Joseph Pham's markup copy

written material

going to grab this data from gh: 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.

```
!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 45.8 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.

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

This cell imported pandas and numpy for our python code to run

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

In this cell, we defined two seperate variables for two different urls . The first variable, url is linked to the product list csv file from our ulta project. The second variable, url_m, linked the matrix csv fil.

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

In this cell, we created and defined the data frame that we wil be use. We did this by having pandas read a csv file of our choice which in this case was url_m as predefined earlier.

```
df_m
```

	City	1	2	3	4	5	6	7	8	9	...	32	33	34	35	36	37	38	39	40	41
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	1340	6923	3082	5617	3555	1341	1756	7598	1509	1861
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	4424	8813	6655	3986	2805	4601	4449	5727	2315	8822
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	5430	1601	9145	1493	9807	2652	9296	2815	4886	7458
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	9169	7829	6879	4166	7935	2605	9982	3338	9116	3875
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	1556	5533	1884	2088	3657	2158	4469	2513	8135	6963
5	Hoover	9741	7377	9410	9790	8864	2522	5347	9145	8402	...	6031	7673	8403	7588	9748	7224	4628	8107	6143	1671
6	Dothan	7646	2060	4911	4976	7851	4277	7423	6183	6641	...	8253	1565	6052	5802	5650	4400	7842	4006	9335	3571
7	Auburn	4326	2659	6928	4656	1828	5199	5331	6294	3076	...	6128	3737	7785	3281	4387	6890	2833	5083	9707	2116
8	Decatur	3786	2891	8124	2469	3704	3623	2409	8287	2032	...	6622	9742	9382	8413	9305	6509	6848	5408	3707	8744
9	Madison	1934	3628	9190	3275	9344	5778	1256	3523	1781	...	6619	6128	5325	9976	1746	4470	7054	6573	3556	1374
10	Florence	8017	3187	1128	4706	9962	7547	4440	4530	9569	...	8306	1392	1363	5545	5929	1123	7306	8746	4000	6943
11	Gadsden	2290	6402	8598	7547	5158	9731	8038	4435	7357	...	4488	3591	1683	7343	2549	5175	5997	9608	7230	9731
12	Vestavia Hills	9471	9142	4419	3846	2016	5069	4853	6336	9062	...	4613	2942	7408	9484	5142	9619	9601	8099	1391	6276
13	Prattville	6039	8003	6180	4610	3548	7115	6720	8512	9954	...	8225	7278	7358	2997	1591	4401	3457	4245	4341	2573

In this cell, we ran df_m and saw that it outputs the csv file as spreadsheet. We also see that it tells use how many rows and columns are present in this spread sheet.

```
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')
```

list all cities in the matrix dataframe

In the above cells, we asked df_m.column essentially, "tell us how many columns are present in the data frame that was called up. The resulting output tells us what is being filled in for each of the 42 cells.

```
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

In the above cell, we asked the data fram to tell us what is being populated in each of the cells under the 'City' column of the csv.

```
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

In this cell, we wanted to know that is what objects are being populated in the cells. In this case, we want to see what quantiles for each display 1 for each store.

```
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

In this cell, we wanted to break out each quantile into quarters, 25, 50, and 75% After which we wanted to see its value across each of the display.

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

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

In this cell, we transposed a row of data into a column of data using the T. Transposing data essentially flips a column on its side to become a row, or flips a row into a column.

```
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

In this cell, we transposed a column of data which in for this cell was the average performance of each quartile.

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

```
3535.24
```

In this cell, we used the [] to specifically find a quartile from the mean matrix. In this case, we wanted to call on the 25% quartile.

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

```
5826.36
```

In this cell, we again used the [ ] to target a specfic value in the df_3.T.mean() command. For this cell, we wanted the 50% or .5 value.

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

```
7953.0
```

Double-click (or enter) to edit

In this cell, we again used the [ ] to target a specfic value in the df_3.T.mean() command. For this cell, we wanted the 75% or .75 value.

```
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

13 stores are under the 25%

```
# 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
```

In the cell above we wanted to see how many displays are preforming at or below the 25%. shape tells us how many items are in each row. For our case, we have on item in each row which would be the percentage in sales.

```
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
7     79.5
```

In the cell above, we want to display each of the quartiles, 25,50 and 75 for each of the 24 respective cities in Alabama. We do this by define a printable variable for each quartile and have them round to the nearest tenth before outputing.

```
# df_m
```

We redefine our dataframe here.

```
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

In this cell, we now display our data in a more friendly interface. We set up our end_set such that at the top of each column, it will have the city, and each of the quartiles we want to see.

create a choropleth for each store

```
#choropleth:
import pandas as pd

# Create a sample dataframe
data = {'City': ['Birmingham', 'Montgomery', 'Mobile', 'Huntsville', 'Tuscaloosa', 'Hoover', 'Dothan', 'Auburn', 'Decatur', 'Madison', 'Flor
        'Zip Code': ['35201','36101','36601','35801','35401','35216','36301','36830','35601','35756','35630','35901','35216','36066','36867'

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

In this cell, we start to create the chloropleths by creating a new data frame, df that will pull information such as city names and zipcodes. we also create a variable called zip_codes that contains a matrix of zipcodes that we will call later on. we then print df_m to produce the tables.

```
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')
```

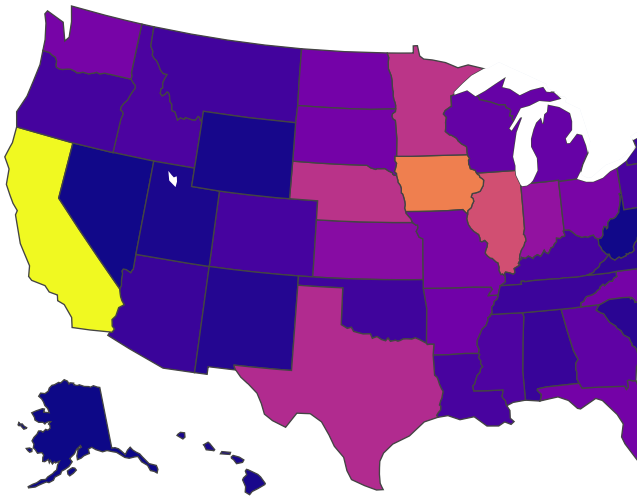
here we are simply running the df_m.column to see wht it will print out.

```
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()
```



we import plotly express as px and pandas as pd. Plotly express allows us to create graphical images with the data we feed it. Fig = px.chloropleth is the image that is produced above once we fill in the rest of the required information. df_demo is pulling from csv file that includes the various agricultural exports by each state and the amount.

```
df_demo
```

	code	state	category	total exports	beef	pork	poultry	dairy	fruits fresh	fruits proc	total fruits	veggies fresh	veggies proc	total veggies	corn	whea
0	AL	Alabama	state	1390.63	34.4	10.6	481.0	4.06	8.0	17.1	25.11	5.5	8.9	14.33	34.9	70
1	AK	Alaska	state	13.31	0.2	0.1	0.0	0.19	0.0	0.0	0.00	0.6	1.0	1.56	0.0	0
2	AZ	Arizona	state	1463.17	71.3	17.9	0.0	105.48	19.3	41.0	60.27	147.5	239.4	386.91	7.3	48
3	AR	Arkansas	state	3586.02	53.2	29.4	562.9	3.53	2.2	4.7	6.88	4.4	7.1	11.45	69.5	114
4	CA	California	state	16472.88	228.7	11.1	225.4	929.95	2791.8	5944.6	8736.40	803.2	1303.5	2106.79	34.6	249
5	CO	Colorado	state	1851.33	261.4	66.0	14.0	71.94	5.7	12.2	17.99	45.1	73.2	118.27	183.2	400
6	CT	Connecticut	state	259.62	1.1	0.1	6.9	9.49	4.2	8.9	13.10	4.3	6.9	11.16	0.0	0
7	DE	Delaware	state	282.19	0.4	0.6	114.7	2.30	0.5	1.0	1.53	7.6	12.4	20.03	26.9	22
8	FL	Florida	state	3764.09	42.6	0.9	56.9	66.31	438.2	933.1	1371.36	171.9	279.0	450.86	3.5	1
9	GA	Georgia	state	2860.84	31.0	18.9	630.4	38.38	74.6	158.9	233.51	59.0	95.8	154.77	57.8	65
10	HI	Hawaii	state	401.84	4.0	0.7	1.3	1.16	17.7	37.8	55.51	9.5	15.4	24.83	0.0	0
11	ID	Idaho	state	2078.89	119.8	0.0	2.4	294.60	6.9	14.7	21.64	121.7	197.5	319.19	24.0	568
12	IL	Illinois	state	8709.48	53.7	394.0	14.0	45.82	4.0	8.5	12.53	15.2	24.7	39.95	2228.5	223
13	IN	Indiana	state	5050.23	21.9	341.9	165.6	89.70	4.1	8.8	12.98	14.4	23.4	37.89	1123.2	114
14	IA	Iowa	state	11273.76	289.8	1895.6	155.6	107.00	1.0	2.2	3.24	2.7	4.4	7.10	2529.8	3
15	KS	Kansas	state	4589.01	659.3	179.4	6.4	65.45	1.0	2.1	3.11	3.6	5.8	9.32	457.3	1426
16	KY	Kentucky	state	1889.15	54.8	34.2	151.3	28.27	2.1	4.5	6.60	0.0	0.0	0.00	179.1	149
17	LA	Louisiana	state	1914.23	19.8	0.8	77.2	6.02	5.7	12.1	17.83	6.6	10.7	17.25	91.4	78
18	ME	Maine	state	278.37	1.4	0.5	10.4	16.18	16.6	35.4	52.01	24.0	38.9	62.90	0.0	0
19	MD	Maryland	state	692.75	5.6	3.1	127.0	24.81	4.1	8.8	12.90	7.8	12.6	20.43	54.1	55
20	MA	Massachusetts	state	248.65	0.6	0.5	0.6	5.81	25.8	55.0	80.83	8.1	13.1	21.13	0.0	0
21	MI	Michigan	state	3164.16	37.7	118.1	32.6	214.82	82.3	175.3	257.69	72.4	117.5	189.96	381.5	247
22	MN	Minnesota	state	7192.33	112.3	740.4	189.2	218.05	2.5	5.4	7.91	45.9	74.5	120.37	1264.3	538
23	MS	Mississippi	state	2170.80	12.8	30.4	370.8	5.45	5.4	11.6	17.04	10.6	17.2	27.87	110.0	102
24	MO	Missouri	state	3933.42	137.2	277.3	196.1	34.26	4.2	9.0	13.18	6.8	11.1	17.90	428.8	161
25	MT	Montana	state	1718.00	105.0	16.7	1.7	6.82	1.1	2.2	3.30	17.3	28.0	45.27	5.4	1198
26	NE	Nebraska	state	7114.13	762.2	262.5	31.4	30.07	0.7	1.5	2.16	20.4	33.1	53.50	1735.9	292
27	NV	Nevada	state	139.89	21.8	0.2	0.0	16.57	0.4	0.8	1.19	10.6	17.3	27.93	0.0	5
28	NH	New Hampshire	state	73.06	0.6	0.2	0.8	7.46	2.6	5.4	7.98	1.7	2.8	4.50	0.0	0
29	NJ	New Jersey	state	500.40	0.8	0.4	4.6	3.37	35.0	74.5	109.45	21.6	35.0	56.54	10.1	6
30	NM	New Mexico	state	751.58	117.2	0.1	0.3	191.01	32.6	69.3	101.90	16.7	27.1	43.88	11.2	13
31	NY	New York	state	1488.90	22.2	5.8	17.7	331.80	64.7	137.8	202.56	54.7	88.7	143.37	106.1	29
32	NC	North Carolina	state	3806.05	24.8	702.8	598.4	24.90	23.8	50.7	74.47	57.4	93.1	150.45	92.2	200
33	ND	North Dakota	state	3761.96	78.5	16.1	0.5	8.14	0.1	0.2	0.25	49.9	80.9	130.79	236.1	1664
34	OH	Ohio	state	3979.79	36.2	199.1	129.9	134.57	8.7	18.5	27.21	20.4	33.1	53.53	535.1	207
35	OK	Oklahoma	state	1646.41	337.6	265.3	131.1	24.35	3.0	6.3	9.24	3.4	5.5	8.90	27.5	324
36	OR	Oregon	state	1794.57	58.8	1.4	14.2	63.66	100.7	214.4	315.04	48.2	78.3	126.50	11.7	320
37	PA	Pennsylvania	state	1969.87	50.9	91.3	169.8	280.87	28.6	60.9	89.48	14.6	23.7	38.26	112.1	41
38	RI	Rhode Island	state	31.59	0.1	0.1	0.2	0.52	0.9	1.9	2.83	1.2	1.9	3.02	0.0	0
39	SC	South Carolina	state	929.93	15.2	10.9	186.5	7.62	17.1	36.4	53.45	16.3	26.4	42.66	32.1	55
40	SD	South Dakota	state	3770.19	193.5	160.2	29.3	46.77	0.3	0.5	0.80	1.5	2.5	4.06	643.6	704
41	TN	Tennessee	state	1535.13	51.1	17.6	82.4	21.18	2.0	4.2	6.23	9.4	15.3	24.67	88.8	100
42	UT	Utah	state	453.30	27.9	50.9	23.1	48.60	3.9	8.4	12.24	2.5	4.1	6.60	5.3	42

we run df_demo to show what each of the 50 states are exporting, in what quantities, and by what type of export.

```
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')
```

	code	state	category	total exports	beef	pork	poultry	dairy	fruits fresh	fruits proc	total fruits	veggies fresh	veggies proc	total veggies	corn	wheat	cotton
48	WI	Wisconsin	state	3090.23	107.3	38.6	34.5	633.60	42.8	91.0	133.80	56.8	92.2	148.99	460.5	96

here we are checking what are being listed at the top of the columns.

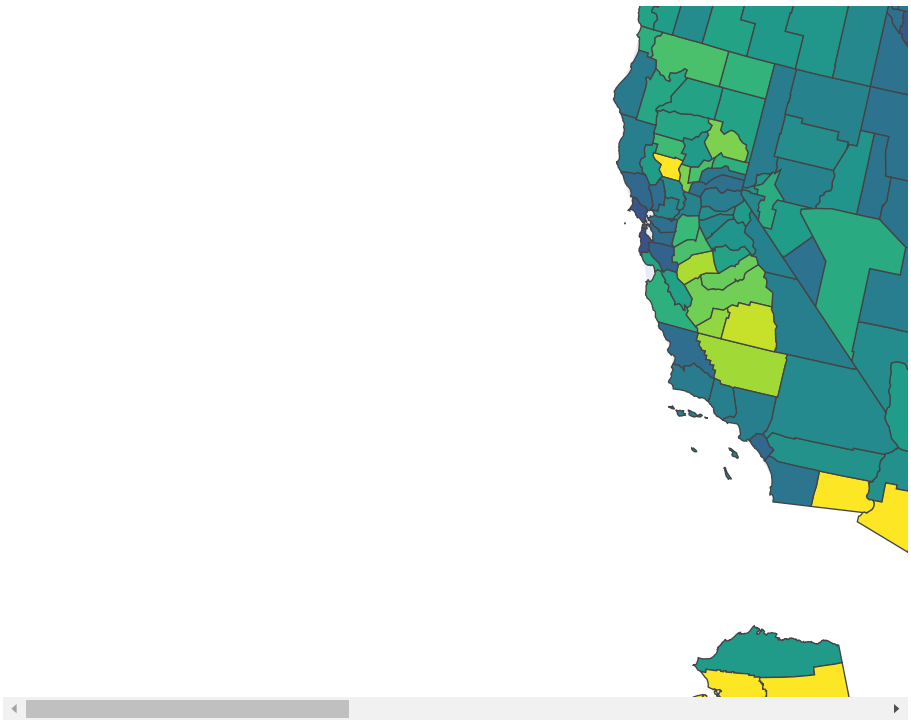
map demo #2: state of AL

```
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()
```



we create another chloropleth, this time showing all the counties in the United States.

we import urlopen to allow us to read json files. we import pandas again to allow us to read our csv file. we import plotly express to allow us to create the figure above of the United States, but this time with counties. we defined our data frame as df_us

```
df_us.columns
```

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

We check to see what are the name of the objects we are working with.

```
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

This then createss a display of data that shows us the fips and percent of unemployed people in each countie.

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

```
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
```

we want now relate each of the counties in Alabama to a FIPS code.

```
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')
```

we again run df_m.column to recall the data frame we had started earlier.

```
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

this displays the data frame df_m now with the quartiles of each store and the zip code that that city is located.

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

```
25
```

we ask how many rows are present in the csv with df_m.shape[] and with the 0, it will only count the first column

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

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

```
25
50
```

we want to know how many counties are in the data frame.

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

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

df_m: all display data, per store

we are asking the data frame to display the county name and the FIPS code for that county.

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

```
25
```

fips codes per county

this is the number of FIPS codes per county in Alabama.

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

```
25
```

this is the number of counties in Alabama.

```
df_counties.columns
```

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

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

```
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	40	41	25qt	50qt	75qt	zip	County	FIPS Code
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	1756	7598	1509	1861	28.6	55.8	77.3	35201	Autauga	01001
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	4449	5727	2315	8822	21.4	55.8	70.5	36101	Baldwin	01003
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	9296	2815	4886	7458	38.1	60.5	79.5	36601	Barbour	01005
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	9982	3338	9116	3875	26.2	51.2	77.3	35801	Bibb	01007
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	4469	2513	8135	6963	21.4	60.5	79.5	35401	Blount	01009

merged_df is merging df_m and df_counties dataframes into one cohesive data frame that now displays the city, the sales per display, the quartile, the county and FIPS code.

use the merged_df as data source for the choropleth

```
merged_df.columns
```

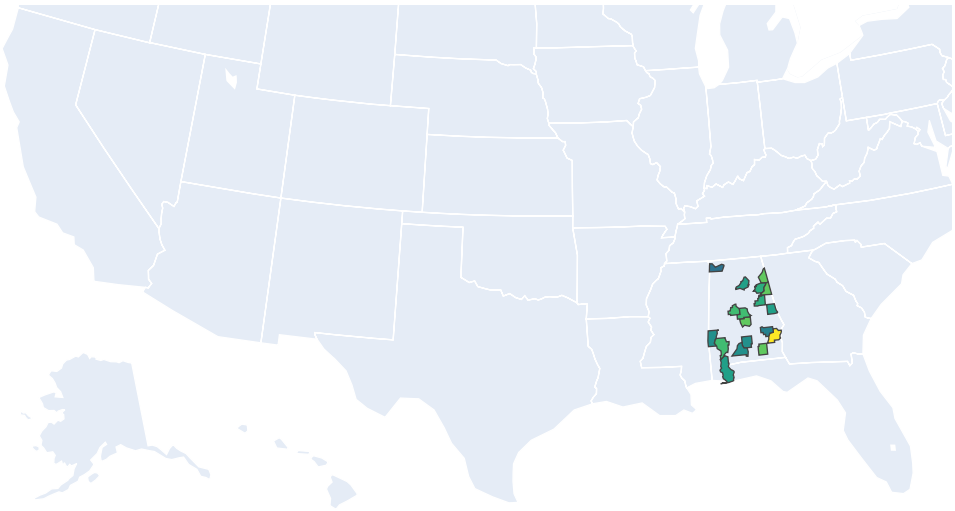
```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41', '25qt', '50qt', '75qt',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

we are checking to see what will be displayed at the top row of the csv file.

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

```
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()
```



we again import plotly express to help us generate the image above and then begin giving it data from our data frames.

```
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()
```