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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
```

This is a command-line instruction that basically tells Python's package manager to install a package. The exclamation mark indicates that the command following it should be run in the system's command line. Pip is Python's package installer. Install is the command and plotly-geo is the name of the package needed to be installed.

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

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

Import pandas as pd line means that it imports the Pandas library and aliases it as pd. It is an open source data analysis and manipulation tool. Import numpy as np is a library for Python adding support for large and multidimensional array of objects.

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

After installing Pandas successfully, the material from the GitHub website is posted onto the GoogleCollab sheet.

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

This is used for reading a Comma-Seperated Values file from a specific URL and loading it to a Data Frame. pd.read_csv is mainly used in Pandas for data manipulation and analysis. url_m contains the url of the csv file you want to load. df_m is the code assigning the dataframe created. The # symbol is a comment used to describe what a line of code looks like or does.

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```
df_m
```

| | City | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | 32 | 33 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Birmingham | 8285 | 5343 | 6738 | 6635 | 5658 | 8118 | 4311 | 8535 | 3436 | ... | 1340 | 6923 | 3( |
| **1** | Montgomery | 1287 | 6585 | 8300 | 8874 | 8208 | 5363 | 3552 | 3387 | 2765 | ... | 4424 | 8813 | 6( |
| **2** | Mobile | 8035 | 5569 | 9492 | 5905 | 5024 | 1107 | 6937 | 5580 | 8044 | ... | 5430 | 1601 | 9' |
| **3** | Huntsville | 6280 | 2841 | 3399 | 5448 | 6173 | 5451 | 7488 | 9981 | 5236 | ... | 9169 | 7829 | 6( |
| **4** | Tuscaloosa | 4079 | 1066 | 3923 | 4177 | 4277 | 4219 | 9436 | 8160 | 4302 | ... | 1556 | 5533 | 1( |
| **5** | Hoover | 9741 | 7377 | 9410 | 9790 | 8864 | 2522 | 5347 | 9145 | 8402 | ... | 6031 | 7673 | 8( |
| **6** | Dothan | 7646 | 2060 | 4911 | 4976 | 7851 | 4277 | 7423 | 6183 | 6641 | ... | 8253 | 1565 | 6( |
| **7** | Auburn | 4326 | 2659 | 6928 | 4656 | 1828 | 5199 | 5331 | 6294 | 3076 | ... | 6128 | 3737 | 7' |
| **8** | Decatur | 3786 | 2891 | 8124 | 2469 | 3704 | 3623 | 2409 | 8287 | 2032 | ... | 6622 | 9742 | 9( |
| **9** | Madison | 1934 | 3628 | 9190 | 3275 | 9344 | 5778 | 1256 | 3523 | 1781 | ... | 6619 | 6128 | 5( |
| **10** | Florence | 8017 | 3187 | 1128 | 4706 | 9962 | 7547 | 4440 | 4530 | 9569 | ... | 8306 | 1392 | 1( |
| **11** | Gadsden | 2290 | 6402 | 8598 | 7547 | 5158 | 9731 | 8038 | 4435 | 7357 | ... | 4488 | 3591 | 1( |
| **12** | Vestavia Hills | 9471 | 9142 | 4419 | 3846 | 2016 | 5069 | 4853 | 6336 | 9062 | ... | 4613 | 2942 | 7( |
| **13** | Prattville | 6039 | 8003 | 6180 | 4610 | 3548 | 7115 | 6720 | 8512 | 9954 | ... | 8225 | 7278 | 7( |
| **14** | Phenix City | 8788 | 8269 | 6838 | 2863 | 6753 | 6608 | 4048 | 8774 | 4513 | ... | 5704 | 8720 | 3( |
| **15** | Alabaster | 1733 | 9767 | 3274 | 7125 | 7437 | 5748 | 5399 | 6513 | 3038 | ... | 7351 | 9503 | 1( |
| **16** | Bessemer | 6559 | 2453 | 1578 | 5158 | 3058 | 8075 | 7066 | 8530 | 8346 | ... | 8921 | 3517 | 4' |
| **17** | Enterprise | 8436 | 7800 | 7234 | 5063 | 4274 | 1948 | 7887 | 6647 | 1320 | ... | 4840 | 6309 | 7( |
| **18** | Opelika | 9998 | 8953 | 7923 | 6176 | 4369 | 9503 | 2126 | 1816 | 9224 | ... | 3217 | 1170 | 9( |
| **19** | Homewood | 2373 | 7188 | 9880 | 9236 | 5969 | 9998 | 8703 | 8440 | 4643 | ... | 8144 | 8091 | 3( |
| **20** | Northport | 3536 | 9231 | 8651 | 6374 | 4842 | 5704 | 8484 | 6322 | 2012 | ... | 2154 | 8484 | 1' |
| **21** | Pelham | 6830 | 3736 | 2734 | 6443 | 8494 | 6206 | 7290 | 8518 | 6176 | ... | 9219 | 4891 | 4( |
| **22** | Trussville | 2794 | 8273 | 9174 | 2850 | 8351 | 3978 | 5995 | 4632 | 7693 | ... | 2582 | 9365 | 8( |
| **23** | Mountain Brook | 8433 | 9368 | 2141 | 2357 | 6566 | 1482 | 4787 | 3900 | 6615 | ... | 4666 | 9227 | 2( |
| **24** | Fairhope | 8114 | 1464 | 2811 | 3090 | 4686 | 7995 | 7676 | 1304 | 7332 | ... | 4911 | 3255 | 2( |

This is a representation of the Pandas data frame. This data fram contains data structured in a table format with rows and columns. The first column is labeled "City" followed by numbered columns from number 1 to 41. City columns contains the names of cities. Numbers 1 through 41 all contain numbers representing statistical data.

```
df_m.columns #dimensionality of the matrix
```

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

This output is an index object listing all the column names in the data frame. This is useful for understanding the structure especially when working with data with many columns.

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 is used with Pandas data frame to access a specific column. It selects the city column from the df_m. It allows you to focus on just that one column.

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
```

This is used to display the data types of each column in the Pandas dataframe. The dtypes returns the data types of each column in the data frame. It helps decide how to handle each column for tasks like data cleaning and analysis.

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

This code performs a quantile calculation on the data frame. It indicates that the quantile calculation only be performed on the columns. df_3 gives a summary of the distribution of the measurements of each city.

per store, the quartile values

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

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

Performs a transpose operation on the dataframe which means swapping its rows and columns. the contents of df_3.T is also stored in variable 1.

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

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

This calculates the average of each column in the transposed dataframe. This operation can be useful for understanding the average for quantile values.

define the global quartile boundary, per q

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

```
3535.24
```

Performs a specific calculation on the transposed dataframe. Originally it had quantiles such as 0.25, 0.50 and 0.75. After selecting 0.25 the result is a single numeric value representing the average of all the 25th percent values from df_3.

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

```
5826.36
```

As stated above, this calculates the average of the 50th percentile values across all transposed dataframe.

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

```
7953.0
```

This also calculates the mean average of the 75th percentile across all transposed dataframe.

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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
```

This calculates the average of each column in the transposed dataframe and stores the result in a variable named kk. The variable kk is a pandas series where each index corresponds to an original entity like a city.

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
```

This calculates the percentage of values in each row of the dataframe that are less than or equal to the 25th percentile. Also uses 1 as true and 0 as false and the divison takes the count of values less or equal to the 25th percentile for each row and divides it by the total number of columns.

```
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)
```

```
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
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
```

This creates three new columns in the dataframe and calculating specific values for them. The line prints the values 1a, 11, and 111 which are rounded percentages of all the percentiles. This is used to analyze how the values in each row compare to certain percentiles.

```
# df_m
```

This means that executed as part of the code. Used to make notes and helpful for future references.

```
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 |

This list specifies the columns you want to select from the dataframe. This is useful if you want to focus on a specific set of columns.

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', 'Flor
        'Zip Code': ['35201','36101','36601','35801','35401','35216','36301','36830','35601','35756','35630','35901','35216','36066','36867'

df = pd.DataFrame(data)

# Create a list of zip codes
zip_codes = ['35201', '36101', '36601', '35801', '35401', '35216',
             '36301', '36830', '35601', '35756', '35630', '35901',
             '35216', '36066', '36867', '35007', '35020',
             '36330', 36801, 35209, 35473, 35124, 35173, 35213, 36532]

# Add the list of zip codes as a new column to the dataframe
# df = df.assign(Zip_Codes=zip_codes)
df_m = df_m.assign(zip=zip_codes)


print(df_m)
```

```
                City     1     2     3     4     5     6     7     8     9  ...  \
0         Birmingham  8285  5343  6738  6635  5658  8118  4311  8535  3436  ...
1         Montgomery  1287  6585  8300  8874  8208  5363  3552  3387  2765  ...
2             Mobile  8035  5569  9492  5905  5024  1107  6937  5580  8044  ...
3         Huntsville  6280  2841  3399  5448  6173  5451  7488  9981  5236  ...
4         Tuscaloosa  4079  1066  3923  4177  4277  4219  9436  8160  4302  ...
5             Hoover  9741  7377  9410  9790  8864  2522  5347  9145  8402  ...
6             Dothan  7646  2060  4911  4976  7851  4277  7423  6183  6641  ...
7             Auburn  4326  2659  6928  4656  1828  5199  5331  6294  3076  ...
8            Decatur  3786  2891  8124  2469  3704  3623  2409  8287  2032  ...
9            Madison  1934  3628  9190  3275  9344  5778  1256  3523  1781  ...
10          Florence  8017  3187  1128  4706  9962  7547  4440  4530  9569  ...
11           Gadsden  2290  6402  8598  7547  5158  9731  8038  4435  7357  ...
12  Vestavia Hills  9471  9142  4419  3846  2016  5069  4853  6336  9062  ...
13       Prattville  6039  8003  6180  4610  3548  7115  6720  8512  9954  ...
14      Phenix City  8788  8269  6838  2863  6753  6608  4048  8774  4513  ...
15        Alabaster  1733  9767  3274  7125  7437  5748  5399  6513  3038  ...
16         Bessemer  6559  2453  1578  5158  3058  8075  7066  8530  8346  ...
17       Enterprise  8436  7800  7234  5063  4274  1948  7887  6647  1320  ...
18          Opelika  9998  8953  7923  6176  4369  9503  2126  1816  9224  ...
19         Homewood  2373  7188  9880  9236  5969  9998  8703  8440  4643  ...
20        Northport  3536  9231  8651  6374  4842  5704  8484  6322  2012  ...
21           Pelham  6830  3736  2734  6443  8494  6206  7290  8518  6176  ...
22       Trussville  2794  8273  9174  2850  8351  3978  5995  4632  7693  ...
23  Mountain Brook  8433  9368  2141  2357  6566  1482  4787  3900  6615  ...
24         Fairhope  8114  1464  2811  3090  4686  7995  7676  1304  7332  ...

      36    37    38    39    40    41  25qt  50qt  75qt    zip
0   3555  1341  1756  7598  1509  1861  28.6  55.8  77.3  35201
```

```
1   2805  4601  4449  5727  2315  8822  21.4  55.8  70.5  36101
2   9807  2652  9296  2815  4886  7458  38.1  60.5  79.5  36601
3   7935  2605  9982  3338  9116  3875  26.2  51.2  77.3  35801
4   3657  2158  4469  2513  8135  6963  21.4  60.5  79.5  35401
5   9748  7224  4628  8107  6143  1671  16.7  34.9  59.1  35216
6   5650  4400  7842  4006  9335  3571  19.0  55.8  90.9  36301
7   4387  6890  2833  5083  9707  2116  23.8  51.2  79.5  36830
8   9305  6509  6848  5408  3707  8744  21.4  46.5  70.5  35601
9   1746  4470  7054  6573  3556  1374  28.6  48.8  75.0  35756
10  5929  1123  7306  8746  4000  6943  26.2  48.8  63.6  35630
11  2549  5175  5997  9608  7230  9731  19.0  41.9  68.2  35901
12  5142  9619  9601  8099  1391  6276  26.2  53.5  70.5  35216
13  1591  4401  3457  4245  4341  2573  23.8  44.2  75.0  36066
14  3520  7654  6845  7738  3828  1202  28.6  48.8  75.0  36867
15  2479  9673  7478  7207  7006  3523  28.6  41.9  84.1  35007
16  4810  7641  5365  3545  6812  9483  14.3  46.5  70.5  35020
17  3461  2640  4375  8634  4917  2830  19.0  41.9  72.7  36330
18  5191  9304  2720  3100  3912  1548  28.6  55.8  72.7  36801
19  8787  5459  8389  5242  2224  6025  19.0  41.9  68.2  35209
20  6947  5401  6681  9018  1668  8307  28.6  53.5  75.0  35473
21  2777  4045  7309  4745  4284  2640  23.8  51.2  72.7  35124
22  1650  9470  6356  4700  3344  8743  33.3  48.8  75.0  35173
23  5765  3653  5198  9266  4945  3935  19.0  53.5  70.5  35213
24  3457  4808  7227  5482  6355  4553  33.3  67.4  86.4  36532

[25 rows x 46 columns]
```

This creates a dataframe with city names and zip codes and then you can attempt to add zip codes as a new column to another dataframe.

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')
```

This provides an index object listing all the names. The colmns with numbers can represent different variables.

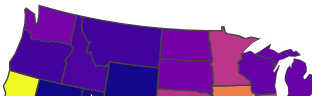
Here this command is used to retrieve the names of the columns.

```
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 code creates a choropleth map using the data in df_demo which reads the material from the GitHub website. The locationmode='USA-states' tells plotly to interpret the locations as a U.S. state, color='total exports' sets the variable that will determine the color of each state and scope='usa' limits the map to just the United States. This code is effective for data visualization such as agricultural exports across different states in the U.S. in 2011.



```
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 |

Double-click (or enter) to edit

Each row in this data represents a state and the columns provide specific details about different types of agriculture produced exported from the U.S.

Double-click (or enter) to edit

```
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')
```

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 25 | MT | Montana | state | 1718.00 | 105.0 | 16.7 | 1.7 | 6.82 | 1.1 | 2.2 |

Based on the data provided earlier, the output df_demo.columns would be an index objext listing all the column headers in the dataframe.

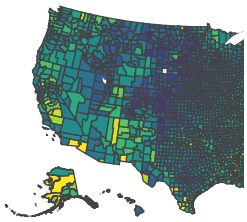
map demo #2: state of AL

```
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()
```



This is creating a choropleth map using Plotly Express. This map shows the unemployment rate across different counties of the United States. with urlopen ('...) as a response statement opens a URL to get GeoJSON data.

```
df_us.columns
```

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

This command when used in Pandas dataframe returns the names of the columns in the dataframe.

```
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

Here each row in the dataframe represents a county identified by its FIPS code along with its corresponding unemployment rate. For instance, the first row of 01001 indicates that the county with that FIPS code had an unemployement rate od 5.3%

Double-click (or enter) to edit

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
```

The list of al_fips contains a total of 25 items each. Maps out the county name to its corresponding FIPS.

```
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')
```

This dataframe is a mix of city names, numerical data across 42 columns, percentile calculations and zip codes.

Double-click (or enter) to edit

```
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 | 9100 | 3275 | 9344 | 5778 | 1256 | 3523 | 1781 | ... | 1746 | 4470 | 76 |

df_m represents the dataframe when using the pandas library and here it contains data for 25 different cities with information across 46 different columns.

Double-click (or enter) to edit

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

```
25
```

This is used to find number of rows in the dataframe. In pandas, shape attribute returns a tuple representing the dimensoinality of the data. The output 25 indicates that the dataframe contains 25 rows.

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **18** | Opelika | 9998 | 8953 | 7923 | 6176 | 4369 | 9503 | 2126 | 1816 | 9224 | ... | 5191 | 9304 | 27 |

Double-click (or enter) to edit

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
```

This expression is used to print the length of the list al_fips which is the number of items in the list. Given the output is 25 it returns 50.

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

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

This prints the name of the counties in the dataframe.

df_m: all display data, per store

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

```
25
```

This is used to find number of rows in the dataframe. In pandas, shape attribute returns a tuple representing the dimensoinality of the data. The output 25 indicates that the dataframe contains 25 rows.

Double-click (or enter) to edit

fips codes per county

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

```
25
```

There are 25 different entries in the df_counties dataframe.

Double-click (or enter) to edit

```
df_counties.columns
```

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

This is structured with two columns one for county names and another for the corresponding FIPS. The column names are presented in a pandas index.

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 | 813 |

This merges two dataframes into one named merged_df using pandas concat function.

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')
```

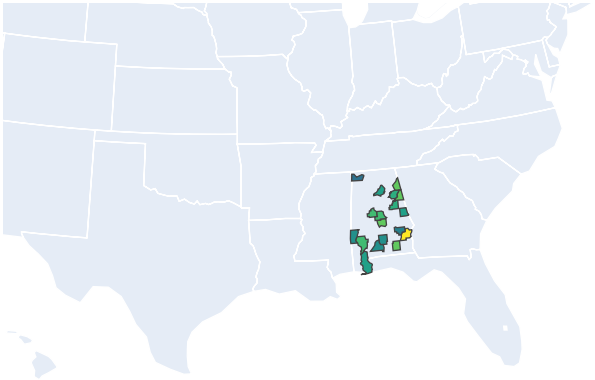
This shows the column names of the merged dataframe. Representing columns from the numbers 1 through 41, columns representing percentiles, counties, and fips code. Useful to analyze both sets of data.

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()
```



This code sets up a choropleth map using plotly integrating the merged dataframe merged_df with GeoJSON object ('counties')

```
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()
```

This provides a choropleth map of Albama's counties showing unemployment rates using plotly. The csv file containing unemployment rate data would be loaded into the pandas dataframe. The data includes fips codes and px.choropleth() creates the map using df and counties for the geographical layout.