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University in face of AI – an introduction to the analysis

> The development of full artificial intelligence could spell the end
> of the human race… It would take off on its own, and re-design itself
> at an ever increasing rate. Humans, who are limited by slow biological
> evolution, couldn't compete, and would be superseded.
>
> Stephen Hawking, BBC

The university undoubtedly belongs to an institution with a long tradition and wide social influence. For many years it was treated as an institution educating the intellectual elite and had a monopoly in this area. It seems, however, that it is currently in a deep crisis of its own identity, as classically understood academic education is increasingly being replaced by modern and dynamic forms of education. Many of them are accessible via the Internet, which has become especially important in the era of a global pandemic. What's more, currently, solutions based on machine learning and even artificial intelligence algorithms are used on a large scale in the technical area. These changes also concern the educational area of various levels, including higher education and academic research practice. The dissemination of this type of practice coincided with the process of cloud computing development (Chmielecki 2019a). It is therefore worth asking in this context about the type and scale of the impact of artificial intelligence (AI) and machine learning (ML) on the future of the university institution.

Ivory Tower decomposition

The university is an institution with a long tradition dating back to the Middle Ages and, according to some researchers, even to earlier ancient philosophical schools.[1] From the beginning of its existence, the university was focused on conducting scientific research and educating staff (administration, medics, clergy) for the needs of the state and the community. Despite the passage of time and the changing conditions in which the university functioned, the university lasted almost

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[1] We can mention here, for example, the Pythagorean Union, the Academy of Plato or the Lyceum of Aristotle, which were a kind of "proto" form or pattern of the university in its classical understanding. Incidentally, it is also worth adding that not only the mentioned European institutions should be taken into account, but also the philosophical and religious schools known in the culture of the Far East.

unchanged and due to this "permanence" it is sometimes called the "ivory tower" (cf. Côté, Allahar 2007: 183). The term can be read in at least two ways. Positive as an impregnable "fortress" and "temple of truth" that is immune to temporary fashions and violent revolutions. Then again, it can be a place of retreat where "deaf" are taught for the needs of practice and the demands of today. Nevertheless, regardless of the interpretation adopted, the university had a monopoly for carrying out research and higher education for many years. The situation started to change approximately over a dozen years ago, when numerous institutions for vocational education were established in a full-time mode, but also in the online formula. Platforms providing various on-demand courses (Education on Demand, EoD) were also gradually gaining popularity. As a result of these changes, the university found itself in a difficult position to compete in the educational services market. However, the turning point was the situation of the global SARS-CoV-2 pandemic at the turn of 2019/2020, which completely changed the educational and research landscape in the entire world.[2]

The global pandemic has shown how the paradigm of education and research in higher education is changing (Chmielecki 2021). From the only traditional form, there was a transition to hybrid (combined) forms to implement a completely remote formula with full lockdown. The pandemic has also shown that many universities are not ready for this form. Unfortunately, this led to the collapse of many of them, and if not, at least to significant losses in the area of finances, number of students and institution prestige. Alternatively, this situation has become a good basis for the development of modern forms of teaching that use a number of the latest technological solutions, including elements of AI and ML.

AI/ML boost

When considering artificial intelligence, it is worth making an initial distinction between artificial intelligence and machine learning. They are definitely not the same, but closely related and influencing each other. AI is definitely a more extensive collection that includes ML and other solutions such as deep learning or the decision-making paradigm. We can use the example of speech recognition technology in a mobile device (smartphone, tablet, etc.), where AI would mean the device's

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[2] During the World Economic Forum 2021 (Davos Agenda) Suzanne Fortier, the Principal and Vice-Chancellor of McGill University in Montreal and a fellow of the American Association for the Advancement of Science, pointed out that COVID did the massive changes to the academic landscape: "We have a lot of learners who are at different stages of their academic and career journeys. Those newer students, who had come to us recently and were just starting their experience of university, are really missing the dynamic nature of life on campus. But those who come to us for upskilling and reskilling, typically people who are already in the workforce, have found many advantages in the flexibility that we now offer. So that's been a positive impact. A large part of that is because of the tools and technology we can use to deliver remote learning and support online collaborations. Related to that is another positive impact. And that's the extent to which researchers across disciplines around the world have been able to work together and really learn about this virus, its impact and how to address it" (Fleming 2021).

ability to learn and interpret the voice commands of a specific user, and ML would be responsible for backend algorithms that enable recognition of commands and execution of specific functions in the device (Mueller, Massaron 2016: 9). Operations performed by ML algorithms are used to process raw data and to draw some results with a certain amount of probability (for example after an anomaly detection due to linear regression). These can then be used by AI as input material for further analysis. Thus, it can be briefly said that thanks to the work done by ML algorithms it is possible to implement AI solutions more widely.

ML is more common today than many people realize. There are more and more chatbots, the mechanisms recommending content on streaming and shopping websites are more and more accurate – and all this is based on the ML solutions. According to the report "The Gartner Hype Cycle for Emerging Technologies 2020", in the next 2–3 years and further 5–10 years, the development of AI will significantly progress (Panetta 2021). The development of AI solutions also forces the improvement of ML algorithms that analyze large data sets obtained from different and unstructured data.

When talking about AI, we may see futuristic visions straight from American cinematography such as *Terminator* or *Blade Runner*. However, such a vision is unlikely, or even unrealistic. Currently, we are closer to the use of AI in the area of automation of selected human works, such as domestic help (cleaning robots), production of items (robots on the assembly line) or customer service (chatbots) (cf. Microsoft 2018: 11). Currently, solutions in the field of augmented, mixed and virtual reality (AR, MR, VR) are also developing, which will constitute a broad base for the implementation of ML solutions. Work is also underway on autonomous vehicles that use AI elements, although we won't see them soon. The current solutions do not include in any way the development of artificial awareness and independent thinking of androids, but rather constitute a kind of service platform working for the benefit of humans (Mueller, Massaron 2016: 13). ML-based AI solutions are now largely limited to multivariate analysis of large data sets, which is beyond human capabilities. The machine will complete this task much faster and will not bother with it, especially if we take into account the virtually unlimited hardware resources of the largest cloud vendors[3] (Microsoft[4],

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[3] It is worth to mention that in the report "The Forrester Wave™: Notebook-Based Predictive Analytics and Machine Learning, Q3 2020" authors evaluated 26-criterion of predictive analytics and machine learning (PAML) providers, and identified the twelve most significant ones – Amazon Web Services, Anaconda, Civis Analytics, Cloudera, Databricks, Domino Data Lab, Google, MathWorks, Microsoft, OpenText, Oracle, and RStudio – and researched, analyzed, and scored them. The report shows how each provider measures up and helps application development and delivery (AD&D) professionals select the right one for their needs. Among the leaders authors mentioned: Microsoft, Google, Cloudera and Domino Data Lab (cf. Carlsson, Gualtieri, Sridharan, Perdoni 2020).

[4] "Microsoft provides coding data scientists with all the bells and whistles. From what was a collection of disparate PAML offerings – Azure ML Workbench, Azure ML Studio, and Azure Batch AI – Microsoft has forged a new unified offering, Microsoft Azure Machine Learning. The result is transformational. Microsoft Azure Machine Learning offers a full suite of enterprise PAML capabilities, from centralized model registries to hyperparameter tuning and modular model training and deployment pipelines. Microsoft has paid particular attention

Google[5], Amazon Web Services[6], Alibaba, etc.). However, questionable issue in this area may be the care for data security and privacy, especially personal or sensitive data (cf. Awol 2018: 18).

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to collaboration – e.g., making it possible for users to work simultaneously in the same note-book, and integrations with Jenkins and GitHub interactions to enable MLOps capabilities as well as fairness and responsible machine learning – e.g., building in capabilities to test models on sensitive variables like age and gender, recommending mitigation models, and protecting data by adding noise or enabling eyes-off training. Microsoft Azure Machine Learning also has AutoML wizards, drag-and-drop tools for building ML pipelines, and integrations to build models within SQL editors to support developers, data analysts, and other non-data scientists who want to build and deploy models. The major cloud vendors have long had a gap in offer-ing a comprehensive PAML platform that meets the full set of enterprise data science team needs, to the detriment of bewildered customers who have had to build or find their own solutions. Microsoft has filled that gap and then some. Between the strength of its sales teams, size of its existing customer base, and Microsoft's own massive internal usage of Microsoft Azure Machine Learning, the success of Microsoft's PAML strategy is a near certainty. Indeed, its future is azure'd" (Carlsson, Gualtieri, Sridharan, Perdoni 2020).

[5] "Google offers one-stop AI shopping on Google Cloud Platform. Google's AI Platform Notebooks offering, made generally available in March 2020, lets data scientists rapidly spin up a JupyterLab notebook environment – preconfigured for a range of open source ML frame-works – that has built-in integrations with Google's AI Platform. These related services in-clude BigQuery (for data storage), Dataprep (for data preparation), Dataproc (for large scale data processing), Data Labeling (for labeling data), AI Platform Training (for training jobs), AI Platform Prediction (for deploying models), Kubeflow (for deploying models on-premises), and the What-If Tool (for explainability). Google has services to support the full AI life-cycle, and it develops a host of AI innovations in both hardware and software that it often shares with the open source community, such as TensorFlow. Google's AI Platform Notebooks service is a convenient, scalable tool for data scientists looking to leverage Google Cloud Plat-form for training or deploying models, especially deep learning models. However, to be more competitive, it needs more modeling, collaboration, and ModelOps capabilities" (Carlsson, Gualtieri, Sridharan, Perdoni 2020).

[6] "Amazon Web Services weaves a web of sagacious ML services. From its not-so--humble beginnings in late 2017 as a collection of ML algorithms offered as a cloud service, AWS SageMaker has developed into a more complete PAML offering that covers the PAML lifecycle. Indeed, it is starting to outpace competitors by introducing innovative capabilities to support the broader lifecycle of an AI application. These include Ground Truth (a data labeling service), the Step Functions Data Science SDK (for rapidly building data and ML deployment pipelines), Model Monitor (for monitoring ML models in production), Augmented AI (human review for low-confidence predictions), and, to the delight of anyone training deep learning models, SageMaker Debugger. (See note 3) For model development, SageMaker Studio offers an increasingly comprehensive and integrated notebook environment, and SageMaker Autopilot distinguishes itself as an AutoML capability by creating fully transparent notebooks for each model it trains. Given AWS's popularity for data storage and application development, it always had a head start when it comes to attracting cloud ML workloads, and it has built a widening set of frequently innovative PAML capabilities. To be more competitive, AWS needs to further integrate these services into a unified offering that can more seamlessly support the end-to-end workflow of enterprise data science teams. Amazon Web Services declined to participate in the full Forrester Wave evaluation process (Carlsson, Gualtieri, Sridharan, Perdoni 2020).

Elements of AI, or at least ML algorithms, are used not only in strictly technological solutions or in the area of services understood in general, but also in the academic dimension, where they support scientists in working with large data sets. Statistical analysis present in social sciences or probability and heuristic analysis are just some of the possible applications of ML. Evolutionary algorithms learned on the basis of data volume analysis allows user to choose the solution that best suits the given criteria. In this respect, the algorithm's work is paralleled on many parallel paths, which may resemble the model of the work of brain neurons. The conducted analysis contributes to the selection of the solution closest to the given criteria and at the same time improves the accuracy of the algorithm that learns based on the analyses and comparisons carried out. Even more advanced AI algorithms, like reinforcement learning, which bases on *trial-and-error* paradigm cannot perform 100 per cent accurate actions (Castaño 2018: 635). Thus, ML alone is unable to make the final decision that is attributed to the human-scientist. Thus, even in this seemingly dehumanized area, the final decision is assigned to a person who, based on the collected data and the ML obtained results of analyses, can make a more informed decision and launch actions. This principle also applies to the Artificial General Intelligence which applies to more common and general situations (Arel 2012: 90). However, I will focus massively on this particular area in my considerations, because it is too broad a topic for the purpose of this study.

Issues on AI correctness typically happen when people relay on the "clear" model based on "idealized assumptions" which should guarantee expected results (usually the assumptions required by their available theoretical or technical tools) (Wang 2012: 319). In practice, however, we know that such laboratory conditions are practically non-existent and when analyzing the impact and significance of ML and AI, one should take into account the importance of a number of distractors that will distort the assessment of the situation, as well as the risk of incompleteness of the cognitive perspective, caused for example by insufficient input data.

Adjusting university

Although I have already raised the question about the role of the university in the technical world in another study (Chmielecki 2019b), however in the face of AI and ML, the question of developing the shape of a modern university still seems to be open. Perhaps the most problematic area now is the distinction between a university and other educational institutions (higher, vocational, general, etc.). It seems that the "humanistic element" that distinguished university, as well as the concern for learning universal truth and respect for cultural heritage and universal values are disappearing somewhere. In the face of these changes, the university itself is slowly transforming into one of the many institutions of vocational education in accordance with the requirements of the labour market and publicly expressed social expectations. This formula is not much different from EoD courses offered on streaming platforms such as Udemy or Pluralsight, where the student becomes a passive recipient of the content prepared by the teacher. There are many institutions of this type on the educational market, but the university should not be one of

them, but rather stand out among them. The university, in a way, necessarily adapts to changes, including technological changes (Mainardes, Alves, Raposo 2011: 140), so as not to persist as a particular entity in a backwater of the world. While it is understandable that modern university adapts to changes, uses technology, migrates to cloud computing to improve its efficiency, it is difficult to accept turning away from its rich and long tradition and abandoning its mission. Certainly, a university can and should use new technologies, including AI, but these should not obscure its mission and role in the culture of his time.

Final round: will AI replace human scientist?

In the final part of the article, it is worth asking the question about the future of the university in the face of AI and ML development. In the light of the above analyses, it can be concluded that ML does not have to be a threat to the educational process or scientific research conducted by scientists. ML solutions will rather be a good tool to supplement the portfolio of analytical tools and at the same time a kind of "relief" for teachers and researchers in the implementation of simple and repeatable analyses on large data sets. Indeed, this is precisely the application of ML and the other mechanisms that compose AI to facilitate his or her work as the researcher. Certainly, ML will not replace people at work, but will complement their work, leaving room for deeper analysis and creative work (Mueller, Massaron 2016: 27). Therefore, it is not a threat to the academic space, but rather a way to optimize it and improve work efficiency, because tedious research work (such as comparing data, searching for connections, etc.) will already be done by the algorithm. It seems to be a revolution similar to the computer revolution, where files in the computer and special applications replaced sheets of paper and counting data on calculators. In that case, many scientists were feared of this shift, however now, I suppose many of us find it difficult to imagine the necessity to revert to these classical methods of scientific work. It is a bit different when it comes to AI. Here, the situation seems to be more complex, as the psychological barrier of working "with" or "for" the machine may be an obstacle. In this understanding, AI can affect the shape and scope of human work, but it certainly should not limit people to only carrying out assigned tasks, ignoring human experience and creativity (Mueller, Massaron 2016: 40; Russel, Norvig 2010: 5–16). Therefore, ML and AI solutions should be treated as tools needed to perform the work of a scientist. These tools should facilitate daily duties and provide important support in many manual activities. Thus, the future human-machine collaboration does not look as bad as the fatalistic visions proclaim.

Bibliography

Arel Itamar. 2012. Deep Reinforcement Learning as Foundation for Artificial General Intelligence. In: Theoretical Foundations of Artificial General Intelligence. Pei Wang, Ben Goertzel (eds.). Amsterdam, Paris and Beijing. 89–103.

Awol Amy. 2018. How to Become Anonymous, Secure and Free Online. New York.

Carlsson Kjell, Gualtieri Mike, Sridharan Srividya, Perdoni Robert. 2020. The Forrester Wave™: Notebook-Based Predictive Analytics and Machine Learning, Q3 2020. https://reprints2.forrester.com/#/assets/2/108/RES157464/report. (accessed: 3.03.2022).

Chmielecki Przemysław. 2019a. "Machine Learning Based on Cloud Solutions". Edukacja Technika Informatyka no. 1. 132–138.

Chmielecki Przemysław. 2019b. "Technicized University – Are the Technological Changes an Opportunity or a Threat?". Zagadnienia Naukoznawstwa no. 1. 103–111.

Chmielecki Przemysław. 2021. "Global YouTube University – uwagi o robotyzacji szkolnictwa wyższego". Humanistyczne Korpus no. 39. 149–154.

Côté James, Allahar Anton L. 2007. Ivory Tower Blues: A University System in Crisis. Toronto.

Fleming Sean. 2021. This Is How University Students Can Emerge from the Pandemic Stronger. https://www.weforum.org/agenda/2021/01/online-learning-universities-covid-suzanne-fortier/. (accessed: 3.03.2022).

Mainardes Emerson Wagner, Alves Helena, Raposo Mario. 2011. "The Process of Change in University Management: From the 'Ivory Tower' to Entrepreneurialism". Transylvanian Review of Administrative Sciences no. 33. 124–149.

Microsoft. 2018. AI in Action. Three Technical Case Studies Show How Developers Are Using Azure AI to Create the Next Generation of Apps. Redmond.

Mueller John Paul, Massaron Luca. 2016. Machine Learning for Dummies. New Jersey.

Panetta Kasey. 2021. The Gartner Hype Cycle for Emerging Technologies, 2020 Highlights 30 Technology Profiles That Will Significantly Change Society and Business Over the Next Five to Ten Years. https: //www.gartner.com/smarterwithgartner/5-trends-drive-the-gartner-hype-cycle-for-emerging-technologies-2020/. (accessed: 9.08.2021).

Pérez Castaño Arnaldo. 2018. Practical Artificial Intelligence. Machine Learning, Bots, and Agent Solutions Using C#. Havana.

Russel Stuart, Norvig Peter. 2010. Artificial Intelligence. A Modern Approach. New Jersey.

Wang Pei. 2012. Theories of Artificial Intelligence – Meta-Theoretical Considerations. In: Theoretical Foundations of Artificial General Intelligence. Pei Wang, Ben Goertzel (eds.). Amsterdam, Paris and Beijing. 305–322.

Abstract

The article addresses the problem of the university's crisis in the face of technological changes, including the particularly dynamically developing artificial intelligence and machine learning. In such a frame of reference, the university seems to lose the rudiments of its own identity and is placed in line with narrow professional education institutions. The development of artificial intelligence may constitute both a threat and a potential field for development for a university, but this status is currently heterogeneous. This article is an attempt to sketch out the impact of artificial intelligence and machine learning on the academic areas (both educational and research).

Uniwersytet wobec AI – wstęp do analiz

Streszczenie

Artykuł porusza problem kryzysu uniwersytetu w obliczu zmian technologicznych, w tym szczególnie dynamicznie rozwijającej się sztucznej inteligencji i uczenia maszynowego. W takim układzie odniesienia uniwersytet zdaje się gubić rudymenty własnej tożsamości i jest stawiany w jednym szeregu z wąskimi instytucjami kształcenia profesjonalnego. Rozwój sztucznej inteligencji może stanowić dla uniwersytetu zarówno zagrożenie, jak i potencjalne pole do rozwoju, lecz status ten jest obecnie niejednorodny. Niniejszy artykuł stanowi próbę szkicowego nakreślenia wpływu sztucznej inteligencji i uczenia maszynowego na przestrzeń akademicką (edukacyjną i badawczą).

Key words: artificial intelligence, machine learning, university, education, science

Słowa kluczowe: sztuczna inteligencja, uczenie maszynowe, uniwersytet, edukacja, nauka

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