```
!pip install datasets
Collecting datasets
       Downloading datasets-2.17.0-py3-none-any.whl (536 kB)
     Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from datasets) (3.13.1)
     Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from datasets) (1.23.5)
     Collecting pyarrow>=12.0.0 (from datasets)
       Downloading pyarrow-15.0.0-cp310-cp310-manylinux_2_28_x86_64.whl (38.3 MB)
     Requirement already satisfied: pyarrow-hotfix in /usr/local/lib/python3.10/dist-packages (from datasets) (0.6)
     Collecting dill<0.3.9,>=0.3.0 (from datasets)
       Downloading dill-0.3.8-py3-none-any.whl (116 kB)
                                                      116.3/116.3 kB 10.0 MB/s eta 0:00:00
     Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from datasets) (1.5.3)
     Requirement already satisfied: requests>=2.19.0 in /usr/local/lib/python3.10/dist-packages (from datasets) (2.31.0)
     Requirement already satisfied: tqdm>=4.62.1 in /usr/local/lib/python3.10/dist-packages (from datasets) (4.66.1)
     Requirement already satisfied: xxhash in /usr/local/lib/python3.10/dist-packages (from datasets) (3.4.1)
     Collecting multiprocess (from datasets)
       Downloading multiprocess-0.70.16-py310-none-any.whl (134 kB)
     Requirement already satisfied: fsspec[http]<=2023.10.0,>=2023.1.0 in /usr/local/lib/python3.10/dist-packages (from datasets) (2023.6
     Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-packages (from datasets) (3.9.3)
     Requirement already satisfied: huggingface-hub>=0.19.4 in /usr/local/lib/python3.10/dist-packages (from datasets) (0.20.3)
     Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from datasets) (23.2)
     Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from datasets) (6.0.1)
     Requirement already satisfied: aiosignal>=1.1.2 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.3.1)
     Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp-vdatasets) (23.2.0)
     Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.4.1)
     Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (6.0.5)
     Requirement already satisfied: yarl<2.0,>=1.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.9.4)
     Requirement already satisfied: async-timeout<5.0,>=4.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (4.0.3)
     Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.10/dist-packages (from huggingface-hub>=0.19.4-
     Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->datasets
     Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->datasets) (3.6)
     Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->datasets) (2.0 Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->datasets) (2024)
     Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas->datasets) (2.8.2)
     Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->datasets) (2023.4)
     Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas->datasets)
     Installing collected packages: pyarrow, dill, multiprocess, datasets
       Attempting uninstall: pyarrow
         Found existing installation: pyarrow 10.0.1
         Uninstalling pyarrow-10.0.1:
           Successfully uninstalled pyarrow-10.0.1
     ibis-framework 7.1.0 requires pyarrow<15,>=2, but you have pyarrow 15.0.0 which is incompatible. pandas-gbq 0.19.2 requires google-auth-oauthlib>=0.7.0, but you have google-auth-oauthlib 0.4.6 which is incompatible.
     Successfully installed datasets-2.17.0 dill-0.3.8 multiprocess-0.70.16 pyarrow-15.0.0
import pandas as pd
import re
import nltk
from datasets import load_dataset
dataset = load_dataset("mystic-leung/medical_cord19")
                                                                 70.8M/70.8M [00:06<00:00,
dataset
             num rows: 210000
```

```
features: ['input', 'output'],
num_rows: 45000
         test: Dataset({
    features: ['input', 'output'],
             num_rows: 45000
train_dataset = dataset['train']
train_dataset
         features: ['input', 'output'],
         num_rows: 210000
print("Features: ",train_dataset.features)
print("Number of Rows: ",train_dataset.num_rows)
                {'input': Value(dtype='string', id=None), 'output': Value(dtype='string', id=None)}
     Number of Rows: 210000
    Data Preprocessing
Converting the dictionary to a Pandas Dataframe
train_df_full = pd.DataFrame(train_dataset)
train_df = train_df_full.head(1000)
train_df.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 1000 entries, 0 to 999
     Data columns (total 2 columns):
         Column Non-Null Count Dtype
      0 input 1000 non-null
1 output 1000 non-null
     dtypes: object(2)
     memory usage: 15.8+ KB
train_df.drop_duplicates(inplace = True)
     <ipython-input-38-6f145123ae15>:1: SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a \operatorname{DataFrame}
       train_df.drop_duplicates(inplace = True)
```

Text cleaning

Removing punctuations, Special characters, Email, Hashtags, Usernames, Leading white spaces, Case conversion,

```
def preprocessing_1(data:str):
 data = data.strip()
 data = data.lower()
 data = re.sub(r'\s+', ' ', data)
 url_pattern = re.compile(r"https?://\S+|www\.\S+")
 data = re.sub(url_pattern, "", data)
 username_pattern = re.compile(r"@\w+")
 data = re.sub(username_pattern, "", data)
 hashtag_pattern = re.compile(r"#\w+'
 data = re.sub(hashtag_pattern, "", data)
 data = re.sub(r"([a-zA-Z])\1\{2,\}", r'\1', data)
  data = re.sub(r'[^a-zA-Z\s]',"",data)#Remove special characters
  return data
```

```
#Assingning this way always converts to Series.Best to avaoid this method and instead use slicing
####input_data = train_df['input']# Similar to X
####output_data = train_df['output']# Similar to Y
X = pd.DataFrame()
Y = pd.DataFrame()
X['text'] = train_df['input'].apply(preprocessing_1)# Similar to X
Y['summary']=train_df['output'].apply(preprocessing_1)
       0
              cardiovascular disease is the leading cause of..
       2
             ethnopharmacological relevance the subtribe hy.
       4
               objectives to report epidemiological features ...
      995 background nurses and midwives have a professi...
      997
                a global public health crisis caused by the n...
             the pandemic from covid causes a health threat.
Tokenization, Removing stopwords etc
nltk.download('punkt')
     [nltk_data] Downloading package punkt to /root/nltk_data...
     [nltk_data] Package punkt is already up-to-date!
nltk.download('averaged_perceptron_tagger')
nltk.download('wordnet')
     [n]{\tt ltk\_data}] \ {\tt Downloading} \ {\tt package} \ {\tt averaged\_perceptron\_tagger} \ {\tt to}
     [nltk_data]
                      /root/nltk_data...
     [nltk_data]
                    Package averaged_perceptron_tagger is already up-to-
     [nltk_data]
     [nltk_data] Downloading package wordnet to /root/nltk_data...
     [nltk_data] Package wordnet is already up-to-date!
     True
nltk.download('stopwords')
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
     [nltk_data] Downloading package stopwords to /root/nltk_data...
     [nltk_data] Package stopwords is already up-to-date!
def preprocessing_2(data:str):
  data = nltk.word_tokenize(data.lower())
  def get_pos(word):
        tag = nltk.pos_tag([word])[0][1].upper()
        tag_dict = {"N":"n","V":"v","R":"r","J":"a"}
        return tag_dict.get(tag,"n")
  lemma = nltk.stem.WordNetLemmatizer()
  data = [lemma.lemmatize(word,pos=get_pos(word))for word in data]
  data = [word for word in data if word.isalnum() and word not in stop_words]
  return data
X['text'] = train_df['input'].apply(preprocessing_2)# Similar to X
Y['summary']=train_df['output'].apply(preprocessing_2)
X['text'] = X['text'].apply(lambda x : " ".join(x))
Y['summary'] = Y['summary'].apply(lambda x : " ".join(x))
```

```
0
              cardiovascular disease leading cause death glo..
       2
             ethnopharmacological relevance subtribe hyptid...
       4
                 objective report epidemiological feature clini...
      995
              background nurse midwife professional obligati...
                global public health crisis caused 2019 novel .
      997
            pandemic cause health threat many country requ..
print(X['text'][1])
     novel coronavirus disease 2019 continues affect pregnant woman concern adverse maternal fetal outcome rapidly spreading throughout
print(Y['summary'][1])
     consequence disease maternal perinatal neonatal outcome retrospective observational cohort study
        medication adherence cardiovascular medicine
#X['text'] = X['text'].apply(lambda x: " ".join(["".join(sentence) for sentence in x]))
 \begin{tabular}{ll} #Y['summary'] = Y['summary'].apply(lambda x: " ".join([" ".join(sentence) for sentence in x])) \end{tabular} 
for i in range(5):
    print("Review:",X['text'][i])
    print("Summary:",Y['summary'][i])
    print("\n")
     Review: cardiovascular disease leading cause death globally pharmacological advancement improved morbidity mortality associated card
     Summary: medication adherence cardiovascular medicine
     Review: novel coronavirus disease 2019 continues affect pregnant woman concern adverse maternal fetal outcome rapidly spreading thre
     Summary: consequence disease maternal perinatal neonatal outcome retrospective observational cohort study
     Review: ethnopharmacological relevance subtribe hyptidinae contains approximately 400 accepted specie distributed 19 genus hyptis er
     Summary: subtribe hyptidinae promising source bioactive metabolite
     Review: estimate medium term impact six major past pandemic crisis co2 emission energy transition renewable electricity result show
     Summary: impact past pandemic co emission transition renewable energy
     Review: objective report epidemiological feature clinical characteristic outcome human rhinovirus hrv infection comparison community
     Summary: impact seasonality human rhinovirus infection hospitalized patient two consecutive year
input = nltk.word_tokenize(X['text'][0])
input
     ['cardiovascular',
       'disease',
      'leading',
      'death',
```

```
'globally
       'pharmacological',
       'improved',
'morbidity',
       'mortality
       'associated'
       'cardiovascular',
       'disease',
'prescribed',
       'treatment',
       'remains'
       'improved',
       'patient',
       'outcome',
       'variety',
'strategy',
       'medication',
       'adherence',
       'tested'
       'clinical',
       'trial',
'include',
       'following',
       'improving',
       'patient',
       'education',
       'implementing',
       'testing',
       'cognitive'
       'behavioral',
       'reducing',
       'medication',
       'cost',
       'utilizing',
'healthcare',
       'team',
'member'
       'streamlining',
       'dosing',
'regimen',
       'review',
       'describe',
       'specific',
output = nltk.word_tokenize(Y['summary'][0])
output
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

→ TF - IDF Vectorizer

tfidf = TfidfVectorizer()
result_1 = tfidf.fit_transform(input)
result_2 = tfidf.transform(output)
tfidf_embeddings_1 = result_1.toarray()
tfidf_embeddings_2 = result_2.toarray()
#print('\nInput Column : idf values:')
for ele1, ele2 in zip(tfidf.get_feature_names_out(), tfidf.idf_):
#print(tfidf_embeddings_1)
#print(tfidf_embeddings_2)
#print('\nOutput Column :idf values:')
for ele1, ele2 in zip(tfidf.get_feature_names_out(), tfidf.idf_):
    print(ele1, ':', ele2)
print(tfidf_embeddings_1)
      adherence : 3.970414465569701
```

```
also: 4.663561646129646
associated : 4.663561646129646
barrier : 4.663561646129646
behavioral : 4.663561646129646
cardiovascular : 3.970414465569701
category: 4.258096538021482
cause: 4.663561646129646
clinical: 4.663561646129646
cognitive : 4.663561646129646
cost : 4.663561646129646
death: 4.663561646129646
describe: 4.663561646129646
disease : 3.970414465569701
dosing : 4.663561646129646
education : 4.663561646129646
examine : 4.663561646129646
following: 4.663561646129646
future: 4.663561646129646
globally: 4.663561646129646
healthcare: 4.663561646129646
highlight: 4.663561646129646
impact : 4.663561646129646
implementing : 4.663561646129646
improve : 4.663561646129646
improved: 4.258096538021482
improving : 4.258096538021482
include : 4.663561646129646
inquiry: 4.663561646129646
intervention : 4.663561646129646
leading : 4.663561646129646
line: 4.663561646129646
medication : 3.4107986776342782
member: 4.663561646129646
morbidity: 4.663561646129646
mortality : 4.663561646129646
ongoing : 4.663561646129646
outcome : 4.663561646129646
patient : 3.970414465569701
pharmacological : 4.663561646129646
prescribed : 4.663561646129646
reducing : 4.663561646129646
regimen : 4.663561646129646
remains : 4.663561646129646
reminder: 4.663561646129646
review: 4.663561646129646
significant: 4.663561646129646
specific : 4.663561646129646
strategy: 4.663561646129646
streamlining : 4.663561646129646
team : 4.663561646129646
tested : 4.663561646129646
testing : 4.663561646129646
treatment: 4.663561646129646
trial: 3.970414465569701
utilizing: 4.663561646129646
```

!pip install -U altair

```
Requirement already satisfied: altair in /usr/local/lib/python3.10/dist-packages (4.2.2)
Collecting altair
 Downloading altair-5.2.0-py3-none-any.whl (996 kB)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from altair) (3.1.3)
Requirement already satisfied: jsonschema>=3.0 in /usr/local/lib/python3.10/dist-packages (from altair) (4.19.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from altair) (1.23.5)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from altair) (23.2)
Requirement already satisfied: pandas>=0.25 in /usr/local/lib/python3.10/dist-packages (from altair) (1.5.3)
Requirement already satisfied: toolz in /usr/local/lib/python3.10/dist-packages (from altair) (0.12.1)
Requirement already satisfied: typing-extensions>=4.0.1 in /usr/local/lib/python3.10/dist-packages (from altair) (4.9.0)
Requirement already satisfied: attrs>=22.2.0 in /usr/local/lib/python3.10/dist-packages (from jsonschema>=3.0->altair) (23.2.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in /usr/local/lib/python3.10/dist-packages (from jsonschema>=3.
Requirement already satisfied: referencing>=0.28.4 in /usr/local/lib/python3.10/dist-packages (from jsonschema>=3.0->altair) (0.33.6
Requirement already satisfied: rpds-py>=0.7.1 in /usr/local/lib/python3.10/dist-packages (from jsonschema>=3.0->altair) (0.17.1)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.25->altair) (2.8.2
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.25->altair) (2023.4)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->altair) (2.1.5)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas>=0.25->altai
Installing collected packages: altair
  Attempting uninstall: altair
    Found existing installation: altair 4.2.2
    Uninstalling altair-4.2.2:
      Successfully uninstalled altair-4.2.2
lida 0.0.10 requires kaleido, which is not installed.
lida 0.0.10 requires python-multipart, which is not installed.
lida 0.0.10 requires uvicorn, which is not installed.
Successfully installed altair-5.2.0
```

```
print(len(tfidf_embeddings_1))
print(len(tfidf_embeddings_2))
      4
  Bag of Words
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer()
bow_matrix_1 = vectorizer.fit_transform(input)
input_bow = vectorizer.transform()
bow_embeddings_1 = bow_matrix_1.toarray()
print(bow_embeddings_1)
from \ sklearn.feature\_extraction.text \ import \ CountVectorizer
bow_matrix_2= vectorizer.fit_transform(output)
bow embeddings 2 = bow matrix 2.toarray()
print(bow_embeddings_2)
      [[0 0 0 ... 0 0 0]
        \begin{bmatrix} 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 0 & \dots & 0 & 0 & 0 \end{bmatrix} 
      [0 0 0 ... 0 0 0]]
[[0 0 1 0]
       [1 0 0 0]
        [0 1 0 0]
        [0 0 0 1]]
from sklearn.metrics.pairwise import cosine_similarity
cs = cosine_similarity(tfidf_embeddings_1, tfidf_embeddings_1)
               [0., 1., 0., ..., 0., 0., 1.],
[0., 0., 1., ..., 0., 0., 0.],
  Word2Vec
from gensim.models import Word2Vec
word2vec_model_1 = Word2Vec([input], vector_size=200, window=7, min_count=1, workers=4)
word2vec_embeddings_1 = [word2vec_model_1.wv[word] for word in input]
print(word2vec_embeddings_1)
print("CBOW input Word Vectors:")
for word in word2vec_model_1.wv.index_to_key:
     print(word, ':', word2vec_model_1.wv[word])
word2vec_model_2 = Word2Vec([output], vector_size=200, window=7, min_count=1, workers=4)
word2vec_embeddings_2 = [word2vec_model_2.wv[word] for word in output]
print(word2vec_embeddings_1)
print("CBOW input Word Vectors:")
for word in word2vec_model_1.wv.index_to_key:
     print(word, ':', word2vec_model_1.wv[word])
      Streaming output truncated to the last 5000 lines.
                2.73144874e-03, -4.88970662e-04, 1.46124672e-04, 1.07236300e-03,
               3.64232506e-03, 8.67599389e-04, 1.49445295e-05, 2.62066396e-03, -1.14890805e-03, 4.91765328e-03, 1.44274859e-03, 1.43793947e-03,
               1.79356057e-03, -1.33768225e-03, 3.00990720e-03, -3.23401368e-03, 3.67726176e-03, -3.96257453e-03, 2.25142910e-04, 1.90282718e-03, -4.27433476e-03, -2.45355093e-03, -3.12529551e-03, -2.21793377e-03,
               4.85354755e-03, -6.03405351e-04, 6.59228361e-04, 3.02102242e-04, 3.71419312e-03, -8.69793002e-04, 2.62665120e-03, 4.52925358e-03,
                3.51981423e-03, -2.01778719e-03, -1.87341985e-03,
                                                                             1.01616792e-03,
```

```
-4.45311842e-03, -4.84207738e-03, -1.65213854e-03, -4.38045943e-03,
                                       1.89710304e-03, -3.00770835e-03, 1.61952735e-03, -2.18944717e-03, 3.62433121e-03, -3.28776572e-04, -9.08664835e-04, 7.25332531e-04,
                                     -1.03188970e-03, -3.35709797e-03, 1.42141664e-03, 7.82564515e-04, -8.42687616e-04, -4.19954071e-03, -1.89533562e-03, -1.07767619e-03,
                                       4.53935796e-03, 2.98528094e-03, 4.05227952e-03, -2.24618649e-04,
                                      -4.42429818e-03, 1.68785686e-03, -2.01124093e-03, -2.73194863e-03, 4.38377232e-04, 2.08066963e-03, -4.13119141e-03, 4.84894961e-03,
                                      3.60024883e-03, 1.48247648e-03, -3.89444572e-03, 4.79171844e-03, -1.82902766e-03, 3.34102544e-03, -5.82411340e-05, 2.69562867e-03,
                                   -1.82902766e-03, 3.34102544e-03, -5.82411340e-05, 2.69562867e-03, -4.97974595e-03, -2.26341726e-04, -1.85428374e-03, -2.52061035e-03, 1.81353756e-03, 3.76515463e-03, -1.23920932e-03, -4.85930406e-03, 4.75250231e-03, 2.98563298e-03, -8.56885046e-04, 4.39230632e-03, 8.67392519e-04, -1.66126108e-03, 1.24680507e-03, 3.01609514e-03, -4.82995575e-03, -7.08100619e-04, 2.57068477e-03, -3.53983673e-03, 3.45219905e-03, 1.29821431e-03, 3.40202660e-03, -4.47224127e-03, 2.68770941e-03, -1.27026055e-03, 1.86251744e-03, -4.81107691e-03, -4.49218322e-03, 2.48919544e-03, -5.87784511e-04, 3.69686796e-03, -4.67617344e-03, 4.92656091e-03, -2.98282481e-03, 2.78733409e-04, 2.31816573e-03, -1.11581967e-03,
                                     -2.98282481e-03, 2.78733409e-04, 2.31816573e-03, -1.11581967e-03, 3.65994871e-03, 2.49042292e-04, -1.46448624e-03, -5.61784487e-04,
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                                       2.66192621e-03, 5.44470851e-04, -1.20554038e-03, -1.74746756e-03],
                                 dtype=float32), array([-2.43397895e-04, 1.17722622e-04, 2.549574016
-4.63713100e-03, -3.56551376e-03, 3.25163547e-03, 4.51285159e-03,
                                                                                                                                                                                                                2.54957401e-03, 4.51032910e-03,
                                    -2.51565920e-03, -1.87524175e-03, 3.68385087e-03, -7.91448576e-04, -2.28561554e-03, 3.30337812e-03, -2.45855120e-03, -8.97895603e-04, 1.44319597e-03, 5.16223197e-04, -4.14273888e-03, -4.76494711e-03, 3.67238838e-03, 2.54630856e-03, 3.39660444e-03, 3.99898883e-04, 3.17395572e-03, -1.69626612e-03, -4.67148609e-04, 2.87643191e-03, 3.27376200, 2.374178009e-04, 2.87643191e-03, 3.273762000e-03, 2.40308760e-04, 2.87643191e-03, 3.27376200e-03, 2.40308760e-03, 2.40308760e-04, 2.87643191e-03, 2.40308760e-04, 2.87643191e-03, 2.40308760e-04, 2.87643191e-03, 2.40308760e-04, 2.87643191e-03, 2.40308760e-04, 2.87643191e-04, 2.40308760e-04, 2.87643191e-04, 2.40308760e-04, 2.87643191e-04, 2.40308760e-04, 2.4030
                                       -3.77776939e-03, -1.97092374e-03, -3.76178417e-03, -4.60139854e-04,
                                        4.80629224e-03, -3.69808194e-03, -1.16402062e-03, -9.47833061e-04,
        Continuous Bag of Words (CBOW) (CountVectorizer)
from gensim.models import Word2Vec
cbow_model_1 = Word2Vec(sentences=[input], vector_size=200, window=7, sg=0, min_count=1, workers=4)
cbow_embeddings_1 = [cbow_model_1.wv[word] for word in input]
print("CBOW input Word Vectors:")
for word in cbow_model_1.wv.index_to_key:
           print(word, ':', cbow_model_1.wv[word])
cbow_model_2 = Word2Vec(sentences=[output], vector_size=200, window=7, sg=0, min_count=1, workers=4)
cbow_embeddings_2 = [cbow_model_2.wv[word] for word in output]
print("CBOW output Word Vectors:")
for word in cbow_model_2.wv.index_to_key:
            print(word, ':', cbow_model_2.wv[word])
               CBOW input Word Vectors:
                medication: [-2.43397895e-04 1.17722622e-04 2.54957401e-03 4.51032910e-03
                  -4.63713100e-03 -3.56551376e-03 3.25163547e-03 4.51285159e-03 -2.51505920e-03 -1.87524175e-03 3.68385087e-03 -7.91448576e-04
                   -2.28501554e-03 3.30337812e-03 -2.45855120e-03 -8.97895603e-04
                     1.44319597e-03 5.16223197e-04 -4.14273888e-03 -4.76494711e-03
                     3.67238838e-03 2.54630856e-03 3.39660444e-03 3.99898883e-04
                      3.17395572e-03 -1.69626612e-03 -4.67148609e-04 2.87643191e-03
                   -3.77776939e-03 -1.97092374e-03 -3.76178417e-03 -4.60139854e-04
                     4.80629224e-03 -3.69808194e-03 -1.16402062e-03 -9.47833061e-04
                     4.05259524e-03 -2.99035665e-03 1.09780931e-05 -2.39576166e-03
                    -4.80683148e-03 2.50480813e-03 -4.38536284e-03 -2.20403029e-03
                     1.88924969e-05 -1.42462290e-04 -3.85450828e-03 4.78526717e-03
                   2.51330575e-03 4.61710291e-03 -4.09376854e-03 2.24235514e-03 -2.07241438e-03 4.17237519e-04 4.27090051e-03 -2.24921876e-03
                     2.25209980e-03 -3.40690790e-03 -1.78425375e-03 4.69333772e-03
                    -7.88534817e-04 1.37734110e-04 -2.06553284e-03 -3.83562851e-03
                   -7.78124609e-04 1.23975298e-03 -4.38545278e-04 2.78540351e-03
                   -1.38571335e-03
                                                                    1.15438027e-03 2.73136212e-03
                                                                                                                                                                      4.19077557e-03
                    -7.14538<mark>153e-04 -4.59928</mark>019e-03 2.20764824e-03 2.8664<mark>2520e-04</mark>
                     3.75571800e-03 -4.28719999e-04 -1.32302812e-03 -4.38319100e-03
```

```
2.68909056e-03
                     1.41345477e-03
   -4.39121126e-04
                                                       3.53308907e-03
   -2.87524308e-03 9.09364200e-04 3.05670057e-03 -2.38309987e-03
   -1.56574394e-03 3.40214814e-03 8.28593154e-04 1.11142916e-04
    1.75784691e-03 1.10478606e-04 4.83453181e-03 2.53630080e-03
   -4.46916185e-03 -3.52568692e-03 4.57892282e-04 3.22038820e-03
   -4.31144377e-03 1.84189912e-03 2.60584126e-03 2.87447963e-03
    3.74397356e-03 -3.10777430e-03 5.74485632e-04
                                                       3.02756508e-03
   -1.44191715e-03 -3.11041973e-03 -2.11135295e-04 -4.20971727e-03
   -2.80767889e-03 3.55624827e-03 1.69188564e-03 3.60373151e-03
    3.38935899e-03 3.75725096e-03 -1.89743156e-03 -3.04426212e-04
    1.17409974e-03 -2.23785383e-03 4.19765199e-03 -4.95673670e-03
    3.37124383e-03 1.46347238e-03 -2.45913374e-03 2.20782938e-03
   -8.72436387e-04 3.35487491e-03 5.00583043e-03 -2.18794867e-03
    -2.98978674e-04 -2.85634911e-03 1.92003627e-03 1.40955846e-03
    3.44955968e-03 3.03705735e-03 4.77960985e-03 4.63266019e-03
    3.97557020e-03 -3.51917115e-03 -4.59417980e-03 -1.69987426e-04
   -1.54050183e-03 3.95821454e-03 2.95688468e-03 -7.84859119e-04
    7.73602689e-04 8.82107997e-04 3.92382313e-03 -4.76300390e-03
    -8.56025654e-05 1.74036995e-03 -4.88541089e-04 4.21383325e-03
    4.51653032e-03 3.27931903e-03 -3.58422607e-04 3.86370439e-03
   -4.25695069e-03 1.61562045e-03 -2.33184779e-03 -2.54722708e-03
    1.81438320e-03 2.69636628e-03 3.87762417e-03 -2.88636587e-03 3.70907574e-03 3.30382166e-03 -1.87198480e-03 -4.37592203e-03
    2.72473064e-03 3.26694781e-03 -3.79896461e-04 -3.34426272e-03
   -3.55738821e-03 -1.23994565e-03 2.58348254e-03 -1.82270515e-03
   -4.69964137e-03 1.91476638e-03 2.43521831e-03 -3.20625957e-03
    6.11510535e-04 -1.03400263e-03 3.57953504e-05 -4.93346481e-03
    1.36854884e-03 -2.38839886e-03 5.61250141e-04 -7.58533657e-04
    1.09596422e-03 -3.95021867e-03 -1.34896149e-03 1.35245186e-03 2.69268872e-03 -1.20098062e-03 -4.74680401e-03 2.23622331e-03]
  cardiovascular: [5.5819572e-05 1.5382001e-03 -3.4035724e-03 -6.8600645e-04
    3.8408015e-03 3.6693064e-03 -1.8291188e-03 1.3336225e-03
    -4.1608596e-03 3.1034756e-03 -2.3193690e-03 -1.5921145e-03
    4.6495600e-03 4.4818191e-04 3.7358576e-03 -3.0309972e-03 2.5796790e-03 4.9703326e-03 -4.2296192e-03 -2.5848746e-03
    -3.5276520e-03 -2.4290096e-03 -1.8822814e-03 -4.2624054e-03
    3.9766789e-03 -2.4183090e-03 4.2147082e-03 2.6268591e-03
Skip-gram
```

```
from gensim.models import Word2Vec

skipgram_model_1 = Word2Vec(sentences=[input], vector_size=200, window=7, sg=1, min_count=1, workers=4)
skipgram_embeddings_1 = [skipgram_model_1.wv[word] for word in input]

print("\nSkip-gram Word Vectors:")
for word in skipgram_model_1.wv.index_to_key:
    print(word, ':', skipgram_model_1.wv[word])

skipgram_model_2 = Word2Vec(sentences=[output], vector_size=200, window=7, sg=1, min_count=1, workers=4)
skipgram_embeddings_2 = [skipgram_model_2.wv[word] for word in output]

print("\nSkip-gram Word Vectors:")
for word in skipgram_model_1.wv.index_to_key:
    print(word, ':', skipgram_model_1.wv[word])

Streaming output truncated to the last 5000 lines.
```

```
-6.80438359e-04 5.10229776e-03 -3.28734022e-04 -1.21548066e-04
-1.02306413e-03 -4.19426151e-03 -4.80649900e-03 2.58191326e-03
-3.30611854e-03 1.54280942e-03 1.43309624e-03 -3.59228114e-03
-1.69031660e-03 -2.96740397e-03 -4.30572871e-03 3.84130180e-05
5.13059273e-03 -3.57472035e-03 -2.14961520e-03 4.31996258e-03
4.76301834e-03 4.77772998e-03 -5.03549585e-03 2.38854392e-03
-3.38240224e-03 3.45636043e-03 3.04419384e-03 -1.73290388e-03
3.70362308e-03 -3.88695113e-03 2.09534029e-03 2.15477799e-03 3.08935507e-03 2.97126803e-03 -1.43272954e-03 1.93556119e-03
-3.06088151e-03 -3.22365202e-03 1.52587309e-03 -4.87774843e-03
-1.63232777e-04 4.72362532e-04 3.94014409e-03 -3.53522715e-03
-1.14526448e-03 -2.17681774e-03 -2.57988530e-03 -2.31732687e-04
2.16885586e-03 -2.46788329e-03 -8.03708390e-04 4.47648298e-03
-7.39487470e-04 -1.66929315e-03 3.70274158e-03 7.38279894e-04
-1.17875054e-04 4.78436705e-03 4.23447369e-03
                                                  1.70411274e-03
1.89667800e-03 -1.29248330e-03 4.00650268e-03 2.45350855e-03
-2.78733368e-03 -3.06073623e-03 -3.95584939e-04 -3.93713638e-03
1.53752987e-03 -4.73904656e-03 -6.71714195e-04 1.75296923e-03
```

1.43463269e-03 1.56716770e-03 -4.45947144e-03 1.82660914e-03 2.81956908e-03 1.78901502e-03 4.07189876e-03 8.93058721e-04 3.06205009e-03 4.37871786e-03 -4.53186512e-04 -2.66135728e-04 1.09547668e-03 -3.71676474e-03 2.86919624e-03 -2.54350482e-03 -1.55348214e-03 -1.12105394e-03 4.25003935e-03 1.19283912e-03 -6.07984664e-04 -1.61452964e-03 -1.66016721e-03 8.51000834e-04 -2.58320803e-03 -2.02282495e-03 2.01815201e-04 2.20483961e-03

-3.70453321e-03 3.09954002e-03 3.47817712e-03 -3.22162313e-03

3.41231981e-03

8.34827835e-04

2.52359943e-03 3.26795201e-03 2.15621642e-03 4.16612579e-03 1.44511426e-03 -5.81645581e-04 -1.24258036e-03 2.78728991e-03

https://colab.research.google.com/drive/1FTleFD9PjcHgO3i8DFsapYL9Vl5u5UyH#scrollTo=jz4FzvnRGaVx&printMode=true

3.33503034e-04 -1.75742176e-03

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 -3.98625759e-03 -4.63391142e-03 -4.63720877e-03 -1.79253489e-04 -3.75555974e-04 2.24391813e-04 -7.78056798e-04 4.58918186e-03
 4.45333496e-03 -3.10695660e-03 4.27327910e-03 -4.58967220e-03
 -5.65015129e-04 1.20668125e-03 5.75605009e-05 -1.95428752e-03
 3.31026735e-04 5.63134032e-04 -4.84150276e-03 -2.30588671e-03
 -3.80731095e-03 1.93056825e-03 -4.53185843e-04 -3.71493935e-03
 2.88090901e-03 1.96302964e-04 1.24558900e-03 2.69120978e-03
-2.00923975e-03 4.02055634e-03 -3.94624891e-03 -1.74556917e-03 -3.72356270e-03 4.38054994e-04 -3.79773439e-03 4.50119143e-03
 2.81994417e-03 -3.53641901e-03 3.20350332e-03 3.40460823e-03 -3.78236338e-03 2.38672178e-03 -3.80887673e-03 4.77143936e-03
2.25756317e-03 -7.39999596e-05 -4.54879785e-03 -4.20057564e-04 -9.58975070e-05 4.72341577e-04 4.47895704e-03 -1.33679202e-03
 -4.18825261e-03 -4.46341420e-03 -4.06744075e-04 8.76497361e-04
 -9.13901204e-06 -1.14589732e-03 4.35298542e-03 1.95895336e-04
  3.33761564e-03 1.95616996e-03 -3.53504601e-03 -1.16232724e-03]
remains : [-3.8556790e-03 -3.3799619e-03 -1.5693560e-03 3.2881303e-03
-3.7658264e-04 4.4078762e-03 -1.1062599e-03 -2.5894120e-03
 1.9418295e-03 1.0957106e-03 -1.5454009e-04 -1.2615781e-03 -3.0327898e-03 2.0590588e-03 -3.8543362e-03 -4.4230875e-03
 -4.5981179e-03 4.2327400e-03 2.0038730e-03 3.4631814e-03
 4.9613966e-03 -3.6027736e-03 2.0696847e-03 1.4275101e-03
  3.0600044e-03 -1.6664518e-03 4.6823416e-03 -2.9241620e-03
  3.4873618e-03 3.4618550e-03 -1.9533971e-04 2.5304654e-03
```

▼ BERT - Capturing contextual relatioships & Understand complex sentences

```
output
```

```
['medication', 'adherence', 'cardiovascular', 'medicine']
```

```
from transformers import BertTokenizer, BertModel
import torch
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
tokens = tokenizer(input, padding=True, truncation=True, return_tensors='pt')
model = BertModel.from_pretrained('bert-base-uncased')
with torch.no_grad():
    out = model(**tokens)
bert_embeddings = out.last_hidden_state
for i, word in enumerate(input):
        print(word, ':', bert_embeddings[i].numpy())
```

```
vocab.txt: 100%
                                                          466k/466k [00:00<00:00, 16.6MB/s]
                                                            440M/440M [00:02<00:00,
from transformers import BertTokenizer, BertModel
import torch
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
tokens_1 = tokenizer(output, padding=True, truncation=True, return_tensors='pt')
model_1 = BertModel.from_pretrained('bert-base-uncased')
with torch.no_grad():
   out_1 = model_1(**tokens_1)
bert_embeddings_1 = out_1.last_hidden_state
for i, word in enumerate(output):
       print(word, ':', bert_embeddings_1[i].numpy())
    0.25458854]
     [ 0.8551517
                   0.12936395 -0.42021742 ... 0.05498876 -0.6903206
       -0.3861094 ]]
     adherence : [[-0.38320982  0.27525085  0.03545895  ...  0.1297458  0.09269787
       0.25569412]
     [-0.21068221 \ -0.12006158 \ \ 0.2886017 \ \ \dots \ \ 0.35808176 \ \ 0.4607638
     [ 0.97147644  0.08883908 -0.25682253 ...  0.29493722 -0.8092183
       -0.22931008]]
     cardiovascular : [[-0.42869335  0.09234771 -0.16442394 ... -0.05152808 -0.06069821
       0.21705684]
      [-0.52572745 -0.5550029 -0.5810933 ... 0.11191379 -0.09953394
       -0.08235869]
                  0.04642388 -0.2991941 ... 0.26279926 -0.8247325
      [ 1.0284969
       -0.135454011]
    \texttt{medicine} \,:\, [[\ \textbf{0.03120169} \ \textbf{0.42934826} \ \textbf{-0.44671717} \ \dots \ \textbf{-0.27408144} \ \textbf{0.13439642}
```

```
0.64538777]
      [ 0.1565493
                    0.38183063 -0.50650716 ... -0.5074962
                                                            0.3653871
       -0.30214646]
                    0.08833586 -0.2898354 ... -0.02793229 -0.9207077
       -0.1900469 ]]
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.2,random_state=42)
#train_df,test_df = train_test_split(df,test_size=0.2,random_state=42)
text_word_count = []
summary_word_count = []
for i in X['text']:
      text_word_count.append(len(i.split()))
for i in Y['summary']:
      summary_word_count.append(len(i.split()))
import matplotlib.pyplot as plt
length\_df = pd.DataFrame(\{'text':text\_word\_count, \ 'summary':summary\_word\_count\})
length_df.hist(bins = 30)
plt.show()
```

