written material

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

we are grabbing the data from the above url to understand the information better and answer questions. This url is given from going to github and going to the raw data page.

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
```

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

These lines are used to bring in the functionality of pandas and NumPy, which are two fundamental libraries for working with structured data in Python.

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

These lines bring in the information given by thr professor on github so we can acess the data tables and get a better look into the information provided. For example we could pull numbers from the top selling stores or the lowest selling stores.

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

This code reads the CSV file located at the specified URL and returns a DataFrame containing the data from that file. the line of code assigns the resulting DataFrame to the variable df_m. You can then use the df_m variable to perform various operations and analyses on the data stored in the DataFrame. DataFrame will represent that table, and you can use pandas methods to explore and manipulate the data, such as filtering rows, selecting columns, calculating statistics, and more.

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

This variable is used to perform various operations and analyses on the data stored in the DataFrame.

```
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	3(
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	4424	8813	6(
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	5430	1601	9
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	9169	7829	6
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	1556	5533	1
5	Hoover	9741	7377	9410	9790	8864	2522	5347	9145	8402	...	6031	7673	8
6	Dothan	7646	2060	4911	4976	7851	4277	7423	6183	6641	...	8253	1565	6(
7	Auburn	4326	2659	6928	4656	1828	5199	5331	6294	3076	...	6128	3737	7
8	Decatur	3786	2891	8124	2469	3704	3623	2409	8287	2032	...	6622	9742	9
9	Madison	1934	3628	9190	3275	9344	5778	1256	3523	1781	...	6619	6128	5
10	Florence	8017	3187	1128	4706	9962	7547	4440	4530	9569	...	8306	1392	1
11	Gadsden	2290	6402	8598	7547	5158	9731	8038	4435	7357	...	4488	3591	1(
12	Vestavia Hills	9471	9142	4419	3846	2016	5069	4853	6336	9062	...	4613	2942	7
13	Prattville	6039	8003	6180	4610	3548	7115	6720	8512	9954	...	8225	7278	7
14	Phenix City	8788	8269	6838	2863	6753	6608	4048	8774	4513	...	5704	8720	3
15	Alabaster	1733	9767	3274	7125	7437	5748	5399	6513	3038	...	7351	9503	1(
16	Bessemer	6559	2453	1578	5158	3058	8075	7066	8530	8346	...	8921	3517	4
17	Enterprise	8436	7800	7234	5063	4274	1948	7887	6647	1320	...	4840	6309	7

The code will show the list of column names and then go through each column name, allowing you to perform specific operations or analyses on each column of the DataFrame.

```
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')
```

This code 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
```

investigate quartile as an analytic tool

This code retrieves the data types of each column in the DataFrame df_m. The result is a pandas Series where the index corresponds to the column names, and the values corresponds to the data types of the respective columns.

```
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

method in pandas to calculate specific quantiles for the numeric columns in a DataFrame. [0.25, 0.5, 0.75]: This specifies the quantiles to calculate. In this case, it calculates the 25th (Q1), 50th (Q2 or median), and 75th (Q3) percentiles. numeric_only=True: This parameter ensures that only numeric columns are considered. If a DataFrame has both numeric and non-numeric columns, this parameter filters out non-numeric columns from the calculation. axis=1: This parameter specifies that the quantiles should be calculated along columns. The result, df_3, is a DataFrame containing the calculated quantiles for each numeric column.

```
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	...	
0.25	3082.0	3633.0	2236.0	3473.0	3657.0	4628.0	4254.0	3588.0	3704.0	3451.0	...	344
0.50	5343.0	5431.0	5311.0	5771.0	5131.0	7588.0	5156.0	5331.0	6589.0	5875.0	...	647
0.75	7242.0	8074.0	7508.0	7935.0	7490.0	9145.0	6840.0	7606.0	8221.0	7783.0	...	743

3 rows × 25 columns

per store, the quartile values

df_3.T: Transposes the DataFrame. .columns: Gets the column names of the transposed DataFrame. l = ...: Assigns the column names to the variable l

After executing this code, the variable l will contain the column names of the original DataFrame df_3 (before transposition). These column names are extracted after calculating quantiles and transposing the DataFrame.

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

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

df_3.T: This part transposes the DataFrame df_3. Transposing swaps the rows and columns of the DataFrame.

.mean(): This part is a pandas method that calculates the mean along a specified axis.

The result is a pandas Series where each element corresponds to the mean value of the corresponding column in the original DataFrame df_3 (before transposition). Each element in the Series is associated with a column name.

```
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

df_3.T: This part transposes the DataFrame df_3. Transposing swaps the rows and columns of the DataFrame.

[0.25]: This part selects the row corresponding to the 50th percentile (median) from the transposed DataFrame.

.mean(): This part calculates the mean of the values in the selected row. Since this is a pandas Series (a single row in this case), it calculates the mean of the values in that row

the boundry is from zero to .25q

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

```
3535.24
```

df_3.T: This part transposes the DataFrame df_3. Transposing swaps the rows and columns of the DataFrame.

[0.50]: This part selects the row corresponding to the 50th percentile (median) from the transposed DataFrame.

.mean(): This part calculates the mean of the values in the selected row. Since this is a pandas Series (a single row in this case), it calculates the mean of the values in that row

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

```
5826.36
```

df_3.T: This part transposes the DataFrame df_3. Transposing swaps the rows and columns of the DataFrame.

[0.75]: This part selects the row corresponding to the 50th percentile (median) from the transposed DataFrame.

.mean(): This part calculates the mean of the values in the selected row. Since this is a pandas Series (a single row in this case), it calculates the mean of the values in that row

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

```
7953.0
```

df_3.T: This part transposes the DataFrame df_3. Transposing swaps the rows and columns of the DataFrame.

.mean(): This part is a pandas method that calculates the mean along the default axis (axis=0), which means it calculates the mean for each column.

kk = ...: This part assigns the resulting pandas Series (containing mean values for each column) to the variable kk.

kk: This line by itself is likely used to display the contents of the kk variable.

After executing this code, the variable kk will contain a pandas Series with mean values for each column in the original DataFrame df_3 (before transposition). Each element in the Series is associated with a column name, representing the average value across the specified quantiles.

```
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

```
# 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
```

```
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
```

```
# df_m
```

end_set: This is a list of column names specified as ['City', '25qt', '50qt', '75qt']. These column names seem to represent different aspects of the data, such as a city name and the 25th, 50th, and 75th quantiles.

df_m[end_set]: This part of the code uses the list of column names (end_set) to select and create a new DataFrame containing only the columns specified in the list. It subsets the original DataFrame df_m based on the specified column names.

So, after executing this code, end_set will be a new DataFrame containing only the columns 'City', '25qt', '50qt', and '75qt' from the original DataFrame df_m. It's a way to focus on a specific subset of columns for further analysis or visualization.

```
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

create a choropleth for each store

8	Decatur	21.4	46.5	70.5

```
#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

```
df_m.columns
```

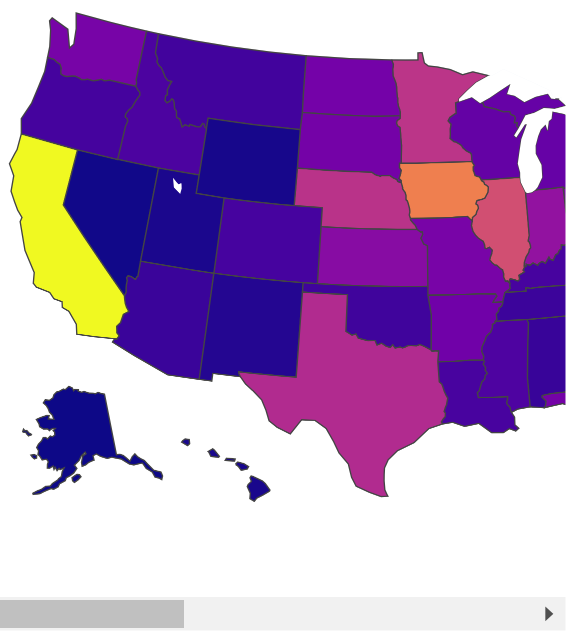
```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41', '25qt', '50qt', '75qt', '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
0	AL	Alabama	state	1390.63	34.4	10.6	481.0	4.06	8.0
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
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
5	CO	Colorado	state	1851.33	261.4	66.0	14.0	71.94	5.7
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
9	GA	Georgia	state	2860.84	31.0	18.9	630.4	38.38	74.6
10	HI	Hawaii	state	401.84	4.0	0.7	1.3	1.16	17.7
11	ID	Idaho	state	2078.89	119.8	0.0	2.4	294.60	6.9
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
18	ME	Maine	state	278.37	1.4	0.5	10.4	16.18	16.6
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
21	MI	Michigan	state	3164.16	37.7	118.1	32.6	214.82	82.3
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
24	MO	Missouri	state	3933.42	137.2	277.3	196.1	34.26	4.2

```
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')
```

Hampshire

map demo #2: state of AL

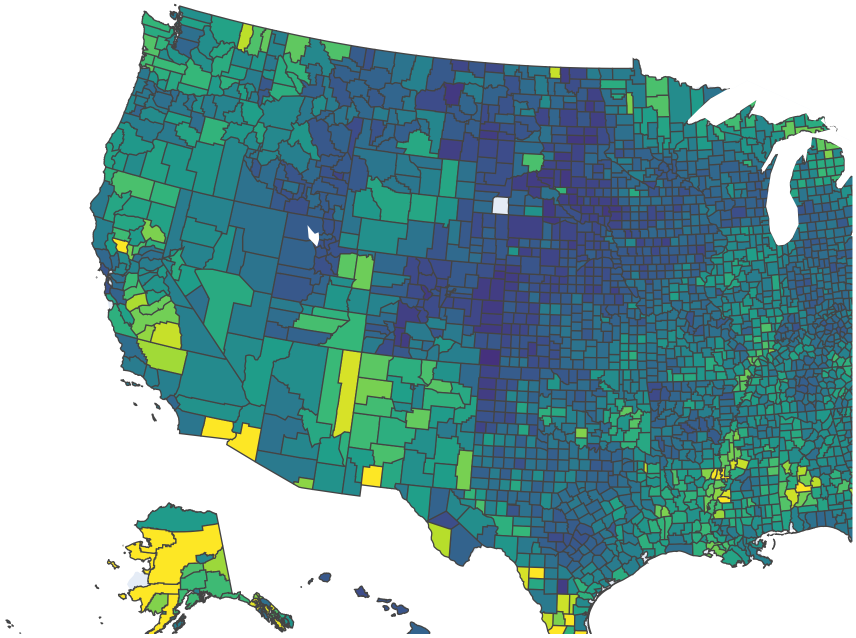
30	NM	New Mexico	state	751.58	117.2	0.1	0.3	191.01	32.6

```
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()
```



```
df_us.columns
```

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

```
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

```
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
```

```
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')
```

```
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

df_m: This is assumed to be a pandas DataFrame, and the variable name is df_m.

.shape: This is an attribute of a DataFrame that returns a tuple representing the dimensions of the DataFrame. The first element of the tuple is the number of rows, and the second element is the number of columns.

[0]: Indexing is used to access the first element of the tuple, which corresponds to the number of rows.

So, df_m.shape[0] specifically retrieves the number of rows in the DataFrame df_m. If you use this code, it will return an integer representing the total number of rows in the DataFrame.

Vestavia

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

```
25
```

14	Phenix City	8788	8269	6838	2863	6753	6608	4048	8774	4513	...	3520	7654	68

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

len(al_fips): Prints the length (number of elements) of the iterable al_fips. df_counties = pd.DataFrame(al_fips): Creates a DataFrame using the elements in al_fips. df_counties.size: Returns the total number of elements in the DataFrame. The printed length and the size of the DataFrame can be useful for understanding the size and structure of the data in al_fips. If al_fips is a list of FIPS codes or some other data, len(al_fips) gives you the count of elements, and df_counties.size gives you the total count of elements in the DataFrame.

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

```
25
50
```

df_counties: This is assumed to be a pandas DataFrame, and the variable name is df_counties.

.columns: This is an attribute of a DataFrame that returns an Index object containing the column names of the DataFrame.

print(df_counties.columns): This line prints the column names of the DataFrame df_counties to the console.

So, if you have executed this code, it would display the names of the columns in the DataFrame df_counties. The printed result will be the Index object containing the column names.

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

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

df_m: all display data, per store

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

```
25
```

fips codes per county

df_m: This is assumed to be a pandas DataFrame, and the variable name is df_m.

.shape: This is an attribute of a DataFrame that returns a tuple representing the dimensions of the DataFrame. The first element of the tuple is the number of rows, and the second element is the number of columns.

[0]: Indexing is used to access the first element of the tuple, which corresponds to the number of rows.

So, df_m.shape[0] specifically retrieves the number of rows in the DataFrame df_m. If you use this code, it will return an integer representing the total number of rows in the DataFrame.

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

```
25
```

df_counties: This is assumed to be a pandas DataFrame, and the variable name is df_counties.

.columns: This is an attribute of a DataFrame that returns an Index object containing the column names of the DataFrame.

So, df_counties.columns specifically retrieves the column names of the DataFrame df_counties. The result will be an Index object containing the names of all the columns in the DataFrame. If you print or otherwise inspect this, you'll see a list of column names.

```
df_counties.columns
```

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

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

pd.concat([df_m, df_counties], axis=1): The pd.concat function concatenates DataFrames along a specified axis. In this case, axis=1 indicates concatenation along columns (horizontally). The function takes a list of DataFrames ([df_m, df_counties]) to concatenate. The result is a new DataFrame (merged_df) containing columns from both df_m and df_counties.

merged_df.head(): This line displays the first few rows of the newly created DataFrame merged_df using the head() method. This is a common practice to quickly inspect the combined DataFrame.

So, the overall purpose of the code is to horizontally concatenate the columns of df_m and df_counties and store the result in a new DataFrame merged_df. This could be useful when you want to combine information from different DataFrames that share a common index or column values.

```
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

use the merged_df as data source for the choropleth

merged_df: This is assumed to be a pandas DataFrame, and the variable name is merged_df. This DataFrame is created by concatenating two DataFrames, df_m and df_counties, horizontally along their columns.

.columns: This is an attribute of a DataFrame that returns an Index object containing the column names of the DataFrame.

So, merged_df.columns specifically retrieves the column names of the DataFrame merged_df. The result will be an Index object containing the names of all the columns in the merged DataFrame. If you print or otherwise inspect this, you'll see a list of column names that includes columns from both df_m and df_counties.

```
merged_df.columns
```

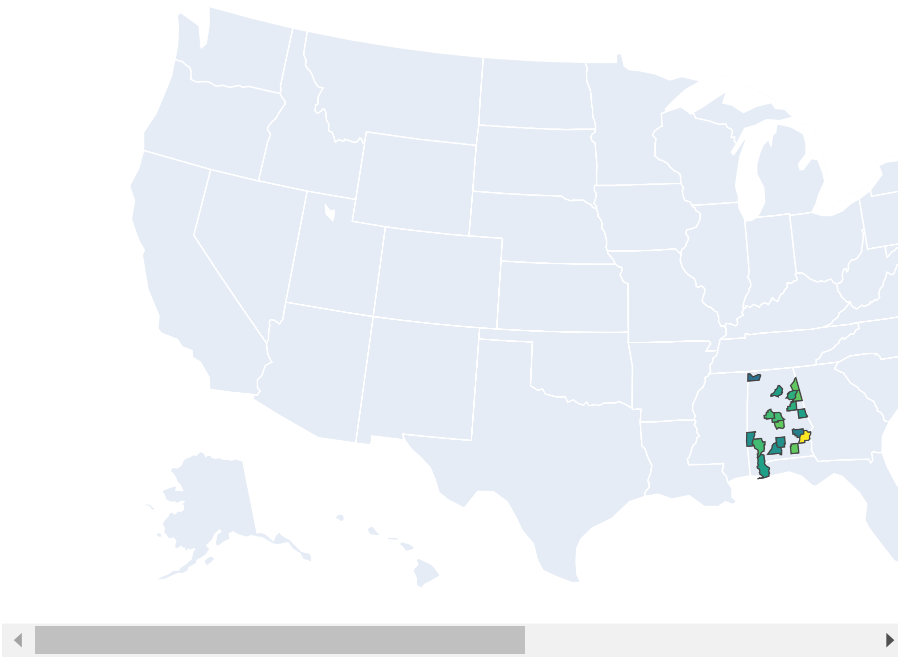
```
Index(['City', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12',
       '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23', '24',
       '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '35', '36',
       '37', '38', '39', '40', '41', '25qt', '50qt', '75qt',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

the code uses Plotly Express to create an interactive choropleth map visualizing data from the DataFrame merged_df. The map displays color-coded regions (counties) based on the values in the '25qt' column, and additional information is provided in the hover tooltip. The layout is adjusted to remove margins around the plot.

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()
```



```
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()
```