Sentiment Analysis Model Analysis Report

Model-1:

Statistcal model(Only machine learning model)

1. Introduction

- **The sentiment analysis model aims to predict the intensity of emotions (anger, fear, joy, sadness) in textual data. This report provides an in-depth analysis of the model development, training, testing, and evaluation, including algorithm selection, feature engineering, and performance assessment.**

2. Data Preprocessing

- **Exploratory Data Analysis (EDA) was conducted to understand the distribution of emotions and explore potential features for model training. Features such as word count, character count, and punctuation count were initially considered. Additionally, text cleaning techniques, including the removal of special characters, URLs, and stopwords, were applied to preprocess the textual data.**

3. Model Training

- **Various regression models were trained using different algorithms, including linear regression, ridge regression, Bayesian ridge, KNN regression, decision tree regression, and support vector regression (SVR). Additionally, two vectorization techniques, Bag of Words (BoW) and TF-IDF, were explored to represent the textual data as numerical features. The training process involved utilizing the training dataset and testing the models on the development dataset to identify the optimal algorithm and vectorization method. The SVR model with TF-IDF vectorization demonstrated the lowest error and was selected as the final model.**

4. Model Testing

- **Each emotion was assigned its own model trained on the combined training and development datasets. The performance of the models was evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Pearson correlation on separate test datasets for each emotion.**

5. Evaluation and Analysis

- **The performance of the sentiment analysis model was analyzed in detail. The models exhibited better results compared to random intensity selection, with a noticeable positive linear relationship between predicted and actual intensity. However, variations in performance were observed across different emotions, with the anger model demonstrating the lowest errors and the joy model showing the highest errors. Pearson correlation analysis revealed a linear positive relationship between predicted and actual intensity, although lower correlation results were observed when considering gold scores only between 0.5-1, indicating reduced model performance for tweets with higher actual intensities.**

6. Results

Model Training Results:

BoW-Linear Regression:

- Mean Absolute Error: 0.1503
- Mean Squared Error: 0.0368
- Root Mean Squared Error: 0.1919

Tfidf-Linear Regression:

- Mean Absolute Error: 0.1514
- Mean Squared Error: 0.0367
- Root Mean Squared Error: 0.1915

BoW-Ridge Regression:

- Mean Absolute Error: 0.1419

- Mean Squared Error: 0.0326
- Root Mean Squared Error: 0.1805

Tfidf-Ridge Regression:

- Mean Absolute Error: 0.1350
- Mean Squared Error: 0.0294
- Root Mean Squared Error: 0.1714

BoW-Knn Regression:

- Mean Absolute Error: 0.1501
- Mean Squared Error: 0.0358
- Root Mean Squared Error: 0.1893

Tfidf-Knn Regression:

- Mean Absolute Error: 0.1523
- Mean Squared Error: 0.0349
- Root Mean Squared Error: 0.1867

BoW-Decision Tree Regression:

- Mean Absolute Error: 0.1492
- Mean Squared Error: 0.0331
- Root Mean Squared Error: 0.1820

Tfidf-Decision Tree Regression:

- Mean Absolute Error: 0.1548
- Mean Squared Error: 0.0353
- Root Mean Squared Error: 0.1878

BoW-SVR:

- Mean Absolute Error: 0.1296
- Mean Squared Error: 0.0263
- Root Mean Squared Error: 0.1622

Tfidf-SVR:

- Mean Absolute Error: 0.1256
- Mean Squared Error: 0.0249
- Root Mean Squared Error: 0.1577

Model Testing Results:

Anger Model:

- Mean Absolute Error: 0.1194
- Mean Squared Error: 0.0218
- Root Mean Squared Error: 0.1477

Fear Model:

- Mean Absolute Error: 0.1423
- Mean Squared Error: 0.0304

- Root Mean Squared Error: 0.1744

Sadness Model:

- Mean Absolute Error: 0.1358
- Mean Squared Error: 0.0269
- Root Mean Squared Error: 0.1641

Joy Model:

- Mean Absolute Error: 0.1558
- Mean Squared Error: 0.0364
- Root Mean Squared Error: 0.1908

7. Conclusion

- **The sentiment analysis model shows promise in predicting emotion intensity in textual data. Despite achieving promising results, there are areas for improvement, including addressing inaccuracies in extreme intensity predictions and enhancing performance across different emotions. Recommendations for improvement include spell correction, increasing training data, and developing emotion-specific models to improve performance.**

8. Future Directions

- **Future directions for research could focus on refining the model architecture, incorporating advanced natural language processing (NLP) techniques, and exploring ensemble methods to further enhance prediction accuracy. Additionally, the model could be extended to handle multiclass classification tasks and applied to diverse domains beyond social media sentiment analysis.**

Model-2:

Convolutional Neural Network (CNN) Sentiment Analysis Model Report

1. Introduction

- **This report presents the development and evaluation of a Convolutional Neural Network (CNN) model for sentiment analysis, specifically predicting the intensity of emotions including anger, fear, joy, and sadness in textual data. The model was implemented using TensorFlow and Python, leveraging various NLP techniques for text preprocessing and feature extraction.**

2. Model Architecture and Training

- **The CNN model consists of multiple layers including Embedding, Conv1D, MaxPooling1D, Flatten, Dense, and Dropout. Text data preprocessing involved cleaning the text by removing special characters, URLs, and non-alphabetic characters, followed by tokenization and padding to ensure uniform length sequences. The model was trained using a combination of training and validation datasets, with early stopping and learning rate scheduling employed to prevent overfitting and optimize training performance. Mean squared error (MSE) was chosen as the loss function, and mean absolute error (MAE) was used as the evaluation metric during training.**

3. Model Evaluation

- T**he trained CNN model was evaluated on test datasets for each emotion category (anger, fear, joy, sadness). Evaluation metrics included mean absolute error (MAE), Pearson correlation, and Spearman correlation. The model exhibited varying performance across different emotions, with anger achieving the lowest MAE and fear demonstrating the highest MAE. Pearson correlation coefficients ranged from approximately 0.19 to 0.33, indicating a positive linear relationship between predicted and actual intensity for each emotion. Spearman correlation scores were consistent with Pearson correlations, reflecting the strength and direction of monotonic relationships between predicted and actual intensity.**

4. Analysis and Insights

- **The CNN model shows potential for accurately predicting emotion intensity in textual data, with lower MAE and higher correlation scores indicating better performance. Anger and fear emotions had relatively lower MAE and higher correlation coefficients compared to joy and sadness, suggesting that the model performs better on certain emotions. The model may benefit from further optimization and fine-tuning of hyperparameters to improve performance across all emotion categories. Future research could explore ensemble methods, transfer learning, and larger datasets to enhance model generalization and robustness.**

Model Results:

Mean Absolute Error (MAE) for each emotion category:

- Anger: 0.1386
- Fear: 0.1556
- Joy: 0.1764
- Sadness: 0.1587

Pearson Correlation for each emotion category:

- Anger: 0.2461
- Fear: 0.3272
- Joy: 0.1928
- Sadness: 0.3292

Spearman Correlation for each emotion category:

- Anger: 0.2246
- Fear: 0.3168
- Joy: 0.1942
- Sadness: 0.3167

Pearson Correlation on High Intensity Subset:

- High Intensity Subset: 0.2432
- Spearman Correlation on High Intensity Subset:
- High Intensity Subset: 0.2310

5. Conclusion

- **The CNN sentiment analysis model demonstrates promising performance in predicting emotion intensity in textual data. While further improvements are possible, the model represents a valuable tool for understanding and analyzing sentiment in various domains.**

6. Future Directions

Future research directions may include:

- **Experimenting with different CNN architectures and hyperparameters to improve model performance. Incorporating advanced NLP techniques such as attention mechanisms and transformer models for enhanced feature extraction. Extending the model to handle multiclass classification tasks and exploring applications in real-world scenarios such as social media monitoring and customer sentiment analysis.**

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