Project 1

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Effect of Rain on Subway Ridership on Weekdays

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In [3]:
```
from __future__ import absolute_import
from __future__ import division
from __future__ import print_function
from __future__ import unicode_literals

import pandas as pd
import numpy as np
import scipy as sp
import ggplot as gp
import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import statsmodels.formula.api as sm

%matplotlib inline
```

In [4]:
```
# Data Source: https://www.dropbox.com/s/
# meyki2wl9xfa7yk/turnstile_data_master_with_weather.csv

df = pd.read_csv('turnstile_weather_v2.csv')
```

0. References

- Python for Data Analysis: Data Wrangling with Pandas, NumPy, and IPython by Wes McKinney
- Share label between subplots http://stackoverflow.com/a/26892326/965648
- Haversine formula details http://en.wikipedia.org/wiki/Haversine_formula

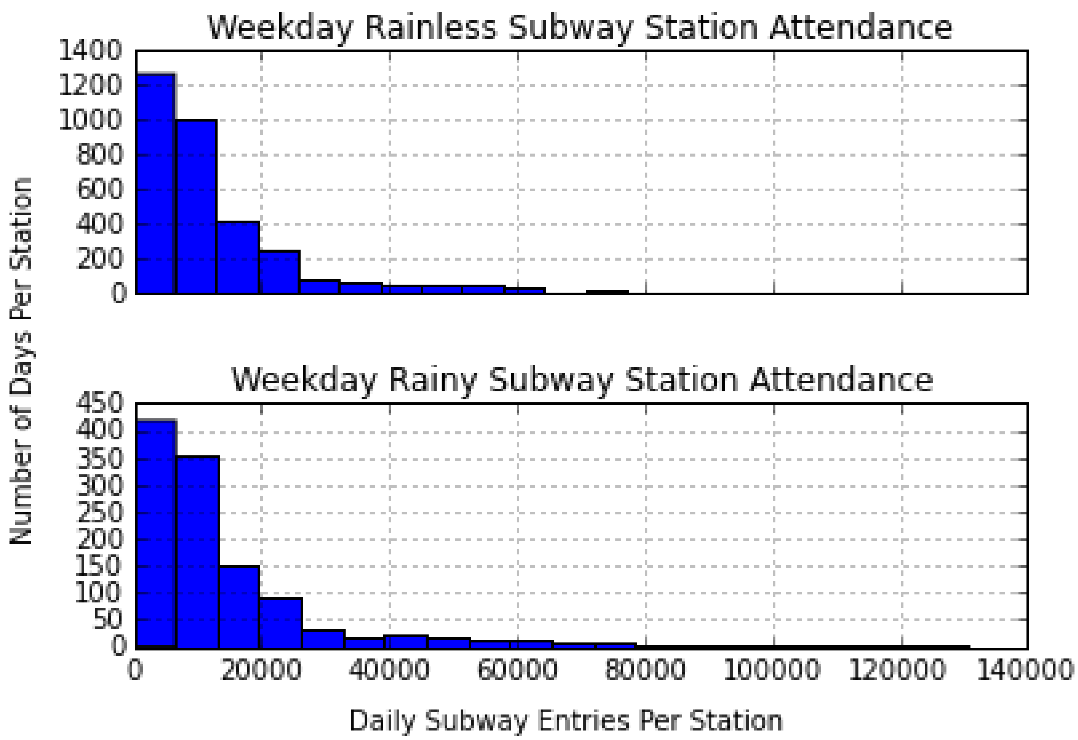
1. Statistical Test

First, check if the data is normal by graphing it.

In [5]:
```
# Monday is 0, ... Saturday is 5, Sunday is 6
week_days = df[pd.to_datetime(df['DATEn']).dt.dayofweek < 5]
week_days = week_days[['station', 'DATEn', 'rain', 'ENTRIESn_hourly']]
grouped_days = week_days.groupby(['station', 'DATEn'])

# Add a column, rainy, that annotates if it was rainy at that station at all during that day
```

```
def add_rainy_day(group):
    group['rainy_day'] = 1 in group['rain'].values
    return group

df_with_rainy = grouped_days.apply(add_rainy_day)
by_day = df_with_rainy.groupby(['DATEn', 'station', 'rainy_day'], as_index=False)
by_day = by_day['ENTRIESn_hourly'].sum()

rain = by_day[by_day['rainy_day'] == True]['ENTRIESn_hourly']
no_rain = by_day[by_day['rainy_day'] == False]['ENTRIESn_hourly']
```

In [6]:
```
fig, axes = plt.subplots(2, sharex=True)

no_rain.hist(ax=axes[0], bins=20).set_title('Weekday Rainless Subway Station Attendance')
rain.hist(ax=axes[1], bins=20).set_title('Weekday Rainy Subway Station Attendance')
fig.subplots_adjust(hspace=.45)

# Apply the labels just as text as it isn't obvious how to share a label among two subplots
# Code from http://stackoverflow.com/a/26892326/965648
fig.text(0.5, 0.02, 'Daily Subway Entries Per Station', ha='center')
fig.text(0.02, 0.5, 'Number of Days Per Station', va='center', rotation='vertical')

plt.show()
```



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?

The two-tailed Mann-Whitney U Test is used to compare the two samples. We will use a p-critical value of .05.

Null hypothesis: The hourly entry rate is the same on rainy and non-rainy days. Alternative hypothesis: The hourly entry rate is different on rainy and non-rainy days.

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.

Data is clearly not normal, so the Mann-Whitney U Test was chosen instead of a t-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.

See results below.

```
In [11]: U, p = sp.stats.mannwhitneyu(rain, no_rain)

         print('Mean hourly entries on a rainy day:', rain.mean())
         print('Mean hourly entries on a non-rainy day:', no_rain.mean())
         print('U statistic:', U)
         print('p-value:', p)
```

```
Mean hourly entries on a rainy day: 15091.9598291
Mean hourly entries on a non-rainy day: 14280.8696556
U statistic: 1914829.0
p-value: 0.0754622901355
```

1.4 What is the significance and interpretation of these results?

Due to the P value of 7.5%, we fail to reject the null.

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

Statsmodel OLS through the Pandas interface.

```
In [12]: # Produce a dataset that groups all of the entries at a particular time together
         # This way, the station/unit isn't considered

         total_hourly_entries = \
             df.groupby(['weekday', 'hour', 'rain'], as_index=False)[['ENTRIESn_hourly']].mean()

         y = total_hourly_entries['ENTRIESn_hourly']
         x = total_hourly_entries[['hour', 'weekday', 'rain']]
         # This is just statsmodel OLS, but we use the pandas interface to it
         print(pd.stats.ols.OLS(y, x))
```

```
-------------------------Summary of Regression Analysis-------------------------

Formula: Y ~ <hour> + <weekday> + <rain> + <intercept>

Number of Observations:         24
Number of Degrees of Freedom:   4

R-squared:         0.5588
Adj R-squared:     0.4926
```

```
Rmse:            844.0648

F-stat (3, 20):     8.4422, p-value:     0.0008

Degrees of Freedom: model 3, resid 20

-----------------------Summary of Estimated Coefficients------------------------
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
          hour   101.2211    25.2213       4.01     0.0007    51.7874   150.6547
       weekday  1046.1914   344.5880       3.04     0.0065   370.7989  1721.5838
          rain   -15.4076   344.5880      -0.04     0.9648  -690.8001   659.9848
     intercept   108.0618   390.7261       0.28     0.7850  -657.7613   873.8848
---------------------------------End of Summary---------------------------------
```

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

Input variables were weekday, hour, and rain. Rain was a dummy variable.

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.

The regression was done using hour, weekday, and rain as independent variables. Hour and weekday were chosen as habit and routine are the most likely significant driver of subway usage. Rain was included as it was relevant to the assignment.

2.4 What are the coefficients (or weights) of the non-dummy features in your linear regression model?

The hour coefficient was 101.2211 and the weekday coefficient was 1046.1914

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

The R2 value is 0.5588.

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?

The above ordinary least squares analysis shows that 55.2% of the variance in the global hourly subway entries is explained by the hour and if it is a weekday. This suggests a good relationship between if it is weekday, the time of day, and the number of people that enter the subway in New York City at that time.

3. Visualization

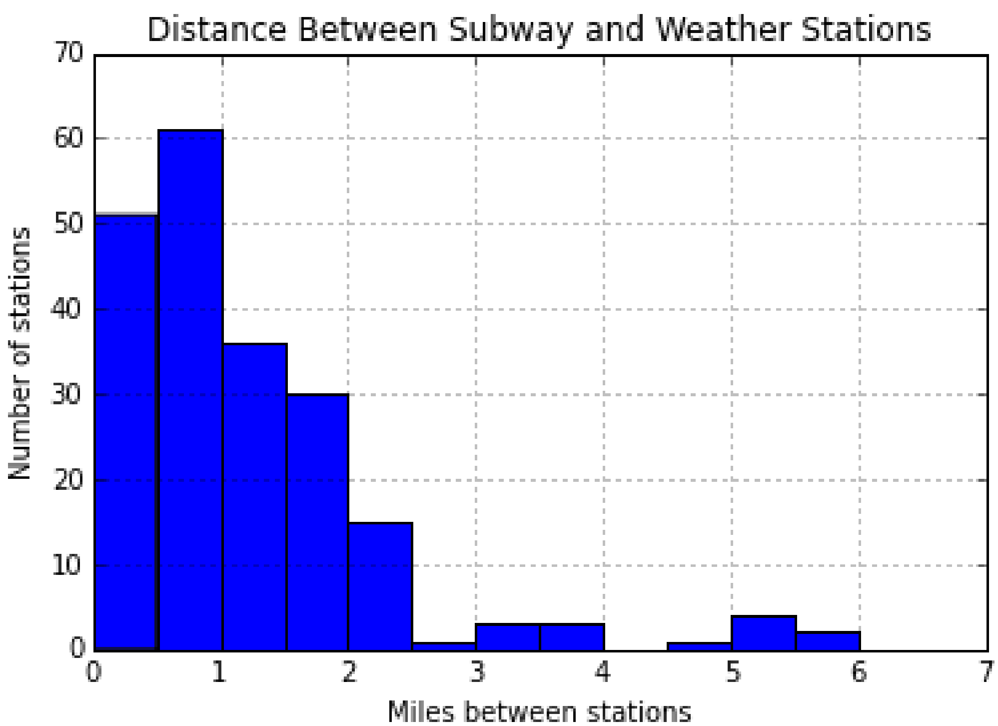
3.1 One visualization should contain two histograms: one of ENTRIESn_hourly for rainy days and one of ENTRIESn_hourly for non-rainy days.

This was included above. It was used to justify the Mann-Whitney U Test, so it was more appropriate in that section.

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

In [9]:
```
# Our goal is to show how close the weather stations are to the subway stations that they provi
# weather data for. To do this, we use the latitude and longitude of each to determine where th
# on the Earth. From these points, we use the Haversine formula to calculate the distance. Whil
# formula assumes the Earth is a sphere, it should be more than good enough for our purposes

# Formula from http://en.wikipedia.org/wiki/Haversine_formula
```

```python
# Implementation my own
def haversine(radius, lat1, lat2, lon1, lon2):
    """Haversine formula. All angle variables are in radians"""
    inner = np.sqrt(np.sin((lat2 - lat1)/2)**2
                    + (np.cos(lat1) * np.cos(lat2) * np.sin((lon2 - lon1)/2)**2))
    return 2 * radius * np.arcsin(inner)

# This function was tested by plugging some values into this and
# comparing with Google Maps walking distance
def earth_distance(row):
    """Variables are GPS coordinates"""
    # Average Earth radius
    EARTH_RADIUS_MILES = 3959
    return haversine(EARTH_RADIUS_MILES, *np.deg2rad(row))

coords = df.groupby('station')[['latitude', 'weather_lat', 'longitude', 'weather_lon']]
per_station_coords = coords.last()
per_station_coords['dist'] = \
    np.apply_along_axis(earth_distance, 1, per_station_coords.values)

axis = per_station_coords['dist'].hist(bins=np.arange(0, 7, .5))
axis.set_xlabel('Miles between stations')
axis.set_ylabel('Number of stations')
axis.set_title('Distance Between Subway and Weather Stations')
None
```



The above visualization shows the distance between the weather station and the subway station it provides data for. Large distances suggest the weather data is not as representative of the actual weather near the subway station. Luckily, all of the weather stations are within 6 miles, with the vast majority being within 2.5 miles.

```
In [10]: # These calculations are used in the sections below
         coord_list = per_station_coords[['latitude', 'longitude']].values
         max_dist = max([earth_distance([x[0], y[0], x[1], y[1]])
                         for x in coord_list for y in coord_list])
         print("Maximum distance between two stations: {:.2f} miles".format(max_dist))

         has_data = not df[(df['station'] == 'CYPRESS HILLS')
                           & (df['datetime'] == '5/6/11 8:00')].empty
         print("Exists data for Cypress Hills at 5/6/11 8:00am: {}".format(has_data))
```

```
Maximum distance between two stations: 22.01 miles
Exists data for Cypress Hills at 5/6/11 8:00am: False
```

4. Conclusion

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?

It does not appear that there is a statistically significant relationship between rain and subway ridership.

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.

The Mann-Whitney U Test between means had a p-value of 7.5%, which is too high to be significant. Mann-Whitney U Test performed compared the mean weekday daily ridership between stations. However, this is sensitive to noise. If a busy station had a couple of rainy days, the rainy mean could be brought up significantly. The effect of this could be reduced if more than a month of data was used.

The ordinary least squares regression also suggested against rain being a factor. It only appeared to impact global daily ridership by about 16 people, as the coefficient was -15.4. The p-value was also very high, suggesting that -15.4 was just noise.

5. Reflection

5.1 Please discuss potential shortcomings of the methods of your analysis, including: Dataset, Analysis, such as the linear regression model or statistical test.

The dataset used is only from the month of May in 2011. One month is not a lot of data, a couple of baseball games could throw off these numbers significantly. This is the largest weakness of this dataset. More data across a larger frame would greatly increase its usefulness.

There also appears to be missing data points. For example, Cypress Hills doesn't have any value at 5/6/11 at 8:00am. This throws off calculations like per-station daily values that were used in the above analysis.

The analysis methods used were powerful but rudimentary. The dependent variables were picked based on a hunch. Only linear relationships between variables were considered. More complicated relationships likely exist. An r-squared value of .56 is good, but a better value is almost certainly achievable.