SOCIAL MEDIA POPULARITY PREDICTION BASED ON MULTI-MODAL SELF-ATTENTION MECHANISMS

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Abstract:
Popularity prediction using social media is an important task because of its wide range of real-world applications such as advertisements, recommendation systems, and trend analysis. However, this task is challenging because social media is affected by multiple factors that cannot be easily modeled (e.g. quality of content, relevance to viewers, real-life events). Usually, other methods adopt the greedy approach to include as many modalities and factors as possible into their model but treat these features equally. To solve this phenomenon, our proposed method leverages the self-attention mechanism to effectively and automatically fuse different features to achieve better performance for the popularity prediction of a post, where the features used in our model can be mainly categorized into two modalities, semantic (text) and numeric features. With extensive experiments and ablation studies on the training and testing data of the challenging ACM Multimedia SMPD 2020 Challenge dataset, the evaluation results demonstrate the effectiveness of the proposed approach as compared with other methods.

Keywords : Social networking (online) , Feature extraction, Semantics , Numerical models , Multimedia Web sites , Image databases , Task analysis

1.INTRODUCTION

Social media provides a public platform to easily exchange information with each other, and nowadays people spend a lot of time every day on various social media platforms. Since social media occupies a large part of the daily lives of modern people, many people are interested in researching how to extract data from social media. An example of information that could be gained from social media is the popularity score. Specifically, this score tells how many people viewed a post, and a larger number of views means more influence. Social media popularity prediction (SMP) is the task of estimating the popularity score using the available data of a given social media post.

Estimating the popularity score is hard because of the many and complex factors that affect popularity. Quality of content and relevance to viewers are some of the factors, and these are difficult to measure. Other factors such as real-life events are tough to include in a prediction model. Recent SMP methods attempt to tackle these complex factors by adding more modalities such as images relationship networks temporal context tags, and categories.

Although increasing the number of modalities is a good approach to the works, it also increases the complexity of the model, in terms of architecture, memory consumption, number of modules, etc. Alternatively, the paper is also a multi-modal approach but in its pipeline, it represented images as captions (i.e. texts). Different modalities could be converted to another modality using existing technologies. Image captioning converts images to texts. There exist speech-to-text methods already. From the social graph of a post, we could extract different numeric values, such as the number of the neighbors for each node.

Moreover, the popularity of posts may be affected by user information. Many studies have shown that there is a high correlation between image popularity and users. One of the reasons is that the users have their own followers, different users may have different numbers of followers. Generally, posts written by the user with more followers have a higher chance to receive more views and likes. And the temporal and spatial information may affect the popularity as well, the earlier post should get more people's attention, and if the user uploads the post in a special location, it will attract more attention too.

In this paper, we proposed a network that exploits semantic (text) and numerical (number) modalities to estimate the popularity of a social media post based on the self-attention mechanism. Due to the data type discrepancy, we divided the data into semantic and numerical branches. In the semantic branch, the image contents are transferred to caption texts and tags, all of the textual features are converted into tokens, each token has an associated with word embedding since the attention mechanism is shown effective to extract contextual information, to better aggregate the sequence of embedding, we also develop a feature attention mechanism for the purpose, which can deal with dispensing recurrence, and convolutions entirely. Using only the semantic features modality is not sufficient for some types of social media posts, so we used the numerical features as well which can be easily converted into scalars, such as timestamps, geo location. After preprocessing, we extracted and fused the features in both modalities respectively, and assemble two models to calculate the popularity score. The contributions of this work are 3 fold:

_We designed a network that adopts an attention mechanism and exploits multiple features in two modalities to perform model ensemble, the network can be easily extended to include more different modalities furthermore, which is able to solve problems with heavy categories.

_We analyzed the influence of semantic features on the model performance. Moreover, we generated additional numerical features, the result indicates the derived features are beneficial to improve our network performance.

_We demonstrated that our method outperforms the other state-of-the-art methods in Social Media Popularity Dataset.

2.LITERATURE SURVEY

2.1DIFFERENT AUTHORS DISCUSSION

Social media popularity prediction receives much attention, there is a lot of research on this topic in both academia and industry. These studies cover a wide range of applications such as recommendations, image and video annotation, personality detection, human behavior prediction, and media popularity prediction. They share a common way to figure out the final popularity score which involves feature extraction and using regression models [34, 35].

Khosla et al. [1] used the image content and the user context to predict the image popularity based on millions of images. They methodically analyzed the impact of low-level, middle-level, and high-level features on prediction accuracy. Wu et al. [2] merged multiple time-scale dynamics into a sequential prediction of popularity. In [3], Hessel et al. [4] analyzed that the combination of visual and textual modalities generally leads to the best accuracies for predicting relative popularity on Reddit. Mazloom et al. [5] proposed that there are several important features, called engagement parameters, such as sentiment, vividness, and entertainment. They used these parameters for predicting the popularity of brand-related posts on Instagram

2.2 DOMAIN DESCRIPTION

It is focuses on creating algorithms and models that enable computers to learn from data and improve their performance on a specific task over time,without being explicitly programmed. It involves the development of systems that can recognize patterns, make decisions, and improve their abilities through experience

3. PROBLEM STATEMENT

3.1 EXISTING SYSTEM

In Existing system, Li et al presented a Doc2Vec model and an effective text-based feature fusion engineering, but these works only concatenated the different types of features then fed them to the regression model, they did not consider the correlation between different features, Hsu et al proposedan iterative refinement method to compensate for prediction error and computed the view count of apost by residual learning, However, this works only adopted limited types of social media data there are still a lot of useful data that can improve the performance of prediction, Van Zwol studied the characteristics of users' social behaviour on Flickr, He revealed that photos received the majorityof their views within the first two days of being uploaded, They share a common way to figure out the final popularity score which involves feature extraction and using regression models, Yeh et al [38] proposed a visual attention module to enhance image classification Capability, Ortis et al [40] considered visual and textual information to perform sentiment analysis through the SVM classifier,and Katsurai et al [41] exploited the SentiWordNet to retrieve sentiment information and fused the visual and textual views to classify the post belongs positive or negative via SVM as well, however,the SVM model cannot afford the large-scale dataset, and it is hard to apply to high dimensional data, In 2016, He et al. [10] proposed a novel deep learning architecture, Residual Network generally, the deeper network will get better performance, however, there exists a degradation problem: when the number of layers increases, the accuracy will decrease, ResNet has an identity

mapping mechanism to solve problems of gradient vanishing and explosion.

3.2 DISADVANTAGE OF EXISTINTG SYSTEM:

An existing methodology doesn't implement SEMANTIC FEATURE EXTRACTIONmethod.
The system not implemented ENSEMBLE REGRESSOR MODEL for the datasets.

4. PROPOSED SYSTEM

4.1 PROPOSED SYSTEM

In The Proposed System we proposed a network that exploits semantic and numerical modalities to estimate the popularity of a social media post based on the self-attention mechanism. Due to the data type discrepancy, we divided the data into semantic and numerical branches, self attention mechanism is shown effective to extract contextual information, to better aggregate the sequence ofembedding we also Feature Attention Mechanism for this purpose, our method using Spearman's Rho ranking correlation to measure the correlation between actual probability and predicted probabilities, features used in our model can be mainly categorized into two modalities, semantic (text) and numeric features and self-attention mechanism to effectively and automatically fuse different features to achieve better performance for the popularity prediction of a post.

4.2ADVANTAGES IN PROPOSED SYSTEM :

Caption Features : Social media posts could have images or videos attached, to simplify the pipeline of our method, these attached images and videos are converted to text using a pre-trainedcaptioning and are treated similarly as textual features.

User-Related Features : User-related information is directly related to the user who created thesocial media post. For simplicity, we used two features in this type:

- User ID
- Pro-Member Flag

Numerical Features : Features that could be expressed quantitatively (i.e. ordinal, interval, ratio). Examples of these features in terms of a social media post are timestamps, longitude, and latitude. Other numeric values could be computed using the existing features such as tag count andposting frequency.

Tag Features : Tag features are composed of several keywords given by the user when they arecreating a post, the tags are arbitrary information, for Example the styles, location ,or holiday.

5. IMPLEMENTATION

5.1 Service Provider:

In this module, the Service Provider has to login by using valid user name and password,after login successful he can do some operations such as:

Login, Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar chart, View Trained and Tested Accuracy Results, View Predicted social media popularity Results, View Predicted social media popularity Ratio, Download Predicted Data Sets, View All Remote Users, Logout

View and Authorize Users:

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations Once user registers, their details will be stored to the database, After registration successful, he has to login by using authorized user name and password. Once Login is successfuluser will do some operations like REGISTER AND LOGIN, PREDICTED SOCIAL MEDIA POPULARITY, VIEW YOUR PROFILE

6. ARCHITECTURE

7. CONCLUSION

In this paper, we proposed a social media popularity prediction method with multi-modal input and attention-based mechanisms Specifically, our method uses semantic and numerical features to compute the popularity score, Semantic features are text-based and sequential hence attention-based networks (i.e. Transformer) have good synergy with this task, We also convertedimages to semantic features using existing image captioning algorithms, Furthermore, we augmented the existing numerical features to increase the performance of our model, We showcased that our method performs reasonably well against other state-of-the-art methods.

8. FUTURE ENHANCEMENT

To solve this phenomenon, our proposed method leverages the self-attention mechanism to effectively and automatically fuse different features to achieve better performance for the popularity prediction of a post, where the features used in our model can be mainly categorizedinto two modalities, semantic (text) and numeric features. With extensive experiments and ablation studies on the training and testing data of the challenging In this paper, we proposed asocial media popularity prediction method with multi-modal input and attention-based mechanisms. Specifically, our method uses semantic and numerical features to compute the popularity score. Semantic features are text-based and sequential hence attention-based networks (Transformer) have good synergy with this task. We also converted images to semantic features using existing image captioning algorithms. Furthermore, we augmented theexisting numerical features to increase the performance of our model. We showcased that our method performs reasonably well against other state-of-the-art methods.

Although increasing the number of modalities is a good approach to the works, it also increasesthe complexity of the model, in terms of architecture, memory consumption, number of modules,etc. Alternatively, the paper [7, 26, 27, 28, 29, 30] is also a multi-modal approach but in its pipeline, it represented images as captions (texts). Different modalities could be converted to another modality using existing technologies. Image captioning converts images to texts there exist speech-to-text methods already. From the socialgraph of a post, we could extract different numeric values, such as the number of the neighbours for each node, In this paper, we proposed a network that exploits semantic (text) and numerical (number) modalities to estimate the popularity of a social media post based on the data into semantic andnumerical branches.

In the semantic branch, the image contents are transferred to caption texts and tags, all of the textual features are converted into tokens, each token has an associated with word embedding [23], since the attention mechanism [9] is shown effective to extract contextual information, tobetter aggregate the sequence of embedding, we also develop a feature attention mechanism for the purpose, which can deal with dispensing recurrence, and convolutions entirely. Using only the semantic features modality is not sufficient for some types of social media posts, so we usedthe numerical features as well which can be easily converted into scalars, such as timestamps, geolocation. After preprocessing, we extracted and fused the features in both modalities respectively, and assemble two models to calculate the popularity score, The contributions of this work are three fold:

• We designed a network that adopts an attention mechanism and exploits multiple features in two modalities to perform model ensemble, the network can be easily extended to includemore different modalities furthermore, which is able to solve problems with heavy categories.

• We analyzed the influence of semantic features on the model performance. Moreover, we generated additional numerical features, the result indicates the derived features are beneficial to improve our network performance.

• We demonstrated that our method outperforms the other state-of-the-art methods in SocialMedia Popularity Dataset.

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4.PROPOSED SYSTEM

4.1 PROPOSED SYSTEM

In this paper, we propose a novel Sybil attack detection scheme using proofs of work and location. The main idea is that when a vehicle encounters an RSU, the RSU should issue authorized time-stamped tag which is a concatenation of time of appearance and anonymous location tag of that RSU. As the vehicle keeps moving, it creates its trajectory by combining a set of consecutive authorized time-stamped tags that are chronologically chained to each other. That trajectory is used as an anonymous identity of the vehicle. Since RSUs have the main responsibility to issue proof of location to vehicles, the scheme should resist against RSU compromise attack so we design the trajectory so that not only one RSU is capable of creating trajectories for the vehicles. To achieve this, threshold signature is adopted so that each RSU is only able to generate a partial signature on a set of time-stamped tags. Once a vehicle travels along a certain threshold number of RSUs, a standard signature representing a proof of location can be generated. Upon receiving an authorized message from an RSU, the vehicle should use it as a seed to solve a puzzle using a proof-of-work algorithm, similar to the one used in Bitcoin .The core idea of PoW is to provide a proof to RSUs so they can ensure that the vehicle solved the puzzle correctly. Comparing to Footprint using PoW limits the ability of a malicious vehicles to create multiple trajectories.

To detect Sybil trajectories, upon receiving an event from other vehicles, the event manager first applies a set of heuristics to construct a connected graph of Sybil nodes, then it uses the maximum clique algorithm to detect all Sybil nodes in that grap

4.2 ADVANTAGE OF PROPOSED SYSTEM:

The system used threshold signatures to resist RSU compromise attacks. The attacker needs to compromise an infeasible number of RSUs to be able to create fake trajectories.

_ The system used the PoW algorithm with Machine learning classifiers to limit the ability of a malicious vehicle to create multiple forged trajectories, and more importantly, to reduce the detection time for detecting Sybil trajectories which is a critical concern in traffic management applications.

_ The system carefully analyzed the probabilistic nature of PoW based scheme by examining the affecting parameters (e.g travel time between two consecutive RSUs) experimentally, and then we developed a mathematical model that can be used for adjusting these parameters so that the ability of a malicious vehicle to create forged trajectories is reduced significantly.

_ By experiments, we prove that using the proof of work algorithm reduces the ability of a malicious vehicle to maintain actual multiple trajectories simultaneously. Further simulations, analysis, and practical experiments are conducted to evaluate the proposed scheme and compare it with the Footprint the results indicate that the

proposed scheme can successfully detect and defend against Sybil attacks in VANETs and more efficiently compared to the Footprint.

5.IMPLEMENTATION

5.1 Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Browse and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Attack Status, View Attack Status Ratio, Download Trained Data Sets, View Attack Status Ratio Results, View All Remote Users.

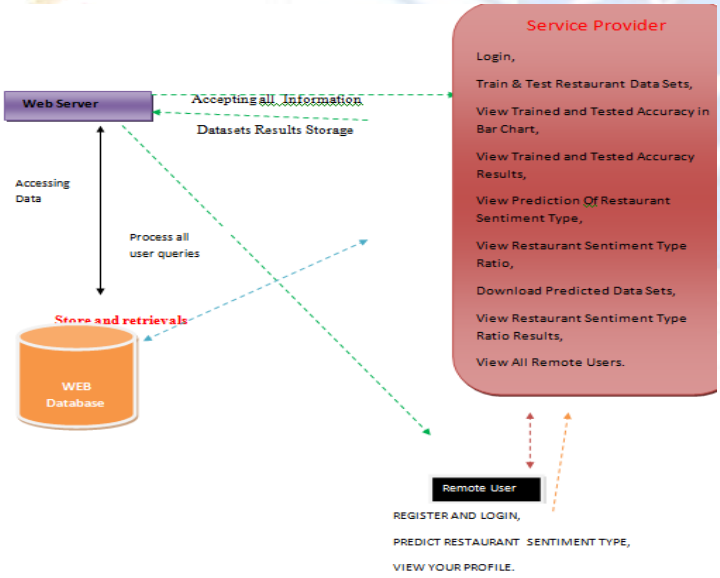
5.2 View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

5.3 Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT ATTACK STATUS TYPE, VIEW YOUR PROFILE.

6. ARCHITECTURE



8.CONCLUSION

Sybil attacks can cause disastrous consequences in VANETS. In this paper, we have introduced a novel approach for detecting Sybil attacks using proofs of work and location. An anonymous trajectory of a vehicle is formed by obtaining a consecutive proof of locations from multiple RSUs which Sybil attacks can cause disastrous consequences in VANETS. In this paper, we have introduced a novel approach for detecting Sybil attacks using proofs of work and location. An anonymous trajectory of a vehicle is formed by obtaining a consecutive proof of locations from multiple RSUs which it encounters. Instead of allowing only one RSU to issue authorized messages for vehicles, at least t RSUs are required for creating a proof of location message using threshold signature to mitigate the RSU compromise attack. Also, the use of proof-of-work algorithm can limit the ability of malicious vehicles to create forged trajectories. Our evaluations have demonstrated that our scheme can detect Sybil attacks with high rate and low false negative rate. Moreover, the communication and computation overhead of the exchanged packets are acceptable.

9. FUTURE ENHANCEMENT

As the vehicle keeps moving, it creates its trajectory by combining a set of consecutive authorized time-stamped tags that are chronologically chained to each other. That trajectory is used as an anonymous identity of the vehicle. Since RSUs have the main responsibility to issue proof of location to vehicles, the scheme should resist against RSU compromise attack so we design the trajectory so that not only one RSU is capable of creating trajectories for the vehicles. To achieve this, threshold signature is adopted so that each RSU is only able to generate a partial signature on a set of time-stamped tags. Once a vehicle travels along a certain threshold number of RSUs, a standard signature representing a proof of location can be generated. Upon receiving an authorized message from an RSU, the vehicle should use it as a seed to solve a puzzle using a proof-of-work algorithm, similar to the one used in Bitcoin .

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