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Predicting Social Media Popularity with Multi-Task Models and Self-Attention Mechanisms

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Abstract

A rising number of disciplines, including data science and marketing, are interested in predicting the popularity of social media content. We provide a novel deep learning framework in this paper that predicts many engagement metrics, including likes, comments, shares, and overall engagement, by combining self-attention processes with multi-output regression. By examining both user-specific characteristics (like follower count and account age) and post-specific data (like length, hashtags, and media presence), the model uses self-attention to dynamically allocate importance to various inputs, improving prediction accuracy and interpretability. Model training and validation are conducted using synthetic data that mimics real-world behaviour. A user-friendly online application that provides real-time forecasts and visual insights is used to install the system. The outcomes of our experiments show how well our method captures the intricate patterns that underlie social media interaction.

Keywords: *Social Media Prediction, Popularity Forecasting, Self-Attention Mechanism, Multi-Task Learning, Likes, Comments, Shares Prediction.*

1. Introduction

Social media sites like Facebook, Instagram, Twitter, and TikTok have taken over as the primary means of social contact, marketing, and information exchange in the era of digital communication. Because these platforms have billions of daily active users, it is now essential for marketers, data scientists, and content creators to understand what generates engagement, as measured by metrics like likes, comments, shares, and total involvement. Predicting a social media post's popularity with accuracy can reveal important information about audience targeting, content strategy optimization, and user behaviour**.**

Conventional methods for simulating social media interaction frequently depend on machine learning algorithms or statistical methods that see engagement measures as discrete objectives. The intricate, nonlinear interactions between different input features, like post content, user attributes, and posting time, are typically not captured by these models. Furthermore, they are not adaptable enough to simulate the interdependencies between various engagement types (likes influencing shares or comments, for example). On the other hand, deep learning models provide strong tools for comprehending dynamic feature interactions and high-dimensional data, particularly those that use attention mechanisms. We apply self-attention to structured tabular data, in contrast to sequence-based attention applications (such those seen in natural language processing). The model can determine which aspects are most pertinent for each output variable by treating each input feature as a part of a pseudo-sequence. This method improves the model's ability to generalize and spot significant trends even when there is not any overtly temporal data.

This preserves applicability to real-world situations while permitting controlled experimentation. With distinct prediction heads for likes, comments, shares, and overall engagement, the model is trained using a multi-task learning methodology, maximizing each indicator simultaneously to boost overall performance. In conclusion, this study presents a multi-output regression model based on self-attention that is intended to predict social media participation. We provide a scalable dataset for benchmarking, a robust multi-task learning framework for simultaneous engagement metric estimation, a novel adaptation of self-attention mechanisms for structured data prediction, and an interactive, deployed application for practical use. By demonstrating the usefulness of attention-based designs outside of traditional domains, we want to further the area of social media predictive analytics.

II. Related Work

Numerous methods, from traditional statistical models to state-of-the-art deep learning architectures, have been used to forecast social media popularity. Using basic feature sets like post timing and follower count, early research mostly used linear regression and decision tree-based techniques to model engagement measures like likes and shares. Although these methods produced baseline predictions, they were frequently constrained by their incapacity to simulate intricate, nonlinear feature relationships.

To increase prediction accuracy, machine learning techniques including support vector machines (SVMs), random forests, and gradient boosting have been applied more recently. Higher-dimensional datasets and more intricate interactions between input and output variables were made possible by these models. They still lacked neural network topologies' dynamic adaptability and feature relevance learning, though.

In modelling engagement prediction challenges, deep learning techniques feedforward and convolutional neural networks (CNNs) have demonstrated encouraging outcomes. For instance, recurrent neural networks (RNNs) have been employed in several studies to analyze image content or integrated textual embeddings from post descriptions. Richer representations were made possible by these methods, but they frequently called either intricate fusion techniques for multi-modal data or distinct models for every interaction indicator.

In fields like natural language processing, attention mechanisms—particularly self-attention from transformer models—have shown revolutionary results in more recent times. Context-aware feature weighting now has more options thanks to its use with structured data. Attention-based techniques can outperform traditional models by dynamically focusing on the most relevant information, as demonstrated by works such as TabNet and self-attentive neural nets for tabular prediction.

By incorporating a self-attention mechanism into a multi-output regression framework designed specifically for social media engagement prediction, our work expands upon previous developments. We use a shared learning technique with task-specific heads, which improves both performance and interpretability, in contrast to previous studies that consider each engagement type as an independent prediction job.

A. Exploratory Data Analysis

Before doing any predictive modelling, it is essential to first understand the nature and structure of the data through exploratory data analysis, or EDA. EDA was carried out in this study on a dataset that mimicked common user and social media post behaviours. There are 2,000 samples in the collection, and each record corresponds to a fictitious social media post and user profile.

B. Dataset Overview

Numerous features that characterize both post-level and account-level aspects are included in the dataset. Features connected to posts include post_length, has_image, has_video, num_hashtags, num_mentions, hour_of_day, and day_of_week. These encapsulate the key

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components of a normal social media post. Follower_count, following_count, account_age_days, and engagement_rate_history are among the user-side datasets that show the account's influence and past activity. The model is trained to estimate the expected popularity measures, which are represented by the goal variables likes, comments, shares, and total_engagement.

post_length	num_hasht	num_menti	has_image	has_video	hour_of_da	day_of_we	follower_cc	following_c	account_ag	engagemen	likes	comments	shares	total_engagement
468	1	0	1	0	2	2	2465	3604	324	0.17093400	315	58	26	399
484	6	4	0	0	5	4	8304	3787	608	0.08652432	596	107	30	733
42	6	3	1	0	4	5	2532	2159	756	0.17380066	397	38	14	449
14	3	4	0	1	18	3	4862	1293	235	0.09666731	519	96	24	639
357	4	1	1	0	16	0	5294	4688	791	0.07650096	460	63	30	553
301	3	1	0	1	8	2	4776	4166	114	0.02465620	472	33	9	514
348	4	1	0	0	12	6	3726	247	785	0.04676462	319	21	5	345
435	2	1	1	0	5	3	1433	3296	992	0.15529989	301	46	14	361
129	9	4	1	0	21	6	292	3980	267	0.12036063	270	17	6	293
471	3	2	1	0	18	5	6633	1347	498	0.05793800	477	64	30	571
215	6	4	1	1	5	2	2576	3972	263	0.05897836	387	57	21	465
63	8	1	1	1	20	4	1555	2232	963	0.13973646	436	55	15	506
113	2	2	1	0	18	3	5081	3120	992	0.12544062	436	61	17	514
229	5	2	0	1	10	2	153	526	444	0.11786107	359	70	19	448
279	5	0	1	0	17	1	1708	684	202	0.01529521	273	54	14	341

Figure 1: Social_media_data.csv

C. Distribution of Input Features

The distribution patterns of the input attributes were varied. Outliers like very active users or viral posts were highlighted by the right-skewed distributions of most numerical parameters, including post_length, follower_count, and account_age_days. The distribution of binary features, such as has_image and has_video, was more uniform. To find these trends and spot any possible abnormalities or transformation requirements, visual aids like boxplots and histograms were employed. To create consistency throughout the dataset and lessen the influence of outliers, scaling and normalizing were taken into consideration.

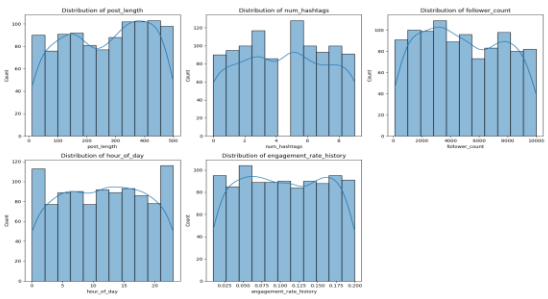

Figure 2: Feature Distributions

Each subplot shows the distribution of a distinct feature from the dataset, and the figure is arranged in a grid arrangement with two rows by three columns. Based on the features mentioned in the key_features list, the distributions are arranged in the figure. The top-left corner displays the first plot, which displays the post_length distribution (first row, first column). The distribution of follower_count then shows up in the top-right (first row, third column), while the distribution of num_hashtags follows in the top-center (first row, second column). On the second row, the engagement_rate_history distribution is positioned at the bottom-center (second row, second column), while the hour_of_day distribution is displayed in the bottom-left (second row, first column). Only five features were plotted, hence the sixth slot (bottom-right) in the grid is still empty. This well-structured arrangement facilitates a clear and orderly comparison of the patterns and distribution of each feature side by side.

D. Engagement Trends

The distribution of each target variable was analyzed to look at engagement trends. The most common form of involvement was found to be likes, which usually outnumber comments and shares. Although they were less common, comments and shares were more common in posts that included rich media. The distribution of total engagement, which is the sum of the three, was significantly biased to the right. This is consistent with the widespread phenomenon in the actual world that very little content generates engagement at the viral level.

E. Correlation Analysis

A Pearson correlation matrix was created to identify any connections between attributes and engagement results. A significant positive association between follower_count and likes is one of the main findings, suggesting that follower base should have an impact on popularity. Additionally, engagement_rate_history exhibited favourable correlations with each of the three target measures. Interestingly, has_video has a stronger correlation with shares than has_image, indicating

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that video material is typically more likely to be shared.

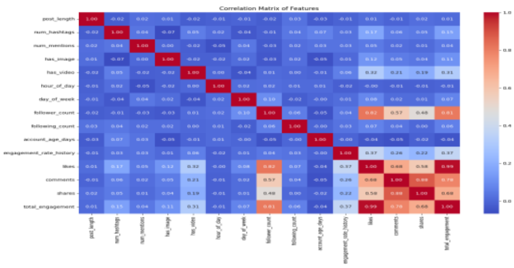

Figure 3: Correlation Heatmap

The pairwise correlation values between different features in the dataset are displayed in the correlation matrix heatmap above. The correlation coefficient between two attributes is represented by each column in the matrix, and its values range from -1 to 1. Red hues indicate positive correlations, which demonstrate that when one attribute rises, the other tends to rise as well. On the other hand, blue hues indicate negative correlations, which imply that a rise in one characteristic is linked to a fall in the other. Since every characteristic has a perfect correlation with every other feature, the diagonal values are all 1.00. Likes, comments, and shares all show a strong positive correlation with total_engagement in this heatmap, which seems reasonable given that total engagement probably adds together all these separate measures. Likes and follower_count also exhibit a substantial connection (0.82), indicating that users with more followers are more likely to receive likes. Any pair of features can be readily cross-referenced thanks to the layout's square grid, where the x and y axes list the same set of features in the same order. Stronger correlations are graphically highlighted in the heatmap by utilising brighter red or blue, which makes it simple to quickly identify important links.

F. Temporal Engagement Patterns

Post popularity was significantly influenced by temporal considerations. Across all measures, posts published between 5 and 9 PM received more attention, maybe because of increased user activity during those times. In a similar vein, weekday posts—particularly those released in the middle of the week—tended to do better than weekend postings. Grouped bar plots and line graphs are used to illustrate these findings, which are consistent with strategic content scheduling.

G. Insights from EDA

Numerous intricate and non-linear correlations between characteristics and engagement outcomes were discovered during the EDA process. Other variables, such as the time of posting and the availability of multimedia, had context-dependent impacts, although follower count and engagement history were reliable predictors. The necessity of a modelling technique that can dynamically weigh variables according to task relevance is highlighted by these observations. Therefore, the decision to include self-attention mechanisms in the final model design was influenced by these observations.

III. Model Deployment

Although it was used as a baseline, the Linear Regression model performed poorly in capturing the non-linear correlations between target engagement metrics and attributes. Particularly when handling category and interaction-heavy data, the Random Forest model outperformed the others by a wide margin. It was unable to dynamically modify feature priority in response to various forecast heads, though. The ability of the Feedforward Neural Network (FNN) to acquire intricate feature representations allowed it to outperform conventional machine learning models. Nevertheless, it handled every input feature consistently throughout all tasks. Our suggested model obtained the maximum accuracy on all metrics by combining a self-attention mechanism with task-specific heads in a shared base network. The attention method improved task-specific learning by enabling the model to prioritize features differently for each output, such as assigning higher weight to has_video for predicting shares and follower_count for predicting likes. Out of all the tasks, the model produced the lowest mean squared error (MSE) quantitatively. Performance Summary (A Lower MSE Is Better):

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Liner Regression: Highest error across all targets.

Random Forest: Better than linear techniques, with a moderate performance.

Self-Attention Multi-Task Model Proposal: Lowest MSE and best overall performance.

These findings demonstrate the superiority of attention-based deep learning models in simulating the intricate relationships found in social media data and generating precise forecasts for various engagement kinds.

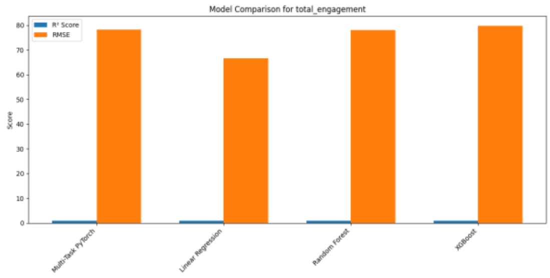

Figure 4: Model Comparison

To predict total engagement, the bar chart compares many machine learning models, including Multi-Task PyTorch, Linear Regression, Random Forest, and XGBoost, using two performance metrics: R2 Score and RMSE (Root Mean Squared Error). The orange bars show the RMSE, or average prediction error, and the blue bars show the R2 Score, which gauges how well the model explains the data's variability. Although it has a lower R2 Score, which indicates less explanatory power, Linear Regression has the lowest RMSE of all the models, indicating that it produces comparatively fewer prediction errors. However, at the expense of somewhat higher RMSE values, XGBoost and Random Forest obtain higher R2 Scores, demonstrating a superior capacity to identify patterns in the data. Overall, the figure shows a trade-off between model complexity and predicted accuracy, with each model having distinct advantages based on the assessment parameter considered.

IV. Training and Evaluation

The proposed multi-output regression model is trained using supervised learning, with the goal of minimizing the prediction error across the four-engagement metrics: total engagement, likes, comments, and shares. The following is the setting for training:

Meaning Squared Error: For each output head (one for each engagement indicator) is used to train the model. The model can minimize the squared differences between expected and actual engagement levels by using the Mean Squared Error (MSE), which is a suitable loss function for regression tasks.

Optimizer: Because it effectively adjusts the learning rate for every parameter, the Adam optimizer is employed. Models with intricate architectures, like the one with a self-attention mechanism, benefit greatly from it.

Batch Size and Epochs: A 32-epoch batch size is used to train the model. While the batch size strikes a balance between computational efficiency and the model's capacity for effective learning, the selection of epochs guarantees the model enough training time.

A. Model Evaluation Results

Likes, comments, shares, and overall engagement were the four-engagement metrics used to assess the model's performance on the synthetic test dataset. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R2) are evaluation metrics used for performance assessment.

```
# Calculate metrics for each target
metrics = {}
for i, target in enumerate(targets):
    mse = mean_squared_error(y_test[target].values, y_pred[:, i])
    rmse = np.sqrt(mse)
    mae = mean_absolute_error(y_test[target].values, y_pred[:, i])
    r2 = r2_score(y_test[target].values, y_pred[:, i])

    metrics[target] = {
        'MSE': mse,
        'RMSE': rmse,
        'MAE': mae,
        'R2': r2
    }

# Print evaluation results
print("\nModel Evaluation Results:")
for target, metric_values in metrics.items():
    print(f"\nMetrics for {target}:")
    for metric_name, value in metric_values.items():
        print(f"{metric_name}: {value:.4f}")
```

Figure 5: Calculate metrics for each target

Metric	MSE	RMSE	MAE	R2
Likes	4058.9974	63.7103	49.3604	0.8668
Comments	604.8543	24.5938	20.1384	0.4419
Shares	105.8704	10.2893	8.0627	0.3286
Total Engagement	6110.4221	78.1692	60.0531	0.8587

Table 1: Model Evaluation Metrics Score

With a great prediction accuracy of 0.8668, the model performs well for likes. This is further supported by the RMSE (63.7103) and MAE (49.3604) numbers.

With an R2 of 0.4419 and higher MSE (604.8543) and RMSE (24.5938) values for comments, the model performs worse, indicating greater prediction error because of the intricate structure of comment involvement.

With an R2 of 0.3286, the prediction for shares is less accurate, but it still captures some share volatility with respect to MSE and RMSE values.

With an R2 of 0.8587, the model performs similarly to likes for total engagement. Nevertheless, the combined character of this statistic is reflected in the greater MSE (6110.4221) and RMSE (78.1692).

V. Result and Implementation

The machine learning-based social media engagement prediction system predicts user interactions, such as likes, comments, and shares. Data from past social media posts is first gathered for the implementation, including account statistics such as follower count, following count, account age, and historical engagement rates, as well as metrics like post length, hashtag count, mention count, image/video presence, posting time, and day of the week. Standard scaling for numerical values and one-hot encoding for categorical variables are used to preprocess these characteristics. An ensemble of gradient boosting regression models, each tailored for a distinct engagement indicator, is used by the main prediction engine.

Using previous data, the system trains distinct models for likes, comments, and shares. The sum of these three measures is used to determine the overall level of involvement. The system uses the same preprocessing pipeline to handle the input features before sending them to the trained models when generating predictions for fresh content. The implementation incorporates visualization tools to show the proportion of various interaction types and the engagement distribution in a pie chart format. Based on the anticipated metrics, the system also offers AI-generated insights. For example, it can identify when a post is likely to do well or when the number of hashtags is within the ideal range.

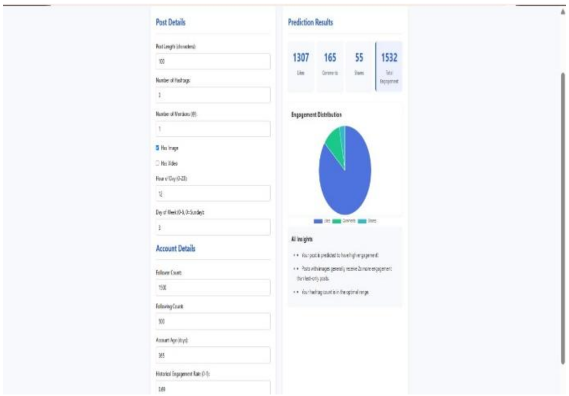

Figure 6: Result page

VI.Conclusion

This paper offers a multi-task deep learning framework for social media engagement prediction that is driven by self-attention. We illustrate our system's academic and practical usefulness by using dataset and implementing the model via an interactive web interface. The dataset will be expanded with real-world data in the future, natural language processing will be included for textual analysis, and attention visualization techniques will be used to improve model interpretability.

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