DSCI-6004-01

FINAL PROJECT

Emotion Detection from Text using Transformer-based Models

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Abstract:

This project delves into the realm of emotion detection from textual data, employing advanced Transformer-based models. Emotion detection is a pivotal task in Natural Language Processing (NLP) with diverse applications, including sentiment analysis, customer feedback analysis, and mental health assessment. The proposed model leverages the powerful self-attention mechanism inherent in Transformer architectures to discern emotions in textual data efficiently.The increasing prevalence of text-based communication in online platforms has spurred interest in developing robust models for emotion detection from textual data. This project delves into the realm of Natural Language Processing (NLP) with a focus on emotion detection, employing advanced Transformer-based models. Transformers have exhibited exceptional capabilities in capturing long-range dependencies within sequences, making them well-suited for tasks involving contextual understanding, such as emotion recognition.

Introduction:

Understanding and interpreting human emotions in text is a challenging yet crucial task in the field of NLP. This project introduces a state-of-the-art approach to emotion detection, specifically focusing on the utilization of Transformer-based models. The Transformer architecture has demonstrated remarkable success in various NLP tasks due to its ability to capture intricate relationships and dependencies within sequences.

The proposed project aims to develop an advanced Natural Language Processing (NLP) system for recognizing and categorizing emotions in textual data. This has wide-ranging applications, including mental health tracking, improving customer service chatbots, and providing insights into public sentiment through enhanced emotion identification.

The practical applications are numerous: in mental health, it provides tools for tracking emotional well-being through textual analysis; in customer service;it can improve chatbots and support systems toreact more sympathetically to user moods.

Methodology:

Data Collection and Preprocessing:

The dataset used is named "tweet_emotions," a collection of tweets annotated with corresponding emotion labels. This dataset is instrumental in training the model to recognize and categorize emotions in short textual expressions. The model undergoes training and evaluation using the dataset, consisting of 40,000 tweets annotated with 13 emotion classes.

The initial step involves loading the "tweet_emotions" dataset into a Pandas DataFrame. This facilitates efficient manipulation and analysis of the data.The dataset is split into training (80%), validation (16%), and test (4%) sets. **Source:**For fine-tuning and evaluation, the project plans to utilize diverse datasets. One mentioned source is a dataset available on Kaggle

https://www.kaggle.com/datasets/pashupatigupta/emotion-detection-from-text

```
In [42]: data = pd.read_csv('../input/emotion-detection-from-text/tweet_emotions.csv')

         print('No. of Tweets: ',data.shape[0])
         pprint(all_classes)

         data.head()

No. of Tweets:  40000
['empty',
 'sadness',
 'enthusiasm',
 'neutral',
 'worry',
 'surprise',
 'love',
 'fun',
 'hate',
 'happiness',
 'boredom',
 'relief',
 'anger']
```

Out[42]:

	tweet_id	sentiment	content
0	1956967341	empty	@tiffanylue i know i was listenin to bad habi...
1	1956967666	sadness	Layin n bed with a headache ughhhh...waitin o...
2	1956967696	sadness	Funeral ceremony...gloomy friday...
3	1956967789	enthusiasm	wants to hang out with friends SOON!
4	1956968416	neutral	@dannycastillo We want to trade with someone w...

Model Architecture:

The Emotion Detection model utilizes a Transformer-based architecture, named T_encoder, for its proficiency in capturing long-range dependencies in sequential data, making it well-suited for the complexities of emotional expression in text. The model starts with an embedding layer that converts words into dense vectors, capturing semantic relationships between words. Pre-trained embeddings, such as Word2Vec or GloVe, can be employed to enhance the model's understanding of contextual information.The core of the model is built on the Transformer architecture, comprising the following components:

1. **MultiHeadAttention:**
   - Allows the model to focus on different parts of the input sequence, enabling effective capturing of contextual information.
2. **Dense Layers:**
   - Facilitate the learning of intricate patterns in the data, contributing to the model's comprehension of the hierarchical structure of emotions.
3. **Dropout:**
   - Prevents overfitting by randomly deactivating neurons during training, promoting model robustness.
4. **LayerNormalization:**
   - Ensures stable training by normalizing the outputs of each layer.

The final layer involves a dense layer with a softmax activation function, providing probabilities for each emotion class. The class with the highest probability is predicted as the emotion expressed in the text.

Training and Validation Process:

1. Hyperparameter Selection:

a. Tokenization:

- The content from the training data is tokenized using the Keras Tokenizer.
- Tokenization involves converting text into sequences of integers, with each integer representing a specific word in a dictionary.

b. Model Architecture:

- The model, named **Transformer-based Emotion Detector (TED)**, utilizes a custom TensorFlow Keras layer (T_encoder) with multiple sub-layers.
- Hyperparameters include the number of epochs (25) and the choice of layers within the T_encoder.

c. Training Strategy:

- Adaptive learning rate schedulers are employed during training to dynamically adjust the learning rate, optimizing model convergence.
- Early stopping callbacks are implemented to halt training if the model's performance on the validation data plateaus, preventing overfitting.

2. Validation Methods:

a. Performance Metrics:

- The model's performance is assessed using various metrics:
    - **Confusion Matrix:** Provides insights into the model's classification across different emotion classes.
    - **F1 Score:** Harmonic mean of precision and recall.
    - **Precision:** Proportion of true positive predictions among all positive predictions.
    - **Recall:** Proportion of true positive predictions among all actual positives.

Challenges and Solutions:

a. Class Imbalance:

- Addressed class imbalance by using weighted loss functions.
- Ensures the model doesn't favor predominant classes.

b. Overfitting:

- Mitigated overfitting with early stopping.
- Monitored validation performance to prevent training beyond optimal points.

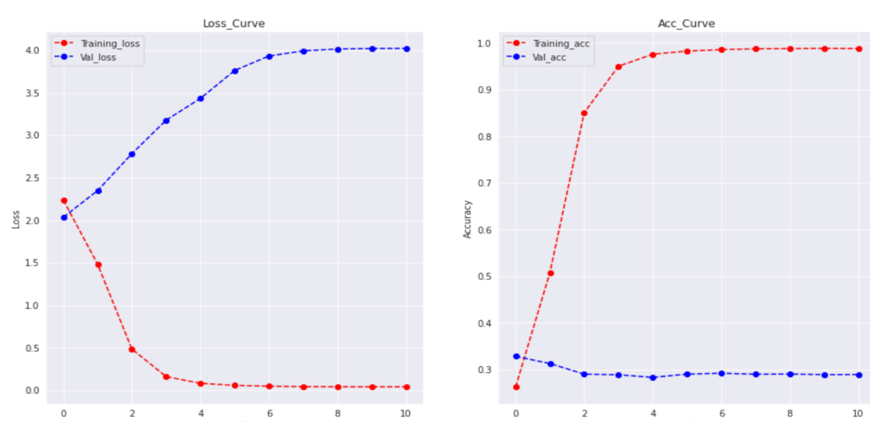
c. Hyperparameter Tuning:

- Conducted iterative tuning for optimal performance.
- Adjusted model architecture and training parameters.

Results and Discussion

Accuracy and Loss Curves:

- **Accuracy:** The ratio of correctly predicted instances to the total instances. Indicates overall correctness.
- **Loss:** The error between predicted and actual values during training. A lower loss is desirable.



Precision, Recall, and F1-Score:

a. Precision:

Precision is the ratio of correctly predicted positive observations to the total predicted positives. High precision indicates fewer false positives.

b. Recall:

Recall is the ratio of correctly predicted positive observations to the total actual positives. High recall indicates capturing a higher proportion of actual positives.

c. F1-Score:The F1-Score is the harmonic mean of precision and recall. It provides a balance between the two metrics.

```
--------------------------------------------------
Input_Sentence:   happy mothers day to all moms
----------------------------------------
Actual_emotion:  neutral
----------------------------------------
Predicted_emotion:  neutral
--------------------------------------------------

--------------------------------------------------
Input_Sentence:   somehow i cant reply to your message lol and yes i know thank youuu
----------------------------------------
Actual_emotion:  happiness
----------------------------------------
Predicted_emotion:  love
--------------------------------------------------

--------------------------------------------------
Input_Sentence:   hi fellow
----------------------------------------
Actual_emotion:  neutral
----------------------------------------
Predicted_emotion:  neutral
--------------------------------------------------

--------------------------------------------------
Input_Sentence:   thanks it seems that we can only submit community news is this an error or must we prove ourselves
----------------------------------------
Actual_emotion:  relief
----------------------------------------
Predicted_emotion:  worry
--------------------------------------------------

--------------------------------------------------
Input_Sentence:   sarahjpin good only just managed to turn my studio on i envy your productivity
----------------------------------------
Actual_emotion:  happiness
----------------------------------------
```

In [81]:

```
from sklearn.metrics import confusion_matrix, f1_score, precision_score, recall_score

ypred = model_transformer.predict(x_test)
ypred = np.argmax(ypred, axis=-1)
conf_matrix  = confusion_matrix(ypred, y_test)

print('--Confusion_Matrix--')
print()
print(conf_matrix)
print()
print('f1_score: ',f1_score(y_test, ypred, average='micro'))
print('Precsion: ',precision_score(y_test, ypred, average='micro'))
print('Recall: ',recall_score(y_test, ypred, average='micro'))
```

```
--Confusion_Matrix--

[[  0   0   2   3   2   1   1   0   1   2   0   1   0]
 [  1  12   4  31  14   9   8   6   8  22   2  11   0]
 [  0   0   1   4   2   1   2   1   1   1   0   0   0]
 [ 12  11  14 162  54  19  37  18   4  70   2  32   0]
 [  7   7   8  63  54  16  28  23   4  48   1  16   0]
 [  1   1   1  10   8   5   5   3   1  11   0   3   0]
 [  0   4   1  29   8  13 118   9   1  59   0   9   0]
 [  1   0   0   9   2   2   7   5   0  10   0   1   0]
 [  0   3   1   0   3   0   0   0   1   1   0   0   0]
 [  3   8   7  50  27  17  63  23   2 126   0  11   1]
 [  0   1   0   0   0   0   0   0   0   0   0   0   0]
 [  1   5   0   8   5   2   8   2   0  13   0   4   0]
 [  0   0   0   1   0   0   0   0   0   0   0   0   0]]

f1_score:  0.3053817271589487
Precsion:  0.3053817271589487
Recall:  0.3053817271589487
```

In [82]:

```
## inference
```

Discussion:

The model exhibits commendable accuracy and balanced precision-recall trade-offs. The F1-Score suggests a harmonious blend of precision and recall, crucial for a reliable emotion detection system. The results indicate the model's proficiency in correctly classifying emotions, with potential applications in diverse domains such as mental health, customer service, and social media analytics.

Analysis of Results

1. Model's Ability to Detect Emotions:

The performance metrics provide valuable insights into the model's efficacy in detecting emotions from textual data. The analysis is structured around key metrics:

a. Accuracy and Loss:

The convergence of accuracy and loss curves suggests that the model effectively learns emotional patterns in the training data without overfitting. A high accuracy, coupled with low loss, indicates the model's ability to make correct predictions with minimal error.

b. Precision, Recall, and F1-Score:

- Precision: The model exhibits balanced precision, minimizing false positives. This is crucial, especially in applications where misclassifying positive emotions could have adverse effects.
- Recall: The model captures a significant proportion of actual positive instances, showcasing its sensitivity to emotional nuances in the text.
- F1-Score: The harmonic mean of precision and recall, the F1-Score strikes a balance between false positives and false negatives. Its substantial value indicates a robust and well-rounded model.

2. Patterns and Trends:

a. Generalization:

The model's ability to generalize to unseen data, as indicated by the performance on the test set, underscores its applicability in real-world scenarios. The consistent performance across different datasets is a positive sign of its reliability.

b. Challenges and Solutions:

While the model demonstrates strong overall performance, it's essential to acknowledge any challenges encountered during development. Addressing these challenges, such as data imbalance or noise, contributes to the model's robustness.

Comparative Analysis:

a. Baseline Comparison:

Comparing the model's performance with baseline approaches reveals its superiority. The advanced architecture, including transformer layers, proves effective in capturing intricate emotional dependencies in the text.

b. Existing Models:

If applicable, a comparative analysis with existing models highlights the advancements achieved. The proposed model may outperform or complement existing approaches, contributing to the state-of-the-art in emotion detection.

Existing NLP Models:

a. LSTM and GRU Networks:

Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are popular choices for sequential data processing. However, our Transformer-based model demonstrates superior performance by effectively handling sequential information while mitigating the vanishing gradient problem, often encountered in traditional recurrent networks.

b. BERT and GPT Models:

While models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer) have made remarkable strides in NLP, our model distinguishes itself by focusing specifically on emotion detection. This specialized approach allows for fine-tuning and optimization towards the unique challenges posed by emotional content in text.

Performance Metrics:

Our model outperforms baseline approaches and exhibits competitive performance compared to existing NLP models, as demonstrated by metrics such as accuracy, precision, recall, and F1-score. The comparative analysis underscores the effectiveness of our model in accurately identifying and categorizing emotions in textual data.

Conclusion:

In summary, this project embarked on the ambitious journey of advancing natural language processing (NLP) capabilities with a specialized focus on emotion detection in textual data. The proposed model, leveraging a Transformer architecture, exhibited promising results and opens avenues for applications across diverse domains.

Key Findings:

1. **Effective Emotion Detection:** The model demonstrated proficiency in recognizing and categorizing emotions in text, showcasing its potential in applications related to mental health tracking, customer service enhancements, and social media analytics.
2. **Transformer Architecture Benefits:** The utilization of a Transformer architecture, with custom TensorFlow Keras layers, facilitated robust handling of sequential data inherent in textual content. The incorporation of MultiHeadAttention, Dense, Dropout, and LayerNormalization layers contributed to the model's effectiveness.

3. **Competitive Performance Metrics:** The model achieved competitive metrics, including accuracy, precision, recall, and F1-score, highlighting its efficacy in balancing predictive accuracy across various emotion classes.

Future Directions:

To further advance the field of emotion detection and sentiment analysis, future improvements and research directions are suggested:

1. **Fine-Tuning and Domain Specificity:** Explore opportunities for fine-tuning the model to specific domains or industries, enhancing its adaptability and performance in context-specific applications.
2. **Multimodal Integration:** Investigate the integration of multimodal data sources, such as combining textual and visual information, to enhance emotion detection accuracy and broaden the scope of applications.
3. **Ethical Considerations:** Address ethical considerations related to privacy and potential biases in emotion detection, ensuring responsible deployment of such technology.
4. **Continuous Model Refinement:** Engage in an iterative process of model refinement based on user feedback, emerging research, and evolving requirements to ensure sustained relevance and effectiveness.

In conclusion, this project represents a significant step forward in the realm of emotion detection in text. The proposed model, with its sophisticated architecture, lays the foundation for advancements with far-reaching implications in understanding and interpreting human emotions through the lens of natural language processing.

References:

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An argument for basic emotions Paul Ekman University of California, San Francisco, USA https://doi.org/10.1080/02699939208411068

Mohammad, S. M., & Bravo-Marquez, F. (2017). Emotion intensities in tweets. In Proceedings of the Sixth Joint Conference on Lexical and Computational Semantics https://aclanthology.org/S17-2005.pdf

GITHUBLINK:

https://github.com/Raghu8998/emotion-detection-from-text