final

May 15, 2023

1 Analysing dialogues between speakers of different ages

1.1 Task 1: Description of Data and Methods (10/50) – (~max 600 words)

BNC2014spoken-xml v1.1 dataset contains the following files that are used for this project:

- spoken
  - tagged : all the tagged data in xml format. Contains individual words for each utterances and their attributes.
  - untgged : all the untagged data in xml format. Contains utterances and speakers for that particualr dialogues.
  - metadata : text and XML files containing corpus metadata

Q1. What basic preprocessing steps would be needed to work with this data (e.g. tokenization, embeddings etc)

Ans: The basic preprocessing steps that would be needed to work with this data are:

- Data Gathering : The dataset is in xml format and is split into tagged and untagged data. We need to gather the data that is required for our analysis and store it in a dataframe.

- Data Cleaning : The data contains a lot of unnecessary information that is not required for our analysis. We need to clean the data and remove the unnecessary information.

- Data Preprocessing : The data contains a lot of noise and we need to remove the noise from the data. We need to remove the stop words, punctuations, special characters, etc. from the data. This contains the tokenization of the data and extracting the features from the data.

Q2. What feature extraction or analysis methods can you use to gain insights into the data before modeling? (basic counts like sentence length, proposition of pos tags, using linguistic resources, or clustering)

Ans: What I did was I am collecting the utterance from the xml file and calculating a list of linguistic features for each utterance. The features that I am calculating are:

- Lexical Diversity : to check the uniqueness
- Sentence Length : to check the length of the sentence
- Discourse Markers Count : the number of discourse markers in the sentence
- Fillers Count : the number of fillers in the sentence
- Hesitation Count : the number of hesitation in the sentence
- Speech Rate : the speech rate of the sentence

All of these features are calculated in the function 'extract_linguistic_features' which takes a preprocessed utterance(stop words, punctuations, special characters removed) as input and returns a sictionary of linguistic features. Visualizations of these features are also included.

Q3. What are common deep learning approaches to extracting information from textual data, what challenges and trade-offs are there when making an appropriate choice?

Ans: Some of the DL approaches are Long Short Term Memory (LSTM), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Transformer models like BERT, etc. I have also included BERT model in my analysis. The challenges are huge when it comes to DL approaches.

- Data Abailability : The data that is required for DL approaches is huge and it is not always available. We need to have a huge amount of data to train the model.
- Data Quality : The data that is required for DL approaches should be of high quality. The data should be clean and should not contain any noise.
- Model Complexity : The model that is used for DL approaches is very complex and it is very difficult to understand the model.
- Computational Power : Requires a lot of computational power to train the model.

and many more.

Q4. How would you evaluate machine learning systems that generate or classify text data where the gold standard can vary? or, how can you examine errors? (e.g. metrics of fluency, faithfulness, or use of confusion matrices, precision, recall, F1 score, evaluating performance in different subsets of data)

Ans:

- Confusion Matrix : We can use the confusion matrix to evaluate the performance of the machine learning systems. This will help us to understand the performance of the machine learning systems and we can use this information to improve the performance of the machine learning systems.

- Precision : Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.

- Recall : Recall is the ratio of correctly predicted positive observations to the all observations in actual class.

- F1 Score : F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account.

- Accuracy : Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations.

1.2 Task 2: Investigate, model, and report on insights from friends dialogue data (40/50) – (~max

1800 words)

[1]:
```
import os
import re
import pandas as pd
```

```python
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score

# Set the path to the BNC2014 dataset
bnc_path = "bnc2014spoken-xml"
```

[2]:
```python
import nltk
nltk.download("punkt")
nltk.download("stopwords")
nltk.download("wordnet")
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\abhij\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\abhij\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\abhij\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

[2]:
```
True
```

[3]:
```python
dir_corpus = 'bnc2014spoken-xml/spoken/untagged/'
print(dir_corpus)
f_names = os.listdir(dir_corpus)
f_paths = [f"{dir_corpus}{f_name}" for f_name in f_names]

# f_paths = ['bnc2014spoken-xml/spoken/untagged/S2A5.xml']

f_paths
```

```
bnc2014spoken-xml/spoken/untagged/
```

[3]:
```
['bnc2014spoken-xml/spoken/untagged/S23A.xml',
 'bnc2014spoken-xml/spoken/untagged/S24A.xml',
 'bnc2014spoken-xml/spoken/untagged/S24D.xml',
 'bnc2014spoken-xml/spoken/untagged/S24E.xml',
 'bnc2014spoken-xml/spoken/untagged/S263.xml',
 'bnc2014spoken-xml/spoken/untagged/S26N.xml',
 'bnc2014spoken-xml/spoken/untagged/S27D.xml',
 'bnc2014spoken-xml/spoken/untagged/S28F.xml',
 'bnc2014spoken-xml/spoken/untagged/S29Q.xml',
 'bnc2014spoken-xml/spoken/untagged/S29X.xml',
```

```
 'bnc2014spoken-xml/spoken/untagged/STK7.xml',
 'bnc2014spoken-xml/spoken/untagged/STKH.xml',
 'bnc2014spoken-xml/spoken/untagged/STKV.xml',
 …]
```

[4]:
```python
dialogue_data = []
for path in f_paths: # for each of the dialogues
    print(path)
    df_utts = pd.read_xml(path, xpath="//u")
    df_speakers = pd.read_xml(path, xpath="//speaker")
    dialogue_data.append((df_utts, df_speakers))
    # break
```

```
bnc2014spoken-xml/spoken/untagged/S23A.xml
bnc2014spoken-xml/spoken/untagged/S24A.xml
bnc2014spoken-xml/spoken/untagged/S24D.xml
bnc2014spoken-xml/spoken/untagged/S24E.xml
bnc2014spoken-xml/spoken/untagged/S263.xml
bnc2014spoken-xml/spoken/untagged/S26N.xml
bnc2014spoken-xml/spoken/untagged/S27D.xml
bnc2014spoken-xml/spoken/untagged/S28F.xml
bnc2014spoken-xml/spoken/untagged/S29Q.xml
bnc2014spoken-xml/spoken/untagged/S29X.xml
bnc2014spoken-xml/spoken/untagged/S2A5.xml
bnc2014spoken-xml/spoken/untagged/S2AJ.xml
bnc2014spoken-xml/spoken/untagged/S2AX.xml
bnc2014spoken-xml/spoken/untagged/S2B5.xml
bnc2014spoken-xml/spoken/untagged/S2C9.xml
bnc2014spoken-xml/spoken/untagged/S2CY.xml
bnc2014spoken-xml/spoken/untagged/S2DD.xml
bnc2014spoken-xml/spoken/untagged/S2E2.xml
bnc2014spoken-xml/spoken/untagged/S2EF.xml
bnc2014spoken-xml/spoken/untagged/S2FQ.xml
bnc2014spoken-xml/spoken/untagged/S2FT.xml
bnc2014spoken-xml/spoken/untagged/S2GC.xml
bnc2014spoken-xml/spoken/untagged/S2GS.xml
bnc2014spoken-xml/spoken/untagged/S2JK.xml
bnc2014spoken-xml/spoken/untagged/S2JV.xml
bnc2014spoken-xml/spoken/untagged/S2K6.xml
bnc2014spoken-xml/spoken/untagged/S2K7.xml
bnc2014spoken-xml/spoken/untagged/S2KP.xml
bnc2014spoken-xml/spoken/untagged/S2LC.xml
bnc2014spoken-xml/spoken/untagged/S2LD.xml
bnc2014spoken-xml/spoken/untagged/S2NQ.xml
bnc2014spoken-xml/spoken/untagged/S2PS.xml
bnc2014spoken-xml/spoken/untagged/S2PY.xml
bnc2014spoken-xml/spoken/untagged/S2QU.xml
```

```
bnc2014spoken-xml/spoken/untagged/SZLE.xml
bnc2014spoken-xml/spoken/untagged/SZME.xml
bnc2014spoken-xml/spoken/untagged/SZNA.xml
bnc2014spoken-xml/spoken/untagged/SZNG.xml
bnc2014spoken-xml/spoken/untagged/SZNP.xml
bnc2014spoken-xml/spoken/untagged/SZP6.xml
bnc2014spoken-xml/spoken/untagged/SZPS.xml
bnc2014spoken-xml/spoken/untagged/SZQ9.xml
bnc2014spoken-xml/spoken/untagged/SZQX.xml
bnc2014spoken-xml/spoken/untagged/SZR7.xml
bnc2014spoken-xml/spoken/untagged/SZRJ.xml
bnc2014spoken-xml/spoken/untagged/SZT4.xml
bnc2014spoken-xml/spoken/untagged/SZVB.xml
bnc2014spoken-xml/spoken/untagged/SZVC.xml
bnc2014spoken-xml/spoken/untagged/SZW4.xml
bnc2014spoken-xml/spoken/untagged/SZXQ.xml
bnc2014spoken-xml/spoken/untagged/SZYV.xml
```

[5]:
```python
# Concatenate all speakers dataframes into one
df_all_speakers = pd.concat([speaker_data[1] for speaker_data in dialogue_data])
df_all_speakers
```

[5]:
```
      id exactage age1994 agerange gender                  nat
0  S0021       27   25_34    19_29      F              British  \
1  S0032       28   25_34    19_29      M              British
2  S0094       33   25_34    30_39      F              British
3  S0095       33   25_34    30_39      M              British
0  S0261       41   35_44    40_49      M  British/New Zealand
..   …        …       …        …      …                    …
1  S0510       47   45_59    40_49      F              British
0  S0058       23   15_24    19_29      F              British
1  S0120       23   15_24    19_29      M     British & German
0  S0428       27   25_34    19_29      F              British
1  S0432       23   15_24    19_29      F        White British

                 birthplace birthcountry       l1    lingorig  …
0                   Swindon      England  English     England  …  \
1                    Yoevil      England  English     England  …
2                   Swindon      England  English     England  …
3                 Camarthen     Scotland  English     England  …
0                Wellington  New Zealand  English  England/NZ  …
..                        …            …        …           …  …
1                   England      England  English     England  …
0   Sunderland, Tyne and Wear      England  English     England  …
1             Pembury, Kent      England  English     England  …
0  Aylesbury, Buckinghamshire      England  English     England  …
1                   Lincoln      England  English     England  …
```

```
  dialect_l2   dialect_l3    dialect_l4      edqual
0     england        south     southwest  5_postgrad  \
1     england        south     southwest  4_graduate
2     england        south     southwest  5_postgrad
3       wales        wales         wales  5_postgrad
0      non_uk       non_uk        non_uk  4_graduate
..        …            …             …           …
1     england        south   unspecified  5_postgrad
0     england        north     northeast  4_graduate
1     england        south   unspecified  5_postgrad
0     england        south  eastern_engl  5_postgrad
1     england  unspecified   unspecified  4_graduate

                          occupation socgrade  nssec      l2
0                            Teacher        B      2    None  \
1                 Software developer        A    1_2    None
2                        PhD student        A    1_2  German
3                Self employed maker        E  uncat    None
0                       Entrepreneur        A    1_2     NaN
..                                 …      …      …       …
1                       Receptionist        D      6     NaN
0               Corpus Administrator        B      2     NaN
1             Graduate Civil Engineer       C1      4     NaN
0    Language Research Co-ordinator        A    1_2     NaN
1   Language Research Administrator        A    1_2     NaN

                                                    fls in_core
0                                                  None       y
1                                                  None       y
2                                     Welsh -- Beginner       y
3                                                  None       y
0                                                  None       n
..                                                    …      …
1                                                   NaN       y
0                                                  None       n
1                  German -- Advanced; French -- Advanced       n
0   Spanish -- level unspecified; Italian -- level…       y
1   Spanish -- level unspecified; Chinese -- level…       n

[3593 rows x 25 columns]
```

[6]:
```
# Concatenate all utterances dataframes into one
df_all_utts = pd.concat([utt_data[0] for utt_data in dialogue_data])
df_all_utts
```

[6]:
```
       n    who                                        u
0      1  S0094                                    words  \
1      2  S0095  it's a games word? like a computer games word?
2      3  S0032                                yeah yeah
3      4  S0095                                       oh
4      5  S0032                        I it's something I
..   …     …                                        …
315  316  S0432                                      but
316  317  S0428                                     None
317  318  S0432                  I'll just stick with it yeah
318  319  S0428                                     None
319  320  S0432                                       mm

              unclear    trans whoConfidence  vocal foreign  anon  pause
0                None     None          None    NaN    None   NaN    NaN  \
1                None     None          None    NaN    None   NaN    NaN
2                None     None          None    NaN    None   NaN    NaN
3       oh that's nice     None          None    NaN    None   NaN    NaN
4    have really heard  overlap          None    NaN    None   NaN    NaN
..                 …       …             …      …       …     …      …
315             Mai Li     None          None    NaN     NaN   NaN    NaN
316             Sha Li     None          None    NaN     NaN   NaN    NaN
317               None  overlap          None    NaN     NaN   NaN    NaN
318               None  overlap          None    NaN     NaN   NaN    NaN
319               None  overlap          None    NaN     NaN   NaN    NaN

    trunc  shift  event
0    None    NaN    NaN
1    None    NaN    NaN
2    None    NaN    NaN
3    None    NaN    NaN
4    None    NaN    NaN
..    …      …      …
315  None    NaN    NaN
316  None    NaN    NaN
317   let    NaN    NaN
318  None    NaN    NaN
319  None    NaN    NaN

[1248110 rows x 13 columns]
```

[7]:
```python
def get_speaker_age(speakerid):
    # get the age of the speaker with the given speakerid
    age = df_all_speakers[df_all_speakers['id'] == speakerid]['agerange'].values
    if len(age) == 0:
        return None
    else:
```

```python
        return age[0]

get_speaker_age('S0432')
```

[7]: '19_29'

[8]:
```python
def preprocess_utterance(utterance):
    if utterance is None:
        return ''
    # Remove punctuation and numbers from the conversation transcript
    utterance = re.sub(r'[^\w\s]', '', utterance)  # Remove punctuation
    utterance = re.sub(r'\d+', '', utterance)  # Remove numbers
    utterance = utterance.strip()  # Remove leading/trailing whitespaces
    return utterance

preprocess_utterance("yeah I know but that's why we're an hour late isn't it?")
```

[8]: 'yeah I know but thats why were an hour late isnt it'

[9]:
```python
from nltk.tokenize import word_tokenize

def extract_linguistic_features(preprocessed_conversation):
    # Extract linguistic features from the preprocessed conversation
    if preprocessed_conversation is None:
        return ""

    # Vocabulary Features
    tokens = word_tokenize(preprocessed_conversation)

    word_freq = nltk.FreqDist(tokens)
    lexical_diversity = len(word_freq) / len(tokens) if len(tokens) > 0 else 0
    # specific_word_usage = word_freq['specific_word'] if 'specific_word' in␣
 ↪word_freq else 0

    # Syntactic Features
    sentences = nltk.sent_tokenize(preprocessed_conversation)
    sentence_length = sum(len(word_tokenize(sentence)) for sentence in␣
 ↪sentences) / len(sentences) if len(sentences) > 0 else 0

    # Discourse Features
    discourse_markers = ['like', 'you know', 'basically']
    discourse_marker_count = sum(preprocessed_conversation.lower().
 ↪count(marker) for marker in discourse_markers)
    fillers = ['uh', 'um', 'hmm', 'huh', 'er', 'ah', 'eh', 'mm']
    filler_count = sum(preprocessed_conversation.lower().count(filler) for␣
 ↪filler in fillers)
    hesitation_count = discourse_marker_count + filler_count
```

```python
    # Speech Rate
    words = word_tokenize(preprocessed_conversation)
    speech_rate = len(words) / len(sentences) if len(sentences) > 0 else 0

    # Return the extracted linguistic features as a dictionary
    linguistic_features = {
        'lexical_diversity': lexical_diversity, # each word is unique
        # 'specific_word_usage': specific_word_usage, # use of specific words
        'sentence_length': sentence_length,
        'discourse_marker_count': discourse_marker_count,
        'filler_count': filler_count,
        'hesitation_count': hesitation_count,
        'speech_rate': speech_rate
    }

    # Convert the dictionary to a string representation
    features_string = " ".join([f"{key}:{value}" for key, value in␣
 ↪linguistic_features.items()])

    return features_string, linguistic_features

extract_linguistic_features(preprocess_utterance("yeah I know but that's why␣
 ↪we're an hour late isn't it?"))[0]
```

[9]: 'lexical_diversity:1.0 sentence_length:12.0 discourse_marker_count:0
filler_count:2 hesitation_count:2 speech_rate:12.0'

[10]:
```python
# loop through each df_all_speakers and get the age of each speaker
# Initialize lists to store speaker information and extracted features

speaker_ids = []
age_labels = []
utterances = []
linguistic_features = []

for i in df_all_utts.index:
    speaker_id = df_all_utts["who"].iloc[i]
    age = get_speaker_age(speaker_id)

    utterance = df_all_utts["u"].iloc[i]
    preprocessed_utterance = preprocess_utterance(utterance)
    # Step 3: Feature Extraction
    linguistic_feature = extract_linguistic_features(preprocessed_utterance)[0]

    speaker_ids.append(speaker_id)
    age_labels.append(age)
```

```
    utterances.append(preprocessed_utterance)
    linguistic_features.append(linguistic_feature)

# Create a DataFrame to store the speaker-level data
df = pd.DataFrame({"SpeakerID": speaker_ids, "AgeLabel": age_labels,␣
 ↪"Utterance": utterances, "Features": linguistic_features})
```

[11]:
```
df
```

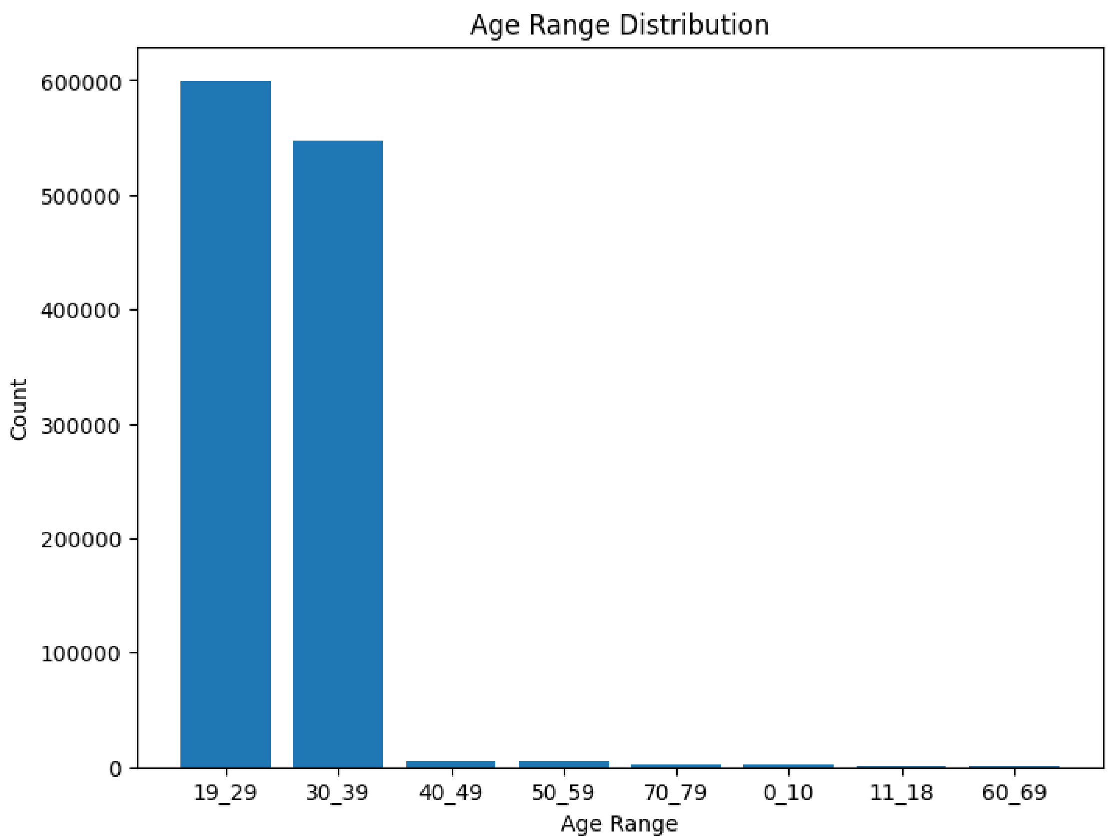
[11]:
```
        SpeakerID AgeLabel                                          Utterance
0           S0094    30_39                                              words  \
1           S0095    30_39        its a games word like a computer games word
2           S0032    19_29                                          yeah yeah
3           S0095    30_39                                                 oh
4           S0032    19_29                                 I its something I
…             …        …                                                  …
1248105     S0021    19_29                                        I have like
1248106     S0094    30_39
1248107     S0032    19_29
1248108     S0021    19_29   I have like tomato ketchup emergencies if I ru…
1248109     S0032    19_29   thats not as bad as the barbecue that we had t…

                                                  Features
0        lexical_diversity:1.0 sentence_length:1.0 disc…
1        lexical_diversity:0.6666666666666666 sentence_…
2        lexical_diversity:0.5 sentence_length:2.0 disc…
3        lexical_diversity:1.0 sentence_length:1.0 disc…
4        lexical_diversity:0.75 sentence_length:4.0 dis…
…                                                    …
1248105  lexical_diversity:1.0 sentence_length:3.0 disc…
1248106  lexical_diversity:0 sentence_length:0 discours…
1248107  lexical_diversity:0 sentence_length:0 discours…
1248108  lexical_diversity:0.7391304347826086 sentence_…
1248109  lexical_diversity:0.9090909090909091 sentence_…

[1248110 rows x 4 columns]
```

1.2.1 Visualization

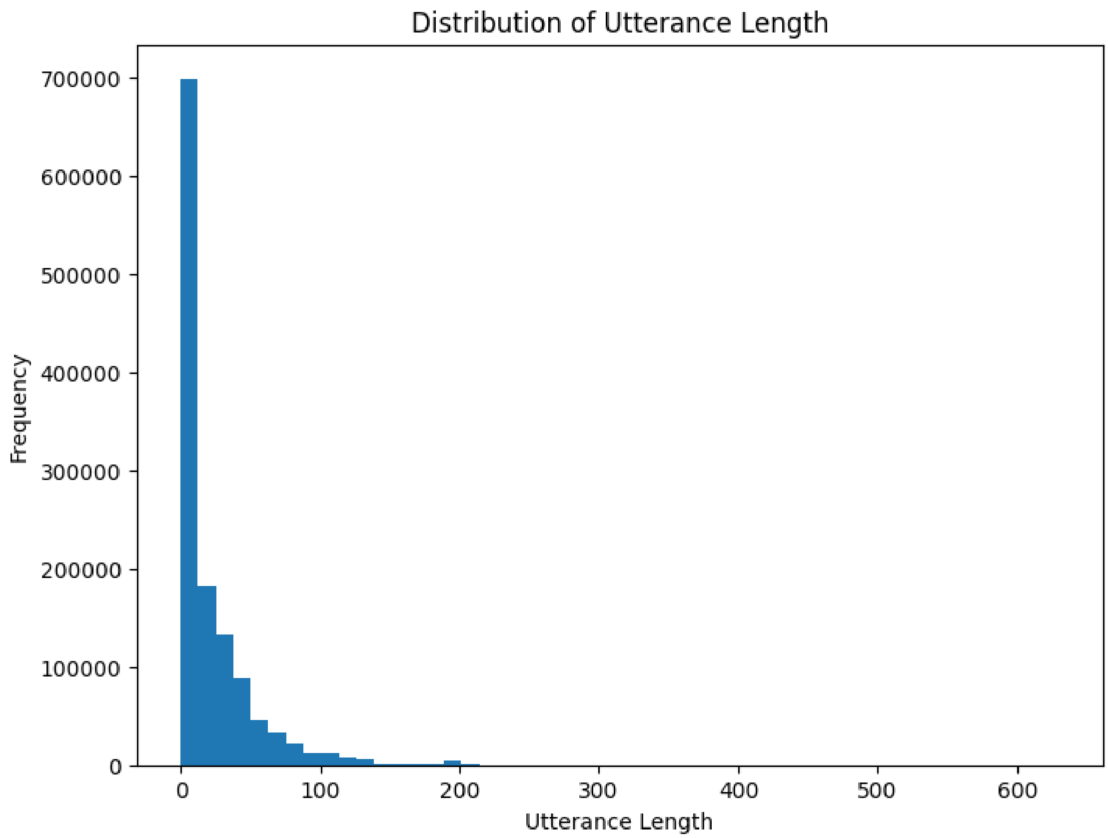
[12]:
```
df_vis = df.copy()
```

[13]:
```
import matplotlib.pyplot as plt

# Count the occurrences of each age range category
age_counts = df_vis['AgeLabel'].value_counts()

# Create a bar plot
```

```
plt.figure(figsize=(8, 6))
plt.bar(age_counts.index, age_counts.values)
plt.xlabel('Age Range')
plt.ylabel('Count')
plt.title('Age Range Distribution')
plt.show()
```



[14]:
```
import matplotlib.pyplot as plt

# Compute the length of each utterance
df_vis['utterance_length'] = df_vis['Utterance'].apply(len)

# Create a histogram
plt.figure(figsize=(8, 6))
plt.hist(df_vis['utterance_length'], bins=50)
plt.xlabel('Utterance Length')
plt.ylabel('Frequency')
plt.title('Distribution of Utterance Length')
plt.show()
```

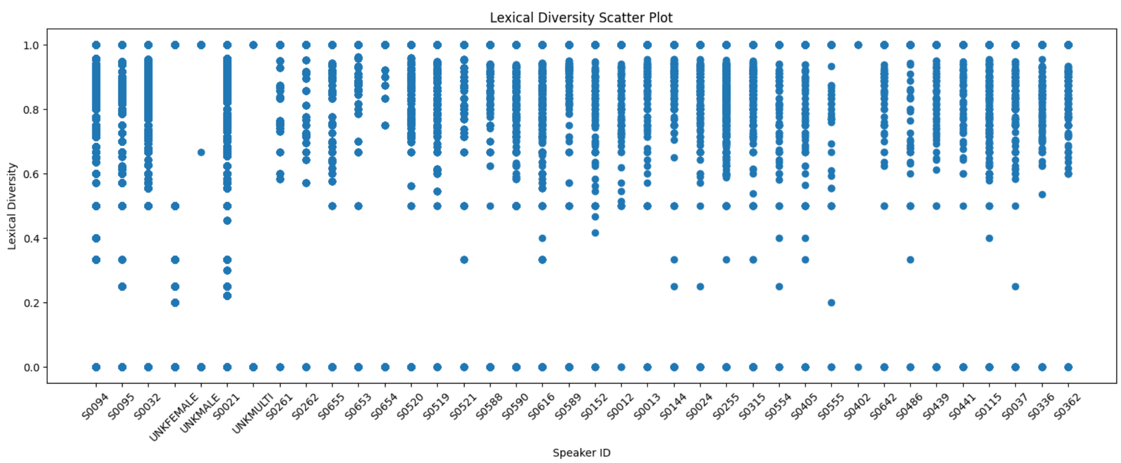


[15]:
```
def compute_lexical_diversity(text):
    # Tokenize the text into individual words
    tokens = nltk.word_tokenize(text)

    # Calculate the number of unique words (vocabulary)
    vocabulary_size = len(set(tokens))

    # Calculate the lexical diversity as the ratio of unique words to total␣
↪words
    lexical_diversity = vocabulary_size / len(tokens) if len(tokens) > 0 else 0

    return lexical_diversity


# Compute the lexical diversity for each utterance
df_vis['lexical_diversity'] = df_vis['Utterance'].
↪apply(compute_lexical_diversity)
```

[16]:
```
def compute_word_frequency(text):
    # Tokenize the text into individual words
```

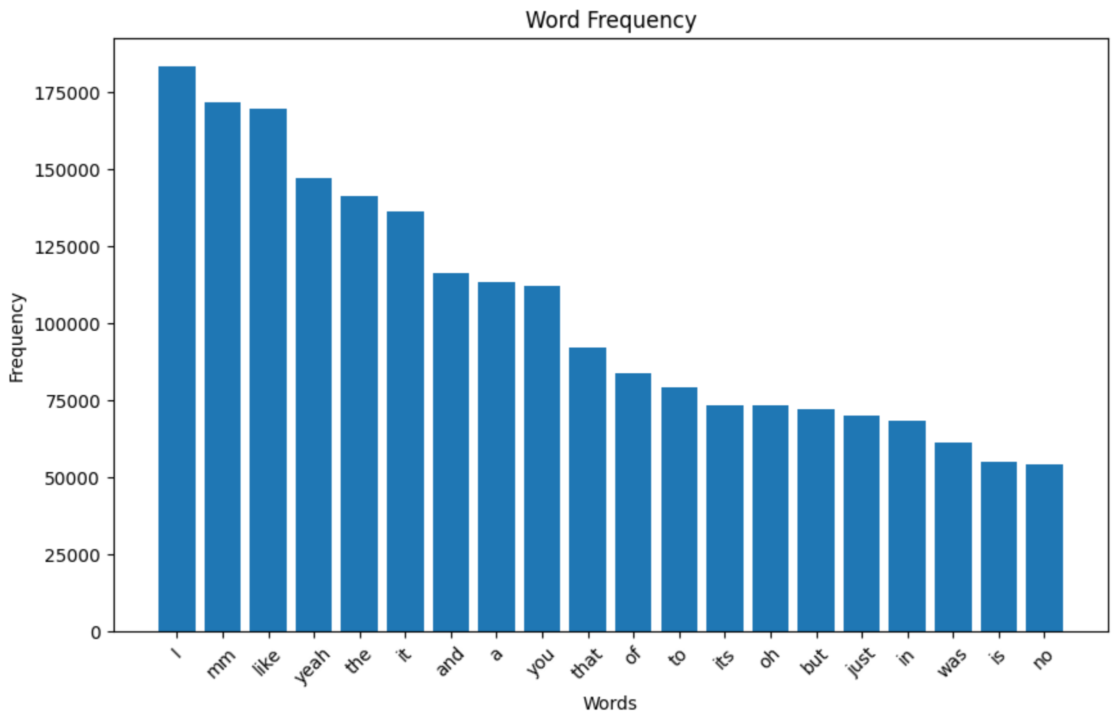
```python
    tokens = nltk.word_tokenize(text)

    # Compute the word frequency distribution
    word_freq = nltk.FreqDist(tokens)

    return word_freq
```

[17]:
```python
import matplotlib.pyplot as plt

# Create a scatter plot
plt.figure(figsize=(18, 6))
plt.scatter(df_vis['SpeakerID'], df_vis['lexical_diversity'])
plt.xlabel('Speaker ID')
plt.ylabel('Lexical Diversity')
plt.title('Lexical Diversity Scatter Plot')
plt.xticks(rotation=45)
plt.show()
```



[18]:
```python
import matplotlib.pyplot as plt
from nltk import FreqDist

# Calculate word frequency
word_freq = compute_word_frequency(df_vis['Utterance'].str.cat(sep=' '))

# Get the most common words and their frequencies
most_common = word_freq.most_common(20)
words = [word[0] for word in most_common]
frequencies = [freq[1] for freq in most_common]

# Plot the word frequency
plt.figure(figsize=(10, 6))
```

```
plt.bar(words, frequencies)
plt.xlabel('Words')
plt.ylabel('Frequency')
plt.title('Word Frequency')
plt.xticks(rotation=45)
plt.show()
```



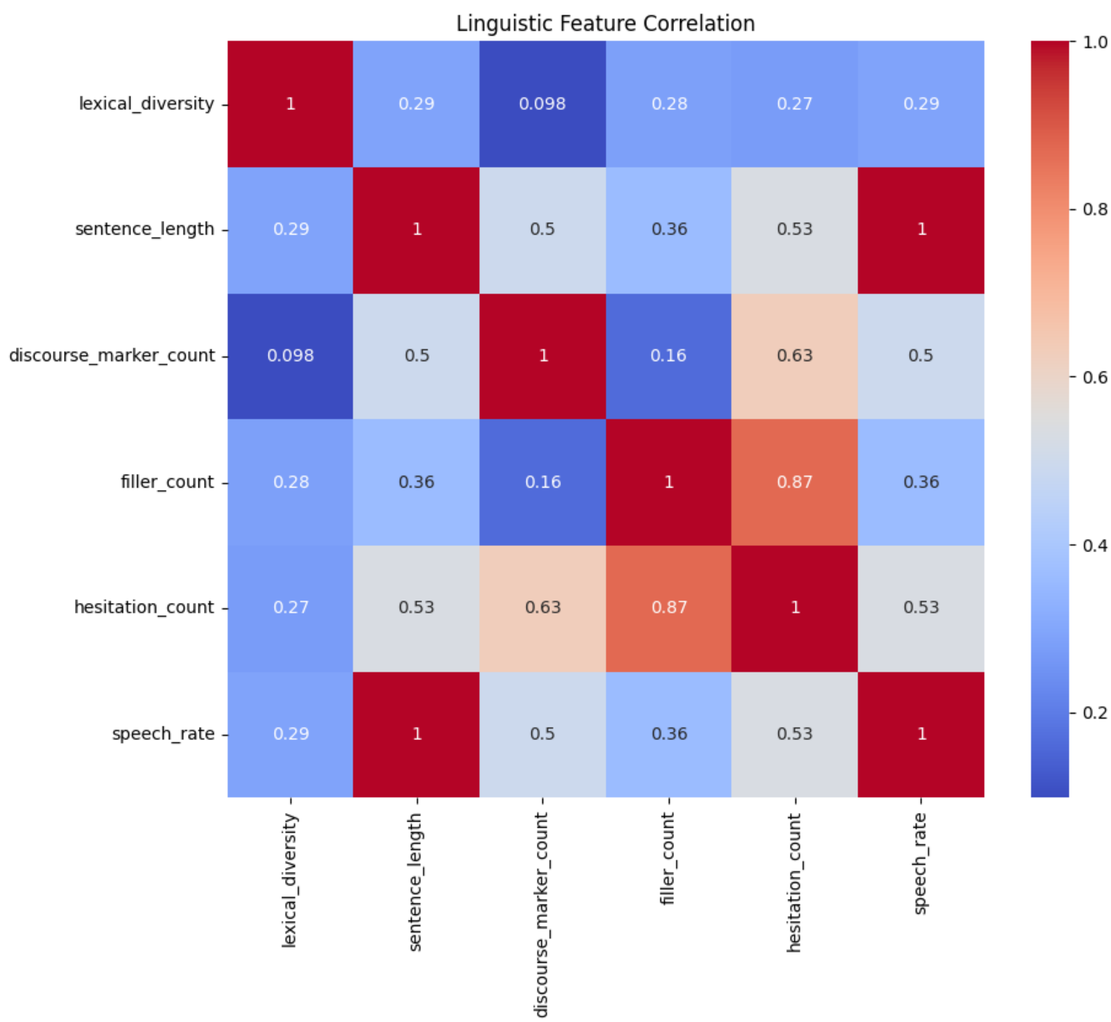
[19]:
```
for index, row in df_vis.iterrows():
    utterance = row['Utterance']
    features = extract_linguistic_features(utterance)[1]
    for feature, value in features.items():
        df_vis.loc[index, feature] = value
```

[20]:
```
list(extract_linguistic_features(utterance)[1].keys())
```

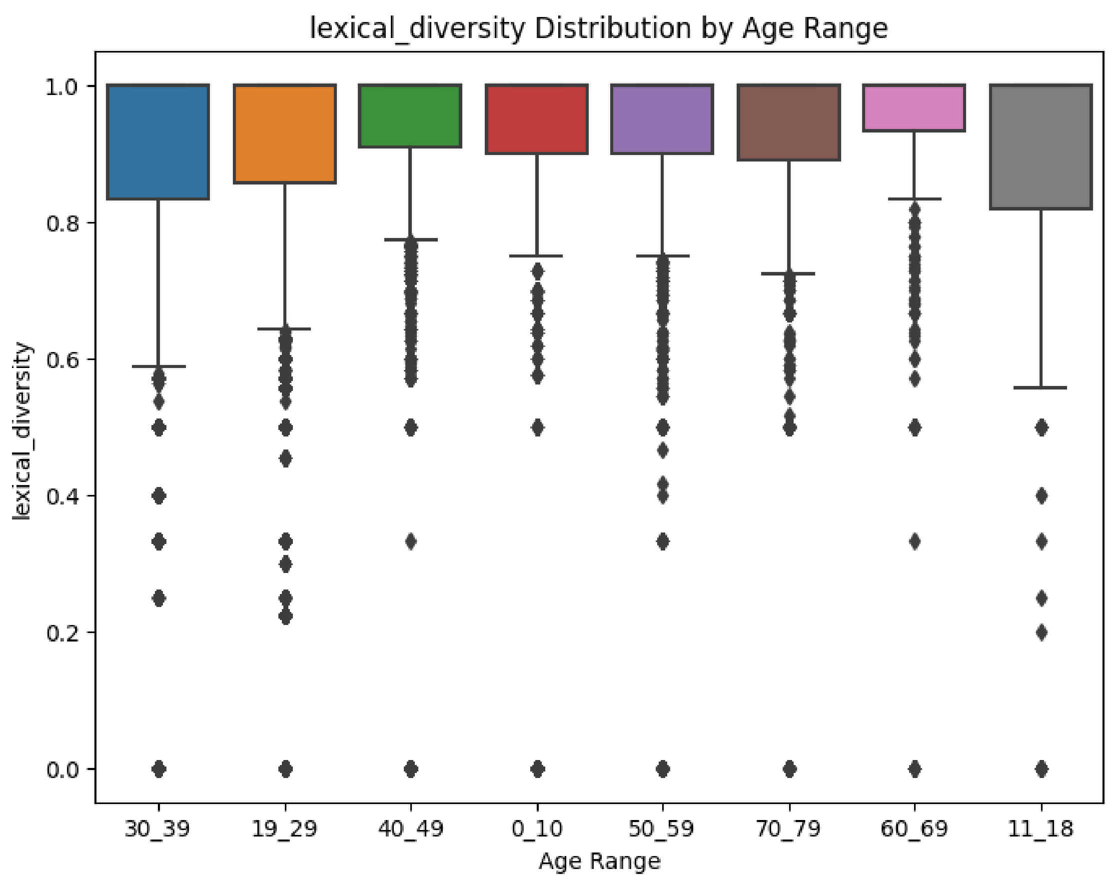
[20]:
```
['lexical_diversity',
 'sentence_length',
 'discourse_marker_count',
 'filler_count',
 'hesitation_count',
 'speech_rate']
```

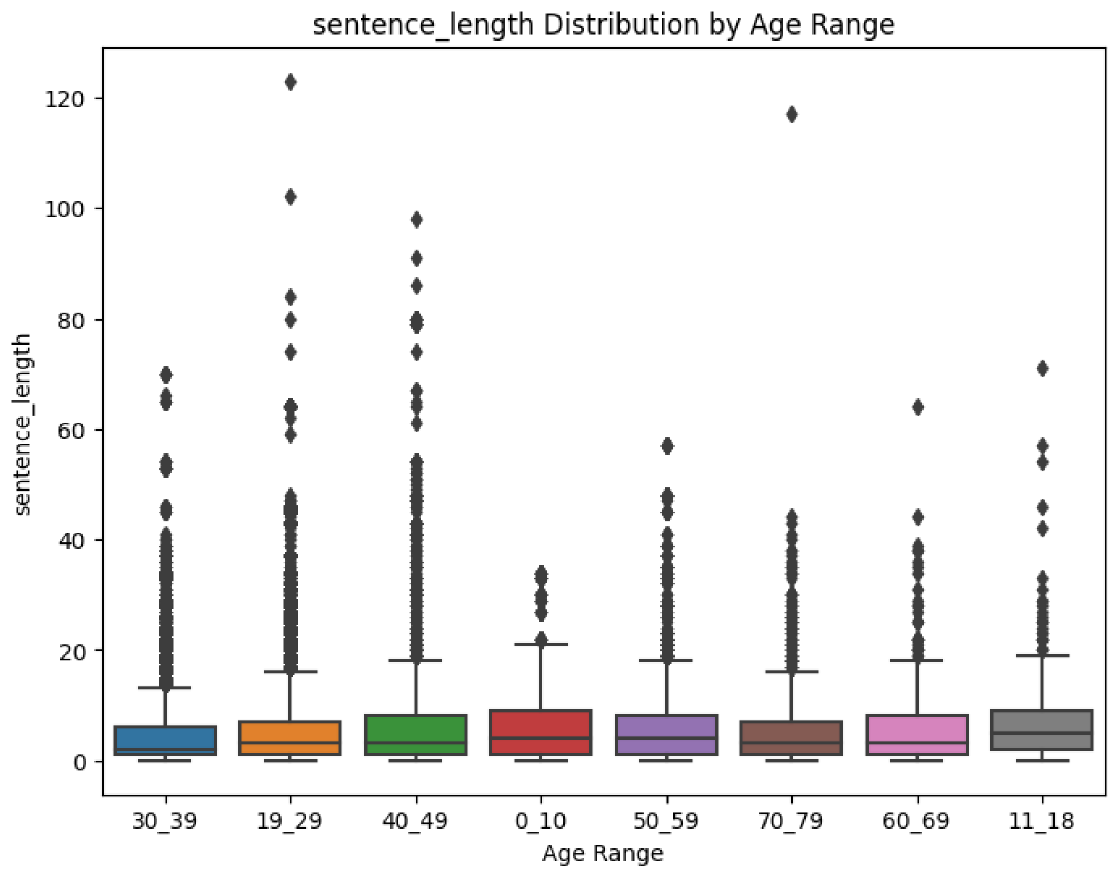
[21]:

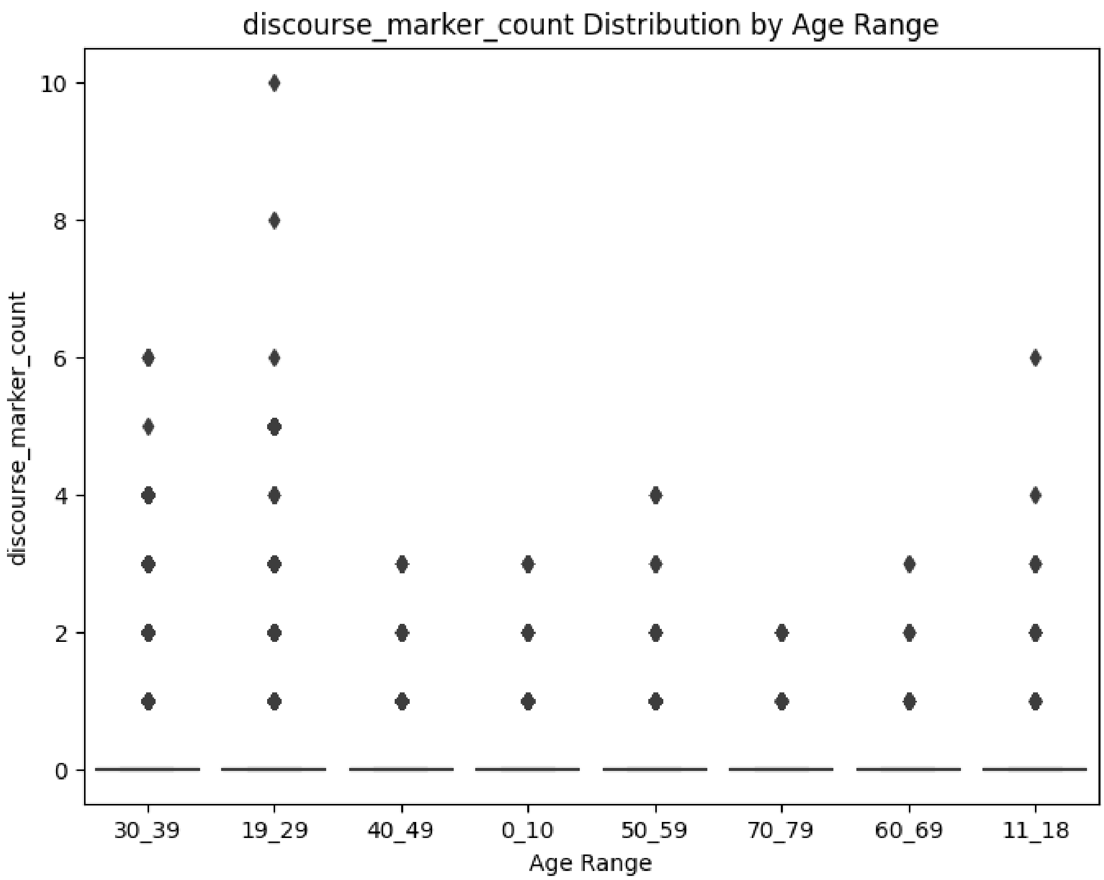
```
import seaborn as sns
import matplotlib.pyplot as plt

# Select the columns containing the linguistic features
linguistic_feature_columns = list(extract_linguistic_features(utterance)[1].
  ↪keys())

# Calculate the correlation matrix
correlation_matrix = df_vis[linguistic_feature_columns].corr()

# Create the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', square=True)
plt.title('Linguistic Feature Correlation')
plt.show()
```

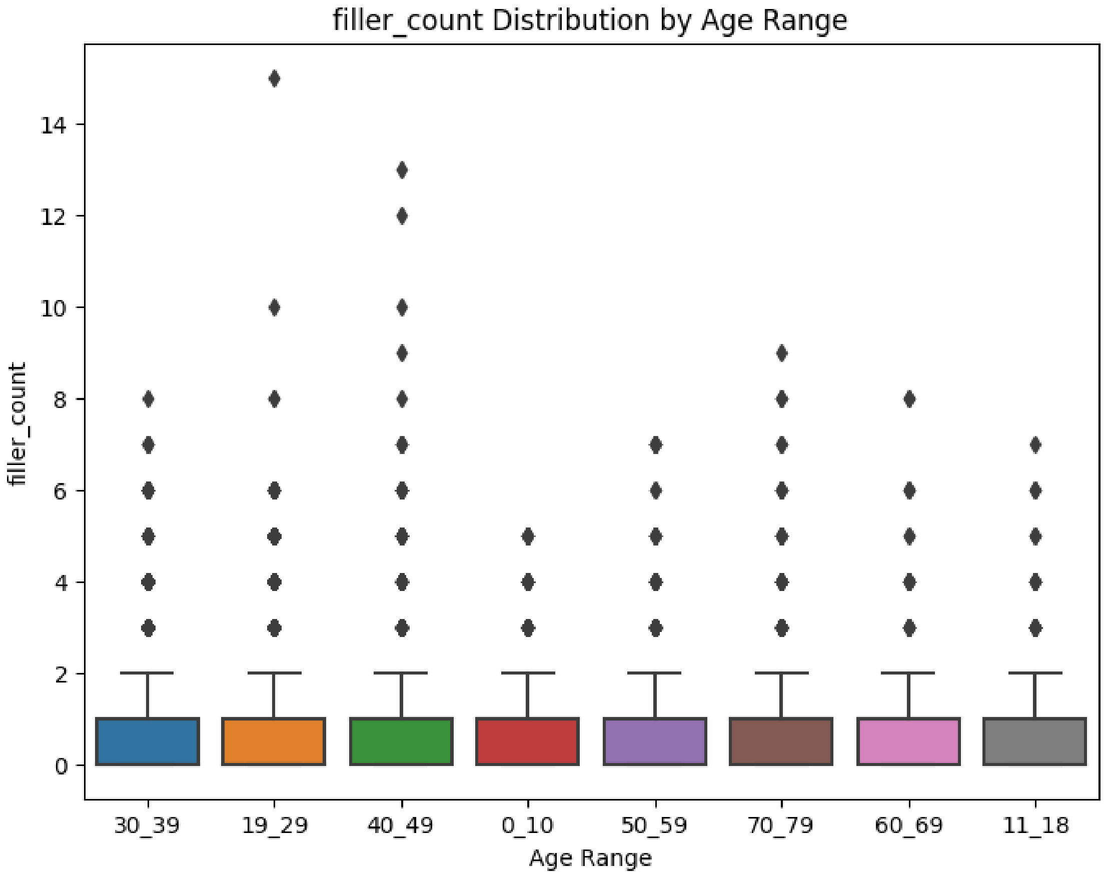


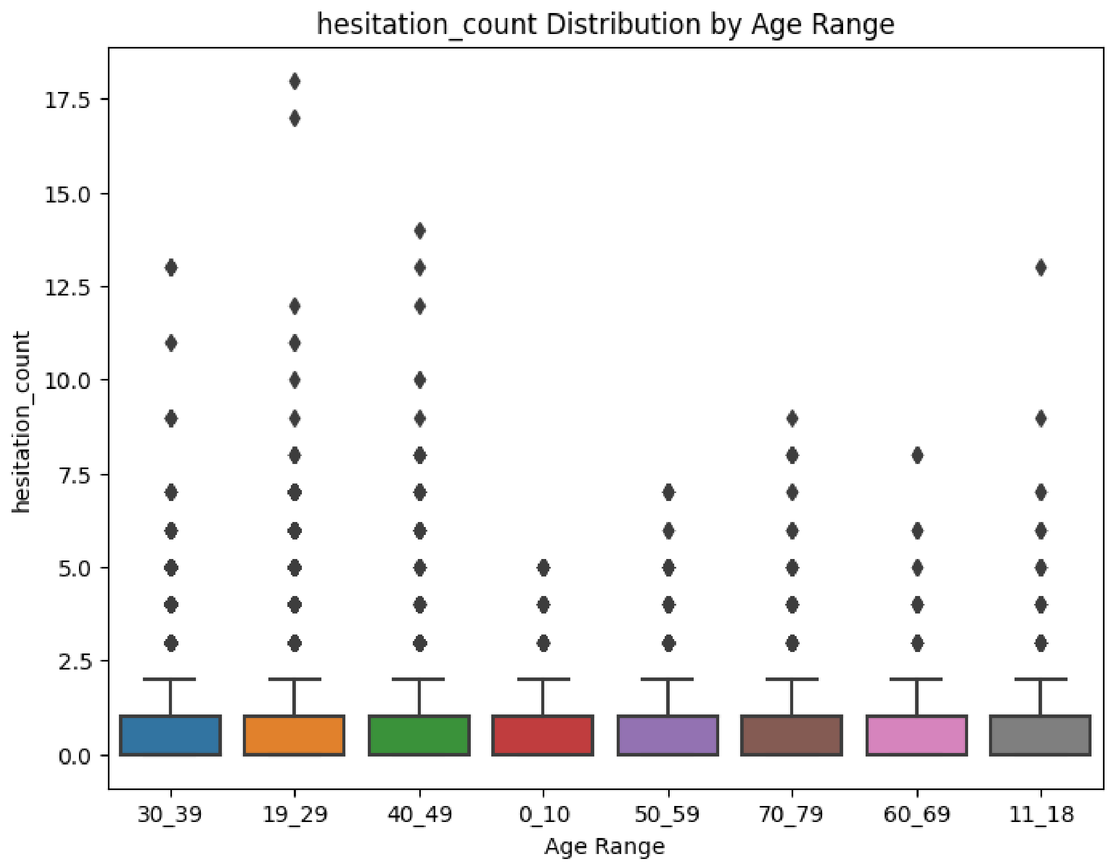
[22]:
```python
import seaborn as sns
import matplotlib.pyplot as plt


features = list(extract_linguistic_features(utterance)[1].keys())

for feature in features:
    plt.figure(figsize=(8, 6))
    sns.boxplot(x='AgeLabel', y=feature, data=df_vis)
    plt.title(f'{feature} Distribution by Age Range')
    plt.xlabel('Age Range')
    plt.ylabel(feature)
    plt.show()
```

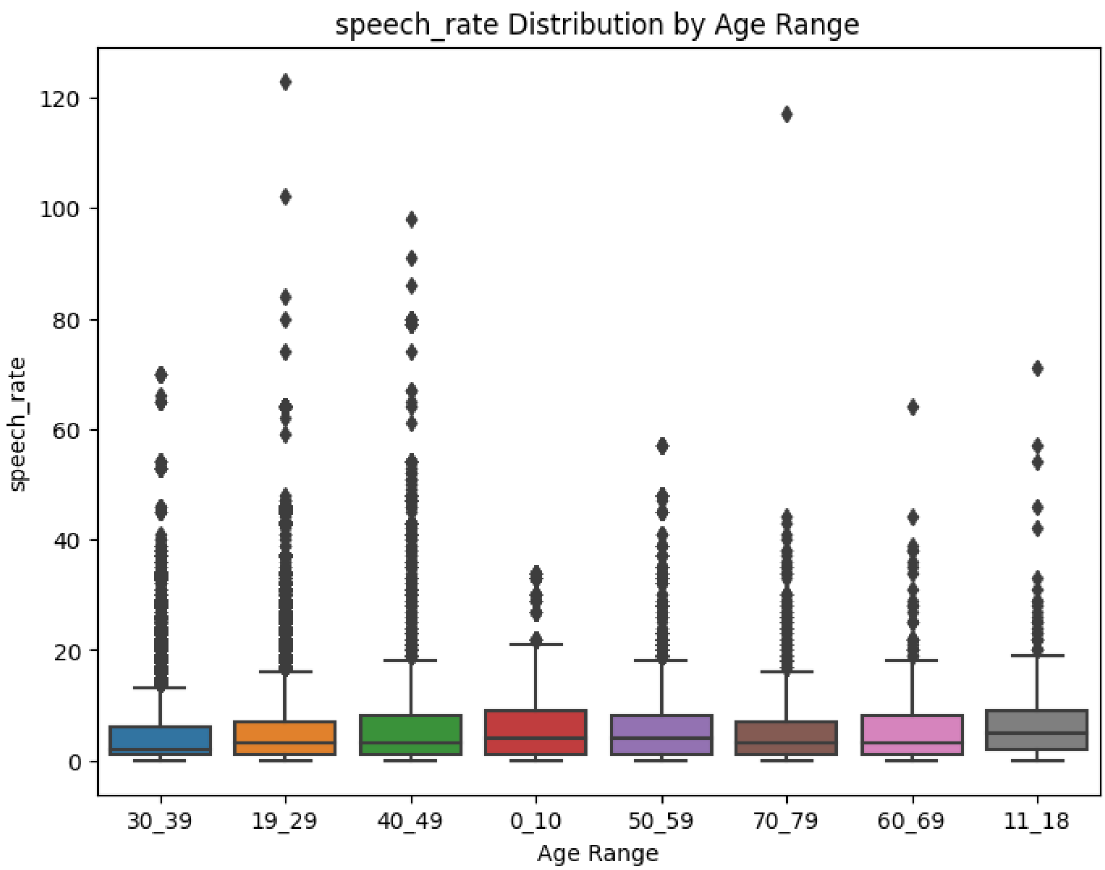



sentence_length Distribution by Age Range
sentence_length
Age Range
0
20
40
60
80
100
120
30_39
19_29
40_49
0_10
50_59
70_79
60_69
11_18


discourse_marker_count Distribution by Age Range
discourse_marker_count
Age Range
30_39
19_29
40_49
0_10
50_59
70_79
60_69
11_18
0
2
4
6
8
10


filler_count Distribution by Age Range
filler_count
0
2
4
6
8
10
12
14
30_39
19_29
40_49
0_10
50_59
70_79
60_69
11_18
Age Range


hesitation_count Distribution by Age Range
hesitation_count
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
30_39
19_29
40_49
0_10
50_59
70_79
60_69
11_18
Age Range



[23]:
```
len(list(extract_linguistic_features(utterance)[1].keys()))
```

[23]: 6

[24]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Select the relevant features for clustering
selected_features = list(extract_linguistic_features(utterance)[1].keys())

# Extract the selected features from the dataset
X = df_vis[selected_features].values

# Scale or normalize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

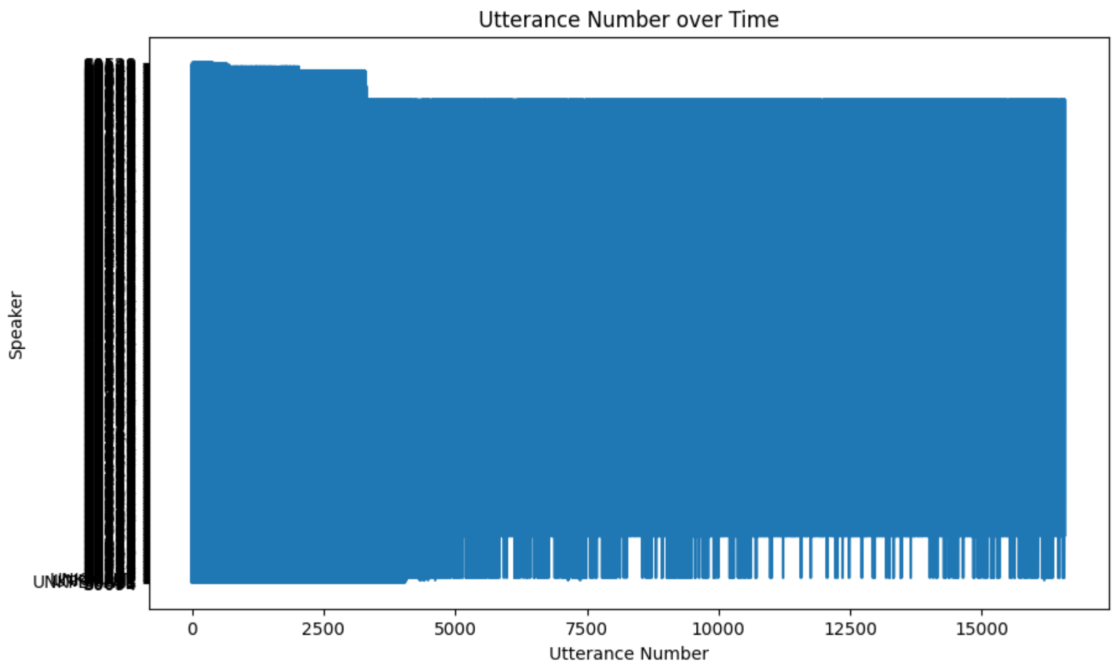
```python
# Choose the number of clusters
num_clusters = 6

# Apply K-means clustering
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
clusters = kmeans.fit_predict(X_scaled)

# Add the cluster labels to the dataframe
df_vis['Cluster'] = clusters

plt.figure(figsize=(20, 3))

# Visualize the clusters
plt.scatter(X[:, 0], X[:, 1], c=clusters)
for i, txt in enumerate(selected_features):
    plt.annotate(txt, (X[i, 0], X[i, 1]), fontsize=10)
plt.title('Clustering Results')
plt.show()
```

```
c:\Users\abhij\.conda\envs\dmassessment\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  warnings.warn(
```

[105]:
```python
# get the time variables from untagged and create a time-series analysis on
↪dialogue data
df_time = df_all_utts.copy()

# drop unclear, trans, whoConfidence, vocal, foreign, anon, pause, trunc,
↪shift, event
df_time.drop(['unclear', 'trans', 'whoConfidence', 'vocal', 'foreign', 'anon',
↪'pause', 'trunc', 'shift', 'event'], axis=1, inplace=True)

df_time.set_index('n', inplace=True)

print(df_time.columns)
```

```python
# Plot the time-series data
plt.figure(figsize=(10, 6))
plt.plot(df_time['who'])
plt.title('Utterance Number over Time')
plt.xlabel('Utterance Number')
plt.ylabel("Speaker")
plt.show()
```

```
Index(['who', 'u'], dtype='object')
```



[25]:
```python
# get a copy of the dataframe
df_copy = df.copy()

# Replace age label values
df_copy['AgeLabel'].replace({'19_29': 'young', '50_59': 'old', '60_69': 'old',␣
↪'70_79': 'old', '80_89': 'old', '90_99': 'old'}, inplace=True)
# Drop rows with remaining age labels
df_copy = df_copy[df_copy['AgeLabel'].isin(['young', 'old'])]

# remove all the None values from Utterance column
df_copy = df_copy.dropna(subset=['Utterance'])

df_copy
```

[25]:
```
        SpeakerID AgeLabel                                           Utterance
2           S0032    young                                          yeah yeah  \
4           S0032    young                                  I its something I
6           S0032    young
10          S0032    young
12          S0021    young
…             …        …                                                  …
1248104     S0032    young                                         no its not
1248105     S0021    young                                        I have like
1248107     S0032    young
1248108     S0021    young  I have like tomato ketchup emergencies if I ru…
1248109     S0032    young  thats not as bad as the barbecue that we had t…

                                                  Features
2        lexical_diversity:0.5 sentence_length:2.0 disc…
4        lexical_diversity:0.75 sentence_length:4.0 dis…
6        lexical_diversity:0 sentence_length:0 discours…
10       lexical_diversity:0 sentence_length:0 discours…
12       lexical_diversity:0 sentence_length:0 discours…
…                                                    …
1248104  lexical_diversity:1.0 sentence_length:3.0 disc…
1248105  lexical_diversity:1.0 sentence_length:3.0 disc…
1248107  lexical_diversity:0 sentence_length:0 discours…
1248108  lexical_diversity:0.7391304347826086 sentence_…
1248109  lexical_diversity:0.9090909090909091 sentence_…

[607368 rows x 4 columns]
```

[26]:
```python
df_copy['AgeLabel'].unique()
```

[26]:
```
array(['young', 'old'], dtype=object)
```

[27]:
```python
import pandas as pd
from sklearn.utils import resample

# Define the input features (X) and target variable (y)
X = df_copy[['Utterance']]
y = df_copy['AgeLabel']

# Combine X and y into a single DataFrame
df = pd.concat([X, y], axis=1)

# Separate the majority and minority classes
young_class = df[df['AgeLabel'] == 'young']
old_class = df[df['AgeLabel'] == 'old']

# Undersample the majority class
```

```
young_undersampled = resample(young_class, replace=False,␣
 ↪n_samples=len(old_class), random_state=42)

# Combine the undersampled majority class and the minority class
balanced_data = pd.concat([young_undersampled, old_class])

# Separate the features (X) and the target variable (y)
X_balanced = balanced_data[['Utterance']]
y_balanced = balanced_data['AgeLabel']
```

[28]:
```
X_balanced.shape, y_balanced.shape
```

[28]:
```
((15528, 1), (15528,))
```

[29]:
```
y_balanced.value_counts()
```

[29]:
```
AgeLabel
young    7764
old      7764
Name: count, dtype: int64
```

[30]:
```
X_train, X_test, y_train, y_test = train_test_split(X_balanced, y_balanced,␣
 ↪test_size=0.2, random_state=42)
```

[31]:
```
X_train.shape
```

[31]:
```
(12422, 1)
```

[32]:
```
X_test.shape
```

[32]:
```
(3106, 1)
```

[33]:
```
print(y_train.value_counts())
```

```
AgeLabel
old      6220
young    6202
Name: count, dtype: int64
```

[34]:
```
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

# Initialize the vectorizer (choose either CountVectorizer or TfidfVectorizer)
vectorizer = CountVectorizer()  # or TfidfVectorizer()

# Fit the vectorizer on the training data
X_train_text = X_train['Utterance']  # assuming 'Utterance' column contains the␣
 ↪text data
```

```
X_train_vectorized = vectorizer.fit_transform(X_train_text)

# Transform the testing data using the fitted vectorizer
X_test_text = X_test['Utterance']  # assuming 'Utterance' column contains the␣
↪text data
X_test_vectorized = vectorizer.transform(X_test_text)
```

[35]:
```
# Step 6: Model Training with no Linguistic Features
model = LogisticRegression()
model.fit(X_train_vectorized, y_train)
```

```
c:\Users\abhij\.conda\envs\dmassessment\Lib\site-
packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[35]:
```
LogisticRegression()
```

[36]:
```
# Step 7: Model Evaluation for old class
y_pred = model.predict(X_test_vectorized)
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, pos_label="old")
recall = recall_score(y_test, y_pred, pos_label="old")
f1 = f1_score(y_test, y_pred, pos_label="old")

print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1}")
```

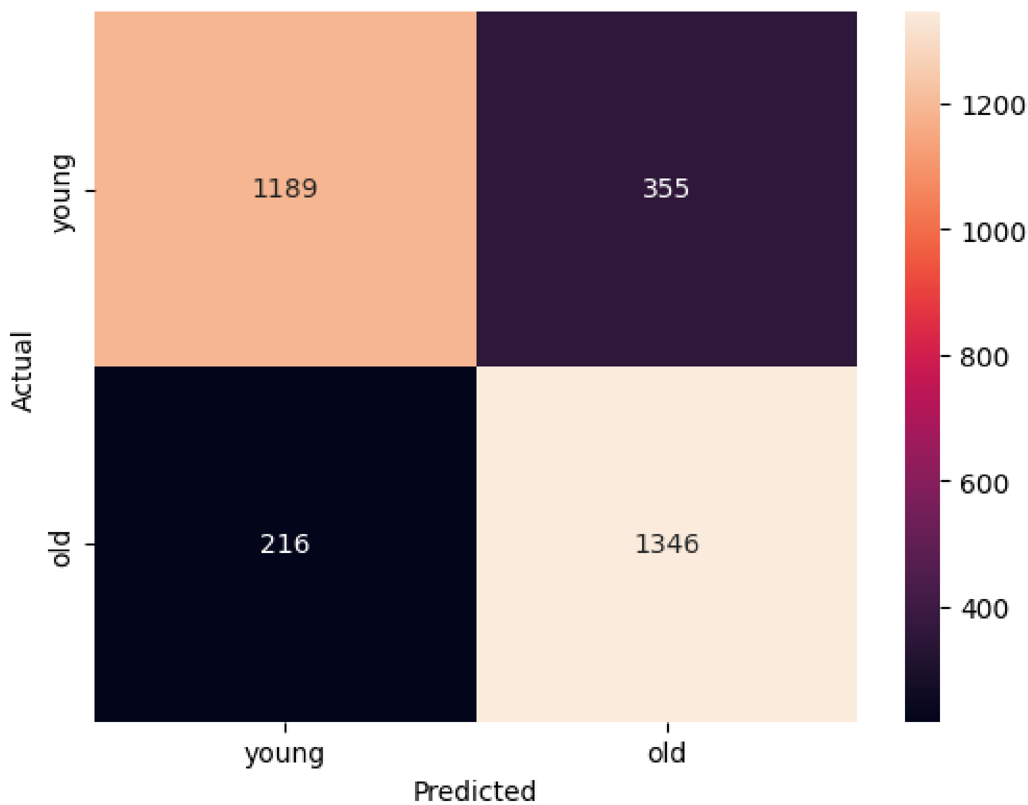
```
Accuracy: 0.8161622665808114
Precision: 0.8462633451957295
Recall: 0.7700777202072538
F1 Score: 0.8063750423872499
```

[37]:
```
# Step 7: Model Evaluation for young class
y_pred = model.predict(X_test_vectorized)
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, pos_label="young")
recall = recall_score(y_test, y_pred, pos_label="young")
```

```python
f1 = f1_score(y_test, y_pred, pos_label="young")

print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1}")
```

```
Accuracy: 0.8161622665808114
Precision: 0.7912992357436802
Recall: 0.8617157490396927
F1 Score: 0.8250076616610481
```

[38]:
```python
# plot confusion matrix
from sklearn.metrics import confusion_matrix
import seaborn as sns

conf_mat = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_mat, annot=True, fmt='d', xticklabels=['young', 'old'],␣
 ↪yticklabels=['young', 'old'])
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```



[39]:
```
df_vis.shape
```

[39]:
```
(1248110, 12)
```

[40]:
```
df_vis['AgeLabel'].value_counts()
```

[40]:
```
AgeLabel
19_29    599604
30_39    547325
40_49      4896
50_59      4478
70_79      2818
0_10       2180
11_18       470
60_69       468
Name: count, dtype: int64
```

[41]:
```
# get a copy of the dataframe
df_with_features = df_vis.copy()

# convert the AgeLabel column, 19_29 to young and 50_59, 60_69, 70_79, 80_89,␣
↪90_99 to old
df_with_features['AgeLabel'].replace({'19_29': 'young', '50_59': 'old', '60_69':
↪ 'old', '70_79': 'old', '80_89': 'old', '90_99': 'old'}, inplace=True)

# drop rows with remaining age labels
df_with_features = df_with_features[df_with_features['AgeLabel'].isin(['young',␣
↪'old'])]
```

[42]:
```
df_with_features['AgeLabel'].value_counts()
```

[42]:
```
AgeLabel
young    599604
old        7764
Name: count, dtype: int64
```

[43]:
```
df_with_features
```

[43]:
```
        SpeakerID AgeLabel                                        Utterance
2           S0032    young                                        yeah yeah  \
4           S0032    young                                I its something I
6           S0032    young
10          S0032    young
12          S0021    young
…           …      …                                                  …
1248104     S0032    young                                        no its not
```

```
1248105     S0021    young                                       I have like
1248107     S0032    young
1248108     S0021    young  I have like tomato ketchup emergencies if I ru…
1248109     S0032    young  thats not as bad as the barbecue that we had t…

                                                      Features  utterance_length
2        lexical_diversity:0.5 sentence_length:2.0 disc…                 9  \
4        lexical_diversity:0.75 sentence_length:4.0 dis…                17
6        lexical_diversity:0 sentence_length:0 discours…                 0
10       lexical_diversity:0 sentence_length:0 discours…                 0
12       lexical_diversity:0 sentence_length:0 discours…                 0
…                                                    …               …
1248104  lexical_diversity:1.0 sentence_length:3.0 disc…                10
1248105  lexical_diversity:1.0 sentence_length:3.0 disc…                11
1248107  lexical_diversity:0 sentence_length:0 discours…                 0
1248108  lexical_diversity:0.7391304347826086 sentence_…               119
1248109  lexical_diversity:0.9090909090909091 sentence_…                51

         lexical_diversity  sentence_length  discourse_marker_count
2                 0.500000              2.0                     0.0  \
4                 0.750000              4.0                     0.0
6                 0.000000              0.0                     0.0
10                0.000000              0.0                     0.0
12                0.000000              0.0                     0.0
…                      …                …                    …
1248104           1.000000              3.0                     0.0
1248105           1.000000              3.0                     1.0
1248107           0.000000              0.0                     0.0
1248108           0.739130             23.0                     2.0
1248109           0.909091             11.0                     0.0

         filler_count  hesitation_count  speech_rate  Cluster
2                 2.0               2.0          2.0        3
4                 0.0               0.0          4.0        1
6                 0.0               0.0          0.0        0
10                0.0               0.0          0.0        0
12                0.0               0.0          0.0        0
…              …                 …          …      …
1248104           0.0               0.0          3.0        1
1248105           0.0               1.0          3.0        4
1248107           0.0               0.0          0.0        0
1248108           2.0               4.0         23.0        2
1248109           0.0               0.0         11.0        1

[607368 rows x 12 columns]
```

[44]:
```
df_with_features.columns
```

[44]: Index(['SpeakerID', 'AgeLabel', 'Utterance', 'Features', 'utterance_length',
       'lexical_diversity', 'sentence_length', 'discourse_marker_count',
       'filler_count', 'hesitation_count', 'speech_rate', 'Cluster'],
      dtype='object')

[45]:
```
df_with_features.describe()
```

[45]:

```
       utterance_length  lexical_diversity  sentence_length  \
count     607368.000000      607368.000000    607368.000000
mean          24.330457           0.810971         5.234224
std           31.979818           0.357185         6.622813
min            0.000000           0.000000         0.000000
25%            2.000000           0.857143         1.000000
50%           13.000000           1.000000         3.000000
75%           35.000000           1.000000         7.000000
max          630.000000           1.000000       123.000000

       discourse_marker_count   filler_count  hesitation_count    speech_rate  \
count           607368.000000  607368.000000     607368.000000  607368.000000
mean                 0.169834       0.519395          0.689230       5.234224
std                  0.498674       0.737525          0.975447       6.622813
min                  0.000000       0.000000          0.000000       0.000000
25%                  0.000000       0.000000          0.000000       1.000000
50%                  0.000000       0.000000          0.000000       3.000000
75%                  0.000000       1.000000          1.000000       7.000000
max                 10.000000      15.000000         18.000000     123.000000

             Cluster
count  607368.000000
mean        2.015722
std         1.481856
min         0.000000
25%         1.000000
50%         1.000000
75%         3.000000
max         5.000000
```

[46]:
```
# get X and y
X = df_with_features[['Utterance', 'utterance_length', 'lexical_diversity',␣
 ↪'sentence_length', 'discourse_marker_count', 'filler_count',␣
 ↪'hesitation_count', 'speech_rate']]
y = df_with_features['AgeLabel']

# balance the dataset
young_class = df_with_features[df_with_features['AgeLabel'] == 'young']
old_class = df_with_features[df_with_features['AgeLabel'] == 'old']
```

```python
young_undersampled = resample(young_class, replace=False,␣
↪n_samples=len(old_class), random_state=42)

balanced_data = pd.concat([young_undersampled, old_class])

# separate the features (X) and the target variable (y)
X_balanced = balanced_data[['Utterance', 'utterance_length',␣
↪'lexical_diversity', 'sentence_length', 'discourse_marker_count',␣
↪'filler_count', 'hesitation_count', 'speech_rate']]
y_balanced = balanced_data['AgeLabel']

X_balanced.shape, y_balanced.shape
```

[46]: ((15528, 8), (15528,))

[47]:
```python
# split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_balanced, y_balanced,␣
↪test_size=0.2, random_state=42)
```

[48]:
```python
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[48]: ((12422, 8), (3106, 8), (12422,), (3106,))

[49]:
```python
y_train.value_counts()
```

[49]:
```
AgeLabel
old      6220
young    6202
Name: count, dtype: int64
```

[50]:
```python
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

# Initialize the vectorizer (choose either CountVectorizer or TfidfVectorizer)
vectorizer = CountVectorizer()  # or TfidfVectorizer()

# Fit the vectorizer on the training data
X_train_text = X_train['Utterance']  # assuming 'Utterance' column contains the␣
↪text data
X_train_vectorized = vectorizer.fit_transform(X_train_text)

# Transform the testing data using the fitted vectorizer
X_test_text = X_test['Utterance']  # assuming 'Utterance' column contains the␣
↪text data
X_test_vectorized = vectorizer.transform(X_test_text)
```

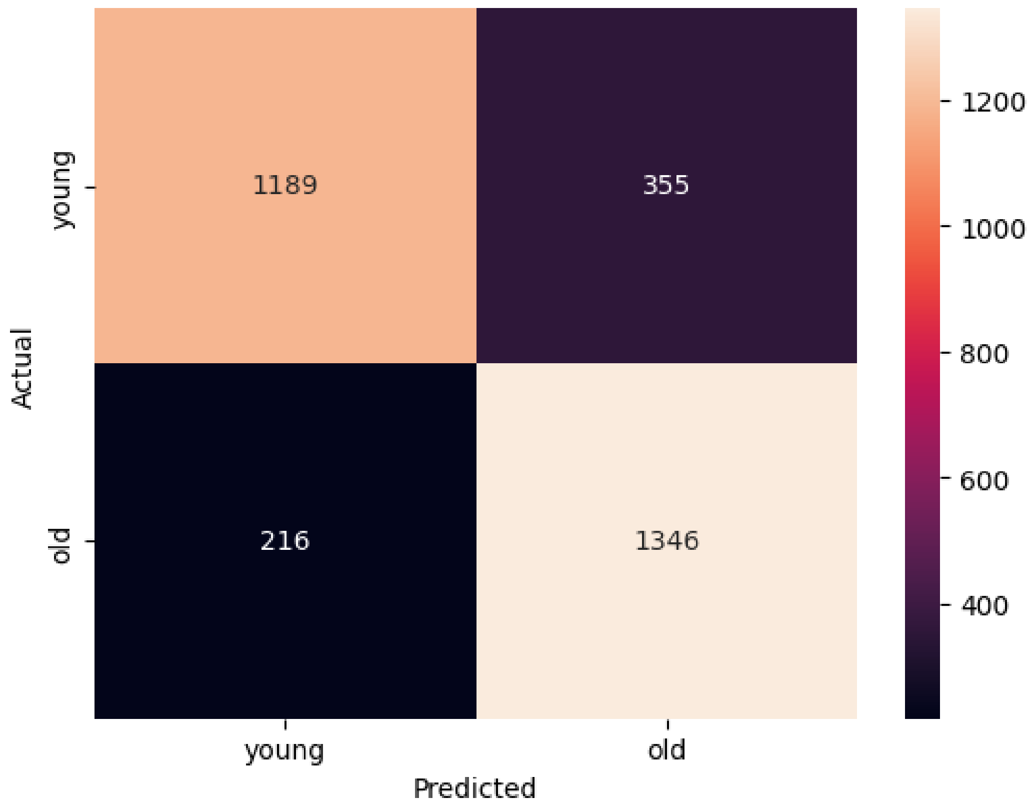
[51]:
```
# Step 6: Model Training with Linguistic Features
model2 = LogisticRegression(max_iter=1000)
model2.fit(X_train_vectorized, y_train)
```

[51]:
```
LogisticRegression(max_iter=1000)
```

[52]:
```
# Step 7: Model Evaluation
from sklearn.metrics import classification_report


y_pred = model2.predict(X_test_vectorized)

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         old       0.85      0.77      0.81      1544
       young       0.79      0.86      0.83      1562

    accuracy                           0.82      3106
   macro avg       0.82      0.82      0.82      3106
weighted avg       0.82      0.82      0.82      3106
```

[53]:
```
# plot confusion matrix
from sklearn.metrics import confusion_matrix
import seaborn as sns

conf_mat = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_mat, annot=True, fmt='d', xticklabels=['young', 'old'],␣
 ↪yticklabels=['young', 'old'])
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```



By comparing both models, one with just utterances and the utterances and features, we expect to see a difference in the performance of the models. But in this case, the performance of the model is almost the same. I assume this is because the data is not large enough to make a difference in the performance of the model. If we had a large dataset, then we would have seen a difference in the performance of the model.

[54]:
```
# predictions for the first 5 test samples

X_test_transformed = vectorizer.inverse_transform(X_test_vectorized)

predictions = model.predict(X_test_vectorized)

# for i in range(len(X_test_transformed)):
for i in range(5):
    sentence = " ".join(X_test_transformed[i])
    predicted_output = predictions[i]
    real_output = y_test.iloc[i]

    print("Input Sentence: ", sentence)
    print("Predicted Output: ", predicted_output)
    print("Real Output: ", real_output)
```

```
    print()
```

```
Input Sentence:  he
Predicted Output:  old
Real Output:  young

Input Sentence:  and need no pool swimming the thing whole you
Predicted Output:  old
Real Output:  old

Input Sentence:
Predicted Output:  young
Real Output:  young

Input Sentence:  mm
Predicted Output:  young
Real Output:  young

Input Sentence:  mm
Predicted Output:  young
Real Output:  old
```

[55]:
```
# get the predictions for the whole test set and display the results in a␣
 ↪dataframe
X_test_transformed = vectorizer.inverse_transform(X_test_vectorized)
predictions = model.predict(X_test_vectorized)

results_df = pd.DataFrame({'Input Sentence': [' '.join(sentence) for sentence␣
 ↪in X_test_transformed],
                           'Predicted Output': predictions,
                           'Real Output': y_test.values})

results_df
```

[55]:
```
                                      Input Sentence Predicted Output  \
0                                                 he              old
1     and need no pool swimming the thing whole you              old
2                                                               young
3                                                 mm            young
4                                                 mm            young
…                                                …              …
3101                                            yeah              old
3102                         is it so time whatever            young
3103                             did make these you            young
3104                                    ill speak to              old
3105                    across did er just oh the to              old
```

```
     Real Output
0          young
1            old
2          young
3          young
4            old
…          …
3101         old
3102       young
3103         old
3104         old
3105         old

[3106 rows x 3 columns]
```

[56]:

```
wrong_predictions = results_df[results_df['Predicted Output'] !=␣
 ↪results_df['Real Output']]
wrong_predictions
```

[56]:

```
                Input Sentence Predicted Output Real Output
0                           he              old       young
4                           mm            young         old
11                        yeah              old       young
18     an day eight hour thats            young         old
19                          er              old       young
…                          …               …       …
3083        didnt help it last            young         old
3088                        so            young         old
3096                is it yeah              old       young
3098                     where            young         old
3103        did make these you            young         old

[571 rows x 3 columns]
```

[57]:

```
# # Get feature names
# import numpy as np

# # Retrieve the coefficients from the trained model
# coefficients = model2.coef_[0]

# # Get feature names from the vectorizer
# feature_names = vectorizer.get_feature_names()

# print(len(feature_names))

# # Get feature names
```

```
# feature_names = ['Utterance', 'utterance_length', 'lexical_diversity',␣
↪'sentence_length',
#                  'discourse_marker_count', 'filler_count', 'hesitation_count',
#                  'speech_rate']

# # Plot the feature importances
# plt.figure(figsize=(10, 6))
# plt.barh(range(len(feature_names)), np.abs(coefficients), align='center')
# plt.yticks(range(len(feature_names)), feature_names)
# plt.xlabel('Coefficient Magnitude')
# plt.ylabel('Features')
# plt.title('Feature Importance for Logistic Regression')
# plt.tight_layout()
# plt.show()
```

[58]:

```
# predictions for the first 5 test samples

X_test_transformed = vectorizer.inverse_transform(X_test_vectorized)

predictions = model.predict(X_test_vectorized)

# for i in range(len(X_test_transformed)):
for i in range(5):
    sentence = " ".join(X_test_transformed[i])
    predicted_output = predictions[i]
    real_output = y_test.iloc[i]

    print("Input Sentence: ", sentence)
    print("Predicted Output: ", predicted_output)
    print("Real Output: ", real_output)
    print()
```

```
Input Sentence:  he
Predicted Output:  old
Real Output:  young

Input Sentence:  and need no pool swimming the thing whole you
Predicted Output:  old
Real Output:  old

Input Sentence:
Predicted Output:  young
Real Output:  young

Input Sentence:  mm
Predicted Output:  young
Real Output:  young
```

```
Input Sentence:  mm
Predicted Output:  young
Real Output:  old
```

[59]:
```python
# get the predictions for the whole test set and display the results in a␣
↪dataframe
X_test_transformed = vectorizer.inverse_transform(X_test_vectorized)
predictions = model.predict(X_test_vectorized)

results_df = pd.DataFrame({'Input Sentence': [' '.join(sentence) for sentence␣
↪in X_test_transformed],
                           'Predicted Output': predictions,
                           'Real Output': y_test.values})

results_df
```

[59]:
```
                                     Input Sentence Predicted Output  \
0                                                he              old
1       and need no pool swimming the thing whole you              old
2                                                              young
3                                                mm            young
4                                                mm            young
…                                               …              …
3101                                           yeah              old
3102                           is it so time whatever            young
3103                               did make these you            young
3104                                     ill speak to              old
3105                     across did er just oh the to              old

     Real Output
0          young
1            old
2          young
3          young
4            old
…            …
3101         old
3102       young
3103         old
3104         old
3105         old

[3106 rows x 3 columns]
```

```
[60]: wrong_predictions = results_df[results_df['Predicted Output'] !=
      results_df['Real Output']]
      wrong_predictions
```

```
[60]:                Input Sentence Predicted Output Real Output
      0                          he              old       young
      4                          mm            young         old
      11                       yeah              old       young
      18     an day eight hour thats            young         old
      19                         er              old       young
      …                           …                …           …
      3083       didnt help it last            young         old
      3088                       so            young         old
      3096               is it yeah              old       young
      3098                    where            young         old
      3103        did make these you            young         old

      [571 rows x 3 columns]
```

2 Using Bert Model

```
[61]: df.columns
```

```
[61]: Index(['Utterance', 'AgeLabel'], dtype='object')
```

```
[62]: import pandas as pd
      from sklearn.model_selection import train_test_split
      from transformers import BertTokenizer, BertForSequenceClassification, AdamW
      import torch

      # Split the data into training and testing sets
      train_df, test_df = train_test_split(df, test_size=0.2, random_state=42)

      # Get the training and testing utterances and labels
      train_texts = train_df['Utterance'].tolist()
      train_labels = train_df['AgeLabel'].tolist()
      test_texts = test_df['Utterance'].tolist()
      test_labels = test_df['AgeLabel'].tolist()
```

```
c:\Users\abhij\.conda\envs\dmassessment\Lib\site-packages\tqdm\auto.py:21:
TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

```
[63]: import numpy as np
```

```
train_labels = np.array(train_labels)
test_labels = np.array(test_labels)
```

[64]:
```
# Load the BERT tokenizer
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

# Load the BERT model for sequence classification
model = BertForSequenceClassification.from_pretrained('bert-base-uncased',␣
 ↪num_labels=2)
```

```
Some weights of the model checkpoint at bert-base-uncased were not used when
initializing BertForSequenceClassification: ['cls.seq_relationship.weight',
'cls.predictions.transform.LayerNorm.weight', 'cls.seq_relationship.bias',
'cls.predictions.bias', 'cls.predictions.transform.dense.weight',
'cls.predictions.decoder.weight', 'cls.predictions.transform.LayerNorm.bias',
'cls.predictions.transform.dense.bias']
- This IS expected if you are initializing BertForSequenceClassification from
the checkpoint of a model trained on another task or with another architecture
(e.g. initializing a BertForSequenceClassification model from a
BertForPreTraining model).
- This IS NOT expected if you are initializing BertForSequenceClassification
from the checkpoint of a model that you expect to be exactly identical
(initializing a BertForSequenceClassification model from a
BertForSequenceClassification model).
Some weights of BertForSequenceClassification were not initialized from the
model checkpoint at bert-base-uncased and are newly initialized:
['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it
for predictions and inference.
```

[66]:
```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
train_labels = label_encoder.fit_transform(train_labels)
test_labels = label_encoder.transform(test_labels)
```

[89]:
```
test_labels
```

[89]:
```
array([1, 1, 1, …, 1, 1, 1])
```

[67]:
```
# Tokenize and encode the training utterances
train_encodings = tokenizer(train_texts, truncation=True, padding=True)

# Tokenize and encode the testing utterances
test_encodings = tokenizer(test_texts, truncation=True, padding=True)

# Create torch tensors for the encoded data and labels
```

```
train_dataset = torch.utils.data.TensorDataset(
    torch.tensor(train_encodings['input_ids']),
    torch.tensor(train_encodings['attention_mask']),
    torch.tensor(train_labels)
)
test_dataset = torch.utils.data.TensorDataset(
    torch.tensor(test_encodings['input_ids']),
    torch.tensor(test_encodings['attention_mask']),
    torch.tensor(test_labels)
)
```

[68]:
```
# Define the training parameters
batch_size = 16
epochs = 3

# Create a DataLoader for the training and testing datasets
train_loader = torch.utils.data.DataLoader(train_dataset,␣
 ↪batch_size=batch_size, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size)
```

[69]:
```
# import torch
# import torch.cuda

# # Set the max_split_size_mb parameter
# torch.cuda.set_per_process_memory_fraction(fraction=0.2)

# torch.cuda.empty_cache()
```

[70]:
```
# import gc

# gc.collect()

# torch.cuda.empty_cache()
```

[71]:
```
# # Set the maximum memory split size in megabytes
# torch.backends.cuda.max_split_size_mb = 2000  # Adjust the value as needed
```

[72]:
```
# import torch
# from GPUtil import showUtilization as gpu_usage
# from numba import cuda

# def free_gpu_cache():
#     print("Initial GPU Usage")
#     gpu_usage()

#     torch.cuda.empty_cache()
```

```
#     cuda.select_device(0)
#     cuda.close()
#     cuda.select_device(0)

#     print("GPU Usage after emptying the cache")
#     gpu_usage()

# free_gpu_cache()
```

[73]:
```
# gpu_usage()
```

[74]:
```
# torch.cuda.device_count()
# cuda.select_device(0)
```

[75]:
```
# import os
# os.environ['CUDA_LAUNCH_BLOCKING'] = '1'
```

[76]:
```
# torch.cuda.memory_allocated()
```

[77]:
```
# Set the device (CPU or GPU)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Move the model to the device
model.to(device)

# Set the optimizer and learning rate
optimizer = AdamW(model.parameters(), lr=1e-5)

# Training loop
model.train()
for epoch in range(epochs):
    for batch in train_loader:
        input_ids, attention_mask, labels = batch
        print("Input ids:", input_ids.shape, "Attention mask:", attention_mask.
 ↪shape, "Labels:", labels.shape)
        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)
        labels = labels.to(torch.long)

        optimizer.zero_grad()

        outputs = model(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss
        loss.backward()
        optimizer.step()
```

```
torch.Size([16])
Input ids: torch.Size([16, 139]) Attention mask: torch.Size([16, 139]) Labels:
torch.Size([16])
Input ids: torch.Size([16, 139]) Attention mask: torch.Size([16, 139]) Labels:
torch.Size([16])
Input ids: torch.Size([16, 139]) Attention mask: torch.Size([16, 139]) Labels:
torch.Size([16])
Input ids: torch.Size([16, 139]) Attention mask: torch.Size([16, 139]) Labels:
torch.Size([16])
Input ids: torch.Size([16, 139]) Attention mask: torch.Size([16, 139]) Labels:
torch.Size([16])
Input ids: torch.Size([6, 139]) Attention mask: torch.Size([6, 139]) Labels:
torch.Size([6])
```

[83]:
```
# save the model
model.save_pretrained('models/bert_model')
```

[84]:
```
# get model from saved
model = BertForSequenceClassification.from_pretrained('models/bert_model',␣
 ↪num_labels=2)

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

model.to(device)

# evaluate the model
model.eval()
with torch.no_grad():
    correct = 0
    total = 0
    for batch in test_loader:
        input_ids, attention_mask, labels = batch
        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)

        outputs = model(input_ids, attention_mask=attention_mask)
        _, predicted = torch.max(outputs.logits, dim=1)

        total += labels.size(0)
        correct += (predicted == labels).sum().item()

    accuracy = correct / total
    print('Accuracy on test data: {:.2f}%'.format(accuracy * 100))
```

```
Accuracy on test data: 99.47%
```

[85]:
```
# Confusion matrix
from sklearn.metrics import confusion_matrix

model.eval()
y_pred = []
y_true = []
with torch.no_grad():
    for batch in test_loader:
        input_ids, attention_mask, labels = batch
        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)

        outputs = model(input_ids, attention_mask=attention_mask)
        _, predicted = torch.max(outputs.logits, dim=1)

        y_pred.extend(predicted.tolist())
        y_true.extend(labels.tolist())

cm = confusion_matrix(y_true, y_pred)
print(cm)
```

```
[[   997    572]
 [    71 119834]]
```

[87]:
```
# get all the predictions for test data
model.eval()
y_pred = []
y_true = []
X_input = []
with torch.no_grad():
    for batch in test_loader:
        input_ids, attention_mask, labels = batch
        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)

        outputs = model(input_ids, attention_mask=attention_mask)
        _, predicted = torch.max(outputs.logits, dim=1)

        X_input.extend(input_ids.tolist())
        y_pred.extend(predicted.tolist())
        y_true.extend(labels.tolist())

# create a dataframe with the predictions
bert_results_df = pd.DataFrame({'text': test_texts, 'label': y_true,␣
 ↪'prediction': y_pred})
```

[91]:
```python
# convert the label and prediction to the actual class names
bert_results_df['label'] = bert_results_df['label'].apply(lambda x: 'young' if␣
↪x == 1 else 'old')
bert_results_df['prediction'] = bert_results_df['prediction'].apply(lambda x:␣
↪'young' if x == 1 else 'old')

bert_results_df
```

[91]:
```
                                          text  label prediction
0        that wed be able to drink together no  young      young
1                            yeah yeah coming  young      young
2        think we drank it all though didnt we  young      young
3                                               young      young
4                       yeah all good thank you  young      young
…                                          …      …          …
121469                                      mm  young      young
121470                                      mm  young      young
121471                                     erm  young      young
121472                           for Christmas  young      young
121473      suppose theyre made out of paper  young      young

[121474 rows x 3 columns]
```

[92]:
```python
# get all the wrong predictions
wrong_predictions_df = bert_results_df[bert_results_df['label'] !=␣
↪bert_results_df['prediction']]
wrong_predictions_df
```

[92]:
```
                 text label prediction
134             right   old      young
458              okay   old      young
762              yeah   old      young
1517               mm   old      young
1579             yeah   old      young
…                 …    …         …
120317           yeah   old      young
120515  oh right yeah   old      young
120667           yeah   old      young
120853                  old      young
121406                  old      young

[643 rows x 3 columns]
```