Link Prediction for Wikipedia Articles based on Temporal Article Embedding

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Abstract: Wikipedia articles contain a vast number of hyperlinks (internal links) connecting subjects to other Wikipedia articles. It is useful to predict future links for newly created articles. Suggesting new links from/to existing articles can reduce editors' burdens, by prompting editors about necessary or missing links in their updates. In this paper, we discuss link prediction on linked and versioned articles. We propose new graph embeddings utilizing temporal random walk, which is biased by timestamp difference and semantic difference between linked and versioned articles. We generate article sequences by concatenating the article titles and category names on each random walk path. A pretrained language model is further trained to learn contextualized embeddings of article sequences. We design our link prediction experiments by predicting future links between new nodes and existing nodes. For evaluation, we compare our model's prediction results with three random walk-based graph embedding models DeepWalk, Node2vec, and CTDNE, through ROC AUC score, PRC AUC score, Precision@k, Recall@k, and F1@k as evaluation metrics. Our experimental results show that our proposed TLPRB outperforms these models in all the evaluation metrics.

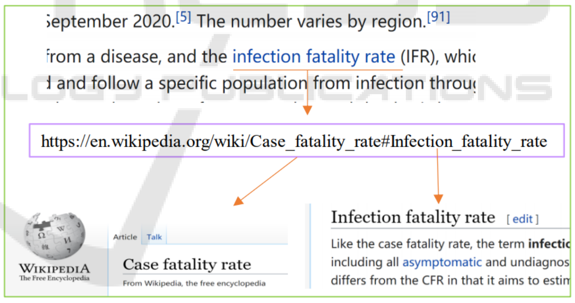
1 INTRODUCTION

Wikipedia is now one of the most popular multilingual online encyclopedias all over the world (Zesch et al., 2007). A large number of volunteers actively create and edit articles to expand shared knowledge. Wikipedia editors keep modifying articles reflecting significant topics and improving quality through various maintenance tasks. Updating an article creates a timestamped version of the article. Wikipedia article links are essential for readers to find relevant articles via navigation. Also, the link structure of Wikipedia is a prime source of knowledge graphs. Since articles are newly created and updated, system-support for suggesting new links from/to existing articles is necessary to reduce editors' burdens.

Figure 1 shows an example of an internal link. The article "COVID-19 pandemic"contains the phrase "infection fatality rate," which is linked to one section of another Wikipedia article "Case fatality rate."

Categories in Wikipedia play an important role in classifying articles into multiple hierarchies of diverse topics. Properly assigning categories to newly created articles is also an important but costly task for human editors.

The evolutional aspect of internal links of Wikipedia can be modeled as a temporal link graph,


eptember 2020.[5] The number varies by region.[91]
rom a disease, and the infection fatality rate (IFR), whi
d and follow a specific population from infection throu

https://en.wikipedia.org/wiki/Case_fatality_rate#Infection_fatality_rate

Article Talk
Case fatality rate
From Wikipedia, the free encyclopedia

Infection fatality rate [edit]
Like the case fatality rate, the term infectio
including all asymptomatic and undiagnos
differs from the CFR in that it aims to estim

Figure 1: Example of Wikipedia internal link.

which is a series of graphs where nodes represent articles, and edges represent links, and each graph is indexed by a timestamp. In this paper, we discuss a new method for predicting links between newly added articles and existing articles. The temporal link graph of Wikipedia shows the following characteristics: 1) The number of articles of hot topics is mostly continuously growing. 2) New articles are likely to be linked to other articles under a common category. 3) New links are more likely to be created between two articles having a high semantic similarity.

We dicuss link prediction based on temporal graph embeddings which can extract temporal, structural and semantical similarities of linked articles, which have not been considered in existing temporal/non-

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temporal link predictions. Major contributions of this paper are summarized below:

- We propose temporal link prediction methods based on new node embeddings that consist of two temporal random walk strategies: Random walk biased by similarity on common categories and random walk biased by semantic similarity.
- For temporal random walk biased by semantic similarity, we propose generating node embeddings from token sequences of article texts along walk paths. We utilize two document embedding methods: FastText (Bojanowski et al., 2017) with character n-gram and further pre-training of RoBERTa (Liu et al., 2019).
- Our proposed algorithms are evaluated on real temporal link graphs extracted from Wikipedia dump, consisting of article sets on three topics from January 1st to July 20th, 2020. Our rigorous evaluations on prediction accuracy show that our proposed RoBERTa-based method outperforms major link prediction algorithms.

The rest of this paper is organized as follows. Section 2 covers related work. Section 3 defines our temporal link prediction task. Section 4 shows the proposed methods. Section 5 explains experimental designs and evaluation results. Section 6 concludes this paper.

2 RELATED WORK

The survey (Yue et al., 2020) covers link prediction methods based on graph embeddings. Graph embedding methods can be grouped into three categories: Matrix factorization-based, random walk-based, and neural network-based methods. After obtaining node embeddings, the downstream prediction tasks in these categories are basically the same.

DeepWalk (Perozzi et al., 2014) learns latent representations of nodes in a network. Given a current start node, DeepWalk randomly samples a node from its neighbors as the next visit node and repeats this process until the visit sequence length meets a preset condition. After obtaining a sufficient number of node walking sequences, SkipGram is applied to generate node embeddings.

Node2vec (Grover and Leskovec, 2016) learns a mapping of nodes to a low-dimensional space of features that maximizes the likelihood of preserving network neighborhoods of nodes. Node2vec uses a biased random walk, which sets two hyperparameters p and q to control the strategy of the random walk. After sampling node sequences, the remaining steps are the same with DeepWalk.

The in-depth survey (Divakaran and Mohan, 2019) of temporal link prediction shows comparisons of the following embedding-based temporal link prediction algorithms. CTDNE (Nguyen et al., 2018) utilizes continuous-time dynamic network embedding to address the problem of learning an appropriate network representation for improving the accuracy of predictive models. They extend the definition of static graph random walk to temporal graph random walk and propose several effective biased random walk strategies.

DynamicTriad (Zhou et al., 2018) preserves structural information and evolution patterns of a given network. The general idea of the model is to impose a triad to model the dynamic changes of network structures. They model how a closed triad develops from an open triad, which is called a triad closure process and is a fundamental mechanism in the formation and evolution of dynamic networks.

DynGEM (Goyal et al., 2018) employs a deep autoencoder as its core and leverages the advances in deep learning to generate highly non-linear embeddings. The major advantages of DynGEM include: The embeddings are stable over time, can handle newly added nodes in dynamic graphs, and has better running time than using static embedding methods on each snapshot of a series of dynamic graphs.

A crucial problem of the above methods is that their embeddings are intended to preserve link neighborhoods, but deep features nodes are representing, such as semantic similarities, are not considered. If a node represents an article, link neighbors as well as semantic neighbors can be useful for the link prediction task. Since Wikipedia articles are texts, we argue that semantic similarity measured on representative parts of article texts, such as titles and categories, can be exploited for this task. Thus, we discuss graph embeddings that can reflect both link structures and textual similarities between nodes.

3 OBJECTIVES AND PRELIMINARIES

Given a series of graph snapshots $[G_0, G_1, ..., G_{T-1}]$, where suffix obeys timestamp order, our goal is to predict links between new nodes in the next graph G_T and nodes existing before T. Each node in each graph snapshot has two attributes; one is a word sequence called *article text*, and the other is a set of word sequences called *category*. The article texts and categories of nodes may also change between snapshots.

Figure 2 left (Snapshots) illustrates our objectives. Since new articles are constantly created, we aim to predict new links between newly added articles (the orange node at $t = 2$) and existing articles in the last graph G_T.

For convenience, we unify the series of graph snapshots $[G_0, G_1, ..., G_T]$ into one temporal (multi-) graph $G = (V, E)$, where N is a set of nodes corresponding to a subset of Wikipedia articles. Let E be the set of edges, representing Wikipedia article links, where each link $e_i = (u, v, t_s) \in E$ means that there is a link from node u to node v at time t_s.

Figure 2 right shows an example of a unified temporal graph $G = (V, E)$. The light blue node has an edge to the purple node at timestamps $t = 1$ and $t = 2$. After unifying the snapshots, the light blue node will have two edges directed to the purple node, where the edges are labeled with timestamps 1 and 2.

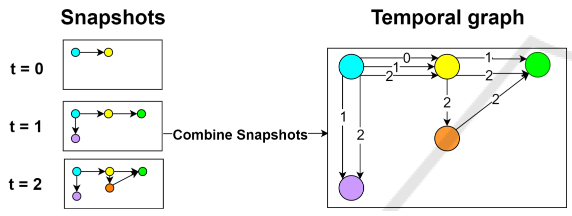


Figure 2: Example of generating the temporal graph.

The set of *temporal neighbors* of a node v at time t_s is defined as $\Gamma_{t_s}(v) = \{(w, t') \mid \exists e = (v, w, t') \in E \text{ such that } T(e) \geqslant t_s\}$, where $t' = T(e)$ is the timestamp of edge e.

4 METHODOLOGIES

Our method consists of three main parts: Temporal random walk, learning node (article) embeddings, and link prediction. After article embeddings are generated, a conventional link prediction method is applied.

4.1 Article Sequences

The random walk part has two steps. Step 1 is selecting an initial random walk edge, and Step 2 is executing temporal random walks. For Step 1, we propose a biased strategy for edge selection. For Step 2, we propose two strategies, which are random walk by common categories and random walk by semantic similarity.

After one random walk is executed, the walk path shows a node sequence, from which we can generate an *article sequence*, which is the concatenation of the article texts along the walk path. The article sequences are utilized as sentences for training node embeddings.

Since typical Wikipedia articles are quite long and complex, we should extract important article components that are useful for link prediction. The following article components are well summarizing topics of one article or one link, thus suitable as article texts: (1) article title, (2) leading k tokens of the article, (3) category names, (4) the title of a link, and (5) the text around the target of a link. Considering random walk length and the length limit of 512 tokens of the BERT/RoBERTa encoder, for article texts we choose (1) article title and (3) category names, which are representing the topics of one article than the other article components.

4.2 Random Walk Strategies

4.2.1 Initial Edge Selection

Given a temporal graph $G = (V, E)$, we first need to select an edge as the initial edge of a random walk. To deal with this problem, we utilize *temporal bias* in sedge election (Nguyen et al., 2018), such that each edge is given a weight according to freshness of its timestamp. Specifically, each weight is given by a softmax function on the exponential distribution of timestamp decay. Each edge $e_i = (u, v, t_s) \in E$ is assigned with the following probability:

$$Pr(e_i) = \frac{e^{(T(e_i) - t_{min})}}{\sum_{e' \in E} e^{(T(e') - t_{min})}} \tag{1}$$

where t_{min} is the minimum edge timestamp in graph G, and $T(e_i)$ denotes the timestamp of edge e_i. The above defines a distribution that heavily favors edges appearing later in time.

4.2.2 Temporal Random Walk

After selecting an initial edge $e_i = (u, v, t_s)$ at time t_s for initiating a temporal random walk, we need to select the next node to visit by the random walk. The main principle of our temporal random walk is that the timestamp of the next edge must not be less than the current time.

We design two techniques to bias temporal random walks by sampling the next node via calculating each neighbor probability based on common categories (Section 4.2.3) and semantic similarity (Section 4.2.4).

We generate an article sequence along each random walk path. For example, when walking to node v at timestamp t_s, we append the article text (Section 4.1) of v into the article sequence of the random walk until the walk length reaches the max walk length.

4.2.3 Random Walk by Common Categories

Figure 3 shows a partial list of categories in Wikipedia[1].

2020 United States presidential election, Donald Trump 2020 presidential campaign, Donald Trump, Mike Pence, Joe Biden 2020 presidential campaign, Joe Biden, Kamala Harris

Figure 3: Categories of article 2020 United States Presidential Election (partial).

The degree of common categories can be measured by the Jaccard coefficient of the current node's categories and the next neighbor node's categories:

$$Jaccard(v,w,t_s,T(w)) = \frac{|n_v^{cat}(t_s) \cap n_w^{cat}(T(w))|}{|n_v^{cat}(t_s) \cup n_w^{cat}(T(w))|} \quad (2)$$

where $n_v^{cat}(t_s)$ represents the categories of article v at timestamp t_s, and $n_w^{cat}(T(w))$ represents the categories of a candidate article w at timestamp $T(w)$. Symbols "$\cap$" and "$\cup$," respectively, denote the intersection and union of two article categories, respectively, where the exact category names are used as identifiers. Symbol $|\cdot|$ is the number of categories in this set.

We define the probability of selecting node v's temporal neighbor $w \in \Gamma_{t_s}(v)$ as:

$$Pr(w) = \frac{e^{T(w)-t_s+\lambda \times Jaccard(v,w,t_s,T(w))}}{\sum_{w' \in \Gamma_{t_s}(v)} e^{T(w')-t_s+\lambda \times Jaccard(v,w',t_s,T(w'))}} \quad (3)$$

The difference $T(w) - t_s$ is the time span between the current timestamp t_s and the next link's timestamp $T(w)$. λ is a hyperparameter to control the influence of time span bias and common categories bias.

4.2.4 Random Walk by Semantic Similarity

Another bias strategy for the temporal random walk is to consider semantic similarity between two nodes, which can be measured by cosine similarity on document embeddings of two nodes. We generate the embedding vector of node v from its article sequence, by utilizing the pretrained language model RoBERTa (Liu et al., 2019), which is an improved version of the pretrained language model BERT. Compared with BERT (Devlin et al., 2019), RoBERTa uses dynamic masking and byte-level BPE (Byte-Pair Encoding), where BPE can cope with out-of-vocabulary words by subword decomposition.

[1]https://en.wikipedia.org/wiki/2020_United_States_presidential_election

To generate node embeddings $Emb(v)$ by RoBERTa, we enter the article sequence of v into RoBERTa, where the article sequence is truncated to fit into the length limitation of 512 tokens of RoBERTa. The output at $<s>$ token is a 768-dimensional vector, which can be used as the node (article) embedding.

Now suppose our current node of a random walk is v, and one candidate neighbor is node w. We introduce the following probability function combining time decay and semantic similarity, for the probability of walking to this candidate node w.

$$Pr(w) = \frac{e^{T(w)-t_s+\alpha \times cosine(Emb(v),Emb(w))}}{\sum_{w' \in \Gamma_{t_s}(v)} e^{T(w')-t_s+\alpha \times cosine(Emb(v),Emb(w'))}} \quad (4)$$

Here, t_s is the current timestamp, and $T(w)$ is the timestamp of edge (v,w). $T(w) - t_s$ is the time difference of the current timestamp t_s and the next link's timestamp $T(w)$. α is a hyperparameter to control the weight of timestamp difference and semantic similarity of articles.

4.3 Learning Node Embeddings

In this paper, we propose training of node embeddings from article sequences collected along random walk paths, so that semantic neighbors and link neighbors are smoothly integrated into a single embedding space.

In Section 4.2.4, document embedding $Emb(v)$ from the article text of a node v was introduced. However, for temporal link prediction we introduce different node embeddings, denoted as $Emb^{TC}(v[t])$ for the embedding of node v at timestamp t. Node embeddings $Emb^{TC}(v[t])$ are trained from article sequences along temporal random walk paths, so that temporal, structural, and semantic similarities are smoothly integrated into a single node representation. We consider two embedding algorithms, FastText (Bojanowski et al., 2017) and further pre-training of RoBERTa for training of $Emb^{TC}(v[t])$.

4.3.1 FastText with Character N-gram

The word embedding model word2vec does not distinguish the words "apple" and "apples." To overcome this problem, FastText (Bojanowski et al., 2017) uses a bag of character-level n-grams to represent a word. For the word "apple," suppose the value of n is 3, then its trigram decomposition is "<ap," "app," "ppl," "ple," "le>." Thus, we can represent the word vector of "apple" by superimposing the vectors of the five trigrams.

In temporal random walk, we generate article sequences by concatenating article texts along each walk path. Then we apply FastText with character n-gram to train embeddings from these article sequences.

4.3.2 Further Pretraining of RoBERTa by Article Sequences

We can construct a corpus consisting of the sentences where each sentence corresponds to the article sequence along each temporal random walk path. Then on this corpus, we perform further pre-training of RoBERTa by the Masked Langrage Model (MLM), such that word tokens are generated by the RoBERTa tokenizer with byte-pair encoding, and dynamically mask randomly selected tokens in each input sequence with a special token [*MASK*]. The objective of MLM is the cross-entropy loss on predicting the masked tokens.

By the above further pretraining on the corpus, the RoBERTa model will learn contextualized embeddings of article sequences. In our case, the RoBERTa model will produce embeddings $Emb^{TC}(v[t])$ such that texts appearing in link neighbors of v will have higher similarities with $Emb^{TC}(v[t])$ than texts that are remote from v in the temporal link graph.

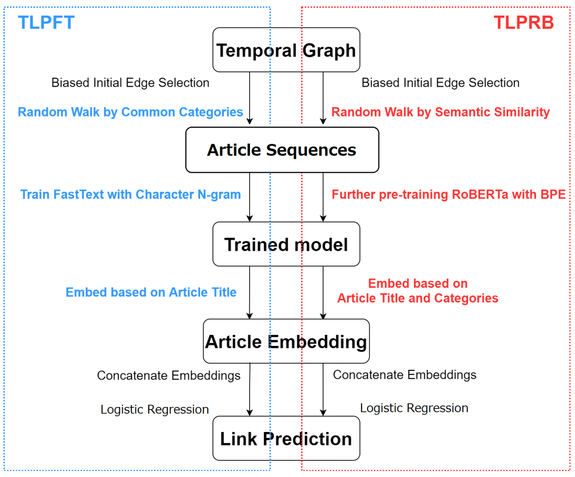
4.4 Two Link Prediction Methods

Since our targets are directed graphs, following (Crichton et al., 2018), we adopt the concatenation method to construct the feature vector of each directed edge. Given a link from u to v at time t, we obtain $Emb^{TC}(u[t])$ and $Emb^{TC}(v[t])$, namely the embeddings of the article sequences of nodes u and v at time t. Then the concatenation $[Emb^{TC}(u[t]), Emb^{TC}(v[t])]$ of these embeddings is used as the feature vector of the link from u to v. Temporal link prediction is performed by a logistic regression classifier on the feature vectors regarding a target article node.

We summarize our proposed temporal link prediction methods into TLPFT and TLPRB. TLPFT (**T**emporal **L**ink **P**rediction with **F**ast**T**ext) is the method with the biased initial edge selection strategy (1), random walk with common categories (3), and learning node embeddings through FastText with character n-grams.

TLPRB (**T**emporal **L**ink **P**rediction with **R**o**B**ERTa) is the method with the biased initial edge selection strategy (1), random walk by semantic similarity (4), and learning node embeddings through further pre-training RoBERTa by article sequences along walk paths. Then we apply these embeddings for link prediction in the same way.

Figure 4 contrasts the differences between TLPFT and TLPRB.


TLPFT
TLPRB
Temporal Graph
Biased Initial Edge Selection
Random Walk by Common Categories
Biased Initial Edge Selection
Random Walk by Semantic Similarity
Article Sequences
Train FastText with Character N-gram
Further pre-training RoBERTa with BPE
Trained model
Embed based on Article Title
Embed based on Article Title and Categories
Article Embedding
Concatenate Embeddings
Logistic Regression
Concatenate Embeddings
Logistic Regression
Link Prediction
Figure 4: Pipelines of TLPFT and TLPRB.

5 EXPERIMENTS

5.1 Datasets

Now we describe the construction of our evaluation datasets, which are sampled from Wikimedia dump. The time span from 2020-01-01 to 2020-07-20 is extracted, consisting of thirteen snapshots in the English Wikipedia server.

We select three topics: **2020 Protests, 2020 United States Presidential Election, COVID-19 Pandemic**, and extract all the articles in these topics from each snapshot in the Wikimedia dump. We extracted three types of information for building our temporal graph: The title of each article at each timestamp, the category lists of each article at each timestamp, and the hyperlinks between all the articles at each timestamp.

The detailed descriptions of our three datasets are summarized in Table 1. Each row of the table corresponds to a timestamp. The columns Nodes and Edges, respectively, are the numbers of nodes and edges, respectively, of the graph at each timestamp.

5.2 Baseline Models

As our baseline models, we choose the following three graph embedding algorithms which are also based on random walk:

- DeepWalk (Perozzi et al., 2014): This model is a basic random walk graph embedding method that can be applied for a directed or undirected un-

Table 1: Statistics of the three datasets.

	2020 Protests		2020 U.S. Presidential Election		COVID-19 Pandemic	
	Nodes	Edges	Nodes	Edges	Nodes	Edges
Jan.1	676	19456	1220	90465	1778	17890
Jan.20	695	20786	1226	93924	1853	18982
Feb.1	704	21286	1229	95755	1911	19876
Feb.20	712	21896	1245	98824	2040	22456
Mar.1	715	22009	1250	99800	2120	25486
Apr.1	726	22523	1276	102608	2759	208020
Apr.20	731	22610	1296	105270	3006	276751
May.1	733	23140	1303	106657	3127	314667
May.20	739	24424	1311	108050	3278	367660
Jun.1	768	25604	1314	108421	3351	382105
Jun.20	925	43502	1322	108704	3431	405540
Jul.1	951	51982	1331	110250	3471	429762
Jul.20	976	55594	1342	112344	3554	456680

weighted graph. However, temporal information is not utilized by DeepWalk.

- Node2vec (Grover and Leskovec, 2016): This model introduces two hyperparameters p and q for a biased random walk. Parameter p controls the probability of repeating the node just visited, and parameter q controls whether the walk is outward or inward on edge direction. Node2vec also does not consider temporal information.
- CTDNE (Nguyen et al., 2018): This model is designed for temporal graph embedding. CTDNE provides three temporal random walk strategies, which are uniform, exponential, and linear.

We choose two versions of the original CTDNE model, in terms of temporal random walk strategies for bias on initial edge selection and bias on neighbor edge selection, denoted as CTDNE (none-none) and CTDNE (none-exponential).

CTDNE can deal with temporal graphs, but DeepWalk and Node2vec are applicable for static graphs. To make the results more descriptive, we unify all the graphs in the training set into one graph and apply DeepWalk and Node2vec on this unified graph for static link prediction.

For comparison, we set the random walk parameters of all models to be the same. Table 2 shows the parameter values used in the experiments. To show the effectiveness of further pre-training RoBERTa by article sequences, we added a new comparative model RoBERTa Embedding that just uses the pre-trained RoBERTa for obtaining node embeddings from article sequences, without further pretraining by MLM.

5.3 Design of Experiments

For evaluating prediction results, we adopt AUC (Area Under the Curve) of ROC, which is one of the most important evaluation metrics for checking any classification model's performance (Yang et al., 2015), where a higher AUC score means better prediction performance.

Table 2: Parameter values of radom walk.

Parameter	Description	Value
window_size	used for the SkipGram algorithm	5
walk_length	max random walk path length	20
num_walks	how many times random walk start per node	30
embedding_size	graph embedding vector dimension	768
p	used for random walk bias strategy in Node2vec	2
q	used for random walk bias strategy in Node2vec	0.5

We also measure Precision@k, Recall@k, and F1@k, which respectively mean precision, recall, and F1-score on the top-k links predicted by a method. The micro-averages of these metrics on the test nodes are shown.

Figure 5 illustrates the split of the test and training sets in our experiments. The construction of the training and test link sets is as follows. The newly added links at the last timestamp (July 20th) are held out as the test link set. The remaining links in the last timestamp, and all the links in the preceeding timestamps, where the test link set is excluded, constitute the training link sets. Biased temporal random walk is carried out on the training link set, and article sequences along the walk paths are extracted for training node embeddings by our TLPFT or TLPRB.

We use the concatenation method to generate edge features, and label them with 1 or 0 based by whether there is a directed link.

Finally, we use logistic regression as a classifier for link prediction. The evaluation metrics are ROC AUC score, PRC AUC score, and micro–averages of Precision@K, Recall@K, and F1@K.

The number of node pairs in the training and testing datasets are shown in Table 3.

Table 3: Number of node pairs in train and test datasets.

Dataset	Node Pairs in Training Set	Node Pairs in Test Set
2020 Protests	107228	48231
2020 United Presidential Election	222812	29383
COVID-19 Pandemic	877544	582975

The random walk of DeepWalk and Node2vec

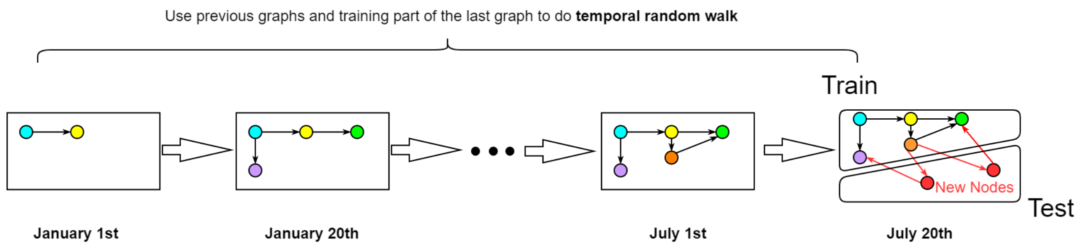

Use previous graphs and training part of the last graph to do temporal random walk
Train
New Nodes
Test
January 1st
January 20th
July 1st
July 20th

Figure 5: Split of train and test link sets.

Table 4: Experimental results on three datasets.

Methods	2020 Protests		2020 United States Presidential Election		COVID-19 Pandemic	
	ROC AUC	PRC AUC	ROC AUC	PRC AUC	ROC AUC	PRC AUC
DeepWalk	0.712	0.111	0.661	0.046	0.921	0.378
Node2vec	0.719	0.118	0.69	0.058	0.938	0.461
CTDNE(None-None)	0.727	0.1	0.727	0.092	0.926	0.488
CTDNE(None-Exponential)	0.725	0.098	0.725	0.063	0.918	0.379
RoBERTa Embedding	0.759	0.095	0.756	0.089	0.977	0.574
TLPFT	0.773	0.115	0.773	0.088	0.976	0.594
TLPRB	**0.791**	**0.12**	**0.79**	**0.105**	**0.981**	**0.678**

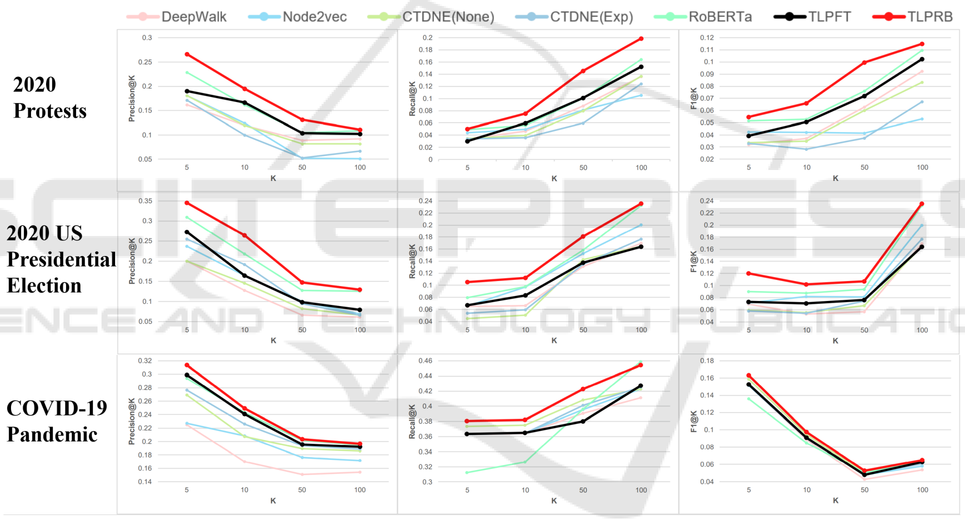


Figure 6: Micro-averaged Precision@k, Recall@k, and F1@k on three datasets.

needs to reach newly created nodes, to learn structure information of the new nodes. So 1% of randomly selected edges in the training set are allocated to the new nodes, and each non-isolated new node is assigned at least one adjacent edge.

The parameters p and q of the walking strategy in DeepWalk are fixed to 1, while for Node2vec grid search is used to find the best combination of parameters p and q from $0.25, 0.5, 1, 2, 4$.

5.4 Experimental Results and Analysis

Table 4 shows the ROC AUC and PRC AUC scores of the models on the three datasets.

As shown in the above experimental results, we can draw the following conclusions.

Node2vec is better than DeepWalk in all the cases, but CTDNE is better than the static graph embedding methods DeepWalk and Node2vec. One reason is that CTDNE learns temporal evolution pattern of link structure through temporal random walk. The pre-trained RoBERTa model was trained by raw English Wikipedia articles (Liu et al., 2019). So, RoBERTa Embedding can appropriately produce embedding vectors of articles. The results indicate that temporal random walk coupled with semantic similarity is showing an apparent improvement over the three graph embedding models.

As for our proposed models, the results show that both TLPFT and TLPRB outperform the baselines by a significant margin. By comparing TLPRB and RoBERTa Embedding, it can be seen that further pretraining RoBERTa by MLM on article sequences is significantly improving the performance, indicating that TLPRB is learning contexutality in sequences of titles and category names, which benefits prediction of neighboring new nodes.

TLPFT is better than the baseline models, indicating that semantic similarity captured by FastText, which is capable of embedding out-of-vocabulary words in article texts by k-gram decomposition, and TLPFT is even surpassing RoBERTa Embedding. However, TLPFT is not as effective as TLPRB, indicating that embeddings of FastText do not capture contexts in article sequences, while TLPRB is further pretrained by a large number of article sequences, to learn semantic similarity and contextual relationship between neighboring articles.

Figure 6 shows micro-averaged Precision@k, Recall@k, and F1@k curves with k=5, 10, 50, 100 on the three datasets. Combining the results on the aggregated performance by the AUC scores and the ranking performance by the Top-K results, our overall conclusion is that TLPRB performs best in both AUC and Top-K evaluations, and TLPFT performs the next in the AUC evaluation.

6 CONCLUSION AND FUTURE WORK

In this paper, we proposed a new method for predicting article links in Wikipedia, which utilizes temporal random walk to generate graph embeddings. Our graph embedding model is based on temporal random walk, biased by temporal feature and semantic relationships of article texts between node pairs. We evaluated on three temporal graph datasets extracted from Wikipedia dump. Our experimental results show that our proposed model TLPRB outperforms the baselines and simple RoBERTa-based model in this temporal link prediction on versioned articles.

For future work, we consider that the current definition of common categories is based on identical category names. Semantic similarity and hierarchical relationships between categories can be explored.

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