What Do We Know about Learning – Conversations with chatGPT

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***Abstract* – We are witnessing a major achievement of machine learning – appearance of several chatbots which are able to produce human-quality conversation. Appearance of such 'fluid conversationalists' has aroused big interest especially among teachers, since they have already passed several exams designed for humans and have been used by students in winter fall 2022 exams. Their performance is not based on linguistic research, but is an achievement of data science. This performance cannot yet be rationally explained (it is based on interplay of billions of variables), thus in the following are used conversations with the currently most visible member of this family – the chatGPT to clear some myths around these programs.**

Keywords – learning, statistics, language, neural net, chatGPT, WordNet

I. INTRODUCTION

We are living in an era of catastrophes – climate catastrophe, exhaustion of natural resources, population explosion, the 'Knowledge Explosion' [1] (predicted already in Bible, Daniel 12:4 [2]).

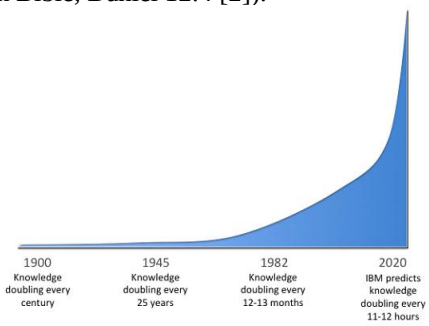

Figure 1. The 'Knowledge-Explosion' graphically

And at the end of the last year begin the explosion of chatbots capable to produce fluent text in natural languages (Croatian, Estonian, Finnish - not only on English!): on Nov.30, 2022 OpenAi announced chatGPT (General Purpose Transformer – transforms text to text) [3]; as a response to this Google announced of Feb 6, 2023 a rival – Bard [4] and on Feb 7, 2023 Microsoft announced new, AI-based (Artificial Intelligence) search engine and homepage Bing [5].

These 'super-polyglots' are based on research in neural networks and presented as 'deep machine learning'; in recent years have appeared umpteen papers proposing new methods of deep machine learning.

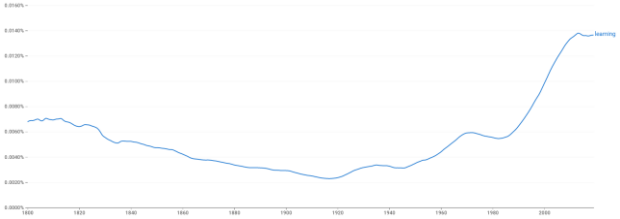

Figure 2. The world-wide interest in learning has in recent decade grown more than twice [6]:

With such explosion of new learning theories the old ones becomes quickly obsolete [7] and many teachers may be confused – should I now start working entirely differently – in a new, 'innovative', 'deep' way?

In the following is presented brief overview our understanding of learning – the 'classical' theories and the new, 'deep' ones..

II. CLASSICAL THEORIES OF LEARNING

Human brain contains ca 10^{11} neurons and each neuron is directly connected via synapses with ca 10^3 other neurons [8]. When learning something, brain constantly rearranges this network. Although this structure has been extensively studied by neurobiologists, teachers, computer scientists, mathematicians, physicists, psychologists, linguists etc. We still do not have workable theories and models of brain, since we can follow brain only from 'outside', follow processes (neuron activations), assuming inner workings of brain, what current methods of neurophysiology cannot yet explain.

Many theories are trying to explain human learning mechanisms [9], [10]. All these theories: the behaviorist learning theory (good students receive positive reinforcement - a prize or a gold star - primitive gamification), Cognitivism (learning is based on changes in the brain), Constructivism (learners construct their understanding of the world through experiences and interactions), Social Learning theory (emphasizes the role of society), the transfer theory (learning occurs when applying already existing knowledge in new situations) etc. are all trying to explain our experience, century's old practice of teaching-learning. They are not 'rules for action' – 'do this, then do that' – they only allow to reflect on our practice. Every teacher is a jazz artist who has

momentarily respond to current situation in class – who did what, who asked what. Learning and teaching both are hard work based mainly on improvising.

III. BOTTOM-UP VS TOP-DOWN

As every process/action, learning can be described from several perspectives. For humans is important the main direction of knowledge acquisition – top-down (from description of external features of the process, describing 'how?') or form bottom-up – from description of inner mechanisms, forces, structures what drive the whole process, describing 'why?'.

The classical learning/teaching is considered in bottom-up manner. You have first learn the basics – learn to read and write, math, laws of physics. Nobody can learn to drive a bicycle by listening lectures on bicycle construction and angular momentums (the top-down approach); you have to try to run a bicycle (bottom-up approach).

With overall advance of computers – the humanity's first 'Tool for Intellect' - many basic intellectual skills are now questioned – could they be performed by computers? In several countries handwriting (calligraphy) has been replaced with drawing 'block letters' (e.g. in USA handwriting become not compulsory in many states already in 2010), ability to calculate is questioned – "everyone has a mobile device which can do all these calculations!" and Google is trying to nullify even ability to read, replacing everything with video - in search results the YouTube videos are always placed first. The 'how it looks' is considered more important than 'how human does it'.

Currently we are witnessing the next step in 'top-down' revolution in considering human thinking – the neural-net revolution of handling natural (English, Croatian, Estonian, Finnish etc.) languages.

We still do not understand our natural languages enough to use them with computers. With computers we have to use mysterious sequences of strange symbols with lot of hidden meaning; what makes programming difficult to learn and understand. For example one line (in Python) [11], [12]

$$a_2, a_1, a_0 = \text{np.polyfit}(x, y, 2)$$

is sufficient to calculate second-order approximation

$$y = a_0 + a_1 x + a_2 x^2$$

This one line hides (in libraries) 18378 other lines of Python code [11], thus from the code is visible only 0.0000979431-th part and it is very difficult to understand. Everything were much simpler, if we could address computers with human languages.

But "If the Mountain won't go to Mohammed, then Mohammed must come to the Mountain" – while we still fight computer languages, computers learned to speak human languages.

IV. THE MACHINE LEARNING REVOLUTION

The 'machine learning' approach to human learning is totally top-down – computers are mimicking the order of tokens (characters, syllables, words) what humans have used in their texts, they do not understand their meaning. Linguists are not involved, the computer scientist Frederick Jelinek (studied automatic speech recognition) boasted: "Every time I fire a linguist, the performance of the speech recognizer goes up".

The beginning of machine learning was discovery of neurons in 1990-s. Neurons are discrete entities, conducting their impulses in one direction only, down their axon and receiving information through dendrites. American neurophysiologist Warren McCulloch and mathematician Walter Pitts presented in 1943 a model of neuron functioning.

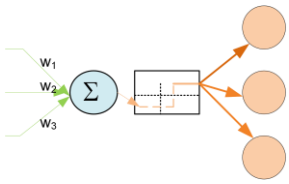

Figure 3. Neuron fires (sens signal to next neurons) if sum of its weighted inputs becomes sufficient.

Donald Hebb took the idea further and proposed that information is processed in brain step-by-step: neurons activate others (fire) by layers and neural pathways strengthen over each successive use (connectionism).

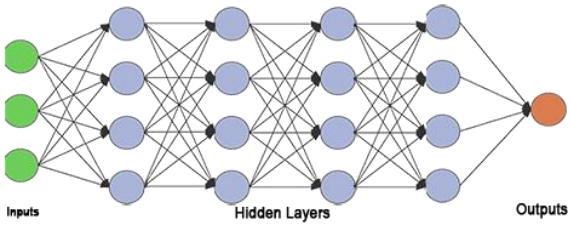

Figure 4. Neural net

Neural nets are devices for classification, compressing large amounts of data into small set of classes, e.g. recognizing an object in a visual scene or understanding the meaning of a sentence or phrase. In statistics these tasks were called clustering, but neural net researchers started to use term 'learning' and since modern neural nets use in the process large number of layers and parameters (weights), the (machine) learning is stated as 'deep'. At the end of the last century were proved universality results – neural nets can approximate any continuous function [13],[14],[15]. Unfortunately this result is often cited not correctly (even by Google), omitting the essential word 'continuous'. Neurons are helpless with e.g. the XOR function [16].

In NLP (Natural Language Processing) and machine learning are used Recurrent Neural Nets (RNN), which have also backward links to implement short-term memory. In text producing the main problem is prediction of the next word (or character) [17]. For prediction is used information - which token follows which one – derived from earlier (human-generated) texts, thus every machine

learning project begins with collecting a large corpus of human-produced text, e.g. from WWW.

Everything is based on statistics about 'what follows what' and only on this, the program does not use linguistic information – word types, sentence parts etc. This information is distilled by a neural net from the corpus, stored in a large number of parameters and called 'text model', e.g. the text model GPT-3 which was used for creating chatGPT has 175 billion parameters.

Text model creation (inferring tokens order information) is based on simple statistics. Suppose we already have a sequence of words:

$$w_1, w_2, ..., w_{i-2}, w_{i-1}$$

The next word w_i could not be arbitrary, it depends on preceding words. The next word could be guessed maximizing the relative probability [18]:

$$\max(w_i \in V) P(w_i \mid w_1, ..., w_{i-1})$$

Here $P(w_i \mid w_1, ..., w_{i-1})$ is the conditional probability that after words $w_1, ..., w_{i-1}$ follows the word w_i. In practice probabilities are estimated from frequencies in the corpus, i.e. the relative probability of a word following previous words is calculated from the frequencies of use of these words in the corpus:

$$P(w_i \mid w_1, ..., w_{i-1}) \approx \frac{Fr(w_1, ..., w_{i-1}, w_i)}{Fr(w_1, ..., w_i)}$$

The probability of the whole phrase is the product of probabilities, i.e. probability of the beginning phrase $P(w_1, ..., w_{i-1})$ and the conditional probability that it is followed by the word w_i:

$$P(w_1, ..., w_i) = P(w_1, ..., w_{i-1}) P(w_i \mid w_1, ..., w_{i-1})$$

Human language is often considered as a process with limited memory (a Markov process), assuming that the meaning of the next word depends only on a limited number of preceding words. This is generally not true, we expect often that the reader/listener already knows the meaning of many words which have been use. But applying the Markov process assumption '*probability of word depends only on few number of previous words*' simplifies programs and is used in NLP (Natural Language Processing) everywhere. Thus for prediction of the next word is used only a sequence of fixed length *k* (the Bayes assumption) and the search goal is

$$\arg\max(w_i \in V) P(w_i \mid w_{i-k}, ..., w_{i-1}) \qquad (1)$$

After replacement $i - k \to 1$ we are looking for

$$P(w_1, ..., w_i) \approx P(w_1, ..., w_{i-1}) P(w_i \mid w_1, ..., w_{i-1})$$

Probability of the first word/phrase could be expressed the same way or those words are given as a seed.

In practice (to speed up calculations) the last formula is simplified even more. By the Bayes conditional independence assumption the probabilities $P(w_j \mid w_{j-1})$ are independent. So in language models are often used only binary probabilities (a very rough assumption, but gives huge speed-up of calculations), thus

$$P(w_1, ..., w_n) = P(w_1) \prod_{i=2}^{n} P(w_{i-1} \mid w_i) \qquad (2)$$

The formula (2) allows to create new texts – give some words $w_1, ..., w_{i-1}$ as a seed and find a word w_i which maximizes probability $P(w_i \mid w_1, ..., w_{i-1})$, then shift the 'action window' one step to right and repeat the process with sequence $w_2, ..., w_{i-1} w_i$. The value of the parameter *n* is big, e.g. in chatGPT n=2048 (see below).

Chaining words which in some context did follow each other could produce expressions which have opposite meaning to the meaning which was expressed in original sentences. For instance, with (2) from sentences:

John loves Mary. Mary loves Marc

would follow (using the underlined pairs of words):

John loves Marc

In the corpus could be also a statement

John hates Marc

But the program would not "see" it – it does not have any pairs of words which could be used for linking with the words from the first two sentences, thus the program would produce a wrong statement. For instance from a corpus containing texts of presentations from the "Mipro.CE" conference was produced nonsence [12]:

Students are not included in the process of e- learning in the context of the process of teaching and learning.

For arithmetical expressions does not hold the Universality Theorem - they do not implement a continuous function except for unary representation, thus they cannot be learned by neural networks. Some websites [19] claim it is possible: "You'll get to 99+% validation accuracy after ~30 epochs". This holds only for expressions with similar structure and length, testing their program with expressions of different length gives rather different results:

```
Q 49+232  T 1    - 0
Q 134+19  T 1    - 0
Q 450+29  T 1    - 0
Q 0+364   T 0    OK 0
…
Correct: 56%
```

With small modifications: multiplying binary strings using variables gives already a very poor result:

```
x=101001  y=1101011010  z=x*y        A:  z=1000100101101010      -
z=1000100111110110
x=1000111 y=1001 z=x*y     A: z=1001111111    - z=1001100011
…
Correct = 7.0%
```

The probabilities $P(w_j \mid w)$ allow to consider the whole vocabulary as an *n*-dimensional space (*n* – the size of the vocabulary) with distances between words determined by these probabilities. For instance, the list of

word vectors of the popular GloVe model from Stanford [20] contains 19171496 lines (one for every word) of length ~ca 2587; the upper-left corner (first 8 elements from first 3 lines; the first word is comma ',') is:

, 0.18378 -0.12123 -0.11987 0.015227 -0.19121 -0.066074 -2.9876 ...
the -0.20838 -0.14932 -0.017528 -0.028432 -0.060104 -0.2646 -4.1445 ...
and -0.09611 -0.25788 -0.3586 -0.32887 0.5795 -0.51774 -4.1582 -....

Creating text model from a text corpus is not a "rocket science", but already a rather common adventure using many openly available programs [21]. Big models show also some semantic relationships, e.g. in the 'vocabulary cloud' created from Mipro.CE presentations 2016-2021 appeared several groups of closely related words:

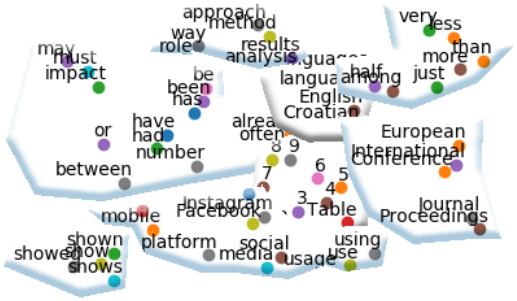

Figure 5. Some semantic groups from the 270021-dimensional space of the vocabulary of Mipro.Ce English-language presentations [22]

V. CHATCBT AND OTHERS

The models created from large text corpuses using openly available algorithms can produce amazingly good, 'human-like' texts. Nobody has not yet presented good explanation, why adding to a word another word which sometimes has followed it could produce 'human-like' text, but many people are over-exited. Professor of the USA university said that he “fell in love” with chatGPT after reading its answers to MBA exam questions [23].

In the following are considered some features of chatbots produced by neural nets. These features hold for all of them (the reasons are the same), but are here illustrated by answers produced on Feb.7-9, 2023 by the chatGPT program itself; its answers are not edited (copy-pasted from the program's window), only a bit reduced in order to comply with length limitations for this paper.

A. chatGPT does not have any understanding of truth

Authors of the chatGPT warned already in their first announcement [3]: "ChatGPT sometimes writes plausible-sounding but incorrect or nonsensical answers."

To check the truthfulness of chatGPT we asked chatGPT itself:

We: *"Can you say false statements ?"*

chatGPT: *" ...I can't guarantee that all the information is true or up-to-date."*

The program cannot distinguish between true and false statements.

We: *"Can You check truth of your statements ?"*

chatGPT: *"I do not have the capability to verify the truth of my own statements. It is ultimately up to the person receiving the information to critically evaluate and verify its accuracy. "*

Some prestigious Internet publications state "ChatGPT lies about scientific results" [24]. This is an over-reaction: lying is a deliberate action, but chatGPT does not know that it lies.

B. chatGPT can not learn

We: *"Are You learning ?"*

chatGPT: *"As an AI language model, I am not capable of learning ..."*

This is the second important difference between chatbots and humans – humans learn constantly, but the chatbot's 'learning' (usually called 'training') is one big computation in order to create the text model. Cost of computation of the chatGPT-s text model GPT-3 having 175 billion parameters was 46 million USD; cost of using GPT-3 (full model) is ca 14400 USD per month [25]; after training the model is fixed, cannot be re-trained.

C. Chatbots are circular

Chatbots are finite deterministic programs (if they were not deterministic, then the computer is severely broken); every finite deterministic system is circular [26].

We: *"What is the definition of set ?"*

chatGPT *"... a set is a well-defined collection..."*

We: *"What is ' a well-defined collection of distinct objects' ?"*

chatGPT: *"A well-defined collection of distinct objects refers to a set"*

Thus '*set*' = '*well-defined collection*' = '*set*', i.e '*set*' is a '*set*'.

D. Chatbot will eventually fall in loop

Every finite and deterministic dynamic system falls in loop, starts repeating itself:

We: *"As a finite system you start looping when producing very long statements ?"*

chatGPT: *"Yes, as a finite machine learning system, I can repeat patterns or get stuck in loops..."*

E. chatGPT (sometimes) does not know math:

The language model produced by neural net cannot guarantee correct math (the same problem was reported in [23]). In our first conversation with chatGPT it made several mistakes.

We: *"Calculate 17*7-26!"*

chatGPT: *"The answer is 69"*

Wrong, 17*7-26 = 89

We: *"Calculate 237.3+36.2*7-382.3!"*

chatGPT: *"The answer is 176.4"*

Not correct, should be 108.4.

After some days chatGPT calculated correctly and produced fluent explanations:

We: *"Please add 24/6 to 12*5!"*

chatGPT: *"To add 24/6 to 12 * 5, first we need to simplify 24/6 to a whole number. Dividing both the numerator and denominator by 6, we get:*

24/6 = 4

*Next, we can multiply 12 * 5 to find the value of the second term:*

*12 * 5 = 60*

Finally, we can add these two values together:

4 + 60 = 64

*So, the result of 24/6 + 12 * 5 is 64."*

F. chatGPT can explain itself

We: *"What is the size of the text corpus which was used to create your text model?"*

chatGPT: *"As an AI language model trained by OpenAI, I was trained on a large text corpus called the "WebText" corpus. This corpus consists of over 8 million web pages and contains a diverse range of content, including articles, books, and websites on a variety of topics.*

The specific version of the WebText corpus that I was trained on contains approximately 40 GB of uncompressed text data. However, it's worth noting that the exact size of the corpus and the training process can vary depending on the specific version of the model and the training configurations used."

We: *"How many tokens to you link to construct your answers ?"*

chatGPT: *"... the maximum number of tokens I can use in a single response is 2048, which is the maximum sequence length that my training allows.*

To give you an idea, an average sentence in English consists of around 15-20 tokens, so I can typically construct a response using anywhere from a few sentences to a few paragraphs, depending on the question."

Google announced on Feb 6, 2023 its own chatbot Bard; it made an error already in its very first demo what resulted in Google's parent company Alphabet loosing $100 billion in market value [27]. Microsoft demoed its new AI-powered search engine Bing on Feb 7, 2023 and placed all the responsibility to user: "Make sure to check the facts!" What is the sense of using expensive chatbot if every its statement should be checked for truth?

G. chatGPT can respond to several languages

Currently Internet is already not only in English – there are texts from many languages and if these texts were included in the text corpus used to train language model, the resulting model will also respond to other languages. This does not mean, that it understands anything – it just links together words/characters/syllables what in some text were following each other:

We: *"Objasnite mi - što je ljudsko učenje i po čemu se razlikuje od strojnog učenja?"*

chatGTP: *"Ljudsko učenje je proces učenja koji se odvija kroz iskustva i interakciju s okolinom. To može uključivati učenje putem iskustva, učenje od drugih, obrazovanje i mnogo drugih oblika učenja. Ljudsko učenje obično zahtijeva nekoliko puta da se nešto uči i da se stekne iskustvo kako bi se steklo znanje.*

Strojno učenje je oblik računalne tehnologije koja omogućuje računalima da nauče iz podataka bez eksplicitnog programiranja. Umjesto da se računalu eksplicitno kaže kako riješiti problem, strojno učenje koristi algoritme koji automatski identificiraju značajne značajke iz podataka i stvaraju modele koji se mogu koristiti za predviđanje ili klasifikaciju. Strojno učenje zasniva se na korištenju velikih količina podataka i računalne snage da bi model bio učinkovit.

Zaključno, razlika između ljudskog i strojnog učenja je u tome što ljudsko učenje uključuje interakciju s okolinom i stjecanje iskustva kroz mnoge učenje, dok strojno učenje zasniva se na automatskom identificiranju značajki i stvaranju modela na temelju velikih količina podataka."

VI. CONCLUSIONS – SHOULD TEACHERS USE CHATBOTS ?

Chatbots as many other inventions did not appear to answer a specific need, but as a result of human curiosity, so now the problem is "What should we do with this?" In terms of Gartner's hype cycle [28], chatbots are currently close to the 'Peak of Inflated Expectations'; it takes time until they move to 'Plateau of Productivity'.

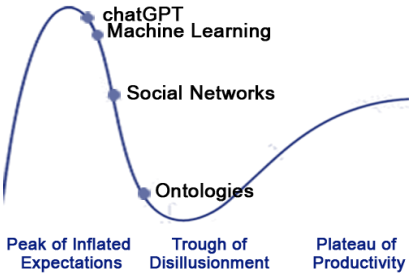

Figure 6. Some popular technologies in Gartner's 'hype cycle' scheme (according to results from Google Trends).

Although teachers did not participate in development of chatGPT (at least there is no information), chatbots will certainly affect our education, e.g. cheating has become incredibly easy. The program was able to pass MBA exam with result B..B- [23] and approach or exceed the score needed to pass three tests of the US Medical Licensing Exam (USMLE) [29] (this also says something about those exams); 17% of prestigious Stanford University students confessed that they used chatGPT to assist with their assignments and exams [30].

The 'demons of cheating' have forced several strong actions: the New York City's education department and growing number of other educational institutions blocked the site on its networks [31], a question and answer site

for programmers StackOverflow banned chatGPT after a week of test use [32].

But 'the troll is already out of bottle'. Universities are accepting the new technology and modified their academic integrity policies. Several possibilities for chatbots are investigated, e.g. if they could be used as automated training and grading systems [33], [34].

We: "*Should the AI tools (such as this program) be used in schools?"*

chatGPT: *"The use of AI tools in education is a complex issue with potential benefits and drawbacks.*

On the one hand, AI can help schools in many ways, such as by providing personalized learning experiences, assisting with grading and assessment, and streamlining administrative tasks. AI can also provide access to vast amounts of educational resources and can help to engage students in new and innovative ways.

On the other hand, the use of AI in education raises concerns about privacy, bias, and the potential for job loss in the education sector. It is also important to ensure that students develop critical thinking skills and are able to critically evaluate information, rather than becoming overly reliant on technology.

In conclusion, the use of AI in education can be beneficial in many ways, but it is important to carefully consider the potential drawbacks and to implement AI in a way that supports student learning and well-being. AI should be used as a tool to support and enhance education, rather than replacing human teachers and other educators."

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