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SOCIAL MEDIA POPULARUTY PREDICTIONBASED ON MULTI-MODELING SELF ATTENTION MECHANISM

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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.

1.INTRODUCTION

Many individuals currently spend a significant portion of their day on different types of social media, which serve as public venues for the easy flow of information. There has been a lot of interest in studying ways to extract data from social media because of the pervasiveness of these platforms in people's everyday lives. The popularity score is one piece of data that might be gleaned from social media. In particular, this score indicates the number of individuals that saw a post; obviously, more views equal more impact. Using the data provided for a specific social media post, the goal of social media popularity prediction (SMP) is to estimate the post's popularity score.

The various and complicated aspects that influence popularity make it difficult to estimate the popularity score. Content quality and audience relevance are two of the characteristics that could be hard to quantify. Adding more variables, such actual occurrences, to a prediction model is challenging. More modalities, including pictures, relationship networks, temporal context tags, and categories, have been included into recent SMP approaches in an effort to address these intricate issues.

The model's design, memory usage, number of modules, etc. all become more complicated as the number of modalities rises, even if this is a sensible way to approach the task. On the other hand, the article is multi-modal as well, but it used captions (texts) to represent pictures in its pipeline. It is possible to change one modality into another with current technology. Photo captioning is a way to turn pictures into words. A number of speech-to-text technologies are currently available. It is possible to get various numerical information, such the number of neighbors for each node, from a post's social network.

In addition, user data may influence the visibility of postings. Numerous studies have shown a strong relationship between the number of users and the popularity of images. A possible explanation is because each person has their own unique set of followers, and the quantity of followers a given user has could vary greatly. Posts made by users who already have a large following tend to do better in terms of engagement. The post that was uploaded earlier should get more attention from people, and if the user posts it in a certain area, it will also draw more attention. Additionally, geographical and temporal information might influence the popularity.

In this research, we present a network that uses the self-attention mechanism to predict how popular a social media post will be by combining textual and numerical modalities. We split the data into numerical and semantic branches because of the data type conflict. We develop a feature attention mechanism that can handle recurrence and convolutions entirely. In the semantic branch, we transfer the image contents to caption texts and tags. All of the textual features are converted into tokens, and each token is associated with a word embedding. Since the attention mechanism is effective in extracting contextual information, we also aggregate the sequence of embeddings better. Since the semantic characteristics modality alone is insufficient for some kinds of social media postings, we supplemented it with numerical data, including timestamps and geolocation, that can be readily turned into scalars. Following the preprocessing phase, we constructed two models to determine the popularity score by extracting and fusing features from the two modalities, respectively. This work contributes in three ways: first, we built a network that uses an attention mechanism to perform model ensemble using multiple features in two modalities; second, it's easily extensible to incorporate more modalities; and third, it solves problems involving heavy categories.

2.LITERATURE SURVEY

In their paper "What makes an image popular?," Aditya Khosla, Atish Das Sarma, and Raffay Hamid discussed this same topic at the International Conference on the World Wide Web. year 2014. On a daily basis, several photo-sharing and social media websites publish hundreds of thousands of images to the internet. Some photos become viral, attracting millions of views, while others go unnoticed. In the same individuals' accounts, various photos might have vastly different views. So, we have to ask: what is it about an image that makes it popular? Is it possible to estimate how many people will see a picture before they even post it? We try to answer some of these questions in this piece. In this study, we look at the picture content and social environment, two important factors that influence an image's appeal. By combining picture content with social signals, we are able to accurately forecast the normalized view count of photographs using a dataset consisting of around 2.3 million images from Flickr. Our rank correlation for this prediction is 0.81. Several social signals, such as the amount of friends or the amount of photographs posted, contribute to an image's popularity, and we demonstrate in this work how important visual cues like color, gradients, deep learning features, and the collection of objects present are. [2] "Timematters: Multi-scale temporalization of social media popularity," ACM International Conference on

Multimedia, pp. 1336–1344, by Bo Wu, Wen-Huang Cheng, Yongdong Zhang, and Tao Mei. 2016.
A massive social media popularity prediction dataset, Temporal Popularity Image Collection (TPIC) contains 680,000 social media postings including photographs from anonymous Flickr.com users whose photo-sharing histories span three years. At the same time, TPIC is a complex social media collection that includes photo information, user profiles, and picture pictures. Our rescaled and normalized popularity numbers are calculated from the total number of views for each post on the internet. User and post identity was anonymized and post timestamps were transformed to time segments with integer indices to safeguard users' privacy and their sharing patterns.

3. EXISTING SYSTEM

Khosla et al. predicted the popularity of photographs using user context and image content using millions of images. Accuracy in predictions was studied carefully with respect to low-level, middle-level, and high-level characteristics. To create a sequential popularity forecast, Wu et al. combined dynamics over many time scales. The traits of Flickr members' social behavior were examined by Van Zwol in. He said that most people saw images within the first two days they were posted. The owners' social circles and personal connections also had a role in how successful their photographs became. Various works have also been examined on different platforms. According to research by Hessel et al., the most accurate methods for forecasting Reddit users' relative popularity include combining visual and textual modalities. Sentiment, vividness, and amusement are a few of the engagement metrics that Mazloom et al. deemed relevant. They utilized these metrics to forecast how many people would like Instagram posts featuring their business. Based on the ACM Multimedia Challenge 2019 or before, several studies have forecasted the growth of social media. For instance, in order to encode the textual information and picture semantic attributes retrieved from image captions, Hsu et al. used word-to-vector models. Ding et al. employed deep neural network methods to forecast the popularity score by combining numerical and textural data. While Li et al. did provide a Doc2Vec model and some excellent text-based feature fusion engineering, their efforts only combined various features and put them into a regression model without taking feature correlation into account. In order to account for prediction error, Hsu et al. suggested an iterative refining strategy and used residual learning to calculate a post's view count. Although this study only used a subset of the available social media data, there is a wealth of other information that might greatly enhance prediction accuracy.

Rapid advancements in machine learning and deep learning have led to several publications presenting vision-based applications; for instance, Lin et al. used numerous residual dense blocks to eliminate patterns. A visual attention module was suggested by Yeh et al. to improve picture categorization capacity. Katsurai et al. used SentiWordNet to retrieve sentiment information and fused the visual and textual views to classify the post belongs positive or negative via SVM as well. Ortis et al. considered both visual and textual information to perform sentiment analysis through the SVM classifier. However, the SVM model is not suitable for large-scale datasets and has difficulty applying to high-dimensional data.

In 2016, He et al. introduced ResNet, a new architecture for deep learning. In general, a deeper network would perform better, but there is a degradation problem: the accuracy decreases as the number of layers grows. To address issues with gradient vanishing and explosion, ResNet includes an identity mapping technique.

Disadvantages

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

3.1 PROPOSED SYSTEM:

In this paper, we proposed a network that exploits semantic (estimation of a social media post's popularity using the self-attention mechanism based on text and numerical modalities. We split the data into numerical and semantic branches because of the data type conflict. The semantic branch involves transforming image contents into caption texts and tags. All textual features are then turned into tokens, and each token is linked to a word embedding [23]. Since the attention mechanism [9] is effective at extracting contextual information, we can improve the aggregation of embedding sequences and create a feature attention mechanism that handles recurrence and convolutions entirely. Since the semantic characteristics modality alone is insufficient for some kinds of social media postings, we supplemented it with numerical data, including timestamps and geolocation, that can be readily turned into scalars. Following the pre-processing, we constructed two models to determine the popularity score by extracting and fusing features from the two modalities, respectively. There are three main benefits of this work:

Our network can handle issues with heavy categories because it uses an attention mechanism and takes use of many characteristics in two modalities to conduct model ensemble. What's more, it can be simply expanded to include other modalities. The impact of semantic characteristics on the model's performance was examined. We also improved our network's performance by generating more numerical features, and the results show that these features are useful. In the Social Media Popularity Dataset, we proved that our technique is superior to the other cutting-edge methodologies.

The benefits

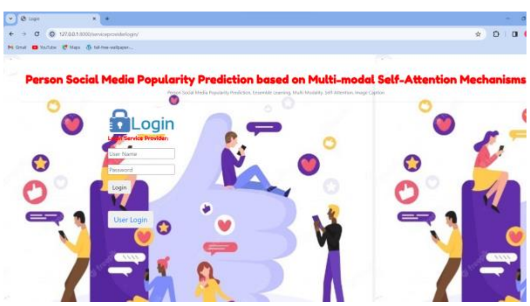
Social media postings may include connected photos or videos with caption features. Our method's pipeline is made simpler by treating the associated videos and pictures as textual characteristics after converting them to text using a pre-trained captioning model [7, 12]. Personal Information About the User—This section focuses on details about the person who made the social media post. Just to keep things simple, we used two characteristics from this type: Separate User ID and Pro-member Status (for Flickr Premium subscribers). For example, due to their intrinsic reputation, superstars often enjoy more popularity than other individuals; this knowledge might be helpful for our model when using the user ID to differentiate distinct users. The data also shows that the promember user tends to have a higher popularity rating overall. Features that fall into predefined categories—There are a number of ways that a social media post could be classified. There are three tiers of classification for Flickr posts in this article: main category, subcategory, and idea descriptions. Concept descriptions are organized into 668 classes,

with 11 classes for categories and 77 classes for subcategories.
The user specifies a number of keywords, such as "styles," "location," or "holiday," while making a post; these tags may be any kind of information.

.4. OUTPUT SCREENS

HOME PAGE:

ADMIN PAGE:



LOGIN PAGE:

REGESTRATION PAGE:

5. CONCLUSION

Our study presents a social media popularity prediction system that utilizes attention-based processes and multi-modal data. In order to determine the popularity score, our technique employs both numerical and semantic characteristics. The attention-based networks, such as Transformer, perform well with semantic characteristics since they are text-based and sequential. Utilizing pre-existing picture captioning methods, we also transformed photos into semantic characteristics. In addition, we improved our model's performance by supplementing the pre-existing numerical characteristics. We demonstrated that, when compared to other cutting-edge approaches, ours does quite well.

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