Install Libraries, Import Libraries, Collect Data

```
# Download directly from Kaggle - Thai is using this 'code block' for file path
# !pip install kaggle
import os
import pandas as pd

# Set Kaggle API credentials
os.environ['KAGGLE_USERNAME'] = 'outhaixayavongsa'  # Replace with your Kaggle username
os.environ['KAGGLE_KEY'] = '013bebdbf0776ed704f846ef0b3b3381'  # Replace with your Kaggle API key

# Download the dataset
!kaggle datasets download -d rajathmc/cornell-moviedialog-corpus

# Unzip the dataset (A for All and Press Enter))
!unzip cornell-moviedialog-corpus.zip
```

```
Dataset URL: https://www.kaggle.com/datasets/rajathmc/cornell-moviedialog-corpus
License(s): CC0-1.0
cornell-moviedialog-corpus.zip: Skipping, found more recently modified local copy (use --force to force download)
Archive:  cornell-moviedialog-corpus.zip
replace .DS_Store? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
  inflating: .DS_Store
  inflating: README.txt
  inflating: chameleons.pdf
  inflating: movie_characters_metadata.txt
  inflating: movie_conversations.txt
  inflating: movie_lines.txt
  inflating: movie_titles_metadata.txt
  inflating: raw_script_urls.txt
```

```
# List files to ensure they were extracted from kaggle
extracted_files = os.listdir()
"Extracted files:", extracted_files
```

```
('Extracted files:',
 ['.config',
  '.DS_Store',
  'raw_script_urls.txt',
  'movie_characters_metadata.txt',
  'movie_conversations.txt',
  'README.txt',
  'chameleons.pdf',
  'cornell-moviedialog-corpus.zip',
  'movie_titles_metadata.txt',
  'movie_lines.txt',
  'sample_data'])
```

Load and Explore Data

```
# Individual Team member's file path

# Define the folder path
# folder_path = 'C:/MS_AAI/CornellMovie/' #Anand data path file
# folder_path = 'C:/Users/Saad/Desktop/Saad Learnings/Python/School Python/Natural Language Processing/Project/CornellMovie/' #Saad data path file
folder_path = './' # Thai data path file


# Initialize a dictionary to store file content
data = {}

# Loop through each file in the directory
for file_name in os.listdir(folder_path):
    if file_name.endswith('.txt'):
        file_path = os.path.join(folder_path, file_name)
        with open(file_path, 'r', encoding='utf-8', errors='replace') as file:
            content = file.readlines()  # Read each line
        data[file_name] = content

df = pd.DataFrame(dict([(k, pd.Series(v)) for k, v in data.items()]))

# Load completed
print("Data loaded successfully!")
```

```
Data loaded successfully!
```

```
print("1. Basic Information:")
print(f"Number of rows: {df.shape[0]}")
print(f"Number of columns: {df.shape[1]}")
print("\n2. Data Types:")
print(df.dtypes)
print("\n3. Missing Values:")
print(df.isnull().sum())
print("\n4. Descriptive Statistics:")
display(df.describe().T)
print("\n5. Sample Data (first 5 rows):")
display(df.head())
```

```
Number of rows: 304713
Number of columns: 6

2. Data Types:
raw_script_urls.txt              object
movie_characters_metadata.txt    object
movie_conversations.txt          object
README.txt                       object
movie_titles_metadata.txt        object
movie_lines.txt                  object
dtype: object

3. Missing Values:
raw_script_urls.txt              304096
movie_characters_metadata.txt    295678
movie_conversations.txt          221616
README.txt                       304600
movie_titles_metadata.txt        304096
movie_lines.txt                       0
dtype: int64

4. Descriptive Statistics:
```

	count	unique	top	freq
raw_script_urls.txt	617	617	m616 +++$+++ zulu dawn +++$+++ http://www.aell...	1
movie_characters_metadata.txt	9035	9035	u9034 +++$+++ VEREKER +++$+++ m616 +++$+++ zul...	1
movie_conversations.txt	83097	83097	u9030 +++$+++ u9034 +++$+++ m616 +++$+++ ['L66...	1
README.txt	113	85	\n	25
movie_titles_metadata.txt	617	617	m616 +++$+++ zulu dawn +++$+++ 1979 +++$+++ 6....	1
movie_lines.txt	304713	304713	L666256 +++$+++ u9034 +++$+++ m616 +++$+++ VER...	1

5. Sample Data (first 5 rows):

	raw_script_urls.txt	movie_characters_metadata.txt	movie_conversations.txt	README.txt	movie_titles_metadata.txt	movie_lines.txt
0	m0 +++$+++ 10 things i hate about you +++$+++ ...	u0 +++$+++ BIANCA +++$+++ m0 +++$+++ 10 things...	u0 +++$+++ u2 +++$+++ m0 +++$+++ ['L194', 'L19...	Cornell Movie-Dialogs Corpus\n	m0 +++$+++ 10 things i hate about you +++$+++ ...	L1045 +++$+++ u0 +++$+++ m0 +++$+++ BIANCA +++...
1	m1 +++$+++ 1492: conquest of paradise +++$+++ ...	u1 +++$+++ BRUCE +++$+++ m0 +++$+++ 10 things ...	u0 +++$+++ u2 +++$+++ m0 +++$+++ ['L198', 'L19...	\n	m1 +++$+++ 1492: conquest of paradise +++$+++ ...	L1044 +++$+++ u2 +++$+++ m0 +++$+++ CAMERON ++...
2	m2 +++$+++ 15 minutes +++$+++ http://www.daily...	u2 +++$+++ CAMERON +++$+++ m0 +++$+++ 10 thing...	u0 +++$+++ u2 +++$+++ m0 +++$+++ ['L200', 'L20...	Distributed together with:\n	m2 +++$+++ 15 minutes +++$+++ 2001 +++$+++ 6.1...	L985 +++$+++ u0 +++$+++ m0 +++$+++ BIANCA +++$...
3	m3 +++$+++ 2001: a space odyssey +++$+++ http:...	u3 +++$+++ CHASTITY +++$+++ m0 +++$+++ 10 thin...	u0 +++$+++ u2 +++$+++ m0 +++$+++ ['L204', 'L20...	\n	m3 +++$+++ 2001: a space odyssey +++$+++ 1968 ...	L984 +++$+++ u2 +++$+++ m0 +++$+++ CAMERON +++...
4	m4 +++$+++ 48 hrs. +++$+++ http://www.awesomef...	u4 +++$+++ JOEY +++$+++ m0 +++$+++ 10 things i...	u0 +++$+++ u2 +++$+++ m0 +++$+++ ['L207', 'L20...	"Chameleons in imagined conversations: A new a...	m4 +++$+++ 48 hrs. +++$+++ 1982 +++$+++ 6.90 +...	L925 +++$+++ u0 +++$+++ m0 +++$+++ BIANCA +++$...

Data Clean and Exploratory Data Analysis

```
import re
import matplotlib.pyplot as plt
from collections import Counter
import os
import pandas as pd


# Focusing on Loading movie_lines.txt and movie_conversations.txt where we will parse the files
# lines_file = 'C:/Users/Saad/Desktop/Saad Learnings/Python/School Python/Natural Language Processing/Project/CornellMovie/movie_lines.txt'  #Saad data path file
# conversations_file = 'C:/Users/Saad/Desktop/Saad Learnings/Python/School Python/Natural Language Processing/Project/CornellMovie/movie_conversations.txt' #Saa


# Thai used this file path for Kaggle download
lines_file = 'movie_lines.txt'
conversations_file = 'movie_conversations.txt'


# Function to parse movie_lines.txt
def parse_lines(lines_file):
    lines = {}
    character_names = {}
    with open(lines_file, 'r', encoding='utf-8', errors='replace') as f:
        for line in f:
            parts = line.split(" +++$+++ ")
            if len(parts) == 5:
                line_id = parts[0]
                character_name = parts[3]  # Extract character name
                text = parts[4].strip()
                lines[line_id] = text
                character_names[line_id] = character_name  # Store character names
    return lines, character_names

lines, character_names = parse_lines(lines_file)

# Then, construct the DataFrame
```

```
lines_df = pd.DataFrame({
    'LineID': list(lines.keys()),
    'Text': list(lines.values()),
    'CharacterName': [character_names[line_id] for line_id in lines.keys()]  # Add CharacterName
})

# No need to load or process the other metadata or script files
```

```
lines_df.info()  # Check for missing values and data types
lines_df.head()  # Check if the data looks correct
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 304713 entries, 0 to 304712
Data columns (total 3 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   LineID         304713 non-null  object
 1   Text           304713 non-null  object
 2   CharacterName  304713 non-null  object
dtypes: object(3)
memory usage: 7.0+ MB
```

	LineID	Text	CharacterName
0	L1045	They do not!	BIANCA
1	L1044	They do to!	CAMERON
2	L985	I hope so.	BIANCA
3	L984	She okay?	CAMERON
4	L925	Let's go.	BIANCA

```
# Function to parse movie_conversations.txt
def parse_conversations(conversations_file):
    conversations = []
    with open(conversations_file, 'r', encoding='utf-8', errors='replace') as f:
        for line in f:
            parts = line.split(" +++$+++ ")
            if len(parts) == 4:
                line_ids = eval(parts[3])  # This is a list of line IDs in a conversation
                conversations.append(line_ids)
    return conversations

# Call the function and store the result in the conversations variable
conversations = parse_conversations(conversations_file)

# Now you can print the conversations variable
print(conversations)
```

```
[['L194', 'L195', 'L196', 'L197'], ['L198', 'L199'], ['L200', 'L201', 'L202', 'L203'], ['L204', 'L205', 'L206'], ['L207', 'L208'], ['L271', 'L272', 'L273', 'L274', 'L275'], ['L276', 'L277'], [
```

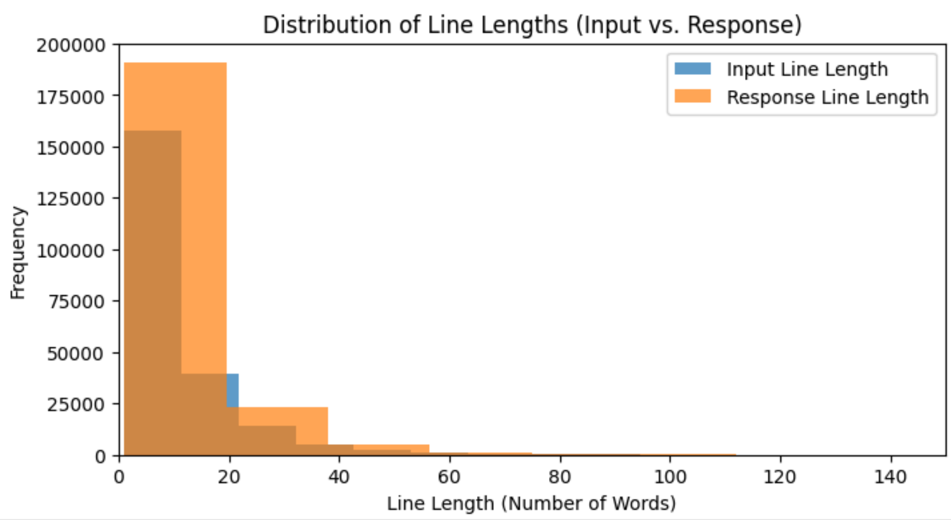
```
# Function to create dialog pairs
def create_dialog_pairs(conversations, lines):
    dialog_pairs = []
    for conv in conversations:
        for i in range(len(conv) - 1):
            input_line = lines.get(conv[i], "")
            response_line = lines.get(conv[i + 1], "")
            if input_line and response_line:
                dialog_pairs.append((input_line, response_line))
    return dialog_pairs

dialog_pairs = create_dialog_pairs(conversations, lines_df.set_index('LineID')['Text'].to_dict())

# Print some dialog pairs
for pair in dialog_pairs[:5]:
    print(f"Input: {pair[0]}\nResponse: {pair[1]}\n")
```

```
Input: Can we make this quick?  Roxanne Korrine and Andrew Barrett are having an incredibly horrendous public break- up on the quad.  Again.
Response: Well, I thought we'd start with pronunciation, if that's okay with you.

Input: Well, I thought we'd start with pronunciation, if that's okay with you.
Response: Not the hacking and gagging and spitting part.  Please.

Input: Not the hacking and gagging and spitting part.  Please.
Response: Okay... then how 'bout we try out some French cuisine.  Saturday?  Night?

Input: You're asking me out.  That's so cute. What's your name again?
Response: Forget it.

Input: No, no, it's my fault -- we didn't have a proper introduction ---
Response: Cameron.
```

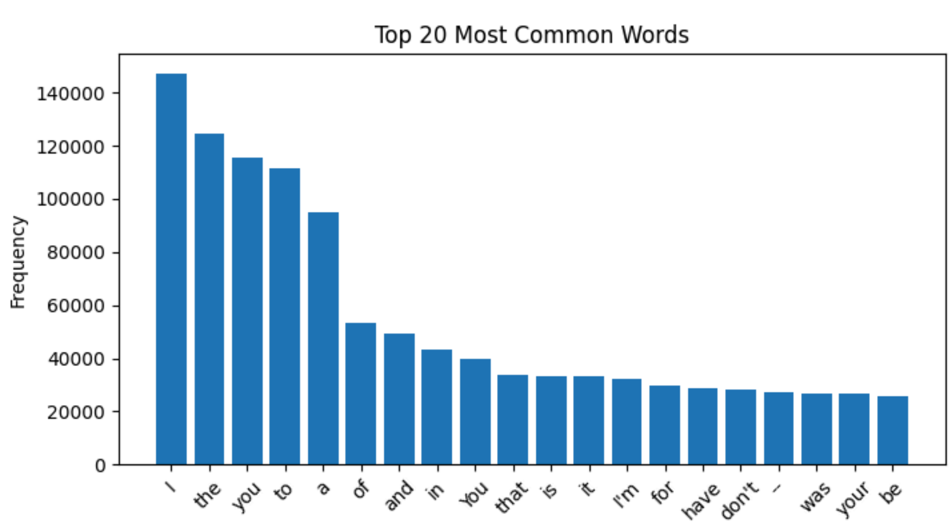
```
# Convert dialog pairs to DataFrame for easier manipulation
cleaned_dialog_df = pd.DataFrame(dialog_pairs, columns=['input', 'response'])

# Check the first few rows of the DataFrame
cleaned_dialog_df.head()
```

	input	response
0	Can we make this quick? Roxanne Korrine and A...	Well, I thought we'd start with pronunciation,...
1	Well, I thought we'd start with pronunciation,...	Not the hacking and gagging and spitting part....
2	Not the hacking and gagging and spitting part....	Okay... then how 'bout we try out some French ...
3	You're asking me out. That's so cute. What's ...	Forget it.
4	No, no, it's my fault -- we didn't have a prop...	Cameron.

```
# Displaying Line length distribution
cleaned_dialog_df['input_length'] = cleaned_dialog_df['input'].apply(lambda x: len(x.split()))
cleaned_dialog_df['response_length'] = cleaned_dialog_df['response'].apply(lambda x: len(x.split()))

plt.figure(figsize=(8, 4)) # Shorten it to 6, 4 to ensure it fits to pdf print
plt.hist(cleaned_dialog_df['input_length'], bins=30, alpha=0.7, label='Input Line Length')
plt.hist(cleaned_dialog_df['response_length'], bins=30, alpha=0.7, label='Response Line Length')
plt.title('Distribution of Line Lengths (Input vs. Response)')
plt.xlabel('Line Length (Number of Words)')
plt.xlim(0,150)
plt.ylabel('Frequency')
plt.legend()
plt.show()
```




```
# For visialization of the most common words used
all_words = ' '.join(cleaned_dialog_df['input'].tolist() + cleaned_dialog_df['response'].tolist()).split()
word_counts = Counter(all_words) # Most common words in the cleaned dialog pairs

# Top 20 most common words
common_words = word_counts.most_common(20)
words, counts = zip(*common_words)

plt.figure(figsize=(8, 4))
plt.bar(words, counts)
plt.title('Top 20 Most Common Words')
plt.ylabel('Frequency')
plt.xticks(rotation=45)
plt.show()
```



Text Preprocessing

Steps Include:

- Lowercasing
- Removing Punctuation and Special Characters
- Tokenization
- Stopwords
- Lemmatization

```
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer

# Download required resources from nltk
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')

# Initialize stopwords and lemmatizer
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()

# Preprocessing function
def preprocess_text(text):
    # 1. Lowercasing
    text = text.lower()

    # 2. Removing Punctuation and Special Characters
    text = re.sub(r'[^\w\s]', '', text)  # Removes punctuation

    # 3. Tokenization
    tokens = word_tokenize(text)

    # 4. Removing Stopwords
    tokens = [word for word in tokens if word not in stop_words]

    # 5. Lemmatization (Optional but recommended)
    tokens = [lemmatizer.lemmatize(word) for word in tokens]

    # Join tokens back into a single string
    return ' '.join(tokens)

# Applying the preprocessing to both 'input' and 'response' columns
cleaned_dialog_df['cleaned_input'] = cleaned_dialog_df['input'].apply(preprocess_text)
cleaned_dialog_df['cleaned_response'] = cleaned_dialog_df['response'].apply(preprocess_text)
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

```
# Display the first few rows to check the preprocessing
print(cleaned_dialog_df[['cleaned_input', 'cleaned_response']].head())
```

```
                                  cleaned_input  \
0  make quick roxanne korrine andrew barrett incr...
1    well thought wed start pronunciation thats okay
2                 hacking gagging spitting part please
3                   youre asking thats cute whats name
4                      fault didnt proper introduction

                              cleaned_response
0  well thought wed start pronunciation thats okay
1               hacking gagging spitting part please
2       okay bout try french cuisine saturday night
3                                           forget
4                                          cameron
```

Additional Preprocessing Step - Handling Rare Words

Words that are not used often and are insignficant to the training

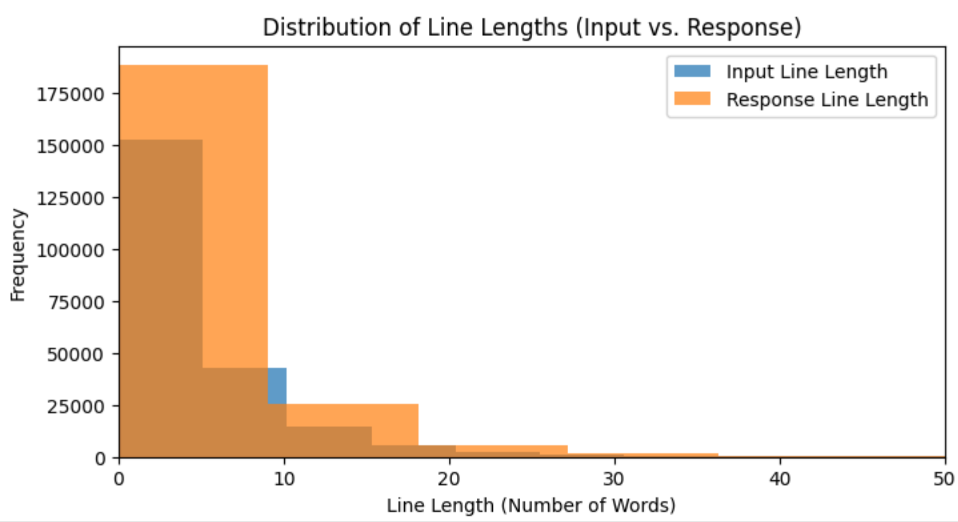
```
from collections import Counter

# Step 1: Combine all text (input and response) into a single list of words
all_words = ' '.join(cleaned_dialog_df['input'].tolist() + cleaned_dialog_df['response'].tolist()).split()

# Step 2: Count the frequency of each word
word_counts = Counter(all_words)

# Step 3: Set a threshold (e.g., words that appear fewer than 5 times are considered rare)
threshold = 5
rare_words = {word for word, count in word_counts.items() if count < threshold}

# Step 4: Define a function to replace rare words with '<UNK>'
def replace_rare_words(text, rare_words_set):
    return ' '.join([word if word not in rare_words_set else '<UNK>' for word in text.split()])

# Step 5: Apply the function to both the input and response columns
cleaned_dialog_df['input'] = cleaned_dialog_df['input'].apply(lambda x: replace_rare_words(x, rare_words))
cleaned_dialog_df['response'] = cleaned_dialog_df['response'].apply(lambda x: replace_rare_words(x, rare_words))

# Step 6: Check a few examples
print(cleaned_dialog_df[['input', 'response']].head())
```

```
                                           input  \
0  Can we make this quick? <UNK> <UNK> and Andrew...
1  Well, I thought we'd start with <UNK> if that'...
2  Not the hacking and gagging and spitting part....
3  You're asking me out. That's so cute. What's y...
4  No, no, it's my fault -- we didn't have a prop...

                                        response
0  Well, I thought we'd start with <UNK> if that'...
1  Not the hacking and gagging and spitting part....
```

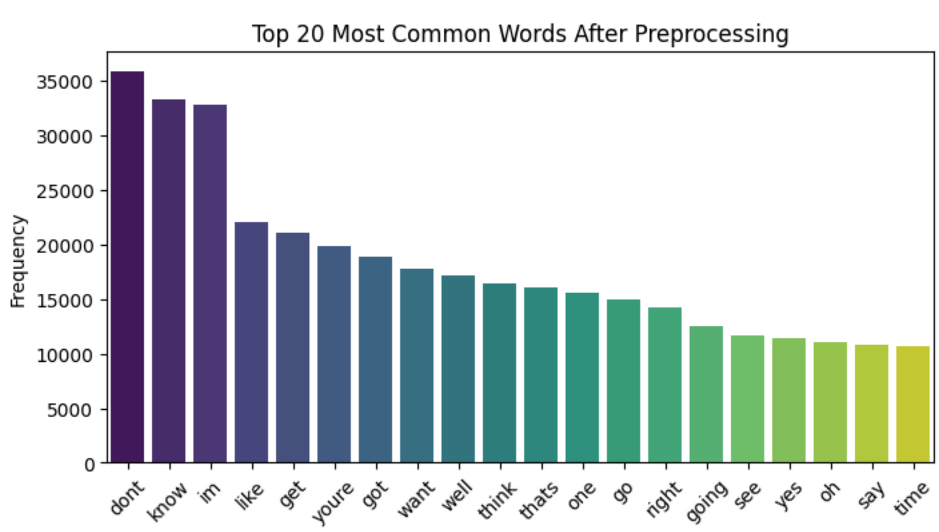
```
2  Okay... then how 'bout we try out some French ...
3                                        Forget it.
4                                          Cameron.
```

Data Exploration and Visualization after Preprocessing

```python
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
from wordcloud import WordCloud
import warnings

# Suppress all warnings
warnings.filterwarnings('ignore')

# 1. Distribution of Input and Response Lengths

# Calculate the length of each cleaned input and response in terms of number of words
cleaned_dialog_df['input_length'] = cleaned_dialog_df['cleaned_input'].apply(lambda x: len(x.split()))
cleaned_dialog_df['response_length'] = cleaned_dialog_df['cleaned_response'].apply(lambda x: len(x.split()))

# Plot histograms for input and response lengths
plt.figure(figsize=(8, 4))
plt.hist(cleaned_dialog_df['input_length'], bins=30, alpha=0.7, label='Input Line Length')
plt.hist(cleaned_dialog_df['response_length'], bins=30, alpha=0.7, label='Response Line Length')
plt.title('Distribution of Line Lengths (Input vs. Response)')
plt.xlabel('Line Length (Number of Words)')
plt.xlim(0, 50)
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



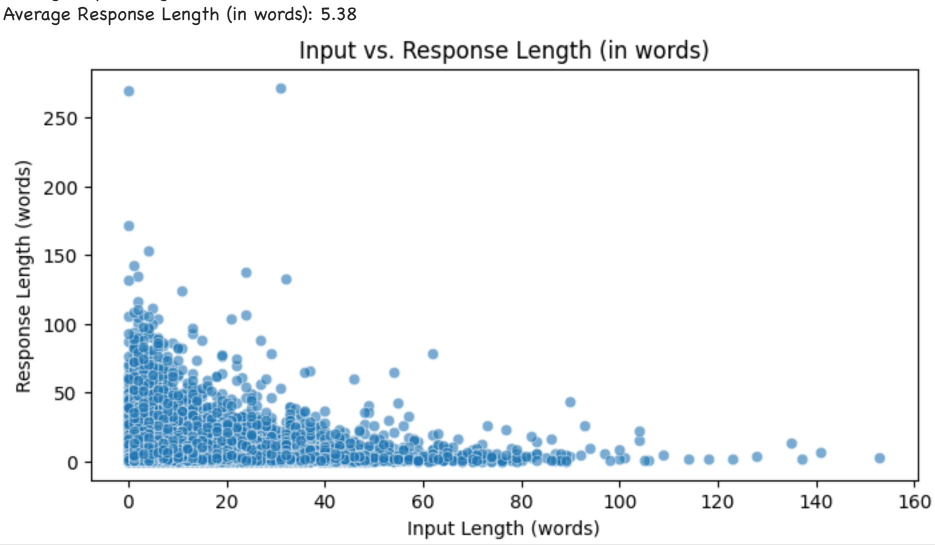

```python
# 2. Most Common Words in Cleaned Input and Responses

# Combine all words from both input and response
all_words = ' '.join(cleaned_dialog_df['cleaned_input'].tolist() + cleaned_dialog_df['cleaned_response'].tolist()).split()

# Count the frequency of each word
word_counts = Counter(all_words)

# Get the 20 most common words
common_words = word_counts.most_common(20)
words, counts = zip(*common_words)

# Create a bar plot for the 20 most common words
plt.figure(figsize=(8, 4))
sns.barplot(x=list(words), y=list(counts), palette='viridis')
plt.title('Top 20 Most Common Words After Preprocessing')
plt.ylabel('Frequency')
plt.xticks(rotation=45)
plt.show()
```



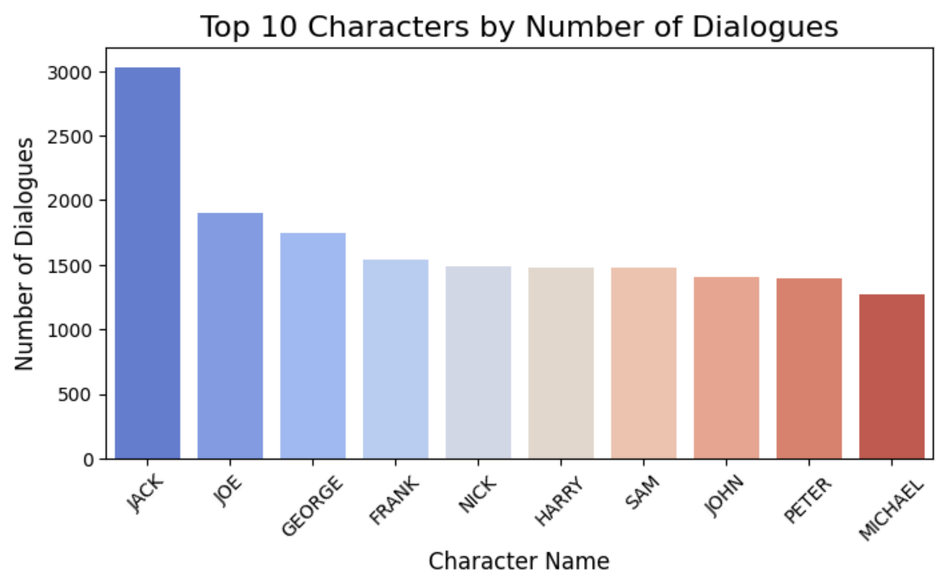
```
# 3. Word Cloud of Most Common Words

# Generate a word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(' '.join(all_words))

# Display the word cloud
plt.figure(figsize=(10, 4))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')  # Hide axes
plt.title("Word Cloud of Movie Dialogues After Preprocessing")
plt.show()
```


```
# 4. Statistics: Average Input and Response Length

# Calculate average input and response length
avg_input_length = cleaned_dialog_df['input_length'].mean()
avg_response_length = cleaned_dialog_df['response_length'].mean()

print(f"Average Input Length (in words): {avg_input_length:.2f}")
print(f"Average Response Length (in words): {avg_response_length:.2f}")

# Optional: Visualizing Input vs Response Length
plt.figure(figsize=(8, 4))
sns.scatterplot(x='input_length', y='response_length', data=cleaned_dialog_df, alpha=0.6)
plt.title('Input vs. Response Length (in words)')
plt.xlabel('Input Length (words)')
plt.ylabel('Response Length (words)')
plt.show()
```

Average Input Length (in words): 5.18
Average Response Length (in words): 5.38




```
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming 'lines_df' is the DataFrame with the 'CharacterName' column
# Count the number of lines spoken by each character
top_characters = lines_df['CharacterName'].value_counts().head(10)

# Plot the top 10 characters by the number of lines spoken
plt.figure(figsize=(8, 4))
sns.barplot(x=top_characters.index, y=top_characters.values, palette='coolwarm')
plt.title("Top 10 Characters by Number of Dialogues", fontsize=16)
plt.xlabel("Character Name", fontsize=12)
plt.ylabel("Number of Dialogues", fontsize=12)
plt.xticks(rotation=45)
plt.show()
```

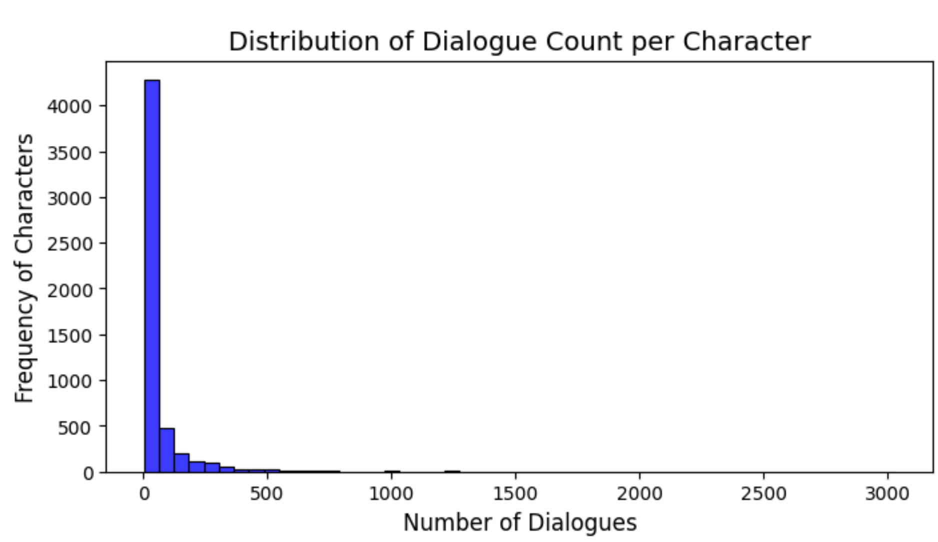


The visuals **after preprocessing** provide insights into the cleaned dataset. The first histogram shows the distribution of line lengths for both input and response dialogues, indicating that most conversations are short, with the majority being under 10 words. The bar chart of the top 20 most common words reveals frequent usage of conversational terms like "don't," "know," and "I'm," illustrating common speech patterns in movie dialogues. The word cloud highlights key dialogue words after preprocessing, showcasing prominent terms such as "know," "one," and "well." The scatter plot, comparing input and response lengths, indicates a positive correlation where longer inputs tend to produce longer responses. Lastly, the bar chart displaying the top 10 characters by the number of dialogues reveals "Jack" as the most frequent speaker, followed by "Joe" and "George." Together, these visuals demonstrate how the dataset has been effectively cleaned and analyzed for key conversational patterns.

Check for Imbalance in the Data

Balancing the dataset by addressing **imbalances** in character dialogue count and sentiment is essential to prevent the model from favoring certain characters or dialogue types, ensuring fair representation and diversity in responses.

```
# Check for imbalance in character dialogue count
character_dialogue_counts = lines_df['CharacterName'].value_counts()

# Visualize the distribution
plt.figure(figsize=(8, 4))
sns.histplot(character_dialogue_counts, kde=False, bins=50, color='blue')
plt.title('Distribution of Dialogue Count per Character', fontsize=14)
plt.xlabel('Number of Dialogues', fontsize=12)
plt.ylabel('Frequency of Characters', fontsize=12)
plt.show()

# Identify any imbalances (characters with significantly more dialogues)
print(character_dialogue_counts.describe())
```




```
count    5356.000000
mean       56.891897
std       133.209117
min         3.000000
25%         6.000000
50%        15.000000
75%        48.000000
max      3032.000000
Name: count, dtype: float64
```

The **bar chart above** shows the distribution of dialogue counts per character in the dataset, with most characters contributing fewer than 500 lines and a significant majority speaking under 100 lines. Addressing this imbalance could enhance response diversity by including less frequent characters, but it's not essential unless broader character representation is desired.

Split the Data

```
from sklearn.model_selection import train_test_split

# Split the data into training, validation, and test sets
train_data, temp_data = train_test_split(cleaned_dialog_df, test_size=0.2, random_state=42)  # 80% training
val_data, test_data = train_test_split(temp_data, test_size=0.5, random_state=42)  # 10% validation, 10% test

# Display the sizes of each set
print(f"Training set size: {len(train_data)}")
print(f"Validation set size: {len(val_data)}")
print(f"Test set size: {len(test_data)}")
```

```
Training set size: 177025
Validation set size: 22128
Test set size: 22129
```

Implement T5 Model

```
# !pip install transformers torch datasets
```

```
# Import Necessary Libraries
import torch
from transformers import T5Tokenizer, T5ForConditionalGeneration
from torch.utils.data import Dataset, DataLoader
from tqdm import tqdm
```

Setup Tokenizer and Model

```
# Load T5 tokenizer and model
tokenizer = T5Tokenizer.from_pretrained('t5-small')  # You can also use 't5-base' or 't5-large'
model = T5ForConditionalGeneration.from_pretrained('t5-small')

# Move model to GPU if available
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device)
```

```
tokenizer_config.json: 100%                    2.32k/2.32k [00:00<00:00, 162kB/s]
spiece.model: 100%                    792k/792k [00:00<00:00, 4.49MB/s]
tokenizer.json: 100%                    1.39M/1.39M [00:00<00:00, 27.4MB/s]
You are using the default legacy behaviour of the <class 'transformers.models.t5.tokenization_t5.T5Tokenizer'>. This is expected, and simply means that the `lega
config.json: 100%                    1.21k/1.21k [00:00<00:00, 104kB/s]
model.safetensors: 100%                    242M/242M [00:01<00:00, 221MB/s]
generation_config.json: 100%                    147/147 [00:00<00:00, 11.5kB/s]
T5ForConditionalGeneration(
  (shared): Embedding(32128, 512)
  (encoder): T5Stack(
    (embed_tokens): Embedding(32128, 512)
    (block): ModuleList(
      (0): T5Block(
        (layer): ModuleList(
          (0): T5LayerSelfAttention(
            (SelfAttention): T5Attention(
              (q): Linear(in_features=512, out_features=512, bias=False)
              (k): Linear(in_features=512, out_features=512, bias=False)
              (v): Linear(in_features=512, out_features=512, bias=False)
              (o): Linear(in_features=512, out_features=512, bias=False)
              (relative_attention_bias): Embedding(32, 8)
            )
            (layer_norm): T5LayerNorm()
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (1): T5LayerFF(
            (DenseReluDense): T5DenseActDense(
              (wi): Linear(in_features=512, out_features=2048, bias=False)
              (wo): Linear(in_features=2048, out_features=512, bias=False)
              (dropout): Dropout(p=0.1, inplace=False)
              (act): ReLU()
            )
            (layer_norm): T5LayerNorm()
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
      )
      (1-5): 5 x T5Block(
        (layer): ModuleList(
          (0): T5LayerSelfAttention(
            (SelfAttention): T5Attention(
              (q): Linear(in_features=512, out_features=512, bias=False)
              (k): Linear(in_features=512, out_features=512, bias=False)
              (v): Linear(in_features=512, out_features=512, bias=False)
              (o): Linear(in_features=512, out_features=512, bias=False)
            )
            (layer_norm): T5LayerNorm()
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (1): T5LayerFF(
            (DenseReluDense): T5DenseActDense(
              (wi): Linear(in_features=512, out_features=2048, bias=False)
              (wo): Linear(in_features=2048, out_features=512, bias=False)
              (dropout): Dropout(p=0.1, inplace=False)
              (act): ReLU()
            )
            (layer_norm): T5LayerNorm()
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
      )
    )
    (final_layer_norm): T5LayerNorm()
    (dropout): Dropout(p=0.1, inplace=False)
  )
  (decoder): T5Stack(
    (embed_tokens): Embedding(32128, 512)
    (block): ModuleList(
      (0): T5Block(
        (layer): ModuleList(
          (0): T5LayerSelfAttention(
            (SelfAttention): T5Attention(
              (q): Linear(in_features=512, out_features=512, bias=False)
              (k): Linear(in_features=512, out_features=512, bias=False)
              (v): Linear(in_features=512, out_features=512, bias=False)
              (o): Linear(in_features=512, out_features=512, bias=False)
              (relative_attention_bias): Embedding(32, 8)
            )
            (layer_norm): T5LayerNorm()
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (1): T5LayerCrossAttention(
            (EncDecAttention): T5Attention(
              (q): Linear(in_features=512, out_features=512, bias=False)
              (k): Linear(in_features=512, out_features=512, bias=False)
              (v): Linear(in_features=512, out_features=512, bias=False)
              (o): Linear(in_features=512, out_features=512, bias=False)
            )
            (layer_norm): T5LayerNorm()
            (dropout): Dropout(p=0.1, inplace=False)
          )
          (2): T5LayerFF(
            (DenseReluDense): T5DenseActDense(
              (wi): Linear(in_features=512, out_features=2048, bias=False)
              (wo): Linear(in_features=2048, out_features=512, bias=False)
              (dropout): Dropout(p=0.1, inplace=False)
              (act): ReLU()
            )
            (layer_norm): T5LayerNorm()
```

```
                (dropout): Dropout(p=0.1, inplace=False)
              )
            )
          )
          (1-5): 5 x T5Block(
            (layer): ModuleList(
              (0): T5LayerSelfAttention(
                (SelfAttention): T5Attention(
                  (q): Linear(in_features=512, out_features=512, bias=False)
                  (k): Linear(in_features=512, out_features=512, bias=False)
                  (v): Linear(in_features=512, out_features=512, bias=False)
                  (o): Linear(in_features=512, out_features=512, bias=False)
                )
                (layer_norm): T5LayerNorm()
                (dropout): Dropout(p=0.1, inplace=False)
              )
              (1): T5LayerCrossAttention(
                (EncDecAttention): T5Attention(
                  (q): Linear(in_features=512, out_features=512, bias=False)
                  (k): Linear(in_features=512, out_features=512, bias=False)
                  (v): Linear(in_features=512, out_features=512, bias=False)
                  (o): Linear(in_features=512, out_features=512, bias=False)
                )
                (layer_norm): T5LayerNorm()
                (dropout): Dropout(p=0.1, inplace=False)
              )
              (2): T5LayerFF(
                (DenseReluDense): T5DenseActDense(
                  (wi): Linear(in_features=512, out_features=2048, bias=False)
                  (wo): Linear(in_features=2048, out_features=512, bias=False)
                  (dropout): Dropout(p=0.1, inplace=False)
                  (act): ReLU()
                )
                (layer_norm): T5LayerNorm()
                (dropout): Dropout(p=0.1, inplace=False)
              )
            )
          )
        )
        (final_layer_norm): T5LayerNorm()
        (dropout): Dropout(p=0.1, inplace=False)
      )
      (lm_head): Linear(in_features=512, out_features=32128, bias=False)
    )
```

Modify Dataset Class for T5

```
class DialogDataset(Dataset):
    def __init__(self, data, tokenizer, max_length=512):
        self.data = data
        self.tokenizer = tokenizer
        self.max_length = max_length

    def __len__(self):
        return len(self.data)

    def __getitem__(self, idx):
        input_text = self.data.iloc[idx]['cleaned_input']
        response_text = self.data.iloc[idx]['cleaned_response']

        # Prepare the text-to-text task in T5 format (input: "dialogue: <input> </s>" and target: "<response> </s>")
        input_text = "dialogue: " + input_text + " </s>"
        response_text = response_text + " </s>"

        # Tokenize inputs and responses
        input_ids = self.tokenizer.encode(input_text, return_tensors='pt', max_length=self.max_length, padding='max_length', truncation=True)
        target_ids = self.tokenizer.encode(response_text, return_tensors='pt', max_length=self.max_length, padding='max_length', truncation=True)

        return input_ids.squeeze(), target_ids.squeeze()
```

Create DataLoader for Training and Validation

```
# Split dataset into training and validation
train_size = int(0.8 * len(cleaned_dialog_df))
val_size = len(cleaned_dialog_df) - train_size

train_dataset = DialogDataset(train_data, tokenizer=tokenizer, max_length=50)
val_dataset = DialogDataset(val_data, tokenizer=tokenizer, max_length=50)

# DataLoader
train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=8)
```

Model Training

```
from tqdm import tqdm

# Define optimizer
optimizer = torch.optim.AdamW(model.parameters(), lr=1e-4)

# Training loop
num_epochs = 15  # Adjust the number of epochs as needed
```

```
for epoch in range(num_epochs):
    model.train()  # Set model to training mode
    total_loss = 0

    # Loop through the training data
    for batch in tqdm(train_loader, desc=f"Training Epoch {epoch+1}/{num_epochs}"):
        input_ids, target_ids = batch
        input_ids = input_ids.to(device)
        target_ids = target_ids.to(device)

        # Forward pass
        outputs = model(input_ids=input_ids, labels=target_ids)
        loss = outputs.loss

        # Backward pass and optimization
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

    avg_train_loss = total_loss / len(train_loader)
    print(f"Epoch {epoch+1}/{num_epochs}, Average Training Loss: {avg_train_loss:.4f}")
```

```
Training Epoch 1/15: 100%|██████████████████| 22129/22129 [21:27<00:00, 17.18it/s]
Epoch 1/15, Average Training Loss: 0.8695
Training Epoch 2/15: 100%|██████████████████| 22129/22129 [21:23<00:00, 17.24it/s]
Epoch 2/15, Average Training Loss: 0.8331
Training Epoch 3/15: 100%|██████████████████| 22129/22129 [21:24<00:00, 17.22it/s]
Epoch 3/15, Average Training Loss: 0.8185
Training Epoch 4/15: 100%|██████████████████| 22129/22129 [21:21<00:00, 17.27it/s]
Epoch 4/15, Average Training Loss: 0.8078
Training Epoch 5/15: 100%|██████████████████| 22129/22129 [21:22<00:00, 17.26it/s]
Epoch 5/15, Average Training Loss: 0.7990
Training Epoch 6/15: 100%|██████████████████| 22129/22129 [21:23<00:00, 17.25it/s]
Epoch 6/15, Average Training Loss: 0.7913
Training Epoch 7/15: 100%|██████████████████| 22129/22129 [21:21<00:00, 17.27it/s]
Epoch 7/15, Average Training Loss: 0.7839
Training Epoch 8/15: 100%|██████████████████| 22129/22129 [21:24<00:00, 17.23it/s]
Epoch 8/15, Average Training Loss: 0.7770
Training Epoch 9/15: 100%|██████████████████| 22129/22129 [21:22<00:00, 17.26it/s]
Epoch 9/15, Average Training Loss: 0.7708
Training Epoch 10/15: 100%|██████████████████| 22129/22129 [21:24<00:00, 17.23it/s]
Epoch 10/15, Average Training Loss: 0.7645
Training Epoch 11/15: 100%|██████████████████| 22129/22129 [21:20<00:00, 17.28it/s]
Epoch 11/15, Average Training Loss: 0.7587
Training Epoch 12/15: 100%|██████████████████| 22129/22129 [21:24<00:00, 17.23it/s]
Epoch 12/15, Average Training Loss: 0.7528
Training Epoch 13/15: 100%|██████████████████| 22129/22129 [21:23<00:00, 17.25it/s]
Epoch 13/15, Average Training Loss: 0.7471
Training Epoch 14/15: 100%|██████████████████| 22129/22129 [21:22<00:00, 17.25it/s]
Epoch 14/15, Average Training Loss: 0.7418
Training Epoch 15/15: 100%|██████████████████| 22129/22129 [21:23<00:00, 17.23it/s]Epoch 15/15, Average Training Loss: 0.7359
```

Model Evaluation

```
# Function to evaluate model and print metrics
def evaluate_model(model, dataloader, device):
    model.eval()  # Set model to evaluation mode
    total_loss = 0
    all_predictions = []
    all_targets = []

    with torch.no_grad():  # Disable gradient calculation for evaluation
        for batch in tqdm(dataloader, desc="Evaluating"):
            input_ids, target_ids = batch
            input_ids = input_ids.to(device)
            target_ids = target_ids.to(device)

            # Forward pass
            outputs = model(input_ids=input_ids, labels=target_ids)
            val_loss = outputs.loss

            total_loss += val_loss.item()

            # Collect predictions and targets for metrics calculation
            predicted_ids = torch.argmax(outputs.logits, dim=-1).cpu().numpy().flatten()
            all_predictions.extend(predicted_ids)
            all_targets.extend(target_ids.cpu().numpy().flatten())

    avg_loss = total_loss / len(dataloader)
    return avg_loss, all_predictions, all_targets

# Evaluate model on validation data after training
val_loss, val_predictions, val_targets = evaluate_model(model, val_loader, device)
print(f"Validation Loss: {val_loss:.4f}")
```

```
Evaluating: 100%|██████████████████| 2766/2766 [01:00<00:00, 45.46it/s]Validation Loss: 0.7966
```

Model Metrics

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_scor
import matplotlib.pyplot as plt
```