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

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This is a command to install plotly visualization library. This command is in python language to install plotly-geo library. It is used to create geographical maps and visualizations.

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

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

Here we will be using pandas and numpy. We imported the two libraries which are used for analysis and manipulation from python. This tells google cloud what we are going to use.

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

Here we are downloading the date from a github repository. This is the data we'll be using for the assignment. This involves the url for the matrix.

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

Here we'll be making a pandas data frame. This is a python code that will download the data from GitHub which will then result in the afromentioned 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
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

Here we can see the data of the different cities and their raw sales in real terms. It's interesting being able to compare the different stores to each other i've never really looked at data like this before.

```
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')
```

Brook

This code here displays the column names of the panda dataframe. From these columns we get the dimensionality of the matrix.

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
```

This code helps us to see a series in the panda dataframe. The output of this code displays the city names in the columns.

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
```

All of these columns are integers. It says its an object but its really a word, or its a string data type. Its a combination of complex characters.

Quantiles for each display, all stores

Double-click (or enter) to edit

```
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

Right here we express quantils as a 25th, 50th, 75th. We make the quantils based on the numeric columns, and then we do it amongst the column axis. Quantils become the rows and cities become the columns. 25 columns one column per city.

per store, the quartile values

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

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

This code is used to tranpose the pandas data frame df_3. This is used to get the column names of the transposed dataframe. This will be a list of column names.

```
df_3.T.mean()
```

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

We wanna establish a mean/an average per quantal. This code gets the mean of the quartile values of the matrix. The output will be a series of mean values.

define the global quartile boundary, per q

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

```
3535.24
```

This code is used to calculate the mean of the 25th quartile from the matrix. The T function is used to transposw the dataframe.

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

```
5826.36
```

This code is just like the one before but calculates the 50th quartile of the matrix. The output of this code is a float value.

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

```
7953.0
```

Once again this calculates the mean of the 75th quartile of the matrix.

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

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

This code is used to calculate the mean of the quartile values of the matrix. The df_f is a tranposed dataframe of the quantities of the matrix.

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
```

Here this code is used to calculate the percentage of displays that are at or below the 25th quartile, per store. The iloc function is used to select all rows and columns from 1 to the end of the dataframe. The shape function is used to get the dimensions of the dataframe. This shows how weak each store is performing.

```
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)
```

```
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
```

```
20    75.0
21    72.7
22    75.0
23    70.5
24    86.4
dtype: float64
```

The first line of code is used to calculate the percentage of displays that are at or below the 25th quartile per store. Each following line does the same just with the 50th and 75th quartile. Each series shows which ones are at or below the 25th,50th, and 75th quartile.

```
# df_m


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

Here we have a date frame called end set where we can make something visual. It means we can attach the 25th quartile calculation to the city. Then we can see what percentage of the displays in that store are underperforming.

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', 'Florei
        '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]
```

Here we begin to work with chloropleths. This a mock data frame for pracitce, an experiment with zip codes. From here we can start to think about making a chloropleths.

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')
```

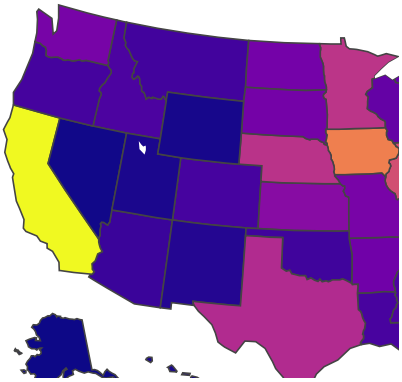
Here is a list of column labels of a panda dataframe. The dataframe contains sales information from the different stores. It shows the sales of how certain stores are doing according to their displays. The firs column represents city names and the next 41 represent sales and the last 3 represent the quartiles.

```
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()
```



Chloropleths are actually not built off of zip codes but rather Fips codes which are the area codes of the county established by the us government. This is called a hover where as you hover above the state it'll display data.

```
df_demo
```

	code	state	category	total exports	beef	pork	poultry	dairy	fruits fresh	fruits proc
0	AL	Alabama	state	1390.63	34.4	10.6	481.0	4.06	8.0	17.1
1	AK	Alaska	state	13.31	0.2	0.1	0.0	0.19	0.0	0.0
2	AZ	Arizona	state	1463.17	71.3	17.9	0.0	105.48	19.3	41.0
3	AR	Arkansas	state	3586.02	53.2	29.4	562.9	3.53	2.2	4.7
4	CA	California	state	16472.88	228.7	11.1	225.4	929.95	2791.8	5944.6
5	CO	Colorado	state	1851.33	261.4	66.0	14.0	71.94	5.7	12.2
6	CT	Connecticut	state	259.62	1.1	0.1	6.9	9.49	4.2	8.9
7	DE	Delaware	state	282.19	0.4	0.6	114.7	2.30	0.5	1.0
8	FL	Florida	state	3764.09	42.6	0.9	56.9	66.31	438.2	933.1
9	GA	Georgia	state	2860.84	31.0	18.9	630.4	38.38	74.6	158.9
10	HI	Hawaii	state	401.84	4.0	0.7	1.3	1.16	17.7	37.8
11	ID	Idaho	state	2078.89	119.8	0.0	2.4	294.60	6.9	14.7
12	IL	Illinois	state	8709.48	53.7	394.0	14.0	45.82	4.0	8.5
13	IN	Indiana	state	5050.23	21.9	341.9	165.6	89.70	4.1	8.8
14	IA	Iowa	state	11273.76	289.8	1895.6	155.6	107.00	1.0	2.2
15	KS	Kansas	state	4589.01	659.3	179.4	6.4	65.45	1.0	2.1
16	KY	Kentucky	state	1889.15	54.8	34.2	151.3	28.27	2.1	4.5
17	LA	Louisiana	state	1914.23	19.8	0.8	77.2	6.02	5.7	12.1
18	ME	Maine	state	278.37	1.4	0.5	10.4	16.18	16.6	35.4
19	MD	Maryland	state	692.75	5.6	3.1	127.0	24.81	4.1	8.8
20	MA	Massachusetts	state	248.65	0.6	0.5	0.6	5.81	25.8	55.0
21	MI	Michigan	state	3164.16	37.7	118.1	32.6	214.82	82.3	175.3
22	MN	Minnesota	state	7192.33	112.3	740.4	189.2	218.05	2.5	5.4
23	MS	Mississippi	state	2170.80	12.8	30.4	370.8	5.45	5.4	11.6
24	MO	Missouri	state	3933.42	137.2	277.3	196.1	34.26	4.2	9.0
25	MT	Montana	state	1718.00	105.0	16.7	1.7	6.82	1.1	2.2
26	NE	Nebraska	state	7114.13	762.2	262.5	31.4	30.07	0.7	1.5
27	NV	Nevada	state	139.89	21.8	0.2	0.0	16.57	0.4	0.8
28	NH	New Hampshire	state	73.06	0.6	0.2	0.8	7.46	2.6	5.4
29	NJ	New Jersey	state	500.40	0.8	0.4	4.6	3.37	35.0	74.5
30	NM	New Mexico	state	751.58	117.2	0.1	0.3	191.01	32.6	69.3
31	NY	New York	state	1488.90	22.2	5.8	17.7	331.80	64.7	137.8
32	NC	North Carolina	state	3806.05	24.8	702.8	598.4	24.90	23.8	50.7
33	ND	North Dakota	state	3761.96	78.5	16.1	0.5	8.14	0.1	0.2
34	OH	Ohio	state	3979.79	36.2	199.1	129.9	134.57	8.7	18.5
35	OK	Oklahoma	state	1646.41	337.6	265.3	131.1	24.35	3.0	6.3
36	OR	Oregon	state	1794.57	58.8	1.4	14.2	63.66	100.7	214.4
37	PA	Pennsylvania	state	1969.87	50.9	91.3	169.8	280.87	28.6	60.9

The map is organized by state we can see from this data above. This data shows the total exports and as you hover above a state it'll display that. With these codes, states, and exports it provides us with some good data.

```
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')
```

Here we have code that provides the columun labels from the panda dataframe that contains the exports of different good from the states.

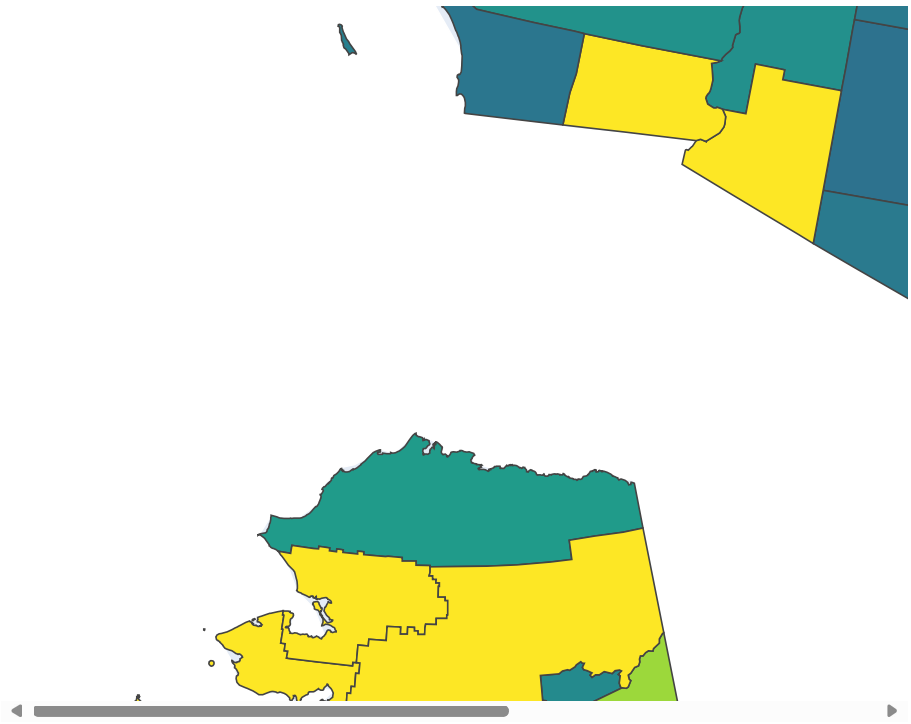
map demo #2: state of AL

```
from urllib.request import urlopen
import json
with urlopen('https://raw.githubusercontent.com/plotly/datasets/master/geojson-counties-fips.json') as response:
    counties = json.load(response)

import pandas as pd
df_us = pd.read_csv("https://raw.githubusercontent.com/plotly/datasets/master/fips-unemp-16.csv",
                    dtype={"fips": str})

import plotly.express as px

fig = px.choropleth(df_us, geojson=counties, locations='fips', color='unemp',
                           color_continuous_scale="Viridis",
                           range_color=(0, 12),
                           scope="usa",
                           labels={'unemp':'unemployment rate'})
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
fig.show()
```



We made a national map then we are going want to highlight alabama. If we worked in California we can look up California. But since we are working witht he sells from Alabama we are going to focus on Alabama.

```
df_us.columns
```

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

With this information we have the unemployment rate of different countries in the US using the Fips codes.

```
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

Here with have the fips codes along with the unemployment rate. As long as we have this two point data structure we can make a choropleth.

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
```

Here we have all the fips codes for the different counties in the state of alabama. Each county has its own corresponding fips code. This list contains 67 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')
```

Here we have code that provides information about the sales of different store in alabama.

```
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	4
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	9807	2652	9
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	7935	2605	9
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	3657	2158	4
5	Hoover	9741	7377	9410	9790	8864	2522	5347	9145	8402	...	9748	7224	4
6	Dothan	7646	2060	4911	4976	7851	4277	7423	6183	6641	...	5650	4400	7
7	Auburn	4326	2659	6928	4656	1828	5199	5331	6294	3076	...	4387	6890	2
8	Decatur	3786	2891	8124	2469	3704	3623	2409	8287	2032	...	9305	6509	6
9	Madison	1934	3628	9190	3275	9344	5778	1256	3523	1781	...	1746	4470	7
10	Florence	8017	3187	1128	4706	9962	7547	4440	4530	9569	...	5929	1123	7
11	Gadsden	2290	6402	8598	7547	5158	9731	8038	4435	7357	...	2549	5175	5
12	Vestavia Hills	9471	9142	4419	3846	2016	5069	4853	6336	9062	...	5142	9619	9
13	Prattville	6039	8003	6180	4610	3548	7115	6720	8512	9954	...	1591	4401	3
14	Phenix City	8788	8269	6838	2863	6753	6608	4048	8774	4513	...	3520	7654	6
15	Alabaster	1733	9767	3274	7125	7437	5748	5399	6513	3038	...	2479	9673	7
16	Bessemer	6559	2453	1578	5158	3058	8075	7066	8530	8346	...	4810	7641	5
17	Enterprise	8436	7800	7234	5063	4274	1948	7887	6647	1320	...	3461	2640	4
18	Opelika	9998	8953	7923	6176	4369	9503	2126	1816	9224	...	5191	9304	2
19	Homewood	2373	7188	9880	9236	5969	9998	8703	8440	4643	...	8787	5459	8
20	Northport	3536	9231	8651	6374	4842	5704	8484	6322	2012	...	6947	5401	6
21	Pelham	6830	3736	2734	6443	8494	6206	7290	8518	6176	...	2777	4045	7
22	Trussville	2794	8273	9174	2850	8351	3978	5995	4632	7693	...	1650	9470	6
23	Mountain Brook	8433	9368	2141	2357	6566	1482	4787	3900	6615	...	5765	3653	5

We assgined cities to their respective counties. We want to show what a store looks like within a county within a city, with an economic output.

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

```
25
```

The output of this code is 25 representing the number of rows in the dataframe.

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
```

The al_fips is the alabama fips codes for all the counties in alabama. We wanna put these codes with our data set to get a realistic feel. We'll have one data frame for all the counties containing the fips codes

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

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

We use the fips codes for the counties in various data system and applications.

df_m: all display data, per store

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

```
25
```

The shape is the number of rows associated with the data frame. The df_m contains all the displays.

fips codes per county

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

```
25
```

We wanna marry dfm with df counties in some meaningful way

```
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	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

Here we merge the dfm with the counties along the columns and all the data we've been building in order to make a choropleth. in plotly.

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()
```

Here we have the quartiles and the fips codes, and then we are grabbing plotly which is a python library for all sorts of charts. We wanna incorporate color. The counties that are doing badly will we brigthter and the ones thats are doing better will be darker. With a color scheme of 34 different gradients.

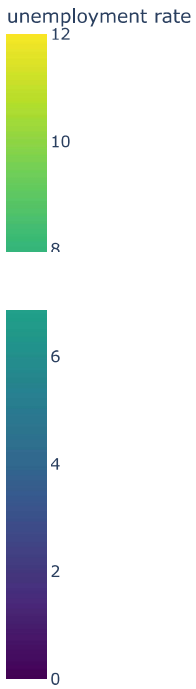
```
import plotly.express as px
import requests
import json
import pandas as pd

# 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()
```



Here we added more of an extensive look by adding more counties.