

# Hurricane Sandy: 311 open data analysis of pre and post

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## Final Paper: Foundation Module

### TEAM MEMBERS

1. Kim, Tae ([thk301@nyu.edu](mailto:thk301@nyu.edu))
2. Putro, Dimas Rinarso ([drp354@nyu.edu](mailto:drp354@nyu.edu))
3. Zhuang, Yuzheng ([yz2611@nyu.edu](mailto:yz2611@nyu.edu))

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## 1. Introduction

New York City has its own story on how it bounced back from one of the biggest disasters ever hit the East Coast since the 20th Century, Hurricane Sandy. With 147 direct deaths reported, in which 72 of them occurred in the mid-Atlantic and Northeastern US, Hurricane Sandy caused the biggest direct fatalities related to tropical cyclones outside the southern areas since 1972 (Eric et al., 2013). This assignment paper examines 311 dataset changes and patterns in the year 2011, 2012, and 2013 respective to the time range close to Hurricane Sandy (between October 1<sup>st</sup> – December 31<sup>st</sup>), to see unseen patterns that can be extracted from the event.

In this team I worked together with Tae Kim ([thk301@nyu.edu](mailto:thk301@nyu.edu)) and Yuzheng Zhuang ([yz2611@nyu.edu](mailto:yz2611@nyu.edu)). My part is to filter and clean the data for other team members. The other tasks were to make visual presentation using Bokeh library in Python and produce correlation analysis using Pandas, Numpy and Statsmodel package in Python.

## 2. Time series plot

Our first step is to categorize the complaints by agency and plot the time series to find visually see the patterns. From figure 1 to figure 4 we could see that regardless of the scale of number of complaints, NYPD and TLC were showing minimum response to the event of disaster, constantly maintained the trend without noticeable peaks. DPR, on the other hand showed peaks in 2011 and 2012 in figure 2 and figure 3 respectively, with in 2012 it reached maximum value of 4400. This provided us hints that DPR trends in 2011 and 2012 differ compared to 2013. Another clue provided by this time series plot is that the negatives trends NYPD complaints in 2012 when DPR reached it peak value. From this we understood that we wanted to limit our scope of observation to only DPR and the next step to statistically confirm the state of abnormalities for DPR.

### 3. ACF and PACF test

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) was before conducting auto regression. We would like to also see, through the correlogram tools, whether in specific year DPR presents abnormal behavior, specified by the level of randomness between data point in certain time interval. This could be achieved by observing the relation of the data at  $t$  and  $t-h$ , where  $h$  is a time lag and in this case was set in the range of 1-20 days, and then see whether it falls within certain threshold of level of confidence (95%):

$$\rho_h = \text{Corr}(y_t, y_{t-h}) = \frac{\gamma_h}{\gamma_0}.$$

The denominator  $\gamma_0$  is the lag 0 covariance. The autocorrelation function (ACF) for a time series  $y_t$ ,  $t = 1, \dots, N$ , is the sequence  $\rho_h$ ,  $h = 1, 2, \dots, N - 1$ . The partial autocorrelation function (PACF) is the sequence  $\phi_{h,h}$ ,  $h = 1, 2, \dots, N - 1$ . The lag- $h$  autocorrelation would be then obtained by:

$$\hat{\rho}_h = \frac{\sum_{t=h+1}^T (y_t - \bar{y})(y_{t-h} - \bar{y})}{\sum_{t=1}^T (y_t - \bar{y})^2}.$$

To visually observe this, we could see the correlogram presented in figure 5. We could see from ACF (left) figure that in 2011 and 2012, the lag equal to 0 and 1 fell outside the confidence level threshold, while in 2013 lag = 1 was within the boundaries. This means that in 2011 and 2012, at any given point, the 1 day lag of that time might still be correlated. In addition, we could see that in 2013, the autocorrelation value for DPR fluctuates in smaller periodic in respect to time intervals. This was caused by increased randomness driven by number of complaints scattered.

From the figure none of the correlation value pass the confidence limit test (all within 95% confidence level), although ACF for 2012 when lag  $h$  is equal to 1 passed the confidence limit test. We also figured out that PACF did not result any correlation except to itself (lag = 0), therefore, PACF could not be used, and consequently ACF test was not valid for autoregression. Therefore, in principle we could not fit any model. However, ACF test might be useful to provide visual representation on how the characteristic of the data in 2011, 2012 and 2013 differs.

## 4. The use of maps and visual representations

Since we know that statistically there were different in patterns of DPR's number of complaints in 2011-2012 versus 2013, we could not tell what is the particular reason why the pattern was different and what variables were correlated. Thus, we did visual representations by plotting the number of DPR complaints per zip code by longitude and latitude given in 311 dataset, and plot it on the map. The result can be seen in figure 6, 7 and 8. From here we could observe that while Sandy's effect is apparent in 2012, there were significant influx of complaints in Staten Island on 2011, while in 2013 is mostly flat. This might be related to the snow storms that in vast majority occurred in Staten Island in October 2011 (Silive, 2011). The next step is to find good predictor for regression analysis and build the model.

## 5. Bivariate regression analysis

### 5.1. Number of tree VS number of complaints

First, we obtained the number of trees data in New York City and try to find the correlation by running bivariate regression model with both linear and second order

polynomial regression. This is to confirm that the 2 disasters, snowstorm in 2011 and Sandy in 2012 were assumed largely affected by trees. In this paper we use linear regression equation as follows:

$$Y' = \beta x + \text{const}$$

Where  $\beta$  is linear coefficient and *const* is the constants. Second order polynomial, on the other hand, was given in standard polynomial equation:

$$\sum_{i=0}^n a_i x^i$$

or, equally:

$$a_n x^n + a_{n-1} x^{n-1} + \dots + a_2 x^2 + a_1 x + a_0,$$

where  $a_2$  and  $a_1$  in the statistics represent  $\beta_0$  and  $\beta_1$  and  $a_0$  represents the constants. Our finding shows that in 2011 and 2012, in figure 9 and 10, characterized by increased R-squared value at 0.59 and 0.81 for both linear and second order polynomial fit, respectively. This indicates that the model explains most of the variability of the sample data around its mean. R-squared with the value 0.59 means 59% of the number of DPR complaints were affected by the change of by the number of value. Linear fit, represented by black bold line, pointed an increased value from  $\beta = 1.30$  to  $\beta = 1.83$  from 2011 to 2012, while it decreased to to from  $\beta = 0.77$  in 2013, when there was no disaster events. 2011-2012 presented indication of super linearity correlation, meaning that the number of DPR complaints has more increased rate relative to the number of trees. However, 95% confidence level, as shown in figure 12-14 fell between 0.932 - 1.670 and 1.543 - 2.126 in 2011 and 2012 respectively, which tells us in 2011 there under the 95% level of confidence there was a possibility of sub linear characteristics ( $\beta < 1$ ).

The other interesting finding from the tree and DPR number of complaints is that the both of the model, linear and second order polynomial could maintain the similar result, confirming that tree and the number of complaints do scale linearly and therefore no need to

use more sophisticated model. This resonates with some emphasis given in class that “in most cases linear approach is the best model to start with”, as linear regression approach was also an interesting subject explored by other urban planners such as in identify the famous “economic of scale” concept proposed in (Luis and Geoffrey, 2007).

## 5.2. Number of accidents VS number of complaints

Again we ran bivariate regression test with both linear and second order polynomial regression against number of road accidents for each year in 2012 and 2013 due to the limitation that 2011 data is not available. Moreover we were not interested in comparing 2011 because it also refers to other disaster which can state bias. We would like to compare Sandy and non-disaster state, hence 2012-2013 was chosen. Our finding in figure 15 and 16, show correlations characterized by weak R-squared value at 0.01 and 0.04 for 2012 and 2013, respectively. The low R-squared hinted that there relation of accident and DPR complaints were not statistically significant. Moreover, since we know from observation 5.1 that trees are strongly correlated to DPR, we could imply that number of trees does not necessarily correlate with number of accident.

## 6. Conclusions

In this foundation module final paper we could see how basic applied statistics learned in the class could help us detect abnormality in 311 complaints data in the case of disaster. Moreover, it helped us analyzing some unique phenomenon that have happened during Sandy and be able to provide us hints on which visual representations might be applicable and which new set of predictors could be added before we can evaluate statistically by observing R-squared and so on. For instance, it guided us to the conclusions



that tree is the root cause of top 311 complaints during disaster, although, however, it did not cause traffic accident. This capability of manually observe and pick more meaningful model and predictors is essential feature in basic applied statistics when compared to the likes of neural network and other pattern recognition methods.

Table of figures

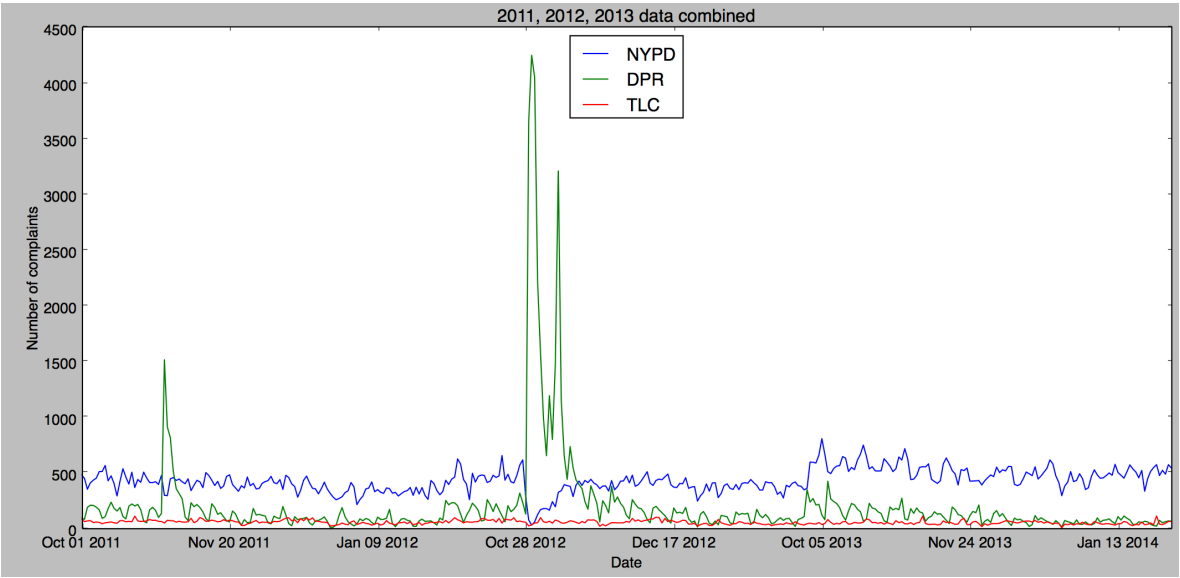


Figure 1 All time series 2011-2014

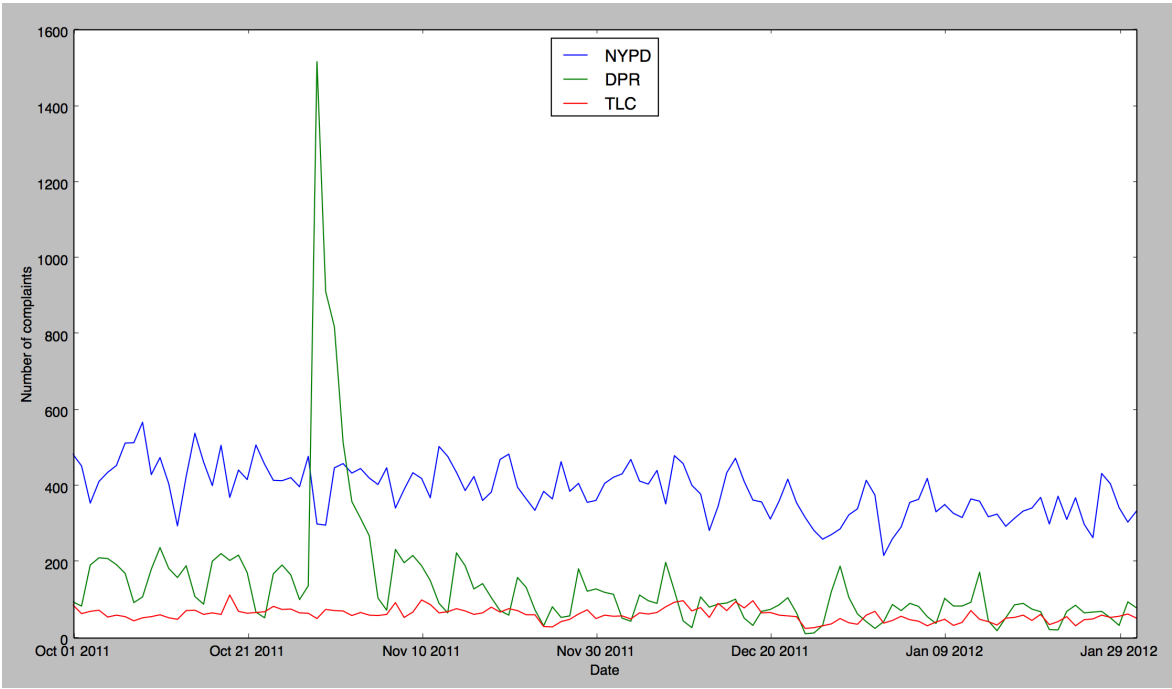


Figure 2 2011 time series plot of top 3 complaints to agency in New York City

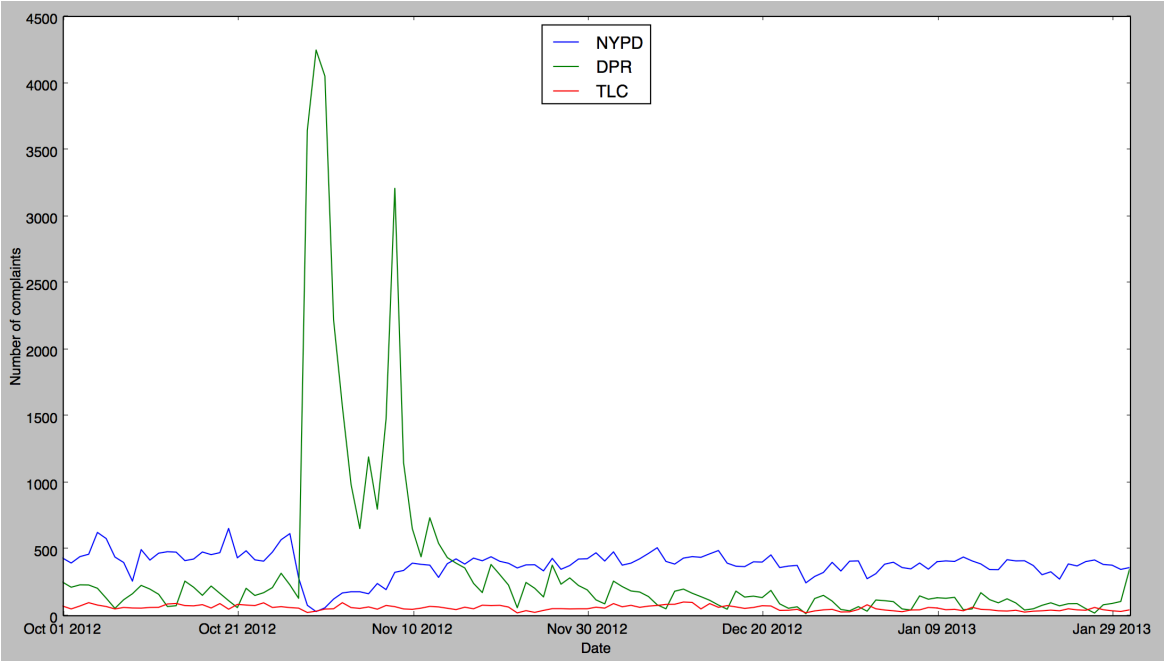


Figure 3 2012 time series plot of top 3 complaints to agency in New York City

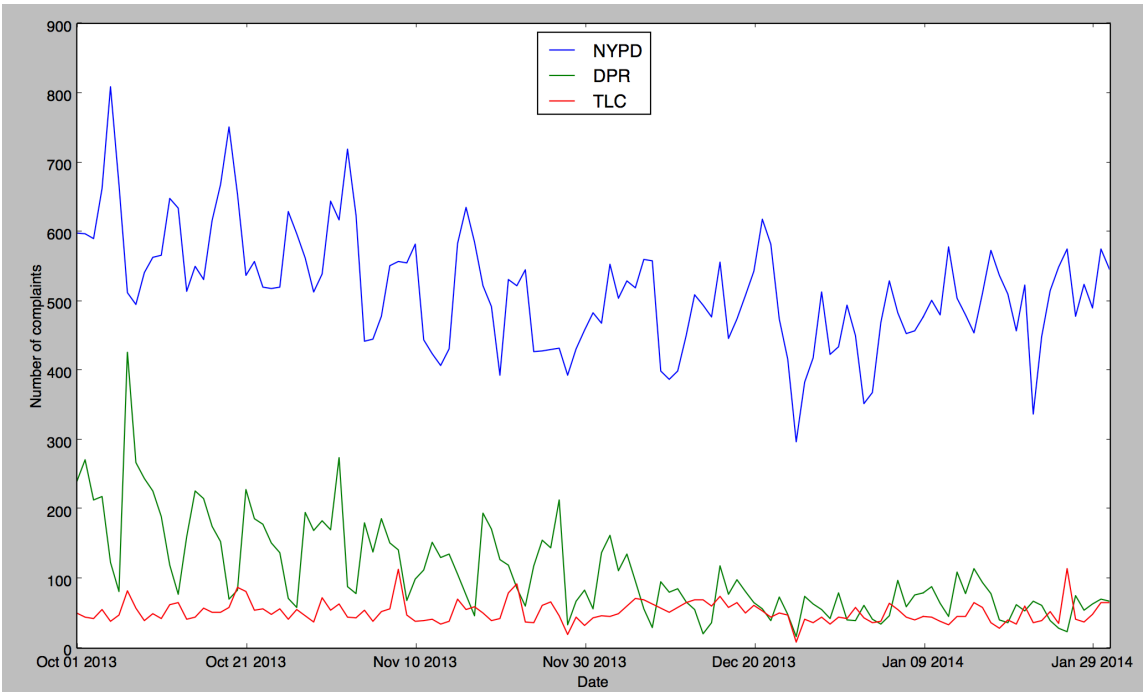


Figure 4 2013 time series plot of top 3 complaints to agency in New York City

ARMA(311 Complaints for DPR in 2011,2012,2013 Oct & Nov): Autocorrelation (left) and Partial Autocorrelation (right)

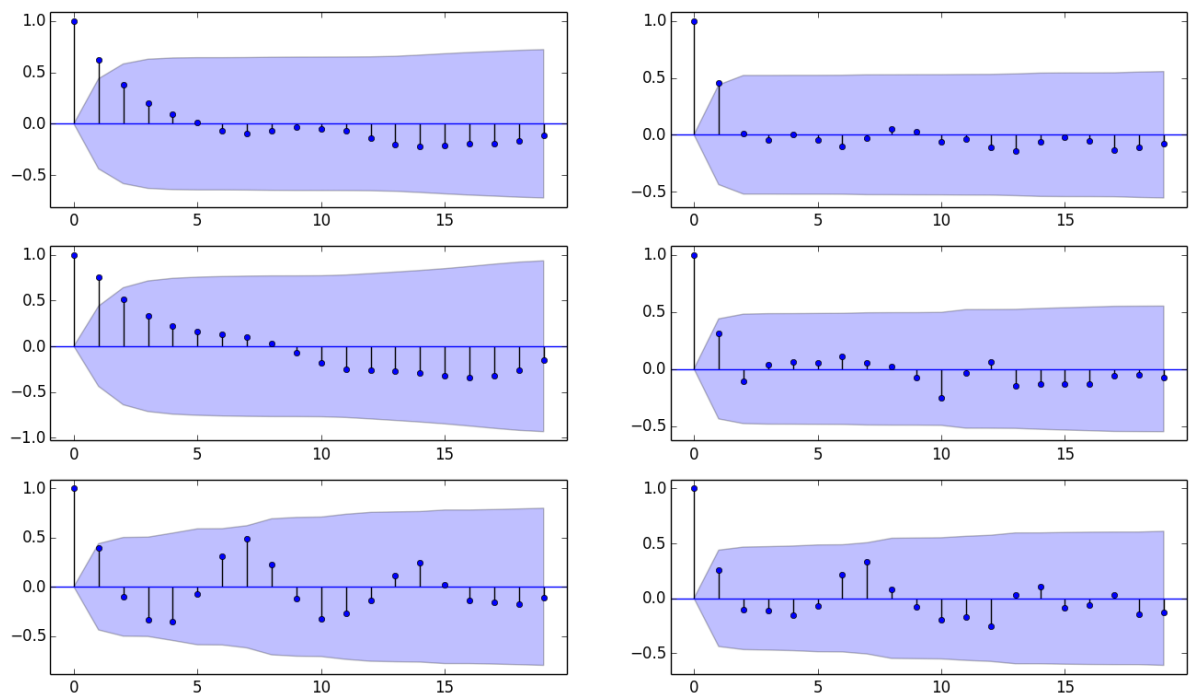


Figure 5 ACF (left) and PACF (Right) of the DPR complaints for Oct and Nov 2011 (top), 2012 (middle), 2013 (bottom)

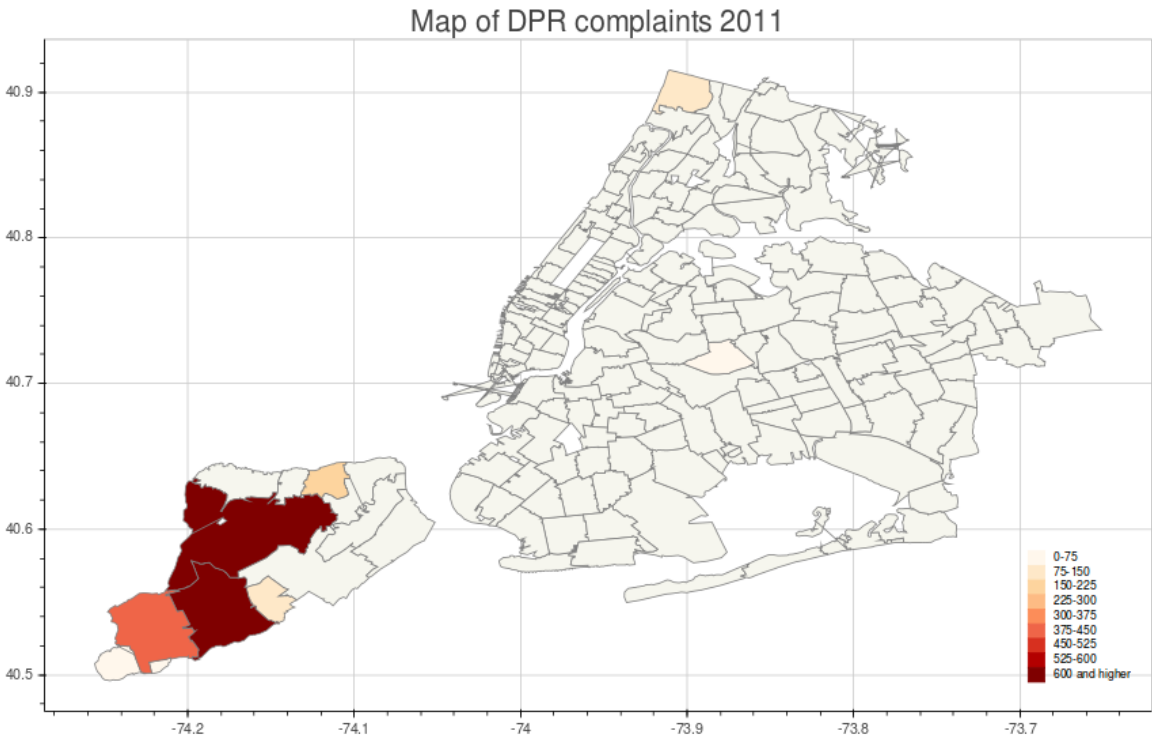


Figure 6 Map of DPR complaints 2011

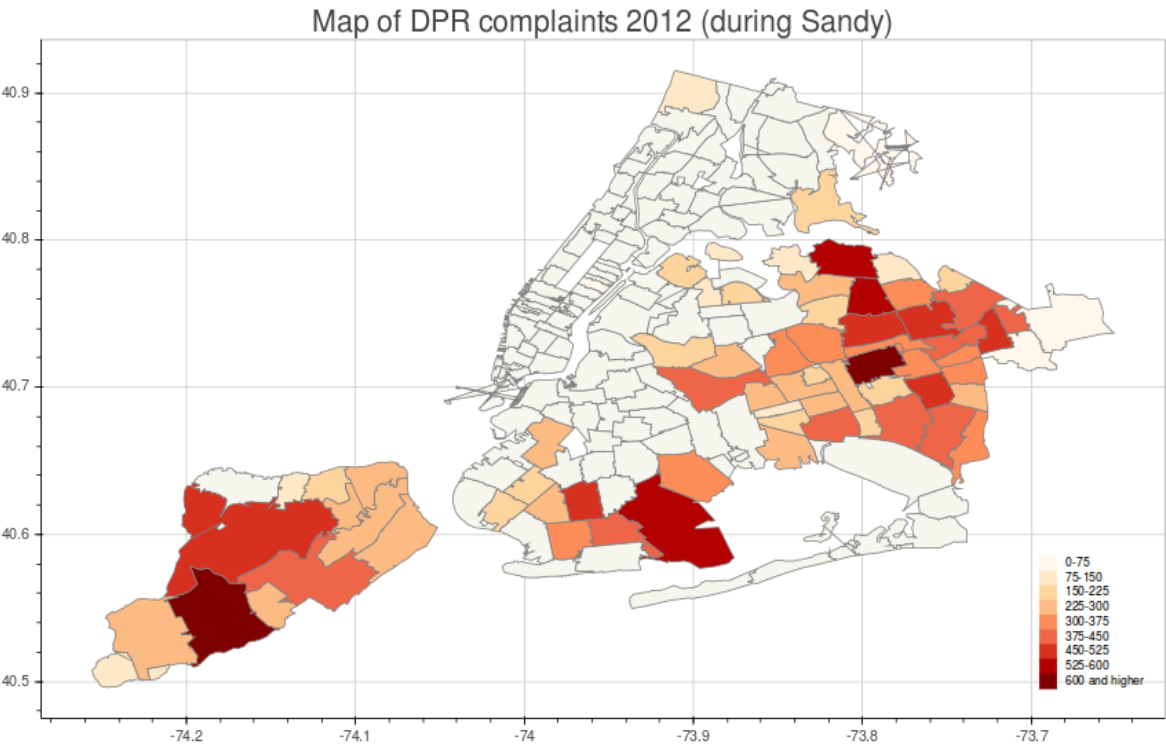


Figure 7 Map of DPR complaints 2012

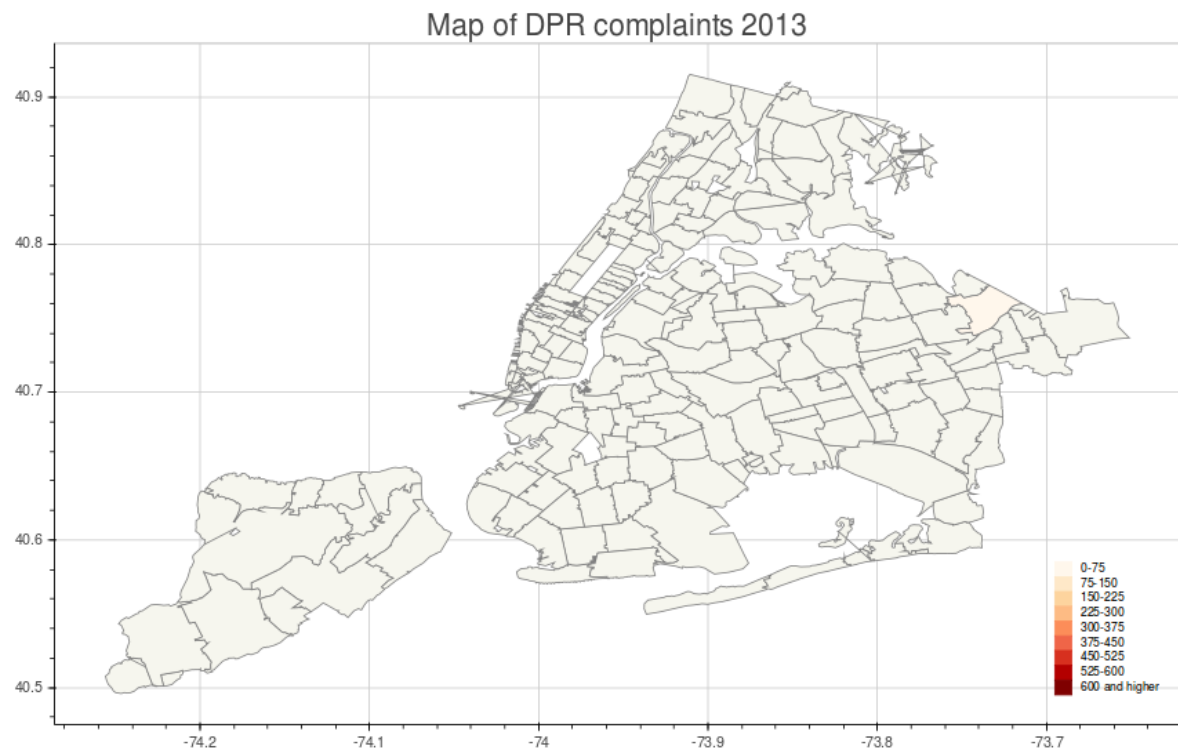


Figure 8 Map of DPR complaints 2013

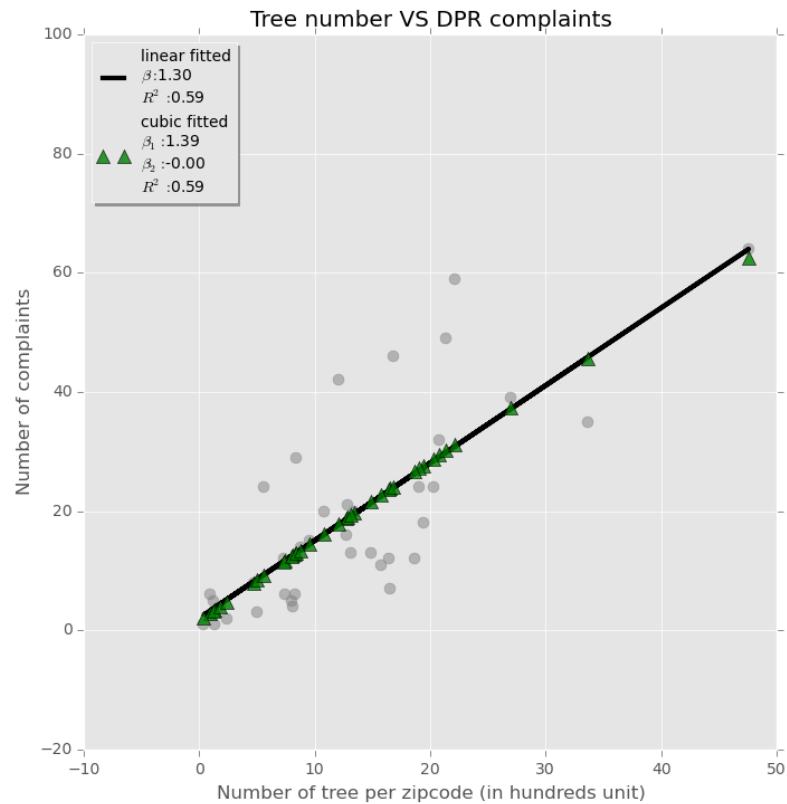


Figure 9 number of trees VS number of DPR complaints 2011

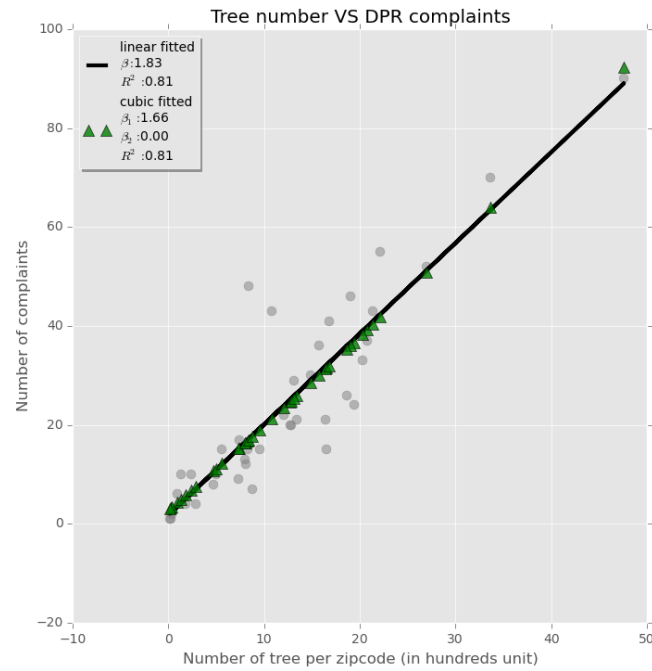


Figure 10 number of trees VS number of DPR complaints 2012

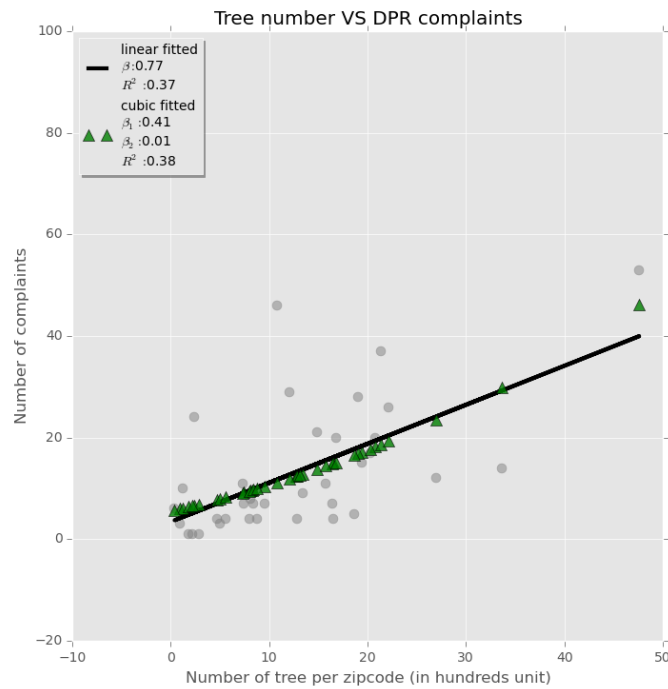


Figure 11 number of trees VS number of DPR complaints 2013

```

=====
                        OLS Regression Results
=====
Dep. Variable:          num      R-squared:                0.587
Model:                  OLS      Adj. R-squared:           0.576
Method:                 Least Squares      F-statistic:        51.20
Date:                   Thu, 27 Nov 2014      Prob (F-statistic):    2.05e-08
Time:                   01:57:23      Log-Likelihood:       -142.86
No. Observations:       38      AIC:                  289.7
Df Residuals:           36      BIC:                  293.0
Df Model:                1
=====
                        OLS Regression Results
=====
                        coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
const                2.0704        2.932        0.706      0.485      -3.875      8.016
counter              1.3011        0.182        7.156      0.000        0.932      1.670
=====
Omnibus:                9.272      Durbin-Watson:        1.961
Prob(Omnibus):          0.010      Jarque-Bera (JB):      8.296
Skew:                   1.085      Prob(JB):              0.0158
Kurtosis:               3.729      Cond. No.              27.4
=====

=====
                        OLS Regression Results
=====
Dep. Variable:          num      R-squared:                0.588
Model:                  OLS      Adj. R-squared:           0.564
Method:                 Least Squares      F-statistic:        24.94
Date:                   Thu, 27 Nov 2014      Prob (F-statistic):    1.85e-07
Time:                   01:57:23      Log-Likelihood:       -142.84
No. Observations:       38      AIC:                  291.7
Df Residuals:           35      BIC:                  296.6
Df Model:                2
=====
                        OLS Regression Results
=====
                        coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
Intercept             1.5269        4.040        0.378      0.708      -6.676      9.729
counter               1.3873        0.472        2.941      0.006        0.430      2.345
I(counter ** 2.0)    -0.0022        0.011       -0.199      0.844      -0.025      0.021
=====
Omnibus:                8.495      Durbin-Watson:        1.971
Prob(Omnibus):          0.014      Jarque-Bera (JB):      7.417
Skew:                   1.032      Prob(JB):              0.0245
Kurtosis:               3.649      Cond. No.              1.11e+03
=====

Warnings:
[1] The condition number is large, 1.11e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

```

Figure 12 Statistics summary for tree VS DPR complaints 2011



OLS Regression Results						
Dep. Variable:	num	R-squared:	0.810			
Model:	OLS	Adj. R-squared:	0.805			
Method:	Least Squares	F-statistic:	162.5			
Date:	Thu, 27 Nov 2014	Prob (F-statistic):	2.68e-15			
Time:	02:00:45	Log-Likelihood:	-142.63			
No. Observations:	40	AIC:	289.3			
Df Residuals:	38	BIC:	292.6			
Df Model:	1					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	1.7568	2.262	0.777	0.442	-2.822	6.336
tree	1.8343	0.144	12.748	0.000	1.543	2.126
Omnibus:	17.896	Durbin-Watson:		2.111		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		26.930		
Skew:	1.247	Prob(JB):		1.42e-06		
Kurtosis:	6.152	Cond. No.		25.7		
OLS Regression Results						
Dep. Variable:	num	R-squared:	0.812			
Model:	OLS	Adj. R-squared:	0.802			
Method:	Least Squares	F-statistic:	79.88			
Date:	Thu, 27 Nov 2014	Prob (F-statistic):	3.75e-14			
Time:	02:00:45	Log-Likelihood:	-142.47			
No. Observations:	40	AIC:	290.9			
Df Residuals:	37	BIC:	296.0			
Df Model:	2					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
Intercept	2.7921	2.980	0.937	0.355	-3.246	8.830
tree	1.6562	0.360	4.599	0.000	0.927	2.386
I(tree ** 2.0)	0.0048	0.009	0.541	0.592	-0.013	0.023
Omnibus:	19.755	Durbin-Watson:		2.080		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		30.815		
Skew:	1.374	Prob(JB):		2.04e-07		
Kurtosis:	6.308	Cond. No.		996.		

Figure 13 Statistics summary for tree VS DPR complaints 2012

OLS Regression Results						
Dep. Variable:	num	R-squared:	0.367			
Model:	OLS	Adj. R-squared:	0.350			
Method:	Least Squares	F-statistic:	21.42			
Date:	Thu, 27 Nov 2014	Prob (F-statistic):	4.43e-05			
Time:	02:02:34	Log-Likelihood:	-143.53			
No. Observations:	39	AIC:	291.1			
Df Residuals:	37	BIC:	294.4			
Df Model:	1					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	3.4246	2.642	1.296	0.203	-1.928	8.777
tree	0.7677	0.166	4.628	0.000	0.432	1.104
Omnibus:	18.019	Durbin-Watson:		2.272		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		23.554		
Skew:	1.399	Prob(JB):		7.68e-06		
Kurtosis:	5.582	Cond. No.		26.7		
OLS Regression Results						
Dep. Variable:	num	R-squared:	0.381			
Model:	OLS	Adj. R-squared:	0.346			
Method:	Least Squares	F-statistic:	11.06			
Date:	Thu, 27 Nov 2014	Prob (F-statistic):	0.000180			
Time:	02:02:34	Log-Likelihood:	-143.09			
No. Observations:	39	AIC:	292.2			
Df Residuals:	36	BIC:	297.2			
Df Model:	2					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
Intercept	5.6142	3.590	1.564	0.127	-1.667	12.896
tree	0.4137	0.426	0.972	0.338	-0.450	1.277
I(tree ** 2.0)	0.0092	0.010	0.903	0.372	-0.011	0.030
Omnibus:	20.469	Durbin-Watson:		2.234		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		29.947		
Skew:	1.509	Prob(JB):		3.14e-07		
Kurtosis:	6.053	Cond. No.		1.08e+03		

## Warnings:

[1] The condition number is large, 1.08e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Figure 14 Statistics summary for tree VS DPR complaints 2012

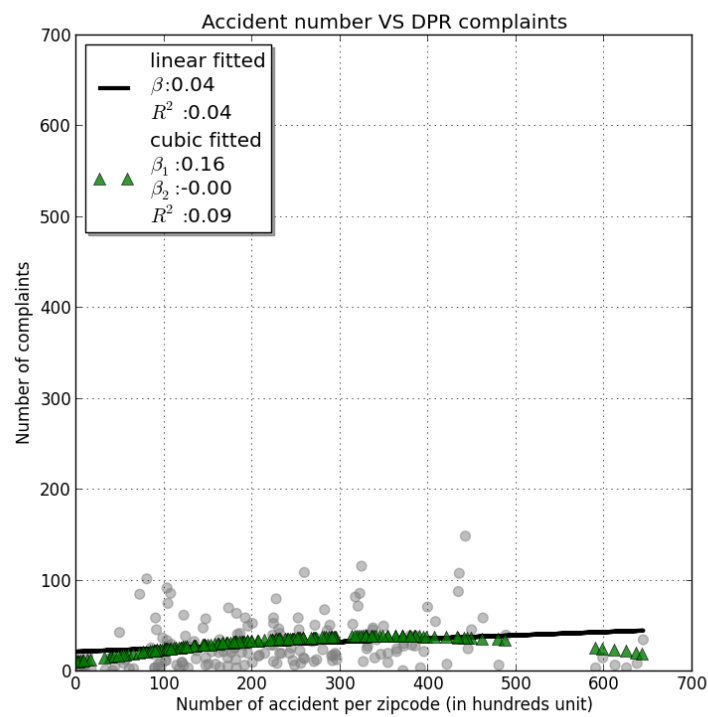


Figure 15 Accident VS DPR complaints 2013

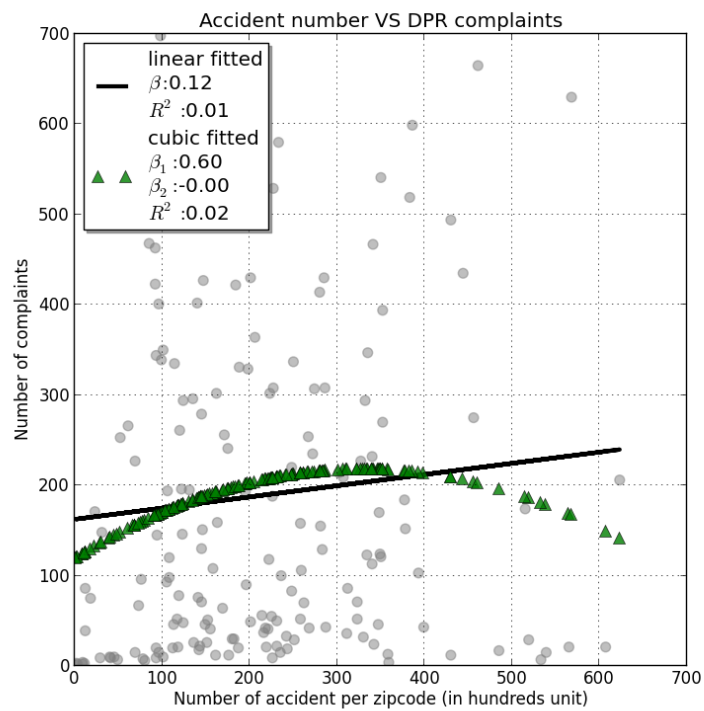


Figure 16 Accident VS DPR complaints 2012

### OLS Regression Results

```

=====
Dep. Variable:          num      R-squared:          0.041
Model:                  OLS      Adj. R-squared:         0.035
Method:                 Least Squares      F-statistic:          7.354
Date:                   Sat, 06 Dec 2014    Prob (F-statistic):    0.00736
Time:                   13:16:53           Log-Likelihood:       -819.77
No. Observations:      176              AIC:                1644.
Df Residuals:          174              BIC:                1650.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
const	21.3198	3.713	5.742	0.000	13.992 28.648
accident	0.0288	0.011	2.712	0.007	0.008 0.050

```

=====
Omnibus:                55.258      Durbin-Watson:          1.237
Prob(Omnibus):          0.000      Jarque-Bera (JB):       110.711
Skew:                   1.479      Prob(JB):               9.11e-25
Kurtosis:               5.519      Cond. No.               671.
=====

```

#### Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

### OLS Regression Results

```

=====
Dep. Variable:          num      R-squared:          0.089
Model:                  OLS      Adj. R-squared:         0.079
Method:                 Least Squares      F-statistic:          8.499
Date:                   Sat, 06 Dec 2014    Prob (F-statistic):    0.000301
Time:                   13:16:53           Log-Likelihood:       -815.16
No. Observations:      176              AIC:                1636.
Df Residuals:          173              BIC:                1646.
Df Model:               2
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
Intercept	9.4318	5.326	1.771	0.078	-1.080 19.9
accident	0.1199	0.032	3.791	0.000	0.057 0.1
I(accident ** 2.0)	-0.0001	4.11e-05	-3.049	0.003	-0.000 -4.42e-

```

=====
Omnibus:                63.173      Durbin-Watson:          1.255
Prob(Omnibus):          0.000      Jarque-Bera (JB):       144.648
Skew:                   1.615      Prob(JB):               3.89e-32
Kurtosis:               6.048      Cond. No.               5.24e+05
=====

```

#### Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.24e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Figure 17 Statistics summary accident VS DPR complaints 2013

## OLS Regression Results

```

=====
Dep. Variable:          num    R-squared:          0.007
Model:                  OLS    Adj. R-squared:        0.002
Method:                 Least Squares    F-statistic:        1.313
Date:                  Sat, 06 Dec 2014    Prob (F-statistic):    0.253
Time:                  13:22:43    Log-Likelihood:      -1188.8
No. Observations:      178    AIC:                2382.
Df Residuals:          176    BIC:                2388.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	162.4972	27.187	5.977	0.000	108.843	216.152
accident	0.1240	0.108	1.146	0.253	-0.090	0.338

```

=====
Omnibus:                32.153    Durbin-Watson:          0.848
Prob(Omnibus):          0.000    Jarque-Bera (JB):       43.202
Skew:                   1.165    Prob(JB):               4.16e-10
Kurtosis:               3.626    Cond. No.                471.
=====

```

## Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

## OLS Regression Results

```

=====
Dep. Variable:          num    R-squared:          0.019
Model:                  OLS    Adj. R-squared:        0.008
Method:                 Least Squares    F-statistic:        1.733
Date:                  Sat, 06 Dec 2014    Prob (F-statistic):    0.180
Time:                  13:22:43    Log-Likelihood:      -1187.7
No. Observations:      178    AIC:                2381.
Df Residuals:          175    BIC:                2391.
Df Model:               2
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]	
Intercept	118.7172	40.354	2.942	0.004	39.074	198.361
accident	0.5989	0.342	1.752	0.082	-0.076	1.273
I(accident ** 2.0)	-0.0009	0.001	-1.464	0.145	-0.002	0.000

```

=====
Omnibus:                33.539    Durbin-Watson:          0.831
Prob(Omnibus):          0.000    Jarque-Bera (JB):       45.758
Skew:                   1.195    Prob(JB):               1.16e-10
Kurtosis:               3.675    Cond. No.                2.72e+05
=====

```

## Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.72e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Figure 18 Statistics summary accident VS DPR complaints 2013

## 7. References

1. Blake, Eric S., Kimberlain, Todd B., J. Berg, Robery, P. Cagnialosi, John, and L. Beven II, John, 2013. “*Tropical Cyclone Report: Hurricane Sandy*,” National Hurricane Center, *National Hurricane Center* February 12, 2013.
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3. Silive 2011, *October snow storm pounds Staten Island with 2 inches*. Last updated on November 03 2011.  
[http://www.silive.com/news/index.ssf/2011/10/october\\_surprise\\_2\\_inches\\_of\\_s.html](http://www.silive.com/news/index.ssf/2011/10/october_surprise_2_inches_of_s.html).
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