Report - COVID19 papers (CORD-19)

In [1]:
```
# Itamar Fradkin - 312531064
# Ron Boxer - 321219008
```

first you need to download the files from Here

Note- After downloading the zip file -

Unzip - metadata.csv & pdf_json folder (Keep the sturcted folder((document_parses)).

Insert this files into 'data' folder & create new folder named- 'minidataset' in 'document_parses' folder

We created several utilits which can be found in 'utils' folder.

let`s load and take a look on the metadata.

In [2]:
```
import json
import os
import cotools
import shutil
import pandas as pd
import numpy as np
```

In [3]:
```
DATASET_PATH = 'data/'
METADATA_PATH = 'data/metadata.csv'
MINI_DATASET_JSON_PATH = 'data/document_parses/minidataset'
```

In [4]:
```
import utils.dataset as ut
df = ut.load_metadata()
```

```
C:\Users\ronbo\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3338: DtypeWarning: Columns (1,4,5,6,13,14,15,16) have mixed types.Specify dtype option on import or set low_memory=False.
  if (await self.run_code(code, result,  async_=asy)):
```

In [5]:
```
df
```

Out[5]:

sha	cord_uid	source_x	title	doi	pmcid	pubmed_id	license	abstract	publish_time	authors	journal	mag_id	who_covidence_id	arxiv_id	pdf_json_
d7ea1370848eac2a4e421c20fc30a69dfa69566e	9w762whh	Elsevier; PMC; WHO	Patients With Myocarditis Associated With COVI...	10.1016/j.jacc.2022.02.004	PMC8958986	NaN	els-covid	NaN	2022-04-05	Rosner, Carolyn M.; Atkins, Melany; Saeed, Ibr...	Journal of the American College of Cardiology	NaN	NaN	NaN	document_parses/pdf_json/d7ea1370848eac2a4e4
e4494dc889fcaadde2f5c0fcf401e7e8a3d96a63	6ltgimq0	Elsevier; Medline; PMC; WHO	Electrochemical immunosensor for rapid and hig...	10.1016/j.talanta.2022.123211	PMC8730781	3.49993e+07	no-cc	A label-free electrochemical biosensing approa...	2022-04-01	Mehmandoust, Mohammad; Gumus, Z. Pinar; Soylak...	Talanta	NaN	NaN	NaN	document_parses/pdf_json/e4494dc889fcaadde2f
12bc48af0b3196eef7e887807130b8553e8d7190	vmsyu6w7	Elsevier; Medline; PMC; WHO	Entrepreneurial Interventions for crisis manag...	10.1016/j.ijdrr.2022.102830	PMC8865137	3.5229e+07	no-cc	This article investigates both the negative an...	2022-04-01	Krishnan, Commander S. Navaneetha; Ganesh, L.S...	Int J Disaster Risk Reduct	NaN	NaN	NaN	document_parses/pdf_json/12bc48af0b3196eef7e
fea63a0a7eb45059214491c2cb894f7a98b5f65c	tx49s7f8	Medline; PMC; WHO	A Qualitative Examination of COVID-19's Impact...	10.1177/08901171211053845	PMC8851044	3.4787e+07	no-cc	PURPOSE: The COVID-19 pandemic is correlated w...	2022-03-31	Brannon, Grace Ellen; Mitchell, Sophia; Ray, M...	Am J Health Promot	NaN	NaN	NaN	document_parses/pdf_json/fea63a0a7eb45059214
631cf2b3762bf36ecfe686765b08cbc34351fbd9	aagrsfeh	Elsevier; PMC; WHO	Population Mobility and Socioeconomic Indicato...	10.1016/j.ijid.2021.12.061	PMC8884814	NaN	els-covid	Purpose To explore the extent that socioeconom...	2022-03-31	Marwah, A.; Feldman, J.; Moineddin, R.; Thomas...	International Journal of Infectious Diseases	NaN	NaN	NaN	document_parses/pdf_json/631cf2b3762bf36ecfe
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
cbd8c8f742fb5a032e1b041da900a8a51623cc79	htwp70hc	Medline; PMC; WHO	Comparison of chest CT severity scoring system...	10.1007/s00330-021-08432-5	PMC8760133	3.50318e+07	no-cc	PURPOSE: To compare the diagnostic performance...	2022-01-15	Elmokadem, Ali H.; Mounir, Ahmad M.; Ramadan, ...	Eur Radiol	NaN	NaN	NaN	document_parses/pdf_json/cbd8c8f742fb5a032e1
5bacfca63b11318e9788197ca3005a1135138956	4jqcl0ny	PMC	Regarding the articles on home spirometry	10.1016/j.jcf.2022.01.002	PMC8760931	35042654	no-cc	NaN	2022-01-15	Curley, Rachael; Campbell, Michael J; Walters,...	J Cyst Fibros	NaN	NaN	NaN	document_parses/pdf_json/5bacfca63b11318e978
637abda16edb7c7245861431108ff8f25aeea80f	7221cj12	Medline; PMC	Missed opportunities to identify cryptococcosi...	10.1177/20499361211066363	PMC8771738	3.50703e+07	cc-by-nc	SARS-CoV-2 may activate both innate and adapti...	2022-01-15	Chastain, Daniel B.; Henao-Martínez, Andrés F....	Ther Adv Infect Dis	NaN	NaN	NaN	document_parses/pdf_json/637abda16edb7c72458
49ae4f05cc3d5dadcd9ee8d7df2a6cbe6afcb8fb	33c5rxm2	Medline; PMC	Using Simulation Optimization to Solve Patient...	10.3390/healthcare10010164	PMC8775607	3.50523e+07	cc-by	This study investigates patient appointment sc...	2022-01-15	Chen, Ping-Shun; Chen, Gary Yu-Hsin; Liu, Li-W...	Healthcare (Basel)	NaN	NaN	NaN	document_parses/pdf_json/49ae4f05cc3d5dadcd9
a4bb5b7bfd9cf309d443cf439d29502ccd30e1a5	tbhb2lhc	Elsevier; Medline; PMC; WHO	Livelihood challenges and healthcare-seeking b...	10.1016/j.aquaculture.2021.737348	PMC8414286	3.44939e+07	no-cc	The outbreak of coronavirus disease (COVID-19)...	2022-01-15	Hossain, Md. Tanvir; Lima, Taposhi Rabya; Ela,...	Aquaculture	NaN	NaN	NaN	document_parses/pdf_json/a4bb5b7bfd9cf309d44

27000 rows × 18 columns

As we only need some of the data, we move a small cohort into an entirely separate folder. (It will take a while :))

In [6]:
```
ut.move_files(df)
```

Now we will use outsource package - 'cord-19-tools' to help us load the papers effitiantly.

In [7]:
```
pip install cord-19-tools
```

```
Requirement already satisfied: cord-19-tools in c:\users\ronbo\anaconda3\lib\site-packages (0.3.3)
Requirement already satisfied: xmltodict in c:\users\ronbo\anaconda3\lib\site-packages (from cord-19-tools) (0.12.0)
Note: you may need to restart the kernel to use updated packages.
```

In [8]:
```
# Load papers
import cotools
data = cotools.Paperset(MINI_DATASET_JSON_PATH)
```

In [9]:
```
covid_df = ut.load_papers_into_df(data, size=20000)
covid_df.head()
```

Out[9]:

	title	paper_id	abstract	body_text
0	Recruitment methods and yield rates in a clini...	000e6f401f0f46b240cc81f2c9ef41914bfb9e06	Background: Although the prevalence of hyperte...	The prevalence of hypertension is increasing w...
1	Impact of the COVID-19 Pandemic on Daily Life:...	0012308e8c02792b907c31935868f1afbff2c59b	Using a mixed methods design, this study aimed...	travel restrictions. These measures aimed to p...
2	Colchicine Against SARS-CoV-2 Infection: What ...	0015cecc2298c3bdb9bda0e0b84b38ebdcca716f	Coronavirus disease 2019 caused by the severe ...	Systemic inflammation is the hallmark of coron...
3	Use and misuse of prescription stimulants by u...	001716d1b1c1e9d9c1c8b3751e620371f2ddf2d4	Background: Misuse of prescription stimulants ...	Global Drug Survey, an increase of neuroenhanc...
4	A Neural Phillips Curve and a Deep Output Gap	001746ab8ab396aa3a7bc6b45ba75f26ec860fa9	Many problems plague the estimation of Phillip...	Few equations are as central to modern macroec...

Part A - Paper Similarity using gzip as our compresing method on text data only

Normalized compression distance (NCD) is a way of measuring the similarity between two objects, be it two documents, two letters, two emails, two music scores, two languages, two programs, two pictures, two systems, two genomes, to name a few. Such a measurement should not be application dependent or arbitrary. A reasonable definition for the similarity between two objects is how difficult it is to transform them into each other. Further information can be found on this blog post

If two objects compress better together than separately, it means they share common patterns and are similar!!

here is the formula-

NCD Formula

Let's take a paper as an example. Calculate the NCD distance to all other papers and take the 10 closest papers.

In [10]:
```
import utils.model as model
paper_id = '88b80f02e54d2ed8c9f05f422b45f4810a6a405b' # Example
k = 10
similarity_df = model.k_similar_papers(paper_id, k, covid_df,txt_to_encode='abstract')
similarity_df
```

Out[10]:

	title	paper_id	abstract	body_text	ncd_distance
14448	Explainable machine learning to predict long-t...	88b80f02e54d2ed8c9f05f422b45f4810a6a405b	Background: Machine learning (ML) model is inc...	The long-term outcome is currently an emerging...	0.037691
14255	Comparative analysis of explainable machine le...	8710f527c4706f1ae42013a4d7688b1ec03f73aa	Background: Machine learning (ML) holds the pr...	underlying structure of the data, while ML mod...	0.777518
2529	Prediction of 3-year risk of diabetic kidney d...	18a795e30445a0f4ab3eb1be1198a805deb0e1fa	Background: Established prediction models of D...	clinical decision-making. Understanding the ri...	0.795195
9839	Predicting the necessity of oxygen therapy in ...	5d6ad19f8d11971024d1b7a4a23e6cd7378cd15b	Medical oxygen is a critical element in the tr...	Since the spread of COVID-19 in December 2019,...	0.805654
9625	Article 852736 1 (2022) A Promising Preoperati...	5b9d41960cd05dbc62122130019030e29f1b4ae2	Background: The non-invasive preoperative diag...	Hepatocellular carcinoma (HCC) is one of the m...	0.807205
10705	Mortality Predictive Value of APACHE II and SO...	6621c2bde72488b15a577d92fb8613a77461266b	Background. COVID-19 pandemic has become a glo...	In December 2019, severe acute respiratory syn...	0.813725
5295	Journal Pre-proofs Can we reliably automate cl...	32d17d06540281827e8a013e51f98e953e7f114f	Background: Building Machine Learning (ML) mod...	What was already known on the topic: Classic...	0.818610
14952	Predicting ionized hypocalcemia: External vali...	8dd1465054a2ef6c952fedf0ed9af361ea1a38ef	Background: Ionized hypocalcemia is common in ...	New York City was the epicenter of the COVID-1...	0.824499
15770	Early changes in laboratory tests predict live...	959423993ae9a583d8f26edf1842128dc086ae06	Background: Most patients with coronavirus dis...	. Studies have shown that COVID-19 can affect ...	0.828033
8813	Comparing different machine learning technique...	53d8d480246f79239ebc56e87c0384a8085ba514	Background: Coronavirus disease 2019 (COVID-19...	Coronavirus disease 2019 (COVID-19) has been a...	0.828685
24656	Comparison of Regression and Machine Learning ...	e997ad775d1eed1188a65bc0b60f50a87cf46851	Background: Depression is highly prevalent and...	Depression is the most common psychiatric diso...	0.828889

In this example, we found some similar papers using the comparison method. our paper was in the field of machine learning From the results, we can see that we got papers in the field of machine learning are also represented.

Part B - Clustering using Compression method from Part A

Our idea is to make several features based on the compression method. we saw in part A that actually, we can get some similar papers based on this method. so we decided to enrich the idea and create 3 features based on compression on the title, paper body text, and abstract text. we think this logic will find clusters with similar papers.

In [11]:
```
import gzip

def compress(x):
    x = str(x).encode()
    l_x = len(gzip.compress(x))
    return l_x


# Apply Compression method from Part A
train = covid_df.copy()
train['comp_title'] = train['title'].apply(compress)
train['comp_body'] = train['body_text'].apply(compress)
train['comp_abstract'] = train['abstract'].apply(compress)
```

In [12]:
```
# Pre- prossece before clustering - Normalization
from sklearn.preprocessing import StandardScaler , MinMaxScaler

normalizer = MinMaxScaler()
paper_ids =  covid_df['paper_id']
train = train[['paper_id','comp_title','comp_body','comp_abstract']]
train['comp_title'] = normalizer.fit_transform(train[['comp_title']])
train['comp_body'] = normalizer.fit_transform(train[['comp_body']])
train['comp_abstract'] = normalizer.fit_transform(train[['comp_abstract']])
train
```

Out[12]:

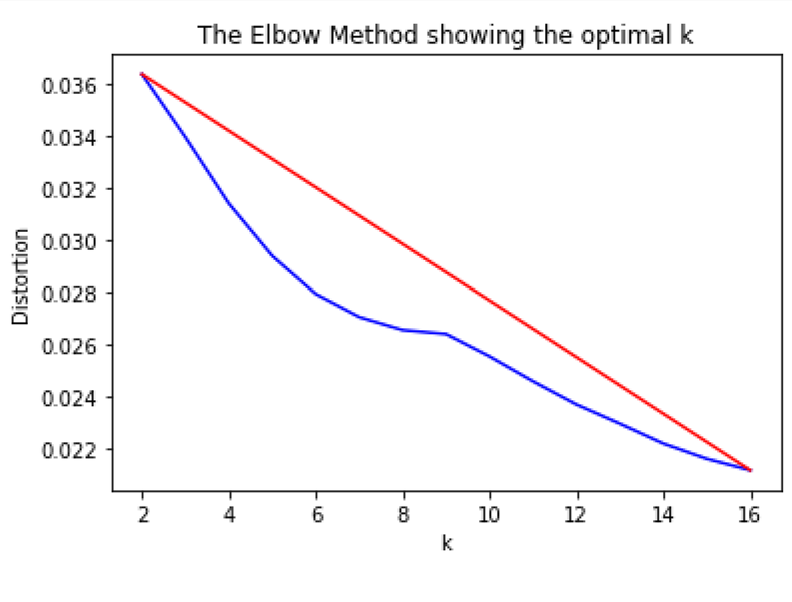
	paper_id	comp_title	comp_body	comp_abstract
0	000e6f401f0f46b240cc81f2c9ef41914bfb9e06	0.135011	0.026254	0.075546
1	0012308e8c02792b907c31935868f1afbff2c59b	0.092677	0.050131	0.030028
2	0015cecc2298c3bdb9bda0e0b84b38ebdcca716f	0.069794	0.027313	0.050121
3	001716d1b1c1e9d9c1c8b3751e620371f2ddf2d4	0.127002	0.036918	0.055819
4	001746ab8ab396aa3a7bc6b45ba75f26ec860fa9	0.050343	0.141596	0.166362
...	...	...	...	...
26979	ffeb944868a31900fb661d78835ae1b22655fb22	0.137300	0.021210	0.072404
26980	ffeba2e1ac4c562c93da63f732f73cea26327793	0.081236	0.031219	0.047636
26986	fff951fc332133ecdffe8506d630494b552b126b	0.077803	0.049735	0.010156
26988	fffacb29c594a89c2e2db9a844a496c540ad913c	0.148741	0.022383	0.000658
26990	fffed5cd958beb441f517c58f6d04990fe62c7c2	0.141876	0.019907	0.058815

17664 rows × 4 columns

Choose optimal K - Elbow method

In [13]:
```
from sklearn import metrics
from scipy.spatial.distance import cdist
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# run kmeans with many different k
distortions = []
K = range(2, 17)

data = train[['comp_title','comp_body','comp_abstract']]

for k in K:
    k_means = KMeans(n_clusters=k, random_state=42).fit(data)
    k_means.fit(data)
    distortions.append(sum(np.min(cdist(data, k_means.cluster_centers_, 'euclidean'), axis=1)) / train.shape[0])
```

In [14]:
```
X_line = [K[0], K[-1]]
Y_line = [distortions[0], distortions[-1]]

# Plot the elbow
plt.plot(K, distortions, 'b-')
plt.plot(X_line, Y_line, 'r')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```

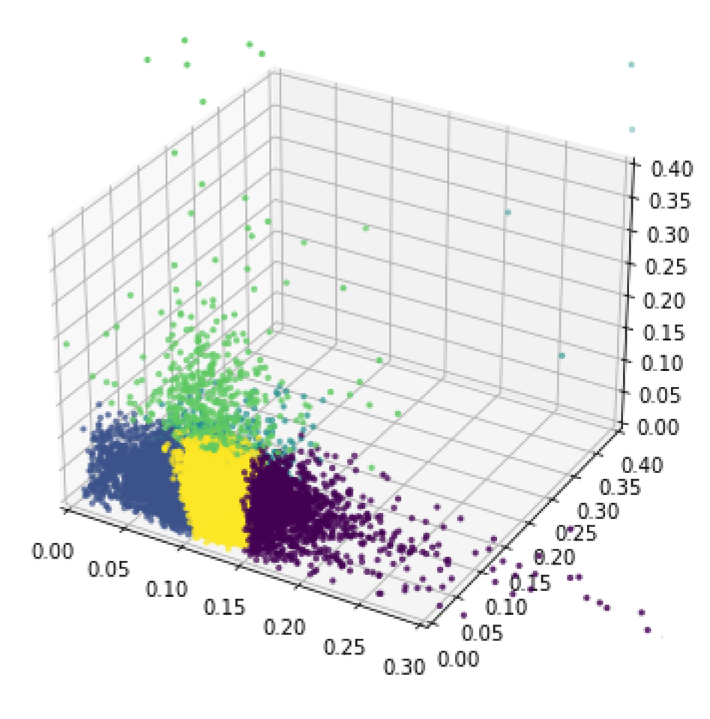


Final Clustering K= 5

In [15]:
```
kmeans = KMeans(n_clusters=5, random_state=0)

#predict the labels of clusters.
label = kmeans.fit_predict(train[['comp_title','comp_body','comp_abstract']])
```

Visualizatoion

In [16]:
```
import matplotlib.pyplot as plt
import numpy as np


fig = plt.figure(1, figsize=(25, 6))
ax = plt.axes(projection = '3d')
ax.scatter(data.iloc[:, 0], data.iloc[:, 1], data.iloc[:, 2], marker='.', c = label)
plt.xlim([0, 0.3])
plt.ylim([0, 0.4])
ax.set_zlim(0, 0.4);
```



Looks like a good separation

Analysis

In order to see if the clusters actually presenting similar papers we will take the example from part A and check if they are in the same cluster.

In [17]:
```
example_paper = '88b80f02e54d2ed8c9f05f422b45f4810a6a405b'
example_paper_raw_data = train[train['paper_id'] == example_paper]
predicted_cluster_example_paper = kmeans.predict(example_paper_raw_data[['comp_title','comp_body','comp_abstract']])[0]
counter = 0

for similar_paper in similarity_df['paper_id'].values[1:]:
    paper_raw_data = train[train['paper_id'] == similar_paper]
    paper_raw_data = paper_raw_data[['comp_title','comp_body','comp_abstract']]
    paper_pridiction = kmeans.predict(paper_raw_data)
    if paper_pridiction == predicted_cluster_example_paper:
        counter += 1
counter
```

Out[17]: 7

Wow! Seven out of ten were in the same cluster. In addition, we saw in Part A an example paper in the field of machine learning. therefore, This cluster seems to represent a good collection of papers in the field of machine learning.

Furhter Work

Based only on the compression method and using only text data in this work, we got pretty good results. For future work, we would like to add some more methods, such as word embedding (DOC2VEC), and create a model that incorporates both methods and more metadata features. Using this approach, we believe that we will achieve better performance and similarity.