Houses

August 8, 2020

1 Introduction

Lab 2 focuses on Time Series Forecasting. First we focus our attention on four metro areas in Arkansas. The metro areas have different zipcodes associated with them, so we have to aggragate the data by metro area in order to be able to visualize the trends over time per metro area. Secondly, the lab asks us to find which three zipcodes we should invest in. The lab does not crearly state the metrics necessary to do choose, but through simple analysis, we can determine the best metric for the job.

2 Imports

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        import statsmodels.api as sm  # statistical models (including regression)
        import statsmodels.formula.api as smf  # R-like model specification
```

3 Path

```
In [2]: pwd

Out[2]: '/Users/ramosem/Documents/SyracuseUniversity/4th_Quarter/IST718/Lab2'

In [3]: path = '/Users/ramosem/Documents/SyracuseUniversity/4th_Quarter/IST718/Lab2/'
```

4 Read Data

```
In [4]: fileName = 'Zip_Zhvi_SingleFamilyResidence'

In [93]: df = pd.read_csv(path + fileName + '.csv')

In [6]: df.head()

Out[6]:    RegionID  SizeRank  RegionName RegionType StateName State      City  \
        0     61639         0       10025        Zip        NY    NY  New York
```

```
1      84654          1       60657         Zip        IL     IL   Chicago
2      61637          2       10023         Zip        NY     NY  New York
3      91982          3       77494         Zip        TX     TX      Katy
4      84616          4       60614         Zip        IL     IL   Chicago

                            Metro       CountyName  1996-01-31  ...  \
0       New York-Newark-Jersey City  New York County         NaN  ...
1          Chicago-Naperville-Elgin      Cook County    364892.0  ...
2       New York-Newark-Jersey City  New York County         NaN  ...
3  Houston-The Woodlands-Sugar Land    Harris County    200475.0  ...
4          Chicago-Naperville-Elgin      Cook County    546663.0  ...

   2019-06-30  2019-07-31  2019-08-31  2019-09-30  2019-10-31  2019-11-30  \
0   1413747.0   1405862.0   1402547.0   1390420.0   1381621.0   1375725.0
1    974693.0    975616.0    975734.0    975251.0    974238.0    973104.0
2   1528603.0   1514894.0   1502233.0   1492429.0   1486122.0   1480426.0
3    335536.0    335878.0    335940.0    336092.0    336119.0    336083.0
4   1207765.0   1208853.0   1208481.0   1206304.0   1204013.0   1201182.0

   2019-12-31  2020-01-31  2020-02-29  2020-03-31
0   1374714.0   1381453.0   1385737.0   1389268.0
1    971908.0    972038.0    973671.0    975642.0
2   1476509.0   1478980.0   1479301.0   1474994.0
3    336154.0    335860.0    336037.0    336483.0
4   1198879.0   1198277.0   1199900.0   1200980.0

[5 rows x 300 columns]
```

5 PreAnalyze

In [7]:
```
df['RegionID'].nunique()
```

Out[7]:
```
30464
```

In [8]:
```
df.describe()
```

Out[8]:
```
             RegionID      SizeRank    RegionName    1996-01-31    1996-02-29  \
count    30464.000000  30464.000000  30464.000000  1.322400e+04  1.347200e+04
mean     80411.444032  15971.949875  48773.301110  1.287668e+05  1.284274e+05
std      25500.467961   9602.814124  27437.793823  8.932606e+04  8.923079e+04
min      58001.000000      0.000000    501.000000  1.067200e+04  1.065500e+04
25%      68822.750000   7688.000000  25867.250000  7.188575e+04  7.167675e+04
50%      79170.500000  15497.000000  48313.500000  1.083435e+05  1.078815e+05
75%      89238.250000  24073.000000  71740.500000  1.604298e+05  1.598525e+05
max     753844.000000  35187.000000  99929.000000  1.749532e+06  1.744909e+06

         1996-03-31    1996-04-30    1996-05-31    1996-06-30    1996-07-31  \
count  1.351000e+04  1.353200e+04  1.361700e+04  1.365200e+04  1.367500e+04
```

```
mean   1.283393e+05  1.283755e+05  1.284372e+05  1.284450e+05  1.287817e+05
std    8.908503e+04  8.891757e+04  8.878505e+04  8.866373e+04  9.173599e+04
min    1.067300e+04  1.066800e+04  1.067700e+04  1.059500e+04  1.047700e+04
25%    7.167450e+04  7.179450e+04  7.187400e+04  7.197175e+04  7.207500e+04
50%    1.077805e+05  1.078935e+05  1.078990e+05  1.080335e+05  1.082100e+05
75%    1.596290e+05  1.595368e+05  1.595160e+05  1.598925e+05  1.601715e+05
max    1.726037e+06  1.696812e+06  1.649586e+06  1.602308e+06  2.920398e+06

       ...    2019-06-30    2019-07-31    2019-08-31    2019-09-30  \
count  ...  3.046400e+04  3.046400e+04  3.046400e+04  3.046400e+04
mean   ...  2.316270e+05  2.322013e+05  2.328094e+05  2.334704e+05
std    ...  2.744219e+05  2.745258e+05  2.745434e+05  2.747149e+05
min    ...  1.051600e+04  1.056000e+04  1.059900e+04  1.067800e+04
25%    ...  1.035932e+05  1.040092e+05  1.043135e+05  1.046772e+05
50%    ...  1.608075e+05  1.614010e+05  1.621690e+05  1.627390e+05
75%    ...  2.621595e+05  2.631830e+05  2.641112e+05  2.649178e+05
max    ...  8.665174e+06  8.704005e+06  8.653878e+06  8.558984e+06

         2019-10-31    2019-11-30    2019-12-31    2020-01-31    2020-02-29  \
count  3.046400e+04  3.046400e+04  3.046400e+04  3.046400e+04  3.046400e+04
mean   2.341255e+05  2.347233e+05  2.353932e+05  2.361603e+05  2.370185e+05
std    2.748821e+05  2.751632e+05  2.759450e+05  2.772066e+05  2.787410e+05
min    1.073700e+04  1.086000e+04  1.103500e+04  1.121800e+04  1.137200e+04
25%    1.049818e+05  1.052908e+05  1.056270e+05  1.058540e+05  1.061430e+05
50%    1.634350e+05  1.640095e+05  1.645335e+05  1.650715e+05  1.655705e+05
75%    2.658900e+05  2.666098e+05  2.674230e+05  2.683828e+05  2.692755e+05
max    8.451378e+06  8.356810e+06  8.303433e+06  8.293072e+06  8.271645e+06

         2020-03-31
count  3.046400e+04
mean   2.378982e+05
std    2.801460e+05
min    1.149200e+04
25%    1.064082e+05
50%    1.660700e+05
75%    2.702558e+05
max    8.221444e+06

[8 rows x 294 columns]
```

In [9]:
```
dates = df.columns.values[9:]
```

6 Part 1:

Provide an initial data analysis to include (but not limited to): Develop time series plots for the following Arkansas metro areas: Hot Springs, Little Rock, Fayetteville, Searcy Present all values from 1997 to present Average at the metro area level

6.1 Get the Subset of The Metro Areas

```
In [10]: cityOfInterst = ['Hot Springs', 'Little Rock', 'Fayetteville', 'Searcy']

In [11]: arCity = df.loc[df['Metro'].isin(cityOfInterst)].reset_index(drop=True)

In [12]: arCity['Metro'].unique()

Out[12]: array(['Fayetteville', 'Hot Springs', 'Searcy'], dtype=object)
```

6.1.1 Little Rock Does Not Have a Metro Area Named after it

```
In [13]: df.loc[df['City'] == 'Little Rock'].head(2)

Out[13]:       RegionID  SizeRank  RegionName RegionType StateName State         City  \
         2610     89442      2628       72204        Zip        AR    AR  Little Rock
         3176     89446      3203       72209        Zip        AR    AR  Little Rock

                                             Metro      CountyName  1996-01-31  ...  \
         2610  Little Rock-North Little Rock-Conway  Pulaski County     47506.0  ...
         3176  Little Rock-North Little Rock-Conway  Pulaski County     48395.0  ...

               2019-06-30  2019-07-31  2019-08-31  2019-09-30  2019-10-31  2019-11-30  \
         2610     72297.0     72162.0     72250.0     72332.0     72976.0     73492.0
         3176     73613.0     73328.0     72997.0     72800.0     73261.0     73445.0

               2019-12-31  2020-01-31  2020-02-29  2020-03-31
         2610     74355.0     75124.0     76106.0     76895.0
         3176     73738.0     73768.0     74577.0     75424.0

         [2 rows x 300 columns]
```

Little Rock Metro area is called Little Rock-North Little Rock-Conway.

```
In [14]: lr = df.loc[[False if pd.isnull(x) else x for x in df['Metro'].str.contains('Little Ro
```

We append the Little Rock metro area to our dataset

```
In [15]: arCity = pd.concat([arCity, lr])

In [16]: arCity.head()

Out[16]:    RegionID  SizeRank  RegionName RegionType StateName State          City  \
         0     69849       215       28314        Zip        NC    NC  Fayetteville
         1     89249       332       71913        Zip        AR    AR   Hot Springs
         2     69842      1309       28306        Zip        NC    NC  Fayetteville
         3     69902      1457       28376        Zip        NC    NC       Raeford
         4     69847      1535       28311        Zip        NC    NC  Fayetteville

                     Metro        CountyName  1996-01-31  ...  2019-06-30  2019-07-31  \
```

```
0  Fayetteville  Cumberland County     91738.0  ...    124299.0    124389.0
1   Hot Springs     Garland County     91204.0  ...    158061.0    158528.0
2  Fayetteville  Cumberland County    113111.0  ...    159607.0    159496.0
3  Fayetteville        Hoke County         NaN  ...    178186.0    178673.0
4  Fayetteville  Cumberland County     99811.0  ...    135627.0    135708.0

   2019-08-31  2019-09-30  2019-10-31  2019-11-30  2019-12-31  2020-01-31  \
0    124643.0    124785.0    125022.0    125708.0    126576.0    127449.0
1    159213.0    160118.0    161110.0    161806.0    162347.0    163134.0
2    159711.0    160011.0    160450.0    161232.0    162215.0    163196.0
3    179091.0    179431.0    179704.0    179780.0    179884.0    179991.0
4    136097.0    136413.0    136634.0    137330.0    138309.0    139264.0

   2020-02-29  2020-03-31
0    127791.0    128149.0
1    164485.0    166238.0
2    163748.0    164245.0
3    180248.0    180527.0
4    139653.0    140037.0

[5 rows x 300 columns]
```

```
In [17]: arCity['Metro'].unique()
```

```
Out[17]: array(['Fayetteville', 'Hot Springs', 'Searcy',
                'Little Rock-North Little Rock-Conway'], dtype=object)
```

6.2 Only look at 1997 onwards

```
In [18]: on97 = [x for x in dates if np.datetime64(x) >= np.datetime64('1997-01')]
```

```
In [19]: on97[:5]
```

```
Out[19]: ['1997-01-31', '1997-02-28', '1997-03-31', '1997-04-30', '1997-05-31']
```

```
In [20]: on97Dates = [np.datetime64(x) for x in on97] # Convert Strings to np.datetime64
```

6.3 Group By Metro Area

```
In [21]: arCityAv = arCity[['Metro']+on97].groupby(['Metro']).agg(np.nanmean)
```

```
In [22]: arCityAv
```

```
Out[22]:                                        1997-01-31     1997-02-28  \
         Metro
         Fayetteville                        100072.230769  100048.923077
         Hot Springs                          77182.600000   77657.400000
         Little Rock-North Little Rock-Conway  87378.959184   87692.673469
         Searcy                               57560.583333   57887.666667
```

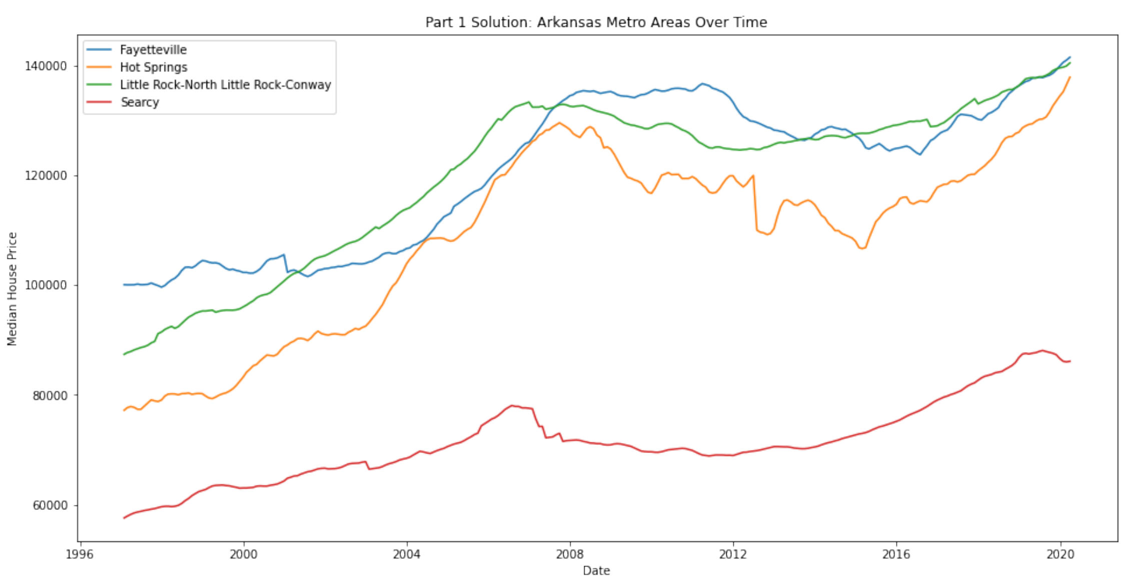
```
                                       1997-03-31     1997-04-30  \
Metro
Fayetteville                          100061.769231  100058.000000
Hot Springs                            77872.800000   77722.000000
Little Rock-North Little Rock-Conway   87890.285714   88178.959184
Searcy                                 58211.000000   58466.000000

                                       1997-05-31     1997-06-30  \
Metro
Fayetteville                          100183.769231  100066.923077
Hot Springs                            77370.400000   77363.800000
Little Rock-North Little Rock-Conway   88397.102041   88617.755102
Searcy                                 58640.083333   58765.833333

                                       1997-07-31     1997-08-31  \
Metro
Fayetteville                          100088.615385  100135.538462
Hot Springs                            77931.200000   78521.000000
Little Rock-North Little Rock-Conway   88776.408163   89037.326531
Searcy                                 58921.583333   59028.333333

                                       1997-09-30     1997-10-31  ...  \
Metro                                                              ...
Fayetteville                          100378.076923  100122.692308  ...
Hot Springs                            79080.400000   78898.800000  ...
Little Rock-North Little Rock-Conway   89457.693878   89739.448980  ...
Searcy                                 59160.333333   59267.333333  ...

                                       2019-06-30     2019-07-31  \
Metro
Fayetteville                          137884.812500  137801.062500
Hot Springs                           130194.714286  130269.714286
Little Rock-North Little Rock-Conway  137957.419355  137967.725806
Searcy                                 87910.222222   88080.166667

                                       2019-08-31     2019-09-30  \
Metro
Fayetteville                          138057.625000  138239.375000
Hot Springs                           130643.285714  131520.857143
Little Rock-North Little Rock-Conway  138232.258065  138562.548387
Searcy                                 87890.888889   87739.555556

                                       2019-10-31     2019-11-30  \
Metro
Fayetteville                          138617.500000  139208.687500
Hot Springs                           132674.000000  133555.714286
Little Rock-North Little Rock-Conway  139092.919355  139401.790323
```

```
Searcy                                   87566.888889   87297.888889

                                           2019-12-31     2020-01-31  \
Metro
Fayetteville                            139931.437500  140591.125000
Hot Springs                             134451.857143  135230.142857
Little Rock-North Little Rock-Conway    139585.387097  139714.419355
Searcy                                   86611.722222   86112.388889

                                           2020-02-29     2020-03-31
Metro
Fayetteville                            140992.875000  141523.312500
Hot Springs                             136497.142857  137892.571429
Little Rock-North Little Rock-Conway    139935.032258  140491.000000
Searcy                                   86010.611111   86115.611111

[4 rows x 279 columns]
```

6.4 Plot Time Series

In [23]:
```
plt.figure(figsize=(16,8))

for idx, row in arCityAv.iterrows():
    plt.plot(on97Dates, row[on97].values, label=idx)
plt.legend()
plt.title('Part 1 Solution: Arkansas Metro Areas Over Time')
plt.xlabel('Date')
plt.ylabel('Median House Price')
```

Out[23]:
```
Text(0, 0.5, 'Median House Price')
```



7 Part 2:

The research question is can we predict which three zip codes provide the best investment opportunity for the Syracuse Real Estate Investment Trust (SREIT)?

7.1 Get Rid Of Columns Before 1997

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

```
Out[24]: Index(['RegionID', 'SizeRank', 'RegionName', 'RegionType', 'StateName',
                'State', 'City', 'Metro', 'CountyName', '1996-01-31',
                ...
                '2019-06-30', '2019-07-31', '2019-08-31', '2019-09-30', '2019-10-31',
                '2019-11-30', '2019-12-31', '2020-01-31', '2020-02-29', '2020-03-31'],
               dtype='object', length=300)
```

7.2 Analyze Dataset

7.2.1 Check for Duplicates

```
In [25]: df['RegionID'].value_counts().sort_values().max()
```

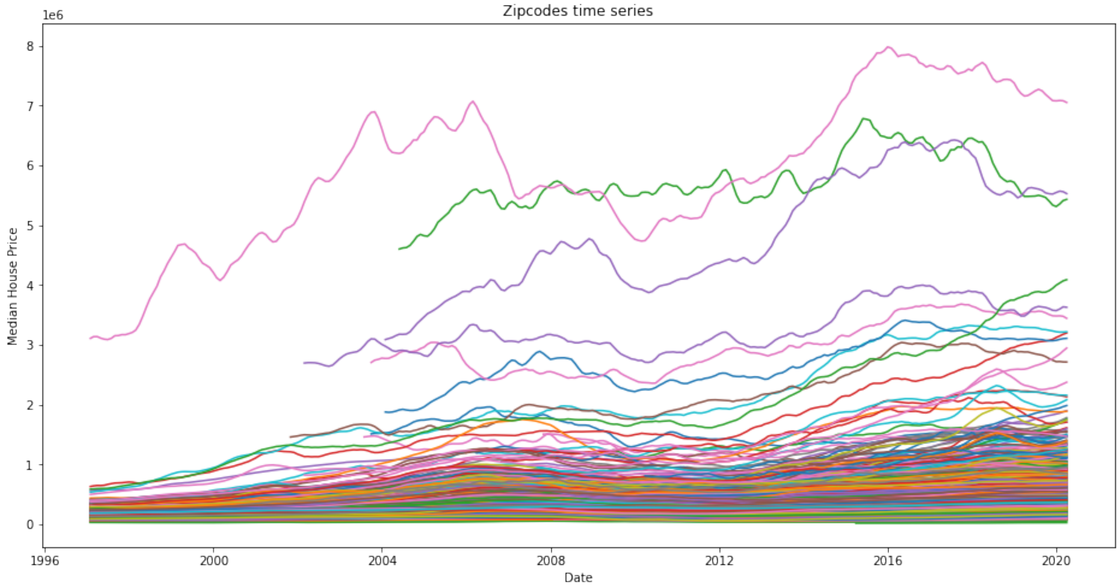
```
Out[25]: 1
```

There are no duplicate regions.

7.2.2 Time Series Plot

```
In [26]: plt.figure(figsize=(16,8))

         for idx, row in df.iloc[:1000].iterrows():
             plt.plot(on97Dates, row[on97].values, label=idx)
         # plt.legend()
         plt.title('Zipcodes time series')
         plt.xlabel('Date')
         plt.ylabel('Median House Price')
```

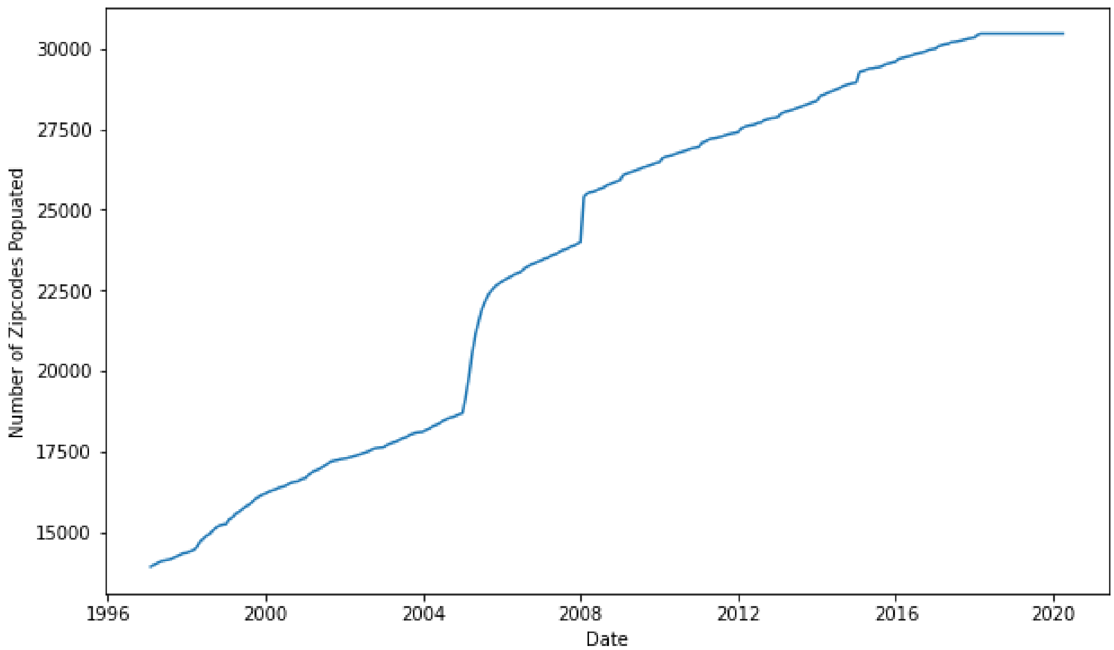
```
Out[26]: Text(0, 0.5, 'Median House Price')
```



Most zipcodes are below a million dollars.

7.2.3 Check When all Zipcodes have values

```
In [27]: counts = []
         for date in on97:
             counts.append(df[date].count())
         on97Counts = pd.DataFrame(zip(on97, counts), columns=['Date', 'Count'])
         on97Counts['Date'] = on97Counts['Date'].astype(np.datetime64)

In [28]: plt.figure(figsize=(10,6))
         plt.plot(on97Counts['Date'], on97Counts['Count'])
         plt.xlabel('Date')
         plt.ylabel('Number of Zipcodes Popuated')

Out[28]: Text(0, 0.5, 'Number of Zipcodes Popuated')
```




```
In [29]: on97Counts.loc[on97Counts['Count'] == len(df)].head()
```

```
Out[29]:           Date  Count
         253 2018-02-28  30464
         254 2018-03-31  30464
         255 2018-04-30  30464
         256 2018-05-31  30464
         257 2018-06-30  30464
```

Starting 2018, all zipcodes are finally populated. Since we will be predicting the latest date, we do not have to drop any zip codes from the analysis. We will have to preprocess some zipcodes since they are not fully populated till a certain time. This might lower our accuracy in zipcodes that only have data for a small amount of time.

```
In [30]: on97Counts.loc[on97Counts['Date'].astype(str).str.contains('2020')].tail(3)
```

```
Out[30]:           Date  Count
         276 2020-01-31  30464
         277 2020-02-29  30464
         278 2020-03-31  30464
```

2020 has a total of 30464 zip codes populated.

```
In [31]: on97Counts.loc[on97Counts['Date'].astype(str).str.contains('1997')].head(3)
```

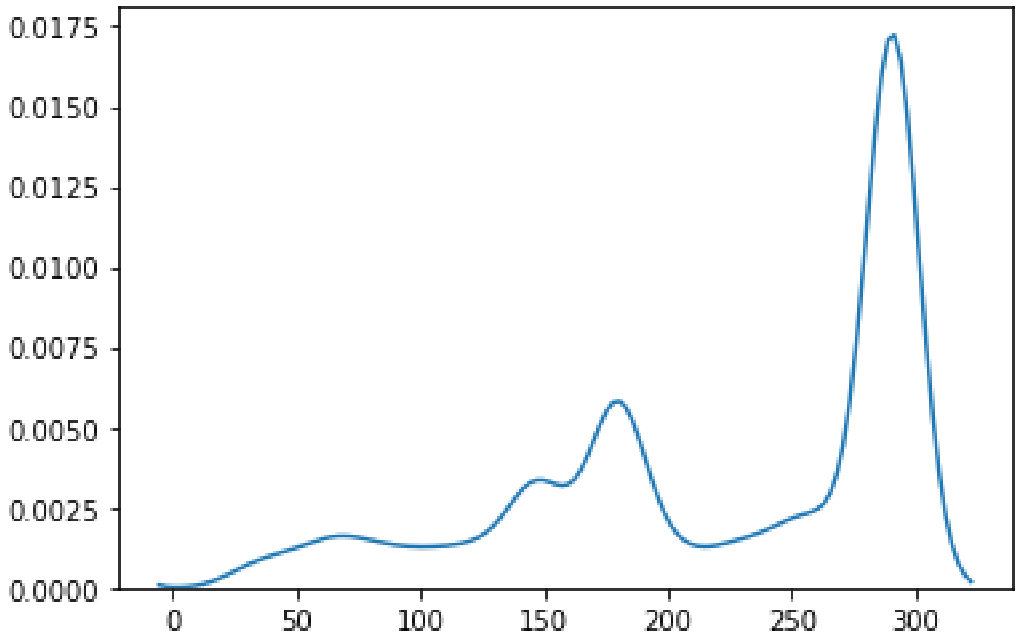
```
Out[31]:         Date  Count
         0 1997-01-31  13913
         1 1997-02-28  13961
         2 1997-03-31  14019
```

1997 only has 13913 zip codes populated..

7.3 Look at Counts Per Zip Code

First we need to perform some transformations in the data in order to calculate the counts per zip code

```
In [32]: dd = df.drop(['SizeRank', 'RegionName', 'RegionType', 'StateName', 'State', 'City', 'I

In [33]: dd = dd.set_index('RegionID')

In [34]: dp = dd.transpose()

In [35]: dp.head()

Out[35]: RegionID    61639     84654   61637     91982     84616    91940   61616  \
         1996-01-31    NaN  364892.0     NaN  200475.0  546663.0  97521.0    NaN
         1996-02-29    NaN  364162.0     NaN  200723.0  546231.0  97513.0    NaN
         1996-03-31    NaN  363605.0     NaN  200526.0  545451.0  97471.0    NaN
         1996-04-30    NaN  362963.0     NaN  199337.0  545391.0  97491.0    NaN
         1996-05-31    NaN  361660.0     NaN  198200.0  543066.0  97486.0    NaN

         RegionID      91733    93144     84640  ...  59484  59376  60758  58084  \
         1996-01-31  97381.0  82374.0  254388.0  ...    NaN    NaN    NaN    NaN
         1996-02-29  97405.0  82330.0  252774.0  ...    NaN    NaN    NaN    NaN
         1996-03-31  97330.0  82300.0  251468.0  ...    NaN    NaN    NaN    NaN
         1996-04-30  97323.0  82263.0  248948.0  ...    NaN    NaN    NaN    NaN
         1996-05-31  97280.0  82344.0  246695.0  ...    NaN    NaN    NaN    NaN

         RegionID    58112  58111  58115  58117  58121  58125
         1996-01-31    NaN    NaN    NaN    NaN    NaN    NaN
         1996-02-29    NaN    NaN    NaN    NaN    NaN    NaN
         1996-03-31    NaN    NaN    NaN    NaN    NaN    NaN
         1996-04-30    NaN    NaN    NaN    NaN    NaN    NaN
         1996-05-31    NaN    NaN    NaN    NaN    NaN    NaN

         [5 rows x 30464 columns]

In [36]: zipCount = dp.count()

In [37]: sns.kdeplot(zipCount)

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff26af3c978>
```




```
In [38]: zipCount.describe()
```

```
Out[38]: count    30464.000000
         mean       221.713892
         std         78.132404
         min         26.000000
         25%        170.000000
         50%        256.000000
         75%        291.000000
         max        291.000000
         dtype: float64
```

We can see how most of the zipcodes have between 250 to 300 values populate in the dataset. Since they have more data, it will likely increase its prediction accuracy.

7.4 Group Zip Code by Year and Check if there is any correlation

```
In [39]: dyear = dp.copy()
```

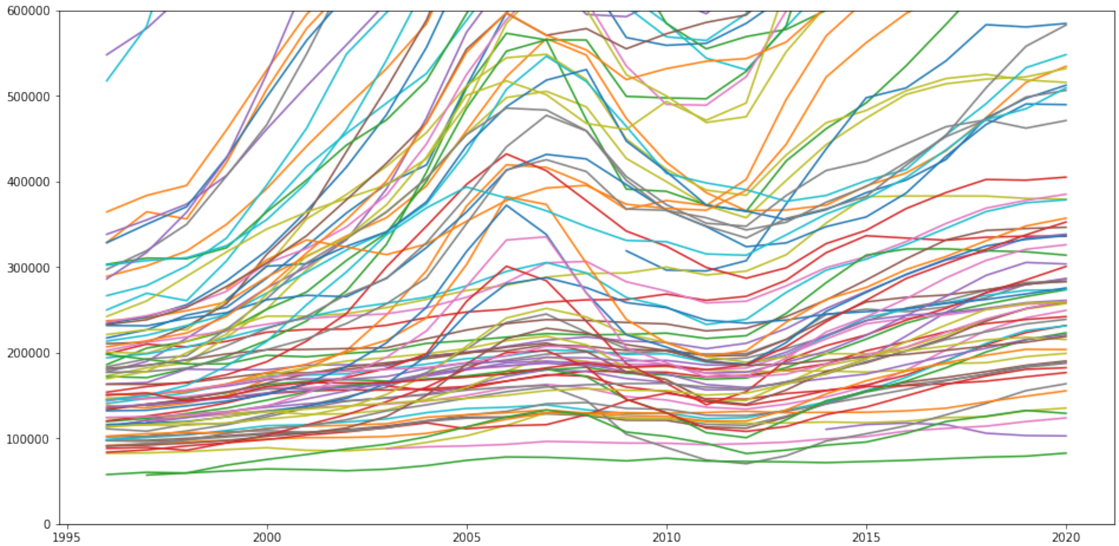
```
In [40]: dyear.index.name = 'ds'
         dyear = dyear.reset_index(drop=False)
```

```
In [41]: dyear['year'] = dyear['ds'].astype(str).str[0:4]
```

```
In [42]: dyear = dyear.groupby(['year']).mean().reset_index(drop=False)
```

```
In [43]: plt.figure(figsize=(16,8))
         for col in dyear.columns[1:100]:
             plt.plot(dyear['year'].astype(int), dyear[col])

         plt.ylim(-5, 600000)
```

```
Out[43]: (-5.0, 600000.0)
```



We are all aware of the 2008 housing crisis which lowered the price of the housing market significatly. In the chart above, we see a huge drop among a big subset of zipcodes. Now because of the lack of computing power and the since this drop can cause a lack of accuracy, we will only fit the models with data past a certain date. On 2010, we see the data start to plateu, but around 2011, it started going back up again. Therefore, we will use 2011 as our lower limit for the modeling.

```
In [44]: lowerDataLim = np.datetime64('2011-01-01')
```

7.5 Split Train and Test Dataset

In order to create the model we need to create a training set and a test set. The test set is going to be the most recent date as the target while the training dataset is going to use the data from 6 months prior as the target.

7.5.1 Find the most recent date.

```
In [45]: testDate = on97Counts['Date'].max()
         print('Test Date on Dataset: ', testDate)
```

```
Test Date on Dataset:  2020-03-31 00:00:00
```

```
In [46]: trainDate = on97Counts['Date'].max() - np.timedelta64(6, 'M')
         trainDate = on97Counts.loc[on97Counts['Date'] < trainDate]['Date'].values[-1]
         print('Train Target Date on Dataset: ', trainDate)
```

```
Train Target Date on Dataset:  2019-09-30T00:00:00.000000000
```

7.6 Create Facebook Profet Model

```
In [47]: from fbprophet import Prophet
```

```
ERROR:fbprophet:Importing plotly failed. Interactive plots will not work.
```

7.6.1 Convert Dataset To Prophet Format

To input the data to the prophet, we need to convert the Data Frame into a friendly format for the prophet to work.

```
In [48]: dp.columns.name = None # Get rid of column name
         dp.index.names = ['ds'] # Convert Date columns to ds

In [49]: zipCodes = dp.columns # Get list of Zip Codes

In [50]: zipCodes = np.sort(zipCodes)

In [53]: dp = dp.reset_index(drop=False) # Make Date a column rather than the index

In [54]: dp['ds'] = dp['ds'].astype(np.datetime64)
```

7.6.2 Create Data Frame with Predicted Values

```
In [55]: future = pd.DataFrame([trainDate, testDate], columns=['ds'])

In [56]: future
```

```
Out[56]:           ds
         0 2019-09-30
         1 2020-03-31
```

7.6.3 Fit Model Using The Target Training Date

```
In [57]: dp = dp.loc[((dp['ds'] <= trainDate) & (dp['ds'] >= lowerDataLim))].reset_index(drop=

In [92]: predictions = []
         count = 0
         for zip in zipCodes:
             m = Prophet(uncertainty_samples=0, interval_width=0.95, weekly_seasonality=False,

             dtemp = dp[['ds', zip]].rename(columns={zip: 'y', 'ds': 'ds'}) # Convert columns
```

```
            dtemp = dtemp.dropna(axis=0) # Drop unpopulated dates

            m.fit(dtemp) # Fit series

            preds = m.predict(future)[['ds', 'yhat']] # Predict the train date and test date


            predictions.append([zip, dtemp.loc[dtemp['ds'] == trainDate]['y'].values[0],
                                preds['yhat'].values[0], preds['yhat'].values[1]]) # append dat

            count += 1
```

```
In [68]: len(predictions)
```

```
Out[68]: 2500
```

7.7 Calucate Accuracy and Opportunity of Growth

7.7.1 Create DataFrame with Zip Code information

```
In [69]: zipPred = pd.DataFrame(predictions, columns=['zipcode', 'train', 'train_pred', 'test_
```

```
In [70]: # zipPred.to_csv(path + 'PredictionData.csv') # Save Prediction to a CSV file since w
```

```
In [79]: zipPred = pd.read_csv(path + 'all_preds.csv')
```

```
In [80]: zipPred.head()
```

Out[80]:

	Unnamed: 0	Unnamed: 0.1	zipcode	train	train_pred	test_pred
0	0	0	99896	170972.0	171056.661470	175758.447514
1	1	1	99897	288141.0	288810.105902	300880.428270
2	2	2	99898	345708.0	347049.233058	361007.685087
3	3	3	99899	187753.0	186323.733684	193046.967531
4	4	4	99900	169052.0	169479.033910	178694.019347

```
In [81]: print(len(zipPred))
```

```
30464
```

7.7.2 Calcualte Error In Training Prediction

By Calculating the error in the training prediction, we can find out the risk associated with investing in a specific zipcode. If a zipcode is volatile, the prediction will have a high error. Therefore, if we see a high prediction on the training target date, we should be causious in investing there. On the other hand, if the prediction is very accurate, the risk factor shoudl be greatly reduced.

```
In [82]: zipPred['trainError'] = 100*(zipPred['train'] - zipPred['train_pred']) / zipPred['tra
```

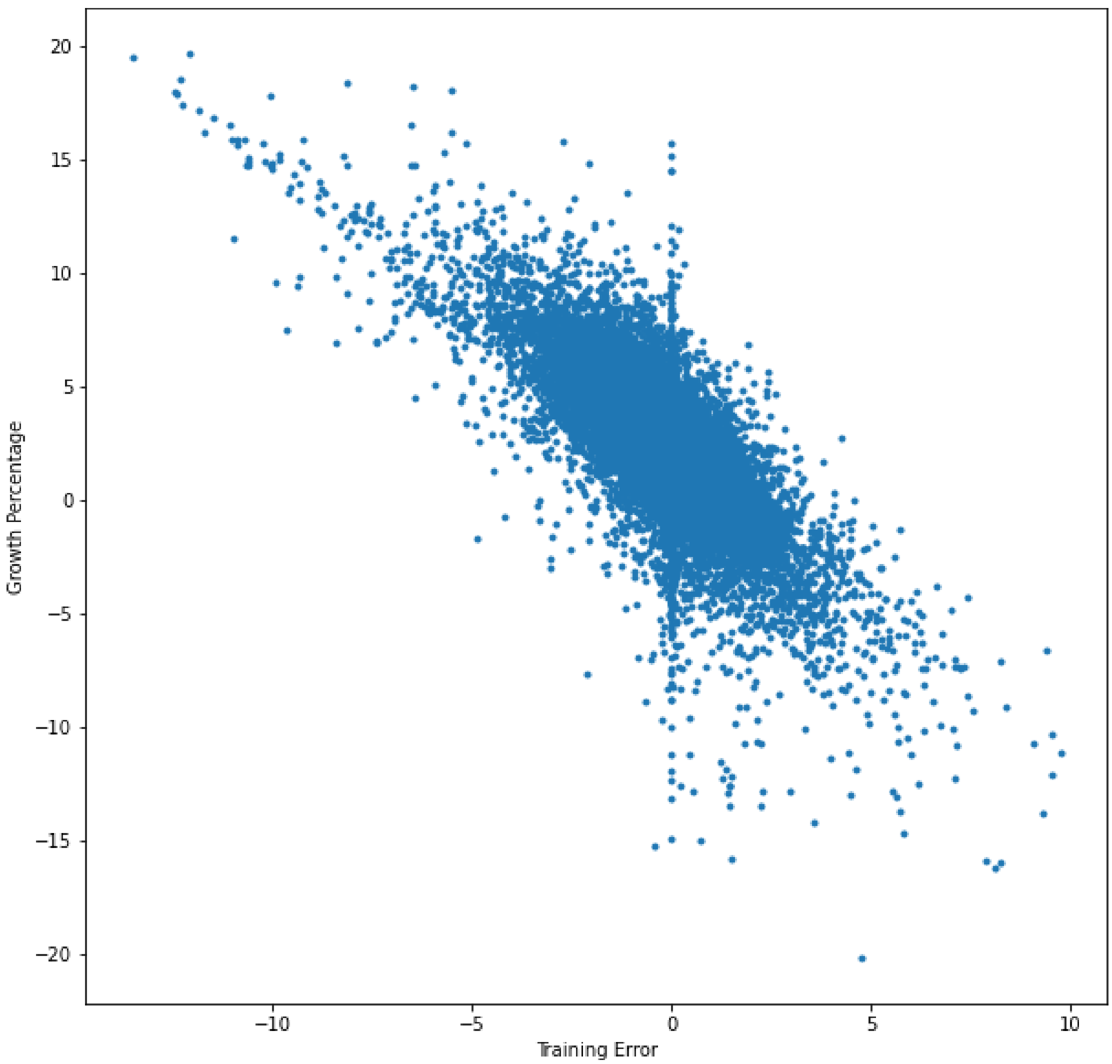
7.7.3 Calculate Growth Percentage

The growth percentage comes from the test target date. We want to see if there is any potential growth in the zipcode. To do this, we use the model's prediction for six months from the training target date. Then we get the percentage increased or decreased. We want to avoid all decreased growth. Conversely, we want the most return possible from an investment which would be indicated by a big percentage increase or a high percent growth.

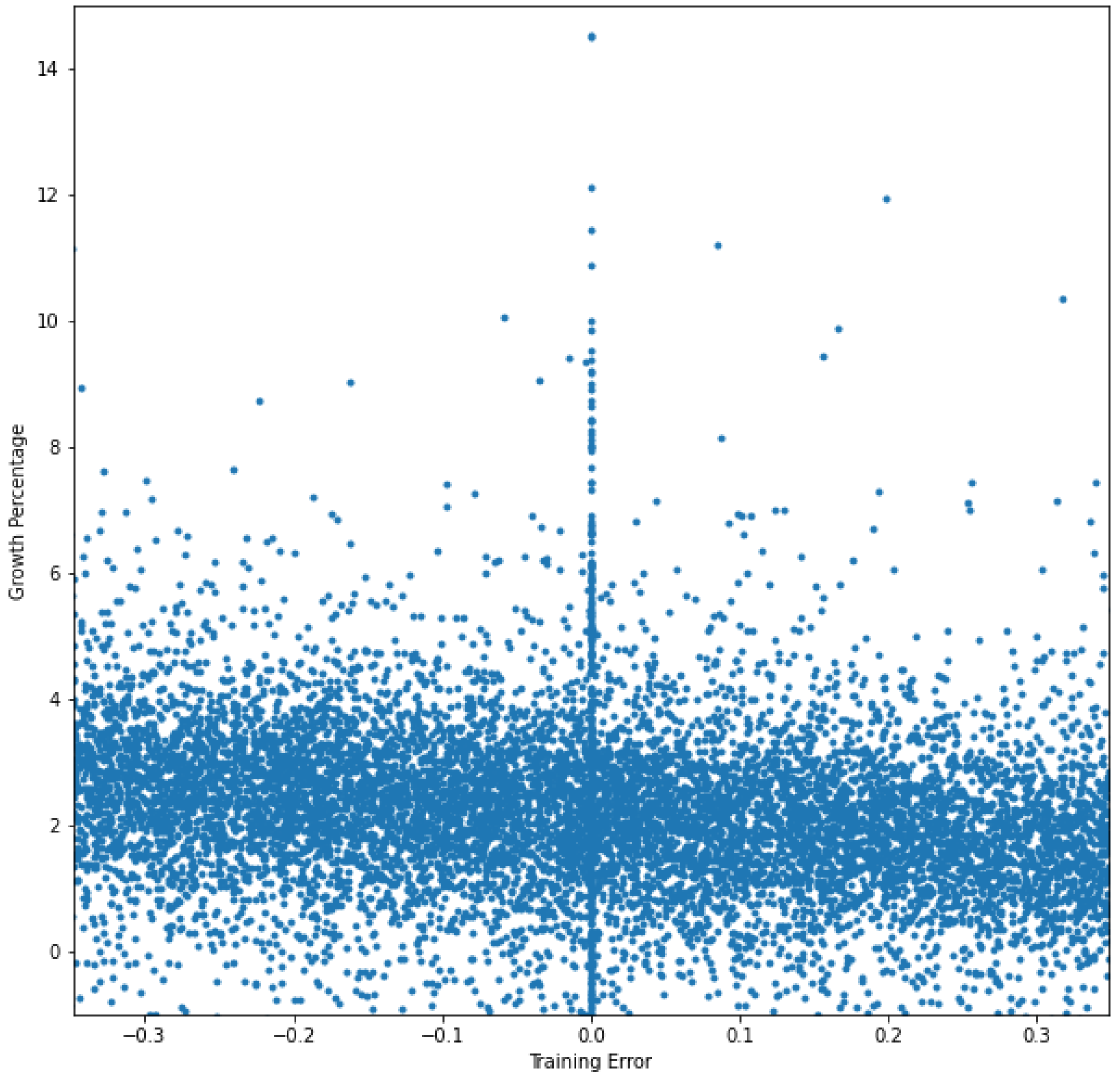
```
In [83]: zipPred['GrowthPerc'] = 100*(zipPred['test_pred'] - zipPred['train']) / zipPred['trai
```

8 Find the Best Zip Codes

```
In [84]: plt.figure(figsize=(10,10))

         plt.plot(zipPred['trainError'],zipPred['GrowthPerc'], lw=0, marker='.')

         plt.xlabel('Training Error')
         plt.ylabel('Growth Percentage')

Out[84]: Text(0, 0.5, 'Growth Percentage')
```




```
In [85]: plt.figure(figsize=(10,10))

         plt.plot(zipPred['trainError'],zipPred['GrowthPerc'], lw=0, marker='.')

         plt.xlabel('Training Error')
         plt.ylabel('Growth Percentage')

         plt.xlim(-.348, .348)
         plt.ylim(-1, 15)

Out[85]: (-1.0, 15.0)
```



The chart above shows us the best zipcodes. The closest to the x-axis and the farthest up corresponds to the zipcodes that we should be investing in since there is almost no risk and there is a big growth opportunity.

```
In [86]: zipPred['trainError'].describe()

Out[86]: count    30464.000000
         mean        -0.210522
         std          1.347398
         min        -13.524418
         25%         -0.755930
         50%         -0.122969
         75%          0.388458
         max          9.779789
         Name: trainError, dtype: float64
```

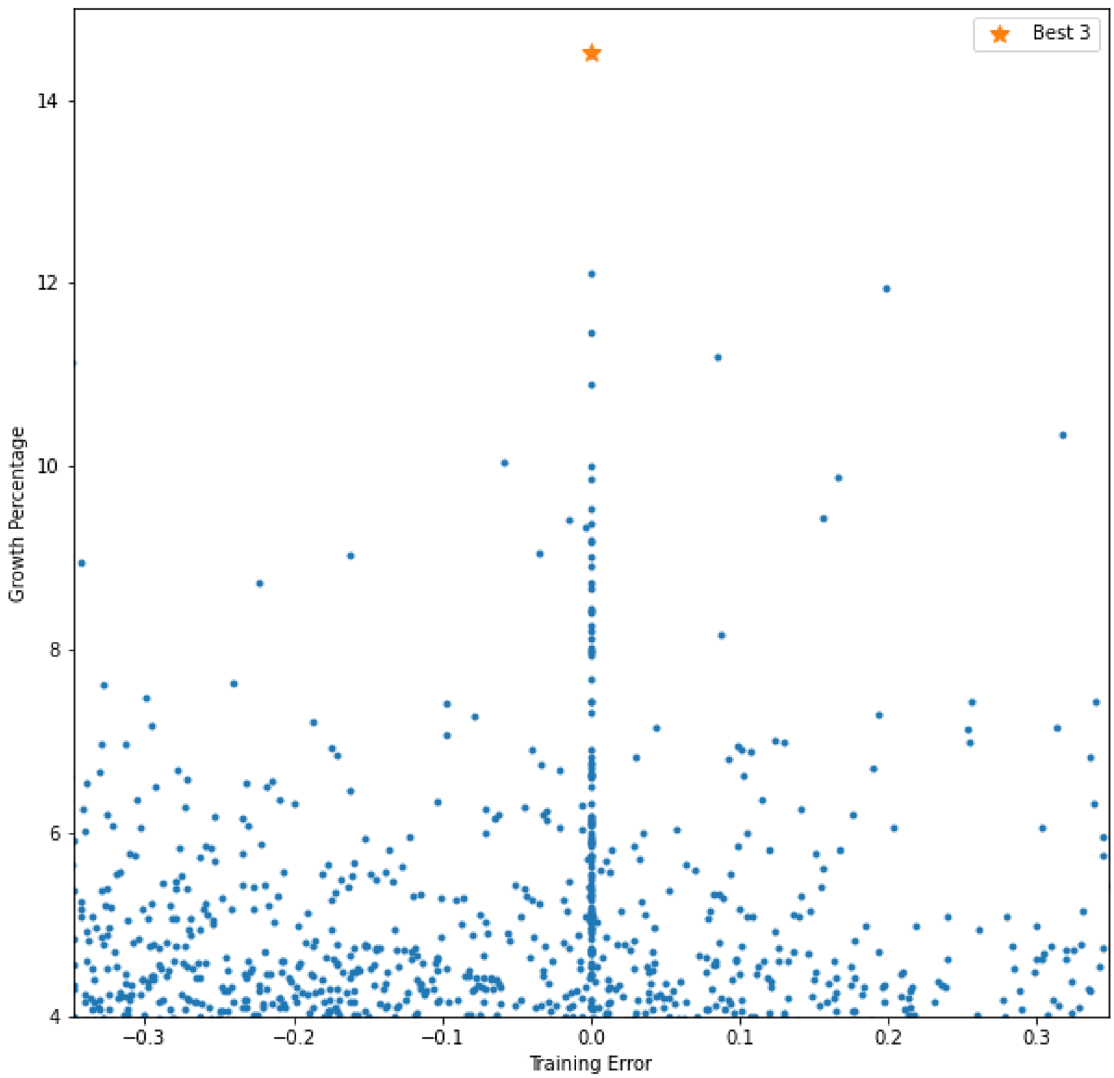
```
In [87]: zipPred.loc[((zipPred['trainError'] < .09) & (zipPred['trainError'] > -0.09))].sort_va
```

```
Out[87]:        Unnamed: 0  Unnamed: 0.1  zipcode    train  train_pred     test_pred  \
         20761       20996           253    92440  65473.0     65473.0  75733.108783
         5945         5945           631    86144  70463.0     70463.0  81134.813276
         7125         7125          1811    87700  51992.0     51992.0  59541.848612

                  trainError  GrowthPerc
         20761  9.557105e-13   15.670748
         5945   0.000000e+00   15.145272
         7125  -6.997190e-14   14.521174
```

```
In [88]: best3 = zipPred.loc[((zipPred['trainError'] < .09) & (zipPred['trainError'] > -0.09))]
```

```
In [90]: plt.figure(figsize=(10,10))

         plt.plot(zipPred['trainError'],zipPred['GrowthPerc'], lw=0, marker='.')

         plt.plot(best3['trainError'],best3['GrowthPerc'], lw=0, marker='*', markersize=10, lal

         plt.xlabel('Training Error')
         plt.ylabel('Growth Percentage')
         plt.legend()
         plt.xlim(-.348, .348)
         plt.ylim(4, 15)
```

```
Out[90]: (4.0, 15.0)
```



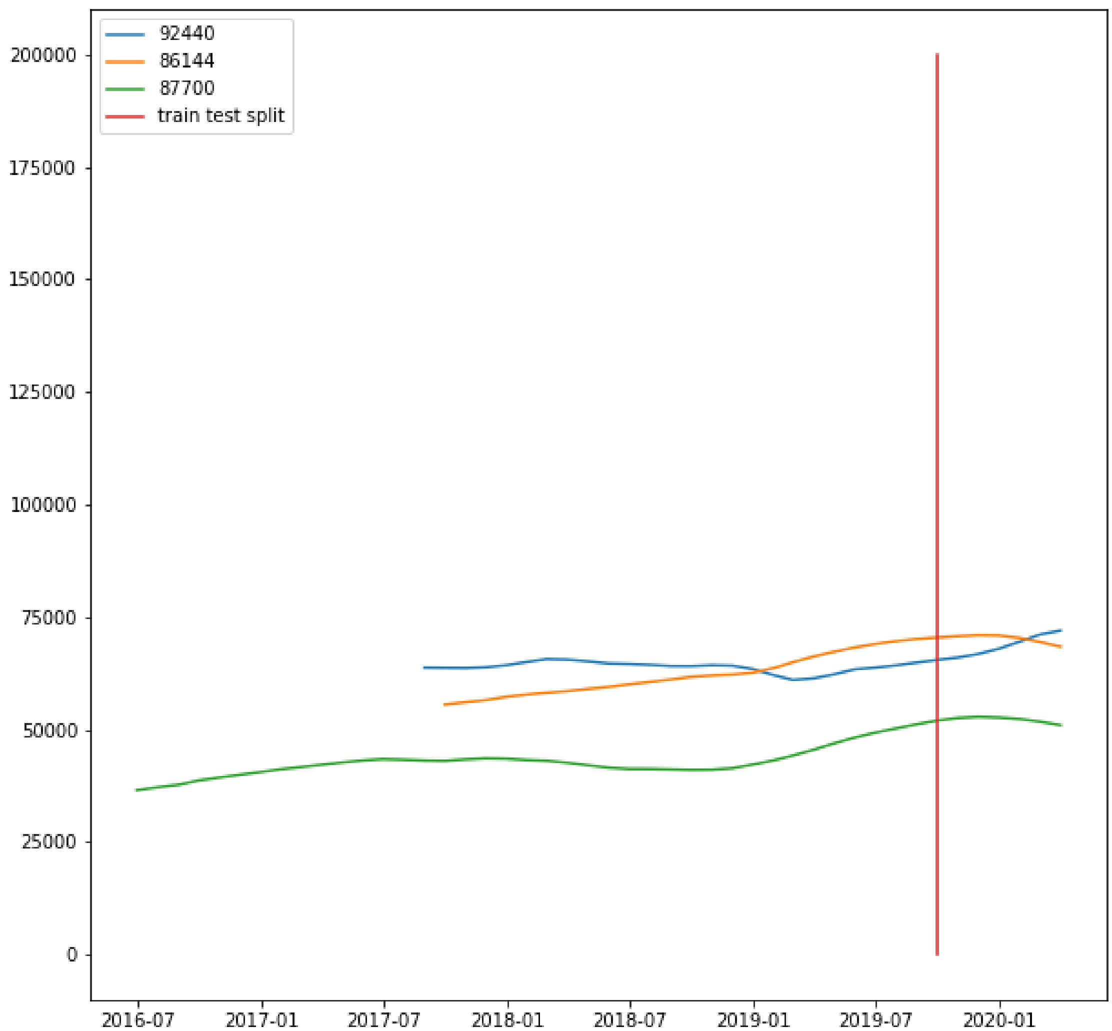
To find the best zipcodes, we first take a look at the subset with the smallest risk or the training error closest to 0. Then we sort by the Growth Percentage in Descending order and we are left with 3 zipcodes.

8.1 Conclusion

```
In [94]: plt.figure(figsize=(10,10))

         for zip in best3['zipcode']:

             temp = df.loc[df['RegionID'] == zip]

             dateL = []
             dateS = []
             for col in on97:
```

```
            if pd.isnull(df.loc[df['RegionID'] == zip][col].values[0]):
                continue
            else:
                dateS.append(col)
                dateL.append(np.datetime64(col))

        plt.plot(dateL, df.loc[df['RegionID'] == zip][dateS].values[0], label=zip)

    plt.plot([trainDate, trainDate],[0, 200000], label='train test split')

    plt.legend()
```

Out[94]: <matplotlib.legend.Legend at 0x7ff25e016470>



When we compare to the actual growth in six months, we actually see that the only one out of the three zipcode candidates actually improved in median house hold prices. Therefore, we would have ended up in a loss. It is also important to note that the loses started happenning once the pandemic started, so it is an unpredictable event. Otherwise before 2020, the median household prices kept increasing.