Time Series

November 6, 2018

1 Time Series

As an example of time series we will be looking at weather data which is easily obtained. The data set we will look at is from the Global Historical Climatology Network (GHCN): 2005-2015 New York Region

The data comes from http://www.ncdc.noaa.gov/cdo-web/datasets

Air Temperature: (tenths of degrees Celsius) * MNTM - Monthly mean temperature * MMNT - Monthly Mean minimum temperature * MMXT - Monthly Mean maximum temperature * EMNT - Extreme minimum daily temperature * EMXT - Extreme maximum daily temperature

Precipitation: (tenths of mm) * TPCP - Total precipitation * EMXP - Extreme maximum daily precipitation

Snow: (mm) * TSNW - Total snow fall * MXSD - Maximum snow depth

Note that one of the great strengths of Pandas is time series. Pandas is particularly helpful. Using version is not 0.23.4 here so keep that in mind.

```
In [1]: # load pandas
        import pandas as pd
        # check the version
        pd.__version__
```

```
Out[1]: '0.23.4'
```

```
In [2]: # load in csv file of data from online and put it into the ghcn dataframe object
        ghcn = pd.read_csv('https://raw.githubusercontent.com/story645/ams_tutorials/master/da
```

```
In [3]: #view the first 5 rows of the data
        ghcn.head()
```

```
In [4]: #get data types and counts of variables
        ghcn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1625 entries, 0 to 1624
Data columns (total 11 columns):
STATION_NAME    1625 non-null object
DATE            1625 non-null int64
EMXP            1625 non-null int64
MXSD            1625 non-null int64
```

```
TPCP            1625 non-null int64
TSNW            1625 non-null int64
EMXT            1625 non-null int64
EMNT            1625 non-null int64
MMXT            1625 non-null int64
MMNT            1625 non-null int64
MNTM            1625 non-null int64
dtypes: int64(10), object(1)
memory usage: 139.7+ KB
```

```
In [5]: #view column names
        ghcn.columns
```

```
Out[5]: Index(['STATION_NAME', 'DATE', 'EMXP', 'MXSD', 'TPCP', 'TSNW', 'EMXT', 'EMNT',
               'MMXT', 'MMNT', 'MNTM'],
              dtype='object')
```

1.1 Indexing

Pandas gives us different ways and great flexibility at indexing our data. We can create slices like in numpy. First we select the columns we want to index and then we can choose, for example, from the 6th row to the 15th row, skipping every other row.

```
In [6]: ghcn[['MMNT','TSNW']][5:15:2]
```

Here we specify the same range/slice of rows and a range of column headings.

```
In [7]: # use .loc for row, column order
        ghcn.loc[5:15:2,'TSNW':'MNTM']
```

```
In [8]: #use .iloc for numerical indexing on rows and cols
        ghcn.iloc[5:15:2,5:10]
```

1.2 Summary Statistics & Distributions

Pandas has a number of built in statistical functions, more than we find in pure bandas. We have min, max, mean, std, but there is also mean and quantile.

```
In [9]: ghcn['MMNT'].min(), ghcn['MMNT'].max(), ghcn['MMNT'].mean(), ghcn['MMNT'].median(), gh
```

```
Out[9]: (-9999, 239, -2825.9304615384617, 19.0, -9999.0)
```

```
In [10]: import numpy as np
         np.__version__
```

```
Out[10]: '1.15.3'
```

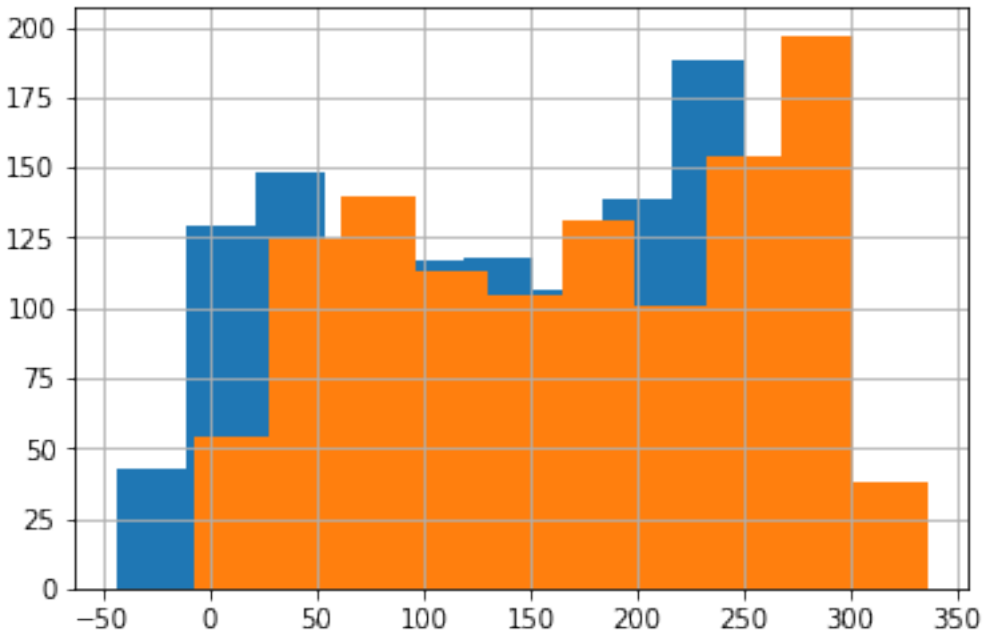
```
In [11]: # mask missing values by replacing -9999 with np.nan
         ghcn.replace(-9999,np.nan,inplace=True)
```

```
In [12]: # Compute the summary statistics of the average temperature:
         ghcn['TPCP'].describe()
```

```
Out[12]: count    1622.000000
         mean      977.469174
         std       665.199628
         min         0.000000
         25%       553.000000
         50%       880.500000
         75%      1250.000000
         max      4813.000000
         Name: TPCP, dtype: float64
```

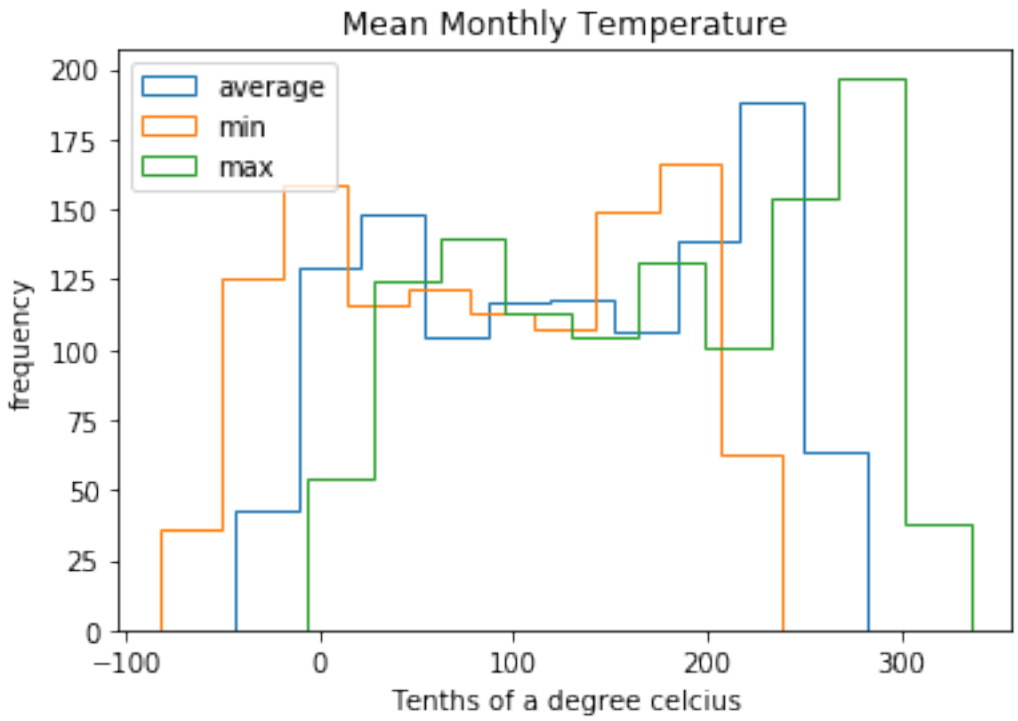
```
In [13]: #use matplotlib inline to show the distribution
         %matplotlib inline
         # We will need this later
         import matplotlib.pyplot as plt

         # plot the histogram of the MNTM column and the MMXT column to compare them
         ghcn['MNTM'].hist()
         ghcn['MMXT'].hist()
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x121f28358>
```



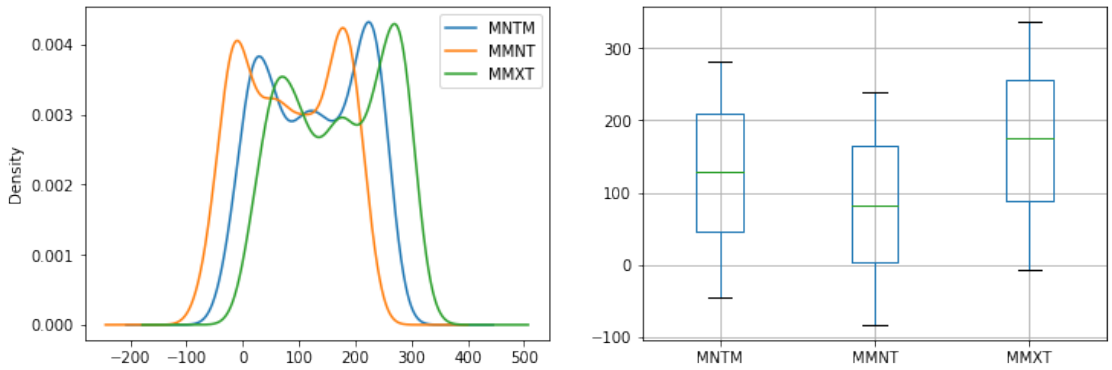
Note that because the histograms are solid we cannot see through them. One way we can deal with this is to change the histogram type to 'step'. This just give us the outline. In order to show them on the same graph we explicitly create the 'axis' using subplots and pass it to each plot. We also use the 'label' attribute to identify each of the plots for use in the legend.

```
In [14]: # plot the histogram of all three temperature variables
         fig, ax = plt.subplots()
         _ = ghcn['MNTM'].hist(histtype='step', ax=ax, label='average')
         _ = ghcn['MMNT'].hist(histtype='step', ax=ax, label='min')
         _ = ghcn['MMXT'].hist(histtype='step', ax=ax, label='max')
         _ = ax.legend(loc='upper left')
         _ = ax.set_title("Mean Monthly Temperature")
         _ = ax.set_xlabel('Tenths of a degree celcius')
         ax.set_ylabel('frequency')
         ax.grid(False)
```



The histogram is an approximation to a probability density. The bin makes it a probability distribution (discrete bins) that approaches a probability density (continuous) as the bins get very small. We have two other ways of looking at it. The kde plot takes the data and by setting up effectively normal densities around each data point, approximates the smooth probability density of the data. The boxplot just gives the summary statistics in visual form showing the max, min, median, first and third quartile. In some ways by showing less, the box plot makes it easier to compare the overall stats better although the kde is better at showing the comparative shapes of the density.

```
In [15]: fig, (ax1, ax2) = plt.subplots(figsize=(12,4), ncols=2)
         _ = ghcn[['MNTM','MMNT','MMXT']].plot.kde(ax=ax1)
         _ = ghcn[['MNTM','MMNT','MMXT']].boxplot(ax=ax2)
```




```
In [16]: #summary for entire dataset
         ghcn.describe()
```

Not all stations have the same number of measurements. Some stations are newer while others may have been retired. Lets see which stations have the longest time series in the data.

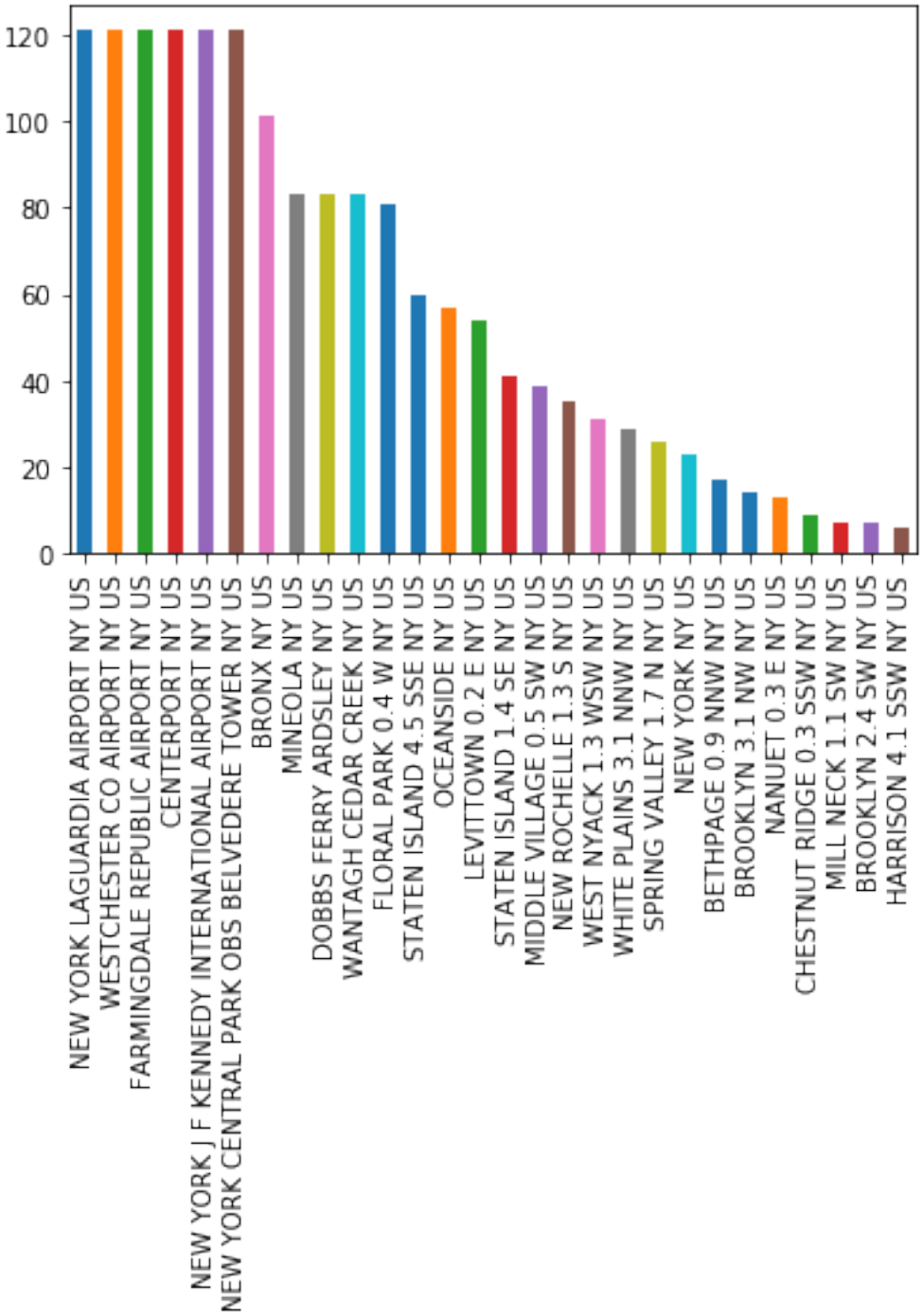
```
In [17]: ghcn['STATION_NAME'].value_counts()
```

```
Out[17]: NEW YORK LAGUARDIA AIRPORT NY US                    121
         WESTCHESTER CO AIRPORT NY US                       121
         FARMINGDALE REPUBLIC AIRPORT NY US                 121
         CENTERPORT NY US                                   121
         NEW YORK J F KENNEDY INTERNATIONAL AIRPORT NY US   121
         NEW YORK CENTRAL PARK OBS BELVEDERE TOWER NY US    121
         BRONX NY US                                        101
         MINEOLA NY US                                       83
         DOBBS FERRY ARDSLEY NY US                           83
         WANTAGH CEDAR CREEK NY US                           83
         FLORAL PARK 0.4 W NY US                             81
         STATEN ISLAND 4.5 SSE NY US                         60
         OCEANSIDE NY US                                     57
         LEVITTOWN 0.2 E NY US                               54
         STATEN ISLAND 1.4 SE NY US                          41
         MIDDLE VILLAGE 0.5 SW NY US                         39
         NEW ROCHELLE 1.3 S NY US                            35
         WEST NYACK 1.3 WSW NY US                            31
         WHITE PLAINS 3.1 NNW NY US                          29
         SPRING VALLEY 1.7 N NY US                           26
         NEW YORK NY US                                      23
         BETHPAGE 0.9 NNW NY US                              17
         BROOKLYN 3.1 NW NY US                               14
         NANUET 0.3 E NY US                                  13
         CHESTNUT RIDGE 0.3 SSW NY US                         9
         MILL NECK 1.1 SW NY US                               7
```

```
BROOKLYN 2.4 SW NY US                                   7
HARRISON 4.1 SSW NY US                                  6
Name: STATION_NAME, dtype: int64
```

This is nice but to see the pattern of value counts it would be much easier to represent this as a bar graph. We can do this with the bar chart built into Pandas.

```
In [18]: ghcn['STATION_NAME'].value_counts().plot.bar()

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1a23fc1470>
```

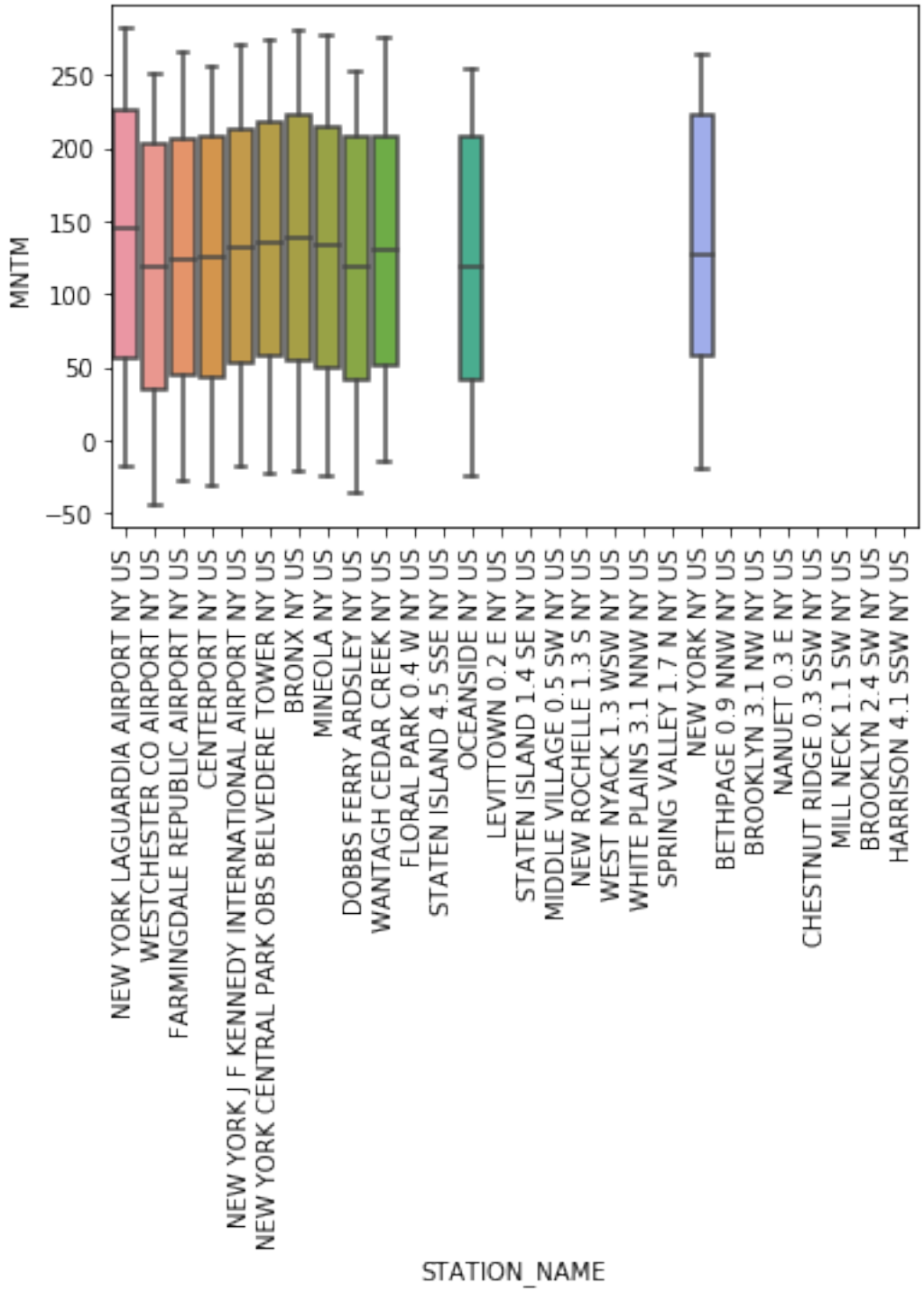


Harrison station looks particularly short on measurements. Let's have a look.

```
In [19]: ghcn[ghcn['STATION_NAME'].str.contains('HARRISON')]
```

Definitely we can see Harrison station has view measurements and many NaN. Lets look at boxplots for all the stations but only the Monthly Mean Temperature distributions. Clearly as with Harrison there may be missing boxplots due to missing measurements.

```
In [20]: import seaborn as sns
         g=sns.boxplot(y='MNTM', x='STATION_NAME', data=ghcn,
                       order=ghcn['STATION_NAME'].value_counts().keys())
         _ = g.set_xticklabels(g.get_xticklabels(), rotation=90)
```



Potentially we could have filtered out the stations which had no measurements. Now lets examine the dates.

1.3 Fixing Dates

The dates read from the csv file are just formated as ints. We print out the first 5 to learn the format:

```
In [21]: ghcn['DATE'].head()

Out[21]: 0    20050601
         1    20050701
         2    20050801
         3    20050901
         4    20051001
         Name: DATE, dtype: int64
```

This gives us the opportunity to see how the formating works. It is year month then date. We specify the format in the 'to_datetime' method and this gives us a way to format this as date objects right into the pandas object.

```
In [22]: ghcn['date']=pd.to_datetime(ghcn['DATE'],format='%Y%m%d')
         # Note we keep "DATE" in its original form but just at a 'date' column of the new typ
         ghcn['date'].head()

Out[22]: 0   2005-06-01
         1   2005-07-01
         2   2005-08-01
         3   2005-09-01
         4   2005-10-01
         Name: date, dtype: datetime64[ns]

In [23]: stations = dict(list(ghcn.groupby('STATION_NAME')))
         print('\n'.join(stations.keys()))

BETHPAGE 0.9 NNW NY US
BRONX NY US
BROOKLYN 2.4 SW NY US
BROOKLYN 3.1 NW NY US
CENTERPORT NY US
CHESTNUT RIDGE 0.3 SSW NY US
DOBBS FERRY ARDSLEY NY US
FARMINGDALE REPUBLIC AIRPORT NY US
FLORAL PARK 0.4 W NY US
HARRISON 4.1 SSW NY US
LEVITTOWN 0.2 E NY US
MIDDLE VILLAGE 0.5 SW NY US
MILL NECK 1.1 SW NY US
MINEOLA NY US
```