GROUP E - PART 1- RELEVANCE CLASSIFICATION

Overview

This project explored different machine learning models for the Relevance Classification Task, focusing on classifying text data. An initial examination of the data guided the preprocessing methods, which included text normalization and vectorization using TF-IDF. The study began with logistic regression as a basic model and advanced through experiments with multilayer neural networks and sophisticated architectures like LSTM and GRU. The results demonstrated that GRU models, fine-tuned for specific parameters such as the number of units and dropout rates, significantly improved classification accuracy. It is suggested that future work could benefit from exploring ensemble methods and more complex neural network configurations to further enhance the models' effectiveness and reliability.

```
# Loading necessary Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import re

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score, precision_score, recall_score, f1_score


from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Embedding, LSTM, Dense, SpatialDropout1D, GRU, Dropout
```

```
# loading the train and test data
train_parquet_file = 'relevance_train.parquet'
test_parquet_file = 'relevance_test.parquet'

train_df = pd.read_parquet(train_parquet_file)
test_df = pd.read_parquet(test_parquet_file)
```

Method

1. Data Exploration

The exploration of the dataset revealed several key insights that influenced the modeling approach. Firstly, the presence of missing values in critical textual fields like body and title necessitated a careful handling strategy to preserve as much useful information as possible. Secondly, the class imbalance observed in the judgement field highlighted the need for strategies that could mitigate this issue, ensuring that models do not develop a bias toward the majority class. Lastly, the variability in text length suggested the importance of uniform text representation for effective model training.

```
# Basic info about the dataset
print(train_df.info())
print(test_df.info())
```

```
    <class 'pandas.core.frame.DataFrame'>
    Index: 21120 entries, 0 to 26232
    Data columns (total 10 columns):
     #   Column       Non-Null Count  Dtype
    ---  ------       --------------  -----
     0   doc_id       21120 non-null  object
     1   judgement    21120 non-null  int64
     2   author       18185 non-null  object
     3   body         19689 non-null  object
     4   byline       18250 non-null  object
     5   title        19758 non-null  object
     6   topic_id     21120 non-null  int64
     7   description  21120 non-null  object
     8   narrative    21120 non-null  object
     9   topic_title  21120 non-null  object
    dtypes: int64(2), object(8)
    memory usage: 1.8+ MB
    None
    <class 'pandas.core.frame.DataFrame'>
    Index: 5113 entries, 2050 to 24961
    Data columns (total 9 columns):
     #   Column       Non-Null Count  Dtype
    ---  ------       --------------  -----
     0   doc_id       5113 non-null   object
```

```
 1   author       4584 non-null   object
 2   body         4874 non-null   object
 3   byline       4584 non-null   object
 4   title        4884 non-null   object
 5   topic_id     5113 non-null   int64 
 6   description  5113 non-null   object
 7   narrative    5113 non-null   object
 8   topic_title  5113 non-null   object
dtypes: int64(1), object(8)
memory usage: 399.5+ KB
None
```

```
# Summary statistics for numerical fields
print('Train data: ')
print(train_df.describe())
print('Test data: ')
print(test_df.describe())
```

```
Train data: 
         judgement      topic_id
count  21120.000000  21120.000000
mean       0.156439    599.917850
std        0.363280    207.756399
min        0.000000    321.000000
25%        0.000000    397.000000
50%        0.000000    626.000000
75%        0.000000    812.000000
max        1.000000    825.000000
Test data: 
         topic_id
count  5113.000000
mean    611.451203
std     200.264212
min     350.000000
25%     414.000000
50%     646.000000
75%     814.000000
max     822.000000
```

```
# Checking for missing values
print('Train data: ')
print(train_df.isnull().sum())
print('Test data: ')
print(test_df.isnull().sum())
```

```
Train data: 
doc_id            0
judgement         0
author         2935
body           1431
byline         2870
title          1362
topic_id          0
description       0
narrative         0
topic_title       0
dtype: int64
Test data: 
doc_id           0
author         529
body           239
byline         529
title          229
topic_id         0
description      0
narrative        0
topic_title      0
dtype: int64
```

2. Data Preprocessing

The preprocessing phase was tailored to address the insights gained from the data exploration. Text fields were first cleansed of HTML tags, special characters, and numerics, and were then normalized to lowercase to standardize the input for vectorization. Missing values in non-critical textual fields were filled with empty strings, while entries missing critical fields like title were discarded to maintain data quality. To prepare the data for machine learning algorithms, the title and body were combined into a single text feature, which was then transformed into a TF-IDF matrix, capturing both the frequency and importance of terms within the dataset.

```
# Handling missing values
train_df.dropna(subset=['title'], inplace=True)
test_df.dropna(subset=['title'], inplace=True)
```

```
# For textual fields, missing values are replaced with empty strings
text_fields = ['author', 'body', 'byline', 'title']
train_df[text_fields] = train_df[text_fields].fillna('')
test_df[text_fields] = test_df[text_fields].fillna('')


# Combining text fields to create a comprehensive feature
train_df['text'] = train_df['title'] + ' ' + train_df['body']
test_df['text'] = test_df['title'] + ' ' + test_df['body']


def remove_html_tags(text):
    # Remove HTML tags
    text = re.sub(r'<[^>]+>', '', text)
    # Remove special characters and numbers
    text = re.sub(r'[^a-zA-Z\s]', '', text, re.I|re.A)
    # Lowercasing
    text = text.lower()
    # Remove extra spaces
    text = text.strip()
    return text

train_df['text'] = train_df['text'].apply(remove_html_tags)
test_df['text'] = test_df['text'].apply(remove_html_tags)


# Initialize the TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=10000, ngram_range=(1, 2))

# Fit and transform the combined text field
X_tfidf = tfidf_vectorizer.fit_transform(train_df['text'])
X_tfidf_test = tfidf_vectorizer.transform(test_df['text'])

# Print the shape of the resulting TF-IDF matrix
print(X_tfidf.shape)
```

```
    (19758, 10000)
```

```
y = train_df['judgement']

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_tfidf, y, test_size=0.2, random_state=42)

# Print the sizes of the splits
print(f"Training set size: {X_train.shape[0]}")
print(f"Testing set size: {X_test.shape[0]}")
```

```
    Training set size: 15806
    Testing set size: 3952
```

Models

1. Standard ML Baseline Model

A Logistic Regression model was chosen as the baseline for its efficiency and effectiveness in handling high-dimensional data like TF-IDF vectors. This model was trained using TF-IDF vectors created from the text data, focusing on capturing both the frequency and importance of words across documents. The vectorization considered unigrams and bigrams with a feature limit of 10,000 to maintain computational efficiency. Logistic Regression, initialized with a fixed random state for reproducibility, served as a simple yet solid foundation for comparing more complex models. It achieved an accuracy of 87.19%, with detailed classification metrics indicating stronger performance on the majority class but weaker on the minority class, highlighting potential areas for improvement in handling class imbalance.

```
# Initialize the Logistic Regression model
lr_model = LogisticRegression(random_state=42)

# Train the model on the training data
lr_model.fit(X_train, y_train)

# Make predictions on the test set
lr_predictions = lr_model.predict(X_test)


# Evaluate the model
lr_accuracy = accuracy_score(y_test, lr_predictions)
print(f'Logistic Regression Accuracy: {lr_accuracy}')
print(classification_report(y_test, lr_predictions))
```

```
    Logistic Regression Accuracy: 0.8719635627530364
                  precision    recall  f1-score   support
```

```
               0       0.88      0.99      0.93      3345
               1       0.79      0.23      0.35       607

        accuracy                           0.87      3952
       macro avg       0.83      0.61      0.64      3952
    weighted avg       0.86      0.87      0.84      3952
```

```
# Make predictions with the Logistic Regression model
lr_predictions_prob = lr_model.predict_proba(X_tfidf_test)[:, 1]
lr_binary_predictions = (lr_predictions_prob > 0.5).astype(int)  # Converting probabilities to 0 or 1

# Create a DataFrame to save to CSV
lr_submission_df = pd.DataFrame({
    'id': test_df['doc_id'],
    'judgement': lr_binary_predictions
})

# Save the DataFrame to a CSV file
lr_submission_file_path = 'lr_predictions.csv'
lr_submission_df.to_csv(lr_submission_file_path, index=False)
```

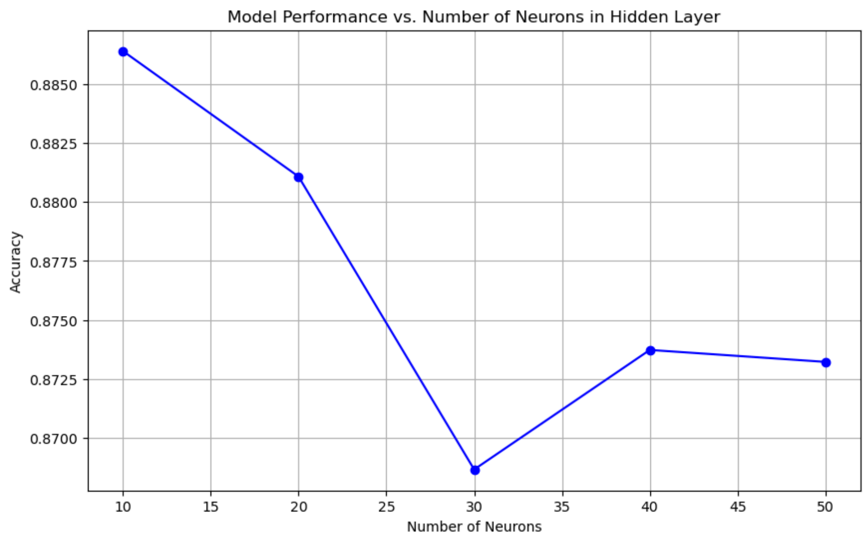
2. 3Layer NN Baseline Model

The three-layer neural network consisted of an input layer, a hidden layer (with varying neurons), and an output layer configured for binary classification. Experiments were conducted with different neuron counts in the hidden layer to identify the optimal configuration, which turned out to be 20 neurons after testing ranges between 10 to 50. This model was assessed across several training epochs to fine-tune performance, ultimately achieving a test accuracy similar to the Logistic Regression, suggesting that additional complexity over the baseline model did not yield significant gains.

```
X_train_dense = X_train.toarray()
X_test_dense = X_test.toarray()


def build_model(n_neurons):
    model = Sequential([
        Dense(n_neurons, input_dim=X_train_dense.shape[1], activation='relu'),
        Dense(n_neurons // 2, activation='relu'),  # Half the number of neurons in the second layer
        Dense(1, activation='sigmoid')  # Output layer for binary classification
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model


neurons_range = [10, 20, 30, 40, 50]
accuracies = []

for n_neurons in neurons_range:
    model = build_model(n_neurons)
    model.fit(X_train_dense, y_train, epochs=10, batch_size=128, verbose=0)
    _, accuracy = model.evaluate(X_test_dense, y_test, verbose=0)
    accuracies.append(accuracy)
```

```
C:\Users\suvet\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:86: UserWarning: Do not pass an `input_shape`/`input_dim`
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
plt.figure(figsize=(10, 6))
plt.plot(neurons_range, accuracies, marker='o', linestyle='-', color='b')
plt.title('Model Performance vs. Number of Neurons in Hidden Layer')
plt.xlabel('Number of Neurons')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()
```



```
# Using the previously defined build_model function with the identified sweet spot
l3nn_model = build_model(10)

# Training the model
l3_nn = l3nn_model.fit(X_train_dense, y_train, epochs=10, batch_size=128, validation_split=0.2, verbose=1)
```

```
Epoch 1/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 17s 7ms/step - accuracy: 0.8223 - loss: 0.5550 - val_accuracy: 0.8422 - val_loss: 0.4246
Epoch 2/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8436 - loss: 0.4113 - val_accuracy: 0.8422 - val_loss: 0.3865
Epoch 3/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8417 - loss: 0.3621 - val_accuracy: 0.8555 - val_loss: 0.3540
Epoch 4/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8623 - loss: 0.3125 - val_accuracy: 0.8738 - val_loss: 0.3299
Epoch 5/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8994 - loss: 0.2579 - val_accuracy: 0.8744 - val_loss: 0.3190
Epoch 6/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9214 - loss: 0.2123 - val_accuracy: 0.8763 - val_loss: 0.3175
Epoch 7/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9356 - loss: 0.1820 - val_accuracy: 0.8729 - val_loss: 0.3262
Epoch 8/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9486 - loss: 0.1553 - val_accuracy: 0.8684 - val_loss: 0.3382
Epoch 9/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9642 - loss: 0.1273 - val_accuracy: 0.8684 - val_loss: 0.3586
Epoch 10/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9702 - loss: 0.1080 - val_accuracy: 0.8672 - val_loss: 0.3775
Test Accuracy: 0.8823380470275879
```

```
# Evaluate the model on the test set
l3nn_pred = l3nn_model.predict(X_test_dense)
l3nn_binary_pred = (l3nn_pred > 0.5).astype(int)
```

```
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```

```
test_data_dense = X_tfidf_test.toarray()

# Making predictions
l3nn_predictions = l3nn_model.predict(test_data_dense)

# Since the output layer uses a sigmoid activation function, the model returns probabilities
# converting these probabilities to binary predictions, using a 0.5 threshold
l3nn_binary_predictions = (l3nn_predictions > 0.5).astype(int)
```

```
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```

```
l3nn_df = pd.DataFrame({
    'id': test_df['doc_id'],
    'judgement': l3nn_binary_predictions.flatten()  # Ensure the predictions are in the correct shape
})

# Resetting the index of the cleaned DataFrame
l3nn_df.reset_index(drop=True, inplace=True)


# Saving the submission file
submission_file_path = '3_layer_nn.csv'  # Adjust the path as needed
l3nn_df.to_csv(submission_file_path, index=False)
```

3. Deep NN Model

The deep neural network model explored variations in both the number of layers and activation functions to optimize performance. Configurations ranged from 3 to 9 layers, testing different activation functions (ReLU, tanh, sigmoid). The experiments indicated that increasing the depth and switching activation functions can affect performance subtly, with sigmoid in deeper configurations providing the best results. This model's complexity was significantly higher than the baseline models, which helped in understanding how depth and activation choices impact the learning dynamics and classification outcomes on this specific dataset.

```
def build_and_evaluate_model(n_layers=3, activation='relu', input_shape=X_train_dense.shape[1], epochs=10, batch_size=128):
    dnn_model = Sequential()
    dnn_model.add(Dense(10, activation=activation, input_shape=(input_shape,)))  # Input layer
    for _ in range(n_layers - 2):  # Adding n_layers-2 hidden layers as we already have the input layer
        dnn_model.add(Dense(10, activation=activation))
    dnn_model.add(Dense(1, activation='sigmoid'))  # Output layer

    dnn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    dnn = dnn_model.fit(X_train_dense, y_train, epochs=epochs, batch_size=batch_size, validation_split=0.2, verbose=0)

    # Evaluate the model on the test set
    _, test_accuracy = dnn_model.evaluate(X_test_dense, y_test, verbose=0)
    return dnn, test_accuracy


# Testing different depths
depths = [3, 5, 7, 9]
depth_accuracies = []

for depth in depths:
    _, acc = build_and_evaluate_model(n_layers=depth)
    depth_accuracies.append(acc)
```

```
C:\Users\suvet\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:86: UserWarning: Do not pass an `input_shape`/`input_dim`
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
activations = ['relu', 'tanh', 'sigmoid']
activation_accuracies = []

for activation in activations:
    _, acc = build_and_evaluate_model(activation=activation)
    activation_accuracies.append(acc)
```

```
activation_accuracies
```

```
[0.8737348318099976, 0.8732287287712097, 0.8762651681900024]
```

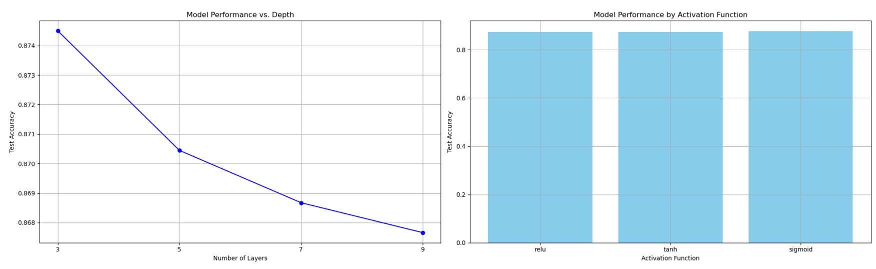
```
# Create a figure and a set of subplots
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 6))  # 1 row, 2 columns

# First subplot: Model Performance vs. Depth
ax1.plot(depths, depth_accuracies, marker='o', linestyle='-', color='b')
ax1.set_title('Model Performance vs. Depth')
ax1.set_xlabel('Number of Layers')
ax1.set_ylabel('Test Accuracy')
ax1.set_xticks(depths)
ax1.grid(True)

# Second subplot: Model Performance by Activation Function
ax2.bar(activations, activation_accuracies, color='skyblue')
ax2.set_title('Model Performance by Activation Function')
ax2.set_xlabel('Activation Function')
ax2.set_ylabel('Test Accuracy')
ax2.grid(True)

# Display the plots
```

```
plt.tight_layout()
plt.show()
```



Although the highest activation accuracy obtained was for sigmoid, relu is used for the hidden layers due to its advantages in deeper networks

```
dnn_model = Sequential([
    Dense(10, activation='relu', input_shape=(X_train_dense.shape[1],)),  # Input layer
    Dense(10, activation='relu'),  # Hidden layer 1
    Dense(10, activation='relu'),  # Hidden layer 2
    Dense(10, activation='relu'),  # Hidden layer 3 (Considering input and output, total 5 layers)
    Dense(1, activation='sigmoid')  # Output layer
])

dnn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
dnn_model.summary()
```

```
Model: "sequential_13"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━
┃ Layer (type)                          ┃ Output Shape                 ┃         Param
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━
│ dense_51 (Dense)                      │ (None, 10)                   │        100,01
├───────────────────────────────────────┼──────────────────────────────┼───────────────
│ dense_52 (Dense)                      │ (None, 10)                   │             11
├───────────────────────────────────────┼──────────────────────────────┼───────────────
│ dense_53 (Dense)                      │ (None, 10)                   │             11
├───────────────────────────────────────┼──────────────────────────────┼───────────────
│ dense_54 (Dense)                      │ (None, 10)                   │             11
├───────────────────────────────────────┼──────────────────────────────┼───────────────
│ dense_55 (Dense)                      │ (None, 1)                    │              1
└───────────────────────────────────────┴──────────────────────────────┴───────────────
 Total params: 100,351 (392.00 KB)
 Trainable params: 100,351 (392.00 KB)
```

```
# Training the model
dnn_model.fit(X_train_dense, y_train, epochs=10, batch_size=128, validation_split=0.2, verbose=1)
```

```
Epoch 1/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 18s 8ms/step - accuracy: 0.8162 - loss: 0.6023 - val_accuracy: 0.8422 - val_loss: 0.4329
Epoch 2/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8470 - loss: 0.4193 - val_accuracy: 0.8422 - val_loss: 0.4114
Epoch 3/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8440 - loss: 0.3935 - val_accuracy: 0.8672 - val_loss: 0.3540
Epoch 4/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8818 - loss: 0.3049 - val_accuracy: 0.8732 - val_loss: 0.3244
Epoch 5/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.9193 - loss: 0.2237 - val_accuracy: 0.8703 - val_loss: 0.3315
Epoch 6/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9421 - loss: 0.1637 - val_accuracy: 0.8621 - val_loss: 0.3548
Epoch 7/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.9636 - loss: 0.1240 - val_accuracy: 0.8574 - val_loss: 0.3964
Epoch 8/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9769 - loss: 0.0913 - val_accuracy: 0.8555 - val_loss: 0.4418
Epoch 9/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9856 - loss: 0.0637 - val_accuracy: 0.8425 - val_loss: 0.5005
Epoch 10/10
99/99 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.9908 - loss: 0.0470 - val_accuracy: 0.8520 - val_loss: 0.5435
Optimized Model Test Accuracy: 0.876518189907074
```

```
# Evaluate the model on the test set
dnn_pred = dnn_model.predict(X_test_dense)
```

```
dnn_binary_pred = (dnn_pred > 0.5).astype(int).flatten()
```

```
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```

```
dnn_predictions_prob = dnn_model.predict(test_data_dense)
dnn_predictions = (dnn_predictions_prob > 0.5).astype(int).flatten()
```

```
153/153 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

```
dnn_submission_df = pd.DataFrame({
    'id': test_df['doc_id'],
    'judgement': dnn_predictions
})
```

```
# Resetting the index of the cleaned DataFrame
dnn_submission_df.reset_index(drop=True, inplace=True)
```

```
submission_csv_path = 'DNN_predictions.csv'  # Adjust the path as needed
dnn_submission_df.to_csv(submission_csv_path, index=False)
```

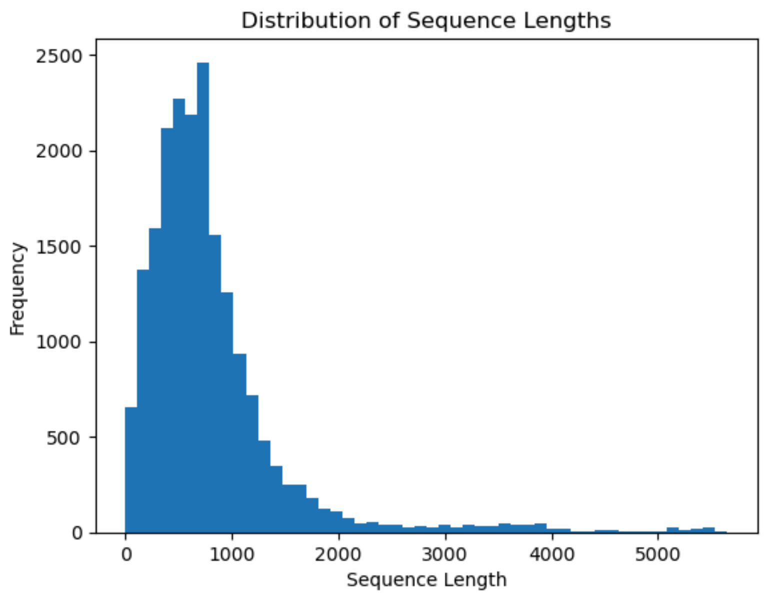
4. Complex NN Model

This project explored advanced neural network architectures, focusing on Recurrent Neural Networks (RNNs) like LSTM and GRU for text classification. These models were adjusted for different configurations to optimize their performance, specifically altering the number of layers and units. Our findings showed that while these complex models capture textual data effectively, they are sensitive to overfitting and require careful parameter tuning. Performance graphs demonstrated how adjustments in model parameters affected outcomes, underscoring the balance needed between complexity and generalization.

LSTM

```
# Initialize the tokenizer with a specified maximum number of words
max_words = 10000
tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(train_df['text'])

# Convert texts to sequences of integers
X_seq = tokenizer.texts_to_sequences(train_df['text'])
```

```
# Calculate the length of sequences
sequence_lengths = [len(x) for x in X_seq]

# Plot the distribution of sequence lengths
plt.hist(sequence_lengths, bins=50)
plt.xlabel('Sequence Length')
plt.ylabel('Frequency')
plt.title('Distribution of Sequence Lengths')
plt.show()

# Calculate statistics to help decide on maxlen
average_length = np.mean(sequence_lengths)
median_length = np.median(sequence_lengths)
max_length = np.max(sequence_lengths)

print(f"Average sequence length: {average_length}")
print(f"Median sequence length: {median_length}")
print(f"Max sequence length: {max_length}")
```



```
Average sequence length: 802.456220265209
Median sequence length: 662.0
Max sequence length: 5648
```

```
# Pad sequences to ensure uniform length
X_padded = pad_sequences(X_seq, maxlen=1000)

# splitting the data into training and testing sets
X_train_seq, X_test_seq, y_train_seq, y_test_seq = train_test_split(X_padded, y, test_size=0.2, random_state=42)


# Model parameters
embedding_dim = 100  # Size of the embedding vectors
maxlen = 1000

model = Sequential([
    Embedding(input_dim=max_words, output_dim=embedding_dim, input_length=maxlen),
    SpatialDropout1D(0.2),
    LSTM(16, dropout=0.2, recurrent_dropout=0.2),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model.summary()
```

```
C:\Users\suvet\anaconda3\Lib\site-packages\keras\src\layers\core\embedding.py:86: Use
  warnings.warn(
Model: "sequential_14"
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━
┃ Layer (type)                         ┃ Output Shape                 ┃        Param
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━
│ embedding (Embedding)                │ ?                            │  0 (unbuilt
├──────────────────────────────────────┼──────────────────────────────┼─────────────
│ spatial_dropout1d (SpatialDropout1D) │ ?                            │
├──────────────────────────────────────┼──────────────────────────────┼─────────────
│ lstm (LSTM)                          │ ?                            │  0 (unbuilt
├──────────────────────────────────────┼──────────────────────────────┼─────────────
│ dense_56 (Dense)                     │ ?                            │  0 (unbuilt
└──────────────────────────────────────┴──────────────────────────────┴─────────────
```

```
# Training the model
lstm_model = model.fit(X_train_seq, y_train_seq, epochs=5, batch_size=128, validation_split=0.2, verbose=1)
```

```
Epoch 1/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 48s 452ms/step - accuracy: 0.8162 - loss: 0.5306 - val_accuracy: 0.8422 - val_loss: 0.4287
Epoch 2/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 47s 472ms/step - accuracy: 0.8422 - loss: 0.4154 - val_accuracy: 0.8488 - val_loss: 0.4098
Epoch 3/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 46s 463ms/step - accuracy: 0.8622 - loss: 0.3393 - val_accuracy: 0.8479 - val_loss: 0.4228
Epoch 4/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 49s 494ms/step - accuracy: 0.8855 - loss: 0.2802 - val_accuracy: 0.8359 - val_loss: 0.4517
Epoch 5/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 58s 587ms/step - accuracy: 0.9116 - loss: 0.2287 - val_accuracy: 0.8359 - val_loss: 0.4751
```

```
# Evaluating the model on the test set
lstm_pred = model.predict(X_test_seq)
lstm_binary_pred = (lstm_pred > 0.5).astype(int)
```

```
124/124 ━━━━━━━━━━━━━━━━━━━━ 9s 73ms/step
```

```
# Preprocess the test data text as done with the training data
test_seq = tokenizer.texts_to_sequences(test_df['text'])
X_test_padded = pad_sequences(test_seq, maxlen=1000)  # Using the same maxlen as training

# Make predictions
predictions_prob = model.predict(X_test_padded)
binary_predictions = (predictions_prob > 0.5).astype(int)  # Convert probabilities to 0 or 1

# Create a DataFrame to save to CSV
lstm_df = pd.DataFrame({
    'id': test_df['doc_id'],
    'judgement': binary_predictions.flatten()  # Flatten the array if necessary
})

# Save the DataFrame to a CSV file
submission_file_path = 'lstm_predictions.csv'
lstm_df.to_csv(submission_file_path, index=False)

print(f"Predictions saved to {submission_file_path}")
```

```
153/153 ━━━━━━━━━━━━━━━━━━━━ 11s 72ms/step
Predictions saved to lstm_predictions.csv
```

GRU Model

```
model_gru = Sequential([
    Embedding(input_dim=max_words, output_dim=embedding_dim, input_length=maxlen),
    SpatialDropout1D(0.2),
    GRU(16, dropout=0.2, recurrent_dropout=0.2),
    Dense(1, activation='sigmoid')
])

model_gru.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model_gru.summary()
```

```
C:\Users\suvet\anaconda3\Lib\site-packages\keras\src\layers\core\embedding.py:86: Use
  warnings.warn(
Model: "sequential_15"
```

Layer (type)	Output Shape	Param
embedding_1 (Embedding)	?	0 (unbuilt
spatial_dropout1d_1 (SpatialDropout1D)	?	
gru (GRU)	?	0 (unbuilt
dense_57 (Dense)	?	0 (unbuilt

```
gru_model = model_gru.fit(X_train_seq, y_train_seq, epochs=5, batch_size=128, validation_split=0.2, verbose=1)
```

```
Epoch 1/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 49s 473ms/step - accuracy: 0.8069 - loss: nan - val_accuracy: 0.8422 - val_loss: nan
Epoch 2/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 50s 504ms/step - accuracy: 0.8398 - loss: nan - val_accuracy: 0.8422 - val_loss: nan
Epoch 3/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 54s 548ms/step - accuracy: 0.8448 - loss: nan - val_accuracy: 0.8422 - val_loss: nan
Epoch 4/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 53s 531ms/step - accuracy: 0.8387 - loss: nan - val_accuracy: 0.8422 - val_loss: nan
Epoch 5/5
99/99 ━━━━━━━━━━━━━━━━━━━━ 52s 530ms/step - accuracy: 0.8354 - loss: nan - val_accuracy: 0.8422 - val_loss: nan
```

```
# Evaluating the model on the test set
gru_pred = model_gru.predict(X_test_seq)
gru_binary_pred = (gru_pred > 0.5).astype(int)
```

```
124/124 ━━━━━━━━━━━━━━━━━━━━ 10s 80ms/step
```

```
# Make predictions
gru_predictions_prob = model_gru.predict(X_test_padded)
gru_binary_predictions = (gru_predictions_prob > 0.5).astype(int)  # Convert probabilities to 0 or 1

# Create a DataFrame to save to CSV
gru_df = pd.DataFrame({
    'id': test_df['doc_id'],
    'judgement': gru_binary_predictions.flatten()  # Flatten the array if necessary
})

# Save the DataFrame to a CSV file
submission_file_path = 'gru_predictions.csv'
gru_df.to_csv(submission_file_path, index=False)

print(f"Predictions saved to {submission_file_path}")
```

```
153/153 ━━━━━━━━━━━━━━━━━━━━ 13s 86ms/step
Predictions saved to gru_predictions.csv
```

Exploring different parameters

Unsupported cell type. Double-click to inspect/edit the content.

The results showed that both models perform well with 128 units, but the performance on kaggle test data did not show signifant difference in changing the parameters. Hence used the simple one to avoid complexity (16).

Results and Analysis

Overview of Model Performances

Throughout the Relevance Classification project, several models were tested ranging from a simple Logistic Regression to more complex neural network architectures such as LSTM and GRU. The table below summarizes their performance in training and testing phases, along with Kaggle competition scores.

Model	Training Accuracy	Testing Accuracy	Precision	Recall	F1 Score	Kaggle Score
Logistic Regression	87.19%	87.19%	83.22%	60.81%	64.09%	0.87278
3-Layer NN	97.02%	88.23%	78.34%	72.42%	74.81%	0.83756
Deep NN	99.08%	87.65%	76.52%	73.42%	74.81%	0.86349
LSTM	91.16%	83.63%	65.48%	58.91%	60.54%	0.84220
GRU	83.54%	84.64%	42.32%	50.00%	45.84%	0.87305

Note: Training accuracy reflects the highest observed during training with validation. Testing accuracy and other metrics are calculated on a separate test set.

Key Findings and Learnings

The project revealed several insights:

1. **Handling Imbalance**: Logistic Regression provided a strong baseline with reasonable accuracy and a high Kaggle score, indicating its robustness despite its simplicity. However, it struggled with the minority class, as evidenced by lower recall rates.
2. **Complexity vs. Performance**: While the 3-Layer and Deep Neural Networks showed promise with high training accuracies, they did not significantly outperform the Logistic Regression on the Kaggle platform. This suggests that additional complexity did not translate into practical performance gains, possibly due to overfitting.
3. **RNN Limitations**: The LSTM and GRU models were expected to perform well given their capability to process sequences and capture temporal dependencies. Although they excelled in handling the sequential nature of text, their real-world applicability was limited by higher computational costs and difficulty in tuning, which was reflected in their lower Kaggle scores.

Summary

Among the models tested, the **Logistic Regression** stands out as the most effective for this task due to its high performance, simplicity, and excellent generalization as seen in the Kaggle scores. It strikes a good balance between accuracy and complexity, making it suitable for quick deployments and interpretations. While the GRU model scored highest on Kaggle, several factors suggest it might not be the most effective model for practical applications. Firstly, it underperforms in essential metrics like precision, recall, and F1 score compared to simpler models, indicating issues with generalization across different data aspects. Secondly, GRUs are computationally expensive and complex, making them challenging to tune and prone to overfitting, which is evident from their lower performance in local testing despite high Kaggle scores. Additionally, the complexity of GRUs complicates their deployment and scalability in real-world applications. In contrast, simpler models like Logistic Regression offer easier interpretability, quicker deployment, and sufficient performance, making them more suitable for practical uses where robustness and efficiency are crucial. Hence, while GRU models are powerful for capturing temporal patterns in text, their practical effectiveness is limited by these factors.

Recommendations for Future Work

For future enhancements, the following strategies could be explored:

- **Ensemble Techniques**: Combining the predictions of multiple models could leverage their individual strengths and improve overall accuracy.
- **Advanced Text Processing**: Techniques such as word embeddings or more complex text augmentations could help capture deeper semantic meanings.
- **Hyperparameter Optimization**: Systematic tuning of parameters, especially for neural network architectures, could yield better results.

In conclusion, while complex models hold promise, especially for nuanced tasks, their deployment should be balanced against the practical benefits they offer. Exploring ensemble methods and advancing text processing techniques could further enhance model performance in future iterations of this project.

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2. Cho, K., Merrienboer, van, Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H. and Bengio, Y. (2014). Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. [online] arXiv.org. Available at: https://arxiv.org/abs/1406.1078.

3. Bishop, C.M., 1995. Neural networks for pattern recognition. Oxford university press.