Project 2

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```
import numpy as np
np.random.seed(42)
import random
random.seed(42)
from sklearn.datasets import fetch_20newsgroups

from sklearn.feature_extraction.text import TfidfTransformer,
CountVectorizer
from sklearn.decomposition import TruncatedSVD
from sklearn.decomposition import NMF
from sklearn.metrics.cluster import contingency_matrix
from sklearn.metrics.cluster import adjusted_mutual_info_score,
adjusted_rand_score, homogeneity_score, v_measure_score,
completeness_score

from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
import itertools
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors as colors

from scipy.optimize import linear_sum_assignment
from sklearn.metrics import confusion_matrix
```

Part 1

```
topics = ['comp.graphics', 'comp.os.ms-windows.misc',
'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware', 'rec.autos',
'rec.motorcycles','rec.sport.baseball', 'rec.sport.hockey']
data = fetch_20newsgroups(subset = 'all', categories=topics,
remove=('headers', 'footers'))
```

Question 1

Dimensions of the TF-IDF matrix: (7882, 23522)

```
count_vect = CountVectorizer(stop_words='english', min_df=3)
X_train_counts = count_vect.fit_transform(data.data)

tfidf_transformer = TfidfTransformer()
```

```
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
print(X_train_tfidf.shape)
```

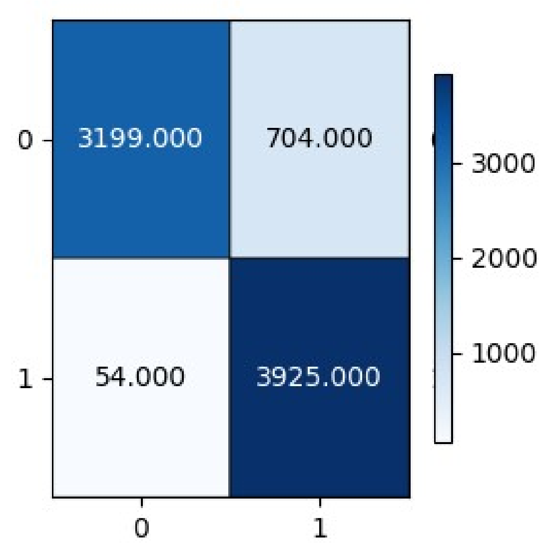
```
(7882, 23522)
```

Question 2

The contingency matrix does not always have to be square shaped. For example in multiclass classification there can be a different number of actual classes versus the classes that are predicted. It will have dimensions based on the number of classes involved.

```
def plot_mat(mat, xticklabels = None, yticklabels = None, pic_fname =
None, size=(3,3), if_show_values = True, colorbar = True, grid = 'k',
xlabel = None, ylabel = None, title = None, vmin=None, vmax=None):
  if size == (-1, -1):
    size = (mat.shape[1] / 3, mat.shape[0] / 3)

  fig = plt.figure(figsize=size)
  ax = fig.add_subplot(1,1,1)

  # im = ax.imshow(mat, cmap=plt.cm.Blues)
  im = ax.pcolor(mat, cmap=plt.cm.Blues, linestyle='-', linewidth=0.5,
edgecolor=grid, vmin=vmin, vmax=vmax)
  if colorbar:
    plt.colorbar(im,fraction=0.046, pad=0.06)
  # tick_marks = np.arange(len(classes))
  # Ticks
  lda_num_topics = mat.shape[0]
  nmf_num_topics = mat.shape[1]
  yticks = np.arange(lda_num_topics)
  xticks = np.arange(nmf_num_topics)
  ax.set_xticks(xticks + 0.5)
  ax.set_yticks(yticks + 0.5)
  if xticklabels is None:
    xticklabels = [str(i) for i in xticks]
  if yticklabels is None:
    yticklabels = [str(i) for i in yticks]
  ax.set_xticklabels(xticklabels)
  ax.set_yticklabels(yticklabels)

  # Minor ticks
  # ax.set_xticks(xticks, minor=True);
  # ax.set_yticks(yticks, minor=True);
  # ax.set_xticklabels([], minor=True)
  # ax.set_yticklabels([], minor=True)
  # ax.grid(which='minor', color='k', linestyle='-', linewidth=0.5)

  # tick labels on all four sides
  ax.tick_params(labelright = True, labeltop = False)
```

```
  if ylabel:
    plt.ylabel(ylabel, fontsize=15)
  if xlabel:
    plt.xlabel(xlabel, fontsize=15)
  if title:
    plt.title(title, fontsize=15)

  # im = ax.imshow(mat, interpolation='nearest', cmap=plt.cm.Blues)
  ax.invert_yaxis()

  # thresh = mat.max() / 2

  def show_values(pc, fmt="%.3f", **kw):
    pc.update_scalarmappable()
    ax = pc.axes
    for p, color, value in itertools.zip_longest(pc.get_paths(),
pc.get_facecolors(), pc.get_array()):
      x, y = p.vertices[:-2, :].mean(0)
      if np.all(color[:3] > 0.5):
        color = (0.0, 0.0, 0.0)
      else:
        color = (1.0, 1.0, 1.0)
      ax.text(x, y, fmt % value, ha="center", va="center",
color=color, **kw,fontsize=10)
  if if_show_values:
    show_values(im)
  # for i, j in itertools.product(range(mat.shape[0]),
range(mat.shape[1])):
  # ax.text(j, i, "{:.2f}".format(mat[i, j]), fontsize = 4,
  # horizontalalignment="center",
  # color="white" if mat[i, j] > thresh else "black")

  plt.tight_layout()
  if pic_fname:
    plt.savefig(pic_fname, dpi=300, transparent=True)
  plt.show()
  plt.close()

from sklearn.metrics.cluster import contingency_matrix
from sklearn.cluster import KMeans

actual_y = [i//4 for i in data.target]

kmeans = KMeans(n_clusters=2, max_iter=1000, n_init=30)
pred_y = kmeans.fit_predict(X_train_tfidf)
cont_matrix = contingency_matrix(actual_y,pred_y)

plot_mat(cont_matrix)
```



Question 3

The scores are reported below:

Adjusted mutual information score: 0.5949789645310989

Adjusted Rand score: 0.6522758110761804

Homogeneity score: 0.588461885635887

V-measure score: 0.5950164541990309

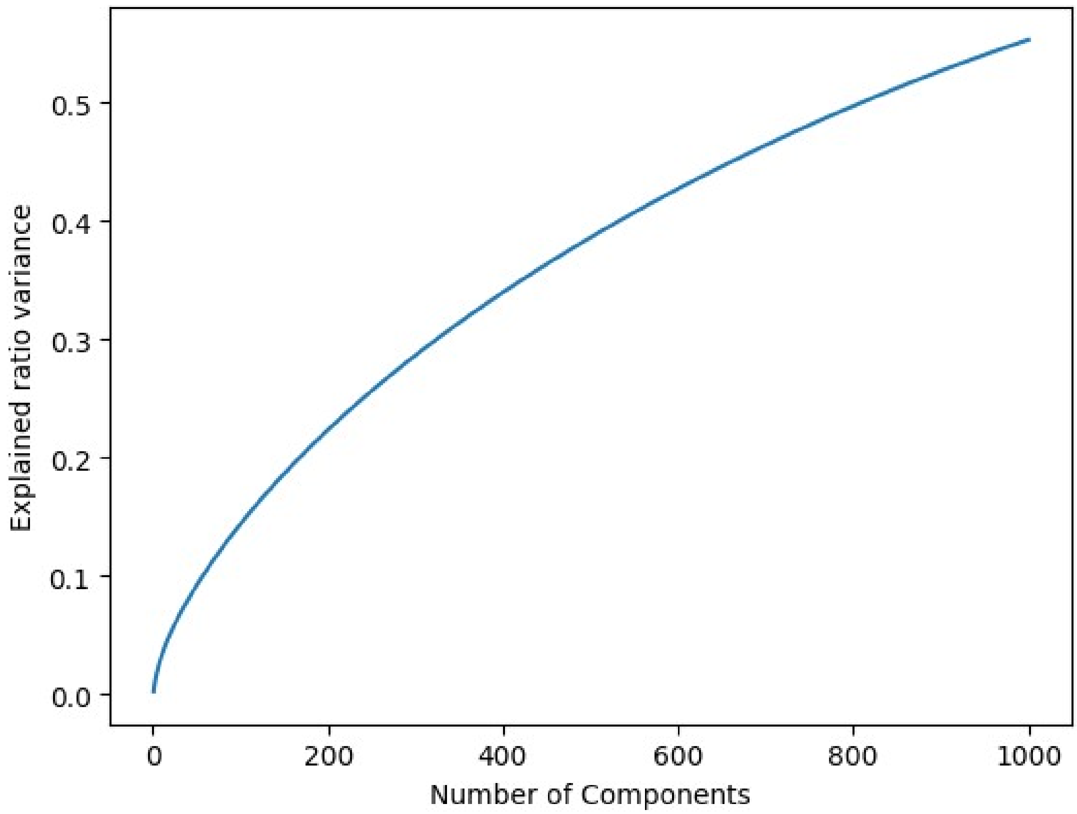
Completeness score: 0.6017186832840086

```
from sklearn.metrics.cluster import adjusted_mutual_info_score,
adjusted_rand_score, homogeneity_score, v_measure_score,
completeness_score

print("Adjusted mutual information score:
",adjusted_mutual_info_score(actual_y,pred_y))
print("Adjusted Rand score: ",adjusted_rand_score(actual_y,pred_y))
print("Homogeneity score: ", homogeneity_score(actual_y,pred_y))
print("V-measure score: ",v_measure_score(actual_y,pred_y))
print("Completeness score: ",completeness_score(actual_y,pred_y))

Adjusted mutual information score:  0.5949789645310989
Adjusted Rand score:  0.6522758110761804
Homogeneity score:  0.588461885635887
V-measure score:  0.5950164541990309
Completeness score:  0.6017186832840086
```

Question 4

```
from sklearn.decomposition import TruncatedSVD

svd_evr = TruncatedSVD(n_components=1000)
X_train_reduced = svd_evr.fit_transform(X_train_tfidf)

plt.plot(np.arange(1000)+1,svd_evr.explained_variance_ratio_.cumsum())
plt.xlabel("Number of Components");
plt.ylabel("Explained ratio variance")
```

```
Text(0, 0.5, 'Explained ratio variance')
```



Question 5

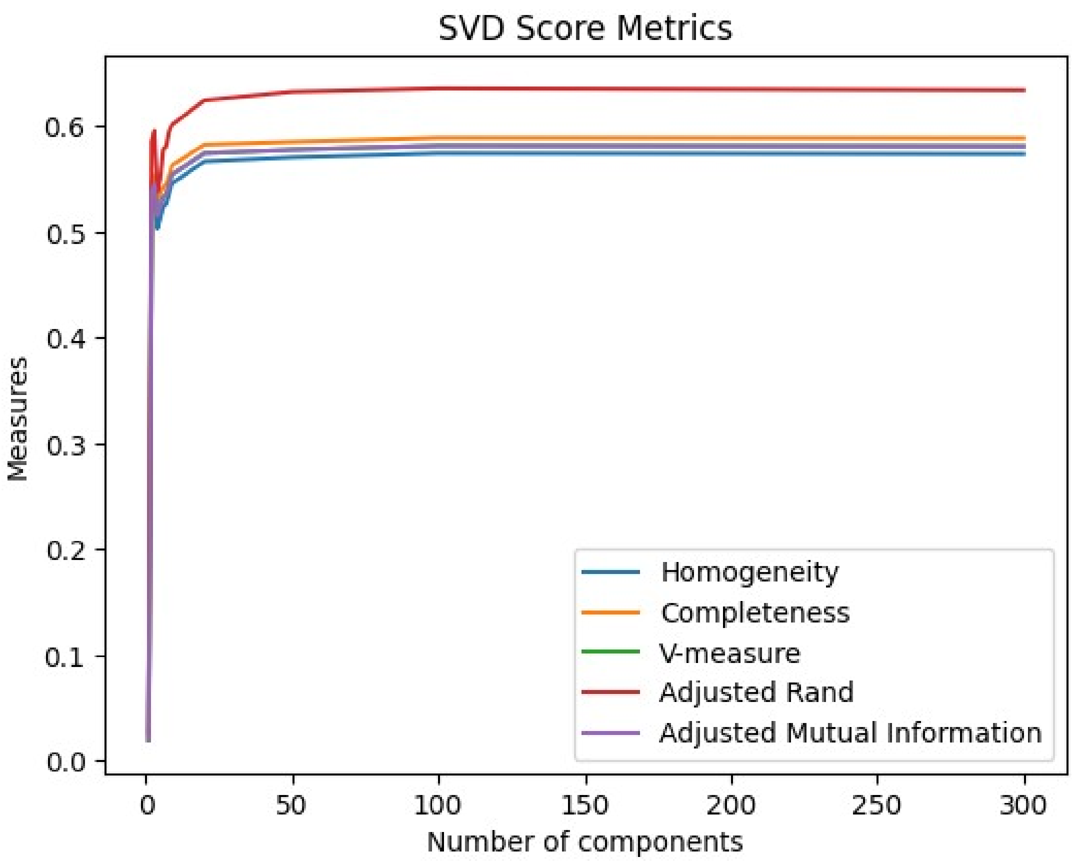
Good Choice for R for SVD: 100

Good Choice for R for NMF: 2

```
poss_r = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 50, 100, 300]
all_hom = []
all_complet = []
all_v = []
all_adj_rand = []
all_adj_mut_inf = []
for r in poss_r:
  svd = TruncatedSVD(n_components=r)
```

```python
  reduced = svd.fit_transform(X_train_tfidf)
  pred_y = kmeans.fit_predict(reduced)
  all_hom.append(homogeneity_score(actual_y,pred_y))
  all_complet.append(completeness_score(actual_y,pred_y))
  all_v.append(v_measure_score(actual_y,pred_y))
  all_adj_rand.append(adjusted_rand_score(actual_y,pred_y))
  all_adj_mut_inf.append(adjusted_mutual_info_score(actual_y,pred_y))

fig, ax = plt.subplots()
ax.plot(poss_r,all_hom, label='Homogeneity')
ax.plot(poss_r, all_complet, label='Completeness')
ax.plot(poss_r, all_v, label='V-measure')
ax.plot(poss_r,all_adj_rand,label='Adjusted Rand')
ax.plot(poss_r,all_adj_mut_inf, label='Adjusted Mutual Information')
ax.legend(loc='best')
plt.xlabel("Number of components")
plt.ylabel("Measures");
plt.title("SVD Score Metrics")
```

```
Text(0.5, 1.0, 'SVD Score Metrics')
```



```python
print("SVD")
print(all_hom)
print(all_complet)
print(all_v)
print(all_adj_rand)
print(all_adj_mut_inf)
```

```
SVD
[0.019096193923968514, 0.5290568591667072, 0.5371352366502093,
0.5030528872950297, 0.5124799770662565, 0.5239219943949754,
0.5263787702409716, 0.5364702886260979, 0.5455819022758501,
0.5475492679846266, 0.566568437426003, 0.5704687479252654,
0.5742537772924552, 0.5736906948793236]
[0.019424232697599873, 0.5466431001230211, 0.5537146886789862,
0.5283850694664373, 0.5363748027677557, 0.5423608376746923,
0.544542750494941, 0.5529862276905418, 0.562774091282195,
0.5646704937854108, 0.5823768459620671, 0.5849519708894831,
0.5887504944765372, 0.5885048109042065]
[0.01925881652670827, 0.5377062240054302, 0.5452989699761482,
0.5154078983737596, 0.5241552060521457, 0.532981987911606,
0.5353067200520797, 0.5446030690208484, 0.5540446590407202,
0.5559781010052695, 0.5743638872633166, 0.5776195856554346,
0.5814117859114925, 0.5810033376094367]
[0.026084881482977705, 0.585225410661106, 0.5957562066257983,
0.53769534393471, 0.550424300845874, 0.5778711366972836,
0.580962008813044, 0.5953644999156059, 0.6012536146031909,
0.6032230837153093, 0.6242973911050828, 0.6323439557028129,
0.6355770200022988, 0.6339594657351051]
[0.019168264152131194, 0.5376632083842705, 0.5452567087593242,
0.5153624433205805, 0.5241106490370318, 0.532938492313225,
0.5352634550847156, 0.5445607447464621, 0.5540031978925944,
0.5559368244003476, 0.5743243835675167, 0.5775804314964481,
0.5813729859748422, 0.5809644889949032]
```

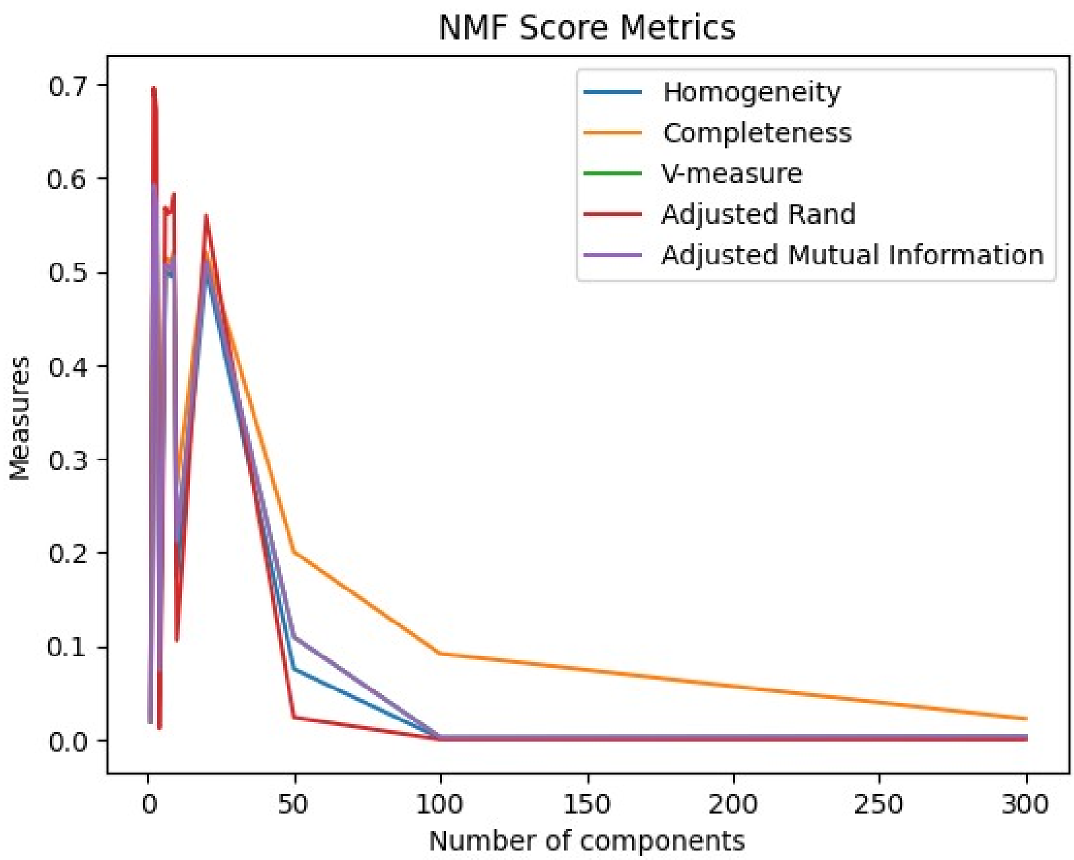
```python
from sklearn.decomposition import NMF

poss_r = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 50, 100, 300]
all_hom = []
all_complet = []
all_v = []
all_adj_rand = []
all_adj_mut_inf = []
for r in poss_r:
  nmf = NMF(n_components=r)
  reduced = nmf.fit_transform(X_train_tfidf)
  pred_y = kmeans.fit_predict(reduced)
  all_hom.append(homogeneity_score(actual_y,pred_y))
  all_complet.append(completeness_score(actual_y,pred_y))
  all_v.append(v_measure_score(actual_y,pred_y))
  all_adj_rand.append(adjusted_rand_score(actual_y,pred_y))
```

```
  all_adj_mut_inf.append(adjusted_mutual_info_score(actual_y,pred_y))

fig, ax = plt.subplots()
ax.plot(poss_r,all_hom, label='Homogeneity')
ax.plot(poss_r, all_complet, label='Completeness')
ax.plot(poss_r, all_v, label='V-measure')
ax.plot(poss_r,all_adj_rand,label='Adjusted Rand')
ax.plot(poss_r,all_adj_mut_inf, label='Adjusted Mutual Information')
ax.legend(loc='best')
plt.xlabel("Number of components")
plt.ylabel("Measures");
plt.title("NMF Score Metrics")
```

```
Text(0.5, 1.0, 'NMF Score Metrics')
```




```
print("NMF")
print(all_hom)
print(all_complet)
print(all_v)
print(all_adj_rand)
print(all_adj_mut_inf)
```

```
NMF
[0.019040345186437314, 0.5924052178662683, 0.571964768502695,
0.0478894086185501, 0.25237744829807296, 0.5006103911725807,
0.4981309476292966, 0.49501073087650027, 0.5103640144416155,
0.17360104220942446, 0.5031739025983972, 0.07527152459454531,
0.001287719557284094, 0.0017907521907223854]
[0.019373010847691004, 0.5939554127512687, 0.5749266623105408,
0.16476153146633502, 0.32650230586382484, 0.514960969107947,
0.513868313365936, 0.508822534264248, 0.5229564919380246,
0.272770470376064, 0.5211440987157528, 0.20047349213771662,
0.09172942657306825, 0.022121728829021674]
[0.01920523754877913, 0.5931793025036739, 0.5734418908009519,
0.07420923981676063, 0.28469407756935783, 0.5076842893886468,
0.5058772664357665, 0.5018216138459274, 0.5165835245811654,
0.2121696237600764, 0.5120013699466501, 0.10944854469410262,
0.002539785007186993, 0.003313293533232974]
[0.02600279267228016, 0.6964515122674229, 0.6725166723140447,
0.011695995753767235, 0.20298968653560295, 0.5686478147251656,
0.5621596514597169, 0.5648266930314535, 0.5832854020584197,
0.10604983248580083, 0.5602585137133101, 0.0235449263662378,
5.5204716378877675e-05, -9.426256698064189e-05]
[0.01911466726971035, 0.5931420092491568, 0.5734027383536108,
0.07407775568160181, 0.28462019682241535, 0.5076385803378457,
0.5058313253107508, 0.501775377432165, 0.516538727893312,
0.21208145268948356, 0.5119559091035821, 0.10932990886341483,
0.0023487932906809993, 0.0031433978879044987]
```

Question 6

KMeans tend to not perform well with higher dimensionality when training on data. As we increase the number of components, the dimensions when clustering KMeans rise too. This issue in poor performance with higher dimensionality can be seen when the Euclidean distance becomes not as useful in higher dimensions(since points will be shown to be equidistant). As shown on the graph, after a certain r value, increasing the number of components doesn't provide any useful information to KMeans, which results in the non-monotonic behavior.

Question 7

Homogeneity: The one computed in question 3 has a higher score(0.588461885635885), then SVD has next higher score on average(0.5046932167962661), then NMF has the lowest(0.3030655866958848).

Completeness: The one computed in question 3 has a higher score(0.6017186832840064), then SVD has next higher score on average(0.5211757440638475), then NMF has the lowest(0.3463118891819598).

V-measure: The one computed in question 3 has a higher score(0.5950164541990287), then SVD has next higher score on average(0.5127957320288846), then NMF has the lowest(0.3154406471023053).

Adjusted Rand: The one computed in question 3 has a higher score(0.6522758110761804), then SVD has next higher score on average(0.5557170228457285), then NMF has the lowest(0.32702788825233003).

Adjusted mutual information: The one computed in question 3 has a higher score(0.5949789645310966), then SVD has next higher score on average(0.5127504484374558), then NMF has the lowest(0.31535720287040236).

Question 8

```
svd_r = 100
nmf_r = 2

best_svd =
TruncatedSVD(n_components=svd_r).fit_transform(X_train_tfidf)
plt.figure()
plt.scatter(best_svd[:,0],best_svd[:,1],c=actual_y)
plt.title("SVD Labeled Ground Truth(R=100)")
plt.legend()

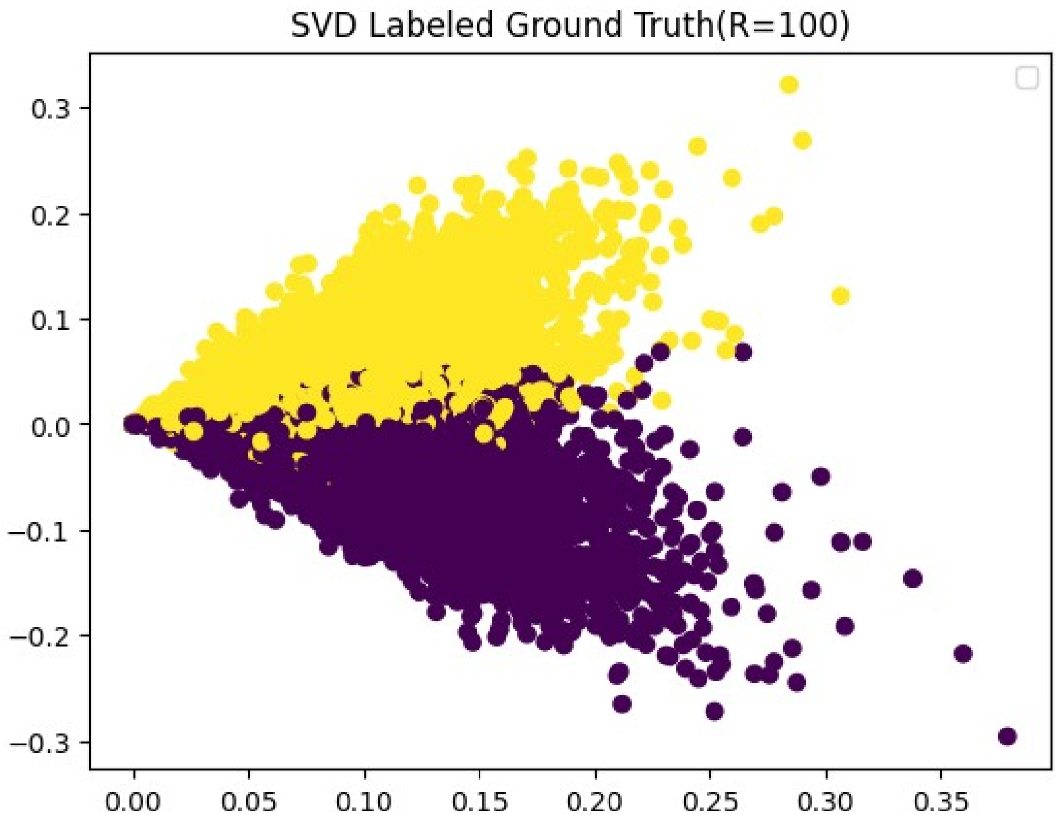
model = KMeans(n_clusters=2, max_iter=1000, n_init=30)
svd_pred = model.fit_predict(best_svd)
plt.figure()
plt.scatter(best_svd[:,0],best_svd[:,1],c=svd_pred)
plt.title("SVD Labeled Predictions Clustering(R=100)")

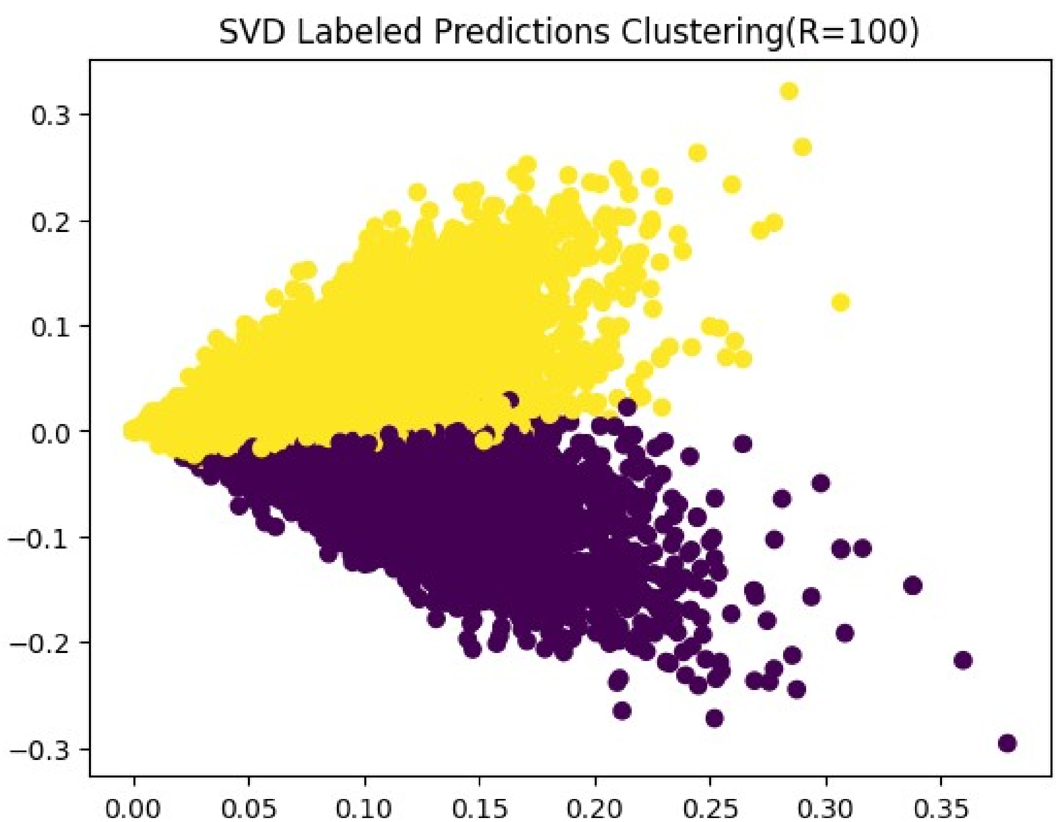
best_nmf =
NMF(n_components=nmf_r,init='random',random_state=0).fit_transform(X_t
rain_tfidf)
plt.figure()
plt.scatter(best_nmf[:,0],best_nmf[:,1],c=actual_y)
plt.title("NMF Labeled Ground Truth(R=2)")

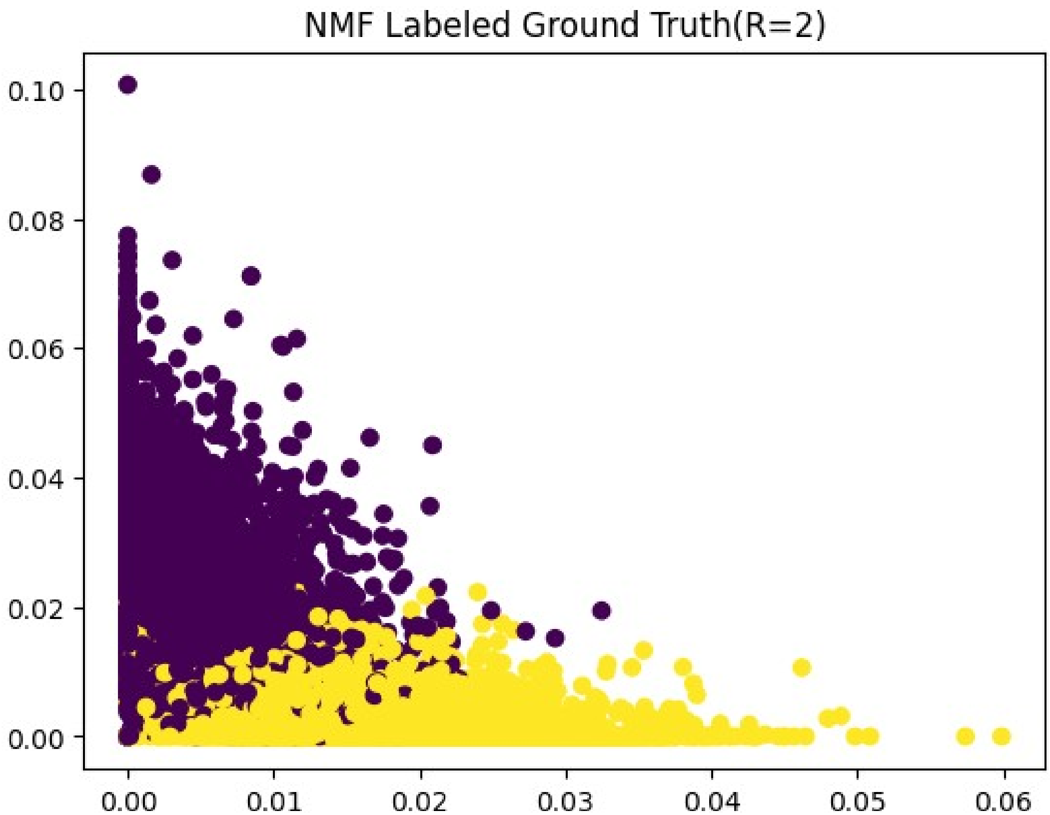
nmf_pred = model.fit_predict(best_nmf)
plt.figure()
plt.scatter(best_nmf[:,0],best_nmf[:,1],c=nmf_pred)
plt.title("NMF Labeled Predictions Clustering(R=2)")
```

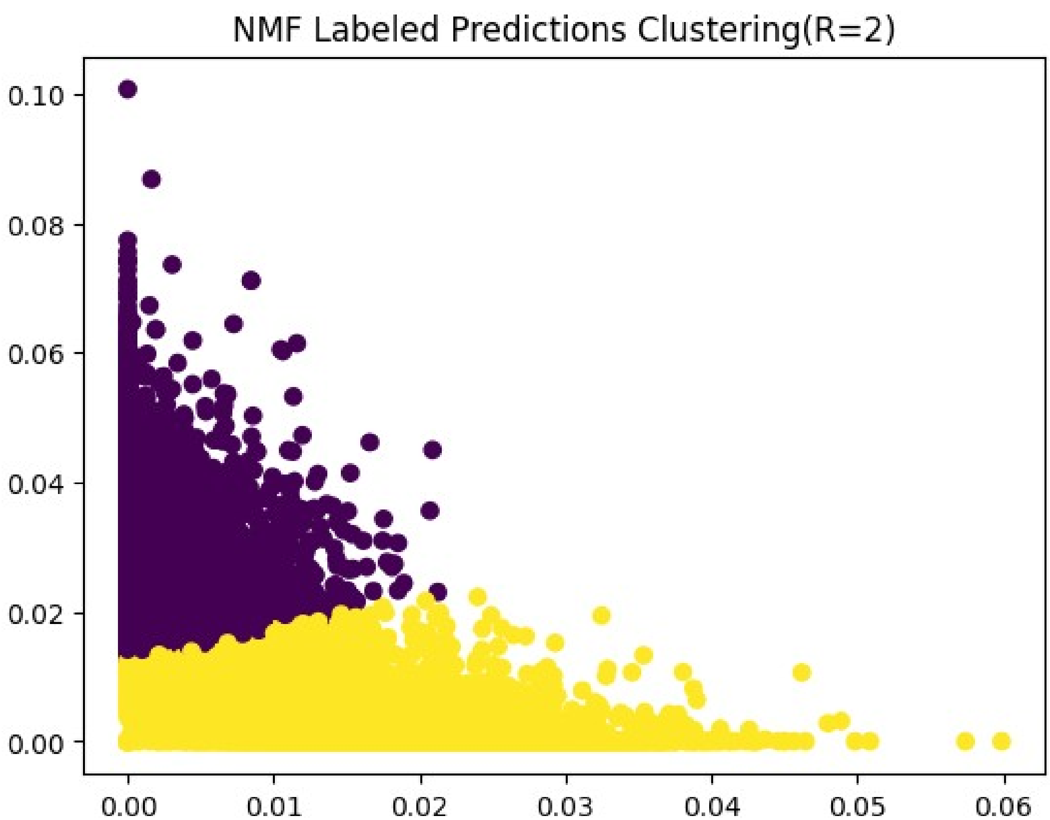
```
WARNING:matplotlib.legend:No artists with labels found to put in
legend.  Note that artists whose label start with an underscore are
ignored when legend() is called with no argument.
```

```
Text(0.5, 1.0, 'NMF Labeled Predictions Clustering(R=2)')
```


SVD Labeled Ground Truth(R=100)
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35


SVD Labeled Predictions Clustering(R=100)
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35


NMF Labeled Ground Truth(R=2)
0.10
0.08
0.06
0.04
0.02
0.00
0.00
0.01
0.02
0.03
0.04
0.05
0.06


NMF Labeled Predictions Clustering(R=2)
0.10
0.08
0.06
0.04
0.02
0.00
0.00
0.01
0.02
0.03
0.04
0.05
0.06

Question 9

CHECK!!In all the graphs there seems to be a sort of clear division of data. I would say the distribution of the data is ideal for K-Means clustering since just by observation we can see that there are two separate areas for the data. My only concern is that there could be some overlap between both classes, which might result in some error for K-Means Clustering.

Question 10

Load documents with the same configuration as in Question 1, but for ALL 20 categories. Construct the TF-IDF matrix, reduce its dimensionality using BOTH NMF and SVD (specify settings you choose and why), and perform K-Means clustering with k=20 . Visualize the contingency matrix and report the five clustering metrics (DO BOTH NMF AND SVD).

```
dataset = fetch_20newsgroups(subset = 'all',shuffle =
True,remove=('headers','footers'))
count_vect = CountVectorizer(stop_words='english',min_df=3)
tfidf_transformer = TfidfTransformer()
X_train_counts = count_vect.fit_transform(dataset.data)
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)

X_train_tfidf.shape

(18846, 45365)

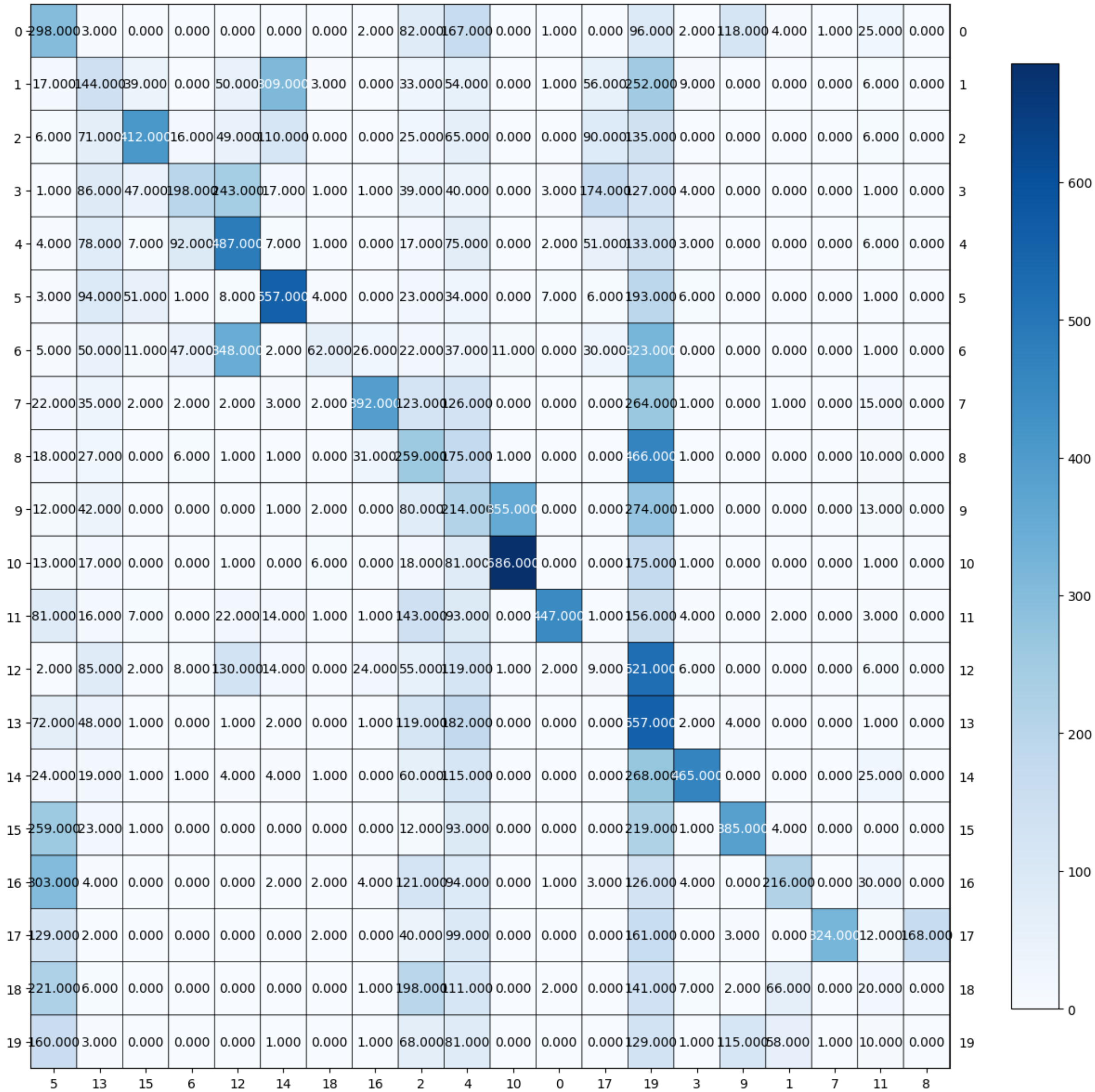
dataset.target

array([10,  3, 17, ...,  3,  1,  7])
```

For SVD we choose the setting n_components equal to 100. From the plot in question 5, we can see that this setting has the highest clustering metrics.

```
svd = TruncatedSVD(n_components=100)
X_train_svd = svd.fit_transform(X_train_tfidf)
km = KMeans(n_clusters=20, max_iter=1000, n_init=30)
pred_svd = km.fit_predict(X_train_svd)
cm = contingency_matrix(dataset.target, pred_svd)
rows, cols = linear_sum_assignment(cm, maximize=True)
plot_mat(cm[rows[:, np.newaxis], cols], xticklabels=cols,
yticklabels=rows, size=(12,12))

print("Homogeneity: %0.3f" % homogeneity_score(dataset.target,
pred_svd))
print("Completeness: %0.3f" % completeness_score(dataset.target,
pred_svd))
print("V-measure: %0.3f" % v_measure_score(dataset.target, pred_svd))
print("Adjusted Rand-Index: %.3f"% adjusted_rand_score(dataset.target,
pred_svd))
print("Adjusted Mutual Information Score: %.3f"%
adjusted_mutual_info_score(dataset.target, pred_svd))
```



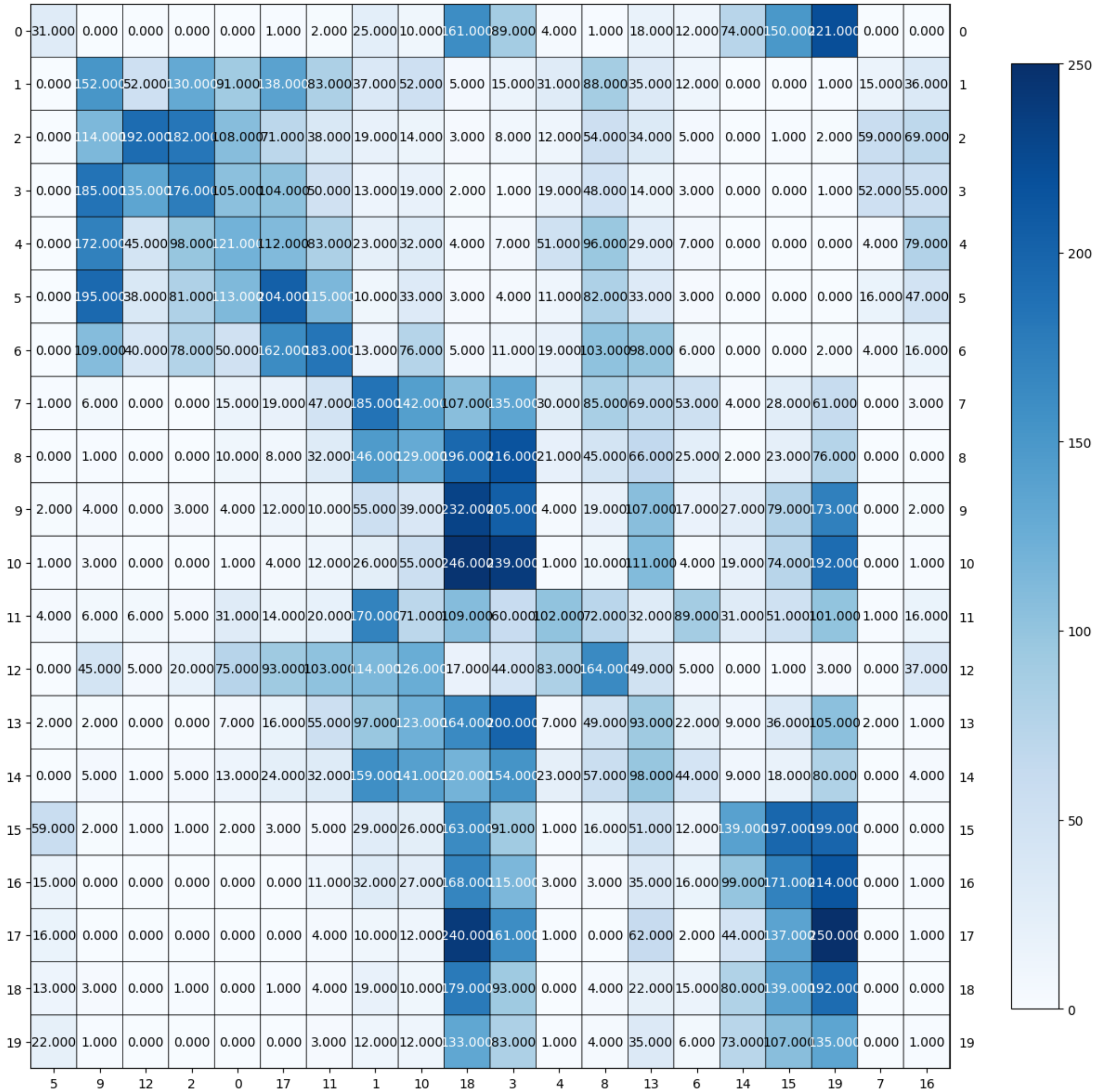

```
Homogeneity: 0.328
Completeness: 0.380
V-measure: 0.352
Adjusted Rand-Index: 0.117
Adjusted Mutual Information Score: 0.349
```

Likewise for NMF, we choose the setting n_components = 2 because the plot in question 5 shows it has the highest values for the clustering metrics.

```
nmf = NMF(n_components=2)
X_train_nmf = nmf.fit_transform(X_train_tfidf)
km = KMeans(n_clusters=20, max_iter=1000, n_init=30)
```

```
pred_nmf = km.fit_predict(X_train_nmf)
cm = contingency_matrix(dataset.target,pred_nmf)
rows, cols = linear_sum_assignment(cm, maximize=True)
plot_mat(cm[rows[:, np.newaxis], cols], xticklabels=cols,
yticklabels=rows, size=(12,12))

print("Homogeneity: %0.3f" % homogeneity_score(dataset.target,
pred_nmf))
print("Completeness: %0.3f" % completeness_score(dataset.target,
pred_nmf))
print("V-measure: %0.3f" % v_measure_score(dataset.target, pred_nmf))
print("Adjusted Rand-Index: %.3f"% adjusted_rand_score(dataset.target,
pred_nmf))
print("Adjusted Mutual Information Score: %.3f"%
adjusted_mutual_info_score(dataset.target, pred_nmf))
```



```
Homogeneity: 0.190
Completeness: 0.202
V-measure: 0.196
Adjusted Rand-Index: 0.056
Adjusted Mutual Information Score: 0.193
```

QUESTION 11

Reduce the dimension of your dataset with UMAP. Consider the following settings: n components = [5, 20, 200], metric = ”cosine” vs. ”euclidean”. If ”cosine” metric fails, please look at the FAQ at the end of this spec. Report the permuted contingency matrix and the five clustering evaluation metrics for the different combinations (6 combinations).

```
!pip install umap-learn

!pip install umap-learn[plot]
!pip install holoviews
!pip install -U ipykernel
```

```
Collecting umap-learn
  Downloading umap-learn-0.5.5.tar.gz (90 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 90.9/90.9 kB 3.4 MB/s eta
0:00:00
etadata (setup.py) ... ent already satisfied: numpy>=1.17 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.1 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.11.4)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.2.2)
Requirement already satisfied: numba>=0.51.2 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (0.58.1)
Collecting pynndescent>=0.5 (from umap-learn)
  Downloading pynndescent-0.5.11-py3-none-any.whl (55 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 55.8/55.8 kB 7.4 MB/s eta
0:00:00
ent already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from umap-learn) (4.66.1)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba>=0.51.2->umap-
learn) (0.41.1)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pynndescent>=0.5->umap-
learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22-
>umap-learn) (3.2.0)
Building wheels for collected packages: umap-learn
  Building wheel for umap-learn (setup.py) ... ap-learn:
filename=umap_learn-0.5.5-py3-none-any.whl size=86832
sha256=9a7b63fa268b405e1b75898f28ca3f3bb20dad2e9d532a9bd0e8d962abd572c
c
  Stored in directory:
/root/.cache/pip/wheels/3a/70/07/428d2b58660a1a3b431db59b806a10da73661
2ebbc66c1bcc5
Successfully built umap-learn
Installing collected packages: pynndescent, umap-learn
Successfully installed pynndescent-0.5.11 umap-learn-0.5.5
Requirement already satisfied: umap-learn[plot] in
/usr/local/lib/python3.10/dist-packages (0.5.5)
Requirement already satisfied: numpy>=1.17 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.23.5)
Requirement already satisfied: scipy>=1.3.1 in
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```
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.11.4)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.2.2)
Requirement already satisfied: numba>=0.51.2 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.58.1)
Requirement already satisfied: pynndescent>=0.5 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.5.11)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-
packages (from umap-learn[plot]) (4.66.1)
Requirement already satisfied: pandas in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.5.3)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(3.7.1)
Collecting datashader (from umap-learn[plot])
  Downloading datashader-0.16.0-py2.py3-none-any.whl (18.3 MB)
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ent already satisfied: bokeh in /usr/local/lib/python3.10/dist-
packages (from umap-learn[plot]) (3.3.4)
Requirement already satisfied: holoviews in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.17.1)
Requirement already satisfied: colorcet in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(3.0.1)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.13.1)
Requirement already satisfied: scikit-image in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.19.3)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba>=0.51.2->umap-
learn[plot]) (0.41.1)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pynndescent>=0.5->umap-
learn[plot]) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22-
>umap-learn[plot]) (3.2.0)
Requirement already satisfied: Jinja2>=2.9 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(3.1.3)
```

```
Requirement already satisfied: contourpy>=1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(1.2.0)
Requirement already satisfied: packaging>=16.8 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(23.2)
Requirement already satisfied: pillow>=7.1.0 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(9.4.0)
Requirement already satisfied: PyYAML>=3.10 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(6.0.1)
Requirement already satisfied: tornado>=5.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(6.3.2)
Requirement already satisfied: xyzservices>=2021.09.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(2023.10.1)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas->umap-
learn[plot]) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas->umap-
learn[plot]) (2023.4)
Requirement already satisfied: pyct>=0.4.4 in
/usr/local/lib/python3.10/dist-packages (from colorcet->umap-
learn[plot]) (0.5.0)
Requirement already satisfied: dask in /usr/local/lib/python3.10/dist-
packages (from datashader->umap-learn[plot]) (2023.8.1)
Requirement already satisfied: multipledispatch in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (1.0.0)
Requirement already satisfied: param in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (2.0.2)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (2.31.0)
Requirement already satisfied: toolz in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (0.12.1)
Requirement already satisfied: xarray in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (2023.7.0)
Requirement already satisfied: pyviz-comms>=0.7.4 in
/usr/local/lib/python3.10/dist-packages (from holoviews->umap-
learn[plot]) (3.0.1)
Requirement already satisfied: panel>=0.13.1 in
/usr/local/lib/python3.10/dist-packages (from holoviews->umap-
```

```
learn[plot]) (1.3.8)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (4.48.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (1.4.5)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (3.1.1)
Requirement already satisfied: networkx>=2.2 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (3.2.1)
Requirement already satisfied: imageio>=2.4.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (2.31.6)
Requirement already satisfied: tifffile>=2019.7.26 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (2024.1.30)
Requirement already satisfied: PyWavelets>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (1.5.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from Jinja2>=2.9->bokeh-
>umap-learn[plot]) (2.1.5)
Requirement already satisfied: markdown in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (3.5.2)
Requirement already satisfied: markdown-it-py in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (3.0.0)
Requirement already satisfied: linkify-it-py in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (2.0.3)
Requirement already satisfied: mdit-py-plugins in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (0.4.0)
Requirement already satisfied: bleach in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (6.1.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (4.9.0)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1-
>pandas->umap-learn[plot]) (1.16.0)
```

```
Requirement already satisfied: click>=8.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (8.1.7)
Requirement already satisfied: cloudpickle>=1.5.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (2.2.1)
Requirement already satisfied: fsspec>=2021.09.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (2023.6.0)
Requirement already satisfied: partd>=1.2.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (1.4.1)
Requirement already satisfied: importlib-metadata>=4.13.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (7.0.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (2024.2.2)
Requirement already satisfied: zipp>=0.5 in
/usr/local/lib/python3.10/dist-packages (from importlib-
metadata>=4.13.0->dask->datashader->umap-learn[plot]) (3.17.0)
Requirement already satisfied: locket in
/usr/local/lib/python3.10/dist-packages (from partd>=1.2.0->dask-
>datashader->umap-learn[plot]) (1.0.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.10/dist-packages (from bleach->panel>=0.13.1-
>holoviews->umap-learn[plot]) (0.5.1)
Requirement already satisfied: uc-micro-py in
/usr/local/lib/python3.10/dist-packages (from linkify-it-py-
>panel>=0.13.1->holoviews->umap-learn[plot]) (1.0.2)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.10/dist-packages (from markdown-it-py-
>panel>=0.13.1->holoviews->umap-learn[plot]) (0.1.2)
Installing collected packages: datashader
Successfully installed datashader-0.16.0
Requirement already satisfied: holoviews in
/usr/local/lib/python3.10/dist-packages (1.17.1)
Requirement already satisfied: param<3.0,>=1.12.0 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (2.0.2)
Requirement already satisfied: numpy>=1.0 in
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/usr/local/lib/python3.10/dist-packages (from holoviews) (1.23.5)
Requirement already satisfied: pyviz-comms>=0.7.4 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (3.0.1)
Requirement already satisfied: panel>=0.13.1 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (1.3.8)
Requirement already satisfied: colorcet in
/usr/local/lib/python3.10/dist-packages (from holoviews) (3.0.1)
Requirement already satisfied: packaging in
/usr/local/lib/python3.10/dist-packages (from holoviews) (23.2)
Requirement already satisfied: pandas>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (1.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0-
>holoviews) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0-
>holoviews) (2023.4)
Requirement already satisfied: bokeh<3.4.0,>=3.2.0 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (3.3.4)
Requirement already satisfied: xyzservices>=2021.09.1 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (2023.10.1)
Requirement already satisfied: markdown in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
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/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (3.0.0)
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/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (2.0.3)
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/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
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/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (2.31.0)
Requirement already satisfied: tqdm>=4.48.0 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (4.66.1)
Requirement already satisfied: bleach in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (6.1.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (4.9.0)
Requirement already satisfied: pyct>=0.4.4 in
/usr/local/lib/python3.10/dist-packages (from colorcet->holoviews)
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(0.5.0)
Requirement already satisfied: Jinja2>=2.9 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (3.1.3)
Requirement already satisfied: contourpy>=1 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (1.2.0)
Requirement already satisfied: pillow>=7.1.0 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (9.4.0)
Requirement already satisfied: PyYAML>=3.10 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (6.0.1)
Requirement already satisfied: tornado>=5.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (6.3.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1-
>pandas>=0.20.0->holoviews) (1.16.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.10/dist-packages (from bleach->panel>=0.13.1-
>holoviews) (0.5.1)
Requirement already satisfied: uc-micro-py in
/usr/local/lib/python3.10/dist-packages (from linkify-it-py-
>panel>=0.13.1->holoviews) (1.0.2)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.10/dist-packages (from markdown-it-py-
>panel>=0.13.1->holoviews) (0.1.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (2024.2.2)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from Jinja2>=2.9-
>bokeh<3.4.0,>=3.2.0->panel>=0.13.1->holoviews) (2.1.5)
Requirement already satisfied: ipykernel in
/usr/local/lib/python3.10/dist-packages (5.5.6)
Collecting ipykernel
  Downloading ipykernel-6.29.2-py3-none-any.whl (116 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 116.1/116.1 kB 4.0 MB/s eta
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m>=0.1.1 (from ipykernel)
  Downloading comm-0.2.1-py3-none-any.whl (7.2 kB)
Requirement already satisfied: debugpy>=1.6.5 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (1.6.6)
Requirement already satisfied: ipython>=7.23.1 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (7.34.0)
Requirement already satisfied: jupyter-client>=6.1.12 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (6.1.12)
Requirement already satisfied: jupyter-core!=5.0.*,>=4.12 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.7.1)
Requirement already satisfied: matplotlib-inline>=0.1 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (0.1.6)
Requirement already satisfied: nest-asyncio in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (1.6.0)
Requirement already satisfied: packaging in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (23.2)
Requirement already satisfied: psutil in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.9.5)
Collecting pyzmq>=24 (from ipykernel)
  Downloading pyzmq-25.1.2-cp310-cp310-manylinux_2_28_x86_64.whl (1.1
MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.1/1.1 MB 13.7 MB/s eta
0:00:00
ent already satisfied: tornado>=6.1 in /usr/local/lib/python3.10/dist-
packages (from ipykernel) (6.3.2)
Requirement already satisfied: traitlets>=5.4.0 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.7.1)
Requirement already satisfied: setuptools>=18.5 in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (67.7.2)
Collecting jedi>=0.16 (from ipython>=7.23.1->ipykernel)
  Downloading jedi-0.19.1-py2.py3-none-any.whl (1.6 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.6/1.6 MB 24.1 MB/s eta
0:00:00
ent already satisfied: decorator in /usr/local/lib/python3.10/dist-
packages (from ipython>=7.23.1->ipykernel) (4.4.2)
Requirement already satisfied: pickleshare in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (0.7.5)
Requirement already satisfied: prompt-toolkit!=3.0.0,!
=3.0.1,<3.1.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from
ipython>=7.23.1->ipykernel) (3.0.43)
Requirement already satisfied: pygments in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (2.16.1)
Requirement already satisfied: backcall in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (0.2.0)
Requirement already satisfied: pexpect>4.3 in
```

```
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1->ipykernel) (4.9.0)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.10/dist-packages (from jupyter-client>=6.1.12->ipykernel) (2.8.2)
Requirement already satisfied: platformdirs>=2.5 in
/usr/local/lib/python3.10/dist-packages (from jupyter-core!=5.0.*,>=4.12->ipykernel) (4.2.0)
Requirement already satisfied: parso<0.9.0,>=0.8.3 in
/usr/local/lib/python3.10/dist-packages (from jedi>=0.16->ipython>=7.23.1->ipykernel) (0.8.3)
Requirement already satisfied: ptyprocess>=0.5 in
/usr/local/lib/python3.10/dist-packages (from pexpect>4.3->ipython>=7.23.1->ipykernel) (0.7.0)
Requirement already satisfied: wcwidth in
/usr/local/lib/python3.10/dist-packages (from prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0->ipython>=7.23.1->ipykernel) (0.2.13)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.1->jupyter-client>=6.1.12->ipykernel) (1.16.0)
Installing collected packages: pyzmq, jedi, comm, ipykernel
  Attempting uninstall: pyzmq
    Found existing installation: pyzmq 23.2.1
    Uninstalling pyzmq-23.2.1:
      Successfully uninstalled pyzmq-23.2.1
  Attempting uninstall: ipykernel
    Found existing installation: ipykernel 5.5.6
    Uninstalling ipykernel-5.5.6:
      Successfully uninstalled ipykernel-5.5.6
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the following dependency conflicts.
google-colab 1.0.0 requires ipykernel==5.5.6, but you have ipykernel 6.29.2 which is incompatible.
notebook 6.5.5 requires pyzmq<25,>=17, but you have pyzmq 25.1.2 which is incompatible.
Successfully installed comm-0.2.1 ipykernel-6.29.2 jedi-0.19.1 pyzmq-25.1.2
```

{"pip_warning":{"packages":["zmq"]}}

```python
import umap
import umap.plot
```

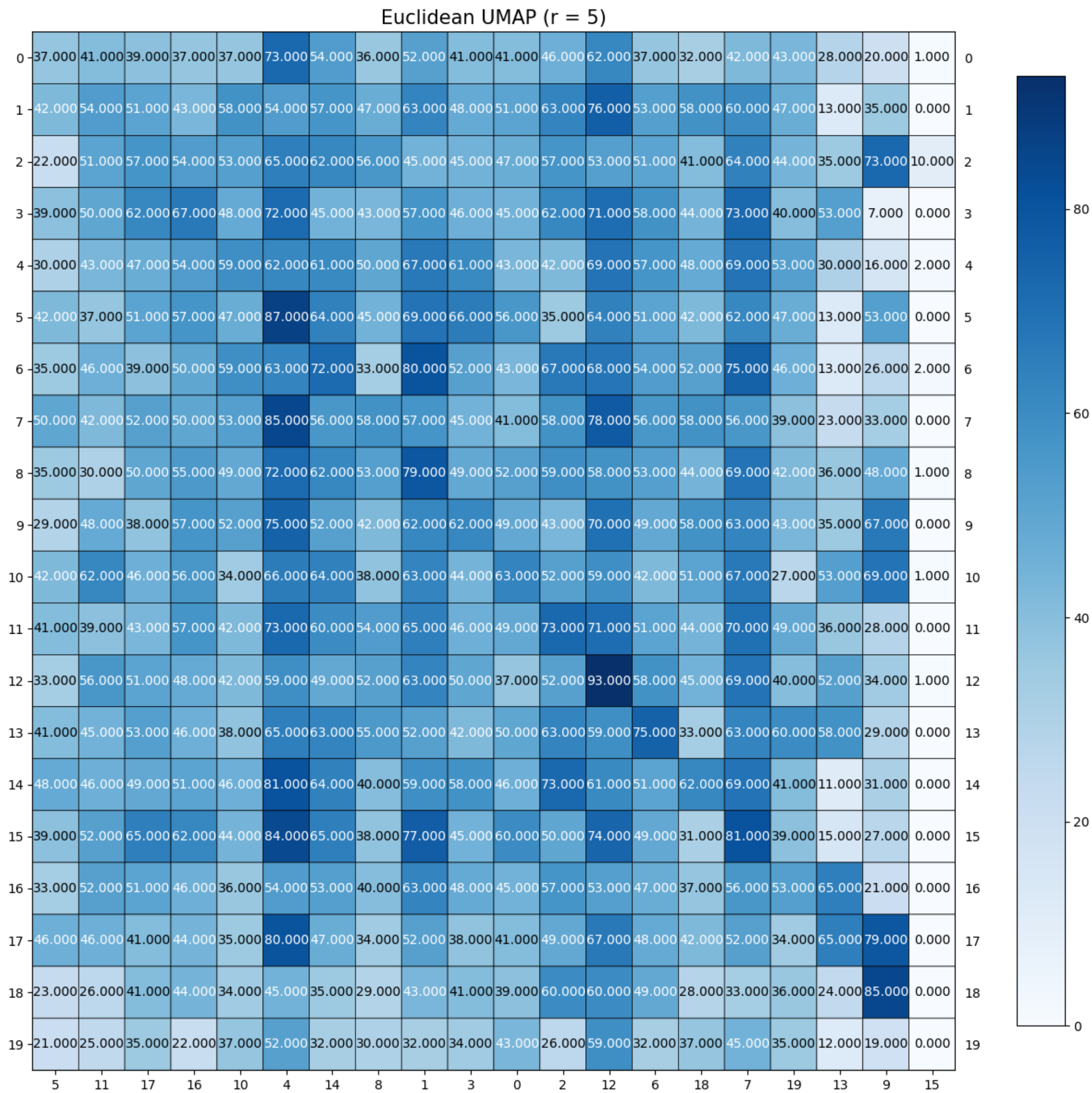
```
/usr/local/lib/python3.10/dist-packages/umap/plot.py:203: NumbaDeprecationWarning: The keyword argument 'nopython=False' was supplied. From Numba 0.59.0 the default is being changed to True and use of 'nopython=False' will raise a warning as the argument will have no effect. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#depr
```

```
ecation-of-object-mode-fall-back-behaviour-when-using-jit for details.
  @numba.jit(nopython=False)
```

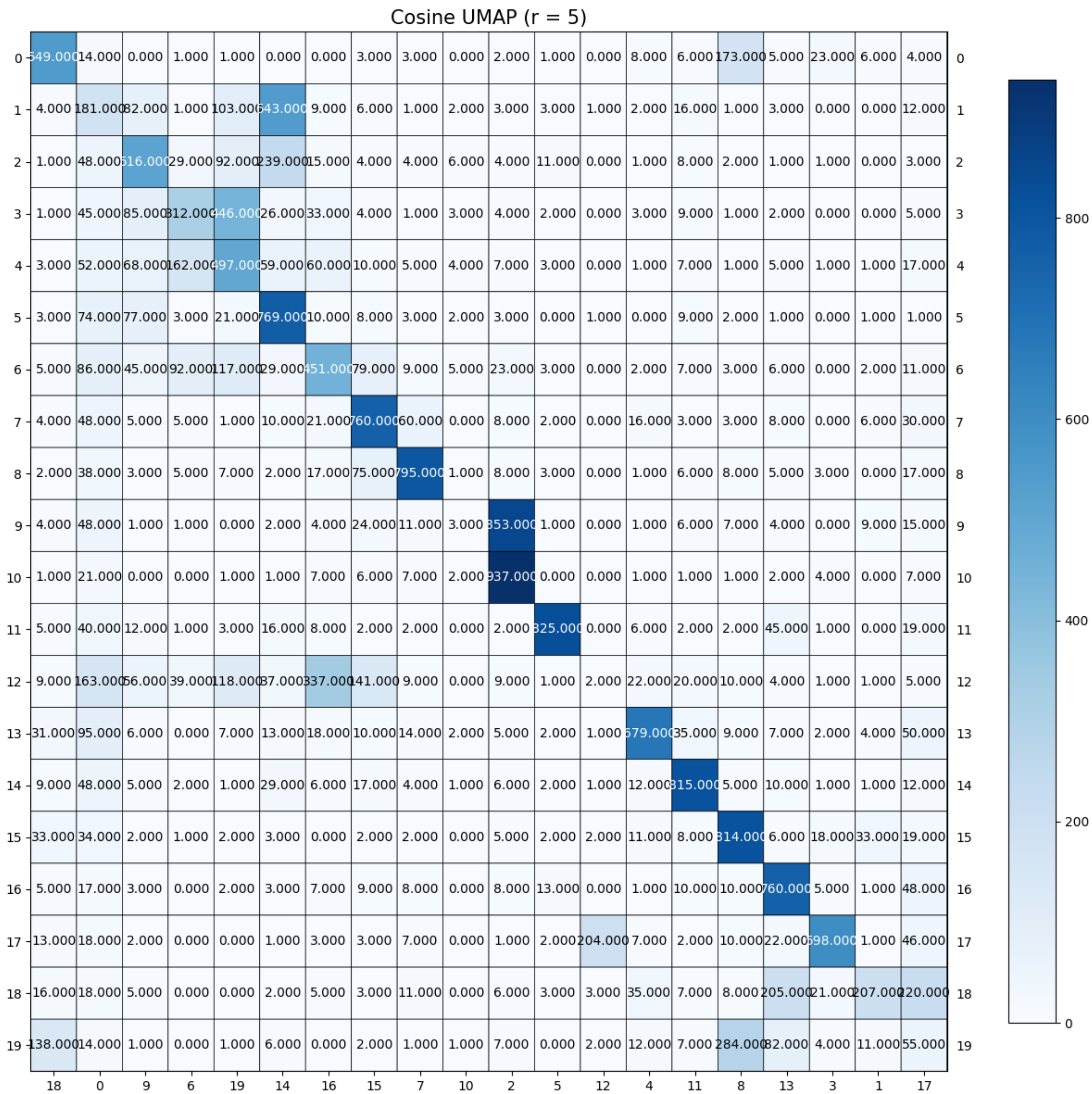
```
poss_n = [5, 20, 200]
km = KMeans(n_clusters=20, max_iter=1000, n_init=30)

for n in poss_n:
  Umap_euc = umap.UMAP(n_components=n,
metric='euclidean').fit_transform(X_train_tfidf)
  kmean_euc = km.fit(Umap_euc)
  cm = contingency_matrix(dataset.target, kmean_euc.labels_)
  rows, cols = linear_sum_assignment(cm, maximize=True)
  plot_mat(cm[rows[:, np.newaxis], cols], xticklabels=cols,
yticklabels=rows, title = 'Euclidean UMAP (r = %i)' %n, size=(12,12))
  print("Euclidean - Homogeneity: %0.3f" %
homogeneity_score(dataset.target, kmean_euc.labels_))
  print("Euclidean - Completeness: %0.3f" %
completeness_score(dataset.target, kmean_euc.labels_))
  print("Euclidean - V-measure: %0.3f" %
v_measure_score(dataset.target, kmean_euc.labels_))
  print("Euclidean - Adjusted Rand-Index: %.3f"%
adjusted_rand_score(dataset.target, kmean_euc.labels_))
  print("Euclidean - Adjusted Mutual Information Score: %.3f"%
adjusted_mutual_info_score(dataset.target, kmean_euc.labels_))

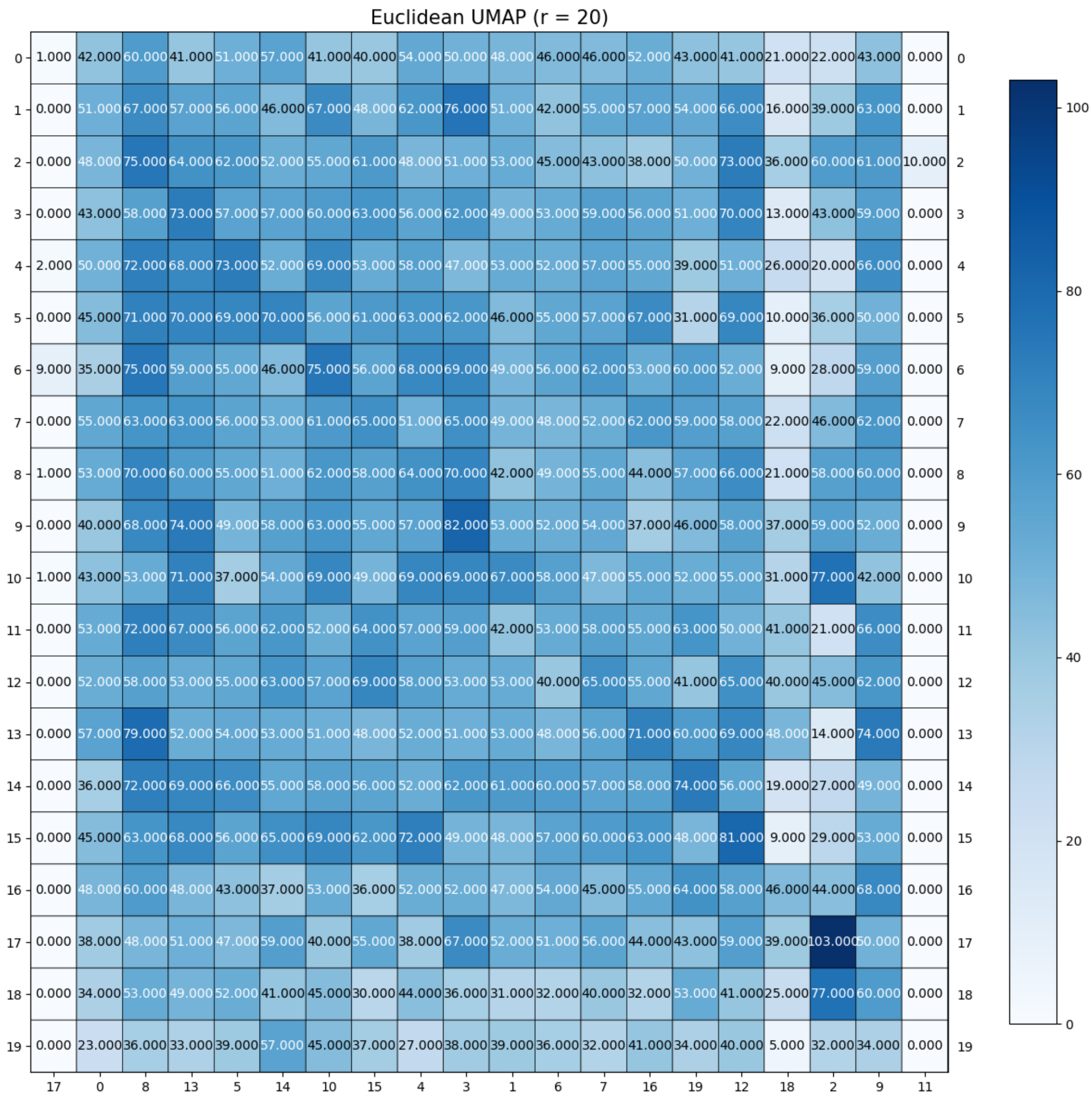
  Umap_cos = umap.UMAP(n_components=n,
metric='cosine').fit_transform(X_train_tfidf)
  kmean_cos = km.fit(Umap_cos)
  cm = contingency_matrix(dataset.target, kmean_cos.labels_)
  rows, cols = linear_sum_assignment(cm, maximize=True)
  plot_mat(cm[rows[:, np.newaxis], cols], xticklabels=cols,
yticklabels=rows, title = 'Cosine UMAP (r = %i)' %n, size=(12,12))
  print("Cosine - Homogeneity: %0.3f" %
homogeneity_score(dataset.target, kmean_euc.labels_))
  print("Cosine - Completeness: %0.3f" %
completeness_score(dataset.target, kmean_euc.labels_))
  print("Cosine - V-measure: %0.3f" % v_measure_score(dataset.target,
kmean_euc.labels_))
  print("Cosine - Adjusted Rand-Index: %.3f"%
adjusted_rand_score(dataset.target, kmean_euc.labels_))
  print("Cosine - Adjusted Mutual Information Score: %.3f"%
adjusted_mutual_info_score(dataset.target, kmean_euc.labels_))
```



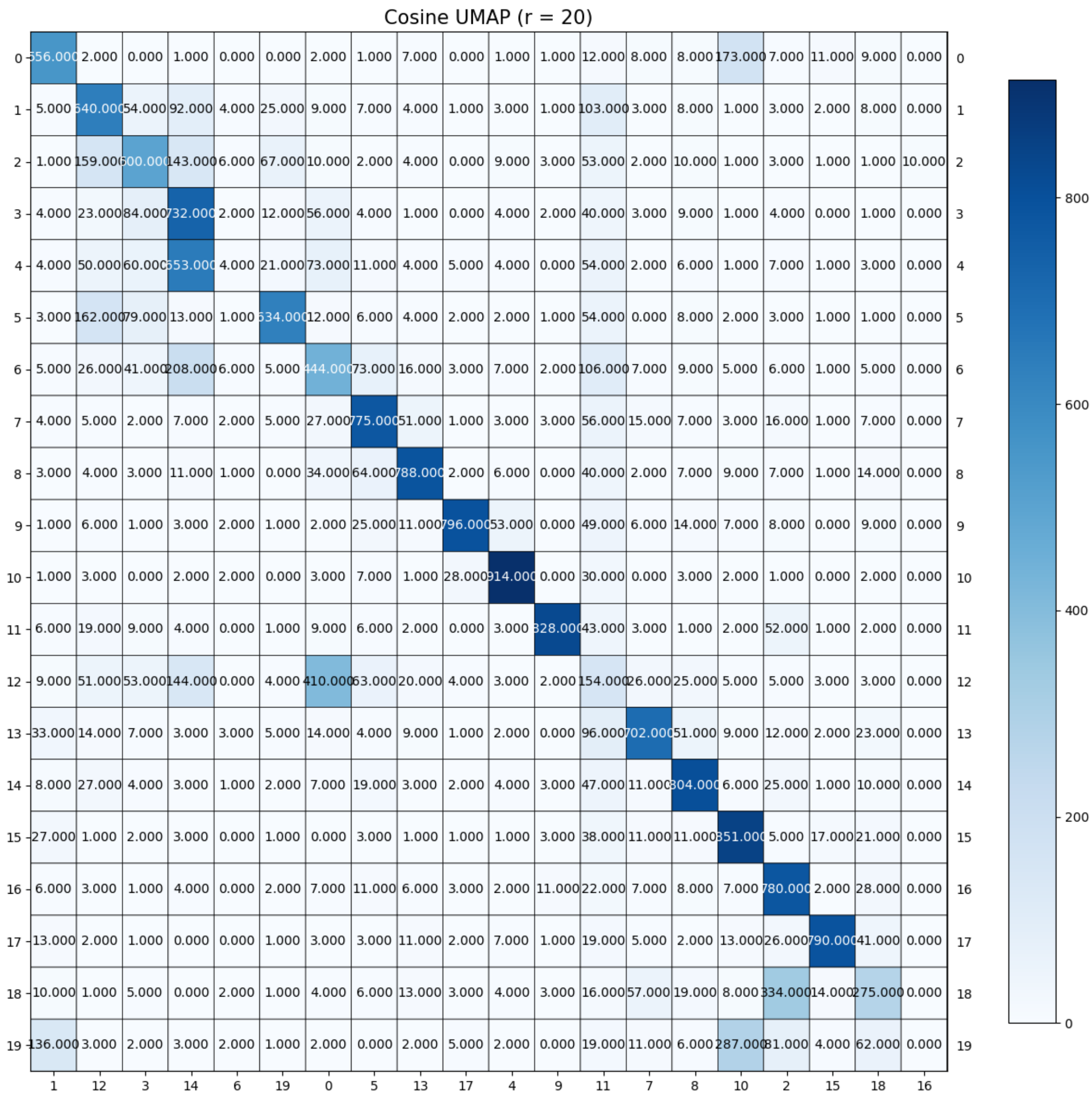

```
Euclidean - Homogeneity: 0.008
Euclidean - Completeness: 0.008
Euclidean - V-measure: 0.008
Euclidean - Adjusted Rand-Index: 0.001
Euclidean - Adjusted Mutual Information Score: 0.005
```



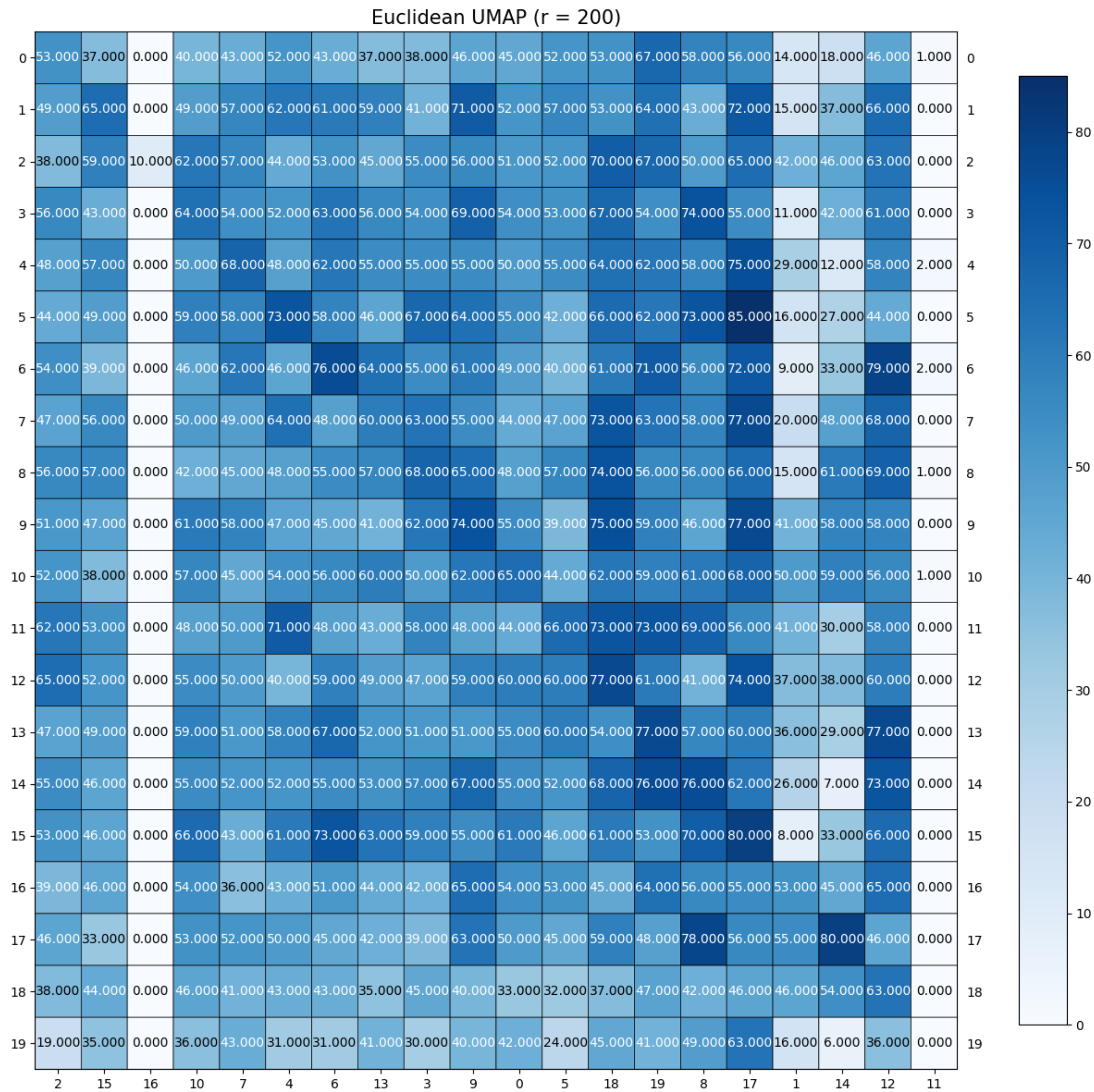

```
Cosine - Homogeneity: 0.553
Cosine - Completeness: 0.579
Cosine - V-measure: 0.566
Cosine - Adjusted Rand-Index: 0.428
Cosine - Adjusted Mutual Information Score: 0.564
```



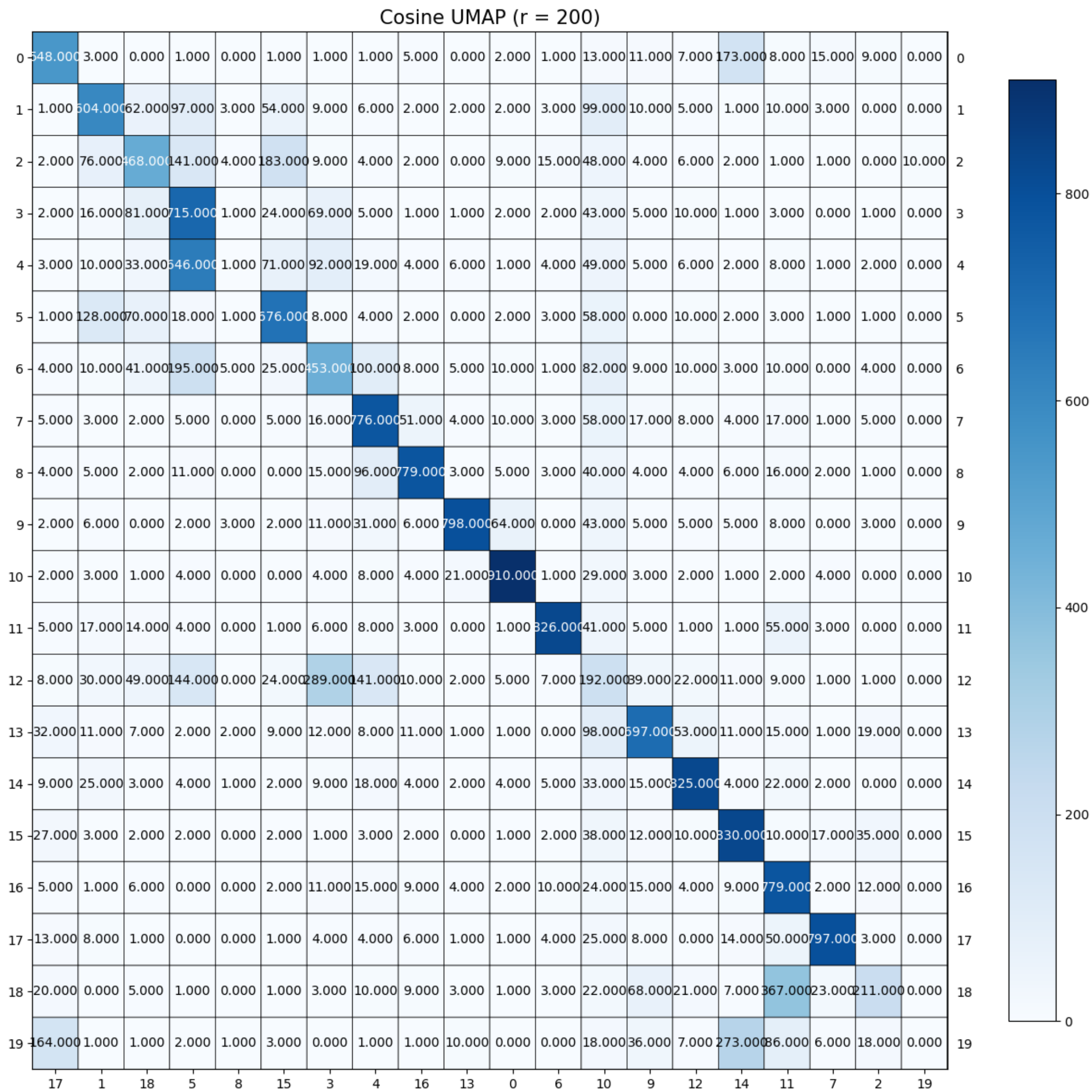

```
Euclidean - Homogeneity: 0.007
Euclidean - Completeness: 0.008
Euclidean - V-measure: 0.007
Euclidean - Adjusted Rand-Index: 0.001
Euclidean - Adjusted Mutual Information Score: 0.004
```




```
Cosine - Homogeneity: 0.578
Cosine - Completeness: 0.604
Cosine - V-measure: 0.591
Cosine - Adjusted Rand-Index: 0.469
Cosine - Adjusted Mutual Information Score: 0.590
```




```
Euclidean - Homogeneity: 0.007
Euclidean - Completeness: 0.007
Euclidean - V-measure: 0.007
Euclidean - Adjusted Rand-Index: 0.001
Euclidean - Adjusted Mutual Information Score: 0.004
```




```
Cosine - Homogeneity: 0.569
Cosine - Completeness: 0.597
Cosine - V-measure: 0.582
Cosine - Adjusted Rand-Index: 0.460
Cosine - Adjusted Mutual Information Score: 0.581
```

QUESTION 12

Analyze the contingency matrices. Which setting works best and why? What about for each metric choice?

Cosine metric with 200 n components works the best. From the contingency matrices we can see that this setting has the most prominent diagonal and the five clustering measures are also the highest.

For both metrics, euclidean and cosine, the best setting is n components of 200. This makes sense since the more n components there are, the closer the data is to the original dimensions.

QUESTION 13

So far, we have attempted K-Means clustering with 4 different representation learning techniques (sparse TF-IDF representation, PCA-reduced, NMF-reduced, UMAP-reduced). Compare and contrast the clustering results across the 4 choices, and suggest an approach that is best for the K-Means clustering task on the 20-class text data. Choose any choice of clustering metrics for your comparison.

Umap with cosine metric is by far the best approach for clustering with kmeans on the 20-class text data. The 2nd best is SVD, then NMF, and finally umap with euclidean metric is the worst. This ranking is true for any of the five clustering metrics.

QUESTION 14

Use UMAP to reduce the dimensionality properly, and perform Agglomerative clustering with n_clusters=20 . Compare the performance of "ward" and "single" linkage criteria. Report the five clustering evaluation metrics for each case.

```
  Umap_cos = umap.UMAP(n_components=200,
metric='cosine').fit_transform(X_train_tfidf)

ac_ward = AgglomerativeClustering(n_clusters=20,
linkage='ward').fit(Umap_cos)
ac_single = AgglomerativeClustering(n_clusters=20,
linkage='single').fit(Umap_cos)

print("Ward - Homogeneity: %0.3f" % homogeneity_score(dataset.target,
ac_ward.labels_))
print("Ward - Completeness: %0.3f" %
completeness_score(dataset.target, ac_ward.labels_))
print("Ward - V-measure: %0.3f" % v_measure_score(dataset.target,
ac_ward.labels_))
print("Ward - Adjusted Rand-Index: %.3f"%
adjusted_rand_score(dataset.target, ac_ward.labels_))
print("Ward - Adjusted Mutual Information Score: %.3f"%
adjusted_mutual_info_score(dataset.target, ac_ward.labels_))
print()
print("Single - Homogeneity: %0.3f" %
homogeneity_score(dataset.target, ac_single.labels_))
print("Single - Completeness: %0.3f" %
completeness_score(dataset.target, ac_single.labels_))
print("Single - V-measure: %0.3f" % v_measure_score(dataset.target,
ac_single.labels_))
print("Single - Adjusted Rand-Index: %.3f"%
```

```
adjusted_rand_score(dataset.target, ac_single.labels_))
print("Single - Adjusted Mutual Information Score: %.3f"%
adjusted_mutual_info_score(dataset.target, ac_single.labels_))
```

```
Ward - Homogeneity: 0.547
Ward - Completeness: 0.584
Ward - V-measure: 0.565
Ward - Adjusted Rand-Index: 0.419
Ward - Adjusted Mutual Information Score: 0.564

Single - Homogeneity: 0.016
Single - Completeness: 0.374
Single - V-measure: 0.031
Single - Adjusted Rand-Index: 0.000
Single - Adjusted Mutual Information Score: 0.027
```

Ward linkage criteria produces better results in all five clustering metrics.

QUESTION 15

Apply HDBSCAN on UMAP-transformed 20-category data

```
!pip install hdbscan
```

```
Collecting hdbscan
  Downloading hdbscan-0.8.33.tar.gz (5.2 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5.2/5.2 MB 21.5 MB/s eta
0:00:00
ents to build wheel ... etadata (pyproject.toml) ...  hdbscan)
  Using cached Cython-0.29.37-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.manylinux_2_24_x86_64.whl
(1.9 MB)
Requirement already satisfied: numpy>=1.20 in
/usr/local/lib/python3.10/dist-packages (from hdbscan) (1.23.5)
Requirement already satisfied: scipy>=1.0 in
/usr/local/lib/python3.10/dist-packages (from hdbscan) (1.11.4)
Requirement already satisfied: scikit-learn>=0.20 in
/usr/local/lib/python3.10/dist-packages (from hdbscan) (1.2.2)
Requirement already satisfied: joblib>=1.0 in
/usr/local/lib/python3.10/dist-packages (from hdbscan) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20-
>hdbscan) (3.2.0)
Building wheels for collected packages: hdbscan
  Building wheel for hdbscan (pyproject.toml) ... e=hdbscan-0.8.33-
cp310-cp310-linux_x86_64.whl size=3039276
sha256=9550a7195e3e205aec859f046044c1cc1c5559ac484b6f000cea9d46ec119e9
b
  Stored in directory:
/root/.cache/pip/wheels/75/0b/3b/dc4f60b7cc455efaefb62883a7483e76f09d0
```

```
6ca81cf87d610
Successfully built hdbscan
Installing collected packages: cython, hdbscan
  Attempting uninstall: cython
    Found existing installation: Cython 3.0.8
    Uninstalling Cython-3.0.8:
      Successfully uninstalled Cython-3.0.8
Successfully installed cython-0.29.37 hdbscan-0.8.33
```

```
import hdbscan

min_cluster = [20, 100, 200]

for m in min_cluster:
  hdb = hdbscan.HDBSCAN(min_cluster_size=m).fit(Umap_cos)
  print("min_cluster_size = %i" %m)
  print("Homogeneity: %0.3f" % homogeneity_score(dataset.target,
hdb.labels_))
  print("Completeness: %0.3f" % completeness_score(dataset.target,
hdb.labels_))
  print("V-measure: %0.3f" % v_measure_score(dataset.target,
hdb.labels_))
  print("Adjusted Rand-Index: %.3f"%
adjusted_rand_score(dataset.target, hdb.labels_))
  print("Adjusted Mutual Information Score: %.3f"%
adjusted_mutual_info_score(dataset.target, hdb.labels_))
  print()
```

```
min_cluster_size = 20
Homogeneity: 0.417
Completeness: 0.439
V-measure: 0.428
Adjusted Rand-Index: 0.071
Adjusted Mutual Information Score: 0.416

min_cluster_size = 100
Homogeneity: 0.408
Completeness: 0.611
V-measure: 0.490
Adjusted Rand-Index: 0.183
Adjusted Mutual Information Score: 0.488

min_cluster_size = 200
Homogeneity: 0.418
Completeness: 0.622
V-measure: 0.500
Adjusted Rand-Index: 0.209
Adjusted Mutual Information Score: 0.499
```

QUESTION 16

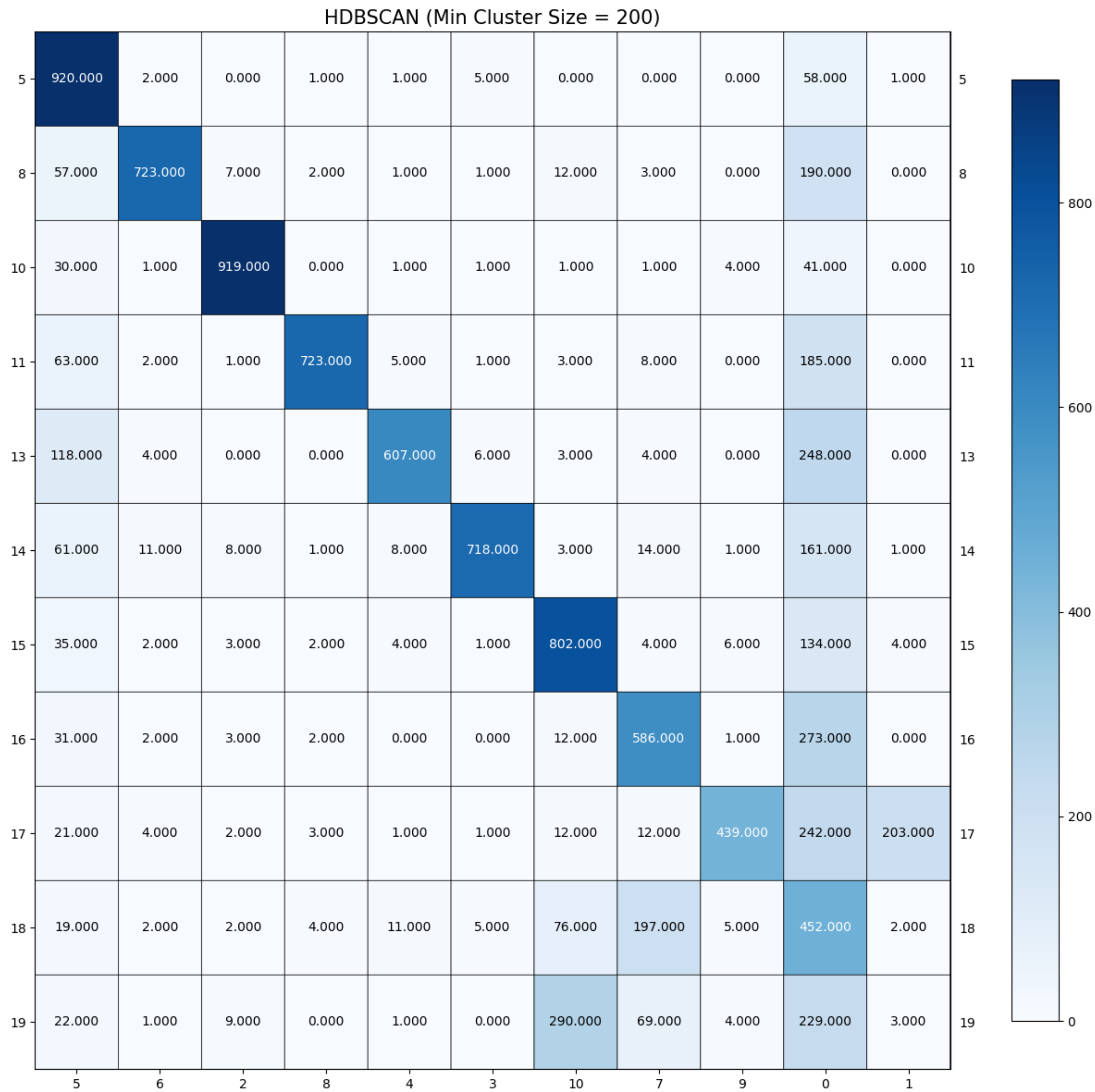
Plot the contingency matrix for the best clustering model from Question 15. How many clusters are given by the model? What does "-1" mean for the clustering labels? Interpret the contingency matrix considering the answer to these questions.

The best clustering model is with minimum cluster size of 200. The model gives 9 clusters. "-1" as a clustering label means that the data point is essentially noise and not assigned to any cluster.

We can see from the below matrix that the diagonal is prominent for only 10 of the 11 classes, with class 18 predictions being spread out. We also see that column 0 stands out with many data points predicted to belong to that cluster.

```
hdb = hdbscan.HDBSCAN(min_cluster_size=200).fit(Umap_cos)
print('Number of Clusters: %i' % hdb.labels_.max())
cm = contingency_matrix(dataset.target, hdb.labels_)
rows, cols = linear_sum_assignment(cm, maximize=True)
plot_mat(cm[rows[:, np.newaxis], cols], xticklabels=cols,
yticklabels=rows, title = 'HDBSCAN (Min Cluster Size = 200)',
size=(12,12))
```

```
Number of Clusters: 9
```



QUESTION 17

Based on your experiments, which dimensionality reduction technique and clustering methods worked best together for 20-class text data and why? Follow the table below.

The best dimensionality reduction techinique and clustering method pair is Umap cosine metric with 200 components and kmeans with k of 20.

Umap is nonlinear so it will preserve more complex relationships in the data set which helps with clustering, compared to svd which is linear. For this data set, we know that there are 20 classes so kmeans and agglomerative clustering will perform better than dbscan since we can define the number of clusters using the parameters.

Part 2

```
import numpy as np
np.random.seed(42)
import random
random.seed(42)
from sklearn.datasets import fetch_20newsgroups

from sklearn.feature_extraction.text import TfidfTransformer, 
CountVectorizer
from sklearn.decomposition import TruncatedSVD
from sklearn.decomposition import NMF
from sklearn.metrics.cluster import contingency_matrix
from sklearn.metrics.cluster import adjusted_mutual_info_score, 
adjusted_rand_score, homogeneity_score, v_measure_score, 
completeness_score

from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
import itertools
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors as colors

from scipy.optimize import linear_sum_assignment
from sklearn.metrics import confusion_matrix

import torch
import torch.nn as nn
from torchvision import transforms, datasets
from torch.utils.data import DataLoader, TensorDataset
import numpy as np
import matplotlib.pyplot as plt

from tqdm import tqdm
import requests
import os
import tarfile

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import confusion_matrix, adjusted_rand_score, 
adjusted_mutual_info_score
from sklearn.pipeline import Pipeline
from sklearn.base import TransformerMixin

!pip install umap-learn

!pip install umap-learn[plot]
```

```
!pip install holoviews
!pip install -U ipykernel

Collecting umap-learn
  Downloading umap-learn-0.5.5.tar.gz (90 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 90.9/90.9 kB 3.2 MB/s eta
0:00:00
etadata (setup.py) ... ent already satisfied: numpy>=1.17 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.1 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.11.4)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (1.2.2)
Requirement already satisfied: numba>=0.51.2 in
/usr/local/lib/python3.10/dist-packages (from umap-learn) (0.58.1)
Collecting pynndescent>=0.5 (from umap-learn)
  Downloading pynndescent-0.5.11-py3-none-any.whl (55 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 55.8/55.8 kB 7.5 MB/s eta
0:00:00
ent already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from umap-learn) (4.66.1)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba>=0.51.2->umap-
learn) (0.41.1)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pynndescent>=0.5->umap-
learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22-
>umap-learn) (3.2.0)
Building wheels for collected packages: umap-learn
  Building wheel for umap-learn (setup.py) ... ap-learn:
filename=umap_learn-0.5.5-py3-none-any.whl size=86832
sha256=b122af249153970305b08eff0d22f863599ea5004d6f7a4a87740e0f35ec113
e
  Stored in directory:
/root/.cache/pip/wheels/3a/70/07/428d2b58660a1a3b431db59b806a10da73661
2ebbc66c1bcc5
Successfully built umap-learn
Installing collected packages: pynndescent, umap-learn
Successfully installed pynndescent-0.5.11 umap-learn-0.5.5
Requirement already satisfied: umap-learn[plot] in
/usr/local/lib/python3.10/dist-packages (0.5.5)
Requirement already satisfied: numpy>=1.17 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.23.5)
Requirement already satisfied: scipy>=1.3.1 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.11.4)
Requirement already satisfied: scikit-learn>=0.22 in
```

```
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.2.2)
Requirement already satisfied: numba>=0.51.2 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.58.1)
Requirement already satisfied: pynndescent>=0.5 in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.5.11)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-
packages (from umap-learn[plot]) (4.66.1)
Requirement already satisfied: pandas in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.5.3)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(3.7.1)
Collecting datashader (from umap-learn[plot])
  Downloading datashader-0.16.0-py2.py3-none-any.whl (18.3 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 18.3/18.3 MB 62.8 MB/s eta
0:00:00
ent already satisfied: bokeh in /usr/local/lib/python3.10/dist-
packages (from umap-learn[plot]) (3.3.4)
Requirement already satisfied: holoviews in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(1.17.1)
Requirement already satisfied: colorcet in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(3.0.1)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.13.1)
Requirement already satisfied: scikit-image in
/usr/local/lib/python3.10/dist-packages (from umap-learn[plot])
(0.19.3)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba>=0.51.2->umap-
learn[plot]) (0.41.1)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pynndescent>=0.5->umap-
learn[plot]) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22-
>umap-learn[plot]) (3.2.0)
Requirement already satisfied: Jinja2>=2.9 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(3.1.3)
Requirement already satisfied: contourpy>=1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(1.2.0)
Requirement already satisfied: packaging>=16.8 in
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/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(23.2)
Requirement already satisfied: pillow>=7.1.0 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(9.4.0)
Requirement already satisfied: PyYAML>=3.10 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(6.0.1)
Requirement already satisfied: tornado>=5.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(6.3.2)
Requirement already satisfied: xyzservices>=2021.09.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh->umap-learn[plot])
(2023.10.1)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas->umap-
learn[plot]) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas->umap-
learn[plot]) (2023.4)
Requirement already satisfied: pyct>=0.4.4 in
/usr/local/lib/python3.10/dist-packages (from colorcet->umap-
learn[plot]) (0.5.0)
Requirement already satisfied: dask in /usr/local/lib/python3.10/dist-
packages (from datashader->umap-learn[plot]) (2023.8.1)
Requirement already satisfied: multipledispatch in
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learn[plot]) (1.0.0)
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learn[plot]) (2.0.2)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (2.31.0)
Requirement already satisfied: toolz in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (0.12.1)
Requirement already satisfied: xarray in
/usr/local/lib/python3.10/dist-packages (from datashader->umap-
learn[plot]) (2023.7.0)
Requirement already satisfied: pyviz-comms>=0.7.4 in
/usr/local/lib/python3.10/dist-packages (from holoviews->umap-
learn[plot]) (3.0.1)
Requirement already satisfied: panel>=0.13.1 in
/usr/local/lib/python3.10/dist-packages (from holoviews->umap-
learn[plot]) (1.3.8)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
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/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (4.48.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (1.4.5)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->umap-
learn[plot]) (3.1.1)
Requirement already satisfied: networkx>=2.2 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (3.2.1)
Requirement already satisfied: imageio>=2.4.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (2.31.6)
Requirement already satisfied: tifffile>=2019.7.26 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (2024.1.30)
Requirement already satisfied: PyWavelets>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-image->umap-
learn[plot]) (1.5.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from Jinja2>=2.9->bokeh-
>umap-learn[plot]) (2.1.5)
Requirement already satisfied: markdown in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (3.5.2)
Requirement already satisfied: markdown-it-py in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (3.0.0)
Requirement already satisfied: linkify-it-py in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (2.0.3)
Requirement already satisfied: mdit-py-plugins in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (0.4.0)
Requirement already satisfied: bleach in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (6.1.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews->umap-learn[plot]) (4.9.0)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1-
>pandas->umap-learn[plot]) (1.16.0)
Requirement already satisfied: click>=8.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (8.1.7)
Requirement already satisfied: cloudpickle>=1.5.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (2.2.1)
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Requirement already satisfied: fsspec>=2021.09.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (2023.6.0)
Requirement already satisfied: partd>=1.2.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (1.4.1)
Requirement already satisfied: importlib-metadata>=4.13.0 in
/usr/local/lib/python3.10/dist-packages (from dask->datashader->umap-
learn[plot]) (7.0.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->datashader-
>umap-learn[plot]) (2024.2.2)
Requirement already satisfied: zipp>=0.5 in
/usr/local/lib/python3.10/dist-packages (from importlib-
metadata>=4.13.0->dask->datashader->umap-learn[plot]) (3.17.0)
Requirement already satisfied: locket in
/usr/local/lib/python3.10/dist-packages (from partd>=1.2.0->dask-
>datashader->umap-learn[plot]) (1.0.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.10/dist-packages (from bleach->panel>=0.13.1-
>holoviews->umap-learn[plot]) (0.5.1)
Requirement already satisfied: uc-micro-py in
/usr/local/lib/python3.10/dist-packages (from linkify-it-py-
>panel>=0.13.1->holoviews->umap-learn[plot]) (1.0.2)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.10/dist-packages (from markdown-it-py-
>panel>=0.13.1->holoviews->umap-learn[plot]) (0.1.2)
Installing collected packages: datashader
Successfully installed datashader-0.16.0
Requirement already satisfied: holoviews in
/usr/local/lib/python3.10/dist-packages (1.17.1)
Requirement already satisfied: param<3.0,>=1.12.0 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (2.0.2)
Requirement already satisfied: numpy>=1.0 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (1.23.5)
Requirement already satisfied: pyviz-comms>=0.7.4 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (3.0.1)
Requirement already satisfied: panel>=0.13.1 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (1.3.8)
Requirement already satisfied: colorcet in
/usr/local/lib/python3.10/dist-packages (from holoviews) (3.0.1)
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Requirement already satisfied: packaging in
/usr/local/lib/python3.10/dist-packages (from holoviews) (23.2)
Requirement already satisfied: pandas>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from holoviews) (1.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0-
>holoviews) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.20.0-
>holoviews) (2023.4)
Requirement already satisfied: bokeh<3.4.0,>=3.2.0 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (3.3.4)
Requirement already satisfied: xyzservices>=2021.09.1 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (2023.10.1)
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>holoviews) (3.5.2)
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>holoviews) (0.4.0)
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/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (2.31.0)
Requirement already satisfied: tqdm>=4.48.0 in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (4.66.1)
Requirement already satisfied: bleach in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (6.1.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.10/dist-packages (from panel>=0.13.1-
>holoviews) (4.9.0)
Requirement already satisfied: pyct>=0.4.4 in
/usr/local/lib/python3.10/dist-packages (from colorcet->holoviews)
(0.5.0)
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/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (3.1.3)
Requirement already satisfied: contourpy>=1 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (1.2.0)
Requirement already satisfied: pillow>=7.1.0 in
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/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (9.4.0)
Requirement already satisfied: PyYAML>=3.10 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (6.0.1)
Requirement already satisfied: tornado>=5.1 in
/usr/local/lib/python3.10/dist-packages (from bokeh<3.4.0,>=3.2.0-
>panel>=0.13.1->holoviews) (6.3.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1-
>pandas>=0.20.0->holoviews) (1.16.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.10/dist-packages (from bleach->panel>=0.13.1-
>holoviews) (0.5.1)
Requirement already satisfied: uc-micro-py in
/usr/local/lib/python3.10/dist-packages (from linkify-it-py-
>panel>=0.13.1->holoviews) (1.0.2)
Requirement already satisfied: mdurl~=0.1 in
/usr/local/lib/python3.10/dist-packages (from markdown-it-py-
>panel>=0.13.1->holoviews) (0.1.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->panel>=0.13.1-
>holoviews) (2024.2.2)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from Jinja2>=2.9-
>bokeh<3.4.0,>=3.2.0->panel>=0.13.1->holoviews) (2.1.5)
Requirement already satisfied: ipykernel in
/usr/local/lib/python3.10/dist-packages (5.5.6)
Collecting ipykernel
  Downloading ipykernel-6.29.2-py3-none-any.whl (116 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 116.1/116.1 kB 3.6 MB/s eta
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m>=0.1.1 (from ipykernel)
  Downloading comm-0.2.1-py3-none-any.whl (7.2 kB)
Requirement already satisfied: debugpy>=1.6.5 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (1.6.6)
Requirement already satisfied: ipython>=7.23.1 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (7.34.0)
Requirement already satisfied: jupyter-client>=6.1.12 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (6.1.12)
Requirement already satisfied: jupyter-core!=5.0.*,>=4.12 in
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/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.7.1)
Requirement already satisfied: matplotlib-inline>=0.1 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (0.1.6)
Requirement already satisfied: nest-asyncio in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (1.6.0)
Requirement already satisfied: packaging in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (23.2)
Requirement already satisfied: psutil in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.9.5)
Collecting pyzmq>=24 (from ipykernel)
  Downloading pyzmq-25.1.2-cp310-cp310-manylinux_2_28_x86_64.whl (1.1
MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.1/1.1 MB 58.1 MB/s eta
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ent already satisfied: tornado>=6.1 in /usr/local/lib/python3.10/dist-
packages (from ipykernel) (6.3.2)
Requirement already satisfied: traitlets>=5.4.0 in
/usr/local/lib/python3.10/dist-packages (from ipykernel) (5.7.1)
Requirement already satisfied: setuptools>=18.5 in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (67.7.2)
Collecting jedi>=0.16 (from ipython>=7.23.1->ipykernel)
  Downloading jedi-0.19.1-py2.py3-none-any.whl (1.6 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.6/1.6 MB 85.3 MB/s eta
0:00:00
ent already satisfied: decorator in /usr/local/lib/python3.10/dist-
packages (from ipython>=7.23.1->ipykernel) (4.4.2)
Requirement already satisfied: pickleshare in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (0.7.5)
Requirement already satisfied: prompt-toolkit!=3.0.0,!
=3.0.1,<3.1.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from
ipython>=7.23.1->ipykernel) (3.0.43)
Requirement already satisfied: pygments in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (2.16.1)
Requirement already satisfied: backcall in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (0.2.0)
Requirement already satisfied: pexpect>4.3 in
/usr/local/lib/python3.10/dist-packages (from ipython>=7.23.1-
>ipykernel) (4.9.0)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.10/dist-packages (from jupyter-client>=6.1.12-
>ipykernel) (2.8.2)
Requirement already satisfied: platformdirs>=2.5 in
/usr/local/lib/python3.10/dist-packages (from jupyter-core!
=5.0.*,>=4.12->ipykernel) (4.2.0)
Requirement already satisfied: parso<0.9.0,>=0.8.3 in
/usr/local/lib/python3.10/dist-packages (from jedi>=0.16-
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>ipython>=7.23.1->ipykernel) (0.8.3)
Requirement already satisfied: ptyprocess>=0.5 in
/usr/local/lib/python3.10/dist-packages (from pexpect>4.3-
>ipython>=7.23.1->ipykernel) (0.7.0)
Requirement already satisfied: wcwidth in
/usr/local/lib/python3.10/dist-packages (from prompt-toolkit!=3.0.0,!
=3.0.1,<3.1.0,>=2.0.0->ipython>=7.23.1->ipykernel) (0.2.13)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.1-
>jupyter-client>=6.1.12->ipykernel) (1.16.0)
Installing collected packages: pyzmq, jedi, comm, ipykernel
  Attempting uninstall: pyzmq
    Found existing installation: pyzmq 23.2.1
    Uninstalling pyzmq-23.2.1:
      Successfully uninstalled pyzmq-23.2.1
  Attempting uninstall: ipykernel
    Found existing installation: ipykernel 5.5.6
    Uninstalling ipykernel-5.5.6:
      Successfully uninstalled ipykernel-5.5.6
ERROR: pip's dependency resolver does not currently take into account
all the packages that are installed. This behaviour is the source of
the following dependency conflicts.
google-colab 1.0.0 requires ipykernel==5.5.6, but you have ipykernel
6.29.2 which is incompatible.
notebook 6.5.5 requires pyzmq<25,>=17, but you have pyzmq 25.1.2 which
is incompatible.
Successfully installed comm-0.2.1 ipykernel-6.29.2 jedi-0.19.1 pyzmq-
25.1.2
```

{"pip_warning":{"packages":["zmq"]}}

```
!pip install hdbscan
```

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Collecting hdbscan
  Downloading hdbscan-0.8.33.tar.gz (5.2 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0.0/5.2 MB ? eta -:--:--
━╺━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0.2/5.2 MB 4.7 MB/s eta
0:00:02 ━━━━━━━━━━━━━━━━━━━━━━━━━━╸━━━━━━━━━━━━━ 3.5/5.2 MB 51.1 MB/s
eta 0:00:01 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 5.2/5.2 MB 50.4
MB/s eta 0:00:00
ents to build wheel ... etadata (pyproject.toml) ...  hdbscan)
  Using cached Cython-0.29.37-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.manylinux_2_24_x86_64.whl
(1.9 MB)
Requirement already satisfied: numpy>=1.20 in
/usr/local/lib/python3.10/dist-packages (from hdbscan) (1.23.5)
Requirement already satisfied: scipy>=1.0 in
/usr/local/lib/python3.10/dist-packages (from hdbscan) (1.11.4)
Requirement already satisfied: scikit-learn>=0.20 in
/usr/local/lib/python3.10/dist-packages (from hdbscan) (1.2.2)
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Requirement already satisfied: joblib>=1.0 in
/usr/local/lib/python3.10/dist-packages (from hdbscan) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.20-
>hdbscan) (3.2.0)
Building wheels for collected packages: hdbscan
  Building wheel for hdbscan (pyproject.toml) ... e=hdbscan-0.8.33-
cp310-cp310-linux_x86_64.whl size=3039281
sha256=4c13586c3e0278480a5b2f4df28f072dc52a5c779dd37097ea13fc7e8bd3898
f
  Stored in directory:
/root/.cache/pip/wheels/75/0b/3b/dc4f60b7cc455efaefb62883a7483e76f09d0
6ca81cf87d610
Successfully built hdbscan
Installing collected packages: cython, hdbscan
  Attempting uninstall: cython
    Found existing installation: Cython 3.0.8
    Uninstalling Cython-3.0.8:
      Successfully uninstalled Cython-3.0.8
Successfully installed cython-0.29.37 hdbscan-0.8.33
```

```
import umap
import umap.plot
```

```
/usr/local/lib/python3.10/dist-packages/umap/plot.py:203:
NumbaDeprecationWarning: The keyword argument 'nopython=False' was
supplied. From Numba 0.59.0 the default is being changed to True and
use of 'nopython=False' will raise a warning as the argument will have
no effect. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#depr
ecation-of-object-mode-fall-back-behaviour-when-using-jit for details.
  @numba.jit(nopython=False)
```

```
import hdbscan
```

```
topics = ['comp.graphics', 'comp.os.ms-windows.misc',
'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware', 'rec.autos',
'rec.motorcycles','rec.sport.baseball', 'rec.sport.hockey']
data = fetch_20newsgroups(subset = 'all', categories=topics,
remove=('headers', 'footers'))
```

```
count_vect = CountVectorizer(stop_words='english', min_df=3)
X_train_counts = count_vect.fit_transform(data.data)
```

```
tfidf_transformer = TfidfTransformer()
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
print(X_train_tfidf.shape)
```

```
(7882, 23522)
```

Question 19, 20

```
filename = './flowers_features_and_labels.npz'

if os.path.exists(filename):
    file = np.load(filename)
    f_all, y_all = file['f_all'], file['y_all']

else:
    if not os.path.exists('./flower_photos'):
        # download the flowers dataset and extract its images
        url =
'http://download.tensorflow.org/example_images/flower_photos.tgz'
        with open('./flower_photos.tgz', 'wb') as file:
            file.write(requests.get(url).content)
        with tarfile.open('./flower_photos.tgz') as file:
            file.extractall('./')
        os.remove('./flower_photos.tgz')

    class FeatureExtractor(nn.Module):
        def __init__(self):
            super().__init__()

            vgg = torch.hub.load('pytorch/vision:v0.10.0', 'vgg16',
pretrained=True)

            # Extract VGG-16 Feature Layers
            self.features = list(vgg.features)
            self.features = nn.Sequential(*self.features)
            # Extract VGG-16 Average Pooling Layer
            self.pooling = vgg.avgpool
            # Convert the image into one-dimensional vector
            self.flatten = nn.Flatten()
            # Extract the first part of fully-connected layer from
VGG16
            self.fc = vgg.classifier[0]

        def forward(self, x):
            # It will take the input 'x' until it returns the feature
vector called 'out'
            out = self.features(x)
            out = self.pooling(out)
            out = self.flatten(out)
            out = self.fc(out)
            return out

    # Initialize the model
    assert torch.cuda.is_available()
    feature_extractor = FeatureExtractor().cuda().eval()
```

```
    dataset = datasets.ImageFolder(root='./flower_photos',

transform=transforms.Compose([transforms.Resize(224),

transforms.CenterCrop(224),

transforms.ToTensor(),

transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224,
0.225])]))
    dataloader = DataLoader(dataset, batch_size=64, shuffle=True)

    # Extract features and store them on disk
    f_all, y_all = np.zeros((0, 4096)), np.zeros((0,))
    for x, y in tqdm(dataloader):
        with torch.no_grad():
            f_all = np.vstack([f_all,
feature_extractor(x.cuda()).cpu()])
            y_all = np.concatenate([y_all, y])
    np.savez(filename, f_all=f_all, y_all=y_all)
```

```
Downloading: "https://github.com/pytorch/vision/zipball/v0.10.0" to
/root/.cache/torch/hub/v0.10.0.zip
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:2
08: UserWarning: The parameter 'pretrained' is deprecated since 0.13
and may be removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:2
23: UserWarning: Arguments other than a weight enum or `None` for
'weights' are deprecated since 0.13 and may be removed in the future.
The current behavior is equivalent to passing
`weights=VGG16_Weights.IMAGENET1K_V1`. You can also use
`weights=VGG16_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth"
to /root/.cache/torch/hub/checkpoints/vgg16-397923af.pth
100%|██████████| 528M/528M [00:03<00:00, 179MB/s]
100%|██████████| 58/58 [00:31<00:00,  1.84it/s]
```

QUESTION 19:

In a brief paragraph discuss: If the VGG network is trained on a dataset with perhaps totally different classes as targets, why would one expect the features derived from such a network to have discriminative power for a custom dataset?

- The features learned from the VGG network are generic representations of the image data, in other words, the general image pattern and structure. We can use these patterns to classify images of a different problem as it has the ability to analysis image data with the pre-trained patterns. Therefore, the VGG network trained with a dataset different from our custom dataset can still read the image information and output the feature.

QUESTION 20:

In a brief paragraph explain how the helper code base is performing feature extraction.

- The feature extraction of the helper code starts with downloading the training data './flowers_features_and_labels.npz' after checking if it is not downloaded yet.
- The Feature Extractor class contains a sequential neural network that performs pooling, flattening, and classifying by using VGG16 for the forward path.
- The usage of GPU is enabled as cuda, so when running this function, user should remeber to connect to the gpu.
- For the downloaded dataset './flower_photos', the code trasforms the dataset into a trainable shape, by resizing the image by 224x224, crop the image by te center, convert the data into a tensor and normalize them. After trasformation, it uses the DataLoader function to enable iterations within the data.
- Finally the Feature Extractor class operates over the processed data and vectorizes the feature into a length of 4096 vector, and saves the VGG feature vectors and the labels into a .npz file.

Question 21, 22

```
from PIL import Image

filepath2 =
"/content/flower_photos/daisy/10172379554_b296050f82_n.jpg"

img1 = Image.open (filepath2)

width1, height1 = img1.size

print ("The dimensions of the image are:", width1, "x", height1) # 320
x 215 = 68800

The dimensions of the image are: 320 x 215

print(f_all.shape, y_all.shape)
num_features = f_all.shape[1]
print(num_features)

(3670, 4096) (3670,)
4096
```

QUESTION 21:

How many pixels are there in the original images?

- width x height = 320 x 215
- 68800 pixels

How many features does the VGG network extract per image; i.e what is the dimension of each feature vector for an image sample?

- 4096 features

QUESTION 22:

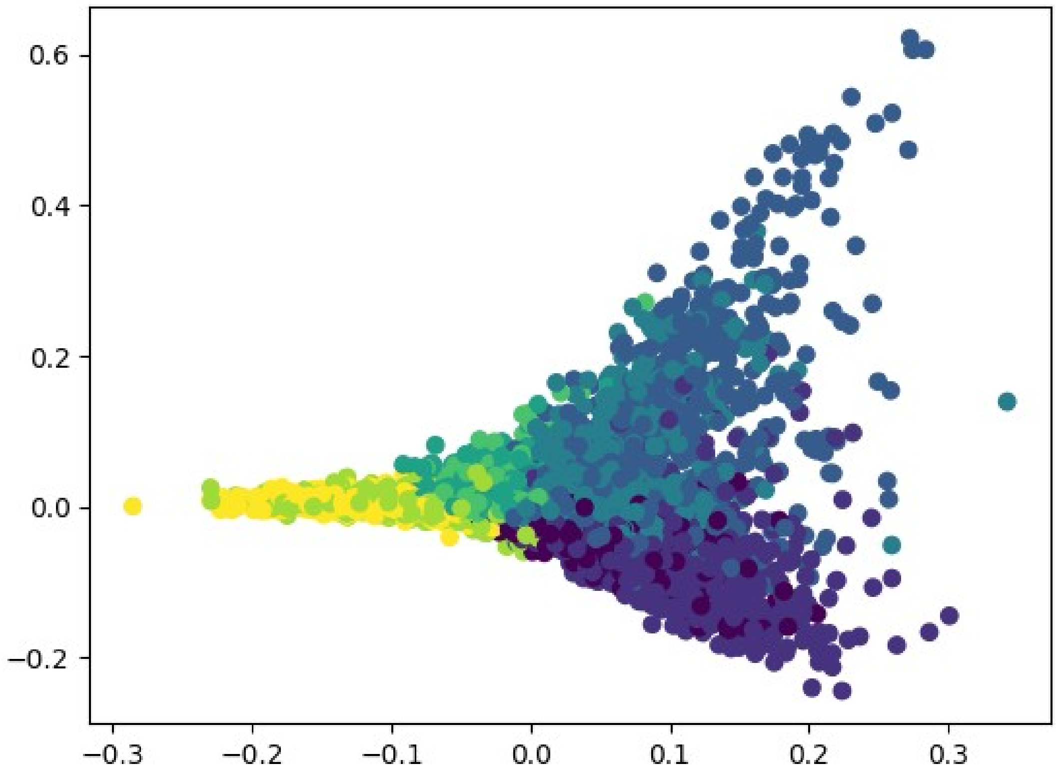
Are the extracted features dense or sparse? (Compare with sparse TF-IDF features in text.)

- The extracted features for the image data is dense.

```
A = np.squeeze(np.asarray(X_train_tfidf.todense()))

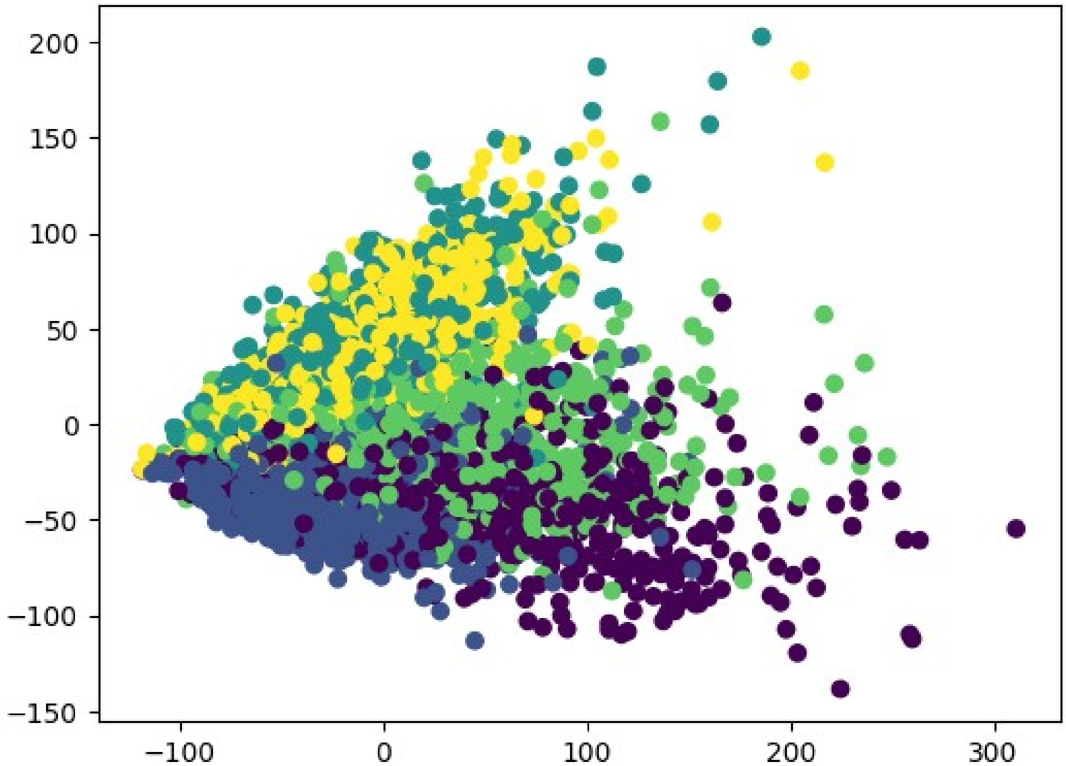
t_pca = PCA(n_components=2).fit_transform(A)
plt.scatter(*t_pca.T, c=data.target)

<matplotlib.collections.PathCollection at 0x7d8182f365f0>
```




```
f_pca = PCA(n_components=2).fit_transform(f_all)
plt.scatter(*f_pca.T, c=y_all)

<matplotlib.collections.PathCollection at 0x7d817c6b5480>
```



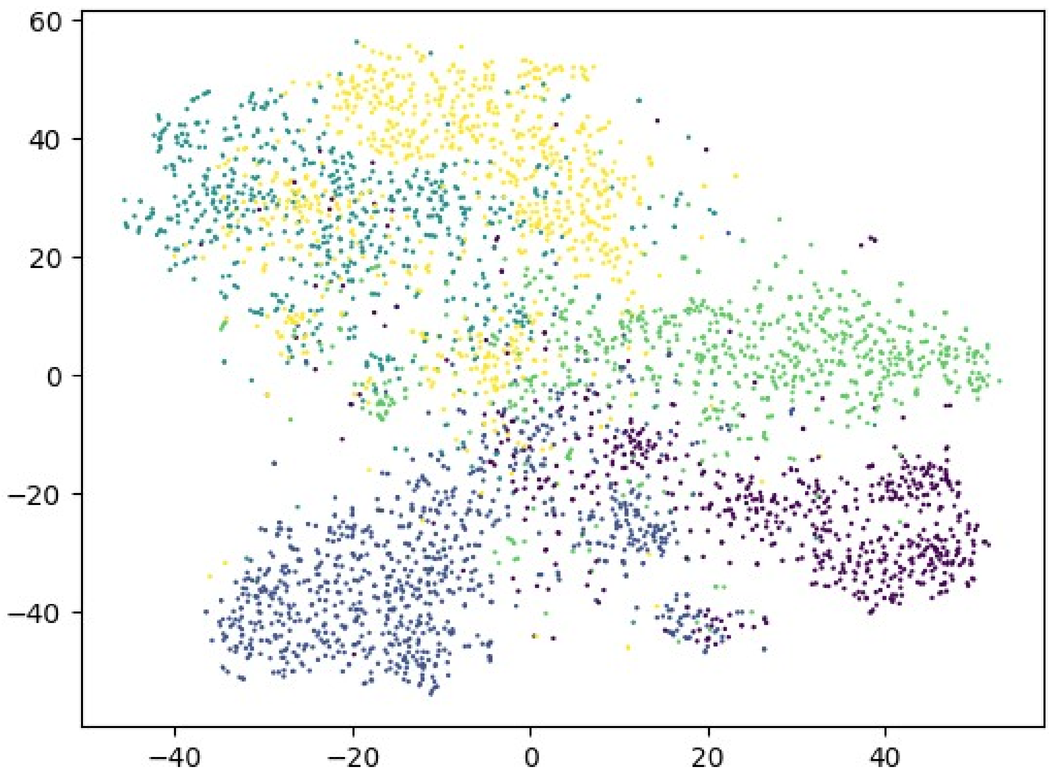
Question 23

```
import matplotlib.pyplot as plt

from sklearn.manifold import TSNE

data = np.load('flowers_features_and_labels.npz')

tsne = TSNE(n_components=2)
X_tsne = tsne.fit_transform(data['f_all'])
plt.scatter(X_tsne[:, 0], X_tsne[:, 1], s = 0.5, c = data['y_all'])
plt.show()
```



QUESTION 23: In order to inspect the high-dimensional features, t-SNE is a popular off-the-shelf choice for visualizing Vision features. Map the features you have extracted onto 2 dimensions with t-SNE. Then plot the mapped feature vectors along x and y axes. Color-code the data points with ground-truth labels. Describe your observation.

- There are five different classes as colored differently. As the different colored data point clusters are mostly seperable based on the area, we can see classification based on clutering is properly visualized by the t-SNE.

Question 24

QUESTION 24: Report the best result (in terms of rand score) within the table below.

Module	Alternatives	Hyperparameters
Dimensionality Reduction	None	N/A
	SVD	r = 50
	UMAP	n_components = 50
	Autoencoder	num_features = 50
Clustering	K-Means	k = 5
	Agglomerative Clustering	n_clusters = 5
	HDBSCAN	min_cluster_size & min_samples

For HDBSCAN, introduce a conservative parameter grid over min cluster size and min samples.

For HDBSCAN, trying min_cluster_size = [5, 10, 20, 50], and min_samples = [1, 5, 10, 20]

The best results were

HDBSCAN_Parameters	min_cluster_size	min_samples	adjusted_rand_score
None & HDBSCAN	10	1	0.0150142
SVD & HDBSCAN	5	1	0.0202971
UMAP & HDBSCAN	5	1	0.19748
Autoencoder & HDBSCAN	10	1	0.00701562

From the given table, using UMAP and K-Means gave the best result, adjusted random score 0.467592.

	K-Means	Agglomerative	HDBSCAN
None	0.190619	0.21845	0.0150142
SVD	0.188837	0.19439	0.0202971
UMAP	0.467592	0.45096	0.19748
Autoencoder	0.232811	0.216423	0.00701562

```
class Autoencoder(torch.nn.Module, TransformerMixin):
    def __init__(self, n_components):
        super().__init__()
        self.n_components = n_components
        self.n_features = None  # to be determined with data
        self.encoder = None
        self.decoder = None

    def _create_encoder(self):
        return nn.Sequential(
            nn.Linear(4096, 1280),
            nn.ReLU(True),
            nn.Linear(1280, 640),
            nn.ReLU(True), nn.Linear(640, 120), nn.ReLU(True),
nn.Linear(120, self.n_components))

    def _create_decoder(self):
        return nn.Sequential(
            nn.Linear(self.n_components, 120),
            nn.ReLU(True),
            nn.Linear(120, 640),
            nn.ReLU(True),
            nn.Linear(640, 1280),
            nn.ReLU(True), nn.Linear(1280, 4096))

    def forward(self, X):
        encoded = self.encoder(X)
        decoded = self.decoder(encoded)
        return decoded
```

```
    def fit(self, X):
        X = torch.tensor(X, dtype=torch.float32, device='cuda')
        self.n_features = X.shape[1]
        self.encoder = self._create_encoder()
        self.decoder = self._create_decoder()
        self.cuda()
        self.train()

        criterion = nn.MSELoss()
        optimizer = torch.optim.Adam(self.parameters(), lr=1e-3,
weight_decay=1e-5)

        dataset = TensorDataset(X)
        dataloader = DataLoader(dataset, batch_size=128, shuffle=True)

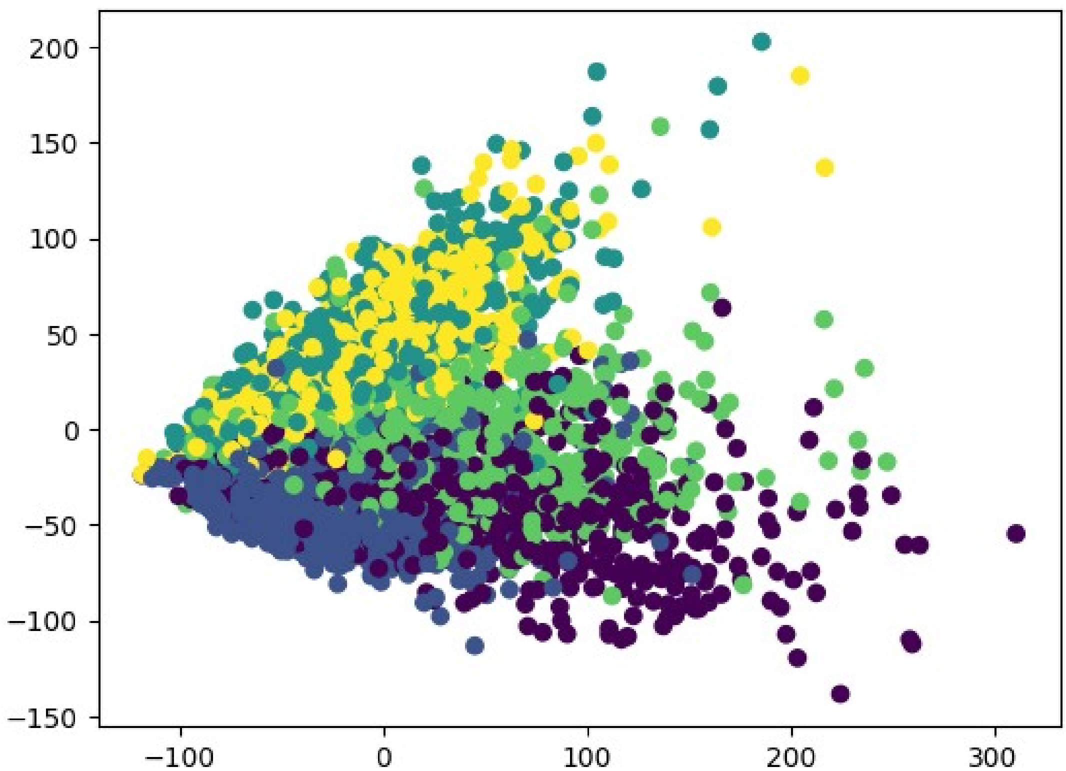
        for epoch in tqdm(range(100)):
            for (X_,) in dataloader:
                X_ = X_.cuda()
                # ===================forward=====================
                output = self(X_)
                loss = criterion(output, X_)
                # ===================backward====================
                optimizer.zero_grad()
                loss.backward()
                optimizer.step()

        return self

    def transform(self, X):
        X = torch.tensor(X, dtype=torch.float32, device='cuda')
        self.eval()
        with torch.no_grad():
            return self.encoder(X).cpu().numpy()

f_pca = PCA(n_components=2).fit_transform(f_all)
plt.scatter(*f_pca.T, c=y_all)
```

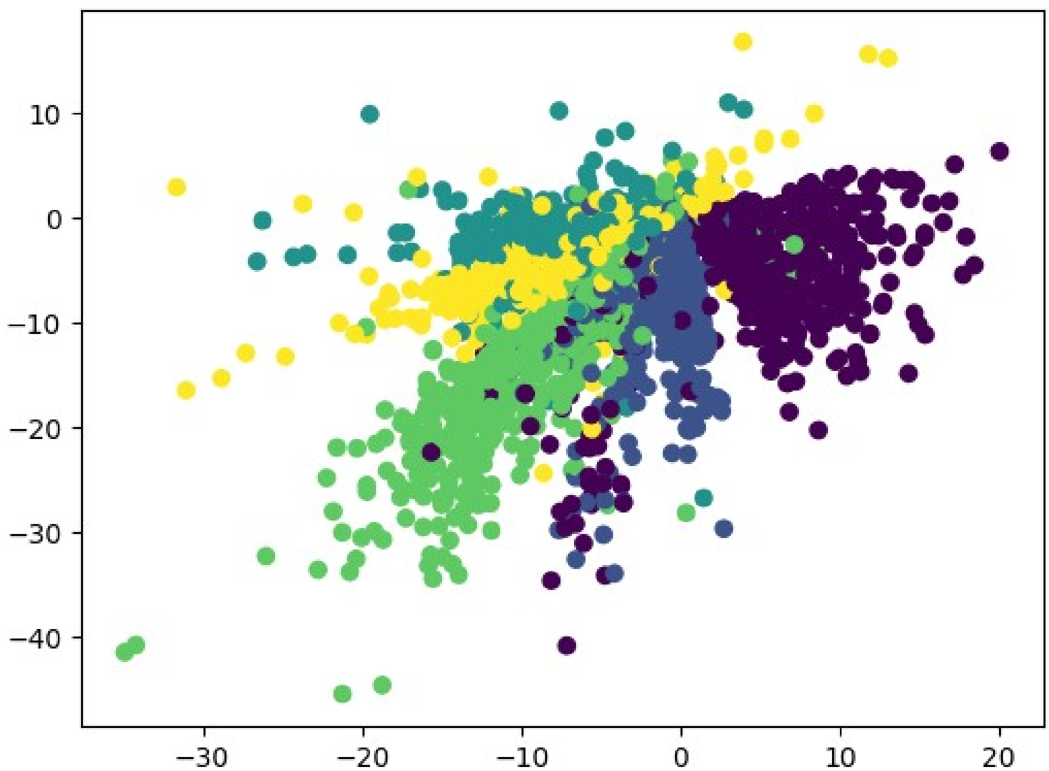
```
<matplotlib.collections.PathCollection at 0x7d817c75f5e0>
```




```
X_em =Autoencoder(2).fit_transform(f_all)
plt.scatter(*X_em.T, c=y_all)
```

```
100%|██████████| 100/100 [00:19<00:00,  5.15it/s]
```

```
<matplotlib.collections.PathCollection at 0x7d8182fb5c30>
```




```
X_data = data["f_all"]
y_data = data["y_all"]

X_svd = TruncatedSVD(n_components=50,
random_state=0).fit_transform(X_data)
X_umap = umap.UMAP(n_components=50, metric =
'cosine').fit_transform(X_data)
X_autoencoder = Autoencoder(50).fit_transform(X_data)

100%|██████████| 100/100 [00:18<00:00,  5.32it/s]
```

Testing HDBSCAN

```
from tabulate import tabulate

hdb = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=1,
prediction_data=True).fit(X_data)
label_none_hdb = hdb.labels_
None_HDBSCAN_5_1 = adjusted_rand_score(y_data, label_none_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=5,
prediction_data=True).fit(X_data)
label_none_hdb = hdb.labels_
None_HDBSCAN_5_5 = adjusted_rand_score(y_data, label_none_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=10,
```

```
prediction_data=True).fit(X_data)
label_none_hdb = hdb.labels_
None_HDBSCAN_5_10 = adjusted_rand_score(y_data, label_none_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=20,
prediction_data=True).fit(X_data)
label_none_hdb = hdb.labels_
None_HDBSCAN_5_20 = adjusted_rand_score(y_data, label_none_hdb)

print('None & HDBSCAN : ', None_HDBSCAN_5_1)
print('None_HDBSCAN_5_5 : ', None_HDBSCAN_5_5)
print('None_HDBSCAN_5_10 : ', None_HDBSCAN_5_10)
print('None_HDBSCAN_5_20 : ', None_HDBSCAN_5_20)
```

```
None & HDBSCAN :  0.014983034591038287
None_HDBSCAN_5_5 :  0.006675668759554497
None_HDBSCAN_5_10 :  0.0
None_HDBSCAN_5_20 :  0.0
```

```
hdb = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=1,
prediction_data=True).fit(X_data)
label_none_hdb = hdb.labels_
None_HDBSCAN_5 = adjusted_rand_score(y_data, label_none_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=10, min_samples=1,
prediction_data=True).fit(X_data)
label_none_hdb = hdb.labels_
None_HDBSCAN_10 = adjusted_rand_score(y_data, label_none_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=20, min_samples=1,
prediction_data=True).fit(X_data)
label_none_hdb = hdb.labels_
None_HDBSCAN_20 = adjusted_rand_score(y_data, label_none_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=50, min_samples=1,
prediction_data=True).fit(X_data)
label_none_hdb = hdb.labels_
None_HDBSCAN_50 = adjusted_rand_score(y_data, label_none_hdb)

print('None & HDBSCAN : ', None_HDBSCAN_5)
print('None_HDBSCAN_10 : ', None_HDBSCAN_10)
print('None_HDBSCAN_20 : ', None_HDBSCAN_20)
print('None_HDBSCAN_50 : ', None_HDBSCAN_50)
```

```
None & HDBSCAN :  0.014983034591038287
None_HDBSCAN_10 :  0.015014212771105666
None_HDBSCAN_20 :  0.0
None_HDBSCAN_50 :  0.0
```

```
hdb = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=1,
prediction_data=True).fit(X_svd)
```

```
label_svd_hdb = hdb.labels_
SVD_HDBSCAN_5 = adjusted_rand_score(y_data, label_svd_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=10, min_samples=1,
prediction_data=True).fit(X_svd)
label_svd_hdb = hdb.labels_
SVD_HDBSCAN_10 = adjusted_rand_score(y_data, label_svd_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=1,
prediction_data=True).fit(X_umap)
label_umap_hdb = hdb.labels_
UMAP_HDBSCAN_5 = adjusted_rand_score(y_data, label_umap_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=10, min_samples=1,
prediction_data=True).fit(X_umap)
label_umap_hdb = hdb.labels_
UMAP_HDBSCAN_10 = adjusted_rand_score(y_data, label_umap_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=1,
prediction_data=True).fit(X_autoencoder)
label_auto_hdb = hdb.labels_
Autoencoder_HDBSCAN_5 = adjusted_rand_score(y_data, label_auto_hdb)

hdb = hdbscan.HDBSCAN(min_cluster_size=10, min_samples=1,
prediction_data=True).fit(X_autoencoder)
label_auto_hdb = hdb.labels_
Autoencoder_HDBSCAN_10 = adjusted_rand_score(y_data, label_auto_hdb)

print('SVD & HDBSCAN_5 : ', SVD_HDBSCAN_5)
print('SVD & HDBSCAN_10 : ', SVD_HDBSCAN_10)
print('UMAP & HDBSCAN_5 : ', UMAP_HDBSCAN_5)
print('UMAP & HDBSCAN_10 : ', UMAP_HDBSCAN_10)
print('Autoencoder & HDBSCAN_5 : ', Autoencoder_HDBSCAN_5)
print('Autoencoder & HDBSCAN_10 : ', Autoencoder_HDBSCAN_10)
```

```
SVD & HDBSCAN_5 :  0.02253331412884546
SVD & HDBSCAN_10 :  0.027262268805319737
UMAP & HDBSCAN_5 :  0.18535162364353452
UMAP & HDBSCAN_10 :  0.0945246169287157
Autoencoder & HDBSCAN_5 :  0.005276810618061742
Autoencoder & HDBSCAN_10 :  0.0240887657265409
```

```
input = [X_data, X_svd, X_umap, X_autoencoder]
best_mincluster = [10, 5, 5, 10]
best_minsample = [1, 1, 1, 1]
scores = [None_HDBSCAN_10, SVD_HDBSCAN_5, UMAP_HDBSCAN_5,
Autoencoder_HDBSCAN_10]

col_names = ["HDBSCAN_Parameters", "min_cluster_size", "min_samples",
"adjusted_rand_score"]
```

```
data = [["None & HDBSCAN",best_mincluster[0], best_minsample[0],
scores[0]],
        ["SVD & HDBSCAN",best_mincluster[1], best_minsample[1],
scores[1]],
        ["UMAP & HDBSCAN",best_mincluster[2], best_minsample[2],
scores[2]],
        ["Autoencoder & HDBSCAN",best_mincluster[3],
best_minsample[3], scores[3]]]

print(tabulate(data, headers=col_names))
```

```
HDBSCAN_Parameters       min_cluster_size    min_samples
adjusted_rand_score
---------------------  ------------------  -------------
---------------------
None & HDBSCAN                         10              1
0.0150142
SVD & HDBSCAN                           5              1
0.0225333
UMAP & HDBSCAN                          5              1
0.185352
Autoencoder & HDBSCAN                  10              1
0.0240888
```

Score comparison

```
# None and KMeans
kmeans = KMeans(n_clusters=5).fit(X_data)
label_none_kmeans = kmeans.labels_
None_Kmeans = adjusted_rand_score(y_data, label_none_kmeans)

# SVD and KMeans
kmeans = KMeans(n_clusters=5).fit(X_svd)
label_svd_kmeans = kmeans.labels_
SVD_Kmeans = adjusted_rand_score(y_data, label_svd_kmeans)

# UMAP and KMeans
kmeans = KMeans(n_clusters=5).fit(X_umap)
label_umap_kmeans = kmeans.labels_
UMAP_Kmeans = adjusted_rand_score(y_data, label_umap_kmeans)

# Autoencoder and KMeans
kmeans = KMeans(n_clusters=5).fit(X_autoencoder)
label_auto_kmeans = kmeans.labels_
Autoencoder_Kmeans = adjusted_rand_score(y_data, label_auto_kmeans)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
_kmeans.py:870: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly
to suppress the warning
```

```
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870
: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870
: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870
: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
warning
  warnings.warn(
```

```
# None and Agglomerative
agg = AgglomerativeClustering(n_clusters = 5,
linkage='ward').fit(X_data)
label_none_agg = agg.labels_
None_Agglomerative = adjusted_rand_score(y_data, label_none_agg)

# SVD and Agglomerative
agg = AgglomerativeClustering(n_clusters = 5,
linkage='ward').fit(X_svd)
label_svd_agg = agg.labels_
SVD_Agglomerative = adjusted_rand_score(y_data, label_svd_agg)

# UMAP and Agglomerative
agg = AgglomerativeClustering(n_clusters = 5,
linkage='ward').fit(X_umap)
label_umap_agg = agg.labels_
UMAP_Agglomerative = adjusted_rand_score(y_data, label_umap_agg)

# Autoencoder and Agglomerative
agg = AgglomerativeClustering(n_clusters = 5,
linkage='ward').fit(X_autoencoder)
label_auto_agg = agg.labels_
Autoencoder_Agglomerative = adjusted_rand_score(y_data,
label_auto_agg)

print('None & Kmeans : ', None_Kmeans)
print('SVD & Kmeans: ', SVD_Kmeans)
print('UMAP & Kmeans : ', UMAP_Kmeans)
print('Autoencoder & Kmeans: ', Autoencoder_Kmeans)
print('-----------------------')
print('None & Agglomerative : ', None_Agglomerative)
print('SVD & Agglomerative: ', SVD_Agglomerative)
```

```
print('UMAP & Agglomerative : ', UMAP_Agglomerative)
print('Autoencoder & Agglomerative: ', Autoencoder_Agglomerative)
```

```
None & Kmeans :  0.19289005000734466
SVD & Kmeans:  0.19647718797412642
UMAP & Kmeans :  0.46649835671936546
Autoencoder & Kmeans:  0.19562086490499953
-----------------------
None & Agglomerative :  0.2184499487113686
SVD & Agglomerative:  0.1427161050758648
UMAP & Agglomerative :  0.4734899990171398
Autoencoder & Agglomerative:  0.25719450849712766
```

```
col_names = ["K-Means", "Agglomerative", "HDBSCAN"]

data = [["None", None_Kmeans, None_Agglomerative, None_HDBSCAN_10],
        ["SVD", SVD_Kmeans, SVD_Agglomerative, SVD_HDBSCAN_5],
        ["UMAP", UMAP_Kmeans, UMAP_Agglomerative, UMAP_HDBSCAN_5],
        ["Autoencoder", Autoencoder_Kmeans, Autoencoder_Agglomerative,
Autoencoder_HDBSCAN_10]]

print(tabulate(data, headers=col_names))
```

```
               K-Means    Agglomerative    HDBSCAN
-----------  ---------  ---------------  ---------
None          0.19289          0.21845   0.0150142
SVD           0.196477         0.142716  0.0225333
UMAP          0.466498         0.47349   0.185352
Autoencoder   0.195621         0.257195  0.0240888
```

Question 25

QUESTION 25:

Report the test accuracy of the MLP classifier on the original VGG features.

- The test accuracy is 0.9169. (2nd trail : 0.9046)

Report the same when using the reduced-dimension features (you have freedom in choosing the dimensionality reduction algorithm and its parameters). Does the performance of the model suffer with the reduced-dimension representations? Is it significant? Does the success in classification make sense in the context of the clustering results obtained for the same features in Question 24.

- The accuracy for the reduced-dimension features is 0.8379 (2nd trial : 0.8678). Yes, the accuracy drops by 0.08 (to 0.04)when the dimensions are reduced. This is in contrast to the results in question 24 where UMAP improved the adjusted random score.

```
class MLP(torch.nn.Module):
    def __init__(self, num_features):
        super().__init__()
```

```
        self.model = nn.Sequential(
            nn.Linear(num_features, 1280),
            nn.ReLU(True),
            nn.Linear(1280, 640),
            nn.ReLU(True),
            nn.Linear(640, 5),
            nn.LogSoftmax(dim=1)
        )
        self.cuda()


    def forward(self, X):
        return self.model(X)

    def train(self, X, y):
        X = torch.tensor(X, dtype=torch.float32, device='cuda')
        y = torch.tensor(y, dtype=torch.int64, device='cuda')

        self.model.train()

        criterion = nn.NLLLoss()
        optimizer = torch.optim.Adam(self.parameters(), lr=1e-3,
weight_decay=1e-5)

        dataset = TensorDataset(X, y)
        dataloader = DataLoader(dataset, batch_size=128, shuffle=True)

        for epoch in tqdm(range(100)):
            for (X_, y_) in dataloader:
                optimizer.zero_grad()

                output = self(X_)
                loss = criterion(output, y_)

                loss.backward()
                optimizer.step()
                #raise NotImplementedError
        return self

    def eval(self, X_test, y_test):
        self.model.eval()

        num_correct = 0

        X_test = torch.tensor(X_test, dtype=torch.float32,
device='cuda')
        y_test = torch.tensor(y_test, dtype=torch.int64,
device='cuda')

        output = self(X_test)
```

```
        _, predictions = torch.max(output, 1)

        num_correct += torch.sum(predictions == y_test)
        num_examples = len(y_test)
        accuracy = num_correct / num_examples
        return accuracy
        #raise NotImplementedError

# test original dataset
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_data, y_data,
test_size=0.2)


MLP_classification = MLP(num_features = 4096).train(X_train, y_train)
MLP_classification.eval(X_test, y_test)

100%|██████████| 100/100 [00:07<00:00, 14.13it/s]

tensor(0.9046, device='cuda:0')

# test dimensionally reduced dataset
X_umap = umap.UMAP(n_components=50, metric =
'cosine').fit_transform(X_data)

X_train_umap, X_test_umap, y_train, y_test = train_test_split(X_umap,
y_data, test_size=0.2)


print(X_umap.shape)

(3670, 50)

print(X_train_umap.shape)
print(X_test_umap.shape)
print(y_train.shape)
print(y_test.shape)

(2936, 50)
(734, 50)
(2936,)
(734,)

MLP_classification = MLP(num_features = 50).train(X_train_umap,
y_train)
MLP_classification.eval(X_test_umap, y_test)

100%|██████████| 100/100 [00:05<00:00, 18.04it/s]

tensor(0.8678, device='cuda:0')
```

Part 3 (Seperate notebook)

QUESTION 26: Try to construct various text queries regarding types of Pokemon (such as ”type: Bug”, ”electric type Pok´emon” or ”Pok´emon with fire abilities”) to find the relevant images from the dataset. Once you have found the most suitable template for queries, please find the top five most relevant Pokemon for type Bug, Fire and Grass. For each of the constructed query, please plot the five most relevant Pokemon horizontally in one figure with following specifications:

• the title of the figure should be the query you used;

• the title of each Pokemon should be the name of the Pokemon and its first and second type.

Repeat this process for Pokemon of Dark and Dragon types. Assess the effectiveness of your queries in these cases as well and try to explain any differences.

```
!pip install datasets transformers numpy pandas Pillow matplotlib
!pip install torch tqdm scipy
!pip install git+https://github.com/openai/CLIP.git
!pip install plotly umap-learn

from datasets import load_dataset
from transformers import CLIPProcessor, CLIPModel
import numpy as np
import pandas as pd
from glob import glob
from PIL import Image
import matplotlib.pyplot as plt
import clip
import torch
from tqdm import tqdm
from scipy.special import softmax
import plotly.express as px
import plotly.graph_objects as go
from sklearn.manifold import TSNE

# load csv file and image paths to construct pokedex, use
type_to_load=None to load all types, else use a list of types 1 to
load
def construct_pokedex(csv_path='Pokemon.csv', image_dir='./images/',
type_to_load=None):
    pokedex = pd.read_csv(csv_path)
    image_paths = []

    for pokemon_name in pokedex["Name"]:
        imgs = glob(f"{image_dir}/{pokemon_name}/0.jpg")
        if len(imgs) > 0:
            image_paths.append(imgs[0])
        else:
            image_paths.append(None)
```

```
    pokedex["image_path"] = image_paths
    pokedex =
pokedex[pokedex["image_path"].notna()].reset_index(drop=True)

    # only keep pokemon with distinct id
    ids, id_counts = np.unique(pokedex["ID"], return_counts=True)
    ids, id_counts = np.array(ids), np.array(id_counts)
    keep_ids = ids[id_counts == 1]

    pokedex =
pokedex[pokedex["ID"].isin(keep_ids)].reset_index(drop=True)
    pokedex["Type2"] = pokedex["Type2"].str.strip()
    if type_to_load is not None:
        pokedex =
pokedex[pokedex["Type1"].isin(type_to_load)].reset_index(drop=True)
    return pokedex

# load clip model
def load_clip_model():
    device = "cuda" if torch.cuda.is_available() else "cpu"
    model, preprocess = clip.load("ViT-L/14", device=device)
    return model, preprocess, device

# inference clip model on a list of image path
def clip_inference_image(model, preprocess, image_paths, device):
    image_embeddings = []
    with torch.no_grad():
        for img_path in tqdm(image_paths):
            img = Image.open(img_path)
            img_preprocessed = preprocess(img).unsqueeze(0).to(device)
            image_embedding =
model.encode_image(img_preprocessed).detach().cpu().numpy()
            image_embeddings += [image_embedding]

    image_embeddings = np.concatenate(image_embeddings, axis=0)
    image_embeddings /= np.linalg.norm(image_embeddings, axis=-1,
keepdims=True)
    return image_embeddings

# inference clip model on a list of texts
def clip_inference_text(model, preprocess, texts, device):
    with torch.no_grad():
        text_embeddings =
model.encode_text(clip.tokenize(texts).to(device)).detach().cpu().nump
y()
    text_embeddings /= np.linalg.norm(text_embeddings, axis=-1,
keepdims=True)
    return text_embeddings
```

```
# compute similarity of texts to each image
def compute_similarity_text_to_image(image_embeddings,
text_embeddings):
    similarity = softmax((100.0 * image_embeddings @
text_embeddings.T), axis=-1)
    return similarity

# compute similarity of iamges to each text
def compute_similarity_image_to_text(image_embeddings,
text_embeddings):
    similarity = softmax((100.0 * image_embeddings @
text_embeddings.T), axis=0)
    return similarity

# Use TSNE to project CLIP embeddings to 2D space
def umap_projection(image_embeddings, n_neighbors=15, min_dist=0.1,
metric='cosine'):
    distance_matrix = np.zeros((image_embeddings.shape[0],
image_embeddings.shape[0]))
    for i in range(image_embeddings.shape[0]):
        for j in range(image_embeddings.shape[0]):
            if i == j:
                distance_matrix[i, j] = 1
            else:
                distance_matrix[i, j] = np.dot(image_embeddings[i],
image_embeddings[j])
    distance_matrix = 1 - distance_matrix
    reducer = TSNE(n_components=2, metric="precomputed",
init="random", random_state=42)
    visualization_data = reducer.fit_transform(distance_matrix)
    return visualization_data
```

QUESTION 27: Randomly select 10 Pokemon images from the dataset and use CLIP to find the most relevant types (use your preferred template, e.g "type: Bug"). For each selected Pokemon, please plot it and indicate:

• its name and first and second type;

• the five most relevant types predicted by CLIP and their predicted probabilities.

```

```

QUESTION 28: In the first and second question, we investigated how CLIP creates 'clusters' by mapping images and texts of various Pokemon into a high-dimensional space and explored neighborhood of these items in this space. For this question, please use t-SNE to visualize image clusters, specifically for Pokemon types Bug, Fire, and Grass. You can use scatter plot from python package plotly. For the visualization, color-code each point based on its first type type 1 using the 'color'argument, and label each point with the Pokemon's name and types using

’hover name’. This will enable you to identify each Pokemon represented in your visualization. After completing the visualization, analyze it and discuss whether the clustering of Pokemon types make sense to you.