Analyzing the NYC Subway Dataset

Overview

In this analysis, I am taking data from May 2011 NYC MTA Subway as provided in the Udacity 'Introduction to Data Science' class and testing the hypothesis that whether rainy days impacts ridership based on problem sets 2 to 5.

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?

The NYC subway data was analyzed with the Mann-Whitney U-Test. A two-tail p-value was used as no prior assumptions are made about the contrast in the distributions of ridership on rainy and non-rainy days.
The p-value returned by scipy.stats.mannwhitneyu is one-tailed as noted here:

http://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.stats.mannwhitneyu.html

In order to use a two-tailed test, the one-tailed p-value returned by scipy.stats.mannwhitneyu must be multiplied by 2.

The p-critical value used was 0.05 (i.e. 5% chance of observing a result as least as extreme).

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.

The question being asked is whether subway ridership varies with the weather. The provided dataset allows hourly entries to MTA turnstiles to be spliced into two different samples, entries with and without rain. The Mann-Whitney U-Test tests the null hypothesis that the two samples being compared are derived from the same population. This null hypothesis allows us to test whether there is a statistically significant difference in ridership on rainy and non-rainy days (i.e., are the hourly entries derived from the same population).

Furthermore, exploratory data analysis (see Section 3.1) has shown that the data is not normally distributed. The Mann-Whitney U-Test does not assume normality of the data, making this test appropriate.

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.

The numerical results of the Mann-Whitney U-Test are the following:

Mean entries, with rain	Mean entries, without rain	Mann-Whitney Test Statistic	two-tailed p-value
1105.44637675	1090.27878015	1924409167.0	0.0249999127935

1.4 What is the significance and interpretation of these results?

```
# Significance level defined in Section 1.1
alpha = 0.05

# two-tailed test
if (p * 2) < alpha:
    print 'Reject the null hypothesis'
else:
    print 'Fail to reject null hypothesis'
```

Reject the null hypothesis

With this small p-value, we reject the null hypothesis of the Mann-Whitney U-Test. In other words, the distribution of the number of entries is statistically different between rainy and non-rainy days.

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?

a. **Gradient descent (as implemented in exercise 3.5)**
b. **OLS using Statsmodels**
c. **Or something different?**

Ordinary Least Squares (OLS) is chosen to solve the linear regression model. The normal equation is implemented directly without the use of the Statsmodel package.

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

The following features are taken directly from the turnstile_master dataset:

- rain
- fog
- Hour
- Meantempi

```
# select features
features = turnstile_master[['rain', 'fog', 'Hour', 'meantempi']]
```

The following features are created by transforming data:

- precipi – The square root of the 'precipi' field in the turnstile_master dataset

```
# needed to prevent warning about chained assignment
features.is_copy = False

# create polynomial features
features['precipi'] = turnstile_master['precipi']**0.5
```

Dummy variables are used to include categorical data as features in a linear model. **The dummy variables include:**

- **UNIT** - Taken directly from the turnstile_master dataset
- **weekday** - The day of the week as an integer [0:6] (Monday = 0, Tuesday = 1, …)

ref - https://docs.python.org/2/library/datetime.html#datetime.datetime.weekday

```
# UNIT
dummy_units = pd.get_dummies(turnstile_master['UNIT'], prefix='unit')
features = features.join(dummy_units)

# weekday
from datetime import datetime

# use lambda function to get weekday from 'DATEn' field
f = lambda x: datetime.strptime(x, "%Y-%m-%d").weekday()

dummy_units = pd.get_dummies(turnstile_master['DATEn'].apply(f), prefix='w
eekday')
features = features.join(dummy_units)
```

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 R^2 value."**

meantempi is chosen as a feature as temperature is a component of the weather that affects people's decision making. A given temperature may affect how long and how much effort it takes to clothe in the morning. A person may simply choose to stay indoors due to discomfort with a given temperature.

Hour and weekday features were chosen as it is easily observed how ridership varies with time of day and day of week. A phenomenon supporting the Hour feature is the daily rush hours that mass transit systems and roadways exhibit and accommodate. An observation supporting the use of weekday is how the MTA train schedule varies between weekdays and weekends, with trains arriving with more infrequency on Saturday and Sunday.

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

- Rain: 0.14
- Fog: 0.17
- Hour: 0.017
- Meantempi: 0.0051

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

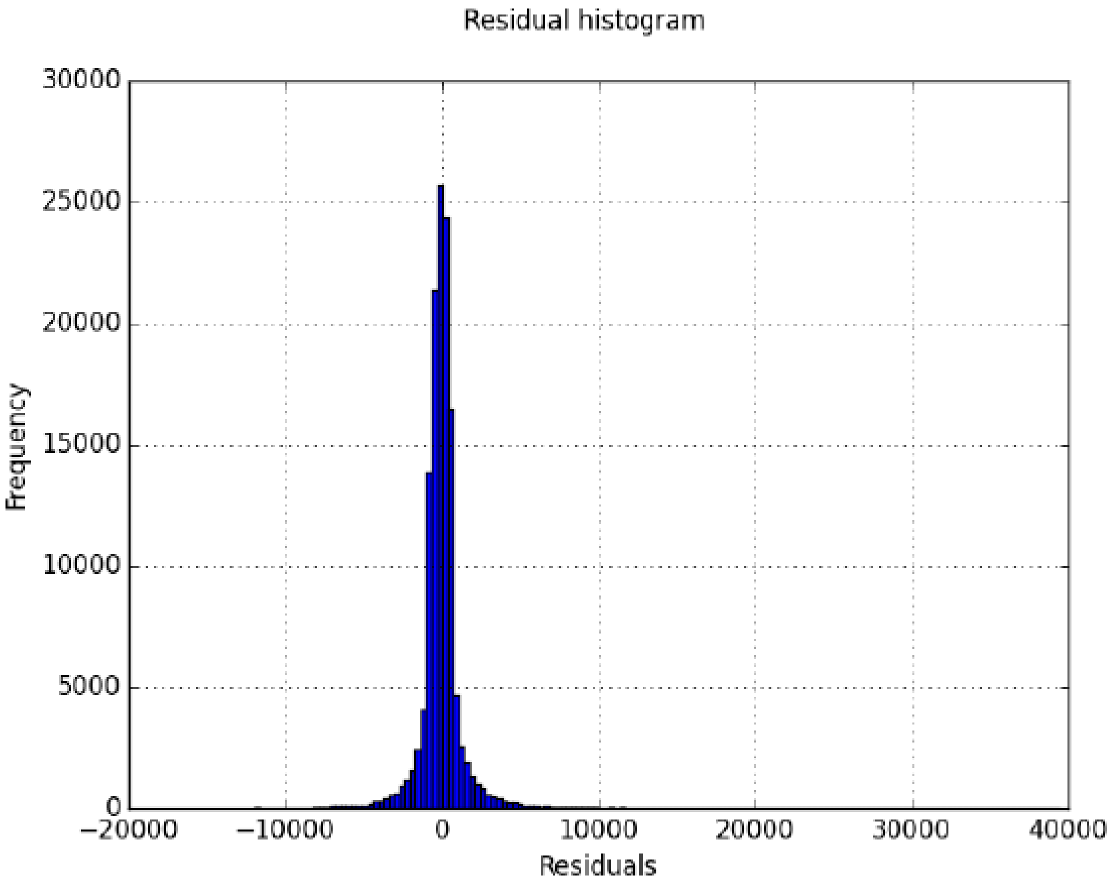
The R^2 of the model is 0.470491013765

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?

R-squared (R^2) is essentially the percentage of variance that is explained, and is a quantitative measure of the "goodness of fit". While it only explains 47% of variation, I think a better metric is to plot the residuals. (Figure below)

To decisively conclude whether or not this model was a good fit certainly depends on the context and use case for the prediction data. If this were a use case that had safety and security concerns, it would certainly be insufficient! The residual plot shows that most of the residuals were close to 0 +/- 5,000. Qualitatively, and for the objective of being able to "ballpark" ridership, the liner model is sufficient.

Further and advance study could include more features or utilize polynomial regressions. However, this might lead to significant over-fitting, and the model may fail on new data sets. In that case, regularization would be a good method to attenuate any over-fitting.

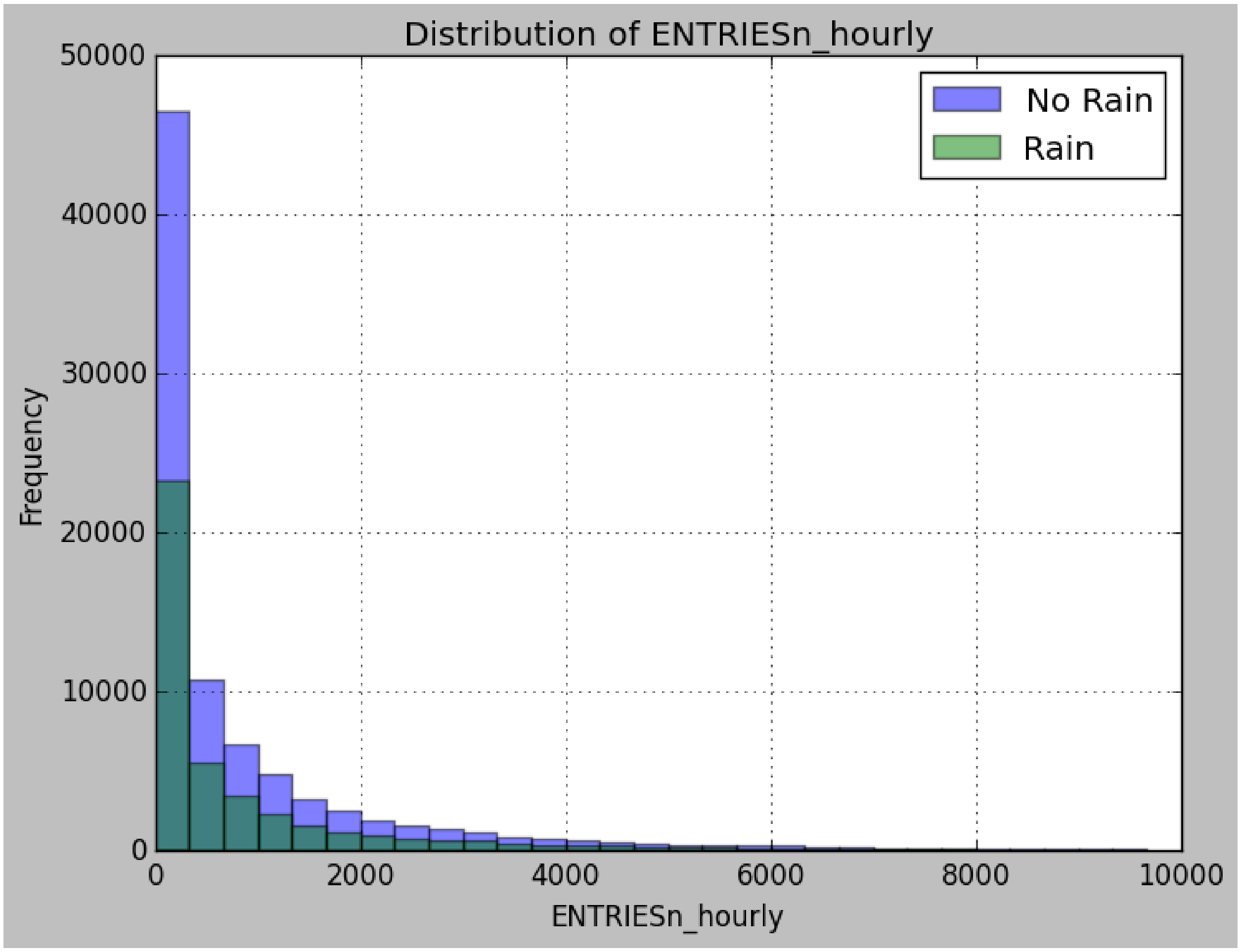


R-squared (R^2) statistic, some of its limitations, and uncover some surprises along the way. For instance, low R-squared values are not always bad and high R-squared values are not always good!

Section-3: Visualization

Please include two visualizations that show the relationships between two or more variables in the NYC subway data. You should feel free to implement something that we discussed in class (e.g., scatter plots, line plots, or histograms) or attempt to implement something more advanced if you'd like.

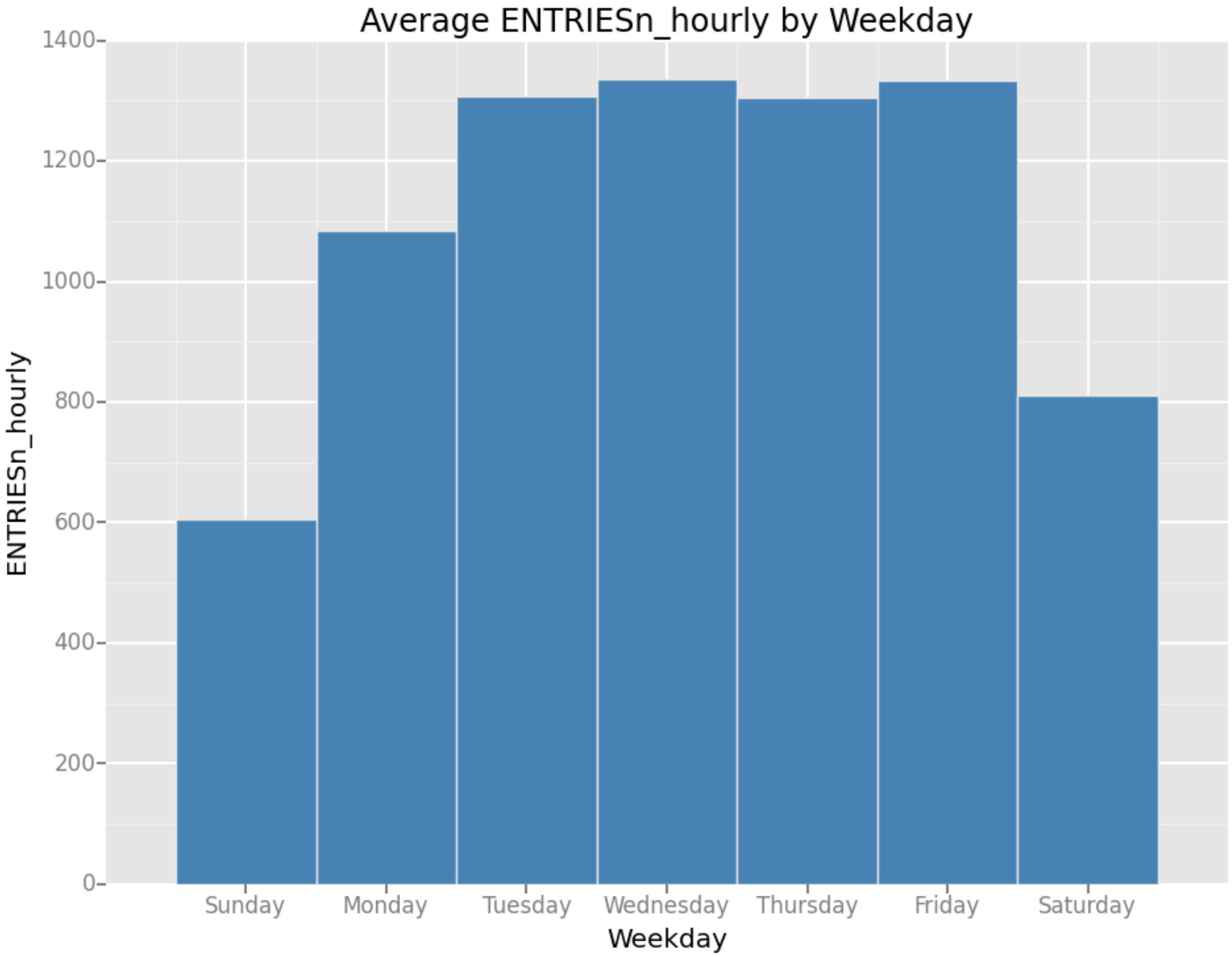
3.1 One visualization should contain two histograms: one of ENTRIESn_hourly for rainy days and one of ENTRIESn_hourly for non-rainy days.



The distribution of ENTRIESn_hourly appears to not be normally distributed and skewed to the right on both rainy and non-rainy days. The mode appears to be within the smallest bin for both distributions. There are far fewer observations on rainy days than non-rainy days.

3.2 One visualization can be more freeform.

Average Hourly Ridership by Day of Week



The above bar chart shows the average hourly ridership by day of week. The sum of ENTRIESn_hourly by day of week was divided by the count of rows for a given day of week (as each row represents an hour’s worth of data). The bar chart shows that the average hourly ridership is higher on weekdays than weekends, with Saturday seeing significantly higher ridership than Sunday. It appears that the average hourly ridership on Monday is significantly different than the rest of the weekdays. This may be due to a seasonal effect of Monday holidays. The given data set is a sample from May 2011. There is at least one major holiday that falls on Monday in the month of May: Memorial Day.

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?

Based on this analysis, I believe that more people ride the NYC subway when it is raining.

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 consider the regression results it remains unclear if rain and ridership have a linear relationship. The model that we have created, with a coefficient of determination of ~47%, seems rather insufficient to prove that weather has any correlation with ridership. But if we take a look at Figure in section 3.1, we can observe that there is a small correlation.

As seen in Section 1.3, the mean of ENTRIESn_hourly is greater for hours with rain than without (1,105 vs. 1,090). Additionally, a Mann-Whitney U-Test shows that the ENTRIESn_hourly sample with rain appears to be drawn from a different distribution (or population) than the ENTRIESn_hourly sample from hours without rain.

Thus, although this does not prove that rain causes more entries. It proves that on rainy hours, there is a higher chance of entries. **It is conscientious to claim that rain increases subway ridership.**

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:

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

Sample size- The data set provided contains only one month of MTA data. This smaller data set is subject to effects of seasonality, as the time of year may also affect ridership.

If the provided data was from different months or years, we could see if May was a typical month or perhaps there is some sort of seasonality (Monday holiday, which appears to have an effect on the data in the visualizations in Section 3.2 and Section 4). May be ridership is higher in the winter as opposed to the summer when people are on vacation and the weather is sunny outside.

Other weather conditions- this analysis only considers rainy and non-rainy condition, but other weather may also impact ridership.

The largest shortcoming I see with this data set is that it appears that the MTA component of the data is produced on an hourly basis, but it is joined to daily weather data. For example, if it rained at any point in a given day, every hour of that day will reflect that it rained. This prevents a truly granular analysis of how the weather can affect ridership within a day.

One immediate red flag that was presented while exploring the data was that there were more 'entries' than there were 'exits'. The only logical explanations could be that there were miscounts, or some turnstiles/stations were not included in the data set. Presumably, this would have had an equivalent effect on both rain and no-rain data sets, so for the purposes of this study, it likely had little to no effect.

A combination of increased sample size (larger data set) and normalization by location/turnstile ID could have potentially increased the confidence of both the Mann-Whitney U test and the linear regression model. As we saw from examining the 'UNIT' column, ridership varied greatly. Simply put, some stations and turnstiles were naturally more active than others. The Mann-Whitney U test did not take this into account, and only looked at the subway entry distributions for rain and no-rain. Examining how the same stations at the same day and time varied by rain could have increased the fidelity of the test.

The linear regression model was adequate for the purpose of the study, but could certainly have been improved. It's possible that the region of study had a linear relationship, but it is still an assumption and simplification. Considering the extreme, subway ridership certainly has an asymptotic limit; only so many riders can get on the subways!

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

I think that an interesting investigation would be to use gradient descent with logistics regression to see if one might be able to predict if it rained or not given various parameters, to include turnstile location/ID, time of day and subway entries. Intuitively, this might produce false positives or negatives on special days (e.g. holidays, city events, marathon runs, etc).

REFERENCES

- Welch's t-test
  http://en.wikipedia.org/wiki/Welch%27s_t_test

- Mann-Whitney test
  http://www.real-statistics.com/non-parametric-tests/mann-whitney-test/
  http://ocw.umb.edu/psychology/psych-270/other-materials/RelativeResourceManager.pdf
  http://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.mannwhitneyu.html

- R2 - linear regression
  http://www.graphpad.com/guides/prism/6/curve-fitting/index.htm?r2_ameasureofgoodness_of_fitoflinearregression.htm