Lab2_JacobDineen_IST718

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1 Zillow

1.1 Import Packages

In [62]:
```
import pandas as pd  # data frame operations
import numpy as np #arrays and math functions
import statsmodels.api as sm #stat models (regression)
import matplotlib.pyplot as plt #2d plotting
from pandas.tools.plotting import scatter_matrix  # scatter plot matrix
import numpy as np  # arrays and math functions
from scipy.stats import uniform  # for training-and-test split
import statsmodels.api as sm  # statistical models (including regression)
import statsmodels.formula.api as smf  # R-like model specification
from sklearn.tree import DecisionTreeRegressor  # machine learning tree
from sklearn.ensemble import RandomForestRegressor # ensemble method
from sklearn.preprocessing import Imputer
%config IPCompleter.greedy=True #tabbing for autocomplete
import seaborn as sns  # PROVIDES TRELLIS AND SMALL MULTIPLE PLOTTING
from pandas import Series
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.arima_model import ARIMAResults
from math import sqrt
from pandas import DataFrame
from scipy.stats import boxcox
import warnings
from mpl_toolkits.basemap import Basemap
import matplotlib.pyplot as plt
pd.options.mode.chained_assignment = None
!pip install cufflinks
import cufflinks as cf
import plotly.plotly as py
import plotly.graph_objs as go
from plotly import tools
from plotly.offline import iplot, init_notebook_mode
init_notebook_mode()
init_notebook_mode(connected=True)
```

```
Requirement already satisfied: cufflinks in c:\programdata\anaconda3\lib\site-packages
Requirement already satisfied: colorlover>=0.2 in c:\programdata\anaconda3\lib\site-packages (
Requirement already satisfied: pandas in c:\programdata\anaconda3\lib\site-packages (from cuff
Requirement already satisfied: plotly>=2.0.0 in c:\programdata\anaconda3\lib\site-packages (fr
Requirement already satisfied: python-dateutil>=2 in c:\programdata\anaconda3\lib\site-package
Requirement already satisfied: pytz>=2011k in c:\programdata\anaconda3\lib\site-packages (from
Requirement already satisfied: numpy>=1.7.0 in c:\programdata\anaconda3\lib\site-packages (fro
Requirement already satisfied: decorator>=4.0.6 in c:\programdata\anaconda3\lib\site-packages
Requirement already satisfied: nbformat>=4.2 in c:\programdata\anaconda3\lib\site-packages (fr
Requirement already satisfied: requests in c:\programdata\anaconda3\lib\site-packages (from pl
Requirement already satisfied: six in c:\programdata\anaconda3\lib\site-packages (from plotly>
Requirement already satisfied: ipython_genutils in c:\programdata\anaconda3\lib\site-packages
Requirement already satisfied: traitlets>=4.1 in c:\programdata\anaconda3\lib\site-packages (f
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in c:\programdata\anaconda3\lib\site-pa
Requirement already satisfied: jupyter_core in c:\programdata\anaconda3\lib\site-packages (fro
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in c:\programdata\anaconda3\lib\site-pack
Requirement already satisfied: idna<2.7,>=2.5 in c:\programdata\anaconda3\lib\site-packages (f
Requirement already satisfied: urllib3<1.23,>=1.21.1 in c:\programdata\anaconda3\lib\site-pack
Requirement already satisfied: certifi>=2017.4.17 in c:\programdata\anaconda3\lib\site-package


IOPub data rate exceeded.
The notebook server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--NotebookApp.iopub_data_rate_limit`.
```

1.1.1 Read in Data

In [2]:
```
#Read CSV File in from the web
## files.zillowstatic.com/research/public/Zip/Zip_Zhvi_SingleFamilyResidence.csv

url = 'http://files.zillowstatic.com/research/public/Zip/Zip_Zhvi_SingleFamilyResidenc
data = pd.read_csv(url) #pandas read csv function
print(str("You have read in a"),'' ,type(data))  #Printing object type
```

```
You have read in a  <class 'pandas.core.frame.DataFrame'>
```

1.1.2 High Level Look at data

In [3]:
```
print(str("This dataframe currently have"), '', np.shape(data)[0], '', str("rows"), ''
      np.shape(data)[1], str("columns")) #printing dimensions of current dataframe

    #Change RegionID to Zipcode to avoid confusion
data.rename(columns={'RegionID' : 'Zipcode', 'RegionName' : 'Region',
                    'CountyName' : 'County'}, inplace=True)
```

```
        data.head(n=2) #calling first 2 rows
```

```
This dataframe currently have  15338  rows  and 268 columns
```

```
Out[3]:    Zipcode  Region     City State    Metro County  SizeRank   1996-04  \
        0    84654   60657  Chicago    IL  Chicago   Cook         1  420800.0
        1    84616   60614  Chicago    IL  Chicago   Cook         2  542400.0

             1996-05   1996-06   ...     2017-03  2017-04  2017-05  2017-06  2017-07  \
        0  423500.0  426200.0   ...     1087500  1080200  1073700  1064100  1052600
        1  546700.0  551700.0   ...     1526300  1527000  1524600  1516600  1512500

           2017-08  2017-09  2017-10  2017-11  2017-12
        0  1047600  1047700  1047600  1048800  1051600
        1  1513700  1513600  1508100  1502300  1496300

        [2 rows x 268 columns]
```

1.1.3 Create dataframe with no missing values

```
In [4]: df_cleaned = data.dropna()
        warnings.filterwarnings("ignore")
        df_cleaned["Zipcode"] = df_cleaned["Zipcode"].astype('category')
        df_cleaned["Region"] = df_cleaned["Region"].astype('category')
        df_cleaned["City"] = df_cleaned["City"].astype('category')
        df_cleaned["State"] = df_cleaned["State"].astype('category')
        df_cleaned["Metro"] = df_cleaned["Metro"].astype('category')
        df_cleaned["County"] = df_cleaned["County"].astype('category')
        df_cleaned["SizeRank"] = df_cleaned["SizeRank"].astype('category')

        print(str("This dataframe currently has"), '', np.shape(df_cleaned)[0], '', str("rows"
              np.shape(df_cleaned)[1], str("columns"))
        #printing dimensions of cleaned dataframe.


        allminusmissing = (np.shape(data)[0])-(np.shape(df_cleaned)[0])
        print(allminusmissing,'',
                  str("observations lost by removing all missing values - Circle back if this i

        df_cleaned.describe() #print summary stats of all columns
```

```
This dataframe currently has  10638  rows  and 268 columns
4700  observations lost by removing all missing values - Circle back if this impacts accuracy.
```

```
Out[4]:             1996-04       1996-05       1996-06       1996-07       1996-08  \
        count  1.063800e+04  1.063800e+04  1.063800e+04  1.063800e+04  1.063800e+04
        mean   1.251639e+05  1.252531e+05  1.253337e+05  1.254029e+05  1.254891e+05
        std    7.921874e+04  7.906851e+04  7.900210e+04  7.896861e+04  7.896923e+04
        min    2.450000e+04  2.450000e+04  2.480000e+04  2.530000e+04  2.540000e+04
        25%    7.720000e+04  7.730000e+04  7.730000e+04  7.730000e+04  7.740000e+04
        50%    1.063000e+05  1.067000e+05  1.068500e+05  1.070000e+05  1.072500e+05
        75%    1.495000e+05  1.497000e+05  1.499000e+05  1.499000e+05  1.499000e+05
        max    1.769000e+06  1.768100e+06  1.766900e+06  1.764200e+06  1.762200e+06

                    1996-09       1996-10       1996-11       1996-12       1997-01  \
        count  1.063800e+04  1.063800e+04  1.063800e+04  1.063800e+04  1.063800e+04
        mean   1.256099e+05  1.257817e+05  1.260264e+05  1.263751e+05  1.269054e+05
        std    7.900314e+04  7.906898e+04  7.917073e+04  7.941154e+04  7.984216e+04
        min    2.530000e+04  2.560000e+04  2.600000e+04  2.620000e+04  2.680000e+04
        25%    7.760000e+04  7.770000e+04  7.780000e+04  7.810000e+04  7.830000e+04
        50%    1.075000e+05  1.077000e+05  1.079500e+05  1.082000e+05  1.084000e+05
        75%    1.502000e+05  1.503000e+05  1.506000e+05  1.510000e+05  1.515750e+05
        max    1.762600e+06  1.763900e+06  1.763800e+06  1.764400e+06  1.765800e+06

                   ...           2017-03       2017-04       2017-05       2017-06  \
        count      ...      1.063800e+04  1.063800e+04  1.063800e+04  1.063800e+04
        mean       ...      2.858859e+05  2.870511e+05  2.882186e+05  2.892460e+05
        std        ...      2.805536e+05  2.817050e+05  2.830268e+05  2.840960e+05
        min        ...      3.340000e+04  3.340000e+04  3.360000e+04  3.370000e+04
        25%        ...      1.377000e+05  1.385000e+05  1.392000e+05  1.394000e+05
        50%        ...      2.041000e+05  2.053000e+05  2.063000e+05  2.069500e+05
        75%        ...      3.301750e+05  3.318250e+05  3.328750e+05  3.344250e+05
        max        ...      5.654600e+06  5.716900e+06  5.777700e+06  5.810900e+06

                    2017-07       2017-08       2017-09       2017-10       2017-11  \
        count  1.063800e+04  1.063800e+04  1.063800e+04  1.063800e+04  1.063800e+04
        mean   2.901185e+05  2.912461e+05  2.928014e+05  2.945772e+05  2.963288e+05
        std    2.849095e+05  2.861074e+05  2.875850e+05  2.905396e+05  2.947448e+05
        min    3.370000e+04  3.400000e+04  3.430000e+04  3.450000e+04  3.450000e+04
        25%    1.400000e+05  1.405250e+05  1.410000e+05  1.416250e+05  1.427000e+05
        50%    2.077000e+05  2.089000e+05  2.101000e+05  2.112500e+05  2.125000e+05
        75%    3.356750e+05  3.367750e+05  3.384750e+05  3.399750e+05  3.408500e+05
        max    5.786300e+06  5.756100e+06  5.745600e+06  5.852400e+06  6.028700e+06

                    2017-12
        count  1.063800e+04
        mean   2.977196e+05
        std    2.980834e+05
        min    3.450000e+04
        25%    1.433000e+05
        50%    2.132000e+05
        75%    3.428000e+05
```

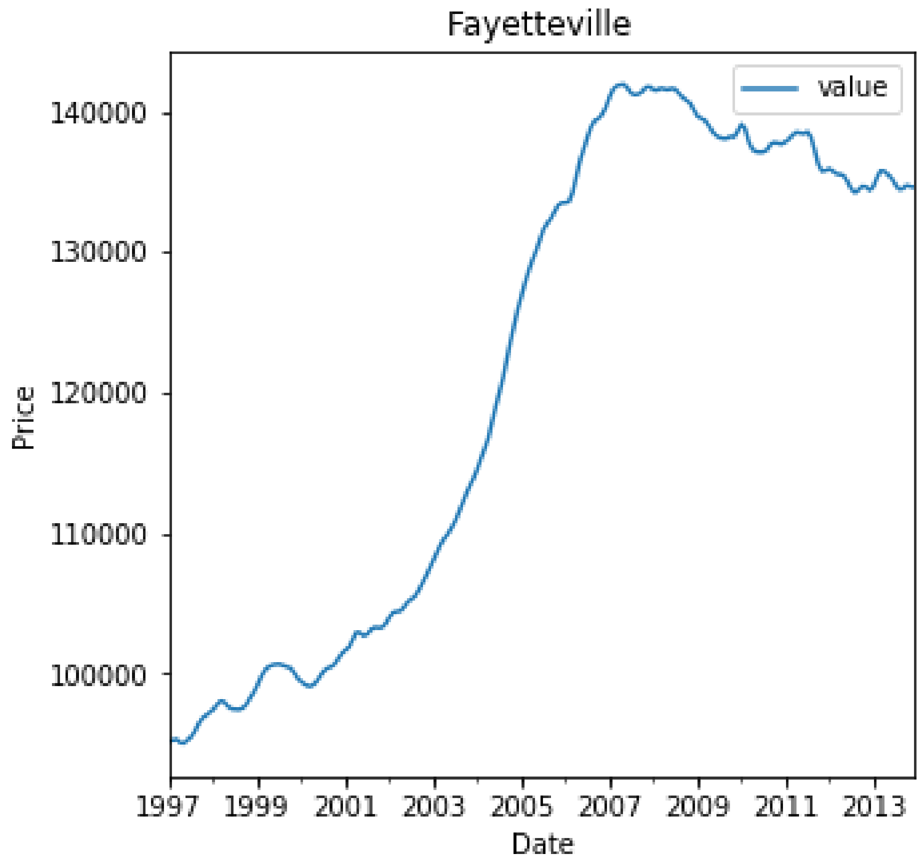
```
max    6.142100e+06

[8 rows x 261 columns]
```

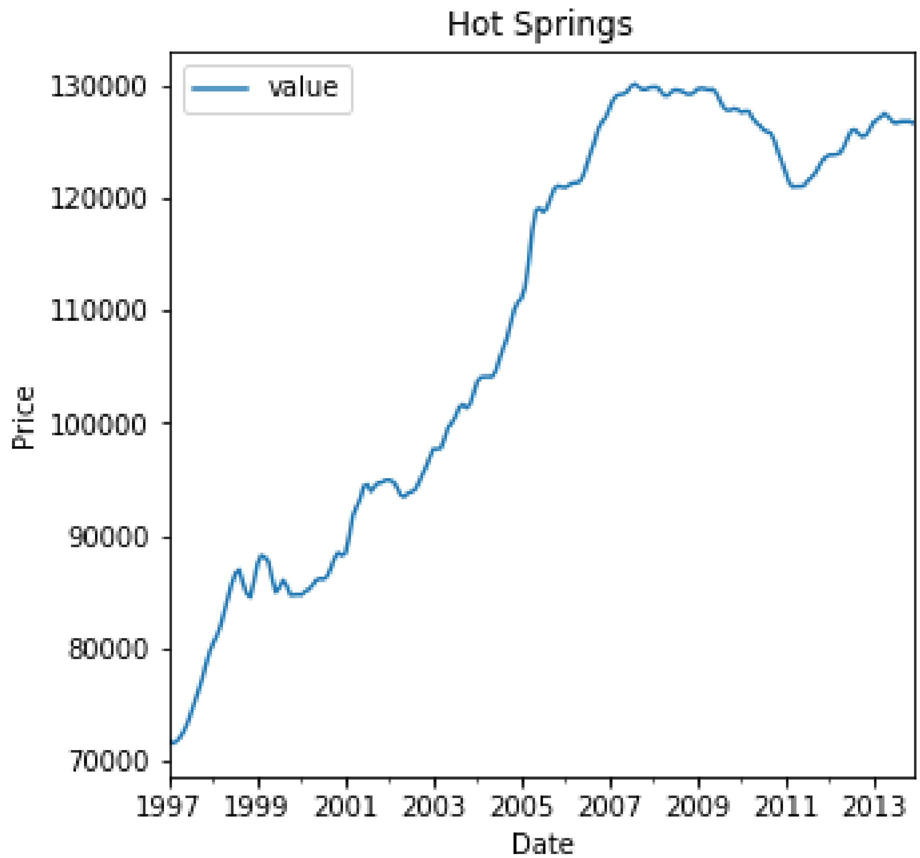
1.1.4 Develop time series plots for the following Arkansas metro areas:

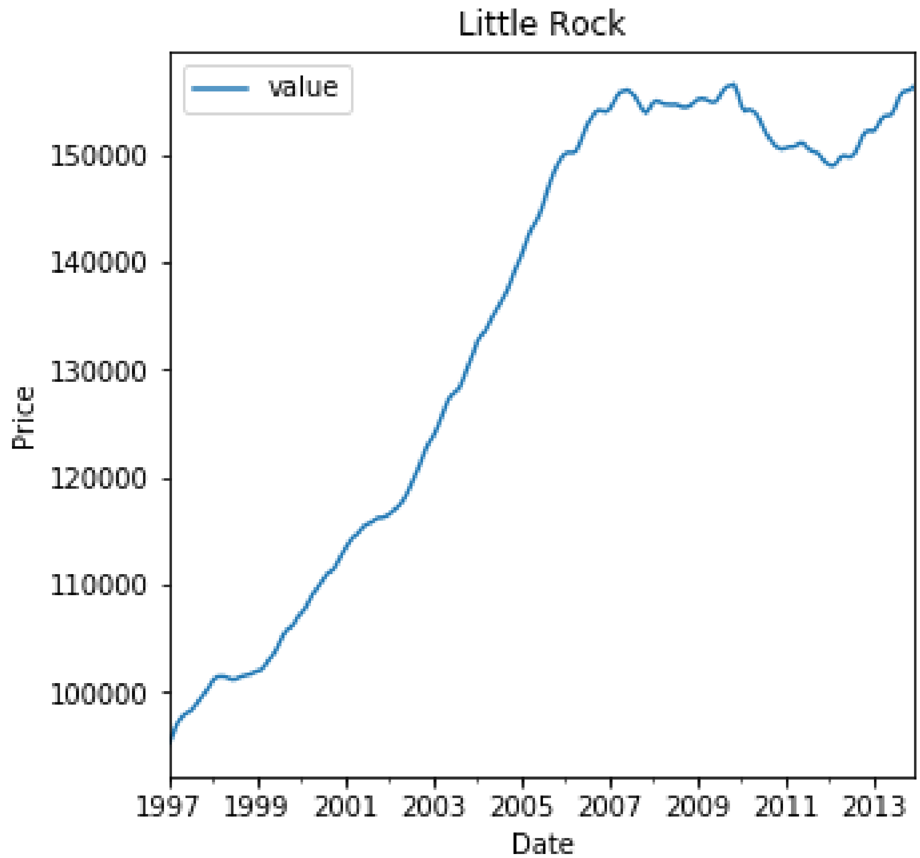
Hot Springs, Little Rock, Fayetteville, Searcy. Present all values from 1997 to 2013. Average at the metro-area level.

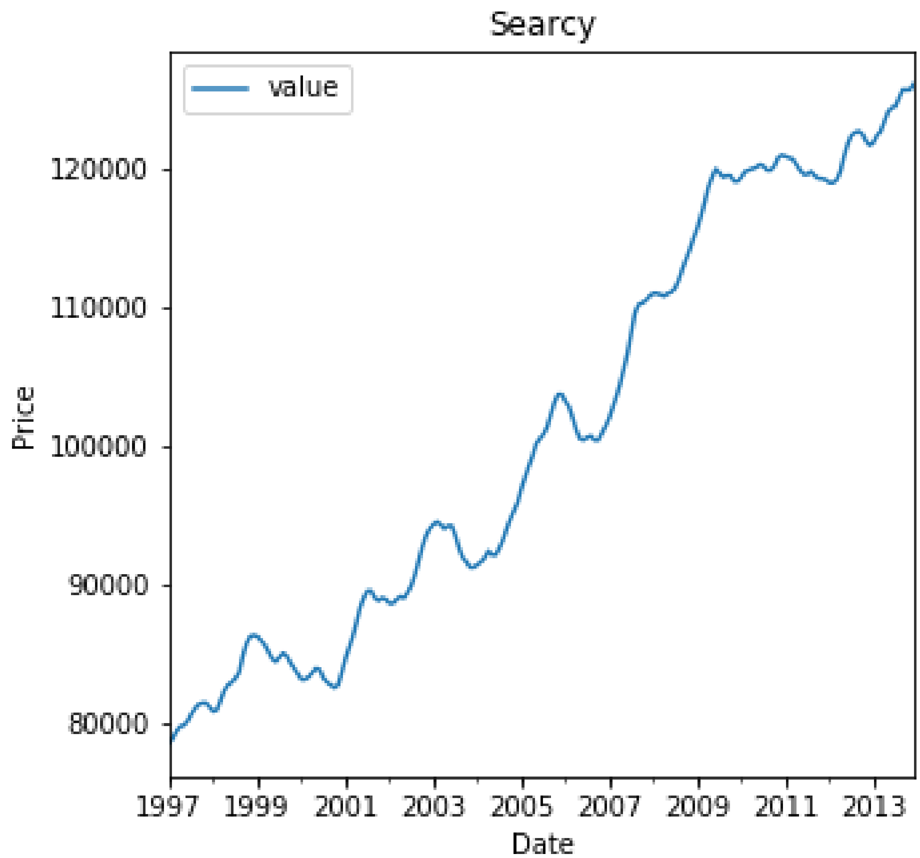
```
In [5]: # We can clean data to reduce size/shape

        #Only looking at 4 cities
        filter_list = ['Hot Springs', 'Little Rock', 'Fayetteville', 'Searcy']
        #df_cleaned[df_cleaned.City.isin(filter_list)]
                                                     #http://www.ritchieng.com/pandas-m
        df_ark = pd.DataFrame(df_cleaned[df_cleaned.City.isin(filter_list)])
        df_ark1 = df_ark.loc[:, 'Metro']


        #need to shave columns < 1997
        #df_ark.columns.get_loc('1997-01') #find index of 1997
        df_ark2 =  df_ark.loc[:, '1997-01' : '2013-12'] #use .loc to index labels
                                                     #https://stackoverflow.com/questio

        #Merge two sets of columns together on index/zip
        #pd.concat([df_ark1, df_ark2], axis=1, join='outer')
        df_ark = pd.concat([df_ark1, df_ark2], axis=1, join='outer') #https://pandas.pydata.or

        np.shape(df_ark)# 26 observations w/ data from 1997 - Latest



        #Grouping By + Mean
        df_ark = df_ark.groupby(['Metro']).mean()
        df_ark #There is a Fayetteville in Atlanta, Remove
        df_ark = df_ark.drop('Atlanta', 0) #(0 for rows and 1 for columns.)

        #separate dfs and out in 'tab
        fay = pd.melt((df_ark.filter(like = 'Fayette', axis=0)))
        hotspr = pd.melt((df_ark.filter(like = 'Hot', axis=0)))
        littlerock = pd.melt((df_ark.filter(like = 'Little Rock', axis=0)))
        searcy = pd.melt((df_ark.filter(like = 'Searcy', axis=0)))

        fay['variable'] = pd.to_datetime(fay['variable'])
        hotspr['variable'] = pd.to_datetime(hotspr['variable'])
        littlerock['variable'] = pd.to_datetime(littlerock['variable'])
        searcy['variable'] = pd.to_datetime(searcy['variable'])

In [6]: from pylab import rcParams
```

```python
rcParams['figure.figsize'] = 5, 5

#Fayetteville
fay.plot(x = 'variable')
plt.title('Fayetteville')
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()

#Hot Springs
hotspr.plot(x = 'variable')
plt.title('Hot Springs')
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()

#Little Rock
littlerock.plot(x = 'variable')
plt.title('Little Rock')
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()

#Searcy
searcy.plot(x = 'variable')
plt.title('Searcy')
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()
```


Fayetteville
value
140000
130000
120000
110000
100000
Price
1997
1999
2001
2003
2005
2007
2009
2011
2013
Date


Hot Springs
value
Price
Date
130000
120000
110000
100000
90000
80000
70000
1997
1999
2001
2003
2005
2007
2009
2011
2013

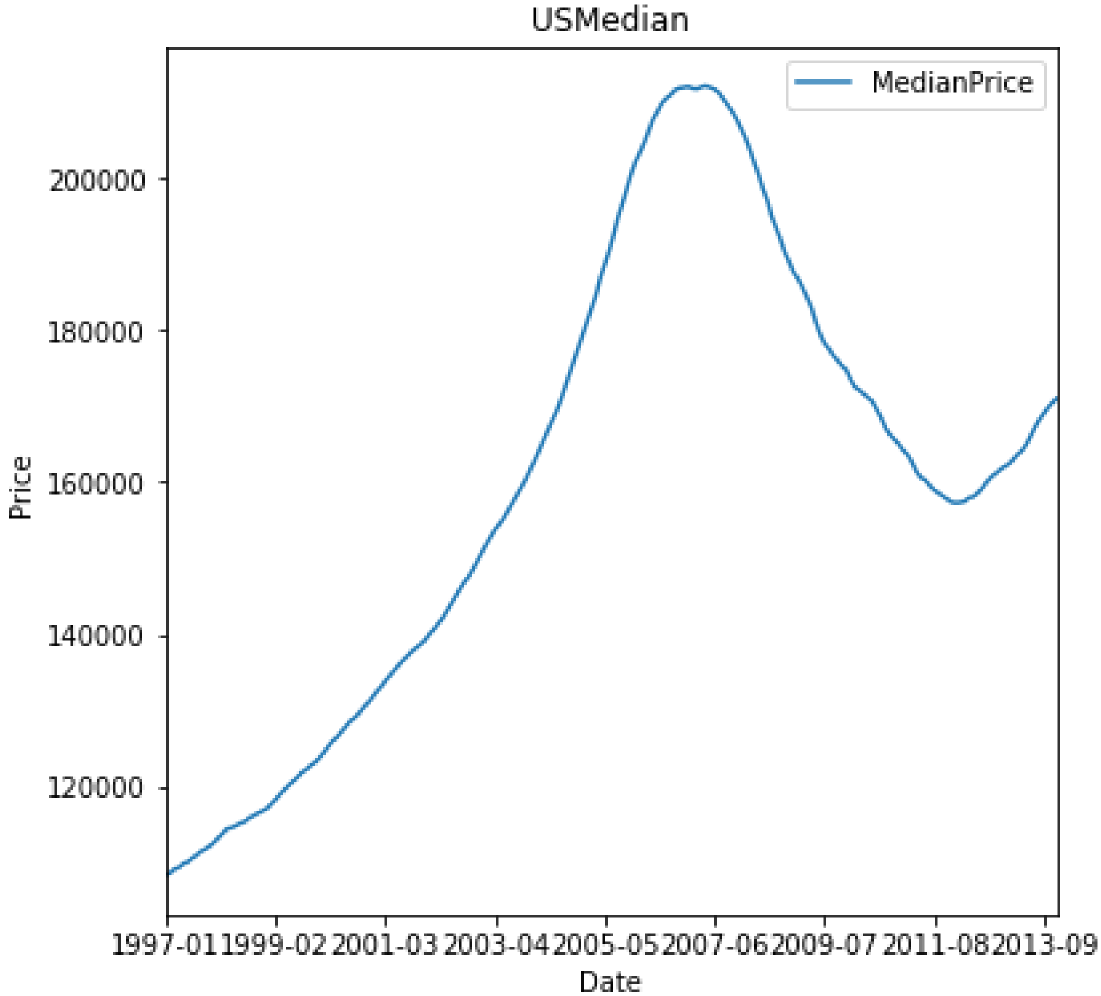

Little Rock
value
Price
150000
140000
130000
120000
110000
100000
1997
1999
2001
2003
2005
2007
2009
2011
2013
Date

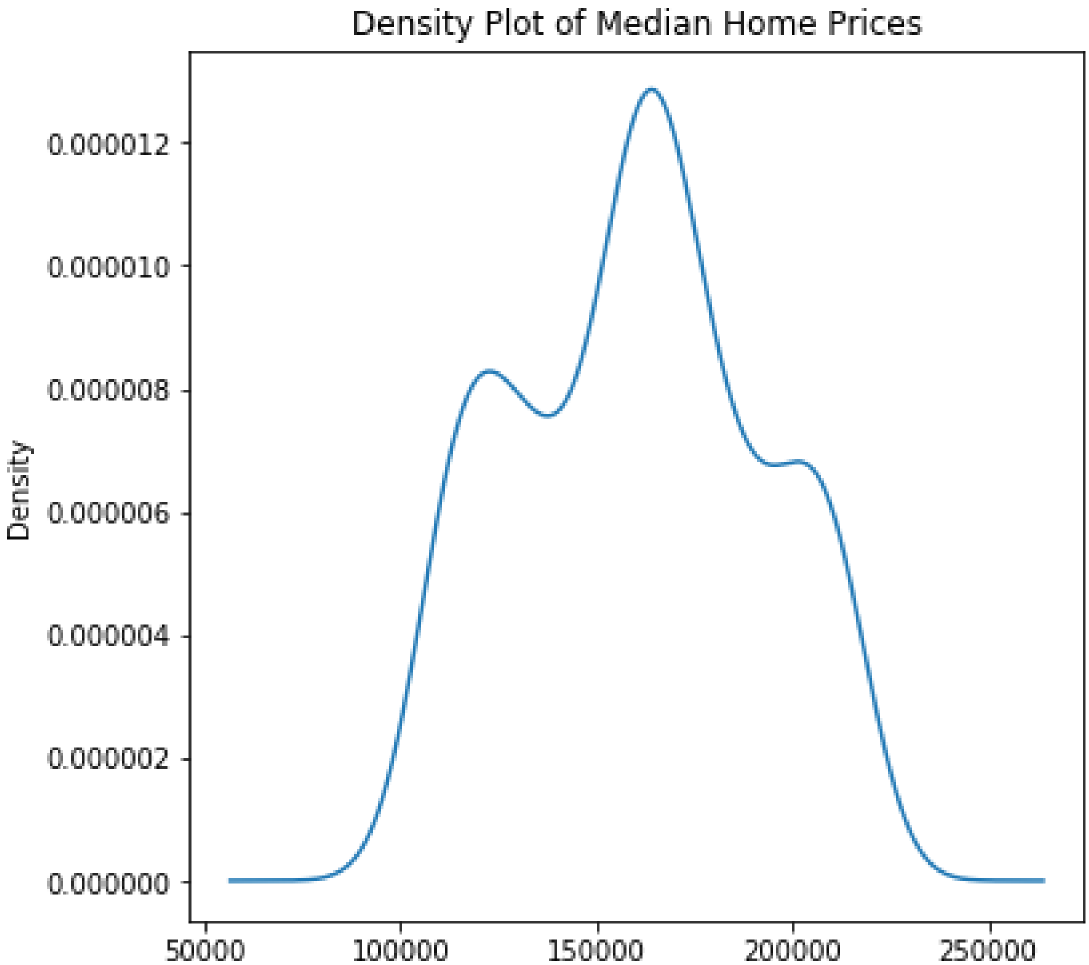


1.1.5 Autocorrelation / Partial Autocorrelation (Using Median)

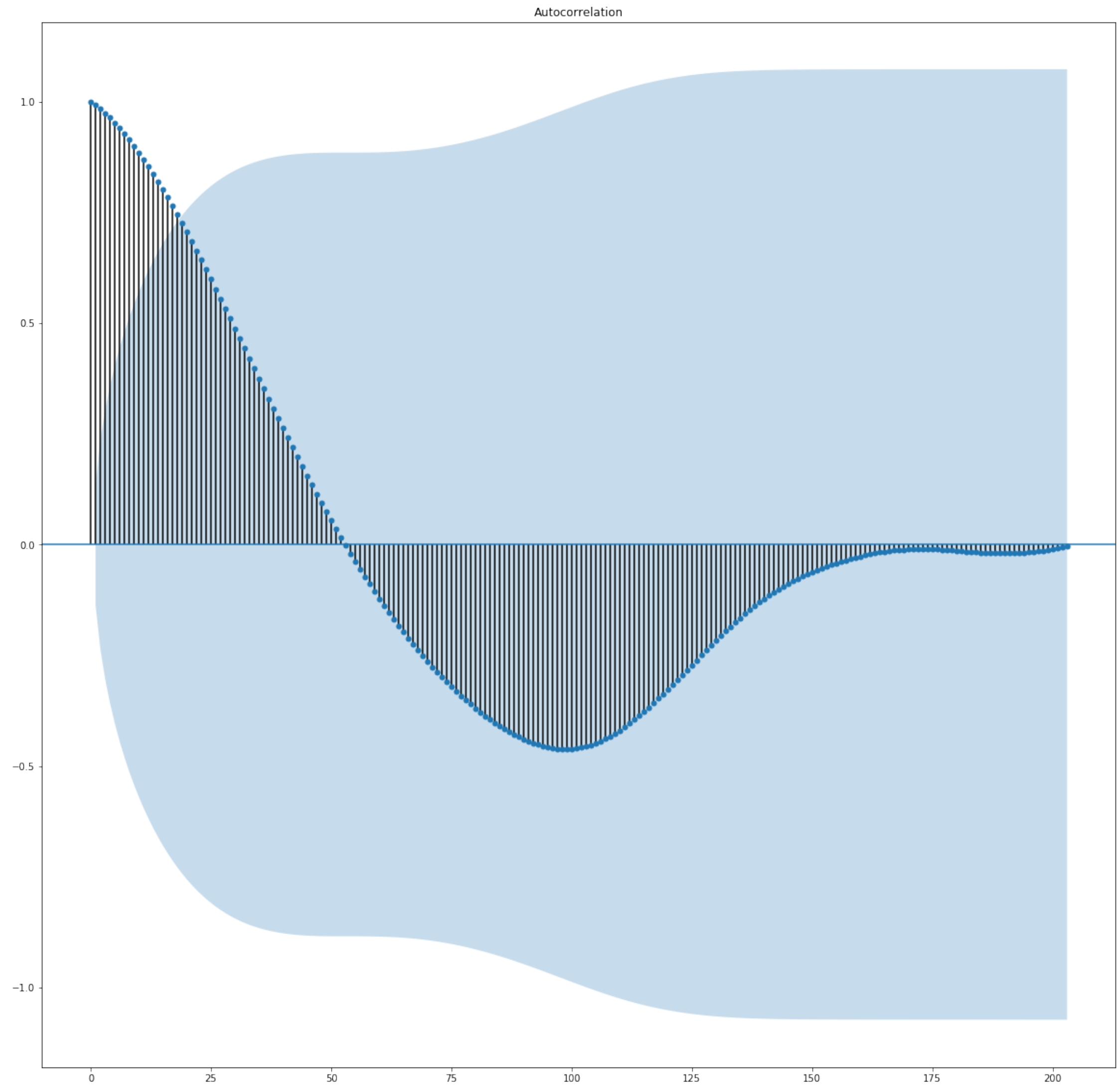
In [7]:
```
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf

from pylab import rcParams
rcParams['figure.figsize'] = 6,6


#Create melted dataframe taking median house price per t
df = df_cleaned.loc[:, '1997-01' : '2013-12']

dfmedian = pd.DataFrame(df.median(), columns= ['MedianPrice'])
dfmedian['MedianPrice'] = round(dfmedian['MedianPrice'], 2)

plt.hist(dfmedian.MedianPrice, bins = 10)
plt.title('Histogram of Median HH Price')
plt.xlabel('Price')
plt.ylabel('Frequency')
```

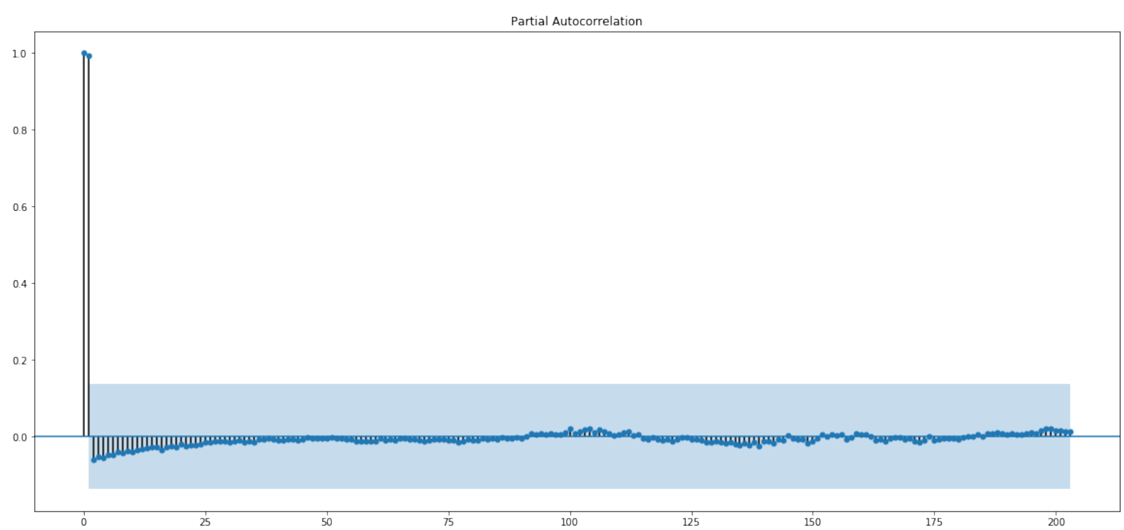
```
#Plot US Median House price per t
dfmedian.plot(y = 'MedianPrice')
plt.title('USMedian')
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()


dfmedian.MedianPrice.plot(kind = 'kde')
plt.title('Density Plot of Median Home Prices')
plt.show()
dfmediantest = df_cleaned.loc[:, '2014-01' : '2014-12']
dfmediantest = pd.DataFrame(dfmediantest.median(), columns= ['MedianPrice'])
dfmediantest['MedianPrice'] = round(dfmediantest['MedianPrice'], 2)
dfmediantest = dfmediantest.astype('float32')
```


USMedian
MedianPrice
200000
180000
160000
140000
120000
Price
1997-01
1999-02
2001-03
2003-04
2005-05
2007-06
2009-07
2011-08
2013-09
Date



In [8]:
```
from matplotlib import pyplot
rcParams['figure.figsize'] = 10,10

#ACF and PACF to get P/Q for ARIMA model and show clusters
plot_acf(dfmedian.MedianPrice, ax=pyplot.gca())
pyplot.show()

pyplot.subplot(212)

plot_pacf(dfmedian.MedianPrice, ax=pyplot.gca())
pyplot.show()
```

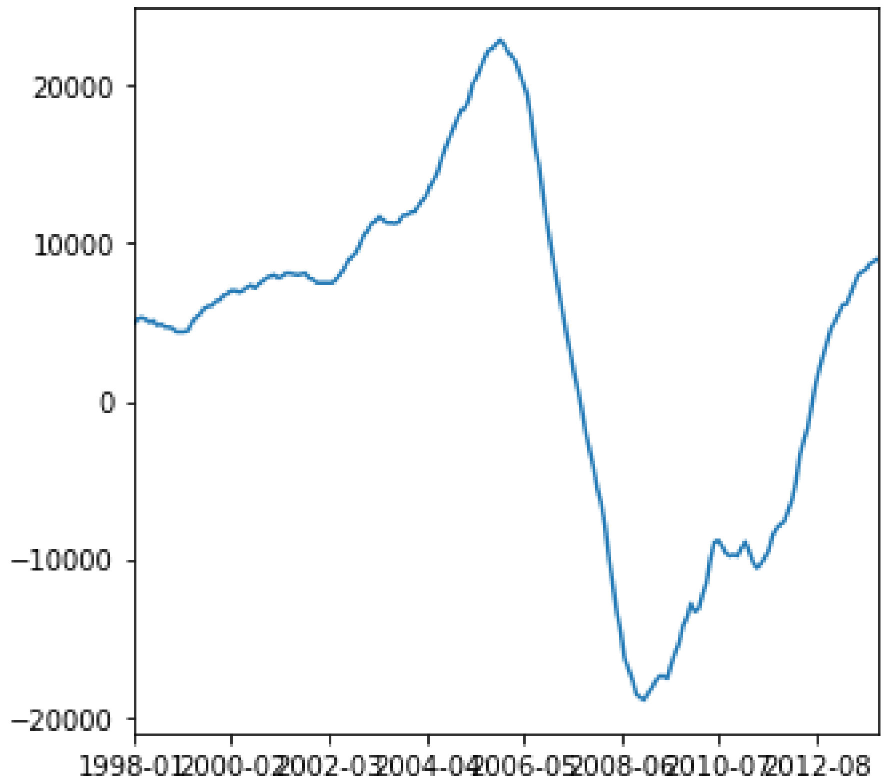

Autocorrelation
1.0
0.5
0.0
−0.5
−1.0
0
25
50
75
100
125
150
175
200


Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
0
25
50
75
100
125
150
175
200

1.1.6 Augmented Dickey Fuller Test (Using median)

In [9]:
```
from statsmodels.tsa.stattools import adfuller
rcParams['figure.figsize'] = 5,5

# create a differenced series
def difference(dataset, interval=1):
        diff = list()
        for i in range(interval, len(dataset)):
                value = dataset[i] - dataset[i - interval]
                diff.append(value)
        return Series(diff)

X = dfmedian.MedianPrice
X = X.astype('float32')
# difference data
months_in_year = 12
stationary = difference(X, months_in_year)
stationary.index = dfmedian.index[months_in_year:]
# check if stationary
result = adfuller(stationary)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
        print('\t%s: %.3f' % (key, value))
# save
stationary.to_csv('stationary.csv')
# plot
stationary.plot()
pyplot.show()
```

```
ADF Statistic: -2.459017
p-value: 0.125767
Critical Values:
        1%: -3.468
        5%: -2.878
        10%: -2.576
```



1.1.7 Develop ARIMA Model. (Using Median HH Price as dependent var)

```
In [10]: # Find Best Orders of Magnitude for ARIMA Model
         import warnings
         import numpy


         # create a differenced series
         def difference(dataset, interval=1):
                 diff = list()
                 for i in range(interval, len(dataset)):
                         value = dataset[i] - dataset[i - interval]
                         diff.append(value)
                 return numpy.array(diff)

         # invert differenced value
         def inverse_difference(history, yhat, interval=1):
                 return yhat + history[-interval]

         # evaluate an ARIMA model for a given order (p,d,q) and return RMSE
         def evaluate_arima_model(X, arima_order):
```

```
        # prepare training dataset
        X = X.astype('float32')
        train_size = int(len(X) * 0.50)
        train, test = X[0:train_size], X[train_size:]
        history = [x for x in train]
        # make predictions
        predictions = list()
        for t in range(len(test)):
                # difference data
                months_in_year = 12
                diff = difference(history, months_in_year)
                model = ARIMA(diff, order=arima_order)
                model_fit = model.fit(trend='nc', disp=0)
                yhat = model_fit.forecast()[0]
                yhat = inverse_difference(history, yhat, months_in_year)
                predictions.append(yhat)
                history.append(test[t])
        # calculate out of sample error
        mse = mean_squared_error(test, predictions)
        rmse = sqrt(mse)
        return rmse

# evaluate combinations of p, d and q values for an ARIMA model
def evaluate_models(dataset, p_values, d_values, q_values):
        dataset = dataset.astype('float32')
        best_score, best_cfg = float("inf"), None
        for p in p_values:
                for d in d_values:
                        for q in q_values:
                                order = (p,d,q)
                                try:
                                        mse = evaluate_arima_model(dataset, order)
                                        if mse < best_score:
                                                best_score, best_cfg = mse, order
                                        print('ARIMA%s RMSE=%.3f' % (order,mse))
                                except:
                                        continue
        print('Best ARIMA%s RMSE=%.3f' % (best_cfg, best_score))

# load dataset
series = df
# evaluate parameters
p_values = range(0, 7)
d_values = range(0, 3)
q_values = range(0, 7)
warnings.filterwarnings("ignore")
evaluate_models(dfmedian.MedianPrice, p_values, d_values, q_values)
```

```
ARIMA(0, 1, 1) RMSE=613.689
ARIMA(0, 1, 2) RMSE=550.229
ARIMA(0, 1, 3) RMSE=481.406
ARIMA(0, 1, 6) RMSE=446.062
ARIMA(0, 2, 1) RMSE=418.071
ARIMA(0, 2, 2) RMSE=421.484
ARIMA(0, 2, 3) RMSE=424.801
ARIMA(0, 2, 4) RMSE=421.630
ARIMA(0, 2, 5) RMSE=425.519
ARIMA(1, 1, 0) RMSE=414.813
ARIMA(1, 1, 4) RMSE=418.963
ARIMA(1, 1, 5) RMSE=421.974
ARIMA(1, 1, 6) RMSE=433.609
ARIMA(1, 2, 0) RMSE=420.045
ARIMA(1, 2, 1) RMSE=418.463
ARIMA(2, 1, 0) RMSE=415.276
ARIMA(2, 2, 0) RMSE=420.417
ARIMA(3, 2, 0) RMSE=424.107
ARIMA(3, 2, 1) RMSE=423.149
ARIMA(4, 2, 0) RMSE=424.884
ARIMA(4, 2, 1) RMSE=422.987
ARIMA(5, 1, 0) RMSE=421.624
ARIMA(5, 2, 0) RMSE=426.506
ARIMA(5, 2, 1) RMSE=424.070
ARIMA(5, 2, 2) RMSE=415.215
ARIMA(6, 1, 0) RMSE=424.042
ARIMA(6, 1, 1) RMSE=422.772
ARIMA(6, 2, 0) RMSE=424.590
Best ARIMA(1, 1, 0) RMSE=414.813
```

In [11]:
```python
#evaluate manually configured ARIMA model with Best ARIMA fit

# create a differenced series
def difference(dataset, interval=1):
        diff = list()
        for i in range(interval, len(dataset)):
                value = dataset[i] - dataset[i - interval]
                diff.append(value)
        return diff

# invert differenced value
def inverse_difference(history, yhat, interval=1):
        return yhat + history[-interval]


# prepare data
X = dfmedian.MedianPrice
```

```python
	X = X.astype('float32')
	train_size = int(len(X) * 0.80)
	train, test = X[0:train_size], X[train_size:]

	# walk-forward validation
	history = [x for x in train]
	predictions = list()
	for i in range(len(test)):
		# difference data
		months_in_year = 12
		diff = difference(history, months_in_year)
		# predict
		model = ARIMA(diff, order=(5,2,2))
		model_fit = model.fit(trend='nc', disp=0)
		yhat = model_fit.forecast()[0]
		yhat = inverse_difference(history, yhat, months_in_year)
		predictions.append(yhat)
		# observation
		obs = test[i]
		history.append(obs)
		print('>Predicted=%.3f, Expected=%3.f' % (yhat, obs))

	# report performance
	rmse = sqrt(mean_squared_error(test, predictions))
	print('RMSE: %.3f' % rmse)
```

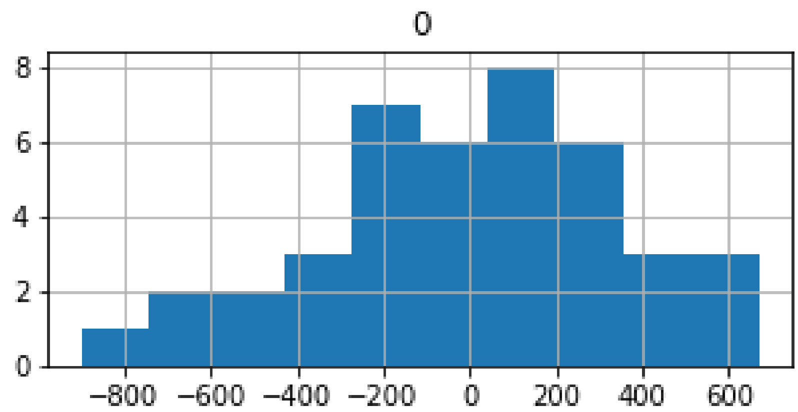
```
>Predicted=169348.906, Expected=168450
>Predicted=167536.555, Expected=167100
>Predicted=166153.890, Expected=166250
>Predicted=165380.285, Expected=165600
>Predicted=165092.054, Expected=165000
>Predicted=163708.802, Expected=164200
>Predicted=163400.108, Expected=163600
>Predicted=163188.350, Expected=162600
>Predicted=161610.161, Expected=161400
>Predicted=160406.613, Expected=160600
>Predicted=159731.783, Expected=160300
>Predicted=159512.069, Expected=159600
>Predicted=159119.271, Expected=159000
>Predicted=158060.829, Expected=158600
>Predicted=158142.862, Expected=158200
>Predicted=157647.272, Expected=157800
>Predicted=157475.728, Expected=157400
>Predicted=157019.921, Expected=157300
>Predicted=157521.260, Expected=157350
>Predicted=157158.249, Expected=157500
>Predicted=157281.242, Expected=157950
>Predicted=158310.535, Expected=158100
```

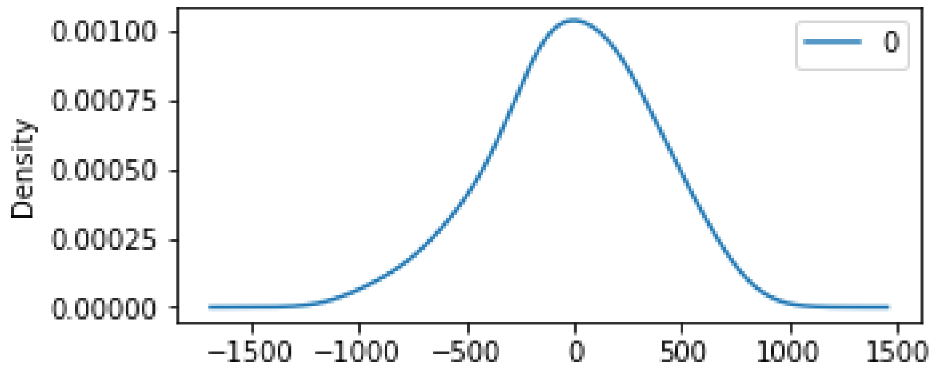
```
>Predicted=158675.091, Expected=158600
>Predicted=158774.479, Expected=159200
>Predicted=159712.501, Expected=160000
>Predicted=160973.237, Expected=160650
>Predicted=161638.958, Expected=161100
>Predicted=161775.506, Expected=161600
>Predicted=161932.740, Expected=162000
>Predicted=162477.989, Expected=162350
>Predicted=162969.009, Expected=162900
>Predicted=163806.304, Expected=163600
>Predicted=164784.919, Expected=164100
>Predicted=164511.481, Expected=164900
>Predicted=165810.924, Expected=166000
>Predicted=166918.798, Expected=167200
>Predicted=168615.387, Expected=168200
>Predicted=169362.574, Expected=169000
>Predicted=169787.563, Expected=169800
>Predicted=170540.343, Expected=170450
>Predicted=170916.717, Expected=171000
RMSE: 348.342
```

In [12]:
```
#summarize ARIMA forecast residuals
# create a differenced series
def difference(dataset, interval=1):
        diff = list()
        for i in range(interval, len(dataset)):
                value = dataset[i] - dataset[i - interval]
                diff.append(value)
        return diff

# invert differenced value
def inverse_difference(history, yhat, interval=1):
        return yhat + history[-interval]



# prepare data
X = dfmedian.MedianPrice
X = X.astype('float32')
train_size = int(len(X) * 0.80)
train, test = X[0:train_size], X[train_size:]
# walk-forward validation
history = [x for x in train]
predictions = list()
for i in range(len(test)):
        # difference data
        months_in_year = 12
```

```python
            diff = difference(history, months_in_year)
            # predict
            model = ARIMA(diff, order=(5, 2, 2))
            model_fit = model.fit(trend='nc', disp=0)
            yhat = model_fit.forecast()[0]
            yhat = inverse_difference(history, yhat, months_in_year)
            predictions.append(yhat)
            # observation
            obs = test[i]
            history.append(obs)

    # errors
    residuals = [test[i]-predictions[i] for i in range(len(test))]
    residuals = DataFrame(residuals)

    print(residuals.describe())
    # plot
    plt.figure()
    plt.subplot(211)
    residuals.hist(ax=plt.gca())
    plt.subplot(212)
    residuals.plot(kind='kde', ax=plt.gca())
    plt.show()
```

```
                0
count   41.000000
mean    -5.884525
std    352.619424
min   -898.905717
25%   -206.304336
50%     12.436856
75%    219.715159
max    668.758458
```





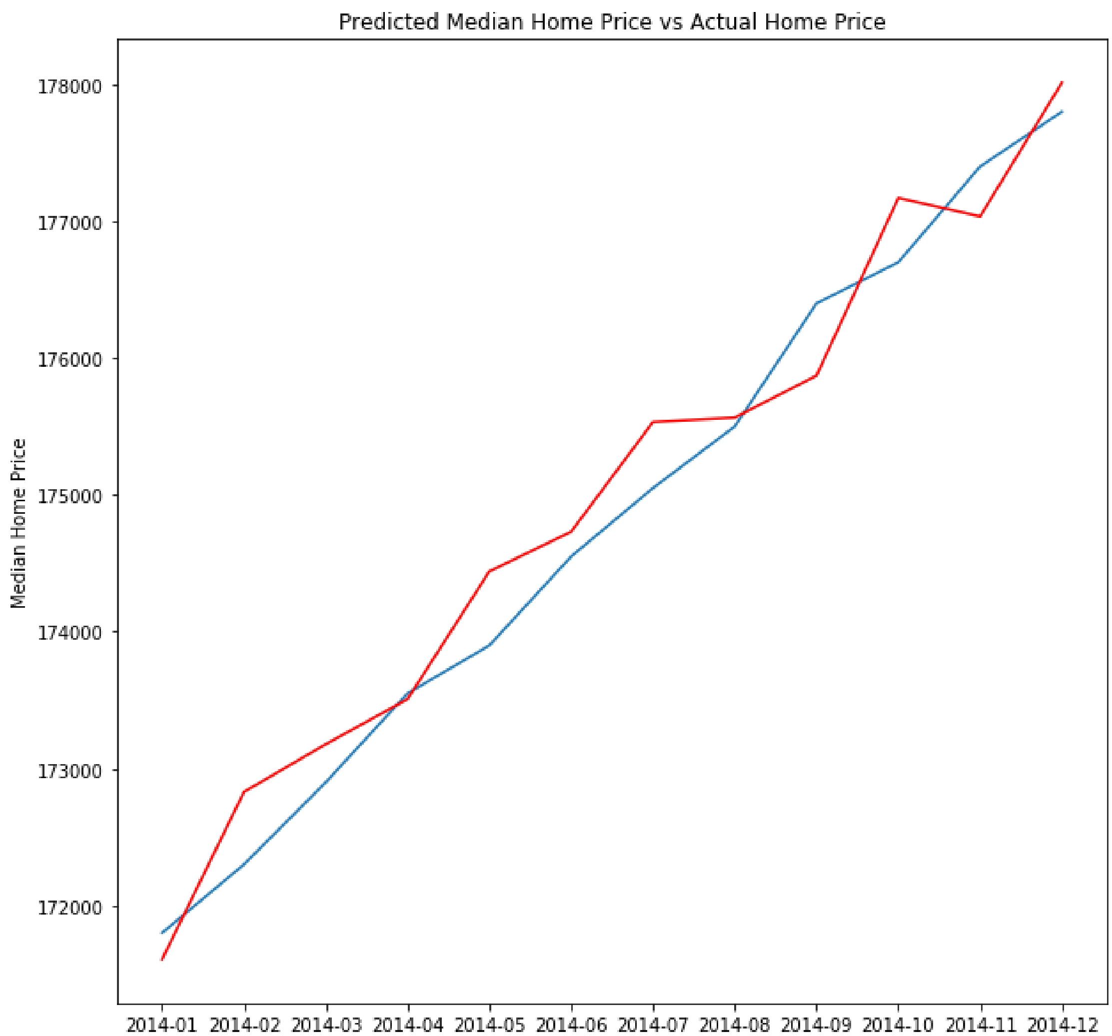
In [26]:
```
#Save finalized model

# monkey patch around bug in ARIMA class
def __getnewargs__(self):
    return ((self.endog),(self.k_lags, self.k_diff, self.k_ma))

ARIMA.__getnewargs__ = __getnewargs__

# create a differenced series
def difference(dataset, interval=1):
    diff = list()
    for i in range(interval, len(dataset)):
        value = dataset[i] - dataset[i - interval]
        diff.append(value)
    return diff

# prepare data
X = dfmedian.MedianPrice
X = X.astype('float32')

# difference data
```

```
months_in_year = 12
diff = difference(X, months_in_year)

# fit model
model = ARIMA(diff, order=(5,2,2)) # Using the best RMSE
model_fit = model.fit(trend='nc', disp=0)

# bias constant, could be calculated from in-sample mean residual
bias = 74.2230 # Using the residual model mean as our bias

# save model
model_fit.save('model.pkl')
np.save('model_bias.npy', [bias])
```

In [27]:
```
#Validating Forecasts against averaged testing data

# create a differenced series
def difference(dataset, interval=1):
        diff = list()
        for i in range(interval, len(dataset)):
                value = dataset[i] - dataset[i - interval]
                diff.append(value)
        return diff

# invert differenced value
def inverse_difference(history, yhat, interval=1):
        return yhat + history[-interval]

# load and prepare datasets
X = dfmedian.MedianPrice.astype('float32')
history = [x for x in X]
months_in_year = 12
y = dfmediantest.MedianPrice.astype('float32')

# load model
model_fit = ARIMAResults.load('model.pkl')
bias = np.load('model_bias.npy')

# make first prediction
predictions = list()
yhat = float(model_fit.forecast()[0])
yhat = bias + inverse_difference(history, yhat, months_in_year)
predictions.append(yhat)
history.append(y[0])
print('>Predicted=%.3f, Expected=%3.f' % (yhat, y[0]))

# rolling forecasts
for i in range(1, len(y)):
```

```
        # difference data
        months_in_year = 12
        diff = difference(history, months_in_year)
        # predict
        model = ARIMA(diff, order=(5,2,2)) # Using the mest ARIMA
        model_fit = model.fit(trend='nc', disp=0)
        yhat = model_fit.forecast()[0]
        yhat = bias + inverse_difference(history, yhat, months_in_year)
        predictions.append(yhat)
        # observation
        obs = y[i]
        history.append(obs)
        print('>Predicted=%.3f, Expected=%3.f' % (yhat, obs))

    pred_dates = ['2014-01','2014-02', '2014-03']
    # Send the prediction to csv file
    #predictions.to_csv('predictions.csv')

    # report performance
    rcParams['figure.figsize'] = 10,10
    rmse = sqrt(mean_squared_error(y, predictions))
    print('RMSE: %.3f' % rmse)
    plt.plot(y)
    plt.plot(predictions, color='red')
    plt.title('Predicted Median Home Price vs Actual Home Price')
    plt.ylabel('Median Home Price')
    plt.show()
```

```
>Predicted=171607.271, Expected=171800
>Predicted=172829.884, Expected=172300
>Predicted=173178.683, Expected=172900
>Predicted=173508.167, Expected=173550
>Predicted=174441.667, Expected=173900
>Predicted=174731.049, Expected=174550
>Predicted=175532.727, Expected=175050
>Predicted=175565.889, Expected=175500
>Predicted=175871.634, Expected=176400
>Predicted=177170.930, Expected=176700
>Predicted=177035.143, Expected=177400
>Predicted=178012.340, Expected=177800
RMSE: 369.689
```



1.1.8 Consolidate monthly data into an annual average (By State/Zip).

In [30]:
```
import datetime
rcParams['figure.figsize'] = 6,6

dftest = df_cleaned
dftest.head()

dfstatemedian = round(dftest.groupby(['State', 'Zipcode']).median() ,2)
dfstatemedian = dfstatemedian.reset_index(level = 'State')
dfstatemedian = dfstatemedian.reset_index(level = 'Zipcode')
dfstatemedian = dfstatemedian.dropna(how='any')

#Melted DF for plotting/vis. Grouped by state by average HH price
dfstatemedian1 = pd.melt(dfstatemedian, id_vars=['State', 'Zipcode'])
```

```
dfstatemedian1.rename(columns = {'variable' : 'Date', 'value': 'Price'}, inplace=True

dfstatemedian1.head()
```

Out[30]:

	State	Zipcode	Date	Price
0	AK	100478	1996-04	238900.0
1	AL	73257	1996-04	84800.0
2	AL	73258	1996-04	62200.0
3	AL	73260	1996-04	107400.0
4	AL	73270	1996-04	90000.0

1.2 Layer in Secondary data sources

In [16]:

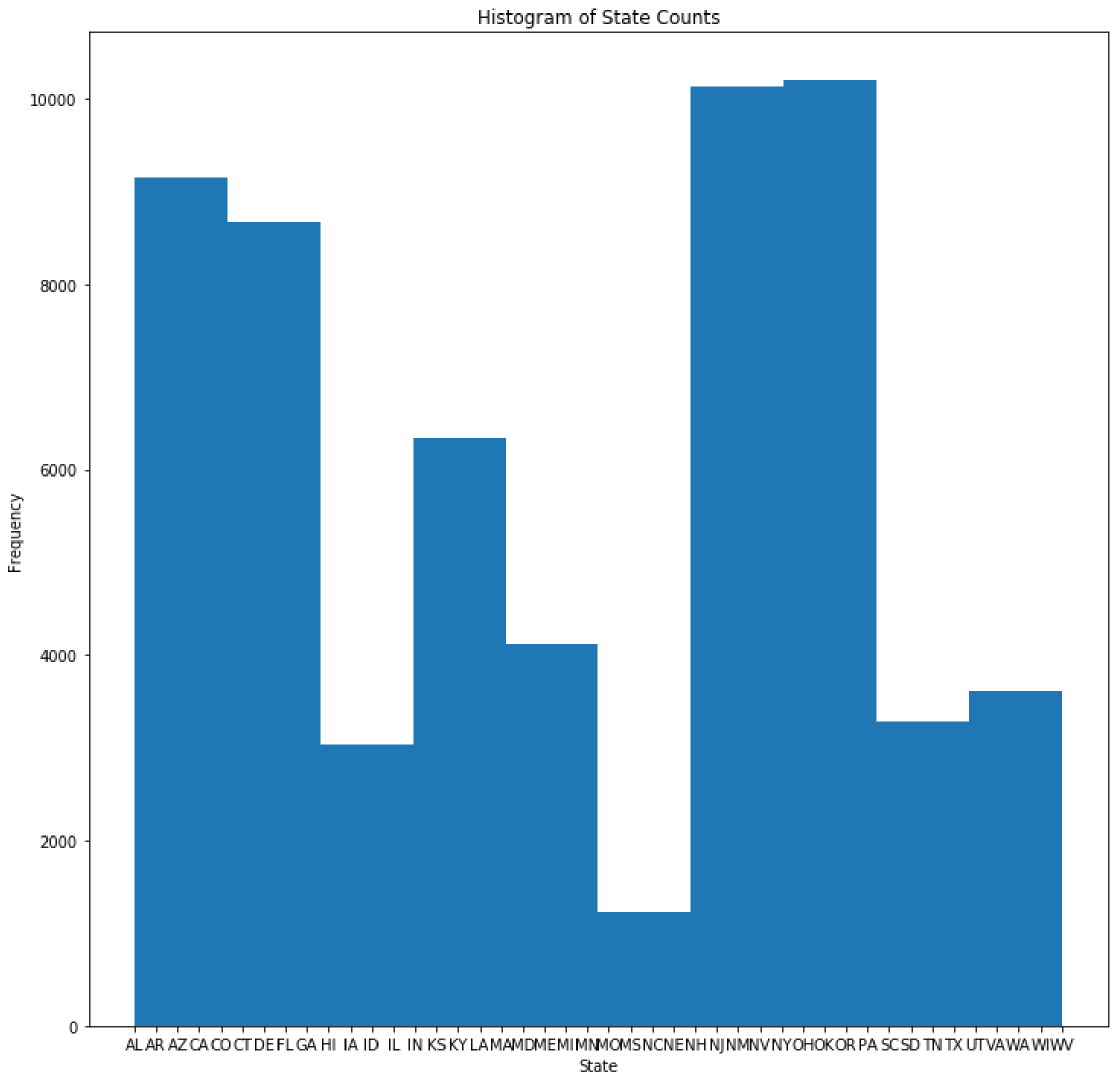
```
#df
dfstatemedian1.head(10)

#Tax data from IRS
tax = pd.read_csv('Tax2016.csv')
CensusEst = pd.read_csv('Census2015.csv') #https://factfinder.census.gov/faces/tables
external = pd.merge(tax, CensusEst, on= 'Zipcode', how= 'inner')
external.head()

dfstatemedian2 = pd.merge(dfstatemedian1, external, on= 'Zipcode', how= 'inner')

dfstatemedian2 = dfstatemedian2.groupby(['Zipcode', 'Date', 'State']).mean()
dfstatemedian2 = dfstatemedian2.reset_index()
dfstatemedian2

#Break out datetime into month/year
dfstatemedian2['Date'] = pd.to_datetime(dfstatemedian2['Date'])
dfstatemedian2['Date'] = pd.to_datetime(dfstatemedian2['Date'])
dfstatemedian2['year'], dfstatemedian2['month'] = dfstatemedian2['Date'].dt.year, dfs
```

Create Training Dataset

In [41]:

```
train = dfstatemedian2
train = train.groupby(['year', 'Zipcode', 'State']).mean()
train = train.reset_index()
train
train["Zipcode"] = train["Zipcode"].astype('category')
train["State"] = train["State"].astype('category')
train.head()
train.drop('month', 1, inplace= True)


rcParams['figure.figsize'] = 12,12
```

```
plt.hist(train.State)
plt.title('Histogram of State Counts')
plt.xlabel('State')
plt.ylabel('Frequency')
plt.show()
```



Create Test dataframe. Use the average of 2014–2001, 2014–2002, and 2014–2003

```
In [42]: test = dfstatemedian2

         test1 =test[(test['Date'] > '2000-12-01') & (test['Date'] < '2015-1-01')]
         test2 =  test[(test['Date'] > '2001-12-01') & (test['Date'] < '2015-1-01')]
         test3 = test[(test['Date'] > '2002-12-01') & (test['Date'] < '2015-1-01')]
```

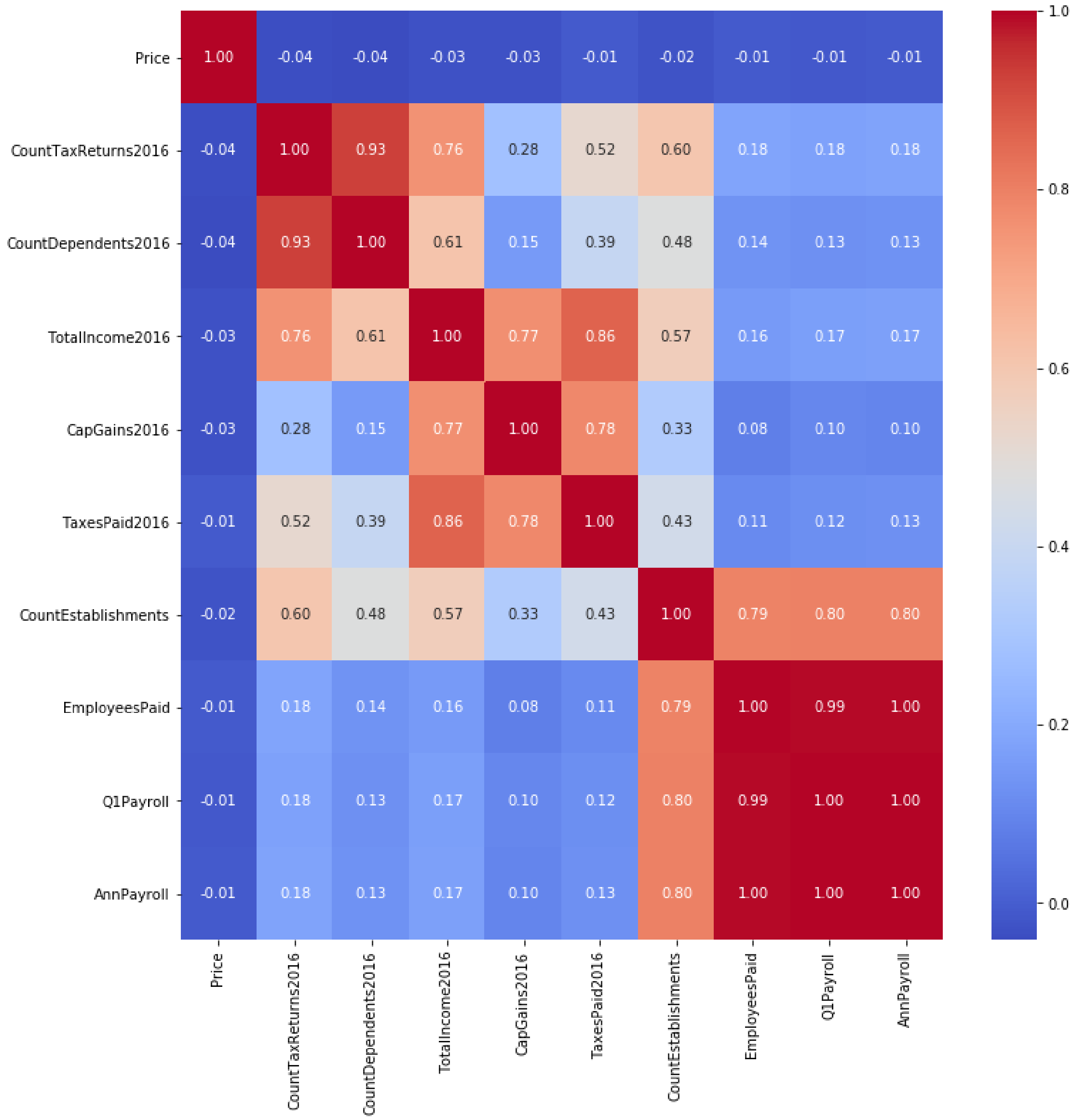
```
df_concat = pd.concat((test1,test2,test3))
df_concat1 = pd.concat((test1,test2,test3))



df_concat["year"] = 2014

df_concat = df_concat.groupby(['year', 'Zipcode', 'State']).mean()
df_concat = df_concat.reset_index()
df_concat["year"] = df_concat["year"].astype('category')
df_concat["State"] = df_concat["State"].astype('category')
df_concat.drop('month', 1, inplace= True)

df_concat.head()
```

Out[42]:

```
   year  Zipcode State          Price  CountTaxReturns2016  \
0  2014    58201    MA  243180.341880              19850.0
1  2014    58204    MA  228205.341880                570.0
2  2014    58212    MA  222174.786325                200.0
3  2014    58214    MA  226433.333333                200.0
4  2014    58220    MA  247868.589744               1110.0

   CountDependents2016  AdjGrossIncome2016  TotalIncome2016  CapGains2016  \
0               9550.0           1399173.0        1422651.0       49689.0
1                740.0             26639.0          23930.0          47.0
2                 70.0             10973.0          11454.0         607.0
3                 70.0             11523.0          11701.0          86.0
4                590.0             73212.0          76260.0        2467.0

   TaxesPaid2016  CountEstablishments  EmployeesPaid  Q1Payroll  AnnPayroll
0        32675.0               1103.0        22841.0   198226.0    856206.0
1            0.0                  8.0           20.0      150.0       741.0
2            0.0                 14.0          121.0     1096.0      4933.0
3            0.0                  7.0           39.0      314.0      1567.0
4          723.0                108.0          818.0     6348.0     37807.0
```

In [43]:

```
#Correlation matrix https://www.kaggle.com/yassineghouzam/titanic-top-4-with-ensemble
g = sns.heatmap(train[["Price","CountTaxReturns2016","CountDependents2016","TotalInco
plt.show()
```



1.3 Build/Test Model

```
In [65]: #train['logprice'] = np.log(train['Price'])

         #did a stepwise regression here
         #my_model1 = str('Price ~ State + year + Zipcode  + CapGains2016')
         my_model1 = str('Price ~ State + year + Zipcode  + CountTaxReturns2016 + CountDepende

         train_model_fit1 = smf.ols(my_model1, data = train).fit()
         model_summary =(train_model_fit1.summary())
         model_params =(train_model_fit1.params)
         train['predict_price'] = train_model_fit1.fittedvalues
```

```
#Store model weights in a csv
modelparams = pd.DataFrame(train_model_fit1.params)
modelparams.to_csv('Model.csv')
```

In [47]:
```
#Run on testset/predict + calculate RMSE

train_model_fit1.predict(df_concat)
df_concat['predictedprice2014'] = train_model_fit1.predict(df_concat)

df_concat['error2014'] = (df_concat['Price']- df_concat['predictedprice2014'])

from sklearn.metrics import mean_squared_error
from math import sqrt

rms = sqrt(mean_squared_error(df_concat['Price'], df_concat['predictedprice2014']))
rms
```

Out[47]:
```
38172.75482853015
```

1.4 Recommendation for SREIT

In [48]:
```
#Estimating house prices per 2020 and determining net difference between 2014 price a

df_concat_2020 = df_concat
df_concat_2020["year"] = 2020
df_concat_2020['predictedprice2020'] = train_model_fit1.predict(df_concat_2020)
df_concat_2020['IncreaseInPrice'] = (df_concat_2020['predictedprice2020']- df_concat_
df_concat_2020['%IncreaseInPrice'] = (df_concat_2020['predictedprice2020']/ df_concat

winners = df_concat_2020.sort_values(by=[ 'IncreaseInPrice'],ascending=False).head(3)
winners.loc[:, ['Zipcode', 'State', 'Price', 'predictedprice2020', 'IncreaseInPrice',
```

Out[48]:
```
      Zipcode State          Price  predictedprice2020  IncreaseInPrice  \
1550    76270    KY  134132.905983       234131.642574     99998.736591
1958    81601    WI  193997.649573       292736.187752     98738.538180
1981    83401    SD  203696.581197       302258.663053     98562.081857

      %IncreaseInPrice
1550        174.551980
1958        150.896770
1981        148.386714
```

In [50]:
```
#Create dataframe to render map
train.head()

df123 = train.groupby(['State']).mean()
df123 = pd.DataFrame(df123.iloc[:, :2])
df123.drop('year', 1, inplace= True)
```

```
df123.head()
df123 = df123.reset_index()
df123 = df123.rename(columns={'State':'state'})

df123.head()
df123['state'] = df123['state'].apply(str)
df123.head()
df123.dtypes
df123['state'] = df123['state'].astype('str')
df123.dtypes
```

Out[50]:
```
state     object
Price    float64
dtype: object
```

1.4.1 Visual Depection of Median home price (1997-2013)

In [63]:
```
# Code was borrowed from the below link, and supplied w/ the help of Amara Moosa
#https://www.kaggle.com/abigaillarion/police-fatalities-in-united-states

# Create a subset data frame of the dataset
data = df123[['state', 'Price']]

# Median home price per 100,000 people in state
median_price = np.round(df123.Price, 2)

# Create a collor scale for the visualization
color_scale = [[0, 'rgb(229, 239, 245)'], [1, 'rgb(1, 97, 156)']]

# Define the dataset
data = [dict(
        type = 'choropleth',
        autocolorscale = False,
        colorscale = color_scale,
        showscale = False,
        locations = df123.state,
        locationmode = 'USA-states',
        z = median_price,
        marker = dict(
            line = dict(
                color = 'rgb(255, 255, 255)',
                width = 2)
            ),
        )]

# Define the layout of the map
layout = dict(
         title = 'Median home price (1997-2013)',
```

```python
        geo = dict(
            scope = 'usa',
            projection = dict(type = 'albers usa'),
            countrycolor = 'rgb(255, 255, 255)',
            showlakes = True,
            lakecolor = 'rgb(255, 255, 255)')
        )

# Display the final map
figure = dict(data = data, layout = layout)
plot = iplot(figure)
plot
```