Deep learning, deep change? Mapping the development of a General Purpose Technology

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Abstract

General Purpose Technologies (GPTs) that can be applied in a broad range of sectors are an important driver of economic growth. However, the geographical aspects of their development and diffusion have not received significant attention in the literature even though their impact on economic geography and the geography of innovation could be substantial. We address this with an analysis of the geography of Deep Learning (DL), a new paradigm for Artificial Intelligence (AI) research which has been identified as a GPT in recent research. We use a novel dataset from `arXiv`, a preprints website widely used by scientific and engineering researchers, which we analyze using Natural Language Processing. After confirming that DL passes the three tests of a GPT (*rapid growth*, *rapid diffusion into new fields*, *impact in new fields*), we consider its geographical dimensions. First, we show evidence of changes in the international rankings of DL research, with China rising in importance while several European countries experience relative decline. Second, we show that those fields of computer science that have adopted DL techniques more rapidly have experienced more volatility in their patterns of geographical clustering than those fields yet to adopt these methods. Finally, we explore the drivers of DL clustering, showing that diversity in the research and industrial base both appear to play a role in the emergence of DL clusters, consistent with the idea that multiple capabilities on the supply and demand side can help a location develop a GPT cluster. We conclude by considering the policy implications of our analysis.

Contents

1 Introduction

What do the steam engine, the electric motor and the semiconductor have in common? They have all been identified as General Purpose Technologies (GPTs) that can be applied in many parts of the economy, potentially transforming the fortunes of industries and nations [1].

In spite of GPT's analytical and policy importance, the geographical aspects of their diffusion and development have not received much attention in the literature, and there is limited empirical evidence about key questions such as their role in transforming the geography of production and innovation, or the local conditions which are more favorable for the development and diffusion of GPTs. Although some important concepts in economic geography and regional science such as dominant designs and cluster life-cycles refer to innovations that disrupt spatial patterns of production and open up 'windows of opportunity' for new entrants, their focus is on individual technologies and industries [2, 3]. Yet the defining feature of GPTs is that they are widely applicable. This is the reason why they are economically important, and why policymakers support their deployment to overcome potential coordination failures between suppliers and adopters ([4]). Any analysis of the geography of technology or innovation which does not take into account this generalizability will be of limited use for our understanding of how GPTs develop, their impact and their policy implications.

In this paper, we seek to address this gap in the literature with an analysis of the geography of Deep Learning (DL) research, a core technique underpinning fast improvements in Artificial Intelligence (AI) technologies that have been identified as the latest example of a transformational GPT and received the attention of scholars, policymakers and the wider public [5]. In particular, we analyze the geography of DL research and how it has evolved, and the underlying drivers for this evolution paying particular attention to the role of research and industrial diversity, two factors that could be particularly important for the development of GPTs with a wide range of research and industrial applications.

To do this, we draw on a novel combination of data sources and analytical methodologies: we obtain our data from `arXiv`, a preprints site used intensively by DL researchers in academia and industry, and identify DL papers with `CorEX`, a state-of-the-art natural language processing method that detects clusters of related words in corpora of text, enabling more robust classification of papers in topics than keyword-based approaches [6]. We use `DBSCAN`, a density-based clustering algorithm to identify geographical clusters of DL activity in the data and `CrunchBase`, a directory of technology companies, to generate measures of industrial activity and diversity which could explain the emergence of DL clusters. Together, the data and analytical pipeline developed for this projects illustrate the opportunities that new data science methods open up for the analysis of emerging technologies such as DL. All the code we have used in our analysis is available for review in `http://www.github.com/....`

The structure of the paper is as follows: The rest of this section reviews relevant literatures in economics and economic geography, and overviews the field of AI and DL, presenting the reasons why it has been identified as a GPT. Section 2 describes how we collected and enriched the data and classified papers into the relevant categories. Section 4 presents the findings of our analysis in three steps. First, we test if DL fulfills the three key features of a GPT (rapid growth, rapid diffusion into new fields, and impact in new fields). Second, we explore the geographical aspects of the diffusion of DL. Third, we model the emergence of DL geographical clusters to understand some of their drivers. Section 5 concludes with a discussion of the findings, limitations of the analysis and issues for further research.

1.1 General Purpose Technologies as engines of growth

GPTs are technologies or clusters of related technologies characterized by their dynamism and broad applicability [1, 7]. They enable productivity improvements in multiple industries by automating or vastly improving the efficiency of common production tasks such as the use of energy to do work, or the transfer and processing of information. The steam engine replaced human and animal motor power in mining, textiles and transport [8]. The electric grid cheaply illuminated homes and workplaces, and the combustion engine gave motorists more freedom in their traveling [9]. The semiconductor transformed the speed and scale of computation across the economy.

GPTs generate new opportunities and complementary innovations in the sectors that deploy them, some of which may also be widely applicable. For example, Information and Communication Technologies (ICTs) based on cheap semiconductors eventually gave birth to the video-games industry, which subsequently spurred the development of Graphical Processing Units (GPUs) that are now used to facilitate parallel processing of information in other sectors. If we imagine the technology system as a network of ideas being constantly recombined, then we will find GPTs sitting near its center [10]. It is however important to note that the discovery of complementary innovations in sectors deploying GPTS involves a process of trial-and-error that can take time. For example, US factories did not start to realize the benefits of electric power until they reorganized their layout to harness the flexibility of small electric motors, decades after the introduction of electricity [9].

The creation of GPTs is subject to important economies of scale: Their successful deployment requires substantial investments in infrastructure and standards with public good characteristics, and creates the risk of lock-in [11] to legacy systems that may be hard to replace in the future. Private actors may lack incentives to invest in these transformational technologies because their benefits will be hard to capture, or because they will damage established business models [4]. Enforcing Intellectual Property Rights to improve incentives risks slowing down GPT diffusion, specially in those sectors where valuable applications can only be discovered through trial-and-error . All these factors explain why policymakers seek to actively encourage and manage the development of GPTs.

1.2 Towards a geography of GPTs?

It is well known that technology clustering and industrial clustering go hand in hand. Agglomeration economies attract workers skilled in a technology to the industrial clusters where there is demand for them, and thick talent pools improve the efficiency of the labor market. Knowledge about technology improvements and good practices diffuse through collaboration, imitation and labor flows between organizations located close to each other **[12, 13]**.

How does this relate to GPTs? The dynamics of slow-building, increasing concentration implicit in the notions of agglomeration economies and knowledge spillovers contrasts with the idea of GPT emergence as a dramatic, disruptive event which can even mark the economic ascent and decline of whole nations. Abrupt changes in economic geography can however happen when incremental technology trajectories experience discontinuities that render longstanding sources of competitive advantage obsolete, and make the places that rely on them stagnant [14, 15]. These radical changes create 'windows of opportunity' that can be harnessed by new entrants and locations [16].

In the dominant design model, these technological trajectories shape the business dynamics of the industries that use them, and their geography [17]: Early in a product life-cycle, there is a stage of entrepreneurial entry and exploration where many entrants explore in parallel potential solutions for a market need (the paradigmatic example being the early days in the history of the automobile) [18]. Afterwards, the industry converges on a standard or dominant design and process innovation becomes more important than product innovation, leading to a 'shake-out' in the industry and concentration of activity in a small number of players. This process reshapes economic and innovation geographies: the initial, exploratory stages of an industry benefit from geographical proximity which facilitates imitation and knowledge spillovers between neighboring innovators. In later stages, proximity loses importance in favor of access to cheap production inputs, resulting in geographical dislocation and off-shoring.

The cluster life-cycle framework considers the regional implications of this process [19]. If the initial burst of entrepreneurial energy in a location is not renewed, industrial clusters can enter a phase of stagnation and decline as the business models of their core industries are disrupted by cheaper locations, or locations with businesses that have adopted new 'competence-destroying' ways of doing things [20].

Although these models capture the disruptive effects of the emergence of a GPT, they do not consider their generalizable aspects, which could be associated to outcomes and drivers quite different from those we see in specialized technologies. By approaching new GPTs as an exogenous shock, it also has little to say about the factors behind their emergence, an area of great interest for policymakers [21, 22].

New advances in evolutionary economic geography, and in particular concepts such as economic complexity and related variety, have given us other useful lenses to study the emergence and contributions of GPTs [23, 24]. These frameworks operationalize economic development as 'moves' in a product or technology space where local capabilities that can be combined more easily (for example because they share the same knowledge base) appear closer to each other. Industrial ecosystems which are more diverse and complex (i.e. contain a wider range of unique capabilities) are able to generate new technological combinations, and are more resilient to changes in the landscape. The spatial proximity between GPT developer and adopter sectors in these ecosystems might help bridge the cognitive and organizational distance between them, enabling a faster and more effective exploration of the economic possibilities that a GPT creates and increasing the prospects for its successful deployment [25]. Conversely, we also expect GPTs to contribute to the resilience of those ecosystems by making it possible to redeploy general technologies in response to declines in existing industries and the emergence of new ones.

1.3 Artificial Intelligence and Deep Learning definitions and economics

Having discussed the concept of GPT and its geography, we now turn our attention to the field where we will be focusing our analysis: Artificial Intelligence, and more specifically the Deep Learning paradigm behind recent, fast improvements in its performance.

Artificial Intelligence (AI) systems comprise *"self-training structures of Machine Learning predictors that automate and accelerate human tasks"* [26]. Machine Learning (ML) has been defined as *"the field that thinks about how to automatically build robust predictions from complex data"* [26]. It emerged in the 1970s in response to the failure of rule-based approaches to developing 'intelligent machines' where human experts sought to hard-code knowledge into those systems [27]. ML's approach is to instead develop algorithms which are able to learn automatically from data with less need for human intervention. This learning can be applied to the prediction of values or generation of labels based on selected features in the data, such as the automatic identification of words in an e-mail which are suggestive of a 'spam' label. Economic analyses of AI focus on its ability to reduce the costs of prediction, a common production tasks which makes any advances in these technologies widely applicable [28].

Deep Learning (DL) is a new ML technique where algorithms are used not only for prediction, but also to identify features in the data that can be used as an input into those predictive tasks [29]. This involves processing the data through networks of synthetic 'neurons' where subsequent layers learn to represent the data in increasingly abstract ways. Although the literature on neural networks goes back to the 1950s, this approach only became feasible in recent years with the availability of large, labeled datasets from the web, and powerful GPUs. Since the early 2010s, Deep Learning has been proven to be 'unreasonably effective' in many applications, from image and video recognition to translation and gaming, fueling another surge of interest in AI [30].

Ultimately, AI researchers strive for generality: developing algorithms that can transfer their predictive prowess across domains, and respond effectively to completely new situations. Unsurprisingly, sustained progress towards that goal has led a growing number of economists to declare AI (and in particular, DL) a new GPT that will revolutionize the economy and society [31]. Analyses of publication, patenting and venture capital investment support this view, with fast growth and diffusion in DL activity compared to other domains of Computer Science and older methods of AI research [6]. Slow productivity growth in the face of rapidly improving AI technologies has been justified by the need to undertake large complementary investments and business reorganization for the effective deployment of the AI GPT [31]. Economists of innovation have also argued that DL represents an *'invention in the methods of invention'* that could transform the process through which new ideas are discovered, vastly expanding the productivity of R&D in fields such as drug discovery, genomics or material sciences [6, 32]. Our analysis of DL as a GPT in Section 4 contributes to this body of research.

Recent work about international trade and AI suggests that economies of scale and localization in knowledge spillovers provide a rationale for national policies to support AI development, including through investments in complementary regulations (namely, privacy regulations that are permissive with the use of personal data in ML/AI algorithms) [5]. Government across the world seem to share this view, and the 'global AI race' has become an important topic of debate. Many countries have published national strategies to develop their AI industries. Less attention has been paid to the sub-national aspects of AI geography, its evolution and drivers. These are some of the questions that we address in this paper

2 Data collection

We generate a dataset for our analysis by matching three non-proprietary open data sources; `arXiv`, Microsoft Academic Graph (`MAG`), and the Global Research Identifier Database (`GRID`). The data sources are matched in the following order, according to the procedure described in Sections 2.1-2.3:

$$\{\texttt{arXiv} \xrightarrow{\text{matched to}} \texttt{MAG}\} \xrightarrow{\text{matched to}} \texttt{GRID}$$

By following this pipeline of data collection, we create a dataset with the features described in Table 1 for further processing as described in Section ??.

Feature	**Data source**	**Comments**
Article title	`arXiv`	Assured to be consistent with `MAG` title after matching procedure.
Article abstract text	`arXiv`	To be used for topic modeling (Section 3).
Subject classification	`arXiv`	Assigned by the author.
Is article published in a journal?	`MAG`	Always true, as implicitly assured by match to `MAG`.
Publication date	`MAG`	Journal publication date, rather than `arXiv` submission date.
Citation count	`MAG`	Used for cross-check by selecting 'high quality' publications (Section ??).
Institute affiliation (all authors)	`MAG`	This replaces the potentially incomplete set of authors from `arXiv`.
Institute location	`GRID`	

TABLE 1: *Features extracted in the data collection procedure.*

2.1 `arXiv`

`arXiv` is a 'real-time' open archive of academic preprints widely used by researchers in quantitative, physical and computational science fields. Data from each of over 1.3 million papers can be accessed programmatically via the `arXiv` API. As `arXiv` papers are self-registered, we ensure that papers are not simply 'junk' articles by requiring that all papers are matched to a journal publication or conference proceeding, as presented in Section 2.2. We also have anecdotal evidence that the archive contains high quality papers, since a short study of conference proceeding from the prestigious AI Conference on Neural Information Processing Systems in 2017 reveals that over 55% of these were published on `arXiv`.

Using `arXiv` data as the root source of data has a number of advantages compared with accessing data directly from `MAG`. We can demonstrate this by considering that `MAG` requires keyword inputs for finding publications. Even if it was possible to select the exact set of keywords which are most predictive of DL papers, it is not clear how one would also generate data for non-DL papers within the same field. Furthermore, it would not be trivial to identify comparator fields that have not adopted DL (an important component of our analytical strategy). The 'Subject classification' field in the `arXiv` data naturally allows for such controls to be generated, once the topic modeling procedure (described in Section 3) has been implemented.

From the initial set of over 1.3 million papers, approximately 134,000 have been selected for analysis as they fall under the broad category of 'Computer Science' (`cs`) or the specific category of 'Statistics - Machine Learning' (`stat.ML`).

2.2 Microsoft Academic Graph (`MAG`)

Microsoft Academic Graph (`MAG`) is an open API offering access to 140 million academic papers and documents compiled by Microsoft and available as part of its 'Cognitive Services'. For the purpose of this paper, `MAG` helps to ensure that article retrieved from `arXiv` have been published in a journal or conference proceeding, as well as providing citation counts, publication date and author affiliations. The matching of the `arXiv` dataset described in Section 2.1 is performed in two steps.

We begin by matching the publication title from `arXiv` to the `MAG` database. The database can be queried by paper title, although fuzzy-matching[1] or near-matches are not possible with this service. Furthermore, since paper titles in `MAG` have been preprocessed, one is required to apply a similar preprocessing prior to querying the `MAG` database. There is no public formula for achieving this, so we explicitly describe the following steps to emulate the `MAG` preprocessing:

1. Identify any 'foreign' characters (for example, Greek or accented letters) as non-symbolic;
2. Replace all symbolic characters with spaces; and
3. Ensure no more than one space separates characters.

This procedure leads to a match rate of 90%, for the set of `arXiv` articles used in this paper. We speculate that papers could be missing for several reasons: the titles on `arXiv` could significantly different from those on `MAG`; the latter procedure may be insufficient for some titles; the `arXiv` paper may not be published in a journal; and `MAG` may not otherwise contain the publication. It may be possible to recuperate some of these papers, however this is currently not a limiting factor in our analysis.

2.3 Global Research Identifier Database (`GRID`)

The Global Research Identifier Database (`GRID`) is used to enrich the dataset with geographical information, specifically a latitude and longitude coordinate for each affiliation. The `GRID` data is particularly useful since it provides institute names and aliases (for example, the institute name in foreign languages). Each institute name from `MAG` is matched to the comprehensive list from `GRID` as follows:

1. If there is an exact match amongst the institute names or aliases, then extract the coordinates of this match. Assign a 'score' of 1 to this match (see step 3. for the definition of 'score').
2. Otherwise, check whether a match has previously been found. If so, extract the coordinates and score of this previous match.
3. Otherwise, find the `GRID` institute name with the highest matching score, by convoluting the scores from various fuzzy-matching algorithms in the following manner:

$$\frac{1}{\sqrt{N}}\sqrt{\sum_{n=0}^{N} F_n(w_{\texttt{MAG}}, W_{\texttt{GRID}})^2} \tag{1}$$

[1] 'Fuzzy-matching' refers to the process of finding a likely match for a set of text (such as a word or sentence) amongst a choice of texts. A naive example would be comparing the ratio of the number of characters between texts, and identifying the texts with the highest ratio as a match.

where N is the number of fuzzy-matching algorithms to use, F_n returns a fuzzy-matching score (in the range $0 \to 1$) from the n^{th} algorithm, $w_{\texttt{MAG}}$ is the name from MAG to be matched and $W_{\texttt{GRID}}$ is the comprehensive list of institutes in the GRID data.

The form of Equation 1 ensures that effect of a single poor fuzzy-matching score is to vastly reduce the preference for a given match. Therefore, good matches are defined according to Equation 1 as having multiple good fuzzy-matching scores, as measured according to different algorithms. We opt to use a prepackaged set of fuzzy-matching algorithms implementing the Levenshtein Distance metric [33], and specifically we use two algorithms applying a token-sort-ratio and a partial-ratio respectively.

After this stage of data matching, approximately 140,000 unique institute-publication matches are found for analysis.

3 Topic modeling

We analyze the abstracts in our corpus using Natural Language Processing to identify papers related to DL. This involves tokenizing the text of the abstracts and removing common stop-words, very rare words and punctuation. We lemmatize the tokens based on their part-of-speech tag, and we create bi-grams and tri-grams. Documents with less than twenty tokens are removed from the sample. After these steps, there are over 168,000 features (unique 'words') in the dataset.

There are different approaches to identify DL papers in this preprocessed corpus. Previous work has used a keyword-search approach based on a predefined vocabulary of terms [6]. Here, we follow an alternative topic modeling strategy which identifies clusters of words in the data without an initial vocabulary, and provides a score for each topic in a document, simplifying the labeling process.

More specifically, we use the Correlation Explanation (`CorEx` [34]) algorithm, which takes an information-theoretic approach to generate n combinations of features in the data which maximally describe correlations in the dataset. Using a one-hot bag-of-words representation, we optimally find $n = 28$ topics by tuning n with respect to the 'total correlation' variable, as advised by the `CorEx` authors. The generated topics contain words which are sorted in terms of their contribution of each feature to total correlation. We assign topics to documents if the following condition is satisfied:

$$\sum_{i=0}^{N^j} T_i^j(w_i, W_k) \geq \gamma \, T_{\max}^j \tag{2}$$

where:

$$T_i^j(w_i, W_k) = \begin{cases} T_i^j & \text{if } w_i \in W_k \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

the form of the above ensures that at least the most important components, or sufficient components. Clearly, larger choice of γ leads to "higher probability" to contain the "true" topic.

After inspecting the model outputs, we identify two topics related to DL, containing keywords such as `neural_network`, `deep_learning`, or `convolutional_neural_networks`. We label as 'Deep Learning' those papers where either of these topics is present with a γ above 0.2, giving us a set of 30,652 DL papers (23% of the total).[2].

[2]We also generate a more restrictive DL category containing only those papers where both DL topics are simultaneously present with a γ above 0.2, resulting in a total of 8,051 papers. A visual inspection of a random sample of papers in both groups does not show significant differences in the precision of the classification so we opt to focus on the larger set. This is further motivated by our interest in understanding the diffusion of DL methods in various domains of computer science.

4 Analysis

4.1 GPT aspects of DL research in arXiv

The literature suggests that AI (and in particular the latest wave of powerful DL techniques) is a GPT that can be rapidly improved and applied to many sectors, where it generates high-impact complementary innovations. We begin our analysis by testing whether this is the case in the arXiv data. In doing this, we expand a growing empirical literature about the GPT nature of AI which has so far monitored AI trends in publication and patent data using a keyword-based approach [6].

The first test for whether a technology is a GPT is *rapid growth*: GPTs with broad applicability should see rapid increases in activity as multiple agents explore their potential. Figure 1 presents the evolution of publication activity in arXiv distinguishing between DL and non-DL papers. It shows that arXiv is becoming an increasingly popular venue for the publication of computer science research, and that DL is gaining relative importance in its corpus. The share of DL papers in the total has almost tripled, from 10% of the total before 2012, to 28% after 2012 [3].

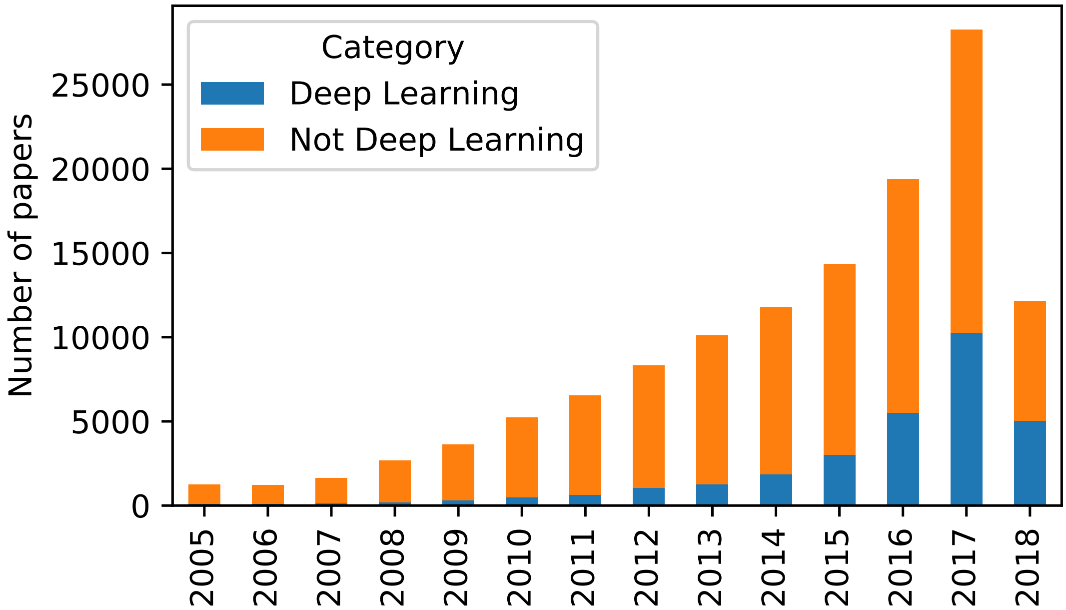

FIGURE 1: *Publication activity in arXiv (2005-2012)*

The second GPT test for a technology is *rapid diffusion in new fields*: is the technology being adopted across multiple domains or restricted to a small number of areas? To verify this, we count the number of DL papers in different categories of Computer Science research based on their arXiv category[4].

Figure 3 presents the results. The top panel displays yearly changes in the shares of DL by arXiv category (based on 3 year moving averages), and the second panel compares shares of DL activity in a category before and after 2012 for the top 35 computer science categories in arXiv by total levels of activity.

Our findings suggest that DL also passes this second GPT test, with a visible upward trend in the relative importance of DL in multiple sub-disciplines of computer science, specially since 2012, the year of publication for [35], a landmark paper in the use of DL in computer vision. In fact, all of the computer science categories presented in the bottom panel have seen an increase in the relative importance of DL research since 2012. This is particularly visible in the case of disciplines

[3]These results hold if we restrict our analysis to the most highly cited papers every year.
[4]Most papers are labeled with multiple arXiv categories. We allocate a paper to a cs category if it appears in it at least once.

that specialize in the development of AI technologies, such as `cs.NE` (Neural Networks), `cs.LG` (Learning), `stat.ML` (Machine Learning) or `cs.AI` (Artificial Intelligence) as well as disciplines working with large amounts of unstructured data such as images (`cs.CV` - Computer Vision) and text (`cs.CL` - Computer Language), two domains where DL's ability to recognize patterns without human intervention have proven particularly valuable [29].

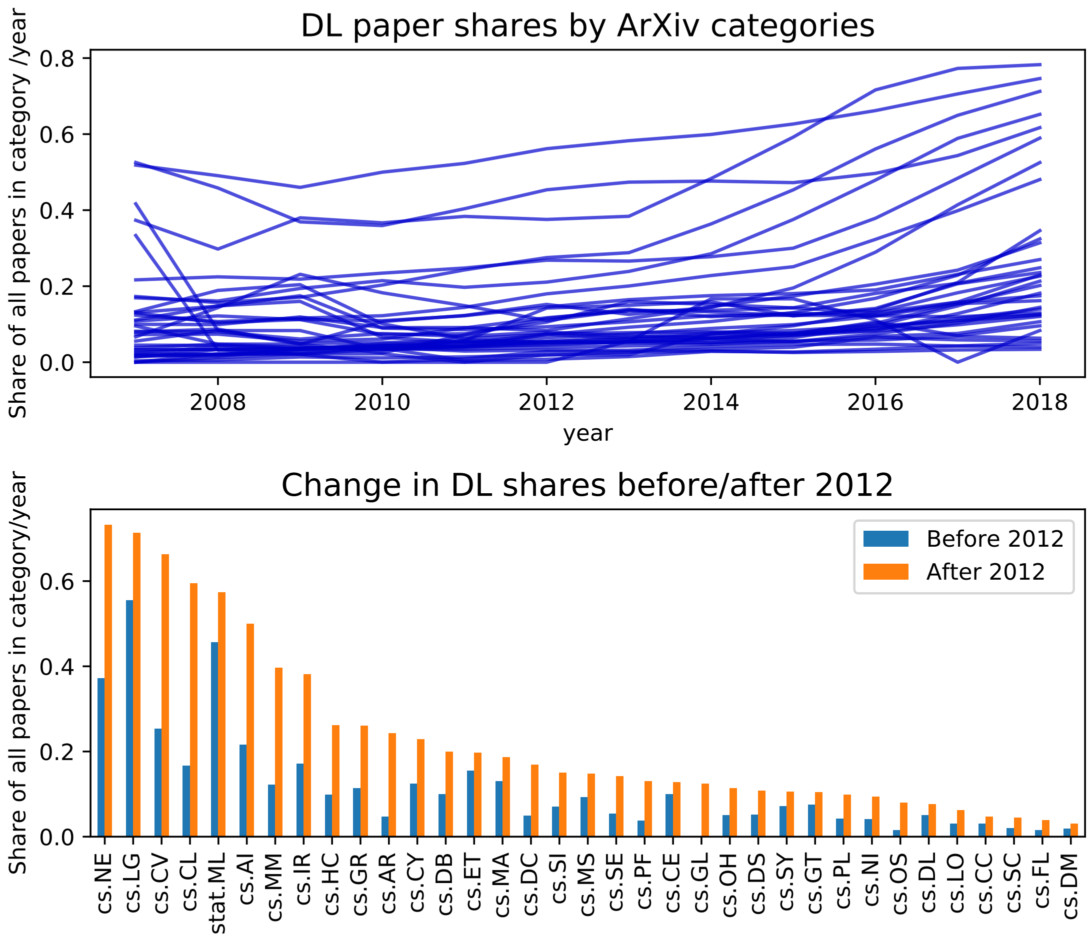

FIGURE 2: *DL as a share of activity in different* `arXiv` *categories*

The third GPT test is *impact in new fields*: it DL generating follow-on innovations in the fields that adopt it? To look at this question, we have calculated the level of 'citation competitiveness' CC_i of DL papers in each computer science sub-discipline i.

$$CC_i = \frac{S_i^h}{S_i} - 1 \tag{4}$$

Here S_i^h represents the share of highly cited DL papers in category i, and S_i represents the share of DL papers in the category [5]. A positive score means that DL papers are overrepresented amongst the highly cited papers in the `arXiv` category. We consider this a proxy for impact [6].

Once again, the results of our analysis support the idea that DL is a GPT: CC_i is greater than zero for most of the `arXiv` categories, suggesting that DL papers are overrepresented among the most influential and impactful papers published in a wide range of computer science sub-disciplines since 2012.

Together, the results in this section support the idea that DL is a GPT: levels of activity in it are growing rapidly, it is spreading into a wide-ranging number of fields, and it is generating an

[5]We define highly cited papers as those in the top quartile of citations for the considered period.

[6]We focus this part of the analysis on papers published after 2012 in order to control for the fact that as 1 showed, most DL papers were published in recent years and have therefore had less time to receive citations

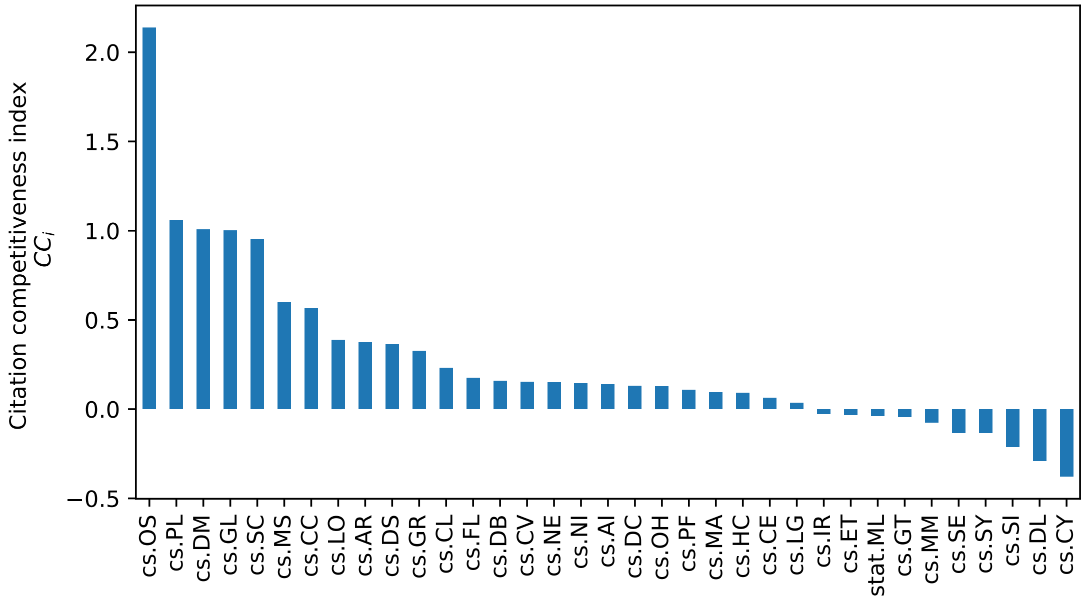

FIGURE 3: *Citation competitiveness of DL papers in the top 35* **arXiv** *categories by total number of publications in the period 2012-2018*

impact (or at least attracts attention, in terms of the number of citations it receive) in the new fields where it is applied. We now turn to the geographical aspects of its development.

4.2 Evolution in the Geography of DL research

In this section, we study the geographical aspects of the development and diffusion of DL. Our prior is that they will follow the patterns identified in the literature on technological trajectories and cluster life-cycles, with an initial disruption in established geographies of activity followed by a 'shake-out' and increase in concentration.

We begin by exploring these two questions using countries as the unit of analysis, and considering changes in their relative comparative advantage in DL research. We define the RCA_{dl} of a country i as:

$$RCA_{dl,i} = \frac{(\frac{A_{dl,i}}{A_{c,i}})}{(\frac{A_{dl,n}}{A_{c,n}})} \tag{5}$$

Where $A_{dl,i}$ and $A_{c,i}$ respectively represent the research activity of the country in DL and all `arXiv` categories, and $A_{dl,n}$ and $A_{c,n}$ represent DL activity and activity in all `arXiv` categories in all countries. A $RCA_{dl,i}$ above 1 implies that the country has a comparative advantage in DL, while the opposite is true if the $RCA_{dl,i}$ is below 1. The use of RCAs allows us to measure changes in DL research while controlling for rapid growth in overall computer science activity.

Figure 4 compares the RCA index in DL before and after 2012 for the 25 countries most active in `arXiv`, restricting our analysis to papers in the top 50 percentile of citations in each year [7]. It shows rapid improvements in DL competitiveness in three Asian countries: China, Hong Kong and Singapore. Canada has also seen a significant increase in its RCA_dl, overtaking the USA. Meanwhile, EU countries such as UK, Netherlands, Belgium or Spain have experienced a relative decline from initial positions of high specialization. France, Germany and Italy retain low levels of specialization through the period.

[7] This has the goal of removing low quality papers from the analysis.

The changes we observe are consistent with the idea of volatility in the early stages of GPT development, with some countries climbing up in the rankings rapidly while others fall behind. It is also interesting to note, qualitatively, that the trends we observe in the data reflect some the narrative in policy documents and the popular press about the current state of the 'AI race', with China and Canada rapidly becoming two global leaders in AI, and EU countries lagging behind. After an initial slow response to the emergence of DL, the US is rapidly becoming more competitive in this technology [6].

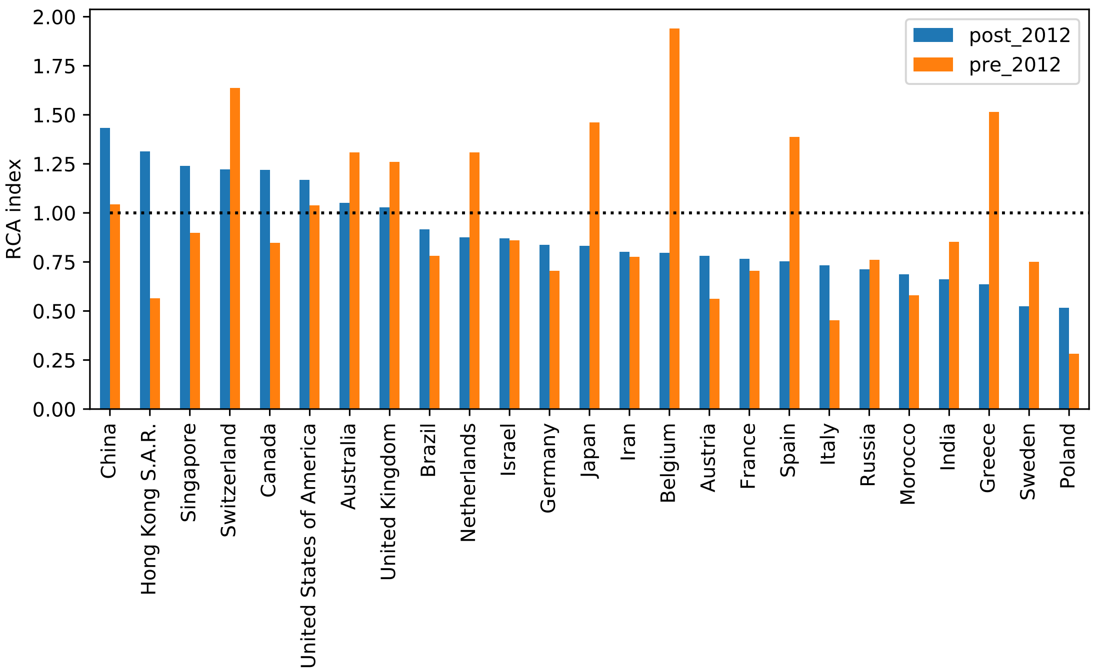

FIGURE 4: *Changes in Relative Comparative Advantage index before/after 2012 for top 25 countries by level of activity in* `arXiv`*, focusing on papers in the 50 percentile in citations for the considered periods.*

Have these shifts led to international consolidation? Figure 5 compares the shares of DL and overall computer science activity in `arXiv` accounted by countries with different positions in the rankings before and after 2012. It shows that in the last 6 years, DL research has become more concentrated, specially when we compare it with what happened in other computer science disciplines. In the period after 2012, the top 5 countries in DL activity comprised 68% of all highly cited publications, 5% more than they did in the period before 2012. The Herfindahl index of concentration for DL has gone from 0.15 to 0.161 (an increase of 3%) compared to a decline of 13% in computer science overall.

Our initial focus on countries and DL research has some limitations. First, it ignores the fact that DL research could cluster at the sub-national level, or across national boundaries [5]. Second, it does not allow us to consider how the adoption of DL is changing the geography of other computer science disciplines, which is what we would expect if it was having an impact on them.

To address this, we expand our geographical analysis using micro-geographical data about the locations of institutions that `arXiv` authors are affiliated with, obtained from the `GRID` database, which we analyze using the `DBSCAN` clustering algorithm which identifies clusters of observations based on their spatial density [36]. Instead of focusing on the evolution of clusters in DL, we benchmark computer science fields that have adopted DL more intensively against fields that that have not (we define high adoption fields as those that have more than 40% of the papers in DL, and low adoption fields as those where less than 10% of the papers are DL) [8]. Our prior is that

[8] The use of a comparator group in the analysis has the added advantage of allowing us to control for the hyper-parameters in the `DBSCAN` algorithm, which we assume should be similar across computer science domains, and for the increase of activity in `arXiv`.

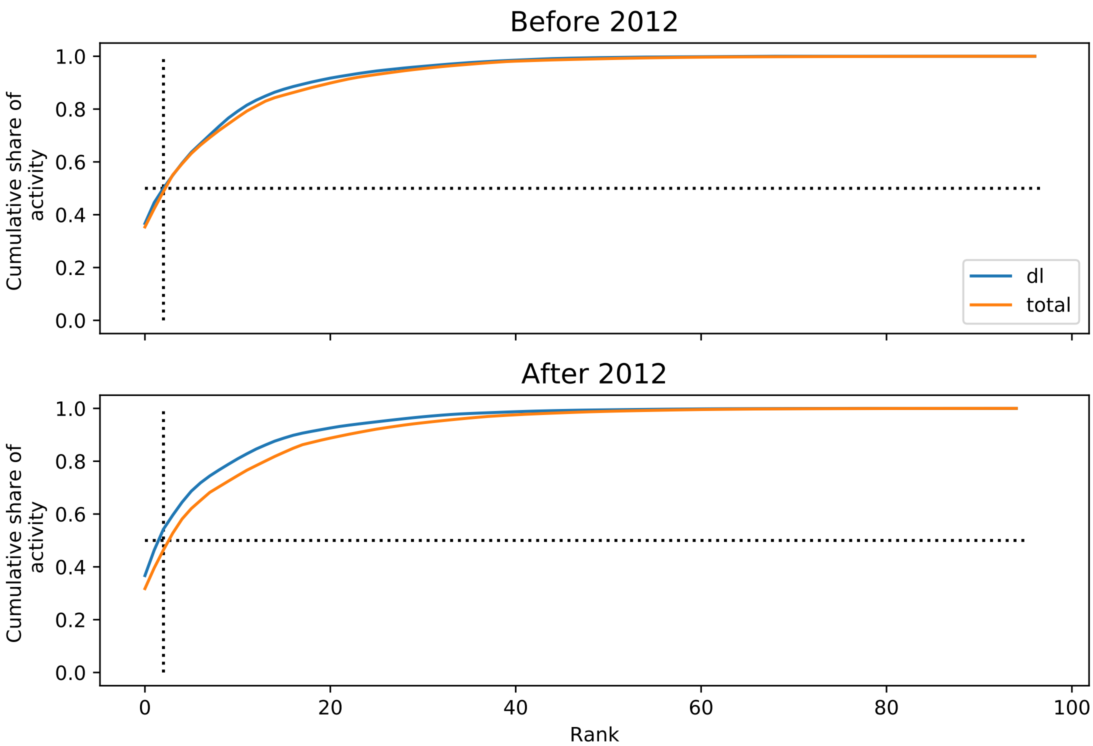

FIGURE 5: *Changes in research concentration before/after 2012 for papers above the 50 percentile in citations for the considered periods.*

strong adopters should have experienced more volatility initially, followed by a stronger increase in concentration afterwards.

We use the following metrics for benchmarking:

1. *Initial cluster coverage*: The percentage of observations in clusters period 2 included in clusters in period 1 (a measure of stability (negative volatility)
2. *Cluster entry*: The number of clusters present in Period 2 that were not present in period 1 (a measure of volatility)
3. *Concentration change*: Changes in the total share of activity in identified clusters between period 1 and period 2
4. *Citation concentration change*: As above, but focusing on highly cited papers.

The results, which we present in 6, are in line with our expectations: strong adopters of DL such as `cs.LG`, `stat.ML` and `cs.LG` experience less stability (a larger fraction of the activity in period 2 happens outside the clusters identified in period 1), more entry by new clusters, and faster growth in the levels of concentration, both for the total number of paper, and for highly influential papers.

4.3 Drivers of DL cluster emergence

Previous subsections have shown that DL research `arXiv` is fast-improving, widely applicable and impactful in new fields, consistent with the definition of a GPT. Our analysis of geographical trends at the national and micro-levels suggests that the advent of DL also follows the hypothesized patterns, with initial volatility followed by a tendency towards concentration as the field consolidates.

In this section, we explore some of the drivers for the emergence of DL clusters. Our expectation is that those locations which are more diverse in their research and industrial base, and include a

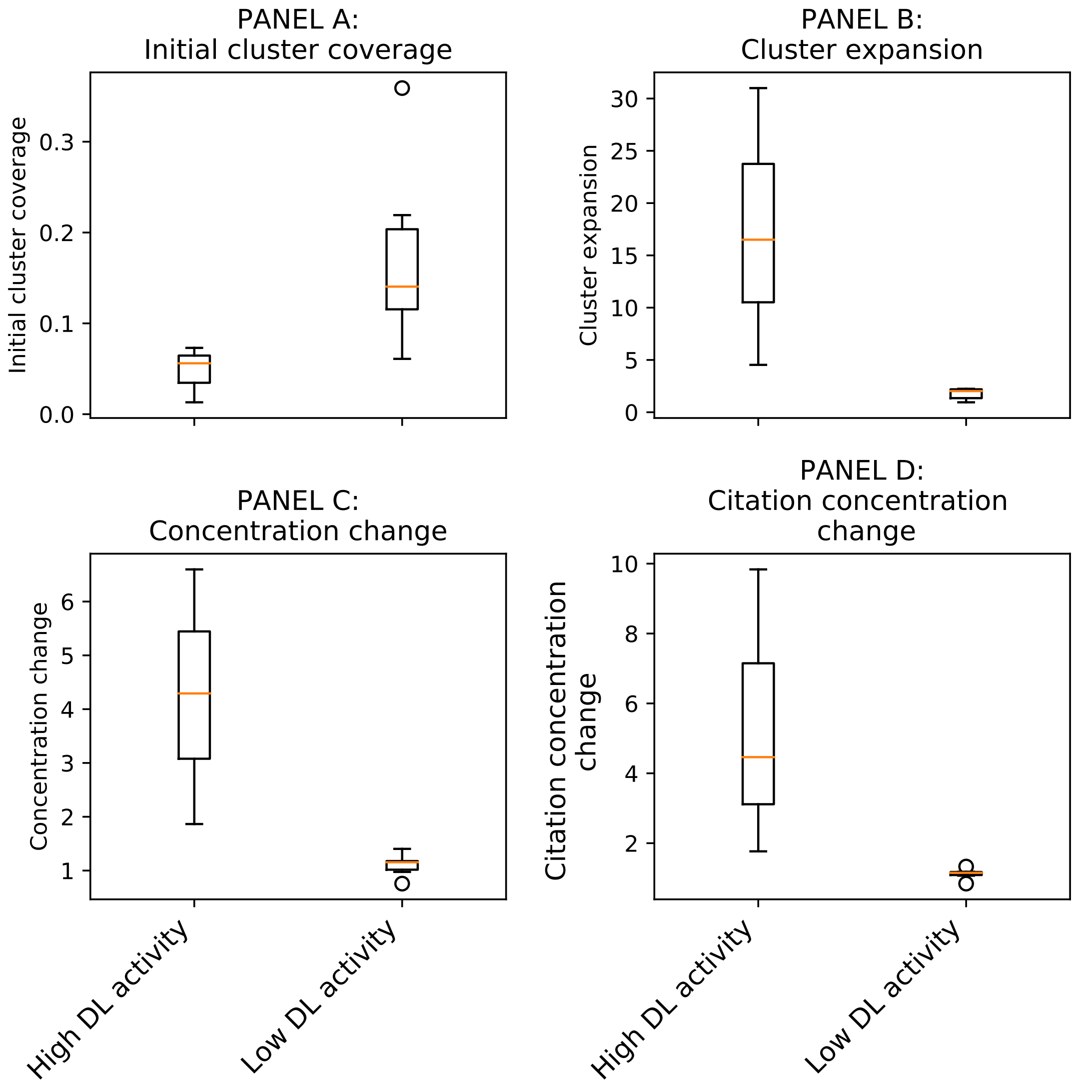

FIGURE 6: *A comparison between* `arXiv` *categories in 4 dimensions: Initial cluster coverage (Panel A), Cluster entry (Panel B), Concentration change (Panel C) and Citation concentration change (Panel C)*

combination of 'developer' and 'adopter' sectors will be better able to explore the broad space of opportunity opened up by the AI GPT.

The dependent variable y in our model is the count of DL clusters that are identified in the region since 2012, based on the same density-based analysis we used in Section 4.2. We set the hyper-parameters of `DBSCAN` at 100 minimum samples and a radius ϵ of 10km. We classify papers and clusters into regions at the administrative level. In total, we identify 88 administrative areas with at least one DL cluster. Table 2 displays the top 15 areas.

This analysis reveals 25 countries with at least 1 DL cluster. 20 administrative areas with at least 1 DL cluster are in the UK, 10 in China, 8 in Great Britain, 5 in France and Australia and 4 in Germany. It is important to note that these metrics are not normalized by the total levels of `arXiv` activity in different countries as we did with the national results we reported in Section 4.2. They do in any case underscore the importance of considering the sub-national picture when analyzing DL research trends.

We construct our independent variables (measures of local capabilities and controls) using data from `arXiv` and `CrunchBase`, a global directory of technology ventures which is increasingly being used in the analysis of digital entrepreneurship and innovation [37]. In addition to calculating total

Administrative area (country)	**Number of DL clusters**
California (US)	6
New York (US)	3
New Jersey (US)	3
Michigan (US)	2
Virginia (US)	2
Texas (US)	2
Maryland (US)	2
Massachusetts (US)	2
Florida (US)	2
Illinois (US)	2
Ontario (CA)	2
Pennsylvania (US)	2
Washington (US)	2
London Borough of Tower Hamlets (GB)	1
Edinburgh (GB)	1
Oxfordshire (GB)	1

TABLE 2: *Number of DL clusters in top 15 administrative areas*

measures of activity in `arXiv` and `CrunchBase` before 2012 (`arXiv_totals` and `cb_totals`), we also consider metrics of diversity in local `arXiv` and `CrunchBase` activity (`arxiv_diversity` and `cb_diversity` using Shannon entropy. Our prior is that those locations that are more diversified in their research and industrial base might be able to apply GPT in a broader range of domains. Our controls include whether a country is China or not (`is_china`), and the geographical size of an administrative area (`area`), to account for the fact that larger areas may be able to physically host more clusters. We log all totals, take the z-score of all variables and focus on areas with at least one `arXiv` paper for the whole period (since these are the only areas that would have been able to develop a DL cluster). In our final analysis, we consider 701 administrative areas.

Table 3 is the correlation matrix between the considered variables. It shows that the bivariate correlation coefficients are consistent with our priors: those locations with more research and industrial activity, and with more research and industrial diversity before 2012 display a stronger propensity to develop a DL cluster.

	y	`arxiv_totals`	`arxiv_diversity`	`cb_totals`	`cb_diversity`	`is_china`
y	1.000	0.516	0.413	0.374	0.314	0.111
`arxiv_totals`	0.516	1.000	0.852	0.627	0.631	0.030
`arxiv_entropy`	0.413	0.852	1.000	0.557	0.571	0.042
`cb_totals`	0.374	0.627	0.557	1.000	0.942	0.021
`cb_entropy`	0.314	0.631	0.571	0.942	1.000	-0.018
`is_china`	0.111	0.030	0.042	0.021	-0.018	1.000

TABLE 3: *Correlation matrix*

We also notice a very strong correlation between absolute measures and diversity measures for both `arXiv` and `CrunchBase`. This is consistent with the idea that those locations with a higher volume of research and industrial activity tend to develop more diversified ecosystems. Unfortunately, these strong correlations also create the risk of multicolinearity between variables. We address this by excluding the total levels of `arXiv` and `CrunchBase` activity from the analysis. This creates the risk of confounding since we would expect the total level of activity in a location to influence both its diversity and its propensity to develop a DL cluster. We try to address this issue in the comparative analysis between DL and low-intensity adopters of DL at the end of the section.

Since we are modeling a distribution of skewed counts, we use a Poisson regression. We cluster our standard errors on countries to account for intra-country similarities. Table 4 presents the outputs of the model.

Dep. Variable:	y	**No. Observations:**	701
Model:	Poisson	**Df Residuals:**	696
Method:	MLE	**Df Model:**	4
Date:	Sun, 01 Jul 2018	**Pseudo R-squ.:**	0.3608
Time:	12:18:09	**Log-Likelihood:**	-207.87
converged:	True	**LL-Null:**	-325.22

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
intercept	-3.6225	0.376	-9.645	0.000	-4.359	-2.886
arxiv_diversity	1.4927	0.270	5.520	0.000	0.963	2.023
cb_diversity	0.8366	0.490	1.707	0.088	-0.124	1.797
is_china	1.0942	0.171	6.413	0.000	0.760	1.429
admin_area	0.0027	0.002	1.235	0.217	-0.002	0.007

TABLE 4: *Poisson Regression Results*

The results suggest that higher levels of diversity in the research and industrial base are both associated to a higher number of DL clusters in a region. Diversity in the research base is more strongly associated with the development of DL clusters, which is what we would expect at the earlier stages in the emergence of a DL cluster. We note that our `is_china` dummy is positively associated to a region's ability to develop a DL cluster. This could be explained by an increase in overall levels of computer science activity in China, or with Chinese policies to support the development of DL. We consider this question next, by benchmarking the estimated parameters for the development of DL clusters with other `arXiv` categories with lower levels of DL adoption.

Figure 7 presents the results of this comparison, using the same model specification as above. Interestingly, the model shows that high levels of research diversity are equally likely for all the disciplines we are considering. This result may be driven by the link between absolute levels of `arXiv` activity and diversity which we mentioned above. When we look at the level of diversity in `CrunchBase`, we find that industrial diversity is more strongly associated with the development of DL clusters in at least some of the disciplines we consider. Chinese regions also appear to be stronger in the development of DL clusters than in other computer science disciplines, which is what we could have expected given the strategic emphasis on developing AI capabilities exhibited by the Chinese government.

5 Conclusion

5.1 Discussion and implications

We have studied the geographical aspects of the emergence of DL, a new paradigm for AI. Our analysis of `arXiv`, a preprints website widely used by the AI research community supports the idea that DL has the features of a GPT technology: it has experienced rapid growth and is being applied

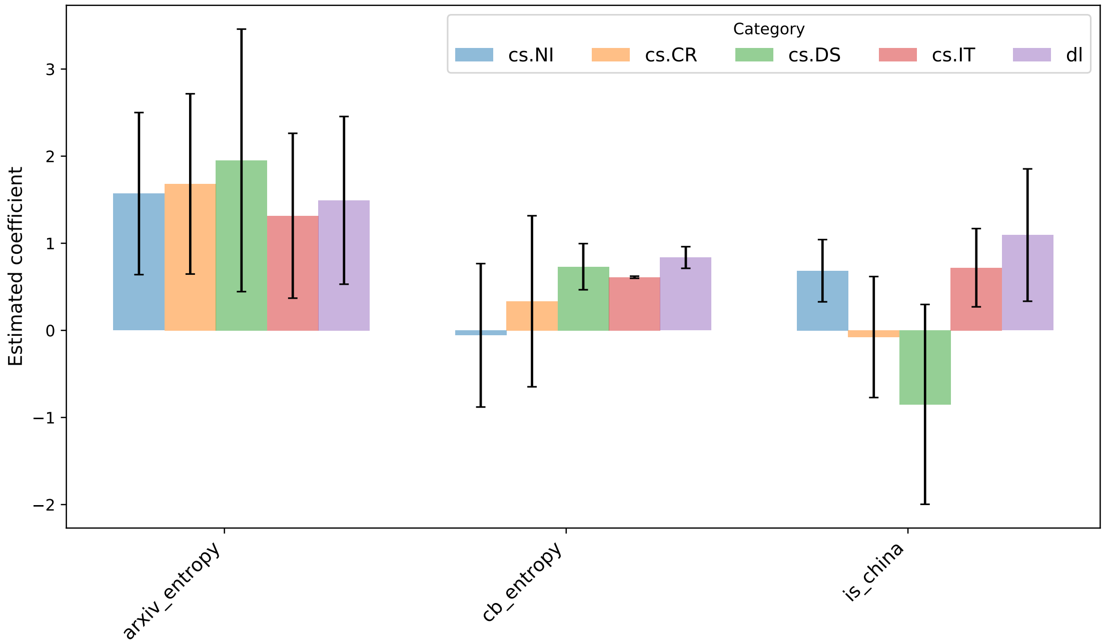

Figure 7: *Poisson regression comparing DL with low-DL activity computer science categories*

in an increasing number of computer science sub-disciplines where it has generated high-impact work (proxied with citations). This confirms the conclusions of previous studies such as [6], and also suggests that in spite of recent criticisms of the DL paradigm, and in particular the lack of robustness stemming from its 'black box nature' [38]), researchers in multiple domains of computer science who are perhaps less likely to be swayed by hype than policymakers and entrepreneurs, are applying it in ways that their peers find interesting and useful.

If DL is a GPT, what are the geographical dimensions of its development and diffusion? In our review of the literature on technological trajectories and dominant designs we posited that we would expect the emergence of a GPT to involve an initial shift in the geography of research as new 'entrants' come into the scene, followed by consolidation as central hubs of activity become dominant. Our analysis at the national and micro level lend support to this thesis: we see international shifts in activity since 2012, when DL started to gain visibility, followed by a geographical concentration of activity. Interestingly, this contrasts with the situation in computer science overall, which has become more dispersed internationally in the same period. These results supports the hypothesis in [5] that knowledge spillovers in AI research are localized, potentially motivating national and sub-national policies to support its development.

Finally, we have modeled the drivers for the emergence of DL clusters in a multivariate framework. Although our results support the idea that both supply side factors (the presence of a strong and diversified research base) and demand-side factors (co-location with a wide-range of industries which are able to explore different channels to apply the AI GPT) play a role in the emergence of DL clusters, it is difficult to disentangle the effects of diversity and size (which is a driver of diversity) in our data. The results of our comparison between DL and other computer science categories with a lower propensity to adopt DL are not clear-cut either. Interestingly, industrial diversity seems to play a role in the development of clusters in these other computer science categories too. One potential explanation is that even though these benchmark sub-disciplines are not strongly deploying DL, they retain an strong element of generality which benefits from co-location with multiple industries and research sub-fields. In future work, we will benchmark DL with other disciplines outside of computer science.

In terms of policy, our findings suggest that the attention that DL is attracting from national and regional policymakers could be warranted given its GPT nature. What is less clear is the extent to which the 'window of opportunity' to enter the field remains open given the growing concentration of DL research activity that we have identified. Our findings are also in line with current views about the emergence of China and Canada as global AI leaders (together with the USA), while EU countries lag behind. While the results of our analysis of the drivers of DL cluster development are more ambiguous, they broadly support the idea that diversified ecosystems of research and industrial activity could offer a fertile ground for the development of GPT technologies that rely on new combinations of ideas from various fields, and are applicable in multiple domains. Proximity between researchers and businesses could help to address some of the coordination failures between developers and adopters of GPT technologies identified in the literature [1]. The challenge for policymakers will be to manage the complexity of research and development policies often fragmented across disciplines and geographies.

5.2 Limitations and issues for further research

Our use of `arXiv` data raises multiple questions. To begin with, this is a publication venue with 'low barriers for entry'. This raises the risk of noise in the data, for example, if the trendy DL field attracts an inordinate amount of low quality contributions. We have sought to address this problem by matching the `arXiv` data with `MAG`, and focusing key parts of our analysis on highly cited, higher quality papers. Future work should expand and further validate our conclusions in other data sources such as patents or open source software development projects.

Second, to which extent are we capturing changes in research trends, or broader technology development and business diffusion questions? Although anecdotal evidence suggests high level of industry participation in `arXiv`, there is risk of biases if different research communities or countries display variation in their propensity to publish their work in `arXiv`. Although we find a strong correlation (ρ=0.87) between the shares of activity in `arXiv` and `CrunchBase`, further triangulation of `arXiv` data with other sources, including peer-reviewed research in comparable disciplines, would help to address concerns about biases.

The use of the `DBSCAN` algorithm in the micro-clustering analysis is also experimental, and further tuning of its hyper-parameters would be desirable. A challenge here is determining what is the 'natural' span and critical mass of a computer science research cluster. While we believe that the use of benchmark categories in the analysis helps to control for the selection of hyper-parameters, this relies in the assumption that clusters in different computer science disciplines have a similar span and density. It would be possible to test this assumption by, for example considering the average distance between co-authors in different categories.

There are many possible extensions for our analysis of the drivers of cluster development. In addition to some we already mentioned, such as incorporating into the analysis proxies for research and business mass which are less strongly correlated with diversity (for example, population, research workforce or number of research institutes) and using non-computer science sub-disciplines as benchmarks in the regression analysis, it would also be desirable to refine some of our measures of diversity, and our analysis of cluster emergence. For example, the measure of diversity we are currently using (Shannon Entropy) does not take into account that some computer science disciplines or `CrunchBase` business categories could be quite similar to each other in a way that leads us to overestimate diversity. We are also ignoring the fact that a mix of specialization in some disciplines and diversity in others could be conducive to the development of a DL cluster, as suggested by the Related Variety concept [23].

Finally, our analysis takes a siloed view of the development of computer science clusters, only considering geographical proximity to other DL researchers and digital businesses as a source of valuable knowledge about new techniques and business applications. In truth, researchers access this knowledge through many other channels with broader geographical spans, and engage in collaborations with other teams located faraway. Going forward, we will address this by studying the network of co-authorships and citations in our data, and trying to understand the role of international conferences in the dissemination of knowledge and geography of DL. This analysis might reveal cross-country flows of ideas and collaboration going against the narrative of a zero-sum global AI race dominating current debates about the geography of AI.

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