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FEATURES, PROBLEMS AND PROSPECTS OF THE APPLICATION OF DEEP MACHINE LEARNING IN LINGUISTICS

Abstract. In its nascent years, artificial intelligence (AI) largely focused on expert systems based on knowledge in the form of production rules, which solved mainly diagnostic problems, but also design-type problems (using the previously manually collected and formalized knowledge/experience of human experts in specific subject area). However, this type of intelligent systems had numerous drawbacks, including the subjectivity of experts' opinions, which eventually led to their loss of mass popularity [1]. In addition, this technology practically could not be adapted to mass and effective use either in scientific philological research or in practical effective linguistics.

As the scale and volume of data has increased, these methods have been replaced by a more controlled and objective data-oriented approach – machine learning [2]. Machine learning is a set of algorithms and methods that helps machines understand the hidden patterns in data and use the structure and essence of these hidden patterns in the data/heuristics to make logical inference/prediction about a specific task. Currently, there is a diverse range of such methods/algorithms, with the help of which machines seek to understand these basic patterns such as association, sequence, classification, clustering, regression prediction, finding anomalies in data [3].

If we systematically consider the history of the development of computational analytics and analyze its perspective, it becomes clear that deep learning is a further evolution and subdomain of machine learning. Thanks to the emergence of architectures with increased computing power (GPU and TPU) and large sets of semi-structured and unstructured data, specialized architectures and corresponding deep learning algorithms are able to independently learn hidden patterns in linguistic data and even perform generative functionality (Large Language Models).

However, recently there has been a growing misconception that deep learning is a competing technology to classical machine learning. Deep learning is not a single possible approach, but rather a class of algorithms and topologies, that can be applied to a wide range of scientific and practical problems (especially in machine linguistics).

This article investigates and conducts a comparative analysis not only of this hypothesis, but also presents the results of thorough research on the advantages, problems, and features of effective deep machine learning in philology, namely in machine linguistics.

Keywords: machine linguistics, natural language processing, machine learning, deep machine learning, deep neural network.

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ОСОБЛИВОСТІ, ПРОБЛЕМИ ТА ПЕРСПЕКТИВИ ЗАСТОСУВАННЯ ГЛИБОКОГО МАШИННОГО НАВЧАННЯ В ЛІНГВІСТИЦІ

Анотація. У роки свого зародження штучний інтелект (AI) значною мірою зосереджувався на експертних системах, заснованих на знаннях у вигляді продукційних правил, які вирішували головним

чином діагностичні задачі, але і задачі проектного типу (використовуючи заздалегідь вручну зібрані та формалізовані знання/досвід людей-експертів у конкретній предметній області). Однак такий тип інтелектуальних систем мав численні недоліки, в тому числі суб'єктивізм думок експертів, що врешті призвело до того, що вони втратили масову популярність [1]. Крім того, ця технологія практично не могла бути пристосована до масового та ефективного використання ні у наукових філологічних дослідженнях, ні у практичній ефективній лінгвістиці.

Зі збільшенням масштабу та обсягу даних ці методи були замінені підходом, більш керованим та орієнтованим на об'єктивні дані – машинним навчанням [2]. Машинне навчання — це набір алгоритмів і інструментів, які допомагають машинам розуміти приховані закономірності в даних і використовувати структуру та суть цих прихованих закономірностей, що лежить в даних/евристиках, для виконання логічного висновку/передбачення щодо певного конкретного завдання. Наразі є різноманітний діапазон таких методів/алгоритмів, за допомогою яких машини прагнуть зрозуміти ці базові закономірності типу асоціації, послідовності, класифікації, кластеризації, прогнозу регресії, пошуку аномалій в даних [3].

Якщо розглянути системно історію розвитку обчислювальної аналітики та проаналізувати її перспективу, глибинне навчання є подальшою еволюцією і піддоменом машинного навчання. Саме завдяки появі архітектур підвищеної обчислювальної потужності (GPU та TPU) та великим наборам напівструктурованих та неструктурованим даних - спеціалізовані архітектури та відповідні алгоритми глибокого навчання здатні самостійно вивчати приховані шаблони в лінгвістичних даних та виконувати, навіть, генеративний функціонал (Large Language Models).

Проте, останнім часом зростає помилкове уявлення, що глибоке навчання є конкурентною технологією для класичного машинного навчання. Глибоке навчання — це не єдиний можливий підхід, а радше клас алгоритмів і топологій, які можна застосувати до широкого спектру наукових проблем та практичних задач (особливо у машинній лінгвістиці).

У цій статті досліджено та проведений порівняльний аналіз не тільки щодо цієї гіпотези, але і викладено результати ґрунтовних досліджень щодо переваг, проблем та особливостей ефективного глибокого машинного навчання у філології, а саме у машинній лінгвістиці.

Ключові слова: машинна лінгвістика, обробка природної мови, машинне навчання, глибоке машинне навчання, глибока нейронна мережа.

Formulation of the problem.

Deep learning is a machine learning technique that

- automatically extracts features (Feature extraction automatically identifies/selects the most discriminating characteristics of signals, which are more easily exploited by machine learning or a deep learning algorithm. Feature extraction is a very difficult to automate and time-consuming process of converting raw data into numerical features (e.g. recognition of conversation recordings), that can be processed by keeping information in the original dataset.

- learns hidden patterns directly from big data.

Such Big Data for deep machine learning can be not only texts, speech recordings or other signals that are tied to time, place, frequency (for example, sound, time series, signals from various microphones and other sensors) [4].

Although deep machine learning was first formulated in the last century, there are the following main reasons why the use of deep learning has grown dramatically in recent years:

Firstly, deep learning methods are now more accurate and more objective than human experts, particularly in natural language processing (NLP).

Secondly, Deep Learning requires significant computing power. That is why the emergence of high-performance GPUs and TPUs with parallel architectures are effective for deep learning. When combined with clusters or cloud computing, this allows development teams to reduce training time for a deep learning network from weeks to hours or less.

Thirdly, in the past few years, large amounts of labeled data have become available for deep learning [5].

Fourthly, the stormy interest, and therefore the investments from the corporate and state scientific communities contributed to the advancement in this area and the effective continuation of relevant research.

The vast majority of deep learning methods use various architectures and training algorithms of artificial neural networks.

Although a shallow artificial neural network with one or more layers can still make approximate predictions, an additional increase in the number of internal layers in a DNN can greatly help to optimize and improve its performance, even on unstructured big data [6].

The term "*deep*" usually refers to the number of hidden layers of such a neural network. Traditional shallow neural networks contain only 2-3 hidden layers, while deep networks can have up to 150.

Therefore, the term "*deep*" in deep learning is associated with these deeply hidden layers, and its effectiveness follows precisely from this. The choice of the number of hidden layers depends on the nature and complexity of the problem and the size and characteristics of the data set.

Thus, deep learning programs have many layers of interconnected layers of artificial neurons, with each layer building on the previous one to refine and optimize regression or classification predictions. This is similar to how our human brain works to solve problems – it runs queries through various hierarchies of concepts and related questions to find an answer. It is the number of layers of data processing in the hidden layers through which the input data must pass that gave rise to the term "*deep*".

However, both deep learning algorithms are incredibly complex, and deep neural network architectures are very specific and variable for solving a range of very different problems.

As outlined above, both classical machine learning and deep learning technologies use data for training, but the key difference: what data they use, how they process that data, and how they learn from it with what architecture configuration.

Analysis of recent research and publications. The fundamental questions of the theory of classical machine learning were revealed in their works by such scientists as: Nils J. Nilsson, Trevor Hastie & Robert Tibshirani & Jerome H. Friedman, Pedro Domingos, Ian H. Witten & Eibe Frank, Ethem Alpaydin, David J. C. MacKay, Richard O. Duda and Peter E. Hart, Christopher Bishop, Stuart Russell & Peter Norvig, Ray Solomonoff, Kevin P. Murphy.

The main foundations of the theory of deep machine learning were considered in their works by such scientists as: Schulz Hannes & Behnke Sven, LeCun Yann & Bengio Yoshua & Hinton Geoffrey, Marblestone Adam H. & Wayne Greg & Kording, Konrad P., Deng L. & Yu, D. Zhang W.J. & Yang G. & Ji C. & Gupta, M.M. Bengio Yoshua, Bengio Y. & Courville A. & Vincent, P. LeCun Yann & Bengio Yoshua & Hinton Geoffrey, Schmidhuber J., Hinton G.E. and other.

However, the urgent question of an effective choice between machine and deep machine learning in philology, and the question of analyzing the advantages, problems and features of deep machine learning in linguistics remained unresolved.

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The purpose of the article. Considering the above, the actual and initial goal of the current comprehensive interdisciplinary collective scientific research was not only to offer recommendations on the choice between machine and deep machine learning in linguistics, but also to offer methodological and practical recommendations on the advantages, problems and features of deep machine learning in philological scientific research and practical linguistic projects.

The main part of the research.

The results of the study of important differences between classical machine learning and deep learning technologies are:

1. Machine learning involves using thousands of data points, while deep learning uses millions of data points. Machine learning algorithms typically work well with relatively small sets of labeled and structured data. Machine learning algorithms are also better when data is scarce. Conversely, deep learning needs very large volumes of unlabeled or partially labeled data that have semi-structured or unstructured data format to understand the data and perform better than traditional machine learning algorithms.

2. Machine learning algorithms solve problems using explicit programming (algorithms for building decision trees and forests, finding association rules, finding regression equation coefficients, kNN, SVM and Naive Bayes classifiers, hierarchical and non-hierarchical cluster analysis, etc.). That is, classical machine learning offers a wide variety of methods and algorithms that can be chosen depending on the specifics of the subject industry, the specific task, the nature of the structured data that are processing, and the type of a problem. However, deep learning algorithms solve all problems after a complex process of learning hidden deep layers of neural networks of special architectures and their further use in a “black box” mode.

3. Machine learning algorithms take relatively less time to train, from a few seconds to a few hours. On the other hand, deep learning algorithms take a long time to train an artificial neural network, from a few days to many months.

4. Classical machine learning involves the possibility of using very different methods/algorithms (algorithms for building trees and decision forests, finding association rules, finding coefficients of regression equations, kNN, SVM and Naive Bayes classifiers, hierarchical and non-hierarchical cluster analysis, etc.); while deep machine learning involves the use of exclusively artificial neural networks of special architectures.

5. Classic machine learning requires an interactive process of interaction with the analyst at all stages of the project, unlike deep machine

learning. Deep learning networks do not require human intervention, as multi-level layers in neural networks contain data in a hierarchy of different concepts that eventually learn from their own mistakes, i.e. are capable of self-learning over time. However, even these can be misleading if the data quality is not good enough.

6. Both in classical machine learning and in deep machine learning, the quality and representativeness of the input data significantly affect the quality of such learning, however, given the minimal intervention of expert analysts in the auto ML mode of deep learning, the risks for it. Due to low-quality and incomplete data are significantly bigger.

7. Classic machine learning with time and/or the appearance of significant changes (either systemic or force majeure) in the studied subject area requires re-training of the model - but exclusively on new sets of collected data, in which such changes should be reflected.

8. Since machine learning algorithms are able to learn only according to pre-programmed set criteria and require labeled data, they are not suitable for solving innovative complex scientific queries in free search mode, which involve a significant amount of unlabeled semi-structured and unstructured data (for example, deciphering and understanding completely unknown languages). In other words, cases where deep learning excels include situations where there is a large amount of unlabeled data, lack of domain understanding for feature discovery/extraction, or more complex problems such as speech recognition and NLP.

9. Classical machine learning does not require the same expensive high-quality computing machines and high-performance processors (GPU and TPU) as for deep learning.

10. After all, many data scientists choose traditional machine learning over deep learning because of its superior interpretability or ability to understand solutions. On the contrary, deep learning models are complex, they work like a "black box", that is, it is actually difficult to explain the course of the decision and prove the result.

11. Deep learning is a subset of machine learning that is distinguished by the way it solves problems. Machine learning requires an expert in the field to define most applied functions. Deep learning, on the other hand, understands hidden functions incrementally, in an offline mode, thus eliminating the need for domain expertise and the systematic intervention of a human expert analyst. Because of this, deep learning algorithms take much longer to train than machine learning algorithms, which only take a few seconds to a few hours. However, the opposite happens during testing. Deep learning algorithms take much less time to run tests than machine learning algorithms, whose test time increases with the size of the data.

12. Retraining for classical machine learning may turn out to be a more urgent problem on modern data sets, given the automatic ability of shallow hidden layers of a deep neural network to level the impact of noise and anomalies in big data and the ability of subsequent, deeper hidden layers to generalize on really big data.

The benefits of deep learning (important for machine linguistics) include the following:

1. Automatic learning/extraction of features from big data.

Deep learning systems can perform feature extraction from data automatically, i.e they do not need supervision to add new features. Deep learning algorithms can save time by not requiring humans to manually extract features from raw data. Deep learning will perform in auto ML mode most of the previous interactive "manual" data processing that is usually associated with machine learning. These algorithms can accept and process unstructured data, such as text and images, and automate feature extraction, removing some reliance on human experts.

2. Discovery/search for hidden regularities/patterns in big data.

Deep learning systems can intelligently and deeply analyze large volumes of data and detect complex patterns in images, text and audio recordings of conversations, other signals, in order to extract hidden, non-trivial and useful regularities/patterns.

3. Ability to effectively process and analyze highly variable/unstable features in big data.

Deep learning systems can classify and sort data sets that have very large variations. Volatile/unstable data sets have large variations and/or noise.

4. Automatic marking/labeling of new data.

Deep learning requires marked/labeled data for training. After training, a DNN can independently label new data and identify different types, categories, or values of new portions of data.

5. Effective processing of unstructured data.

Classical machine learning techniques find unstructured data, such as conversation recordings, difficult for automated processing and analysis because the training dataset can have infinite variations. Deep learning models, on the other hand, can take in unstructured data and make general observations without manually extracting features. For example, a neural network can recognize that these two different input sentences have the same meaning:

- Tell me how to make the payment?
- How should I transfer the money?

This does not necessarily mean that classical machine learning does not use unstructured data; it simply means that in this case the unstructured data requires a rather long, complex and time-consuming procedure of pre-processing the incoming unstructured data for the purpose of manual extraction of features, their quantification, normalization and organization into a structured format (which is acceptable for classical machine learning methods).

Also, it should be noted that simple architectures of deep neural networks are also able to process structured data if there is an appropriate amount of it.

6. Accuracy.

Adding additional hidden layers to DNNs helps optimize deep learning models to provide greater accuracy.

7. Faster debugging of AutoML mode compared to classical machine learning.

Compared to conventional machine learning processes, deep learning requires much less human intervention and manual experimentation, and can automatically analyze types and volumes of data that classical machine learning cannot handle and analyze.

8. More effective and functional unsupervised machine learning.

Deep learning models can learn and improve over time based on user behavior and their own experience. They do not require large variations of labeled datasets. For example, let's consider a neural network that automatically corrects or suggests words by analyzing someone's typing behavior. Let's suppose that a DNN has been trained in English and can check the spelling of English words. However, if the user frequently types/speaks non-English words like *danke*, a trained (according to someone's behavior and characteristics) deep neural network will automatically identify such common misprints/spellings errors mistakes and automatically and correctly correct them.

While deep learning has gained popularity over the past few years, it comes with its own set of challenges that the community is working hard to solve.

Deep learning projects and cases may also have systemic flaws and certain limitations (for machine linguistics), in particular:

The problem of biases in input data for training and its verification. If a model is trained on insufficiently large and representative data that is obtained from different and independent sources, the data may contain biases and shifts, and the trained model will reproduce these biases in its subsequent predictions. This is especially a threat to convolutional DNNs with an unreasonably large number of hidden layers - which can often be prone to overgeneralization.

Optimal configuration of DML hyperparameters, in particular of learning speed. Choosing the optimal learning rate also becomes a serious challenge for deep learning models. If the speed is too high, the model converges too quickly, producing not always optimal and accurate model. If the learning rate is too low, the learning process may take too much time (and therefore exceed the operating budget). In addition, a suboptimal learning rate can lead the model to fall into local or sub-global optima. Another problem with slow learning rates is the threat of overfitting. However, even in the case of a deep learning model transfer strategy (which is currently a popular practice and seems to be able to solve the above threats), retraining a pre-trained deep neural network on new data will still require much more time and computing power than in the case of using classical machine learning.

High requirements for the global financial and operational parameters of the Data Center and its equipment. Multi-core high-performance specialized processors (GPU and TPU) and other relevant accompanying high-performance hardware are necessary to ensure the comprehensive cost-effectiveness of the DML project. However, this hardware not only requires significant investment, but is currently in short supply. Complex conditions of a data processing center with such equipment should also take into account the main item of the operating cost of such projects - the price of electricity.

The need for large volumes of large-dimensional data, including verified marked data. To obtain high-quality DNNs in real conditions of big data, there is a need for a large amount of prepared data of the maximum dimension. And to solve the problems of regression forecasting in such conditions, it is even more difficult to satisfy the need for a large number of prepared and verified correctly marked/labeled data of the maximum dimension. Obtaining which will be an expensive, difficult task that requires considerable time and labor costs.

The need for large amounts of high-quality data. Deep learning algorithms give better results if they are trained on large volumes of high-quality data. Outliers, errors, lack of representativeness and adequacy of input big data, other errors in big data – as a rule, will significantly affect the process of deep learning. To avoid such problems, in the case of deep learning, data engineering, namely ETL/ELT, is very important and responsible. Such pre-processing of input big data for deep machine learning requires a lot of time, labor, and computing power.

Lack of multitasking/ universality of trained DNN in real conditions of its use over time. In order to obtain quality DML - machine learning problem statement, the relevant data for training and testing should generally be as specific/targeted/aimed at solving one specific narrow task/problem as possible. This can lead to the loss of even the limited/conditional universality of the obtained model - and, therefore, to further limitations in the mode of using the trained DNN in real, current conditions (which will contain/reflect objective needs due to even a slight change in the macro environment of the organization/project/company with the time flow).

Lack of adequacy of trained DNN with real new actual data. To obtain quality results DML – machine learning problem statement, suitable big data for training and testing must be cleaned and prepared. This can lead to the loss of even the limited/conditional universality/adequacy of the model trained on such data - and therefore to further errors in the mode of using the trained DNN on new, real and relevant data, especially in the conditions of big data (which naturally will definitely contain anomalies and information noise that were filtered out in the ETL/ELT step before training the DNN).

Lack of transparency of deep machine learning results. While the algorithm is looking at millions of data points to find hidden patterns during this training, it will likely be very difficult to understand how the neural network arrives at its decision. The lack of transparency in how DNNs process data in both training mode and usage mode makes it much more difficult for human experts to detect unwanted biases and explain predictions. Despite the fact that deep learning algorithms surpass the accuracy of human thinking, there is no clear and distinct way to go back (reverse reasoning - deduction) and justifications to explain how exactly, step by step, each made prediction was obtained on the basis of a new portion of input data. This makes it difficult to use DML in some types of scientific research, where the obtained result must be clearly explained and justified.

Behavioral fairness of reinforcement learning agents. Another aspect that tends to be a problem with reinforcement learning models is the presence of meaningful/behavioral/systematic biases/distortions in the input data itself, which can lead to poor/suboptimal performance of the model trained on them due to its suboptimal learning trajectory. Software agents learning using a reward-based mechanism sometimes stop behaving ethically/fairly/ constructively because all they need to do to minimize the aggregate error is to maximize the reward they receive. In the literature, such an example is mentioned, when the software agent simply stopped playing the game and got into an endless cycle of collecting prize points. While this may be partially acceptable in a game scenario, wrong or unethical decisions can have profound negative consequences in the real world. Thus, it is relevant to have additional control of training results with reinforcement for obtaining balanced/constructive/ethical results.

To do this, there are specialized open source toolkits for detecting, investigating, and eliminating such systematic errors in deep learning algorithms and data. It is important for deep learning researchers and users to keep these potential issues in mind when planning and conducting reinforcement deep learning experiments.

Running deep learning algorithms on cloud infrastructure can overcome many DML problems. You can use deep learning in the cloud to more effectively design, develop, and train deep learning applications. Cloud computing services help make deep learning more accessible by making it easier to manage large data sets and train algorithms on distributed hardware.

Considering the above, it is worth noting that the most practical effectiveness in the field of philology is the option of using cloud services for DML in the field of machine linguistics.

In machine linguistics, a deep learning model can enable machines to understand and produce human language. Some of the main types of deep learning problems in machine linguistics include:

- *Automatic Text Generation* – A deep learning model can learn a corpus of text and these trained models (up to training Large Language Models) can automatically generate new text like resumes, essays.

- *Language translation*: Deep learning models can translate text from one language to another, making it possible to communicate with people from different linguistic backgrounds.

- *Sentiment analysis*: Deep learning models can analyze the sentiment of a piece of text, allowing it to determine whether the text is positive, negative, or neutral. This is used in applications such as customer service, social media monitoring and political analysis.

- *Speech recognition*: Deep learning models can recognize and transcribe spoken words, enabling tasks such as speech-to-text, voice search, and voice-controlled devices.

Conclusions. There are two popular in the recent past and fundamentally different approaches to the implementation of classical machine linguistics problems: rule-based and statistical, or based on statistics. Until recently, these classical approaches using classical machine learning allowed to achieve acceptable accuracy and quality.

However, the emergence of new challenges in machine linguistics:

- translation between languages with significant differences in grammar, vocabulary and syntax, as well as in areas with specific terminology and even sign language translation [7, 8];

- taking into account the context and emotional coloring of the text or spoken language [9];

- consideration of exceptions in grammar and vocabulary, idioms;

- exponential growth of Big semi-structured and unstructured linguistic data (including streaming)

do not allow classical methods/algorithms of machine learning to effectively and efficiently respond to the above challenges.

Summarizing, we can say that it is the hybrid use of deep machine learning [10] (which involves the use of deep neural networks of various specialized architectures) and classical methods of machine learning in different ensemble modes (that will allow not only to solve the current problems of machine linguistics productively and quickly, but also to correctly) is appropriate to respond to the above challenges and problems of machine linguistics.

Considering the above, it is also worth emphasizing the perspective of innovative new directions of scientific linguistic research - for example, hybrid-ensemble Large Language Models.

All of the above results become more relevant due to the already existing specialization and recent successes of hardware manufacturers for fast and more accessible deep machine learning (including in experimental modes for determining the optimal hyper parameters of machine learning and configurations of its architecture).

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