Exploring the Confounding Factors of Academic Career Success: An Empirical Study with Deep Predictive Modeling

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Abstract—Understanding determinants of success in academic careers is critically important to both scholars and their employing organizations. While considerable research efforts have been made in this direction, there is still a lack of a quantitative approach to modeling the academic careers of scholars due to the massive confounding factors. To this end, in this paper, we try to mine the key factors of academic career success through an empirical and predictive modeling perspective, with a focus on two typical career honors, i.e. IEEE Fellow and ACM Fellow. Specifically, we first analyze the candidate’s nomination carefully and extract the probable factors of being a Fellow, e.g., scholarly productivity, scientific impact, gender, etc. Then for a scholar, we define the “scholarly distance” to measure the ability that he/she can recommend appropriate endorsers from existing Fellows as his/her nominators. Third, we propose both classification and regression models based on the same underlying neural network structure with self-attention mechanism, called Cls-Fellow and Reg-Fellow, to predict whether a candidate will be elected as a Fellow at current year and how many additional years it will take to be a Fellow. These two models could be helpful for scholars’ self-assessment. Extensive experiments on two Fellow datasets (IEEE Fellow and ACM Fellow) show that our proposed models can achieve great performance. Finally, we analyze the importance of different factors quantitatively, and obtain some insightful findings, such as the evolution of co-author networks between candidates and Fellows, the inequality of gender. We hope these derived factors and findings can help the scholars to improve their competitiveness and develop well in their academic career.

Index Terms—fellow election, scholarly productivity evaluation, coauthorship networks

I. INTRODUCTION

Academic career success is the pursuit of every scholar. Exploring determinants of success in academic careers can not only help scholars to develop themselves better, but also guide their employing organizations to evaluate and manage talents scientifically. Recently, considerable researchers have explored the impact of various factors on academic careers, such as co-author network [1], [2] and scientific impact [3], [4], etc. However, scholars’ academic careers are affected by massive confounding factors. It is challenging to modeling the academic careers of scholars with a quantitative and systematic approach. To this end, in this paper, we try to explore the determinants of academic career success through an empirical and predictive modeling perspective. In particular, we focus our study on IEEE Fellow and ACM Fellow which are two typical career honors.

Taking the IEEE Fellow as an example, to be elected as a Fellow, the candidate must have accrued a sustained level of contribution over time with clear impact that extends well beyond his/her own organization, and must secure endorsements from 5-8 IEEE members, preferably individuals who are themselves IEEE Fellows or have otherwise achieved distinction in the field [5]. Specifically, the candidate will submit a nomination, which includes 1) his/her educational background, 2) his/her most significant professional accomplishments and their foundational, technical, commercial, or other achievements, and 3) his/her most significant leadership roles and awards in IEEE or other service activities. Moreover, the candidate must recommend 5-8 Referees to write supporting letters for her. Then the Fellow Committee will rate each nominee numerically on the basis of the above information and recommend nominees according to some criteria. The detailed flowchart for IEEE Fellowship election [6] is shown in Fig. 1.

However, after submitting the nominations, the candidates do not know whether and how they are elected as a Fellow, because the evaluation criteria and rating process are complicated, and even secret to candidates. Moreover, the evaluation
With a focus on two typical career honors, namely IEEE Fellow and ACM/IEEE Fellow, we discuss the importance of determining whether a candidate can receive good evaluations from the Fellow Committee and to recommend the endorsers based on our datasets and models. The election of ACM/IEEE Fellow involves the recommendation of endorsers, and the challenge is whether the candidate can be elected as an ACM/IEEE Fellow in a specific year. Specifically, the challenge is that the election criteria of ACM/IEEE Fellow is changing over time because the candidates have to face severe global competition. For instance, the evaluation criteria of Fellow candidates in 1980 is totally different with that in 2016. Therefore, our model should be time-related and dynamic, and can be explained from two aspects. First, the nomination becomes more fiercer with the rapid growth of talented candidates, thus the criteria becomes higher and higher. It means that our model should pay more attention to the latest data of recent elected Fellows, because the latest data indicates more precise criteria of Fellow election. Second, a candidate will have higher probability of being elected as a Fellow if he/she spends more years on research, that is, the accumulation of his/her scholarly outcomes and impacts will help him/her to be more competitive. To address the above problems, we design a base neural network structure with self-attention mechanism. By connecting different output layers, we construct a classification model (named Cls-Fellow model) and a regression model (named Reg-Fellow model) to answer Question (II). Extensive experiments show that our proposed models can achieve great performance.

This is the first work that focuses on data-driven method to mine the key factors for Fellow career path. Our main research contributions are summarized as follows:

- With a focus on two typical career honors, namely IEEE Fellow and ACM Fellow, we quantitatively analyze the factors contributing to academic career success.
- We propose two self-attention based neural network models to predict whether a Fellow candidate will be elected as a Fellow at current year and how many additional years it will take his/her if he/she could not be named Fellow, which can be used for scholars’ self-assessment.
- Based on our datasets and models, we discuss the importance of different factors in academic career. Moreover, we discover some interesting phenomena, e.g., the evolution of co-author networks between candidates and Fellows and the inequality of gender, etc. These findings could be helpful for scholars to improve their competitiveness and develop well in their academic career.

II. RELATED WORK

A. Quantitative analysis of career trajectory of scientists.

How to evaluate a scientist’s professional accomplishments quantitatively is a key question during his/her career trajectory.
tory. Recently, many studies try to handle it by considering scientists’ scholarly productivity [7]–[9] and scientific impact [4], [8]–[10] from data perspective. For example, Petersen et al. [12] modeled the productivity and fluctuations over the academic career and found the persistence and uncertainty in the academic community. Way et al. [4] demonstrated that 2/3 faculties exhibited a rich diversity of productivity patterns, rather than simple “rise-down” pattern. Nie et al. [3] identified the academic rising star by using the increment of a scholar’s comprehensive evaluation score and a non-iterative hierarchical citation-based model. Min et al. [13] introduced a perspective of dynamic citation process to identify citation patterns of scientific breakthroughs. Besides, some papers study the inequality of gender, knowledge in program review, peer review, hiring network, etc. For instance, Kevin et al. [14] proposed the intelligent distance affected program review, i.e., reviewers in the same research field tend to give a lower score for program review. Ginther et al. [15] reported the inequality of race and ethnicity in NIH research awards. [4], [9], [16] showed the inequality of gender in peer review and hiring network of the faculty.

B. Data mining for talents.

Recently, how to use data mining techniques to address human resource management have attracted researchers’ much attention in data mining and machine learning communities [17], [18]. For example, By employing deep learning techniques such as convolutional neural networks, recurrent neural networks, and pretrained language models, researchers have achieved significant performance in various recruitment tasks, including person-job fitting [19]–[22], intelligent job interview [23], [24], job description generation [25], and resume understanding [26]. Based on graph neural network, Zha et al. [27] proposed an uncertainty-aware graph autoencoder framework for modeling the mobility patterns of talents across different job titles. Ye et al. [28] proposed to utilize Graph Convolutional Network [29] to extract the local information of employees in their organizational social network for high-potential talent identification and Wu et al. [1] propose a Mate-path Hierarchical Heterogeneous Graph Convolution Network for high-potential scholar recognition.

Differing from the above studies, we not only try to analyze the factors of Fellow career trajectory quantitatively but also propose both classification and regression models to predict whether a candidate will be elected as a Fellow at current year and how many additional years it will take he/she to be a Fellow.

III. DATA AND FACTORS

Up to the date (10/26/2020), there are 10,483 IEEE Fellows (including 425 females) and 1,221 ACM Fellows (including 155 females), spanning from 1934 to 2020 for IEEE Fellow and from 1994 to 2019 for ACM Fellow. First, we collected the basic information (e.g., name, region, country, gender, etc) of each Fellow from IEEE website and ACM website. Second, we collected their publications (including title, authors, journal, year, etc) from Microsoft Academic Search and the corresponding citation metrics (such as citations of each paper, h-index, i10-index) from Google Scholar. Then we removed the Fellows who had no more than 300 citations or were elected less than 8 years since his/her first publication because of noisy data. Fourth, we also collected scholars in ACM Distinguished Members and Aminer Highly cited Scholars Library who are not IEEE/ACM Fellows as negative examples (named non-Fellow) for our classification model. We collected non-Fellow data (same field as Fellows) from ACM website and Aminer website. Finally, we obtained three datasets consisting of 7,191 (877 female) talented researchers with 1,377,907 publications. Some basic statistics of the three datasets are shown in Table I.

After checking the material of Fellow nomination carefully and considering the factors mentioned in Reference [5], we describe the important factors used in our model and provide some statistical information as follows to answer the Question (I).

Table: The details of the Fellow datasets

| Fellow | Dataset | Source | Male | Female | Avg. Pubs | Avg. Cites |
|--------|---------|--------|------|--------|-----------|-----------|
| ACM    | ACM Fellow | https://awards.acm.org/award_winners | 820  | 121  | 143.5     | 10,388.8   |
| IEEE   | IEEE Fellow | https://gct.aminer.cn/eb/series?name=高引学者系列| 4,044 | 275  | 145.7     | 4,322.8   |
| non    | ACM DIST. | https://awards.acm.org/distinguished-members/award-winners | 363  | 54   | 151.0     | 6,952.0   |
| non    | Aminer   | https://scholar.google.com | 1,135 | 427  | 139.1     | 10,397.9   |

Accumulation time. How many years does it cost a talented scientist to achieve his/her academic accumulation and to be elected as an ACM/IEEE Fellow after his/her first publication? In this paper, we define the years as $t_i = e_{yi} - s_{yi}$, where $e_{yi}$ is the year when Fellow $i$ in our datasets was elected as an ACM/IEEE Fellow and $s_{yi}$ is the year when his/her first paper was published.

Scholarly productivity. Similar to previous studies [8], [12], we model the academic career trajectory as a sequence of scientific outcomes which arrive at the variable rate $n_i(t)$. Here $n_i(t)$ is the annual productivity of Fellow $i$ at $t$-th year after his/her first publication. Generally, the reputation of a scientist is typically a cumulative representation of his/her contributions, we consider the cumulative production $N_i(t) = \sum_{t'=1}^{t} n_i(t')$ as a proxy for career achievement. $N_i(t)$ is the total number of papers Fellow $i$ publishes up to time $t$ after his/her first publication, which asymptotically follows $N_i(t) \sim t^{\alpha_1}$. The $\alpha_1$ quantifies the career trajectory dynamics and $\alpha_1 > 1$ indicates on average a steady increase in his/her productivity with $t$. Note that productivity is only one metric in our model and higher productivity is not equal to higher impact. For scholarly productivity of Fellow $i$, we consider 4

References:

[1] https://www.ieee.org/membership/fellows/fellows-directory.html
[2] https://awards.acm.org/award_winners
[3] https://academic.microsoft.com
[4] https://scholar.google.com
[5] https://awards.acm.org/distinguished-members/award-winners
[6] https://gct.aminer.cn/eb/series?name=高引学者系列[2016]

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factors: annual publications $n_i(t)$, annual average publications $\bar{n}_i(t)$, the total number of publications $N_i(cy)$ and $\alpha_i(t)$.

**Scientific impact.** Existing measures of scientific impact believe that citations offer a quantitative proxy of the importance of findings or a scientist’s standing in the research community [10], [30]. Like previous studies, we take the total number of citations and annual citations [10] into account. Besides, $h$-index [30] and $i10$-index are also widely used metrics for the evaluation of scientific impact. The $h$-index incorporates productivity as well as citation impact, and $i10$-index is the number of publications with at least 10 citations [31]. Actually, these measures of scientific impact are often debated. In our models, we include above measures and let the model consider the scientific impact of candidates, comprehensively.

**Scholarly distance.** When submitting his/her nomination, a candidate has to recommend 5-8 existing ACM/IEEE Fellows who are familiar with his/her fields as endorsers. How to measure the social ability that the candidate can recommend appropriate endorsers is one key challenge. Generally, candidates recommend endorsers by their co-author network. To address this challenge, we define a scholarly distance score $sd_i$ between a candidate $i$ and existing Fellows by applying co-author network and node2vec [11], as shown in Eq. 1.

$$ sd_i = \frac{\sum_{j=1}^{N} \cos(x_i, x_j)}{N}, \quad (1) $$

where $x_i$, $x_j$ are the low-dimensional graph embedding vectors learned by node2vec [11] of candidate $i$ and Fellow $j$ from their co-author networks, respectively; $N$ is the total number of Fellows. Generally, a higher scholarly distance score indicates that the candidate owns a better co-author network with existing Fellows, thus he/she can recommend more appropriate endorsers for his/her nomination.

**Scholarly circle.** Ye et al. [28] proposed a data-driven approach for identifying high potential talents (HIPOs) from the newly-enrolled employees by modeling the dynamics of their behaviors in organizational social networks and they found that HIPOs can promote their social centrality factors more effectively in terms of both speed and numerical value.

In this paper, we utilize Hierarchical Graph Convolutional Network (GCN) [29] to extract candidates’ co-author network (graph) information. Singh et al. [32] found that author pairs who have a co-authorship distance $d \leq 3$ significantly affect each other’s citations, but this effect falls off rapidly for longer distances in the co-author network. Thus, for each candidate, we build co-author graph with his/her co-authors (within co-authorship distance $d \leq 3$) and number of cooperation. In each graph, each node represents a scholar and each edge represents the co-author relationship between two scholars. We label each node with values 0, 1 and 2 representing non-Fellow, Fellow and current candidate, respectively. The weight of each edge is the number of cooperation between two scholars.

**Field of Research.** Due to the different development trends in various research fields, the difficulty of election is not the same. For example, candidates can be organized by 39 societies which focus on different research fields in IEEE. The larger Societies have more nominations and competition tends to be more severe. Meanwhile, the score tends to be high normally because of less competition in a small Society [5]. Owing to the significant impact of the research fields, we define a research field vector $rf$ representing candidates’ fields. For IEEE Fellow candidates, the field vector $rf$ is based on the research fields of 39 IEEE Societies. And 34 child topics of “Computer Science” in Microsoft Academic topics are used to generate the field vector $rf$ for ACM Fellow candidates. However, the categories of IEEE Societies and Microsoft Academic topics often overlaps in research fields. Overlapping categories can make it difficult to classify candidates and their publications. Therefore, we combined IEEE Societies and Microsoft topics into 8 broader categories based on the similarity of research fields, independently. For example, the “Computer graphics” and the “Computer vision” are combined into one broader category. Then, based on conferences and journals related to IEEE Societies and Microsoft Academic topics, we collected 2000 high-cited papers for each of the broad category as a field-related dataset. Finally, we trained a BERT-based [33] text classification model (named Field_Cls) using the field-related dataset we collected. The accuracy of the Field_Cls model can reach 76.1% on the ACM categories data and reach 87.0% on the IEEE categories data. For a candidate $i$, his/her research field vector $rf_i$ can be calculated by inputting his/her paper data into the Field_Cls, as shown in Eq. 2.

$$ rf_i = \frac{\sum_{j=1}^{N} Field_Cls(p_j)}{N}, \quad (2) $$

where $N$ is the total number of papers of candidate $i$; $p_j$ represents the information of a certain paper $j$ which belongs to candidate $i$; $Field_Cls(p_j)$, a 8-dimensional vector, is the classification result of the Field_Cls model on $p_j$.

**Place of Employment.** Generally, a reputed employer of the candidate also gives the Fellow Committee members a better first impression [5]. Therefore, in our models, candidates’ employment information is represented using 4-dimensional vector embedding (named employ_emb).

**Gender.** The last factor is the gender of candidates. Previous studies show that gender bias [34] exists in academia, such as faculty hiring [9], [16], grant proposal [35] and peer review [36]. In this paper, our aim is to estimate the influence of gender on the Fellow selection, therefore gender is another factor to be considered in our model.

Finally, for each candidate $i$ in a given calendar year $cy$, we can represent him/her by a 36-dimensional vector $x_i^{cy}$, with details as follows:

- **Accumulation time:** $t_i = cy - sy_i$, where $sy_i$ is the calendar year when candidate $i$ published his/her first paper.
- **Gender:** 1 for male and 0 for female.

7https://www.ieee.org/communities/societies/index.html
8https://academic.microsoft.com/topics/41008148
• **Scholarly productivity**: It has 4 factors. They are the number of publications in the given calendar year ($n_i(cy)$), the $\alpha$ value of publications ($\alpha_i(cy)$), the total number of publications $N_i(cy)$, and the average publications $\tau_i(cy)$ from his/her first publication year to the given calendar year, respectively.

• **Scientific impact**: It consists of 5 factors. They are the total citations of Fellow $i$ ($c_i(cy)$), the $\alpha$ value of citations in the given calendar year $\alpha_i(cy)$, the average citations $\tau_i(cy)$ from his/her first publication year to the given calendar year, the $h$-index $h_i(cy)$ and $i$10-index $i10_i(cy)$ in the given calendar year, respectively.

• **Scholarly distance**: the current $sd_i(cy)$ in the given calendar year.

• **Scholarly circle**: the current co-author network embedding $cn_i(cy)$ with 12-dimensions in the given calendar year.

• **Field of Research**: the current $rf_i(cy)$ with 8-dimensions in the given calendar year.

• **Place of Employment**: the current $employ_{emb_i}(cy)$ with 4-dimensions in the given calendar year.

For **Accumulation time**, **Gender**, **Scholarly productivity**, **Scientific impact** and **Scholarly distance**, their each dimension is normalized by $z$-score. Finally, the candidate $i$ can be represented as time series vectors $X_i$ from the year of his/her first publication to 2020, as shown in Eq. 3

$$X_i = \{x_i^{s_y_1}, \cdots, x_i^{s_y_{2020}}\},$$

where $s_y_i$ is the year of his/her first publication. For example, “Michael I. Jordan” started to publish his first paper in 1981, so his vectors are as follows, $\{x_{1981}^i, \cdots, x_{2020}^i\}$.

In addition, for the above factors, we conduct preliminary statistics and analysis, which can be found in Appendix A.

**IV. PREDICTIVE MODEL**

To answer the Question (II), we need to model the Fellow election: build a classification model to predict whether a candidate will be elected as a Fellow, and build a regression model to predict how many more years it will take a candidate to be a Fellow if he/she could not be named Fellow at current year.

The prediction of the Fellow election is related to and affected by time. Therefore, our models are based on the same underlying neural network structure with multi-head self-attention mechanism. The graphical structure of the proposed models is shown in Fig. 2. Noticed the excellent performance of Transformer [37] on the seq2seq tasks, multi transformer encode layers are used on the front of the models. By flattening the output of the last encode layer, the information of a candidate can be transformed into one vector as a high-level representation. Finally, different fully connected layers are connected to the flatten layers. We expect these two models are able to capture the correlation between election results and the candidate’s performance, as well as the underlying trend and evolving phenomena.

For co-author network information extraction, two GCN layers are used. By aggregating the output of second GCN layer, the co-author network can be represented by a 12-dimensional vector. After co-author network embedding, we concat co-author network vector and other factor vectors for academic trajectory processing.

**V. EXPERIMENTS**

Our Cls-Fellow model can predict whether a candidate will be elected as a Fellow in the current year. If candidates are classified as non-Fellow by Cls-model, it means that they may not named Fellow in the current year. For these candidates, our Reg-model can predict how many additional years it will take them to be Fellows. In this section, we compare our proposed Cls-Fellow model and Reg-model with some state-of-the-art baselines on ACM and IEEE Fellow datasets. During the training and testing, the examples are used in the same way for Cls-Fellow model and the rest baselines. Specifically, the examples are represented as time series vectors, as explained in Section III. The sequence of data is flattened for some baseline methods which cannot take sequence as input.

According to the task type (classification or regression) and Fellow type (ACM or IEEE), we prepare four sub-datasets, namely ACM/IEEE classification datasets and ACM/IEEE regression datasets, respectively.

**A. Baseline Methods**

Multiple transformer encode layers are used in the Cls-Fellow and Reg-Fellow. To evaluate the performance of transformer encode layers and the robustness of feature selection, we compared Cls-Fellow and Reg-Fellow with multiple baselines.

For the classification task, 8 kinds of classification models are used as baselines. They are $\epsilon$-Support Vector classifier (SVM) [38], Linear Regression (LR), Ridge Regression, Decision Tree classifier (DT), Random Forest classifier (RF), Graph Convolutional Network (GCN) [29], Multi-layer Perceptron classifier (MLP) [39] and Attention-RNN [40], [41].

For the regression task, six kinds of regression models are used as baselines. They are Ridge Regression, $\epsilon$-Support Vector Regression (SVR) [38], Multi-layer Perceptron regressor (MLP) [39], Decision Tree regressor (DT) and Attention-RNN [40], [41]. Some of them are the same as in classification baselines.

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Fig. 2: Graphical illustration of the proposed models.
B. Results and Analysis

For classification task, CIs-Fellow model is supposed to classify Fellow or non-Fellow. The F1 scores on IEEE/ACM classification datasets are shown in Table II and Table III. The results are as follows:

TABLE II: The F1 Score of Classification on ACM Classification Datasets

| Method     | F1 Score | Rank |
|------------|----------|------|
| CIs-Fellow |          |      |
| Attn-RNN   |          |      |
| GCN        |          |      |
| LR         |          |      |
| Ridge      |          |      |
| RF         |          |      |
| DT         |          |      |
| SVM        |          |      |
| MLP        |          |      |

| Year | F1 Score | Rank |
|------|----------|------|
| 2015 |          |      |
| 2016 |          |      |
| 2017 |          |      |
| 2018 |          |      |
| 2019 |          |      |

As shown in Table II and Table III, generally, the earlier calendar year $cy$ is, the lower F1 scores of models is. The reason is that when the dataset is spilted by an earlier calendar year $cy$, more “future” Fellows elected after $cy$ will be labeled as non-Fellow. Thus, they are very similar to the Fellow-labeled examples and it is difficult to be classified.

- CIs-Fellow and Attention-RNN based model achieve better results, which are significantly better than other models. It demonstrates that time sequence model is more suitable for Fellow classification. The performance of attention-RNN based model and CIs-Fellow is very close, and on the IEEE classification dataset, former is slightly better.

- GCN only use candidates’ co-author network information. The average F1 score of GCN can reach 79.9% on IEEE dataset and 81.0% in ACM dataset. It implies that the development of scholarly circle can represent candidates’ academic level to some extent.

For regression task, models are supposed to predict how many additional years it will take a candidate to become an IEEE/ACM Fellow. The Mean Absolute Error (MAE) on IEEE and ACM regression dataset is shown in Table IV and Table V. The observations are as follows:

- It can be seen that Reg-Fellow model and attention-RNN based model achieves the lowest average MAE on the two regression datasets. Moreover, when the MAE of Reg-Fellow is less than 1, the calendar years are earlier than other models. Similar to the classification task, attention-RNN based model and our transformer encoder based model perform closely.

- For some traditional models, such as Ridge and SVM, although they handled the sequence data by taking the flattened data as input, they achieved worse performance.

- We noticed that the later calendar year $cy$ is, the smaller MAE gap between the GCN based model and Reg-Fellow model is. It may imply that the scholarly circle factor is more important in the late academic careers of candidates.

VI. DISCUSSION

A. The Contribution of Factors

In Section III, we consider 8 kinds of factors with 36-dimensions to model the election of Fellows. Generally, some factors are essential to improve the competitiveness of candidates. Here we try to explore the contribution of different factors by visualizing the decision tree.

Here, we visualize the structures of the decision trees in IEEE Fellow classification and ACM Fellow classification, which are shown in Fig. 3 and Fig. 4. To facilitate visualization, these trees are trained on the calendar year $cy$ data (one year data) and also achieved acceptable performance (F1 score > 80%). The conditions of each internal node in these trees are the key factors when distinguishing Fellow from non-Fellow. From Fig. 3 and Fig. 4, we can find that:

- In both in IEEE/ACM Fellow classification, the condition of accumulation time is always at the root. It means that, in the view of decision tree, the accumulation time is the most critical factor. ACM candidates with more than 24 years of accumulation and IEEE candidates with more than 18 years of accumulation are generally more likely to be elected as Fellows.

- Total citations is also worthy of attention. In the ACM decision tree, as shown in Fig. 4, the total number of citations and accumulation time are combined as the rule for ACM fellow classification: Candidates with more than 24 years of academic output and more than 6,119 citations are more likely to be elected as Fellows and IEEE/ACM Fellow.
the rising stars (candidates with shorter accumulation time) are able to be very competitive due to a higher number of citations. It means that academic accumulation and influence are comprehensively considered in Fellow elections. We also notice that candidates with less than 6903 citations are usually difficult to be elected as ACM Fellows.

- Candidates’ embedding scores in some research fields, such as Computing and Processing (Hardware/Software) in IEEE, are used as conditions, especially in IEEE decision tree. It shows that the difficulty of becoming a Fellow in various research fields may be different. As we all know, compared with ACM, IEEE’s research fields are broader and more diverse, which may be a factor that the field embedding scores are usually used as conditions in IEEE decision tree.
- Scholary distance plays an important role in IEEE Fellow election, which indicate candidates need to strengthen academic cooperation and develop their academic social networks.

B. The evolution of co-author networks

With the accumulation of candidates’ publications, their co-author networks are also growing. The close cooperation between candidate and elected Fellows not only makes it easier for candidate to find endorsers during the Fellow election, but also imply that the candidate’s research work is excellent. In Section III, we introduce Scholarly distance to measure the distance between a candidate and existing Fellows and calculate the co-author network embedding for Scholarly circle representation. Although, scholarly distance and scholarly circle play important roles in Fellow regression task and Fellow classification task, they are not intuitive for human understanding and reference. Here, we introduce the number of collaborations with Fellows ($N_{collab}$) and the number of Fellow co-authors ($N_{neighbor}$) to indicate the distance between candidates and existing Fellows, we explore the difference between IEEE Fellows, ACM Fellows and non-Fellows by
analyzing the evolution of their \( N_{\text{collab}} \) and \( N_{\text{neighbor}} \) over the accumulation time.

We define three scopes, namely 1-hop, 2-hop and 3-hop, which are used to limit the scope when calculating each candidate’s co-author network. 1-hop only includes candidate’s direct co-authors. The scholars in 1-hop and their direct co-authors are included in 2-hop. 3-hop is the widest scope which covers 1-hop and 2-hop and includes direct co-authors of scholars in them. For each scholar we selected from IEEE Fellow, ACM Fellow and non-Fellow dataset, we calculate their \( N_{\text{collab}} \) and \( N_{\text{neighbor}} \) over the accumulation time. The evolution of them over the accumulation time in three scopes are shown in Fig. 5. From the Fig. 5, we have the following findings:

- Both IEEE/ACM Fellows and non-Fellows can promote their close collaboration with existed Fellows.
- Although non-Fellows are outstanding, compared with IEEE or ACM Fellows, their co-author networks with existed Fellows grow slowly in terms of speed and value.
- The difference between non-Fellows and IEEE/ACM Fellows in the first 5 years is not obvious, and the difference starts to show up in 5-10 years. In the early 10 years, IEEE/ACM Fellows usually have had the direct cooperation with existed Fellows. Previous studies [2] find that junior researchers who coauthor work with top scientists enjoy a persistent competitive advantage throughout the rest of their careers. It implies that cooperation with existed Fellows in candidates’ early careers play a key role for their academic development.
- In 2-hop scope and 3-hop scope, non-Fellows and IEEE Fellows are relatively close in the first 10 years. However, as shown in sub-figure (a) and sub-figure (d) of Fig. 5, in the first 10 years, IEEE Fellows usually have had direct cooperation with existed Fellows, but non-Fellows have not. It implies that an important challenge of becoming a Fellow is how to transform Fellows who have indirect cooperation with candidates into their direct collaborators.
- As show in Fig. 5, the \( N_{\text{collab}} \) and \( N_{\text{neighbor}} \) of ACM Fellows are usually more than that of IEEE Fellows. It may be caused by the fact that the research fields of ACM are more concentrated than those in IEEE, which is more conducive to cooperation.

C. The Inequality of Gender

To check the inequality of gender, we divide the Fellows into two groups according to their genders, and we calculate the \( \bar{\alpha} \) values and standard deviation \( \sigma(N'(t)) \) of the average productivity \( <N'(t)> \) between male Fellows and female ones. Here \( <N'(t)> \) is the average properties of \( N_i(t) \) for all scientists in one group by defining the normalized average trajectory as follows:

\[
<N'(t)> = \frac{1}{I} \sum_{j=1}^{I} \frac{N_j(t)}{\bar{\pi}_j},
\]

where \( <N'(t)> \approx t^\alpha \), \( \bar{\pi}_j \) is the average annual production of scientist \( i \) and \( \sigma(N'(t)) \) is the standard deviation of \( N'(t) \).

The two lines in Fig. 6 show the relationship between \( <N'(t)> \) and \( t \) (log scale) for male Fellows and female Fellows, respectively. We can observe that female Fellows are significantly different to male Fellows in terms of \( \bar{\alpha} \) value (\( p = 2 \times 10^{-5} < 0.001 \), Mann-Whitney Test). It indicates that female Fellows need to put in more effort than male Fellows if they are elected as Fellows. Moreover, the two curves show the trends between \( \sigma(N'(t)) \) and \( t \). Generally, a broad peak is a likely signature of career shocks that can significantly alter the career trajectory [12]. In the early years of their careers, male Fellows have higher academic productivity than female Fellows. However, female candidates are growing faster.

Based on our data, the above results indicate that the inequality of gender does exist in the Fellow selection, like the inequality in faculty hiring network, grant proposal, etc.

VII. CONCLUSION AND FUTURE WORK

In this paper, we tried to explore the key factors of Fellow selection and proposed two self-attention based model to classify Fellows or non-Fellows and predict how many years it takes a talented candidate to be elected as a Fellow. Moreover, we analyzed the factors of the Fellow nomination qualitatively and defined a scholarly distance to measure the co-author network between a candidate and existing Fellows. We also discover some interesting phenomena from the Fellow datasets, such as the evolution of co-author networks between candidates and Fellows, and inequality of gender. It is worth noting that the conclusions and observations are reached based on the current datasets, which maybe are not inconsistent with the practical process of Fellow election. However, we believe that the talented researchers and Fellow Committees can benefit from our findings for Fellow election and nomination. Despite we only focus on the data of IEEE/ACM Fellows in this paper, the relevant research ideas and models can be extended to other data. In the future, when the data is available, we are pleased to explore on other dataset.
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A. Data Statistics and Analysis

1) Accumulation Time: We compute the distribution of accumulation time $t$ for all Fellows in our datasets, as shown in Fig. 7. We can observe that the distributions of $t$ of IEEE and ACM Fellows both obey normal distribution appropriately. From a gender perspective, we can find that: (1) The $\sigma$ of females are lower than that of males ($\sigma_{male}^{IEEE} = 7.61, \sigma_{female}^{IEEE} = 4.61, \sigma_{male}^{ACM} = 7.45, \sigma_{female}^{ACM} = 6.31$). (2) IEEE male Fellows and IEEE female Fellows have the similar means $\mu$ ($\mu_{male}^{IEEE} = 20.50, \mu_{female}^{IEEE} = 20.23$). However, in ACM, female Fellows have a slightly smaller mean $\mu$ than male Fellows ($\mu_{male}^{ACM} = 24.65, \mu_{female}^{ACM} = 23.45$). We also use the Mann-Whitney Test [42] to explore the difference of accumulation time between male Fellows and female Fellows. It shows that there is no significant difference of years between male Fellows and female Fellows ($p_{IEEE}^{male-female} = 0.48 > 0.05, p_{ACM}^{male-female} = 0.12 > 0.05$, Mann-Whitney Test [42]). Moreover, we also observe that ACM Fellows spend more 3 to 4 years than IEEE Fellows on average. The above results demonstrate that time plays a more important role in Fellow election for different organizations, rather than different genders. In our proposed model, for each candidate, we consider the accumulation years from his/her first publication year to a given year as one factor.

2) Scholarly Productivity: As described in Section III, we calculate $\alpha$ to quantify the scholarly productivity. Fig. 8 shows three Fellows with different $\alpha$ values. It is obvious that the publications of Prof. Philip S. Yu increase much faster than Prof. David Boggs and George W. Furnas and his scholarly productivity increases almost twofold during his career, while the increase is slower for Prof. Kahan, William. We can divide the Fellows into ultrahigh-productivity ($\alpha \geq 2$), high-productivity ($1 < \alpha < 2$), and modest-productivity ($\alpha \leq 1$) ones manually according to the value of $\alpha$, and the ratio among the three categories is 2.7 : 2.5 : 1. We can find that 84% Fellows in our datasets have a steady increase in their productivity with time $t$.

3) Visualization: We want to explore the differences in the difficulty of becoming a Fellow in different research fields. To this end, for Fellows in each research field, we calculate the average and third quartile of their academic features. Considering that the criteria of ACM/IEEE Fellow election are evolving over time, the data we calculate are grouped by time. The academic features of Fellows are the factors we consider in Section III, including $h$ = index, $\alpha$ of citations, etc., which can be used as the goals for candidates. The Fig. 9 shows the difference in citations of IEEE Fellows from various research fields and reveals the evolution of citations over time. As can be seen from the Fig. 9, the number of citations of candidates from aerospace field is generally less than candidates from computing and processing (Hardware/Software) field, when they were both elected as IEEE Fellow in the same year. We also plot histograms about other academic features for IEEE/ACM Fellows in the website. We believe that these histograms can help people understand the trend of the IEEE/ACM Fellow election and realize the gap between themselves and IEEE/ACM Fellows.

Fig. 7: The distributions of the years to be selected as ACM and IEEE Fellows (best viewed in color).

Fig. 8: The scholarly productivity measured by $\alpha$ of three Fellows (best viewed in color).

Fig. 9: The third quartile of citations when IEEE Fellows were elected.