Institutional Hierarchy and Asymmetry in Brazilian Computer Science Faculty Hiring Network

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Abstract. *Scientific academia is often shaped by invisible hierarchies that influence career trajectories and institutional prestige. This study examines the prestige and faculty migration of professors affiliated with Brazilian Graduate Programs in Computer Science from 60 institutions. We identify the relationship between the institution's prestige, hiring patterns, and scientific productivity metrics, tracking the migration of 1084 Professors using data from the 2022 CAPES Graduate Programs evaluation report, Lattes curriculum, and OpenAlex profiles. Our analysis reveals an extreme asymmetry: 90% of professors originate from just 20% of institutions, with only 2.31% professors being hired by more prestigious institutions than their doctorate ones.*

1. Introduction

The Science of Science (SciSci) is a transdisciplinary approach to investigate the structure of science, applying quantitative and computational methods to study the mechanisms underlying scientific discovery, collaboration and impact [Fortunato et al. 2018]. Recent advances in the field leverage the availability of bibliographic data in different large-scale databases, namely OpenAlex [Priem et al. 2022], Web of Science, and Scopus, with investigations ranging from the discovery of hierarchical structures in academia [Wapman et al. 2022] to the mobility of scientists [FitzGerald et al. 2023, Murray et al. 2023, Sugimoto et al. 2017] and predictions of productivity [Acuna et al. 2012, Dong et al. 2016, Sinatra et al. 2016].

One aspect of scientific ecosystems is the mobility of researchers, especially the transition from doctoral training to faculty positions. In [FitzGerald et al. 2023], this transition is examined within the mathematics community, where the authors build a network from mathematicians and their Ph.D. supervisors. The network nodes are math departments, and weighted directed links connect the department where researchers obtained their Ph.D. to where they became faculty. The analysis reveals that the graduate faculty transition rate is decaying over time, showing that it is becoming harder for Ph.D. holders to become faculty, even for historically well-placed departments. The main factors influencing this transition are gender, the hiring year, and the number of students advised by the Ph.D. advisor. Recently, [Wapman et al. 2022] investigated the career mobility of tenured or tenured faculty employed in the years 2011–2020 at 368 PhD-granting universities in the US, annotating their doctoral and faculty institutions. They built networks whose nodes are institutions, and directed links go from the institution where the professor got their doctorate to where they were hired as faculty. They found that 80% of all domestically trained faculty were trained in just 20.4% universities. In addition, people are usually hired in lower-rank institutions compared to where they got a Ph.D.

While these studies provide insights into the US academic landscape, the dynamics of faculty hiring and prestige in other national contexts remain relatively unexplored. In Brazil, the Coordination for the Improvement of Higher Education Personnel (CAPES) plays a central role in evaluating graduate programs [Capes 2024]. CAPES conducts quadrennial evaluations, assigning scores from 1 to 7 based on various criteria, including scholarly output, student enrollment, and successful thesis defenses. Scores of 1 and 2 indicate programs unfit to operate, 3 allows for Master's programs, 4 to 7 permit PhD programs, and 6 and 7 denote programs of excellence. This structured evaluation system provides a unique opportunity to examine the interplay between institutional prestige, hiring patterns, and research productivity.

This paper investigates the prestige hierarchies and asymmetries within the Brazilian Graduate Programs in Computer Science (BRGPCS) hiring network. We construct a directed hiring network encompassing $n = 1,084$ professors across 60 BRGPCS institutions, drawing data from three primary sources: the 2022 CAPES evaluation report, Lattes curriculum (the Brazilian national researcher database), and OpenAlex profiles. Notably, OpenAlex [Priem et al. 2022], a fully open catalog of the global research system, encompassing millions of entities (authors, works, institutions, topics) interconnected by billions of relationships, and its well-documented API, facilitates in-depth exploration of our research questions, supplementing the structured data from CAPES and Lattes.

Our study is motivated by three research questions. The first (RQ1) is how unequal is the distribution of faculty production and hiring within the BRGPCS network? Can we identify systemic patterns of inequality and self-reinforcement among elite institutions? The second (RQ2) asks if a significant prestige hierarchy does exist within the BRGPCS network, and how does its steepness compare to established patterns (such as in US academia)? And the third (RQ3) ask how strongly does institutional prestige, as determined by network analysis, correlate with established scientific productivity indicators, such as CAPES scores and bibliometric measures?

To address these questions, we employ a combination of quantitative methods, including the calculation of Gini coefficients of inequality, hierarchical violation rates, and the application of the SpringRank algorithm [Bacco et al. 2018] for network analysis, inspired by [Wapman et al. 2022] and [Clauset et al. 2015], to properly rank institutions based on their hires and production of scientists.

The contributions of this work are a comprehensive analysis of the BRGPCS faculty hiring network, quantifying the extent of inequality in faculty production and hiring. By evaluating the existence and characteristics of a prestige hierarchy within the Brazilian context, we offer a comparative perspective to studies focused on the US system. We also investigate the relationship between network-derived prestige and traditional measures of scientific productivity, shedding light on the potential for prestige to influence evaluation metrics. Finally, we demonstrate the utility of combining data from diverse sources (CAPES, Lattes, and OpenAlex) for studying the dynamics of national academic systems, highlighting how this can impact scientific development in countries outside the usual US-Europe axis.

Our analysis reveals a highly unequal distribution of faculty production within the BRGPCS, with a striking 90% of professors originating from just 20% of the institutions, reflected in a Gini coefficient of $G = 0.81$. This pronounced asymmetry persists even after accounting for institutional age and the number of graduate programs ($G = 0.74 - 0.79$). Furthermore, we find evidence of a steep prestige hierarchy, where upward mobility is exceptionally limited: only 2.31% of hires represent movement to a more prestigious institution than the professor's doctoral origin, a rate significantly lower than the 5-23% observed in US-based studies [Wapman et al. 2022, Clauset et al. 2015].

2. Data and Methodology

This study investigates faculty production inequality and prestige hierarchies within BRGPCS. We frame this investigation as a network analysis problem, where institutions are represented as nodes and faculty hiring patterns are represented as directed, weighted edges. Our analysis is based on a comprehensive dataset constructed from three primary sources: the 2022 CAPES Evaluation Report, Lattes curricula, and OpenAlex. We detail the data collection, processing, and analysis methods below.

2.1. Data Collection

We collected the faculty record of 1,511 professors hired as faculty in at least one Brazilian Graduate Program in Computer Science in 2022. To be eligible to participate in the study, one must have at least a doctorate degree in order to qualify as a supervisor. The list of professors comes from the 2022 CAPES Evaluation Report of Brazilian Graduate Programs available at Sucupira[1], serving as the primary source for the identification of affiliated professors. The list of professors was then cross-referenced with their Lattes curriculum[2], extracting each professor's doctorate and current faculty institution. Only professors from graduate programs with CAPES score between 3 and 7 are included, ensuring alignment with nationally recognized quality standards. The starting year and the CAPES score for each Brazilian Graduate Program in Computer Science were also recorded in the CAPES Evaluation Report. In instances where institutions maintained multiple Graduate Programs in Computer Science, the oldest program was assumed as the reference year, and a mean CAPES score was calculated, weighted by the number of professors within each graduate program.

Using the list of institutions and professors compiled from the CAPES and Lattes databases, we also retrieved from OpenAlex the academic profiles of professors through its public API[3]. The extracted data included the institution's full name and acronym and the list of works published by the institution's faculty affiliated with Computer Science GPs. This list of works was used to calculate scientific productivity metrics, such as the number of papers, the h index and the $i10$ index, treating the sampled faculty as a group for calculations. To maintain data quality, only journal articles and conference papers published up to 2022 were included, excluding works categorized as paratexts or retracted. We also annotated, for each sampled institution, the number of professors trained outside Brazil to calculate international hiring rates, but internationally trained professors were removed from the mobility network. Although the initial data included 1,511 professors,

[1]Available at: https://sucupira.capes.gov.br/sucupira/. Accessed on 15/05/2025.
[2]Available at: https://lattes.cnpq.br/. Accessed on 12/05/2025.
[3]Available at: https://docs.openalex.org/. Accessed on 12/05/2025.

only 1,084 (72%) remained in the final sample, as eligibility required earning a doctorate from and holding a faculty position at a Brazilian institution, keeping the focus on domestic training. The final dataset consists of $n = 1,084$ professors affiliated with Brazilian Graduate Programs in Computer Science from 60 institutions.

2.2. Network Construction and Analysis

A graph $G(V, E)$ contains $N = |V|$ vertices (nodes) and $L = |E|$ edges (links), usually represented by an adjacency matrix A_{ij}, with $A_{ij} = 1$ when nodes i and j are connected and $A_{ij} = 0$ otherwise [Barabási and Pósfai 2016]. For digraphs (directed graphs), the source and target nodes have distinct roles, and link directions matter. One might quantify the number of links, known as node degree, that arrive k_i^{in} and leave k_i^{out} node i, as follows:

$$k_i^{in} = \sum_{j=1}^{N} A_{ij}, \quad k_i^{out} = \sum_{j=1}^{N} A_{ji}. \tag{1}$$

Node strength is a more general concept that considers the total weight incident to a node:

$$f_i^{in} = \sum_{j=1}^{N} W_{ij}, \quad f_i^{out} = \sum_{j=1}^{N} W_{ji}. \tag{2}$$

The matrix W_{ij} contains any real-valued number of the weight between pairs of nodes in contrast to unweighted networks. We show later a network whose nodes represent institutions, and its weighted connections are numbers of professors that obtained a Ph.D. in i and later became a faculty in j. The entries are integer numbers but could be real-valued if one were interested in rates instead.

To investigate the hiring patterns of professors in the Brazilian Graduate Programs in Computer Science, we built a directed graph describing the hiring network. Institutions were modeled as nodes and directed edges were drawn from a faculty member's doctoral institution to their employing institution, weighted by the number of individuals moving between the two. So, given two institutions i and j, if w professors earned their Ph.D. from i and were later hired as faculty at j, we create the edge $i \to j$, with weight w. In the case of a professor being hired by their doctorate institution, we consider this as a self-hire, linking the institution to itself as $i \to i$. The resulting network consisted of 60 nodes (institutions) and 318 edges (hiring relationship).

Likewise, the prestige hierarchy in BRGPCSs was explored by calculating the number of professors hired that violated the prestige hierarchy. A faculty hired by a more prestigious institution than their doctorate institution describes upward mobility in prestige, or a violation of prestige, contradicting the expected prestige flow saw in [Wapman et al. 2022, Clauset et al. 2015]. In a perfectly hierarchical network, no institution would hire a professor from a lower-ranking institution. From this perspective, an institution is regarded as more prestigious if its trained professors secure faculty positions at other prestigious institutions. To obtain a network that closely approximates a perfectly aligned hierarchy of prestige, we applied the SpringRank algorithm as done by [Wapman et al. 2022], assigning ranks to each institution.

2.3. SpringRank Algorithm for Prestige Ranking

SpringRank is a network ranking algorithm that simulates a physical spring system, designed to infer hierarchical structures from directed edge patterns [Bacco et al. 2018]. Each node i is embedded with a rank s_i connected by springs (edges) exerting a force proportional to the deviation from its resting length. The algorithm assumes that edges inherently encode status differences: a directed edge $i \to j$ implies that node i has a higher prestige than node j. A directed edge $i \to j$ has its associated energy defined as:

$$H_{ij} = \frac{1}{2}(s_i - s_j - 1)^2, \tag{3}$$

where s_i and s_j represent the ranks of nodes i and j, respectively. Equation (3) can be minimized when $s_i - s_j = 1$. The optimal ranking s^* of the nodes can be given by minimizing the total energy of the system, described by:

$$H(s) = \frac{1}{2}\sum_{i,j} A_{ij}(s_i - s_j - 1)^2, \tag{4}$$

where A_{ij} denotes the weight of the directed edge $i \to j$. Setting the gradient $\nabla H(s)$ to zero, we can obtain the optimal rank s^* by solving the linear system:

$$[D^{out} + D^{in} - (A + A^T)]s^* = [D^{out} - D^{in}]\mathbf{1}, \tag{5}$$

where D^{out} and D^{in} are diagonal matrices of out-degrees and in-degrees, respectively, and $\mathbf{1}$ is a vector of ones.

The algorithm then fixes the rank of one of the nodes and solves the remaining equation using a sparse iterative solver. This characteristic allows SpringRank to solve Equation (5) almost in linear time, with $\mathcal{O}(L)$ with L as the number of nonzero edges in A, making it applicable to large-scale networks with millions of nodes [Bacco et al. 2018]. Finally, we obtain the real value ranking s^* of the network by solving Equation (5). The implementation of the SpringRank algorithm we use is described by [Bacco et al. 2018] and can be accessed at: `https://github.com/LarremoreLab/SpringRank`.

With node rankings that approximate a perfectly aligned hierarchy of prestige, we calculate the number of violations of the prestige hierarchy, as previously described. To evaluate whether the observed violations in our network are lower than expected by chance, randomized networks were created using a null model based on the configuration model. Specifically, it randomly rewires the edges, preserving the nodes' in and out degrees, thus generating randomized versions of the original network. This process ensures that the global connectivity structure remains unchanged, but that any hierarchical constraints present in the original network are disrupted. We generated $n = 10,000$ networks in total, annotating the fraction of hierarchical violations for each randomized network and comparing the distribution with the fraction of violations in the original network.

All data and source code used in this study are publicly available and can be accessed at: `https://github.com/augustofgui/prestige-hierarchy`.

3. Results and Discussion

This section presents and discusses the results of our analysis, focusing on two primary aspects: faculty production inequality and the prestige hierarchy within Brazilian Graduate Programs in Computer Science (BRGPCS). We connect these findings to the research questions outlined in the Introduction.

3.1. Faculty Production Inequality

Our first research question (RQ1) concerned the extent of inequality in faculty production within the BRGPCS network. The Brazilian Graduate Programs in Computer Science exhibit a high level of inequality in faculty production. An overwhelming 90% of professors were trained in just 20% of the institutions (12 units). This concentration is significantly higher than what is observed in US academia as a whole, where 20.4% of institutions account for 80% of all trained professors [Wapman et al. 2022]. Furthermore, this inequality is significantly higher than what is observed in the US domains of Computer Science, History, and Business, where 25% of the institutions were responsible for training between 71% and 86% of faculty members [Clauset et al. 2015]. Our results show a greater concentration, with fewer institutions producing a larger share of professors, highlighting a high degree of inequality in faculty production in the Brazilian Computer Science academic field.

To quantify the observed inequality, we calculated the Gini coefficient, a standard measure of statistical dispersion. The Gini coefficient ranges from 0 to 1, where $G = 0$ indicates a perfect equality where all institutions produce the same number of faculty, and $G = 1$ represents a maximum inequality where all faculty are trained in a single institution. Our analysis yielded a $G = 0.81$, indicating a highly unequal distribution of faculty production, as shown in Figure 1. In comparison, in the US. academia as a whole, the Gini coefficient for faculty production has been found to be around $G = 0.75$ as reported by [Wapman et al. 2022].

Older institutions would have more time to develop their research infrastructure and attract faculty, which could partially explain the concentration of faculty production. To assess whether the inequality in faculty production could be attributed to the age of an institution, we tested the influence of the institution's age on faculty production by normalizing their faculty production rates by the corresponding institution age. We found $G = 0.74$ after normalizing for age, indicating that a significant component of inequality in faculty production still remains, even with a reduction in the magnitude of the inequality. Additionally, since some institutions contain multiple Graduate Programs, we also analyzed the influence of the number of Graduate Programs on the production inequality, resulting in $G = 0.79$. However, the lack of a significant influence from institution age or the number of Graduate Programs suggests that the observed inequality is likely driven by other social factors.

The domination of the hiring network by few institutions is also observed in faculty hiring, self-hiring, and international hiring rates. The highest producing institution also tends to hire more faculty (Pearson $\rho = 0.75$, $p < 10^{-5}$). Moreover, these institutions show a tendency to train a high degree of their own faculty (Spearman $\rho = 0.86$, $p < 10^{-5}$) and to hire professors trained outside of Brazil (Spearman $\rho = 0.73, p < 10^{-5}$).

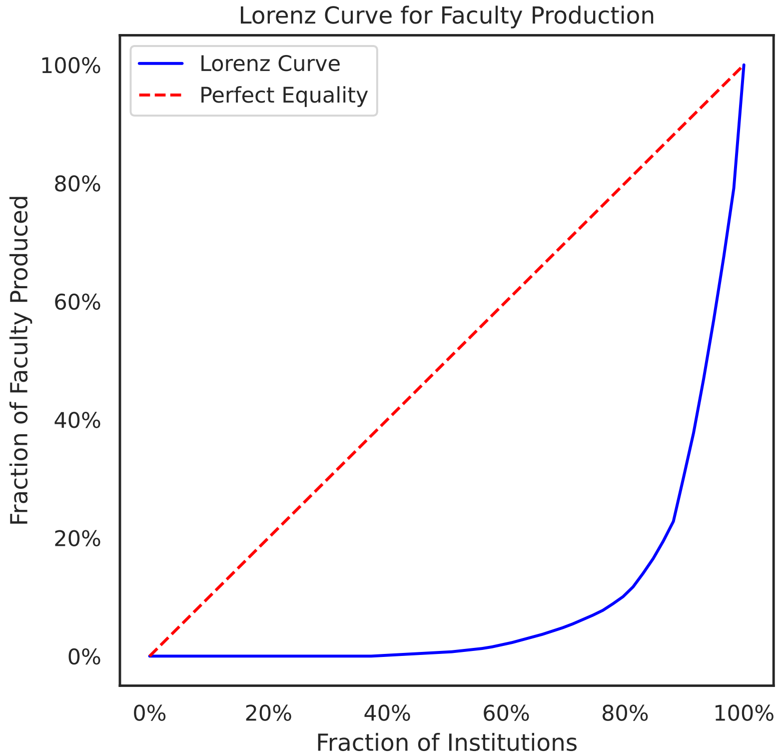

Figure 1. Lorenz curve, in blue, of the fraction of the cumulative sum of the faculty produced by institutions ordered from lower to higher Spring Rank. The line of equality, in red, indicates perfect equality in faculty production. The further the Lorenz curve is from the line of equality, the greater the inequality observed.

This underscores the rigidity and self-reinforcing cycle in which top-tier institutions dominate faculty production and hiring of the BRGPCSs network.

3.2. Prestige Hierarchy

Our second research question (RQ2) focused on the existence and steepness of a prestige hierarchy within the BRGPCS hiring network. To investigate such a hierarchy of prestige in the BRGPCSs hiring network, the SpringRank algorithm was applied to assign a rank to each institution in the network, as discussed in Section 2.3. Figure 2 presents the BRGPCS hiring network with mobility of professors trained in one institution and hired as faculty in another, considering the BRGPCS from 60 institutions. The institutions are sorted by their prestige, as in their corresponding SpringRank value, starting from PUC-RIO and going clockwise to the smallest values, and grouped by the major regions in Brazil by color. It suggests that the more prestigious institutions in each major region seem to function as the primary source of Professors for other institutions in their respective regions.

In this context, we observed the fraction of professors who were hired by an institution more prestigious than their doctorate institution, qualifying this mobility, from lower to higher prestige, as a violation of prestige hierarchy. Only 2.31% of the professors violated the hierarchy, being hired by more prestigious institutions, demonstrating the very steep hierarchical structure of the BRGPCSs hiring network. In comparison,

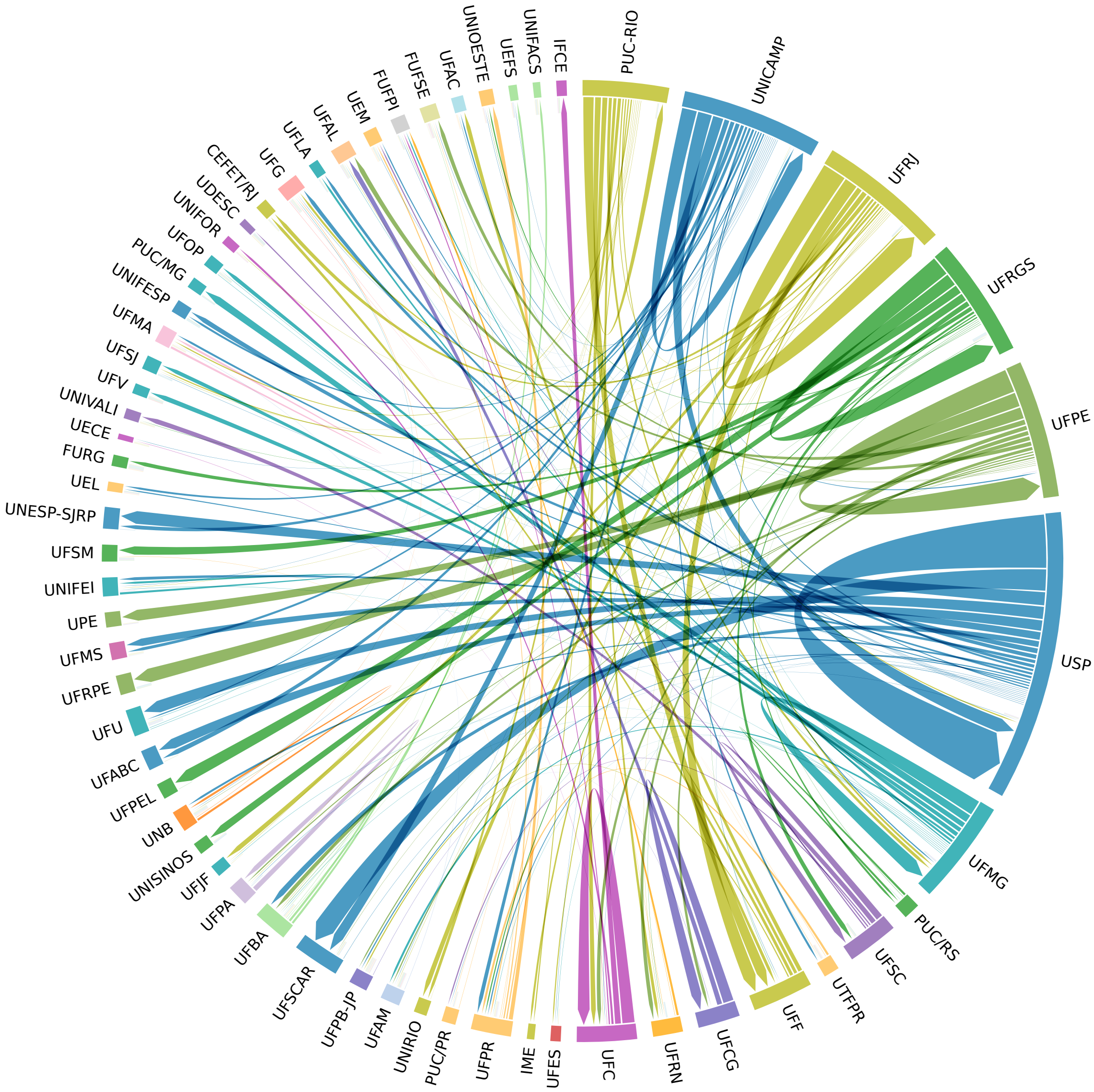

Figure 2. Chord diagram of the BRGPCSs faculty hiring network, ordered by SpringRank rankings, going clockwise starting from PUC-RIO. The color indicates institutions grouped by major regions. The arrows describe the flow of professor trained in an institution that were hired as faculty by the pointed institution.

US academia shows that 5 to 23% professors violated the prestige hierarchy within all domains and fields sampled [Wapman et al. 2022], 13% in the domain of Mathematics and Computing[Wapman et al. 2022], and 9 to 14% in the fields of Computer Science, History, and Business [Clauset et al. 2015].

Figure 3 shows that the fraction of prestige violations in the original network is much lower than the null model distribution, lying in the extreme left tail of the null distribution ($p < 10^{-5}$). This indicates that the steep hierarchy of prestige, with low rates of upward mobility, is structurally inherent in the system.

Moreover, 25.18% of the professors were self-hired, as in the fraction of professors hired as faculty by their own doctoral institutions. More prestigious universities have

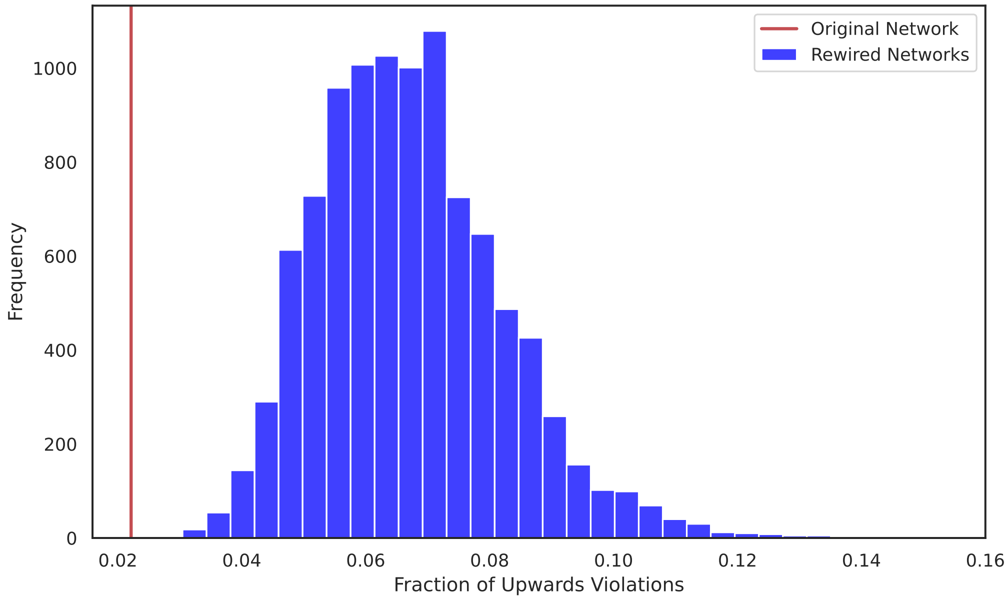

Figure 3. Fraction of prestige violations in the original network (red) and the null model distributions for the fraction of prestige violations (blue).

a small tendency to hire more of their own students (Pearson $\rho = 0.60$, $p < 10^{-5}$) and to hire more talent outside of Brazil (Pearson $\rho = 0.73$, $p < 10^{-5}$). These tendencies further consolidate the hierarchy prestige in the BRGPCSs network by limiting upward mobility for domestically trained academics.

Finally, our third research question (RQ3) explored the correlation between network-derived prestige (SpringRank) and established scientific productivity indicators. The rankings derived from the SpringRank algorithm seemed to approximate the hierarchy of scientific productivity. The top ranked institutions usually had a higher weighted CAPES score (Pearson $\rho = 0.78$, $p < 10^{-5}$), higher h index (Pearson $\rho = 0.75$, $p < 10^{-5}$), $i10$ index (Pearson $\rho = 0.71$, $p < 10^{-3}$) and greater number of articles published by the faculty of an institution (Pearson $\rho = 0.72$, $p < 10^{-5}$). This relationship suggests that productivity metrics and CAPES scores may not only reflect program quality but also signal the existence of a hierarchical structure to scientific impact and output. Although this study focuses on hiring patterns, future research could analyze co-authorship and collaboration networks between these institutions, revealing if prestige hierarchies and inequality in scientific impact manifest in collaborative practices of BRGPCSs.

4. Conclusions

This study investigated the asymmetry and prestige hierarchy within Brazilian Graduate Programs in Computer Science (BRGPCS), focusing on faculty hiring patterns and evaluating how these phenomena compare with the US academia observed by [Wapman et al. 2022] and [Clauset et al. 2015]. By analyzing data from $n = 1,084$ BRGPCS professors in 60 institutions, we constructed a directed hiring network and applied the SpringRank algorithm to rank institutions, quantifying institutional prestige hierarchy and dynamics of inequality within the network.

Our findings revealed an inequality in faculty production, with 90% of professors trained by only 20% of institutions, with a Gini coefficient of $G = 0.81$ indicating an extreme inequality. This asymmetry is present in the data even after normalizing for institutional age or accounting for the number of graduate programs ($G = 0.74 - 0.79$). Furthermore, the hiring network showed a steep prestige hierarchy, with only 2.31% of the hires representing upward mobility, significantly lower than the rates observed in US academia (5-23%) [Wapman et al. 2022, Clauset et al. 2015]. This steep hierarchy, validated through comparison with null models ($p < 10^{-5}$), emphasizes institutional self-reinforcement, as more prestigious programs dominate faculty production, preferentially hire their own graduates (25.18% self-hires), and attract more international talent, strongly correlating with higher scientific productivity metrics, such as h index, $i10$ index, and CAPES scores.

4.1. Limitations

Although our study offers insight into the structure and inequality of the BRGPCS hiring network, it contains limitations. We captured only a cross-sectional snapshot based on the 2022 CAPES evaluation and publications up to that year, overlooking temporal dynamics that may influence hiring patterns. We included only doctoral-holding professors due to the nature of our dataset, which contains only professors affiliated with Graduate Programs. This design choice excludes those with master's degrees and potentially omits early-career faculty whose hiring dynamics might differ. [FitzGerald et al. 2023] and [Wapman et al. 2022] also consider doctoral-holding researchers, since the graph edges connect departments or institutions where the researchers obtained their Ph.D. to where they became faculty. We also focused on Computer Science programs, limiting generalization to other academic fields as hiring pattern can vary widely across disciplines.

4.2. Future Works

In future work, longitudinal hiring networks could be studied by compiling data from multiple CAPES evaluations from different years to track changes in faculty production concentration, prestige hierarchies, and mobility patterns over time. Furthermore, to determine whether the extreme inequality and steep prestige gradients observed in CS are widespread in Brazilian academia or discipline-specific, one could encompass all CAPES-accredited graduate programs in Brazil.

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