Natural Language Processing

HomeWork 3

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Introduction

Explanations:

In this project, we have implemented a classification problem on sentiment analysis both on a document and text level on the Taaghche comments dataset. Taaghche is an Iranian online ebook marketplace featuring user comments on each book. Based on a dataset of scores and comments from users and other users' likes in the comments, we implemented a classifier for sentiment analysis of the text. We use both base models like LSTM or SVM and also Transfomer-based models.

In addition, we also wrote a crawler Taaghche website to crawl all the book pages and get the book information like name and author names so that we can have a list of NER for them.

Crawlers

Explanations:

In the first part, we implemented a crawler on the Taaghche website to get all the book info. The crawler downloads the pages of all books on the website by iterating on the "id" in the URL and saving the result as HTML. We then feed the results into an extractor module written using BeautifulSoup to extract the main parts of book info, including name, publication, author, translator, etc., and save them into CSV files for further use.

crawler.py

```python
base_url = "https://taaghche.com/book/"
def save_page(book_id, thread_exceptions):
    url = f"{base_url}{book_id}/"
    try:
        response = requests.get(url)

        if response.status_code == 404:
            print(book_id," : 404")
            return

        with open(os.path.join(output_dir, f"{book_id}.html"), 'w', encoding='utf-8') as f:
            print(f'Saving book with id: {book_id}')
            f.write(response.text)
    except Exception as e:
        print(e)
        thread_exceptions.append(book_id)
```

Explanations:

This is the main part of the crawler that sends requests to Taagche to get the book pages and save them into files. We also used Python threading features to make the whole process faster.

extactor.py

```python
    def extract_data_from_html(file_path):
    with open(file_path, 'r', encoding='utf-8') as file:
        soup = BeautifulSoup(file, 'html.parser')
        script_tag = soup.find('script', type='application/ld+json')
        if script_tag:
            try:
                json_data = json.loads(script_tag.string)
                book_name = json_data.get('name', '')
                authors = ' $ '.join([author['name'] for author in json_data.get('author', [])])
```

```
                translators = ' $ '.join(
                    [translator['name'] for translator in json_data.get('workExample', {}).get('translator', [])])
                publisher = json_data.get('workExample', {}).get('publisher', {}).get('name', '')
                data.append({
                    'name': book_name,
                    'author': authors,
                    'translator': translators,
                    'publisher': publisher
                })
            except json.JSONDecodeError:
                pass

    for x in os.listdir(input_dir):
    file_name = x
    file_path = os.path.join(input_dir, file_name)
    if os.path.isfile(file_path) and file_path.endswith('.html'):
        extract_data_from_html(file_path)
    if len(data) >= 10000:
        df = pd.DataFrame(data)
        output_file = os.path.join(output_dir, f'books_data_part_{part_number}.csv')
        df.to_csv(output_file, index=False, encoding='utf-8')
        data = []
        part_number += 1
        print("index put into files: ", file_name)

if data:
    df = pd.DataFrame(data)
    output_file = os.path.join(output_dir, f'books_data_part_{part_number}.csv')
    df.to_csv(output_file, index=False, encoding='utf-8')
    data = []
    part_number += 1
    print("index put into files: ", file_name)
    data = []
```

Explanations:

The main part of extracor.py is `extract_data_from_html` function. This function uses BS4 to find the JSON section that includes book data in the HTML and save data json data into a python dictionary. This data is then fed into a Pandas Dataframe and we save it into a csv file.

Document Classifier - Base Model

The base model is in `DocClassifier_Base.ipynb`. We investigate each segment in the following sections.

Note: Some parts of the explanations of code from here to the end of the document are written by partially ChatGPT to help us write clear and unambiguous descriptions.

Loading and Preparing Data

```
# Import the pandas library for data manipulation
import pandas as pd

# Load the CSV file into a pandas DataFrame
# The file 'taghche.csv' is located in the 'datasets/' directory
data = pd.read_csv('datasets/taghche.csv')

# Remove any duplicate rows in the DataFrame
data = data.drop_duplicates()

# Drop rows where the 'comment' or 'rate' columns have missing values (NaN)
data.dropna(subset=['comment', 'rate'], inplace=True)

# Print the first 5 rows of the cleaned DataFrame
```

```
print(data.head())


def label_sentiment(rate, positive_threshold, neutral_threshold):
"""
Labels sentiment based on rating thresholds.

Args:
- rate (int or float): The numerical rating to evaluate.
- positive_threshold (int or float): The minimum rating value that qualifies as 'positive'.
- neutral_threshold (int or float): The minimum rating value that qualifies as 'neutral'; ratings
    below this are considered 'negative'.

Returns:
- str: The sentiment label ('positive', 'neutral', or 'negative') based on the rating.
"""
# Check if the rating is greater than or equal to the positive threshold
if rate >= positive_threshold:
return 'positive'
# If the rating is not 'positive', check if it is greater than or equal to the neutral threshold
elif rate >= neutral_threshold:
return 'neutral'
# If the rating is neither 'positive' nor 'neutral', label the sentiment as 'negative'
else:
return 'negative'
```

Explanations:

At first, we load data using Pandas Library. We then define a fucntion to label the sentiment of each comment based on its rating and threshold. note that we have two thresholds, one for positive, and one for neutral comments. everything below neutral is considered negative.

Balancing Data

```
    # Function to prepare data and labels based on given thresholds
def prepare_data(positive_threshold, neutral_threshold):
    """
    Prepares the data and labels based on given thresholds for sentiment classification.

    Args:
    - positive_threshold (int or float): The minimum rating value that qualifies as 'positive'.
    - neutral_threshold (int or float): The minimum rating value that qualifies as 'neutral';
        ratings below this are considered 'negative'.

    Returns:
    - tuple: A tuple containing:
        - pandas.Series: The comments from the balanced dataset.
        - pandas.Series: The corresponding sentiment labels from the balanced dataset.
    """
    # Create a copy of the original data to avoid modifying it
    labeled_data = data.copy()

    # Apply the label_sentiment function to the 'rate' column to create a new 'sentiment' column
    labeled_data['sentiment'] = labeled_data['rate'].apply(lambda x: label_sentiment(x,
        positive_threshold, neutral_threshold))

    # Combine the 'comment' and 'sentiment' columns into a single DataFrame
    df = pd.concat([labeled_data['comment'], labeled_data['sentiment']], axis=1)

    # Separate the DataFrame into three classes based on sentiment
    positive = df[df['sentiment'] == 'positive']
    neutral = df[df['sentiment'] == 'neutral']
    negative = df[df['sentiment'] == 'negative']

    # Determine the size of the smallest class to balance the dataset
```

```python
    min_class_size = min(len(positive), len(neutral), len(negative))

    # Downsample each class to the size of the smallest class to ensure balance
    positive_downsampled = resample(positive, replace=False, n_samples=min_class_size, random_state
        =42)
    neutral_downsampled = resample(neutral, replace=False, n_samples=min_class_size, random_state
        =42)
    negative_downsampled = resample(negative, replace=False, n_samples=min_class_size, random_state
        =42)

    # Combine the downsampled classes into a single DataFrame
    df_balanced = pd.concat([positive_downsampled, neutral_downsampled, negative_downsampled])

    # Shuffle the balanced DataFrame to mix the rows
    df_balanced = df_balanced.sample(frac=1, random_state=42).reset_index(drop=True)

    # Return the 'comment' and 'sentiment' columns as separate pandas Series
    return df_balanced['comment'], df_balanced['sentiment']
```

Explanations:

- The function starts by creating a copy of the original dataset to avoid modifying it:

```python
        labeled_data = data.copy()
```

- It applies the `label_sentiment` function to the `rate` column to create a new `sentiment` column:

```python
        labeled_data['sentiment'] = labeled_data['rate'].apply(lambda x: label_sentiment(
            x, positive_threshold, neutral_threshold))
```

- The function then combines the `comment` and `sentiment` columns into a single DataFrame:

```python
        df = pd.concat([labeled_data['comment'], labeled_data['sentiment']], axis=1)
```

- It separates the DataFrame into three classes based on sentiment:

```python
        positive = df[df['sentiment'] == 'positive']
        neutral = df[df['sentiment'] == 'neutral']
        negative = df[df['sentiment'] == 'negative']
```

- The function determines the size of the smallest class to balance the dataset:

```python
        min_class_size = min(len(positive), len(neutral), len(negative))
```

- It down-samples each class to the size of the smallest class to ensure balance:

```python
        positive_downsampled = resample(positive, replace=False, n_samples=min_class_size
            , random_state=42)
        neutral_downsampled = resample(neutral, replace=False, n_samples=min_class_size,
            random_state=42)
        negative_downsampled = resample(negative, replace=False, n_samples=min_class_size
            , random_state=42)
```

- The function combines the down-sampled classes into a single DataFrame:

```python
        df_balanced = pd.concat([positive_downsampled, neutral_downsampled,
            negative_downsampled])
```

- It shuffles the balanced DataFrame to mix the rows:

```python
        df_balanced = df_balanced.sample(frac=1, random_state=42).reset_index(drop=True)
```

- Finally, the function returns the `comment` and `sentiment` columns as separate pandas Series:

```python
        return df_balanced['comment'], df_balanced['sentiment']
```

Preprocess

```python
    # Function to preprocess and normalize the text
def preprocess(text):
    """
    Preprocesses and normalizes text data by removing special characters,
    non-Persian characters, digits, and multiple spaces.

    Args:
    - text (str): Input text to be processed.

    Returns:
    - str: Processed text with normalized format.
    """
    # Replace one or more newline characters with a single newline
    pattern = re.compile(r"\n+")
    text = pattern.sub("\n", text)

    # Replace '\n' and '\n' with a single space
    text = re.sub(r'\\n|\n', ' ', text)

    # Remove non-Persian characters and digits
    text = re.sub(r'[^-\s]', ' ', text)

    # Replace one or more spaces with a single space
    pattern = re.compile(r" +")
    text = pattern.sub(" ", text)

    return text

# Apply the preprocess function to the 'comment' column in the DataFrame data
data['comment'] = data['comment'].apply(preprocess)
# Remove any duplicate rows in the DataFrame
data = data.drop_duplicates()

# Drop rows where the 'comment' or 'rate' columns have missing values (NaN)
data.dropna(subset=['comment', 'rate'], inplace=True)
```

Explanations:

- The function starts by replacing one or more newline characters with a single newline:

```python
        pattern = re.compile(r"\n+")
        text = pattern.sub("\n", text)
```

- Next, it replaces occurrences of the newline character (`\n`) and escaped newline (`\\n`) with a single space:

```python
        text = re.sub(r'\\n|\n', ' ', text)
```

- The function then removes all non-Persian characters and digits. This is done using a regular expression that matches any character not in the Persian alphabet (-) or whitespace:

```python
        text = re.sub(r'[^-\s]', ' ', text)
```

- Finally, it replaces one or more spaces with a single space to normalize the spacing in the text:

```python
        pattern = re.compile(r" +")
        text = pattern.sub(" ", text)
```

- The processed text is then returned by the function.

The following lines apply the `preprocess` function to the `comment` column of the DataFrame `data`:

```python
    # Apply the preprocess function to the 'comment' column in the DataFrame data
    data['comment'] = data['comment'].apply(preprocess)

    # Remove any duplicate rows in the DataFrame
    data = data.drop_duplicates()

    # Drop rows where the 'comment' or 'rate' columns have missing values (NaN)
    data.dropna(subset=['comment', 'rate'], inplace=True)
```

- The `preprocess` function is applied to each entry in the `comment` column to clean and normalize the text.
- After preprocessing, any duplicate rows in the DataFrame are removed using:

```python
        data = data.drop_duplicates()
```

- Finally, rows where the `comment` or `rate` columns have missing values (NaN) are dropped:

```python
        data.dropna(subset=['comment', 'rate'], inplace=True)
```

TF IDF - Logistic Regression

Next, we implement a TF-IDF vectorizer and use logistic regression for the task. Based on our study and the papers we investigated, logistic regression is the best base model for this task.

```python
    # Create a pipeline with TF-IDF and logistic regression
logReg_PL = Pipeline([
    ("tfidf", TfidfVectorizer()),
    ("logreg", LogisticRegression(max_iter=500, solver='newton-cg'))
])

# Define the parameter grid for GridSearchCV
param_grid = {
    'tfidf__ngram_range': [(1, 1), (1, 2), (1, 3)],
    'tfidf__max_features': [5000, 10000],
    'logreg__C': [0.01, 0.1, 1, 10]
}

# Custom GridSearchCV implementation to iterate over parameter grid
best_score = 0
best_params = None

# Thresholds to evaluate
rate_thresholds = [(1, 2), (1, 3), (1, 4), (2, 3), (2, 4), (3, 4)]

# Iterate over each pair of thresholds and perform GridSearchCV
for neutral_threshold, positive_threshold in tqdm(rate_thresholds):
    # Prepare the data using the specified thresholds
    X_prepared, y_prepared = prepare_data(positive_threshold, neutral_threshold)

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X_prepared, y_prepared, test_size=0.1,
        random_state=42)

    # Initialize GridSearchCV with the pipeline and parameter grid
    grid_search = GridSearchCV(logReg_PL, param_grid, cv=5, scoring='accuracy')

    # Fit GridSearchCV on the training data
    grid_search.fit(X_train, y_train)

    # Get the best score and parameters from GridSearchCV
    score = grid_search.best_score_

    # Update the best score and best parameters if the current score is better
```

```python
    if score > best_score:
        best_score = score
        best_params = grid_search.best_params_
        best_params['positive_threshold'] = positive_threshold
        best_params['neutral_threshold'] = neutral_threshold

# Print the best parameters found by GridSearchCV
print("Best parameters for TF-IDF model are:", best_params)

# Prepare the data using the best parameters found from GridSearchCV
X_prepared, y_prepared = prepare_data(best_params['positive_threshold'], best_params['neutral_threshold'])

# Split the prepared data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_prepared, y_prepared, test_size=0.1, random_state=42)

# Create a pipeline for the best Logistic Regression model with the best parameters
best_logReg_model = Pipeline([
    ("tfidf", TfidfVectorizer(ngram_range=best_params['tfidf__ngram_range'], max_features=best_params['tfidf__max_features'])),
    ("logreg", LogisticRegression(C=best_params['logreg__C'], max_iter=500, solver='newton-cg'))
])

# Fit the best Logistic Regression model on the training data
best_logReg_model.fit(X_train, y_train)

# Predict the labels on the test set using the best model
y_test_pred = best_logReg_model.predict(X_test)

# Calculate the accuracy score of the best model on the test set
test_accuracy = accuracy_score(y_test, y_test_pred)

# Print the test accuracy score of the best Logistic Regression model
print("Test accuracy of Logistic Regression model:", test_accuracy)
```

Explanations:

```python
        logReg_PL = Pipeline([
            ("tfidf", TfidfVectorizer()),
            ("logreg", LogisticRegression(max_iter=500, solver='newton-cg'))
        ])
```

- The pipeline `logReg_PL` is created with two steps:
  1. `TfidfVectorizer()`: Converts text data into TF-IDF features.
  2. `LogisticRegression()`: Applies logistic regression for classification, with a maximum of 500 iterations and the 'newton-cg' solver.

```python
        # Define the parameter grid for GridSearchCV
        param_grid = {
            'tfidf__ngram_range': [(1, 1), (1, 2), (1, 3)],
            'tfidf__max_features': [5000, 10000],
            'logreg__C': [0.01, 0.1, 1, 10]
        }
```

- The `param_grid` defines the hyperparameters for GridSearchCV to search over:
  - `tfidf__ngram_range`: N-gram ranges (unigrams, bigrams, trigrams).
  - `tfidf__max_features`: Maximum number of features (5000 or 10000).
  - `logreg__C`: Inverse of regularization strength (0.01, 0.1, 1, 10).

```python
        # Custom GridSearchCV implementation to iterate over parameter grid
        best_score = 0
        best_params = None

        # Thresholds to evaluate
        rate_thresholds = [(1, 2), (1, 3), (1, 4), (2, 3), (2, 4), (3, 4)]
```

- `best_score` and `best_params` are initialized to store the best score and corresponding parameters.
- `rate_thresholds` contains pairs of thresholds to evaluate for neutral and positive sentiment classification.

```python
        # Iterate over each pair of thresholds and perform GridSearchCV
        for neutral_threshold, positive_threshold in tqdm(rate_thresholds):
            # Prepare the data using the specified thresholds
            X_prepared, y_prepared = prepare_data(positive_threshold, neutral_threshold)

            # Split the data into training and testing sets
            X_train, X_test, y_train, y_test = train_test_split(X_prepared, y_prepared,
                test_size=0.1, random_state=42)

            # Initialize GridSearchCV with the pipeline and parameter grid
            grid_search = GridSearchCV(logReg_PL, param_grid, cv=5, scoring='accuracy')

            # Fit GridSearchCV on the training data
            grid_search.fit(X_train, y_train)

            # Get the best score and parameters from GridSearchCV
            score = grid_search.best_score_

            # Update the best score and best parameters if the current score is better
            if score > best_score:
                best_score = score
                best_params = grid_search.best_params_
                best_params['positive_threshold'] = positive_threshold
                best_params['neutral_threshold'] = neutral_threshold

        # Print the best parameters found by GridSearchCV
        print("Best parameters for TF-IDF model are:", best_params)
```

- The code iterates over each pair of thresholds in `rate_thresholds`.
- For each pair:
  1. `prepare_data` is called to prepare the dataset with the current thresholds.
  2. The data is split into training and testing sets using `train_test_split`.
  3. `GridSearchCV` is initialized with the pipeline and parameter grid, and fitted to the training data.
  4. The best score and parameters are retrieved from the grid search results.
  5. If the current score is better than the best score, update `best_score` and `best_params`.

```python
        # Prepare the data using the best parameters found from GridSearchCV
        X_prepared, y_prepared = prepare_data(best_params['positive_threshold'], best_params['
            neutral_threshold'])

        # Split the prepared data into training and testing sets
        X_train, X_test, y_train, y_test = train_test_split(X_prepared, y_prepared, test_size
            =0.1, random_state=42)

        # Create a pipeline for the best Logistic Regression model with the best parameters
        best_logReg_model = Pipeline([
            ("tfidf", TfidfVectorizer(ngram_range=best_params['tfidf__ngram_range'],
                max_features=best_params['tfidf__max_features'])),
```

```python
            ("logreg", LogisticRegression(C=best_params['logreg__C'], max_iter=500, solver='
                newton-cg'))
        ])

        # Fit the best Logistic Regression model on the training data
        best_logReg_model.fit(X_train, y_train)

        # Predict the labels on the test set using the best model
        y_test_pred = best_logReg_model.predict(X_test)

        # Calculate the accuracy score of the best model on the test set
        test_accuracy = accuracy_score(y_test, y_test_pred)

        # Print the test accuracy score of the best Logistic Regression model
        print("Test accuracy of Logistic Regression model:", test_accuracy)
```

- The data is prepared using the best parameters found by GridSearchCV.
- The prepared data is split into training and testing sets.
- A pipeline is created for the best logistic regression model with the best parameters.
- The model is fitted to the training data.
- Predictions are made on the test set.
- The accuracy of the model is calculated on the test set.
- The test accuracy is printed.

Evaluation Metrics

```python
def evaluate_model(y_true, y_pred, class_names):
    """
    Evaluates the performance of a classification model using various metrics and visualizations.

    Args:
    - y_true (array-like): True labels of the data.
    - y_pred (array-like): Predicted labels of the data.
    - class_names (list): List of class names in the same order as the confusion matrix.

    Returns:
    - pd.DataFrame: DataFrame containing the classification report.
    """
    # Generate and print the classification report
    report = classification_report(y_true, y_pred, target_names=class_names, output_dict=True)
    report_df = pd.DataFrame(report).transpose()
    print("Classification Report:\n", report_df)

    # Generate and display the confusion matrix as a heatmap
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(10, 7))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=
        class_names)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()

    # Calculate and print overall metrics: accuracy, precision, recall, and F1 score
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred, average='weighted')
    recall = recall_score(y_true, y_pred, average='weighted')
    f1 = f1_score(y_true, y_pred, average='weighted')
```

```python

    metrics = {
        "Accuracy": accuracy,
        "Precision": precision,
        "Recall": recall,
        "F1 Score": f1
    }

    print("\nOverall Metrics:")
    for metric, value in metrics.items():
        print(f"{metric}: {value:.4f}")

    return report_df

# Evaluate the model
report_df = evaluate_model(y_test, y_test_pred, ["Negative", "Neutral", "Positive"])
```

Explanations:

The `evaluate_model` function evaluates the performance of a classification model using various metrics and visualizations.

- The function takes three arguments:
  - `y_true`: The true labels of the data.
  - `y_pred`: The predicted labels of the data.
  - `class_names`: A list of class names in the same order as the confusion matrix.
- The function returns a pandas DataFrame containing the classification report.

Classification Report

- The classification report is generated using `classification_report` from scikit-learn and printed:

```python
    report = classification_report(y_true, y_pred, target_names=class_names, output_dict=True)
    report_df = pd.DataFrame(report).transpose()
    print("Classification Report:\n", report_df)
```

Confusion Matrix

- The confusion matrix is generated and displayed as a heatmap using seaborn:

```python
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(10, 7))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()
```

Overall Metrics

- The function calculates and prints overall metrics including accuracy, precision, recall, and F1 score:

```python
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred, average='weighted')
    recall = recall_score(y_true, y_pred, average='weighted')
    f1 = f1_score(y_true, y_pred, average='weighted')

    metrics = {
        "Accuracy": accuracy,
```

```python
        "Precision": precision,
        "Recall": recall,
        "F1 Score": f1
    }

    print("\nOverall Metrics:")
    for metric, value in metrics.items():
        print(f"{metric}: {value:.4f}")
```

- These metrics are printed in a readable format.

Function Return

- The function returns the classification report DataFrame:

```python
    return report_df
```

Model Evaluation

- The `evaluate_model` function is called to evaluate the model:

```python
    report_df = evaluate_model(y_test, y_test_pred, ["Negative", "Neutral", "Positive"])
```

0.0.1 Results and Interesting Notes

For the results section, we analyzed different approaches to the data to check whether we could get a better result. At first, we tested it without any special technique and got an accuracy of about 0.61 on the whole data. Another approach we tested is removing stopwords, but it seems stopwords are important for our task, and after removing them, our accuracy dropped.

Another approach was to use a formalizer to change the text into a formal Persian text. We used a formalizer based on T5 using models from previous semesters, but we got worse results. It is predictable, though, because some informal Persian slang can significantly change the sentiment of a sentence, and they lose their meaning even from a human perspective when we formalize them.

We also used another approach for formalization: giving the Persian text to Google Translate to translate it into English and then back to Persian. It didn't work fine either.

One of the things we find in papers that seem good for this task is a lemmatizer. We tried to use it on our data, but unfortunately, Hazm was very slow on our 70K database, so we could not use this technique for our task.

It seems our result is good enough, though. As it is a multiclass classification and the best results are for ParsBERT on a significantly larger database than ours that is near 70%, it seems our accuracy of 61% is good enough.

The code used for formalization based on T5 is as follows:

```python
  from transformers import (T5ForConditionalGeneration, AutoTokenizer, pipeline)
  import torch

  model = T5ForConditionalGeneration.from_pretrained('parsi-ai-nlpclass/PersianTextFormalizer')
  tokenizer = AutoTokenizer.from_pretrained('parsi-ai-nlpclass/PersianTextFormalizer')

  pipe = pipeline(task='text2text-generation', model=model, tokenizer=tokenizer)
  def formalizer(text):
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    model.to(device)
    formalized = ""
    for line in text.splitlines():

        inputs = tokenizer.encode("informal: " + line, return_tensors='pt', max_length=128,
            truncation=True, padding='max_length')
        inputs = inputs.to(device)

        outputs = model.generate(inputs, max_length=128, num_beams=4)
```

```
        formalized = formalized + tokenizer.decode(outputs[0], skip_special_tokens=True) + " "
    return formalized

data['comment'] = data['comment'].apply(formalizer)
```

The code used for formalization based on Google Translate is as follows:

```
import googletrans as gt
translator = gt.Translator()

def translation(text):
    en_translated = translator.translate(text, 'en', 'fa')
    fa_translated = translator.translate(en_translated.text, 'fa', 'en')
    return fa_translated.text

data['comment'] = data['comment'].apply(translation)
```

Figure 1: Results of running Logistic Regression on 10000 rows of dataset - With Formalization

```
Best parameters for TF-IDF model are: {'logreg__C': 1, 'tfidf__max_features': 10000, 'tfidf__ngram_range': (1, 2), 'positive_threshold': 4,
'neutral_threshold': 2}
Test accuracy of Logistic Regression model:  0.5208333333333334
              precision    recall  f1-score   support

    negative       0.48      0.49      0.49       117
     neutral       0.56      0.55      0.55       137
    positive       0.52      0.52      0.52       130

    accuracy                           0.52       384
   macro avg       0.52      0.52      0.52       384
weighted avg       0.52      0.52      0.52       384
```

Figure 2: Results of running Logistic Regression on 10000 rows of dataset - Without Formalization

```
Best parameters for TF-IDF model are: {'logreg__C': 0.1, 'tfidf__max_features': 5000, 'tfidf__ngram_range': (1, 3), 'positive_threshold': 4,
'neutral_threshold': 2}
Test accuracy of Logistic Regression model:  0.5416666666666666
              precision    recall  f1-score   support

    negative       0.47      0.56      0.52       117
     neutral       0.54      0.50      0.52       137
    positive       0.62      0.57      0.59       130

    accuracy                           0.54       384
   macro avg       0.55      0.54      0.54       384
weighted avg       0.55      0.54      0.54       384
```

Figure 3: Results of running Logistic Regression on 10000 rows of dataset - without stopwords

```
Best parameters for TF-IDF model are: {'logreg__C': 0.1, 'tfidf__max_features': 10000, 'tfidf__ngram_range': (1, 1), 'positive_threshold':
4, 'neutral_threshold': 2}
Test accuracy of Logistic Regression model:  0.4713541666666667
              precision    recall  f1-score   support

    negative       0.40      0.60      0.48       117
     neutral       0.47      0.42      0.44       137
    positive       0.63      0.41      0.50       130

    accuracy                           0.47       384
   macro avg       0.50      0.48      0.47       384
weighted avg       0.50      0.47      0.47       384
```

+ Code + Markdown

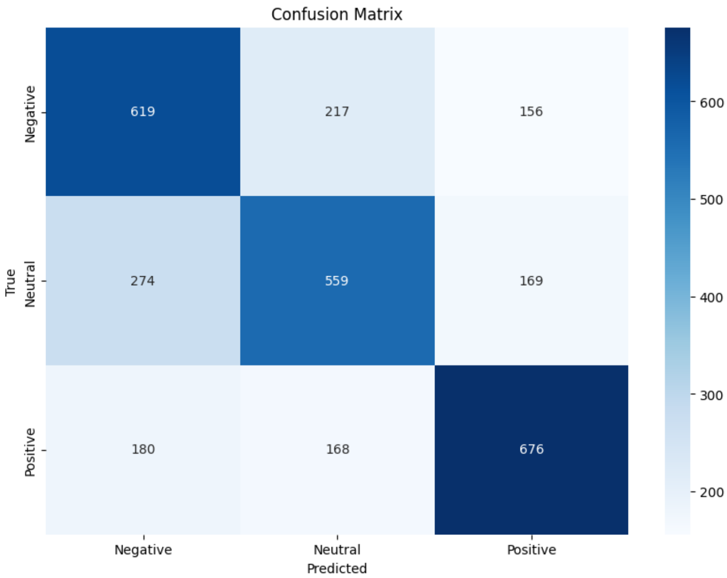
Figure 4: Results of running Logistic Regression on 70000 rows of dataset - without stopwords

```
Best parameters for TF-IDF model are: {'logreg__C': 0.1, 'tfidf__max_features': 10000, 'tfidf__ngram_range': (1, 2), 'positive_threshold': 4, 'neutral_threshold': 2}
Test accuracy of Logistic Regression model:  0.5606361829025845
              precision    recall  f1-score   support

    negative       0.53      0.59      0.56      1020
     neutral       0.52      0.52      0.52       987
    positive       0.65      0.58      0.61      1011

    accuracy                           0.56      3018
   macro avg       0.56      0.56      0.56      3018
weighted avg       0.57      0.56      0.56      3018
```

And the Final Result is as follows:

```
  Classification Report:
  precision    recall  f1-score     support
Negative       0.576887  0.623992  0.599516   992.000000
Neutral        0.592161  0.557884  0.574512  1002.000000
Positive       0.675325  0.660156  0.667654  1024.000000
accuracy       0.614314  0.614314  0.614314     0.614314
macro avg      0.614791  0.614011  0.613894  3018.000000
weighted avg   0.615358  0.614314  0.614333  3018.000000
```

Figure 5: Confusion Matrix




```
Overall Metrics:
Accuracy: 0.6143
Precision: 0.6154
Recall: 0.6143
F1 Score: 0.6143
```

Document Classifier - Transfomer Model

The Transformer model is in `DocClassifier_transformer.ipynb`. We investigate each segment in the following sections.

The first part of code is simply loading data and doing simple stuff like droping missing values.

```
# Import required packages
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score
from sklearn.utils import shuffle
import hazm
from cleantext import clean
import plotly.express as px
import plotly.graph_objects as go
from tqdm.notebook import tqdm
import os
import re
import json
import copy
import collections
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score,
    precision_score, recall_score, f1_score
from transformers import BertConfig, BertTokenizer
from transformers import TFBertModel, TFBertForSequenceClassification
from transformers import glue_convert_examples_to_features
import tensorflow as tf

# Import the pandas library for data manipulation and analysis
import pandas as pd
```

```
# Load the CSV file into a DataFrame
data = pd.read_csv('/kaggle/input/taghchemain/taghche.csv')

# Select only the 'comment' and 'rate' columns for further analysis
data = data[['comment', 'rate']]

# Display the first 10 rows of the DataFrame to get an overview of the data
data.head(10)

# Print the general information about the DataFrame
print('data information')
print(data.info(), '\n')

# Print the statistics of missing values in the DataFrame
print('missing values stats')
print(data.isnull().sum(), '\n')

# Print the first 5 rows where the 'rate' column has missing values
print('some missing values')
print(data[data['rate'].isnull()].iloc[:5], '\n')


# Handle conflicts in the dataset structure
# For simplicity, remove invalid data combinations

# Replace ratings that are 6 or higher with None
# This assumes that valid ratings should be between 0 and 5
data['rate'] = data['rate'].apply(lambda r: r if r < 6 else None)

# Drop rows where the 'rate' column has missing values
data = data.dropna(subset=['rate'])

# Drop rows where the 'comment' column has missing values
data = data.dropna(subset=['comment'])

# Remove duplicate comments, keeping only the first occurrence
data = data.drop_duplicates(subset=['comment'], keep='first')

# Reset the index of the DataFrame
data = data.reset_index(drop=True)

# Print the general information about the DataFrame
print('data information')
print(data.info(), '\n')

# Print the statistics of missing values in the DataFrame
print('missing values stats')
print(data.isnull().sum(), '\n')

# Print the first 5 rows where the 'rate' column has missing values
print('some missing values')
print(data[data['rate'].isnull()].iloc[:5], '\n')
```

Preprocess

Explanations:

Preprocessing

The comments have different lengths based on words. Detecting the most normal range could help us find the maximum length of the sequences for the preprocessing step. On the other hand, we suppose that the minimum word combination for having a meaningful phrase for our learning process is 1.

```
# Calculate the length of comments based on the number of words
# This uses hazm's word_tokenize function to split comments into words and then counts
```

```
    the number of words
data['comment_len_by_words'] = data['comment'].apply(lambda t: len(hazm.word_tokenize(t)))

# Determine the minimum and maximum comment lengths
# This provides insights into the range of comment lengths in the dataset
min_max_len = data["comment_len_by_words"].min(), data["comment_len_by_words"].max()

# Print the minimum and maximum comment lengths
# This helps understand the variation in comment lengths
print(f'Min: {min_max_len[0]} \tMax: {min_max_len[1]}')
```

First, the code calculates the length of each comment based on the number of words. It uses the `word_tokenize` function from the `hazm` library to split comments into words. The minimum and maximum lengths of the comments are then determined and printed to understand the variation in comment lengths.

```
def data_gl_than(data, less_than=100.0, greater_than=0.0, col='comment_len_by_words'):
    """
    Calculate the percentage of comments with lengths greater than 'greater_than' and
        less than or equal to 'less_than'.

    Parameters:
    data (DataFrame): The DataFrame containing the data.
    less_than (float): The upper bound for the comment length.
    greater_than (float): The lower bound for the comment length.
    col (str): The column name that contains the comment lengths.

    Returns:
    None
    """
    # Extract the lengths of the comments from the specified column
    data_length = data[col].values

    # Count the number of comments that have a length greater than 'greater_than' and
        less than or equal to 'less_than'
    data_glt = sum([1 for length in data_length if greater_than < length <= less_than])

    # Calculate the percentage of such comments relative to the total number of comments
    data_glt_rate = (data_glt / len(data_length)) * 100

    # Print the result
    print(f'Texts with word length of greater than {greater_than} and less than {
        less_than} includes {data_glt_rate:.2f}% of the whole!')

# Call the function with specific bounds
data_gl_than(data, 256, 0)
```

The function `data_gl_than` calculates the percentage of comments with lengths greater than a specified lower bound and less than or equal to an upper bound. This is used to analyze the distribution of comment lengths within a specified range.

```
# Define minimum and maximum limits for comment length
minlim, maxlim = 0, 256

# Remove comments with a length of fewer than three words or more than 256 words
data['comment_len_by_words'] = data['comment_len_by_words'].apply(lambda len_t: len_t if
     minlim < len_t <= maxlim else None)

# Drop rows where the 'comment_len_by_words' column has missing values
data = data.dropna(subset=['comment_len_by_words'])

# Reset the index of the DataFrame
data = data.reset_index(drop=True)
```

Comments with a length of fewer than three words or more than 256 words are removed. The DataFrame is then updated to drop rows with missing values in the `comment_len_by_words` column, and the index is reset.

```python
# This initializes an empty figure to which we will add traces
fig = go.Figure()

# Add a histogram trace to the figure
# The x-axis data is taken from the 'comment_len_by_words' column
fig.add_trace(go.Histogram(
    x=data['comment_len_by_words'],
    marker=dict(
        color='rgb(0, 123, 255)',  # Set bar color to a blue shade
        line=dict(
            color='rgb(8, 48, 107)',  # Set bar border color to a darker blue
            width=1.5,  # Set the width of the bar borders
        ),
    ),
    opacity=0.75,  # Set the opacity of the bars for a slight transparency effect
))

# Update the layout of the figure
# This includes setting titles for the plot and axes, and customizing the appearance
fig.update_layout(
    title=dict(
        text='Distribution of Word Counts Within Comments',  # Set the title of the plot
        font=dict(size=24),  # Set the font size of the title
        x=0.5,  # Center the title on the plot
    ),
    xaxis=dict(
        title=dict(
            text='Word Count',  # Set the x-axis title
            font=dict(size=18),  # Set the font size of the x-axis title
        ),
        tickfont=dict(size=14),  # Set the font size of the x-axis tick labels
    ),
    yaxis=dict(
        title=dict(
            text='Frequency',  # Set the y-axis title
            font=dict(size=18),  # Set the font size of the y-axis title
        ),
        tickfont=dict(size=14),  # Set the font size of the y-axis tick labels
    ),
    bargap=0.2,  # Set the gap between individual bars
    bargroupgap=0.2,  # Set the gap between groups of bars
    template='plotly_white'  # Use the 'plotly_white' template for a cleaner look
)

# Show the figure
fig.show()
```

A histogram is created to visualize the distribution of word counts within comments. The layout of the figure is customized, including setting titles for the plot and axes, and using the `plotly_white` template for a cleaner look. The figure is then displayed.

```python
# Extract unique 'rate' values from the 'data' DataFrame, sort them, and convert them
    into a list
unique_rates = list(sorted(data['rate'].unique()))

# Print the number of unique rates and the list of unique rates
print(f'We have {len(unique_rates)} unique rates: {unique_rates}')


# Create a figure for the plot
fig = go.Figure()

# Group the data by 'rate' and count the occurrences of each rate
groupby_rate = data.groupby('rate')['rate'].count()

# Add a bar trace to the figure
```

```
    fig.add_trace(go.Bar(
        x=list(sorted(groupby_rate.index)),  # Set the x-axis data to the sorted unique
            rates
        y=groupby_rate.tolist(),  # Set the y-axis data to the frequency counts of each rate
        text=groupby_rate.tolist(),  # Display the frequency counts as text on the bars
        textposition='auto',  # Automatically position the text within the bars
        marker=dict(
            color='rgb(255, 123, 0)',  # Set bar color to an orange shade
            line=dict(
                color='rgb(107, 48, 8)',  # Set bar border color to a darker orange/brown
                width=1.5,  # Set the width of the bar borders
            ),
        ),
        opacity=0.75  # Set the opacity of the bars for a slight transparency effect
    ))

    # Update the layout of the figure
    # This includes titles for the plot and axes, as well as setting bar gaps
    fig.update_layout(
        title=dict(
            text='Distribution of Rates Within Comments',  # Set the title of the plot
            font=dict(size=24),  # Set title font size
            x=0.5,  # Center the title
        ),
        xaxis=dict(
            title=dict(
                text='Rate',  # Set the x-axis title
                font=dict(size=18),  # Set x-axis title font size
            ),
            tickfont=dict(size=14),  # Set x-axis tick font size
        ),
        yaxis=dict(
            title=dict(
                text='Frequency',  # Set the y-axis title
                font=dict(size=18),  # Set y-axis title font size
            ),
            tickfont=dict(size=14),  # Set y-axis tick font size
        ),
        bargap=0.2,  # Set the gap between individual bars
        bargroupgap=0.2,  # Set the gap between groups of bars
        template='plotly_white'  # Set the plot template for a cleaner look
    )

    # Show the figure
    fig.show()
```

A bar chart is created to visualize the distribution of rates within comments. The layout of the figure is customized, including setting titles for the plot and axes, and using the `plotly_white` template for a cleaner look. The figure is then displayed.

```
    # Function to label the sentiment based on rating thresholds
    def label_sentiment(rate, positive_threshold, neutral_threshold):
        """
        Labels sentiment based on rating thresholds.

        Args:
        - rate (int or float): The numerical rating to evaluate.
        - positive_threshold (int or float): The minimum rating value that qualifies as '
            positive'.
        - neutral_threshold (int or float): The minimum rating value that qualifies as '
            neutral'; ratings below this are considered 'negative'.

        Returns:
        - str: The sentiment label ('positive', 'neutral', or 'negative') based on the
            rating.
        """
        # Check if the rating is greater than or equal to the positive threshold
```

```
        if rate >= positive_threshold:
            return 'positive'
        # If the rating is not 'positive', check if it is greater than or equal to the neutral threshold
        elif rate >= neutral_threshold:
            return 'neutral'
        # If the rating is neither 'positive' nor 'neutral', label the sentiment as 'negative'
        else:
            return 'negative'

    # Apply the label_sentiment function to the 'rate' column to create a new 'label' column
    data['label'] = data['rate'].apply(lambda t: label_sentiment(t, 4.0, 2.0))
    # Print unique labels
    labels = list(sorted(data['label'].unique()))
    # Display the first 5 rows of the DataFrame to get an overview of the data
    data.head()
```

The function `label_sentiment` is defined to label the sentiment based on rating thresholds. Ratings are classified as *positive*, *neutral*, or *negative* based on specified thresholds. The function is applied to the `rate` column to create a new `label` column.

```
    def preprocess(text):
        """
        Preprocess and normalize the given text string by performing several transformations.

        Args:
        text (str): The text string to be preprocessed.

        Returns:
        str: The preprocessed and normalized text string.
        """
        # Define a regular expression pattern that matches one or more newline characters
        pattern = re.compile(r"\n+")

        # Replace multiple newlines with a single newline
        text = pattern.sub("\n", text)

        # Remove special characters and replace newline characters with spaces
        text = re.sub(r'\\n|\n', ' ', text)

        # Remove non-Persian characters and digits
        text = re.sub(r'[^-\s\u200c]', ' ', text)

        # Define a regular expression pattern that matches one or more spaces
        pattern = re.compile(r" +")

        # Replace multiple spaces with a single space
        text = pattern.sub(" ", text)

        return text

    # Apply the preprocess function to the 'comment' column of the DataFrame
    data['cleaned_comment'] = data['comment'].apply(preprocess)

    # Remove duplicate rows from the DataFrame
    data = data.drop_duplicates()

    # Drop rows with empty or NaN values in the 'comment' or 'rate' columns
    data.dropna(subset=['comment', 'rate'], inplace=True)

    # Display the first 10 rows of the cleaned DataFrame
    data.head(10)
```

The function `preprocess` is defined to preprocess and normalize the text. It performs several transformations, including replacing multiple newlines with a single newline, removing special characters, and removing non-Persian characters and digits. The function is applied to the `comment` column. Duplicate rows are removed from the DataFrame, and rows with empty or NaN values in the `comment` or `rate` columns are dropped.

```
        # Create a figure for the plot
        fig = go.Figure()

        # Group the data by 'label' and count the occurrences of each label
        groupby_label = data.groupby('label')['label'].count()

        # Add a bar trace to the figure
        fig.add_trace(go.Bar(
            x=list(sorted(groupby_label.index)),  # Set the x-axis data to the sorted unique
                labels
            y=groupby_label.tolist(),  # Set the y-axis data to the frequency counts of each
                label
            text=groupby_label.tolist(),  # Display the frequency counts as text on the bars
            textposition='auto',  # Automatically position the text within the bars
            marker=dict(
                color='rgb(0, 123, 255)',  # Set bar color to a blue shade
                line=dict(
                    color='rgb(8, 48, 107)',  # Set bar border color to a darker blue
                    width=1.5,  # Set the width of the bar borders
                ),
            ),
            opacity=0.75  # Set the opacity of the bars for a slight transparency effect
        ))

        # Update the layout of the figure
        fig.update_layout(
            title=dict(
                text='Distribution of Labels Within Comments',  # Set the title of the plot
                font=dict(size=24),  # Set title font size
                x=0.5,  # Center the title
            ),
            xaxis=dict(
                title=dict(
                    text='Label',  # Set the x-axis title
                    font=dict(size=18),  # Set x-axis title font size
                ),
                tickfont=dict(size=14),  # Set x-axis tick font size
            ),
            yaxis=dict(
                title=dict(
                    text='Frequency',  # Set the y-axis title
                    font=dict(size=18),  # Set y-axis title font size
                ),
                tickfont=dict(size=14),  # Set y-axis tick font size
            ),
            bargap=0.2,  # Set the gap between individual bars
            bargroupgap=0.2,  # Set the gap between groups of bars
            template='plotly_white'  # Set the plot template for a cleaner look
        )

        # Show the figure
        fig.show()
```

The code creates a bar chart to visualize the distribution of sentiment labels within the comments. The layout is customized, and the plot is displayed.

Balancing the Labels via Resampling

```
        # Filter data into separate DataFrames based on 'label' values
        negative_data = data[data['label'] == 'negative']
        positive_data = data[data['label'] == 'positive']
        neutral_data = data[data['label'] == 'neutral']

```

```
        # Determine the smallest length among the three filtered DataFrames
        cutting_point = min(len(negative_data), len(positive_data), len(neutral_data))

        # If the cutting_point is less than or equal to the length of negative_data, sample
            down negative_data
        if cutting_point <= len(negative_data):
            negative_data = negative_data.sample(n=cutting_point).reset_index(drop=True)

        # If the cutting_point is less than or equal to the length of positive_data, sample
            down positive_data
        if cutting_point <= len(positive_data):
            positive_data = positive_data.sample(n=cutting_point).reset_index(drop=True)

        # If the cutting_point is less than or equal to the length of neutral_data, sample
            down neutral_data
        if cutting_point <= len(neutral_data):
            neutral_data = neutral_data.sample(n=cutting_point).reset_index(drop=True)

        # Concatenate the sampled DataFrames back into a single DataFrame
        new_data = pd.concat([negative_data, positive_data, neutral_data])

        # Shuffle the rows of the new DataFrame
        new_data = new_data.sample(frac=1).reset_index(drop=True)

        # Display summary information about the new DataFrame
        new_data.info()
```

The code balances the dataset by resampling each sentiment label to have an equal number of samples. This is done by determining the smallest length among the sentiment labels and sampling down the other labels to match this length. The DataFrames are concatenated, and the rows are shuffled.

Distribution of Labels Within Comments After Balancing

```
        # Create a figure for the plot
        fig = go.Figure()

        # Group the data by 'label' and count the occurrences of each label
        groupby_label = new_data.groupby('label')['label'].count()

        # Add a bar trace to the figure
        fig.add_trace(go.Bar(
            x=list(sorted(groupby_label.index)),  # Set the x-axis data to the sorted unique
                labels
            y=groupby_label.tolist(),  # Set the y-axis data to the frequency counts of each
                label
            text=groupby_label.tolist(),  # Display the frequency counts as text on the bars
            textposition='auto',  # Automatically position the text within the bars
            marker=dict(
                color='rgb(0, 123, 255)',  # Set bar color to a blue shade
                line=dict(
                    color='rgb(8, 48, 107)',  # Set bar border color to a darker blue
                    width=1.5,  # Set the width of the bar borders
                ),
            ),
            opacity=0.75  # Set the opacity of the bars for a slight transparency effect
        ))

        # Update the layout of the figure
        fig.update_layout(
            title=dict(
                text='Distribution of Labels Within Comments After Balancing Labels via
                    Resampling',  # Set the title of the plot
                font=dict(size=24),  # Set title font size
                x=0.5,  # Center the title
            ),
            xaxis=dict(
                title=dict(
```

```
                    text='Label',  # Set the x-axis title
                    font=dict(size=18),  # Set x-axis title font size
                ),
                tickfont=dict(size=14),  # Set x-axis tick font size
            ),
            yaxis=dict(
                title=dict(
                    text='Frequency',  # Set the y-axis title
                    font=dict(size=18),  # Set y-axis title font size
                ),
                tickfont=dict(size=14),  # Set y-axis tick font size
            ),
            bargap=0.2,  # Set the gap between individual bars
            bargroupgap=0.2,  # Set the gap between groups of bars
            template='plotly_white'  # Set the plot template for a cleaner look
        )

        # Show the figure
        fig.show()
```

A second bar chart is created to visualize the distribution of sentiment labels within the comments after balancing the dataset via resampling. The layout is customized, and the plot is displayed.

Training Configuration

Explanations:

Mapping Labels to Numerical IDs and Data Splitting

```
    # Map labels to numerical ids and add a new column 'label_id' to new_data
    new_data['label_id'] = new_data['label'].apply(lambda t: labels.index(t))

    # Split new_data into train and test sets (80% train, 20% test), stratified by 'label'
    train, test = train_test_split(new_data, test_size=0.2, random_state=1, stratify=
        new_data['label'])

    # Further split test set into test and validation sets (50% test, 50% validation),
        stratified by 'label'
    test, valid = train_test_split(test, test_size=0.5, random_state=1, stratify=test['label
        '])

    # Reset index for train, validation, and test sets to ensure continuous integer indices
    train = train.reset_index(drop=True)
    valid = valid.reset_index(drop=True)
    test = test.reset_index(drop=True)

    # Extract comments and label_ids for train, validation, and test sets
    x_train, y_train = train['comment'].values.tolist(), train['label_id'].values.tolist()
    x_valid, y_valid = valid['comment'].values.tolist(), valid['label_id'].values.tolist()
    x_test, y_test = test['comment'].values.tolist(), test['label_id'].values.tolist()

    # Print shapes of train, validation, and test sets to verify sizes
    print(train.shape)
    print(valid.shape)
    print(test.shape)
```

The code maps the text labels to numerical IDs and adds a new column 'label_id' to the DataFrame. The data is then split into train (80%), test (20%), and validation (50% of the test set) sets, ensuring stratification by label to maintain the distribution of classes in each subset. The indices of each set are reset, and the comments and label IDs are extracted for each set. Finally, the shapes of the train, validation, and test sets are printed to verify the sizes.

Configuration Parameters for BERT Model Training

```python
# General configuration parameters
MAX_LEN = 128                # Maximum sequence length
TRAIN_BATCH_SIZE = 64        # Batch size for training
VALID_BATCH_SIZE = 64        # Batch size for validation
TEST_BATCH_SIZE = 64         # Batch size for testing

EPOCHS = 3                   # Number of epochs for training
EVERY_EPOCH = 1000          # Number of steps to print progress during each epoch
LEARNING_RATE = 2e-5         # Learning rate for the optimizer
CLIP = 0.0                   # Gradient clipping threshold

MODEL_NAME_OR_PATH = 'HooshvareLab/bert-fa-base-uncased'  # Pre-trained model name or
    path
OUTPUT_PATH = '/content/bert-fa-base-uncased-sentiment-taaghceh/pytorch_model.bin'  #
    Path to save the trained model

# Create the directory to save the trained model if it does not exist
os.makedirs(os.path.dirname(OUTPUT_PATH), exist_ok=True)
```

The general configuration parameters for training the BERT model are defined. This includes the maximum sequence length, batch sizes for training, validation, and testing, the number of epochs, learning rate, gradient clipping threshold, the pre-trained model path, and the path to save the trained model. The output directory is created if it does not already exist.

Label Mapping Dictionaries and BERT Configuration

```python
# Create a dictionary mapping labels to numerical ids
label2id = {label: i for i, label in enumerate(labels)}

# Create a dictionary mapping numerical ids back to labels
id2label = {v: k for k, v in label2id.items()}

# Print label2id dictionary
print(f'label2id: {label2id}')

# Print id2label dictionary
print(f'id2label: {id2label}')

# Initialize a BERT tokenizer using the pre-trained model specified in
    MODEL_NAME_OR_PATH
tokenizer = BertTokenizer.from_pretrained(MODEL_NAME_OR_PATH, force_download=True)

# Create a BERT configuration object using the pre-trained model and additional custom
    settings
config = BertConfig.from_pretrained(
    MODEL_NAME_OR_PATH,  # Specify the pre-trained model name or path
    **{                  # Additional custom settings passed as keyword arguments
        'label2id': label2id,  # Mapping from labels to numerical ids
        'id2label': id2label   # Mapping from numerical ids back to labels
    })

# Print the configuration details in JSON format
print(config.to_json_string())
```

Label mapping dictionaries are created to map labels to numerical IDs and vice versa. These mappings are printed for verification. A BERT tokenizer and configuration object are initialized using the specified pre-trained model path and the custom label mappings. The configuration details are printed in JSON format.

Explanations:

Preparing Datasets for BERT Model Training

```python
import tensorflow as tf
import numpy as np
from tqdm import tqdm
from transformers import glue_convert_examples_to_features

class InputExample:
    """ A single example for simple sequence classification. """

    def __init__(self, guid, text_a, text_b=None, label=None):
        """ Constructs an InputExample. """
        self.guid = guid
        self.text_a = text_a
        self.text_b = text_b
        self.label = label

def make_examples(tokenizer, x, y=None, maxlen=128, output_mode="classification", is_tf_dataset=True):
    """
    Converts input texts and labels into examples and features suitable for BERT model training.

    Args:
    tokenizer (transformers.PreTrainedTokenizer): Tokenizer object for tokenizing input texts.
    x (list): List of input texts or tuples of input texts (for sequence classification).
    y (list, optional): List of labels corresponding to input texts. Default is None.
    maxlen (int, optional): Maximum sequence length for input texts. Default is 128.
    output_mode (str, optional): Output mode for the task (e.g., "classification"). Default is "classification".
    is_tf_dataset (bool, optional): Whether to return a TensorFlow dataset or numpy arrays. Default is True.

    Returns:
    tf.data.Dataset or tuple of numpy arrays: Depending on is_tf_dataset, returns either a TensorFlow dataset
                                              or a tuple of numpy arrays containing input_ids, attention_masks,
                                              token_type_ids, and labels.
    list: List of features converted from InputExamples.
    """
    examples = []
    y = y if isinstance(y, list) or isinstance(y, np.ndarray) else [None] * len(x)

    # Create InputExamples from input texts and labels
    for i, (_x, _y) in tqdm(enumerate(zip(x, y)), position=0, total=len(x)):
        guid = "%s" % i
        label = int(_y)

        if isinstance(_x, str):
            text_a = _x
            text_b = None
        else:
            assert len(_x) == 2
            text_a = _x[0]
            text_b = _x[1]

        examples.append(InputExample(guid=guid, text_a=text_a, text_b=text_b, label=label))

```

```
        # Convert InputExamples to features using glue_convert_examples_to_features function
        features = glue_convert_examples_to_features(
            examples,
            tokenizer,
            maxlen,
            output_mode=output_mode,
            label_list=list(np.unique(y)))

        all_input_ids = []
        all_attention_masks = []
        all_token_type_ids = []
        all_labels = []

        # Process features into input arrays for TensorFlow dataset or numpy arrays
        for f in tqdm(features, position=0, total=len(examples)):
            if is_tf_dataset:
                all_input_ids.append(tf.constant(f.input_ids))
                all_attention_masks.append(tf.constant(f.attention_mask))
                all_token_type_ids.append(tf.constant(f.token_type_ids))
                all_labels.append(tf.constant(f.label))
            else:
                all_input_ids.append(f.input_ids)
                all_attention_masks.append(f.attention_mask)
                all_token_type_ids.append(f.token_type_ids)
                all_labels.append(f.label)

        if is_tf_dataset:
            # Create TensorFlow dataset from input arrays
            dataset = tf.data.Dataset.from_tensor_slices(({
                'input_ids': all_input_ids,
                'attention_mask': all_attention_masks,
                'token_type_ids': all_token_type_ids
            }, all_labels))

            return dataset, features

        # Return tuple of numpy arrays if is_tf_dataset=False
        xdata = [np.array(all_input_ids), np.array(all_attention_masks), np.array(
            all_token_type_ids)]
        ydata = all_labels

        return [xdata, ydata], features

    # Create training dataset and examples using make_examples function
    train_dataset_base, train_examples = make_examples(tokenizer, x_train, y_train, maxlen
        =128)

    # Create validation dataset and examples using make_examples function
    valid_dataset_base, valid_examples = make_examples(tokenizer, x_valid, y_valid, maxlen
        =128)

    # Create test dataset and examples using make_examples function
    test_dataset_base, test_examples = make_examples(tokenizer, x_test, y_test, maxlen=128)

    # Create test dataset and examples as numpy arrays (not TensorFlow dataset)
    [xtest, ytest], test_examples = make_examples(tokenizer, x_test, y_test, maxlen=128,
        is_tf_dataset=False)

    # Iterate over the first example in the train_dataset_base
    for value in train_dataset_base.take(1):
        # Print input_ids tensor
        print(f'     input_ids: {value[0]["input_ids"]}')
        # Print attention_mask tensor
        print(f'attention_mask: {value[0]["attention_mask"]}')
        # Print token_type_ids tensor
        print(f'token_type_ids: {value[0]["token_type_ids"]}')
```

```
        # Print target (label) tensor
        print(f'         target: {value[1]}')
```

The code defines an 'InputExample' class for creating input examples for sequence classification and a 'make_examples' function to convert texts and labels into examples and features suitable for BERT model training. It creates TensorFlow datasets for training, validation, and testing, and prints the first example in the training dataset to verify correctness.

Building and Training the BERT Model

```
    def get_training_dataset(dataset, batch_size):
        """
        Creates a training dataset pipeline.

        Args:
        dataset (tf.data.Dataset): TensorFlow dataset containing training examples.
        batch_size (int): Batch size for training.

        Returns:
        tf.data.Dataset: Processed training dataset ready for model training.
        """
        # Repeat the dataset indefinitely
        dataset = dataset.repeat()
        # Shuffle the dataset with a buffer size of 2048
        dataset = dataset.shuffle(2048)
        # Batch the dataset with the specified batch size
        dataset = dataset.batch(batch_size)

        return dataset

    def get_validation_dataset(dataset, batch_size):
        """
        Creates a validation dataset pipeline.

        Args:
        dataset (tf.data.Dataset): TensorFlow dataset containing validation examples.
        batch_size (int): Batch size for validation.

        Returns:
        tf.data.Dataset: Processed validation dataset ready for model evaluation.
        """
        # Batch the dataset with the specified batch size
        dataset = dataset.batch(batch_size)

        return dataset

    # Create training dataset using get_training_dataset function
    train_dataset = get_training_dataset(train_dataset_base, TRAIN_BATCH_SIZE)

    # Create validation dataset using get_validation_dataset function
    valid_dataset = get_validation_dataset(valid_dataset_base, VALID_BATCH_SIZE)

    # Calculate steps per epoch for training and validation
    train_steps = len(train_examples) // TRAIN_BATCH_SIZE
    valid_steps = len(valid_examples) // VALID_BATCH_SIZE

    # Print the calculated steps for training and validation
    print(train_steps, valid_steps)

    def build_model(model_name, config, learning_rate=3e-5):
        """
        Builds a TensorFlow model for sequence classification using a pre-trained BERT model
            .

        Args:
        model_name (str): Pre-trained model name or path.
```

```
        config (transformers.PretrainedConfig): Configuration object for the BERT model.
        learning_rate (float, optional): Learning rate for optimizer. Default is 3e-5.

        Returns:
        tf.keras.Model: Compiled BERT-based model for sequence classification.
        """
        # Load pre-trained BERT model for sequence classification
        model = TFBertForSequenceClassification.from_pretrained(model_name, force_download=
            True, config=config)

        # Define optimizer, loss function, and metrics for the model
        optimizer = tf.keras.optimizers.Adam(learning_rate=learning_rate)
        loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
        metric = tf.keras.metrics.SparseCategoricalAccuracy('accuracy')

        # Compile the model with optimizer, loss function, and metrics
        model.compile(optimizer=optimizer, loss=loss, metrics=[metric])

        return model

    # Build BERT-based model for sequence classification
    model = build_model(MODEL_NAME_OR_PATH, config, learning_rate=LEARNING_RATE)

    %%time

    # Train the BERT-based model
    r = model.fit(
        train_dataset,                          # Training dataset
        validation_data=valid_dataset,          # Validation dataset
        steps_per_epoch=train_steps,            # Number of steps per epoch for training
        batch_size=128,                         # Batch size for training
        validation_steps=valid_steps,           # Number of steps per epoch for validation
        epochs=EPOCHS,                          # Number of epochs
        verbose=1                               # Verbosity mode (1 for progress bar)
    )

    # Extract validation accuracy from training history
    final_accuracy = r.history['val_accuracy']
    print('FINAL ACCURACY MEAN: ', np.mean(final_accuracy))

    # Save the trained model
    model.save_pretrained(os.path.dirname(OUTPUT_PATH))
```

The ‘get_training_dataset‘ and ‘get_validation_dataset‘ functions create data pipelines for training and validation. The ‘build_model‘ function builds and compiles a BERT-based model for sequence classification. The model is then trained, and its validation accuracy is printed and the trained model is saved.

0.0.2 Results

Results are generated using the following code

Explanations:

```
        def evaluate_model(y_true, y_pred, class_names):
            """
            Evaluates the performance of a classification model using various metrics and
                visualizations.

            Args:
            - y_true (array-like): True labels of the data.
            - y_pred (array-like): Predicted labels of the data.
            - class_names (list): List of class names in the same order as the confusion
                matrix.

            Returns:
```

```python
        - pd.DataFrame: DataFrame containing the classification report.
        """
        # Generate and print the classification report
        report = classification_report(y_true, y_pred, target_names=class_names,
            output_dict=True)
        report_df = pd.DataFrame(report).transpose()
        print("Classification Report:\n", report_df)

        # Generate and display the confusion matrix as a heatmap
        cm = confusion_matrix(y_true, y_pred)
        plt.figure(figsize=(10, 7))
        sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names,
            yticklabels=class_names)
        plt.xlabel('Predicted')
        plt.ylabel('True')
        plt.title('Confusion Matrix')
        plt.show()

        # Calculate and print overall metrics: accuracy, precision, recall, and F1 score
        accuracy = accuracy_score(y_true, y_pred)
        precision = precision_score(y_true, y_pred, average='weighted')
        recall = recall_score(y_true, y_pred, average='weighted')
        f1 = f1_score(y_true, y_pred, average='weighted')

        metrics = {
            "Accuracy": accuracy,
            "Precision": precision,
            "Recall": recall,
            "F1 Score": f1
        }

        print("\nOverall Metrics:")
        for metric, value in metrics.items():
            print(f"{metric}: {value:.4f}")

        return report_df

    # Perform predictions on the test dataset
    predictions = model.predict(xtest)

    # Extract predicted labels from predictions
    ypred = predictions[0].argmax(axis=-1).tolist()

    # Evaluate the model
    report_df = evaluate_model(ytest, ypred, ["Negative", "Neutral", "Positive"])
```

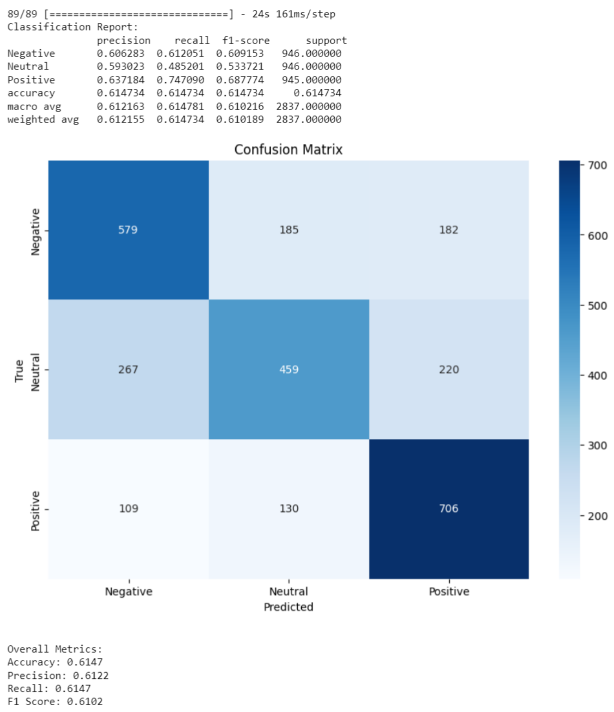
The ‘evaluate_model‘ function assesses the performance of a classification model using various metrics and visualizations. It generates a classification report, displays a confusion matrix as a heatmap, and calculates overall metrics such as accuracy, precision, recall, and F1 score. The function prints these metrics and returns the classification report as a DataFrame.

The code performs predictions on the test dataset using the trained BERT model, extracts the predicted labels, and evaluates the model's performance by calling the ‘evaluate_model‘ function. The function is provided with the true labels, predicted labels, and class names for evaluation.

The following steps are performed:

1. The ‘evaluate_model‘ function generates a classification report and displays it.
2. A confusion matrix is generated and visualized as a heatmap.
3. Overall metrics (accuracy, precision, recall, and F1 score) are calculated and printed.
4. The classification report is returned as a DataFrame.

Figure 6: Results of running Transformer on Dataset



Word Classifier - Base Model

The base model is in `WordClassifier_Base.ipynb`. We investigate each segment in the following sections.

Initial Preprocessing

Explanations:

```
prepared_data: pd.DataFrame = pd.read_csv(url + 'datasets/taghche.csv')
prepared_data = prepared_data[['comment', 'bookname', 'bookID']]
```

The script reads a CSV file containing text data and selects specific columns: `comment`, `bookname`, and `bookID`.

```
chars_stop_words = ''
with open(url + 'stopwords/chars (without digits).txt', 'r', encoding='utf-8') as file
    :
    chars_stop_words = ''.join(file.read().splitlines())

chars_stop_words = chars_stop_words.replace('[', '\[')
chars_stop_words = chars_stop_words.replace(']', '\]')
chars_pattern = re.compile(f'[{chars_stop_words}]')
chars_pattern
```

The script reads a file containing stop words (characters to be removed) and creates a regular expression pattern to match these characters.

```
emojis_pattern = re.compile("["
                            u"\U0001F600-\U0001F64F"  # emoticons
                            u"\U0001F300-\U0001F5FF"  # symbols & pictographs
                            u"\U0001F680-\U0001F6FF"  # transport & map symbols
                            u"\U0001F1E0-\U0001F1FF"  # flags (iOS)
                            "]+")
```

The script defines a regular expression pattern to match emojis using Unicode ranges.

```
def elementary_preprocess(text):
    global chars_pattern, emojis_pattern

```

```
        text = str(text)
        text = chars_pattern.sub(r' ', text)
        text = emojis_pattern.sub(r' ', text)
        return text.translate(str.maketrans('0123456789', ''))
```

The `elementary_preprocess` function removes unwanted characters and emojis from the text and translates digits to Persian numerals.

```
    def higher_preprocess(text, is_informal=False):
        global normalizer

        text = str(text)

        if is_informal:
            text = informal_normalizer_function(text)
            # progress_bar.update(1)
        else:
            text = normalizer.normalize(text)

        text = word_tokenize(text)
        return text
```

The `higher_preprocess` function normalizes the text. If `is_informal` is `True`, it uses an informal normalizer; otherwise, it uses a standard normalizer. The function tokenizes the normalized text.

```
    def informal_normalizer_function(text):
        global informal_normalizer
        text = str(text)

        informal_normalizer = InformalNormalizer()
        text = Normalizer.normalize(informal_normalizer, text)
        sents = [
            informal_normalizer.word_tokenizer.tokenize(sentence)
            for sentence in informal_normalizer.sent_tokenizer.tokenize(text)
        ]

        normalized = [[informal_normalizer.normalized_word(word)[0] for word in sent] for
            sent in sents]
        normalized = np.array(normalized, dtype=object)
        return np.hstack(normalized)

    normalizer = Normalizer()
    informal_normalizer = InformalNormalizer()
```

The `informal_normalizer_function` customizes the normalization process for informal text. It tokenizes sentences and words, then normalizes each word.

```
    for column in prepared_data.columns:
        if column == 'bookID':
            continue

        print(f'Column: {column}')
        prepared_data[column] = prepared_data[column].progress_apply(elementary_preprocess
            )
```

The script applies the `elementary_preprocess` function to each column of the data except `bookID`.

```
    for column in prepared_data.columns:
        if column == 'bookID':
            continue

        print(f'Column: {column}')
        prepared_data[column] = prepared_data[column].progress_apply(higher_preprocess)
```

Next, the script applies the `higher_preprocess` function to each column of the data except `bookID`.

```
    before_dropping = len(prepared_data)
    prepared_data = prepared_data[prepared_data['comment'].apply(lambda x: len(x)) != 0]
```

```
        print(f'Dropped {before_dropping - len(prepared_data)} rows with empty comment.')

        before_dropping = len(prepared_data)
        prepared_data = prepared_data.dropna(subset=['bookID'])
        print(f'Dropped {before_dropping - len(prepared_data)} rows with NaN bookID.')
```

Finally, the script removes rows with empty comments and rows with missing `bookID` values, printing the number of dropped rows.

Using Crawled Data

Explanations:

The following Python script processes and normalizes a dataset containing book data. It combines multiple CSV files into a single DataFrame, sorts and processes author names, removes duplicates and rows with missing IDs, and normalizes text data.

```
ALL_PARTS_LEN = 19
crawled_data: pd.DataFrame = pd.read_csv(url + 'datasets/books data/books_data_part_1.csv'
    )
for i in range(2, ALL_PARTS_LEN + 1):
    crawled_data = pd.concat([crawled_data, pd.read_csv(url + f'datasets/books data/
        books_data_part_{i}.csv')],
                             ignore_index=True)
```

The script first reads the initial CSV file into a DataFrame called `crawled_data`. It then iteratively reads and concatenates additional CSV files into this DataFrame. The variable `ALL_PARTS_LEN` determines the number of parts to be combined.

```
new_author_function = lambda x: ' $ '.join(sorted(str(x).split(' $ ')))
crawled_data['author'] = crawled_data['author'].apply(new_author_function)
```

This section of the code defines a lambda function to sort the author names within each entry. The authors are separated by the delimiter `' $ '`. The lambda function sorts the names alphabetically and joins them back together with the same delimiter.

```
before_dropping = len(crawled_data)
crawled_data = crawled_data.drop_duplicates()
print(f'Dropped {before_dropping - len(crawled_data)} duplicates.')
```

The script removes duplicate rows from `crawled_data` and prints the number of duplicates dropped.

```
before_dropping = len(crawled_data)
crawled_data = crawled_data.dropna(subset=['id'])
print(f'Dropped {before_dropping - len(crawled_data)} rows with NaN id.')
```

Rows with missing `id` values are dropped, and the number of such rows is printed.

```
new_author_function = lambda x: set(x.split(' $ '))
crawled_data['author'] = crawled_data['author'].apply(new_author_function)
```

The script redefines the lambda function to convert the list of authors into a set, effectively eliminating duplicate authors within each entry.

```
crawled_data = crawled_data.explode('author')
crawled_data = crawled_data.reset_index(drop=True)
```

The `explode` method is used to transform each author into a separate row, enabling independent processing of each author in the comments. The index is reset to maintain a clean DataFrame.

```
for column in crawled_data.columns:
    if column == 'id':
        continue

    print(f'Column: {column}')
    crawled_data[column] = crawled_data[column].progress_apply(elementary_preprocess)
```

The script applies the `elementary_preprocess` function to each column of the `crawled_data` DataFrame, excluding the `id` column. This function removes unwanted characters and emojis and translates digits to Persian numerals.

```
    for column in crawled_data.columns:
        if column == 'id':
            continue

        print(f'Column: {column}')
        crawled_data[column] = crawled_data[column].progress_apply(higher_preprocess)
```

The script then applies the `higher_preprocess` function to each column of the `crawled_data` DataFrame, again excluding the `id` column. This function normalizes and tokenizes the text.

The following Python script merges two datasets, identifies unavailable books, and saves a list of unavailable book IDs to a file. The datasets are preprocessed to remove duplicates and missing values before being merged.

```
data: pd.DataFrame = pd.merge(prepared_data, crawled_data, left_on='bookID', right_on='id')
data = data.drop(columns=['bookID'])

print(f'Prepared data: {len(prepared_data)}\nCrawled data: {len(crawled_data)}\nMerged data: {
    len(data)}')
data.head()
```

The script merges the `prepared_data` and `crawled_data` DataFrames using a common key: `bookID` from `prepared_data` and `id` from `crawled_data`. After merging, the `bookID` column is dropped from the merged DataFrame. The script then prints the lengths of the prepared, crawled, and merged datasets and displays the first few rows of the merged dataset.

```
crawled_books = set(crawled_data['id'].values)
prepared_books = prepared_data[['bookID']].copy()

unavailable_books = prepared_books[~prepared_books['bookID'].apply(lambda x: x in
    crawled_books)]
unavailable_books = unavailable_books.drop_duplicates()
print(f'Unavailable books (The page has 404 error): {len(unavailable_books)}')
unavailable_books
```

The script identifies books in the `prepared_data` DataFrame that are not present in the `crawled_data` DataFrame. It creates a set of book IDs from `crawled_data` and compares it to the `bookID` column in `prepared_data`. Books not found in `crawled_data` are considered unavailable. The script removes duplicate entries and prints the number of unavailable books.

```
with open('unavailable_books_list.txt', 'w', encoding='utf-8') as file:
    unavailable_books_list = unavailable_books['bookID'].values.flatten()
    unavailable_books_list = unavailable_books_list[~np.isnan(unavailable_books_list)]
    unavailable_books_list = unavailable_books_list.astype(int)
    unavailable_books_list = unavailable_books_list.tolist()
    unavailable_books_list = sorted(list(set(unavailable_books_list)))
    file.write(str(unavailable_books_list))
```

The script writes the list of unavailable book IDs to a text file. It flattens the array of book IDs, removes any NaN values, converts the IDs to integers, and sorts them. Finally, it saves the sorted list of unique unavailable book IDs to a file named `unavailable_books_list.txt`.

Explanations:

The following Python script processes a dataset to label parts of text related to books, authors, translators, and publishers. It then visualizes the distribution of these labels and removes rows with insufficient labels.

```
    labeled_data = data.copy()
    labeled_data['label'] = [[0]] * len(labeled_data)
```

```
labeled_data.head()

tags = ['name', 'author', 'translator', 'publisher']
```

The script begins by copying the `data` DataFrame to `labeled_data` and initializes a new column, `label`, with zero values. It also defines a list of tags representing different entities in the dataset.

```
def get_label(tag):
    if tag == 'name':
        return 'Book'
    elif tag == 'author':
        return 'Author'
    elif tag == 'translator':
        return 'Translator'
    elif tag == 'publisher':
        return 'Publisher'
    else:
        return None
```

The `get_label` function maps each tag to its corresponding entity label. This function helps in converting tag names to more descriptive labels.

```
def convert_index_to_label(index, tag):
    labels = []

    for i in range(len(index)):
        if index[i] == -1:
            labels.append('O')
        else:
            if i == 0 or index[i - 1] == -1 or index[i] - index[i - 1] != 1:
                labels.append(f'B-{get_label(tag)}')
            else:
                labels.append(f'I-{get_label(tag)}')

    return labels
```

The `convert_index_to_label` function converts a list of indexes to labels. It uses the BIO (Beginning, Inside, Outside) tagging scheme to mark the beginning (`B-`) and continuation (`I-`) of entities. If the index is -1, it assigns the label `O` (Outside).

```
def combine_labels(labels):
    global tags

    result = []

    for i in range(len(labels[tags[0]])):
        name = labels[tags[0]][i] if len(labels[tags[0]]) > 0 else 'O'
        author = labels[tags[1]][i] if len(labels[tags[1]]) > 0 else 'O'
        translator = labels[tags[2]][i] if len(labels[tags[2]]) > 0 else 'O'
        publisher = labels[tags[3]][i] if len(labels[tags[3]]) > 0 else 'O'

        if name != 'O':
            result.append(name)
        elif author != 'O':
            result.append(author)
        elif translator != 'O':
            result.append(translator)
        elif publisher != 'O':
            result.append(publisher)
        else:
            result.append('O')

    return result
```

The `combine_labels` function combines labels for different tags into a single list. It prioritizes the `name` tag, followed by `author`, `translator`, and `publisher`, and assigns the label `O` if no other label is present.

```python
def get_labels(row):
    indexes = {
        tag: []
        for tag in tags
    }
    labels = {
        tag: []
        for tag in tags
    }

    for tag in tags:
        cell = row[tag]
        if cell == {np.nan}:
            continue

        filled_indexes = set()
        for word in row['comment']:
            try:
                current_index = cell.index(word)
                if current_index in filled_indexes:
                    raise ValueError
                indexes[tag].append(current_index)
                filled_indexes.add(current_index)
            except ValueError:
                indexes[tag].append(-1)

        labels[tag] = convert_index_to_label(indexes[tag], tag)

    return combine_labels(labels)

labeled_data['label'] = labeled_data.progress_apply(get_labels, axis=1)
```

The `get_labels` function generates labels for each row in the dataset. It finds the indexes of words in the `comment` column for each tag and converts them to labels using the `convert_index_to_label` function. The labels are then combined using the `combine_labels` function. The `progress_apply` method is used to apply this function to each row in `labeled_data`.

```python
percentage_of_o = [len([tag for tag in label if tag == 'O']) / len(label) for label in
    labeled_data['label']]
fig = px.histogram(percentage_of_o, title='Percentage of O in Each Label List Histogram')
fig.update_layout(showlegend=False)
fig.show()
```

The script calculates the percentage of `O` labels in each label list and creates a histogram to visualize this distribution using Plotly.

```python
before_dropping = len(labeled_data)
labeled_data = labeled_data[[percentage < 0.99 for percentage in percentage_of_o]]
print(f'Dropped {before_dropping - len(labeled_data)} rows with more than 99% O.')
print(f'New length: {len(labeled_data)}')
```

Finally, the script removes rows from `labeled_data` where the percentage of `O` labels exceeds 99

Training

Explanations:

```python
    import tensorflow as tf
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import LabelEncoder
    from sklearn.metrics import classification_report
    from tensorflow.keras.preprocessing.sequence import pad_sequences
    from tensorflow.keras.models import Sequential
```

```python
        from tensorflow.keras.layers import Embedding, LSTM, Bidirectional, SpatialDropout1D,
            InputLayer
        from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, TensorBoard
        from livelossplot.tf_keras import PlotLossesCallback

        words = list(set([word for comment in labeled_data['comment'] for word in comment]))
        words.append('STARTPAD')
        words_size = len(words)
        words_size

        tags = sorted(list(set([tag for label in labeled_data['label'] for tag in label])))
        tags_size = len(tags)
        tags_size, tags

        sentences = labeled_data.progress_apply(
            lambda row: [(word, label) for word, label in zip(row['comment'], row['label'])],
                axis=1)
        sentences = sentences.progress_apply(lambda sentence: sentence + [('STARTPAD', 'O')])

        word2idx = {word: idx for idx, word in enumerate(words)}
        tag2idx = {tag: idx for idx, tag in enumerate(tags)}
        idx2tag = {idx: tag for tag, idx in tag2idx.items()}

        fig = px.histogram([len(sentence) for sentence in sentences], title='Sentence Length
            Histogram')
        fig.update_layout(showlegend=False)
        fig.show()
```

The script begins by importing necessary libraries and defining words and tags used in the labeled data. It calculates the unique words and tags and their respective sizes. It then creates a list of sentences from the labeled data and appends a special token 'STARTPAD' to each sentence. It also maps words and tags to unique indices.

```python
        # Based on the last hist.
        max_length = 210

        comments_less_than_max_length = len([sentence for sentence in sentences if len(
            sentence) <= max_length])
        print(f'Number of comments less than {max_length}: {comments_less_than_max_length}')
        print(f'Remainder: {len(sentences) - comments_less_than_max_length}')
```

The script determines the maximum sentence length based on the histogram of sentence lengths and counts the number of sentences that are shorter than this maximum length.

```python
        X = [[word2idx[word[0]] for word in sentence] for sentence in sentences]
        X = pad_sequences(X, maxlen=max_length, padding='post', value=words_size-1)

        y = [[tag2idx[word[1]] for word in sentence] for sentence in sentences]
        y = pad_sequences(y, maxlen=max_length, padding='post', value=tag2idx['O'])

        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state
            =42)
        X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size=0.5,
            random_state=42)
```

Next, the script converts the sentences into sequences of word indices and pads them to ensure uniform length. It also converts the tags into sequences of tag indices and pads them similarly. The data is then split into training, validation, and test sets.

```python
        ## Create Bidirectional LSTM Model

        model = Sequential()
        model.add(InputLayer((max_length)))
        model.add(Embedding(input_dim=words_size, output_dim=max_length, input_length=
            max_length))
        model.add(SpatialDropout1D(0.1))
```

```
        model.add(Bidirectional(LSTM(units=300, return_sequences=True)))

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

        tf.keras.utils.plot_model(
            model, to_file='resources/model.png', show_shapes=True, show_dtype=False,
            show_layer_names=True, rankdir='LR', expand_nested=True, dpi=300,
        )
```

The script defines a Bidirectional LSTM model using TensorFlow's Keras API. The model consists of an embedding layer, a spatial dropout layer, and a bidirectional LSTM layer. The model is compiled with the Adam optimizer and sparse categorical cross-entropy loss. A summary of the model architecture is displayed, and the model is visualized and saved as an image.

```
        logdir = 'logs/'
        tensorboard_callback = TensorBoard(log_dir=logdir)

        model_checkpoint = ModelCheckpoint('resources/model.keras', monitor='val_loss',
            verbose=1, save_best_only=True,
                                            save_weights_only=True)
        early_stopping = EarlyStopping(monitor='val_accuracy', min_delta=0, patience=1,
            verbose=1, mode='max', baseline=None)
        plot_losses = PlotLossesCallback()

        history = model.fit(X_train[:10], y_train[:10], validation_data=(X_val[:10], y_val
            [:10]), batch_size=32, epochs=3, verbose=1,
                              callbacks=[tensorboard_callback, model_checkpoint, early_stopping,
                                   plot_losses])
```

The script sets up callbacks for TensorBoard logging, model checkpointing, early stopping, and live loss plotting. Finally, the model is trained on a subset of the data with the specified callbacks, batch size, and number of epochs. The training process includes validation on a separate validation set.

Evaluation

Explanations:

The following Python script is used to make predictions with a trained Bidirectional LSTM model and evaluate its performance. It includes functions for predicting and printing predictions, as well as evaluating the model on a test dataset.

```
    def pred_y(x):
        p = model.predict(np.array([x]))
        p = np.argmax(p, axis=-1)
        return p

    def print_prediction(x, y):
        print("{:15}{:5}\t {}\n".format("Word", "True", "Pred"))
        print("-" *30)
        for w, true, pred in zip(x, y, pred_y(x)):
            try:
                print("{:15}{}\t{}".format(words[w-1], tags[true], tags[pred]))
            except IndexError:
                print("{:15}{}\t{}".format(words[w-1], tags[true], 'O'))
```

The `pred_y` function takes an input sequence `x`, makes a prediction using the trained model, and returns the predicted tags. The `print_prediction` function prints the words along with their true and predicted tags for a given input sequence.

```
    sample_X = 'some persian text'
    sample_X = higher_preprocess(elementary_preprocess(sample_X))
    sample_X = [[word2idx[word] if word in word2idx else -1 for word in sample_X]]
```

```
    sample_X = pad_sequences(sample_X, maxlen=max_length, padding='post', value=words_size-1)

    p = pred_y(sample_X[0])
    print("{:15}\t {}\n".format("Word", "Pred"))
    print("-" *30)
    for w, pred in zip(sample_X[0], p[0]):
        try:
            print("{:15}\t{}".format(words[w-1], tags[pred]))
        except IndexError:
            print("{:15}\t{}".format(words[w-1], 'O'))
```

A sample Persian sentence is preprocessed using the `higher_preprocess` and `elementary_preprocess` functions. The sentence is converted to a sequence of word indices and padded to the maximum sequence length. Predictions are made for the sample sentence, and the words along with their predicted tags are printed.

```
    i = np.random.randint(0, X_test.shape[0])
    print("This is sentence:",i)
    p = model.predict(np.array([X_test[i]]))
    p = np.argmax(p, axis=-1)

    print("{:15}{:5}\t {}\n".format("Word", "True", "Pred"))
    print("-" *30)
    for w, true, pred in zip(X_test[i], y_test[i], p[0]):
        try:
            print("{:15}{}\t{}".format(words[w-1], tags[true], tags[pred]))
        except IndexError:
            print("{:15}{}\t{}".format(words[w-1], tags[true], 'O'))
```

A random sentence from the test set is selected, and predictions are made for it. The words along with their true and predicted tags are printed.

```
    y_pred = model.predict(X_test)

    y_pred_index = np.argmax(y_pred, axis=-1)

    X_test_list = X_test.tolist()
    y_test_list = y_test.tolist()
    y_pred_list = y_pred_index.tolist()

    start_pad_index = word2idx['STARTPAD']
    # progress_bar = tqdm(range(len(X_test)))
    for i in range(len(X_test_list)):
        x_start_pad = X_test_list[i].index(start_pad_index)
        X_test_list[i] = X_test_list[i][:x_start_pad]
        y_test_list[i] = y_test_list[i][:x_start_pad]

        y_pred_list[i] = y_pred_list[i][:x_start_pad]
        y_pred_list[i] = [tag if tag <= 8 else 8 for tag in y_pred_list[i]]
```

The script then makes predictions for the entire test set. It converts the predictions to tag indices and removes the padding from the sequences. It ensures that any tag indices greater than the maximum tag index are set to the maximum tag index.

```
    y_test_flatten = []
    for y in y_test_list:
        y_test_flatten.extend(y)

    y_pred_flatten = []
    for y in y_pred_list:
        y_pred_flatten.extend(y)

    print(classification_report(y_test_flatten, y_pred_flatten))
```

Finally, the true and predicted tags are flattened, and a classification report is generated to evaluate the model's performance.

Figure 7: Percentage of O in Each Label List Histogram

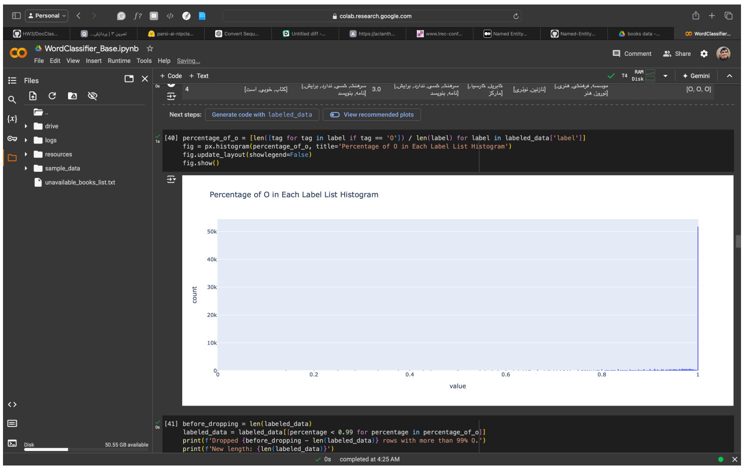


Figure 8: Tag Distribution with O

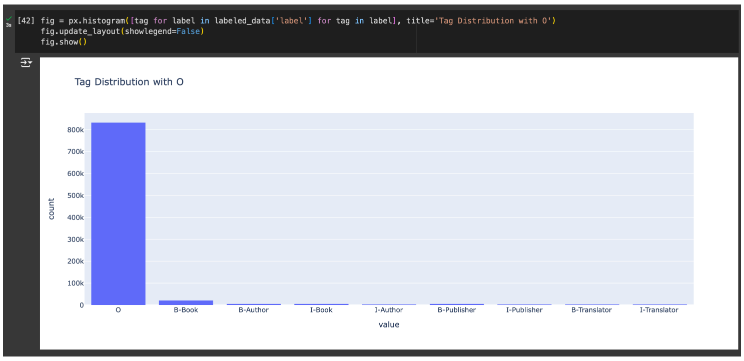


Figure 9: Tag distribution without O

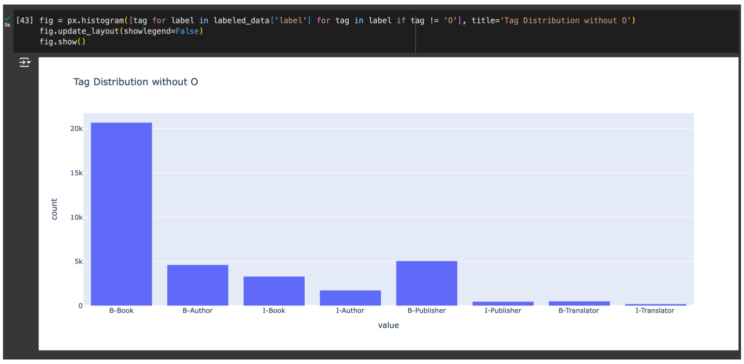


Figure 10: Sentence (Comment) Length Histogram

Figure 11: LSTM Model

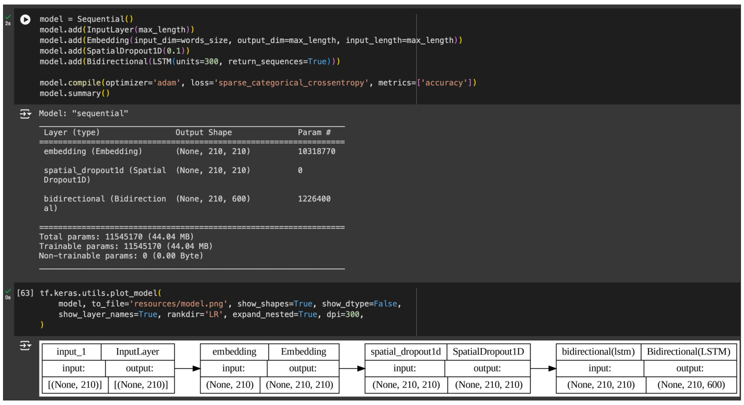


Figure 12: Accuracy and Loss During Training

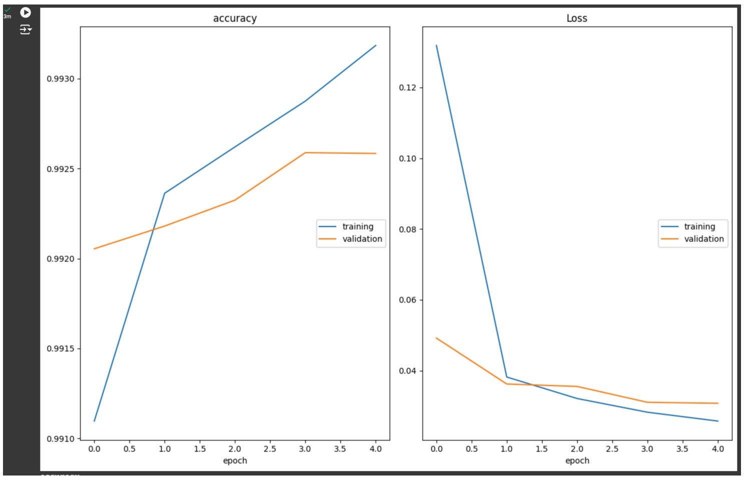
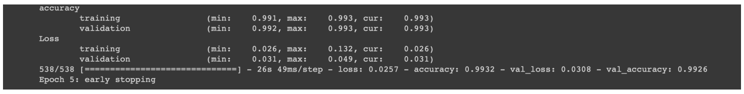


Figure 13: Text of Running the Model



Word Classifier - Transfomer Model

The first part is exactly similar to the previous section. The only difference is that BERT is used as a normalizer. So, we explain only the transformer model in this section.

Explanations:

```python
from transformers import BertConfig
from transformers import TFBertForTokenClassification, InputFeatures
import tensorflow as tf
from livelossplot.tf_keras import PlotLossesCallback
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix,
    precision_score, recall_score, f1_score
```

First, the necessary libraries are imported. We use the Hugging Face Transformers library for BERT, TensorFlow for training, and various scikit-learn utilities for data handling and evaluation.

```python
tags = sorted(list(set([tag for label in labeled_data['label'] for tag in label])))
tags_size = len(tags)
tags_size, tags

tag2idx = {tag: idx for idx, tag in enumerate(tags)}
idx2tag = {idx: tag for tag, idx in tag2idx.items()}
```

Figure 14: The Sentence in the Doc

```
[73] 1/1 [==============================] - 0s 40ms/step
Word              Pred
------------------------------
من                O
پارسال            O
موقع              O
عید               O
کتاب              O
جز                O
از                O
کل                O
رو                O
از                O
انتشارات          B-Publisher
چشمه              O
خوندم             O
باید              O
بگم               O
که                O
موقع              O
خوندنش            O
واقعا             O
محو               O
قلم               O
استیو             B-Book
تولتز             O
شده_بودم          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
STARTPAD          O
```

Figure 15: Classification Report

```
              precision    recall  f1-score   support

           0       0.65      0.64      0.65       442
           1       0.50      0.11      0.18      2033
           2       0.53      0.18      0.27       483
           3       0.00      0.00      0.00        40
           4       0.50      0.28      0.36       155
           5       0.39      0.15      0.22       319
           6       0.00      0.00      0.00        42
           7       0.00      0.00      0.00        12
           8       0.97      0.99      0.98     76751

    accuracy                           0.96     80277
   macro avg       0.39      0.26      0.29     80277
weighted avg       0.95      0.96      0.95     80277

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavio

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavio

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavio
```

The tags used for labeling are extracted and encoded into indices. The `tag2idx` and `idx2tag` dictionaries map tags to indices and vice versa.

```
X_train, X_test, y_train, y_test = train_test_split(labeled_data['comment'], labeled_data['label'], test_size=0.2)
X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size=0.5)

train = pd.DataFrame({'comment': X_train, 'label': y_train})
val = pd.DataFrame({'comment': X_val, 'label': y_val})
```

Figure 16: Confusion matrix

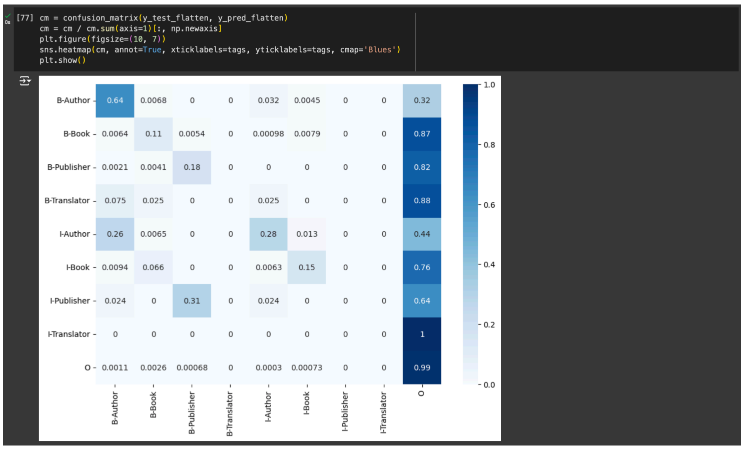


Figure 17: Metrics

```
Accuracy: 0.9594279806171132

Micro Precision: 0.9594279806171132
Macro Precision: 0.3934900376200633
Weighted Precision: 0.9455743349730555

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning:

Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning:

Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

Micro Recall: 0.9594279806171132
Macro Recall: 0.26183398222539545
Weighted Recall: 0.9594279806171132

Micro F1-score: 0.9594279806171132
Macro F1-score: 0.2949953149539064
Weighted F1-score: 0.9484172831756426
```

```
test = pd.DataFrame({'comment': X_test, 'label': y_test})

train = train[:64]
val = val[:64]
test = test[:64]

train = train.reset_index(drop=True)
val = val.reset_index(drop=True)
test = test.reset_index(drop=True)
```

The labeled data is split into training, validation, and test sets using an 80-20 split, with the test set further split in half for validation. For demonstration purposes, only the first 64 rows of each dataset are used.

```
def add_padding(data: pd.DataFrame, max_length: int):
    progress_bar = tqdm(range(len(data)))

    for i in progress_bar:
        data['comment'][i] = data['comment'][i][:max_length]
        data['label'][i] = data['label'][i][:max_length]

        if len(data['comment'][i]) < max_length:
            data['comment'][i] += ['[PAD]'] * (max_length - len(data['comment'][i]))
            data['label'][i] += ['O'] * (max_length - len(data['label'][i]))

    return data

max_length = 128

train = add_padding(train, max_length)
val = add_padding(val, max_length)
test = add_padding(test, max_length)
```

The `add_padding` function ensures all comments and labels in the data are padded to a fixed length (`max_length`). Padding is necessary for BERT to handle inputs of consistent length.

```
## Convert to GLUE Format

```

```python
class InputExample:
    def __init__(self, guid, text_a, text_b=None, label=None):
        self.guid = guid
        self.text_a = text_a
        self.text_b = text_b
        self.label = label
```

The `InputExample` class is defined to structure each data example with a unique ID, the text, and the label.

```python
def convert_data_to_examples(data: pd.DataFrame):
    examples = []

    for i in range(len(data)):
        guid = i
        text_a = data['comment'][i]
        label = data['label'][i]
        examples.append(InputExample(guid=guid, text_a=text_a, label=label))

    return examples


def convert_examples_to_features(examples, tokenizer, max_length, task=None):
    features = []

    for example in examples:
        input_dict = tokenizer.encode_plus(
            example.text_a,
            add_special_tokens=True,
            max_length=max_length,
            return_token_type_ids=True,
            return_attention_mask=True,
            padding='max_length',
            truncation=True
        )

        input_ids = input_dict['input_ids']
        attention_mask = input_dict['attention_mask']
        token_type_ids = input_dict['token_type_ids']

        label = example.label

        if task is not None:
            label = [tag2idx[tag] for tag in label]

        features.append(
            InputFeatures(
                input_ids=input_ids,
                attention_mask=attention_mask,
                token_type_ids=token_type_ids,
                label=label
            )
        )

    return features


def convert_data_to_features(data: pd.DataFrame, tokenizer, max_length, task=None):
    examples = convert_data_to_examples(data)
    return convert_examples_to_features(examples, tokenizer, max_length, task)
```

Functions are provided to convert data into examples and then into features suitable for BERT. These functions tokenize the text, add special tokens, and ensure padding and truncation to the maximum length.

```python
def convert_data_to_tf_dataset(data: pd.DataFrame, tokenizer, max_length, task=None):
    features = convert_data_to_features(data, tokenizer, max_length, task)

    all_input_ids = []
```

```python
        all_attention_masks = []
        all_token_type_ids = []
        all_labels = []

        for feature in features:
            all_input_ids.append(feature.input_ids)
            all_attention_masks.append(feature.attention_mask)
            all_token_type_ids.append(feature.token_type_ids)
            all_labels.append(feature.label)

        return (
            tf.data.Dataset.from_tensor_slices((
                {
                    'input_ids': all_input_ids,
                    'attention_mask': all_attention_masks,
                    'token_type_ids': all_token_type_ids
                },
                all_labels
            ))
        )
```

The `convert_data_to_tf_dataset` function converts the features into a TensorFlow dataset suitable for training.

```python
    max_length = 128
    task = 'ner'

    train_dataset = convert_data_to_tf_dataset(train, tokenizer, max_length, task=task)
    val_dataset = convert_data_to_tf_dataset(val, tokenizer, max_length, task=task)
    test_dataset = convert_data_to_tf_dataset(test, tokenizer, max_length, task=task)

    train_dataset = train_dataset.shuffle(100).batch(32).repeat(2)
    val_dataset = val_dataset.batch(64)
    test_dataset = test_dataset.batch(64)

    train_dataset.element_spec, val_dataset.element_spec, test_dataset.element_spec
```

The datasets for training, validation, and testing are prepared, shuffled, and batched appropriately.

```python
    config = BertConfig.from_pretrained(MODEL_NAME_OR_PATH, num_labels=tags_size, id2label=
        idx2tag, label2id=tag2idx)

    model = TFBertForTokenClassification.from_pretrained(MODEL_NAME_OR_PATH, config=config)
    model.summary()

    multi_label_loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
    model.compile(optimizer='adam', loss=multi_label_loss, metrics=['accuracy'])

    plot_losses = PlotLossesCallback()

    model.fit(train_dataset, epochs=1, validation_data=val_dataset, callbacks=[plot_losses])
```

The BERT model is configured and initialized for token classification. The model is compiled with a loss function and accuracy metric, and training is initiated with the `fit` method, including a callback for plotting the training losses.

Results and Imporatnt Notes

We must note that we tried to use Hazm's Informal Normalizer but it was very slow. So, e customized the Hazm Informal Normalizer. It returns a 3D array in which the third dimension is a candidate for the formal word. We picked the first candidate directly by customizing the Hazm library. Now, it returns a 2D array, and its performance has improved.

For labeling, we iterate over comments and check if the word is in, as an example, in the book name or not. If it was in the book names list, we appended the index of the word in the book names list to a list. So now we have a list of indexes. Then, we tried to find all consecutive ascending sequences in the list. Then we tag them by BIO, or if they are -1, we tag them by O.

Another important note is related to the distribution of tags. The "O" tag completely dominates other tags by count, and therefore, it impacts our results. You can see the distribution in the following figures.

Figure 18: Percentage of O in Each Label List Histogram

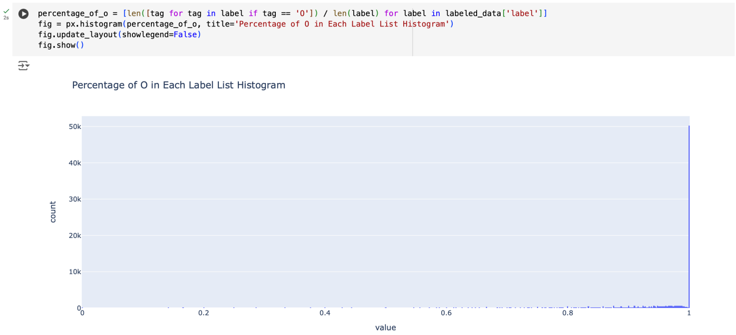


Figure 19: Tag Distribution with O

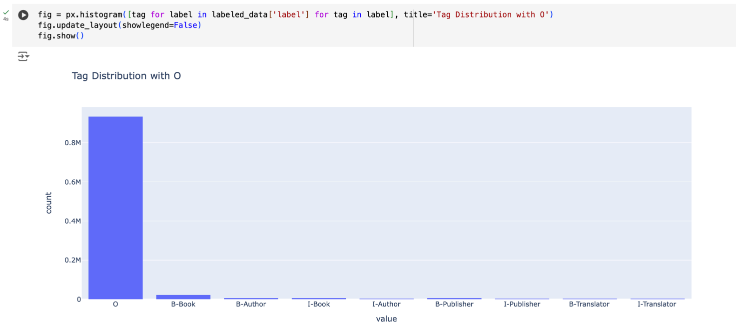


Figure 20: Tag distribution without O

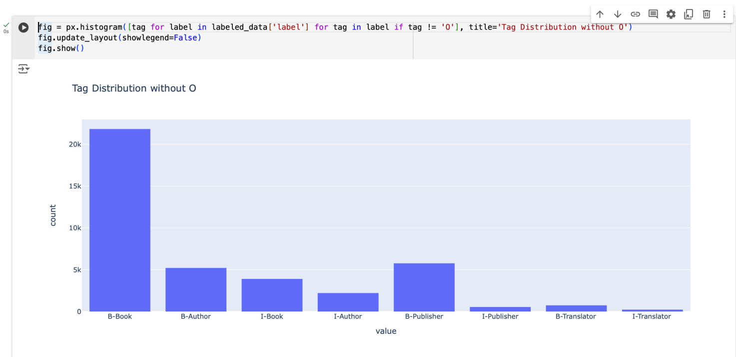


Figure 21: Transfomer Model

```
[71] config = BertConfig.from_pretrained(MODEL_NAME_OR_PATH, num_labels=tags_size, id2label=idx2tag, label2id=tag2idx)

/usr/local/lib/python3.10/dist-packages/huggingface_hub/file_download.py:1132: FutureWarning: `resume_download` is deprecated and will be removed in
  warnings.warn(

[72] model = TFBertForTokenClassification.from_pretrained(MODEL_NAME_OR_PATH, config=config)
     model.summary()

tf_model.h5: 100% 963M/963M [01:08<00:00, 15.0MB/s]
All model checkpoint layers were used when initializing TFBertForTokenClassification.

Some layers of TFBertForTokenClassification were not initialized from the model checkpoint at HooshvareLab/bert-fa-base-uncased and are newly initial:
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
Model: "tf_bert_for_token_classification"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 bert (TFBertMainLayer)      multiple                  162250752

 dropout_37 (Dropout)        multiple                  0 (unused)

 classifier (Dense)          multiple                  6921

=================================================================
Total params: 162257673 (618.96 MB)
Trainable params: 162257673 (618.96 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure 22: Accuracy and Loss During Training

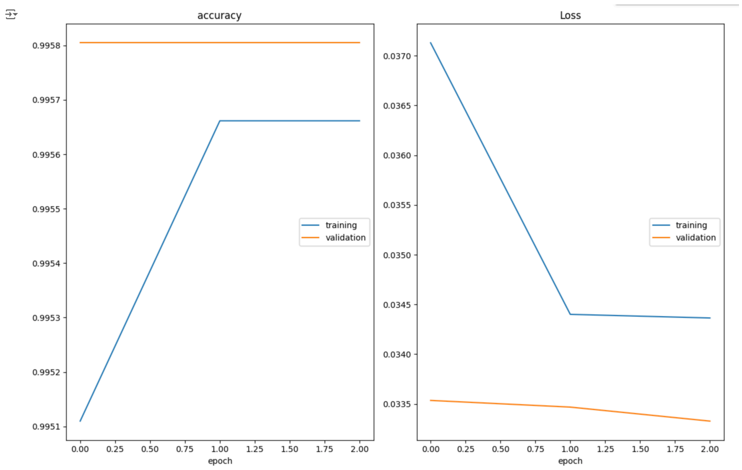


Figure 23: Some Evaluations

```
accuracy
        training                 (min:    0.995, max:    0.996, cur:    0.996)
        validation               (min:    0.996, max:    0.996, cur:    0.996)
Loss
        training                 (min:    0.034, max:    0.037, cur:    0.034)
        validation               (min:    0.033, max:    0.034, cur:    0.033)
3720/3720 [==============================] - 3207s 862ms/step - loss: 0.0344 - accuracy: 0.9957 - val_loss: 0.0333 - val_accuracy: 0.9958
<tf_keras.src.callbacks.History at 0x7f1c77613b20>
```

Figure 24: Classification Report

```
[77] model.evaluate(test_dataset)

117/117 [==============================] - 60s 514ms/step - loss: 0.0341 - accuracy: 0.9957
[0.034096114337444305, 0.9956721067428589]

[78] y_pred = model.predict(test_dataset)
     y_pred = np.argmax(y_pred.logits, axis=2)
     y_pred = [[idx2tag[idx] for idx in row] for row in y_pred]
     y_true = test['label'].values

117/117 [==============================] - 70s 514ms/step

     y_pred = [tag for row in y_pred for tag in row]
     y_true = [tag for row in y_true for tag in row]

     print(classification_report(y_true, y_pred))

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and be
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and be
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

    B-Author       0.00      0.00      0.00       506
      B-Book       0.00      0.00      0.00      2282
 B-Publisher       0.00      0.00      0.00       638
B-Translator       0.00      0.00      0.00        74
    I-Author       0.00      0.00      0.00       206
      I-Book       0.00      0.00      0.00       360
 I-Publisher       0.00      0.00      0.00        36
I-Translator       0.00      0.00      0.00        19
           O       1.00      1.00      1.00    948071

    accuracy                           1.00    952192
   macro avg       0.11      0.11      0.11    952192
weighted avg       0.99      1.00      0.99    952192

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and be
  _warn_prf(average, modifier, msg_start, len(result))
```

Figure 25: Confusion matrix