PREP: Pre-training with Temporal Elapse Inference for Popularity Prediction

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ABSTRACT
Predicting the popularity of online content is a fundamental problem in various applications. One practical challenge takes roots in the varying length of observation time or prediction horizon, i.e., a good model for popularity prediction is desired to handle various prediction settings. However, most existing methods adopt a separate training paradigm for each prediction setting and the obtained model for one setting is difficult to be generalized to others, causing a great waste of computational resources and a large demand for downstream labels. To solve the above issues, we propose a novel pre-training framework for popularity prediction, namely PREP, aiming to pre-train a general representation model from the readily available unlabeled diffusion data, which can be effectively transferred into various prediction settings. We design a novel pretext task for pre-training, i.e., temporal elapse inference for two randomly sampled time slices of popularity dynamics, impelling the representation model to learn intrinsic knowledge about popularity dynamics. Experimental results conducted on two real datasets demonstrate the generalization and efficiency of the pre-training framework for different popularity prediction task settings.

CCS CONCEPTS
• Human-centered computing → Social media; Social networks.

KEYWORDS
Popularity Prediction, Pre-training, Temporal Elapse Inference

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1 INTRODUCTION
The prevalence of social platforms, e.g., Twitter, Sina Weibo, has brought great convenience for the production and dissemination of user-generated online content. Every day there are tens of millions of online content generated on these platforms [2, 15]. Faced with such a large amount of information, predicting the future popularity of online content in advance plays an important role in various applications [7, 14], e.g., social recommendation, online advertisement, information retrieval.

One practical challenge for popularity prediction takes roots in the different settings of popularity prediction tasks in different situation [8], shown in Figure 1 (a). Specifically, there may be different settings of the observation time window, varying from 1 hour (predict the future popularity with an observation time of 1 hour) to 2 hours or other more [3, 4, 13, 16], while there may also be different prediction horizons [2, 7, 15]. Even the type of prediction label may change from binary classification (e.g., predict whether the popularity will double in the future) [5, 10] to regression (predict exact future popularity) [2, 4, 9]. Such a situation brings great challenges to practical application, i.e., a good popularity prediction model is desired to handle various prediction task settings.

Existing methods for popularity prediction mainly fall into three categories [7]: feature-based methods, generative methods, and deep learning based methods. Feature-based methods generally extract various hand-crafted features for popularity prediction [5, 14], while generative methods regard the popularity dynamics as an arrival point process and model the intensity function by different assumptions [11, 15]. The performance of these methods heavily depends on the heuristically extracted features or the unknown assumption, limiting their prediction performance. Recently, deep learning based methods have emerged and achieved state-of-the-art performance.
prediction performance [2, 3, 6, 9, 12, 13, 16], which train a separate model for each prediction task under the guidance of downstream labels (Figure 1 (b)). The obtained model for one prediction task setting is difficult to be generalized to other task settings, causing a great waste of training time and computational resources, as well as a large demand for downstream labels.

To inherit the powerful ability of deep learning based methods while eliminating the limitation of separate training paradigm, we propose a novel pre-training framework for popularity prediction, see Figure 1 (c). Instead of training a separate prediction model through massive downstream labels for each task setting, the proposed framework aims to pre-train a general representation model from readily available unlabeled diffusion data, which can be effectively transferred into different popularity prediction tasks. As the key of pre-training framework mainly lies in the design of self-supervised pretext task, we propose a novel pretext task for pre-training, i.e., temporal elapse inference for two randomly sampled time slices of popularity dynamics. Such a designed pretext task enforces the deep model to capture the intrinsic evolution pattern of popularity dynamics, so as to benefit various downstream task settings.

Note that, the pre-trained representation model only needs to be fine-tuned by few downstream labels when transferred into different downstream settings. Experiments conducted on both Sina Weibo and Twitter demonstrate that when compared with the prediction model under a separate training paradigm, the proposed framework is much more efficient and generalizable while achieving comparable performance. When compared with the random initialization, the pre-trained representation model achieves significant improvement on downstream popularity prediction tasks, further demonstrating the effectiveness of the pre-training framework.

2 METHODS

Since temporal information is the dominant factor for popularity prediction [5] and can be easily generalized across different platforms, here we focus on time-aware popularity prediction scenario.

Time-aware popularity prediction task \( T \): Given the observed retweet sequence of online content \( m \) within observation time \( T \), i.e., \( C^m_T = \{t_1, t_2, ..., t_N^m\} \) where \( N^m \) is the total number of retweets, it aims to predict the popularity label \( y_m \) at a prediction horizon \( T_p \).

Different settings of observation time \( T \), prediction horizon \( T_p \), and popularity label \( y_m \) form different popularity prediction tasks.

2.1 Overview of Pre-training Framework

Given a set of popularity prediction tasks \( \{T_i\}_{i=1}^{N_{tasks}} \) and a set of corresponding datasets with massive task labels \( \{D^i\}_{i=1}^{max} \), existing paradigm trains a separate prediction model \( f_0 \) using \( D^i \) for each task \( T_i \), which is both computational resource-consuming and massive label-demanding.

In contrast, the pre-training for popularity prediction aims to pre-train one general deep representation model \( f_0 \) using unlabeled diffusion data \( D \) based on a pretext task \( T_{pre} \), such that the pre-trained model \( f_0 \) can be effectively transformed into various (unseen) downstream popularity prediction tasks \( \{T_i\}_{i=1}^{N_{tasks}} \), via fine-tuned by few downstream labels \( D^i_{few} \). In this paper, we take the superior Temporal Convolutional Neural Networks (TCN) [1, 13] as the base deep model and transfer the input retweet sequence \( C^m_T \) into popularity dynamics \( X^m_T = [x^m_1, x^m_2, ..., x^m_T] \), which describes the incremental popularity \( x^m_i \) per time unit \( i \) to serve as the input of TCN.

2.2 Pretext Taks: Temporal Elapse Inference

To learn a satisfactory general representation model, the key lies in the design of the pretext task \( T_{pre} \). Considering that the popularity dynamics may have fluctuations in each time slice but remains relatively stable in temporal evolution, we propose a novel temporal elapse inference (TEI) as the pretext task. TEI randomly samples pairs of time slices of popularity dynamics and aims to infer the time elapsed between these two time slices, see Figure 2 to have an intuitive understanding. In order to accurately predict the temporal elapse between two time slices, the deep representation model needs to understand the temporal context information and capture the evolution pattern of popularity dynamics varying with time. Such ability is critical for downstream popularity prediction tasks, which is the reason why the pre-trained deep representation model can be beneficial to downstream tasks. Next, we formally define the designed pretext task of temporal elapse inference.

2.2.1 Temporal Context Sampling. We first segment the input popularity dynamics into several time slices. Let \( ΔT \) denote the length of each time slice, then the popularity dynamics of online content \( m \) can be segmented as: \( \{X^m_{\Delta T} = [x^m_1, ..., x^m_{\Delta T}], ..., x^m_s, ΔT\} \), where \( T \) is the length of observation time, \( s = \lceil T/ΔT \rceil \) denotes the total number of time slices, and \( X^m_{\Delta T} \) denote the \( i \)-th slice of popularity dynamics. Let \( L_{t} \) denote the temporal elapse between the \( A \)-th time slice and \( B \)-th time slice, i.e., \( L_{t} = B - A \).

Intuitively, two time slices that are too far away may make the temporal elapse inference too difficult to confuse the deep representation model, while two overlapping time slices may result in a simple prediction problem that can be easily solved without learning any general knowledge. Based on the above intuition, we set a maximum temporal elapse \( l_{max} \) and then uniformly sample the temporal elapse \( L_{t} \sim P_{t} \), where \( p(t) = \frac{1}{\min(s, l_{max})} \), \( i = 1, 2, ..., \min(s, l_{max}) \). To make sure that the sampled time slices contain sufficient observation, we assign higher sampling probability to earlier time slices, i.e., the \( A \)-th time slice is sampled with the probability \( p_A(A) \propto f(A) \), where \( f(\cdot) \) is monotone decreasing, and then \( B = L_{t} + A \).

2.2.2 Temporal Elapse Inference. For the sampled pair of time slice \( A \) and \( B \), we apply TCN with \( L \) layers [1, 13] on the two time slices of popularity dynamics \( X^m_{\Delta T, A} \) and \( X^m_{\Delta T, B} \) respectively to obtain their representations, i.e.,
We conduct experiments on two real datasets for various task settings. The code is publicly available in Github \(^1\).

### 3.1 Experimental Setup

#### 3.1.1 Datasets

We experiment with two real datasets. The first is Sina Weibo, where we collect all the original messages produced between June 1, 2016 and June 10, 2016, containing 710,554 online content in total. We sort all the online content by their publication time, and take the first 75% for training, 15% for validation, and the last 10% as test set following \([2, 15]\).

#### 3.1.2 Downstream Popularity Prediction Tasks

For separate training paradigm with massive labels, TCN shows outstanding performance on all downstream popularity prediction task settings, which is consistent with the reported results in \([13]\). We cannot perform DeepHawkes and CasCN on Twitter since this dataset lacks the structure information of diffusion subgraph. Since Seismic is sensitive to outliers and can only predict the final popularity, we omit results of MRSE and task \(T_1\).

#### 3.1.3 Baselines

We choose state-of-the-art methods for time-aware popularity prediction as strong baselines, i.e., Feature-based \([5]\); Seismic \([15]\) as a typical generative method; DeepHawkes \([2]\), CasCN \([4]\), TCN \([13]\) as powerful deep learning based methods.

#### 3.1.4 Evaluation Metrics

We adopt two commonly used evaluation metrics for regression task, i.e., loss function MRSE \([3, 14]\), and R-Acc \([7]\) that measures the fraction of content that are correctly predicted under a given tolerance of error:

\[
\text{R-Acc} = \frac{1}{M} \sum_{m=1}^{M} I [\text{APE}_m \leq \epsilon]
\]

where \(\text{APE}_m = \frac{|y_m - \hat{y}_m|}{y_m}\) and \(\epsilon = 0.3\). As for classification task, we take the widely used evaluation metrics for binary classification, i.e., classification accuracy (denoted as C-Acc) and F1 score.

### 3.2 Effectiveness of Pre-training Framework

We conduct experiments with various downstream popularity prediction tasks with the following observations, see Table 2:

- **For separate training paradigm with massive labels**, TCN shows outstanding performance on all downstream popularity prediction task settings, which is consistent with the reported results in \([13]\). We cannot perform DeepHawkes and CasCN on Twitter since this dataset lacks the structure information of diffusion subgraph. Since Seismic is sensitive to outliers and can only predict the final popularity, we omit results of MRSE and task \(T_1\).

- **When transferring the pre-trained model into downstream tasks with few labels**, i.e., 0.1% downstream labels in Sina Weibo and 0.5% on Twitter, our pre-trained TCN model significantly outperforms the random initialized TCN model. That is, PREP-TCN significantly outperforms TCN-f, and PREP-TCN also significantly outperforms TCN, demonstrating the effectiveness of our pre-training framework for downstream tasks.

- **The PREP-TCN which is fine-tuned with few downstream labels even achieves comparable prediction performance when compared with TCN trained with massive downstream labels under the paradigm of separate training**. For example, 0.232 vs 0.238 MRSE and 47.4% vs 47.8% R-Acc for task \(T_1\) on Sina Weibo. However, the separate training of TCN for various downstream prediction settings is much more time resource-consuming than the pre-training framework (See section 3.3).

### 3.3 Efficiency of Pre-training Framework

We conduct efficiency experiments on a single GPU (NVIDIA Tesla K80) and first analyze the training time on downstream tasks, shown in Figure 3. Even taking into account the time of pre-training, PREP-TCN and PREP-TCN-f is much more efficient than the separately trained TCN with massive downstream labels. Such efficiency advantages of the pre-training framework will be more significant with the increase of the number of tasks.
To deeper the understanding of efficiency advantages of the pre-training framework, we further analyze whether it can accelerate the convergence of model training. Figure 4 (left) shows that the loss of the pre-trained model decreases quickly at early training steps and then gradually tends to be stable, demonstrating the benefits of the pre-training framework for model convergence.

### 3.4 Analysis of Pre-training Task

To demonstrate the superiority of temporal elapse inference (TEI) as the pre-training task, we conduct experiments with replaced pre-training tasks, i.e., take one of the downstream tasks $T_j$ as the pre-training task. Besides, we also replace the sampling strategies in TEI with purely random sampling.

Experimental results are shown in Figure 4 (right). For model pre-trained with task $T_j$, it achieves a comparable prediction performance when the downstream tasks exactly match the pre-training task, i.e., the downstream task is also $T_j$, but achieves poor prediction performance for other downstream tasks. These results show that it is difficult to transfer or generalize the learned model across different downstream tasks. When removing the designed sampling strategy, the pre-trained model performs not as well as the original TEI, validating the effectiveness of the sampling strategies in Section 2.2.1. The model pre-trained with TEI gains the best performance, demonstrating the effectiveness of TEI as the pretext task to capture the rich knowledge contained in popularity dynamics for various downstream prediction tasks.

## 4 CONCLUSION

To the best of our knowledge, we are the first to propose a pre-training framework for popularity prediction, which can be effectively transferred into different popularity prediction tasks. We design a novel temporal elapse inference as the pretext task for pre-training, impelling the pre-trained model to effectively capture characteristics of popularity dynamics. Experiments conducted on two real datasets with various downstream tasks demonstrate both the effectiveness and generality of the pre-trained model. In the future, we aim to extend the pre-training framework to more scenarios and replace the TCN model with more advanced deep models that also consider user, content, and structure information.

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