1. Load and Filter Data

This section loads the original dataset and filters sentences where the 'fuel' column has a negative sentiment.

```
import pandas as pd
import os
import nltk
# Load the dataset
file_path = "./data/train_preprocess.csv"
df = pd.read_csv(file_path)

# Filter sentences where fuel is negative
negative_fuel_df = df[df['fuel'] == 'negative'][['sentence']]

# Display a sample of the filtered dataset
print(negative_fuel_df.head())
nltk_data_dir = "./nltk_data"
os.makedirs(nltk_data_dir, exist_ok=True)

# Download stopwords to the specified directory
nltk.download('stopwords', download_dir=nltk_data_dir)
```

```
                                              sentence
1    Avanza kenapa jadi boros bensin begini dah ah....
38   dari segi kenyamanan cortez oke lah, tapi baha...
113  kalau sudah di atas 120 km / jam boros banget ...
116          Rush konde konsumsi BBM yang tetap irit .
124  pengalaman saya punya avanza bahan bakar nya l...

[nltk_data] Downloading package stopwords to ./nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.

True
```

2. Text Summarization

This section performs text summarization using the TextRank algorithm from the Sumy library.

```
import spacy
import networkx as nx
import numpy as np
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.feature_extraction.text import TfidfVectorizer

# Load the SpaCy Indonesian model
nlp = spacy.blank('id')
nlp.add_pipe('sentencizer')
```

```
def custom_tokenizer(text):
    return [token.text for token in nlp(text)]


def enhanced_tokenizer(text):
    # Remove stopwords and non-meaningful tokens
    from nltk.corpus import stopwords
    try:
        stop_words = set(stopwords.words('indonesian'))
    except:
        import nltk
        nltk.download('stopwords')
        stop_words = set(stopwords.words('indonesian'))


    # Your existing custom_tokenizer logic here, plus:
    tokens = custom_tokenizer(text)
    # Remove stopwords and very short tokens
    tokens = [
        token for token in tokens if token not in stop_words and
len(token) > 2]
    return tokens

def textrank_summarizer(text, num_sentences=5):
    # Tokenize sentences
    doc = nlp(text)
    sentences = [sent.text for sent in doc.sents]

    # Convert sentences to TF-IDF vectors
    vectorizer = TfidfVectorizer(tokenizer=enhanced_tokenizer,
stop_words=None)
    tfidf_matrix = vectorizer.fit_transform(sentences)

    # Compute cosine similarity matrix
    similarity_matrix = cosine_similarity(tfidf_matrix)

    # Build the graph and rank sentences
    nx_graph = nx.from_numpy_array(similarity_matrix)
    scores = nx.pagerank(nx_graph)

    # Rank sentences by their TextRank score
    ranked_sentences = sorted(((scores[i], s) for i, s in
enumerate(sentences)), reverse=True)

    # Create a DataFrame with sentence scores
    sentence_scores_df = pd.DataFrame(ranked_sentences,
columns=["Score", "Sentence"])

    # Return summary and sentence scores
```

```
    summary = " ".join([sent for _, sent in
ranked_sentences[:num_sentences]])

    return summary, sentence_scores_df



example_text = "semenjak saya pakai toyota calya dompet ku enggak lagi
bocor alias bbm nya irit banget . dan enggak sering mengisi bbm
lagi ."

print("Example Text:")
print(example_text)

# Tokenize the example text
# Display the example text
print("Tokenized Example Text:")
print(enhanced_tokenizer(example_text))



# Combine sentences into one large text for summarization
text = " ".join(negative_fuel_df['sentence'])
text


# Apply TextRank summarization
summary, sentence_scores = textrank_summarizer(text, 5)

# Display summary
print("Summary:")
print(summary)

# # Display sentence scores
sentence_scores.head()
```

```
Example Text:
semenjak saya pakai toyota calya dompet ku enggak lagi bocor alias bbm
nya irit banget . dan enggak sering mengisi bbm lagi .
Tokenized Example Text:
['semenjak', 'pakai', 'toyota', 'calya', 'dompet', 'bocor', 'alias',
'bbm', 'nya', 'irit', 'banget', 'mengisi', 'bbm']
Summary:
ampun deh punya xenia uang habis cuma buat konsumsi bensin livina di
tempat gue bensin nya asli boros banget kalau soal ngelitik memang iya
avanza bahan bakar nya boros banget pengalaman saya punya avanza bahan
bakar nya lebih hemat daripada ketika saya punya xenia sudah harga nya
mahal, fortuner ini juga konsumsi bahan bakar nya lumayan menguras
dompet Asli avanza saya boros akhir-akhir ini walaupun secara
```

```
keseluruha oke tapi kalo bensinnya boros jadi malas beli ertiga gaya nya oke banget, tarikan juga mantap dan bandel tapi sayang nya boros banget pakai new avanza bu . secara keseluruhan avanza bagus kecuali pemakaian bensin yang boros sekali Masa konsumsi bensin Toyota Avanza Veloz 12,5 liter per kilometer , boros banget anjing kalo gak mau boros jangan beli scoopy xenia 1:8 - 9 boros juga ya juragan , karena bodi besar nya dan cc kecil mungkin ya . dari segi kenyamanan cortez oke lah, tapi bahan bakar nya itu loh boros banget kalau sudah di atas 120 km / jam boros banget avanza saya , terus kopling nya memang agak keras juragan . Baru diisi sudah mau setengah saja .
```

```
/home/nicho/MachineLearningENV/lib/python3.12/site-packages/sklearn/feature_extraction/text.py:517: UserWarning: The parameter 'token_pattern' will not be used since 'tokenizer' is not None'
  warnings.warn(
```


```
{"columns":[{"name":"index","rawType":"int64","type":"integer"},{"name":"Score","rawType":"float64","type":"float"},{"name":"Sentence","rawType":"object","type":"string"}],"conversionMethod":"pd.DataFrame","ref":"4247dbbc-2883-4e08-85b1-90b93a22650c","rows":[["0","0.12678790364909412","ampun deh punya xenia uang habis cuma buat konsumsi bensin livina di tempat gue bensin nya asli boros banget kalau soal ngelitik memang iya avanza bahan bakar nya boros banget"],["1","0.1150688142610501","pengalaman saya punya avanza bahan bakar nya lebih hemat daripada ketika saya punya xenia sudah harga nya mahal, fortuner ini juga konsumsi bahan bakar nya lumayan menguras dompet Asli avanza saya boros akhir-akhir ini walaupun secara keseluruha oke tapi kalo bensinnya boros jadi malas beli ertiga gaya nya oke banget, tarikan juga mantap dan bandel tapi sayang nya boros banget pakai new avanza bu ."],["2","0.10974510347616118","secara keseluruhan avanza bagus kecuali pemakaian bensin yang boros sekali Masa konsumsi bensin Toyota Avanza Veloz 12,5 liter per kilometer , boros banget anjing kalo gak mau boros jangan beli scoopy xenia 1:8 - 9 boros juga ya juragan , karena bodi besar nya dan cc kecil mungkin ya ."],["3","0.10188125889590718","dari segi kenyamanan cortez oke lah, tapi bahan bakar nya itu loh boros banget kalau sudah di atas 120 km / jam boros banget avanza saya , terus kopling nya memang agak keras juragan ."],["4","0.1","Baru diisi sudah mau setengah saja ."]],"shape":{"columns":2,"rows":5}}
```


3. Text Similarity

This section computes text similarity between sentences where the fuel column has a negative sentiment.

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
```

```
# Convert text data to TF-IDF features
vectorizer = TfidfVectorizer()
tfidf_matrix = vectorizer.fit_transform(negative_fuel_df['sentence'])

# Compute cosine similarity matrix
similarity_matrix = cosine_similarity(tfidf_matrix)

# Display similarity matrix
import pandas as pd
sim_df = pd.DataFrame(similarity_matrix,
index=negative_fuel_df['sentence'],
columns=negative_fuel_df['sentence'])
print(sim_df)
```

```
sentence                                                Avanza kenapa jadi
boros bensin begini dah ah. Baru diisi sudah mau setengah saja .  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
1.000000
dari segi kenyamanan cortez oke lah, tapi bahan...
0.013448
kalau sudah di atas 120 km / jam boros banget a...
0.093155
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.028798
sudah harga nya mahal, fortuner ini juga konsum...
0.062352
Asli avanza saya boros akhir-akhir ini
0.056262
walaupun secara keseluruha oke tapi kalo bensin...
0.096638
ertiga gaya nya oke banget, tarikan juga mantap...
0.012664
pakai new avanza bu . Boros bensin haha
0.112813
yamaha lexi speed nya gila, tarikan nya juara, ...
0.028442
secara keseluruhan avanza bagus kecuali pemakai...
0.090878
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.077425
kalo gak mau boros jangan beli scoopy
0.120673
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.011639
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.013199
```

```
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.132082
vario jauh lebih boros daripada mio
0.019689
Dari semua merek mobil yang pernah saya pakai ,...
0.091465
ampun deh punya xenia uang habis cuma buat kons...
0.035234
livina di tempat gue bensin nya asli boros bang...
0.046680
avanza bahan bakar nya boros banget
0.096074

sentence                                                dari segi
kenyamanan cortez oke lah, tapi bahan bakar nya itu loh boros
banget  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.013448
dari segi kenyamanan cortez oke lah, tapi bahan...
1.000000
kalau sudah di atas 120 km / jam boros banget a...
0.066794
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.124784
sudah harga nya mahal, fortuner ini juga konsum...
0.162354
Asli avanza saya boros akhir-akhir ini
0.017364
walaupun secara keseluruha oke tapi kalo bensin...
0.155417
ertiga gaya nya oke banget, tarikan juga mantap...
0.257034
pakai new avanza bu . Boros bensin haha
0.020445
yamaha lexi speed nya gila, tarikan nya juara, ...
0.071597
secara keseluruhan avanza bagus kecuali pemakai...
0.016470
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.051302
kalo gak mau boros jangan beli scoopy
0.018659
xenia 1:8 - 9 boros juga ya juragan , karena bo...
```

0.035203
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.039921
kata orang yang XI malah lebih irit dari yang L...
0.065117
Ini gue saja yang merasa bensin Xenia boros ban...
0.055222
vario jauh lebih boros daripada mio
0.020455
Dari semua merek mobil yang pernah saya pakai ,...
0.080620
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.080207
avanza bahan bakar nya boros banget
0.401044

sentence kalau sudah di atas 120 km / jam boros banget avanza saya , terus kopling nya memang agak keras juragan . \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.093155
dari segi kenyamanan cortez oke lah, tapi bahan...
0.066794
kalau sudah di atas 120 km / jam boros banget a...
1.000000
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.132843
sudah harga nya mahal, fortuner ini juga konsum...
0.100861
Asli avanza saya boros akhir-akhir ini
0.109522
walaupun secara keseluruha oke tapi kalo bensin...
0.012831
ertiga gaya nya oke banget, tarikan juga mantap...
0.114502
pakai new avanza bu . Boros bensin haha
0.059101
yamaha lexi speed nya gila, tarikan nya juara, ...
0.061481
secara keseluruhan avanza bagus kecuali pemakai...
0.047609
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.072565

```
kalo gak mau boros jangan beli scoopy
0.016023
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.089614
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.034280
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.108383
vario jauh lebih boros daripada mio
0.017565
Dari semua merek mobil yang pernah saya pakai ,...
0.060468
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.268526
avanza bahan bakar nya boros banget
0.202001

sentence                                                Rush konde
konsumsi BBM yang tetap irit .  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.000000
dari segi kenyamanan cortez oke lah, tapi bahan...
0.000000
kalau sudah di atas 120 km / jam boros banget a...
0.000000
Rush konde konsumsi BBM yang tetap irit .
1.000000
pengalaman saya punya avanza bahan bakar nya le...
0.000000
sudah harga nya mahal, fortuner ini juga konsum...
0.071223
Asli avanza saya boros akhir-akhir ini
0.000000
walaupun secara keseluruha oke tapi kalo bensin...
0.000000
ertiga gaya nya oke banget, tarikan juga mantap...
0.000000
pakai new avanza bu . Boros bensin haha
0.000000
yamaha lexi speed nya gila, tarikan nya juara, ...
0.000000
secara keseluruhan avanza bagus kecuali pemakai...
0.073462
```

```
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.072516
kalo gak mau boros jangan beli scoopy
0.000000
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.000000
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.000000
kata orang yang XI malah lebih irit dari yang L...
0.226482
Ini gue saja yang merasa bensin Xenia boros ban...
0.067369
vario jauh lebih boros daripada mio
0.000000
Dari semua merek mobil yang pernah saya pakai ,...
0.063082
ampun deh punya xenia uang habis cuma buat kons...
0.079947
livina di tempat gue bensin nya asli boros bang...
0.000000
avanza bahan bakar nya boros banget
0.000000

sentence                                                pengalaman saya
punya avanza bahan bakar nya lebih hemat daripada ketika saya punya
xenia  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.028798
dari segi kenyamanan cortez oke lah, tapi bahan...
0.124784
kalau sudah di atas 120 km / jam boros banget a...
0.132843
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
1.000000
sudah harga nya mahal, fortuner ini juga konsum...
0.146920
Asli avanza saya boros akhir-akhir ini
0.162230
walaupun secara keseluruha oke tapi kalo bensin...
0.000000
ertiga gaya nya oke banget, tarikan juga mantap...
0.045511
pakai new avanza bu . Boros bensin haha
0.043781
yamaha lexi speed nya gila, tarikan nya juara, ...
```

0.064791
secara keseluruhan avanza bagus kecuali pemakai...
0.035269
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.030048
kalo gak mau boros jangan beli scoopy
0.000000
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.064456
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.023717
kata orang yang XI malah lebih irit dari yang L...
0.058926
Ini gue saja yang merasa bensin Xenia boros ban...
0.054386
vario jauh lebih boros daripada mio
0.192872
Dari semua merek mobil yang pernah saya pakai ,...
0.101851
ampun deh punya xenia uang habis cuma buat kons...
0.215826
livina di tempat gue bensin nya asli boros bang...
0.024916
avanza bahan bakar nya boros banget
0.328311

sentence sudah harga nya mahal, fortuner ini juga konsumsi bahan bakar nya lumayan menguras dompet \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.062352
dari segi kenyamanan cortez oke lah, tapi bahan...
0.162354
kalau sudah di atas 120 km / jam boros banget a...
0.100861
Rush konde konsumsi BBM yang tetap irit .
0.071223
pengalaman saya punya avanza bahan bakar nya le...
0.146920
sudah harga nya mahal, fortuner ini juga konsum...
1.000000
Asli avanza saya boros akhir-akhir ini
0.068151
walaupun secara keseluruha oke tapi kalo bensin...
0.000000
ertiga gaya nya oke banget, tarikan juga mantap...
0.150855

```
pakai new avanza bu . Boros bensin haha
0.000000
yamaha lexi speed nya gila, tarikan nya juara, ...
0.141244
secara keseluruhan avanza bagus kecuali pemakai...
0.000000
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.055073
kalo gak mau boros jangan beli scoopy
0.000000
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.093053
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.169105
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.059281
vario jauh lebih boros daripada mio
0.000000
Dari semua merek mobil yang pernah saya pakai ,...
0.121081
ampun deh punya xenia uang habis cuma buat kons...
0.060716
livina di tempat gue bensin nya asli boros bang...
0.054318
avanza bahan bakar nya boros banget
0.344548

sentence                                                Asli avanza saya
boros akhir-akhir ini  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.056262
dari segi kenyamanan cortez oke lah, tapi bahan...
0.017364
kalau sudah di atas 120 km / jam boros banget a...
0.109522
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.162230
sudah harga nya mahal, fortuner ini juga konsum...
0.068151
Asli avanza saya boros akhir-akhir ini
1.000000
walaupun secara keseluruha oke tapi kalo bensin...
0.018570
```

```
ertiga gaya nya oke banget, tarikan juga mantap...
0.016352
pakai new avanza bu . Boros bensin haha
0.085535
yamaha lexi speed nya gila, tarikan nya juara, ...
0.000000
secara keseluruhan avanza bagus kecuali pemakai...
0.068904
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.058703
kalo gak mau boros jangan beli scoopy
0.023189
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.015028
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.017042
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.093461
vario jauh lebih boros daripada mio
0.025421
Dari semua merek mobil yang pernah saya pakai ,...
0.157451
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.120301
avanza bahan bakar nya boros banget
0.124048

sentence                                                walaupun secara
keseluruha oke tapi kalo bensinnya boros jadi malas beli  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.096638
dari segi kenyamanan cortez oke lah, tapi bahan...
0.155417
kalau sudah di atas 120 km / jam boros banget a...
0.012831
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.000000
sudah harga nya mahal, fortuner ini juga konsum...
0.000000
Asli avanza saya boros akhir-akhir ini
0.018570
```

```
walaupun secara keseluruha oke tapi kalo bensin...
1.000000
ertiga gaya nya oke banget, tarikan juga mantap...
0.146356
pakai new avanza bu . Boros bensin haha
0.021866
yamaha lexi speed nya gila, tarikan nya juara, ...
0.000000
secara keseluruhan avanza bagus kecuali pemakai...
0.118352
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.015007
kalo gak mau boros jangan beli scoopy
0.248212
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.012933
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.014666
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.016153
vario jauh lebih boros daripada mio
0.021877
Dari semua merek mobil yang pernah saya pakai ,...
0.015126
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.015408
avanza bahan bakar nya boros banget
0.031711

sentence                                                ertiga gaya nya
oke banget, tarikan juga mantap dan bandel tapi sayang nya boros
banget  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.012664
dari segi kenyamanan cortez oke lah, tapi bahan...
0.257034
kalau sudah di atas 120 km / jam boros banget a...
0.114502
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.045511
sudah harga nya mahal, fortuner ini juga konsum...
```

```
0.150855
Asli avanza saya boros akhir-akhir ini
0.016352
walaupun secara keseluruha oke tapi kalo bensin...
0.146356
ertiga gaya nya oke banget, tarikan juga mantap...
1.000000
pakai new avanza bu . Boros bensin haha
0.019253
yamaha lexi speed nya gila, tarikan nya juara, ...
0.202100
secara keseluruhan avanza bagus kecuali pemakai...
0.015510
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.083408
kalo gak mau boros jangan beli scoopy
0.017571
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.165350
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.113658
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.089781
vario jauh lebih boros daripada mio
0.019263
Dari semua merek mobil yang pernah saya pakai ,...
0.013318
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.137495
avanza bahan bakar nya boros banget
0.282983

sentence                                                pakai new avanza
bu . Boros bensin haha  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.112813
dari segi kenyamanan cortez oke lah, tapi bahan...
0.020445
kalau sudah di atas 120 km / jam boros banget a...
0.059101
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
```

```
0.043781
sudah harga nya mahal, fortuner ini juga konsum...
0.000000
Asli avanza saya boros akhir-akhir ini
0.085535
walaupun secara keseluruha oke tapi kalo bensin...
0.021866
ertiga gaya nya oke banget, tarikan juga mantap...
0.019253
pakai new avanza bu . Boros bensin haha
1.000000
yamaha lexi speed nya gila, tarikan nya juara, ...
0.043241
secara keseluruhan avanza bagus kecuali pemakai...
0.138162
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.117709
kalo gak mau boros jangan beli scoopy
0.027304
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.017695
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.020067
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.074403
vario jauh lebih boros daripada mio
0.029933
Dari semua merek mobil yang pernah saya pakai ,...
0.139055
ampun deh punya xenia uang habis cuma buat kons...
0.053567
livina di tempat gue bensin nya asli boros bang...
0.070968
avanza bahan bakar nya boros banget
0.146062

sentence                                            ...  \
sentence                                            ...
Avanza kenapa jadi boros bensin begini dah ah. ...  ...
dari segi kenyamanan cortez oke lah, tapi bahan...  ...
kalau sudah di atas 120 km / jam boros banget a...  ...
Rush konde konsumsi BBM yang tetap irit .           ...
pengalaman saya punya avanza bahan bakar nya le...  ...
sudah harga nya mahal, fortuner ini juga konsum...  ...
Asli avanza saya boros akhir-akhir ini              ...
walaupun secara keseluruha oke tapi kalo bensin...  ...
ertiga gaya nya oke banget, tarikan juga mantap...  ...
pakai new avanza bu . Boros bensin haha             ...
```

```
yamaha lexi speed nya gila, tarikan nya juara, ...  ...
secara keseluruhan avanza bagus kecuali pemakai...  ...
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...  ...
kalo gak mau boros jangan beli scoopy               ...
xenia 1:8 - 9 boros juga ya juragan , karena bo...  ...
Grand Livina XV AT 2008 ngelitik nya parah kak ...  ...
kata orang yang XI malah lebih irit dari yang L...  ...
Ini gue saja yang merasa bensin Xenia boros ban...  ...
vario jauh lebih boros daripada mio                 ...
Dari semua merek mobil yang pernah saya pakai ,...  ...
ampun deh punya xenia uang habis cuma buat kons...  ...
livina di tempat gue bensin nya asli boros bang...  ...
avanza bahan bakar nya boros banget                 ...

sentence                                            kalo gak mau boros
jangan beli scoopy  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.120673
dari segi kenyamanan cortez oke lah, tapi bahan...
0.018659
kalau sudah di atas 120 km / jam boros banget a...
0.016023
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.000000
sudah harga nya mahal, fortuner ini juga konsum...
0.000000
Asli avanza saya boros akhir-akhir ini
0.023189
walaupun secara keseluruha oke tapi kalo bensin...
0.248212
ertiga gaya nya oke banget, tarikan juga mantap...
0.017571
pakai new avanza bu . Boros bensin haha
0.027304
yamaha lexi speed nya gila, tarikan nya juara, ...
0.000000
secara keseluruhan avanza bagus kecuali pemakai...
0.021995
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.018739
kalo gak mau boros jangan beli scoopy
1.000000
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.016149
Grand Livina XV AT 2008 ngelitik nya parah kak ...
```

0.018314
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.020171
vario jauh lebih boros daripada mio
0.027318
Dari semua merek mobil yang pernah saya pakai ,...
0.018887
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.019240
avanza bahan bakar nya boros banget
0.039599

sentence xenia 1:8 - 9
boros juga ya juragan , karena bodi besar nya dan cc kecil mungkin ya . \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.011639
dari segi kenyamanan cortez oke lah, tapi bahan...
0.035203
kalau sudah di atas 120 km / jam boros banget a...
0.089614
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.064456
sudah harga nya mahal, fortuner ini juga konsum...
0.093053
Asli avanza saya boros akhir-akhir ini
0.015028
walaupun secara keseluruha oke tapi kalo bensin...
0.012933
ertiga gaya nya oke banget, tarikan juga mantap...
0.165350
pakai new avanza bu . Boros bensin haha
0.017695
yamaha lexi speed nya gila, tarikan nya juara, ...
0.061966
secara keseluruhan avanza bagus kecuali pemakai...
0.014254
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.012144
kalo gak mau boros jangan beli scoopy
0.016149

```
xenia 1:8 - 9 boros juga ya juragan , karena bo...
1.000000
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.081776
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.065087
vario jauh lebih boros daripada mio
0.017704
Dari semua merek mobil yang pernah saya pakai ,...
0.012240
ampun deh punya xenia uang habis cuma buat kons...
0.053274
livina di tempat gue bensin nya asli boros bang...
0.036299
avanza bahan bakar nya boros banget
0.074708

sentence                                                Grand Livina XV AT
2008 ngelitik nya parah kak sekarang juga lumayan boros  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.013199
dari segi kenyamanan cortez oke lah, tapi bahan...
0.039921
kalau sudah di atas 120 km / jam boros banget a...
0.034280
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.023717
sudah harga nya mahal, fortuner ini juga konsum...
0.169105
Asli avanza saya boros akhir-akhir ini
0.017042
walaupun secara keseluruha oke tapi kalo bensin...
0.014666
ertiga gaya nya oke banget, tarikan juga mantap...
0.113658
pakai new avanza bu . Boros bensin haha
0.020067
yamaha lexi speed nya gila, tarikan nya juara, ...
0.070271
secara keseluruhan avanza bagus kecuali pemakai...
0.016165
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.013772
```

```
kalo gak mau boros jangan beli scoopy
0.018314
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.081776
Grand Livina XV AT 2008 ngelitik nya parah kak ...
1.000000
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.014824
vario jauh lebih boros daripada mio
0.020076
Dari semua merek mobil yang pernah saya pakai ,...
0.079127
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.202900
avanza bahan bakar nya boros banget
0.084721

sentence                                          kata orang yang XI
malah lebih irit dari yang LI nih .  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.000000
dari segi kenyamanan cortez oke lah, tapi bahan...
0.065117
kalau sudah di atas 120 km / jam boros banget a...
0.000000
Rush konde konsumsi BBM yang tetap irit .
0.226482
pengalaman saya punya avanza bahan bakar nya le...
0.058926
sudah harga nya mahal, fortuner ini juga konsum...
0.000000
Asli avanza saya boros akhir-akhir ini
0.000000
walaupun secara keseluruha oke tapi kalo bensin...
0.000000
ertiga gaya nya oke banget, tarikan juga mantap...
0.000000
pakai new avanza bu . Boros bensin haha
0.000000
yamaha lexi speed nya gila, tarikan nya juara, ...
0.000000
secara keseluruhan avanza bagus kecuali pemakai...
0.112164
```

```
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.000000
kalo gak mau boros jangan beli scoopy
0.000000
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.000000
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.000000
kata orang yang XI malah lebih irit dari yang L...
1.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.102861
vario jauh lebih boros daripada mio
0.095333
Dari semua merek mobil yang pernah saya pakai ,...
0.162229
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.000000
avanza bahan bakar nya boros banget
0.000000

sentence                                            Ini gue saja yang
merasa bensin Xenia boros banget apa memang iya sih  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.132082
dari segi kenyamanan cortez oke lah, tapi bahan...
0.055222
kalau sudah di atas 120 km / jam boros banget a...
0.108383
Rush konde konsumsi BBM yang tetap irit .
0.067369
pengalaman saya punya avanza bahan bakar nya le...
0.054386
sudah harga nya mahal, fortuner ini juga konsum...
0.059281
Asli avanza saya boros akhir-akhir ini
0.093461
walaupun secara keseluruha oke tapi kalo bensin...
0.016153
ertiga gaya nya oke banget, tarikan juga mantap...
0.089781
pakai new avanza bu . Boros bensin haha
0.074403
yamaha lexi speed nya gila, tarikan nya juara, ...
0.031944
```

```
secara keseluruhan avanza bagus kecuali pemakai...
0.121081
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.091353
kalo gak mau boros jangan beli scoopy
0.020171
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.065087
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.014824
kata orang yang XI malah lebih irit dari yang L...
0.102861
Ini gue saja yang merasa bensin Xenia boros ban...
1.000000
vario jauh lebih boros daripada mio
0.022113
Dari semua merek mobil yang pernah saya pakai ,...
0.128629
ampun deh punya xenia uang habis cuma buat kons...
0.106115
livina di tempat gue bensin nya asli boros bang...
0.345139
avanza bahan bakar nya boros banget
0.117192

sentence                                          vario jauh lebih
boros daripada mio  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.019689
dari segi kenyamanan cortez oke lah, tapi bahan...
0.020455
kalau sudah di atas 120 km / jam boros banget a...
0.017565
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.192872
sudah harga nya mahal, fortuner ini juga konsum...
0.000000
Asli avanza saya boros akhir-akhir ini
0.025421
walaupun secara keseluruha oke tapi kalo bensin...
0.021877
ertiga gaya nya oke banget, tarikan juga mantap...
0.019263
pakai new avanza bu . Boros bensin haha
0.029933
```

```
yamaha lexi speed nya gila, tarikan nya juara, ...
0.000000
secara keseluruhan avanza bagus kecuali pemakai...
0.024112
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.020543
kalo gak mau boros jangan beli scoopy
0.027318
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.017704
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.020076
kata orang yang XI malah lebih irit dari yang L...
0.095333
Ini gue saja yang merasa bensin Xenia boros ban...
0.022113
vario jauh lebih boros daripada mio
1.000000
Dari semua merek mobil yang pernah saya pakai ,...
0.020705
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.021092
avanza bahan bakar nya boros banget
0.043410

sentence                                                Dari semua merek
mobil yang pernah saya pakai , terios baru ini lumayan boros .  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.091465
dari segi kenyamanan cortez oke lah, tapi bahan...
0.080620
kalau sudah di atas 120 km / jam boros banget a...
0.060468
Rush konde konsumsi BBM yang tetap irit .
0.063082
pengalaman saya punya avanza bahan bakar nya le...
0.101851
sudah harga nya mahal, fortuner ini juga konsum...
0.121081
Asli avanza saya boros akhir-akhir ini
0.157451
walaupun secara keseluruha oke tapi kalo bensin...
0.015126
ertiga gaya nya oke banget, tarikan juga mantap...
0.013318
```

```
pakai new avanza bu . Boros bensin haha
0.139055
yamaha lexi speed nya gila, tarikan nya juara, ...
0.000000
secara keseluruhan avanza bagus kecuali pemakai...
0.073925
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.014203
kalo gak mau boros jangan beli scoopy
0.018887
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.012240
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.079127
kata orang yang XI malah lebih irit dari yang L...
0.162229
Ini gue saja yang merasa bensin Xenia boros ban...
0.128629
vario jauh lebih boros daripada mio
0.020705
Dari semua merek mobil yang pernah saya pakai ,...
1.000000
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.014583
avanza bahan bakar nya boros banget
0.030014

sentence                                          ampun deh punya
xenia uang habis cuma buat konsumsi bensin  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.035234
dari segi kenyamanan cortez oke lah, tapi bahan...
0.000000
kalau sudah di atas 120 km / jam boros banget a...
0.000000
Rush konde konsumsi BBM yang tetap irit .
0.079947
pengalaman saya punya avanza bahan bakar nya le...
0.215826
sudah harga nya mahal, fortuner ini juga konsum...
0.060716
Asli avanza saya boros akhir-akhir ini
0.000000
walaupun secara keseluruha oke tapi kalo bensin...
0.000000
```

```
ertiga gaya nya oke banget, tarikan juga mantap...
0.000000
pakai new avanza bu . Boros bensin haha
0.053567
yamaha lexi speed nya gila, tarikan nya juara, ...
0.111790
secara keseluruhan avanza bagus kecuali pemakai...
0.043151
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.098582
kalo gak mau boros jangan beli scoopy
0.000000
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.053274
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.000000
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.106115
vario jauh lebih boros daripada mio
0.000000
Dari semua merek mobil yang pernah saya pakai ,...
0.000000
ampun deh punya xenia uang habis cuma buat kons...
1.000000
livina di tempat gue bensin nya asli boros bang...
0.037746
avanza bahan bakar nya boros banget
0.000000

sentence                                                livina di tempat
gue bensin nya asli boros banget kalau soal ngelitik memang iya  \
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.046680
dari segi kenyamanan cortez oke lah, tapi bahan...
0.080207
kalau sudah di atas 120 km / jam boros banget a...
0.268526
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.024916
sudah harga nya mahal, fortuner ini juga konsum...
0.054318
Asli avanza saya boros akhir-akhir ini
0.120301
```

```
walaupun secara keseluruha oke tapi kalo bensin...
0.015408
ertiga gaya nya oke banget, tarikan juga mantap...
0.137495
pakai new avanza bu . Boros bensin haha
0.070968
yamaha lexi speed nya gila, tarikan nya juara, ...
0.104295
secara keseluruhan avanza bagus kecuali pemakai...
0.057169
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.087137
kalo gak mau boros jangan beli scoopy
0.019240
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.036299
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.202900
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.345139
vario jauh lebih boros daripada mio
0.021092
Dari semua merek mobil yang pernah saya pakai ,...
0.014583
ampun deh punya xenia uang habis cuma buat kons...
0.037746
livina di tempat gue bensin nya asli boros bang...
1.000000
avanza bahan bakar nya boros banget
0.170215

sentence                                                avanza bahan bakar
nya boros banget
sentence

Avanza kenapa jadi boros bensin begini dah ah. ...
0.096074
dari segi kenyamanan cortez oke lah, tapi bahan...
0.401044
kalau sudah di atas 120 km / jam boros banget a...
0.202001
Rush konde konsumsi BBM yang tetap irit .
0.000000
pengalaman saya punya avanza bahan bakar nya le...
0.328311
sudah harga nya mahal, fortuner ini juga konsum...
0.344548
```

```
Asli avanza saya boros akhir-akhir ini
0.124048
walaupun secara keseluruha oke tapi kalo bensin...
0.031711
ertiga gaya nya oke banget, tarikan juga mantap...
0.282983
pakai new avanza bu . Boros bensin haha
0.146062
yamaha lexi speed nya gila, tarikan nya juara, ...
0.151944
secara keseluruhan avanza bagus kecuali pemakai...
0.117662
Masa konsumsi bensin Toyota Avanza Veloz 12,5 l...
0.179339
kalo gak mau boros jangan beli scoopy
0.039599
xenia 1:8 - 9 boros juga ya juragan , karena bo...
0.074708
Grand Livina XV AT 2008 ngelitik nya parah kak ...
0.084721
kata orang yang XI malah lebih irit dari yang L...
0.000000
Ini gue saja yang merasa bensin Xenia boros ban...
0.117192
vario jauh lebih boros daripada mio
0.043410
Dari semua merek mobil yang pernah saya pakai ,...
0.030014
ampun deh punya xenia uang habis cuma buat kons...
0.000000
livina di tempat gue bensin nya asli boros bang...
0.170215
avanza bahan bakar nya boros banget
1.000000

[23 rows x 23 columns]
```

4. Text Clustering

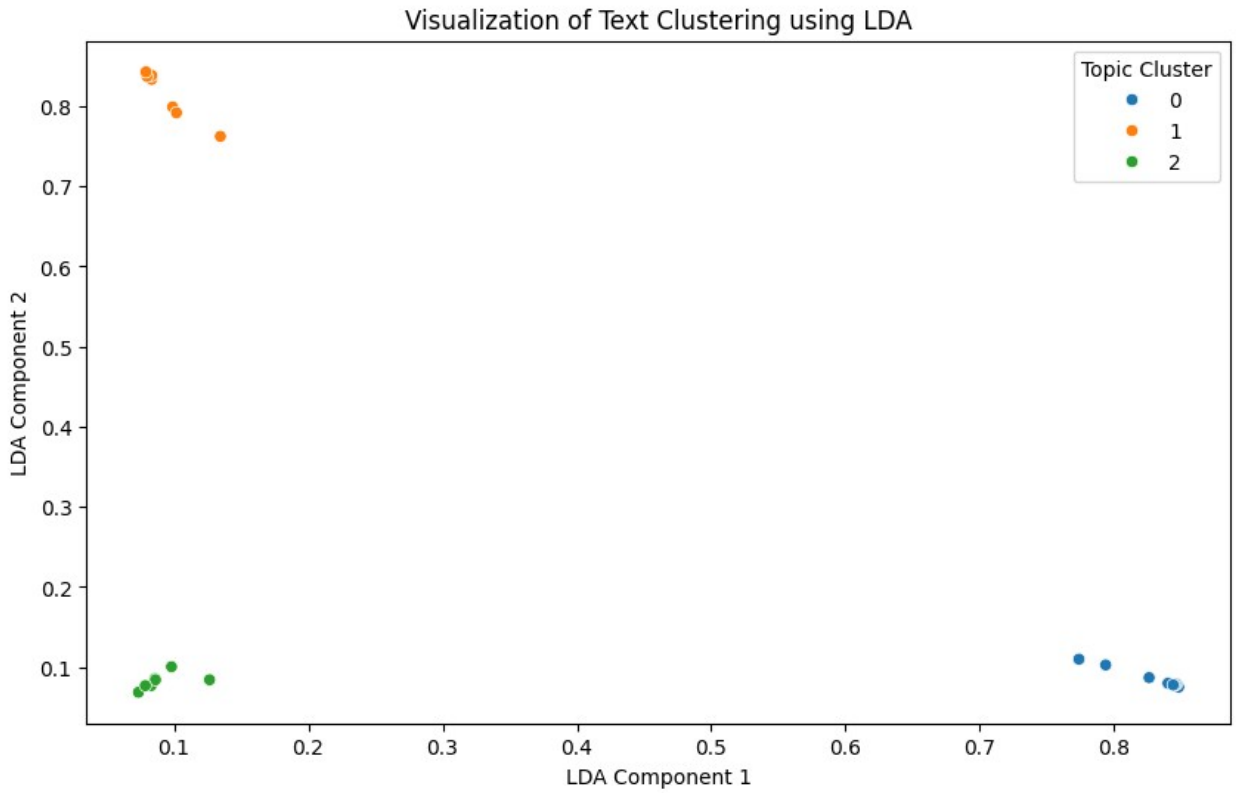
This section applies clustering techniques on sentences where the fuel column has a negative sentiment.

```python
from sklearn.cluster import KMeans

# Choose number of clusters (can be adjusted)
num_clusters = 3

# Apply KMeans clustering
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
```

```
negative_fuel_df['cluster'] = kmeans.fit_predict(tfidf_matrix)

# Display clustered sentences
print(negative_fuel_df[['sentence',
'cluster']].sort_values(by='cluster'))


import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.decomposition import LatentDirichletAllocation

# Perform LDA for topic modeling
num_topics = 3  # Adjust the number of topics as needed
lda = LatentDirichletAllocation(n_components=num_topics,
random_state=42)
lda_matrix = lda.fit_transform(tfidf_matrix)

# Assign the most probable topic to each sentence
negative_fuel_df['LDA_Topic'] = np.argmax(lda_matrix, axis=1)

# Visualize the clustering
plt.figure(figsize=(10, 6))
sns.scatterplot(x=lda_matrix[:, 0], y=lda_matrix[:, 1],
hue=negative_fuel_df['LDA_Topic'], palette="tab10")
plt.xlabel("LDA Component 1")
plt.ylabel("LDA Component 2")
plt.title("Visualization of Text Clustering using LDA")
plt.legend(title="Topic Cluster")
plt.show()
```

	sentence	cluster
762	avanza bahan bakar nya boros banget	0
38	dari segi kenyamanan cortez oke lah, tapi baha...	0
113	kalau sudah di atas 120 km / jam boros banget ...	0
157	sudah harga nya mahal, fortuner ini juga konsu...	0
342	walaupun secara keseluruha oke tapi kalo bensi...	0
385	ertiga gaya nya oke banget, tarikan juga manta...	0
394	yamaha lexi speed nya gila, tarikan nya juara,...	0
499	Grand Livina XV AT 2008 ngelitik nya parah kak...	0
448	xenia 1:8 - 9 boros juga ya juragan , karena b...	0
632	ampun deh punya xenia uang habis cuma buat kon...	1
626	Dari semua merek mobil yang pernah saya pakai ...	1
581	vario jauh lebih boros daripada mio	1
555	Ini gue saja yang merasa bensin Xenia boros ba...	1
1	Avanza kenapa jadi boros bensin begini dah ah....	1
418	Masa konsumsi bensin Toyota Avanza Veloz 12,5 ...	1

```
641  livina di tempat gue bensin nya asli boros ban...        1
390            pakai new avanza bu . Boros bensin haha        1
276             Asli avanza saya boros akhir-akhir ini        1
124  pengalaman saya punya avanza bahan bakar nya l...        1
419              kalo gak mau boros jangan beli scoopy        1
407  secara keseluruhan avanza bagus kecuali pemaka...        1
517  kata orang yang XI malah lebih irit dari yang ...        2
116          Rush konde konsumsi BBM yang tetap irit .        2
```




```python
# Function to display the top words for each topic
def display_topics(model, feature_names, num_words=10):
    topics = {}
    for topic_idx, topic in enumerate(model.components_):
        topics[f"Topic {topic_idx}"] = [feature_names[i] for i in
topic.argsort()[:-num_words - 1:-1]]

    # Convert topics to a DataFrame for display
    topics_df = pd.DataFrame(topics)

    return topics_df

# Get feature names from the TF-IDF vectorizer
feature_names = vectorizer.get_feature_names_out()

# Display the top words in each topic
```

```
topics = display_topics(lda, feature_names)
topics.head()
```

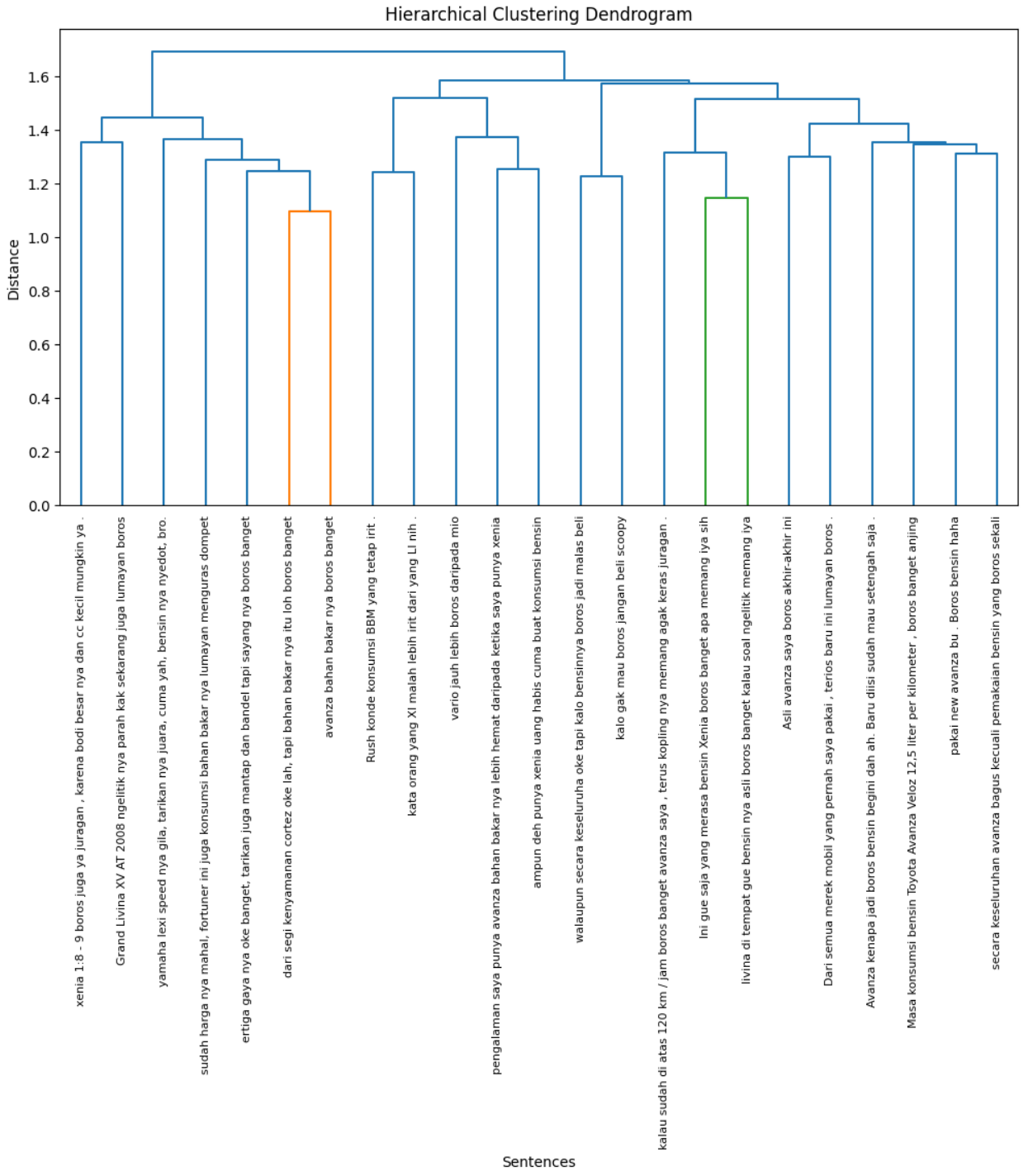

```
{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"Topic 0","rawType":"object","type":"string"},{"name":"Topic
1","rawType":"object","type":"string"},{"name":"Topic
2","rawType":"object","type":"string"}],"conversionMethod":"pd.DataFra
me","ref":"25b8986a-72e9-4410-be4c-77b24184e92a","rows":
[["0","nya","boros","punya"],["1","avanza","juga","memang"],
["2","boros","nya","xenia"],["3","bakar","ya","yang"],
["4","bahan","oke","saya"]],"shape":{"columns":3,"rows":5}}
```


```
# Function to display the top words for each topic per cluster
def display_cluster_topics(model, feature_names, num_words=10):
    topics = {}
    for topic_idx, topic in enumerate(model.components_):
        topics[f"Topic {topic_idx}"] = [feature_names[i] for i in
topic.argsort()[:-num_words - 1:-1]]

    # Convert topics to a DataFrame for display
    topics_df = pd.DataFrame(topics)

    # Associate topics with clusters
    cluster_topics = negative_fuel_df[['sentence',
'LDA_Topic']].copy()
    cluster_topics['Topic Words'] =
cluster_topics['LDA_Topic'].apply(lambda x: ",
".join(topics_df[f"Topic {x}"]))

    return cluster_topics

# Get feature names from the TF-IDF vectorizer
feature_names = vectorizer.get_feature_names_out()

# Display the top words in each topic per cluster
topic_cluster = display_cluster_topics(lda, feature_names)
topic_cluster.head()
```


```
{"columns":[{"name":"index","rawType":"int64","type":"integer"},
{"name":"sentence","rawType":"object","type":"string"},
{"name":"LDA_Topic","rawType":"int64","type":"integer"},{"name":"Topic
Words","rawType":"object","type":"string"}],"conversionMethod":"pd.Dat
aFrame","ref":"df593378-50f2-4a49-ad11-2f8b08609634","rows":
[["1","Avanza kenapa jadi boros bensin begini dah ah. Baru diisi sudah
mau setengah saja .","0","nya, avanza, boros, bakar, bahan, banget,
akhir, bensin, ini, baru"],["38","dari segi kenyamanan cortez oke lah,
tapi bahan bakar nya itu loh boros banget","0","nya, avanza, boros,
bakar, bahan, banget, akhir, bensin, ini, baru"],["113","kalau sudah
di atas 120 km / jam boros banget avanza saya , terus kopling nya
memang agak keras juragan .","2","punya, memang, xenia, yang, saya,
```

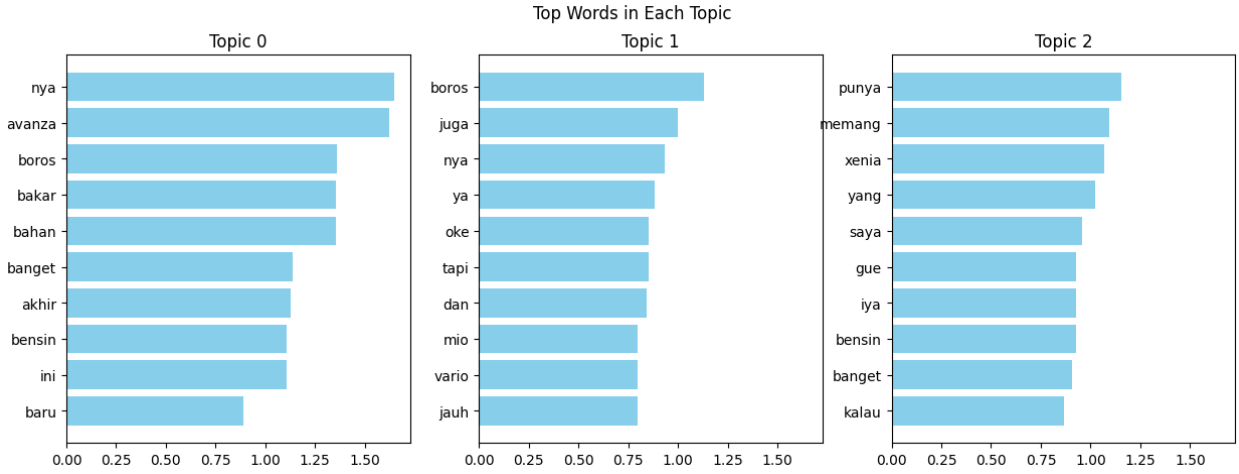
gue, iya, bensin, banget, kalau"],["116","Rush konde konsumsi BBM yang tetap irit .","1","boros, juga, nya, ya, oke, tapi, dan, mio, vario, jauh"],["124","pengalaman saya punya avanza bahan bakar nya lebih hemat daripada ketika saya punya xenia","2","punya, memang, xenia, yang, saya, gue, iya, bensin, banget, kalau"]],"shape":{"columns":3,"rows":5}}

```
import scipy.cluster.hierarchy as sch
import matplotlib.pyplot as plt

# Perform hierarchical clustering
linkage_matrix = sch.linkage(tfidf_matrix.toarray(), method='ward')

# Plot the dendrogram
plt.figure(figsize=(12, 6))
sch.dendrogram(linkage_matrix,
labels=negative_fuel_df['sentence'].values, leaf_rotation=90,
leaf_font_size=8)
plt.title("Hierarchical Clustering Dendrogram")
plt.xlabel("Sentences")
plt.ylabel("Distance")
plt.show()
```




```
from wordcloud import WordCloud
import matplotlib.pyplot as plt
import numpy as np

# Function to plot word clouds for topics
def plot_word_clouds(model, feature_names, num_words=10):
    fig, axes = plt.subplots(1, model.n_components, figsize=(15, 5))
```

```
    for topic_idx, topic in enumerate(model.components_):
        word_freqs = {feature_names[i]: topic[i] for i in
topic.argsort()[:-num_words - 1:-1]}
        wordcloud =
WordCloud(background_color="white").generate_from_frequencies(word_fre
qs)
        axes[topic_idx].imshow(wordcloud, interpolation='bilinear')
        axes[topic_idx].axis("off")
        axes[topic_idx].set_title(f"Topic {topic_idx}")
    plt.suptitle("Topic Word Clouds")
    plt.show()

# Function to plot bar charts of top words per topic
def plot_top_words(model, feature_names, num_words=10):
    fig, axes = plt.subplots(1, model.n_components, figsize=(15, 5),
sharex=True)
    for topic_idx, topic in enumerate(model.components_):
        top_features_indices = topic.argsort()[:-num_words - 1:-1]
        top_features = [feature_names[i] for i in
top_features_indices]
        top_weights = topic[top_features_indices]

        axes[topic_idx].barh(top_features, top_weights,
color='skyblue')
        axes[topic_idx].invert_yaxis()
        axes[topic_idx].set_title(f"Topic {topic_idx}")

    plt.suptitle("Top Words in Each Topic")
    plt.show()

# Get feature names from the TF-IDF vectorizer
feature_names = vectorizer.get_feature_names_out()

# Plot word clouds and top words for topics
plot_word_clouds(lda, feature_names)
plot_top_words(lda, feature_names)
```



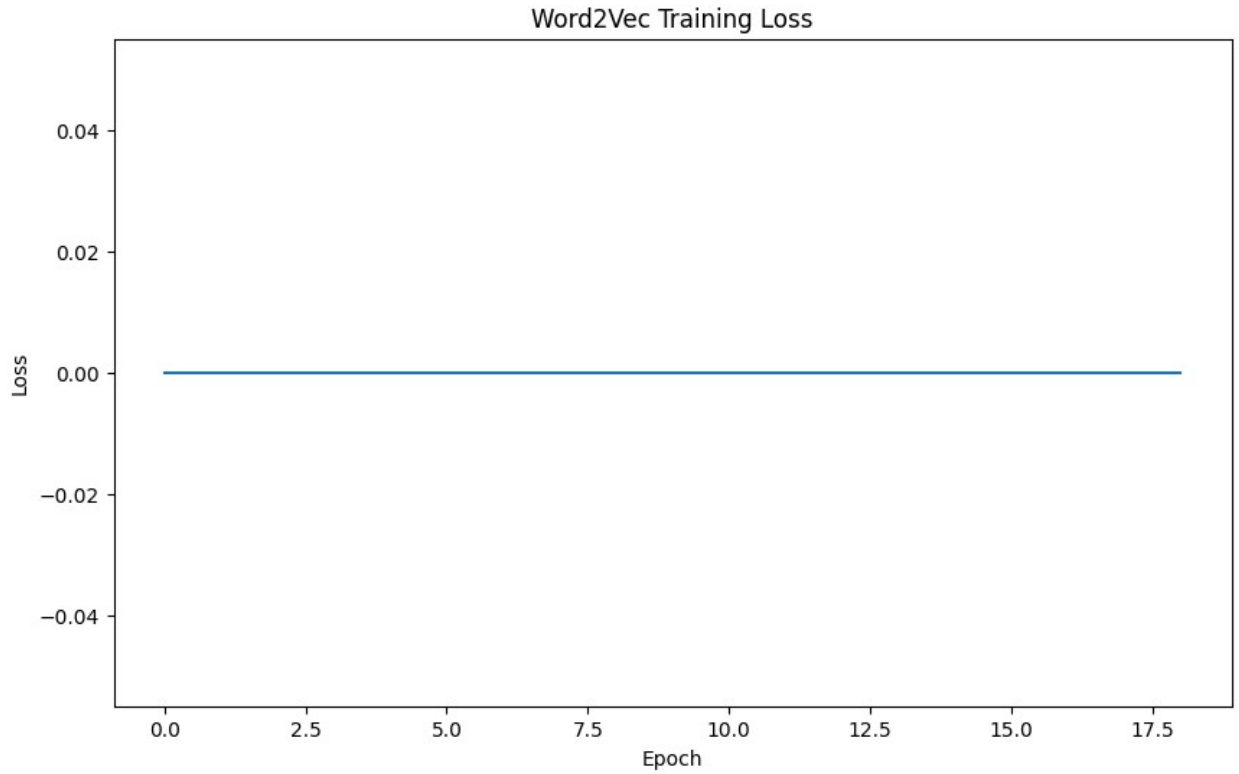
5. Clustering using word2vec

```
def average_word_vectors(words, model, vocabulary, num_features):
    feature_vector = np.zeros((num_features,), dtype="float64")
    nwords = 0.0

    for word in words:
        if word in vocabulary:
            nwords += 1.0
            feature_vector = np.add(feature_vector, model.wv[word])

    if nwords:
        feature_vector = np.divide(feature_vector, nwords)

    return feature_vector


# Function to vectorize sentences using the Word2Vec model
def averaged_word_vectorizer(corpus, model, num_features):
    vocabulary = set(model.wv.index_to_key)  # Get vocabulary words
    features = [
        average_word_vectors(tokenized_sentence, model,
                             vocabulary, num_features)
        for tokenized_sentence in corpus
    ]
    return np.array(features)

import gensim
from gensim.models import Word2Vec
from gensim.models.callbacks import CallbackAny2Vec
import numpy as np
import matplotlib.pyplot as plt

# Loss tracking callback
class EpochLogger(CallbackAny2Vec):
    def __init__(self):
```

```
        self.epoch = 0
        self.losses = []

    def on_epoch_end(self, model):
        loss = model.get_latest_training_loss()
        if self.epoch == 0:
            self.loss_previous_step = loss
        else:
            current_loss = loss - self.loss_previous_step
            self.losses.append(current_loss)
            self.loss_previous_step = loss
            print(f'Epoch: {self.epoch}, Loss: {current_loss}')
        self.epoch += 1




all_sentences = []
for df in [df, negative_fuel_df]:
    if 'sentence' in df.columns:
        tokenized = [enhanced_tokenizer(sent) for sent in
df['sentence']]
        all_sentences.extend(tokenized)

# Initialize callback
epoch_logger = EpochLogger()

# Train an enhanced Word2Vec model
w2v_model = Word2Vec(
    sentences=all_sentences,
    vector_size=200,         # Increased from 100
    window=6,                # Context window size
    min_count=2,             # Ignore words that appear less than this
    sg=1,                    # Use skip-gram (1) instead of CBOW (0)
    hs=0,                    # Use negative sampling instead of
hierarchical softmax
    negative=10,             # Number of negative samples per positive
sample
    ns_exponent=0.75,        # Negative sampling distribution exponent
    seed=42,                 # For reproducibility
    workers=4,               # Parallel processing
    epochs=20,               # More training iterations
    callbacks=[epoch_logger] # Track training progress
)

# Plot training loss
plt.figure(figsize=(10, 6))
plt.plot(epoch_logger.losses)
plt.title('Word2Vec Training Loss')
```

```
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()



# Evaluate similarity for key terms
test_words = ["mobil", "bensin", "boros", "avanza", "bbm", "konsumsi"]
for word in test_words:
    if word in w2v_model.wv:
        similar = w2v_model.wv.most_similar(word, topn=10)
        print(f"\nWords similar to '{word}':")
        for term, score in similar:
            print(f"  {term}: {score:.4f}")

# Visualization of word embeddings using PCA
```

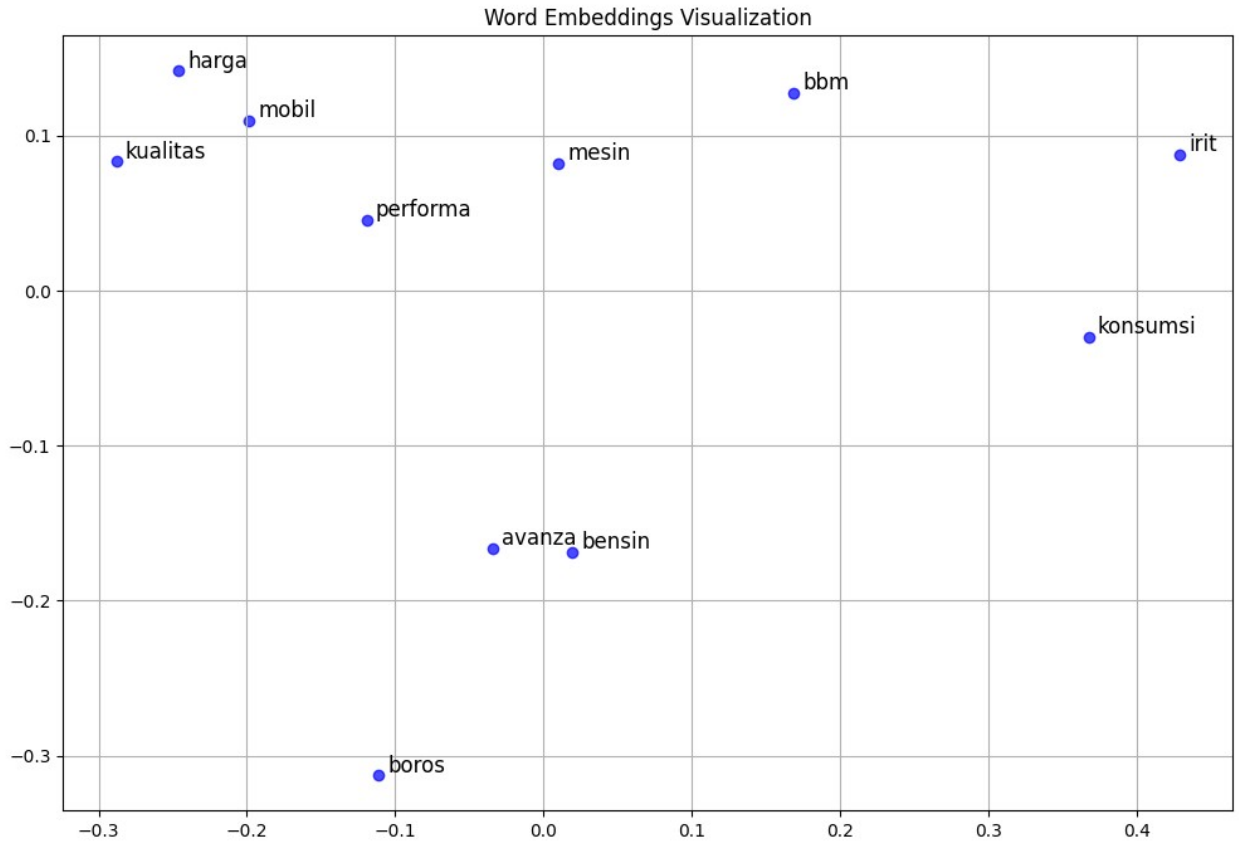
```
Epoch: 1, Loss: 0.0
Epoch: 2, Loss: 0.0
Epoch: 3, Loss: 0.0
Epoch: 4, Loss: 0.0
Epoch: 5, Loss: 0.0
Epoch: 6, Loss: 0.0
Epoch: 7, Loss: 0.0
Epoch: 8, Loss: 0.0
Epoch: 9, Loss: 0.0
Epoch: 10, Loss: 0.0
Epoch: 11, Loss: 0.0
Epoch: 12, Loss: 0.0
Epoch: 13, Loss: 0.0
Epoch: 14, Loss: 0.0
Epoch: 15, Loss: 0.0
Epoch: 16, Loss: 0.0
Epoch: 17, Loss: 0.0
Epoch: 18, Loss: 0.0
Epoch: 19, Loss: 0.0
```




```
Words similar to 'mobil':
  lcgc: 0.9937
  Confero: 0.9937
  murahan: 0.9933
  bangga: 0.9930
  Harga: 0.9929
  juta: 0.9929
  memilih: 0.9928
  indonesia: 0.9928
  Formo: 0.9927
  ragu: 0.9926

Words similar to 'bensin':
  liter: 0.9878
  12,5: 0.9846
  kak: 0.9841
  boros: 0.9838
  xenia: 0.9832
  kilometer: 0.9827
  ngelitik: 0.9825
  BBM: 0.9824
  menguras: 0.9821
  dompet: 0.9814

Words similar to 'boros':
```

```
  avanza: 0.9841
  bensin: 0.9838
  ngelitik: 0.9816
  kak: 0.9815
  120: 0.9804
  liter: 0.9799
  diisi: 0.9787
  penuh: 0.9786
  jam: 0.9775
  12,5: 0.9774

Words similar to 'avanza':
  penuh: 0.9876
  juragan: 0.9875
  nya: 0.9865
  cortez: 0.9849
  120: 0.9841
  boros: 0.9841
  mewah: 0.9837
  kenyamanan: 0.9836
  diisi: 0.9830
  menguras: 0.9830

Words similar to 'bbm':
  kota: 0.9915
  lumayan: 0.9874
  BBM: 0.9857
  dompet: 0.9837
  dikendarai: 0.9831
  Rush: 0.9828
  Beat: 0.9818
  dipakai: 0.9816
  bawa: 0.9812
  terbukti: 0.9811

Words similar to 'konsumsi':
  hemat: 0.9879
  irit: 0.9870
  Rush: 0.9732
  Calya: 0.9691
  lumayan: 0.9675
  bakar: 0.9655
  bahan: 0.9648
  bbm: 0.9638
  kendaraan: 0.9629
  dompet: 0.9628

from sklearn.decomposition import PCA
```

```
def plot_word_vectors(model, words):
    # Extract vectors for the words
    word_vectors = [model.wv[word] for word in words if word in
model.wv]
    words_found = [word for word in words if word in model.wv]

    # Apply PCA to reduce to 2 dimensions
    pca = PCA(n_components=2)
    reduced_vectors = pca.fit_transform(word_vectors)

    # Plot
    plt.figure(figsize=(12, 8))
    plt.scatter(reduced_vectors[:, 0],
                reduced_vectors[:, 1], c='blue', alpha=0.7)

    # Add labels for each point
    for i, word in enumerate(words_found):
        plt.annotate(word, xy=(reduced_vectors[i, 0],
reduced_vectors[i, 1]),
                     xytext=(5, 2), textcoords='offset points',
                     fontsize=12, color='black')

    plt.title('Word Embeddings Visualization')
    plt.grid(True)
    plt.show()


# Visualize vectors for automotive terms
automotive_terms = ["mobil", "bensin", "bahan_bakar", "avanza", "bbm",
"konsumsi",
                    "boros", "irit", "mesin", "performa", "harga",
"kualitas"]
plot_word_vectors(w2v_model, automotive_terms)
```




```
from sklearn.cluster import AffinityPropagation
from sklearn.decomposition import PCA
# Tokenize the sentences for word2vec vectorization
tokenized_sentences = [enhanced_tokenizer(sent) for sent in
negative_fuel_df['sentence']]

# Generate feature vectors using Word2Vec model
w2v_feature_array = averaged_word_vectorizer(
    corpus=tokenized_sentences, model=w2v_model,
num_features=w2v_model.vector_size
)
```

Clustering using KMeans and DBSCAN on word2vec embeddings of sentences where the fuel column has a negative sentiment.

```
from sklearn.cluster import KMeans, DBSCAN
from sklearn.metrics import silhouette_score
import pandas as pd
import numpy as np
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Apply KMeans clustering to the word2vec features
```

```python
def apply_kmeans_clustering(feature_array, max_clusters=10):
    """
    Apply KMeans clustering with evaluation metrics to find optimal
number of clusters
    """
    # Metrics for evaluation
    silhouette_scores = []
    inertias = []

    # Try different numbers of clusters
    for n_clusters in range(2, max_clusters+1):
        kmeans = KMeans(n_clusters=n_clusters, random_state=42,
n_init=10)
        cluster_labels = kmeans.fit_predict(feature_array)

        # Calculate evaluation metrics
        silhouette = silhouette_score(feature_array, cluster_labels)
        inertia = kmeans.inertia_

        silhouette_scores.append(silhouette)
        inertias.append(inertia)

        print(f"KMeans with {n_clusters} clusters - Silhouette:
{silhouette:.4f}, Inertia: {inertia:.4f}")

    # Plot silhouette scores and inertia (elbow method)
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))

    ax1.plot(range(2, max_clusters+1), silhouette_scores, 'o-')
    ax1.set_xlabel('Number of clusters')
    ax1.set_ylabel('Silhouette Score')
    ax1.set_title('Silhouette Score vs. Number of Clusters')
    ax1.grid(True)

    ax2.plot(range(2, max_clusters+1), inertias, 'o-')
    ax2.set_xlabel('Number of clusters')
    ax2.set_ylabel('Inertia')
    ax2.set_title('Elbow Method for Optimal k')
    ax2.grid(True)

    plt.tight_layout()
    plt.show()

    # Determine optimal number of clusters based on silhouette score
    optimal_clusters = silhouette_scores.index(max(silhouette_scores))
+ 2
    print(f"Optimal number of clusters based on silhouette score:
{optimal_clusters}")
```

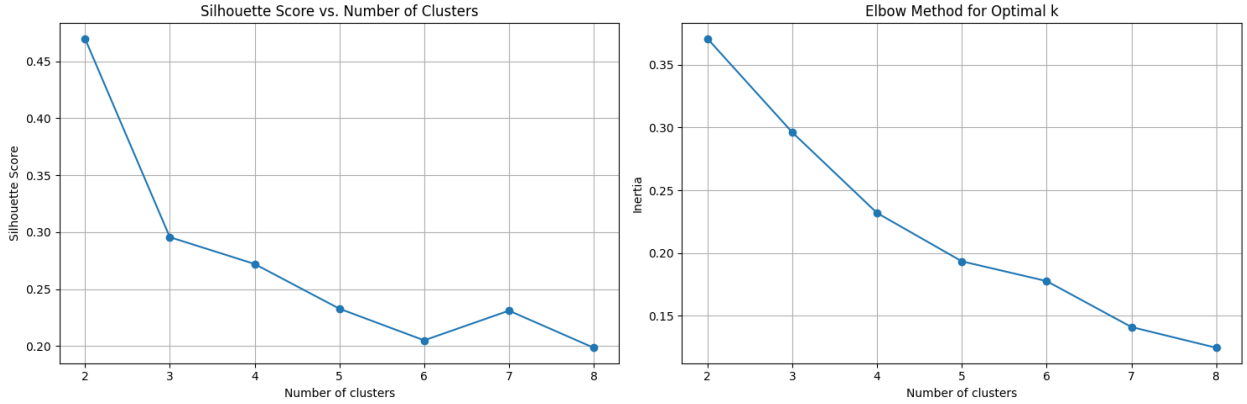
```
    return optimal_clusters

# Apply DBSCAN clustering to the word2vec features
def apply_dbscan_clustering(feature_array, eps_range=(0.1, 1.0),
min_samples_range=(2, 10)):
    """
    Apply DBSCAN clustering with parameter tuning
    """
    best_silhouette = -1
    best_params = {}
    best_labels = None

    # Try different combinations of eps and min_samples
    for eps in np.linspace(eps_range[0], eps_range[1], 10):
        for min_samples in range(min_samples_range[0],
min_samples_range[1]+1):
            dbscan = DBSCAN(eps=eps, min_samples=min_samples)
            labels = dbscan.fit_predict(feature_array)

            # Skip if all points are classified as noise (-1) or only
one cluster
            unique_labels = set(labels)
            if len(unique_labels) <= 1 or (len(unique_labels) == 2 and
-1 in unique_labels):
                continue

            # Calculate silhouette score (ignoring noise points)
            if -1 in labels:
                non_noise_mask = labels != -1
                if sum(non_noise_mask) <= 1:  # Skip if only one non-
noise point
                    continue
                score = silhouette_score(
                    feature_array[non_noise_mask],
                    labels[non_noise_mask]
                )
            else:
                score = silhouette_score(feature_array, labels)

            print(f"DBSCAN eps={eps:.2f}, min_samples={min_samples}:
clusters={len(unique_labels)-(-1 in unique_labels)},
silhouette={score:.4f}, noise={sum(labels==-1)}")

            if score > best_silhouette:
                best_silhouette = score
                best_params = {'eps': eps, 'min_samples': min_samples}
                best_labels = labels

    if best_params:
```

```
        print(f"Best DBSCAN parameters: {best_params}, Silhouette:
{best_silhouette:.4f}")
    else:
        print("Could not find suitable DBSCAN parameters. Using
default parameters.")
        dbscan = DBSCAN(eps=0.5, min_samples=3)
        best_labels = dbscan.fit_predict(feature_array)
        best_params = {'eps': 0.5, 'min_samples': 3}

    return best_params, best_labels



# Main clustering workflow
# Find optimal number of clusters for KMeans
optimal_k = apply_kmeans_clustering(w2v_feature_array, max_clusters=8)

# Apply KMeans with optimal k
kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=10)
kmeans_labels = kmeans.fit_predict(w2v_feature_array)

# Add KMeans labels to the dataframe
negative_fuel_df['W2V_KMeans_Cluster'] = kmeans_labels

# Display KMeans clustering results
print("\nKMeans Clustering Results:")
for cluster in range(optimal_k):
    print(f"\nCluster {cluster}:")
    cluster_sentences =
negative_fuel_df[negative_fuel_df['W2V_KMeans_Cluster'] == cluster]
['sentence'].values
    for sentence in cluster_sentences[:3]:  # Show first 3 sentences
in each cluster
        print(f"- {sentence}")
    if len(cluster_sentences) > 3:
        print(f"  ... and {len(cluster_sentences) - 3} more
sentences")

# Apply DBSCAN with parameter tuning
dbscan_params, dbscan_labels = apply_dbscan_clustering(
    w2v_feature_array,
    eps_range=(0.3, 0.8),
    min_samples_range=(2, 5)
)

# Add DBSCAN labels to the dataframe
negative_fuel_df['W2V_DBSCAN_Cluster'] = dbscan_labels

# Display DBSCAN clustering results
print("\nDBSCAN Clustering Results:")
```

```
clusters = sorted(set(dbscan_labels))
for cluster in clusters:
    cluster_name = "Noise" if cluster == -1 else f"Cluster {cluster}"
    print(f"\n{cluster_name}:")
    cluster_sentences =
negative_fuel_df[negative_fuel_df['W2V_DBSCAN_Cluster'] == cluster]
['sentence'].values
    for sentence in cluster_sentences[:3]:  # Show first 3 sentences
in each cluster
        print(f"- {sentence}")
    if len(cluster_sentences) > 3:
        print(f"  ... and {len(cluster_sentences) - 3} more
sentences")

# Visualize both clustering results using PCA for dimensionality
reduction
pca = PCA(n_components=2)
reduced_features = pca.fit_transform(w2v_feature_array)

# Create a figure with two subplots for KMeans and DBSCAN
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 7))

# Plotting KMeans results
scatter1 = ax1.scatter(reduced_features[:, 0], reduced_features[:, 1],
c=kmeans_labels, cmap='viridis', alpha=0.7, s=100)
ax1.set_title('KMeans Clustering of Word2Vec Embeddings')
ax1.set_xlabel('PCA Component 1')
ax1.set_ylabel('PCA Component 2')
legend1 = ax1.legend(*scatter1.legend_elements(), title="KMeans
Clusters")
ax1.add_artist(legend1)

# Plotting DBSCAN results - Handle case with all noise points
if len(set(dbscan_labels)) > 1 or (len(set(dbscan_labels)) == 1 and
list(set(dbscan_labels))[0] != -1):
    scatter2 = ax2.scatter(reduced_features[:, 0], reduced_features[:,
1], c=dbscan_labels, cmap='viridis', alpha=0.7, s=100)
    ax2.set_title('DBSCAN Clustering of Word2Vec Embeddings')
    ax2.set_xlabel('PCA Component 1')
    ax2.set_ylabel('PCA Component 2')
    legend2 = ax2.legend(*scatter2.legend_elements(), title="DBSCAN
Clusters")
    ax2.add_artist(legend2)
else:
    ax2.scatter(reduced_features[:, 0], reduced_features[:, 1],
alpha=0.7, s=100, color='gray')
    ax2.set_title('DBSCAN Clustering - All Points Classified as
Noise')
    ax2.set_xlabel('PCA Component 1')
    ax2.set_ylabel('PCA Component 2')
```

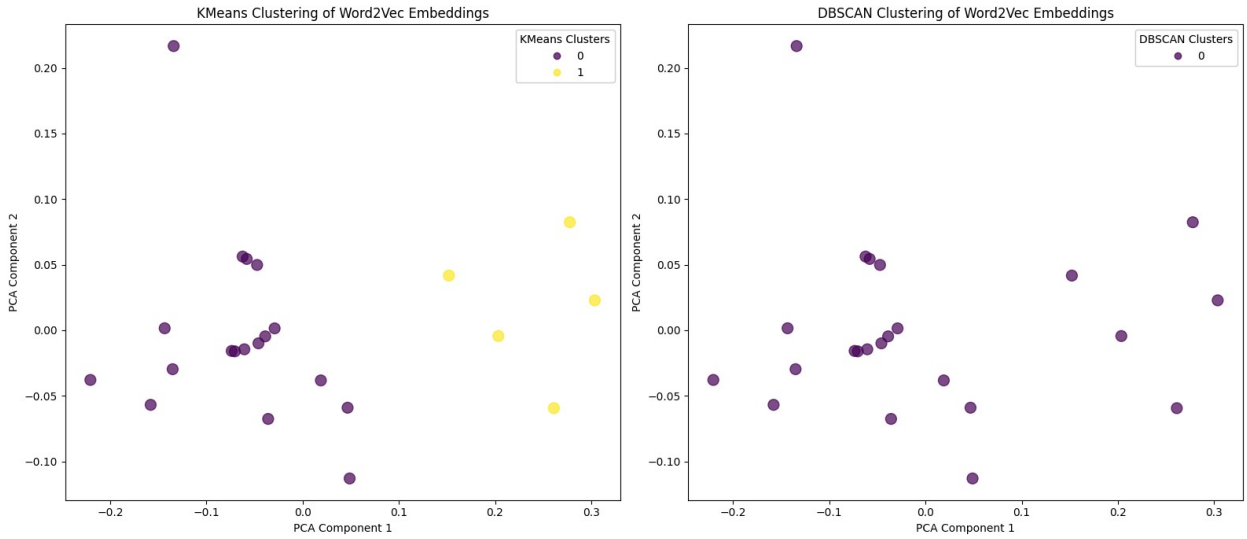
```
plt.tight_layout()
plt.show()

# Compare clustering results
comparison_df = pd.DataFrame({
    'Sentence': negative_fuel_df['sentence'],
    'KMeans Cluster': kmeans_labels,
    'DBSCAN Cluster': dbscan_labels
})

# Print comparison table
print("\nCluster Comparison:")
print(comparison_df.head(10))
```

```
KMeans with 2 clusters - Silhouette: 0.4699, Inertia: 0.3707
KMeans with 3 clusters - Silhouette: 0.2956, Inertia: 0.2961
KMeans with 4 clusters - Silhouette: 0.2720, Inertia: 0.2319
KMeans with 5 clusters - Silhouette: 0.2327, Inertia: 0.1935
KMeans with 6 clusters - Silhouette: 0.2049, Inertia: 0.1777
KMeans with 7 clusters - Silhouette: 0.2310, Inertia: 0.1412
KMeans with 8 clusters - Silhouette: 0.1984, Inertia: 0.1247
```




```
Optimal number of clusters based on silhouette score: 2

KMeans Clustering Results:

Cluster 0:
- Avanza kenapa jadi boros bensin begini dah ah. Baru diisi sudah mau setengah saja .
- kalau sudah di atas 120 km / jam boros banget avanza saya , terus kopling nya memang agak keras juragan .
- Asli avanza saya boros akhir-akhir ini
  ... and 15 more sentences

Cluster 1:
- dari segi kenyamanan cortez oke lah, tapi bahan bakar nya itu loh
```

```
boros banget
- Rush konde konsumsi BBM yang tetap irit .
- pengalaman saya punya avanza bahan bakar nya lebih hemat daripada
ketika saya punya xenia
  ... and 2 more sentences
Could not find suitable DBSCAN parameters. Using default parameters.

DBSCAN Clustering Results:

Cluster 0:
- Avanza kenapa jadi boros bensin begini dah ah. Baru diisi sudah mau
setengah saja .
- dari segi kenyamanan cortez oke lah, tapi bahan bakar nya itu loh
boros banget
- kalau sudah di atas 120 km / jam boros banget avanza saya , terus
kopling nya memang agak keras juragan .
  ... and 20 more sentences
```




```
Cluster Comparison:
                                                Sentence  KMeans Cluster
\
1    Avanza kenapa jadi boros bensin begini dah ah....                0

38   dari segi kenyamanan cortez oke lah, tapi baha...                1

113  kalau sudah di atas 120 km / jam boros banget ...                0

116          Rush konde konsumsi BBM yang tetap irit .                1

124  pengalaman saya punya avanza bahan bakar nya l...                1

157  sudah harga nya mahal, fortuner ini juga konsu...                1
```

```
276              Asli avanza saya boros akhir-akhir ini                0
342  walaupun secara keseluruha oke tapi kalo bensi...                 0
385  ertiga gaya nya oke banget, tarikan juga manta...                 0
390             pakai new avanza bu . Boros bensin haha                0
```

	DBSCAN Cluster
1	0
38	0
113	0
116	0
124	0
157	0
276	0
342	0
385	0
390	0

AFFINITY PROPAGATION for word2vec

```python
# Apply Affinity Propagation clustering with optimized parameters
def apply_optimized_affinity_propagation(feature_array):
    """
    Apply Affinity Propagation clustering with optimized parameters
for Word2Vec embeddings
    """
    ## damping is a parameter that controls the degree of damping in
the algorithm.
    # Higher values lead to more stable clusters, but may miss some
fine-grained structures
    # Lower values can capture more clusters but may be less stable.
    damping_values = [0.7, 0.75, 0.8, 0.85, 0.9, 0.95]
    best_silhouette = -1
    best_labels = None
    best_damping = None
    best_n_clusters = 0

    for damping in damping_values:
        print(f"Testing Affinity Propagation with damping={damping}")
        try:
            # Apply Affinity Propagation
            ap = AffinityPropagation(
                damping=damping,
                max_iter=1000,
                convergence_iter=50,
                random_state=42
```

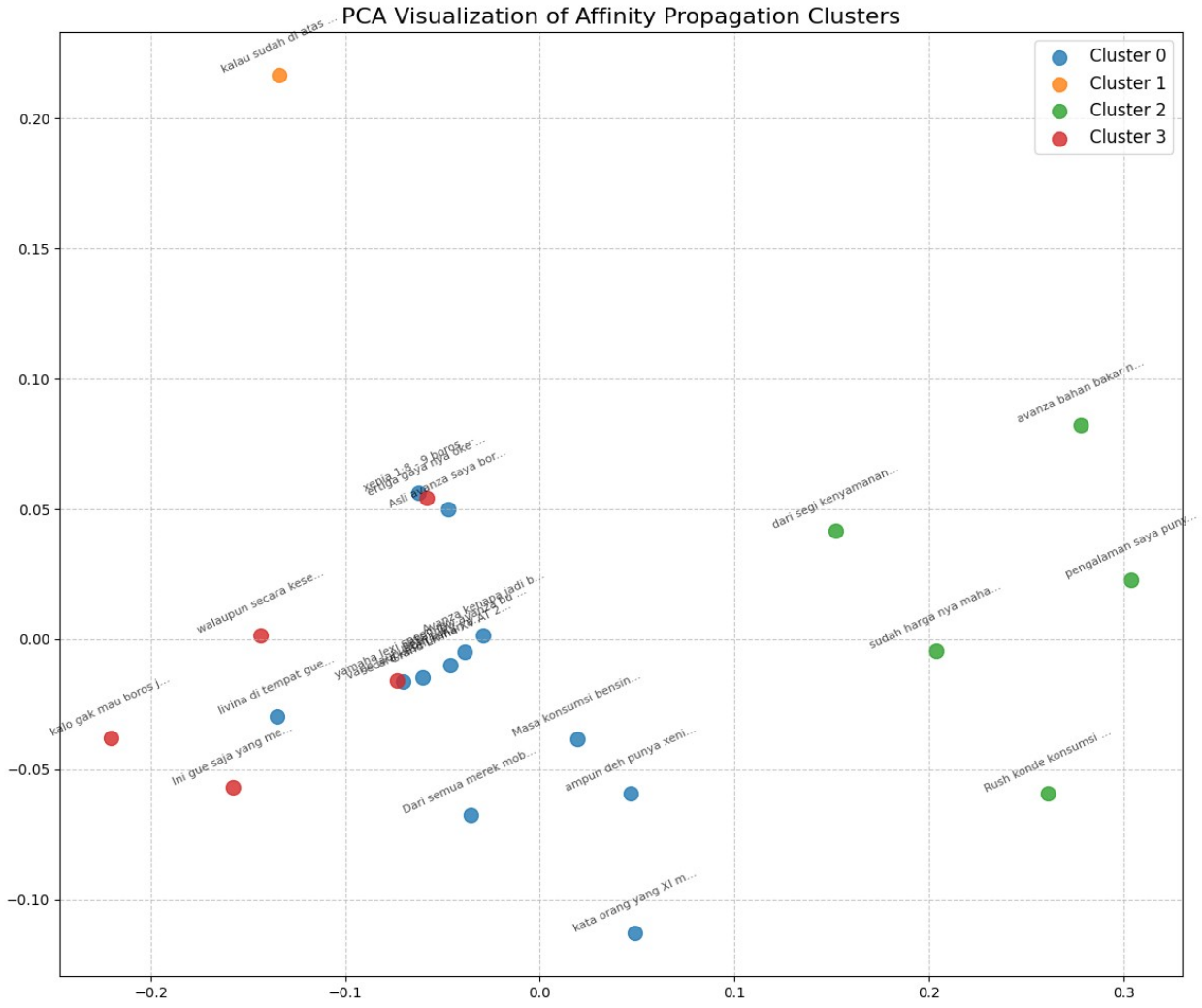
```
            )

            # Fit and predict
            labels = ap.fit_predict(feature_array)
            n_clusters = len(set(labels)) - (1 if -1 in labels else 0)

            # If only one cluster is found, skip evaluation
            if n_clusters <= 1:
                print(f"  Only {n_clusters} clusters found,
skipping.")
                continue

            # Evaluate using silhouette score
            silhouette = silhouette_score(feature_array, labels)
            print(f"  Found {n_clusters} clusters with silhouette
score: {silhouette:.4f}")

            # Update best parameters if better score is found
            if silhouette > best_silhouette:
                best_silhouette = silhouette
                best_labels = labels
                best_damping = damping
                best_n_clusters = n_clusters

        except Exception as e:
            print(f"  Error with damping={damping}: {e}")

    if best_labels is None:
        print("Could not find good clusters with Affinity Propagation.
Using default parameters.")
        ap = AffinityPropagation(random_state=42)
        best_labels = ap.fit_predict(feature_array)
        best_damping = 0.5
        best_n_clusters = len(set(best_labels)) - (1 if -1 in
best_labels else 0)

    print(f"\nBest Affinity Propagation results:")
    print(f"  Damping: {best_damping}")
    print(f"  Number of clusters: {best_n_clusters}")
    print(f"  Silhouette score: {best_silhouette:.4f}")

    return best_labels, best_n_clusters

# Apply the optimization
ap_labels, n_ap_clusters =
apply_optimized_affinity_propagation(w2v_feature_array)

# Add the cluster labels to the DataFrame
negative_fuel_df['W2V_AP_Cluster'] = ap_labels
```

```
# Display cluster statistics
cluster_counts = negative_fuel_df['W2V_AP_Cluster'].value_counts()
print("\nCluster distribution:")
print(cluster_counts)

# Visualize clusters using dimensionality reduction
# First try PCA for cleaner visualization
pca = PCA(n_components=2, random_state=42)
pca_result = pca.fit_transform(w2v_feature_array)

# If we have many clusters, try t-SNE as an alternative visualization
if n_ap_clusters > 5:
    print("\nApplying t-SNE for better visualization of many
clusters...")
    tsne = TSNE(n_components=2, perplexity=5, n_iter=1000,
random_state=42)
    tsne_result = tsne.fit_transform(w2v_feature_array)

    # Plot t-SNE results
    plt.figure(figsize=(12, 10))
    for cluster in range(n_ap_clusters):
        # Get points in this cluster
        indices = negative_fuel_df['W2V_AP_Cluster'] == cluster

        # Plot points
        plt.scatter(
            tsne_result[indices, 0],
            tsne_result[indices, 1],
            s=100,
            alpha=0.8,
            label=f'Cluster {cluster}'
        )

    plt.title('t-SNE Visualization of Affinity Propagation Clusters',
fontsize=16)
    plt.legend(fontsize=12)
    plt.grid(True, linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()

# Plot PCA results
plt.figure(figsize=(12, 10))
for cluster in range(n_ap_clusters):
    # Get points in this cluster
    indices = negative_fuel_df['W2V_AP_Cluster'] == cluster

    # Plot points
    plt.scatter(
        pca_result[indices, 0],
        pca_result[indices, 1],
```

```
        s=100,
        alpha=0.8,
        label=f'Cluster {cluster}'
    )

# Add sentence texts as annotations
for i, (x, y) in enumerate(pca_result):
    txt = negative_fuel_df['sentence'].iloc[i][:20] + '...'
    cluster = negative_fuel_df['W2V_AP_Cluster'].iloc[i]
    plt.annotate(
        txt,
        (x, y),
        fontsize=8,
        alpha=0.7,
        ha='center',
        va='bottom',
        rotation=25
    )

plt.title('PCA Visualization of Affinity Propagation Clusters',
fontsize=16)
plt.legend(fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Print examples from each cluster
print("\nExamples from each cluster:")
for cluster in range(n_ap_clusters):
    print(f"\nCluster {cluster}:")
    cluster_sentences =
negative_fuel_df[negative_fuel_df['W2V_AP_Cluster'] == cluster]
['sentence'].values
    for sentence in cluster_sentences[:3]:  # Show first 3 sentences
in each cluster
        print(f"- {sentence}")
    if len(cluster_sentences) > 3:
        print(f"  ... and {len(cluster_sentences) - 3} more
sentences")

# Extract and analyze common words per cluster
def extract_common_words(cluster_sentences, top_n=10):
    """Extract most common words for a set of sentences"""
    all_words = []
    for sentence in cluster_sentences:
        all_words.extend(enhanced_tokenizer(sentence))

    # Count word frequencies
    word_counts = {}
    for word in all_words:
```

```
        if word not in word_counts:
            word_counts[word] = 0
        word_counts[word] += 1

    # Sort by frequency
    sorted_words = sorted(word_counts.items(), key=lambda x: x[1],
reverse=True)
    return sorted_words[:top_n]

print("\nCommon words per cluster:")
for cluster in range(n_ap_clusters):
    cluster_sentences =
negative_fuel_df[negative_fuel_df['W2V_AP_Cluster'] == cluster]
['sentence'].values
    common_words = extract_common_words(cluster_sentences)
    print(f"\nCluster {cluster} common words:")
    for word, count in common_words:
        print(f"  {word}: {count}")
```

```
Testing Affinity Propagation with damping=0.7
  Found 5 clusters with silhouette score: 0.2288
Testing Affinity Propagation with damping=0.75
  Found 5 clusters with silhouette score: 0.2288
Testing Affinity Propagation with damping=0.8
  Found 4 clusters with silhouette score: 0.2708
Testing Affinity Propagation with damping=0.85
  Found 4 clusters with silhouette score: 0.2708
Testing Affinity Propagation with damping=0.9
  Found 4 clusters with silhouette score: 0.2708
Testing Affinity Propagation with damping=0.95
  Found 4 clusters with silhouette score: 0.2708

Best Affinity Propagation results:
  Damping: 0.8
  Number of clusters: 4
  Silhouette score: 0.2708

Cluster distribution:
W2V_AP_Cluster
0    12
2     5
3     5
1     1
Name: count, dtype: int64
```




```
Examples from each cluster:

Cluster 0:
- Avanza kenapa jadi boros bensin begini dah ah. Baru diisi sudah mau
setengah saja .
- Asli avanza saya boros akhir-akhir ini
- pakai new avanza bu . Boros bensin haha
  ... and 9 more sentences

Cluster 1:
- kalau sudah di atas 120 km / jam boros banget avanza saya , terus
kopling nya memang agak keras juragan .

Cluster 2:
- dari segi kenyamanan cortez oke lah, tapi bahan bakar nya itu loh
boros banget
- Rush konde konsumsi BBM yang tetap irit .
```

```
- pengalaman saya punya avanza bahan bakar nya lebih hemat daripada
ketika saya punya xenia
  ... and 2 more sentences

Cluster 3:
- walaupun secara keseluruha oke tapi kalo bensinnya boros jadi malas
beli
- ertiga gaya nya oke banget, tarikan juga mantap dan bandel tapi
sayang nya boros banget
- yamaha lexi speed nya gila, tarikan nya juara, cuma yah, bensin nya
nyedot, bro.
  ... and 2 more sentences

Common words per cluster:

Cluster 0 common words:
  boros: 9
  bensin: 6
  avanza: 3
  nya: 3
  Avanza: 2
  pakai: 2
  konsumsi: 2
  banget: 2
  xenia: 2
  ngelitik: 2

Cluster 1 common words:
  120: 1
  jam: 1
  boros: 1
  banget: 1
  avanza: 1
  kopling: 1
  nya: 1
  keras: 1
  juragan: 1

Cluster 2 common words:
  nya: 5
  bahan: 4
  bakar: 4
  boros: 2
  banget: 2
  konsumsi: 2
  avanza: 2
  segi: 1
  kenyamanan: 1
  cortez: 1
```

```
Cluster 3 common words:
  nya: 5
  boros: 4
  banget: 3
  oke: 2
  kalo: 2
  beli: 2
  tarikan: 2
  bensin: 2
  keseluruha: 1
  bensinnya: 1
```

Hamming Distance

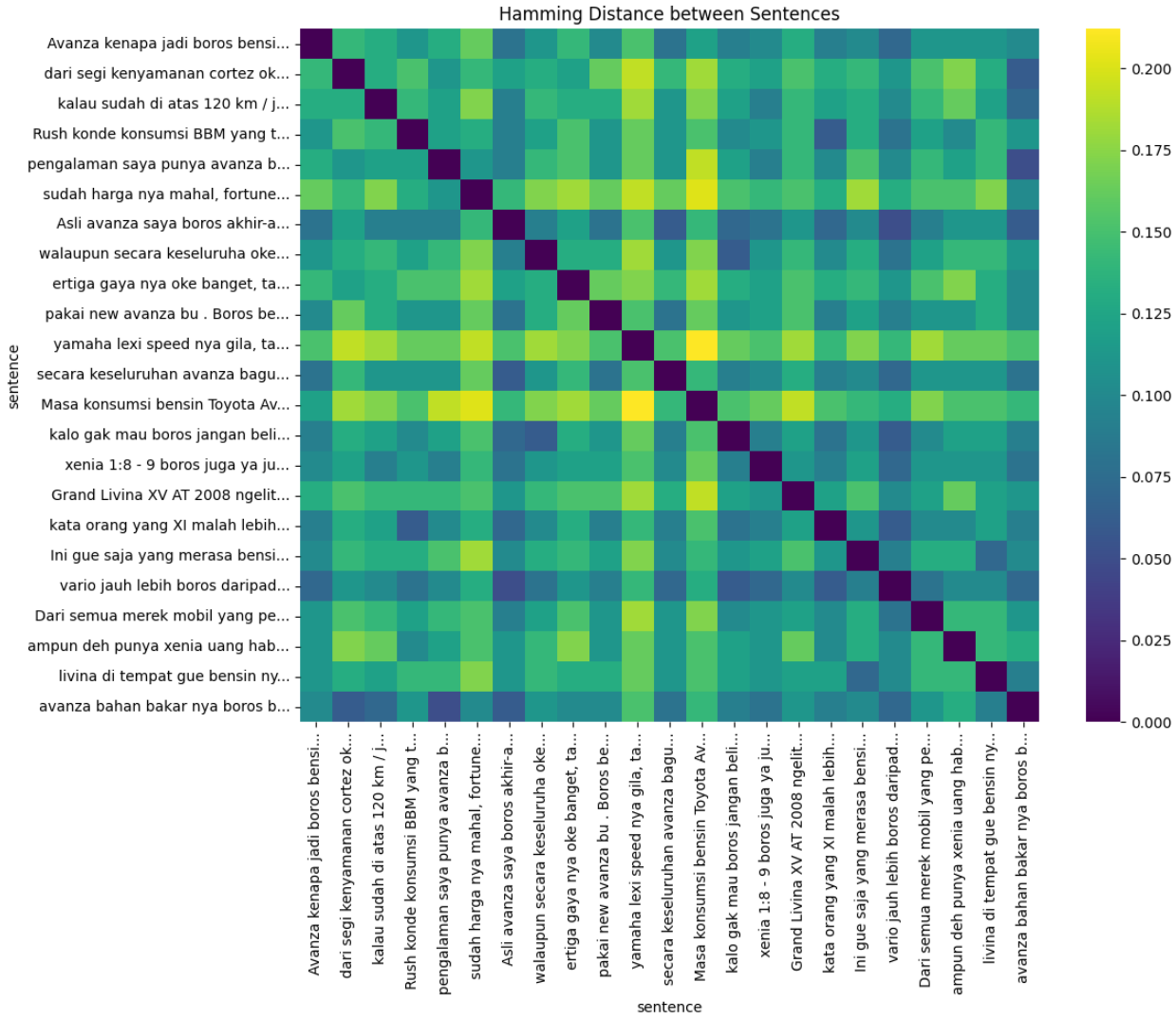
```
from scipy.spatial.distance import hamming
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Create binary representations of sentences for hamming distance
(word level)
# We'll convert each sentence into a binary vector showing
presence/absence of words
all_words = set()
for sent in negative_fuel_df['sentence']:
    tokens = enhanced_tokenizer(sent)
    all_words.update(tokens)

# Create binary vectors for each sentence
binary_vectors = []
sentences = negative_fuel_df['sentence'].values

for sent in sentences:
    tokens = set(enhanced_tokenizer(sent))
    vector = [1 if word in tokens else 0 for word in all_words]
    binary_vectors.append(vector)

# Calculate Hamming distances between all pairs
n_sentences = len(sentences)
hamming_matrix = np.zeros((n_sentences, n_sentences))

for i in range(n_sentences):
    for j in range(n_sentences):
        hamming_matrix[i, j] = hamming(binary_vectors[i],
binary_vectors[j])

# Character-level Hamming distance function (new)
def char_hamming_distance(str1, str2):
    """Calculate Hamming distance between two strings at character
```

```
level"""
    # Make strings the same length by padding shorter one
    max_len = max(len(str1), len(str2))
    str1 = str1.ljust(max_len)
    str2 = str2.ljust(max_len)

    # Count positions where characters differ
    distance = sum(c1 != c2 for c1, c2 in zip(str1, str2))
    return distance / max_len  # Normalize by length

# Calculate character-level Hamming distance for words
def demo_char_hamming():
    word_pairs = [
        ("avanza", "pajero"),
        ("bensin", "bensol"),
        ("boros", "bolos"),
        ("mobil", "motor")
    ]

    print("Character-level Hamming Distance:")
    for word1, word2 in word_pairs:
        dist = char_hamming_distance(word1, word2)
        print(f"'{word1}' vs '{word2}': {dist:.4f}")

        # Show character by character comparison
        print("  Character comparison:")
        for i, (c1, c2) in enumerate(zip(word1.ljust(max(len(word1),
len(word2))),
                                         word2.ljust(max(len(word1),
len(word2))))):
            match = "✓" if c1 == c2 else "✗"
            print(f"    Position {i}: '{c1}' vs '{c2}' {match}")
        print()

# Run the character-level demo
demo_char_hamming()

# Create a DataFrame for better visualization
hamming_df = pd.DataFrame(
    hamming_matrix,
    index=negative_fuel_df['sentence'].str[:30] + '...',
    columns=negative_fuel_df['sentence'].str[:30] + '...'
)

# Plot the Hamming distance matrix
plt.figure(figsize=(12, 10))
sns.heatmap(hamming_df, cmap='viridis')
plt.title('Hamming Distance between Sentences')
plt.tight_layout()
plt.show()
```

```python
# Find the most similar sentences based on Hamming distance
def find_most_similar_levenshtein(idx, top_n=5):
    distances = [(i, hamming_matrix[idx, i]) for i in
range(n_sentences) if i != idx]
    similar = sorted(distances, key=lambda x: x[1])[:top_n]
    return similar

# Print some examples of similar sentences
for idx in [0, 5, 10]:
    print(f"\nSentence: {sentences[idx][:50]}...")
    similar_idx = find_most_similar_levenshtein(idx)
    print("Most similar sentences:")
    for sim_idx, distance in similar_idx:
        print(f"Distance {distance:.4f}: {sentences[sim_idx]
[:50]}...")
```

```
Character-level Hamming Distance:
'avanza' vs 'pajero': 1.0000
  Character comparison:
    Position 0: 'a' vs 'p' ✗
    Position 1: 'v' vs 'a' ✗
    Position 2: 'a' vs 'j' ✗
    Position 3: 'n' vs 'e' ✗
    Position 4: 'z' vs 'r' ✗
    Position 5: 'a' vs 'o' ✗

'bensin' vs 'bensol': 0.3333
  Character comparison:
    Position 0: 'b' vs 'b' ✓
    Position 1: 'e' vs 'e' ✓
    Position 2: 'n' vs 'n' ✓
    Position 3: 's' vs 's' ✓
    Position 4: 'i' vs 'o' ✗
    Position 5: 'n' vs 'l' ✗

'boros' vs 'bolos': 0.2000
  Character comparison:
    Position 0: 'b' vs 'b' ✓
    Position 1: 'o' vs 'o' ✓
    Position 2: 'r' vs 'l' ✗
    Position 3: 'o' vs 'o' ✓
    Position 4: 's' vs 's' ✓

'mobil' vs 'motor': 0.6000
  Character comparison:
    Position 0: 'm' vs 'm' ✓
    Position 1: 'o' vs 'o' ✓
    Position 2: 'b' vs 't' ✗
    Position 3: 'i' vs 'o' ✗
```

```
    Position 4: 'l' vs 'r' ✗
```




```
Sentence: Avanza kenapa jadi boros bensin begini dah ah. Bar...
Most similar sentences:
Distance 0.0707: vario jauh lebih boros daripada mio...
Distance 0.0808: Asli avanza saya boros akhir-akhir ini...
Distance 0.0808: secara keseluruhan avanza bagus kecuali pemakaian ...
Distance 0.0909: kalo gak mau boros jangan beli scoopy...
Distance 0.0909: kata orang yang XI malah lebih irit dari yang LI n...

Sentence: sudah harga nya mahal, fortuner ini juga konsumsi ...
Most similar sentences:
Distance 0.1010: avanza bahan bakar nya boros banget...
Distance 0.1111: pengalaman saya punya avanza bahan bakar nya lebih...
```

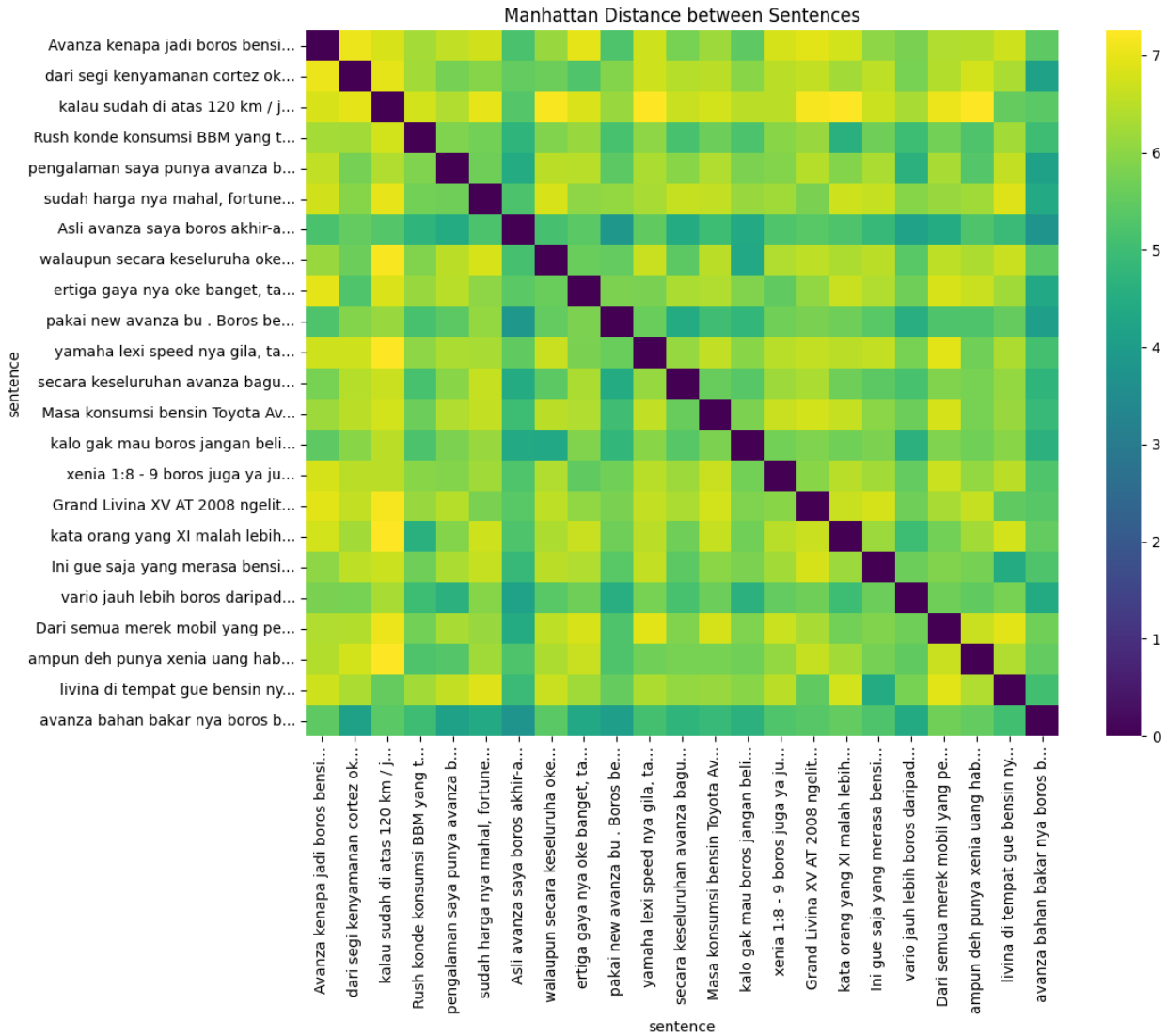
```
Distance 0.1313: Rush konde konsumsi BBM yang tetap irit ....
Distance 0.1313: kata orang yang XI malah lebih irit dari yang LI n...
Distance 0.1313: vario jauh lebih boros daripada mio...

Sentence: yamaha lexi speed nya gila, tarikan nya juara, cum...
Most similar sentences:
Distance 0.1414: kata orang yang XI malah lebih irit dari yang LI n...
Distance 0.1414: vario jauh lebih boros daripada mio...
Distance 0.1515: Avanza kenapa jadi boros bensin begini dah ah. Bar...
Distance 0.1515: Asli avanza saya boros akhir-akhir ini...
Distance 0.1515: pakai new avanza bu . Boros bensin haha...
```

Manhattan Distance

```
from scipy.spatial.distance import cityblock
import numpy as np
import pandas as pd
import seaborn as sns

import matplotlib.pyplot as plt

# Character-level Manhattan distance function
def char_manhattan_distance(str1, str2):
    """Calculate Manhattan distance between two strings at character
level"""
    # Make strings the same length by padding shorter one
    max_len = max(len(str1), len(str2))
    str1 = str1.ljust(max_len)
    str2 = str2.ljust(max_len)

    # Sum of absolute differences between ASCII values of characters
    distance = sum(abs(ord(c1) - ord(c2)) for c1, c2 in zip(str1,
str2))
    return distance

# Calculate Manhattan distances between all pairs of sentences
n_sentences = len(negative_fuel_df)
manhattan_matrix = np.zeros((n_sentences, n_sentences))

# Convert sparse matrix to dense for calculations
tfidf_dense = tfidf_matrix.toarray()

for i in range(n_sentences):
    for j in range(n_sentences):
        # Calculate using cityblock distance (Manhattan)
        manhattan_matrix[i, j] = cityblock(tfidf_dense[i],
tfidf_dense[j])

# Create a DataFrame for better visualization
manhattan_df = pd.DataFrame(
```

```
    manhattan_matrix,
    index=negative_fuel_df['sentence'].str[:30] + '...',
    columns=negative_fuel_df['sentence'].str[:30] + '...'
)

# Plot the Manhattan distance matrix
plt.figure(figsize=(12, 10))
sns.heatmap(manhattan_df, cmap='viridis')
plt.title('Manhattan Distance between Sentences')
plt.tight_layout()
plt.show()

# Find the most similar sentences based on Manhattan distance
def find_most_similar_manhattan(idx, top_n=5):
    distances = [(i, manhattan_matrix[idx, i]) for i in
range(n_sentences) if i != idx]
    similar = sorted(distances, key=lambda x: x[1])[:top_n]
    return similar



# Demonstrate character-level Manhattan distance
def demo_char_manhattan():
    word_pairs = [
        ("avanza", "pajero"),
        ("bensin", "bensol"),
        ("boros", "bolos"),
        ("mobil", "motor")
    ]

    print("Character-level Manhattan Distance (ASCII differences):")
    for word1, word2 in word_pairs:
        dist = char_manhattan_distance(word1, word2)
        print(f"'{word1}' vs '{word2}': {dist}")

        # Show character by character comparison
        print("  Character comparison:")
        for i, (c1, c2) in enumerate(zip(word1.ljust(max(len(word1),
len(word2))),
                                         word2.ljust(max(len(word1),
len(word2))))):
            diff = abs(ord(c1) - ord(c2))
            print(f"    Position {i}: '{c1}' vs '{c2}' (diff:
{diff})")
        print()

# Compare with other distance metrics
example_idx = 22  # "avanza bahan bakar nya boros banget"
example_sent = negative_fuel_df['sentence'].iloc[example_idx]
```

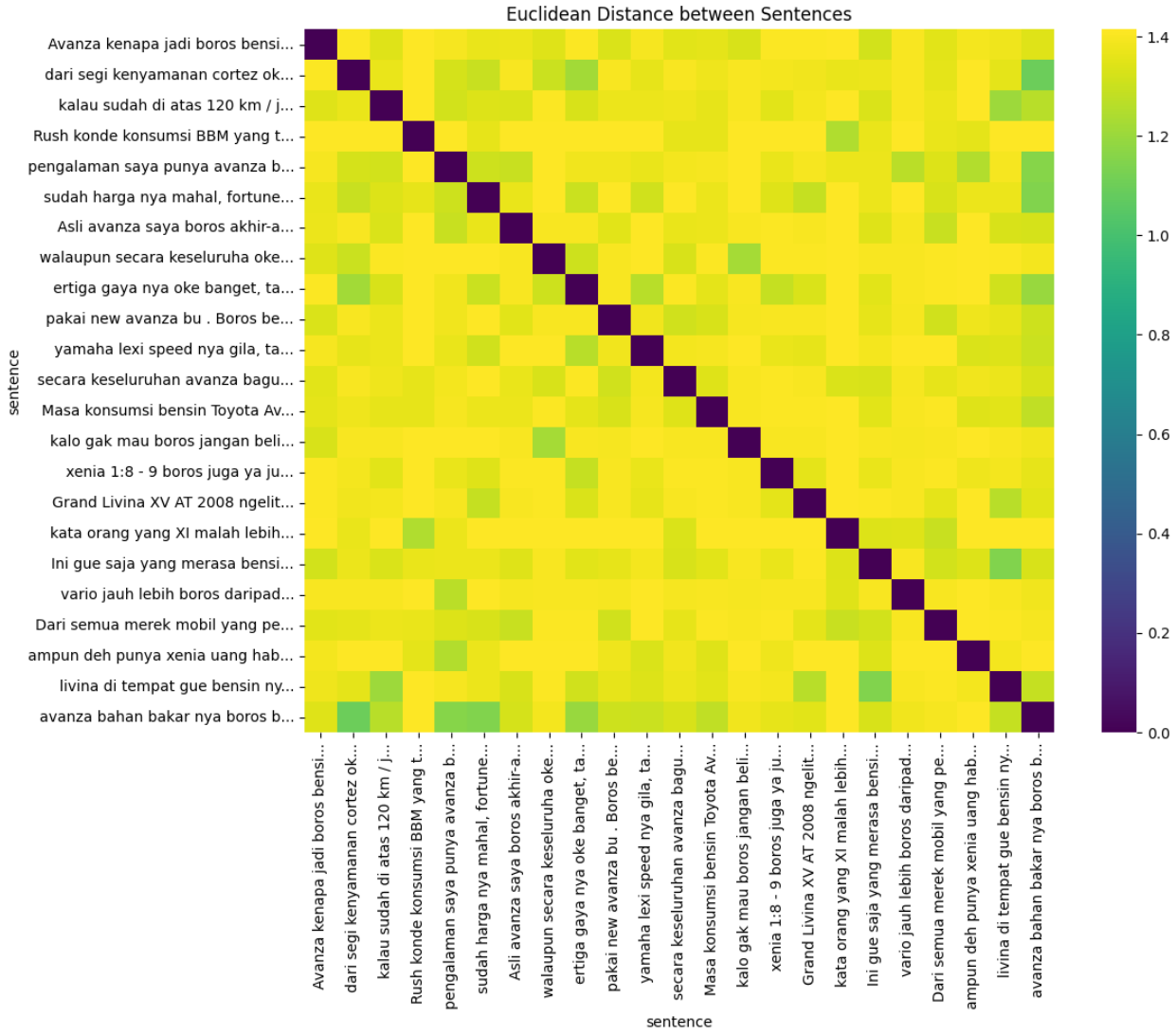
```python
# Get similar sentences using all metrics
manhattan_similar = find_most_similar_manhattan(example_idx, 3)


# Display results
print(f"\nComparison for: {example_sent}")
print("\nTop similar sentences by Manhattan distance:")
for idx, dist in manhattan_similar:
    print(f"- {negative_fuel_df['sentence'].iloc[idx][:50]}...
(distance: {dist:.4f})")



# Run the character-level demo
demo_char_manhattan()
```



```
Comparison for: avanza bahan bakar nya boros banget

Top similar sentences by Manhattan distance:
- Asli avanza saya boros akhir-akhir ini... (distance: 3.7527)
- pakai new avanza bu . Boros bensin haha... (distance: 4.0381)
- dari segi kenyamanan cortez oke lah, tapi bahan ba... (distance:
4.1355)
Character-level Manhattan Distance (ASCII differences):
'avanza' vs 'pajero': 76
  Character comparison:
    Position 0: 'a' vs 'p' (diff: 15)
    Position 1: 'v' vs 'a' (diff: 21)
    Position 2: 'a' vs 'j' (diff: 9)
    Position 3: 'n' vs 'e' (diff: 9)
    Position 4: 'z' vs 'r' (diff: 8)
    Position 5: 'a' vs 'o' (diff: 14)

'bensin' vs 'bensol': 8
  Character comparison:
    Position 0: 'b' vs 'b' (diff: 0)
    Position 1: 'e' vs 'e' (diff: 0)
    Position 2: 'n' vs 'n' (diff: 0)
    Position 3: 's' vs 's' (diff: 0)
    Position 4: 'i' vs 'o' (diff: 6)
    Position 5: 'n' vs 'l' (diff: 2)

'boros' vs 'bolos': 6
  Character comparison:
    Position 0: 'b' vs 'b' (diff: 0)
    Position 1: 'o' vs 'o' (diff: 0)
    Position 2: 'r' vs 'l' (diff: 6)
    Position 3: 'o' vs 'o' (diff: 0)
    Position 4: 's' vs 's' (diff: 0)

'mobil' vs 'motor': 30
  Character comparison:
    Position 0: 'm' vs 'm' (diff: 0)
    Position 1: 'o' vs 'o' (diff: 0)
    Position 2: 'b' vs 't' (diff: 18)
    Position 3: 'i' vs 'o' (diff: 6)
    Position 4: 'l' vs 'r' (diff: 6)


from scipy.spatial.distance import euclidean

# Calculate Euclidean distances between all pairs of sentences
n_sentences = len(negative_fuel_df)
euclidean_matrix = np.zeros((n_sentences, n_sentences))
```

```
# Convert sparse matrix to dense for calculations
tfidf_dense = tfidf_matrix.toarray()

for i in range(n_sentences):
    for j in range(n_sentences):
        # Calculate using the direct manual formula
        euclidean_matrix[i, j] =
np.sqrt(np.sum(np.square(tfidf_dense[i] - tfidf_dense[j])))

# Create a DataFrame for better visualization
euclidean_df = pd.DataFrame(
    euclidean_matrix,
    index=negative_fuel_df['sentence'].str[:30] + '...',
    columns=negative_fuel_df['sentence'].str[:30] + '...'
)

# Plot the Euclidean distance matrix
plt.figure(figsize=(12, 10))
sns.heatmap(euclidean_df, cmap='viridis')
plt.title('Euclidean Distance between Sentences')
plt.tight_layout()
plt.show()

# Find the most similar sentences based on Euclidean distance
def find_most_similar_euclidean(idx, top_n=5):
    distances = [(i, euclidean_matrix[idx, i]) for i in
range(n_sentences) if i != idx]
    similar = sorted(distances, key=lambda x: x[1])[:top_n]
    return similar

# Print some examples of similar sentences
for idx in [0, 5, 10]:
    print(f"\nSentence: {negative_fuel_df['sentence'].iloc[idx]
[:50]}...")
    similar_idx = find_most_similar_euclidean(idx)
    print("Most similar sentences (Euclidean):")
    for sim_idx, distance in similar_idx:
        print(f"Distance {distance:.4f}:
{negative_fuel_df['sentence'].iloc[sim_idx][:50]}...")


# Get a specific sentence
example_idx = 22  # "avanza bahan bakar nya boros banget"
example_sent = negative_fuel_df['sentence'].iloc[example_idx]

# Identify most similar sentences by both metrics
euclidean_similar = find_most_similar_euclidean(example_idx, 3)
cosine_similar = [(i, 1-similarity_matrix[example_idx, i]) for i in
range(n_sentences) if i != example_idx]
cosine_similar = sorted(cosine_similar, key=lambda x: x[1])[:3]
```

```
# Display results
print(f"\nComparison for: {example_sent}")
print("\nTop similar by Euclidean distance:")
for idx, dist in euclidean_similar:
    print(f"- {negative_fuel_df['sentence'].iloc[idx][:50]}...
(distance: {dist:.4f})")

print("\nTop similar by Cosine distance:")
for idx, dist in cosine_similar:
    print(f"- {negative_fuel_df['sentence'].iloc[idx][:50]}...
(distance: {dist:.4f})")

idx1 = 22  # "avanza bahan bakar nya boros banget"
idx2 = 1   # One of the most similar sentences

print("\nManual calculation example:")
print(f"Sentence 1: {negative_fuel_df['sentence'].iloc[idx1]}")
print(f"Sentence 2: {negative_fuel_df['sentence'].iloc[idx2]}")

manual_dist = np.sqrt(np.sum(np.square(tfidf_dense[idx1] -
tfidf_dense[idx2])))

print(f"Manual formula distance: {manual_dist:.6f}")

print("\nDetailed calculation steps:")
diff = tfidf_dense[idx1] - tfidf_dense[idx2]
squared_diff = np.square(diff)
sum_squared_diff = np.sum(squared_diff)
euclidean_distance = np.sqrt(sum_squared_diff)

print(f"1. Calculate difference between vectors")
print(f"2. Square each element: sum of squares =
{sum_squared_diff:.6f}")
print(f"3. Take square root: final distance =
{euclidean_distance:.6f}")
```




```
Sentence: Avanza kenapa jadi boros bensin begini dah ah. Bar...
Most similar sentences (Euclidean):
Distance 1.3175: Ini gue saja yang merasa bensin Xenia boros banget...
Distance 1.3261: kalo gak mau boros jangan beli scoopy...
Distance 1.3321: pakai new avanza bu . Boros bensin haha...
Distance 1.3441: walaupun secara keseluruha oke tapi kalo bensinnya...
Distance 1.3446: avanza bahan bakar nya boros banget...

Sentence: sudah harga nya mahal, fortuner ini juga konsumsi ...
Most similar sentences (Euclidean):
Distance 1.1449: avanza bahan bakar nya boros banget...
Distance 1.2891: Grand Livina XV AT 2008 ngelitik nya parah kak sek...
Distance 1.2943: dari segi kenyamanan cortez oke lah, tapi bahan ba...
Distance 1.3032: ertiga gaya nya oke banget, tarikan juga mantap da...
Distance 1.3062: pengalaman saya punya avanza bahan bakar nya lebih...
```

```
Sentence: yamaha lexi speed nya gila, tarikan nya juara, cum...
Most similar sentences (Euclidean):
Distance 1.2633: ertiga gaya nya oke banget, tarikan juga mantap da...
Distance 1.3023: avanza bahan bakar nya boros banget...
Distance 1.3105: sudah harga nya mahal, fortuner ini juga konsumsi ...
Distance 1.3328: ampun deh punya xenia uang habis cuma buat konsums...
Distance 1.3384: livina di tempat gue bensin nya asli boros banget ...

Comparison for: avanza bahan bakar nya boros banget

Top similar by Euclidean distance:
- dari segi kenyamanan cortez oke lah, tapi bahan ba... (distance:
1.0945)
- sudah harga nya mahal, fortuner ini juga konsumsi ... (distance:
1.1449)
- pengalaman saya punya avanza bahan bakar nya lebih... (distance:
1.1590)

Top similar by Cosine distance:
- dari segi kenyamanan cortez oke lah, tapi bahan ba... (distance:
0.5990)
- sudah harga nya mahal, fortuner ini juga konsumsi ... (distance:
0.6555)
- pengalaman saya punya avanza bahan bakar nya lebih... (distance:
0.6717)

Manual calculation example:
Sentence 1: avanza bahan bakar nya boros banget
Sentence 2: dari segi kenyamanan cortez oke lah, tapi bahan bakar nya
itu loh boros banget
Manual formula distance: 1.094492

Detailed calculation steps:
1. Calculate difference between vectors
2. Square each element: sum of squares = 1.197912
3. Take square root: final distance = 1.094492
```

Eucledean Distance

LEVENSHTEIN EDIT DISTANCE

```python
def levenshtein_distance(s1, s2):
    """
    Calculate the Levenshtein edit distance between two strings
    with visualization of the distance matrix
    """
    # Create a matrix
    rows = len(s1) + 1
    cols = len(s2) + 1
```

```
    distance_matrix = [[0 for _ in range(cols)] for _ in range(rows)]

    # Initialize the first row and column
    for i in range(rows):
        distance_matrix[i][0] = i
    for j in range(cols):
        distance_matrix[0][j] = j

    # Fill in the rest of the matrix
    for i in range(1, rows):
        for j in range(1, cols):
            if s1[i-1] == s2[j-1]:
                cost = 0
            else:
                cost = 1

            distance_matrix[i][j] = min(
                distance_matrix[i-1][j] + 1,      # deletion
                distance_matrix[i][j-1] + 1,      # insertion
                distance_matrix[i-1][j-1] + cost  # substitution
            )

    return distance_matrix

# Example with a single word
word1 = "avanza"
word2 = "Pajero"

# Calculate distance matrix
distance_matrix = levenshtein_distance(word1, word2)

# Print the matrix with row and column labels
print(f"Levenshtein Edit Distance Matrix between '{word1}' and
'{word2}'")
print("    " + " ".join(f"{c:2}" for c in [''] + list(word2)))
for i, row in enumerate(distance_matrix):
    label = word1[i-1] if i > 0 else ''
    print(f"{label:2} {' '.join(f'{cell:2d}' for cell in row)}")

# Determine the edit operations needed
i, j = len(word1), len(word2)
operations = []

while i > 0 or j > 0:
    if i > 0 and j > 0 and word1[i-1] == word2[j-1]:
        operations.append(f"Match '{word1[i-1]}'")
        i -= 1
        j -= 1
    elif i > 0 and j > 0 and distance_matrix[i][j] ==
distance_matrix[i-1][j-1] + 1:
```

```
        operations.append(f"Substitute '{word1[i-1]}' → '{word2[j-
1]}'")
        i -= 1
        j -= 1
    elif i > 0 and distance_matrix[i][j] == distance_matrix[i-1][j] +
1:
        operations.append(f"Delete '{word1[i-1]}'")
        i -= 1
    elif j > 0 and distance_matrix[i][j] == distance_matrix[i][j-1] +
1:
        operations.append(f"Insert '{word2[j-1]}'")
        j -= 1

print("\nEdit operations (from end to beginning):")
for op in operations:
    print(f"- {op}")

print(f"\nTotal edit distance: {distance_matrix[len(word1)]
[len(word2)]}")
```

```
Levenshtein Edit Distance Matrix between 'avanza' and 'Pajero'
       P  a  j  e  r  o
    0  1  2  3  4  5  6
a   1  1  1  2  3  4  5
v   2  2  2  2  3  4  5
a   3  3  2  3  3  4  5
n   4  4  3  3  4  4  5
z   5  5  4  4  4  5  5
a   6  6  5  5  5  5  6

Edit operations (from end to beginning):
- Substitute 'a' → 'o'
- Substitute 'z' → 'r'
- Substitute 'n' → 'e'
- Substitute 'a' → 'j'
- Substitute 'v' → 'a'
- Substitute 'a' → 'P'

Total edit distance: 6
```

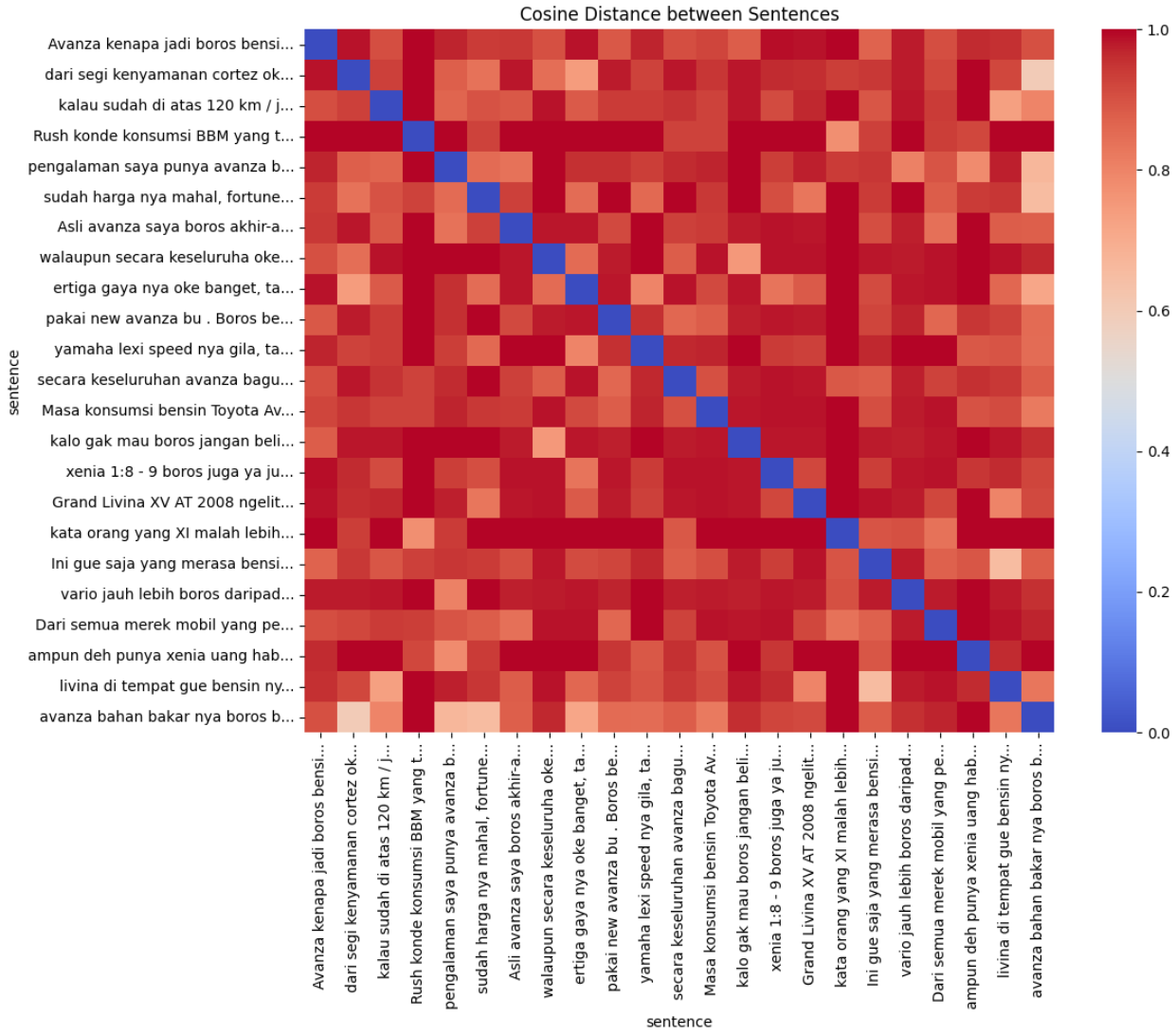
Cosine Distance

```
from sklearn.metrics.pairwise import cosine_distances
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Calculate cosine distances between all pairs of sentences
n_sentences = len(negative_fuel_df)
```

```
cosine_distance_matrix = cosine_distances(tfidf_matrix)

# Create a DataFrame for better visualization
cosine_distance_df = pd.DataFrame(
    cosine_distance_matrix,
    index=negative_fuel_df['sentence'].str[:30] + '...',
    columns=negative_fuel_df['sentence'].str[:30] + '...'
)

# Plot the cosine distance matrix as a heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(cosine_distance_df, cmap='coolwarm')
plt.title('Cosine Distance between Sentences')
plt.tight_layout()
plt.show()

# Find the most similar sentences based on Cosine distance
def find_most_similar_cosine(idx, top_n=5):
    distances = [(i, cosine_distance_matrix[idx, i]) for i in
range(n_sentences) if i != idx]
    similar = sorted(distances, key=lambda x: x[1])[:top_n]
    return similar

# Character-level cosine similarity function
def char_cosine_similarity(str1, str2):
    """Calculate cosine similarity between two strings at character
level"""
    # Create character sets of both strings
    chars = set(str1 + str2)

    # Create character frequency vectors
    vec1 = np.array([str1.count(c) for c in chars])
    vec2 = np.array([str2.count(c) for c in chars])

    # Compute cosine similarity
    dot_product = np.dot(vec1, vec2)
    norm_vec1 = np.linalg.norm(vec1)
    norm_vec2 = np.linalg.norm(vec2)

    similarity = dot_product / (norm_vec1 * norm_vec2) if norm_vec1 *
norm_vec2 != 0 else 0
    return similarity

# Compare word pairs with character-level cosine similarity
def demo_char_cosine():
    word_pairs = [
        ("avanza", "pajero"),
        ("bensin", "bensol"),
        ("boros", "bolos"),
        ("mobil", "motor")
```

```
    ]

    print("Character-level Cosine Similarity:")
    for word1, word2 in word_pairs:
        similarity = char_cosine_similarity(word1, word2)
        distance = 1 - similarity

        print(f"'{word1}' vs '{word2}':")
        print(f"  Cosine similarity: {similarity:.4f}")
        print(f"  Cosine distance: {distance:.4f}")

        # Show character frequencies
        chars = sorted(set(word1 + word2))
        print(f"  Character counts: {', '.join([f'{c}:
{word1.count(c)}/{word2.count(c)}' for c in chars])}")
        print()

# Compare with other distance metrics
example_idx = 22  # "avanza bahan bakar nya boros banget"
example_sent = negative_fuel_df['sentence'].iloc[example_idx]

# Get similar sentences using cosine distance
cosine_similar = find_most_similar_cosine(example_idx, 3)

# Display comparison results
print(f"\nComparison for: {example_sent}")

print("\nTop similar by Cosine distance:")
for idx, dist in cosine_similar:
    print(f"- {negative_fuel_df['sentence'].iloc[idx][:50]}...
(distance: {dist:.4f})")

print("\nTop similar by Euclidean distance:")
for idx, dist in find_most_similar_euclidean(example_idx, 3):
    print(f"- {negative_fuel_df['sentence'].iloc[idx][:50]}...
(distance: {dist:.4f})")

print("\nTop similar by Levenshtein distance:")
for idx, dist in find_most_similar_levenshtein(example_idx, 3):
    print(f"- {negative_fuel_df['sentence'].iloc[idx][:50]}...
(distance: {dist:.4f})")

# Run the character-level demo
demo_char_cosine()

# Calculate cosine similarity between sentences
def sentence_cosine_similarity(sent1, sent2):
    vectorizer = TfidfVectorizer()
    tfidf_matrix = vectorizer.fit_transform([sent1, sent2])
    similarity = cosine_similarity(tfidf_matrix[0:1],
```

```
tfidf_matrix[1:2])[0][0]
    return similarity

# Compare sentence pairs with both word-level and character-level
cosine similarity
sentence_pairs = [
    (negative_fuel_df['sentence'].iloc[22],
negative_fuel_df['sentence'].iloc[1]),  # Similar sentences
    (negative_fuel_df['sentence'].iloc[22],
negative_fuel_df['sentence'].iloc[3])   # Dissimilar sentences
]

print("Sentence Comparison - Word vs Character Level:")
for sent1, sent2 in sentence_pairs:
    word_sim = sentence_cosine_similarity(sent1, sent2)
    char_sim = char_cosine_similarity(sent1, sent2)

    print(f"\nSentence 1: {sent1[:50]}...")
    print(f"Sentence 2: {sent2[:50]}...")
    print(f"Word-level cosine similarity: {word_sim:.4f}")
    print(f"Character-level cosine similarity: {char_sim:.4f}")
    print(f"Word-level cosine distance: {1-word_sim:.4f}")
    print(f"Character-level cosine distance: {1-char_sim:.4f}")
```




```
Comparison for: avanza bahan bakar nya boros banget

Top similar by Cosine distance:
- dari segi kenyamanan cortez oke lah, tapi bahan ba... (distance:
0.5990)
- sudah harga nya mahal, fortuner ini juga konsumsi ... (distance:
0.6555)
- pengalaman saya punya avanza bahan bakar nya lebih... (distance:
0.6717)

Top similar by Euclidean distance:
- dari segi kenyamanan cortez oke lah, tapi bahan ba... (distance:
1.0945)
- sudah harga nya mahal, fortuner ini juga konsumsi ... (distance:
1.1449)
- pengalaman saya punya avanza bahan bakar nya lebih... (distance:
```

```
1.1590)

Top similar by Levenshtein distance:
- pengalaman saya punya avanza bahan bakar nya lebih... (distance:
0.0505)
- dari segi kenyamanan cortez oke lah, tapi bahan ba... (distance:
0.0606)
- Asli avanza saya boros akhir-akhir ini... (distance: 0.0606)
Character-level Cosine Similarity:
'avanza' vs 'pajero':
  Cosine similarity: 0.3536
  Cosine distance: 0.6464
  Character counts: a:3/1, e:0/1, j:0/1, n:1/0, o:0/1, p:0/1, r:0/1,
v:1/0, z:1/0

'bensin' vs 'bensol':
  Cosine similarity: 0.7217
  Cosine distance: 0.2783
  Character counts: b:1/1, e:1/1, i:1/0, l:0/1, n:2/1, o:0/1, s:1/1

'boros' vs 'bolos':
  Cosine similarity: 0.8571
  Cosine distance: 0.1429
  Character counts: b:1/1, l:0/1, o:2/2, r:1/0, s:1/1

'mobil' vs 'motor':
  Cosine similarity: 0.5071
  Cosine distance: 0.4929
  Character counts: b:1/0, i:1/0, l:1/0, m:1/1, o:1/2, r:0/1, t:0/1

Sentence Comparison - Word vs Character Level:

Sentence 1: avanza bahan bakar nya boros banget...
Sentence 2: dari segi kenyamanan cortez oke lah, tapi bahan ba...
Word-level cosine similarity: 0.3967
Character-level cosine similarity: 0.9052
Word-level cosine distance: 0.6033
Character-level cosine distance: 0.0948

Sentence 1: avanza bahan bakar nya boros banget...
Sentence 2: Rush konde konsumsi BBM yang tetap irit ....
Word-level cosine similarity: 0.0000
Character-level cosine similarity: 0.6185
Word-level cosine distance: 1.0000
Character-level cosine distance: 0.3815
```

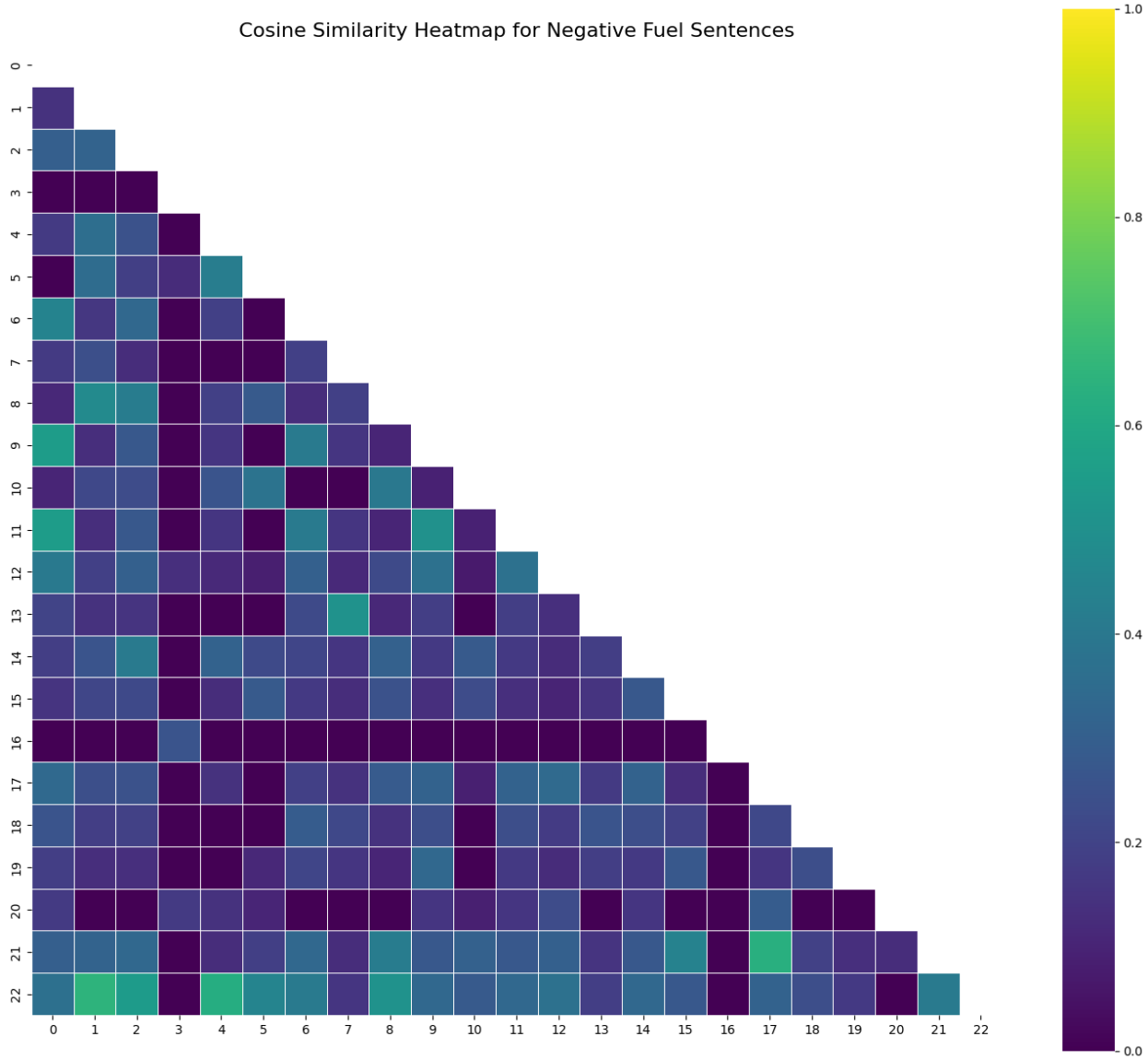
COSINE SIMILARITY

```
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.feature_extraction.text import CountVectorizer
```

```
# Import necessary libraries
import matplotlib.pyplot as plt

# Create a cosine similarity matrix for sentence comparison using
CountVectorizer
def create_cosine_similarity_matrix(sentences):
    # Create count vectorizer
    count_vectorizer = CountVectorizer(tokenizer=enhanced_tokenizer,
stop_words=None)
    count_matrix = count_vectorizer.fit_transform(sentences)

    # Calculate cosine similarity
    cosine_sim_matrix = cosine_similarity(count_matrix)

    return cosine_sim_matrix, count_vectorizer

# Generate the similarity matrix
sentences = negative_fuel_df['sentence'].values
cosine_sim_matrix, count_vectorizer =
create_cosine_similarity_matrix(sentences)

# Create a heatmap visualization
plt.figure(figsize=(14, 12))
mask = np.triu(np.ones_like(cosine_sim_matrix, dtype=bool))
sns.heatmap(cosine_sim_matrix,
            mask=mask,
            cmap='viridis',
            vmin=0,
            vmax=1,
            center=0.5,
            square=True,
            linewidths=.5)
plt.title('Cosine Similarity Heatmap for Negative Fuel Sentences',
fontsize=16)
plt.tight_layout()
plt.show()

# Find the most similar pairs of sentences
def find_most_similar_pairs(similarity_matrix, sentences, top_n=10):
    n = len(sentences)
    similarity_pairs = []

    # Collect all pairs and their similarity scores
    for i in range(n):
        for j in range(i+1, n):
            if similarity_matrix[i, j] > 0:  # Only consider non-zero
similarities
                similarity_pairs.append((i, j, similarity_matrix[i,
j]))
```

```
    # Sort by similarity in descending order
    similarity_pairs.sort(key=lambda x: x[2], reverse=True)

    # Return the top_n pairs
    return similarity_pairs[:top_n]

# Get the most similar pairs
top_similar_pairs = find_most_similar_pairs(cosine_sim_matrix,
sentences)

# Display the results
print("Top similar sentence pairs by cosine similarity:")
print("-" * 80)
for i, j, score in top_similar_pairs:
    print(f"Similarity: {score:.4f}")
    print(f"Sentence 1: {sentences[i]}")
    print(f"Sentence 2: {sentences[j]}")
    print("-" * 80)

# Calculate average similarity within the dataset
avg_similarity = np.sum(cosine_sim_matrix) / (len(sentences)**2 -
len(sentences))
print(f"Average cosine similarity across all sentence pairs:
{avg_similarity:.4f}")
```

```
/home/nicho/MachineLearningENV/lib/python3.12/site-packages/sklearn/
feature_extraction/text.py:517: UserWarning: The parameter
'token_pattern' will not be used since 'tokenizer' is not None'
  warnings.warn(
```




```
Top similar sentence pairs by cosine similarity:
--------------------------------------------------------------------------------
Similarity: 0.6455
Sentence 1: dari segi kenyamanan cortez oke lah, tapi bahan bakar nya itu loh boros banget
Sentence 2: avanza bahan bakar nya boros banget
--------------------------------------------------------------------------------
Similarity: 0.6299
Sentence 1: Ini gue saja yang merasa bensin Xenia boros banget apa memang iya sih
Sentence 2: livina di tempat gue bensin nya asli boros banget kalau soal ngelitik memang iya
--------------------------------------------------------------------------------
```

```
----------
Similarity: 0.6172
Sentence 1: pengalaman saya punya avanza bahan bakar nya lebih hemat
daripada ketika saya punya xenia
Sentence 2: avanza bahan bakar nya boros banget
--------------------------------------------------------------------
----------
Similarity: 0.5477
Sentence 1: Avanza kenapa jadi boros bensin begini dah ah. Baru diisi
sudah mau setengah saja .
Sentence 2: pakai new avanza bu . Boros bensin haha
--------------------------------------------------------------------
----------
Similarity: 0.5477
Sentence 1: Avanza kenapa jadi boros bensin begini dah ah. Baru diisi
sudah mau setengah saja .
Sentence 2: secara keseluruhan avanza bagus kecuali pemakaian bensin
yang boros sekali
--------------------------------------------------------------------
----------
Similarity: 0.5443
Sentence 1: kalau sudah di atas 120 km / jam boros banget avanza
saya , terus kopling nya memang agak keras juragan .
Sentence 2: avanza bahan bakar nya boros banget
--------------------------------------------------------------------
----------
Similarity: 0.5103
Sentence 1: ertiga gaya nya oke banget, tarikan juga mantap dan bandel
tapi sayang nya boros banget
Sentence 2: avanza bahan bakar nya boros banget
--------------------------------------------------------------------
----------
Similarity: 0.5071
Sentence 1: walaupun secara keseluruha oke tapi kalo bensinnya boros
jadi malas beli
Sentence 2: kalo gak mau boros jangan beli scoopy
--------------------------------------------------------------------
----------
Similarity: 0.5000
Sentence 1: pakai new avanza bu . Boros bensin haha
Sentence 2: secara keseluruhan avanza bagus kecuali pemakaian bensin
yang boros sekali
--------------------------------------------------------------------
----------
Similarity: 0.4743
Sentence 1: dari segi kenyamanan cortez oke lah, tapi bahan bakar nya
itu loh boros banget
Sentence 2: ertiga gaya nya oke banget, tarikan juga mantap dan bandel
tapi sayang nya boros banget
```

```
--------------------------------------------------------------------------
----------
Average cosine similarity across all sentence pairs: 0.2229
```

Hellinger-Bhattacharyya Distance

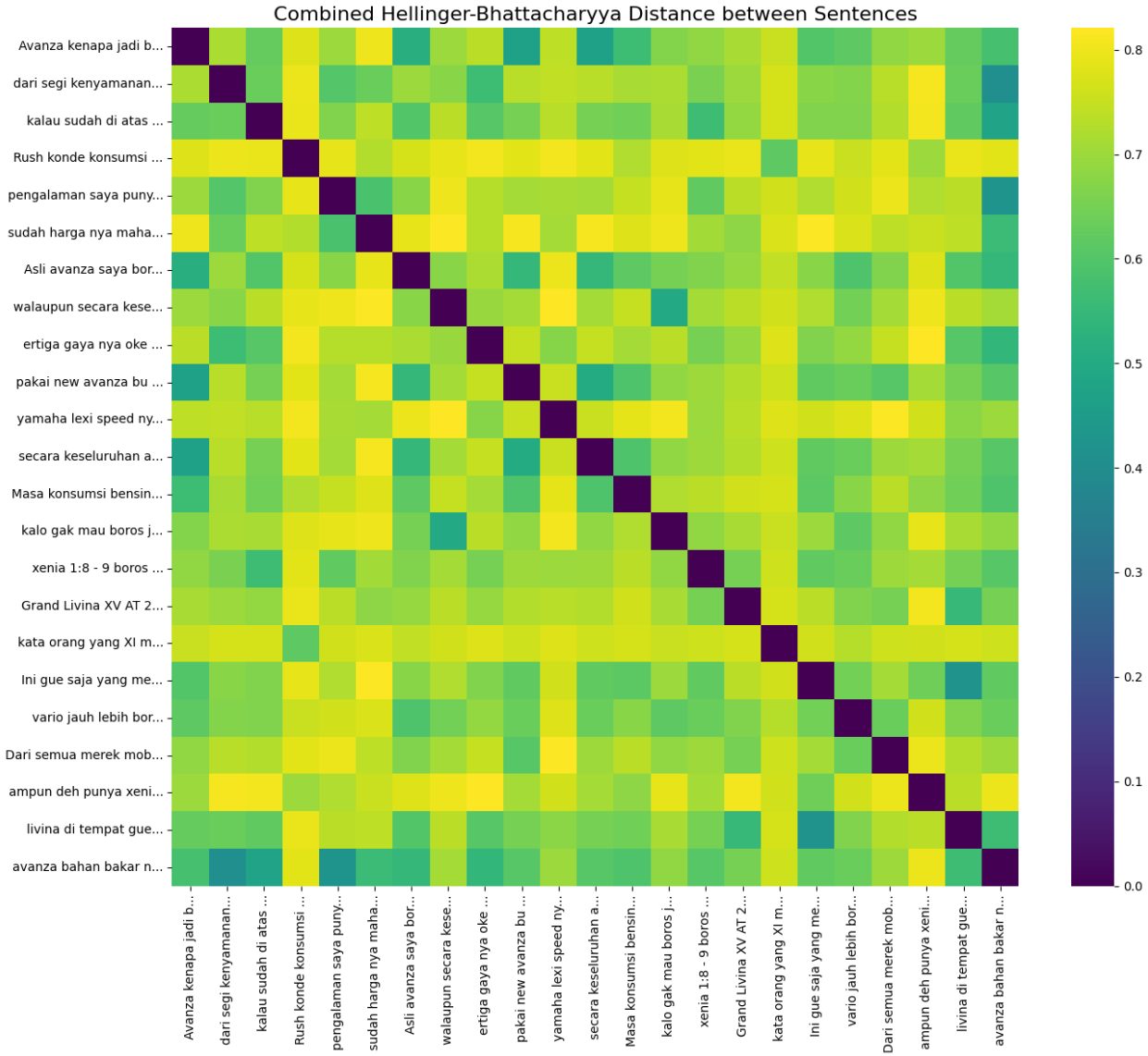
```
from scipy.sparse import csr_matrix
from sklearn.feature_extraction.text import TfidfVectorizer,
CountVectorizer

import matplotlib.pyplot as plt

# Function to calculate Hellinger distance between probability
distributions
def hellinger_distance(p, q):
    """
    Calculate the Hellinger distance between two probability
distributions.
    Input vectors need to be normalized (sum to 1)
    """
    return np.sqrt(0.5 * np.sum((np.sqrt(p) - np.sqrt(q)) ** 2))

# Function to calculate Bhattacharyya distance
def bhattacharyya_distance(p, q):
    """
    Calculate the Bhattacharyya distance between two probability
distributions.
    Input vectors need to be normalized (sum to 1)
    """
    return -np.log(np.sum(np.sqrt(p * q)))

# Function to calculate combined Hellinger-Bhattacharyya distance
def combined_hellinger_bhattacharyya_distance(p, q, alpha=0.5):
    """
    Calculate a weighted combination of Hellinger and Bhattacharyya
distances.

    Parameters:
    - p, q: Probability distributions
    - alpha: Weight for Hellinger distance (1-alpha for Bhattacharyya)
             Must be between 0 and 1

    Returns:
    - Combined distance score
    """
    # Normalize Bhattacharyya to [0,1] range for fair combination
    # Bhattacharyya is unbounded, so we use exponential transformation
    h_dist = hellinger_distance(p, q)
    b_dist = bhattacharyya_distance(p, q)
```

```
    # Transform Bhattacharyya to [0,1] using 1-exp(-b)
    normalized_b = 1 - np.exp(-b_dist)

    # Weighted combination
    return alpha * h_dist + (1 - alpha) * normalized_b

# Calculate distances between all sentence pairs
n_sentences = len(negative_fuel_df)
hellinger_matrix = np.zeros((n_sentences, n_sentences))
bhattacharyya_matrix = np.zeros((n_sentences, n_sentences))
combined_matrix = np.zeros((n_sentences, n_sentences))

# Use Count Vectorizer to get term frequencies (better for probability
distributions)
count_vectorizer = CountVectorizer(tokenizer=enhanced_tokenizer,
min_df=1)
count_matrix =
count_vectorizer.fit_transform(negative_fuel_df['sentence'])

# Convert to probability distributions by normalizing each document
vector
normalized_counts = []
for i in range(count_matrix.shape[0]):
    row = count_matrix[i].toarray().flatten()
    # Add smoothing to avoid zeros (which cause problems with
Bhattacharyya)
    row = row + 0.01
    normalized_counts.append(row / np.sum(row))  # Normalize to sum to
1

# Calculate distance matrices
for i in range(n_sentences):
    for j in range(n_sentences):
        hellinger_matrix[i, j] =
hellinger_distance(normalized_counts[i], normalized_counts[j])
        bhattacharyya_matrix[i, j] =
bhattacharyya_distance(normalized_counts[i], normalized_counts[j])
        combined_matrix[i, j] =
combined_hellinger_bhattacharyya_distance(
            normalized_counts[i], normalized_counts[j], alpha=0.6
        )

# Visualize the combined distance matrix
plt.figure(figsize=(14, 12))
sns.heatmap(combined_matrix,
            cmap='viridis',
            xticklabels=[s[:20] + '...' for s in
negative_fuel_df['sentence']],
            yticklabels=[s[:20] + '...' for s in
```

```
negative_fuel_df['sentence']])
plt.title('Combined Hellinger-Bhattacharyya Distance between
Sentences', fontsize=16)
plt.tight_layout()
plt.show()

# Find most similar sentences by combined distance
def find_most_similar_combined(idx, top_n=5):
    distances = [(i, combined_matrix[idx, i]) for i in
range(n_sentences) if i != idx]
    similar = sorted(distances, key=lambda x: x[1])[:top_n]
    return similar

# Find most similar sentences by Hellinger distance
def find_most_similar_hellinger(idx, top_n=5):
    distances = [(i, hellinger_matrix[idx, i]) for i in
range(n_sentences) if i != idx]
    similar = sorted(distances, key=lambda x: x[1])[:top_n]
    return similar

# Compare with other distance metrics for a sample sentence
example_idx = 22  # "avanza bahan bakar nya boros banget"
example_sent = negative_fuel_df['sentence'].iloc[example_idx]

print(f"\nComparison for: {example_sent}")
print("\nTop similar by Combined Hellinger-Bhattacharyya distance:")
for idx, dist in find_most_similar_combined(example_idx, 3):
    print(f"- {negative_fuel_df['sentence'].iloc[idx][:50]}...
(distance: {dist:.4f})")

print("\nTop similar by Hellinger distance:")
for idx, dist in find_most_similar_hellinger(example_idx, 3):
    print(f"- {negative_fuel_df['sentence'].iloc[idx][:50]}...
(distance: {dist:.4f})")

# Compare the effectiveness of the combined metric vs individual
metrics
def compare_metric_effectiveness():
    # Analyze how the metrics rank the same pairs differently
    example_indices = [22, 1, 9]  # Sample indices to compare

    print("\nMetric comparison for selected sentences:")
    for idx in example_indices:
        sent = negative_fuel_df['sentence'].iloc[idx]
        print(f"\nSentence: {sent[:50]}...")

        # Get top 3 most similar by each metric
        hell_similar = find_most_similar_hellinger(idx, 3)
        bhat_similar = sorted([(i, bhattacharyya_matrix[idx, i]) for i
in range(n_sentences) if i != idx],
```

```
                                key=lambda x: x[1])[:3]
        comb_similar = find_most_similar_combined(idx, 3)

        # Compare rankings
        print("Top by Hellinger:")
        for i, (similar_idx, dist) in enumerate(hell_similar):
            print(f"{i+1}.
{negative_fuel_df['sentence'].iloc[similar_idx][:30]}...
({dist:.4f})")

        print("\nTop by Bhattacharyya:")
        for i, (similar_idx, dist) in enumerate(bhat_similar):
            print(f"{i+1}.
{negative_fuel_df['sentence'].iloc[similar_idx][:30]}...
({dist:.4f})")

        print("\nTop by Combined:")
        for i, (similar_idx, dist) in enumerate(comb_similar):
            print(f"{i+1}.
{negative_fuel_df['sentence'].iloc[similar_idx][:30]}...
({dist:.4f})")

# Run the comparison
compare_metric_effectiveness()
```

```
/home/nicho/MachineLearningENV/lib/python3.12/site-packages/sklearn/
feature_extraction/text.py:517: UserWarning: The parameter
'token_pattern' will not be used since 'tokenizer' is not None'
  warnings.warn(
```




```
Comparison for: avanza bahan bakar nya boros banget

Top similar by Combined Hellinger-Bhattacharyya distance:
- dari segi kenyamanan cortez oke lah, tapi bahan ba... (distance:
0.4070)
- pengalaman saya punya avanza bahan bakar nya lebih... (distance:
0.4247)
- kalau sudah di atas 120 km / jam boros banget avan... (distance:
0.4771)

Top similar by Hellinger distance:
- dari segi kenyamanan cortez oke lah, tapi bahan ba... (distance:
0.5070)
- pengalaman saya punya avanza bahan bakar nya lebih... (distance:
```

```
0.5244)
- kalau sudah di atas 120 km / jam boros banget avan... (distance:
0.5749)

Metric comparison for selected sentences:

Sentence: avanza bahan bakar nya boros banget...
Top by Hellinger:
1. dari segi kenyamanan cortez ok... (0.5070)
2. pengalaman saya punya avanza b... (0.5244)
3. kalau sudah di atas 120 km / j... (0.5749)

Top by Bhattacharyya:
1. dari segi kenyamanan cortez ok... (0.2971)
2. pengalaman saya punya avanza b... (0.3216)
3. kalau sudah di atas 120 km / j... (0.4012)

Top by Combined:
1. dari segi kenyamanan cortez ok... (0.4070)
2. pengalaman saya punya avanza b... (0.4247)
3. kalau sudah di atas 120 km / j... (0.4771)

Sentence: dari segi kenyamanan cortez oke lah, tapi bahan ba...
Top by Hellinger:
1. avanza bahan bakar nya boros b... (0.5070)
2. ertiga gaya nya oke banget, ta... (0.6521)
3. pengalaman saya punya avanza b... (0.6873)

Top by Bhattacharyya:
1. avanza bahan bakar nya boros b... (0.2971)
2. ertiga gaya nya oke banget, ta... (0.5538)
3. pengalaman saya punya avanza b... (0.6395)

Top by Combined:
1. avanza bahan bakar nya boros b... (0.4070)
2. ertiga gaya nya oke banget, ta... (0.5613)
3. pengalaman saya punya avanza b... (0.6014)

Sentence: pakai new avanza bu . Boros bensin haha...
Top by Hellinger:
1. Avanza kenapa jadi boros bensi... (0.5638)
2. secara keseluruhan avanza bagu... (0.5967)
3. Asli avanza saya boros akhir-a... (0.6387)

Top by Bhattacharyya:
1. Avanza kenapa jadi boros bensi... (0.3825)
2. secara keseluruhan avanza bagu... (0.4402)
3. Asli avanza saya boros akhir-a... (0.5240)

Top by Combined:
```

```
1. Avanza kenapa jadi boros bensi... (0.4654)
2. secara keseluruhan avanza bagu... (0.5005)
3. Asli avanza saya boros akhir-a... (0.5463)
```