Banking Chat Intent Clustering Project

```
!huggingface-cli login
环 🛦 Warning: 'huggingface-cli login' is deprecated. Use 'hf auth login' instead.
         To log in, `huggingface_hub` requires a token generated from <a href="https://huggingface.co/settings/tokens">https://huggingface.co/settings/tokens</a>.
     Enter your token (input will not be visible):
     Add token as git credential? (Y/n) Y
     Token is valid (permission: fineGrained).
     The token `noname` has been saved to /root/.cache/huggingface/stored_tokens
     Cannot authenticate through git-credential as no helper is defined on your machine.
     You might have to re-authenticate when pushing to the Hugging Face Hub.
     Run the following command in your terminal in case you want to set the 'store' credential helper as default.
     git config --global credential.helper store
     Read https://git-scm.com/book/en/v2/Git-Tools-Credential-Storage for more details.
     Token has not been saved to git credential helper.
     Your token has been saved to /root/.cache/huggingface/token
     Login successful.
     The current active token is: `noname`
pip install datasets huggingface_hub
      Show hidden output
from datasets import load_dataset
# Replace with your username/dataset name
dataset = load_dataset("atulgupta002/banking_customer_service_query_intent")
# See available splits
print(dataset)
# Convert to DataFrame
df = dataset['train'].to_pandas()
df=df[["query","intent"]]
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
     The secret `HF_TOKEN` does not exist in your Colab secrets.
     To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set
     You will be able to reuse this secret in all of your notebooks.
     Please note that authentication is recommended but still optional to access public models or datasets.
       warnings.warn(
     DatasetDict({
         train: Dataset({
             features: ['Unnamed: 0', 'query', 'intent'],
             num_rows: 5000
         })
     })
        Unnamed: 0
                 0 Could you please help me reset my account pass..
     1
                                 What company charged my account last?
                 2 How do I schedule an appointment to discuss lo...
     2
                                           Which loans 2day suited me?
     3
     4
                 4 Do you have any updated timelines for my loan ...
                   intent
     0
           password_reset
        transaction_query
     1
             loan_inquiry
     3
             loan inquiry
     4
             loan_inquiry
df=df[["query","intent"]]
df.sample(4)
```

```
→
                                                auerv
                                                                    intent
      1058 I would appreciate assistance in understanding... credi_card_application
      2103
             Could you assist in determining if my account ...
                                                                 loan_inquiry
      1323
                          pls reset pass b4 i lose my mind
                                                             password_reset
       679
                               how do i apply 4 biz credit?
                                                                 loan inquiry
df["intent"].value_counts()
₹
                             count
                    intent
           loan_inquiry
                              1600
           fraud_report
                              1249
        transaction_query
                              1210
         balance_inquiry
                               323
      credi_card_application
                               318
         password_reset
                               300
     dtype: int64
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import warnings
warnings.filterwarnings('ignore')
nltk.download('stopwords')
nltk.download('punkt_tab')
nltk.download('wordnet')
→ [nltk_data] Downloading package stopwords to /root/nltk_data...
     [nltk_data] Package stopwords is already up-to-date!
     [nltk_data] Downloading package punkt_tab to /root/nltk_data...
     [nltk_data]
                   Package punkt_tab is already up-to-date!
     [nltk\_data] \ \ Downloading \ package \ wordnet \ to \ /root/nltk\_data...
     [nltk_data] Package wordnet is already up-to-date!
     True
Start coding or generate with AI.
→ [nltk_data] Downloading package stopwords to /root/nltk_data...
     [nltk_data] Package stopwords is already up-to-date!
     [nltk_data] Downloading package punkt_tab to /root/nltk_data...
     [nltk_data]
                   Package punkt_tab is already up-to-date!
     [nltk_data] Downloading package wordnet to /root/nltk_data...
     [nltk_data] Package wordnet is already up-to-date!
df.shape
→ (5000, 2)
df.isnull().sum()
\overline{2}
             0
      query 0
      intent 0
     dtype: int64
df.info()
```

Text Preprocessing

```
df.sample(5)
₹
                                                     query
                                                                       intent
       1858 Was the most recent transaction completed with... transaction_query
       4035
                                         ayo yall hacked me
                                                                  fraud_report
       4736
                             my pass expired, how do i reset?
                                                               password_reset
       1743
                What is the present financial status of my sav...
                                                               balance_inquiry
       1882
                May I ask for a thorough explanation of your I...
                                                                  loan_inquiry
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()
list(stop_words)[:10]
→ ['and',
       "she's",
      'is',
       "it's",
       "shouldn't",
       't',
'if',
       "they'd",
       'had',
       "aren't"]
def preprocess_text(text):
```

```
def preprocess_text(text):
    # 1. Lowercase
    text = text.lower()

# 2. Remove punctuation and numbers
    text = re.sub(r'[^a-z\s]', '', text) # keeps only letters and spaces

# 3. Tokenize
    words = nltk.word_tokenize(text)

# 4. Remove stopwords
    words = [word for word in words if word not in stop_words]

# 5. Remove special characters
    words = [word for word in words if word.isalnum()==1]

# 6. Lemmatize
    words = [lemmatize(word) for word in words]
```

```
# 7. Re-join words into a string
return ' '.join(words)

for i in range(len(df)):
    df["query"][i]=preprocess_text(df["query"][i])

preprocess_text("ayo yall hacked me")

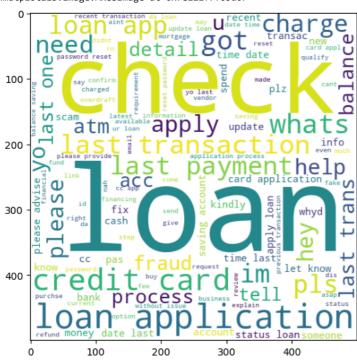
    'ayo yall hacked'

from wordcloud import WordCloud
wc=WordCloud(width=500,height=500,min_font_size=10,background_color="white")

AI_wc=wc.generate(df["query"].str.cat(sep=" "))

plt.figure(figsize=(6,6))
plt.imshow(AI_wc)
```

<matplotlib.image.AxesImage at 0x7e111f7f65d0>



Feature Engineering

```
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf=TfidfVectorizer(max_features=300, ngram_range=(1,3))

X=tfidf.fit_transform(df["query"]).toarray()

X.shape

(4974, 300)

from sentence_transformers import SentenceTransformer

model = SentenceTransformer('all-MiniLM-L6-v2')
embeddings = model.encode(df['query'].tolist())

from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
df['cluster'] = kmeans.fit_predict(embeddings) # or 'embeddings' for SBERT
```

import hdbscan

```
clusterer = hdbscan.HDBSCAN(min_cluster_size=100)
df['cluster'] = clusterer.fit_predict(embeddings)

from sklearn.metrics import silhouette_score

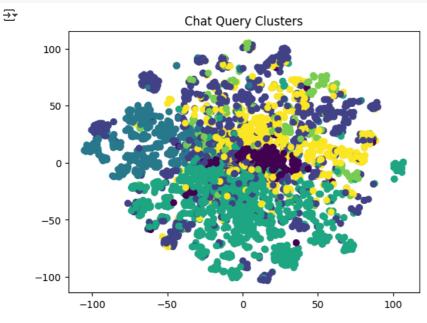
# For vectorized data
score = silhouette_score(embeddings, df['cluster']) # or 'embeddings'
print(f"Silhouette Score: {score:.2f}") # Aim for >0.5
```

→ Silhouette Score: 0.09

```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

tsne = TSNE(n_components=2, random_state=42)
vis_data = tsne.fit_transform(X)

plt.scatter(vis_data[:, 0], vis_data[:, 1], c=df['cluster'], cmap='viridis')
plt.title("Chat Query Clusters")
plt.show()
```



#pip install gensim

```
→ Collecting gensim
                 Downloading gensim-4.3.3-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (8.1 kB)
            Collecting numpy<2.0,>=1.18.5 (from gensim)
                 Downloading numpy-1.26.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (61 kB)
                                                                                                                                         61.0/61.0 kB 1.5 MB/s eta 0:00:00
            Collecting scipy<1.14.0,>=1.7.0 (from gensim)
                 Downloading scipy-1.13.1-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (60 kB)
                                                                                                                                        - 60.6/60.6 kB 2.3 MB/s eta 0:00:00
            Requirement already satisfied: smart-open>=1.8.1 in /usr/local/lib/python3.11/dist-packages (from gensim) (7.3.0.post1)
            Requirement already satisfied: wrapt in /usr/local/lib/python3.11/dist-packages (from smart-open>=1.8.1->gensim) (1.17.3)
            Downloading gensim-4.3.3-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (26.7 MB)
                                                                                                                                   - 26.7/26.7 MB 31.5 MB/s eta 0:00:00
            Downloading numpy-1.26.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (18.3 MB)
                                                                                                                                   - 18.3/18.3 MB 39.6 MB/s eta 0:00:00
            Downloading scipy-1.13.1-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (38.6 MB)
                                                                                                                                  - 38.6/38.6 MB 8.6 MB/s eta 0:00:00
            Installing collected packages: numpy, scipy, gensim
                 Attempting uninstall: numpy
                      Found existing installation: numpy 2.0.2
                      Uninstalling numpy-2.0.2:
                            Successfully uninstalled numpy-2.0.2
                 Attempting uninstall: scipy
                      Found existing installation: scipv 1.16.1
                      Uninstalling scipy-1.16.1:
                            Successfully uninstalled scipy-1.16.1
            ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is
            opencv-contrib-python \ 4.12.0.88 \ requires \ numpy < 2.3.0, >= 2; \ python\_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ is \ incompared to the python_version >= "3.9", \ but \ you \ have \ numpy \ 1.26.4 \ which \ you \ y
            opencv-python 4.12.0.88 requires numpy<2.3.0,>=2; python_version >= "3.9", but you have numpy 1.26.4 which is incompatible.
            thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.26.4 which is incompatible.
            tsfresh 0.21.0 requires scipy>=1.14.0; python_version >= "3.10", but you have scipy 1.13.1 which is incompatible.
            opencv-python-headless 4.12.0.88 requires numpy<2.3.0,>=2; python_version >= "3.9", but you have numpy 1.26.4 which is incompart of the second of the second
            Successfully installed gensim-4.3.3 numpy-1.26.4 scipy-1.13.1
```

from nltk.tokenize import word_tokenize

5000 rows × 2 columns

df

```
₹
                                                                          intent
                                                        query
        0
             Could you please help me reset my account pass...
                                                                  password_reset
        1
                      What company charged my account last? transaction_query
        2
              How do I schedule an appointment to discuss lo...
                                                                     loan_inquiry
        3
                                  Which loans 2day suited me?
                                                                     loan_inquiry
        4
              Do you have any updated timelines for my loan ...
                                                                     loan_inquiry
      4995
                      Was the transaction processed correctly? transaction query
      4996
                      Apple Pay charges I didn't make-fraud!!
                                                                     fraud report
      4997
              Can you provide detailed steps on how to begin...
                                                                     loan inquiry
      4998
                           what's the acc say? nervous chuckle
                                                                  balance inquiry
      4999
                              why'd my transac get dunked on? transaction_query
```

```
₹
```

w2v_model.wv['check']

0.00007400 0.4000440 0.00007646 0.44746446 0.0000666

```
Banking Chat Intent.ipynb - Colab
  ט.טסטט/482, -ט.טסטטטטטט, -ט.טסטטטטטט, -ט.טסטטטטטט, -ט.טסטטטטטט,
  0.12359828, \ -0.06053425, \ \ 0.03908334, \ \ 0.04258515, \ -0.09026598,
   \hbox{0.12591277, -0.02877494, -0.0278694, -0.06337349, -0.0172609, } \\
 -0.11444492, 0.05766811, 0.1260676, -0.05855938, 0.07825004, 0.09201267, 0.04196916, 0.00710163, -0.12322395, 0.0706398,
  0.07292578, \quad 0.08281413, \quad -0.14102271, \quad 0.09434362, \quad -0.00499564,
 0.18015322, 0.06761307, 0.02011781, 0.07370505, -0.03664183, -0.16926664, 0.02060376, -0.07399998, 0.02030248, -0.09433614,
  0.09839907, -0.00811235, \quad 0.09650765, -0.16685827, -0.08007952, \\
 -0.0062323 , -0.05684746 , 0.0520971 , -0.08130912 , 0.05558424 , 0.00258068 , -0.1123684 , 0.08319373 , -0.19050603 , 0.13416585 ,
 -0.1100857 , -0.06889507, -0.02476717, 0.18819547, 0.17773835, -0.03387957, -0.03506389, 0.01173825, 0.24117164, 0.03916995,
  0.08060808, \ -0.06059883, \ \ 0.0255092 \ , \ \ 0.05085579, \ \ 0.12130864,
                                                                        , 0.12838209,
  0.14836572, 0.14520921, -0.03680674, -0.07277
 \hbox{-0.05760913, -0.03922096, -0.00625797, 0.05260391, 0.00605842,}
 \hbox{-0.14735614,} \quad \hbox{0.03005108,} \quad \hbox{0.01942448,} \quad \hbox{-0.06786844,} \quad \hbox{-0.03596085,}
 -0.1255352 , -0.06717985 , 0.05114658 , 0.07063763 , 0.09512886 , 0.09014269 , 0.01000162 , -0.01996969 , 0.10169414 , -0.11314784 ,
  0.00635214, \quad 0.08405048, \quad 0.06247025, \quad -0.05004987, \quad -0.03075552,
  0.13315478, \quad 0.03132945, \quad -0.17855564, \quad -0.08928069, \quad 0.08867704,
   \hbox{0.15002197, 0.22491665, 0.06825162, -0.142501, 0.11248266, } \\
   0.05815551, \ -0.02215566, \ -0.05753402, \ -0.28935173, \ -0.1073303 \ , 
 \hbox{-0.06780231, -0.06042719, 0.00780021, 0.04599118, 0.17170632,}
 \hbox{-0.15027045, -0.09992228, -0.01804444, 0.00607619, -0.13384832,}\\
 \hbox{-0.06030835, -0.14139393, 0.01912612, 0.03418608, 0.0011703,}\\
  0.08823892, -0.21435651, -0.02992686, 0.01625939, 0.09992211,
   0.08922045, \ -0.02571659, \ -0.09545876, \ \ 0.02679662, \ -0.16964468, 
   0.04496613, \quad 0.06892719, \quad 0.1362786 \ , \ -0.04137455, \quad 0.25539932, 
 \hbox{-0.05382124, 0.00921551, 0.08995181, 0.10762193, 0.09171587,}\\
  0.12721686, 0.0447987, -0.14698721, -0.00759032, 0.07522756,
  0.04211498, 0.07298534, -0.11130349, -0.10016432, -0.05972821,
 -0.03809527, 0.2420915, 0.13757108, -0.05645635, -0.21128252,
 0.10414475, 0.09749319, -0.14725031, 0.07266144, 0.04379525, -0.10359757, -0.01876608, -0.12233123, 0.01370681, -0.06685211,
 \hbox{-0.20239952, -0.05333187, 0.02983568, -0.04365081, -0.1136435 ,}\\
 -0.09790797, -0.02202103, -0.03198808, 0.04528502, -0.03544129, -0.0322194, -0.08054534, -0.17277747, -0.01997566, -0.04152491,
 \hbox{-0.22001834, -0.13074744, -0.2677888, -0.16012755, -0.05151961,}
 0.04621465, 0.10063493, -0.1069029, -0.03691696, -0.11325835, -0.04678367, 0.059754, -0.02392766, -0.17169589, 0.11237822,
  0.01425483, \ -0.05468687, \ -0.09279235, \ \ 0.1527461 \ , \ -0.07922108,
  0.04868382, 0.06405529, 0.02595069, 0.03560789, -0.26492673, 0.03376934, -0.02923445, -0.04274911, -0.03762026, 0.04080937,
 -0.11811687, 0.0562453, -0.01940629, 0.10643192, -0.03013926, 0.09165271, -0.02913047, 0.04234148, -0.03087159, -0.20593645,
 \hbox{-0.02830286,} \quad \hbox{0.17284308,} \quad \hbox{-0.0777771 ,} \quad \hbox{-0.24632865,} \quad \hbox{-0.11375698,}
  0.06621087, 0.16783036, 0.13950938, -0.262561 , -0.20037189, 0.07623817, -0.00869674, 0.05241466, -0.08989535, -0.00063426,
   0.02333372, \quad 0.05453069, \quad 0.0844 \qquad , \quad 0.0197862 \ , \quad 0.0504894 \ , \\
 0.15895598, 0.09731191, 0.01605176, -0.1981894, -0.06992178, -0.01161425, -0.06605342, -0.07593374, 0.08435901, 0.08565657,
 \hbox{-0.08661163, -0.09424403, 0.08685389, 0.00815491, 0.15802093,}\\
  0.0327177, 0.24190313, 0.06422476, 0.00985391, 0.18354377, 0.16362043, 0.04242164, -0.01480162, 0.12421991, -0.02877424],
dtyne=float32)
```

```
w2v model.wv.most similar('loan')
```

```
→ [('line', 0.9629036784172058),
     ('approval', 0.962518036365509),
     ('submit', 0.9612851142883301),
     ('credit', 0.9605515003204346),
     ('steps', 0.9584606289863586),
     ('on', 0.9576819539070129),
     ('personal', 0.9573211669921875),
     ('required', 0.9554418921470642),
     ('application', 0.954888641834259),
     ('regarding', 0.9509759545326233)]
```

```
import numpy as np
vocab_set = set(w2v_model.wv.index_to_key)
vector_size = w2v_model.vector_size
X_w2v = np.zeros((len(df), vector_size))
for i, text in enumerate(df['query']):
    vectors = [w2v_model.wv[word] for word in text if word in vocab_set]
    if vectors:
        X w2v[i] = np.mean(vectors, axis=0)
```

X w2v

 $\overline{2}$

```
array([[-0.0146107 , 0.10901842, -0.04898347, ..., -0.05695681, 0.1084467 , -0.06725479],

[-0.01396885, 0.11685753, -0.0434003 , ..., -0.07728344, 0.12547073, -0.05353657],

[-0.015592 , 0.1243165 , -0.05252567, ..., -0.06686812, 0.11984246, -0.07384428],

...,

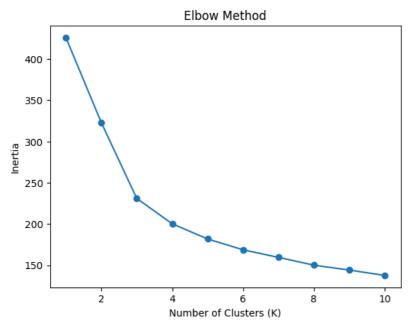
[-0.0171927 , 0.13332888, -0.03586521, ..., -0.08481096, 0.12746266, -0.06543156],

[-0.01875741, 0.11218677, -0.04241446, ..., -0.0511254 , 0.11027022, -0.06501191],

[-0.01163105, 0.12245308, -0.06470449, ..., -0.06999706, 0.12881836, -0.068672 ]])
```

```
from sklearn.cluster import KMeans
inertias = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_w2v)
    inertias.append(kmeans.inertia_)

import matplotlib.pyplot as plt
plt.plot(range(1, 11), inertias, marker='o')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.title('Elbow Method')
plt.show()
```



```
from sklearn.metrics import silhouette_score
silhouette_scores = []
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    clusters = kmeans.fit_predict(X_w2v)
    score = silhouette_score(X_w2v, clusters)
    silhouette_scores.append(score)
    print(f"K={k}, Silhouette Score={score:.2f}")
```

```
K=2, Silhouette Score=0.24
K=3, Silhouette Score=0.26
K=4, Silhouette Score=0.21
K=5, Silhouette Score=0.19
K=6, Silhouette Score=0.17
K=7, Silhouette Score=0.17
K=8, Silhouette Score=0.17
K=9, Silhouette Score=0.15
K=10, Silhouette Score=0.15
```

```
from sklearn.decomposition import TruncatedSVD from sklearn.cluster import AgglomerativeClustering
```

```
# ==== 4. Agglomerative Clustering ====
n_clusters = 4 # you can change this
```

```
agg_clust = AgglomerativeClustering(n_clusters=n_clusters)
cluster_labels = agg_clust.fit_predict(X_w2v)

df['Agg_cluster'] = cluster_labels
from sklearn.metrics import silhouette_score
# ==== 5. Evaluation ====
sil_score = silhouette_score(X_w2v, cluster_labels)

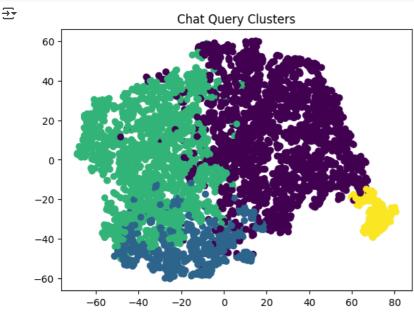
print(f"Silhouette Score: {sil_score:.3f}")
```

→ Silhouette Score: 0.204

```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

tsne = TSNE(n_components=2, random_state=42)
vis_data = tsne.fit_transform(X_w2v)

plt.scatter(vis_data[:, 0], vis_data[:, 1], c=cluster_labels, cmap='viridis')
plt.title("Chat Query Clusters")
plt.show()
```



```
# kmeans clustering
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=4, random_state=42)
df['kmeans_cluster'] = kmeans.fit_predict(X_w2v)

sil_score = silhouette_score(X_w2v, df['kmeans_cluster'])
print(f"Silhouette Score: {sil_score:.3f}")
```

→ Silhouette Score: 0.215

```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

tsne = TSNE(n_components=2, random_state=42)
vis_data = tsne.fit_transform(X_w2v)

plt.scatter(vis_data[:, 0], vis_data[:, 1], c=df['kmeans_cluster'], cmap='viridis')
plt.title("Chat Query Clusters")
plt.show()
```



Chat Query Clusters 60 40 20 0 -20 -40-60 -60 -40 -20 0 20 40 60 80

```
# DBSCAN clustering
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps=0.1, min_samples=5) # Adjusted parameters
df['dbscan_cluster'] = dbscan.fit_predict(X_w2v)

# Check the number of unique clusters found by DBSCAN
num_clusters = len(np.unique(df['dbscan_cluster']))

if num_clusters > 1:
    sil_score = silhouette_score(X_w2v, df['dbscan_cluster'])
    print(f"Silhouette Score: {sil_score:.3f}")
else:
    print("DBSCAN found only one cluster. Try adjusting eps and min_samples.")
```

→ Silhouette Score: -0.043

df ∑•

| • | | query | intent | Agg_cluster | kmeans_cluster | dbscan_cluster | |
|---|------|------------------------------------------------|-------------------|-------------|----------------|----------------|--|
| | 0 | Could you please help me reset my account pass | password_reset | 1 | 1 | 0 | |
| | 1 | What company charged my account last? | transaction_query | 2 | 1 | 0 | |
| | 2 | How do I schedule an appointment to discuss lo | loan_inquiry | 0 | 0 | 0 | |
| | 3 | Which loans 2day suited me? | loan_inquiry | 2 | 0 | 0 | |
| | 4 | Do you have any updated timelines for my loan | loan_inquiry | 2 | 0 | 0 | |
| | | | | | | | |
| | 4995 | Was the transaction processed correctly? | transaction_query | 0 | 2 | 0 | |
| | 4996 | Apple Pay charges I didn't make—fraud!! | fraud_report | 0 | 2 | 0 | |
| | 4997 | Can you provide detailed steps on how to begin | loan_inquiry | 2 | 0 | 0 | |
| | 4998 | what's the acc say? nervous chuckle | balance_inquiry | 0 | 1 | -1 | |
| | 4999 | why'd my transac get dunked on? | transaction_query | 0 | 2 | 0 | |

5000 rows × 5 columns

```
import re
from sklearn.feature_extraction.text import TfidfVectorizer

# Function to clean text

def clean_text(text):
    text = text.lower() # lowercase
    text = re.sub(r"[^a-zA-Z\s]", "", text) # remove punctuation/numbers
    text = re.sub(r"\s+", " ", text).strip() # remove extra spaces
    return text

# Apply cleaning
```

```
8/17/25, 10:19 PM
                                                               Banking_Chat_Intent.ipynb - Colab
    df["clean_query"] = df["query"].apply(clean_text)
    # Vectorize using TF-IDF
    vectorizer = TfidfVectorizer(stop_words="english", max_features=1000)
    X_tfidf = vectorizer.fit_transform(df["clean_query"])
    print("Shape of TF-IDF matrix:", X_tfidf.shape)
    → Shape of TF-IDF matrix: (5000, 1000)
    from sklearn.decomposition import PCA
    # Reduce dimensions for clustering
    pca = PCA(n_components=50, random_state=42) # keep top 50 components
    X_pca = pca.fit_transform(X_tfidf.toarray())
    print("Shape after PCA:", X_pca.shape)
    → Shape after PCA: (5000, 50)
    !pip install sentence-transformers
    from sentence_transformers import SentenceTransformer
    # Load pre-trained SBERT model
    model = SentenceTransformer('all-MiniLM-L6-v2')
    # Encode sentences
    X_embeddings = model.encode(df["clean_query"], show_progress_bar=True)
    print("Shape of SBERT embeddings:", X_embeddings.shape)
```

```
Requirement already satisfied: sentence-transformers in /usr/local/lib/python3.11/dist-packages (5.1.0)
    Requirement already satisfied: transformers<5.0.0,>=4.41.0 in /usr/local/lib/python3.11/dist-packages (from sentence-transformers
    Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (from sentence-transformers) (4.67.1)
    Requirement already satisfied: torch>=1.11.0 in /usr/local/lib/python3.11/dist-packages (from sentence-transformers) (2.6.0+
    Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (from sentence-transformers) (1.6.1)
    Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from sentence-transformers) (1.13.1)
    Requirement already satisfied: huggingface-hub>=0.20.0 in /usr/local/lib/python3.11/dist-packages (from sentence-transformer
    Requirement already satisfied: Pillow in /usr/local/lib/python3.11/dist-packages (from sentence-transformers) (11.3.0)
    Requirement already satisfied: typing_extensions>=4.5.0 in /usr/local/lib/python3.11/dist-packages (from sentence-transforme
    Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.20.0->sentence-t
    Requirement already satisfied: fsspec>=2023.5.0 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.20.0->se
    Requirement already satisfied: packaging>=20.9 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.20.0->ser
    Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.20.0->sentence
    Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.20.0->sentence-t
    Requirement already satisfied: hf-xet<2.0.0,>=1.1.3 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.20.0
    Requirement already satisfied: networkx in /usr/local/lib/python3.11/dist-packages (from torch>=1.11.0->sentence-transformer
    Requirement already satisfied: jinja2 in /usr/local/lib/python3.11/dist-packages (from torch>=1.11.0->sentence-transformers)
    Collecting nvidia-cuda-nvrtc-cu12==12.4.127 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia_cuda_nvrtc_cu12-12.4.127-py3-none-manylinux2014_x86_64.whl.metadata (1.5 kB)
    Collecting nvidia-cuda-runtime-cu12==12.4.127 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia_cuda_runtime_cu12-12.4.127-py3-none-manylinux2014_x86_64.whl.metadata (1.5 kB)
    Collecting nvidia-cuda-cupti-cu12==12.4.127 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia cuda cupti cu12-12.4.127-py3-none-manylinux2014 x86 64.whl.metadata (1.6 kB)
    Collecting nvidia-cudnn-cu12==9.1.0.70 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia_cudnn_cu12-9.1.0.70-py3-none-manylinux2014_x86_64.whl.metadata (1.6 kB)
    Collecting nvidia-cublas-cu12==12.4.5.8 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia_cublas_cu12-12.4.5.8-py3-none-manylinux2014_x86_64.whl.metadata (1.5 kB)
    Collecting nvidia-cufft-cu12==11.2.1.3 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia_cufft_cu12-11.2.1.3-py3-none-manylinux2014_x86_64.whl.metadata (1.5 kB)
    Collecting nvidia-curand-cu12==10.3.5.147 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia_curand_cu12-10.3.5.147-py3-none-manylinux2014_x86_64.whl.metadata (1.5 kB)
    Collecting nvidia-cusolver-cu12==11.6.1.9 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia_cusolver_cu12-11.6.1.9-py3-none-manylinux2014_x86_64.whl.metadata (1.6 kB)
    Collecting nvidia-cusparse-cu12==12.3.1.170 (from torch>=1.11.0->sentence-transformers)
      Downloading nvidia_cusparse_cu12-12.3.1.170-py3-none-manylinux2014_x86_64.whl.metadata (1.6 kB)
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    Collecting nvidia-nccl-cu12==2.21.5 (from torch>=1.11.0->sentence-transformers)
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    Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.11/dist-packages (from torch>=1.11.0->sentence-transf
    Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from sympy==1.13.1->torch>=1.1
    Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.11/dist-packages (from transformers<5.0.0,>=4.41.0->ser
    Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.11/dist-packages (from transformers<5.0.0,>=4.41
    Requirement already satisfied: tokenizers<0.22,>=0.21 in /usr/local/lib/python3.11/dist-packages (from transformers<5.0.0,>=
    Requirement already satisfied: safetensors>=0.4.3 in /usr/local/lib/python3.11/dist-packages (from transformers<5.0.0,>=4.41
    Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->sentence-transfo
    Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn->sentence-
    Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from jinja2->torch>=1.11.0->sent@
    Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->huggingfa
    Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->huggingface-hub>=0.20
    Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->huggingface-huk
    Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests->huggingface-huk
    Downloading nvidia_cublas_cu12-12.4.5.8-py3-none-manylinux2014_x86_64.whl (363.4 MB)
                                               - 363.4/363.4 MB 1.3 MB/s eta 0:00:00
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                                               - 13.8/13.8 MB 98.8 MB/s eta 0:00:00
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                                                883.7/883.7 kB 51.5 MB/s eta 0:00:00
    Downloading nvidia_cudnn_cu12-9.1.0.70-py3-none-manylinux2014_x86_64.whl (664.8 MB)
                                               664.8/664.8 MB 966.7 kB/s eta 0:00:00
    Downloading nvidia_cufft_cu12-11.2.1.3-py3-none-manylinux2014_x86_64.whl (211.5 MB)
                                               - 211.5/211.5 MB 3.2 MB/s eta 0:00:00
    Downloading nvidia_curand_cu12-10.3.5.147-py3-none-manylinux2014_x86_64.whl (56.3 MB)
                                               56.3/56.3 MB 9.6 MB/s eta 0:00:00
    Downloading nvidia_cusolver_cu12-11.6.1.9-py3-none-manylinux2014_x86_64.whl (127.9 MB)
                                                127.9/127.9 MB 4.5 MB/s eta 0:00:00
    Downloading nvidia_cusparse_cu12-12.3.1.170-py3-none-manylinux2014_x86_64.whl (207.5 MB)
                                               207.5/207.5 MB 4.4 MB/s eta 0:00:00
    Downloading nvidia_nccl_cu12-2.21.5-py3-none-manylinux2014_x86_64.whl (188.7 MB)
                                               - 188.7/188.7 MB 4.8 MB/s eta 0:00:00
    Downloading nvidia_nvjitlink_cu12-12.4.127-py3-none-manylinux2014_x86_64.whl (21.1 MB)
                                               21.1/21.1 MB 88.7 MB/s eta 0:00:00
    Installing collected packages: nvidia-nvjitlink-cu12, nvidia-nccl-cu12, nvidia-curand-cu12, nvidia-cufft-cu12, nvidia-cuda-r
      Attempting uninstall: nvidia-nvjitlink-cu12
        Found existing installation: nvidia-nvjitlink-cu12 12.5.82
        Uninstalling nvidia-nvjitlink-cu12-12.5.82:
          Successfully uninstalled nvidia-nvjitlink-cu12-12.5.82
      Attempting uninstall: nvidia-nccl-cu12
        Found existing installation: nvidia-nccl-cu12 2.23.4
        Uninstalling nvidia-nccl-cu12-2.23.4:
```

```
Successfully uninstalled nvidia-nccl-cu12-2.23.4
 Attempting uninstall: nvidia-curand-cu12
   Found existing installation: nvidia-curand-cu12 10.3.6.82
   Uninstalling nvidia-curand-cu12-10.3.6.82:
     Successfully uninstalled nvidia-curand-cu12-10.3.6.82
 Attempting uninstall: nvidia-cufft-cu12
   Found existing installation: nvidia-cufft-cu12 11.2.3.61
   Uninstalling nvidia-cufft-cu12-11.2.3.61:
     Successfully uninstalled nvidia-cufft-cu12-11.2.3.61
 Attempting uninstall: nvidia-cuda-runtime-cu12
   Found existing installation: nvidia-cuda-runtime-cu12 12.5.82
   Uninstalling nvidia-cuda-runtime-cu12-12.5.82:
     Successfully uninstalled nvidia-cuda-runtime-cu12-12.5.82
 Attempting uninstall: nvidia-cuda-nvrtc-cu12
   Found existing installation: nvidia-cuda-nvrtc-cu12 12.5.82
   Uninstalling nvidia-cuda-nvrtc-cu12-12.5.82:
     Successfully uninstalled nvidia-cuda-nvrtc-cu12-12.5.82
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   Uninstalling nvidia-cuda-cupti-cu12-12.5.82:
     Successfully uninstalled nvidia-cuda-cupti-cu12-12.5.82
 Attempting uninstall: nvidia-cublas-cu12
   Found existing installation: nvidia-cublas-cu12 12.5.3.2
   Uninstalling nvidia-cublas-cu12-12.5.3.2:
     Successfully uninstalled nvidia-cublas-cu12-12.5.3.2
 Attempting uninstall: nvidia-cusparse-cu12
   Found existing installation: nvidia-cusparse-cu12 12.5.1.3
   Uninstalling nvidia-cusparse-cu12-12.5.1.3:
     Successfully uninstalled nvidia-cusparse-cu12-12.5.1.3
 Attempting uninstall: nvidia-cudnn-cu12
   Found existing installation: nvidia-cudnn-cu12 9.3.0.75
   Uninstalling nvidia-cudnn-cu12-9.3.0.75:
     Successfully uninstalled nvidia-cudnn-cu12-9.3.0.75
 Attempting uninstall: nvidia-cusolver-cu12
   Found existing installation: nvidia-cusolver-cu12 11.6.3.83
   Uninstalling nvidia-cusolver-cu12-11.6.3.83:
     Successfully uninstalled nvidia-cusolver-cu12-11.6.3.83
Successfully installed nvidia-cublas-cu12-12.4.5.8 nvidia-cuda-cupti-cu12-12.4.127 nvidia-cuda-nvrtc-cu12-12.4.127 nvidia-cu
Batches: 100%
                                                     157/157 [00:32<00:00. 8.68it/s]
Shape of SBERT embeddings: (5000, 384)
```

```
from sklearn.cluster import KMeans
import numpy as np

# Choose embeddings (pick X_pca or X_embeddings)

#X = X_embeddings # if using SBERT

X = X_pca  # if using TF-IDF + PCA

# Define KMeans
kmeans = KMeans(n_clusters=6, random_state=42, n_init=10)
clusters = kmeans.fit_predict(X)

# Add cluster labels to dataframe
df["cluster"] = clusters

# Check some results
df[["query", "intent", "cluster"]].sample(20)
```



| | query | intent | cluster |
|------|---------------------------------------------------|------------------------|---------|
| 2335 | Something looks off with my last few transacti | fraud_report | 1 |
| 3594 | i never used atm that night | fraud_report | 1 |
| 62 | What vendor processed my most recent charge? | transaction_query | 1 |
| 67 | too many charges poppin up | fraud_report | 1 |
| 2364 | I have forgotten my password; please help me r | password_reset | 1 |
| 3467 | Did the app break? WHY CAN'T I SEE MY SAVINGS?! | balance_inquiry | 5 |
| 1386 | Was the last payment made correctly? | transaction_query | 1 |
| 3564 | business lending types? | loan_inquiry | 1 |
| 1845 | whut loan solutions do u have? | loan_inquiry | 2 |
| 3141 | Was the previous transaction done without issues? | transaction_query | 5 |
| 3083 | I'm having a crisis—SAVINGS BALANCE IMMEDIATELY! | balance_inquiry | 1 |
| 306 | Did the most recent transaction finalize witho | transaction_query | 5 |
| 318 | wuts dis brand lol | fraud_report | 1 |
| 570 | yo, any sign on my loan app progressin'? | loan_inquiry | 2 |
| 4122 | I'd like to learn about in-branch application | credi_card_application | 1 |
| 4594 | they said my data is leaking, pay up or else | fraud_report | 1 |
| 827 | Has my loan request been forwarded to the appr | loan_inquiry | 2 |
| 1081 | transacshun? panics in millennial | transaction_query | 1 |
| 3049 | overdraft woes galore | fraud_report | 1 |
| 4232 | Please guide me through the password reset pro | password_reset | 1 |

```
from sklearn.metrics import adjusted_rand_score, normalized_mutual_info_score

# True labels (ground truth)
y_true = df["intent"]

# Predicted cluster labels
y_pred = df["cluster"]

# Adjusted Rand Index (ARI): how well clustering matches true labels (0 = random, 1 = perfect)
ari = adjusted_rand_score(y_true, y_pred)

# Normalized Mutual Information (NMI): measures shared information (0 to 1)
nmi = normalized_mutual_info_score(y_true, y_pred)

print("Adjusted Rand Index (ARI):", ari)
print("Normalized Mutual Information (NMI):", nmi)
sil_score = silhouette_score(X, df['cluster'])

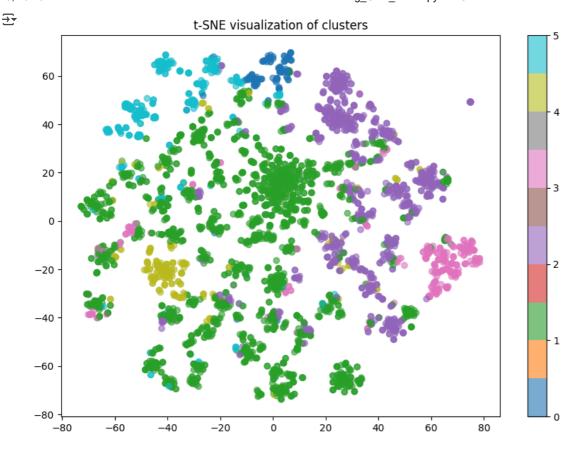
print(f"Silhouette Score: {sil_score:.3f}")
```

Adjusted Rand Index (ARI): 0.2206192099643765
Normalized Mutual Information (NMI): 0.3840869184207783
Silhouette Score: 0.103

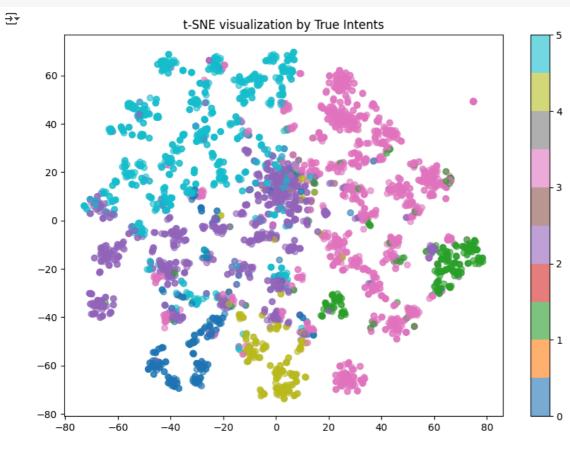
```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

# Reduce embeddings to 2D for visualization
tsne = TSNE(n_components=2, random_state=42, perplexity=30)
X_2d = tsne.fit_transform(X)

# Plot clusters
plt.figure(figsize=(10,7))
plt.scatter(X_2d[:,0], X_2d[:,1], c=df["cluster"], cmap="tab10", alpha=0.6)
plt.colorbar()
plt.title("t-SNE visualization of clusters")
plt.show()
```







from sentence_transformers import SentenceTransformer
from sklearn.cluster import KMeans

```
# Load a pre-trained sentence embedding model
model = SentenceTransformer("all-MiniLM-L6-v2")
# Encode all queries
embeddings = model.encode(df["query"].tolist(), show_progress_bar=True)
# Cluster
kmeans = KMeans(n_clusters=4, random_state=42)
df["cluster"] = kmeans.fit_predict(embeddings)
→
    Batches: 100%
                                                   157/157 [00:37<00:00, 7.24it/s]
from hdbscan import HDBSCAN
clusterer = HDBSCAN(min_cluster_size=10, metric='euclidean')
df["cluster"] = clusterer.fit_predict(embeddings)
warnings.warn(
    /usr/local/lib/python3.11/dist-packages/sklearn/utils/deprecation.py:151: FutureWarning: 'force_all_finite' was renamed to
      warnings.warn(
from sklearn.metrics import adjusted_rand_score, normalized_mutual_info_score
ari = adjusted_rand_score(df["intent"], df["cluster"])
nmi = normalized_mutual_info_score(df["intent"], df["cluster"])
print("ARI:", ari)
print("NMI:", nmi)
```

ARI: 0.21203621492640584 NMI: 0.4686243542822578

V UMAP & T-SNE

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import warnings
warnings.filterwarnings('ignore')
nltk.download('all')
```

Show hidden output

```
from datasets import load_dataset

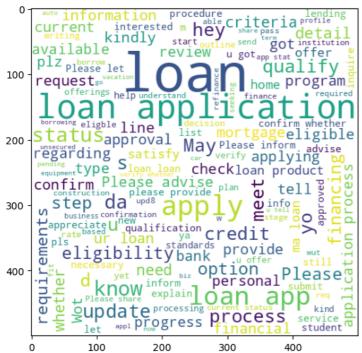
# Replace with your username/dataset name
dataset = load_dataset("atulgupta002/banking_customer_service_query_intent")

# See available splits
print(dataset)

# Convert to DataFrame
df = dataset['train'].to_pandas()
df=df[["query", "intent"]]
```

```
README.md: 100%
                                                                     312/312 [00:00<00:00, 34.1kB/s]
                                                326k/? [00:00<00:00, 16.6MB/s]
      (...) ervice\_intent\_classification\_dataset.csv:
     Generating train split: 100%
                                                                            5000/5000 [00:00<00:00, 108007.09 examples/s]
     DatasetDict({
          train: Dataset({
              features: ['Unnamed: 0', 'query', 'intent'],
              num_rows: 5000
          })
     })
df
∓
                                                                      intent
                                                     query
        0
             Could you please help me reset my account pass...
                                                               password reset
        1
                      What company charged my account last? transaction_query
        2
              How do I schedule an appointment to discuss lo...
                                                                  loan_inquiry
        3
                                Which loans 2day suited me?
                                                                  loan_inquiry
        4
              Do you have any updated timelines for my loan ...
                                                                  loan_inquiry
      4995
                      Was the transaction processed correctly?
                                                             transaction_query
      4996
                      Apple Pay charges I didn't make—fraud!!
                                                                  fraud_report
      4997
              Can you provide detailed steps on how to begin...
                                                                  loan_inquiry
      4998
                          what's the acc say? nervous chuckle
                                                               balance_inquiry
      4999
                             why'd my transac get dunked on? transaction_query
     5000 rows × 2 columns
df.columns=["t","i"]
df["n_c"]=df["t"].apply(len)
df["n_w"]=df["t"].apply(lambda x:len(nltk.word_tokenize(x)))
df["n_s"]=df["t"].apply(lambda x:len(nltk.sent_tokenize(x)))
from wordcloud import WordCloud
wc=WordCloud(width=500,height=500,min_font_size=10,background_color="white")
AI_wc=wc.generate(df[df["i"]=="loan_inquiry"]["t"].str.cat(sep=" "))
plt.figure(figsize=(6,6))
plt.imshow(AI_wc)
```

<matplotlib.image.AxesImage at 0x7a7dc8422f90>

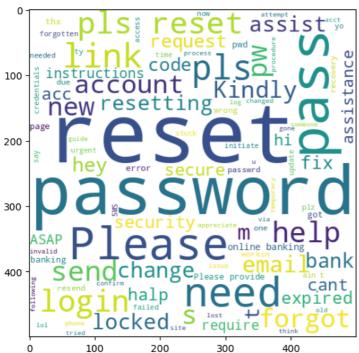


df[df["i"]=="loan_inquiry"][["n_c","n_w","n_s"]].describe()

| _ | | n_c | n_w | n_s |
|--------------|-------|-------------|-------------|-------------|
| | count | 1600.000000 | 1600.000000 | 1600.000000 |
| | mean | 47.361250 | 10.124375 | 1.011875 |
| | std | 21.274983 | 3.323524 | 0.108357 |
| | min | 12.000000 | 3.000000 | 1.000000 |
| | 25% | 28.000000 | 7.000000 | 1.000000 |
| | 50% | 44.000000 | 10.000000 | 1.000000 |
| | 75% | 64.250000 | 13.000000 | 1.000000 |
| | max | 112.000000 | 20.000000 | 2.000000 |

```
AI_wc=wc.generate(df[df["i"]=="password_reset"]["t"].str.cat(sep=" "))
plt.figure(figsize=(6,6))
plt.imshow(AI_wc)
```

<matplotlib.image.AxesImage at 0x7a7dc5e0a490>



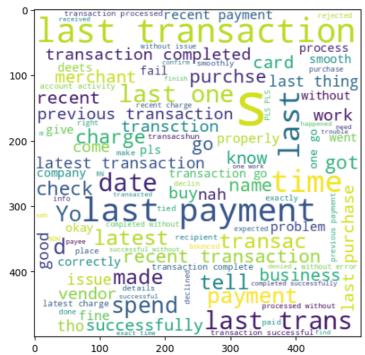
```
df[df["i"]=="password_reset"][["n_c","n_w","n_s"]].describe()
```

```
₹
                    n_c
                                n_w
                                            n_s
     count 300.000000
                        300.000000
                                     300.000000
     mean
              40.050000
                           8.613333
                                       1.233333
      std
              11.561418
                           2.258501
                                       0.461446
      min
              20.000000
                           4.000000
                                       1.000000
      25%
              31.000000
                           7.000000
                                       1.000000
      50%
              37.000000
                           9.000000
                                       1.000000
              49.000000
                          10.000000
                                       1.000000
      75%
              76.000000
                          14.000000
                                       3.000000
      max
```

```
AI_wc=wc.generate(df[df["i"]=="transaction_query"]["t"].str.cat(sep=" "))
```

plt.figure(figsize=(6,6))
plt.imshow(AI_wc)

<matplotlib.image.AxesImage at 0x7a7d65317ad0>

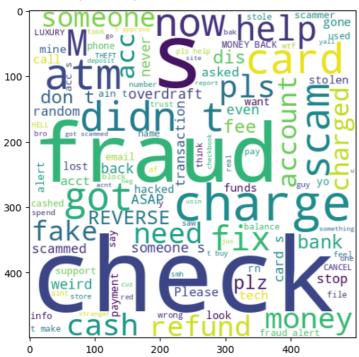


df[df["i"]=="transaction_query"][["n_c","n_w","n_s"]].describe()

| _ | | n_c | n_w | n_s |
|--------------|-------|-------------|-------------|-------------|
| | count | 1210.000000 | 1210.000000 | 1210.000000 |
| | mean | 40.805785 | 8.990083 | 1.090083 |
| | std | 10.304919 | 2.380629 | 0.286419 |
| | min | 16.000000 | 3.000000 | 1.000000 |
| | 25% | 32.000000 | 7.000000 | 1.000000 |
| | 50% | 40.000000 | 9.000000 | 1.000000 |
| | 75% | 49.000000 | 10.000000 | 1.000000 |
| | max | 68.000000 | 17.000000 | 2.000000 |

```
# fraud_report
AI_wc=wc.generate(df[df["i"]=="fraud_report"]["t"].str.cat(sep=" "))
plt.figure(figsize=(6,6))
plt.imshow(AI_wc)
```

<matplotlib.image.AxesImage at 0x7a7d44d08d10>

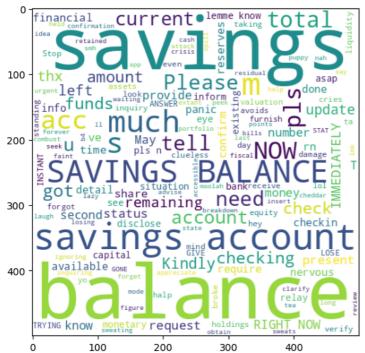


 $\label{eq:dfdf} \texttt{df[df["i"]=="fraud_report"][["n_c","n_w","n_s"]].describe()}$

| ₹ | | n_c | n_w | n_s |
|---|-------|-------------|-------------|-------------|
| | count | 1249.000000 | 1249.000000 | 1249.000000 |
| | mean | 37.662930 | 9.349880 | 1.495596 |
| | std | 14.487204 | 4.348418 | 0.673577 |
| | min | 9.000000 | 2.000000 | 1.000000 |
| | 25% | 25.000000 | 6.000000 | 1.000000 |
| | 50% | 38.000000 | 9.000000 | 1.000000 |
| | 75% | 46.000000 | 12.000000 | 2.000000 |
| | max | 91.000000 | 25.000000 | 4.000000 |

AI_wc=wc.generate(df[df["i"]=="balance_inquiry"]["t"].str.cat(sep=" "))
plt.figure(figsize=(6,6))
plt.imshow(AI_wc)

<matplotlib.image.AxesImage at 0x7a7d44d7bf50>

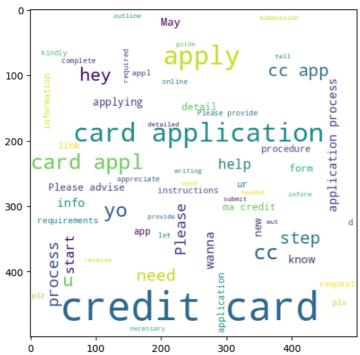


df[df["i"]=="balance_inquiry"][["n_c","n_w","n_s"]].describe()

| | | n_c | n_w | n_s |
|-------------|-------|------------|------------|------------|
| | count | 323.000000 | 323.000000 | 323.000000 |
| | mean | 43.894737 | 9.674923 | 1.448916 |
| | std | 8.727486 | 2.121223 | 0.695833 |
| | min | 7.000000 | 1.000000 | 1.000000 |
| | 25% | 37.000000 | 9.000000 | 1.000000 |
| | 50% | 46.000000 | 10.000000 | 1.000000 |
| | 75% | 50.000000 | 11.000000 | 2.000000 |
| | max | 74.000000 | 16.000000 | 7.000000 |

```
AI_wc=wc.generate(df[df["i"]=="credi_card_application"]["t"].str.cat(sep=" "))
plt.figure(figsize=(6,6))
plt.imshow(AI_wc)
```

<matplotlib.image.AxesImage at 0x7a7d44d6ccd0>



df[df["i"]=="credi_card_application"][["n_c","n_w","n_s"]].describe()

| → | | n_c | n_w | n_s |
|----------|-------|------------|------------|------------|
| | count | 318.000000 | 318.000000 | 318.000000 |
| | mean | 52.924528 | 11.327044 | 1.022013 |
| | std | 22.129971 | 3.370866 | 0.146956 |
| | min | 11.000000 | 4.000000 | 1.000000 |
| | 25% | 31.000000 | 8.000000 | 1.000000 |
| | 50% | 51.000000 | 12.000000 | 1.000000 |
| | 75% | 72.000000 | 14.000000 | 1.000000 |
| | max | 107.000000 | 19.000000 | 2.000000 |

df

| _ | | t | i | n_c | n_w | n_s |
|--------------|---------|-------------------------------------------------------|-------------------|-----|-----|-----|
| | 0 | Could you please help me reset my account pass | password_reset | 51 | 10 | 1 |
| | 1 | What company charged my account last? | transaction_query | 37 | 7 | 1 |
| | 2 | How do I schedule an appointment to discuss lo | loan_inquiry | 67 | 13 | 1 |
| | 3 | Which loans 2day suited me? | loan_inquiry | 27 | 6 | 1 |
| | 4 | Do you have any updated timelines for my loan \dots | loan_inquiry | 55 | 11 | 1 |
| | | | | | | |
| | 4995 | Was the transaction processed correctly? | transaction_query | 40 | 6 | 1 |
| | 4996 | Apple Pay charges I didn't make—fraud!! | fraud_report | 39 | 10 | 2 |
| | 4997 | Can you provide detailed steps on how to begin | loan_inquiry | 66 | 13 | 1 |
| | 4998 | what's the acc say? nervous chuckle | balance_inquiry | 35 | 9 | 2 |
| | 4999 | why'd my transac get dunked on? | transaction_query | 31 | 9 | 1 |
| | 5000 rc | ows × 5 columns | | | | |

from sentence_transformers import SentenceTransformer
Load a pre-trained sentence embedding model
model = SentenceTransformer("all-MiniLM-L6-v2")

```
# Encode all queries
embeddings = model.encode(df["t"].tolist(), show_progress_bar=True)
     modules.json: 100%
                                                                    349/349 [00:00<00:00, 24.3kB/s]
      config_sentence_transformers.json: 100%
                                                                                      116/116 [00:00<00:00, 6.46kB/s]
      README.md:
                       10.5k/? [00:00<00:00, 595kB/s]
      sentence_bert_config.json: 100%
                                                                               53.0/53.0 [00:00<00:00, 3.56kB/s]
      config.json: 100%
                                                                  612/612 [00:00<00:00, 39.3kB/s]
      model.safetensors: 100%
                                                                         90.9M/90.9M [00:01<00:00, 80.1MB/s]
      tokenizer_config.json: 100%
                                                                           350/350 [00:00<00:00, 9.62kB/s]
                   232k/? [00:00<00:00, 5.55MB/s]
      vocab.txt:
      tokenizer.json:
                       466k/? [00:00<00:00, 22.7MB/s]
                                                                              112/112 [00:00<00:00, 8.01kB/s]
      special_tokens_map.json: 100%
      config.json: 100%
                                                                  190/190 [00:00<00:00, 4.87kB/s]
      Batches: 100%
                                                                157/157 [00:02<00:00, 140.24it/s]
embeddings
 → array([[-0.03671908, -0.07597653, -0.01249438, ..., 0.0780434,
               -0.02108414, -0.10642095],
             [\ 0.00080891,\ -0.01177414,\ -0.02466845,\ \dots,\ -0.11604776,
               0.04516524, -0.01950026],
             [\ 0.0100682\ ,\ -0.00434602,\ -0.00085265,\ \dots,\ 0.02112929,
              -0.09129895, -0.06690539],
             [\ 0.0392577\ ,\ 0.03649173,\ -0.0212892\ ,\ \ldots,\ 0.08284812,
               -0.02740316, -0.06003959],
             [-0.08713641, -0.00544636, 0.02045082, ..., 0.06934794,
               0.02031212, -0.03548901],
             [ 0.01072836, -0.02365415, 0.05852266, ..., -0.01786028,
               -0.05420143, 0.01089964]], dtype=float32)
X_new=pd.concat([pd.DataFrame(embeddings),df[["n_w","n_s","n_c"]]], axis=1)
X new
\overline{2}
                     0
                                1
                                           2
                                                      3
                                                                            5
                                                                                       6
                                                                                                  7
                                                                                                             8
                                                                                                                        9 ...
                                                                                                                                      377
             -0.036719 -0.075977 -0.012494
                                             -0.026569 -0.027302
                                                                    0.059690
                                                                               0.018057
                                                                                           0.017092
                                                                                                      0.009097
                                                                                                                -0 017147
                                                                                                                                -0.002832 -0
        0
                                                                                                               -0.022968
        1
             0.000809 -0.011774 -0.024668
                                              -0.013851
                                                          0.042000
                                                                    -0.004458
                                                                               0.054191 -0.037227
                                                                                                      0.062161
                                                                                                                                 0.024998 - 0
                       -0.004346
                                  -0.000853
                                              0.005554
                                                         -0.081639
                                                                    -0.049284
                                                                               -0.025041
                                                                                           0.039795
                                                                                                      0.041797
                                                                                                                -0.043278
        2
             0.010068
                                                                                                                                 -0.023813
        3
                                   -0.049527
                                              -0.010081
                                                         -0.017726
                                                                                           0.025617
                                                                                                     -0.020526
                                                                                                                -0.030805
                                                                                                                                 0.073519 -0
             0.006883
                       -0.046947
                                                                    -0.069042
                                                                                0.014642
        4
             -0.024798 -0.058147
                                   0.058895
                                              -0.019508
                                                         0.016510
                                                                    -0.078348 -0.142908 -0.036995
                                                                                                     -0.023168
                                                                                                                -0.022636
                                                                                                                                -0.027766 0
      4995
             -0.008571
                        0.079681
                                   -0.018899
                                              -0.001861
                                                         -0.077694
                                                                    -0.096329
                                                                                0.055912 -0.053277
                                                                                                     -0.016167
                                                                                                                 0.009940
                                                                                                                                -0.021826
      4996
             -0.064108
                        0.057621
                                   0.095225
                                              -0.035204
                                                          0.021385
                                                                    -0.050942
                                                                                0.103024 -0.074215
                                                                                                      0.074222
                                                                                                                 0.040593
                                                                                                                                 -0.053427
      4997
             0.039258
                        0.036492
                                   -0.021289
                                              -0.051159
                                                         -0.079778
                                                                    -0.003736
                                                                               -0.049690
                                                                                           0.070004
                                                                                                     -0.063574
                                                                                                                -0.018668
                                                                                                                                 0.015649
      4998
             -0.087136 -0.005446
                                   0.020451
                                              0.068807 -0.009414
                                                                    -0.018395
                                                                                0.171198 -0.017964
                                                                                                     -0.037767
                                                                                                                -0.092763
                                                                                                                                 -0.015286 -0
      4999
             0.010728 -0.023654
                                   0.058523
                                              0.026812 -0.065386 -0.091657
                                                                                0.141122
                                                                                          0.073431
                                                                                                      0.008429
                                                                                                                 0.023026
                                                                                                                                -0.013210 -0
     5000 rows × 387 columns
X_new.columns=[f"f{i}" for i in range(len(X_new.columns))]
 # min max scaler
 from sklearn.preprocessing import MinMaxScaler
 scaler=MinMaxScaler()
 {\it X=scaler.fit\_transform(X\_new)}
```

```
x_df=pd.DataFrame(X)
x_df
₹
                                                                                                 7
                    0
                                          2
                                                     3
                                                                           5
                                                                                      6
                                                                                                            8
                                                                                                                       9 ...
                                                                                                                                                378
                               1
                                                                                                                                     377
            0.492873 \quad 0.214210 \quad 0.485070 \quad 0.365148 \quad 0.357505 \quad 0.731027 \quad 0.438363 \quad 0.542738 \quad 0.502959
                                                                                                                            ... 0.488209 0.132130
                                                                                                              0.461707
       0
                                                                                                                            ... 0.576576 0.162620
            0.596808 \quad 0.394395 \quad 0.448255 \quad 0.409578 \quad 0.580055 \quad 0.522454 \quad 0.518197 \quad 0.368965 \quad 0.671973 \quad 0.440499
       1
       2
             0.622453 0.415242 0.520274 0.477369 0.183014 0.376707 0.343146 0.615369
                                                                                                   0.607112 0.366491
                                                                                                                                          0.632755
                                                                                                                            ... 0.421590
       3
             0.613632 0.295682
                                  0.373082  0.422748  0.388259  0.312467  0.430820
                                                                                        0.570011
                                                                                                    0.408602
                                                                                                               0.411942
                                                                                                                            ... 0.730642
                                                                                                                                          0.440928
             0.525889
                      0.264249
                                 0.700952  0.389816  0.498201  0.282210  0.082741  0.369708  0.400187
                                                                                                              0.441707
                                                                                                                                0.409039
                                                                                                                                          0.547073
      4995
           0.570830 0.651066 0.465703 0.451462 0.195682 0.223745 0.521998 0.317616 0.422487
                                                                                                              0.560408
                                                                                                                            ... 0.427901 0.631873
            0.417018 \quad 0.589153 \quad 0.810812 \quad 0.334985 \quad 0.513854 \quad 0.371316 \quad 0.626084 \quad 0.250635 \quad 0.710390
                                                                                                               0.672105
                                                                                                                               0.327560
                                                                                                                                          0.389714
      4997
            0.703294 \quad 0.529854 \quad 0.458474 \quad 0.279246 \quad 0.188991 \quad 0.524803 \quad 0.288689 \quad 0.712010 \quad 0.271489
                                                                                                               0.456166
                                                                                                                               0.546890 0.707440
      4998 0.353239 0.412154 0.584696 0.698333 0.414951 0.477141 0.776704 0.430590 0.353689 0.186175
                                                                                                                            ... 0.448667 0.230691
      4999 0.624281 0.361054 0.699825 0.551631 0.235206 0.238936 0.710254 0.722974 0.500829 0.608095
                                                                                                                            ... 0.455256 0.262249
     5000 rows × 387 columns
```

from sklearn.cluster import KMeans from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score

KMeans

```
from sklearn.manifold import TSNE
# Apply t-SNE for dimension reduction
tsne = TSNE(n_components=2, random_state=42, perplexity=60,learning_rate=100) # You can adjust n_components and perplexity
X_tsne = tsne.fit_transform(X_new)
print("Shape after t-SNE:", X_tsne.shape)
Shape after t-SNE: (5000, 2)
from sklearn.cluster import KMeans
kmeans = KMeans(
    n clusters=4.
    init="k-means++",
    random state=42,
    n_init=50
)
clusters = kmeans.fit_predict(X_tsne)
# Add cluster labels to dataframe
df['Kmeans'] = clusters
# Unsupervised evaluation
silhouette = silhouette score(X tsne, clusters)
calinski = calinski_harabasz_score(X_tsne, clusters)
davies = davies_bouldin_score(X_tsne, clusters)
print(f"Silhouette Score: {silhouette:.3f}")
print(f"Calinski-Harabasz Score: {calinski:.3f}")
print(f"Davies-Bouldin Score: {davies:.3f}")
# Inspect cluster examples
for i in range(4):
    print(f"\nCluster {i} examples:")
    print(df[df['Kmeans'] == i]['t'].sample(5).to_list())
```

Silhouette Score: 0.488
Calinski-Harabasz Score: 6494.805
Davies-Bouldin Score: 0.666

```
Cluster 1 examples:
['What are the minimum credit requirements to apply for a loan?', '$700 TO "VIP EVENTS"? I WATCH NETFLIX IN PAJAMAS—STOP THI

Cluster 2 examples:
['tell me dats a joke', 'hey dude, reset my banking pw', 'how to avoid overdraft?', 'my acc got hacked pls help!!!', 'any mc

Cluster 3 examples:
['there's a $50 charge i don't recognize—pls fix', 'I'm considering a loan—what options do you have?', 'I seek the current 1
```

Agglomerative

from sklearn.decomposition import TruncatedSVD

```
from sklearn.cluster import AgglomerativeClustering

# === 4. Agglomerative Clustering ====
n_clusters = 4 # you can change this
agg_clust = AgglomerativeClustering(n_clusters=n_clusters)
cluster_labels = agg_clust.fit_predict(X_tsne)

df['Agg_cluster'] = cluster_labels

# ==== 5. Evaluation ====
sil_score = silhouette_score(X_tsne, cluster_labels)
calinski_score = calinski_harabasz_score(X_tsne, cluster_labels)
davies_score = davies_bouldin_score(X_tsne, cluster_labels)

print(f"Silhouette Score: {sil_score:.3f}")
print(f"Calinski-Harabasz Score: {calinski_score:.3f}")
print(f"Davies-Bouldin Score: {davies_score:.3f}")
```

Silhouette Score: 0.453
Calinski-Harabasz Score: 6572.894
Davies-Bouldin Score: 0.710

```
from sklearn.manifold import TSNE
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, calinski_harabasz_score, davies_bouldin_score
import pandas as pd
results = []
# Define parameter grid
perplexities = [5, 10,15,20,25,30,40,50,60,80]
learning_rates = [10,20,30,40,50,70,90,100]
n_clusters_list = [2,3,4,5,6,7]
for perplexity in perplexities:
    for lr in learning_rates:
        # Apply t-SNE
        tsne = TSNE(n_components=2, perplexity=perplexity, learning_rate=lr, random_state=42)
        X_tsne = tsne.fit_transform(X_new)
        for n_clusters in n_clusters_list:
            kmeans = KMeans(n_clusters=n_clusters, random_state=42, n_init=20)
            clusters = kmeans.fit_predict(X_tsne)
            # Evaluate
            silhouette = silhouette_score(X_tsne, clusters)
            calinski = calinski_harabasz_score(X_tsne, clusters)
            davies = davies_bouldin_score(X_tsne, clusters)
            results.append({
                'perplexity': perplexity,
                'learning_rate': lr,
                'n_clusters': n_clusters,
                'silhouette': silhouette,
                'calinski': calinski,
                'davies': davies
```

```
# Convert results to DataFrame
results_df = pd.DataFrame(results)

# Rank by silhouette (higher is better)
best_params = results_df.sort_values(by="silhouette", ascending=False).head(5)
print(best_params)
```

| ₹ | | perplexity | learning_rate | n_clusters | silhouette | calinski | davies |
|---|-----|------------|---------------|------------|------------|-------------|----------|
| | 428 | 60 | 100 | 4 | 0.502517 | 7893.368652 | 0.679381 |
| | 416 | 60 | 70 | 4 | 0.499660 | 7624.535645 | 0.690614 |
| | 470 | 80 | 90 | 4 | 0.499212 | 8536.618164 | 0.676886 |
| | 464 | 80 | 70 | 4 | 0.498247 | 8186.384277 | 0.681496 |
| | 476 | 80 | 100 | 4 | 0.497959 | 8470.266602 | 0.682969 |
| | | | | | | | |

df

→*

| 7 | | t | i | n_c | n_w | n_s | Kmeans | Agg_cluster | HBDSCAN |
|---|------|-------------------------------------------------------|-------------------|-----|-----|-----|--------|-------------|---------|
| | 0 | Could you please help me reset my account pass | password_reset | 51 | 10 | 1 | 3 | 0 | 2 |
| | 1 | What company charged my account last? | transaction_query | 37 | 7 | 1 | 0 | 2 | 2 |
| | 2 | How do I schedule an appointment to discuss lo | loan_inquiry | 67 | 13 | 1 | 1 | 3 | 3 |
| | 3 | Which loans 2day suited me? | loan_inquiry | 27 | 6 | 1 | 2 | 1 | -1 |
| | 4 | Do you have any updated timelines for my loan \dots | loan_inquiry | 55 | 11 | 1 | 3 | 0 | 2 |
| | | | | | | | | | |
| | 4995 | Was the transaction processed correctly? | transaction_query | 40 | 6 | 1 | 0 | 0 | 2 |
| | 4996 | Apple Pay charges I didn't make—fraud!! | fraud_report | 39 | 10 | 2 | 0 | 2 | 2 |
| | 4997 | Can you provide detailed steps on how to begin | loan_inquiry | 66 | 13 | 1 | 1 | 3 | 3 |
| | 4998 | what's the acc say? nervous chuckle | balance_inquiry | 35 | 9 | 2 | 0 | 2 | 2 |
| | 4999 | why'd my transac get dunked on? | transaction_query | 31 | 9 | 1 | 0 | 2 | -1 |

from sklearn.manifold import TSNE

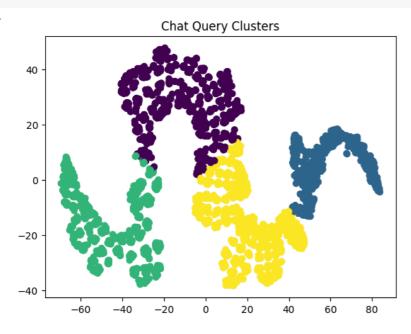
5000 rows × 8 columns

import matplotlib.pyplot as plt

tsne = TSNE(n_components=2, random_state=42, perplexity=60,learning_rate=100) # You can adjust n_components and perplexity vis_data = tsne.fit_transform(X_new)

plt.scatter(vis_data[:, 0], vis_data[:, 1], c=df['Kmeans'], cmap='viridis')
plt.title("Chat Query Clusters")
plt.show()





Inspect cluster examples
for i in range(4):

```
print(f"\nCluster {i} examples:")
print(df[df['Kmeans'] == i]['t'].sample(5).to_list())
```



Cluster 0 examples:

['How do I call up the loan app process?', 'Was the last payment processed correctly?', 'i need to check how much mony i hav

Cluster 1 examples:

['Would you confirm my eligibility for a turnkey project loan?', 'Can you please confirm the current phase of my loan applic

Cluster 2 examples:

['new cust loan apply? how?', 'cant login, pass sucks now', 'How do I go abt gettin a loan?', 'transac went poof—why?', 'no

Cluster 3 examples:

['Was the previous transaction successful without issues?', 'Can you tell me the time of my last transaction?', 'Did the mos

```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

#tsne = TSNE(n_components=2, random_state=42, perplexity=60,learning_rate=100) # You can adjust n_components and perplexity
#vis_data = tsne.fit_transform(X_new)

plt.scatter(vis_data[:, 0], vis_data[:, 1], c=df['Agg_cluster'], cmap='viridis')
plt.title("Chat Query Clusters")
plt.show()
```



Chat Query Clusters 40 - 20 - 0 - -20 - -40 - -20 0 20 40 60 80

```
# Inspect cluster examples
for i in range(4):
    print(f"\nCluster {i} examples:")
    print(df[df['Agg_cluster'] == i]['t'].sample(5).to_list())
```

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Cluster 0 examples:

['This is unacceptable—ANSWER MY SAVINGS INQUIRY!', 'What are the requirements to apply for an unsecured loan?', 'What's the

Cluster 1 examples:

['do i meet payday alt criteria?', 'do i check ur loan boxes?', 'do i ring as loan material?', 'still no reset email, resenc

Cluster 2 examples:

['recent transction? cries silently', 'someone's takin loans in my name—HELP!!', 'Loan application—how do I get started?',

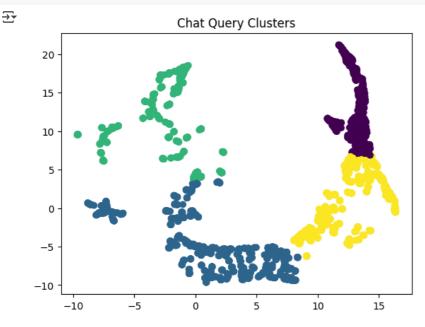
Cluster 3 examples:

['\$450 AT "FITNESS FREAK"? I HATE GYMS—REVERSE THIS OR I'M CLOSING MY ACCOUNT!', 'WHO'S "LUXURY LIVING"? I LIVE IN A STUDIO-

```
# size of local neighborhood (controls balance of local/global structure)
    n_neighbors=15,
    min_dist=0.1,
                          # how tightly UMAP packs points together
    random state=42
X_umap = umap_model.fit_transform(X_new)
print("Shape after UMAP:", X_umap.shape)
# Step 2: Cluster with KMeans
kmeans = KMeans(n_clusters=4, random_state=42, n_init=20)
clusters = kmeans.fit_predict(X_umap)
# Step 3: Add cluster labels to dataframe
df["UMAP_KMeans"] = clusters
# Step 4: Evaluate clustering
silhouette = silhouette_score(X_umap, clusters)
calinski = calinski_harabasz_score(X_umap, clusters)
davies = davies_bouldin_score(X_umap, clusters)
print(f"Silhouette Score: {silhouette:.3f}")
print(f"Calinski-Harabasz Score: {calinski:.3f}")
print(f"Davies-Bouldin Score: {davies:.3f}")
```

Shape after UMAP: (5000, 2)
Silhouette Score: 0.488
Calinski-Harabasz Score: 6494.805
Davies-Bouldin Score: 0.666

```
plt.scatter(X_umap[:, 0], X_umap[:, 1], c=df['UMAP_KMeans'], cmap='viridis')
plt.title("Chat Query Clusters")
plt.show()
```



```
# Inspect cluster examples
for i in range(4):
    print(f"\nCluster {i} examples:")
    print(df[df['UMAP_KMeans'] == i]['t'].sample(5).to_list())
```

Cluster 0 examples:
['What are the steps to apply for a startup seed funding loan?', 'How do I request a credit card application package by mail
Cluster 1 examples:
['last transction—am i in debt now', 'Did that last payment go through or not?', 'do i got shiine 4 loan approval?', 'check

Cluster 2 examples: ['card said no. why?', 'did i pass prequal or nah?', 'this not how i roll', 'atm hacked or smth', 'gotta block dis ASAP']

Cluster 3 examples:

['Please advise on how I may reset my password.', 'What was the time and date on my last purchase?', 'That check deposit was