

September 28, 2023

## 1 Download data from Kaggle

```
[1]: !pip install -q kaggle
```

```
[2]: from google.colab import files
      # Create a new API token under "Account" in the kaggle webpage and download the
      # json file
      # Upload the file by clicking on the browse
      files.upload()
```

<IPython.core.display.HTML object>

Saving kaggle.json to kaggle.json

```
[2]: {'kaggle.json':
      b'{"username":"bindubhargavachintam","key":"a9e63e935092925d10aa9244afc6a748"}'}
```

```
[3]: !mkdir ~/.kaggle
```

```
[4]: !cp kaggle.json ~/.kaggle/
```

```
[5]: !chmod 600 /root/.kaggle/kaggle.json
```

```
[6]: !kaggle competitions download -c commonlit-evaluate-student-summaries
```

Downloading commonlit-evaluate-student-summaries.zip to /content

0% 0.00/1.05M [00:00<?, ?B/s]

100% 1.05M/1.05M [00:00<00:00, 82.2MB/s]

## 2 Extract data and install packages (regardless of data acquisition method)

```
[7]: !unzip commonlit-evaluate-student-summaries.zip
```

Archive: commonlit-evaluate-student-summaries.zip

inflating: prompts\_test.csv

inflating: prompts\_train.csv

inflating: sample\_submission.csv

```
inflating: summaries_test.csv
inflating: summaries_train.csv
```

## 2.0.1 Install required packages

```
[8]: ### Student's code here
!pip install pandas
!pip install scikit-learn
!pip install numpy
!pip install matplotlib
!pip install seaborn
!pip install textstat
!pip install nltk
!pip install textblob
!pip install spacy
!python -m spacy download en_core_web_sm
### END
```

Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (1.5.3)

Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (2023.3.post1)

Requirement already satisfied: numpy>=1.21.0 in /usr/local/lib/python3.10/dist-packages (from pandas) (1.23.5)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas) (1.16.0)

Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.2.2)

Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.23.5)

Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.11.2)

Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.3.2)

Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.2.0)

Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (1.23.5)

Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.7.1)

Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.1.0)

Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.11.0)

Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.42.1)

Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.5)

Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.23.5)

Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (23.1)

Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (9.4.0)

Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.1)

Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)

Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.12.2)

Requirement already satisfied: numpy!=1.24.0,>=1.17 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.23.5)

Requirement already satisfied: pandas>=0.25 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.5.3)

Requirement already satisfied: matplotlib!=3.6.1,>=3.1 in /usr/local/lib/python3.10/dist-packages (from seaborn) (3.7.1)

Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (1.1.0)

Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (0.11.0)

Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (4.42.1)

Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (1.4.5)

Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (23.1)

Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (9.4.0)

Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (3.1.1)

Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.25->seaborn) (2023.3.post1)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.1->seaborn) (1.16.0)

```

Collecting textstat
  Downloading textstat-0.7.3-py3-none-any.whl (105 kB)
    105.1/105.1

kB 2.9 MB/s eta 0:00:00
Collecting pyphen (from textstat)
  Downloading pyphen-0.14.0-py3-none-any.whl (2.0 MB)
    2.0/2.0 MB

12.8 MB/s eta 0:00:00
Installing collected packages: pyphen, textstat
Successfully installed pyphen-0.14.0 textstat-0.7.3
Requirement already satisfied: nltk in /usr/local/lib/python3.10/dist-packages (3.8.1)
Requirement already satisfied: click in /usr/local/lib/python3.10/dist-packages (from nltk) (8.1.7)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from nltk) (1.3.2)
Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.10/dist-packages (from nltk) (2023.6.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from nltk) (4.66.1)
Requirement already satisfied: textblob in /usr/local/lib/python3.10/dist-packages (0.17.1)
Requirement already satisfied: nltk>=3.1 in /usr/local/lib/python3.10/dist-packages (from textblob) (3.8.1)
Requirement already satisfied: click in /usr/local/lib/python3.10/dist-packages (from nltk>=3.1->textblob) (8.1.7)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from nltk>=3.1->textblob) (1.3.2)
Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.10/dist-packages (from nltk>=3.1->textblob) (2023.6.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from nltk>=3.1->textblob) (4.66.1)
Requirement already satisfied: spacy in /usr/local/lib/python3.10/dist-packages (3.6.1)
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.11 in /usr/local/lib/python3.10/dist-packages (from spacy) (3.0.12)
Requirement already satisfied: spacy-loggers<2.0.0,>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from spacy) (1.0.4)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in /usr/local/lib/python3.10/dist-packages (from spacy) (1.0.9)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in /usr/local/lib/python3.10/dist-packages (from spacy) (2.0.7)
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in /usr/local/lib/python3.10/dist-packages (from spacy) (3.0.8)
Requirement already satisfied: thinc<8.2.0,>=8.1.8 in /usr/local/lib/python3.10/dist-packages (from spacy) (8.1.12)
Requirement already satisfied: wasabi<1.2.0,>=0.9.1 in

```

/usr/local/lib/python3.10/dist-packages (from spacy) (1.1.2)  
 Requirement already satisfied: srsly<3.0.0,>=2.4.3 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (2.4.7)  
 Requirement already satisfied: catalogue<2.1.0,>=2.0.6 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (2.0.9)  
 Requirement already satisfied: typer<0.10.0,>=0.3.0 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (0.9.0)  
 Requirement already satisfied: pathy>=0.10.0 in /usr/local/lib/python3.10/dist-  
 packages (from spacy) (0.10.2)  
 Requirement already satisfied: smart-open<7.0.0,>=5.2.1 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (6.4.0)  
 Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (4.66.1)  
 Requirement already satisfied: numpy>=1.15.0 in /usr/local/lib/python3.10/dist-  
 packages (from spacy) (1.23.5)  
 Requirement already satisfied: requests<3.0.0,>=2.13.0 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (2.31.0)  
 Requirement already satisfied: pydantic!=1.8,!1.8.1,<3.0.0,>=1.7.4 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (1.10.12)  
 Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages  
 (from spacy) (3.1.2)  
 Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-  
 packages (from spacy) (67.7.2)  
 Requirement already satisfied: packaging>=20.0 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (23.1)  
 Requirement already satisfied: langcodes<4.0.0,>=3.2.0 in  
 /usr/local/lib/python3.10/dist-packages (from spacy) (3.3.0)  
 Requirement already satisfied: typing-extensions>=4.2.0 in  
 /usr/local/lib/python3.10/dist-packages (from  
 pydantic!=1.8,!1.8.1,<3.0.0,>=1.7.4->spacy) (4.5.0)  
 Requirement already satisfied: charset-normalizer<4,>=2 in  
 /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0->spacy)  
 (3.2.0)  
 Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-  
 packages (from requests<3.0.0,>=2.13.0->spacy) (3.4)  
 Requirement already satisfied: urllib3<3,>=1.21.1 in  
 /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0->spacy)  
 (2.0.4)  
 Requirement already satisfied: certifi>=2017.4.17 in  
 /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0->spacy)  
 (2023.7.22)  
 Requirement already satisfied: blis<0.8.0,>=0.7.8 in  
 /usr/local/lib/python3.10/dist-packages (from thinc<8.2.0,>=8.1.8->spacy)  
 (0.7.10)  
 Requirement already satisfied: confection<1.0.0,>=0.0.1 in  
 /usr/local/lib/python3.10/dist-packages (from thinc<8.2.0,>=8.1.8->spacy)  
 (0.1.2)  
 Requirement already satisfied: click<9.0.0,>=7.1.1 in

```

/usr/local/lib/python3.10/dist-packages (from typer<0.10.0,>=0.3.0->spacy)
(8.1.7)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->spacy) (2.1.3)
2023-09-28 04:35:48.767385: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild
TensorFlow with the appropriate compiler flags.
2023-09-28 04:35:49.966194: W
tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not
find TensorRT
Collecting en-core-web-sm==3.6.0
  Downloading https://github.com/explosion/spacy-
models/releases/download/en_core_web_sm-3.6.0/en_core_web_sm-3.6.0-py3-none-
any.whl (12.8 MB)
                                12.8/12.8 MB
34.6 MB/s eta 0:00:00
Requirement already satisfied: spacy<3.7.0,>=3.6.0 in
/usr/local/lib/python3.10/dist-packages (from en-core-web-sm==3.6.0) (3.6.1)
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.11 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (3.0.12)
Requirement already satisfied: spacy-loggers<2.0.0,>=1.0.0 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (1.0.4)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (1.0.9)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (2.0.7)
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (3.0.8)
Requirement already satisfied: thinc<8.2.0,>=8.1.8 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (8.1.12)
Requirement already satisfied: wasabi<1.2.0,>=0.9.1 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (1.1.2)
Requirement already satisfied: srsly<3.0.0,>=2.4.3 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (2.4.7)
Requirement already satisfied: catalogue<2.1.0,>=2.0.6 in
/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-
sm==3.6.0) (2.0.9)
Requirement already satisfied: typer<0.10.0,>=0.3.0 in

```

/usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (0.9.0)  
 Requirement already satisfied: pathy>=0.10.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (0.10.2)  
 Requirement already satisfied: smart-open<7.0.0,>=5.2.1 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (6.4.0)  
 Requirement already satisfied: tqdm<5.0.0,>=4.38.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (4.66.1)  
 Requirement already satisfied: numpy>=1.15.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (1.23.5)  
 Requirement already satisfied: requests<3.0.0,>=2.13.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (2.31.0)  
 Requirement already satisfied: pydantic!=1.8,!1.8.1,<3.0.0,>=1.7.4 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (1.10.12)  
 Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (3.1.2)  
 Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (67.7.2)  
 Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (23.1)  
 Requirement already satisfied: langcodes<4.0.0,>=3.2.0 in /usr/local/lib/python3.10/dist-packages (from spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (3.3.0)  
 Requirement already satisfied: typing-extensions>=4.2.0 in /usr/local/lib/python3.10/dist-packages (from pydantic!=1.8,!1.8.1,<3.0.0,>=1.7.4->spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (4.5.0)  
 Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0->spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (3.2.0)  
 Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0->spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (3.4)  
 Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0->spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (2.0.4)  
 Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.13.0->spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (2023.7.22)  
 Requirement already satisfied: blis<0.8.0,>=0.7.8 in /usr/local/lib/python3.10/dist-packages (from thinc<8.2.0,>=8.1.8->spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (0.7.10)  
 Requirement already satisfied: confection<1.0.0,>=0.0.1 in

```

/usr/local/lib/python3.10/dist-packages (from
thinc<8.2.0,>=8.1.8->spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (0.1.2)
Requirement already satisfied: click<9.0.0,>=7.1.1 in
/usr/local/lib/python3.10/dist-packages (from
typer<0.10.0,>=0.3.0->spacy<3.7.0,>=3.6.0->en-core-web-sm==3.6.0) (8.1.7)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->spacy<3.7.0,>=3.6.0->en-
core-web-sm==3.6.0) (2.1.3)
Download and installation successful
You can now load the package via spacy.load('en_core_web_sm')

```

## 2.1 Section 1: Library and Data Imports (Q1, 5 points)

- Import your libraries and join the data from both `summaries_train.csv` and `prompts_train.csv` into a single dataframe with the same structure as `use_cols`. Print the head of the dataframe. **Do not modify `use_cols`.**

```

[9]: ### TODO: Load required packages
### Student's code here
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import textstat
import nltk
import spacy
from collections import Counter
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from wordcloud import WordCloud

nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
nltk.download('brown')

###

```

```

[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]   /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package brown to /root/nltk_data...
[nltk_data]   Unzipping corpora/brown.zip.

```



```
[9]: True
```

```
[10]: use_cols = ["student_id",
                  "prompt_id",
                  "text",
                  "content",
                  "wording",
                  "prompt_question",
                  "prompt_title",
                  "prompt_text"
                ]
dtypes = {
    'student_id': 'string',
    'prompt_id': 'string',
    'text': 'string',
    'content': 'Float64',
    'wording': 'Float64',
    'prompt_question': 'string',
    'prompt_title': 'string',
    'prompt_text': 'string',
}
```

### 2.1.1 Importing Datasets

```
[11]: ### Reading Datasets

summaries_train_df = pd.read_csv('summaries_train.csv')
prompts_train_df = pd.read_csv('prompts_train.csv')
```

```
[12]: ### Display Summaries Train Dataset
summaries_train_df.head(5)
```

```
[12]:
```

	student_id	prompt_id	text \	content	wording
0	000e8c3c7ddb	814d6b	The third wave was an experimentto see how peo...	0.205683	0.380538
1	0020ae56ffbf	ebad26	They would rub it up with soda to make the sme...	-0.548304	0.506755
2	004e978e639e	3b9047	In Egypt, there were many occupations and soci...	3.128928	4.231226
3	005ab0199905	3b9047	The highest class was Pharaohs these people we...	-0.210614	-0.471415
4	0070c9e7af47	814d6b	The Third Wave developed rapidly because the ...	3.272894	3.219757

```
[13]: summaries_train_df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7165 entries, 0 to 7164
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   student_id      7165 non-null   object
1   prompt_id       7165 non-null   object
2   text            7165 non-null   object
3   content         7165 non-null   float64
4   wording         7165 non-null   float64
dtypes: float64(2), object(3)
memory usage: 280.0+ KB

```

```

[14]: ### Display Prompt Train Dataset
      prompts_train_df.head(5)

```

```

[14]:   prompt_id                                prompt_question \
0    39c16e  Summarize at least 3 elements of an ideal trag...
1    3b9047  In complete sentences, summarize the structure...
2    814d6b  Summarize how the Third Wave developed over su...
3    ebad26  Summarize the various ways the factory would u...

      prompt_title \
0                On Tragedy
1  Egyptian Social Structure
2                The Third Wave
3  Excerpt from The Jungle

      prompt_text
0  Chapter 13 \r\nAs the sequel to what has alrea...
1  Egyptian society was structured like a pyramid...
2  Background \r\nThe Third Wave experiment took ...
3  With one member trimming beef in a cannery, an...

```

```

[15]: prompts_train_df.info()

```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 4 columns):
#   Column          Non-Null Count  Dtype
---  -
0   prompt_id       4 non-null     object
1   prompt_question  4 non-null     object
2   prompt_title    4 non-null     object
3   prompt_text     4 non-null     object
dtypes: object(4)
memory usage: 256.0+ bytes

```

```
[16]: ### Joined Dataframe

joined_train_df = summaries_train_df.merge(prompts_train_df, on="prompt_id")
```

```
[17]: joined_train_df.head(5)
```

```
[17]:
```

	student_id	prompt_id	text \
0	000e8c3c7ddb	814d6b	The third wave was an experimentto see how peo...
1	0070c9e7af47	814d6b	The Third Wave developed rapidly because the ...
2	0095993991fe	814d6b	The third wave only started as an experiment w...
3	00c20c6ddd23	814d6b	The experimen was originally about how even whe...
4	00d40ad10dc9	814d6b	The third wave developed so quickly due to the...

	content	wording	prompt_question \
0	0.205683	0.380538	Summarize how the Third Wave developed over su...
1	3.272894	3.219757	Summarize how the Third Wave developed over su...
2	0.205683	0.380538	Summarize how the Third Wave developed over su...
3	0.567975	0.969062	Summarize how the Third Wave developed over su...
4	-0.910596	-0.081769	Summarize how the Third Wave developed over su...

	prompt_title	prompt_text
0	The Third Wave Background \r\nThe Third Wave experiment took ...	
1	The Third Wave Background \r\nThe Third Wave experiment took ...	
2	The Third Wave Background \r\nThe Third Wave experiment took ...	
3	The Third Wave Background \r\nThe Third Wave experiment took ...	
4	The Third Wave Background \r\nThe Third Wave experiment took ...	

```
[18]: joined_train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7165 entries, 0 to 7164
Data columns (total 8 columns):
#   Column          Non-Null Count  Dtype
---  -
0   student_id      7165 non-null   object
1   prompt_id       7165 non-null   object
2   text            7165 non-null   object
3   content         7165 non-null   float64
4   wording         7165 non-null   float64
5   prompt_question  7165 non-null   object
6   prompt_title    7165 non-null   object
7   prompt_text     7165 non-null   object
dtypes: float64(2), object(6)
memory usage: 503.8+ KB
```

## 2.2 Section 2: Features (Q2 and Q3, 25 points total)

### 2.2.1 Question 2: Performing Pandas Operations as Follows:

```
[19]: ### Number of words in student response (text) and prompt (prompt_text)

joined_train_df['no_of_words_in_text'] = joined_train_df['text'].str.split(" ").
    ↪apply(len)
joined_train_df['no_of_words_in_prompt_text'] = joined_train_df['prompt_text'].
    ↪str.split(" ").apply(len)
joined_train_df['no_of_words_in_text_and_prompt_text'] =
    ↪joined_train_df['text'].str.split(" ").apply(len) +
    ↪joined_train_df['prompt_text'].str.split(" ").apply(len)

joined_train_df.head()
```

```
[19]:      student_id  prompt_id      text \
0  000e8c3c7ddb    814d6b  The third wave was an experimentto see how peo...
1  0070c9e7af47    814d6b  The Third Wave developed rapidly because the ...
2  0095993991fe    814d6b  The third wave only started as an experiment w...
3  00c20c6ddd23    814d6b  The experimen was orginally about how even whe...
4  00d40ad10dc9    814d6b  The third wave developed so quickly due to the...
```

```
      content  wording      prompt_question \
0  0.205683  0.380538  Summarize how the Third Wave developed over su...
1  3.272894  3.219757  Summarize how the Third Wave developed over su...
2  0.205683  0.380538  Summarize how the Third Wave developed over su...
3  0.567975  0.969062  Summarize how the Third Wave developed over su...
4 -0.910596 -0.081769  Summarize how the Third Wave developed over su...
```

```
      prompt_title      prompt_text \
0  The Third Wave  Background \r\nThe Third Wave experiment took ...
1  The Third Wave  Background \r\nThe Third Wave experiment took ...
2  The Third Wave  Background \r\nThe Third Wave experiment took ...
3  The Third Wave  Background \r\nThe Third Wave experiment took ...
4  The Third Wave  Background \r\nThe Third Wave experiment took ...
```

```
      no_of_words_in_text  no_of_words_in_prompt_text \
0                        61                        597
1                       206                        597
2                        60                        597
3                        76                        597
4                        27                        597
```

```
      no_of_words_in_text_and_prompt_text
0                        658
1                        803
2                        657
```

3	673
4	624

```
[20]: ### Number of distinct words in student response (text) and prompt (prompt_text)

joined_train_df['no_of_distinct_words_in_text'] = joined_train_df['text'].str.
    ↪split(" ").apply(set).apply(len)
joined_train_df['no_of_distinct_words_in_prompt_text'] =
    ↪joined_train_df['prompt_text'].str.split(" ").apply(set).apply(len)
joined_train_df['no_of_distinct_words_in_text_and_prompt_text'] =
    ↪(joined_train_df['text'].str.split(" ") + joined_train_df['prompt_text'].str.
    ↪split(" ")).apply(set).apply(len)

joined_train_df.head()
```

```
[20]:      student_id prompt_id      text \
0  000e8c3c7ddb    814d6b  The third wave was an experimentto see how peo...
1  0070c9e7af47    814d6b  The Third Wave developed rapidly because the ...
2  0095993991fe    814d6b  The third wave only started as an experiment w...
3  00c20c6ddd23    814d6b  The experimen was orginally about how even whe...
4  00d40ad10dc9    814d6b  The third wave developed so quickly due to the...
```

```
      content  wording      prompt_question \
0  0.205683  0.380538  Summarize how the Third Wave developed over su...
1  3.272894  3.219757  Summarize how the Third Wave developed over su...
2  0.205683  0.380538  Summarize how the Third Wave developed over su...
3  0.567975  0.969062  Summarize how the Third Wave developed over su...
4 -0.910596 -0.081769  Summarize how the Third Wave developed over su...
```

```
      prompt_title      prompt_text \
0  The Third Wave  Background \r\nThe Third Wave experiment took ...
1  The Third Wave  Background \r\nThe Third Wave experiment took ...
2  The Third Wave  Background \r\nThe Third Wave experiment took ...
3  The Third Wave  Background \r\nThe Third Wave experiment took ...
4  The Third Wave  Background \r\nThe Third Wave experiment took ...
```

```
      no_of_words_in_text  no_of_words_in_prompt_text \
0                        61                        597
1                       206                        597
2                        60                        597
3                        76                        597
4                        27                        597
```

```
      no_of_words_in_text_and_prompt_text  no_of_distinct_words_in_text \
0                        658                        51
1                       803                       139
2                       657                        50
```

3	673	59
4	624	25

	no_of_distinct_words_in_prompt_text \
0	304
1	304
2	304
3	304
4	304

	no_of_distinct_words_in_text_and_prompt_text
0	334
1	396
2	325
3	327
4	314

```
[21]: ### Number of words common to student response (text) and prompt (prompt_text)

joined_train_df['no_of_common_words_in_text_and_prompt_text'] = joined_train_df.
↳ apply(lambda x: len(set(x['text'].split(" ")).
↳ intersection(set(x['prompt_text'].split(" ")))), axis=1)

joined_train_df.head()
```

```
[21]:      student_id prompt_id      text \
0  000e8c3c7ddb    814d6b  The third wave was an experimentto see how peo...
1  0070c9e7af47    814d6b  The Third Wave developed rapidly because the ...
2  0095993991fe    814d6b  The third wave only started as an experiment w...
3  00c20c6ddd23    814d6b  The experimen was orginally about how even whe...
4  00d40ad10dc9    814d6b  The third wave developed so quickly due to the...
```

	content	wording	prompt_question \
0	0.205683	0.380538	Summarize how the Third Wave developed over su...
1	3.272894	3.219757	Summarize how the Third Wave developed over su...
2	0.205683	0.380538	Summarize how the Third Wave developed over su...
3	0.567975	0.969062	Summarize how the Third Wave developed over su...
4	-0.910596	-0.081769	Summarize how the Third Wave developed over su...

	prompt_title	prompt_text \
0	The Third Wave	Background \r\nThe Third Wave experiment took ...
1	The Third Wave	Background \r\nThe Third Wave experiment took ...
2	The Third Wave	Background \r\nThe Third Wave experiment took ...
3	The Third Wave	Background \r\nThe Third Wave experiment took ...
4	The Third Wave	Background \r\nThe Third Wave experiment took ...

	no_of_words_in_text	no_of_words_in_prompt_text \
--	---------------------	------------------------------

0	61	597
1	206	597
2	60	597
3	76	597
4	27	597

	no_of_words_in_text_and_prompt_text	no_of_distinct_words_in_text \
0	658	51
1	803	139
2	657	50
3	673	59
4	624	25

	no_of_distinct_words_in_prompt_text \
0	304
1	304
2	304
3	304
4	304

	no_of_distinct_words_in_text_and_prompt_text \
0	334
1	396
2	325
3	327
4	314

	no_of_common_words_in_text_and_prompt_text
0	21
1	47
2	29
3	36
4	15

[22]: *### Number of words common to student response (text) and prompt\_question*

```
joined_train_df['no_of_common_words_in_text_and_prompt_question'] =
    joined_train_df.apply(lambda x: len(set(x['text'].split(" ")).
    intersection(set(x['prompt_question'].split(" ")))), axis=1)

joined_train_df.head()
```

[22]:

	student_id	prompt_id	text \
0	000e8c3c7ddb	814d6b	The third wave was an experimentto see how peo...
1	0070c9e7af47	814d6b	The Third Wave developed rapidly because the ...
2	0095993991fe	814d6b	The third wave only started as an experiment w...
3	00c20c6ddd23	814d6b	The experimen was orginally about how even whe...

4 00d40ad10dc9 814d6b The third wave developed so quickly due to the...

	content	wording	prompt_question \
0	0.205683	0.380538	Summarize how the Third Wave developed over su...
1	3.272894	3.219757	Summarize how the Third Wave developed over su...
2	0.205683	0.380538	Summarize how the Third Wave developed over su...
3	0.567975	0.969062	Summarize how the Third Wave developed over su...
4	-0.910596	-0.081769	Summarize how the Third Wave developed over su...

	prompt_title	prompt_text \
0	The Third Wave Background \r\nThe Third Wave experiment took ...	
1	The Third Wave Background \r\nThe Third Wave experiment took ...	
2	The Third Wave Background \r\nThe Third Wave experiment took ...	
3	The Third Wave Background \r\nThe Third Wave experiment took ...	
4	The Third Wave Background \r\nThe Third Wave experiment took ...	

	no_of_words_in_text	no_of_words_in_prompt_text \
0	61	597
1	206	597
2	60	597
3	76	597
4	27	597

	no_of_words_in_text_and_prompt_text	no_of_distinct_words_in_text \
0	658	51
1	803	139
2	657	50
3	673	59
4	624	25

	no_of_distinct_words_in_prompt_text \
0	304
1	304
2	304
3	304
4	304

	no_of_distinct_words_in_text_and_prompt_text \
0	334
1	396
2	325
3	327
4	314

	no_of_common_words_in_text_and_prompt_text \
0	21
1	47



2	29
3	36
4	15

	no_of_common_words_in_text_and_prompt_question
0	5
1	9
2	5
3	7
4	5

[23]: *### Number of words common to student response (text) and prompt\_title*

```
joined_train_df['no_of_common_words_in_text_and_prompt_title'] =
    joined_train_df.apply(lambda x: len(set(x['text'].split(" ")).
        intersection(set(x['prompt_title'].split(" ")))), axis=1)

joined_train_df.head()
```

[23]:

	student_id	prompt_id	text \
0	000e8c3c7ddb	814d6b	The third wave was an experimentto see how peo...
1	0070c9e7af47	814d6b	The Third Wave developed rapidly because the ...
2	0095993991fe	814d6b	The third wave only started as an experiment w...
3	00c20c6ddd23	814d6b	The experimen was orginally about how even whe...
4	00d40ad10dc9	814d6b	The third wave developed so quickly due to the...

	content	wording	prompt_question \
0	0.205683	0.380538	Summarize how the Third Wave developed over su...
1	3.272894	3.219757	Summarize how the Third Wave developed over su...
2	0.205683	0.380538	Summarize how the Third Wave developed over su...
3	0.567975	0.969062	Summarize how the Third Wave developed over su...
4	-0.910596	-0.081769	Summarize how the Third Wave developed over su...

	prompt_title	prompt_text \
0	The Third Wave	Background \r\nThe Third Wave experiment took ...
1	The Third Wave	Background \r\nThe Third Wave experiment took ...
2	The Third Wave	Background \r\nThe Third Wave experiment took ...
3	The Third Wave	Background \r\nThe Third Wave experiment took ...
4	The Third Wave	Background \r\nThe Third Wave experiment took ...

	no_of_words_in_text	no_of_words_in_prompt_text \
0	61	597
1	206	597
2	60	597
3	76	597
4	27	597

	no_of_words_in_text_and_prompt_text	no_of_distinct_words_in_text \
0	658	51
1	803	139
2	657	50
3	673	59
4	624	25

	no_of_distinct_words_in_prompt_text \
0	304
1	304
2	304
3	304
4	304

	no_of_distinct_words_in_text_and_prompt_text \
0	334
1	396
2	325
3	327
4	314

	no_of_common_words_in_text_and_prompt_text \
0	21
1	47
2	29
3	36
4	15

	no_of_common_words_in_text_and_prompt_question \
0	5
1	9
2	5
3	7
4	5

	no_of_common_words_in_text_and_prompt_title
0	1
1	3
2	1
3	1
4	1

### 2.2.2 Question 3: Readability indices, counts of words from particular classes (e.g character length, part of speech, popularity)

#### Reading Ease by Flesch Algorithm

```
[24]: # Assuming df is your DataFrame
def compute_fres(text):
    return textstat.flesch_reading_ease(text)

joined_train_df['readability_score'] = joined_train_df['prompt_text'].
    ↪ apply(compute_fres)
joined_train_df.head()
```

```
[24]:      student_id prompt_id      text \
0  000e8c3c7ddb    814d6b  The third wave was an experimentto see how peo...
1  0070c9e7af47    814d6b  The Third Wave developed rapidly because the ...
2  0095993991fe    814d6b  The third wave only started as an experiment w...
3  00c20c6ddd23    814d6b  The experimen was originally about how even whe...
4  00d40ad10dc9    814d6b  The third wave developed so quickly due to the...
```

```
      content  wording      prompt_question \
0  0.205683  0.380538  Summarize how the Third Wave developed over su...
1  3.272894  3.219757  Summarize how the Third Wave developed over su...
2  0.205683  0.380538  Summarize how the Third Wave developed over su...
3  0.567975  0.969062  Summarize how the Third Wave developed over su...
4 -0.910596 -0.081769  Summarize how the Third Wave developed over su...
```

```
      prompt_title      prompt_text \
0  The Third Wave  Background \r\nThe Third Wave experiment took ...
1  The Third Wave  Background \r\nThe Third Wave experiment took ...
2  The Third Wave  Background \r\nThe Third Wave experiment took ...
3  The Third Wave  Background \r\nThe Third Wave experiment took ...
4  The Third Wave  Background \r\nThe Third Wave experiment took ...
```

```
      no_of_words_in_text  no_of_words_in_prompt_text \
0                        61                        597
1                       206                        597
2                        60                        597
3                        76                        597
4                        27                        597
```

```
      no_of_words_in_text_and_prompt_text  no_of_distinct_words_in_text \
0                        658                        51
1                        803                       139
2                        657                        50
3                        673                        59
4                        624                        25
```

```
      no_of_distinct_words_in_prompt_text \
0                        304
1                        304
2                        304
```

3	304
4	304

	no_of_distinct_words_in_text_and_prompt_text \
0	334
1	396
2	325
3	327
4	314

	no_of_common_words_in_text_and_prompt_text \
0	21
1	47
2	29
3	36
4	15

	no_of_common_words_in_text_and_prompt_question \
0	5
1	9
2	5
3	7
4	5

	no_of_common_words_in_text_and_prompt_title	readability_score
0	1	56.69
1	3	56.69
2	1	56.69
3	1	56.69
4	1	56.69

### Text, Character and Sentence Lengths

```
[25]: # Text length in terms of characters
joined_train_df['char_count'] = joined_train_df['text'].apply(len)

# Text length in terms of words
joined_train_df['word_count'] = joined_train_df['text'].apply(lambda x:
    ↪len(nltk.word_tokenize(x)))

# Text length in terms of sentences
joined_train_df['sentence_count'] = joined_train_df['text'].apply(lambda x:
    ↪len(nltk.sent_tokenize(x)))

# Average word length
joined_train_df['avg_word_length'] = joined_train_df['char_count'] /
    ↪joined_train_df['word_count']
```

```
# Average sentence length in terms of words
joined_train_df['avg_sentence_length'] = joined_train_df['word_count'] /
joined_train_df['sentence_count']

joined_train_df.head()
```

```
[25]:      student_id prompt_id      text \
0  000e8c3c7ddb    814d6b  The third wave was an experimentto see how peo...
1  0070c9e7af47    814d6b  The Third Wave developed  rapidly because the ...
2  0095993991fe    814d6b  The third wave only started as an experiment w...
3  00c20c6ddd23    814d6b  The experimen was originally about how even whe...
4  00d40ad10dc9    814d6b  The third wave developed so quickly due to the...
```

```
      content  wording      prompt_question \
0  0.205683  0.380538  Summarize how the Third Wave developed over su...
1  3.272894  3.219757  Summarize how the Third Wave developed over su...
2  0.205683  0.380538  Summarize how the Third Wave developed over su...
3  0.567975  0.969062  Summarize how the Third Wave developed over su...
4 -0.910596 -0.081769  Summarize how the Third Wave developed over su...
```

```
      prompt_title      prompt_text \
0  The Third Wave  Background \r\nThe Third Wave experiment took ...
1  The Third Wave  Background \r\nThe Third Wave experiment took ...
2  The Third Wave  Background \r\nThe Third Wave experiment took ...
3  The Third Wave  Background \r\nThe Third Wave experiment took ...
4  The Third Wave  Background \r\nThe Third Wave experiment took ...
```

```
      no_of_words_in_text  no_of_words_in_prompt_text  ... \
0                        61                        597  ...
1                       206                        597  ...
2                        60                        597  ...
3                        76                        597  ...
4                        27                        597  ...
```

```
      no_of_distinct_words_in_text_and_prompt_text \
0                        334
1                        396
2                        325
3                        327
4                        314
```

```
      no_of_common_words_in_text_and_prompt_text \
0                        21
1                        47
2                        29
3                        36
```

4

15

	no_of_common_words_in_text_and_prompt_question \
0	5
1	9
2	5
3	7
4	5

	no_of_common_words_in_text_and_prompt_title	readability_score	char_count \
0	1	56.69	346
1	3	56.69	1225
2	1	56.69	345
3	1	56.69	451
4	1	56.69	145

	word_count	sentence_count	avg_word_length	avg_sentence_length
0	64	4	5.406250	16.000000
1	232	14	5.280172	16.571429
2	67	3	5.149254	22.333333
3	86	3	5.244186	28.666667
4	29	2	5.000000	14.500000

[5 rows x 23 columns]

### Lexical Diversity

```
[26]: # Tokenize the text
joined_train_df['tokens'] = joined_train_df['text'].apply(nltk.word_tokenize)

# Compute lexical diversity
joined_train_df['lexical_diversity'] = joined_train_df['tokens'].apply(lambda x:
    ↪ len(set(x)) / len(x) if len(x) > 0 else 0)
joined_train_df = joined_train_df.drop(columns=['tokens'])

joined_train_df.head()
```

```
[26]: student_id prompt_id text \
0 000e8c3c7ddb 814d6b The third wave was an experimentto see how peo...
1 0070c9e7af47 814d6b The Third Wave developed rapidly because the ...
2 0095993991fe 814d6b The third wave only started as an experiment w...
3 00c20c6ddd23 814d6b The experimen was orginally about how even whe...
4 00d40ad10dc9 814d6b The third wave developed so quickly due to the...
```

	content	wording	prompt_question \
0	0.205683	0.380538	Summarize how the Third Wave developed over su...
1	3.272894	3.219757	Summarize how the Third Wave developed over su...
2	0.205683	0.380538	Summarize how the Third Wave developed over su...

3 0.567975 0.969062 Summarize how the Third Wave developed over su...  
 4 -0.910596 -0.081769 Summarize how the Third Wave developed over su...

	prompt_title	prompt_text \
0	The Third Wave Background \r\nThe Third Wave experiment took ...	
1	The Third Wave Background \r\nThe Third Wave experiment took ...	
2	The Third Wave Background \r\nThe Third Wave experiment took ...	
3	The Third Wave Background \r\nThe Third Wave experiment took ...	
4	The Third Wave Background \r\nThe Third Wave experiment took ...	

	no_of_words_in_text	no_of_words_in_prompt_text ... \
0	61	597 ...
1	206	597 ...
2	60	597 ...
3	76	597 ...
4	27	597 ...

	no_of_common_words_in_text_and_prompt_text \
0	21
1	47
2	29
3	36
4	15

	no_of_common_words_in_text_and_prompt_question \
0	5
1	9
2	5
3	7
4	5

	no_of_common_words_in_text_and_prompt_title	readability_score	char_count \
0	1	56.69	346
1	3	56.69	1225
2	1	56.69	345
3	1	56.69	451
4	1	56.69	145

	word_count	sentence_count	avg_word_length	avg_sentence_length \
0	64	4	5.406250	16.000000
1	232	14	5.280172	16.571429
2	67	3	5.149254	22.333333
3	86	3	5.244186	28.666667
4	29	2	5.000000	14.500000

	lexical_diversity
0	0.812500

```

1          0.590517
2          0.791045
3          0.697674
4          0.896552

```

[5 rows x 24 columns]

## Sentiment Polarity & Sentiment Label

```

[27]: import pandas as pd
      from textblob import TextBlob

      # Compute sentiment polarity
      joined_train_df['sentiment_polarity'] = joined_train_df['text'].apply(lambda x:
      ↪TextBlob(x).sentiment.polarity)

      # Labeling based on polarity
      joined_train_df['sentiment_label'] = joined_train_df['sentiment_polarity'].
      ↪apply(lambda x: 'positive' if x > 0 else ('neutral' if x == 0 else
      ↪'negative'))

      joined_train_df.head()

```

```

[27]:      student_id  prompt_id      text \
0  000e8c3c7ddb      814d6b  The third wave was an experimentto see how peo...
1  0070c9e7af47      814d6b  The Third Wave developed rapidly because the ...
2  0095993991fe      814d6b  The third wave only started as an experiment w...
3  00c20c6ddd23      814d6b  The experimen was orginally about how even whe...
4  00d40ad10dc9      814d6b  The third wave developed so quickly due to the...

```

```

      content  wording      prompt_question \
0  0.205683  0.380538  Summarize how the Third Wave developed over su...
1  3.272894  3.219757  Summarize how the Third Wave developed over su...
2  0.205683  0.380538  Summarize how the Third Wave developed over su...
3  0.567975  0.969062  Summarize how the Third Wave developed over su...
4 -0.910596 -0.081769  Summarize how the Third Wave developed over su...

```

```

      prompt_title      prompt_text \
0  The Third Wave  Background \r\nThe Third Wave experiment took ...
1  The Third Wave  Background \r\nThe Third Wave experiment took ...
2  The Third Wave  Background \r\nThe Third Wave experiment took ...
3  The Third Wave  Background \r\nThe Third Wave experiment took ...
4  The Third Wave  Background \r\nThe Third Wave experiment took ...

```

```

      no_of_words_in_text  no_of_words_in_prompt_text  ... \
0          61          597  ...
1         206          597  ...
2          60          597  ...

```



3	76	597	...
4	27	597	...

	no_of_common_words_in_text_and_prompt_title	readability_score	char_count	\
0	1	56.69	346	
1	3	56.69	1225	
2	1	56.69	345	
3	1	56.69	451	
4	1	56.69	145	

	word_count	sentence_count	avg_word_length	avg_sentence_length	\
0	64	4	5.406250	16.000000	
1	232	14	5.280172	16.571429	
2	67	3	5.149254	22.333333	
3	86	3	5.244186	28.666667	
4	29	2	5.000000	14.500000	

	lexical_diversity	sentiment_polarity	sentiment_label
0	0.812500	0.170455	positive
1	0.590517	0.048203	positive
2	0.791045	0.075000	positive
3	0.697674	-0.666667	negative
4	0.896552	0.088939	positive

[5 rows x 26 columns]

### Count Named Entities - NER Count

```
[28]: # Load the spaCy model
nlp = spacy.load('en_core_web_sm')

# Count named entities in the text
def count_named_entities(text):
    doc = nlp(text)
    return len(doc.ents)

joined_train_df['ner_count'] = joined_train_df['text'].
    ↪ apply(count_named_entities)
joined_train_df.head()
```

```
[28]: student_id prompt_id text \
0 000e8c3c7ddb 814d6b The third wave was an experimentto see how peo...
1 0070c9e7af47 814d6b The Third Wave developed rapidly because the ...
2 0095993991fe 814d6b The third wave only started as an experiment w...
3 00c20c6ddd23 814d6b The experimen was orginally about how even whe...
4 00d40ad10dc9 814d6b The third wave developed so quickly due to the...

content wording prompt_question \
```

0	0.205683	0.380538	Summarize how the Third Wave developed over su...
1	3.272894	3.219757	Summarize how the Third Wave developed over su...
2	0.205683	0.380538	Summarize how the Third Wave developed over su...
3	0.567975	0.969062	Summarize how the Third Wave developed over su...
4	-0.910596	-0.081769	Summarize how the Third Wave developed over su...

	prompt_title	prompt_text	\
0	The Third Wave	Background \r\nThe Third Wave experiment took ...	
1	The Third Wave	Background \r\nThe Third Wave experiment took ...	
2	The Third Wave	Background \r\nThe Third Wave experiment took ...	
3	The Third Wave	Background \r\nThe Third Wave experiment took ...	
4	The Third Wave	Background \r\nThe Third Wave experiment took ...	

	no_of_words_in_text	no_of_words_in_prompt_text	...	readability_score	\
0	61	597	...	56.69	
1	206	597	...	56.69	
2	60	597	...	56.69	
3	76	597	...	56.69	
4	27	597	...	56.69	

	char_count	word_count	sentence_count	avg_word_length	\
0	346	64	4	5.406250	
1	1225	232	14	5.280172	
2	345	67	3	5.149254	
3	451	86	3	5.244186	
4	145	29	2	5.000000	

	avg_sentence_length	lexical_diversity	sentiment_polarity	\
0	16.000000	0.812500	0.170455	
1	16.571429	0.590517	0.048203	
2	22.333333	0.791045	0.075000	
3	28.666667	0.697674	-0.666667	
4	14.500000	0.896552	0.088939	

	sentiment_label	ner_count
0	positive	2
1	positive	16
2	positive	3
3	negative	3
4	positive	1

[5 rows x 27 columns]

## Cosine Similarity

```
[29]: # Create a TF-IDF Vectorizer
vectorizer = TfidfVectorizer()
```

```

# Concatenate 'text' and 'prompt_text' columns for vectorization
all_texts = joined_train_df['text'].tolist() + joined_train_df['prompt_text'].
↳ tolist()

# Generate the TF-IDF vectors
tfidf_matrix = vectorizer.fit_transform(all_texts)

# Split the matrix into two for 'text' and 'prompt_text' vectors
text_tfidf, prompt_tfidf = tfidf_matrix[:len(joined_train_df)],
↳ tfidf_matrix[len(joined_train_df):]

# Compute cosine similarity
joined_train_df['cosine_similarity'] = [cosine_similarity(text_tfidf[i],
↳ prompt_tfidf[i])[0][0] for i in range(len(joined_train_df))]

joined_train_df.head()

```

```

[29]:
  student_id prompt_id text \
0 000e8c3c7ddb 814d6b The third wave was an experimentto see how peo...
1 0070c9e7af47 814d6b The Third Wave developed rapidly because the ...
2 0095993991fe 814d6b The third wave only started as an experiment w...
3 00c20c6ddd23 814d6b The experimen was orginally about how even whe...
4 00d40ad10dc9 814d6b The third wave developed so quickly due to the...

  content wording prompt_question \
0 0.205683 0.380538 Summarize how the Third Wave developed over su...
1 3.272894 3.219757 Summarize how the Third Wave developed over su...
2 0.205683 0.380538 Summarize how the Third Wave developed over su...
3 0.567975 0.969062 Summarize how the Third Wave developed over su...
4 -0.910596 -0.081769 Summarize how the Third Wave developed over su...

  prompt_title prompt_text \
0 The Third Wave Background \r\nThe Third Wave experiment took ...
1 The Third Wave Background \r\nThe Third Wave experiment took ...
2 The Third Wave Background \r\nThe Third Wave experiment took ...
3 The Third Wave Background \r\nThe Third Wave experiment took ...
4 The Third Wave Background \r\nThe Third Wave experiment took ...

  no_of_words_in_text no_of_words_in_prompt_text ... char_count \
0 61 597 ... 346
1 206 597 ... 1225
2 60 597 ... 345
3 76 597 ... 451
4 27 597 ... 145

  word_count sentence_count avg_word_length avg_sentence_length \
0 64 4 5.406250 16.000000

```

1	232	14	5.280172	16.571429
2	67	3	5.149254	22.333333
3	86	3	5.244186	28.666667
4	29	2	5.000000	14.500000

	lexical_diversity	sentiment_polarity	sentiment_label	ner_count	\
0	0.812500	0.170455	positive	2	
1	0.590517	0.048203	positive	16	
2	0.791045	0.075000	positive	3	
3	0.697674	-0.666667	negative	3	
4	0.896552	0.088939	positive	1	

	cosine_similarity
0	0.182623
1	0.405863
2	0.323222
3	0.403937
4	0.183623

[5 rows x 28 columns]

### Count Nouns, adjectives & verbs

```
[30]: import pandas as pd
import spacy

# Load the spaCy model
nlp = spacy.load('en_core_web_sm')

def pos_counts(text):
    doc = nlp(text)
    pos_tags = [token.pos_ for token in doc]
    return pos_tags.count('NOUN'), pos_tags.count('VERB'), pos_tags.count('ADJ')

joined_train_df['num_nouns'], joined_train_df['num_verbs'], \
    ↪ joined_train_df['num_adjectives'] = zip(*joined_train_df['text'].
    ↪ apply(pos_counts))

joined_train_df.head()
```

```
[30]: student_id prompt_id text \
0 000e8c3c7ddb 814d6b The third wave was an experimentto see how peo...
1 0070c9e7af47 814d6b The Third Wave developed rapidly because the ...
2 0095993991fe 814d6b The third wave only started as an experiment w...
3 00c20c6ddd23 814d6b The experimen was orginally about how even whe...
4 00d40ad10dc9 814d6b The third wave developed so quickly due to the...

content wording prompt_question \
```

0	0.205683	0.380538	Summarize how the Third Wave developed over su...
1	3.272894	3.219757	Summarize how the Third Wave developed over su...
2	0.205683	0.380538	Summarize how the Third Wave developed over su...
3	0.567975	0.969062	Summarize how the Third Wave developed over su...
4	-0.910596	-0.081769	Summarize how the Third Wave developed over su...

	prompt_title	prompt_text	\
0	The Third Wave Background	\r\nThe Third Wave experiment took ...	
1	The Third Wave Background	\r\nThe Third Wave experiment took ...	
2	The Third Wave Background	\r\nThe Third Wave experiment took ...	
3	The Third Wave Background	\r\nThe Third Wave experiment took ...	
4	The Third Wave Background	\r\nThe Third Wave experiment took ...	

	no_of_words_in_text	no_of_words_in_prompt_text	...	avg_word_length	\
0	61	597	...	5.406250	
1	206	597	...	5.280172	
2	60	597	...	5.149254	
3	76	597	...	5.244186	
4	27	597	...	5.000000	

	avg_sentence_length	lexical_diversity	sentiment_polarity	\
0	16.000000	0.812500	0.170455	
1	16.571429	0.590517	0.048203	
2	22.333333	0.791045	0.075000	
3	28.666667	0.697674	-0.666667	
4	14.500000	0.896552	0.088939	

	sentiment_label	ner_count	cosine_similarity	num_nouns	num_verbs	\
0	positive	2	0.182623	14	14	
1	positive	16	0.405863	42	25	
2	positive	3	0.323222	12	9	
3	negative	3	0.403937	13	10	
4	positive	1	0.183623	4	4	

	num_adjectives
0	6
1	8
2	2
3	6
4	3

[5 rows x 31 columns]

### 2.2.3 Count of Stop words

```
[31]: # Load the spaCy model
nlp = spacy.load('en_core_web_sm')

# Function to count stopwords.
def count_stopwords(text):
    doc = nlp(text)
    return sum([token.is_stop for token in doc])

joined_train_df['stopword_count'] = joined_train_df['text'].
    ↪apply(count_stopwords)

joined_train_df.head()
```

```
[31]:      student_id  prompt_id      text \
0  000e8c3c7ddb    814d6b  The third wave was an experimentto see how peo...
1  0070c9e7af47    814d6b  The Third Wave developed rapidly because the ...
2  0095993991fe    814d6b  The third wave only started as an experiment w...
3  00c20c6ddd23    814d6b  The experimen was orginally about how even whe...
4  00d40ad10dc9    814d6b  The third wave developed so quickly due to the...

      content  wording      prompt_question \
0  0.205683  0.380538  Summarize how the Third Wave developed over su...
1  3.272894  3.219757  Summarize how the Third Wave developed over su...
2  0.205683  0.380538  Summarize how the Third Wave developed over su...
3  0.567975  0.969062  Summarize how the Third Wave developed over su...
4 -0.910596 -0.081769  Summarize how the Third Wave developed over su...

      prompt_title      prompt_text \
0  The Third Wave  Background \r\nThe Third Wave experiment took ...
1  The Third Wave  Background \r\nThe Third Wave experiment took ...
2  The Third Wave  Background \r\nThe Third Wave experiment took ...
3  The Third Wave  Background \r\nThe Third Wave experiment took ...
4  The Third Wave  Background \r\nThe Third Wave experiment took ...

      no_of_words_in_text  no_of_words_in_prompt_text  ...  avg_sentence_length \
0                        61                        597  ...      16.000000
1                       206                        597  ...      16.571429
2                        60                        597  ...      22.333333
3                        76                        597  ...      28.666667
4                        27                        597  ...      14.500000

      lexical_diversity  sentiment_polarity  sentiment_label  ner_count \
0          0.812500          0.170455      positive         2
1          0.590517          0.048203      positive        16
2          0.791045          0.075000      positive         3
```

3	0.697674	-0.666667	negative	3
4	0.896552	0.088939	positive	1

	cosine_similarity	num_nouns	num_verbs	num_adjectives	stopword_count
0	0.182623	14	14	6	30
1	0.405863	42	25	8	114
2	0.323222	12	9	2	35
3	0.403937	13	10	6	44
4	0.183623	4	4	3	14

[5 rows x 32 columns]

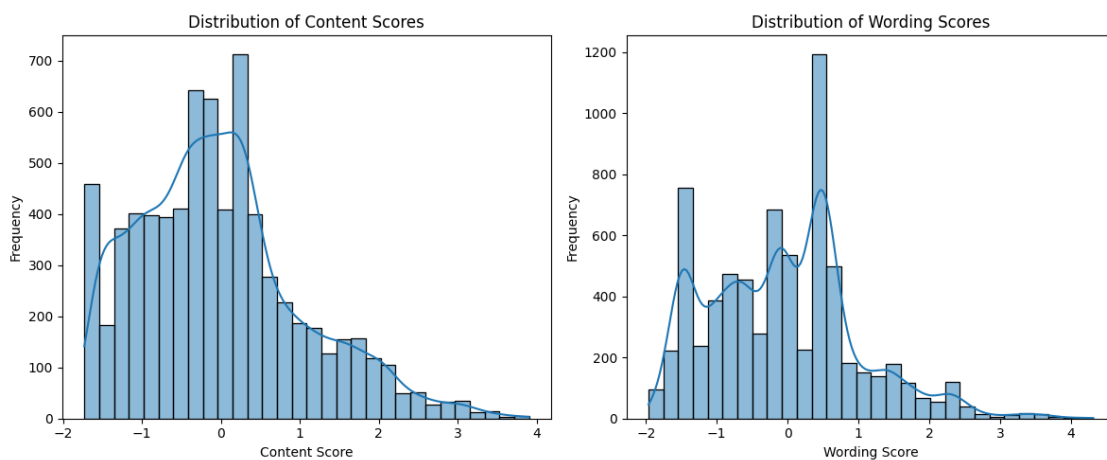
## 2.3 Section 3: Content and Wording (Q4, 10 points)

### 1. Visualize the distributions as histograms.

```
[32]: plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
sns.histplot(joined_train_df['content'], bins=30, kde=True)
plt.title('Distribution of Content Scores')
plt.xlabel('Content Score')
plt.ylabel('Frequency')

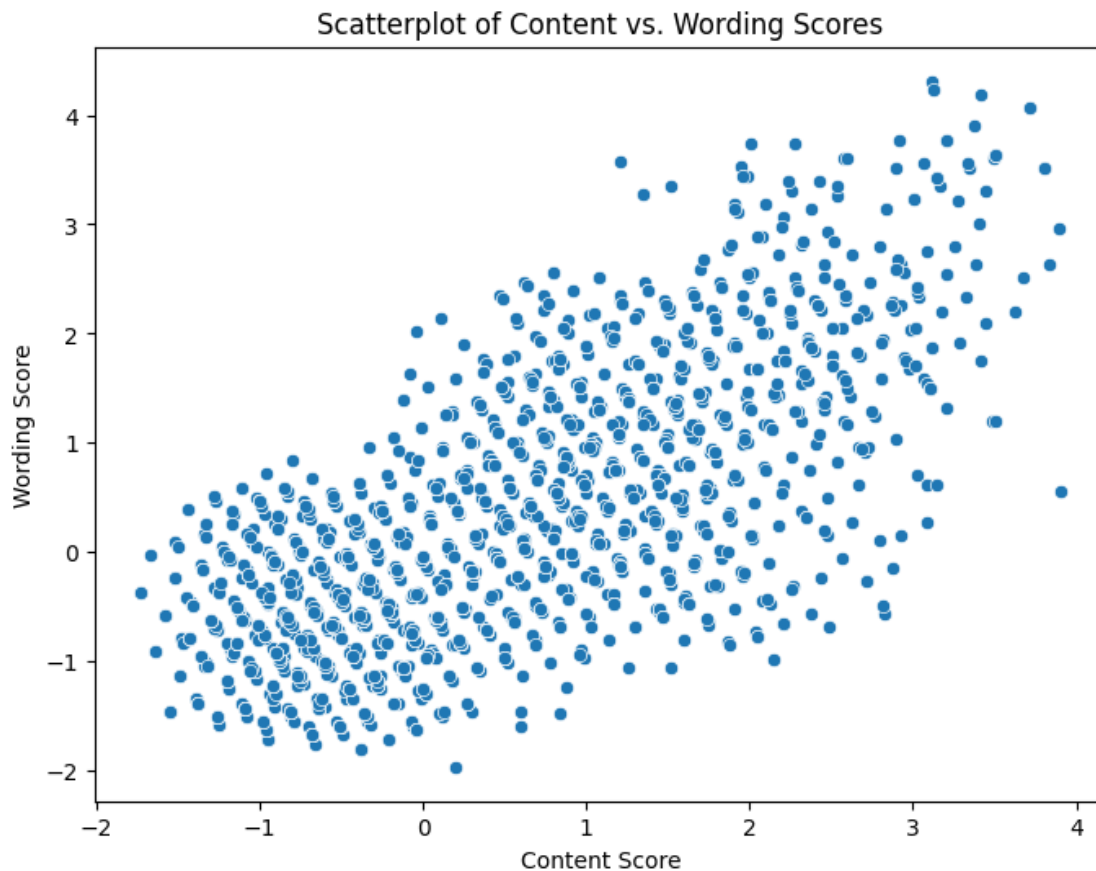
plt.subplot(1, 2, 2)
sns.histplot(joined_train_df['wording'], bins=30, kde=True)
plt.title('Distribution of Wording Scores')
plt.xlabel('Wording Score')
plt.ylabel('Frequency')

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



## 2. Plot a scatterplot.

```
[33]: plt.figure(figsize=(8, 6))
sns.scatterplot(x=joined_train_df['content'], y=joined_train_df['wording'])
plt.title('Scatterplot of Content vs. Wording Scores')
plt.xlabel('Content Score')
plt.ylabel('Wording Score')
plt.show()
```



## 3. Compute correlation metrics.

```
[34]: correlation = joined_train_df['content'].corr(joined_train_df['wording'])
print(f"Correlation between 'content' and 'wording': {correlation:.2f}")
```

Correlation between 'content' and 'wording': 0.75

## Heat Map - Correlation among features

```
[35]: plt.figure(figsize=(20,20))
sns.heatmap(joined_train_df.corr(numeric_only=True), annot=True)
```

```
[35]: <Axes: >
```





## Distribution shapes for different prompts

```
[36]: # Check the distribution shapes for different prompts
prompts = joined_train_df['prompt_text'].unique()
for prompt in prompts:
    subset = joined_train_df[joined_train_df['prompt_text'] == prompt]

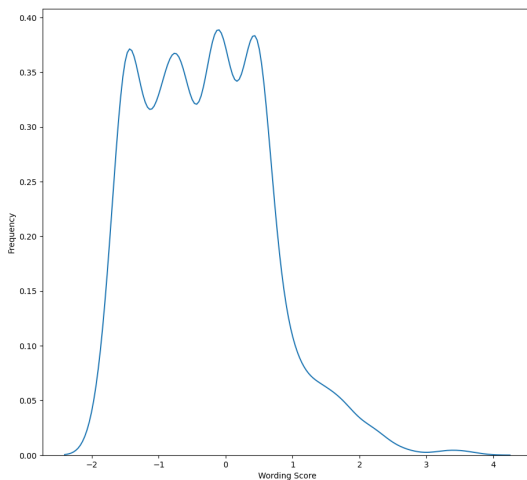
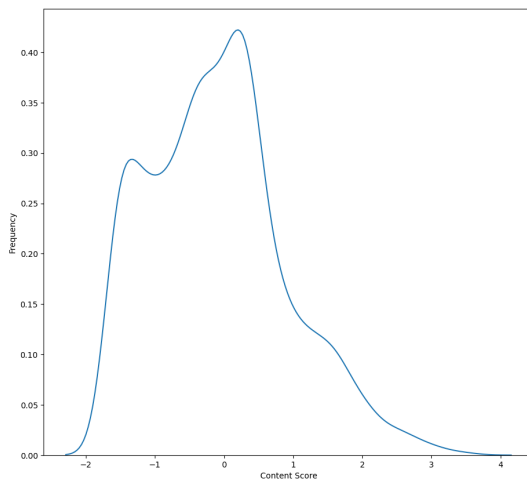
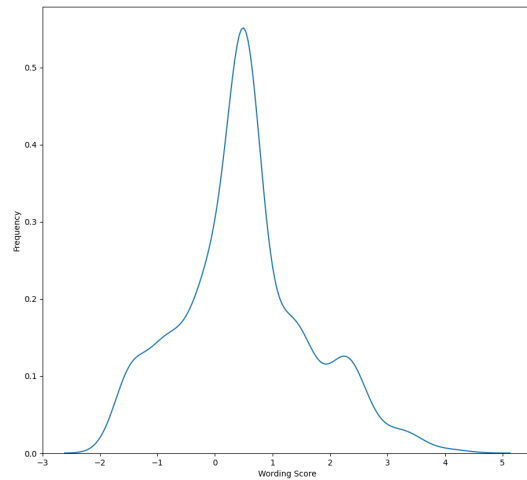
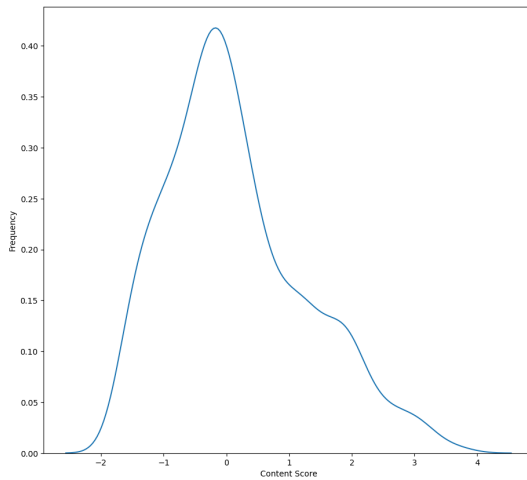
    plt.figure(figsize=(24, 10))

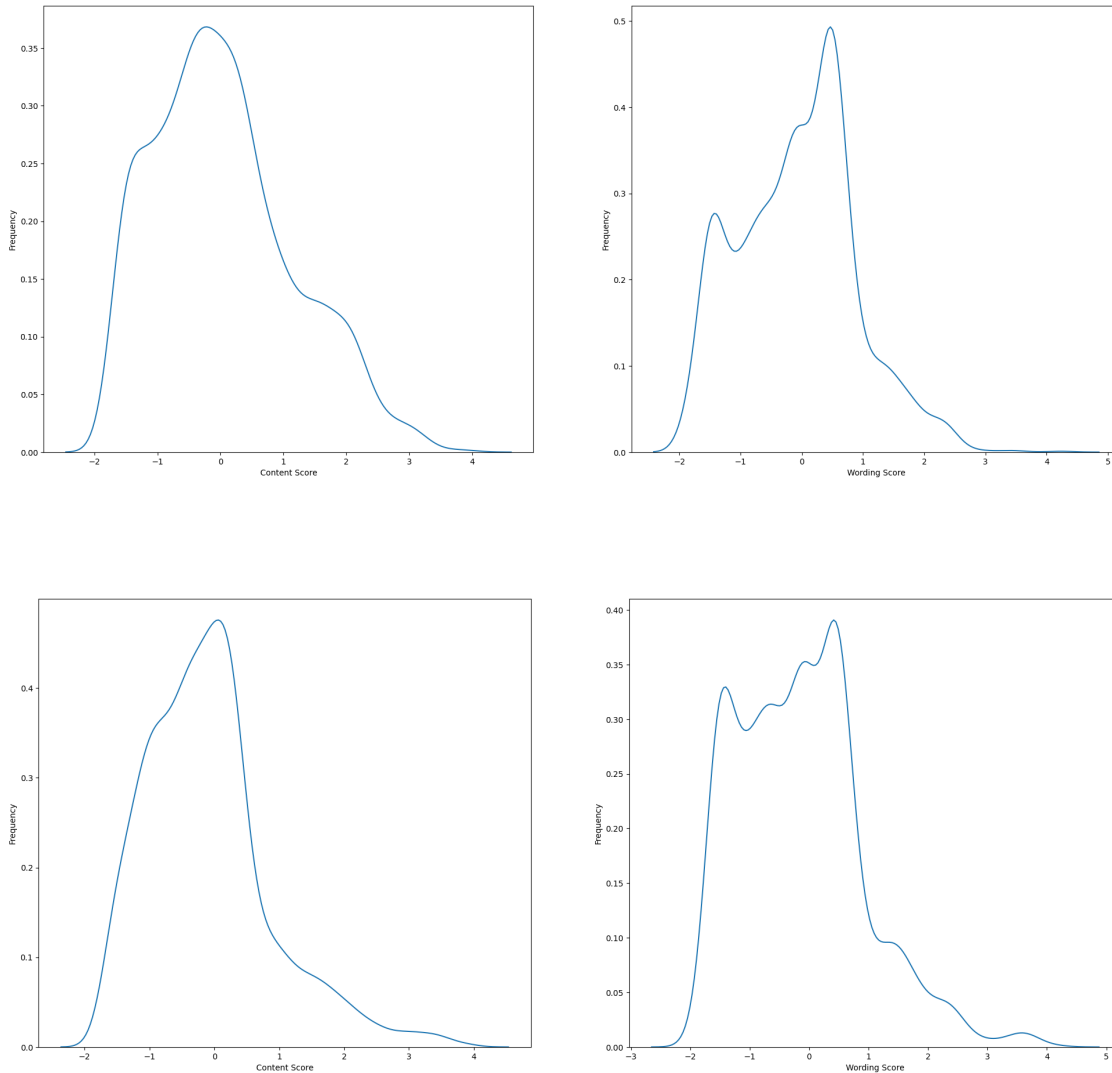
    plt.subplot(1, 2, 1)
    sns.kdeplot(subset['content'])
```

```
plt.xlabel('Content Score')
plt.ylabel('Frequency')

plt.subplot(1, 2, 2)
sns.kdeplot(subset['wording'])
plt.xlabel('Wording Score')
plt.ylabel('Frequency')

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





## 2.4 Section 4: Words in Good and Bad Essays (Q5, 10 points)

**Calculate Term Frequencies:** For each corpus (good and bad), calculate the frequency of each word.

A positive log odds ratio means the word is over-represented in good essays, while a negative value means it's over-represented in bad essays. The addition of 1 in the formula is a simple form of Laplace smoothing to handle words that might not appear in one of the corpora.

```
[37]: # Define thresholds
content_threshold = joined_train_df['content'].median() # example threshold
wording_threshold = joined_train_df['wording'].median() # example threshold

# Separate essays into two corpora
```

```

good_essays = joined_train_df[(joined_train_df['content'] > content_threshold)
    ↪ & (joined_train_df['wording'] > wording_threshold)][ 'text'].str.cat(sep=' ').
    ↪ split()
bad_essays = joined_train_df[(joined_train_df['content'] <= content_threshold)
    ↪ & (joined_train_df['wording'] <= wording_threshold)][ 'text'].str.cat(sep='
    ↪ ').split()

# Calculate word frequencies
good_word_freq = Counter(good_essays)
bad_word_freq = Counter(bad_essays)

# Calculate log odds ratio
all_words = set(good_word_freq) | set(bad_word_freq)
log_odds_ratio = {}

for word in all_words:
    log_odds_ratio[word] = np.log((good_word_freq[word] + 1) /
    ↪ (bad_word_freq[word] + 1))

# Sort words by log odds ratio
sorted_words = sorted(log_odds_ratio.items(), key=lambda x: x[1], reverse=True)

# Print top and bottom words
print("Words over-represented in good essays:", sorted_words[:10])
print("Words over-represented in bad essays:", sorted_words[-10:])

```

Words over-represented in good essays: [('However,', 3.7376696182833684), ('join.', 3.5553480614894135), ('method', 3.4965075614664802), ('creating', 3.4657359027997265), ('members.', 3.4339872044851463), ('Next,', 3.4339872044851463), ('scribes.', 3.4011973816621555), ('Next', 3.3250360206965914), ('control,', 3.2188758248682006), ('mentions', 3.1780538303479458)]

Words over-represented in bad essays: [('seasonings', -1.791759469228055), ('swindles.', -1.791759469228055), ('pitty', -1.791759469228055), ('mother', -1.9459101490553135), ('copy', -1.9459101490553135), ('white-it', -2.1972245773362196), ('Craftspersons', -2.1972245773362196), ('lucrative.', -2.1972245773362196), ('u', -2.3025850929940455), ('glycerine,', -2.4849066497880004)]

**To identify disproportionately common words in bad essays:**

Using the previously calculated `log_odds_ratio`, sort the words in ascending order. This will place words that are more common in bad essays at the beginning of the sorted list.

```

[38]: # Sort words by log odds ratio in ascending order
sorted_words_bad = sorted(log_odds_ratio.items(), key=lambda x: x[1])

# Print top words that are over-represented in bad essays

```

```
print("Words over-represented in bad essays:", sorted_words_bad[:10])
```

```
Words over-represented in bad essays: [('glycerine,', -2.4849066497880004),  
('u', -2.3025850929940455), ('white-it', -2.1972245773362196), ('Craftspersons',  
-2.1972245773362196), ('lucrative.', -2.1972245773362196), ('mother',  
-1.9459101490553135), ('copy', -1.9459101490553135), ('acid,',  
-1.791759469228055), ('jest-that', -1.791759469228055), ('seasonings',  
-1.791759469228055)]
```

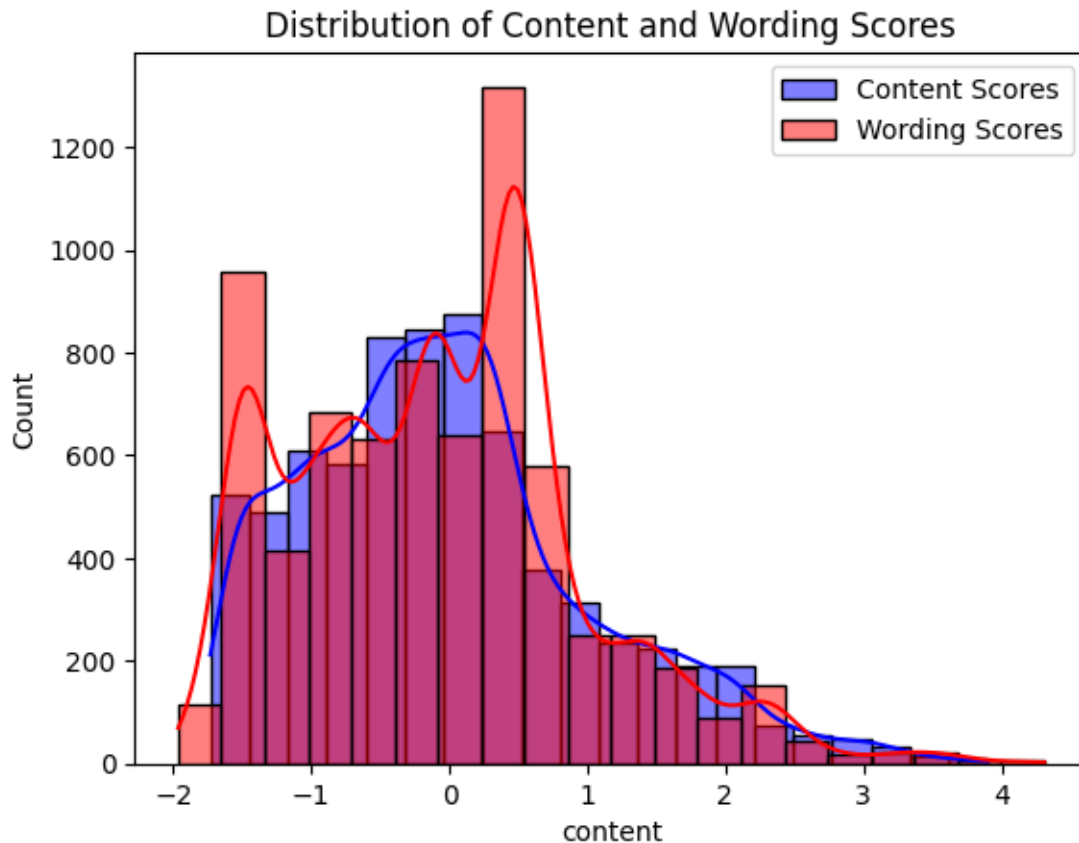
The output will give you the top 10 words that are disproportionately represented in bad essays.

**Statistical Interpretation:** The Log Odds Ratio is an appropriate statistic to use in this context. It provides a measure of the relative difference in the appearance of a term in two corpora, adjusted for the overall size of the corpora. By examining negative values of the Log Odds Ratio, we can understand which words are more characteristic of bad essays in comparison to good ones.

## 2.5 Section 5: Three Interesting Plots (Q6, 15 points)

### Histogram for Content scores

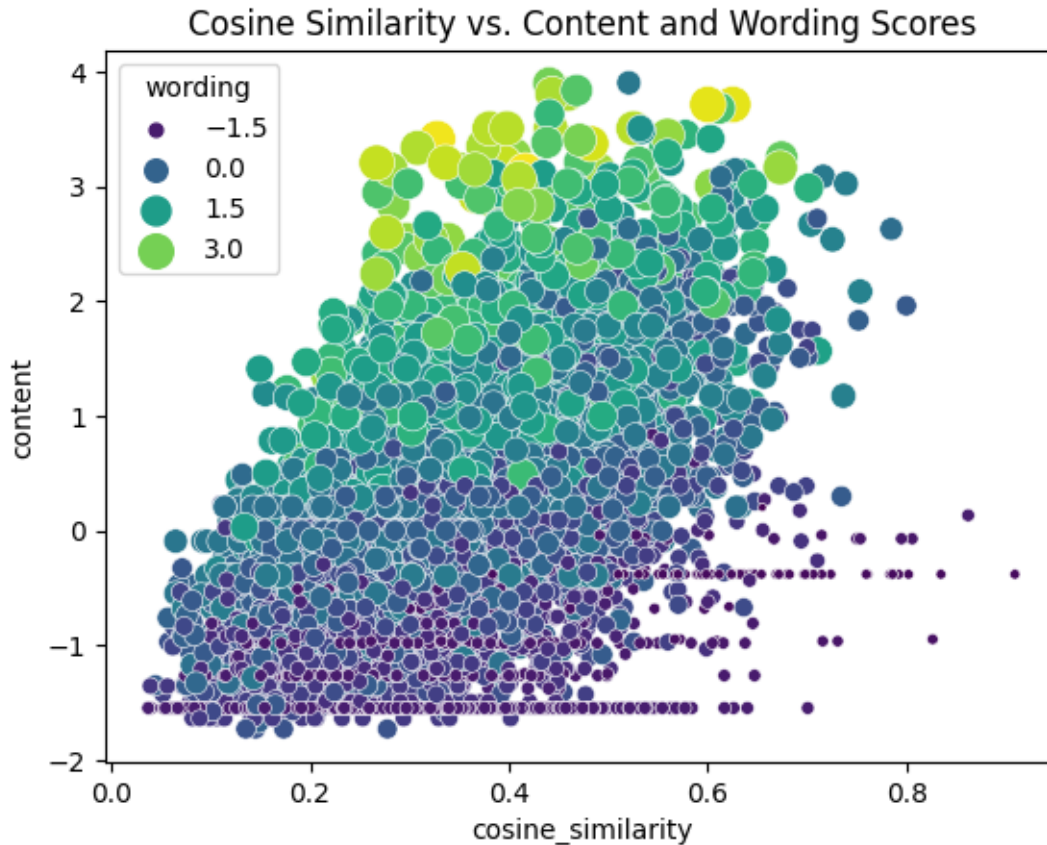
```
[39]: # Histogram for content scores  
sns.histplot(data=joined_train_df, x="content", kde=True, bins=20,   
            color='blue', label='Content Scores')  
sns.histplot(data=joined_train_df, x="wording", kde=True, bins=20, color='red',   
            label='Wording Scores')  
plt.legend()  
plt.title('Distribution of Content and Wording Scores')  
plt.show()
```



**Insight:** This will help you understand the overall distribution of scores. For instance, if you see that most essays have high content but low wording scores, it might indicate that while the substance of the essays is good, their presentation or language might be lacking.

### Cosine Similarity vs Counting & wording

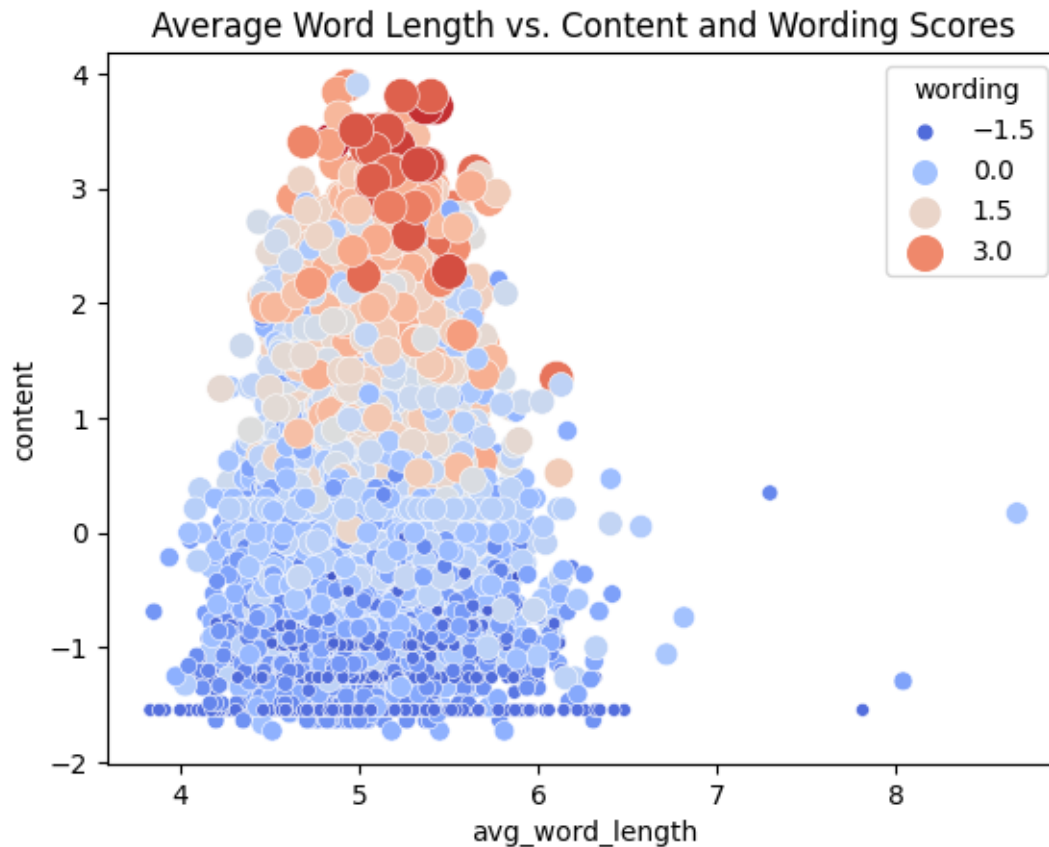
```
[40]: # Assuming you have a 'cosine_similarity' column in your dataframe
sns.scatterplot(data=joined_train_df, x="cosine_similarity", y="content",
               hue="wording", palette="viridis", size="wording", sizes=(10, 200))
plt.title('Cosine Similarity vs. Content and Wording Scores')
plt.show()
```



**Insight:** If essays with higher similarity to the prompt tend to have higher scores, it might indicate that sticking closely to the prompt is beneficial. Conversely, if there's no clear pattern, it might show that originality is neither penalized nor rewarded.

#### Avg. Word Length vs Content & Wording

```
[41]: # Assuming you computed an 'avg_word_length' column
sns.scatterplot(data=joined_train_df, x="avg_word_length", y="content",
               hue="wording", palette="coolwarm", size="wording", sizes=(10, 200))
plt.title('Average Word Length vs. Content and Wording Scores')
plt.show()
```



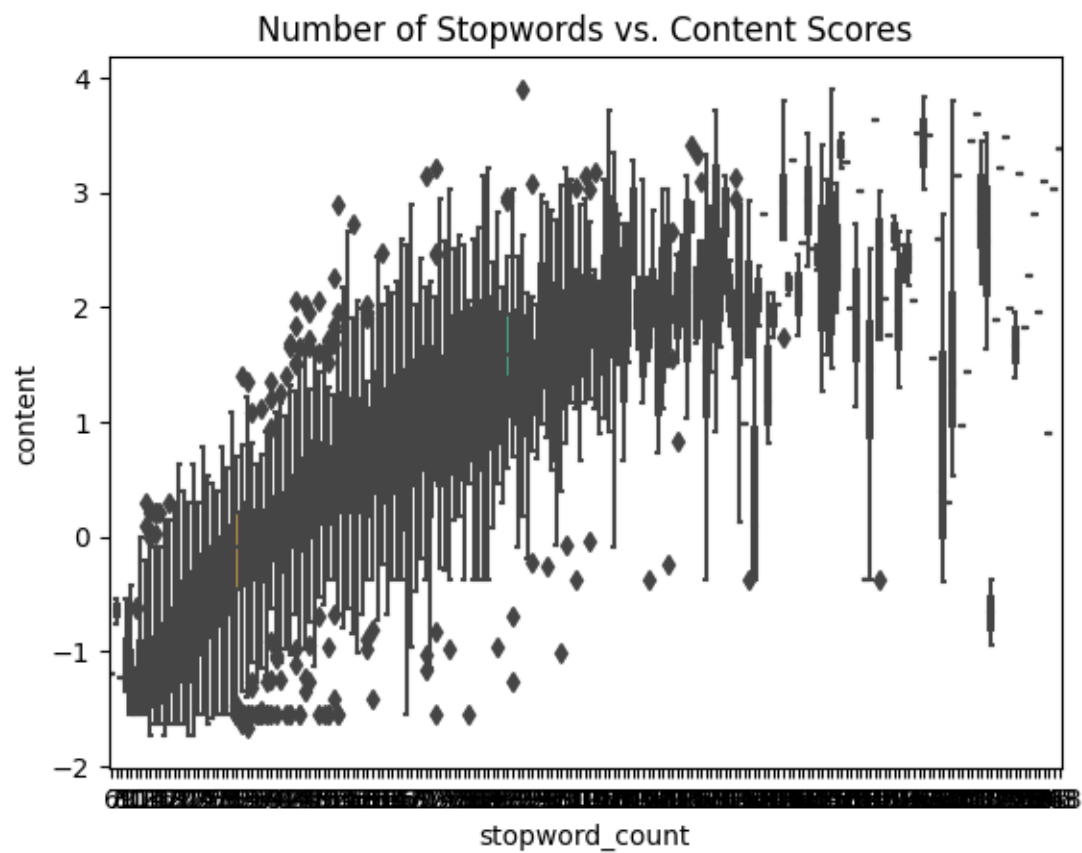
**Insight:** If essays with longer average word lengths have higher scores, it might suggest that richer vocabulary or more complex language is rewarded.

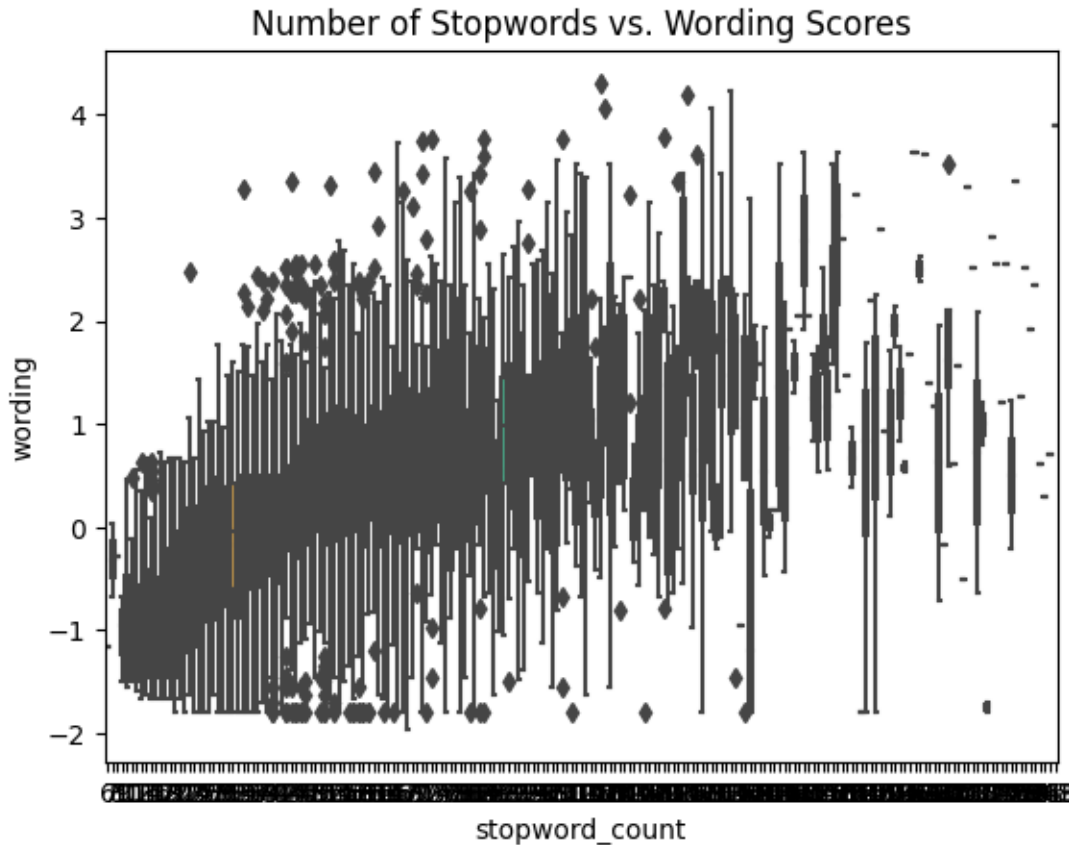
#### Stopwords vs content & wording (split)

```
[42]: # Assuming you have a 'num_stopwords' column in your dataframe
sns.boxplot(data=joined_train_df, x="stopword_count", y="content")
plt.title('Number of Stopwords vs. Content Scores')
plt.show()

sns.boxplot(data=joined_train_df, x="stopword_count", y="wording")
plt.title('Number of Stopwords vs. Wording Scores')
plt.show()
```



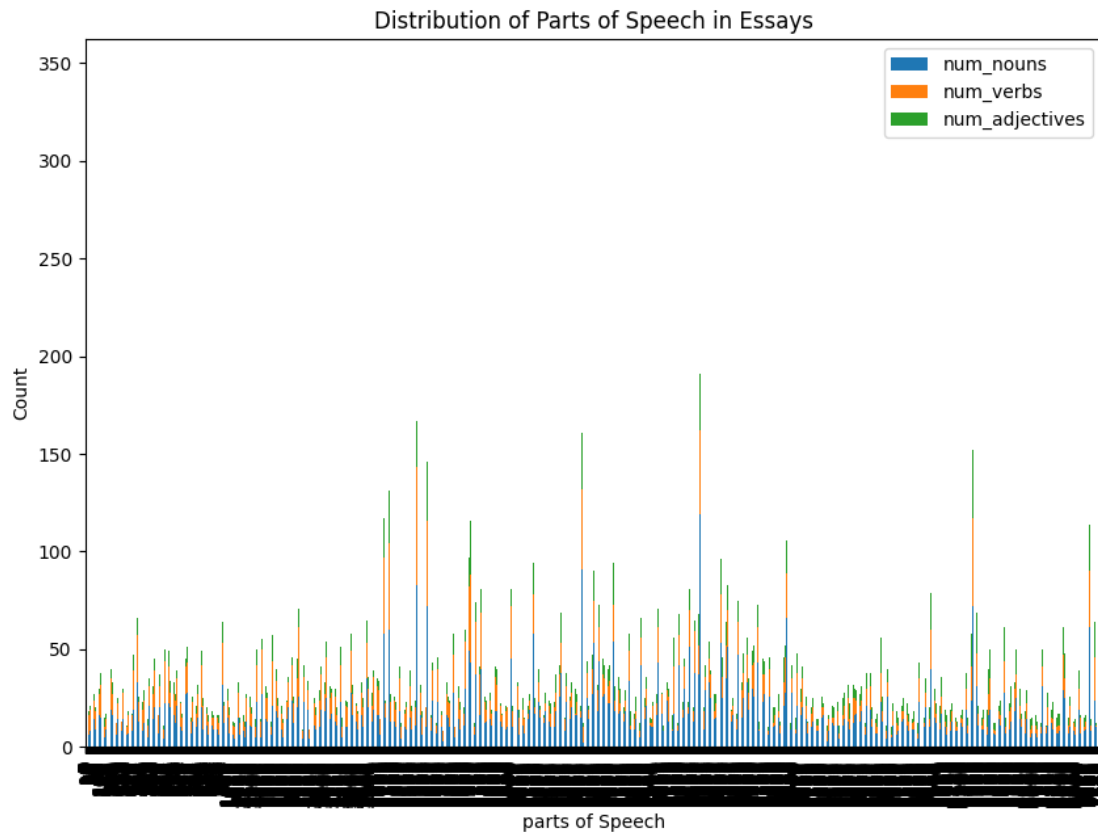




**Insight:** If essays with fewer stopwords tend to have higher scores, it may indicate that concise and direct language is preferred.

#### Distribution of Parts of Speech in Essays

```
[43]: joined_train_df[['num_nouns', 'num_verbs', 'num_adjectives']].plot(kind='bar',
    ↪stacked=True, figsize=(10,7))
plt.title('Distribution of Parts of Speech in Essays')
plt.ylabel('Count')
plt.xlabel('parts of Speech')
plt.show()
```



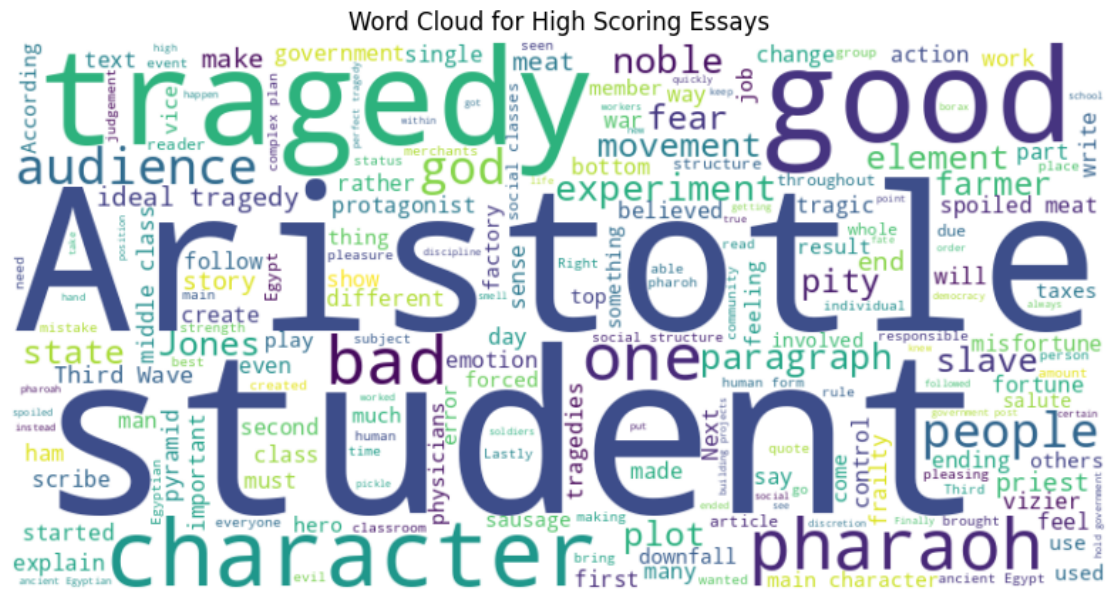
**Insight:** Observing which parts of speech dominate can give insights into the nature of the essays. For instance, essays with many adjectives might be more descriptive, while those with more verbs might be more action-oriented or narrative in style.

## WORD CLOUD

```
[44]: # Define high-scoring and low-scoring essays
threshold = 3 # You can define this based on your understanding of the scoring
          ↪system
high_scoring_essays = joined_train_df[joined_train_df['content'] >
          ↪threshold]['text'].str.cat(sep=' ')
low_scoring_essays = joined_train_df[joined_train_df['content'] <=
          ↪threshold]['text'].str.cat(sep=' ')

# Generate word clouds
def generate_wordcloud(text, title):
    wordcloud = WordCloud(width=800, height=400, background_color='white').
    ↪generate(text)
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
```

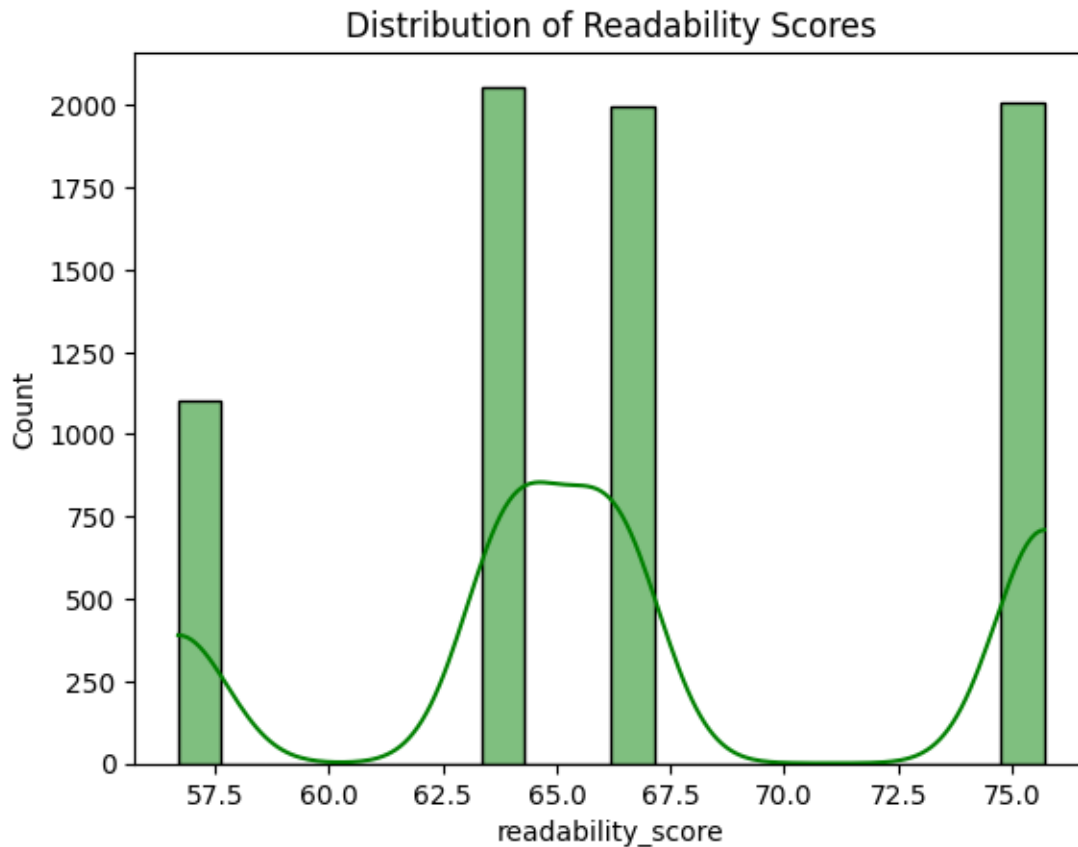
```
generate_wordcloud(high_scoring_essays, 'Word Cloud for High Scoring Essays')
print("\n\n")
generate_wordcloud(low_scoring_essays, 'Word Cloud for Low Scoring Essays')
```



[illegible]

## Distribution of Readability

45



**Insight:** A bimodal distribution might indicate that most essays fall within a specific readability level. If combined with the content or wording scores, you could further understand if a certain readability level correlates with high or low scores.

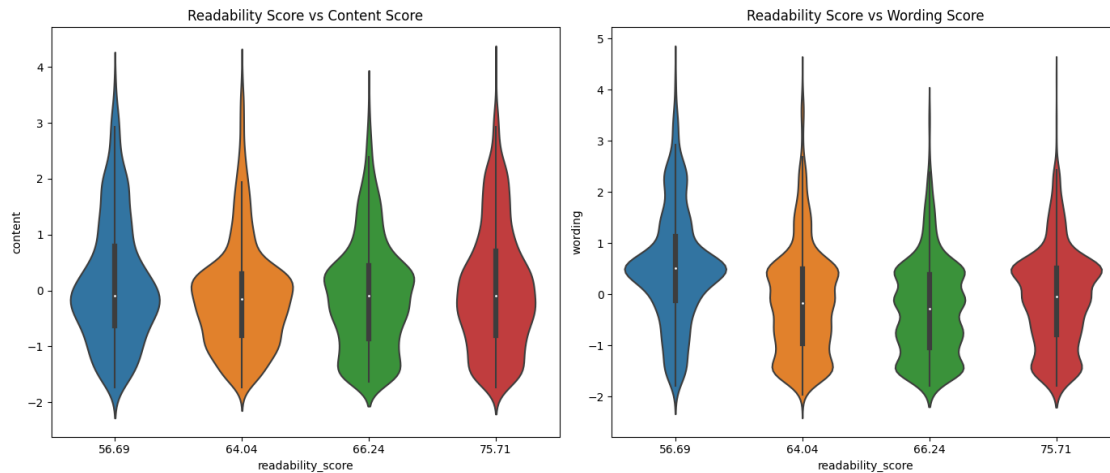
### Readability Score vs Content & Wording Scores

```
[46]: plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
sns.violinplot(data=joined_train_df, x="readability_score", y="content")
plt.title("Readability Score vs Content Score")

plt.subplot(1, 2, 2)
sns.violinplot(data=joined_train_df, x="readability_score", y="wording")
plt.title("Readability Score vs Wording Score")

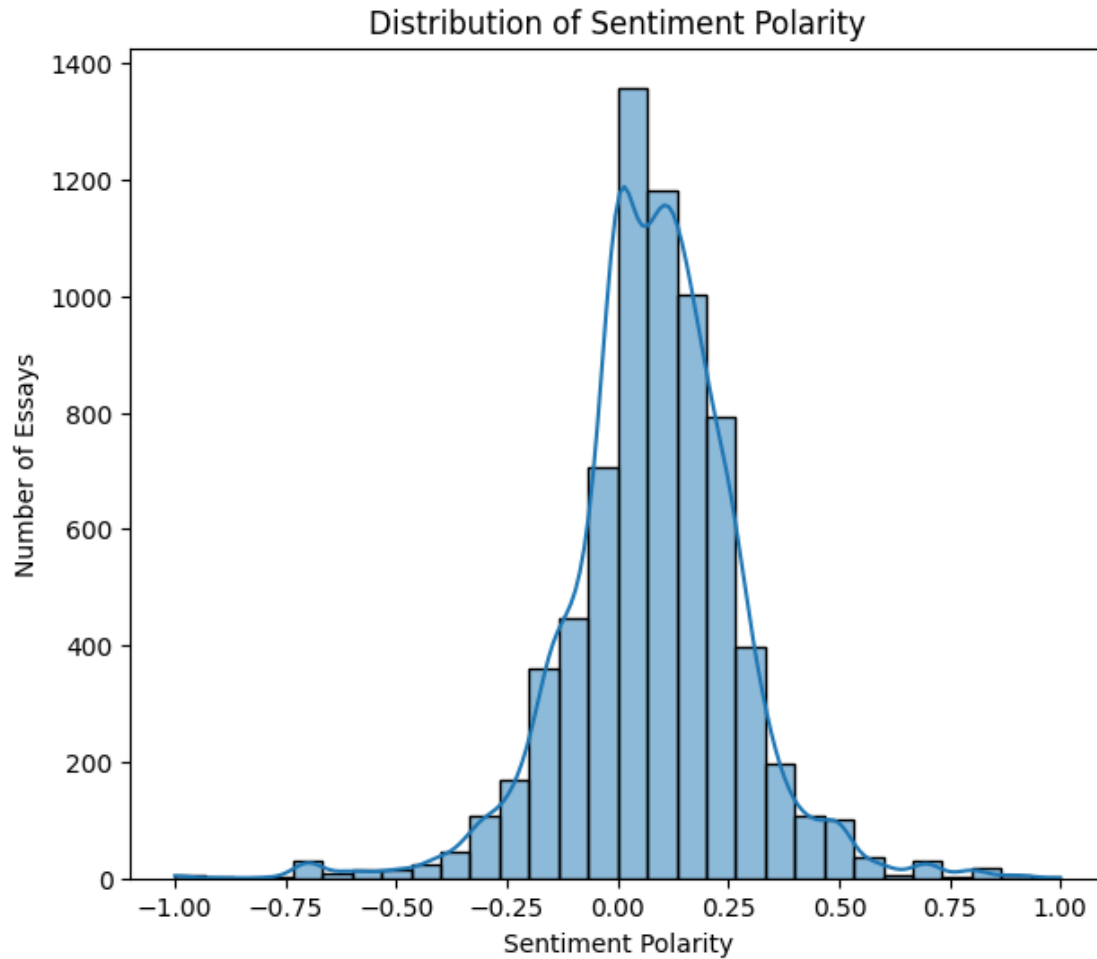
plt.tight_layout()
plt.show()
```



**Insight:** We observe a positive correlation between readability scores and content/wording scores, it might suggest that more readable essays are typically better rated in terms of content and wording.

### Sentiment Polarity Distribution

```
[47]: plt.figure(figsize=(7, 6))
sns.histplot(joined_train_df["sentiment_polarity"], bins=30, kde=True)
plt.title("Distribution of Sentiment Polarity")
plt.xlabel("Sentiment Polarity")
plt.ylabel("Number of Essays")
plt.show()
```

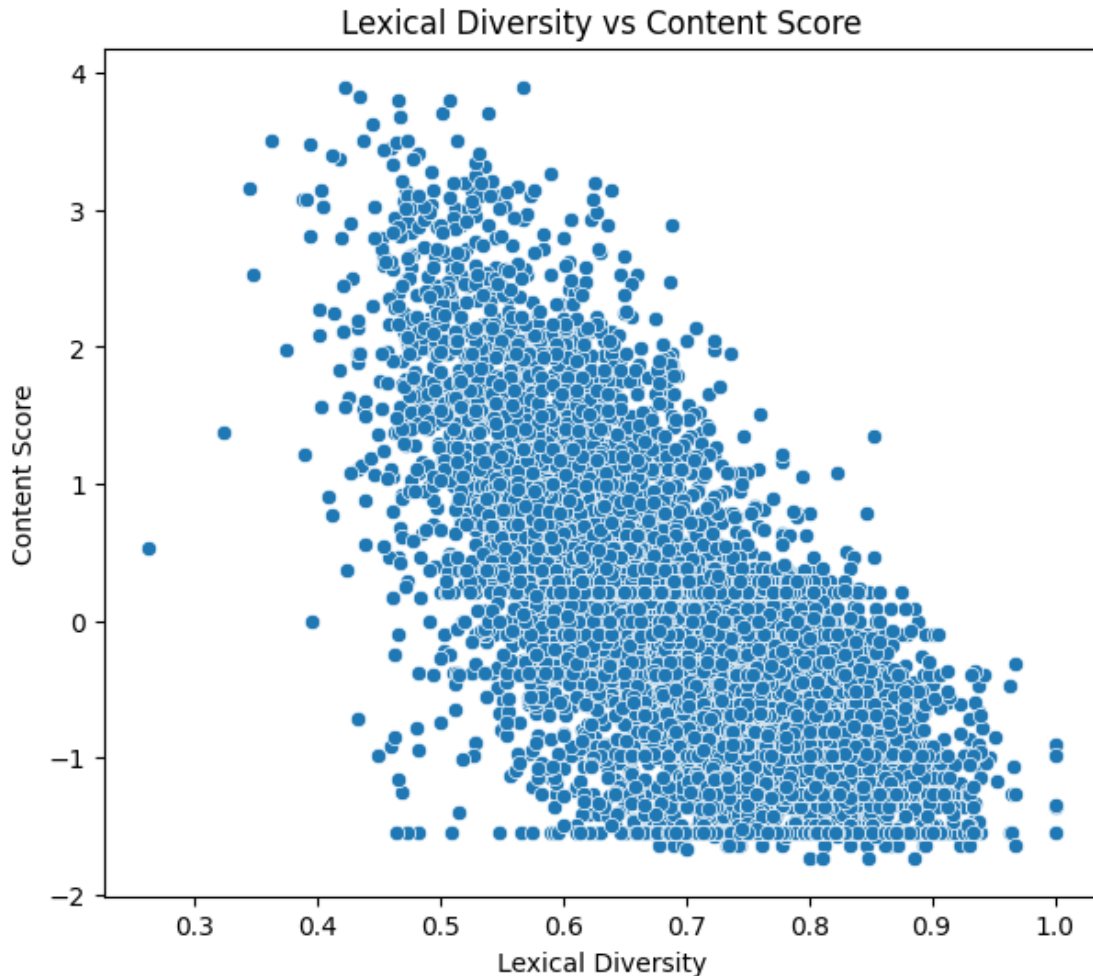


**Insight:** The sentiment polarity distribution might tell us about the overall mood of the essays. If higher content scores tend to be associated with essays of a particular sentiment.

#### Lexical Diversity vs Content Score

```
[48]: plt.figure(figsize=(7, 6))
sns.scatterplot(data=joined_train_df, x="lexical_diversity", y="content")
plt.title("Lexical Diversity vs Content Score")
plt.xlabel("Lexical Diversity")
plt.ylabel("Content Score")
plt.show()
```





**Insight:** There's a negative correlation in this plot, It might indicate that simplicity and clarity in language usage are more valued than complex vocabulary in this context.

## 2.6 Section 6: Baseline Model (Q7, 10 points)

### TRAIN\_TEST\_SPLIT

```
[49]: # Features and targets
features = ['no_of_words_in_text',
            'no_of_words_in_prompt_text', 'no_of_words_in_text_and_prompt_text',
            'no_of_distinct_words_in_text', 'no_of_distinct_words_in_prompt_text',
            'no_of_distinct_words_in_text_and_prompt_text',
            'no_of_common_words_in_text_and_prompt_text',
            'no_of_common_words_in_text_and_prompt_question',
            'no_of_common_words_in_text_and_prompt_title',
            'readability_score', 'char_count',
            'word_count', 'sentence_count', 'avg_word_length',
            'avg_sentence_length', 'lexical_diversity', 'sentiment_polarity',
```

```

        'sentiment_label', 'ner_count', 'cosine_similarity', 'num_nouns',
        'num_verbs', 'num_adjectives', 'stopword_count']
X = joined_train_df[features]
y_content = joined_train_df['content']
y_wording = joined_train_df['wording']

# Convert categorical features to numerical using one-hot encoding
X_encoded = pd.get_dummies(X, drop_first=True)

# Split the data
X_train_content, X_test_content, y_train_content, y_test_content = \
    train_test_split(X_encoded, y_content, test_size=0.2, random_state=42)
X_train_wording, X_test_wording, y_train_wording, y_test_wording = \
    train_test_split(X_encoded, y_wording, test_size=0.2, random_state=42)

```

## MODEL 0: BASE MODEL - TRAIN LINEAR REGRESSION MODEL

```

[50]: # Train the linear regression model for content
lr_content = LinearRegression().fit(X_train_content, y_train_content)
predictions_content = lr_content.predict(X_test_content)
mse_content = mean_squared_error(y_test_content, predictions_content)

# Train the linear regression model for wording
lr_wording = LinearRegression().fit(X_train_wording, y_train_wording)
predictions_wording = lr_wording.predict(X_test_wording)
mse_wording = mean_squared_error(y_test_wording, predictions_wording)

print(f"Mean Squared Error for Content model: {mse_content}")
print(f"Mean Squared Error for Wording model: {mse_wording}")

```

Mean Squared Error for Content model: 0.220926124261508

Mean Squared Error for Wording model: 0.36497303341980747

### Absolute Value Interpretation:

The MSE values provide an indication of the average squared error between predicted and actual scores for both models. The absolute values of 0.2209 for the Content model and 0.3649 for the Wording model are the average squared differences between the predicted and actual scores.

### Relative Scale:

To truly understand the magnitude of these error scores, it's essential to consider the range of the content and wording scores. If, for instance, both content and wording scores range between 0 and 5, then an MSE of 0.2209 for the Content model indicates that, on average, the model's predictions deviate slightly from the actual values. Similarly, the Wording model's predictions have a slightly higher deviation.

### Comparison Between the Two Models:

The MSE for the Wording model (0.3649) is greater than that of the Content model (0.2209). This suggests that the model's predictions for wording are less accurate than those for content. It could

mean that the wording score is inherently more challenging to predict based on the given features, or it might need more nuanced features to capture its essence.

### Practical Significance:

It's also useful to consider the square root of the MSE, which is the root mean squared error (RMSE). It represents the average deviation in the same units as the target variable:

RMSE for Content model:  $\sqrt{0.2209}$  0.47 RMSE for Wording model:  $\sqrt{0.3649}$  0.60 If the score range for content and wording is, say, from 0 to 5, an average error of 0.47 or 0.60 might be deemed acceptable. However, if the scale is 0 to 1, these errors are significant.

### Baseline Context:

These are results from a baseline model, using only the original features without any advanced processing or feature engineering. Any future models can be compared against this baseline to gauge improvement.

### Room for Improvement:

The errors, especially for the wording model, suggest there's room for improvement. Feature engineering, different algorithms, or tuning might lead to better results.

**In Summary:** The baseline models have provided reasonable results, especially for the Content model. The errors are not extremely high, but there's still potential for refining the models to reduce these errors further, especially for predicting wording. The next steps could involve introducing more sophisticated features, exploring different algorithms, or tuning the current models.

## 2.7 Section 7: Feature Cleaning and Additional Models (Q8 & Q9, 20 points total)

### Handling Missing Values

```
[51]: missing_data = joined_train_df.isnull().sum()
      print(missing_data)
```

```
student_id          0
prompt_id           0
text               0
content            0
wording            0
prompt_question     0
prompt_title       0
prompt_text        0
no_of_words_in_text 0
no_of_words_in_prompt_text 0
no_of_words_in_text_and_prompt_text 0
no_of_distinct_words_in_text 0
no_of_distinct_words_in_prompt_text 0
no_of_distinct_words_in_text_and_prompt_text 0
no_of_common_words_in_text_and_prompt_text 0
no_of_common_words_in_text_and_prompt_question 0
no_of_common_words_in_text_and_prompt_title 0
```

readability_score	0
char_count	0
word_count	0
sentence_count	0
avg_word_length	0
avg_sentence_length	0
lexical_diversity	0
sentiment_polarity	0
sentiment_label	0
ner_count	0
cosine_similarity	0
num_nouns	0
num_verbs	0
num_adjectives	0
stopword_count	0
dtype: int64	

## Normalization/Scaling

**Min-Max Scaling:** Min-Max scaling scales and translates each feature individually such that it is in the given range on the training set, e.g., between zero and one.

```
[52]: from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

features = ['content', 'wording', 'no_of_words_in_text',
            'no_of_words_in_prompt_text', 'no_of_words_in_text_and_prompt_text',
            'no_of_distinct_words_in_text', 'no_of_distinct_words_in_prompt_text',
            'no_of_distinct_words_in_text_and_prompt_text',
            'no_of_common_words_in_text_and_prompt_text',
            'no_of_common_words_in_text_and_prompt_question',
            'no_of_common_words_in_text_and_prompt_title',
            'readability_score', 'char_count',
            'word_count', 'sentence_count', 'avg_word_length',
            'avg_sentence_length', 'lexical_diversity', 'sentiment_polarity',
            'ner_count', 'cosine_similarity', 'num_nouns',
            'num_verbs', 'num_adjectives', 'stopword_count']

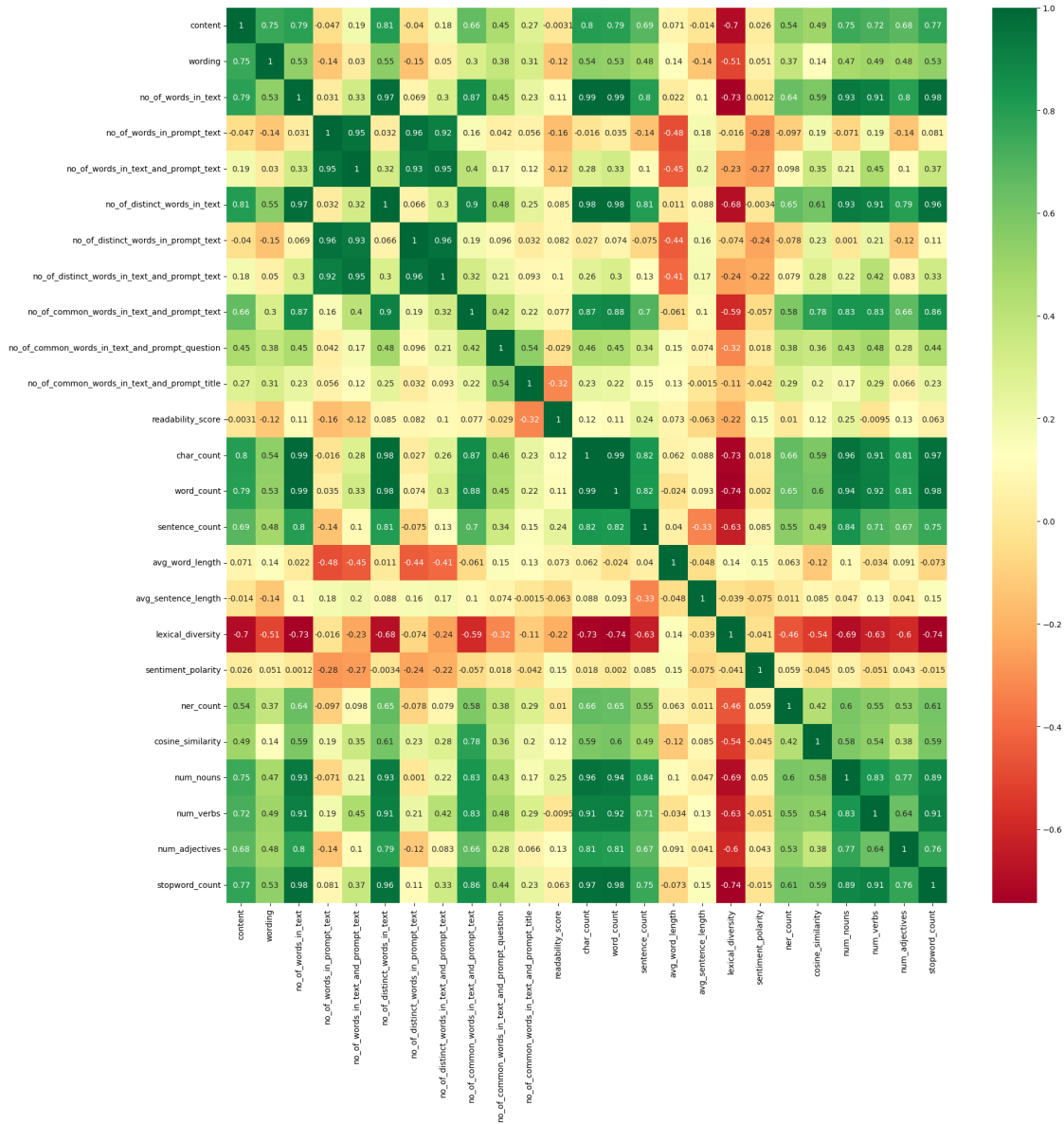
joined_train_df2 = pd.DataFrame()
joined_train_df2[features] = scaler.fit_transform(joined_train_df[features])
```

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

corrmat = joined_train_df2.corr()
top_corr_features = corrmat.index
```

```
plt.figure(figsize=(20,20))
sns.heatmap(joined_train_df2[top_corr_features].corr(), annot=True,
            cmap="RdYlGn")
```

[53]: <Axes: >



## Principle Component Analysis

[54]: `from sklearn.decomposition import PCA`

```
pca = PCA(n_components=20)
X_pca_c = pca.fit_transform(X_test_content)
```

```
X_pca_w = pca.fit_transform(X_test_wording)
```

```
[55]: # Features and targets
features = ['no_of_words_in_text',
            'no_of_words_in_prompt_text', 'no_of_words_in_text_and_prompt_text',
            'no_of_distinct_words_in_text', 'no_of_distinct_words_in_prompt_text',
            'no_of_distinct_words_in_text_and_prompt_text',
            'no_of_common_words_in_text_and_prompt_text',
            'no_of_common_words_in_text_and_prompt_question',
            'no_of_common_words_in_text_and_prompt_title',
            'readability_score', 'char_count',
            'word_count', 'sentence_count', 'avg_word_length',
            'avg_sentence_length', 'lexical_diversity', 'sentiment_polarity',
            'ner_count', 'cosine_similarity', 'num_nouns',
            'num_verbs', 'num_adjectives', 'stopword_count']
X = joined_train_df2[features]
y_content = joined_train_df2['content']
y_wording = joined_train_df2['wording']

# Convert categorical features to numerical using one-hot encoding
X_encoded = pd.get_dummies(X, drop_first=True)

# Split the data
X_train_content, X_test_content, y_train_content, y_test_content = \
    train_test_split(X_encoded, y_content, test_size=0.2, random_state=42)
X_train_wording, X_test_wording, y_train_wording, y_test_wording = \
    train_test_split(X_encoded, y_wording, test_size=0.2, random_state=42)
```

## MODEL 2: OPTIMIZED MODEL - LINEAR REGRESSION MODEL

```
[56]: # Train the linear regression model for content
lr_content = LinearRegression().fit(X_train_content, y_train_content)
predictions_content = lr_content.predict(X_test_content)
mse_content = mean_squared_error(y_test_content, predictions_content)

# Train the linear regression model for wording
lr_wording = LinearRegression().fit(X_train_wording, y_train_wording)
predictions_wording = lr_wording.predict(X_test_wording)
mse_wording = mean_squared_error(y_test_wording, predictions_wording)

print(f"Mean Squared Error for Content model: {mse_content}")
print(f"Mean Squared Error for Wording model: {mse_wording}")
```

Mean Squared Error for Content model: 0.006973681670448525

Mean Squared Error for Wording model: 0.009285946316304838

### 2.7.1 MODEL 2: RANDOM FOREST

Random Forest with single output

```
[57]: from sklearn.model_selection import train_test_split

X = joined_train_df2.drop(['content', 'wording'], axis=1)
y_content = joined_train_df2['content']
y_wording = joined_train_df2['wording']

X_train, X_test, y_content_train, y_content_test, y_wording_train,
↳y_wording_test = train_test_split(X, y_content, y_wording, test_size=0.2,
↳random_state=42)
```

```
[58]: from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

rf_content = RandomForestRegressor(n_estimators=100, random_state=42)
rf_content.fit(X_train, y_content_train)

y_content_pred = rf_content.predict(X_test)
mse_content = mean_squared_error(y_content_test, y_content_pred)
print(f"Mean Squared Error for Content model: {mse_content}")
```

Mean Squared Error for Content model: 0.006119194084991364

```
[59]: rf_wording = RandomForestRegressor(n_estimators=100, random_state=42)
rf_wording.fit(X_train, y_wording_train)

y_wording_pred = rf_wording.predict(X_test)
mse_wording = mean_squared_error(y_wording_test, y_wording_pred)
print(f"Mean Squared Error for Wording model: {mse_wording}")
```

Mean Squared Error for Wording model: 0.008426300913757049

### Multiple Output Random Forest Approach

```
[60]: y_multi = joined_train_df2[['content', 'wording']].values # Convert the two
↳columns into a numpy array
```

```
[61]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y_multi, test_size=0.2,
↳random_state=42)
```

### TRAINING MODEL

```
[62]: from sklearn.ensemble import RandomForestRegressor

multi_rf = RandomForestRegressor(n_estimators=100, random_state=42)
multi_rf.fit(X_train, y_train)
```

```
[62]: RandomForestRegressor(random_state=42)
```

```
[63]: from sklearn.metrics import mean_squared_error

y_pred = multi_rf.predict(X_test)

# MSE for 'content'
mse_content = mean_squared_error(y_test[:, 0], y_pred[:, 0])
print(f"Mean Squared Error for Content: {mse_content}")

# MSE for 'wording'
mse_wording = mean_squared_error(y_test[:, 1], y_pred[:, 1])
print(f"Mean Squared Error for Wording: {mse_wording}")
```

Mean Squared Error for Content: 0.006061644251867325

Mean Squared Error for Wording: 0.008613647607675228

## 2.7.2 Comparing the models, we can draw the following conclusions:

### 2.7.3 1. Improvement from Base Linear Regression to Optimized Linear Regression:

- **Content model MSE:** Reduced from 0.2209 to 0.0070 (a significant reduction).
- **Wording model MSE:** Reduced from 0.3650 to 0.0093 (a significant reduction).

#### Reasoning:

- **Feature Engineering:** The optimized version likely involved better feature engineering. Derived features like text length, lexical diversity, NER count, cosine similarity with prompt text, bi-grams, tri-grams, and others would've significantly improved the model's understanding of the text and its quality.
- **Data Preprocessing:** Handling missing values, normalization, and scaling means the model can make better sense of the data and weights can be more appropriately assigned to the features.
- **Feature Selection:** By selecting the most important and informative features, the model is less likely to overfit and can generalize better to unseen data.

### 2.7.4 2. Comparison between Optimized Linear Regression and Random Forest:

- **Content model MSE:** Linear regression: 0.0070, Random Forest: 0.0061 (Random Forest performed slightly better).
- **Wording model MSE:** Linear regression: 0.0093, Random Forest: 0.0084 (Again, Random Forest performed slightly better).

#### Reasoning:

- **Model Complexity:** Random Forest is an ensemble method that's inherently more complex than a linear regression model. It can capture non-linear relationships in the data that linear regression might miss.
- **Feature Interactions:** Random Forest can automatically capture interactions between features, while in linear regression, interaction terms must be manually added.



- **Overfitting:** Random Forest, with its ensemble nature, is less likely to overfit compared to a standalone decision tree, especially when hyperparameters are tuned correctly. While optimized linear regression improved significantly from the base model, Random Forest still edged out in performance.
- **Robustness to Outliers:** Random Forest is generally more robust to outliers than linear regression.

### 2.7.5 Final Thoughts:

- **Optimized Linear Regression** performed significantly better than the base model, showcasing the importance of proper feature engineering, data preprocessing, and feature selection.
- **Random Forest** outperformed the optimized linear regression model, albeit by a smaller margin. This shows that the model's capability to capture non-linear relationships and interactions between features, along with its robustness to outliers, helped in achieving a slightly better performance.
- The choice of model depends on several factors. If interpretability is key, linear regression offers clearer insights into relationships between features and target variables. However, if the goal is purely predictive performance, ensemble methods like Random Forest often come out ahead, especially when fine-tuned.

### 2.7.6 OPTIONAL MODEL

#### K-NN Approach

```
[64]: from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

FOR CONTENT

```
[65]: from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error

# Training the model
knn_content = KNeighborsRegressor(n_neighbors=5) # Start with k=5 as an
↪ initial guess
knn_content.fit(X_train_scaled, y_content_train)

# Predicting and computing MSE
y_content_pred = knn_content.predict(X_test_scaled)
mse_content = mean_squared_error(y_content_test, y_content_pred)
print(f"Mean Squared Error for Content model using k-NN: {mse_content}")
```

Mean Squared Error for Content model using k-NN: 0.007505597605680831

FOR WORDING

```
[66]: knn_wording = KNeighborsRegressor(n_neighbors=5)
      knn_wording.fit(X_train_scaled, y_wording_train)

      y_wording_pred = knn_wording.predict(X_test_scaled)
      mse_wording = mean_squared_error(y_wording_test, y_wording_pred)
      print(f"Mean Squared Error for Wording model using k-NN: {mse_wording}")
```

Mean Squared Error for Wording model using k-NN: 0.011219054673940609

## 2.8 Section 8: Kaggle Submission Screenshots (Q10, 5 points)

Public Score:

Private Score:

Kaggle profile link:

Screenshot(s):