

# 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.

1. [http://pandas.pydata.org/pandas-docs/stable/generated/pandas.get\\_dummies.html](http://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html) - to understand how to create dummy data
2. <http://docs.scipy.org/doc/scipy-0.15.1/reference/generated/scipy.stats.mannwhitneyu.html> - for the MannWhitneyU test syntax
3. [https://storage.googleapis.com/supplemental\\_media/udacityu/649959144/MannWhitneyUTest.pdf?GoogleAccessId=1069728276824-fdhtlb98k1m9qrmdgj4jgc7gjp2l1lsm@developer.gserviceaccount.com&Expires=1432263445&Signature=IR2iiPm347gZ080ezCRaSrAcD/Wi2PhKd2uXzIORN2TeimihvXRdBTBFLBqXqCmDJdy7aqeRtJActr7fLkGHTjukG/NcOuaE3XPlmZ58RAar06DsDB9OuL5rbQBQG%2BaPrsH9pivB6mMaDAlo%2Ba6m58MK3l/k/nkg5JOWbqLkM9U%3D](https://storage.googleapis.com/supplemental_media/udacityu/649959144/MannWhitneyUTest.pdf?GoogleAccessId=1069728276824-fdhtlb98k1m9qrmdgj4jgc7gjp2l1lsm@developer.gserviceaccount.com&Expires=1432263445&Signature=IR2iiPm347gZ080ezCRaSrAcD/Wi2PhKd2uXzIORN2TeimihvXRdBTBFLBqXqCmDJdy7aqeRtJActr7fLkGHTjukG/NcOuaE3XPlmZ58RAar06DsDB9OuL5rbQBQG%2BaPrsH9pivB6mMaDAlo%2Ba6m58MK3l/k/nkg5JOWbqLkM9U%3D) - To understand the MannWhitney U test
- 4.

### 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 determine whether there would be significant difference in the subway ridership on the days it rained versus the days without rain. I used the two-tailed P value because we are only concerned with whether or not the two samples come from the same population. The null hypothesis is that the two samples (with and without rain) would be identical that is they come from the same population. That is:

H-nought:  $x = y$  (where x and y are the two samples)

H-Alternate:  $x < y$  or  $x > y$

The P critical value was 0.05 (alpha level of 0.05).

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 Mann Whitney U test is applicable because we can't make any assumptions about the distribution of ridership in the two samples. Also the sample sizes could be significantly different.

1.2 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 of the two samples, the MannWhitneyU value and the P-value were as follows:

Mean of entries with rain:	1105.4463767458733,
Mean of entries without rain:	1090.278780151855,
MannWhitneyU:	1924409167.0,
P-value:	0.024999912793489721

1.4 What is the significance and interpretation of these results?

The P-value of 0.0499 (we multiple the P-value by 2 for a two-sided test) indicates that we should reject the null at a P-Critical value of 0.05. This indicates that there IS a statistically significant difference in the subway ridership when it is raining versus when it is not raining. It is worth noting that the P-value was very close to the threshold that I had set to determine whether or not the value is statistically significant.

## 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 used OLS using Statsmodels. This model gave me a better  $R^2$  than the Linear Gradient Descent (which was .4662) for the same set of features.

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

I first tried  $R^2$  with just 'UNIT' in the features list. I got an  $R^2$  value of 0.4482

Next I tried adding 'rain' and 'fog' to the features. The  $R^2$  values changed only slightly to 0.4490.

Next I tried with only 'Hour' and 'UNIT' in the features. The  $R^2$  went to 0.4822 which tells me that in addition to the station, the hour of the day is a significant indicator of the ridership.

I then added 'rain' and 'fog' back in along with 'Hour' and 'UNIT' to the features. The  $R^2$  changed slightly to 0.4830. This tells me that the rain and fog have impact (albeit small) on ridership.

I then tried 'UNIT', 'Hour', 'rain' and 'meantempi' as the features. I got a  $R^2$  of 0.4833, which tells me that the temperature has a slightly more significant impact than fog on the ridership.

Next I tried 'UNIT', 'Hour', 'rain', 'meantempi' and 'meanwindspdi' as the features. I got a  $R^2$  of 0.4838.

Next I tried 'UNIT', 'Hour', 'rain', 'fog', 'meantempi' and 'meanwindspdi' as the features. I got a  $R^2$  of 0.4849 (making progress!).

Adding 'thunder' to the above did not change the  $R^2$  score at all, which tells me that the ridership was not impacted by whether there was thunder or not.

I added 'meandewpti', 'meanpressurei' to the above (excluded 'thunder') and got an  $R^2$  of .4850.

I then tried 'UNIT', 'Hour', 'rain', 'fog', 'mintempi', 'maxtempi', 'meanwindspdi', 'maxdewpti', 'mindewpti', 'maxpressurei', 'minpressurei' and got a  $R^2$  score of .4865.

I then normalized the non-dummy features and then removed 1 of the dummy variables from the features data frame. I found that the  $R^2$  value jumped to .578.

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 tried various combinations of features (see above) to see how adding or removing them would change the  $R^2$  value. I found that UNIT and Hour had the most impact but the other features also contributed slightly (about 5%) to the  $R^2$  score. I also found that by normalizing the non-dummy features, the error regarding a potential multi-collinearity in the model went away. Also removing just one of the dummy variables from the features seemed to help improve the value of  $R^2$ .

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

When I exclude the dummy variable, and don't normalize the features I get the following:

OLS Regression Results			
=====			
Dep. Variable:	ENTRIESn_hourly	R-squared:	0.208
Model:	OLS	Adj. R-squared:	0.208
Method:	Least Squares	F-statistic:	263.0
Date:	Wed, 27 May 2015	Prob (F-statistic):	0.00

Time: 18:53:36 Log-Likelihood: -91290.  
 No. Observations: 10000 AIC: 1.826e+05  
 Df Residuals: 9990 BIC: 1.827e+05  
 Df Model: 10  
 Covariance Type: nonrobust

```
=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----+-----
Hour          55.7828        3.232       17.259     0.000        49.447    62.118
rain        -108.0636       72.866       -1.483     0.138       -250.895    34.768
fog          179.6255       76.512        2.348     0.019        29.647   329.604
mintempi    -26.6995       11.292       -2.365     0.018       -48.833    -4.566
maxtempi       7.0879        5.617        1.262     0.207        -3.923    18.099
meanwindspdi  42.4883       12.127        3.503     0.000        18.716    66.260
maxdewpti     20.2353        9.896        2.045     0.041         0.837    39.634
mindewpti     -7.9576        7.173       -1.109     0.267       -22.017     6.102
maxpressurei  744.7955      438.160        1.700     0.089       -114.086  1603.677
minpressurei -733.2743      439.772       -1.667     0.095      -1595.316   128.768
=====
```

Omnibus: 11157.795 Durbin-Watson: 1.345  
 Prob(Omnibus): 0.000 Jarque-Bera (JB): 1224831.396  
 Skew: 5.702 Prob(JB): 0.00  
 Kurtosis: 56.005 Cond. No. 3.53e+03  
 =====

#### Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 3.53e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Your R^2 value is: 0.0339755953001

Can you beat the 0.4 R<sup>2</sup> value that we achieved with gradient descent?

When I normalize the non-dummy variables and exclude the dummy variables, I get the following values:

```

                                OLS Regression Results
=====
Dep. Variable:          ENTRIESn_hourly    R-squared:                0.028
Model:                  OLS                Adj. R-squared:         0.027
Method:                 Least Squares      F-statistic:              28.83
Date:                  Thu, 28 May 2015    Prob (F-statistic):       3.21e-55
Time:                  05:14:10           Log-Likelihood:           -92316.
No. Observations:      10000             AIC:                     1.847e+05
Df Residuals:          9990              BIC:                     1.847e+05
Df Model:              10
Covariance Type:       nonrobust

=====
                    coef    std err          t      P>|t|      [95.0% Conf. Int.]
-----
Hour                385.2343     24.735     15.574     0.000     336.749     433.720
rain                -56.4811     38.306     -1.474     0.140    -131.569     18.607
fog                 60.9746     31.956      1.908     0.056     -1.665    123.615
mintempi          -201.3315     82.172     -2.450     0.014    -362.405    -40.258
maxtempi           68.2454     48.662      1.402     0.161     -27.142    163.633
meanwindspdi       78.3658     26.870      2.917     0.004      25.696    131.036
maxdewpti         144.2691     98.577      1.464     0.143     -48.963    337.501
mindewpti         -41.2067     95.101     -0.433     0.665    -227.624    145.211
maxpressurei       63.5229     65.621      0.968     0.333     -65.108    192.154
minpressurei     -119.3004     72.802     -1.639     0.101    -262.007     23.406

=====
Omnibus:            11162.053    Durbin-Watson:           1.095
Prob(Omnibus):      0.000      Jarque-Bera (JB):        1227438.269
Skew:              5.705      Prob(JB):                0.00

```

Kurtosis: 56.063 Cond. No. 10.5

=====

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Note that there is no warning about potential multicollinearity in the above, however, the  $R^2$  value has now dropped to .028.

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

The highest  $R^2$  score I got was .571. Here is the summary:

OLS Regression Results

=====

Dep. Variable: ENTRIESn\_hourly R-squared: 0.571

Model: OLS Adj. R-squared: 0.549

Method: Least Squares F-statistic: 26.71

Date: Thu, 28 May 2015 Prob (F-statistic): 0.00

Time: 05:18:03 Log-Likelihood: -88231.

No. Observations: 10000 AIC: 1.774e+05

Df Residuals: 9526 BIC: 1.808e+05

Df Model: 474

Covariance Type: nonrobust

=====

	coef	std err	t	P> t	[95.0% Conf. Int.]	
Hour	431.6455	17.312	24.933	0.000	397.710	465.581
rain	-45.4625	26.647	-1.706	0.088	-97.697	6.772
fog	52.3587	22.241	2.354	0.019	8.762	95.955
mintempi	-160.1259	57.215	-2.799	0.005	-272.279	-47.973
maxtempi	16.1255	33.819	0.477	0.634	-50.167	82.418
meanwindspdi	58.5070	18.730	3.124	0.002	21.791	95.223
maxdewpti	254.0944	68.498	3.710	0.000	119.825	388.364

mindewpti	-164.7691	66.022	-2.496	0.013	-294.187	-35.352
maxpressurei	14.2347	45.672	0.312	0.755	-75.292	103.761
minpressurei	-38.5183	50.683	-0.760	0.447	-137.867	60.831
unit_R002	497.4693	486.004	1.024	0.306	-455.201	1450.140
unit_R003	272.2407	507.980	0.536	0.592	-723.509	1267.991
unit_R004	641.2801	507.683	1.263	0.207	-353.887	1636.447
unit_R005	980.0455	467.147	2.098	0.036	64.338	1895.753
unit_R006	678.7972	595.481	1.140	0.254	-488.472	1846.067
unit_R007	285.5227	421.027	0.678	0.498	-539.780	1110.825
~						
unit_R548	150.2592	231.269	0.650	0.516	-303.078	603.596
unit_R549	12.6980	54.381	0.234	0.815	-93.900	119.296
unit_R550	15.0537	72.058	0.209	0.835	-126.194	156.302
unit_R551	92.2285	112.249	0.822	0.411	-127.803	312.260
unit_R552	127.6401	107.391	1.189	0.235	-82.869	338.150

```

=====
Omnibus:                9113.198    Durbin-Watson:                1.798
Prob(Omnibus):           0.000    Jarque-Bera (JB):            1167818.916
Skew:                    3.911    Prob(JB):                     0.00
Kurtosis:                55.360    Cond. No.                     94.7
=====

```

#### Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Your R<sup>2</sup> value is: 0.476014497048

Can you beat the 0.4 R<sup>2</sup> value that we achieved with gradient descent?

2.6 What does this R<sup>2</sup> 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<sup>2</sup> value?

The R<sup>2</sup> score of .571 indicates that 57.10% of the variability in the data can be attributed to the features chosen. While there is still a lot of variability in the predicted values, a value over 57% is a good

fit. The model shows that much of the variation can be attributed to the station rather than any of the weather related data, although the weather does contribute to variability in ridership to a small extent.

## Section 3. Visualization

Please include two visualizations that show the relationships between two or more variables in the NYC subway data.

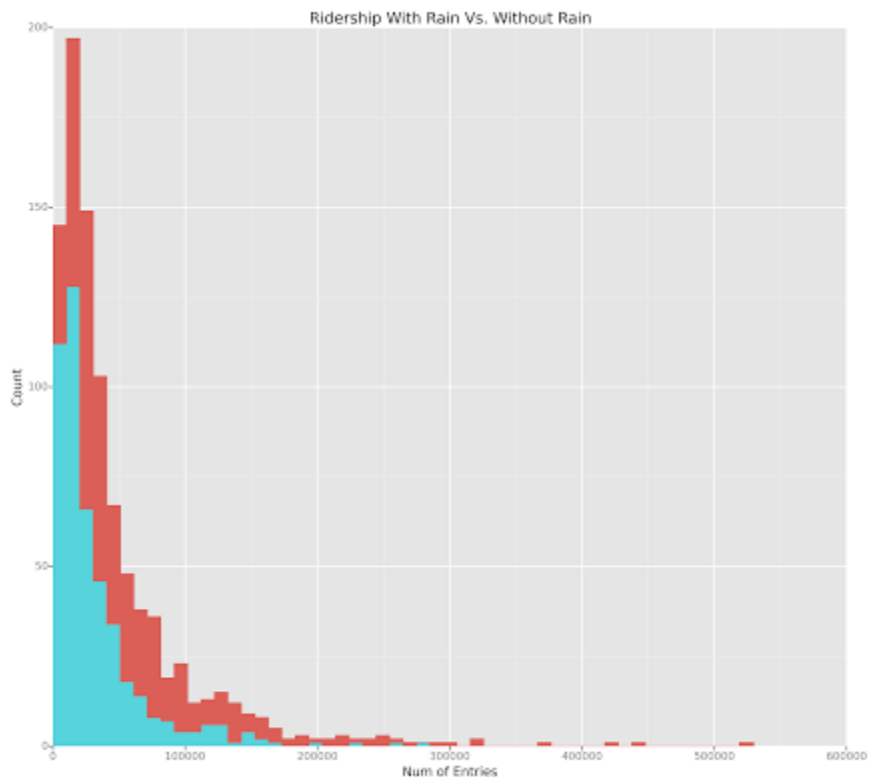
Remember to add appropriate titles and axes labels to your plots. Also, please add a short description below each figure commenting on the key insights depicted in the figure.

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 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.

The histogram produced was as follows:



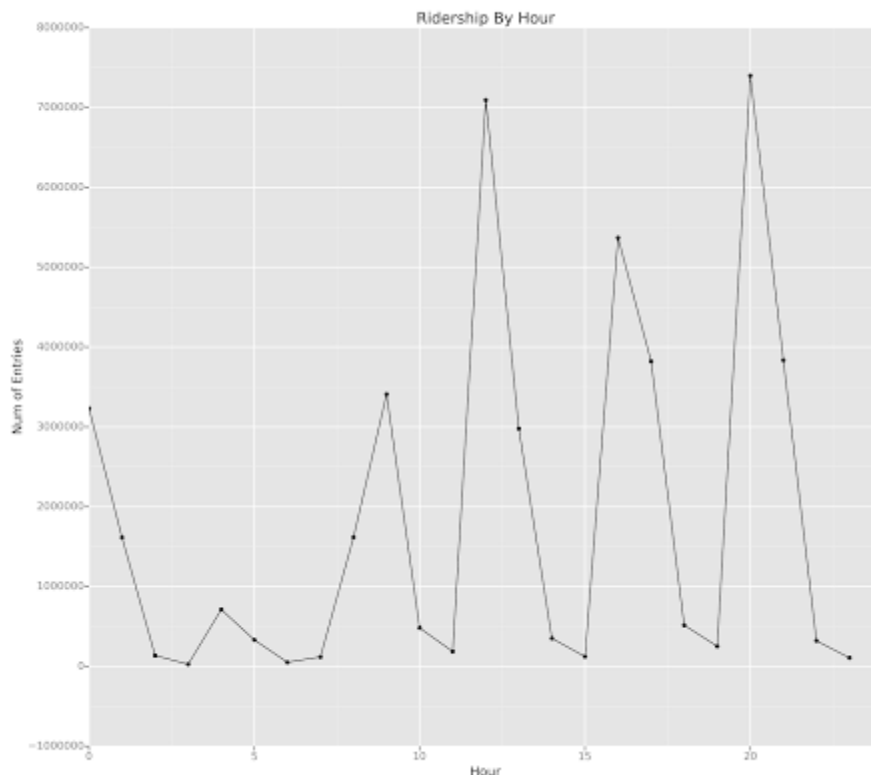


The blue bar represent Number of Entries when it was raining and the red represents Number of Entries without rain. The Number of Entries for each Unit were grouped together and summed for with and without rain. We see from the histogram that there is a noticeable difference in the ridership when it rains vs. when it does not rain across all stations. It appears that the ridership decreases when it is raining.

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

I plotted the graph of ridership by time of day. The result was as follows:



The plot above shows that when mapped across all stations, the ridership peaks around 1 PM and 8 PM with the next significant number being around 4-5 PM and 9 PM.

## 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?

The histogram clearly shows that there are more riders when it is not raining than when it is raining when the data is aggregated over all the stations. This appears to be in conflict with the mean values of entries when it rains vs. when it does not rain in the sample provided, as was seen in 3.3 (mean of entries with rain = 1105.45 and mean of entries without rain = 1090.28), but that might be due to outliers in the sample data set. The data in the histogram was aggregated over all stations and mapped by frequency of occurrence of a given number of entries, thus removing any station specific variability.

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 MannWhiteyU statistic was used to determine that there *IS* a statistically significant difference in the ridership when it is raining or when it is not raining. Although the P-value was almost equal to the P-critical value that I used for my threshold, it still proved that the difference was significant.

When I used the OLS method for linear regression, I used rain as one of the features to predict the value. The coefficient for 'rain' was a -45.46 and the P value was 0.088. The confidence interval was towards the negative as well, which I think indicates that there was an inverse relationship between rain and ridership (or entries).

Hence both the statistics support the conclusion that the ridership decreases 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.

I have thus far only run the code in Udacity's test environment (IDE provided) and hence the models were likely only run against a subset of the data (~10%). I would like to set up an environment on my local machine and rerun some of the code locally to see if I get different results. That would indicate how consistent my model was against different datasets.

Also, in the OLS model used to predict ridership, a large part of the variability is due to the dummy variables (or stations ). Hence the effect of weather related features is overshadowed and cannot be interpreted properly.

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