Institute of Business Administration
Introduction to Text Analytics
Assignment 02 – K-Means Clustering Assessment

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Report each experiment's detail and scores for k = 5, 9, and 13. You are required to perform ten experiments for each 'k' (number of clusters). Please set random seed value to your ERP ID for each K-Means clustering experiment.

*The first four entries in the table are provided for reference only. Hence, the scores do not interpret anything and have been entered randomly. Replace these entries while submitting.

PLEASE NOTE

Due to the excessive cases, the readability of the table is difficult. Thus I have attached the excel sheet (which also contains the case numbers) I maintained to my submission. I have removed the case numbers here. I have also maintained a github repository with the notebooks committed for EACH CASE.
You can view them here: https://github.com/z-aqib/text-analytics.git

THE YELLOW HIGHLIGHTED IS THE BEST SILL/WSS FOR THAT VECTORIZER

k (Number of clusters)	Vectorizer Type and Details	Stemming (Yes/No)	Lemmatization (Yes/No)	N-Grams Utilized	Stop words (Yes/No)	Silhouette Score	WSS Score
5	BOW: CountVectorizer (TP)	Yes	No	unigram	Yes	0.013282	3473.43
	BOW: CountVectorizer (TP)	Yes	No	unigram	No	0.016872	4258.04
	BOW: CountVectorizer (TP)	Yes	No	bigram	Yes	-0.03306	3152.58
	BOW: CountVectorizer (TP)	Yes	No	bigram	No	-0.07444	4153.87
	BOW: CountVectorizer (TP)	No	Yes	unigram	Yes	0.001199	3477.07
	BOW: CountVectorizer (TP)	No	Yes	unigram	No	0.015732	4203.41
	BOW: CountVectorizer (TP)	No	Yes	bigram	Yes	-0.03326	3127.11

BOW: CountVectorizer (TP)	No	Yes	bigram	No	-0.07196	4098.04
BOW: CountVectorizer (TF)	Yes	No	unigram	Yes	0.009557	3548.97
BOW: CountVectorizer (TF)	Yes	No	unigram	No	0.025306	4388.59
BOW: CountVectorizer (TF)	Yes	No	bigram	Yes	-0.03325	3155.58
BOW: CountVectorizer (TF)	Yes	No	bigram	No	-0.07469	4159.86
BOW: CountVectorizer (TF)	No	Yes	unigram	Yes	0.014238	3501.15
BOW: CountVectorizer (TF)	No	Yes	unigram	No	0.005123	4363.45
BOW: CountVectorizer (TF)	No	Yes	bigram	Yes	-0.03326	3127.11
BOW: CountVectorizer (TF)	No	Yes	bigram	No	0.000191	4093.68
BOW: TF-IDF	Yes	No	unigram	Yes	0.00393	440.559
BOW: TF-IDF	Yes	No	unigram	No	0.003238	438.559
BOW: TF-IDF	Yes	No	bigram	Yes	0.00485	445.19
BOW: TF-IDF	Yes	No	bigram	No	0.002056	446.498
BOW: TF-IDF	No	Yes	unigram	Yes	0.003872	441.06
BOW: TF-IDF	No	Yes	unigram	No	0.003327	432.287
BOW: TF-IDF	No	Yes	bigram	Yes	0.004559	445.258
BOW: TF-IDF	No	Yes	bigram	No	0.002796	446.139
TruncatedSVD (n_components = 50)	Yes	No	unigram	Yes	0.152272	103.365
TruncatedSVD (n_components = 50)	Yes	No	unigram	No	0.034948	106.905
TruncatedSVD (n_components = 50)	Yes	No	bigram	Yes	0.453867	66.6053
TruncatedSVD (n_components = 50)	Yes	No	bigram	No	0.554426	66.826

	TruncatedSVD (n_components = 50)	No	Yes	unigram	Yes	0.054367	102.359
	TruncatedSVD (n_components = 50)	No	Yes	unigram	No	0.054062	104.212
	TruncatedSVD (n_components = 50)	No	Yes	bigram	Yes	0.611437	66.04
	TruncatedSVD (n_components = 50)	No	Yes	bigram	No	0.495226	66.1592
	TruncatedSVD (n_components = 100)	Yes	No	unigram	Yes	0.058368	176.812
	TruncatedSVD (n_components = 100)	Yes	No	unigram	No	0.010665	180.852
	TruncatedSVD (n_components = 100)	Yes	No	bigram	Yes	-0.00459	120.402
	TruncatedSVD (n_components = 100)	Yes	No	bigram	No	0.321782	122.915
	TruncatedSVD (n_components = 100)	No	Yes	unigram	Yes	0.005729	175.121
	TruncatedSVD (n_components = 100)	No	Yes	unigram	No	0.025373	177.703
	TruncatedSVD (n_components = 100)	No	Yes	bigram	Yes	-0.01228	120.295
	TruncatedSVD (n_components = 100)	No	Yes	bigram	No	0.263086	123.649
	TruncatedSVD (n_components = 200)	Yes	No	unigram	Yes	0.002308	287.157
	TruncatedSVD (n_components = 200)	Yes	No	unigram	No	0.003627	289.395
	TruncatedSVD (n_components = 200)	Yes	No	bigram	Yes	-0.0162	221.752
	TruncatedSVD (n_components = 200)	Yes	No	bigram	No	-0.00372	225.001

	TruncatedSVD (n_components = 200)	No	Yes	unigram	Yes	-0.0147	284.989
	TruncatedSVD (n_components = 200)	No	Yes	unigram	No	0.010122	284.571
	TruncatedSVD (n_components = 200)	No	Yes	bigram	Yes	-0.01698	221.746
	TruncatedSVD (n_components = 200)	No	Yes	bigram	No	0.000446	224.948
9	BOW: CountVectorizer (TP)	Yes	No	unigram	Yes	-0.0036	3457.41
	BOW: CountVectorizer (TP)	Yes	No	unigram	No	0.016511	4125.94
	BOW: CountVectorizer (TP)	Yes	No	bigram	Yes	-0.03111	3117.21
	BOW: CountVectorizer (TP)	Yes	No	bigram	No	-0.07107	4098.74
	BOW: CountVectorizer (TP)	No	Yes	unigram	Yes	-0.00902	3426.18
	BOW: CountVectorizer (TP)	No	Yes	unigram	No	0.00829	4085.34
	BOW: CountVectorizer (TP)	No	Yes	bigram	Yes	-0.04772	3082.5
	BOW: CountVectorizer (TP)	No	Yes	bigram	No	-0.06917	4043.13
	BOW: CountVectorizer (TF)	Yes	No	unigram	Yes	0.002473	3477.09
	BOW: CountVectorizer (TF)	Yes	No	unigram	No	-0.00307	4269.57
	BOW: CountVectorizer (TF)	Yes	No	bigram	Yes	-0.0325	3117.39
	BOW: CountVectorizer (TF)	Yes	No	bigram	No	-0.07133	4104.73

	BOW: CountVectorizer (TF)	No	Yes	unigram	Yes	0.007316	3476.03
	BOW: CountVectorizer (TF)	No	Yes	unigram	No	0.003109	4277.8
	BOW: CountVectorizer (TF)	No	Yes	bigram	Yes	-0.04772	3082.5
	BOW: CountVectorizer (TF)	No	Yes	bigram	No	-0.06943	4049.11
	BOW: TF-IDF	Yes	No	unigram	Yes	0.004994	433.455
	BOW: TF-IDF	Yes	No	unigram	No	0.004518	426.227
	BOW: TF-IDF	Yes	No	bigram	Yes	0.005695	440.075
	BOW: TF-IDF	Yes	No	bigram	No	0.004948	440.601
	BOW: TF-IDF	No	Yes	unigram	Yes	0.005264	433.752
	BOW: TF-IDF	No	Yes	unigram	No	0.004401	426.32
	BOW: TF-IDF	No	Yes	bigram	Yes	0.008202	439.087
	BOW: TF-IDF	No	Yes	bigram	No	0.005882	440.325
	TruncatedSVD (n_components = 50)	Yes	No	unigram	Yes	0.100574	94.459
	TruncatedSVD (n_components = 50)	Yes	No	unigram	No	0.101465	101.311
	TruncatedSVD (n_components = 50)	Yes	No	bigram	Yes	0.418285	59.524
	TruncatedSVD (n_components = 50)	Yes	No	bigram	No	0.561402	59.8563
	TruncatedSVD (n_components = 50)	No	Yes	unigram	Yes	0.077142	93.9194
	TruncatedSVD (n_components = 50)	No	Yes	unigram	No	0.056393	96.8025
	TruncatedSVD (n_components = 50)	No	Yes	bigram	Yes	0.535079	59.3088
	TruncatedSVD (n_components = 50)	No	Yes	bigram	No	0.485763	60.247
	TruncatedSVD (n_components = 100)	Yes	No	unigram	Yes	0.017778	170.097

	TruncatedSVD (n_components = 100)	Yes	No	unigram	No	0.010862	173.8
	TruncatedSVD (n_components = 100)	Yes	No	bigram	Yes	0.017498	114.278
	TruncatedSVD (n_components = 100)	Yes	No	bigram	No	0.258557	117.456
	TruncatedSVD (n_components = 100)	No	Yes	unigram	Yes	0.042785	166.474
	TruncatedSVD (n_components = 100)	No	Yes	unigram	No	4.08E-05	171.309
	TruncatedSVD (n_components = 100)	No	Yes	bigram	Yes	-0.05811	114.596
	TruncatedSVD (n_components = 100)	No	Yes	bigram	No	0.346014	116.539
	TruncatedSVD (n_components = 200)	Yes	No	unigram	Yes	0.005805	280.828
	TruncatedSVD (n_components = 200)	Yes	No	unigram	No	0.007101	280.68
	TruncatedSVD (n_components = 200)	Yes	No	bigram	Yes	-0.00569	217.876
	TruncatedSVD (n_components = 200)	Yes	No	bigram	No	-0.03617	221.3
	TruncatedSVD (n_components = 200)	No	Yes	unigram	Yes	-0.00557	278.34
	TruncatedSVD (n_components = 200)	No	Yes	unigram	No	-0.0017	278.288
	TruncatedSVD (n_components = 200)	No	Yes	bigram	Yes	0.000785	216.63
	TruncatedSVD (n_components = 200)	No	Yes	bigram	No	-0.0198	221.329
13	BOW: CountVectorizer (TP)	Yes	No	unigram	Yes	-0.00456	3407.49

	BOW: CountVectorizer (TP)	Yes	No	unigram	No	0.017478	4045.31
	BOW: CountVectorizer (TP)	Yes	No	bigram	Yes	-0.04603	3078.22
	BOW: CountVectorizer (TP)	Yes	No	bigram	No	-0.05229	4033.53
	BOW: CountVectorizer (TP)	No	Yes	unigram	Yes	-0.00799	3345.04
	BOW: CountVectorizer (TP)	No	Yes	unigram	No	0.007993	4012.53
	BOW: CountVectorizer (TP)	No	Yes	bigram	Yes	-0.0454	3045.55
	BOW: CountVectorizer (TP)	No	Yes	bigram	No	-0.05317	3999.18
	BOW: CountVectorizer (TF)	Yes	No	unigram	Yes	0.002217	3414.45
	BOW: CountVectorizer (TF)	Yes	No	unigram	No	-0.00142	4182.39
	BOW: CountVectorizer (TF)	Yes	No	bigram	Yes	-0.10687	3082.15
	BOW: CountVectorizer (TF)	Yes	No	bigram	No	-0.0538	4045.44
	BOW: CountVectorizer (TF)	No	Yes	unigram	Yes	-0.01178	3416.53
	BOW: CountVectorizer (TF)	No	Yes	unigram	No	-0.00081	4212.12
	BOW: CountVectorizer (TF)	No	Yes	bigram	Yes	-0.0454	3045.55
	BOW: CountVectorizer (TF)	No	Yes	bigram	No	-0.05344	4005.17
	BOW: TF-IDF	Yes	No	unigram	Yes	0.006173	426.959
	BOW: TF-IDF	Yes	No	unigram	No	0.004518	426.227
	BOW: TF-IDF	Yes	No	bigram	Yes	0.010892	434.539
	BOW: TF-IDF	Yes	No	bigram	No	0.00726	434.88

	BOW: TF-IDF	No	Yes	unigram	Yes	0.006527	427.368
	BOW: TF-IDF	No	Yes	unigram	No	0.004401	426.32
	BOW: TF-IDF	No	Yes	bigram	Yes	0.009156	434.682
	BOW: TF-IDF	No	Yes	bigram	No	0.008489	434.212
	TruncatedSVD (n_components = 50)	Yes	No	unigram	Yes	0.11596	86.9302
	TruncatedSVD (n_components = 50)	Yes	No	unigram	No	0.080295	94.1874
	TruncatedSVD (n_components = 50)	Yes	No	bigram	Yes	0.4655	52.537
	TruncatedSVD (n_components = 50)	Yes	No	bigram	No	0.587086	53.4737
	TruncatedSVD (n_components = 50)	No	Yes	unigram	Yes	0.112176	85.6851
	TruncatedSVD (n_components = 50)	No	Yes	unigram	No	0.079903	88.9609
	TruncatedSVD (n_components = 50)	No	Yes	bigram	Yes	0.525883	52.3797
	TruncatedSVD (n_components = 50)	No	Yes	bigram	No	0.414504	53.9709
	TruncatedSVD (n_components = 100)	Yes	No	unigram	Yes	0.026357	162.914
	TruncatedSVD (n_components = 100)	Yes	No	unigram	No	0.016508	166.313
	TruncatedSVD (n_components = 100)	Yes	No	bigram	Yes	0.039934	108.439
	TruncatedSVD (n_components = 100)	Yes	No	bigram	No	0.281876	111.899
	TruncatedSVD (n_components = 100)	No	Yes	unigram	Yes	0.034725	160.228
	TruncatedSVD (n_components = 100)	No	Yes	unigram	No	0.011416	165.463
	TruncatedSVD (n_components = 100)	No	Yes	bigram	Yes	-0.04799	108.721

TruncatedSVD (n_components = 100)	No	Yes	bigram	No	0.270533	110.034
TruncatedSVD (n_components = 200)	Yes	No	unigram	Yes	0.005824	275.258
TruncatedSVD (n_components = 200)	Yes	No	unigram	No	0.011844	274.21
TruncatedSVD (n_components = 200)	Yes	No	bigram	Yes	-0.02986	212.562
TruncatedSVD (n_components = 200)	Yes	No	bigram	No	-0.0229	215.924
TruncatedSVD (n_components = 200)	No	Yes	unigram	Yes	0.005614	270.774
TruncatedSVD (n_components = 200)	No	Yes	unigram	No	0.003762	272.886
TruncatedSVD (n_components = 200)	No	Yes	bigram	Yes	-0.01827	212.411
TruncatedSVD (n_components = 200)	No	Yes	bigram	No	-0.01596	216.737

Analysis & Interpretation:

- **Identify which embedding technique resulted in the best clustering.**
- **Discuss how preprocessing choices impacted the results.**
- **Provide sample headlines from different clusters to analyze coherence.**

So I did around 48 for each k, from that these are the best sillhoutte scores and WSS,

	k=5	k=9	k=13
smallest WSS	66.04	59.31	52.38
	43	43	43
largest SILL	0.611	0.561	0.587
	43	31	31

This table shows that the smallest WSS was found in case 43 for all k's, (best was k=13). That case was: **LSA 50, lemmatization, bigrams and removed stop words**.
The best silhouette score was found again in cases 43 and 31. Again, the best was k=5 in case 43. Case 31 was **LSA 50, stemming, bigrams, and not removing stop words**.

- So the best embedding technique was hands down LSA 50.
  - LSA 50 gave WSS in 50-100, whereas
  - BOW was in 3500-4000.
  - LSA 100 was 100-200 and
  - LSA 200 was 200-300.
  - TFIDF was 400-500.

- So the best was LSA 50. The silhouette scores were also the highest in LSA 50.

- I noticed that when we applied bigrams, we got more columns, and silhouette falled into a negative FOR BOW. However for the rest bigrams performed better, it gave a higher silhouette and lower WSS
- However removing stop words was ALWAYS good, whenever I didn't remove, I had more columns and very high WSS and low silhouette
- Lemmatization performed slightly better than stemming
- LSA 50 was faster than LSA 200. It took slightly longer to run LSA 200.

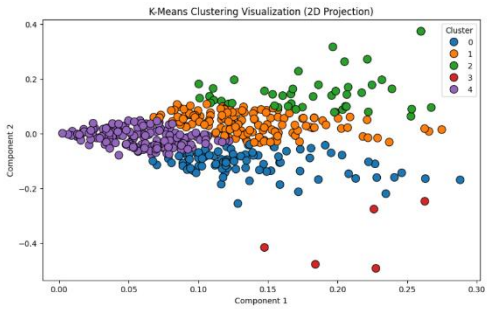
```
import re
import unicodedata

def clean_text(text):
    text = text.encode('ascii', 'ignore').decode()  # Remove non-ASCII characters
    text = unicodedata.normalize("NFKD", text)  # Normalize Unicode text

    # Separate numbers attached to words
    text = re.sub(r'(?<=\d)(?=[a-zA-Z])', ' ', text)  # number-word
    text = re.sub(r'(?<=[a-zA-Z])(?=\d)', ' ', text)  # word-number

    text = text.replace("-", " ") # replace hyphens with spaces to tokenize the numbers and words
    text = re.sub(r'[^\w\s,]', '', text)  # Remove everything except words, numbers, and commas
    text = re.sub(r'\s+', ' ', text).strip()   # remove extra spaces

    return text
```

✓ 0.0s

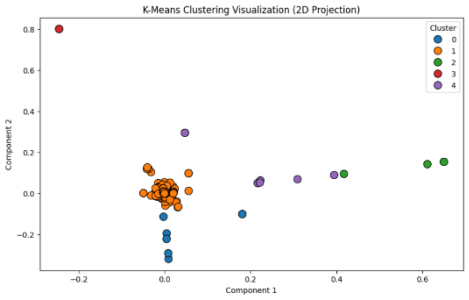
```
documents = [clean_text(text) for text in documents]
documents
```

✓ 0.0s

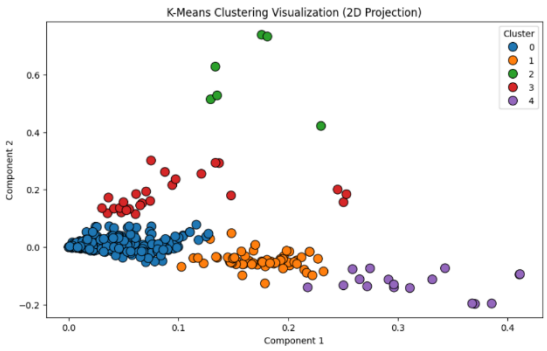
- Values were much better after the data was cleaned. Here is the cleaning code:
- I ran it on my own laptop on VS code and it did not have any errors or problems, running time for each was an average of 1-2 seconds, sometimes even less than 1 second
- I generated the graph for each iteration, and this is what I found:



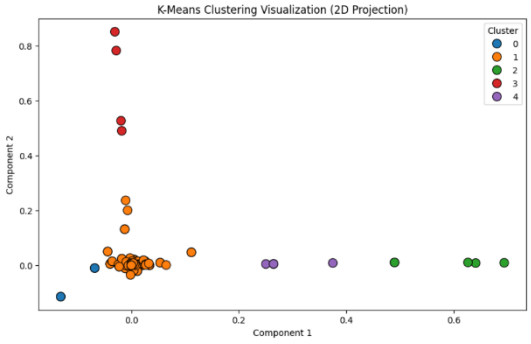
This is for ALL words, UNI gram



This is for ALL words, BI gram



This is for STOP words removed, UNI gram



This is for STOP words removed, BI gram

So from this we can see that unigrams have a more spreadout values while bigrams have more concise values with same context

This was the graph generation code:

```
def display_k_means(k, data):
    print(f"Displaying {k} start time:", get_current_datetime())

    svd = TruncatedSVD(n_components=2, random_state=42)
    data = svd.fit_transform(data)

    kmeans = KMeans(n_clusters=k, random_state=erp)
    labels = kmeans.fit_predict(data)

    # Convert to DataFrame for visualization
    df_viz = pd.DataFrame({'X': data[:, 0], 'Y': data[:, 1], 'Cluster': labels})

    # Scatter plot of clusters
    plt.figure(figsize=(10, 6))
    sns.scatterplot(data=df_viz, x='X', y='Y', hue='Cluster', palette='tab10', s=100, edgecolor='black')
    plt.title("K-Means Clustering Visualization (2D Projection)")
    plt.xlabel("Component 1")
    plt.ylabel("Component 2")
    plt.legend(title="Cluster")
    plt.show()

    print("Finished displaying at:", get_current_datetime(), "\n")
```

Here are some sample headlines:

```
Executing 5 start time: 2025-02-23 20:12:01
K=5: Silhouette Score and WSS=0.6114    66.0400
copied to clipboard

Cluster 0:
- Justice Sarfraz Dogar sworn in as acting chief justice of IHC
- Justice Sarfraz Dogar takes oath as acting Chief Justice of IHC

Cluster 1:
- Oil prices decline on optimism over potential Russia-Ukraine peace agreement
- US, India strike deal for F-35 stealth fighter jets amid growing defense ties
- Harassment experiences in Pakistan: the need to speak up
- UK Pound further climbs up against Pakistani rupee – 14 February 2025
- Burnt body of missing Karachi young man found

Cluster 2:
- Pakistan’s 2nd polio case of 2025 reported in Badin
- Second polio case of 2025 reported from Badin

Cluster 3:
- KP govt prepares to launch first air ambulance service
- K-P prepares to launch first air ambulance, test flight completed

Cluster 4:
- Bureaucrats will also have to declare their assets
- Bureaucrats will also have to declare their assets
Displaying 5 start time: 2025-02-23 20:12:01
```

So from these cluster headlines (for each case I have generated 5 headlines for every k. this is headlines for k=5 and case 43 (THE BEST CASE)):

- I can see the first cluster is of politics/chief justice
- Second cluster is a bit mixed, mostly for world affairs
- Third cluster is of polio cases
- Forth cluster is of air ambulance
- Fifth is of bereaucrats

So we can say there is some sense of coherence in the clusters.

SO OVERALL the best is

- LSA 50
- Bigrams
- Lemmatization
- And stop words removed