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
```

双击（或按回车键）即可修改

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

Using an alias is a common practice to simplify code, making it shorter and more readable. 'pandas' (aliased as pd) is used for structured data handling, while 'numpy' (aliased as np) supports numerical computations.

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

Defines two URLs and points to CSV files and can be used to retrieve data for further processing or analysis in a the environment.

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

Use the 'pandas' library to read the CSV file from the URL and create a DataFrame named df_m. The DataFrame is a tabular data structure commonly used in data analysis with pandas.

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

Read and display a DataFrame (df_m). The data shows numeric values associated with different cities.

```
df_m
```

	City	1	2	3	4	5	6	7	8	9	...	32	33	34	35	36	37	38	39	40	4
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	1340	6923	3082	5617	3555	1341	1756	7598	1509	186
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	4424	8813	6655	3986	2805	4601	4449	5727	2315	882
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	5430	1601	9145	1493	9807	2652	9296	2815	4886	745
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	9169	7829	6879	4166	7935	2605	9982	3338	9116	387
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	1556	5533	1884	2088	3657	2158	4469	2513	8135	696
5	Hoover	9741	7377	9410	9790	8864	2522	5347	9145	8402	...	6031	7673	8403	7588	9748	7224	4628	8107	6143	167
6	Dothan	7646	2060	4911	4976	7851	4277	7423	6183	6641	...	8253	1565	6052	5802	5650	4400	7842	4006	9335	357
7	Auburn	4326	2659	6928	4656	1828	5199	5331	6294	3076	...	6128	3737	7785	3281	4387	6890	2833	5083	9707	211
8	Decatur	3786	2891	8124	2469	3704	3623	2409	8287	2032	...	6622	9742	9382	8413	9305	6509	6848	5408	3707	874
9	Madison	1934	3628	9190	3275	9344	5778	1256	3523	1781	...	6619	6128	5325	9976	1746	4470	7054	6573	3556	137
10	Florence	8017	3187	1128	4706	9962	7547	4440	4530	9569	...	8306	1392	1363	5545	5929	1123	7306	8746	4000	694

Retrieves the column labels of the DataFrame df_m, indicating the dimensionality of the matrix.

12 Vestavia Hills 9471 9142 4419 3846 2016 5069 4853 6336 9062 ... 4613 2942 7408 9484 5142 9619 9601 8099 1391 627

```
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')
```

17 Enterprise 8436 7800 7234 5063 4274 1948 7887 6647 1320 ... 4840 6309 7334 9880 3461 2640 4375 8634 4917 283

list all cities in the matrix dataframe

This Series contains the names of the cities associated with the data in the matrix.

20 Northport 3536 9231 8651 6374 4842 5704 8484 6322 2012 ... 2154 8484 1742 8443 6947 5401 6681 9018 1668 830

```
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

'df_m.dtypes' returns the data types of each column in the DataFrame 'df_m'.

```
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

A new DataFrame was created from 'df_m' using the quantile method, showcasing the 25th, 50th, and 75th percentiles for each city across numeric features.

```
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	...
0.50	5343.0	5431.0	5311.0	5771.0	5131.0	7588.0	5156.0	5331.0	6589.0	5875.0	...
0.75	7242.0	8074.0	7508.0	7935.0	7490.0	9145.0	6840.0	7606.0	8221.0	7783.0	...

3 rows × 25 columns

per store, the quartile values

The variable l contains the column names of the transposed DataFrame df_3, representing the features for which percentiles were calculated.

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

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

The code calculates the mean value for each feature (column) in the transposed DataFrame 'df_3'.

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

```
3535.24
```

双击（或按回车键）即可修改

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

```
5826.36
```

双击（或按回车键）即可修改

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

```
7953.0
```

The variable 'kk' stores the mean values calculated from the transposed DataFrame 'df_3'. It is a Pandas Series containing the mean values for each feature.

```
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

It calculates the percentage of values in each row of the DataFrame 'df_m' that is less than or equal to the 25th percentile (Q1) and stores the result in the variable 'n'.

For example, store 0 has approximately 28.57% of its displays at or below the 25th quartile.

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

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

The variables 'la', 'll', and 'lll' represent the percentage of displays at or below the 25th, 50th, and 75th quartiles, respectively, for each store. The values are rounded to one decimal place.

```
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
```

```
# df_m
```

The DataFrame 'df_m' now consists of the columns 'City', '25qt', '50qt', and '75qt', representing the respective quartile percentages for each store.

```
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

create a choropleth for each store

The DataFrame df_m has been augmented with an additional column named 'zip,' incorporating the provided list of zip codes.

```
#choropleth:
import pandas as pd

# Create a sample dataframe
data = {'City': ['Birmingham', 'Montgomery', 'Mobile', 'Huntsville', 'Tuscaloosa', 'Hoover', 'Dothan', 'Auburn', 'Decatur', 'Madison', 'Floren
         'Zip Code': ['35201','36101','36601','35801','35401','35216','36301','36830','35601','35756','35630','35901','35216','36066','36867','350

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

Display the columns of the DataFrame 'df_m'.

```
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')
```

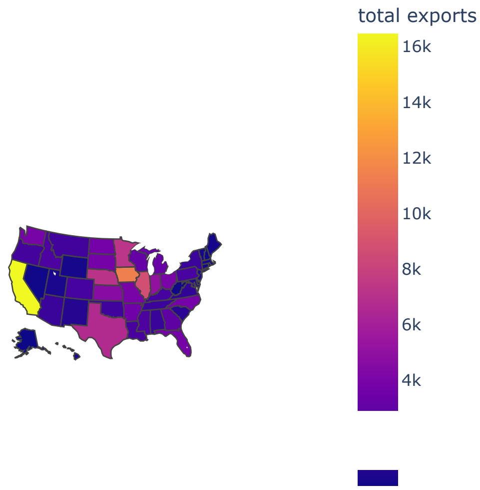
Uses Plotly Express to create a choropleth map with U.S. states and their total exports.

```
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()
```



Display DataFrame 'df_demo'.

```
df_demo
```

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.
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.
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	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.
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.
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.
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.
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.
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.
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.
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.
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.
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.
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.
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.
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.
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.
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.
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.
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.
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.

The columns in the DataFrame 'df_demo' for the choropleth map.

```
df_demo.columns
```

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

map demo #2: state of AL

This code produces an interactive choropleth map of the U.S., where the color intensity represents the unemployment rate in different counties.

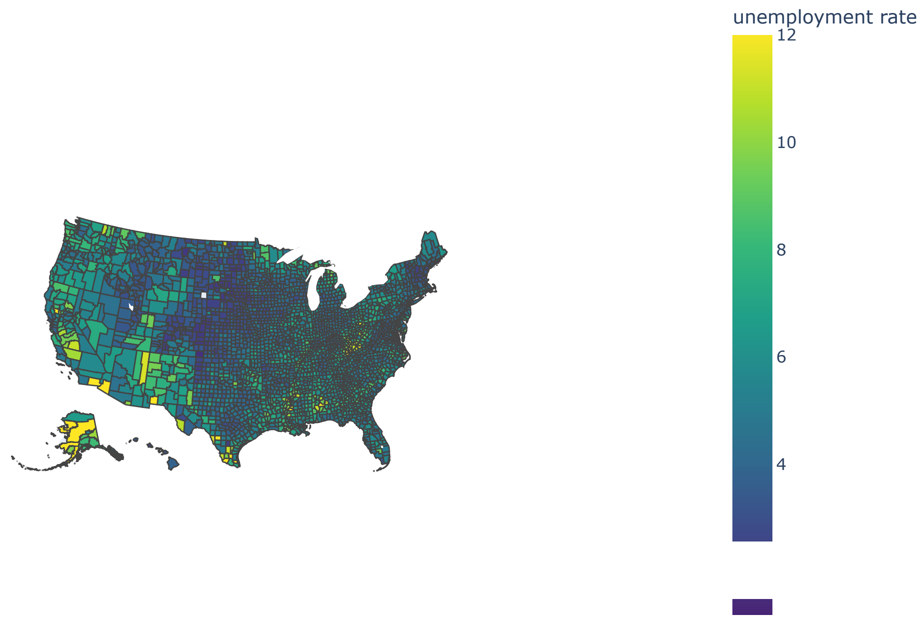
29	NJ	New Jersey	state	500.40	0.8	0.4	4.6	3.37	35.0	74.5	109.45	21.6	35.0	56.54	10.

```
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()
```



Print the columns of DataFrame 'df_us'.

```
df_us.columns
```

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

Display DataFrame 'df_us'.

```
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

The list 'al_fips' is a collection of dictionaries, where each dictionary represents information about a county in Alabama.

```
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
```

Print the columns of DataFrame 'df_m'.

```
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')
```

Display DataFrame 'df_m'.

```
df_m
```

	City	1	2	3	4	5	6	7	8	9	...	36	37	38	39	40	41	25qt	50qt	75qt	z
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	3555	1341	1756	7598	1509	1861	28.6	55.8	77.3	352
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	2805	4601	4449	5727	2315	8822	21.4	55.8	70.5	361
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	9807	2652	9296	2815	4886	7458	38.1	60.5	79.5	366
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	7935	2605	9982	3338	9116	3875	26.2	51.2	77.3	358
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	3657	2158	4469	2513	8135	6963	21.4	60.5	79.5	354
5	Hoover	9741	7377	9410	9790	8864	2522	5347	9145	8402	...	9748	7224	4628	8107	6143	1671	16.7	34.9	59.1	352
6	Dothan	7646	2060	4911	4976	7851	4277	7423	6183	6641	...	5650	4400	7842	4006	9335	3571	19.0	55.8	90.9	363
7	Auburn	4326	2659	6928	4656	1828	5199	5331	6294	3076	...	4387	6890	2833	5083	9707	2116	23.8	51.2	79.5	368

Returns the number of rows in the DataFrame 'df_m'. It gives the count of cities in the dataset.

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

```
25
```

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

It is the count of counties in Alabama.

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

```
25
50
```

19 Homewood 2373 7188 9880 9236 5969 9998 8703 8440 4643 ... 8787 5459 8389 5242 2224 6025 19.0 41.9 68.2 352

Prints the column names of the DataFrame 'df_counties'.

```
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_counties.shape[0]
```

```
25
```

Attribute returns an Index object that contains the column labels of the DataFrame 'df_counties'

```
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
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	1756	7598	1509	1861	28.6	55.8	77.3	35201	Autauga
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	4449	5727	2315	8822	21.4	55.8	70.5	36101	Baldwin
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236		9982	3338	9116	3875	26.2	51.2	77.3	35801	Bibb

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')
```

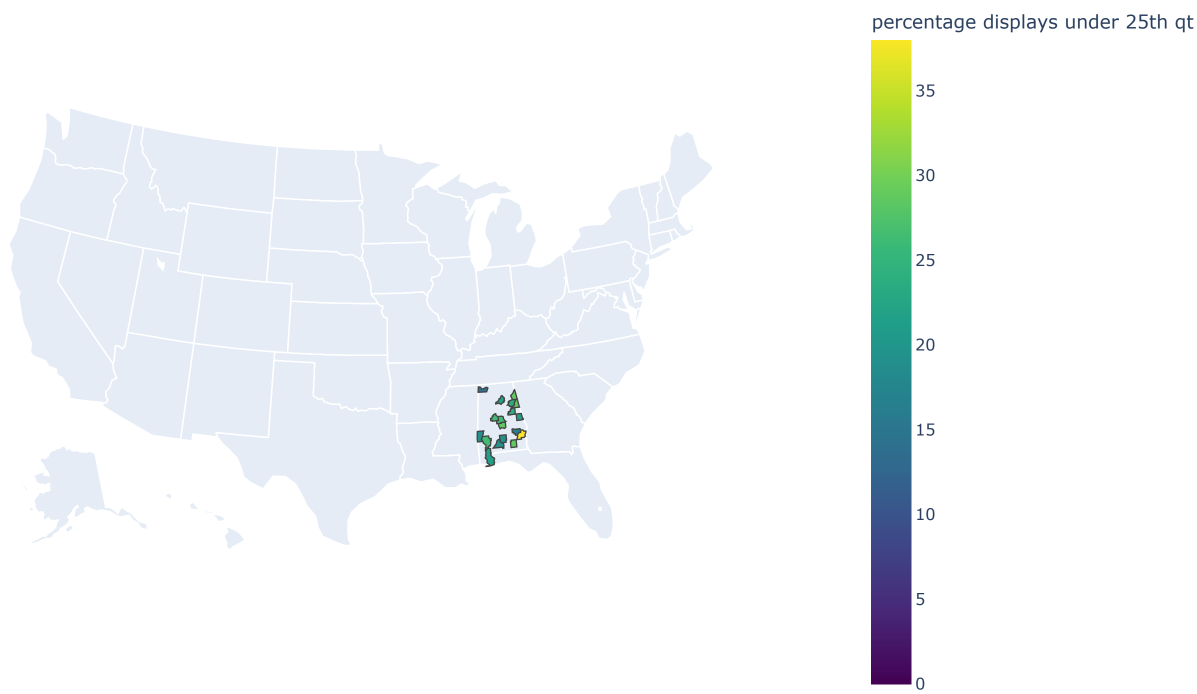
双击（或按回车键）即可修改

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

The map visualizes the percentage of displays under the 25th quartile in different cities, with each city being represented by its corresponding FIPS Code.

```
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()
```



This code is using the Plotly Express library to create a choropleth map of unemployment rates in Alabama's counties.

Load GeoJSON Data: The script starts by making a request to get GeoJSON data for all U.S. counties from a GitHub repository.

Filter GeoJSON Data: It then filters this data to include only Alabama's counties based on the FIPS code (Federal Information Processing Standards).

Load Sample Data: The script loads sample data for Alabama's counties from another URL. This data includes the unemployment rate for each county.

Create Choropleth Map: Using Plotly Express (px), it creates a choropleth map with the specified GeoJSON data and the sample data. The unemployment rate is used as the color scale.

Display the Map: The resulting map is displayed.

```
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()
```