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The large language models in the service of education

Abstract

The name artificial intelligence (AI) appeared in the 1950s (McCarthy 1956), but mankind had a much older desire to perform certain tasks with machines. AI permeates our everyday lives, so the widest possible layers of society must acquire knowledge about artificial intelligence. The understanding and acceptance of AI are crucial for social development, equality, and innovation. For these reasons, the Hungarian Artificial Intelligence Coalition was founded in 2018, the main goal of which is to bring technology closer to all actors in society. As a result of the coalition's work, the Artificial Intelligence Strategy of Hungary was published in May 2020, in which one of the important segments of the priority AI research and development directions is the development of language technology. Our research aims to provide a comprehensive overview of the development and functioning of the large language models, focusing on the specific challenges and opportunities that arise in the field of Hungarian language models. In addition, we would like to show how these models can be used effectively in education and how they can help students improve their language skills, support their studies, or even create intelligent systems for educators.

Keywords: artificial intelligence, large language models, natural language processing, digitization, education

Introduction

Perhaps one of the most exciting and dynamically developing fields in the history of mankind is artificial intelligence (AI). In recent decades, and even more so in recent years, technological progress has given impetus to a revolution that is changing our daily lives. Innovations and developments supported by artificial intelligence permeate everything from industrial processes through personal assistants to medicine and the financial sector.

According to Daugherty and Wilson (2018), companies that realize how to utilize AI will gain an advantage, while others will be left behind. The field of AI is changing and developing so rapidly that possibilities that previously seemed unimaginable are now part of our everyday lives. Taking machine learning[1] and data analysis to a new level, the development of autonomous vehicles, natural language processing (NLP) and robotics are just a few examples of the innovations taking place within the field. Technological innovations not only create new opportunities but also transform industries, workplaces and society. In this rapidly changing environment, AI is not just a scientific or technological field, but a full-scale paradigm shift that fundamentally reshapes the way we think, work and live (Ford 2022). Therefore, it is essential to constantly monitor developments and understand their effects and possibilities. Navigating the world permeated by artificial intelligence is not only a challenge but also an exciting opportunity for all of us.

The rapid development in the field prompted us to review the various stages of AI development. In the present study, as part of secondary research, we focus on natural language processing, as one of the key areas of AI, and we review the usability of these applications in education. The development of large language models will be presented, highlighting the models trained in the Hungarian language.

Historical overview

The history of artificial intelligence goes back to ancient times, the discoveries of many scientists have contributed to the fact that this technology permeates all areas of life today (Buzás 2021). The concept of artificial intelligence (AI) appeared in the 1950s, but mankind had a much older desire to perform certain tasks with machines. This was first described by Aristotle (1969) in his work Politics, in which he stated that the device he called an automaton was able to perform the work of slaves. His idea was never realized, but it served as a basis for the development of different types of artificial intelligence. uring the development of AI, several eras can be identified, in which different techniques and methods alternated.

The term itself was first used by John McCarthy in 1956 at a summer conference at Dartmouth College. In his reading, the definition of artificial intelligence is:

> "*Artificial Intelligence aims to create machine systems capable of human-level intelligent behaviour such as perception, linguistic communication, decision-making, and learning*" (McCarthy 2007).

[1] In machine learning, algorithms are taught to find patterns and correlations in large data sets and make the best decisions and predictions based on this analysis, without being programmed to do so. A machine learning model can be supervised, unsupervised, semi-supervised or reinforced.

In addition to all this, Searle (1980) talks about weak and strong artificial intelligence according to a different approach. Weak AI refers to systems that act as if they are intelligent, but it cannot be determined whether they have a mind. On the other hand, he uses the term strong AI for systems that think. An important role in the emergence of AI is attributed to Alan Mathison Turing, who in the 1930s developed the mathematical model of the programmable computer (Turing 1936), which was then named after him the Turing machine. A Turing machine can be considered a theoretical model of a simplified computer, not a real machine, but an abstract automaton. Turing's 1950 paper "Computing Machinery and Intelligence" is about the idea that if we programmed a computer so well that it could communicate on any subject on a human level with another human, and that person would not be able to tell that it was actually a machine or talking to a living person, then we should consider this machine intelligent. This concept is known as the Turing test (Turing 1950).

In 1958, Frank Rosenblatt built the Perceptron. The Perceptron represented the development of a neural network, which was an important milestone in the development of artificial intelligence. This algorithm was used to create machines that could recognize and categorize images. Machine learning appeared in the 1960s, the essence of which is that machines learn from data without being specifically programmed to do so. This resulted in the first chatbot developed by Joseph Weizenbaum in 1966 and named ELIZA. Perceptron did not live up to expectations, and researchers recognized the limitations of AI technologies. A nearly 10-year period followed when research in the field received less support. Expert systems appeared in this period.

In the development of AI, the 1990s brought a new turn with the wide spread of the Internet, which made it possible to use large amounts of data for research. In 1997, the DEEP BLUE computer developed by IBM beat the world chess champion Garry Kasparov (Hsu 1999; Newborn 2012). Deep learning[2] appeared in the 2000s (Goodfellow et al. 2016). Algorithms based on this have been used in many areas, such as image and speech recognition or natural language processing. In the 2010s, developments in the field of neural networks and machine learning appeared, which marked a great advance in the field of natural language processing[3] (Khurana et al. 2023) and computer vision. In 2016, the AlphaGo (URL1) program developed by Google beat the then-Go world champion Lee Sedol.

2 Deep learning is actually machine learning, which enables the learning of systems with artificial neural networks.

3 Natural language processing is the area of cooperation between AI and linguistics, where natural (human) languages are processed using different computer methods.

The further development of neural network machine learning resulted in new developments in the field of natural language processing. Large language models were published, which then enabled the public presentation of ChatGpt (URL2) developed by OpenAI in November 2022. The development in Artificial Intelligence research is so fast that some new developments appear almost every day, which are then integrated into our everyday. The technological singularity, or the hypothetical point in the future when Artificial Intelligence and other advanced technologies develop to the point where they surpass human capabilities, may occur in the not-so-distant future. This concept was first used by Raymond Kurzweil (2013). According to him, the explosive growth of computing capacity will lead to a point where the development of technology will be so fast that it will be difficult to predict exactly what will happen. Raymond Kurzweil (2013) predicts this date as 2045.

When we talk about Artificial Intelligence (Figure 1), we mean, for example, machine learning, deep learning, natural language processing, image and voice recognition, data mining and many other systems based on intelligent algorithms. The Hungarian Artificial Intelligence Coalition (Digital Prosperity Program, URL3) was founded in 2018, the main goal of which is to bring technology closer to all actors in society. It is very important to be aware of what the technology is capable of, what we can use it for, and what we should pay attention to when using it (Tilesch and Hatamleh 2021). As a result of the coalition's work, Hungary's Artificial Intelligence Strategy (URL4) was published in May 2020, in which one of the important segments of the priority AI research and development directions is the development of language technology. Among these developments, the interpretation of spoken and written texts is one of the fastest-developing areas. Nowadays, a greater percentage of communication takes place on digital channels in natural language, so it is very important to expect that machine systems have adequate language skills. Most of the developments in language technology focus on the English language, but it is a legitimate expectation of all societies to be able to communicate in their own mother tongue in the digital space. The application and development of technologies related to the Hungarian language is a priority of national interest. One of the key tools for this is the development of a Hungarian teaching corpus.[4] Digitization of the Hungarian language is very important.

[4] A corpus is a collection of actually occurring written or recorded spoken language data. The texts are selected and arranged according to some aspect. It does not necessarily contain entire texts, and it is not only a repository of texts, but also contains their bibliographic data and marks the structural units (paragraph, sentence). (URL5).

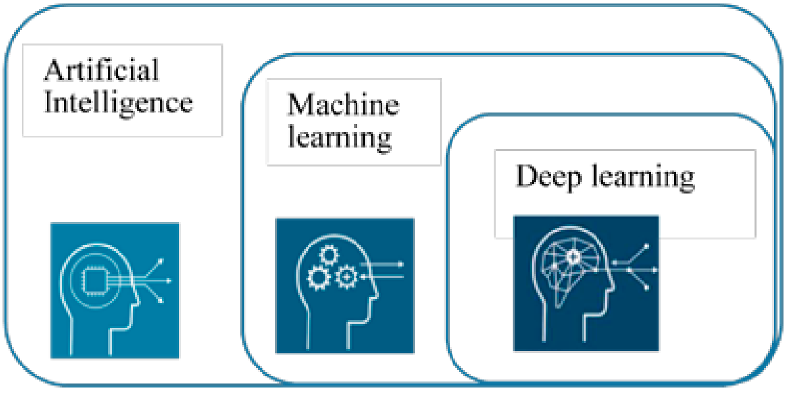

Figure 1. The relationship between Artificial Intelligence, machine learning and deep learning.

Language models

Natural language processing (NLP) is present in almost all areas of life, we can meet it when using Internet search engines or in the case of machine translators. Such NLP applications have been integrated into many tools, such as name recognition or sentiment analysis[5]. First, let's clarify what a language model is. An algorithm trained on a large amount of data is able to recognize linguistic connections and, based on these, generates an output that can be interpreted by the machine. The key element of the system is the learning process. What does it take to create a large language model? The learning process requires a very large computer capacity. To start learning, you need a lot of diverse and clean data. Of course, a person with expertise is a very important factor in this process. Different models were used when processing natural languages, we will now review them in chronological order.

[5] Analysis of the emotional content of a given text. The texts are classified into 2 or 3 groups based on the emotional charge, which can be positive, or negative, and the 3rd group is neutral (Pang and Lee 2008). Sentiment analysis is the study of the emotional assessment of conversational, transactional and social media texts. The emotions appearing in the texts are determined by considering the intention of the text writer, the topic, the use of language, the context and the context of the text. By exploring emotions, the copywriter can better understand the audience's emotions, attitudes, and preferences, and shape their communication accordingly. Text generated by Puligpt.

Rule-based models

Language features are described by rules, these rules are the basis of deterministic algorithms[6]. The system for describing linguistic features is very complicated, as a result of which more and more complex systems were created, which became unmanageable over time. The essence of rule-based solutions is to transfer the code from one code to another according to some rule. In the case of rule-based language systems, working solutions have been created to solve the task of spam filtering, noun element recognition, and word class clarity. Promising research was carried out in the implementation of opinion mining, meaning clarification, syntactic analysis, machine translation, information extraction, and coreference[7] resolution tasks. Answering the question, creating a paraphrase,[8] extracting text, and creating a dialogue were only among the long-term goals in the case of rule-based models. It was an important expectation that each language should have its own basic language research kit (BLARK). It was created by the Hungarian Language and Speech Technology Center. Hungary has joined CLARIN, Europe's largest infrastructure of this kind. The paper The Hungarian Language in the Digital Age (Rehm and Uszkoreit 2012) was published. It has been stated that the processing of the English language is the best, but Hungarian ranks quite high behind English. Among the rule-based solutions are analyzers [Humor (Prószéky and Tihanyi 1996), HunMorph (Trón et al. 2005)], machine translators [webforditas.hu, MetaMorpho (Prószéky and Tihanyi 2002)], part-of-speech disambiguators [HunPOS (Halácsy et al. 2007), PurePOS (Orosz and Novák 2012)] were prepared in Hungarian. The first text corpora were completed (Orwell 1984,[9] BUSZI[10]), although they were still small in size, they became the starting basis for statistical models.

Statistical models

When large amounts of data were available, rule-based models were replaced by statistical models. For these models, we do not describe rules, but the

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[6] Algorithms that always give the same output for a specific input.

[7] Coreference is a linguistic term that refers to when two or more linguistic terms refer to the same entity in a text. Coreference resolution means identifying all occurrences of an entity in the text (Vincze et al. 2015; Vadász and Nyéki 2023).

[8] We say the same sentence in different words.

[9] Orwell's 1984 it was his work that was translated into almost every language and was a good starting point for machine linguistics research.

[10] Budapest sociolinguistic interview, text corpus made from spoken texts.

models are created using machine learning through examples. The examples, i.e. the input, are labelled data, where the labels describe relevant features. For these models, it is difficult to find relevant features (feature engineering). Hand- or machine-annotated[11] text corpora (Sass 2016) appear as input, which are processed using statistical methods during machine learning, and the output is generated from this, which is, for example, the prediction of what other word may follow a given word. In the case of statistical language systems, working solutions have been created for solving tasks such as spam filtering, noun element recognition, and word type disambiguation. Acceptable solutions have already been prepared for the implementation of opinion mining, meaning clarification, syntactic analysis, machine translation, information extraction, and co-reference resolution tasks. In the tasks of answering questions, creating paraphrases, extracting text, and creating dialogues, which seemed very distant with rule-based systems, promising research has already been conducted here. In this period, text corpora in Hungarian were created, such as the monolingual Webcorpus (Halácsy et al. 2004), the annotated Szeged corpus (Csendes et al. 2003), the bilingual Hunglish (Halácsy et al. 2005), the Pázmány corpus (Endrédy and Prószéky 2016), Hungarian National Dictionary (Váradi 2002), and small-scale historical corpus (Ómagyar corpus) and speech corpus have also been prepared (BEA). Very easy-to-use applications have appeared in the field of transport and telephone customer service. During this period, e-magyar.hu was created (Váradi et al. 2017), which contains the basic tools for machine analysis of the Hungarian language.

Language processing with neural networks

The first mathematical description of a neural network was made by Warren McCulloch and his colleagues in 1943. They realized that the nervous system works on an “all or nothing” basis, so it can be modelled mathematically. According to their idea, this is how the artificial neuron can be created. Figure 2 shows a human and an artificial neuron. In the case of the artificial neuron, the input (x1 (n), ... xm(n)) is a known m-dimensional vector. n is n. denotes a moment in time. The w1(n), ... wm(n) are the weights that the goal is to determine. b(n) is the distortion, it is also unknown, it must be determined.

[11] Annotation means that we assign data to text units, such as paragraphs, sentences, and words, according to some aspect. For example, the type of word for words, the type of sentence for sentences, the emotional charge for a paragraph, and its author for a document. Annotation can be manual, machine, or a combination of the two.

The summation node produces a weighted sum of the inputs. The activation or transfer function is a function that we have to choose according to the task. The output is the value assigned by the neuron to the input.

The models are taught using a neural network system, where the neural network is a set of interconnected neurons (Fazekas 2013). Figure 3 shows the structure of the multilayer neural network. In deep learning, we use such a multilayer neural network. With neural network solutions, we do not need to specify rules, nor do we need to label the input data. The input is raw text, of which an ever-increasing amount is available with the rise of the Internet. In the process of learning, the machine system (Beszédes et al. 2021) invents the features itself.

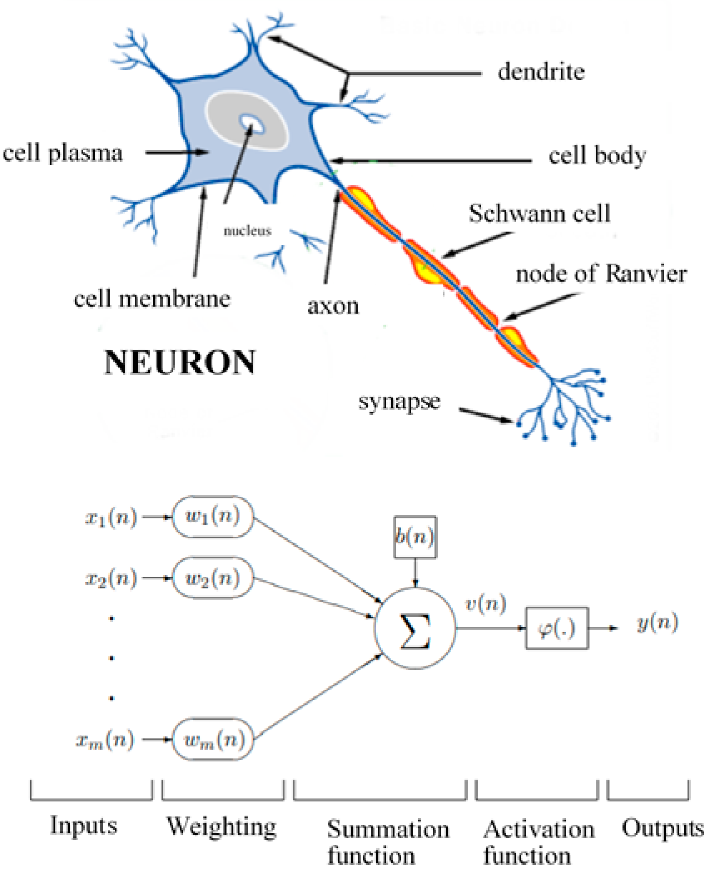

Figure 2. A natural (source: URL6.) and an artificial neuron (source: URL7. page 16).

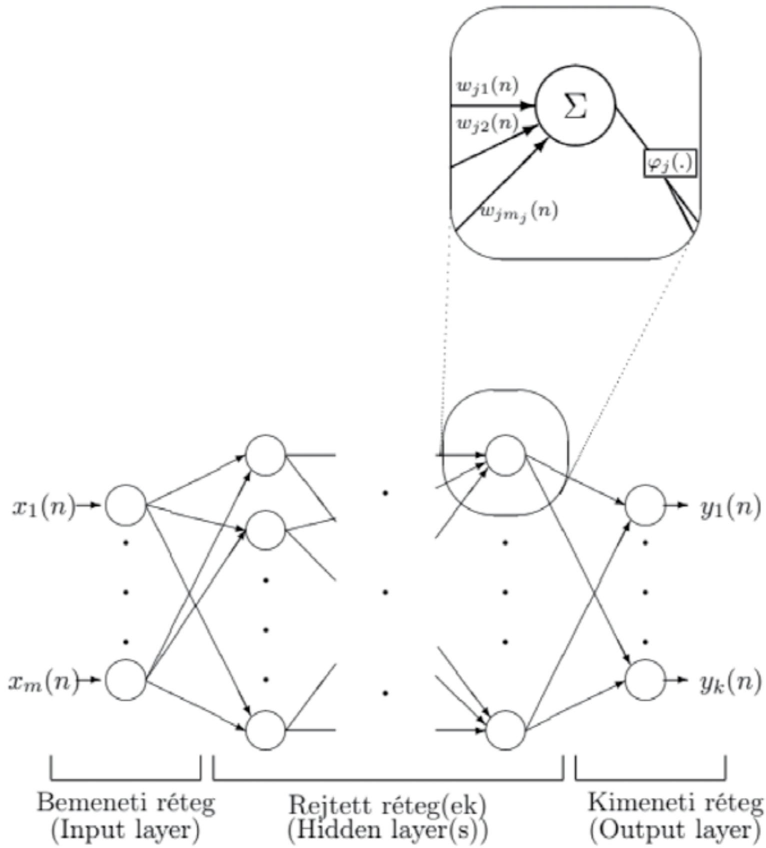

Figure 3. Structure of the multilayer neural network (source: URL7. page 32).

In the case of language models, it is very important what data they were taught with. This teaching dataset is called a corpus. The Hungarian National Dictionary aims to be a general-purpose representative corpus of today's Hungarian written vernacular. Huge high-quality text corpora are available (Sass 2016), but models can be further fine-tuned with smaller specialized text corpora. Figure 4 shows the corpora available on the National Corpus Portal in the chronological order of their creation.

The neural network models already had acceptable solutions for the tasks of answering questions, creating paraphrases, extracting text, and creating dialogues. The basis of neural network systems was the appearance of word vector representations. Such word vector representations are

2023	ParlaMint 4.0
2023	MoMa – Moldvai magyar korpusz
2023	KED – Középmagyar emlékirat- és drámakorpusz
2016	„új" Magyar történeti szövegtár
2015	Mikes-szótár
2014	MNSZ2
2014	Történeti Magánéleti Korpusz
2013	Ómagyar korpusz
2012	BUSZI
2010	Hunglish Korpusz
2009	Mazsola
2006	Webkorpusz
2005	MNSZ1
1999	Orwell: 1984

Figure 4. Text corpora are available on the National Corpus Portal (source: URL8).

word2vec (Mikolov 2013), fasttext. The dynamic language models (mBERT, HuBERT) were published. The meaning of words is closely related to their environment (distributional semantics). Linguistic elements are points in the vector space, and semantically or morphologically similar words are also close to each other in the vector space. During the operation of the system, the deep learning neural network assigns a multidimensional vector to each word (elementary unit, token) of the text entered as input, the i-th element of which shows that the text is examined i. the probability that certain elements of the text occur in the environment of its element. Anyone can test how a neural network learns (URL9). With the support of Microsoft Hungary, the Institute of Linguistics and the University of Pécs prepared the Hungarian adaptation of the BERT-large model, the HILBERT (Feldmann et al. 2021) model. More and more speech corpora are being prepared, in addition to BEA, for example, BEKK and HuTongue speech corpus appear.

In 2017, the emergence of the transformer architecture (Vaswani et al. 2017) brought great progress in machine translation. The transformer architecture can be analytical (encoder) or generative (decoder). Many tasks can be solved with the generative language model: creating a summary, translating, writing program code, etc. Analytical language models must be fine-tuned separately for each task, with labeled data. Encoder models analyze the text coming to their input, such as the BERT, RoBERTa, ELECTRA, ALBERT language models. The decoder models are suitable for text generation, the first one was the GPT model, but this is the PaLM MT-NLG. Encoder-decoder type model is T5, BART, Marian. The language model is the set of weights produced at the end of learning. In Table 1, we compare some large language models based on the number of parameters and the size of the text corpus used for learning.

Table 1. Characteristics of some large language models

Model Name	Company	Number of Parameters	Size of Training Corpus
GPT-2	OpenAI	1.5 billion	40 GB
GPT-3,5	OpenAI	175 billion	45 TB
BERT	Google	340 million	3.3 billion text pieces
XLNet	Google	340 million	126 GB
RoBERTa	Facebook	355 million	160 GB
Megatron	Nvidia	8.3 billion	512 GB
ALBERT	Google	11 million	3.3 billion text pieces
T5	Google	11 billion	750 GB
T-NLG	Microsoft	17 billion	568 GB
ELECTRA	Google	110 million	1.7 TB
LaMDA	Google	137 billion	1.56 billion words
GPT-4	OpenAI	~ 600 billion	~ 120 TB
mT5	Google	580 million	29 TB
ProphetNet	Microsoft	550 million	160 GB
DeBERTa	Microsoft	1.5 billion	160 GB
PEGASUS	Google	568 million	750 GB

(source: own editing)

Nowadays, more and more language models are appearing. There is huge competition between the big companies. The development of language models involves enormous technological and financial challenges, which is why only large companies can afford the development of huge language models. The goal is to create large language models that are capable of solving all kinds of linguistic tasks (extraction, sentiment analysis, translation, tagging, name element recognition, anonymization[12] etc.) even without fine-tuning. Figure 5 shows some of the more important language models.

[12] The process of converting personal data into anonymous data, as a result of which the data subject can no longer be identified – National Legal Code 2021 XCI. law (URL10).

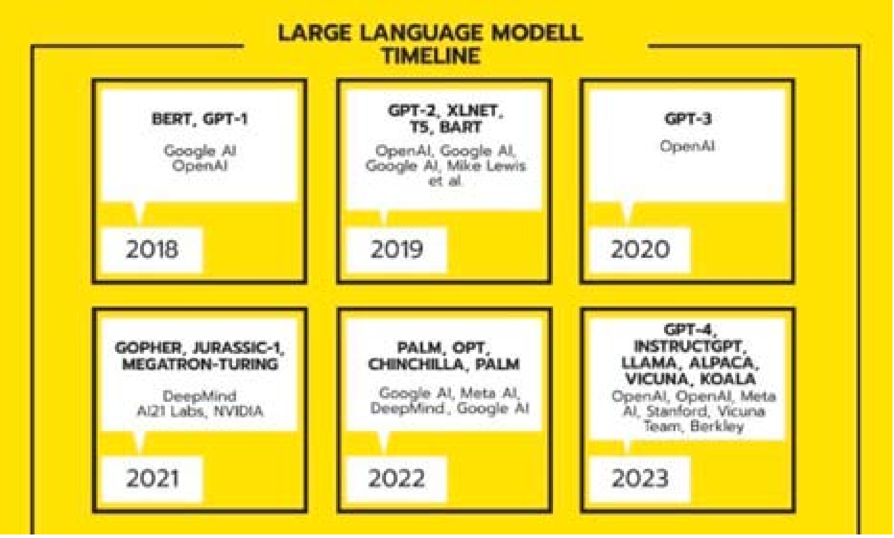

Figure 5. The major language models (URL11).

More important Hungarian language models

In the shadow of the greats, they also developed Hungarian language models with a more modest infrastructure. huBERT was completed in 2020 (Nemeskey 2021), which was based on the BERT Base model. 110 million is the number of parameters of the model, the teaching corpus was the webcorpus 2.0. HILBERT was completed in 2021 with the support of HILANCO and Microsoft (Feldmann et al. 2021), which was based on the BERT Large model with 340 million parameters. The teaching corpus consists of 3.67 billion words. The HILANCO language model, which is bilingual (English, Hungarian), was introduced in 2022. The number of parameters is 6.7 billion and the teacher's corpus is 127 billion words, of which 102 billion are English words and 25 billion are Hungarian words. In the same year, the language model PULI GPT 3SX (Yang et al. 2023a) with 6.7 billion parameters was published. The teacher's corpus was 32.5 billion Hungarian words. The trilingual PULI GPTrio was completed in 2023 (Yang et al. 2023b), which also has 6.7 billion parameters. The three languages are Hungarian, English and Chinese, and the teaching corpus was 200 billion words. The parameter number means that the system can assign so many characteristics to a grammatical element. If we think about how many different characteristics we can specify for an object, then the order of billions shows how much technology is capable of. Table 2 shows a comparison of some Hungarian language models based on the number of parameters and the size of the teaching corpus.

Table 2. Characteristics of some Hungarian language models

Model Name	Number of Parameters	Size of Training Corpus
huBERT	110 million	10 billion words (webcorpus 2.0)
HILBERT	340 million	3.67 billion words
HILANCO	6.7 billion	127 billion words (English, Hungarian)
PULI GPT 3SX	6.7 billion	32.5 billion words (Hungarian)
PULI GPTrio	6.7 billion	200 billion words (Hungarian, English and Chinese)

(source: own editing)

The complicated grammatical structure of the Hungarian language poses a difficulty when creating Hungarian language models. Sentences do not have a fixed word order, a sentence can be written in several different word orders. There are many exceptions to the rules, and handling them is not easy either. There are many turns of phrase and expressions in the Hungarian language, the meaning of which is not always clear (Arató–Balázs 2022, 2023). Language models must understand and take into account the cultural and social context of the Hungarian language, they must be able to correctly interpret the texts and give appropriate answers to them. The Hungarian language has different dialects and accents, which is an additional difficulty for models. In the case of ChatGPT, which is not specifically taught in Hungarian but understands Hungarian, the size of the teaching corpus is a limitation, which is limited to 128 million Hungarian text fragments. In contrast, in the case of PULI, teaching was carried out with 32.5 billion text fragments. It is very important to create Hungarian teaching corpora of the right size (Balázs 1997; Prószéky and Váradi 2023).

Language models in education

By fine-tuning language models with specialized texts, applications based on these models will be able to generate and analyze high-quality specialized texts. In the case of subjects belonging to different scientific fields, these fine-tuned models can be of great help in preparing the curriculum. Language models could be prepared for each discipline, which would be fine-tuned for professional texts in addition to general knowledge. In the case of universities, the theses stored electronically could be the teaching texts for fine-tuning. What can we use applications based on language models?

Sentiment analysis (Laki and Yang 2022a; Yang and Laki 2023): You can decide whether a given text has a positive, negative or neutral charge. In education, for example, sentiment analysis can be used to filter out positive and negative opinions in the evaluation of students by instructors. In the case of correspondence with students, such a mood analysis could also be prepared, and depending on the result, additional benefits could be brought. The staff of the Linguistics Research Center created a sentiment analysis application that anyone can try (URL12).

Chatbots: They are virtual assistants for students who can answer their questions immediately. It is most beneficial for students who do not dare to ask their questions in class. Chatbots can also provide explanations of definitions, but they can also give students study tips. Chatbots can also help students in their academic affairs and answer administrative questions. The best-known chatbot is ChatGPT (URL2), but there is also a Hungarian counterpart called PULI GPT (URL13).

Translation: translating texts from one language to another. In the case of teaching materials in a foreign language, it can help students translate the text. They can also play an important role in maintaining contact with foreign students, and can also be useful in case of participation in international programs. Like students, they can also provide teachers with great help in getting to know and understanding research results in a foreign language. A demo of a translation program is available on the website of the Linguistics Research Center (Laki and Yang 2022b) (URL14).

Summarizing: very useful for extracting essential information from long texts. It can help students prepare for the exam by reviewing the essential parts of the curriculum. For summarizing the content of a topic when preparing teaching material for teachers. It is also a great help for students when writing their theses, and for instructors when preparing publications, since these papers always include a summary of the work done. These applications produce digests of given long texts (Yang 2022) (URL15).

Question-answer: generates appropriate answers to the questions we ask. Both teachers and students can use these applications, although it is important to be critical of the answers to the question. An example of this is the command PULI (Yang et al. 2023b, Yang et al. 2024a, Yang et al. 2024b) (URL16).

Content creation: these applications are able to produce content on a wide variety of topics based on specified criteria and parameters.

Applications based on GPT models are all suitable for this. Since these models do not copy texts from some source, but are able to produce their own texts as a result of learning, it is therefore very important to treat the produced content critically.

Speech recognition: this is an application that transforms spoken language into written text (Németh and Olaszy 2010). The final result is greatly influenced by ambient noise. It can be very useful for instructors to be able to immediately create a written text from their lectures, and the digital content for the subject is already ready. The hearing-impaired are assisted by the textual transcripts of the presentations given in the preface.

Tagging: keywords are important information for searchers in the case of studies. During tagging, we add tags and keywords to a specified text using the applications created for this purpose. A good choice of tags assigned to long texts can also help students when searching for content (Yang et al. 2020) (URL17).

Language learning support: A chatbot working with language models as part of an application helps you learn a language interactively, for example by doing conversational exercises or giving grammar explanations (Porkoláb and Fekete 2023). Some popular AI-based language learning apps are TalkPal, Duolingo, Rosetta Stone, Babbel, and Mondly. These apps use machine learning algorithms and other artificial intelligence technologies to provide a personalized and interactive learning experience.

Summary

The rapid development of artificial intelligence (AI) today represents an extremely exciting and diverse field. The application of AI is already present in almost every sector, including healthcare, finance, automotive and education. Newer models, such as large language models and deep learning algorithms, are constantly improving and enabling new forms of human-machine interactions. Large language models are revolutionizing education with their wide applicability and interactive features. One of their main advantages is the ability to learn from a wide and diverse range of sources, allowing learners to access different knowledge bases and expertise through a single platform. In addition, large language models can also be used interactively in education. These models allow students to ask and answer questions, participate in simulations or engage in dialogue with virtual characters. This improves students' communication and problem-solving skills. However, it is important to recognize that these models are not perfect. Sometimes they may give wrong or inaccurate information, which can be misleading for students. In addition, ethical issues also arise, such as personal data protection and the protection of students' intellectual property. It is important that users critically examine and contextualize the information provided by such models. Overall, large language models have great potential in education if they are properly used and critically evaluated. It is important that teachers are prepared to use models and consciously integrate them into the educational process in order to provide maximum benefits to students while taking into account possible challenges and limitations.

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