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ИНОСТРАННЫЙ ЯЗЫК
АНГЛИЙСКИЙ ЯЗЫК

ARTIFICIAL INTELLIGENCE
IN MANUFACTURING

Учебное пособие

Санкт-Петербург
2024

Министерство науки и высшего образования Российской Федерации
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Высшая школа технологии и энергетики

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Утверждено Редакционно-издательским советом ВШТЭ СПбГУПТД

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Учебное пособие соответствует программам и учебным планам дисциплины «Иностранный язык. Английский язык» для студентов 2 курса, обучающихся по направлению подготовки 09.03.03 «Прикладная информатика», профиль «Искусственный интеллект в информационных системах».

Пособие содержит 16 уроков с текстами для устного и письменного перевода, с лексическими и грамматическими заданиями по темам III и IV семестров, грамматические таблицы для самостоятельной подготовки, а также словарь.

Учебное пособие предназначено для подготовки бакалавров очной формы обучения.

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ОГЛАВЛЕНИЕ

ВВЕДЕНИЕ

Учебное пособие предназначено для студентов 2 курса очной формы обучения, обучающихся по программе бакалавриата по направлению подготовки 09.03.03 «Прикладная информатика», профиль «Искусственный интеллект в информационных системах». Пособие подготовлено в соответствии с рабочей программой и учебным планом дисциплины «Иностранный язык. Английский язык», утвержденными в Высшей школе технологии и энергетики.

Тематика текстов из разделов отражает рекомендованную для неязыковых вузов программу обучения иностранному языку и соответствует требованиям нового государственного стандарта высшего образования.

Пособие состоит из 16 уроков с текстами для устного и письменного перевода, с лексическими и грамматическими заданиями по темам III и IV семестров, содержит грамматические таблицы для самостоятельной подготовки, а также глоссарии к текстам. В конце пособия представлен словарь для перевода узкоспециальных текстов.

LESSON 1

1. Words and word combinations to be remembered.
Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. approach (n.)
2. artificial (adj.)
3. assumption (n.)
4. behavior (n.)
5. concern (v.)
6. control software
7. corresponding (adj.)
8. current (adj.)
9. deal with (v.)
10. define (v.)
11. definition (n.)
12. determine (v.)
13. disadvantage (n.)
14. distinguishable (adj.)
15. entail (v.)
16. evidence (n.)
17. execute (v.)
18. execution (n.)
19. expected reward
20. in order to
21. intelligence (n.)
22. interact (v.)
23. introduce (v.)
24. logic-based representations
25. mention (v.)
26. numerous (adj.)
27. objective (n.)
28. perform (v.)
29. provide (v.)
30. readable (adj.)
31. refer to (v.)
32. require (v.)
33. resort to (v.)
34. select (v.)
35. several (adj.)
36. software agent
37. uncertainty (n.)
38. underlie (v.)
39. usefulness (n.)
40. verification (n.)

2. Read the words in transcription, translate them into Russian.
[ɑːtɪˈfɪʃ(ə)l], [ˈkʌr(ə)nt], [kəˈrekt], [dɪˈtɜːmɪn], [ˈfʌŋkʃ(ə)n], [ˌɪntərˈækt], [ˈseɪftɪ].

3. Read and translate the rows of the same root words, defining the part of speech.
Artifice, artificer, artificial, artificially, unartificial.
Behave, misbehave, behaviour, behaviouristic.
Distinguish, distinguishable, distinguishability, undistinguishable.
Perform, performing, performed, performance, performable.
Read, readings, readable, unreadable, readability.
Certain, certainly, certainty, uncertainty.
Use, useful, useless, usefulness, uselessness.

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Software systems engineering, intelligent software agents, automated reasoning systems, reasoning mechanisms, safety system controller, safety-relevant system, work surface, field test.

5. Match the following words with their correct definitions.

1. Assumption
2. Corresponding
3. Current
4. Disadvantage
5. Distinguishable
6. Entail
7. Numerous
8. Readable
9. Uncertainty
10. Verification

a) Clear or able to be identified as different.
b) Existing in large numbers.
c) Something that one cannot be sure about.
d) A belief or idea accepted without proof.
e) To involve something that cannot be avoided.
f) Happening or existing now.
g) Clear and easy to read.
h) The act of showing or checking that something is true or accurate.
i) Referring to something that is related or matched.
j) Something that makes a situation more difficult, or makes you less likely to succeed.

6. Revise the passive voice and translate the following sentences.

1. The corresponding tasks is performed / will be performed / is being performed / had been performed / will have been performed by pure software agents.

2. The Turing test must be mentioned / had to be mentioned / will have to be mentioned / could be mentioned / doesn’t have to be mentioned in this context.

3. The state that has the maximum usefulness was being determined. / has been determined / will be determined / should be determined.

7. Translate the sentences into Russian defining the functions of the infinitives.

1. We have included mathematical formulas and pseudocode algorithms to make the key ideas concrete
2. These models can be used as is, or can serve as a baseline to be customized with your particular data for your particular application.
3. Advanced techniques are required just to make the essentially continuous search space finite.
4. As AI systems find application in the real world, it has become necessary to consider a wide range of risks and ethical consequences.
5. A challenge for the future is to more smoothly combine learning and prior knowledge.

6. Ironically, the new back-propagation learning algorithms that were to cause an enormous resurgence in neuralnet research in the late 1980s and again in the 2010s had already been developed in other contexts in the early 1960s.
7. Goals organize behavior by limiting the objectives and hence the actions to be considered.
8. As a general rule, it is better to design performance measures according to what one actually wants to be achieved in the environment, rather than according to how one thinks the agent should behave.

8. Read and translate the text.

What is Artificial Intelligence?

Artificial Intelligence (AI) is a discipline that is concerned with the generation of software systems that provide functions, the execution of which requires what is typically referred to by the word *intelligence*. Thereby, the corresponding tasks can be performed by pure software agents as well as by physical systems, such as robots or self-driving cars.

As the term ‘intelligence’ is already very difficult to define, the definition of AI is, of course, correspondingly difficult and numerous definitions can be found in the literature. Among them are several approaches that are based on human behavior or thinking. For example, the Turing test introduced by Alan Turing in 1950, in which the actions generated by the system or robot should not be distinguishable from those generated by humans, has to be mentioned in this context. Such a Turing test for systems interacting with humans would then mean, for example, that a human could no longer determine whether a conversation partner on the telephone is a human or software.

However, most current AI systems aim to generate agents that think or act rationally. To realize systems that think rationally, logic-based representations and reasoning systems are often used. The basic assumption here is that rational thinking entails rational action if the reasoning mechanisms used are correct.

Another group of definitional approaches deals with the direct generation of rational actions. In such systems, the underlying representations often are not human-readable or easily understood by humans. They often use a goal function that describes the usefulness of states. The task of the system is then to maximize this objective function, that is, to determine the state that has the maximum usefulness or that, in case of uncertainties, maximizes the future expected reward. If, for example, one chooses the cleanliness of the work surface minus the costs for the executed actions as the objective function for a cleaning robot, then in the ideal case this leads to the robot selecting the optimal actions in order to keep the work surface as clean as possible. This already shows the strength of the approach to generate rational behavior compared to the approach to generate human behavior. A robot striving for rational behavior can simply become more effective than one that merely imitates human behavior, because humans, unfortunately, do not show the optimal behavior in all cases. The disadvantage lies in the fact that the interpretation of the representations or structures learned by the system typically is not easy, which makes verification difficult. Especially in the case of safety-relevant systems, it is often necessary to provide evidence of the safety of, for example, the control software. However, this can be very difficult and generally even impossible to do analytically, so one has to rely on statistics. In the case of self-driving cars, for example, one has to resort to extensive field tests in order to be able to prove the required safety of the systems.

9. Answer the questions to the text.

1. What is AI concerned with?
2. Why is it difficult to define AI?
3. What is the Turing test based on?
4. What approach is used to realise systems that think rationally?
5. What is the task of the system based on direct generation of rational actions?
6. Why might a robot that strives for rational behavior be more effective than one that imitates human behavior?
7. What is the disadvantage of direct generation of rational actions?

10. Decide whether the statements below are true or false.

1. The Turing test was introduced in 1950 by Alan Turing.
2. Current AI systems are mainly focused on mimicking human behavior rather than rational action.
3. Rational thinking does not necessarily lead to rational action.
4. Rational behavior can sometimes be less effective than imitating human behavior.
5. Verification of AI systems can often be done analytically.

11. Fill in the gaps with the correct form of the verb (sometimes more than one variant is possible). Translate the sentences into Russian.

Entail, interact, introduce, perform, provide, require, resort to, underlie.

1. The researcher had to ……… a new method for classifying the data to improve the accuracy of the model.
2. The software is designed to ……. various tasks automatically without human intervention.
3. This algorithm may ………. additional computing resources due to its complexity.
4. When the data is incomplete, we often have to ………. estimation techniques to fill the gaps.
5. To ensure smooth operation, AI systems must be able to ………. efficiently with their environment.
6. The safety protocols ………. a series of checks to be carried out before deployment.
7. The basic principles that ………. artificial intelligence are derived from computer science and cognitive psychology.
8. The final step is to ……… the most appropriate solution based on the criteria provided.

12. Translate the text in writing with a dictionary.

Historically, researchers have pursued several different versions of AI. Some have defined intelligence in terms of fidelity to human performance, while others prefer an abstract, formal definition of intelligence called rationality – loosely speaking, doing the “right thing”. The subject matter itself also varies: some consider intelligence to be a property of internal thought processes and reasoning, while others focus on intelligent behavior, an external characterization. From these two dimensions – human vs. rational and thought vs. behavior – there are four possible combinations, and there have been adherents and research programs for all four. The methods used are necessarily different: the pursuit of human-like intelligence must be in part an empirical science related to psychology, involving observations and hypotheses about actual human behavior and thought processes; a rationalist approach, on the other hand, involves a combination of mathematics and engineering, and connects to statistics, control theory, and economics. The various groups have both disparaged and helped each other.

LESSON 2

1. Words and word combinations to be remembered.
Write out the transcription and translation of the following words and word combinations from the dictionary. Memorize their pronunciation and meaning.

1. activity (n.)
2. advent (n.)
3. apply (v.)
4. currently (adv.)
5. destination (n.)
6. environment (n.)
7. however (adv.)
8. impact (n.)
9. improve (v.)
10. incidentally (adv.)
11. increasingly (adv.)
12. initially (adv.)
13. machine learning
14. participant (n.)
15. precisely (adv.)
16. property (n.)
17. record (v.)
18. remarkable (adj.)
19. renowned (adj.)
20. result from (v.)
21. robust (adj.)
22. significant (adj.)
23. solution (n.)
24. substantial (adj.)
25. successful (adj.)
26. upswing (n.)
27. usher in (v.)
28. various (adj.)
29. workshop (n.)

2. Read the words in transcription, translate them into Russian.

[ɔ:lˈðəu], [ˈkʌrəntlɪ], [hauˈevə], [ɪˈnɪʃ(ə)lɪ], [məˈʃi:n], [rɪˈnaund], [rəʊˈbʌst], [səkˈsesf(ə)l].

3. Read and translate the rows of the same root words, defining the part of speech.

Develop, developer, development, developed, underdeveloped, developing.

Incident, incidental, incidentally, coincidentally.
Increase, increase, increased, increasing, increasingly.
Sign, signify, significant, significance, significantly.
Remark, remarkable, unremarkable.
Vary, variation, variety, various.

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Knowledge processing, knowledge representation, machine learning techniques, support vector machines, classification problem, pattern recognition and image processing, recognition algorithms, paradigm shift.

5. Translate the sentences into Russian defining the functions of *it*.

1. Breadth-first search expands the shallowest nodes first; it is complete, optimal for unit action costs, but has exponential space complexity.
2. One way to deal with a continuous state space is to discretize it.
3. For this reason, it is common to characterize the performance of online search algorithms in terms of the size of the entire state space rather than just the depth of the shallowest goal.
4. To avoid traveling all the way to a distant state to expand the next node, it seems better to expand nodes in a local order.
5. It was the success of the AlexNet deep learning system in the 2012 ImageNet competition that propelled deep learning into the limelight.

6. Translate the sentences into Russian defining the functions of the infinitives.

1. The first question to answer is whether there is a finite horizon or an infinite horizon for decision making.
2. One of the main criticisms of AI is that while computers can be trained to do a limited number of things very well, it is much harder to teach a computer to be adaptive in its learning.
3. The Turing Test, a foundational analysis to determine if responses to questions are created by a human or machine, is implicitly biased toward language use as a measure of intelligence.
4. AI is increasingly used to monitor our daily lives.
5. A larger issue that ethicists and philosophers raise is whether it is morally acceptable to create sentient life for the sole purpose of having it serve the needs of humans.
6. Researchers involved in the development of artificial intelligence systems should work together to prioritize safety.

7. Read and translate the text.

The History of Artificial Intelligence

Historically, the term AI dates back to 1956, when at a summer workshop called the Dartmouth Summer Research Project on Artificial Intelligence, renowned scientists met in the state of New Hampshire, USA, to discuss AI. The basic idea was that any aspect of learning or other properties of intelligence could be described so precisely that machines can be used to simulate them. In addition, the participants wanted to discuss how to get computers to use language and abstract concepts, or simply improve their own behavior. This meeting is still considered today to have been extremely successful and has led to a large number of activities in the field of AI. For example, in the 1980s, there was a remarkable upswing in AI in which questions of knowledge representation and knowledge processing played an important role. In this context expert systems became popular. Such systems used a large corpus of knowledge, represented in terms of facts and rules, to draw conclusions and provide solutions to problems. Although there were initially quite promising successes with expert systems, these successes then waned quite a bit, leading to a so-called demystification of AI and ushering in the AI winter. It was not until the 1990s when mathematical and probabilistic methods increasingly took hold and a new upswing could be recorded. A prominent representative of this group of methods is Bayesian networks. The systems resulting from this technique were significantly more robust than those based on symbolic techniques. This period also started the advent of machine learning techniques based on probabilistic and mathematical concepts. For example, support vector machines revolutionized machine learning. Until a few years ago, they were considered one of the best performing approaches to classification problems. This radiated to other areas, such as pattern recognition and image processing. Face recognition and also speech recognition algorithms found their way into products we use in our daily lives, such as cameras or even cell phones. Cameras can automatically recognize faces and cell phones can be controlled by speech. These methods have been applied in automobiles, for example when components can be controlled by speech. However, there are also fundamental results from the early days of AI that have a substantial influence on today's products. These include the ability of navigation systems to plan the shortest possible routes and navigate us effectively to our destination based on given maps. Incidentally, the same approaches play a significant role in computer games, especially when it comes to simulating intelligent systems that can effectively navigate the virtual environment. At the same time, there was also a paradigm shift in robotics. The probabilistic methods had a significant impact, especially on the navigation of mobile robots, and today, thanks to this development, it is well understood how to build mobile systems that move autonomously in their environment. This currently has an important influence on various areas, such as self-driving cars or transport systems in logistics, where extensive innovations can be expected in the coming years.

8. Answer the questions to the text.

1. What was the basic idea of the Dartmouth Summer Research Project on Artificial Intelligence?
2. Under what circumstances did expert systems become popular?
3. What are the characteristics of expert systems?
4. What is a prominent representative of mathematical and probabilistic method in context of AI?

5. What revolutionized machine learning?
6. Where are face and speech recognition algorithms used nowadays?

9. Decide whether the statements below are true or false.

1. The focus of the 1956 Dartmouth workshop was primarily on developing expert systems using large knowledge databases.
2. Expert systems, which became popular in the 1980s, used probabilistic methods to draw conclusions.
3. Bayesian networks are an example of probabilistic methods that gained importance in the 1990s.
4. Support vector machines were once considered among the best-performing approaches for pattern recognition and image processing.
5. Probabilistic methods had no significant impact on the development of mobile robots and self-driving cars.

10. Fill in the gaps with the missing words, translate the text into Russian.

Applied, increasingly, recorded, activities, solutions

The advancements in AI have been 1)……… in various fields, from healthcare to finance. Researchers have 2) ……… these technologies to real-world problems, leading to 3) ……… innovative 4) …….. that improve efficiency and accuracy. These developments have been well-5)…….. in recent years, showing a clear trend toward greater integration of AI in daily life.

11. Translate the text in writing with a dictionary.

The Inception of Artificial Intelligence

The first work that is now generally recognized as AI was done by Warren McCulloch and Walter Pitts (1943). Inspired by the mathematical modeling work of Pitts's advisor Nicolas Rashevsky (1936, 1938), they drew on three sources: knowledge of the basic physiology and function of neurons in the brain; a formal analysis of propositional logic due to Russell and Whitehead; and Turing's theory of computation. They proposed a model of artificial neurons in which each neuron is characterized as being "on" or "off," with a switch to "on" occurring in response to stimulation by a sufficient number of neighboring neurons. The state of a neuron was conceived of as "factually equivalent to a proposition which proposed its adequate stimulus." They showed, for example, that any computable function could be computed by some network of connected neurons, and that all the logical connectives (AND, OR, NOT, etc.) could be implemented by simple network structures. McCulloch and Pitts also suggested that suitably defined networks could learn. Donald Hebb (1949) demonstrated a simple updating rule for modifying the connection strengths between neurons. His rule, now called Hebbian learning, remains an influential model to this day.

LESSON 3

1. Words and word combinations to be remembered.
Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. achieve (v.)
2. agenda (n.)
3. articulate (v.)
4. capability (n.)
5. circumstance (n.)
6. detect (v.)
7. exactly (adv.)
8. extrapolate (v.)
9. independently (adv.)
10. influential (adj.)
11. interrogator (n.)
12. objection (n.)
13. perceive (v.)
14. persuasive (adj.)
15. plenty (n.)
16. pose (v.)
17. quest (n.)
18. response (n.)
19. rigorously (adv.)
20. sidestep (v.)
21. store (v.)
22. subsequent (adj.)
23. succeed (v.)
24. surplus (n.)
25. vagueness (n.)
26. warn (v.)

2. Read the words in transcription, translate them into Russian.
[ɪkˈsperɪmənt], [ˌkeɪpəˈbɪləti], [ˈpɜːsn], [ˈhjuːmən], [ʌnˈnesəsəri], [ˌɪntərˈækʃn], [səkˈsiːd], [ˈtəʊtl], [ˌeərəʊdaɪˈnæmɪks], [ˌeərəˈnɔːtɪkl].

3. Read and translate the rows of the same root words, defining the part of speech.
Experiment, experimental, experimentally experimentation, experimenter.
Vague, vaguely, vagueness.
Question, questionable, questionnaire, questioner.
Interrogate, interrogated, interrogative, interrogator, interrogation.
Rigour, rigorous, rigorously.
Necessary, necessarily, unnecessary, necessity, necessitate.

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Thought experiment, natural language processing, knowledge representation, reinforcement learning, computer vision, speech recognition, neural network computer.

5. Translate the sentences into Russian paying attention to the translation of the word *most*.
1. The most important property of many computer-based systems is dependability.
2. For most AI researchers, the goal was not merely to create programs that processed information in such a way that the product or outcome appeared to be the result of intelligent behavior.

3. Bias in algorithmic systems has become one of the most critical concerns surrounding the ethics of artificial intelligence.
4. Social concerns surrounding artificial intelligence and harm to humans have most famously been represented by Isaac Asimov's Three Laws of Robotics.
5. General AI, the kind most often encountered in science fiction, does not yet exist in the real world.
6. Most new applications are based on machine learning (ML), and most of the AI examples cited in the news are related to this subset of technologies.

6. Translate the sentences into Russian paying attention to Complex Subject.
1. A good component is likely to be good in a variety of different designs.
2. This kind of reasoning is said to exhibit nonmonotonicity, because the set of beliefs does not grow monotonically over time as new evidence arrives.
3. If the degree of deviation is statistically unlikely (usually taken to mean a 5 % probability or less), then that is considered to be good evidence for the presence of a significant pattern in the data.
4. Given the hypothesis prior, any other prediction is expected to be correct less often.
5. If the environment is partially observable, however, then it could appear to be nondeterministic.
6. Currently, deep neural networks are very popular in this role and have proved to be effective even when the input is a raw image with no human-designed feature extraction at all.
7. These mechanisms are thought to form the basis for learning in the brain.

7. Read and translate the text.

The Turing Test Approach

The Turing test, proposed by Alan Turing (1950), was designed as a thought experiment that would sidestep the philosophical vagueness of the question "Can a machine think?". A computer passes the test if a human interrogator, after posing some written questions, cannot tell whether the written responses come from a person or from a computer.

Programming a computer to pass a rigorously applied test provides plenty to work on. The computer would need the following capabilities:

– natural language processing to communicate successfully in a human language;
– knowledge representation to store what it knows or hears;
– automated reasoning to answer questions and to draw new conclusions;
– machine learning to adapt to new circumstances and to detect and extrapolate patterns.

Turing viewed the *physical* simulation of a person as unnecessary to demonstrate intelligence. However, other researchers have proposed a total Turing test, which requires interaction with objects and people in the real world. To pass the total Turing test, a robot will need:

– computer vision and speech recognition to perceive the world;
– robotics to manipulate objects and move about.

These six disciplines compose most of AI. Yet AI researchers have devoted little effort to passing the Turing test, believing that it is more important to study the underlying principles of intelligence. The quest for “artificial fight” succeeded when engineers and inventors stopped imitating birds and started using wind tunnels and learning about aerodynamics. Aeronautical engineering texts do not define the goal of their field as making “machines that fly so exactly like pigeons that they can fool even other pigeons.”

8. Answer the questions to the text.

1. What is the major objective of the Turing test?
2. What capabilities does a computer require to pass the Turing test?
3. What are the peculiarities of the total Turing test?
4. What have AI researches devoted little attention to passing the Turing test?
5. What analogy is used at the end of the text to explain the goal of AI research?

9. Decide whether the statements below are true or false.

1. The Turing test was proposed to answer the question “Can a machine think?”
2. A computer that passes the Turing test must physically resemble a human.
3. Natural language processing is necessary for a computer to communicate in a human language.
4. The total Turing test requires a robot to interact with objects and people in the real world.
5. AI researchers believe that imitating birds is the best way to achieve artificial flight.

10. Fill in the gaps with the correct word. Translate the sentences into Russian.

Simulate, capabilities, underlying, total, interaction, successfully

1. The Turing test checks if a computer can …… communicate in a human language.
2. To pass the …… Turing test, a robot must interact with the real world.
3. Natural language processing is one of the essential …… needed for the Turing test.
4. AI researchers focus on the …….. principles of intelligence rather than just passing the test.
5. The total Turing test involves …….. with objects and people.
6. Turing believed it was unnecessary for a computer to physically …….. a person to demonstrate intelligence.

11. Match the following words with their correct definitions.

1. Circumstance	a) A person who asks questions, especially in a formal situation.
2. Detect	b) The quality of being unclear or not fully defined.
3. Exactly	c) To avoid answering or dealing with something directly.
4. Extrapolate	d) A situation or condition that affects what happens.
5. Interrogator	e) To notice something that is not immediately obvious.
6. Perceive	f) To imagine or predict based on known information.
7. Plenty	g) In a precise or accurate manner.
8. Rigorously	h) To understand or interpret something in a particular way.
9. Sidestep	i) A large or sufficient amount of something.
10. Vagueness	j) In a strict or thorough manner.

12. Translate the text in writing with a dictionary.

Two undergraduate students at Harvard, Marvin Minsky and Dean Edmonds, built the first neural network computer in 1950. The SNARC, as it was called, used 3000 vacuum tubes and a surplus automatic pilot mechanism from a B-24 bomber to simulate a network of 40 neurons. Later, at Princeton, Minsky studied universal computation in neural networks. His Ph.D. committee was skeptical about whether this kind of work should be considered mathematics, but von Neumann reportedly said, “If it isn’t now, it will be someday.” There were a number of other examples of early work that can be characterized as AI, including two checkers-playing programs developed independently in 1952 by Christopher Strachey at the University of Manchester and by Arthur Samuel at IBM. However, Alan Turing’s vision was the most influential. He gave lectures on the topic as early as 1947 at the London Mathematical Society and articulated a persuasive agenda in his 1950 article “Computing Machinery and Intelligence.” Therein, he introduced the Turing test, machine learning, genetic algorithms, and reinforcement learning. He dealt with many of the objections raised to the possibility of AI. He also suggested that it would be easier to create human-level AI by developing learning algorithms and then teaching the machine rather than by programming its intelligence by hand. In subsequent lectures he warned that achieving this goal might not be the best thing for the human race.

LESSON 4

1. Words and word combinations to be remembered.
Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. AC
2. acquire (v.)
3. aid (n., v.)
4. capture (v.)
5. condition (n.)
6. conduct (v.)
7. contain (v.)
8. daunting (adj.)
9. DC
10. distinguish (v.)
11. elicit (v.)
12. emerge (v.)
13. experiential (adj.)
14. express (v.)
15. implementation (n.)
16. pole (n.)
17. pose (v.)
18. reasoning (n.)
19. relevant (adj.)
20. retrieve (v.)
21. solution (n.)
22. statement (n.)
23. store (v.)

2. Read the words in transcription, translate them into Russian.
[ˈjuːʒəli], [ɪˈmɜːdʒ], [tekˈniːk], [kærəktəˈrɪstɪk], [ˈælgərɪðəm], [ˈnɒlɪdʒ], [dɪˈzaɪn], [dɪˈsɪʒn], [məˈnɪpjuleɪt].

3. Read and translate the rows of the same root words, defining the part of speech.
Human, humane, humanitarian, humanize, humanization.
Emerge, emerging, emergence, emergent.
Differ, different, indifferent, difference, differentiate.
Explain, explained, explanation, explanatory, self-explanatory.
Infer, inference, inferential, inferentially, inferencer.
Acquire, acquiring, acquired, unacquired, acquisition.

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Knowledge base, inference engine, inference process, promising application technique, artificial intelligence research, computer-based knowledge system, knowledge acquisition process.

5. Translate the sentences into Russian paying attention to modal verbs.
1. The problem-solving strategy must be preliminarily structured as part of the program.
2. Asimov's Three Laws of Robotics often are cited as guiding principles for artificial intelligence and robotics: 1) A robot may not injure a human being or, through inaction, allow a human being to come to harm. 2) A robot must obey orders given to it by human beings except where such orders would conflict with the First Law.

3) A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

3. Superintelligences must be developed for the larger good of humanity, and not only to advance the goals of one company or nation.
4. Voice recognition must be able to identify each unique individual user.
5. One of the main criticisms of AI is that while computers can be trained to do a limited number of things very well, it is much harder to teach a computer to be adaptive in its learning.
6. While computers can store vast quantities of information, they can only utilize what has actually been programmed into them. In other words, they cannot adapt to situations that programmers didn't foresee.
7. A superintelligence should want to grant humankind happiness and fulfillment and might even make the hard decisions that benefit the whole community over the individual.

6. Translate the sentences into Russian paying attention to Complex Object.

1. We can let the inference procedure operate on the axioms and problem-specific facts to derive the facts we are interested in knowing.
2. Some consider intelligence to be a property of internal thought processes and reasoning, while others focus on intelligent behavior, an external characterization.
3. These considerations have led researchers to consider how to embed default reasoning within probability theory or utility theory.
4. Every choice of ordering yields a valid algorithm, but different orderings cause different intermediate factors to be generated during the calculation.
5. A proportional controller can cause the robot to apply too much force, overshooting the desired path and zig-zagging back and forth.
6. The incorporation of learning allows one to design a single rational agent that will succeed in a vast variety of environments.

7. Read and translate the text.

Expert Systems (1)

Expert systems solve problems that are usually solved by human experts. They emerged as one of the most promising application techniques in the first decades of artificial intelligence research. The basic idea is to capture the knowledge of an expert into a computer-based knowledge system.

Several characteristics of expert systems can be distinguished:

– They use knowledge rather than data.
– Knowledge is often heuristic (e.g., the experiential knowledge that can be expressed as rules of thumb) rather than algorithmic.
– The task of representing heuristic knowledge in expert systems is daunting.
– Knowledge and the program are generally separated so that the same program can operate on different knowledge bases.

– Expert systems should be able to explain their decisions, represent knowledge symbolically, and have and use meta knowledge, that is, knowledge about knowledge.

Expert systems almost always represent knowledge from a specific domain. One popular application for expert systems is from the field of engineering and engineering design, which attempts to capture the heuristic knowledge of the design process in designing motors and generators. The expert system aids in the first step of the design, where decisions such as the number of poles, AC or DC, and so on are determined.

Two components define the basic structure of expert systems: the knowledge base and the inference engine. While the knowledge base contains the knowledge of the expert, the inference engine uses the knowledge base to arrive at decisions. The knowledge is in this manner separated from the program that is used to manipulate it. In creating the expert systems, knowledge first must be acquired and then understood, classified, and stored. It is retrieved based on given criteria to solve problems. Four general steps in the construction of an expert system can be distinguished: acquiring knowledge, representing that knowledge, controlling reasoning with an inference engine, and explaining the expert systems' solution.

8. Answer the questions to the text.

1. What is the basic idea of expert systems?
2. What are the characteristics of expert systems?
3. Could you provide an example of the use of expert systems?
4. What components define the basic structure of expert systems?
5. How is the knowledge retrieved?
6. What are the basic steps in constructing an expert system?

9. Decide whether the statements below are true or false.

1. Expert systems only work with data, not knowledge.
2. Heuristic knowledge is often expressed as rules of thumb.
3. The knowledge base and the program are the same in expert systems.
4. An expert system can explain its decisions.
5. The expert system in engineering design helps in determining the design process details.

10. Match the following words with their correct definitions.

1. Expert system
2. Inference engine
3. Meta knowledge
4. Knowledge base
5. Algorithmic

a) Knowledge about knowledge, such as planning, tagging, and learning.
b) A computer program that uses AI technologies to simulate the judgment and behavior of a human or an organization that has expertise in a particular field.
c) A component that uses the knowledge base to make decisions.
d) A structured collection of expert knowledge.
e) Relating to a step-by-step procedure for solving problem

11. Fill in the gaps with the necessary word. Translate the sentences into Russian.

Explain, inference, knowledge, constructing, decisions, separately, data, representing

1. Expert systems use …… rather than ..… to solve problems.
2. The ……. engine is responsible for using the knowledge base to make…. .
3. One characteristic of expert systems is that they should be able to …… their decisions.
4. The process of …… an expert system involves acquiring knowledge, …… that knowledge, controlling reasoning with an inference engine, and explaining the solution.
5. In expert systems, knowledge is generally represented …… from the program.

12. Translate the text in writing with a dictionary.

Representation of domain knowledge can be done using production (rule based) or non-production systems. In rule-based systems, the rules in the form of IF-THEN-ELSE statements represent knowledge. The inference process is conducted by going through the rules recursively either using a forward chaining mechanism or backward chaining mechanism. Given that the condition and rules are known to be true, forward chaining asks what would happen next. Backward chaining asks why this happened, going from a goal to the rules we know to be true. In simpler terms, when the left side of the rule is evaluated first, that is, when the conditions are checked first and the rules are executed left to right, then it is called forward chaining (also known as data-driven inference). When the rules are evaluated from the right side, i.e., when the results are checked first, it is called backward chaining (also known as goal-driven inference).

LESSON 5

1. Words and word combinations to be remembered.
Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. assist (v.)
2. available (adj.)
3. backtrack (v.)
4. choice (v.)
5. come up with (v.)
6. deliver (v.)
7. encapsulate (v.)
8. entity (n.)
9. expectation (n.)
10. helpful (adj.)
11. implementation (n.)
12. imply (v.)
13. initially (adv.)
14. inside (prep.)
15. lighting (n.)
16. modeling (n.)
17. object-oriented (adj.)
18. predicate (adj.)
19. procedural (adj.)
20. shell (n.)
21. taper off (v.)
22. though (conj.)
23. totally (adv.)
24. uncertainty (n.)
25. unique (adj.)
26. user-friendly (adj.)
27. voltage (n.)

2. Read the words in transcription, translate them into Russian.
[ˌɪntərˈæktɪv], [ˈpærədaɪm], [wɪˈðaʊt], [ˈpaʊəfʊl], [faʊnˈdeɪʃ(ə)n], [ˈθɪərɪ], [ˈfʌzɪ], [ˈkæptʃə], [ˈmeɪnt(ə)nəns].

3. Read and translate the rows of the same root words, defining the part of speech.
Assist, assistant, assistance, assistive, assisting, assisted.
Certain, certainly, certainty, uncertainty, ascertain.
Imply, implied, implying, implication, implicit.
Maintain, maintained, maintaining, maintenance, maintainability.
Implement, implemented, implementing, implementation, implementer.

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Interactive development environments, user-friendly graphical user interfaces, logic programming paradigm, expert system shell, real-world scenario, real-world entities, Object Inference Knowledge Specification Language.

5. Translate the sentences into Russian, paying attention to *because of* and *because*.
1. This strategy worked initially because microworlds contained very few objects and hence very few possible actions and very short solution sequences.
2. A third difficulty arose because of some fundamental limitations on the basic structures being used to generate intelligent behavior.
3. Fully observable environments are convenient because the agent need not maintain any internal state to keep track of the world.
4. An environment might be partially observable because of noisy and inaccurate sensors or because parts of the state are simply missing from the sensor data.
5. Episodic environments are much simpler than sequential environments because the agent does not need to think ahead.
6. Many authors have studied this problem because of its importance in planning.

6. Translate the sentences into Russian paying attention to infinitives and infinitive constructions.
1. It is important to note that bias in and of itself is not always problematic: bias can be designed into a system in an effort to correct an unfair system or reality.
2. The idea is that it is impossible for programmers to anticipate every scenario that a machine equipped with AI may face congruent with its actions and so it must be able to adapt.
3. Without the ability to monitor and replan, an agent's behavior is likely to be fragile if it relies on absolute correctness of its model.
4. As artificial intelligences are programmed to learn from their own experiences and data input, they are arguably becoming more autonomous.
5. A process of feature selection can be performed to discard attributes that appear to be irrelevant.

6. A controller is said to be stable if small perturbations lead to a bounded error between the robot and the reference signal. It is said to be strictly stable if it is able to return to and then stay on its reference path upon such perturbations. Our P controller appears to be stable but not strictly stable, since it fails to stay anywhere near its reference trajectory.

7. Read and translate the text.

Expert Systems (2)

Expert systems can be developed in several ways. Interactive development environments involve user-friendly graphical user interfaces to assist programmers as they code. Expert system development may also involve special languages. Two of the most popular choices are Prolog (Programming in Logic) and LISP (List Programming). Prolog is based on predicate logic, and thus prolog language belongs to the logic programming paradigm. LISP is one of the earliest programming languages in use for artificial intelligence applications. Programmers often rely on expert system shells. A shell gives an environment where the knowledge can be coded into the system. The shell, as the name implies, is a layer without the knowledge base. JESS (Java Expert System Shell) is an expert shell written in the powerful Java language.

There have been many attempts to combine different paradigms and come up with hybrid systems. The object-oriented approach attempts to integrate logic-based systems with object-oriented systems. Though object orientation lacks a formal mathematical foundation, it is quite helpful in the modeling of real-world scenarios. Knowledge is represented in the form of objects that encapsulate the data as well as the methods to work on them. Object-oriented systems model real-world entities more closely than procedural programming. One specific approach is OI-KSL Object Inference Knowledge Specification Language. Even though other languages such as Visual Prolog had integrated object-oriented programming, the approach taken in OI-KSL is unique. In Visual Prolog, the backtracking is inside the objects; that is, the methods backtracked. In OI-KSL, backtracking is taken to a totally different level, and the object themselves are backtracked. Sometimes probability theory, heuristics, or fuzzy logic are used to deal with uncertainties in the available information. One example of an implementation of fuzzy logic using Prolog involved a fuzzy electric lighting system, in which the amount of natural light determined the voltage that passed to the electric bulb. This made it possible for the system to reason under uncertainty and with less information.

In the late 1990s, interest in expert systems began tapering off, in part because expectations for the technology were initially so high and because of the cost of maintenance. Expert systems could not deliver what they promised. Still, many areas in data science, chatbots, and machine intelligence today continue to use technology first developed in expert systems research. Expert systems seek to capture the corporate knowledge that has been acquired by humanity through centuries of learning, experience, and practice.

8. Answer the questions to the text.

1. What are the most popular special languages for the development of expert systems? What are they based on?
2. What is the aim of the object-oriented approach?
3. Does procedural programming model real-world entities better than object-oriented programming?
4. What does the abbreviation OI-KSL stand for?
5. What the example of an implementation of fuzzy logic using Prolog provided in the text?
6. Why did the interest in expert systems decline?

9. Decide whether the statements below are true or false.

1. Prolog is based on object-oriented programming.
2. Expert systems were able to fully deliver on their initial promises.
3. Object-oriented programming lacks a formal mathematical foundation but is useful in modeling real-world scenarios.
4. JESS is a programming language used in expert systems.
5. Fuzzy logic allows expert systems to handle uncertainty in information.

10. Match the following words with their correct definitions.

1. Backtrack	a) A conceptual framework or approach.
2. Encapsulate	b) To move backward or reconsider a previous decision.
3. Entity	c) The state of being unsure or unpredictable.
4. Initially	d) Happening first, in the beginning.
5. Modeling	e) To express or communicate an idea concisely.
6. Object-oriented	f) Denoting a system, programming language, etc., that supports the use of objects, as an entire image, a routine, or a data structure.
7. Paradigm	g) An element in a system, especially in an expert system.
8. Uncertainty	h) The degree of electrical potential in a circuit.
9. User-friendly	i) The representation, often mathematical, of a process, concept, or operation of a system.
10. Voltage	j) Easy for people to use, especially those with limited technical skills.

11. Fill in the gaps with the necessary word. Translate the sentences into Russian.

Shell, languages, fuzzy, logic-based, corporate

1. Prolog and LISP are two of the most popular ….. used in expert system development.
2. An expert system ….. provides an environment where knowledge can be coded into the system.
3. The object-oriented approach integrates ….. systems with object-oriented systems.
4. ….. logic is used to reason under uncertainty and with less information.

5. Expert systems seek to capture the ….. knowledge accumulated through centuries of human learning and experience.

12. Translate the text in writing with a dictionary.

Expert system architectures based on nonproduction architectures may involve associative/semantic networks, frame representations, decision trees, or neural networks. An associative/semantic network is made up of nodes and is useful for representing hierarchical knowledge. In frame architectures, frames are structured sets of closely related knowledge. Decision tree architectures represent knowledge in a top-down fashion. Blackboard system architectures involve complicated systems where the direction of the inference process may be chosen during runtime.

Case-based reasoning involves attempts to analyze and look for solutions from stored solved cases for a given problem. A vague analogy can be drawn between case-based reasoning and judicial law, where the judgment of a similar but past case is referred to in solving a present legal case. Case-based reasoning is typically implemented as a frame and requires a more complicated process to match and retrieve.

There are three alternatives to building the knowledge base manually. Using interactive programs, the knowledge may be elicited by way of an interview with a computer. A second alternative to manual construction of knowledge bases involves text scanning programs that read books into memory. A third option still under development is machine learning programs that develop mastery on their own, with or without supervision from a human expert.

LESSON 6

1. Words and word combinations to be remembered.
Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. application (n.)
2. approximate (v.)
3. approximation error
4. attribute (n.)
5. boosting (n.)
6. clustering (n.)
7. data (n., pl.)
8. determine (v.)
9. explicit (adj.)
10. guess (n., v.)
11. involve (v.)
12. map (v.)
13. memorize (v.)
14. moreover (adv.)
15. performance (n.)
16. predominant (adj.)
17. present (v.)
18. procedure (n.)
19. random forest (n.)
20. require (v.)
21. supervised learning
22. thereof (adv.)
23. unsupervised learning

2. Read the words in transcription, translate them into Russian.

[ˈtɪpɪkəlɪ], [mɔ:'rəuvə], [prə'si:ʤə], [ðe(ə)'rɔv], [ˈmɪnɪmaɪz], [ˈdʒen(ə)rəlaɪz], [sɜːtʃ], [skweəd], [ʌnˈsiːn].

3. Read and translate the rows of the same root words, defining the part of speech.
Decide, decided, undecided, decision, decisive, decisively.
Determine, determined, predetermined, determining, determination.
Involve, involved, uninvolved, involving, involvement.
Memory, memorize, memorable, memorably, memorization.
Dominate, dominant, predominant, dominance, predominance.
Require, requirer, required, unrequired, requirement.

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Decision trees, support vector machines, dimensionality reduction, market segmentation, market basket analysis, image compression, recommendation engines, data input, preprocessing data stage.

5. Translate the sentences into Russian defining the functions of *one*.
1. The Greek philosopher Aristotle was one of the first to attempt to codify "right thinking" – that is, irrefutable reasoning processes.
2. Aristotle developed an informal system of syllogisms for proper reasoning, which in principle allowed one to generate conclusions mechanically, given initial premises.
3. One might say that to solve a hard problem, you have to almost know the answer already.
4. A rational agent is one that does the right thing.
5. Surveys regularly rank AI as one of the most interesting and fastest-growing fields.
6. A rational agent is one that acts so as to achieve the best outcome or, when there is uncertainty, the best expected outcome.
7. For example, in designing a self-driving car, one might think that the objective is to reach the destination safely.

6. Translate the sentences into Russian, define the type of conditional sentences used.
1. If there are any patterns in the data other than the overall slope of a line, a linear function will not be able to represent those patterns.
2. If we knew the data represented, say, the number of hits to a Web site that grows from day to day, but also cycles depending on the time of day, then we might favor the sinusoidal function.
3. If we knew the data was definitely not cyclic but had high noise, that would favor the linear function.
4. If the problem is realizable, then variance decreases towards zero as the number of training examples increases.
5. We don't know what would have happened if there had been no human in the loop.
6. If the agent uses some randomization to choose its actions, then we would have to try each sequence many times to identify the probability of each action.

7. Read and translate the text.

Machine Learning

Machine learning typically involves developing algorithms to improve the performance of procedures based on data or examples and without explicit programming. One of the predominant applications of machine learning is that of classification. Here the system is presented with a set of examples and their corresponding classes. The system must now learn a function that maps the properties or attributes of the examples to the classes with the goal of minimizing the classification error. Of course, one could simply memorize all the examples, which would automatically minimize the classification error, but such a procedure would require a lot of space and, moreover, would not generalize to examples not seen before. In principle, such an approach can only guess. The goal of machine learning is rather to learn a compact function that performs well on the given data and also generalizes well to unseen examples. In the context of classification, examples include decision trees, random forests, a generalization thereof, support vector machines, or boosting. These approaches are considered supervised learning because the learner is always given examples including their classes.

Another popular supervised learning problem is regression. Here, the system is given a set of points of a function with the task of determining a function that approximates the given points as well as possible. Again, one is interested in functions that are as compact as possible and minimize the approximation error. In addition, there is also unsupervised learning, where one searches for a function that explains the given data as well as possible. A typical unsupervised learning problem is clustering, where one seeks centers for a set of points in the plane such that the sum of the squared distances of all points from their nearest center is minimized.

8. Answer the questions to the text.

1. What does the term ‘machine learning’ involve?
2. What is the major application of machine learning?
3. What does classification mean?
4. What is the goal of machine learning?
5. What are the examples of supervised learning provided in the text?
6. What are the characteristics of unsupervised learning?

9. Decide whether the statements below are true or false.

1. Machine learning always involves explicit programming to improve performance.
2. Memorizing examples is an effective way to ensure that a system generalizes well to unseen data.
3. Support vector machines are an example of unsupervised learning.
4. Regression is concerned with finding a function that approximates a set of given points.
5. Clustering is a common problem in supervised learning.

10. Fill in the gaps with the necessary word. Translate the sentences into Russian.

Procedures, performance, attributes, supervised, approximation, random.

1. The ….. of the machine learning model improved significantly after applying the new algorithm.
2. The ….. error was higher than expected, indicating that the model did not generalize well to unseen data.
3. ….. forests are commonly used in machine learning to increase prediction accuracy.
4. Each example in the dataset has several ….. that describe its characteristics.
5. The ….. of the clustering algorithm were chosen to minimize the sum of squared distances.

11. Match each term with its correct definition.

1. Algorithm	a) The task of finding a function that best approximates a set of points.
2. Classification	b) A type of learning where the system is provided with examples and their corresponding outputs.
3. Generalization	c) Grouping a set of points such that the sum of squared distances from their nearest center is minimized.
4. Regression	d) The process of mapping attributes of examples to their classes to minimize errors.
5. Supervised learning	e) A procedure or set of rules used to solve a problem or perform a task.
6. Unsupervised learning	f) The ability of a system to perform well on unseen examples, not just on the training data.
7. Clustering	g) A type of learning where the system is not given specific labels or outputs for the data.

12. Translate the text in writing with a dictionary.

What Is Unsupervised Learning?

Unsupervised learning uses machine learning algorithms to analyze and cluster unlabeled data sets. These algorithms discover hidden patterns in data without the need for human intervention (hence, they are “unsupervised”).

Unsupervised learning models are used for three main tasks: clustering, association and dimensionality reduction.

Clustering is a data mining technique for grouping unlabeled data based on their similarities or differences. For example, K-means clustering algorithms assign similar data points into groups, where the K value represents the size of the grouping and granularity. This technique is helpful for market segmentation, image compression, and so on.

Association is another type of unsupervised learning method that uses different rules to find relationships between variables in a given data set. These methods are frequently used for market basket analysis and recommendation engines, along the lines of “Customers Who Bought This Item Also Bought” recommendations.

Dimensionality reduction is a learning technique that is used when the number of features (or dimensions) in a given data set is too high. It reduces the number of data inputs to a manageable size while also preserving the data integrity. Often, this technique is used in the preprocessing data stage, such as when autoencoders remove noise from visual data to improve picture quality.

LESSON 7

1. Words and word combinations to be remembered.
Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. computational (adj.)
2. consideration (n.)
3. constant (adj.)
4. convergence (n.)
5. decrease (v.)
6. dimensionality (n.)
7. diminishing returns
8. ensure (v.)
9. entire (adj.)
10. escape (v.)
11. estimate (v.)
12. exhibit (v.)
13. in favor of
14. inaccurate (adj.)
15. incorporate (v.)
16. instability (n.)
17. militate (adj.)
18. minibatch (n.)
19. mitigate (v.)
20. modify (v.)
21. momentum (n.)
22. overall (adj.)
23. overfit (v.)
24. overflow (v., n.)
25. parallelism (n.)
26. particularly (adv.)
27. proceed (v.)
28. randomly (adv.)
29. solution (n.)
30. stochasticity (n.)
31. tanh (n.)
32. training set
33. underflow (n., v.)
34. variance (n.)
35. with respect to

2. Read the words in transcription, translate them into Russian.
[ˈmɒdɪfaɪ], [kənˌsɪdəˈreɪʃn], [ədˈvɑːntɪdʒ], [ˌɪndɪˈpendəntli], [ˈləʊkl], [ˈkɒmpenseɪt], [ˈvænɪʃ], [səˈluːʃn], [ˈʃedjuːl], [əˈdɪʃənl].

3. Read and translate the rows of the same root words, defining the part of speech.
Optimize, optimization, optimized, optimizing, optimal, suboptimal.
Train, training, trained, retrain, self-training, trainable.
Calculate, calculation, calculated, calculating, recalculate, precalculation.
Classify, classification, classified, reclassify, misclassification.
Validate, validation, validated, validator, revalidate.
Incorporate, incorporation, incorporated, incorporating, reincorporate**.**

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Loss function, training set, optimization algorithm, gradient descent process, gradient contribution, stochastic gradient descent optimization algorithm, small minibatch size, deep learning research, neural network parameter modification, numerical instability mitigation strategies.

5. Translate the sentences into Russian, paying attention to the functions of *that* and *those*.
1. Machine learning is a subfield of AI that studies the ability to improve performance based on experience.
2. Since that time, each generation of computer hardware has brought an increase in speed and capacity and a decrease in price.
3. It was not until 2011, however, that deep learning methods really took off.
4. The agent-design problems in multiagent environments are often quite different from those in single-agent environments.
5. One reason that the problem of consciousness is hard is that it remains ill-defined, even after centuries of debate.
6. The field of AI will need to develop technical and ethical standards at least comparable to those prevalent in other engineering and healthcare disciplines where people's lives are at stake.

6. Translate the sentences into Russian, define the type of conditional sentences used.
1. If there are roughly equal numbers of examples for all four combinations of input values, then neither attribute will be informative.
2. If we were only going to create one hypothesis, then this approach would be sufficient.
3. If we are trying to predict a numerical output value, such as the price of an apartment, then we need a regression tree rather than a classification tree.
4. A classifier with a 1 % error rate, where almost all the errors were classifying spam as non-spam, would be better than a classifier with only a 0.5% error rate, if most of those errors were classifying non-spam as spam.
5. If the test had failed, processing would have continued with the next test in the list.

7. Read and translate the text.

Learning Algorithms

Training a neural network consists of modifying the network's parameters so as to minimize the loss function on the training set. In principle, any kind of optimization algorithm could be used. In practice, modern neural networks are almost always trained with some variant of stochastic gradient descent (SGD).

Here, the goal is to minimize the loss *L (w)*, where *w* represents all of the parameters of the network. Each update step in the gradient descent process looks like this:

$w \leftarrow w - \alpha \nabla w L(w)$,

where α is the learning rate. For standard gradient descent, the loss *L* is defined with respect to the entire training set. For SGD, it is defined with respect to a minibatch of *m* examples chosen randomly at each step.

It is worth mentioning a few important considerations that are particularly relevant to training neural networks:

– For most networks that solve real-world problems, both the dimensionality of *w* and the size of the training set are very large. These considerations militate strongly in favor of using SGD with a relatively small minibatch size *m*: stochasticity helps the algorithm escape small local minima in the high-dimensional weight space; and the small minibatch size ensures that the computational cost of each weight update step is a small constant, independent of the training set size.

– Because the gradient contribution of each training example in the SGD minibatch can be computed independently, the minibatch size is often chosen so as to take maximum advantage of hardware parallelism in GPUs or TPUs.

– To improve convergence, it is usually a good idea to use a learning rate that decreases over time. Choosing the right schedule is usually a matter of trial and error.

– Near a local or global minimum of the loss function with respect to the entire training set, the gradients estimated from small minibatches will often have high variance and may point in entirely the wrong direction, making convergence difficult. One solution is to increase the minibatch size as training proceeds; another is to incorporate the idea of momentum, which keeps a running average of the gradients of past minibatches in order to compensate for small minibatch sizes.

– Care must be taken to mitigate numerical instabilities that may arise due to overflow, underflow, and rounding error. These are particularly problematic with the use of exponentials in softmax, sigmoid, and tanh activation functions, and with the iterated computations in very deep networks and recurrent networks that lead to vanishing and exploding activations and gradients.

Overall, the process of learning the weights of the network is usually one that exhibits diminishing returns. We run until it is no longer practical to decrease the test error by running longer. Usually this does not mean we have reached a global or even a local minimum of the loss function. Instead, it means we would have to make an impractically large number of very small steps to continue reducing the cost, or that additional steps would only cause overfitting, or that estimates of the gradient are too inaccurate to make further progress.

8. Answer the questions to the text.

1. How is training a neural network implemented?
2. What is the goal of SGD?
3. What does the small minibatch size ensure?
4. What method is used in order to improve convergence?
5. Why do numerical instabilities arise?

6. Why does the process of learning the weights of the network usually exhibit diminishing returns?

9. Decide whether the statements below are true or false.

1. Stochastic Gradient Descent works by updating the parameters based on the entire training set at once.
2. The use of small minibatches is always recommended, regardless of the hardware being used.
3. A learning rate that decreases over time can help improve convergence.
4. Momentum helps in compensating for small minibatch sizes by maintaining a running average of past gradients.
5. Numerical instabilities are commonly caused by the use of activation functions like softmax and sigmoid.

10. Match the following words with their correct definitions.

1. Stochastic Gradient Descent (SGD)
2. Learning Rate (α)
3. Momentum
4. Minibatch
5. Numerical instability
6. Overfitting

a) The process of training a network to minimize the loss function using a random subset of training data at each step.
b) A very small dataset used at each step of stochastic gradient descent.
c) A tuning parameter that controls how much the network's parameters change during each update.
d) A scenario where machine learning models perform well on training data but poorly on unseen data.
e) A technique to improve convergence by keeping a running average of past gradients.
f) Errors that occur due to limitations in how numbers are represented in computer hardware.

11. Fill in the gaps with the verbs in the appropriate form. Translate the sentences into Russian.

Decrease, estimate, exhibit, militate, modify, proceed.

1. Training a neural network consists of …….. the network's parameters to minimize the loss function.
2. The use of a learning rate that …….. over time is usually a good idea to improve convergence.
3. One solution to improve training is to …….. with a larger minibatch size as the process continues.
4. These considerations strongly ……… in favor of using stochastic gradient descent.
5. The process of learning the weights often …….. diminishing returns over time.
6. Gradient values …….. based on a minibatch of examples chosen at each step.

12. Translate the text in writing with a dictionary.

Choosing a Network Architecture

A great deal of effort in deep learning research has gone into finding network architectures that generalize well. Indeed, for each particular kind of data – images, speech, text, video, and so on – a good deal of the progress in performance has come from exploring different kinds of network architectures and varying the number of layers, their connectivity, and the types of node in each layer.

Some neural network architectures are explicitly designed to generalize well on particular types of data: convolutional networks encode the idea that the same feature extractor is useful at all locations across a spatial grid, and recurrent networks encode the idea that the same update rule is useful at all points in a stream of sequential data. To the extent that these assumptions are valid, we expect convolutional architectures to generalize well on images and recurrent networks to generalize well on text and audio signals.

LESSON 8

1. Words and word combinations to be remembered.
Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. absence (n.)
2. according to (prep.)
3. although (conj.)
4. application (n.)
5. assume (v.)
6. autonomous (adj.)
7. decision (n.)
8. derive (v.)
9. direct (adj.)
10. ground truth
11. guidance (n.)
12. interact (v.)
13. label (n.)
14. latter (adj.)
15. mimic (v.)
16. pseudo (adj.)
17. reinforcement (n.)
18. response (n.)
19. sequence (n.)
20. sequential (adj.)
21. state-action-reward
22. trial and error
23. tuple (n.)
24. uncertain (adj.)
25. underlie (v.)

2. Read the words in transcription, translate them into Russian.

[ɪnˈvaɪrənmənt], [daɪˈrekt/dəˈrekt], [ɔːˈtɒnəməs], [sɪˈkwenʃ(ə)l], [kənˈtrɑːst], [ˌbaɪəˈlɒdʒɪkl], [truːθ], [ˌmæksɪmaɪˈzeɪʃn].

3. Read and translate the rows of the same root words, defining the part of speech.

Reinforce, reinforced, reinforcing, reinforcer, reinforcement.
Autonomy, autonomous, autonomously, autonomize.
Absent, absently, absence, absentee, absenteeism.

Guide, guided, guiding, guideline, guidance.
Actual, actually, actualize, actualized, actualizing, actualization.

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Reinforcement learning algorithms, decision-making settings, sequential decision-making problems, artificial intelligence development, prediction accuracy maximization, real-world biological learning methods, classification method, output variables validation, recommendation engine.

5. Translate the sentences into Russian, paying attention to *as well as, as long as, as soon as.*
1. In this section we discuss exact algorithms for computing posterior probabilities as well as the complexity of this task.
2. Decision trees have a lot going for them: ease of understanding, scalability to large data sets, and versatility in handling discrete and continuous inputs as well as classification and regression.
3. As long as we keep track of paths and cut off ones that are cycles, eventually we will reach every reachable state.
4. As soon as you successfully classify a batch of spam messages, the spammers will see what you have done and change their tactics, sending a new type of message you haven't seen before.

6. Translate the conditional sentences into Russian, paying attention to the conjunctions used.
1. Grey rectangles represent time intervals during which an action may be executed, provided that the ordering constraints are respected.
2. Thus the first ultraintelligent machine is the last invention that man need ever make, provided that the machine is docile enough to tell us how to keep it under control.
3. But unless there are obviously no errors, it is better to formally evaluate your system by running it on a test suite of queries and measuring how many you get right.
4. Typically, this approach is slow, unless the domain is small.
5. The software for a self-driving car wouldn't be considered safe unless it can handle unusual situations.

7. Read and translate the text.

Reinforcement Learning

In reinforcement learning, an agent learns to make decisions by interacting with an environment. It is used in robotics and other decision-making settings.

Reinforcement learning (RL) is a type of machine learning process that focuses on decision making by autonomous agents. An autonomous agent is any system that can make decisions and act in response to its environment independent of direct instruction by a human user. Robots and self-driving cars are examples of autonomous agents. In reinforcement learning, an autonomous agent learns to perform a task by trial and error in the absence of any guidance from a human user. It particularly addresses sequential decision-making problems in uncertain environments, and shows promise in artificial intelligence development.

Literature often contrasts reinforcement learning with supervised and unsupervised learning.

Supervised and unsupervised learning methods assume each record of input data is independent of other records in the dataset but that each record actualizes a common underlying data distribution model. These methods learn to predict with model performance measured according to prediction accuracy maximization.

By contrast, reinforcement learning learns to act. It assumes input data to be interdependent tuples – i.e. an ordered sequence of data – organized as state-action-reward. Many applications of reinforcement learning algorithms aim to mimic real-world biological learning methods through positive reinforcement.

It should be noted that, although the two are not often compared in literature, reinforcement learning is distinct from self-supervised learning as well. The latter is a form of unsupervised learning that uses pseudo labels derived from unlabeled training data as a ground truth to measure model accuracy. Reinforcement learning, however, does not produce pseudo labels or measure against a ground truth – it is not a classification method but an action learner. The two have been combined however with promising results.

8. Answer the questions to the text.

1. Where is reinforcement learning used?
2. What is an autonomous agent? Could you provide examples?
3. What is reinforcement learning usually contrasted with?
4. What distinguishes reinforcement learning from self-supervised learning?
5. Is it possible to combine the two aforementioned methods?

9. Decide whether the statements below are true or false.

1. Reinforcement learning is used primarily for classification tasks.
2. In reinforcement learning, the agent learns by following human instructions.
3. Self-supervised learning uses pseudo labels to train a model.
4. Sequential decision-making problems are particularly addressed by reinforcement learning.
5. Supervised learning and reinforcement learning assume input data are interdependent.

10. Fill in the gaps with the correct verb in active or passive voice. Translate the sentences into Russian.

Address, assume, derive, focus on, mimic, predict.

1. Reinforcement learning …….. decision-making by autonomous agents.
2. Autonomous agents …….. real-world biological learning methods through trial and error.

3. Supervised and unsupervised learning methods ……… that each record of input data is independent of others.
4. Sequential decision-making problems in uncertain environments ……… by reinforcement learning.
5. In unsupervised learning, pseudo labels ………. from unlabeled training data.
6. Supervised and unsupervised learning methods learn to ………. with high accuracy.

11. Match the following terms with their correct definitions.

1. Reinforcement learning
2. Autonomous agent
3. Sequential decision-making
4. Interdependent tuples
5. Positive reinforcement
6. Ground truth

a) A system that can make decisions and act independently of direct human instruction.
b) A method where an agent learns by interacting with its environment and receiving feedback.
c) An ordered sequence of data points that depend on each other.
d) A scenario where decisions must be made in a specific order over time.
e) The actual or known correct information used to measure model accuracy.
f) The framework used in reinforcement learning where actions are chosen based on the current situation to maximize future rewards.

12. Translate the text in writing with a dictionary.

The Main Difference between Supervised and Unsupervised Learning: Labeled Data

The main distinction between the two approaches is the use of labeled data sets. To put it simply, supervised learning uses labeled input and output data, while an unsupervised learning algorithm does not.

In supervised learning, the algorithm “learns” from the training data set by iteratively making predictions on the data and adjusting for the correct answer. While supervised learning models tend to be more accurate than unsupervised learning models, they require upfront human intervention to label the data appropriately. For example, a supervised learning model can predict how long your commute will be based on the time of day, weather conditions and so on. But first, you must train it to know that rainy weather extends the driving time.

Unsupervised learning models, in contrast, work on their own to discover the inherent structure of unlabeled data. Note that they still require some human intervention for validating output variables. For example, an unsupervised learning model can identify that online shoppers often purchase groups of products at the same time. However, a data analyst would need to validate that it makes sense for a recommendation engine to group baby clothes with an order of diapers, applesauce, and sippy cups.

LESSON 9

1. Words and word combinations to be remembered. Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meanings.

1. adapt (v.)
2. advantage (n.)
3. approximation (n.)
4. attractive (adj.)
5. capability (n.)
6. computable (adj.)
7. computation (n.)
8. consequently (adv.)
9. conventional (adj.)
10. cumbersome (adj.)
11. detection (n.)
12. diagnosis (n.)
13. effortless (adj.)
14. emerge (v.)
15. employ (v.)
16. especially (adv.)
17. fault (n.)
18. heuristic (adj.)
19. impractical (adj.)
20. intermediate (adj.)
21. learning coefficient ratio
22. learning rule
23. multilayered perceptron (MLP)
24. multiple input-multiple output (MIMO)
25. necessary (adj.)
26. nonlinear (adj.)
27. numerical (adj.)
28. obtain (v.)
29. owing to (prep.)
30. possess (v.)
31. prior (adj.)
32. properly (adv.)
33. Quickprop and Resilient Back-propagation (RPROP)
34. readily (adv.)
35. response (n.)
36. run (n.)
37. sensor (n.)
38. solely (adv.)
39. specify (n.)
40. steady-state (adj.)
41. uncertainty (n.)
42. unnecessary (adj.)
43. utilize (v.)
44. weight (n.)
45. yield (n.)

2. Read the words in transcription, translate them into Russian.

[ˈdekeɪd], [ɪˈspeʃ(ə)lɪ], [ˈpraɪə], [fɪˌnɒmɪˈnɒlədʒɪ], [jiːld], [aɪˌdentɪfɪˈkeɪʃ(ə)n], [kærəktəˈrɪstɪks], [əˈdʒʌst], [ˈnjʊərɒn], [ˌkəʊɪˈfɪʃ(ə)nt].

3. Work with word formation. Fill in the table with the necessary nouns, verbs or adjectives.

Noun	Verb	Adjective
	attract	
computation		
		necessary
	relate	
utilization		
		adaptable
	know	

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.

Nonlinear process modeling, conventional regression model, model-free approximation capabilities, generalization ability, soft sensor building, yield maximization, fault detection and diagnosis, causal process variables, error-back-propagation, transfer function, learning coefficient ratio, random number seed, root-mean-squared-error.

5. Translate the sentences into Russian paying attention to passive voice.

1. Agents move through search space based on averaged velocity vectors that are influenced by the global and local best-known solutions (positive feedback), the agent's previous direction, and a randomized direction.
2. Financial services are also affected by the introduction of many AI-related innovations, such as roboadvisors.
3. The moment where AI takes over its own selfimprovement is referred to as the Singularity or artificial superintelligence (ASI).
4. The Dartmouth Conference was followed by an international conference on the "Mechanisation of Thought Processes" at the British National Physical Laboratory (NPL) in 1958.
5. When problems come up, they are dealt with.
6. While the rough distinctions outlined above between automated, semiautonomous, and autonomous systems are generally agreed upon, ambiguity exists where these system categories are present in actual systems.

6. Translate the sentences into Russian defining the functions of the gerunds.

1. Most nonparametric models have the advantage that it is easy to do leave-one-out cross-validation without having to recompute everything.
2. Having a reliable, flexible, secure, data-handling pipeline is more critical to success than the exact details of the machine learning algorithm.
3. We do agree that behaving intelligently will require some degree of awareness, which will differ from task to task, and that tasks involving interaction with humans will require a model of human subjective experience.
4. Critics contend that the Turing Test doesn't measure intelligence; rather, it measures how well a machine can simulate being a human.
5. Autonomous machines learn from their experiences and are in some ways capable of reaching beyond their initial programming.
6. Chatbots can be written in almost any programming language, and there are a variety of techniques available for creating them.

7. Read and translate the text.

Artificial Neural Networks

In the last decade, artificial neural networks (ANNs) have emerged as attractive tools for nonlinear process modeling, especially in situations where the development of phenomenological or conventional regression models becomes impractical or cumbersome. ANN is a computer modeling approach that learns from examples through iterations without requiring a prior knowledge of the relationships of process parameters and is, consequently, capable of adapting to a changing environment. It is also capable of dealing with uncertainties, noisy data, and nonlinear relationships.

ANN modeling has been known as effortless computation and readily used extensively because of its model-free approximation capabilities of complex decision-making processes. The advantages of an ANN-based model are the following:

1. It can be constructed solely from the historic process input-output data (example set).

2. Detailed knowledge of the process phenomenology is unnecessary for model development.

3. A properly trained model possesses excellent generalization ability owing to which it can accurately predict outputs for a new input data set.

4. Even multiple input-multiple output (MIMO) nonlinear relationships can be approximated simultaneously and easily.

Owing to their several attractive characteristics, ANNs have been widely used in chemical engineering applications such as steady-state and dynamic process modeling, soft sensor building, process identification, yield maximization, nonlinear control, and fault detection and diagnosis.

The most widely utilized ANN paradigm is the multilayered perceptron (MLP) that approximates nonlinear relationships existing between an input set of data (causal process variables) and the corresponding output (dependent variables) data set. A three-layered MLP with a single intermediate (hidden) layer housing a sufficiently large number of nodes (also termed neurons or processing elements) can approximate (map) any nonlinear computable function to an arbitrary degree of accuracy. It learns the approximation through a numerical procedure called network training, wherein network parameters (weights) are adjusted iteratively such that the network, in response to the input patterns in an example set, accurately produces the corresponding outputs. There exists a number of algorithms – each possessing certain positive characteristics – to train an MLP network, for example, the most popular error-back-propagation (EBP), Quickprop and Resilient Back-propagation (RPROP). Training of an ANN involves minimizing a nonlinear error function (e.g., root-mean-squared-error, RMSE) that may possess several local minima. Thus, it becomes necessary to employ a heuristic procedure involving multiple training runs to obtain an optimal ANN model whose parameters (weights) correspond to the global or the deepest local minimum of the error function. The building of a backpropagation network involved the specification of the number of hidden layers and the number of neurons in each hidden layer. In addition, several parameters, including the learning rule, the transfer function, the learning coefficient ratio, the random number seed, the error minimization algorithm, and the number of learning cycles had to be specified.

8. Answer the questions to the text.

1. What is ANN modeling?
2. What are the advantages of an ANN-based model?
3. Where can ANNs be used?

4. What is MLP and what is its function?
5. What algorithms are used to train an MLP network?
6. What did the building of a backpropagation network involve?

9. Decide whether the statements below are true or false.

1. ANNs require detailed knowledge of the process phenomenology for successful modeling.
2. MLPs can only approximate linear relationships.
3. Backpropagation is the most commonly used method for training an MLP network.
4. An ANN with strong generalization ability can accurately predict new input-output pairs that were not part of the training data.
5. Weights in a neural network remain constant throughout the training process.
6. The process of training an ANN may involve multiple runs to find the global minimum of the error function.

10. Match the following words with their correct definitions.

1. Phenomenological model
2. Generalization ability
3. Backpropagation
4. Hidden layer
5. Neurons (nodes)
6. Weights
7. Root-mean-squared-error

a) The numerical values that determine the strength and direction of connections between neurons in artificial neural networks.
b) The layer in a neural network where information is processed between input and output layers.
c) A mathematical procedure that allows ANNs to learn by updating weights based on the error in prediction.
d) A numerical measure used to quantify the error in a model's prediction.
e) The ability of a trained model to correctly predict unseen data.
f) Elements or processing units in a neural network that receive and process input data.
g) A model built based on observed phenomena, rather than pure theory or calculation.

11. Find in the text and translate:

a) sentences with the gerund as an adverbial modifier;
b) sentences with participle I as an attribute;
c) sentences with verbs in passive voice;
d) sentences with adjectives with negative affixes.

12. Translate the text in writing with a dictionary.

Network Architecture

The MLP network usually consists of three layers of nodes. The layers described as input, hidden, and output layers comprise N, L, and K number of processing nodes, respectively. Each node in the input (hidden) layer is linked to all the nodes in the hidden (output) layer using weighted connections. In addition to the N and L number of input and hidden nodes, the MLP architecture also houses a bias node (with fixed output of +1) in its input and hidden layers; the bias nodes are also connected to all the nodes in the subsequent layer, and they provide additional adjustable parameters (weights) for the model fitting. The number of nodes (N) in the MLP network's input layer is equal to the number of inputs in the process whereas the number of output nodes (K) equals the number of process outputs. However, the number of hidden nodes (L) is an adjustable parameter whose magnitude is determined by issues, such as the desired approximation and generalization capabilities of the network model.

LESSON 10

1. Words and word combinations to be remembered. Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meanings.

1. break down (v.)
2. complete (adj., v.)
3. extract (v.)
4. hierarchical (adj.)
5. immense (adj.)
6. intricate (adj.)
7. lack (v.)
8. multiple (adj.)
9. permit (v.)
10. prearranged (adj.)
11. precede (v.)
12. refers to (v.)
13. shallow(adj.)
14. storage(n.)
15. subsequent (adj.)
16. subset (n.)

2. Read the words in transcription, translate them into Russian.

[ˈmeθəd], [ˈʃæləʊ], [ˈvɪʒ(ə)n], [ɪkˈsaɪtɪŋ], [ˈnjʊərɒn], [ˈmʌltɪp(ə)l], [ʌnˈstrʌktʃəd], [ˈsɪəriːz], [ˌpriːəˈreɪndʒd], [ˌhaɪəˈrɑːkɪkl].

3. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.

Machine learning networks, computer hardware advances, speech recognition task performance, deep learning algorithm complexity, natural language processing application, multi-layered learning algorithm depth, fully connected layer structure.

4. Work with word formation. Fill in the table with the necessary nouns, verbs or adjectives.

Noun	Verb	Adjective
	complete	
vision		
		recognizable
	extract	
association		
		structural
	store	
excitement		

5. Translate the sentences paying attention to the functions of *have*.

1. Unmanned vehicles are either preprogrammed by algorithms or remotely controlled by a human operator, and they can have varying degrees of autonomy in their operations.
2. Obviously, if the environment is unknown, the agent will have to learn how it works in order to make good decisions.
3. Since the 1950s, researchers have explored two major avenues to artificial intelligence: connectionism and symbolic representation.
4. There are two opposing opinions on the long-term effect that the development of AI-based technologies will have on automation and human labor.
5. One might say that to solve a hard problem, you have to almost know the answer already.
6. The problem-solving approach has been applied to a vast array of task environments.

6. Translate the sentences into Russian defining the functions of the gerunds.

1. It’s possible to reduce the layer size simply by having a fully connected layer with fewer units than the preceding layer.
2. Having multiple sensors increases performance in general, and is particularly important in conditions of poor visibility.
3. Making correct inferences is sometimes part of being a rational agent, because one way to act rationally is to deduce that a given action is best and then to act on that conclusion.
4. Having a belief about the human’s goal helps the robot anticipate what next actions the human will take.
5. The concept of pruning – eliminating possibilities from consideration without having to examine them – is important for many areas of AI.
6. Ambiguity in definitions of semiautonomous and autonomous systems mirrors the many challenges in designing optimized user interfaces for these systems.

7. Read and translate the text.

Deep Learning (1)

Deep learning is a subset of methods, tools, and techniques in artificial intelligence or machine learning. Learning in this case involves the ability to derive meaningful information from various layers or representations of any given data-set in order to complete tasks without human instruction. *Deep* refers to the depth of a learning algorithm, which usually involves many layers. Machine learning networks involving many layers are often considered to be deep, while those with only a few layers are considered shallow. The recent rise of deep learning over the 2010s is largely due to computer hardware advances that permit the use of computationally expensive algorithms and allow storage of immense datasets. Deep learning has produced exciting results in the fields of computer vision, natural language, and speech recognition.

Artificial neural networks are the most common form of deep learning. Neural networks extract information through multiple stacked layers commonly known as hidden layers. These layers contain artificial neurons, which are connected independently via weights to neurons in other layers. Neural networks often involve dense or fully connected layers, meaning that each neuron in any given layer will connect to every neuron of its preceding layer. This allows the network to learn increasingly intricate details or be trained by the data passing through each subsequent layer. Part of what separates deep learning from other forms of machine learning is its ability to work with unstructured data. Unstructured data lacks prearranged labels or features. Using many stacked layers, deep learning algorithms can learn to associate its own features from the given unstructured datasets. This is accomplished by the hierarchical way a deep multi-layered learning algorithm provides progressively intricate details with each passing layer, allowing for it to break down a highly complex problem into a series of simpler problems. This allows the network to learn increasingly intricate details or be trained by the data passed through subsequent layers.

8. Answer the questions to the text.

1. What is deep learning?
2. What machine learning networks are considered to be deep?
3. Why have hardware advances been crucial to the rise of deep learning in the 2010s?
4. What are some of the fields where deep learning has shown significant results?
5. What is the most common form of deep learning?
6. Does deep learning provide for working with unstructured data?

9. Decide whether the statements below are true or false.

1. Deep learning is a subset of artificial intelligence that works with only structured data.
2. Fully connected layers in neural networks mean that each neuron in a layer connects to every neuron in the preceding layer.
3. A shallow neural network is one with many layers of neurons.
4. Deep learning can process unstructured data, making it unique compared to traditional machine learning.
5. Deep learning breaks down highly complex problems into simpler problems by processing data in layers.
6. Computer vision is a field that has seen advancements due to deep learning

10. Find in the text and translate:

- **a) a sentence with the infinitive as an adverbial modifier of purpose;**
- **b) sentences with Complex Object and Complex Subject;**
- **c) sentences with participle I as an attribute;**
- **d) a sentence with adjectives in superlative degree.**

11. Match the following terms with their correct definitions.

1. Deep learning
2. Unstructured data
3. Shallow networks
4. Computer vision
5. Data-set
6. Natural Language Processing (NLP)

a) A field of artificial intelligence that enables computers to interpret and understand visual information from the world.
b) A collection of structured or unstructured data used to train AI and machine learning models.
c) Networks involving a few layers in their architecture.
d) A method in machine learning that uses many layers to learn from data without human guidance.
e) The application of computational techniques to the analysis and synthesis of natural language and speech.
f) Data that lacks predefined labels or structured organization.

12. Fill in the gaps with the appropriate adjectives given below. Translate the sentences into Russian.

Individual, hierarchical, connected, shallow, unstructured, significant

1. A deep neural network uses dense or fully …… layers, where each neuron connects to every neuron in the previous layer.
2. …….. learning allows deep learning algorithms to break down complex problems into a series of simpler tasks using a multi-layered approach.
3. The primary advantage of deep learning is that it can handle …… data, extracting features without human intervention.
4. Neurons are …….. processing units in artificial neural networks that pass information between layers.
5. …….networks only involve a few layers, while deep networks have many.
6. Deep learning has achieved ………. breakthroughs in fields like computer vision and speech recognition.

13. Translate the text in writing with a dictionary.

A network is trained through the following steps: first, small batches of labeled data are passed forward through the network. The network's loss is calculated by comparing predictions versus the actual labels. Any discrepancies are calculated and relayed back to the weights through back propagation. Weights are slightly altered with the goal of continuously minimizing loss during each round of predictions. The process repeats until optimal minimization of loss occurs and the network achieves a high accuracy of correct predictions.

Deep learning's ability to self-optimize its layers is what gives it an edge over many machine learning techniques or shallow learning networks. Since machine or shallow learning algorithms involve only a few layers at most, they require human intervention in the preparation of unstructured data for input, also known as feature engineering. This can be quite an arduous process and might take too much time to be worthwhile, especially if the dataset is quite large.

For these reasons, it may appear as though machine learning algorithms might become a method of the past. But deep learning algorithms come at a cost. The ability to find their own features requires a vast amount of data that might not always be available. Also, as data sizes increase, so too does the processing power and training time requirements needed since the network will have much more data to sort through. Training time will also increase depending on the amount and types of layers used. Luckily, online computing, where access to powerful computers can be rented for a fee, allows anyone the ability to execute some of the more demanding deep learning networks.

LESSON 11

1. Words and word combinations to be remembered. Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. associate (v.)
2. concise (adj.)
3. convnet (n.)
4. convolutional (adj.)
5. currently (adv.)
6. extra (adj.)
7. gain (v.)
8. intricate (adj.)
9. invariant (n.)
10. kernel (n.)
11. parse (v.)
12. pooling (n.)
13. repeat (v.)
14. retain (v.)
15. sampling (n.)

2. Read the words in transcription, translate them into Russian.

[ˌkɒnvəˈluːʃn], [ˈkʌrəntli], [ˈkɜːn(ə)l], [ˈsʌbsɪkw(ə)nt], [ˈɪmɪdʒ], [lə(ʊ)ˈkeɪt], [wɪðˈaʊt], [ʌnˈstrʌktʃəd], [ˈænəlaɪz], [ˈveəriəs].

3. Work with word formation. Fill in the table with the necessary nouns, verbs or adjectives.

Noun	Verb	Adjective
	inform	
automation		
		complete
	repeat	
meaning		
		general
	compute	
ability		

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.

Convolutional neural network architecture, deep learning computer vision projects, low-level feature extraction process, higher-level feature detection techniques, image classification task, intricate detail analysis process.

5. Translate the sentences paying attention to the functions of *to be.*

1. Propositional logic is a simple language consisting of proposition symbols and logical connectives.
2. In each case, the algorithm reaches a point at which no progress is being made.
3. One way to construct the library is to learn the methods from problem-solving experience.
4. Ironically, the new back-propagation learning algorithms that were to cause an enormous resurgence in neuralnet research in the late 1980s and again in the 2010s had already been developed in other contexts in the early 1960s.
5. Unfortunately, propositional logic is limited in what it can say.
6. What programming languages lack is a general mechanism for deriving facts from other facts; each update to a data structure is done by a domain-specific procedure whose details are derived by the programmer from his or her own knowledge of the domain.
7. The idea is to understand the scope of the knowledge base, as determined by the task, and to understand how the domain actually works.
8. Lyapunov analysis was originally developed in the 1890s for the stability analysis of general nonlinear systems, but it was not until the early 1930s that control theorists realized its true potential.

6. Translate the sentences into Russian, paying attention to the complex gerundial constructions.

1. The scientists' recombining different network architectures helped to explore new possibilities.
2. The researchers focused on automating the task of architecture selection, knowing that their choosing the right network architecture would be challenging without clear guidelines.
3. The team discussed the scientists' recombining different network architectures.
4. By their treating the architectural possibilities as a continuous space, they were able to apply gradient descent more effectively.
5. They attributed the project's success to the team's using evolutionary algorithms for neural architecture search.
6. The key to speeding up the process lay in their learning a heuristic evaluation function.
7. The team's using evolutionary algorithms for neural architecture search led to more efficient network design.

7. Read and translate the text.

Deep Learning (2)

Convolutional neural networks (CNNs) require extra types of hidden layers not discussed in the basic neural network architecture. This type of deep learning is most often associated with computer vision projects and is currently the most widely used method in that field. Basic convnet networks will generally use three types of layers in order to gain insight from the image: convolutional layers, pooling layers, and dense layers. Convolutional layers work by shifting a window, or convolutional kernel, across the image in order to gain information from low-level features such as edges or curves. Subsequent stacked convolutional layers will repeat this process over the newly formed layers of low-level features searching for progressively higher-level features until it forms a concise understanding of the image. Varying the size of the kernel or the distance in which it slides over the image are various hyperparameters that can be changed in order to locate different types of features. Pooling layers allow a network to continue to learn progressively higher-level features of an image by downsampling the image along the way.

Without a pooling layer implemented among convolutional layers, the network might become too computationally expensive as each progressive layer analyzes more intricate details. Also, the pooling layer shrinks an image while retaining important features. These features become translation invariant, meaning that a feature found in one part of an image can be recognized in a completely new area of a second. For an image classification task, the convolutional neural network's ability to retain positional information is vital. Again, the power of deep learning regarding convolutional neural networks is shown through its ability to parse through the unstructured data automatically to find local features that it deems important while retaining positional information about how these features interact with one another.

8. Answer the questions to the text.

1. Where are convolutional neural networks mainly used?
2. What types of layer are generally used for basic convnet networks?
3. Why are hyperparameters like kernel size and stride important in convolutional neural networks?
4. What is the function of the pooling layer?
5. What is the significance of translation invariance in convolutional neural networks?

9. Decide whether the statements below are true or false.

1. Convolutional layers in CNNs scan the image using a small sliding window called a kernel.
2. Dense layers in CNNs connect each neuron in one layer to every neuron in the previous layer.
3. The kernel size in a convolutional layer is a fixed value and cannot be changed.
4. Pooling layers are optional but help prevent CNNs from becoming too computationally expensive.

5. High-level features are detected in the early layers of a CNN, while low-level features are detected in the later layers.
6. CNNs are able to parse through unstructured data like images automatically.

10. Find in the text and translate:

a) **sentences with the infinitive as an adverbial modifier of purpose;**
b) **sentences with verbs in passive voice;**
c) **sentences with participle I as an adverbial modifier;**
d) **sentences with the gerund as an adverbial modifier.**

11. Match the following terms with their correct definitions.

1. Convolutional neural network
2. Pooling layer
3. Convolutional kernel
4. Low-level features
5. High-level features
6. Downsampling
7. Translation invariance

a) Features such as edges or curves found in the earlier layers of a convolutional neural network.
b) A technique that reduces the size of an image while preserving important features.
c) A deep learning network structure primarily used in computer vision tasks.
d) The ability of a network to recognize a feature in different locations within an image.
e) A small sliding window used to detect patterns or features in an image.
f) Features such as shapes or objects found in later layers of a convolutional neural network.
g) A layer that reduces the computational complexity by downsampling the input while retaining important information.

12. Translate the text in writing with a dictionary.

Recurrent neural networks are excellent at sequence-based tasks such as finishing sentences or predicting stock prices. The underlying premise is that – unlike the earlier examples of networks where neurons only pass information forward – neurons in recurrent neural networks feed information forward and also periodically loop back the output to itself during a time step. Since each time step provides recurrent information of all previous time steps, recurrent neural networks can be thought of as having a basic form of memory. This is often used with natural language projects, as recurrent neural networks can process text in a method more akin to humans. Instead of looking at a sentence as merely a bunch of separate words, a recurrent neural network can begin to process the sentence’s sentiment or even autonomously write the next sentence based on what was previously said.

LESSON 12

1. Words and word combinations to be remembered. Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meanings.

1. attempt (n.)
2. attribute (n., v.)
3. challenge (n.)
4. choice (n.)
5. complete (adj., v.)
6. continuous (adj.)
7. cover (v.)
8. deploy (v.)
9. depth (n.)
10. determine (v.)
11. differentiable (adj.)
12. eliminate (v.)
13. estimate (v.)
14. frame (n., v.)
15. GPU
16. guideline (n.)
17. hill climbing
18. hyperparameter (n.)
19. improve (v.)
20. join (v.)
21. judgment (n.)
22. multiple (adj.)
23. mutation (n.)
24. possibility (n.)
25. predict (v.)
26. procedure (n.)
27. recombination (n.)
28. reduce (v.)
29. remove (v.)
30. retain (v.)
31. retrain (v.)
32. score (n.)
33. sensible (adj.)
34. share (n., v.)
35. solution (n.)
36. speed up (v.)
37. straightforward (adj.)
38. subgraph (n.)
39. treat (v.)
40. tuning (n.)

2. Read the words in transcription, translate them into Russian.

[ʌnˈfɔːtʃ(ə)nətlɪ], [ˌiːvəˈluːʃ(ə)n(ə)rɪ], [ˈɔːtəmeɪt], [ˈgaɪdlaɪn], [riːˌkɒmbɪˈneɪʃ(ə)n], [bætʃ], [sɜːtʃ], [ˈriːz(ə)nəb(ə)l], [ˈtʃælɪn(d)ʒ], [ˈnetwɜːk].

3. Work with word formation. Fill in the table with the necessary nouns, verbs or adjectives.

Noun	Verb	Adjective
success		
	select	
		popular
value		
	continue	
		different
validation		
	predict	

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.

Neural architecture search, search techniques, architecture selection process, parameter value, mutation operation, heuristic evaluation function, complete training procedure, signal value, validation set.

5. Translate the sentences paying attention to the conjunctions *both… and…, either… or…, neither… nor…* and to the determiners *both, either, neither.*

1. A variety of cognitive architectures have been developed in both academic and industrial environments.
2. Hybrid networks with both discrete and continuous variables were investigated.
3. In both of these problems, there is a wide path to the goal.
4. The problem is that we know neither the assignments nor the parameters.
5. Neither forward nor backward search is efficient without a good heuristic function.
6. Neither strategy is optimal.
7. In standard logics, every sentence must be either true or false in each possible world – there is no "in between."
8. Unmanned vehicles are either preprogrammed by algorithms or remotely controlled by a human operator.
9. The search is complete in either case.

6. Translate the sentences into Russian; decide whether the Ving-form used is a gerund or a participle. Define the functions of Ving-forms.

1. Having specified the syntax of propositional logic, we now specify its semantics.
2. Social concerns surrounding artificial intelligence and harm to humans have most famously been represented by Isaac Asimov's Three Laws of Robotics.
3. Acquiring domain knowledge posed the biggest challenge to the expert system.
4. Many factors play a role in making the acquisition step difficult, but the complexity of representing heuristic and experiential knowledge is probably the most significant challenge.
5. The model's performance improved significantly thanks to their training the network on a smaller dataset.
6. The creators of the Asilomar principles, noting the high stakes involved, included principles covering longer term issues.
7. The system having detected an anomaly, the AI alerted the team to potential issues.

7. Read and translate the text.

Neural Architecture Search

Unfortunately, there is no clear set of guidelines to help one choose the best network architecture for a particular problem. Success in deploying a deep learning solution requires experience and good judgment.

From the earliest days of neural network research, attempts have been made to automate the process of architecture selection. We can think of this as a case of hyperparameter tuning, where the hyperparameters determine the depth, width, connectivity, and other attributes of the network. However, there are so many choices to be made that simple approaches like grid search can't cover all possibilities in a reasonable amount of time.

Therefore, it is common to use neural architecture search to explore the state space of possible network architectures. Many of the search techniques and learning techniques have been applied to neural architecture search.

Evolutionary algorithms have been popular because it is sensible to do both recombination (joining parts of two networks together) and mutation (adding or removing a layer or changing a parameter value). Hill climbing can also be used with these same mutation operations. Some researchers have framed the problem as reinforcement learning, and some as Bayesian optimization. Another possibility is to treat the architectural possibilities as a continuous differentiable space and use gradient descent to find a locally optimal solution.

For all these search techniques, a major challenge is estimating the value of a candidate network. The straightforward way to evaluate an architecture is to train it on a test set for multiple batches and then evaluate its accuracy on a validation set. But with large networks that could take many GPU-days.

Therefore, there have been many attempts to speed up this estimation process by eliminating or at least reducing the expensive training process. We can train on a smaller data set. We can train for a small number of batches and predict how the network would improve with more batches. We can use a reduced version of the network architecture that we hope retains the properties of the full version. We can train one big network and then search for subgraphs of the network that perform better; this search can be fast because the subgraphs share parameters and don't have to be retrained.

Another approach is to learn a heuristic evaluation function (as was done for A$*$ search). That is, start by choosing a few hundred network architectures and train and evaluate them. That gives us a data set of (network, score) pairs. Then learn a mapping from the features of a network to a predicted score. From that point on we can generate a large number of candidate networks and quickly estimate their value. After a search through the space of networks, the best one(s) can be fully evaluated with a complete training procedure.

8. Answer the questions to the text.

1. Why is choosing a network architecture for a particular problem quite a difficult task?
2. What search and learning techniques have been applied to neural architecture search?
3. What is the straightforward way to evaluate an architecture and why is it unsuitable for large networks?
4. How can the estimation process of the network architecture be sped up?
5. What is a heuristic evaluation function in the context of neural architecture search, and how does it help in searching for the best network architecture?

9. Decide whether the statements below are true or false.

1. Neural architecture search is essentially a type of hyperparameter tuning.
2. Grid search is the most effective approach to neural architecture search.
3. Hill climbing methods incrementally adjust parameters to find local optima in neural architecture search.
4. Training a large number of candidate networks to full completion is the fastest way to evaluate network architectures.
5. Gradient descent can be applied to neural architecture search by treating the search space as differentiable.
6. Subgraphs are small, fully trained networks that are created to speed up evaluation during neural architecture search.

10. Match the following terms with their correct definitions.

1. Hyperparameter tuning	a) A type of optimization that searches through potential solutions based on learned probabilities.
2. Evolutionary algorithm	b) A search method that finds a local optimum by incrementally changing the current solution.
3. Bayesian optimization	c) An algorithm that improves a solution by combining or mutating network parts.
4. Hill climbing	d) A function that predicts the value of a candidate network without fully training it.
5. Gradient descent	
6. Heuristic evaluation	e) A parameter optimization technique that involves adjusting aspects like depth or width of a neural network.
	f) The process of updating network parameters by computing the error gradient and moving in the direction that minimizes the error.

11. Fill in the gaps with an appropriate verb given below. Translate the sentences into Russian.

To speed up, to predict, to automate, to evaluate, to search for, to explore

1. Neural architecture search is used ……. the process of finding the best neural network architecture.
2. Techniques like evolutionary algorithms and hill climbing allow the search process ……… network architectures in a systematic way.
3. The challenge of computation time arises when attempting …… large network architectures due to the computational time needed for training.
4. One way …… the search process is to train on a smaller data set, which reduces the size of the training data.
5. An alternative approach to training large networks fully is …… subgraphs that share parameters and evaluate them.
6. Another method involves building a dataset of architectures and scores and then using heuristic evaluation ……. the performance of new networks.

12. Find in the text and translate:

a) **sentences with the infinitive as an attribute;**
b) **sentences with an infinitive as an adverbial modifier of purpose;**
c) **a sentences with verbs in passive voice;**
d) **a sentence with “have” as a modal verb equivalent;**
e) **sentences with the gerund as an adverbial modifier.**

13. Translate the text in writing with a dictionary.

A feedforward network, as the name suggests, has connections only in one direction that is, it forms a directed acyclic graph with designated input and output nodes. Each node computes a function of its inputs and passes the result to its successors in the network. Information flows through the network from the input nodes to the output nodes, and there are no loops.

A recurrent network, on the other hand, feeds its intermediate or final outputs back into its own inputs. This means that the signal values within the network form a dynamical system that has internal state or memory.

Boolean circuits, which implement Boolean functions, are an example of feedforward networks. In a Boolean circuit, the inputs are limited to 0 and 1, and each node implements a simple Boolean function of its inputs, producing a 0 or a 1. In neural networks, input values are typically continuous, and nodes take continuous inputs and produce continuous outputs. Some of the inputs to nodes are parameters of the network; the network learns by adjusting the values of these parameters so that the network as a whole fits the training data.

LESSON 13

1. Words and word combinations to be remembered. Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meanings.

1. assess (v.)
2. conditionally (adv.)
3. consideration (n.)
4. delineate (v.)
5. distinct (adj.)
6. distinguish (v.)
7. former (adj.)
8. in advance
9. inclusive (adj.)
10. intent (n.)
11. latter (adj.)
12. obstruction (n.)
13. overlap (v.)
14. path (n.)
15. predetermine (v.)
16. proceed (v.)
17. receive (v.)
18. reliance (n.)
19. response (n.)
20. select (v.)
21. somewhere (adv.)
22. tie (v.)
23. via (prep.)

2. Read the words in transcription, translate them into Russian.

[ˌsɛmiɔːˈtɒnəməs], [kəˈmɑːnd], [ˈsʌmweə], [sɜːkəmˈstænʃ(ə)l], [ɪnˈtɜːn(ə)l], [ˈkætəg(ə)rɪ], [ɪntərˈækʃ(ə)n], [ˈeksɪkjuːt], [əˈsesmənt].

3. Work with word formation. Fill in the table with the necessary nouns, verbs or adjectives.

Noun	Verb	Adjective
		multiple
activity		
	rely	
		alternative
extent		
	receive	
		inclusive
sensor		
	obstruct	

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.

Behavior regulation, decision-making capability, user interface, user input, user intent, real-world example, robotics applications, manufacturing facility assembly line, interplanetary exploration applications.

5. Translate the sentences into Russian, paying attention to the underlined verbals.

A chatbot is a computer program that uses artificial intelligence to engage in conversations with humans. The conversations can take place using text or voice input. In some cases, chatbots are also designed to perform automated actions, such as launching an application or sending an email, in response to input from a human. Most chatbots aim to simulate the conversational behavior of a human being, although to date no chatbot has achieved that goal perfectly.

6. Translate the sentences paying attention to the linking words of contrast.

1. Ideal AutoML methods may not have been developed as yet *despite* some promising early examples.
2. *Whereas* roboethics, like computer ethics before it, considers technology to be a more or less transparent tool or instrument of human moral decision-making and action, robot ethics is concerned with the design and development of artificial moral agents.
3. *Although* not in widespread use, caregiver robots are considered important in nations with growing elderly populations.
4. In non-scalable decentralized systems, all-to-all communication is an essential part of the coordination scheme that would, *however*, form a bottleneck in systems with too many agents.

5. The ability to generalize knowledge or skills, however, is so far still pretty much only a human achievement. *Nevertheless*, an enormous amount of research in General AI is currently underway.
6. Some have defined intelligence in terms of fidelity to human performance, while others prefer an abstract, formal definition of intelligence called rationality – loosely speaking, doing the "right thing."

7. Read and translate the text.

Autonomous and Semiautonomous Systems

Autonomous and semiautonomous systems are generally distinguished by their reliance on external commands for decision-making. They are related to conditionally autonomous systems and automated systems. Autonomous systems are capable of decision-making within a specified domain of activity without human input, whereas semiautonomous systems rely upon a human user somewhere "in the loop" for decision-making, behavior regulation, or circumstantial interventions. Conditionally autonomous systems function autonomously under certain conditions.

Semiautonomous and autonomous systems (autonomy) are also distinct from automated systems (automation). The former systems include decision-making capability inclusive of assessing contextual inputs, whereas the latter systems' actions are predetermined sequences directly tied to specified inputs. Systems are considered automated when their actions, and alternatives for action, are predetermined in advance as responses to specific inputs. An example of an automated system is an automatic garage door that stops closing when a sensor detects an obstruction in the path of the door. Inputs can be received via not only sensors but also user interaction. An example of a user-initiated automatic system would be an automatic dishwasher or clothes washer where the human user specifies the sequences of events and behaviors through a user interface, and the machine then proceeds to execute the commands according to predetermined mechanical sequences.

In contrast, autonomous systems are those systems wherein the ability to evaluate circumstances and select actions is internal to the system. Like an automated system, the autonomous system still relies upon sensors, cameras, or user input to provide information, but the system's responses can be characterized by more complex decision-making based upon the situated assessment of multiple simultaneous inputs such as user intent, environment, and capability.

In considering real-world examples of systems, automated, semiautonomous, and autonomous are categories that have some overlap depending on the nature of the tasks under consideration and upon the specifics of decision-making. These categories aren't always clearly or precisely delineated. Lastly, the extent to which these categories apply depends upon the scale and level of the activity under consideration.

8. Answer the questions to the text.

1. What is the difference between autonomous, semiautonomous and conditionally autonomous systems?
2. What are the peculiarities of automated systems?
3. What is the example of an automated system provided in the text?
4. Do autonomous systems have to rely on sensors, cameras or user input to provide information?
5. Why is the distinction between automated, semiautonomous, and autonomous systems not always clear?
6. What factors determine whether a system is automated, semiautonomous, or autonomous?

9. Find in the text and translate:

- **a) sentences with verbs in passive voice;**
- **b) sentences with participle II as an attribute;**
- **c) a sentence with the infinitive as an adverbial modifier of purpose;**
- **d) a sentence with the gerund as an adverbial modifier.**

10. Fill in the gaps with the correct form of the verbs below. Translate the sentences into Russian.

Predetermine, delineate, distinguish, overlap, proceed, select, assess

1. Autonomous systems can …… circumstances and make decisions without human intervention.
2. The categories of autonomous, semiautonomous, and automated systems sometimes ……. depending on the nature of the tasks.
3. It can be challenging to ……. the boundaries between semiautonomous and automated systems due to their similarities.
4. When certain conditions are met, an automated system ……. according to a predetermined sequence of actions.
5. The human operator is required to ……. specific parameters when setting up a semiautonomous system.
6. In an automated system, the actions to be taken …… in response to specific inputs.
7. The characteristics that ……. autonomous systems from automated systems include the ability to evaluate inputs and make decisions.

11. Match the following words with their correct definitions.

1. Autonomous system	a) A system that requires human intervention for certain decisions or actions.
2. Semiautonomous system	b) A system that operates without human input but within a specified domain of activity.
3. Conditionally autonomous system	c) A devices that detects and measures environmental conditions, providing input to systems.
4. Automated system	d) A system that functions autonomously but only under specific conditions.
5. Decision-making	e) A mechanism through which a human user interacts with and controls a system.
6. Sensor	f) A system that performs actions based on pre-programmed responses to specific inputs.
7. User interface	g) The process of evaluating inputs and choosing a course of action.
8. Predetermined sequences	h) Actions and responses that are planned and programmed in advance.

12. Translate the text in writing with a dictionary.

Autonomous Robotics

Examples of autonomous systems can be found across the field of robotics for a variety of purposes. There are a number of reasons that it is desirable to replace or augment humans with autonomous robots, and some of the reasons include safety (for example, spaceflight or planetary surface exploration), undesirable circumstances (monotonous tasks such as domestic chores and strenuous labor such as heavy lifting), or where human action is limited or impossible (search and rescue in confined conditions). As with automotive applications, robotics applications may be considered autonomous within the constraints of a narrowly defined domain or activity space, such as a manufacturing facility assembly line or home. Like autonomous vehicles, the degree of autonomy is conditional upon the specified domain, and in many cases excludes maintenance and repair. However, unlike automated systems, an autonomous robot within such a defined activity structure will act to complete a specified goal through sensing its environment, processing circumstantial inputs, and regulating behavior accordingly without necessitating human intervention. Current examples of autonomous robots span an immense variety of applications and include domestic applications such as autonomous lawn care robots and interplanetary exploration applications such as the MER-A and MER-B Mars rovers.

LESSON 14

1. Words and word combinations to be remembered. Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meanings.

1. apply (v.)
2. availability (n.)
3. commonly (adv.)
4. deploy (v.)
5. digital (adj.)
6. discrete (adj.)
7. discretization (n.)
8. emerge (v.)
9. ensemble (n.)
10. equation (n.)
11. error (n.)
12. evaluate (v.)
13. exploration (n.)
14. injection (n.)
15. intensive (adj.)
16. intrinsic (adj.)
17. look for (v.)
18. multiple (adj.)
19. nonetheless (adv.)
20. open-source (adj.)
21. plentiful (adj.)
22. random (adj.)
23. range (n., v.)
24. randomness (n.)
25. relatively (adv.)
26. remove (v.)
27. stochastic (adj.)
28. tune (v.)
29. unravel (v.)
30. variable (n.)

2. Read the words in transcription, translate them into Russian.

[ˈeərɪə], [ˈlaɪbrərɪ], [ˈpaɪplaɪn], [dɪˈskriːt], [pəˈræmɪtə], [ɒnˈsɒmb(ə)l], [ˈrændəmnɪs], [ɪnˈtɜːprɪt], [sɪstəˈmætɪk], [ˈmeθəd].

3. Work with word formation. Fill in the table with the necessary nouns, verbs or adjectives.

Noun	Verb	Adjective
power		
	explore	
		random
equation		
	vary	
		familiar
creation		
	detect	

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.

Open-source machine learning libraries, high-performance computing, software package, machine learning pipelines, feature transformation algorithm, feature engineering algorithm, ensemble methods, linear support vector machine, grid search, configuration variables.

5. Translate the sentences into Russian, paying attention to the underlined verbals.

Chatbots can help <u>to address</u> a variety of needs across a range of settings. Perhaps most obvious is their ability <u>to save</u> time and resources for humans <u>by using</u> a computer program <u>to collect</u> or <u>dispense</u> information instead of <u>requiring</u> a human <u>to perform</u> these tasks. For example, a company might create a customer support chatbot that responds to customer questions with information that the chatbot determines, <u>using</u> artificial intelligence, <u>to be relevant</u> based on queries from customers. In this way, the chatbot eliminates the need <u>for a human operator to provide</u> this type of customer support.

6. Translate the sentences into Russian defining the part of speech of the words *in italics.*

1. In a compositional language, the meaning of a sentence is a *function* of the meaning of its parts.
2. Semiautonomous systems are found near the middle of the spectrum. These systems may be able to *function* independently of a human being, but only in limited ways.
3. Genetic algorithms involve the *use* of software to simulate and apply Darwinian evolutionary theories to *search* and optimization problems in artificial intelligence.
4. A planner can be seen either as a program that *searches* for a solution or as one that proves the existence of a solution.
5. The *use* of networks to represent probabilistic information began early in the 20th century.
6. We can *use* decision theory to build a system that makes decisions by considering all possible actions and choosing the one that leads to the best expected outcome.
7. The widespread growth of applications to real-world problems led to the development of a wide *range* of representation and reasoning tools.
8. The applications of AI *range* from microelectronic devices to robotic planetary explorers to online services with billions of users.

7. Read and translate the text.

Automated Machine Learning (1)

Automated machine learning is a relatively new area of study that has emerged as a result of the availability of powerful open-source machine learning libraries and plentiful high-performance computing. There are now multiple open-source and commercial AutoML software packages available for use. Many of these packages enable the exploration of machine learning pipelines that can include feature transformation algorithms such as discretization (transforming continuous equations, functions, models, and variables into discrete equations, functions, and so forth for digital computers), feature engineering algorithms such as principal components analysis (a process that removes large dimension “less important” data while retaining a subset of “more important” variables), feature selection algorithms such as ReliefF (a technique that minimizes error), and multiple different machine learning algorithms along with their parameter settings. Stochastic search algorithms used in AutoML have included Bayesian optimization, ensemble methods, and genetic programming. Stochastic search algorithms may be deployed in computational problems with intrinsic random noise or deterministic problems unraveled by injection of randomness. New approaches to remove the “signal from the noise” in datasets, and find insights and make predictions, are being actively developed and evaluated.

One of the challenges of machine learning is that each algorithm looks at data in a different way. That is, each algorithm detects and characterizes different patterns. Some algorithms such as linear support vector machines are good at detecting linear patterns while k-nearest neighbor algorithms can detect nonlinear patterns. The challenge is that scientists do not know when they begin their work which algorithm(s) to use because they do not know what patterns they are looking for in the data. What most people do is choose an algorithm they are familiar with or choose one that seems to work well across a wide range of datasets. Some may choose an algorithm because the models that are generated are easy to interpret. There are lots of different reasons that certain algorithms are chosen for a data analysis. Nonetheless, the chosen algorithm may not be ideal for a given data- set.

One approach to this problem is to perform a grid search. Here, multiple machine learning algorithms and parameter settings are applied to a dataset in a systematic way and the results compared to identify a best algorithm. This is a commonly used approach and can yield good results. The challenge with the grid search is that it can be computationally intensive if many algorithms, each with several parameter settings, need to be evaluated. Random forests are classification algorithms built from multiple decision trees that have several commonly used parameters that must be tuned for optimal performance on a given dataset. Parameters are configuration variables that the adopted machine learning technique uses to adjust the data. A common parameter is the maximum number of features that will be permitted in the decision trees that are created and evaluated.

8. Answer the questions to the text.

1. What is automated machine learning?
2. What can machine learning pipelines include?
3. Where can stochastic search algorithms be deployed?
4. What challenge does AutoML address in machine learning?
5. Why is it difficult for scientists to choose a machine learning algorithm at the beginning of a project?
6. What is grid search and what is its primary limitation?
7. How do random forests and decision trees function within the context of AutoML?

9. Decide whether the statements below are true or false.

1. Principal components analysis is used to increase the number of variables in a dataset.
2. Stochastic search algorithms introduce randomness in order to find solutions in deterministic problems.
3. Grid search is computationally intensive because it involves applying only a single algorithm to multiple datasets.

4. Random forests are built from multiple decision trees, and their performance can be optimized by tuning specific parameters.

10. Find in the text and translate:

a) sentences with the infinitive as an adverbial modifier of purpose;
b) sentences with verbs in passive voice;
c) sentences with participle II as an attribute.

11. Match the following words with their correct definitions.

1. Discretization
2. Principal components analysis
3. ReliefF
4. Stochastic search algorithms
5. Grid search
6. Random forest

a) A classification algorithm that combines multiple decision trees.
b) A feature selection algorithm used to minimize error in machine learning.
c) The process of transforming continuous variables into discrete ones for use in digital computers.
d) A process that reduces data dimensionality by retaining only important variables.
e) A systematic method of applying different machine learning algorithms and comparing results.
f) Methods deployed in problems with randomness to search for solutions.

12. Fill in the gaps with an appropriate noun given below. Translate the sentences into Russian.

Algorithms, number, randomness, transformation, parameter, data

1. Stochastic search algorithms are used when noise or ……. needs to be introduced in machine learning problems.
2. A grid search is a method of selecting the best machine learning algorithm by testing multiple ……. and parameter settings.
3. Feature ……. algorithms like discretization convert continuous ……. into discrete forms.
4. A common ……. in random forest models is the maximum ……. of features allowed in decision trees.

13. Translate the text in writing with a dictionary.

Neuro-Fuzzy Systems

Neuro-fuzzy system (NFS) is a hybrid intelligent model that combines the excellent predicting capabilities of the ANN with the human-like reasoning of the fuzzy inference system (FIS). It is a realization of the fuzzy system by a connectionist structure of an ANN. The amalgamation of two methods generates a learning system that provides the advantages of both of the involved techniques while at the same time dealing with their drawbacks. Another appealing property for the process industry application of the NFS models is that the technique is based on receptive fields and thus intrinsically provides means for the building of local models. The evolving variants of NFS are very well suited to dealing with dynamic environment.

These systems are called evolving because they adapt automatically together with the changing environment represented by the data. An evolving system is thought to be able to change its structure, to grow and shrink and to update its parameter. In this way, the model is able to deploy new local models related to new states of the input data if necessary.

LESSON 15

1. Words and word combinations to be remembered. Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. additional (adj.)
2. beforehand (adv.)
3. combinatorial explosion
4. comparison (n.)
5. computational (adj.)
6. cross-validation (n.)
7. depend on (v.)
8. employ (v.)
9. examine (v.)
10. expensive (adj.)
11. exploration (n.)
12. explore (v.)
13. govern (v.)
14. guide (n.)
15. heuristic (adj., n.)
16. improve (v.)
17. limit (n., v.)
18. manage (v.)
19. manageable (adj.)
20. modify (v.)
21. objective (n.)
22. prohibitive (adj.)
23. repeat (v.)
24. sample (n., v.)
25. setting (n.)
26. single (adj.)
27. so-called (adj.)
28. specify (v.)
29. suffer (v.)
30. value (n.)

2. Read the words in transcription, translate them into Russian.

[bɪˈfɔːhænd], [ˈsɑːmp(ə)l], [ˌhaipəpəˈræmɪtə], [ˈfiːtʃə], [ˌhjʊ(ə)ˈrɪstɪk], [stəˈkastɪk], [ˈɡʌv(ə)n], [ˈsaɪəntɪst], [əˈlaʊ], [əbˈdʒektɪv].

3. Work with word formation. Fill in the table with the necessary nouns, verbs or adjectives.

Noun	Verb	Adjective
explosion		
	separate	
		minimal
repetition		
	combine	
		manageable
user		
	set	

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Parameter settings, hyperparameter configurations, hyperparameter combinations, hyperparameter setting combinations, cross-validation strategy, random number generator, stochastic search algorithm, performance objective.

5. Translate the sentences into Russian, paying attention to the underlined verbals.

Ambiguity in definitions of semiautonomous and autonomous systems mirrors the many challenges in <u>designing</u> <u>optimized</u> user interfaces for these systems. In the case of vehicles, for example, <u>ensuring</u> that the user and the system (as <u>developed</u> by a system's designers) share a common model of the capabilities <u>being automated</u> (and the <u>expected</u> distribution and extent of control) is critical for safe transference of control responsibility. Autonomous systems are theoretically simpler user-interface challenges insofar as once an activity domain is defined, control and responsibility are binary (either the system or the human user is responsible). Here the challenge is reduced to <u>specifying</u> the activity and <u>handing</u> over control.

6. Translate the sentences paying attention to the connectors of cause and effect.

1. *Since* the set of possible deals is finite, the agents cannot negotiate indefinitely.
2. These simple approaches can lead to errors *due to* the approximate nature of the evaluation function.
3. Even with these algorithms, perfect rationality is usually unachievable in practice *because of* computational complexity.
4. Roboethics is often utilized to identify a professional ethics for roboticists and *therefore* is similar to other professional, applied ethics formulations such as bioethics or computer ethics.
5. Operations on symbols are mechanical and *thus* can be assigned to computers.
6. *Because* the human experts' knowledge is a mixture of skills, experience, and formal knowledge, it is difficult to formalize the knowledge acquisition process. *Consequently*, the experts' knowledge is modeled rather than directly transferred from human experts to the programming system.
7. The agents may be software agents or embodied agents in the form of robots, *hence* forming a multi-robot system.

7. Read and translate the text.

Automated Machine Learning (2)

Automated machine learning can help manage the complex, computationally expensive combinatorial explosion in specific analyses that need to be run. A single parameter might have, for example, ten different settings. A second parameter could be the number of decision trees to be included in the forest, perhaps another ten different settings. A third parameter could be the minimum number of samples that will be allowed in the "leaves" of the decision trees, another ten different settings. This example yields 1000 different possible parameter settings assuming the exploration of only three parameters. A data scientist investigating ten different machine learning algorithms, each with 1000 possible parameter settings, would need to run 10,000 specific analyses.

On top of these analyses are so-called hyperparameters, which involve characteristics of the analyses that are set beforehand and thus not learned from the data. They are often specified by the data scientist using various rules of thumbs or values drawn from other problems. Hyperparameter configurations might involve comparisons of several different cross-validation strategies or examine the effect of sample size on results. In a typical example, hundred hyperparameter combinations might need to be evaluated. The combination of machine learning algorithms, parameter settings, and hyperparameter settings could in this way yield a total of one million analyses that the data scientist would need to perform. Depending on the sample size of the data to be analyzed, the number of features, and the types of machine learning algorithms selected, so many separate analyses could be prohibitive given the computing resources that are available to the user.

An alternative approach is to use a stochastic search to approximate the best combination of machine learning algorithms, parameter settings, and hyperparameter settings. A random number generator is used to sample from all possible combinations until some computational limit is reached. The user manually explores additional parameter and hyperparameter settings around the best method before making a final choice. This has the advantage of being computationally manageable but suffers from the stochastic element where chance might not explore the optimal combinations.

A solution to this is to add a heuristic element – a practical method, guide, or rule – to create a stochastic search algorithm that can adaptively explore algorithms and settings while improving over time. Approaches that employ stochastic searches with heuristics are called automated machine learning because they automate the search for optimal machine learning algorithms and settings. A stochastic search might start by randomly generating a number of machine learning algorithm, parameter setting, and hyperparameter setting combinations and then evaluating each one using cross-validation, a technique for testing the effectiveness of a machine learning model. The best of these is selected, randomly modified, and then evaluated again. This process is repeated until a computational limit or a performance objective is reached. The heuristic algorithm governs this process of stochastic search. The development of optimal search strategies is an active area of research.

8. Answer the questions to the text.

1. What problems does automated machine learning (AutoML) help to solve when running analyses with multiple parameters?
2. What are hyperparameters, and how do they differ from parameters in machine learning?
3. What can hyperparameter configurations involve?
4. Why can running multiple analyses with different algorithms, parameters, and hyperparameters be prohibitive for data scientists?
5. Why are approaches employing stochastic searches with heuristics called automated machine learning?

6. What is cross-validation and how is it used in the context of evaluating machine learning models during stochastic searches?

9. Find in the text and translate:

a) sentences with infinitives as 1) an attribute, 2) predicative;
b) sentences with verbs in passive voice;
c) sentences with modal verbs of possibility;
d) **sentences with participle I as an adverbial modifier.**

10. Fill in the gaps with the correct form of the verbs in active or passive voice. Translate the sentences into Russian.

Examine, govern, specify, depend on, modify, explore, employ

1. The computational limits of automated machine learning …… the resources available for analysis and the number of possible parameter settings.
2. Stochastic search approaches often …… heuristic methods to improve the exploration of machine learning algorithms over time.
3. Various cross-validation strategies ……. to determine their effect on the model's performance.
4. Data scientists …… different parameter settings to optimize machine learning models.
5. The heuristic algorithm ……. the stochastic search process by directing the selection of parameter and hyperparameter settings.
6. Parameter settings ……. to find a configuration that meets the desired performance objectives.
7. Data scientists often ……. the values of hyperparameters based on rules of thumb or experience with similar problems.

11. Match the following terms with their correct definitions.

1. Hyperparameters
2. Cross-validation
3. Heuristic
4. Combinatorial explosion
5. Random Number Generator
6. Performance objective

a) A rule or guide that helps to find a solution more quickly, though not necessarily perfectly.
b) A type of algorithm or hardware device that can produce a series of arbitrary numbers.
c) Characteristics set before running an analysis, not learned from the data.
d) An exponential increase in possible combinations when multiple variables are considered.
e) The limit or goal set for a machine learning model to achieve optimal performance.
f) A technique for testing the effectiveness of a model by splitting data into training and testing sets.

12. Translate the text in writing with a dictionary.

The AutoML approach has numerous advantages. First, it can be more computationally efficient than the exhaustive grid search approach. Second, it makes machine learning more approachable because it takes some of the guesswork out of selecting an optimal machine learning algorithm and its many settings for a given dataset. This helps bring machine learning to the novice user. Third, it can yield more reproducible results if generalizability metrics are built into the heuristic that is used. Fourth, it can yield more interpretable results if complexity metrics are built into the heuristic. Fifth, it can yield more actionable results if expert knowledge is built into the heuristic.

Of course, there are some challenges with AutoML approaches. First is the challenge of overfitting – producing an analysis that corresponds too closely to known data but does not fit or predict unseen or new data – due to the evaluation of many different algorithms. The more analytical methods that are applied to a dataset, the higher the chance of learning the noise in the data that leads to a model unlikely to generalize to independent data. This needs to be rigorously addressed with any AutoML method. Second, AutoML can be computationally intensive in its own right. Third, AutoML methods can generate very complex pipelines that include multiple different machine learning methods. This can make interpretation much more difficult than picking a single algorithm for the analysis. Fourth, this field is still in its infancy. Ideal AutoML methods may not have been developed as yet despite some promising early examples.

LESSON 16

1. Words and word combinations to be remembered. Write out the transcription and translation of the following words from the dictionary. Memorize their pronunciation and meaning.

1. accountability (n.)
2. acknowledge (v.)
3. adopt (v.)
4. applicability (n.)
5. assistance (n.)
6. avoid (v.)
7. beneficial (adj.)
8. combustion (n.)
9. commonly-cited (adj.)
10. communicate (v.)
11. contemplate (v.)
12. crop management
13. cut off (v.)
14. disruptive (adj.)
15. emission (n.)
16. employment (n.)
17. enforce (v.)
18. engender (v.)
19. execution (n.)
20. fairness (n.)
21. fission (n.)
22. governance (n.)
23. ignore (v.)
24. implication (n.)
25. inequality (n.)
26. intend (v.)
27. measurement (n.)
28. obligation (n.)
29. on-shore (adj.)
30. opportunity (n.)
31. pollution (n.)
32. prevention (n.)

33. privacy (n.)
34. promote (v.)
35. recover (v.)
36. responsibility (n.)
37. stakeholder (n.)
38. tedious (adj.)
39. transparency (n.)
40. unintended (adj.)
41. uphold (v.)
42. vague (adj.)
43. virtue (n.)
44. wealth (n.)

2. Read the words in transcription, translate them into Russian.
[ˌriːˈsaɪklɪŋ], [ˌɒptɪmaɪˈzeɪʃən], [məʊˈbɪlətɪ], [ˈækses], [welθ], [səˈsaɪəti], [kəˌlæbəˈreɪʃn], [ˈɪʃuː], [ˈkʌltʃə], [əkˈnɒlɪdʒ].

3. Work with word formation. Fill in the table with the necessary nouns, verbs or adjectives.

Noun	Verb	Adjective
obligation		
	ignore	
		preventive
assistance		
	respect	
		applicable
destruction		
	contribute	

4. Translate the attribute chains. Mind that the main word in these "chains" is the last noun and all the previous nouns are used as attributes to the last one.
Pollution monitoring, fossil fuel emissions, internal combustion engine, low-cost manufacturing, automated manufacturing facilities, governance decisions, software or hardware systems, AI developers.

5. Match the following nouns with their correct definitions.

1. Accountability
2. Applicability
3. Employment
4. Governance
5. Implication
6. Prevention
7. Responsibility
8. Transparency

a) The state or fact of having a duty to deal with something or of having control over someone.
b) The way that organizations or countries are managed at the highest level, and the systems for doing this
c) The fact of affecting or relating to a person or thing.
d) The work that is available in a country or area.
e) The quality of being easy to perceive or detect.
f) The act of stopping something from happening or of stopping someone from doing something
g) The effect that an action or decision will have on something else in the future.
h) The fact of being responsible for what you do and able to give a satisfactory reason for it.

6. Translate the sentences into Russian, paying attention to the underlined verbals.

The autonomy of AI programs is not the only aspect of autonomy that is <u>being considered</u> with the advent of the technology. There are also concerns about the impact on human autonomy as well as concerns about complacency <u>regarding</u> the machines. As AI systems become better adapted to <u>anticipating</u> the desires and preferences of the people, they serve the people who benefit from the choice of the machine <u>becoming</u> moot as they no longer have <u>to make</u> choices.

7. Translate the sentences paying attention to the connectors of addition.

1. A system deployed with an incorrect objective will have negative consequences. *Moreover*, the more intelligent the system, the more negative the consequences.
2. A robot can use inverse reinforcement learning to learn a good policy for itself, by understanding the actions of an expert. *In addition*, the robot can learn the policies used by other agents in a multiagent domain.
3. So convolution with multiple kernels finds multiple patterns; *furthermore*, composite patterns can be detected by applying another layer to the output of the first layer.
4. Artificial intelligence experts viewed human cognitive processes as a model for their programs, and *likewise*, they believed AI would offer insight into human psychology.
5. *Besides* the technical innovations must give a lot of credit to big data and big computation.
6. Writing code that can process natural language is a challenging task that requires expertise in computer science and linguistics, *as well as* extensive programming.

8. Read and translate the text.

The Ethics of AI

Given that AI is a powerful technology, we have a moral obligation to use it well, to promote the positive aspects and avoid or mitigate the negative ones.

The positive aspects are many. For example, AI can save lives through improved medical diagnosis, new medical discoveries, better prediction of extreme weather events, and safer driving with driver assistance and (eventually) self-driving technologies. There are also many opportunities to improve lives, such as applying AI to recovering from natural disasters, pollution monitoring, measurement of fossil fuel emissions, crisis counseling, suicide prevention, recycling, and other issues.

AI applications in crop management and food production help feed the world. Optimization of business processes using machine learning will make businesses more productive, increasing wealth and providing more employment. Automation can replace the tedious and dangerous tasks that many workers face, and free them to concentrate on more interesting aspects. People with disabilities will benefit from AI-based assistance in seeing, hearing, and mobility. Machine translation already allows people from different cultures to communicate. Software-based AI solutions have near zero marginal cost of production, and so have the potential to democratize access to advanced technology (even as other aspects of software have the potential to centralize power).

Despite these many positive aspects, we shouldn't ignore the negatives. Many new technologies have had unintended negative side effects: nuclear fission brought Chernobyl and the threat of global destruction; the internal combustion engine brought air pollution, global warming, and the paving of paradise. Other technologies can have negative effects even when used as intended. Automation will create wealth, but under current economic conditions much of that wealth will flow to the owners of the automated systems, leading to increased income inequality. This can be disruptive to a well-functioning society. In developing countries, the traditional path to growth through low-cost manufacturing for export may be cut off, as wealthy countries adopt fully automated manufacturing facilities on-shore. Our ethical and governance decisions will dictate the level of inequality that AI will engender.

All scientists and engineers face ethical considerations of what projects they should or should not take on, and how they can make sure the execution of the project is safe and beneficial. Every organization that creates AI technology, and everyone in the organization, has a responsibility to make sure the technology contributes to good, not harm. The most commonly-cited principles are:

– Ensuring safety
– Ensuring fairness
– Respecting privacy
– Promoting collaboration
– Providing transparency
– Limiting harmful uses of AI
– Establishing accountability
– Upholding human rights and values
– Avoiding concentration of power
– Acknowledging legal/policy implications
– Contemplate implications for employment

It should be noted that many of the principles, such as "ensure safety," have applicability to all software or hardware systems, not just AI systems. Several principles are worded in a vague way, making them difficult to measure or enforce. That is in part because AI is a big field with many subfields, each of which has a different set of historical norms and different relationships between the AI developers and the stakeholders.

9. Answer the questions to the text.

1. What are some positive aspects of AI mentioned in the text?
2. How does AI help improve people's lives in the medical field?
3. What are some applications of AI that can help address environmental issues?
4. What are some of the negative side effects of AI that we should be aware of?
5. How might automation in wealthy countries negatively impact developing countries?

6. What is the role of ethical and governance decisions in shaping the impact of AI on income inequality?
7. What are some of the key ethical principles for AI development mentioned in the text?
8. What responsibility do organizations and individuals developing AI technology have?
9. Why does the text compare AI to other technologies like nuclear fission and the internal combustion engine?

10. Decide whether the statements below are true or false.

1. AI can help prevent natural disasters.
2. AI has the potential to increase income inequality under current economic conditions.
3. Automation can lead to job loss in wealthy countries, but it will have little impact on developing countries.
4. AI-based assistance can help people with disabilities in areas like mobility and communication.
5. Ensuring transparency and avoiding the concentration of power are important ethical principles in AI development.
6. All AI ethical principles are clear and easy to measure and enforce.

11. Find in the text and translate:

a) sentences with infinitives as attributes;
b) sentences with participle I as an adverbial modifier;
c) sentences with the gerund as an adverbial modifier;
d) sentences with verbs in passive voice.

12. Fill in the gaps with the correct form of the verbs in active or passive voice. Translate the sentences into Russian.

Cut off, improve, suggest, ensure, generate

1. AI has the potential to …… medical diagnosis, new medical discoveries, and technologies like driver assistance.
2. Despite its benefits, AI can lead to income inequality if the wealth it ….. flows primarily to the owners of automated systems.
3. In developing countries, the traditional path to growth through low-cost manufacturing may …… due to the adoption of fully automated manufacturing facilities in wealthy countries.
4. Some principles, such as "….. safety", apply to both software systems and AI systems.
5. It …… that the ethical and governance decisions we make will affect how AI impacts income inequality.

13. Translate the text in writing with a dictionary.

Machine ethics is the ethical discipline that scrutinizes the theoretical and ethical issues that Artificial Morality raises. It involves a meta-ethical and a normative dimension. Meta-ethical issues concern conceptual, ontological, and epistemic aspects of Artificial Morality like what moral agency amounts to, whether artificial systems can be moral agents and, if so, what kind of entities artificial moral agents are, and in which respects human and artificial moral agency diverge.

Normative issues in machine ethics can have a narrower or wider scope. In the narrow sense, machine ethics is about the moral standards that should be implemented in artificial moral agents, for instance: should they follow utilitarian or deontological principles? Does a virtue ethical approach make sense? Can we rely on moral theories that are designed for human social life, at all, or do we need new ethical approaches for artificial moral agents? Should artificial moral agents rely on moral principles at all or should they reason case-based?

In the wider sense, machine ethics comprises the deliberation about the moral implications of Artificial Morality on the individual and societal level. Is Artificial Morality a morally good thing at all? Are there filads of application in which artificial moral agents should not be deployed, if they should be used at all? Are there moral decisions that should not be delegated to machines? What is the moral and legal status of artificial moral agents? Will artificial moral agents change human social life and morality if they become more pervasive?

TEXTS FOR FURTHER READING

TEXT 1

Big Data

Remarkable advances in computing power and the creation of the World Wide Web have facilitated the creation of very large data sets – a phenomenon sometimes known as big data. These data sets include trillions of words of text, billions of images, and billions of hours of speech and video, as well as vast amounts of genomic data, vehicle tracking data, clickstream data, social network data, and so on.

This has led to the development of learning algorithms specially designed to take advantage of very large data sets. Often, the vast majority of examples in such data sets are unllabeled; for example, in Yarowsky's (1995) influential work on word-sense disambiguation, occurrences of a word such as "plant" are not labeled in the data set to indicate whether they refer to flora or factory. With large enough data sets, however, suitable learning algorithms can achieve an accuracy of over 96 % on the task of identifying which sense was intended in a sentence. Moreover, Banko and Brill (2001) argued that the improvement in performance obtained from increasing the size of the data set by two or three orders of magnitude outweighs any improvement that can be obtained from tweaking the algorithm.

A similar phenomenon seems to occur in computer vision tasks such as filling in holes in photographs – holes caused either by damage or by the removal of ex-friends. A clever method for doing this was developed by blending in pixels from similar images; it was found that the technique worked poorly with a database of only thousands of images but crossed a threshold of quality with millions of images. Soon after, the availability of tens of millions of images in the ImageNet database sparked a revolution in the field of computer vision.

The availability of big data and the shift towards machine learning helped AI recover commercial attractiveness. Big data was a crucial factor in the 2011 victory of IBM's Watson system over human champions in the Jeopardy! Quiz game, an event that had a major impact on the public's perception of AI.

TEXT 2

What Is Supervised Learning?

Supervised learning, also known as supervised machine learning, is a subcategory of machine learning and artificial intelligence. It is defined by its use of labeled data sets to train algorithms to classify data or predict outcomes accurately.

As input data is fed into the model, it adjusts its weights until the model has been fitted appropriately, which occurs as part of the cross validation process. Supervised learning helps organizations solve for a variety of real-world problems at scale, such as classifying spam in a separate folder from your inbox. It can be used to build highly accurate machine learning models.

Supervised learning uses a training set to teach models to yield the desired output. This training dataset includes inputs and correct outputs, which allow the model to learn over time. The algorithm measures its accuracy through the loss function, adjusting until the error has been sufficiently minimized.

Supervised learning can be separated into two types of problems when data mining – classification and regression.

Classification uses an algorithm to accurately assign test data into specific categories. It recognizes specific entities within the dataset and attempts to draw some conclusions on how those entities should be labeled or defined. Common classification algorithms are linear classifiers, support vector machines (SVM), decision trees, k-nearest neighbor, and random forest.

Regression is used to understand the relationship between dependent and independent variables. It is commonly used to make projections, such as for sales revenue for a given business. Linear regression, logistical regression, and polynomial regression are popular regression algorithms.

TEXT 3

Deep Learning

Deep learning is a technique that can learn from massive amounts of data to provide effective solutions to a variety of machine learning problems. One of the most popular approaches is the so-called deep neural networks. They are based on the neural networks whose introduction dates back to Warren McCulloch and Walter Pitts in 1943. At that time, they tried to reproduce the functioning of neurons of the brain by using electronic circuits, which led to the artificial neural networks. The basic idea was to build a network consisting of interconnected layers of nodes. Here, the bottom layer is considered the input layer, and the top layer is considered the output layer. Each node now executes a simple computational rule, such as a simple threshold decision. The outputs of each node in a layer are then passed to the nodes in the next layer using weighted sums. These networks were already extremely successful and produced impressive results, for example, in the field of optical character recognition. However, even then there were already pioneering successes from today’s point of view, for example in the No Hands Across America project, in which a minivan navigated to a large extent autonomously and controlled by a neural network from the east coast to the west coast of the United States. Until the mid-80s of the last century, artificial neural networks played a significant role in machine learning, until they were eventually replaced by probabilistic methods and, for example, Bayesian networks, support vector machines, or Gaussian processes. These techniques have dominated machine learning for more than a decade and have also led to numerous applications, for example in image processing, speech recognition, or even human–machine interaction. However, they have recently been superseded by the deep neural networks, which are characterized by having a massive number of layers that can be effectively trained on modern hardware, such as graphics cards. These deep networks learn representations of the data at different levels of abstraction at each layer. Particularly in conjunction with large data sets (big data), these networks can use efficient algorithms such as backpropagation to optimize the parameters in a single layer based on the previous layer to identify structures in data. Deep neural networks have led to tremendous successes, for example in image, video, or speech processing. But they have also been used with great success in other tasks, such as in the context of object recognition or deep data interpretation.

TEXT 4

What is backpropagation?

In machine learning, backpropagation is an effective algorithm used to train artificial neural networks, especially in feed-forward neural networks.

Backpropagation is an iterative algorithm, that helps to minimize the cost function by determining which weights and biases should be adjusted (Figure). During every epoch, the model learns by adapting the weights and biases to minimize the loss by moving down toward the gradient of the error. Thus, it involves the two most popular optimization algorithms, such as gradient descent or stochastic gradient descent.

Computing the gradient in the backpropagation algorithm helps to minimize the cost function and it can be implemented by using the mathematical rule called chain rule from calculus to navigate through complex layers of the neural network.

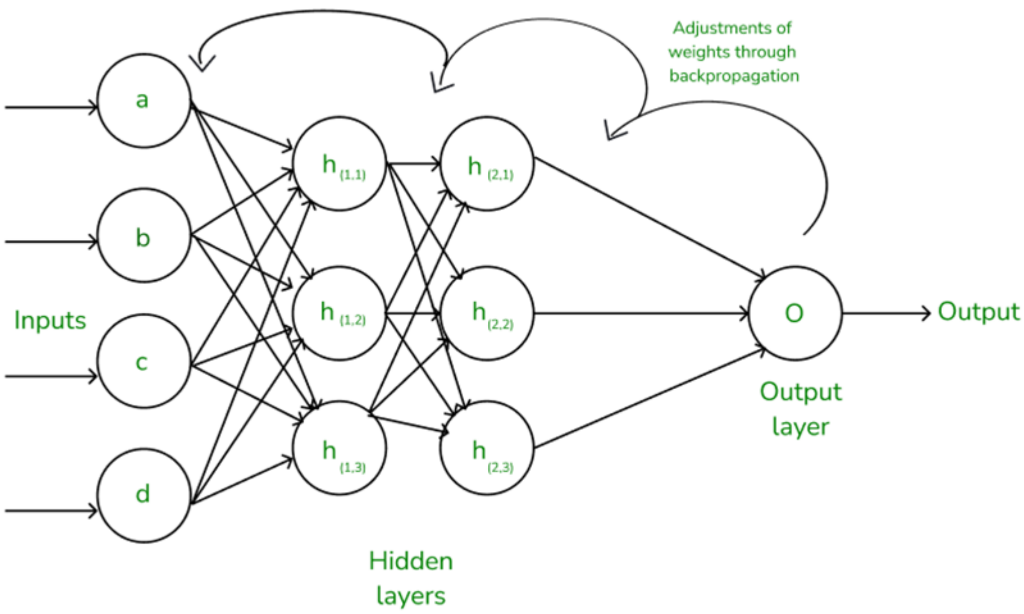

Figure – A simple illustration of how the backpropagation works by adjustments of weights

Backpropagation as a fundamental algorithm in training neural networks offers several advantages that make it a preferred choice for many machine learning tasks. Let us consider them in more detail.

1) Backpropagation does not require prior knowledge of neural networks, making it accessible to beginners. Its straightforward nature simplifies the programming process, as it primarily involves adjusting weights based on error derivatives.

2) The algorithm's simplicity allows it to be applied to a wide range of problems and network architectures. Its flexibility makes it suitable for various scenarios, from simple feedforward networks to complex recurrent or convolutional neural networks.

3) Backpropagation accelerates the learning process by directly updating weights based on the calculated error derivatives. This efficiency is particularly advantageous in training deep neural networks, where learning features of a function can be time-consuming.

4) Backpropagation enables neural networks to generalize well to unseen data by iteratively adjusting weights during training. This generalization ability is crucial for developing models that can make accurate predictions on new, unseen examples.

5) Backpropagation scales well with the size of the dataset and the complexity of the network. This scalability makes it suitable for large-scale machine learning tasks, where training data and network size are significant factors.

TEXT 5

Navigation

Mobile robots must be able to navigate their environments effectively in order to perform various tasks effectively. Consider, for example, a robotic vacuum cleaner or a robotic lawnmower. Most of today's systems do their work by essentially navigating randomly. As a result, as time progresses, the probability increases that the robot will have approached every point in its vicinity once so that the task is never guaranteed but very likely to be completed if one waits for a sufficiently long time. Obviously, such an approach is not optimal in the context of transport robots that are supposed to move an object from the pickup position to the destination as quickly as possible. Several components are needed to execute such a task as effectively as possible. First, the robot must have a path planning component that allows it to get from its current position to the destination point in the shortest possible path. Methods for this come from AI and are based, for example, on the well-known A* algorithm for the effective computation of shortest paths. For path planning, robotic systems typically use maps, either directly in the form of roadmaps or by subdividing the environment of the robot into free and occupied space in order to derive roadmaps from this representation. However, a robot can only assume under very strong restrictions that the once planned path is actually free of obstacles. This is, in particular, the case if the robot operates in a dynamic environment, for example in one used by humans. In dynamic, real-world environments the robot has to face situations in which doors are closed, that there are obstacles on the planned path or that the environment has changed and the given map is, therefore, no longer valid. One of the most popular approaches to attack this problem is to equip the robot with sensors that allow it to measure the distance to obstacles and thus avoid obstacles. Additionally, an approach is used that avoids collisions and makes dynamic adjustments to the previously planned path. In order to navigate along a planned path, the robot must actually be able to accurately determine its position on the map and on the planned path (or distance from it). For this purpose, current navigation systems for robots use special algorithms based on probabilistic principles, such as the Kalman filter or the particle filter algorithm. Both approaches and their variants have been shown to be extremely robust for determining a probability distribution about the position of the vehicle based on the distances to obstacles determined by the distance sensor and the given obstacle map. Given this distribution, the robot can choose its most likely position to make its navigation decisions. The majority of autonomously navigating robots that are not guided by induction loops, optical markers, or lines utilize probabilistic approaches for robot localization. A basic requirement for the components discussed thus far is the existence of a map. But how can a robot obtain such an obstacle map? In principle, there are two possible solutions for this. First, the user can measure the environment and use it to create a map with the exact positions of all objects in the robot's workspace. This map can then be used to calculate the position of the vehicle or to calculate paths in the environment. The alternative is to use a so-called SLAM (Simultaneous Localization and Mapping) method. Here, the robot is steered through its environment and, based on the data gathered throughout this process, automatically computes the map. Incidentally, this SLAM technique is also known in photogrammetry where it is used for generating maps based on measurements. These four components: path planning, collision avoidance and replanning, localization, and SLAM for map generation are key to today's navigation robots and also self-driving cars.

TEXT 6

Autonomous Vehicles

Machine learning and AI are foundational elements of autonomous vehicle systems. Vehicles are trained on complex data (e.g., the movement of other vehicles, road signs) with machine learning, which helps to improve the algorithms they operate under. AI enables vehicles' systems to make decisions without needing specific instructions for each potential situation.

In order to make autonomous vehicles safe and effective, artificial simulations are created to test their capabilities. To create such simulations, black-box testing is used, in contrast to white-box validation. White-box testing, in which the internal structure of the system being tested is known to the tester, can prove the absence of failure. Black-box methods are much more complicated and involve taking a more adversarial approach. In such methods, the internal design of the system is unknown to the tester, who instead targets the external design and structure. These methods attempt to find weaknesses in the system to ensure that it meets high safety standards.

As of 2024, fully autonomous vehicles are not available for consumer purchase. Certain obstacles have proved challenging to overcome. For example, maps of almost four million miles of public roads in the United States would be needed for an autonomous vehicle to operate effectively, which presents a daunting task for manufacturers. Additionally, the most popular cars with a "self-driving" feature, those of Tesla, have raised safety concerns, as such vehicles have even headed toward oncoming traffic and metal posts. AI has not progressed to the point where cars can engage in complex interactions with other drivers or with cyclists or pedestrians. Such "common sense" is necessary to prevent accidents and create a safe environment.

In October 2015 Google's self-driving car, Waymo (which the company had been working on since 2009) completed its first fully driverless trip with one passenger. The technology had been tested on one billion miles within simulations, and two million miles on real roads. Waymo, which boasts a fleet of fully electric-powered vehicles, operates in San Francisco and Phoenix, where users can call for a ride, much as with Uber or Lyft. The steering wheel, gas pedal, and brake pedal operate without human guidance, differentiating the technology from Tesla's autonomous driving feature. Though the technology's valuation peaked at $175 billion in November 2019, it had sunk to just $30 billion by 2020. Waymo is being investigated by the U.S. National Highway Traffic Safety Administration (NHTSA) after more than 20 different reports of traffic violations. In certain cases, the vehicles drove on the wrong side of the road and in one instance, hit a cyclist.

TEXT 7

AI-based Quality Control and Inspection

Artificial Intelligence (AI) is transforming quality control and inspection in industrial manufacturing by enhancing accuracy, consistency, and efficiency. AI-driven systems, particularly those utilizing machine learning and computer vision, are revolutionizing the way defects are detected and quality is ensured throughout the production process.

One of the primary applications of AI in quality control is visual inspection. Traditional inspection methods rely heavily on human inspectors, who can be prone to fatigue and subjective judgment. AI-powered visual inspection systems, on the other hand, use advanced image recognition algorithms to analyze products in real-time. These systems can identify defects, such as surface imperfections, misalignments, and structural anomalies, with a level of precision and speed that far surpasses human capabilities.

Machine learning plays a crucial role in improving the accuracy of these inspections. By training on vast datasets of images and defect patterns, machine learning models learn to recognize even the subtlest deviations from quality standards. Over time, these models continue to improve as they are exposed to more data, becoming increasingly adept at identifying defects that might have previously gone unnoticed.

Consistency is another significant benefit of AI in quality control. Human inspectors may have varying levels of expertise and may perform differently under different conditions. AI systems, however, provide a consistent level of performance regardless of external factors, ensuring that each product is inspected to the same high standard.

AI also enhances efficiency in the inspection process. Automated inspection systems can operate continuously without breaks, significantly increasing the throughput of inspected items. This continuous operation not only speeds up the production line but also reduces the likelihood of bottlenecks caused by manual inspection processes.

Furthermore, AI systems are capable of analyzing complex patterns and correlations that might be missed by human inspectors. For instance, in the semiconductor industry, AI can detect minute defects and variations in microchips that are critical to the functionality of electronic devices. This capability is crucial in industries where even the smallest defect can lead to significant product failures.

AI-driven quality control systems also facilitate real-time feedback and process adjustments. When a defect is detected, the system can immediately alert operators or automatically adjust the production parameters to correct the issue. This real-time intervention minimizes the production of defective products and reduces waste.

In addition to visual inspection, AI is used in non-destructive testing (NDT) methods such as ultrasonic, radiographic, and thermal imaging inspections. AI algorithms analyze the data from these tests to identify internal defects that are not visible to the naked eye, further ensuring the integrity and reliability of the final product.

Thus, AI is revolutionizing quality control and inspection by providing unparalleled accuracy, consistency, and efficiency. By leveraging machine learning and computer vision, AI systems enhance defect detection, improve inspection speed, and ensure high-quality standards across various industries. This transformation not only boosts productivity but also ensures that products meet stringent quality requirements, ultimately leading to greater customer satisfaction and reduced costs associated with defective products.

TEXT 8

Automated AI-Based Predictive Maintenance

An automated AI-based Predictive Maintenance solution can prevent asset failures and unplanned downtime. It consists of IIoT hardware that connects physical assets to each other, and an advanced analytics platform that analyzes the complex machine data to predict failures and prevent unplanned downtime. AI-based Predictive Maintenance solutions ensure remote condition monitoring and facilitate proactive asset maintenance.

The goal of an automated AI-based Predictive Maintenance system is to maintain and improve the performance of critical industrial assets, resulting in fewer failures, reduced downtime, increased production and improved workplace safety. The AI-based system uses machine output data, including historical performance as well as real-time contextual data, and analyses it using machine learning algorithms to notify maintenance and reliability professionals of the maintenance needs of different equipment sets.

Automated AI-based Predictive Maintenance System is a powerful tool that can help the maintenance & reliability professionals to streamline the extraction of actionable information from the machine health and performance data, to improve the overall manufacturing operations.

Automated AI-based Predictive Maintenance offers myriad benefits to the manufacturing industry.

The first big benefit of Artificial Intelligence in predictive maintenance is the ability to detect faults before they happen. This means that organizations can prevent costly equipment failures before they occur. This helps companies to save costs that are associated with frequent maintenance activities.

AI-based predictive maintenance systems also help companies prevent production losses from faulty equipment, and with fewer repairs needed, companies will spend less on hiring outside contractors and service technicians.

Furthermore, it helps companies save time as it eliminates the need for manual inspection checks or trips to the shop floor for diagnostics.

It also improves the workplace safety for engineers and technicians by collecting automatically data from the machines in complex and hard-to-reach places.

All these factors make AI a much more cost-effective option than traditional maintenance methods and other forms of redundancy like backups or replacements.

ГРАММАТИЧЕСКИЕ ТАБЛИЦЫ

Таблица 1 – Глагол “to be”

Функция в предложении и значение	**Примеры**	**Перевод**
1. Смысловой глагол «быть», «являться», «находиться».	1. A bit <u>is</u> the smallest part of information. 2. Many memorizing elements <u>are</u> on one chip.	1. Бит <u>является</u> самой малой частью информации. 2. Много запоминающих элементов <u>находится</u> на одном чипе.
2. Вспомогательный глагол для образования сложных глагольных времен (группа Continuous и Passive Voice). Самостоятельно не переводится.	1. Computer <u>is storing</u> information. 2. Bits <u>are grouped</u> in units that <u>are called</u> bytes.	1. Компьютер <u>хранит</u> информацию. 2. Биты <u>объединяются</u> в единицы, которые <u>называются</u> байты.
3. Модальный глагол (в сочетании с инфинитивом другого глагола с частицей "to"). «Должен», «нужно».	The results of the experiment <u>are to be checked.</u>	Результаты эксперимента <u>должны быть</u> проверены.
4. В конструкции "there is (are)" – «существует», «имеется», «есть».	<u>There are</u> two methods of solving this problem.	<u>Существует</u> два метода решения этой задачи.

Таблица 2 – Глагол “to have”

Функция в предложении и значение	Примеры	Перевод
1. Смысловой глагол «иметь».	Each memory location has its own unique address	Каждая ячейка памяти имеет свой единственный адрес. (У каждой ячейки памяти есть свой единственный адрес.)
2. Вспомогательный глагол для образования сложных глагольных времен (группа времен Perfect). Самостоятельно не переводится.	The invention has made people's work easier.	Изобретение облегчило труд людей.
3. Модальный глагол (в сочетании с инфинитивом другого глагола с частицей "to"). «Должен», «вынужден».	For digital computer the information has to be in the form of digits or numbers.	Для цифрового компьютера информация должна быть в виде цифр или чисел.

Таблица 3 – Страдательный (пассивный) залог: глагол to be + Participle II

Способы перевода	Примеры	Перевод
1. Сочетание глагола «быть» с кратким страдательным причастием прошедшего времени с суффиксом -н или -т. Глагол "быть" в настоящем времени не употребляется.	The device is made by us. was made has been made had been made will be made	Прибор делается нами. был сделан был сделан был сделан будет сделан
2. Глагол на -ся в соответствующем времени, лице и числе.	The machine-tool is operated by the new electronic system.	Станок приводится в действие новой электронной системой.
3. Глагол действительного залога в 3 лице множественного числа в неопределенно-личном предложении.	The experiment was made last year.	Эксперимент провели в прошлом году.
4. Глаголы с относящимися к ним предлогам, которые переводятся также глаголами с предлогом: **to depend on** – зависеть от; **to insist on** – настаивать на; **to look at** – смотреть на; **to refer to** – ссылаться на; **to rely on** – полагаться на; t**o speak of (about)** – говорить о; **to send for –** послать за; **to deal with** – иметь дело с и другие. Переводятся глаголами в неопределенно-личной форме, причем соответствующий предлог ставится перед английским подлежащим.	This discovery is often referred to. This system is much spoken of.	**На** это открытие часто ссылаются. **Об** этой системе много говорят.
5. Глаголы без предлогов, которые переводятся глаголами с предлогами: to affect – влиять на; **to act** – действовать на; **to answer** – отвечать на; **to attend** – присутствовать на; **to follow** – следовать за; **to influence** – влиять на и другие. Переводятся глаголами в действительном (активном) залоге, причем перевод надо начинать с предлога, поставив его **перед** английским подлежащим.	The work of this device is affected by electricity.	**На** работу этого прибора влияет электричество.

Таблица 4 – Модальные глаголы

Модальный глагол и его эквивалент	Значение	Времена		
		Present	Past	Future
must **to have to**	должен, надо, нужно, вынужден, приходится	must work have (has) to work	– had to work	– shall /will have to work
can **to be able to**	могу, умею	can work am (is, are) able to work	could work was (were) able to work	– shall /will be able to work
may **to be allowed to**	могу, можно, разрешено	may work am (is, are) allowed to work	might work was (were) allowed to work	– shall /will be allowed to work
to be to	должен, предстоит (обусловлено заранее намеченным планом)	am (is, are) to work	was (were) to work	–
should	должен, должен бы, следует, следовало бы (рекомендация)	This device should be handled carefully. – С этим прибором следует обращаться осторожно.		
ought to	должен, следует (совет, моральный долг)	The result of this experiment ought to be checked. – Результат этого эксперимента следует проверить		

Таблица 5 – Причастия

Вид причастия, примеры	Функция в предложении и перевод		
	Часть сказуемого	Определение	Обстоятельство
1	2	3	4
1. Participle I, active voice. **solving, writing**	He is solving a problem. Он решает задачу. (Для образования времен группы Continuous. Самостоятельно не переводится).	The engineer solving this problem works hard. Инженер, решающий эту задачу, работает много. The operator examined the device showing the disturbances. Оператор осмотрел прибор, показавший нарушения в работе. (Причастия на -щий, -вший).	(When, while) solving the problem he read many books. Решая задачу, он прочитал много книг. (Деепричастие на -а, -я).
2. Participle I, passive voice. **being solved, being written**	The problem is being solved. Задача решается. (Для образования времен группы Continuous пассивного залога. Самостоятельно не переводится).	The problem being solved was difficult. Решаемая задача была трудная. (Причастия на -емый и -имый).	(While) being solved, the problem offered some unexpected aspects. Когда ее решали (во время решения), задача представила некоторые неожиданные стороны. (Придаточное обстоятельственное предложение или обстоятельство, выраженное существительным с предлогом).

1	2	3	4
3. Participle II, passive voice. **solved, written**	1) He has <u>solved</u> the problem. Он решил задачу. (Для образования времен Perfect. <u>Самостоятельно не переводится</u>). 2) The problem is <u>solved</u>. Задача решена. (Для образования пассивного залога. <u>Самостоятельно не переводится</u>).	1) The problem <u>solved</u> turned out to be fundamental. <u>Решенная</u> задача оказа-лась фундаментальной. 2) The problem <u>discussed</u> there yesterday is very important. Проблема, <u>обсужденная</u> (<u>обсуждавшаяся</u>) вчера, очень важна. (<u>Причастие на -щийся, -мый, -ный</u>, <u>-тый, -вшийся</u>).	If <u>solved</u>, the problem will offer numerous consequences. <u>Если ее решить</u>, задача будет иметь многочисленные последствия. (<u>Обстоятельственное придаточное предложение</u>).
4. Perfect Participle, active voice. **having solved, having written**	–	–	<u>Having solved</u> the problem he left the classroom. <u>Решив</u> задачу, он ушел из класса. <u>(Деепричастие на -ив, -ав).</u>
5. Perfect Participle, passive voice. **having been solved, having been written**	–	–	<u>Having been solved</u>, the problem offered some unexpected consequences. <u>После того, как задача была решена,</u> обнаружились некоторые ее неожиданные следствия. (<u>Придаточное обстоятельственное предложение).</u>

Таблица 6 – Независимый причастный оборот

Примеры	Перевод
1) The problem ***being*** difficult, they worked hard.	***Так как*** задача ***была*** трудная, они работали много.
2) The experiment ***being carried out***, he cannot leave the laboratory.	***Когда (т. к.)*** эксперимент ***идет***, он не может уйти из лаборатории.
3) *With* the results *being* different, scientists had to repeat their experiment.	***Поскольку*** результаты ***были*** разными, ученым пришлось повторить свой эксперимент.
4) He read two articles on this subject, the latter ***being*** more interesting.	Он прочитал две статьи на эту тему, ***причем*** последняя ***была*** более интересной.

Таблица 7 – Герундий

Функция в предложении	Примеры	Перевод
1. Подлежащее	Supervising the production is very important.	Наблюдение (наблюдать) за производством очень важно. (Существительное, инфинитив).
2. Часть сказуемого	The main task is switching off the system in time.	Главная задача – выключение (выключить) систему вовремя. (Существительное, инфинитив).
3. Прямое дополнение	The production requires utilizing supervisory system.	Производство требует использования (использовать) системы наблюдения. (Существительное, инфинитив).
4. Определение (обычно с предлогами of, for после существительного)	The property of influencing the production run is studied carefully.	Свойство влиять на ход производства тщательно изучается. (Инфинитив).
5. Обстоятельство (обычно с предлогами in – при, в то время как; on (upon) – по, после; after – после; before – перед; by – творительный падеж; instead of – вместо того, чтобы; for – для и т.д.)	The operator examined the machine without diminishing its speed.	Оператор осмотрел машину, не уменьшая (без уменьшения) ее скорости. (Существительное, деепричастие).

Таблица 8 – Инфинитив

Функция	Примеры	Перевод
1. Подлежащее.	To design a good control system is not easy	Спроектировать хорошую систему (проектирование хорошей системы) управления непросто. (Инфинитив, существительное).
2. Часть сказуемого: а) после глагола-связки; б) после модального глагола.	а) Their aim is to improve the control system. б) You have to improve the control system.	а) Их цель – (состоит в том, чтобы) усовершенствовать систему управления. (Инфинитив). б) Вы должны усовершенствовать систему управления. (Инфинитив).
3. Дополнение.	The operator prefers to use the new device.	Оператор предпочитает использовать новое устройство (использование нового устройства). (Инфинитив, существительное).
4. Определение.	1) They have the possibility to use this system. 2) The new equipment to be used at our laboratory has just arrived. 3) He was the first to begin this experiment.	1) У них есть возможность использовать эту систему. (Инфинитив, существительное). 2) Новое оборудование, которое будет (должно быть) использовано в нашей лаборатории, только что прибыло. (Определительное придаточное предложение со сказуемым, выражающим действие, которое должно быть или будет совершено). 3) Он первым начал этот эксперимент.
5. Обстоятельство цели.	To design a good control system, you must have good knowledge of electronics.	Чтобы спроектировать хорошую систему управления, вы должны иметь хорошие знания электроники. (Инфинитив с союзами чтобы, для того, чтобы).

Таблица 9 – Инфинитивные обороты

<table>
<tr><th colspan="3">Примеры</th><th colspan="2">Перевод</th></tr>
<tr><td colspan="5">I. Сложное подлежащее</td></tr>
<tr><td colspan="3">1</td><td colspan="2">2</td></tr>
<tr><td colspan="3"></td><td colspan="2">Переводится двумя способами:
1. Дополнительным придаточным предложением с союзами «что», «чтобы», «как». Инфинитив переводится личной глагольной формой.</td></tr>
<tr><td>This device</td><td>is known
is likely
is certain
is found
is reported
is assumed
is considered
is expected
appears
seems
proved</td><td>to work very efficiently.</td><td>Известно
Вероятно
Несомненно
Обнаружено
Сообщают
Допускается
Считается
Ожидается
Оказывается
Кажется
Доказано</td><td>, что это устройство работает очень эффективно.</td></tr>
<tr><td colspan="3"></td><td colspan="2">2. Простым предложением с вводным словом, соответствующим сказуемому английского предложения.</td></tr>
<tr><td colspan="3">This device is known to work very efficiently.</td><td colspan="2">Это устройство, как известно, работает очень эффективно.</td></tr>
</table>

Окончание табл. 9

<table>
<tr><th colspan="2">II. Сложное дополнение</th></tr>
<tr><td>1</td><td>2</td></tr>
<tr><td>1) They want (like) the plan to be fulfilled.
2) * They see (hear) the engineer leave the room.

3) * They order, allow (let), cause, force (make) these data to be processed immediately.</td><td rowspan="2">1) Они хотят, чтобы план был выполнен.
2) Они видят (слышат), что инженер уходит из комнаты.
3) Они приказывают (позволяют, заставляют), чтобы эти данные были обработаны немедленно.
Переводится придаточным предложением с союзами «что», «чтобы», «как». Инфинитив переводится личной глагольной формой.</td></tr>
<tr><td>* После глаголов чувственного восприятия (see, hear, feel и т. д.), а также глаголов let, make, have используется инфинитив без частицы "to".</td></tr>
</table>

Таблица 10 – Многофункциональное слово “one”

Функция, значение	Примеры		Перевод	
1. Числительное «один», «одна», «одно».	This design is one of the oldest.		Эта конструкция – одна из самых старых.	
2. Формальное подлежащее в неопределенно-личных предложениях. Самостоятельно не переводится.	One knows One believes One can expect One must expect One may expect One should expect	that the machine will work well.	Известно Считают Можно ожидать Нужно ожидать Можно ожидать Следует ожидать	, что машина будет работать хорошо.
3. Словозаменитель. Переводится тем существительным, которое заменяет, или опускается в переводе.	The new way of processing data differs from the old one.		Новый способ обработки данных отличается от старого (способа).	
4. Местоимения в форме притяжательного падежа one's - свой, собственный, чей-то.	No one likes when somebody reads one’s letters.		Никому не нравится, когда кто-либо читает его письма.	

Таблица 11 – Многофункциональные слова “that”, “those”, “this”, “these”

Функция и значение	Примеры	Перевод
	“that” – “those”	
1. Указательное местоимение «тот» – «те», «этот» – «эти».	**Those** computers are used in manufacturing process.	**Эти (те)** компьютеры используются в производственном процессе.
2. Слово-заменитель, переводится тем существительным, которое оно заменяет. Иногда опускается.	The efficiency of the old apparatus is low compared with **that** of the new device.	Производительность старого прибора низкая по сравнению с **производительностью** нового устройства (с новым устройством).
3. “that” – союзное слово «который».	The device **that** was installed in our laboratory is efficient.	Устройство, **которое** было установлено в нашей лаборатории, эффективно.
4. “that” – союз «что», «чтобы».	One can say **that** this apparatus is the most useful.	Можно сказать, **что** этот прибор самый нужный.
	“this” – “these”	
1. Указательное местоимение «этот» – «эти».	**These** systems will be installed at our mill.	**Эти** системы будут установлены на нашем заводе.
2. These – "они", заменитель существительного.	The elements of the Periodic group IA are called "the alkali metals". **These** are alike in having a single electron on the outermost shell.	Элементы периодической системы группы IA называются "щелочными металлами". **Они** сходны тем, что имеют по одному электрону на внешней оболочке.

Таблица 12 – Многофункциональное слово “it”

Функция и значение	Примеры	Перевод
1. Личное местоимение «он», «она», «оно» (неодушевленный предмет).	A new device is created in the laboratory. **It** will be very efficient.	Новый прибор создан в лаборатории. **Он** будет очень эффективным.
2. Указательное местоимение «это».	The temperature is rising slowly. **It** means that…	Температура медленно поднимается. **Это** означает, что…
3. Формальное подлежащее безличного предложения. Самостоятельно не переводится.	It is a common practice It is essential It is impossible It is important It is expected to use this tool.	Обычно принято Важно Невозможно Важно Ожидается использовать этот инструмент (использование этого инструмента)
4. Формальное дополнение после некоторых глаголов. Не переводится.	The method makes **it** possible to obtain good productivity.	Метод делает возможным получение хорошей производительности.
5. Часть эмфатической (выделительной) конструкции "**it is … that (which)**". Переводится «именно», «это», «только», и т. д.	**It is** in our laboratory **that** the new design was created. **It was** not until 1950 **that** the new technique entered into practice.	**Именно (это)** в нашей лаборатории был создан новый проект. **Только** в 1950 г. новый метод вошел в употребление.

Таблица 13 – Типы условных придаточных предложений

Тип условного придаточного, употребляемые времена	Пример	Перевод
0. Нулевое условие для описания фактов После союза (if) – Present Simple, в главном предложении – Present Simple	If you take the ice out of the refrigerator, it melts	Если достать лед из холодильника, он тает.
1. Реальное условие. После союза (if) – Present Simple, в главном предложении – Future Simple	If you give him the book, he will read it.	Если вы дадите ему книгу, он ее прочитает.
2. Не вполне реальное условие. После союза (if) – Past Simple, в главном предложении– should, would, could, might + Infinitive	If you gave him the book, he would read it.	Если бы вы дали ему книгу, он прочитал бы ее.
3. Нереальное условие в прошлом. После союза (if) – Past Perfect, в главном предложении– should, would, could, might + have + Participle II смыслового глагола	If you had given him the book yesterday, he would have read it.	Если бы вы дали ему вчера книгу, он прочитал бы ее.
4. Смешанный тип. а) Нереальная ситуация в прошлом с условием, справедливым для настоящего. После союза (if) – Past Simple, в главном предложении– should, would, could, might + have + Participle II смыслового глагола. б) Нереальная ситуация в настоящем или будущем с условием в прошлом, После союза (if) – Past Perfect, в главном предложении– should, would, could, might + have + Infinitive смыслового глагола	If I were clever enough, I wouldn't have done this. If I had won that lottery, I would now live in France	Будь я достаточно умен, я бы так не поступил. Если бы я выиграл в той лотерее, я бы сейчас жил во Франции.

СЛОВАРЬ

А		
absence (n.)	ˈæbs(ə)ns	отсутствие
absentee (n.)	ˌæbsənˈtiː	прогульщик
AC (alternating current)	ˈɔ:ltəneıtıŋˈ kʌrənt	переменный ток
accelerate (v.)	əkˈseləreıt	ускорять(ся)
acceptable (adj.)	əkˈseptəbl	приемлемый
access (n.)	ˈækses	доступ
accessible (adj.)	əkˈsesəb(ə)l	доступный, достижимый
accident (n.)	ˈæksıd(ə)nt	случай
according to (prep.)	əˈkɔ:dıŋtə	согласно, в соответствии с
accordingly (adv.)	əˈkɔ:dıŋlı	соответственно
accountability (n.)	əˈkauntəˈbılıtı	отчетность, отслеживаемость
accuracy (n.)	ˈækjərəsı	точность, корректность
accurate (adj.)	ˈækjərət	точный, достоверный
achieve (v.)	əˈʧi:v	достигать
acknowledge (v.)	əkˈnɔlıʤ	подтверждать, признавать
acquire (v.)	əˈkwaıə	получать, приобретать
acquisition (n.)	ˌækwıˈzıʃn	приобретение
action (n.)	ˈækʃ(ə)n	действие
actionable (adj.)	ˈækʃ(ə)nəb(ə)l	выполнимый, осуществимый
activity (n.)	ækˈtıvıtı	действие, работа, активность
actual (adj.)	ˈækʧuəl	фактический, действительный
actualize (v.)	ˈæktʃuəlaız	осуществлять, реализовывать
actually (adv.)	ˈækʧ(u)əlı	фактически, на самом деле
acyclic (adj.)	əˈsaıklık	ацикличный, непериодический
adapt (v.)	əˈdæpt	настраивать, приспосабливать
additional (adj.)	əˈdıʃ(ə)nəl	дополнительный, вспомогательный
additionally (adv.)	əˈdıʃ(ə)nəlı	дополнительно, кроме того
address (v.)	əˈdres	обращаться, рассматривать
adept (adj.)	æˈdept	опытный, подходящий
adherent (adj.) (n.)	ədˈhı(ə)rənt	прилегающий приверженец, последователь
adjust (v.)	əˈʤʌst	регулировать, выверять
adjustable (adj.)	əˈʤʌstəb(ə)l	регулируемый, приспосабливаемый
adjustment (n.)	əˈʤʌstmənt	регулировка, настройка
adopt (v.)	əˈdɔpt	принимать, вводить
advance (n.) (v.) in advance	ədˈvɑ:ns	достижение, улучшение; продвигаться, происходить; заранее

advanced (adj.)	ədˈvɑ:nst	передовой, высокотехнологичный
advantage (n.) take advantage of	ədˈvɑ:ntɪʤ	преимущество; воспользоваться
advantageous (adj.)	ˌædvənˈteɪdʒəs	выгодный, благоприятный
advent (n.)	ˈædvent	появление, наступление
adversarial (adj.)	ˌædvɜːˈsɛərɪəl	конфликтующий
agenda (n.)	əˈʤendə	повестка дня, проблематика
agent (n.) software agent	ˈeɪʤ(ə)nt	агент, контроллер, устройство управления; программный агент
aid (n., v.)	eɪd	помощь, подкрепление, средство
aim (n.) aim to (v.)	eɪm	цель, задача, намерение; быть направленным на, иметь целью
akin (adj.)	əˈkɪn	похожий, близкий
alert (adj.)	əˈlɜ:t]	сигнальный, предупредительный
allow (v.)	əˈlau	разрешать, допускать
alter (v.)	ˈɔ:ltə	изменять(ся)
although (conj.)	ɔ:lˈðəu	хотя, несмотря на
amalgamation (n.)	əˈmælgəˈmeɪʃ(ə)n	объединение, слияние
ambiguity (n.)	ˌæmbɪˈgjuːəti	неясность, двусмысленность
amount (n.) amount to (v.)	əˈmaunt	количество, величина, объем; составлять, равняться
ANN (artificial neural network)		искусственная нейронная сеть
anomaly (n.)	əˈnɔməlɪ	аномалия, отклонение, искажение
anticipate (v.)	ænˈtɪsɪpeɪt	предвидеть, предугадать
appealing (adj.)	əˈpi:lɪŋ	привлекательный, вызывающий интерес
appearance (n.)	əˈpɪ(ə)rəns	внешность; появление
applicability (n.)	əˈplɪkəˈbɪlɪtɪ	применимость, пригодность
application (n.)	ˈæplɪˈkeɪʃ(ə)n	применение, приложение
apply (v.)	əˈplaɪ	применять
approach (n.)	əˈprəuʧ	подход
approachable (adj.)	əˈprəuʧəb(ə)l	доступный, достижимый
appropriately (adv.)	əˈprəuprɪɪtlɪ	должным образом, адекватно
approximate (v.) (adj.)	əˈprɒksɪmeɪt əˈprɒksɪmət	приближенно равняться, приближаться; приблизительный, аппроксимирующий

approximation (n.)	əˈprɔksɪˈmeɪʃ(ə)n	аппроксимация, приближенная величина
arbitrary (adj.)	ˈɑ:bɪtrərɪ	произвольно выбранный, произвольный, стохастический
arduous (adj.)	ˈɑ:djuəs	трудный, изнурительный
area (n.)	ˈe(ə)rɪə	область, поле
arguably (adv.)	ˈɑːgjuəbli	вероятно; по мнению некоторых
arise (v.)	əˈraɪz	возникать, являться результатом
articulate (v.) (adj.)	ɑːˈtɪkjuleɪt ɑːˈtɪkjələt	четко формулировать; ясный, четкий
artificer (n.)	ɑːˈtɪfɪsə	мастер, механик
artificial (adj.)	ˈɑ:tɪˈfɪʃ(ə)l	искусственный
assembly (n.)	əˈsemblɪ	сборка; комплект приборов
assess (v.)	əˈses	оценивать, определять
assets (n., pl.)	ˈæsets	ресурсы, активы, фонды
assign (v.)	əˈsaɪn	определять, задавать, присваивать
assignment (n.)	əˈsaɪnmənt	задание
assist (v.)	əˈsɪst	помогать, содействовать
assistance (n.)	əˈsɪst(ə)ns	помощь, содействие
associate (v.)	əˈsəʊsieɪt, əˈsəʊʃieɪt	объединять(ся), ассоциировать
association (n.)	əˌsəʊsiˈeɪʃən, əˌsəʊʃiˈeɪʃən	связь, сопряжение, соединение, ассоциация
assume (v.)	əˈsju:m	допускать, принимать
assumption (n.)	əˈsʌmpʃ(ə)n	предположение, допущение
attack (v.)	əˈtæk	приступать к решению
attempt (n.) (v.)	əˈtempt	пытаться, делать попытку; попытка
attractive (adj.)	əˈtræktɪv	привлекательный, перспективный
attractiveness (n.)	əˈtræktɪvnɪs	привлекательность
attribute (n.) (v.)	ˈætrɪbju:t əˈtrɪbjuːt	элемент, признак, критерий; приписывать, относить
autoencoder (n.)	ˈɔ:təu ɪnˈkəudə	автокодировщик
automate (v.)	ˈɔ:təmeɪt	автоматизировать, подвергать автоматической обработке
autonomous (adj.)	ɔːˈtɔnəməs	автономный
availability (n.)	əˈveɪləˈbɪlɪtɪ	доступность, наличие
available (adj.)	əˈveɪləb(ə)l	доступный, имеющийся в наличии
avenue (n.)	ˈævənjuː	путь, метод
avoid (v.)	əˈvɔɪd	избегать, обходить

avoidance (n.)	əˈvɔɪd(ə)ns	избежание, обход
awareness (n.)	əˈweənəs	информированность, учёт особенностей
B		
backpropagation (n.)	bæk ˈprɔpəˈgeɪʃ(ə)n	обратное распространение ошибки
backtrack (v.)	ˈbæktræk	отслеживать в обратном порядке, отслеживать с возвратом
backtracking (n.)	ˈbækˌtrækɪŋ	механизм перебора с возвратом
backup (n.)	ˈbækʌp	резервная копия, техническое обслуживание
baseline (n.)	ˈbeɪslaɪn	основа, ориентир
batch (n.)	bæʧ	пакет данных, партия
because (conj.) because of (prep.)	bɪˈkɔz]	потому что; из-за
beforehand (adv.)	bɪˈfɔ:hænd	заранее, предварительно
behavior (n.)	bɪˈheɪvjə, -jər	поведение, характер, режим работы
belief (n.)	bɪˈliːf	убеждение
belong (v.)	bɪˈlɔŋ	принадлежать, быть частью
beneficial (adj.)	ˈbenɪˈfɪʃ(ə)l	полезный, эффективный
besides (prep.) (adv.)	bɪˈsaɪdz	кроме; помимо этого
bias (n.)	ˈbaɪəs	систематическая ошибка выборки, смешение, отклонение
biased (adj.)	bɪˈsaɪdz	необъективный
binary (adj.)	ˈbaɪnəri	двоичный, бинарный
blackboard	ˈblækbɔːd	доска объявлений, информационная доска
black-box	ˌblæk ˈbɒks	«черный ящик», объект исследования с неизвестными свойствами
boost (v.)	bu:st	повышать, увеличивать
boosting (n.)	ˈbuːstɪŋ	повышение, усиление
bottleneck (n.)	ˈbɔtlnek	препятствие, уязвимое место
bottom (n.)	ˈbɔtəm	низ
brake (n.)	breɪk	тормоз
break (n.)	breɪk	перебой, перерыв
break down (v.)	ˈbreɪkˈdaun	ломать(ся)
breakthrough (n.)	ˈbreɪkθruː	открытие, прорыв
bulb (n.)	bʌlb	лампочка

C		
calculate (v.)	ˈkælkjuleɪt	вычислять, подсчитывать
calculus (n.)	ˈkælkjuləs	вычисление, исчисление
capability (n.)	ˈkeɪpəˈbɪlɪtɪ	способность, техническая возможность
capable (adj.)	ˈkeɪpəb(ə)l	способный
capture (v.)	ˈkæpʧə	собирать (данные)
case (n.)	keɪs	случай, кейс, пример, прецедент
causal (adj.)	ˈkɔ:z(ə)l	каузальный
certain (adj.)	ˈsɜ:tn	конкретный, определенный, некоторый
chain	tʃeɪn	цепь
challenge (n.)	ˈʧælɪnʤ	задача, трудность, вызов
chaining backward chaining	'tʃeiniŋ	сцепление; обратный логический вывод
challenging (adj.)	ˈʧælɪnʤɪŋ	трудный, но интересный, требующий особого подхода
choice (n.)	ʧɔɪs	выбор
circuit (n.)	ˈsɜ:kɪt	схема
circumstance (n.)	ˈsɜ:kəmstæns	обстоятельство
cite (v.)	saɪt	цитировать, ссылаться на
classifier (n.)	ˈklæsɪfaɪə	классификатор
cleanliness (n.)	ˈklenlɪnɪs	чистота
clickstream (n.)	ˈklɪkˌstri:m	история посещений
cluster (v.)	ˈklʌstə	объединять(ся) в кластеры, кластеризовать(ся)
clustering (n.) K-means clustering	ˈklʌstərɪŋ	кластеризация, группирование кластеризация методом k-средних
cluttered (adj.)	ˈklʌtəd	приведенный в беспорядок
codify (v.)	ˈkəʊdɪfaɪ	кодировать, шифровать
coexist (v.)	kəʊigˈzist	сосуществовать
coincidentally (adv.)	kəʊˌɪnsɪˈdentəli	случайно, по случайному совпадению
collaboration (n.)	kəˈlæbəˈreɪʃ(ə)n	сотрудничество, совместная работа
collision (n.)	kəˈlɪʒ(ə)n	столкновение, авария
combine (v.)	kəmˈbaɪn	объединять, сочетать
combustion (n.)	kəmˈbʌsʧ(ə)n	горение
come up with (v.)		предлагать, придумывать
commonly (adv.)	ˈkɔmənlɪ	обычно, как правило
commonly-cited (adj.)	ˈkɔmənlɪ ˈsaɪtɪd	часто упоминающийся
communicate (v.)	kəˈmjuːnɪkeɪt	сообщать(ся), передавать

comparable (adj.)	ˈkɒmpərəbl	сопоставимый
compare (v.)	kəmˈpeə	сравнивать, сопоставлять
comparison (n.)	kəmˈpærɪs(ə)n	сравнение
complacency (n.)	kəmˈpleɪsnsi	самоуверенность, беспечность
complete (adj.) (v.)	kəmˈpli:t	полный; завершать, выполнять
complex (adj.)	kəmˈpleks / ˈkɑːmpleks	сложный, комплексный
complexity (n.)	kəmˈpleksɪtɪ	сложность
complicated (adj.)	ˈkɔmplɪkeɪtɪd	сложный, осложненный
compression (n.)	kəmˈpreʃ(ə)n	сжатие, компрессия
comprise (v.)	kəmˈpraɪz	составлять, включать в себя
computable (adj.)	kəmˈpju:təb(ə)l	вычислимый, машиночитаемый
computation (n.)	ˈkɔmpjuˈteɪʃ(ə)n	вычисление
computational (adj.)	ˈkɔmpjuˈteɪʃ(ə)nəl	вычислительный
computing (n.)	kəmˈpju:tɪŋ	применение компьютеров, информационные технологии
conceive (v.)	kənˈsi:v	понимать, полагать
concern (v.) be concerned with (n.)	kənˈsɜ:n	касаться, заниматься; иметь дело с, быть связанным; интерес, важность, значение
concise (adj.)	kənˈsaɪs	краткий, сжатый
conclusion (n.) draw conclusions	kənˈkluːʒn	заключение, вывод; делать выводы
condition (n.)	kənˈdɪʃ(ə)n	условие, состояние
conditionally (adv.)	kənˈdɪʃ(ə)nəlɪ	условно, при определенных условиях
conduct (v.) (n.)	kənˈdʌkt ˈkɒndʌkt	проводить, вести; поведение
confine (v.)	ˈkɔnfaɪn	ограничивать
congruent (adj.)	ˈkɒŋgruənt	согласованный, конгруэнтный
conjunction (n.)	kənˈʤʌŋkʃ(ə)n	сочетание, соединение
connect (v.)	kəˈnekt	соединять, связывать
connection (n.)	kəˈnekʃ(ə)n	соединение, связь
connectionism (n.)	kəˈnekʃənɪzəm	связность
connectionist (adj.)	kəˈnekʃ(ə)nɪst	нейросетевой, ассоциативный
connective (n.)	kəˈnektɪv	логическая связка, выражение
connectivity (n.)	ˌkɒnɛkˈtɪvəti	связь, связность
consciousness (n.)	ˈkɒnʃəsnəs	сознание
consequently (adv.)	ˈkɔnsɪkwəntlɪ	следовательно, таким образом
consider (v.)	kənˈsɪdə	считать, рассматривать
consideration (n.) under cosideration	kənˈsɪdəˈreɪʃ(ə)n	рассмотрение, соображение; рассматриваемый, данный
consist (v.)	ˈkɔnsɪst	состоять;

consist in		заключаться
consistency (n.)	kənˈsɪst(ə)nsɪ	последовательность, логичность
constant (adj.)	ˈkɔnstənt	постоянный
constraint (n.)	kənˈstreɪnt	ограничение
contain (v.)	kənˈteɪn	содержать
contemplate (v.)	ˈkɔntəmpleɪt	рассматривать
content (n.)	kˈɔntent	содержание, содержимое, информация
continuous (adj.)	kənˈtɪnjuəs	непрерывный
continuously (adv.)	kənˈtɪnjuəslɪ	непрерывно, постоянно
contractor (n.)	kənˈtræktə	подрядчик, разработчик, исполнитель
contribution (n.)	ˈkɔntrɪˈbjuːʃ(ə)n	вклад, распределение
convenience (n.)	kənˈviːnɪəns	удобство, польза, выгода
convenient (adj.)	kənˈviːniənt	удобный
conventional (adj.)	kənˈvenʃ(ə)nəl	обычный, простой
convergence (n.)	kənˈvɜːʤ(ə)ns	сходимость
convnet (n.) convolution neural network	ˈkɔnvˈnet	конволюционная нейронная сеть
convolutional (adj.)	ˈkɔnvəˈluːʃən (ə)l	конволюционный
correct (adj.) (v.)	kəˈrekt	правильный, соответствующий; исправлять
correctness (n.)	kəˈrektnəs	корректность, правильность
correlation (n.)	ˈkɔrɪˈleɪʃ(ə)n	соотношение, взаимосвязь, корреляция
correspond (v.)	ˈkɔrɪˈspɔnd	соответствовать
correspondingly (adv.)	ˌkɒrɪsˈpɒndɪŋlɪ	соответственно
cost (n.) (v.)	kɒst	цена, стоимость, расход; стоить
cover (v.)	ˈkʌvə	охватывать, покрывать
create (v.)	krɪˈeɪt	создавать
creation (n.)	kriːˈeɪʃ(ə)n	создание
critical (adj.)	ˈkrɪtɪkl	крайне важный
crop (n.)	krɔp	сельскохозяйственная культура
cross-validation (n.)	ˌkrɒsˌvælɪˈdeɪʃn	перекрестная проверка (на достоверность)
crucial (adj.)	ˈkruːʃ(ə)l	важный, существенный, значимый
cumbersome (adj.)	ˈkʌmbəs(ə)m	громоздкий, трудоемкий
current (adj.)	ˈkʌrənt	текущий, активный
currently (adv.)	ˈkʌrəntlɪ	в текущий момент, в данное время, сейчас

customize (v.)	ˈkʌstəmaɪz	настраивать, модифицировать (в соответствии с требованиями заказчика)
cut off (v.)	ˈkʌtˈɔf	прекращать, отключать
cycle (n.)	ˈsaɪk(ə)l	цикл, фаза
	D	
data (n.) input data output data unlabeled data	ˈdeɪtə /ˈdɑːtə	данные, информация; вводные данные; выходные данные; неразмеченные данные
dataset (n.)	ˈdeɪtəˈset	массив данных
daunting (adj.)	ˈdɔːntɪŋ	негативный, пугающий
DC direct current	daɪˈrekt ˈkʌr(ə)nt	постоянный ток
deal with (v.)	di:l	иметь дело с, рассматривать
decade (n.)	ˈdekeɪd	десятилетие
decision (n.)	dɪˈsɪʒ(ə)n]	решение
decrease (v.) (n.)	di:krˈi:s ˈdi:kri:s	снижаться, убывать; снижение, убывание
deduce (v.)	dɪˈdjuːs	выводить, заключать
define (v.)	dɪˈfaɪn	определять, устанавливать
definition (n.)	ˈdefɪˈnɪʃ(ə)n	определение; разрешение
deliberation (n.)	dɪˈlɪbəˈreɪʃ(ə)n	обсуждение, осмотрительность
delineate (v.)	dɪˈlɪnɪeɪt]	очерчивать, определять
deliver (v.)	dɪˈlɪvə	доставлять, добиваться результата
demanding (adj.)	dɪˈmɑːndɪŋ	трудный, трудоемкий
denote (v.)	dɪˈnəʊt	обозначать
dense (adj.)	dens	плотный
depend (v.) depending on	dɪˈpend	зависеть; в зависимости от
dependability (n.)	dəˌpendəˈbɪlətɪ	(функциональная) надёжность
dependent (adj.)	dɪˈpendənt	зависимый
depict (v.)	dɪˈpɪkt	описывать, изображать
deploy (v.)	dɪˈplɔɪ	применять, использовать
depth (n.)	depθ	глубина
derivative (n.)	dɪˈrɪvətɪv	производная (величина)
derive (v.)	dɪˈraɪv	получать, выводить
descent (n.) gradient descent	dɪˈsent	спуск; градиентный спуск
describe (v.)	dɪsˈkraɪb	описывать
design (n.) (v.)	dɪˈzaɪn	проект, конструкция; проектировать, конструировать;

engineering design		техническое проектирование
designate (v.)	ˈdezɪgneɪt	обозначать, определять
desired (adj.)	dɪˈzaɪəd	желательный, нужный
despite (prep.)	dɪsˈpaɪt	несмотря на
destination (n.)	ˈdestɪˈneɪʃ(ə)n	цель, конечная точка
detect (v.)	dɪˈtekt	обнаруживать, выявлять
detection (n.)	dɪˈtekʃ(ə)n	обнаружение, определение
determine (v.)	dɪˈtɜ:mɪn	определять, устанавливать
development (n.)	dɪˈveləpmənt	развитие, разработка
deviation (n.)	ˈdi:vɪˈeɪʃ(ə)n	отклонение
device (n.) imaging device interpreting device sensing device	dɪˈvaɪs	устройство, аппарат; устройство обработки изображений; сенсорное устройство
diagnosis (n.)	ˈdaɪəgˈnəusɪs	диагностика, обнаружение неисправностей
difference (n.)	ˈdɪf(ə)rəns	отличие
differentiable (adj.)	ˌdɪfəˈrɛnʃiəbl	дифференцируемый
differentiate (v.)	ˌdɪfəˈrenʃieɪt	различать, дифференцировать
digital (adj.)	ˈdɪʤɪt(ə)l	цифровой
dimension (n.)	d(a)ɪˈmenʃ(ə)n	измерение, размеры
dimensionality (n.)	daɪˌmɛnʃəˈnæləti / dəˌmɛnʃəˈnæləṱi	размерность; число измерений
diminish (v.)	dɪˈmɪnɪʃ	уменьшать(ся)
direct (adj.) (v.)	d(a)ɪˈrekt	прямой, непосредственный направлять, ориентировать
direction (n.)	d(a)ɪˈrekʃ(ə)n	направление
directly (adv.)	d(a)ɪˈrektlɪ	напрямую, непосредственно
disadvantage (n.)	ˈdɪsədˈvɑ:ntɪʤ	недостаток
disambiguation (n.)	ˌdɪsæmbɪgjʊˈeɪʃən	разрешение противоречий
discrepancy (n.)	dɪsˈkrep(ə)nsɪ	несоответствие, расхождение
discrete (adj.)	dɪsˈkri:t	дискретный
discretization (n.)	dɪsˌkri:t(a)ɪˈzeɪʃ(ə)n	дискретизация
discretize (v.)	ˈdiskri:taiz	дискретизировать
disparage (v.)	dɪsˈpærɪʤ	умалять, негативно отзываться
disruptive (adj.)	dɪsˈrʌptɪv	деструктивный, разрушительный
distance (n.)	ˈdɪst(ə)ns	расстояние
distinct (adj.)	dɪsˈtɪŋ(k)t	отличный, четкий, явный
distinction (n.)	dɪsˈtɪŋ(k)ʃ(ə)n	отличие
distinguish (v.)	dɪsˈtɪŋgwɪʃ	отличать, выделять
distinguishability (n.)	disˌtiŋgwiʃəˈbiɪiti	отличимость, распознаваемость

distinguishable (adj.)	dɪsˈtɪŋgwɪʃəbl	различимый, заметный
distribution (n.)	ˈdɪstrɪˈbju:ʃ(ə)n	распределение
diverge (v.)	daɪˈvɜ:ʤ	отклоняться
docile (adj.)	ˈdəʊsaɪl	поддающийся, способный
domain (n.)	dəˈmeɪn	область
downsample (v.)	daunˈsɑ:mp(ə)l	снижать разрешение
downtime (n.)	ˈdauntaɪm	простой, длительность отказа
draw on (v.)	ˈdrɔ:ˈɔn	исходить, основываться на
drawback (n.)	ˈdrɔ:bæk	недостаток
	E	
edge (n.)	eʤ	граница, край
effort (n.)	ˈefət	усилие
effortless (adj.)	ˈefətlɪs	не требующий усилий, беспрепятственный
elicit (v.)	ɪˈlɪsɪt	извлекать, выводить
eliminate (v.)	ɪˈlɪmɪneɪt	исключать, устранять, ликвидировать
emerge (v.)	ɪˈmɜ:ʤ	возникать, появляться
emission (n.)	ɪˈmɪʃ(ə)n	выброс
employ (v.)	ɪmˈplɔɪ	использовать, применять; нанимать
employment (n.)	ɪmˈplɔɪmənt	занятость, трудоустройство
enable (v.)	ɪˈneɪb(ə)l	давать возможность, позволять
enabler (n.)	ɪˈneɪblə(r)	способствующий фактор
encapsulate (v.)	ɪnˈkæpsjuleɪt	заключать в себе
encounter (n.) (v.)	ɪnˈkaʊntə	встреча, столкновение; встречать, сталкиваться
enforce (v.)	ɪnˈfɔ:s	приводить в исполнение
engender (v.)	ɪnˈʤendə	порождать, производить
engine (n.) inference engine recommendation engine	ˈenʤɪn	механизм, компонент, машина, двигатель; механизм логического вывода; рекомендательный сервис
engineering (n.)	endʒɪˈnɪərɪŋ	конструирование, машиностроение
enhance (v.)	ɪnˈhɑ:ns	усиливать, совершенствовать
enormous (adj.)	ɪˈnɔːməs	огромный
ensemble (n.)	ɔnˈsɔmb(ə)l	ансамбль
ensure (v.)	ɪnˈʃuə	обеспечивать, гарантировать
entail (v.)	ɪnˈteɪl	влечь за собой, вызывать
enter (v.)	ˈentə	вводить
entire (adj.)	ɪnˈtaɪə	целый, полный, весь
entity (n.)	ˈentɪtɪ	единица, субъект

environment (n.)	ɪnˈvaɪ(ə)rənmənt	(окружающая) среда, условия
envision (v.)	ɪnˈvɪʒ(ə)n	задумывать, предусматривать
epoch (n.)	ˈi:pɔk	эпоха, отдельная итерация
equal (adj.) (v.)	ˈi:kwəl	равный; равняться
equation (n.)	ɪˈkweɪʒ(ə)n	уравнение, выражение
equip (v.)	ɪˈkwɪp	оборудовать, укомплектовывать
error (n.) approximation error; classification error; root-mean-squared-error (RMSE)	ˈerə	ошибка; ошибка аппроксимации; ошибка классификации; средняя квадратическая ошибка
error-back-propagation (EBP)		обратное распространение ошибки
escape (v.)	ɪˈskeɪp	избегать, уходить от
especially (adv.)	ɪˈspeʃ(ə)lɪ	особенно, главным образом
essentially (adv.)	ɪˈsenʃ(ə)lɪ	по существу, существенным образом
estimate (v.) (n.)	ˈɛstɪˌmeɪt ˈɛstɪmɪt	оценивать, подсчитывать; оценка, подсчет
estimation (n.)	ˈestɪˈmeɪʃ(ə)n	оценка, вычисление оценки
evaluate (v.)	ɪˈvæljueɪt	оценивать, вычислять
eventually (adv.)	ɪˈvenʧu(ə)lɪ	в итоге, в результате
evidence (n.)	ˈevɪd(ə)ns	свидетельство, основание
evolve (v.)	ɪˈvɔlv	развивать(ся), вырабатывать
exactly (adv.)	ɪgˈzæktli	точно, именно
examine (v.)	ɪgˈzæmɪn	исследовать, анализировать
exclude (v.)	ɪkˈsklu:d	исключать
execute (v.)	ˈeksɪkju:t	выполнять
execution (n.)	ˈeksɪˈkju:ʃ(ə)n	выполнение, проведение
exhaustive (adj.)	ɪgˈzɔ:stɪv	исчерпывающий, всесторонний
exhibit (v.)	ɪgˈzɪbɪt	показывать, демонстрировать
expand (v.)	ɪkˈspænd	расширять(ся)
expectation (n.)	ˈekspekˈteɪʃ(ə)n	ожидание
expected reward		ожидаемый выигрыш
expensive (adj.)	ɪkˈspensɪv	дорогой
experience (n.) (v.)	ɪkˈspɪəriəns	опыт; испытывать
experiential (adj.)	ɪkˈspɪ(ə)rɪˈenʃ(ə)l	опытный, практический, эмпирический
expert system	ˈekspɜːt ˈsɪstəm	экспертная система, система обработки экспертных знаний

expertise (n.)	ˈekspɜːˈtiːz	экспертные знания, компетентность
explicit (adj.)	ɪkˈsplɪsɪt	явный, четкий
explicitly (adv.)	ɪkˈsplɪsɪtlɪ	явно, однозначно
explode (v.)	ɪkˈspləʊd	взрывать, разбивать на части
exploration (n.)	ˈekspləˈreɪʃ(ə)n	исследование
explore (v.)	ɪkˈsplɔː	изучать, исследовать
explosion (n.) combinatorial explosion	ɪkˈspləʊʒn	взрыв; комбинаторный взрыв; лавинообразное увеличение затрат машинного времени при незначительном усложнении задачи
exponential (adj.)	ˌekspəˈnenʃ(ə)l	экспоненциальный
expose to (v.)	ɪkˈspəuz	подвергать (воздействию)
express (v.)	ɪkˈspres	выражать
extent (n.)	ɪkˈstent	степень, объем
external (adj.)	ɪkˈstɜːn(ə)l	внешний
extract (v.)	ɪksˈtrækt	извлекать
extraction (n.) feature extraction	ɪkˈstrækʃ(ə)n	извлечение; извлечение признаков
extractor (n.) feature extractor	ɪkˈstræktə	программа для получения информации; блок выделения (характерных) признаков
extrapolate (v.)	ɪkˈstræpəleɪt	обобщать, распространять в другую область, экстраполировать
extremely (adv.)	ɪkˈstriːmlɪ	крайне, чрезвычайно
	F	
face (v.)	feɪs	сталкиваться
facial (adj.)	ˈfeɪʃ(ə)l	лицевой
facilitate (v.)	fəˈsɪlɪteɪt	способствовать, облегчать
facility (n.)	fəˈsɪlɪtɪ	предприятие, оборудование
fail (v.)	feɪl	давать сбой, терпеть неудачу
failure (n.)	ˈfeɪljə	неисправность, отказ, сбой
fairness (n.)	ˈfeənɪs	справедливость
fatigue (n.)	fəˈtiːg	утомление, усталость
fault (n.)	fɔːlt	неисправность, отказ
favour (n.) (v.) in favour of	ˈfeɪvə|	польза, интерес; поддерживать, одобрять; в пользу, в поддержку
feature (n.)	ˈfiːʧə	особенность, характеристика, признак

feed (v.)	fi:d	подавать, передавать
feedback (n.)	ˈfi:dbæk	обратная связь
feed-forward (n.)	ˈfi:dˈfɔ:wəd	прямая связь, упреждение
fidelity (n.)	fɪˈdelɪtɪ	достоверность
field (n.)	fi:ld	поле, область
field test		испытания в условиях эксплуатации
finite (adj.)	ˈfaɪnaɪt	конечный
fission (n.)	ˈfɪʃ(ə)n	деление, (ядерный) распад
fit (v.)	fɪt	подходить, подбирать, подгонять, устанавливать
fitting (n.)	ˈfɪtɪŋ	подбор, подгонка
flexibility (n.)	ˈfleksəˈbɪlɪtɪ	гибкость
flexibly (adv.)	ˈfleksɪblɪ	гибко
focus (v.)	ˈfəukəs	концентрировать(ся), сосредотачивать(ся)
former (adj.)	ˈfɔ:mə	бывший, первый (из двух)
forward chaining		с прямым логическим выводом
foundational (adj.)	faunˈdeɪʃ(ə)nəl	основополагающий
fragile (adj.)	ˈfrædʒaɪl	хрупкий
frame (n.), (v.)	freɪm	каркас, фрейм; преподносить
framework (n.)	ˈfreɪmwɜːk	основа; комплекс инструментов
frequent (adj.)	ˈfri:kwənt	частый
frequently (adv.)	ˈfriːkwəntli	часто, регулярно
function (n.) goal function loss function cost function transfer function be a function of (v.)	ˈfʌŋkʃn	функция; целевая функция; функция потерь; функция потерь, критерий оптимальности; передаточная функция; зависеть от; работать, действовать
furthermore (adv.)	ˌfɜːðəˈmɔː	кроме того, также
fuzzy inference system (FIS)		система нечеткого логического вывода
G		
gain (v.)	geɪn	получать
gather (v.)	ˈgæðə]	собирать
general (adj.)	ˈʤen(ə)rəl	общий, основной
generalization (n.)	ˈʤen(ə)rəlaɪˈzeɪʃ(ə)n	обобщение
given (prep.)	ˈgɪv(ə)n	учитывая, при условии
goal (n.)	gəul	цель, задача
goal-driven (adj.)	ˈgəʊlˈdrɪvən	управляемый целями

govern (v.)	ˈgʌvən	руководить, регулировать, направлять
governance (n.)	ˈgʌvənəns	управление, руководство
GPU, graphics processing unit		графический процессор
gradient	ˈgreɪdɪənt	градиент
granularity (n.)	ˌgrænjuˈlærəti	глубина детализации, уровень модульности
graph (n.)	græf	граф, график
grasp (v.)	grɑ:sp	схватывать, уяснять
grid (n.)	grɪd	сетка
ground truth		эталонные данные
guess (n.) (v.)	ges	предположение, приблизительный подсчет; предполагать, приблизительно подсчитывать
guesswork (n.)	ˈgɛswɜːk	догадки, предположения
guidance (n.)	ˈgaɪd(ə)ns	руководство, управление
guide (n.) (v.)	gaɪd	руководство, набор инструкций; направлять, определять
guideline (n.)	ˈgaɪdlaɪn	принцип, общий курс
H		
handle (v.)	ˈhænd(ə)l	обрабатывать, манипулировать
hardware (n.)	ˈhɑ:dweə	технические средства, оборудование, аппаратное обеспечение
head toward (v.)	ˌhed təˈwɔːd	направляться
heavily (adv.)	ˈhevɪlɪ	существенным образом
helpful (adj.)	ˈhelpf(ə)l	полезный, ценный
hence (adv.)	hens	следовательно
heuristic (n.) (adj.)	hjuˈrɪstɪk	эвристический алгоритм; эвристический
hierarchical (adj.)	ˌhaɪˈrɑːkɪkl	иерархический
hill climbing	ˌhɪl ˈklaɪmɪŋ	поиск восхождением к вершине, поиск максимума (функции)
hit (n.)	hɪt	совпадение, результат поиска
house (v.)	hauz	вмещать
however (adv.)	hauˈevə	однако, тем не менее, как бы то ни было
human (n.)	ˈhju:mən	человек
hyperparameter (n.)	ˌhaipəpəˈræmɪtə	гиперпараметр

I		
identifier (n.)	aɪˈdentɪfaɪə	идентификатор
identify (v.)	aɪˈdentɪfaɪ	распознавать, определять
ignore (v.)	ɪgˈnɔ:	пренебрегать, пропускать
IIoT, industrial internet of things		промышленный интернет вещей
image (n.)	ˈɪmɪʤ	образ, изображение
immediately (adv.)	ɪˈmi:dɪətlɪ	немедленно, моментально
immense (adj.)	ɪˈmens	огромный
impact (n.) (v.)	ˈɪmpækt ɪmˈpækt	воздействие, влияние; влиять, воздействовать
imperfection (n.)	ˈɪmpəˈfekʃ(ə)n	несовершенство, изъян
implement (v.)	ˈɪmplɪment	внедрять, осуществлять, выполнять
implementation (n.)	ˈɪmplɪmənˈteɪʃ(ə)n	исполнение, внедрение, реализация
implication (n.)	ˌɪmplɪˈkeɪʃ(ə)n	последствие, нюанс
implicitly (adv.)	ɪmˈplɪsɪtlɪ	непрямо, косвенно
imply (v.)	ɪmˈplaɪ	подразумевать, предполагать
impossible (adj.)	ɪmˈpɔsəb(ə)l	невыполнимый, невозможный
impractical (adj.)	ɪmˈpræktɪk(ə)l	непрактичный, нецелесообразный
impressive (adj.)	ɪmˈpresɪv	впечатляющий, внушительный
improve (v.)	ɪmˈpru:v	улучшать
in order to		чтобы
inaccurate (adj.)	ɪnˈækjurɪt	неточный
inception (n.)	ɪnˈsepʃ(ə)n	начало
incidental (adj.)	ˌɪnsɪˈdentl	случайный, эпизодичный
incidentally (adv.)	ˈɪnsɪˈdent(ə)lɪ	периодически; кстати
include (v.)	ɪnˈklu:d	включать
inclusive (of) (adj.)	ɪnˈklu:sɪv	заключающий (в себе), с учётом
incorporate (v.)	ɪnˈkɔ:p(ə)reɪt	включать (в состав), объединять
incorporation (n.)	ɪnˌkɔ:pəˈreɪʃn	включение, объединение
increase (n.) (v.)	ˈɪŋkri:s	увеличение, рост; повышать(ся), увеличивать(ся)
increasingly (adv.)	ɪnˈkri:sɪŋlɪ	всё больше, всё чаще
indeed (adv.)	ɪnˈdi:d	действительно, в самом деле
independent (adj.)	ˈɪndɪˈpendənt	независимый, автономный
independently (adv.)	ˈɪndɪˈpendəntlɪ	независимо, автономно, самостоятельно
independently (adv.)	ˌɪndɪˈpendəntli	независимо
industry (n.)	ˈɪndəstrɪ	промышленность, отрасль

inequality (n.)	ˌɪnɪˈkwɒləti	неравенство
infancy (n.)	ˈɪnfənsɪ	начальная стадия развития
inference (n.)	ˈɪnf(ə)rəns	логический вывод, заключение
inferencer (n.)	ˈɪnf(ə)rən(t)sə	механизм вывода
infinite (adj.)	ˈɪnfɪnət	бесконечный
influential (adj.)	ˌɪnflʊˈenʃ(ə)l	авторитетный, влиятельный
inherent (adj.)	ɪnˈhɪ(ə)rənt	свойственный, присущий
initially (adv.)	ɪˈnɪʃ(ə)lɪ	первоначально
injection (n.)	ɪnˈʤekʃ(ə)n	введение, ввод
input (n.) (v.)	ˈɪnput]	сигнал на входе; вводить
inside (adv., prep.)	ˈɪnsaɪd	внутри; в
insight (n.)	ˈɪnsaɪt	понимание
insofar as (conj.)	ˌɪnsəˈfɑːr əz	настолько, в той мере
inspection (n.)	ɪnˈspekʃ(ə)n	проверка, осмотр
inspire (v.)	ɪnˈspaɪə	вдохновлять, внушать
instability (n.)	ˌɪnstəˈbɪləti	неустойчивость
instance (n.) for instance	ˈɪnstəns	пример, образец; например
instead (adv.) instead of (prep.)	ɪnˈsted	вместо этого, вместе с тем; вместо
integrity (n.)	ɪnˈtegrɪtɪ	целостность, полнота
intelligence (n.)	ɪnˈtelɪʤ(ə)ns	интеллект, разум
intend (v.)	ɪnˈtend	намереваться, предназначать
intensive (adj.)	ɪnˈtensɪv	затратный, ёмкий
intent (n.)	ɪnˈtent	намерение, план
interact (v.)	ˈɪntəˈrækt	взаимодействовать
interconnected (adj.)	ˌɪntəkəˈnɛktɪd	взаимосвязанный, соединенный
intermediate (adj.)	ˌɪntəˈmiːdiət	промежуточный
internal (adj.)	ɪnˈtɜ:nl	внутренний
interpret (v.)	ɪnˈtɜ:prɪt	интерпретировать, толковать, дешифровывать
interpretable (adj.)	ɪnˈtɜːprɪtəbl	интерпретируемый, объяснимый
interrogation (n.)	ɪnˌterəˈgeɪʃ(ə)n	опрос, получение справки
interrogative (adj.)	ˌɪntəˈrɒgətɪv	вопросительный
interrogator (n.)	ɪnˈterəgeɪtə	устройство опрашивания, система опроса
intervention (n.)	ɪntəˈvenʃ(ə)n	вмешательство
intricate (adj.)	ˈɪntrɪkeɪt	сложный, замысловатый
intrinsic (adj.)	ɪnˈtrɪnsɪk	характерный, свойственный
intrinsically (adv.)	ɪnˈtrɪnsɪk(ə)lɪ	в сущности, в действительности
introduce (v.)	ɪntrəˈdjuːs	вводить

invariant (n.)	ɪnˈve(ə)rɪənt	инвариант
involve (v.)	ɪnˈvɔlv	включать в себя, повлечь, предусматривать
irrefutable (adj.)	ˌɪrɪˈfju:təbl/ɪˈrefjətəbl	неоспоримый
issue (n.)	ˈɪʃu: / ˈɪsjuː	проблема, вопрос
iterative (adj.)	ˈɪtərətɪv	повторяющийся, итератинвый, циклический
iteratively (adv.)	ˈɪtərətɪvlɪ	многократно, итеративно
J		
join (v.)	ʤɔɪn	объединять, связывать
judgment (n.)	ˈdʒʌdʒmənt	суждение, рассудительность
judicial (adj.)	ʤu:ˈdɪʃ(ə)l	судебный, правовой
K		
keep track		отслеживать
kernel (n.)	kɜ:nl	ядро
knowledge (n.)	ˈnɔlɪʤ	знания
L		
label (v.) (n.)	ˈleɪb(ə)l	размечать; ярлык
labor (n.)	ˈleɪbə(r)	труд
lack (v.)	læk	испытывать недостаток, нуждаться
latter (adj.)	ˈlætə	последний из двух
layer (n.) pooling layer	ˈleɪə	слой; объединяющий слой
lead to (v.)	li:d	приводить к
learning (n.) reinforcement learning supervised learning unsupervised learning	ˈlɜːnɪŋ	обучение; обучение с подкреплением; машинное обучение без учителя
level (n.)	ˈlev(ə)l	уровень
leverage (v.)	ˈlevərɪdʒ /|ˈliːv(ə)rɪdʒ	эффективно использовать, оптимизировать
library (n.)	ˈlaɪbr(ə)rɪ	библиотека
lighting (n.)	ˈlaɪtɪŋ	освещение, освещенность
lightweight (adj.)	ˈlaɪtweɪt	легкий, упрощенный
likelihood (n.)	ˈlaɪklɪhud	вероятность, правдоподобие
likewise (adv.)	ˈlaɪkwaɪz	аналогично, сходным образом
limelight (n.)	ˈlaɪmlaɪt	центр внимания
limit (n.) (v.)	ˈlɪmɪt	предел; ограничивать
limitation (n.)	lɪmɪˈteɪʃ(ə)n	ограничение
line (n.)	laɪn	линия, контур;

assembly line		(конвейерная) линия сборки
linear (adj.)	ˈlɪniə	линейный
link (n.) (v.)	lɪŋk	связь, звено, ссылка; соединять, связывать
localization (n.)	ˈləukəlaɪˈzeɪʃ(ə)n	локализация, позиционирование, расположение
location (n.)	ləuˈkeɪʃ(ə)n	местонахождения, обнаружение местоположения
look for (v.)	lʊkˈfɔː(r)	искать
loop (n.) induction loop loop back (v.)	lu:p	петля, контур, цепь; индукционная петля; возврат к началу цикла
loosely (adv.)	ˈlu:slɪ	условно, примерно
loss (n.)	lɔs	потеря
M		
machine learning	məˈʃi:n	машинное обучение
magnitude (n.)	ˈmægnɪtju:d	величина
maintenance predictive maintenance	ˈmeɪnt(ə)nəns	техническое обслуживание, поддержание, сопровождение; диагностическое обслуживание, ТО по текущему состоянию
majority (n.)	məˈʤɔrɪtɪ	большинство
manage (v.)	ˈmænɪʤ	управлять, регулировать
management (n.)	ˈmænɪdʒmənt	управление
manageable (adj.)	ˈmænɪʤəb(ə)l	удобный в управлении, управляемый, приемлемый
manual (adj.)	ˈmænjuəl	ручной
manually (adv.)	ˈmænjuəli	вручную, в ручном режиме
map to (v.)	mæp	проецировать, устанавливать соответствие
mapping (n.)	ˈmæpɪŋ	проекция, соотнесение, преобразование данных
marginal	ˈmɑ:ʤɪnl	предельный
market basket		потребительская корзина
mastery (n.)	ˈmɑ:st(ə)rɪ	усвоение, владение
match (n.) (v.)	mæʧ	совпадение; совпадать, приводить в соответствие, подбирать
mean (v.)	mi:n	означать
means (n., pl.)	mi:nz	способ, средство
measure (n.) (v.)	ˈmeʒə	мера, степень, критерий; измерять

measurement (n.)	ˈmeʒəmənt	измерение, вычисление
meet (v.) meet standards	miːt	отвечать, соответствовать соответствовать стандартам
memorize (v.)	ˈmeməraɪz	запоминать, передавать в память
mention (v.)	ˈmenʃ(ə)n	упоминать, ссылаться на
merely (adv.)	ˈmɪəlɪ	просто, только
metric (n.)	ˈmetrɪk	показатель
microchip (n.)	ˈmaɪkrə(u)ʧɪp	микрочип, микропроцессор
militate (v.)	ˈmɪlɪteɪt	свидетельствовать
mimic (v.)	ˈmɪmɪk	повторять, имитировать, моделировать
minibatch (n.)	ˈmɪnɪˈbæʧ	мини-батч (небольшое подмножество тренировочного набора)
mining (n.) data mining	ˈmaɪnɪŋ	добыча, поиск, анализ; добыча данных, извлечение информации из массива данных; анализ и обработка данных
minute (adj.)	maɪˈnjuːt	мельчайший
mirror (v.)	ˈmɪrə	отражать
misalignment (n.)	ˈmɪsəˈlaɪnmənt	несовпадение, нестыковка, отклонение от оси
misbehave (v.)	ˌmɪsbɪˈheɪv	неправильно функционировать
miss (v.)	mɪs	пропускать, не попадать
mitigate (v.)	ˈmɪtɪgeɪt	смягчать, уменьшать, нивелировать
modeling (n.)	ˈmɔdlɪŋ	моделирование
modern (adj.)	mɔdn	современный, новый
modify (v.)	ˈmɔdɪfaɪ	изменять, модифицировать
momentum (n.)	mə(u)ˈmentəm	импульс, толчок
monotonous (adj.)	məˈnɔt(ə)nəs	монотонный, однообразный
moot (adj.)	muːt	спорный
moreover (adv.)	mɔːˈrəuvə	более того, наряду с этим, к тому же
motion (n.)	ˈməuʃ(ə)n	движение, ход
movement (n.)	ˈmuːvmənt	движение, перемещение
multilayered perceptron (MLP)	ˌmʌltiˈleɪəd pəˈseptrɔn	многослойный персептрон
multiple (adj.)	ˈmʌltɪp(ə)l	многочисленный, многократный, серийный
multiple input-multiple output (MIMO)	ˈmʌltɪp(ə)l ˈɪnpʊt ˈmʌltɪp(ə)l ˈaʊtpʊt	многоканальный вход – многоканальный выход

mutation (n.)	mjuːˈteɪʃ(ə)n	мутация, изменение
myriad (n.)	ˈmɪrɪəd	неисчислимое множество
N		
naked eye	ˈneɪkɪdˈaɪ	невооруженный глаз
navigate (v.)	ˈnævɪgeɪt	перемещать(ся), ориентироваться
necessarily (adv.)	ˈnesəs(ə)rɪlɪ	обязательно, неизбежно
necessary (adj.)	ˈnesɪs(ə)rɪ	необходимый
necessitate (n.)	nɪˈsesɪteɪt	требовать, делать необходимым
negotiate (v.)	nɪˈgəʊʃieɪt	договариваться, обсуждать условия
network (n.) associative network; feed-forward neural network; semantic network	ˈnetwɜːk	сеть; ассоциативная сеть; нейронная сеть прямого распространения; семантическая сеть
neuro-fuzzy	ˈnju(ə)rə(u) ˈfʌzɪ	нейро-нечёткий
neuron (n.)	ˈnju(ə)rɔn	нейрон
nevertheless (adv.)	ˌnevəðəˈles	тем не менее
node (n.) input node output node	nəʊd	узел; входной узел; узел вывода
non-destructive testing (NDT)		неразрушающий метод контроля, дефектоскопия
nondeterministic (adj.)	ˌnɒndɪˌtɜːmɪˈnɪstɪk	недетерминистский
nonetheless (adv.)	ˈnʌnðəˈles	тем не менее
nonlinear (adj.)	ˌnɒnˈlɪniə	нелинейный
nonmonotonicity (n.)	ˌnɒnˌmɒnətəˈnɪsəti	немонотонность
nonparametric (adj.)	ˌnɒnˌpærəˈmɛtrɪk	непараметрический
non-scalable (adj.)	ˌnɒnˈskeɪləbl	немасштабируемый
notable (adj.)	ˈnəutəb(ə)l	значительный, примечательный
notify (v.)	ˈnəutɪfaɪ	уведомлять, извещать
novel (adj.)	ˈnɒv(ə)l	новый, инновационный
novice (adj.)	ˈnɔvɪs	неопытный
number (n.) a number of	ˈnʌmbə	число, количество; ряд, несколько
numerical (adj.)	njuːˈmerɪk(ə)l	числовой, численный
numerous (adj.)	ˈnjuːm(ə)rəs	многочисленный

O		
objection (n.)	əbˈʤekʃ(ə)n	возражение
objective (n.)	əbˈʤektɪv	цель, задача
objective function		целевая функция
object-oriented (adj.)	ˈɒbdʒɪktˌɔːriɛntɪd	объектно-ориентированный
obligation (n.)	ˌɒblɪˈgeɪʃn	обязательство
observable (adj.)	əbˈzɜːvəbl	наблюдаемый, различимый
observation (n.)	ˈɔbzəˈveɪʃ(ə)n	наблюдение; соблюдение
observe (v.)	əbˈzɜːv	наблюдать; соблюдать
obstacle (n.)	ˈɔbstək(ə)l	помеха, препятствие
obstruction (n.)	əbˈstrʌkʃ(ə)n	препятствие, затруднение
obtain (v.)	əbˈteɪn	получать, достигать
obviously (adv.)	ˈɔbvɪəslɪ	очевидно, явно
occupy (v.)	ˈɔkjupaɪ	занимать
occur (v.)	əˈkɜː	случаться, происходить
occurrence (n.)	əˈkʌr(ə)ns	частотность; случай
offer (n.) (v.)	ˈɔfə	предложение; предлагать
OI-KSL (Object Inference Knowledge Specification Language)		язык спецификации знаний
once (adv.) (n.) (prep.)	wʌns	однажды, когда-то; один раз; как только
oncoming (adj.)	ˈɔnˈkʌmɪŋ	приближающийся, будущий
on-shore (adv.)	ˈɒnʃɔː	на суше, на берегу
open-source	ˌəʊpən ˈsɔːs	общедоступный; с открытым исходным кодом
operate (v.)	ˈɔpəreɪt	управлять, работать
opportunity (n.)	ˌɒpəˈtjuːnəti	возможность
outcome (n.)	ˈaʊtkʌm	результат
outline (v.)	ˈaʊtlaɪn	кратко излагать
output (n.) (v.)	ˈautput	выходная величина; выводить
outweigh (v.)	ˌaʊtˈweɪ	перевешивать, превосходить
overall (adj.)	ˌəʊvərˈɔːl	итоговый, общий, результирующий
overcome (v.)	ˌəʊvəˈkʌm	преодолевать
overfitting (n.)	ˌəuvə ˈfɪtɪŋ	перетренировка (нейронной сети); чрезмерное обучение
overflow (n.) (v.)	ˌəʊvəˈfləʊ	переполнение; переполнять
overlap (n.)	ˌəʊvəˈlæp	частичное пересечение;

(v.)		частично совпадать
owing to (prep.)	ˈəʊɪŋtu	из-за, вследствие, благодаря
P		
package (n.) software package	ˈpækɪdʒ	совокупность, пакет; пакет программного обеспечения
paradigm (n.)	ˈpærədaɪm	парадигма, подход
parallelism (n.)	ˈpærəlɛlɪzəm	параллелизм
parse (v.)	pɑːz	анализировать (синтаксис)
participant (n.)	pɑːˈtɪsɪpənt	участник
particular (adj.)	pəˈtɪkjulə	частный, отдельный, конкретный
particularly (adv.)	pəˈtɪkjuləlɪ	особенно, в частности
path (n.)	pɑːθ	путь, маршрут
pattern (n.)	ˈpætn	шаблон, образец, образ
pedestrian (n.)	pɪˈdestrɪən	пешеход
perceive (v.)	pəˈsi:v	воспринимать, понимать
perception (n.)	pəˈsepʃn	восприятие
perform (v.)	pəˈfɔ:m	выполнять, работать, функционировать
performable (adj.)	pəˈfɔːməbl	выполнимый
performance (n.)	pəˈfɔ:məns	эффективность, производительность, исполнение
permit (v.)	pəˈmɪt	позволять, разрешать
persuasive (adj.)	pəˈsweɪsɪv	убедительный
photogrammetry (n.)	ˈfəutəuˈgræmɪtrɪ	фотограмметрия
pickup (n.) pickup position	ˈpɪkʌp	взятие, захват; зажим губок схвата
pipeline (n.)	ˈpaɪplaɪn	конвейер
plentiful (adj.)	ˈplentɪf(ə)l	более чем достаточный, обильный
plenty (n.)	ˈplentɪ]	множество, масса
point (n.) data point	pɔɪnt	точка, пункт; точка (ввода) данных
pole (n.)	pəul	полюс
pollution (n.)	pəˈluːʃn	загрязнение
polynomial (adj.)	ˈpɔlɪˈnəumɪəl	полиноминальный, многочленный
pool (v.)	ˈpuːl	объединять, накапливать
pose (v.) pose challenges	pəuz	задавать, порождать; быть проблематичным
possess (v.)	pəˈzes	обладать
possibility (n.)	ˈpɔsəˈbɪlɪtɪ	возможность, вероятность

posterior (adj.)	pɒˈstɪərɪə	последующий
power (computing power)	ˈpaʊə	сила, мощность
powerful (adj.)	ˈpaʊəfʊl	мощный, сильный, эффективный
prearranged (adj.)	ˌpriːəˈreɪndʒd	запланированный, предусмотренный заранее
precalculation (n.)	ˌpriːˌkælkjuˈleɪʃn	предварительный подсчёт
precede (v.)	prɪˈsi:d	предшествовать
precisely (adv.)	prɪˈsaɪslɪ	точно
predetermine (v.)	ˌpriːdɪˈtɜːmɪn	предопределять
predicate (adj.)	ˈpredɪkət	предикатный
predict (v.)	prɪˈdɪkt	прогнозировать, предвычислять
prediction (n.)	prɪˈdɪkʃ(ə)n	прогноз, предвычисление
predictive	prɪˈdɪktɪv	прогностический
predominant (adj.)	prɪˈdɔmɪnənt	преобладающий
prefer (v.)	prɪˈfɜː	предпочитать
preference (n.)	ˈprefrəns	предпочтение
premise (n.)	ˈpremɪs	предпосылка, условие
preprocessing (n.)	ˈpri:ˈprəusesɪŋ	предварительная обработка
present (v.) (adj.)	prɪˈzent ˈpreznt	представлять; настоящий, данный
preserve (v.)	prɪˈzɜ:v	сохранять
prevalent (adj.)	ˈprevələnt	преобладающий
prevent (v.)	prɪˈvent	предотвращать
prevention (n.)	prɪˈvenʃn	предотвращение, упреждение
previously (adv.)	pri:vɪəslɪ	ранее, до этого
primarily (adv.)	ˈpraɪm(ə)rɪlɪ / praɪˈmerəlɪ	в первую очередь, главным образом
prior (adj.)	ˈpraɪə	предшествующий, прежний
privacy (n.)	ˈpraɪvəsi / ˈprɪvəsi	конфиденциальность, тайна личной жизни
proactive (adj.)	prəʊˈæktɪv	активный, упреждающий
probabilistic (adj.)	ˈprɔbəbəˈlɪstɪk	вероятностный
probability (n.)	ˌprɒbəˈbɪləti	вероятность
probably (adv.)	ˈprɒbəbli	вероятно
procedural (adj.)	prəˈsi:ʤ(ə)rəl	процедурный
procedure (n.)	prəˈsi:ʤə	процедура
proceed (v.)	prəˈsi:d	продолжать(ся), приступать
process (v.)	ˈprəʊses	обрабатывать
processing (n.)	ˈprəusesɪŋ	обработка
progress (v.)	prəˈgres	происходить, продвигаться
prohibitive (adj.)	prəˈhɪbɪtɪv	невозможный, недопустимый

projection (n.)	prəˈʤekʃ(ə)n	план, перспективный прогноз
prominent (adj.)	ˈprɔmɪnənt	выдающийся
promise (v.)	ˈprɔmɪs	обещать
promising (adj.)	ˈprɔmɪsɪŋ	перспективный, имеющий потенциал
promote (v.)	prəˈməʊt	продвигать, способствовать
prone to (adj.)	prəun	склонный
proof (n.)	pruːf	доказательство
propel (v.)	prəˈpel	стимулировать, двигать
properly (adv.)	ˈprɔpəlɪ	должным образом, правильно
property (n.)	ˈprɔpətɪ	свойство
proposition (n.)	ˌprɒpəˈzɪʃ(ə)n	пропозиция, высказывание, утверждение
prove (v.)	pru:v	доказывать; оказываться
provide (v.)	prəˈvaɪd	обеспечивать, предоставлять
pruning (n.)	ˈpruːnɪŋ	отсечение (ветвей в дереве поиска или перебора)
pseudo- (adj.)	ˈsju:dəu	псевдо-
pseudocode (n.)	ˈsjuːdəʊˌkəʊd	псевдокод, символический код
purchase (n.) (v.)	ˈpɜːʧɪs	покупка; покупать, приобретать
purpose (n.)	ˈpɜ:pəs	цель, назначение
pursue (v.)	pəˈsju:	преследовать, придерживаться
pursuit (n.)	pəˈsju:t	поиск, стремление
Q		
quality (n.)	ˈkwɔlɪtɪ	качество, свойство
query (n.)	ˈkwɪəri / ˈkwɪri	запрос
quest (n.)	kwest	поиски
questionable (adj.)	ˈkwestʃənəbl	непроверенный, сомнительный
questionnaire (n.)	ˌkwestʃəˈneə	анкета
quickprop	kwɪkpˈrɔp	алгоритм быстрого распространения
R		
radiate to (v.)	ˈreɪdɪeɪt	распространяться
raise (v.)	reɪz	повышать
random (adj.)	ˈrændəm]	случайный
random forest		случайные деревья решений, алгоритм случайного леса
randomization (n.)	ˈrændəmaɪˈzeɪʃ(ə)n	рандомизайия, хаотизация
randomize (v.)	ˈrændəmaɪz	рандомизировать, вносить элемент случайности
randomly (adv.)	ˈrændəmli	случайным образом, произвольно
randomness (n.)	ˈrændəmnɪs	произвольность, случайность

range (n.) (v.)	reɪnʤ	диапазон; варьироваться, находиться в диапазоне
rate (n.)	reɪt	скорость, темп
ratio (n.)	ˈreɪʃiəʊ	коэффициент, степень
reachable (adj.)		
readable (adj.)	ˈri:dəb(ə)l	читаемый, считываемый
readily (adv.)	ˈredɪlɪ	легко, оперативно
reading (n.)	ˈri:tʃəbl	достижимый
realizable (adj.)	ˈriːəlaɪzəbl	осуществимый
reason (n.)	ˈri:z(ə)n	причина
reasoning (n.) case-based reasoning	ˈri:z(ə)nɪŋ	построение логического вывода, формирование рассуждений; рассуждение на основе прецедентов/аналогичных случаев
recalculate (v.)	ˌriːˈkælkjuleɪt	пересчитывать
receive (v.)	rɪˈsi:v	получать
recent (adj.)	ˈri:s(ə)nt	недавний, последний
receptive (adj.)	rɪˈseptɪv	восприимчивый, способный принимать
reclassify (v.)	ˌriːˈklæsɪfaɪ	переклассифицировать
recognition (n.) pattern recognition	ˈri:ekəgˈnɪʃ(ə)n	распознавание; признание; распознавание образов
recognize (v.)	ˈrekəgnaɪz	распознавать, признавать
recombination (n.)	ˈri:kɔmbɪˈneɪʃ(ə)n	рекомбинация
recompute (v.)	ˌriːˈklæsɪfaɪ	вычислять заново
record (n.) (v.)	ˈrekɔ:d rɪˈkɔːd	запись, данные; записывать, фиксировать
recover (v.)	rɪˈkʌvə	восстанавливать; извлекать
rectangle (n.)	ˈrektæŋgl	прямоугольник
recurrent (adj.)	rɪˈkʌrənt	рекуррентный, циклический, повторяющийся
recursively (adv.)	rɪˈkɜːsɪvli	рекурсивно, рекуррентно
reduce (v.)	rɪˈdju:s	снижать, сокращать
reduction (n.) dimensionality reduction	rɪˈdʌkʃ(ə)n	снижение, сокращение; сокращение размерности
redundancy (n.)	rɪˈdʌndənsi	дублирование, резервирование, запас мощности
refer to (v.) refer to as	rɪˈfɜ:	ссылаться, упоминать; называть, обозначать
regard (v.)	rɪˈgɑ:d	рассматривать

regardless (adv.)	rɪˈgɑ:dlɪs]	независимо от, несмотря на
regression (n.) polynomial regression	rɪˈgreʃ(ə)n	регрессия; полиноминальная регрессия
reinforce (v.)	ˌriːɪnˈfɔːs	подкреплять, усиливать
reinforcement (n.)	ˈri:ɪnˈfɔ:smənt	подкрепление, усиление
relate (v.) relate to	rɪˈleɪt	устанавливать отношение; касаться
related (adj.)	rɪˈleɪtɪd	связанный, сопутствующий
relationship (n.)	rɪˈleɪʃ(ə)nʃɪp	(взаимо)отношение, связь
relatively (adv.)	ˈrelətɪvlɪ]	относительно
relay (v.)	ˌriːˈleɪ	передавать, транслировать
relevant (adj.)	ˈrelɪv(ə)nt	актуальный, соответствующий
reliability (n.)	rɪˈlaɪəˈbɪlɪtɪ	надежность, безотказность
reliance (n.)	rɪˈlaɪəns]	зависимость, полагание
rely on (v.)	rəˈlaɪ ɒn	полагаться на
remain (v.)	rɪˈmeɪn	оставаться, сохраняться
remarkable (adj.)	rɪˈmɑ:kəb(ə)l	значительный, заметный
remote (adj.)	rɪˈməut	удалённый
remotely (adv.)	rɪˈməʊtli	удалённо
remove (v.)	rɪˈmu:v	удалять, устранять
renowned (adj.)	rɪˈnaund	известный, выдающийся
rent (v.)	rent	арендовать
repair (n.) (v)	rɪˈpeə	ремонт, исправление; ремонтировать, исправлять
repeat (v.)	rɪˈpi:t	повторять
replace (v.)	rɪˈpleɪs	заменять
replacement (n.)	rɪˈpleɪsmənt	замена
replan (v.)	ˌriːˈplæn]	перепланировать
replicate (v.)	ˈreplɪkeɪt	повторять, дублировать
represent (v.)	ˈreprɪˈzent	представлять, изображать
representation (n.) knowledge representation	ˈreprɪzenˈteɪʃ(ə)n	представление, изображение; представление знаний
reproduce (v.)	ˈri:prəˈdju:s	воспроизводить, дублировать
reproducible (adj.)	ˌriːprəˈdjuːsəb	воспроизводимый, повторяемый
request (n.) (v.)	rɪˈkwest	запрос, просьба; требовать, отправлять запрос
require (v.)	rɪˈkwaɪə	требовать, нуждаться
requirement (n.)	rɪˈkwaɪəmənt	требование
requirer (n.)		проситель
rescue (n.) (v.)	ˈreskju:	спасение; спасать, избавлять
researcher (n.)	rɪˈsɜ:ʧə	исследователь

resilient (adj.)	rɪˈzɪlɪənt	отказоустойчивый
resort to (v.)	rɪˈzɔːt	прибегать к, обращаться
respect with respect to	rɪˈspekt	внимание, отношение; что касается, в отношении
respectively (adv.)	rɪˈspektɪvli	соответственно
response (n.)	rɪˈspɒns	ответ, реакция
responsibility (n.)	rɪˌspɒnsəˈbɪləti	ответственность
restriction (n.)	rɪˈstrɪkʃn	ограничение
result (v.) result from result in	rɪˈzʌlt	происходить (в результате); являться результатом; приводить к
retain (v.)	rɪˈteɪn	сохранять
retrain (v.)	riːˈtreɪn	переобучать
retrieve (v.)	rɪˈtriːv	получать, извлекать
return (v.) (n.)	rɪˈtɜːn	возвращать(ся); доход, эффект
revalidate (v.)	ˌriːˈvalɪdeɪt	перепроверять, подтверждать
reward (n.)	rɪˈwɔːd	вознаграждение
rigorous (adj.)	ˈrɪg(ə)rəs	строгий, тщательный
rigorously (adv.)	ˈrɪgərəslɪ	строго, тщательно
rigour (n.)	ˈrɪgə	строгость, точность
roadmap (n.)	ˌrəʊdˈmæp	стратегический план, ориентир
robust (adj.)	rəʊˈbʌst	крепкий, надежный, устойчивый
roughly (adv.)	ˈrʌfli	приблизительо
route (n.)	ruːt	маршрут
rule (n.) chain rule learning rule rule of thumb		правило; цепное правило; обучающее правило; практическое правило
run (n.) (v.)	rʌn	прогон (программы); запускать, функционировать, проводить
runtime (n.)	ˈrʌntaɪm	время выполнения программы
	S	
safe (adj.)	seɪf	безопасный, надежный
safety-relevant (adj.)	ˈseɪftɪ ˈrelɪv(ə)nt	важный/существенный для безопасности
sample (n.) (v.)	ˈsɑːmp(ə)l	образец, выборка; проводить выборку, испытывать
sampling (n.)	ˈsɑːmpəlɪŋ	проведение выборки
satisfaction (n.)	ˌsætɪsˈfækʃn	удовлетворение, выполнение (условий)

scalability (n.)	ˌskeɪləˈbɪləti	масштабируемость
scale (n.)	skeɪl	масштаб; шкала
scope (n.)	skəʊp	диапазон, область
score (n.)	skɔ:	оценка
scrutinize (v.)	ˈskruːtənaɪz	тщательно проверять, внимательно изучать
search (n.) breadth-first search grid search	sɜːtʃ	поиск; поиск в ширину/поиск по вершинам поддеревьев; сеточный поиск, перебор параметров по сетке
secure (adj.) (v.)	sɪˈkjʊə	безопасный; обеспечивать, защищать
seed (n.)	si:d	начальное число
seek (v.)	si:k	искать, стремиться
select (v.)	sɪˈlekt	выбирать
semiconductor (n.)	ˌsemikənˈdʌktə(r)	полупроводник
sense (n.) (v.) make sense	sens	смысл; ощущать, считывать; иметь смысл
sensible (adj.)	ˈsensəbl	разумный, целесообразный
sensor (n.)	ˈsensə	датчик
sentiment (n.)	ˈsentɪmənt	эмоциональная окраска, тональность
separate (v.) (adj.)	ˈsepəreɪt ˈseprət	разделять, различать; отдельный
sequence (n.)	ˈsiːkwəns	последовательность
sequential (adj.)	sɪˈkwenʃl	последовательностный, многостадийный
service (n.)	ˈsɜːvɪs	служба, услуга
set (n.) (v.) data set validation set	set	набор; устанавливать; объем данных, набор данных; валидационное множество
setting (n.)	ˈsetɪŋ	установка; параметр настройки
several (adj.)	ˈsevrəl	несколько
shallow (adj.)	ˈʃæləʊ	невысокий, малой мощности
share (n.) (v.)	ʃeə	доля; делить(ся)
shift (n.) (v.)	ʃɪft	смена, сдвиг; смещать, переносить
shell (n.) expert system shell	ʃel	оболочка; оболочка экспертной системы,

		незаполненная (пустая) экспертная система
shop floor	ˌʃɒp ˈflɔː(r)	производственный цех
shrink (v.)	ʃrɪŋk	уменьшать(ся), сворачивать
sidestep (v.)	ˈsaɪdstep	оттеснять, уклоняться от
sigmoid (adj.)	ˈsɪgmɔɪd	сигмоидальный
significant (adj.)	sɪgˈnɪfɪkənt	значительный, существенный
significantly (adv.)	sɪgˈnɪfɪkəntli	значительно
signify (v.)	ˈsɪgnɪfaɪ	обозначать
similar (adj.)	ˈsɪmɪlə|	похожий, подобный
similarity (n.)	ˌsɪməˈlærəti	подобие, сходство
simplicity (n.)	sɪmˈplɪsəti	простота
simplify (v.)	ˈsɪmplɪfaɪ	упрощать
simulate (v.)	ˈsɪmjuleɪt	имитировать, моделировать, воспроизводить
simultaneous (adj.)	ˌs(a)ɪmlˈteɪniəs	одновременный
since (conj.)	sɪns	с тех пор, как; так как, поскольку
single (adj.)	ˈsɪŋg(ə)l	один, единственный
slope (n.)	sləʊp	наклон (функции)
smoothly (adv.)	ˈsmuːðli	плавно
SNARC (Stochastic Neural Analog Reinforcement Calculator)		стохастический нейронный аналоговый калькулятор с подкреплением
so-called (adj.)	ˌsəʊ ˈkɔːld	так называемый
softmax	ˈsɒftˌmæks	многопеременная логистическая функция
software (n.) control software	ˈsɔftweə	программное обеспечение; управляющее программное обеспечение
solely (adv.)	ˈsəʊlli	исключительно, только
solution (n.)	səˈluːʃn	решение
solve (v.)	sɒlv	решать
somewhere (adv.)	ˈsʌmweə	где-то
span (v.)	spæn	охватывать
space (n.)	speɪs	пространство
spatial (adj.)	ˈspeɪʃl	пространственный
specify (n.)	ˈspesɪfaɪ	определять, устанавливать
speed up (v.)	spiːdˈʌp	ускорять
state (n) (v.)	steɪt	состояние; утверждать
statement (n.)	ˈsteɪtmənt	утверждение

steady-state (adj.)	ˈstedɪˈsteɪt	установившийся, сравнительно устойчивый
steer (v.)	stɪə	управлять, направлять
stochastic (adj.)	stəˈkæstɪk	стохастический, вероятностный, случайный
stochastic gradient descent (SGD)		стохастический градиентный спуск
stochasticity (n.)	ˌstɒkæˈstɪsəti	стохастичность
storage (n.)	ˈstɔːrɪdʒ	запоминание; хранилище
store (v.)	stɔː	хранить, вмещать
straightforward (adj.)	ˌstreɪtˈfɔːwəd	прямой, непосредственный
stream (n.)	striːm	поток
streamline (v.)	ˈstriːmlaɪn	модернизировать, совершенствовать
strength (n.)	streŋkθ	сила, прочность, преимущество
strenuous (adj.)	ˈstrenjuəs	требующий усилий, напряженный
stringent (adj.)	ˈstrɪndʒənt	жесткий, строгий
strive (v.)	straɪv	стараться, прилагать усилия
subgraph (n.)	ˈsʌbgrɑːf, -græf	подграф
subsequent (adj.)	ˈsʌbsɪkwənt	последующий
subset (n.)	ˈsʌbset	подкласс, подгруппа
substantial (adj.)	səbˈstænʃl	существенный
subtle (adj.)	ˈsʌtl	неуловимый, едва различимый
succeed (v.)	səkˈsiːd	добиться успеха
successful (adj.)	səkˈsesfl	успешный
successor (n.)	səkˈsesə	преемник
suffer (v.)	ˈsʌfə	страдать, подвергаться воздействию
sufficiently (adv.)	səˈfɪʃntli	достаточно
suggest (n.)	səˈdʒest	предлагать; предполагать
suit (v.) suited	s(j)u:	подходить, удовлетворять
suitable (adj.)	ˈs(j)u:təb(ə)l	подходящий
suitably (adv.)	ˈs(j)u:təblɪ	должным образом, достаточно
supersede (v.)	ˌs(j)u:pə'si:d	заменять, вытеснять
supervise (v.)	ˈsuːpəvaɪz	контролировать, выполнять диспетчерские функции
support vector machines		машина опорных векторов; метод опорных векторов
suppose (v.)	səˈpəʊz	предполагать
surface (n.)	ˈsɜːfɪs	поверхность
surpass (v.)	səˈpɑːs	превосходить
surplus (n.)	ˈsɜːpləs	избыток

surround (v.)	səˈraʊnd	окружать
survey (n.)	ˈsɜːveɪ	опрос
switch (v.) (n.)	swɪʧ	переключать; переключатель
T		
tailor (v.)	ˈteɪlə	адаптировать, приспосабливать, специально разрабатывать
tanh (hyperbolic tangent)		гиперболический тангенс
taper off (v.)	'teɪpə(r)'ɔf	уменьшать(ся), сокращать(ся)
target (n.) (v)	ˈtɑːɡɪt	цель; иметь целью
technician (n.) service technician	tekˈnɪʃn	технический специалист; специалист по обслуживанию оборудования
technique (n.)	tekˈniːk	техника, методы, приём
tedious (adj.)	ˈtiːdiəs	утомительный, трудоемкий
tend (v.)	tend	иметь тенденцию, быть склонным
term (v.)	tɜːm	называть, именовать
themselves (pron.)	ðəmˈselvz	сами
thereby (adv.)	ðeəˈbaɪ	таким образом, тем самым
therefore (adv.)	ˈðeəfɔː	поэтому, следовательно
thereof (adv.)	ˌðeərˈɒv	соответственно, в данном отношении
though (conj.)	ðəʊ	хотя
threshold (n.)	ˈθreʃ(h)əʊld	пороговая/предельная величина
through (prep.)	θruː	через
throughout (prep., adv.)	θruːˈaʊt	в течение; на всём протяжении
throughput (n.)	ˈθruːpʊt	производительность, пропускная способность
thus (adv.)	ðʌs	таким образом
tie (v.)	taɪ	привязывать
time-consuming (adj.)	ˈtaɪm kənsjuːmɪŋ	трудоемкий, отнимающий много времени
tool (n.)	tuːl	инструмент
toolbox (n.)	ˈtuːlbɒks	инструментарий, набор инструментов
totally (adv.)	ˈtəʊtəli	полностью
toward (prep.)	təˈwɔːd	к, в направлении
TPU (tensor processing unit)		тензорный процессор

tracking (n.)	ˈtrækɪŋ	отслеживание, сопровождение
train (v.)	treɪn	обучать
training set		набор данных для (машинного) обучения
transfer (n.) (v.)	ˈtrænsfɜː(r) trænsˈfɜː(r)	передача, перенос; переносить, передавать
transform (v.)	trænsˈfɔːm	преобразовывать
transparency (n.)	trænsˈpærənsi	прозрачность
treat (v.)	triːt	трактовать, рассматривать, обрабатывать
tree (n.) classification tree decision tree regression tree	triː	дерево, древовидная схема; дерево классификации; дерево (поиска) решений; дерево регрессии
tremendous (adj.)	trəˈmendəs	огромный
trial and error	ˈtraɪəl ənd ˈerə	метод проб и ошибок
tune (v.)	tjuːn	регулировать
tuning (n.)	ˈtjuːnɪŋ	регулирование
tuple (n.)	ˈtjuːp(ə)l	кортеж
turn into (v.)	tɜːn ˈɪntə	превращать
tweaking (n.)	ˈtwiːkɪŋ	оптимизация, тонкая настройка, подстройка
U		
ultrasonic (adj.)	ˌʌltrəˈsɒnɪk	ультразвуковой
unartificial (adj.)	ˌʌnˌɑːtɪˈfɪʃl	естественный, натуральный
uncertain (adj.)	ʌnˈsɜːtn	неопределенный
uncertainty (n.)	ʌnˈsɜːtnti	неопределенность
underflow (n.)	ˈʌndəfləʊ	исчезновение значащих рядов, потеря значимости
underlie (v.)	ˌʌndəˈlaɪ	лежать в основе
undistinguishable (adj.)	ˌʌndɪˈstɪŋgwɪʃəb(ə)l	неразличимый
unfair (adj.)	ʌnˈfeə	несправедливый
unfortunately (adv.)	ʌnˈfɔːtʃənətli	к сожалению
unintended (adj.)	ˌʌnɪnˈtendɪd	непреднамеренный, непредусмотренный
unique (adj.)	juˈniːk	уникальный
unit (n.)	ˈjuːnɪt	единица
unlabeled (adj.)	ʌn'leɪbld	непомеченный
unlike (prep.)	ˌʌnˈlaɪk	в отличие от
unlikely (adj.)	ʌnˈlaɪkli	маловероятный
unmanned (adj.)	ʌnˈmænd	беспилотный, автоматический
unnecessary (adj.)	ʌnˈnesəsəri	ненужный
unparalleled (adj.)	ʌn'pærəleld	исключительный, непревзойденный

unpredictable (adj.)	ˌʌnprɪˈdɪktəbl	непредсказуемый
unravel (v.)	ʌnˈrævl	объяснять, разгадывать
unreadable (adj.)	ʌnˈri:dəb(ə)l	несчитываемый
unremarkable (adj.)	ˌʌnrɪˈmɑːkəbl	незаметный
unseen (adj.)	ˌʌnˈsiːn	невидимый; неактивный
unsupervised (adj.)	ˌʌnˈsuːpəvaɪzd	без учителя, неконтролируемый
unsure (adj.)	ʌnˈʃʊə	неуверенный, ненадёжный
update (v.)	ˌʌpˈdeɪt	обновлять
update rule		правило обновления
upfront (adj.)	ˌʌpˈfrʌnt	предшествующий
uphold (v.)	ʌpˈhəʊld	соблюдать, поддерживать
upswing (n.)	ˈʌpswɪŋ	подъем, повышение
usefulness (n.)	ˈjuːsflnəs	полезность
usefulness (n.)	ˈjuːsflnəs	полезность
uselessness (n.)	ˈjuːsləsnəs	нецелесообразность
user-friendly (adj.)	ˌjuːzə'frɛndli	удобный для пользователя
usher in (v.)	ˈʌʃə	возвещать, объявлять
utilitarian (adj.)	ju:'tɪlɪ'te(ə)rɪən	практичный
utilize (v.)	ˈjuːtəlaɪz	использовать
V		
vague (adj.)	veɪg	неясный, неопределенный
vagueness (n.)	ˈveɪgnəs	неопределенность, нечеткость
valid (adj.)	ˈvælɪd	действительный, достоверный
validation (n.) cross validation leave-one-out cross-validation	ˌvælɪˈdeɪʃn	проверка, подтверждение достоверности; перекрестная проверка результата на достоверность; метод исключения одного объекта
valuation (n.)	ˌvæljuˈeɪʃn	оценка, определение ценности
value (n.)	ˈvæljuː	значение, параметр, величина
vanishing	ˈvænɪʃ	исчезать
variable (n.) dependent variable	ˈveəriəbl	 зависимая переменная
variable (n.) process variable		переменная величина; регулируемая переменная, параметр процесса
variance (n.)	ˈveəriəns	отклонение
variety (n.)	vəˈraɪəti	разнообразие
various (adj.)	ˈveəriəs	различный, разнообразный
vary (v.)	ˈveəri	варьироваться, изменяться
vehicle (n.)	ˈviːəkl / ˈviːhɪkl	транспортное средство, автомобиль

velocity (n.)	vəˈlɒsəti	скорость
verification (n.)	ˌverɪfɪˈkeɪʃn	проверка, испытание, подтверждение корректности
versatility (n.)	ˌvɜːsəˈtɪləti	универсальность
versus (prep.)	ˈvɜːsəs	в сопоставлении с, против
via (prep.)	ˈvaɪə / ˈviːə	через
vicinity (n.)	vəˈsɪnəti	окружающее пространство
violation (n.)	ˌvaɪəˈleɪʃn	нарушение (правил), отклонение
virtue (n.)	ˈvɜːtʃuː	мораль, нравственность
visibility (n.)	ˌvɪzəˈbɪləti	видимость
vision (n.) computer vision	ˈvɪʒn	зрение; машинное зрение
voltage (n.)	ˈvəʊltɪdʒ	напряжение
	W	
warn (v.)	wɔːn	предупреждать
waste (n.) (v.)	weɪst	отходы производства, потери; терять, тратить
weakness (n.)	ˈwiːknəs	уязвимость, недостаток
wealth (n.)	welθ	материальные блага, состояние
weight (n.) (v.)	weɪt	вес; присваивать вес
weighted sum (n.)	ˈweɪtɪd ˈsʌm	взвешенная сумма
wheel (n.) steering wheel	wiːl	колесо; руль управления
whereas (conj.)	ˌweərˈæz	в то время, как
whether (conj.)	ˈweðə	ли
while (conj.)	waɪl	пока; в то время как
white-box (n.)		белый ящик (объект исследования с полностью известными или полностью принимаемыми во внимание свойствами)
widespread (adj.)	ˈwaɪdspred	распространенный
with respect to		в отношении; применительно к
without (prep.)	wɪˈðaʊt	без
workshop (n.)	ˈwɜːkʃɒp	семинар, совещание рабочей группы
worthwhile (adj.)	ˌwɜːθˈwaɪl	целесообразный, оправданный
	Y	
yield (n.) (v.)	jiːld	выход, объем выпуска; давать (на выходе)

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