Predicting the Citations of Scholarly Paper

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Abstract

Citation prediction of scholarly papers is of great significance in guiding funding allocations, recruitment decisions, and rewards. However, little is known about how citation patterns evolve over time. By exploring the inherent involution property in scholarly paper citation, we introduce the Paper Potential Index (PPI) model based on four factors: inherent quality of scholarly paper, scholarly paper impact decaying over time, early citations, and early citers’ impact. In addition, by analyzing factors that drive citation growth, we propose a multi-feature model for impact prediction. Experimental results demonstrate that the two models improve the accuracy in predicting scholarly paper citations. Compared to the multi-feature model, the PPI model yields superior predictive performance in terms of range-normalized RMSE. The PPI model better interprets the changes in citation, without the need to adjust parameters. Compared to the PPI model, the multi-feature model performs better prediction in terms of Mean Absolute Percentage Error and Accuracy; however, their predictive performance is more dependent on the parameter adjustment.

Keywords: Scholarly Paper, Paper Potential Index, Multi-feature Model

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1. Introduction

There is an increasing interest in understanding the citation dynamics of scholarly paper and the evolution in science (Xia et al., 2017). So far, studies in this field have primarily been focused on success of science (Xia et al., 2016; Bai et al., 2016; Cao et al., 2016; Fiala and Tutoky, 2018; Zhang et al., 2017), academic collaboration networks (Panagopoulos et al., 2017), team science (Heidi, 2015) and scientific impact prediction (Bai et al., 2017). While citation serves as a popular indicator for measuring the research outcome, it is often required to estimate the future impact as well. For instance, research impact prediction helps in effective allocation of research funds (Clauset et al., 2017). An important challenge in scientific impact prediction is to characterize the change in citations over time, and it is important to identify the factors that affect citations of scholarly papers.

Previous studies have mainly focused on predicting the citations or analyzing future citation distributions. Some studies utilize machine learning algorithms such as Gradient Boosting Decision Tree (Sandulescu and Chiru, 2016), Support Vector Machine (Adankon and Cheriet, 2010), and XGBoost (Chen and Guestrin, 2016). To train the validity of the predictive models, crucial features have been identified for citation prediction, including early citations, journal impact factor, authors’ authority, journal reputation, topic of scholarly paper, and age (Petersen et al., 2014; Sarigöl et al., 2014; Yu et al., 2014). Some citation prediction studies have applied generative model to reflect the observation that older papers typically attracted higher citations (Newman, 2008), or to address some citation patterns that come with an initial period of growth followed by a gradual declined over time (Wang et al., 2008, 2013). More recently, Xiao et al. (2016) proposed a point process model to predict the long-term impact of individual publications based on early citations. Furthermore, Singh et al. (2017) has found that early influential citers negatively affected long-term scientific impact, possibly due to attention stealing, whereas non-influential early citers positively affected long-term scientific impact.

Inspired by the prior work Wang et al. (2008, 2013); Xiao et al. (2016); Singh et al. (2017), we model the Paper Potential Index (PPI) by considering the following factors: inherent quality of scholarly paper, scholarly paper impact decaying over time, early citations, and early citers’ impact. The PPI predictive model combines these factors and expands the Hawkes process, and it mainly depends on the inherent involution mechanism of paper cita-
tions with the following three properties: (1) Paper citation declines along with the decay of paper novelty over time; (2) The early citer’s impact can increase scholarly paper impact in the predictive model; (3) Early citations help retaining long term citations.

In addition, we propose a multi-feature predictive model, which considers author-based features, journal-based features, and citations feature. We compare the prediction results of the two models in terms of mean absolute error, root mean squared error, range-normalized RMSE, mean absolute percentage error and accuracy.

Main contributions of this paper include: (1) Introduction of PPI which reflects the potential impact of a scholarly article; (2) Consideration of scholarly paper impact decaying over time, scholarly papers’ quality, early citations, and early citing authors’ impact, to quantify the potential impact of scholarly articles; (3) Discussions on how PPI outperforms the existing multi-feature models in citation prediction.

2. Related work

Citation prediction of scholarly papers has been extensively investigated, and these studies are mostly based on the analysis of mixture of features, including author-based features (the number of authors, the country of the author’s institution, authors’ authority, etc.), journal-based features (the total citations of the journal, journal impact factor, keyword frequency of each journal, etc.), paper-based features (the topic of scholarly paper, scholarly paper length, keyword repetition in the abstract of a paper, the number of references, etc.), and other features such as institutional features (institutional rankings and reputation, etc.) In addition, Altmetrics are also employed to predict the citations of scholarly paper. Various investigations have been conducted to explore the correlation between Twitter activities and citation patterns [Peoples et al. 2016, Timilsina et al. 2016, Erdt et al. 2016]. Seminal examples in citation prediction using mixture of features are summarized in Table 1. The three categories of features: author-based features, journal-based features, and citations feature are used in our multi-feature predictive model. In order to improve the performance of prediction, Author Impact Factor (AIF), Q value, H-index, Journal Impact Factor and citations are used to predict the citations of scholarly paper. The main difference between our multi-feature predictive model and the prior studies is the selection of features.
| source | author features | journal features | paper features | other features |
|--------|----------------|-----------------|----------------|----------------|
| Haslam et al. (2008) | the number of authors, first author gender | journal prestige | title length, the number of references | first author institution’s prestige |
| Bornmann et al. (2012) | the number of authors, the reputation of the authors | the language of the publishing journal | citation count | citation performance of the cited references, reviewers’ ratings of importance |
| Livne et al. (2013) | H-index, g-index | journal prestige | citations | content similarity, graph density, clustering coefficient |
| Yu et al. (2014) | the number of authors, the country of the author’s institution, H-index | journal impact factor, total citations, 5-year impact factor, the cited half-life | the number of references, the reciprocal of the first-cited age of this paper | the document type |
| Singh et al. (2015) | H-index, author rank, past influence of authors, productivity, sociality, authority, versatility | journal rank, journal centrality, past influence of journals | publication count, citation count, novelty, topic rank, diversity | average countX, average citeWords |
| Robson and Mousquès (2016) | the number of authors, author name | the number of journal pages, journal prestige | the year of publication, title length, abstract length | special issue |
| Sohrabi and Iraj (2017) | the number of authors | | title length, abstract length | SCImago quartile |
In order to analyze the efficiency of multi-feature for citation prediction, regression models are often used. Popular regression models for citation prediction include quantile regression (Robson and Mousquès, 2016), semi-continuous regression (Sohrabi and Iraj, 2017) and Gradient Boosted Regression Trees (GBDT) (Chen and Zhang, 2015). Generative models can also be used to predict the citations of scholarly papers (Li et al., 2015; Zhang et al., 2016). Wang et al. (2013) proposed a point process by identifying three fundamental mechanisms in paper impact prediction: preferential attachment (highly cited papers are more likely be cited again), decay rate, and fitness (capturing the inherent differences between papers) to predict the probability of a paper being cited. To characterize the citation dynamics of scientific papers, a nonlinear stochastic model of citation dynamics based on the copying-redirection-triadic closure mechanism was reported by Golosovsky and Solomon (2017).

3. Modeling citing behavior as a point process

3.1. Dataset

The American Physical Society (APS) dataset includes all papers published in 9 journals, including Physical Review A, Physical Review B, Physical Review C, Physical Review D, Physical Review E, Physical Review I, Physical Review L, Physical Review ST and Review of Modern Physics, from 1970 to 2013 (http://publish.aps.org/datasets). Each record in the APS dataset includes paper title, author names, author affiliations, date of publication, and a list of cited papers. Because the APS dataset does not provide unique author identifiers, we first do name disambiguation based on the method proposed by Sinatra et al. (2016) in our experiments. Two authors are considered to be the same individual if all of the following three conditions are fulfilled: (1) Last names of two authors are identical; (2) First names are identical or with the matched initial; (3) One of the following is true: the two authors cited each other at least once; the two authors share at least one co-author; The two authors share at least one similar affiliation. We select 183,336 papers as experimental data in the APS dataset from 1978 to 1998. Scholarly papers with greater or equal to 5 citations within the first 5 years of publication are used as the training data, and their citations in the subsequent 10 years are used as the testing data.
3.2. Prediction model

**Intrinsic potential** Citations reflect the impact of a research paper, which correspond to the authors’ impact which can be quantified as $Q_i$ for an author $i$ (Sinatra et al., 2016). A scholar with high $Q_i$ is expected to publish high-impact publications. In this paper, we use the parameter $Q_i$ to indicate the intrinsic potential of a paper’s impact.

**Paper impact decaying over time** As new ideas presented of each paper further grow in follow-up studies, the novelty fades away eventually and the impact of papers decays over time (Wang et al., 2013). Figure 1 shows the citation pattern of individual scholarly papers over time. The vertical axis is the yearly citations of 100 randomly selected scholarly papers published between 1978 and 1997 in the APS dataset. The color represents to the publication year of each scholarly paper. According to Figure 1 each paper has its own inherent citation trend and the pattern may not correlate to one another.

![Figure 1: Citation pattern of individual scholarly papers over time.](image)

**Early citers’ impact** Some prior studies have ignored the citers’ impact to the citation dynamics (Wang et al., 2013). According to the study in Singh et al. (2017), influential early citers might negatively affect long-term scientific impact of papers due to attention stealing, whereas non-influential early citers could positively affect the long-term scientific impact of papers. Inspired by this idea, the early citers’ impact is used in PPI to model the citation pattern of a scholarly paper.

**Early citation** Based on the behavior that high early citations lead to more citations in the future, we model the Paper Potential Index $\lambda_d(t)$ of a
scholarly paper $d$ by extending a self-exciting Hawkes process:

$$\lambda_d(t) = \beta_d Q_{dMax} e^{-w_1 t} + \alpha_d \sum_{j, t_j < t} D_j e^{-w_2 (t - t_j)}$$

(1)

where parameter $\beta_d$ is the coefficient of paper $d$ impact decaying over time. $Q_{dMax}$ indicates the maximum value of authors’ impact of paper $d$, and $e^{-w_1 t}$ indicates the decay of a paper impact over time. Parameter $\alpha_d$ is the coefficient that triggers the current impact of paper $d$. $D_j$ indicates the early citers’ impact on paper $d$’s citations. $e^{-w_2 (t - t_j)}$ indicates the decay of the current citation.

In equation (1), the $Q$ value reflects an author’s influence to the impact of a paper (Sinatra et al. (2016)), and it is a constant in a scientist’s career.

$$Q_i = e^{(\langle \log c_{i\alpha} \rangle - \mu_p)}$$

(2)

where $Q_i$ represents the $Q$ value of author $i$. $\langle \log c_{i\alpha} \rangle$ represents the average logarithmic citations of all papers published by author $i$. $\alpha$ represents author $i$’s $\alpha$-th paper. $\mu_p$ is equal to $\langle \hat{p} \rangle$.

In order to explore the correlation between early citers’ impact and paper citations, we conduct experiments based on the method proposed by (Singh et al., 2017). We first get the maximum $Q$ value among citers for each paper since it is published for two years. Next, we verify the correlation between the maximum $Q$ value for citers with high impact and citations of paper published for 5, 8, 10, 12 and 15 years. We also verify the correlation between the maximum $Q$ value for citers with low impact and citations of paper. Our experimental results show that early citing authors with low impact is more relevant to the long-term scientific impact of papers than early citing authors with high impact. The results are consistent with the finding in Singh et al. (2017) that attention stealing exists. In accordance with the positive correlation between them, we define $D_j$ in equation (2) as:

$$D_j = 1 + \frac{Q_j}{Q_{jMax}}$$

(3)

where $Q_j$ is the maximum $Q$ value among all authors of a citing paper $j$, and $Q_{jMax}$ represents the highest impact among all citers.

3.3. Model learning and prediction

In order to obtain the optimal values of parameters $\alpha$, $\beta$, $w_1$, $w_2$ in the PPI model, we adopt the maximum likelihood estimation method. Namely,
given that the reached probability of the $i-1$th citation at time $t_i-1$, we maximize the reached probability of the $i$th citation at time $t_i$. The concept can be formulated as follows:

$$p(t_i|t_{i-1}) = \exp\left(-\int_{t_{i-1}}^{t_i} \lambda(t)dt\right) \lambda(t_i)$$

then we use the maximum likelihood estimation method to calculate the likelihood function on the cited sequence of each article, and take the logarithmic function of the maximum likelihood estimate:

$$\log \prod_{i=1}^{n} p(t_i|t_{i-1}) = \sum_{i=1}^{n} \log \lambda(t_i) - \int_{0}^{T} \lambda(t)dt$$  

where $n$ is the citation count of a scholarly paper, $t_i$ is the time that the $i$th citation occurs, and $T$ is a period of time that a paper is cited. The maximum value of the log-likelihood function is obtained by calculating the minimum of its dual equation. Equation (4) is brought into the above formula, and add a sparse regularized term $\|\beta\|_1$, we get the objective function $L_\beta$:

$$L_\beta = -\sum_{d=1}^{N} \left\{ \sum_{i=1}^{n} \log(\beta_s d e^{-w_1 d t_i} + \sum_{j=1}^{i-1} \alpha_d D_j e^{-w_2 d(t_i-t_j)}) \right\} \beta_s d (1 - e^{-w_1 d T}) - \frac{\alpha_d}{w_2 d} \sum_{i=1}^{n} D_i - \sum_{i=1}^{n} \sum_{i=1}^{n} D_i - e^{-w_2 d(T-t_i)}\} + \lambda\|\beta\|_1$$

where $N$ is the number of papers in the experimental data, $s_d$ is the features of a paper. Adding the regularization term makes the objective function non-differentiable, we use the Alternating Direction Method of Multipliers (ADMM) to decompose the original optimization problem into a few simpler sub-problems. By introducing the auxiliary variable $z$, the optimization problem in equation (6) can be formulated by the following constraint optimization:

$$\min L + \lambda\|z\|_1 \quad s.t. \quad \beta = z$$

The corresponding augmented Lagrangian is:

$$L_\rho = L + \lambda\|z\|_1 + \rho \mu(\beta - z) + \frac{\rho}{2}\|\beta - z\|_2^2$$

where $\mu$ is the dual variable or Lagrange multiplier; $\rho$ is the penalty coefficient, which is usually used as an iterative step to update the dual variable.
The steps to solve the above augmented Lagrange optimization problem using the ADMM algorithm are as follows:

$$\begin{align*}
(\beta^{l+1}, \alpha^{l+1}) &= \arg \min_{\beta \geq 0, \alpha \geq 0} L_\rho(\beta^l, \alpha^l, z^l, u^l) \\
z^{l+1} &= S_{\lambda/\rho}(\beta^{l+1} + \alpha^{l+1}) \\
u^{l+1} &= u^l + \beta^l - z^{l+1}
\end{align*}$$

(9)

(10)

(11)

where $S_{\lambda/\rho}$ is a soft critical value function. The ADMM algorithm is similar to the dual ascent algorithm, including a parameter minimization process, such as equation (9); an auxiliary parameter minimization process, such as equation (10); and a dual parameter update process, such as equation (11).

In order to efficiently solve the optimization problem in equation (9), we use the EM framework to update the parameters $\alpha$ and $\beta$. Given the probability that feature $k$ activates event $i$ is $p_{ki}$, the probability that event $i$ activates event $j$ is $p_{ij}$, the EM algorithm is as follows:

$$\begin{align*}
p_{ki}^{l+1} &= \frac{\beta_k s_{sk} e^{-w_1d_i}}{\lambda(t_i)} \\
p_{ij}^{l+1} &= \frac{\alpha_d D_j e^{-w_2d(t_i-t_j)}}{\lambda(t_i)} \\
\beta_k^{l+1} &= \frac{-B + \sqrt{B^2 + 4\rho \sum_{d=1}^N \sum_{i=1}^n p_{ki}^d}}{2\rho} \\
\alpha_d^{l+1} &= \frac{\sum_{i=1}^n \sum_{j=1}^{i-1} p_{ij}^d}{\sum_{i=1}^n (D_i - e^{-w_2d(T-t_i)})/w_2d}
\end{align*}$$

(12)

(13)

(14)

(15)

where $B = \sum_{d=1}^N s_{dk}(1 - e^{-w_1dT})/w_{1d} + \rho(u_k - z_k)$. Equation (12) represents the probability that the value of the $k$th feature $S_{sk}$ and the coefficient $\beta_k$ corresponding to the feature $k$ affect the citations of the paper when a paper is cited $i$ times. Equation (13) represents the probability that the $j$-th ($j \geq i$) citation affects the citations of a paper when it is cited $i$ times. Therefore, $\sum_{d=1}^N \sum_{i=1}^n \lambda(t_i) p_{ki}^d$ indicates the expectation that the coefficient $\beta_k$ corresponding to the feature $k$ affects citations of the paper on the entire
data set. $\sum_{i=1}^{n} \sum_{j=1}^{i-1} \lambda(t_i)p_{ij}^d$ indicates the expectation that the number of existing citations of the paper affects its citations. In equation (8), we find the maximum of these two expectations and derive the partial derivatives for $\alpha$ and $\beta$. When the partial derivative is zero, equations (14) and (15) are obtained. By iterating until convergence, we get the optimal values of the parameters $\alpha$ and $\beta$. After that, the new values of $\alpha$ and $\beta$ are brought back to the values of $u$ and $z$ in the ADMM algorithm.

After obtaining the parameters $\alpha$ and $\beta$, the parameters $w_1$ and $w_2$ of each paper are solved by the gradient descent method. The gradient of the objective function with respect to $w_1$ and $w_2$ is as follows:

$$\frac{\partial L_p}{\partial w_1} = \sum_{i=1}^{n} \frac{\beta s t i e^{-w_1 t_i}}{\lambda(t_i)} + \frac{\beta s}{w_1^2} (e^{-w_1 T} + T \cdot w_1 \cdot e^{-w_1 T} - 1) \tag{16}$$

$$\frac{\partial L_p}{\partial w_2} = \sum_{i=1}^{n} \sum_{j=1}^{i-1} \frac{(t_i - t_j) \alpha D_j e^{-w_2(t_i - t_j)}}{\lambda(t_i)}
+ \frac{\alpha}{w_2^2} [w_2(T - t_i) e^{-w_2(T - t_i)} + e^{-w_2(T - t_i)} - 1] \tag{17}$$

After obtaining the optimal values of all parameters $\alpha$, $\beta$, $w_1$ and $w_2$, we estimate the citations of a scholarly paper after a certain period of time by taking the integral of the intensity function $\lambda(t)$.

4. Multi-features predictive model

4.1. Features that drive the increase of citations

Author-based features.

- Author Impact Factor (AIF).

Similar to the concept of journal impact factor, an author’s AIF in year $T$ is the average citations of published papers in a period of $\Delta T$ years before year $T$. Based on the APS dataset, we compute each author’s AIF value according to the author’s publishing history and use the statistics of all authors’ AIF of a given institution 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 is calculated according to equation 2.

• 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.

**Journal-based feature.**
Journal Impact Factor is a quantitative index to evaluate the impact of journal. It is actually the ratio of citations of a journal and papers published of the journal.

**Citations feature.**
The historical citations of each paper are used to predict the impact of a paper.

4.2. Feature selection
In order to investigate the effect of author-based feature, journal-based feature and citations feature, we evaluate the importance of features (see Table 2).

4.3. Learning algorithm
In this section, we describe the multi-feature predictive model, which integrates author-based feature, journal-based feature and citations to the Gradient boosting decision trees (GBDT). The GBDT model suits for a mass of features and no-linear relationships between the predictor variables and the target variable. In terms of the multi-feature predictive model, parameters adjustment is crucial for the performance of predictive model. Main parameters include:
(1) **learning rate**: namely the model’s learning speed on the distribution characteristics of the sample, expressed as the weight of the regression tree for each iteration in the algorithm. The larger the learning rate is, the faster the algorithm converges. The smaller the learning rate is, the slower the algorithm converges, but the prediction accuracy may increase.
(2) **number of iterations**: the number of iterations is the number of weak learners obtained in the model. In general, the number of iterations depends on the learning rate.
Table 2: Features used in the prediction model.

| Feature       | Description      | Feature       | Description      |
|---------------|------------------|---------------|------------------|
| c1            | one-year citations | max(H-index)  | maximum of H-index |
| c2            | two-year citations | min(H-index)  | minimum of H-index |
| c3            | three-year citations | avg(H-index)  | average of H-index |
| c4            | four-year citations | med(H-index)  | median of H-index |
| c5            | five-year citations | dev(H-index)  | deviation of H-index |
| sum(Q)        | sum of Q value   | sum(AIF)      | sum of AIF       |
| max(Q)        | maximum of Q value | max(AIF)      | maximum of AIF   |
| min(Q)        | minimum of Q value | min(AIF)      | minimum of AIF   |
| avg(Q)        | average of Q value | avg(AIF)      | average of AIF   |
| med(Q)        | median of Q value | med(AIF)      | median of AIF    |
| dev(Q)        | deviation of Q value | dev(AIF)      | deviation of AIF |
| sum(H-index)  | sum of H-index   | JIF           | journal impact factor |

(3) *minimum samples of leaf nodes*: this parameter defines the conditions under which the subtree continues to be divided. If the number of samples on the leaf node is smaller than the set value, the node will not be further divided.

(4) *maximum depth of decision tree*: this parameter is used to control the maximum depth of the decision tree generated by each round iteration. The purpose is to prevent over-fitting.

(5) *Sampling rate*: this parameter indicates the proportion of training samples used in each training, and its value ranges from 0 to 1. When the value is 1, it indicates that all the samples are involved training. The main role of this parameter is to add sample perturbation to prevent over-fitting. The sampling rate of general samples is set between 0.5 and 0.8. If the value is too large, the risk of over-fitting will be increased. If the value is too small, correct samples may not be learned due to too few samples, and the model deviations will increase.

We used the Grid Search method to adjust the above mentioned parameters. The value of the learning rate ranges from 0.0005 to 0.5 and the step size is 0.0005. The number of iterations ranges from 500 to 3000 and the step size is 500. The value of leaf node minimum sample number value ranges...
from 10 to 80 and the step size is 10. The maximum depth of the decision tree ranges from 5 to 7 and the step size is 1. Sampling rate ranges from 0.5 to 1.0 and the step size is 0.1.

According to the range of values and the step size of each parameter, the grid covered parameter space is generated for grid search. Each point on the grid is traversed, and the parameter combination corresponding to the point is used to train the model on the training set. Correspondingly, prediction is performed on the validation set, and the predictive accuracy is calculated as an estimate of the prediction performance of the model under the set of parameters. After traversing all the parameter combinations, the set of parameters with the highest prediction accuracy on the corresponding verification set is taken as the parameter of the final model.

5. Results and discussion

5.1. Evaluation metrics

In this subsection, we introduce several evaluation metrics for validating the PPI prediction model.

**Mean absolute error (MAE).**

MAE quantifies how close the predictions is to the ground truth. MAE is given by:

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |e_i|
\]  

The mean absolute error is an average of the absolute errors $|e_i|$, which is equal to $|f_i - y_i|$, where $f_i$ is the prediction, and $y_i$ is the true value. $n$ represents the number of predictions.

**Root mean squared error (RMSE).**

RMSE is similar to MAE, which is defined as follows:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} e_i^2}
\]  

RMSE also provides the average error and quantify the overall error rate. In some cases, we need to compare results across activities, but RMSE can not give an indication of the relative error. We need a normalized error, such as Range-normalized RMSE.
**Range-normalized RMSE (NRMSE).**

\[ NRMSE = \frac{RMSE}{\max(y_i) - \min(y_i)} \]  

(20)

where \( \max(y_i) \) and \( \min(y_i) \) represent the maximum and minimum functions, which are calculated by all ground-truth values of the test instances.

**Mean absolute percentage error (MAPE)**

An useful normalized metric is MAPE, which normalizes each error value for each prediction. This metric shows the average deviation between predicted output and true output from the \( n \) experimental data. MAPE is defined as follows:

\[ MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|e_i|}{y_i} \]  

(21)

**Accuracy**

Accuracy shows the fraction of papers correctly predicted for a given error tolerance \( \epsilon \):

\[ Accuracy = \frac{1}{n} \sum_{i=1}^{n} \frac{|e_i|}{y_i} \leq \epsilon \]  

(22)

5.2. Feature importance analysis

Figure 2 shows the feature importance score of all features to predict the 15th year’s citations of the published papers. The features \( c_5, c_4, c_3 \) and \( c_2 \) rank first to fourth in the feature importance rankings, and their values are 0.3495, 0.0963, 0.0783 and 0.0618. The minimum, median, average, maximum of authors’ \( Q \) value, JIF, authors’ \( Q \) value’ sum, respectively, their values are 0.0608, 0.0527, 0.0441, 0.0338, 0.0331, and 0.0317. The feature importance score for predicting 6th-14th year citations of the published papers are shown in the appendix.
Based on all features’ importance in predicting 6th-15th year citations of papers, we selected the top 10 feature retraining model, the prediction accuracy remains high. There are differences in feature importance scores for different predictive years (see appendix). Figure 3 shows the top 10 feature importance score for predicting the 15th year citations of the published papers. The features $c_5$ and $c_4$ rank first to third in the feature importance rankings. Their importance scores are 0.3425 and 0.1079, respectively. The authors’ $Q$ value’s minimum ranks fourth, and its value is 0.0969. Other feature importance scores are less than 0.0950.

Figure 3: Importance scores of top 10 features.
According to Figure 2 and Figure 3, we observe that citations in the first five years after the publication of the paper, author’s $Q$ value, and JIF are ranked in the top 10 of the list of feature importance ranking. Author H-index related features and author AIF related features are located behind the list of feature importance rankings.

In summary, we observe that historical citations play an important role for predicting the impact of the paper. Besides, author-based features are important in predicting the paper impact, especially the authors’ $Q$ value.

5.3. Comparing performances of different models and discussion

To test the validity of PPI prediction model, its predictive performance is compared against four competing models: PPI, NECAI, GBDT_All, GBDT_10 and PLI_Science published by Wang et al. (2013). The comparison is made in terms of MAE, RMSE, NRMSE, MAPE, and accuracy.

Figure 4 shows the MAE value of the five models. According to Figure 4, we observe that PPI outperforms all competing models with lower MAE values for predicting citations after a scholarly paper is published for 5 years. We also observe that MAE values of all five models increase along with the year, indicating that the predictive performance of all five models degrades over time.

Figure 4: Comparing MAE for different models.
Figure 5 shows the RMSE value of the five models. Similar to the MAE comparisons, that the PLI_Science model falls behind all competing models in terms of RMSE. RMSE performance of all other models are mixed, with PPI yields lower RMSE than other models between 2 to 6 years, indicating it performs well in short term citation prediction but its performance fails behind GBDT_All and GBDT_10 for long term citation prediction. Similar to study based on MAE, the predictive performance in terms of RMSE of all five models gradually declines over time.

![Graph showing RMSE values of different models over time.](image)

Figure 5: Comparing RMSE for different models.

Figure 6 shows NRMSE values of the five models. For PPI model and PPI_NECAI model, their NRMSE values are about 0.006. The NRMSE values of GBDT_All model and GBDT_10 model shows increasing trends, and their NRMSE values are about 0.018 in future the 10th years after the fifth year of scholarly paper published. The NRMSE values of the PLI_Science model show a decaying trend. In term of NRMSE, the predictive performance of the PPI model is better than other four models.

Figure 7 shows the MAPE values of the five models. We observe that the MAPE values of GBDT_All model and GBDT_10 model are below the other three models. The MAPE value of the PPI model is slightly higher than GBDT_All model and GBDT_10 model.

Figure 8 shows the accuracy of the five models. The accuracy values of
Figure 6: Comparing NRMSE for different models.

Figure 7: Comparing MAPE for different models.
PPI prediction model are higher than PPI-NECAI model and PLI-Science model, but are slightly below than GBDT_All model and GBDT_10 model. From 3 to 10 years after the fifth year of scholarly paper published, the predictive accuracy of PPI-NECAI model is lower than other four models. The predictive accuracy of all models shows a decaying trend.

By comparing PPI and PPI-NECAI, we observe that early citing authors’ impact contributes to improved prediction of scholarly paper impact. PPI yields superior citation prediction over PPI-NECAI, GBDT_All, GBDT_10 and PLI-Science in terms of MAE and NRMSE. Although the predictive performances of the GBDT_All model and the GBDT_10 model are better than other three models in terms of MAPE and accuracy, the proposed PPI prediction model gives a clear explanation for the predictive effect of the model by the following factors: inherent quality of scholarly paper, scholarly paper impact decaying over time, early citations, and early citers’ impact.

Compared to PPI-NECAI and PLI-Science, PPI more accurately predicts the scholarly paper impact. Although considering early citers’ impact can improve the predictive performance of PPI model, other factors exist, such as author’s team impact, journal impact, authors’ cooperation relationship, and disciplinary differences. In addition, due to the fact that the APS dataset only contains local citations, this might limit the predictive accuracy of this work. Uncovering the essence of paper potential index is a promising future
work, which might improve the predictive performance of PPI model, and it could provide a better understanding of the evolution of scholarly paper impact.

6. Conclusion

Based on point estimation process, we present the PPI predictive model, which considers the following four factors: (1) inherent quality of scholarly paper; (2) scholarly paper impact decaying over time; (3) early citations; and (4) early citers' impact. Experimental results indicate that the PPI model improves citation prediction of scholarly papers. The predictive performance of PPI is better than PPI-NECAI, which reflects that early citing author’s impact is important for predicting the citations of scholarly paper. Although the predictive performance of the GBDT_All model and GBDT_10 model is better than other three models in terms of MAPE and accuracy, the proposed PPI predictive model give a clear explanation for the predictive effect, indicating that an ultimate understanding of long-term impact of scholarly paper will benefit from understanding the inherent evolutionary mechanism of citations of scholarly papers.

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