

Notebook

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1 Election Analysis

Names: Shiyuan Zhang, Shuoyuan Gao

1.1 1. Introduction and Dataset Research

1. Discovering hidden patterns: For example, in the 2016 U.S. election dataset may contain multidimensional data such as voter's voting behavior, socio-economic characteristics, and geographic information. Unsupervised learning, clustering as we using in below, can help identify underlying patterns between different groups of voters, such as voters with similar voting behavior or voters with similar socioeconomic characteristics. Then as we found the patterns, we can understand better for the voter trends. This can tell us more deeper analysis and predictions of election outcomes and voter preferences."
2. Discovering outliers: In the 2016 U.S. election dataset, there may be some unusual voting patterns like precincts with unusually high or low turnout. We can identified the outliers using algorithms. This can letting people know more about the precinct characteristics. In Gaussian Mixture Models, "the GMM from sklearn calculates the score of an observation based on the density of each point's location in that space. Thus, points in higher density regions are less likely to be outliers, and vice versa."
3. Data exploration and visualization: unsupervised learning can also be used as a data exploration and visualization tool to help researchers better understand the structure and distribution of data in the 2016 U.S. election dataset. For example, cluster analysis allows for the division of voters into different clusters and the generation of visualization charts to show the relationships between these clusters. This helps researchers better understand voter behavior and attitudes, identify potential voting patterns or trends, and extract interesting insights from the dataset.

Motivation: We want to use the voting data to determine if different counties are clustered according to the state they are in. We also want to explore the distribution of candidates supported in each cluster. The specific method is: we take the information of the real state where the county is located as the pre-defined label, and then check whether the predicted clusters are related to our pre-defined Location_State by different clustering algorithms. Then we analyze each cluster in detail to explore the components with high candidate support.

Citation:

1.Delua, Julianna. "Supervised vs. Unsupervised Learning: What's the Difference?" IBM, 12 Mar. 2021, <https://www.ibm.com/cloud/blog/supervised-vs-unsupervised-learning>.

2.Santos, Gustavo. “Using Unsupervised Learning to Find Outliers.” Medium, Towards Data Science, 2 Nov. 2022, <https://towardsdatascience.com/using-unsupervised-learning-to-find-outliers-670e07396599>.

3.Verbeeck, Nico et al. “Unsupervised machine learning for exploratory data analysis in imaging mass spectrometry.” Mass spectrometry reviews vol. 39,3 (2020): 245-291. doi:10.1002/mas.21602

The dataset is from Professor provided. Background is from 2016 USA president election, it contains the Democrat candidates and Republicans candidates counts.

voting information include all of the U.S. counties in the 2016 U.S. presidential election. For each county, the percentage and number of votes that went to each primary presidential candidate is listed.

```
[1]: pip install sklearn
```

```
Requirement already satisfied: sklearn in  
/Users/gj/miniconda3/lib/python3.10/site-packages (0.0.post4)
```

```
[notice] A new release of pip is  
available: 23.0.1 -> 23.1.2
```

```
[notice] To update, run:
```

```
pip install --upgrade pip
```

```
Note: you may need to restart the kernel to use updated packages.
```

1.2 2. Data Cleaning and Data Manipulation

```
[3]: import numpy as np  
import matplotlib.pyplot as plt  
import seaborn as sns  
import pandas as pd  
  
from sklearn.preprocessing import MinMaxScaler  
from sklearn.manifold import TSNE  
from sklearn.metrics import adjusted_rand_score  
from sklearn.datasets import load_digits  
from sklearn.cluster import KMeans  
from sklearn.metrics import adjusted_rand_score  
from sklearn.datasets import make_blobs  
from sklearn.mixture import GaussianMixture  
from sklearn.cluster import KMeans  
  
from matplotlib.patches import Ellipse  
  
from sklearn.metrics import silhouette_samples, silhouette_score  
  
from sklearn.cluster import KMeans  
from sklearn.metrics import silhouette_score  
from sklearn.manifold import TSNE
```

```

from sklearn.cluster import AgglomerativeClustering
from scipy.spatial.distance import pdist
from scipy.cluster.hierarchy import linkage, dendrogram, cophenet
from sklearn.preprocessing import StandardScaler

from scipy.spatial.distance import pdist, squareform
from sklearn.neighbors import NearestNeighbors
from sklearn.cluster import DBSCAN
from pyclustertend import hopkins
from sklearn.metrics import silhouette_score, calinski_harabasz_score
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

```

```

[126]: #read data
df = pd.read_csv('election.csv')
df = df.drop('Location_State_Abbreviation',axis =1)
df

```

```

[126]:
   Location_County Location_State Vote_Data_Ben_Carson_Number_of_Votes \
0      Abbeville  South Carolina                                305
1         Abbot      Maine                                           0
2      Abington  Massachusetts                                53
3        Acadia    Louisiana                                           0
4      Accomack    Virginia                                411
...
4211         Yuma    Arizona                                           0
4212         Yuma    Colorado                                           0
4213        Zapata    Texas                                             4
4214        Zavala    Texas                                             0
4215        Ziebach  South Dakota                                           0

   Vote_Data_Ben_Carson_Party Vote_Data_Ben_Carson_Percent_of_Votes \
0      Republican            8.3
1      Republican            0.0
2      Republican            2.5
3      Republican            0.0
4      Republican            9.5
...
4211      Republican            0.0
4212      Republican            0.0
4213      Republican            4.7
4214      Republican            0.0
4215      Republican            0.0

   Vote_Data_Bernie_Sanders_Number_of_Votes Vote_Data_Bernie_Sanders_Party \
0                                312      Democrat
1                                1      Democrat

```

2	1352	Democrat
3	1087	Democrat
4	682	Democrat
...	...	...
4211	2156	Democrat
4212	33	Democrat
4213	685	Democrat
4214	373	Democrat
4215	132	Democrat

	Vote_Data_Bernie_Sanders_Percent_of_Votes \
0	17.0
1	100.0
2	53.4
3	31.4
4	27.4
...	...
4211	31.5
4212	39.3
4213	23.6
4214	18.1
4215	58.9

	Vote_Data_Carly_Fiorina_Number_of_Votes	Vote_Data_Carly_Fiorina_Party \
0	0	Republican
1	0	Republican
2	0	Republican
3	0	Republican
4	0	Republican
...	...	...
4211	0	Republican
4212	0	Republican
4213	0	Republican
4214	0	Republican
4215	0	Republican

	...	Vote_Data_Rand_Paul_Percent_of_Votes \
0	...	0.0
1	...	0.0
2	...	0.0
3	...	0.0
4	...	0.0
...	...	...
4211	...	0.0
4212	...	0.0
4213	...	0.0
4214	...	0.0

4215 ... 0.0

	Vote_Data_Rick_Santorum_Number_of_Votes	Vote_Data_Rick_Santorum_Party \
0	0	Republican
1	0	Republican
2	0	Republican
3	0	Republican
4	0	Republican
...	...	...
4211	0	Republican
4212	0	Republican
4213	0	Republican
4214	0	Republican
4215	0	Republican

	Vote_Data_Rick_Santorum_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
4211	0.0
4212	0.0
4213	0.0
4214	0.0
4215	0.0

	Vote_Data_Ted_Cruz_Number_of_Votes	Vote_Data_Ted_Cruz_Party \
0	876	Republican
1	0	Republican
2	208	Republican
3	1454	Republican
4	685	Republican
...	...	...
4211	2556	Republican
4212	0	Republican
4213	32	Republican
4214	0	Republican
4215	25	Republican

	Vote_Data_Ted_Cruz_Percent_of_Votes \
0	23.9
1	0.0
2	9.9
3	38.2
4	15.9

```
...
4211      28.8
4212      0.0
4213      37.2
4214      0.0
4215      21.7
```

```

Vote_Data_Uncommitted_Number_of_Votes Vote_Data_Uncommitted_Party \
0      0      NaN
1      0      NaN
2      0      NaN
3      0      NaN
4      0      NaN
...
4211      0      NaN
4212      0      NaN
4213      0      NaN
4214      0      NaN
4215      0      NaN
```

```

Vote_Data_Uncommitted_Percent_of_Votes
0      0.0
1      0.0
2      0.0
3      0.0
4      0.0
...
4211      0.0
4212      0.0
4213      0.0
4214      0.0
4215      0.0
```

[4216 rows x 50 columns]

```
[6]: df = df.fillna(0)
```

```
[7]: #check total vote number
sum_column = df.filter(regex='Number',axis =1).sum(axis=1) ->
df['Vote_Data_No_Preference_Number_of_Votes']
df['sum_column'] = sum_column
df['sum_column'].sort_values(ascending=False)
```

```
[7]: 2214      1268622
677      760894
831      678313
1630      537303
```

```

2318      464471
...
3113      0
146      0
3852      0
1492      0
4170      0
Name: sum_column, Length: 4216, dtype: int64

```

1.2.1 number extreme value which will cause inaccurate

```
[8]: #calculate the average amount of vote of each states
df['sum_column'].mean()
```

```
[8]: 13460.871679316888
```

```
[9]: #filter the low vote number state
df_filtered = df[df['sum_column'] > 100]
df = df_filtered.drop('sum_column', axis=1)
df
```

```
[9]:
```

	Location_County	Location_State	Location_State_Abbreviation	\
0	Abbeville	South Carolina		SC
2	Abington	Massachusetts		MA
3	Acadia	Louisiana		LA
4	Accomack	Virginia		VA
5	Acton	Massachusetts		MA
...	...	...	...	...
4210	Yuba	California		CA
4211	Yuma	Arizona		AZ
4213	Zapata	Texas		TX
4214	Zavala	Texas		TX
4215	Ziebach	South Dakota		SD

	Vote_Data_Ben_Carson_Number_of_Votes	Vote_Data_Ben_Carson_Party	\
0	305	Republican	
2	53	Republican	
3	0	Republican	
4	411	Republican	
5	54	Republican	
...	...	...	...
4210	0	Republican	
4211	0	Republican	
4213	4	Republican	
4214	0	Republican	
4215	0	Republican	

	Vote_Data_Ben_Carson_Percent_of_Votes \
0	8.3
2	2.5
3	0.0
4	9.5
5	2.3
...	...
4210	0.0
4211	0.0
4213	4.7
4214	0.0
4215	0.0

	Vote_Data_Bernie_Sanders_Number_of_Votes	Vote_Data_Bernie_Sanders_Party \
0	312	Democrat
2	1352	Democrat
3	1087	Democrat
4	682	Democrat
5	2557	Democrat
...	...	...
4210	1730	Democrat
4211	2156	Democrat
4213	685	Democrat
4214	373	Democrat
4215	132	Democrat

	Vote_Data_Bernie_Sanders_Percent_of_Votes \
0	17.0
2	53.4
3	31.4
4	27.4
5	46.8
...	...
4210	51.1
4211	31.5
4213	23.6
4214	18.1
4215	58.9

	Vote_Data_Carly_Fiorina_Number_of_Votes	...	\
0	0	...	
2	0	...	
3	0	...	
4	0	...	
5	0	...	
...	...	...	
4210	0	...	

4211	0	...
4213	0	...
4214	0	...
4215	0	...

	Vote_Data_Rand_Paul_Percent_of_Votes	\
0	0.0	
2	0.0	
3	0.0	
4	0.0	
5	0.0	
...	...	
4210	0.0	
4211	0.0	
4213	0.0	
4214	0.0	
4215	0.0	

	Vote_Data_Rick_Santorum_Number_of_Votes	Vote_Data_Rick_Santorum_Party	\
0	0	Republican	
2	0	Republican	
3	0	Republican	
4	0	Republican	
5	0	Republican	
...	...	...	
4210	0	Republican	
4211	0	Republican	
4213	0	Republican	
4214	0	Republican	
4215	0	Republican	

	Vote_Data_Rick_Santorum_Percent_of_Votes	\
0	0.0	
2	0.0	
3	0.0	
4	0.0	
5	0.0	
...	...	
4210	0.0	
4211	0.0	
4213	0.0	
4214	0.0	
4215	0.0	

	Vote_Data_Ted_Cruz_Number_of_Votes	Vote_Data_Ted_Cruz_Party	\
0	876	Republican	
2	208	Republican	

3	1454	Republican
4	685	Republican
5	203	Republican
...	...	...
4210	318	Republican
4211	2556	Republican
4213	32	Republican
4214	0	Republican
4215	25	Republican

	Vote_Data_Ted_Cruz_Percent_of_Votes \
0	23.9
2	9.9
3	38.2
4	15.9
5	8.7
...	...
4210	8.2
4211	28.8
4213	37.2
4214	0.0
4215	21.7

	Vote_Data_Uncommitted_Number_of_Votes	Vote_Data_Uncommitted_Party \
0	0	0.0
2	0	0.0
3	0	0.0
4	0	0.0
5	0	0.0
...	...	...
4210	0	0.0
4211	0	0.0
4213	0	0.0
4214	0	0.0
4215	0	0.0

	Vote_Data_Uncommitted_Percent_of_Votes
0	0.0
2	0.0
3	0.0
4	0.0
5	0.0
...	...
4210	0.0
4211	0.0
4213	0.0
4214	0.0

4215

0.0

[3592 rows x 51 columns]

```
[10]: #delete the col including the number, we would like to use the percentage for
      ↪cluster
df = df.drop(df.filter(regex='Number', axis=1).columns, axis=1)
df
```

```
[10]:      Location_County Location_State Location_State_Abbreviation \
0      Abbeville      South Carolina      SC
2      Abington      Massachusetts      MA
3      Acadia      Louisiana      LA
4      Accomack      Virginia      VA
5      Acton      Massachusetts      MA
...      ...      ...      ...
4210      Yuba      California      CA
4211      Yuma      Arizona      AZ
4213      Zapata      Texas      TX
4214      Zavala      Texas      TX
4215      Ziebach      South Dakota      SD

      Vote_Data_Ben_Carson_Party Vote_Data_Ben_Carson_Percent_of_Votes \
0      Republican      8.3
2      Republican      2.5
3      Republican      0.0
4      Republican      9.5
5      Republican      2.3
...      ...      ...
4210      Republican      0.0
4211      Republican      0.0
4213      Republican      4.7
4214      Republican      0.0
4215      Republican      0.0

      Vote_Data_Bernie_Sanders_Party \
0      Democrat
2      Democrat
3      Democrat
4      Democrat
5      Democrat
...      ...
4210      Democrat
4211      Democrat
4213      Democrat
4214      Democrat
4215      Democrat
```

	Vote_Data_Bernie_Sanders_Percent_of_Votes	Vote_Data_Carly_Fiorina_Party \
0	17.0	Republican
2	53.4	Republican
3	31.4	Republican
4	27.4	Republican
5	46.8	Republican
...	...	...
4210	51.1	Republican
4211	31.5	Republican
4213	23.6	Republican
4214	18.1	Republican
4215	58.9	Republican

	Vote_Data_Carly_Fiorina_Percent_of_Votes	Vote_Data_Christie_Party \
0	0.0	Republican
2	0.0	Republican
3	0.0	Republican
4	0.0	Republican
5	0.0	Republican
...	...	...
4210	0.0	Republican
4211	0.0	Republican
4213	0.0	Republican
4214	0.0	Republican
4215	0.0	Republican

	...	Vote_Data_No_Preference_Party \
0	...	0.0
2	...	0.0
3	...	0.0
4	...	0.0
5	...	0.0
...	...	...
4210	...	0.0
4211	...	0.0
4213	...	0.0
4214	...	0.0
4215	...	0.0

	Vote_Data_No_Preference_Percent_of_Votes	Vote_Data_Rand_Paul_Party \
0	0.0	Republican
2	1.2	Republican
3	0.0	Republican
4	0.0	Republican
5	0.2	Republican
...	...	...

4210	0.0	Republican
4211	0.0	Republican
4213	0.0	Republican
4214	0.0	Republican
4215	0.0	Republican

	Vote_Data_Rand_Paul_Percent_of_Votes	Vote_Data_Rick_Santorum_Party \
0	0.0	Republican
2	0.0	Republican
3	0.0	Republican
4	0.0	Republican
5	0.0	Republican
...	...	...
4210	0.0	Republican
4211	0.0	Republican
4213	0.0	Republican
4214	0.0	Republican
4215	0.0	Republican

	Vote_Data_Rick_Santorum_Percent_of_Votes	Vote_Data_Ted_Cruz_Party \
0	0.0	Republican
2	0.0	Republican
3	0.0	Republican
4	0.0	Republican
5	0.0	Republican
...	...	...
4210	0.0	Republican
4211	0.0	Republican
4213	0.0	Republican
4214	0.0	Republican
4215	0.0	Republican

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	23.9	0.0
2	9.9	0.0
3	38.2	0.0
4	15.9	0.0
5	8.7	0.0
...	...	...
4210	8.2	0.0
4211	28.8	0.0
4213	37.2	0.0
4214	0.0	0.0
4215	21.7	0.0

	Vote_Data_Uncommitted_Percent_of_Votes
0	0.0

2	0.0
3	0.0
4	0.0
5	0.0
...	...
4210	0.0
4211	0.0
4213	0.0
4214	0.0
4215	0.0

[3592 rows x 35 columns]

```
[11]: df_num = df.select_dtypes(include='number')
df_num
```

```
[11]: Vote_Data_Ben_Carson_Percent_of_Votes \
0      8.3
2      2.5
3      0.0
4      9.5
5      2.3
...
4210   0.0
4211   0.0
4213   4.7
4214   0.0
4215   0.0
```

	Vote_Data_Bernie_Sanders_Percent_of_Votes \
0	17.0
2	53.4
3	31.4
4	27.4
5	46.8
...	...
4210	51.1
4211	31.5
4213	23.6
4214	18.1
4215	58.9

	Vote_Data_Carly_Fiorina_Percent_of_Votes \
0	0.0
2	0.0
3	0.0
4	0.0

5	0.0
...	...
4210	0.0
4211	0.0
4213	0.0
4214	0.0
4215	0.0

	Vote_Data_Chris_Christie_Percent_of_Votes	\
0	0.0	
2	0.0	
3	0.0	
4	0.0	
5	0.0	
...	...	
4210	0.0	
4211	0.0	
4213	0.0	
4214	0.0	
4215	0.0	

	Vote_Data_Donald_Trump_Percent_of_Votes	\
0	36.9	
2	57.9	
3	44.5	
4	47.9	
5	28.2	
...	...	
4210	82.8	
4211	49.5	
4213	39.5	
4214	0.0	
4215	68.7	

	Vote_Data_Hillary_Clinton_Percent_of_Votes	\
0	81.8	
2	44.6	
3	53.7	
4	72.0	
5	52.8	
...	...	
4210	46.4	
4211	63.7	
4213	67.8	
4214	75.5	
4215	41.1	

	Vote_Data_Jeb_Bush_Percent_of_Votes \
0	6.4
2	0.0
3	0.0
4	0.0
5	0.0
...	...
4210	0.0
4211	0.0
4213	0.0
4214	0.0
4215	0.0

	Vote_Data_John_Kasich_Percent_of_Votes \
0	4.3
2	14.2
3	3.4
4	4.9
5	32.5
...	...
4210	5.1
4211	5.9
4213	0.0
4214	0.0
4215	9.6

	Vote_Data_Marco_Rubio_Percent_of_Votes \
0	20.2
2	12.7
3	10.6
4	20.9
5	24.9
...	...
4210	0.0
4211	0.0
4213	12.8
4214	0.0
4215	0.0

	Vote_Data_Martin_OMalley_Percent_of_Votes \
0	0.0
2	0.0
3	0.0
4	0.0
5	0.0
...	...
4210	0.0

4211	0.0
4213	0.0
4214	0.0
4215	0.0

	Vote_Data_Mike_Huckabee_Percent_of_Votes	Vote_Data_No_Preference_Party \
0	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
5	0.0	0.0
...	...	...
4210	0.0	0.0
4211	0.0	0.0
4213	0.0	0.0
4214	0.0	0.0
4215	0.0	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
0	0.0
2	1.2
3	0.0
4	0.0
5	0.2
...	...
4210	0.0
4211	0.0
4213	0.0
4214	0.0
4215	0.0

	Vote_Data_Rand_Paul_Percent_of_Votes \
0	0.0
2	0.0
3	0.0
4	0.0
5	0.0
...	...
4210	0.0
4211	0.0
4213	0.0
4214	0.0
4215	0.0

	Vote_Data_Rick_Santorum_Percent_of_Votes \
0	0.0
2	0.0

3	0.0
4	0.0
5	0.0
...	...
4210	0.0
4211	0.0
4213	0.0
4214	0.0
4215	0.0

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	23.9	0.0
2	9.9	0.0
3	38.2	0.0
4	15.9	0.0
5	8.7	0.0
...	...	...
4210	8.2	0.0
4211	28.8	0.0
4213	37.2	0.0
4214	0.0	0.0
4215	21.7	0.0

	Vote_Data_Uncommitted_Percent_of_Votes
0	0.0
2	0.0
3	0.0
4	0.0
5	0.0
...	...
4210	0.0
4211	0.0
4213	0.0
4214	0.0
4215	0.0

[3592 rows x 18 columns]

1. We first read the dataset.
2. Drop the NA value.
3. Then check total vote number.
4. We calculate the average amount of vote of each states to drop the filter the low vote number state.
5. We filter the total vote number below the 100, which filter the extreme values out of the dataset.
6. Finally, Delete the col including the number, we would like to use the percentage for cluster.

Now, we have the percentage columns that only have the total vote number greater than 100,

“df_num”.

1.3 3. Basic Descriptive Analytics

1.3.1 3.1 For numerical attributes, calculate basic summary statistics about each attribute.

```
[12]: df_basic = df_num.describe()  
df_basic
```

```
[12]:      Vote_Data_Ben_Carson_Percent_of_Votes  \  
count                                3592.000000  
mean                                 2.699807  
std                                  3.589121  
min                                  0.000000  
25%                                 0.000000  
50%                                 0.000000  
75%                                 5.400000  
max                                  21.700000  
  
      Vote_Data_Bernie_Sanders_Percent_of_Votes  \  
count                                3592.000000  
mean                                 47.883404  
std                                  18.395268  
min                                  0.000000  
25%                                 36.875000  
50%                                 48.600000  
75%                                 56.800000  
max                                  100.000000  
  
      Vote_Data_Carly_Fiorina_Percent_of_Votes  \  
count                                3592.000000  
mean                                 0.067054  
std                                  0.481854  
min                                  0.000000  
25%                                 0.000000  
50%                                 0.000000  
75%                                 0.000000  
max                                  11.700000  
  
      Vote_Data_Christie_Percent_of_Votes  \  
count                                3592.000000  
mean                                 0.053931  
std                                  0.436933  
min                                  0.000000  
25%                                 0.000000  
50%                                 0.000000  
75%                                 0.000000
```

max 8.719532

Vote_Data_Donald_Trump_Percent_of_Votes \

count	3592.000000
mean	46.237583
std	15.930844
min	0.000000
25%	35.000000
50%	45.400000
75%	55.700000
max	91.500000

Vote_Data_Hillary_Clinton_Percent_of_Votes \

count	3592.000000
mean	49.293099
std	18.057093
min	0.000000
25%	40.000000
50%	48.650000
75%	59.800000
max	100.000000

Vote_Data_Jeb_Bush_Percent_of_Votes \

count	3592.000000
mean	0.192129
std	1.137126
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	12.100000

Vote_Data_John_Kasich_Percent_of_Votes \

count	3592.000000
mean	12.111225
std	10.649826
min	0.000000
25%	3.900000
50%	8.450000
75%	17.500000
max	63.900000

Vote_Data_Marco_Rubio_Percent_of_Votes \

count	3592.000000
mean	10.275768
std	9.123062
min	0.000000

25%	0.000000
50%	10.000000
75%	17.200000
max	62.700000

	Vote_Data_Martin_OMalley_Percent_of_Votes \
count	3592.000000
mean	0.022884
std	0.366343
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	13.200000

	Vote_Data_Mike_Huckabee_Percent_of_Votes \
count	3592.000000
mean	0.066676
std	0.479296
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	9.600000

	Vote_Data_No_Preference_Party \
count	3592.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
count	3592.000000
mean	0.063363
std	0.243077
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	3.000000

	Vote_Data_Rand_Paul_Percent_of_Votes \
count	3592.000000

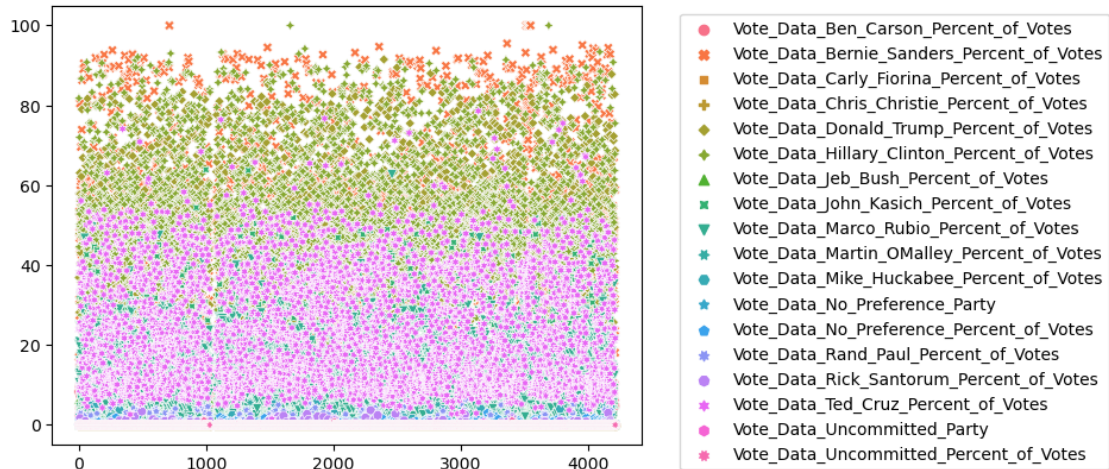
mean	0.093875
std	0.621383
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	9.600000

	Vote_Data_Rick_Santorum_Percent_of_Votes \
count	3592.000000
mean	0.027450
std	0.232522
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	7.300000

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
count	3592.000000	3592.0
mean	24.025030	0.0
std	13.759378	0.0
min	0.000000	0.0
25%	12.000000	0.0
50%	21.700000	0.0
75%	34.700000	0.0
max	78.600000	0.0

	Vote_Data_Uncommitted_Percent_of_Votes
count	3592.000000
mean	0.001253
std	0.036195
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.300000

```
[13]: sns.scatterplot(data=df_num)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



1.3.2 3.2 For any categorical attributes, count up the number of observations of each type.

```
[14]: df['Location_State'].value_counts().sort_values(ascending=False)
```

```
[14]: Massachusetts      346
      Texas              253
      Vermont            229
      Connecticut        169
      Georgia            159
      Virginia           133
      Kentucky           120
      Missouri           115
      Illinois           103
      North Carolina     100
      Iowa               99
      Tennessee          95
      Nebraska           93
      Indiana            92
      Ohio               88
      Michigan           83
      Mississippi        82
      Oklahoma           77
      Arkansas           74
      Wisconsin          72
      Alabama            67
      Florida            67
      Pennsylvania       67
      South Dakota       66
      Louisiana          64
```

New York	62
California	58
Montana	56
West Virginia	55
South Carolina	46
Idaho	44
Colorado	43
Rhode Island	41
Washington	39
Alaska	38
Oregon	36
New Mexico	33
Utah	29
Maryland	24
New Jersey	21
Nevada	16
Arizona	15
New Hampshire	10
Kansas	4
Hawaii	4
Delaware	3
Wyoming	1
Maine	1

Name: Location_State, dtype: int64

```
[15]: df['Location_County'].value_counts().sort_values(ascending=False)
```

```
[15]: Washington      28
      Jefferson      25
      Franklin       24
      Lincoln        22
      Jackson        21
      ..
      Seward         1
      Seymour        1
      Shackelford    1
      Shaftsbury     1
      Ziebach        1
      Name: Location_County, Length: 2215, dtype: int64
```

```
[16]: df['Vote_Data_Ben_Carson_Party'].value_counts().sort_values(ascending=False)
```

```
[16]: Republican      3592
      Name: Vote_Data_Ben_Carson_Party, dtype: int64
```

```
[17]: df['Vote_Data_Bernie_Sanders_Party'].value_counts().sort_values(ascending=False)
```

```
[17]: Democrat      3592
      Name: Vote_Data_Bernie_Sanders_Party, dtype: int64
```

```
[18]: df['Vote_Data_Rick_Santorum_Party'].value_counts().sort_values(ascending=False)
```

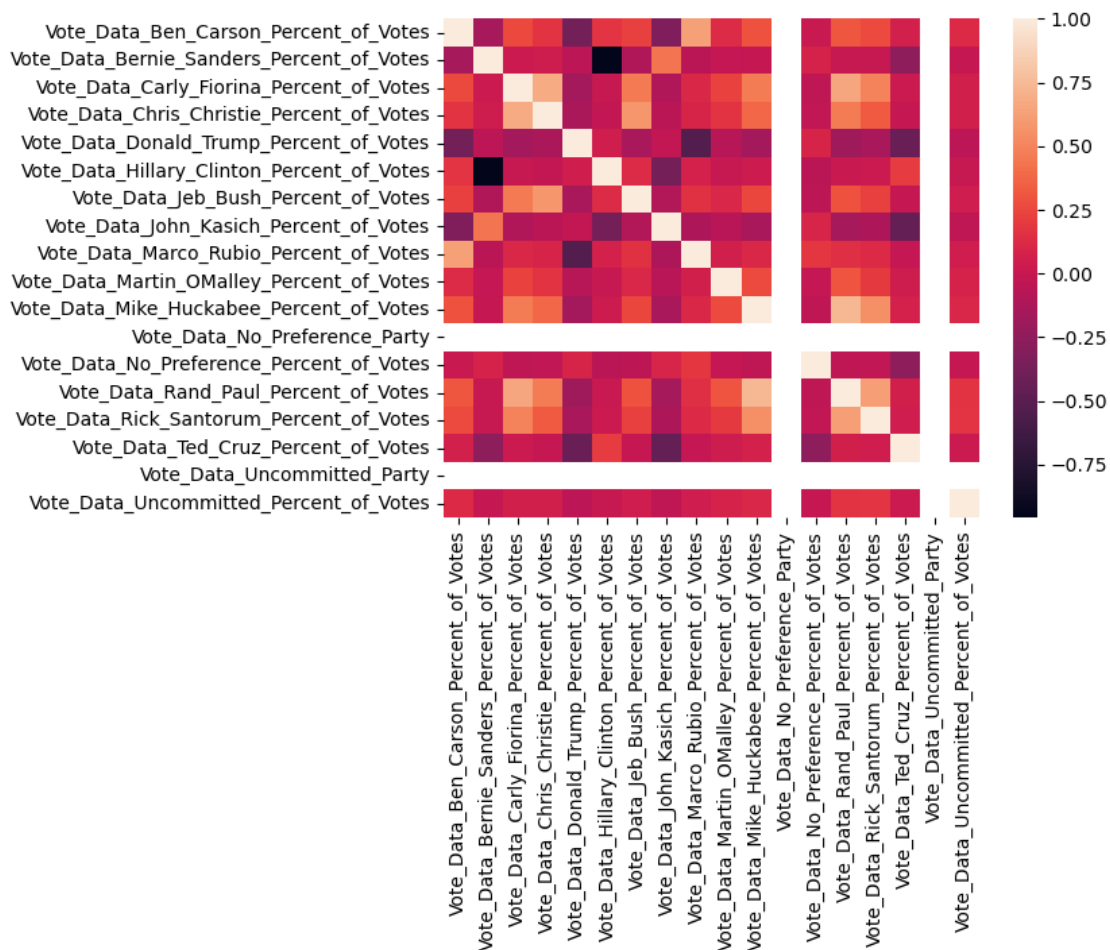
```
[18]: Republican      3592
      Name: Vote_Data_Rick_Santorum_Party, dtype: int64
```

```
[19]: df['Vote_Data_Ted_Cruz_Party'].value_counts().sort_values(ascending=False)
```

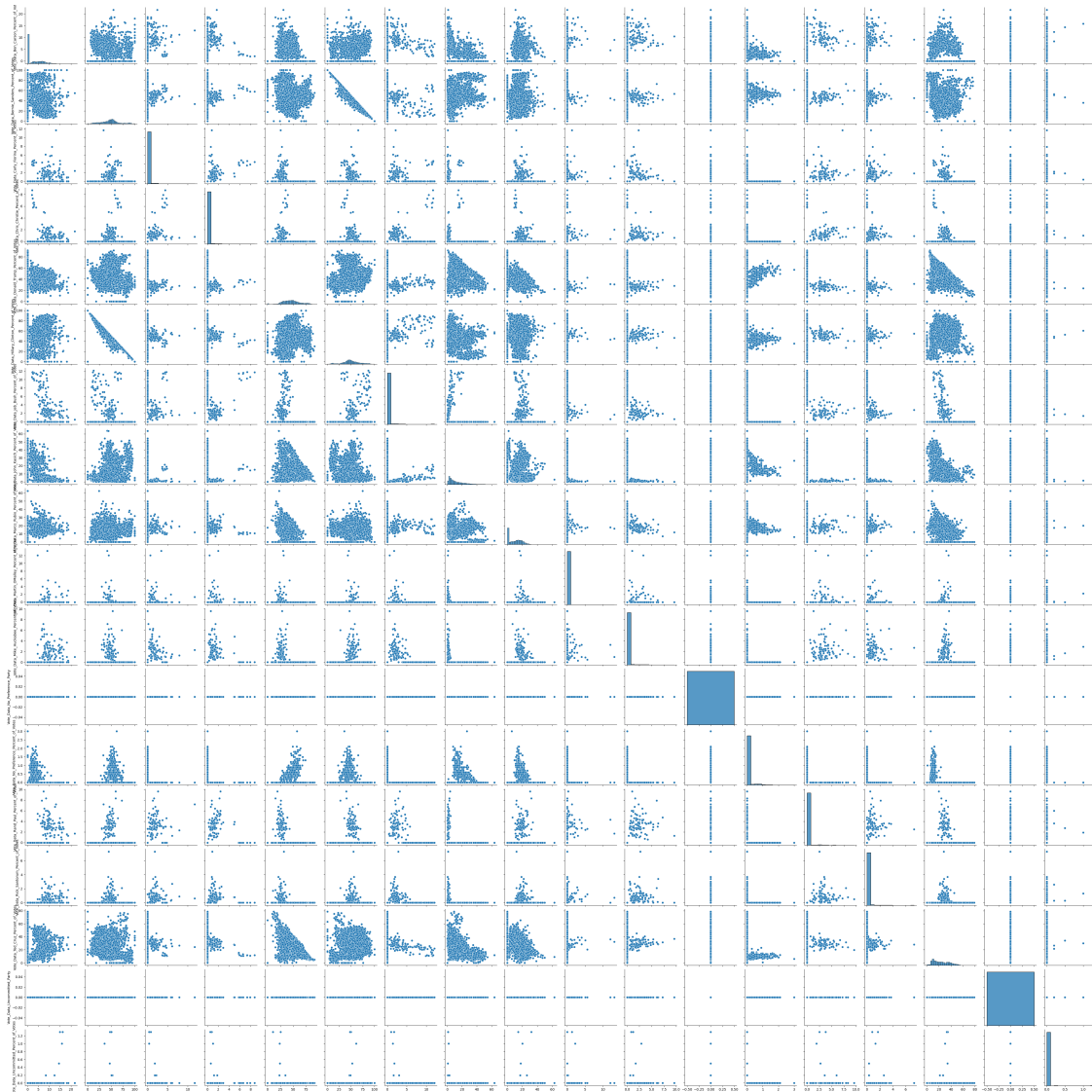
```
[19]: Republican      3592
      Name: Vote_Data_Ted_Cruz_Party, dtype: int64
```

1.3.3 3.3 Determine if there exist are any strong pairwise relationships between the variables in your dataset

```
[20]: sns.heatmap(df_num.corr())
      plt.show()
```



```
[21]: sns.pairplot(data = df)
plt.show()
```



From the above graph, we can see there are no strong relationship between most variable. However, the 'Vote_Data_Bernie_Sanders_Percent_of_Votes' and 'Vote_Data_Hillary_Clinton_Percent_of_Votes' have strong negative relation, which means if the extend of people want to vote for Bernie Sanders, the extend of Hillary Clinton will decrease.

1.4 4. Dataset Scaling Decisions

Scaling data using the Min-Max Scaler means scaling the data to a fixed range of values, usually $[0,1]$ or $[-1,1]$. The difference between the two scaling methods using Standard Scaler and Min-Max

Scaler is that the scaling range of the data is different: Standard Scaler scales the data to a normal distribution with a mean of 0 and a standard deviation of 1, while Min-Max Scaler scales the data to a specified minimum and maximum value range.

The distribution range of the data is different: If the distribution range of the data is large, using Standard Scaler may scale the data to a smaller range, resulting in the loss of some characteristic information of the data. While using Min-Max Scaler can scale the data to a specified range and keep more information about the data features.

Outliers in the data: If there are outliers in the data, using Standard Scaler may cause the scaling range of the data to be affected by the outliers, thus affecting the performance of the model. Using the Min-Max Scaler avoids this problem by scaling the outliers to a specified range.

Model requirements: Different models have different requirements for data scaling. For example, some models (e.g., SVM) are more sensitive to data scaling, while others (e.g., decision trees) are less sensitive to data scaling. Therefore, the needs of the model used need to be considered when choosing a data scaling method.

In general, the choice of which scaling method to use should be based on the specific data set and model. If the distribution of the data is relatively large or there are outliers, it is recommended to use the Min-Max Scaler; if the distribution of the data is closer to normal or the model is not sensitive to data scaling, the Standard Scaler can be used.

```
[22]: scale = StandardScaler()
      df_scale1 = scale.fit_transform(df_num)
      df_scale1
```

```
[22]: array([[ 1.56054152, -1.67911137, -0.13917705, ..., -0.00908819,
           0.          , -0.03461736],
       [-0.05567791,  0.29993386, -0.13917705, ..., -1.02671774,
           0.          , -0.03461736],
       [-0.75232422, -0.89619238, -0.13917705, ...,  1.0303477 ,
           0.          , -0.03461736],
       ...,
       [ 0.55737084, -1.3202735 , -0.13917705, ...,  0.95765988,
           0.          , -0.03461736],
       [-0.75232422, -1.61930506, -0.13917705, ..., -1.74632721,
           0.          , -0.03461736],
       [-0.75232422,  0.59896542, -0.13917705, ..., -0.16900141,
           0.          , -0.03461736]])
```

```
[23]: Z = pd.DataFrame(df_scale1, columns=df_num.columns)
      Z
```

```
[23]:      Vote_Data_Ben_Carson_Percent_of_Votes  \
0      1.560542
1     -0.055678
2     -0.752324
3      1.894932
4     -0.111410
```

```

...
3587 -0.752324
3588 -0.752324
3589 0.557371
3590 -0.752324
3591 -0.752324

Vote_Data_Bernie_Sanders_Percent_of_Votes \
0 -1.679111
1 0.299934
2 -0.896192
3 -1.113670
4 -0.058904
...
3587 0.174884
3588 -0.890755
3589 -1.320274
3590 -1.619305
3591 0.598965

Vote_Data_Carly_Fiorina_Percent_of_Votes \
0 -0.139177
1 -0.139177
2 -0.139177
3 -0.139177
4 -0.139177
...
3587 -0.139177
3588 -0.139177
3589 -0.139177
3590 -0.139177
3591 -0.139177

Vote_Data_Christie_Christie_Percent_of_Votes \
0 -0.123449
1 -0.123449
2 -0.123449
3 -0.123449
4 -0.123449
...
3587 -0.123449
3588 -0.123449
3589 -0.123449
3590 -0.123449
3591 -0.123449

```

```
Vote_Data_Donald_Trump_Percent_of_Votes \
```


0	-0.586214
1	0.732167
2	-0.109086
3	0.104367
4	-1.132400
...	...
3587	2.295390
3588	0.204815
3589	-0.422986
3590	-2.902798
3591	1.410192

	Vote_Data_Hillary_Clinton_Percent_of_Votes \
0	1.800480
1	-0.259940
2	0.244088
3	1.257681
4	0.194239
...	...
3587	-0.160242
3588	0.797964
3589	1.025053
3590	1.451538
3591	-0.453796

	Vote_Data_Jeb_Bush_Percent_of_Votes \
0	5.460023
1	-0.168983
2	-0.168983
3	-0.168983
4	-0.168983
...	...
3587	-0.168983
3588	-0.168983
3589	-0.168983
3590	-0.168983
3591	-0.168983

	Vote_Data_John_Kasich_Percent_of_Votes \
0	-0.733563
1	0.196160
2	-0.818083
3	-0.677216
4	1.914737
...	...
3587	-0.658433
3588	-0.583304

3589	-1.137381
3590	-1.137381
3591	-0.235833

	Vote_Data_Marco_Rubio_Percent_of_Votes \
0	1.087969
1	0.265763
2	0.035545
3	1.164709
4	1.603219
...	...
3587	-1.126508
3588	-1.126508
3589	0.276725
3590	-1.126508
3591	-1.126508

	Vote_Data_Martin_OMalley_Percent_of_Votes \
0	-0.062475
1	-0.062475
2	-0.062475
3	-0.062475
4	-0.062475
...	...
3587	-0.062475
3588	-0.062475
3589	-0.062475
3590	-0.062475
3591	-0.062475

	Vote_Data_Mike_Huckabee_Percent_of_Votes	Vote_Data_No_Preference_Party \
0	-0.139132	0.0
1	-0.139132	0.0
2	-0.139132	0.0
3	-0.139132	0.0
4	-0.139132	0.0
...	...	...
3587	-0.139132	0.0
3588	-0.139132	0.0
3589	-0.139132	0.0
3590	-0.139132	0.0
3591	-0.139132	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
0	-0.260707
1	4.676696
2	-0.260707

3	-0.260707
4	0.562193
...	...
3587	-0.260707
3588	-0.260707
3589	-0.260707
3590	-0.260707
3591	-0.260707

	Vote_Data_Rand_Paul_Percent_of_Votes \
0	-0.151096
1	-0.151096
2	-0.151096
3	-0.151096
4	-0.151096
...	...
3587	-0.151096
3588	-0.151096
3589	-0.151096
3590	-0.151096
3591	-0.151096

	Vote_Data_Rick_Santorum_Percent_of_Votes \
0	-0.118069
1	-0.118069
2	-0.118069
3	-0.118069
4	-0.118069
...	...
3587	-0.118069
3588	-0.118069
3589	-0.118069
3590	-0.118069
3591	-0.118069

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	-0.009088	0.0
1	-1.026718	0.0
2	1.030348	0.0
3	-0.590591	0.0
4	-1.113943	0.0
...	...	...
3587	-1.150287	0.0
3588	0.347082	0.0
3589	0.957660	0.0
3590	-1.746327	0.0
3591	-0.169001	0.0

	Vote_Data_Uncommitted_Percent_of_Votes
0	-0.034617
1	-0.034617
2	-0.034617
3	-0.034617
4	-0.034617
...	...
3587	-0.034617
3588	-0.034617
3589	-0.034617
3590	-0.034617
3591	-0.034617

[3592 rows x 18 columns]

```
[24]: df['Location_State']
```

```
[24]: 0      South Carolina
      2      Massachusetts
      3      Louisiana
      4      Virginia
      5      Massachusetts
      ...
      4210     California
      4211     Arizona
      4213     Texas
      4214     Texas
      4215     South Dakota
      Name: Location_State, Length: 3592, dtype: object
```

```
[25]: df.reset_index(inplace=True)
      C = df['Location_State']
      frames = [C,Z]
      df_label_standard = pd.concat(frames,axis = 1)
      df_label_standard
```

	Location_State	Vote_Data_Ben_Carson_Percent_of_Votes \
0	South Carolina	1.560542
1	Massachusetts	-0.055678
2	Louisiana	-0.752324
3	Virginia	1.894932
4	Massachusetts	-0.111410
...	...	...
3587	California	-0.752324
3588	Arizona	-0.752324
3589	Texas	0.557371

3590	Texas	-0.752324
3591	South Dakota	-0.752324

	Vote_Data_Bernie_Sanders_Percent_of_Votes \
0	-1.679111
1	0.299934
2	-0.896192
3	-1.113670
4	-0.058904
...	...
3587	0.174884
3588	-0.890755
3589	-1.320274
3590	-1.619305
3591	0.598965

	Vote_Data_Carly_Fiorina_Percent_of_Votes \
0	-0.139177
1	-0.139177
2	-0.139177
3	-0.139177
4	-0.139177
...	...
3587	-0.139177
3588	-0.139177
3589	-0.139177
3590	-0.139177
3591	-0.139177

	Vote_Data_Chris_Christie_Percent_of_Votes \
0	-0.123449
1	-0.123449
2	-0.123449
3	-0.123449
4	-0.123449
...	...
3587	-0.123449
3588	-0.123449
3589	-0.123449
3590	-0.123449
3591	-0.123449

	Vote_Data_Donald_Trump_Percent_of_Votes \
0	-0.586214
1	0.732167
2	-0.109086
3	0.104367

4	-1.132400
...	...
3587	2.295390
3588	0.204815
3589	-0.422986
3590	-2.902798
3591	1.410192

	Vote_Data_Hillary_Clinton_Percent_of_Votes \
0	1.800480
1	-0.259940
2	0.244088
3	1.257681
4	0.194239
...	...
3587	-0.160242
3588	0.797964
3589	1.025053
3590	1.451538
3591	-0.453796

	Vote_Data_Jeb_Bush_Percent_of_Votes \
0	5.460023
1	-0.168983
2	-0.168983
3	-0.168983
4	-0.168983
...	...
3587	-0.168983
3588	-0.168983
3589	-0.168983
3590	-0.168983
3591	-0.168983

	Vote_Data_John_Kasich_Percent_of_Votes \
0	-0.733563
1	0.196160
2	-0.818083
3	-0.677216
4	1.914737
...	...
3587	-0.658433
3588	-0.583304
3589	-1.137381
3590	-1.137381
3591	-0.235833

	Vote_Data_Marco_Rubio_Percent_of_Votes \
0	1.087969
1	0.265763
2	0.035545
3	1.164709
4	1.603219
...	...
3587	-1.126508
3588	-1.126508
3589	0.276725
3590	-1.126508
3591	-1.126508

	Vote_Data_Martin_OMalley_Percent_of_Votes \
0	-0.062475
1	-0.062475
2	-0.062475
3	-0.062475
4	-0.062475
...	...
3587	-0.062475
3588	-0.062475
3589	-0.062475
3590	-0.062475
3591	-0.062475

	Vote_Data_Mike_Huckabee_Percent_of_Votes	Vote_Data_No_Preference_Party \
0	-0.139132	0.0
1	-0.139132	0.0
2	-0.139132	0.0
3	-0.139132	0.0
4	-0.139132	0.0
...	...	...
3587	-0.139132	0.0
3588	-0.139132	0.0
3589	-0.139132	0.0
3590	-0.139132	0.0
3591	-0.139132	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
0	-0.260707
1	4.676696
2	-0.260707
3	-0.260707
4	0.562193
...	...
3587	-0.260707

3588	-0.260707
3589	-0.260707
3590	-0.260707
3591	-0.260707

	Vote_Data_Rand_Paul_Percent_of_Votes \
0	-0.151096
1	-0.151096
2	-0.151096
3	-0.151096
4	-0.151096
...	...
3587	-0.151096
3588	-0.151096
3589	-0.151096
3590	-0.151096
3591	-0.151096

	Vote_Data_Rick_Santorum_Percent_of_Votes \
0	-0.118069
1	-0.118069
2	-0.118069
3	-0.118069
4	-0.118069
...	...
3587	-0.118069
3588	-0.118069
3589	-0.118069
3590	-0.118069
3591	-0.118069

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	-0.009088	0.0
1	-1.026718	0.0
2	1.030348	0.0
3	-0.590591	0.0
4	-1.113943	0.0
...	...	...
3587	-1.150287	0.0
3588	0.347082	0.0
3589	0.957660	0.0
3590	-1.746327	0.0
3591	-0.169001	0.0

	Vote_Data_Uncommitted_Percent_of_Votes
0	-0.034617
1	-0.034617

2	-0.034617
3	-0.034617
4	-0.034617
...	...
3587	-0.034617
3588	-0.034617
3589	-0.034617
3590	-0.034617
3591	-0.034617

[3592 rows x 19 columns]

```
[26]: scaler = MinMaxScaler()
df_scale = pd.DataFrame(scaler.fit_transform(df_num), columns=df_num.columns,);
df_num =df_scale.copy()
df_scale
```

```
[26]:      Vote_Data_Ben_Carson_Percent_of_Votes  \
0      0.382488
1      0.115207
2      0.000000
3      0.437788
4      0.105991
...      ...
3587    0.000000
3588    0.000000
3589    0.216590
3590    0.000000
3591    0.000000
```

```
      Vote_Data_Bernie_Sanders_Percent_of_Votes  \
0      0.170
1      0.534
2      0.314
3      0.274
4      0.468
...      ...
3587    0.511
3588    0.315
3589    0.236
3590    0.181
3591    0.589
```

```
      Vote_Data_Carly_Fiorina_Percent_of_Votes  \
0      0.0
1      0.0
2      0.0
```

3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Chris_Christie_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Donald_Trump_Percent_of_Votes \
0	0.403279
1	0.632787
2	0.486339
3	0.523497
4	0.308197
...	...
3587	0.904918
3588	0.540984
3589	0.431694
3590	0.000000
3591	0.750820

	Vote_Data_Hillary_Clinton_Percent_of_Votes \
0	0.818
1	0.446
2	0.537
3	0.720
4	0.528
...	...
3587	0.464
3588	0.637
3589	0.678
3590	0.755
3591	0.411

	Vote_Data_Jeb_Bush_Percent_of_Votes \
0	0.528926
1	0.000000
2	0.000000
3	0.000000
4	0.000000
...	...
3587	0.000000
3588	0.000000
3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_John_Kasich_Percent_of_Votes \
0	0.067293
1	0.222222
2	0.053208
3	0.076682
4	0.508607
...	...
3587	0.079812
3588	0.092332
3589	0.000000
3590	0.000000
3591	0.150235

	Vote_Data_Marco_Rubio_Percent_of_Votes \
0	0.322169
1	0.202552
2	0.169059
3	0.333333
4	0.397129
...	...
3587	0.000000
3588	0.000000
3589	0.204147
3590	0.000000
3591	0.000000

	Vote_Data_Martin_OMalley_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...

3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Mike_Huckabee_Percent_of_Votes	Vote_Data_No_Preference_Party \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
...	...	...
3587	0.0	0.0
3588	0.0	0.0
3589	0.0	0.0
3590	0.0	0.0
3591	0.0	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
0	0.000000
1	0.400000
2	0.000000
3	0.000000
4	0.066667
...	...
3587	0.000000
3588	0.000000
3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_Rand_Paul_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Rick_Santorum_Percent_of_Votes \
0	0.0

1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	0.304071	0.0
1	0.125954	0.0
2	0.486005	0.0
3	0.202290	0.0
4	0.110687	0.0
...	...	...
3587	0.104326	0.0
3588	0.366412	0.0
3589	0.473282	0.0
3590	0.000000	0.0
3591	0.276081	0.0

	Vote_Data_Uncommitted_Percent_of_Votes
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

[3592 rows x 18 columns]

```
[27]: X = pd.DataFrame(df_scale, columns=df_num.columns)
X
```

```
[27]: Vote_Data_Ben_Carson_Percent_of_Votes \
0      0.382488
1      0.115207
2      0.000000
3      0.437788
```

4	0.105991
...	...
3587	0.000000
3588	0.000000
3589	0.216590
3590	0.000000
3591	0.000000

	Vote_Data_Bernie_Sanders_Percent_of_Votes	\
0	0.170	
1	0.534	
2	0.314	
3	0.274	
4	0.468	
...	...	
3587	0.511	
3588	0.315	
3589	0.236	
3590	0.181	
3591	0.589	

	Vote_Data_Carly_Fiorina_Percent_of_Votes	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	
...	...	
3587	0.0	
3588	0.0	
3589	0.0	
3590	0.0	
3591	0.0	

	Vote_Data_Chris_Christie_Percent_of_Votes	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	
...	...	
3587	0.0	
3588	0.0	
3589	0.0	
3590	0.0	
3591	0.0	

	Vote_Data_Donald_Trump_Percent_of_Votes \
0	0.403279
1	0.632787
2	0.486339
3	0.523497
4	0.308197
...	...
3587	0.904918
3588	0.540984
3589	0.431694
3590	0.000000
3591	0.750820

	Vote_Data_Hillary_Clinton_Percent_of_Votes \
0	0.818
1	0.446
2	0.537
3	0.720
4	0.528
...	...
3587	0.464
3588	0.637
3589	0.678
3590	0.755
3591	0.411

	Vote_Data_Jeb_Bush_Percent_of_Votes \
0	0.528926
1	0.000000
2	0.000000
3	0.000000
4	0.000000
...	...
3587	0.000000
3588	0.000000
3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_John_Kasich_Percent_of_Votes \
0	0.067293
1	0.222222
2	0.053208
3	0.076682
4	0.508607
...	...
3587	0.079812

3588	0.092332
3589	0.000000
3590	0.000000
3591	0.150235

	Vote_Data_Marco_Rubio_Percent_of_Votes \
0	0.322169
1	0.202552
2	0.169059
3	0.333333
4	0.397129
...	...
3587	0.000000
3588	0.000000
3589	0.204147
3590	0.000000
3591	0.000000

	Vote_Data_Martin_OMalley_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Mike_Huckabee_Percent_of_Votes	Vote_Data_No_Preference_Party \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
...	...	...
3587	0.0	0.0
3588	0.0	0.0
3589	0.0	0.0
3590	0.0	0.0
3591	0.0	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
0	0.000000
1	0.400000

2	0.000000
3	0.000000
4	0.066667
...	...
3587	0.000000
3588	0.000000
3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_Rand_Paul_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Rick_Santorum_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	0.304071	0.0
1	0.125954	0.0
2	0.486005	0.0
3	0.202290	0.0
4	0.110687	0.0
...	...	...
3587	0.104326	0.0
3588	0.366412	0.0
3589	0.473282	0.0
3590	0.000000	0.0

3591	0.276081	0.0
------	----------	-----

	Vote_Data_Uncommitted_Percent_of_Votes
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

[3592 rows x 18 columns]

```
[28]: C = df['Location_State']
frames = [C,X]
df_label = pd.concat(frames,axis = 1)
df_label
```

	Location_State	Vote_Data_Ben_Carson_Percent_of_Votes	\
0	South Carolina	0.382488	
1	Massachusetts	0.115207	
2	Louisiana	0.000000	
3	Virginia	0.437788	
4	Massachusetts	0.105991	
...	...	...	
3587	California	0.000000	
3588	Arizona	0.000000	
3589	Texas	0.216590	
3590	Texas	0.000000	
3591	South Dakota	0.000000	

	Vote_Data_Bernie_Sanders_Percent_of_Votes	\
0	0.170	
1	0.534	
2	0.314	
3	0.274	
4	0.468	
...	...	
3587	0.511	
3588	0.315	
3589	0.236	
3590	0.181	
3591	0.589	

	Vote_Data_Carly_Fiorina_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Chris_Christie_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Donald_Trump_Percent_of_Votes \
0	0.403279
1	0.632787
2	0.486339
3	0.523497
4	0.308197
...	...
3587	0.904918
3588	0.540984
3589	0.431694
3590	0.000000
3591	0.750820

	Vote_Data_Hillary_Clinton_Percent_of_Votes \
0	0.818
1	0.446
2	0.537
3	0.720
4	0.528
...	...

3587	0.464
3588	0.637
3589	0.678
3590	0.755
3591	0.411

	Vote_Data_Jeb_Bush_Percent_of_Votes \
0	0.528926
1	0.000000
2	0.000000
3	0.000000
4	0.000000
...	...
3587	0.000000
3588	0.000000
3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_John_Kasich_Percent_of_Votes \
0	0.067293
1	0.222222
2	0.053208
3	0.076682
4	0.508607
...	...
3587	0.079812
3588	0.092332
3589	0.000000
3590	0.000000
3591	0.150235

	Vote_Data_Marco_Rubio_Percent_of_Votes \
0	0.322169
1	0.202552
2	0.169059
3	0.333333
4	0.397129
...	...
3587	0.000000
3588	0.000000
3589	0.204147
3590	0.000000
3591	0.000000

	Vote_Data_Martin_OMalley_Percent_of_Votes \
0	0.0

1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Mike_Huckabee_Percent_of_Votes	Vote_Data_No_Preference_Party \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
...	...	...
3587	0.0	0.0
3588	0.0	0.0
3589	0.0	0.0
3590	0.0	0.0
3591	0.0	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
0	0.000000
1	0.400000
2	0.000000
3	0.000000
4	0.066667
...	...
3587	0.000000
3588	0.000000
3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_Rand_Paul_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0

```

3590          0.0
3591          0.0

```

```

Vote_Data_Rick_Santorum_Percent_of_Votes \
0          0.0
1          0.0
2          0.0
3          0.0
4          0.0
...
3587      ...
3587          0.0
3588          0.0
3589          0.0
3590          0.0
3591          0.0

```

```

Vote_Data_Ted_Cruz_Percent_of_Votes  Vote_Data_Uncommitted_Party \
0          0.304071          0.0
1          0.125954          0.0
2          0.486005          0.0
3          0.202290          0.0
4          0.110687          0.0
...
3587      ...
3587          0.104326          0.0
3588          0.366412          0.0
3589          0.473282          0.0
3590          0.000000          0.0
3591          0.276081          0.0

```

```

Vote_Data_Uncommitted_Percent_of_Votes
0          0.0
1          0.0
2          0.0
3          0.0
4          0.0
...
3587      ...
3587          0.0
3588          0.0
3589          0.0
3590          0.0
3591          0.0

```

```
[3592 rows x 19 columns]
```

```

[29]: df_cata = df.select_dtypes(include=['object', 'category'])
df_cata = [df_cata,X]
df_cata = pd.concat(df_cata,axis = 1)

```

```
df_cata = df_cata.drop(['Location_County'],axis = 1)
df_cata.head()
```

```
[29]: Location_State Location_State_Abbreviation Vote_Data_Ben_Carson_Party \
0 South Carolina SC Republican
1 Massachusetts MA Republican
2 Louisiana LA Republican
3 Virginia VA Republican
4 Massachusetts MA Republican

Vote_Data_Bernie_Sanders_Party Vote_Data_Carly_Fiorina_Party \
0 Democrat Republican
1 Democrat Republican
2 Democrat Republican
3 Democrat Republican
4 Democrat Republican

Vote_Data_Chris_Christie_Party Vote_Data_Donald_Trump_Party \
0 Republican Republican
1 Republican Republican
2 Republican Republican
3 Republican Republican
4 Republican Republican

Vote_Data_Hillary_Clinton_Party Vote_Data_Jeb_Bush_Party \
0 Democrat Republican
1 Democrat Republican
2 Democrat Republican
3 Democrat Republican
4 Democrat Republican

Vote_Data_John_Kasich_Party ... Vote_Data_Marco_Rubio_Percent_of_Votes \
0 Republican ... 0.322169
1 Republican ... 0.202552
2 Republican ... 0.169059
3 Republican ... 0.333333
4 Republican ... 0.397129

Vote_Data_Martin_OMalley_Percent_of_Votes \
0 0.0
1 0.0
2 0.0
3 0.0
4 0.0

Vote_Data_Mike_Huckabee_Percent_of_Votes Vote_Data_No_Preference_Party \
0 0.0 0.0
```

1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
0	0.000000
1	0.400000
2	0.000000
3	0.000000
4	0.066667

	Vote_Data_Rand_Paul_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

	Vote_Data_Rick_Santorum_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	0.304071	0.0
1	0.125954	0.0
2	0.486005	0.0
3	0.202290	0.0
4	0.110687	0.0

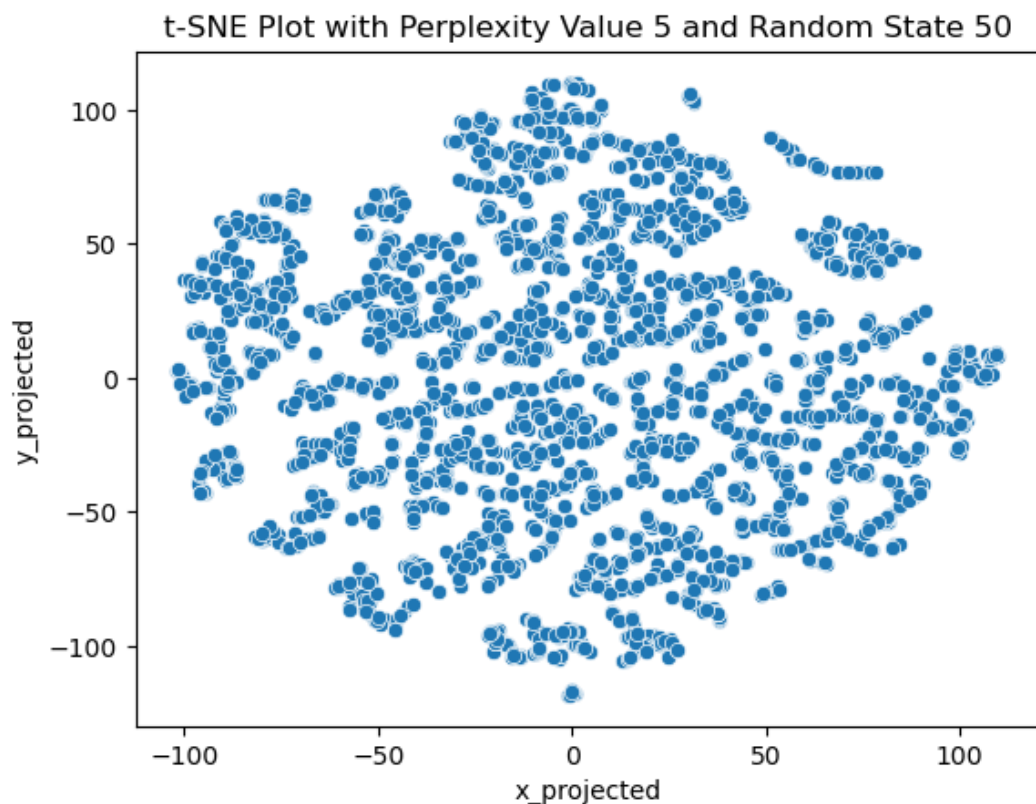
	Vote_Data_Uncommitted_Percent_of_Votes
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

[5 rows x 34 columns]

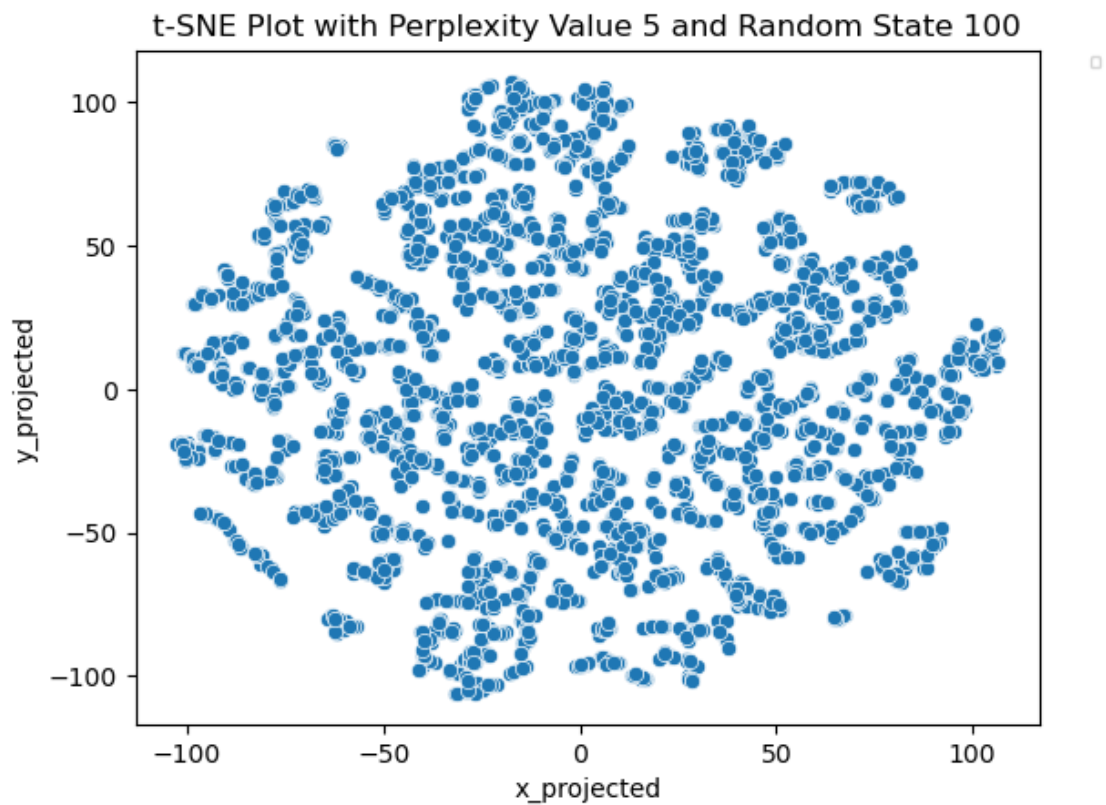
1.5 5. Clusterability and Clustering Structure Questions

```
[28]: for perp in [5,10, 20, 30, 40, 50]:  
      for rs in [50,100]:  
          tsne = TSNE(n_components=2, perplexity=perp, random_state=rs)  
          data_tsne = tsne.fit_transform(X)  
          df_tsne = pd.DataFrame(data_tsne, columns=['x_projected',  
          ↪ 'y_projected'])  
          df_combo = pd.concat([df_label, df_tsne], axis=1)  
          sns.scatterplot(x='x_projected',y='y_projected', data=df_combo)  
          plt.title('t-SNE Plot with Perplexity Value %s and Random State %s'  
          ↪%(perp, rs))  
          plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)  
          plt.show()  
      print('-----')
```

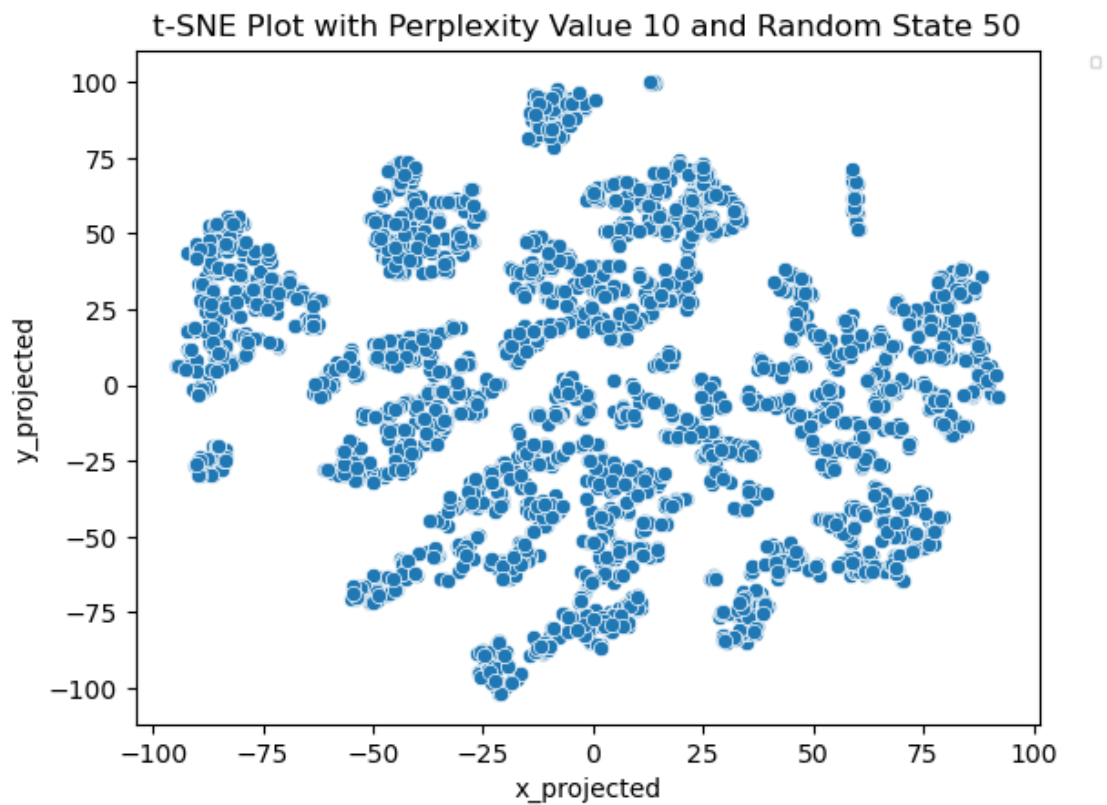
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



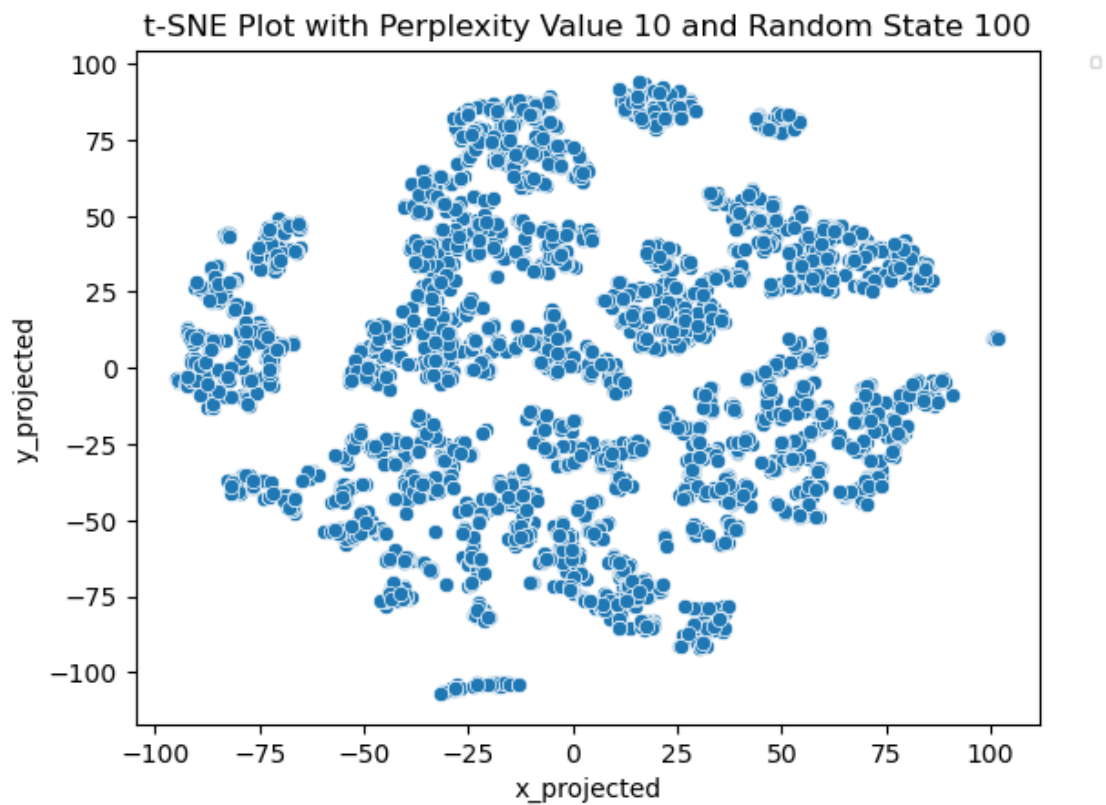
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



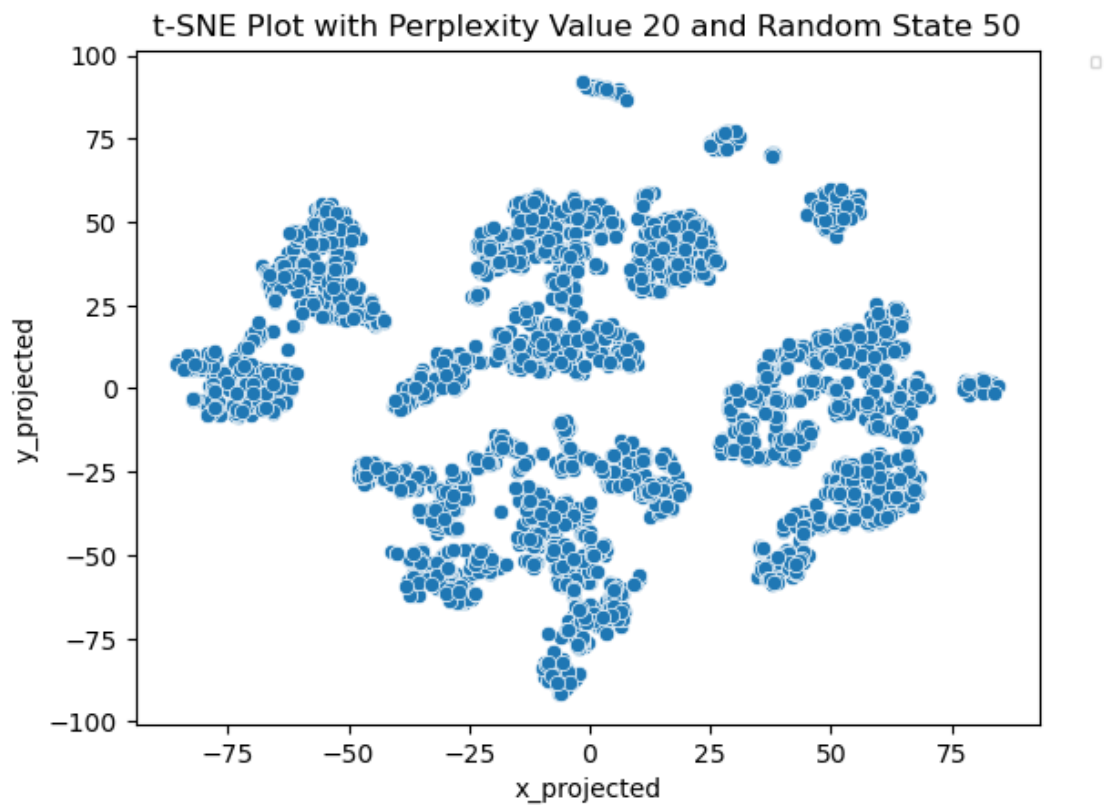
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



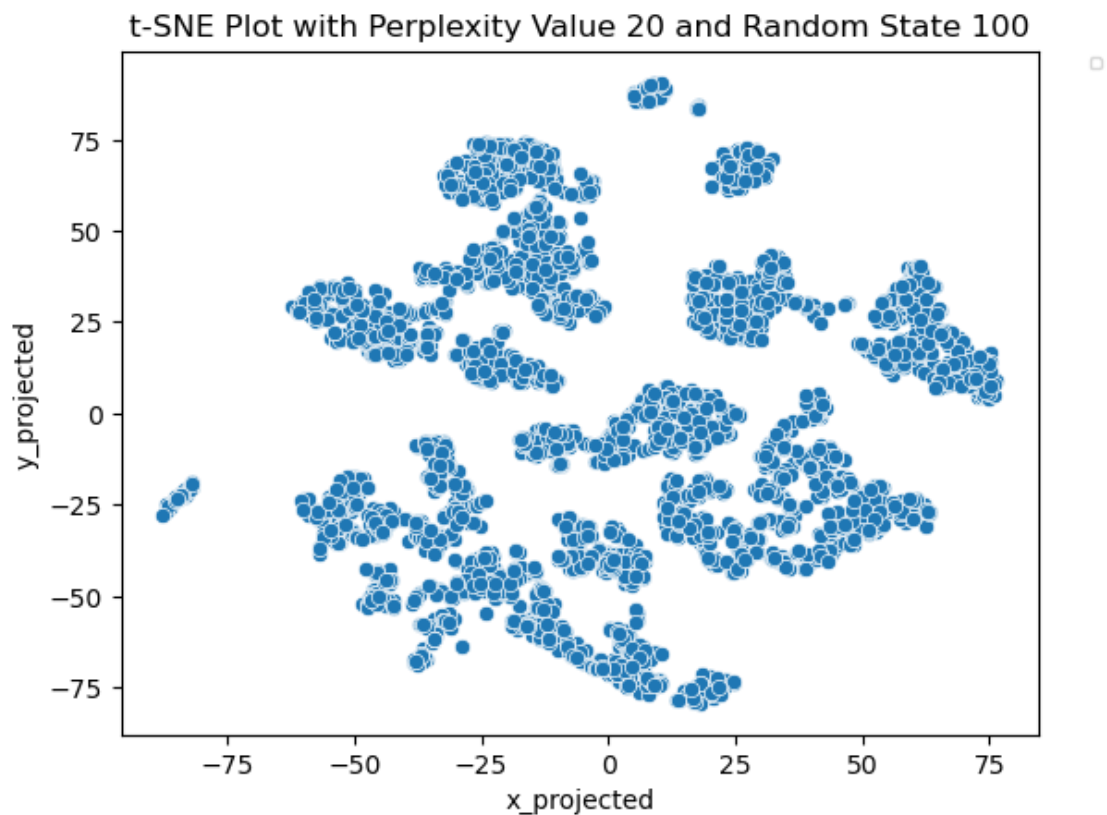
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



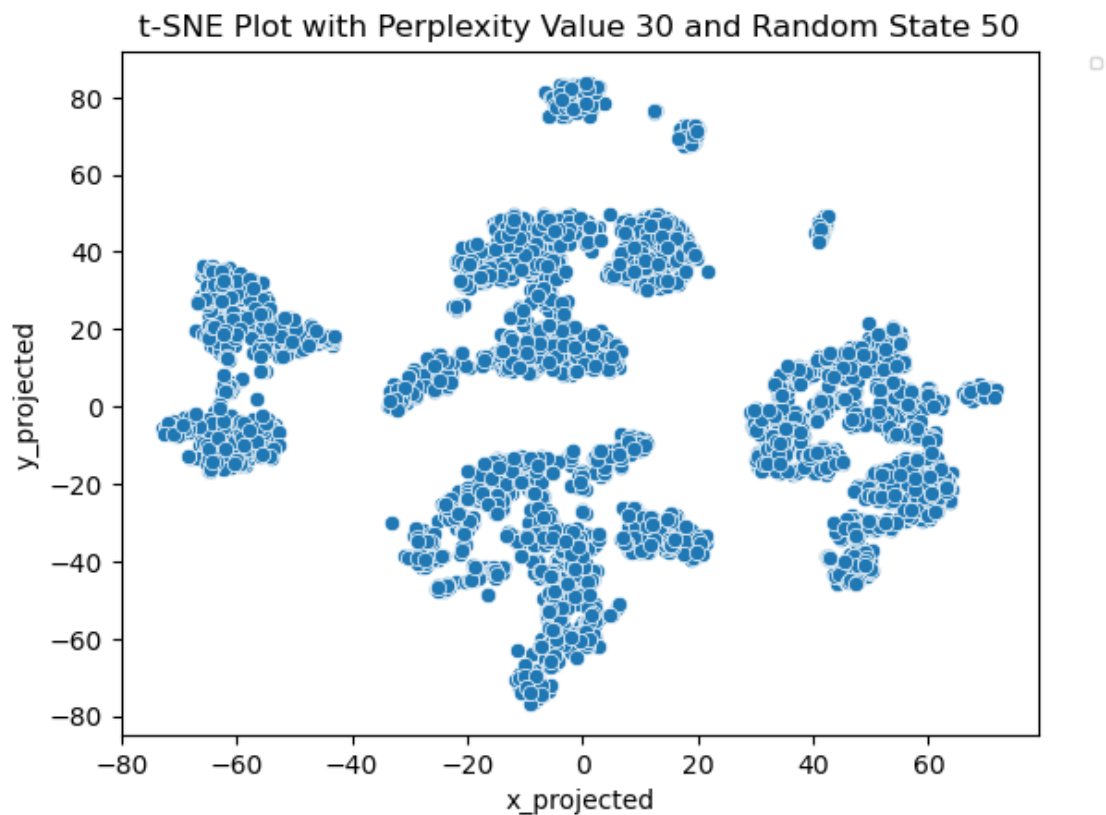
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



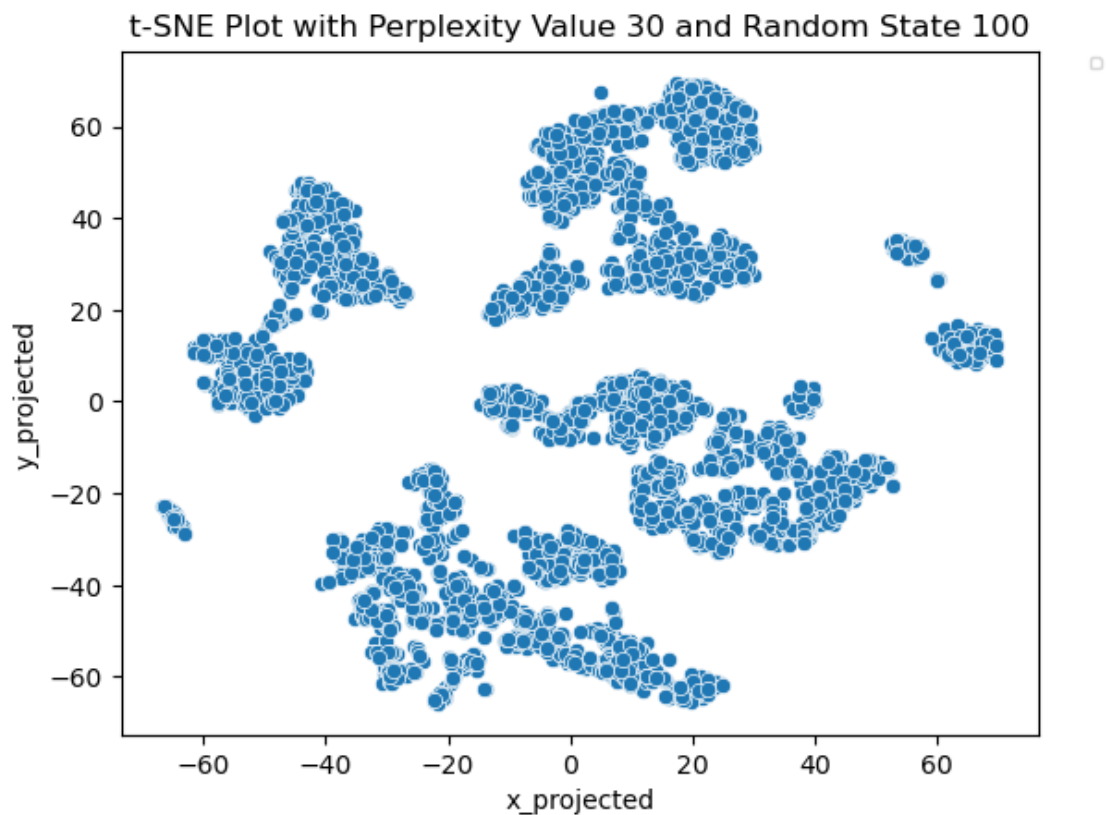
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when `legend()` is called with no argument.



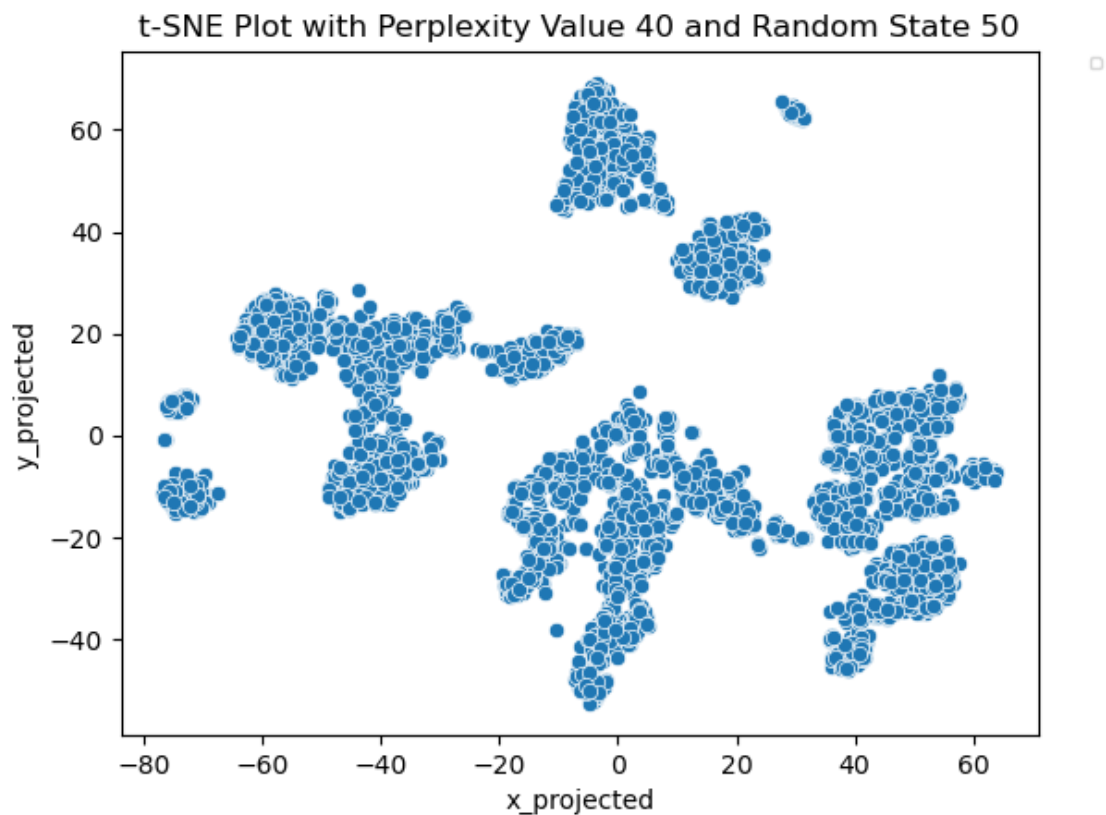
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



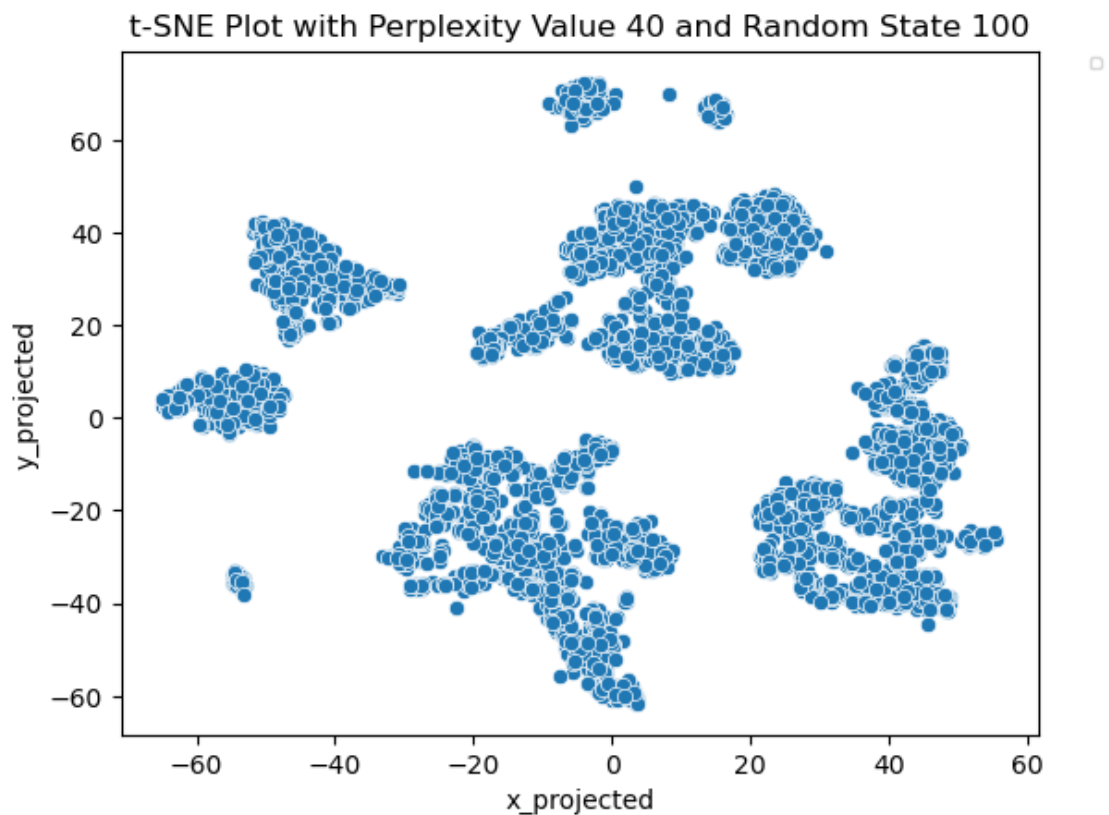
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



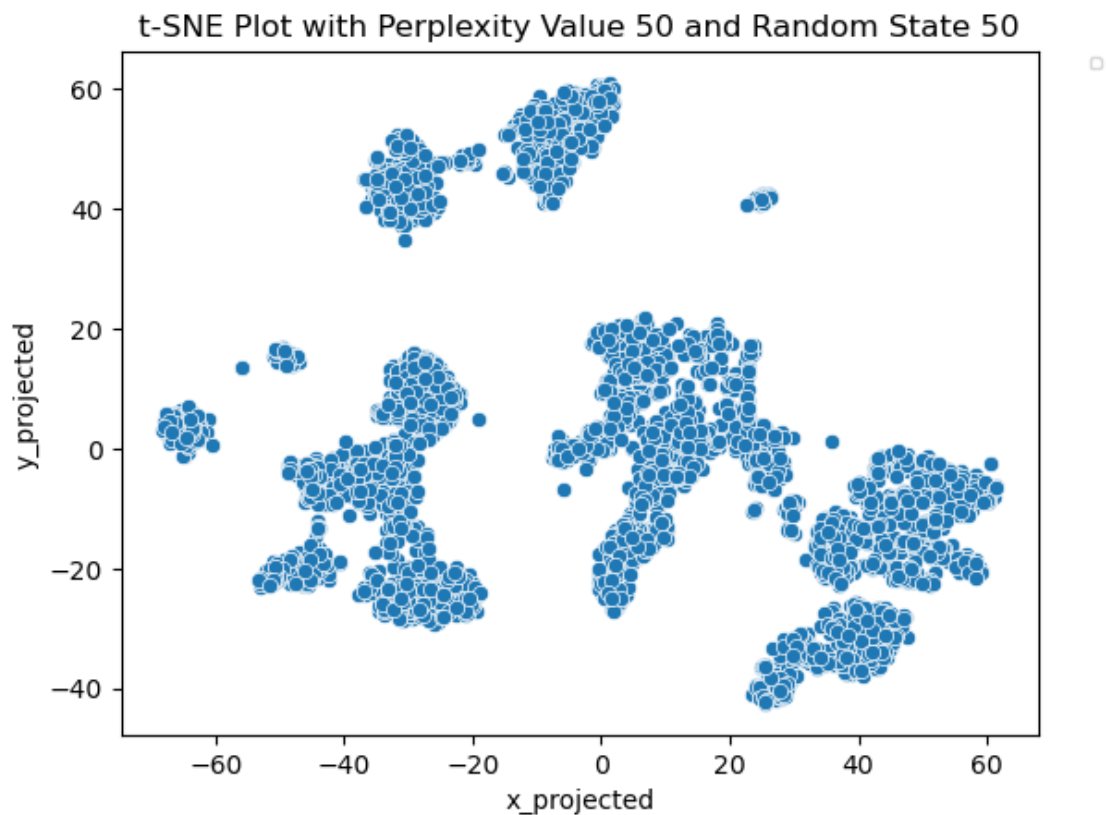
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



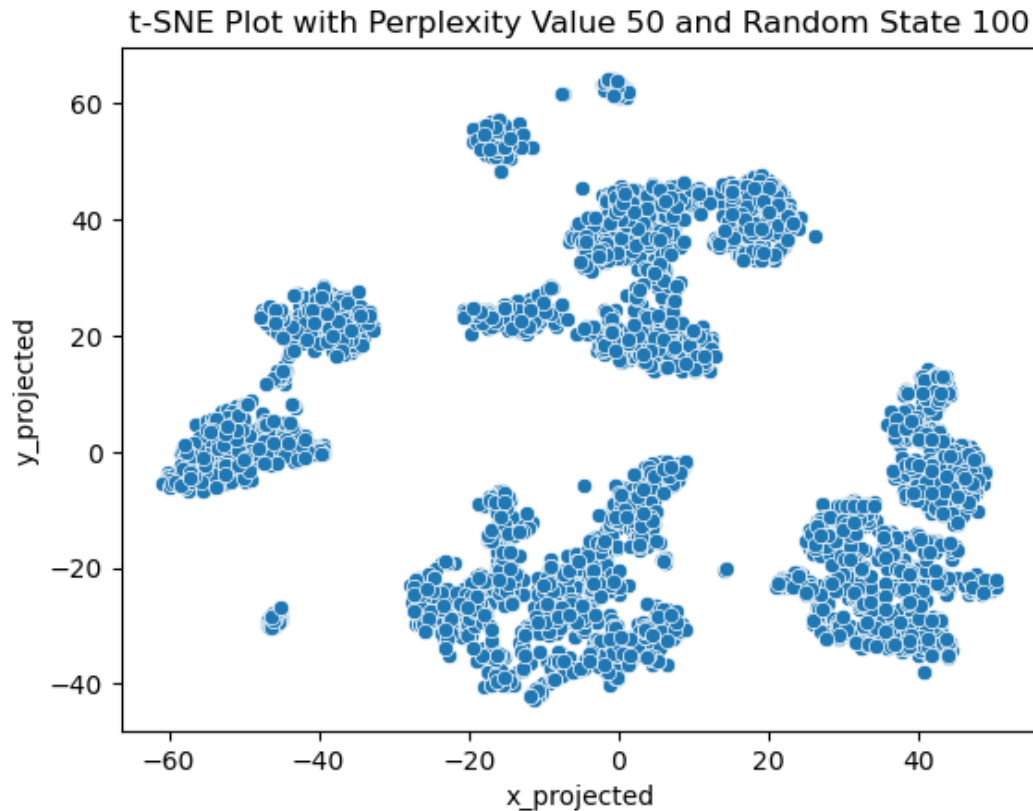
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when `legend()` is called with no argument.



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.

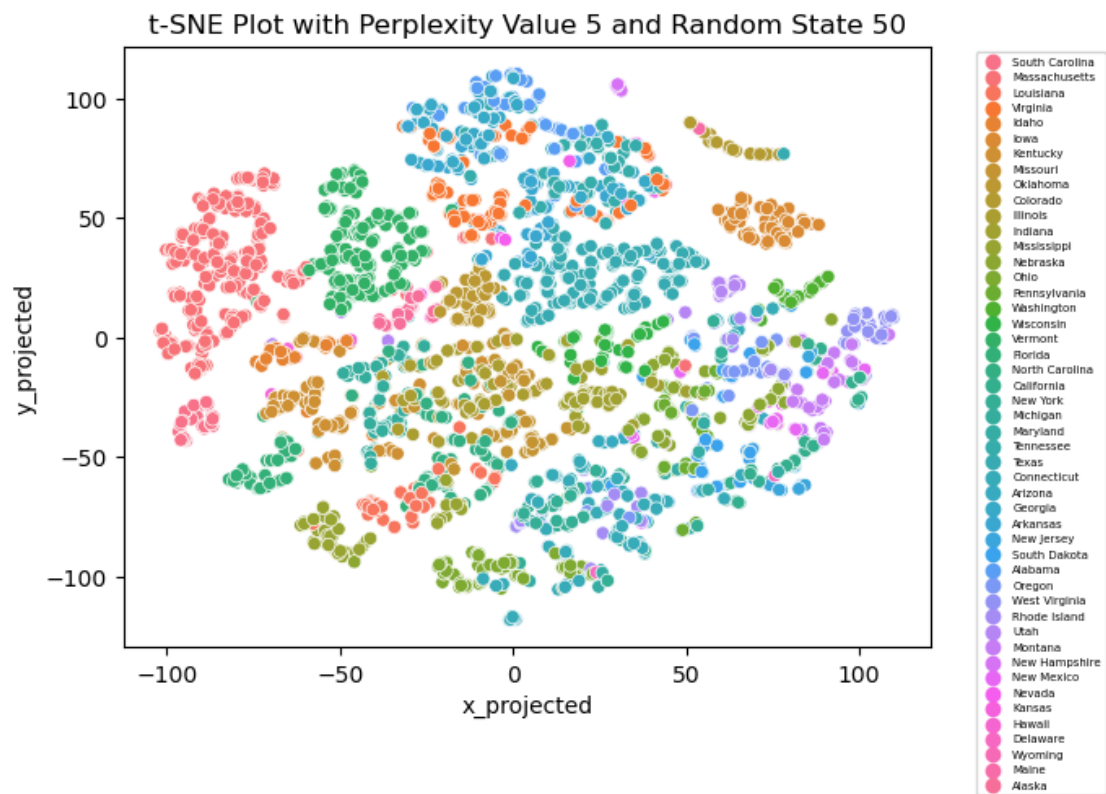


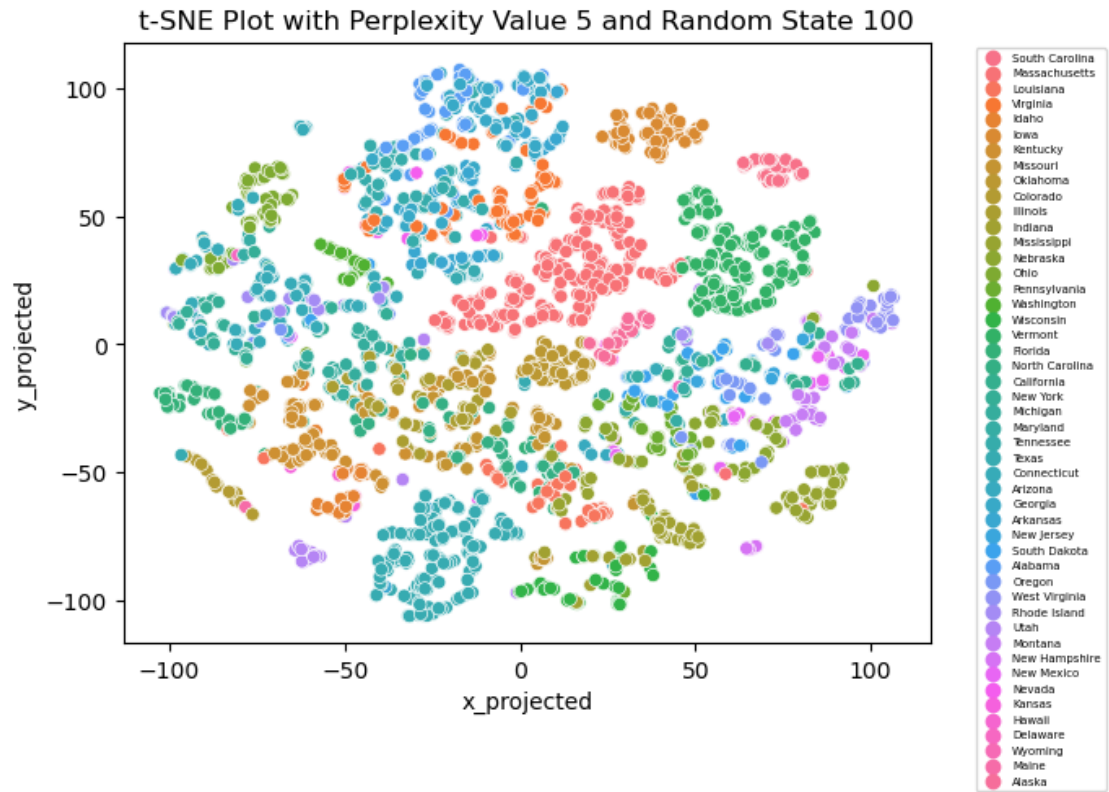
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.

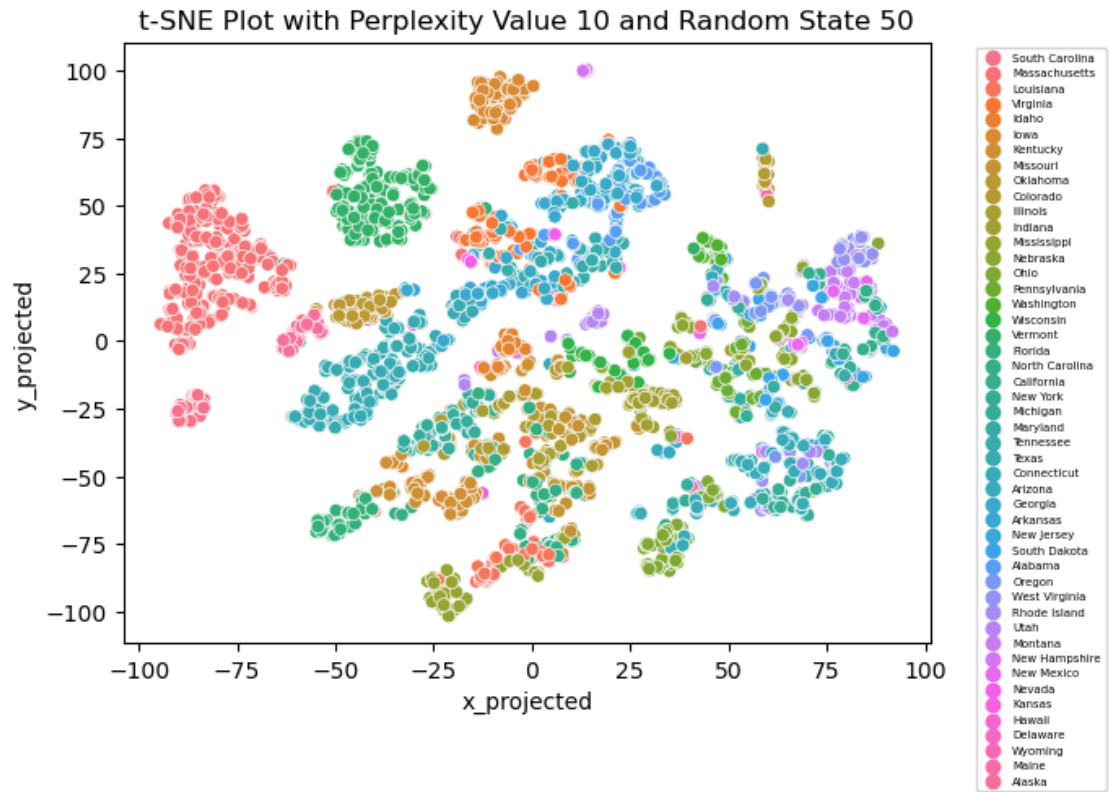


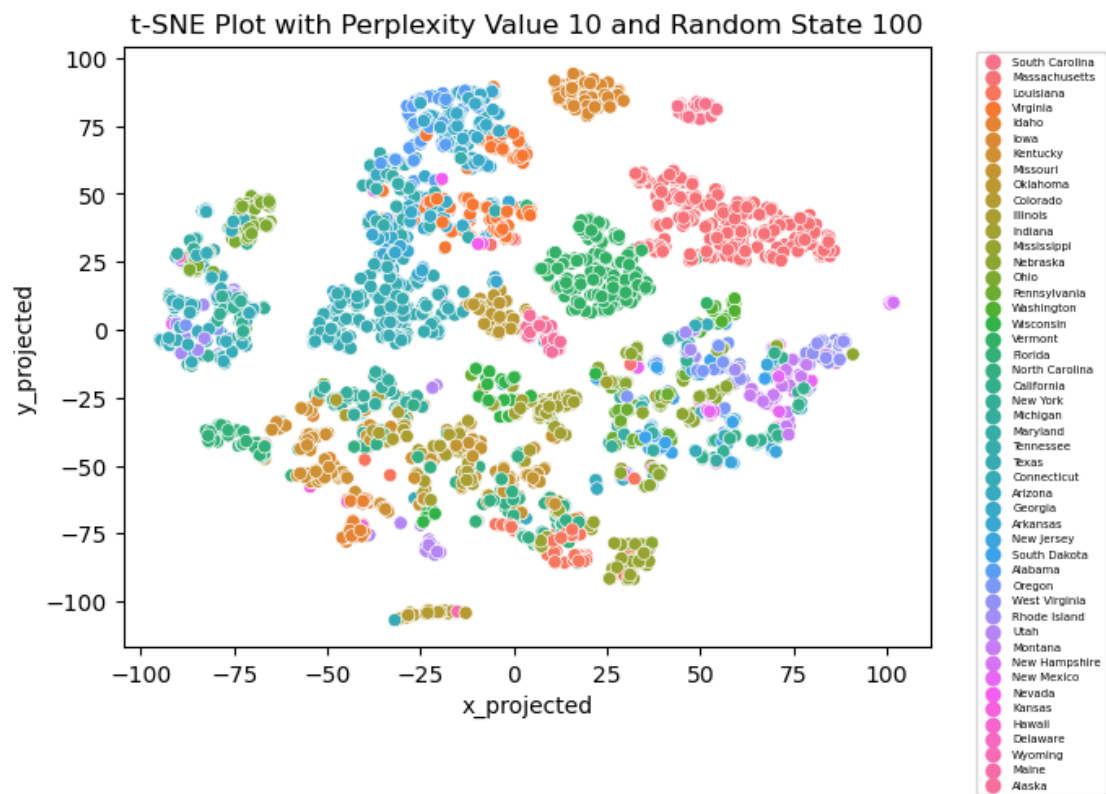
```
[29]: # if we choose the location of state is the pre-assigned label and colorer it
      ↪ in the t-sne plot

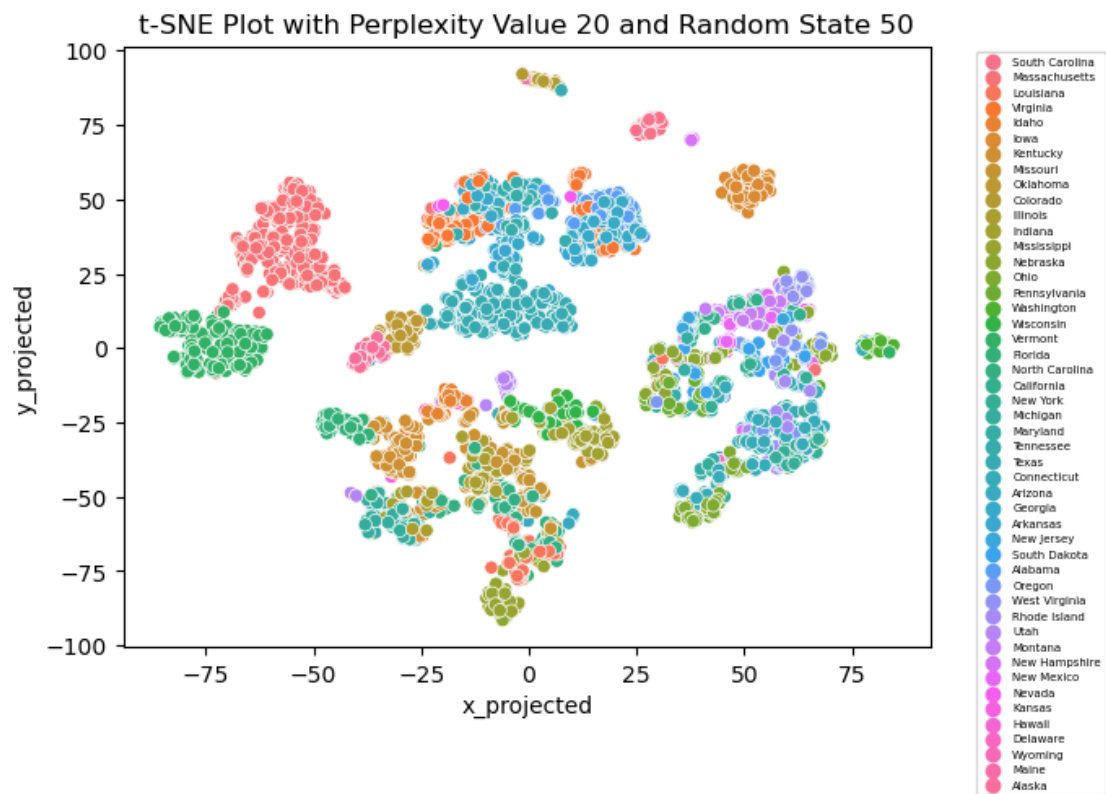
for perp in [5,10, 20, 30, 40, 50]:
    for rs in [50,100]:
        tsne = TSNE(n_components=2, perplexity=perp, random_state=rs)
        data_tsne = tsne.fit_transform(X)
        df_tsne = pd.DataFrame(data_tsne, columns=['x_projected',
        ↪ 'y_projected'])
        df_combo = pd.concat([df_label, df_tsne], axis=1)
        sns.scatterplot(x='x_projected',y='y_projected', hue =
        ↪ "Location_State",data=df_combo)
        plt.title('t-SNE Plot with Perplexity Value %s and Random State %s'
        ↪ (perp, rs))
        plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
        plt.show()
        print('-----')
```

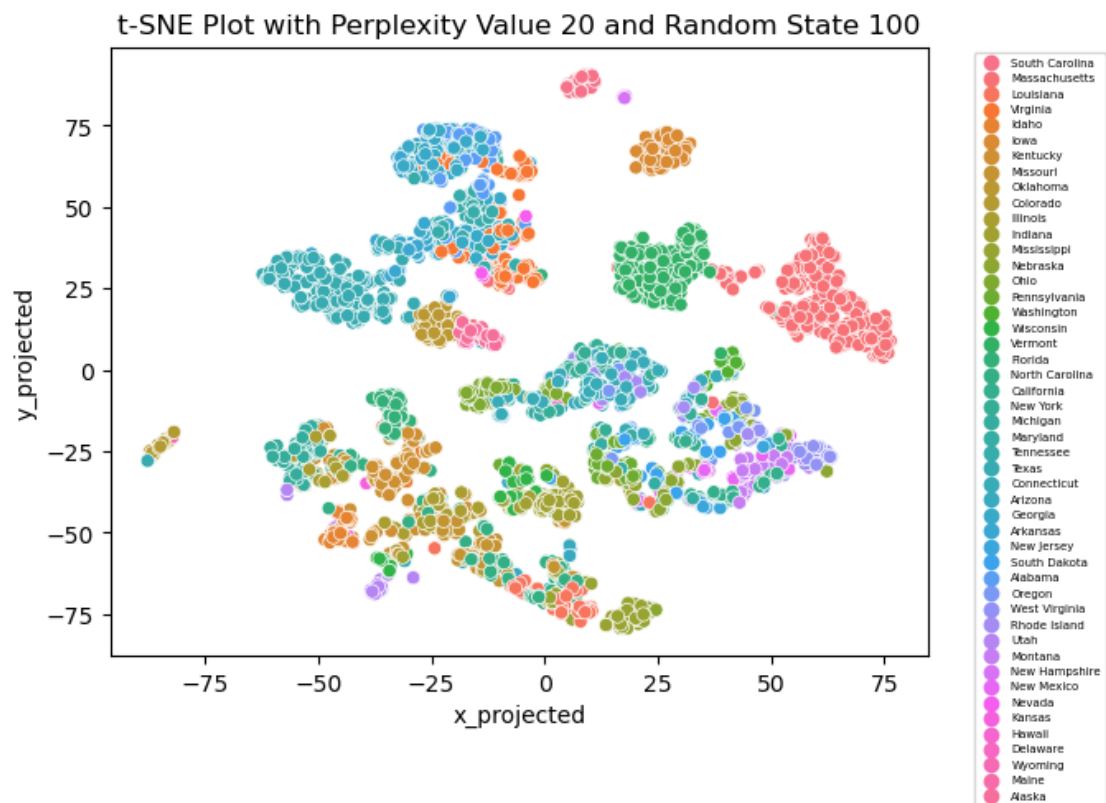


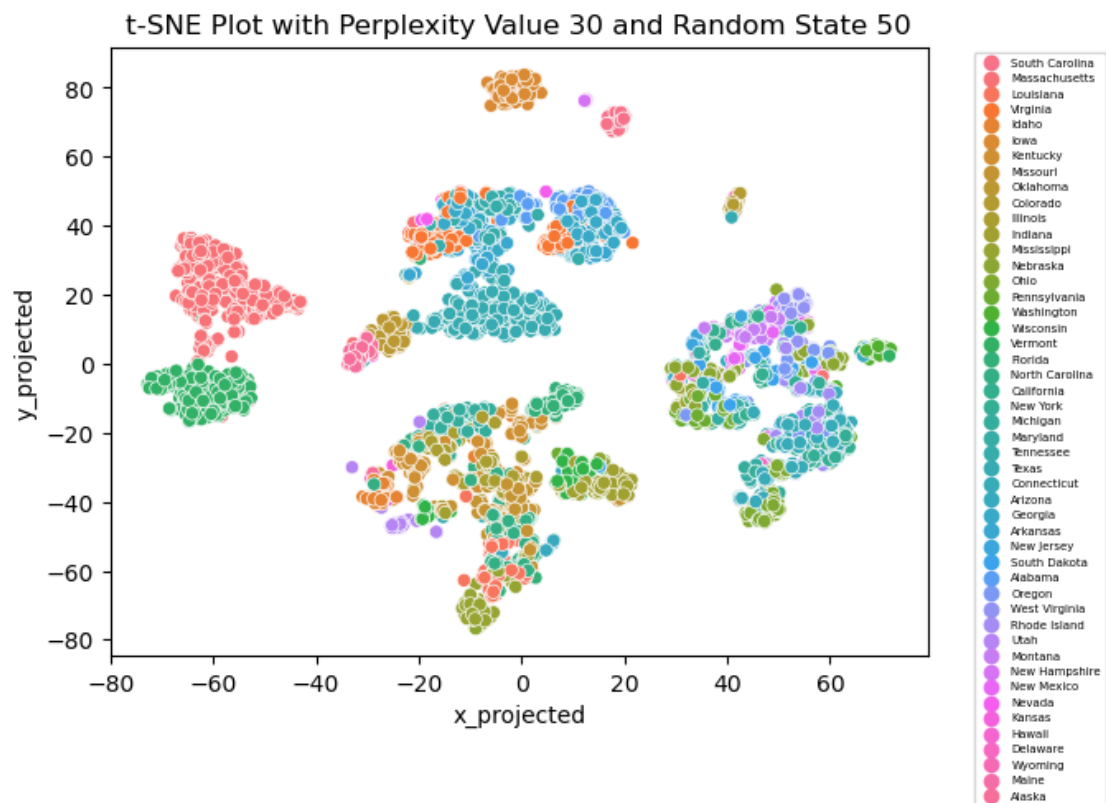


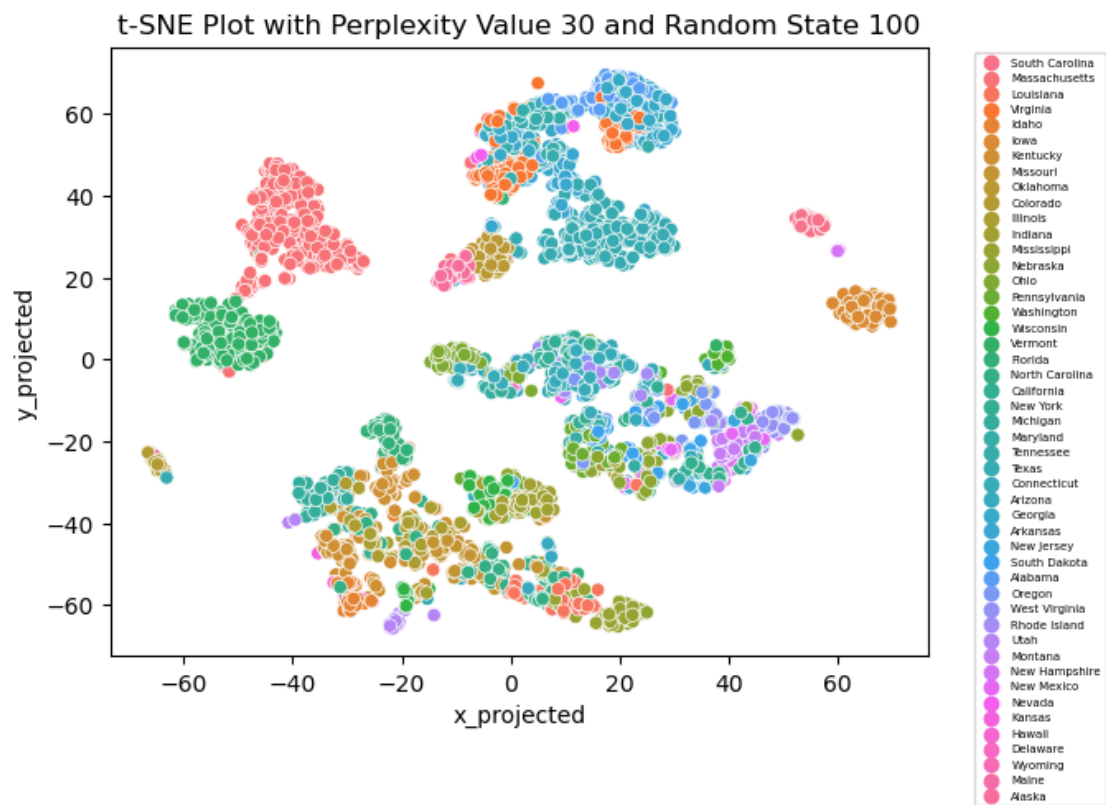


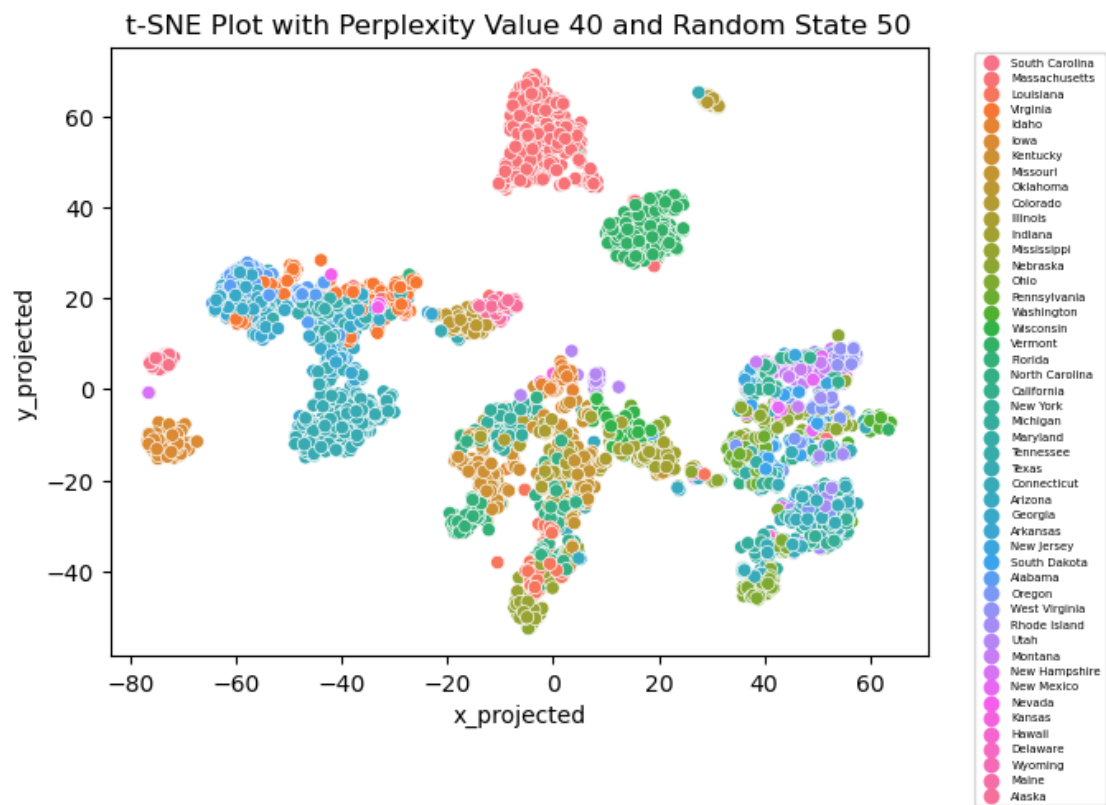


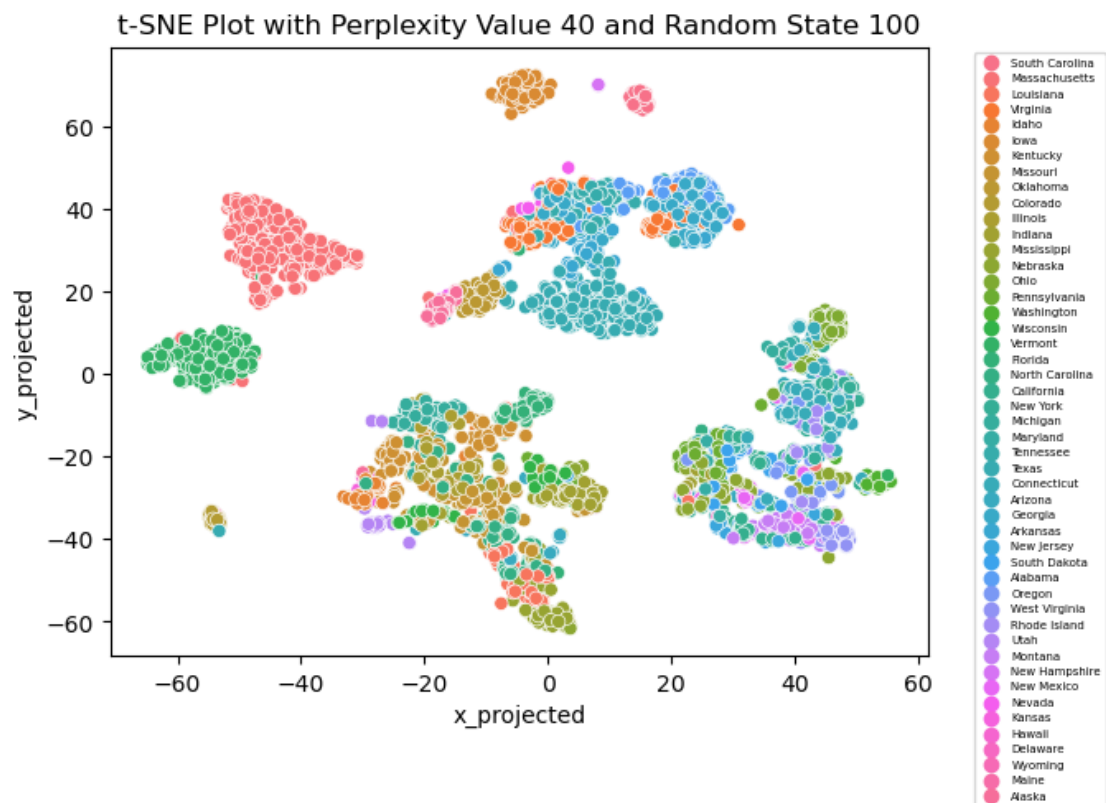


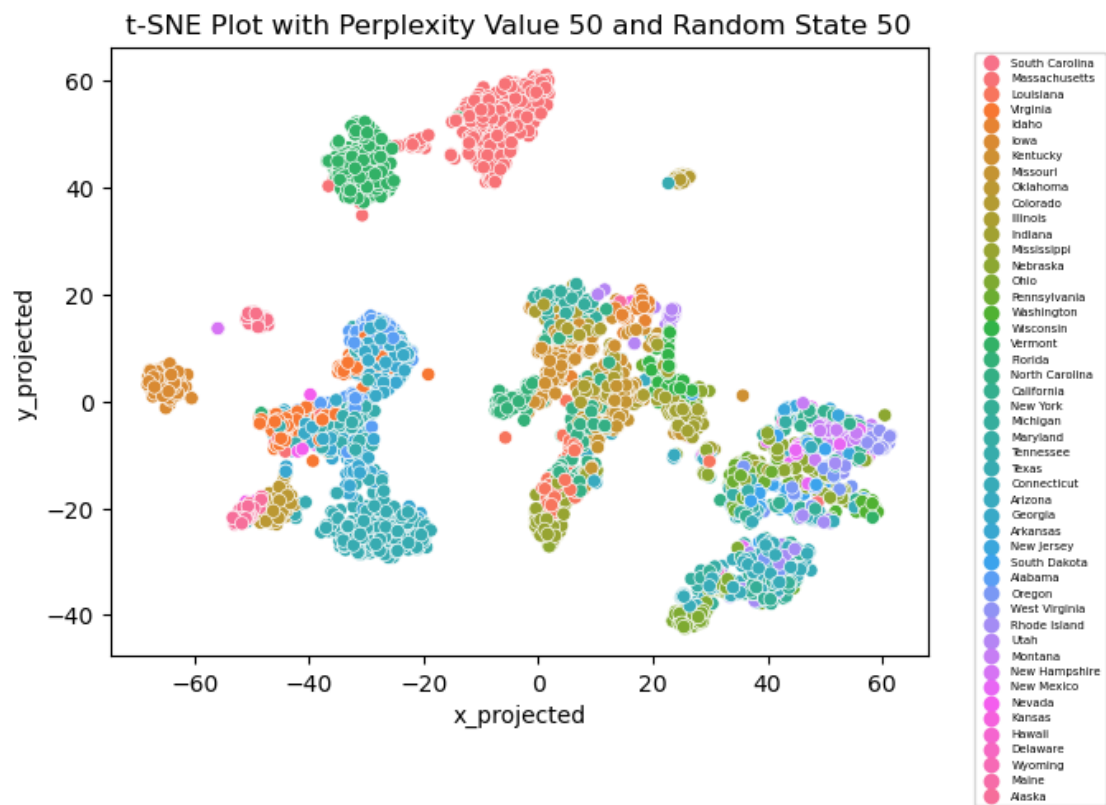


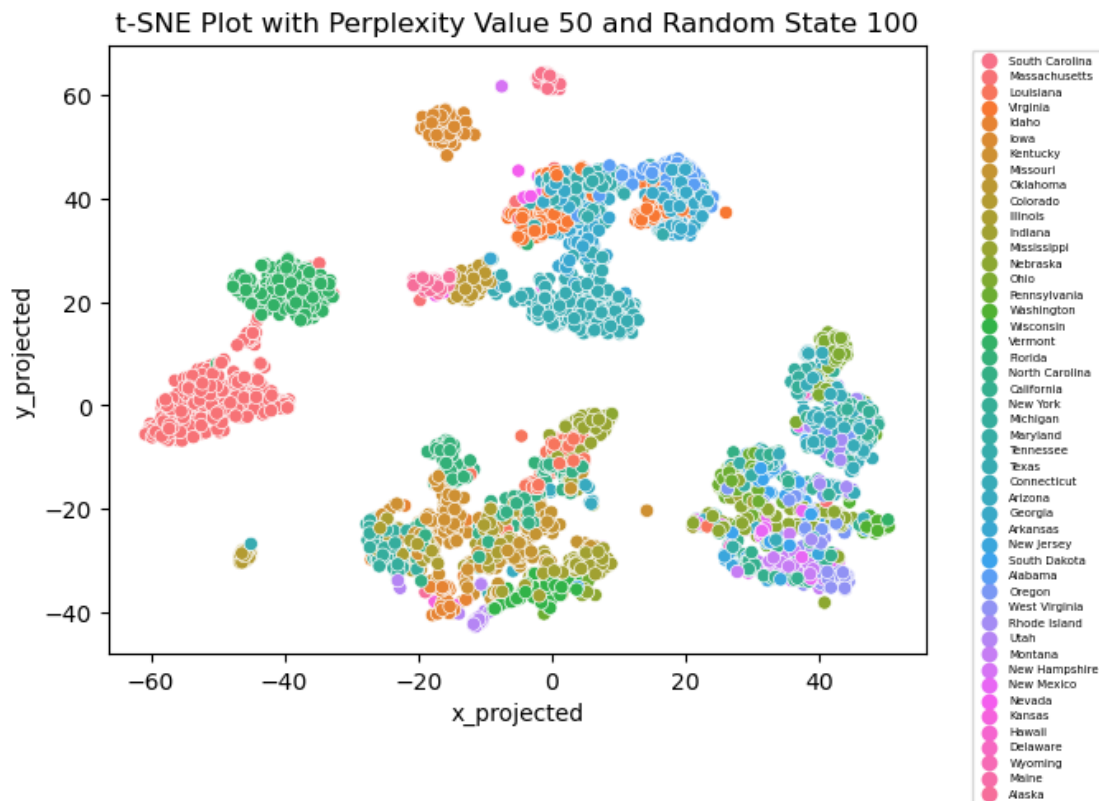












```
[30]: num_trials=10
hopkins_stats=[]
for i in range(0,num_trials):
    n = len(X)
    p = int(0.1 * n)
    hopkins_stats.append(hopkins(X,p))
print(hopkins_stats)
```

```
[0.04070630045751869, 0.03929863065307637, 0.0397228717346078,
0.03817619119068465, 0.03718203368349326, 0.04121653438793144,
0.04139403559241479, 0.042184529046137245, 0.03970703705773819,
0.03955241995398281]
```

Because many of these Hopkins statistics are closer to 0 than they are to 0.5, the Hopkin's statistic suggests that the dataset is clusterable.

```
[31]: X.shape
```

```
[31]: (3592, 18)
```


1.6 6. Algorithm Selection Motivation

We chose K-means and HAC algorithms

We perform clustering analysis for the pre-assigned label of location state, so the clustering algorithm is what we need to present. Secondly we throw out the ranks of number, so the data is presented as a percentage. The values of percentages float from 0-1, plus we removed the states with small numbers so it is not easy to have outliers.

The type variable only represents the party that the voter is running for, and given that the type variables for parties are in a repeating pattern, they are less meaningful for classification. We do not consider the analysis of type variables

By looking at our t-SNE plot, we can see that this dataset is clusterable. This is very suitable for using simple and practical clustering algorithms like k-means.

K-means is a commonly used unsupervised learning algorithm for clustering data points based on their similarity. K-means can be a useful algorithm for analyzing presidential election datasets, but its applicability depends on the specific structure and characteristics of the data and the selection of Other unsupervised learning algorithms such as hierarchical clustering, principal component analysis (PCA) and t-SNE may also be worth considering, depending on the specific structure and characteristics of the data and the selection of features used for clustering. Other unsupervised learning algorithms such as hierarchical clustering, principal component analysis (PCA) and t-SNE may also be worth considering, depending on the goals of the analysis and the nature of the data.

Hierarchical classification: This is a clustering algorithm that creates a hierarchy of clusters that can be visualized as a tree diagram, called a dendrogram. Hierarchical classification can be performed using either the aggregation method or the segmentation method. Aggregative clustering starts with each data point as its own cluster and then iteratively merges the most similar clusters until a single cluster is obtained that contains all data points. Split clustering, on the other hand, starts with all data points in one cluster and then iteratively divides that cluster into smaller clusters until each data point is in its own cluster. Hierarchical clustering is useful for identifying relationships between clusters, and for identifying subgroups within larger clusters.

1.7 7. Clustering K-means

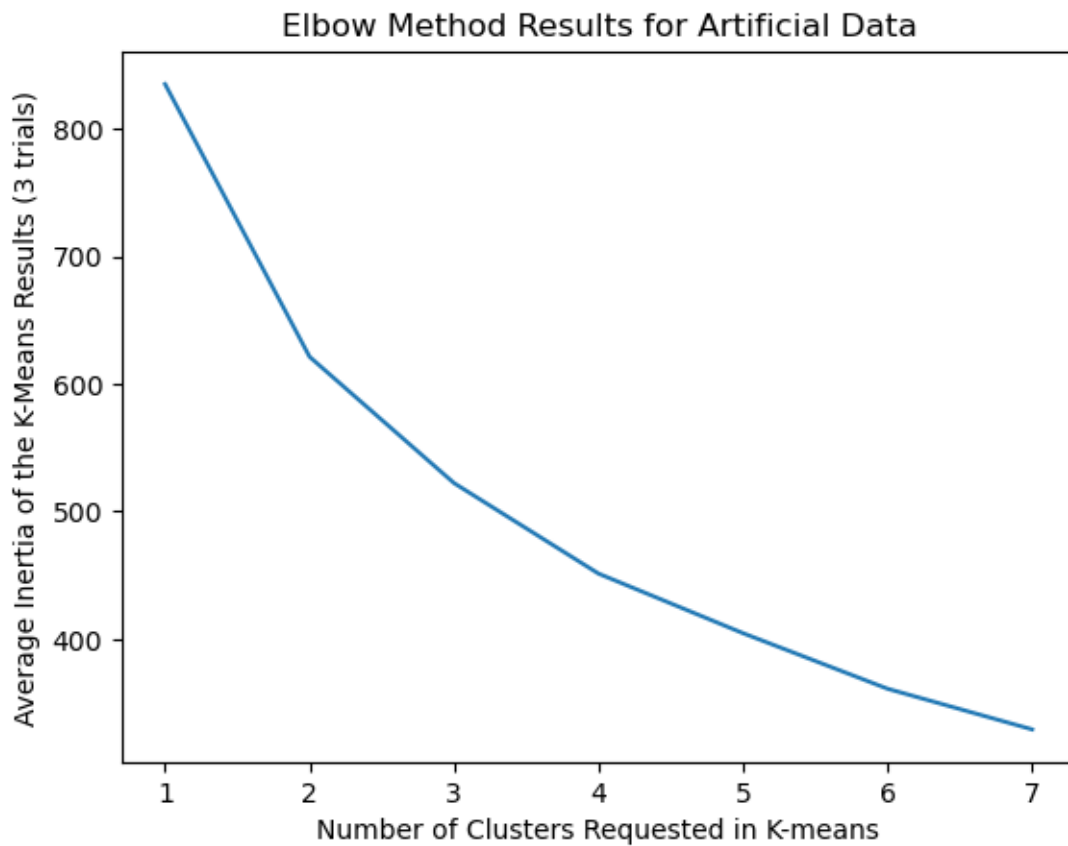
1.7.1 7.1. Parameter Selection

```
[47]: cluster_num_list=range(1,8)
      avg_inertia_list=[]
      for k in cluster_num_list:
          print('k= '+str(k))
          sub_inertia_list=[]
          for i in range(0,3):
              kmeans=KMeans(n_clusters=k).fit(X)
              sub_inertia_list.append(kmeans.inertia_)
          avg_inertia_list.append(np.average(sub_inertia_list))

      plt.plot(cluster_num_list,avg_inertia_list)
      plt.xlabel('Number of Clusters Requested in K-means')
      plt.ylabel('Average Inertia of the K-Means Results (3 trials)')
```

```
plt.title('Elbow Method Results for Artificial Data')
plt.show()
```

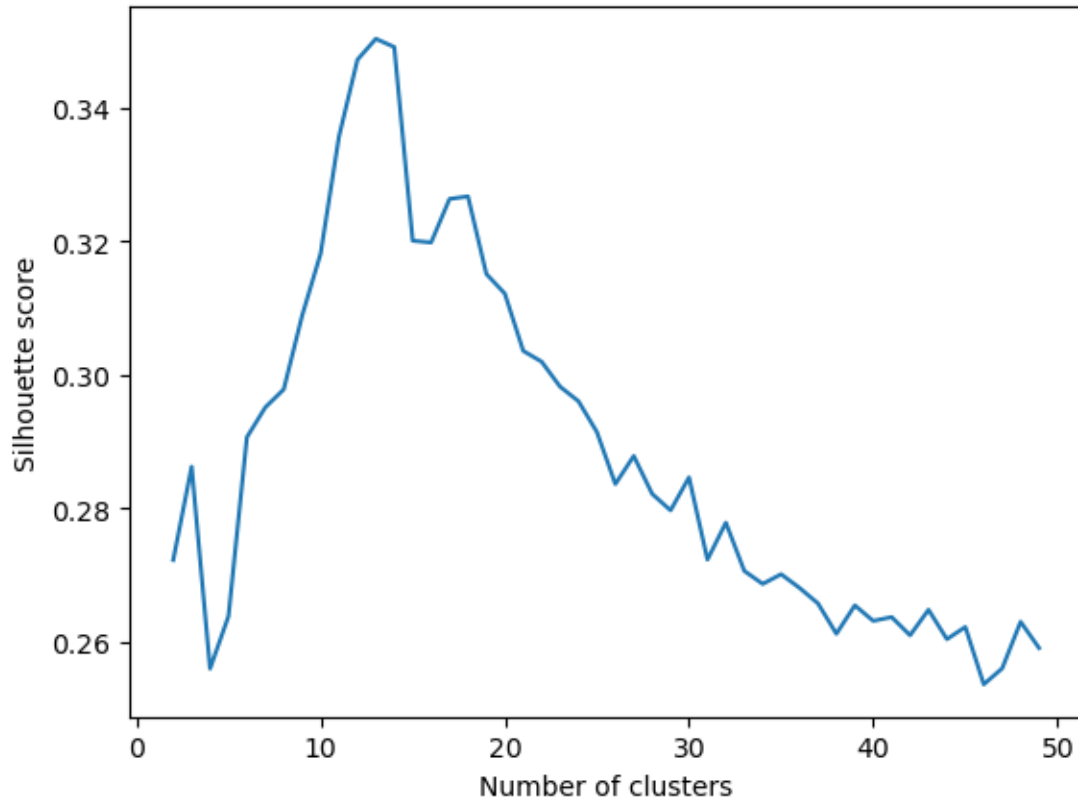
```
k= 1
k= 2
k= 3
k= 4
k= 5
k= 6
k= 7
```



```
[120]: %matplotlib inline
silhouette_scores = []
for k in range(2, 50):
    kmeans = KMeans(n_clusters=k, random_state=0)
    labels = kmeans.fit_predict(X)
    score = silhouette_score(X, labels)
    silhouette_scores.append(score)

#
```

```
plt.plot(range(2, 50), silhouette_scores)
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette score')
plt.show()
```



We are choosing Silhouette score at around 0.35, which cluster $K = 13$. Because we can see the elbow plot didn't give us a good vision of the cluster. Thus, it is reasonable to choose $k = 13$.

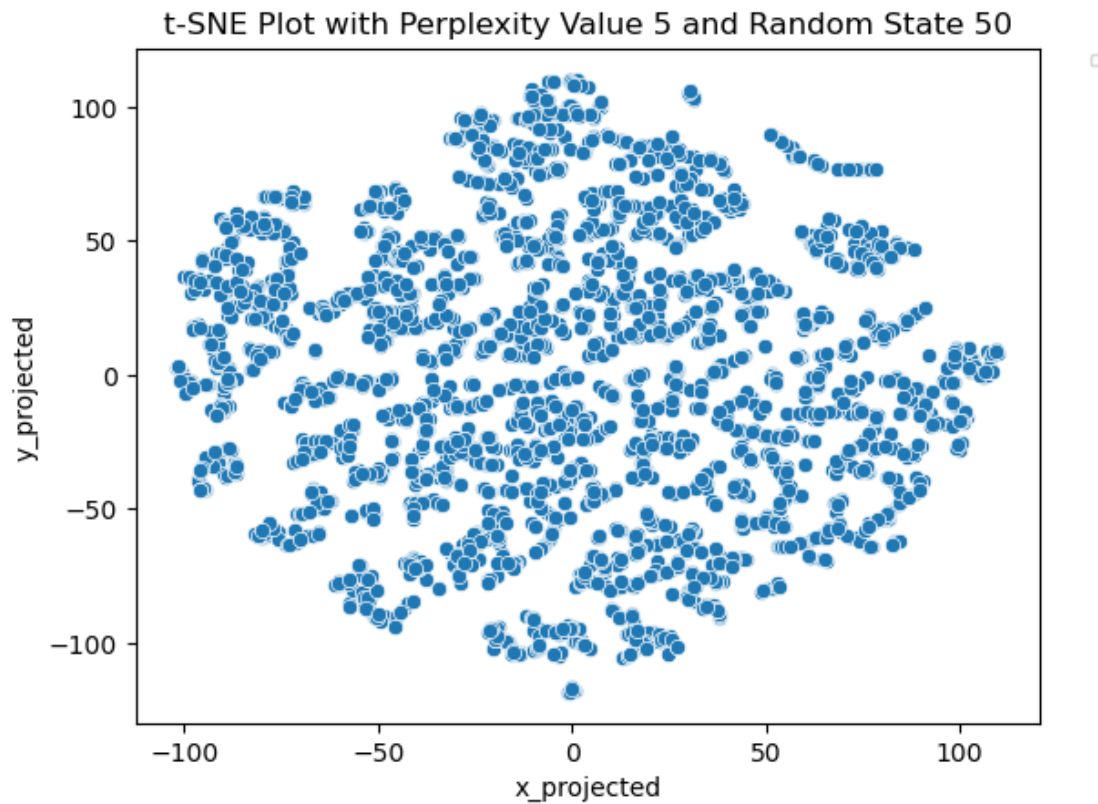
1.7.2 7.2. Clustering Algorithm

Recall the t-SNE plot, we find the perp with 40 and random state with 100, it has a pretty good clusterable structure.

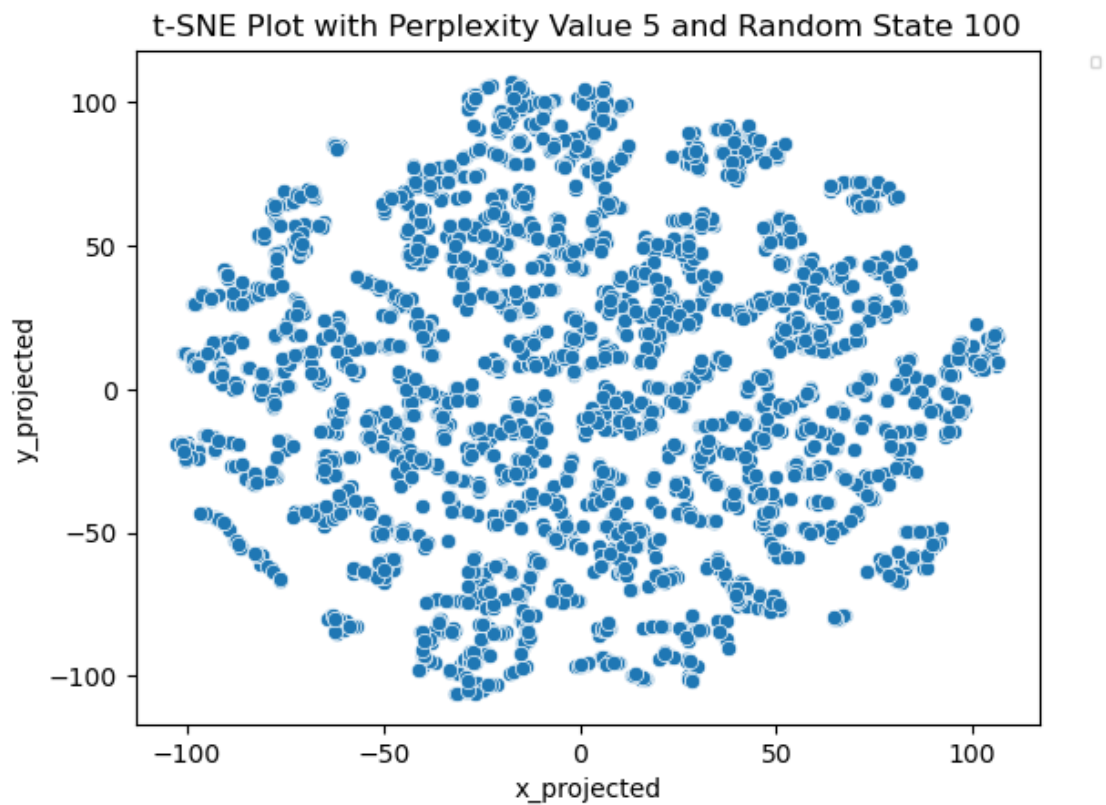
```
[49]: for perp in [5,10, 20, 30, 40, 50]:
      for rs in [50,100]:
          tsne = TSNE(n_components=2, perplexity=perp, random_state=rs)
          data_tsne = tsne.fit_transform(X)
          df_tsne = pd.DataFrame(data_tsne, columns=['x_projected', 'y_projected'])
          df_combo = pd.concat([df_label, df_tsne], axis=1)
          sns.scatterplot(x='x_projected',y='y_projected', data=df_combo)
```

```
plt.title('t-SNE Plot with Perplexity Value %s and Random State %s'␣
↪%(perp, rs))
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
plt.show()
print('-----')
```

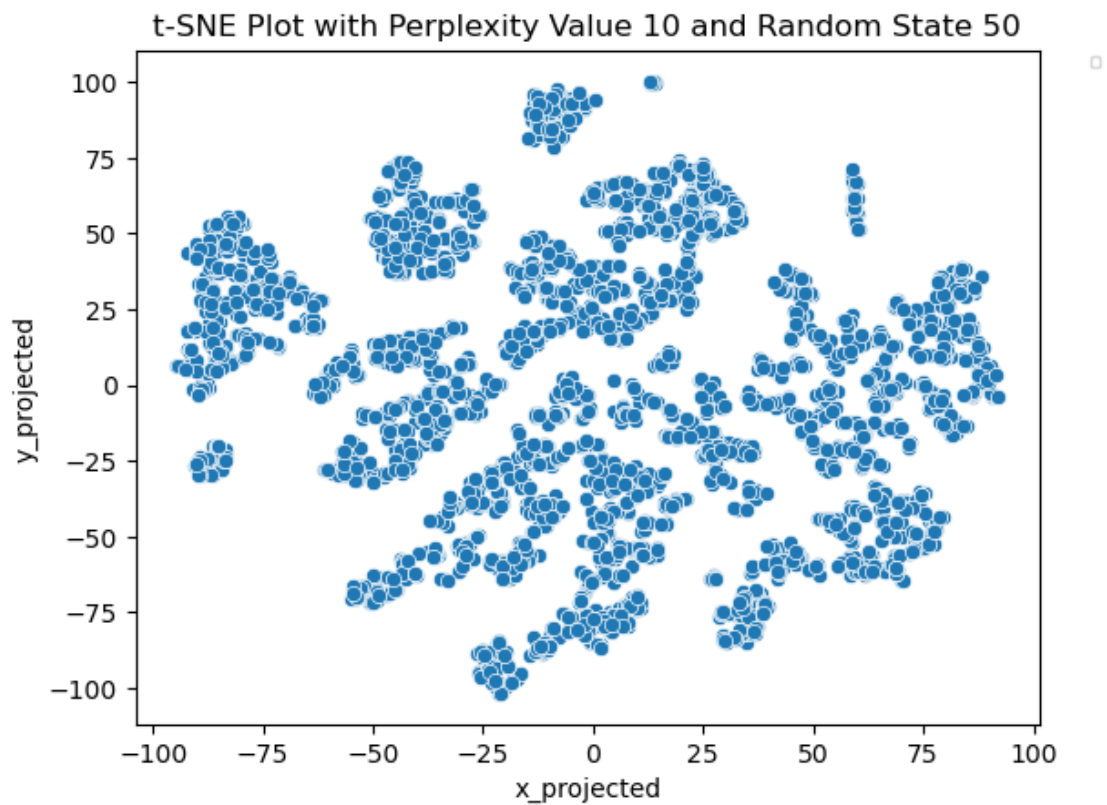
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



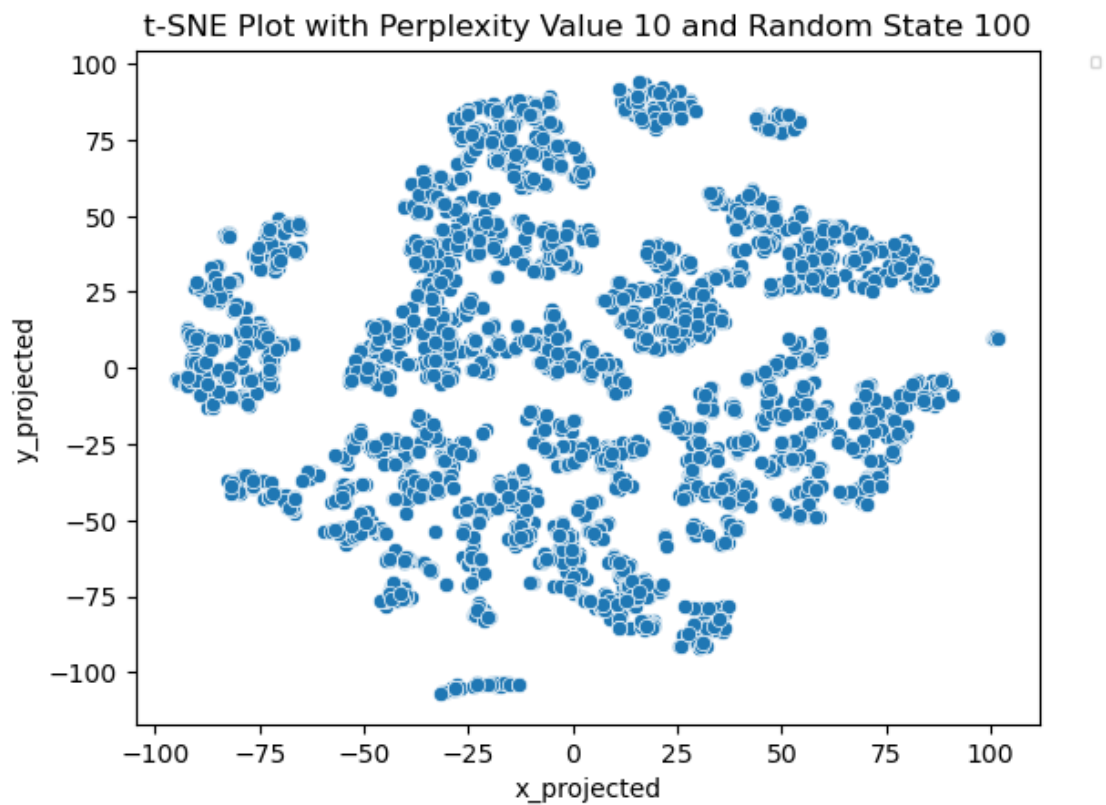
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



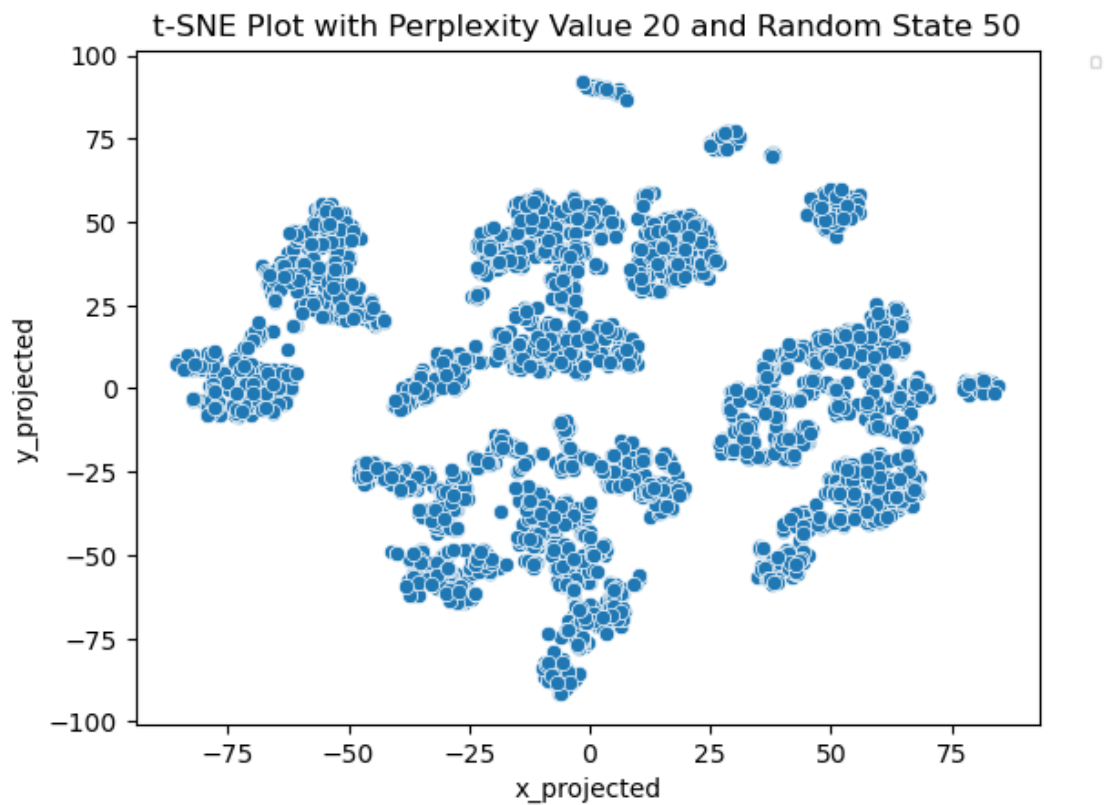
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



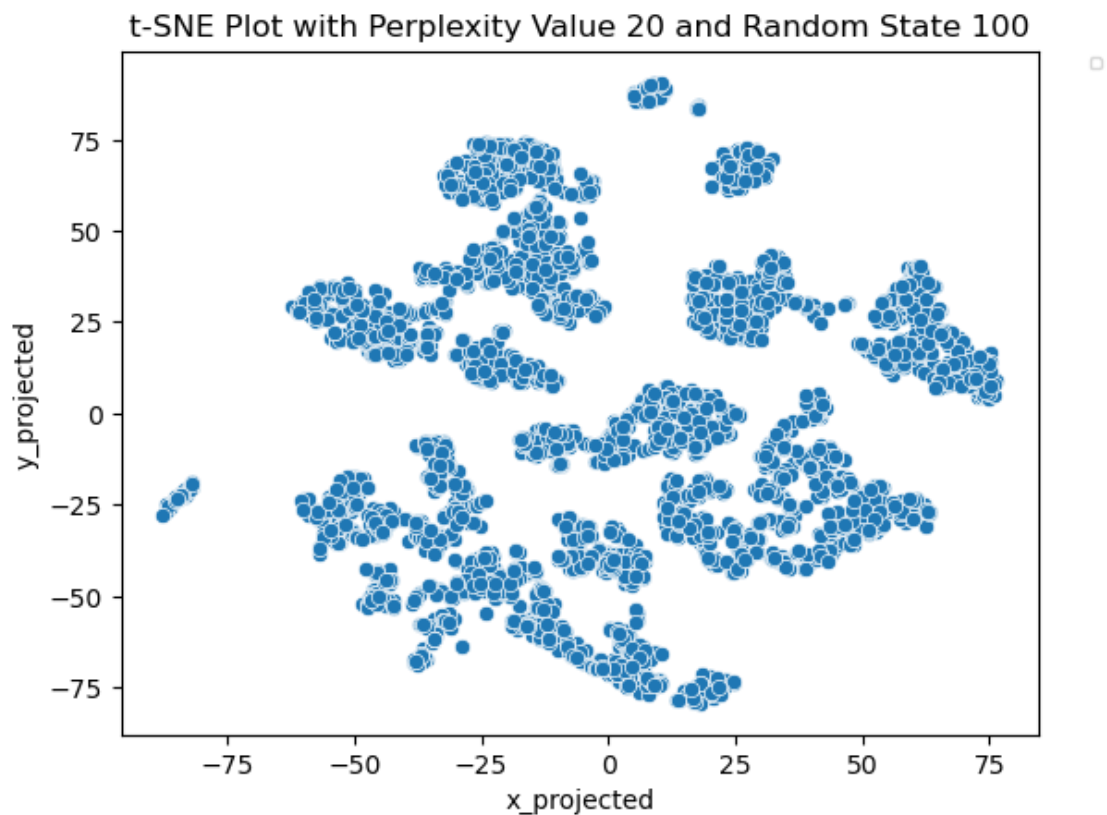
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



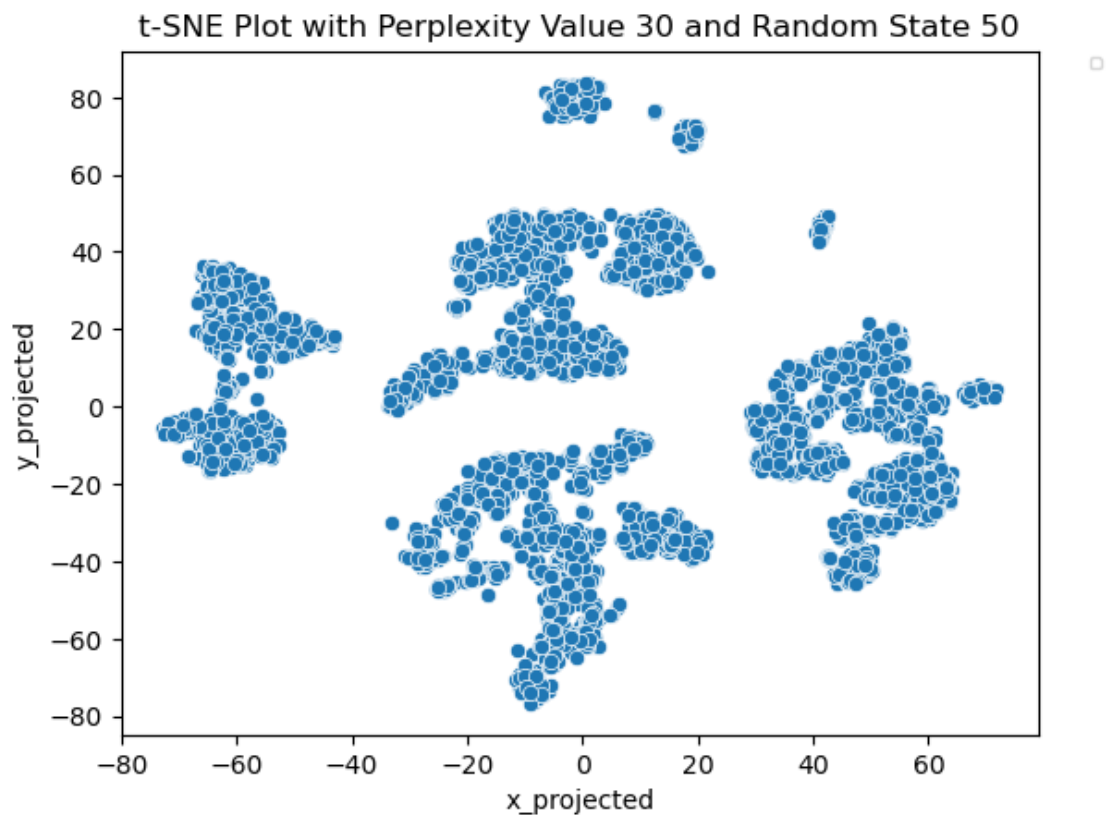
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



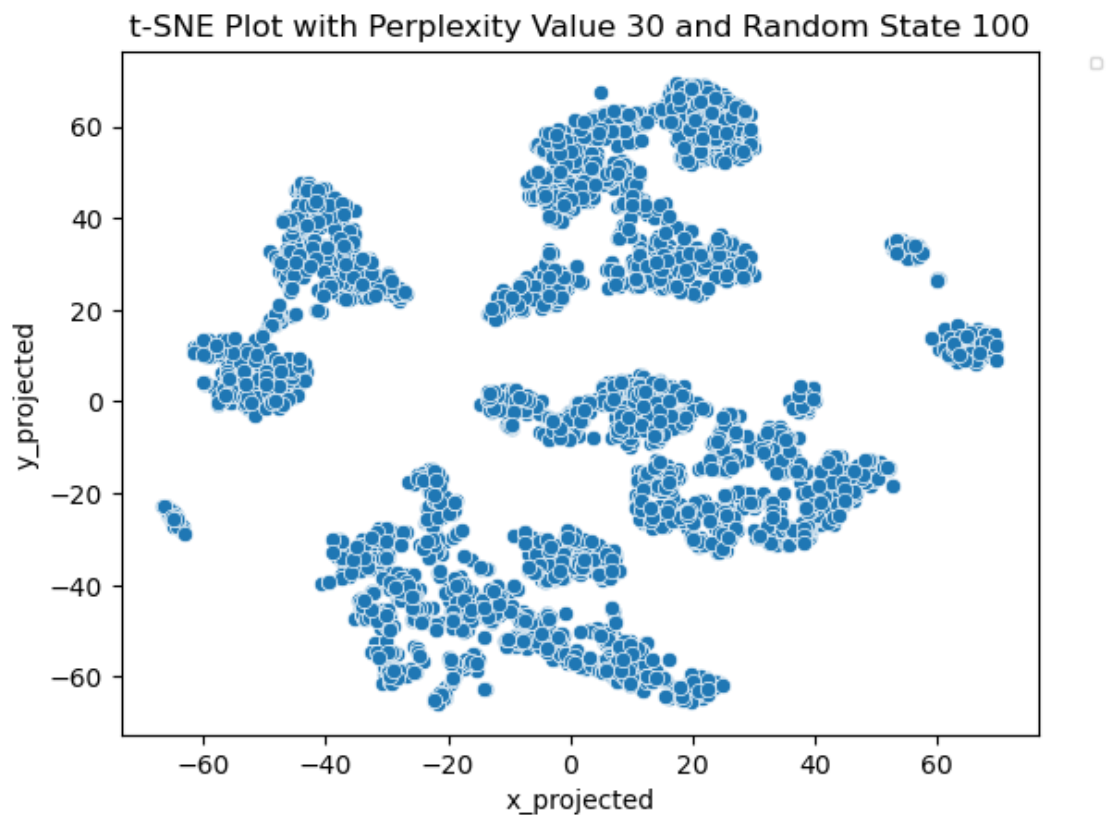
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when `legend()` is called with no argument.



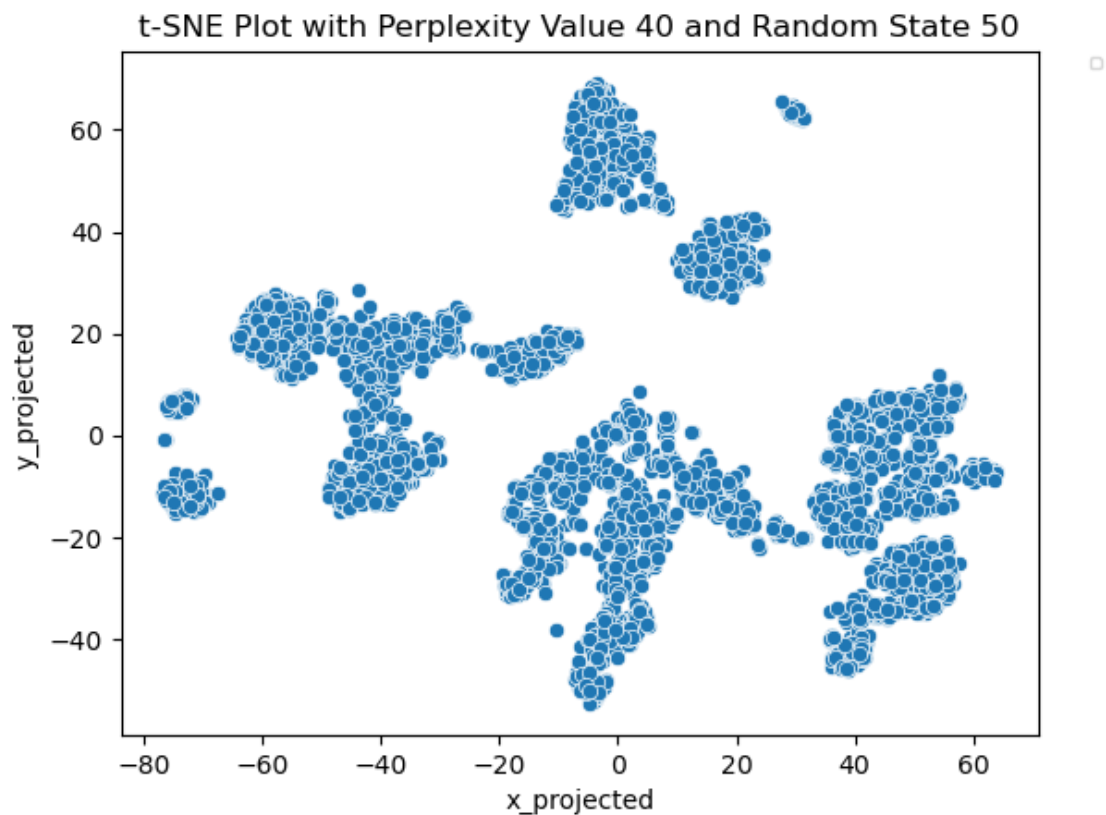
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



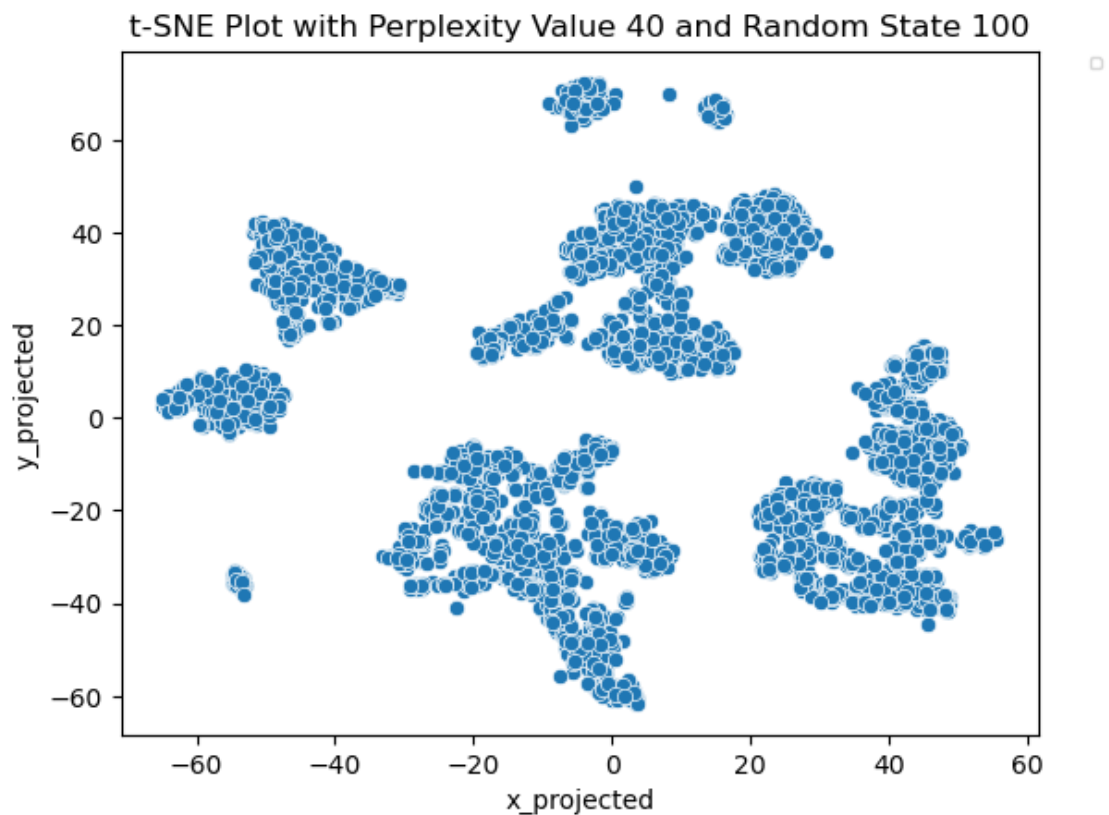
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



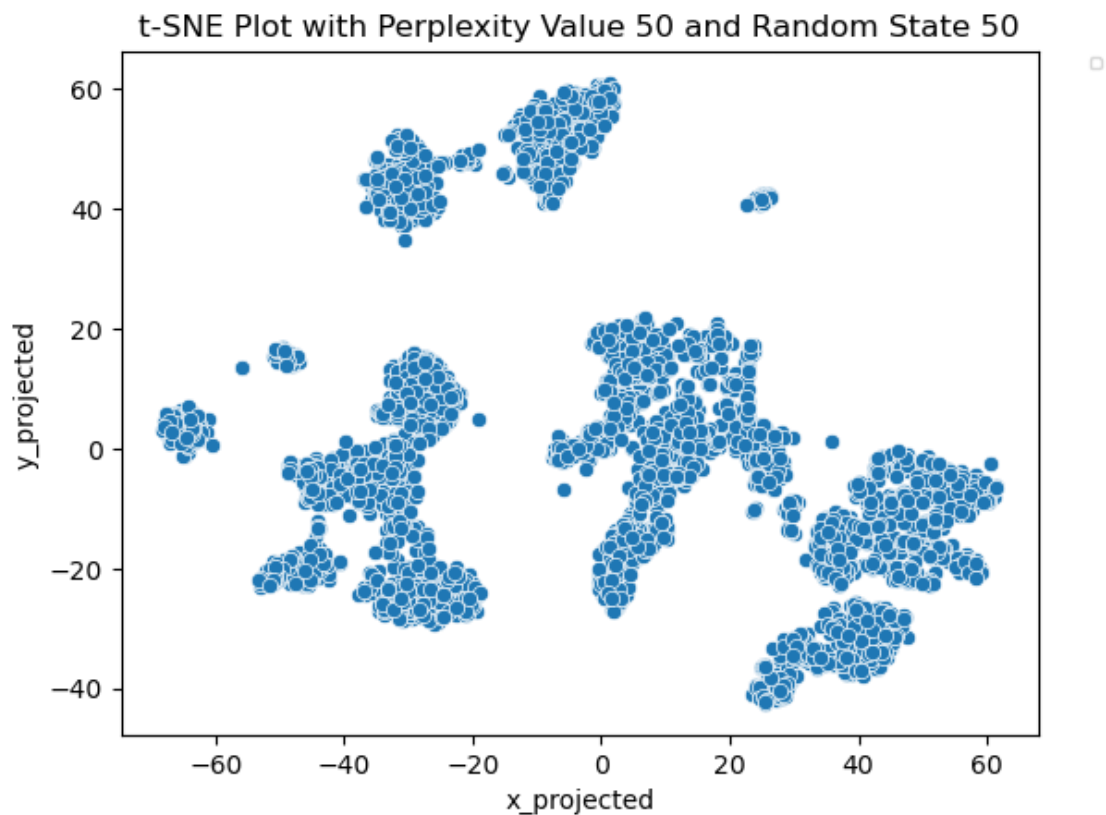
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



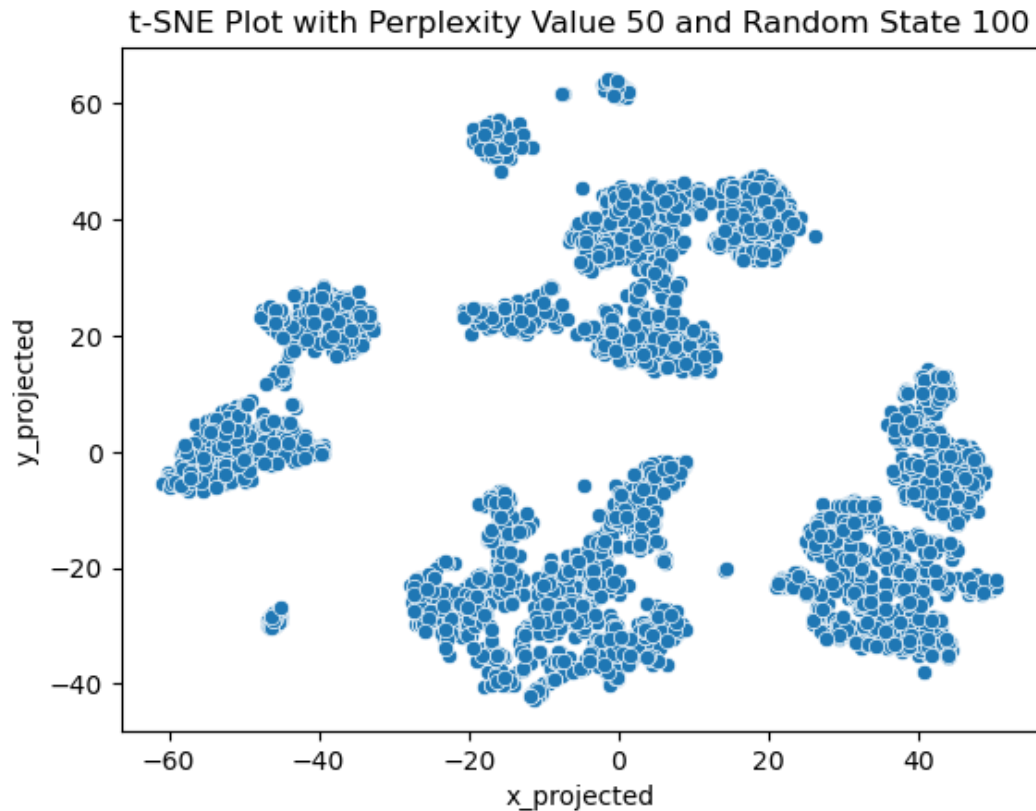
No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when `legend()` is called with no argument.



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.



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.



From the 7.1, we've already decided to use parameters of $k = 13$. And the random state = 100 may let the data has more clear cluster sturcture. So we would use them to perform k-means below.

```
[50]: kmeans=KMeans(n_clusters=13).fit(X)
labels = kmeans.fit_predict(X)
df_kmeans_label = X.copy()
df_kmeans_label['label'] = labels
df_kmeans_label
```

```
[50]: Vote_Data_Ben_Carson_Percent_of_Votes \
0      0.382488
1      0.115207
2      0.000000
3      0.437788
4      0.105991
...      ...
3587    0.000000
3588    0.000000
3589    0.216590
3590    0.000000
```

3591 0.000000

	Vote_Data_Bernie_Sanders_Percent_of_Votes \
0	0.170
1	0.534
2	0.314
3	0.274
4	0.468
...	...
3587	0.511
3588	0.315
3589	0.236
3590	0.181
3591	0.589

	Vote_Data_Carly_Fiorina_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Chris_Christie_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Donald_Trump_Percent_of_Votes \
0	0.403279
1	0.632787
2	0.486339
3	0.523497
4	0.308197

...	...
3587	0.904918
3588	0.540984
3589	0.431694
3590	0.000000
3591	0.750820

	Vote_Data_Hillary_Clinton_Percent_of_Votes \
0	0.818
1	0.446
2	0.537
3	0.720
4	0.528
...	...
3587	0.464
3588	0.637
3589	0.678
3590	0.755
3591	0.411

	Vote_Data_Jeb_Bush_Percent_of_Votes \
0	0.528926
1	0.000000
2	0.000000
3	0.000000
4	0.000000
...	...
3587	0.000000
3588	0.000000
3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_John_Kasich_Percent_of_Votes \
0	0.067293
1	0.222222
2	0.053208
3	0.076682
4	0.508607
...	...
3587	0.079812
3588	0.092332
3589	0.000000
3590	0.000000
3591	0.150235

	Vote_Data_Marco_Rubio_Percent_of_Votes \
--	--

0	0.322169
1	0.202552
2	0.169059
3	0.333333
4	0.397129
...	...
3587	0.000000
3588	0.000000
3589	0.204147
3590	0.000000
3591	0.000000

	Vote_Data_Martin_OMalley_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Mike_Huckabee_Percent_of_Votes	Vote_Data_No_Preference_Party \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
...	...	...
3587	0.0	0.0
3588	0.0	0.0
3589	0.0	0.0
3590	0.0	0.0
3591	0.0	0.0

	Vote_Data_No_Preference_Percent_of_Votes \
0	0.000000
1	0.400000
2	0.000000
3	0.000000
4	0.066667
...	...
3587	0.000000
3588	0.000000

3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_Rand_Paul_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Rick_Santorum_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	0.304071	0.0
1	0.125954	0.0
2	0.486005	0.0
3	0.202290	0.0
4	0.110687	0.0
...	...	...
3587	0.104326	0.0
3588	0.366412	0.0
3589	0.473282	0.0
3590	0.000000	0.0
3591	0.276081	0.0

	Vote_Data_Uncommitted_Percent_of_Votes	label
0	0.0	5
1	0.0	10
2	0.0	11

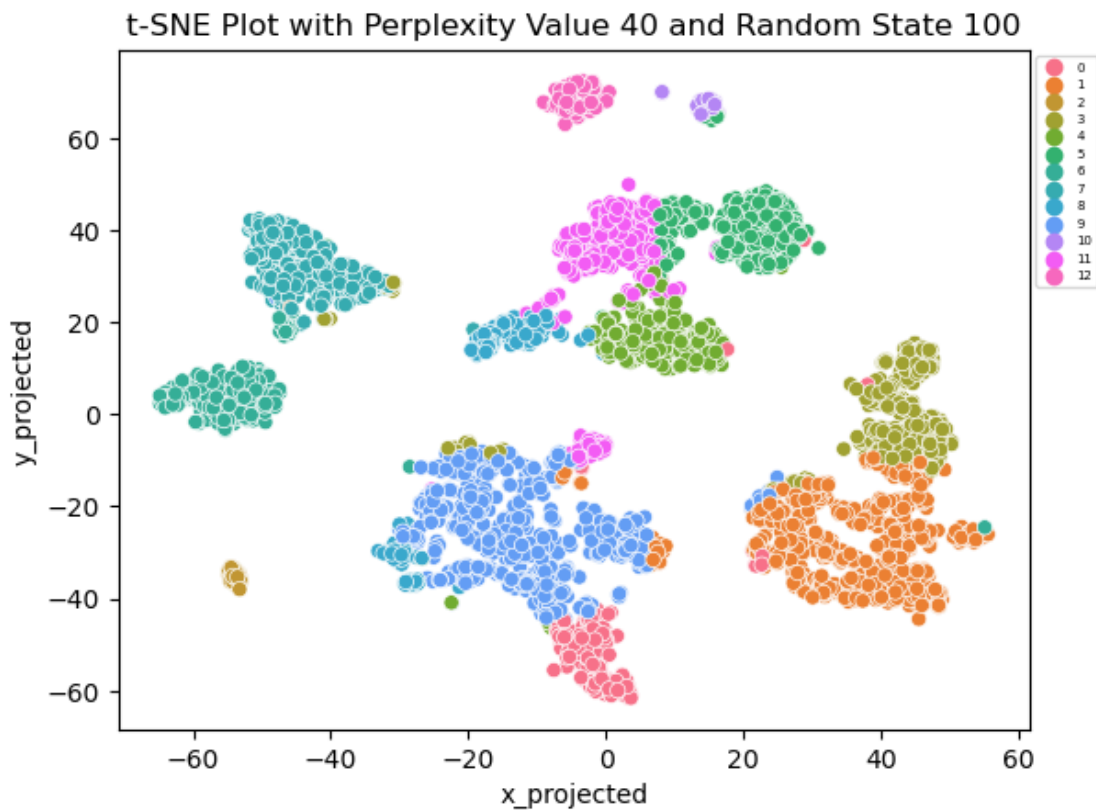
3	0.0	6
4	0.0	10
...	...	...
3587	0.0	3
3588	0.0	11
3589	0.0	4
3590	0.0	9
3591	0.0	3

[3592 rows x 19 columns]

1.7.3 7.3. Clustering Algorithm Results Presentation

```
[121]: perp = 40
rs = 100

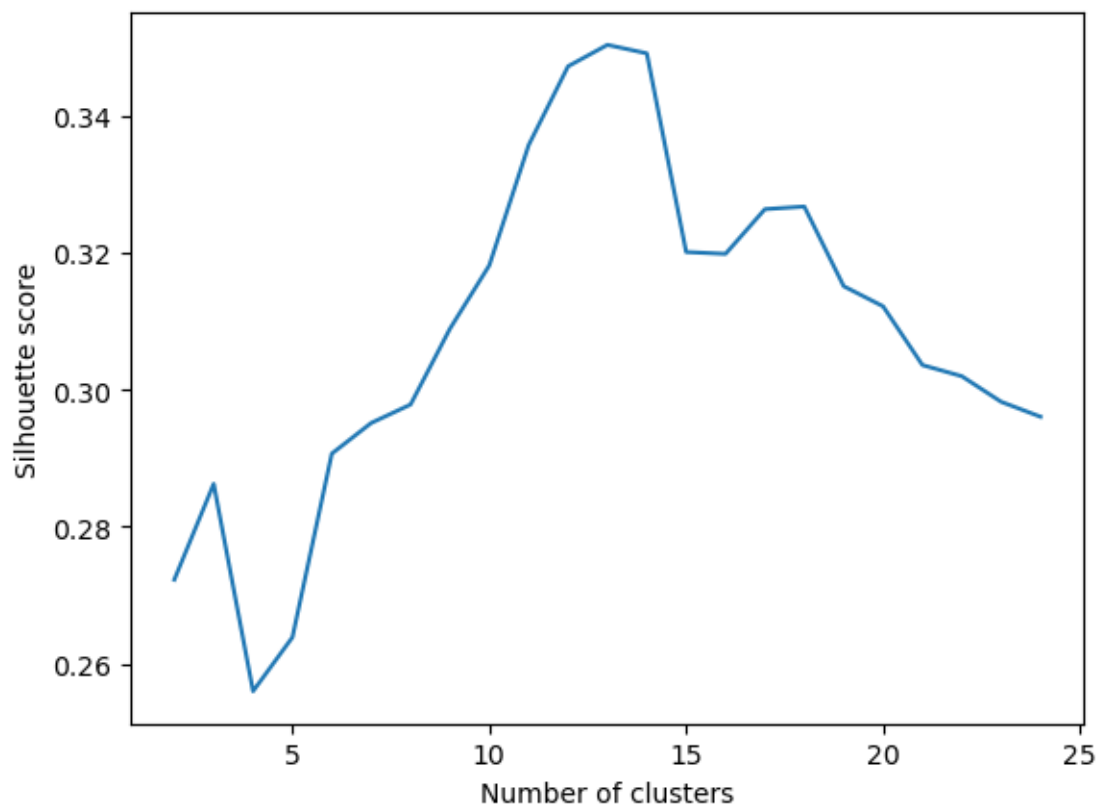
kmeans = KMeans(n_clusters=13, random_state=100).fit(X)
df_combo["label"] = kmeans.labels_
sns.scatterplot(x='x_projected',y='y_projected',hue = "label",palette=sns.
    color_palette('husl', 13), data=df_combo)
plt.title('t-SNE Plot with Perplexity Value %s and Random State %s' %(perp, rs))
plt.legend(bbox_to_anchor=(1, 1), loc='upper left', fontsize = 5)
plt.show()
```



1.7.4 7.4. Assessing Clustering Separation and Cohesion

```
[52]: silhouette_scores = []
      for k in range(2, 25):
          kmeans = KMeans(n_clusters=k, random_state=0)
          labels = kmeans.fit_predict(X)
          score = silhouette_score(X, labels)
          silhouette_scores.append(score)

      #
      plt.plot(range(2, 25), silhouette_scores)
      plt.xlabel('Number of clusters')
      plt.ylabel('Silhouette score')
      plt.show()
```



```
[53]: def show_silhouette_plots(X, cluster_labels):

      # This package allows us to use "color maps" in our visualizations
```

```

import matplotlib.cm as cm

#How many clusters in your clustering?
n_clusters=len(np.unique(cluster_labels))

# Create a subplot with 1 row and 2 columns
fig, ax1 = plt.subplots(1, 1)
fig.set_size_inches(18, 7)

# The 1st subplot is the silhouette plot
# The silhouette coefficient fcan range from -1, 1 but in this example all
# lie within [-0.1, 1]
ax1.set_xlim([-0.1, 1])
# The (n_clusters+1)*10 is for inserting blank space between silhouette
# plots of individual clusters, to demarcate them clearly.
ax1.set_ylim([0, len(X) + (n_clusters + 1) * 10])

# The silhouette_score gives the average value for all the samples.
# This gives a perspective into the density and separation of the formed
# clusters
silhouette_avg = silhouette_score(X, cluster_labels)
print("For n_clusters =", n_clusters,
      "The average silhouette_score is :", silhouette_avg)

# Compute the silhouette scores for each sample
sample_silhouette_values = silhouette_samples(X, cluster_labels)

y_lower = 10
for i in range(n_clusters):
    # Aggregate the silhouette scores for samples belonging to
    # cluster i, and sort them
    ith_cluster_silhouette_values = \
        sample_silhouette_values[cluster_labels == i]

    ith_cluster_silhouette_values.sort()

    size_cluster_i = ith_cluster_silhouette_values.shape[0]
    y_upper = y_lower + size_cluster_i

    color = cm.nipy_spectral(float(i) / n_clusters)
    ax1.fill_betweenx(np.arange(y_lower, y_upper),
                      0, ith_cluster_silhouette_values,
                      facecolor=color, edgecolor=color, alpha=0.7)

    # Label the silhouette plots with their cluster numbers at the middle

```

```

ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

# Compute the new y_lower for next plot
y_lower = y_upper + 10 # 10 for the 0 samples

ax1.set_title("The silhouette plot for the various clusters.")
ax1.set_xlabel("The silhouette coefficient values")
ax1.set_ylabel("Cluster label")

# The vertical line for average silhouette score of all the values
ax1.axvline(x=silhouette_avg, color="red", linestyle="--")

ax1.set_yticks([]) # Clear the yaxis labels / ticks
ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])

plt.show()

return

```

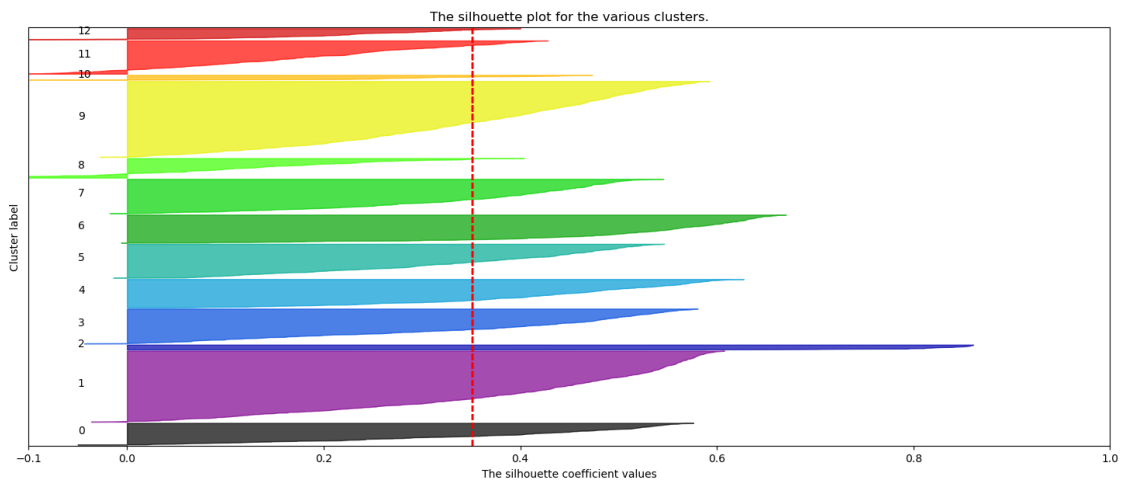
```
[54]: kmeans=KMeans(n_clusters=13, random_state=100).fit(X)
      cluster_labels = kmeans.labels_

```

```
[55]: show_silhouette_plots(X,cluster_labels)

```

For n_clusters = 13 The average silhouette_score is : 0.35128092983387776



a.) each of the clusters and

b.) the overall clustering. Are there are any objects that have poor cohesion with their assigned cluster? Explain.

a. We can see cluster 12 and 8 are quite same, but the score is at 0.4, which indicate they have a

poor separation and cohesion. Cluster 9, 1, 4, 0 and 3 are similar, the score is 0.6 which have a moderate separation and cohesion. Cluster 10 is at score 0.5, is a median in separation and cohesion. Cluster 6 is in a second place which have relatively good separation and cohesion. Cluster 2 have the highest score which is 0.9, well-separated and well-matched.

- b. In this case, the average silhouette score of 0.351 indicates that the clusters are not fairly well-separated and data points within each cluster are not well-matched. The score is not particularly high, which suggests that there may be some overlap or ambiguity between the clusters, or that the clusters are not perfectly optimized for the data.

1.7.5 7.5. Additional Analysis

```
[56]: from sklearn.metrics import adjusted_rand_score, homogeneity_score, \
      ↪completeness_score
```

```
[57]: ari = adjusted_rand_score(df_label["Location_State"], df_kmeans_label["label"])
      ari
```

```
[57]: 0.3469780328175856
```

```
[58]: homogeneity = homogeneity_score(df_label["Location_State"], \
      ↪df_kmeans_label["label"])
      homogeneity
```

```
[58]: 0.5464057466437389
```

```
[59]: completeness = completeness_score(df_label["Location_State"], \
      ↪df_kmeans_label["label"])
      completeness
```

```
[59]: 0.8269716937056959
```

The adjusted RAND index score of 0.357 indicates a moderate level of agreement between the true and predicted labels. The homogeneity score of 0.542 suggests that each cluster contains members of multiple classes, while the completeness score of 0.811 indicates that members of each class are not all assigned to the same cluster. These results suggest that while there is some agreement between the true and predicted labels, the clustering may not be capturing all of the underlying patterns in the data. It may be worth exploring other clustering methods or tweaking the parameters of the k-means algorithm to improve the results.

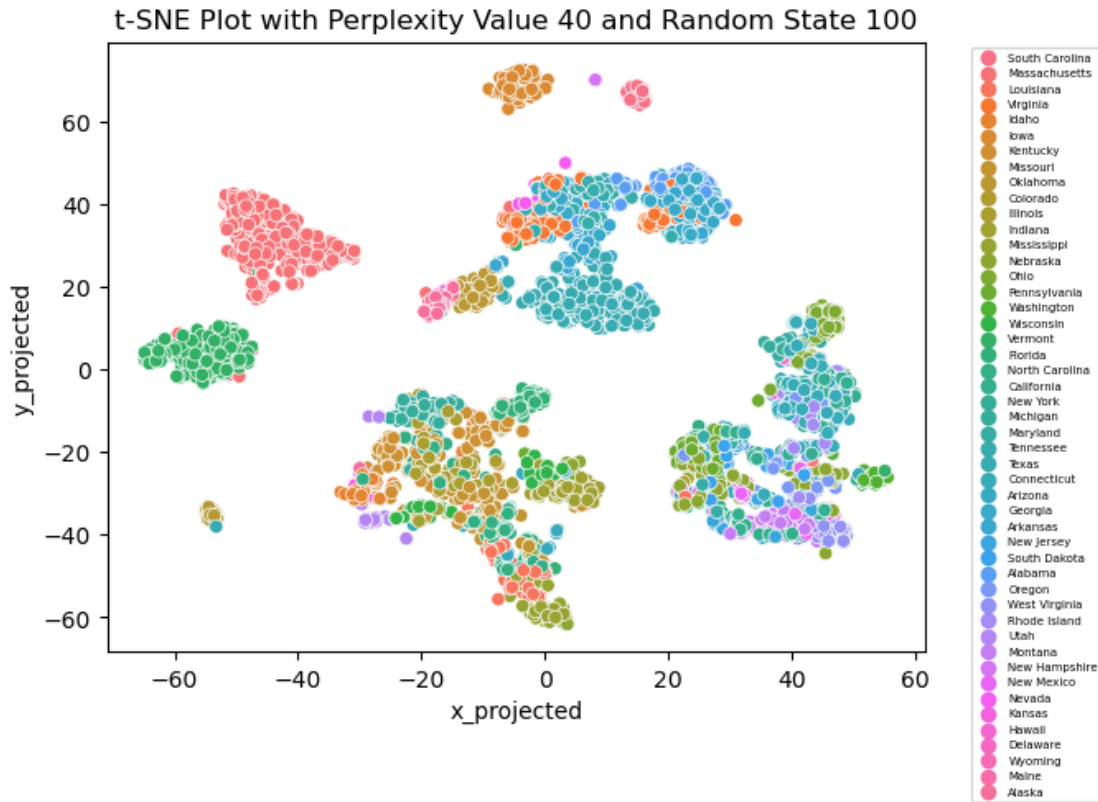
```
[100]: for perp in [40]:
      for rs in [100]:
          tsne = TSNE(n_components=2, perplexity=perp, random_state=rs)
          data_tsne = tsne.fit_transform(X)
          df_tsne = pd.DataFrame(data_tsne, columns=['x_projected', \
      ↪'y_projected'])
          df_combo = pd.concat([df_label, df_tsne], axis=1)
          sns.scatterplot(x='x_projected', y='y_projected', hue = \
      ↪"Location_State", data=df_combo)
```



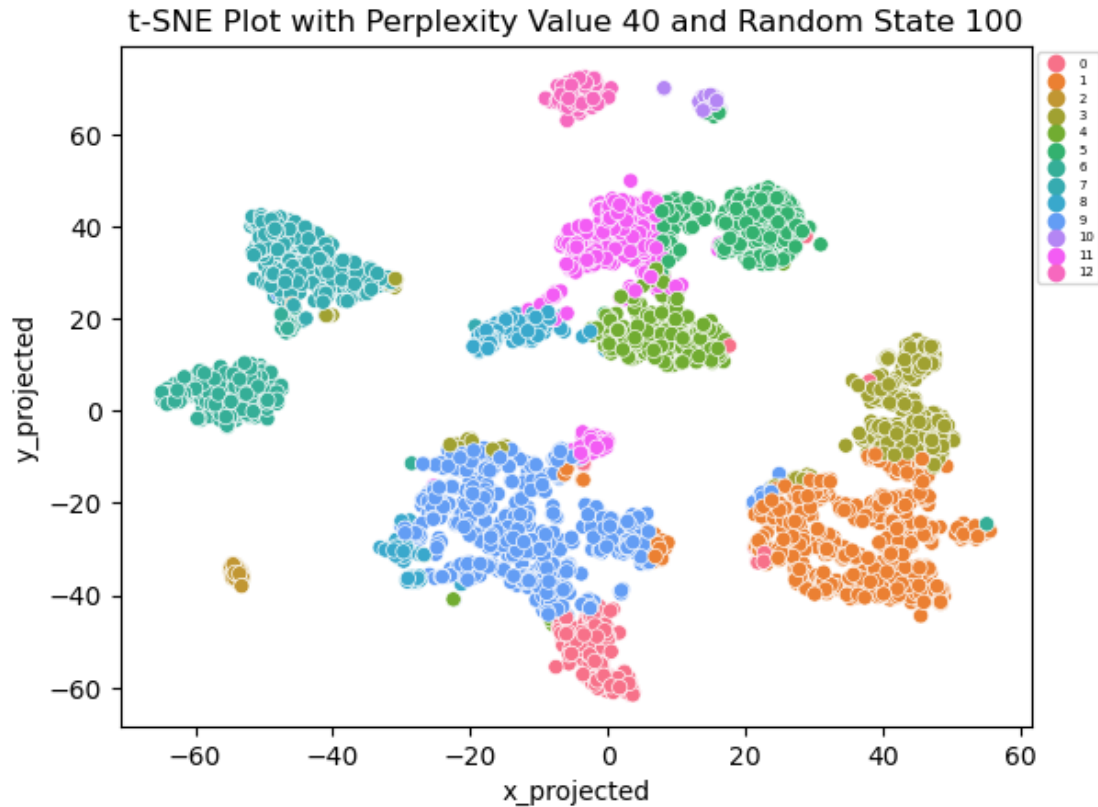
```

plt.title('t-SNE Plot with Perplexity Value %s and Random State %s' %
↳(perp, rs))
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
plt.show()
print('-----True Label-----')
#Color code the points in your t-sne plot by cluster labels and code the
↳"style" of the marker with your class labels.
kmeans = KMeans(n_clusters=13, random_state=100).fit(X)
df_combo["label"] = kmeans.labels_
sns.scatterplot(x='x_projected',y='y_projected',hue = "label",palette=sns.
↳color_palette('husl', 13), data=df_combo)
plt.title('t-SNE Plot with Perplexity Value %s and Random State %s' %(perp, rs))
plt.legend(bbox_to_anchor=(1, 1), loc='upper left', fontsize = 5)
plt.show()
print('-----Predicted Label-----')

```



-----True Label-----

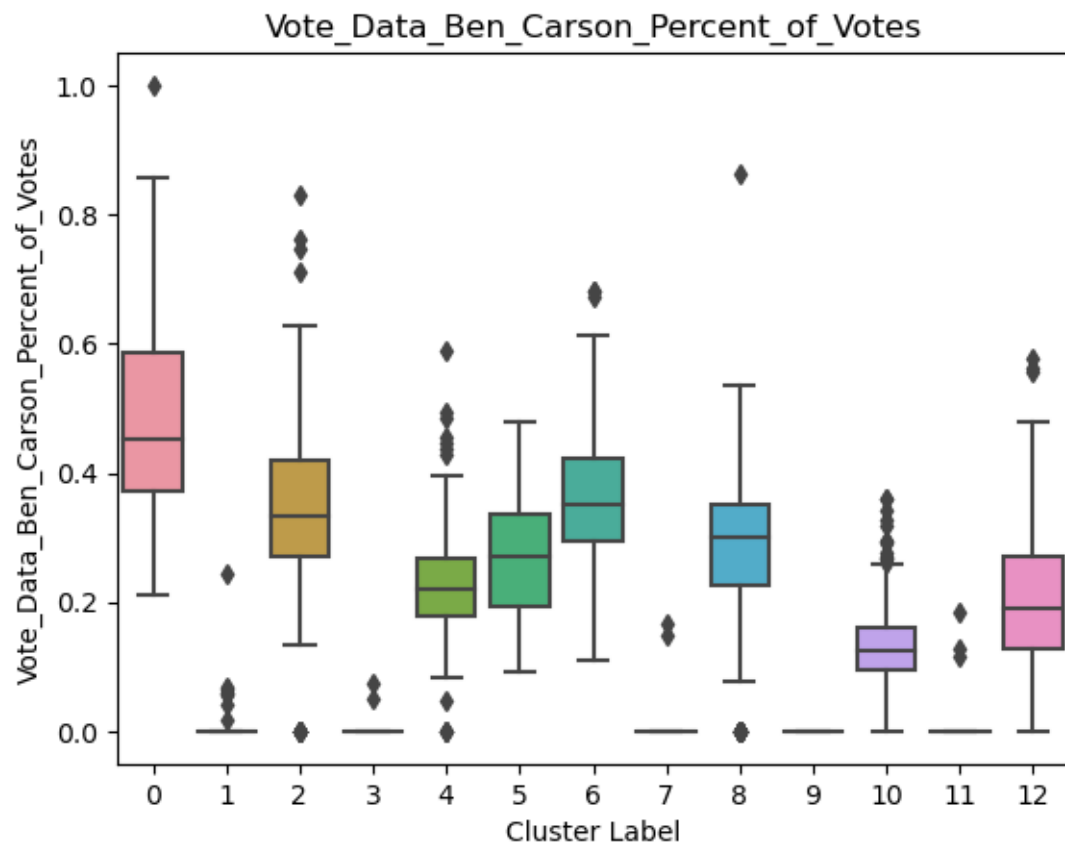


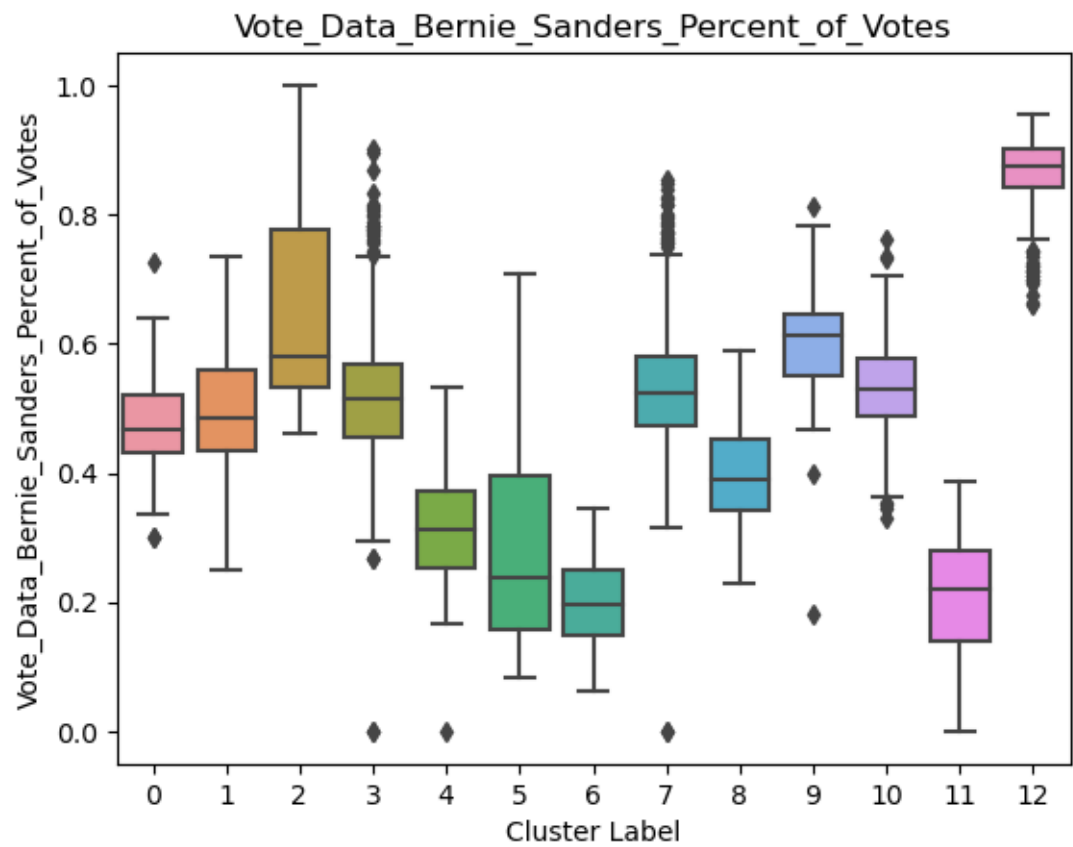
-----Predicted Label-----

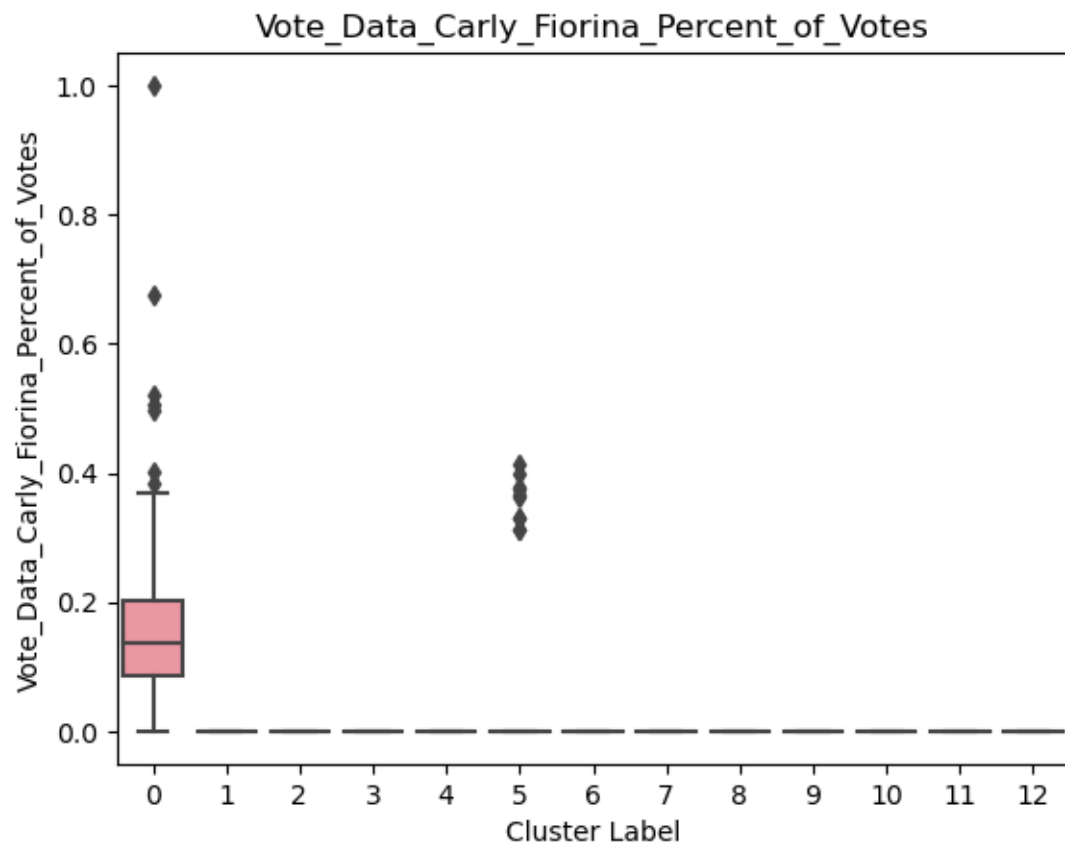
There is a bit difference between true label. We can see the left-up corner have a connect with the down one. But, the true label is not.

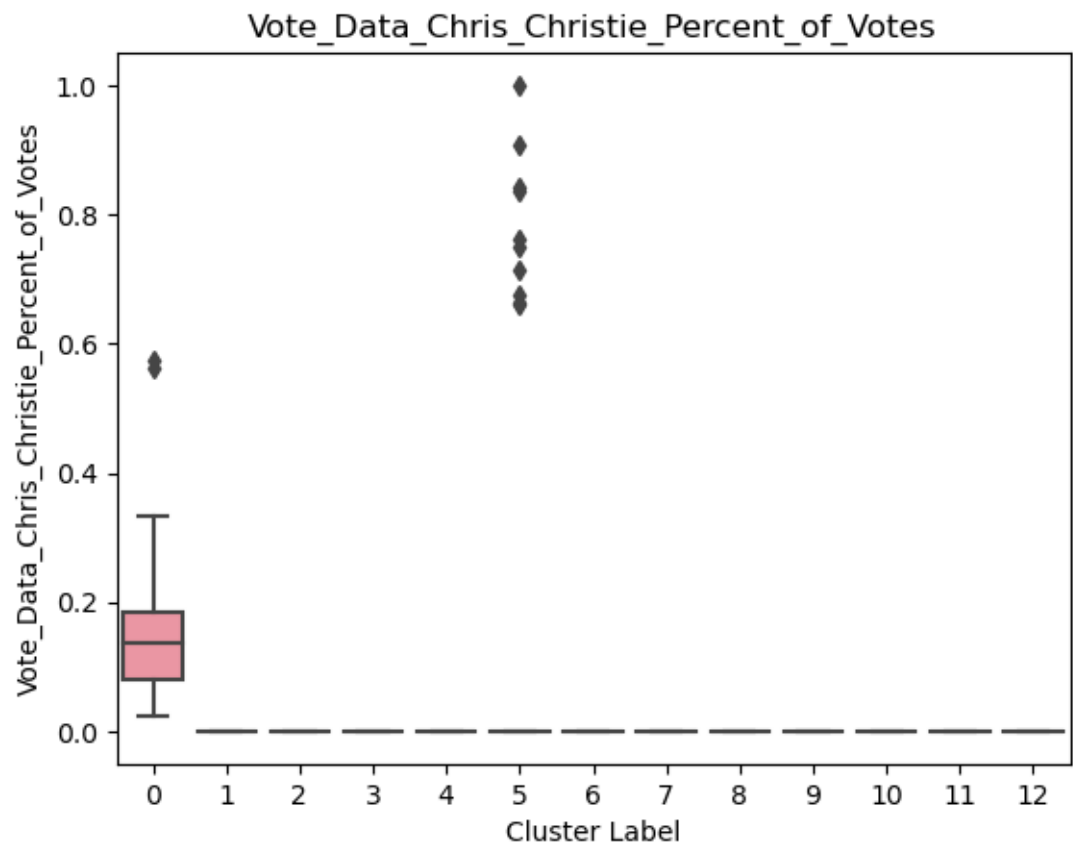
1.7.6 7.6. Describing Each of the Clusters

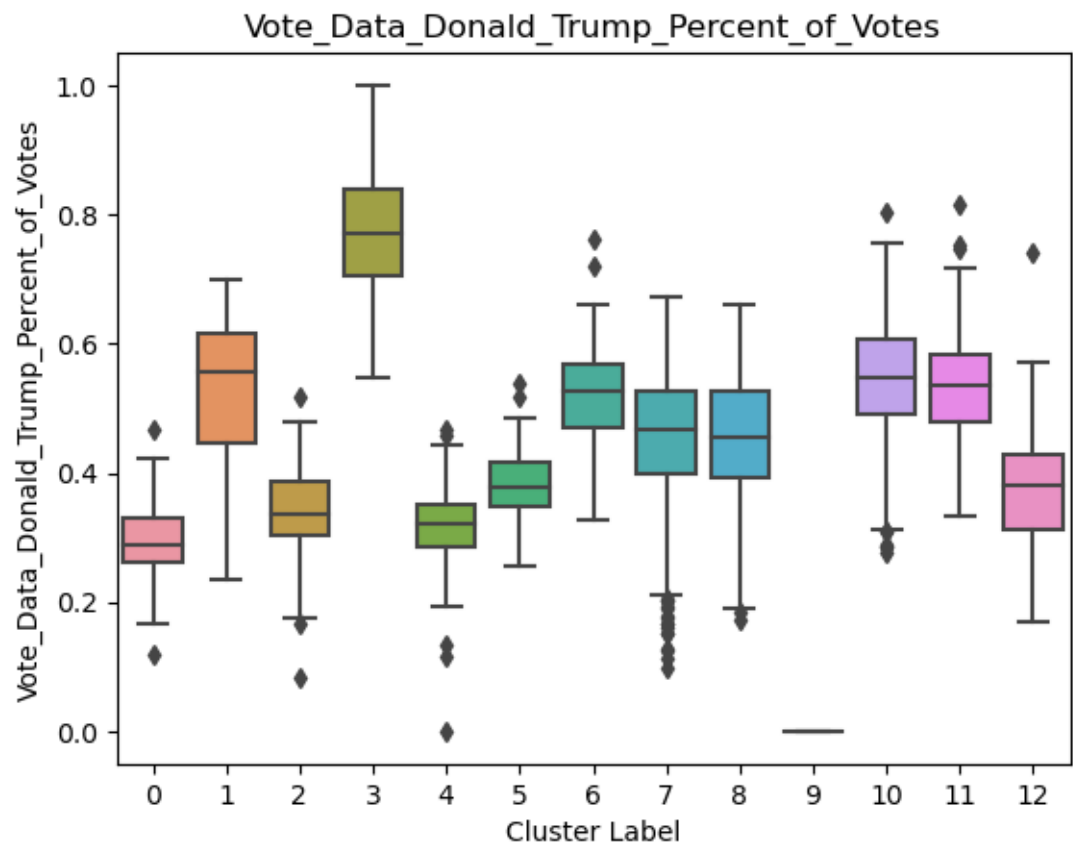
```
[115]: for col in df_kmeans_label.columns[:-1]:
        plt.figure()
        plt.title(col)
        sns.boxplot([df_kmeans_label.loc[df_kmeans_label['label'] == label, col]
        ↪for label in range(13)])
        plt.xlabel('Cluster Label')
        plt.ylabel(col)
        plt.show()
```

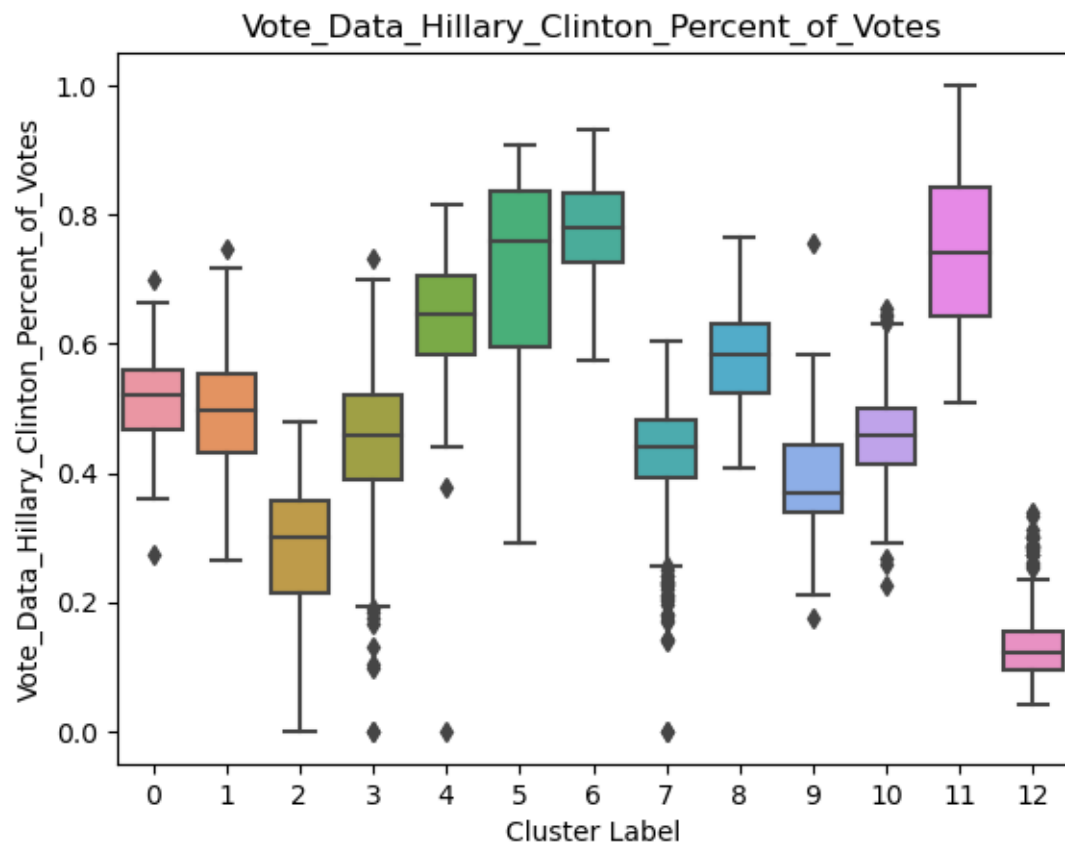


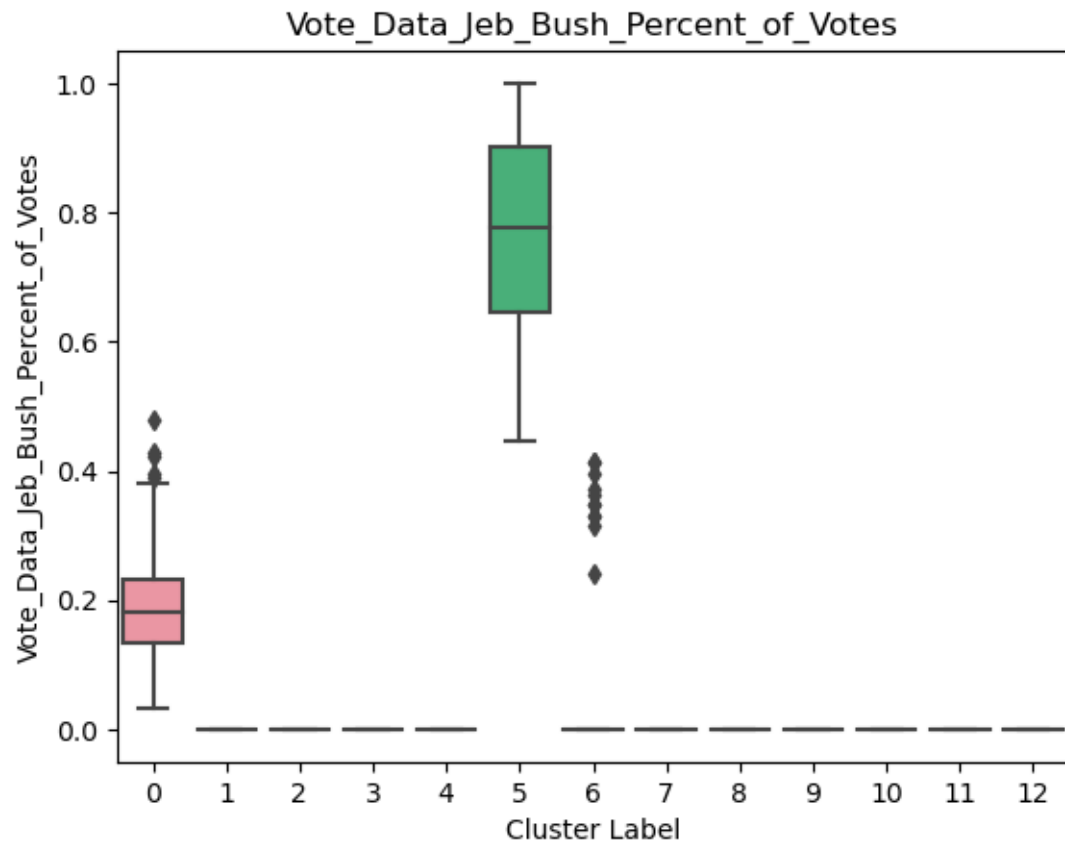


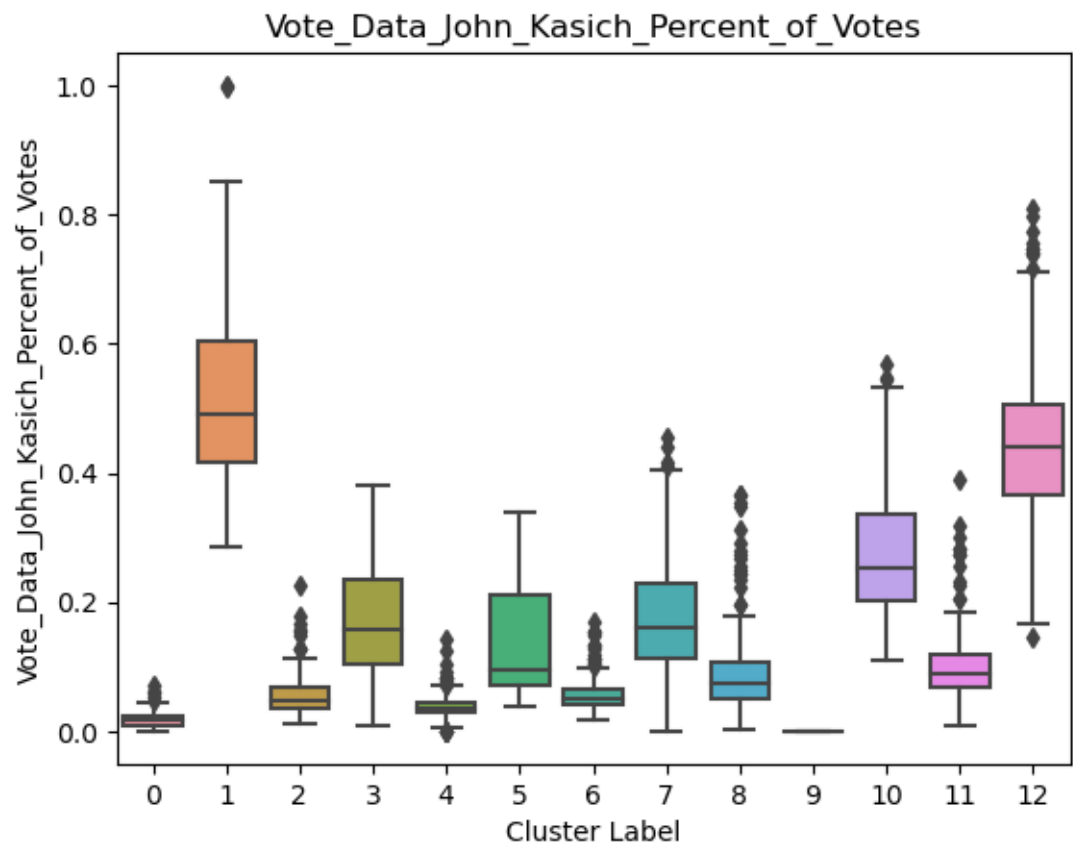


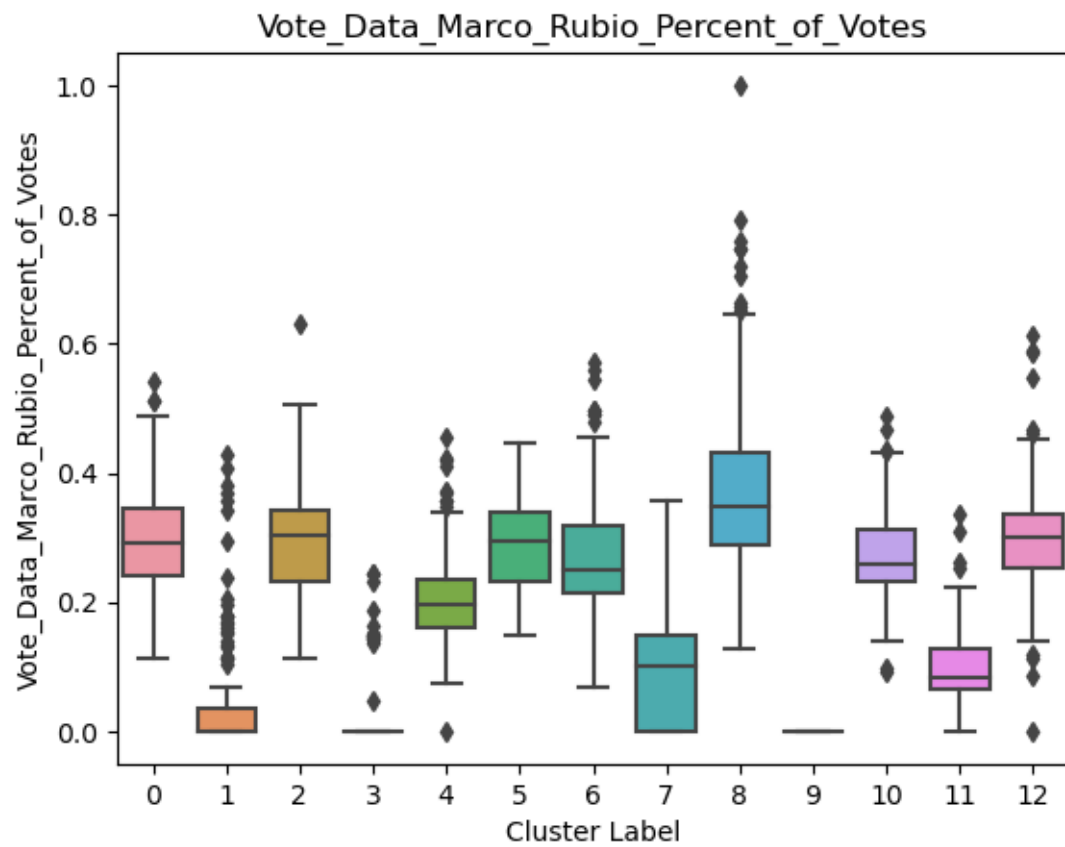


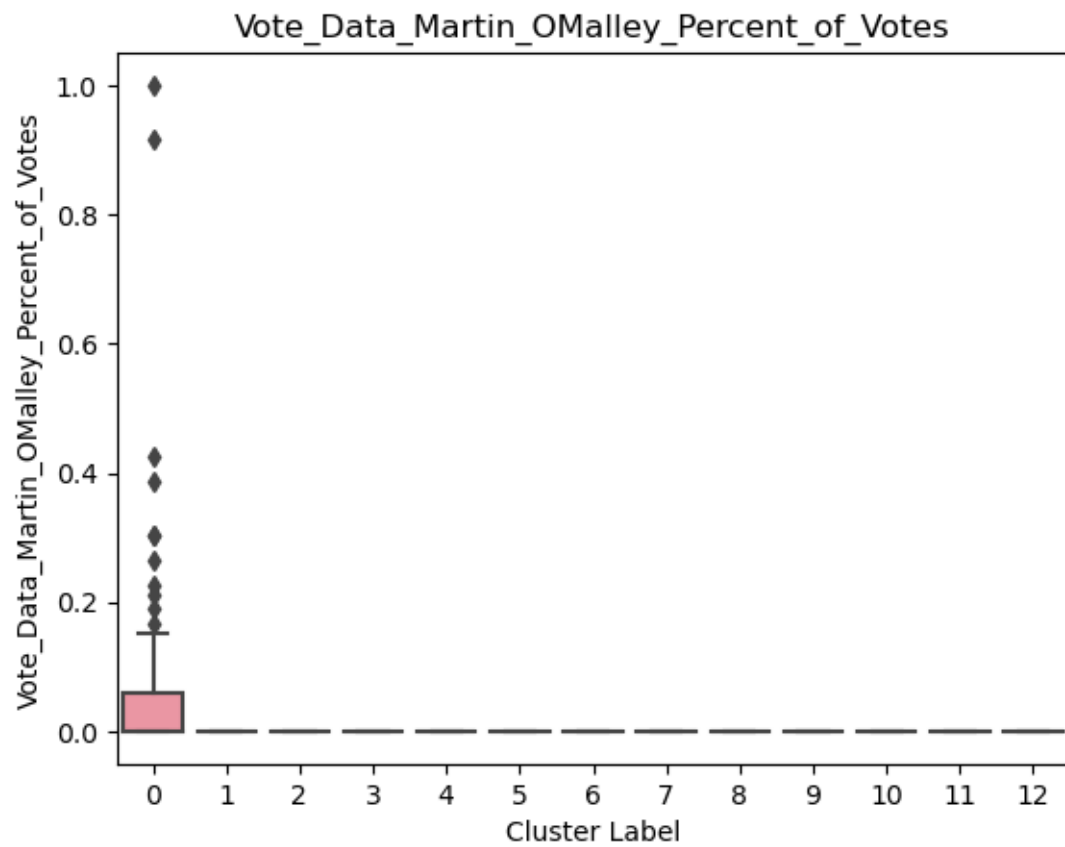


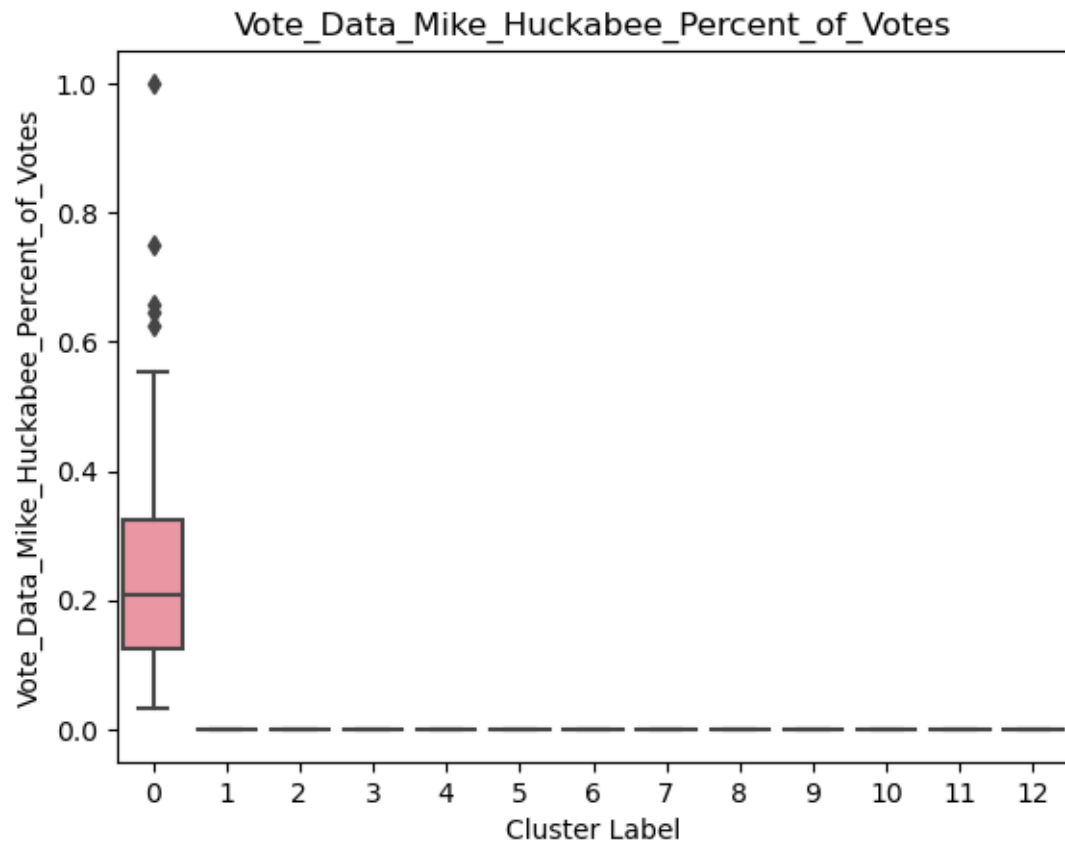


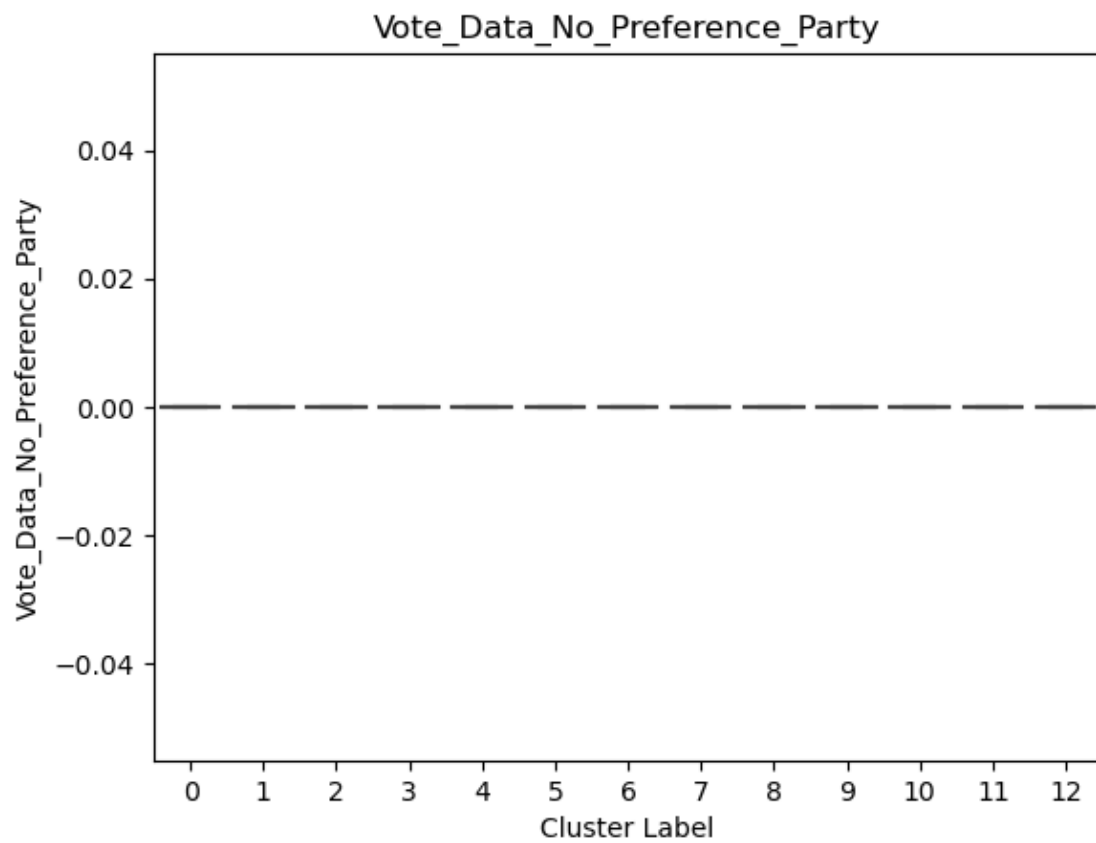


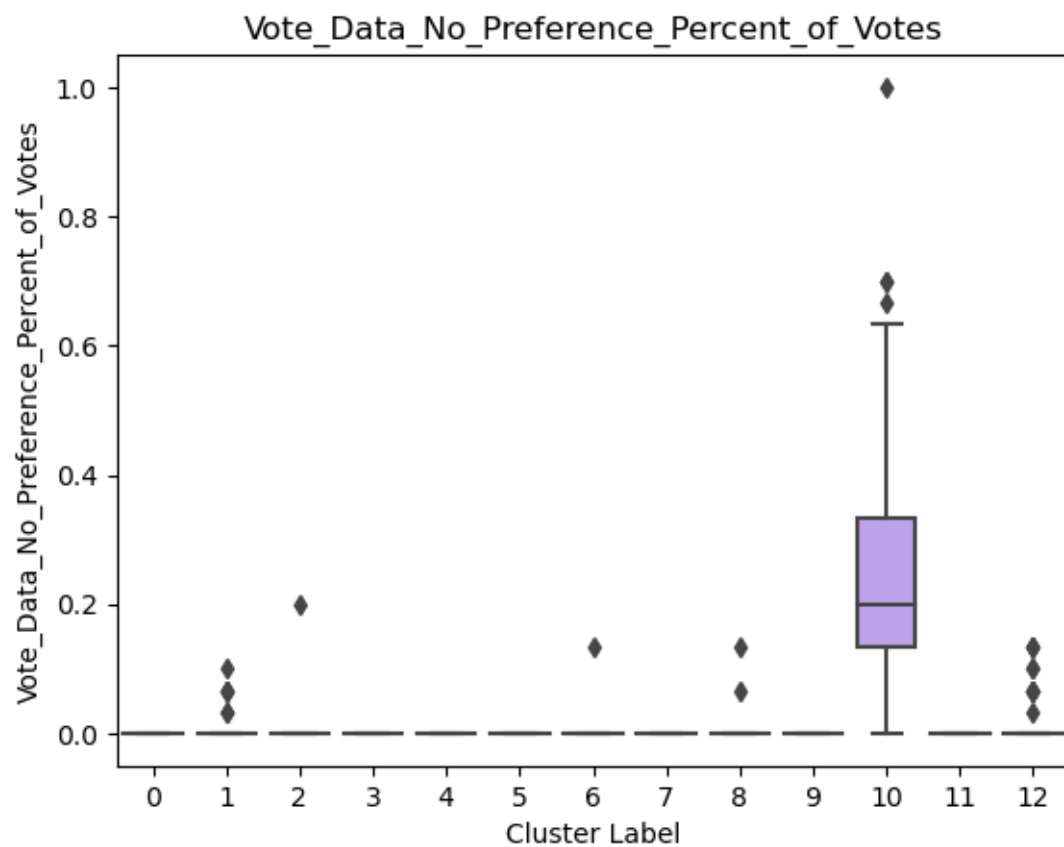


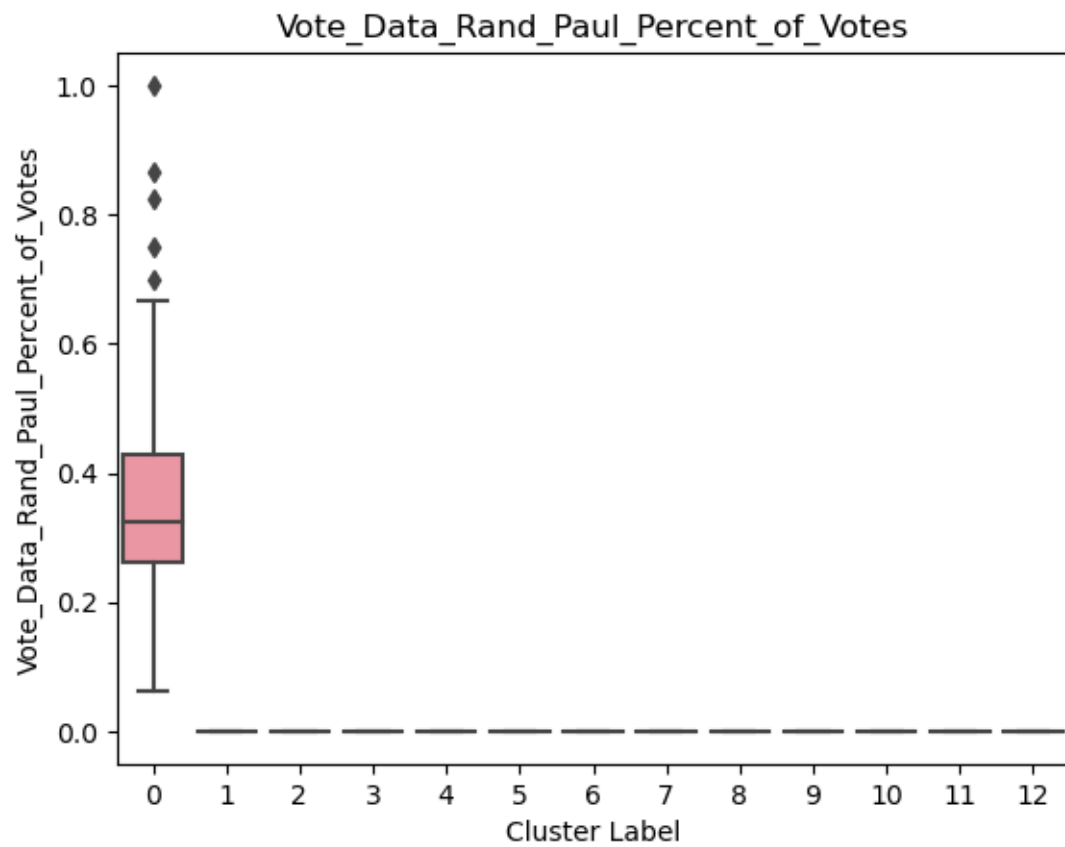


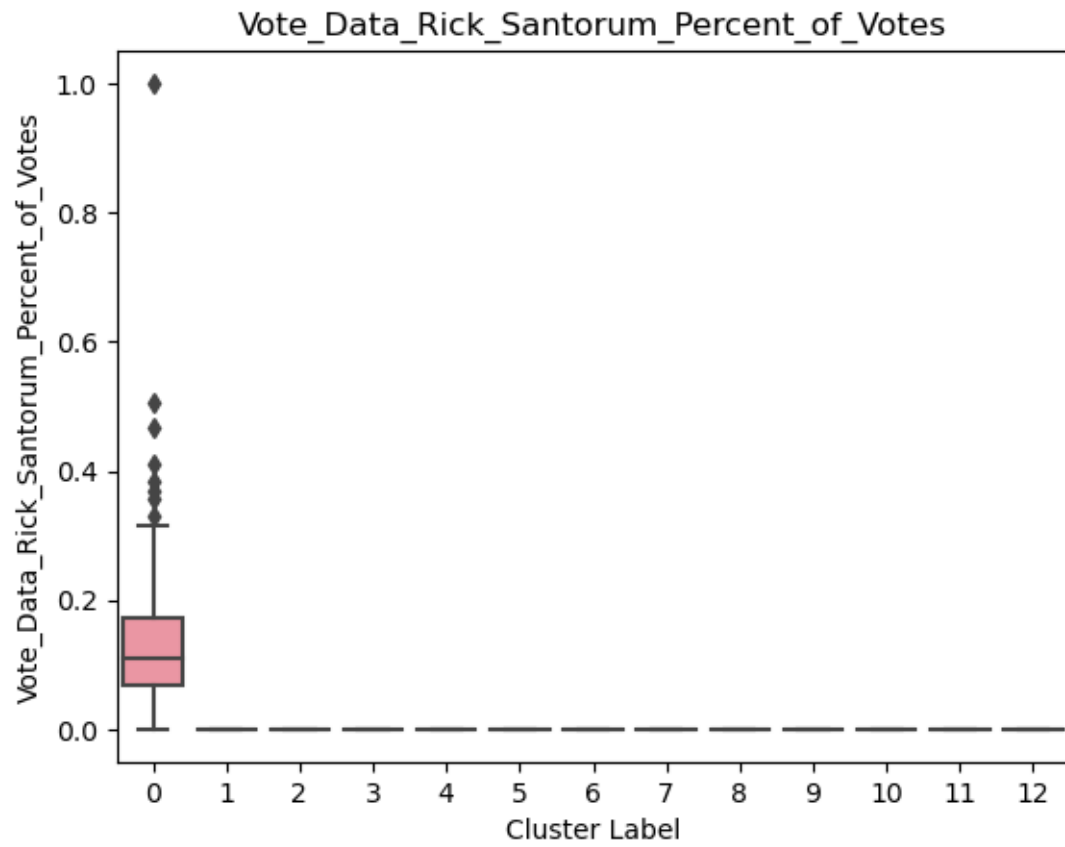


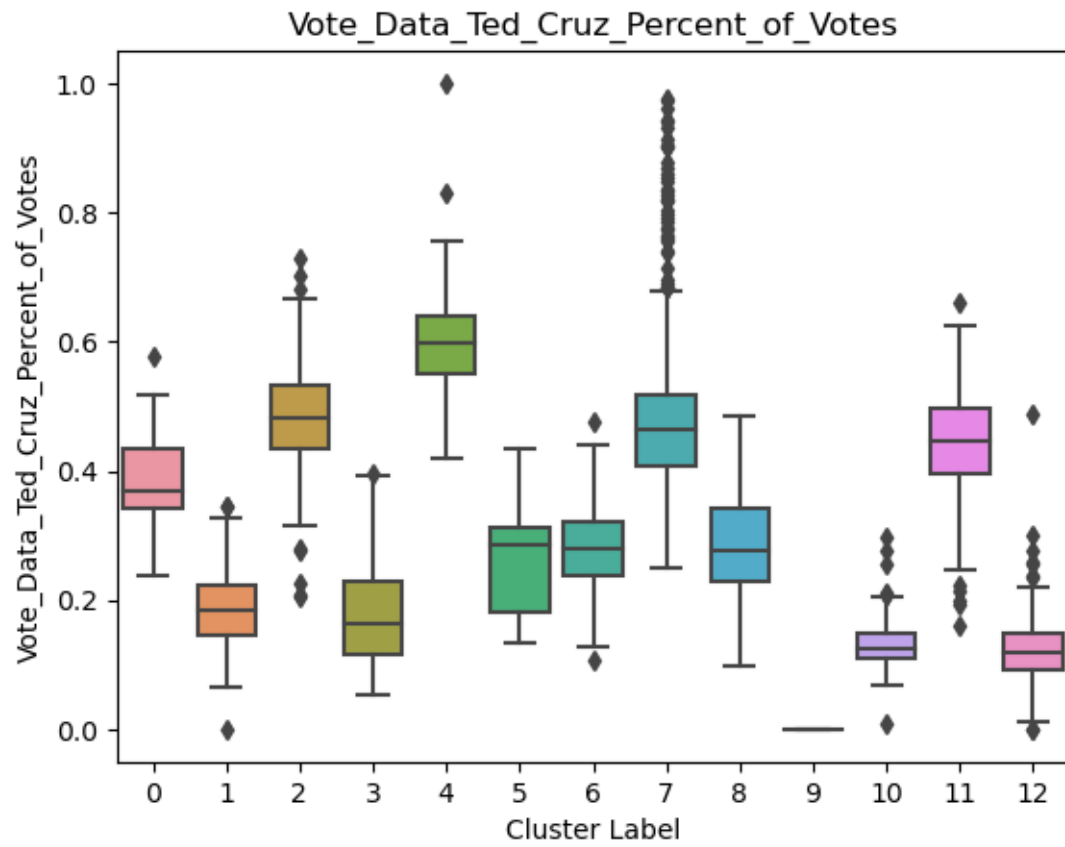


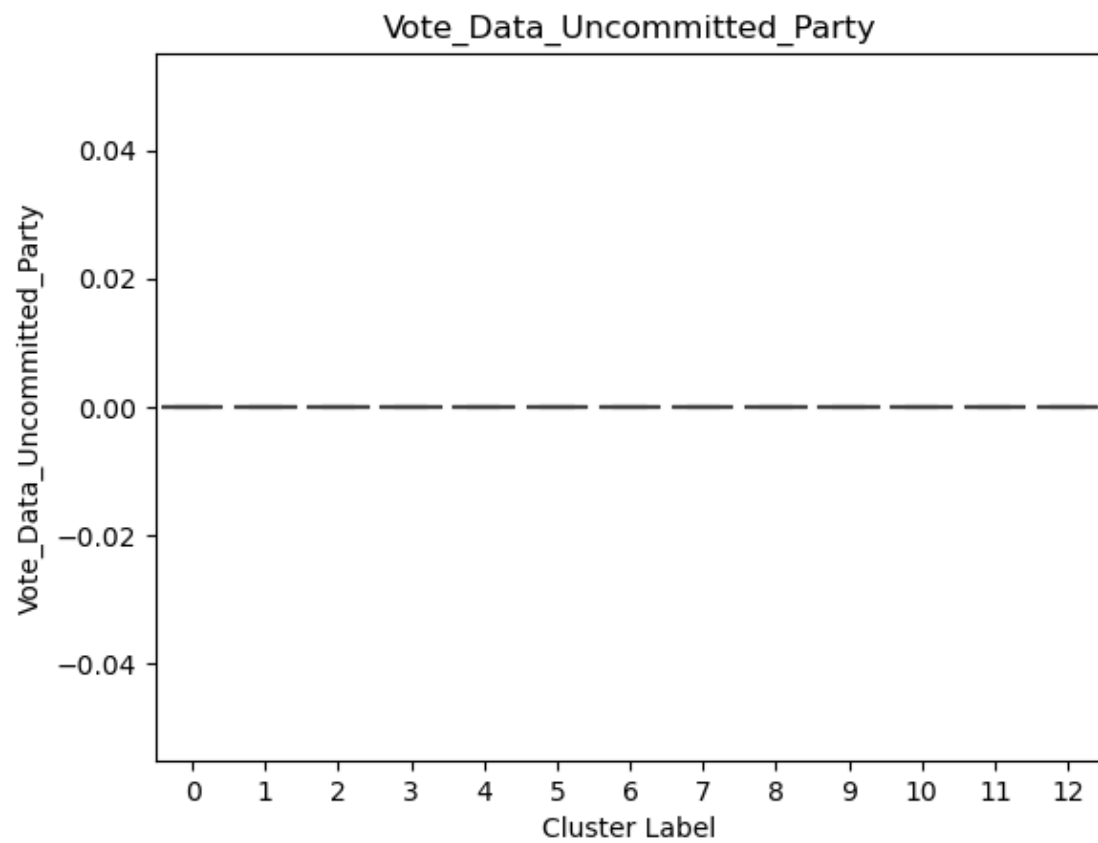


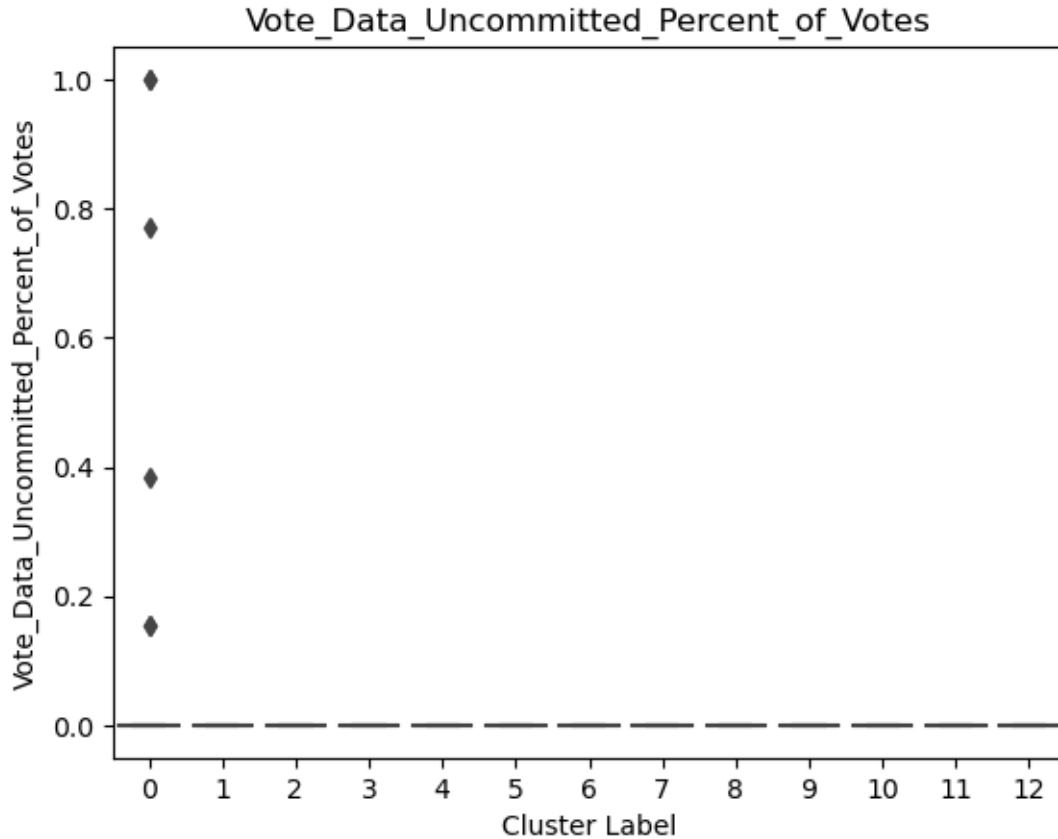








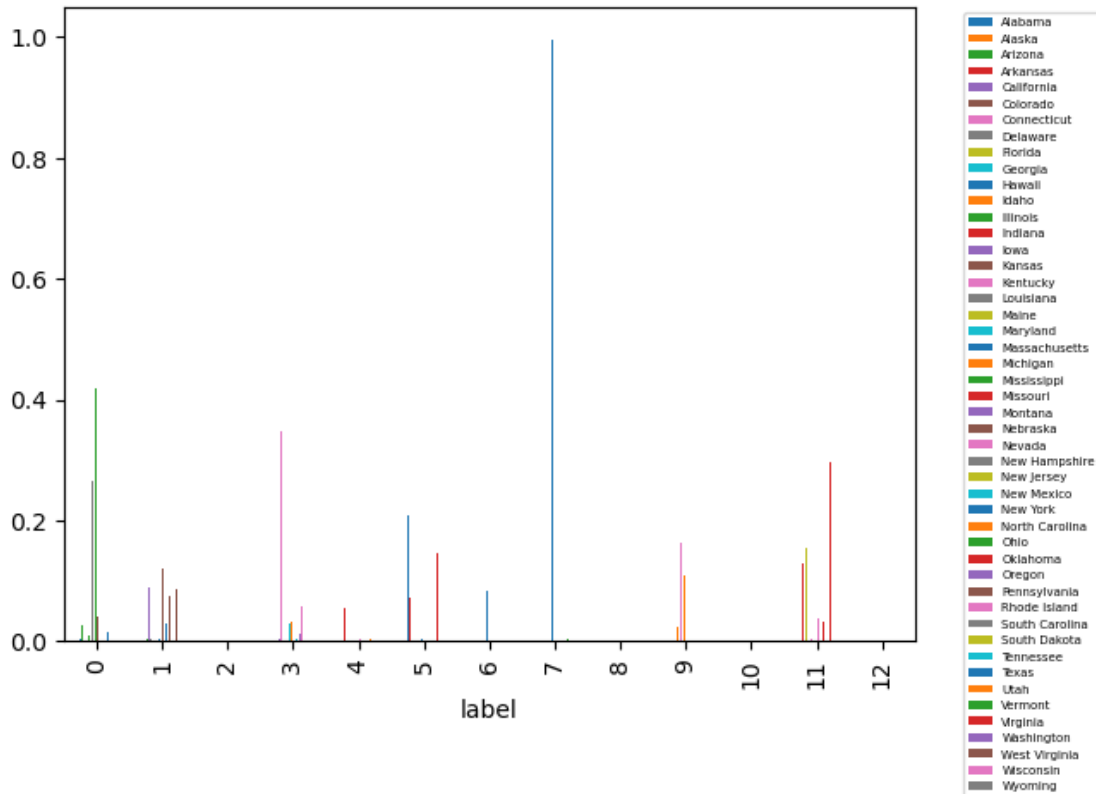




1. Ben Carson has the highest value of 0.5 in cluster 0 and the lowest cluster is 10.
2. Bernie Sanders is distributed in cluster 12 with a maximum value of 0.9 and the lowest cluster is cluster 6.
3. Carly Fiorina is mainly distributed in Cluster 0, have 0.1.
4. Chris Christie is mainly distributed in Cluster 0 have 0.1.
5. Donald Trump, is mainly distributed in Cluster 3–0.8. Then he has a very low approval rating in Cluster 0.
6. Hillary Clinton is mainly in 11, with a value of 0.7 and lowest is in 12.
7. Jeb Bush has very high support in cluster 5, with a value of 0.8 Very low support in cluster 0.
8. John Kasich's approval rating is only high in 1 and 12, with values of 0.5 and 0.5 respectively, while the rest are very low.
9. Marco Rubio has a relatively high approval rate of 8, with a value of 0.4, but the rest are quite average.
10. Mike Huckabee and Martin O'Malley are in the 0 distribution, the others are not.
11. Rand Paul's approval rating is at cluster 0.
12. Rick Santorum's approval rating is at cluster 0.
13. Ted Cruz's approval rating is highest at cluster 4 with a value of 0.6, lowest cluster is 12.

There is no centralized distribution for both unintentional and nonpartisan data, and very little data.

```
[103]: ctab=pd.crosstab(df_combo['label'],
    ↪df_combo['Location_State'],normalize='index')
ctab.plot.bar()
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
plt.show()
```



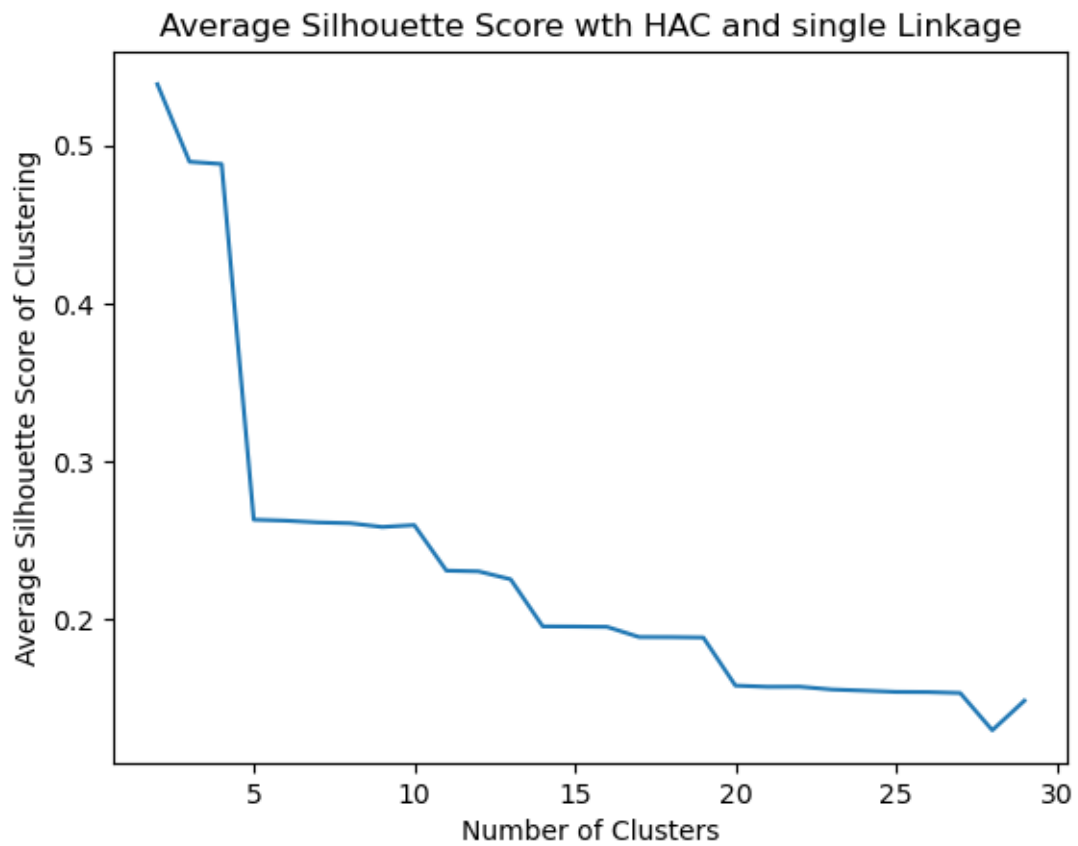
We can see that cluster 7 is composed of one state. But there are some clusters are not agree with motivation, for example, clusters 0, 1 and 11 have a lot of different states in their distribution. This shows that also the cohesion is a little bit unsatisfactory.

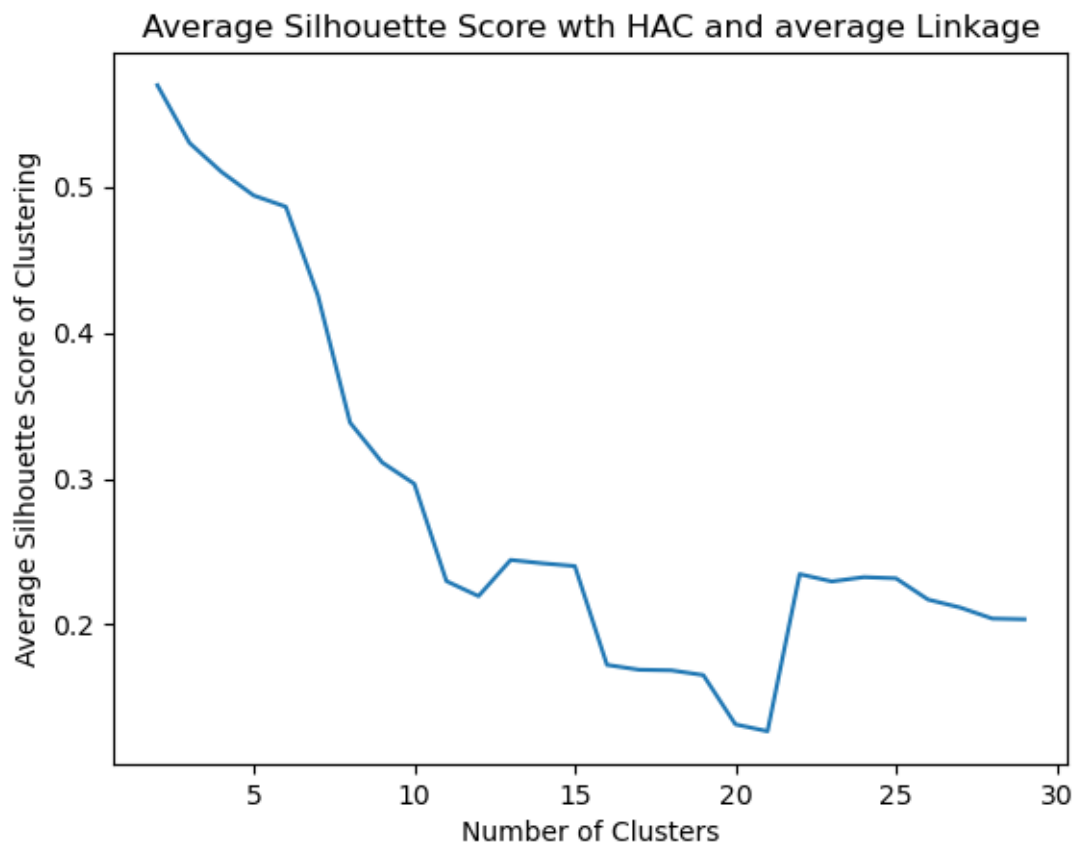
1.8 8. Clustering Algorithm 2 (change name to the algorithm you chose)

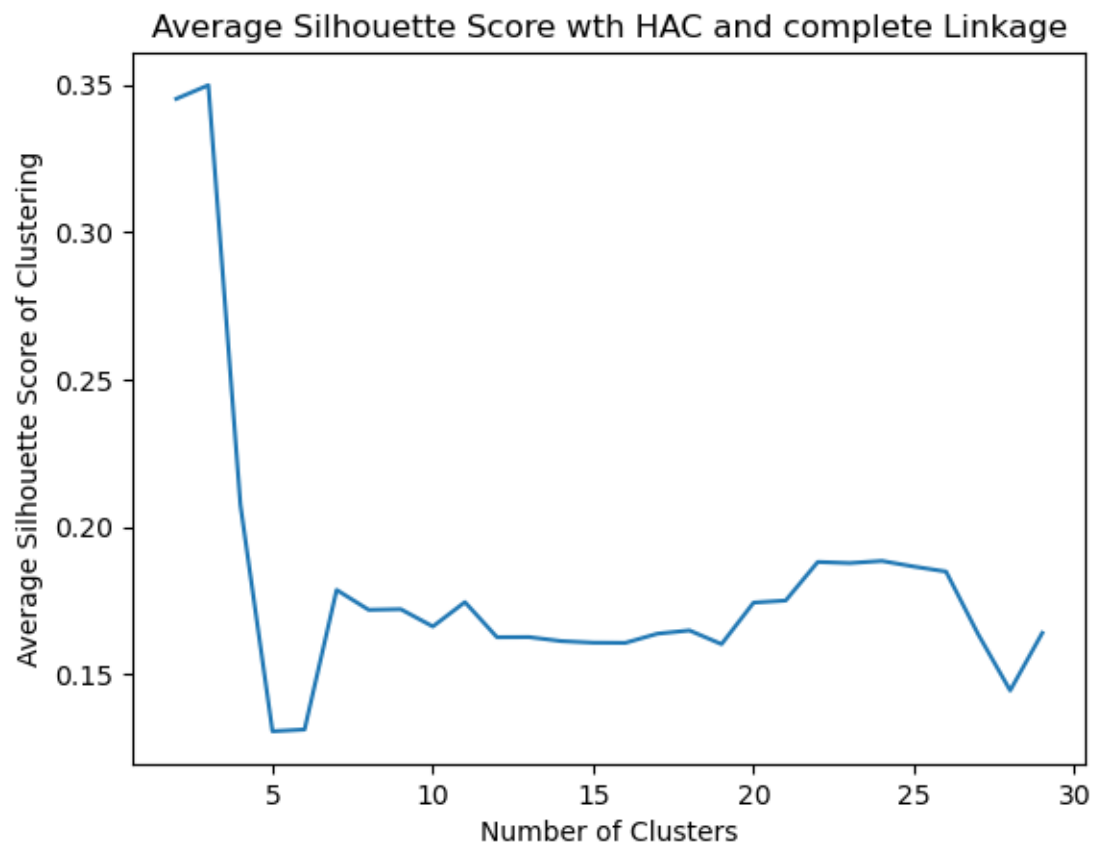
1.8.1 8.1. Parameter Selection

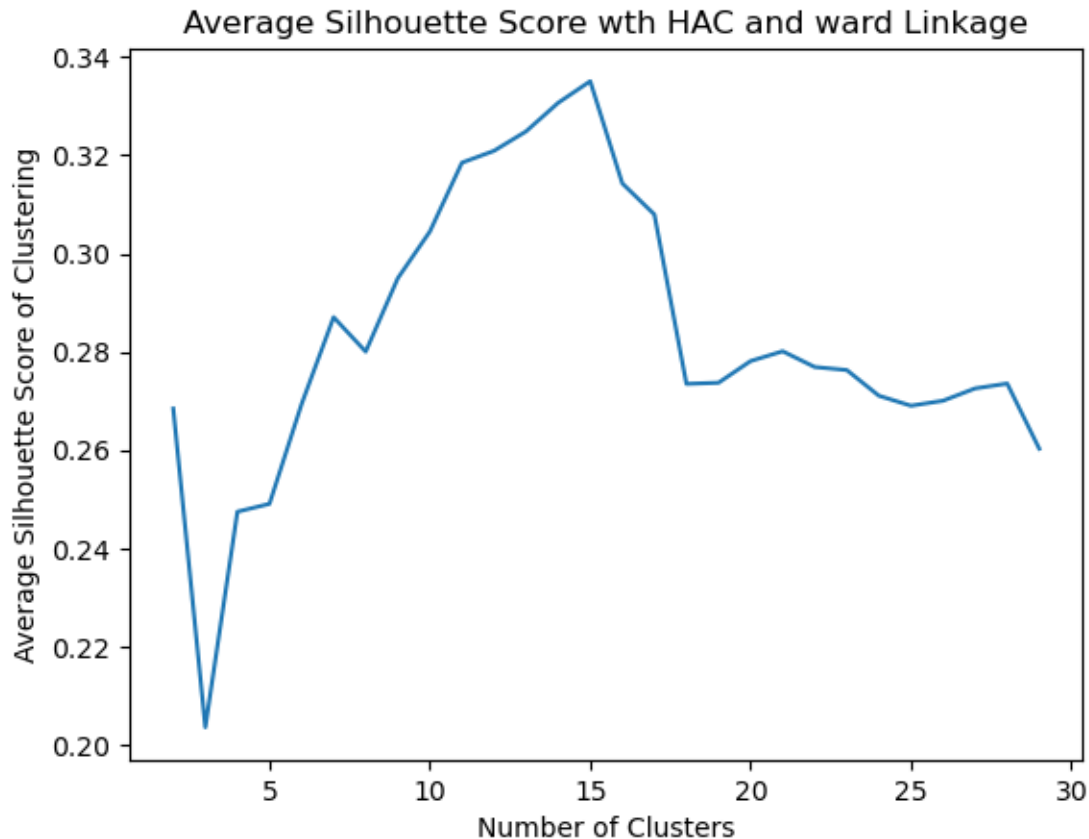
```
[62]: for link in ['single', 'average', 'complete', 'ward']:
    avg_ss=[]
    for k in range(2,30):
        hac = AgglomerativeClustering(n_clusters=k, affinity='euclidean',
    ↪linkage=link)
        Y_pred = hac.fit_predict(df_num)
        avg_ss.append(silhouette_score(df_num, Y_pred))
```

```
plt.plot(range(2,30), avg_ss)
plt.title('Average Silhouette Score wth HAC and %s Linkage'%link)
plt.xlabel('Number of Clusters')
plt.ylabel('Average Silhouette Score of Clustering')
plt.show()
```





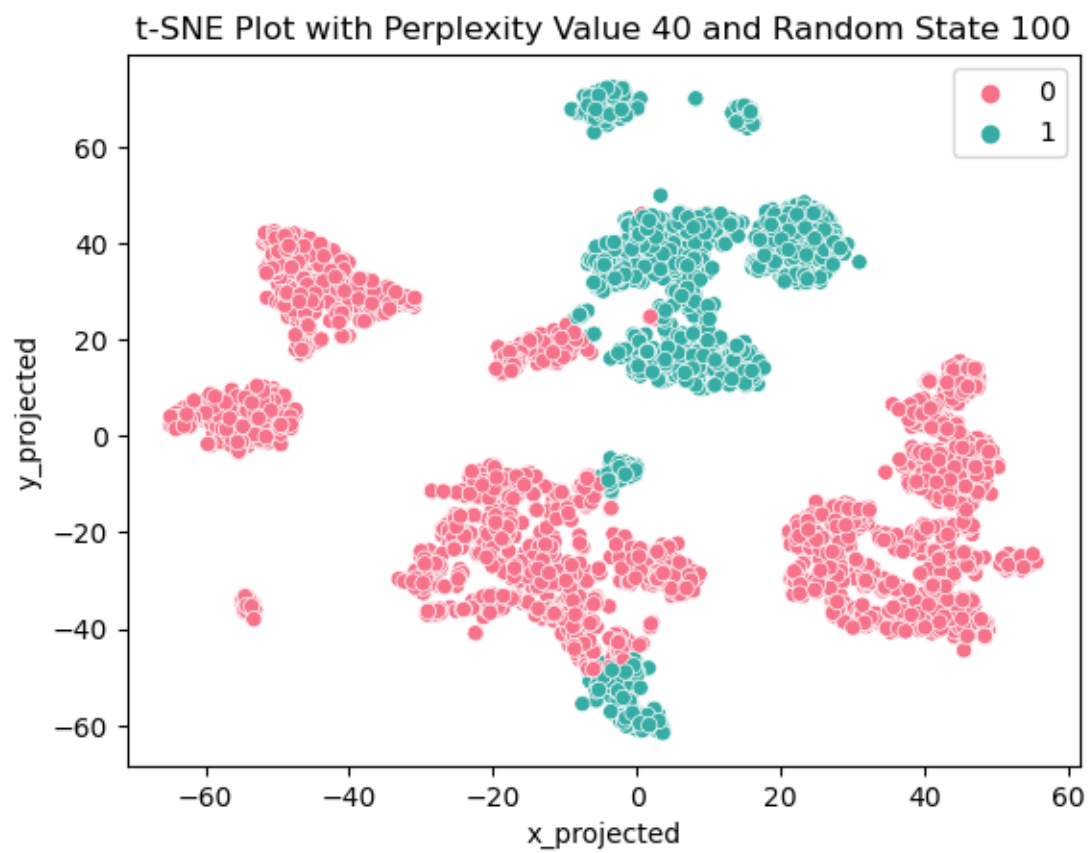


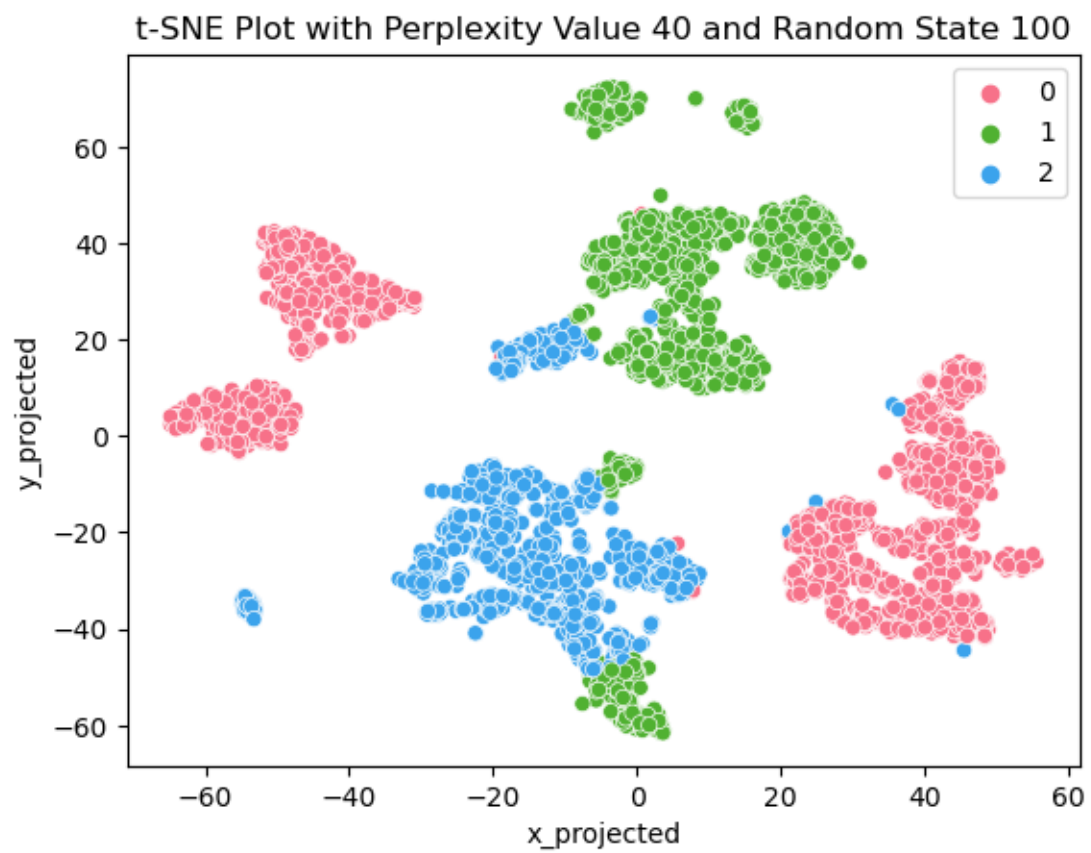


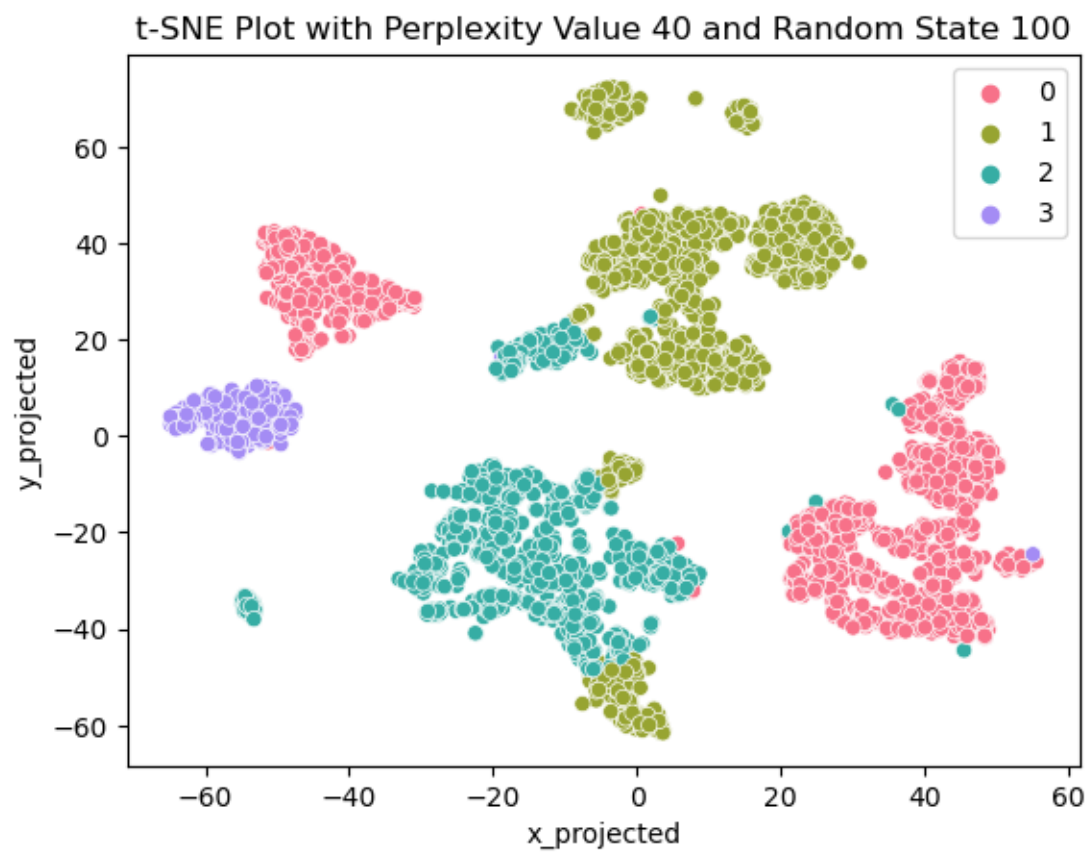
We think the cluster number should approach the number of states. If we only choose the highest Average Silhouette Score from above with low number of cluster, it is unreasonable. Thus, we selected ward linkage which $K = 15$. The ward linkage have the average highest score, which the score is bigger than $k = 7$.

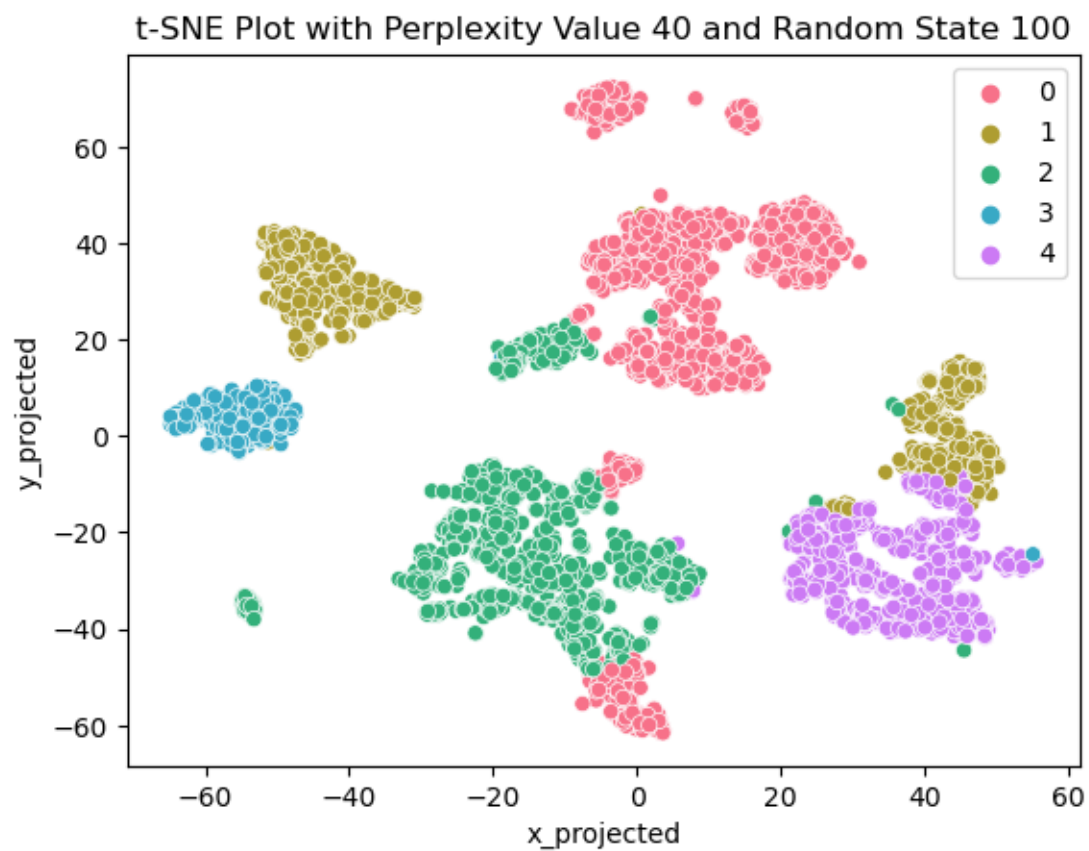
```
[63]: for k in range(2,30):
        #Clustering from dendrogram with k clusters
        hac = AgglomerativeClustering(n_clusters=k, affinity='euclidean',
        ↪linkage='ward')
        df_combo['predicted_cluster'] = hac.fit_predict(df_num)

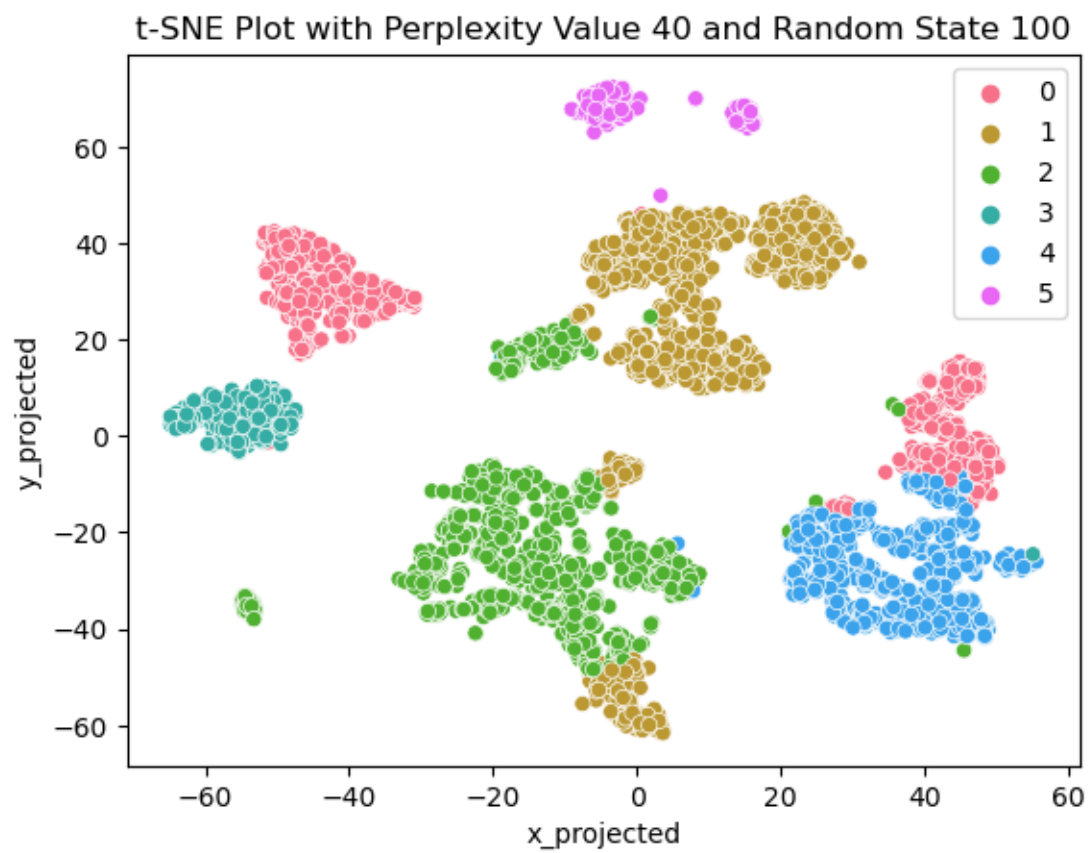
        #Map the resulting cluster labels onto our chosen t-SNE plot
        sns.scatterplot(x='x_projected',y='y_projected', hue='predicted_cluster',
        ↪palette=sns.color_palette("husl", k), data=df_combo)
        plt.title('t-SNE Plot with Perplexity Value %s and Random State %s' %(40,
        ↪100))
        plt.legend(bbox_to_anchor=(1,1))
        plt.show()
```

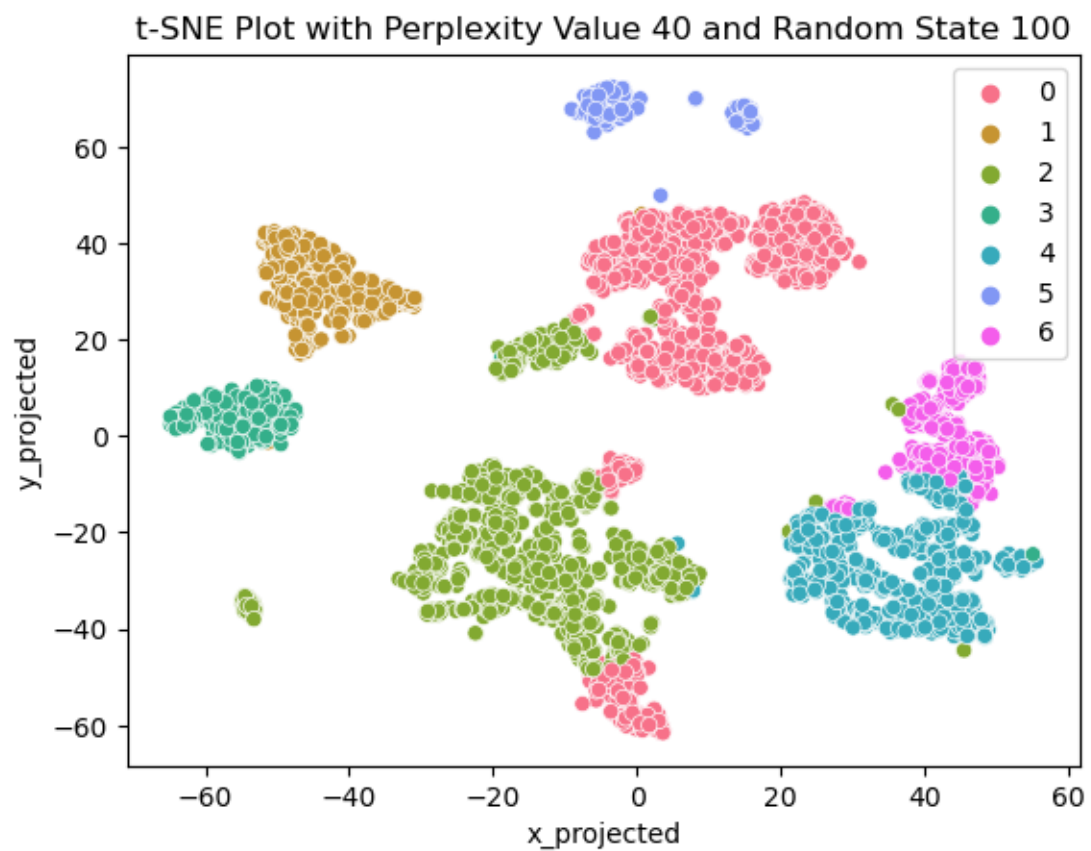


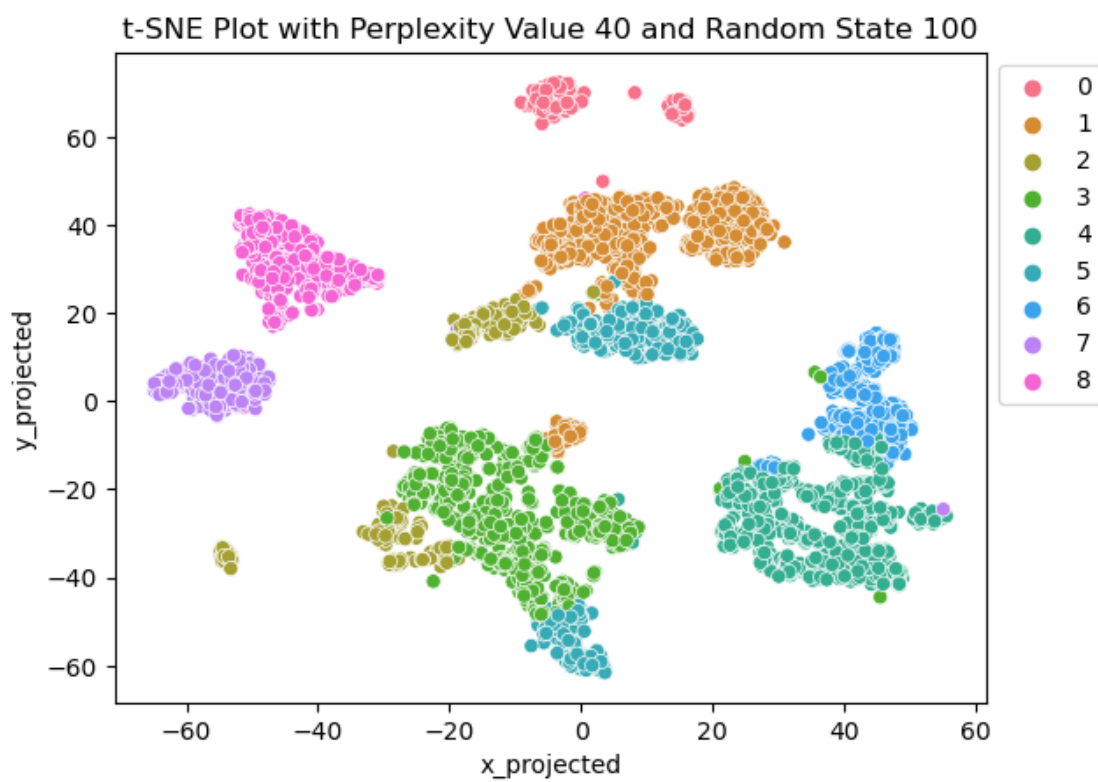
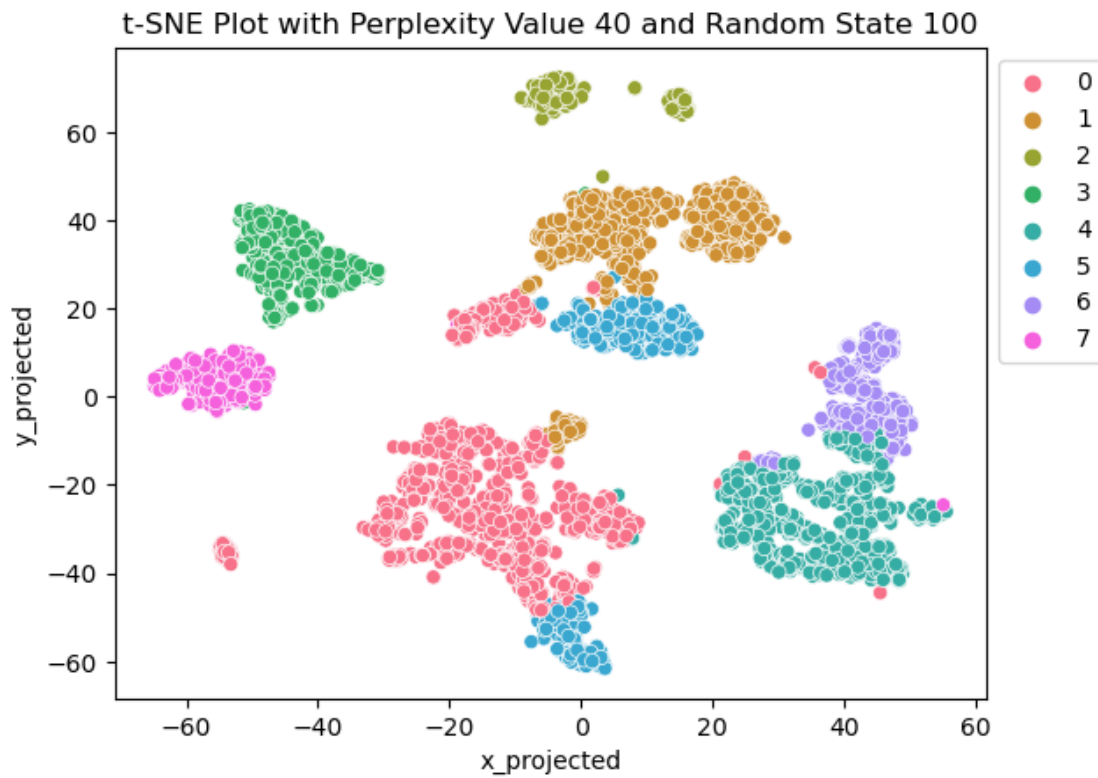


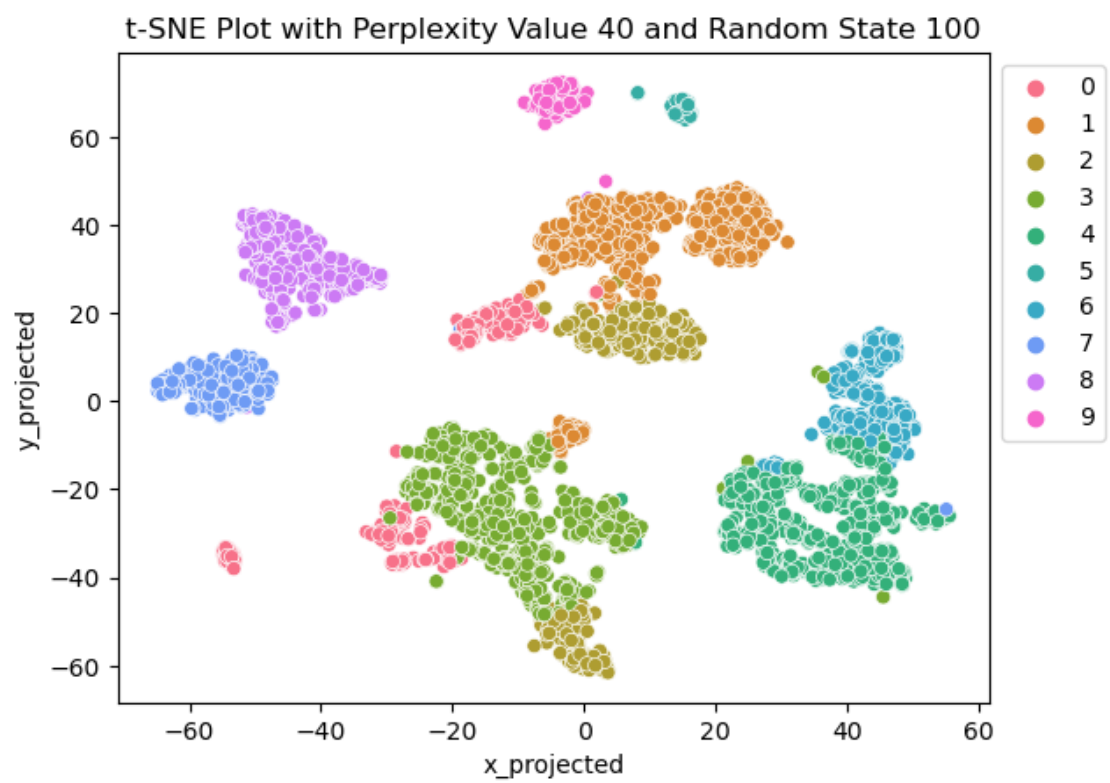


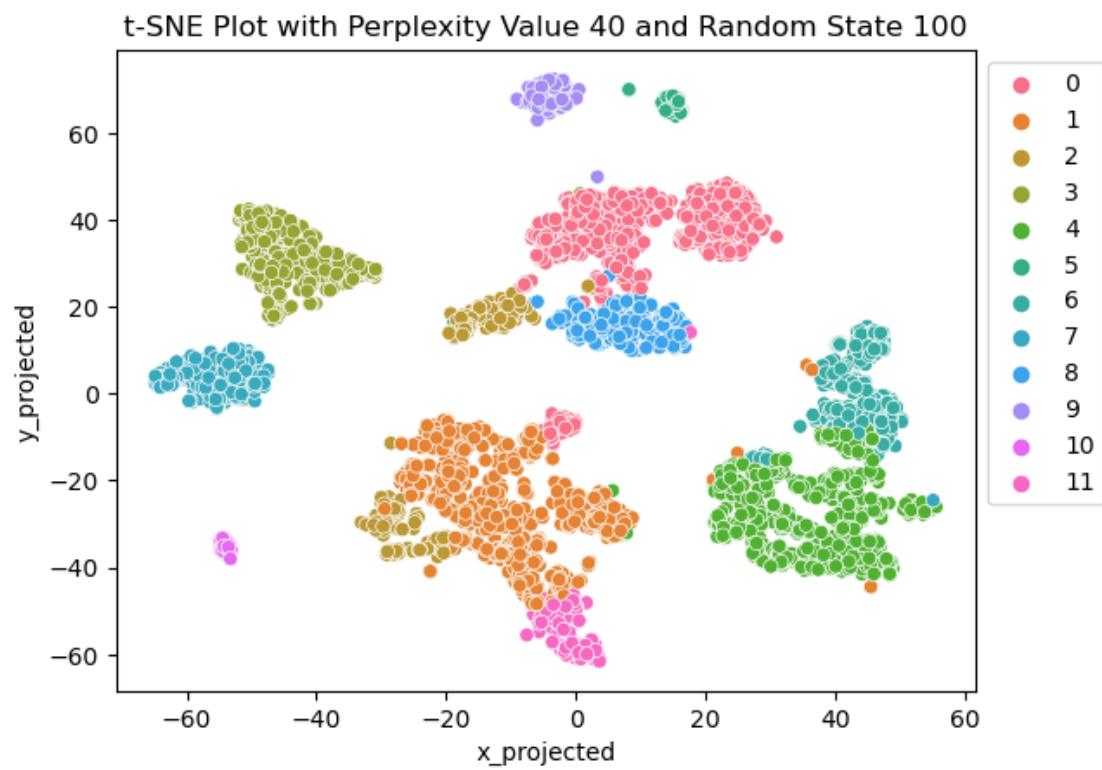
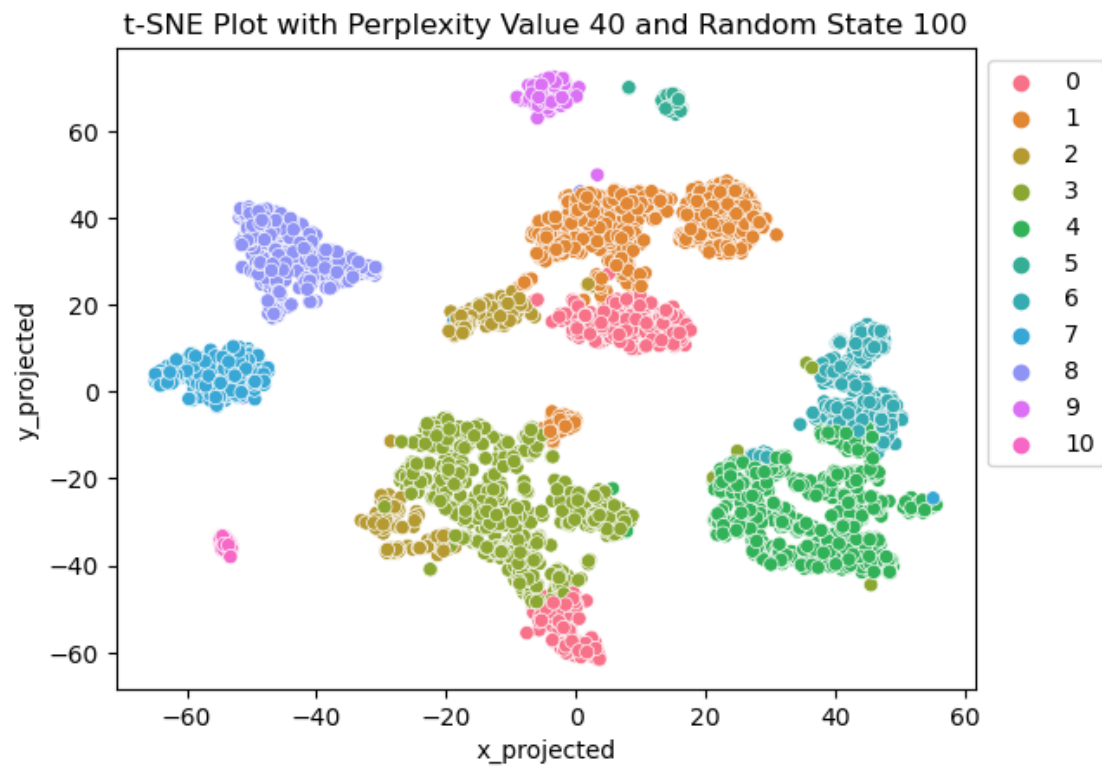


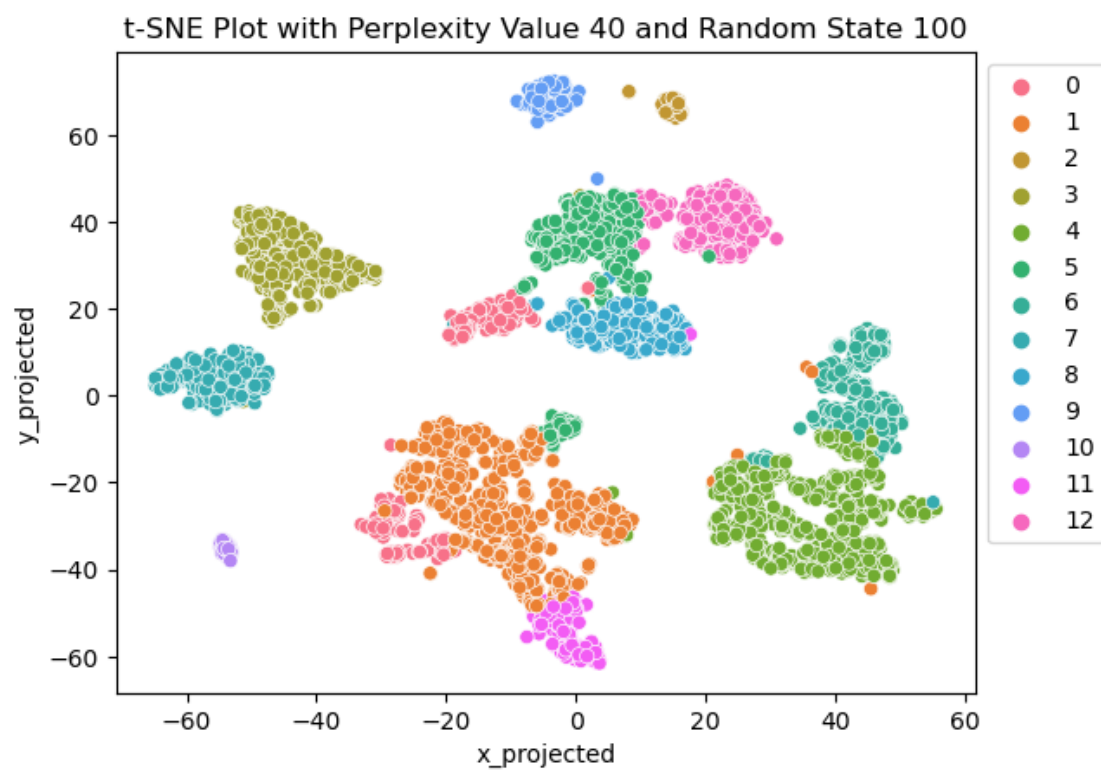


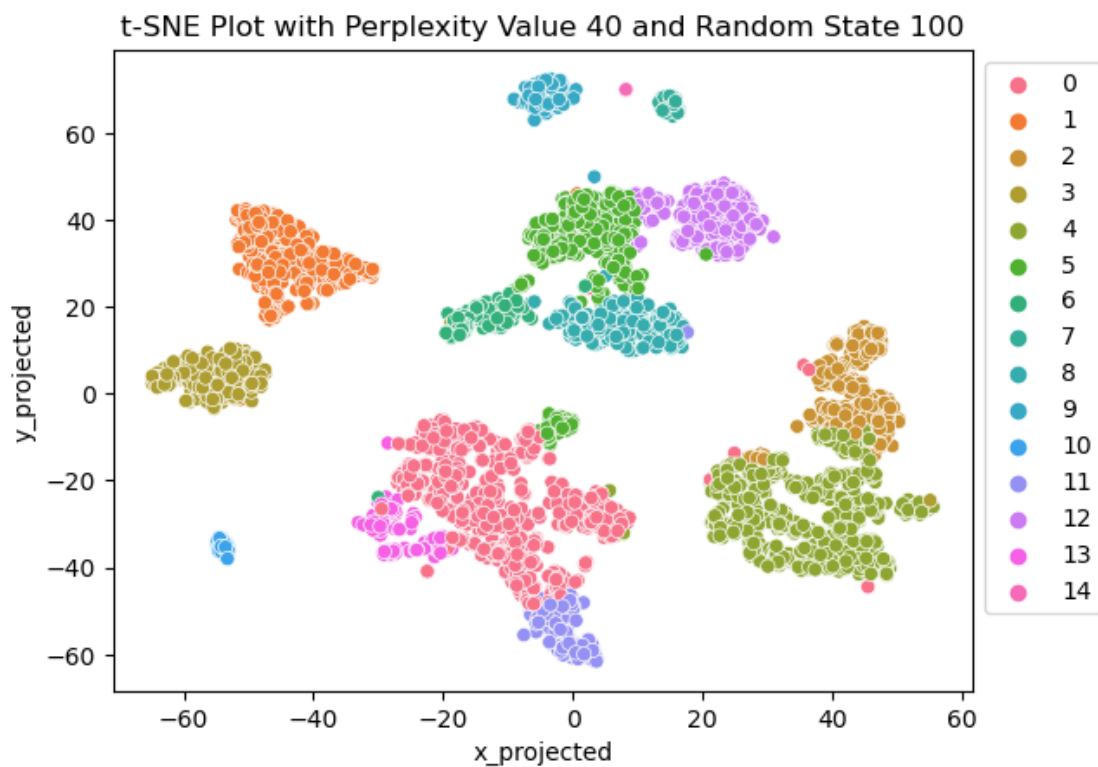
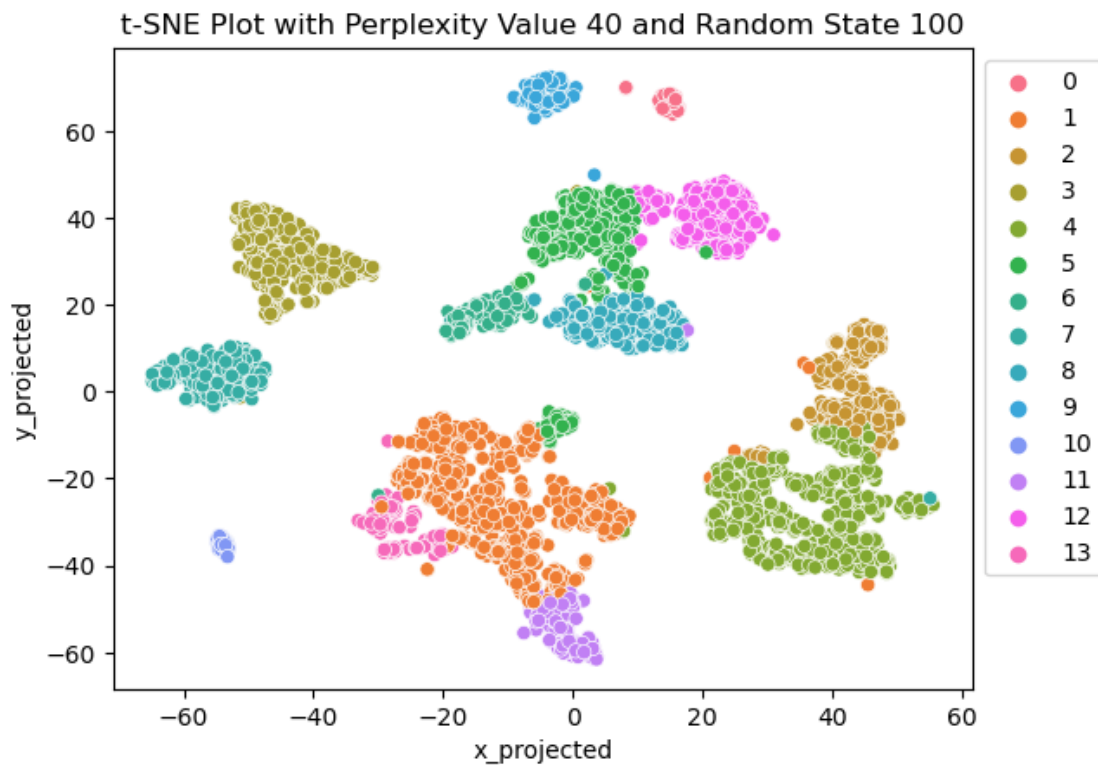


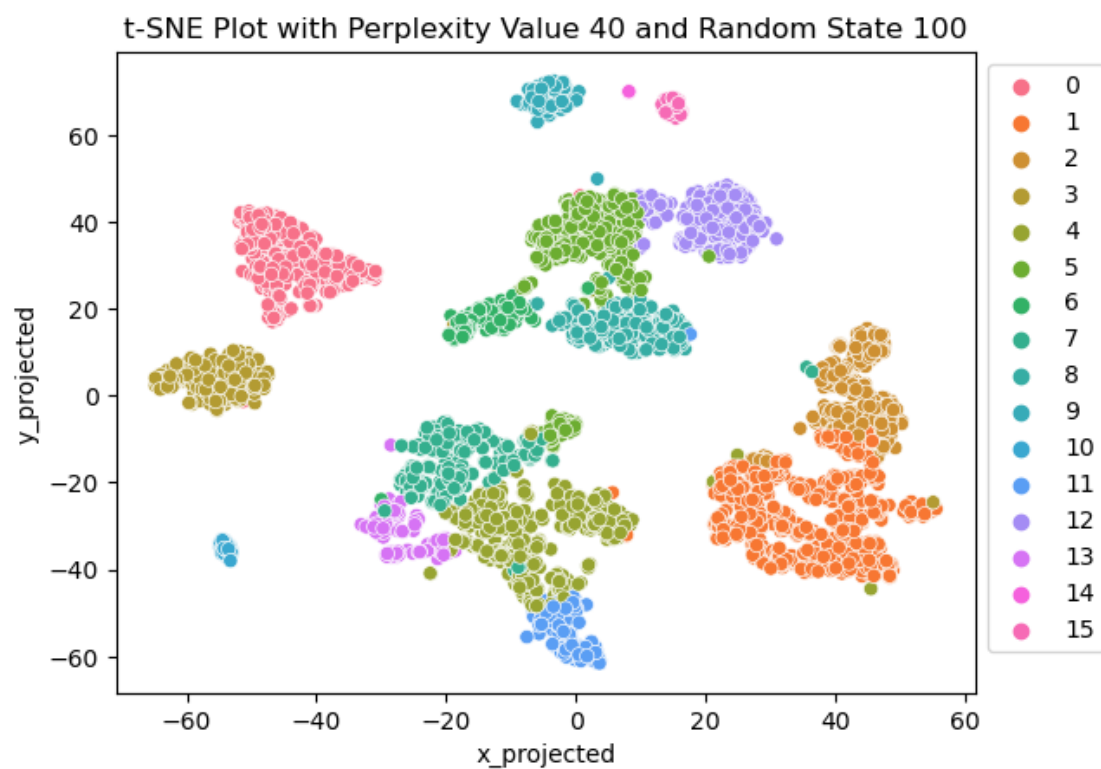


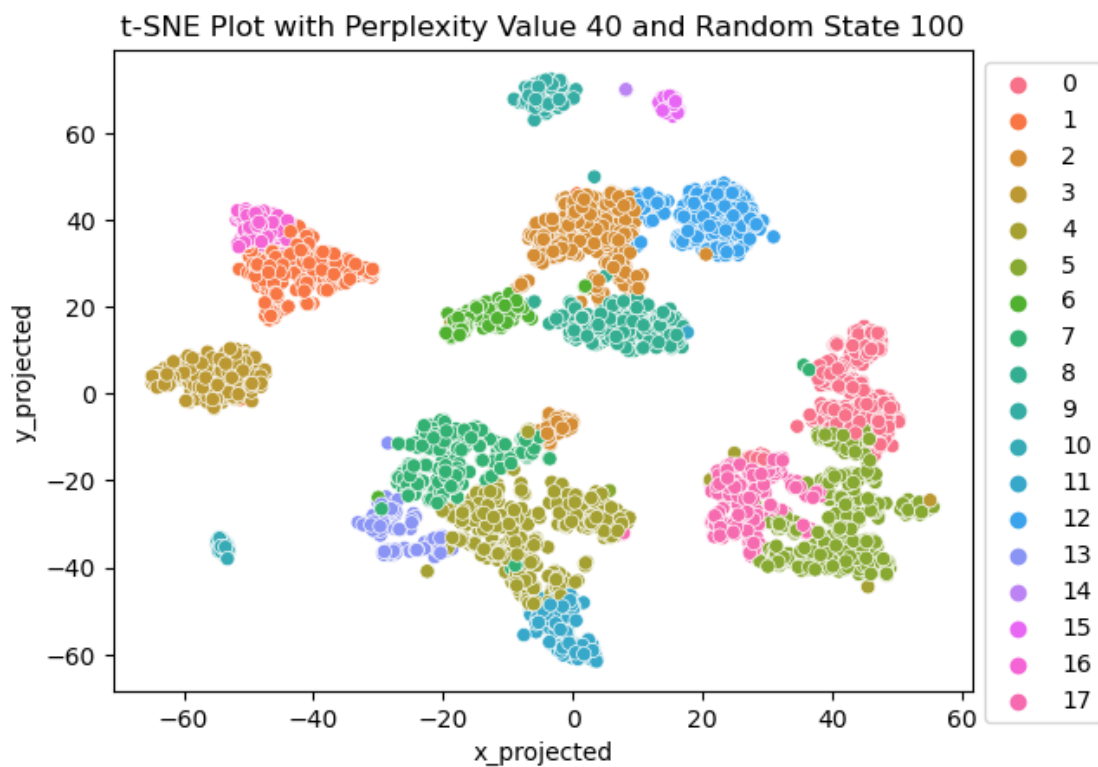
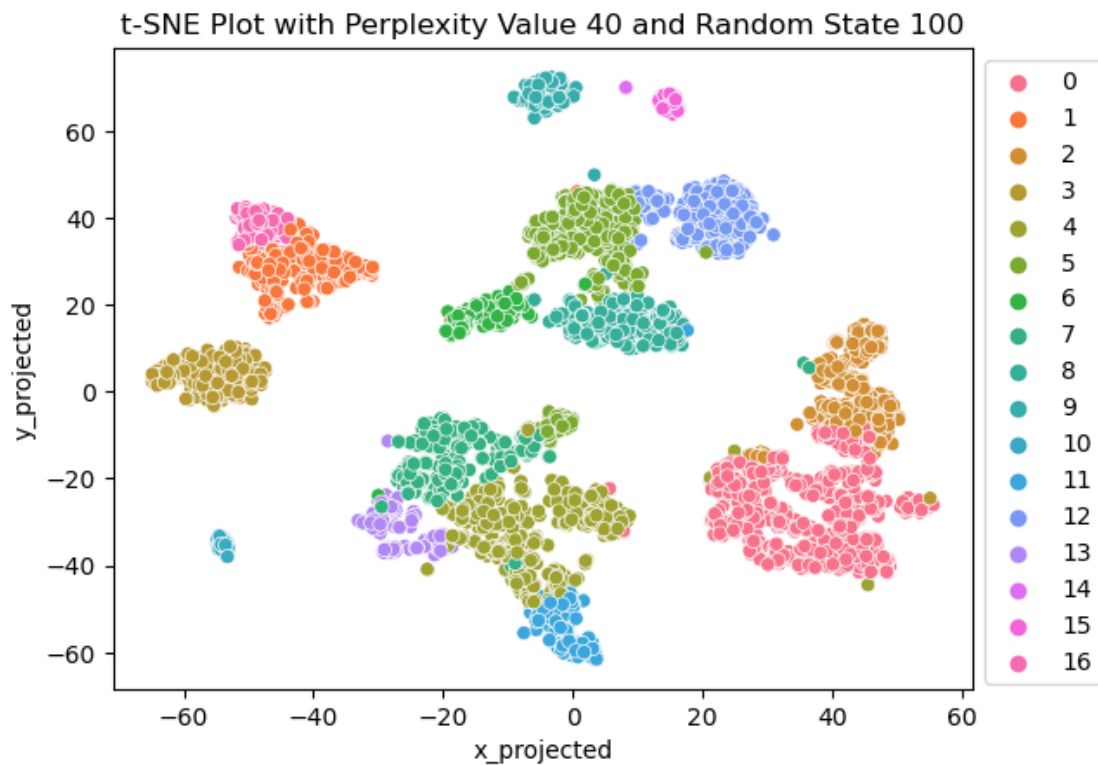


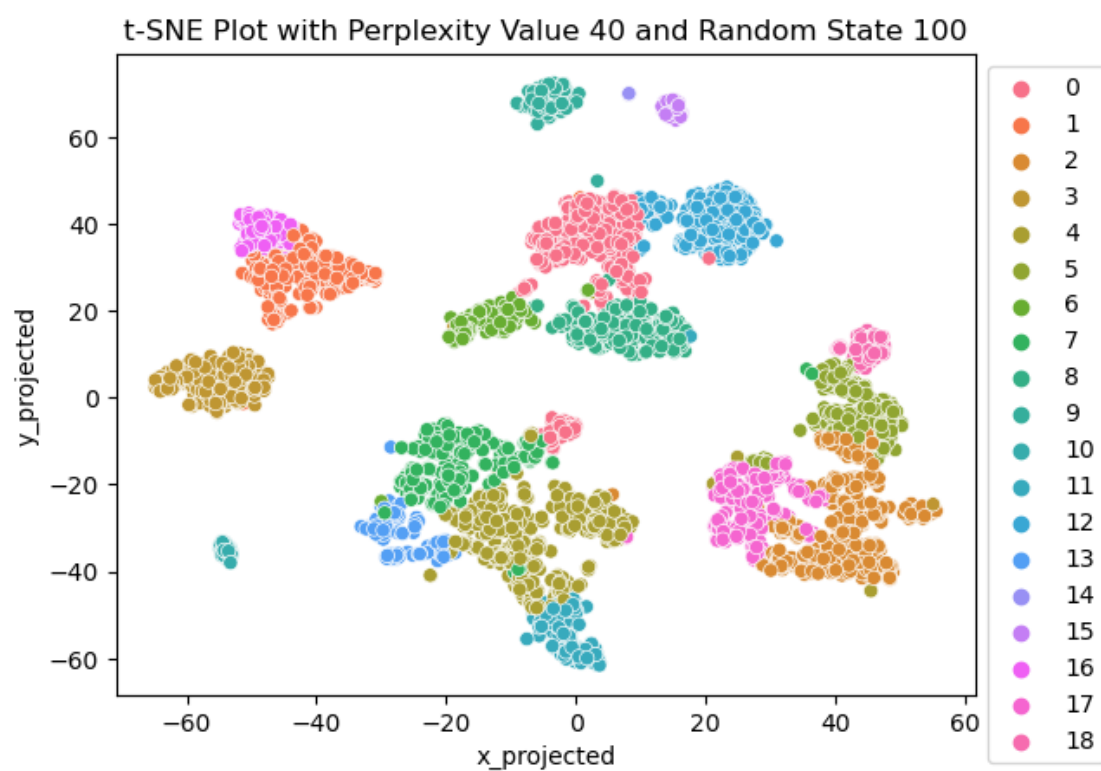


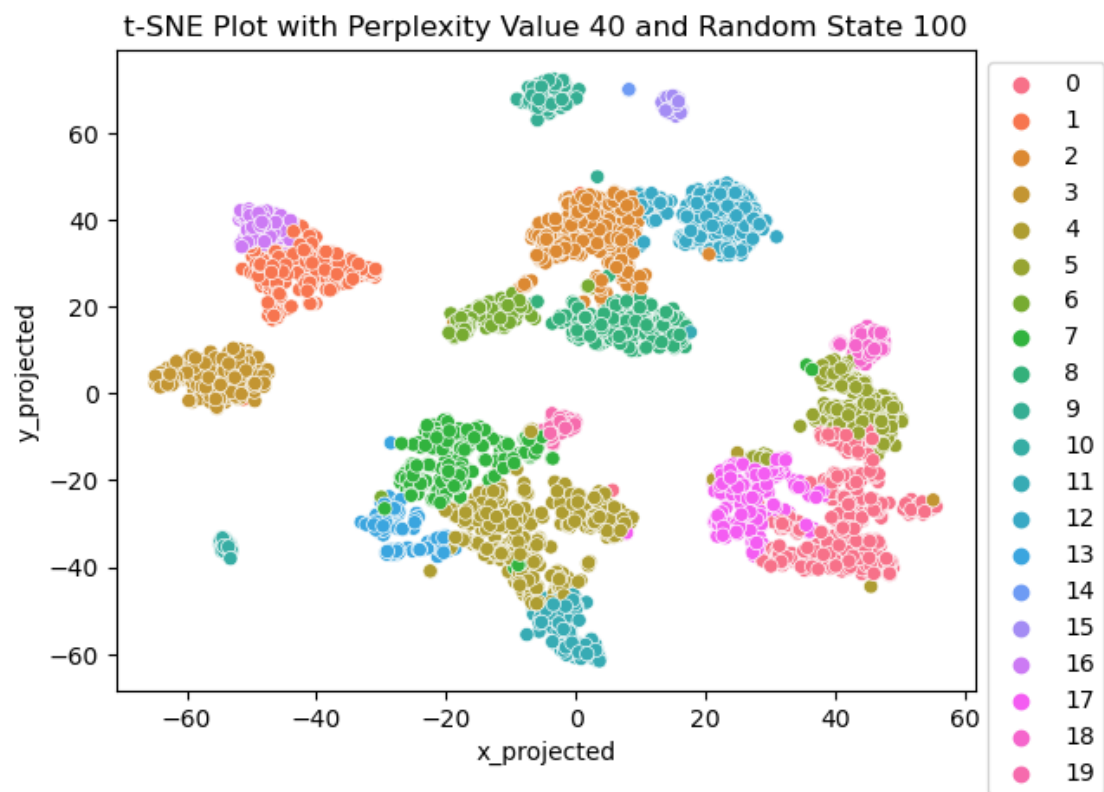


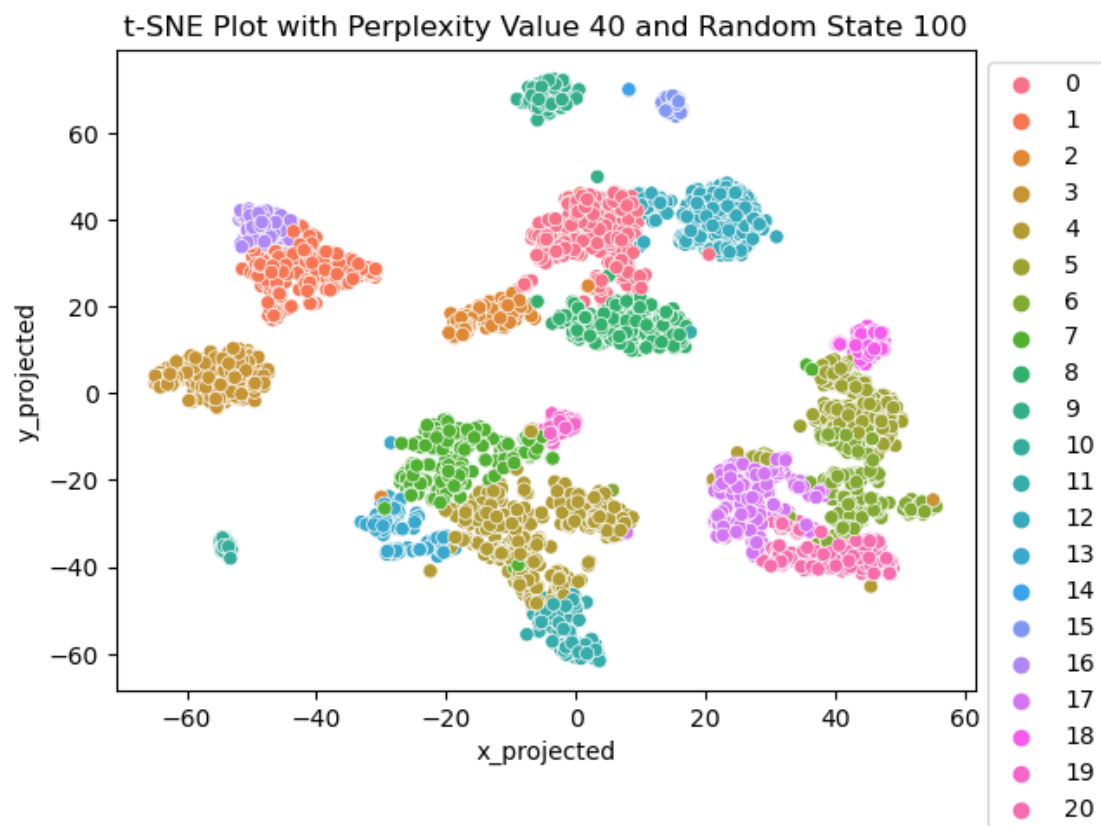


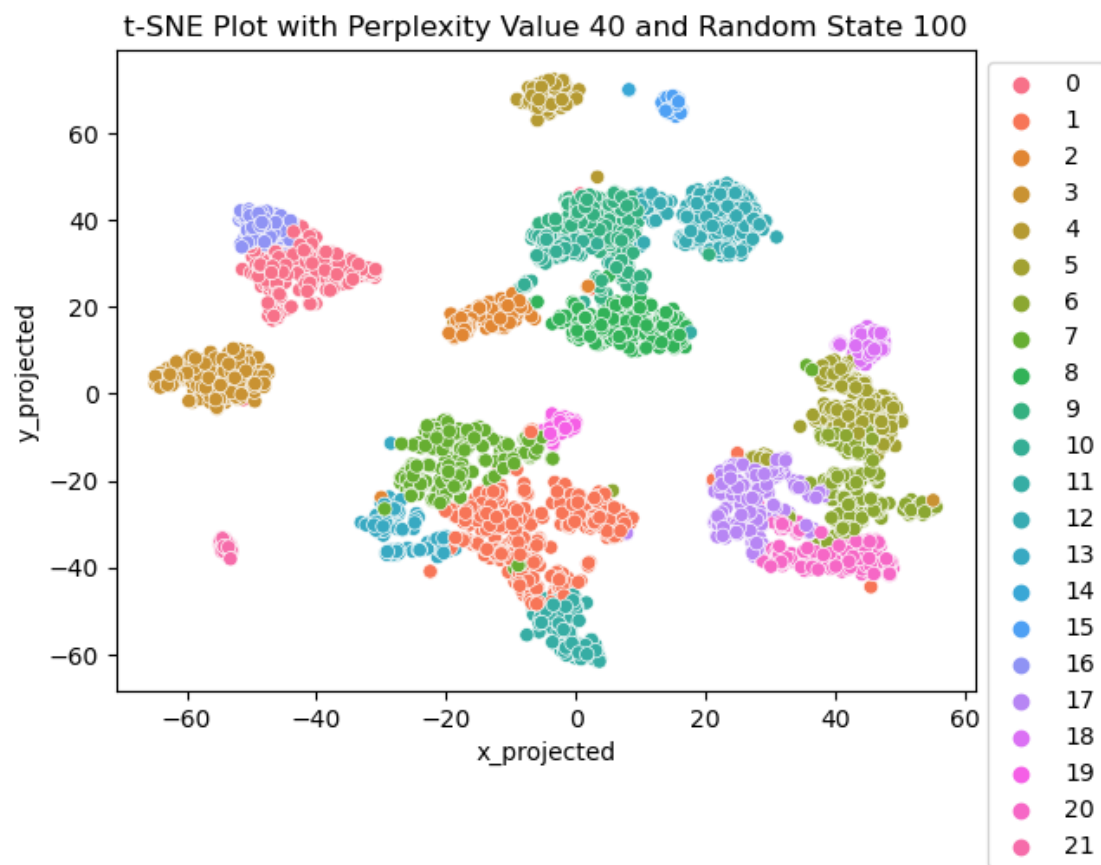


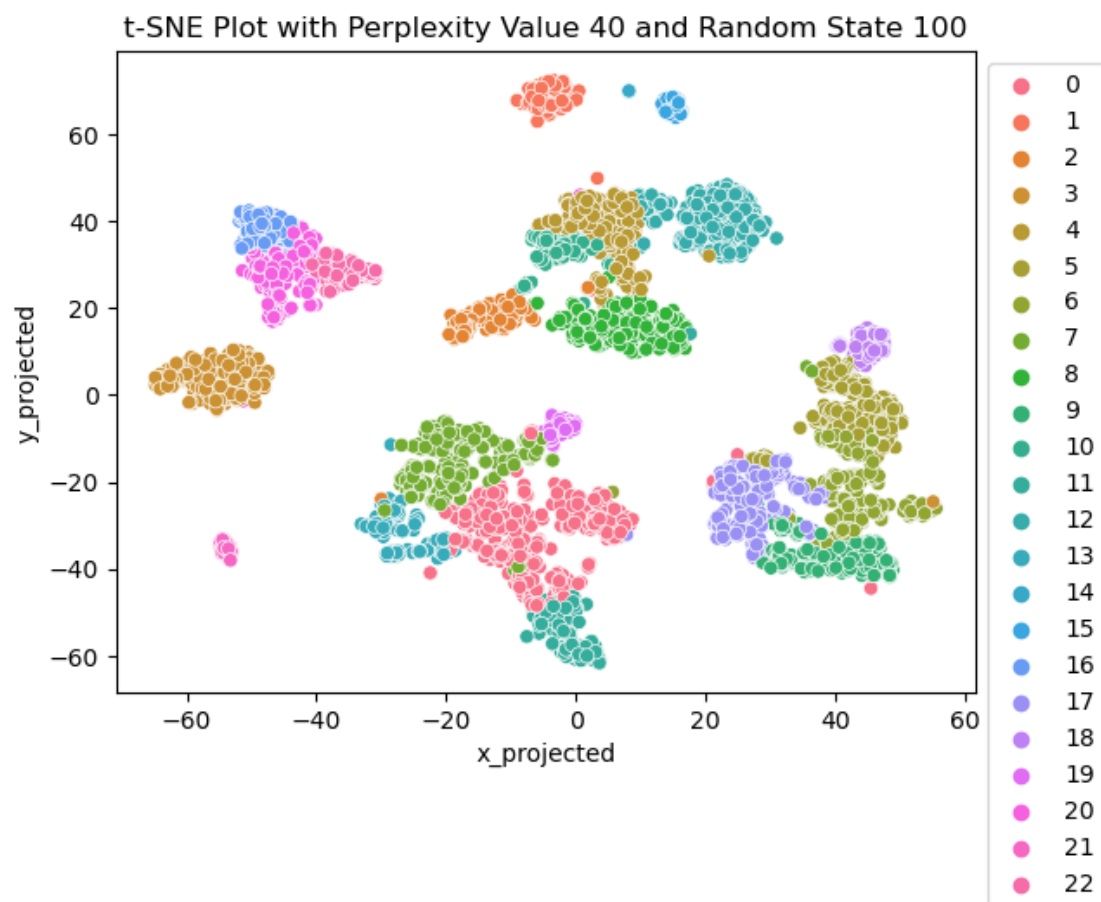


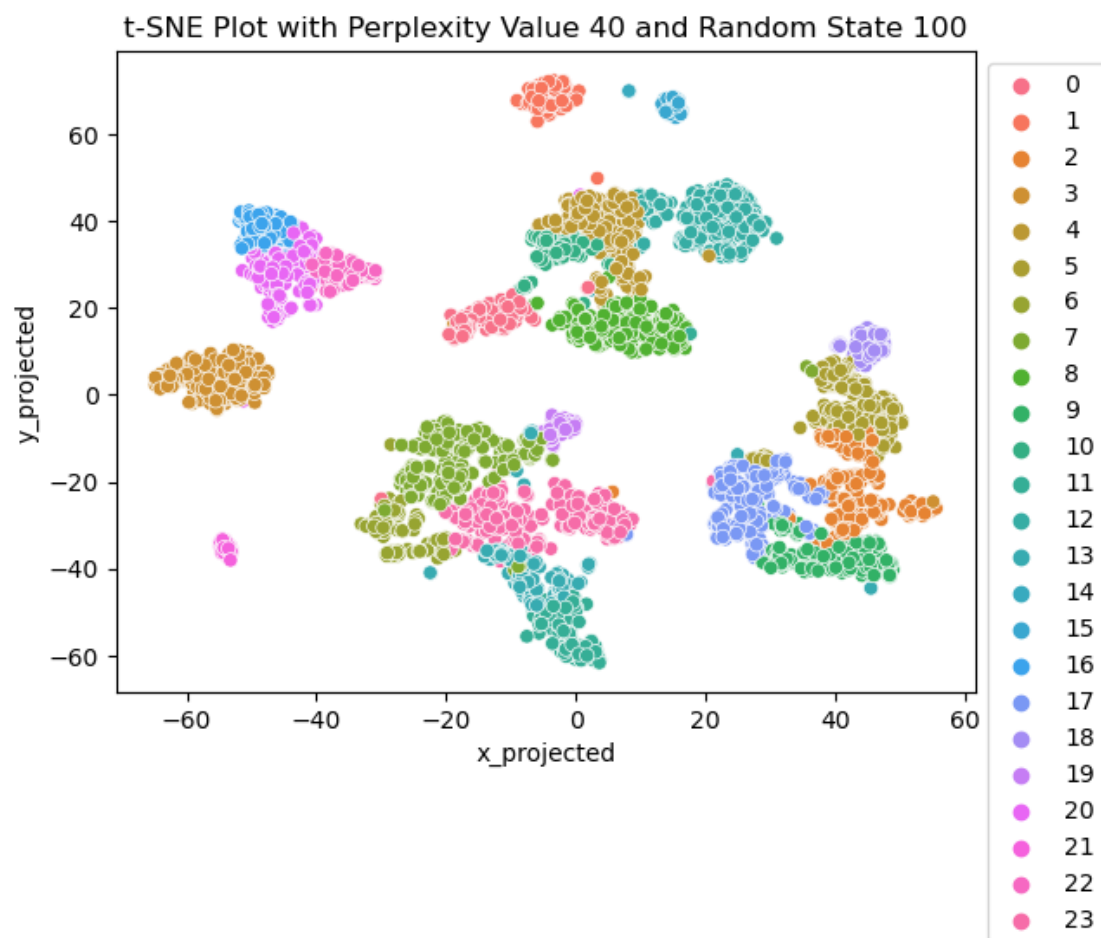


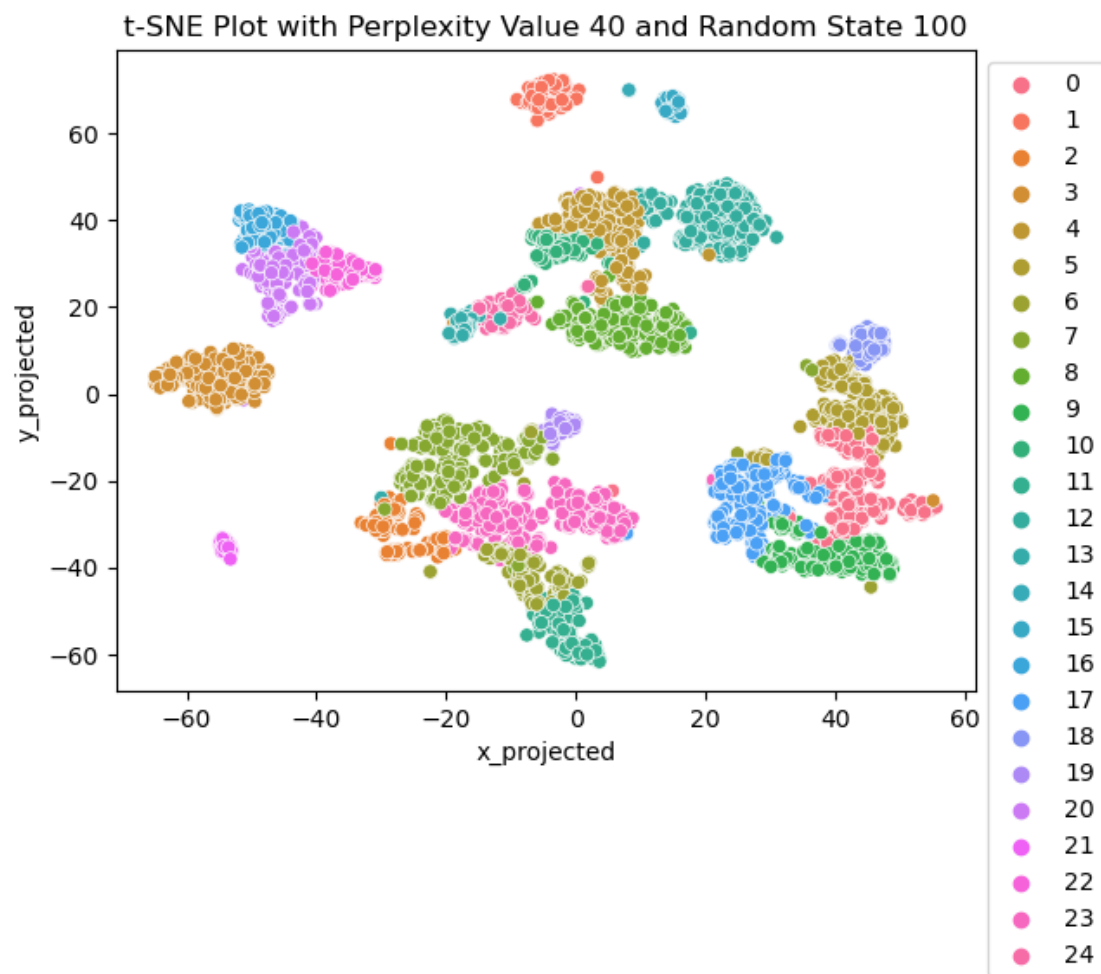


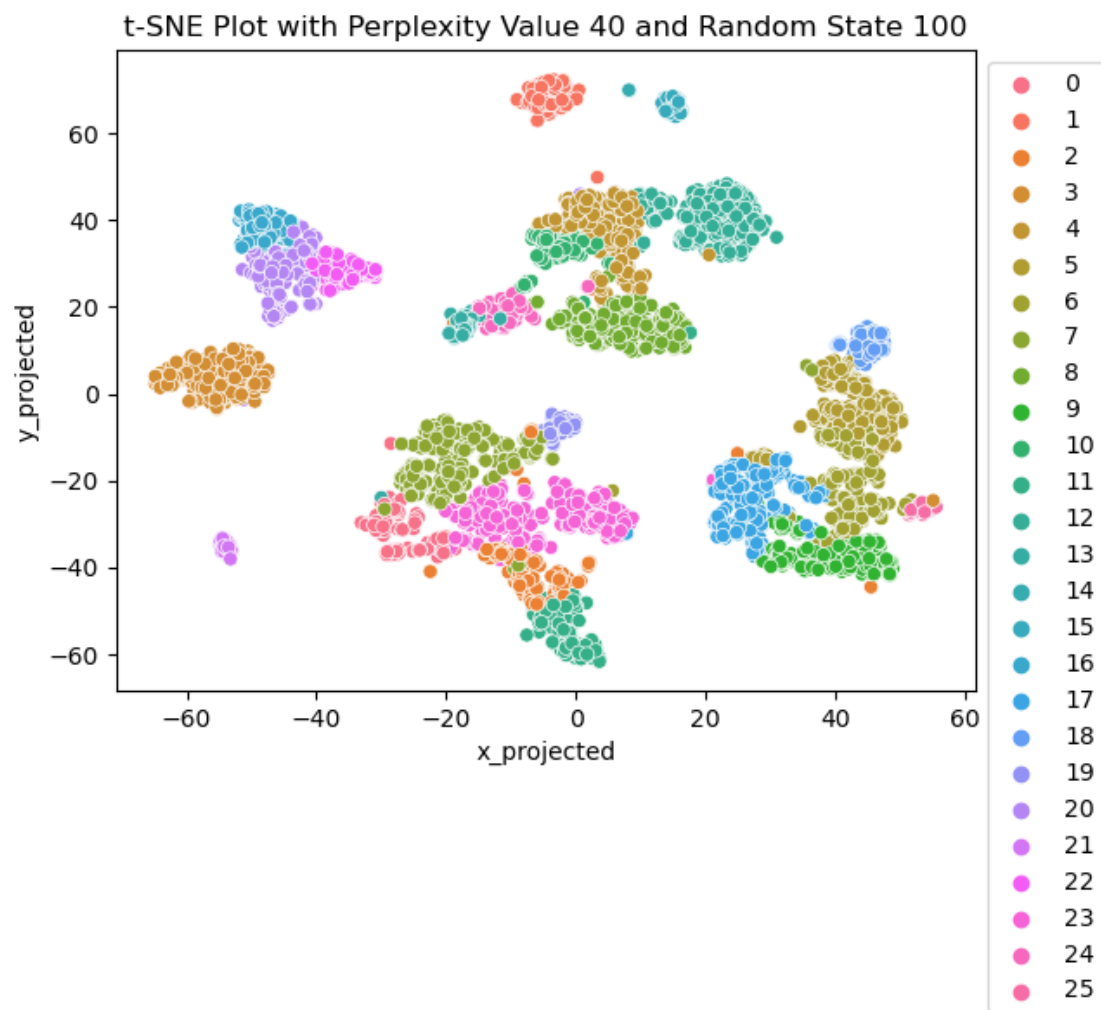


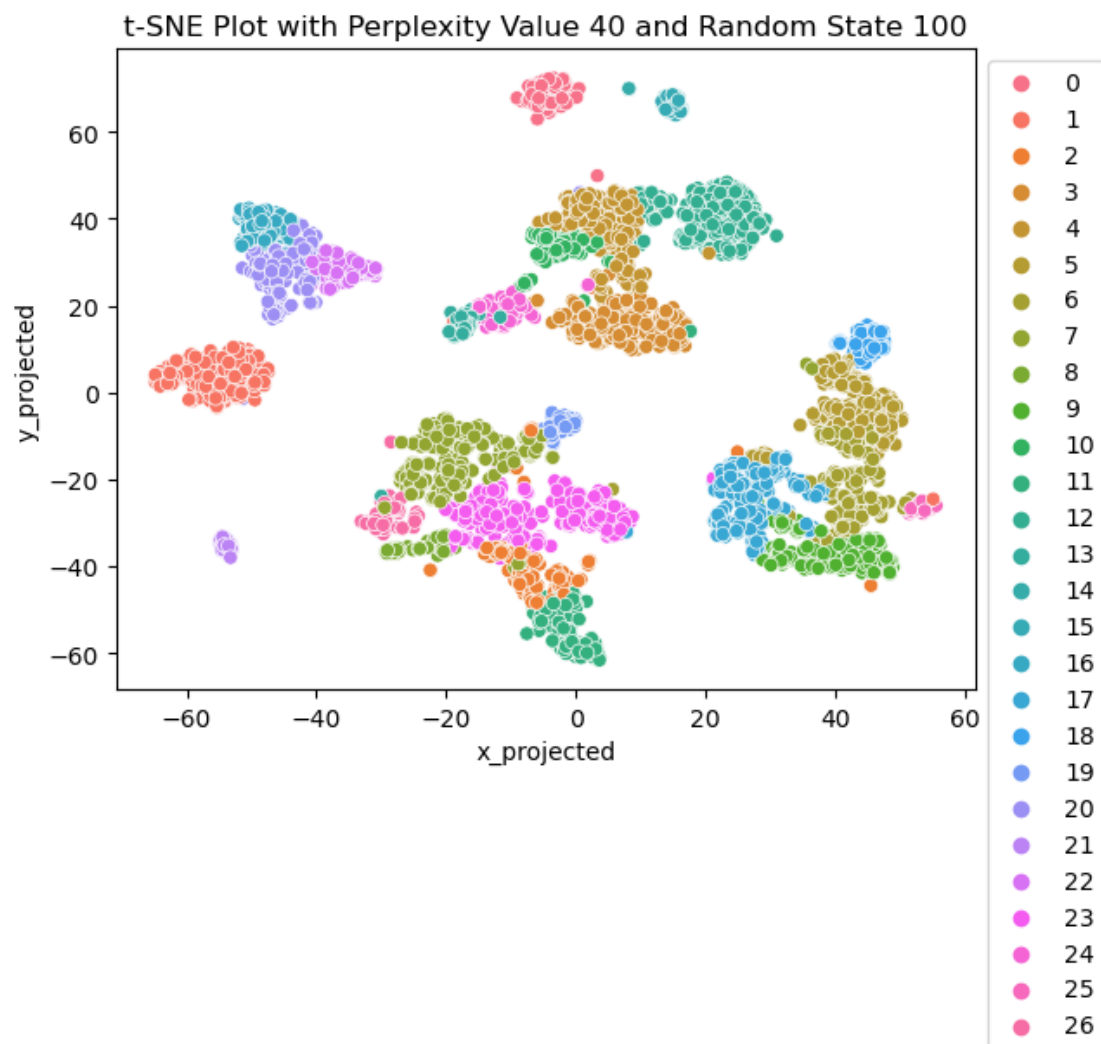


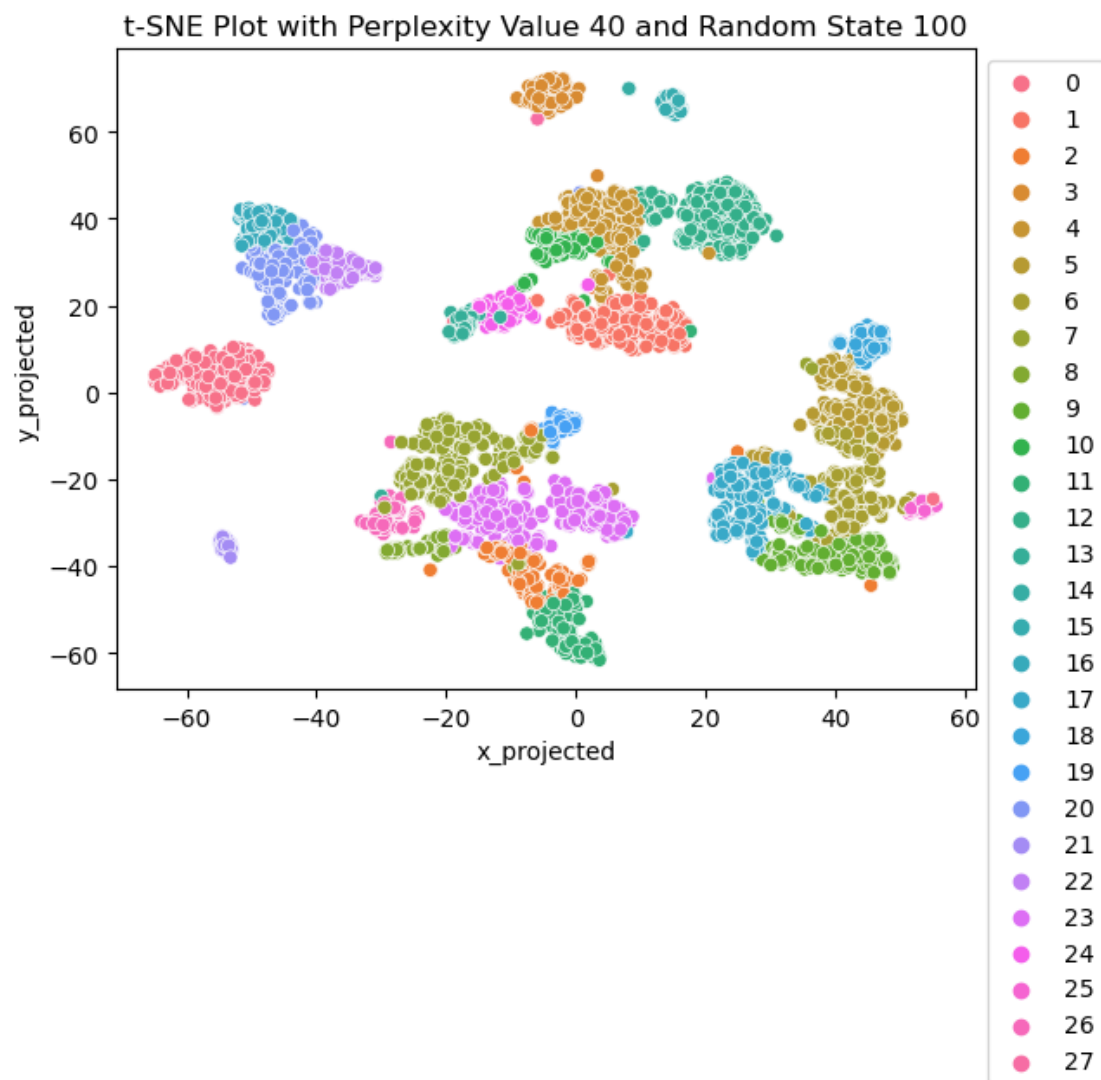


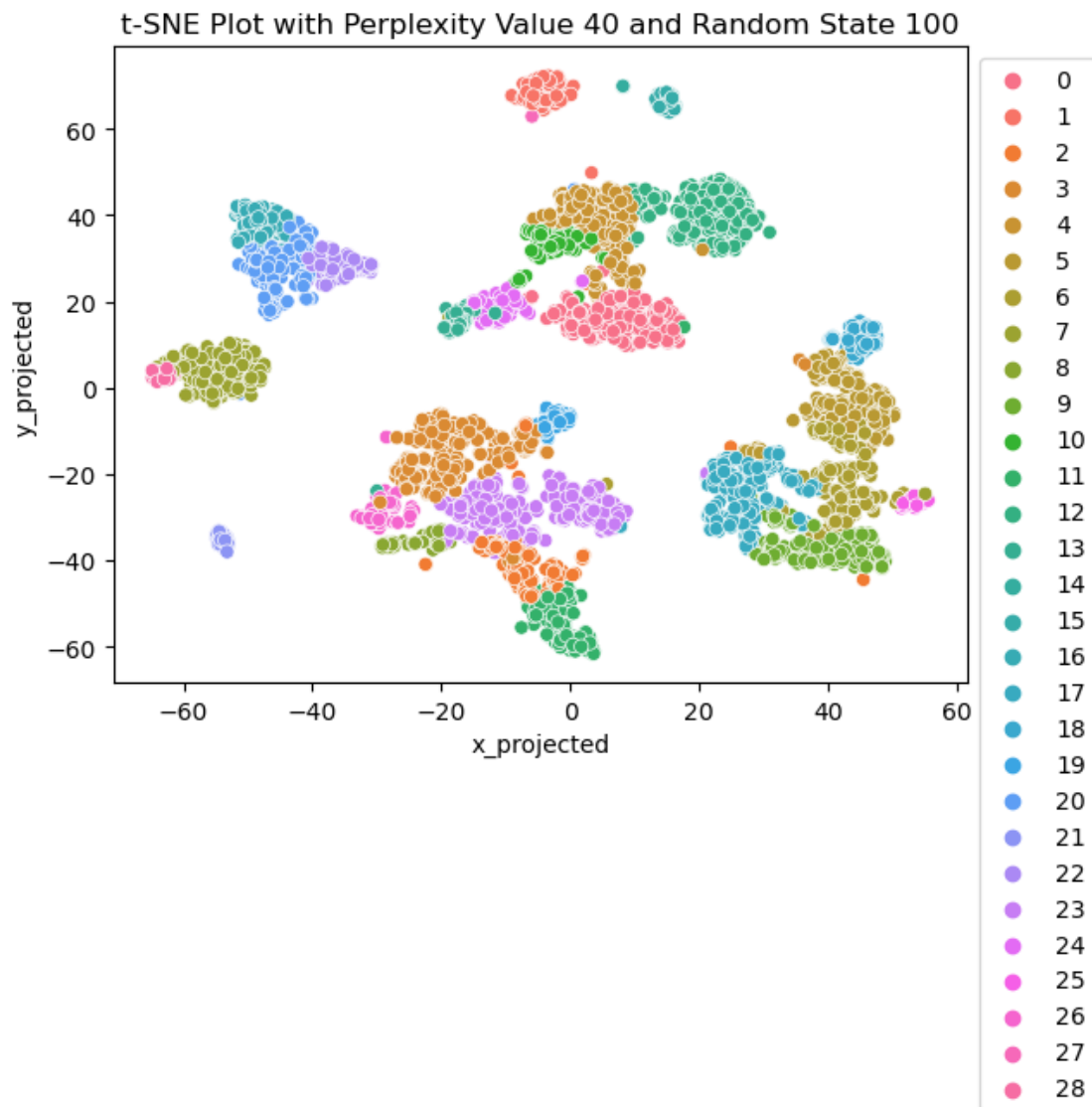












1.8.2 8.2. Clustering Algorithm

```
[79]: #Clustering from dendrogram with 6 clusters
hac = AgglomerativeClustering(n_clusters=15, affinity='euclidean',
                               linkage='ward')
df_combo['predicted_cluster'] = hac.fit_predict(df_num)
```

```
[80]: df_combo
```

```
[80]:   Location_State  Vote_Data_Ben_Carson_Percent_of_Votes  \
0   South Carolina                                0.382488
1   Massachusetts                                0.115207
```

2	Louisiana	0.000000
3	Virginia	0.437788
4	Massachusetts	0.105991
...	...	...
3587	California	0.000000
3588	Arizona	0.000000
3589	Texas	0.216590
3590	Texas	0.000000
3591	South Dakota	0.000000

	Vote_Data_Bernie_Sanders_Percent_of_Votes \
0	0.170
1	0.534
2	0.314
3	0.274
4	0.468
...	...
3587	0.511
3588	0.315
3589	0.236
3590	0.181
3591	0.589

	Vote_Data_Carly_Fiorina_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Christie_Percent_of_Votes \
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0

3591 0.0

	Vote_Data_Donald_Trump_Percent_of_Votes \
0	0.403279
1	0.632787
2	0.486339
3	0.523497
4	0.308197
...	...
3587	0.904918
3588	0.540984
3589	0.431694
3590	0.000000
3591	0.750820

	Vote_Data_Hillary_Clinton_Percent_of_Votes \
0	0.818
1	0.446
2	0.537
3	0.720
4	0.528
...	...
3587	0.464
3588	0.637
3589	0.678
3590	0.755
3591	0.411

	Vote_Data_Jeb_Bush_Percent_of_Votes \
0	0.528926
1	0.000000
2	0.000000
3	0.000000
4	0.000000
...	...
3587	0.000000
3588	0.000000
3589	0.000000
3590	0.000000
3591	0.000000

	Vote_Data_John_Kasich_Percent_of_Votes \
0	0.067293
1	0.222222
2	0.053208
3	0.076682
4	0.508607

...	...
3587	0.079812
3588	0.092332
3589	0.000000
3590	0.000000
3591	0.150235

	Vote_Data_Marco_Rubio_Percent_of_Votes	...	\
0		0.322169	...
1		0.202552	...
2		0.169059	...
3		0.333333	...
4		0.397129	...
...		...	...
3587		0.000000	...
3588		0.000000	...
3589		0.204147	...
3590		0.000000	...
3591		0.000000	...

	Vote_Data_No_Preference_Party	Vote_Data_No_Preference_Percent_of_Votes	\
0	0.0	0.000000	
1	0.0	0.400000	
2	0.0	0.000000	
3	0.0	0.000000	
4	0.0	0.066667	
...	...	...	
3587	0.0	0.000000	
3588	0.0	0.000000	
3589	0.0	0.000000	
3590	0.0	0.000000	
3591	0.0	0.000000	

	Vote_Data_Rand_Paul_Percent_of_Votes	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	
...	...	
3587	0.0	
3588	0.0	
3589	0.0	
3590	0.0	
3591	0.0	

Vote_Data_Rick_Santorum_Percent_of_Votes \

0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
3587	0.0
3588	0.0
3589	0.0
3590	0.0
3591	0.0

	Vote_Data_Ted_Cruz_Percent_of_Votes	Vote_Data_Uncommitted_Party \
0	0.304071	0.0
1	0.125954	0.0
2	0.486005	0.0
3	0.202290	0.0
4	0.110687	0.0
...	...	...
3587	0.104326	0.0
3588	0.366412	0.0
3589	0.473282	0.0
3590	0.000000	0.0
3591	0.276081	0.0

	Vote_Data_Uncommitted_Percent_of_Votes	x_projected	y_projected \
0	0.0	15.333004	65.792213
1	0.0	-48.632351	38.450615
2	0.0	-7.403143	-43.584099
3	0.0	17.125759	43.247463
4	0.0	-32.474995	27.306452
...	...	...	...
3587	0.0	40.149212	-39.740902
3588	0.0	0.413865	-43.407272
3589	0.0	13.933252	18.729895
3590	0.0	-53.272396	-38.035904
3591	0.0	42.094490	-25.580858

	predicted_cluster
0	7
1	1
2	0
3	12
4	1
...	...
3587	4
3588	0

```

3589             8
3590            10
3591             4

```

```
[3592 rows x 22 columns]
```

1.8.3 8.3. Clustering Algorithm Results Presentation

We randomly selected 100 values. The purpose is that because the dataset is too large, the hierarchical diagram in jupyter notebook running HAC is too intricate and complex. So we randomly selected 100 does not affect the algorithm itself, just for the aesthetics of the data visualization.

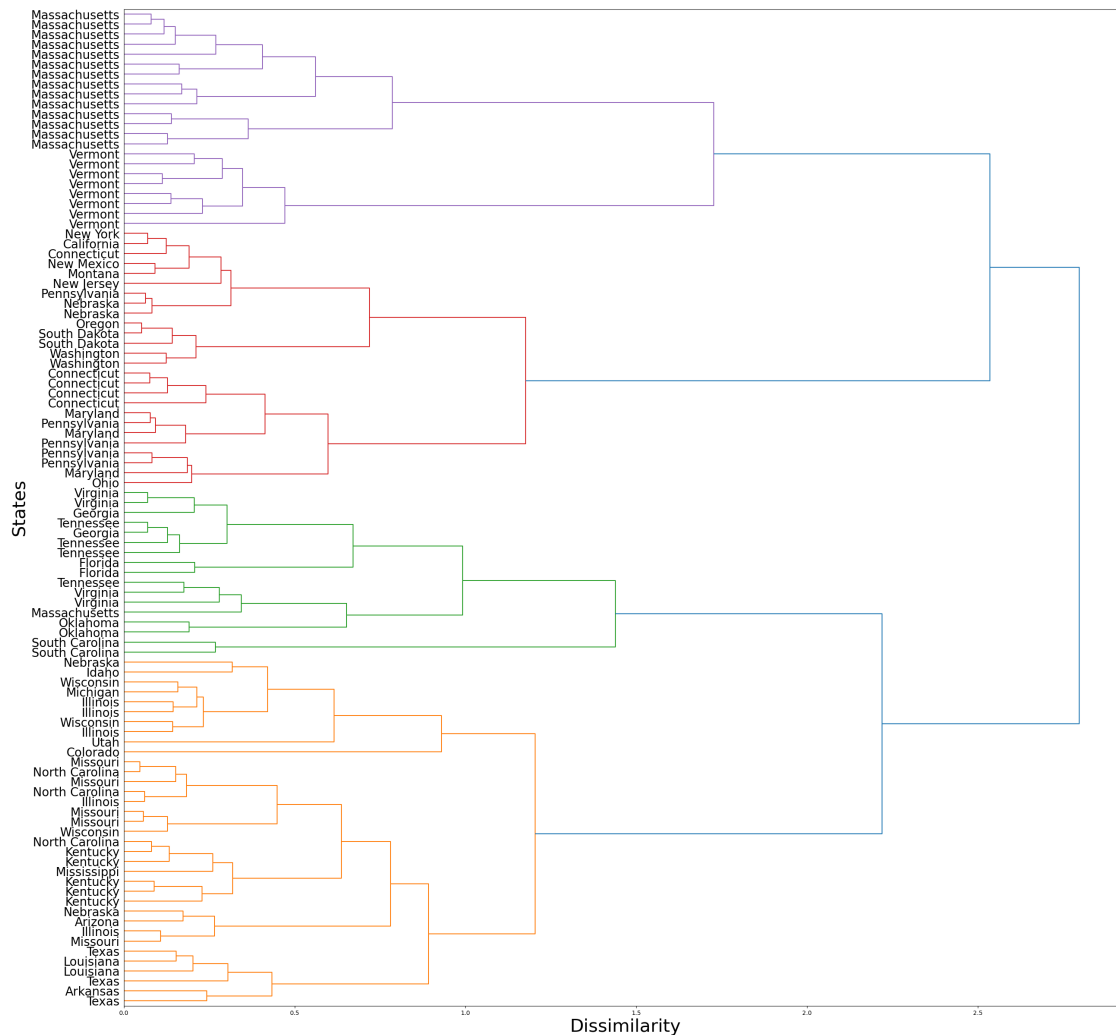
```

[81]: df_random = df_label.sample(100).reset_index(drop=True)
df_random_num = df_random.drop(['Location_State'], axis = 1)
df_random_num

dm = pdist(df_random_num, metric='euclidean')
S = linkage(dm, method='ward')

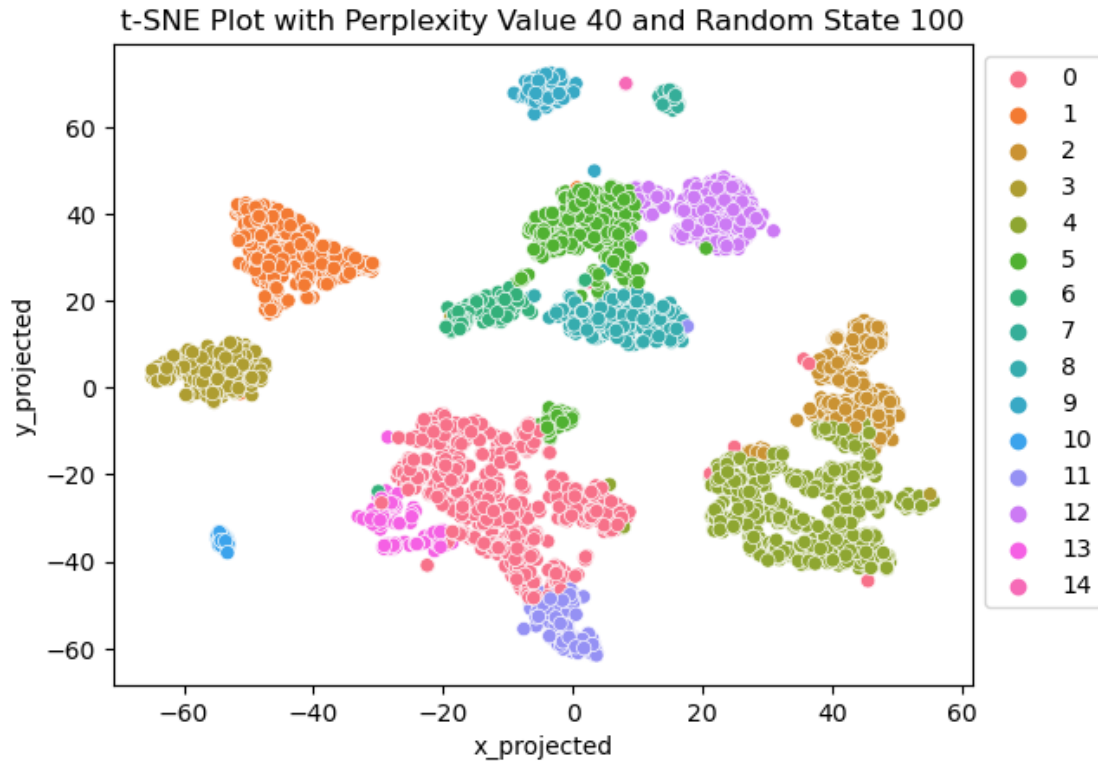
fig, ax = plt.subplots(figsize=(30, 30))
d = dendrogram(S, orientation='right', labels=df_random['Location_State'].
    ↳array, ax=ax)
ax.set_xlabel('Dissimilarity', fontsize=30)
ax.set_ylabel('States', fontsize=30)
ax.set_yticklabels(ax.get_yticklabels(), fontsize=20)
plt.show()

```



```
[82]: for k in [15]:
    #Clustering from dendrogram with k clusters
    hac = AgglomerativeClustering(n_clusters=k, affinity='euclidean',
    ↪linkage='ward')
    df_combo['predicted_cluster'] = hac.fit_predict(df_num)

    #Map the resulting cluster labels onto our chosen t-SNE plot
    sns.scatterplot(x='x_projected',y='y_projected', hue='predicted_cluster',
    ↪palette=sns.color_palette("husl", k), data=df_combo)
    plt.title('t-SNE Plot with Perplexity Value %s and Random State %s' %(40,
    ↪100))
    plt.legend(bbox_to_anchor=(1,1))
    plt.show()
```



1.8.4 8.4. Assessing Clustering Separation and Cohesion

```
[68]: def show_silhouette_plots(X, cluster_labels):

    # This package allows us to use "color maps" in our visualizations
    import matplotlib.cm as cm

    #How many clusters in your clustering?
    n_clusters=len(np.unique(cluster_labels))

    # Create a subplot with 1 row and 2 columns
    fig, ax1 = plt.subplots(1, 1)
    fig.set_size_inches(18, 7)

    # The 1st subplot is the silhouette plot
    # The silhouette coefficient fcan range from -1, 1 but in this example all
    # lie within [-0.1, 1]
    ax1.set_xlim([-0.1, 1])
    # The (n_clusters+1)*10 is for inserting blank space between silhouette
    # plots of individual clusters, to demarcate them clearly.
    ax1.set_ylim([0, len(X) + (n_clusters + 1) * 10])
```



```

# The silhouette_score gives the average value for all the samples.
# This gives a perspective into the density and separation of the formed
# clusters
silhouette_avg = silhouette_score(X, cluster_labels)
print("For n_clusters =", n_clusters,
      "The average silhouette_score is :", silhouette_avg)

# Compute the silhouette scores for each sample
sample_silhouette_values = silhouette_samples(X, cluster_labels)

y_lower = 10
for i in range(n_clusters):
    # Aggregate the silhouette scores for samples belonging to
    # cluster i, and sort them
    ith_cluster_silhouette_values = \
        sample_silhouette_values[cluster_labels == i]

    ith_cluster_silhouette_values.sort()

    size_cluster_i = ith_cluster_silhouette_values.shape[0]
    y_upper = y_lower + size_cluster_i

    color = cm.nipy_spectral(float(i) / n_clusters)
    ax1.fill_betweenx(np.arange(y_lower, y_upper),
                      0, ith_cluster_silhouette_values,
                      facecolor=color, edgecolor=color, alpha=0.7)

    # Label the silhouette plots with their cluster numbers at the middle
    ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

    # Compute the new y_lower for next plot
    y_lower = y_upper + 10  # 10 for the 0 samples

    ax1.set_title("The silhouette plot for the various clusters.")
    ax1.set_xlabel("The silhouette coefficient values")
    ax1.set_ylabel("Cluster label")

    # The vertical line for average silhouette score of all the values
    ax1.axvline(x=silhouette_avg, color="red", linestyle="--")

    ax1.set_yticks([])  # Clear the yaxis labels / ticks
    ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])

plt.show()

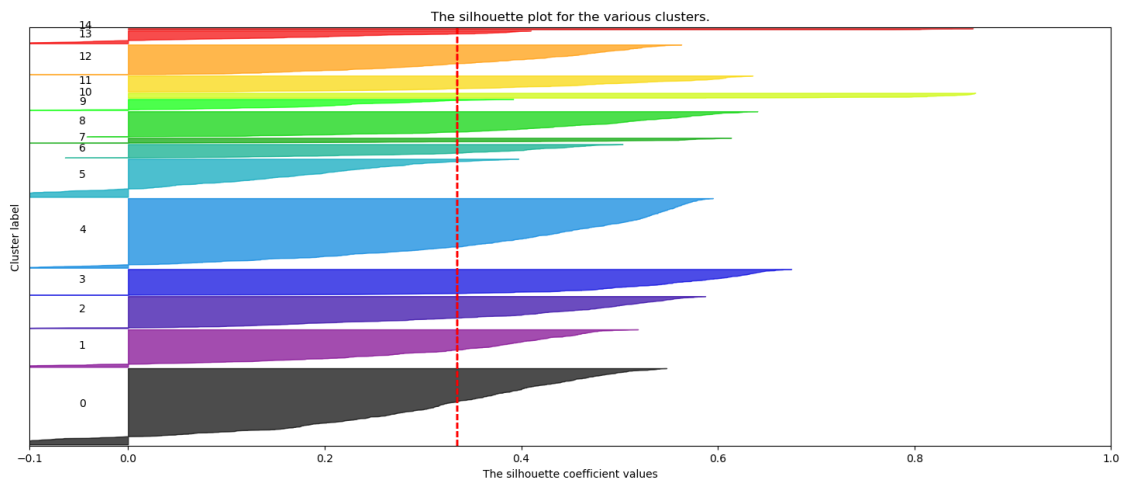
```

```
return
```

```
[104]: #Clustering from dendrogram with 15 clusters
hac = AgglomerativeClustering(n_clusters=15, affinity='euclidean',
    ↪linkage='ward')
df_compare = df_num.copy()
df_compare = hac.fit_predict(df_num)

show_silhouette_plots(X,df_compare)
```

For n_clusters = 15 The average silhouette_score is : 0.3350670274512757



a.) each of the clusters and b.) the overall clustering. Are there are any objects that have poor cohesion with their assigned cluster? Explain.

- We can see cluster 5 and 9 the score is at 0.4, which indicate they have a poor separation and cohesion. Cluster 1 and 6 have the score at 0.5, which said they got a moderate separation and cohesion. Cluster 7, 4 and 2 are similar, the score is 0.6 which have a moderate separation and cohesion. Cluster 11 and 8 at score 0.65, is a median in separation and cohesion. Cluster 3 is in a second place which have score at 0.7, relatively good separation and cohesion. Cluster 13 and 14 have the highest score which is 0.9, well-separated and well-matched.
- In the case, the average silhouette score of 0.269 for n_clusters = 6 suggests that the clustering results are not very compact and well-separated. It is generally recommended to aim for a silhouette score closer to 1, indicating better clustering results. However, the choice of the number of clusters depends on the context and the specific problem you are trying to solve.

1.8.5 8.5. Additional Analysis

```
[70]: from sklearn.metrics import adjusted_rand_score, homogeneity_score,   
      ↪completeness_score
```

```
[71]: ari = adjusted_rand_score(df_label["Location_State"], df_compare)   
      ari
```

```
[71]: 0.45900746908678663
```

```
[72]: homogeneity = homogeneity_score(df_label["Location_State"], df_compare)   
      homogeneity
```

```
[72]: 0.6642166230977945
```

```
[73]: completeness = completeness_score(df_label["Location_State"], df_compare)   
      completeness
```

```
[73]: 0.7704005551052056
```

The adjusted Rand index (ARI) is a measure of the similarity between two clusterings. It ranges from -1 (no agreement) to 1 (perfect agreement). In this case, the ARI value of 0.459 indicates a moderate agreement between the true labels and the predicted labels.

The homogeneity score measures how well each cluster contains only samples that are members of a single class. It ranges from 0 (low homogeneity) to 1 (high homogeneity). The score of 0.664 indicates a moderate level of homogeneity.

The completeness score measures how well all members of a given class are assigned to the same cluster. It ranges from 0 (low completeness) to 1 (high completeness). The score of 0.770 indicates a high level of completeness.

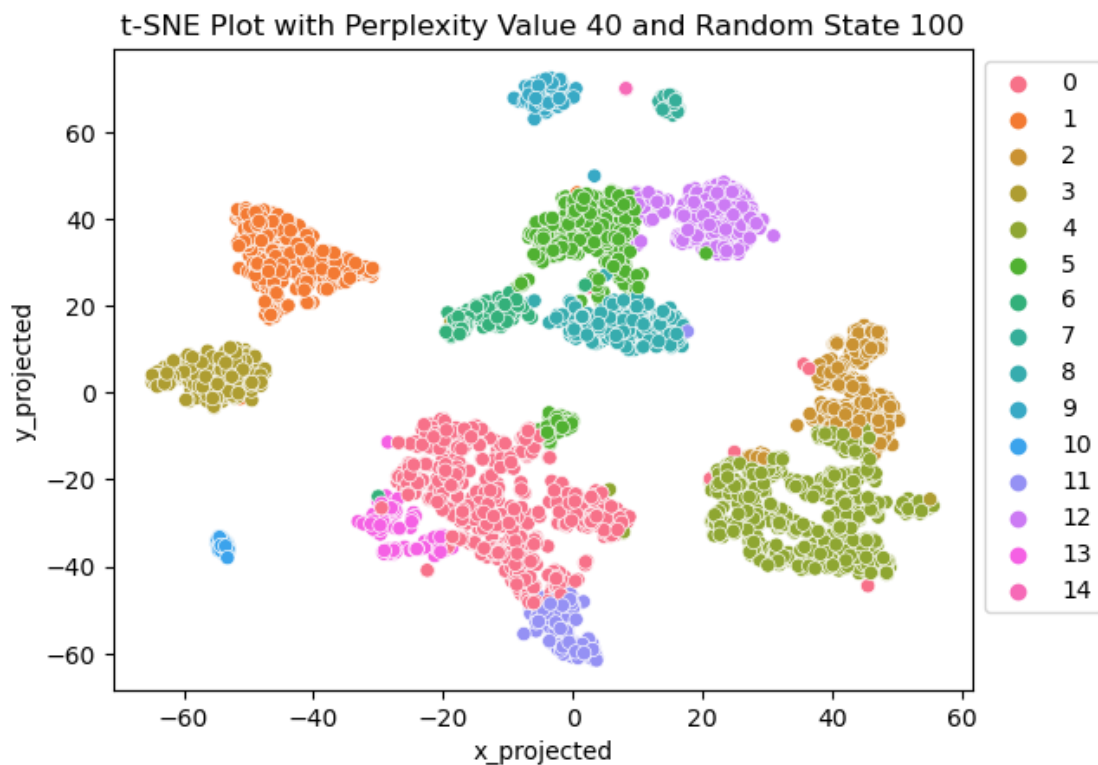
In summary, the ARI and homogeneity scores suggest that the clustering results have moderate agreement with the true labels and moderate homogeneity, while the completeness score suggests that the clustering results have high completeness.

```
[105]: for k in [15]:   
      #Clustering from dendrogram with k clusters   
      hac = AgglomerativeClustering(n_clusters=k, affinity='euclidean',   
      ↪linkage='ward')   
      df_combo['predicted_cluster'] = hac.fit_predict(df_num)   
   
      #Map the resulting cluster labels onto our chosen t-SNE plot   
      sns.scatterplot(x='x_projected',y='y_projected', hue='predicted_cluster',   
      ↪palette=sns.color_palette("husl", k), data=df_combo)   
      plt.title('t-SNE Plot with Perplexity Value %s and Random State %s' %(40,   
      ↪100))   
      plt.legend(bbox_to_anchor=(1,1))   
      plt.show()   
      print('-----Predicted Label-----')
```

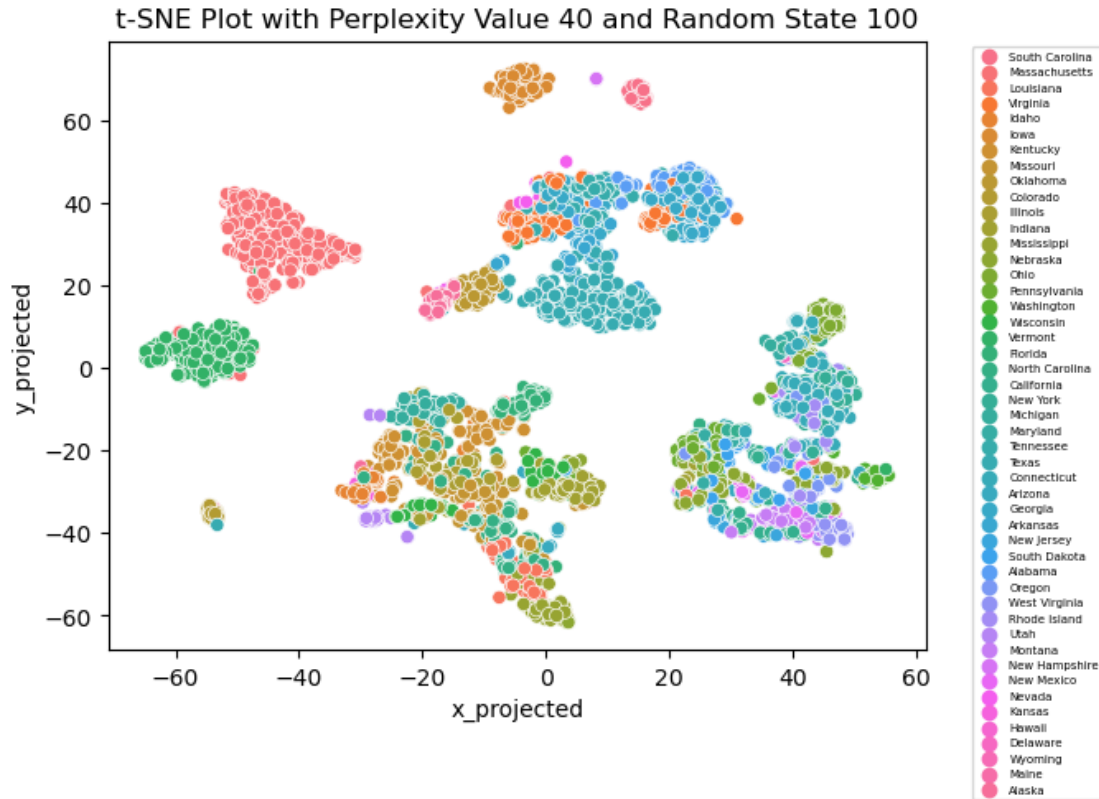
```

for perp in [40]:
    for rs in [100]:
        tsne = TSNE(n_components=2, perplexity=perp, random_state=rs)
        data_tsne = tsne.fit_transform(X)
        df_tsne = pd.DataFrame(data_tsne, columns=['x_projected',
↪ 'y_projected'])
        df_combo = pd.concat([df_label, df_tsne], axis=1)
        sns.scatterplot(x='x_projected', y='y_projected', hue =
↪ "Location_State", data=df_combo)
        plt.title('t-SNE Plot with Perplexity Value %s and Random State %s'
↪ (perp, rs))
        plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
        plt.show()
print('-----True Label-----')

```



-----Predicted Label-----



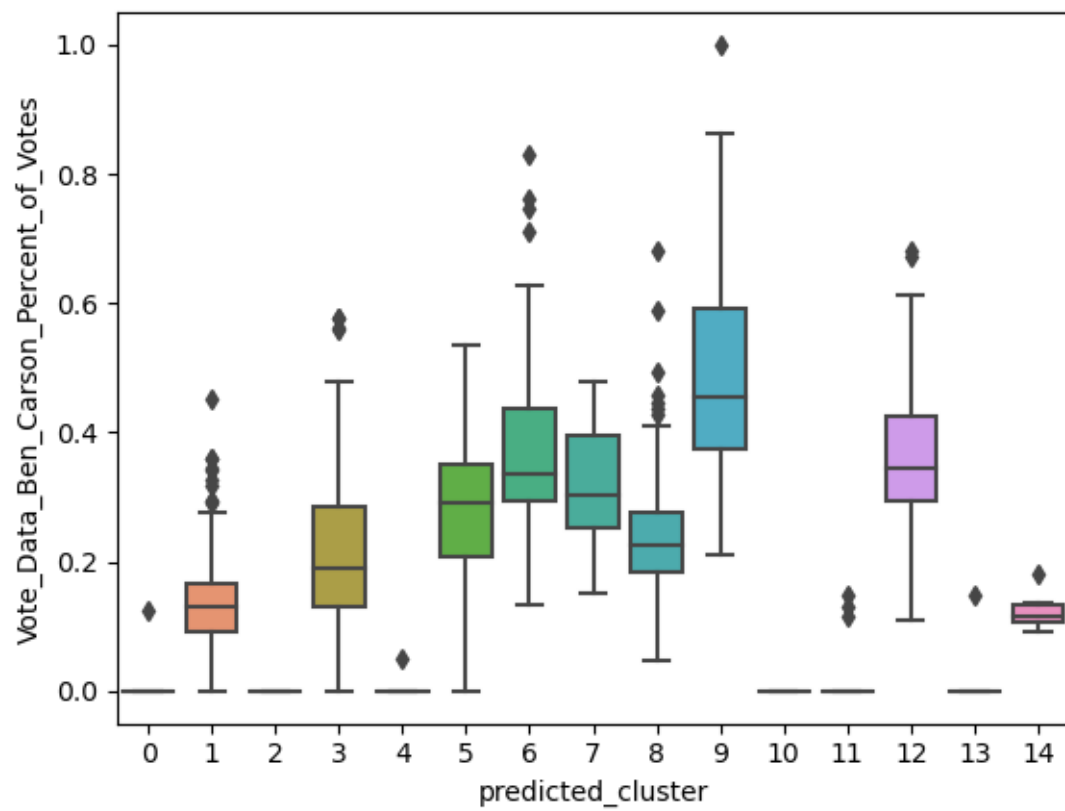
-----True Label-----

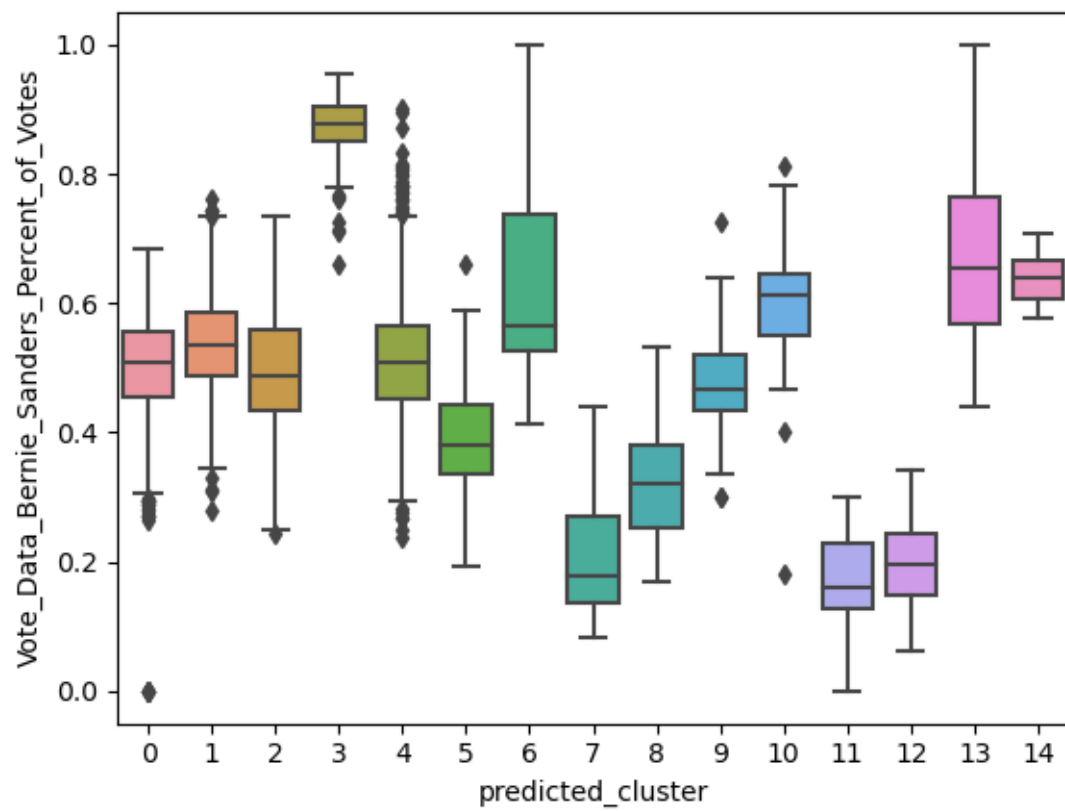
We can see there are somewhat different between the true label. For example, you can see the left up corner, there are three cluster being seperated.

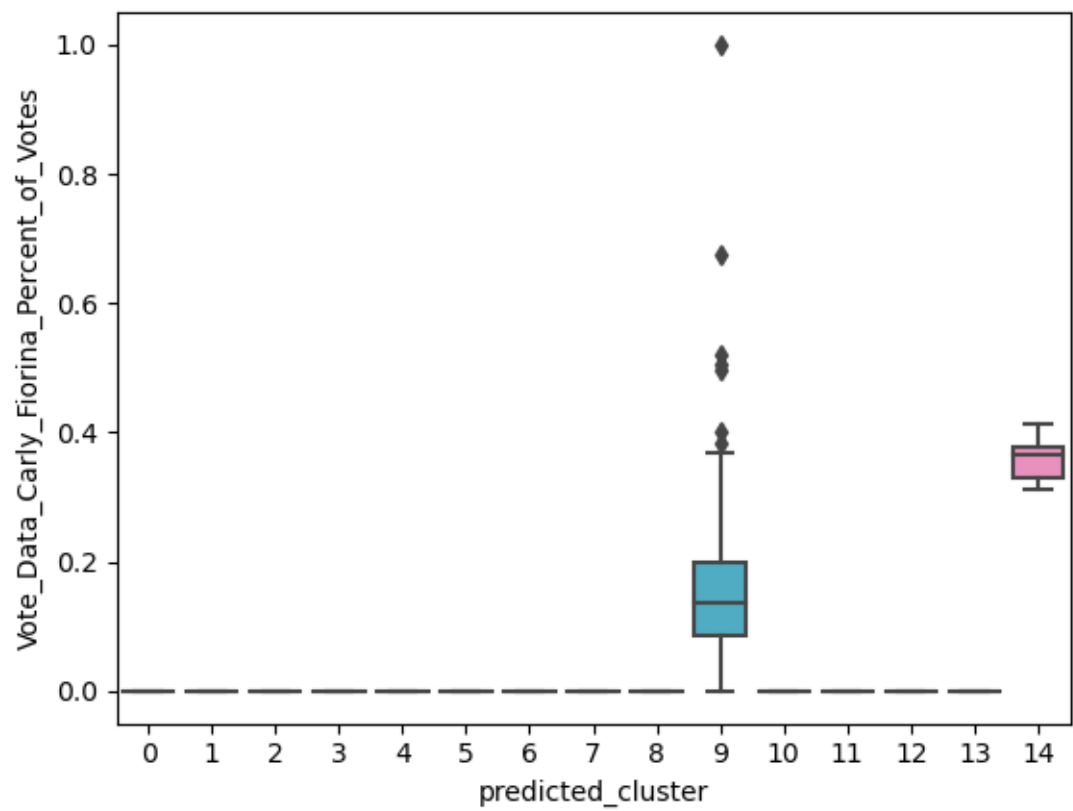
1.8.6 8.6. Describing Each of the Clusters

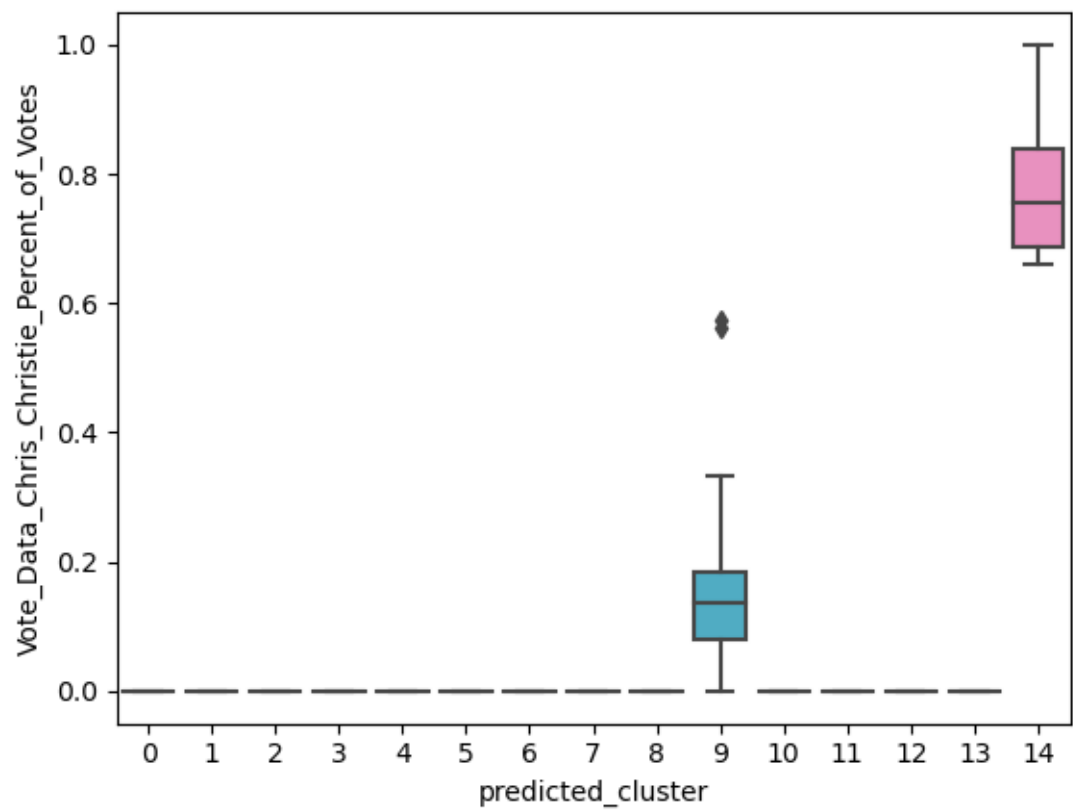
```
[108]: #Clustering from dendrogram with k clusters
hac = AgglomerativeClustering(n_clusters=15, affinity='euclidean',
                               linkage='ward')
df_combo['predicted_cluster'] = hac.fit_predict(df_num)

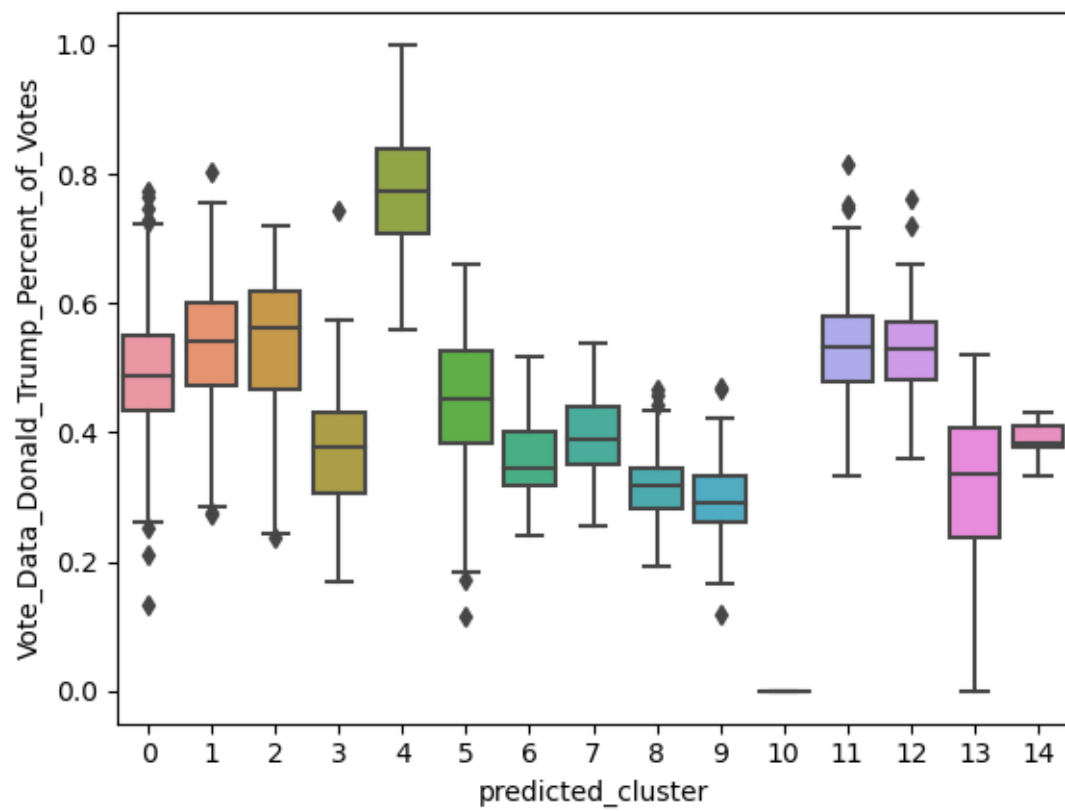
[109]: for col in df_label.columns[1:18]:
        sns.boxplot(x="predicted_cluster", y=col, data=df_combo)
        plt.show()
```

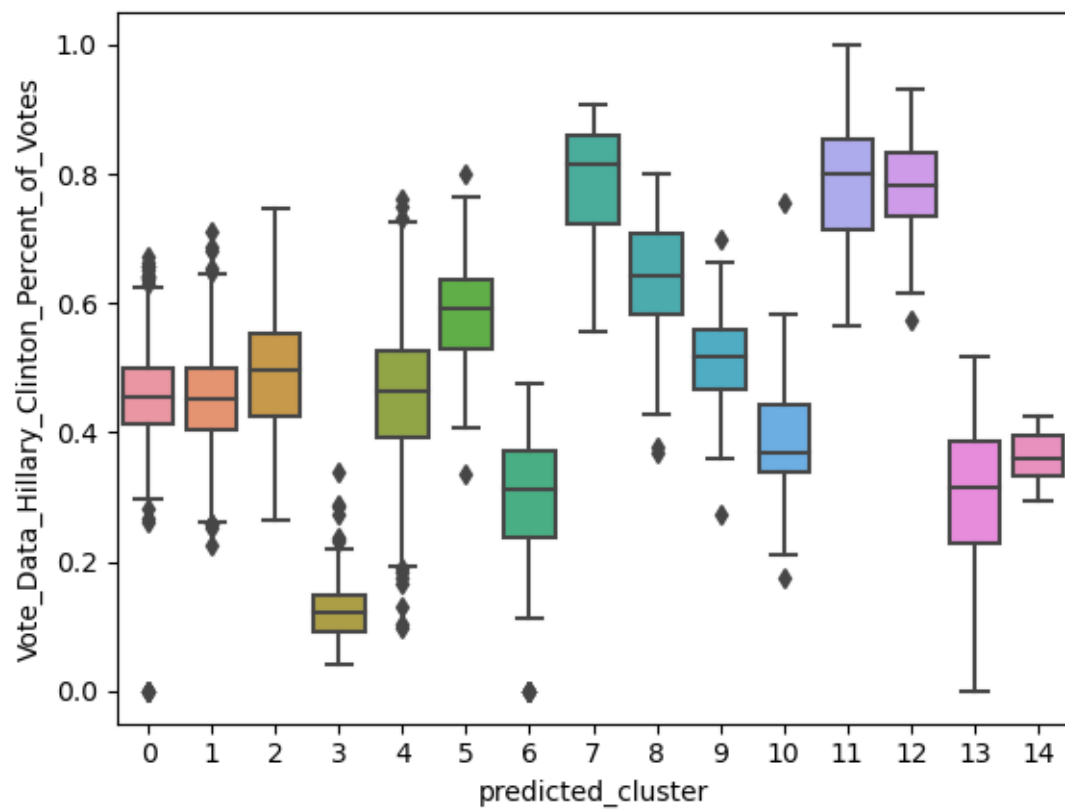


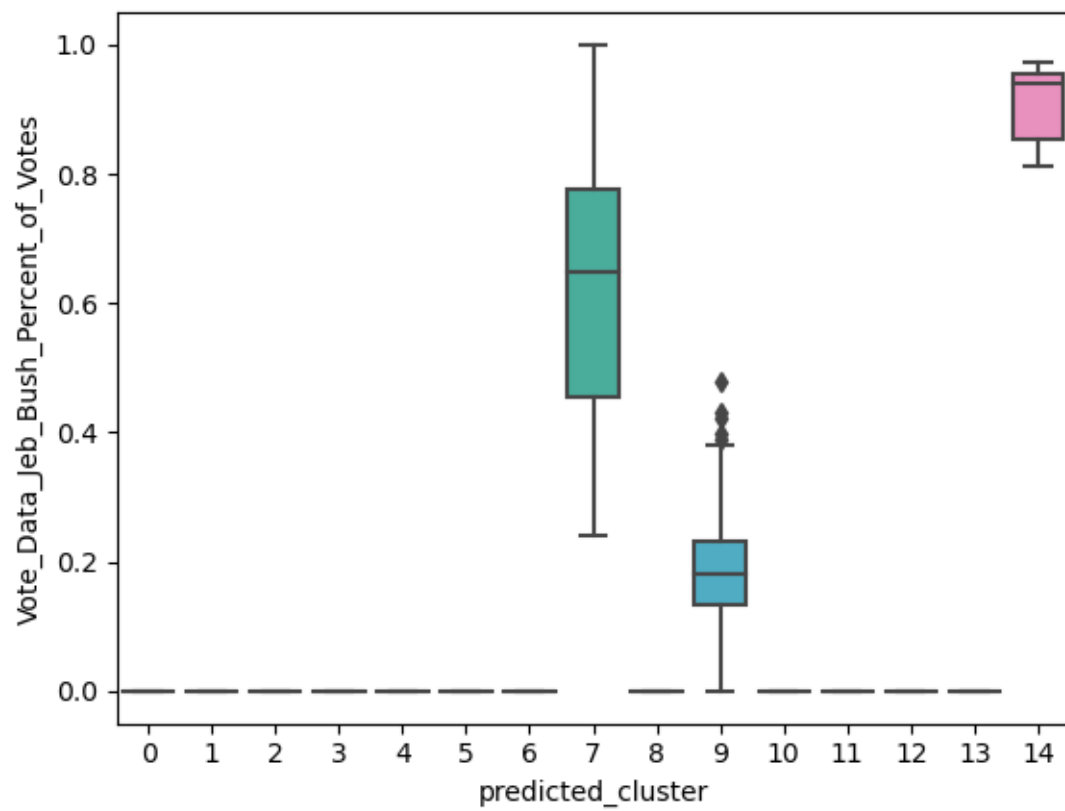


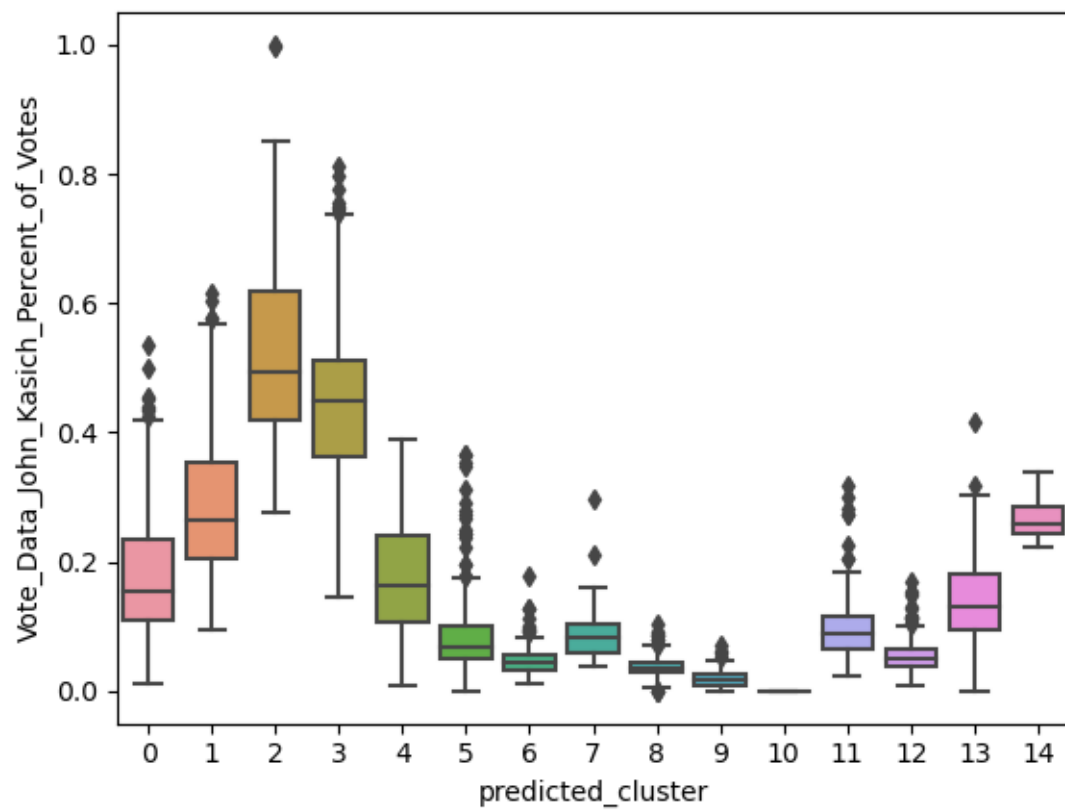


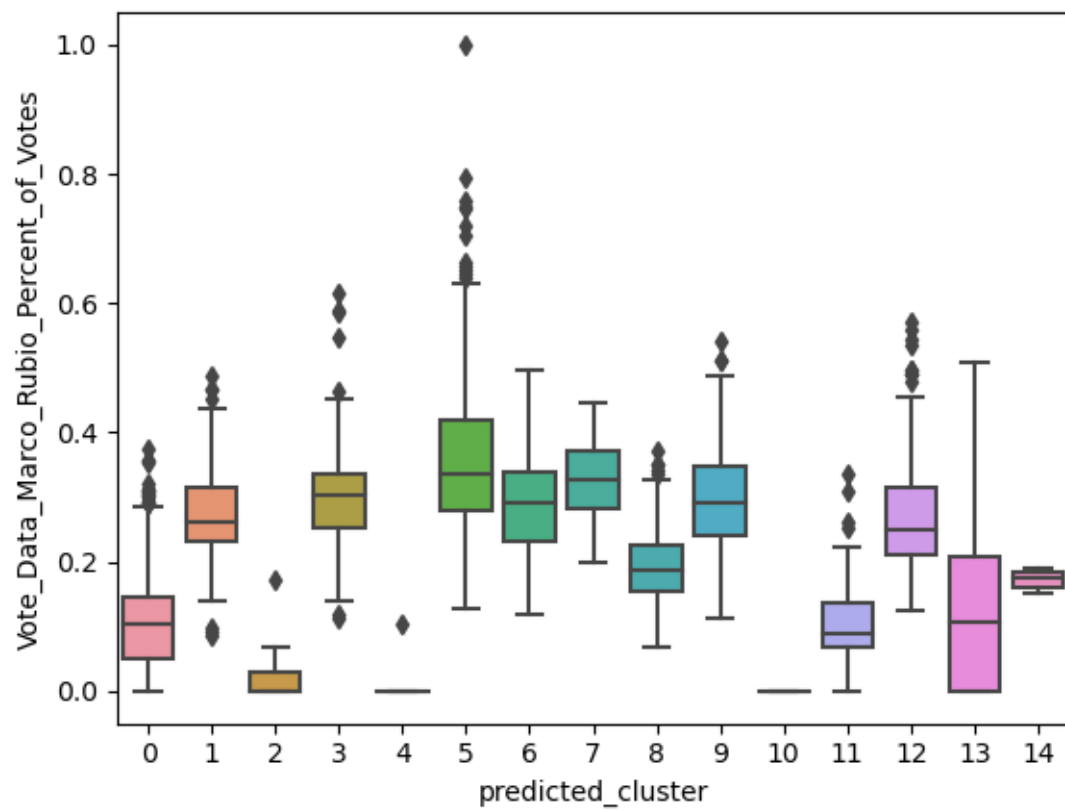


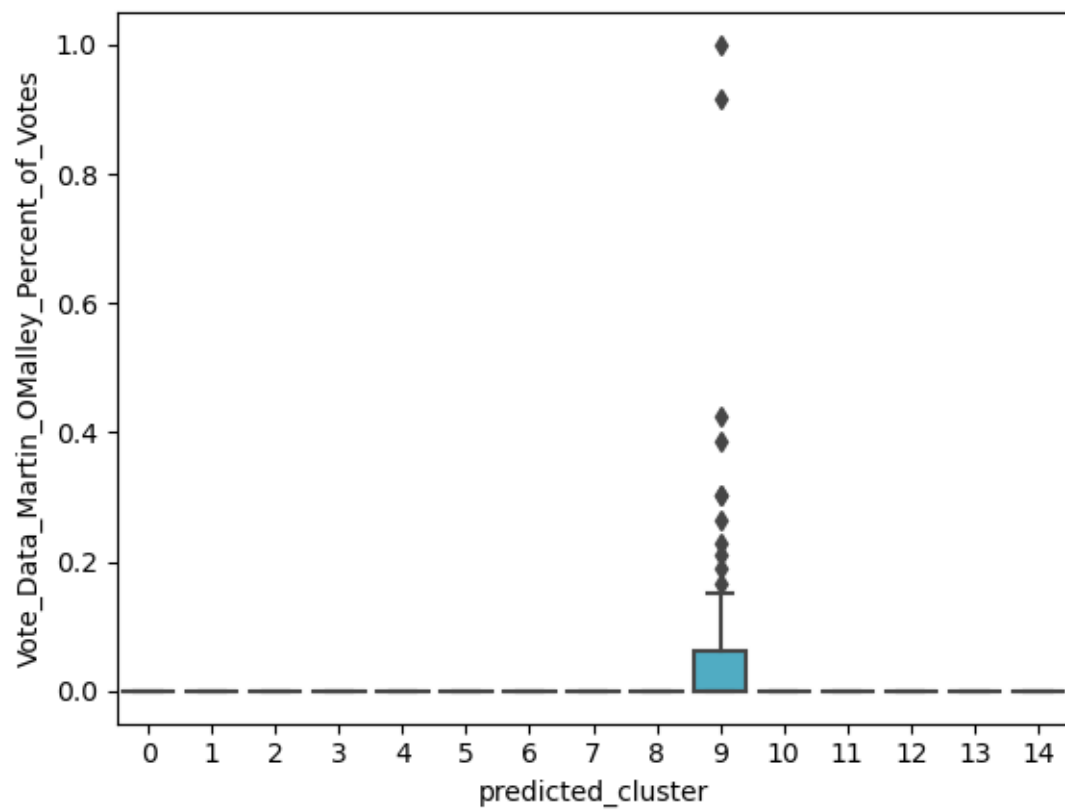


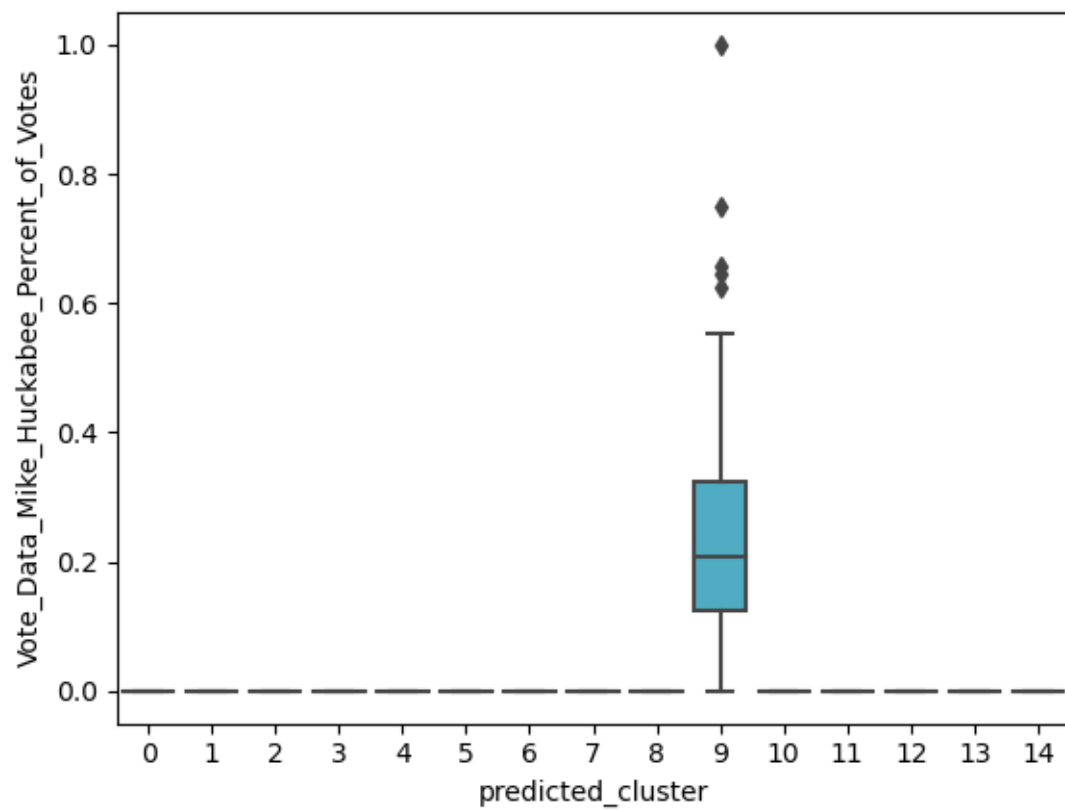


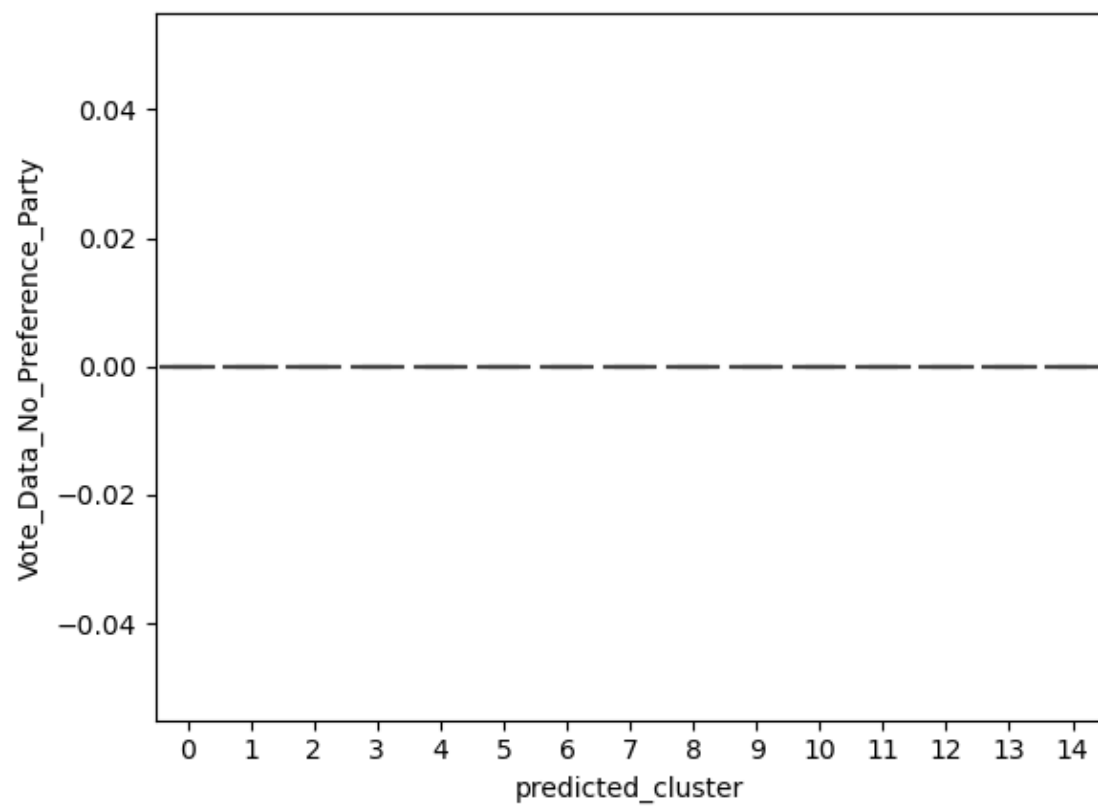


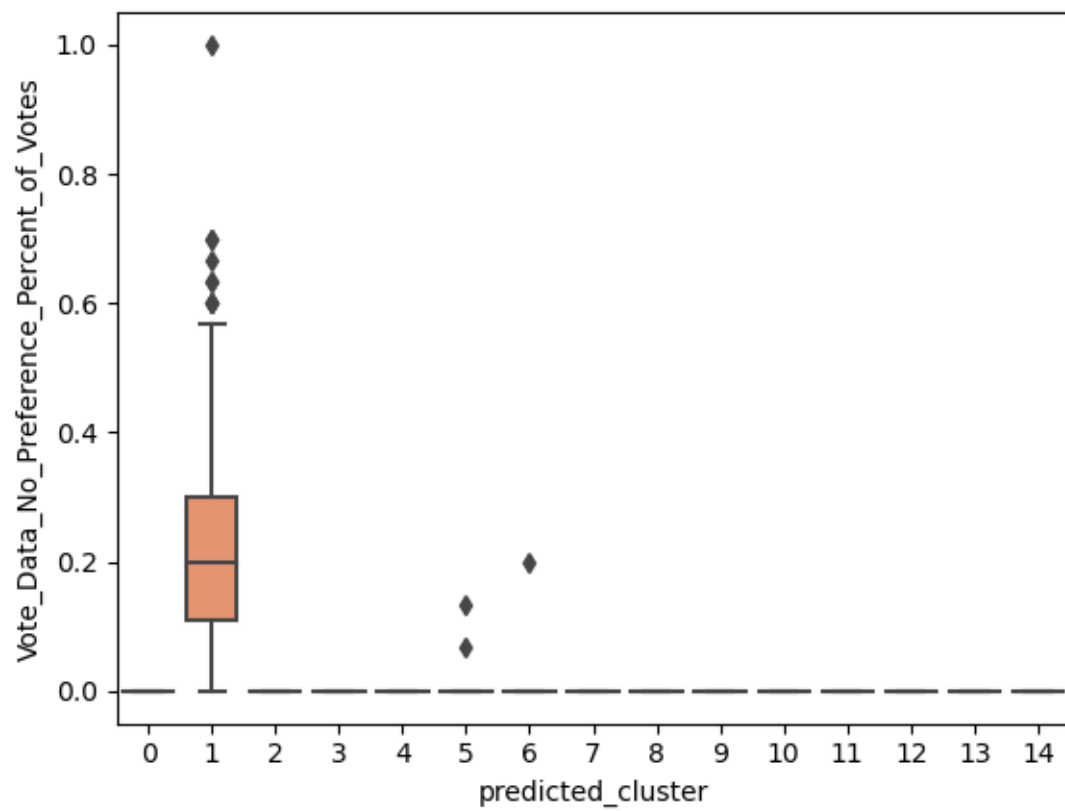


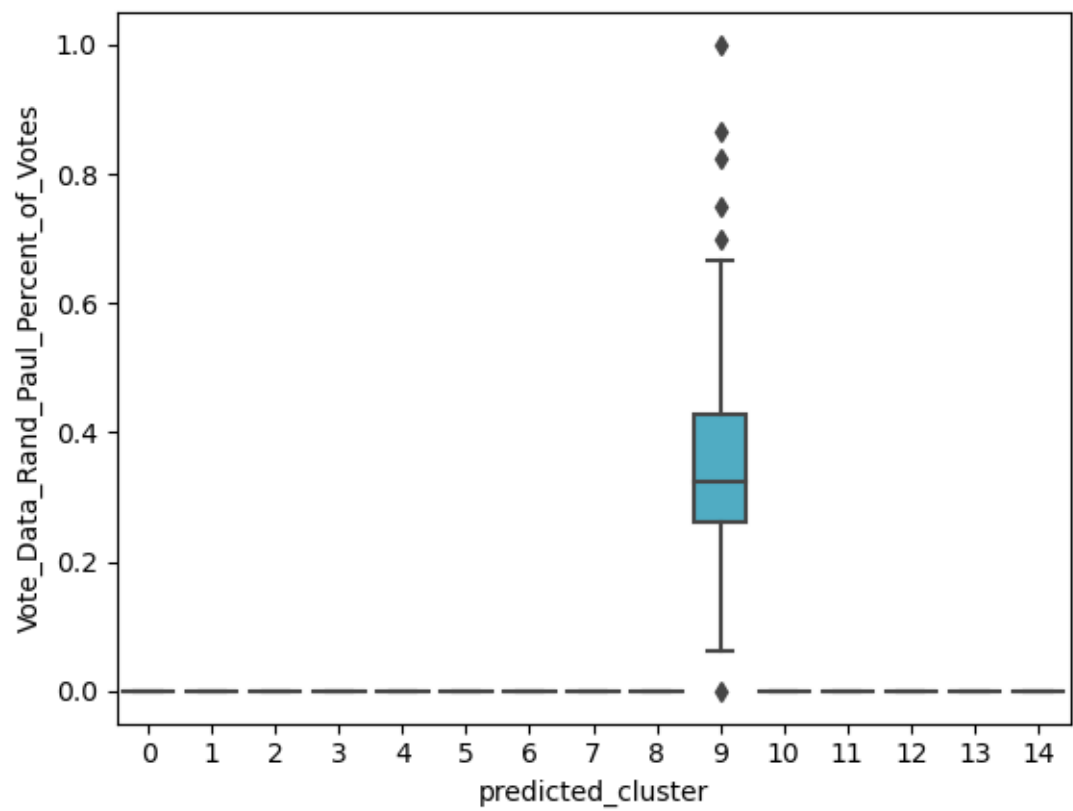


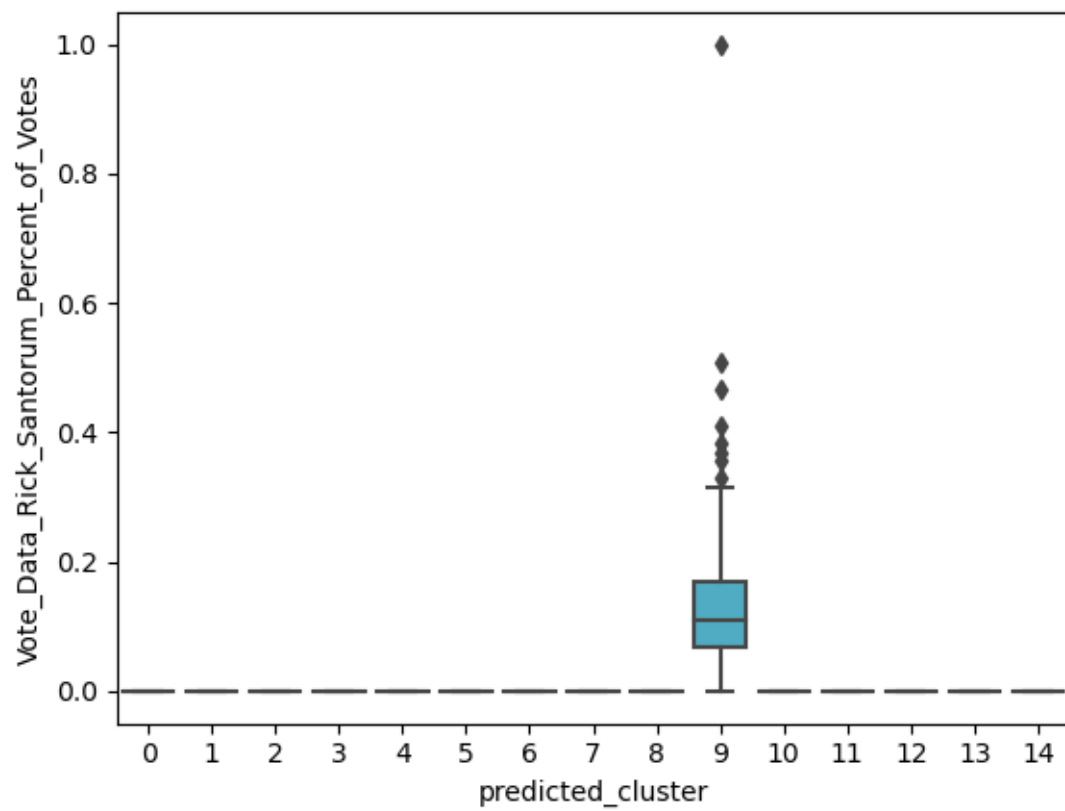


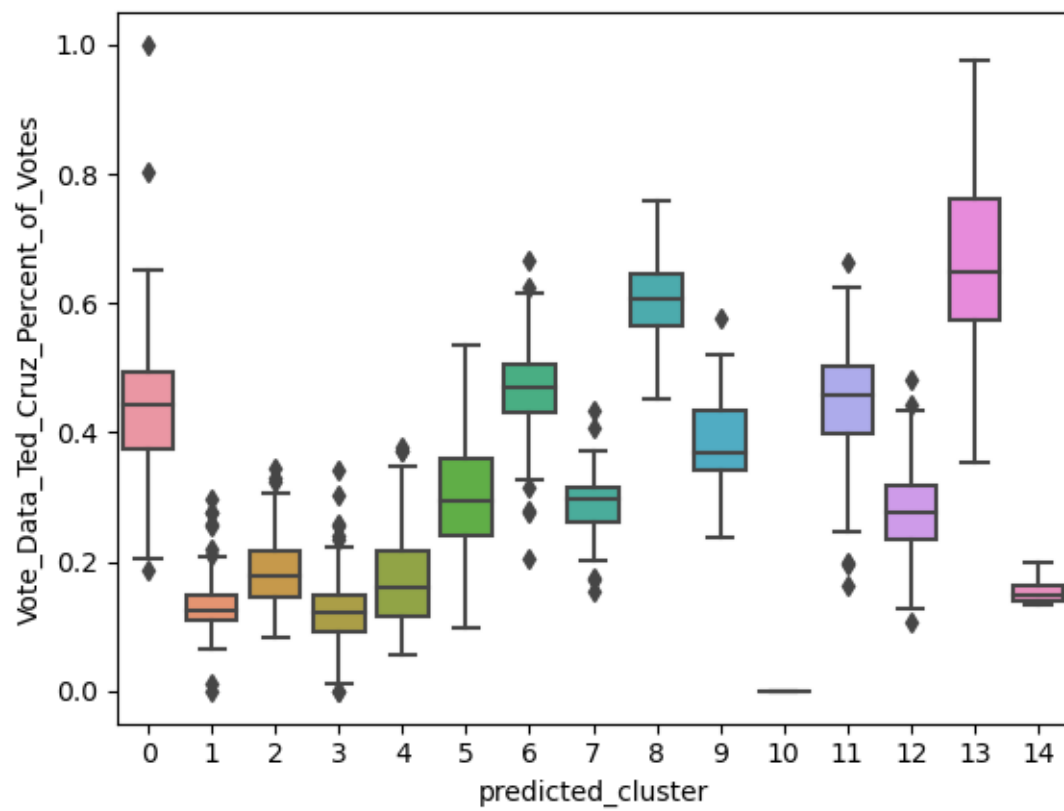


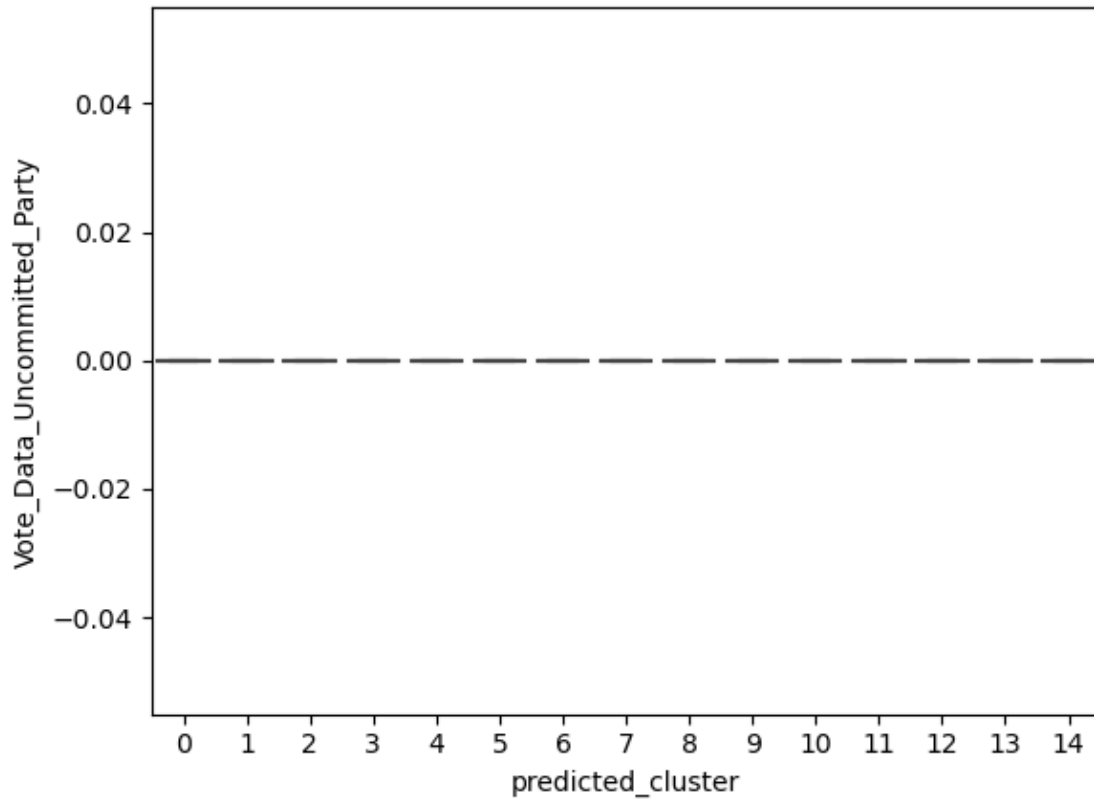








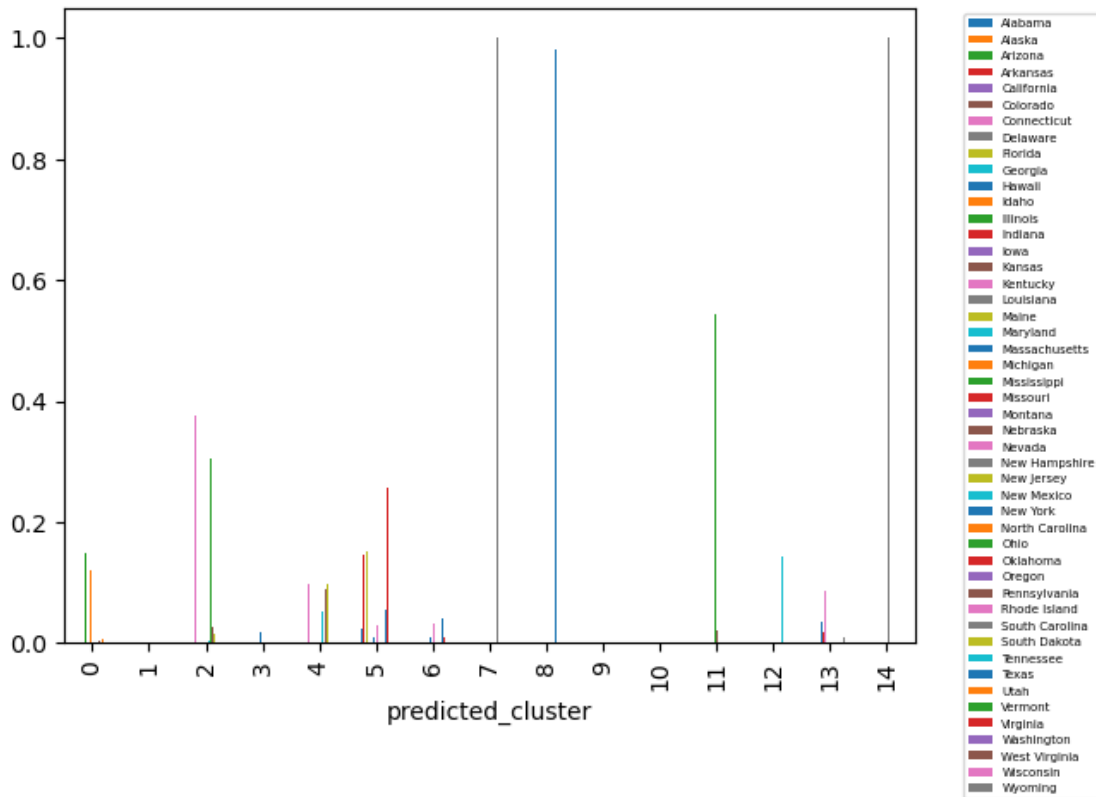




1. The vote for Bernie Sanders are mainly distributed in cluster 3 and 13 which apporctch to 0.9. But cluster 11 and 12 have the lowest which is 0.1.
2. For Carly Fiorina, it is mainly distriubated in Cluster 14, have 0.35.
3. For Chris Christie iy is mainly in cluster 14 have 0.75
4. For Donald Trump, mainly distributed in cluster 0, 9 and 17 which apporctch to 0.8. But cluster 2 are very low.
5. HillaryCliton mostly distributed in cluster 11, 12 and 15. But less distributed in 3 and 13.
6. Jeb Bush had a lot of support on cluster 14 and 15, but cluster 1 very low support.
7. John's approval rating is only high among 18, and the others are very low.
8. Marco Rubio has a very high rating in cluster 10 but the rest are vert low.
9. Mike Huckabee and Martin OMalley are only distributed in cluster 9 and none of the others.

Unaffiliated and nonpartisan data are not centrally distributed and data are scarce.

```
[90]: ctab=pd.crosstab(df_combo['predicted_cluster'],
    ↪df_combo['Location_State'],normalize='index')
ctab.plot.bar()
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
plt.show()
```



We can see from the bar plot that clusters 7, 8, 11, 12 and 14 are composed of one state. But in clusters 2, 4 and 5, there are multiple states. So the bar plot of HAC also shows that the cohesion is a little bit unsatisfactory. The cluster structure goes to K=15, plus our additional analysis said the ARI and homogeneity scores suggest that the clustering results have moderate agreement with the true labels and moderate homogeneity, while the completeness score suggests that the clustering results have high completeness which fit with the bar plot.

1.9 9. Analysis Summary and Conclusion

1.9.1 9.1. Algorithm Comparison Summary

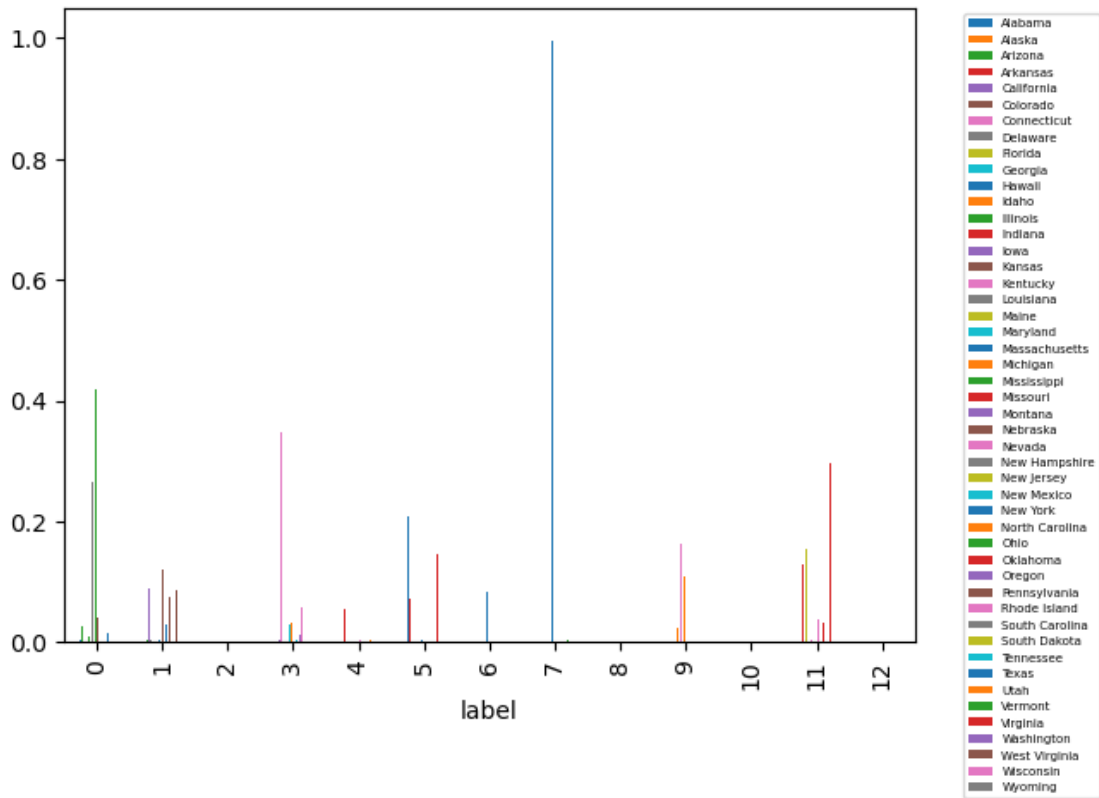
9.1.1. Comparing Algorithm Performance recall the bar plot in 7.6 and 8.6 first.

```
[114]: kmeans = KMeans(n_clusters=13, random_state=100).fit(X)
df_combo["label"] = kmeans.labels_
ctab=pd.crosstab(df_combo['label'],
                 df_combo['Location_State'],normalize='index')
ctab.plot.bar()
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
plt.show()
print('-----Bar for Kmeans-----')
```

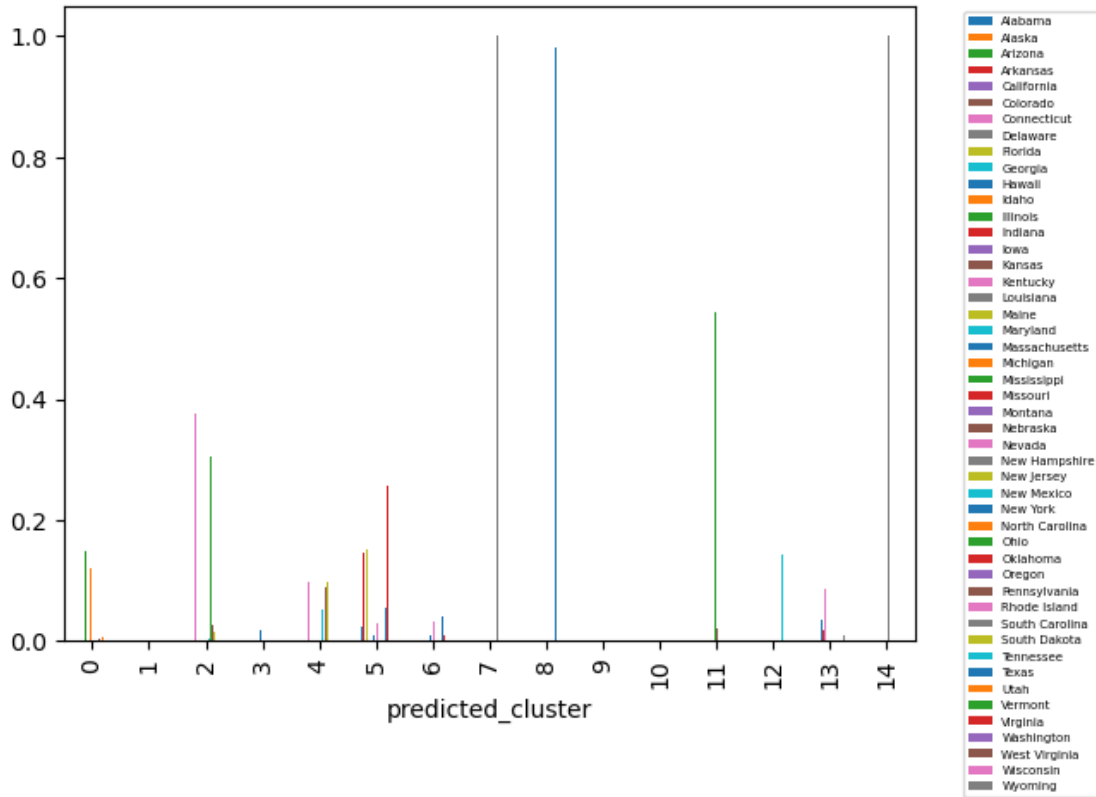
```

ctab=pd.crosstab(df_combo['predicted_cluster'],
    ↪df_combo['Location_State'],normalize='index')
ctab.plot.bar()
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
plt.show()
print('-----Bar for HAC-----')

```



-----Bar for Kmeans-----



-----Bar for HAC-----

Given your research goals and motivation stated at the beginning of your analysis, **compare and contrast the performance of your two clustering algorithms.** recall the Motivation: We want to use the voting data to determine if different counties are clustered according to the state they are in. We also want to explore the distribution of candidates supported in each cluster. The specific method is: we take the information of the real state where the county is located as the pre-defined label, and then check whether the predicted clusters are related to our pre-defined Location_State by different clustering algorithms. Then we analyze each cluster in detail to explore the components with high candidate support.

Looking first at the k-means, we can see that cluster 7 is composed of one state. But we can see that some clusters are not conceived with motivation, for example, clusters 5 and 11 have different states in their distribution. This shows that also the separation and cohesion is a little bit unsatisfactory, especially the cohesion.

Next is the HAC, where we can see that clusters 7, 8, 11, 12 and 14 are composed of one state. But in clusters 2 and 5, there are multiple states. So the bar plot of HAC also shows that the cohesion is a little bit unsatisfactory.

9.1.2. Comparing Algorithm Results

```

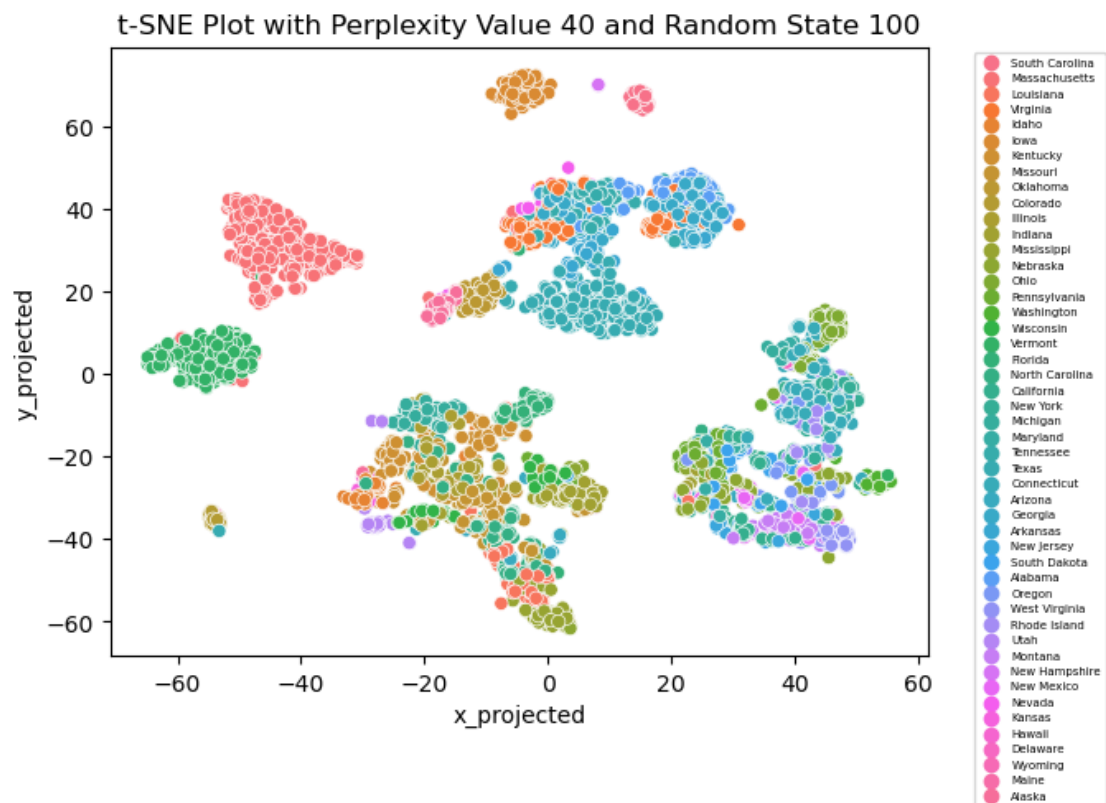
[111]: for perp in [40]:
        for rs in [100]:
            tsne = TSNE(n_components=2, perplexity=perp, random_state=rs)
            data_tsne = tsne.fit_transform(X)
            df_tsne = pd.DataFrame(data_tsne, columns=['x_projected',
↪ 'y_projected'])
            df_combo = pd.concat([df_label, df_tsne], axis=1)
            sns.scatterplot(x='x_projected',y='y_projected', hue =
↪ "Location_State",data=df_combo)
            plt.title('t-SNE Plot with Perplexity Value %s and Random State %s'
↪ %(perp, rs))
            plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', fontsize = 5)
            plt.show()
            print('          -----True Label-----')

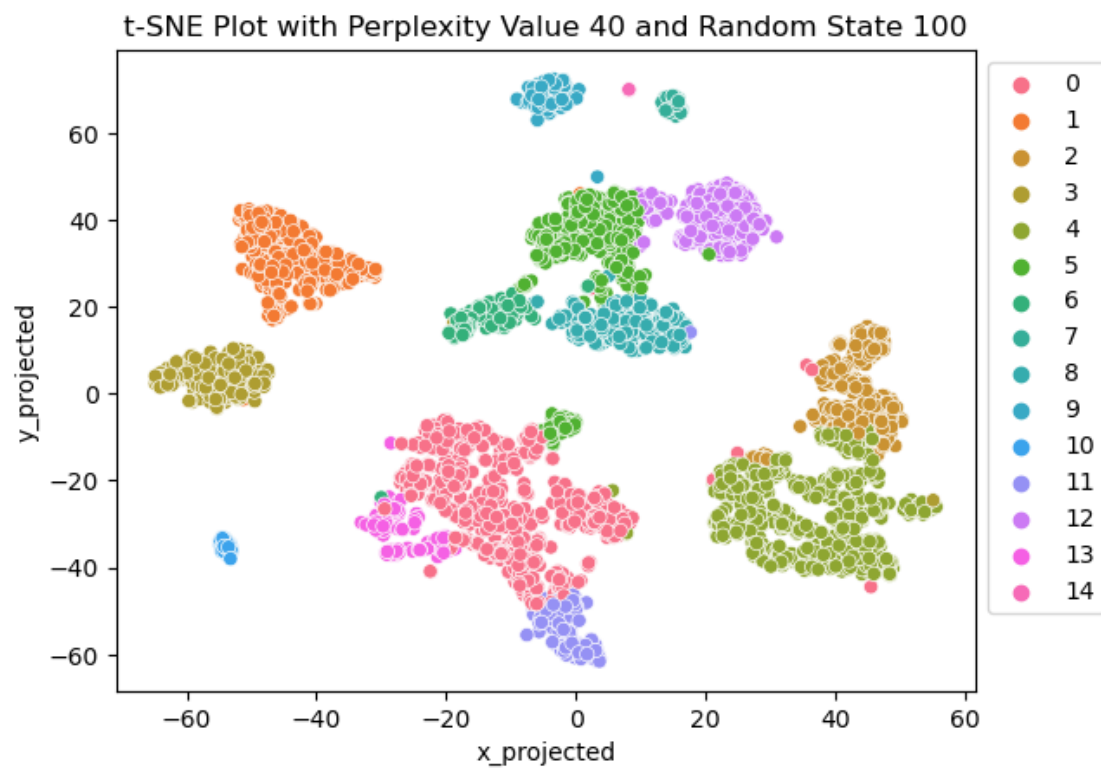
for k in [15]:
    #Clustering from dendrogram with k clusters
    hac = AgglomerativeClustering(n_clusters=k, affinity='euclidean',
↪ linkage='ward')
    df_combo['predicted_cluster'] = hac.fit_predict(df_num)

    #Map the resulting cluster labels onto our chosen t-SNE plot
    sns.scatterplot(x='x_projected',y='y_projected', hue='predicted_cluster',
↪ palette=sns.color_palette("husl", k), data=df_combo)
    plt.title('t-SNE Plot with Perplexity Value %s and Random State %s' %(40,
↪ 100))
    plt.legend(bbox_to_anchor=(1,1))
    plt.show()
    print('          -----Predicted Label
↪ HAC-----')

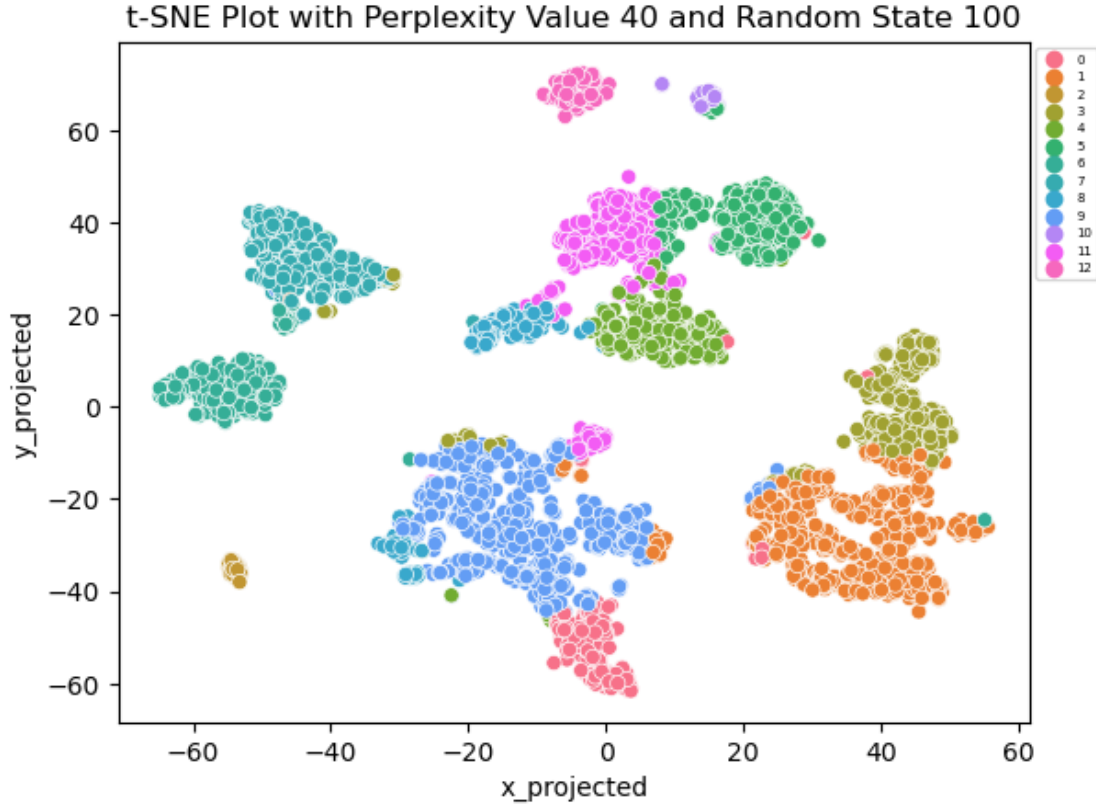
#Color code the points in your t-sne plot by cluster labels and code the
↪ "style" of the marker with your class labels.
kmeans = KMeans(n_clusters=13, random_state=100).fit(X)
df_combo["label"] = kmeans.labels_
sns.scatterplot(x='x_projected',y='y_projected',hue = "label",palette=sns.
↪ color_palette('husl', 13), data=df_combo)
plt.title('t-SNE Plot with Perplexity Value %s and Random State %s' %(perp, rs))
plt.legend(bbox_to_anchor=(1, 1), loc='upper left', fontsize = 5)
plt.show()
print('          -----Predicted Label
↪ K-means-----')

```





-----Predicted Label HAC-----



-----Predicted Label K-means-----

Average silhouette_score is 0.35 from k-means, 0.33 from hac ward linkage. These values are quiet similar, however, the K-means are better.

And we compare the t-SNE plot, from the t-SNE plot, HAC and K-means are similar too with $k=13$ and $k=15$. Also their distribution is also similar by the t-SNE plot. In addition, those two plot have strong relation with the location_state. Both of this two algos have proved that our goal in the motivation which is the vote preference in each county may be similar according to their state.

All in all, these two algorithms are pretty similar. However, the K-means has higher average silhouette score. A higher average silhouette score indicates better clustering performance, where each data point is more similar to other data points in the same cluster than to data points in other clusters. Also, K-means have more balanced clusters. But the HAC shows more clusters, which are more close to the real number of states. The difference between them are not huge, they are both good algo in this situation as far as I am concerned.

1.9.2 9.2. Conclusion and Insights Summary

In conclusion, we have used clustering algorithms to explore the distribution of vote preference in each county and determine if they are clustered according to the state they in. The K-means and HAC clustering algorithms were used, and their performance was compared based on the average

silhouette score and t-SNE plot. The results showed that both algorithms have strong relations with the location_state and are good in this situation. However, K-means had a higher average silhouette score, indicating better clustering performance, and more balanced clusters with a greater distribution shape. On the other hand, HAC showed more clusters, which were more close to the real number of states. In general, the results suggest that the vote preference in each county may be similar according to their state, but with some variations that need to be explored further.

1.10 10. Group Contribution Report

Project Name: Election Analysis

Team Members:

[Shuoyuan Gao]

[Shiyuan Zhang]

Contributions:

[Shuoyuan Gao] - [Part1, Part2, Part3, Part4, Part8, Part9] - 60%

[Shiyuan Zhang] - [Part5, Part6, Part7, part10] - 40%

This notebook was converted with convert.ploomber.io