Double-click (or enter) to edit

### written material

going to grab this data from gh: [https://raw.githubusercontent.com/stefanbund/py3100/main/ProductList_118.csv](https://raw.githubusercontent.com/stefanbund/py3100/main/ProductList_118.csv)

## The Ulta Beauty Problem

our work entails designing and delivering a business intelligence application that serves a major retail enterprise. The system ....

first, install the plotly visualization library.

Google collab is running lixus machine

```
!pip install plotly-geo
```

```
Collecting plotly-geo
  Downloading plotly_geo-1.0.0-py3-none-any.whl (23.7 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 23.7/23.7 MB 48.7 MB/s eta 0:00:00
Installing collected packages: plotly-geo
Successfully installed plotly-geo-1.0.0
```

Double-click (or enter) to edit

our system depends on the use of the pandas and numpy libraries.

This is how we import the major libraries that we're going to be working on

```
import pandas as pd
import numpy as np
```

Here we download the date from github

```
url ='https://raw.githubusercontent.com/stefanbund/py3100/main/ProductList_118.csv'
url_m = 'https://raw.githubusercontent.com/stefanbund/py3100/main/matrix.csv'
```

we make a pandas dataframe from url m as in matrix

```
df_m = pd.read_csv(url_m) #make a pandas dataframe
```

we're going to inspect the data frame that we have, such as cities etc

```
df_m
```

| | City | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | 32 | 33 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Birmingham | 8285 | 5343 | 6738 | 6635 | 5658 | 8118 | 4311 | 8535 | 3436 | ... | 1340 | 6923 |
| **1** | Montgomery | 1287 | 6585 | 8300 | 8874 | 8208 | 5363 | 3552 | 3387 | 2765 | ... | 4424 | 8813 |
| **2** | Mobile | 8035 | 5569 | 9492 | 5905 | 5024 | 1107 | 6937 | 5580 | 8044 | ... | 5430 | 1601 |
| **3** | Huntsville | 6280 | 2841 | 3399 | 5448 | 6173 | 5451 | 7488 | 9981 | 5236 | ... | 9169 | 7829 |
| **4** | Tuscaloosa | 4079 | 1066 | 3923 | 4177 | 4277 | 4219 | 9436 | 8160 | 4302 | ... | 1556 | 5533 |
| **5** | Hoover | 9741 | 7377 | 9410 | 9790 | 8864 | 2522 | 5347 | 9145 | 8402 | ... | 6031 | 7673 |
| **6** | Dothan | 7646 | 2060 | 4911 | 4976 | 7851 | 4277 | 7423 | 6183 | 6641 | ... | 8253 | 1565 |
| **7** | Auburn | 4326 | 2659 | 6928 | 4656 | 1828 | 5199 | 5331 | 6294 | 3076 | ... | 6128 | 3737 |
| **8** | Decatur | 3786 | 2891 | 8124 | 2469 | 3704 | 3623 | 2409 | 8287 | 2032 | ... | 6622 | 9742 |
| **9** | Madison | 1934 | 3628 | 9190 | 3275 | 9344 | 5778 | 1256 | 3523 | 1781 | ... | 6619 | 6128 |
| **10** | Florence | 8017 | 3187 | 1128 | 4706 | 9962 | 7547 | 4440 | 4530 | 9569 | ... | 8306 | 1392 |
| **11** | Gadsden | 2290 | 6402 | 8598 | 7547 | 5158 | 9731 | 8038 | 4435 | 7357 | ... | 4488 | 3591 |
| **12** | Vestavia Hills | 9471 | 9142 | 4419 | 3846 | 2016 | 5069 | 4853 | 6336 | 9062 | ... | 4613 | 2942 |
| **13** | Prattville | 6039 | 8003 | 6180 | 4610 | 3548 | 7115 | 6720 | 8512 | 9954 | ... | 8225 | 7278 |
| **14** | Phenix City | 8788 | 8269 | 6838 | 2863 | 6753 | 6608 | 4048 | 8774 | 4513 | ... | 5704 | 8720 |

these are the columns that represent the dimension of the matrix

```
df_m.columns #dimensionality of the matrix
```

```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41'],
      dtype='object')
```

here is a list of every city

list all cities in the matrix dataframe

this below provides a way to explore inside the dataframe

```
df_m['City'] #explore a Series inside the dataframe
```

```
0         Birmingham
1         Montgomery
2             Mobile
3         Huntsville
4         Tuscaloosa
5             Hoover
6             Dothan
7             Auburn
8            Decatur
9            Madison
10          Florence
11           Gadsden
12    Vestavia Hills
13        Prattville
14       Phenix City
15         Alabaster
16          Bessemer
17        Enterprise
18           Opelika
19          Homewood
20         Northport
21            Pelham
22        Trussville
23    Mountain Brook
24          Fairhope
Name: City, dtype: object
```

investigate quartile as an analytic tool

next we have the data types, a combination of characters

```
df_m.dtypes
# df_m.columns
```

```
City    object
1        int64
2        int64
3        int64
4        int64
5        int64
6        int64
7        int64
8        int64
9        int64
10       int64
11       int64
12       int64
13       int64
14       int64
15       int64
16       int64
17       int64
18       int64
19       int64
20       int64
21       int64
22       int64
23       int64
24       int64
25       int64
26       int64
27       int64
28       int64
29       int64
30       int64
31       int64
32       int64
33       int64
34       int64
35       int64
36       int64
37       int64
38       int64
39       int64
40       int64
41       int64
dtype: object
```

Quantiles for each display, all stores

Double-click (or enter) to edit

here we are expressing quantiles 0.25, 0.5, 0.75 only based on numeric columns creating quantile is only going across

```
df_3 = df_m.quantile([0.25, 0.5, 0.75], numeric_only=True, axis=1)
df_3
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | 15 | 16 | 17 | 18 | 19 | 20 | 21 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0.25** | 3082.0 | 3633.0 | 2236.0 | 3473.0 | 3657.0 | 4628.0 | 4254.0 | 3588.0 | 3704.0 | 3451.0 | ... | 3449.0 | 4246.0 | 4375.0 | 3217.0 | 4259.0 | 2468.0 | 3646.0 |
| **0.50** | 5343.0 | 5431.0 | 5311.0 | 5771.0 | 5131.0 | 7588.0 | 5156.0 | 5331.0 | 6589.0 | 5875.0 | ... | 6478.0 | 5944.0 | 6315.0 | 5341.0 | 6472.0 | 5472.0 | 5779.0 |
| **0.75** | 7242.0 | 8074.0 | 7508.0 | 7935.0 | 7490.0 | 9145.0 | 6840.0 | 7606.0 | 8221.0 | 7783.0 | ... | 7437.0 | 8331.0 | 8436.0 | 8472.0 | 8389.0 | 7877.0 | 8373.0 |

3 rows × 25 columns

per store, the quartile values

the quantiles establish cortiles

```
l = df_3.T.columns  #transpose, T
l
```

```
Float64Index([0.25, 0.5, 0.75], dtype='float64')
```

quartiles establish ranges, we decided to go with the mean here

```
df_3.T.mean()
```

```
0.25    3535.24
0.50    5826.36
0.75    7953.00
dtype: float64
```

define the global quartile boundary, per q

you get the mean by following this code, type .25 to get the mean

```
df_3.T[0.25].mean()
```

```
3535.24
```

Double-click (or enter) to edit

the mean for 05 is 5826.36

```
df_3.T[0.5].mean()
```

```
5826.36
```

Double-click (or enter) to edit

then the mean for 0.75 is 7953.0

```
df_3.T[0.75].mean()
```

```
7953.0
```

Double-click (or enter) to edit

the 3 means that we found are listed below

```
kk = df_3.T.mean()
kk #series
```

```
0.25    3535.24
0.50    5826.36
0.75    7953.00
dtype: float64
```

what percentage of displays are at or below the 25th quartile, per store? exercise

the code below explains that we are going into the matrix and its going one row at a time. then we are grabbing the sums and dividing items of the row then times 100. then we have all of the stores listed below and they show the stores that are underperforming under the 25 quartile

```
# n =
((df_m.iloc[:, 1:] <= kk[0.25]).sum(axis=1) / df_m.shape[1]) * 100
# print(round(n))
```

```
0     28.571429
1     21.428571
2     38.095238
3     26.190476
4     21.428571
5     16.666667
6     19.047619
7     23.809524
8     21.428571
9     28.571429
10    26.190476
11    19.047619
12    26.190476
13    23.809524
14    28.571429
15    28.571429
16    14.285714
17    19.047619
18    28.571429
19    19.047619
20    28.571429
21    23.809524
22    33.333333
23    19.047619
24    33.333333
dtype: float64
```

here are the code that we use to assign the QT. la, ll, lll. they all have a meaning behind them

```
la = df_m['25qt'] = round(((df_m.iloc[:, 1:] <= kk[0.25]).sum(axis=1) / df_m.shape[1]) * 100,1)
ll = df_m['50qt'] = round(((df_m.iloc[:, 1:] <= kk[0.50]).sum(axis=1) / df_m.shape[1]) * 100,1)
lll = df_m['75qt'] = round(((df_m.iloc[:, 1:] <= kk[0.75]).sum(axis=1) / df_m.shape[1]) * 100,1)
print(la, ll, lll)
```

```
0     28.6
1     21.4
2     38.1
3     26.2
4     21.4
5     16.7
6     19.0
7     23.8
8     21.4
9     28.6
10    26.2
11    19.0
12    26.2
13    23.8
14    28.6
15    28.6
16    14.3
17    19.0
18    28.6
19    19.0
20    28.6
21    23.8
22    33.3
23    19.0
24    33.3
dtype: float64 0     55.8
1     55.8
2     60.5
3     51.2
4     60.5
5     34.9
6     55.8
7     51.2
8     46.5
9     48.8
10    48.8
11    41.9
12    53.5
13    44.2
14    48.8
15    41.9
16    46.5
17    41.9
18    55.8
19    41.9
20    53.5
```

```
21    51.2
22    48.8
23    53.5
24    67.4
dtype: float64 0     77.3
1     70.5
2     79.5
3     77.3
4     79.5
5     59.1
6     90.9
```

Double-click (or enter) to edit

this is a comment saying that we are moving towards the matrix

```
# df_m
```

now we have a dataframe call end_set, with this is possible to make the data visible. such as graphs, charts, maps, etc. it also means that we are isolating some features with this command

```
end_set = ['City','25qt','50qt','75qt']
df_m[end_set]
```

| | City | 25qt | 50qt | 75qt |
|---|---|---|---|---|
| 0 | Birmingham | 28.6 | 55.8 | 77.3 |
| 1 | Montgomery | 21.4 | 55.8 | 70.5 |
| 2 | Mobile | 38.1 | 60.5 | 79.5 |
| 3 | Huntsville | 26.2 | 51.2 | 77.3 |
| 4 | Tuscaloosa | 21.4 | 60.5 | 79.5 |
| 5 | Hoover | 16.7 | 34.9 | 59.1 |
| 6 | Dothan | 19.0 | 55.8 | 90.9 |
| 7 | Auburn | 23.8 | 51.2 | 79.5 |
| 8 | Decatur | 21.4 | 46.5 | 70.5 |
| 9 | Madison | 28.6 | 48.8 | 75.0 |
| 10 | Florence | 26.2 | 48.8 | 63.6 |
| 11 | Gadsden | 19.0 | 41.9 | 68.2 |
| 12 | Vestavia Hills | 26.2 | 53.5 | 70.5 |
| 13 | Prattville | 23.8 | 44.2 | 75.0 |
| 14 | Phenix City | 28.6 | 48.8 | 75.0 |
| 15 | Alabaster | 28.6 | 41.9 | 84.1 |
| 16 | Bessemer | 14.3 | 46.5 | 70.5 |
| 17 | Enterprise | 19.0 | 41.9 | 72.7 |
| 18 | Opelika | 28.6 | 55.8 | 72.7 |
| 19 | Homewood | 19.0 | 41.9 | 68.2 |
| 20 | Northport | 28.6 | 53.5 | 75.0 |
| 21 | Pelham | 23.8 | 51.2 | 72.7 |
| 22 | Trussville | 33.3 | 48.8 | 75.0 |
| 23 | Mountain Brook | 19.0 | 53.5 | 70.5 |
| 24 | Fairhope | 33.3 | 67.4 | 86.4 |

create a choropleth for each store

Double-click (or enter) to edit

here we get started with a choropleth map, and what this code below is saying is that we're making a mock dataframe, then we also provide the zip codes

```
#choropleth:
import pandas as pd

# Create a sample dataframe
data = {'City': ['Birmingham', 'Montgomery', 'Mobile', 'Huntsville', 'Tuscaloosa', 'Hoover', 'Dothan', 'Auburn', 'Decatur', 'Mac
        'Zip Code': ['35201','36101','36601','35801','35401','35216','36301','36830','35601','35756','35630','35901','35216','36

df = pd.DataFrame(data)

# Create a list of zip codes
zip_codes = ['35201', '36101', '36601', '35801', '35401', '35216',
             '36301', '36830', '35601', '35756', '35630', '35901',
             '35216', '36066', '36867', '35007', '35020',
             '36330', 36801, 35209, 35473, 35124, 35173, 35213, 36532]

# Add the list of zip codes as a new column to the dataframe
# df = df.assign(Zip_Codes=zip_codes)
df_m = df_m.assign(zip=zip_codes)


print(df_m)
```

```
              City     1     2     3     4     5     6     7     8     9  ...  \
0       Birmingham  8285  5343  6738  6635  5658  8118  4311  8535  3436  ...
1       Montgomery  1287  6585  8300  8874  8208  5363  3552  3387  2765  ...
2           Mobile  8035  5569  9492  5905  5024  1107  6937  5580  8044  ...
3       Huntsville  6280  2841  3399  5448  6173  5451  7488  9981  5236  ...
4       Tuscaloosa  4079  1066  3923  4177  4277  4219  9436  8160  4302  ...
5           Hoover  9741  7377  9410  9790  8864  2522  5347  9145  8402  ...
6           Dothan  7646  2060  4911  4976  7851  4277  7423  6183  6641  ...
7           Auburn  4326  2659  6928  4656  1828  5199  5331  6294  3076  ...
8          Decatur  3786  2891  8124  2469  3704  3623  2409  8287  2032  ...
9          Madison  1934  3628  9190  3275  9344  5778  1256  3523  1781  ...
10        Florence  8017  3187  1128  4706  9962  7547  4440  4530  9569  ...
11         Gadsden  2290  6402  8598  7547  5158  9731  8038  4435  7357  ...
12  Vestavia Hills  9471  9142  4419  3846  2016  5069  4853  6336  9062  ...
13      Prattville  6039  8003  6180  4610  3548  7115  6720  8512  9954  ...
14     Phenix City  8788  8269  6838  2863  6753  6608  4048  8774  4513  ...
15       Alabaster  1733  9767  3274  7125  7437  5748  5399  6513  3038  ...
16        Bessemer  6559  2453  1578  5158  3058  8075  7066  8530  8346  ...
17      Enterprise  8436  7800  7234  5063  4274  1948  7887  6647  1320  ...
18          Opelika  9998  8953  7923  6176  4369  9503  2126  1816  9224  ...
19        Homewood  2373  7188  9880  9236  5969  9998  8703  8440  4643  ...
20       Northport  3536  9231  8651  6374  4842  5704  8484  6322  2012  ...
21          Pelham  6830  3736  2734  6443  8494  6206  7290  8518  6176  ...
22      Trussville  2794  8273  9174  2850  8351  3978  5995  4632  7693  ...
23  Mountain Brook  8433  9368  2141  2357  6566  1482  4787  3900  6615  ...
24        Fairhope  8114  1464  2811  3090  4686  7995  7676  1304  7332  ...

      36    37    38    39    40    41  25qt  50qt  75qt    zip
0   3555  1341  1756  7598  1509  1861  28.6  55.8  77.3  35201
1   2805  4601  4449  5727  2315  8822  21.4  55.8  70.5  36101
2   9807  2652  9296  2815  4886  7458  38.1  60.5  79.5  36601
3   7935  2605  9982  3338  9116  3875  26.2  51.2  77.3  35801
4   3657  2158  4469  2513  8135  6963  21.4  60.5  79.5  35401
5   9748  7224  4628  8107  6143  1671  16.7  34.9  59.1  35216
6   5650  4400  7842  4006  9335  3571  19.0  55.8  90.9  36301
7   4387  6890  2833  5083  9707  2116  23.8  51.2  79.5  36830
8   9305  6509  6848  5408  3707  8744  21.4  46.5  70.5  35601
9   1746  4470  7054  6573  3556  1374  28.6  48.8  75.0  35756
10  5929  1123  7306  8746  4000  6943  26.2  48.8  63.6  35630
11  2549  5175  5997  9608  7230  9731  19.0  41.9  68.2  35901
12  5142  9619  9601  8099  1391  6276  26.2  53.5  70.5  35216
13  1591  4401  3457  4245  4341  2573  23.8  44.2  75.0  36066
14  3520  7654  6845  7738  3828  1202  28.6  48.8  75.0  36867
15  2479  9673  7478  7207  7006  3523  28.6  41.9  84.1  35007
16  4810  7641  5365  3545  6812  9483  14.3  46.5  70.5  35020
17  3461  2640  4375  8634  4917  2830  19.0  41.9  72.7  36330
18  5191  9304  2720  3100  3912  1548  28.6  55.8  72.7  36801
19  8787  5459  8389  5242  2224  6025  19.0  41.9  68.2  35209
20  6947  5401  6681  9018  1668  8307  28.6  53.5  75.0  35473
21  2777  4045  7309  4745  4284  2640  23.8  51.2  72.7  35124
22  1650  9470  6356  4700  3344  8743  33.3  48.8  75.0  35173
23  5765  3653  5198  9266  4945  3935  19.0  53.5  70.5  35213
24  3457  4808  7227  5482  6355  4553  33.3  67.4  86.4  36532
```

```
[25 rows x 46 columns]
```

experiment with chloropleths

this is just how we number the chart, each number a city

```
df_m.columns
```

```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41', '25qt', '50qt', '75qt', 'zip'],
      dtype='object')
```

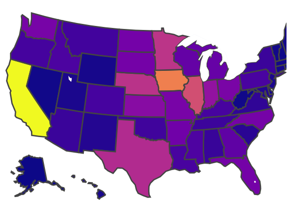
choropleth is build of off fisps codes. fisps codes are the area code of the county. then you can hoover over the map and get some brief info regarding eah state.

```
import plotly.express as px
import pandas as pd

# Load data
df_demo = pd.read_csv('https://raw.githubusercontent.com/plotly/datasets/master/2011_us_ag_exports.csv')

# Create choropleth map
fig = px.choropleth(df_demo, locations='code', locationmode='USA-states', color='total exports', scope='usa')

# Show map
fig.show()
```



here we organized this map based on states or a code of the state and total exports.

```
df_demo
```

| | code | state | category | total exports | beef | pork | poultry | dairy | fruits fresh | frui pr |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | AL | Alabama | state | 1390.63 | 34.4 | 10.6 | 481.0 | 4.06 | 8.0 | 1 |
| **1** | AK | Alaska | state | 13.31 | 0.2 | 0.1 | 0.0 | 0.19 | 0.0 | |
| **2** | AZ | Arizona | state | 1463.17 | 71.3 | 17.9 | 0.0 | 105.48 | 19.3 | 4 |
| **3** | AR | Arkansas | state | 3586.02 | 53.2 | 29.4 | 562.9 | 3.53 | 2.2 | |
| **4** | CA | California | state | 16472.88 | 228.7 | 11.1 | 225.4 | 929.95 | 2791.8 | 594 |
| **5** | CO | Colorado | state | 1851.33 | 261.4 | 66.0 | 14.0 | 71.94 | 5.7 | 1 |
| **6** | CT | Connecticut | state | 259.62 | 1.1 | 0.1 | 6.9 | 9.49 | 4.2 | |
| **7** | DE | Delaware | state | 282.19 | 0.4 | 0.6 | 114.7 | 2.30 | 0.5 | |
| **8** | FL | Florida | state | 3764.09 | 42.6 | 0.9 | 56.9 | 66.31 | 438.2 | 93 |
| **9** | GA | Georgia | state | 2860.84 | 31.0 | 18.9 | 630.4 | 38.38 | 74.6 | 15 |
| **10** | HI | Hawaii | state | 401.84 | 4.0 | 0.7 | 1.3 | 1.16 | 17.7 | 3 |
| **11** | ID | Idaho | state | 2078.89 | 119.8 | 0.0 | 2.4 | 294.60 | 6.9 | 1 |
| **12** | IL | Illinois | state | 8709.48 | 53.7 | 394.0 | 14.0 | 45.82 | 4.0 | |
| **13** | IN | Indiana | state | 5050.23 | 21.9 | 341.9 | 165.6 | 89.70 | 4.1 | |
| **14** | IA | Iowa | state | 11273.76 | 289.8 | 1895.6 | 155.6 | 107.00 | 1.0 | |
| **15** | KS | Kansas | state | 4589.01 | 659.3 | 179.4 | 6.4 | 65.45 | 1.0 | |
| **16** | KY | Kentucky | state | 1889.15 | 54.8 | 34.2 | 151.3 | 28.27 | 2.1 | |
| **17** | LA | Louisiana | state | 1914.23 | 19.8 | 0.8 | 77.2 | 6.02 | 5.7 | 1 |
| **18** | ME | Maine | state | 278.37 | 1.4 | 0.5 | 10.4 | 16.18 | 16.6 | 3 |
| **19** | MD | Maryland | state | 692.75 | 5.6 | 3.1 | 127.0 | 24.81 | 4.1 | |
| **20** | MA | Massachusetts | state | 248.65 | 0.6 | 0.5 | 0.6 | 5.81 | 25.8 | 5 |
| **21** | MI | Michigan | state | 3164.16 | 37.7 | 118.1 | 32.6 | 214.82 | 82.3 | 17 |
| **22** | MN | Minnesota | state | 7192.33 | 112.3 | 740.4 | 189.2 | 218.05 | 2.5 | |
| **23** | MS | Mississippi | state | 2170.80 | 12.8 | 30.4 | 370.8 | 5.45 | 5.4 | 1 |
| **24** | MO | Missouri | state | 3933.42 | 137.2 | 277.3 | 196.1 | 34.26 | 4.2 | |
| **25** | MT | Montana | state | 1718.00 | 105.0 | 16.7 | 1.7 | 6.82 | 1.1 | |
| **26** | NE | Nebraska | state | 7114.13 | 762.2 | 262.5 | 31.4 | 30.07 | 0.7 | |
| **27** | NV | Nevada | state | 139.89 | 21.8 | 0.2 | 0.0 | 16.57 | 0.4 | |
| **28** | NH | New Hampshire | state | 73.06 | 0.6 | 0.2 | 0.8 | 7.46 | 2.6 | |
| **29** | NJ | New Jersey | state | 500.40 | 0.8 | 0.4 | 4.6 | 3.37 | 35.0 | 7 |
| **30** | NM | New Mexico | state | 751.58 | 117.2 | 0.1 | 0.3 | 191.01 | 32.6 | 6 |
| **31** | NY | New York | state | 1488.90 | 22.2 | 5.8 | 17.7 | 331.80 | 64.7 | 13 |
| **32** | NC | North Carolina | state | 3806.05 | 24.8 | 702.8 | 598.4 | 24.90 | 23.8 | 5 |
| **33** | ND | North Dakota | state | 3761.96 | 78.5 | 16.1 | 0.5 | 8.14 | 0.1 | |
| **34** | OH | Ohio | state | 3979.79 | 36.2 | 199.1 | 129.9 | 134.57 | 8.7 | 1 |
| **35** | OK | Oklahoma | state | 1646.41 | 337.6 | 265.3 | 131.1 | 24.35 | 3.0 | |
| **36** | OR | Oregon | state | 1794.57 | 58.8 | 1.4 | 14.2 | 63.66 | 100.7 | 21 |
| **37** | PA | Pennsylvania | state | 1969.87 | 50.9 | 91.3 | 169.8 | 280.87 | 28.6 | 6 |
| **38** | RI | Rhode Island | state | 31.59 | 0.1 | 0.1 | 0.2 | 0.52 | 0.9 | |
| **39** | SC | South Carolina | state | 929.93 | 15.2 | 10.9 | 186.5 | 7.62 | 17.1 | 3 |
| **40** | SD | South Dakota | state | 3770.19 | 193.5 | 160.2 | 29.3 | 46.77 | 0.3 | |
| **41** | TN | Tennessee | state | 1535.13 | 51.1 | 17.6 | 82.4 | 21.18 | 2.0 | |
| **42** | TX | Texas | state | 6648.22 | 961.0 | 42.7 | 339.2 | 240.55 | 31.9 | 6 |
| **43** | UT | Utah | state | 453.39 | 27.9 | 59.0 | 23.1 | 48.60 | 3.9 | |
| **44** | VT | Vermont | state | 180.14 | 6.2 | 0.2 | 0.9 | 65.98 | 2.6 | |

here is the info of our chart and what is gooing to contain.

```
df_demo.columns
```

```
Index(['code', 'state', 'category', 'total exports', 'beef', 'pork', 'poultry',
       'dairy', 'fruits fresh', 'fruits proc', 'total fruits', 'veggies fresh',
       'veggies proc', 'total veggies', 'corn', 'wheat', 'cotton'],
      dtype='object')
```

map demo #2: state of AL

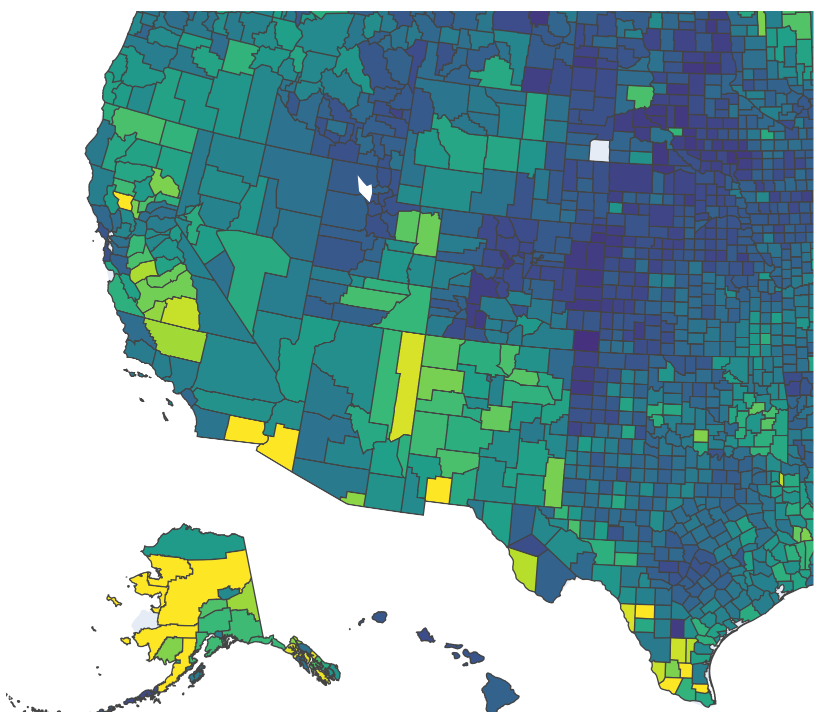
here are the steps of how we got the second demostration.

```
from urllib.request import urlopen
import json
with urlopen('https://raw.githubusercontent.com/plotly/datasets/master/geojson-counties-fips.json') as response:
    counties = json.load(response)

import pandas as pd
df_us = pd.read_csv("https://raw.githubusercontent.com/plotly/datasets/master/fips-unemp-16.csv",
                   dtype={"fips": str})

import plotly.express as px

fig = px.choropleth(df_us, geojson=counties, locations='fips', color='unemp',
                           color_continuous_scale="Viridis",
                           range_color=(0, 12),
                           scope="usa",
                           labels={'unemp':'unemployment rate'})
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
fig.show()
```



here is the code for the fips and this provide us with the county codes.

```
df_us.columns
```

```
Index(['fips', 'unemp'], dtype='object')
```

with this information, we can make a choropleth. we get this info by putting the code above.

```
df_us
```

| | fips | unemp |
|---|---|---|
| 0 | 01001 | 5.3 |
| 1 | 01003 | 5.4 |
| 2 | 01005 | 8.6 |
| 3 | 01007 | 6.6 |
| 4 | 01009 | 5.5 |
| ... | ... | ... |
| 3214 | 72145 | 13.9 |
| 3215 | 72147 | 10.6 |
| 3216 | 72149 | 20.2 |
| 3217 | 72151 | 16.9 |
| 3218 | 72153 | 18.8 |

3219 rows × 2 columns

documentation here, with more discusssion here, and specifially to do counties, here

county **list** for ulta stores in Alabama, by FIPS code

here we started to look up the fips code for various county

```
al_fips =[
    {'County': 'Autauga', 'FIPS Code': '01001'},
    {'County': 'Baldwin', 'FIPS Code': '01003'},
    {'County': 'Barbour', 'FIPS Code': '01005'},
    {'County': 'Bibb', 'FIPS Code': '01007'},
    {'County': 'Blount', 'FIPS Code': '01009'},
    {'County': 'Bullock', 'FIPS Code': '01011'},
    {'County': 'Butler', 'FIPS Code': '01013'},
    {'County': 'Calhoun', 'FIPS Code': '01015'},
    {'County': 'Chambers', 'FIPS Code': '01017'},
    {'County': 'Cherokee', 'FIPS Code': '01019'},
    {'County': 'Chilton', 'FIPS Code': '01021'},
    {'County': 'Choctaw', 'FIPS Code': '01023'},
    {'County': 'Clarke', 'FIPS Code': '01025'},
    {'County': 'Clay', 'FIPS Code': '01027'},
    {'County': 'Cleburne', 'FIPS Code': '01029'},
    {'County': 'Coffee', 'FIPS Code': '01031'},
    {'County': 'Colbert', 'FIPS Code': '01033'},
    {'County': 'Conecuh', 'FIPS Code': '01035'},
    {'County':'Greene', 'FIPS Code' : '28073'},
    {'County':'Hale', 'FIPS Code' : '28065'},
    {'County':'Henry','FIPS Code' : '28067'},
    {'County':'Houston', 'FIPS Code' : '28069'},
    {'County':'Jackson', 'FIPS Code' : '28071'},
    {'County':'Jefferson', 'FIPS Code' : '28073'},
    {'County':'Lamar', 'FIPS Code' : '28073'}]
len(al_fips)
```

```
25
```

here is the code for the columns for each county and city

```
df_m.columns
```

```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41', '25qt', '50qt', '75qt', 'zip'],
      dtype='object')
```

then here we assigned the city with the county, creating a clean chart with the correct info.

```
df_m
```

| | City | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | 36 | 37 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Birmingham | 8285 | 5343 | 6738 | 6635 | 5658 | 8118 | 4311 | 8535 | 3436 | ... | 3555 | 1341 | 17 |
| **1** | Montgomery | 1287 | 6585 | 8300 | 8874 | 8208 | 5363 | 3552 | 3387 | 2765 | ... | 2805 | 4601 | 44 |
| **2** | Mobile | 8035 | 5569 | 9492 | 5905 | 5024 | 1107 | 6937 | 5580 | 8044 | ... | 9807 | 2652 | 92 |
| **3** | Huntsville | 6280 | 2841 | 3399 | 5448 | 6173 | 5451 | 7488 | 9981 | 5236 | ... | 7935 | 2605 | 99 |
| **4** | Tuscaloosa | 4079 | 1066 | 3923 | 4177 | 4277 | 4219 | 9436 | 8160 | 4302 | ... | 3657 | 2158 | 44 |
| **5** | Hoover | 9741 | 7377 | 9410 | 9790 | 8864 | 2522 | 5347 | 9145 | 8402 | ... | 9748 | 7224 | 46 |
| **6** | Dothan | 7646 | 2060 | 4911 | 4976 | 7851 | 4277 | 7423 | 6183 | 6641 | ... | 5650 | 4400 | 78 |
| **7** | Auburn | 4326 | 2659 | 6928 | 4656 | 1828 | 5199 | 5331 | 6294 | 3076 | ... | 4387 | 6890 | 28 |
| **8** | Decatur | 3786 | 2891 | 8124 | 2469 | 3704 | 3623 | 2409 | 8287 | 2032 | ... | 9305 | 6509 | 68 |
| **9** | Madison | 1934 | 3628 | 9190 | 3275 | 9344 | 5778 | 1256 | 3523 | 1781 | ... | 1746 | 4470 | 70 |
| **10** | Florence | 8017 | 3187 | 1128 | 4706 | 9962 | 7547 | 4440 | 4530 | 9569 | ... | 5929 | 1123 | 73 |
| **11** | Gadsden | 2290 | 6402 | 8598 | 7547 | 5158 | 9731 | 8038 | 4435 | 7357 | ... | 2549 | 5175 | 59 |
| **12** | Vestavia Hills | 9471 | 9142 | 4419 | 3846 | 2016 | 5069 | 4853 | 6336 | 9062 | ... | 5142 | 9619 | 96 |
| **13** | Prattville | 6039 | 8003 | 6180 | 4610 | 3548 | 7115 | 6720 | 8512 | 9954 | ... | 1591 | 4401 | 34 |
| **14** | Phenix City | 8788 | 8269 | 6838 | 2863 | 6753 | 6608 | 4048 | 8774 | 4513 | ... | 3520 | 7654 | 68 |
| **15** | Alabaster | 1733 | 9767 | 3274 | 7125 | 7437 | 5748 | 5399 | 6513 | 3038 | ... | 2479 | 9673 | 74 |
| **16** | Bessemer | 6559 | 2453 | 1578 | 5158 | 3058 | 8075 | 7066 | 8530 | 8346 | ... | 4810 | 7641 | 53 |
| **17** | Enterprise | 8436 | 7800 | 7234 | 5063 | 4274 | 1948 | 7887 | 6647 | 1320 | ... | 3461 | 2640 | 43 |
| **18** | Opelika | 9998 | 8953 | 7923 | 6176 | 4369 | 9503 | 2126 | 1816 | 9224 | ... | 5191 | 9304 | 27 |
| **19** | Homewood | 2373 | 7188 | 9880 | 9236 | 5969 | 9998 | 8703 | 8440 | 4643 | ... | 8787 | 5459 | 83 |
| **20** | Northport | 3536 | 9231 | 8651 | 6374 | 4842 | 5704 | 8484 | 6322 | 2012 | ... | 6947 | 5401 | 66 |
| **21** | Pelham | 6830 | 3736 | 2734 | 6443 | 8494 | 6206 | 7290 | 8518 | 6176 | ... | 2777 | 4045 | 73 |
| **22** | Trussville | 2794 | 8273 | 9174 | 2850 | 8351 | 3978 | 5995 | 4632 | 7693 | ... | 1650 | 9470 | 63 |
| **23** | Mountain Brook | 8433 | 9368 | 2141 | 2357 | 6566 | 1482 | 4787 | 3900 | 6615 | ... | 5765 | 3653 | 51 |
| **24** | Fairhope | 8114 | 1464 | 2811 | 3090 | 4686 | 7995 | 7676 | 1304 | 7332 | ... | 3457 | 4808 | 72 |

shapes are the number of stores associated with the dataframe

```
df_m.shape[0]
```

```
25
```

transform al_fips, the list of county fps codes, into a pandas dataframe

here we want to assigned al to fips. that way we can have the fips associated with each store.

```
print(len(al_fips))
df_counties = pd.DataFrame(al_fips)
df_counties.size
```

```
25
50
```

here we are cobianing fips and the countys

```
print(df_counties.columns)
```

```
Index(['County', 'FIPS Code'], dtype='object')
```

df_m: all display data, per store

here again we are adding more rows to thew dataframe

```
df_m.shape[0]
```

```
25
```

fips codes per county

here we are adding rows to the county so that way we can combined them together

```
df_counties.shape[0]
```

```
25
```

again we are setting everything up for the merging process.

```
df_counties.columns
```

```
Index(['County', 'FIPS Code'], dtype='object')
```

merge the county fips codes with the stores sales results (df_m)

here we are going to merge df_m with the county along with columns and we get our chart below

```
merged_df = pd.concat([df_m, df_counties], axis=1)
merged_df.head()
```

| | City | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | 38 | 39 | 4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Birmingham | 8285 | 5343 | 6738 | 6635 | 5658 | 8118 | 4311 | 8535 | 3436 | ... | 1756 | 7598 | 15( |
| 1 | Montgomery | 1287 | 6585 | 8300 | 8874 | 8208 | 5363 | 3552 | 3387 | 2765 | ... | 4449 | 5727 | 23 |
| 2 | Mobile | 8035 | 5569 | 9492 | 5905 | 5024 | 1107 | 6937 | 5580 | 8044 | ... | 9296 | 2815 | 48 |
| 3 | Huntsville | 6280 | 2841 | 3399 | 5448 | 6173 | 5451 | 7488 | 9981 | 5236 | ... | 9982 | 3338 | 91 |
| 4 | Tuscaloosa | 4079 | 1066 | 3923 | 4177 | 4277 | 4219 | 9436 | 8160 | 4302 | ... | 4469 | 2513 | 81 |

5 rows × 48 columns

we are going to marge all of this information together to develop our choropleth

use the merged_df as data source for the choropleth

```
merged_df.columns
```

```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41', '25qt', '50qt', '75qt', 'zip', 'County',
       'FIPS Code'],
      dtype='object')
```

Double-click (or enter) to edit

use the plotly api, feed it the merged_df information to do a map, with encoded quantile values

merged df has the data, then we are grabbing plotly which is the pythin library for charts. then we are saying the location. we are also grabbing all of our fibs and assigning colors to the choropleth. we use 35 radiants. the ones that are under performing are bright and the ones doing good are darker colors. we have hoovering and legend.

```
import plotly.express as px

fig = px.choropleth(merged_df, geojson=counties, locations='FIPS Code', color='25qt',
                           color_continuous_scale="Viridis",
                           range_color=(0, 38),
                           scope="usa",
                    hover_name="City",
                    hover_data=["City"],
                           labels={'25qt':'percentage displays under 25th qt'}  #
                          )
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
fig.show()
```



here we did an example of a different county. same process diffe

here we did an example of a different county. same process different data.

```
import plotly.express as px
import requests
import json
import pandas as pd

# Load the geojson data for Alabama's counties
r = requests.get('https://raw.githubusercontent.com/plotly/datasets/master/geojson-counties-fips.json')
counties = json.loads(r.text)

# Filter the geojson data to only include Alabama's counties
target_states = ['01']
counties['features'] = [f for f in counties['features'] if f['properties']['STATE'] in target_states]

# Load the sample data for Alabama's counties
df = pd.read_csv('https://raw.githubusercontent.com/plotly/datasets/master/fips-unemp-16.csv', dtype={'fips': str})

# Create the choropleth map
fig = px.choropleth(df, geojson=counties, locations='fips', color='unemp',
                    color_continuous_scale='Viridis', range_color=(0, 12),
                    scope='usa', labels={'unemp': 'unemployment rate'})
fig.update_layout(margin={'r': 0, 't': 0, 'l': 0, 'b': 0})
fig.show()
```