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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.

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The code "!pip install plotly-geo" is a Linux file system that is a collab with Google. The code "!pip" is responsible for the installation of the plotly visualization library. This code also provides geospatial features for the Plotly library. It helps create plots, charts, and geographical data.

```
!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 26.6 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" and "import numpy as np" are used for data manipulation and analysis using two popular libraries. First, this code "import pandas as pd" allows for the Panda library to be imported and it gives it an alias. Not to mention that using an alias makes it easier to reference the library. Last, the code "import numpy as np" gives an alias to the NumPy libary "library for numerical operations in Python" and imports it.

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

This code "url ='https://raw.githubusercontent.com/stefanbund/py3100/main/ProductList_118.csv'" allows us to download the data from a GitHub repository and implant it into our notebook. The other code "url_m = 'https://raw.githubusercontent.com/stefanbund/py3100/main/matrix.csv' " creates a pandas data frame for us to use. url_m means the URL for the matrix which is a two-dimensional data set representation for Alta. We can see the cities and raw sales in the data set.

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

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The code "df_m = pd.read_csv(url_m)" is used to read Comma Separated Values files from a certain URL into a pandas data frame. The part "read_csv" allows us to read data from a CSV into a data frame by using a pandas function. Later, in your Python code, you can use df_m to manipulate, analyze, and visualize the data from the CSV file. This code is used to read the csv.

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

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df_m stands for data frame and with this code, we can see data for multiple factors. such factors that we can see include the cities, their displays, and their raw sales in real terms. With this code, we can use the data to get information from. It is very useful since this data will be essential for the later codes.

```
df_m
```

	City	1	2	3	4	5	6	7	8	9	...	32	33	34	35	36	37
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	1340	6923	3082	5617	3555	1341
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	4424	8813	6655	3986	2805	4601
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	5430	1601	9145	1493	9807	2652
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	9169	7829	6879	4166	7935	2605
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	1556	5533	1884	2088	3657	2158
5	Hoover	9741	7377	9410	9790	8864	2522	5347	9145	8402	...	6031	7673	8403	7588	9748	7224
6	Dothan	7646	2060	4911	4976	7851	4277	7423	6183	6641	...	8253	1565	6052	5802	5650	4400
7	Auburn	4326	2659	6928	4656	1828	5199	5331	6294	3076	...	6128	3737	7785	3281	4387	6890
8	Decatur	3786	2891	8124	2469	3704	3623	2409	8287	2032	...	6622	9742	9382	8413	9305	6509
9	Madison	1934	3628	9190	3275	9344	5778	1256	3523	1781	...	6619	6128	5325	9976	1746	4470
10	Florence	8017	3187	1128	4706	9962	7547	4440	4530	9569	...	8306	1392	1363	5545	5929	1123
11	Gadsden	2290	6402	8598	7547	5158	9731	8038	4435	7357	...	4488	3591	1683	7343	2549	5175
12	Vestavia Hills	9471	9142	4419	3846	2016	5069	4853	6336	9062	...	4613	2942	7408	9484	5142	9619
13	Prattville	6039	8003	6180	4610	3548	7115	6720	8512	9954	...	8225	7278	7358	2997	1591	4401
14	Phenix City	8788	8269	6838	2863	6753	6608	4048	8774	4513	...	5704	8720	3386	1295	3520	7654
15	Alabaster	1733	9767	3274	7125	7437	5748	5399	6513	3038	...	7351	9503	1081	7704	2479	9673
16	Bessemer	6559	2453	1578	5158	3058	8075	7066	8530	8346	...	8921	3517	4121	5295	4810	7641
17	Enterprise	8436	7800	7234	5063	4274	1948	7887	6647	1320	...	4840	6309	7334	9880	3461	2640
18	Opelika	9998	8953	7923	6176	4369	9503	2126	1816	9224	...	3217	1170	9351	1453	5191	9304
19	Homewood	2373	7188	9880	9236	5969	9998	8703	8440	4643	...	8144	8091	3869	4259	8787	5459
20	Northport	3536	9231	8651	6374	4842	5704	8484	6322	2012	...	2154	8484	1742	8443	6947	5401
21	Pelham	6830	3736	2734	6443	8494	6206	7290	8518	6176	...	9219	4891	4276	4976	2777	4045
22	Trussville	2794	8273	9174	2850	8351	3978	5995	4632	7693	...	2582	9365	8305	2147	1650	9470
23	Mountain Brook	8433	9368	2141	2357	6566	1482	4787	3900	6615	...	4666	9227	2858	2083	5765	3653

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With this code "df_m.columns" we can see the columns which are the numbers in between apostrophes for example "'1'". The columns represent the dimensionality of the matrix. This would become very useful since we can calculate and know the precise calculations of the dimensionalities. a matrix is a dimensional array.

```
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

This code allows us to view the list of the cities and count how many we are looking at. This also allows us to explore a series within the data frame. this would come in very helpful later because it enables you to filter, aggregate, or analyze the data in the 'City' column. Overall this code is needed to view what cities we select.

```
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

For this code, it is important to first know that dtypes means data types. All of the columns below the object usually indicating the string data type are integers. Just right below the cities are the data types. With this code, we can figure out both the types and the integers

```
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

what this is used for is reading the values throughout the matrix data frame. this establishes quantiles 20th, 50th, and 75th for the columns. This is more of a summary of the cities and quantiles. Here the quantiles are the rows and the cities are the columns.

```
df_3 = df_m.quantile([0.25, 0.5, 0.75], numeric_only=True, axis=1)
df_3
```

	0	1	2	3	4	5	6	7	8	9	...	15	16	17	
0.25	3082.0	3633.0	2236.0	3473.0	3657.0	4628.0	4254.0	3588.0	3704.0	3451.0	...	3449.0	4246.0	4375.0	32
0.50	5343.0	5431.0	5311.0	5771.0	5131.0	7588.0	5156.0	5331.0	6589.0	5875.0	...	6478.0	5944.0	6315.0	53
0.75	7242.0	8074.0	7508.0	7935.0	7490.0	9145.0	6840.0	7606.0	8221.0	7783.0	...	7437.0	8331.0	8436.0	84

3 rows × 25 columns

per store, the quartile values

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This is used for boundaries and ranges. It creates quantiles which are boundaries and then ranges which are quartiles inside of it.

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

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

This code allows us to use and get the mean or an average per quantile

```
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

This code allows us to transpose the DataFrame df_3, select the 0.25 column, and then calculate the mean of the values in that column.

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

```
3535.24
```

This code allows you to transpose the DataFrame df_3, select the 0.5 column, and then calculate the mean of the values in that column. The expression in this case computes the mean of the column labeled 0.5.

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

```
5826.36
```

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This code allows you to take the code and transpose it to a DataFrame (df_3), then access the row labeled 0.75 and calculate the mean of the values in that row.

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

```
7953.0
```

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This code assigns the mean value of each column in a transposed dataframe to a new variable. Following this line of code, kk will be a pandas Series with each element corresponding to the mean value of a column in the original DataFrame.

```
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

This allows us to determine which stores and the percentage of displays per store are performing below the 25th percentile. It is a temporary value expression that we use to say that we can provide a percentage value to describe weakness and it is used as an 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 25th 50th and 75th have been assigned quickly to variables. These quick variables are very necessary for the following coding.

```
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
```

We have a data frame called an end set here, which allows us to get closer to creating something visual. It enables us to link the 25th quartile calculation to the city and obtain the percentage of displays in the store that are underperforming.

```
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

create a choropleth for each store

This is where you learn how choropleth works and start with a few experiments. It starts by creating a sham data frame. The use of zipcodes is experimental.

20 Northport 28.6 53.5 75.0

```
#choropleth:
import pandas as pd

# Create a sample dataframe
data = {'City': ['Birmingham', 'Montgomery', 'Mobile', 'Huntsville', 'Tuscaloosa', 'Hoover', 'Dothan', 'Auburn', 'Decatur', 'Madison', 'Florence', 'Gads
        'Zip Code': ['35201','36101','36601','35801','35401','35216','36301','36830','35601','35756','35630','35901','35216','36066','36867','35007','35

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

In pandas, is used to retrieve the column labels (names) of a data frame.

```
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')
```

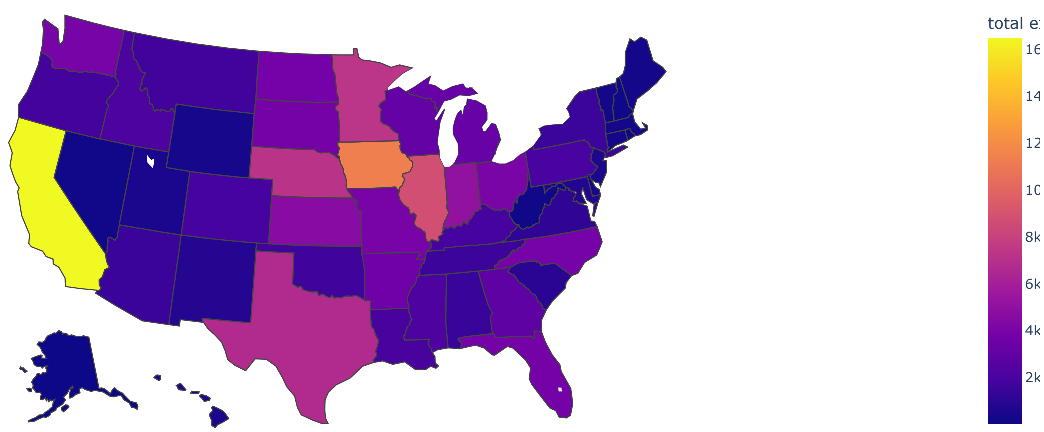
FIPS codes are used here; they are county area codes established by the US government. As an alternative to a zip code, we can obtain a county/state-size area.

```
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()
```



This generates an organized map based on the state or state code and total exports. This map is based on two pieces of data: state and total exports as a number, which allows us to create a two-dimensional map.

```
df_demo
```

	code	state	category	total exports	beef	pork	poultry	dairy	fruits fresh	fruits proc	total fruits	veggies fresh	veggies proc	total veggies	corn	wheat	cotton
0	AL	Alabama	state	1390.63	34.4	10.6	481.0	4.06	8.0	17.1	25.11	5.5	8.9	14.33	34.9	70.0	317.61
1	AK	Alaska	state	13.31	0.2	0.1	0.0	0.19	0.0	0.0	0.00	0.6	1.0	1.56	0.0	0.0	0.00
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	48.7	423.95
3	AR	Arkansas	state	3586.02	53.2	29.4	562.9	3.53	2.2	4.7	6.88	4.4	7.1	11.45	69.5	114.5	665.44
4	CA	California	state	16472.88	228.7	11.1	225.4	929.95	2791.8	5944.6	8736.40	803.2	1303.5	2106.79	34.6	249.3	1064.95
5	CO	Colorado	state	1851.33	261.4	66.0	14.0	71.94	5.7	12.2	17.99	45.1	73.2	118.27	183.2	400.5	0.00
6	CT	Connecticut	state	259.62	1.1	0.1	6.9	9.49	4.2	8.9	13.10	4.3	6.9	11.16	0.0	0.0	0.00
7	DE	Delaware	state	282.19	0.4	0.6	114.7	2.30	0.5	1.0	1.53	7.6	12.4	20.03	26.9	22.9	0.00
8	FL	Florida	state	3764.09	42.6	0.9	56.9	66.31	438.2	933.1	1371.36	171.9	279.0	450.86	3.5	1.8	78.24
9	GA	Georgia	state	2860.84	31.0	18.9	630.4	38.38	74.6	158.9	233.51	59.0	95.8	154.77	57.8	65.4	1154.07
10	HI	Hawaii	state	401.84	4.0	0.7	1.3	1.16	17.7	37.8	55.51	9.5	15.4	24.83	0.0	0.0	0.00
11	ID	Idaho	state	2078.89	119.8	0.0	2.4	294.60	6.9	14.7	21.64	121.7	197.5	319.19	24.0	568.2	0.00
12	IL	Illinois	state	8709.48	53.7	394.0	14.0	45.82	4.0	8.5	12.53	15.2	24.7	39.95	2228.5	223.8	0.00
13	IN	Indiana	state	5050.23	21.9	341.9	165.6	89.70	4.1	8.8	12.98	14.4	23.4	37.89	1123.2	114.0	0.00
14	IA	Iowa	state	11273.76	289.8	1895.6	155.6	107.00	1.0	2.2	3.24	2.7	4.4	7.10	2529.8	3.1	0.00
15	KS	Kansas	state	4589.01	659.3	179.4	6.4	65.45	1.0	2.1	3.11	3.6	5.8	9.32	457.3	1426.5	43.98
16	KY	Kentucky	state	1889.15	54.8	34.2	151.3	28.27	2.1	4.5	6.60	0.0	0.0	0.00	179.1	149.3	0.00
17	LA	Louisiana	state	1914.23	19.8	0.8	77.2	6.02	5.7	12.1	17.83	6.6	10.7	17.25	91.4	78.7	280.42
18	ME	Maine	state	278.37	1.4	0.5	10.4	16.18	16.6	35.4	52.01	24.0	38.9	62.90	0.0	0.0	0.00
19	MD	Maryland	state	692.75	5.6	3.1	127.0	24.81	4.1	8.8	12.90	7.8	12.6	20.43	54.1	55.8	0.00
20	MA	Massachusetts	state	248.65	0.6	0.5	0.6	5.81	25.8	55.0	80.83	8.1	13.1	21.13	0.0	0.0	0.00
21	MI	Michigan	state	3164.16	37.7	118.1	32.6	214.82	82.3	175.3	257.69	72.4	117.5	189.96	381.5	247.0	0.00
22	MN	Minnesota	state	7192.33	112.3	740.4	189.2	218.05	2.5	5.4	7.91	45.9	74.5	120.37	1264.3	538.1	0.00
23	MS	Mississippi	state	2170.80	12.8	30.4	370.8	5.45	5.4	11.6	17.04	10.6	17.2	27.87	110.0	102.2	494.75
24	MO	Missouri	state	3933.42	137.2	277.3	196.1	34.26	4.2	9.0	13.18	6.8	11.1	17.90	428.8	161.7	345.29
25	MT	Montana	state	1718.00	105.0	16.7	1.7	6.82	1.1	2.2	3.30	17.3	28.0	45.27	5.4	1198.1	0.00
26	NE	Nebraska	state	7114.13	762.2	262.5	31.4	30.07	0.7	1.5	2.16	20.4	33.1	53.50	1735.9	292.3	0.00

This indicates that the DataFrame df_demo contains columns named "Name," "Age," and "City." This data can be used for a variety of DataFrame operations and analyses.

```
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

34	OH	Ohio	state	3979.79	36.2	199.1	129.9	134.57	8.7	18.5	27.21	20.4	33.1	53.53	535.1	207.4	0.00

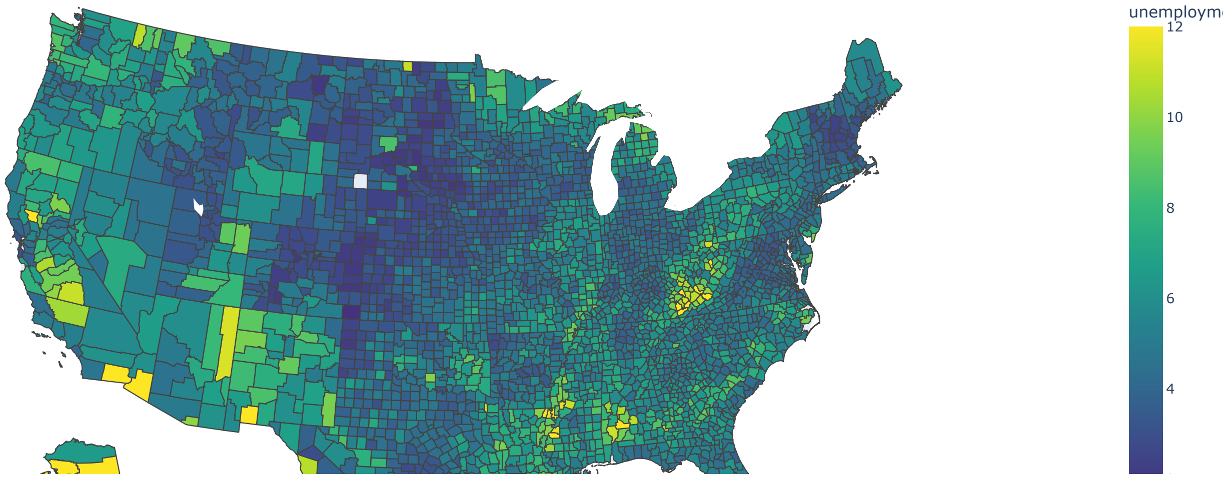
This is used to create a national graph where you can see every state and even your own. It provides a percentage and data for each state/county.

```
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()
```



You get a list or Index object containing the names of all the columns in the DataFrame when you use df_us.columns. This data is useful for understanding the structure of your DataFrame and performing operations on specific columns.

```
df_us.columns
```

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

This code contains the fips, which are the county codes that included the necessary unemployment statistics. We can use this to create a choropleth.

```
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

In this code, we look up and print the fips codes for the various counties 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
```

```
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')
```

We assign cities to prospective counties in this code. With this information, if we ever needed to supply a county, we'd know where to look.

```
df_m
```

	City	1	2	3	4	5	6	7	8	9	...	36	37	38	39	40	41
0	Birmingham	8285	5343	6738	6635	5658	8118	4311	8535	3436	...	3555	1341	1756	7598	1509	1861
1	Montgomery	1287	6585	8300	8874	8208	5363	3552	3387	2765	...	2805	4601	4449	5727	2315	8822
2	Mobile	8035	5569	9492	5905	5024	1107	6937	5580	8044	...	9807	2652	9296	2815	4886	7458
3	Huntsville	6280	2841	3399	5448	6173	5451	7488	9981	5236	...	7935	2605	9982	3338	9116	3875
4	Tuscaloosa	4079	1066	3923	4177	4277	4219	9436	8160	4302	...	3657	2158	4469	2513	8135	6963
5	Hoover	9741	7377	9410	9790	8864	2522	5347	9145	8402	...	9748	7224	4628	8107	6143	1671
6	Dothan	7646	2060	4911	4976	7851	4277	7423	6183	6641	...	5650	4400	7842	4006	9335	3571
7	Auburn	4326	2659	6928	4656	1828	5199	5331	6294	3076	...	4387	6890	2833	5083	9707	2116
8	Decatur	3786	2891	8124	2469	3704	3623	2409	8287	2032	...	9305	6509	6848	5408	3707	8744
9	Madison	1934	3628	9190	3275	9344	5778	1256	3523	1781	...	1746	4470	7054	6573	3556	1374
10	Florence	8017	3187	1128	4706	9962	7547	4440	4530	9569	...	5929	1123	7306	8746	4000	6943
11	Gadsden	2290	6402	8598	7547	5158	9731	8038	4435	7357	...	2549	5175	5997	9608	7230	9731
12	Vestavia Hills	9471	9142	4419	3846	2016	5069	4853	6336	9062	...	5142	9619	9601	8099	1391	6276
13	Prattville	6039	8003	6180	4610	3548	7115	6720	8512	9954	...	1591	4401	3457	4245	4341	2573
14	Phenix City	8788	8269	6838	2863	6753	6608	4048	8774	4513	...	3520	7654	6845	7738	3828	1202
15	Alabaster	1733	9767	3274	7125	7437	5748	5399	6513	3038	...	2479	9673	7478	7207	7006	3523
16	Bessemer	6559	2453	1578	5158	3058	8075	7066	8530	8346	...	4810	7641	5365	3545	6812	9483
17	Enterprise	8436	7800	7234	5063	4274	1948	7887	6647	1320	...	3461	2640	4375	8634	4917	2830
18	Opelika	9998	8953	7923	6176	4369	9503	2126	1816	9224	...	5191	9304	2720	3100	3912	1548
19	Homewood	2373	7188	9880	9236	5969	9998	8703	8440	4643	...	8787	5459	8389	5242	2224	6025
20	Northport	3536	9231	8651	6374	4842	5704	8484	6322	2012	...	6947	5401	6681	9018	1668	8307
21	Pelham	6830	3736	2734	6443	8494	6206	7290	8518	6176	...	2777	4045	7309	4745	4284	2640
22	Trussville	2794	8273	9174	2850	8351	3978	5995	4632	7693	...	1650	9470	6356	4700	3344	8743
23	Mountain Brook	8433	9368	2141	2357	6566	1482	4787	3900	6615	...	5765	3653	5198	9266	4945	3935
24	Fairhope	8114	1464	2811	3090	4686	7995	7676	1304	7332	...	3457	4808	7227	5482	6355	4553

Refers to the columns of a pandas DataFrame object when working with data using the pandas library.

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

```
25
```

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

This code collects all of the fips codes in Alabama and combines them so that we can have a realistic sense of the fips associated with each store and list them in our data sets.

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

```
25
50
```

This would contain the counties' fips codes into rows.

Double-click (or enter) to edit

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

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

df_m: all display data, per store

This code contains all of the displays.

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

```
25
```

fips codes per county

The shape means number of rows associated with the Alabama fips codes data frame

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

```
25
```

This code allows us to create columns for our data.

```
df_counties.columns
```

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

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

This combines the DFM, counties, and columns. Once the data is merged, we can see all of the displays, quantiles, zip codes, fips codes, and counties. So this summarizes all of the data that we required in tabular format to create a choropleth.

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

5 rows × 48 columns

use the merged_df as data source for the choropleth

This code has the quartile and fits code data needed.

```
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')
```

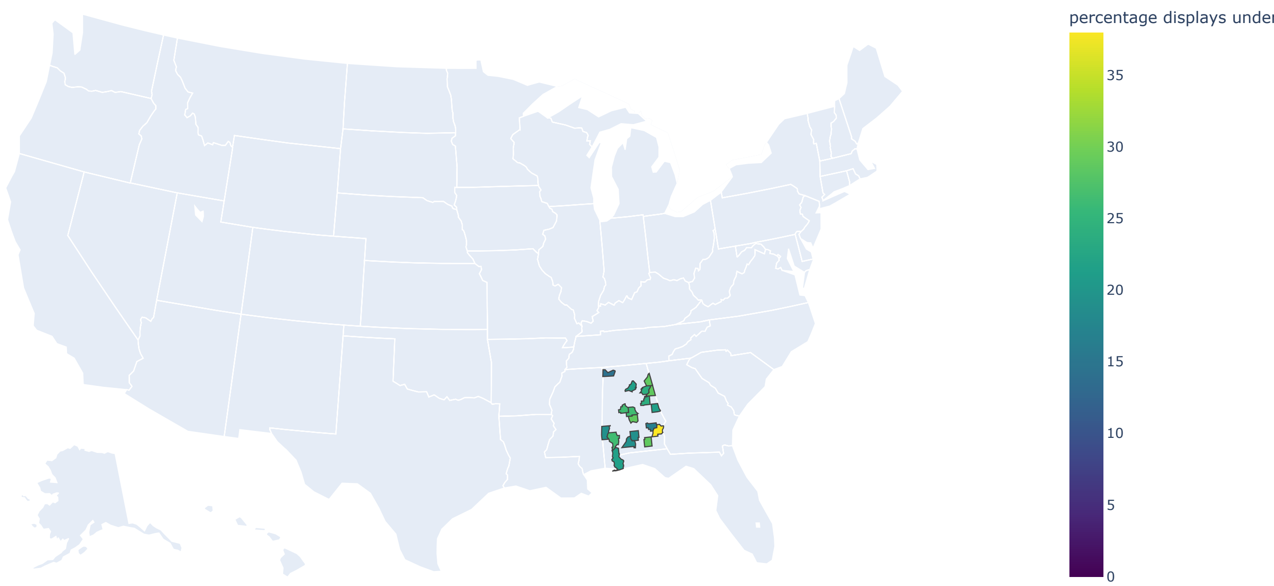
Double-click (or enter) to edit

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

In this code, we use the "merge_df" function to gather the data frame. We take the fips codes from the series and then vary the color per county based on the 25th quartile value. This means that the counties doing the worst will be brighter, while the counties doing well will be darker. This would result in a map that would allow us to view and record data on store performance.

```
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 is an example of how in-depth it would be if every county studied in one place. It is used as an example and a question to be answered.

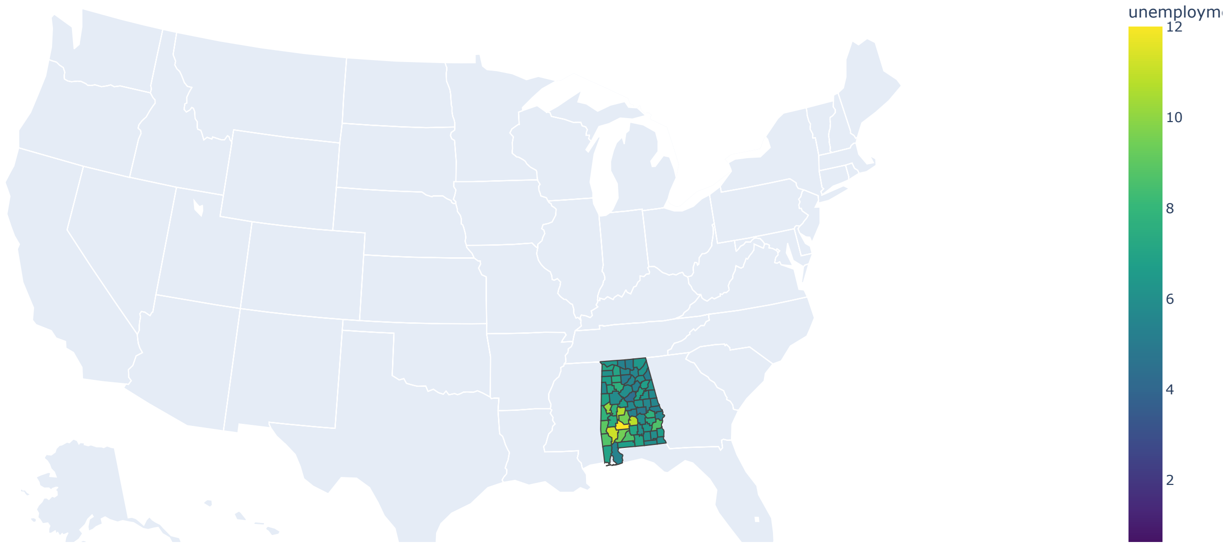
```
import plotly.express as px
import requests
import json
import pandas as pd

# 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()
```


unemployme
12
10
8
6
4
2