2_0_Lexical_Complexity_Binary_Classification_Prediction_Data_Preparat

April 5, 2025

[61]:
```
#@title Install Packages
```

[62]:
```
!pip install -q transformers
!pip install -q torchinfo
!pip install -q datasets
!pip install -q evaluate
!pip install -q nltk
!pip install -q contractions
```

[63]:
```
!sudo apt-get update
! sudo apt-get install tree
```

```
Get:1 https://cloud.r-project.org/bin/linux/ubuntu jammy-cran40/ InRelease
[3,632 B]
Hit:2 https://developer.download.nvidia.com/compute/cuda/repos/ubuntu2204/x86_64
InRelease
Hit:3 http://archive.ubuntu.com/ubuntu jammy InRelease
Get:4 http://security.ubuntu.com/ubuntu jammy-security InRelease [129 kB]
Hit:5 https://r2u.stat.illinois.edu/ubuntu jammy InRelease
Get:6 http://archive.ubuntu.com/ubuntu jammy-updates InRelease [128 kB]
Hit:7 https://ppa.launchpadcontent.net/deadsnakes/ppa/ubuntu jammy InRelease
Hit:8 https://ppa.launchpadcontent.net/graphics-drivers/ppa/ubuntu jammy
InRelease
Hit:9 http://archive.ubuntu.com/ubuntu jammy-backports InRelease
Hit:10 https://ppa.launchpadcontent.net/ubuntugis/ppa/ubuntu jammy InRelease
Fetched 261 kB in 2s (105 kB/s)
Reading package lists… Done
W: Skipping acquire of configured file 'main/source/Sources' as repository
'https://r2u.stat.illinois.edu/ubuntu jammy InRelease' does not seem to provide
it (sources.list entry misspelt?)
Reading package lists… Done
Building dependency tree… Done
Reading state information… Done
tree is already the newest version (2.0.2-1).
0 upgraded, 0 newly installed, 0 to remove and 44 not upgraded.
```

[64]:
```
#@title Imports
import nltk
from nltk.tokenize import RegexpTokenizer

import evaluate
import transformers

import contractions

from torchinfo import summary
from datasets import load_dataset

from transformers import AutoTokenizer, AutoModel,␣
↪AutoModelForSequenceClassification
from transformers import TrainingArguments, Trainer

import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import sklearn
```

[65]:
```
# @title Mount Google Drive
```

[66]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[67]:
```
dir_root = '/content/drive/MyDrive/266-final/'
# dir_data = '/content/drive/MyDrive/266-final/data/'
# dir_data = '/content/drive/MyDrive/266-final/data/se21-t1-comp-lex-master/'
dir_data = '/content/drive/MyDrive/266-final/data/266-comp-lex-master'
dir_models = '/content/drive/MyDrive/266-final/models/'
dir_results = '/content/drive/MyDrive/266-final/results/'
```

[68]:
```
!tree /content/drive/MyDrive/266-final/data/266-comp-lex-master/
```

```
/content/drive/MyDrive/266-final/data/266-comp-lex-master/
  fe-test-labels
  fe-train
  fe-trial-val
  test-labels
      lcp_multi_test.tsv
      lcp_single_test.tsv
```

```
  train
      lcp_multi_train.tsv
      lcp_single_train.tsv
  trial
      lcp_multi_trial.tsv
      lcp_single_trial.tsv

6 directories, 6 files
```

[69]:
```
!ls -R /content/drive/MyDrive/266-final/data/266-comp-lex-master/
```

```
/content/drive/MyDrive/266-final/data/266-comp-lex-master/:
fe-test-labels  fe-train  fe-trial-val  test-labels  train  trial

/content/drive/MyDrive/266-final/data/266-comp-lex-master/fe-test-labels:

/content/drive/MyDrive/266-final/data/266-comp-lex-master/fe-train:

/content/drive/MyDrive/266-final/data/266-comp-lex-master/fe-trial-val:

/content/drive/MyDrive/266-final/data/266-comp-lex-master/test-labels:
lcp_multi_test.tsv  lcp_single_test.tsv

/content/drive/MyDrive/266-final/data/266-comp-lex-master/train:
lcp_multi_train.tsv  lcp_single_train.tsv

/content/drive/MyDrive/266-final/data/266-comp-lex-master/trial:
lcp_multi_trial.tsv  lcp_single_trial.tsv
```

[70]:
```
#@title Import Data
```

[71]:
```
# train_single_df = pd.read_csv(os.path.join(dir_data, "train",␣
↪"lcp_single_train.tsv"), sep="\t")
# train_multi_df = pd.read_csv(os.path.join(dir_data, "train", "lcp_multi_train.
↪tsv"), sep="\t")

# trail_val_single_df = pd.read_csv(os.path.join(dir_data, "trial",␣
↪"lcp_single_trial.tsv"), sep="\t")
# trail_val_multi_df = pd.read_csv(os.path.join(dir_data, "trial",␣
↪"lcp_multi_trial.tsv"), sep="\t")

# test_single_df = pd.read_csv(os.path.join(dir_data, "test-labels",␣
↪"lcp_single_test.tsv"), sep="\t")
# test_multi_df = pd.read_csv(os.path.join(dir_data, "test-labels",␣
↪"lcp_multi_test.tsv"), sep="\t")
```

[72]:

```
# # Try to load the files containing unterminated strings
# try:
#     # Approach 1: Try with the C engine but with error handling
#     multi_test_df = pd.read_csv(
#         os.path.join(dir_data, "test", "lcp_multi_test.tsv"),
#         sep="\t",
#         on_bad_lines='skip'  # Skip bad lines
#     )
#     print("Loaded with skipping bad lines")
# except Exception as e:
#     print(f"First approach failed: {e}")
#     try:
#         # Approach 2: Try with the Python engine which might be more forgiving
#         multi_test_df = pd.read_csv(
#             os.path.join(dir_data, "test", "lcp_multi_test.tsv"),
#             sep="\t",
#             engine="python",
#             quoting=3  # QUOTE_NONE
#         )
#         print("Loaded with Python engine")
```

[73]:

```
# Load train data into train_*_df
train_single_df = pd.read_csv(
    os.path.join(dir_data, "train", "lcp_single_train.tsv"),
    sep = "\t",
    engine = "python",
    quoting = 3
)
train_multi_df = pd.read_csv(
    os.path.join(dir_data, "train", "lcp_multi_train.tsv"),
    sep = "\t",
    engine = "python",
    quoting = 3
)

# Load trial data into trial_val_*_df
trial_val_single_df = pd.read_csv(
    os.path.join(dir_data, "trial", "lcp_single_trial.tsv"),
    sep = "\t",
    engine = "python",
    quoting = 3
)
trial_val_multi_df = pd.read_csv(
    os.path.join(dir_data, "trial", "lcp_multi_trial.tsv"),
    sep = "\t",
    engine = "python",
    quoting = 3
```

```
)

# Load test data (with labels) into test_*_df
test_single_df = pd.read_csv(
    os.path.join(dir_data, "test-labels", "lcp_single_test.tsv"),
    sep = "\t",
    engine = "python",
    quoting = 3
)
test_multi_df = pd.read_csv(
    os.path.join(dir_data, "test-labels", "lcp_multi_test.tsv"),
    sep = "\t",
    engine = "python",
    quoting = 3
)

print("Data successfully loaded into train, trial-val, and test variables")
```

```
Data successfully loaded into train, trial-val, and test variables
```

[74]:
```
#@title EDA
```

[75]:
```
def print_dataframe_summary(df_name, df):
    # Print section header
    print(f"========== {df_name} ==========")

    # Shape and Columns
    print(f"Shape: {df.shape}")
    print(f"Columns: {list(df.columns)}\n")

    # Data Types
    print("Data Types:")
    print(df.dtypes)
    print()

    # Missing Values
    print("Missing Values (by column):")
    print(df.isna().sum())
    print()

    # 'complexity' column stats
    desc = df['complexity'].describe()  # count, mean, std, min, 25%, 50%, 75%,␣
 ↪max
    print("'complexity' Column Stats (incl. quartiles and median):")
    print(desc)

    # Calculate frequency counts for each quartile range
```

```python
    q1 = desc['25%']
    q2 = desc['50%']  # This is the median
    q3 = desc['75%']
    q_max = desc['max']

    # Note: We'll define the ranges as:
    #   <= Q1
    #   > Q1 and <= Q2
    #   > Q2 and <= Q3
    #   > Q3

    freq_q1 = np.sum(df['complexity'] <= q1)
    freq_q2 = np.sum((df['complexity'] > q1) & (df['complexity'] <= q2))
    freq_q3 = np.sum((df['complexity'] > q2) & (df['complexity'] <= q3))
    freq_q4 = np.sum(df['complexity'] > q3)

    print()
    print("Quartile Frequency Counts (tab-separated next to each quartile):")
    print(f"25%: {q1}\tCount (<= Q1): {freq_q1}")
    print(f"50% (Median): {q2}\tCount (Q1 < x <= Q2): {freq_q2}")
    print(f"75%: {q3}\tCount (Q2 < x <= Q3): {freq_q3}")
    print(f"100% (Max): {q_max}\tCount (Q3 < x <= Max): {freq_q4}")

    print("======================================\n")

# Now we call this for each of our dataframes
print_dataframe_summary("train_single_df", train_single_df)
print_dataframe_summary("train_multi_df", train_multi_df)
print_dataframe_summary("trial_val_single_df", trial_val_single_df)
print_dataframe_summary("trial_val_multi_df", trial_val_multi_df)
print_dataframe_summary("test_single_df", test_single_df)
print_dataframe_summary("test_multi_df", test_multi_df)
```

```
========== train_single_df ==========
Shape: (7662, 5)
Columns: ['id', 'corpus', 'sentence', 'token', 'complexity']

Data Types:
id              object
corpus          object
sentence        object
token           object
complexity     float64
dtype: object

Missing Values (by column):
id             0
corpus         0
```

```
sentence      0
token         7
complexity    0
dtype: int64

'complexity' Column Stats (incl. quartiles and median):
count    7662.000000
mean        0.302288
std         0.132977
min         0.000000
25%         0.211538
50%         0.279412
75%         0.375000
max         0.861111
Name: complexity, dtype: float64

Quartile Frequency Counts (tab-separated next to each quartile):
25%: 0.2115384615384615 Count (<= Q1): 1928
50% (Median): 0.2794117647058823        Count (Q1 < x <= Q2): 1937
75%: 0.375      Count (Q2 < x <= Q3): 1984
100% (Max): 0.8611111111111112  Count (Q3 < x <= Max): 1813
======================================

========== train_multi_df ==========
Shape: (1517, 5)
Columns: ['id', 'corpus', 'sentence', 'token', 'complexity']

Data Types:
id             object
corpus         object
sentence       object
token          object
complexity    float64
dtype: object

Missing Values (by column):
id            0
corpus        0
sentence      0
token         0
complexity    0
dtype: int64

'complexity' Column Stats (incl. quartiles and median):
count    1517.000000
mean        0.418362
std         0.155536
min         0.027778
```

```
25%         0.302632
50%         0.409091
75%         0.529412
max         0.975000
Name: complexity, dtype: float64

Quartile Frequency Counts (tab-separated next to each quartile):
25%: 0.3026315789473685 Count (<= Q1): 382
50% (Median): 0.409090909090909 Count (Q1 < x <= Q2): 377
75%: 0.5294117647058824 Count (Q2 < x <= Q3): 380
100% (Max): 0.975       Count (Q3 < x <= Max): 378
========================================

========== trial_val_single_df ==========
Shape: (421, 5)
Columns: ['id', 'subcorpus', 'sentence', 'token', 'complexity']

Data Types:
id             object
subcorpus      object
sentence       object
token          object
complexity    float64
dtype: object

Missing Values (by column):
id            0
subcorpus     0
sentence      0
token         0
complexity    0
dtype: int64

'complexity' Column Stats (incl. quartiles and median):
count    421.000000
mean       0.298631
std        0.137619
min        0.000000
25%        0.214286
50%        0.266667
75%        0.359375
max        0.875000
Name: complexity, dtype: float64

Quartile Frequency Counts (tab-separated next to each quartile):
25%: 0.2142857142857143 Count (<= Q1): 106
50% (Median): 0.2666666666666667        Count (Q1 < x <= Q2): 107
75%: 0.359375   Count (Q2 < x <= Q3): 103
```

```
100% (Max): 0.875       Count (Q3 < x <= Max): 105
======================================

========== trial_val_multi_df ==========
Shape: (99, 5)
Columns: ['id', 'subcorpus', 'sentence', 'token', 'complexity']

Data Types:
id               object
subcorpus        object
sentence         object
token            object
complexity      float64
dtype: object

Missing Values (by column):
id             0
subcorpus      0
sentence       0
token          0
complexity     0
dtype: int64

'complexity' Column Stats (incl. quartiles and median):
count    99.000000
mean      0.417961
std       0.153752
min       0.000000
25%       0.309028
50%       0.421875
75%       0.513932
max       0.825000
Name: complexity, dtype: float64

Quartile Frequency Counts (tab-separated next to each quartile):
25%: 0.3090277777777778 Count (<= Q1): 25
50% (Median): 0.421875  Count (Q1 < x <= Q2): 25
75%: 0.5139318885448916 Count (Q2 < x <= Q3): 24
100% (Max): 0.825       Count (Q3 < x <= Max): 25
======================================

========== test_single_df ==========
Shape: (917, 5)
Columns: ['id', 'corpus', 'sentence', 'token', 'complexity']

Data Types:
id               object
corpus           object
```

```
sentence       object
token          object
complexity    float64
dtype: object

Missing Values (by column):
id            0
corpus        0
sentence      0
token         0
complexity    0
dtype: int64

'complexity' Column Stats (incl. quartiles and median):
count    917.000000
mean       0.296362
std        0.127290
min        0.000000
25%        0.214286
50%        0.276316
75%        0.357143
max        0.777778
Name: complexity, dtype: float64

Quartile Frequency Counts (tab-separated next to each quartile):
25%: 0.2142857142857143 Count (<= Q1): 237
50% (Median): 0.2763157894736842        Count (Q1 < x <= Q2): 224
75%: 0.3571428571428571 Count (Q2 < x <= Q3): 229
100% (Max): 0.7777777777777777  Count (Q3 < x <= Max): 227
======================================

========== test_multi_df ==========
Shape: (184, 5)
Columns: ['id', 'corpus', 'sentence', 'token', 'complexity']

Data Types:
id             object
corpus         object
sentence       object
token          object
complexity    float64
dtype: object

Missing Values (by column):
id            0
corpus        0
sentence      0
token         0
```

```
complexity    0
dtype: int64

'complexity' Column Stats (incl. quartiles and median):
count    184.000000
mean       0.422312
std        0.155785
min        0.000000
25%        0.316667
50%        0.428571
75%        0.527778
max        0.800000
Name: complexity, dtype: float64

Quartile Frequency Counts (tab-separated next to each quartile):
25%: 0.31666666666666666 Count (<= Q1): 47
50% (Median): 0.4285714285714286        Count (Q1 < x <= Q2): 46
75%: 0.5277777777777778 Count (Q2 < x <= Q3): 46
100% (Max): 0.8 Count (Q3 < x <= Max): 45
======================================
```

[76]:
```
print(train_single_df.head())
```

```
                               id corpus
sentence     token  complexity
0  3ZLW647WALVGE8EBR50EGUBPU4P32A  bible  Behold, there came up out of the river
seven c…     river    0.000000
1  34R0BODSP1ZBN3DVY8J8XSIY551E5C  bible  I am a fellow bondservant with you and
with yo…  brothers    0.000000
2  3S1WOPCJFGTJU2SGNAN2Y213N6WJE3  bible  The man, the lord of the land, said to
us, 'By…  brothers    0.050000
3  3BFNCI9LYKQN09BHXHH9CLSX5KP738  bible  Shimei had sixteen sons and six
daughters; but…  brothers    0.150000
4  3G5RUKN2EC3YIWSKUXZ8ZVH95R49N2  bible             "He has put my brothers
far from me.  brothers    0.263889
```

[77]:
```
print(train_multi_df.head())
```

```
                               id corpus
sentence             token  complexity
0  3S37Y8CWI80N8KVM53U4E6JKCDC4WE  bible  but the seventh day is a Sabbath to
Yahweh you…       seventh day    0.027778
1  3WGCNLZJKF877FYC1Q6COKNWTDWD11  bible  But let each man test his own work,
and then h…           own work    0.050000
2  3UOMW19E6D6WQ5TH2HDD74IVKTP5CB  bible  To him who by understanding made the
heavens; …  loving kindness    0.050000
3  36JW4WBR06KF9AXMUL4N476OMF8FHD  bible  Remember to me, my God, this also, and
spare m…  loving kindness    0.050000
```

```
4  3HRWUH63QU2FH9Q8R7MRNFC7JX2N5A  bible  Because your loving kindness is better
than li…  loving kindness    0.075000
```

[78]:
```python
#@title Data Engineering
```

[79]:
```python
# Assuming you have already loaded the DataFrames:
# train_single_df, train_multi_df, trial_val_single_df, trial_val_multi_df,␣
↪test_single_df, test_multi_df

def print_distinct_values(df, column_name):
    """Prints the distinct values of a specified column in a DataFrame."""
    distinct_values = df[column_name].unique()
    print(f"Distinct values in '{column_name}' column:")
    for value in distinct_values:
        print(value)
    print("-" * 30)  # Separator

# Print distinct values for each DataFrame
print_distinct_values(train_single_df, "corpus")
print_distinct_values(train_multi_df, "corpus")
print_distinct_values(trial_val_single_df, "subcorpus")
print_distinct_values(trial_val_multi_df, "subcorpus")
print_distinct_values(test_single_df, "corpus")
print_distinct_values(test_multi_df, "corpus")
```

```
Distinct values in 'corpus' column:
bible
biomed
europarl
------------------------------
Distinct values in 'corpus' column:
bible
biomed
europarl
------------------------------
Distinct values in 'subcorpus' column:
bible
biomed
europarl
------------------------------
Distinct values in 'subcorpus' column:
bible
biomed
europarl
------------------------------
Distinct values in 'corpus' column:
bible
biomed
```

```
europarl
------------------------------
Distinct values in 'corpus' column:
bible
biomed
europarl
------------------------------
```

0.1 standardize column headers: convert trial_val header from 'subcorpus' to 'corpus'

[80]:
```
# Rename the 'subcorpus' column to 'corpus'
trial_val_single_df = trial_val_single_df.rename(columns={'subcorpus':␣
↪'corpus'})
trial_val_multi_df = trial_val_multi_df.rename(columns={'subcorpus': 'corpus'})

# Verify the change (optional)
print(trial_val_single_df.columns)
print(trial_val_multi_df.columns)
```

```
Index(['id', 'corpus', 'sentence', 'token', 'complexity'], dtype='object')
Index(['id', 'corpus', 'sentence', 'token', 'complexity'], dtype='object')
```

[81]:
```
dataframes = [train_single_df, train_multi_df, trial_val_single_df,␣
↪trial_val_multi_df, test_single_df, test_multi_df]

# Get the headers (column names) of the first DataFrame as a reference
reference_headers = list(dataframes[0].columns)

# Loop through the remaining DataFrames and compare headers
all_headers_match = True
for df in dataframes[1:]:
    if list(df.columns) != reference_headers:
        all_headers_match = False
        print(f"Headers do not match for DataFrame: {df.head(0)}")  # Print␣
↪which DataFrame has different headers
        break  # Exit the loop if a mismatch is found

# Print the result
if all_headers_match:
    print("All DataFrames have matching headers.")
else:
    print("Headers do not match for all DataFrames.")
```

```
All DataFrames have matching headers.
```

0.2 Interrogate Span Length by Corpus Value by Data Split

[82]:
```
# Analyzing sentence spans by complexity quartile and corpus

tokenizer = RegexpTokenizer(r'\w+') # setup tokenizer

def analyze_sentence_spans_by_corpus_and_quartile(dfs_dict):
    """
    Analyze sentence spans (length metrics) grouped by corpus and complexity␣
 ↪quartile
    for multiple dataframes.
    """
    results = []

    for df_name, df in dfs_dict.items():
        print(f"Processing {df_name}...")

        # Calculate complexity quartiles for this dataframe
        q1 = df['complexity'].quantile(0.25)
        q2 = df['complexity'].quantile(0.50)
        q3 = df['complexity'].quantile(0.75)

        # Define quartile ranges for labeling
        def get_quartile(x):
            if x <= q1:
                return 'Q1'
            elif x <= q2:
                return 'Q2'
            elif x <= q3:
                return 'Q3'
            else:
                return 'Q4'

        # Add quartile column
        df = df.copy()
        df['quartile'] = df['complexity'].apply(get_quartile)

        # Compute sentence metrics using RegexpTokenizer instead of␣
 ↪word_tokenize
        def compute_span_metrics(sentence):
            if pd.isna(sentence):
                return pd.Series({'word_count': 0, 'char_count': 0,␣
 ↪'avg_word_len': 0})

            # Use our tokenizer that doesn't require punkt_tab
            words = tokenizer.tokenize(sentence)
            word_count = len(words)
```

```
            char_count = len(sentence)
            avg_word_len = np.mean([len(word) for word in words]) if word_count␣
↪> 0 else 0
            return pd.Series({'word_count': word_count, 'char_count':␣
↪char_count, 'avg_word_len': avg_word_len})

        # Apply the function to each sentence
        span_metrics = df['sentence'].apply(compute_span_metrics)
        df = pd.concat([df, span_metrics], axis=1)

        # Get corpus column name (could be 'corpus' or 'subcorpus')
        corpus_col = 'corpus' if 'corpus' in df.columns else 'subcorpus'

        # Group by corpus and quartile
        for corpus_name, corpus_df in df.groupby(corpus_col):
            for quartile, quartile_df in corpus_df.groupby('quartile'):
                # Calculate statistics
                complexity_range = f"{quartile_df['complexity'].min():.
↪3f}-{quartile_df['complexity'].max():.3f}"
                stats = {
                    'Dataframe': df_name,
                    'Corpus': corpus_name,
                    'Quartile': quartile,
                    'Complexity Range': complexity_range,
                    'Count': len(quartile_df),
                    'Avg Words': quartile_df['word_count'].mean(),
                    'Median Words': quartile_df['word_count'].median(),
                    'Min Words': quartile_df['word_count'].min(),
                    'Max Words': quartile_df['word_count'].max(),
                    'Std Words': quartile_df['word_count'].std(),
                    'Avg Chars': quartile_df['char_count'].mean(),
                    'Avg Word Len': quartile_df['avg_word_len'].mean()
                }
                results.append(stats)

    # Convert to DataFrame and sort
    results_df = pd.DataFrame(results)
    results_df = results_df.sort_values(['Dataframe', 'Corpus', 'Quartile'])

    return results_df

# Create dictionary of dataframes
dfs = {
    'train_single_df': train_single_df,
    'train_multi_df': train_multi_df,
    'trial_val_single_df': trial_val_single_df,
    'trial_val_multi_df': trial_val_multi_df,
```

```
    'test_single_df': test_single_df,
    'test_multi_df': test_multi_df
}

# Run analysis
span_analysis = analyze_sentence_spans_by_corpus_and_quartile(dfs)

# Display results
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 1000)
display(span_analysis)

# Save the analysis results
results_path = os.path.join(dir_results, 'sentence_span_analysis.csv')
span_analysis.to_csv(results_path, index=False)
print(f"Analysis saved to: {results_path}")
```

```
Processing train_single_df…
Processing train_multi_df…
Processing trial_val_single_df…
Processing trial_val_multi_df…
Processing test_single_df…
Processing test_multi_df…

               Dataframe    Corpus Quartile Complexity Range  Count  Avg Words ␣
↪Median Words  Min Words  Max Words  Std Words   Avg Chars  Avg Word Len
60         test_multi_df     bible       Q1      0.025-0.317     26  23.076923   ␣
↪       22.0         4.0       48.0  11.831900  118.653846      4.128898
61         test_multi_df     bible       Q2      0.325-0.417     11  20.545455   ␣
↪       17.0         7.0       47.0  12.917923  109.545455      4.209752
62         test_multi_df     bible       Q3      0.432-0.528     18  21.111111   ␣
↪       21.5         4.0       43.0  10.889222  112.777778      4.474206
63         test_multi_df     bible       Q4      0.542-0.694     11  22.363636   ␣
↪       20.0         7.0       51.0  11.935432  126.181818      4.605062
64         test_multi_df    biomed       Q1      0.000-0.312     11  29.818182   ␣
↪       29.0        17.0       47.0   8.388304  195.727273      5.491145
65         test_multi_df    biomed       Q2      0.324-0.417     11  27.090909   ␣
↪       24.0         9.0       47.0  11.449494  171.818182      5.436237
66         test_multi_df    biomed       Q3      0.456-0.528     10  26.900000   ␣
↪       26.5        10.0       49.0  10.712921  177.500000      5.497409
67         test_multi_df    biomed       Q4      0.562-0.800     21  32.285714   ␣
↪       34.0        14.0       56.0  13.598319  209.285714      5.460101
68         test_multi_df  europarl       Q1      0.214-0.303     10  24.700000   ␣
↪       24.5         7.0       56.0  14.189589  146.900000      5.049688
69         test_multi_df  europarl       Q2      0.321-0.429     24  27.833333   ␣
↪       27.0         9.0       73.0  15.352855  172.291667      5.269610
```

70	test_multi_df	europarl	Q3	0.432-0.516	18	32.944444	32.0	6.0	68.0	19.129504	209.888889	5.512245
71	test_multi_df	europarl	Q4	0.531-0.562	13	39.000000	36.0	6.0	95.0	29.631065	237.076923	5.100616
48	test_single_df	bible	Q1	0.000-0.214	79	22.835443	22.0	7.0	49.0	10.602891	116.797468	4.031532
49	test_single_df	bible	Q2	0.217-0.276	68	24.176471	21.0	2.0	77.0	14.393138	125.955882	4.167352
50	test_single_df	bible	Q3	0.278-0.353	67	22.388060	20.0	4.0	63.0	11.306950	119.731343	4.254090
51	test_single_df	bible	Q4	0.359-0.732	69	20.579710	19.0	1.0	55.0	11.264736	110.550725	4.337010
52	test_single_df	biomed	Q1	0.000-0.214	75	27.080000	25.0	10.0	84.0	12.025603	172.893333	5.271985
53	test_single_df	biomed	Q2	0.217-0.275	58	30.275862	26.0	10.0	83.0	15.856587	197.775862	5.434573
54	test_single_df	biomed	Q3	0.278-0.357	66	29.833333	29.0	13.0	85.0	11.754650	191.863636	5.334048
55	test_single_df	biomed	Q4	0.359-0.778	90	31.144444	30.0	14.0	83.0	12.089146	203.055556	5.393138
56	test_single_df	europarl	Q1	0.000-0.214	83	25.337349	21.0	3.0	82.0	16.032191	151.891566	5.044222
57	test_single_df	europarl	Q2	0.217-0.276	98	32.326531	30.0	1.0	97.0	18.707061	195.653061	5.062296
58	test_single_df	europarl	Q3	0.278-0.357	96	33.000000	30.0	3.0	141.0	21.404377	201.760417	5.124551
59	test_single_df	europarl	Q4	0.361-0.583	68	33.235294	29.0	1.0	130.0	20.440023	206.514706	5.164123
12	train_multi_df	bible	Q1	0.028-0.300	163	23.588957	22.0	3.0	67.0	12.429421	124.834356	4.232989
13	train_multi_df	bible	Q2	0.304-0.409	132	24.053030	22.0	6.0	65.0	11.738444	129.575758	4.302615
14	train_multi_df	bible	Q3	0.411-0.529	131	23.770992	23.0	4.0	50.0	11.158691	127.389313	4.324088
15	train_multi_df	bible	Q4	0.533-0.778	79	25.481013	24.0	3.0	81.0	13.490605	139.240506	4.486716
16	train_multi_df	biomed	Q1	0.028-0.303	87	29.091954	28.0	9.0	77.0	11.882792	185.954023	5.276290
17	train_multi_df	biomed	Q2	0.304-0.408	74	30.716216	28.0	11.0	85.0	13.521693	195.864865	5.370313
18	train_multi_df	biomed	Q3	0.411-0.529	111	29.783784	29.0	8.0	61.0	10.912383	193.855856	5.430133
19	train_multi_df	biomed	Q4	0.531-0.975	242	29.595041	28.0	10.0	75.0	12.040443	194.995868	5.534629
20	train_multi_df	europarl	Q1	0.118-0.303	132	29.363636	27.0	3.0	101.0	17.874146	176.553030	5.002618

21	train_multi_df	europarl	Q2	0.304-0.409	171	31.654971	28.0	3.0	108.0	19.099221	195.152047	5.176834
22	train_multi_df	europarl	Q3	0.411-0.529	138	33.398551	30.0	7.0	101.0	18.992715	208.304348	5.286607
23	train_multi_df	europarl	Q4	0.533-0.750	57	34.596491	31.0	6.0	96.0	20.318763	218.350877	5.345891
0	train_single_df	bible	Q1	0.000-0.212	701	23.275321	22.0	4.0	61.0	11.760701	121.607703	4.126789
1	train_single_df	bible	Q2	0.212-0.279	640	23.753125	22.0	3.0	60.0	11.577932	124.576562	4.148961
2	train_single_df	bible	Q3	0.281-0.375	624	23.823718	22.0	3.0	70.0	11.958906	126.230769	4.208102
3	train_single_df	bible	Q4	0.380-0.861	609	23.577997	21.0	3.0	69.0	12.461688	126.518883	4.295608
4	train_single_df	biomed	Q1	0.000-0.212	586	28.534130	27.0	2.0	85.0	12.115387	182.011945	5.319754
5	train_single_df	biomed	Q2	0.212-0.279	583	30.435678	29.0	7.0	92.0	11.872558	193.789022	5.285758
6	train_single_df	biomed	Q3	0.281-0.375	659	29.860395	28.0	4.0	77.0	11.591263	191.050076	5.328161
7	train_single_df	biomed	Q4	0.381-0.861	748	29.176471	28.0	3.0	85.0	12.246613	186.909091	5.298112
8	train_single_df	europarl	Q1	0.025-0.212	641	26.761310	24.0	2.0	107.0	15.230853	159.180967	4.942557
9	train_single_df	europarl	Q2	0.212-0.279	714	30.420168	27.0	1.0	129.0	18.383783	183.093838	4.995672
10	train_single_df	europarl	Q3	0.281-0.375	701	30.523538	28.0	1.0	122.0	18.163026	185.840228	5.114587
11	train_single_df	europarl	Q4	0.381-0.775	456	33.528509	31.0	2.0	235.0	21.704693	203.592105	5.054701
36	trial_val_multi_df	bible	Q1	0.000-0.292	11	26.272727	21.0	13.0	64.0	13.950562	141.363636	4.282457
37	trial_val_multi_df	bible	Q2	0.333-0.400	7	20.571429	23.0	5.0	28.0	7.412987	110.857143	4.279406
38	trial_val_multi_df	bible	Q3	0.425-0.500	5	19.600000	19.0	9.0	32.0	8.905055	109.200000	4.431391
39	trial_val_multi_df	bible	Q4	0.525-0.661	6	22.333333	20.5	9.0	44.0	12.242004	117.833333	4.178525
40	trial_val_multi_df	biomed	Q1	0.083-0.303	6	26.833333	25.0	15.0	49.0	11.771434	159.166667	4.899969
41	trial_val_multi_df	biomed	Q2	0.317-0.422	7	25.428571	21.0	15.0	48.0	11.588171	156.000000	5.194383
42	trial_val_multi_df	biomed	Q3	0.438-0.513	6	37.833333	39.5	26.0	44.0	6.675827	247.500000	5.438593
43	trial_val_multi_df	biomed	Q4	0.537-0.825	14	30.642857	29.5	17.0	43.0	9.849695	211.428571	5.730623

```
44   trial_val_multi_df  europarl       Q1      0.176-0.306       8  30.000000   ␣
  ↪      25.5          4.0          64.0  20.361027  186.750000       5.306837
45   trial_val_multi_df  europarl       Q2      0.312-0.412      11  47.909091   ␣
  ↪      46.0         24.0          78.0  18.651834  296.909091       5.058375
46   trial_val_multi_df  europarl       Q3      0.432-0.500      13  26.307692   ␣
  ↪      26.0          5.0          66.0  18.167666  166.153846       5.263847
47   trial_val_multi_df  europarl       Q4      0.515-0.714       5  26.400000   ␣
  ↪      15.0          6.0          66.0  24.316661  164.600000       4.998182
24  trial_val_single_df     bible       Q1      0.000-0.214      52  26.750000   ␣
  ↪      26.0          5.0          73.0  15.530962  137.230769       4.071006
25  trial_val_single_df     bible       Q2      0.217-0.266      38  24.868421   ␣
  ↪      23.0          7.0          50.0  10.768249  131.236842       4.195550
26  trial_val_single_df     bible       Q3      0.268-0.355      26  22.884615   ␣
  ↪      20.5          5.0          44.0   9.961233  121.269231       4.312026
27  trial_val_single_df     bible       Q4      0.361-0.633      27  25.666667   ␣
  ↪      23.0          6.0          49.0  12.554497  137.555556       4.212685
28  trial_val_single_df    biomed       Q1      0.028-0.214      21  25.571429   ␣
  ↪      21.0         13.0          65.0  11.543706  163.904762       5.305404
29  trial_val_single_df    biomed       Q2      0.217-0.267      28  30.571429   ␣
  ↪      27.5         11.0          57.0  12.099674  198.142857       5.315287
30  trial_val_single_df    biomed       Q3      0.268-0.359      38  32.105263   ␣
  ↪      29.0         11.0          61.0  12.710476  206.947368       5.364934
31  trial_val_single_df    biomed       Q4      0.364-0.875      48  25.145833   ␣
  ↪      25.5          6.0          56.0  11.721937  163.979167       5.439709
32  trial_val_single_df  europarl       Q1      0.050-0.214      33  31.969697   ␣
  ↪      28.0          5.0          81.0  20.356947  185.969697       4.799024
33  trial_val_single_df  europarl       Q2      0.217-0.267      41  28.463415   ␣
  ↪      28.0          4.0          71.0  15.386841  172.780488       4.997706
34  trial_val_single_df  europarl       Q3      0.268-0.359      39  30.282051   ␣
  ↪      28.0          3.0          99.0  20.040681  184.358974       5.086945
35  trial_val_single_df  europarl       Q4      0.367-0.605      30  35.700000   ␣
  ↪      30.5          5.0          77.0  20.142852  215.400000       4.910759

Analysis saved to:
/content/drive/MyDrive/266-final/results/sentence_span_analysis.csv
```

[82]:

```
```

[82]:

```
```

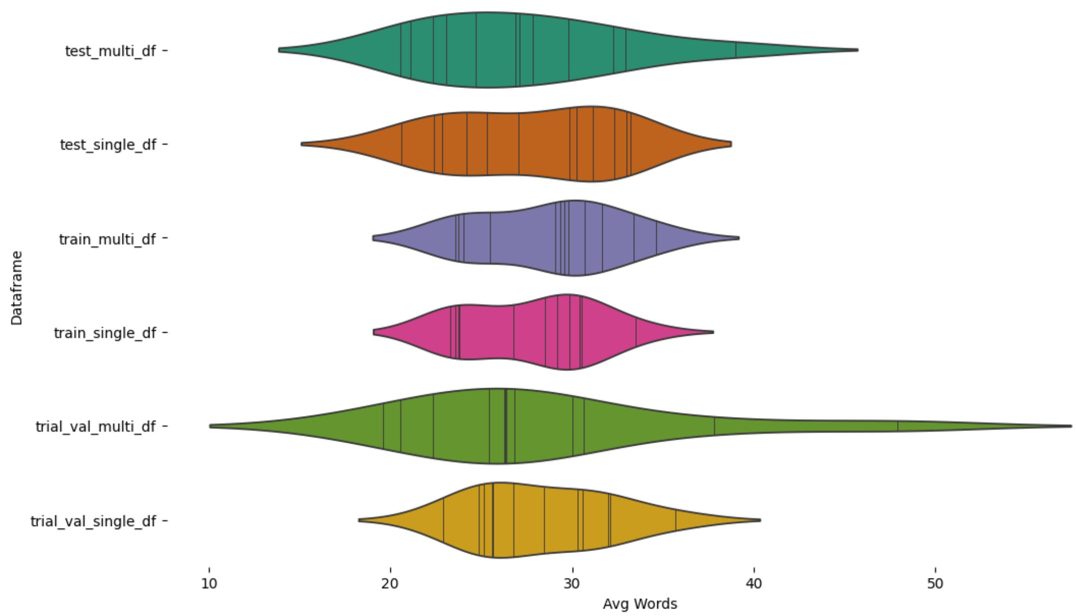
[83]:

```python
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(span_analysis['Dataframe'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(span_analysis, x='Avg Words', y='Dataframe', inner='stick',␣
 ↪palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

<ipython-input-83-00a8ad5642c1>:5: FutureWarning:

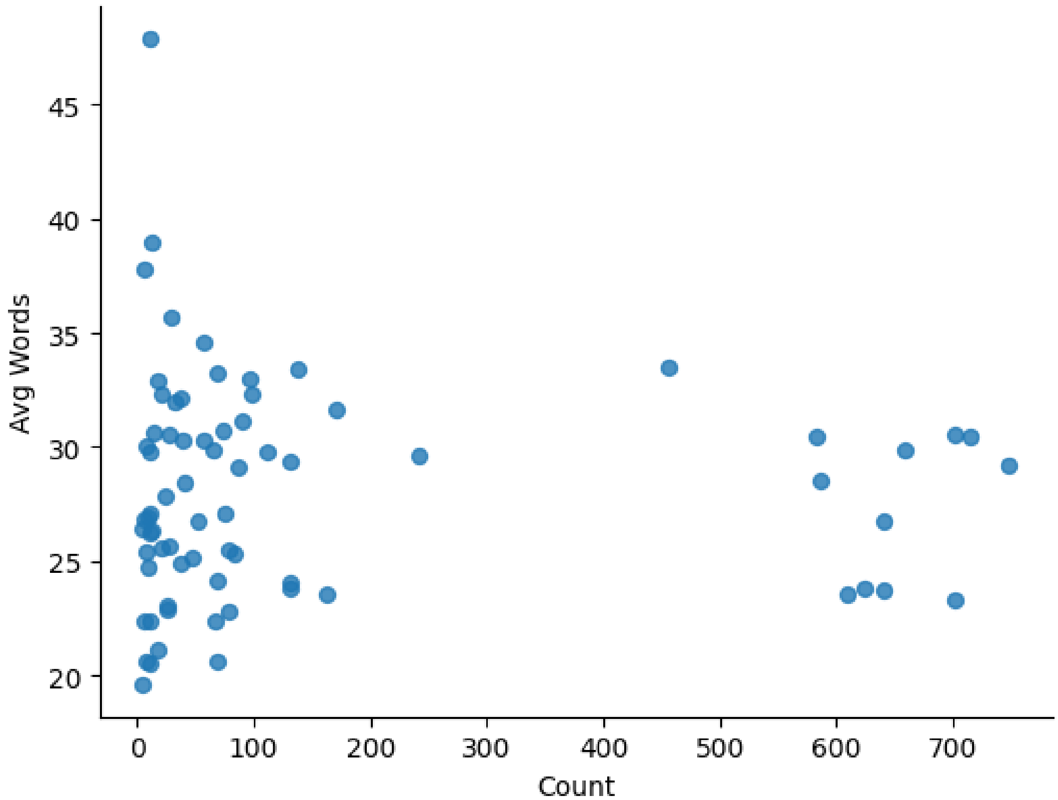
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

```
  sns.violinplot(span_analysis, x='Avg Words', y='Dataframe', inner='stick',
palette='Dark2')
```



[84]:

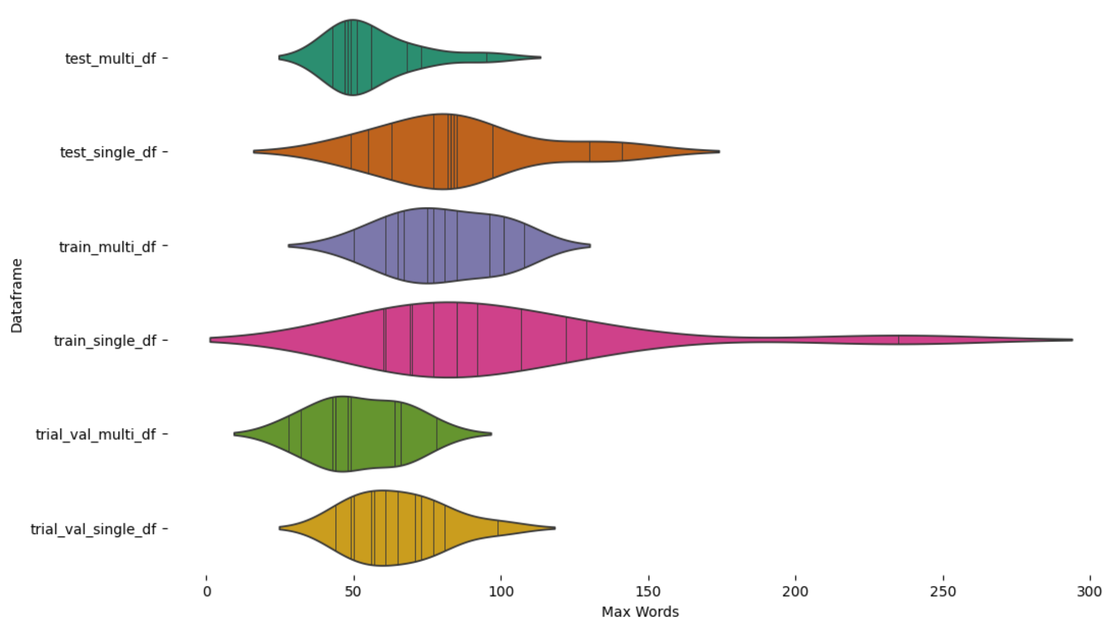
```
from matplotlib import pyplot as plt
span_analysis.plot(kind='scatter', x='Count', y='Avg Words', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```



[85]:

```
from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(span_analysis['Dataframe'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(span_analysis, x='Max Words', y='Dataframe', inner='stick',␣
↪palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```

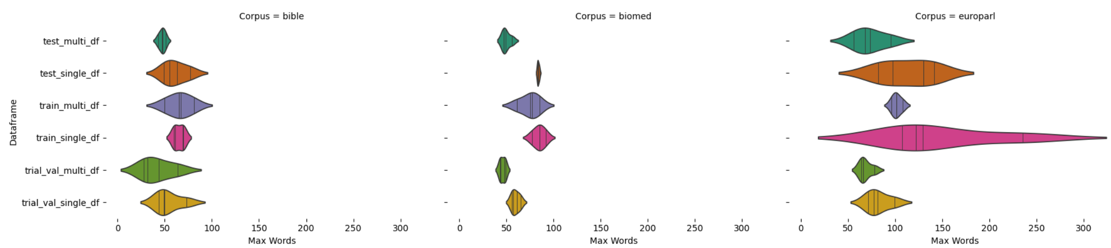
```
<ipython-input-85-01bf0c89d620>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.violinplot(span_analysis, x='Max Words', y='Dataframe', inner='stick',
palette='Dark2')
```



[86]:
```python
# Create a FacetGrid
g = sns.FacetGrid(span_analysis, col="Corpus", col_wrap=3, height=4, aspect=1.
 ↪5)  # Adjust col_wrap and height as needed

# Map the violinplot to the FacetGrid
g.map(sns.violinplot, "Max Words", "Dataframe", inner='stick', palette='Dark2')

# Remove spines for cleaner look
g.despine(top=True, right=True, bottom=True, left=True)

# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/seaborn/axisgrid.py:718: UserWarning:
Using the violinplot function without specifying `order` is likely to produce an
incorrect plot.
  warnings.warn(warning)
/usr/local/lib/python3.11/dist-packages/seaborn/axisgrid.py:854: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  func(*plot_args, **plot_kwargs)
/usr/local/lib/python3.11/dist-packages/seaborn/axisgrid.py:854: FutureWarning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  func(*plot_args, **plot_kwargs)
/usr/local/lib/python3.11/dist-packages/seaborn/axisgrid.py:854: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  func(*plot_args, **plot_kwargs)
```



[86]:

[86]: