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Language Models as Dissertation Assistants: Academic Misconduct or Efficiency Upgrades?

Tiantian Yu[1,a,*]

[1]*Beijing Academy of Social Science, Beijing, China*
[a]*yutiantian0423@outlook.com*
[*]*Corresponding author*

Abstract: *This paper examines the pivotal role of large language models (LLMs) in academic writing and explores their implications for students and educators alike. By tracing the progression from early statistical methods to the current sophisticated deep learning models based on Transformer architectures, LLMs have showcased their capability in a wide array of natural language processing tasks. Prominent examples of such models include the GPT series, PaLM, LLaMA, and T5, each characterized by unique features and applications. The study further investigates the influence of LLMs on higher education, employing theoretical perspectives such as dialectical materialism, neoliberalism, and constructivism. It argues for the creation of an evaluation framework to support the prudent integration of LLMs into educational practices and suggests conducting empirical research to refine this guidance. In conclusion, the paper asserts that LLMs hold significant promise in advancing educational goals.*

Keywords: *Large Language Model, Dissertation Writing, Philosophical Orientation*

1. Introduction

On the afternoon of Tuesday, June 4, 2024, OpenAI's flagship product, the ChatGPT series, suffered a significant system outage that disrupted services for millions of global users for nearly eight hours. OpenAI officially recognized the disruption on its website, stating, "We have experienced a substantial service disruption affecting all ChatGPT users; however, platform.openai.com and our APIs were not impacted." The timing of this outage coincided with the final paper submission deadlines at many universities around the world, leading to lighthearted comments from some users, such as, "Even Prof. ChatGPT couldn't meet this deadline."

Although OpenAI is still investigating the root cause of the system failure, user experiences and feedback suggest that the use of ChatGPT for composing academic papers has far exceeded the developers' initial projections. A systematic literature review by Muhammad Imran et al. examined the role and impact of AI tools, particularly ChatGPT, as writing aids in higher education. Since its release in November 2022, ChatGPT has attracted considerable attention due to its effective text generation capabilities and human-like interactions, which have ignited extensive discussions about its applications in academic and creative writing, language translation, and its broader implications for students and educators.

These conversations underscore several key issues, including concerns over originality and authenticity, threats to academic integrity, and the need for evolving assessment strategies. While large language models offer new possibilities for education and writing, achieving a balance between their benefits and drawbacks, while maintaining academic standards and fairness, remains a critical area for further investigation and the establishment of industry standards.

2. Large Language Model

2.1. Definition, Evolution, and Technical Characteristics of Large Language Models

A large language model (LLM) represents an advanced class of language models trained on extensive text corpora, often comprising billions to hundreds of billions of parameters. Early natural language processing (NLP) research predominantly utilized rule-based and statistical methods.

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However, the advent of increased computational capabilities and the explosion of available data have driven the evolution towards more complex language models powered by deep learning. Since the 1950s, the quest for artificial intelligence capable of comprehending and mastering human language has seen significant milestones, from the initial statistical machine translation systems and neural network models to today's Transformer-based pre-trained frameworks, which now dominate academic inquiry.

In recent years, the expansion of model parameters and the enlargement of training datasets have endowed LLMs with distinctive competencies not found in smaller models, such as contextual learning and multi-step reasoning. Although LLMs share a fundamental Transformer architecture and pre-training objectives with their smaller counterparts, they distinguish themselves through their enlarged scale, more extensive training data, and heightened computational demands. Pre-trained on vast text corpora, these models learn intricate linguistic patterns, which can be further refined through fine-tuning for specialized tasks. The performance gains in LLMs often adhere to a scaling law, where specific emergent capabilities, including context-aware learning, instruction adherence, and sequential reasoning, emerge as the model surpasses a certain size threshold.

Throughout the pre-training stage, the optimization of the model's parameters occurs through exposure to large-scale text data, thereby enhancing its overall modeling capacity. The subsequent fine-tuning phase customizes the model to excel in targeted tasks, aligning with specific needs. Leveraging their immense parameter counts, expansive datasets, and state-of-the-art Transformer architectures and pre-training techniques, LLMs have markedly improved the performance of NLP tasks, demonstrating strong language understanding and generation capabilities.

2.2. Examples of Current Mainstream Large Language Models

In the field of natural language processing (NLP), notable examples of large language models currently in use include the GPT series, PaLM, LLaMA, and T5. These models have attracted considerable attention for their outstanding performance, with each model boasting unique technical attributes and application contexts. Below, we delve into the foundational principles, architectural designs, and salient features of these leading models.

2.2.1. GPT Series

The GPT series of large language models represents a milestone in NLP, developed by OpenAI, a U.S.-based artificial intelligence research laboratory. Based on the Transformer architecture, GPT-3 boasts up to 175 billion parameters. These models undergo pre-training via large-scale unsupervised learning, utilizing extensive text data for language modeling, which can subsequently be fine-tuned for specific tasks. The primary attributes of the GPT models are their robust generative capabilities, high-quality text production, and versatility across multiple language tasks, ranging from text generation to dialogue systems, and extending to code comprehension and creation. The extensive parameter count endows these models with formidable generative capacity and broad knowledge coverage.

2.2.2. PaLM

PaLM (Pathways Language Model) is a large-scale, multimodal pre-trained model developed by Google. Leveraging the Pathways architecture, PaLM facilitates the sharing of representations across multiple tasks, thereby enabling efficient multi-task learning. Boasting 540 billion parameters, PaLM stands as one of the most extensive language models available today. Through unsupervised learning enabled by Pathways technology, PaLM is pre-trained on vast amounts of internet text. This approach employs multi-task and transfer learning methodologies, allowing the model to effectively transfer knowledge across different tasks and domains.

PaLM demonstrates exceptional language understanding and generation capabilities, performing exceptionally well in a broad spectrum of complex NLP tasks. These tasks include text generation, question answering, translation, code comprehension, and tackling problems that require commonsense reasoning. The model’s ability to handle very large-scale data and tasks through shared representations highlights the potential of hyperscale models to significantly enhance the adaptability and practicality of language models.

2.2.3. LLaMA

Meta AI introduced LLaMA, a collection of open-source large language models aimed at aiding the research community in gaining deeper insights into the performance and characteristics of these models.

The LLaMA family includes models with parameter sizes ranging from 7 billion to 65 billion, trained on a diverse dataset that encompasses content in multiple languages. This approach is designed to improve multilingual capabilities and enhance the models' generalizability.

2.2.4. T5

T5 (Text-to-Text Transfer Transformer) is a pre-trained language model developed by Google researchers. Introduced in late 2019 and early 2020, T5 offers a versatile framework capable of addressing a wide array of NLP tasks. One of the key innovations of T5 is its approach to unifying all NLP tasks into a text-to-text format. Tasks such as text classification, semantic similarity judgments, and machine translation are all framed as processes of converting input text into output text [1].

Using this unified approach, Google's research team significantly enhanced the performance of the WMT (Workshop on Machine Translation) English-German translation task, achieving impressive results and notably improving the BLEU score compared to the baseline model. Beyond English-German translation, T5 has also shown excellent performance in translation tasks involving other language pairs, underscoring its robustness and adaptability across different linguistic contexts.

3. LLMs as Dissertation Assistants

3.1. Literature Searching and Reviewing

In the context of academic writing, artificial intelligence (AI), including large language models (LLMs) and other supporting tools, plays a pivotal role in literature search and review. LLMs can swiftly comb through databases and repositories of scholarly resources, aiding researchers in identifying pertinent literature. They are capable of processing numerous search queries more efficiently and comprehensively than traditional manual searches. Leveraging predefined algorithms, these models can filter out the most relevant papers, thereby minimizing the time researchers spend sifting through extraneous material. Searches can be refined using various criteria such as keywords, topics, and publication dates.

Advanced LLMs, such as GPT-3, can digest entire documents and generate summaries, helping researchers rapidly grasp the core content and conclusions of the literature. This capability is especially beneficial when dealing with voluminous bibliographies. Some AI-assisted reading tools go further by analyzing data within the literature to discern research trends and emerging areas of interest. This insight supports researchers in staying abreast of the latest developments in their fields and guiding their research directions. Moreover, these tools offer literature management features that assist in organizing and maintaining bibliographic materials, automating the generation of reference lists, and ensuring the accuracy and consistency of citations. Thanks to user-friendly interfaces, LLMs can serve as collaborative platforms for sharing literature and notes among researchers, thereby fostering teamwork and enhancing research efficiency. Researchers can utilize AI tools to discuss papers, exchange insights, and streamline their workflows.

In essence, the function of AI assistants, particularly LLMs, in literature search and review is to boost productivity, save time, offer in-depth analysis, and support researchers in their academic writing endeavors. They represent a crucial instrument for contemporary academic research, contributing to the advancement of scholarly work.

3.2. Language Revision and Polishing

For non-native speakers, LLMs offer invaluable literature translation services, enabling researchers to comprehend foreign language texts. Additionally, LLMs can provide probabilistic explanations of specialized terms and concepts based on user instructions, thereby enhancing researchers' understanding. For instance, the varied explanations of the same concept by ‘Tongyi Qianwen’ and ChatGPT can deepen a researcher’s grasp and application of the concept.

During the writing process, LLMs can offer suggestions to refine grammar, spelling, and sentence structure. They also provide synonym recommendations to prevent the repetitive use of the same vocabulary, enhancing the richness of the text [2]. In practice, ChatGPT, a widely recognized LLM, significantly contributes to the clarity and coherence of English academic papers. Utilizing its deep understanding of language structure and subtleties, ChatGPT can polish sentences, rectify grammatical errors, and improve the overall fluency and readability of the text. This feature is particularly beneficial

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for non-native English speakers or scholars aiming to refine their work to a high standard, ensuring that their research content and ideas are conveyed effectively and professionally [3]. Moreover, other LLMs such as T5 can assist in identifying and correcting grammatical mistakes, refining sentence structures, and enhancing the fluency and consistency of language, thereby ensuring the clarity and readability of papers, rather than relying on stiff literal translations.

4. Philosophical Boundaries in Academic Applications of LLMs

When integrating AI technologies, such as large language models (LLMs), into the academic domain, it is imperative to consider both philosophical guidance and limitations. Philosophy provides valuable insights into ethics and values, which are essential for ensuring that the use of LLMs is ethical and socially responsible. Key issues such as data privacy, algorithmic bias, and intellectual property must be carefully addressed. Additionally, it is crucial to recognize the limitations of the knowledge these models can provide and how humans interpret and understand the world. As tools, the application of LLMs should be guided by value rationality—focusing on higher moral and ethical goals, rather than prioritizing efficiency and utilitarian outcomes alone.

4.1. Based on Dialectical Materialism

In higher education and academia, the application of large language models (LLMs) has emerged as a dual-edged phenomenon, presenting both significant benefits and substantial challenges. On the positive side, LLMs have markedly enhanced the efficiency of academic research by rapidly processing and analyzing vast datasets, thereby shortening research cycles and accelerating knowledge generation and dissemination [4]. For instance, in conducting literature reviews or data mining, LLMs can swiftly identify and synthesize key information, thereby saving researchers considerable time. Additionally, LLMs facilitate the democratization of expertise by automating content generation, making intricate academic concepts more accessible to a broader audience. The proliferation of this technology holds considerable promise for narrowing the knowledge gap and elevating educational standards universally.

LLMs can serve as catalysts for academic innovation, offering novel research perspectives and methodologies that foster fresh thinking and exploration. These models can uncover patterns and associations that might elude human researchers, potentially opening new frontiers in scientific inquiry. However, given that LLMs are trained on extensive datasets, there is a risk that the content they generate may include inaccuracies or misinformation, making quality assurance a paramount concern. Excessive reliance on LLMs could also erode foundational research skills. If researchers overly depend on these tools for critical thinking and analysis, they might gradually lose the capacity for independent critical thought and deep analytical skills. This poses a significant risk not only to individual researchers but also to the academic community at large. Furthermore, the deployment of LLMs raises a series of ethical issues, including data privacy, intellectual property rights, and algorithmic bias, necessitating careful deliberation and the formulation of appropriate policies and guidelines.

From a Dialectical Materialist perspective, a holistic approach to the application of LLMs in higher education is warranted. This involves acknowledging both the positive impacts and the associated challenges. The challenge lies in leveraging these tools judiciously to maximize their advantages while mitigating or resolving the issues they precipitate [5]. Achieving this equilibrium demands collaborative efforts from policymakers, educators, and researchers to establish norms and standards that ensure the responsible use of LLMs, contributing positively to academic advancement rather than hindering it.

To realize this vision, there is a need for strengthened interdisciplinary collaboration to investigate and establish best practices for LLM utilization. Concurrently, enhancing the training of researchers to improve their understanding and proficiency in using this technology is essential. Through concerted efforts, we can ensure that LLMs fulfill their potential in higher education and academia while minimizing potential negative impacts.

4.2. Based on Neoliberalism

From a Neoliberal perspective, the integration of large language models (LLMs) into higher education is frequently viewed as a market-driven and efficiency-focused innovation. Neoliberalism advocates for market mechanisms, individual liberty, and minimal governmental interference; hence, the adoption of LLMs in this context is characterized by marketization, competition, cost-effectiveness, personalized learning, and innovation-driven practices.

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Proponents of Neoliberalism might argue that the implementation of LLMs fosters greater competition within the education sector, compelling higher education institutions to enhance the quality and efficiency of their offerings to attract students and secure funding. From a cost-effectiveness standpoint, LLMs can reduce educational expenses and optimize the allocation of resources. Automation of certain instructional and assessment procedures can diminish institutional reliance on human instructors, thereby lowering labor costs. Furthermore, neoliberalism places a premium on individual freedom and choice. The deployment of LLMs can facilitate a more personalized learning environment, catering to the diverse needs of students. Advocates may contend that LLMs spur educational innovation and enable higher education institutions to adapt to the rapidly evolving socio-economic landscape.

However, several critiques and concerns arise from a neoliberal viewpoint, including the quality of education, issues of inequality, ethical considerations, and the risks of excessive marketization. Excessive dependence on technology might compromise educational quality, particularly in areas that demand human interaction and critical thinking. Unequal access to technology could lead to disparities in the distribution of educational resources, thereby exacerbating social inequalities. The utilization of LLMs may also provoke ethical and privacy concerns, such as the collection and utilization of student data. The market-oriented logic inherent in neoliberalism can result in the over-commercialization of education, potentially overshadowing its public nature and social responsibilities.

Thus, while the application of LLMs in higher education is perceived as a tool to enhance efficiency and drive innovation, it is imperative to remain vigilant regarding the potential drawbacks concerning educational quality, inequality, and ethical implications [6].

4.3. Based on Constructivism

Mandai et al. observe that while AI technologies, such as ChatGPT, hold significant promise for enhancing the quality and efficacy of education, they also present challenges such as overreliance, diminished creative thinking, and potential inaccuracies in information dissemination [7]. Building upon this observation, this paper synthesizes Dewey's experiential learning theory with Bloom's taxonomy of knowledge mastery to develop a comprehensive, multi-dimensional evaluation framework. This framework aims to guide the judicious application of ChatGPT and similar tools, fostering effective learning among students.

The authors propose conducting surveys to assess the practical usage among educators and learners, thereby refining and adjusting the evaluation criteria to ensure the healthy and beneficial integration of AI technologies within educational contexts. To optimize this evaluation framework, additional empirical research is essential, particularly through gathering insights from the actual users—teachers and students—of these technological innovations. Such qualitative data can illuminate the real-world applications of these tools, revealing both their strengths and limitations, thus enabling the necessary refinement of the assessment framework.

Artificial intelligence in education operates as a double-edged sword, necessitating further exploration of its applications, user experiences, and empirical validation to establish a philosophical value orientation. Under the value orientation of dialectical materialism, to prevent academic misconduct in the deployment of large language models, it is imperative that these models actively prompt users to cite sources, extend their thought processes, and engage in broad divergent or convergent thinking when retrieving research findings.

Within the Neoliberal paradigm, the developers of LLMs must prioritize user experience and feedback, standardize pricing models within commercialization strategies, and offer a variety of algorithmic options to cater to the diverse needs of individuals and institutions. In practical pedagogical scenarios, the application of constructivist principles and generative AI trends towards a systematic evaluation framework. Subsequent research can conduct experiments based on these frameworks and guidelines, and incorporate teacher and student feedback to iteratively update the theoretical framework governing the educational application of Large Language Models.

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