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, 4, and 5 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

Please include a list of references you have used for this project. Please be specific - for example, instead of including a general website such as stackoverflow.com, try to include a specific topic from Stackoverflow that you have found useful.

Section 1: Statistical Test

I used this book as a general reference on statistical methodology:
Herbert Basler: Grundbegriffe der Wahrscheinlichkeitsrechnung und Statistischen Methodenlehre, Physica Verlag, 11. Auflage
Mainly Chapter 3, especially 3.4.2 (t-test) and 3.4.5 (Mann Whitney U-test)

On z-transformation:

http://de.wikipedia.org/wiki/Studentisierung

why chose a significance level of 0.05:

http://www.p-value.info/2013/01/whats-significance-of-005-significance_6.html

http://www.radford.edu/~jaspelme/611/Spring-2007/Cowles-n-Davis_Am-Psyc_orignis-of-05-level.pdf

Interpretation of p-value:

http://stats.stackexchange.com/questions/46856/interpretation-of-p-value-in-hypothesis-testing/46858#46858

Section 2: Linear Regression

Plotting residuals

http://www.itl.nist.gov/div898/handbook/pri/section2/pri24.htm

http://matplotlib.org/users/pyplot_tutorial.html

http://matplotlib.org/api/pyplot_api.html#matplotlib.pyplot.hist

computing R^2
http://docs.scipy.org/doc/numpy/reference/generated/numpy.mean.html

http://docs.scipy.org/doc/numpy/reference/generated/numpy.sum.html

http://en.wikipedia.org/wiki/Gradient_descent

http://en.wikipedia.org/wiki/Coefficient_of_determination

Correlation matrix to find out the best candidates for linear regression:

http://pythonprogramming.net/pandas-statistics-correlation-tables-how-to/

http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.corr.html

Interpretation of R^2
http://blog.minitab.com/blog/adventures-in-statistics/regression-analysis-how-do-i-interpret-r-squared-and-assess-the-goodness-of-fit
http://people.duke.edu/~rnau/rsquared.htm

Section 3: Visualization
Introduction and overview with good examples:
http://opr.princeton.edu/workshops/201501/ggplot2Jan2014DawnKoffman.pdf

overview on existing geoms:
http://docs.ggplot2.org/current/
http://cran.r-project.org/web/packages/ggplot2/ggplot2.pdf

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?

I used the Mann Whitney U-test to find out if there is a significant difference between the number of riders with rain versus the number of riders without rain.

The Mann Whitney U-test assumes that two input variables x and y follow the same distribution with the only difference that there is a lag between them named a: Fy(x) = Fx(x-a). The null-hypothesis states that a = 0, i.e. there is no difference in the variables.

Transferred to our question here: the null-hypothesis says that there is no difference between the number of riders with rain and without rain.

I used the two-tail p-value, because the question in test aims at differences in both directions, there could as well be more riders or less riders when it rains. In the one sided version the p-value would have been halved.

I choose a significance value of 0.05. There is no deterministic reason to pick exactly 0.05 but this has established itself as an agreed level of significance following the idea that an event which occurs 5% of the time or less is rare enough to assume that there is a different cause but mere chance behind it.

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.

Welch´s T-Test postulates that the data set follows a normal distribution. But the histogramm has clearly shown that this is not the case. Therefore Welch´s T-Test is not applicable on this set.

However, the histogramm has shown that the Entries at Rain and the Entries at no Rain follow a very similar distribution. This makes it a candidate fort he Mann Whitney U-test (see assumption above in 1.1., second paragraph).

It has to be considered that the number of without rain occurencies is much higher than the number of with rain occurencies. Therefore the test to choose has to be robust against different sample size. This is true for the Mann Whitney U-test. This is why I picked this test for this data set.

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 mean values between with rain and without rain differ by 1105.4 - 1090.3 = 15.1, which means that the average number of riders with rain is about 15.1 higher than the number of riders without rain.

The question is: can this difference be explained by chance or is it a significant difference? This question shall be answered by a statistical test, in this case the Mann-Whitney U-Test.

Executing this test produces the result of p = 0.025 (rounded).

1.4 What is the significance and interpretation of these results?

The result of our test shows a p-value of 0.025. Compared with our alpha-Value of 0.05 we see that p < alpha.

Based on our siginificance level of 0.05 we have to reject the null-hypothesis that there is no difference between the number of riders with rain and without rain. Thinking of 'Fisher's disjunction': Either a rare event has happened or the null hypothesis is false. Following our approach we think that the event is rare enough to reject the null hypothesis.

The result is that significantly more people use the Subway when it rains.

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:

1. Gradient descent (as implemented in exercise 3.5)
2. OLS using Statsmodels
3. Or something different?

I ussed the the Gradient descent approach.

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 the features 'Hour', 'meanwindspdi' and 'mintempi'. The dummy variable "UNIT" was also added.

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.”

I calculated the correlation coefficient for each variable in relation to the variable ENTRIESn_hourly:

(print(turnstile_weather.corr()))

The result:

	correlation coefficient to ENTRIESn_hourly
Hour	0.175430
ENTRIESn_hourly	1.000.000
EXITSn_hourly	0.744316
maxpressurei	-0.017084
maxdewpti	-0.009893
mindewpti	-0.020135
minpressurei	-0.020517
meandewpti	-0.016198
meanpressurei	-0.016128
fog	0.011368
rain	0.003062
meanwindspdi	0.026627
mintempi	-0.029034
meantempi	-0.022796
maxtempi	-0.014303
precipi	0.009665
thunder	NaN

Taking only the absoulute values into account it shows that the two highest values are ENTRIESn_hourly and EXITSn_hourly. This is trivailly true and self evident. It proves that the approach produces correct results but does not reveal any insight.

The next three variables are hour, meanwindspdi and mintempi. Bevore picking this values one should ask if they seem to make sense judging by intuition: Hour makes sense, otherwise there would be no such thing as a rush hour. Mintempi (negatively correlated) makes sense, because people should be likely to prefer the train instead of walking when temperature decreases (at least in New York, there might be a different situation in the desert). What about meanwindspdi? It is positively correlated to the number of entries. The more wind, the more people riding the train? When I think of women being afraid to ruin their hair-do: It makes sense for me.

So the three variables which showed the highest correlation to the entries (without being trivial) made sense according to my intuition. This is why I picked them for my model.

2.4 What are the coefficients (or weights) of the non-dummy features in your linear regression model?
-1.57248270e+02, -1.55110529e+02,   1.21866703e+03

2.5 What is your model's R^2 (coefficients of determination) value?
I calculated an R^2 Value of 0.464610132035.

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?

R^2 is a measure indicating how well a a statistical model fits to the actual data, where 0 is the worst and 1 is the best possible value. So our value of 0.46 looks like a pretty bad result.

Most authors state that a high R^2 does not necessarily mean that the model is good. But a low R^2 value is never an indicator for a good fitting model, even if in some cases the model might still be helpful to get some insight in the data.

So the result is that the elaborated linear model is not appropriate to predict the number of entries based on the chosen features. It does not necessarily mean that there is no linear relationship at all digged in the data.

Section 3. Visualization

Please include two visualizations that show the relationships between two or more variables in the NYC subway data. Remember to add appropriate titles and axes labels to your plots. Also, please add a short description below each figure commenting on the key insights depicted in the figure.
3.1 One visualization should contain two histograms: one of ENTRIESn_hourly for rainy days and one of ENTRIESn_hourly for non-rainy days.

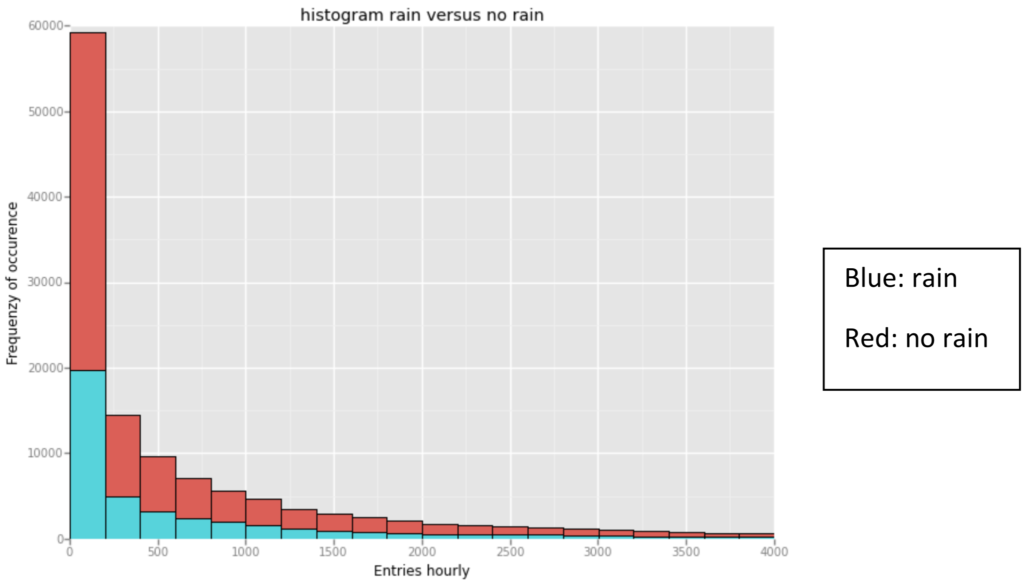
- You can combine the two histograms in a single plot or you can use two separate plots.
- If you decide to use to two separate plots for the two histograms, please ensure that the x-axis limits for both of the plots are identical. It is much easier to compare the two in that case.
- For the histograms, 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.

My solution:

```
plot = ggplot (aes(x='ENTRIESn_hourly', fill = 'rain'), data = df )
plot + stat_bin(binwidth = 200 , color = 'black') \
+ xlim(0, 4000) \
+ ggtitle ("histogram rain versus no rain") \
+ xlab('Entries hourly') \
+ ylab('Frequenzy of occurence')
```

.. creates this plot:



(I could not add an automatic legend in the plot, it seems this feature is not fully implemented in Python.)

This plot shows the hourly entries and their frequenzy of occurence. It can be seen that the frequenzy without rain exceeds the frequenzy with rain for every number of hourly entries, which is not very surprising.

We can further see that the distribution is extremely skewed. The frequenzy of low values with <= 200 entries per hour exceeds the accumulated rest of all entries. This tells us that far most of the overall traffic volume takes place as a „base load“ with a low number of passengers entering the train at a time.

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

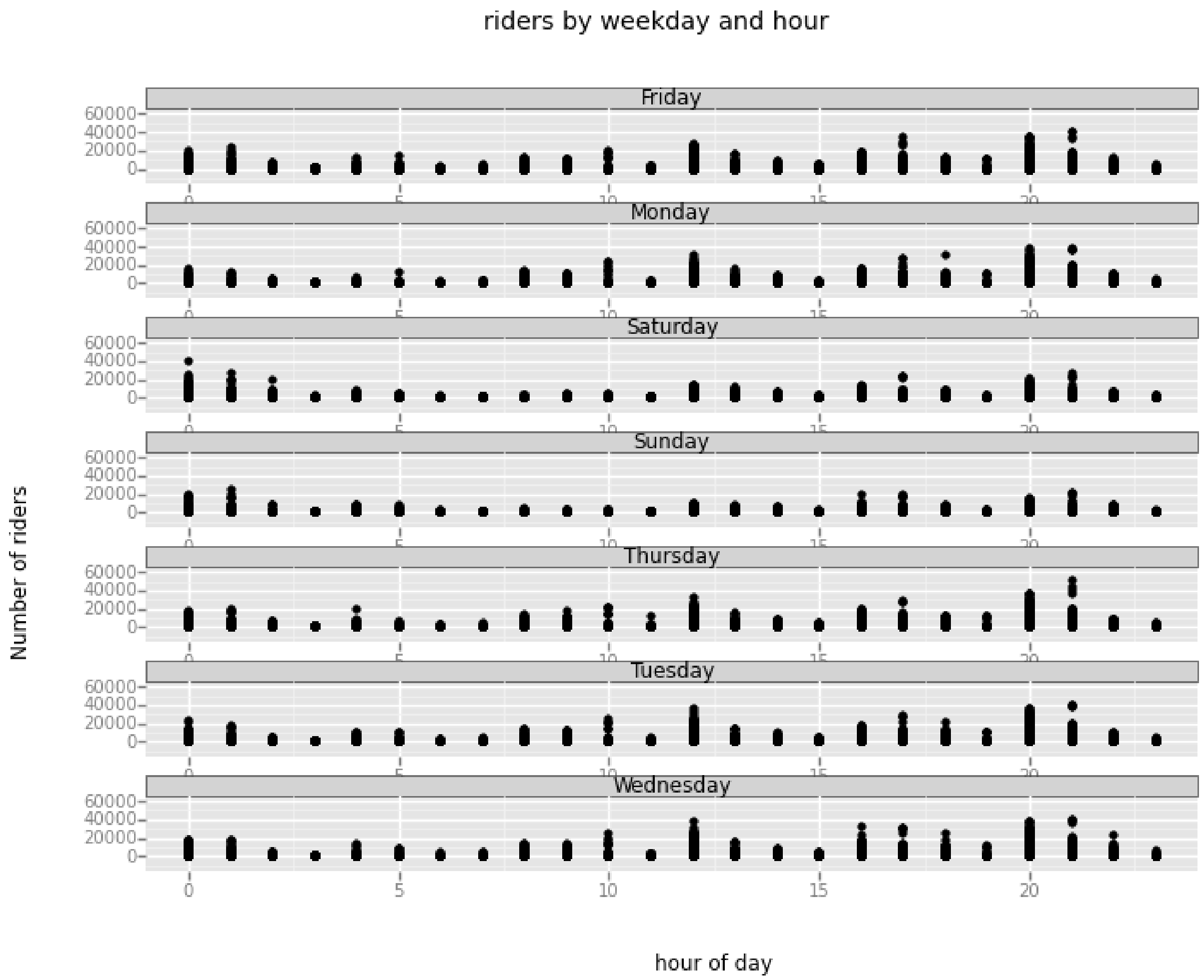
After adding the weekday to the data set:

```
from datetime import datetime
df['Weekday'] = map(lambda dat: datetime.strftime(datetime.strptime(dat, '%Y-%m-%d'), '%A'), df['DATEn'])
```

.. I used the following code:

```
p = ggplot(aes(x='Hour', y='ENTRIESn_hourly'), data=df)
p + geom_point() + facet_grid('Weekday') \
+ xlim(-1, 24) \
+ ggtitle ("riders by weekday and hour") \
+ xlab('hour of day') \
+ ylab('Number of riders')
```

.. to generate this plot:



This plot provides insight in the distribution by time of day as well es weekday. The idea is not to look at the exact values but to get an idea of the patterns the data contains. We see that there is something like a rush hour every evening at 20 h, which decreases on Saturday and Sunday. It can also be noted a peak at 12 h, also being smaller at the weekend days. Instead we find that on Friday, Saturday and Sunday there is a raise around midnight.

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?
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 linear regression I conducted did not provide any valid result. The R^2 value of 0.46 showed clearly that this linear model was not able to explain the number of riders based on linear relationships based on the chosen features. It does not necessarily mean that there is no linear relationship at all digged in the data (see Section 5 for a continuation of this thought).

The statistical test was much more use in this case. Having detected a higher average number of riders with rain compared to no rain, I used the Mann-Whitney U-Test to find out if this difference is statistically significant. The result was that significantly more people use the train when it rains.

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.

The analysis of the residuals of the linear regression showed a better result than the low R^2 value let me expect. So, would this be worth another try? I think so. The problem might have been in the hour-input variable. If we have a look at the second visualization in chapter 3 we see that there is a visible pattern of peaks and lows during the regular day („rush hours“). This effect entails a deeply non-linear relationship between „hour“ and number of riders and will therefore interfere any linear model, as long as the data is modelled like that.

This does not affect the statistical test result, which is valid. More poeple choose the train when it rains.

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

Another oberservation was that there is a high proportion of traffic being conducted as base load (<= 200 riders / hour). This might be a consequence of the fact that there es no differentiation over the different units in the different stations. I would assume that there should be some differences between inner city stations and suburbs. I would expect the rain effect to be lower at long distance rides from the suburbs to the center compared to inner city rides where people can choose between walking or taking the train.