PANDAS 001 - Transforming DataFrames

Inspecting a DataFrame
When you get a new DataFrame to work with, the first thing you need to do is explore it and see what it contains. There are several useful methods and attributes for this.
.head() returns the first few rows (the "head" of the DataFrame).
.info() shows information on each of the columns, such as the data type and number of missing values.
.shape returns the number of rows and columns of the DataFrame.
.describe() calculates a few summary statistics for each column.
homelessness is a DataFrame containing estimates of homelessness in each U.S. state in 2018. The individual column is the number of homeless individuals not part of a family with children. The family_members column is the number of homeless individuals part of a family with children. The state_pop column is the state's total population.

Import Pandas

Print the head of the homelessness DataFrame.

In [21]:

```
import pandas as pd

#load data
homelessness = pd.read_csv('homelessness.csv')#Path to the dataset(file)

# Print the head of the homelessness data
print(homelessness.head())
```

```
   Unnamed: 0              region       state  individuals  family_members  \
0           0  East South Central     Alabama       2570.0           864.0
1           1             Pacific      Alaska       1434.0           582.0
2           2            Mountain     Arizona       7259.0          2606.0
3           3  West South Central    Arkansas       2280.0           432.0
4           4             Pacific  California     109008.0         20964.0

   state_pop
0    4887681
1     735139
2    7158024
3    3009733
4   39461588
```

Print information about the column types and missing values in homelessness

In [22]:

```
# Print information about homelessness
print(homelessness.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Unnamed: 0      51 non-null     int64
 1   region          51 non-null     object
 2   state           51 non-null     object
 3   individuals     51 non-null     float64
 4   family_members  51 non-null     float64
 5   state_pop       51 non-null     int64
dtypes: float64(2), int64(2), object(2)
memory usage: 2.5+ KB
None
```

Print the number of rows and columns in homelessness

In [23]:

```
# Print the shape of homelessness
print(homelessness.shape)
```

```
(51, 6)
```

Print some summary statistics that describe the homelessness DataFrame.

In [24]:

```
#summary statistics
print(homelessness.describe())
```

```
       Unnamed: 0    individuals  family_members     state_pop
count   51.000000      51.000000       51.000000  5.100000e+01
mean    25.000000    7225.784314     3504.882353  6.405637e+06
std     14.866069   15991.025083     7805.411811  7.327258e+06
min      0.000000     434.000000       75.000000  5.776010e+05
25%     12.500000    1446.500000      592.000000  1.777414e+06
50%     25.000000    3082.000000     1482.000000  4.461153e+06
75%     37.500000    6781.500000     3196.000000  7.340946e+06
max     50.000000  109008.000000    52070.000000  3.946159e+07
```

Parts of a DataFrame
To better understand DataFrame objects, it's useful to know that they consist of three components, stored as attributes:

.values: A two-dimensional NumPy array of values.
.columns: An index of columns: the column names.
.index: An index for the rows: either row numbers or row names.
You can usually think of indexes as a list of strings or numbers, though the pandas Index data type allows for more sophisticated options. (These will be covered later in the course.)

TASKS
Print a 2D NumPy array of the values in homelessness.
Print the column names of homelessness.
Print the index of homelessness

In [25]:

```
# Print the values of homelessness
print(homelessness.values)

# Print the column index of homelessness
print(homelessness.columns)

# Print the row index of homelessnes
print(homelessness.index)
```

```
[[0 'East South Central' 'Alabama' 2570.0 864.0 4887681]
 [1 'Pacific' 'Alaska' 1434.0 582.0 735139]
 [2 'Mountain' 'Arizona' 7259.0 2606.0 7158024]
 [3 'West South Central' 'Arkansas' 2280.0 432.0 3009733]
 [4 'Pacific' 'California' 109008.0 20964.0 39461588]
 [5 'Mountain' 'Colorado' 7607.0 3250.0 5691287]
 [6 'New England' 'Connecticut' 2280.0 1696.0 3571520]
 [7 'South Atlantic' 'Delaware' 708.0 374.0 965479]
 [8 'South Atlantic' 'District of Columbia' 3770.0 3134.0 701547]
 [9 'South Atlantic' 'Florida' 21443.0 9587.0 21244317]
 [10 'South Atlantic' 'Georgia' 6943.0 2556.0 10511131]
 [11 'Pacific' 'Hawaii' 4131.0 2399.0 1420593]
 [12 'Mountain' 'Idaho' 1297.0 715.0 1750536]
 [13 'East North Central' 'Illinois' 6752.0 3891.0 12723071]
```

```
 [14 'East North Central' 'Indiana' 3776.0 1482.0 6695497]
 [15 'West North Central' 'Iowa' 1711.0 1038.0 3148618]
 [16 'West North Central' 'Kansas' 1443.0 773.0 2911359]
 [17 'East South Central' 'Kentucky' 2735.0 953.0 4461153]
 [18 'West South Central' 'Louisiana' 2540.0 519.0 4659690]
 [19 'New England' 'Maine' 1450.0 1066.0 1339057]
 [20 'South Atlantic' 'Maryland' 4914.0 2230.0 6035802]
 [21 'New England' 'Massachusetts' 6811.0 13257.0 6882635]
 [22 'East North Central' 'Michigan' 5209.0 3142.0 9984072]
 [23 'West North Central' 'Minnesota' 3993.0 3250.0 5606249]
 [24 'East South Central' 'Mississippi' 1024.0 328.0 2981020]
 [25 'West North Central' 'Missouri' 3776.0 2107.0 6121623]
 [26 'Mountain' 'Montana' 983.0 422.0 1060665]
 [27 'West North Central' 'Nebraska' 1745.0 676.0 1925614]
 [28 'Mountain' 'Nevada' 7058.0 486.0 3027341]
 [29 'New England' 'New Hampshire' 835.0 615.0 1353465]
 [30 'Mid-Atlantic' 'New Jersey' 6048.0 3350.0 8886025]
 [31 'Mountain' 'New Mexico' 1949.0 602.0 2092741]
 [32 'Mid-Atlantic' 'New York' 39827.0 52070.0 19530351]
 [33 'South Atlantic' 'North Carolina' 6451.0 2817.0 10381615]
 [34 'West North Central' 'North Dakota' 467.0 75.0 758080]
 [35 'East North Central' 'Ohio' 6929.0 3320.0 11676341]
 [36 'West South Central' 'Oklahoma' 2823.0 1048.0 3940235]
 [37 'Pacific' 'Oregon' 11139.0 3337.0 4181886]
 [38 'Mid-Atlantic' 'Pennsylvania' 8163.0 5349.0 12800922]
 [39 'New England' 'Rhode Island' 747.0 354.0 1058287]
 [40 'South Atlantic' 'South Carolina' 3082.0 851.0 5084156]
 [41 'West North Central' 'South Dakota' 836.0 323.0 878698]
 [42 'East South Central' 'Tennessee' 6139.0 1744.0 6771631]
 [43 'West South Central' 'Texas' 19199.0 6111.0 28628666]
 [44 'Mountain' 'Utah' 1904.0 972.0 3153550]
 [45 'New England' 'Vermont' 780.0 511.0 624358]
 [46 'South Atlantic' 'Virginia' 3928.0 2047.0 8501286]
 [47 'Pacific' 'Washington' 16424.0 5880.0 7523869]
 [48 'South Atlantic' 'West Virginia' 1021.0 222.0 1804291]
 [49 'East North Central' 'Wisconsin' 2740.0 2167.0 5807406]
 [50 'Mountain' 'Wyoming' 434.0 205.0 577601]]
Index(['Unnamed: 0', 'region', 'state', 'individuals', 'family_members',
       'state_pop'],
      dtype='object')
RangeIndex(start=0, stop=51, step=1)
```

SORTING ROWS
Finding interesting bits of data in a DataFrame is often easier if you change the order of the rows.
You can sort the rows by passing a column name to .sort_values().

In cases where rows have the same value (this is common if you sort on a categorical variable),
you may wish to break the ties by sorting on another column.
You can sort on multiple columns in this way by passing a list of column names.

Sort on … Syntax

one column df.sort_values("breed")
multiple columns df.sort_values(["breed", "weight_kg"])

By combining .sort_values() with .head(), you can answer questions in the form, "What are the top cases where…?".

TASK
Sort homelessness by the number of homeless individuals, from smallest to largest,
and save this as *homelessness_ind.*

Print the head of the sorted DataFrame

Print the head of the sorted DataFrame.

In [26]:

```
# Sort homelessness by individual
homelessness_ind = homelessness.sort_values("individuals")

# Print the top few rows
print(homelessness_ind.head())
```

```
    Unnamed: 0              region         state  individuals  family_members  \
50          50            Mountain       Wyoming        434.0           205.0
34          34  West North Central  North Dakota        467.0            75.0
7            7      South Atlantic      Delaware        708.0           374.0
39          39         New England  Rhode Island        747.0           354.0
45          45         New England       Vermont        780.0           511.0

    state_pop
50     577601
34     758080
7      965479
39    1058287
45     624358
```

TASK

**Sort homelessness by the number of homeless family_members in descending order,
and save this as homelessness_fam.**

Print the head of the sorted DataFrame.

In [27]:

```
# Sort homelessness by descending family members
homelessness_fam = homelessness.sort_values("family_members",ascending = False)

# Print the top few rows
print(homelessness_fam.head())
```

```
    Unnamed: 0              region          state  individuals  \
32          32        Mid-Atlantic       New York      39827.0
4            4             Pacific     California     109008.0
21          21         New England  Massachusetts       6811.0
9            9      South Atlantic        Florida      21443.0
43          43  West South Central          Texas      19199.0

    family_members  state_pop
32         52070.0   19530351
4          20964.0   39461588
21         13257.0    6882635
9           9587.0   21244317
43          6111.0   28628666
```

**Sort homelessness first by region (ascending),
and then by number of family members (descending).
Save this as homelessness_reg_fam.
Print the head of the sorted DataFrame.**

In [28]:

```
# Sort homelessness by region, then descending family members
homelessness_reg_fam = homelessness.sort_values(["region","family_members"],ascending =[
True,False])


# Print the top few rows
print(homelessness_reg_fam.head())
```

```
    Unnamed: 0              region      state  individuals  family_members  \
```

```
13          13  East North Central   Illinois       6752.0          3891.0
35          35  East North Central       Ohio       6929.0          3320.0
22          22  East North Central   Michigan       5209.0          3142.0
49          49  East North Central  Wisconsin       2740.0          2167.0
14          14  East North Central    Indiana       3776.0          1482.0

    state_pop
13   12723071
35   11676341
22    9984072
49    5807406
14    6695497
```

Subsetting columns

When working with data, you may not need all of the variables in your dataset.
Square brackets ([]) can be used to select only the columns that matter to you in an order that makes sense to you.

To select only "col_a" of the DataFrame df, use
df["col_a"]

To select "col_a" and "col_b" of df, use
df[["col_a", "col_b"]]

TAST Create a DataFrame called individuals that contains only the individuals column of homelessness.

Print the head of the result.

In [29]:

```
# Select the individuals column
individuals = homelessness["individuals"]

# Print the head of the result
print(individuals.head())
```

```
0      2570.0
1      1434.0
2      7259.0
3      2280.0
4    109008.0
Name: individuals, dtype: float64
```

Create a DataFrame called *state_fam* that contains only the state and *family_members* columns of *homelessness*, in that order.
Print the head of the result.

In [30]:

```
# Select the state and family_members columns
state_fam = homelessness[["state", "family_members"]]

# Print the head of the result
print(state_fam.head())
```

```
        state  family_members
0     Alabama           864.0
1      Alaska           582.0
2     Arizona          2606.0
3    Arkansas           432.0
4  California         20964.0
```

Create a DataFrame called *ind_state* that contains the individuals and state columns of *homelessness*, in that order.
Print the head of the result.

In [31]:

```
# Select only the individuals and state columns, in that order
ind_state = homelessness[["individuals", "state"]]

# Print the head of the result
print(ind_state.head())
```

```
   individuals       state
0       2570.0     Alabama
1       1434.0      Alaska
2       7259.0     Arizona
3       2280.0    Arkansas
4     109008.0  California
```

Subsetting rows

A large part of data science is about finding which bits of your dataset are interesting.
One of the simplest techniques for this is to find a subset of rows that match some criteria.
This is sometimes known as filtering rows or selecting rows.

There are many ways to subset a DataFrame, perhaps the most common is to use relational operators to return True or False for each row, then pass that inside square brackets.

dogs[dogs["height_cm"] > 60]
dogs[dogs["color"] == "tan"]

You can filter for multiple conditions at once by using the *"bitwise and" operator, &*.

dogs[(dogs["height_cm"] > 60) & (dogs["color"] == "tan")]

...

Tasks

Filter homelessness for cases where the number of individuals is greater than ten thousand, assigning to ind_gt_10k.

View the printed result.

In [32]:

```
# Filter for rows where individuals is greater than 10000
ind_gt_10k = homelessness[homelessness["individuals"]>10000]

# See the result
print(ind_gt_10k)
```

```
    Unnamed: 0              region       state  individuals  family_members  \
4            4             Pacific  California     109008.0         20964.0
9            9      South Atlantic     Florida      21443.0          9587.0
32          32        Mid-Atlantic    New York      39827.0         52070.0
37          37             Pacific      Oregon      11139.0          3337.0
43          43  West South Central       Texas      19199.0          6111.0
47          47             Pacific  Washington      16424.0          5880.0

    state_pop
4    39461588
9    21244317
32   19530351
37    4181886
43   28628666
47    7523869
```

Filter homelessness for cases where the USA Census region is "Mountain", assigning to mountain_reg. View the printed result.

In [33]:

```
# Filter for rows where region is Mountain
mountain_reg = homelessness[homelessness['region']=='Mountain']

# See the result
print(mountain_reg)
```

```
    Unnamed: 0    region       state  individuals  family_members  state_pop
2            2  Mountain     Arizona       7259.0          2606.0    7158024
5            5  Mountain    Colorado       7607.0          3250.0    5691287
12          12  Mountain       Idaho       1297.0           715.0    1750536
26          26  Mountain     Montana        983.0           422.0    1060665
28          28  Mountain      Nevada       7058.0           486.0    3027341
31          31  Mountain  New Mexico       1949.0           602.0    2092741
44          44  Mountain        Utah       1904.0           972.0    3153550
50          50  Mountain     Wyoming        434.0           205.0     577601
```

Filter homelessness for cases where the number of family_members is less than one thousand and the region is "Pacific", assigning to fam_lt_1k_pac. View the printed result.

In [34]:

```
# Filter for rows where family_members is less than 1000
# and region is Pacific
fam_lt_1k_pac = homelessness[(homelessness['family_members']<1000) & (homelessness['regi
on']=='Pacific')]

# See the result
print(fam_lt_1k_pac)
```

```
   Unnamed: 0   region   state  individuals  family_members  state_pop
1           1  Pacific  Alaska       1434.0           582.0     735139
```

Subsetting rows by categorical variables
Subsetting data based on a categorical variable often involves using the "or" operator (|) to select rows from multiple categories.
This can get tedious when you want all states in one of three different regions, for example.
Instead, use the .isin() method, which will allow you to tackle this problem by writing one condition instead of three separate ones.

```
colors = ["brown", "black", "tan"]
condition = dogs["color"].isin(colors)
dogs[condition]
```

...

Filter homelessness for cases where the USA census region is *"South Atlantic"* or it is *"Mid-Atlantic"*, assigning to *south_mid_atlantic*.

View the printed result.

In [35]:

```
# Subset for rows in South Atlantic or Mid-Atlantic regions
li = ["South Atlantic","Mid-Atlantic"]
south_mid_atlantic = homelessness[homelessness['region'].isin(li)]

# See the result
print(south_mid_atlantic)
```

```
    Unnamed: 0          region                state  individuals  \
7            7  South Atlantic             Delaware        708.0
8            8  South Atlantic  District of Columbia       3770.0
9            9  South Atlantic              Florida      21443.0
10          10  South Atlantic              Georgia       6943.0
20          20  South Atlantic             Maryland       4914.0
30          30    Mid-Atlantic           New Jersey       6048.0
32          32    Mid-Atlantic             New York      39827.0
```

```
33          33  South Atlantic        North Carolina       6451.0
38          38    Mid-Atlantic          Pennsylvania       8163.0
40          40  South Atlantic        South Carolina       3082.0
46          46  South Atlantic              Virginia       3928.0
48          48  South Atlantic         West Virginia       1021.0

    family_members  state_pop
7            374.0     965479
8           3134.0     701547
9           9587.0   21244317
10          2556.0   10511131
20          2230.0    6035802
30          3350.0    8886025
32         52070.0   19530351
33          2817.0   10381615
38          5349.0   12800922
40           851.0    5084156
46          2047.0    8501286
48           222.0    1804291
```

Filter homelessness for cases where the USA census state is in the list of Mojave states, canu, assigning to mojave_homelessness.

View the printed result.

In [36]:

```
# The Mojave Desert states
canu = ["California", "Arizona", "Nevada", "Utah"]

# Filter for rows in the Mojave Desert states
mojave_homelessness = homelessness[homelessness["state"].isin(canu)]

# See the result
print(mojave_homelessness)
```

```
    Unnamed: 0    region       state  individuals  family_members  state_pop
2            2  Mountain     Arizona       7259.0          2606.0    7158024
4            4   Pacific  California     109008.0         20964.0   39461588
28          28  Mountain      Nevada       7058.0           486.0    3027341
44          44  Mountain        Utah       1904.0           972.0    3153550
```

Adding new columns
You aren't stuck with just the data you are given. Instead, you can add new columns to a DataFrame. This has many names, such as transforming, mutating, and feature engineering.

You can create new columns from scratch, but it is also common to derive them from other columns, for example, by adding columns together or by changing their units.

...

Add a new column to homelessness, named total, containing the sum of the individuals and family_members columns.

Add another column to homelessness, named p_individuals, containing the proportion of homeless people in each state who are individuals

In [37]:

```
# Add total col as sum of individuals and family_members
homelessness['total'] = homelessness['individuals'] + homelessness['family_members']

# Add p_individuals col as proportion of individuals
homelessness['p_individuals'] = homelessness['individuals']/homelessness['total']

# See the result
print(homelessness)
```

```
    Unnamed: 0             region                 state  individuals  \
```

0	0	East South Central	Alabama	2570.0
1	1	Pacific	Alaska	1434.0
2	2	Mountain	Arizona	7259.0
3	3	West South Central	Arkansas	2280.0
4	4	Pacific	California	109008.0
5	5	Mountain	Colorado	7607.0
6	6	New England	Connecticut	2280.0
7	7	South Atlantic	Delaware	708.0
8	8	South Atlantic	District of Columbia	3770.0
9	9	South Atlantic	Florida	21443.0
10	10	South Atlantic	Georgia	6943.0
11	11	Pacific	Hawaii	4131.0
12	12	Mountain	Idaho	1297.0
13	13	East North Central	Illinois	6752.0
14	14	East North Central	Indiana	3776.0
15	15	West North Central	Iowa	1711.0
16	16	West North Central	Kansas	1443.0
17	17	East South Central	Kentucky	2735.0
18	18	West South Central	Louisiana	2540.0
19	19	New England	Maine	1450.0
20	20	South Atlantic	Maryland	4914.0
21	21	New England	Massachusetts	6811.0
22	22	East North Central	Michigan	5209.0
23	23	West North Central	Minnesota	3993.0
24	24	East South Central	Mississippi	1024.0
25	25	West North Central	Missouri	3776.0
26	26	Mountain	Montana	983.0
27	27	West North Central	Nebraska	1745.0
28	28	Mountain	Nevada	7058.0
29	29	New England	New Hampshire	835.0
30	30	Mid-Atlantic	New Jersey	6048.0
31	31	Mountain	New Mexico	1949.0
32	32	Mid-Atlantic	New York	39827.0
33	33	South Atlantic	North Carolina	6451.0
34	34	West North Central	North Dakota	467.0
35	35	East North Central	Ohio	6929.0
36	36	West South Central	Oklahoma	2823.0
37	37	Pacific	Oregon	11139.0
38	38	Mid-Atlantic	Pennsylvania	8163.0
39	39	New England	Rhode Island	747.0
40	40	South Atlantic	South Carolina	3082.0
41	41	West North Central	South Dakota	836.0
42	42	East South Central	Tennessee	6139.0
43	43	West South Central	Texas	19199.0
44	44	Mountain	Utah	1904.0
45	45	New England	Vermont	780.0
46	46	South Atlantic	Virginia	3928.0
47	47	Pacific	Washington	16424.0
48	48	South Atlantic	West Virginia	1021.0
49	49	East North Central	Wisconsin	2740.0
50	50	Mountain	Wyoming	434.0

	family_members	state_pop	total	p_individuals
0	864.0	4887681	3434.0	0.748398
1	582.0	735139	2016.0	0.711310
2	2606.0	7158024	9865.0	0.735834
3	432.0	3009733	2712.0	0.840708
4	20964.0	39461588	129972.0	0.838704
5	3250.0	5691287	10857.0	0.700654
6	1696.0	3571520	3976.0	0.573441
7	374.0	965479	1082.0	0.654344
8	3134.0	701547	6904.0	0.546060
9	9587.0	21244317	31030.0	0.691041
10	2556.0	10511131	9499.0	0.730919
11	2399.0	1420593	6530.0	0.632619
12	715.0	1750536	2012.0	0.644632
13	3891.0	12723071	10643.0	0.634408
14	1482.0	6695497	5258.0	0.718144
15	1038.0	3148618	2749.0	0.622408
16	773.0	2911359	2216.0	0.651173
17	953.0	4461153	3688.0	0.741594
18	519.0	4659690	3059.0	0.830337

19	1066.0	1339057	2516.0	0.576312
20	2230.0	6035802	7144.0	0.687850
21	13257.0	6882635	20068.0	0.339396
22	3142.0	9984072	8351.0	0.623758
23	3250.0	5606249	7243.0	0.551291
24	328.0	2981020	1352.0	0.757396
25	2107.0	6121623	5883.0	0.641849
26	422.0	1060665	1405.0	0.699644
27	676.0	1925614	2421.0	0.720777
28	486.0	3027341	7544.0	0.935578
29	615.0	1353465	1450.0	0.575862
30	3350.0	8886025	9398.0	0.643541
31	602.0	2092741	2551.0	0.764014
32	52070.0	19530351	91897.0	0.433387
33	2817.0	10381615	9268.0	0.696051
34	75.0	758080	542.0	0.861624
35	3320.0	11676341	10249.0	0.676066
36	1048.0	3940235	3871.0	0.729269
37	3337.0	4181886	14476.0	0.769481
38	5349.0	12800922	13512.0	0.604130
39	354.0	1058287	1101.0	0.678474
40	851.0	5084156	3933.0	0.783626
41	323.0	878698	1159.0	0.721311
42	1744.0	6771631	7883.0	0.778764
43	6111.0	28628666	25310.0	0.758554
44	972.0	3153550	2876.0	0.662031
45	511.0	624358	1291.0	0.604183
46	2047.0	8501286	5975.0	0.657406
47	5880.0	7523869	22304.0	0.736370
48	222.0	1804291	1243.0	0.821400
49	2167.0	5807406	4907.0	0.558386
50	205.0	577601	639.0	0.679186

Combo-attack! You've seen the four most common types of data manipulation: sorting rows, subsetting columns, subsetting rows, and adding new columns.
In a real-life data analysis, you can mix and match these four manipulations to answer a multitude of questions.

In this exercise, you'll answer the question, "Which state has the highest number of homeless individuals per 10,000 people in the state?" Combine your new pandas skills to find out.

Add a column to homelessness, indiv_per_10k, containing the number of homeless individuals per ten thousand people in each state.
Subset rows where indiv_per_10k is higher than 20, assigning to high_homelessness.

Sort high_homelessness by descending indiv_per_10k, assigning to high_homelessness_srt.

Select only the state and indiv_per_10k columns of high_homelessness_srt and save as result. Look at the result.

...

In [38]:

```
# Create indiv_per_10k col as homeless individuals per 10k state pop
homelessness["indiv_per_10k"] = 10000 * (homelessness['individuals'] /homelessness['stat
e_pop'])

# Subset rows for indiv_per_10k greater than 20
high_homelessness = homelessness[homelessness['indiv_per_10k']>20]

# Sort high_homelessness by descending indiv_per_10k
high_homelessness_srt = high_homelessness.sort_values('indiv_per_10k',ascending=False)

# From high_homelessness_srt, select the state and indiv_per_10k cols
result = high_homelessness_srt[['state', 'indiv_per_10k']]

# See the result
print(result)
```

```
                state  indiv_per_10k
```

8	District of Columbia	53.738381
11	Hawaii	29.079406
4	California	27.623825
37	Oregon	26.636307
28	Nevada	23.314189
47	Washington	21.829195
32	New York	20.392363