CodeViolationsSeattle

August 25, 2015

1 What Happened to Code Violations in Seattle?

This is part 1 of a project I initially started as a way of helping me find a new apartment around Seattle. As a recent graduate from UW, I wanted to find a place around U-District to keep me close to the University + Downtown for potential work. U-District is not a pretty place, but go 20 minutes away from campus in any direction and things look much better. By looking at code violations around the city I would get some insight into the quality of local neighborhoods. Combining this with criminal activity throughout Seattle would give me an even better idea of what I was getting myself into, but that's part 2.

But why stop there? The data is already there (and surprisingly well taken!), so I expanded the scope of the project a bit. Right now, part 1 is a way of:

```
<li>Getting an inkling of the quality of each neighborhood</li>
<li>Learning more about using the Pandas Python package</li>
<li>Figuring out why the number of code violation cases drastically dropped in 2010</li>
```

I roughly followed along with a blog post by data scientist Jake Vanderplas at the University of Washington eScience Institute. He does a very thorough analysis of timeseries data of cyclists in Seattle instead, I highly recommend reading his blog to learn more about data science and Python techniques.

1.1 The Data

I use three datasets in part 1. One contains code violations in the Seattle neighborhoods going back ˜15 years. There are 33918 individual code violation cases of various types in this dataset. It includes the type, description, address, geographical location, and various dates of the recorded violation. Many of the earliest cases are missing bits of data such as the date the case was created by the city. The other two datasets contain building permits (here and here) applied for and issued by the city for various projects in the past ˜10 years. There are 81840 permit applications in this dataset. Many are still ongoing projects. They include the type, address, geographical location, and various dates of permit issuing/expiration.

1.2 The Analysis

1.2.1 Creation vs Inspection

This entire analysis will be done using Python3 in a Jupyter notebook. I'll start by importing Pandas, Matplotlib, and Numpy to read in the datasets, then plot & perform operations with it. The data come as CSV files, and Pandas has fabulous features for reading in and parsing properly-formatted CSV files. I will be using the date on which the violation cases were created as the index for timeseries' that I create. This makes later manipulation easier, and makes it easier to keep track of various cases.

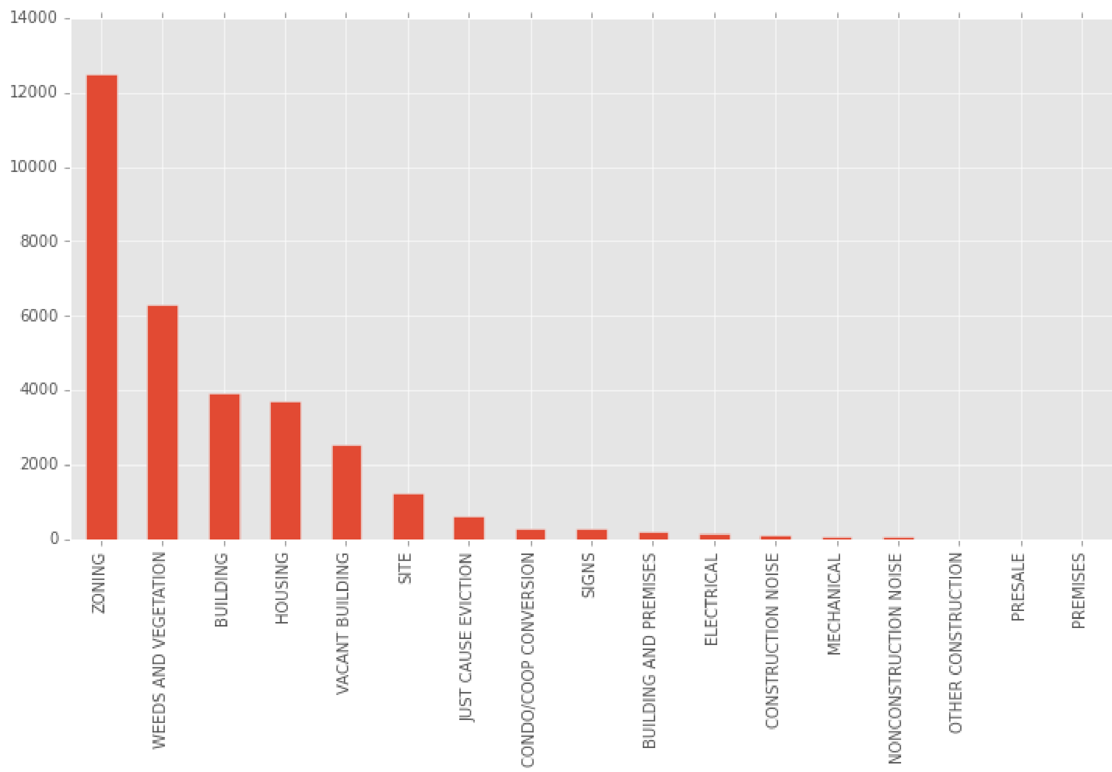
```
In [50]: %matplotlib inline

         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
```

```
plt.style.use('ggplot')

violations = pd.read_csv('violations.csv', header=0, index_col='Date Case Created')
violations.index = pd.DatetimeIndex(violations.index)
```

I can make a histogram of the different code violation cases submitted to the city. These are complaints that were sent in and given an initial inspection by the city. The cases also have dates for any secondary followup inspections that may have happened.

```
In [20]: violations['Case Group'].value_counts().plot(kind='bar', figsize=(12,6))
```

```
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc1ccc1ca90>
```



The overwhelming majority are 'ZONING' violations, followed not-to-closely by 'WEEDS AND VEGETATION' violations. Together, these make up over 50% of all cases.

```
In [3]: violations['Case Group'].value_counts()
```

```
Out[3]: ZONING                    12480
        WEEDS AND VEGETATION       6291
        BUILDING                   3905
        HOUSING                    3700
        VACANT BUILDING            2522
        SITE                       1265
        JUST CAUSE EVICTION         608
        CONDO/COOP CONVERSION       305
        SIGNS                       302
        BUILDING AND PREMISES       212
```

```
ELECTRICAL                 176
CONSTRUCTION NOISE         108
MECHANICAL                  92
NONCONSTRUCTION NOISE       55
OTHER CONSTRUCTION          11
PRESALE                      8
PREMISES                     4
dtype: int64
```

At a glance, it looks like the majority of these violations are from people complaining about their neighbors! Interestingly enough, despite there being constant construction everywhere, there aren't that many complaints about construction related issues. It may be that construction related violations are handled by another government entity.

Each entry of the data includes the type of violation, the location at which the violation took place, the date on which the city opened a case, and outcomes of followup inspections. Though I'll ultimately be using the dates on which cases were created, it's at least interesting to see a little about how inspections are handled by the city as well.

A good way to visualize this data is to setup a timeseries of it, which Pandas is perfect for. At a first glance, the dates on which cases are created aren't regular, and neither are the dates where agents followup on those cases. By counting up all of the cases created/inspected on a given day, I can create a timeseries over the 10 years. Pandas dataframes offer a very convenient way of compiling the two timeseries.

```
In [4]: case_counts = violations.index.value_counts()
        inspec_counts = violations['Last Inspection Date'].value_counts()

        case_dates = pd.to_datetime(case_counts.index, format='%m/%d/%Y')
        inspec_dates = pd.to_datetime(inspec_counts.index, format='%m/%d/%Y')

        inspections = pd.DataFrame({'Case Creation': pd.Series(case_counts.tolist(), index=case_dates),
                                    'Followup Inspection': pd.Series(inspec_counts.tolist(), index=inspe
        inspections.tail(5)
```

```
Out[4]:             Case Creation  Followup Inspection
        2015-08-04             15                   18
        2015-08-05              8                    4
        2015-08-06             11                   13
        2015-08-23            NaN                    1
        2015-12-05            NaN                    1
```

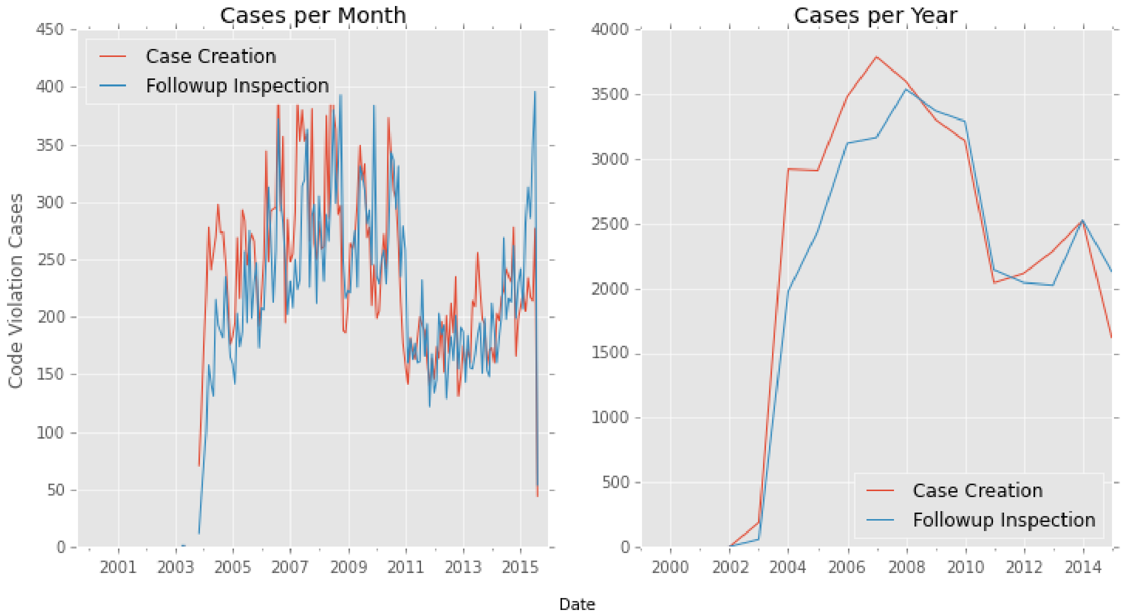
Notice that there are NaNs all throughout where there are either no case creations or followup inspections on that day. I can fix this with a simple replacement of NaNs with 0.

```
In [5]: inspections = inspections.fillna(0)
```

And now the pretty part. Since plotting day by day is messy, I can use Pandas to resample up to monthly and annual cadences.

```
In [6]: fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))
        axes[0].set_ylabel('Code Violation Cases')
        fig.text(0.5, 0.04, 'Date', ha='center', va='center')
        inspections[['Case Creation','Followup Inspection']].resample('M',how='sum').plot(ax=axes[0]).se
        inspections[['Case Creation','Followup Inspection']].resample('A',how='sum').plot(ax=axes[1]).se
```

```
Out[6]: <matplotlib.text.Text at 0x7fc1cf7d2b70>
```



Curiously enough, there are significantly more cases created than are followup inspected by the city. This could be due to a number of things, such as certain cases not requiring in-person followup. However most surprising is the huge drop in cases (>1000 cases), both followed-up and not followed-up, around 2010. That's a pretty blatant anomaly and most likely has some kind of external cause. In fact we can look at the average number of cases per day before and after the drop in 2010.

```
In [9]: print('Pre-2010: '+str(inspections['Case Creation'][:'2010-01-01'].mean()))
        print('Post-2010: '+str(inspections['Case Creation']['2010-01-01':].mean()))
```

```
Pre-2010: 12.192632850241546
Post-2010: 9.453856749311294
```

Weird, right? Before I get any further into this drop, I am going to try to look at the smaller details first. If I'm going to properly use this data, I want to take out as many anomalies as possible to have data that is equally relevant across the entire set. After thinking about it a little, the most obvious sources of small biases are likely to be seasonal variations (who wants to go investigate a case in the dead of winter?) and day of the week (cases might be entered on very specific days). Luckily, Jake Vanderplas has a nifty function for finding seasonal variations, which I will use shortly.

1.2.2 Seasonal and Daily Variations

I can set up a season dictionary for the months to figure out the season for every day on which at least one case appears, as well as for each case itself. This gives a rough initial picture on what kinds of variations there may be during the year in how often cases are investigated, and in how many cases are acknowledged.

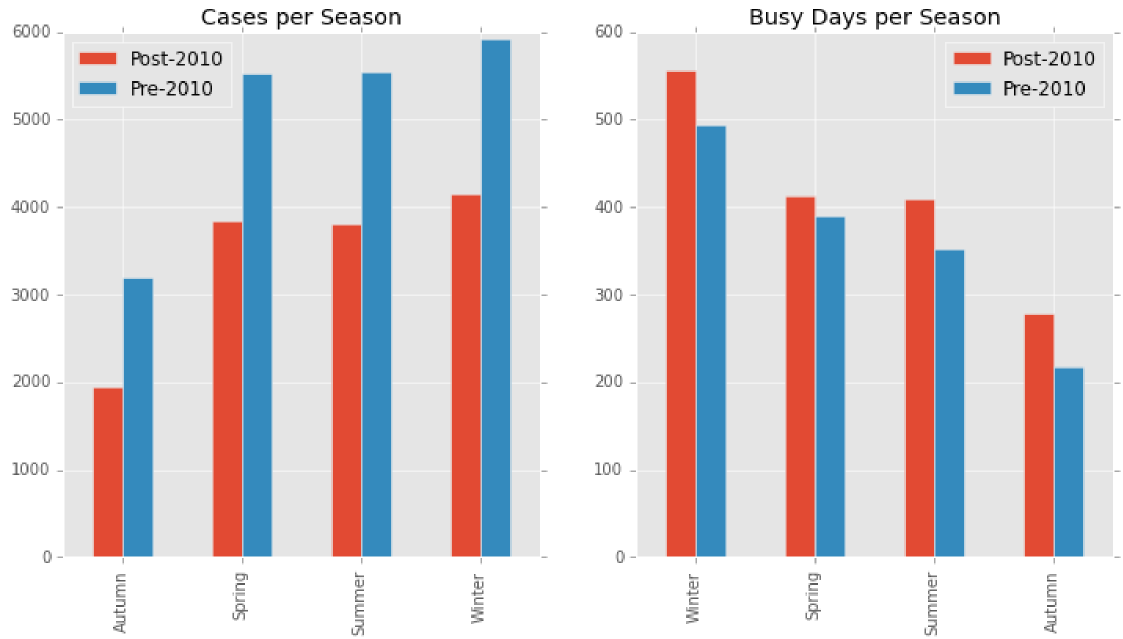
```
In [178]: SEASON = {1:'Winter', 2:'Winter', 3:'Winter', 4:'Spring', 5:'Spring', 6:'Spring',
                    7:'Summer', 8:'Summer', 9:'Summer', 10:'Autumn', 11:'Autumn', 12:'Winter'}

          inspections['Case Season'] = pd.Series([SEASON[i] for i in inspections.index.month], index=ins
          violations['Case Season'] = pd.Series([SEASON[i] for i in violations.index.month],
                                                index=violations.index)
```

Just to make it easier for the next plot, I'll make a couple temporary data frames. A cleaner method for what I want through Pandas wasn't readily obvious.

```
In [225]: df1 = pd.DataFrame({'Pre-2010': violations['Case Season']['2010-01-01':].value_counts(),
                              'Post-2010': violations['Case Season'][:'2010-01-01'].value_counts()})
          df2 = pd.DataFrame({'Pre-2010': inspections['Case Season']['2010-01-01':].value_counts(),
                              'Post-2010': inspections['Case Season'][:'2010-01-01'].value_counts()})
```

```
In [224]: fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))

          df1.plot(kind='bar', ax=axes[0], legend=True)
          df2.plot(kind='bar', ax=axes[1], legend=True)

          axes[1].set_title('Busy Days per Season')
          axes[0].set_title('Cases per Season')
```

```
Out[224]: <matplotlib.text.Text at 0x7f1dbb154dd8>
```



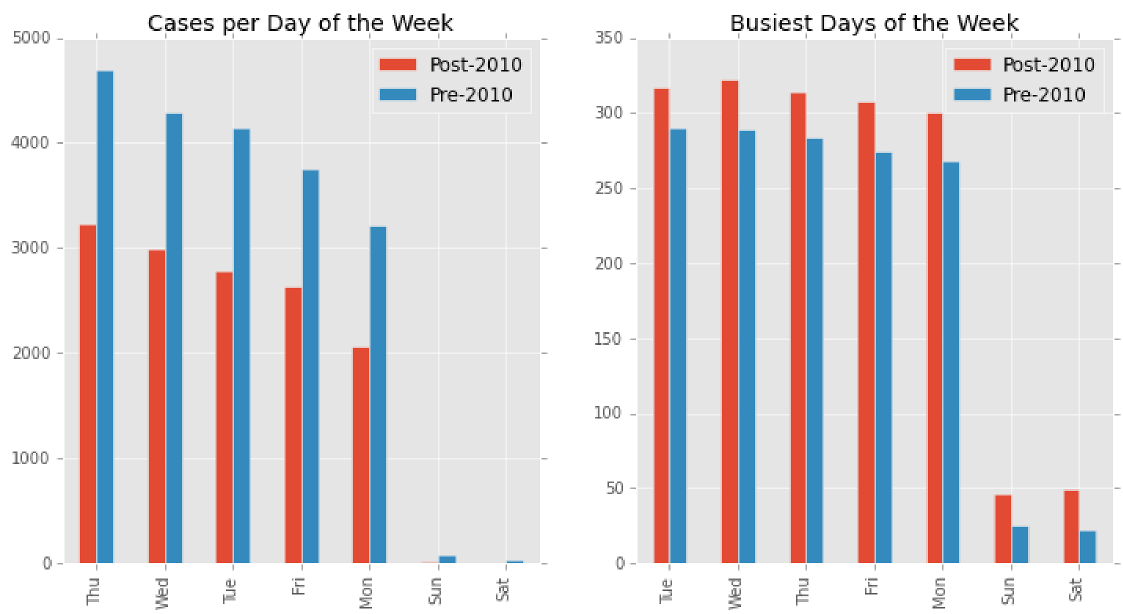
A “busy day” is just a day with at least one case being investigated.

First, winter has a small lead in the sheer number of cases created per season, and a pretty sizable lead on the number of days the city takes to perform an initial followup on the cases. In other words, complaints are roughly as likely to happen in winter, summer, and spring, but may take longer to investigate in the winter. Autumnal cases are much less common and there are fewer days where inspections happen. Post-2010 numbers show a drop by 40% at most in the number of cases being created by the city. There are more “busy days” after the drop, too. This indicates that after the 2010 drop, the city was taking longer to respond to a lower volume of complaints. This kind of activity might be significant enough to warrant subtracting it out.

Furthermore I can check to see if there is variation on a day-to-day basis in an identical way.

```
In [11]: WEEKDAY = {0:'Mon', 1:'Tue', 2:'Wed', 3:'Thu',
                    4:'Fri', 5:'Sat', 6:'Sun'}

         inspections['Case Day'] = pd.Series([WEEKDAY[i] for i in inspections.index.weekday], index=insp
         violations['Case Day'] = pd.Series([WEEKDAY[i] for i in violations.index.weekday], index=viola
```

```
In [48]: df1 = pd.DataFrame({'Pre-2010': violations['Case Day']['2010-01-01':].value_counts(),
                             'Post-2010': violations['Case Day'][:'2010-01-01'].value_counts()})
         df2 = pd.DataFrame({'Pre-2010': inspections['Case Day']['2010-01-01':].value_counts(),
                             'Post-2010': inspections['Case Day'][:'2010-01-01'].value_counts()})

         df1 = df1.sort('Pre-2010', axis=0, ascending=False)
         df2 = df2.sort('Pre-2010', axis=0, ascending=False)

In [53]: fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))

         df1.plot(kind='bar', ax=axes[0], legend=True)
         df2.plot(kind='bar', ax=axes[1], legend=True)

         axes[0].set_title('Cases per Day of the Week')
         axes[1].set_title('Busiest Days of the Week')

Out[53]: <matplotlib.text.Text at 0x7fc1c7bda160>
```



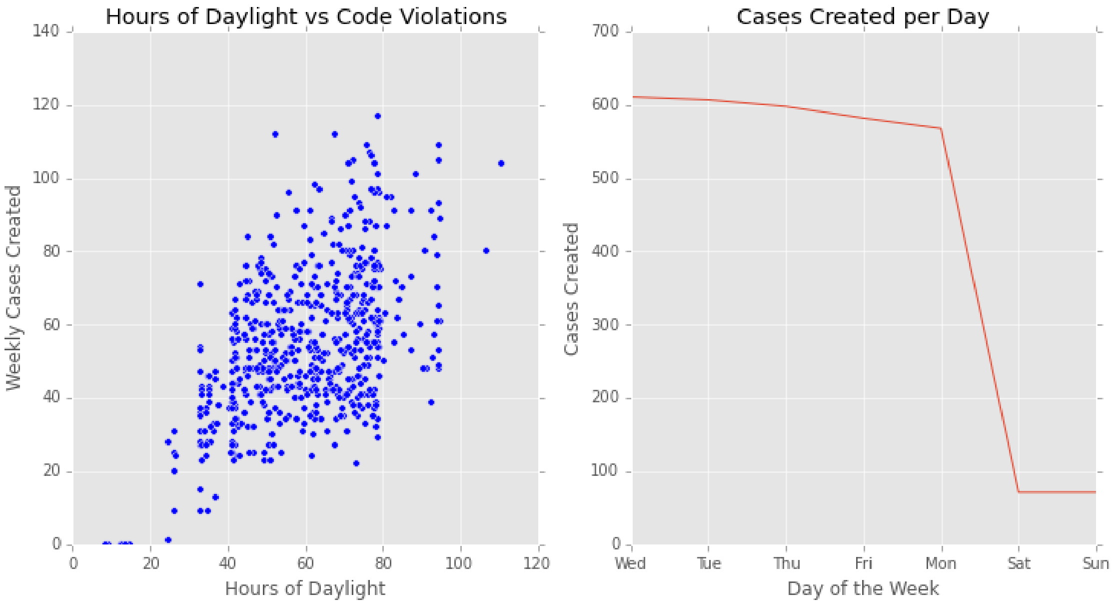
Seasonal and daily patterns still hold after 2010. Cases generally aren't investigated on the weekend, and Thursday is the most popular day for cases to be officially created. Cases are physically investigated roughly equally across all weekdays.

Now for the fun part! I lifted a function from Jake Vanderplas to calculate the daylight hours in Seattle throughout the year. This allows me to find the number of hours of daylight for each individual inspection so that I can subtract out seasonal variations. I can also simultaneosly subtract out the daily variations.

```
In [54]: def hours_of_daylight(date, axis=23.44, latitude=47.61):
             """Compute the hours of daylight for the given date"""
             diff = date - pd.datetime(2000, 12, 21)
             day = diff.total_seconds() / 24. / 3600
             day %= 365.25
             m = 1. - np.tan(np.radians(latitude)) * np.tan(np.radians(axis) * np.cos(day * np.pi / 182
             m = max(0, min(m, 2))
             return 24. * np.degrees(np.arccos(1 - m)) / 180.
```

```
In [55]: fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))

         inspections['Hours Daylight'] = inspections.index.map(hours_of_daylight)
         axes[0].scatter(x=inspections['Hours Daylight'].resample('W', how='sum'),
                         y=inspections['Case Creation'].resample('W', how='sum'))
         axes[0].set_xlabel('Hours of Daylight') ; axes[0].set_ylabel('Weekly Cases Created')
         axes[0].set_ylim(0,)
         axes[0].set_title('Hours of Daylight vs Code Violations')

         inspections['Case Day'].value_counts().plot(ax=axes[1])
         axes[1].set_ylabel('Cases Created') ; axes[1].set_xlabel('Day of the Week')
         axes[1].set_title('Cases Created per Day')
```

```
Out[55]: <matplotlib.text.Text at 0x7fc1c7a91668>
```



scikit-learn is one of few up-to-date packages that properly handles multivariate regression. I can use the tools it provides to fit both the seasonal and daily variations at once. I'll create a new column for the weekday number instead of name (e.g, 0 instead of 'Monday').

```
In [56]: inspections['Case Day Number'] = pd.Series(inspections.index.dayofweek, index=inspections.inde
```

Then I can fit with sklearn:

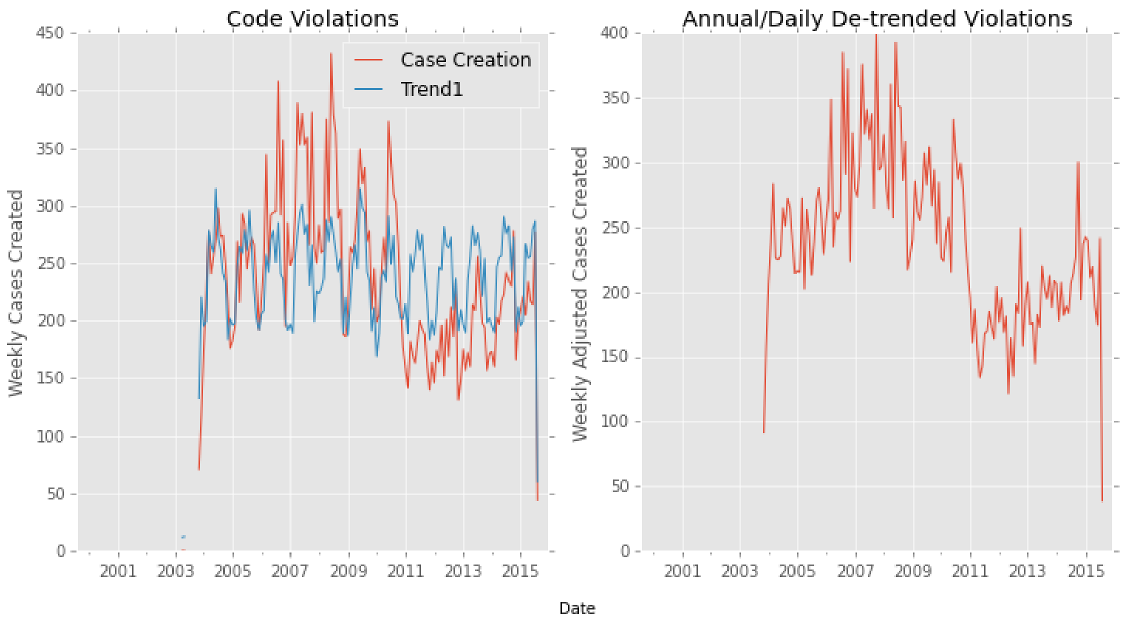
```
In [57]: from sklearn.linear_model import LinearRegression

         fit = LinearRegression().fit(inspections[['Hours Daylight','Case Day Number']], inspections['C
```

Then de-trend:

```
In [58]: fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))

         inspections['Trend1'] = fit.predict(inspections[['Hours Daylight','Case Day Number']])
         inspections[['Case Creation','Trend1']].resample('M', how='sum').plot(ax=axes[0], title='Code 
```

```
inspections['DeTrended1'] = inspections['Case Creation'] - inspections['Trend1'] + inspections
inspections['DeTrended1'].resample('M',how='sum').plot(ax=axes[1], title='Annual/Daily De-tren

axes[0].set_ylabel('Weekly Cases Created')
axes[1].set_ylabel('Weekly Adjusted Cases Created')
axes[1].set_ylim(0,)
fig.text(0.5, 0.04, 'Date', ha='center', va='center')
```

Out[58]: <matplotlib.text.Text at 0x7fc1b776a4a8>




```
In [59]: print('Original RMS: '+str(inspections['Case Creation'].std()))
         print('De-trended RMS: '+str(inspections['DeTrended1'].std()))
```

```
Original RMS: 6.1362216988060805
De-trended RMS: 6.0005391303840945
```

Not a huge difference, but the counts are noticeably lower and the RMS is slightly smaller. The right plot shows how cases would be accepted by the city if there were no seasonal or daily variations.

1.2.3 Permitting & Case Type

There's pretty clearly other forces at play here so I decided to do some Internet sleuthing. I found a memo from the Seattle Department of Planning & Development regarding, among other things, the volume of violation complaints for a few years prior.

```
In [16]: from IPython.display import Image
         Image(filename='violations.png')
```

Out[16]:

Violation Complaint Volumes: The volume of violation complaints by type of issue is shown below. Construction related complaints remain at lower levels than several years ago, consistent with the drop in construction activity. The recession and its ripple effects are likely also a factor. Vacant building complaints have decreased in the past two years, somewhat counter-intuitively, given the higher level of home foreclosures and persistent problems associated with a small number of foreclosed properties.

CODE VIOLATION COMPLAINTS BY TYPE, 2006-2011

Problem Type	2008	2009	2010	2011*
Construction	1,159	994	926	871
Noise**	261	194	190	192
Housing/zoning	**3,900**	**3,701**	**3,454**	**3,110**
Housing	434	461	456	464
Unfit bldg/premises	5	3	2	3
Vacant building	263	250	198	219
Vegetation overgrowth***	1,498	1,221	1,332	1,048
Land Use/Zoning (incl. shoreline)	1,700	1,766	1,466	1,376
Landlord/tenant service calls	**1,833**	**2,662**	**3,729**	**3829**
Tenant Relocation	623	699	846	1173
Rental housing (eviction, emergency order, illegal unit)	607	1,077	1,844	1999
Other	603	886	1,039	657
TOTAL	**7,153**	**7,551**	**8,299**	**8002**

* 2011 data as of Nov. 29, 2011.

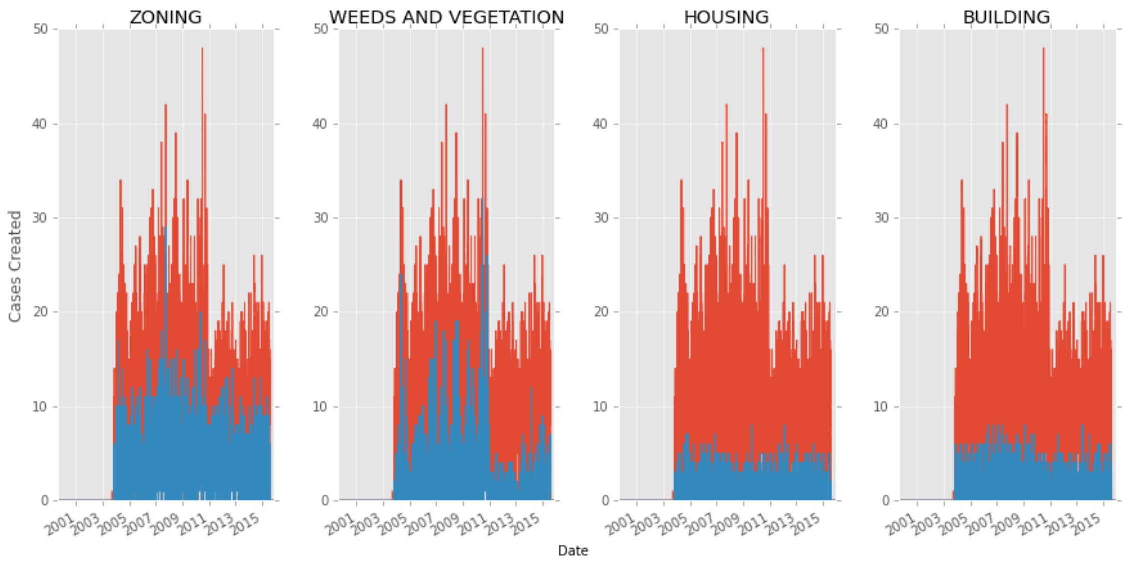
** Noise complaint response is handled in the Operations Division.

*** Vegetation inspection response was reduced in 2011 as a result of staff reductions.

From the looks of it, there are a few factors. They blame the drop on the recession and ensuing construction drop. Construction complaints dropped a bit, but housing/zoning complaints began to drop off more quickly due to vegetation overgrowth inspections being reduced and fewer land use complaints.

Fortunately, the original data allows one to sort by the type of code violation case! Because this is tampering with the initial dataset, I can very readily de-trend everything but whatever seems to be the culprit. If I were doing more important things with this data, I would probably stop before averaging out these kinds of violations – I'm effectively throwing out information. But the end goal is to find a nice place to live, it's not a big deal if it means lower RMS and large scale variations.

```
In [70]: fig, axes = plt.subplots(nrows=1, ncols=4, figsize=(12,6))
         complaints = ['ZONING', 'WEEDS AND VEGETATION', 'HOUSING', 'BUILDING']

         for i in range(len(complaints)):
             inspections[complaints[i]] = violations[violations['Case Group'] == complaints[i]].index.va
             inspections[complaints[i]] = inspections[complaints[i]].fillna(0)
             inspections['Case Creation'].plot(ax=axes[i])
             inspections[complaints[i]].plot(ax=axes[i], title=complaints[i])

         plt.tight_layout()
         axes[0].set_ylabel('Cases Created')
         fig.text(0.5, 0.0, 'Date', ha='center', va='center')

Out[70]: <matplotlib.text.Text at 0x7fc1b53cb048>
```

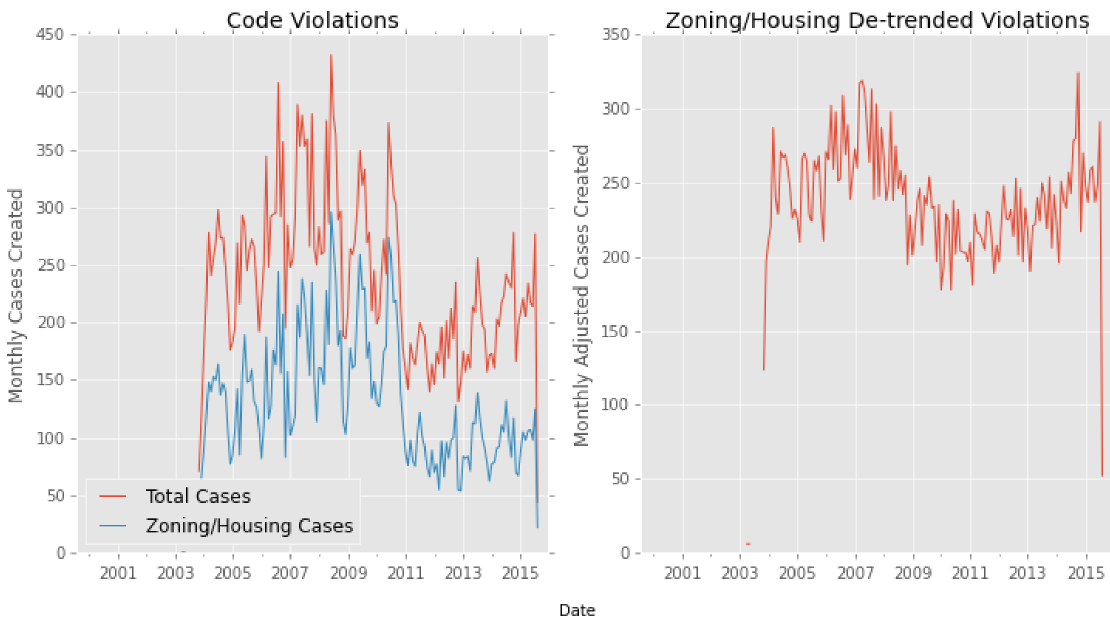


The biggest contributors to the drop are zoning and weeds/vegetation, so I'll ignore the other two to avoid tampering too much with the data.

```
In [73]: complaints = ['ZONING', 'WEEDS AND VEGETATION']
         inspections['Trend2'] = inspections[complaints[0]].add(inspections[complaints[1]], fill_value=
```

And now the plotting:

```
In [74]: fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))

         inspections['Case Creation'].resample('M', how='sum').plot(ax=axes[0], label='Total Cases', leg
         inspections['Trend2'].resample('M', how='sum').plot(ax=axes[0], title='Code Violations',
                                                             label='Zoning/Housing Cases', legend=True)
         inspections['DeTrended2'] = (inspections['Case Creation'] - inspections['Trend2'] + inspection
         inspections['DeTrended2'].resample('M', how='sum').plot(ax=axes[1], title='Zoning/Housing De-t

         axes[0].set_ylabel('Monthly Cases Created')
         axes[1].set_ylabel('Monthly Adjusted Cases Created')
         fig.text(0.5, 0.04, 'Date', ha='center', va='center')

Out[74]: <matplotlib.text.Text at 0x7fc1b541f2b0>
```




```
In [75]: print('Original RMS: '+str(inspections['Case Creation'].std()))
         print('De-trended RMS: '+str(inspections['DeTrended2'].std()))
```

```
Original RMS: 6.1362216988060805
De-trended RMS: 3.1806112199381436
```

Looking much better! The drop is mostly gone and the RMS is roughly halved. There is still a big bump cenetered on 2007, but fortunately there is another piece of the puzzle that wasn't taken into account in this: construction violations. They don't make up as big of a chunk, but I like to cover my bases. For this, I picked up another couple datasets regarding permitting by the city. These are permits for any sort of construction activity. The first is for permits in the past 5 years, and the second is for permits older than 5 years stretching back to about 10 years ago.

```
In [76]: construction1 = pd.read_csv('construction.csv', header=0, index_col='Issue Date')
         construction2 = pd.read_csv('construction2.csv', header=0, index_col='Issue Date')
         construction = pd.concat([construction1,construction2])
```

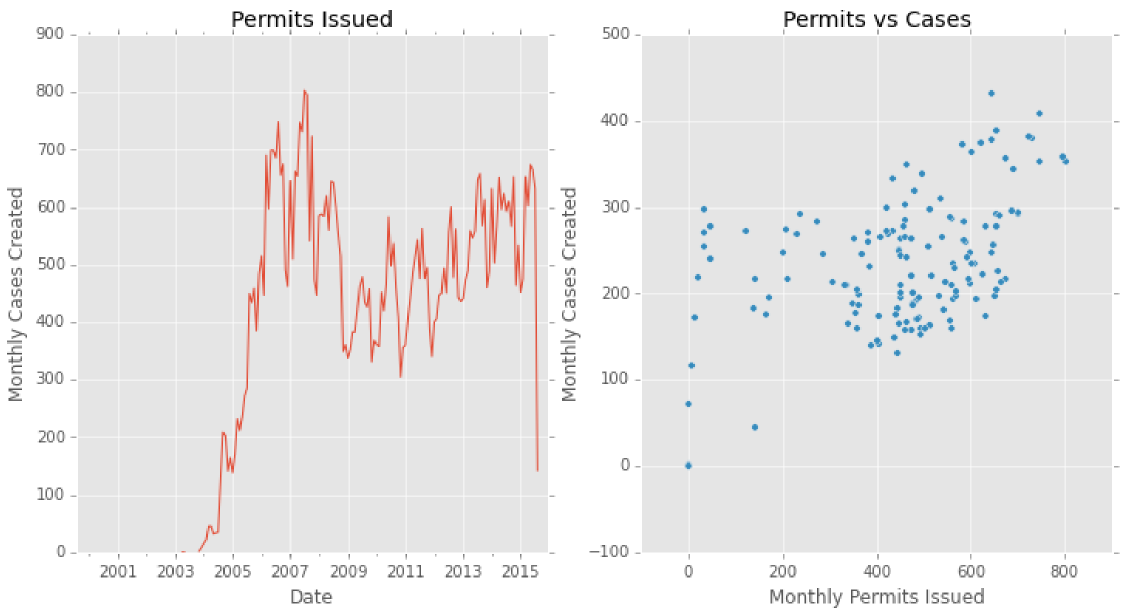
The headers include location, date of application, date of issuing, final projected date, and expiration date. The most relevant one is probably how many permits the city itself acknowledges and gives out, so I make a timeseries for the permit issuing dates.

```
In [77]: issue_counts = construction.index.value_counts()
         issue_dates = pd.to_datetime(issue_counts.index, format='%m/%d/%Y')

         inspections['Issue Permit'] = pd.Series(issue_counts.tolist(), index=issue_dates)
         inspections['Issue Permit'] = inspections['Issue Permit'].fillna(0)
```

```
In [78]: fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))

         inspections['Issue Permit'].resample('M', how='sum').plot(ax=axes[0], title='Permits Issued')
         inspections.resample('M', how='sum').plot(kind='scatter', ax=axes[1], x='Issue Permit',
                                                    y='Case Creation', title='Permits vs Cases')
```

```
        axes[0].set_ylabel('Monthly Cases Created')
        axes[0].set_xlabel('Date')
        axes[1].set_ylabel('Monthly Cases Created')
        axes[1].set_xlabel('Monthly Permits Issued')
```

```
Out[78]: <matplotlib.text.Text at 0x7fc1b2636080>
```



Looks very promising!

1.2.4 Fitting Everything

Using sklearn again, I'll take out biases induced by reduced construction activity. By the looks of the plot, I can set a minimum cutoff date for permit issuing around the start of 2003. There were no violation cases created before that time anyway. The last thing I'll fit for is the large scale variation peaking at 2007, dipping in 2011. I don't know if all of these biases are completely independent, so the best way to approach this is fitting them all at the same time. Using sklearn's multivariate regression capabilities, I'll take into account seasonal and daily variations as well as construction permitting and violation reason all at once. I do this after resampling to monthly cadence since this scales everything to larger, more meaningful numbers.

```
In [93]: inspections['Day Count'] = np.arange(len(inspections))
```

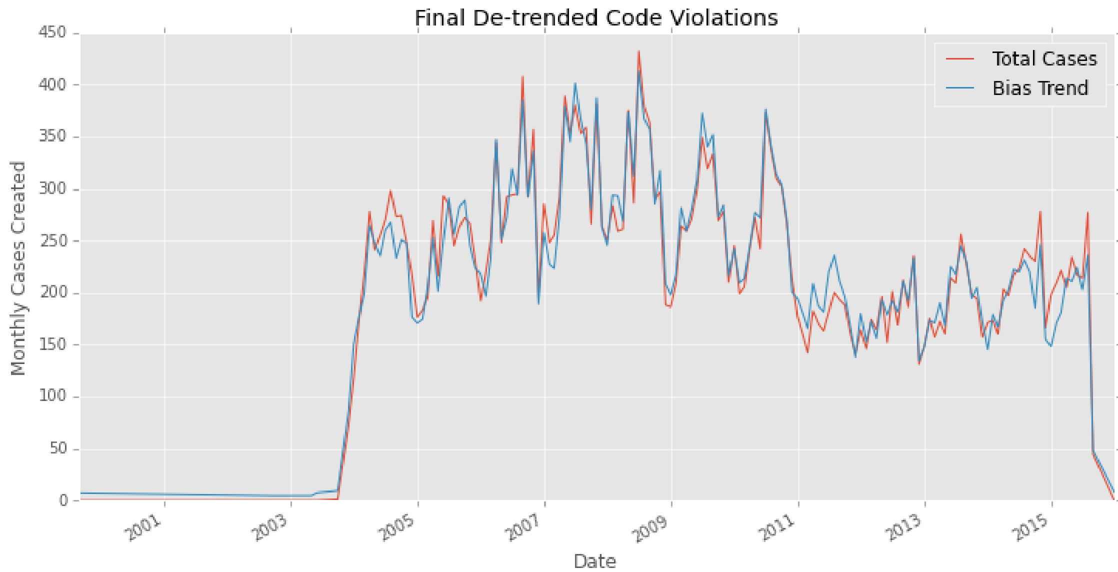
```
In [94]: headers = complaints + ['Day Count', 'Hours Daylight', 'Case Day Number', 'Issue Permit']
         monthly = inspections.resample('M', how='sum').dropna()

         fit = LinearRegression().fit(monthly[headers], monthly['Case Creation'])
```

And here's the de-trended code violation plot:

```
In [95]: monthly['Trend3'] = fit.predict(monthly[headers])
         monthly['DeTrended3'] = monthly['Case Creation'] - monthly['Trend3'] + monthly['Trend3'].mean(

         monthly['Case Creation'].plot(figsize=(12,6), label='Total Cases', legend=True)
```

```
monthly['Trend3'].plot(title='Final De-trended Code Violations',
                                                   label='Bias Trend', legend=True)

plt.ylabel('Monthly Cases Created') ; plt.xlabel('Date')
```

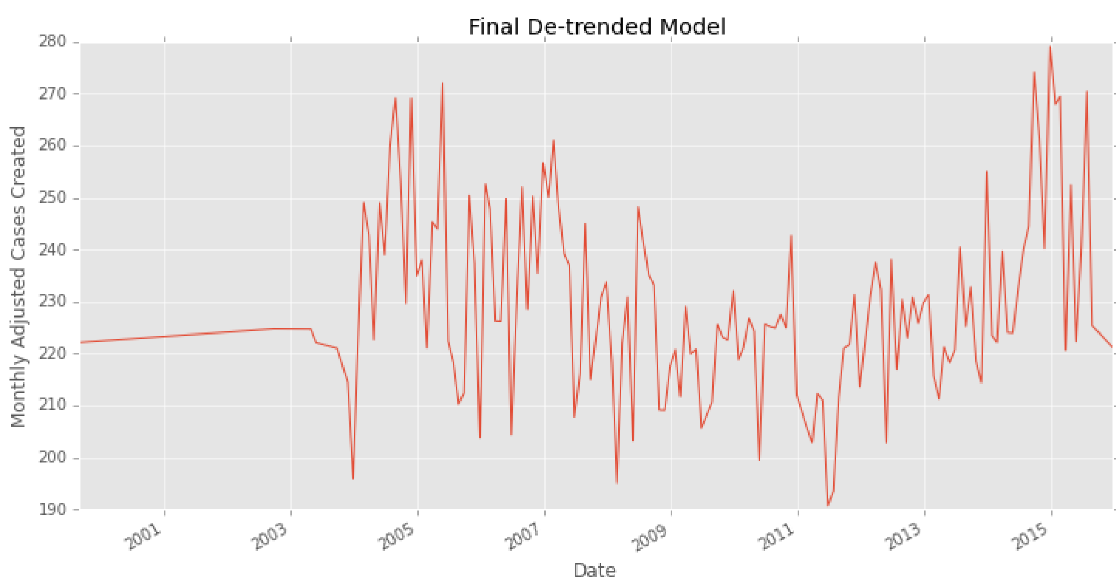
Out[95]: <matplotlib.text.Text at 0x7fc1b4c25cf8>



And the de-trended data plot:

In [96]:
```
monthly['DeTrended3'].plot(title='Final De-trended Model', figsize=(12,6))
plt.ylabel('Monthly Adjusted Cases Created')
plt.xlabel('Date')
```

Out[96]: <matplotlib.text.Text at 0x7fc1b3db6198>



Not half bad! I managed to get most of the variation, and it actually looks like properly de-trended data. The last thing to do is to actually see how legitimate these fits really are, however.

I calculate covariances using the methods in Vanderplas' blog post. The justification for this method can be found here.

```
In [102]: x_i = monthly[headers]
          y = monthly['Case Creation']
          model = monthly['Trend3']

          var_y = np.sum(y.subtract(model,axis=0)** 2) / len(y)
          X = np.hstack([x_i, np.ones((x_i.shape[0], 1))])
          C = var_y * np.linalg.inv(np.dot(X.T, X))
          var_tot = C.diagonal()
```

So now I have the slopes of each quantity in the multivariate regression, as well as their respective variances. I also have the RMS of the de-trended and original monthly data.

```
In [103]: for i in range(len(headers)):
              print(headers[i]+': '+str(fit.coef_[i])+' +/- '+str(np.sqrt(var_tot[i])))

          print('Original RMS: ' + str(monthly['Case Creation'].std()))
          print('De-Trended RMS: ' + str(monthly['DeTrended3'].std()))
```

```
ZONING: 1.1556641837 +/- 0.0798819457264
WEEDS AND VEGETATION: 0.795537574455 +/- 0.049019534943
Day Count: -0.000666613374778 +/- 0.000102175600464
Hours Daylight: 0.0882672481497 +/- 0.0288480745738
Case Day Number: 1.22135907256 +/- 0.193260591968
Issue Permit: 0.0867033259519 +/- 0.0111260194807
Original RMS: 82.30668682931699
De-Trended RMS: 17.780910339386338
```

```
In [104]: for i in range(len(headers)):
              print(headers[i]+' error: '+str(np.sqrt(var_tot[i])*100 / abs(fit.coef_[i]))+'%')
```

```
ZONING error: 6.9122109046%
WEEDS AND VEGETATION error: 6.16181265562%
Day Count error: 15.327565322%
Hours Daylight error: 32.6826486364%
Case Day Number error: 15.8234049519%
Issue Permit error: 12.8322868339%
```

It looks like including seasonal variations wasn't the best idea. The errors in general would be too big for intricate data work, but I'm satisfied with these. I'm not sure why the seasonal variations error is so large, though. On the bright side, I got an 8x decrease in the scatter of the data!

1.2.5 Conclusion

Using NumPy, scikit-learn, Pandas, and Matplotlib, I fit various biases in the data for code violations around Seattle in an attempt to more equalize it for the purpose of finding a new place to live. This was a very rough analysis of a dataset with many more facets than I considered. In this short glance, the biggest contributors to the bias in code violations in Seattle were variations in daily inspections, the number of permits being issued by the city, policy changes to code violations, and general change over time of the creation of cases. Curiously enough, the seasonal variations don't play as big a role as I initially anticipated. There are surely other factors at play here that I did not consider at all. I now have half of the data I want to find a nice place to live, and a better grasp of Pandas. For part 2, I will look at criminal activity and attempt to tie it into this analysis. Thank you for reading my first attempt at a written-up analysis like this, I look forward to doing part 2!