GeoDBLP: Geo-Tagging DBLP for Mining the Sociology of Computer Science

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Abstract

Many collective human activities have been shown to exhibit universal patterns. However, the possibility of universal patterns across timing events of researcher migration has barely been explored at global scale. Here, we show that timing events of migration within different countries exhibit remarkable similarities. Specifically, we look at the distribution governing the data of researcher migration inferred from the web. Compiling the data in itself represents a significant advance in the field of quantitative analysis of migration patterns. Official and commercial records are often access restricted, incompatible between countries, and especially not registered across researchers. Instead, we introduce GeoDBLP where we propagate geographical seed locations retrieved from the web across the DBLP database of 1,080,958 authors and 1,894,758 papers. But perhaps more important is that we are able to find statistical patterns and create models that explain the migration of researchers. For instance, we show that the science job market can be treated as a Poisson process with individual propensities to migrate following a log-normal distribution over the researcher’s career stage. That is, although jobs enter the market constantly, researchers are generally not “memoryless” but have to care greatly about their next move. The propensity to make $k > 1$ migrations, however, follows a gamma distribution suggesting that migration at later career stages is “memoryless”. This aligns well but actually goes beyond scientometric models typically postulated based on small case studies. On a very large, transnational scale, we establish the first general regularities that should have major implications on strategies for education and research worldwide.
1 Introduction

Over the last years, many collective human activities have been shown to exhibit universal patterns, see e.g. [34, 21, 18, 12, 11, 5, 17, 10, 31, 3] among others. However, the possibility of universal patterns across timing events of researcher migration — the event of transfer from one residential location to another by a researcher — has barely been explored at global scale. This is surprising since education and science is, and has always been international. For instance, according to the UNESCO Institute for Statistics, the global number of foreign students pursuing tertiary education abroad increased from 1.6 million in 1999 to 2.8 million in 2008[1]. As the UN notes [30], “there has been an expansion of arrangements whereby universities from high-income countries either partner with universities in developing countries or establish branch campuses there. Governments have supported or encouraged these arrangements, hoping to improve training opportunities for their citizens in the region and to attract qualified foreign students.” Likewise, science thrives on the free exchange of findings and methods, and ultimately of the researchers themselves, as noted by the German Council of Science and Humanities [9]. The European Union even defined the free movement of knowledge in Europe as the “fifth fundamental freedom”[2]. Similarly, the US National Science Foundation argues that “international high-skill migration is likely to have a positive effect on global incentives for human capital investment. It increases the opportunities for highly skilled workers both by providing the option to search for a job across borders and by encouraging the growth of new knowledge”[25]. Generally, due to globalization and rapidly increasing international competition, today’s scientific, social and ecological challenges can only be met on a global scale both in education and science, and are accompanied by political and economic interests. Thus, research on scientist’s migration and understanding it, play key roles in the future development of most computer science departments, research institutes, companies and nations, especially if fertility continues to decline globally [16]. But can we provide decision makers and analysts with statistical regularities of migration? Are there any statistical patterns

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1 United Nations Education, Scientific and Cultural Organization, Data extract (Paris, 2011), accessed on 19 April 2011 at: http://stats.uis.unesco.org/unesco/TableViewer

2 Council of the European Union (2008a), p. 5: “In order to become a truly modern and competitive economy, and building on the work carried out on the future of science and technology and on the modernization of universities, Member States and the EU must remove barriers to the free movement of knowledge by creating a ‘fifth freedom’ ...”
at all?

These questions were the seed that grew into the present report. On first sight, reasons to migrate are manifold and complex: political stability and freedom of science, family influences such as long distance relationships and oversea relatives, and personal preferences such as exploration, climate, improved career, better working conditions, among others. Despite this complex web of interactions, we show in this paper that the timing events of migration within different countries exhibit remarkable simple but strong and similar regularities. Specifically, we look at the distribution governing the data of researcher migration inferred from the web. Compiling the data in itself represents a significant advance in the field of quantitative analysis of migration patterns. Although, efforts to produce comparable and reliable statistics are underway, estimates of researcher flows are inexistent, outdated, or largely inconsistent, for most countries. Moreover, official (NSF, EU, DFG, etc.) and commercial (ISI, Springer, Google, AuthorMapper, ArnetMinder) records are often access restricted and especially not registered across researchers. On top of it, these information sources are often highly noisy. Luckily, bibliographic sites on the Internet such as DBLP are publicly accessible and contain data for millions of publications. Papers are written virtually everywhere in the scientific world, and the affiliations of authors tracked over time could be used as proxy for migration. Unfortunately, many if not most of the prominent bibliographic sites such as DBLP do not provide affiliation information. Instead, we have to infer this information. To do so, we extracted the geographical locations — the cities — for a few seed author-paper-pairs and then propagated them across the DBLP social network of more than one million authors and almost two million papers. We refer to this new dataset as **GeoDBLP**, DBLP augmented with geo-tags. GeoDBLP is the basis for our statistical analysis and has city-tags for most of the 5,033,018 paper-author-pairs in DBLP. Specifically, as partly shown in Fig. 1 we present the first strong regularities for researcher migration in computer science:

- **(R1)** A specific researcher’s propensity to migrate, that means to make the next move, follows a log-normal distribution. That is, researchers are generally not “memoryless” but have to care greatly about their next move. This is plausible due to the dominating early career researchers with non-permanent positions. This regularity of timing events is remarkably stable and similar within different continents and countries across the globe.

- **(R2)** The propensity to make \( k > 1 \) migrations, however, follows a
Figure 1: We infer from the WWW the first strong regularities of timing events in the migration of computer scientists. Due to the many early stage careers, with non-permanent contracts, a specific scientist’s propensity to make the next move follows a log-normal distribution (left). For larger numbers of moves, i.e., for senior scientists this turns into a gamma distribution due to permanent positions (left-middle); migration becomes memoryless. The circulation of expertise, i.e., the time until a researcher returns to the country of her first publication follows a gamma distribution (middle-right). Returning is also memoryless. The inter-city migration frequency distribution, however, follows a power-law (right). That is, cities with a high exchange of researchers will even exchange more researchers in the future. These regularities should have major implications on strategies for research across the world.

gamma distribution suggesting that migration at later career stages is “memoryless”. That is, researchers have to care less about their next move since the majority of positions are permanent in later career stages.

- Since jobs enter the market all the time, R1 and R2 together suggest that the job market can be treated as a Poisson-log-normal process.

- (R3) The brain circulation, i.e., the time until a researcher returns to the country of her first publication, follows a gamma distribution. That is, returning is also memoryless. Researchers cannot plan to return but rather have to pick up opportunities as they arrive.

- (R4) The inter-city migration frequency follows a power-law. That is, cities with a high exchange of researchers will exchange even more researchers in the future. So, investments into migration pay off.

- **Statistical patterns:** Link analysis of the author-migration graph can discover additional statistical patterns such as (SP1) migration sinks, sources and incubators, as well as (SP2) the hottest migration cities.
These results validate and go beyond migration models based on small case studies at a very large, transnational scale. Ultimately, they can provide forecasts of (re-)migration which can help decision makers who seek actively the migration and the return of their researchers to reach better decisions regarding the timing of their efforts.

Already Zipf [34] investigated inter-city migration. He analyzed so called gravity models. These models incorporated terms measuring the masses of each origin and destination and the distance between them and were calibrated statistically using log-linear regression techniques. Over the years, several modifications and alternatives have been postulated, see e.g. [6, 27] and the references in there. Steward [28] reviewed the Poisson-log-normal model for bibliometric/scientometric distributions, i.e., to characterize the productivity of scientists. Sums of Poisson processes and other Poisson regression models as well as ordinary-least-squares have actually a long tradition within migration research, see [29, 24] for recent overviews. All of these approaches, however, have considered small scale data only [24] and have not considered researcher migration in computer science. To the best of our knowledge, the only large-scale migration study was recently presented by Zagheni and Weber [32], analyzing a large-scale e-mail datasets to estimate international migration rates, but not specific to computer scientists. Moreover, they have not presented any statistical regularities nor dealt with missing information. Indeed, as already mentioned, other collective human activities have been the subject of extensive and large-scale planetary mining. Prominent examples are mobility patterns drawn from communication [18, 13] and web services [22], as well as mining blog dynamics [10] and social ties [31]. Our methods and findings complement these results by highlighting the value of using the World Wide Web together with data mining to deal with missing information as a world-wide lens onto researcher migration, enabling the analyst to develop global strategies for research migration and to inform the public debate.

We proceed as follows. We start by discussing the harvesting of our data in detail. Then, we will describe how we made use of multi-label propagation to fill in missing information. Before concluding, we will present our statistical migration models and patterns.

2 Mining the Data from the Web

Bibliographic sites on the Internet such as DBLP are publicly accessible and contain millions of data records on publications. Papers are written
Figure 2: Statistics of the DBLP dump: The number of publications (2a) and authors (2b) per year. As one can see, DBLP has been growing constantly over the past decades from 1970 until 2010.

virtually everywhere in the scientific world, and the affiliations of authors tracked over time could be used as proxy for migration. Unfortunately, many if not most of the prominent bibliographic sites such as DBLP do not provide affiliation information. Instead we have to infer this information. In this section, we will detail the mining of our data. The goal was to tag every of the over 5 million author-paper-pairs in our database with an affiliation. The data collection method utilized an open-source information extraction methodology, namely DBLP, ACM Digital Library, Google’s Geocoding API and large-scale multi-label propagation.

2.1 Harvesting the Data

We used DBLP as a starting point. DBLP is a large index of computer science publications that also offers a manual best-effort entity disambiguation. We used an XML-dump from February 2012 which contained 1,894,758 publications written by 1,080,958 authors. Fig. 2 shows the number of publications and authors per year from this dump. As one can see, the number of computer scientists as well as the productivity have been growing enormously over the past decades. Unfortunately, DBLP does not provide affiliation information for the authors over the years. This information, however, is required in order to develop migration models using author affiliations as proxy. Specifically, we aim to infer geo-tags of the more than 5 million unknown author-paper-pairs.

Luckily, there are other information sources on the web that contain such

http://dblp.uni-trier.de/
information. One of these systems is the ACM Digital Library. Unfortunately, ACM DL does not allow a full download of the data. Consequently, we retrieved the affiliation information of only a few papers from ACM DL which we then had to match with our DBLP dump. This resulted in affiliation information for 479,258 of all author-paper-pairs. In order to fill in the missing information, we resorted to data mining techniques. To do so, however, we have to be a little bit more careful. First, the names of the affiliations in ACM DL are not in canonical form which results in a very large set of affiliation candidates. More precisely, the DBLP dump enhanced with the initial affiliations from ACM DL contained 159,068 different affiliation names in total. Secondly, although we have now partial affiliation information, we still lack exact geo-information of the organizations to identify cities, countries, and continents. Many of the affiliation names may contain a reference to the city or country but these pieces of information are not trivial to extract from the raw strings. Additionally, we want to have latitude and longitude values to enable further analysis and visualization. For example, latitude and longitude data would allow one to calculate exact distances between collaborators. This geo-location issue can easily be resolved using Google’s Geocoding API. Just querying the API using the retrieved affiliation names resulted in geo-locations for 117,942 of the 159,068 strings. The remaining gap primarily rises from the fact that the Google API does not find geo-locations for all the retrieved affiliation strings. This is essentially because the strings contain information not related to the geo-location such as departments, e-mail addresses, among others. In any case, as our empirical results will show, this resulted in enough information to propagate the seed affiliations and in turn the geo-locations across the DBLP network of authors and papers.

2.2 Inferring Missing Data

Before we infer the missing author-paper-pairs, we revise our obtained affiliation data. To further increase the quality of our harvested affiliations, we hypothesized that there are actually not that many relevant organizations in Computer Science and these names need to get de-duplicated. This hypothesis is confirmed by services such as MS Academic Search which currently lists only 13,276 organizations compared to our 150k+ names. Since, we now have the geo-locations for many of the affiliation strings, we can use

4 http://dl.acm.org/
5 https://developers.google.com/maps/documentation/geocoding/
6 http://academic.research.microsoft.com/
Figure 3: Example database.

| Id | A | Y  | Aff | Aff* |
|----|---|----|-----|------|
| 1  | 1 | 2000 | g   | g    |
| 2  | 2 | 2000 | d   | d    |
| 3  | 2 | 2001 | r   | r    |
| 4  | 1,2 | 2002 | ?,,r | r,r  |
| 5  | 1 | 2002 | ?   | r    |
| 6  | 2 | 2003 | r   | r    |
| 7  | 1 | 2004 | r   | r    |
| 8  | 2 | 2004 | g   | g    |

This information for a simple entity resolution which helps resolving this issue. More precisely, we clustered affiliations together for which the retrieved city coincide resulting in 4,254 distinct cities.

The city-based entity resolution resulted in a dataset with approximately 10% of the author-paper-pairs being geo-tagged. Based on these known geo-locations, we will now fill in the missing ones. To do so, we essentially employ Label Propagation \cite{4,33} (LP), a semi-supervised learning algorithm, to propagate the known cities to the unknown author-paper-pairs based on the similarity between the pairs. LP works on a graph based formulation of the problem and propagates node labels along the edges. We define the LP graph as an undirected graph $G = (V,E)$ with nodes $V$ and edges $E$. We have a node in $V$ for every author-paper-pair that we want to label with a city. Every edge $e_{ij} \in E$ between two nodes $i$ and $j$ contains a weight $w_{ij}$ that is proportional to the similarity of the nodes.

We will now explain in detail when two nodes are connected by an edge and how the weight $w_{ij}$ for that edge is set. Intuitively, the weight of an edge is proportional to the similarity of the nodes and we define the similarity of two nodes based on relations such as co-authorship between the authors associated with the nodes. Only those nodes are connected via an edge where $w_{ij} > 0$. Specifically, in order to define the edges, we considered the following functions over the set of nodes that return facts about the nodes: $\text{author}(i)$, $\text{paper}(i)$, and $\text{year}(i)$. For example, $\text{author}(i)$ essentially “returns” the author of an author-paper node. Based on these functions, we can now define logic based rules that add a rule-specific weight $\lambda_k$ to every matching edge $e_{ij}$. Initially, we set all weights $w_{ij}$ to zero. The first rule,

$$w_{ij} = \lambda_1 \text{ if } \text{paper}(i) = \text{paper}(j)$$

\footnote{Indeed, this approach does not distinguishing multiple affiliations per cities such as MIT and Harvard. However, it is simple and effective, and — as our empirical results show — the resolution is sufficient to establish strong regularities in the timing events.}
Figure 4: City Propagation: Missing geo-tags from the example database (see Fig. 3) are estimated by propagating the known cities/geo-locations across the network of authors and papers. The graph for propagating the information (a) is constructed as follows. For each author $A$ and paper $Id$ there is a node. Two nodes are connected if they are written by the same author in the same or subsequent years or if two researchers co-author them. The colors of nodes indicate known cities and white nodes indicate unknown locations. As one can see (b), this significantly improves the content of our database. The number of geo-tagged author-paper-pairs increased significantly, showing the publication activities across the world. (Best viewed in color)

adds a weight between two nodes if the nodes belong to two authors that co-author the paper associated with nodes $i$ and $j$. The second rule,

$$w_{ij} = \lambda_2 \text{ if } \text{author}(i) = \text{author}(j) \land \text{year}(i) = \text{year}(j)$$

adds a weight whenever two nodes corresponds to different publications by the same author in the same year. Finally,

$$w_{ij} = \lambda_3 \text{ if } \text{author}(i) = \text{author}(j) \land \text{year}(i) = \text{year}(j + 1)$$

fires when the nodes belong to two publications of the same author but written in subsequent years. This construction process is depicted in Fig. 4a for the example publication database in Fig. 3. The example database is missing the affiliation information for papers 4 and 5 which is denoted by the “?” in the “Aff”-column.

Based on the constructed graph, we can now build a symmetric $(n \times n)$ similarity matrix $W$ that is used as input to LP. Essentially, LP performs the following matrix-matrix-multiplication until convergence: $Y^{t+1} = W \cdot Y^t$, where $Y^t$ is the labels matrix. In $Y^t$, row $i$ corresponds to a distribution over the possible labels for a node $i$. In $Y^0$, we set a cell $Y_{ij}$ to 1 if we know
that node $i$ has label $j$. All other cells are set to 0. After every iteration, a push-back phase clamps the rows of the known nodes in $Y^t$ to their original distribution as in $Y^0$. This operation is performed until convergence or a maximum number of iterations has been reached. At convergence, the labels of the unknown nodes are read off the labels matrix, i.e. the label of node $i$ is given by $y_i = \arg \max_{0 \leq j \leq n-1} Y_{ij}$. In our context, we call this City Propagation (CP), that is we run LP on the graph, constructed based on logical rules, to get a distribution over the possible cities for every unlabeled node.

Although the implementation of CP is just a simple matrix-matrix-multiplication, this already becomes challenging with $n$ around five million. While the similarity matrix $W$ is very sparse, the labels matrix $Y$ becomes denser with every iteration. Resulting in an almost pure dense matrix if the graph was completely connected. With $4k+$ labels, the labels matrix already requires more than 160GB with 64bit float numbers. Fortunately, one can easily split the labels matrix into chunks and do the multiplications separately. However, we still require an efficient implementation for multiplying a sparse-matrix with a dense-matrix. We implemented CP with the help of LAMA\footnote{http://www.libama.org/}, a very efficient linear algebra library. We ran CP for 100 iterations and determined the maximizing label for every unlabeled node. We used $\lambda_1 = 1$, $\lambda_2 = 3$, and $\lambda_3 = 2$ as weights. They had been found using a grid search on a small subset of the data. After running CP, GeoDBLP contains 4,318,206 geo-tagged author-paper-pairs.

Looking at the last column in our running example in Fig.\ref{running-example} we see that CP fills the unknown cities, i.e. labels the missing affiliations for papers 4 and 5. The effect of running CP on our initial dataset is shown in Fig.\ref{productivity}. One can see that the worldwide productivity increases significantly. The
Figure 6: Individual propensities and (inter-)arrival times illustrated for the two researchers A1 and A2 of our running example. A researchers’s propensity (shown only for A2) is her probability of migrating. The $k$th move propensities are her probability of making $k > 1$ moves. This should not be confused with the (inter-)arrival times of the job market, i.e., of the overall Poisson process. Every node denotes a publication and the node colors denote different affiliations, i.e. there are three affiliations here: green, red, and blue. From this, we can read off migration: A1 moves from green to red, A2 moves from blue to red and from red to green. (Best viewed in color)

Geo-locations of publications alone can already reveal interesting insights such as the most productive research cities in the world, see Fig. 5. The main focus of the paper, however, is the timing of migration.

3 Sketching Migration

Unfortunately, we cannot directly observe the event of transfer from one residential location resp. institution to another by a researcher. Instead, we use the affiliations mentioned in her publication record as a proxy. Nevertheless, even after city propagation, this list may still be noisy and, hence, does not provide the timing information easily. To illustrate this, an author may very well move to a new affiliation and publish a paper with her old affiliation because the work was done while being with the old affiliation. Therefore we considered migration sketches only. Intuitively, a sketch captures only the main stations of her researcher career.

More formally, we define a migration sketch as the set of the unique affiliations of an author ordered by the first appearance in the list of publications. For instance, in our running example, we have [2000 : Aff$_g$, 2002 : Aff$_r$] for author A$_1$ and [2000 : Aff$_b$, 2001 : Aff$_r$, 2004 : Aff$_g$] for author A$_2$. That
is, Author $A_1$ has two different affiliations, $Aff_g$ appearing in 2000 the first time and the first publication with $Aff_r$ in 2002. Of course, this approach has the drawback that we can not capture if a person returns to an earlier affiliation after several years. Finally, we dropped implausible entries from the resulting sketch database. For instance, we dropped sketches with more than ten affiliations. It is very unlikely that a single person has moved more than ten times and these sketches should rather be attributed to an insufficient entity disambiguation. Having the migration sketches at hand, we can now define a migration/move of a researcher as the event of transfer from one residential location to another by a researcher in her migration sketch. Fig. 6 shows the moves of author $A_2$ in our running example. In total, we found 310,282 migrations in GeoDBLP. The number of moves per year is shown in Fig. 7a and it shows that the number of moves increases with the years super-linearly. However, when we normalize the numbers of moves by the number of scientists, we see roughly a linear slop, see Fig. 7b. With this information at hand, we can now start to investigate the statistical properties of researcher migration.

### 4 Regularities of Timing Events

As mentioned above, reasons to migrate are manifold. Despite this complex web of interactions, we now show that researcher migration shows remarkably simple but strong global regularities in the timing.
Figure 8: Migration propensity. The individual migration propensity is best fitted by a log-normal distribution. That is, although jobs enter the market all the time, researchers are generally not “memoryless” but have to care greatly about their next move, and this timing is a multiplicative function of many independently distributed factors.

4.1 (R1) Migration Propensity is Log-Normal

Given the migration sketches, we can now read off timing information. First, we estimate the propensity to transfer to a new residential location or institution across scientists. To do so, let $T_i^j$ be the point in time when a researcher moves from one location to the next one. Let $t_i^j$ be the time between the $T_i^j$ and $T_i^{j-1}$. We call $t_i^j$, i.e. the time between two moves, the migration propensity (see Fig. 6). It reflects the bias of researchers to stay for a specific amount of time until moving on.

Fig. 8 shows the best fitting distribution in terms of log-likelihood and KL-divergence among various distributions such as log-normal, gamma, exponential, inverse-Gauss, and power-law using maximum likelihood estimation for the parameters. It is a log-normal distribution $[1, 28]$. That is, the log of the propensity is normal distribution with density

$$\ln(x) = \frac{1}{x\sqrt{2\pi}\sigma^2} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}. \quad (1)$$

The parameters $\mu$ and $\sigma^2 > 0$ are the mean and the standard deviation of the variable’s natural logarithm. This is a plausible model due to Gibrat’s “law of proportionate effects” $[26]$. The underlying propensity to move is a multiplicative function of many independently distributed factors, such as motivation, open positions, short-term contracts, among others. That is, such factors do not add together but are multiplied together, as a weakness in any one factor reduces the effects of all the other factors. That this leads to log-normality can be seen as follows. Recall that, by the law of large
numbers, the sum of independent random variables becomes a normal distribution regardless of the distribution of the individuals. Since log-normal random variables are transformed to normal random variables by taking the logarithm, when random variables are multiplied, as the sample size increases, the distribution of the product becomes a log-normal distribution regardless of the distribution of the individuals. This might explain why the log-normal distribution is one of the most frequently observed distributions in nature and describes a large number of physical, biological and even sociological phenomena [20]. For example, variations in animal and plant species just as in incomes appear log-normal, i.e. normal when presented as a function of logarithm of the variable. Dose-response relations just as grain sizes from grinding processes show log-normal distributions. Moreover, although the overall job market is a Poisson process, as we will show later on, it is good that the migration propensity is not exponential. It is precisely this non-Poisson that makes it possible to make predictions based on past observations. Since positions are occupied in a rather regularly way, upon taking a position it is very unlikely that you will take up another position soon. In the Poisson case, which is the dividing case between clustered and regular processes, you should be indifferent to the time since the last position.

Based on our data, a computer scientist stays on average 5 years at a place. Thus headhunters, for example, should approach young potentials in their fourth year. On the other hand, one should probably reconsider the common practice, e.g. in the EU and the US, of having projects lasting only
Figure 10: Zooming in on migration propensities: across the most productive
countries they are best fitted by log-normal. Actually, the representative
countries USA, China, Germany, UK, Australia, Singapore, Canada, France,
Italy, and Hong Kong are shown. Except for China, all are best fitted by log-
normal. China’s migration propensity follows a gamma distribution. (Best
viewed in color)

three years to fill in the gap. More importantly, the log-normality of the
propensity can be found across continents and countries of the world, see
Figs. 9 and 10, where we considered only moves originating from a continent
resp. country. Timing research careers has clearly no cultural boundaries!

4.2 (R2) k-th Move Propensities are Gamma

Fig. 11 shows the best fitting distribution in terms of log-likelihood and
KL-divergence among various distributions such as log-normal, gamma, ex-
ponential, inverse-Gauss, and power-law using maximum likelihood estima-
tion for the propensity to make \( k > 1 \) migrations. More precisely, the \( k \)th
move propensity for an author \( A_i \) is defined as \( s_{k}^{i} = \sum_{j=1}^{k} t_{ij} \). It is a gamma
distribution,

\[
g_{\alpha}(x) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} e^{-\frac{x}{\theta}},
\]

with shape \( k > 0 \), scale \( \theta > 0 \), and \( \Gamma(k) = \int_0^\infty s^{k-1}e^{-s}ds \), suggesting
that migration at later career stages is “memoryless”. Why? Well, this
follows from the theory of Poisson processes. For Poisson processes, we know
that the inter-arrival times are independent and obey an exponential form,
\( \text{exp}(t) = \lambda e^{-\lambda t} \), where \( \lambda > 0 \) is called the intensity rate. The important
consequence of this is that the distribution of \( t \) conditioned on \( \{ t > s \} \) is
Figure 11: $k$th move propensities. The $k$th move propensities (left-right, top-down with $k = 2, 3, 4, 5$) are best fitted by gamma distributions. This suggests that migration at later career stages is “memoryless”, i.e., it follows an exponential distribution.

again exponential. That is, the remaining time after we have not moved to a new position at time $s$ has the same distribution as the original time $t$, i.e., it is memoryless. Moreover, we know that the time until the $k$-th move — the $k$th move propensity — has a gamma distribution; it is the sum of the first $k$ propensities of senior researchers. So, the propensities for the next move turn exponential for later career stages. This is plausible, since early career researchers have seldom taken many positions and, hence, we consider here rather senior researchers, which typically have permanent positions; they do not have to greatly care about their moves. As a consequence, e.g. competing universities have to top the current position of a senior researcher if they want to hire her.

4.3 Job Market is Poisson Log-Normal

So far, we have shown that the propensities, let us call it $\delta$, to move to a new residential location resp. institute follow a log-normal distribution. We have also shown that $k$th move propensities follow a gamma distribution, suggesting that propensities of senior researchers are exponential. The latter fact already points towards a Poisson model. More precisely, we postulate
that the job market follows a Poisson-log-normal model [28]. That is, given a specific scientist’s migration propensity $\delta$, her probability of migrating follows a simple Poisson model: $\text{pos}(k) = \frac{1}{k!} \cdot (\delta^k e^{-\delta})$, for $k = 1, 2, 3, 4, \ldots$. Thus the rate of the Poisson process is a function of the migration propensity. The number of migrations for all scientists having the same $\delta$ value will follow the same Poisson process. Moreover, since the sum of Poisson processes is again a Poisson process, we know that every finite sample of scientists with $\delta$s drawn from a log-normal is again following a Poisson process. Thus, assuming the job market to be a Poisson model is plausible. It actually tells us that the arrival of job openings is memoryless. Open positions should always be announced as they come. On a global scale, there is no point in waiting to announce them. There are always researchers ready to take it. And, individual researchers can always look out for new job openings.

4.4 (R3) Brain Circulation is gamma

Brain circulation, or more widely known as brain drain, is the term generically used to describe the mobility of high-level personnel. It is an emerging global phenomenon of significant proportion as it affects the socio-economic and socio-cultural progress of a society and a nation, and the world. Here, we defined it as the time until a researcher returns to the country of her first publication. Only 29,398 out of 193,986 (15%) mobile researchers, i.e., researchers that have moved at least once, and out of a total of 1,080,958 (3%) researchers returned to their roots (in terms of publications). As to be expected from the statistical regularity for $k$th move propensities, it also follows a gamma distribution, as shown in Fig. 12(left). Since a gamma distribution is the sum of exponential distributions, returning is memory less.
Researchers cannot plan to return to their roots but rather have to pick up opportunities as they arrive.

5 Link Analysis of Migration

Link analysis techniques provide an interesting alternative view on our migration data. That is, we view migration as a graph where nodes are cities and directed edges are migration links between cities. More formally, the author-migration graph is a directed graph $G = (V, E)$ where each vertex $v \in V$ corresponds to a city in our database. There is an edge $e \in E$ from vertex $v_1$ to vertex $v_2$ iff there is an author who has moved from an affiliation in city $v_1$ to $v_2$.

5.1 (R4) Inter-City Migration is Power-Law

Triggered by Zipf’s early work and other recent work on inter-city migration \[34, 6, 27\], we investigated the frequency of inter-city researcher migration. The frequency of a connection between two cities can be seen as knowledge exchange rate between the cities. It is a kind of knowledge flow because one can assume that researchers take their acquired knowledge to next affiliation. If one looks at the author-movement-graph as a traffic network, high frequent connections corresponds to highly used streets. Fig. 12(right) shows the distribution with a fitted power-law using maximum likelihood estimation. A likelihood comparison to other distributions such as log-normal and gamma revealed that a power-law is the best fit. Thus, there are only few pairs of cities with frequent researcher exchange and many low-frequent pairs. However, cities with a high exchange of researchers will exchange even more researchers in the future. Investments into migration pay off.

5.2 (SP 1) Migration Authorities and Hubs

Next, we are interested in mining the migration authorities and hubs. To do so, we use Kleinberg’s HITS-algorithm \[14\] on the author-migration graph. The algorithm is an iterative power method and returns two scores for every node in the graph, which are known as hubs and authorities. This terminology arises from the web where hubs and authorities represent websites. Hubs are pages with many outlinks and authorities are pages with many inlinks.

In our context, inlinks correspond to researchers arriving in a city — she picks up a new position — whereas an outlink corresponds to a researcher
Figure 13: (left and middle) Running HITS on the directed author-migration graph reveals sending, receiving, and incubator countries. Shown are representative cities in North America (left) and Europe (middle). The size of spikes encodes the value of the “authority” (blue) and “hub” (red) scores. Incubator cities have well balanced scores. As one can see, the European cities rather send researchers. US cities at the east cost are incubators, and west cost cities receive researchers. (right) Top 25 migration cities ranked by PageRank. Compared to the productivity map in Fig. 5, one can see that productive cities are not necessarily cities with high migration flux. (Best viewed in color)

leaving a city — e.g. funding ends. Hubs can be seen as “sending” cities, i.e., they send out researcher across the world. On the other hand, authorities can either be cities where people want to stay and tenure positions are available or where people drop out of research, i.e. heading to industry. They are “receiving” cities. Moreover, if we make the assumption that only high-quality students and scientists get new positions, one may view sending cities as institutions producing high profile scientists but also cannot hold all of them, due to restricted capacities or low attractiveness. In contrast, receiving cities might have the capacities and reputation to hold many migrating researchers or highly interesting industrial jobs are close by. Cities having generally high scores are incubators: they attract a lot of migration but also send them to other places.

Fig. 13 shows the sending and receiving scores for cities in the representative regions of the US and Europe. The US clearly shows an East-coast/west-coast movement. The east coast aggregates many sending cities while receiving cities dominate the west coast. This is plausible. Not only are there many highly productive universities on the west coast, see also Fig. 5 but labor market for high-tech workers in, say, the Bay Area is the strongest in a decade. Thousands of new positions are being offered by small startups and established tech giants. However, one should view many of the east-coast cities as incubators since they have high overall scores. The scores

9Rendered with WebGL Globe (see http://www.chromeexperiments.com/globe).
of European cities are typically much smaller, see again Fig. [13(right)]. Europe is dominated by sending cities. Few exceptions are Berlin, Munich, Stockholm, and Zurich. The largest receiving city in the world is Singapore. This is also plausible. The city-state is known for its remarkable investment in research in recent years, as e.g. noted by a recent Nature Editorial [7].

In contrast, the largest sending city by far is Beijing. This is also plausible. There has been upsurge in Chinese emigration to Western countries since the mid-first decade of the 21st century [15]. In 2007, China became the biggest worldwide contributor of emigrants.

5.3 (SP2) Moving Cities

Following up on HITS, we also computed PageRank on the author-migration graph. Compared to HITS, PageRank [23] produces only a single score: a page is informative or important if other important pages point to it. More formally, by converting a graph to an ergodic Markov chain, the PageRank of a node $v$ is the (limit) stationary probability that a random walker is at $v$.

In the context of migration, this has a natural and very appealing analogy. The PageRank computes the (limit) stationary probability that a random migrator is at a city.

To compute the MigrationRank of a city, the author-migration graph is transformed into the PageRank-matrix on which a power method is applied to obtain the PageRank-vector, containing a score for every node in the graph. The transformed matrix also contains the stochastic adjustment identical to the random surfer in the original work. That is, a researcher can always migrate from one affiliation to another affiliation, even if no one else did so before. Fig. [13(right)] shows the top 25 cities in the world according to the MigrationRank. Compared to the productive map in Fig. [5], one can clearly see many similarities but although notable differences. The US is not only productive but thrives on migration. Vancouver, B.C., is among the top 25 when it comes to migration but not when it comes to productivity. Generally, productivity does not imply a high migration rank. Beijing, however, is top in both when it comes to productivity and migration. Singapore is higher ranked for migration than for productivity. European cities seem to also thrive on migration more than on productivity. At least there are much more cities in the top 25 than for productivity. However, compared to the US, they are less clustered together.

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10 The recent economic pressure mounting on research communities in Singapore and around the world is not well captured in our data, which lasts to 2010 only.
Figure 14: Prototypical migration career of a computer scientist according to the WWW. Shown are the mean values for \((k\text{th move})\) propensities and brain circulation. That is, on average a scientist makes the next move after 5 years (green). Making two moves takes on average 8 years (red), and three moves 11 years (red). She moves back to her roots, if at all, after 8 years (blue). (Best viewed in color)

6 Conclusions

International mobility among researchers not only benefits the individual development of scientists, but also creates opportunities for intellectually productive encounters, enriching science in its entirety, preparing it for the global scientific challenges lying ahead. Moreover, mobile scientists act as ambassadors for their home country and, after their return, also for their former host country, giving mobility a culture-political dimension. So far, however, no statistical regularities have been established for the timing of migration. In this paper, we have established the first set of statistical regularities and patterns for research migration stemming from inferring and analyzing a large-scale, geo-tagged dataset from the web representing the migration of all researchers listed in DBLP. The methods and findings highlight the value of using the World Wide Web together with data mining to fill in missing data as a world-wide lens onto research migration.

Specifically, we described the creation of GeoDBLP that, in contrast to existing migration research, involved propagation of only few seed locations across bibliographic data, namely the DBLP network of authors and papers. The result was a database of over 5 million unique author-paper-pairs mostly labeled with geo-tags, which was used for a detailed statistical analysis. The statistical regularities and patterns discovered are encouraging: we could estimate statistical regularities for migration propensities that align well but actually go beyond knowledge in the migration and scientometric literature — typically concluded from small-scale, unregistered data only — and establish for the first time that there are no cultural boundaries for
the timing events underlying migration. The statistical regularity remains similar no matter what country you are looking at. Thus, moving on to a new position is a common pattern in terms of timing across different countries from the US to China over Germany, and Australia and independent of geography, ideology, politics or religion. The resulting prototypical migration career is sketched in Fig. [14]. This is interesting, since, if nations want to get back their high-level personnel, they have to do that just before the second move, on average in the 7th year. Otherwise, it is likely that the high-level personnel does not come back anymore. And recall that only 3% of all scientists actually return. If you miss this opportunity, you will have to invest much more, since moving in later stages in a career is memoryless; there is no pressure for high-level personnel to move. On average scientists move every 5 years. This high value is due to dominance of researchers in early academic career stages. For senior scientists, that are the minority, this turns into a gamma distribution. For instance, we make two moves within 8 years on average, while making three moves takes on average 11 years. Analyzing the author-migration graph reveals for instance that China is the largest migration hub in the world, whereas Singapore is the largest migration authority. Generally, the east cost of the US receives and sends out researchers; the east cost is an incubator. In contrast, the west coast of the US is large migration authority, probably due to strong new economy and better climate. People have had this suspicion but we are showing on a very large scale that this insights go beyond folklore.

In general, our findings suggest that the WWW, together with data mining to deal with missing information, may complement existing migration data sources, resolve inconsistencies arising from different definitions of migration, and provide new and rich information on migration patterns of computer scientists. However, a lot remains to be done. One should monitor migration over time and validate gravity models for international migration. One should also investigate the distribution over distances traveled when migrating. It is certainly more complex and most likely follows a mixtures of distributions. Initial results show that there are several modes, indicating that there are cultural boundaries. Other interesting avenues for future work are geographical topic models to discover research trends across the world and to realize expert finding systems that know where the experts are at any time. The most promising direction is to extend our results beyond computer science.

Nevertheless, our results are an encouraging sign that harvesting and inferring data from the web at large-scale may give fresh impetus to demographic research; we have only started to look through the world-wide web
lens onto it.

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