

## AI AS CONTENT NOT TOOL

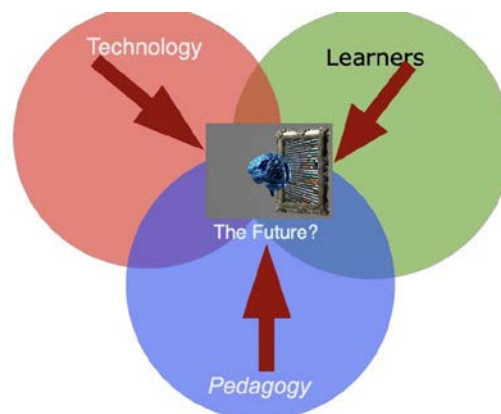
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*Focus Topics: AI and Data Science Competencies*

### Introduction

We find ourselves at a crossroads where learning is increasingly dependent on understanding three aspects of the learning situation, the **learner**, available **pedagogies**, and **technologies**. At the intersection of these three aspects of the learning ecology I claim that the “education of the future” is to be found (see Figure 1). The AI futures of education initially focussed on the ability of AI tools to generate outcomes (text, images, sound) that were difficult to distinguish from the work of a human. The most significant impact of this was to “democratise” access to aid in solving homework and any other type of assessment process that used end-points of an intellectual process as a foundation for assessment of personal development and ability. Thus, AI equalised the playing field, and made it realistic for all students to obtain “made to measure” artefacts to deliver to their instructors in satisfaction of assessment criteria.



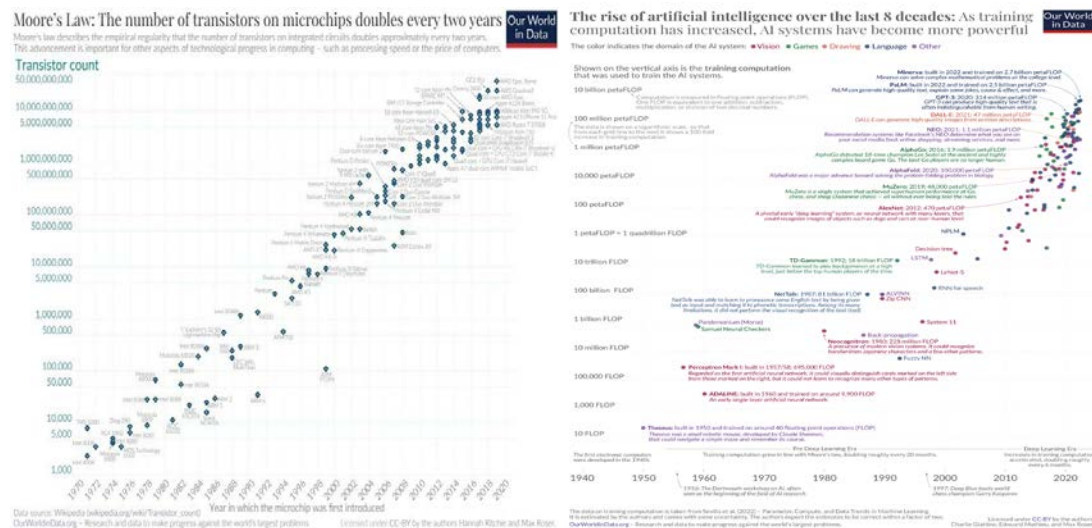
**Figure 1: Education of the Future**

The realisation that a nearly zero-cost alternative to performing the work oneself was readily available to the general population caused consternation in academic circles. How would we detect cheating and plagiarism (if it can be said that AI generated text is a sophisticated approach to generating plagiaries based on combing through the intellectual property contained in the training datasets). However, it behoves us to recall that plagiarism, while a challenge in educational settings, arises from the educational system’s inability to render the learning process relevant and engaging to the learner. I advance the hypothesis that plagiarism is, in fact, the fault of the teacher and educational system, rather than the student, since any relevant exercise developing highly sought after skills provides no incentive for plagiarism, rather the contrary.

### The conundrum of generative AI

Generative AI has experienced unprecedented hype since the release of ChatGPT by OpenAI in 2022. Despite an apparent leap in capability it is important to remember that current systems to a very large extent build on computer science principles that have been known since the 1990’s. Changes in three crucial areas afford systems deployed in 2020 and onward their performance. Firstly, the computational power available through networked GPU clusters and cluster computing vastly increase processing power and speed, the ability to provide access to these clusters through high speed communication networks makes the technology widely available in most affluent areas of the World, and finally access to the vast body of literature, image and sound data available as a result of the digital

communications platform developments, building on the Internet infrastructure, that have emerged over the last 20 years or so. It merely takes a quick review of the trends in the two graphs in Figure 2, to demonstrate the impact of processing power on the emergence of real-time AI solutions.



**Figure 2: Processing power and AI capacity**

While generative AI tools such as the GPT family of language models show considerable promise in terms of text production in a number of well defined areas of the literary corpus they are by no means either omnipotent or infallible (Barocas et al., 2023; Dressel & Farid, 2018). Generative AI systems are in essence extremely complex, multi-layered networks of symbols and statistical weightings. Such networks encode the underlying patterns that they can identify when examining large sets of data which has been appropriately labeled. Labeling is vital to establishing both value and context, linking the AI model to something tangible in our observable world. Based on the patterns discerned from the data upon which it was trained, a generative AI system creates output (in response to well formulated queries) through a highly sophisticated, very fine grain, cut and paste from existing data. In this process, as has been extensively discussed in the literature (Barocas et al., 2023; Dressel & Farid, 2018; Mehrabi et al., 2022), such systems reproduce norms and biases present in the input data sets. Given the scale of the training data, understanding these areas of norm and bias is a non-trivial exercise.

In educational settings generative AI tools have been demonstrated to perform at least as well as an average student, and in many cases significantly better. This demonstrates the unsustainable nature of the educational assessment paradigm that has dominated the last century. Assessment of competence and process based on the attributes of final products (artefacts of the learning process) is a flawed model in a world where all of these outputs can be readily generated by AI tools with very limited learner involvement.

In the current context it is important to shift the discourse from AI as a means to cheat, to AI as a tool which increases the productivity of future professionals. If this is the case, then AI must be taught as content in order for graduates to be prepared for an AI accelerated workplace when they graduate in 3-5 years. This premise implies that all disciplines should prioritise identifying AI related competencies in their disciplinary area, and act to integrate these into degree programmes and courses.

### Why education in AI competencies?

The argument for AI competencies in all disciplines is strong. Emerging forms of generative, and big data based AI, have already shown their contribution in the Nobel Prize conferrals in 2024. In each professional area exists a range of processes or workflows that can be accelerated through strategic deployment of AI services. Examples are many, but to name only a few, medical image analysis of MRI or x-ray images for cancer, protein folding, and design of new materials and alloys are important examples.

Education is under pressure to keep pace with these advancements and to equip graduates with the necessary skills and competencies for their future professions. To meet this demand universities must evolve and redesign education that combines AI related competencies with disciplinary specific skills and knowledge. Higher education, in this context, is under pressure to deliver new content and interdisciplinary knowledge to learners at all levels.

To achieve this reform I postulate that curricula require radical revision in the short term, in order to integrate AI content and thus remain relevant to future employers and the workplace market as a whole. Universities need to both adapt their educational approaches, as well as integrate new AI content into all disciplinary areas in order to serve industry and society well.

### **Advice to the professions**

Computing and Engineering professionals, if not all professionals, will very likely be expected to work with AI-based tools and services during the next few years, and the impact of AI as an accelerator of professional workflows should not be underestimated. McKinsey in their 2023 report (*Generative AI and the Future of Work in America* | McKinsey, n.d.). The impact of automation is expected to increase the productivity of many professions between 6 and 15 percent, with STEM disciplines being those at the top of the scale.

### **Conclusions**

AI education is not about plagiarism and the ability to subvert assessment models that link learning to outcomes! Generative AI can produce very sophisticated artifacts with very little engagement from the prompt generating person. This suggests that education must refocus on assessing process, not product. Inferring elements of process from the characteristics of artifacts has been a long standing practice, and now its day has come.

Future education needs to embrace AI competencies and define them in relation to each professional area. Failure to do this will fundamentally undermine all higher education. The higher education sector needs to take a stance in regard to emerging AI tools and integrate them, where relevant, into courses and degree programmes. This process will require substantial dialogue between universities, the public sector, and society at large. How will we contribute to that debate?

### **References**

- Barocas, S., Hardt, M., & Narayanan, A. (2023). *Fairness and Machine Learning: Limitations and Opportunities*. MIT Press.
- Dressel, J., & Farid, H. (2018). The accuracy, fairness, and limits of predicting recidivism. *Science Advances*, 4(1), eaao5580. <https://doi.org/10.1126/sciadv.aao5580>
- Generative AI and the future of work in America* | McKinsey. (n.d.). Retrieved 12 January 2025, from <https://www.mckinsey.com/mgi/our-research/generative-ai-and-the-future-of-work-in-america>
- Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2022). *A Survey on Bias and Fairness in Machine Learning*. <https://arxiv.org/abs/1908.09635>