- Author: Marco Bours
- Date: Aug 13, 2020
- Context: Final Project for the course 'Making Money with Data' lectured by Jitesh Shah from Microfacturing Institutes in cooperation with the Extension of the University of California, Santa Cruz

Contents

Where is the best place for a teacher to live in California?

In the news you constantly read and hear that teachers in Californian urban areas can barely make a living. Transparent California (https://transparentcalifornia.com/ (https://transparentcalifornia.com/)) offers income data on K-12 Schools to give the Californian inhabitants accountability for the educational spending. Together with cost of living data provided by salary.com (https://www.salary.com/research/cost-of-living/ca (https://www.salary.com/research/cost-of-living/ca)) it is possible to see how teachers fair in different counties. Is it better for a teacher in the country side or is a higher salary in the urban areas worthwhile?

1 What is the cost of living in California?

Let's take a look at the cost of living. To get an idea how the cost of living is distributed over California, the table with cost of living is seperated into 5 categories. Each county is then colored according to the category. From the colorful map we can now see where the cost of living clusters.

1.1 Process the cost of living data

Process the cost of living data to check for completeness and create 5 categories of cost of living

```
In [1]: import pandas as pd
```

```
In [2]: col=pd.read_csv('CostOfLovingCAByCounty.csv')
```

In [3]:
```
col.sort_values(by = 'CostOfLiving')
```

Out[3]:
```
              City         County       State  CostOfLiving
106  Crescent City      Del Norte  California          86.8
 92        Alturas          Modoc  California          86.8
 98     Susanville         Lassen  California          92.8
 91     Bridgeport           Mono  California          93.7
 83          Yreka       Siskiyou  California          94.5
...            ...            ...         ...           ...
  2       San Jose    Santa Clara  California         151.4
 62    Santa Clara    Santa Clara  California         151.4
  3  San Francisco  San Francisco  California         162.5
 96     San Rafael          Marin  California         162.5
 21      Daly City      San Mateo  California         162.5
```

In [4]:
```
# Calculate the minumum and maximum 'CostOfLiving'
# Take the range and divide it into 5 equal categories
col_min=col['CostOfLiving'].min()
col_max=col['CostOfLiving'].max()
col_range=col_max-col_min
bucket_size=col_range/5
limit1=col_min+bucket_size
limit2=col_min + 2*bucket_size
limit3=col_min + 3*bucket_size
limit4=col_max-bucket_size
# print(col_min, col_max, col_range, bucket_size)
```

In [5]:
```
# Create a function to split the 'CostOfLiving' into 5 categories
def color_code(number):
    if number <= limit1:
        return 1
    elif number <= limit2:
        return 2
    elif number <= limit3:
        return 3
    elif number <= limit4:
        return 4
    else:
        return 5
```

In [6]:

```
col['ColorCode']=col['CostOfLiving'].apply(color_code)
col
```

Out[6]:

	City	County	State	CostOfLiving	ColorCode
0	Los Angeles	Los Angeles	California	142.6	4
1	San Diego	San Diego	California	138.6	4
2	San Jose	Santa Clara	California	151.4	5
3	San Francisco	San Francisco	California	162.5	5
4	Fresno	Fresno	California	110.3	2
...	...	...	...	...	...
107	Colusa	Colusa	California	99.9	1
108	San Andreas	Calaveras	California	125.9	3
109	Jackson	Amador	California	120.5	3
110	Markleeville	Alpine	California	111.8	2
111	Oroville	Butte	California	118.5	3

https://en.wikipedia.org/wiki/List_of_counties_in_California (https://en.wikipedia.org/wiki/List_of_counties_in_California)

In [7]:

```
# Verify that the list of counties is complete
counties=pd.read_csv('CACounties.csv')
counties
```

Out[7]:

	County	FIPS code	County seat	Est	Formed from	Etymology	General Law or Charter	Population	Area_sc
0	Yuba	115	Marysville	1850	original	Named either by the Maidu people a local Nativ...	General Law	78668	6
1	Yolo	113	Woodland	1850	original	The Yolan people a local Native American tribe.	General Law	220500	10
2	Ventura	111	Ventura	1872	Santa Barbara	The city of Ventura derived from Mission San B...	General Law	846006	18

In [8]:

```
# Check for typos. E.g. Los Angeles could also bw listed as Los Angelos.
col_counties=col['County'].unique()
col_counties.sort()
col_counties
```

Out[8]:

```
array(['Alameda', 'Alpine', 'Amador', 'Butte', 'Calaveras', 'Colusa',
       'Contra Costa', 'Del Norte', 'El Dorado', 'Fresno', 'Glenn',
       'Humboldt', 'Imperial', 'Inyo', 'Kern', 'Kings', 'Lake', 'Lassen',
       'Los Angeles', 'Madera', 'Marin', 'Mariposa', 'Mendocino',
       'Merced', 'Modoc', 'Mono', 'Monterey', 'Napa', 'Nevada', 'Orange',
       'Placer', 'Plumas', 'Riverside', 'Sacramento', 'San Benito',
       'San Bernardino', 'San Diego', 'San Francisco', 'San Joaquin',
       'San Luis Obispo', 'San Mateo', 'Santa Barbara', 'Santa Clara',
       'Santa Cruz', 'Shasta', 'Sierra', 'Siskiyou', 'Solano', 'Sonoma',
       'Stanislaus', 'Sutter', 'Tehama', 'Trinity', 'Tulare', 'Tuolumne',
       'Ventura', 'Yolo', 'Yuba'], dtype=object)
```

In [9]:

```
# How many counties are there in the list vs how many does Wikipedia say rh
len(col_counties)
```

Out[9]:

```
58
```

In [10]:

```
# If there is a county missing, get the county seat and look up the cost of
# Get all 'County seat'
counties.loc[
    (counties['County'] != col_counties[0]) &
    (counties['County'] != col_counties[1]) &
    (counties['County'] != col_counties[2]) &
    (counties['County'] != col_counties[3]) &
    (counties['County'] != col_counties[4]) &
    (counties['County'] != col_counties[5]) &
    (counties['County'] != col_counties[6]) &
    (counties['County'] != col_counties[7]) &
    (counties['County'] != col_counties[8]) &
    (counties['County'] != col_counties[9]) &
    (counties['County'] != col_counties[10]) &
    (counties['County'] != col_counties[11]) &
    (counties['County'] != col_counties[12]) &
    (counties['County'] != col_counties[13]) &
    (counties['County'] != col_counties[14]) &
    (counties['County'] != col_counties[15]) &
    (counties['County'] != col_counties[16]) &
    (counties['County'] != col_counties[17]) &
    (counties['County'] != col_counties[18]) &
    (counties['County'] != col_counties[19]) &
    (counties['County'] != col_counties[20]) &
    (counties['County'] != col_counties[21]) &
    (counties['County'] != col_counties[22]) &
    (counties['County'] != col_counties[23]) &
    (counties['County'] != col_counties[24]) &
    (counties['County'] != col_counties[25]) &
    (counties['County'] != col_counties[26]) &
    (counties['County'] != col_counties[27]) &
    (counties['County'] != col_counties[28]) &
    (counties['County'] != col_counties[29]) &
    (counties['County'] != col_counties[30]) &
    (counties['County'] != col_counties[31]) &
    (counties['County'] != col_counties[32]) &
    (counties['County'] != col_counties[33]) &
    (counties['County'] != col_counties[34]) &
    (counties['County'] != col_counties[35]) &
    (counties['County'] != col_counties[36]) &
    (counties['County'] != col_counties[37]) &
    (counties['County'] != col_counties[38]) &
    (counties['County'] != col_counties[39]) &
    (counties['County'] != col_counties[40]) &
    (counties['County'] != col_counties[41]) &
    (counties['County'] != col_counties[42]) &
    (counties['County'] != col_counties[43]) &
    (counties['County'] != col_counties[44]) &
    (counties['County'] != col_counties[45]) &
    (counties['County'] != col_counties[46]) &
    (counties['County'] != col_counties[47]) &
    (counties['County'] != col_counties[48]) &
    (counties['County'] != col_counties[49]) &
    (counties['County'] != col_counties[50]) &
    (counties['County'] != col_counties[51]) &
    (counties['County'] != col_counties[52]) &
    (counties['County'] != col_counties[53]) &
    (counties['County'] != col_counties[54]) &
    (counties['County'] != col_counties[55]) &
    (counties['County'] != col_counties[56]) &
    (counties['County'] != col_counties[57])
     ]['County seat']
```

```
Out[10]: Series([], Name: County seat, dtype: object)
```

In [11]:

```
# Get all 'County' to find missing entries in col_counties
counties.loc[
    (counties['County'] != col_counties[0]) &
    (counties['County'] != col_counties[1]) &
    (counties['County'] != col_counties[2]) &
    (counties['County'] != col_counties[3]) &
    (counties['County'] != col_counties[4]) &
    (counties['County'] != col_counties[5]) &
    (counties['County'] != col_counties[6]) &
    (counties['County'] != col_counties[7]) &
    (counties['County'] != col_counties[8]) &
    (counties['County'] != col_counties[9]) &
    (counties['County'] != col_counties[10]) &
    (counties['County'] != col_counties[11]) &
    (counties['County'] != col_counties[12]) &
    (counties['County'] != col_counties[13]) &
    (counties['County'] != col_counties[14]) &
    (counties['County'] != col_counties[15]) &
    (counties['County'] != col_counties[16]) &
    (counties['County'] != col_counties[17]) &
    (counties['County'] != col_counties[18]) &
    (counties['County'] != col_counties[19]) &
    (counties['County'] != col_counties[20]) &
    (counties['County'] != col_counties[21]) &
    (counties['County'] != col_counties[22]) &
    (counties['County'] != col_counties[23]) &
    (counties['County'] != col_counties[24]) &
    (counties['County'] != col_counties[25]) &
    (counties['County'] != col_counties[26]) &
    (counties['County'] != col_counties[27]) &
    (counties['County'] != col_counties[28]) &
    (counties['County'] != col_counties[29]) &
    (counties['County'] != col_counties[30]) &
    (counties['County'] != col_counties[31]) &
    (counties['County'] != col_counties[32]) &
    (counties['County'] != col_counties[33]) &
    (counties['County'] != col_counties[34]) &
    (counties['County'] != col_counties[35]) &
    (counties['County'] != col_counties[36]) &
    (counties['County'] != col_counties[37]) &
    (counties['County'] != col_counties[38]) &
    (counties['County'] != col_counties[39]) &
    (counties['County'] != col_counties[40]) &
    (counties['County'] != col_counties[41]) &
    (counties['County'] != col_counties[42]) &
    (counties['County'] != col_counties[43]) &
    (counties['County'] != col_counties[44]) &
    (counties['County'] != col_counties[45]) &
    (counties['County'] != col_counties[46]) &
    (counties['County'] != col_counties[47]) &
    (counties['County'] != col_counties[48]) &
    (counties['County'] != col_counties[49]) &
    (counties['County'] != col_counties[50]) &
    (counties['County'] != col_counties[51]) &
    (counties['County'] != col_counties[52]) &
    (counties['County'] != col_counties[53]) &
    (counties['County'] != col_counties[54]) &
    (counties['County'] != col_counties[55]) &
    (counties['County'] != col_counties[56]) &
    (counties['County'] != col_counties[57])
     ]['County']
```

Out[11]:

```
Series([], Name: County, dtype: object)
```

In [12]:

```
# Get the entire list of County not in col_counties
# If the list is empty, all counties are in col_counties
counties.loc[
    (counties['County'] != col_counties[0]) &
    (counties['County'] != col_counties[1]) &
    (counties['County'] != col_counties[2]) &
    (counties['County'] != col_counties[3]) &
    (counties['County'] != col_counties[4]) &
    (counties['County'] != col_counties[5]) &
    (counties['County'] != col_counties[6]) &
    (counties['County'] != col_counties[7]) &
    (counties['County'] != col_counties[8]) &
    (counties['County'] != col_counties[9]) &
    (counties['County'] != col_counties[10]) &
    (counties['County'] != col_counties[11]) &
    (counties['County'] != col_counties[12]) &
    (counties['County'] != col_counties[13]) &
    (counties['County'] != col_counties[14]) &
    (counties['County'] != col_counties[15]) &
    (counties['County'] != col_counties[16]) &
    (counties['County'] != col_counties[17]) &
    (counties['County'] != col_counties[18]) &
    (counties['County'] != col_counties[19]) &
    (counties['County'] != col_counties[20]) &
    (counties['County'] != col_counties[21]) &
    (counties['County'] != col_counties[22]) &
    (counties['County'] != col_counties[23]) &
    (counties['County'] != col_counties[24]) &
    (counties['County'] != col_counties[25]) &
    (counties['County'] != col_counties[26]) &
    (counties['County'] != col_counties[27]) &
    (counties['County'] != col_counties[28]) &
    (counties['County'] != col_counties[29]) &
    (counties['County'] != col_counties[30]) &
    (counties['County'] != col_counties[31]) &
    (counties['County'] != col_counties[32]) &
    (counties['County'] != col_counties[33]) &
    (counties['County'] != col_counties[34]) &
    (counties['County'] != col_counties[35]) &
    (counties['County'] != col_counties[36]) &
    (counties['County'] != col_counties[37]) &
    (counties['County'] != col_counties[38]) &
    (counties['County'] != col_counties[39]) &
    (counties['County'] != col_counties[40]) &
    (counties['County'] != col_counties[41]) &
    (counties['County'] != col_counties[42]) &
    (counties['County'] != col_counties[43]) &
    (counties['County'] != col_counties[44]) &
    (counties['County'] != col_counties[45]) &
    (counties['County'] != col_counties[46]) &
    (counties['County'] != col_counties[47]) &
    (counties['County'] != col_counties[48]) &
    (counties['County'] != col_counties[49]) &
    (counties['County'] != col_counties[50]) &
    (counties['County'] != col_counties[51]) &
    (counties['County'] != col_counties[52]) &
    (counties['County'] != col_counties[53]) &
    (counties['County'] != col_counties[54]) &
    (counties['County'] != col_counties[55]) &
    (counties['County'] != col_counties[56]) &
    (counties['County'] != col_counties[57])
     ]
```

Out[12]:

County	FIPS code	County seat	Est	Formed from	Etymology	General Law or Charter	Population	Area_sqmi	Area_km2

In [13]:

```
# This is a helper to find missing counties
# Only print the first 3 columns of county to help match the county with it
counties.iloc[:,0:3]
```

Out[13]:

	County	FIPS code	County seat
0	Yuba	115	Marysville
1	Yolo	113	Woodland
2	Ventura	111	Ventura
3	Tuolumne	109	Sonora
4	Tulare	107	Visalia
5	Trinity	105	Weaverville
6	Tehama	103	Red Bluff
7	Sutter	101	Yuba City
8	Stanislaus	99	Modesto
9	Sonoma	97	Santa Rosa
10	Solano	95	Fairfield
11	Siskiyou	93	Yreka
12	Sierra	91	Downieville
13	Shasta	89	Redding
14	Santa Cruz	87	Santa Cruz
15	Santa Clara	85	San Jose
16	Santa Barbara	83	Santa Barbara
17	San Mateo	81	Redwood City
18	San Luis Obispo	79	San Luis Obispo
19	San Joaquin	77	Stockton
20	San Francisco	75	San Francisco
21	San Diego	73	San Diego
22	San Bernardino	71	San Bernardino
23	San Benito	69	Hollister
24	Sacramento	67	Sacramento
25	Riverside	65	Riverside
26	Plumas	63	Quincy
27	Placer	61	Auburn
28	Orange	59	Santa Ana
29	Nevada	57	Nevada City
30	Napa	55	Napa
31	Monterey	53	Salinas

	County	FIPS code	County seat
32	Mono	51	Bridgeport
33	Modoc	49	Alturas
34	Merced	47	Merced
35	Mendocino	45	Ukiah
36	Mariposa	43	Mariposa
37	Marin	41	San Rafael
38	Madera	39	Madera
39	Los Angeles	37	Los Angeles
40	Lassen	35	Susanville
41	Lake	33	Lakeport
42	Kings	31	Hanford
43	Kern	29	Bakersfield
44	Inyo	27	Independence
45	Imperial	25	El Centro
46	Humboldt	23	Eureka
47	Glenn	21	Willows
48	Fresno	19	Fresno
49	El Dorado	17	Placerville
50	Del Norte	15	Crescent City
51	Contra Costa	13	Martinez
52	Colusa	11	Colusa
53	Calaveras	9	San Andreas
54	Butte	7	Oroville
55	Amador	5	Jackson
56	Alpine	3	Markleeville
57	Alameda	1	Oakland

In [14]:

```
# This is a helper to find missing counties
# Only get the 'County seat' and 'County' to match the county with its seat
counties[['County seat', 'County']]
```

Out[14]:

	County seat	County
0	Marysville	Yuba
1	Woodland	Yolo
2	Ventura	Ventura
3	Sonora	Tuolumne
4	Visalia	Tulare
5	Weaverville	Trinity
6	Red Bluff	Tehama
7	Yuba City	Sutter
8	Modesto	Stanislaus
9	Santa Rosa	Sonoma
10	Fairfield	Solano
11	Yreka	Siskiyou
12	Downieville	Sierra
13	Redding	Shasta
14	Santa Cruz	Santa Cruz
15	San Jose	Santa Clara
16	Santa Barbara	Santa Barbara
17	Redwood City	San Mateo
18	San Luis Obispo	San Luis Obispo
19	Stockton	San Joaquin
20	San Francisco	San Francisco
21	San Diego	San Diego
22	San Bernardino	San Bernardino
23	Hollister	San Benito
24	Sacramento	Sacramento
25	Riverside	Riverside
26	Quincy	Plumas
27	Auburn	Placer
28	Santa Ana	Orange
29	Nevada City	Nevada
30	Napa	Napa
31	Salinas	Monterey

	County seat	County
32	Bridgeport	Mono
33	Alturas	Modoc
34	Merced	Merced
35	Ukiah	Mendocino
36	Mariposa	Mariposa
37	San Rafael	Marin
38	Madera	Madera
39	Los Angeles	Los Angeles
40	Susanville	Lassen
41	Lakeport	Lake
42	Hanford	Kings
43	Bakersfield	Kern
44	Independence	Inyo
45	El Centro	Imperial
46	Eureka	Humboldt
47	Willows	Glenn
48	Fresno	Fresno
49	Placerville	El Dorado
50	Crescent City	Del Norte
51	Martinez	Contra Costa
52	Colusa	Colusa
53	San Andreas	Calaveras
54	Oroville	Butte
55	Jackson	Amador
56	Markleeville	Alpine
57	Oakland	Alameda

1.2 Create a color coded map

Color Scheme:

- 1 Blue - cheapest
- 2 Green - cheap
- 3 Yellow - medium
- 4 Orange - expensive

- 5 Red - most expensive

Fill in the map with colors. Fill ColorCode 1 counties with blue, ColorCode 2 counties with green, ColorCode 3 counties with yellow, ColorCode 4 counties with orange and ColorCode 5 counties with red.

In [15]:

```
# blue
col.loc[col['ColorCode'] == 1].sort_values('CostOfLiving')
```

Out[15]:

	City	County	State	CostOfLiving	ColorCode
92	Alturas	Modoc	California	86.8	1
106	Crescent City	Del Norte	California	86.8	1
98	Susanville	Lassen	California	92.8	1
91	Bridgeport	Mono	California	93.7	1
83	Yreka	Siskiyou	California	94.5	1
88	Quincy	Plumas	California	99.8	1
84	Downieville	Sierra	California	99.9	1
107	Colusa	Colusa	California	99.9	1
97	Madera	Madera	California	101.9	1

```
In [16]: # Green
         col.loc[col['ColorCode'] == 2].sort_values('CostOfLiving')
```

Out[16]:

	City	County	State	CostOfLiving	ColorCode
101	Independence	Inyo	California	106.3	2
89	Nevada City	Nevada	California	108.9	2
75	Visalia	Tulare	California	109.0	2
100	Hanford	Kings	California	109.3	2
51	Pasadena	Los Angeles	California	109.6	2
4	Fresno	Fresno	California	110.3	2
104	Willows	Glenn	California	110.4	2
82	Yuba City	Sutter	California	110.4	2
110	Markleeville	Alpine	California	111.8	2
10	Bakersfield	Kern	California	112.6	2
55	Rialto	San Bernardino	California	113.2	2
56	Riverside	Riverside	California	113.2	2
47	Ontario	San Bernardino	California	113.2	2
41	Moreno Valley	Riverside	California	113.2	2
28	Fontana	San Bernardino	California	113.2	2
19	Corona	Riverside	California	113.2	2
9	Apple Valley	San Bernardino	California	113.2	2
54	Rancho Cucamonga	San Bernardino	California	113.2	2
59	San Bernardino	San Bernardino	California	113.2	2
105	Placerville	El Dorado	California	113.5	2
80	Weaverville	Trinity	California	114.5	2
85	Redding	Shasta	California	114.9	2
81	Red Bluff	Tehama	California	117.0	2

In [17]:

```
# Yellow
col.loc[col['ColorCode'] == 3].sort_values('CostOfLiving')
```

Out[17]:

	City	County	State	CostOfLiving	ColorCode
111	Oroville	Butte	California	118.5	3
15	Chico	Butte	California	118.5	3
79	Sonora	Tuolumne	California	118.5	3
86	San Luis Obispo	San Luis Obispo	California	119.5	3
78	Woodland	Yolo	California	120.5	3
77	Marysville	Yuba	California	120.5	3
109	Jackson	Amador	California	120.5	3
57	Roseville	Placer	California	120.5	3
5	Sacramento	Sacramento	California	120.5	3
25	Elk Grove	Sacramento	California	120.5	3
95	Mariposa	Mariposa	California	121.1	3
103	Eureka	Humboldt	California	122.6	3
52	Petaluma	Sonoma	California	122.6	3
99	Lakeport	Lake	California	122.6	3
66	Santa Rosa	Sonoma	California	122.6	3
39	Modesto	Stanislaus	California	122.6	3
94	Ukiah	Mendocino	California	122.6	3
38	Lompoc	Santa Barbara	California	123.1	3
73	Ventura	Ventura	California	124.8	3
49	Oxnard	Ventura	California	124.8	3
61	Santa Barbara	Santa Barbara	California	125.3	3
108	San Andreas	Calaveras	California	125.9	3
17	Coachella	Riverside	California	125.9	3
67	Simi Valley	Ventura	California	126.4	3
70	Thousand Oaks	Ventura	California	126.4	3
65	Santa Maria	Santa Barbara	California	126.8	3
37	Lancaster	Los Angeles	California	127.0	3
63	Santa Clarita	Los Angeles	California	127.2	3
50	Palmdale	Los Angeles	California	127.3	3
43	Newhall	Los Angeles	California	127.5	3
26	Escondido	San Diego	California	131.5	3
93	Merced	Merced	California	131.6	3

	City	County	State	CostOfLiving	ColorCode
74	Victorville	San Bernardino	California	131.9	3
13	Carlsbad	San Diego	California	132.0	3
46	Oceanside	San Diego	California	132.0	3

In [18]:

```python
# Orange
col.loc[col['ColorCode'] == 4].sort_values('CostOfLiving')
```

Out[18]:

	City	County	State	CostOfLiving	ColorCode
69	Temecula	Riverside	California	132.5	4
42	Murrieta	Riverside	California	132.8	4
102	El Centro	Imperial	California	134.6	4
87	Hollister	San Benito	California	136.1	4
1	San Diego	San Diego	California	138.6	4
16	Chula Vista	San Diego	California	138.6	4
23	El Cajon	San Diego	California	138.6	4
64	Santa Cruz	Santa Cruz	California	139.9	4
11	Berkeley	Alameda	California	141.3	4
18	Concord	Contra Costa	California	141.3	4
45	Oakland	Alameda	California	141.3	4
8	Antioch	Contra Costa	California	141.3	4
27	Fairfield	Solano	California	141.6	4
72	Vallejo	Solano	California	141.6	4
76	West Covina	Los Angeles	California	142.1	4
30	Fullerton	Orange	California	142.1	4
31	Garden Grove	Orange	California	142.1	4
60	Santa Ana	Orange	California	142.1	4
53	Pomona	Los Angeles	California	142.1	4
48	Orange	Orange	California	142.1	4
20	Costa Mesa	Orange	California	142.1	4
36	Irvine	Orange	California	142.1	4
44	Norwalk	Los Angeles	California	142.1	4
7	Anaheim	Orange	California	142.1	4
71	Torrance	Los Angeles	California	142.6	4
0	Los Angeles	Los Angeles	California	142.6	4
35	Inglewood	Los Angeles	California	142.6	4
34	Huntington Beach	Orange	California	142.6	4
32	Glendale	Los Angeles	California	142.6	4
24	El Monte	Los Angeles	California	142.6	4
22	Downey	Los Angeles	California	142.6	4
14	Carson	Los Angeles	California	142.6	4

	City	County	State	CostOfLiving	ColorCode
12	Burbank	Los Angeles	California	142.6	4
6	Long Beach	Los Angeles	California	142.6	4
90	Napa	Napa	California	143.3	4
29	Fremont	Alameda	California	143.3	4
68	Stockton	San Joaquin	California	143.3	4
33	Hayward	Alameda	California	143.3	4
58	Salinas	Monterey	California	144.7	4
40	Monterey	Monterey	California	144.7	4

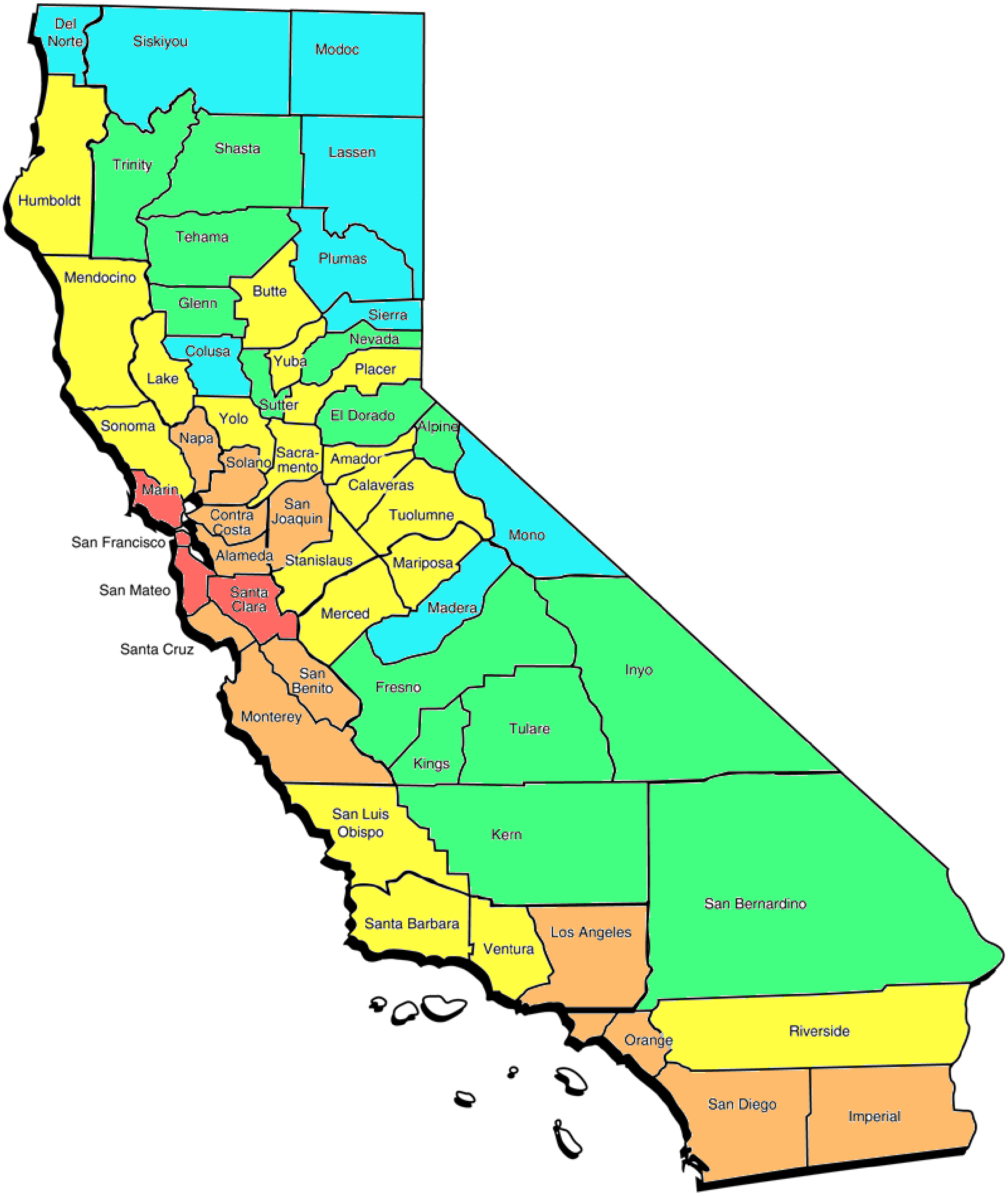
In [19]:

```
# Red
col.loc[col['ColorCode'] == 5].sort_values('CostOfLiving')
```

Out[19]:

	City	County	State	CostOfLiving	ColorCode
2	San Jose	Santa Clara	California	151.4	5
62	Santa Clara	Santa Clara	California	151.4	5
3	San Francisco	San Francisco	California	162.5	5
21	Daly City	San Mateo	California	162.5	5
96	San Rafael	Marin	California	162.5	5

Now let's take a look at the map with all counties colored.



1.3 What can you read from the colorful map?

California has 2 centers where the cost of living is very high: Los Angeles and the San Francisco Bay Area. From the 2 centers, the San Francisco Bay Area has the highest cost of living. In general, it is more expensive at the coast and cheaper to live further north. If you go further away from the 2 centers and the coast, the lower the cost of living gets. The cost of living is the lowest bordering Oregon and Nevada (North East).

2 What does a teacher earn?

Now, that we know, how the cost of living is distributed over the counties of California, let's take a look at teachers salaries. The data offered at Transparent California is quite extensive. Since there are 5 categories for cost of living, the teachers salary should be collection in each category. Since this process is labor intensive and done manually, below is the sample list of counties considered for this project.

Red Category:

- San Francisco (sf)
- Santa Clara (sc)

Orange Category:

- Alameda (ala)
- Orange (oc)

Yellow Category:

- Sacramento (sac)
- Butte (bt)

Green Category:

- Alpine (alp)
- Kern (kc)

Blue Category:

- Mono (mn)
- Modoc (md)

In [20]:

```
# Create a list of the counties in the sample. The abbreviation is used for
# district csv files for 2017 and 2018 each.
sample_counties=[['San Francisco', 'sf', 1],['Santa Clara', 'sc', 33],['Ala
                 ['Orange','oc', 30], ['Sacramento', 'sac', 13], ['Butte',
                 ['Alpine', 'alp', 2],['Kern', 'kc', 45],['Mono', 'mn', 3],
sample_counties
```

Out[20]:

```
[['San Francisco', 'sf', 1],
 ['Santa Clara', 'sc', 33],
 ['Alameda', 'ala', 17],
 ['Orange', 'oc', 30],
 ['Sacramento', 'sac', 13],
 ['Butte', 'bt', 14],
 ['Alpine', 'alp', 2],
 ['Kern', 'kc', 45],
 ['Mono', 'mn', 3],
 ['Modoc', 'md', 3]]
```

2.1 Load and scrub the data

On the Transparent California web page you can download csv files for school districts. The files are grouped by county. Because not all school districts are on top of keeping this data current, the data for 2019 is very sparce. Because it was not clear whether the data for 2018 is complete enough for an analysis, I also collected the data for 2017. A few districts did not include 2018. In that case, I reused the 2017 data for 2018. If 2017 was missing, I used the 2016 data, if available and if not, I reused the 2018 data. If both 2018 and 2017 are not available the school district was skipped.

Once all the csv files where downloaded, I concatenated the files into one (counties/mkall.sh). In this process it was noted, that Orange County and Alameda County included csv files in a different format. I stored them in (county)2(year).csv and they are processed below.

In [21]:

```
# Load all 2018 data
# 10 Counties + 2 counties with extra data = 12
sf2018=  pd.read_csv('counties/san-francisco/all.2018.csv')
sc2018=  pd.read_csv('counties/santa-clara/all.2018.csv')
ala2018= pd.read_csv('counties/alameda/all.2018.csv')
ala22018=pd.read_csv('counties/alameda/all2.2018.csv')
oc2018=  pd.read_csv('counties/orange/all.2018.csv')
oc22018= pd.read_csv('counties/orange/all2.2018.csv')
sac2018= pd.read_csv('counties/sacramento/all.2018.csv')
bt2018=  pd.read_csv('counties/butte/all.2018.csv')
alp2018= pd.read_csv('counties/alpine/all.2018.csv')
kc2018=  pd.read_csv('counties/kern/all.2018.csv')
mn2018=  pd.read_csv('counties/mono/all.2018.csv')
md2018=  pd.read_csv('counties/modoc/all.2018.csv')
```

In [22]:

```
# Load all 2017 data
sf2017=  pd.read_csv('counties/san-francisco/all.2017.csv')
sc2017=  pd.read_csv('counties/santa-clara/all.2017.csv')
ala2017= pd.read_csv('counties/alameda/all.2017.csv')
ala22017=pd.read_csv('counties/alameda/all2.2017.csv')
oc2017=  pd.read_csv('counties/orange/all.2017.csv')
oc22017= pd.read_csv('counties/orange/all2.2017.csv')
sac2017= pd.read_csv('counties/sacramento/all.2017.csv')
bt2017=  pd.read_csv('counties/butte/all.2017.csv')
alp2017= pd.read_csv('counties/alpine/all.2017.csv')
kc2017=  pd.read_csv('counties/kern/all.2017.csv')
mn2017=  pd.read_csv('counties/mono/all.2017.csv')
md2017=  pd.read_csv('counties/modoc/all.2017.csv')
```

When I tried to concatenate the counties Orange and Alameda, there was an error message when reading the csv-file saying the number of columns did not match. I split the files into 2 different csv files. Now let's analyze how they can be joined.

In [23]:

```
oc2018.columns
```

Out[23]:

```
Index(['Employee Name', 'Job Title', 'Base Pay', 'Overtime Pay', 'Other P
ay',
       'Benefits', 'Total Pay', 'Total Pay & Benefits', 'Year', 'Notes',
       'Agency', 'Status'],
      dtype='object')
```

```
In [24]: oc22018.columns
```

```
Out[24]: Index(['Employee Name', 'Job Title', 'Base Pay', 'Overtime Pay', 'Other P
         ay',
                'Benefits', 'Total Pay', 'Pension Debt', 'Total Pay & Benefits',
         'Year',
                'Notes', 'Agency', 'Status'],
               dtype='object')
```

```
In [25]: ala2018.columns
```

```
Out[25]: Index(['Employee Name', 'Job Title', 'Base Pay', 'Overtime Pay', 'Other P
         ay',
                'Benefits', 'Total Pay', 'Total Pay & Benefits', 'Year', 'Notes',
                'Agency', 'Status'],
               dtype='object')
```

```
In [26]: ala22018.columns
```

```
Out[26]: Index(['Employee Name', 'Job Title', 'Base Pay', 'Overtime Pay', 'Other P
         ay',
                'Benefits', 'Total Pay', 'Pension Debt', 'Total Pay & Benefits',
         'Year',
                'Notes', 'Agency', 'Status'],
               dtype='object')
```

Some of the school district include an additional column 'Pension Debt'. Since 'Pension Debt' is not supplied by the other school disticts, this column is removed. While converting the columns into their proper data type, some columns included 'Not Provided' or 'Aggregate'. For simplicity their values are converted to 0.

```
In [27]: # Make the df mergable by removing columns from the <county>2<year> and
         # make sure the data type is the same.
         #
         #flight_data_copy.drop(['TailNum', 'OriginStateFips',
         #                 'DestStateFips', 'Diverted'], axis=1, inplace=True)

         oc22018.drop(['Pension Debt'], axis=1, inplace=True)
         ala22018.drop(['Pension Debt'], axis=1, inplace=True)

         bt2018[bt2018['Benefits'] == 'Not Provided'] = 0
         ala2018[ala2018['Benefits'] == 'Not Provided']=0

         oc2018[oc2018['Other Pay']=='Aggregate'] = 0
         oc22018[oc22018['Other Pay']=='Aggregate'] = 0
         bt2018[bt2018['Other Pay'] == 'Not Provided'] = 0
```

In [28]:

```
oc22017.drop(['Pension Debt'], axis=1, inplace=True)
ala22017.drop(['Pension Debt'], axis=1, inplace=True)

bt2017[bt2017['Benefits'] == 'Not Provided'] = 0
ala2017[ala2017['Benefits'] == 'Not Provided']=0

oc2017[oc2017['Other Pay']=='Aggregate'] = 0
oc22017[oc22017['Other Pay']=='Aggregate'] = 0
bt2017[bt2017['Other Pay'] == 'Not Provided'] = 0
```

```
/Users/marco/opt/anaconda3/lib/python3.7/site-packages/pandas/core/ops/ar
ray_ops.py:253: FutureWarning: elementwise comparison failed; returning s
calar instead, but in the future will perform elementwise comparison
  res_values = method(rvalues)
```

In [29]:

```
# Strip all headers 2018 otherwise the data type can not be converted
sf2018=    sf2018[(  sf2018['Job Title'] != 'Job Title')]
sc2018=    sc2018[(  sc2018['Job Title'] != 'Job Title')]
ala2018=  ala2018[( ala2018['Job Title'] != 'Job Title')]
ala22018=ala22018[(ala22018['Job Title'] != 'Job Title')]
oc2018=    oc2018[(  oc2018['Job Title'] != 'Job Title')]
oc22018=  oc22018[( oc22018['Job Title'] != 'Job Title')]
sac2018=  sac2018[( sac2018['Job Title'] != 'Job Title')]
bt2018=    bt2018[(  bt2018['Job Title'] != 'Job Title')]
alp2018=  alp2018[( alp2018['Job Title'] != 'Job Title')]
kc2018=    kc2018[(  kc2018['Job Title'] != 'Job Title')]
mn2018=    mn2018[(  mn2018['Job Title'] != 'Job Title')]
md2018=    md2018[(  md2018['Job Title'] != 'Job Title')]
```

In [30]:

```
# Strip all headers 2017
sf2017=    sf2017[(  sf2017['Job Title'] != 'Job Title')]
sc2017=    sc2017[(  sc2017['Job Title'] != 'Job Title')]
ala2017=  ala2017[( ala2017['Job Title'] != 'Job Title')]
ala22017=ala22017[(ala22017['Job Title'] != 'Job Title')]
oc2017=    oc2017[(  oc2017['Job Title'] != 'Job Title')]
oc22017=  oc22017[( oc22017['Job Title'] != 'Job Title')]
sac2017=  sac2017[( sac2017['Job Title'] != 'Job Title')]
bt2017=    bt2017[(  bt2017['Job Title'] != 'Job Title')]
alp2017=  alp2017[( alp2017['Job Title'] != 'Job Title')]
kc2017=    kc2017[(  kc2017['Job Title'] != 'Job Title')]
mn2017=    mn2017[(  mn2017['Job Title'] != 'Job Title')]
md2017=    md2017[(  md2017['Job Title'] != 'Job Title')]
```

Prepare all data types to be identical for a concatenation

In [31]:

```
# Convert 'Total Pay' into a float
dtype=float
for column in 'Total Pay', 'Base Pay', 'Overtime Pay','Benefits', 'Total Pa

    sf2018[column]   = sf2018[column].astype(dtype)
    sc2018[column]   = sc2018[column].astype(dtype)
    ala2018[column]  = ala2018[column].astype(dtype)  # 'Benefits' == 'Not
    ala22018[column] = ala22018[column].astype(dtype)
    oc2018[column]   = oc2018[column].astype(dtype)   # 'Other Pay'=='Aggre
    oc22018[column]  = oc22018[column].astype(dtype)  # 'Other Pay'=='Aggre
    sac2018[column]  = sac2018[column].astype(dtype)
    bt2018[column]   = bt2018[column].astype(dtype)   # Other Pay', 'Benefi
    alp2018[column]  = alp2018[column].astype(dtype)
    kc2018[column]   = kc2018[column].astype(dtype)
    mn2018[column]   = mn2018[column].astype(dtype)
    md2018[column]   = md2018[column].astype(dtype)

#sc2018['Total Pay']   = sc2018['Total Pay'].astype(float)
#ala2018['Total Pay']  = ala2018['Total Pay'].astype(float)
#ala22018['Total Pay'] = ala22018['Total Pay'].astype(float)
#oc2018['Total Pay']   = oc2018['Total Pay'].astype(float)
#oc22018['Total Pay']  = oc22018['Total Pay'].astype(float)
#sac2018['Total Pay']  = sac2018['Total Pay'].astype(float)
#bt2018['Total Pay']   = bt2018['Total Pay'].astype(float)
#alp2018['Total Pay']  = alp2018['Total Pay'].astype(float)
#kc2018['Total Pay']   = kc2018['Total Pay'].astype(float)
#mn2018['Total Pay']   = mn2018['Total Pay'].astype(float)
#md2018['Total Pay']   = md2018['Total Pay'].astype(float)
```

In [32]:

```
# Convert 'Total Pay' into a float
dtype=float
for column in 'Total Pay', 'Base Pay', 'Overtime Pay','Benefits', 'Total Pa

    sf2017[column]   = sf2017[column].astype(dtype)
    sc2017[column]   = sc2017[column].astype(dtype)
    ala2017[column]  = ala2017[column].astype(dtype)  # 'Benefits' == 'Not
    ala22017[column] = ala22017[column].astype(dtype)
    oc2017[column]   = oc2017[column].astype(dtype)   # 'Other Pay'=='Aggre
    oc22017[column]  = oc22017[column].astype(dtype)  # 'Other Pay'=='Aggre
    sac2017[column]  = sac2017[column].astype(dtype)
    bt2017[column]   = bt2017[column].astype(dtype)   # Other Pay', 'Benefi
    alp2017[column]  = alp2017[column].astype(dtype)
    kc2017[column]   = kc2017[column].astype(dtype)
    mn2017[column]   = mn2017[column].astype(dtype)
    md2017[column]   = md2017[column].astype(dtype)
```

In [33]:
```
# Convert 'Note' and 'Status' into strings
dtype=str
for column in 'Notes','Status':
    sf2018[column]   = sf2018[column].astype(dtype)
    sc2018[column]   = sc2018[column].astype(dtype)
    ala2018[column]  = ala2018[column].astype(dtype)
    ala22018[column] = ala22018[column].astype(dtype)
    oc2018[column]   = oc2018[column].astype(dtype)
    oc22018[column]  = oc22018[column].astype(dtype)
    sac2018[column]  = sac2018[column].astype(dtype)
    bt2018[column]   = bt2018[column].astype(dtype)
    alp2018[column]  = alp2018[column].astype(dtype)
    kc2018[column]   = kc2018[column].astype(dtype)
    mn2018[column]   = mn2018[column].astype(dtype)
    md2018[column]   = md2018[column].astype(dtype)
```

In [34]:
```
# Convert 'Note' and 'Status' into strings
dtype=str
for column in 'Notes','Status':
    sf2017[column]   = sf2017[column].astype(dtype)
    sc2017[column]   = sc2017[column].astype(dtype)
    ala2017[column]  = ala2017[column].astype(dtype)
    ala22017[column] = ala22017[column].astype(dtype)
    oc2017[column]   = oc2017[column].astype(dtype)
    oc22017[column]  = oc22017[column].astype(dtype)
    sac2017[column]  = sac2017[column].astype(dtype)
    bt2017[column]   = bt2017[column].astype(dtype)
    alp2017[column]  = alp2017[column].astype(dtype)
    kc2017[column]   = kc2017[column].astype(dtype)
    mn2017[column]   = mn2017[column].astype(dtype)
    md2017[column]   = md2017[column].astype(dtype)
```

In [35]:
```
# Convert 'Year' into an integer
dtype=int
sf2018['Year']   = sf2018['Year'].astype(dtype)
sc2018['Year'] = sc2018['Year'].astype(dtype)
ala2018['Year'] = ala2018['Year'].astype(dtype)
ala22018['Year'] = ala22018['Year'].astype(dtype)
oc2018['Year'] = oc2018['Year'].astype(dtype)
oc22018['Year'] = oc22018['Year'].astype(dtype)
sac2018['Year'] = sac2018['Year'].astype(dtype)
bt2018['Year'] = bt2018['Year'].astype(dtype)
alp2018['Year'] = alp2018['Year'].astype(dtype)
kc2018['Year'] = kc2018['Year'].astype(dtype)
mn2018['Year'] = mn2018['Year'].astype(dtype)
md2018['Year'] = md2018['Year'].astype(dtype)
```

In [36]:
```
# Does not work
#
#dtype=int
##dtype=int64
#for column in 'Year' :
#    sf2018[column]   = sf2018[column].astype(dtype)
#    sf2018[column]   = sf2018[column].astype(dtype)
#    ala2018[column]  = ala2018[column].astype(dtype)
#    ala22018[column] = ala22018[column].astype(dtype)
#    oc2018[column]   = oc2018[column].astype(dtype)
#    oc22018[column]  = oc22018[column].astype(dtype)
#    sac2018[column]  = sac2018[column].astype(dtype)
#    bt2018[column]   = bt2018[column].astype(dtype)
#    alp2018[column]  = alp2018[column].astype(dtype)
#    kc2018[column]   = kc2018[column].astype(dtype)
#    mn2018[column]   = mn2018[column].astype(dtype)
#    md2018[column]   = md2018[column].astype(dtype)
```

In [37]:
```
# Convert 'Year' into an integer
# Instead of for loop:
dtype=int
sf2017['Year']   = sf2017['Year'].astype(dtype)
sc2017['Year'] = sc2017['Year'].astype(dtype)
ala2017['Year'] = ala2017['Year'].astype(dtype)
ala22017['Year'] = ala22017['Year'].astype(dtype)
oc2017['Year'] = oc2017['Year'].astype(dtype)
oc22017['Year'] = oc22017['Year'].astype(dtype)
sac2017['Year'] = sac2017['Year'].astype(dtype)
bt2017['Year'] = bt2017['Year'].astype(dtype)
alp2017['Year'] = alp2017['Year'].astype(dtype)
kc2017['Year'] = kc2017['Year'].astype(dtype)
mn2017['Year'] = mn2017['Year'].astype(dtype)
md2017['Year'] = md2017['Year'].astype(dtype)
```

2.3 Concatenate

To get a meaningful result, all counties can only have one data frame. Merge Orange and Alameda county.

In [38]:
```
# concatenate the <county><year> with <county>2<tear>
oc2018=pd.concat([oc2018,oc22018])
ala2018=pd.concat([ala2018,ala22018])

# get rid of the <county>2<year> df
del [oc22018,ala22018]

# Call garbage collection to free up memory
import gc
gc.collect()
```

Out[38]:
```
60
```

In [39]:
```
# concatenate the <county><year> with <county>2<tear>
oc2017=pd.concat([oc2017,oc22017])
ala2017=pd.concat([ala2017,ala22017])

# get rid of the <county>2<year> df
del [oc22017,ala22017]

# Call garbage collection to free up memory
gc.collect()
```

Out[39]:
```
20
```

Clean up the data frames - redo the type conversion for oc2018, oc2017, ala2018, ala2017 This has been reset due to the concatenation

In [40]:
```
dtype=float
for column in 'Total Pay', 'Base Pay', 'Overtime Pay','Benefits', 'Total Pa
    oc2018[column]   = oc2018[column].astype(dtype)
    oc2017[column]   = oc2017[column].astype(dtype)
    ala2018[column]   = ala2018[column].astype(dtype)
    ala2017[column]   = ala2017[column].astype(dtype)
```

In [41]:
```
dtype=str
for column in 'Notes','Status':
    oc2018[column]   = oc2018[column].astype(dtype)
    oc2017[column]   = oc2017[column].astype(dtype)
    ala2018[column]   = ala2018[column].astype(dtype)
    ala2017[column]   = ala2017[column].astype(dtype)
```

In [42]:
```
dtype=int
oc2018['Year'] = oc2018['Year'].astype(dtype)
ala2018['Year'] = ala2018['Year'].astype(dtype)

oc2017['Year'] = oc2017['Year'].astype(dtype)
ala2017['Year'] = ala2017['Year'].astype(dtype)
```

Clean up the data frames - reduce columns

In [43]:
```
sf2018.columns
```

Out[43]:
```
Index(['Employee Name', 'Job Title', 'Base Pay', 'Overtime Pay', 'Other P
ay',
       'Benefits', 'Total Pay', 'Total Pay & Benefits', 'Year', 'Notes',
       'Agency', 'Status'],
      dtype='object')
```

In [44]:

```
# Since the concatenation of oc2018 with oc22018 and ala2018 with ala22018
# drop all columns not needed
# for column in 'Employee Name','Base Pay','Overtime Pay','Other Pay',\
#'Benefits','Total Pay & Benefits','Year','Notes','Agency','Status':
#    sf2018.drop([column], axis=1, inplace=True)
#    sc2018.drop([column], axis=1, inplace=True)
#    ala2018.drop([column], axis=1, inplace=True)
#    ala22018.drop([column], axis=1, inplace=True)
#    oc2018.drop([column], axis=1, inplace=True)
#    oc22018.drop([column], axis=1, inplace=True)
#    sac2018.drop([column], axis=1, inplace=True)
#    bt2018.drop([column], axis=1, inplace=True)
#    alp2018.drop([column], axis=1, inplace=True)
#    kc2018.drop([column], axis=1, inplace=True)
#    mn2018.drop([column], axis=1, inplace=True)
#    md2018.drop([column], axis=1, inplace=True)
```

Clean up the data frames - remove entries tainting the result

In [45]:

```
sc2018.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 42969 entries, 0 to 43000
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Employee Name         42969 non-null  object 
 1   Job Title             42969 non-null  object 
 2   Base Pay              42969 non-null  float64
 3   Overtime Pay          42969 non-null  float64
 4   Other Pay             42969 non-null  float64
 5   Benefits              42969 non-null  float64
 6   Total Pay             42969 non-null  float64
 7   Total Pay & Benefits  42969 non-null  float64
 8   Year                  42969 non-null  int64  
 9   Notes                 42969 non-null  object 
 10  Agency                42969 non-null  object 
 11  Status                42969 non-null  object 
dtypes: float64(6), int64(1), object(5)
memory usage: 4.3+ MB
```

In [46]:

```
# If'Total Pay' <= 0, it is assumed they did not work. Example: Substitute
# 'Total Pay' == 0.01, 0.02 look like a place holder
min_pay=0.02
```

In [47]:
```
# Strip all entries with 'Total Pay' <= min_pay, assuming they did not work
min_pay=0.02
sf2018=    sf2018[(  sf2018['Total Pay'] > min_pay)]
sc2018=    sc2018[(  sc2018['Total Pay'] > min_pay)]
ala2018=  ala2018[( ala2018['Total Pay'] > min_pay)]
oc2018=    oc2018[(  oc2018['Total Pay'] > min_pay)]
sac2018=  sac2018[( sac2018['Total Pay'] > min_pay)]
bt2018=    bt2018[(  bt2018['Total Pay'] > min_pay)]
alp2018=  alp2018[( alp2018['Total Pay'] > min_pay)]
kc2018=    kc2018[(  kc2018['Total Pay'] > min_pay)]
mn2018=    mn2018[(  mn2018['Total Pay'] > min_pay)]
md2018=    md2018[(  md2018['Total Pay'] > min_pay)]
```

In [48]:
```
# Strip all entries with 'Total Pay' <= 0, assuming they did not work.
sf2017=    sf2017[(  sf2017['Total Pay'] > min_pay)]
sc2017=    sc2017[(  sc2017['Total Pay'] > min_pay)]
ala2017=  ala2017[( ala2017['Total Pay'] > min_pay)]
oc2017=    oc2017[(  oc2017['Total Pay'] > min_pay)]
sac2017=  sac2017[( sac2017['Total Pay'] > min_pay)]
bt2017=    bt2017[(  bt2017['Total Pay'] > min_pay)]
alp2017=  alp2017[( alp2017['Total Pay'] > min_pay)]
kc2017=    kc2017[(  kc2017['Total Pay'] > min_pay)]
mn2017=    mn2017[(  mn2017['Total Pay'] > min_pay)]
md2017=    md2017[(  md2017['Total Pay'] > min_pay)]
```

Create lists with all sub-, aide-, monitor- jobs, so they can be excluded from the final result. These jobs do not work full time and with little to no income, taint the result.

In [49]:
```
sub=['Sub', 'sub', 'SUB', 'Aide', 'aide', 'AIDE', 'Monitor', 'monitor', 'MO
     'Non Regular Employees', 'Not Provide', 'Unknown' ]
sf2018_sub=sf2018[sf2018['Job Title'].apply(lambda x: any ([k in x for k in
sf2017_sub=sf2017[sf2017['Job Title'].apply(lambda x: any ([k in x for k in
```

In [50]:
```
sc2018_sub=sc2018[sc2018['Job Title'].apply(lambda x: any ([k in x for k in
sc2017_sub=sc2017[sc2017['Job Title'].apply(lambda x: any ([k in x for k in
```

In [51]:
```
oc2018_sub=oc2018[oc2018['Job Title'].apply(lambda x: any ([k in x for k in
oc2017_sub=oc2017[oc2017['Job Title'].apply(lambda x: any ([k in x for k in
```

In [52]:
```
#oc22018_sub=oc22018[oc22018['Job Title'].apply(lambda x: any ([k in x for
#oc22017_sub=oc22017[oc22017['Job Title'].apply(lambda x: any ([k in x for
```

In [53]:
```
ala2018_sub=ala2018[ala2018['Job Title'].apply(lambda x: any ([k in x for k
ala2017_sub=ala2017[ala2017['Job Title'].apply(lambda x: any ([k in x for k
```

In [54]:
```
#ala22018_sub=ala22018[ala22018['Job Title'].apply(lambda x: any ([k in x f
#ala22017_sub=ala22017[ala22017['Job Title'].apply(lambda x: any ([k in x f
```

In [55]:
```
sac2018_sub=sac2018[sac2018['Job Title'].apply(lambda x: any ([k in x for k
sac2017_sub=sac2017[sac2017['Job Title'].apply(lambda x: any ([k in x for k
```

In [56]:

```
bt2018_sub=bt2018[bt2018['Job Title'].apply(lambda x: any ([k in x for k in
bt2017_sub=bt2017[bt2017['Job Title'].apply(lambda x: any ([k in x for k in
```

In [57]:

```
alp2018_sub=alp2018[alp2018['Job Title'].apply(lambda x: any ([k in x for k
alp2017_sub=alp2017[alp2017['Job Title'].apply(lambda x: any ([k in x for k
```

In [58]:

```
kc2018_sub=kc2018[kc2018['Job Title'].apply(lambda x: any ([k in x for k in
kc2017_sub=kc2017[kc2017['Job Title'].apply(lambda x: any ([k in x for k in
```

In [59]:

```
mn2018_sub=mn2018[mn2018['Job Title'].apply(lambda x: any ([k in x for k in
mn2017_sub=mn2017[mn2017['Job Title'].apply(lambda x: any ([k in x for k in
```

In [60]:

```
md2018_sub=md2018[md2018['Job Title'].apply(lambda x: any ([k in x for k in
md2017_sub=md2017[md2017['Job Title'].apply(lambda x: any ([k in x for k in
```

Combine all lists

In [61]:

```
all2018_subs=list(sf2018_sub) + list(sc2018_sub) + list(oc2018_sub) + \
    list(ala2018_sub) + list(sac2018_sub) + list(bt2018_sub) + \
    list(alp2018_sub) + list(kc2018_sub) + list(mn2018_sub) + list(md2018_s
all2018_subs
```

Out[61]:

```
['Prop "A "Sub Teacher',
 'Child Dev Inst/Aide: Spanish',
 'Child Dev Inst/Aide: Cantonese',
 'Child Develop.- Inst/Aide Prog',
 'Child Dev Inst/Aide: Multiple',
 'Inst. Aide Elem Basic: Spanish',
 'Instruct Aide Pre-K: Spanish',
 'Day-To-Day Sub',
 'Child Dev Inst/Aide: Mandarin',
 'Inst/Aide Computer: Cantonese',
 'Inst/Aide Second Basic:Spanish',
 'Instruct Aide Pre-K Program',
 'Instruct Aide Pre-K: Cantonese',
 'Instructional Aide - Computer',
 'Instruc/Aide Elem-Basic Skills',
 'Inst/Aide Secon Basic:Multiple',
 'Instructional/Aide - Science',
 'Inst/Aide Sec. Basic:Cantonese',
 'Children Center Day-To-Day Sub',
```

In [62]:
```
all2017_subs=list(sf2017_sub) + list(sc2017_sub) + list(oc2017_sub) + \
    list(ala2017_sub) + list(sac2017_sub) + list(bt2017_sub) + \
    list(alp2017_sub) + list(kc2017_sub) + list(mn2017_sub) + list(md2017_s
all2017_subs
```

Out[62]:
```
['Child Develop.- Inst/Aide Prog',
 'Child Dev Inst/Aide: Cantonese',
 'Child Dev Inst/Aide: Spanish',
 'Child Dev Inst/Aide: Mandarin',
 'Child Dev Inst/Aide: Multiple',
 'Instruc/Aide Computer: Spanish',
 'Day-To-Day Sub',
 'Instruct Aide Pre-K Program',
 'Prop "A "Sub Teacher',
 'Instruct Aide Pre-K: Spanish',
 'Inst. Aide Elem Basic: Spanish',
 'Inst/Aide Second Basic:Spanish',
 'Instruct Aide Pre-K: Cantonese',
 'Instructional Aide - Computer',
 'Inst/Aide Computer: Cantonese',
 'Inst/Aide Secon Basic:Multiple',
 'Inst.Aide Elem Basic:Cantonese',
 'Inst/Aide Sec. Basic:Cantonese',
 'Instruc/Aide -Naturalist',
```

In [63]:
```
# Get the length of the sf2018 list and compare it after applying below lam
len(sf2018)
```

Out[63]:
```
12920
```

In [64]:
```
# Strip all 'Job Title' included in the sub list, since they do not work fo
#
# Does not work
# The output show the df is reduced by the sub jobs, but it is not assigned
#
sub=['Sub', 'sub', 'SUB']
sf2018=sf2018[sf2018['Job Title'].apply(lambda x: any ([k not in x for k in
sc2018=sc2018[sc2018['Job Title'].apply(lambda x: any ([k not in x for k in
ala2018=ala2018[ala2018['Job Title'].apply(lambda x: any ([k not in x for k
#ala22018=ala22018[ala22018['Job Title'].apply(lambda x: any ([k not in x f
oc2018=oc2018[oc2018['Job Title'].apply(lambda x: any ([k not in x for k in
#oc22018=oc22018[oc22018['Job Title'].apply(lambda x: any ([k not in x for
sac2018=sac2018[sac2018['Job Title'].apply(lambda x: any ([k not in x for k
bt2018=bt2018[bt2018['Job Title'].apply(lambda x: any ([k not in x for k in
alp2018=alp2018[alp2018['Job Title'].apply(lambda x: any ([k not in x for k
kc2018=kc2018[kc2018['Job Title'].apply(lambda x: any ([k not in x for k in
mn2018=mn2018[mn2018['Job Title'].apply(lambda x: any ([k not in x for k in
md2018=md2018[md2018['Job Title'].apply(lambda x: any ([k not in x for k in
```

In [65]:
```
sf2018[sf2018['Job Title'].apply(lambda x: any ([k in x for k in sub]))]
```

Out[65]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
5355	Melvin D. Ong	Prop "A "Sub Teacher	40435.30	0.0	4845.11	16230.09	45280.41	61510.50	2018	nan
5441	Alan Lovaasen	Prop "A "Sub Teacher	39084.75	0.0	4964.04	15411.00	44048.79	59459.79	2018	nan
5599	Matthew Zephaniah Akuluze	Prop "A "Sub Teacher	33069.73	0.0	5699.58	17029.21	38769.31	55798.52	2018	nan
5654	Bao Duc Dang	Prop "A "Sub Teacher	39058.09	0.0	3787.43	11484.14	42845.52	54329.66	2018	nan
5710	Ronald Wirth Trapp	Day-To-Day Sub	34998.89	0.0	4907.31	12824.57	39906.20	52730.77	2018	nan
...	...	...	...	...	...	...	...	...	...	...
12910	Hilda E Faziola	Day To Day Sub Teacher Retired	0.00	0.0	4.70	0.00	4.70	4.70	2018	nan
12911	Elisa Maria Legon	Day-To-Day Sub	0.00	0.0	4.70	0.00	4.70	4.70	2018	nan
12912	Katherine Elizabeth Williams	Day-To-Day Sub	0.00	0.0	4.70	0.00	4.70	4.70	2018	nan
12921	Valerie Ann Petrache Fernandez	Day-To-Day Sub	0.00	0.0	1.01	0.28	1.01	1.29	2018	nan
12934	Wendy Moreno	Day-To-Day Sub	0.00	0.0	37.63	-130.24	37.63	-92.61	2018	nan

1102 rows × 12 columns

In [66]:
```
len(sf2018)
```

Out[66]:
```
12920
```

The size of sf2018 has not changed. A different approach is necessary.

In [67]:
```
# df[df.country.isin(countries_to_keep)]
# df[~df.country.isin(countries_to_keep)]
#
# isin requires a perfect match. That means, collect all sub jobs with lamb
# use that list with isin
sf2018=sf2018[~sf2018['Job Title'].isin(all2018_subs)]
sc2018=sc2018[~sc2018['Job Title'].isin(all2018_subs)]
ala2018=ala2018[~ala2018['Job Title'].isin(all2018_subs)]
#ala22018=ala22018[~ala22018['Job Title'].isin(all2018_subs)]
oc2018=oc2018[~oc2018['Job Title'].isin(all2018_subs)]
#oc22018=oc22018[~oc22018['Job Title'].isin(all2018_subs)]
sac2018=sac2018[~sac2018['Job Title'].isin(all2018_subs)]
bt2018=bt2018[~bt2018['Job Title'].isin(all2018_subs)]
alp2018=alp2018[~alp2018['Job Title'].isin(all2018_subs)]
kc2018=kc2018[~kc2018['Job Title'].isin(all2018_subs)]
mn2018=mn2018[~mn2018['Job Title'].isin(all2018_subs)]
md2018=md2018[~md2018['Job Title'].isin(all2018_subs)]
```

In [68]:
```
sf2018[sf2018['Job Title'].apply(lambda x: any ([k in x for k in sub]))]
```

Out[68]:

Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes	Agency	Status

In [69]:
```
len(sf2018)
```

Out[69]:
```
10460
```

This time the modification worked.

In [70]:
```
# df[df.country.isin(countries_to_keep)]
# df[~df.country.isin(countries_to_keep)]
#
# isin requires a perfect match. That means, collect all sub jobs with lamb
# use that list with isin
sf2017=sf2017[~sf2017['Job Title'].isin(all2017_subs)]
sc2017=sc2017[~sc2017['Job Title'].isin(all2017_subs)]
ala2017=ala2017[~ala2017['Job Title'].isin(all2017_subs)]
#ala22017=ala22017[~ala22017['Job Title'].isin(all2017_subs)]
oc2017=oc2017[~oc2017['Job Title'].isin(all2017_subs)]
#oc22017=oc22017[~oc22017['Job Title'].isin(all2017_subs)]
sac2017=sac2017[~sac2017['Job Title'].isin(all2017_subs)]
bt2017=bt2017[~bt2017['Job Title'].isin(all2017_subs)]
alp2017=alp2017[~alp2017['Job Title'].isin(all2017_subs)]
kc2017=kc2017[~kc2017['Job Title'].isin(all2017_subs)]
mn2017=mn2017[~mn2017['Job Title'].isin(all2017_subs)]
md2017=md2017[~md2017['Job Title'].isin(all2017_subs)]
```

2.3 The counties

2.3.1 San Fransisco

Comment: In a first approach, I went over the list of 'Job Title' and tried to find those, who are actually teaching. This approach turned out to be to labor intensive for the due date of this project (Santa Clara County has 3800+ different Job Title). The second approach is to use all the jobs and only skip those, whose 'Total Pay' is deemed a real payment (values >0.02)

```
In [71]: # Display all Job Title
         sf2018['Job Title'].unique()
```

```
Out[71]: array(['Superintendent', 'Deputy Superintendent',
                'Chief General Counsel, Sfusd', 'Deputy Director',
                'Special Assistant Xvii', 'Chief Of Financial Officer',
                'Is Director', 'Chief', 'Sr Attorney Civil & Criminal',
                'Chief, Administrative Services', 'Project Manager Iii',
                'Dir Of Facili, Design & Constr', 'Assistant Superintendent',
                '9995 Dir Of Risk Management', 'Special Assistant Xix',
                'Executive Director', '1070 Is Project Director', 'Is Manager',
                'Director', 'School Facilities Planner', 'Project Manager Ii',
                'Educational Policy Analyst', 'Principal High School', 'Manager
         I',
                'Supervising Purchaser', 'Principal Elementary',
                'Special Assistant Xvi', 'Project Manager I', 'Manager Ii',
                'Principal Admin Analyst', 'Program Administrator',
                'Is Business Analyst Principal', 'Maintenance Manager Sfusd',
                'Special Assistant X', 'Architect', 'Rotc Teacher',
                'Executive Asst To Board Of Ed', 'Principal Middle School',
                'Supervisor', 'Assistant Principal Elem. Sch.',
                'Confidential Secretary To Supt', 'Principal,K-8',
```

In [72]:

```
# filter for teacher only
# skipped: teacher special assign, Eed Preschool Teacher, Eed Infant/Toddle
# Teacher Sab Leave, Childrens Center Teacher 4/7, Summer Eed Prek Teacher,
# Summer School Sub Teacher, Prop "A" C C Sub Teacher', 'Day-To-Day Sub', '
#           (sf2018['Job Title'] == 'Day-To-Day Sub') |
#           (sf2018['Job Title'] == 'Day To Day Sub Teacher Retired') |
#           (sf2018['Job Title'] == 'Special Education - Core Sub') |
#           (sf2018['Job Title'] == 'Day-To-Day Student Teacher Sub') |
sf2018_teachers=sf2018.loc[(sf2018['Job Title'] == 'Rotc Teacher') |
           (sf2018['Job Title'] == 'Esl Teacher') |
           (sf2018['Job Title'] == 'Eld Classroom Teacher') |
           (sf2018['Job Title'] == 'Secondary Art Teacher') |
           (sf2018['Job Title'] == 'Regular Classroom Teacher') |

           (sf2018['Job Title'] == 'Librarian Teacher') |
           (sf2018['Job Title'] == 'Bilingual Classroom Teacher') |
           (sf2018['Job Title'] == 'Transitional Kg Teacher') |
           (sf2018['Job Title'] == 'Secondary Music Teacher') |
           (sf2018['Job Title'] == 'Physical Education Teacher') |

           (sf2018['Job Title'] == 'Itinerant Drama Teacher') |
           (sf2018['Job Title'] == 'Itinerant Visual Art Teacher') |
           (sf2018['Job Title'] == 'Teacher/Resource Teacher') |
           (sf2018['Job Title'] == 'Itinerant Dance Teacher') |
           (sf2018['Job Title'] == 'Resource Teacher') |

           (sf2018['Job Title'] == 'Adapted Pe Teacher') |
           (sf2018['Job Title'] == 'Esl/Bilingual Teacher') |
           (sf2018['Job Title'] == 'Prop "A "Sub Teacher') |
           (sf2018['Job Title'] == 'Teacher')
           ]
sf2018_teachers
```

Out[72]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Ye
112	George Ishikata	Rotc Teacher	121449.08	0.0	20442.48	27683.74	141891.56	169575.30	20
181	Leonel Nascimento	Rotc Teacher	119375.66	0.0	11649.53	28284.88	131025.19	159310.07	20
228	Lisa A Ernst	Eld Classroom Teacher	81738.15	0.0	45028.83	27464.32	126766.98	154231.30	20
271	Doug Bullard	Rotc Teacher	118661.11	0.0	4787.61	27146.48	123448.72	150595.20	20
302	Joseph Alter	Secondary Art Teacher	81940.64	0.0	39721.96	27248.72	121662.60	148911.32	20
...	...	...	...	...	...	...	...	...	

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Y
11959	Katerina Maselli Zimman	Regular Classroom Teacher	1020.59	0.0	158.13	0.00	1178.72	1178.72	20
11982	Gloria Gao	Bilingual Classroom Teacher	1063.20	0.0	74.40	0.00	1137.60	1137.60	20
12078	James Marshall Sinkler	Physical Education Teacher	0.00	0.0	1000.00	0.00	1000.00	1000.00	20
12080	Todd J Hohenstein	Regular Classroom Teacher	904.25	0.0	94.22	0.00	998.47	998.47	20
12276	Marie Hew	Regular Classroom Teacher	0.00	0.0	622.94	89.89	622.94	712.83	20

3159 rows × 12 columns

In [73]:

```
# Create a list with unique teacher 'Job Title'
sf_teachers=sf2018.loc[(sf2018['Job Title'] == 'Rotc Teacher') |
           (sf2018['Job Title'] == 'Esl Teacher') |
           (sf2018['Job Title'] == 'Eld Classroom Teacher') |
           (sf2018['Job Title'] == 'Secondary Art Teacher') |
           (sf2018['Job Title'] == 'Regular Classroom Teacher') |

           (sf2018['Job Title'] == 'Librarian Teacher') |
           (sf2018['Job Title'] == 'Bilingual Classroom Teacher') |
           (sf2018['Job Title'] == 'Transitional Kg Teacher') |
           (sf2018['Job Title'] == 'Secondary Music Teacher') |
           (sf2018['Job Title'] == 'Physical Education Teacher') |

           (sf2018['Job Title'] == 'Itinerant Drama Teacher') |
           (sf2018['Job Title'] == 'Itinerant Visual Art Teacher') |
           (sf2018['Job Title'] == 'Teacher/Resource Teacher') |
           (sf2018['Job Title'] == 'Itinerant Dance Teacher') |
           (sf2018['Job Title'] == 'Resource Teacher') |

           (sf2018['Job Title'] == 'Adapted Pe Teacher') |
           (sf2018['Job Title'] == 'Esl/Bilingual Teacher') |
           (sf2018['Job Title'] == 'Prop "A "Sub Teacher') |


           (sf2018['Job Title'] == 'Teacher')
           ]['Job Title'].unique()

# Copy the sf_teachers list to teachers as a base for all other counties.
teachers=sf_teachers.copy()
teachers
```

Out[73]:

```
array(['Rotc Teacher', 'Eld Classroom Teacher', 'Secondary Art Teacher',
       'Regular Classroom Teacher', 'Librarian Teacher',
       'Bilingual Classroom Teacher', 'Transitional Kg Teacher',
       'Esl Teacher', 'Secondary Music Teacher',
       'Physical Education Teacher', 'Itinerant Drama Teacher',
       'Itinerant Visual Art Teacher', 'Teacher/Resource Teacher',
       'Itinerant Dance Teacher', 'Resource Teacher',
       'Adapted Pe Teacher', 'Esl/Bilingual Teacher'], dtype=object)
```

In [74]:

```
# Create the list of teachers with a lambda and a teachers list
# the 'k in x' will also include 'Job Title' where k is a partial match. Me
# If k is 'Teacher' it will find all 'Job Title' with Teacher in it.
# Replace 'k in x' with 'k == x'
sf2018[sf2018['Job Title'].apply(lambda x: any([k == x for k in teachers]))
```

Out[74]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year
112	George Ishikata	Rotc Teacher	121449.08	0.0	20442.48	27683.74	141891.56	169575.30	2018
181	Leonel Nascimento	Rotc Teacher	119375.66	0.0	11649.53	28284.88	131025.19	159310.07	2018
228	Lisa A Ernst	Eld Classroom Teacher	81738.15	0.0	45028.83	27464.32	126766.98	154231.30	2018
271	Doug Bullard	Rotc Teacher	118661.11	0.0	4787.61	27146.48	123448.72	150595.20	2018
302	Joseph Alter	Secondary Art Teacher	81940.64	0.0	39721.96	27248.72	121662.60	148911.32	2018
...	...	...	...	...	...	...	...	...	...
11959	Katerina Maselli Zimman	Regular Classroom Teacher	1020.59	0.0	158.13	0.00	1178.72	1178.72	2018
11982	Gloria Gao	Bilingual Classroom Teacher	1063.20	0.0	74.40	0.00	1137.60	1137.60	2018
12078	James Marshall Sinkler	Physical Education Teacher	0.00	0.0	1000.00	0.00	1000.00	1000.00	2018
12080	Todd J Hohenstein	Regular Classroom Teacher	904.25	0.0	94.22	0.00	998.47	998.47	2018
12276	Marie Hew	Regular Classroom Teacher	0.00	0.0	622.94	89.89	622.94	712.83	2018

3159 rows × 12 columns

In [75]:

```
# Also create a list of 'Job Title' which are not considered teachers. Cont
# evaluate those 'Job Title' not occuring in the teachers and not_teachers
not_teachers=sf2018.loc[(sf2018['Job Title'] != 'Rotc Teacher') |
             (sf2018['Job Title'] != 'Esl Teacher') |
             (sf2018['Job Title'] != 'Eld Classroom Teacher') |
             (sf2018['Job Title'] != 'Secondary Art Teacher') |
             (sf2018['Job Title'] != 'Regular Classroom Teacher') |

             (sf2018['Job Title'] != 'Librarian Teacher') |
             (sf2018['Job Title'] != 'Bilingual Classroom Teacher') |
             (sf2018['Job Title'] != 'Transitional Kg Teacher') |
             (sf2018['Job Title'] != 'Secondary Music Teacher') |
             (sf2018['Job Title'] != 'Physical Education Teacher') |

             (sf2018['Job Title'] != 'Itinerant Drama Teacher') |
             (sf2018['Job Title'] != 'Itinerant Visual Art Teacher') |
             (sf2018['Job Title'] != 'Teacher/Resource Teacher') |
             (sf2018['Job Title'] != 'Itinerant Dance Teacher') |
             (sf2018['Job Title'] != 'Resource Teacher') |

             (sf2018['Job Title'] != 'Adapted Pe Teacher') |
             (sf2018['Job Title'] != 'Esl/Bilingual Teacher') |
             (sf2018['Job Title'] != 'Prop "A "Sub Teacher') |
             (sf2018['Job Title'] != 'Day-To-Day Sub') |
             (sf2018['Job Title'] != 'Day To Day Sub Teacher Retired') |

             (sf2018['Job Title'] != 'Special Education - Core Sub') |
             (sf2018['Job Title'] != 'Day-To-Day Student Teacher Sub') |
             (sf2018['Job Title'] != 'Teacher')
             ]['Job Title'].unique()
not_teachers
```

Out[75]:

```
array(['Superintendent', 'Deputy Superintendent',
        'Chief General Counsel, Sfusd', 'Deputy Director',
        'Special Assistant Xvii', 'Chief Of Financial Officer',
        'Is Director', 'Chief', 'Sr Attorney Civil & Criminal',
        'Chief, Administrative Services', 'Project Manager Iii',
        'Dir Of Facili, Design & Constr', 'Assistant Superintendent',
        '9995 Dir Of Risk Management', 'Special Assistant Xix',
        'Executive Director', '1070 Is Project Director', 'Is Manager',
        'Director', 'School Facilities Planner', 'Project Manager Ii',
        'Educational Policy Analyst', 'Principal High School', 'Manager
I',
        'Supervising Purchaser', 'Principal Elementary',
        'Special Assistant Xvi', 'Project Manager I', 'Manager Ii',
        'Principal Admin Analyst', 'Program Administrator',
        'Is Business Analyst Principal', 'Maintenance Manager Sfusd',
        'Special Assistant X', 'Architect', 'Rotc Teacher',
        'Executive Asst To Board Of Ed', 'Principal Middle School',
        'Supervisor', 'Assistant Principal Elem. Sch.',
        'Confidential Secretary To Supt', 'Principal,K-8',
```

In [76]:

```
# Create the list of not_teachers with a lambda and a teachers list
# the 'k in x' will also include 'Job Title' where k is a partial match. Me
# If k is 'Teacher' it will find all 'Job Title' with Teacher in it.
# Replace 'k in x' with 'k == x'
sf2018[sf2018['Job Title'].apply(lambda x: any([k != x for k in teachers]))
```

Out[76]:

```
array(['Superintendent', 'Deputy Superintendent',
        'Chief General Counsel, Sfusd', 'Deputy Director',
        'Special Assistant Xvii', 'Chief Of Financial Officer',
        'Is Director', 'Chief', 'Sr Attorney Civil & Criminal',
        'Chief, Administrative Services', 'Project Manager Iii',
        'Dir Of Facili, Design & Constr', 'Assistant Superintendent',
        '9995 Dir Of Risk Management', 'Special Assistant Xix',
        'Executive Director', '1070 Is Project Director', 'Is Manager',
        'Director', 'School Facilities Planner', 'Project Manager Ii',
        'Educational Policy Analyst', 'Principal High School', 'Manager
I',
        'Supervising Purchaser', 'Principal Elementary',
        'Special Assistant Xvi', 'Project Manager I', 'Manager Ii',
        'Principal Admin Analyst', 'Program Administrator',
        'Is Business Analyst Principal', 'Maintenance Manager Sfusd',
        'Special Assistant X', 'Architect', 'Rotc Teacher',
        'Executive Asst To Board Of Ed', 'Principal Middle School',
        'Supervisor', 'Assistant Principal Elem. Sch.',
        'Confidential Secretary To Supt', 'Principal,K-8',
```

Now that the county lists are cleaned, we can take a look at the statistics for 'Total Pay'

In [77]:

```
sf2018['Total Pay'].describe()
```

Out[77]:

```
count     10460.000000
mean      51517.705534
std       37456.890517
min           2.370000
25%       17402.052500
50%       50357.325000
75%       80581.512500
max      311549.960000
Name: Total Pay, dtype: float64
```

Notice the $2.37 as minimum pay. And now in contrast the hand picked Job Title:

In [78]:

```
sf2018_teachers['Total Pay'].describe()
```

Out[78]:

```
count      3159.000000
mean      67608.753289
std       26855.050202
min         622.940000
25%       50063.315000
50%       70431.130000
75%       90116.705000
max      141891.560000
Name: Total Pay, dtype: float64
```

The minimum is more realistic, but $622 is still too little for a real teacher's income. Because there is no distiction between a full time and a part time job, it would be a guess on where to put the boundary. Let's look at the lower end of the income and check wether there is a 'Job Title' which should be filter out using the sub list.

In [79]:
```
sf2018.sort_values('Total Pay').head(50)
#sf2018_teachers.sort_values('Total Pay').head(500)
```

Out[79]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	N
12469	Latonia Evette Carpenter	Family Liaison	0.00	0.0	2.37	445.83	2.37	448.20	2018	
12915	Linda T Raskin	Senior Clerk Typist	0.00	0.0	3.30	0.00	3.30	3.30	2018	
12914	Arlene David Lugue	Senior Clerk Typist	0.00	0.0	3.56	0.00	3.56	3.56	2018	
12901	Vidya Karra	Homebound / Hospital Svcs Tchr	0.00	0.0	5.97	0.00	5.97	5.97	2018	
12895	Henry Ton	Sped Ia Sh -All	0.00	0.0	7.87	0.00	7.87	7.87	2018	

2.3.2 Santa Clara

Comment: After I discovered that it is imposible to manually sift out the real teacher jobs, I verified the list sorted by 'Total Pay'. From the first entries, I noticed, some individuals have a negative income, some have no income, and a few have 1 or 2 pennies as income. I removed all those jobs from the data set.

In [80]:

```
# All sc 'Job Title' not in not_teacher
sc_teachers=sc2018[~sc2018['Job Title'].apply(lambda x: any([k == x for k i
sc_teachers
```

Out[80]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year
2	Kolvira Chheng	Assistant Sup (Cl)	184971.48	0.0	0.0	66088.00	184971.48	251059.48	2018
3	Jean Gallagher	Officer Certificated	174459.96	0.0	0.0	66630.24	174459.96	241090.20	2018
4	Sandra F Garcia	Director Ii	153744.00	0.0	0.0	67090.12	153744.00	220834.12	2018
5	Barbara Campbell	Director Ii	156000.96	0.0	0.0	51164.94	156000.96	207165.90	2018
8	Douglas Kleinhenz	Director / Princ Middle	143517.48	0.0	0.0	60768.20	143517.48	204285.68	2018
...	...	...	...	...	...	...	...	...	...
42958	Nick P Weideling	District Business Office	259.50	0.0	0.0	0.00	259.50	259.50	2018
42973	Kaitlyn E Levin	District Business Office	181.17	0.0	0.0	0.00	181.17	181.17	2018
42982	Alec D Leong	District Business Office	162.00	0.0	0.0	0.00	162.00	162.00	2018
42986	Donald M Lindt	Oster School	0.00	0.0	144.0	0.00	144.00	144.00	2018
42992	Diana M Eschman	School Administrative Asst.	62.94	0.0	0.0	0.00	62.94	62.94	2018

33158 rows × 12 columns

In [81]:
```
# All sc 'Job Title' not in teacher
# Effectively all 'Job Title' not in sf county 'Job Title'
# list all 'Job Title' and find the teachers.

# Show complete list, do not abreviate.
import numpy as np
np.set_printoptions(threshold=np.inf)

sc_JobTitles=sc_teachers[~sc_teachers['Job Title'].apply(lambda x: any([k =
sc_JobTitles

# sc_JobTitles is too long: 3858
```

Out[81]:
```
array(['Assistant Sup (Cl)', 'Officer Certificated', 'Director Ii',
        'Director / Princ Middle', 'K-8 Principal',
        'Coordinator, State & Fed', 'Principal/Elementary',
        'Teacher - Elementary', 'Rsp, Special Ed', 'Assistant Principa
l',
        'Teacher-Middle School', 'Princ Spec Assign/ Ele Pr',
        'Coordinator/Dean/Pia', 'Supervisory 12Mo', 'Tosa- Vils Grant',
        'Principal Small Schools', 'Manager/Coordinator', 'Teacher, Coac
h',
        'Teacher, Prep', 'Program Specialist-Sp Ed', 'Sdc, Special Ed',
        'Adapted P.E.', 'Sr Executive Asst - Sup', 'Area President',
        'Behavior Specialist', 'Accountant', 'Sdc, Pre K',
        'Teacher, Music', 'Lead Build Maint Wkr',
        'Academic Emph Counselor', 'Building Maintenance Wkr',
        'Maint Iv - Landscaping', 'Executive Asst', 'Teacher, Resource',
        'Contracted Employee', 'District Nurse', 'Senior Accountant',
        'Maintenance Wkr Iv-Hvac', 'Certification Specialist',
        'Executive Assistant-Csea', 'Lead Cust/Sp Projects',
        'Night Custodian - Element', 'Lead Mechanic',
```

Teaching Job Title in Santa Clara County: - unfinished.

'Teacher - Elementary', 'Rsp, Special Ed', 'Teacher-Middle School', 'Teacher, Coach', 'Teacher, Music', 'Sub-Teacher Regular', 'Sub-Teacher Retiree', 'Teach Comprehensive English Gr', 'Teacher', 'Teahcer', 'Teach Kinder', 'Teacher, Grade 1', 'Teacher, Grade 2', 'Teacher, Grade 3', 'Teacher, Grade 4', 'Teacher, Grade 5', 'Teacher, Grade 6', 'Teacher, Grade 7' Teacher Grade 1', 'Teacher Grade 2', 'Teacher Grade 3', 'Teacher Grade 4', 'Teacher Grade 5', 'Teacher Grade 6','Teacher Grade 7', 'Teach.Combo Class(Any K-3)', 'Teacher,Instrument.Music(4-6)', 'Teach Physcial Ed (7-8)', 'Teacher, Science (7-8)', 'Teacher, General Music (7-8)', 'Teach.Math/Pre Algebra(6-8)', 'Teacher,Lsh', 'Categorical Teacher', 'Teacher-Substitute', 'Teacher-Sp Ed.', 'Teacher, Art Grades 7-8', 'Teacher Physical Education 7-8', 'Teacher Special Classes/Center', 'Teacher Spanish (K-8)', 'Teacher Other Self Cont', 'Teach.Gen.Mathematics/Basic Ma', 'Teacher Art Gr 7-8', 'Teacher Vocal Music', 'Teacher Science 7-8',

In [82]:
```
# Helper to find entries with a specific 'Job Title'
sc_teachers[(sc_teachers['Job Title'] == 'Teach Comprehensive English Gr')]
```

Out[82]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Ye
1550	Parisa B Nunez	Teach Comprehensive English Gr	168195.35	0.0	2529.74	39349.71	170725.09	210074.80	20
1577	Katherine A Wolterbeek	Teach Comprehensive English Gr	115398.18	0.0	5525.00	37802.15	120923.18	158725.33	20
1588	Kristin A Hoppe	Teach Comprehensive English Gr	112903.30	0.0	1250.00	36731.37	114153.30	150884.67	20
1633	Daniel Suarez	Teach Comprehensive English Gr	103209.10	0.0	1725.00	35332.59	104934.10	140266.69	20
1983	Rebecca Raisch	Teach Comprehensive English Gr	51363.53	0.0	-157.34	16676.85	51206.19	67883.04	20
2163	Alfonso Fuentes Jr	Teach Comprehensive English Gr	27852.50	0.0	0.00	0.00	27852.50	27852.50	20
2324	Miguel Pascual	Teach Comprehensive English Gr	6097.50	0.0	0.00	0.00	6097.50	6097.50	20

Skipped 'Tosa- Vils Grant', 'Teacher, Prep', 'Teacher, Resource', 'Spec Para Education 7.5','Teacher On Special Assig', 'Teacher On Special Assig Tosa',

List all 'Job Title' sorted by 'Total Pay'. Take a look at the lowest incomes and determine, wether this 'Job Title' needs to be omitted in the list.

In [83]:
```
sc2018.sort_values('Total Pay').head(50)
```

Out[83]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
34970	Anita Kwock	Teacher	0.00	0.0	2.10	0.00	2.10	2.10	2018	nan
5857	Henry J Buck	Student Worker	5.67	0.0	0.00	0.00	5.67	5.67	2018	nan
25355	Nansi F Olguin	Instructional Assistant	0.00	0.0	7.46	0.00	7.46	7.46	2018	nan
34969	Andreu Maso Barnadas	Teacher	0.00	0.0	7.96	0.00	7.96	7.96	2018	nan
25354	Linda M Lorimor	Instructional Assistant	0.00	0.0	8.22	0.00	8.22	8.22	2018	nan
34968	Scott Brasil	Coach	0.00	0.0	8.57	0.00	8.57	8.57	2018	nan
8551	Rhianna D Costiloe	Inst Asst - Specialized	8.93	0.0	0.00	2.07	8.93	11.00	2018	nan
34967	Michael Adams	Teacher	0.00	0.0	8.97	0.00	8.97	8.97	2018	nan
25352	Anneli K Rullo	Student Help-Instructional	0.00	0.0	10.05	0.00	10.05	10.05	2018	nan
34965	Rodney Simpson	Teacher	0.00	0.0	11.50	0.00	11.50	11.50	2018	nan
34964	Ardsher Ahmed	Teacher	0.00	0.0	11.81	0.00	11.81	11.81	2018	nan
34963	Lauren Christensen	Teacher	0.00	0.0	12.66	0.00	12.66	12.66	2018	nan
34962	Mary Lance	Teacher	0.00	0.0	13.14	0.00	13.14	13.14	2018	nan
34961	Tony Carriles	Teacher	0.00	0.0	13.39	0.00	13.39	13.39	2018	nan
34960	Lok In Lam	Teacher Special Education	0.00	0.0	13.49	0.00	13.49	13.49	2018	nan
34959	Berton Mahardja	Resource Specialist Special Education	0.00	0.0	13.93	0.00	13.93	13.93	2018	nan

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
34958	Lisa Tripoli	Resource Teacher	0.00	0.0	13.97	0.00	13.97	13.97	2018	nan
14493	Julia B Alejo	Noon Duty Sup	13.98	0.0	0.00	0.00	13.98	13.98	2018	nan
34957	Randal Chase	Teacher	0.00	0.0	14.13	0.00	14.13	14.13	2018	nan
34956	Annamarie Travers	Teacher	0.00	0.0	14.35	0.00	14.35	14.35	2018	nan
34955	Zade Shakir	Teacher	0.00	0.0	14.53	0.00	14.53	14.53	2018	nan
25350	Cecilia A Vitug	Adult Education Teacher 11 Mos	14.79	0.0	0.00	2.13	14.79	16.92	2018	nan
34954	Patricia Carrillo	Resource Teacher	0.00	0.0	14.97	0.00	14.97	14.97	2018	nan
25351	Alan M Lopez-Sanchez	Student Assistant I	0.00	0.0	15.00	0.00	15.00	15.00	2018	nan
34952	Raluca Boscaiu	Teacher	0.00	0.0	15.86	0.00	15.86	15.86	2018	nan
34951	Lyndsey Hicks	Teacher	0.00	0.0	16.35	0.00	16.35	16.35	2018	nan
34950	Nicholas Barry	Teacher	0.00	0.0	16.43	0.00	16.43	16.43	2018	nan
34949	Sophia Angeles	Counselor	0.00	0.0	19.16	0.00	19.16	19.16	2018	nan
34948	Elizabeth Keiley	Teacher Special Education	-0.01	0.0	19.24	0.00	19.23	19.23	2018	nan
30393	Victor B Spielberg	Family Engagement Specialist	19.68	0.0	0.00	0.00	19.68	19.68	2018	nan
5856	Sadie Crome	Walk-On/Activity Pay	20.25	0.0	0.00	0.00	20.25	20.25	2018	nan
37433	Hanan A Tahir	Education Assistant, Spec Ed	20.49	0.0	0.00	0.00	20.49	20.49	2018	nan
8549	Rebecca L Kan	Clerical & Office - Personnel	0.00	0.0	21.25	1.63	21.25	22.88	2018	nan
4565	Janice Workman	Noon/Yard Duty Assistant	0.00	0.0	22.00	0.00	22.00	22.00	2018	nan

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
19783	Charles J Ottum	Student Worker	22.00	0.0	0.00	0.00	22.00	22.00	2018	nan
34947	Jeffrey Hardin	Teacher	0.00	0.0	22.10	0.00	22.10	22.10	2018	nan
34946	Kristin Thomas	Resource Teacher Coach	0.00	0.0	22.32	0.00	22.32	22.32	2018	nan
25349	Ruben C Strait	Student Help Cler,Tech&Office	0.00	0.0	22.50	0.00	22.50	22.50	2018	nan
34945	Macaela Mc Clure	Teacher	0.00	0.0	23.32	0.00	23.32	23.32	2018	nan
40277	Jessica G Little	Paraeducator Special Ed	23.40	0.0	0.00	1335.09	23.40	1358.49	2018	nan
18073	Gregory A Gonzalez	Student Worker	0.00	0.0	23.70	0.00	23.70	23.70	2018	nan
34944	Ismael Reynoso	Teacher	0.00	0.0	24.28	0.00	24.28	24.28	2018	nan
22111	Narjessadat Mirrahimi	Student Cafeteria Worker	0.00	0.0	24.34	0.91	24.34	25.25	2018	nan
34943	Ryan Nguyen	Teacher	0.00	0.0	25.05	0.00	25.05	25.05	2018	nan
40509	Emily Espinoza	Student Assistant	26.01	0.0	0.00	0.00	26.01	26.01	2018	nan
34942	Kathryn Brayton	Resource Specialist Special Education	-0.01	0.0	26.06	0.00	26.05	26.05	2018	nan
34941	Dorothy Nguyen	Teacher	0.00	0.0	26.42	0.00	26.42	26.42	2018	nan
13232	Himelda Escudero Holguin	Noon Duty Assistant	27.00	0.0	0.00	0.00	27.00	27.00	2018	nan
34940	Zoe Ingerson	Teacher	0.00	0.0	27.09	0.00	27.09	27.09	2018	nan
34939	Christos Tikelis	Teacher	0.00	0.0	28.72	0.00	28.72	28.72	2018	nan

In [84]:

```
sc2018['Total Pay'].describe()
```

Out[84]:

```
count     34528.000000
mean      58648.281242
std       43996.953044
min           2.100000
25%       20607.392500
50%       55064.695000
75%       93905.137500
max      395078.000000
Name: Total Pay, dtype: float64
```

2.3.3 Orange County

In [85]:

```
my_county=sc2018
```

```
In [86]: my_county.sort_values('Total Pay').head(50)
```

Out[86]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
34970	Anita Kwock	Teacher	0.00	0.0	2.10	0.00	2.10	2.10	2018	nan
5857	Henry J Buck	Student Worker	5.67	0.0	0.00	0.00	5.67	5.67	2018	nan
25355	Nansi F Olguin	Instructional Assistant	0.00	0.0	7.46	0.00	7.46	7.46	2018	nan
34969	Andreu Maso Barnadas	Teacher	0.00	0.0	7.96	0.00	7.96	7.96	2018	nan
25354	Linda M Lorimor	Instructional Assistant	0.00	0.0	8.22	0.00	8.22	8.22	2018	nan
34968	Scott Brasil	Coach	0.00	0.0	8.57	0.00	8.57	8.57	2018	nan
8551	Rhianna D Costiloe	Inst Asst - Specialized	8.93	0.0	0.00	2.07	8.93	11.00	2018	nan
34967	Michael Adams	Teacher	0.00	0.0	8.97	0.00	8.97	8.97	2018	nan
25352	Anneli K Rullo	Student Help-Instructional	0.00	0.0	10.05	0.00	10.05	10.05	2018	nan
34965	Rodney Simpson	Teacher	0.00	0.0	11.50	0.00	11.50	11.50	2018	nan
34964	Ardsher Ahmed	Teacher	0.00	0.0	11.81	0.00	11.81	11.81	2018	nan
34963	Lauren Christensen	Teacher	0.00	0.0	12.66	0.00	12.66	12.66	2018	nan
34962	Mary Lance	Teacher	0.00	0.0	13.14	0.00	13.14	13.14	2018	nan
34961	Tony Carriles	Teacher	0.00	0.0	13.39	0.00	13.39	13.39	2018	nan
34960	Lok In Lam	Teacher Special Education	0.00	0.0	13.49	0.00	13.49	13.49	2018	nan
34959	Berton Mahardja	Resource Specialist Special Education	0.00	0.0	13.93	0.00	13.93	13.93	2018	nan

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
34958	Lisa Tripoli	Resource Teacher	0.00	0.0	13.97	0.00	13.97	13.97	2018	nan
14493	Julia B Alejo	Noon Duty Sup	13.98	0.0	0.00	0.00	13.98	13.98	2018	nan
34957	Randal Chase	Teacher	0.00	0.0	14.13	0.00	14.13	14.13	2018	nan
34956	Annamarie Travers	Teacher	0.00	0.0	14.35	0.00	14.35	14.35	2018	nan
34955	Zade Shakir	Teacher	0.00	0.0	14.53	0.00	14.53	14.53	2018	nan
25350	Cecilia A Vitug	Adult Education Teacher 11 Mos	14.79	0.0	0.00	2.13	14.79	16.92	2018	nan
34954	Patricia Carrillo	Resource Teacher	0.00	0.0	14.97	0.00	14.97	14.97	2018	nan
25351	Alan M Lopez-Sanchez	Student Assistant I	0.00	0.0	15.00	0.00	15.00	15.00	2018	nan
34952	Raluca Boscaiu	Teacher	0.00	0.0	15.86	0.00	15.86	15.86	2018	nan
34951	Lyndsey Hicks	Teacher	0.00	0.0	16.35	0.00	16.35	16.35	2018	nan
34950	Nicholas Barry	Teacher	0.00	0.0	16.43	0.00	16.43	16.43	2018	nan
34949	Sophia Angeles	Counselor	0.00	0.0	19.16	0.00	19.16	19.16	2018	nan
34948	Elizabeth Keiley	Teacher Special Education	-0.01	0.0	19.24	0.00	19.23	19.23	2018	nan
30393	Victor B Spielberg	Family Engagement Specialist	19.68	0.0	0.00	0.00	19.68	19.68	2018	nan
5856	Sadie Crome	Walk-On/Activity Pay	20.25	0.0	0.00	0.00	20.25	20.25	2018	nan
37433	Hanan A Tahir	Education Assistant, Spec Ed	20.49	0.0	0.00	0.00	20.49	20.49	2018	nan
8549	Rebecca L Kan	Clerical & Office - Personnel	0.00	0.0	21.25	1.63	21.25	22.88	2018	nan
4565	Janice Workman	Noon/Yard Duty Assistant	0.00	0.0	22.00	0.00	22.00	22.00	2018	nan

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
19783	Charles J Ottum	Student Worker	22.00	0.0	0.00	0.00	22.00	22.00	2018	nan
34947	Jeffrey Hardin	Teacher	0.00	0.0	22.10	0.00	22.10	22.10	2018	nan
34946	Kristin Thomas	Resource Teacher Coach	0.00	0.0	22.32	0.00	22.32	22.32	2018	nan
25349	Ruben C Strait	Student Help Cler,Tech&Office	0.00	0.0	22.50	0.00	22.50	22.50	2018	nan
34945	Macaela Mc Clure	Teacher	0.00	0.0	23.32	0.00	23.32	23.32	2018	nan
40277	Jessica G Little	Paraeducator Special Ed	23.40	0.0	0.00	1335.09	23.40	1358.49	2018	nan
18073	Gregory A Gonzalez	Student Worker	0.00	0.0	23.70	0.00	23.70	23.70	2018	nan
34944	Ismael Reynoso	Teacher	0.00	0.0	24.28	0.00	24.28	24.28	2018	nan
22111	Narjessadat Mirrahimi	Student Cafeteria Worker	0.00	0.0	24.34	0.91	24.34	25.25	2018	nan
34943	Ryan Nguyen	Teacher	0.00	0.0	25.05	0.00	25.05	25.05	2018	nan
40509	Emily Espinoza	Student Assistant	26.01	0.0	0.00	0.00	26.01	26.01	2018	nan
34942	Kathryn Brayton	Resource Specialist Special Education	-0.01	0.0	26.06	0.00	26.05	26.05	2018	nan
34941	Dorothy Nguyen	Teacher	0.00	0.0	26.42	0.00	26.42	26.42	2018	nan
13232	Himelda Escudero Holguin	Noon Duty Assistant	27.00	0.0	0.00	0.00	27.00	27.00	2018	nan
34940	Zoe Ingerson	Teacher	0.00	0.0	27.09	0.00	27.09	27.09	2018	nan
34939	Christos Tikelis	Teacher	0.00	0.0	28.72	0.00	28.72	28.72	2018	nan

```
In [87]: my_county['Total Pay'].describe()
```

```
Out[87]: count     34528.000000
         mean      58648.281242
         std       43996.953044
         min           2.100000
         25%       20607.392500
         50%       55064.695000
         75%       93905.137500
         max      395078.000000
         Name: Total Pay, dtype: float64
```

2.3.4 Alameda

```
In [88]: my_county=ala2018
```

In [89]:

```
my_county.sort_values('Total Pay').head(50)
```

Out[89]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
13658	Lucia Diaz	Other Class Hourly	2.85	0.00	0.00	0.41	2.85	3.26	2018	nan
13653	Leticia Rice	Other Class Hourly	5.50	0.00	0.00	0.00	5.50	5.50	2018	nan
13651	Paul A Wagner	Cert Teachers Hourly	0.00	0.00	6.50	0.00	6.50	6.50	2018	nan
8550	Ann Margaret M Rohrer	Spec Ed Inst Asst K-5	6.78	0.00	0.00	1.61	6.78	8.39	2018	nan
20742	Rowena Lopez	Class Instruct - Hourly	0.00	0.00	7.71	0.00	7.71	7.71	2018	nan
2808	Xingmei He Wu	Cafeteria Assitant 1	8.08	0.00	0.00	1.25	8.08	9.33	2018	nan
1987	Nabilla Esmat	Noon Supervisor	11.00	0.00	0.00	0.00	11.00	11.00	2018	nan
13646	Veronica Vind	Other Class Hourly	13.75	0.00	0.00	0.00	13.75	13.75	2018	nan
21715	Asmita K Parikh	Other Class Hourly	0.00	0.00	15.11	0.00	15.11	15.11	2018	nan
2807	Robert Arp	Cafeteria Manager	0.00	0.00	18.21	2.83	18.21	21.04	2018	nan
13644	Stephanie Price	Child Nutrition Assistant 1	9.24	0.00	9.24	0.00	18.48	18.48	2018	nan
20741	Raeda Marmash	Other Class Sal - Hourly	0.00	0.00	22.40	0.00	22.40	22.40	2018	nan
20740	Kusham Kumar	Other Class Sal - Hourly	0.00	0.00	23.00	0.00	23.00	23.00	2018	nan
34269	Bonita C Evart	Other Classified Nonillness	0.00	0.00	27.00	0.00	27.00	27.00	2018	nan
34268	Hilario B Reyes Jr	Other Classified Nonillness	0.00	0.00	27.00	0.00	27.00	27.00	2018	nan
4731	Hannah Acevedo-Schiesel	Psychologist, Behavior Special	29.67	0.00	0.00	5386.00	29.67	5415.67	2018	nan
17010	Steve Robles	Noon Supervisor	30.00	0.00	0.00	1.13	30.00	31.13	2018	nan
8548	Shalini Suravarjjala	Otherclass Salaries Hourly	0.00	0.00	30.25	2.26	30.25	32.51	2018	nan

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
8547	Jaimie Dewitt	Literacy Coach	31.18	0.00	0.00	5.08	31.18	36.26	2018	nan
20738	Amanda Medeiros	Classroom Asst Iv Aba	31.77	0.00	0.00	4.94	31.77	36.71	2018	nan
8546	Fazela Hatef	Food Service Worker 6-8	29.81	0.00	2.36	8.02	32.17	40.19	2018	nan
13635	Heidi R Reichner	Cert Teachers Hourly	35.62	0.00	0.00	5.14	35.62	40.76	2018	nan
13636	Patricia L Dutra	Cert Teachers Hourly	35.62	0.00	0.00	5.14	35.62	40.76	2018	nan
13638	Lynnette M Cooper	Campus Supervisor	17.84	0.00	17.84	2.17	35.68	37.85	2018	nan
2806	Mary F Luersen	Teacher	0.00	0.00	36.83	0.00	36.83	36.83	2018	nan
13632	Alexis N Frost	Cert Teachers Hourly	37.28	0.00	0.00	5.38	37.28	42.66	2018	nan
13637	Susan W Carpendale	Teacher-Special Day Class	21.39	0.00	16.07	3.09	37.46	40.55	2018	nan
21714	Malvina Cordoba	Translator	0.00	0.00	37.78	0.00	37.78	37.78	2018	nan
13629	Myrafiel O Pangantihon	Cert Teachers Hourly	39.18	0.00	0.00	5.66	39.18	44.84	2018	nan
13633	Terrie Lopes	Van Driver	18.36	1.52	19.88	2.60	39.76	42.36	2018	nan
20736	Tracey Baron	Other Class Sal - Hourly	0.00	0.00	40.13	0.00	40.13	40.13	2018	nan
2803	Gisella Villafuerte	Cafeteria Assitant 1	39.01	1.20	0.00	6.25	40.21	46.46	2018	nan
20735	Neepa Mehta	Rca I - General	40.43	0.00	0.00	0.00	40.43	40.43	2018	nan
6723	Christian James	Student Worker	42.00	0.00	0.00	0.00	42.00	42.00	2018	nan
6725	Nathaniel Jackson	Student Worker	42.00	0.00	0.00	0.00	42.00	42.00	2018	nan
6724	William Dickson	Student Worker	42.00	0.00	0.00	0.00	42.00	42.00	2018	nan

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
6726	Emily Espinoza	Student Worker	42.00	0.00	0.00	0.00	42.00	42.00	2018	nan
2805	Jacklyn Bittner	Other Classified Salaries	0.00	0.00	44.00	0.00	44.00	44.00	2018	nan
317	Yzabelle V Vargas	Other Cl Studnt/Intern	44.00	0.00	0.00	0.00	44.00	44.00	2018	nan
8545	Uma Kaulgud	Otherclass Salaries Hourly	0.00	0.00	44.00	3.19	44.00	47.19	2018	nan
20733	Lorraine Neira	College & Career Center Tech	29.37	0.00	15.07	6.90	44.44	51.34	2018	nan
13628	Noria Shuja	Other Class Hourly	45.00	0.00	0.00	0.00	45.00	45.00	2018	nan
34263	Deann L Guzman	Classified Support Salaries	-1.00	0.00	47.00	0.00	46.00	46.00	2018	nan
13625	Tasia J Perry	Cert Teachers Hourly	46.55	0.00	0.00	6.72	46.55	53.27	2018	nan
13624	Rochelle Hooks	Cert Teachers Hourly	47.50	0.00	0.00	6.85	47.50	54.35	2018	nan
8543	Amanda M Burr	Teacher	48.73	0.00	0.00	7.94	48.73	56.67	2018	nan
8542	Brenda L Kidd	Spec Ed Inst Asst 9-12	49.37	0.00	0.00	11.76	49.37	61.13	2018	nan
13626	Sheila Mani	Other Class Hourly	49.50	0.00	0.00	0.00	49.50	49.50	2018	nan
17007	Nicole Thomas	Noon Supervisor	52.50	0.00	0.00	3.10	52.50	55.60	2018	nan
13621	Mallory J Byrne	Cert Teachers Hourly	52.72	0.00	0.00	7.61	52.72	60.33	2018	nan

In [90]:
```
my_county['Total Pay'].describe()
```

Out[90]:
```
count     26531.000000
mean      55168.027347
std       38136.513584
min           2.850000
25%       23830.565000
50%       52839.000000
75%       85230.035000
max      345061.520000
Name: Total Pay, dtype: float64
```

2.3.5 Sacramento

In [91]:
```
my_county=sac2018
```

In [92]:
```
my_county.sort_values('Total Pay').head(50)
```

Out[92]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Note
10422	Mackenzie Kerling	Clerical Pool	4.84	0.0	0.00	0.00	4.84	4.84	2018	na
36818	Keri Wanner	Food Service Worker	6.32	0.0	0.00	0.00	6.32	6.32	2018	na
26020	Robert L Jones	Other Classified Salary-Tempor	0.00	0.0	6.37	0.00	6.37	6.37	2018	na
10419	Virginia Sloat	Classroom Teacher, 6Th	8.07	0.0	0.00	1.16	8.07	9.23	2018	na
10418	Colleen Zehnder	Classroom Teacher, 2Nd	8.35	0.0	0.00	1.20	8.35	9.55	2018	na
10417	John Thorn	7/8 Teacher,	8.50	0.0	0.00	1.20	8.50	9.70	2018	na

In [93]:
```
my_county['Total Pay'].describe()
```

Out[93]:
```
count     31780.000000
mean      47992.659175
std       36504.608810
min           4.840000
25%       17156.682500
50%       42161.980000
75%       80016.482500
max      387485.330000
Name: Total Pay, dtype: float64
```

2.3.6 Butte

```
In [94]: my_county=bt2018
```

In [95]:

```
my_county.sort_values('Total Pay').head(50)
```

Out[95]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Ye
4818	Ashlee D Leach	Cafeteria Assistant	0.03	0.0	1.23	0.00	1.26	1.26	20
4817	Kasey L Besson	Cafeteria Assistant	3.90	0.0	0.00	0.00	3.90	3.90	20
4816	Kimberly J Dawkins	IA-Special Education RSP	3.50	0.0	0.42	0.38	3.92	4.30	20
4815	Jessica J Hays	Campus Supervisor	4.39	0.0	0.00	0.00	4.39	4.39	20
4814	Kacie L Holt	Overtime	0.00	0.0	4.65	0.45	4.65	5.10	20
4161	Andrea N Petersen	Overtime	0.00	0.0	4.87	3756.00	4.87	3760.87	20
4813	Kimberly A Egger	Overtime	0.00	0.0	5.12	0.50	5.12	5.62	20
4812	Amy L Gaffney	Cafeteria Assistant	8.90	0.0	0.00	0.00	8.90	8.90	20
4811	Shelby K Plummer	Overtime	0.00	0.0	10.50	0.00	10.50	10.50	20
2249	James Lynch	Student	11.00	0.0	0.00	0.00	11.00	11.00	20
2248	Roberto Medina	Student	11.00	0.0	0.00	0.00	11.00	11.00	20
4810	Oleta M Bryson	Other Cert Salaries	0.00	0.0	12.00	0.00	12.00	12.00	20
4809	Sarena R Kirk	IPS-Healthcare	12.75	0.0	0.00	0.00	12.75	12.75	20
4808	Deanne A Rouse	IPS-Classroom	15.13	0.0	0.00	1.90	15.13	17.03	20
4807	Tammy M Ostrowski	Health Assistant	17.99	0.0	1.62	1.89	19.61	21.50	20
2246	Jorge S Figueroa-Argueta	Mini Corp Tutor	22.00	0.0	0.00	0.00	22.00	22.00	20
5382	Angel B Gonzalez	Classifiedinstructionalsalary	0.00	0.0	22.00	0.00	22.00	22.00	20
5383	Victor M Jimenez	Classifiedinstructionalsalary	0.00	0.0	22.00	0.00	22.00	22.00	20

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Ye
2244	Jack E Zevely-Howlett	Otherclassifiedsalaries	22.00	0.0	0.00	0.00	22.00	22.00	20
2245	Chase A Jeffers	Student	22.00	0.0	0.00	0.00	22.00	22.00	20
4806	Alicia L Trammel	Campus Supervisor	21.94	0.0	0.46	0.00	22.40	22.40	20
4805	Louise Kincheloe	Other Cert Salaries	0.00	0.0	24.00	0.00	24.00	24.00	20
2243	Yuliza Y Ibarra	Student	27.50	0.0	0.00	0.00	27.50	27.50	20
2242	Thomas B Martinez	Student	30.25	0.0	0.00	0.00	30.25	30.25	20
4804	Wesley E Olson	Noon Supervision	0.00	0.0	30.75	0.00	30.75	30.75	20
4802	Sara S Knight	Overtime	0.00	0.0	31.50	0.00	31.50	31.50	20
4801	Lauren A Brown-Kinell	Overtime	0.00	0.0	31.50	0.00	31.50	31.50	20
4803	Marija Savitt	Overtime	0.00	0.0	31.50	0.00	31.50	31.50	20
2234	Kou K Hawj	Otherclassifiedshortterm	32.99	0.0	0.00	5.13	32.99	38.12	20
2238	Andre S Mota	Student	33.00	0.0	0.00	0.00	33.00	33.00	20
2237	Skyler R Conner	Student	33.00	0.0	0.00	0.00	33.00	33.00	20
2239	Ashley J Jordan	Student	33.00	0.0	0.00	0.00	33.00	33.00	20
2240	Silas A Medina	Student	33.00	0.0	0.00	0.00	33.00	33.00	20

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Ye
2241	Joshua A Morris	Student	33.00	0.0	0.00	0.00	33.00	33.00	20
2231	Sandra Reynolds	Classifiedsupportsalaries	34.53	0.0	0.00	5.36	34.53	39.89	20
6729	Amber D Englund	Clericltechniclofficstaff	0.00	0.0	35.00	0.00	35.00	35.00	20
4799	Leilani Frietas	Regular	0.00	0.0	35.13	0.00	35.13	35.13	20
2235	Wade Huffman	Student	35.75	0.0	0.00	0.00	35.75	35.75	20
2236	Kristopher D Titsworth	Student	35.75	0.0	0.00	0.00	35.75	35.75	20
8055	Miranda L Johnson	Otherclassifiedsalaries	0.00	0.0	35.97	5.59	35.97	41.56	20
2233	Lantanya M Veale	Student	38.50	0.0	0.00	0.00	38.50	38.50	20
2232	Ricky L Poindexter	Student	38.50	0.0	0.00	0.00	38.50	38.50	20
4795	Madelynn G Copper	Overtime	0.00	0.0	39.18	0.00	39.18	39.18	20
4796	Zaira A Paredon Nieto	Overtime	0.00	0.0	39.18	0.00	39.18	39.18	20
4797	Barbara K Wise	Overtime	0.00	0.0	39.18	0.00	39.18	39.18	20
4794	Caroline M Chambers	Overtime	0.00	0.0	39.18	0.00	39.18	39.18	20
4793	Katherine L Pace	Overtime	0.00	0.0	39.57	0.00	39.57	39.57	20
4792	Chantelle E John	Overtime	0.00	0.0	39.57	0.00	39.57	39.57	20
4791	Sharon L Gamer	Overtime	0.00	0.0	39.57	0.00	39.57	39.57	20
4790	Sydney Buxbaum	Overtime	0.00	0.0	39.57	0.00	39.57	39.57	20

```
In [96]: my_county['Total Pay'].describe()
```

```
Out[96]: count      6076.000000
         mean      33168.984013
         std       32008.489960
         min           1.260000
         25%        4500.000000
         50%       24217.185000
         75%       55507.862500
         max      284009.760000
         Name: Total Pay, dtype: float64
```

2.3.7 Alpine

```
In [97]: my_county=alp2018
```

```
In [98]: my_county.sort_values('Total Pay').head(50)
```

Out[98]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Not
52	Andrew Voss	Classified Hourly	143.0	0.0	0.0	26.0	143.0	169.0	2018	n
51	Beverly Giannopulos	Classified Contract	179.0	0.0	0.0	0.0	179.0	179.0	2018	n
50	Terrie Peets	Classified Contract	248.0	0.0	0.0	0.0	248.0	248.0	2018	n
30	Anthony Holdridge	Board Member	0.0	0.0	347.0	19767.0	347.0	20114.0	2018	n

```
In [99]: alp2018['Total Pay'].describe()
```

```
Out[99]: count        60.000000
         mean      31938.966667
         std       29906.471061
         min         143.000000
         25%        7949.250000
         50%       25202.500000
         75%       49648.250000
         max      145033.000000
         Name: Total Pay, dtype: float64
```

2.3.8 Kern

In [100]:

```
my_county=kc2018
```

```
In [101]: my_county.sort_values('Total Pay').head(50)
```

```
Out[101]:
```

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes	
20841	Ojilbeh Alcantar	After School Program Leader	1.03	0.0	0.00	0.02	1.03	1.05	2018	nan	V
20839	Kristine Reynaga	Para-Professional Iii	1.22	0.0	0.00	0.19	1.22	1.41	2018	nan	V
26174	Shelby Watts	Student Worker	0.00	0.0	5.50	0.00	5.50	5.50	2018	nan	
20836	Kimberllie Howard	After School Program Leader	6.46	0.0	0.00	0.14	6.46	6.60	2018	nan	V
20835	Carol Nevarez	Dispatcher Senior	7.79	0.0	0.00	1.21	7.79	9.00	2018	nan	V
23828	Jami Dow	Classified - Non Mgmt	0.00	0.0	9.02	0.00	9.02	9.02	2018	nan	
23827	Sandra Warkentin	Classified - Non Mgmt	0.00	0.0	9.06	0.00	9.06	9.06	2018	nan	
15653	Anna Maria Iniguez	Classified - Non Mgmt	0.00	0.0	10.50	0.22	10.50	10.72	2018	nan	I
23822	Lynn Warfield	Classified - Non Mgmt	0.00	0.0	11.00	0.23	11.00	11.23	2018	nan	
23823	Brandon Johnston	Classified - Non Mgmt	0.00	0.0	11.00	0.23	11.00	11.23	2018	nan	
23826	Suganthi Jothikumar	Classified - Non Mgmt	0.00	0.0	11.00	0.00	11.00	11.00	2018	nan	
23825	Clarissa Green	Classified - Non Mgmt	0.00	0.0	11.00	0.23	11.00	11.23	2018	nan	
23824	Danielle Bertrand	Classified - Non Mgmt	0.00	0.0	11.00	0.23	11.00	11.23	2018	nan	
11289	Michelle . Perone	Certificated - Non Mgmt	0.00	0.0	12.78	1.84	12.78	14.62	2018	nan	
14100	Angela Van Vleet	Classified - Non Mgmt	0.00	0.0	12.93	0.00	12.93	12.93	2018	nan	E
14099	Lucinda Wimmer	Classified - Non Mgmt	0.00	0.0	12.93	0.00	12.93	12.93	2018	nan	E

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
23821	Kelsey Hershey	Classified - Non Mgmt	0.00	0.0	14.19	0.00	14.19	14.19	2018	nan
11288	Elizabeth . Ramos	Classified - Non Mgmt	0.00	0.0	15.05	0.32	15.05	15.37	2018	nan
23820	Maranda T. Vitello	Classified - Non Mgmt	0.00	0.0	15.92	0.00	15.92	15.92	2018	nan
23818	Oscar B. Wickliff	Classified - Non Mgmt	0.00	0.0	15.92	0.59	15.92	16.51	2018	nan
21642	Malinda R Rodriguez	Classified - Non Mgmt	0.00	0.0	16.00	0.57	16.00	16.57	2018	nan
23819	Brieanna Verkuyl	Classified - Non Mgmt	0.00	0.0	16.50	0.00	16.50	16.50	2018	nan
14098	Jeri J. Horenstein	Certificated - Non Mgmt	0.00	0.0	17.86	3.57	17.86	21.43	2018	nan
14788	Jasmine Chavarin	Classified - Non Mgmt	0.00	0.0	18.17	0.00	18.17	18.17	2018	nan
23817	Clayton Hoggard	Classified - Non Mgmt	0.00	0.0	19.25	0.40	19.25	19.65	2018	nan
15652	Virginia Gonzalez	Classified - Non Mgmt	0.00	0.0	20.27	0.43	20.27	20.70	2018	nan
23815	Jordyne M. Slater	Classified - Non Mgmt	0.00	0.0	21.00	0.44	21.00	21.44	2018	nan
26173	Hunter Everson	Classified - Non Mgmt	0.00	0.0	21.00	0.00	21.00	21.00	2018	nan
23816	Tess Mcdonald	Classified - Non Mgmt	0.00	0.0	21.00	0.00	21.00	21.00	2018	nan
27027	Kailey Cornell	Classified - Non Mgmt	0.00	0.0	21.00	0.00	21.00	21.00	2018	nan
26172	Hunter Ashford	Student Worker	0.00	0.0	21.67	0.00	21.67	21.67	2018	nan
23811	Michelle Leverett	Classified - Non Mgmt	0.00	0.0	22.00	3.97	22.00	25.97	2018	nan
23814	Fernando H. Villar	Classified - Non Mgmt	0.00	0.0	22.00	0.46	22.00	22.46	2018	nan

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes	
20824	Jillana Ridgeway	Administrative Secretary Sr	22.85	0.0	0.00	3.55	22.85	26.40	2018	nan	V
23813	Destinee Nelson	Classified - Non Mgmt	0.00	0.0	23.15	0.00	23.15	23.15	2018	nan	
20825	Monique Daniels	Cafeteria General Helper	23.32	0.0	0.00	0.49	23.32	23.81	2018	nan	V
24644	Nicole R.. Cambaliza	Classified - Non Mgmt	0.00	0.0	23.64	3.67	23.64	27.31	2018	nan	
23812	Jesse M. Coluna	Classified - Non Mgmt	0.00	0.0	23.78	0.00	23.78	23.78	2018	nan	
14787	Nicole Fernandez	Classified - Non Mgmt	0.00	0.0	24.22	0.00	24.22	24.22	2018	nan	E
26171	Gage Smith	Classified - Non Mgmt	0.00	0.0	24.75	0.00	24.75	24.75	2018	nan	
27026	Davin Davis	Classified - Non Mgmt	0.00	0.0	25.00	0.00	25.00	25.00	2018	nan	
27025	Miriam Moreno	Classified - Non Mgmt	0.00	0.0	25.00	0.00	25.00	25.00	2018	nan	
20823	Mary Fildes	Cafeteria General Helper	25.36	0.0	0.00	3.94	25.36	29.30	2018	nan	V
20822	Elizabeth Sanchez	Noontime Assistant	26.47	0.0	0.00	4.11	26.47	30.58	2018	nan	V
27024	Myriah Mulkern	Classified - Non Mgmt	0.00	0.0	27.50	0.58	27.50	28.08	2018	nan	
23810	Anna Smallwood	Classified - Non Mgmt	0.00	0.0	28.05	0.00	28.05	28.05	2018	nan	
22735	Shirley Callahan	Classified - Non Mgmt	0.00	0.0	28.22	0.00	28.22	28.22	2018	nan	E
20819	Michael Tootle	Custodian	29.79	0.0	0.00	4.63	29.79	34.42	2018	nan	V
11285	Jasmine D. Wright	Certificated - Non Mgmt	0.00	0.0	30.00	4.33	30.00	34.33	2018	nan	

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Notes
11286	Jessica . Valdovinos-Ayala	Certificated - Non Mgmt	0.00	0.0	30.00	4.33	30.00	34.33	2018	nan

In [102]:

```
my_county['Total Pay'].describe()
```

Out[102]:

```
count     22500.000000
mean      41833.961366
std       34891.575214
min           1.030000
25%       10415.975000
50%       35443.875000
75%       68230.972500
max      271945.410000
Name: Total Pay, dtype: float64
```

2.3.9 Mono

In [103]:

```
my_county=mn2018
```

```
In [104]: my_county.sort_values('Total Pay').head(50)
```

Out[104]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year
358	Karen Donahue	Classified Hourly	96.00	0.0	0.00	2.02	96.00	98.02	2018
352	Brianna Brown	Certificated Hourly	375.00	0.0	0.00	67.73	375.00	442.73	2018
351	Patricia Holland	Certificated Contrac	403.00	0.0	0.00	65.53	403.00	468.53	2018
350	Lisa Rosati	Classified Hourly	595.00	0.0	0.00	12.50	595.00	607.50	2018
343	Gil Campos	Certificated Hourly	750.00	0.0	0.00	122.10	750.00	872.10	2018
344	Yvette Garcia	Certificated Hourly	750.00	0.0	0.00	122.10	750.00	872.10	2018
345	Ruth Hensley	Certificated Contrac	750.00	0.0	0.00	122.10	750.00	872.10	2018
342	Emilie Wisner	Certificated Hourly	750.00	0.0	0.00	122.10	750.00	872.10	2018
347	Casey O'Neill	Certificated Hourly	750.00	0.0	0.00	122.10	750.00	872.10	2018
348	Jacklyn Powell	Certificated Hourly	750.00	0.0	0.00	122.10	750.00	872.10	2018
346	April Lowery	Certificated Hourly	750.00	0.0	0.00	122.10	750.00	872.10	2018
143	Gina M Ruiz	Class Hrly	0.00	0.0	768.26	96.65	768.26	864.91	2017

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year
349	Jessica Barker	Classified Hourly	770.00	0.0	0.00	16.17	770.00	786.17	2018
341	Todd Hensley	Certificated Hourly	910.00	0.0	0.00	131.32	910.00	1041.32	2018
142	Julio Aguayo	Class Hrly	0.00	0.0	913.00	0.00	913.00	913.00	2017
141	Jeremy J Veenker	Coach	0.00	0.0	913.00	0.00	913.00	913.00	2017
134	Caleb D Young	Coach	0.00	0.0	1525.00	0.00	1525.00	1525.00	2017
340	Diana Schmidt	Peapod Leader	1825.00	0.0	0.00	38.34	1825.00	1863.34	2018
132	Leslie A Bishop	Class Hrly	0.00	0.0	2096.96	0.00	2096.96	2096.96	2017
128	Charlene Andrews	Coach	0.00	0.0	2438.00	0.00	2438.00	2438.00	2017
122	Amanda R Pelichowski	Class Hrly	0.00	0.0	2528.36	552.80	2528.36	3081.16	2017
338	Monica Hernandez	Classified Confident	2632.00	0.0	0.00	1081.15	2632.00	3713.15	2018
339	Teiya Gleason	Peapod Leader	2690.00	0.0	0.00	56.49	2690.00	2746.49	2018
124	Gary J Nelson	Retired	0.00	0.0	3000.00	0.00	3000.00	3000.00	2017
119	Rosa N Valles	Class Hrly	0.00	0.0	3733.78	0.00	3733.78	3733.78	2017
118	Nestor Vera	Class Hrly	0.00	0.0	4056.00	0.00	4056.00	4056.00	2017
115	Eileen Dews	Retired	0.00	0.0	4500.00	0.00	4500.00	4500.00	2017

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year
114	Shelly L Mosher	Coach	0.00	0.0	4708.00	0.00	4708.00	4708.00	2017
113	James A Rangel	Undefined	0.00	0.0	4764.50	0.00	4764.50	4764.50	2017
112	Jacqueline Russe	Class Hrly	0.00	0.0	4880.37	0.00	4880.37	4880.37	2017
336	Anna Ceruti	Classified Hourly	5075.00	0.0	0.00	106.58	5075.00	5181.58	2018
332	Gordon Thornburg	It Support Technicia	5520.00	0.0	0.00	3109.04	5520.00	8629.04	2018
105	Amanda A Juarez	Class Hrly	0.00	0.0	5569.28	723.11	5569.28	6292.39	2017
106	Skyler Villareal	Coach	0.00	0.0	5621.00	0.00	5621.00	5621.00	2017
334	Jesse Aguilera	It Support Technicia	4569.00	0.0	1541.00	709.65	6110.00	6819.65	2018
104	Monica D Eilts	Teacher Reg Lves	4872.80	0.0	1851.44	0.00	6724.24	6724.24	2017
333	Jackie Miller	Peapod Leader	7098.00	0.0	0.00	262.65	7098.00	7360.65	2018
285	Alonso Escobar	Mes Paraprofessional	8136.36	0.0	0.00	1263.58	8136.36	9399.94	2018
91	Carl A Peake	Class Hrly	0.00	0.0	8753.92	5067.62	8753.92	13821.54	2017
92	Leslie S Mullinax-Distler	Food Service Worker	0.00	0.0	8784.36	4946.18	8784.36	13730.54	2017
95	Kristi Leonguerrero	Class Hrly	0.00	0.0	9849.77	1367.94	9849.77	11217.71	2017
90	Heather Noble	Cust/Maint/Bus Drive	0.00	0.0	9862.06	5559.19	9862.06	15421.25	2017
284	Caroline Arechiga	Mes Paraprofessional	10170.45	0.0	0.00	0.00	10170.45	10170.45	2018

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year
283	Juana Solorio	Mes Food Service Worker I	10200.00	0.0	0.00	0.00	10200.00	10200.00	2018
331	Sherlan Tems	Classified Contract	3906.00	0.0	7687.00	606.59	11593.00	12199.59	2018
282	Sara Vasquez	Mes Paraprofessional	11763.68	0.0	0.00	0.00	11763.68	11763.68	2018
281	Jose Godinez	Mes Food Service Worker I	12352.95	0.0	0.00	0.00	12352.95	12352.95	2018
88	Jennifer E Vandragt	Teacher Reg Lves	12356.10	0.0	0.00	3823.41	12356.10	16179.51	2017
280	Antonia Rangel Guzman	Mms Food Service Worker I	13487.85	0.0	0.00	0.00	13487.85	13487.85	2018
330	Shane Stroud	Classified Contract	12089.00	0.0	1681.00	3967.45	13770.00	17737.45	2018

In [105]:

```
my_county['Total Pay'].describe()
```

Out[105]:

```
count       283.000000
mean      50624.032756
std       35302.484549
min          96.000000
25%       23611.740000
50%       53015.000000
75%       75411.280000
max      288383.760000
Name: Total Pay, dtype: float64
```

2.3.10 Modoc

In [106]:

```
my_county=md2018
```

In [107]:
```
my_county.sort_values('Total Pay').head(50)
```

Out[107]:

	Employee Name	Job Title	Base Pay	Overtime Pay	Other Pay	Benefits	Total Pay	Total Pay & Benefits	Year	Not
434	Alanis M Reep	Other Classified	0.00	0.00	25.50	4.61	25.50	30.11	2018	r
194	Alissa R Young	Classified Support Salary	0.00	0.00	30.25	0.00	30.25	30.25	2018	r
432	Lee J Albright	Teacher'S Salaries	0.00	0.00	60.00	8.66	60.00	68.66	2018	r
433	Michael Hickman	Other Classified	0.00	0.00	63.70	0.00	63.70	63.70	2018	r

In [108]:
```
my_county['Total Pay'].describe()
```

Out[108]:
```
count       323.000000
mean      36169.820279
std       28279.786814
min          25.500000
25%       10613.960000
50%       30481.920000
75%       55836.795000
max      131665.320000
Name: Total Pay, dtype: float64
```

2.4 Data Extraction for analysis

Comment: Now that all data has been gathered, I now have to condense the useful information and extract a conclusion. What is needed? I need the counties with its cost of living and from each county, I need some values from the describe() of Total Pay.

How do I get just the county from the sample_counties list?

In [109]:
```
sample_counties[0][0]
```

Out[109]:
```
'San Francisco'
```

In [110]:

```
# get a counties from sample_counties in the cost of living data frame 'col
col[col['County'].isin(sample_counties[1])]
```

Out[110]:

	City	County	State	CostOfLiving	ColorCode
2	San Jose	Santa Clara	California	151.4	5
62	Santa Clara	Santa Clara	California	151.4	5

In [111]:

```
# How do I get all the counties:
for i in range(10):
    print(col[col['County'].isin(sample_counties[i])][['County','CostOfLivi
```

```
          County  CostOfLiving
3  San Francisco         162.5
         County  CostOfLiving
2   Santa Clara         151.4
62  Santa Clara         151.4
     County  CostOfLiving
11  Alameda         141.3
29  Alameda         143.3
33  Alameda         143.3
45  Alameda         141.3
    County  CostOfLiving
7   Orange         142.1
20  Orange         142.1
30  Orange         142.1
31  Orange         142.1
34  Orange         142.6
36  Orange         142.1
48  Orange         142.1
60  Orange         142.1
        County  CostOfLiving
5   Sacramento         120.5
25  Sacramento         120.5
    County  CostOfLiving
15   Butte         118.5
111  Butte         118.5
     County  CostOfLiving
110  Alpine         111.8
   County  CostOfLiving
10   Kern         112.6
   County  CostOfLiving
91   Mono          93.7
   County  CostOfLiving
92  Modoc          86.8
```

In [112]:

```
col[col['County'] == 'San Francisco'][['County', 'CostOfLiving']]
```

Out[112]:

	County	CostOfLiving
3	San Francisco	162.5

In [113]:
```
col[col['County'] == 'Santa Clara'][['CostOfLiving']]
```

Out[113]:

	CostOfLiving
2	151.4
62	151.4

In [114]:
```
# How to create the mean of the cost of living per county?
col[col['County'] == 'Santa Clara'][['CostOfLiving']].mean()
```

Out[114]:
```
CostOfLiving    151.4
dtype: float64
```

In [115]:
```
for county in sample_counties[1]:
    print(county,(col[col['County'] == county]['CostOfLiving'].mean()) )
```

```
Santa Clara 151.4
sc nan
33 nan
```

In [116]:
```
# How do I get all the counties from the sample_counties list:
for i in range(10):
    print(sample_counties[i][0])
```

```
San Francisco
Santa Clara
Alameda
Orange
Sacramento
Butte
Alpine
Kern
Mono
Modoc
```

How do you capture the individual values from desrcibe():

In [117]:
```
md2018['Total Pay'].describe()[['count', 'mean', 'std', 'min', '25%', '50%'
```

Out[117]:
```
count       323.000000
mean      36169.820279
std       28279.786814
min          25.500000
25%       10613.960000
50%       30481.920000
75%       55836.795000
max      131665.320000
Name: Total Pay, dtype: float64
```

In [118]:

```
# Create an empty data from to collect all the data:
cols = ['County', 'CostOfLiving','count','mean', 'median']
idx = range(10)
result = pd.DataFrame(columns = cols, index = idx)
result2 = pd.DataFrame(columns = cols, index = idx)
result
```

Out[118]:

	County	CostOfLiving	count	mean	median
0	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN	NaN
8	NaN	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	NaN	NaN

In [119]:

```
# Fill the data frame
year=2018
all_de=[]
for i in range(10):
    result['County'][i]=sample_counties[i][0]
    abr=sample_counties[i][1]
    result['CostOfLiving'][i]=col[col['County'].isin(sample_counties[i])]['
    #print(sample_counties[i][0], col[col['County'].isin(sample_counties[i]
    df=abr+str(year)
    #all_df.append(df)

#print(all_df)
cnt=0
for df in sf2018, sc2018, ala2018, oc2018, sac2018, bt2018, alp2018, kc2018
    count=df['Total Pay'].describe()['count']
    result['count'][cnt]=count
    mean=df['Total Pay'].describe()['mean']
    result['mean'][cnt]=mean
    median=df['Total Pay'].describe()['50%']
    result['median'][cnt]=median
    cnt+=1
```

In [120]:

```
result
```

Out[120]:

	County	CostOfLiving	count	mean	median
0	San Francisco	162.5	10460	51517.7	50357.3
1	Santa Clara	151.4	34528	58648.3	55064.7
2	Alameda	142.3	26531	55168	52839
3	Orange	142.162	62572	53559.7	47340
4	Sacramento	120.5	31780	47992.7	42162
5	Butte	118.5	6076	33169	24217.2
6	Alpine	111.8	60	31939	25202.5
7	Kern	112.6	22500	41834	35443.9
8	Mono	93.7	283	50624	53015
9	Modoc	86.8	323	36169.8	30481.9

In [121]:

```
# Normalized data to have the result fall between 0 and 100
# When plotted, the result has the same range.

year=2018
col_max=result['CostOfLiving'].max()
cnt_max=result['count'].max()
mn_max=result['mean'].max()
md_max=result['median'].max()

for i in range(10):
    result2['County'][i]=sample_counties[i][0]
    result2['CostOfLiving'][i]=100*result['CostOfLiving'][i]/col_max
    result2['count'][i]       =100*result['count'][i]/cnt_max
    result2['mean'][i]        =100*result['mean'][i]/mn_max
    result2['median'][i]      =100*result['median'][i]/md_max
result2
```

Out[121]:

	County	CostOfLiving	count	mean	median
0	San Francisco	100	16.7167	87.8418	91.4512
1	Santa Clara	93.1692	55.1812	100	100
2	Alameda	87.5692	42.4008	94.0659	95.958
3	Orange	87.4846	100	91.3235	85.9716
4	Sacramento	74.1538	50.7895	81.8313	76.5681
5	Butte	72.9231	9.71041	56.5558	43.9795
6	Alpine	68.8	0.0958895	54.4585	45.7689
7	Kern	69.2923	35.9586	71.3302	64.3677
8	Mono	57.6615	0.452279	86.318	96.2777
9	Modoc	53.4154	0.516205	61.6724	55.3566

2.5 Visualization

Now that all the data has extracted and condensed into a small table, it always helps to visually display the result. The best way to display the result is a bar diagram with all values from a county in different colors next to each other. It turned out, that the display of the raw data does not let you visualize relationships. The data first has to be normalized to values between 0 and 100.

In [122]:

```
import seaborn as sns
import matplotlib.pyplot as plt
```

In [123]:

```
result.columns
```

Out[123]:

```
Index(['County', 'CostOfLiving', 'count', 'mean', 'median'], dtype='objec
t')
```

In [124]:
```
result.iloc[:,1].values
```

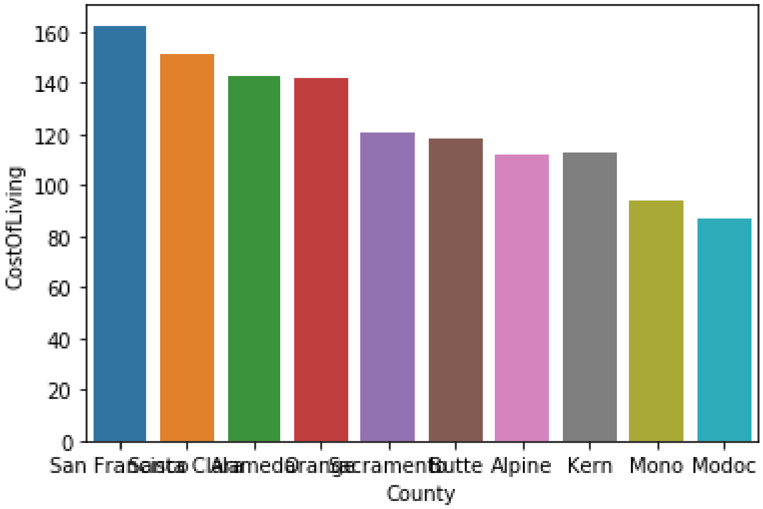
Out[124]:
```
array([162.5, 151.4, 142.3, 142.1625, 120.5, 118.5, 111.8, 112.6, 93.7,
       86.8], dtype=object)
```

In [125]:
```
result['CostOfLiving']
```

Out[125]:
```
0       162.5
1       151.4
2       142.3
3     142.162
4       120.5
5       118.5
6       111.8
7       112.6
8        93.7
9        86.8
Name: CostOfLiving, dtype: object
```

2.5.1 Bar diagram

In [126]:
```
ax=sns.barplot(x=result['County'], y=result['CostOfLiving']);
```



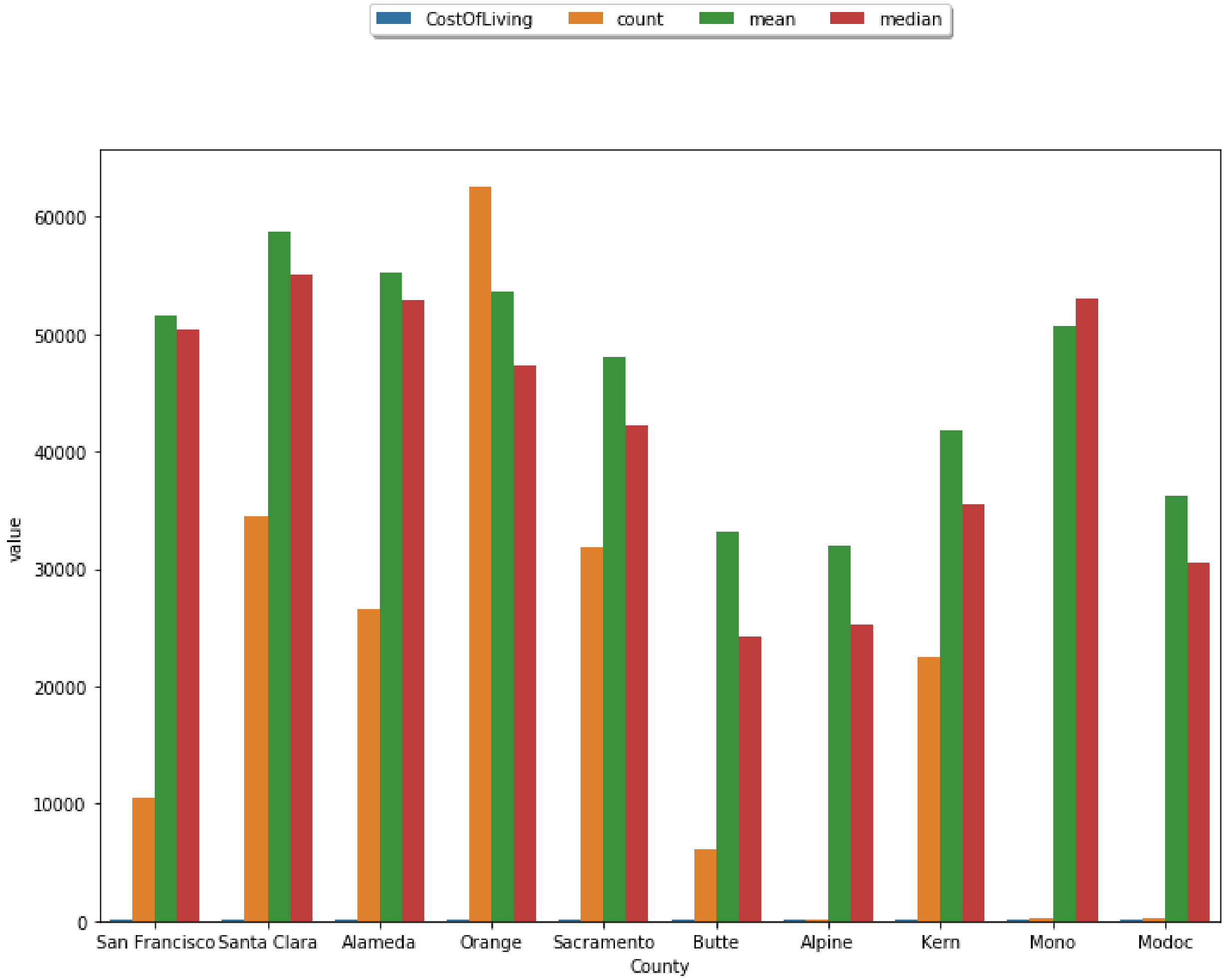
It is nice to see the cost of living ploted by county in a bar chart, but you would like to see the releationship to the other values.

```
In [127]: letter_dims = (11, 8.5)
          a4_dims = (11.7, 8.27)

          fig, ax = plt.subplots(figsize=a4_dims)

          mdf=pd.melt(result,id_vars="County",var_name=['stats'])
          ax = sns.barplot(x="County", y="value", hue="stats", data=mdf, errwidth=0)
          ax.legend(loc='upper center', bbox_to_anchor=(0.5, 1.2), ncol=4, fancybox=T
```

```
Out[127]: <matplotlib.legend.Legend at 0x127bf6b50>
```



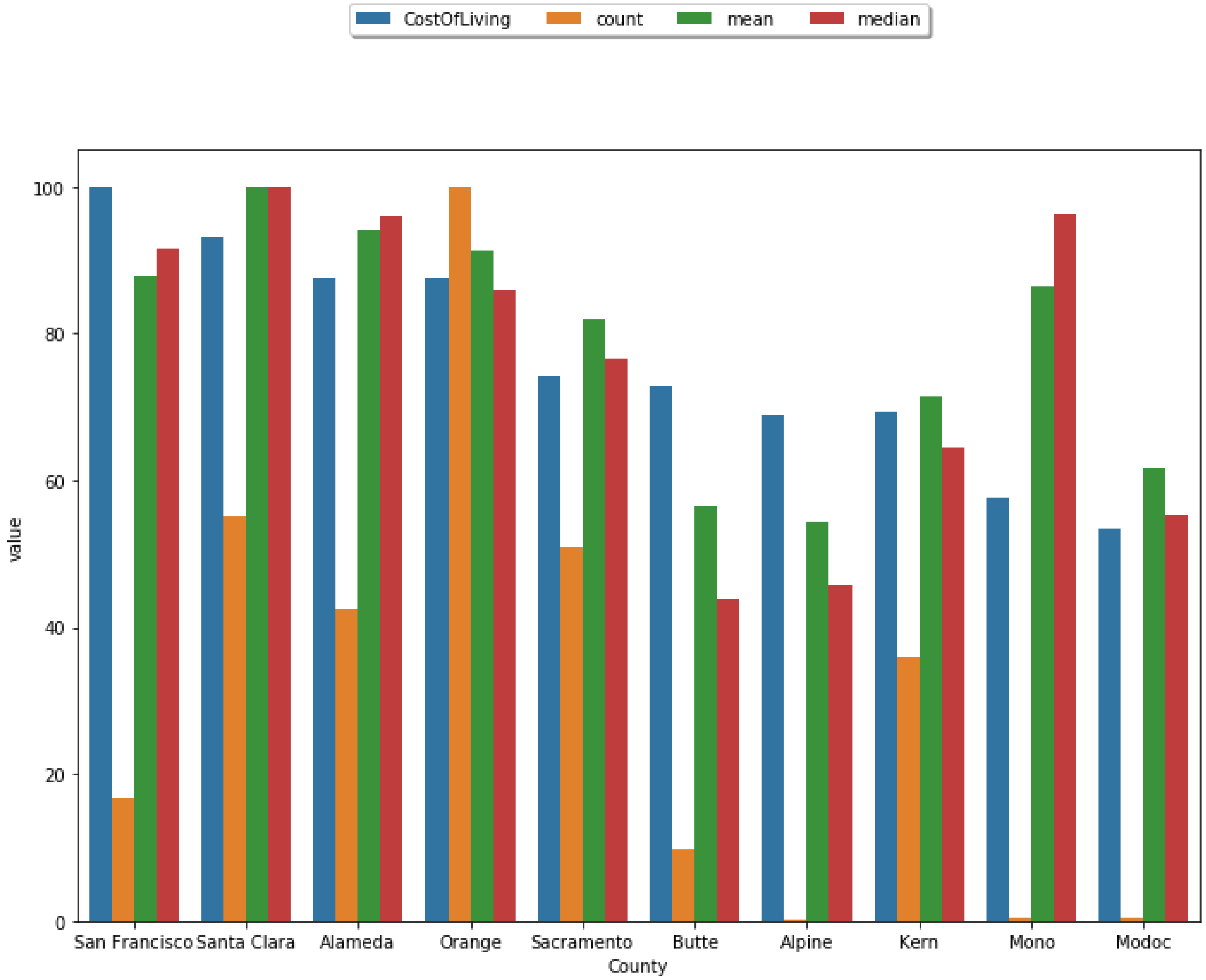
The data has to be normalized to fall in the same range (0-100) in order to get to a conclusion. Notice, that the CostOfLiving is barely visible.

In [128]:
```
letter_dims = (11, 8.5)
a4_dims = (11.7, 8.27)

fig, ax = plt.subplots(figsize=a4_dims)

mdf=pd.melt(result2,id_vars="County",var_name=['stats'])
ax = sns.barplot(ax=ax, x="County", y="value", hue="stats", data=mdf, errwi
ax.legend(loc='upper center', bbox_to_anchor=(0.5, 1.2), ncol=4, fancybox=T
```

Out[128]:
```
<matplotlib.legend.Legend at 0x127bc1f50>
```



Is there a relationship between Cost of Livng, the number of K-12 employees in a county and the mean and median income of a K-12 employee?

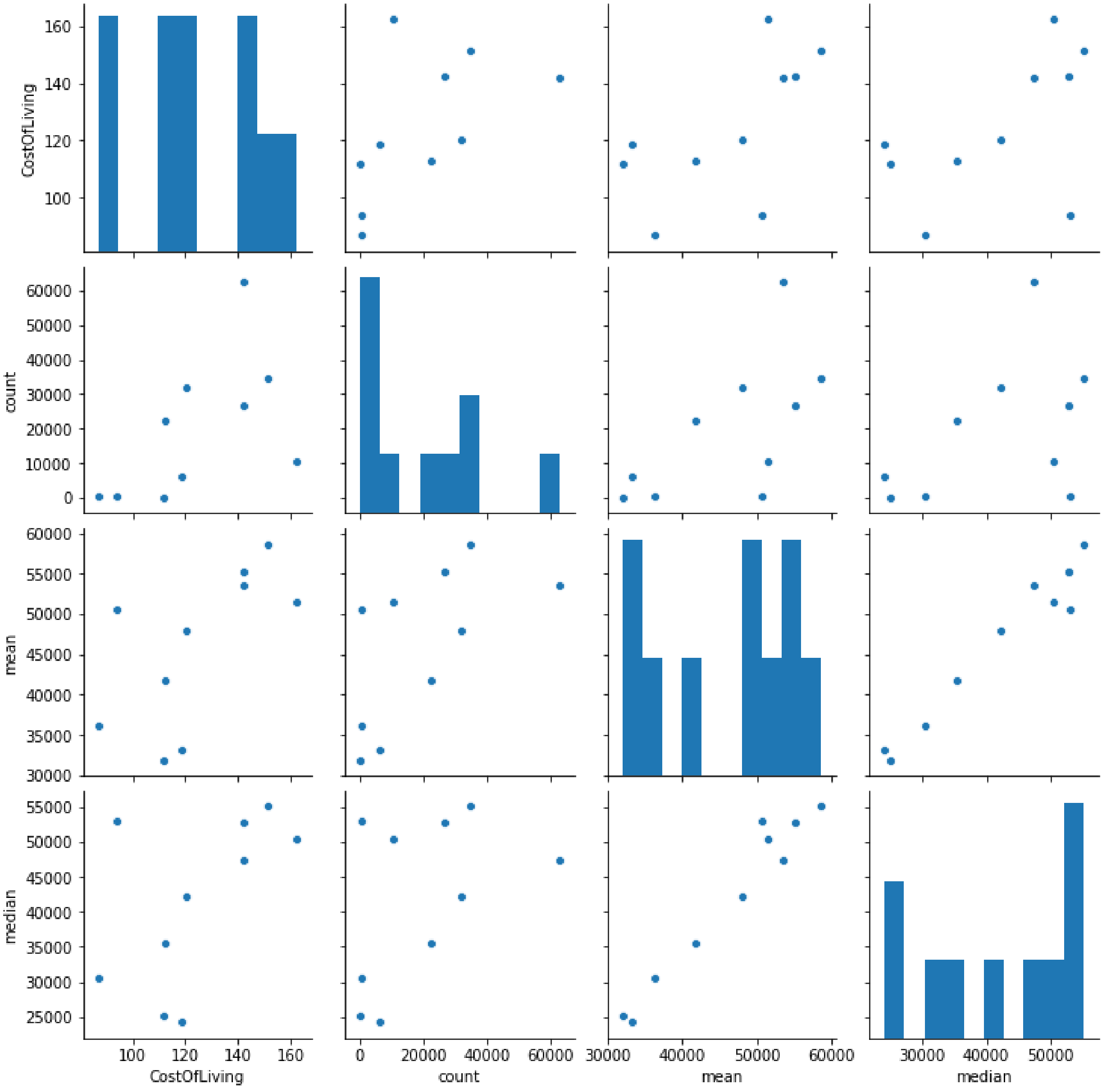
If the world would be without flaw, you believe your income would be adjusted according to your cost of living. San Francisco and Santa Clara have very hight cost of living numbers. The mean and median income in Santa Clara is higher than in San Francisco. That is counter intuitive.

Looking at the cost of living and the mean and median income, the expected correlationship seems to be as expected: the lower the cost of living, the lower the mean/median income. Yet, the last 3 counties destroy the picture. Apparently you can have the same income in Mono County as in Santa Clare, yet have a way lower cost of living.

It begs the question, are the last 3 counties so remote, that you need to get a big stimulus to work/live there?

2.5.2 Pairplot

```
In [129]: sns.pairplot(result.iloc[:, 1:len(result)-1]);
```



From the pairplot it is instantaniously visible, that there is a relationship between mean and median. The other plots do not have an obvious relationship. Looking at e.g. CostOfLiving vs Mean, I could imaging the ideal approximation as Y = mean(all Y), but it could also be a line with a slope and offset (Y = β0 + β1X)

2.6 Mathematical proof of relationship

After the visualization gave us a first insight on the relationship of cost of living with income values, it is now time to take the mathematical approach.

In [130]:

```
import statsmodels.api as sm
```

In [131]:

```
result.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   County        10 non-null     object
 1   CostOfLiving  10 non-null     object
 2   count         10 non-null     object
 3   mean          10 non-null     object
 4   median        10 non-null     object
dtypes: object(5)
memory usage: 528.0+ bytes
```

In [132]:

```
# convert all values to float, int
dtype=float
result['CostOfLiving']   = result['CostOfLiving'].astype(dtype)
result['count']   = result['count'].astype(dtype)
result['mean']   = result['mean'].astype(dtype)
result['median']   = result['median'].astype(dtype)
dtype=int
result['count']   = result['count'].astype(dtype)
result.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   County        10 non-null     object 
 1   CostOfLiving  10 non-null     float64
 2   count         10 non-null     int64  
 3   mean          10 non-null     float64
 4   median        10 non-null     float64
dtypes: float64(3), int64(1), object(1)
memory usage: 528.0+ bytes
```

2.6.1 Correlation Matrix

In [133]:

```
result.iloc[:, 1:len(result)-1]
```

Out[133]:

	CostOfLiving	count	mean	median
0	162.5000	10460	51517.705534	50357.325
1	151.4000	34528	58648.281242	55064.695
2	142.3000	26531	55168.027347	52839.000
3	142.1625	62572	53559.671445	47340.000
4	120.5000	31780	47992.659175	42161.980
5	118.5000	6076	33168.984013	24217.185
6	111.8000	60	31938.966667	25202.500
7	112.6000	22500	41833.961366	35443.875
8	93.7000	283	50624.032756	53015.000
9	86.8000	323	36169.820279	30481.920

In [134]:

```
result.iloc[:, 1:len(result)-1].corr()
```

Out[134]:

	CostOfLiving	count	mean	median
CostOfLiving	1.000000	0.556551	0.639757	0.544473
count	0.556551	1.000000	0.622101	0.454025
mean	0.639757	0.622101	1.000000	0.975380
median	0.544473	0.454025	0.975380	1.000000

In the correlation matrix, a variable does matter when the value is close to +1 or -1. A variable does not matter, whet the value is close to 0. If the value is negative, the relation is reciprocal. If the value is positive, the relation is direct.

From the correlation matrix there is no clear correlation between CostOfLiving and the other variables. There is clear correlation between mean and median as we already discovered from the vizualization.

2.6.2 Ordinary Least Squares (OLS)

In [135]:

```
# all values are neither float nor integer. They have to be converted befor
X=sm.add_constant(result[['count','mean','median']])
Y=result['CostOfLiving']

# Ordinary Least Squares
model=sm.OLS(Y.astype(float),X.astype(float)).fit()

model.summary(xname=['constant','count','mean','median'])
```

```
/Users/marco/opt/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.
py:1535: UserWarning: kurtosistest only valid for n>=20 ... continuing an
yway, n=10
  "anyway, n=%i" % int(n))
```

Out[135]:

OLS Regression Results

Dep. Variable:	CostOfLiving	**R-squared:**	0.602
Model:	OLS	**Adj. R-squared:**	0.403
Method:	Least Squares	**F-statistic:**	3.024
Date:	Fri, 14 Aug 2020	**Prob (F-statistic):**	0.115
Time:	10:03:23	**Log-Likelihood:**	-41.152
No. Observations:	10	**AIC:**	90.30
Df Residuals:	6	**BIC:**	91.52
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
constant	-96.5133	110.151	-0.876	0.415	-366.042	173.015
count	-0.0008	0.001	-0.971	0.369	-0.003	0.001
mean	0.0123	0.007	1.669	0.146	-0.006	0.030
median	-0.0079	0.005	-1.512	0.181	-0.021	0.005

Omnibus:	2.488	**Durbin-Watson:**	1.447
Prob(Omnibus):	0.288	**Jarque-Bera (JB):**	1.040
Skew:	0.789	**Prob(JB):**	0.594
Kurtosis:	2.904	**Cond. No.**	1.23e+06

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.23e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

2.6.2.1 How to read this table

- Constant

Constant is the base value for the accuracy of Y or the value we are looking for.

- Coef

Coef (Coefficient) for the variables is the Beta(β) in Y = β0 + β1X1 + β2 X2 + β3 X3 + .. If the β is positive, it influences X directly If the β is negative, it is reciprocal to X If β is small, its influence is marginal

- t and P

In the OLS Regression Results, if the t is (much) bigger than 2.1 or (much) less than -2.1 as well as the P is less than 0.05, the Null Hypothesis is rejected. In clear text: the factor for this variable is not null and the factor plays a role in determining the Y.

- R-Squared and Adj. R-Squared

R-squared and Adj. R-squared indicate how well the model represents the reality. Adjusted R-squared (which we should use) tells us about the model fit. How good a fit is the model with all the data points. It is just one metric but is not always a very reliable metric. A low R-squared does not mean a bad model. The value ranges from 0 to 1. 0 means poor fit and 1 means a perfect fit.

- Prob(F-stat)

is also a measure of model fit. This should be less than 0.05.

2.6.2.2 Reading the table

- Coef

All of the variables count, mean, median have a marginal effect on the outcome.

- t and P

All t are in between -2.1 and 2.1. All P are bigger than 0.05 That means, the Null hypothesis is accepted. In other words, the variables do not play a role in determining the CostOfLiving.

- Adj R Squared

For a good fit, R needs to be close to 1. In above table R is neither close to 0 nor close to 1. In other words: there is no conclusion possible.

- Prob(F-Stat)

The above value is bigger than 0.05, which means this model is not a good fit.

2.6.3 Variance Inflation Factor (VIF)

VIF measures how much the variance of the estimated regression coefficients are inflated as compared to when the predictor variables are not collinear with each other. This metric is the most reliable way to detect multicollinearity.

Since it already has been determined through the correlation matrix and the Ordinary Least Squares that all variables do not relate to cost of living, there is no need to try and find variables to be eliminated from the model.

3 Conclusion

Ths initial assumption is that the government takes measures to equalize the burden governmental employees have and that at the end you would have the same purchasing power no matter where in California you live.

As we have seen in the vizualization of cost of living with the count/mean/median of 'Total Pay', there is a very marginal to no correlation. This is subsequently confirmed by several statistical models. To say it in a manner a teacher would understand: the total pay you receive, is not adjusted for your cost of living.

Because there is no relationship between cost of living and the total pay, my advise to teachers is not to move to a county with a high cost of living. With a bit of luck the pay in a low cost of living county is equal to the amount paid in the high cost of living county.

There is a note of caution though: the county sample in this document covers all categories of counties, but the sample size is only 10 of 58 counties. The sample size of 10 counties was chosen over all counties, because of a labor intensive manual process to collect the data. Now that the process has been established, I would advise to include more counties, if not all to get a better picture.