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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
```

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

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

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

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

```
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

12	Hills	9471	9142	4419	3846	2016	5069	4853	6336	9062	...	4613	2942	7'

```
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
# 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

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```
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

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

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

```
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

25th quartile of mean data

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

```
3535.24
```

50th quartile of mean data

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

```
5826.36
```

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75th quartile of mean data

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

```
7953.0
```

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```
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

```
# 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)
```

```
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
23    70.5
24    86.4
dtype: float64
```

```
# df_m
```

This is a common operation for data manipulation, where you focus on a specific set of columns within a larger DataFrame.

```
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

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10	Florence	26.2	48.8	63.6

```
#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',

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

choropleth is a type of thematic map that represents data values by using different colors or shading patterns to fill areas. These areas are typically defined by geographic or political boundaries, and the purpose of a choropleth map is to visualize and convey information about a particular variable across these regions. We are using it for displays in these counties.

```
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	frui pr
0	AL	Alabama	state	1390.63	34.4	10.6	481.0	4.06	8.0	1
1	AK	Alaska	state	13.31	0.2	0.1	0.0	0.19	0.0	(
2	AZ	Arizona	state	1463.17	71.3	17.9	0.0	105.48	19.3	4
3	AR	Arkansas	state	3586.02	53.2	29.4	562.9	3.53	2.2	

```
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')
```

8	FL	Florida	state	3764.09	42.6	0.9	56.9	66.31	438.2	93

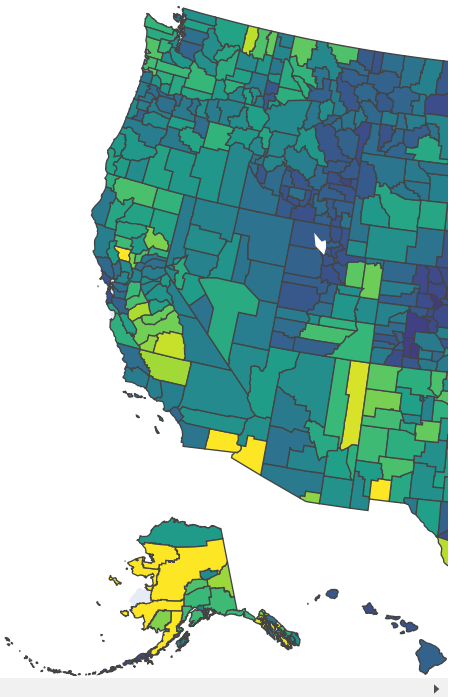
map demo #2: state of AL

```
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()
```



39	SC	South Carolina	state	929.93	15.2	10.9	186.5	7.62	17.1	3(

```
df_us.columns
```

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

43	TX	Texas	state	6648.23	261.0	42.7	239.2	240.55	21.0	9(

```
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
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
23	Brook	8433	9568	2141	2357	6566	1482	4787	3900	6615	...	5765	3653	5

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

```
25
```

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

1. List item
2. List item

All the counties in alabam that we are interested in.

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

```
25
50
```

```
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
```

```
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	4
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	1756	7598	150
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	488
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	813

use the merged_df as data source for the choropleth

```
merged_df.columns
```

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

Double-click (or enter) to edit

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

```
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()
```