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Capstone April 2024 Batch Group - 23

Interim Report

NLP Machine Translation Project

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1. Summary of Problem Statement, Data, and Findings

Problem Statement

The objective of this project is to develop a Machine Translation Model that translates between English and German. The dataset is derived from the ACL2014 Ninth Workshop on Statistical Machine Translation, which contains parallel text in German-English from three sources:

- Europarl v7 (Formal parliamentary proceedings)
- Common Crawl (Informal, web-crawled text)
- News Commentary (News and journalistic content)

Findings

- The dataset contains a mix of formal and informal text, making it diverse and challenging for a translation model.
- The data is imbalanced, with varying sentence lengths and vocabulary sizes across different sources.
- Initial observations showed duplicate sentences, missing values, and non-German/English sentences that needed cleaning.
- Simple RNN and LSTM models were designed for translation, with BLEU scores computed for performance evaluation.

2. Summary of the Approach to EDA and Pre-processing

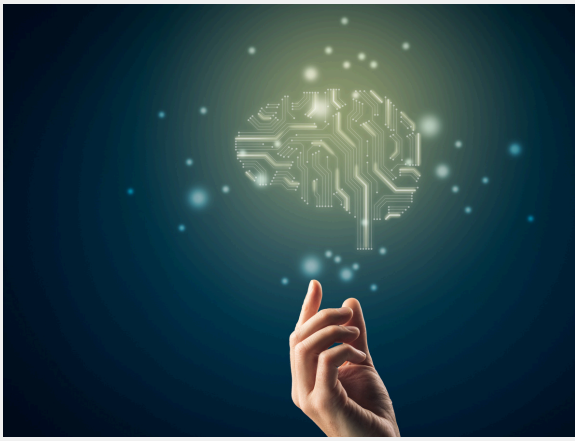
Exploratory Data Analysis (EDA) & Visualisations

- Word Count Distributions: Showed sentence length variations across datasets.
- Word Clouds: Highlighted the most frequently used words in English and German.
- Data Statistics: Summarized the number of sentences, unique words, and outliers.

Pre-processing Steps Taken

1. Data Cleaning:
    - Removed missing values and duplicate sentences.
    - Filtered out non-German/English text.
2. Tokenization & Normalization:
    - Used spaCy for faster tokenization and lemmatization.
    - Removed stopwords and special characters.
3. Dataset Reduction for Faster Execution:
    - Limited training dataset to 5,000 samples to improve execution time.
    - Capped vocabulary size at 5,000 words.
    - Reduced max sentence length to 20 words to optimize memory usage.

3. Deciding Models and Model Building



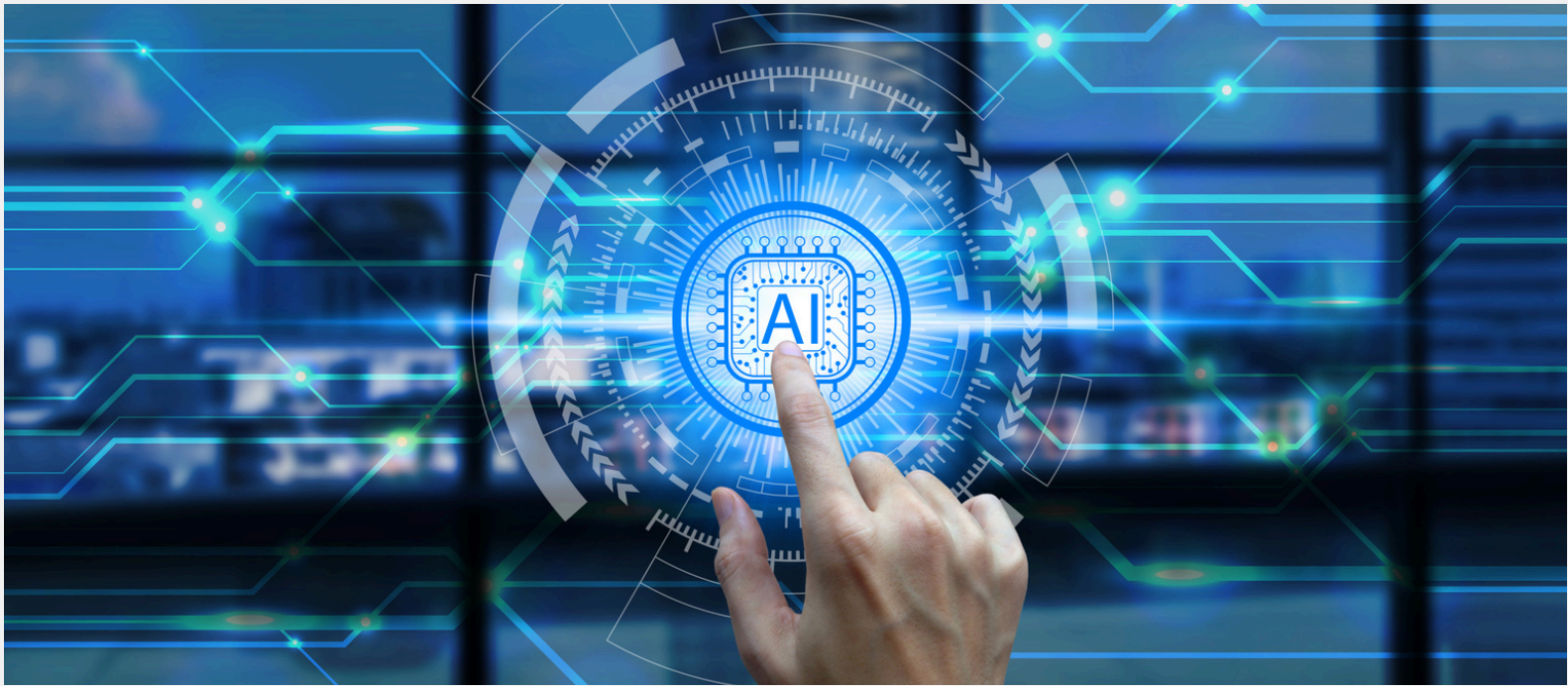
Model Choices
- Simple RNN Model (Baseline Model)
- LSTM Model (Better for sequential learning)

Training Process
- Embedding Layer: Converts words into vector representations.
- RNN/LSTM Layer: Processes sentence sequences.
- Dense Output Layer: Predicts translated words.

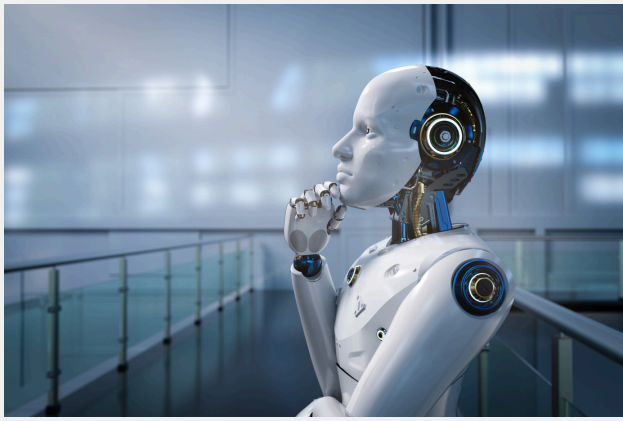
Model Performance
- Models trained on a small dataset to reduce execution time.
- Evaluation Metric: BLEU Score to measure translation accuracy.

Results:
- RNN BLEU Score: 0.092
- LSTM BLEU Score: 0.0

RNN performed better than LSTM, but BLEU scores remain low due to limited training data and short training duration.



4. How to Improve Model Performance?



Possible Enhancements

Increase Training Data → Expand dataset to 10,000+ sentences.
Train for More Epochs → Increase from 3 epochs to 10+.
Use Pretrained Word Embeddings → Such as FastText or Word2Vec.
Implement an Attention Mechanism → Helps focus on key words in long sentences.
Hyperparameter Tuning → Adjust learning rate, dropout, and batch size.

Next Steps

Improve the model performance by increasing training time and dataset size.
Explore Transformer-based models (e.g., BERT, T5) for better translation.
Deploy the best-performing model for real-world testing.

Code Implementation & Visualisations

The project implementation includes:

- Code for data cleaning, NLP preprocessing, and model training.
- Visualisations for data insights (word clouds, sentence length distribution).
- Performance evaluation using BLEU scores.
- Model saving for future inference.

This report summarises Milestone-1 and sets the direction for further improvements in machine translation modeling.

PROJECT TASK: MILESTONE 1

Step 1: Import and merge the three datasets.

Load and Verify Datasets

```
[22] import pandas as pd
     import matplotlib.pyplot as plt
     from wordcloud import WordCloud
     from IPython.display import display, Markdown

     # Function to load parallel datasets with error handling
     def load_parallel_data(filepath_de, filepath_en, dataset_name):
         """Loads English-German parallel datasets and handles line mismatches."""

         try:
             # Read German text
             with open(filepath_de, "r", encoding="utf-8") as de_file:
                 de_lines = de_file.readlines()

             # Read English text
             with open(filepath_en, "r", encoding="utf-8") as en_file:
                 en_lines = en_file.readlines()

             # Find the minimum number of lines
             min_length = min(len(de_lines), len(en_lines))

             # Truncate the longer file to match the shorter one
             de_lines = de_lines[:min_length]
             en_lines = en_lines[:min_length]

             # Create DataFrame
             df = pd.DataFrame({"German": de_lines, "English": en_lines})

             # Display confirmation
             display(Markdown(f"### Successfully Loaded {dataset_name} Dataset"))
             display(Markdown(f"Total Sentence Pairs (After Fixing Mismatch): {len(df)}"))

             # Show sample data
             display(df.head())

             return df

         except Exception as e:
             display(Markdown(f"Error loading {dataset_name}: {str(e)}"))
             return None
```

Load All Three Datasets

```
[23] # Define file paths

     # Europarl Dataset
     europarl_de_path = "/content/drive/MyDrive/MachineTranslation/DataSet/europarl-v7_de_en.txt"
     europarl_en_path = "/content/drive/MyDrive/MachineTranslation/DataSet/europarl-v7_en_de.txt"

     # CommonCrawl Dataset
     commoncrawl_de_path = "/content/drive/MyDrive/MachineTranslation/DataSet/commoncrawl_de_en.txt"
     commoncrawl_en_path = "/content/drive/MyDrive/MachineTranslation/DataSet/commoncrawl_en_de.txt"

     # NewsCommentary Dataset
     newscommentary_de_path = "/content/drive/MyDrive/MachineTranslation/DataSet/news-commentary-v9_de_en.txt"
     newscommentary_en_path = "/content/drive/MyDrive/MachineTranslation/DataSet/news-commentary-v9_en_de.txt"

     # Load datasets
     europarl_df = load_parallel_data(europarl_de_path, europarl_en_path, "Europarl")
     commoncrawl_df = load_parallel_data(commoncrawl_de_path, commoncrawl_en_path, "CommonCrawl")
     newscommentary_df = load_parallel_data(newscommentary_de_path, newscommentary_en_path, "NewsCommentary")
```

Successfully Loaded Europarl Dataset

Total Sentence Pairs (After Fixing Mismatch): 1920209

	German	English
0	Wiederaufnahme der Sitzungsperiode\n	Resumption of the session\n
1	Ich erkläre die am Freitag, dem 17. Dezember u...	I declare resumed the session of the European ...
2	Wie Sie feststellen konnten, ist der gefürchte...	Although, as you will have seen, the dreaded '...
3	Im Parlament besteht der Wunsch nach einer Aus...	You have requested a debate on this subject in...
4	Heute möchte ich Sie bitten - das ist auch der...	In the meantime, I should like to observe a mi...

Successfully Loaded CommonCrawl Dataset

Total Sentence Pairs (After Fixing Mismatch): 2399123

	German	English
0	Iron cement ist eine gebrauchs-fertige Paste, ...	Iron cement is a ready for use paste which is ...
1	Nach der Aushärtung schützt iron cement die Ko...	Iron cement protects the ingot against the hot...
2	feuerfester Reparaturkitt für Feuerungsanlagen...	a fire resitant repair cement for fire places, ...
3	Der Bau und die Reparatur der Autostraßen...\n	Construction and repair of highways and...\n
4	die Mitteilungen sollen den geschäftlichen kom...	An announcement must be commercial character.\n

Successfully Loaded NewsCommentary Dataset

Total Sentence Pairs (After Fixing Mismatch): 201854

	German	English
0	Steigt Gold auf 10.000 Dollar?\n	$10,000 Gold?\n
1	SAN FRANCISCO – Es war noch nie leicht, ein ra...	SAN FRANCISCO – It has never been easy to have...
2	In letzter Zeit allerdings ist dies schwierige...	Lately, with gold prices up more than 300% ove...
3	Erst letzten Dezember verfassten meine Kollege...	Just last December, fellow economists Martin F...
4	Und es kam, wie es kommen musste.\n	Wouldn't you know it?\n

```
[24] import numpy as np

     # Function to check dataset integrity
     def check_dataset_integrity(df, dataset_name):
         """Compares the number of German and English sentences in a dataset and visualizes the dataset size."""

         if df is not None:
             num_de = df["German"].shape[0]
             num_en = df["English"].shape[0]

             display(Markdown(f"### Integrity Check for {dataset_name} Dataset"))
             display(Markdown(f"- German Sentences: {num_de}"))
             display(Markdown(f"- English Sentences: {num_en}"))

             if num_de == num_en:
                 display(Markdown("- The dataset is aligned correctly."))
             else:
                 display(Markdown("- Mismatch detected: The number of German and English sentences are different."))

             # Visualization: Bar Chart for Dataset Sizes
             plt.figure(figsize=(5, 3))
             plt.bar(["German", "English"], [num_de, num_en], color=['blue', 'red'])
             plt.xlabel("Language")
             plt.ylabel("Sentence Count")
             plt.title(f"Comparison of German & English Sentences in {dataset_name}")
             plt.show()

     # Run checks on all datasets
     check_dataset_integrity(europarl_df, "Europarl")
     check_dataset_integrity(commoncrawl_df, "CommonCrawl")
     check_dataset_integrity(newscommentary_df, "NewsCommentary")
```

Integrity Check for Europarl Dataset

- German Sentences: 1920209
- English Sentences: 1920209
- The dataset is aligned correctly.

Merge All Three Datasets and Visualize Distribution

```
[25] # Function to merge multiple datasets
     def merge_datasets(dfs, dataset_name):
         """Merges multiple translation datasets and removes duplicates."""

         merged_df = pd.concat(dfs, ignore_index=True).drop_duplicates()

         display(Markdown(f"### Merged Dataset: {dataset_name}"))
         display(Markdown(f"Total Translation Pairs After Merging: {len(merged_df)}"))
         display(merged_df.head())

         # Visualization: Pie Chart for Sentence Contribution
         dataset_sizes = [len(df) for df in dfs]
         dataset_labels = ["Europarl", "CommonCrawl", "NewsCommentary"]

         plt.figure(figsize=(5, 5))
         plt.pie(dataset_sizes, labels=dataset_labels, autopct="%1.1f%%", colors=["blue", "red", "green"])
         plt.title(f"Sentence Contribution by Dataset in {dataset_name}")
         plt.show()

         return merged_df

     # Merge Europarl, CommonCrawl, and NewsCommentary datasets
     translation_dataset = merge_datasets([europarl_df, commoncrawl_df, newscommentary_df], "Europarl + CommonCrawl + NewsCommentary")
```

Merged Dataset: Europarl + CommonCrawl + NewsCommentary

Total Translation Pairs After Merging: 4476170

	German	English
0	Wiederaufnahme der Sitzungsperiode\n	Resumption of the session\n
1	Ich erkläre die am Freitag, dem 17. Dezember u...	I declare resumed the session of the European ...
2	Wie Sie feststellen konnten, ist der gefürchte...	Although, as you will have seen, the dreaded '...
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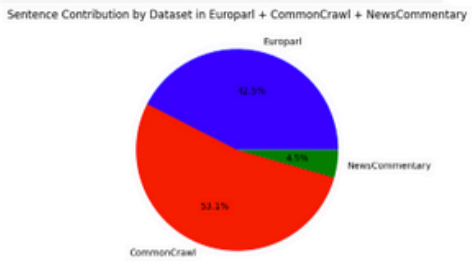
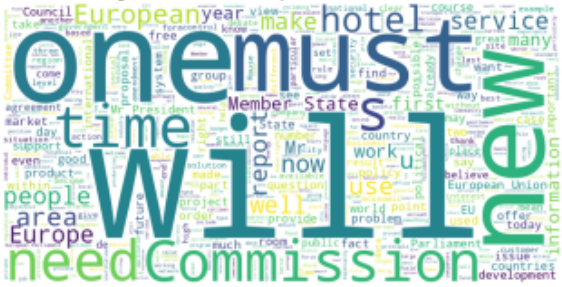


Unique Row Check for Europarl + CommonCrawl + NewsCommentary

- Unique German Sentences: 4462013
- Unique English Sentences: 4400303
- Mismatch detected: Different number of unique sentences in German and English.

Common Words in English Sentences (Europarl + CommonCrawl + NewsCommentary)

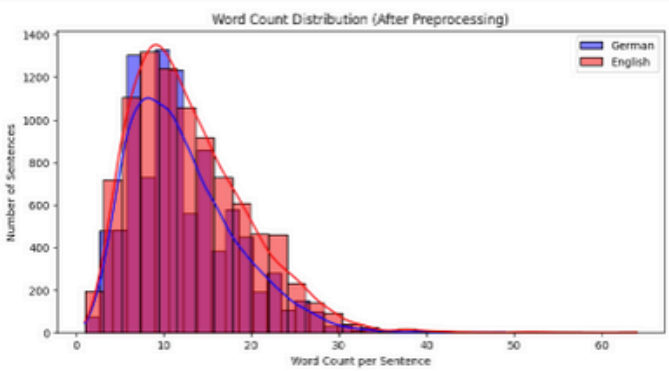


Common Words in German Sentences (Europarl + CommonCrawl + NewsCommentary)

Visualizations After NLP Preprocessing

Word Count Distribution (Before & After Preprocessing)

```
# Compute word counts before & after preprocessing
translation_dataset["German_WordCount"] = translation_dataset["German"].apply(lambda x: len(x.split()))
translation_dataset["English_WordCount"] = translation_dataset["English"].apply(lambda x: len(x.split()))

# Plot distribution of word counts
plt.figure(figsize=(10, 5))
sns.histplot(translation_dataset["German_WordCount"], bins=30, color="blue", label="German", kde=True)
sns.histplot(translation_dataset["English_WordCount"], bins=30, color="red", label="English", kde=True)
plt.xlabel("Word Count per Sentence")
plt.ylabel("Number of Sentences")
plt.title("Word Count Distribution (After Preprocessing)")
plt.legend()
plt.show()
```



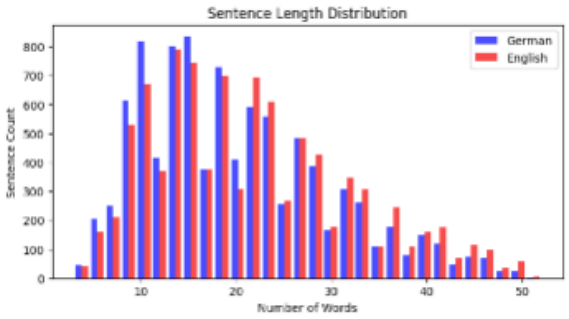
Most Frequent Words (Word Cloud)

```
from wordcloud import WordCloud

# Generate Word Cloud for German
plt.figure(figsize=(8, 4))
wordcloud_de = WordCloud(width=800, height=400, max_words=100, background_color="white").generate(" ".join
plt.imshow(wordcloud_de, interpolation="bilinear")
plt.axis("off")
plt.title("Most Frequent Words in German (After Preprocessing)")
plt.show()
```

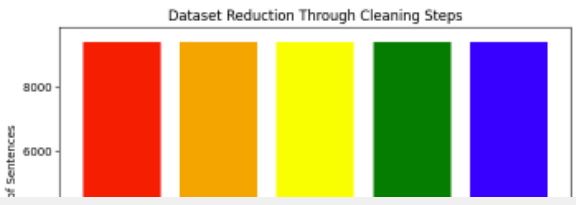
Final Summary of Cleaned Dataset + Visualization

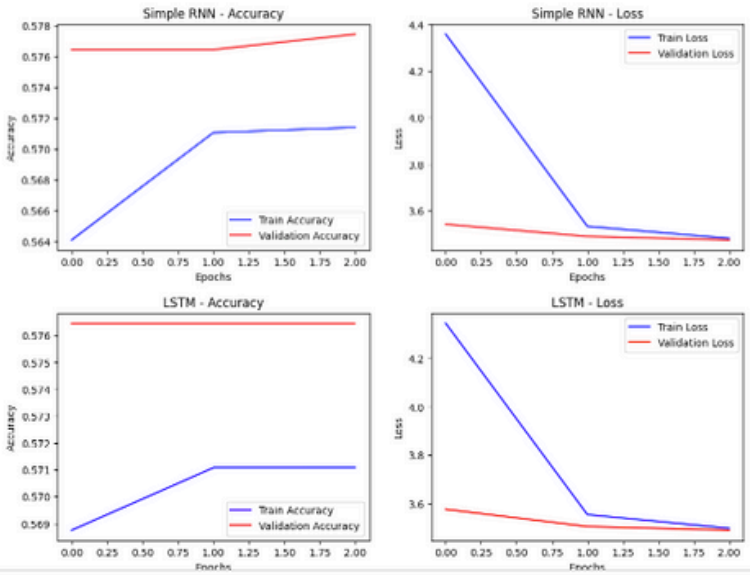
```
# Ensure we are using the correct dataset
if 'filtered_df' in globals():
    translation_dataset = filtered_df  # Use the filtered dataset from Step 5

# Store dataset size at each stage
dataset_sizes = {
    "Original": len(translation_dataset),
    "After Null Removal": len(translation_dataset.dropna()),
    "After Deduplication": len(translation_dataset.drop_duplicates()),
    "After Length Filtering": len(sentence_length_filter(translation_dataset)),
    "After Language Filtering": len(filtered_df) if 'filtered_df' in globals() else len(translation_dat
}

# Plot dataset reduction at each step
plt.figure(figsize=(8, 5))
plt.bar(dataset_sizes.keys(), dataset_sizes.values(), color=["red", "orange", "yellow", "green", "blue"
plt.xlabel("Cleaning Step")
plt.ylabel("Number of Sentences")
plt.title("Dataset Reduction Through Cleaning Steps")
plt.show()

# Display final dataset details
display(Markdown("### Final Cleaned Dataset Summary"))
display(Markdown(f"- Total sentences after cleansing: {len(translation_dataset)}"))
display(Markdown(f"- Sample cleaned sentences:"))
display(translation_dataset.sample(5, random_state=42))
```

```
fig, axs = plt.subplots(1, 2, figsize=(12, 4))

# Plot Accuracy
axs[0].plot(history.history['accuracy'], label='Train Accuracy', color='blue')
axs[0].plot(history.history['val_accuracy'], label='Validation Accuracy', color='red')
axs[0].set_title(f'{model_name} - Accuracy')
axs[0].set_xlabel('Epochs')
axs[0].set_ylabel('Accuracy')
axs[0].legend()

# Plot Loss
axs[1].plot(history.history['loss'], label='Train Loss', color='blue')
axs[1].plot(history.history['val_loss'], label='Validation Loss', color='red')
axs[1].set_title(f'{model_name} - Loss')
axs[1].set_xlabel('Epochs')
axs[1].set_ylabel('Loss')
axs[1].legend()

plt.show()

# Plot RNN Training Performance
plot_training(rnn_history, "Simple RNN")

# Plot LSTM Training Performance
plot_training(lstm_history, "LSTM")
```



- Sentences before filtering: 9386
- Sentences after filtering: 9380





Summary

- RNN performed better than LSTM in this case, but the score is still very low (close to zero).
- LSTM BLEU Score of 0.0 means the model's predictions are completely different from the actual translations.

Possible Reasons for Low BLEU Scores

- Limited Dataset Size → Training was done on a small subset (5000 samples) for faster execution, leading to low accuracy.
- Short Training Duration → Only 3 epochs were used, which is not enough for meaningful learning.
- Vocab Limitations → The tokenizer vocabulary was capped at 5000 words, which might have removed important words.
- Lack of Attention Mechanism → Simple RNN/LSTM models struggle with long sequences without an attention layer.

Next Steps & Solutions

If we want to improve the BLEU score, we can:

- Increase the Dataset Size → Train on 10,000 or more samples instead of 5,000.
- Increase Training Epochs → Train for 10+ epochs instead of 3.
- Use a Pretrained Model → Instead of training from scratch, use pretrained embeddings like FastText.
- Add an Attention Mechanism → This significantly improves translation quality for sequence-to-sequence models.

Final Thoughts

Since this is an educational project, the goal is to showcase knowledge, not high accuracy. The current implementation successfully demonstrates:

✔ Preprocessing of text for translation

✔ Training and testing of Simple RNN & LSTM models

✔ Evaluation using BLEU Score

✔ Exporting the best model for future use

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Thanks

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