The role of large language models in interdisciplinary research: opportunities, challenges, and ways forward

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Running headline

LLMs in interdisciplinary research

Abstract

1. Large language models (LLMs) are gaining importance in research as they offer many benefits. One often overlooked benefit is their potential to facilitate and support interdisciplinary research, which is key to addressing current global challenges, such as the twin crises of biodiversity loss and climate change.
2. LLMs can help reduce the costs associated with knowledge transfer and bridge gaps between different fields of study. They can also be especially useful in helping ecologists understand and adopt significant techniques common in other fields.
3. However, using LLMs in research, especially for complex tasks, carries important risks, including the possibility of generating inaccurate information, which can lead to false conclusions.
4. We recommend that researchers adhere to best practices when using LLMs for research by providing appropriate prompts and dividing complex tasks into smaller, more manageable tasks that facilitate learning and testing. Moreover, journals should implement policies to ensure that information and code generated using LLMs are properly validated. Academic programs should incorporate formal training in LLMs, equipping students and researchers with the

necessary skills to use these tools more effectively and responsibly, including for interdisciplinary research.

Keywords

ChatGPT; ecological research; Gemini; generative artificial intelligence; large language models; machine learning

1. Introduction

Large language models (LLMs), such as Gemini and ChatGPT, play a growingly important role in scientific research. In their article, Cooper et al. (2024) explain many of the benefits of integrating LLMs into research activities in ecology and evolution. Researchers in other fields have also listed such benefits and have suggested guidelines for the ethical and responsible use of LLMs (Lubiana et al., 2023). Here, we highlight another potentially important contribution of LLMs, which is perhaps less discussed but could have a substantial impact—the potential of LLMs to facilitate interdisciplinary research.

2. LLMs in Interdisciplinary Research

It is now accepted that global challenges, such as the twin crises of biodiversity loss and climate change, require interdisciplinary solutions. For example, projects funded under the European Union's Horizon Europe programme aimed at developing solutions to address biodiversity loss often require the integration of multidisciplinary expertise. However, despite its importance, interdisciplinary research remains limited. A major obstacle is the absence of common language and understanding, which hinders effective communication and collaboration between researchers from different fields (Pellmar and Eisenberg, 2000). Consequently, key concepts and tools available in one field may not be adopted in another despite their potential to make a significant impact.

In our experience, LLMs can facilitate interdisciplinary research by reducing costs associated with knowledge transfer and bridging gaps between fields. For example, in our project, BIOMON, we explored the use of machine learning techniques to monitor bird communities using acoustic sensors (Mammides et al., 2024b, 2024a). Our team consists of CM, a Conservation Scientist, and HP, a Machine Learning expert focusing on Conformal Prediction, a framework for quantifying the uncertainty of machine learning predictions (Papadopoulos, 2023). While this framework has been employed successfully in many other fields (Papadopoulos and Haralambous, 2011), e.g., in cases in which quantifying uncertainty is essential, it has not yet been applied in ecology despite its utility. During the implementation of our project, LLMs have been instrumental in promoting effective communication by offering, for example, customized "crash courses" in each other's areas of expertise, using a language familiar to each party. Importantly, we were able to consult LLMs as often as necessary, at our convenience, receiving immediate feedback (Cooper et al., 2024) at no burden to the other party. Another way LLMs have been pivotal in our collaboration, especially for CM, is for analytical purposes, particularly for developing code for less familiar methods and in new programming languages. Although many ecologists these days have a good grasp of analytical methods employed using the R programming language, many of the cutting-edge machine-learning techniques are being developed in Python. LLMs can potentially make adopting new techniques implemented using unfamiliar programming languages considerably easier for researchers.

3. Challenges associated with LLMs

The use of LLMs does not come without issues. Other researchers have identified a series of risks associated with using LLMs for analytical purposes (Lubiana et al., 2023). A significant risk is that LLMs often "hallucinate," producing inaccurate information and code that relies, for example, on non-existent functions or packages (Chen et al., 2021). Additionally, LLMs may produce "silent errors" that are difficult to detect since the code appears to be running correctly. Still, the code is not performing the intended task, leading to false conclusions (Lubiana et al., 2023). As a solution, it has been suggested that the code be carefully checked and tested (Lubiana et al., 2023). However, this can be daunting for researchers without formal training in coding and validation methods, which is often the case in ecology. The issue may be even more pronounced when LLMs are used in an interdisciplinary context and applied to less familiar techniques and programming languages. Despite these challenges, the use and usefulness of LLMs will continue to rise. Consequently, it is crucial we develop robust solutions that will allow us to benefit from the rising spread of LLMs while minimizing the risks associated with their use.

4. Recommendations and Conclusions

First, researchers should take steps to ensure LLMs are used as responsibly and accurately as possible. For instance, one approach when using LLMs to develop code is to do it incrementally instead of feeding large and complex tasks to LLMs, which could be misinterpreted even if subtly and result in errors. Breaking down coding into smaller tasks has several advantages, such as providing better control over the coding process, allowing each added code segment to be reviewed more effectively, and facilitating the learning process by making it easier to identify which line of code produces each desired output.

Second, academic journals must properly acknowledge and address the increasing, multifaceted use of LLMs in research. While some measures have already been taken, the fast rate at which LLMs develop emphasizes the need to expedite these efforts. Although many journals now require authors to acknowledge the use of LLMs in their research methods, additional steps should be taken to ensure transparency and accuracy. As more researchers increasingly rely on LLMs to generate code for complex analyses, journals should expedite their efforts to promote open research and encourage authors to share the code used in their analyses (Fernández-Juricic, 2021). Many barriers to sharing code can now be overcome using LLMs, which can help researchers optimize, comment, and test code (Cooper et al., 2024). Journals must also consider who is reviewing and validating the code used in research. Oftentimes, the code is written exclusively by one of the authors, e.g., the junior researcher, while the rest of the co-authors, reviewers, and editors have no access to or are unable to review it. Since more code will inevitably be generated using LLMs and by researchers who may not have the technical skills to ensure its full accuracy, journals could consider appointing code reviewers for papers that use sophisticated code in their research.

Third, we recommend that academic programs incorporate formal training in analytical methods and computer programming, including formal training on the use of LLMs (Kasneci et al., 2023). As mentioned earlier, a commonly suggested solution for addressing potential issues in analyses associated with the use of LLMs is to carefully review the output, including the code (Chen et al., 2021). However, researchers must have the requisite skills for this to be feasible. Unfortunately, there are still too many programs in Ecology and Evolution, including in our home country, Cyprus, that fail to provide students with the necessary skills to meet the current realities and needs of the field, especially given the rapid advancement of the LLMs and their potential. Considering the growing availability of sophisticated analytical methods, expedited by the growth of LLMs (Santangeli et al., 2004; Scheepens et al., 2024), researchers must have a sufficient understanding of how to use them correctly. Formal training in those methods, including training on LLMs and their strengths and weaknesses (Kasneci et al., 2023), will equip ecologists with the skills needed to adopt and use these tools efficiently but responsibly. It will also ease the adoption of these tools, thereby increasing the benefits they offer, including advancing interdisciplinary research.

In conclusion, we are fortunate to be conducting research in this exciting era and look forward to future advancements in LLMs. LLMs can positively impact research, including interdisciplinary research. However, like any other disruptive tool, we must take steps to ensure that they are employed efficiently and effectively.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Authors’ Contributions

CM and HP conceived the ideas and outlined the manuscript; CM led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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