Time Series Analysis
Recovering A Stochastic Signal

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1 Time Series Analysis

1.1 Recovering A Stochastic Signal

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This is a pretty basic example of how to filter and recover a random signal from a time series that is a combination of confounding noise.

In [72]:
```
#%install_ext https://raw.githubusercontent.com/rasbt/watermark/master/watermark.py
%load_ext watermark
%watermark -p numpy,scipy,pandas,matplotlib
```

```
The watermark extension is already loaded. To reload it, use:
  %reload_ext watermark


numpy 1.10.1
scipy 0.16.0
pandas 0.16.2
matplotlib 1.4.0
```

In [73]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import scipy.signal as signal
%matplotlib inline
```

In [74]:
```
df = pd.read_csv("/home/daniel/OrbitalInsights/data.csv")
```

In [75]:
```
df.head()
```

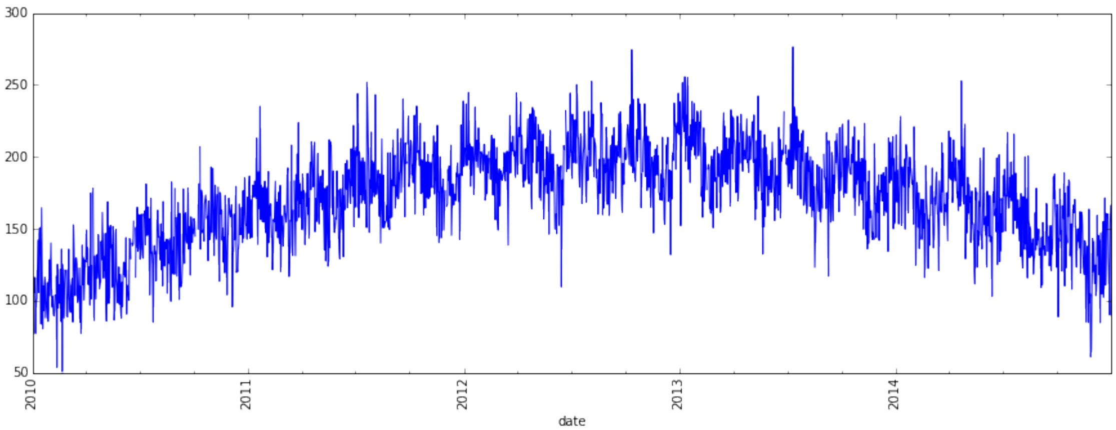
Out[75]:

	date	day.of.week	car.count	weather
0	2010-01-01	friday	94.5	-0.1
1	2010-01-02	saturday	108.4	-2.4
2	2010-01-03	sunday	105.5	-0.5
3	2010-01-04	monday	109.6	-2.1
4	2010-01-05	tuesday	116.1	1.9

In [76]:
```
# like using Pandas b/c of the datetime features, resample or groupby
# but I haven't used date methods in a while and lost some time to redresh my memory
df['date'] = pd.to_datetime(df['date'])
df.set_index(df['date'], inplace=True)
```

1.2 Initial Plot

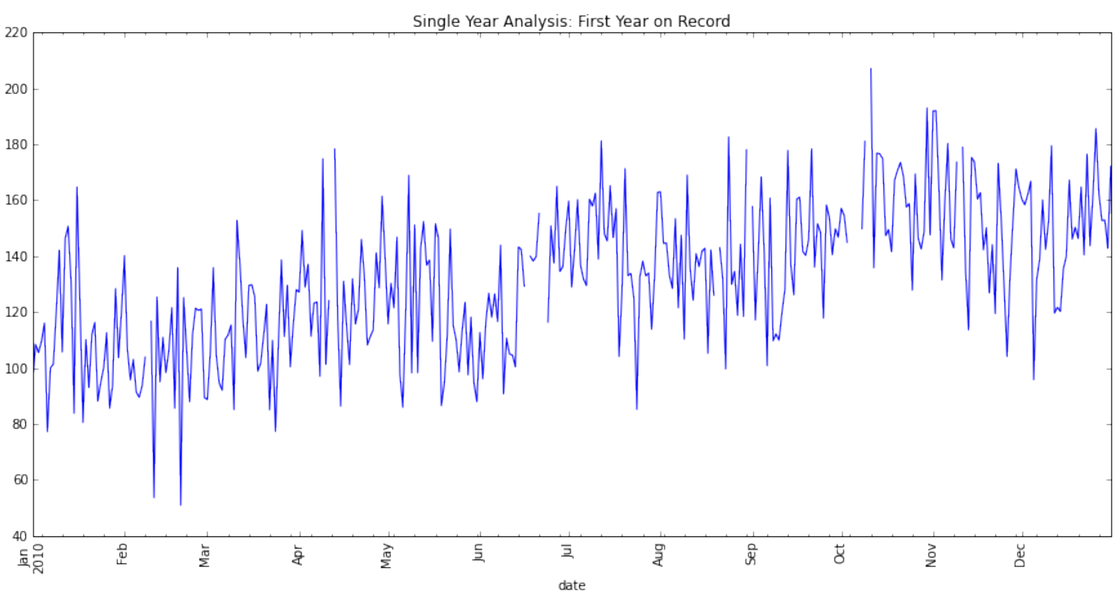
```
In [77]: df['car.count'].plot(rot=90, figsize=(15,5));
```



I'd guess that we have a linear combination of a quadratic, sinusoid and random stochastic signal.

1.2.1 Single Year Analysis: first year in the record

```
In [110]: # year = df['car.count'][0:365]  if you are in a rush
          year = df[df['date'] < pd.to_datetime('20110101')]['car.count']
          year.plot(rot=90, figsize=(15,7), title="Single Year Analysis: First Year on Record");
```



It's not easy to see, but there are missing values in the series. We need to treat those.

```
In [79]: #TODO: add to signal processing module

         def remove_nans(data, return_nan_index=False):
```

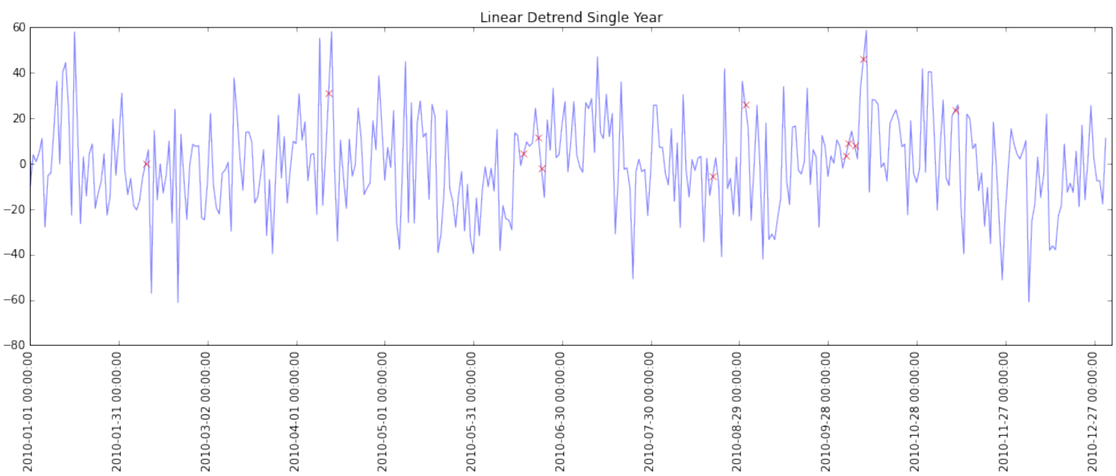
```
    nan_ind = np.nonzero(~np.isfinite(data))[0]
    good_data_ind = np.nonzero(np.isfinite(data))[0]
    good_data = data[good_data_ind]

    new_points = np.interp(nan_ind, good_data_ind, good_data)
    data[nan_ind] = new_points

    if return_nan_index:
        return data, nan_ind
    else:
        return data
```

```
In [80]: year, nan_ind = remove_nans(year.copy(), return_nan_index=True)
         year_linear_det = signal.detrend(year, axis=0, type='linear')
```

Single Year Linear Detrend Time Series

```
In [81]: plt.figure(figsize=(17, 5))
         plt.xticks(np.arange(year.shape[0])[0::30], year.index[0::30], rotation=90)
         plt.plot(year_linear_det, alpha=0.5)
         plt.title("Linear Detrend Single Year")
         plt.plot(nan_ind, year_linear_det[nan_ind], 'rx')
         plt.xlim(0, 366)
```

```
Out[81]: (0, 366)
```



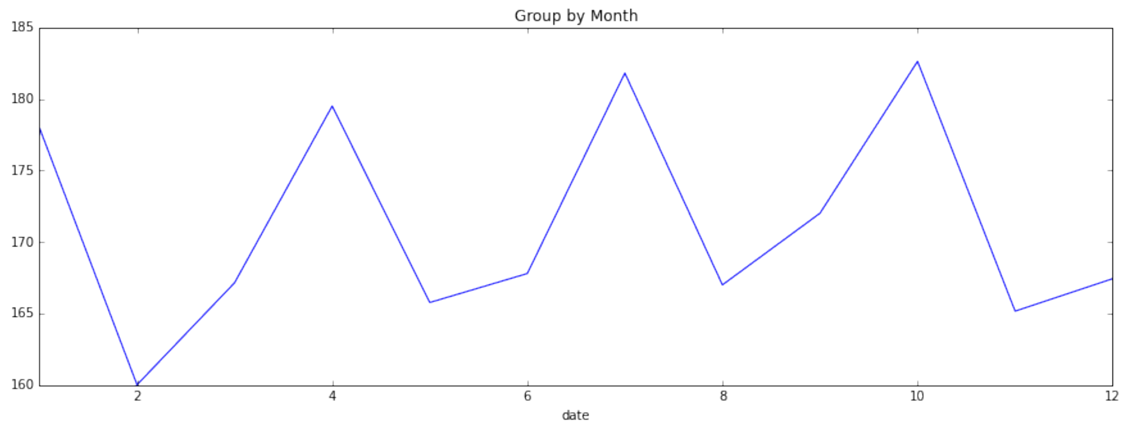
We see a ≈ 90 day period here.
Without more insight about the data we don't know if this is a nuisance or a feature we are looking for.
The NaN replacements look reasonable.

1.3 Group By for Basic Analysis

Grouping the data points into bins and taking the mean, is very simialr to a Fourier Transform.
Pandas makes this easy and there's no reason not to. Especially if the data is related to business trends.

1.3.1 Group by Month: Global monthly trend averaging over the 5 samples of each month

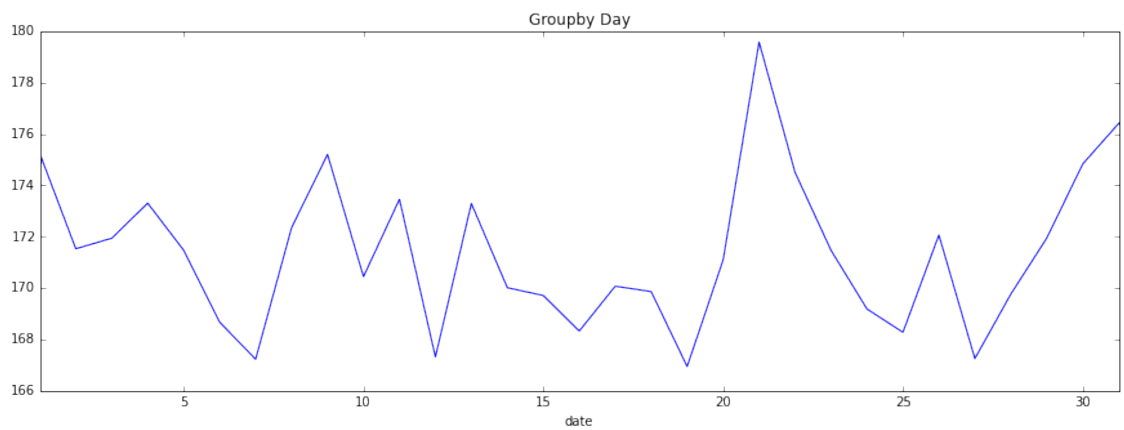
```
In [82]: grp = df.groupby(df.date.map(lambda x:x.month))
         grp.mean()['car.count'].plot(figsize=(15,5), title="Group by Month");
```



A group-by is sort of like a Fourier Transform where we choose just one frequency bin. There's the sinusodial period ≈ 90 days.

1.3.2 Group by Day: Global day trend averaging over the 5 samples of each day

```
In [83]: grp = df.groupby(df.date.map(lambda x:x.day))
         grp.mean()['car.count'].plot(figsize=(15,5), title="Groupby Day");
```



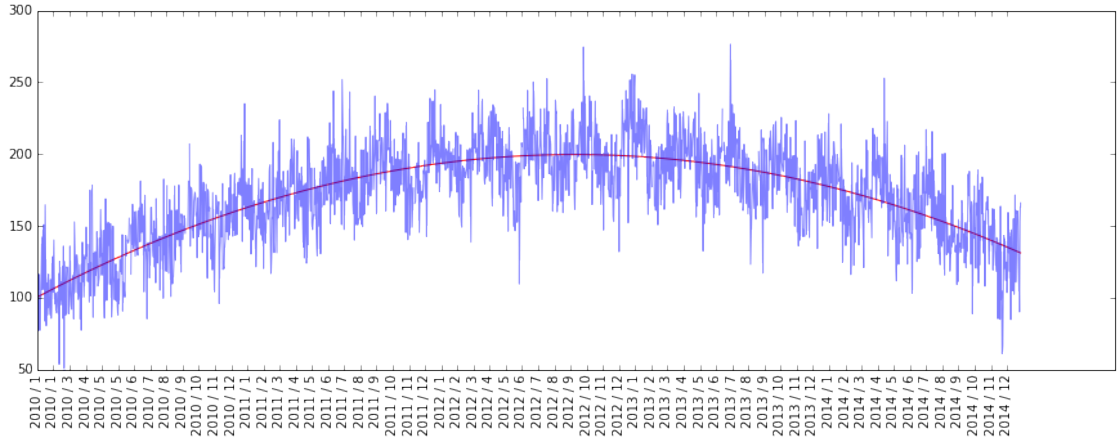
It would appear as though the 21st day of each month saw greater count.

1.4 Removing Confounds

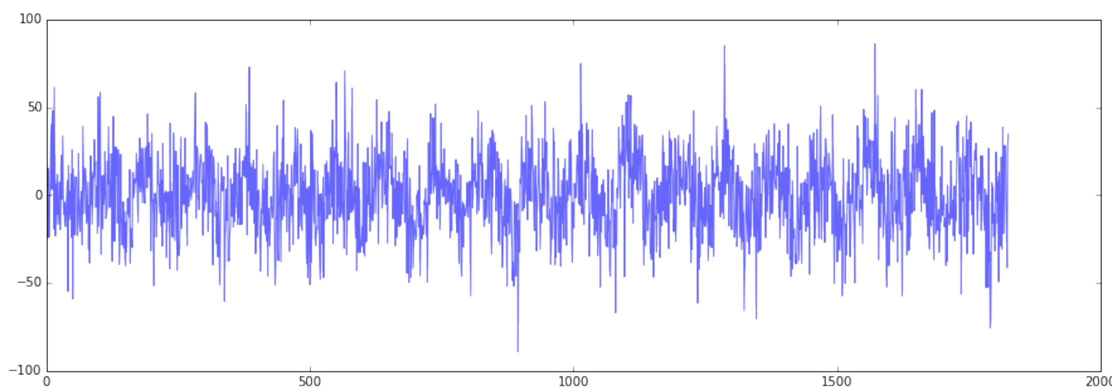
1.4.1 Quadratic Detrend Using PolyFit

```
In [96]: poly =  np.polynomial.polynomial

         t = np.arange(df.shape[0])
         coefs, stats = poly.polyfit(t, counts, deg=2, full=True)
         fit_curve = poly.polyval(t, coefs)
```

```
In [98]: plt.figure(figsize=(15,5))

         plt.plot(fit_curve, 'r')
         plt.plot(t, df['car.count'], alpha=0.5)

         labels = df['date']
         date_str = map(lambda x: str(x.year) + " / "  + str(x.month), labels)
         plt.xticks(t[0::30], date_str[0::30], rotation="vertical");
```




```
In [99]: det_curve = counts - fit_curve
         plt.figure(figsize=(15,5))
         plt.plot(det_curve, alpha=0.6);
```



1.5 Further Confound Removal

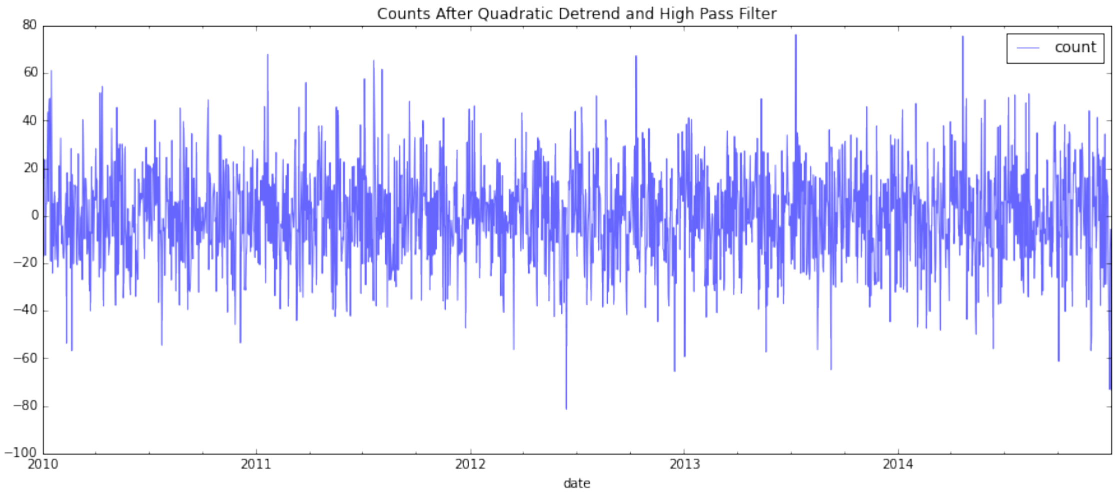
Lets suppose that the quadratic is a measurement error and that the ≈ 90 day sinusodial is a well understood or nuisance, then we'll examine the remainder of the signal.

```
In [100]: import sys
          sys.path.append("/home/daniel/git/Python/MRI/Modules")
          import SignalProcessTools
```

```
sigtools = SignalProcessTools.SignalProcessTools()
```

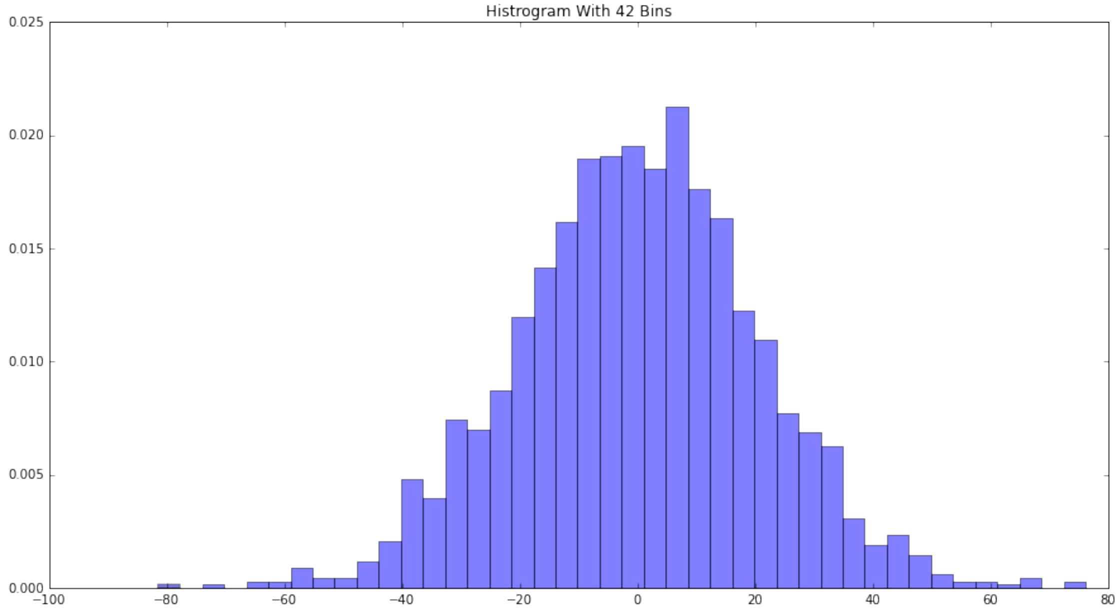
In [101]:
```
frq = 1 / 85.3 # from FFT output above
out = sigtools.hi_pass_filter(det_curve, frq, 1.0, 2)

dff = pd.DataFrame({'count':out}, index=df.index)
dff.plot(title="Counts After Quadratic Detrend and High Pass Filter", figsize=(15,6), alpha=0
```

Out[101]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe0100bc190>
```



In [102]:
```
plt.figure(figsize=(15,8))

nbins = np.floor(np.sqrt(out.shape[0]))
y_counts, bin_x, patch = plt.hist(out, nbins, normed=True, alpha=0.5);
string = "Histrogram With %s Bins" % str(int(nbins))
plt.title(string)
```

Out[102]:
```
<matplotlib.text.Text at 0x7fe010039b10>
```



Perhaps a Gausian

```
In [103]: bin_x = bin_x[1:]# drop the first bin to match the array lengths
```

```
In [104]: from scipy.optimize import curve_fit
```

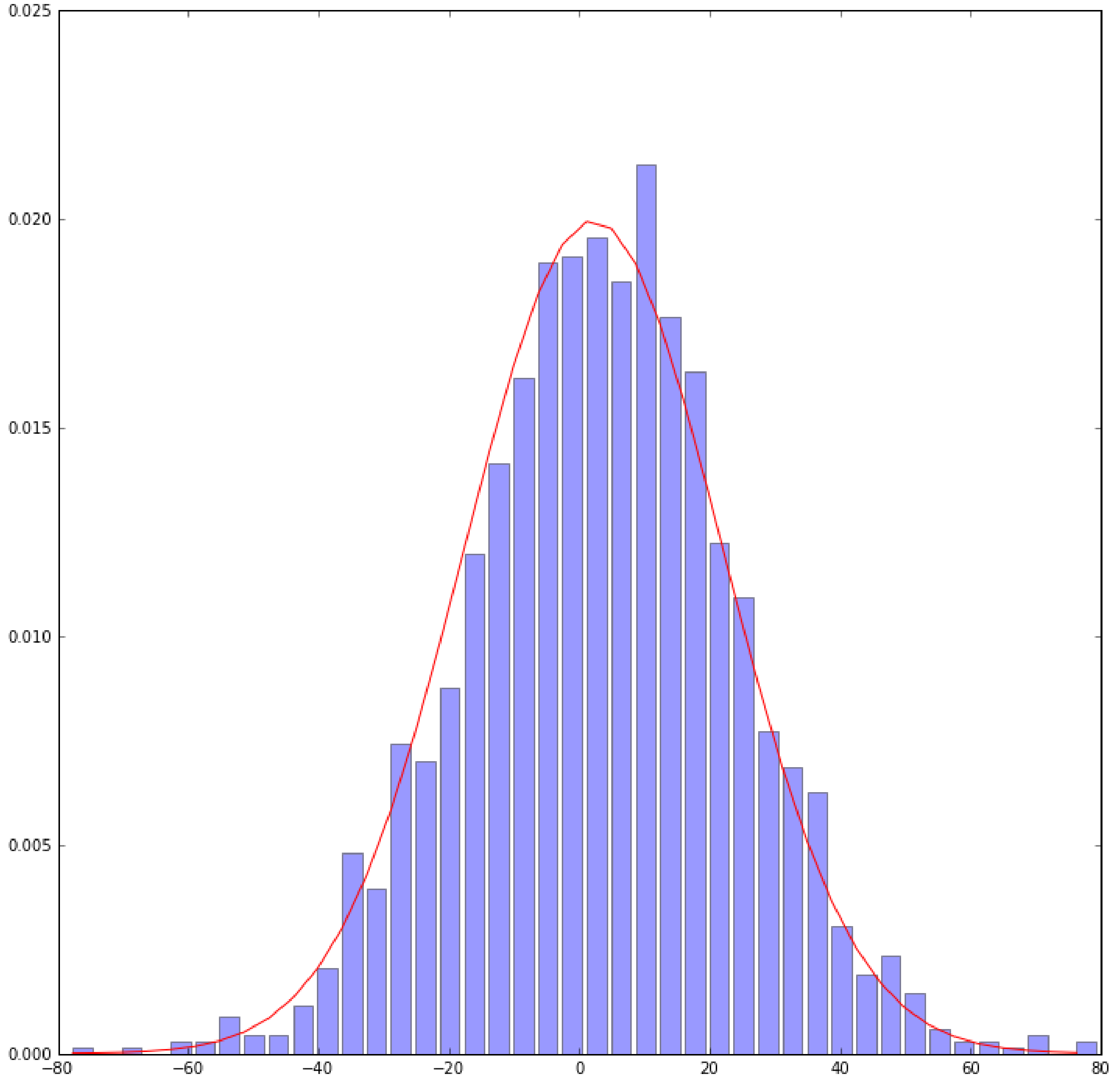
```
In [105]: def gauss(x, *p):
              A, mu, sig = p
              gau = A * np.exp(-(x-mu)**2 / 2.0 * sig**2)
              return gau
```

```
In [108]: coeff, var_matrix = curve_fit(gauss, bin_x, y_counts, p0=[0.1, 0.0, 0.1])
          print "Amplitude:%f  mean:%f   std:%f" %(coeff[0], coeff[1], coeff[2])
```

```
Amplitude:0.019967  mean:2.184505   std:0.050485
```

```
In [107]: fit_gau = gauss(bin_x, *coeff)
          plt.figure(figsize=(12, 12))

          plt.plot(bin_x, fit_gau, 'r')
          plt.bar(bin_x, y_counts, alpha=0.4, width=3)
```

```
Out[107]: <Container object of 42 artists>
```



2 Summary Write Up

Hidden in the periodic noise is the more interesting signal. It's random from a Gaussian distribution.