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Artificial Intelligence Demystified

Summary

The United Nations Secretary General's Strategy on New Technologies recognizes the importance of artificial intelligence (AI) and its promise for the advancement of human welfare, but also the potential risks it may pose for global society. "*AI and robotics promise enhanced economic growth, but they can also exacerbate inequality within and between nations and can contribute to unemployment. Neural networks and deep learning offer the promise of instantaneous translation, bringing us all closer together. But they may also learn and amplify our biases, driving us further apart.*"

Theoretical and practical applications in the field of artificial intelligence accompany a series of concepts, approaches and tools from diverse fields - mathematics, statistics, information theory, data science, biology and cognitive psychology - to create new ways to analyze and understand the data and its hidden qualities and to unlock its potential value to automate and improve business processes and decision-making.

This text aims to provide an overview of the evolution and current state of artificial intelligence, to explain some of the main principles, potential applications and interactions with other advanced technologies, and to demystify the "artificial intelligence" term using down to earth examples. The intention is to lay a foundation for future discussions, projects and collaborations among trade facilitation experts and practitioners, and to support other United Nations Centre for Trade Facilitation and Electronic Business (UN/CEFACT) work items, specifically development of guidance material and, regional and global regulatory documents.

Document ECE/TRADE/C/CEFACT/2021/19 is submitted by the Chair of the Advisory Group on Advanced Technologies in Trade and Logistics to the twenty-seventh session of the Plenary for information.

Contents

I. Introduction

1. Artificial intelligence (AI) is one of the most discussed but also the most misunderstood and underestimated advanced technologies of our time. As with every emerging technology, discussion about AI tends to produce both enthusiasm and scepticism. Today, in this relatively early stage of its practical application, AI is the source of many controversies and grand proclamations. Even now, AI is still perceived as one of the big existential threats to humanity, as famously expressed by Stephen Hawking, *"the development of full artificial intelligence could spell the end of the human race*."[1] Yet, AI can also be perceived as one of humankind's biggest opportunities. If handled well, an AI application can excel in various fields of activity historically reserved for humans - even outperforming them.

2. When human activities (or parts of them) are digitized, their performance and precision are greatly improved. Traditional algorithmic computer programming has dramatically empowered humans in repetitive, procedural activities. An important branch of artificial intelligence - machine learning - empowers humans to address different types of activities such as perception, classification and prediction. In this new application space, computers can operate at a much higher speed and on a larger scale than humans can. Humans performing repetitive perception, classification and prediction tasks are empowered by machines, augmenting our capabilities at unprecedented levels.

3. When AI is mentioned in general discussions, many people still imagine the AI archetype presented in popular media over the last decades - a malevolent out-of-control computer such as the voice of HAL 9000 from 2001: A Space Odyssey; Skynet from Terminator; or Agent Smith from The Matrix - but the banal reality is that artificial intelligence, as the computer science and developer communities understand it, is already all around us in some way or another. It is a part of our everyday lives without most of us even realizing or noticing it.

4. In order to shed some light on this often misunderstood technology, we'll first provide a brief history, outlining the basic principles behind AI and presenting some types of problems it can solve. Next, we'll describe some existing use cases, and conclude by presenting some potential near-future applications relating to international business and other advanced technologies such as the Internet of things (IoT), blockchain and distributed ledger technologies (DLT), and concepts such as the smart city and the Industrial Revolution 4.0.

II. History of artificial intelligence

5. As with many emerging technologies, there is no generally accepted definition of AI. Similar to technology concepts like blockchain, with its combination of multiple factors and technological developments, when trying to define such concepts we are mostly trying to describe them by their features.

6. In simple terms, AI is a system that simulates some aspects of human/biological intelligence in an artificial/machine environment.

7. The High-level Expert group on AI of the European Commission has provided a more formal definition: "*Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge or processing the information derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also*

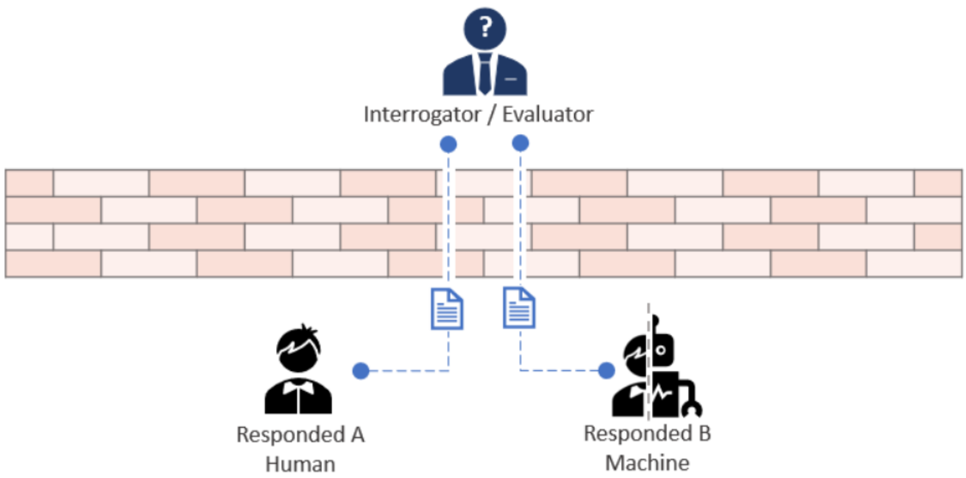
[1] Rory Cellan-Jones, "Stephen Hawking warns artificial intelligence could end mankind", BBC News, 2 December 2014. Available at: https://www.bbc.com/news/technology-30290540

adapt their behaviour by analysing how the environment is affected by their previous actions."[2]

8. The most common explanation of the application of AI is that it's a computer algorithm capable of exploiting a high quantity of external data to identify and recognize patterns and correlations in these data, and able to perform tasks mimicking some qualities of human intelligence such as the ability to observe and learn, to continuously self-correct, to reason, plan, problem-solve and to improve its capability as more inputs are provided. In this way, it demonstrates some aspects akin to those of human intelligence in an artificial (machine and virtual) environment.

9. In 1950, Isaac Asimov published his famous *I, Robot*, a collection of short stories where he introduced 3 laws of robotics[3] - unbreakable ethical principles for artificial beings. In the same year, British mathematician Alan Turing proposed the "imitation game"[4] - the now so-called Turing test - to evaluate if a machine can express intelligent behaviour. Turing proposed a scenario where a machine, human, and evaluator are separated from each other. The evaluator has a natural-language conversation using text-based channels with both the machine and the human, unaware which conversation partner is which. If the evaluator cannot reliably tell the machine from the human, based on the conversation and the responder's behaviour, the machine can be considered to exhibit intelligent behaviour.

Figure 1
The principle of Turing's test



Source: UNECE

10. This test was later disputed by philosopher John Searle and his also famous Chinese room thought experiment[5]. He argued that if a computer simply makes the correct connection between an input (a question in the Chinese language, represented by a series of characters) and the correct output (an answer, again represented by a series of characters) it does not necessarily imply that the machine understands the Chinese language. It would appear to have appropriate answers and pass the Turing test as an intelligent machine, but it would merely simulate understanding; and without understanding, we cannot consider the machine to be thinking or of having a mind. This argument led to the use of concepts such as strong AI and weak AI, distinctions still in use today (to be explained further in this text).

[2] European Commission High-Level Expert Group on Artificial Intelligence, *High Ethics Guidelines for Trustworthy AI*, 8 April 2019. Available at: https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=60419

[3] *A robot may not injure a human being or, through inaction, allow a human being to come to harm. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.*
A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws

[4] See: https://academic.oup.com/mind/article/LIX/236/433/986238

[5] See: http://cogprints.org/7150/1/10.1.1.83.5248.pdf

11. The term "artificial intelligence" was first coined by John McCarthy as *"the science and engineering of making intelligent machines"*[6] in a document created for a conference on the campus of Dartmouth College in 1956. This conference kickstarted the beginning of serious AI research in the upcoming decades.

12. One of the first successful applications of AI algorithms dates back to 1962 and is attributed to another AI pioneer, Arthur Samuel, who coined the term "machine learning" and who created a computer program which could learn and play a game of checkers (drought) with itself, and evolve itself finding new strategies. Eventually, it was able to learn the game to a degree that it was consistently able to beat its creator. This led to a series of famous man vs. machine competitions, in which machines have ultimately been able to slowly conquer one field after another, with possibly more to come.

13. The reason why classic board games are so popular in AI experiments is that their framework and rules are relatively easy to model and transfer to the virtual world. All possible player behaviours are predefined and can therefore be translated to a programming language as a set of conditions and instructions. Moreover, all context is perfectly visible to all players. The game of Checkers is relatively simple due to its rules and the limited number of possible combinations of moves, but more complex games introduce new challenges and require different approaches to transfer their models. Strategic, real-world behaviours (such as driver decisions) introduce many additional sets of variables (e.g. the laws of physics, driving rules and human values) and translating them into algorithms is one of the ultimate challenges of AI.

III. Artificial intelligence – principles

14. In a standard algorithmic approach to solving problems, we define, analyze and understand the problem, create a model of the scenario and construct an algorithm that is able to try different combinations of approaches to solving the problem. One of the fundamental building blocks of any algorithm is a conditional decision: IF some condition occurs, THEN do some action. The complexity depends on the variety of possible inputs and outputs, the number of states that can occur, and the possible outcomes. AI is not primarily based on deterministic logic of conditional decisions, AI is an umbrella term for different kind of technologies. From classical rule-based logic approach (e.g., expert systems) to machine learning, arguably the most relevant approach today, using probabilistic reasoning algorithms, based on observation and statistics.

A. Combinatorial explosion

15. Where some relatively trivial problems can be algorithmically solved, the game of chess is a completely different problem. The complexity (possible variations) of a single game of chess are explained by its lower bound, also known as Shannon Number (10^{120}), which is famously higher than the number of atoms in the observable universe (10^{80}). This means that there isn't enough available matter for the memory demands of a brute-force algorithm trying all possible moves and choosing the best one. This rapid growth in a problem's complexity is known as "combinatorial explosion"; in such scenarios, different approaches must be used. Applications of artificial intelligence use algorithms that autonomously extract correlations from the observed data (e.g. checker moves), building a statistical model that can be later used to predict the best move to perform in a given situation.

B. Types of artificial intelligence

16. Artificial general intelligence (AGI) - also known as strong, deep, true or full AI - is the hypothetical state of artificial intelligence where a machine can learn and understand tasks

[6] John McCarthy, *"*What is Artificial Intelligence?*"*, revised 12 November 2007). Available at: http://jmc.stanford.edu/articles/whatisai/whatisai.pdf

in the same manner as a human being - meaning cognitive abilities, reasoning and problem-solving.

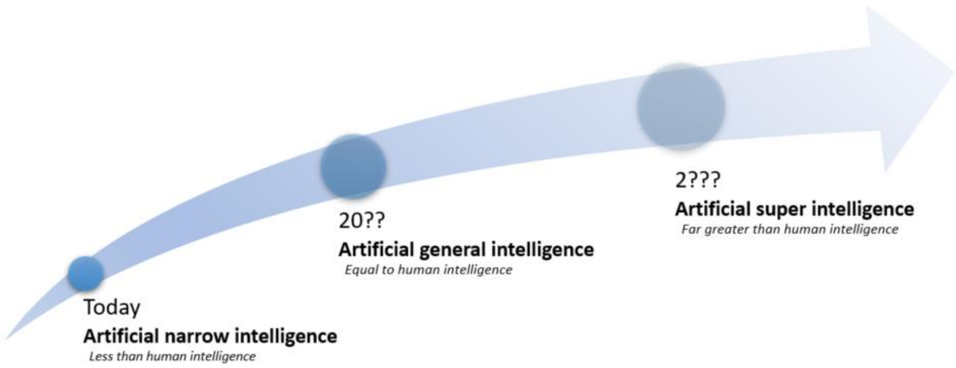
17. Artificial general intelligence is the type of AI that can theoretically pass the Turing test and Chinese room test, and is the type of AI that research is trying to achieve. It is the mainstream understanding of AI reflected in sci-fi works.

18. Artificial superintelligence (ASI) is the next hypothetical step in AI. ASI would not only resemble human intelligence and behaviour, but would be able to exceed and surpass it.

19. Narrow AI (or weak AI) is designed to handle very narrow and specific tasks, while still resembling some aspects of human Intelligence.

Figure 2

Types of artificial intelligence



Source: UNECE

20. At this point, we have only successfully created examples of narrow AI. Examples of general and super intelligence remain to be seen but are being actively pursued and would be considered major scientific and technological milestones.

21. In the field of narrow AI, some applications are proving very effective – to the degree that they are currently being used in many day-to-day operations. Examples of narrow AI applications are: spam email detection, optical character recognition (OCR), automatic video captioning, natural language processing, translation services, image recognition and online assistants. Marketing campaigns and online shopping recommendations are some simple applications of narrow AI that we interact with on a day to day basis, often without even realizing they use some kind of AI as their foundation.

22. Perhaps more visible are popular attempts to create task-specific AI applications that can compete with, and eventually beat, humans in some specific competitive activity such as classic board games.

23. In 1997, chess-playing computer Deep Blue, developed by IBM, famously won a series of matches against reigning world champion Garry Kasparov[7].

24. In 2011, the question-answering computer Watson, developed by IBM, competed in the television quiz show Jeopardy! After a series of matches won against two of the show's most successful contestants[8].

25. Researchers focused on another classic strategic board game, Go, in testing the next step in AI capabilities. Go, compared to chess, offers much more complexity. The board is five times bigger (361 vs 64) and each turn allows an average of 200 legal moves. As such, the number of possible positions on the Go board is around 10^{172}, which is 10 sexdecilion times (53 decimal digits, or 10^{52}) more than the number of combinations in chess.

26. In 2016, Go-playing computer AlphaGo, developed by Google DeepMind, played and won 4 out of 5 matches in a set of games of Go against Lee Sedol, a 9 dan champion[9]

[7] https://www.ibm.com/ibm/history/ibm100/us/en/icons/deepblue/

[8] https://ieeexplore.ieee.org/xpl/tocresult.jsp?reload=true&isnumber=6177717

[9] The highest rank of a professional Go player

considered the top player in the world. In 2017 the improved version of the program, called AlphaGo Zero, beat the previous version by 100 games to 0.[10]

27. These examples illustrate two main messages in AI developments: Firstly, AI algorithms can, with further iterations, improve and solve gradually more complex tasks. Secondly, once the AI algorithms reach a certain level, they dominate and surpass even the best humans in their respective fields. With this in mind, the question about the next field of narrow AI application can be presented as "*what (field it will be)?*" and "*when (will it reach dominance)?*".

IV. Artificial intelligence algorithm process explanation

28. In principle, AI algorithms work by processing a large amount of data and trying to recognize patterns in it. Based on these patterns, algorithms are able to interpret the data or take some predefined action such as to create predictions, classify data based on their features, or suggest or perform some automated action.

29. In its inner workings, the AI algorithm is consuming data and using this data to retrain itself. It does this by creating a model for understanding the data and its attributes, to be used in future decisions. These models are then continuously reviewed, improved, and adapted with more input data and production runs. This simulates learning behaviour as we understand it from our human learning perspective.

30. When AI is asked to perform a task, it uses its previous experience-based model to perform a best guess in understanding the input data and to suggest or perform an action as an output.

A. Machine learning

31. Machine learning (ML) is a subfield of AI that aims to create a learning algorithm to gradually improve itself based on more experience: more algorithm runs, more processed data, and (in some cases) feedback provided from external sources – either by the environment or by a human.

32. Tom Mitchell provides a more modern definition: "*A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.*"[11]

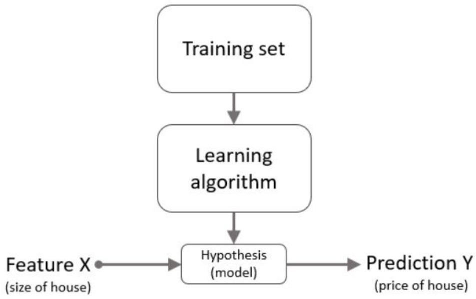
33. Going back to board games, task T is to play a game, experience E is all matches of the game, and P can be win/loss ratio. In other words, the win/loss ratio grows as the algorithm plays more rounds of the game.

B. Types of machine learning: supervised, unsupervised, semi-supervised and reinforced learning

34. Similar to the human approach to learning, where some skills are obtained in school by learning from teachers and subject matter experts, and other skills are discovered in the environment (through our own observations), a machine can also approach learning in different ways – each suited to different problem-solving environments and goals.

[10] Demis Hassabis and David Silver, "AlphaGo Zero: Starting from scratch", Deep Mind, 18 October 2018. Available at: https://deepmind.com/blog/article/alphago-zero-starting-scratch
[11] Tom Mitchell, *Machine Learning* (New York, NY, McGraw Hill, 1997). Page 2.

Figure 3
Basic principle of machine learning



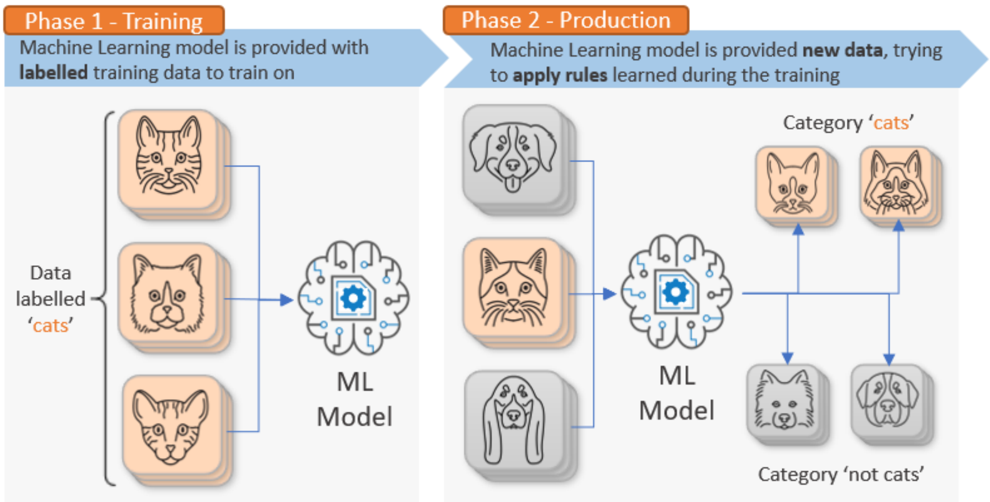
Source: Andrew Ng

1. Supervised learning

35. Supervised learning is like having a trainer. The algorithm is provided with labelled training data that describes the parameters of the input data. The algorithm is then trained to process such data, recognizing patterns in it, and associating the data with the provided labels. This process, which we call training, is performed by skilled professionals to obtain a statistical model of the scenario under study. In the next step, the algorithm is provided with new, unlabeled data. Based on previous observations, the algorithm will attempt to apply a learned mechanism to perform a best guess and assign the unlabeled data with additional parameters, typically sorting it into categories or performing predictions.

36. Supervised machine learning algorithms are the most common type in current commercial use.

Figure 4
Supervised machine learning



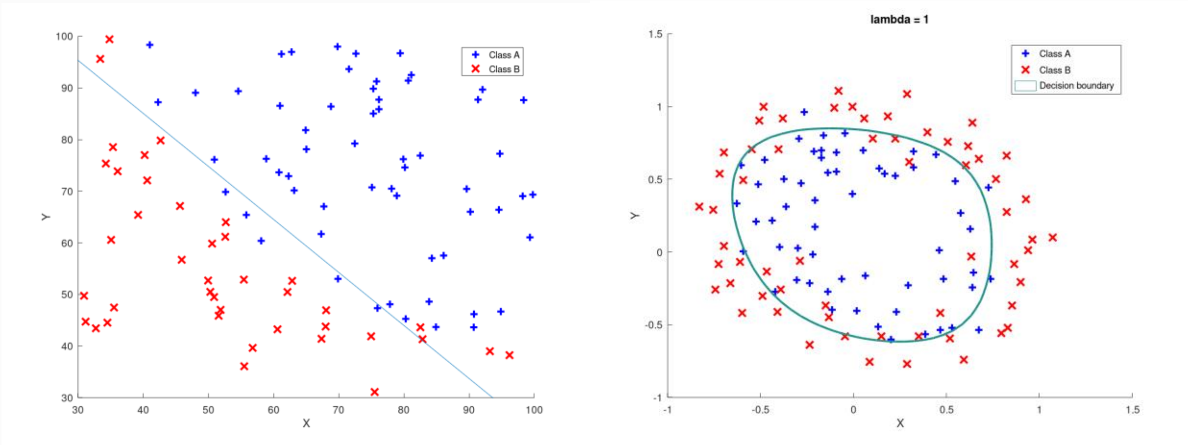
Source: UNECE

37. Classification and regression problems (defined below) are typical cases of supervised learning.

1.1. Classification

38. Classification is the action of identifying and finding patterns in data in order to classify and sort it into different categories – producing discrete value outputs.

Figure 5
Examples of classification problems



Linear binary classification | Nonlinear classification

Source: UNECE

39. A typical example of a supervised learning classification problem is image recognition. An algorithm is supplied with a set of images, for example, containing dogs. It processes the data and recognizes patterns in the supplied data set. Next, it is given unlabeled data and the algorithm attempts to identify and classify pictures with dogs.

40. Optical character recognition is also a type of classification problem where, based on input data, the algorithm classifies each character from the visual data feed and tries to assign them to the proper character category, thus identifying them as a text or numbers.

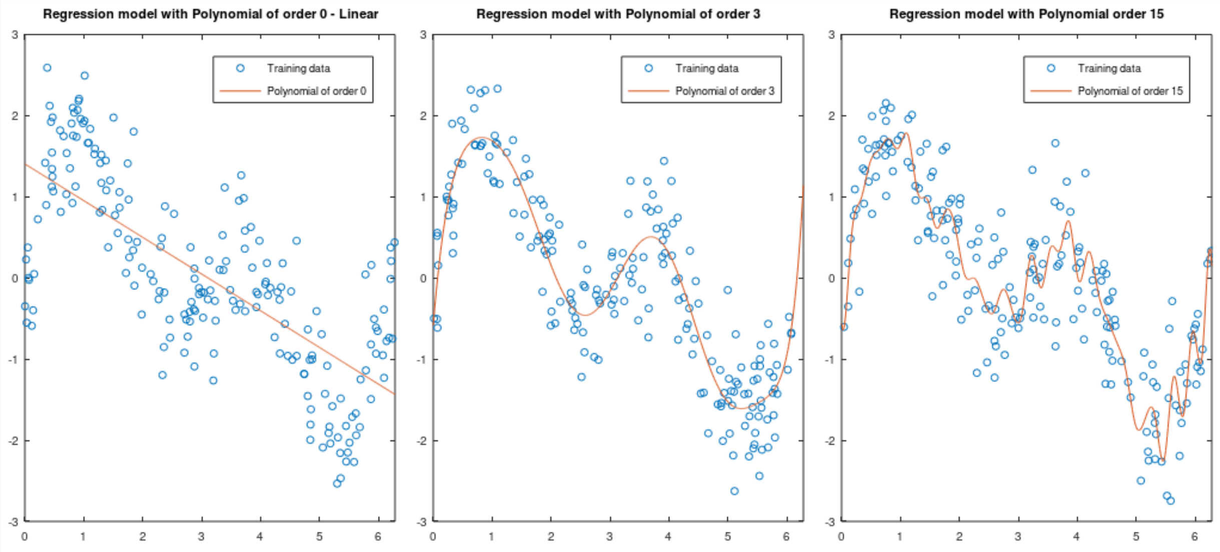
1.2. Regression

41. A regression task is one that analyzes continuous data in an attempt to find relationships between variables (typically between one dependent and several independent variables) to predict a theoretical outcome for which there are no available data measures, such as future predictions.

42. Regression is mostly used in prediction and forecasting models; a prediction algorithm learns and creates its models on the features of current or historical states of variables to create and predict continuous value output.

43. This can lead to a simple linear regression relationship or to a more complex logarithmic, exponential or polynomial relationship of different degrees. By extending values into unknown regions while following discovered variable relationships, we can predict their positions outside of scope available to us in training data sets.

Figure 6
Example of a regression problem



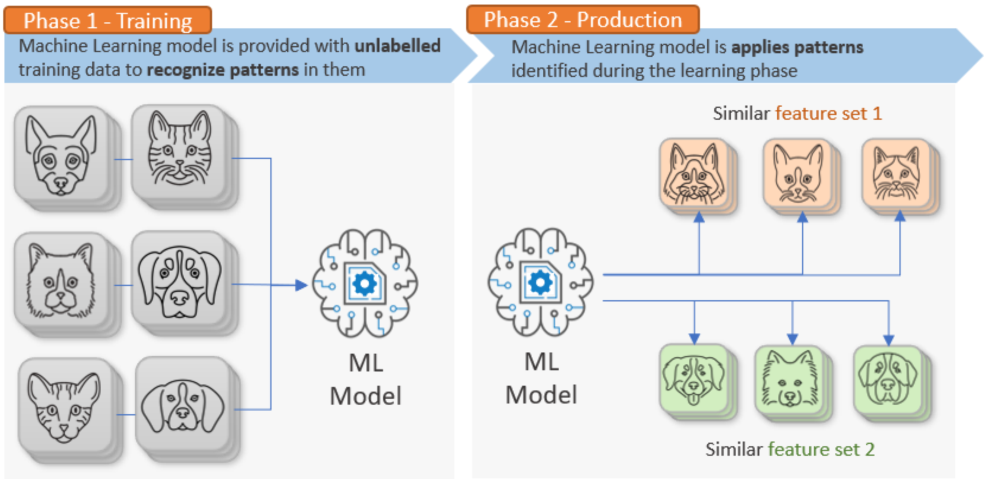
*0-degree polynomial (linear function) shows “**underfitting**” of prediction model to training data, therefore missing most of the data points*
*3rd-degree polynomial fits “**just right**” and follows pattern of training data close enough to predict new data points outside of the training set*
*15th-degree polynomial shows “**overfitting**” of prediction model that aligns too closely to training data but would perform poorly on data outside of the training set*

Source: UNECE

2. Unsupervised learning

44. Unsupervised machine learning, on the other hand, is an approach where a learning algorithm is trained by supplying it with unlabeled input data and without any specific guidance, desired outcome, or correct answer. The algorithm tries to analyze the data on its own to identify data features and to recognize any underlying patterns and structures. In this type of machine learning there is no feedback based on predicted results.

Figure 7
Unsupervised machine learning



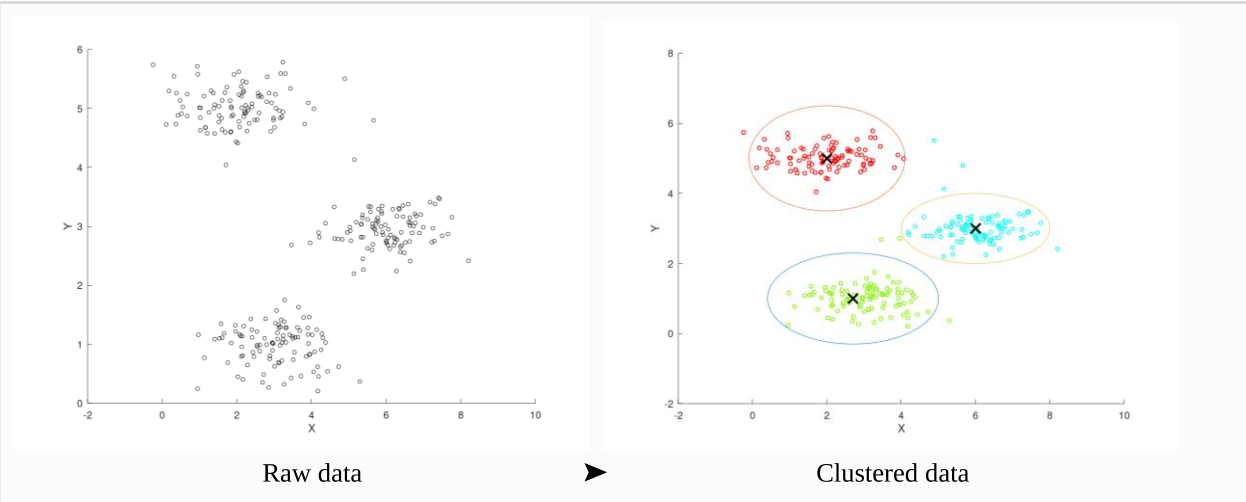
Source: UNECE

45. Output results and data interpretation can be used in modelling methods such as clustering, association, anomaly detection, or dimensionality reduction, as explained below.

2.1. *Clustering*

46. Clustering, in unsupervised learning, involves looking for patterns and common connections in unlabeled data sets and creating groups of data based on common attributes. Clustering can be seen in the marketing sector where it is used for customer segmentation, that is, for creating "buckets" of customers that share some common attributes.

Figure 8
Example of clustering

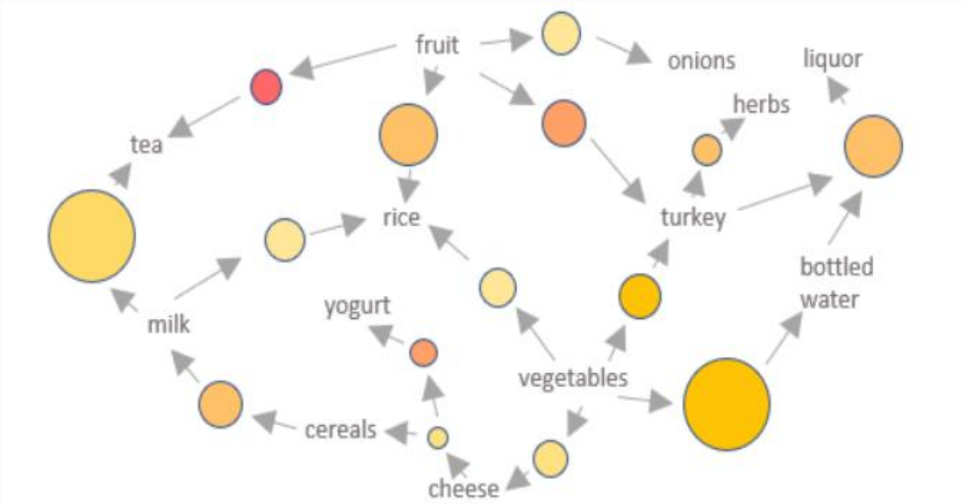


Source: UNECE

2.2. *Association*

47. Detecting association rules in data involves trying to find and describe previously unknown and hidden relationships in data sets. In transaction data, an algorithm can analyze steps and determine how they relate to each other. It can find out which steps precede or succeed other steps more often and assume hidden rules for causality.

Figure 9
Example of an association model



Visualization of association rules from grocery transactions
(larger circle size implies rule's *support (frequency of rule)*; circle colour implies rule's *lift (strength of rule)*

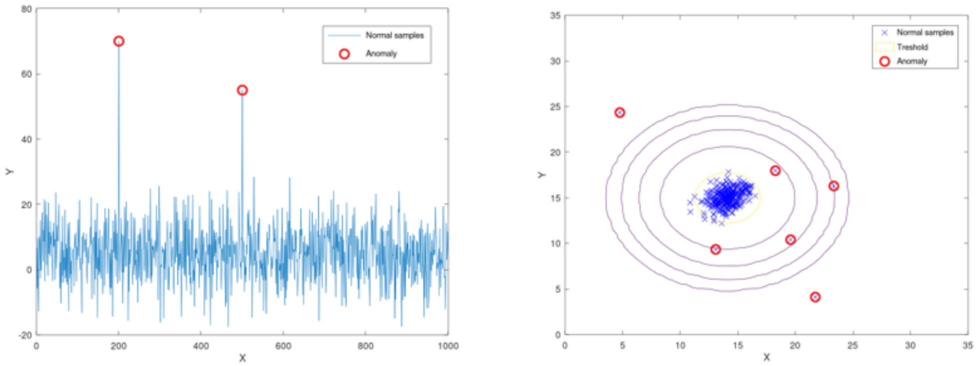
Source: UNECE

48. Association is typically used in retail and online shopping business to analyze and understand customer buying habits and to create a more optimized and targeted marketing strategy. Association rules can be also used in layout planning and design, from shopping layout to urban planning.

2.3. Anomaly detection

49. Recognizing and identifying anomalies in data can have many benefits, assuming that most of the data and flows are statistically coherent. That is, following (for example) Gaussian distribution, where any significant deviation can mean potential issues to investigate and analyze further.

Figure 10
Examples of anomaly detection



Anomaly in time series

Anomaly in Gaussian distribution

Source: UNECE

50. In the financial services sector, anomaly detection can be used to identify fraud, as unusual spending patterns can mean a compromised account or credit card theft. In manufacturing anomaly detection can help with automated quality control, as an anomaly can mean a defective product. In data center management it can identify a faulty machine or

a stuck process. In cybersecurity unusual resource access or network activity can mean a potential security issue or network breach.

51. With the growing scale of Internet of Things (IoT) and concepts such as smart cities depending heavily on increased data inputs from various sensors, anomaly detection could be used to detect real-life incidents (e.g. related to traffic, city infrastructure or shipping). These inputs could possibly trigger alerting systems or enable preventive and corrective actions before the incident occurs.

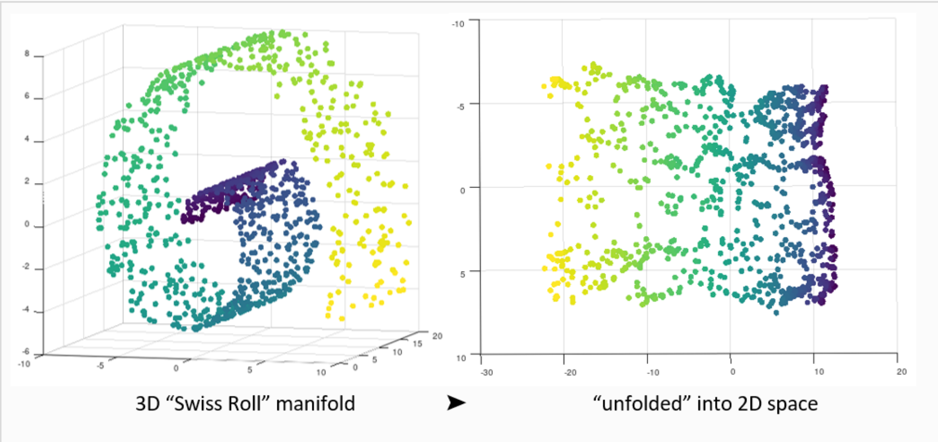
2.4. *Dimensionality reduction*

52. When we analyze data, we may find that it has many dimensions. In healthcare data we usually study all patients' history and physiometric parameters. The insurance industry is trying to create more precise models by taking data from a variety of sources for more accurate risk assessments. Web-streaming data may include hundreds or thousands of different dimensions with strongly correlated data.

53. In very large data sets, typically produced through big data, multiple dimensions may contain redundancies (e.g. height in feet, metres, and centimetres) or data that is irrelevant for a specific need. Dimensionality reduction simplifies data analysis by creating a subset of data features or extracting specific sets of data features to create a new data set.

54. Dimensionality reduction may be used in image recognition. An AI dealing with form recognition might, for example, convert a coloured high-resolution image into a black and white, single colour intensity value per pixel, lower-resolution image that is sufficient for subsequent recognition tasks.

Figure 11
Examples of dimensionality reduction



Source: UNECE

55. Dimensionality reduction is usually intended to improve computational efficiency for subsequent processes. It can help in pre-processing for further training algorithms, or it can find hidden intrinsic patterns in data. Dimensionality reduction can be also used in data compression data visualization of high-dimensional data sets, reduced and displayed as 3D or 2D data visualizations.

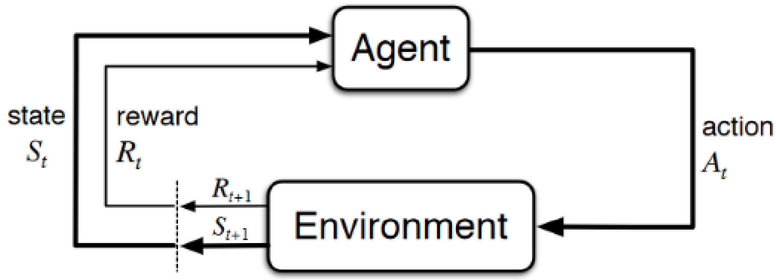
3. Semi-supervised learning

56. Semi-supervised learning, as the name suggests, is a combination of both supervised and unsupervised approaches. A smaller set of labelled data is provided, together with a bigger set of unlabelled data. This helps the training algorithm produce a better model and can, potentially, greatly improve the model's performance in terms of output precision and accuracy.

4. Reinforcement learning

57. In reinforcement learning (RL), an artificial agent maximizes a reward function which is designed to represent success in the domain. The idea at the core of this learning paradigm is that the agent (or system) explores the environment and receives a reward or a penalty depending on the actions it takes. In an example where an agent learns to play a video game, the agent will learn that certain moves lead to a better score while others will make it lose the game.

Figure 12
Example of reinforcement learning – agent training and feedback loop



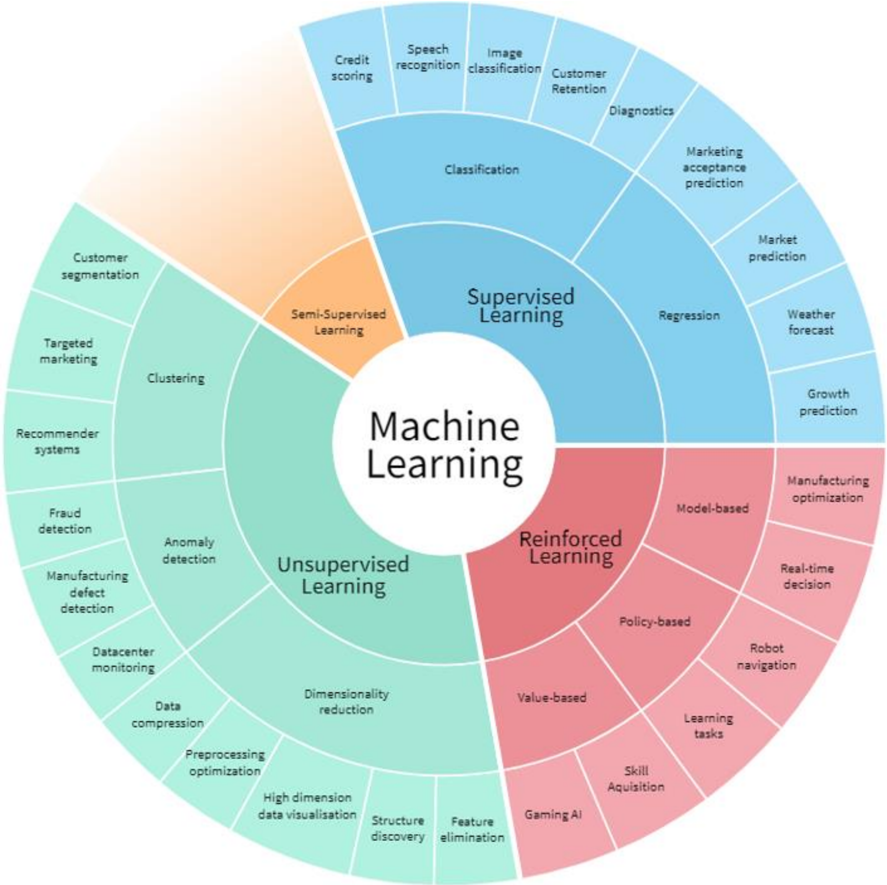
Source: DeepMind

58. One of the most popular algorithms for reinforcement learning is Q-learning where “Q” stands for “quality”, which represents the output value that the algorithm is trying to maximize.

59. Examples of Q-learning applications might include improving a score in a computer game, minimizing a cost, creating a logistic route, or maximizing profit score. In 2015, the team behind Google’s DeepMind project published an article describing the process of teaching AI algorithms, using deep reinforcement learning methods, to learn in situations approaching real-world complexity when playing classic Atari 2600 games. They stated that “*…the deep Q-network agent, receiving only the pixels and the game score as inputs, was able to surpass the performance of all previous algorithms and achieve a level comparable to that of a professional human games tester…*”.[12]

[12] Mnih, V., Kavukcuoglu, K., Silver, D. et al. “Human-level control through deep reinforcement learning”, *Nature*, 25 February 2015.
Available at: https://doi.org/10.1038/nature14236

Figure 13
Summary of different machine learning techniques, problems and applications



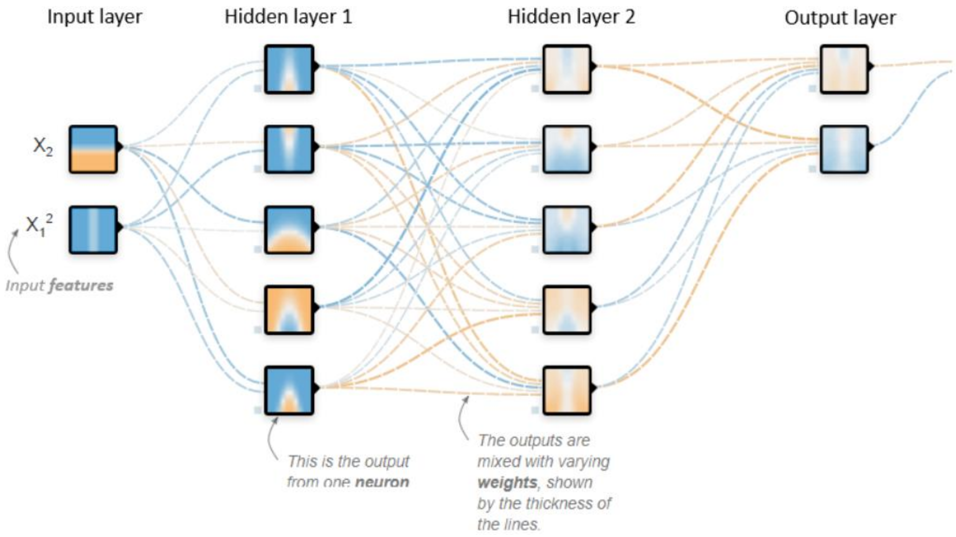
Source: UNECE

C. Neural networks

60. Artificial neural networks (ANN) are virtual network structures that are designed, in their topology and behaviour, in ways that resemble an extremely simplified model of neuron cells and their connections in the biological brain. Thanks to the Internet and big data, today we have access to larger amounts of data to train these neural networks than we had in the past. Combined with extremely powerful processors, we can achieve much higher accuracy in solving problems that traditional methods could not. While some problems can be described as having discrete sets of rules for data features (that is, having no data points, or rules, in common with neighbouring sets) defining rules for image recognition is quite different. For example, to define or create rules to distinguish a cat from a dog in an image is extremely complicated, since they share many common features. That is why we use huge amounts of training to generate these rules; it is thanks to this extensive training, and the huge amount of data, that ANN can become a viable tool for providing a possible solution.

61. These networks consist of nodes: artificial neurons, organized into layers, with weighted connections between neurons in the layers immediately preceding and following them. The neurons in input layers receive the raw data, and the output layers produce the resulting outcome. In between there are typically a series of hidden layers that process the data. They are activated to different degrees based on the data features that the previous layer observed and propagated further. As a result, the output layer can provide some estimated output (with varying degrees of confidence) indicating that input data, based on their observed features, have some specific quality. For example, it could identify a specific character (in OCR), an image as containing a specific object, or an email that has text evaluated as spam.

Figure 14
Topology of artificial neural networks



Source: playground.tensorflow.org

62. Artificial neural networks also utilize more advanced techniques to improve their performance, such as the backpropagation algorithm which retroactively adjusts the weights between neurons by comparing the output of labelled data with the initial input in an attempt to minimize errors and improve the performance of the neural network.

D. Deep learning

63. Some use cases utilizing neural networks, that do not necessarily need complex network topology, can perform well with just a simple structure and one hidden layer. More complex tasks use deep learning methods where the ANNs have multiple hidden layers between the input and output layers. This layered approach allows for different parts of the network to process different data features and can solve more complex problems like autonomous driving, where observing the environment and processing all the signals from vehicle sensors require much more complex network topology.

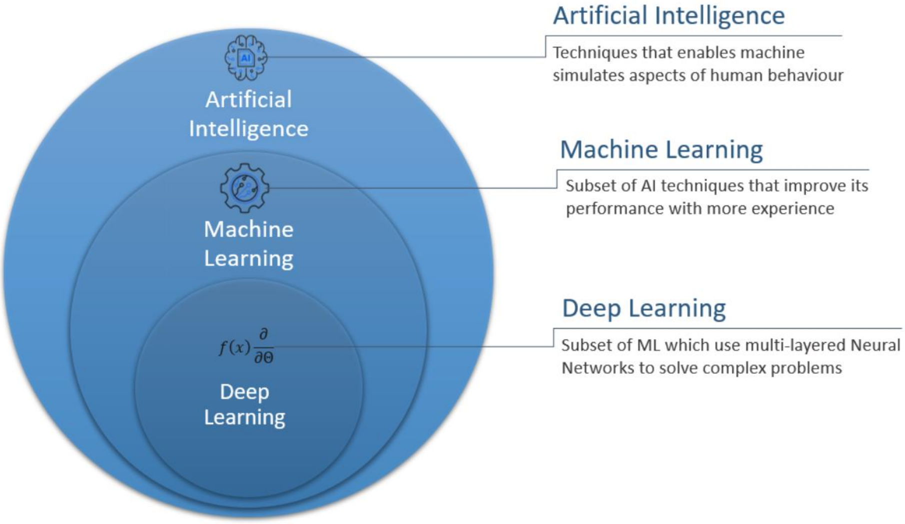
64. The human brain has 100 billion biological neurons and each neuron can be connected to 10,000 other neurons. This creates over 100 trillion synapses. Analogously, in deep learning each layer responds to different features (in image recognition these features may be light, outlines, corners, shapes, forms, movement) and progressive layers build from simple information, such as light, to more complex outcomes such as movement.

65. Two types of ANNs, used in deep learning, are convolutional neural networks and recurrent neural networks:

- **Convolutional neural network (CNN)**: Usually, these neural networks are composed of many layers, each layer breaking down the input data into simple information, such as points. Then, through the different intermediate convolutional levels, information is aggregated to identify structured information such as edges or borders. Gradually the information is composed and recognized as structured objects. These neural networks are used to analyze images and extract information such as the presence or absence of specific objects (for example, the identification of a particular individual's face); and

- **Recurrent neural network (RNN)**: These neural networks can store certain pieces of information and consider the time dimension during the learning phase. They are employed to keep track of the intrinsic knowledge contained within a sequence or time series. For instance, they are employed in dialogue or voice recognition tasks and are useful in formulating meaningful answers.

Figure 15
Relationship between AI, ML and DL



Source: UNECE

E. Generative adversarial networks and generative attacks

66. A generative adversarial network (GAN) is a new form of machine learning that is able to produce content from scratch. Roughly speaking, two systems (a discriminator and a generator, which are usually complex neural networks) compete for a reward. The discriminator should recognize when input is fake or original, while the generator aims to deceive the discriminator by creating content which is as realistic as possible. Initially, the generator is not good at generating content, but in the end, it becomes very good. Good generators[13] are then used to produce a variety of content, from simulated training data for situations where insufficient data is available, to fake content for different media – from text to video they are employed to produce pieces of art or fake news.

67. Spotting this kind of content is very difficult and poses new threats for both human moderators and automatic content moderation systems.

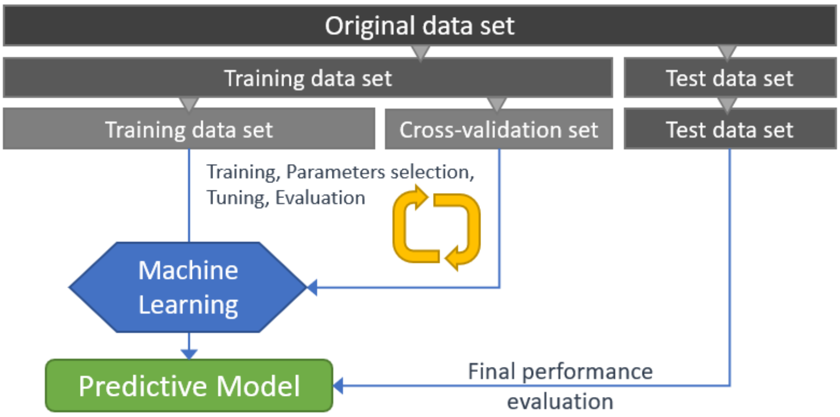
F. Artificial intelligence performance

68. The typical approach when training ML models is to create representative cross-validation and testing data sets from the main data set and use them to verify model performance. The cross-validation data set is used to verify the model while still in development and to tune it by observing the performance and changing the parameters (feature regularization, feature polynomial degree[14], learning rate, etc.). A test data set, which contains the data ML model "never seen before", is used for the final model's performance evaluation.

[13] https://thispersondoesnotexist.com/ and https://openai.com/blog/better-language-models/
[14] Polynomial features are those features created by raising existing features to an exponent. The "degree" of the polynomial (linear, quadratic, cubic ...) is used to control the number of features added, e.g. having features [x, y], a degree of 2 will add [1, x, y, x^2, xy, y^2].

Figure 16

Partition and the original data into training/cross-validation/test data sets and their use



Source: UNECE

69. When AI is assessed, a set of performance metrics is defined that describes how the trained model behaves; this set can be used to tune different model parameters to achieve desired behaviour. For example, the healthcare or aircraft engine manufacturing industries would expect different performance metrics (such as precision) than applications identifying cats and dogs in a photo gallery, or a shop recommending a product.

70. Based on observed outcomes in the final performance evaluation, the following metrics are recorded into a so-called *confusion matrix*:

n = number of samples	Actual Positive (1)	Actual Negative (0)
Predicted Positive (1)	*True Positive*	*False Positive*
Predicted Negative (0)	*False Negative*	*True Negative*

71. The metrics are defined as follows:

- **Accuracy** represents the correct predictions compared to the whole data set (e.g. *from all pictures, how many were identified correctly as having dogs or not having dogs*):

$$Accuracy = \frac{TruePositive + TrueNegative}{n}$$

- **Precision** tells us how many of the samples predicted as positive were identified correctly as positives (*e.g. :how many pictures with dogs, that were predicted to be pictures with dogs were really pictures with dogs?*).

$$Precision(P) = \frac{TruePositive}{TruePositive + Falsepositive} = \frac{TruePositive}{No.\,of predicted positives}$$

- **Recall** (sometimes called sensitivity) tells us what fraction of the total set of actual positives were correctly predicted as positives *(e.g. from all dogs in all pictures, how many were correctly detected).*

$$Recall(R) = \frac{TruePositive}{TruePositive + FalseNegative} = \frac{TruePositive}{No.\,of actual positives}$$

- **Specificity** tells us how many from all actual negatives, have been correctly predicted as negatives (*e.g. from all pictures without dogs, how many were detected as not containing dogs*).

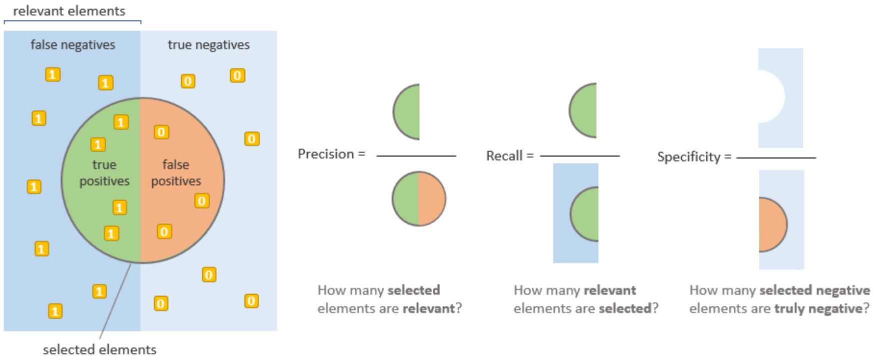
$$Specificity = \frac{FalsePositive}{FalsePositive + TrueNegative}$$

72. Precision can be seen as a measure of quality, and recall as a measure of quantity. Higher precision means that an algorithm returns more relevant results than irrelevant ones,

and high recall means that an algorithm returns most of the total set of relevant results (whether or not irrelevant ones are also returned).[15]

Figure 17

Precision, recall and specificity



Source: UNECE

73. In order to evaluate final performance, we cannot simply use a mean score, as this would provide a biased outcome on data with skewed distribution. (A small number of positive examples in the majority of negative examples will always perform well if we classify everything as negative.) For this purpose, we use an F1 score, which represents the harmonic mean of precision and recall. It is defined as follows:

$$F1score = 2\frac{P * R}{P + R}$$

74. With this performance data, we can set model parameters and other variables (like prediction thresholds for a specific use case), balancing trade-offs between precision and recall - i.e. how much can we afford to miss truly positive cases, compared to identifying some cases as false positive.

G. Data mining

75. Data mining is another recent, popular term in data analytics. So, what is it and how does it relate to the concepts of AI and machine learning? Data mining involves approaches, processes and techniques that use statistical methods for analysing large data sets, looking for relationships between data, identifying patterns and generating new views and information from these data sets.

76. Data mining is usually run on top of big, but relatively stable data sets like open data or data warehouses. In contrast, AI machine learning analysis is typically run on training data sets and then confronted with different, often much larger and structurally different data sets, as part of a continuous stream of data on which an algorithm tries to improve itself.

77. There are of course many overlaps between data mining and machine learning and many data mining principles and techniques have their place in AI and machine learning. For example, data mining is useful in regression field modeling in unsupervised machine learning. In this context, data mining belongs to the AI stack as one of the possible methods or approaches for analysing data as part of machine learning.

H. Business intelligence

78. AI and business intelligence (BI) are overlapping concepts, technologies, and tools in working with business data. Business intelligence focuses on collecting, governing, analysing and reporting business data in order to provide clear and useful views into an organization's data and performance for managers and executives to help them make data-driven, evidence-

[15] https://en.wikipedia.org/wiki/Precision_and_recall

based decisions. Business intelligence systems typically involve monolithic data storage - data warehouses, that use historical data for performing well-defined analytical tasks, focused on process, operational and financial metrics. AI applications can be used in the BI context for additional, typically prescriptive analytic tasks. Currently, popular BI tools such as Microsoft's Power BI, Tableau, or Oracle BI support the most common AI and ML techniques.

I. Big Data

79. Big data has four Vs: volume, variety, velocity, and veracity characteristics. These larger, more complex data sets can be generated from various sources (IoT ecosystems, smart cities, data produced by e-government systems, detailed user activity from Internet traffic, and analytical data from websites and online services) result in predictive and analytical user behaviour models. The efficient handling of big data requires slightly different approaches and system architecture for processing and infrastructure for storing. This typically means high-throughput computing, processing parallelism, distributed storage systems, and others.

80. Large scale AI computing can benefit from concepts and optimization developed for big data. Processing concepts like MapReduce[16] allow for the splitting of big data sets into smaller data chunks that can be processed separately in a parallel, distributed environment. All partial results are then combined (a split-apply-combine strategy) and can be used by AI and ML algorithms during testing and production phases. File systems designed for big data, such as the Hadoop Distributed File System (HDFS)[17], can be also used to handle production data for AI and ML. These allow for the storage of large volumes of data on a distributed network of commodity hardware and reduce the operation and maintenance costs of data storage and processing.

J. Data science

81. While sometimes used interchangeably, data science and artificial intelligence typically have some distinct contextual differences. Data science is the field of studying, analysing, and understanding data. It produces useful insights for their respective business context, typically in data-driven organizations and for data-driven decisions. Data science can also involve the preparation of data inputs for AI through activities such as data cleaning and pre-processing, and AI results interpretation for analysis and visualization.

82. Typically, data science is more business-oriented and utilizes economic and statistical models, whereas AI involves a high degree of scientific processing. AI can analyze and find relationships and patterns in data; data science can then take these output findings and add additional context such as why these relationships and patterns formed, what the benefits may be, etc. In this way, artificial intelligence (and its subset ML) are methods and tools for the data science field.

V. Use cases of artificial intelligence

83. A variety of online assistants utilize AI for natural speech recognition to understand the user's voice input and perform the appropriate action. These assistants can be built into our smartphones, smart speaker devices, smart TVs, cars, personal computers, or any other smart devices that serve as a user interface.

84. Google Assistant recognizes speech input or typed commands and uses Google’s Knowledge Graph to find the answers for questions, organize to-do lists, initiate communication with a user’s contacts and provide news or information about the current location. In addition, it can connect to smart devices and control automated household items: doors, lights, coffee machines etc. Other assistants work in a similar fashion; Alexa from

[16] https://research.google/pubs/pub62/

[17] https://hadoop.apache.org/docs/current/hadoop-project-dist/hadoop-hdfs/HdfsDesign.html

Amazon, Siri from Apple and Cortana from Microsoft typically use features from the ecosystem of their respective companies.

85. AI-powered spam filters are commonly used by email providers. For example, Gmail uses an artificial neural network to detect and block spam emails based on a user's individual behaviour and historical data (features obtained from email communication) and active spam reporting from users. This is an example of a spam filter using the machine learning principle of classification (where the message is classified as spam or not-spam) to continuously improve its accuracy in identifying spam.

86. Translation is another field in which AI is heavily utilized. IBM Watson, for example, uses cognitive AI learning to offer services in translating documents, apps and web pages, to create multilingual chatbots, and uses deep learning techniques to continuously improve translation speed and accuracy[18].

87. Artificial intelligence is also employed to automate moderation of user generated materials. This is useful to prevent unlawful and harmful online behaviour, or at least to mitigate its effect. The use of automatic tools for moderation of online platforms is meant to foster productive, pro-social and lawful interaction of the users.[19] The problem with such an approach is that, inevitably, the evaluation system will produce several prediction errors, thus curtailing some users' freedom of expression. In these cases, procedures and tools to ensure a prompt remediation of the error are needed.

88. Google Translate is using hybrid model architecture, combining a variety of approaches to drive and improve automated translation of 108 supported languages. Neural Machine Translation (NMT) models are trained using examples of translated sentences and documents, which are typically collected from the public web. Massive neural machine translation (M4) has been especially helpful for low-resource languages[20]. M4 uses a single, giant model to translate between all languages and English, showcasing the benefits of co-training with a wide array of other related languages (lower-resource language like Yiddish has the benefit of co-training with a wide array of other related Germanic languages: German, Dutch, Danish, etc.). M4 can also translate almost a hundred other languages that may not share a known linguistic connection, but may provide a useful feedback signal to the model and permit them to transfer learning from monolingual data at a massive scale, to provide relatively coherent translation, even for the lowest-resource of the supported languages[21].

89. A very popular use of AI is in recommender systems - engines that provide product recommendations tailored for each customer. Amazon is one of the technology leaders in this space. Today, Amazon uses sophisticated AI for various use cases to support its business in online purchases. Recommender algorithm "item-based collaborative filtering" generates a unique personalized homepage for each customer based on their purchasing history, interests, and preferences. Another feature, "frequently bought together", is a type of recommendation algorithm that showcases the purchase histories of other customers who purchased the same product. In the physical store "Just Walk Out" experience Amazon Go[22], AI and deep learning models are used together with computer vision to combine data from the shop's surveillance cameras, customer smartphones, and other sensors like entry gates, to automatically keep track of every purchase and shopping activity inside the store - automating the whole shopping process for both the store and the customers.

90. Another use case is Amazon's collaboration with the application StyleSnap. Customers can upload an image and a deep learning AI algorithm detects different apparel items in the image. It identifies and categorizes them and suggests similar items available on Amazon.

91. YouTube uses AI in a few different ways. AI is used to analyze, automatically identify, and flag harmful content using artificial intelligence classifiers. AI is also used to

[18] https://www.ibm.com/watson/services/language-translator/

[19] http://www.europarl.europa.eu/RegData/etudes/STUD/2020/657101/IPOL_STU(2020)657101_EN.pdf

[20] The low-resource language in the context of natural language processing (NLP) is a language that lacks useful training attributes such as supervised data, the number of native speakers or experts, etc.

[21] https://ai.googleblog.com/2020/06/recent-advances-in-google-translate.html

[22] https://towardsdatascience.com/how-the-amazon-go-store-works-a-deep-dive-3fde9d9939e9

automatically and in real-time detect and switch backgrounds in a content creator's videos[23], a task that was historically done manually using greenscreen. YouTube's "Up Next" feature, which suggests what to watch next based on the user's preferences and viewing history, is also powered by an AI recommendation engine that processes all newly uploaded content - up to 300 hours of content every minute.

92. Netflix uses AI, data science, and machine learning in many similar ways. Netflix makes personalized movie recommendations based on viewing history and comparisons to users with similar tastes and preferences. AI is also used to personalize video thumbnails in an attempt to maximize the likelihood of a user clicking on a video. This personalization can draw on past preferences, favourite actors, themes and movie genres, but also demographic and other parameters.

A. Trade facilitation of international trade and e-commerce

93. AI is highly promising for international trade and logistics as many of the routine tasks, business processes, and data flows, can be automated and further optimized using AI and ML techniques. Digital supply chains can be automated, relationships between parties acting in domestic or international areas can be streamlined, and errors caused by manual data entries can be reduced by applying AI to some extent.

94. Documents and data used in international trade, such as invoices, orders, and shipping notifications can be scanned or electronically analyzed to find and extract the machine-readable data they carry.

95. Semantic standards such as the United Nations Core Component Library (UN/CCL) or UN/CEFACT Cross Industry Invoice (CII), can be used for describing and labelling extracted data, which can be used to train ML models. Once the data is in digital format, it can be automatically validated with submitters and checked for any errors or discrepancies. Furthermore, this data can be combined with other data sources and compiled in human and machine-readable formats:

- The raw data can be extracted from source formats such as electronic documents, PDF scans, emails, instant messages;
- Analysed and converted into formats for international trade data exchange such as the United Nations rules for Electronic Data Interchange for Administration, Commerce and Transport (UN/EDIFACT); XML messages as defined by XML Schemas;
- Fed to application programming interfaces (APIs), using data-interchange formats such as JSON;
- And finally used as an input to databases, data warehouses in other data storage formats.

96. Other components, developed by UN/CEFACT, can play a role in leveraging AI and ML; for example, IoT and smart containers can serve as data sources that AI algorithms can analyze for future optimization - using regression, to detect nonstandard handling using anomaly detection.

97. Mechanisms and models, such as single windows, data pipelines, and integrated services for micro, small and medium-sized enterprises can also use multiple AI applications to automatically analyze, process, and verify data. This is mainly beneficial for automated processing - for example by a classification algorithm; for errors and fraud recognition by anomaly detection; and for capacity planning using regression and forecasting.

VI. Ethics in artificial intelligence

98. Removing the burden of preparation and execution of decision-making from humans and moving it to machines brings up many ethical and moral questions: Can the machine be

[23] https://ai.googleblog.com/2018/03/mobile-real-time-video-segmentation.html

seen as equal to a human? Who is responsible for its decision - the machine performing the task, its designer, the manufacturer or the user?

99. There have been many attempts to facilitate understanding of the ethical challenges of AI and to provide a platform for discussing these challenges by organizations such as the Organization for Economic Cooperation and Development (OECD), the European Union (EU), the Group of Seven (G7) and others. One of the latest attempts at a comprehensive recommendation and framework of ethical values comes from the Ad Hoc Expert Group (AHEG) at UNESCO.[24] This recommendation describes a set of principles to be respected by all actors in the AI lifecycle. The principles are proportionality and do no harm; safety and security; fairness and non-discrimination; sustainability; privacy; human oversight and determination; transparency and explainability; responsibility and accountability; awareness and literacy; multi-stakeholder and adaptive governance; and collaboration. The recommendation identifies a few areas for policy action, such as ethical impact assessments; ethical governance and stewardship; data policy; international cooperation; gender; and others.

100. A paper on Ethical Principles, developed as part of The Conference on the Ethics and Law of AI[25], proposed a list of rights deriving from ethical principles and values for the development of applications and systems based on artificial intelligence techniques: accessibility, transparency, reliability, non-discrimination, the dignity of individuals and the collective, confidentiality, identity, social cohesion and pluralism. These are all values that express just as much as many rights.

101. For these rights to actually form part of people's lives, it is necessary that specific institutional authorities, including supranational ones, ensure their enjoyment. The State must ensure a basic level of digital education, the operator must avoid his prejudices becoming discriminatory criteria for the algorithm, and the company building it must ensure the quality of the machine.

102. The best endeavour obligations of companies take on particular significance. Some of them can compete with countries in terms of financial power, potential for steering individuals, and ability to influence public authorities. They must make choices focused on the need for innovations for the benefit of civil development. The suggested obligations of companies, set out by the Conference on the Ethics and Law of AI include:

- The commitment to guarantee the safety of AI systems at different levels of applicability: from the protection of the safety of individuals to the storage of personal data, from the protection and management of physical assets to the structural integrity of the system;
- The duty to ensure the use of AI systems also for special categories of users, such as the non-self-sufficient, disabled and minors, in order to guarantee them conscious use of technology in line with the maximum expression of their potential; and
- The obligation/duty creation of good practices to prevent harm related to the use of AI systems, through risk assessment and management procedures, to identify critical situations and prototype risk scenarios usable by AI.

103. The introduction of redress mechanisms should also be considered on the basis of the principle of "redress by design." A non-defective, perfectly functioning AI system, being a statistical engine that produces probabilistic results, can make incorrect predictions. In these cases, the appeal procedure may not actually exist or, if it does exist, may be ineffective. In order to guarantee effective protection of rights, companies should consider, right from the design phase, the creation of mechanisms to guarantee alternative procedures in order to effectively identify, verify and correct the wrong decisions taken by a non-defective (properly configured, certified and controlled) system[26].

[24] Available at: https://unesdoc.unesco.org/ark:/48223/pf0000373434

[25] Available at: https://fondazioneleonardo-cdm.com/site/assets/files/2450/fle1_booklet_conferenza_eng_gar_311019.pdf

[26] For example to ensure freedom of speech in automatic content moderation systems like those exposed in the "Use cases" section.

104. A redress mechanism is necessary, but not sufficient. The Council of Europe recently released a document "Responsibility and AI"[27], underlining the need for States to guarantee human rights vis-à-vis the growing power of so-called Big Tech companies, particularly given the existing unbalances between corporate actors and individual citizens. There is a need for new institutional mechanisms aimed at preventing the risks that follow from an irresponsible use of AI, both for individual rights and democratic systems.

105. Another example is the "Ethics guidelines for trustworthy AI", developed by the European Commission's High-Level Expert Group on AI. This document states that AI should be (1) lawful - respecting all applicable laws and regulations, (2) ethical - respecting ethical principles and values, and (3) robust - both from a technical perspective, and by taking into account its social environment.[28]

106. This shows there are serious attempts to address AI from an ethical perspective, but for general and widely accepted ethical standards still needs consensus within the international policymakers and global expert communities.

A. Autonomous vehicles

107. A typical thought experiment regarding choice and the potential consequences of AI is the trolley problem: a situation where an observer sees a runaway trolley which will hit and kill five people unless the observer acts and diverts the trolley to a sidetrack where it will kill one person.

108. Fully autonomous vehicles will potentially need to deal with situations where one or more human lives are in danger and the AI algorithm will need to determine whose life will be put in danger - pedestrians, other drivers or its own passengers. Responsibilities and ethics must be fully considered and coded into every potentially harmful autonomous device in every area of human activity.

109. By today's standards this concept of the trolley problem is outdated. when applying AI and ML to potentially dangerous field of our activities, such as autonomous vehicles managing dilemmas in crash avoidance, the part of ethical principles move to the point, where policymakers may accept that the behaviour of connected autonomous vehicles (CAVs) in dilemma situations can organically emerge from principles of continuous statistical risk distribution and inequalities among road users, - cyclists and pedestrians are more exposed and vulnerable and programming must respect this asymmetry of power.

110. Another relevant topic is responsibility: specifically, the obligation to explain something that has happened, and one's role in its occurrence. *"This does not mean that each action of the system should be causally traceable to an individual human action, but rather that each action of the system should be understandable by and explainable to the relevant persons or organizations via reference to the choices and actions of at least one human person along the chain of design, control, and use."*[29] Policymakers should collaborate with researchers, manufacturers and deployers to develop clear and fair criteria for assigning culpability to individual actors or organizations in the event that something goes wrong with CAVs - typically when something is damaged or someone is injured or killed in a crash due to an unjustifiable and inexcusable mistake of some human actor.[30]

B. International security

111. Another potential danger is the weaponization of AI. Recently, the international community, through the United Nations Office on Disarmament Affairs (UNODA), the

[27] Available at: https://rm.coe.int/responsability-and-ai-en/168097d9c5 .
[28] Available at: https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai .
[29] European Commission, Report on the Ethics of Connected and Autonomous Vehicles, (Luxembourg, 2020). Available at: https://ec.europa.eu/info/news/new-recommendations-for-a-safe-and-ethical-transition-towards-driverless-mobility-2020-sep-18_en
[30] Further reading: https://doi.org/10.1007/s10676-019-09519-w

Convention on Conventional Weapons (CCW), the United Nations Institute for Disarmament Research (UNIDIR), the International Committee of the Red Cross (ICRC) and NGOs such as The Campaign to Stop Killer Robots[31], expressed concerns about the developments and initiated dialogue in order to regulate lethal autonomous weapons systems (LAWS). These efforts cover technologies such as drones, tanks and other machinery controlled by a computer, run on artificial intelligence systems, and programmed to select and attack targets without human control.

112. During the Paris Peace Forum, United Nations Secretary-General Antonio Guterres called for a new international treaty to ban LAWs, saying that *"machines that have the power and discretion to kill without human intervention are politically unacceptable and morally despicable."*[32]

C. Private and individual security

113. Yet another potential danger is security and privacy breaches. Promoting regional and international laws that secure AI principles needs to be done through regional or international platforms.

114. These international platforms can be established through already existing international organizations, such as the United Nations Economic Commission for Europe (UNECE) and/or the International Telecommunication Union (ITU). Promoting laws or principles through regional and international platforms ensures continuity and uniformity, better management of security issues, and more accessible information and confidence for citizens.

D. Biases in data causing biased artificial intelligence

115. In recent years, we witnessed a few examples of AI's bad decision-making due to biased data being used for its training. In 2014 Amazon discontinued its hiring engines after it preferred male candidates over female, as it was trained on male-dominated data sets.[33] In 2016 Microsoft turned off its AI chatbot "Tay" after a series of hateful comment incidents. Tay had been taught these hateful ideas by interacting with users who had passed them into Tay's algorithm.[34] Another recent example, from 2019, showed biases in Facebook's advertising algorithm, which decides who to show advertised job offers and behaves in discriminatory ways towards women and minorities.[35]

VII. Next steps for artificial intelligence applications as part of Industrial Revolution 4.0 and beyond

116. The latest progress in multiple advanced technology fields is introducing new synergies between AI and other technologies such as the artificial intelligence of things (AIoT), blockchain technology, distributed ledger technology (DLT), big data, smart cities, robotics and autonomous devices, and potentially others.

[31] https://www.stopkillerrobots.org/

[32] United Nations, "Amid Widening Fault Lines, Broken Relations among Great Powers, World 'in Turmoil', Secretary-General Tells Paris Peace Forum, Calling for New Social Contract", press release, 11 November 2019. Available at: https://www.un.org/press/en/2019/sgsm19852.doc.htm

[33] Jeffrey Dastin, "Amazon scraps secret AI recruiting tool that showed bias against women", Reuters, 10 October 2018. Available at: https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G

[34] Jane Wakefield, "Microsoft chatbot is taught to swear on twitter", BBC News, 24 March 2016. Available at: https://www.bbc.com/news/technology-35890188

[35] Karen Hao, "Facebook's ad-serving algorithm discriminates by gender and race", MIT Technology Review, 5 April 2019. Available at: https://www.technologyreview.com/2019/04/05/1175/facebook-algorithm-discriminates-ai-bias/

A. Artificial intelligence of things

117. With the developments and widespread use of various devices as part of the Internet of things (IoT), AI is the logical addition to this ecosystem as an analytics layer on top of data gathered and produced by IoT devices. These combinations, called the artificial intelligence of things (AIoT), can provide optimization, improve performance, and provide additional business insight into data.

118. For example, cameras can be equipped with various computer vision features, such as facial or posture recognition, which predict a customer's behaviour and intentions. Wearable "smart devices" can be leveraged by combining data they gather about its user and providing a comprehensive lifestyle and health profile, or recommendation based on the user's preferences. "Smart homes" can use AI in a very similar fashion, monitoring and creating profiles based on the user's habits and preferences, optimizing control of house lights, heating, and appliances. Today, many households are equipped with some "smart speaker" products, serving as a gateway and user interface to AI-powered assistants.

119. As part of digital transformation, industries such as manufacturing, warehousing, fulfilment, and other large-facility industries in supply chain and logistics can also use a combination of autonomous robots, building sensors, and staff equipped with sensors and devices to gather and analyze data - using AI techniques to optimize their operations, predict capacity planning, and foresee process bottlenecks, potential errors and hazards.

B. Artificial intelligence, blockchain and distributed ledger technologies

120. Blockchain technology, an immutable distributed cryptography-based public database of transaction records, was originally developed and introduced to the world as the backbone of Bitcoin cryptocurrency. Later, with the introduction of the Ethereum platform, it was opened up to a multitude of uses through the utilization of smart contracts. Today, it generally provides easy-to-use tools so that anyone can create and distribute their own tokens and is slowly getting closer to the real-world economy in an environment called the "token-economy." As blockchain technology, and distributed ledger technologies (DLT) in general, are considered some of the main disruptive technologies of the past decade, the analytical capabilities of AI, then can help them complement each other, unlocking even greater potential in both areas: data storage and transfer coming from DLT and data analytics and decision-making from AI.

121. Using a combination of DLT and AI can maximize their fundamental principles - DLT offering stored data privacy using cryptography, and AI needing data for training its models and predictions. In this relationship, when AI needs to use private or sensitive data, it can be anonymized and obfuscated. As AI only needs feature data, all personal and sensitive details can be stored and encrypted on DLT. This way AI can, for example, analyze healthcare or financial data without knowing to whom it belongs. These details and their keys can be managed by the owners of the data - persons or organizations different from the ones behind the AI.

122. Similarly, AI needs correct and truthful data, and DLT and its protocol can guarantee such truthfulness. When AI is in charge of a certain decision-making scenario, it can benefit from immutability, a complete record history, and other blockchain features like byzantine fault tolerance[36] and other consensus mechanisms that provide truthfulness and correctness in data stored on the blockchain.

123. Another, perhaps more advanced, use case is the combination of self-sovereign identity (SSI) and AI. With SSI implemented on the blockchain, owners of the identity data can control and manage who accesses them, and to which extent, autonomously and without

[36] The byzantine fault tolerance (BFT) in the context of blockchain is the feature of nodes reaching a consensus about particular blocks based on the protocol mechanism - i.e. proof of work, even when some nodes are failing to respond or acting maliciously, trying to misguide the network.

a central authority. AI can then ask for permission to use part of the data managed by the SSI, and data owners can decide and grant access transparently, and to the degree they choose.

124. With more token assets and cryptocurrencies being recognized (to some degree) by legislative frameworks, the rise of tokenomics (the token economy) is benefiting from the main principles of blockchain: immutability and data resiliency, transparency, and the nature of the distributed network.

125. With the tokenization trend (where physical assets are recreated as digital tokens) the new environments consisting of dynamic nature of economies, markets, organizations, and their business process are created anew with the data as their main assets. Since tokenization leads to dematerialization, and to a further digital description of our world, AI applications can be applied to this data in synergistic ways. This can lead to optimized and automated decision-making in a multitude of digitized processes and tasks, such as digital asset management, party interactions that require data exchange, automated trade orders, automated negotiation, fraud detection, marketing, and transactional data analysis. AI is a natural tool in this digital ecosystem.

126. Smart contracts (digitized contracts between parties, implemented as autonomous, self-executing programs) can use data supplied by AI as inputs for their triggers. On the other hand, on a larger-scale, AI can monitor and analyze portfolios of smart contracts, eventually generating and maintaining them.

127. AI can also be used by decentralized applications (dApps), which are applications running on decentralized ecosystems - typically blockchain-based platforms. When compared with smart contracts, dApps can perform a variety of multipurpose activities, but in principle use data provided by AI in a similar way as smart contracts, for example in process execution as event triggers. AI can then monitor and gather data about the behaviour and performance of the dApps and analyze them or create models about them.

128. In a very similar fashion, decentralized autonomous organizations (DAOs) use AI as an advanced data-driven, decision-making process, which effectively simulates and automates the governance, managerial, development, investment, and operational decisions normally done by humans in traditional organizations.

C. Smart cities

129. Smart cities are urban locations that use various technologies to monitor and generate large amounts of data about the states of locations, the environments and flows within it. This generated data, typically having big data qualities, can then be made available to the public as open data, or used as inputs for service providers in the public or private sectors.

130. As smart cities have a large volume of data, generated from various dimensions of social-economic and urban activities, AI can be used for many analytical processing tasks and outputs for domains such as transportation, energy and utilities, environment, healthcare, education, communication, administration, and governance.

131. This combination has led to emerging new products and large scale solutions such as City Brain created by Alibaba. "*Utilizing comprehensive real-time city data, City Brain holistically optimizes urban public resources by instantly correcting defects in urban operations.*"[37] By aggregating data from sources such as government and network data, IoT sensors and image devices, the central data governance can converge data together to create urban government models, service models, and industrial development.

132. Other synergies of AI and smart cities can be in data-generating sensors in advanced vehicle control systems (AVCSs), as well as autonomous drones, that can gather and analyze traffic data and use AI to predict traffic flows, parking capacities, and dynamically suggest adjustments to traffic systems, like the timing of traffic lights.

[37] https://www.alibabacloud.com/solutions/intelligence-brain/city

D. Artificial intelligence and robotics

133. AI has many practical implications for the data world in analysing and working with data, but another field where AI has potential benefits is robotics and advanced software or hardware automation.

134. Robots are physical (hardware-based) or virtual (software-based) machines that replicate certain human movements and functions in order to automate and/or help with some human activity. Traditionally, robots have been used for automating processes and tasks, and their scope has been typically very narrow or specific (e.g. manufacturing or robotic process automation).

135. AI is now heavily used in robotics, as robotic machines can outperform humans in physical feats - from their strength to lift objects to their endurance in repetitive tasks. The combination of robotics and AI opens up many new possibilities. One use case for robotic AI is in observing and mapping the surrounding environment, creating its models, and finding the most efficient paths.

136. Robotics can connect AI and machine learning with the physical world through IoT and autonomous devices. A smart vacuum cleaner can map its environment and generate optimal paths for cleaning; it can determine which places accumulate dirt regularly and create a time schedule for the household to optimize its activity and minimize disturbance. A smart refrigerator can analyze the lifestyle and diet patterns of a household, plan automatic orders, suggest recipes based on available ingredients and adjust them based on the season or for local holidays.

137. An autonomous vehicle is a type of robot that uses supervised learning and artificial neural networks to take data from its sensors, process it and make decisions in open environment. Currently, these experiments still involve a human driver to provide feedback to the vehicle when it makes a mistake in order to improve its decision model with more experience.

E. Artificial intelligence/machine learning as a service

138. The recent progress and practical application of artificial intelligence and machine learning have made it attractive to a broader audience. This has led multiple technology companies to provide frameworks and tools to the public for commercial use[38]. These are typically hosted in a cloud environment as part of a wider service platform and accessed through an as a service (*aaS) deployment model.

139. Microsoft Azure Machine Learning offers a set of machine learning services, such as no-code designer and built-in Jupyter notebooks to support quick model creation; MLOps - DevOps tools, designed for ML, to support production workflows using profilers, pipelines, virtual machine deployments and automation; “responsible ML” - a set of tools to explore and explain model behaviour during training and interfacing; and support for programming languages like Python and R.

- *For more details:* https://azure.microsoft.com/en-us/services/machine-learning

140. Amazon Web Services (AWS) offers Amazon SageMaker, a series of services integrated into the AWS environment, that allows users to build, train and deploy ML models, automate ML capabilities, generate workflows and interfaces for training data sets and run ML in the cloud or at the edge of computing networks.

141. Other products provided by AWS are AI services that can be integrated into applications in order to elevate their AI capabilities. Some examples are text analysis, automated code reviews, chatbots, demand forecasting, document analysis, fraud prevention, image and video analysis, personalized recommendations, real-time translations, text to speech, transcription and others.

[38] The reference to individual products and companies does not imply endorsement by UNECE but is for illustrative purposes only.

142. Amazon Web Services (AWS) also provides Deep Learning Amazon Machine Images (AMIs), a set of virtual computing instances, pre-installed with deep learning frameworks such as TensorFlow, PyTorch Apache MXNet, Keras and others.

- *For more details:* https://aws.amazon.com/machine-learning/

143. Another more business-specific product offered on AWS is Amazon Personalized, this solution offers Amazon's recommendation engine capabilities via APIs and simplifies "*the complex steps required to build, train, tune, and deploy a machine learning recommendation model*".

- *For more details:* https://aws.amazon.com/personalize/

144. Google, as one of the leading companies in AI developments, offers multiple AI-related products and services.

145. ML Kit provides mobile developers with packages that leverage smartphones and other personal devices with AI capabilities running on-device. Vision APIs offer features like face detection, image labelling, object detection and recognition, text recognition, or pose detection. Natural Language APIs provide on-device translations, smart reply suggestions or language ID to identify language from just a small sample of text.

- *For more details:* https://developers.google.com/ml-kit

146. Google Cloud AI Platform offers an end-to-end platform to support machine learning through its learning lifecycle, from preparation and labelling of training data sets, through building machine learning models using AutoML, deployment in the cloud or edge infrastructure and MLOps to manage the whole workflow using pipelines and monitor ML models performance.

- *For more details:* https://cloud.google.com/ai-platform

147. Another service provided by Google is a searchable library of data sets, from a variety of information and data science disciplines, that can be used to build a broad spectrum of ML models and applications.

- *For more details:* https://research.google/tools/datasets/

VIII. Conclusions

148. There are specific tasks that a machine can perform faster and on larger volumes of data compared to what is possible by any human being. These tasks, such as the game of chess, are very well defined and their model and behavioural rules can be described and transformed into the digital world.

149. Today, we can confidently argue that there are specific tasks in which computers, having and using some of the techniques from the artificial intelligence field, can challenge and exceed performances even the best human with all the skills, creativity, and training of a human mind.

150. It is often questioned if it will be possible that, at some point in the future, the number of these tasks will grow into a bigger group of skills that form some comprehensive artificial characteristics resembling consciousness and awareness of the environment and our physical world, forming an artificial mind similar to biological one. In the end, according to some practitioners[39], the human brain is only a very complex biological system, with boundaries and biological, chemical and physical limitations. At some point, and with enough theoretical resources, these practitioners argue, it should be possible to replicate this very complex system in an artificial non-biological environment.

[39] Fischer, Hans Peter. "Mathematical modeling of complex biological systems: from parts lists to understanding systems behavior." Alcohol research & health : the journal of the National Institute on Alcohol Abuse and Alcoholism vol. 31,1 (2008): 49-59. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3860444/

151. Such a possibility has been dismissed as "unrealistic" by the High-Level Expert Group on AI of the European Commission.

152. With the focus on logic, learning and problem-solving intelligence aspects of the mind, we may be able to create an extremely efficient "tasker", that can with an analytical approach outperform humans in specific duties; there are, however, other aspects of the human mind that we cannot as easily define in mathematical, statistical and programming formulas, aspects like emotional and social intelligence, intuition, creativity, imagination, judgement and others, that are key parts of the human mind. These additional layers are not so easy to describe in exact mathematical language and thus very elusive to implement into artificial systems, but progress is made on biological, psychological as well as technical levels with each day and the more we understand ourselves and inner workings of our mind, maybe we will be able to further improve performances of the machines.

153. Even if we can't expect to see artificial general intelligence, in complexity and aspects comparable to our own, progress in this field and practical utilization will be apparent and their relevance increasing in all sectors of economy and society in the coming years.

154. The importance of AI is already starting to be reflected in various area of work at UNECE.

- UNECE's High-Level Group for the Modernisation of Official Statistics (HLG-MOS) launched a Machine Learning Project[40], that aimed to increase the relevance and quality of official statistics and demonstrate the added value of ML (for instance, using ML to improve the efficient production, relevance, timeliness, accuracy, and trustworthiness of data).
- The UNECE Sustainable Transport Division study the potential impact of AI developments on autonomous driving[41], Intelligent Transport Systems (ITS) and vehicle regulations[42].
- In addition to this digital transformation, the ways in which artificial intelligence and robotic process automation (RPA) can enhance the trade facilitation area through automation and optimization of well-established business processes. One of the examples is the UN/CEFACT project, which focuses on the negotiation process between buyer and seller. The inclusion of AI and RPA can ultimately assist in achieving better-negotiating conditions[43].

155. Devising and promoting international best practice or guidance for legal and regulatory frameworks that secure AI principles in line with today's global development challenges and the Agenda 2030 requires an inclusive and multi-stakeholder process of consensus building through regional or international platforms. International organizations with AI-related mandates and workstreams, such as the United Nations Economic Commission for Europe (UNECE), the International Telecommunication Union (ITU), and/or the United Nations Educational, Scientific and Cultural Organization (UNESCO) can offer important contributions to such an endeavour.

156. Regional and international platforms can help deliver on the full potential that *AI promise to enhanced economic growth, while avoiding inequality within and between nations.* By adopting laws and ethical principles they can ensure continuity and uniformity. They can directly address ethical, technical, and security challenges. They can provide guidance and mandates for information accessibility and standardization, allowing for increased capacity building and data literacy that is necessary to build confidence and trust among citizens.

[40] https://statswiki.unece.org/display/ML/HLG-MOS+Machine+Learning+Project
[41] https://unece.org/automated-driving
[42] Paper on Artificial Intelligence and Vehicle Regulations: WP.29-175-21, Available at: https://www.unece.org/fileadmin/DAM/trans/doc/2018/wp29/WP29-175-21e.pdf
[43] https://uncefact.unece.org/display/uncefactpublic/eNegotiation