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Implicit Multi-Feature Learning for Dynamic Time Series Prediction of the Impact of Institutions

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ABSTRACT Predicting the impact of research institutions is an important tool for decision makers, such as resource allocation for funding bodies. Despite significant effort of adopting quantitative indicators to measure the impact of research institutions, little is known that how the impact of institutions evolves in time. Previous studies have focused on using the historical relevance scores of different institutions to predict potential future impact for these institutions. In this paper, we explore the factors that can drive the changes of the impact of institutions, finding that the impact of an institution, as measured by the number of the accepted papers of the institution, more is determined by the authors' influence of the institution. Geographic location of institution feature and state GDP can drive the changes of the impact of institutions. Identifying these features allows us to formulate a predictive model that integrates the effects of individual ability, location of institution, and state GDP. The model unveils the underlying factors driving the future impact of institutions, which can be used to accurately predict the future impact of institutions.

INDEX TERMS Scientific impact, prediction, feature selection, machine learning, scientometrics.

I. INTRODUCTION

With the rapid growth of scholarly big data [1], [2], the scientific future impact often plays an important role, which can help decision-makers to make better decisions. For example, the prediction of the impact of papers, scholars, and institutions can guide government funding allocation and assess the grant proposals.

The evaluation and prediction of scholarly impact are two important aspects of scientific impact [3]. Scholarly impact evaluation focuses on quantifying the previous impact of scholarly entities [4]–[6]. The institution impact evaluation mainly has two categories: full counting and fractional counting. The former considered that all authors had the same contributions for a paper [7], [8]. The latter considered the best journal and highly-cited papers [9]. Due to lack the baseline, the prediction of institution impact is challenging. The KDD CUP 2016 offers a evaluation criterion relying on the number of accepted papers. Previous researchers mainly used the historical relevance scores of each institution to predict the impact of the institution in next year. Based on

the gradient boost decision trees (GBDT) model [10], Sandulescu and Chiru [11] leveraged the following features: the historical relevance scores of the accepted papers of every institution, Author Impact Factor (AIF) [12], and the weighted moving-average of relevance scores from previous years to predict the accepted papers of the institution in next year. Xie [13] used linear regression and gradient boosting decision tree to predict the impact of each institution by integrating four features: accepted paper-rank, program committee membership, cross-conference, and cross-phase. Orouskhani and Tavabi [14] ranked the research institutions based on the annual scores of the institutions.

Compared to the evaluation of scholarly impact, to find future potential impact is more guiding significance. Exploring the factors driving scholarly impact is very crucial. Predicting the impact of papers usually focused on the citations prediction or citation distributions. Early citations as a crucial feature usually were used to predict the potential citations of a paper [15]–[17]. Cao *et al.* [17] predicted future citations of a paper by integrating a short-term citation history to a

Gaussian mixture model. Stegehuis *et al.* [18] predicted the citations distribution of a paper in the future by the two crucial features: early citations and Journal Impact Factor [19]. The prediction of scholars' impact mainly focused on predicting the author's H-index and his (her) citations. Penner *et al.* [20] applied the future impact model based on linear regression to 762 careers from three disciplines: mathematics, physics and biology. They found that their models' prediction performance depended heavily on scientists' career age. Based on linear regression, Dong *et al.* [21] leveraged six factors, including author, content, venue, social information, reference and temporal data to predict an author's H-index [22] in five years. They found that topic authority and venue were two crucial factors, which can determine whether a newly published paper will enhance its authors' H-index. Based on a linear regression with elastic net regularization, Acuna *et al.* [23] constructed a simple model including the number of papers, H-index, years since first publication, and etc.

Intuitively, the previous changing trend of the impact of each institution is the most relevant to future impact of the institution. Therefore, previous scholars mainly consider the historical relevance scores of the accepted papers for each institution to predict future impact of the institution. Namely, the number of the accepted papers for each institution in previous years is used as an important feature to construct the predictive model. However, we find that scholars' impact such as AIF, Q value [24], and H-index are more relevant to predict the impact of institutions for top conferences, compared to the relevance scores of the institution. Svider *et al.* [25] found that there was an association between industry support and academic impact. An interesting phenomenon is that industry payments greater than \$10,000 were related to a greater scholarly impact. Their work inspires us to explore GDP to improve the performance of the predictive model for accurately predicting the potential impact of institutions.

The paper aims to explore the factors driving the changes of the impact of institutions and the contributions of these factors for predicting the impact of the institutions. Via feature selection, we find that the impact of an institution, as measured by the number of the accepted papers of the institution, more is determined by the authors' influence of the institution. Geographic location of institution feature and state GDP can drive the changes of the impact of institutions. At the same time, we also find that the features driving the changing of the impact of institution play different roles for predicting the future potential impact. Based on XGBoost [26], we propose a novel prediction model, which has the ability to generate accurate predictions and explain the prediction performance.

II. METHODS

We now describe our methods on predicting the number of the accepted papers of each institution for top conferences, including the following five parts: prediction task, dataset and

data processing, factors that drive the impact of institutions to increase, feature selection, and predicting the future impact of institutions.

A. PREDICTION TASK

Given the heterogeneous characteristics of scholarly data, our task aims to predict the number of the accepted papers of each institution for top conferences. We consider the problem of the impact of institutions prediction from academic data. Let $Y = \{Y_1, Y_2, \dots, Y_T\}$ be the set of the number of the accepted papers for an institution of a conference in different years, where Y_i corresponds to the number of the accepted papers for an institution in the i^{th} year. Given features X extracted from the experimental data as input, the impact of institution predictor needs to generate $f = (f_1, f_2, \dots, f_T)$ as output, where f_i is the predicted number of the accepted papers of an institution for a top conference in next year.

B. DATASET AND DATA PROCESSING

We use the real-world data from Microsoft Academic Graph (MAG), which is a large and heterogeneous graph. Each paper contains publication date, citation relationships, authors, institutions, journal or conference, and fields of study. In our experiments, we follow KDD-CUP 2016's conference selection, including FSE, ICML, KDD, MM, MobiCom, SIGCOMM, SIGIR and SIGMOD to construct our experimental dataset. Firstly, we retain the data from 2000 to 2015, and add the loss authors' institution information according to the institution information of their previous publication. Secondly, because a small part of the data is incomplete, the data are deleted. Finally, we remove the duplicated institutional information to find the coordinates of these institutions. After the data processing, our experimental dataset includes 33,953 authors with 19,343 papers from 4,524 institutions across years 2000 to 2015.

C. FACTORS THAT DRIVE THE IMPACT OF INSTITUTIONS TO INCREASE

1) AUTHOR-BASED FEATURES

- Author Impact Factor (AIF). Author impact factor is an extension of the journal impact factor to authors. AIF of an author in year T is the average citations of published papers in a period of ΔT years before year T . Based on the eight top conferences selected by KDD-CUP 2016, we compute each author's AIF value according to the author's publishing history and use the statistics of a given institution's all authors' AIF as a group of its features, including sum, maximum, minimum, median, average and deviation. We briefly explore and report the authors' AIF features in this work.
- Q value. The Q value reflects the ability of scientists to enhance the impact of a paper [24], and it is a constant in a scientist's career.

$$Q_i = e^{(\log c_{ia}) - \mu_p} \quad (1)$$



FIGURE 1. The coordinate of different institutions published papers on KDD conference from 2011 to 2014. (a) 2011. (b) 2012. (c) 2013. (d) 2014.

where Q_i indicates a scientist i 's Q value. $\langle \log c_{i\alpha} \rangle$ is the average logarithmic citations of all papers published by scientist i and α indicates scientist i 's α -th paper. μ_p is the mean value of all papers' potential impact.

- H-index. A scholar has an index value of H if the scholar has H papers with at least H citations. H-index can give an estimate of the impact of a scholar's cumulative research contributions. Based on each selected top conference, we calculate each author's H-index value according to his or her published information in all conferences, then calculate the features of a given institution via the same way as authors' AIF.

2) GEOGRAPHIC DISTANCE-BASED FEATURES

Given I represents a set of institutions, $I = \{I_1, I_2, \dots, I_a \dots\}$. L represents a set of the conference location $L = \{L_1, L_2, \dots, L_i \dots\}$. For the geographic distance between an institution I_a with the conference location L_i , d , can be approximated by a spherical model:

$$d = 2R \cdot \arcsin \sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_a) \cdot \cos(\phi_i) \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right)} \quad (2)$$

where R is the Earth's radius, ϕ_a and λ_a are the latitude and longitude values of institute a , and ϕ_i and λ_i are the latitude and longitude values of conference i 's location. $\Delta\phi = |\phi_a - \phi_i|$ and $\Delta\lambda = |\lambda_a - \lambda_i|$.

Figure 1 shows the geographic distributions of institutions and the location of KDD conference from 2011 to 2014. The red dots represent the institutions, and the green dots represent the conference location. We observe that the authors' institutions published papers on KDD conference mainly distribute in North America, Europe and Asian.

3) ECONOMIC FEATURES

The GDP per capita of different countries are obtained from the website: <http://data.worldbank.org>. In our experiments, we use the GDP per capita data from 2000 to 2015.

4) RELEVANCE SCORES-BASED FEATURES

Figure 2 shows an example that the impact of scholarly papers is allocated to different institutions for a given top conference. The relevance score of each institution in different years can be summarized as follows: (1) each accepted paper is considered as the equal importance. (2) each author has same contribution to a paper. (3) if an author has multiple institutions,

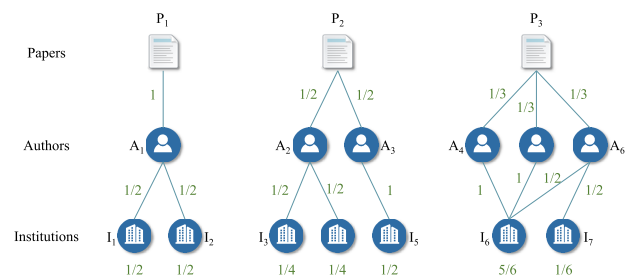


FIGURE 2. A example demonstrating the relevance scores of each institution.

each institution also contributes equally. In addition, we use time trend-based features to weight the relevance scores of each institution in given years. The higher weights are given for the recent years relative to the forecasting year, and the lower weights are given for the years away from predicting year. The weights are normalized, and the sum of weights are set as 1. The time trend-based features are used for windows of four years. We also use distance trend-based features to weight the relevance scores of each institution in given years. The higher weights are given for the institutions farther from the conference's location in the forecasting year.

D. FEATURE SELECTION

In practice, features extracted for machine learning may sometimes be irrelevant or redundant. Selecting the truly correlative features can simplify the predictive model, and even improve the prediction accuracy if there exist some wanted features. To remove the unwanted features, it is necessary to give an importance score for the features of each dimension. In this paper, we use XGBoost feature selection, which can give the score of each feature in the training model, indicating the importance of each feature. The feature score of each feature is the number of times of each feature used in the decision tree nodes partition. The prediction features of impact of institutions are described in Table 1.

E. LEARNING ALGORITHMS

In this section, we describe two algorithms for learning and predicting the impact of institutions for top conferences. One is Gradient boosting decision trees (GBDT), which is a comparison model. The other is XGBoost, which is intended to enhance the prediction performance for predicting the impact of institutions in the future.

TABLE 1. Features used in prediction model.

Feature	Description	Feature	Description
rel y1	relevance scores ¹ in y1 year ²	GDP y2	GDP in y2 year
rel y2	relevance scores in y2 year ²	GDP y3	GDP in y3 year
rel y3	relevance scores in y3 year ²	GDP y4	GDP in y4 year
rel y4	relevance scores in y4 year ²	sum(Q)	sum of Q value
sum(rel)	sum of relevance scores	max(Q)	maximum of Q value
max(rel)	maximum of relevance scores	min(Q)	minimum of Q value
min(rel)	minimum of relevance scores	avg(Q)	average of Q value
avg(rel)	average of relevance scores	med(Q)	median of Q value
med(rel)	median of relevance scores	dev(Q)	deviation of Q value
dev(rel)	deviation of relevance scores	sum(AIF)	sum of AIF
wt(rel)	time weighted relevance scores	max(AIF)	maximum of AIF
wd(rel)	distance weighted relevance scores	min(AIF)	minimum of AIF
sum(H-index)	sum of H-index	avg(AIF)	average of AIF
max(H-index)	maximum of H-index	med(AIF)	median of AIF
min(H-index)	minimum of H-index	dev(AIF)	deviation of AIF
avg(H-index)	average of H-index	distance y1	distance between conference and institution in y1 year
med(H-index)	median of H-index	distance y2	distance between conference and institution in y2 year
dev(H-index)	deviation of H-index	distance y3	distance between conference and institution in y3 year
GDP y1	GDP in y1 year	distance y4	distance between conference and institution in y4 year

¹ relevance scores are the number of the accepted papers for each institution in given year.

² y year represents the predictive year, y1=y-4, y2=y-3, y3=y-2, y4=y-1.

1) GBDT

The GBDT model is used to predict the number of accepted papers for each institution in the eight top conferences in next year. GBDT model suits for dealing with a mass of features and no-linear relationships between the predictor variables and the target variable. GBDT model is the extension of weak decision trees, and the error function selected is the mean square error function when GBDT is used to regression problem. In dealing with the problem of predicting the impact of institutions in next year, Sandulescu and Chiru [11] used three kinds of features: statistics-based features, trend-based features and AIF-based features including time weighted relevance scores and the sum, maximum, minimum, median, average, deviation of relevance scores and authors' AIF.

2) XGBoost

XGBoost is a scalable end-to-end tree boosting system, which runs more than ten times faster than existing currently popular solutions.

XGBoost's tree boosting mainly includes two parts. One is regularized learning objective, the other is gradient tree boosting. For a given dataset D with m examples and n features $D = \{(x_i, y_i)\}$, where $|D| = m, x_i \in R^n, y_i \in R$, the formula of output prediction is as follows:

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^K f_k(x_i), \quad f_k \in F, \quad (3)$$

where $F = \{f_x = \omega_{q(x)}\}(q : R^n \rightarrow T, \omega \in R^T)$ is the space of regression trees. q indicates the structure of each tree, which maps an example to the corresponding leaf index. T is the number of leaves of the tree. f_k is consistent with tree

structure q and leaf weights ω . In order to learn f_k , the following regularized objective is introduced:

$$\Gamma(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k), \quad (4)$$

where $\Omega(f) = \gamma T + \frac{1}{2} \lambda \|\omega\|^2$, Ω controls the complexity of the model to avoid over-fitting. l indicates a loss function, which calculates the difference between the prediction value \hat{y}_i and the true value y_i .

To improve the prediction model according to the equation, f_t is added:

$$\Gamma^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t), \quad (5)$$

where $\hat{y}_i^{(t)}$ is the prediction of the i^{th} instance at the t^{th} iteration.

In the XGBoost model, the second order Taylor expansion is used to accelerate the optimization procedure of the objective function, which is shown as follows:

$$\tilde{\Gamma}^{(t)} = \sum_{i=1}^n [g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2, \quad (6)$$

where $g_i = \partial_{\hat{y}_i^{(t-1)}} l(y_i, \hat{y}_i^{(t-1)})$, and $h_i = \partial_{\hat{y}_i^{(t-1)}}^2 l(y_i, \hat{y}_i^{(t-1)})$ are the first and second order gradient statistics for the loss function.

For an independent tree structure $q(x)$, the optimal weight w_j^* of leaf j is calculated as follows:

$$\omega_j^* = - \frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda}. \quad (7)$$

The corresponding optimal objective function is calculated by the following formula:

$$\tilde{\Gamma}^{(t)} = -\frac{1}{2} \sum_{j=1}^T \frac{(\sum_{i \in I_j} g_i)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma T. \quad (8)$$

Our training data is composed of a sequence of relevant features of the institutional impact $\Lambda = (\theta_1, \theta_2, \theta_3, \dots, \theta_n)$, where θ_i represents the i -th feature. In our experiments, we mainly use historical data in the previous four year to predict the number of the accepted papers in the next year from each institution, and the experiments are conducted across years 2000 to 2010. The features include author-based features, relevance scores-base features, geographic distance-based features, and GDP-based features. We use the number of accepted papers of each institution in prediction year to label each training data to train XGBoost model for the task of institution impact prediction. Our testing data is extracted from the selected conference between 2011 and 2015. We use the extracted features from 2011 to 2014 to predict the number of the accepted papers in 2015. We employ the XGBoost algorithm that can yield accurate prediction for the future impact of each institution.

F. NORMALIZED DISCOUNTED CUMULATIVE GAIN (NDCG) FOR MODEL EVALUATION

NDCG is a normalized measure method of Discounted Cumulative Gain (DCG). NDCG usually is used to indicate the accuracy of prediction model. DCG is given by:

$$DCG_n = \sum_{i=1}^n \frac{rel_i}{\log_2^{i+1}}, \quad (9)$$

where DCG_n is the weighted sum of relevant degree of ranked entities, and its weight is a decreasing function varying according to the ranked position. Variable i is the ranking of an institution, and rel_i is the relevance score of the i -th ranked institution. Via normalizing DCG values, NDCG@N is given by:

$$NDCG_n = \frac{DCG_n}{IDCG_n}, \quad (10)$$

where $IDCG$ is an ideal DCG, which is considered as the simple DCG measure with the best ranking results. Therefore, the probability score of NDCG measurement always are between 0 and 1. In this paper, NDCG reflects the importance of an institution in the given relevant top conference. If an institution is not appeared in the final ranking results, its NDCG value will be set as 0.

III. RESULTS

Considering the historical relevance scores of the accepted papers is a common practice in predicting institutional contribution in a conference [11]. Via feature selection, we find that author-based features introduce more impact, and we observe that the authors' impact of each institution for some

top conferences dominates the impact of the institution. In our experiments, we train the predictive model using top 10%, top 20%, top 30%, ..., and all features including author-based features, relevance scores-based features, geographic distance-based features, and state GDP-based features. Via feature selection, feature importance ranking of different features for the selected conferences is shown in Figure 3. The feature importance ranking indicates the best predictive performance according to the selected features. In Figure 3, we observe that the feature importance scores are different according to features selected to train the predictive model.

Figure 3a shows the feature importance ranking via different percentages of features selection for FSE. We observe that the features related to authors' AIF rank first for using different percentages of features to train the predictive model. Author-based features' importance scores, relevance scores-based features' importance scores, geographical distance-based features' importance scores and GDP-based features' importance scores for FSE are listed in Table 2a. In Table 2a, we observe that author-based features' importance scores are the highest, which are higher than 0.5. Specially, author-based features' importance scores reach 0.9944 via using top 20% features to train the predictive model. Relevance scores-based features' importance scores are lower than 0.25, and geographical distance-based features' importance scores are lower than 0.32. The lowest feature importance scores are from GDP-based features, which are lower than 0.1.

Figure 3b shows feature importance ranking for ICML. We observe that the sum of authors' AIF features rank first in all the features' importance ranking list for ICML. In Table 2b, we observe that author-based features' importance scores are the highest in the four kinds of features: author-based features, relevance scores-based features, geographical distance-based features and GDP-based features. All the author-based features' importance scores exceed 0.48 for using different percentages of features to train the predictive model. Relevance scores-based features' importance scores are between 0.2 and 0.4. For ICML, geographical distance-based features begin to take effect from top 60% features, and GDP-based features' importance scores are from top 20% features.

Figure 3c illustrates the feature importance ranking for KDD. We observe that the sum of authors' AIF features ranks first in terms of feature importance. From Table 2c, we observe that author-based features' importance scores are higher than relevance scores-based features' importance scores except for the top 20% features. Author-based features' importance scores range from 0.3 to 0.6, and relevance scores-based features' importance scores are between 0.2 and 0.7. Compared to ICML, geographical distance-based features begin to take effect earlier when the top 30% features are used. GDP-based features are found after choosing the top 60% features.

Figure 3d shows the feature importance ranking for MM. Compared with FSE, ICML and KDD, the relevant features with authors do not always appear first on the feature

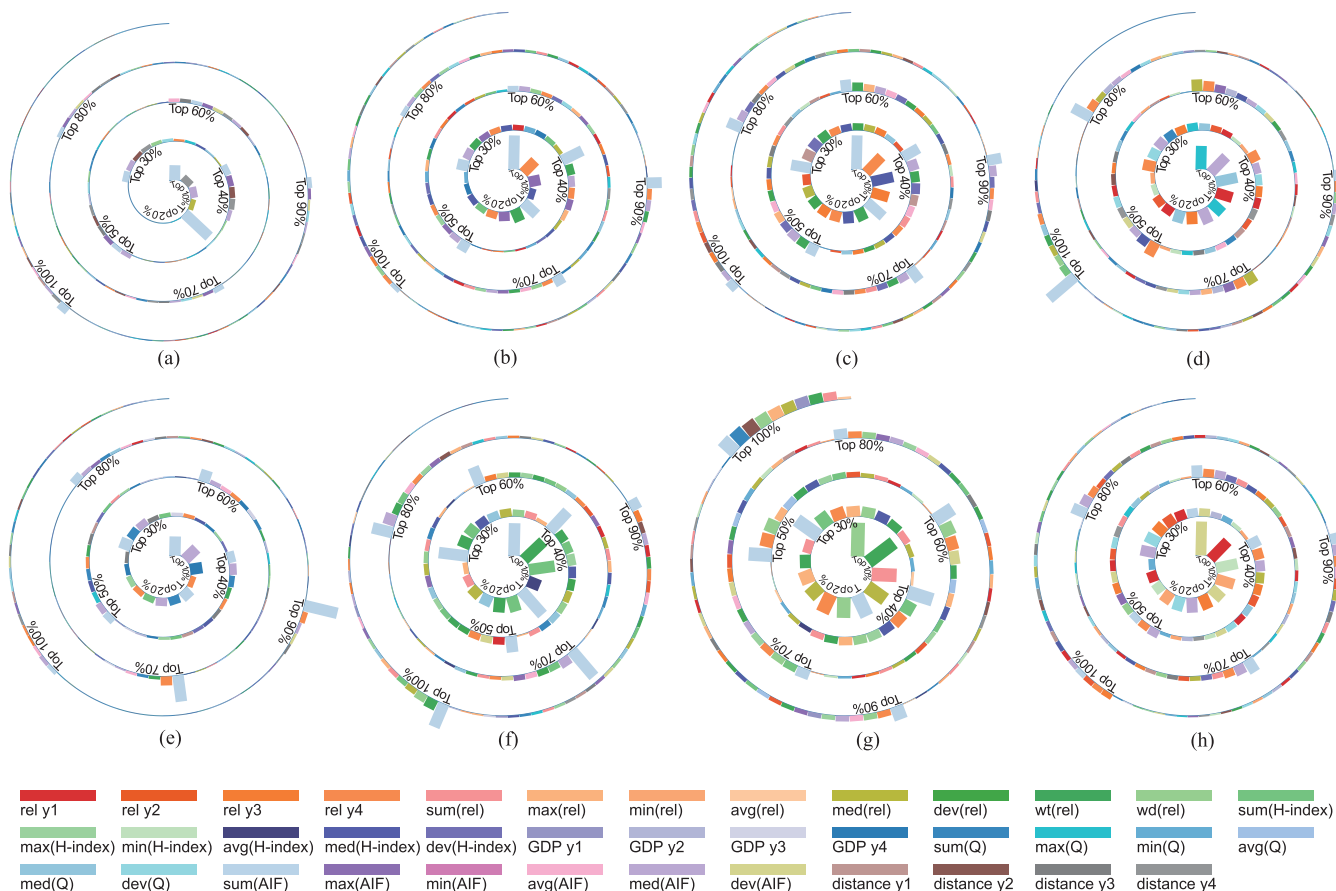


FIGURE 3. Feature importance ranking from four features for different conferences. Notes: the horizontal axis indicates the relevant importance scores, and the vertical axis indicates the features. (a) FSE. (b) ICML. (c) KDD. (d) MM. (e) MobiCom. (f) SIGCOMM. (g) SIGIR. (h) SIGMOD.

importance ranking list, other relevant features such as the historical scores of institutions rank first for top 40%, top 50%, top 60% and top 70% features. In Table 2d, we observe that author-based features’ importance scores are between 0.4 and 0.8, and relevance scores-based features’ importance scores are between 0.2 and 0.5.

Figure 3e illustrates the feature importance ranking for MobiCom. According to Figure 3e, we observe that authors’ AIF features always rank first in feature importance ranking list. In Table 2e, we observe that author-based features’ importance scores are higher than the relevance scores-based features’ importance scores. Like FSE, author-based features’ importance scores are higher than 0.5 for using different percentages of features to train the model. The relevance scores-based features’ importance scores are between 0.1 and 0.3. The geographical distance-based features’ importance scores and GDP-based features’ importance scores range from 0 to 0.3. Compared to FSE, ICML, KDD, and MM, GDP-based features’ importance scores begin to take effect from using top 10% features to train the model.

Figure 3f illustrates the feature importance ranking for SIGCOMM. According to Figure 3f, we observe that authors’ AIF features rank first in feature importance ranking list. Like MobiCom, authors-based features’ importance scores

are higher than the relevance scores-based features’ importance scores for SIGCOMM, which is shown in Table 2f. In Table 2f, we observe that geographical distance-based features and GDP-based features have quite a few effects for improving the predictive model.

Figure 3g shows the feature importance ranking for SIGIR. According to Figure 3g, we observe that the authors-based features rank first excluding the top 10% features. In Table 2g, we observe that author-based features’ importance scores are between 0 and 0.6, and the relevance score-based features’ importance scores are between 0.3 and 1. For less than top 30% features, the relevant score-based features’ importance scores are higher than authors-based features’ importance scores. Like SIGCOMM, geographical distance-based features and GDP-based features have quite a few effects for improving the performance of predictive model.

Figure 3h shows the feature importance ranking for SIGMOD. According to Figure 3h, we observe that authors’ AIF features rank first in feature importance ranking list excluding the case of using all features to train predictive model. In Table 2h, we observe that author-based features’ importance scores are higher than relevance scores-based features’ importance scores. Author-based features’ importance scores are between 0.4 and 0.7, and the

TABLE 2. Four features' importance scores. (a) FSE. (b) ICML. (c) KDD. (d) MM. (e) MobiCom. (f) SIGCOMM. (g) SIGIR. (h) SIGMOD.

(a)					(b)					(c)				
Features	Author	Relevance scores	Distance	GDP	Features	Author	Relevance scores	Distance	GDP	Features	Author	Relevance scores	Distance	GDP
10%	0.6349	0.1451	0.2200	0.0000	10%	0.7547	0.2452	0.0000	0.0000	10%	0.5839	0.4160	0.0000	0.0000
20%	0.9944	0.0029	0.0026	0.0000	20%	0.6272	0.3041	0.0000	0.0687	20%	0.3518	0.6483	0.0000	0.0000
30%	0.5738	0.1999	0.2262	0.0000	30%	0.5966	0.3299	0.0000	0.0735	30%	0.4491	0.4352	0.1155	0.0000
40%	0.5926	0.0948	0.3127	0.0000	40%	0.6198	0.3695	0.0000	0.0107	40%	0.5438	0.3770	0.0792	0.0000
50%	0.5660	0.1149	0.2353	0.0837	50%	0.6174	0.3395	0.0000	0.0431	50%	0.4746	0.4155	0.1097	0.0000
60%	0.5679	0.0913	0.2591	0.0819	60%	0.5553	0.3805	0.0379	0.0263	60%	0.4686	0.4163	0.0861	0.0289
70%	0.6087	0.2068	0.1325	0.0520	70%	0.5464	0.3822	0.0243	0.0470	70%	0.4994	0.3182	0.1446	0.0379
80%	0.5679	0.1953	0.1572	0.0796	80%	0.5266	0.3790	0.0584	0.0363	80%	0.5378	0.2950	0.1324	0.0347
90%	0.5890	0.2307	0.1222	0.0583	90%	0.5814	0.3049	0.0726	0.0412	90%	0.5655	0.2764	0.1252	0.0328
100%	0.5616	0.1765	0.2125	0.0493	100%	0.4883	0.3676	0.0976	0.0465	100%	0.4663	0.3460	0.1535	0.0343

(d)					(e)					(f)				
Features	Author	Relevance scores	Distance	GDP	Features	Author	Relevance scores	Distance	GDP	Features	Author	Relevance scores	Distance	GDP
10%	0.7986	0.2014	0.0000	0.0000	10%	0.6609	0.1069	0.0000	0.2323	10%	0.7282	0.2718	0.0000	0.0000
20%	0.5819	0.4182	0.0000	0.0000	20%	0.7424	0.1079	0.0675	0.0821	20%	0.6050	0.3949	0.0000	0.0000
30%	0.5751	0.4250	0.0000	0.0000	30%	0.7267	0.0688	0.0865	0.1180	30%	0.6077	0.3924	0.0000	0.0000
40%	0.4351	0.3764	0.1884	0.0000	40%	0.6136	0.1382	0.1241	0.1240	40%	0.6347	0.3653	0.0000	0.0000
50%	0.4925	0.3213	0.1863	0.0000	50%	0.6360	0.1704	0.1071	0.0863	50%	0.5527	0.4474	0.0000	0.0000
60%	0.4716	0.3697	0.0865	0.0721	60%	0.5767	0.1855	0.0520	0.1857	60%	0.5559	0.4442	0.0000	0.0000
70%	0.4295	0.4025	0.0833	0.0848	70%	0.6503	0.2559	0.0212	0.0424	70%	0.7734	0.2264	0.0000	0.0000
80%	0.5075	0.2867	0.0739	0.1322	80%	0.5932	0.2067	0.1028	0.0973	80%	0.6440	0.2636	0.0922	0.0000
90%	0.4846	0.3326	0.1166	0.0662	90%	0.7889	0.1165	0.0680	0.0265	90%	0.4482	0.3720	0.1291	0.0508
100%	0.6690	0.3285	0.0017	0.0005	100%	0.5201	0.2693	0.1414	0.0691	100%	0.5137	0.4024	0.0354	0.0484

(g)					(h)				
Features	Author	Relevance scores	Distance	GDP	Features	Author	Relevance scores	Distance	GDP
10%	0.0000	1.0000	0.0000	0.0000	10%	0.5624	0.4377	0.0000	0.0000
20%	0.2068	0.7932	0.0000	0.0000	20%	0.6184	0.3816	0.0000	0.0000
30%	0.4932	0.5067	0.0000	0.0000	30%	0.5646	0.3765	0.0000	0.0591
40%	0.5681	0.4320	0.0000	0.0000	40%	0.4732	0.4470	0.0400	0.0399
50%	0.4802	0.5197	0.0000	0.0000	50%	0.4826	0.4269	0.0552	0.0351
60%	0.5035	0.4964	0.0000	0.0000	60%	0.5033	0.3802	0.0889	0.0277
70%	0.5437	0.4253	0.0311	0.0000	70%	0.4840	0.3575	0.1200	0.0385
80%	0.4988	0.3845	0.1168	0.0000	80%	0.4774	0.3762	0.1088	0.0375
90%	0.4764	0.3616	0.0897	0.0725	90%	0.4915	0.3655	0.1062	0.0368
100%	0.2928	0.5646	0.0717	0.0710	100%	0.4560	0.3753	0.1323	0.0362

relevance scores-based features' importance scores are between 0.3 and 0.5.

Because we find that the historical relevance scores of each institution are not the most important factors for predicting the number of the accepted papers via the feature selection, this drives us to explore the performance of the prediction model without considering the relevant features with the historical relevance scores of each institution. We resume to train the model using features excluding the features relevant to the historical relevance scores of each institution.

Figure 4 shows the feature importance ranking according to different percentages of features excluding the relevant features with the relevant historical scores of each institution.

Figure 4a shows the feature importance ranking for FSE. According to Figure 4a, we observe that authors' AIF features rank first for different percentages of features. In Table 3a, we observe that author-based features' importance scores are the highest, which are between 0.6 and 1. Geographical distance-based features' importance scores are between 0 and 0.4, and GDP-based features' importance scores are between 0 and 0.07.

Figure 4b shows the feature importance ranking for ICML. We observe that the sum of authors' AIF features rank

first in all the features' importance ranking list for ICML. In Table 3b, we observe that author-based features' importance scores are 1 from top 10% to top 40% features. For using different percentages of features to train the predictive model, author-based features play a crucial role, and author-based features' importance scores are beyond 0.75. Distance-based features' importance scores are between 0.04 and 0.16 from top 50% features to top 100% features. GDP-based features only take effect for using top 90% features and top 100% features.

Figure 4c illustrates the feature importance ranking for KDD. we observe that the sum of authors' AIF features rank first in feature importance ranking list. In Table 3c, we observe that author-based features' importance scores are higher than 0.8. Distance-based features' importance scores are less than 0.2, and GDP-based features' importance scores are about 0.05 from using top 80% features to train the predictive model.

Figure 4d shows the feature importance ranking for MM. We observe that the sum of authors' AIF feature ranks first in feature importance ranking list excluding top 50% features. In Table 3d, we observe that author-based features' importance scores are beyond 0.6. Geographical distance-based

TABLE 3. Three features’ importance scores. (a) FSE. (b) ICML. (c) KDD. (d) MM. (e) MobiCom. (f) SIGCOMM. (g) SIGIR. (h) SIGMOD.

(a)				(b)				(c)			
Features	Author	Distance	GDP	Features	Author	Distance	GDP	Features	Author	Distance	GDP
10%	1.0000	0.0000	0.0000	10%	1.0000	0.0000	0.0000	10%	1.0000	0.0000	0.0000
20%	1.0000	0.0000	0.0000	20%	1.0000	0.0000	0.0000	20%	1.0000	0.0000	0.0000
30%	0.7411	0.2589	0.0000	30%	1.0000	0.0000	0.0000	30%	1.0000	0.0000	0.0000
40%	1.0000	0.0000	0.0000	40%	1.0000	0.0000	0.0000	40%	0.8923	0.1076	0.0000
50%	0.6434	0.3566	0.0000	50%	0.9283	0.0718	0.0000	50%	0.8840	0.1160	0.0000
60%	0.7337	0.2186	0.0479	60%	0.9509	0.0491	0.0000	60%	0.8367	0.1632	0.0000
70%	0.6187	0.1636	0.0508	70%	0.9352	0.0648	0.0000	70%	0.8359	0.1641	0.0000
80%	0.7300	0.2029	0.0672	80%	0.8677	0.1324	0.0000	80%	0.8563	0.0933	0.0504
90%	0.7102	0.2128	0.0224	90%	0.7978	0.1586	0.0335	90%	0.8112	0.1342	0.0545
100%	0.7868	0.1526	0.0608	100%	0.8355	0.1065	0.0580	100%	0.8129	0.1284	0.0585

(d)				(e)				(f)			
Features	Author	Distance	GDP	Features	Author	Distance	GDP	Features	Author	Distance	GDP
10%	1.0000	0.0000	0.0000	10%	1.0000	0.0000	0.0000	10%	1.0000	0.0000	0.0000
20%	1.0000	0.0000	0.0000	20%	1.0000	0.0000	0.0000	20%	1.0000	0.0000	0.0000
30%	1.0000	0.0000	0.0000	30%	1.0000	0.0000	0.0000	30%	1.0000	0.0000	0.0000
40%	0.8536	0.1464	0.0000	40%	0.8870	0.0655	0.0474	40%	0.9421	0.0579	0.0000
50%	0.8369	0.1631	0.0000	50%	0.9079	0.0000	0.0920	50%	0.9260	0.0000	0.0074
60%	0.7673	0.1647	0.0679	60%	0.8805	0.0000	0.1194	60%	0.8731	0.0550	0.0719
70%	0.7945	0.1376	0.0681	70%	0.8245	0.0761	0.0996	70%	0.8703	0.0345	0.0954
80%	0.7820	0.1110	0.1071	80%	0.7736	0.1195	0.1069	80%	0.7940	0.0949	0.0671
90%	0.6761	0.2509	0.0731	90%	0.7552	0.1418	0.1030	90%	0.7998	0.1222	0.0779
100%	0.7549	0.1567	0.0884	100%	0.7700	0.1342	0.0954	100%	0.8227	0.1063	0.0709

(g)				(h)			
Features	Author	Distance	GDP	Features	Author	Distance	GDP
10%	1.0000	0.0000	0.0000	10%	1.0000	0.0000	0.0000
20%	1.0000	0.0000	0.0000	20%	1.0000	0.0000	0.0000
30%	0.8220	0.0000	0.1779	30%	1.0000	0.0000	0.0000
40%	0.9120	0.0000	0.0880	40%	0.9229	0.0772	0.0000
50%	0.8638	0.0000	0.1363	50%	1.0000	0.0000	0.0000
60%	0.9026	0.0000	0.0972	60%	0.9116	0.0267	0.0000
70%	0.8772	0.0000	0.1229	70%	0.9298	0.0251	0.0000
80%	0.8991	0.0000	0.1008	80%	0.8883	0.0556	0.0559
90%	0.8354	0.0196	0.1450	90%	0.8793	0.0698	0.0508
100%	0.7953	0.0541	0.1506	100%	0.8206	0.0954	0.0549

TABLE 4. NDCG@20 results for GBDT model.

conference	GBDT
FSE	0.604
ICML	0.851
KDD	0.909
MM	0.790
MobiCom	0.571
SIGCOMM	0.769
SIGIR	0.906
SIGMOD	0.822

features’ importance scores are between 0 and 0.3. GDP-based features’ importance scores are about 0.1 from top 60% features.

Figure 4e illustrates the feature importance ranking for MobiCom. According to Figure 4e, we observe that authors’ AIF features always rank first in feature importance ranking list. In Table 3e, we observe that author-based features’ importance scores are beyond 0.7. Geographical distance-based features’ importance scores and GDP-based features’ importance scores are less than 0.15.

Figure 4f illustrates the feature importance ranking for SIGCOMM. We observe that the sum of authors’ AIF features

rank first in feature importance ranking list. In Table 3f, we observe that author-based features’ importance scores are between 0.7 and 1. Geographical distance-based features’ importance scores are less than 0.2, and GDP-based features’ importance scores are less than 0.1.

Figure 4g illustrates the feature importance ranking for SIGIR. We observe that the sum of authors’ AIF features rank first in feature importance ranking. In Table 3g, we observe that author-based features’ importance scores are higher than 0.7 for using different percentages of features to train the predictive model. geographical distance-based features’ importance scores are less 0.1, and GDP-based features’ importance scores are less than 0.2.

Figure 4h shows the feature importance ranking for SIGMOD. According to Figure 4h, we observe that authors’ AIF features rank first in feature importance ranking. In Table 3h, we observe that author-based features’ importance scores are beyond 0.8. Geographical distance-based features’ importance scores are less than 0.1, and GDP-based features’ importance scores are about 0.05 for using top 80%, top 90% and all the features to train the predictive model. Our experiment result shows that GDP related features are not significant comparing with others. One possible reason is that the proportion of national scientific research in GDP is

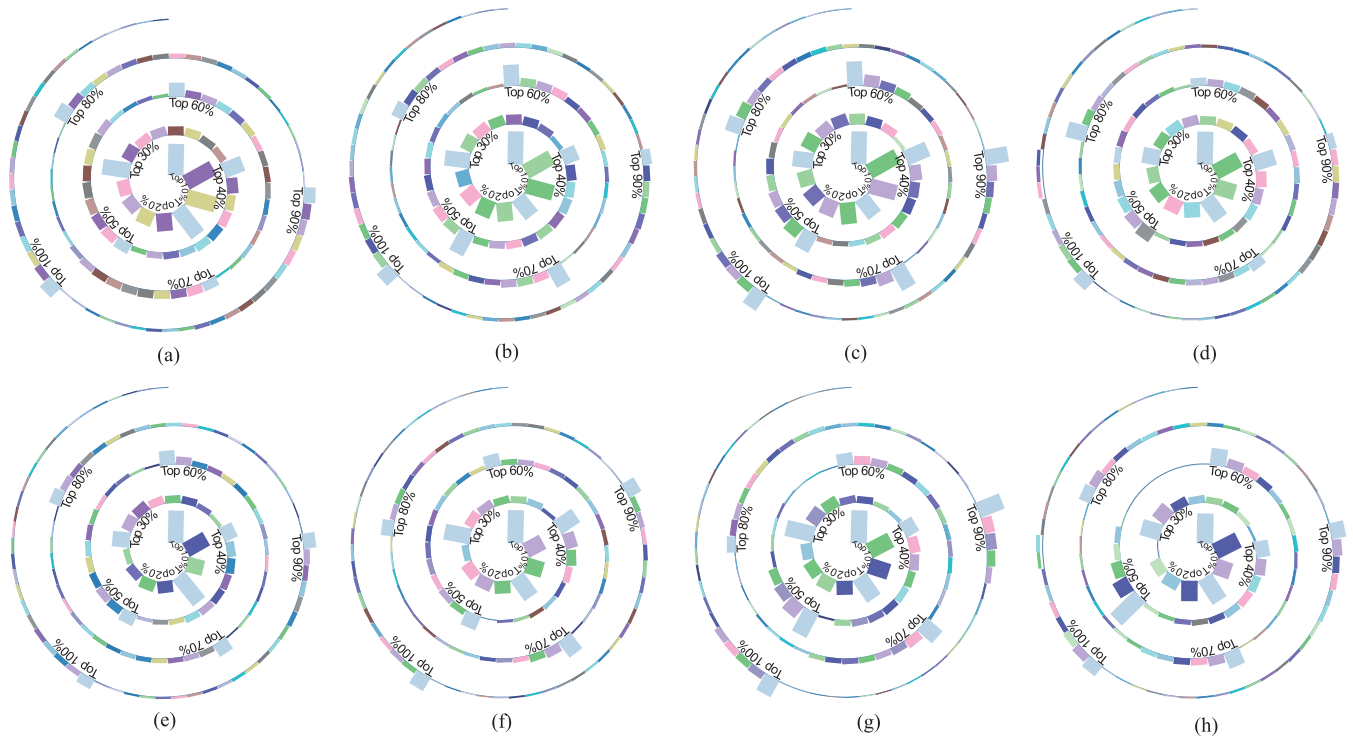


FIGURE 4. Feature importance ranking from three features for different conferences. Notes: the horizontal axis indicates the relevant importance scores, and the vertical axis indicates the features. (a) FSE. (b) ICML. (c) KDD. (d) MM. (e) MobiCom. (f) SIGCOMM. (g) SIGIR. (h) SIGMOD.

TABLE 5. NDCG@20 results for XGBoost model, using top percentages of features with historical relevance scores.

conference	10%	20%	30%	40%	50%	60%	70%	80%	90%	all features
FSE	0.564	0.623	0.683	0.649	0.661	0.686	0.676	0.700	0.696	0.612
ICML	0.901	0.888	0.902	0.915	0.903	0.895	0.893	0.892	0.887	0.923
KDD	0.937	0.939	0.934	0.926	0.930	0.936	0.929	0.928	0.928	0.945
MM	0.858	0.873	0.823	0.816	0.816	0.816	0.854	0.861	0.865	0.846
MobiCom	0.752	0.728	0.642	0.639	0.613	0.604	0.600	0.622	0.677	0.694
SIGCOMM	0.829	0.839	0.829	0.826	0.843	0.840	0.840	0.847	0.849	0.803
SIGIR	0.896	0.922	0.902	0.900	0.889	0.889	0.906	0.908	0.913	0.912
SIGMOD	0.794	0.779	0.822	0.846	0.857	0.854	0.843	0.850	0.849	0.839

very small. Another possible reason is that scientific research depending on funds exists difference in different fields.

An interesting finding is that we still obtain a good predictive performance despite of ignoring the historical relevance scores of institutions. The prediction accuracy NDCG@20 of GBDT model for the selected conferences is presented in Table 4. The prediction accuracy NDCG@20 of XGBoost model with historical relevance scores for the conferences is presented in Table 5. The prediction accuracy NDCG@20 of XGBoost model without historical relevance scores for the conferences is presented in Table 6. In Table 4-6, we observe that the best prediction performance of the impact of institutions is random for different top percentages of features. XGBoost model with or without relevance scores features generally performs much better than GBDT model. XGBoost model with all features including relevance scores of institutions to train data has stronger

predictability for ICML, and KDD. Compared to the prediction result of GBDT with 0.851, the best prediction performance NDCG@20 with XGBoost model with all features is 0.923 for ICML. To KDD, the predictability NDCG@20 of using XGBoost model with all features is 0.945, which is higher than the prediction accuracy NDCG@20 with 0.909 of GBDT model. To FSE, the best prediction accuracy NDCG@20 with 0.727 is from XGBoost model excluding relevance scores of institutions by using top 50% features. However, the prediction performance of GBDT model is only 0.604. To MM, using XGBoost with top 20% features excluding historical relevance scores generates the highest prediction accuracy NDCG@20 with 0.890, While NDCG@20 of using GBDT model is only 0.790. To MobiCom, the prediction accuracy NDCG@20 of GBDT model is 0.571, while NDCG@20 of XGBoost model using top 10% features to train is 0.752. the prediction performance NDCG@20 of

TABLE 6. NDCG@20 results for XGBoost model, using top percentages of features without historical relevance scores.

conference	10%	20%	30%	40%	50%	60%	70%	80%	90%	all features
FSE	0.712	0.680	0.693	0.702	0.727	0.717	0.708	0.716	0.704	0.714
ICML	0.857	0.860	0.861	0.865	0.879	0.866	0.867	0.878	0.870	0.863
KDD	0.919	0.918	0.929	0.935	0.920	0.940	0.940	0.927	0.940	0.941
MM	0.829	0.890	0.886	0.862	0.870	0.847	0.850	0.856	0.854	0.857
MobiCom	0.589	0.573	0.615	0.652	0.633	0.614	0.646	0.640	0.708	0.622
SIGCOMM	0.824	0.835	0.843	0.832	0.852	0.839	0.846	0.840	0.835	0.841
SIGIR	0.889	0.881	0.881	0.887	0.897	0.894	0.899	0.897	0.893	0.887
SIGMOD	0.856	0.846	0.846	0.852	0.847	0.851	0.862	0.844	0.849	0.846

GBDT model is 0.769 for SIGCOMM, while NDCG@20 of the XGBoost model using the top 50% features excluding historical relevance scores is 0.852. To SIGIR, the prediction performance NDCG@20 of XGBoost model using top 20% features is 0.922, which is higher than the prediction result of GBDT with 0.906. For SIGMOD, the prediction performance NDCG@20 of XGBoost model using top 70% features excluding relevance scores of institutions is 0.862.

IV. CONCLUSION

In this paper, we study a data-driven method for predicting the contributions of different institutions in eight top conferences. Previous studies have mainly focused on adopting historical relevance scores of each institution to predict the impact of institutions. Unlike previous researches, by exploring the factors that can drive the changes of the impact of institutions such as author-based features, geographical distance-based features, economic features, and the relevance scores-based features, we have developed a high-performance prediction model, which has the ability to generate accurate predictions and explain which features have contribution to the predictive performance.

Several important findings are listed as follows: (1) the relevance scores of the accepted papers of each institution are not the most crucial factors for the prediction performance for top conferences. Via feature selection, we find that author-based features are critical in determining the number of accepted papers for an institution in the future. Compared to the Q value and H-index, the AIF features are more relevant to the number of accepted papers for an institution. (2) to ICML, KDD, MobiCom, and SIGCOMM, the authors' impact such as AIF, Q value, and H-index are the most relevant factors for predicting the impact of institutions. (3) for the selected top conferences excluding ICML and KDD, the performance of prediction using the fractional features is better than using all the features. (4) for KDD and SIGCOMM, the performance of prediction without using relevance scores of each institution is approximate to using the relevance scores of each institution. (5) geographic location of institution feature and state GDP feature can improve the predictive performance. Therefore, we draw a conclusion that the data-driven methods are crucial to the success of predictive models.

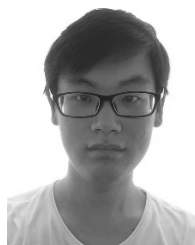
In the future, we will further explore the relationships between the impact of institutions and the features driving the impact of institutions change to enhance the predic-

tion performance. In addition, this work is conducted only on literatures from the eight top conferences based on MAG dataset, examining other conferences for the same observed patterns could widen the significance of our findings.

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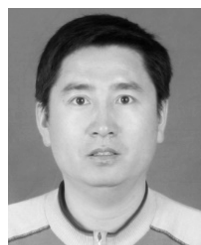


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