Modeling and Predicting Popularity Dynamics via Deep Learning Attention Mechanism

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Abstract

An ability to predict the popularity dynamics of individual items within a complex evolving system has important implications in a wide range of domains. Here we propose a deep learning attention mechanism to model the process through which individual items gain their popularity. We analyze the interpretability of the model with the four key phenomena confirmed independently in the previous studies of long-term popularity dynamics quantification, including the intrinsic quality, the aging effect, the recency effect and the Matthew effect. We analyze the effectiveness of introducing attention model in popularity dynamics prediction. Extensive experiments¹ on a real-large citation data set demonstrate that the designed deep learning attention mechanism possesses remarkable power at predicting the long-term popularity dynamics. It consistently outperforms the existing methods, and achieves a significant performance improvement.

Introduction

In the era of information explosion, it is particularly urgent to find valuable information from the increasingly abundant content and immediately available data. Attention has become a major limiting factor in the consumption of information. Attention economy relies on a competing process through which a few items become popular while most are forgotten over time. Popularity prediction has important applications in a wide range of domains, such as decision making concerning with recruitment and funding in the scientific community, public opinion monitoring in the online social networks, and so on. However, it is arguably very difficult to predict the dynamical popularity of individual items within a complex evolving system. One reason behind this is that the dynamical processes governing individual items appear too noisy to be amenable to quantification (Wang and Barabsi 2013).

The early researches reproducfocus on certain statistical quantities ing over an aggregation of items (Crane and Sornette 2008; Ratkiewicz et al. 2010). These models have been successful in understanding the underlying mechanisms

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of popularity dynamics. Yet, as they do not provide a way to extract item-specific parameters, these models lack of predictive power for the popularity dynamics of individual item. In the past several years, researchers began to analyze and model the popularity dynamics of individual items (Matsubara et al. 2012; Wang and Barabsi 2013). The existing models fall into two main paradigms. One uses networks to model the popularity dynamics and utilizes graph mining techniques to solve the prediction problem (Mcgovern et al. 2003; Yu et al. 2012; Pobiedina and Ichise 2016). The other prevalent line of research formulates the popularity dynamics over time as time series, making predictions by either exploiting temporal correlations (Szabo and Huberman 2010), regression (Yan et al. 2011), or fitting these time series with certain classes of process (Matsubara et al. 2012; Bao et al. 2013), including counting cess (Vu et al. 2011), point process (Xiao et al. 2016) or specific Poisson process (Shen et al. 2014) and so on.

The second kind of time series model has gained widely concern in the academic and research community. Reinforced Poisson Process (RPP) (Shen et al. 2014) is used with a probabilistic framework to model the stochastic popularity dynamics. RPP with self-excited Hawkes Process (Bao et al. 2015; Xiao et al. 2016) considers the aging effect and triggering role of recent citations in the prediction of individual paper citation count over time. Furthermore, the influence-based self-excited Hawkes process (Bao 2016) takes into account the user-specific triggering effect of each forwarding based on the endogenous social influence in the microblogging network. However, one major limitation of the parametric forms of these processes is due to their specialized and restricted expression capability for arbitrary distributed data which trends to be oversimplified or even infeasible for capturing the problem complexity in real applications (Xiao et al. 2017).

Recently, Deep Neural Network (DNN) based models, such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), have received great attention from both the academia and the industry. RNN has been proven to perform extremely well on temporal data series (Sutskever, Vinyals, and Le 2014). The networks with loops in RNN allow information to persist. Due to the vanishing gradient problem, RNN fails to handle the tempo-

¹All the codes and the preprocessed data used in this paper will be available online.

ral contingencies present in the input/output sequences span long intervals (Bengio, Simard, and Frasconi 1994). Long short-term memory (LSTM) is proven to be capable of learning long-term dependencies. So, RNN with LSTM units is suitable for handling long-term temporal data series.

The recent studies in the area of popularity dynamics combine the deep learning with the point process or Hawkes process. DeepHawkes (Cao et al. 2017) leverages end-to-end deep learning to make an analogy to interpretable the three key factors captured in Hawkes process. RNNs with LSTM units are used to model the intensity function of point process without specific parametric form (Xiao et al. 2017). It models various characters of real event data for its application utility under the assumption of point process. Without assuming any specific type of the generative process, adversarial learning of neural network process is used in the latest research for popularity prediction (Xiao et al. 2018).

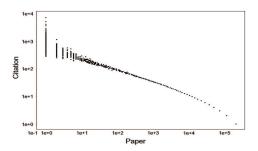


Figure 1: The citation distribution.

In the existing studies, all items are treated equivalently in popularity dynamics prediction. However, the popularity difference between items is very large. A few items become popular while most are forgotten over time. Fig. 1 illustrates the citation distribution (the number of papers vs. citation counts) of about two million papers in AMiner (Tang et al. 2008). It is natural to find that not all publications attract equal attention in the academia. Nature reports that a few research papers accumulate the vast majority of citations, and most of the other papers attract only a few citations (Barabsi, Song, and Wang 2012). Obviously, the papers with large citation counts are needed to be given special emphasis in popularity dynamics prediction.

In this paper, we propose a deep learning attention mechanism to model and predict individual-level popularity dynamics. Due to the effectiveness of RNN with LSTM units, it is used in the proposed model to quantify the hidden mechanisms of the given time series and capture the long-term mechanism of popularity dynamics. It is worth noting that we analyze the interpretability of the model with the four key phenomena confirmed independently in the previous studies of long-term popularity dynamics quantification, including (1) the intrinsic quality, characterizing the inherent competitiveness of an item against others; (2) the aging effect, capturing the fact that each item's novelty fades eventually over time; (3) the recency effect, corresponding to the phenomenon that novel items tend to attract more attentions; (4) the Matthew effect, documenting the well-known "rich-get-

richer" phenomenon. To give emphasis on the history data of highly cited papers, we design a deep learning attention mechanism based on the RNN.

Taking citation system as an exemplary case, we demonstrate the effectiveness of the proposed prediction model using a dataset peculiar in its longitudinality, spanning over 80 years (from 1936 to 2016). Experimental results show that the proposed deep learning attention model consistently outperforms the existing models. The main contributions of this paper are two-fold: (1) we design the deep learning attention model to give emphasis on items with high popularity; (2) we analyze the the interpretability of the proposed model with the four key phenomena of long-term popularity dynamics.

Problem Formulation

The popularity dynamics of an individual item d during time period [0,T] is characterized by a time-stamped sequence $\{n_d^t\}_{t=0}^T$, where n_d^t represents the attention received by item d at time t. In the context of given the historical citation, the goal is to model the popularity dynamics and predict it at any given time.

Definition 1 *Popularity.* The popularity of an item d at time t is defined as the number of attentions n_d^t received by the item d at time t. n_d^t is an integer greater than or equal to zero.

The underlying assumption of the popularity here is that we concern on the accumulated attentions. Although the aging effect exists in the long-term popularity dynamics evaluation, the accumulated attentions make it possible to quantify popularity for different items at different times. Without loss of generality, we have $0=n_d^0 \leq \cdots \leq n_d^t \leq \cdots \leq n_d^T=N_d$.

Definition 2 *Popularity dynamics.* The popularity dynamics of individual item d can be formalized as the following time series $\{n_d^0, \cdots, n_d^t, \cdots, n_d^T\}$.

The **popularity dynamics prediction** problem can be formalized as follows.

Input: For each item d, the input is $\{(x_d^0, n_d^0), \cdots, (x_d^t, n_d^t), \cdots, (x_d^T, n_d^T)\}$ $\in \mathbb{N}^K \times \mathbb{N}$, where $\vec{X} = \{x_d^1, \cdots, x_d^t, \cdots, x_d^T\}$, and x_d^t is expressed as a K-dimensional feature vector, and n_d^t denotes the popularity of the item d at time t.

Learning: The goal of popularity dynamics prediction is to learn a predictive function $f(\mathbb{N}^K \to \mathbb{N})$ to predict the popularity of an item d after a given time period t. Formally, we have

$$f(d|\vec{X},t) \to \hat{n}_d^t,$$
 (1)

where \hat{n}_d^t is the predicted popularity and n_d^t is the actual one. A commonly used prediction function is linear (Yuan et al. 2017), that is, $f(x_d^t) = \omega_t^T x_d^t + b$, where ω_t are parameters to be estimated from the training data and b is a bias term, which can be further absorbed by adding one dimension to ω_t (as b) and one dimension (of value 1) to x_d^t . Thus we have a simple form $f(x_d^t) = \omega_t^T x_d^t$. Extensions to nonlinear functions can be done, for example,

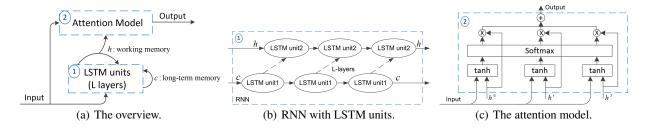


Figure 2: The deep learning attention model.

by using kernel tricks. We will show the performance comparison between the linear function and the nonlinear function in the long-term popularity dynamics prediction. Due to the restricted expression capability of the linear function, it is oversimplified for capturing the embedded rules in the long-term popularity dynamics. The popularity dynamics prediction model we used belongs to the second case.

Prediction: Based on the learned prediction function, we can predict the popular level of a given item in the future time, for example, the popularity of item d at time t is given by $f(d|\vec{X},t)$.

Popularity Dynamics Prediction

We begin by considering the RNN-LSTM solution for popularity dynamics prediction, and then give emphasis on highly cited papers in the proposed deep learning attention mechanism. We further perform detailed analysis to understand the interpretability of each component in the model, and bridge the gap between prediction and understanding of the four key phenomena confirmed in the previous studies of long-term popularity dynamics quantification.

Deep Learning Attention Mechanism

We embed the underlying mechanisms of the long-term popularity dynamics in RNN to produce result. Fig. 2 illustrates the proposed long-term popularity dynamics prediction model. Fig. 2(a) gives an overview of the architecture.

Given a time-stamped sequence $\{n_d^t\}_{t=0}^T$, a K-dimensional feature vector $\vec{X} = \{x_d^0, \cdots, x_d^t, \cdots, x_d^T\}$ needs to be designed as input. The input space of every item with popularity records $\{(x^0, n^0), \cdots, (x^t, n^t), \cdots, (x^T, n^T)\}$ reflects the intrinsic quality of the item. There are two key components in the architecture: the RNN with LSTM units and the attention model. The LSTM units are arranged in the form of RNN with L layers. The parameter L is set as conventional number in deep neural network according to the input scale.

The LSTM unit is used for its popularity and well-know capability for efficient long-range dependency learning (Xiao et al. 2017). We use the LSTM units to capture the aging effect and the Matthew effect in long-term popularity dynamics quantification. Specifically, for enhancing the recency effect through the short-term working memory h, we design an attention model in the framework.

The RNN with LSTM Units. The LSTM units are arrange in the form of RNN as illstrated in Fig. 2(b). There are four major components in a common LSTM unit, including a memory cell, a forget gate Γ_f , an input gate Γ_i , and an output gate Γ_o . The gates are responsible for information processing and storage over arbitrary time intervals. Usually, the outputs of these gates are between 0 and 1. A new study gives suggestions to push the output values of the gates towards 0 or 1. By doing so, the gates are mostly open or closed, instead of in a middle state (Li et al. 2018). Although the LSTM units are arranged in the form of RNN, it avoids the vanishing gradient problem by the introduction of the memory cell. Thus, information can be stored for either short or long time periods in the LSTM unit.

Intuitively, the input gate controls the extent to which a new value flows into the memory cell. A function of the inputs passes through the input gate and is added to the cell state to update it. The following formula for the input gate is used:

$$\Gamma_i^t = \sigma\left(W_i \left[h^{t-1}, x^t\right] + b_i\right),\tag{2}$$

where matrix W_i collects the weights of the input and recurrent connections. The symbol σ represents the Sigmoid function. The values of the vector Γ_i^t are between 0 and 1. If one of the values of Γ_i^t is 0 (or close to 0), it means that this input gate is closed and no new information is allowed into the memory cell at time t. If one of the values is 1, the input gate is open for new coming value at time t. Otherwise, the gate is in the state of half-open half-clearance.

The forget gate controls the extent to which a value remains in the memory cell. It provides a way to get rid of the previously stored memory value. Here is the formulate of the forget gate:

$$\Gamma_f^t = \sigma \left(W_f \left[h^{t-1}, x^t \right] + b_f \right), \tag{3}$$

where W_f are weights that govern the behavior of the forget gate. Similar to Γ_i^t , Γ_f^t is also a vector of values between 0 and 1. If one of the values of Γ_f^t is 0 (or close to 0), it means that the memory cell should remove that piece of information in the corresponding component in the cell. If one of the values is 1, the corresponding information will be kept.

Remembering information for long periods of time is practically the default behavior of LSTM. The long-term accumulative influence is formulated as follows:

$$c^t = \Gamma_f^t * c^{t-1} + \Gamma_i^t * \tilde{c}^t, \tag{4}$$

where * denotes the Hadamard product (the element-wise multiplication of matrices), \tilde{c}^t is calculated as follows:

$$\tilde{c}^t = \tanh\left(W_c\left[h^{t-1}, x^t\right] + b_c\right). \tag{5}$$

That is, the information in memory cell consists of two parts: the retained old information $\Gamma_f^t * c^{t-1}$ (controlled by the forget gate), and the new coming information $\Gamma_i^t * \tilde{c}^t$ (controlled by the input gate).

The output gate controls the extent to which the value in the cell is used to compute the output activation of the LSTM unit. The following output function is used:

$$\Gamma_o^t = \sigma \left(W_o \left[h^{t-1}, x^t \right] + b_o \right). \tag{6}$$

The weight matrices and bias vector parameters are needed to be learned during training. The current working state is updated as the following formula:

$$h^t = \Gamma_o^t * \tanh\left(c^t\right). \tag{7}$$

The Attention Model. The artificial attention mechanism, inspired by the attention behavior in neuroscience (Itti, Koch, and Niebur 1998), has been applied in deep learning for speech recognition, translation, and visual identification of object (Vaswani et al. 2017; Choi et al. 2016). Broadly, attention mechanisms are components of prediction systems that allow the system to sequentially focus on different subsets of the input (Cho, Courville, and Bengio 2015). More specifically, the attention distribution is generated with content-based attention. Only part of a subset of the input information is focused. The attention function needs to be differentiable, so that we focus everywhere of the input, just to different extents.

The deep learning attention mechanism designed in this paper works as follows: given an input $\vec{X} = \{x_d^0, \cdots, x_d^t, \cdots, x_d^T\}$, the aforementioned LSTM units generate $\vec{h} = \{h_1, \cdots, h_t, \cdots, h_T\}$ to represent the hidden patterns of the input. The output is the summary of the h_t focusing on information linked to the input. In this formulation, attention can be seen as producing a fixed-length embedding of the input sequence by computing an adaptive weighted average of the state sequence \vec{h} (Raffel and Ellis 2016).

The graphical representation of the attention model is shown in Fig. 2(c). The input \vec{X} and the hidden layer \vec{h} of LSTM network (a RNN composed of LSTM units) are the input of the attention model. Then, it computes the following formula:

$$a^{t} = \tanh\left(W_{a}\left[x^{t}, h^{t}\right]\right),\tag{8}$$

where W_a is the weight matrix. An important remark here is that each a^t is computed independently without looking at the other $x^{t'}$ for $t' \neq t$ (Raffel and Ellis 2016). Then, each a^t is linked to a Softmax layer, which function is given by:

$$\alpha^t = \frac{e^{a^t}}{\sum_t e^{a^t}}, \text{ for } t = 1, \cdots, T$$
 (9)

where $\sum_t \alpha^t = 1$, the α^t is the softmax of the a^t projected on a learned direction. The output is a weighted arithmetic

mean of the input, and the weights reflects the relevance of \vec{h} and the input. It is calculated as the following formula:

$$O = \sum_{t} \alpha^{t} x_{t}. \tag{10}$$

Finally, the popularity of item d at time t is given by the prediction $f(d|\vec{X},t) = O$.

Key Phenomena in Popularity Dynamics

There are four key phenomena confirmed independently in previous studies of long-term popularity dynamics quantification: the intrinsic quality, the aging effect, the recency effect and the Matthew effect. We analyze the interpretability of the deep learning attention model with these four major phenomena.

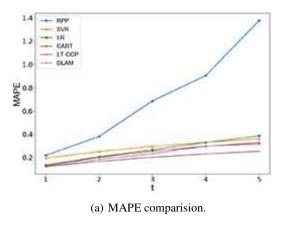
We firstly show the details of them. The intrinsic quality reflects the perceived novelty and importance of an item (Wang and Barabsi 2013). It captures the inherent differences between items. Actually, the items with low quality are more likely to be unpopular, and vice versa. The aging effect represents the accumulation process of popularity recession. In the attention economy, aging accounts for the fact that each item's novelty fades eventually over time. The recency effect indicates that novel items tend to attract more attentions. In the time series modeling of popularity dynamics, the recent items shored in the short-term working state have an advantage over those stored in the long-term memory. Therefore, more emphasis needs to be given on the new popular items, which are stored in the short-term working memory. The Matthew effect of accumulated advantage is summarized by the "rich-get-richer" phenomenon, i.e., previous accumulated attention triggers more subsequent attentions (Crane and Sornette 2008). It is in fact that the highly popular items are more visible and more likely to be viewed than others.

Then, we present how the proposed deep learning attention mechanism captures the four key phenomena of long-term popularity dynamics. We are the first to analyze the interpretability in the deep learning based model for popularity dynamics prediction. The detailed specifications of these four phenomena are formulated as follows:

- (1) **Intrinsic quality**. The intrinsic quality captures the inherent differences between items, accounting for the perceived novelty and importance of an item. In our proposed prediction model, the input space of every item with popularity records $\{(x^0, n^0), \cdots, (x^t, n^t), \cdots\}$ reflects its intrinsic quality.
- (2) **Aging effect.** The aging effect, which captures the fact that each item's novelty fades eventually over time, can be modeled by the forget gate in the LSTM unit. It is formulized as Eq. (3).
- (3) Recency effect. We need to give emphasis on the current popularity state of items, which is given by Eq. (7). In the proposed popularity dynamics prediction model, the recent items shored in the current working state have an advantage in reading over those stored in the long-term memory. Thus, it is possible to capture the Recency effect.

	t = 1		t=2		t = 3		t = 4		t = 5	
Models	MAPE	ACC								
RPP	0.219	0.819	0.381	0.661	0.686	0.524	0.904	0.433	1.376	0.370
SVR	0.195	0.814	0.252	0.664	0.296	0.579	0.331	0.528	0.362	0.493
LR	0.136	0.924	0.207	0.752	0.269	0.629	0.330	0.540	0.386	0.482
CART	0.131	0.913	0.202	0.758	0.256	0.634	0.297	0.549	0.328	0.489
LT-CCP	0.123	0.940	0.185	0.804	0.234	0.703	0.298	0.590	0.317	0.551
DLAM	0.121	0.960	0.168	0.849	0.203	0.757	0.231	0.693	0.255	0.643

Table 1: The performance of various models on the data set.



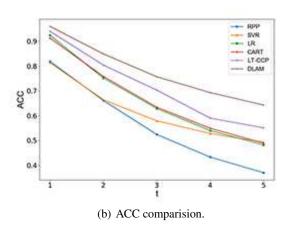


Figure 3: The performance comparison in citation count prediction.

(4) **Matthew effect**. The memory cell in LSTM unit takes the long-term dependencies into consideration. As shown in Eq. (4), previous accumulated attention stored in the long-term memory triggers more subsequent attentions. What's more, the attention model, which focuses on the most popular part of the time series as Eq. (10) does, also capture the Matthew effect.

Experiments

In this section, we demonstrate the effectiveness of the proposed popularity dynamics prediction model via deep learning attention mechanism.

Dataset

Experiments are conducted on a real-world dataset², which is extracted from the academic search and mining platform – AMiner. We select publications in *Computer Science* for more than 80 years (from 1936 to 2016), which consists of 2,092,356 papers authored by 1,712,433 researchers. The full graph of citation network contained in this dataset has 2,092,356 vertices (literature papers) and 8,024,869 edges (citations).

Similar to the protocol in (Wang and Barabsi 2013; Shen et al. 2014; Xiao et al. 2016), we use papers with more than 5 citations during the first 5 years after publication as training data and predict their citations in the next years. As

a result, there are 143,902 papers published in 1956 to 2015 are retained.

Baseline Models and Evaluation Metrics

To compare the predictive performance of the proposed deep learning attention mechanism **DLAM** against other models, we introduce several published models that have been used to model and predict the popularity dynamics. Specifically, the comparison methods in our experiments are listed as follows. **RPP** (Wang and Barabsi 2013; Shen et al. 2014) incorporates three key ingredients: the intrinsic attractiveness, the aging effect, and the reinforcement mechanism using a reinforced Poisson process. **CART** and **SVR** perform better in citation count prediction compared to LR and KNN in the reference (Yan et al. 2011).

Two metrics used for evaluating popularity dynamics in (Shen et al. 2014; Xiao et al. 2016) are also used: Mean Absolute Percentage Error (MAPE) and Accuracy (ACC). Let n_d^t be the observed citations of paper d up to time t, and \hat{n}_d^t be the predicted one. The MAPE measures the average deviation between the predicted and observed citations over all papers. For a dataset of M papers, the MAPE is given by:

MAPE =
$$\frac{1}{M} \sum_{d=1}^{M} \left| \frac{\hat{n}_{d}^{t} - n_{d}^{t}}{n_{d}^{t}} \right|$$
. (11)

ACC measures the fraction of papers correctly predicted under a given error tolerance ϵ . Specifically, the accuracy of

²https://www.aminer.cn/data

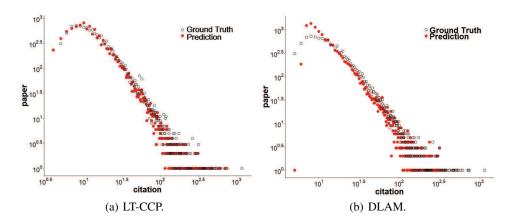


Figure 4: The performance comparison in citation count prediction.

citation prediction over M papers is defined as:

$$ACC = \frac{1}{M} \sum_{d=1}^{M} I\left[\left| \frac{\hat{n}_{d}^{t} - n_{d}^{t}}{n_{d}^{t}} \right| \le \epsilon \right], \tag{12}$$

where $I[\theta]$ is an indicator function which return 1 if the statement θ is true, otherwise return 0. We find that our method always outperforms regardless the value of ϵ . In this paper, we set $\epsilon=0.3$ as (Xiao et al. 2016).

Model Setting

We found in the experiments that the longer the duration of the training set, the better the long-term prediction performance. In this paper, we set the training period as 5 years and then predict the citation counts for each paper from the $1^{\rm st}$ to $5^{\rm th}$ after the training period. For example, t=1 means that the first observation year after the training period. We found that the features with positive contributions are the citation history, the h-index of the paper author and the level of the publication journal. For the convenience of performance comparison, the input feature used here is the citation history for every sub-window of length 10 years. In the experiment, we set L=2. The loss function utilized here is MAPE. We use Adadelta (Zeiler 2012) as the gradient descent optimization algorithm. The attention layer is fully connected and it uses tanh activation.

Results and Discussion

Results. As shown in Table. 1, the proposed DLAM model exhibits the best performance in terms of ACC in all the situation of t=1,2,3,4 and 5. It means that the DLAM consistently achieves the higher accuracy than other models across different observation time. What's more, the DLAM model also exhibits the best performance in terms of MAPE in all the aforementioned situations. That is, the DLAM model achieves the higher accuracy and lower error simultaneously. As shown in Fig. 3(b), the superiority of the DLAM model, compared to the other methods in terms of ACC, increases with the number of years after the training period. When t=5, the proposed DLAM model achieves a significant performance improvement in terms of ACC, about about

42.46% compared to RPP. As illustrated in Fig. 3(a), the models used for comparison all achieve acceptable low error rate, except RPP. This problem can be avoid by RPP with prior (Shen et al. 2014), which incorporates conjugate prior for the fitness parameter. But the RPP with prior doesn't improve the ACC performance. That is to say, our proposed DLAM model also outperforms than RPP with prior in terms of ACC.

Effectiveness of the attention model. We remove the attention model of the proposed model to verify the effectiveness of the attention model. The remainder is RNN with LSTM units (labeled as LT-CCP), which is proven to be effectiveness in long-term popularity dynamics prediction. As shown in Fig. 3, the DLAM consistently outperforms (improving the ACC and decreasing the MAPE) than the LT-CCP. That is, introducing the attention model can improve the prediction ability in popularity dynamics.

Analysis of the citation distribution. We illustrate the actual and the predicted citations distribution when t=5 in Fig. 4. At first glance, it seems that the LT-CCP (shown in Fig. 4(a)) has better fitting effect than the DLAM (shown in Fig. 4(b)). In fact, the LT-CCP only has better fitting effect on the papers with little citation counts. On the contrary, the DLAM has better fitting effect on the highly cited papers. The DLAM achieves better overall performance. It is more accordant with practical prediction requirements that a few papers occupy vast number of citations. It further proves the effectiveness of the attention model.

Conclusion

In the long-term popularity dynamics analysis, it is a fact that a few items become popular while most are forgotten over time. In this paper, we present a deep learning attention mechanism to model and predict long-term popularity dynamics. We analyze the interpretability of the model. It incorporates four key ingredients of long-term popularity dynamics, including the intrinsic quality of publications, the aging effect, the recency effect and the Matthew effect. More importantly, we verify the effectiveness of introducing the attention model in long-term popularity dynamics prediction. Experiments on a real-large citation dataset demon-

strate that our proposed model consistently outperforms the existing prediction models. The results show that the proposed model has better fitting effect on the highly cited papers, and achieves the best overall performance.

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