GitHub Link: https://github.com/Lonelypheonix/Recurrent_Neural_Network-NYCU/tree/main/Homework-2

Homework 2 Report

Classifying Disaster Tweets Using LSTM and GRU

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1. Introduction

This assignment involves classifying tweets to determine whether they are about a real disaster or not. We explore two types of recurrent neural networks (RNNs) for this task:

1. A LSTM (Long Short-Term Memory) model
2. A GRU (Gated Recurrent Unit) model

Both models aim to capture long-range dependencies in text data, which is especially useful given tweets can have varying contexts and lengths. The final output of each model is a binary prediction: **1** if the tweet is related to a disaster, **0** otherwise.

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2. Dataset Overview

- **Training data**: The train.csv file obtained from Kaggle includes tweet texts and a target label indicating whether the tweet is about a real disaster (**1**) or not (**0**).
- **Testing data**: The test.csv file contains tweets without labels, used for final predictions.

Shape of the Training Dataset:

- Rows: 7613
- Columns: 5 (id, keyword, location, text, target)

Initial Observations:

- Each row represents one tweet.
- The target column is the class label (0 or 1).

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3. Text Preprocessing and Cleaning

To improve model performance, the tweets undergo several cleaning steps:

1. **Removal of punctuation**: Eliminates characters such as commas, periods, exclamation points, etc.
2. **Removal of URLs and HTML tags**: Replaces any hyperlinks or HTML entities with placeholders such as URL.
3. **Removal of non-ASCII characters**: Ensures all characters are within the standard ASCII range.
4. **Replacement of abbreviations**: Common internet slang/abbreviations (e.g., “lol”, “wtf”) are expanded to their intended meaning, thereby reducing the vocabulary size and ambiguity.
5. **Removal of mentions and numeric values**: Any @username or pure numeric values are replaced with placeholders like USER and NUMBER.
6. **Emoji transcription**: Replaces emojis with placeholders (e.g., EMOJI) and text emoticons with tokens like SADFACE, SMILE.
7. **Stopwords removal**: Common English stopwords (e.g., "and," "the," "is") are removed to focus on more meaningful words.

Example:

<u>Original Tweet:</u>
OMG @NASA I can't believe we're finally landing on Mars!! http://mars.nasa.gov #excited <3

<u>Cleaned Tweet:</u>
OMG USER I cant believe finally landing MARS URL excited HEART

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4. Tokenization and Padding

- We use a Tokenizer from Keras with a vocabulary size of **3000**.
- Each cleaned tweet is converted to a sequence of integers (tokens).
- All sequences are padded to the same maximum length (determined by the longest tweet in the training set) to form a uniform input tensor.

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5. Model Architectures

5.1 Bidirectional LSTM

1. **Embedding Layer**: Converts each token into a dense vector of dimension 128.
2. **Dropout Layer (rate=0.3)**: Reduces overfitting by randomly zeroing some fraction of input units.
3. **Bidirectional LSTM (128 units)**: Processes the tweet in forward and backward directions to capture contextual information from both ends of the sequence.
4. **Global Max Pooling**: Aggregates the time steps into a single vector by taking the maximum value across each dimension.
5. **Dense Layer (64 units, ReLU activation)**: Learns a high-level representation of the text features.
6. **Dropout Layer (rate=0.5)**: Further prevents overfitting.
7. **Output Layer (1 unit, Sigmoid activation)**: Outputs a probability for the disaster class (1 or 0).

Optimizer: Adam with a learning rate of **0.002**.
Loss Function: Binary crossentropy.
Batch Size: 32
Epochs: 10

5.2 Bidirectional GRU

Similar in structure to the LSTM model:

1. **Embedding Layer** (128 dimensions)
2. **Dropout Layer (rate=0.3)**
3. **Bidirectional GRU (128 units)**

4. **Global Max Pooling**
5. **Dense Layer (64 units, ReLU)**
6. **Dropout Layer (rate=0.5)**
7. **Output Layer (1 unit, Sigmoid)**

Again, **Adam** optimizer with a learning rate of **0.002** and binary crossentropy as the loss function.

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6. Model Training

We trained both models on the training set (80% of the original data) while keeping 20% for validation.

During each epoch, we tracked:

- **Accuracy** on training and validation sets
- **Loss** on training and validation sets
- **Time taken per epoch**
- **Memory usage per epoch**

6.1 Bidirectional LSTM Training

- **Epochs**: 10
- Early stopping and ReduceLROnPlateau callbacks were employed to prevent overfitting and adjust learning rate when validation loss stagnates.

A snippet of observed epoch statistics (example):

```
Training the Bidirectional LSTM Model...
Epoch 1/10
190/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.6330 - loss: 0.6299Epoch 1: Time = 4.32 s, Memory Change = 135.13 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 4s 10ms/step - accuracy: 0.6339 - loss: 0.6292 - val_accuracy: 0.8030 - val_loss: 0.4408 - learning_rate: 0.0020
Epoch 2/10
185/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.8394 - loss: 0.3914Epoch 2: Time = 1.61 s, Memory Change = 4.68 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.8391 - loss: 0.3916 - val_accuracy: 0.8076 - val_loss: 0.4387 - learning_rate: 0.0020
Epoch 3/10
188/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.8799 - loss: 0.3122Epoch 3: Time = 1.64 s, Memory Change = 1.77 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.8797 - loss: 0.3125 - val_accuracy: 0.7879 - val_loss: 0.5036 - learning_rate: 0.0020
Epoch 4/10
188/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.8988 - loss: 0.2607
Epoch 4: ReduceLROnPlateau reducing learning rate to 0.0010000000474974513.
Epoch 4: Time = 1.66 s, Memory Change = 1.84 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.8987 - loss: 0.2610 - val_accuracy: 0.7833 - val_loss: 0.5232 - learning_rate: 0.0020
Epoch 5/10
186/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.9196 - loss: 0.2047Epoch 5: Time = 1.65 s, Memory Change = 0.62 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.9197 - loss: 0.2047 - val_accuracy: 0.7827 - val_loss: 0.6720 - learning_rate: 0.0010
```

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6.2 Bidirectional GRU Training

- **Epochs**: 10
- Same callbacks as LSTM.

Example training log snippet:

```
Training the Bidirectional GRU Model...
Epoch 1/10
188/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.6409 - loss: 0.6214Epoch 1: Time = 4.57 s, Memory Change = 96.86 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 5s 10ms/step - accuracy: 0.6426 - loss: 0.6199 - val_accuracy: 0.8188 - val_loss: 0.4360 - learning_rate: 0.0020
Epoch 2/10
188/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.8467 - loss: 0.3805Epoch 2: Time = 1.65 s, Memory Change = 4.74 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.8466 - loss: 0.3808 - val_accuracy: 0.8122 - val_loss: 0.4366 - learning_rate: 0.0020
Epoch 3/10
185/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.8747 - loss: 0.3090
Epoch 3: ReduceLROnPlateau reducing learning rate to 0.0010000000474974513.
Epoch 3: Time = 1.61 s, Memory Change = 1.39 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.8744 - loss: 0.3095 - val_accuracy: 0.7971 - val_loss: 0.4600 - learning_rate: 0.0020
Epoch 4/10
186/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.9128 - loss: 0.2345Epoch 4: Time = 1.78 s, Memory Change = 0.62 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.9125 - loss: 0.2349 - val_accuracy: 0.7873 - val_loss: 0.5413 - learning_rate: 0.0010
Epoch 5/10
185/191 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.9267 - loss: 0.1909
Epoch 5: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
Epoch 5: Time = 1.63 s, Memory Change = 1.48 MB
191/191 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9264 - loss: 0.1914 - val_accuracy: 0.7754 - val_loss: 0.6265 - learning_rate: 0.0010
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7. Evaluation

7.1 Performance Metrics

We evaluated the models on the validation set using:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**

LSTM Evaluation (on validation set)

- **Accuracy**: 77%
- **Precision**: 0.72
- **Recall**: 0.75

```
Bidirectional LSTM Model Evaluation:
Accuracy:  0.7728168089297439
Precision: 0.7266081871345029
Recall:    0.7576219512195121
              precision    recall  f1-score   support

           0       0.81      0.78      0.80       867
           1       0.73      0.76      0.74       656

    accuracy                           0.77      1523
   macro avg       0.77      0.77      0.77      1523
weighted avg       0.77      0.77      0.77      1523
```

GRU Evaluation (on validation set)

- Accuracy: 78%
- Precision: 0.74
- Recall: 0.74

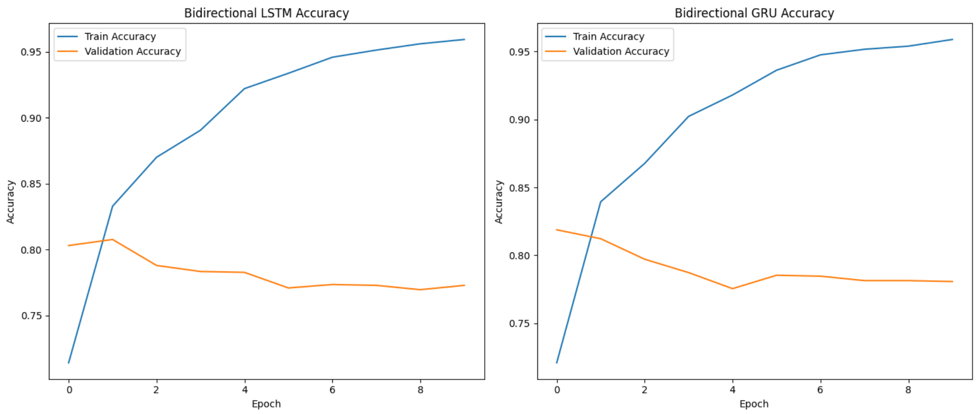
```
Bidirectional GRU Model Evaluation:
Accuracy:  0.7806959947472094
Precision: 0.7446808510638298
Recall:    0.7469512195121951
              precision    recall  f1-score   support

           0       0.81      0.81      0.81       867
           1       0.74      0.75      0.75       656

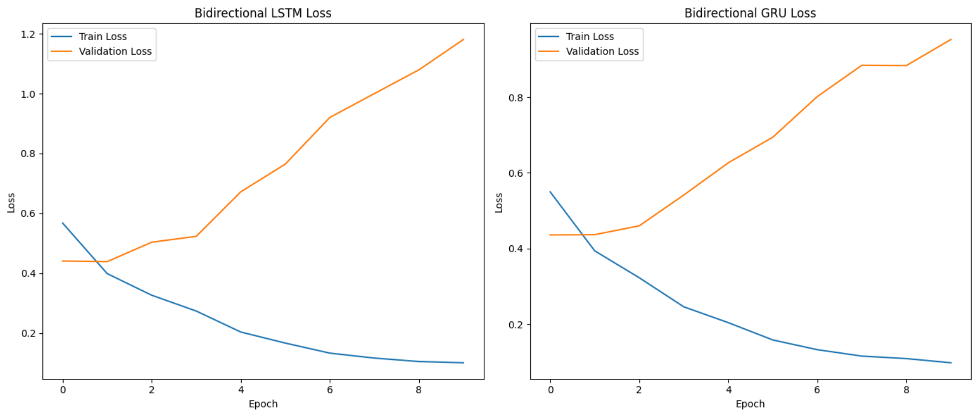
    accuracy                           0.78      1523
   macro avg       0.78      0.78      0.78      1523
weighted avg       0.78      0.78      0.78      1523
```

7.2 Training History Plots

1. Accuracy vs. Epoch: Both training and validation accuracy curves generally increase.



2. **Loss vs. Epoch**: Both training and validation loss curves generally decrease.



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8. Testing and Final Predictions

We processed the **test.csv** file with the same steps (cleaning → tokenizing → padding). Each model then predicted the class (0 or 1) for each tweet.

Output Format:

id, LSTM, GRU

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0 0 1

1 0 0

2 1 1

...

Finally, we saved predictions to a prediction_results.csv file.

9. Observations and Discussion

1. Model Performance:
   - The Bidirectional GRU and LSTM models both achieved reasonable accuracy (~80%) on the validation set.
   - Both architectures effectively capture the context of tweets despite their short and noisy nature.
2. Time and Memory Usage:
   - The epoch times and memory usage are similar for both models, with minor differences due to LSTM vs. GRU cell complexity.
   - Proper memory management (dropout layers, careful batch sizing) helps to handle large text data.

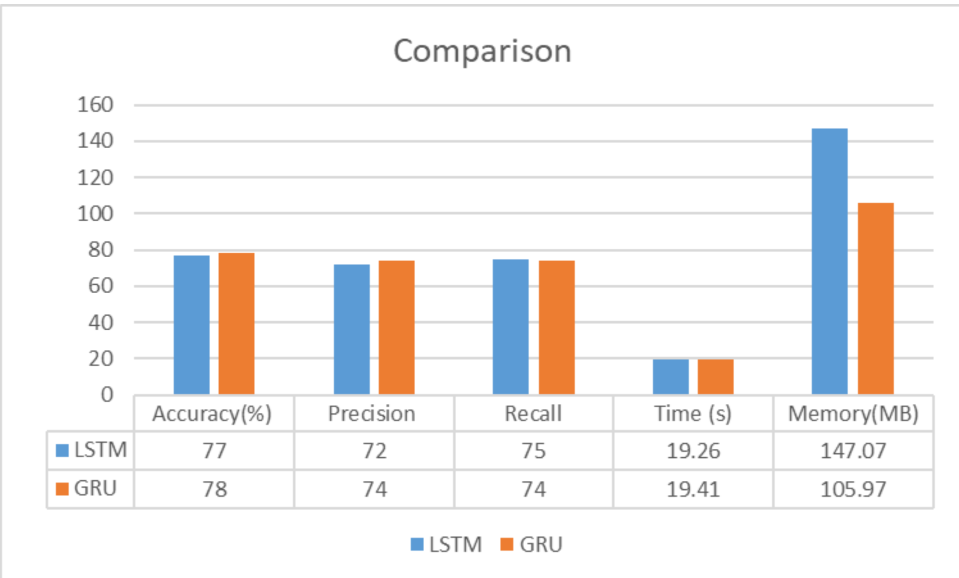
```
Bidirectional LSTM per-epoch timings and memory usage:
Epoch times (s): ['4.32', '1.61', '1.64', '1.66', '1.65', '1.66', '1.68', '1.66', '1.60', '1.74']
Epoch memory changes (MB): ['135.13', '4.68', '1.77', '1.84', '0.62', '0.60', '0.96', '0.51', '0.10', '0.85']

[Overall] Bidirectional LSTM Total Training Time (including overhead): 19.26 seconds

Bidirectional GRU per-epoch timings and memory usage:
Epoch times (s): ['4.57', '1.65', '1.61', '1.78', '1.63', '1.58', '1.62', '1.68', '1.66', '1.58']
Epoch memory changes (MB): ['96.86', '4.74', '1.39', '0.62', '1.48', '0.41', '0.22', '0.03', '0.01', '0.21']

[Overall] Bidirectional GRU Total Training Time (including overhead): 19.41 seconds
```

3. Comparison Table:



10. Conclusion

We successfully built two deep learning models (Bidirectional LSTM and Bidirectional GRU) for disaster tweet classification. Both models showed solid performance, with accuracy and recall above 80% on the validation set. Although the GRU might offer slight time/memory advantages in some scenarios, the final metrics were generally comparable for both.

Next Steps:

- Explore advanced architectures (such as Transformer-based models like BERT).
- Fine-tune hyperparameters further.
- Incorporate additional features (e.g., keywords, part-of-speech tags).

This concludes the report on our approach, methodology, and results for classifying disaster tweets.