This kernel is under active upgradation

Zillow's Mission:

Is to “build the largest, most-trusted, and vibrant home-related marketplace in the world.” Spaulding noted that trust is paramount for a company like Zillow. He brought up how many real estate agents think Zillow is in business to cut brokers out of their industry.

Throughout this notebook. I have used plotly, which is a library built on top of d3.js that has a steep-learning curve JavaScript library. There are Plotly API for Matlab, R, Python that helps us to create interactive visuals and dashboards. In other words, we can manipulate data manipulations in Pandas DataFrame and create interactive visual works easily.

In this notebook I will be focusing on Exploratory Data Analysis on the Price Per Square Feets of the house in the USA. My aim is to do visual analysis of price varrying from State to State and providing some basic answers to general questions about the dataset. ¶

Report Structure:

1. Importing the Libraries
2. Importing the Data Set
3. Exploring the Data Set
4. Basic Q/A Section
5. Data Analysis and Visualisation
6. Conclusion

Section 1:

- Importing the Libraries:

In [1]:
```
# section 1 importing Libs:

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
# my style:
sns.set(style= "whitegrid")

# My favourite Library for visualisation
from plotly import __version__
import cufflinks as cf

from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)

cf.go_offline()

import plotly.figure_factory as ff
import plotly.offline as py
##for online plotting use import plotly.plotly as py
import plotly.graph_objs as go
py.init_notebook_mode(connected=True)
from plotly import tools
```

Section 2:

Importing the Data Set

In [3]:
```
df = pd.read_csv("pricepersqft.csv")
df_rent = pd.read_csv("price.csv")
```

Let's see what both the dataset is about:

A brief information about the PPSFT dataset.

- Number of observations (n) = 11919
- Number of columns (p) = 81
- 5 object type columns, rest are floats

A brief information about the Rent dataset.

- Number of observations (n) = 13131
- Number of columns (p) = 81
- Data Type: float(17), int(60), object(4)

Run dataframe.info() for more details

Head of the Datasets:

In [4]:
```
df.head(10)
```

Out[4]:

	City Code	City	Metro	County	State	Population Rank	November 2010	December 2010	January 2011	February 2011	...	April 2016	May 2016	June 2016	July 2016	August 2016	September 2016	October 2016	November 2016	December 2016	January 2017
0	6181	New York	New York	Queens	NY	1	NaN	NaN	NaN	NaN	...	1.806	1.810	1.816	1.824	1.828	1.836	1.844	1.858	1.866	1.872
1	12447	Los Angeles	Los Angeles	Los Angeles	CA	2	1.578	1.578	1.580	1.582	...	1.990	2.004	2.018	2.026	2.032	2.038	2.042	2.048	2.056	2.064
2	17426	Chicago	Chicago	Cook	IL	3	1.244	1.248	1.254	1.254	...	1.354	1.362	1.370	1.374	1.378	1.380	1.380	1.380	1.376	1.374
3	39051	Houston	Houston	Harris	TX	4	0.788	0.784	0.784	0.786	...	0.984	0.984	0.982	0.980	0.976	0.974	0.974	0.976	0.976	0.974
4	13271	Philadelphia	Philadelphia	Philadelphia	PA	5	0.854	0.858	0.858	0.858	...	0.948	0.956	0.962	0.964	0.964	0.966	0.968	0.972	0.974	0.974
5	40326	Phoenix	Phoenix	Maricopa	AZ	6	0.764	0.766	0.766	0.766	...	0.862	0.870	0.876	0.880	0.882	0.884	0.886	0.890	0.892	0.894
6	18959	Las Vegas	Las Vegas	Clark	NV	7	0.750	0.750	0.748	0.748	...	0.768	0.770	0.772	0.774	0.772	0.774	0.774	0.778	0.780	0.780
7	6915	San Antonio	San Antonio	Bexar	TX	8	0.694	0.698	0.700	0.700	...	0.820	0.822	0.824	0.822	0.822	0.822	0.824	0.830	0.834	0.836
8	54296	San Diego	San Diego	San Diego	CA	9	1.492	1.494	1.492	1.490	...	1.772	1.782	1.788	1.792	1.794	1.796	1.802	1.808	1.814	1.816
9	38128	Dallas	Dallas-Fort Worth	Dallas	TX	10	0.802	0.810	0.818	0.824	...	1.026	1.034	1.040	1.046	1.048	1.050	1.054	1.060	1.062	1.064

10 rows × 81 columns

In [5]:
```
df_rent.head(10)
```

Out[5]:

	City Code	City	Metro	County	State	Population Rank	November 2010	December 2010	January 2011	February 2011	...	April 2016	May 2016	June 2016	July 2016	August 2016	September 2016	October 2016	November 2016	December 2016	January 2017
0	6181	New York	New York	Queens	NY	1	NaN	NaN	NaN	NaN	...	2334	2339	2345	2344	2336	2324	2318	2321	2321	2322
1	12447	Los Angeles	Los Angeles	Los Angeles	CA	2	2184.0	2184.0	2183.0	2188.0	...	2637	2662	2687	2704	2716	2723	2731	2740	2748	2753
2	17426	Chicago	Chicago	Cook	IL	3	1563.0	1555.0	1547.0	1537.0	...	1684	1686	1687	1685	1681	1675	1668	1656	1644	1632
3	39051	Houston	Houston	Harris	TX	4	1198.0	1199.0	1199.0	1200.0	...	1444	1446	1446	1443	1440	1438	1437	1437	1435	1430
4	13271	Philadelphia	Philadelphia	Philadelphia	PA	5	1092.0	1099.0	1094.0	1087.0	...	1206	1211	1218	1222	1223	1220	1216	1211	1209	1212
5	40326	Phoenix	Phoenix	Maricopa	AZ	6	1087.0	1080.0	1071.0	1067.0	...	1228	1236	1240	1240	1238	1238	1239	1241	1244	1247
6	18959	Las Vegas	Las Vegas	Clark	NV	7	1188.0	1183.0	1178.0	1177.0	...	1222	1225	1227	1227	1227	1228	1230	1234	1237	1239
7	6915	San Antonio	San Antonio	Bexar	TX	8	1057.0	1043.0	1037.0	1032.0	...	1244	1245	1245	1241	1236	1234	1235	1239	1245	1250
8	54296	San Diego	San Diego	San Diego	CA	9	2070.0	2059.0	2043.0	2030.0	...	2414	2428	2438	2442	2441	2442	2449	2457	2465	2469
9	38128	Dallas	Dallas-Fort Worth	Dallas	TX	10	1114.0	1135.0	1156.0	1159.0	...	1338	1347	1353	1358	1364	1370	1377	1385	1389	1391

10 rows × 81 columns

A brief description about botht the data sets.

1. PPSFT dataset
2. Rent Dataset

In [6]:
```
df.describe()
```

Out[6]:

	City Code	Population Rank	November 2010	December 2010	January 2011	February 2011	March 2011	April 2011	May 2011	June 2011	...	April 2016	May 2016	June 2016	July 2016	August 2016	September 2016	October 2016	November 2016	Decem 2
count	11919.000000	11919.000000	10600.000000	10600.000000	10600.000000	10744.000000	10829.000000	10878.000000	10885.000000	10885.000000	...	11919.000000	11919.000000	11919.000000	11919.000000	11919.000000	11919.000000	11919.000000	11919.000000	11919.000
mean	77097.011998	5960.000000	0.860989	0.863896	0.865602	0.864939	0.862232	0.860946	0.859769	0.859848	...	0.958509	0.962608	0.964971	0.964989	0.963645	0.962379	0.962570	0.963743	0.964
std	118093.323482	3440.863264	0.286088	0.286489	0.284910	0.281532	0.278903	0.277075	0.275870	0.275311	...	0.371177	0.373848	0.376643	0.378865	0.380334	0.381100	0.381545	0.381775	0.381
min	3300.000000	1.000000	0.360000	0.358000	0.358000	0.358000	0.362000	0.366000	0.366000	0.366000	...	0.394000	0.392000	0.388000	0.384000	0.382000	0.378000	0.378000	0.378000	0.378
25%	18762.000000	2980.500000	0.676000	0.678000	0.680000	0.682000	0.680000	0.678000	0.678000	0.678000	...	0.732000	0.734000	0.734000	0.732000	0.730000	0.728000	0.728000	0.728000	0.730
50%	34637.000000	5960.000000	0.796000	0.799000	0.802000	0.802000	0.800000	0.800000	0.798000	0.800000	...	0.870000	0.872000	0.872000	0.872000	0.870000	0.870000	0.870000	0.870000	0.872
75%	51298.500000	8939.500000	0.972000	0.974000	0.976000	0.972000	0.970000	0.968000	0.968000	0.968000	...	1.072000	1.076000	1.080000	1.082000	1.080000	1.080000	1.082000	1.082000	1.080
max	737791.000000	11919.000000	4.482000	4.508000	4.558000	4.564000	4.548000	4.536000	4.528000	4.536000	...	6.252000	6.342000	6.404000	6.452000	6.476000	6.486000	6.476000	6.470000	6.440

8 rows × 77 columns

In [7]:
```
df_rent.describe()
```

Out[7]:

	City Code	Population Rank	November 2010	December 2010	January 2011	February 2011	March 2011	April 2011	May 2011	June 2011	...	April 2016	May 2016	June 2016	July 2016	August 2016	September 2016	October 2016	November 2016	Decem 2
count	13131.000000	13131.000000	11348.000000	11348.000000	11348.000000	11500.000000	11673.000000	11722.000000	11732.000000	11732.000000	...	13131.000000	13131.000000	13131.000000	13131.000000	13131.000000	13131.000000	13131.000000	13131.000000	13131.000
mean	78126.756454	6566.000000	1327.100458	1331.831953	1334.447744	1331.935217	1327.595819	1323.824518	1321.730822	1321.872826	...	1466.406519	1470.625695	1472.876856	1471.627370	1468.666667	1465.817988	1465.572157	1467.105247	1467.524
std	119604.910806	3790.737527	652.531343	655.822002	653.931315	647.853483	640.168818	636.392831	633.675563	631.981504	...	813.253498	815.322324	819.417181	823.317848	825.885842	826.421670	825.621199	824.678612	821.891
min	3300.000000	1.000000	547.000000	539.000000	536.000000	542.000000	535.000000	533.000000	533.000000	536.000000	...	543.000000	548.000000	547.000000	544.000000	539.000000	532.000000	527.000000	518.000000	517.000
25%	18803.000000	3283.500000	982.000000	984.750000	986.000000	984.000000	979.000000	973.000000	971.000000	972.000000	...	1041.000000	1044.000000	1046.000000	1043.500000	1038.000000	1034.000000	1032.000000	1033.000000	1034.000
50%	34678.000000	6566.000000	1195.000000	1199.000000	1201.500000	1201.000000	1201.000000	1196.000000	1194.000000	1193.000000	...	1275.000000	1277.000000	1278.000000	1276.000000	1270.000000	1268.000000	1266.000000	1267.000000	1267.000
75%	51385.500000	9848.500000	1479.000000	1479.000000	1479.000000	1477.000000	1473.000000	1471.000000	1472.000000	1473.000000	...	1625.000000	1630.000000	1633.000000	1629.000000	1628.000000	1628.000000	1630.500000	1630.000000	1632.000
max	737791.000000	13131.000000	18787.000000	18848.000000	19054.000000	19019.000000	18997.000000	18939.000000	19119.000000	19442.000000	...	21344.000000	20547.000000	20400.000000	20639.000000	20695.000000	20615.000000	20163.000000	19460.000000	18605.000

8 rows × 77 columns

The above Data Frame gives the gerneral specification of the columns: Mean, Standard Deviation, Minimum, Maximum values in every column.

Alot of questions can be answered using the above DF:

1. Minimum, Maximum values in each columns.
2. What is the mean, standard deviation of the columns and get the specifications which we see in a Boxplot.

Section 3

Basic Question and Answer Section:

In [8]:

```python
print("\n"+"In the month of November 2010, Maximum and Minimum Price Per Square Feet ")
print(df[df["November 2010"]==df["November 2010"].max()][["Metro","County", "November 2010"]])
print(df[df["November 2010"]==df["November 2010"].min()][["City","Metro", "County", "November 2010"]])
print("____________________________________________________________")

print("\n"+"In the month January 2011, Maximum and Minimum Price Per Square Feet ")
print(df[df["January 2011"]==df["January 2011"].max()][["City", "County", "January 2011"]])
print(df[df["January 2011"]==df["January 2011"].min()][["City","Metro", "County", "January 2011"]])
print("____________________________________________________________")

print("\n"+"In the month January 2012, Maximum and Minimum Price Per Square Feet ")
print(df[df["January 2012"]==df["January 2012"].max()][["City", "County", "January 2012"]])
print(df[df["January 2012"]==df["January 2012"].min()][["City","Metro", "County", "January 2012"]])
print("____________________________________________________________")

print("\n"+"In the month January 2013, Maximum and Minimum Price Per Square Feet ")
print(df[df["January 2013"]==df["January 2013"].max()][["City", "County", "January 2013"]])
print(df[df["January 2013"]==df["January 2013"].min()][["City","Metro", "County", "January 2013"]])
print("____________________________________________________________")

print("\n"+"In the month January 2014, Maximum and Minimum Price Per Square Feet ")
print(df[df["January 2014"]==df["January 2014"].max()][["City", "County", "January 2014"]])
print(df[df["January 2014"]==df["January 2014"].min()][["City","Metro", "County", "January 2014"]])
print("____________________________________________________________")

print("\n"+"In the month January 2015, Maximum and Minimum Price Per Square Feet ")
print(df[df["January 2015"]==df["January 2015"].max()][["City", "County", "January 2015"]])
print(df[df["January 2015"]==df["January 2015"].min()][["City","Metro", "County", "January 2015"]])
print("____________________________________________________________")

print("\n"+"In the month January 2016, Maximum and Minimum Price Per Square Feet ")
print(df[df["January 2016"]==df["January 2016"].max()][["City", "County", "January 2016"]])
print(df[df["January 2016"]==df["January 2016"].min()][["City","Metro", "County", "January 2016"]])
print("____________________________________________________________")
```

```
In the month of November 2010, Maximum and Minimum Price Per Square Feet
                      Metro      County  November 2010
11627  Miami-Fort Lauderdale  Miami-Dade          4.482
               City     Metro   County  November 2010
6387  Fort Mitchell  Columbus  Russell           0.36
____________________________________________________________

In the month January 2011, Maximum and Minimum Price Per Square Feet
                City      County  January 2011
11627  Fisher Island  Miami-Dade         4.558
               City     Metro   County  January 2011
6387  Fort Mitchell  Columbus  Russell         0.358
____________________________________________________________

In the month January 2012, Maximum and Minimum Price Per Square Feet
                City      County  January 2012
11627  Fisher Island  Miami-Dade         4.602
         City Metro   County  January 2012
8480  Wheeler   NaN  Wheeler         0.358
____________________________________________________________

In the month January 2013, Maximum and Minimum Price Per Square Feet
                City      County  January 2013
11627  Fisher Island  Miami-Dade         4.894
         City Metro   County  January 2013
8480  Wheeler   NaN  Wheeler          0.36
____________________________________________________________

In the month January 2014, Maximum and Minimum Price Per Square Feet
                City      County  January 2014
11627  Fisher Island  Miami-Dade         5.198
            City       Metro County  January 2014
9018  State Road  Mount Airy  Surry         0.378
____________________________________________________________

In the month January 2015, Maximum and Minimum Price Per Square Feet
                City      County  January 2015
11627  Fisher Island  Miami-Dade          5.89
       City       Metro County  January 2015
4312  Elkin  Mount Airy  Surry         0.386
____________________________________________________________

In the month January 2016, Maximum and Minimum Price Per Square Feet
                City      County  January 2016
11627  Fisher Island  Miami-Dade         6.294
       City       Metro County  January 2016
4312  Elkin  Mount Airy  Surry         0.394
____________________________________________________________
```

I hihgly recommend to use SQL to get more detailed and concise abstractions/answers from a data set but we can also do alot in Python. However the block of codes can get huge.

- We can see in the above report The City : Fisher Island, County: Miami- Dade has the highest Price Per Square Feet Rate in the begining of the all the Years.
- While on the other hand the minimum Price Per Sq Ft has varied among the Cities: Fort Mitchell, Wheeler, State Road County: Surry and Elkin.

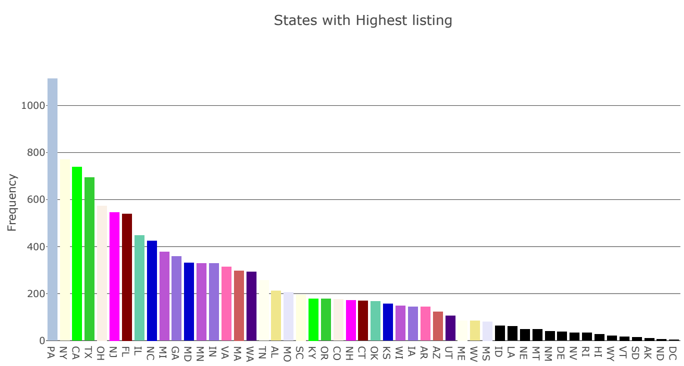
In [ ]:

Section:

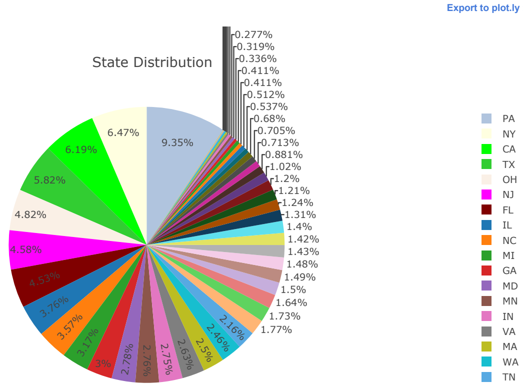
Data Analysis and Visualisation

**** Total number of listing for all the States:***

In [9]:
```
state_count = df["State"].value_counts()

trace = go.Bar(
    x=state_count.index,
    y=state_count.values,
    marker=dict(
        color = (["lightsteelblue", "lightyellow", "lime", "limegreen",
            "linen", "magenta", "maroon", "mediumaquamarine",
            "mediumblue", "mediumorchid", "mediumpurple","mediumblue", "mediumorchid", "mediumpurple", "hotpink", "indianred", "indigo",
            "ivory", "khaki", "lavender","lightyellow", "lime", "limegreen",
            "linen", "magenta", "maroon", "mediumaquamarine",
            "mediumblue", "mediumorchid", "mediumpurple", "hotpink", "indianred", "indigo",
            "ivory", "khaki", "lavender"])))
layout = go.Layout(
    title='States with Highest listing', yaxis = dict(title = 'Frequency'))
data = [trace]
fig = go.Figure(data=data, layout=layout)
py.iplot(fig)



label = state_count.index
size = state_count.values
colors = ["lightsteelblue", "lightyellow", "lime", "limegreen",
            "linen", "magenta", "maroon"]
trace = go.Pie(labels=label,
               values=size,
               marker=dict(colors=colors))
layout = go.Layout(
    title='State Distribution')
data = [trace]
fig = go.Figure(data=data, layout=layout)
py.iplot(fig)



#plt.figure(figsize = (15, 8))
#sns.set_context("paper",font_scale= 2)
#sns.barplot(state_count.index, state_count.values, order = state_count.index)
#plt.xlabel("States")
#plt.xticks(rotation = 90)
#plt.ylabel("Total Number of Listings")
#plt.tight_layout()
#plt.show()
```



Export to plot.ly »

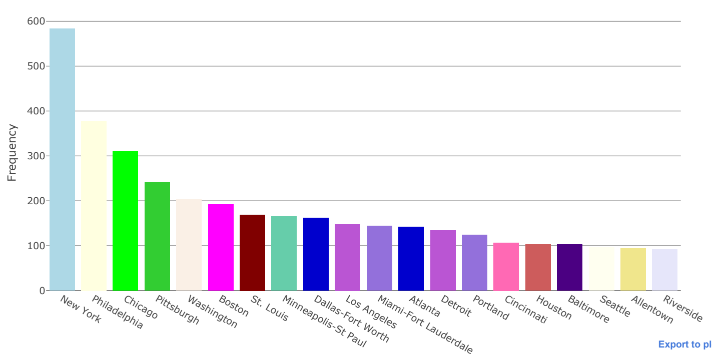


Export to plot.ly »

Top 20 Metro's distribution with highest listings:

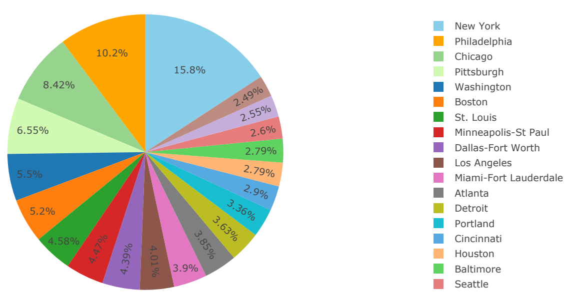
In [10]:
```python
# Highest 20 Metro's
metro_count = df["Metro"].value_counts().head(20)

trace = go.Bar(
    x=metro_count.index,
    y=metro_count.values,
    marker=dict(
        color = (["lightblue", "lightyellow", "lime", "limegreen",
            "linen", "magenta", "maroon", "mediumaquamarine",
            "mediumblue", "mediumorchid", "mediumpurple","mediumblue", "mediumorchid", "mediumpurple", "hotpink", "indianred", "indigo",
            "ivory", "khaki", "lavender" ])))

layout = go.Layout(
    title='20 Metro with Highest listing', yaxis = dict(title = 'Frequency'))

data = [trace]
fig = go.Figure(data=data, layout=layout)
py.iplot(fig)

label = metro_count.index
size = metro_count.values
colors = ['skyblue', 'orange', '#96D38C', '#D0F9B1']
trace = go.Pie(labels=label,
              values=size,
              marker=dict(colors=colors))
layout = go.Layout(
    title='Top 20 Metro Distribution')
data = [trace]
fig = go.Figure(data=data, layout=layout)
py.iplot(fig)


# This block of code for Metro listing count plot is optional. (for my github page)
# As plotly does not work on github.
#plt.figure(figsize=(25,10))
#sns.set_context("paper",font_scale= 2)
#sns.barplot(x=metro_count.index, y= metro_count.values, order= metro_count.index )
#plt.xlabel("Metro")
#plt.xticks(rotation = 90)
#plt.ylabel("Total Number of Listings")
#plt.tight_layout()
#plt.show()
```

20 Metro with Highest listing



Export to plot.ly »

Top 20 Metro Distribution



Export to plot.ly »

Type *Markdown* and LaTeX: α^2

In [11]:
```python
years = list(set([y.split( )[1] for y in df.columns[6:]]))
months = df.columns[6:]
```

1. Let's explore more about Boston Metro:

In [12]:
```python
# Getting a dataframe of boston city only:
boston = df[df["Metro"]=="Boston"]
boston.head()
```

Out[12]:

	City Code	City	Metro	County	State	Population Rank	November 2010	December 2010	January 2011	February 2011	...	April 2016	May 2016	June 2016	July 2016	August 2016	September 2016	October 2016	November 2016	December 2016	January 2017
21	44269	Boston	Boston	Suffolk	MA	22	1.774	1.776	1.798	1.830	...	2.500	2.512	2.520	2.520	2.522	2.522	2.524	2.524	2.522	2.516
286	25659	Lowell	Boston	Middlesex	MA	287	1.156	1.156	1.150	1.140	...	1.358	1.374	1.388	1.398	1.402	1.404	1.412	1.420	1.424	1.426
289	3934	Cambridge	Boston	Middlesex	MA	290	2.128	2.156	2.206	2.266	...	2.656	2.654	2.674	2.696	2.716	2.726	2.732	2.748	2.754	2.756
356	40013	Newton	Boston	Middlesex	MA	357	1.678	1.688	1.700	1.700	...	1.822	1.828	1.840	1.846	1.848	1.846	1.844	1.850	1.854	1.856
357	44328	Brockton	Boston	Plymouth	MA	358	1.042	1.040	1.040	1.048	...	1.288	1.296	1.292	1.276	1.254	1.244	1.244	1.250	1.256	1.258

5 rows × 81 columns

In [13]:
```
boston_r = df_rent[df_rent["Metro"]=="Boston"]
boston_r.head()
```

Out[13]:

	City Code	City	Metro	County	State	Population Rank	November 2010	December 2010	January 2011	February 2011	...	April 2016	May 2016	June 2016	July 2016	August 2016	September 2016	October 2016	November 2016	December 2016	January 2017
21	44269	Boston	Boston	Suffolk	MA	22	1783.0	1771.0	1789.0	1819.0	...	2500	2509	2506	2496	2490	2486	2489	2495	2510	2524
284	25659	Lowell	Boston	Middlesex	MA	285	1658.0	1631.0	1597.0	1565.0	...	1909	1943	1968	1980	1977	1969	1972	1976	1989	2004
287	3934	Cambridge	Boston	Middlesex	MA	288	2011.0	2036.0	2118.0	2200.0	...	2572	2570	2584	2602	2625	2638	2648	2662	2658	2648
354	40013	Newton	Boston	Middlesex	MA	355	3008.0	2977.0	2957.0	2909.0	...	3017	3014	3009	3000	3002	3011	3024	3023	3019	3010
355	44328	Brockton	Boston	Plymouth	MA	356	1414.0	1415.0	1414.0	1415.0	...	1747	1753	1740	1716	1692	1688	1700	1718	1726	1724

5 rows × 81 columns

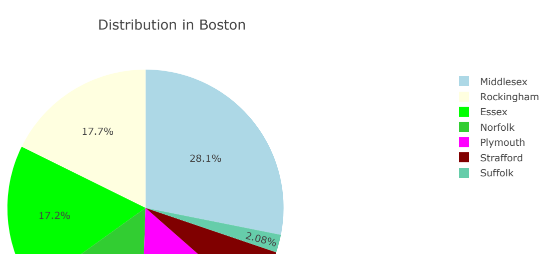
In [14]:
```
boston_r = df_rent[df_rent["Metro"]=="Boston"]
```

In [15]:
```
# Let's see most expensive & least expensice city in boston:
print(" Highest Price Per Square Feet for Jan'10 and Jan'17")
print(boston[boston["November 2010"] == boston["November 2010"].max()][["City", "Metro", "November 2010"]])
print(boston[boston["January 2011"] == boston["January 2011"].max()][["City", "Metro", "January 2011"]])
print(boston[boston["January 2017"] == boston["January 2017"].max()][["City", "Metro", "January 2017"]])
print("_____________________________________________________")

print(" Lowest Price Per Square Feet for Jan'10 and Jan'17")
print(boston[boston["November 2010"] == boston["November 2010"].min()][["City", "Metro", "November 2010"]])
print(boston[boston["January 2011"] == boston["January 2011"].min()][["City", "Metro", "January 2011"]])
print(boston[boston["January 2017"] == boston["January 2017"].min()][["City", "Metro", "January 2017"]])
print("______________________________________________________")
```

```
 Highest Price Per Square Feet for Jan'10 and Jan'17
         City   Metro  November 2010
289  Cambridge  Boston          2.128
         City   Metro  January 2011
289  Cambridge  Boston         2.206
         City   Metro  January 2017
289  Cambridge  Boston         2.756
_____________________________________________________
 Lowest Price Per Square Feet for Jan'10 and Jan'17
        City   Metro  November 2010
9106  Madbury  Boston          0.708
        City   Metro  January 2011
9106  Madbury  Boston         0.726
       City   Metro  January 2017
6094  Auburn  Boston         0.856
______________________________________________________
```

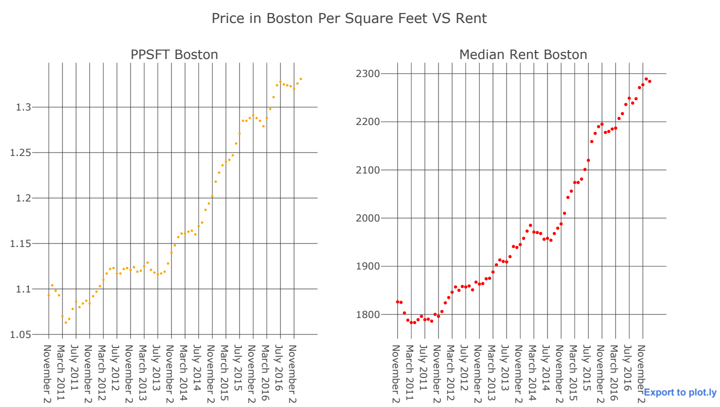
Plot coparison between Median Rent and PPSFT in Boston

In [32]:
```
#Variable assig
bos_pi = boston["County"].value_counts()
colors = ["lightblue", "lightyellow", "lime", "limegreen","magenta", "maroon", "mediumaquamarine"]

# Pie chart
trace = go.Pie(labels=bos_pi.index,
              values = bos_pi.values,
              marker= dict(colors = colors))

layout = go.Layout(title="Distribution in Boston")

data =[trace]
fig = go.Figure(data=data, layout = layout)
py.iplot(fig)

#For Scatter plot
trace = go.Scatter(x = months,
                  y= np.nanmedian(boston[months], axis = 0),
                    mode='markers', marker=dict(size=3,color = ('orange')),
                   name = "Boston Median PPSFT")
```



In [31]:
```
#For Scatter plot
trace1 = go.Scatter(x = months,
                  y= np.nanmedian(boston_r[months], axis = 0),
                   mode='markers', marker=dict(size=4,color = ('red')),
                  name = "Boston Median Rent")


fig = tools.make_subplots(rows=1, cols=2,
                          subplot_titles=('PPSFT Boston','Median Rent Boston'))

fig.append_trace(trace, 1, 1)
fig.append_trace(trace1, 1, 2)

layout = go.Layout(title="Median index price of boston",
                  xaxis= dict(title= "Months"),yaxis=dict(title="PPSFT"))

fig['layout'].update(showlegend=False, title='Price in Boston Per Square Feet VS Rent')
py.iplot(fig)
```

```
This is the format of your plot grid:
[ (1,1) x1,y1 ]  [ (1,2) x2,y2 ]
```



In [ ]:

In [ ]:

2. let's explore about New York Metro

Comparing between New Jersey and New York

In [17]:
```
ny = df[df["Metro"]=="New York"]
ny.head(1)
ny_nj = ny.groupby("State")[months].median()
```

In [ ]:

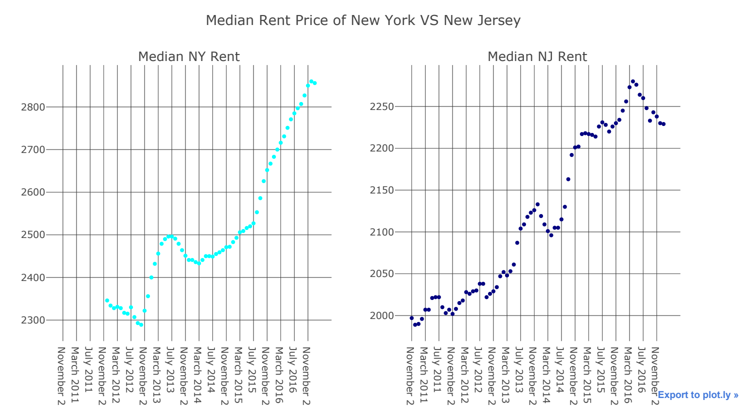
In [18]:
```
ny_rent = df_rent[df_rent["Metro"]=="New York"]
ny_rent.head(1)
ny_nj_rent = ny.groupby("State")[months].median()
```

In [30]:
```
stat1 = list (set([x for x in ny["State"]]))
#np.median(ny[ny["State"]==stat[0]][months], axis = 0)

# For Scatter Plot
trace1 = go.Scatter(x = months,
                  y= np.nanmedian(ny[ny["State"]==stat1[2]][months], axis = 0),
                   mode='markers', marker=dict(size=5,color = ('aqua')),
                  name = "New York")
trace2 = go.Scatter(x = months,
                  y= np.nanmedian(ny[ny["State"]==stat1[0]][months], axis = 0),
                   mode='markers', marker=dict(size=5,color = ('navy')),
                  name = "New Jersey")

layout = go.Layout(title="Median PPSFT price of NY, NJ",
                  xaxis= dict(title= "Months"),yaxis=dict(title="PPSFT"))

data = [trace1, trace2]
fig = go.Figure(data = data, layout=layout)
py.iplot(fig)
```

In [26]:

```
trace1 = go.Scatter(x = months,
                  y= np.nanmedian(ny_rent[ny_rent["State"]==stat1[2]][months], axis = 0),
                   mode='markers', marker=dict(size=5,color = ('aqua')),
                   name = "New York")
trace2 = go.Scatter(x = months,
                  y= np.nanmedian(ny_rent[ny_rent["State"]==stat1[0]][months], axis = 0),
                   mode='markers', marker=dict(size=5,color = ('navy')),
                   name = "New Jersey")



fig = tools.make_subplots(rows= 1 , cols=2, subplot_titles=('Median NY Rent','Median NJ Rent'))
fig.append_trace(trace1, 1,1)
fig.append_trace(trace2, 1,2)

fig['layout'].update(showlegend=False, title='Median Rent Price of New York VS New Jersey')
py.iplot(fig)
```

```
This is the format of your plot grid:
[ (1,1) x1,y1 ]  [ (1,2) x2,y2 ]


/Users/keshavrastogi/anaconda3/lib/python3.6/site-packages/numpy/lib/function_base.py:4033: RuntimeWarning:

All-NaN slice encountered
```

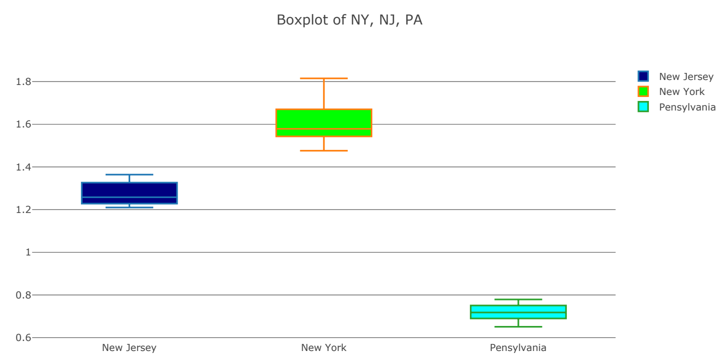


In [ ]:

In [27]:

```
# Box Plot block of code:
ny_gr = ny.groupby("State")[months].median()
print(ny_gr)
trace0 = go.Box(y=ny_gr.loc["NJ"],name="New Jersey",fillcolor='navy')
trace1 = go.Box(y=ny_gr.loc["NY"],name="New York",fillcolor='lime')
trace2 = go.Box(y=ny_gr.loc["PA"],name="Pensylvania",fillcolor='aqua')

layout = go.Layout(title  =" Boxplot of NY, NJ, PA")
data = [trace0, trace1, trace2]
fig = go.Figure(data = data, layout = layout)
py.iplot(fig)
```

```
       November 2010  December 2010  January 2011  February 2011  March 2011  \
State
NJ             1.210          1.220         1.224          1.228       1.232
NY               NaN            NaN           NaN            NaN         NaN
PA             0.738          0.746         0.751          0.750       0.747

       April 2011  May 2011  June 2011  July 2011  August 2011      ...       \
State                                                               ...
NJ          1.234     1.228      1.228      1.226        1.222      ...
NY            NaN       NaN        NaN        NaN          NaN      ...
PA          0.740     0.733      0.730      0.727        0.718      ...

       April 2016  May 2016  June 2016  July 2016  August 2016  \
State
NJ          1.352     1.360      1.362      1.364        1.360
NY          1.732     1.745      1.755      1.763        1.769
PA          0.771     0.771      0.772      0.773        0.776

       September 2016  October 2016  November 2016  December 2016  \
State
NJ              1.362         1.356          1.354          1.356
NY              1.777         1.791          1.802          1.815
PA              0.778         0.779          0.773          0.765

       January 2017
State
NJ            1.350
NY            1.814
PA            0.757

[3 rows x 75 columns]
```



Export to plot.ly »

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Type *Markdown* and LaTeX: α^2

3. Median PPSFT for all States:

In [20]:

```
states = list(df["State"].unique())
state_group = df.groupby("State")[months].median().reset_index()
state_group.head(5)
```

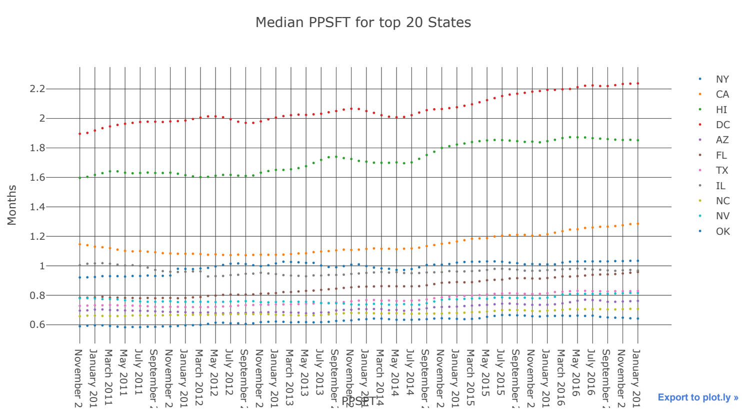
Out[20]:

	State	November 2010	December 2010	January 2011	February 2011	March 2011	April 2011	May 2011	June 2011	July 2011	...	April 2016	May 2016	June 2016	July 2016	August 2016	September 2016	October 2016	November 2016	December 2016	January 2017
0	AK	NaN	NaN	NaN	NaN	0.928	0.936	0.942	0.940	0.932	...	0.964	0.966	0.958	0.956	0.954	0.952	0.950	0.944	0.928	0.900
1	AL	0.598	0.600	0.602	0.601	0.602	0.602	0.604	0.605	0.605	...	0.644	0.646	0.644	0.638	0.634	0.634	0.634	0.634	0.636	0.634
2	AR	0.554	0.562	0.564	0.564	0.562	0.562	0.562	0.562	0.560	...	0.632	0.636	0.634	0.628	0.626	0.624	0.624	0.626	0.624	0.622
3	AZ	0.696	0.698	0.703	0.704	0.700	0.699	0.697	0.696	0.695	...	0.753	0.763	0.770	0.768	0.765	0.756	0.756	0.758	0.760	0.762
4	CA	1.146	1.140	1.130	1.126	1.120	1.110	1.102	1.098	1.100	...	1.246	1.248	1.257	1.260	1.265	1.266	1.270	1.275	1.283	1.286

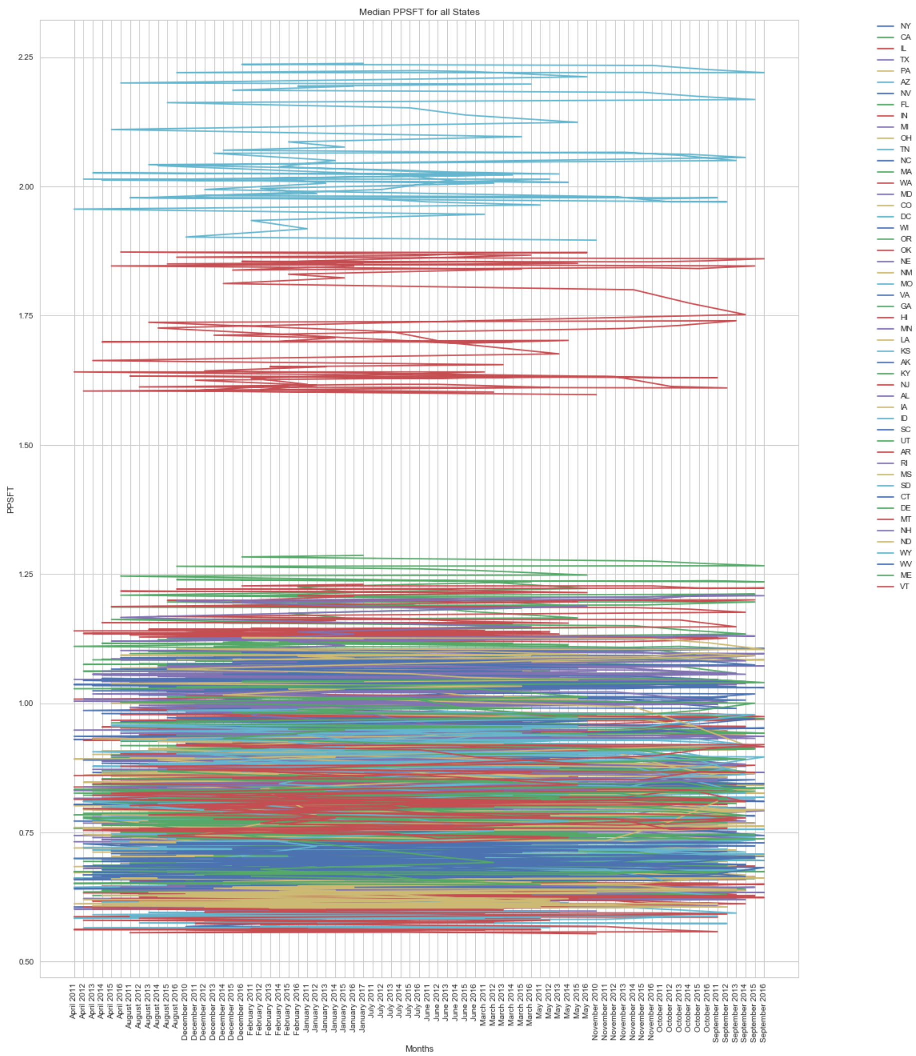
5 rows × 76 columns

In [21]:

```python
trace0 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="NY"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "NY")

trace1 =go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="CA"][months], axis = 0), mode='markers', marker=dict(size=3),
                   name = "CA")
trace2 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="HI"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "HI")

trace3 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="DC"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "DC")

trace4 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="AZ"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "AZ")

trace5 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="FL"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "FL")

trace6 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="TX"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "TX")

trace7 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="IL"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "IL")

trace8 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="NC"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "NC")

trace9 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="NV"][months], axis = 0),
                    mode='markers', marker=dict(size=3),
                    name = "NV")

trace10 = go.Scatter(x= months,
                    y = np.nanmedian(df[df["State"]=="OK"][months], axis = 0),
                     mode='markers', marker=dict(size=3),
                     name = "OK")

layout = go.Layout(title = "Median PPSFT for top 20 States", xaxis= dict(title = "PPSFT"),
                  yaxis = dict(title = "Months"))
data = [trace0, trace1, trace2, trace3, trace4, trace5, trace6, trace7, trace8, trace9, trace10]
fig =go.Figure(data=data, layout = layout)
py.iplot(fig)



#Matplotlib plot
plt.figure(figsize=(17,22))

for st in states:
    st_pick = df[df["State"] == st][months]
    plt.plot(months, np.nanmedian(st_pick, axis=0), label = st)

plt.title("Median PPSFT for all States")
plt.xlabel("Months")
plt.ylabel("PPSFT")
plt.xticks(rotation = 90)
plt.legend(bbox_to_anchor = (1.1, 1), loc = 2, borderaxespad = 0)
plt.show()
```

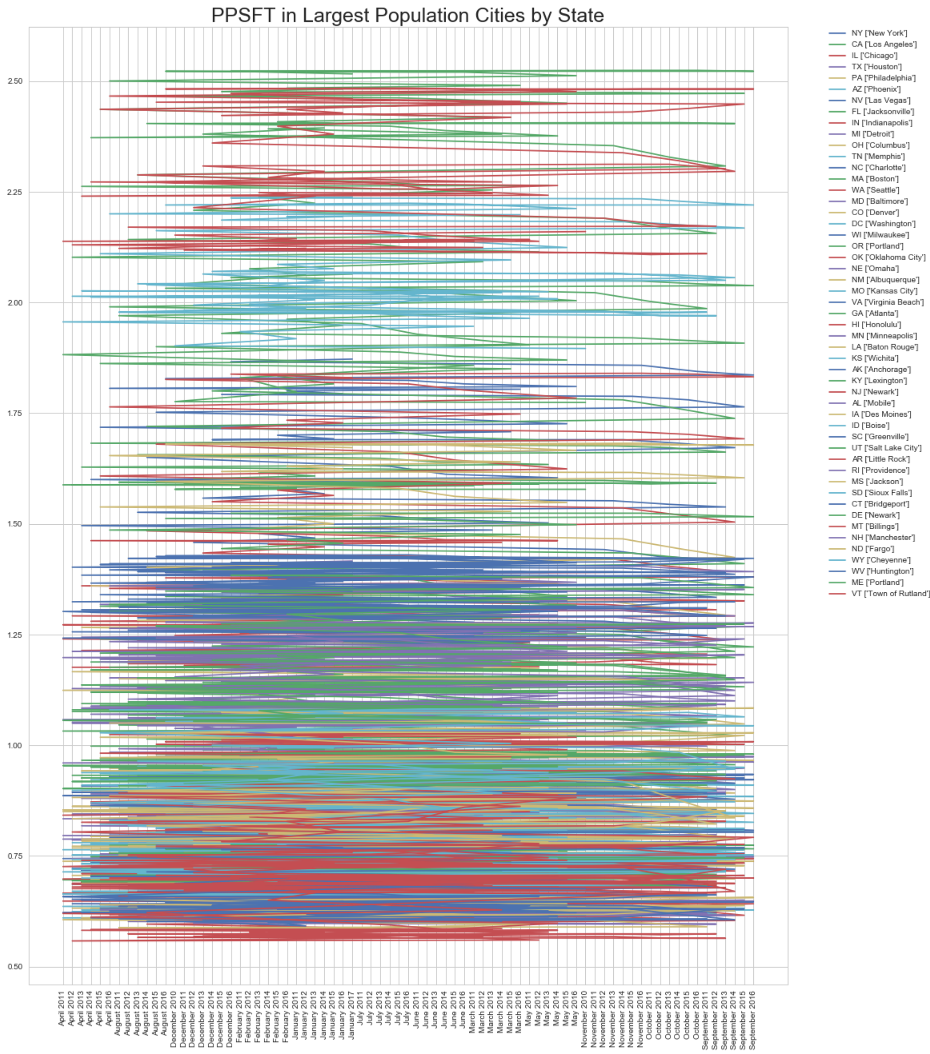



```
/Users/keshavrastogi/anaconda3/lib/python3.6/site-packages/numpy/lib/function_base.py:4033: RuntimeWarning:

All-NaN slice encountered
```



PPSFT of Cities accorind to their Population

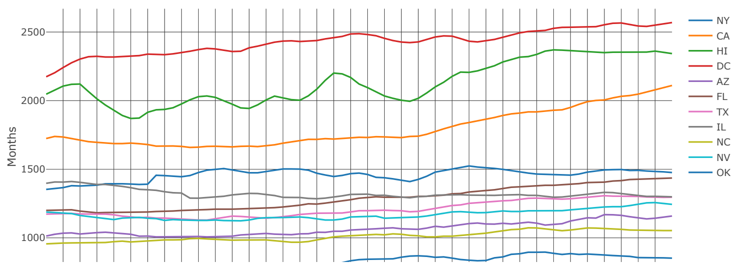
In [22]:
```
plt.figure(figsize = (17, 22))
for s in states:
    pr = df[df["State"] == s]
    r = min(pr["Population Rank"])
    pr = pr[pr["Population Rank"] == r]
    label = "{} {}".format(s, pr["City"].unique())
    pr = pr[months]
    plt.plot(pr.columns, np.transpose(pr.values), label = label)

plt.title("PPSFT in Largest Population Cities by State", fontsize = 25)
plt.xticks(rotation = 90)
plt.legend(bbox_to_anchor = (1.05, 1), loc = 2, borderaxespad = 0.)
plt.show()
```



Median Rent for all States:

In [ ]:

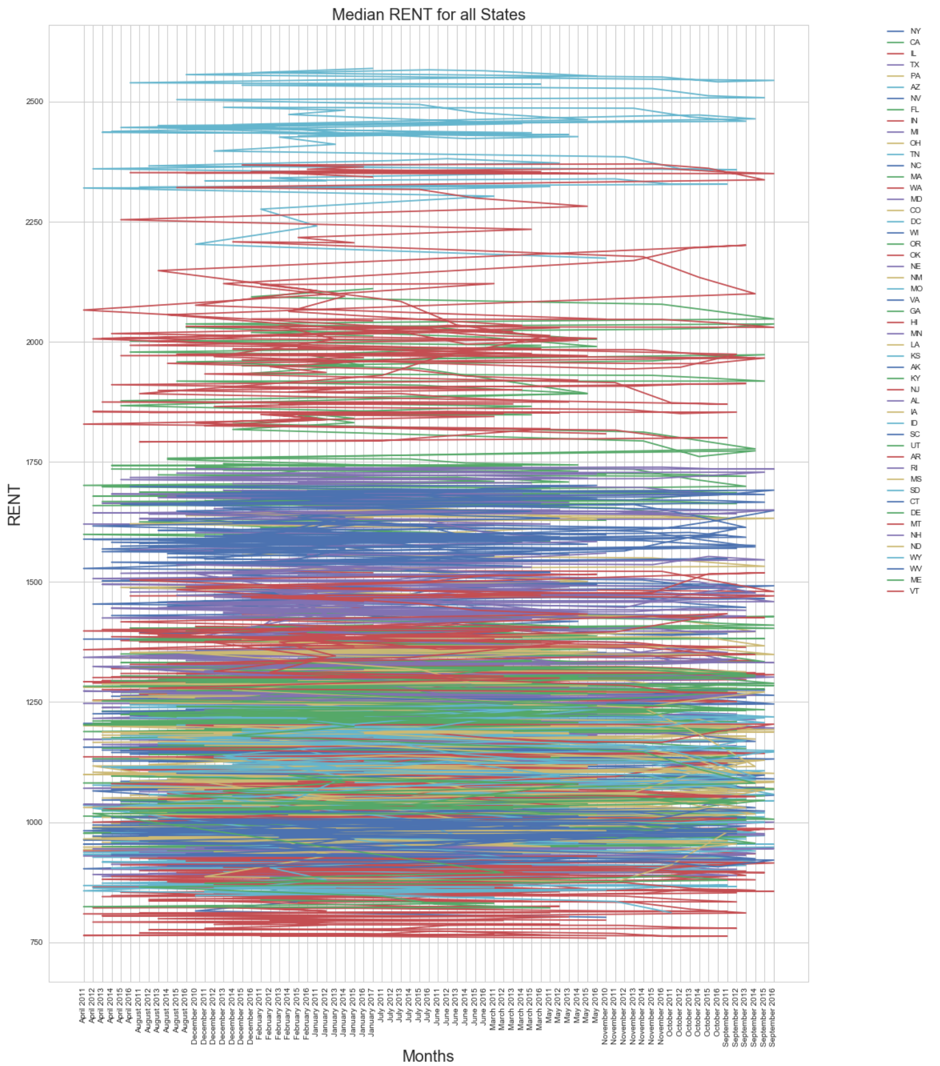
In [34]:
```
trace0 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="NY"][months], axis = 0), name = "NY")

trace1 =go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="CA"][months], axis = 0), name = "CA")
trace2 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="HI"][months], axis = 0), name = "HI")

trace3 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="DC"][months], axis = 0), name = "DC")

trace4 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="AZ"][months], axis = 0), name = "AZ")

trace5 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="FL"][months], axis = 0), name = "FL")

trace6 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="TX"][months], axis = 0), name = "TX")

trace7 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="IL"][months], axis = 0), name = "IL")

trace8 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="NC"][months], axis = 0), name = "NC")

trace9 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="NV"][months], axis = 0), name = "NV")

trace10 = go.Scatter(x= months,
                    y = np.nanmedian(df_rent[df_rent["State"]=="OK"][months], axis = 0), name = "OK")

layout = go.Layout(title = "Median RENT for top 20 States", xaxis= dict(title = "RENT"),
                  yaxis = dict(title = "Months"))
data = [trace0, trace1, trace2, trace3, trace4, trace5, trace6, trace7, trace8, trace9, trace10]
fig =go.Figure(data=data, layout = layout)
py.iplot(fig)
```



In [33]:

```python
#Matplotlib plot
plt.figure(figsize=(17,22))

for st in states:
    st_pick = df_rent[df_rent["State"] == st][months]
    plt.plot(months, np.nanmedian(st_pick, axis=0), label = st)

plt.title("Median RENT for all States", fontsize = 20)
plt.xlabel("Months", fontsize = 20)
plt.ylabel("RENT", fontsize = 20)
plt.xticks(rotation = 90)
plt.legend(bbox_to_anchor = (1.1, 1), loc = 2, borderaxespad = 0)
plt.show()
```

```
/Users/keshavrastogi/anaconda3/lib/python3.6/site-packages/numpy/lib/function_base.py:4033: RuntimeWarning:

All-NaN slice encountered
```



Note: Washington DC has the Highest PPSFT and Rent prince. Following by Hawai at second place.**

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4. Lastly, let's take a look at California State. And, compare few of its metro.

In [24]:
```
cal= df[df["State"]=="CA"]
cal.head(10)
```

Out[24]:

	City Code	City	Metro	County	State	Population Rank	November 2010	December 2010	January 2011	February 2011	...	April 2016	May 2016	June 2016	July 2016	August 2016	September 2016	October 2016	November 2016	December 2016	January 2017
1	12447	Los Angeles	Los Angeles	Los Angeles	CA	2	1.578	1.578	1.580	1.582	...	1.990	2.004	2.018	2.026	2.032	2.038	2.042	2.048	2.056	2.064
8	54296	San Diego	San Diego	San Diego	CA	9	1.492	1.494	1.492	1.490	...	1.772	1.782	1.788	1.792	1.794	1.796	1.802	1.808	1.814	1.816
10	33839	San Jose	San Jose	Santa Clara	CA	11	1.542	1.546	1.540	1.530	...	2.224	2.234	2.242	2.246	2.246	2.240	2.232	2.224	2.210	2.200
12	20330	San Francisco	San Francisco	San Francisco	CA	13	2.502	2.526	2.516	2.468	...	3.594	3.590	3.588	3.580	3.564	3.542	3.518	3.498	3.466	3.442
33	18203	Fresno	Fresno	Fresno	CA	34	0.840	0.838	0.832	0.822	...	0.814	0.816	0.816	0.818	0.820	0.820	0.822	0.822	0.822	0.824
34	20288	Sacramento	Sacramento	Sacramento	CA	35	0.918	0.926	0.928	0.930	...	1.074	1.082	1.088	1.094	1.100	1.104	1.108	1.112	1.114	1.118
36	46298	Long Beach	Los Angeles	Los Angeles	CA	37	1.594	1.590	1.588	1.586	...	1.882	1.888	1.890	1.894	1.898	1.906	1.916	1.928	1.938	1.950
42	13072	Oakland	San Francisco	Alameda	CA	43	1.396	1.404	1.414	1.424	...	2.212	2.244	2.276	2.300	2.318	2.330	2.344	2.356	2.360	2.358
53	16764	Anaheim	Los Angeles	Orange	CA	54	1.464	1.466	1.466	1.466	...	1.754	1.762	1.770	1.776	1.782	1.788	1.792	1.794	1.800	1.806
54	47568	Santa Ana	Los Angeles	Orange	CA	55	1.566	1.564	1.566	1.568	...	1.946	1.956	1.964	1.966	1.966	1.966	1.970	1.972	1.978	1.986

10 rows × 81 columns

In [25]:
```
cal_met= cal["Metro"].unique()
#cal_met

plt.figure(figsize=(17,22))
for met in cal_met:
    met_price = cal[cal["Metro"]== met][months]
    plt.plot(months, np.nanmedian(met_price, axis = 0), label = met)


plt.title("Median PPSFT of Metros in California ", fontsize =20)
plt.xlabel("Months", fontsize = 20)
plt.ylabel("PPSFT", fontsize = 20)
plt.xticks(rotation = 90)
plt.legend(bbox_to_anchor = (1.1, 1), loc = 2, borderaxespad = 0)
plt.show()
```

```
/Users/keshavrastogi/anaconda3/lib/python3.6/site-packages/numpy/lib/function_base.py:4033: RuntimeWarning:

All-NaN slice encountered

/Users/keshavrastogi/anaconda3/lib/python3.6/site-packages/numpy/lib/nanfunctions.py:1018: RuntimeWarning:

Mean of empty slice
```

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Why median prices instead of mean prices:

In their press releases, the Québec Federation of Real Estate Boards and the province's real estate boards are now using the median price to report on the evolution of property prices. Th National Association of Realtors in the United States has been using this measure for quite some time now to discuss property prices. Let us examine why the median is generally a better indicator than the average when dealing with property prices. The median is the middle point that divides a series into two equal parts. In our case, the median price allows you to divide all transactions into two equal parts: 50% of transactions occur at a price that is lower than the median price and the other 50% occur at a price that is higher. For example, a median price of $150,000 indicates that 50 percent of properties sold for$ 150,000 and the other 50% sold for more. The advantage of the median as a measure central tendency is that it is not adversely influenced by extreme numbers. And conversely, the disadvantage of the average is that it can be influenced by extreme numbers, which can lead to major distortions that bias data interpretation. Consider a geographical area in which property prices are generally in the $150,000$200,000 range. If, in one particular month, a property that is not representative of the geographic area sells for $2,000,000, this transaction pulls the average higher and results in an over-estimate of price growth in the area. The median price is not influenced by this$ 2,000,000 transaction. It thereby provides a truer reflection of the market in terms of prices and in terms of growth between two periods. Regardless of whether the median price or the average price is used, the fewer transactions there are on which to base the calculation, the more the data needs to be interpreted with caution. The standard for this calculation is a minimum of 30 transactions. With fewer than 30 transactions, there is increased risk that neither the median price nor the average price will provide a valid measure of the market value of all properties. The QFREB therefore uses this 30-sale minimum rule to determine whether or not to publish a median or average price.

Source: QFREB market analytics department.

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