STAT 306 Project

Prediction for Taxi Transaction Counts
Based on Time and Districts in Thessaloniki, Greece

Team Members

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1.Abstract

The goal of the project is to fit a predictive model for the count of taxi transactions in Thessaloniki, Greece, based on the taxi transaction records in the first three months of 2015. Explanatory variables are Weekday (day of the week), Hour (hour of the day), Holiday (whether a day is a statutory holiday), and Distance_to_Downtown (Euclidian distance from the point of passenger pick up to the geographic centre of the city), which are all categorical variables.

Our analysis shows that interaction terms between explanatory variables are important. Consequently, based on summary statistics like adjusted R^2, root mean square prediction error, AIC and BIC, the best prediction model is:

Log_count ~ weekday + hour + holiday + radius_down_km + I(weekday:hour) + I(hour:holiday) + I(weekday:holiday) + I(hour:radius_down_km)

The model in matrix form:

$$\text{Log(Count)} = C_{weekday} * X_{weekday} + C_{hour} * X_{hour} + C_{holiday} * X_{holiday} + C_{radius\_down\_km} * X_{radius\_down\_km} + C_{weekday:hour} * X_{weekday:hour} + C_{weekday:holiday} * X_{weekday:holiday} + C_{hour:holiday} * X_{hour:holiday} + C_{hour:radius\_down\_km} * X_{hour:radius\_down\_km}$$

*The values of diagonal entries in coefficient matrices are attached in the Appendix.

A categorical variable with n categories/levels, whether describing a single effect or an interaction, is represented by a coefficient matrix C_i, an (n-1) by (n-1) diagonal matrix with diagonal elements equal to the coefficients from the fitted model. Each C_i is paired with a unit vector X_i of length (n-1) that consists of (n-2) zeros and a single one. For example, Figure(1.1) shows the diagonal matrix C_i for the variable weekday, which is 6 by 6 (weekdayMonday chosen as a base), as well as two copies of vector X_i. representing Monday and Tuesday respectively.

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]
[1,]	0.0522	0.0000	0.000	0.000	0.0000	0.00
[2,]	0.0000	-0.0487	0.000	0.000	0.0000	0.00
[3,]	0.0000	0.0000	0.158	0.000	0.0000	0.00
[4,]	0.0000	0.0000	0.000	0.266	0.0000	0.00
[5,]	0.0000	0.0000	0.000	0.000	0.0704	0.00
[6,]	0.0000	0.0000	0.000	0.000	0.0000	-0.16

	[,1]
[1,]	0
[2,]	0
[3,]	0
[4,]	0
[5,]	0
[6,]	0

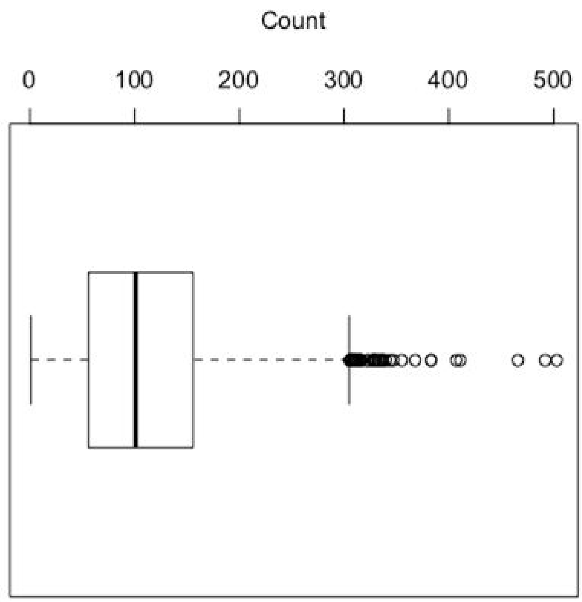
	[,1]
[1,]	1
[2,]	0
[3,]	0
[4,]	0
[5,]	0
[6,]	0

Figure(1.1) Coefficient Matrix($C_{weekday}$) and two copies of Dummy Variable Vector ($X_{weekday}$)

2.Data Description

The main data set is a record of 1.5 million transactions for the first three months in 2015 from a taxi company located in Thessaloniki, Greece. The original response variable is categorical with five revenue classes 1,2,3,4,5 (with 1 representing the lowest revenue and 5 the highest).

Originally we intended to fit a binary response model for predicting the probability of high revenue taxi fares. In the end, we settled for predicting the total counts of transactions within one hour interval. Transaction count is an important measure of demand for taxi services, as well as an indicator of how many vehicles remain vacant. So, higher hourly count of transactions would signal a peak demand time interval, and potential vehicle supply shortage. The counts have been further transformed by the application of natural log in order to make their distribution less skewed.



Figure(2.1) Distribution of Transaction Counts

The reasons for departure from the more obvious logistic regression will become clear upon introducing the available explanatory variables. Some of the variables contain several pieces of information that we extracted for the purposes of our analysis. For example, timestamp was used to extract day of the week and hour. Intertemporal patterns are highly pronounced in the data, e.g., commute hours: most days of the week from 2 to 11 am have significantly fewer transactions (but there are some departures from this pattern, e.g., on Sundays), and Fridays get the most transactions. Potentially, we need to keep in mind that cross terms of weekday and hour will be important.

In addition to timestamp, the original dataset also contained spatial data, i.e., GPS coordinates for the passenger pickup location. Given a GPS latitude-longitude pair, geospatial information (such as neighborhood or street name) can potentially be extracted using APIs (Google Maps or MapQuest to name the most popular). Unfortunately both have a limit on the number of free monthly calls: 5000 and 15000, respectively. As raw GPS data cannot be ranked meaningfully, the next best alternative for sorting coordinates is by distance from some city landmark, for example, geographic centre of the city or the airport. GPS coordinates have been transformed into *Universal Transverse Mercator* format in order to allow the use of Euclidian distance formula. The aggregation of spatial data by radius obviously results in the loss of information. Consequently, our attempt to fit a logistic model resulted in the low predictive power, requiring us to modify the approach and resort to hourly counts of transactions as the response variable.

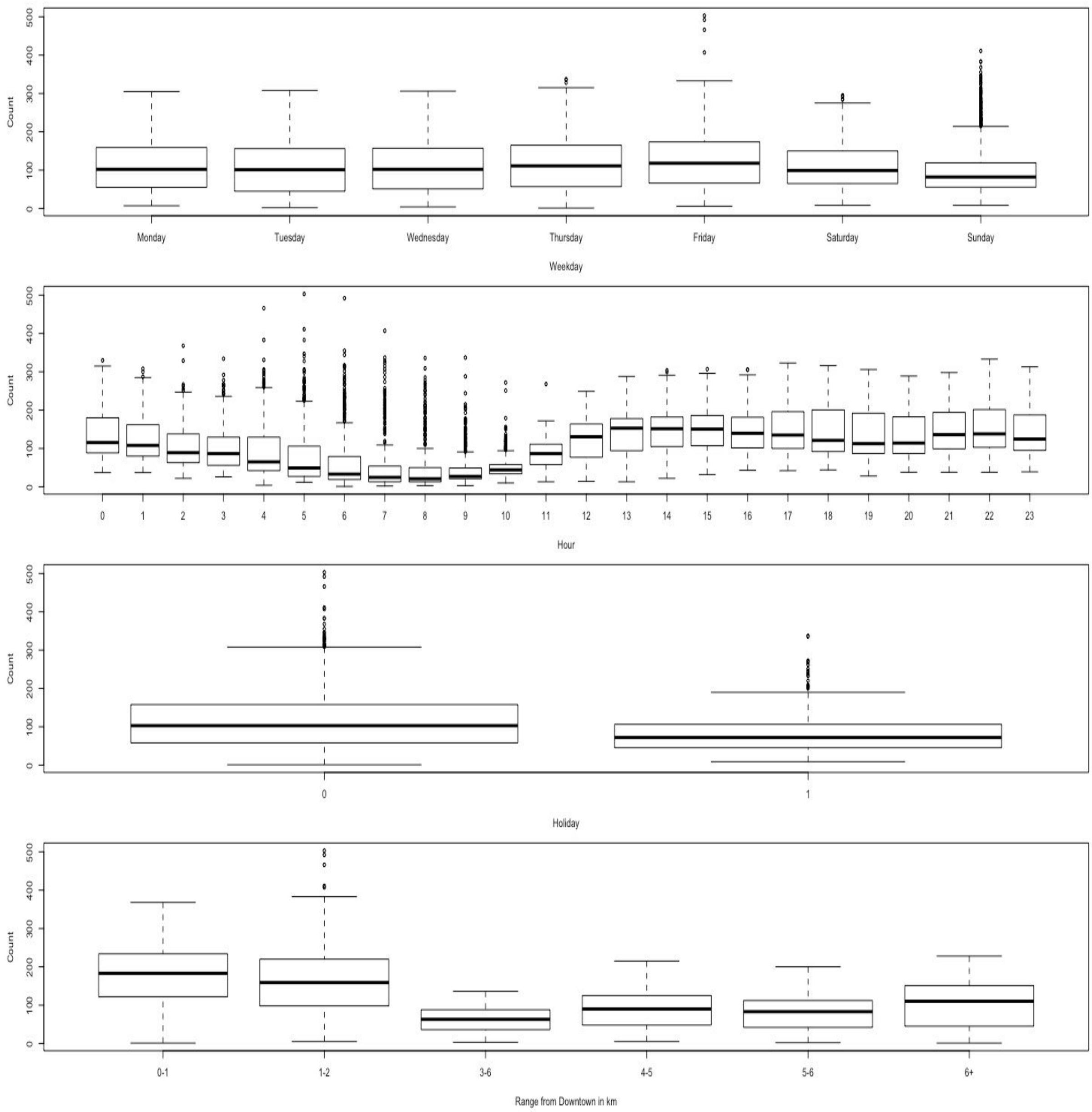


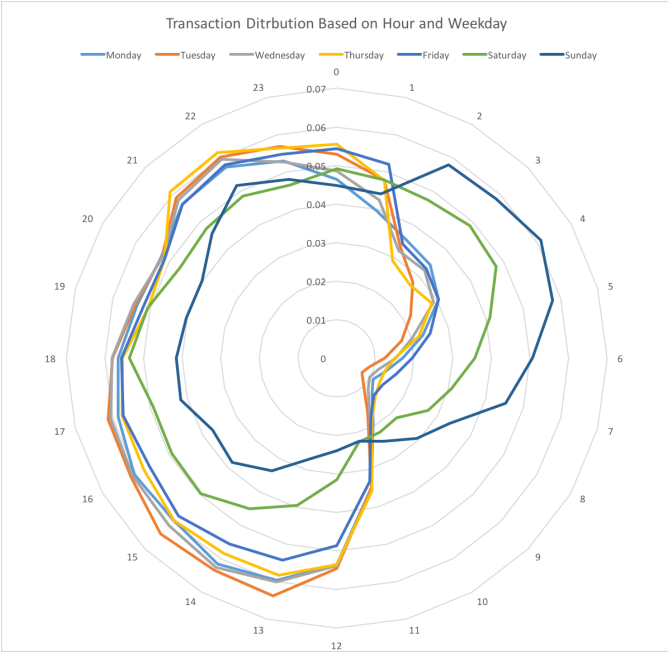
Figure (2.3) Boxplots of Transaction Counts against Weekday, Hour, Holiday and Distance to Downtown (km)

3.Data Analysis and Results

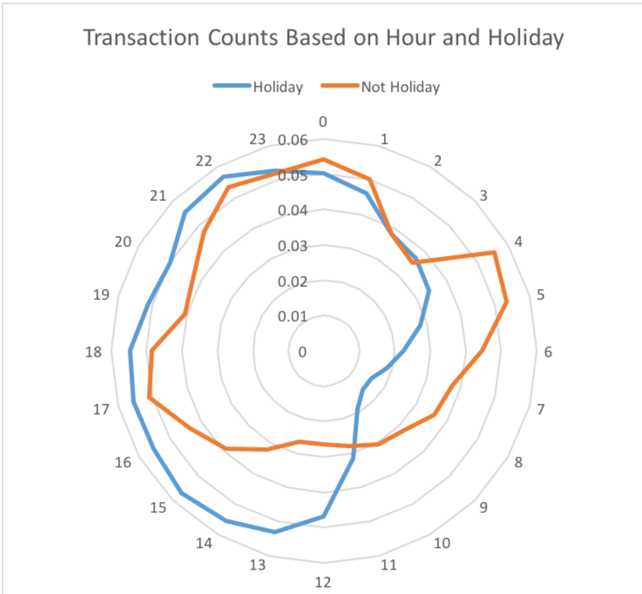
3.1 Comparing Different Models with Different Quadratic Terms

Based on the preliminary data exploration in section 2, we anticipate the importance of quadratic terms, and proceed by comparing models with different combinations of variable interactions. In order to decide which quadratic terms are useful, we resorted to polar plots. For example, Figure(3.1.1) shows that weekend and weekday hourly transaction count patterns are distinctly different. Likewise, Figure(3.1.2) conveys intertemporal differences in hourly transaction counts for statutory holidays, so the quadratic term Hour:Holiday may improve our model's predictive power.

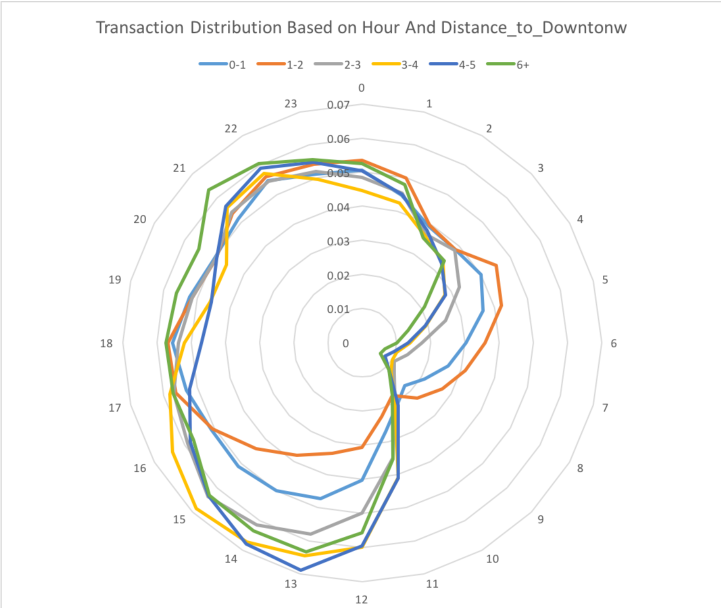
Figure(3.1.3) confirms our belief that physical location is also an important predictor of taxi services demand.



Figure(3.1.1) Transaction Distribution Based On Hour and Weekday



Figure(3.1.2) Transaction Distribution Based On Hour and Holiday



Figure(3.3) Transaction Distribution Based On Hour and Distance to Downtown

The five final candidate models include four with different quadratic terms and a single model with linear terms only: see Table(3.1.1). We tested these models using 3 different training sets and compared their performance using adjusted R^2, AIC, RMSE of training sets and RMSE of holdout sets. Table(3.1.2) summarizes our findings highlighting that Model 3 is the best model overall. According to Table(3.1.2), Models 3,4,5 have very close adjusted R^2, around 0.92 for all of the training sets; they also have similar AIC and RMSE. We finally chose model 3, because it is the simplest model with least number of parameters and quadratic terms, but has the same predictive ability.

Nevertheless, Model 3 has 315 parameters, which raises a valid concern of whether the model is overfitted. To address the issue of potential model overfitting, we compare RMSE of training sets versus RMSE of holdout sets. It turns out that although RMSE for training sets is naturally lower, the difference is not large enough to signal overfitting.

Table(3.1.1) Models with Different Quadratic Terms

Model	**Content of Model**
Model 1	log_count~weekday + hour + radius_down_km + holiday
Model 2	log_count~(weekday + hour + holiday)^2 + radius_down_km
Model 3	log_count~(weekday + hour + holiday)^2 + radius_down_km + I(hour:radius_down_km)

Model 4	log_count~(weekday + hour + holiday)^2 + radius_down_km + I(hour:radius_down_km) + I(weekday:radius_down_km)
Model 5	log_count~(weekday + hour + holiday + radius_down_km)^2

Table(3.1.2) Adjusted R^2, AIC, RMSE of Train Set and RMSE of Holdout set for 5 models

	# of Parameters	Adjusted R^2			AIC			RMSE			RMSE		
		Train Set1	Train Set2	Train Set3	Train Set1	Train Set2	Train Set3	Train Set1	Train Set2	Train Set3	Hold out1	Hold out2	Hold out3
Model1	36	0.7294	0.7268	0.721	11029	11004	11285	0.4185	0.4179	0.4239	0.426	0.4281	0.4073
Model2	200	0.8492	0.8466	0.8455	5345	5393.8	5534.8	0.3098	0.3106	0.3128	0.3192	0.3155	0.3096
Model3	315	0.9234	0.9176	0.9173	-1318	-709	-605.2	0.2195	0.2263	0.2275	0.2439	0.2216	0.2172
Model4	345	0.9248	0.9192	0.9188	-1478	-876.2	-751.4	0.2171	0.2237	0.2251	0.2419	0.2202	0.2149
Model5	350	0.925	0.9193	0.9188	-1490	-879.9	-754.2	0.2168	0.2236	0.225	0.2422	0.22	0.2148

3.2 The Final Regression Model and Results

Table(3.2) Part of Regression Output of Model 3

Call:

lm(formula = logcount ~ (weekday + hour + holiday)^2 + radius_down_km + I(hour:radius_down_km) , data = train)

Residuals:

Min	1Q	Median	3Q	Max
-2.5802	-0.1019	0.0059	0.1079	1.4785

Coefficients:

	Estimate	Std.Error	t value	Pr(>|t|)	
(Intercept)	5.299639	0.037437	141.56	2.00E-16	***
weekdayTuesday	0.071375	0.041061	1.74	0.0822	.
weekdayWednesday	0.044539	0.041085	1.08	0.27836	
weekdayThursday	0.20686	0.040354	5.13	3.00E-07	***
weekdayFriday	0.266442	0.041166	6.47	1.00E-10	***
weekdaySaturday	0.041513	0.040319	1.03	0.30321	
weekdaySunday	-0.204946	0.041198	-4.97	6.60E-07	***
hour1	-0.181998	0.065435	-2.78	0.00542	**
hour2	-0.444281	0.065056	-6.83	9.00E-12	***

hour3	-0.473827	0.065351	-7.25	4.50E-13	***
hour4	-1.05412	0.065171	-16.17	2.00E-16	***
hour5	-1.58424	0.065604	-24.15	2.00E-16	***
...					
hour18:holiday1	-0.270357	0.078878	-3.43	0.00061	***
hour19:holiday1	-0.30512	0.082314	-3.71	0.00021	***
hour20:holiday1	-0.264926	0.079724	-3.32	0.00089	***
hour21:holiday1	-0.290364	0.077777	-3.73	0.00019	***
hour22:holiday1	-0.215056	0.079878	-2.69	0.00711	**
hour23:holiday1	-0.157194	0.07884	-1.99	0.0462	*

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					
Residual standard error: 0.223 on 9685 degrees of freedom					
Multiple R-squared: 0.926,			**Adjusted R-squared:** 0.923		
F-statistic: 385 on 314 and 9685 DF			**p-value:** <2e-16		

*The complete regression result is attached in the Appendix.

Table(3.2) is part of the regression output of Model 3.
Here is a summary of our conclusions drawn from R output:

- Generally, the demand for taxi services is higher from 13:00 pm to 23:00 pm. The demand is much lower from 1:00 am to 11:00 am.
- Thursdays and Fridays have the highest taxi demand, while the demand decreases significantly on Sundays.
- Most Weekday:Hour terms have strongly significant coefficients, meaning that different days of the week have different time patterns for taxi demand.
- On a holiday, the total demand for taxis decreases. However, holiday demand for taxis is higher from 4:00 am to 9:00 am, which is a low-demand period on a regular day.
- Taxi demand is the highest in the center of the city and the lowest in the 3-4 kilometer distance to downtown.
- The quadratic term Hour:Radius_down_km improves the Adjusted R^2 from 0.84 to 0.92, which signals that different districts have different intertemporal patterns of taxi demand.

A variable may be insignificant on its own, but might become significant if combined with other variables into quadratic terms. After playing around with different combinations of quadratic terms, we found the combination of quadratic terms that produces the best results..

3.3 Residuals Analysis

Table(3.3.1): Residual From Model3

Min	1st Qu.	Median	Mean	3rd Qu,	Max
-4.110	-0.101	0.006	0.000	0.108	1.530

Since we have a very large sample size, we take a closer look at the residual subset to check for patterns/abnormalities. In Figure 3.3.1, 1000 residual values are extracted out of the 10000 total residuals in the training set.

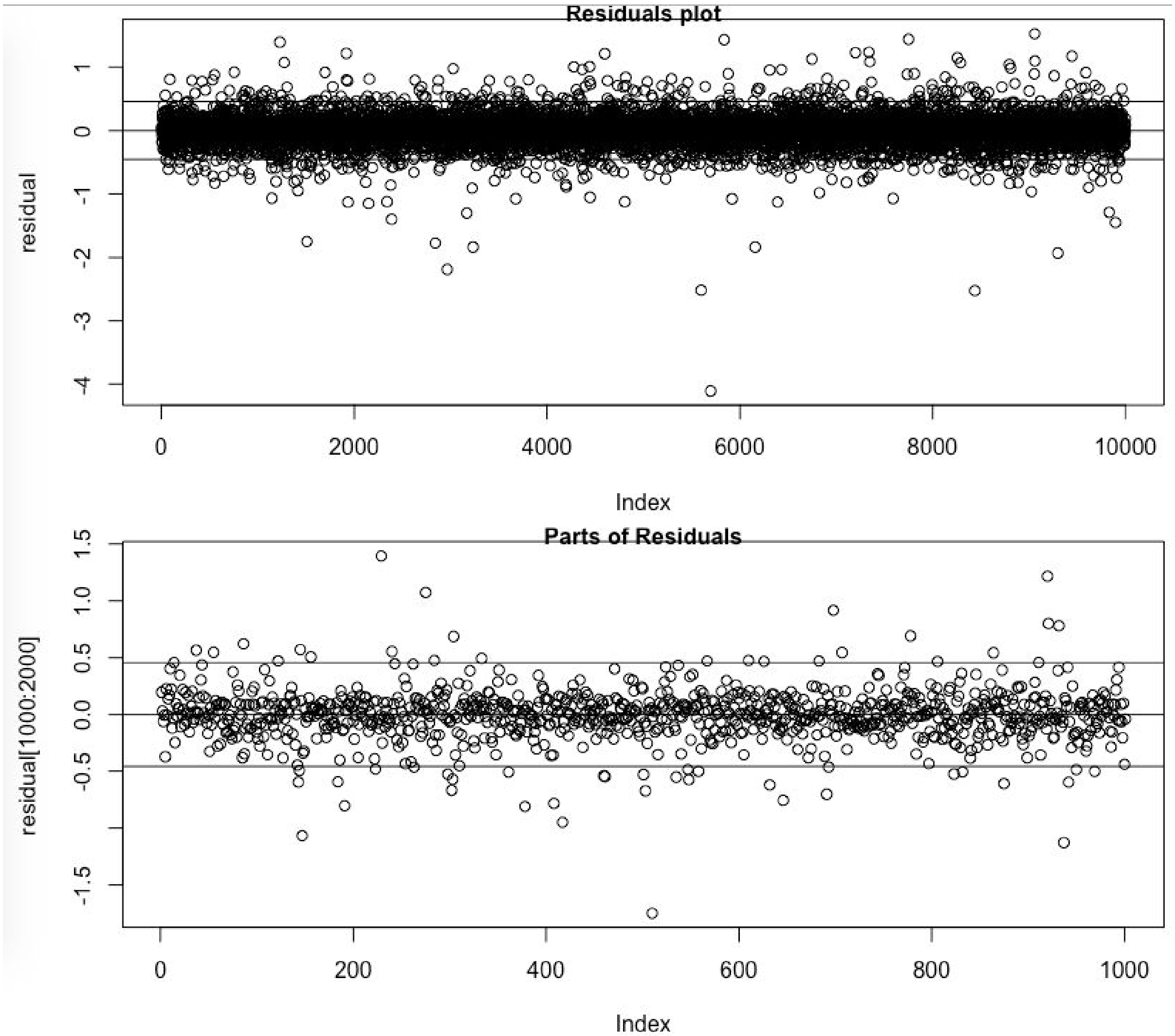


Figure (3.3.1) Plot of residuals of total prediction with 1,001 residuals from a total of 10,000 residuals

Upon closer look at the residual distribution, we conclude that, generally speaking, Model3 does not deviate from the assumption of homoscedasticity. The detailed analysis of residuals follows.

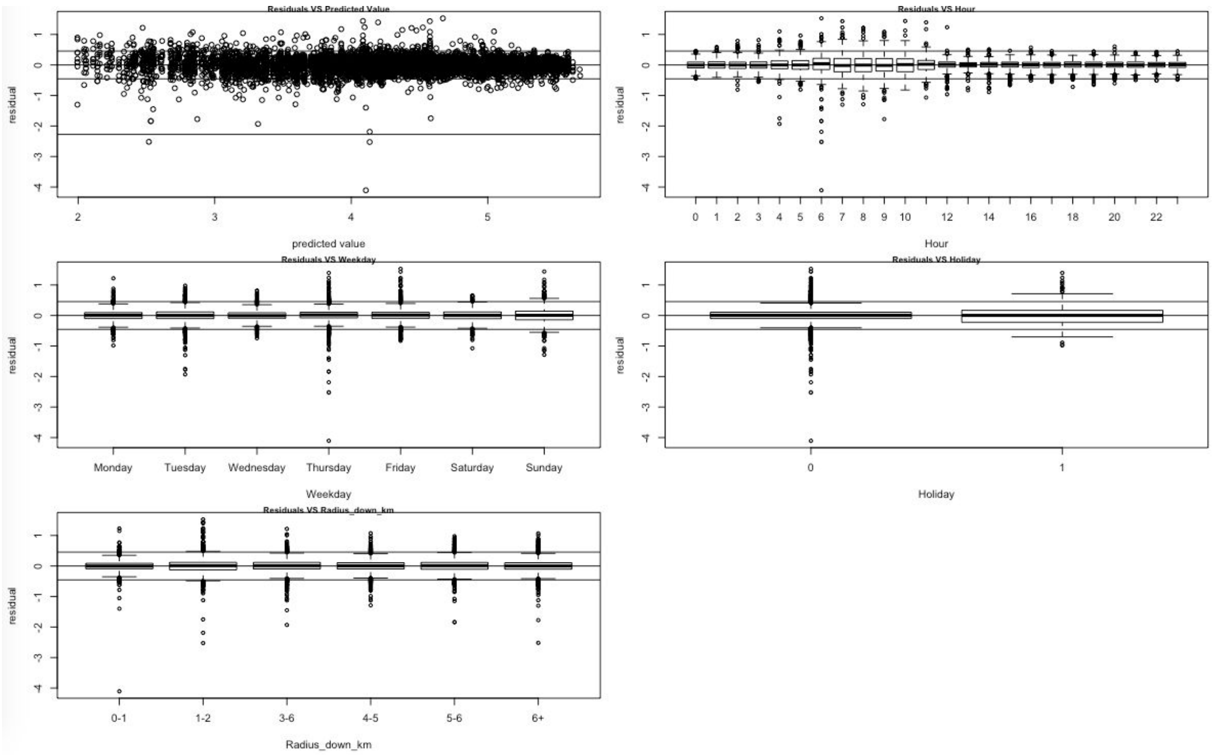


Figure 3.3.2 Residual plots with 5 explanatory variables in a model with quadratic terms of model3

Figure 3.3.2 contains standard plots for the analysis of residuals. Residuals versus predicted values plot shows that most points fall within two standard deviations of zero, and only three extreme outliers appear to fall as far as ten standard deviations below zero.

Table(3.3.2) R output of Studentized Residual of the Data Point with the most Deviation

Fits and Diagnostics for Unusual Observations				
Obs	Logcount	Fit	Resid	Std Resid
5697	0.302	4.409	-4.1070	-18.44
R Large Residual				

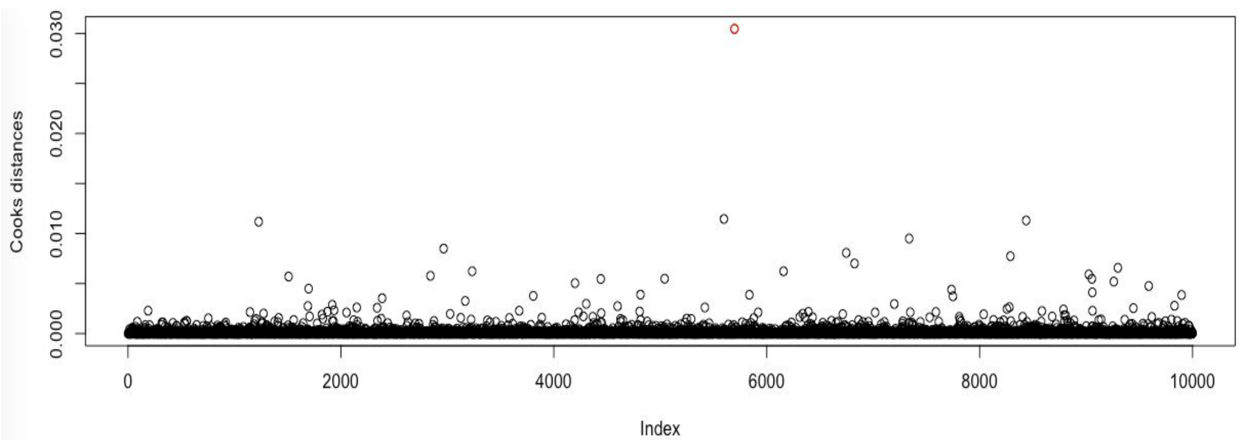


Figure 3.3.3 Using Cook's distance to find one extreme data point (observation 5697)

In order to analyze the impact of the outlier on the model, we fit Model 3 twice: once with and once without the outlier.

Table(3.3.3) R output of Model with the outlier (Model3)

Residuals:				
Min	1Q	Median	3Q	Max
-4.110	-0.101	0.006	0.108	1.530
Residual standard error: 0.23 on 9685 degrees of freedom				
Multiple R-squared: 0.920, Adjusted R-squared: 0.918				

Table(3.3.4) R output of Model without the outlier

Residuals:				
Min	1Q	Median	3Q	Max
-2.6000	-0.1020	0.0062	0.1070	1.500
Residual standard error: 0.23 on 9685 degrees of freedom				
Multiple R-squared: 0.92, Adjusted R-squared: 0.918				

Note: some of the output has been rounded, therefore it might be different from the actual residual result

Comparing the two models, there are hardly any side effects from including the outlier observation. R^2 has barely changed when the outlier was omitted. In either case, the relationship between the response variable and explanatory variables is deemed strong. We conclude that the outlier in question is not influential.

In addition, by checking the plots of residuals versus explanatory variables in Figure 3.3.2 and Figure 3.3.3 (See Appendix), we conclude that the addition of quadratic terms does not cause our model to violate homoscedasticity assumption, and there is no sign of heteroscedasticity or curvilinear relation between the response variable and explanatory variables.

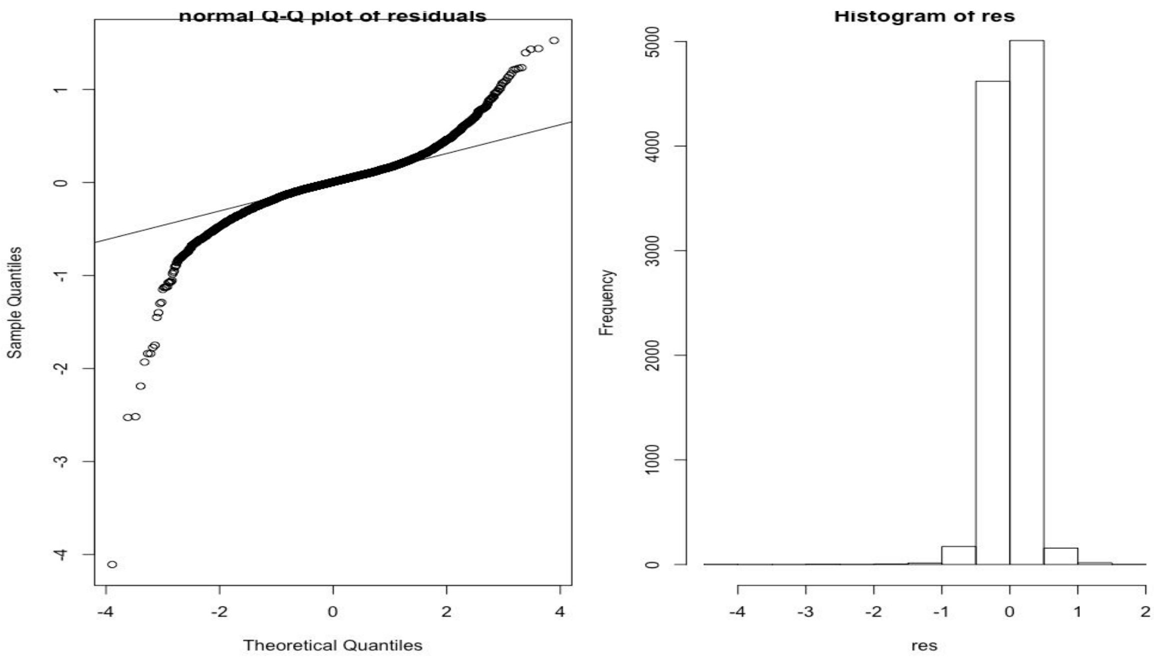


Figure 3.3.4 Normal Quantile-Quantile plot and Quantile-Quantile histogram of residuals

Although comparison of Quantile-Quantile plot in Figure 3.3.4 signals deviations from normality: much thicker tails than expected, the distribution of residuals is still symmetric and not skewed.

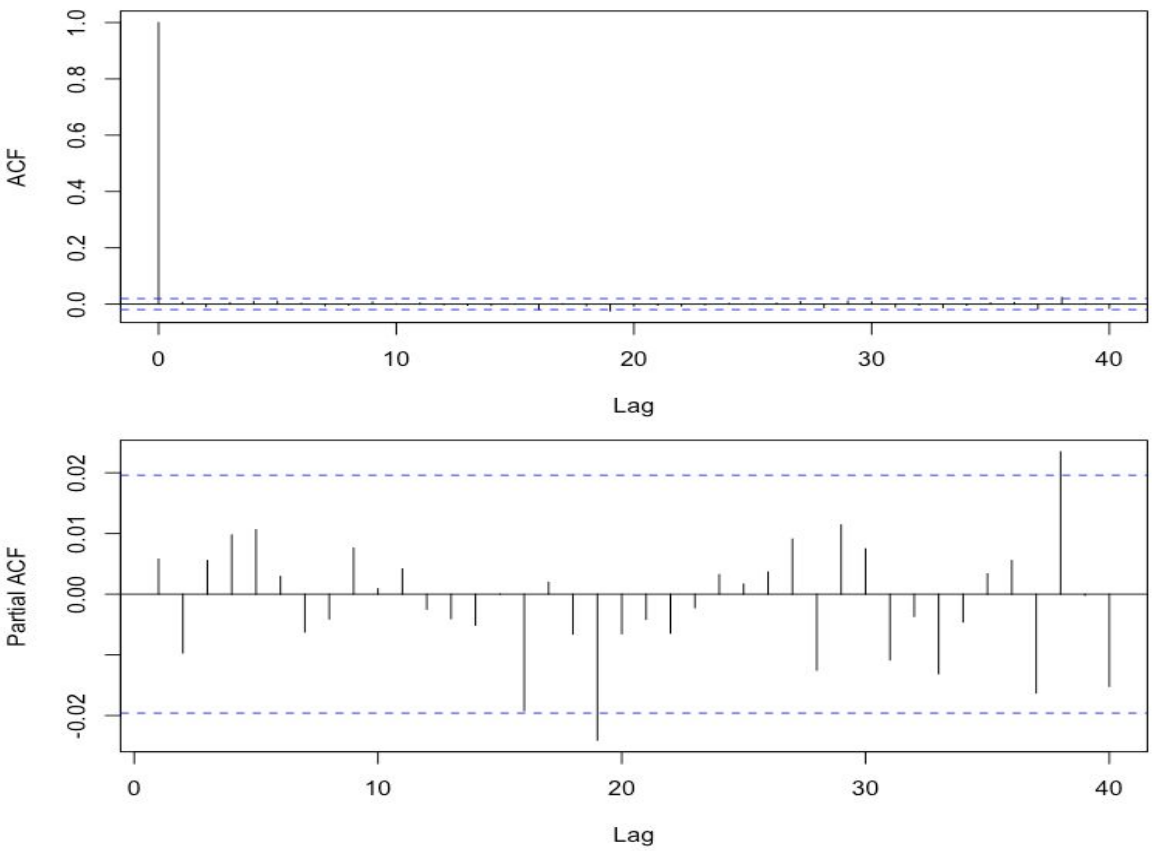


Figure 3.3.5 Plot of Residuals. ACF and PACF plot of Residuals

The residual plots appear to be random without any obvious patterns or trend. ACF plot cuts off at lag 0, implying that residuals follow a white noise process. In the PACF plot, all the values are within the confidence interval limit. These results provide further support that our model gives good prediction.

4.Contributions Section

Our team consists of three BCS (second-degree) students and two undergraduate students. We have known each other from taking various courses together in the first winter term, e.g., MATH 307, CPSC 110.

We quickly realized that the safest way to choose a project topic would be to find an interesting data set that would lend itself to the analytical toolbox of STAT 306. Having examined several data sets on Kaggle, we settled on the records of taxi company transactions, hoping to use logistic regression to predict probability of high revenue transactions from the intertemporal and spatial patterns.

As we gained deeper understanding of the subject, it became clear that extraction of location information from the available GPS coordinates requires the use of APIs (that limit the number of monthly calls), making our original plan of analysis infeasible. The predictive power of logistic model without precise location data was so weak, that we had to resort to transaction aggregation over one hour time intervals.

In retrospect, a better strategy would have been for all team members to be more proactive during the data set search phase and attempt preliminary analysis on several alternative datasets, so that the most promising one is selected for the final version of the project.

The names are ordered alphabetically by surname.

Name	Contribution
Andriy Bolyachevets	Model and analysis brainstorming. Suggested the original project idea and did most of the data wrangling. Laid out R code blueprint for the model selection. Wrote data description (section 2) and contribution sections of the report. Proofread the final version of the report.

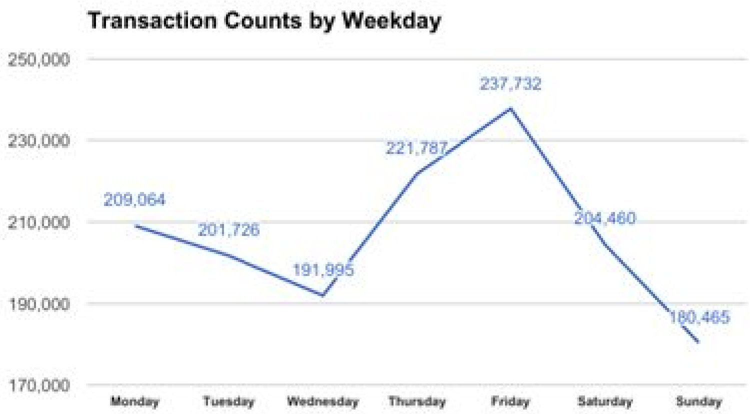
Xiaojing Huang	Model and analysis brainstorming. Corrected shortcomings in the process of transaction aggregation. Performed quadratic term analysis using polar plots. Conducted model selection analysis and wrote most of model analysis (sections 3.1, 3.2). Edited styling of the report.
Siliang Liu	Model and analysis brainstorming. Performed and wrote residual analysis (section 3.3). Edited styling of the report.
Qiyu Wu	Model and analysis brainstorming. Wrote abstract/summary section of the report. Edited appendix (R output table).
Amy Xu	Model and analysis brainstorming. Helped with transaction aggregation. Checked for autocorrelation and contributed to residual analysis. Contributed to data analysis (sections 3.1, 3.2). Edited styling of the report.

Data Sources

- Taxi Revenue Kaggle Data https://inclass.kaggle.com/c/taxi-fare-prediction-challenge-epia-2017
- Public Holiday: https://www.timeanddate.com/holidays/greece/2015
- Geographic/UTM Coordinate Converter: http://home.hiwaay.net/~taylorc/toolbox/geography/geoutm.html
- Local weather data: https://www.wunderground.com/
- Greece gasoline data source: http://www.tradingeconomics.com/greece/gasoline-prices

Appendix

Exhibit (1) Figures and Tables (in chronological order)



Figure(2.2) Transaction Counts by Weekday

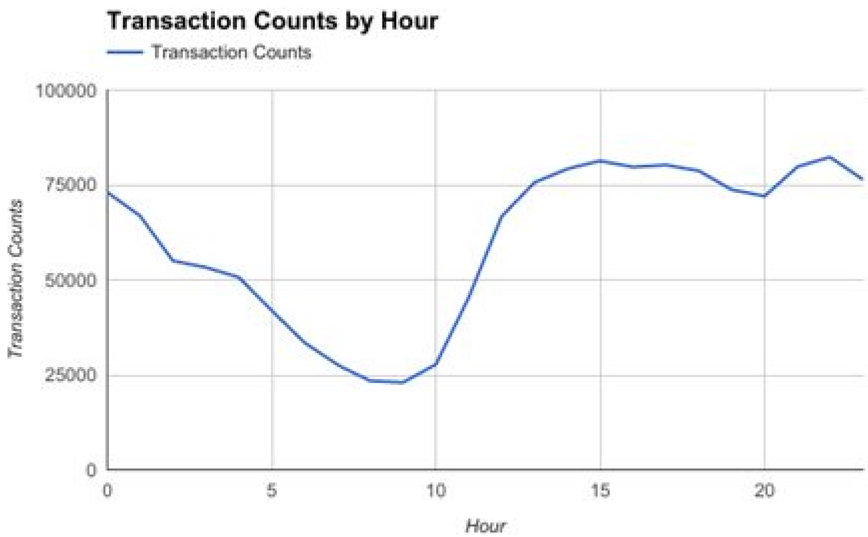


Figure (2.3) Transaction Counts by Hour

Table (2.1) Frequency Table for the explanatory variable Weekday

Weekday	Mon	Tue	Wed	Thur	Fri	Sat	Sun
Counts	209,064	201,726	191,995	221,787	237,732	204,460	180,465

Table (2.2) Frequency Table by Hour

Hour	0	1	2	3	4	...	20	21	22	23
Counts	73050	66850	55019	53288	50689	...	72003	79762	82255	76370

Table (2.3) Transaction Counts across Day of the Week and Hour

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
0	9697	10659	9325	12321	12919	10043	8086
1	8287	9661	8169	10600	12378	9781	7974
2	7443	6697	6172	6453	8107	9690	10457
3	7160	5643	6197	5963	7815	9953	10557
4	6364	4472	5561	6302	7223	9739	11028
5	4826	3526	3904	4894	5954	8397	10446
6	3565	2504	2952	3344	4650	7328	9160
7	2718	1770	2153	2852	3772	6278	8170
8	2295	1521	1890	2842	3279	5567	6099
9	2724	1991	2204	3125	3228	4473	5302
10	3965	3218	3305	4067	4217	4541	4469
11	7258	7007	6793	7900	7848	4593	4021
12	11195	10993	10337	11882	11552	6433	4322
13	12475	12857	11534	12909	12881	8084	4898
14	12897	12801	12019	12964	13228	9214	6070
15	12448	12991	11797	13197	13765	10153	6912
16	12644	12415	11725	12798	13311	10082	6704
17	12261	12354	11628	12774	13597	10043	7532
18	11840	11700	11161	12281	13230	10967	7488
19	11192	10893	10446	11199	12339	10357	7269
20	10953	10544	10017	11419	12228	9585	7257
21	11825	11868	11132	13537	13407	9747	8246
22	11971	12164	11455	13647	13781	9913	9324
23	11061	11477	10119	12517	13023	9499	8674

Table (2.4) Frequency Table by Distance to Downtown(km)

Distance to Downtown(km)	0-1	1-2	2-3	4-5	5-6	6+
Counts	377880	345573	134168	195018	173830	220760

Table (2.5) Frequency Table by Holiday

Holiday	Not Holiday	Holiday
Counts	1401,367	45,862

Table (2.6) Frequency table by Weather

Weather	Bad	Good
Counts	682,447	763,640

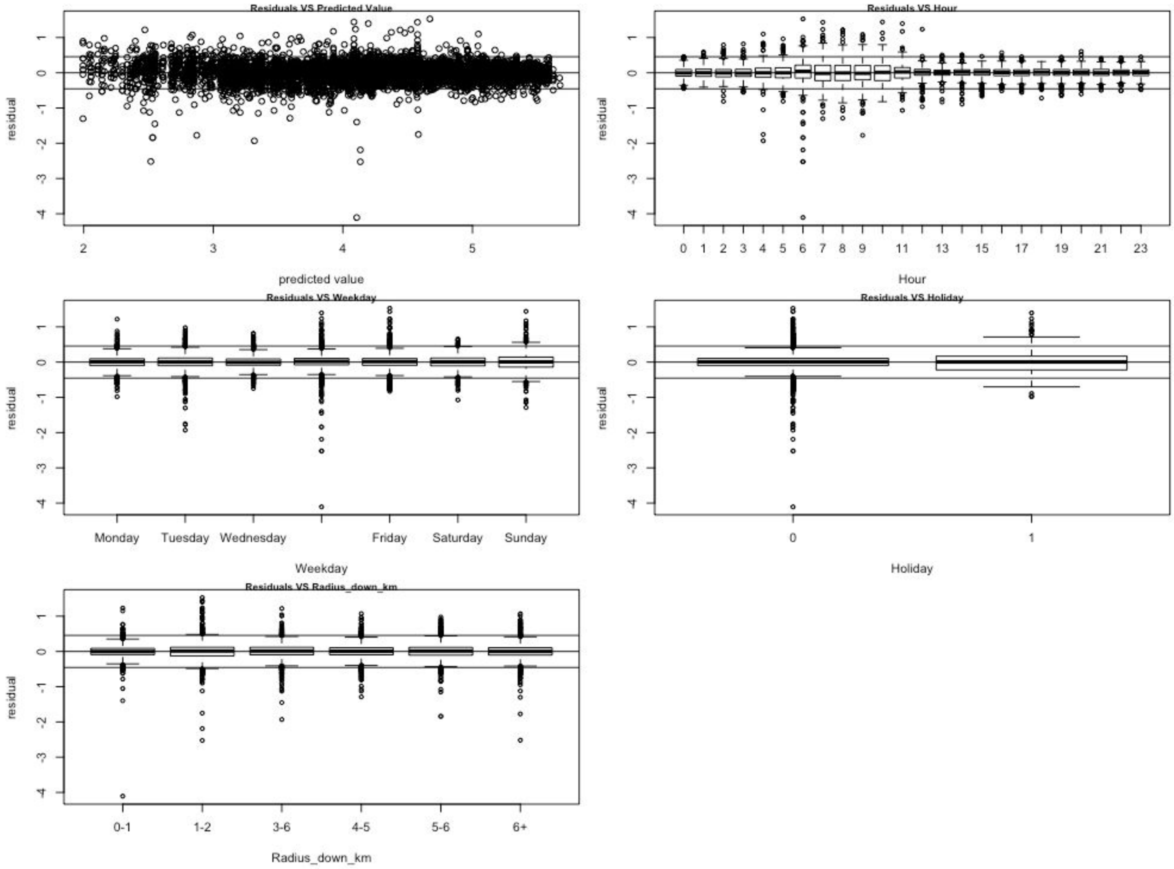


Figure 3.3.3 Standardized residual plots with 5 explanatory variables in a model with quadratic terms of model3

Exhibit (2) R Output

Call:
lm(formula = logcount ~ (weekday + hour + holiday)^2 + radius_down_km + I(hour:radius_down_km) , data = train)
Residuals:
Min 1Q Median 3Q Max

	-2.5802	-0.1019	0.0059	0.1079	1.4785
Coefficients:					
	Estimate	**Std.Error**	**t value**	**Pr(>|t|)**	
(Intercept)	5.299639	0.037437	141.56	2.00E-16	***
weekdayTuesday	0.071375	0.041061	1.74	0.0822	.
weekdayWednesday	0.044539	0.041085	1.08	0.27836	
weekdayThursday	0.20686	0.040354	5.13	3.00E-07	***
weekdayFriday	0.266442	0.041166	6.47	1.00E-10	***
weekdaySaturday	0.041513	0.040319	1.03	0.30321	
weekdaySunday	-0.204946	0.041198	-4.97	6.60E-07	***
hour1	-0.181998	0.065435	-2.78	0.00542	**
hour2	-0.444281	0.065056	-6.83	9.00E-12	***
hour3	-0.473827	0.065351	-7.25	4.50E-13	***
hour4	-1.05412	0.065171	-16.17	2.00E-16	***
hour5	-1.58424	0.065604	-24.15	2.00E-16	***
hour6	-1.961205	0.06435	-30.48	2.00E-16	***
hour7	-2.431233	0.064784	-37.53	2.00E-16	***
hour8	-2.410271	0.06541	-36.85	2.00E-16	***
hour9	-1.614209	0.065027	-24.82	2.00E-16	***
hour10	-1.036952	0.064806	-16	2.00E-16	***
hour11	-0.286688	0.064647	-4.43	9.30E-06	***
hour12	0.289958	0.064264	4.51	6.50E-06	***
hour13	0.432444	0.065235	6.63	3.60E-11	***
hour14	0.401292	0.06514	6.16	7.50E-10	***
hour15	0.311546	0.065529	4.75	2.00E-06	***
hour16	0.258674	0.065754	3.93	8.40E-05	***
hour17	0.202369	0.065001	3.11	0.00186	**
hour18	0.219576	0.065588	3.35	0.00082	***
hour19	0.20338	0.064452	3.16	0.00161	**
hour20	0.172768	0.065033	2.66	0.00791	**
hour21	0.289909	0.064752	4.48	7.60E-06	***
hour22	0.241244	0.065678	3.67	0.00024	***
hour23	0.117928	0.052886	2.23	0.02578	*
holiday1	-0.56329	0.058904	-9.56	2.00E-16	***
radius_down_km1-2	-0.067412	0.037517	-1.8	0.07239	.

radius_down_km3-6	-1.043979	0.03762	-27.75	2.00E-16	***
radius_down_km4-5	-0.694065	0.038167	-18.18	2.00E-16	***
radius_down_km5-6	-0.72499	0.036987	-19.6	2.00E-16	***
radius_down_km6+	-0.473608	0.037536	-12.62	2.00E-16	***
I(hour:radius_down_km)0:1-2	-0.009478	0.053342	-0.18	0.85897	
I(hour:radius_down_km)0:3-6	-0.063352	0.053088	-1.19	0.23277	
I(hour:radius_down_km)0:4-5	-0.114688	0.0535	-2.14	0.03208	*
I(hour:radius_down_km)0:5-6	-0.062765	0.052751	-1.19	0.23415	
I(hour:radius_down_km)0:6+	-0.026189	0.053243	-0.49	0.62282	
I(hour:radius_down_km)1:0-1	-0.00524	0.05367	-0.1	0.92222	
I(hour:radius_down_km)1:1-2	0.032316	0.052919	0.61	0.54143	
I(hour:radius_down_km)1:3-6	-0.018873	0.054137	-0.35	0.72738	
I(hour:radius_down_km)1:4-5	-0.070462	0.054185	-1.3	0.1935	
I(hour:radius_down_km)1:5-6	-0.068816	0.053327	-1.29	0.19692	
I(hour:radius_down_km)2:0-1	0.191759	0.053704	3.57	0.00036	***
I(hour:radius_down_km)2:1-2	0.162032	0.053702	3.02	0.00256	**
I(hour:radius_down_km)2:3-6	0.142473	0.054112	2.63	0.00848	**
I(hour:radius_down_km)2:4-5	0.135713	0.054357	2.5	0.01255	*
I(hour:radius_down_km)2:5-6	0.081662	0.053834	1.52	0.12932	
I(hour:radius_down_km)3:0-1	0.196205	0.053394	3.67	0.00024	***
I(hour:radius_down_km)3:1-2	0.17473	0.054394	3.21	0.00132	**
I(hour:radius_down_km)3:3-6	0.20514	0.054367	3.77	0.00016	***
I(hour:radius_down_km)3:4-5	0.085451	0.054318	1.57	0.11572	
I(hour:radius_down_km)3:5-6	-0.017869	0.05381	-0.33	0.73985	
I(hour:radius_down_km)4:0-1	0.746828	0.052075	14.34	2.00E-16	***
I(hour:radius_down_km)4:1-2	0.843143	0.052455	16.07	2.00E-16	***
I(hour:radius_down_km)4:3-6	0.496989	0.052581	9.45	2.00E-16	***
I(hour:radius_down_km)4:4-5	0.371141	0.053706	6.91	5.10E-12	***
I(hour:radius_down_km)4:5-6	0.332587	0.05268	6.31	2.90E-10	***
I(hour:radius_down_km)5:0-1	1.108645	0.054491	20.35	2.00E-16	***
I(hour:radius_down_km)5:1-2	1.182235	0.053734	22	2.00E-16	***
I(hour:radius_down_km)5:3-6	0.715408	0.054325	13.17	2.00E-16	***
I(hour:radius_down_km)5:4-5	0.472876	0.054496	8.68	2.00E-16	***
I(hour:radius_down_km)5:5-6	0.36458	0.05314	6.86	7.30E-12	***
I(hour:radius_down_km)6:0-1	1.204854	0.053425	22.55	2.00E-16	***

I(hour:radius_down_km)6:1-2	1.219439	0.052869	23.07	2.00E-16	***
I(hour:radius_down_km)6:3-6	0.600298	0.053663	11.19	2.00E-16	***
I(hour:radius_down_km)6:4-5	0.463156	0.054209	8.54	2.00E-16	***
I(hour:radius_down_km)6:5-6	0.36144	0.052351	6.9	5.40E-12	***
I(hour:radius_down_km)7:0-1	1.407724	0.052936	26.59	2.00E-16	***
I(hour:radius_down_km)7:1-2	1.467008	0.053326	27.51	2.00E-16	***
I(hour:radius_down_km)7:3-6	0.715681	0.054117	13.22	2.00E-16	***
I(hour:radius_down_km)7:4-5	0.605851	0.054074	11.2	2.00E-16	***
I(hour:radius_down_km)7:5-6	0.387242	0.052627	7.36	2.00E-13	***
I(hour:radius_down_km)8:0-1	1.205719	0.053673	22.46	2.00E-16	***
I(hour:radius_down_km)8:1-2	1.354385	0.053228	25.45	2.00E-16	***
I(hour:radius_down_km)8:3-6	0.540729	0.053851	10.04	2.00E-16	***
I(hour:radius_down_km)8:4-5	0.580447	0.053872	10.77	2.00E-16	***
I(hour:radius_down_km)8:5-6	0.244999	0.052863	4.63	3.60E-06	***
I(hour:radius_down_km)9:0-1	0.421824	0.053175	7.93	2.40E-15	***
I(hour:radius_down_km)9:1-2	0.57143	0.053547	10.67	2.00E-16	***
I(hour:radius_down_km)9:3-6	0.19275	0.053306	3.62	0.0003	***
I(hour:radius_down_km)9:4-5	0.151871	0.054126	2.81	0.00503	**
I(hour:radius_down_km)9:5-6	0.020198	0.05278	0.38	0.70196	
I(hour:radius_down_km)10:0-1	0.234721	0.053692	4.37	1.20E-05	***
I(hour:radius_down_km)10:1-2	-0.013389	0.053058	-0.25	0.80078	
I(hour:radius_down_km)10:3-6	0.175363	0.053288	3.29	0.001	**
I(hour:radius_down_km)10:4-5	0.231732	0.053904	4.3	1.70E-05	***
I(hour:radius_down_km)10:5-6	0.191869	0.052822	3.63	0.00028	***
I(hour:radius_down_km)11:0-1	-0.135061	0.053565	-2.52	0.0117	*
I(hour:radius_down_km)11:1-2	-0.358836	0.053526	-6.7	2.10E-11	***
I(hour:radius_down_km)11:3-6	0.077443	0.053482	1.45	0.14764	
I(hour:radius_down_km)11:4-5	0.235433	0.054572	4.31	1.60E-05	***
I(hour:radius_down_km)11:5-	0.149826	0.053428	2.8	0.00505	**

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I(hour:radius_down_km)12:0-1	-0.263325	0.053244	-4.95	7.70E-07	***
I(hour:radius_down_km)12:1-2	-0.53189	0.052509	-10.13	2.00E-16	***
I(hour:radius_down_km)12:3-6	-0.05737	0.052883	-1.08	0.27802	
I(hour:radius_down_km)12:4-5	0.150504	0.054172	2.78	0.00548	**
I(hour:radius_down_km)12:5-6	0.044353	0.053308	0.83	0.40543	
I(hour:radius_down_km)13:0-1	-0.253264	0.053565	-4.73	2.30E-06	***
I(hour:radius_down_km)13:1-2	-0.610677	0.053516	-11.41	2.00E-16	***
I(hour:radius_down_km)13:3-6	-0.039221	0.053611	-0.73	0.46444	
I(hour:radius_down_km)13:4-5	0.092948	0.053198	1.75	0.08063	.
I(hour:radius_down_km)13:5-6	0.060778	0.052988	1.15	0.25141	
I(hour:radius_down_km)14:0-1	-0.179007	0.053173	-3.37	0.00076	***
I(hour:radius_down_km)14:1-2	-0.481949	0.052462	-9.19	2.00E-16	***
I(hour:radius_down_km)14:3-6	0.019612	0.053083	0.37	0.7118	
I(hour:radius_down_km)14:4-5	0.142428	0.053909	2.64	0.00826	**
I(hour:radius_down_km)14:5-6	0.057207	0.053148	1.08	0.28179	
I(hour:radius_down_km)15:0-1	-0.156592	0.05382	-2.91	0.00363	**
I(hour:radius_down_km)15:1-2	-0.322248	0.054021	-5.97	2.50E-09	***
I(hour:radius_down_km)15:3-6	0.082212	0.053449	1.54	0.12405	
I(hour:radius_down_km)15:4-5	0.183139	0.054905	3.34	0.00085	***
I(hour:radius_down_km)15:5-6	0.008806	0.053211	0.17	0.86856	

I(hour:radius_down_km)16:0-1	-0.063418	0.053395	-1.19	0.23497	
I(hour:radius_down_km)16:1-2	-0.096227	0.05392	-1.78	0.07435	.
I(hour:radius_down_km)16:3-6	0.131652	0.0546	2.41	0.01592	*
I(hour:radius_down_km)16:4-5	0.19428	0.053797	3.61	0.00031	***
I(hour:radius_down_km)16:5-6	0.028045	0.053083	0.53	0.59729	
I(hour:radius_down_km)17:0-1	-0.015957	0.052767	-0.3	0.76235	
I(hour:radius_down_km)17:1-2	0.008735	0.053526	0.16	0.87037	
I(hour:radius_down_km)17:3-6	0.079107	0.053544	1.48	0.13959	
I(hour:radius_down_km)17:4-5	0.098822	0.05376	1.84	0.06606	.
I(hour:radius_down_km)17:5-6	-0.096499	0.053251	-1.81	0.06999	.
I(hour:radius_down_km)18:0-1	0.005712	0.05439	0.11	0.91636	
I(hour:radius_down_km)18:1-2	-0.021694	0.05411	-0.4	0.68848	
I(hour:radius_down_km)18:3-6	-0.014896	0.054508	-0.27	0.78464	
I(hour:radius_down_km)18:4-5	-0.007744	0.055094	-0.14	0.88822	
I(hour:radius_down_km)18:5-6	-0.201858	0.053807	-3.75	0.00018	***
I(hour:radius_down_km)19:0-1	-0.0192	0.053249	-0.36	0.71843	
I(hour:radius_down_km)19:1-2	-0.075581	0.053515	-1.41	0.15789	
I(hour:radius_down_km)19:3-6	-0.020988	0.054739	-0.38	0.70141	
I(hour:radius_down_km)19:4-5	-0.104681	0.053226	-1.97	0.04924	*
I(hour:radius_down_km)19:5-6	-0.18636	0.053991	-3.45	0.00056	***
I(hour:radius_down_km)20:0-1	-0.028226	0.053471	-0.53	0.5976	

I(hour:radius_down_km)20:1-2	-0.07323	0.053267	-1.37	0.16924	
I(hour:radius_down_km)20:3-6	-0.03706	0.053942	-0.69	0.49208	
I(hour:radius_down_km)20:4-5	-0.074098	0.053353	-1.39	0.16492	
I(hour:radius_down_km)20:5-6	-0.111084	0.052849	-2.1	0.03559	*
I(hour:radius_down_km)21:0-1	-0.132904	0.052898	-2.51	0.01201	*
I(hour:radius_down_km)21:1-2	-0.134955	0.053542	-2.52	0.01173	*
I(hour:radius_down_km)21:3-6	-0.063936	0.053082	-1.2	0.22844	
I(hour:radius_down_km)21:4-5	-0.033246	0.053827	-0.62	0.53682	
I(hour:radius_down_km)21:5-6	-0.085994	0.053852	-1.6	0.11033	
I(hour:radius_down_km)22:0-1	-0.031412	0.053067	-0.59	0.55391	
I(hour:radius_down_km)22:1-2	-0.056326	0.053342	-1.06	0.29103	
I(hour:radius_down_km)22:3-6	-0.040111	0.054158	-0.74	0.45894	
I(hour:radius_down_km)22:4-5	0.042621	0.054276	0.79	0.43232	
I(hour:radius_down_km)22:5-6	-0.014181	0.052832	-0.27	0.78839	
weekdayTuesday:hour1	0.059489	0.057504	1.03	0.30092	
weekdayWednesday:hour1	0.022196	0.058228	0.38	0.70307	
weekdayThursday:hour1	-0.021149	0.05796	-0.36	0.7152	
weekdayFriday:hour1	0.129715	0.058804	2.21	0.02742	*
weekdaySaturday:hour1	0.119797	0.057829	2.07	0.03833	*
weekdaySunday:hour1	0.136421	0.058968	2.31	0.02072	*
weekdayTuesday:hour2	-0.265435	0.057358	-4.63	3.70E-06	***
weekdayWednesday:hour2	-0.191534	0.05752	-3.33	0.00087	***
weekdayThursday:hour2	-0.288013	0.05721	-5.03	4.90E-07	***
weekdayFriday:hour2	-0.213016	0.05805	-3.67	0.00024	***
weekdaySaturday:hour2	0.224867	0.058367	3.85	0.00012	***
weekdaySunday:hour2	0.537248	0.05774	9.3	2.00E-16	***

weekdayTuesday:hour3	-0.346029	0.05748	-6.02	1.80E-09	***
weekdayWednesday:hour3	-0.267366	0.058988	-4.53	5.90E-06	***
weekdayThursday:hour3	-0.31909	0.058016	-5.5	3.90E-08	***
weekdayFriday:hour3	-0.217342	0.058267	-3.73	0.00019	***
weekdaySaturday:hour3	0.288099	0.057866	4.98	6.50E-07	***
weekdaySunday:hour3	0.676972	0.059084	11.46	2.00E-16	***
weekdayTuesday:hour4	-0.530319	0.058096	-9.13	2.00E-16	***
weekdayWednesday:hour4	-0.250301	0.058103	-4.31	1.70E-05	***
weekdayThursday:hour4	-0.285716	0.05717	-5	5.90E-07	***
weekdayFriday:hour4	-0.202058	0.057977	-3.49	0.00049	***
weekdaySaturday:hour4	0.388721	0.056957	6.82	9.30E-12	***
weekdaySunday:hour4	0.782906	0.057684	13.57	2.00E-16	***
weekdayTuesday:hour5	-0.365715	0.058666	-6.23	4.70E-10	***
weekdayWednesday:hour5	-0.241006	0.058261	-4.14	3.60E-05	***
weekdayThursday:hour5	-0.313736	0.058286	-5.38	7.50E-08	***
weekdayFriday:hour5	-0.141619	0.057945	-2.44	0.01454	*
weekdaySaturday:hour5	0.50511	0.057448	8.79	2.00E-16	***
weekdaySunday:hour5	0.984566	0.057241	17.2	2.00E-16	***
weekdayTuesday:hour6	-0.474488	0.05757	-8.24	2.00E-16	***
weekdayWednesday:hour6	-0.166134	0.057322	-2.9	0.00376	**
weekdayThursday:hour6	-0.507654	0.05675	-8.95	2.00E-16	***
weekdayFriday:hour6	-0.07871	0.057045	-1.38	0.16769	
weekdaySaturday:hour6	0.644884	0.056379	11.44	2.00E-16	***
weekdaySunday:hour6	1.149023	0.058602	19.61	2.00E-16	***
weekdayTuesday:hour7	-0.477483	0.057217	-8.35	2.00E-16	***
weekdayWednesday:hour7	-0.236511	0.057639	-4.1	4.10E-05	***
weekdayThursday:hour7	-0.255013	0.056592	-4.51	6.70E-06	***
weekdayFriday:hour7	0.01988	0.058286	0.34	0.73305	
weekdaySaturday:hour7	0.727212	0.056995	12.76	2.00E-16	***
weekdaySunday:hour7	1.237794	0.057837	21.4	2.00E-16	***
weekdayTuesday:hour8	-0.443041	0.058152	-7.62	2.80E-14	***
weekdayWednesday:hour8	-0.221476	0.058335	-3.8	0.00015	***
weekdayThursday:hour8	-0.181399	0.057752	-3.14	0.00169	**
weekdayFriday:hour8	0.018971	0.058348	0.33	0.74508	
weekdaySaturday:hour8	0.641378	0.058238	11.01	2.00E-16	***

weekdaySunday:hour8	1.02523	0.05863	17.49	2.00E-16	***
weekdayTuesday:hour9	-0.399839	0.057952	-6.9	5.50E-12	***
weekdayWednesday:hour9	-0.211279	0.058395	-3.62	0.0003	***
weekdayThursday:hour9	-0.18755	0.056894	-3.3	0.00098	***
weekdayFriday:hour9	-0.161168	0.057751	-2.79	0.00527	**
weekdaySaturday:hour9	0.268263	0.057266	4.68	2.80E-06	***
weekdaySunday:hour9	0.536864	0.05824	9.22	2.00E-16	***
weekdayTuesday:hour10	-0.268581	0.057629	-4.66	3.20E-06	***
weekdayWednesday:hour10	-0.171971	0.059225	-2.9	0.0037	**
weekdayThursday:hour10	-0.292422	0.05743	-5.09	3.60E-07	***
weekdayFriday:hour10	-0.25211	0.058219	-4.33	1.50E-05	***
weekdaySaturday:hour10	-0.02831	0.057034	-0.5	0.61964	
weekdaySunday:hour10	0.114263	0.057543	1.99	0.04709	*
weekdayTuesday:hour11	-0.081655	0.057322	-1.42	0.15433	
weekdayWednesday:hour11	-0.007993	0.057586	-0.14	0.8896	
weekdayThursday:hour11	-0.105374	0.056943	-1.85	0.06427	.
weekdayFriday:hour11	-0.17207	0.057983	-2.97	0.00301	**
weekdaySaturday:hour11	-0.552896	0.057151	-9.67	2.00E-16	***
weekdaySunday:hour11	-0.478119	0.057033	-8.38	2.00E-16	***
weekdayTuesday:hour12	-0.089972	0.057249	-1.57	0.11608	
weekdayWednesday:hour12	-0.043948	0.057609	-0.76	0.44556	
weekdayThursday:hour12	-0.135765	0.058044	-2.34	0.01936	*
weekdayFriday:hour12	-0.292843	0.057566	-5.09	3.70E-07	***
weekdaySaturday:hour12	-0.643332	0.057078	-11.27	2.00E-16	***
weekdaySunday:hour12	-0.814396	0.058648	-13.89	2.00E-16	***
weekdayTuesday:hour13	-0.043257	0.057845	-0.75	0.45459	
weekdayWednesday:hour13	-0.033864	0.057925	-0.58	0.55881	
weekdayThursday:hour13	-0.202543	0.056984	-3.55	0.00038	***
weekdayFriday:hour13	-0.339227	0.05808	-5.84	5.40E-09	***
weekdaySaturday:hour13	-0.546681	0.057103	-9.57	2.00E-16	***
weekdaySunday:hour13	-0.836752	0.058553	-14.29	2.00E-16	***
weekdayTuesday:hour14	-0.086683	0.057144	-1.52	0.12932	
weekdayWednesday:hour14	-0.000862	0.058004	-0.01	0.98814	
weekdayThursday:hour14	-0.224532	0.057112	-3.93	8.50E-05	***
weekdayFriday:hour14	-0.308845	0.057555	-5.37	8.20E-08	***

weekdaySaturday:hour14	-0.438543	0.056863	-7.71	1.40E-14	***
weekdaySunday:hour14	-0.635689	0.05817	-10.93	2.00E-16	***
weekdayTuesday:hour15	-0.029123	0.058419	-0.5	0.61813	
weekdayWednesday:hour15	0.008986	0.058862	0.15	0.87866	
weekdayThursday:hour15	-0.166816	0.056973	-2.93	0.00342	**
weekdayFriday:hour15	-0.2151	0.058662	-3.67	0.00025	***
weekdaySaturday:hour15	-0.296634	0.0585	-5.07	4.00E-07	***
weekdaySunday:hour15	-0.442244	0.058179	-7.6	3.20E-14	***
weekdayTuesday:hour16	-0.099432	0.057598	-1.73	0.08432	.
weekdayWednesday:hour16	-0.034387	0.059155	-0.58	0.56104	
weekdayThursday:hour16	-0.24373	0.057485	-4.24	2.30E-05	***
weekdayFriday:hour16	-0.253422	0.057613	-4.4	1.10E-05	***
weekdaySaturday:hour16	-0.301641	0.057104	-5.28	1.30E-07	***
weekdaySunday:hour16	-0.490996	0.05829	-8.42	2.00E-16	***
weekdayTuesday:hour17	-0.058792	0.057584	-1.02	0.30729	
weekdayWednesday:hour17	0.001991	0.058098	0.03	0.97266	
weekdayThursday:hour17	-0.155272	0.056968	-2.73	0.00643	**
weekdayFriday:hour17	-0.202893	0.057973	-3.5	0.00047	***
weekdaySaturday:hour17	-0.201163	0.058468	-3.44	0.00058	***
weekdaySunday:hour17	-0.28322	0.058123	-4.87	1.10E-06	***
weekdayTuesday:hour18	-0.094167	0.058688	-1.6	0.10863	
weekdayWednesday:hour18	-0.021895	0.059664	-0.37	0.71365	
weekdayThursday:hour18	-0.208445	0.056655	-3.68	0.00024	***
weekdayFriday:hour18	-0.208176	0.058825	-3.54	0.0004	***
weekdaySaturday:hour18	-0.16609	0.059695	-2.78	0.00541	**
weekdaySunday:hour18	-0.293389	0.058302	-5.03	4.90E-07	***
weekdayTuesday:hour19	-0.10258	0.057885	-1.77	0.0764	.
weekdayWednesday:hour19	-0.045946	0.058575	-0.78	0.43282	
weekdayThursday:hour19	-0.238262	0.056879	-4.19	2.80E-05	***
weekdayFriday:hour19	-0.227126	0.057783	-3.93	8.50E-05	***
weekdaySaturday:hour19	-0.206155	0.057483	-3.59	0.00034	***
weekdaySunday:hour19	-0.286576	0.058512	-4.9	9.90E-07	***
weekdayTuesday:hour20	-0.105074	0.057872	-1.82	0.06946	.
weekdayWednesday:hour20	-0.072572	0.058729	-1.24	0.21659	
weekdayThursday:hour20	-0.18607	0.056614	-3.29	0.00102	**

weekdayFriday:hour20	-0.218726	0.057781	-3.79	0.00015	***
weekdaySaturday:hour20	-0.26508	0.056841	-4.66	3.10E-06	***
weekdaySunday:hour20	-0.26571	0.05759	-4.61	4.00E-06	***
weekdayTuesday:hour21	-0.072799	0.058079	-1.25	0.21008	
weekdayWednesday:hour21	-0.041999	0.058788	-0.71	0.47499	
weekdayThursday:hour21	-0.109215	0.057428	-1.9	0.05723	.
weekdayFriday:hour21	-0.211629	0.057769	-3.66	0.00025	***
weekdaySaturday:hour21	-0.315871	0.057409	-5.5	3.80E-08	***
weekdaySunday:hour21	-0.21479	0.058105	-3.7	0.00022	***
weekdayTuesday:hour22	-0.08623	0.058163	-1.48	0.13823	
weekdayWednesday:hour22	-0.035219	0.059294	-0.59	0.55254	
weekdayThursday:hour22	-0.123905	0.057761	-2.15	0.03197	*
weekdayFriday:hour22	-0.182756	0.058389	-3.13	0.00175	**
weekdaySaturday:hour22	-0.303627	0.058368	-5.2	2.00E-07	***
weekdaySunday:hour22	-0.108352	0.058527	-1.85	0.06416	.
weekdayTuesday:hour23	-0.053517	0.058133	-0.92	0.35728	
weekdayWednesday:hour23	-0.055482	0.059212	-0.94	0.34877	
weekdayThursday:hour23	-0.111718	0.057471	-1.94	0.05194	.
weekdayFriday:hour23	-0.150844	0.057675	-2.62	0.00893	**
weekdaySaturday:hour23	-0.219635	0.05696	-3.86	0.00012	***
weekdaySunday:hour23	-0.074206	0.056883	-1.3	0.19208	
weekdayTuesday:holiday1	0.277283	0.032071	8.65	2.00E-16	***
weekdayWednesday:holiday1	0.293135	0.031613	9.27	2.00E-16	***
weekdayThursday:holiday1	0.513691	0.032801	15.66	2.00E-16	***
weekdayFriday:holiday1	NA	NA	NA	NA	
weekdaySaturday:holiday1	NA	NA	NA	NA	
weekdaySunday:holiday1	NA	NA	NA	NA	
hour1:holiday1	0.075016	0.074703	1	0.31532	
hour2:holiday1	0.51791	0.084181	6.15	7.90E-10	***
hour3:holiday1	0.524819	0.084318	6.22	5.00E-10	***
hour4:holiday1	0.731795	0.080967	9.04	2.00E-16	***
hour5:holiday1	0.854902	0.079774	10.72	2.00E-16	***
hour6:holiday1	1.058887	0.079634	13.3	2.00E-16	***
hour7:holiday1	1.171737	0.076868	15.24	2.00E-16	***
hour8:holiday1	0.927688	0.078767	11.78	2.00E-16	***

hour9:holiday1	0.722592	0.07886	9.16	2.00E-16	***
hour10:holiday1	0.198565	0.079138	2.51	0.01212	*
hour11:holiday1	-0.526089	0.07784	-6.76	1.50E-11	***
hour12:holiday1	-0.894469	0.082134	-10.89	2.00E-16	***
hour13:holiday1	-1.001207	0.080019	-12.51	2.00E-16	***
hour14:holiday1	-0.777509	0.07691	-10.11	2.00E-16	***
hour15:holiday1	-0.562039	0.081026	-6.94	4.30E-12	***
hour16:holiday1	-0.4351	0.077791	-5.59	2.30E-08	***
hour17:holiday1	-0.228689	0.079828	-2.86	0.00418	**
hour18:holiday1	-0.270357	0.078878	-3.43	0.00061	***
hour19:holiday1	-0.30512	0.082314	-3.71	0.00021	***
hour20:holiday1	-0.264926	0.079724	-3.32	0.00089	***
hour21:holiday1	-0.290364	0.077777	-3.73	0.00019	***
hour22:holiday1	-0.215056	0.079878	-2.69	0.00711	**
hour23:holiday1	-0.157194	0.07884	-1.99	0.0462	*

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					
Residual standard error: 0.223 on 9685 degrees of freedom					
Multiple R-squared: 0.926,			**Adjusted R-squared:** 0.923		
F-statistic: 385 on 314 and 9685 DF			**p-value:** <2e-16		