# Analyzing the NYC Subway Dataset ¶

Questions

## Overview

This project consists of two parts. In Part 1 of the project, you should have completed the questions in Problem Sets 2, 3, and 4 in the Introduction to Data Science course. This document addresses part 2 of the project. Please use this document as a template and answer the following questions to explain your reasoning and conclusion behind your work in the problem sets. You will attach a document with your answers to these questions as part of your final project submission.

### Section 0. References

https://en.wikipedia.org/wiki/Nonparametric_statistics (https://en.wikipedia.org/wiki/Nonparametric_statistics) https://en.wikipedia.org/wiki/Mann–Whitney_U_test (https://en.wikipedia.org/wiki/Mann–Whitney_U_test) http://dss.princeton.edu/online_help/analysis/interpreting_regression.htm (http://dss.princeton.edu/online_help/analysis/interpreting_regression.htm) https://en.wikipedia.org/wiki/Polynomial_regression (https://en.wikipedia.org/wiki/Polynomial_regression)

### Section 1. Statistical Test

#### *1.1 Which statistical test did you use to analyze the NYC subway data? Did you use a one-tail or a two-tail P value? What is the null hypothesis? What is your p-critical value?*

***ANS :***

```
We choose Mann–Whitney U test two-tail P value.

H0 is "the distribution of Hourly_entries for the two groups are equal"

We define α = 0.05
```

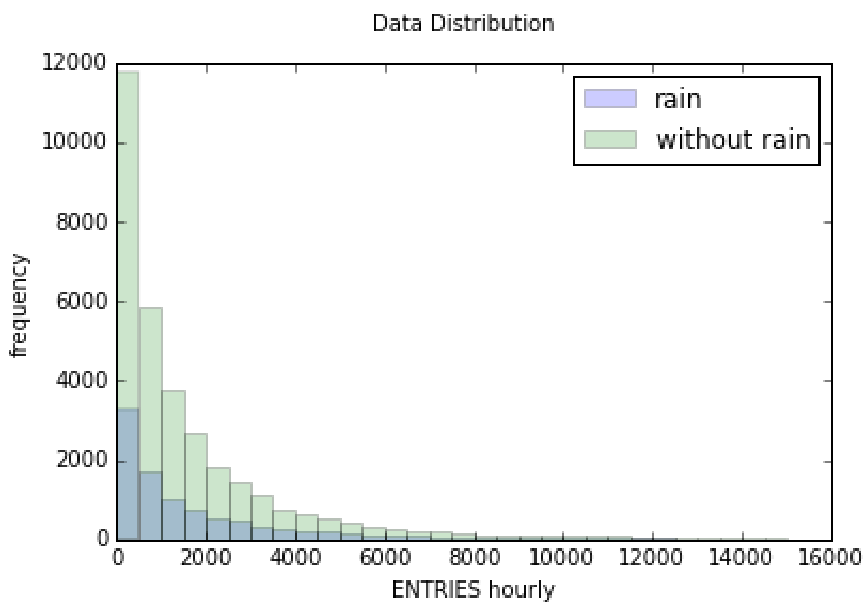
***1.2 Why is this statistical test applicable to the dataset? In particular, consider the assumptions that the test is making about the distribution of ridership in the two samples.***

***ANS :***

In [146]:
```
import pandas as pd
import os
import scipy
import scipy.stats
import numpy as np
import statsmodels.api as sm
alpha = 0.05
filename = r'~/WorkSpace/Udemy-Datascience/IntroductionToDataScienc
e/P2-Analyzing-NYC/turnstile_weather_v2.csv'
turnstile_weather = pd.read_csv(filename)

H0 = "\"the distribution of ENTRIESn_hourly for the two groups are
equal\""
not_H0 = "\"the distribution of ENTRIESn_hourly for the two groups
are not equal\""
```

In [149]:
```
%pylab inline
import matplotlib.pyplot as plt

rain_df = turnstile_weather[turnstile_weather.rain == 1]['ENTRIES
n_hourly']
norain_df = turnstile_weather[turnstile_weather.rain == 0]['ENTRIES
n_hourly']
df_compare = pd.DataFrame({'rain': rain_df,
               'without rain': norain_df})
df_compare.plot(kind='hist', alpha=0.2,bins = range(0, 15000 + 500,
500) ) ##,bins = range(0, 37 + 3, 3)

# plt.set_title('Data Distribution')
plt.suptitle('Data Distribution')
plt.xlabel("ENTRIES hourly")
plt.ylabel("frequency")
plt.show()
print "As you can see, the distribution is not normal."
```

```
Populating the interactive namespace from numpy and matplotlib
```




```
As you can see, the distribution is not normal.
```

In [150]:
```
print "The number of rain data is %s ." % len(rain_df)
print "The number of without rain data is %s ." % len(norain_df)
```

```
The number of rain data is 9585 .
The number of without rain data is 33064 .
```

In [151]:
```
import scipy
w,p = scipy.stats.shapiro(norain_df)
print "The p-value for the hypothesis that the without rain data wa
s drawn from a normal distribution is %.10f ." % p

w,p = scipy.stats.shapiro(rain_df)
print "The p-value for the hypothesis that the with rain data was d
rawn from a normal distribution is %.10f ." % p
```

```
The p-value for the hypothesis that the without rain data was draw
n from a normal distribution is 0.0000000000 .
The p-value for the hypothesis that the with rain data was drawn f
rom a normal distribution is 0.0000000000 .
```

## Conclusion :

Part of the assumption of parametric tests like the T-test is that the distributions are normal.

As you can see the distribution is not normal so we use the Mann-Whitney over the T-test.

Ref: http://vassarstats.net/textbook/parametric.html (http://vassarstats.net/textbook/parametric.html)
Ref: https://en.wikipedia.org/wiki/Mann%E2%80%93Whitney_U_test (https://en.wikipedia.org/wiki/Mann%E2%80%93Whitney_U_test) Ref: https://en.wikipedia.org/wiki/Shapiro%E2%80%93Wilk_test (https://en.wikipedia.org/wiki/Shapiro%E2%80%93Wilk_test)

***1.3 What results did you get from this statistical test? These should include the following numerical values: p-values, as well as the means for each of the two samples under test.***

**ANS:**

In [152]:
```
def test_has_effect(df1,df2 , name_df1, name_df2 ,show_graph= Fals
e):
    U,p = scipy.stats.mannwhitneyu(df1,df2)
    df1_mean = np.mean(df1)
    df2_mean = np.mean(df2)
    #agg = turnstile_weather.groupby(['is_precipi'], as_index=Fals
e).mean()
    if show_graph:
        df_compare = pd.DataFrame({name_df1: df1,
                     name_df2: df2})
        df_compare.plot(kind='hist', alpha=0.2,bins = range(0, 1500
0 + 500, 500) ) ##,bins = range(0, 37 + 3, 3)

        # plt.set_title('Data Distribution')
        plt.suptitle('Data Distribution')
        plt.xlabel("ENTRIES hourly")
        plt.ylabel("frequency")
        plt.show()
        print "As you can see, the distribution is not normal."
    p = 2*p
    print " After we perform mannwhitney t-test the conclusion is:"
    print " p-values for two-tailed is %.9f."%p
    if p < alpha :
        print " We reject the null hypothesis. \n %s" % (not_H0)
    else :
        print " We accept the null hypothesis. \n %s" % (H0)
    print " %s mean is %.10f"% (name_df1,df1_mean )
    print " %s mean is %.10f"% (name_df2,df2_mean )

df1 = turnstile_weather[turnstile_weather.rain == 1]['ENTRIESn_hour
ly']
df2 = turnstile_weather[turnstile_weather.rain == 0]['ENTRIESn_hour
ly']
test_has_effect(df1,df2 , 'with rain', 'without rain' )
```

```
 After we perform mannwhitney t-test the conclusion is:
 p-values for two-tailed is 0.000005482.
 We reject the null hypothesis.
 "the distribution of ENTRIESn_hourly for the two groups are not e
qual"
 with rain mean is 2028.1960354721
 without rain mean is 1845.5394386644
```

### *1.4 What is the significance and interpretation of these results?*

### ANS:

The distribution of "ENTRIESn_hourly" of 2 samples are statistically significance different.

## Section 2. Linear Regression

#### *2.1 What approach did you use to compute the coefficients theta and produce prediction for ENTRIESn_hourly in your regression model:*

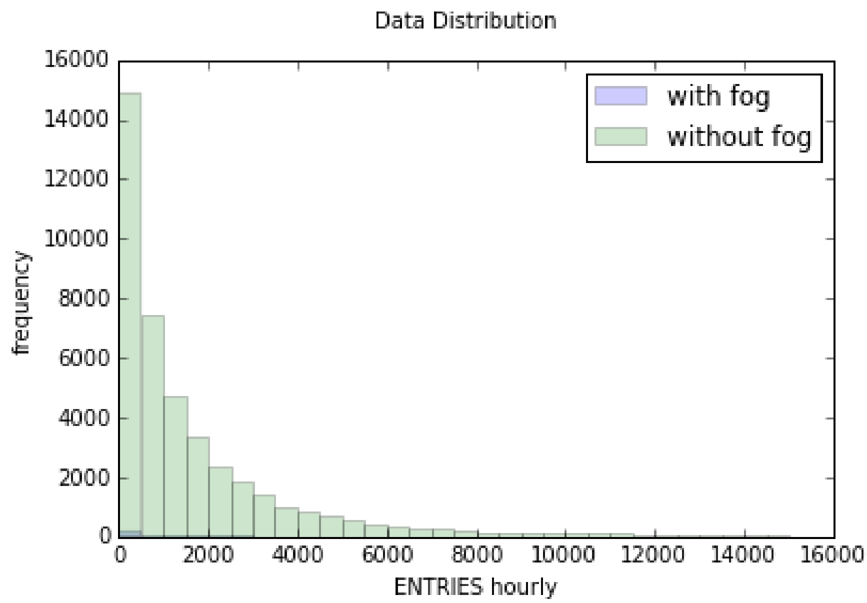
OLS using Statsmodels or Scikit Learn Gradient descent using Scikit Learn Or something different?

ANS: We decide to go for OLS.

#### *2.2 What features (input variables) did you use in your model? Did you use any dummy variables as part of your features?*

#### *ANS :*

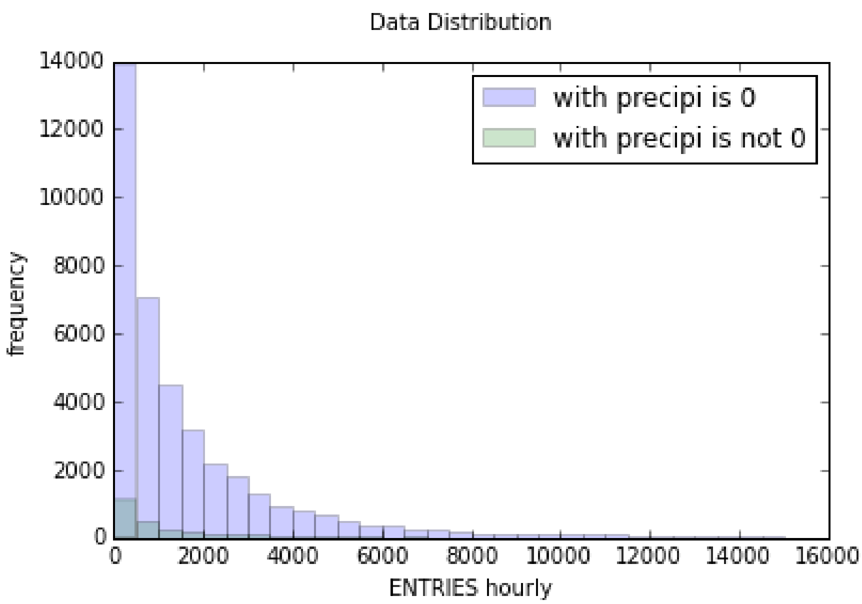
In [153]:
```
df1 = turnstile_weather[turnstile_weather.fog == 1]['ENTRIESn_hourl
y']
df2 = turnstile_weather[turnstile_weather.fog == 0]['ENTRIESn_hourl
y']
test_has_effect(df1,df2 , 'with fog', 'without fog',show_graph=True
)
```




```
As you can see, the distribution is not normal.
 After we perform mannwhitney t-test the conclusion is:
 p-values for two-tailed is 0.006688382.
 We reject the null hypothesis.
 "the distribution of ENTRIESn_hourly for the two groups are not e
qual"
 with fog mean is 1631.9809069212
 without fog mean is 1889.1161496566
```

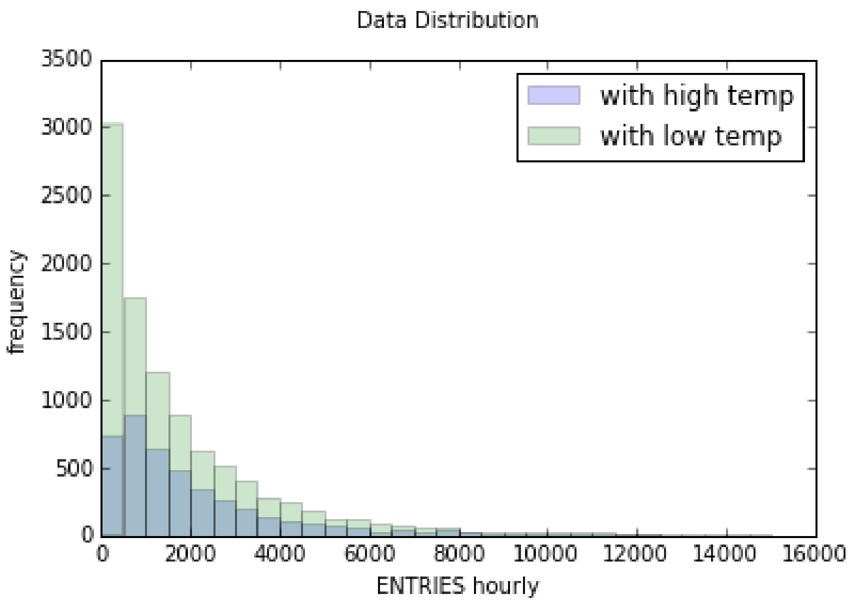
In [154]:
```
resolution = 0.2
turnstile_weather['is_precipi'] =  turnstile_weather['precipi'].app
ly(lambda x: 0 if x == 0 else 1 )


df1 = turnstile_weather[turnstile_weather.is_precipi == 0]['ENTRIES
n_hourly']
df2 = turnstile_weather[turnstile_weather.is_precipi == 1]['ENTRIES
n_hourly']
print "is_precipi == 0 data size is %s "%len(df1)
print "is_precipi == 1 data size is %s "%len(df2)
test_has_effect(df1,df2 , 'with precipi is 0', 'with precipi is not
0' ,show_graph=True)
```

```
is_precipi == 0 data size is 39827
is_precipi == 1 data size is 2822
```



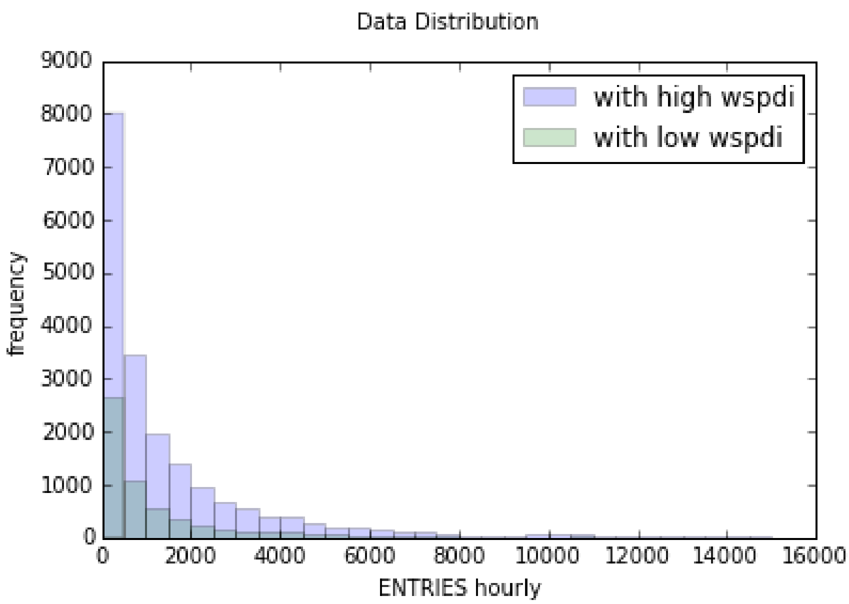

```
As you can see, the distribution is not normal.
 After we perform mannwhitney t-test the conclusion is:
 p-values for two-tailed is 0.000191212.
 We reject the null hypothesis.
 "the distribution of ENTRIESn_hourly for the two groups are not e
qual"
 with precipi is 0 mean is 1896.7423104929
 with precipi is not 0 mean is 1743.3093550673
```

In [155]:
```
resolution = 10
turnstile_weather['tempi_group'] =  turnstile_weather['tempi'].appl
y(lambda x: np.round(x/resolution)*resolution )
agg = turnstile_weather.groupby(['tempi_group'], as_index=False).me
an()
df1 = turnstile_weather[turnstile_weather.tempi_group == 70]['ENTRI
ESn_hourly']
df2 = turnstile_weather[turnstile_weather.tempi_group == 80]['ENTRI
ESn_hourly']

test_has_effect(df1,df2 , 'with low temp', 'with high temp' ,show_g
raph=True)
```




```
As you can see, the distribution is not normal.
 After we perform mannwhitney t-test the conclusion is:
 p-values for two-tailed is 0.000000000.
 We reject the null hypothesis.
 "the distribution of ENTRIESn_hourly for the two groups are not e
qual"
 with low temp mean is 2021.6490019960
 with high temp mean is 2291.7881670534
```

In [156]:
```
resolution = 5
turnstile_weather['wspdi_group'] =  turnstile_weather['wspdi'].appl
y(lambda x: np.round(x/resolution)*resolution )
agg = turnstile_weather.groupby(['wspdi_group'], as_index=False).me
an()

df1 = turnstile_weather[turnstile_weather.wspdi_group == 0]['ENTRIE
Sn_hourly']
df2 = turnstile_weather[turnstile_weather.wspdi_group == 5]['ENTRIE
Sn_hourly']
test_has_effect(df1,df2 , 'with low wspdi', 'with high wspdi' ,sho
w_graph=True)
```




```
As you can see, the distribution is not normal.
 After we perform mannwhitney t-test the conclusion is:
 p-values for two-tailed is 0.000000000.
 We reject the null hypothesis.
 "the distribution of ENTRIESn_hourly for the two groups are not e
qual"
 with low wspdi mean is 1549.0320479863
 with high wspdi mean is 1715.1301188904
```

### *Conclusion :*

We use rain, fog, tempi as features in our model and add UNIT, hour, wspdi and day_week to features using dummy varible.

In [157]:
```
features = turnstile_weather[['rain','fog','tempi']]
dummy_units = pd.get_dummies(turnstile_weather['UNIT'], prefix='uni
t')
features = features.join(dummy_units)
dummy_hour = pd.get_dummies(turnstile_weather['hour'], prefix='hou
r')
features = features.join(dummy_hour)
dummy_day_week = pd.get_dummies(turnstile_weather['day_week'], pref
ix='day_week')
features = features.join(dummy_day_week)
# dummy_tempi = pd.get_dummies(turnstile_weather['tempi_group'], pr
efix='tempi_group')
# features = features.join(dummy_tempi)
dummy_wspdi = pd.get_dummies(turnstile_weather['wspdi_group'], pref
ix='wspdi_group')
features = features.join(dummy_wspdi)
```

#### *2.3 Why did you select these features in your model? We are looking for specific reasons that lead you to believe that*

the selected features will contribute to the predictive power of your model.

Your reasons might be based on intuition. For example, response for fog might be: “I decided to use fog because I thought that when it is very foggy outside people might decide to use the subway more often.”

Your reasons might also be based on data exploration and experimentation, for example: “I used feature X because as soon as I included it in my model, it drastically improved my R2 value.”

**ANS:**

UNIT,Hour,day of week has obviously effect the ENTRIESn_hourly.

We decide to do not use station because it corresponding to the remote unit.

"rain,fog,tempi and precipi" has an effect by the t-test conclusion.

#### *2.4 What are the parameters (also known as "coefficients" or "weights") of the non-dummy features in your linear regression model?*

In [186]:
```
X = features
y = np.array(turnstile_weather['ENTRIESn_hourly'])
X = sm.add_constant(X)
olsmod = sm.OLS(y, X)
olsres = olsmod.fit()
ynewpred = olsres.predict(X)
intercept , params = olsres.params[0],olsres.params[1:]
print(olsres.summary())
```

```
                            OLS Regression Results
==================================================================
============
Dep. Variable:                      y   R-squared:
0.546
Model:                            OLS   Adj. R-squared:
0.543
Method:                 Least Squares   F-statistic:
197.2
Date:                Tue, 10 Nov 2015   Prob (F-statistic):
0.00
Time:                        00:04:28   Log-Likelihood:
-3.8448e+05
No. Observations:               42649   AIC:
7.695e+05
Df Residuals:                   42390   BIC:
7.717e+05
Df Model:                         258
Covariance Type:            nonrobust
==================================================================
==================
                       coef    std err          t      P>|t|
[95.0% Conf. Int.]
------------------------------------------------------------------
------------------
const             1772.8534     63.005     28.138      0.000
1649.363  1896.344
rain               -32.4710     25.903     -1.254      0.210
-83.241    18.299
fog               -182.0574    100.800     -1.806      0.071
-379.628    15.513
tempi              -14.7173      1.362    -10.807      0.000
-17.386   -12.048
unit_R003        -1693.6559    153.828    -11.010      0.000
-1995.161 -1392.150
unit_R004        -1326.0177    150.816     -8.792      0.000
-1621.620 -1030.416
unit_R005        -1341.2832    152.123     -8.817      0.000
-1639.446 -1043.120
unit_R006        -1162.6273    148.755     -7.816      0.000
-1454.189  -871.065
unit_R007        -1526.3967    153.030     -9.974      0.000
-1826.339 -1226.454
unit_R008        -1528.3240    153.465     -9.959      0.000
-1829.118 -1227.530
unit_R009        -1526.5142    150.828    -10.121      0.000
-1822.140 -1230.888
unit_R011         5563.9756    146.934     37.867      0.000
5275.983  5851.969
unit_R012         6915.9853    146.146     47.322      0.000
6629.536  7202.435
unit_R013          814.4261    146.146      5.573      0.000
527.977  1100.875
```

```
unit_R016        -1009.1465    146.935     -6.868       0.000
-1297.143  -721.150
unit_R017         2429.4207    146.146     16.623       0.000
2142.971  2715.870
unit_R018         5997.2138    146.620     40.903       0.000
5709.836  6284.591
unit_R019         1464.7466    146.336     10.009       0.000
1177.925  1751.568
unit_R020         4605.5175    146.146     31.513       0.000
4319.068  4891.967
unit_R021         2915.5924    146.933     19.843       0.000
2627.601  3203.584
unit_R022         7749.9100    146.146     53.029       0.000
7463.461  8036.359
unit_R023         4385.0874    146.146     30.005       0.000
4098.638  4671.537
unit_R024         1426.6750    146.728      9.723       0.000
1139.085  1714.265
unit_R025         3561.6390    146.336     24.339       0.000
3274.817  3848.461
unit_R027         1199.5229    146.146      8.208       0.000
913.074  1485.972
unit_R029         5461.4960    146.146     37.370       0.000
5175.047  5747.945
unit_R030         1331.6896    146.146      9.112       0.000
1045.240  1618.139
unit_R031         2583.4584    146.146     17.677       0.000
2297.009  2869.908
unit_R032         2678.1519    146.538     18.276       0.000
2390.934  2965.370
unit_R033         6466.4691    146.146     44.247       0.000
6180.020  6752.918
unit_R034         -651.9222    152.836     -4.266       0.000
-951.484  -352.361
unit_R035         1028.8096    146.933      7.002       0.000
740.819  1316.800
unit_R036        -1057.2232    149.884     -7.054       0.000
-1350.999  -763.447
unit_R037         -933.6930    147.407     -6.334       0.000
-1222.613  -644.773
unit_R038        -1587.3834    150.723    -10.532       0.000
-1882.803 -1291.964
unit_R039        -1067.9196    154.730     -6.902       0.000
-1371.194  -764.645
unit_R040         -533.4530    147.011     -3.629       0.000
-821.598  -245.308
unit_R041         1331.5014    146.146      9.111       0.000
1045.052  1617.951
unit_R042        -1185.1288    148.549     -7.978       0.000
-1476.287  -893.970
unit_R043         1118.6358    146.146      7.654       0.000
832.186  1405.085
unit_R044         2910.0444    146.146     19.912       0.000
2623.595  3196.494
```

```
unit_R046          6576.4960    146.146     44.999      0.000
6290.047  6862.945
unit_R049          1004.3078    146.146      6.872      0.000
717.859  1290.757
unit_R050          2259.2547    146.935     15.376      0.000
1971.258  2547.251
unit_R051          3366.0498    146.146     23.032      0.000
3079.600  3652.499
unit_R052          -585.4247    152.039     -3.851      0.000
-883.423  -287.426
unit_R053          1392.0730    147.017      9.469      0.000
1103.917  1680.229
unit_R054          -307.8866    146.932     -2.095      0.036
-595.877   -19.896
unit_R055          6557.1628    146.226     44.843      0.000
6270.557  6843.769
unit_R056          -322.9592    146.934     -2.198      0.028
-610.952   -34.966
unit_R057          3114.4369    146.146     21.310      0.000
2827.988  3400.886
unit_R058         -1125.9778    146.541     -7.684      0.000
-1413.201  -838.755
unit_R059          -585.5432    149.796     -3.909      0.000
-879.147  -291.940
unit_R060          -982.7879    148.547     -6.616      0.000
-1273.943  -691.633
unit_R061         -1186.9780    154.195     -7.698      0.000
-1489.204  -884.752
unit_R062           968.2971    146.146      6.626      0.000
681.848  1254.746
unit_R063          -640.1265    153.744     -4.164      0.000
-941.468  -338.785
unit_R064          -931.9130    150.217     -6.204      0.000
-1226.340  -637.486
unit_R065          -940.5654    151.949     -6.190      0.000
-1238.388  -642.743
unit_R066         -1546.9678    152.839    -10.122      0.000
-1846.535 -1247.400
unit_R067          -937.0028    154.285     -6.073      0.000
-1239.404  -634.601
unit_R068         -1346.2432    154.291     -8.725      0.000
-1648.657 -1043.829
unit_R069          -851.8829    151.597     -5.619      0.000
-1149.016  -554.750
unit_R070            19.2756    146.146      0.132      0.895
-267.174   305.725
unit_R080          1843.6035    146.146     12.615      0.000
1557.154  2130.053
unit_R081          1794.3124    146.933     12.212      0.000
1506.321  2082.304
unit_R082          -266.2321    146.933     -1.812      0.070
-554.223    21.759
unit_R083          1358.0121    146.146      9.292      0.000
1071.563  1644.461
```

```
unit_R084          8262.2863    146.146     56.534       0.000
7975.837  8548.736
unit_R085           843.5019    146.935      5.741       0.000
555.507  1131.497
unit_R086           831.6035    146.146      5.690       0.000
545.154  1118.053
unit_R087          -539.9019    147.735     -3.655       0.000
-829.465  -250.338
unit_R089         -1255.3585    146.935     -8.544       0.000
-1543.355  -967.362
unit_R090         -1370.5178    154.287     -8.883       0.000
-1672.923 -1068.113
unit_R091          -658.5260    152.920     -4.306       0.000
-958.252  -358.800
unit_R092           219.1146    150.312      1.458       0.145
-75.499   513.729
unit_R093           247.3605    151.163      1.636       0.102
-48.922   543.643
unit_R094            -7.9565    147.012     -0.054       0.957
-296.102   280.189
unit_R095           398.7608    148.222      2.690       0.007
108.243   689.279
unit_R096           585.2179    146.614      3.992       0.000
297.851   872.585
unit_R097          1206.2517    146.620      8.227       0.000
918.874  1493.629
unit_R098            66.1627    146.146      0.453       0.651
-220.287   352.612
unit_R099           623.1896    146.146      4.264       0.000
336.740   909.639
unit_R100         -1211.7167    147.823     -8.197       0.000
-1501.452  -921.982
unit_R101          1057.5820    146.146      7.236       0.000
771.133  1344.031
unit_R102          1946.4207    146.146     13.318       0.000
1659.971  2232.870
unit_R103          -377.8285    152.029     -2.485       0.013
-675.808   -79.849
unit_R104          -418.4314    147.008     -2.846       0.004
-706.571  -130.292
unit_R105          1596.1197    146.146     10.921       0.000
1309.670  1882.569
unit_R106          -711.6355    154.284     -4.612       0.000
-1014.036  -409.235
unit_R107         -1303.7224    154.759     -8.424       0.000
-1607.054 -1000.391
unit_R108          3485.2863    146.146     23.848       0.000
3198.837  3771.736
unit_R111          1482.4100    146.146     10.143       0.000
1195.961  1768.859
unit_R112           -73.0956    146.614     -0.499       0.618
-360.462   214.271
unit_R114          -858.9462    146.731     -5.854       0.000
-1146.541  -571.351
```

```
unit_R115         -487.7642    146.336     -3.333      0.001
-774.586  -200.943
unit_R116         1461.5552    146.146     10.001      0.000
1175.106  1748.004
unit_R117         -899.2615    153.821     -5.846      0.000
-1200.754  -597.769
unit_R119           92.4627    149.038      0.620      0.535
-199.654   384.580
unit_R120         -249.0357    151.154     -1.648      0.099
-545.301    47.229
unit_R121         -283.3014    150.220     -1.886      0.059
-577.736    11.133
unit_R122          817.9531    148.227      5.518      0.000
527.425  1108.482
unit_R123         -114.8121    148.549     -0.773      0.440
-405.972   176.348
unit_R124        -1103.4509    152.389     -7.241      0.000
-1402.137  -804.765
unit_R126          123.4638    146.146      0.845      0.398
-162.986   409.913
unit_R127         3064.1734    146.146     20.967      0.000
2777.724  3350.623
unit_R137          703.0714    146.226      4.808      0.000
416.465   989.678
unit_R139          798.1584    146.540      5.447      0.000
510.937  1085.380
unit_R163         1599.9100    146.146     10.947      0.000
1313.461  1886.359
unit_R172          165.9476    146.146      1.135      0.256
-120.502   452.397
unit_R179         5046.7218    146.146     34.532      0.000
4760.273  5333.171
unit_R181           23.1992    148.959      0.156      0.876
-268.763   315.162
unit_R183        -1020.1679    154.745     -6.593      0.000
-1323.471  -716.865
unit_R184         -758.2779    152.836     -4.961      0.000
-1057.839  -458.717
unit_R186         -653.5763    148.139     -4.412      0.000
-943.933  -363.220
unit_R188          599.8546    146.538      4.093      0.000
312.636   887.073
unit_R189         -343.3938    149.795     -2.292      0.022
-636.995   -49.793
unit_R194          262.1646    148.965      1.760      0.078
-29.809   554.138
unit_R196         -400.7090    147.331     -2.720      0.007
-689.481  -111.937
unit_R198          383.7891    146.934      2.612      0.009
95.796   671.782
unit_R199        -1016.0686    148.963     -6.821      0.000
-1308.039  -724.098
unit_R200         -690.4024    147.910     -4.668      0.000
-980.310  -400.495
```

```
unit_R202          490.4928    147.013      3.336      0.001
202.345   778.641
unit_R203           29.8105    150.643      0.198      0.843
-265.454   325.075
unit_R204         -272.5524    146.146     -1.865      0.062
-559.002    13.897
unit_R205         -228.9959    147.817     -1.549      0.121
-518.720    60.728
unit_R207          277.4172    146.540      1.893      0.058
-9.803   564.638
unit_R208          773.3186    147.810      5.232      0.000
483.608  1063.029
unit_R209         -964.1558    153.738     -6.271      0.000
-1265.485  -662.827
unit_R210        -1199.4997    149.801     -8.007      0.000
-1493.113  -905.886
unit_R211          684.8777    146.146      4.686      0.000
398.428   971.327
unit_R212          -35.0703    146.538     -0.239      0.811
-322.288   252.147
unit_R213         -576.2380    149.375     -3.858      0.000
-869.016  -283.460
unit_R214        -1089.2390    154.199     -7.064      0.000
-1391.472  -787.006
unit_R215         -126.4400    146.934     -0.861      0.390
-414.434   161.554
unit_R216         -955.4743    146.933     -6.503      0.000
-1243.465  -667.483
unit_R217         -752.0586    153.741     -4.892      0.000
-1053.395  -450.722
unit_R218          249.6617    146.618      1.703      0.089
-37.712   537.035
unit_R219         -469.3956    147.013     -3.193      0.001
-757.543  -181.248
unit_R220         -240.3965    146.146     -1.645      0.100
-526.846    46.053
unit_R221         -342.2014    154.201     -2.219      0.026
-644.438   -39.965
unit_R223          389.1639    146.614      2.654      0.008
101.797   676.531
unit_R224         -999.5511    150.222     -6.654      0.000
-1293.988  -705.114
unit_R225        -1148.2865    148.142     -7.751      0.000
-1438.648  -857.925
unit_R226        -1039.8991    152.920     -6.800      0.000
-1339.626  -740.172
unit_R227         -621.1330    146.146     -4.250      0.000
-907.582  -334.684
unit_R228         -607.4424    153.291     -3.963      0.000
-907.896  -306.989
unit_R229        -1176.1316    152.388     -7.718      0.000
-1474.816  -877.448
unit_R230        -1215.1252    150.644     -8.066      0.000
-1510.390  -919.860
```

```
unit_R231          -754.9510    148.139     -5.096      0.000
-1045.307  -464.595
unit_R232          -720.6861    151.949     -4.743      0.000
-1018.510  -422.862
unit_R233          -653.2971    155.132     -4.211      0.000
-957.359  -349.235
unit_R234         -1443.0872    153.750     -9.386      0.000
-1744.441 -1141.733
unit_R235           852.1249    146.541      5.815      0.000
564.902  1139.348
unit_R236          -213.2885    147.813     -1.443      0.149
-503.004    76.427
unit_R237         -1106.3668    153.361     -7.214      0.000
-1406.957  -805.776
unit_R238           371.6645    146.618      2.535      0.011
84.291   659.038
unit_R239          -823.9717    146.146     -5.638      0.000
-1110.421  -537.522
unit_R240           935.0171    147.330      6.346      0.000
646.248  1223.786
unit_R242         -1183.5001    149.380     -7.923      0.000
-1476.289  -890.711
unit_R243          -368.5493    151.593     -2.431      0.015
-665.674   -71.424
unit_R244          -135.5100    151.589     -0.894      0.371
-432.627   161.607
unit_R246         -1067.5961    153.289     -6.965      0.000
-1368.045  -767.147
unit_R247         -1617.8973    156.083    -10.366      0.000
-1923.823 -1311.971
unit_R248          1380.4881    146.540      9.421      0.000
1093.267  1667.709
unit_R249          -369.0032    148.548     -2.484      0.013
-660.161   -77.845
unit_R250          -758.4554    149.375     -5.078      0.000
-1051.234  -465.677
unit_R251          -450.9028    147.331     -3.060      0.002
-739.674  -162.132
unit_R252          -765.3310    146.932     -5.209      0.000
-1053.322  -477.341
unit_R253          -998.3039    152.054     -6.565      0.000
-1296.332  -700.276
unit_R254           858.1375    146.620      5.853      0.000
570.760  1145.515
unit_R255          -969.8776    147.916     -6.557      0.000
-1259.797  -679.959
unit_R256          -658.5975    146.933     -4.482      0.000
-946.589  -370.606
unit_R257           163.2003    146.146      1.117      0.264
-123.249   449.650
unit_R258          -201.1006    147.331     -1.365      0.172
-489.872    87.671
unit_R259          -800.6017    148.547     -5.390      0.000
-1091.757  -509.446
```

```
unit_R260          -653.5131    159.531     -4.096       0.000
-966.196  -340.830
unit_R261          -185.0256    149.878     -1.235       0.217
-478.790   108.738
unit_R262         -1308.2648    156.078     -8.382       0.000
-1614.180 -1002.349
unit_R263         -1597.9984    149.374    -10.698       0.000
-1890.774 -1305.222
unit_R264         -1251.1566    146.540     -8.538       0.000
-1538.378  -963.936
unit_R265          -884.8970    152.393     -5.807       0.000
-1183.589  -586.205
unit_R266          -828.7194    146.615     -5.652       0.000
-1116.088  -541.351
unit_R269          -843.9177    146.935     -5.743       0.000
-1131.913  -555.923
unit_R270         -1265.1981    153.288     -8.254       0.000
-1565.645  -964.751
unit_R271         -1381.9898    152.834     -9.042       0.000
-1681.547 -1082.432
unit_R273          -378.7498    153.745     -2.463       0.014
-680.093   -77.406
unit_R274          -787.9245    151.945     -5.186       0.000
-1085.740  -490.109
unit_R275          -854.2737    149.888     -5.699       0.000
-1148.057  -560.490
unit_R276          -314.2621    146.146     -2.150       0.032
-600.711   -27.813
unit_R277         -1339.9156    157.531     -8.506       0.000
-1648.679 -1031.153
unit_R278         -1380.1016    152.397     -9.056       0.000
-1678.802 -1081.401
unit_R279          -985.4616    149.042     -6.612       0.000
-1277.587  -693.336
unit_R280         -1114.6907    156.551     -7.120       0.000
-1421.534  -807.848
unit_R281          -450.9962    148.544     -3.036       0.002
-742.145  -159.847
unit_R282          -143.6877    146.935     -0.978       0.328
-431.683   144.308
unit_R284          -956.9343    146.932     -6.513       0.000
-1244.925  -668.944
unit_R285         -1186.5201    154.374     -7.686       0.000
-1489.096  -883.944
unit_R287         -1221.9907    154.663     -7.901       0.000
-1525.133  -918.848
unit_R291            78.9691    146.146      0.540       0.589
-207.480   365.418
unit_R294          -800.4005    149.798     -5.343       0.000
-1094.007  -506.794
unit_R295         -1179.9310    169.657     -6.955       0.000
-1512.463  -847.399
unit_R300           488.0336    146.146      3.339       0.001
201.584   774.483
```

```
unit_R303          -503.7708    148.551     -3.391       0.001
-794.934  -212.608
unit_R304          -645.3072    146.934     -4.392       0.000
-933.301  -357.314
unit_R307         -1454.3298    154.751     -9.398       0.000
-1757.644 -1151.016
unit_R308          -979.1828    151.601     -6.459       0.000
-1276.324  -682.042
unit_R309          -943.8603    151.171     -6.244       0.000
-1240.158  -647.563
unit_R310          -492.7003    152.909     -3.222       0.001
-792.404  -192.996
unit_R311         -1356.7305    150.650     -9.006       0.000
-1652.008 -1061.453
unit_R312         -1406.0248    147.332     -9.543       0.000
-1694.799 -1117.251
unit_R313         -1747.1601    155.213    -11.257       0.000
-2051.381 -1442.939
unit_R318         -1199.7076    147.735     -8.121       0.000
-1489.271  -910.144
unit_R319          -396.9874    148.960     -2.665       0.008
-688.952  -105.023
unit_R321          -649.3696    146.146     -4.443       0.000
-935.819  -362.920
unit_R322            30.9239    148.962      0.208       0.836
-261.044   322.892
unit_R323          -497.0385    151.950     -3.271       0.001
-794.863  -199.214
unit_R325         -1435.9524    150.749     -9.525       0.000
-1731.424 -1140.481
unit_R330          -765.4439    149.794     -5.110       0.000
-1059.043  -471.845
unit_R335         -1428.0644    155.802     -9.166       0.000
-1733.439 -1122.690
unit_R336         -1782.2849    155.804    -11.439       0.000
-2087.663 -1476.907
unit_R337         -1726.7415    153.940    -11.217       0.000
-2028.466 -1425.017
unit_R338         -1853.5135    151.268    -12.253       0.000
-2150.001 -1557.026
unit_R341         -1263.0971    147.523     -8.562       0.000
-1552.245  -973.950
unit_R344         -1310.4959    155.589     -8.423       0.000
-1615.453 -1005.538
unit_R345         -1297.5825    150.651     -8.613       0.000
-1592.861 -1002.304
unit_R346          -516.5363    151.075     -3.419       0.001
-812.647  -220.426
unit_R348         -1660.5788    151.154    -10.986       0.000
-1956.844 -1364.314
unit_R354         -1621.9985    154.387    -10.506       0.000
-1924.600 -1319.397
unit_R356          -681.1600    150.413     -4.529       0.000
-975.973  -386.347
```

```
unit_R358         -1588.2745    154.383    -10.288        0.000
-1890.869 -1285.680
unit_R370         -1290.9864    150.216     -8.594        0.000
-1585.413  -996.560
unit_R371         -1075.1879    151.950     -7.076        0.000
-1373.012  -777.364
unit_R372         -1092.1437    153.289     -7.125        0.000
-1392.593  -791.695
unit_R373         -1144.8127    153.732     -7.447        0.000
-1446.131  -843.495
unit_R382          -888.3056    149.967     -5.923        0.000
-1182.245  -594.367
unit_R424         -1442.6820    155.141     -9.299        0.000
-1746.762 -1138.602
unit_R429          -768.6038    147.409     -5.214        0.000
-1057.529  -479.679
unit_R453           -12.8098    156.543     -0.082        0.935
-319.637   294.017
unit_R454         -1689.8554    154.199    -10.959        0.000
-1992.088 -1387.622
unit_R455         -1743.6190    153.748    -11.341        0.000
-2044.968 -1442.270
unit_R456         -1557.9066    149.800    -10.400        0.000
-1851.518 -1264.295
unit_R459         -1723.8581    212.426     -8.115        0.000
-2140.218 -1307.499
unit_R464         -1919.0066    153.449    -12.506        0.000
-2219.770 -1618.243
hour_0             -146.5138     22.942     -6.386        0.000
-191.482  -101.546
hour_4            -1262.6161     23.046    -54.787        0.000
-1307.786 -1217.446
hour_8             -933.0556     25.152    -37.096        0.000
-982.355  -883.757
hour_12            1556.9001     27.914     55.774        0.000
1502.188  1611.613
hour_16             853.3062     28.019     30.455        0.000
798.389   908.223
hour_20            1704.8326     23.671     72.021        0.000
1658.436  1751.229
day_week_0          201.5390     24.149      8.346        0.000
154.207   248.871
day_week_1          611.4333     26.223     23.317        0.000
560.036   662.831
day_week_2          637.1959     27.351     23.297        0.000
583.588   690.804
day_week_3          638.0988     26.061     24.485        0.000
587.019   689.179
day_week_4          609.2279     27.107     22.475        0.000
556.098   662.357
day_week_5         -286.9554     27.344    -10.494        0.000
-340.550  -233.361
day_week_6         -637.6860     24.220    -26.329        0.000
-685.157  -590.215
```

```
wspdi_group_0.0    407.5296     43.545      9.359      0.000
322.180   492.879
wspdi_group_5.0    420.9405     37.125     11.338      0.000
348.175   493.706
wspdi_group_10.0   439.0652     37.128     11.826      0.000
366.293   511.838
wspdi_group_15.0   447.9262     40.897     10.953      0.000
367.767   528.085
wspdi_group_20.0   425.9491     69.628      6.118      0.000
289.477   562.421
wspdi_group_25.0  -368.5571    166.255     -2.217      0.027
-694.421   -42.694
==================================================================
============
Omnibus:                    30246.342   Durbin-Watson:
1.525
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1103688.475
Skew:                           2.979   Prob(JB):
0.00
Kurtosis:                      27.199   Cond. No.
1.36e+17
==================================================================
============

Warnings:
[1] Standard Errors assume that the covariance matrix of the error
s is correctly specified.
[2] The smallest eigenvalue is 9.36e-27. This might indicate that
there are
strong multicollinearity problems or that the design matrix is sin
gular.
```

**ANS:**

In [159]:

```
print "rain coefficients is %.10f"%params[0]
print "fog coefficients is %.10f"%params[1]
```

```
rain coefficients is -32.4709952114
fog coefficients is -182.0574321738
```

### *2.5 What is your model's R2 (coefficients of determination) value?*

In [160]:

```
print olsres.rsquared
```

```
0.545517676888
```

In [161]:
```
def plot_residuals(turnstile_weather, predictions):
    name_df1 = "Prediction by our models"
    df1 = (turnstile_weather['ENTRIESn_hourly'] - predictions)

    name_df2 = "Predict by mean value"
    df2 = (turnstile_weather['ENTRIESn_hourly'] - turnstile_weathe
r['ENTRIESn_hourly'].mean())
    df_compare = pd.DataFrame({name_df1: df1,
                name_df2: df2})


    df_compare = pd.DataFrame({name_df1: df1,
                name_df2: df2})
    df_compare.plot(kind='hist', alpha=0.2,bins = range(-6000, 6000
, 300))




    plt.suptitle('Predict ENTRIESn_hourly Error compare between Our
model and Mean')
    plt.xlabel("ENTRIES hourly Error")
    plt.ylabel("frequency")
    fig = matplotlib.pyplot.gcf()
    fig.set_size_inches(18.5, 10.5, forward=True)
    plt.show()
    return
```

**ANS:**

In statistics, the coefficient of determination, denoted R2 or r2 and pronounced R squared, is a number that indicates how well data fit a statistical model.

Our model's R2 is 0.54629540704.

The result indicates that the model explains 54.63% of the variability of the response data around its mean.

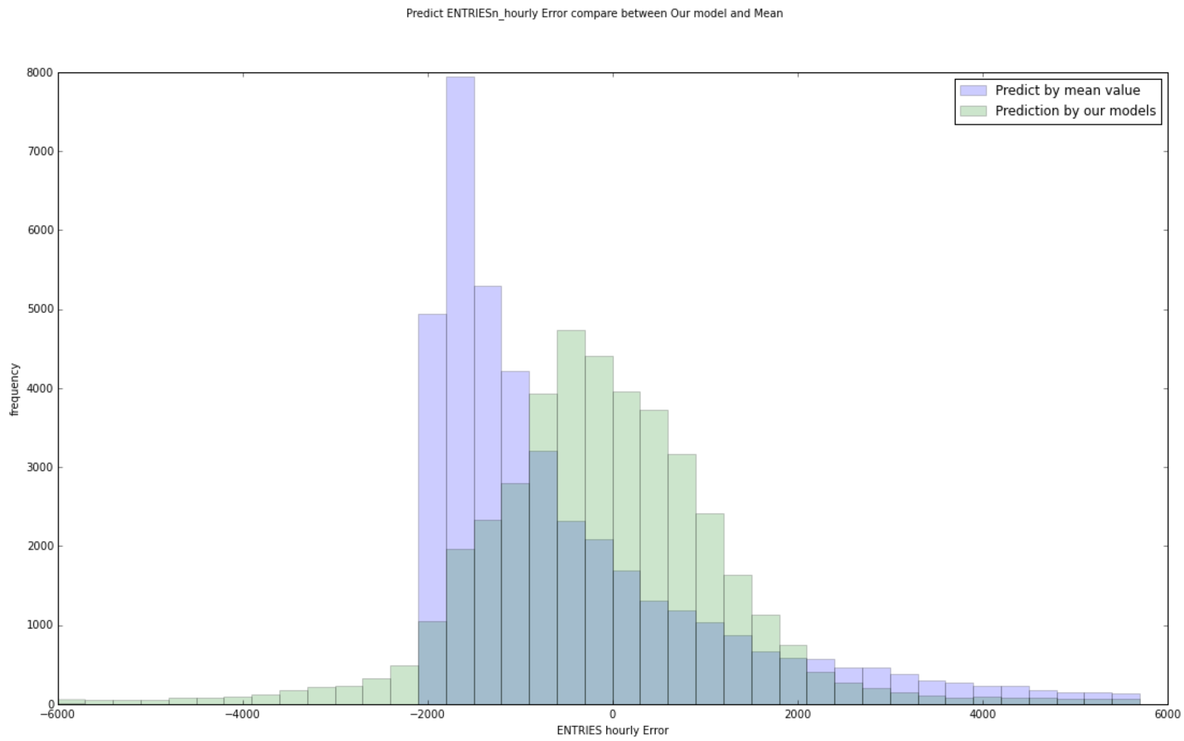
#### *2.6 What does this R2 value mean for the goodness of fit for your regression model? Do you think this linear model to predict ridership is appropriate for this dataset, given this R2 value?*

In [162]:
```
predictions = ynewpred
```

**ANS :**

Our R2(0.546) indicates that the regression line fits the data more than any other models that R2 less than 0.546 and still has the chance to improve the model for make it closer to 1.

In [163]:
```
plot_residuals(turnstile_weather, predictions)
```




As you can see our model's prediction is obviously better than predict by mean.

# Section 3. Visualization

### *3.1 One visualization should contain two histograms: one of ENTRIESn_hourly for rainy days and one of ENTRIESn_hourly for non-rainy days.*

You can combine the two histograms in a single plot or you can use two separate plots.

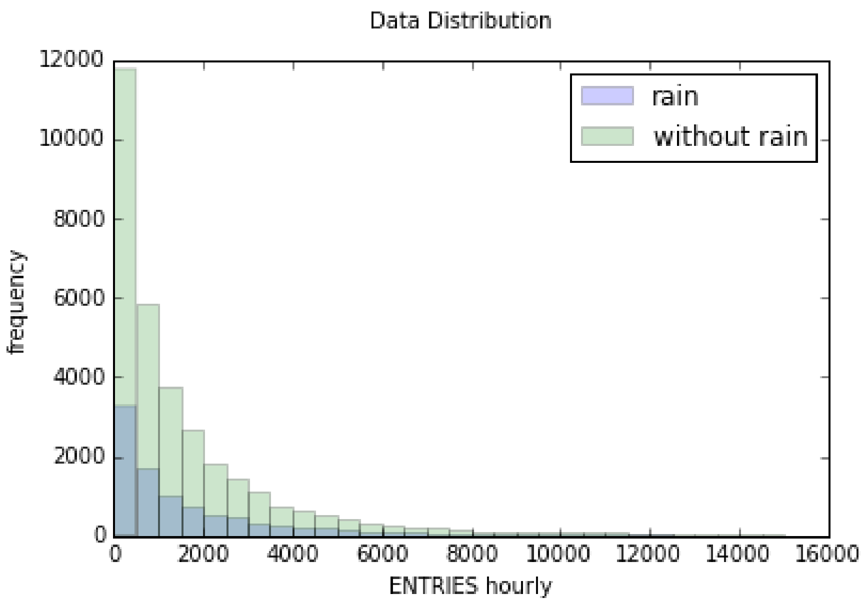
If you decide to use to two separate plots for the two histograms, please ensure that the x-axis limits for both of the plots are identical. It is much easier to compare the two in that case.

For the histograms, you should have intervals representing the volume of ridership (value of ENTRIESn_hourly) on the x-axis and the frequency of occurrence on the y-axis. For example, each interval (along the x-axis), the height of the bar for this interval will represent the number of records (rows in our data) that have ENTRIESn_hourly that falls in this interval.

Remember to increase the number of bins in the histogram (by having larger number of bars). The default bin width is not sufficient to capture the variability in the two samples.

**ANS:**

In [164]:
```
rain_df = turnstile_weather[turnstile_weather.rain == 1]['ENTRIES
n_hourly']
norain_df = turnstile_weather[turnstile_weather.rain == 0]['ENTRIES
n_hourly']
df_compare = pd.DataFrame({'rain': rain_df,
               'without rain': norain_df})
df_compare.plot(kind='hist', alpha=0.2,bins = range(0, 15000 + 500,
500) ) ##,bins = range(0, 37 + 3, 3)

plt.xlabel("ENTRIES hourly")
plt.suptitle('Data Distribution')
plt.ylabel("frequency")
plt.show()

print "As you can see, the distribution is not normal."
```




```
As you can see, the distribution is not normal.
```

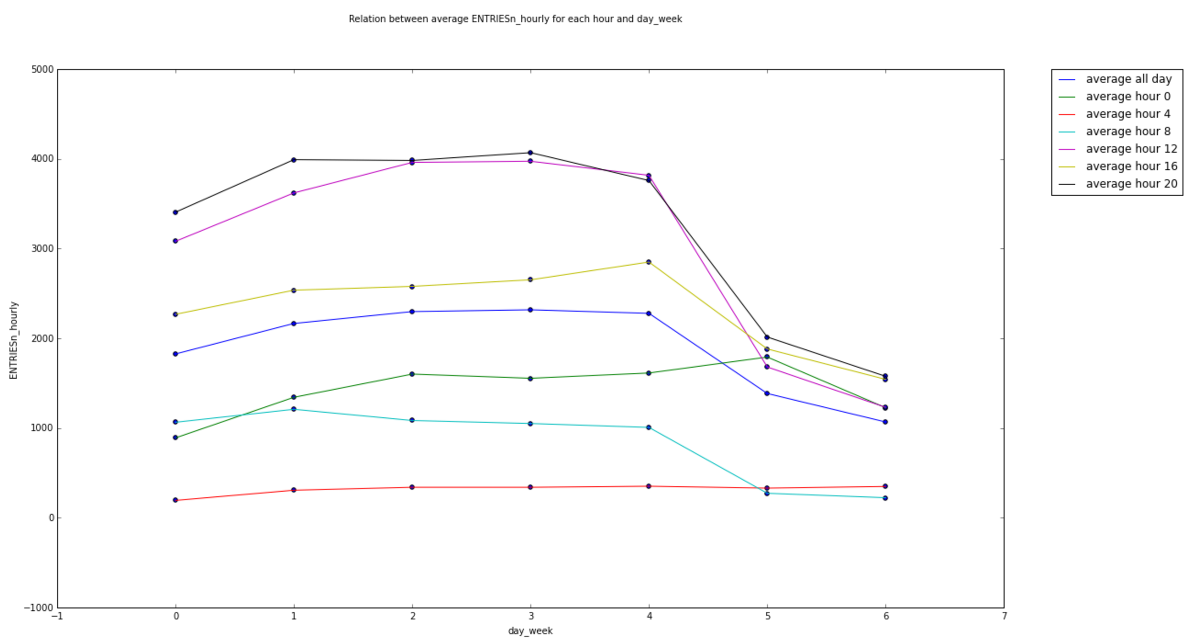
#### *3.2 One visualization can be more freeform. You should feel free to implement something that we discussed in class (e.g., scatter plots, line plots) or attempt to implement something more advanced if you'd like. Some suggestions are:*

Ridership by time-of-day

Ridership by day-of-week

**ANS:**

In [165]:
```
agg = turnstile_weather.groupby(['day_week'], as_index=False).mea
n()

x_data  = agg['day_week']
y_data = agg['ENTRIESn_hourly']
plt.plot(x_data, y_data,label="average all day")
plt.scatter(x=agg['day_week'], y=agg['ENTRIESn_hourly'])

for hour in range(0,25):
    agg = turnstile_weather[turnstile_weather.hour == hour].groupb
y(['day_week'], as_index=False).mean()
    x_data  = agg['day_week']
    y_data = agg['ENTRIESn_hourly']
    if np.mean(y_data) > 0  :
        plt.plot(x_data, y_data, label="average hour %s"%hour)
        plt.scatter(x=agg['day_week'], y=agg['ENTRIESn_hourly'])

plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)

plt.suptitle('Relation between average ENTRIESn_hourly for each hou
r and day_week')
plt.xlabel("day_week")
plt.ylabel("ENTRIESn_hourly")
fig = matplotlib.pyplot.gcf()
fig.set_size_inches(18.5, 10.5, forward=True)
plt.show()
print "As you can see the average ENTRIESn_hourly of hour 20 and 12
is obviously higher than other"
```




As you can see the average ENTRIESn_hourly of hour 20 and 12 is ob
viously higher than other

# Section 4. Conclusion

Please address the following questions in detail. Your answers should be 1-2 paragraphs long.

#### 4.1 From your analysis and interpretation of the data, do more people ride the NYC subway when it is raining or when it is not raining?

## ANS:

From rain's coeffiecent(-54.5780521669) in linear regression and P value is 0.210 so we conclude that :

**Rain are not associated with changes in the response ( ENTRIESn_hourly ).**

#### 4.2 What analyses lead you to this conclusion? You should use results from both your statistical tests and your linear regression to support your analysis.

## ANS:

From the null hypothesis testing results with 2 samples rain and with out rain return p value = 0.00000274106957 it mean that the possibility of distribution different has occured by chance is about 0.0002741% so we assume that

***The distributions of both populations are not equal.***

But the p-value from linear regression summary (0.210) is greater than the common alpha level of 0.05, which indicates that:

***Rain is not statistically significant effect on ENTRIESn_hourly.***

# Section 5. Reflection

Please address the following questions in detail. Your answers should be 1-2 paragraphs long.

#### 5.1 Please discuss potential shortcomings of the methods of your analysis, including:

Dataset, Analysis, such as the linear regression model or statistical test.

**ANS**

#### *Dataset:*

Folowing the data :

The data has only one month data and I quite sure that "month" has an effect on "ENTRIESn_hourly" so If we have more data in every month is possible that our model is more fit on the different month.

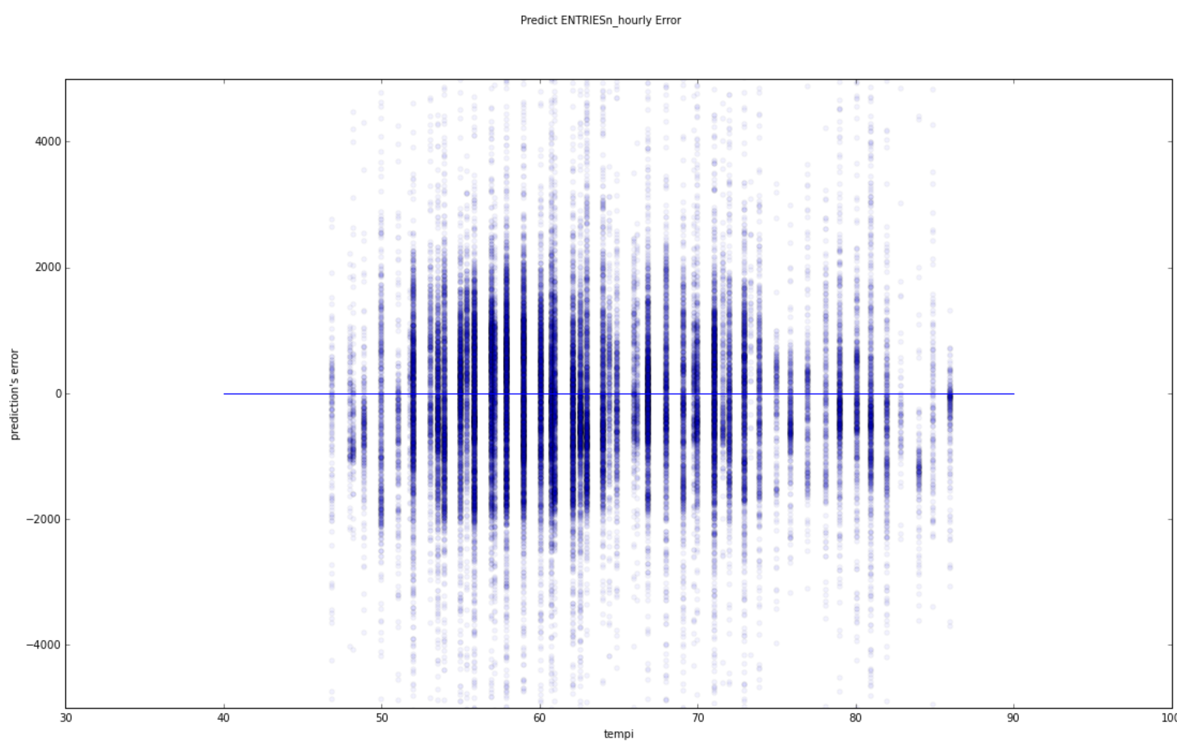
I am quite sure that "public holiday" has an effect on "ENTRIESn_hourly" so If we has the parameter, our prediction will be more significant accurate.

#### *Statistical Test:*

The Statistical Test is only comparing the differences between the conditions of one feature;rain, when clearly other are other variables that seem to affect the ridership even more.

#### *Regression Model*

In [187]:
```
def plot_residuals2(turnstile_weather, effect_parameter='tempi'):
    name_df1 = "Prediction by our models"
    turnstile_weather['Predict_ENTRIESn_hourly_error'] = (turnstil
e_weather['ENTRIESn_hourly'] - predictions)
    agg = turnstile_weather
#     agg = turnstile_weather.groupby([effect_parameter], as_inde
x=False).mean()
    agg = agg.sort([effect_parameter])
    x_data  = agg[effect_parameter]
    y_data = agg['Predict_ENTRIESn_hourly_error']
    fig = matplotlib.pyplot.gcf()
    fig.set_size_inches(18.5, 10.5, forward=True)
#     plt.plot(x_data, y_data)
    plt.plot([40,90], [0,0])
    plt.xlabel("tempi")
    plt.ylabel("prediction's error")
    plt.suptitle('Predict ENTRIESn_hourly Error')
    plt.scatter(x=agg[effect_parameter], y=agg['Predict_ENTRIESn_ho
urly_error'], alpha = 0.05)
    x1,x2,y1,y2 = plt.axis()
    plt.axis((x1,x2,-5000,5000))
    plt.show()

    return

plot_residuals2(turnstile_weather, effect_parameter='tempi')
```



As you see "Predict ENTRIESn_hourly" is quite acurrate (0 horizontal line draw through the middle of intense blue dot cluster) so I think linear model in this context is good enough.

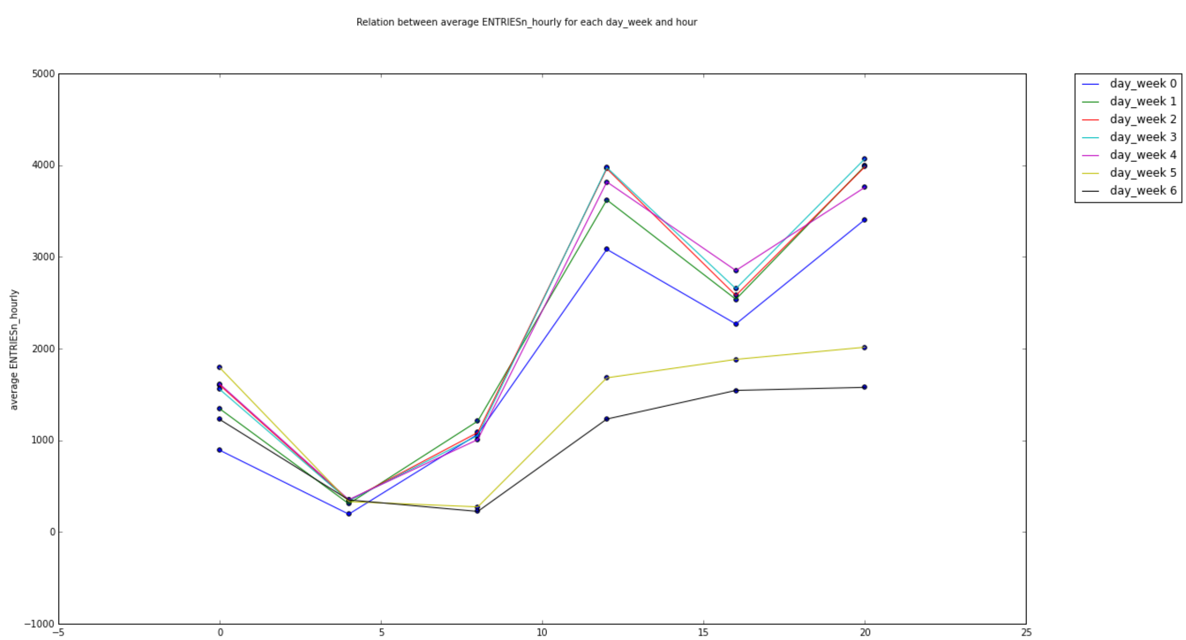
Any way if we find out other pattern such as cyclic or polynomial the linear model will be less appropriate.

### *5.2 (Optional) Do you have any other insight about the dataset that you would like to share with us?*

### ANS:

In [188]:

```
for day_week in range(0,7):
    agg = turnstile_weather[turnstile_weather.day_week == day_week].groupby(['hour'], as_index=False).mean()
    x_data  = agg['hour']
    y_data = agg['ENTRIESn_hourly']
    if np.mean(y_data) > 0  :
        plt.plot(x_data, y_data, label="day_week %s"%day_week)
        plt.scatter(x=agg['hour'], y=agg['ENTRIESn_hourly'])
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
plt.xlabel("hour")
plt.ylabel("average ENTRIESn_hourly")
plt.suptitle('Relation between average ENTRIESn_hourly for each day_week and hour')
fig = matplotlib.pyplot.gcf()
fig.set_size_inches(18.5, 10.5, forward=True)
plt.show()
```



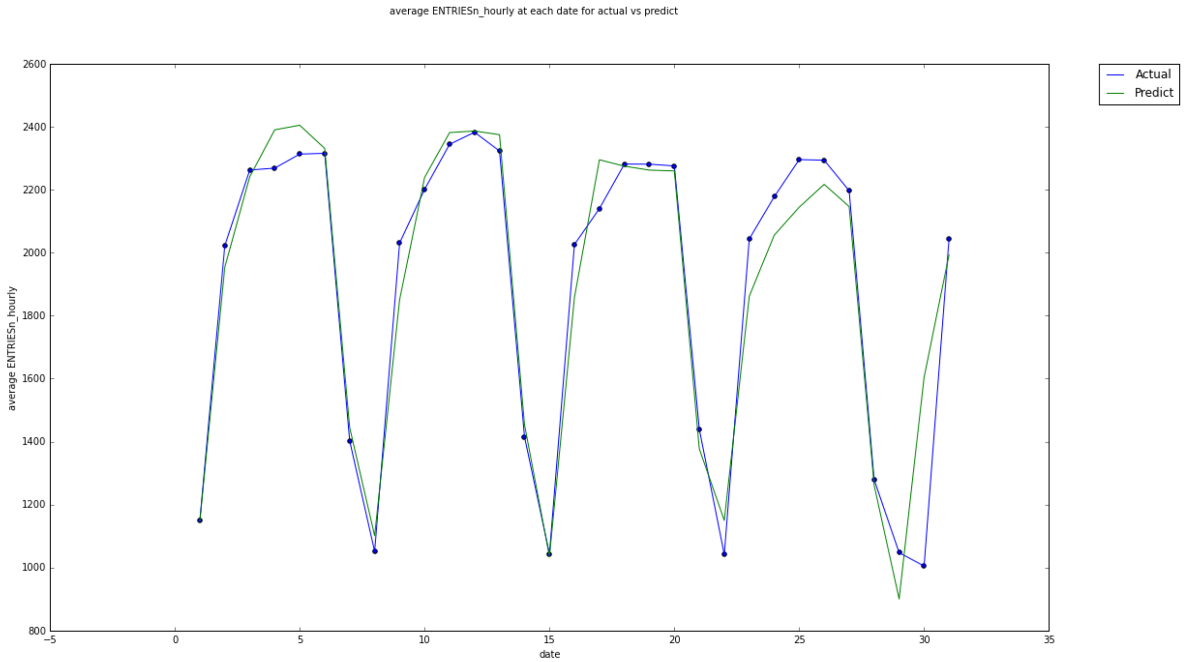
There are 2 patterns of Hourly_entries by hour first is day_week 0-4 second is dayweek 5-6.

Peek Hour for Hourly_entries are about at 12:00 and 20:00.

In [189]:
```
# agg2 = turnstile_weather.groupby(['conds'])
# for key, cond  in agg2['conds']:
# #     print key
#     if key in ['Clear','Light Drizzle','Heavy Rain','Light Rai
n']:
#         agg = turnstile_weather[turnstile_weather.conds == key].g
roupby(['hour'], as_index=False).mean()
#         x_data  = agg['hour']
#         y_data = agg['ENTRIESn_hourly']
# #         print np.mean(y_data)
#         if np.mean(y_data) > 0  :
#             plt.plot(x_data, y_data, label="cond %s"%key)
#             plt.scatter(x=agg['hour'], y=agg['ENTRIESn_hourly'])

# plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
# plt.xlabel("hour")
# plt.ylabel("average ENTRIESn_hourly")
# plt.suptitle('Relation between average ENTRIESn_hourly for each c
ond and hour')
# fig = matplotlib.pyplot.gcf()
# fig.set_size_inches(18.5, 10.5, forward=True)
# plt.show()
```

In [190]:

```
fig = matplotlib.pyplot.gcf()
fig.set_size_inches(18.5, 10.5)

turnstile_weather['predict_ENTRIESn_hourly'] = predictions
agg = turnstile_weather.groupby(['DATEn'], as_index=False).mean()
# agg['datetime_obj']  = pd.to_datetime(agg['DATEn'])
# agg['datetime_obj']  = pd.DatetimeIndex (agg['DATEn'])
# agg['datetime_obj']  = agg['DATEn'].astype('datetime64[ns]')
from time import strptime
# agg = agg[:30]
agg['datetime_obj']  = pd.to_datetime(agg['DATEn'])
# print agg['datetime_obj'][0].day
agg['datetime_num']  =  agg['datetime_obj'].apply(lambda x: x.day )

agg = agg.sort(['datetime_num'])
# print len(agg)

import matplotlib.dates as mdates
x_data = agg['datetime_num']
y_data = agg['ENTRIESn_hourly']
y2_data = agg['predict_ENTRIESn_hourly']

plt.scatter(x=agg['datetime_num'], y=agg['ENTRIESn_hourly'])
plt.plot(agg['datetime_num'], agg['ENTRIESn_hourly'],label="Actua
l")

plt.plot(agg['datetime_num'], agg['predict_ENTRIESn_hourly'],labe
l="Predict")
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)

plt.xlabel("date")
plt.ylabel("average ENTRIESn_hourly")
plt.suptitle('average ENTRIESn_hourly at each date for actual vs pr
edict')
plt.show()
```




The pattern are cyclic.

```
In [ ]:
```