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

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 50.3 MB/s eta 0:00:00
Installing collected packages: plotly-geo
Successfully installed plotly-geo-1.0.0
```

Installs a tool "poltly-geo"

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

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

These two are both java librarys. Pandas is a java data library tool structures for storing and manipulating large datasets. It is widely used in data science, machine learning, and finance applications. NumPy is a fundamental java library tool for scientific computing, typically used alongside Pandas.

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

The above are links to professor Stefan Bund's GitHub data sets (used previously for Excel)

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

The above code reads a CSV file from a URL, then creates DataFrame object named df_m using pandas.

The pd.read_csv() function is reads data from the given CSV file into a DataFrame. it converts it into columns and provides a number of options for handling missing data, specifying column names, and more, much like Excel.

```
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
14	Phenix City	8788	8269	6838	2863	6753	6608	4048	8774	4513		5704	8720	3386	1295	3520	7654	6845	7738	3828	1202

Similarly to the previous code, df_m takes the data from the CSV and converts it into table; but this is the more display output aspect of the computation, whereas the previous code was in the input.

```
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')
```

The above code returns specifically the columns aspect from the CSV. Rather than reading and outputting everything, it shows based on the [columns] parameter.

list all cities in the matrix 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
```

Similarly to the previous code, rather than taking the data from the CSV and outputting the [columns] parameter, we are using a parameter with a search-like funciton with [City] as the following for the keyword of the search.

investigate quartile as an analytic tool

```
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
```

Displays the data type of each column for the output specified.

Quantiles for each display, all stores

```
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

Calculates the quartiles of the given data columns.

per store, the quartile values

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

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

Converts the data so that the rows become columns and the columns become rows.

```
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

Calculates the mean of each quartile of the dataset.

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

```
3535.24
```

Calculates the mean of all of the first quartile of the dataset.

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

```
5826.36
```

Calculates the mean of the second quartile of the dataset.

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

```
7953.0
```

Calculates the mean of the third quartile of the dataset.

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

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

Calculates the mean of each column under the 'kk' object.

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

```
# 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
```

Calculates the percentage of the values in *each* row of the df_m dataframe less than or equal to the first quartile.

```
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)
```

```
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
8     70.5
9     75.0
10    63.6
11    68.2
12    70.5
13    75.0
14    75.0
15    84.1
16    70.5
17    72.7
18    72.7
19    68.2
20    75.0
21    72.7
22    75.0
```

df_m.iloc[:, 1:] selects all columns of the DataFrame except the first index column. kk[0.25] (first quartile), kk[0.50] (second quartile), and kk[0.75] (third quartile) selects the values less than or equal to the quartiles. sum(axis=1) sums the number of True values in each row, which then the result is divided by the total number of columns using (df_m.shape[1]). round() rounds the percentages to the first decimal place, then the results are stored in new columns 25qt, 50qt, and 75qt.

```
# df_m
```

Commented out command that once again displays the data set from the CSV.

```
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

end_set lists the column names df_m[end_set] is selects only the columns from [end].

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]
```

The first data command with the parameters listed within the colons creates a sample data set. pd.DataFrames creates another parameter to specify by called zip codes.

experiment with chloropleths

```
df_m.columns
```

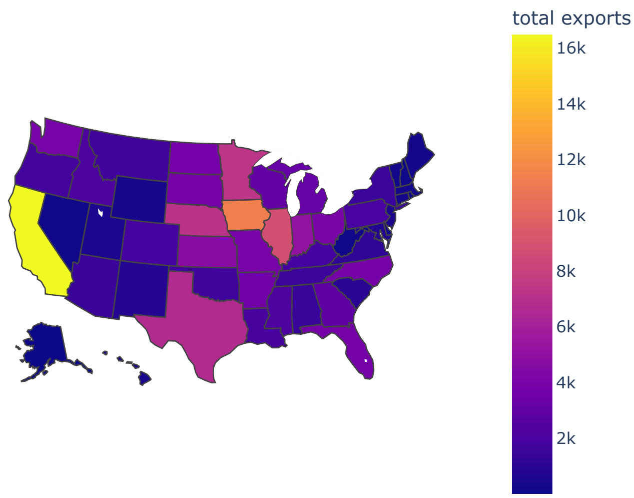
```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41', '25qt', '50qt', '75qt',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

```
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()
```




```
df_demo
```

	code	state	category	total exports	beef	pork	poultry	dairy	fruits fresh	fruits proc	total fruits	veggies fresh	veggies proc	total veggies	corn	wh
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	
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	
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	
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	1
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	2
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	4
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	
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	
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	
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	
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	
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	5
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	2
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	1
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	
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	14
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	1
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	
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	
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	
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	
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	2
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	5
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	1
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	1
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	11
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	2
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	
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	
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	
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	
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	
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	2
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	16
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	2
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	3
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	3
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	

Creates, loads, and outputs the data into map format followed by the data as an outputted table.

```
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')
```

Creates a new index using specified parameters, similarly to creating parameters for finding specified data from the CSV earlier.

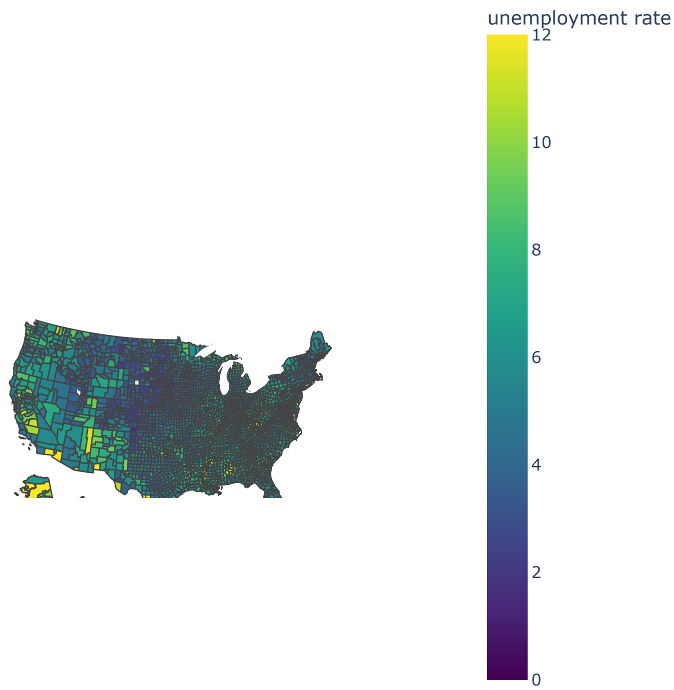
map demo #2: state of AL

```
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()
```



Creates a new map output, this time using new commands to import from another data source. it imports json, a data interchanging formatter to make the data easier to read, then uses the link listed above as a response to be its input. after importing pandas again, it reads a ne data set, then imports a new tool called "plotly.express". Fig is a method unique to the choropoleth function and adjusts the output for the map.

```
df_us.columns
```

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

creates an output of more columns from the df_us dataset.

```
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

Another command to output a table from the CSV.

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

3219 rows × 2 columns

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
```

Creates a county list using a FIPS code for each set county.

```
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')
```

Creates another index for outputting a table specified by the city as each column.

```
df_m
```

	City	1	2	3	4	5	6	7	8	9	...	36	37	38	39	40	41	25qt	50qt	75qt	zip
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	3555	1341	1756	7598	1509	1861	28.6	55.8	77.3	35201
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	2805	4601	4449	5727	2315	8822	21.4	55.8	70.5	36101
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	9807	2652	9296	2815	4886	7458	38.1	60.5	79.5	36601
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	7935	2605	9982	3338	9116	3875	26.2	51.2	77.3	35801
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	3657	2158	4469	2513	8135	6963	21.4	60.5	79.5	35401
5	Hoover	9741	7377	9410	9790	8864	2522	5347	9145	8402	...	9748	7224	4628	8107	6143	1671	16.7	34.9	59.1	35216
6	Dothan	7646	2060	4911	4976	7851	4277	7423	6183	6641	...	5650	4400	7842	4006	9335	3571	19.0	55.8	90.9	36301
7	Auburn	4326	2659	6928	4656	1828	5199	5331	6294	3076	...	4387	6890	2833	5083	9707	2116	23.8	51.2	79.5	36830
8	Decatur	3786	2891	8124	2469	3704	3623	2409	8287	2032	...	9305	6509	6848	5408	3707	8744	21.4	46.5	70.5	35601
9	Madison	1934	3628	9190	3275	9344	5778	1256	3523	1781	...	1746	4470	7054	6573	3556	1374	28.6	48.8	75.0	35756
10	Florence	8017	3187	1128	4706	9962	7547	4440	4530	9569	...	5929	1123	7306	8746	4000	6943	26.2	48.8	63.6	35630
11	Gadsden	2290	6402	8598	7547	5158	9731	8038	4435	7357	...	2549	5175	5997	9608	7230	9731	19.0	41.9	68.2	35901
12	Vestavia Hills	9471	9142	4419	3846	2016	5069	4853	6336	9062	...	5142	9619	9601	8099	1391	6276	26.2	53.5	70.5	35216
13	Prattville	6039	8003	6180	4610	3548	7115	6720	8512	9954	...	1591	4401	3457	4245	4341	2573	23.8	44.2	75.0	36066
14	Phenix City	8788	8269	6838	2863	6753	6608	4048	8774	4513	...	3520	7654	6845	7738	3828	1202	28.6	48.8	75.0	36867
15	Alabaster	1733	9767	3274	7125	7437	5748	5399	6513	3038	...	2479	9673	7478	7207	7006	3523	28.6	41.9	84.1	35007
16	Bessemer	6559	2453	1578	5158	3058	8075	7066	8530	8346	...	4810	7641	5365	3545	6812	9483	14.3	46.5	70.5	35020
17	Enterprise	8436	7800	7234	5063	4274	1948	7887	6647	1320	...	3461	2640	4375	8634	4917	2830	19.0	41.9	72.7	36330
18	Opelika	9998	8953	7923	6176	4369	9503	2126	1816	9224	...	5191	9304	2720	3100	3912	1548	28.6	55.8	72.7	36801
19	Homewood	2373	7188	9880	9236	5969	9998	8703	8440	4643	...	8787	5459	8389	5242	2224	6025	19.0	41.9	68.2	35209
20	Northport	3536	9231	8651	6374	4842	5704	8484	6322	2012	...	6947	5401	6681	9018	1668	8307	28.6	53.5	75.0	35473
21	Pelham	6830	3736	2734	6443	8494	6206	7290	8518	6176	...	2777	4045	7309	4745	4284	2640	23.8	51.2	72.7	35124
22	Trussville	2794	8273	9174	2850	8351	3978	5995	4632	7693	...	1650	9470	6356	4700	3344	8743	33.3	48.8	75.0	35173

The output for the previous code.

24	Fairhope	8114	1464	2811	3090	4686	7995	7676	1304	7332	...	3457	4808	7227	5482	6355	4553	33.3	67.4	86.4	36532

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

```
25
```

Returns the number of rows for the previous command; there are 25 rows as seen on the bottom of the previous output, as why there is an output of 25.

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
```

"Prints" or shows an output of the number of rows followed by the number of FIPS codes.

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

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

Prints the number of county columns in the data set.

df_m: all display data, per store

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

```
25
```

Prints the number of columns once again, but this time using the parameter [shape].

fips codes per county

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

```
25
```

Prints the number of columns once again, using [shape] again as well, but specified to the counties in the data set.

```
df_counties.columns
```

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

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

Creates a parameter which associates the FIPS codes with the sales results into columns.

```
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 Co
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	1756	7598	1509	1861	28.6	55.8	77.3	35201	Autauga	01(
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	4449	5727	2315	8822	21.4	55.8	70.5	36101	Baldwin	01(
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	9296	2815	4886	7458	38.1	60.5	79.5	36601	Barbour	01(
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	9982	3338	9116	3875	26.2	51.2	77.3	35801	Bibb	01(
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	4469	2513	8135	6963	21.4	60.5	79.5	35401	Blount	01(

5 rows × 48 columns

merged_df.head() method displays the first few rows. merged_df.describe() method summarizes each column.

use the merged_df as data source for the choropleth

```
merged_df.columns
```

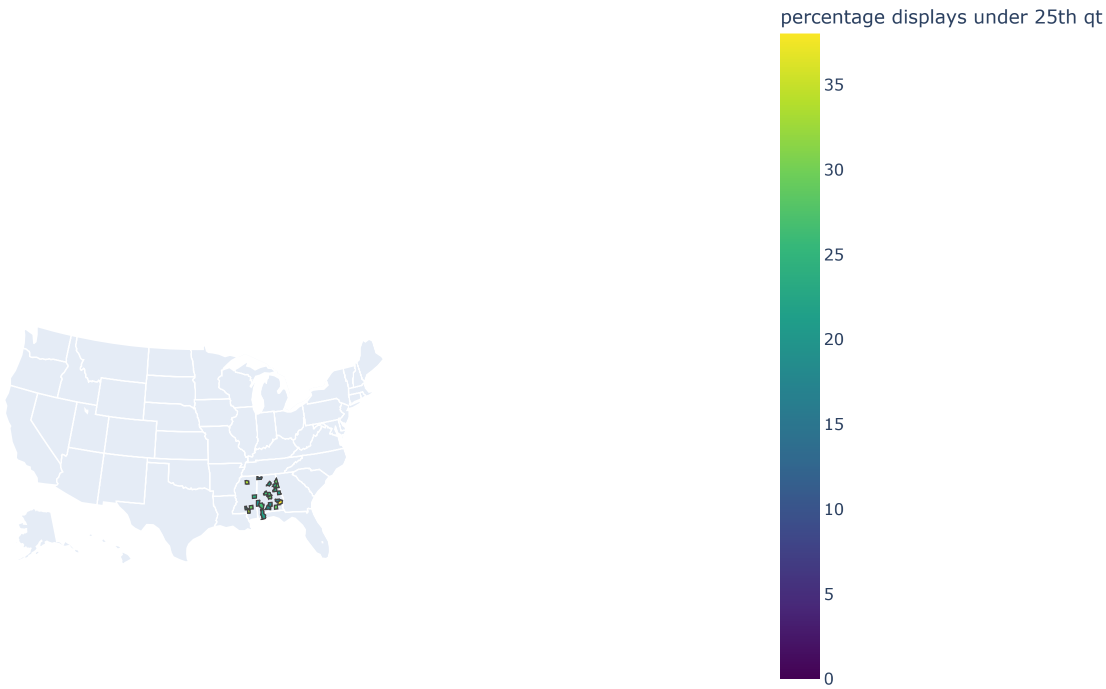
```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41', '25qt', '50qt', '75qt',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

Creates an index of the data sorted by the city.

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()
```



Imports plotly.express as a tool for outputting a map. fig changes the parameters for the output display of the map.

```
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()
```

Creates another map output. json to format the data, reimporting panda, then uses the geojson for data input on the Alabama counties data. After importing, it filters by county, then loads sample data and then finally creates the choropleth map output.