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Predicting Social Media Popularity Using Multi Model Self Attention Machanisms

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ABSTRACT:

Advertising, recommendation systems, and trend research are just a few of the many real-world uses for social media popularity prediction. This isn't an easy process to do, however, since there are a lot of unmodelable aspects that impact social media (such as content quality, audience relevance, and real-life occurrences). Most other approaches take a greedy tack and try to pack as many elements and modalities as possible into their model without giving any special consideration to any of them. There are two main types of features used in our model—semantic (text) features and numerical features—and our suggested method takes advantage of the self-attention mechanism to automatically fuse different features in order to improve performance when predicting a post's popularity. The success of the suggested strategy is shown by the assessment findings, which are based on extensive experiments and ablation studies conducted on the training and testing data of the demanding ACM Multimedia SMPD 2020 Challenge dataset.

INTRODUCTION

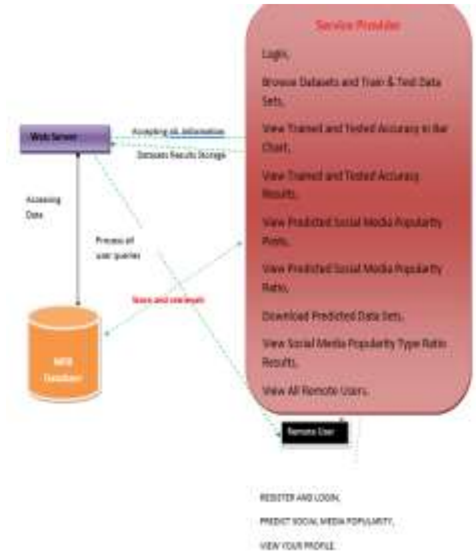
People increasingly spend a significant amount of time each day on different social media platforms, which give a public platform for effortlessly exchanging information with one other. A lot of individuals are curious about studying ways to glean data from social media since these platforms are so integral to people's everyday lives. To illustrate the kind of data that may be retrieved from social media, consider the popularity score. A higher number of views indicates greater impact, and this score specifically informs you how many individuals saw a post. Predicting a social media post's popularity score using the data that is already available is known as social media popularity prediction (SMP).

Due to the various and complicated elements influencing popularity, estimating the popularity score is difficult. Some of the characteristics, such material quality and audience relevance, are hard to quantify. It is difficult to include other variables, such actual occurrences, into a prediction model. More modalities, such as images[14,39], connection networks[25], temporal context[13], tags, and categories, have been included into recent SMP approaches in an effort to address these complicated variables [4, 5, 7, 12, 17.]

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 paper 7, 26, 27, 28, 29, 30 likewise used a multi-modal method, but it portrayed pictures as captions (i.e. words) in its pipeline. It is possible to change one modality into another with current technology. Captioning photographs turns them become words. Existing approaches exist for speech-to-text conversion. Numeric information, such as the number of neighbors for each node, might be extracted 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 [20, 32, 33]. The fact that each user has their own unique number of followers is one explanation. Posts made by users who already have a large following tend to do better in terms of engagement. Additionally, the post's temporal and geographical information may influence its popularity; for example, a post uploaded at a certain time and place will likely get more views than one uploaded later.

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. The disparity in data types prompted us to partition the information into numerical and semantic subsets. The semantic branch handles the translation of image contents into caption texts and tags. All textual features are tokenized and linked to word embeddings [23]. To further aggregate the sequence of embeddings, we also develop a feature attention mechanism that can handle recurrence and convolutions entirely. This is because the attention mechanism [9] has been proven effective in extracting contextual information. 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. We assembled two models to determine the popularity score after preprocessing, and we retrieved and fused features in each modalities, respectively. There are three main benefits of this work:Using an attention mechanism and a combination of features from two modalities, we built a network that can solve problems involving heavy categories and is easily extensible to include more modalities. We also examined how semantic features affected the model's performance. Also, we improved our network's performance by generating extra numerical features, and the results show that these features are useful.We showed that, when tested on the Social Media Popularity Dataset, our strategy beats the other top-tier algorithms.

SYSTEM ARCHITECTURE



METHODOLOGY

ALGORITHMS:

```
class
SocialMediaPopularityPredictor(nn.Module):
def _init_(self):
super(SocialMediaPopularityPredictor,
self)._init_()
self.bert = BertModel.from_pretrained('bert-
base-uncased')
self.fc1 = nn.Linear(768, 256)
self.fc2 = nn.Linear(256, 1)
self.sigmoid = nn.Sigmoid()
def forward(self, input_ids, attention_mask):
bert_outputs = self.bert(input_ids,
attention_mask=attention_mask)
pooled_output = bert_outputs[1]
x = self.fc1(pooled_output)
x = nn.ReLU()(x)
x = self.fc2(x)
x = self.sigmoid(x)
return x
```

SVM ALGORITHM

```
import numpy as np
```

```
import pandas as pd
from sklearn.feature_extraction.text import
TfidfVectorizer
from sklearn.model_selection import
train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score,
precision_score, recall_score, f1_score
# Example dataset (replace with actual data)
data = {
'text': ["Post text 1", "Post text 2", "Post text 3"],
'image_feature': [0.1, 0.2, 0.3], # Example
image features
'user_feature': [5, 10, 15], # Example user
features
'temporal_feature': [0, 1, 2], # Example
temporal features
'popularity': [0, 1, 1] # Popularity labels
(0 = not popular, 1 = popular)
}
# Convert to DataFrame
df = pd.DataFrame(data)
# Feature extraction for text data
vectorizer = TfidfVectorizer()
text_features =
vectorizer.fit_transform(df['text']).toarray()
# Combine all features into a single feature
matrix
eatures = np.hstack((text_features,
df[['image_feature', 'user_feature',
'temporal_feature']].values))
# Labels
labels = df['popularity'].values
# Train-test split
X_train, X_test, y_train, y_test =
train_test_split(features, labels, test_size=0.2,
random_state=42)
# Initialize and train SVM model
svm_model = SVC(kernel='linear', C=1.0) #
You can try different kernels and
hyperparameters
svm_model.fit(X_train, y_train)
# Make predictions
y_pred = svm_model.predict(X_test)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1-Score: {f1}")
```

Service Provider

The Service Provider must provide their username and password in order to access this module. After he successfully logs in, he will be able to perform things likeDatasets for Browsing and Training and Testing, Browse All Remote Users, View Trained and Tested Accuracy in Bar Chart, View Results for Trained and Tested Accuracy, Browse Social Media Popularity in Posts and Ratio, Download Data Sets for Predictions, View Results for Social Media Popularity in Types, and Download Data Sets for Predictions.

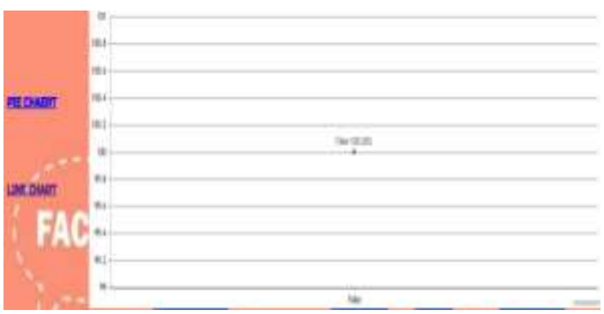
View and Grant Access to Users

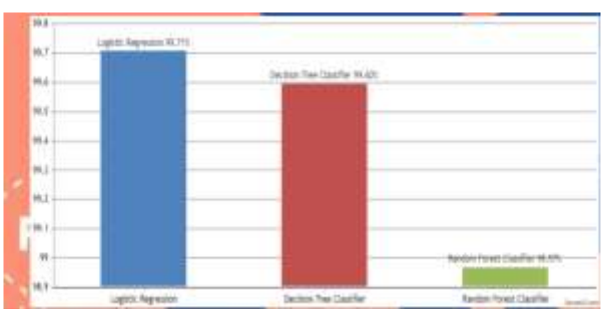
The admin can get a complete rundown of all registered users in this section. Here, the administrator may see the user's information (name, email, and address) and grant them access.

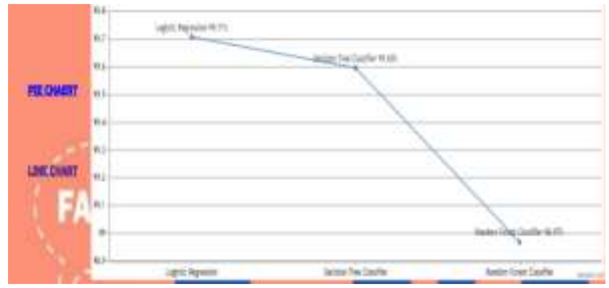
Remote User

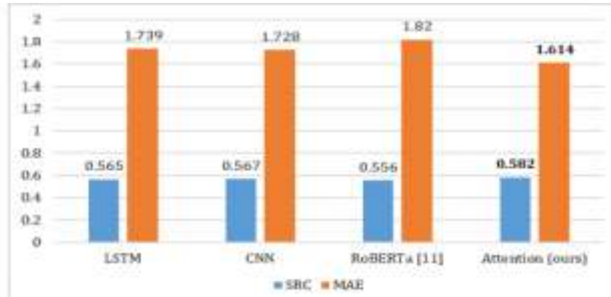
All all, there are n users in this module. Before doing any actions, the user is required to register. The user's information will be entered into the database after they register. He will need to log in using the permitted username and password when registration is completed. After logging in, users will be able to do things like register and log in, predict the popularity of social media vie and more.

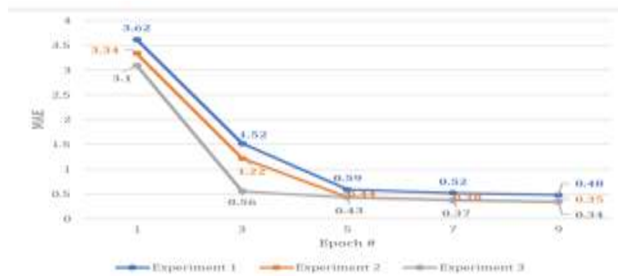
RESULT ANALYSIS:











CONCLUSION

Using attention-based processes and multi-modal information, we provide a social media popularity prediction approach in this work. In particular, our approach calculates the popularity score by combining numerical and semantic factors. Transformer and other attention-based networks function well with text-based and sequential semantic data. Using preexisting picture captioning methods, we also transformed images 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 state-of-the-art approaches, ours does quite well.

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