Project 1: Analyzing the NYC Subway Data Set

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0. References

http://matplotlib.org/1.3.0/examples/pylab_examples/histogram_demo_extended.html

http://stackoverflow.com/questions/6986986/bin-size-in-matplotlib-histogram

http://discussions.udacity.com/t/project-1-section-3-1-creating-2-histograms-for-entries-on-rainy-days-vs-non-rainy-days/18027/3

http://stackoverflow.com/questions/2849286/python-matplotlib-subplot-how-to-set-the-axis-range

https://pypi.python.org/pypi/ggplot/

http://matplotlib.org/examples/statistics/histogram_demo_multihist.html

http://stackoverflow.com/questions/29268134/how-to-merge-rows-in-dataframe-according-to-unique-elements-and-get-averages?rq=1 (to find average entries by hour)

http://discussions.udacity.com/t/written-project-should-be-based-on-results-obtained-in-problem-sets-1-5/17878

http://blog.minitab.com/blog/adventures-in-statistics/regression-analysis-how-do-i-interpret-r-squared-and-assess-the-goodness-of-fit

An Introduction to Statistical Learning with Applications in R, by Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani

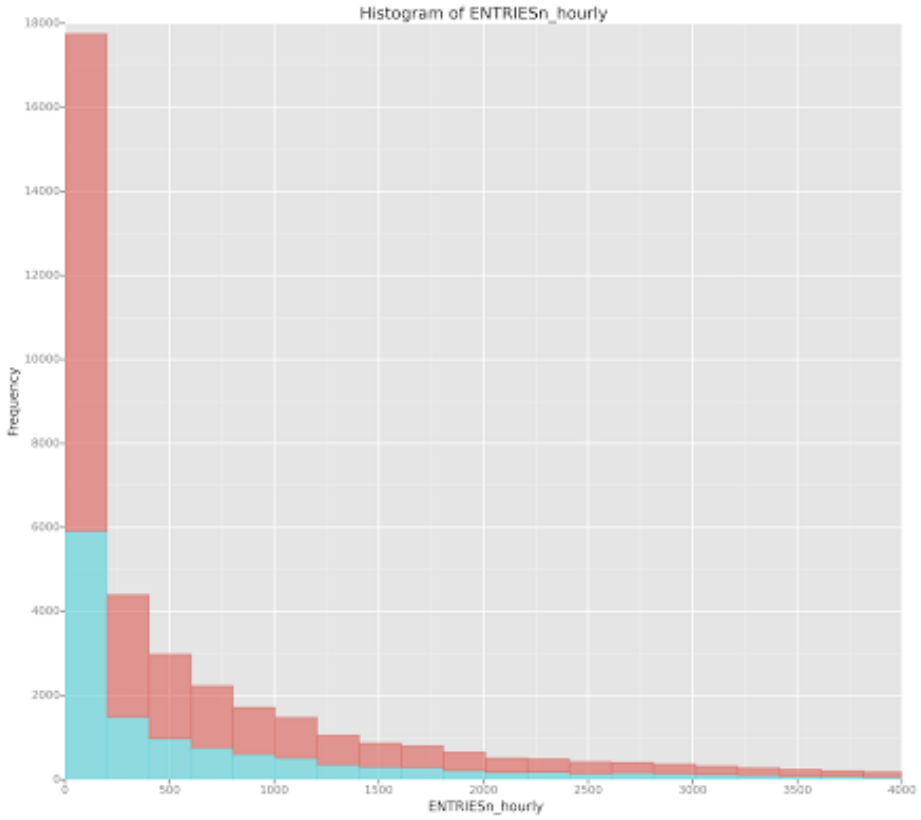
1. Statistical Test

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?**

I used the Mann Whitney U-test to analyze the NYC subway data on the original data set. I used a two-tail P value as we are only checking for change in ridership caused by rain and cannot assume before-hand that it will increase or decrease. My null hypothesis is that, both the distributions (rainy day ridership and non rainy day ridership) are from the same population. In other words, mean ridership of the NYC subway remains the same on rainy days and non-rainy days. The p-critical value is 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.**

When we charted out the ridership data ('ENTRIESn_hourly' for Raining vs Non Rainy days) we saw that the data was not normally distributed hence we cannot use the Welch's t-test which assumes normal distribution.



Code used to generate the above histogram:

```
plot = ggplot(turnstile_weather,
aes(x='ENTRIESn_hourly',colour='rain',fill='rain' )) + \
```

```
geom_histogram(binwidth=200, alpha=0.6) + \
ggtitle('Histogram of ENTRIESn_hourly') + \
xlim(0, 4000) + xlab('ENTRIESn_hourly') + ylab('Frequency')
```

It should be noted that just because non-rainy day's frequency of ridership is more in the above histogram, we cannot conclude that people use the subway more on non-rainy days. When we look at the actual data we can see that there are more non-rainy days overall. We will also see later that the mean of rainy days ridership is more than non-rainy day's ridership.

I also did the Shapiro-Wilk test to find out if the two distributions were Gaussian. The null hypothesis was that the data is drawn from a normal distribution. For both the distributions I got a P value of 0.0 and thus rejected the null hypothesis.

The Mann Whitney U-test is a non-parametric test which can be used on distributions that are not normal.

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.**
Using the code in problem set 3.3 we got:

Mean ridership on rainy day	1105.45
Mean ridership on non-rainy day	1090.28
P value (one-tail)	0.024999912793489721 ~ 0.025
P value (two-tail)	0.049999825586979442 ~ 0.05

1.4. **What is the significance and interpretation of these results?**
If we do not round up the two-tail p value it is less than our threshold of 0.05. So we reject the null hypothesis that the distributions are from the same population. We accept the alternate hypothesis that the distributions are from two different populations. In other words they are statistically different and that rain actually does have an effect on ridership. We can also see that the mean ridership on rainy days is more than on non-rainy days

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? Gradient descent, OLS or something else?**
I used gradient descent to compute the coefficients theta and produce prediction for ENTRIESn_hourly in my regression model as implemented in exercise 3.5

2.2. **What features (input variables) did you use in your model? Did you use any dummy variables as part of your features?**
I used *'rain', 'precipi', 'Hour', 'meantempi', 'fog', 'meanwindspdi'* as features in my model. I used 'UNIT' as my dummy variables as it's a categorical 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.**

From the Mann Whitney U-test I performed I chose the above features based on intuition and also by trial and error by looking at their effect on R^2

- 'rain' this is the factor which is part of our null hypothesis so it was natural to select this. Also I assumed that on a rainy day people would be more prone to use the subway instead of being stuck in traffic jams and for safety. I know I would!
- 'precipi' was included because if it's just a drizzle then it may not affect people's choice of whether to use the subway but if it's raining heavily that may affect ridership.
- 'Hour' is a feature because there are peak usage hours during the day – morning rush to offices and evening rush back home as we will see in our visualization below.
- 'fog' obviously impacts visibility and as opposed to being in a car, the subway has its fixed tracks and routes and is much safer. Hence this might also influence people's choice.
- 'meanwindtspi' gave a slight improvement to the R^2 value. My intuition behind this was that on a very windy day people may also choose not to use cars. Since I saw a positive effect after adding it, I left it as a feature
- 'UNIT' also is important because certain stations may have more entries than others because of location. When we remove UNIT we can see that R^2 really goes down. It is used as a dummy variable because we can't do any numerical calculations on this – it's a categorical variable.

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

Coefficients of non-dummy features

Feature	Coefficient
'rain'	-1.01382395e+01
'precipi'	-2.48062493e+01
'Hour'	4.68435930e+02
'meantempi'	-5.37848030e+01
'fog'	7.31131541e+01
'meanwindspdi'	6.40183862e+01

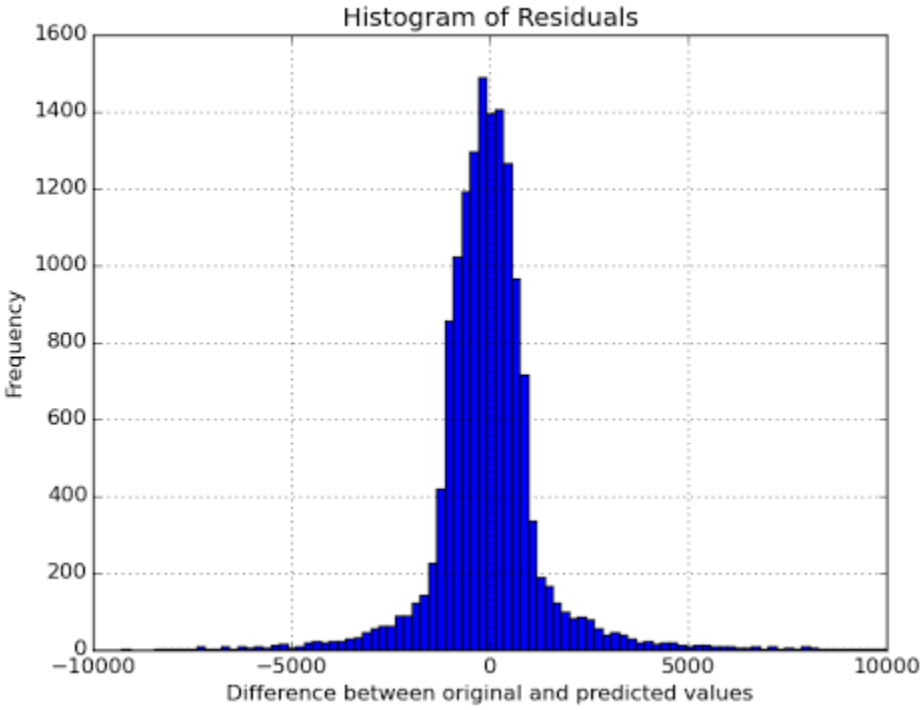
2.5 What is your model's R^2 (coefficients of determination) value?

My R^2 value is 0.465094157151

2.6 What does this R^2 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 R^2 value?

Our R^2 value means that 46.5% of the variation in the value of my dependent variable, ENTRIESn_hourly, is explained by the variation in my features. However when we look at the histogram plot of the residuals (problem set 3.6) we can see a non-linear pattern. The long tails on either side means our regression model is highly over- or under-estimating our predicted values.

This pronounced non-linear pattern cannot be modeled accurately using linear regression.



Code for histogram

```
plt.figure()
(turnstile_weather['ENTRIESn_hourly'] - predictions).hist(bins=200)
plt.xlabel('Difference between original and predicted values')
plt.ylabel('Frequency')
plt.title('Histogram of Residuals')
plt.xlim([-10000,10000])
```

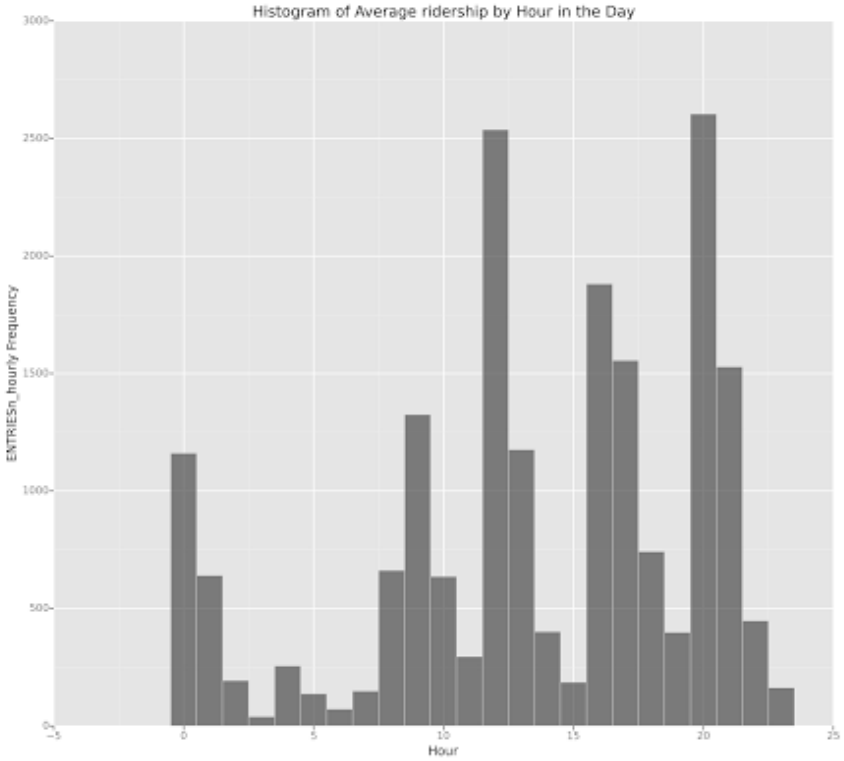
3 Visualization

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

Histogram for ENTRIESn_hourly is shown in Section 1.2

3.2 One visualization can be more freeform.

Free form plot average ridership by time-of-day



We can see that there are peak hours during noon and evening. It could be people going out for lunch or for other personal activities during lunch break (and leaving their cars). We see a peak around 8pm which isn't really the time when people are leaving office so it could be people going out for leisure activities in the evening. Looks like time of the day also affects ridership volume.

```
df2 =   turnstile_weather.groupby(['Hour'])['ENTRIESn_hourly'].mean().reset_index()
plot = ggplot(df2, aes(x='Hour', y='ENTRIESn_hourly')) + \
geom_bar(alpha=0.60, stat='bar') + \
ggtitle('Histogram of Average ridership by Hour in the Day') + \
xlab('Hour') + ylab('ENTRIESn_hourly Frequency')
```

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?

Statistically the Mann Whitney U-Test result of 0.049 shows that the two distributions are from a different population – that there is more ridership on a rainy day versus on non-rainy days. But the p-value is very close to our p-critical value of 0.05 and our r~2 is only 0.465 (the closer it is to 1 the better fit it is). So we cannot definitely conclude that rainy days have more 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.

If we look at the difference in mean of ridership on rainy vs non rainy days there is only a difference of about 15 people per hour, which is around a 1% difference. In real world that's really not a lot. In our regression model too, keeping all the features I selected above, I played around with 'rain' and 'percipi' and removing them didn't make a significant change to the regression value.

I moved rain to a dummy variable too as its either raining or not and used precipitation as a feature and we can numerically measure the amount of rain through this. The extremely minor change to the r^2 value means we cannot confidently conclude that rain is causing any effect whatsoever at all. The biggest change in r^2 value was obtained by UNIT as a dummy variable which means that certain UNITs have more ridership than others.

r^2	Rain/percipi
0.465083550449	without rain/with percipi as feature
0.464964580824	without rain /without percipi as features
0.465021310938	with rain as a dummy variable / no percipi as feature

5 Reflection

5.1 Please discuss potential shortcomings of the methods of your analysis, including: Dataset, Linear regression model or statistical test

The features I selected may have correlation example a very rainy day may also be very windy and may have low temperatures. There may be a lot of other variables that influence ridership which weren't available in the data. Weather conditions also very by the hour. It could also be that during a rainy day more people prefer to stay home for safety but the percentage of ridership (based on mean) is higher. Other events like public holidays, parades, election-day, summer holidays, weekends, fuel costs, car taxes etc. may also influence the choice to opt for or against the subway.

We also have data for only one month which isn't a long enough interval to make any serious conclusions.

When we fit a linear regression model to a particular data set, many problems may occur. Most common among these are the following:

1. Non-linearity of the response-predictor relationships.
2. Correlation of error terms.
3. Non-constant variance of error terms.
4. Outliers.
5. High-leverage points.
6. Collinearity.

As we saw in 3.6 we do have the issue of non-linearity when we look at our residuals chart. This could mean that the error values associated with our predicted value are very high.