Philosophy at Scale: Introducing OpenAlex Mapper

Maximilian Noichl [1], Andrea Loettgers [2] and Tarja Knuuttila [2]

[1] *Department of Philosophy and Religious Studies, Utrecht University, The Netherlands*
[2] *Department of Philosophy, University of Vienna, Austria*

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This paper presents OpenAlex Mapper, a novel computational tool for the investigation of transdisciplinary practices and processes in the sciences. Developed with an eye on the ubiquitousness of cross-disciplinary model and template transfer, our approach leverages recent advances in language modeling, dimensionality reduction, and interactive visualization to map the dissemination of models, concepts and methods as they can be found in the OpenAlex-database across different scientific domains. While traditional methods in the philosophy of science—such as detailed historical case studies and, more recently, ethnographic observations—offer rich, fine-grained insights into scientific reasoning, they are limited in their ability to capture large-scale patterns, and to reliably locate themselves in them. Our method complements these historical and empirical approaches by enabling highly scalable and empirically grounded investigation of how modeling practices evolve and migrate across fields. Through three different short case studies we demonstrate how OpenAlex Mapper can trace the migration of model templates, reveal conceptual shifts, and investigate the distribution of modeling subcultures. We situate our contribution within the growing field of computational philosophy of science. By integrating digital tools with philosophical analysis, OpenAlex Mapper enables the exploration of scientific landscapes and disciplinary restructuring in science.

1 Introduction

Philosophers of science seek to understand science. Their appraisals should align actual scientific methods, requiring knowledge of what is rare versus common, core versus peripheral, and stable versus transient in scientific practice. Achieving such knowledge is a tall order, given that contemporary science is a global, rapidly evolving collective enterprise characterized by diverse methods, models, theories, and technological frameworks.

The demand that philosophical arguments grounded in an understanding of science's large-scale structures has spurred the integration of computational methods into the philosophy of science[1]. As a result, digital humanities have become a lively and quickly growing area of study in this field. Digital methods enable the systematic examination of large-scale phenomena significant to philosophers, which are otherwise challenging to study empirically. In recent years, digital methods have significantly advanced empirical approaches in philosophy of science. Philosophers have investigated phenomena such as shifts in scientific research focus (Malaterre, Chartier, and Lareau, 2020; Malaterre, Pulizzotto, and Lareau, 2020; Meyns, 2020; Pence, 2019), the diffusion of techniques and innovations across disciplines (Herfeld and Doehne, 2019; Noichl, 2023), and the evolution of perceptions (Jiménez-Pazos, 2022), concepts (Malaterre and Chartier, 2021; Zichert and Wüthrich, 2024), research networks (Wüthrich, 2023, and virtues (Mizrahi, 2021). By using digital methods, philosophers have become able to analyze a broader and less biased range of cases, addressing limitations inherent in traditional case studies[2]. The use of digital methods in philosophy of science has been facilitated by improvements in digital tools, growing interdisciplinary collaboration, and increased interest in practice-oriented, more data-driven research.

The present paper has three interconnected objectives: First, it introduces OpenAlexMapper as a flexible novel computational tool for the study of the large scale patterns in the sciences. Second, it briefly applies this method to three different cases: the migration of model templates, and the distribution of the concept of emergence and modeling subcultures across different scientific domains. Third, it demonstrates a new way in which AI-assisted methods can enrich philosophical understanding of scientific practice, without transforming philosophy of science into metascience or scientometrics.

We proceed as follows: the specifics of OpenAlex Mapper are introduced in Section 2. OpenAlex Mapper works by projecting arbitrary searches within the OpenAlex database, including for terms found in full texts, works that cite specific other works, or research output from individuals, journals or institutions. The results are then projected onto a base map of the sciences (drawn from a random sample from OpenAlex), showing how the searched result is distributed over the whole of the scientific landscape. This makes interdisciplinary relationships visible at a glance. As the base map is designed to be interactively explorable, it enables philosophers of science not only to identify macro patterns of interdisciplinary work, but also to drill down and investigate specific areas that stand out to them with very little additional effort.

The three case studies applying OpenAlexMapper will be introduced and discussed in Section 3. We will start with the dissemination of model templates across disciplines. The development of the OpenAlexMapper was originally inspired by the work on computational and model templates by Humphreys, 2002, 2004 and Knuuttila and Loettgers, 2014, 2016, 2023. Model templates are mathematical and conceptual constructs that serve as the basis for model construction across different

[1] For an expansion of this argument see Pence and Ramsey, 2018, as well as Betti, 2016, who makes this argument more generally for the history of ideas

[2] See Mizrahi, 2020 for a critique of the case studies-method from this perspective

scientific contexts. Unlike domain-specific models, model templates are not tightly bound to a single empirical system but instead provide generalizable structures—such as the Ising model or the Lotka–Volterra equations—which can be applied to diverse phenomena exhibiting similar interaction patterns. We study as examples, the Ising model, the Sherrington–Kirkpatrick (SK) spin-glass model, and the Hopfield model. All three originate in statistical physics but have since been employed in a wide array of domains, including neuroscience, computer science, and the social sciences. Our analysis reveals distinct disciplinary trajectories for each model, shaped by the epistemic functions they support and the kinds of questions they enable researchers to pose.

Second, we turn to the concept of emergence, a longstanding concern in the philosophy of science, particularly in discussions of reductionism and explanation. Traditionally treated as a metaphysical puzzle, emergence has recently become the subject of empirical investigation through computational methods. Using OpenAlex Mapper, we map how the concept of emergence is distributed across disciplines and show how its meaning shifts depending on local research contexts—from physical systems and phase transitions to biological organization and cognitive dynamics.

Finally, we explore the distribution of modeling cultures by comparing the use of two widely employed modeling techniques: logistic regression and random forests. These methods—representing classical statistics and machine learning, respectively—are often contrasted in debates about interpretability, mechanistic explanation, and predictive power. Drawing on earlier sociological work on epistemic cultures (Cetina, 1999), we use OpenAlex Mapper to show how different disciplines adopt and prefer different modeling strategies, possibly reflecting deeper epistemic commitments and methodological norms. The resulting map provides empirical support for the claim that modeling practices are culturally embedded and not universally transferable – even though models and methods travel and may be shared. Taken together, these three cases illustrate how OpenAlex Mapper provides a scalable, empirically grounded method for studying the dissemination and transformation of models, concepts, and methods in science. Rather than replacing traditional philosophical or historical approaches, our method complements them by enabling researchers to identify patterns, generate new research questions, and contextualize local studies within broader "scientific landscapes". In doing so, we contribute to a growing interest in computational approaches to the philosophy of science, while advancing the analysis of model-based reasoning, conceptual migration, and the organization of transdisciplinary knowledge.

2 Introducing OpenAlex Mapper

OpenAlex Mapper aims to solve a simple problem: to allow philosophers to interactively explore in which parts of science a certain model, concept, or method has appeared; in which areas a person or work has been influential; or where an institution has been active.

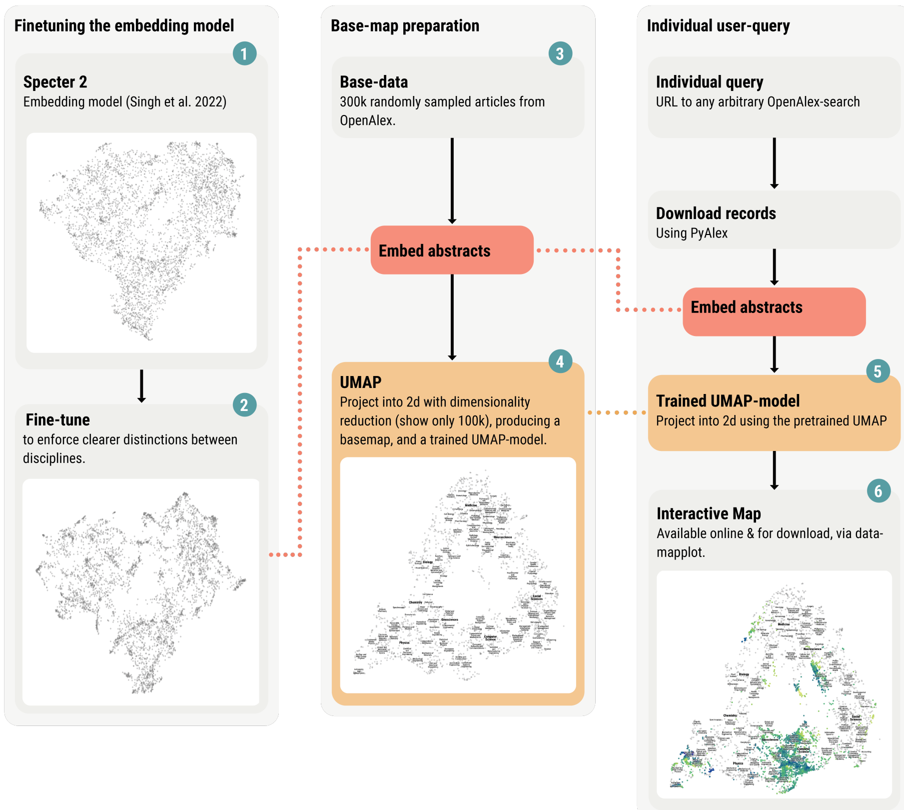

Figure 1: Workflow behind OpenAlexMapper. We begin with the Specter 2 language model trained on a vast corpus of scientific literature (1), which we fine-tune to better distinguish between disciplines (here visualized using a UMAP of the training data). We then use this finetuned model to embed 300,000 randomly sampled articles from OpenAlex (3) and project them into two dimensions using UMAP (4), creating a base-map of the scientific landscape. This UMAP model which has learned the general structure of the OpenAlex-database is then used to project new data onto the base-map (5), which is then made available to the user in an interactive map (6).

To solve this problem, we make use of the OpenAlex database, available under OpenAlex.org, a comprehensive and publicly available repository of scientific literature. Our web-mask accepts arbitrary queries to this database, and projects them onto a global map of science which we construct (the base-map).

To build this basemap, we randomly sample scholarly material from the whole OpenAlex database. We then use this material to build a base-map of the disciplinary organization of science, by embedding the abstracts of the randomly chosen texts using a language-model, and nonlinear dimensionality reduction. Finally, we establish an online pipeline that projects the abstracts of new articles that resulted from a search-query to OpenAlex onto our basemap, which allows users of the method to investigate their distribution This allows us to visualize the interdisciplinary distribution and temporal spread of a search-query in a detailed and interactively accessible format. The pipeline integrates a large language model, a fine-tune of the Specter 2 embedding model, and dimensionality reduction through UMAP, as well as an interactive environment using Gradio and DataMapPlot, hosted on HuggingFace. The whole workflow is visualized in Figure 1, the tool is freely available under https://huggingface.co/spaces/m7n/openalex_mapper.

2.1 OpenAlex

The source of data for all components of this project is the OpenAlex database. OpenAlex, which takes its name from the library of Alexandria, is a recent database of scholarly material containing articles, preprints, books, and similar documents, alongside standard metadata and, in many cases, data on citations and research topics or areas, in a wide range of languages (Céspedes et al., 2025). OpenAlex succeeds the Microsoft Academic Graph (Scheidsteger and Haunschild, 2023) and is, in most respects, comparable to other major scholarly databases such as Google Scholar, Web of Science, and Scopus (Culbert et al., 2024). Like Google Scholar, OpenAlex tends to be more inclusive than traditional databases (Ortega and Delgado-Quirós, 2024; Priem et al., 2022; Simard et al., 2024), thus it may contain additional relevant material but also occasionally include items that lack clear academic provenance. At the time of writing, OpenAlex archives approximately 250 million works. To access OpenAlex via its free API, this project uses PyAlex (De Bruin, 2023).

2.2 Finetuning Specter 2

To transform abstracts from text into a format that allows the computer to assess textual similarity, we employ an embedding model called *Specter 2*, which has been trained specifically for the purpose of generating adequate representations of scientific material (Singh et al., 2023). The primary training process of *Specter 2* sets with a basic transformer-based embedding (BERT-style) model, an artificial neural network that has been trained on a task of prediction of words from their context in scientific texts. It then continues learning by predicting, based on the title, journal, and abstract of an article, which of two other articles that it is presented with, are cited by the original article. To make this process more challenging, the model also needs to learn to distinguish between directly cited, and citation once-removed articles. This provides challenging training examples, as in many cases the one-citation-removed articles will still be very similar, enabling the model to better learn detailed structures in the scientific literature. Subsequently, the model is further trained for improved performance on various additional tasks such as classification, regression, and co-authorship prediction.

We had already achieved strong results using *Specter 2* but often found qualitatively that assignments into disciplinary groupings were not as clear as we had hoped in our base map. Therefore, we continued training *Specter 2* using an additional dataset of abstracts sampled from OpenAlex, aiming to teach the model clearer distinctions between disciplines. To accomplish this, we needed data with explicit disciplinary assignments; this was challenging, as disciplines tend to be somewhat vague and socially contested entities. To handle this ambiguity, we combined two signals indicating disciplinary belonging: publication in the same journal and topic-based assignment to the same research field by OpenAlex. We created equally proportioned pairs of articles from all OpenAlex discipline labels, each pair sharing both the same disciplinary label and journal. We then fine-tuned *Specter 2* by presenting it with one matching example and one randomly selected contrasting example, encouraging it to focus on disciplinary belonging as opposed to topical similarity.

We note that *Specter 2*'s original performance on this task was already quite good, which is not surprising, as the model was trained on citation-data, which can be assumed to reflect a good deal of disciplinary structure. Thus, we aimed only for subtle enhancements, lightly guiding the model toward clearer disciplinary distinctions to improve the overall quality of our base map. The effect of this training-procedure can be glanced from the mappings provided in Figure 1.

2.3 Building a base-map

To build our base map, we first download 300,000 randomly selected items from the OpenAlex database. The only requirements for inclusion in this random sample are that each item has an abstract available, is of adequate textual quality and length, and is written in English. We then encode all of these abstracts using our custom Specter2 fine-tune. This means each abstract is transformed into a 768-dimensional vector.

To move from these high-dimensional vectors to a two-dimensional map of disciplines, we employ a dimensionality reduction method called *Uniform Manifold Approximation and Projection* (UMAP, McInnes et al., 2018). The UMAP algorithm starts by constructing a k-nearest-neighbor graph of the base dataset. Each data point (in our case, each abstract/article) is linked to its k nearest neighbors, defined by greatest similarity. Similarity here refers specifically to cosine similarity, which measures the angle between two vectors and is commonly used in embedding contexts since it is robust to variations in vector magnitude and handles high-dimensional data well.

Initially, this nearest-neighbor graph is weighted according to these similarity values.

UMAP then readjusts these weights to adapt them to the local connectivity of the graph.

UMAP completes dimensionality reduction by arranging the resulting re-weighted graph into the target lower-dimensional space, which in our application is two-dimensional. To do this, UMAP uses a network layout algorithm in which nodes connected by strongly weighted links are drawn closer, while nodes generally push each other apart. The result is a two-dimensional representation that approximates the structure found among articles in the original high-dimensional space.

It is important to note here that the UMAP procedure involves some inherent trade-offs. Clearly, 768 dimensions cannot be perfectly represented in two dimensions, meaning the algorithm must approximate certain relationships. Furthermore, the layout process itself is stochastic. Each run produces structurally similar layouts, but details and global orientations vary. Consequently, although our map is displayed as a scatterplot, it does not have axis labels. The X and Y axes are not interpretable, but simply reflect arbitrary outcomes of the layout process.

We note that the resulting base map (Represented in Figure 3 by the grey points) forms a ring-like structure. This structure encodes a circular gradient of the sciences arranged systematically: physics appears at the bottom left, leading upward through chemistry towards the life sciences via biochemistry and microbiology, and into the broader life sciences positioned near the top. These in turn transition into medicine and health sciences toward the upper right. From there, neurology and psychology lead downward into a cluster formed by the social sciences and humanities, including philosophy and history toward the upper regions, and economics and finance toward the lower right of that grouping. Continuing through organization science and logistics, this cluster connects further to computer science and informatics, and finally—via applied and pure mathematics—completes the circle back into physics. The labels on the base-map are identical to the labels used by OpenAlex itself, and placed over the approximate medians of that cluster.

This ring-like organization not only aligns well with common assumptions about the composition and explanatory ordering of the sciences (see Humphreys, 2002), but also corresponds closely to the topology of maps produced in Börner et al., 2012; Klavans and Boyack, 2009 (see especially the reproduction of that work in Börner, 2010). Through entirely different analyses of journal citation data, their work indicates that this map indeed captures at least one highly salient and plausible representation of the organization of the sciences.

2.4 UMAP as projective method

The key innovation of our proposed method, which is enabled by the UMAP-package, is that new data can now be projected onto this base map as if it were already present during the map's initial creation, thus immediately showing how samples of scientific materials are distributed across it.

On a technical level, this works by embedding all new texts gathered from OpenAlex

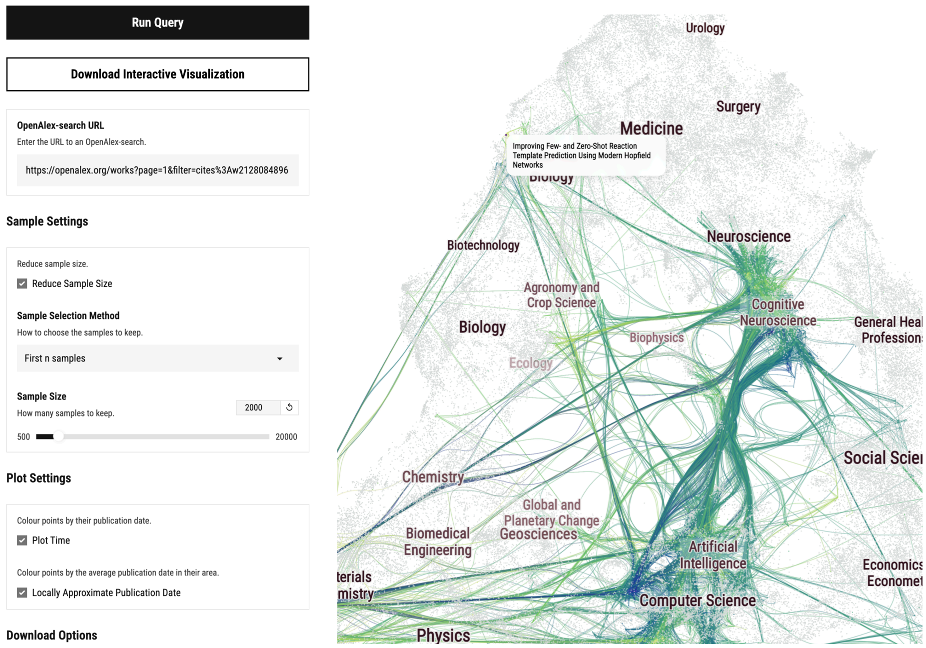

Figure 2: A screenshot of the tool in action. The displayed map is fully interactive, allowing users to zoom, pan, and investigate individual data-points by hovering. Clicking on individual data points will direct the user to the respective paper, if it is available online.

using the same language model that created the original map. We then use UMAP's functionality for projecting novel data to determine the appropriate positions of these new data points.

Specifically, this involves identifying each new data point's nearest neighbors in the original map along with their respective distances. We then perform the same reweighting step as initially conducted, reapplying the previously established UMAP parameters. Finally, we optimize the positions of the new data points onto the original map to best reflect these weighted distances with respect to their nearest neighbors. Throughout all these calculations, the base-map remains completely static.

2.5 Interactive implementation

We initially suggested that our method would be useful to philosophers of science, as it would allow them to easily gather further intuition about large-scale relationships and structures within the sciences and fostering a deeper understanding of the phenomenon of science as a whole. For this promise to be fulfilled, however, the entire workflow had to be made available to philosophers of science in the most approachable way possible.

This is not trivial, as our workflow crucially depends on high-powered graphical processing units (GPUs) for the embedding step. For the interactive version, we made us of Hugging Face's ZeroGPU offering and implemented our system as a Hugging Face Space using gradio (Abid et al., 2019). Figure 2 shows the user interface that is available through a web-browser. ZeroGPU allows users access to GPUs only for the limited durations required by active usage, which lowers the barrier of entry for users significantly. The whole program can also be run locally if adequate computational resources are available for a specific research project. Both the static and the interactive maps are plotted using DataMapPlot (McInnes, 2025).

2.6 Advantages and Shortcomings

Our method has several advantages over previous attempts to incorporate digital methods into philosophy, specifically studies based on topic modeling, network analyses, or the analysis of the occurrence of individual words. First, it directly connects to one of the largest existing databases of scientific material, and can not only draw subsamples from this database, but also relate its outputs to the database as a whole. Another advantage is its fully interactive integration, which allows philosophers to progress significantly in data-driven philosophy of science project without having to write code or develop computational skills.

However, certain drawbacks associated with our method must be acknowledged. First, we have already discussed potential interpretability issues regarding the UMAP algorithm.An additional related issue is that not all data points we receive from OpenAlex neatly fit into the map. Sometimes, web-site html may be incorrectly included as abstracts—due, for example, to errors in web scraping on the side of OpenAlex. In these cases, the language model is ill-equipped to handle them, producing meaningless embeddings. These embeddings usually scatter data points in the central area of the plot, as they do not strongly relate to any other data, and are roughly equivalently close to everything. Although relatively rare for most applications, this issue should be kept in mind when employing OpenAlex Mapper.

Another limitation particularly relevant for historical data is that we are restricted to recent scientific literature in which abstracts or semantically rich titles are available. Texts also must be in English, as the language model currently cannot process multiple languages.[3] Some of these constraints, for example, the choice of a relatively efficient language model for the embeddings and the selection of 300,000 nearest neighbors, instead of a larger subsample in the base-map, were made in view oft their computational efficiency, making the interactive interface practical. However, these are not fundamental issues and can be addressed in dedicated studies.

3 Applying OpenAlexMapper

This section explores how the computational tool OpenAlex Mapper can be used to trace and analyze key epistemic structures in contemporary science—namely, the

[3]This limitation might be addressed in the future through the use of multilingual embedding-models.

dissemination of model templates, the conceptual evolution of emergence, and the distribution of modeling cultures.

Building on the notion of a model templates as transdisciplinary modeling frameworks, we first investigate the dissemination trajectories of the Ising, Sherrington–Kirkpatrick, and Hopfield models across scientific fields. These models not only illustrate how mathematical structures travel between domains but also reveal how their associated concepts—such as cooperativity and phase transitions—are reinterpreted in new contexts. We then turn to the concept of emergence, a longstanding concern in the philosophy of science, and demonstrate how computational mapping allows us to track its diverse and evolving meanings across disciplines. Finally, we examine the distribution of modeling practices related to machine learning and classical statistics, shedding light on the presence of distinct modeling cultures. In each of these cases, OpenAlex Mapper enables a broader, empirically grounded perspective into the structure and transformation of scientific domains, complementing philosophical, historical and more traditional empirical approaches by providing large-scale insights not accessible by the other more conventional approaches.

3.1 The Dissemination of Model Templates

Figure 3 illustrates the disciplinary dissemination of the Ising (Ising, 1925, orange dots), Sherrington–Kirkpatrick (SK) (Kirkpatrick and Sherrington, 1978, red dots), and Hopfield (Hopfield, 1982, red dots) models. According to our framework, all three qualify as model templates. As discussed by Knuuttila and Loettgers, 2014, 2016, 2023, model templates offer a powerful unit of analysis for transdisciplinary modeling practices. The concept draws inspiration from Paul Humphreys' work on computational templates and the central role of computational methods in scientific advancement (Humphreys, 2004). Knuuttila and Loettgers extend Humphreys' notion by emphasizing the importance of conceptual scaffolding: a model template provides a formal foundation for constructing minimal models, coupled with a general conceptual framework that remains independent of any particular empirical domain (Knuuttila and Loettgers, 2014).

The concept of a model template is designed to capture how mathematical structures and associated computational tools are integrated with theoretical concepts to represent general mechanisms—mechanisms that can, in principle, be applied across domains that share similar interaction patterns. Returning to the Ising, SK, and Hopfield models, we observe that all three share overlapping ontological and conceptual foundations. Ontologically, each involves interacting binary variables arranged in grid-like or networked structures, with cooperativity playing a central conceptual role. Cooperative phenomena describe macroscopic effects—such as magnetization—that emerge from microscopic interactions among system components, independent of their specific physical realization. A prominent example is the phase transition, a qualitative shift in system behavior that cannot be directly reduced to micro-level dynamics.

The Ising model, originally developed to describe a phase transition from para-

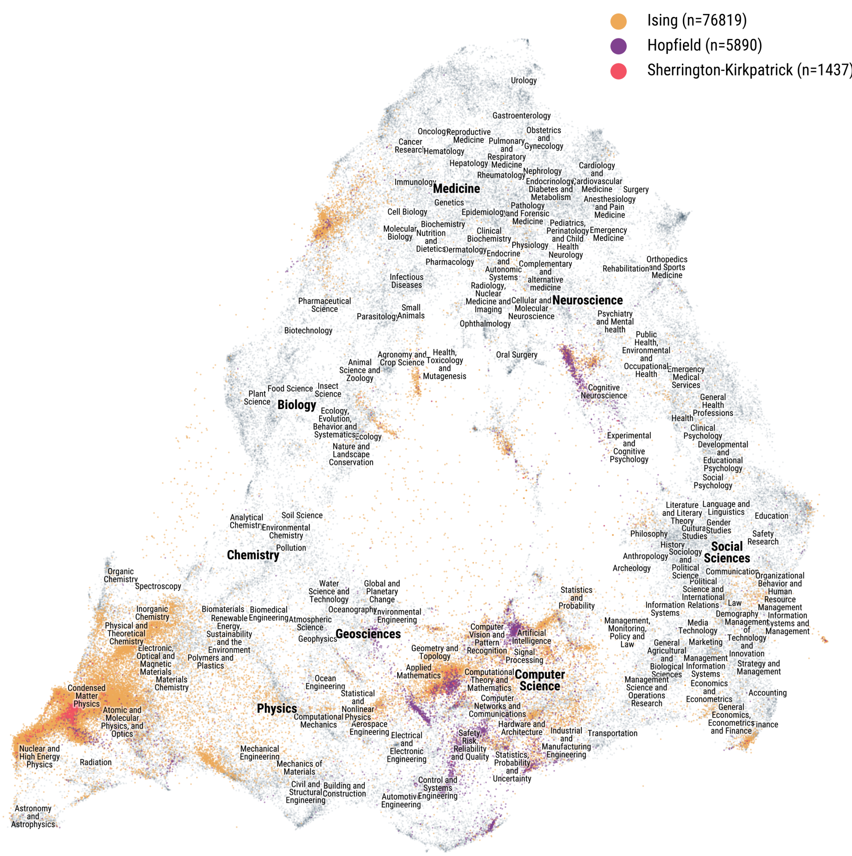

Figure 3: The results of three search queries to OpenAlex Mapper are overlaid on top of each other. Each represents a full-text search for mentions of the Ising model, the Hopfield model, and the Sherrington–Kirkpatrick model. Since OpenAlex Mapper allows the downloading of the full dataset along with coordinates, it is straightforward to re-plot the data sets together.

magnetism to ferromagnetism at a critical temperature (T_C), has been crucial to the understanding of critical phenomena and was foundational to the development of renormalization group methods in statistical physics (Hughes, 1999,Niss, 2005, 2009, 2011). Disregarding microscopic details—which were not known at the time and whose absence was only later justified through the introduction of the renormalization group method—facilitated the model's adoption across various domains, from materials science to sociology.

Our computational analysis reveals distinct dissemination patterns for these three model templates. The Ising model forms a large cluster in physics, particularly condensed matter physics, but also appears in computational theory, mathematics, and artificial intelligence, as well as in smaller clusters within the social sciences, finance, cognitive neuroscience, and molecular biology. The SK model's dissemination remains more focused within physics, especially condensed matter physics, with modest extensions into computer science and social science. In contrast, the Hopfield model displays a broad interdisciplinary reach, appearing in fields as varied as atomic and molecular physics, optics, information theory, computer science, cognitive neuroscience, geoscience, and cell biology.

While these models share foundational similarities, their dissemination trajectories reflect the specific epistemic functions and research questions each supports. The SK model, derived from the Ising model, was designed to describe disordered systems—specifically, metallic alloys with randomly distributed magnetic atoms. Although these alloys have limited practical applications, their complex thermodynamic behavior, such as long relaxation times and frozen disorder, attracted significant attention from theoretical physicists. Giorgio Parisi's work on spin glasses, for which he received the 2021 Nobel Prize in Physics, extended the SK model and revealed a new class of phase transitions (Mezard et al., 1987; Parisi, 1980).

The Hopfield model, at first glance, seems far removed from these physical systems. Introduced as a model of associative memory, it emerged from John Hopfield's effort to explore computation in biological systems using tools from statistical physics (Hey, 2018). Influenced by the SK model's rugged energy landscapes and metastable states, Hopfield constructed a mathematical framework in which these metastable states correspond to stored patterns encoded in neuron-like binary variables. Pattern recognition, in this context, is framed as a cooperative phenomenon, with simulations demonstrating reliable retrieval of stored patterns. This prompted physicists to ask whether such retrieval behavior constitutes a phase transition—a question that animated much of the early theoretical work on the model (Amit and Amit, 1989).

Our analysis of the Hopfield model's dissemination shows how its origins in statistical physics generated questions that would seem remote from neuroscience, such as the nature and detectability of phase transitions. This raises a broader philosophical question: Should the Hopfield model be understood primarily as a physicist's approach to pattern recognition—limited in neuroscientific relevance but significant for computer science—or more broadly, as a model of emergent cooperative phenomena with interdisciplinary implications (Loettgers, 2007)?

This example also illustrates a key strength of our method: the ability to trace how embedded concepts evolve and take on new meanings in transdisciplinary contexts. In the case of the Hopfield model, concepts like pattern, pattern recognition, phase transition, and the critical point required reinterpretation. What physicists described as attractors in an energy landscape became ”memories” in neural systems, while phase transitions were framed as shifts from reliable retrieval to chaotic dynamics as system parameters crossed critical thresholds. Although rooted in statistical mechanics, these concepts migrated and transformed as they were applied in computer science and neuroscience.

A preliminary comparison of dissemination maps reveals notable differences between the Hopfield model and the concept of phase transitions. While phase transitions cluster heavily in physics, the Hopfield model forms a more prominent presence in computer science. The only substantial overlap appears in molecular and cell biology, where researchers reference phase transitions in conjunction with the Hopfield model but often without strong ties to its physical foundations. This suggests that the concept of phase transition may have entered these contexts indirectly, with the Hopfield model serving as a vehicle for its adaptation as a pattern formation framework within nonlinear dynamics.

3.2 Tracing the concept of emergence

The concept of emergence has long played a central role in the philosophy of science, particularly in debates concerning reductionism, explanation, and the ontological status of higher-level phenomena. Traditional philosophical accounts have focused on clarifying whether emergence should be understood as a metaphysical or epistemological phenomenon, and on assessing its compatibility with physicalism and scientific realism. These analyses commonly distinguish between strong emergence, where higher-level properties exhibit novel causal powers irreducible to lower-level processes, and weak emergence, where complex behavior resists prediction but remains reducible in principle (Kim, 1999; Wimsatt, 2007). Philosophers such as Batterman, 2001 have analyzed emergence in the context of phase transitions, while Craver and Bechtel, 2007, have advanced accounts of mechanistic emergence grounded in neuroscience. While such work has deepened our conceptual understanding, it typically relies on a limited set of detailed case studies and aims at theoretical clarity and generality.

In recent years, however, the introduction of computational methods has shifted how emergence is studied—moving from abstract conceptual analysis to the empirical mapping of how the term is used across scientific practice. To test whether our tool, OpenAlex Mapper, could support this shift, we analyzed the dissemination of the concept of emergence across disciplines (see Figure 4). Drawing from prior studies on the Ising, Sherrington–Kirkpatrick, and Hopfield models, and considering the influential role of Philip Anderson's paper “More is Different” (Anderson, 1972)—which revived interest in emergence within physics—we initially expected to find the concept strongly clustered in physics-related fields. Yet our analysis reveals that “emergence” is more prominently used in biology, medicine, neuroscience, and the

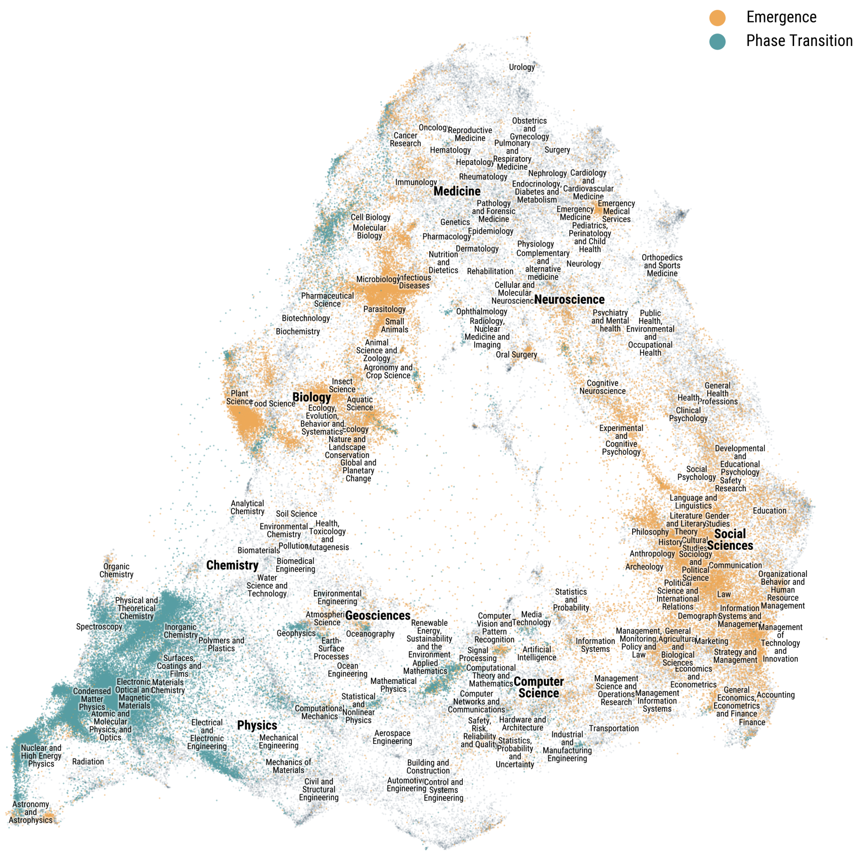

Figure 4: Searches for "emergence" and "phase transition" (n=50000 each) in the OpenAlex database, projected onto our base-map. We note how the concepts occupy largely distinct areas of the map, with some trading-gounds.

social sciences. In these domains, the term diverges from the formal and collective behavior framework typical of physics, instead referring to phenomena such as biological organization, cognitive development, or social dynamics.

Our findings relate with the results of Christophe Malaterre and Jean-François Chartier (Malaterre and Chartier, 2021), who conducted a large-scale text-mining study of over 70,000 articles from BioMed Central to trace how concepts such as theory," "model," "mechanism," and "explanation" are used across scientific disciplines. Their analysis uncovered significant variation among the disciplines in the uses of these concepts.

While Malaterre and Chartier provide a rich account within the life sciences, a key advantage of our approach is its broader empirical scope. By drawing on the OpenAlex database, using OpenAlex Mapper, we can easily analyze a larger and more heterogeneous set of publications across the scientific landscape. Our interactive mapping interface enables dynamic, multi-scale exploration of both model templates and associated epistemic concepts, helping to reveal conceptual proximities, disciplinary clustering, and potential paths of translation and reinterpretation. Crucially, the interface also allows users to "look behind the dots" on the map by directly accessing the research papers linked to each data point. This makes it possible to investigate in greater detail how the term emergence is used in specific contexts—for instance, in the framing of hypotheses, the construction of models, or the interpretation of simulation results.

This shift—from treating emergence as a metaphysical puzzle to analyzing it as a practice-dependent and empirically traceable phenomenon—has important implications for philosophical analysis. Rather than seeking a single, universally correct definition, philosophers can instead attend to how scientific communities actively employ the concept in the production of knowledge. Computational methods thus offer powerful tools for investigating how emergence functions as an epistemic operator: a flexible concept that helps coordinate inquiry across scales, disciplines, and modeling frameworks.

Importantly, this computational and empirical turn does not displace traditional philosophical debates on reduction, explanation, or causal structure. Instead, it complements and re-contextualizes them—embedding these longstanding concerns within a broader framework that is attentive to the evolving, plural, and domain-specific uses of emergence in actual scientific practice.

3.3 Modeling Cultures

Another example that can be investigated using OpenAlex Mapper is the distribution of subcultures in science that are of philosophical interest. One topic that has received recurring attention in debates is the use of machine learning/AI, as opposed to more classical statistical methods in science (see also Bzdok et al., 2018). Here, classical statistical approaches—those that rely on strong assumptions about the nature of the data-generation process (e.g., underlying distributions)—are contrasted with more flexible machine learning methods, which often surpass them in predictive power but sacrifice interpretability and, arguably, any sense of mechanistic understanding (Andrews, 2023; Räz and Beisbart, 2024; Sullivan, 2022).

However, philosophical discussions of this tension often focus on a small set of well-known examples, such as the use of neural networks to classify medical images. Such generalizations tend to obscure the diversity of modeling cultures across scientific domains. This is where earlier work from the sociology of science, particularly Cetina, 1999 notion of epistemic cultures, offers a helpful analytical approach. Epistemic cultures refer to the heterogeneous configurations of practices, instruments, norms, and social structures through which different scientific communities produce and validate knowledge. Rejecting the idea of a unified scientific method, Knorr Cetina demonstrates—through comparative ethnography of high-energy physics and molecular biology—that even within the natural sciences, knowledge-making practices are organized in radically different ways. Physics tends to rely on large-scale, collaborative experimentation and abstract statistical frameworks, whereas biology emphasizes localized, exploratory practices and visual evidence. The concept of epistemic cultures has broad philosophical significance, supporting methodological pluralism and challenging universalist accounts of rationality and explanation. It also provides an analytical framework for understanding how different modeling practices are negotiated in interdisciplinary contexts.

Our use of OpenAlex Mapper offers a scalable and complementary approach to such ethnographically grounded studies. In an initial application, we examined how the two modeling cultures that emerge from the machine learning versus classical statistics debate are distributed across scientific disciplines. Specifically, we compared the use of two modeling techniques—random forests (representing machine learning) and logistic regression (representing classical statistics)—following the framing proposed by Breiman, 2001. These methods are often used for similar predictive tasks but reflect different epistemic commitments and assumptions.

The resulting map in Figure 5 shows a clear disciplinary divergence. Random forests are widely employed in computer science, bioinformatics, geosciences, astronomy, and parts of cell biology and neuroscience. In contrast, logistic regression dominates in the health sciences, especially medicine, epidemiology, psychology, and clinical research, and unsurprisingly, in statistical literature itself. These differences suggest the presence of distinct epistemic cultures across disciplines—each shaped by different goals, constraints, and methodological values. At the same time, the diffusion of these methods to different often distant domains indicates that modeling methods can transform cultures and draw them closer to each other. OpenAlex Mapper thus allows us to empirically trace the distribution of modeling practices across fields, offering new tools for philosophers and historians of science to investigate the dynamics of scientific pluralism at scale.

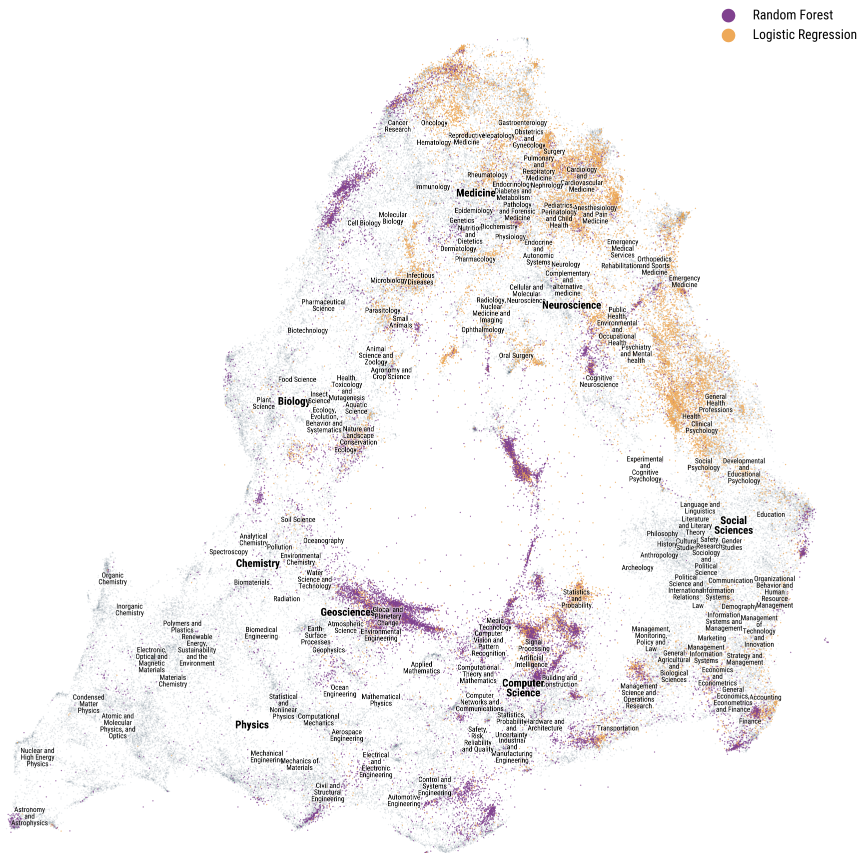

Figure 5: Searches for "random forest" and "logistic regression" (n=50000 each) in the OpenAlex database, projected onto our base-map. We note that quite a complicated pattern of differing communities choosing specific modeling approaches.

4 OpenAlex Mapper for scientific landscapes

Our application of the OpenAlex Mapper to the transdisciplinary dissemination of model templates and the associated transfer of concepts demonstrates both the importance of model and template transfer and its decisive role in reorganizing disciplinary matrices. This process—where the models, methods, commitments, and conceptual resources of scientific fields evolve—has recently been conceptualized in the philosophy of science through the notion of scientific landscapes. The landscape metaphor provides a powerful analytical framework for understanding disciplinary transformation, expanding upon Thomas Kuhn's (Kuhn, 2009) original notion of the disciplinary matrix, which consists of shared exemplars, values, and methodological assumptions that structure research within a scientific community. While Kuhn primarily focused on paradigm shifts internal to a given field, the scientific landscape framework draws attention to broader and more dynamic transformations—including transdisciplinary movements, conceptual migration, and methodological innovation.

We suggest that model templates and computational structures serve as key vehicles for transformations taking place among different disciplines. In a sense, this has always been the case with modeling practices; nonetheless, the development of powerful computational methods has further escalated this phenomenon. As models and methods migrate across disciplinary boundaries, they reshape the epistemic terrains by introducing new problem framings, methodologies, and explanatory norms. This reconfiguration of disciplinary matrices is not only methodological and conceptual but also organizational, as seen in the evolving roles of key epistemic concepts. For instance, as Christophe Malaterre's studies demonstrate, concepts change meaning and function as they circulate across disciplines, adapting to local practices and contributing to shifting epistemic boundaries.

Recent philosophical work further emphasizes that scientific landscapes cannot be understood in terms of static maps but rather as dynamic terrains shaped by external pressures such as data infrastructures, digital technologies, and computational methods. Massimi, 2022), for example, has developed the idea of perspectival pluralism, using the landscape metaphor to explore how diverse epistemic perspectives coexist and interact productively within shared scientific spaces. It is in this context that OpenAlex Mapper provides a novel and empirically grounded tool for analyzing how models and concepts disseminate, evolve, and contribute to the transformation of scientific landscapes. By mapping large-scale patterns in the use of models, methods and concepts across disciplines, OpenAlex Mapper enables philosophers of science to investigate not just individual case studies but also the more comprehensive ecologies of modeling that structure scientific practices. This approach complements traditional methods in integrated history and philosophy of science—such as detailed historical case studies (e.g. Chang, 2004; Steinle, 2016) and ethnographic investigations (e.g. Cetina, 1999)—by offering a scalable method for tracing conceptual and methodological dynamics across large scientific corpora. While historical and ethnographic approaches yield rich, fine-grained insights into specific scientific contexts, they are necessarily limited in scope. OpenAlex Mapper, by contrast, allows researchers to visualize the movement and transformation of model templates, epistemic concepts and modeling methods across entire fields, thereby offering a broader perspective on the architecture of scientific change.

New possibilities for philosophical analysis come into view. Rather than replacing traditional methodologies, OpenAlex Mapper enhances them by enabling new types of questions about the trajectories, patterns, and epistemic functions of models, methods and concepts. In doing so, it contributes to a deeper understanding of how scientific knowledge is shaped not only by local experimental and theoretical practices but also by the circulation, recombination, and reuse of model templates that drive interdisciplinary innovation and the reconfiguration of scientific domains.

5 Conclusion

Computational methods can enrich the philosophy of science by offering new questions, so far unfamiliar phenomena to analyze and novel forms of empirical grounding for philosophical analysis. As we have argued, the mapping of model templates and their conceptual trajectories provides a means to study scientific reasoning not only through exemplary cases but also through broader disciplinary patterns. This contributes to a shift from anecdotal to scalable analysis and strengthens the empirical relevance of philosophical reflections on modeling, interdisciplinarity, and concept evolution. By leveraging large-language models alongside topological machine-learning, we offer an interactive platform that enables philosophers and historians of science to examine methodological and conceptual dynamics in ways that are both systematic and adaptable. This approach not only complements existing digital efforts, but also extends their scope by enabling fine-grained comparative studies across a wider scientific landscape.

Looking ahead, the method we propose could be further refined, and applied to other foundational concepts and modeling frameworks in contemporary science. Future applications might explore the dissemination of computational paradigms such as agent-based modeling, the role of network structures in systems biology, or the circulation of epistemic virtues like robustness and simplicity. Beyond these empirical inquiries, our approach also invites new forms of collaboration between philosophers, digital humanists, and data scientists, pointing toward a richer, more integrated vision of computational philosophy of science.

We are also aware that the usefulness of digital methods in the philosophy of science has been questioned from various angles. One central concern is that such methods risk oversimplifying complex philosophical problems: topic models or statistical clusters may fail to capture theoretical depth, argumentative structure, or normative dimensions, and the results they produce often require substantial interpretation. Moreover, how do choices concerning data, corpora, or modeling parameters shape the results and their interpretation? Digital tools are not epistemically neutral—they carry embedded assumptions about language, meaning, and relevance that can shape outcomes in subtle but significant ways. We fully acknowledge the importance of these concerns and agree that they must be taken seriously when applying digital methods in philosophical research. However, we also contend that these challenges cannot be entirely avoided. The most productive way to address them is through a complementary approach, complementing close reading and conventional empirical methods by revealing long-term trends, conceptual shifts, and patterns of influence (Lamers et al., 2020; Pence and Ramsey, 2018). While this may not eliminate all methodological challenges, it allows us to examine so far largely unexamined questions such as the extent to which model templates and modeling methods have in fact spread to different, often distant domains. Results like this could have profound philosophical ramifications.

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