Parking Meters at Carnegie Mellon University

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Section 1: Introduction

Research Question and Motivation

Coin parking meters are becoming a rarity in today's technologically advanced era, so why at Carnegie Mellon has there not been a technological improvement in terms of parking on its campus since CMU is known for being such a big tech hub? *Parking Meters at Carnegie Mellon University* is a survey regarding on campus parking meters to determine if there is a high frequency in unpaid meters. Additionally, it would be interesting to see if there are any correlations between other factors, such as the estimated value of the vehicle, time of day, day of week, color of vehicle, etc.

Traffic and parking are topics already on the minds of many at Carnegie Mellon University. Members of the Heinz College have put together Traffic21, a multi-disciplinary research initiative of Carnegie Mellon University. Their goal is to, "design, test, deploy and evaluate information and communications technology based solutions to address the problems facing the transportation system of the Pittsburgh region." As students at Carnegie Mellon, we would love to see some of their research efforts geared towards the campus community. cite?

It is not a question that metered parking is becoming an old technology. Recently the Pittsburgh Parking Authority has voted to spend $6.8 million for 500 new metering devices that allow payment methods of cash and/or credit cars. These new meters will also require that the driver enter a license plate number in order to pay for the parking spot. The meters will be multi-space meters and although will require drivers to walk a little farther to the meter, the new technology is anticipated to be well worth it. We believe that technology like this, if brought to Carnegie Mellon will help to improve the current parking situation. cite?

This new technology boom in metered parking is already having effects down south. This past year Texas Christian University installed new smart park parking meters allowing people to use their credit and debit cards. Although each new parking meter cost $7,000 each, parking manager for the Fort Worth City Council, Peter Elliot believes it has been well worth the investment. "Streamlining [parking meters] so that people can use their credit cards can only be seen as a good thing. It is just exchanging one form of technology with something newer." The city has been providing the university with real-time data on how frequently the spaces on campus were being used and for how long. This a feature that was not possible with the older parking meters, which allows researchers to asses cost-benefit analysis for the new parking system. The research that Texas Christian University affiliates are conducting with their new smart park parking system ignites innovation and truly incentivize other colleges and universities across the nation to jump on the bandwagon and get hip with the new technology. cite?

This project is also relevant for the portion of Carnegie Mellon community members who uses the parking meters on campus, and especially those who have been ticketed for parking violations. This survey is significant, because it looks at the bigger picture. Through effective investigation and research, the results illustrate exactly how efficient the parking system at Carnegie Mellon University Pittsburgh campus actually is.

Overview

The main focus of this survey was to see if there is an abundance of people parking illegally. The time of day was also considered to see if there are certain times of day or certain days of the week that was correlated to a higher frequency of illegal parking. The state the vehicle is registered in was also recorded in order to see if there was a difference of out of state individuals versus Pennsylvania residents. Other variables such as make/model and color were noted in order to see if there is any connection with these factors and illegal parking.

This survey looked at different aspects of metered parking at Carnegie Mellon University and included the questions below amongst many others.

a. How frequent do people not pay meters
b. Are certain days/times more likely to have unpaid meters
c. Are different types (color/brand/model) of vehicles more likely to be at an unpaid meter
d. Are vehicles registered with Pennsylvania stickers or outside states (by checking license plate) more likely to be at an unpaid meter

Parking Meters at Carnegie Mellon University surveyed all campus parking meters at various hours in the day and on multiple days while recording how frequently the meters are unpaid and which types of vehicles are parked at those unpaid meters. Due to our findings, Carnegie Mellon University should strive to seek alternative methods to coin operated parking meters for its campus community members.

Summary of Results

We found from regression analysis that certain days, streets, and time of day were more likely to have more unpaid meters than other areas. We found some variables to disregard because of its inability to accurately predict the probability of unpaid meters on campus. In the end, the inefficiency of coined meter parking can be inferred from our census of Carnegie Mellon’s parking meters. They are too expensive, inconvenient and thus are operating at a third of its capacity. The cost to commuters who pay compensation for parking time compared to the cost of commuters who run the risk of getting caught not paying fair compensation do not account for factors like cost of risk. Hence some commuters find it worthwhile to run the risk at a discount rate.

In our analysis we find that the Pittsburgh Parking Authority and Carnegie Mellon Parking Management would find it beneficial to lower the cost of meter parking as well as increase ticket fines. We also find that integrating new technologies to our meters, such as the use of mobile/online payment programs, in the long run will save our management the cost of meter operation and maintenance. We also expect more commuters to find new utility in the convenience of smart meters once integrated and increase each meter's productivity rate.

Section 2: Methods

Target Population

The target population was parking meters on Frew, Tech, Margaret Morrison Street, and the University Center, and behind Morewood Gardens. These are all of the on campus parking meters, and since the target population is not overwhelmingly large in size, all units in the target population were observed.

Population Description

There are total of 224 parking meters on campus:

Margaret Morrison Street	5
Tech Street	29
Frew Street	168
University Center	6
Morewood Parking Lot	16

The sampling scheme is a census of all 224 parking meters. The results from a census are more reliable than the ones we would obtain from doing a random sample since there is theoretically no error in a census. Since a census of all campus parking meters was conducted, the sample size was 224 and the margin of error was zero.

Survey Method

The survey was conducted by checking each parking meter at varying times and on different days, whilst recording the observations. An Excel spreadsheet was used (using a small lap-top) to record the findings. A copy of this Excel spreadsheet can be found in Appendix 2. Below is a general grouping of the aspects that were surveyed:

Questions related to the parking meter

1. Is there a vehicle parked at the parking meter?
2. Is the vehicle parked at an expired meter?
3. Is the meter broken?

Questions related to the vehicle

1. What color is the vehicle?
2. Type of vehicle (compact, minivan, truck, etc.)
3. Make of vehicle (Chevy, Ford, BMW, Mazda, Honda, Pontiac, etc.)
4. Model of vehicle (Accord, Focus, Protégé, Sunfire)
5. What state is their license plate from?
6. Does the vehicle have a ticket?
    a. How much is the ticket?
    b. What were they ticketed for?
7. Is the vehicle clean or dirty?
8. Do they have registration? (tag located on license place)
    a. Is the registration expired?
9. Do they have their vehicle inspected? (tag located on windshield)
    a. Is their inspection expired?
10. Does the vehicle have any after-market additions? (fancy exhaust system, suspension lift, spoiler, fancy rims)
11. Is the vehicle parked at a handicapped parking spot?
    a. Do they have a handicapped tag/license plate
12. Does the vehicle have any major dents, scrapes, or shattered windows?
13. Is the vehicle driving on a spare tire?
14. Does the vehicle have a parking pass to park on another on-campus location?

Questions not related to either the meter or the vehicle

1. What day of the week is it?
2. What is the time?
3. What street is the vehicle parked on?
4. What is the weather like? (sunny, rainy, cold, hot, etc.)
5. Total percentage of vehicles parked on each street/region

A reference sheet of most vehicle makes was created in a column format in order to be most efficient during the survey process. Specific to the questionnaire, most of the questions were "yes" or "no" questions, so coding "1" for "yes" and "0" and "no" was used. For the "type of vehicle" question, the following coding was used: 1 for a car/sedan, 2 for a truck, 3 for SUV, 4 for VAN, 5 for motorcycle/scooter, 6 for other. Unique coding was used for all but four questions in our survey in order to conduct the survey in the most efficient manner.

Since parking meter fees apply between 8:00am and 10:00pm for the Skibo/Baker parking meters, 8:00am until 5:00pm for the meters behind Morewood, and 24 hours at the University Center meters, two surveying groups were comprised in order to administer the census. The first group surveyed morning commuters, from 8:00am to 12:00pm, and the second group surveyed afternoon commuters, from 12:00pm to 5:00pm.

These subgroups cover some key demographics of student, faculty, and visitors for presence on campus which led to some interesting differences between morning commuters versus afternoon commuters' behavior towards paying parking meters on campus. In each of the subgroups, a full sample of all parking meters on campus (Frew Street, Tech Street, Margaret Morrison Street, University Center, behind Morewood Gardens) was recorded. The schedule of data collection times is below:

Monday, Wednesday, and Friday census collection		
Jungmoon/Nancy/Victor	Morning	9:00-12:00pm
Victor/Nancy	Afternoon	3:30-6:30pm
Tuesday and Thursday census collection		
Jeff	Morning	9:30-12:00pm
Kaylee/Nancy	Afternoon	12:00-3:00pm

Given the survey census design, there were two cluster variables- Time and Location. First, there were two time variables, Day of the Weekday (M,T,W,TH,F) and Time of Day (Morning, Afternoon). Since commuters to Carnegie Mellon are probably very specific on what time they are on campus, each subgroup was aimed to yield similar responses. Second, location variable of parking meter spaces (Tech St., Frew St., Margret Morrison St., Morewood Parking Lot, Frew St.). Since parking meters are very location specific, we found that people who park at meters were different between and similar within each location. We surveyed for one week, and the calculations in Appendix 1 showcase why we believe one week was enough time to collect the data we need.

The appx was great, thanks. Note that a bit more words in appx 1 would be helpful, so we know (a) what X is supposed to be counting, (b) that the expected value of X under these assumptions is 78.4, etc...

Post Survey Processing

After we compiled a data set from our 10 different runs of parking meters on campus, we examined that some variables became of little use whereas others were obviously correlated with non-paid parking meters on campus.

Coding categorical for expected change in not paid meters and which reference category type will be set to 0:
Color: Use black. (e.g. a car that is red may have more or less expected unpaid meters compared to black cars)
Car type: Use 1, Sedan type (e.g. a SUV may have more or less expected unpaid meters compared to sedans)
Registration state: Use PA, Pennsylvania (e.g. a car registered in Ohio may have more or less expected unpaid meters compared to cars registered in Pennsylvania)

Categorical variables with yes or no responses we will set no as the reference.
Clean: use dirty (e.g. a clean car will have more or less expected unpaid meters compared to dirty car)
Handicapped: Use not handicapped (e.g. a handicapped reserved space will have more or less expected unpaid meters compared to a non-reserved space)

Imputation: There was minor imputation needed for our data, yet it was mostly housekeeping. Our data entry varied in certain aspects depending on who was collecting data so we needed to organize our data in a systematic way so that we could run the data in R. An example was the state category, some filled in the abbreviation while others typed in the whole state. Other issues were capital and lowercase letters as well as leaving cells empty or inserting a zero.

Section 3: Results

Either here or in the appendices need to include a glossaryof variable names and their meanings...

General Results

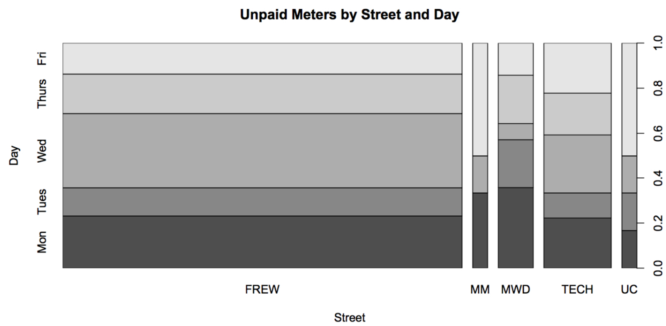
Upon analyzing the results of the survey, we found relevant correlations that will illustrate how many members of the Carnegie Mellon University community park at a parking meter, and which of those individuals parking at a parking meter actually pay for parking.

Number of Meters: 2240
Number of Commuters Using Meters: 794 (**35.4464%**)
Number of Commuters who failed to pay for meters: 213 (**9.5089%**)
Number of Commuters who parked at broken meters: 74 (**3.3036%**)

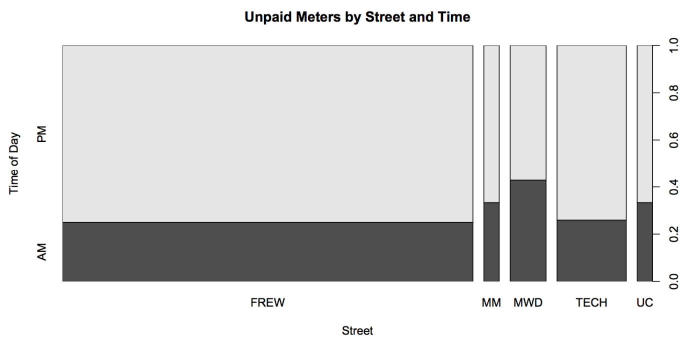
provide std errors based on replicating census 10 times?

(here and throughout...)

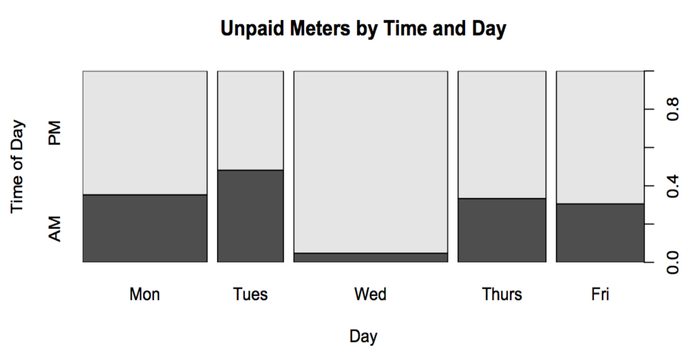
Number of Commuters who received a ticket: 30 (**1.3392%**)



We see that Frew Street on Wednesdays has the most observed upaid meters whereas Margret Morrison on Wednesdays had no observed unpaid meters.



We can see that there were more commuters who failed to pay for meters in the afternoon. Frew Street in the afternoon had the most unpaid meters whereas Margret Morrison and the UC meters in the morning had the least unpaid meters.



Commuters were very unlikely to have unpaid meters Wednesday mornings but are very likely to have meters unpaid during the afternoon.

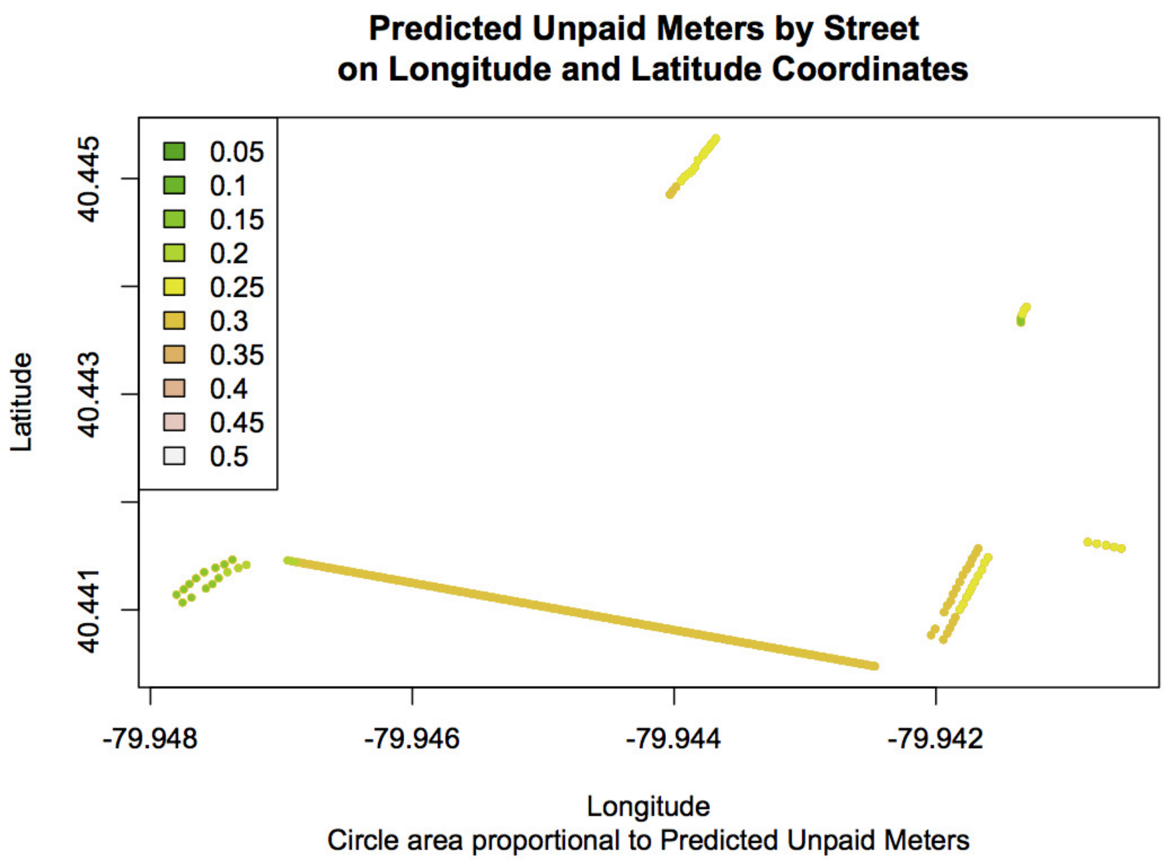
By Street: Rsq=0.4224 P-value=0.1065

meter=0.25512-0.04083MM-0.11786MWD-0.03561TECH-0.0733UC
By Day: Rsq= 0.4055 P-value=2.2e-16
meter= 0.27273+0.05630M-0.18619T+0.1549W-0.06096TH
By Time Rsq= 0.4072 P-value=2.2e-16
meter: 0.12051 +0.23217PM

These look like nice analyses, but in the appx it looks like more than half the data was dropped because of missing values -- you should've run the analyses on the cleaned-up data with no missingness after post-survey processing (and/or explained in the post-survey processing section above why it is OK to deal with missingness by just case-wise deletion (MCAR assumption!)....

By Time and Street: Rsq=0.4047 P-value=2.2e-16
By Time and Day: Rsq= 0.3968 P-value= 2.2e-16
By Street and Day: Rsq=0.4041 P-value= 2.2e-16
By Street, Day, and Time: Rsq=0.394 P-value= 2.2e-16
Additional Regression, to ease interpretation of our variable, unpaid meters, we chose not to transform meters. (see Appendix 7 Part B and C)

Holding for Frew Street: Rsq= 0.3402 P-value: 0.07927
Ticket= 0.10625-0.10625MM+0.17946MWD+0.15301TECH+0.06042UC



nice

Map above explained on the next page.

Heat map of predicted unpaid meters with street as its predictor variables. The green areas, values near 0, represent paid meters, where as yellower areas represent areas of unpaid meters. None of the predicted vales of meter were over 0.5, which represents 50% of all commuters who used meters on these streets did not pay.

Conclusions about our research question

Below are some calculations displaying why some commuters may have the tendency to not pay for the meter:

this calculation is a very nice idea.

Assuming our variables are all independent variables:
Parking Tickets cost $30
Parking Meters cost 8 minutes for $0.25
If we say the average commuter parks for about 2.5 hours it costs about $4.69

On any given length of weekday at Carnegie Mellon (Monday - Friday):
Predicted Meter Revenue: $3723.86
Predicted Lost Meter Revenue: $6781.74
Predicted Lost Meter Revenue on Broken Meters: $347.06
Predicted Ticket Revenue: $900.

I can't tell where these numbers are coming from.

Explain to reader!

Chances of Commuters receiving a ticket: 14.08%
Expected cost of risk: $4.23

Therefore, some commuters find that it is worth it to run the risk of not paying for meter, since $4.23 is less than $4.69.

As a result, Carnegie Mellon and Pittsburgh Parking Authority need to find new ways to allow commuters to easily pay for meters. An average commuter who utilizes parking meters correctly will in fact boost meter revenue whereas resorting to ticketing and enforcing meters will result in long-run gross loss.

Section 4: Discussion

Our Research Questions

The survey *Parking Meters at Carnegie Mellon University* analyzed campus parking meters in order to find meaningful correlations between the frequency of unpaid meters along with any correlations between other factors, such as the estimated value of the vehicle, time of day, day of week, color of vehicle, etc. Our hope is to be able to provide relevant insight to the Pittsburgh Parking Authority in how to make parking and monitoring more efficient. Many results from the survey beg the question, why is Carnegie Mellon University in tandem with the Pittsburgh Parking Authority not actively searching for new ways of implementing technological improvements in terms of parking on its campus in order to monitor parking in the most efficient and cutting-edge manner?

a. How frequent do people not pay meters?

9.5089%

b. Are certain days/times more likely to have unpaid meters?

Holding Friday as the comparison variable, we expect with 95% confidence Monday to be between 0.827% and 10.433%, Tuesday to be between -22.83% and -14.408%, Wednesday to be between 10.665% and 20.315%, Thursday to be between -10.801% and -1.391%. Overall we expect Wednesday to have most unpaid meters and Tuesday to have most paid meters.

c. Are different types (color/brand/model) of vehicles more likely to be at an unpaid meter?

Listed top most likely with count percentages.
Brands: Toyota (12.20%), Honda(10.32%), Ford (10.32%), Chevy (7.98%)
Models: Mini Cooper (5.63%), Honda Civic (5.16%), Toyota Corolla (3.76%), Ford Focus (3.29%)
Color: Black (20.66%), Blue (15.02%), Silver (14.08%), White (12.68%)

d. Are vehicles registered with Pennsylvania stickers or outside states (by checking license plate) more likely to be at an unpaid meter?

State: PA(82.63%), NY (1.88%), CA(1.88%)

Surprising Results

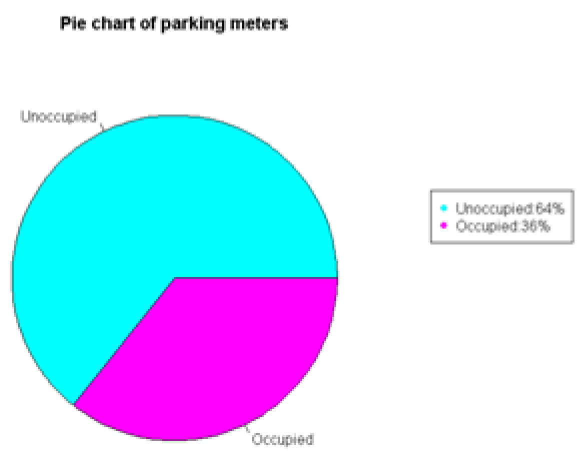
Upon conducting our census survey, the lack of vehicles parked at the parking meters was overwhelming and quite surprising. Furthermore, an even greater surprise came from the proportion of those vehicles that were parked at a campus parking meter and did not pay. We found that only 40% of the parking meters on campus were being used, and of that forty percent, over 30% did not put money in the meter they were parked at. It is easy to see that this is an extremely inefficient system for the Pittsburgh Parking Authority and it should be addressed by the parking authority immediately.

Meaningful Results

Possible explanations for our findings can be drawn from the increase in price per hour for parking and the time limitations now in place that does not allow one to park in a given parking zone for more than four hours a day are quite evident. Both of these aspects, along with various other stipulations now being enforced on those who chose to park on campus, are ultimately affecting the effectiveness of parking on campus. The next logical step to take is to find what other options Carnegie Mellon University can offer its campus community.

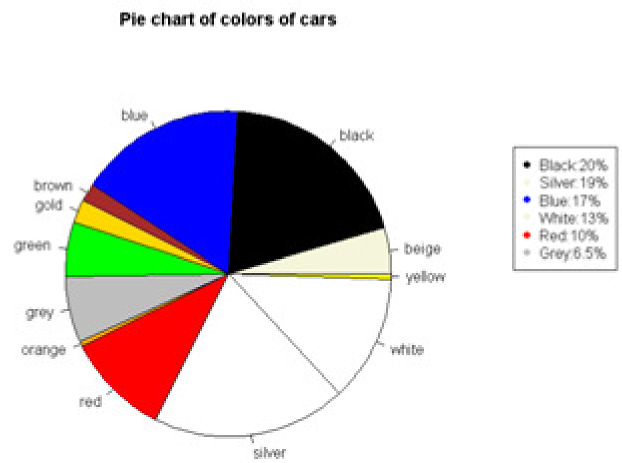
Fun Facts

After completing our census, we created some pie charts to displays some interesting features we have observed:

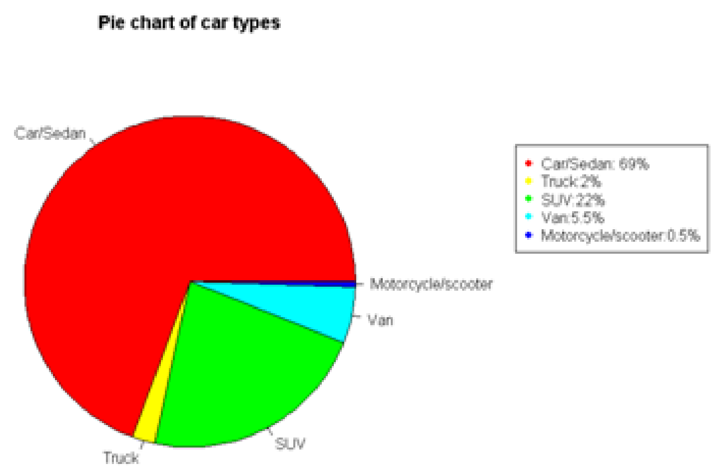


First, out of 2233 parking meters we observed (224 parking meter *10 times, but excluding ineligible units), only about 36% were occupied. The ineligible units were 4 zipcar, 3 cars which parking fees were already covered, and 1 CMU police car.

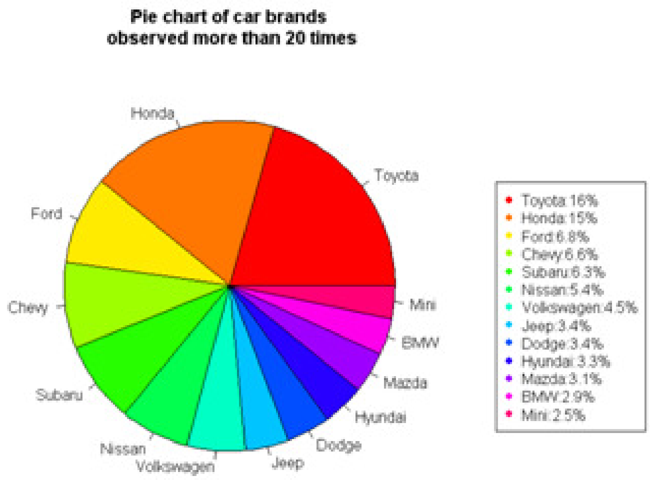
Next pie chart on the following page.



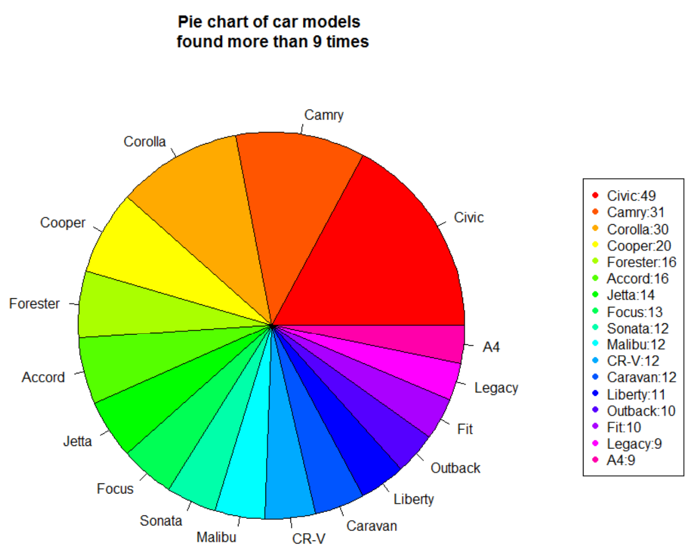
Next, we made a pie chart for the colors of cars. We found, out of 803 we observed, 20% of the cars were black while 19% of them were silver, followed by blue and then white. Overall, cars with a type of white shade were most commonly found. It may be because white cars pay lower insurance fee compared to other colored-cars.



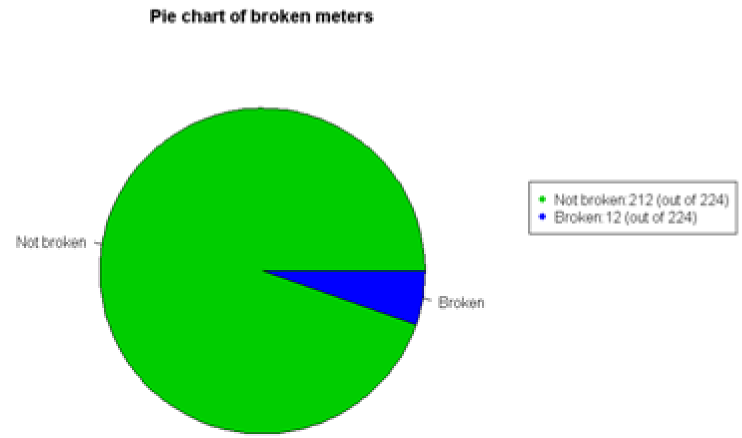
Moving on, out of 803 cars we observed, more than half, in fact, 69% of them were car/sedan. We only saw 3 motorcycles/scooters.



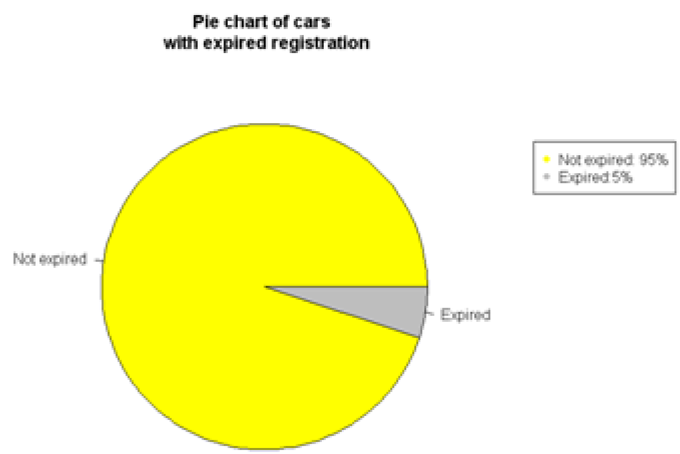
We observed many different car brands, but above pie chart only displays car makes that were seen more than 20 times. The top three most popular car brands at CMU are Toyota, Honda and Ford. The fifth and sixth mostly found car brands were subaru and nissan, which indicated that people at CMU tend to prefer Japanese-makes cars.



Above is the pie chart of car models found more than 9 times. As we have seen in the pie chart of car brands found more than 20 times, we saw 49 Civic, 31 Camry, and 30 Camry which are all from Japanese brands (Civic is from Honda, Camry and Corolla are from Toyota.) It was interesting to see quite so many Mini coopers (about 20).



Out of 224 parking meters, 12 of them were broken and it was interesting to see how these broken parking meters were always occupied.



Another interesting feature we observed is the proportion of cars with expired registeration. Out of 796, 40 of them had expired registration and none of them got tickets for it.

Weaknesses

Although we conducted a census, there are still some errors coming from ineligible units. First of all, we considered cars parked in between spaces as ineligible units. Usually, parking meters define parking spaces. However, there are sometimes spaces that are large enough so that a car can park but no parking meter is present, and the driver gets a free pass for the day. We noticed that this was the usual case for cars parked on Frew Street. Also, there were issues with double parking; a car parked in two parking spaces, which we considered as an ineligible unit in one spot and parked in another. Sometimes, there were cars parked, but drivers were sitting in their cars, and we marked them as “not present” in our data. Another example of an ineligible unit is CMU Transportation cars parked in parking spaces behind Morewood, which is administered by CMU and they were exempted from paying the parking meters. Also, cars parking at meters that we already had passed by and marked as "not present" remained to be "not present."

Another error that arose was measurement error, in the sense that there was no way of knowing if a parking meter is really broken or not. If the meter was broken, the driver was obviously not able to pay and in some cases it was impossible to identify if the driver has not paid because the meter itself was broken or for some other reasons, all reflecting some aspect of measurement error.

Another source of error comes from missing values. Some cars did not have registration or inspection plates or sometimes both and there was no way for us to figure out whether the registration or inspection had expired or not. Therefore, we recorded such data as N/A. Also, there are some possible errors with making best judgment on colors of cars. Interestingly, as we were out there collecting data, people seemed to notice that we were making notes on cars and parking meters, and some drivers seemed to drive away from us, which could have resulted higher rate of no cars being parked at parking meters. Also, on Monday and Wednesday afternoon, cars behind Porter were unpaid for a particular reason (refer to Data Collection Stories below).

Strengths

There were many strengths to our census project. When we had originally estimated the time it would take to complete each census we projected 3 hours. After we got the hang of our collection technique we were able to complete the surveys in 2 hours or less. Another strength that we had was that the weather during the week we collected data was consistent. It would have been interesting to see how weather affected parking, but due to the amount of times that we could collect the data it was nice to have this variable constant. A benefit that our group gained after completing the census was that we learned where the broken meters are located so that we will now be able to take advantage of free parking.

Data Collection Stories

1. ***"The Badge"***

On the first afternoon of Sampling, we (Victor and Nancy) were in the middle of recording data on a black Chevy Avalanche, when we were approached by a man inquiring what our business was. He acted tough and said we should be careful who we are spying on, then proceeded to show us his badge. From there we explained how we were only recording observational data about vehicles parked at meters and that it was for a class. Once he realized that we were doing nothing wrong he left us alone and went back into the building to resume the criminal justice class he was teaching.

2. ***"Cooper for Sale"***

On the third (Wednesday) afternoon of data collection, while on tech street collecting data on a Mini Cooper, the tech guy from Tepper tried to sell us the car. He was on break and noticed us closely observing his vehicle, not realizing we were just surveying he thought we were very interested in his car. He told us about all the great features, the low mileage, and the near pristine condition, he also said he planned on buying a new Mini Cooper after he sold that one. Once we explained we were just surveying for a class he began to tell us some personal accounts of parking. He was parked at a broken meter. He said that he knows where all the broken meters are so that he can avoid paying for parking. If his main broken meter spot is taken he tends to move his car around to different spots throughout the day, whereas if he gets the one on Tech Street he will not move all day. He also told us that CMU had at one time was in charge of on street parking on all three on campus roads with meters. He also said that before the price raise the streets were always filled and there were days he would have to park in Schenley Park for work.

3. ***"Granny"***

On Wednesday morning, as I was on Tech St collecting data, an old lady parked in the parking space that I haven't yet passed by. However, since she was getting her stuff out of her car, and taking some time, I decided that I will come back to it and as I passed by, she was putting some coins in the meter. But, when I actually came back to take some notes on her car and checked the meter, the meter was unpaid. She was merely pretending that she was paying the meter because I think she realized that I was looking at people's cars and making notes.

Take Home Message

There is a serious issue dealing with on campus parking meters. There is a very low rate of cars parked at meters on campus. Of the cars that do park on campus there is a significant amount that do not pay for parking. Although we are not sure of the underlying causes, one main concern is that hourly parking has recently had a hike in the rates. Consequently, the parking system is very inefficient and changes should be made.

References

missing 2 references?

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Section 5: Appendices

Appendix 1: Census Sample Size Calculation

N=224
P=.35
X=?
SD= Sqrt(224xPx(1-P)
SD=7.13
n=10 (number of Census)
*ME= (2*SD)/(sqr(n))*
*=(2*7.13)/(sqrt10)*
ME= 4.5

Appendix 2: Survey Questionnaire (next page)

	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	Location	Parking Meter	Vehicle Present?	Color?	Type?	Make?	Model?	State of license plate?	Expired meter?	Broken meter?	Ticket?	What for?	How much?	Clean (1) or Dirty (0)?	Registration (license plate)?	Registration expired?	Inspected (windsheild)?	Inspection expired?	Handicapp spot?
2	Margaret Morrison St	1	1	black	3	toyota	rav4 4wd	pa	1	0	0	0	0	1	1	1		0	
3		2	0																
4		3	0																
5	Total % of cars	4	0																
6		5	0																
7	Tech St	1	1	white	2	honda	ridgeline 4wd	pa	0	0	0	0	0	1	1	0	1	0	
8		2	1	gray	1	toyota	camry le	il	1	0	1	notpaid	30	0	1	0	1	0	
9		3	0																
10		4	1	dark gray	1	toyota	corolla	pa	0	0	0	0	0	0	1	0	1	1	
11		5	1	white	1	volkswager	golf tdi	pa	0	0	0	0	0	0	1	0	1	0	
12		6	0																
13		7	1	blue	3	chrysler	pacifica	pa	0	0	0	0	0	1	1	0	1	0	
14		8	0																
15		9	0																
16		10	0																
17		11	0																
18		12	0																
19		13	1	black	3	toyota	4 runner	west virginia	0	1	0	0	0	1	1	0	1	0	
20		14	0																
21		15	0																
22		16	0																
23		17	0																
24		18	1	silver	1	benz	s430 4matic	pa	0	0	0	0	0	1	1	0	1	0	
25		19	0																

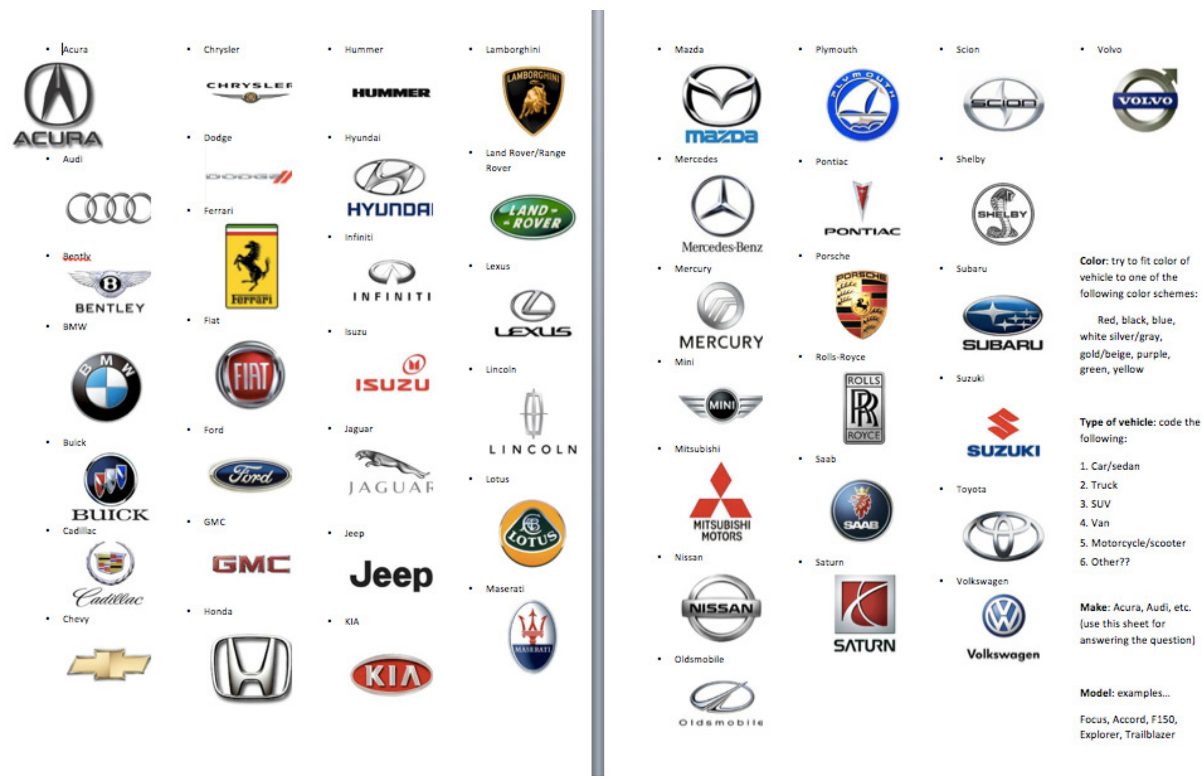
1) Vehicle Present?
2) Color?
3) Type?
    - Car/Sudan/Cross-over
    - Truck
    - SUV
    - Van
    - Motorcycle/Scooter
    - Other
4) Make?
5) Model?
6) State of license plate?
7) Expired meter?
8) Broken meter?
9) Ticket?
10) What for?
11) How much?
12) Clean/Dirty?
13) Registration present?
14) Registration expired?
15) Inspection present?
16) Inspection expired?
17) Handicapped spot?

18) Handicapped plate/tag?
19) Fancy market additions?
    - Tinted windows
    - Rims
    - Wing
    - Etc.
20) Major dents or scratches on vehicle?
21) Any cracked or shattered windows?
22) Vehicle driving on spare tire?
23) Vehicle has parking pass for another on-campus location?

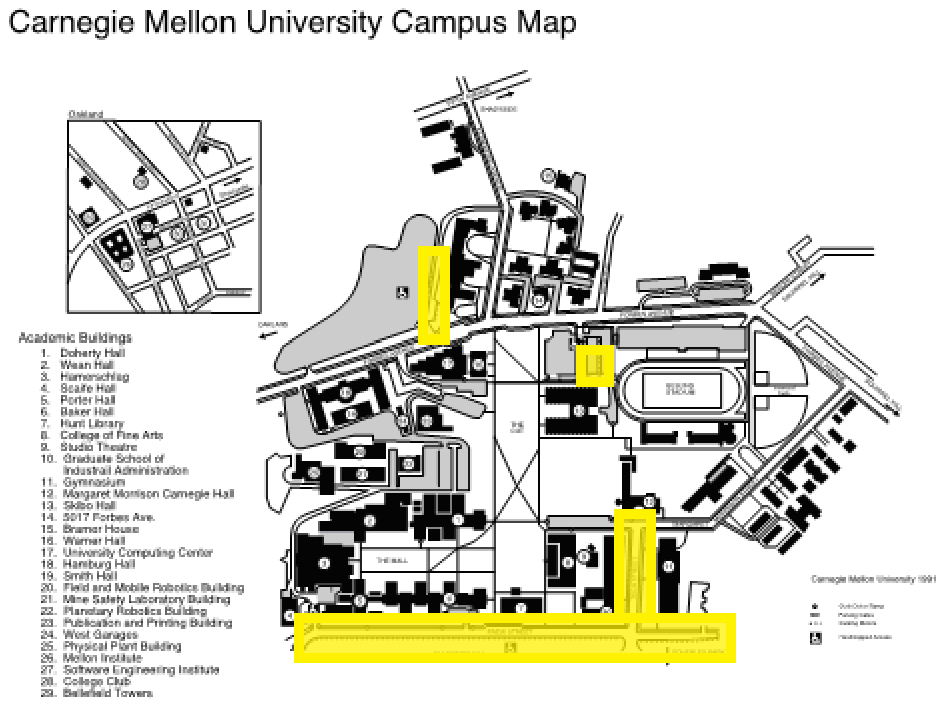
GENERAL QUESTIONS in addition to vehicle/parking meter questions:

1. Date
2. Day of week
3. Surveyors
4. Outside temperature
5. Start time
6. End time

Appendix 3: Reference Sheet



Appendix 4: Carnegie Mellon University Campus Map



Appendix 5: R code for Pie charts

```
library(MASS)
parking<-read.csv("parking-1.csv", header=T)
attach(parking)

table(color)
pie(table(color))

col<-c(36, 155, 133, 14, 18, 43, 52, 4, 82, 153, 100, 4)
col<-matrix(col)
rownames(col)<-c("beige", "black", "blue", "brown", "gold",
"green", "grey", "orange",  "red", "silver", "white", "yellow")

pie(col,main="Pie chart of colors of cars", col=c("beige", "black", "blue", "brown", "gold",
"green", "grey", "orange", "red", "white", "white", "yellow"),
labels=c("beige", "black", "blue", "brown", "gold",
"green", "grey", "orange", "red", "silver", "white", "yellow"))
legend(locator(1), c("Black:20%", "Silver:19%", "Blue:17%", "White:13%", "Red:10%", "Grey:6.5%"),
col=c("black", "beige", "blue", "beige", "red", "grey"), pch=16)

sum(col)
sum(36, 155, 133, 14, 18, 43, 52, 4, 82, 153,100,4)
col.prop<-signif((col/794)*100, 2)

car.type<-c(552, 18, 178, 44, 4)
car.type<-matrix(car.type)
rownames(car.type)<-c("Car/Sedan", "Truck", "SUV", "Van", "Motorcycle/scooter")
pie(car.type, labels=c("Car/Sedan", "Truck", "SUV", "Van", "Motorcycle/scooter"),
col=rainbow(6), main="Pie chart of car types")
```

```
legend(locator(1), c("Car/Sedan: 69%", "Truck:2%", "SUV:22%", "Van:5.5%", "Motorcycle/scooter:0.5%"),
col=rainbow(6), pch=16)

car.type.prop<-signif((car.type/797)*100, 3)
names(parking)
table(make)
sort(table(make))

brand<-c(130, 117, 54, 53, 50, 43, 36, 27, 27, 26, 25, 23, 20 )
brand<-matrix(brand)
rownames(brand)<-c("Toyota", "Honda", "Ford", "Chevy", "Subaru",
"Nissan", "Volkswagen", "Jeep", "Dodge", "Hyundai", "Mazda",
"BMW", "Mini")

pie(brand, col=rainbow(13), labels=c("Toyota", "Honda", "Ford", "Chevy", "Subaru",
"Nissan", "Volkswagen", "Jeep", "Dodge", "Hyundai", "Mazda",
"BMW", "Mini"), main="Pie chart of car brands\n observed more than 20 times")
legend(locator(1), c("Toyota:16%", "Honda:15%", "Ford:6.8%", "Chevy:6.6%", "Subaru:6.3%",
"Nissan:5.4%", "Volkswagen:4.5%", "Jeep:3.4%", "Dodge:3.4%", "Hyundai:3.3%", "Mazda:3.1%",
"BMW:2.9%", "Mini:2.5%"), col=rainbow(13), pch=16)

brand.prop<-signif((brand/797)*100, 2)
table(present)
occupied<-c(1432,796)
occupied<-matrix(occupied)
rownames(occupied)<-c("Unoccupied", "Occupied")
occupied
pie(occupied, main="Pie chart of parking meters", labels=c("Unoccupied", "Occupied"), col=c(5,6))
legend(locator(1), c("Unoccupied:64%", "Occupied:36%"), col=c(5,6), pch=16)

table(broken)
morn<-parking[1:224,13]
length(which(morn=="1"))

broke<-c(212, 12)
broke<-matrix(broke)
rownames(broke)<-c("Not broken", "Broken")
pie(broke, col=c(3,4), labels=c("Not broken", "Broken"), main="Pie chart of broken meters")
legend(locator(1), c("Not broken:212 (out of 224)", "Broken:12 (out of 224)"), col=c(3,4), pch=16)

sum(table(state))-1444
sort(signif((table(state)/796)*100, 2))
state.car<-c(85, 2, 1.6, 1.6, 1, 1, 1)
state.car<-matrix(state.car)
rownames(state.car)<-c("PA", "NY", "OH", "NJ", "VA", "IL", "CA")

pie(state.car, labels=c("PA", "NY", "OH", "NJ", "VA", "IL", "CA"),
col=rainbow(7), main="Pie chart of states \n found more than 8 times" )
legend(locator(1), c("PA:85%", "NY:2%", "OH:1.6%", "NJ:1.6%", "VA:1%", "IL:1%", "CA:1%"),
col=rainbow(7), pch=16)

table(regist.expire)
regist<-c(753, 40)
regist<-matrix(regist)
pie(regist, labels=c("Not expired", "Expired"), main="Pie chart of cars \n with expired registration",
col=c(7,8))
legend(locator(1), c("Not expired: 95%", "Expired:5%"), col=c(7,8), pch=16)

model<-c(49, 31, 30, 20, 16, 16, 14, 13, 12, 12, 12, 12, 11, 10, 10,  9, 9)
model<-as.matrix(model)
```

```
model
pie(model, col=rainbow(18), main="Pie chart of car models \n found more than 9 times",
labels=c("Civic", "Camry", "Corolla", "Cooper", "Forester", "Accord", "Jetta", "Focus", "Sonata", "Malibu",
"CR-V", "Caravan", "Liberty", "Outback", "Fit", "Legacy", "A4"))
legend(locator(1), c("Civic:49", "Camry:31", "Corolla:30", "Cooper:20", "Forester:16", "Accord:16", "Jetta:14", "Focus:13",
"Sonata:12", "Malibu:12",
"CR-V:12", "Caravan:12", "Liberty:11", "Outback:10", "Fit:10", "Legacy:9", "A4:9"), col=rainbow(18), pch=16)
```

Appendix 6: R code for Regression Analysis

Part A

```
length(which(present==1))
[1] 794

length(which(present==1&meter==1))
[1] 213

length(which(present==1&broken==1))
[1] 74
length(which(present==1&ticket==1))
[1] 30
```

Part B

All the models below are great examples of models with significant F statistics (so better than no model) because of the large sample size, but really the models are not that great (very low R^2's for example). This is pretty typical of regression analysis for social science data!

```
fit.street=lm(meter~street)
summary(fit.street)

Call:
lm(formula = meter ~ street)

Residuals:
    Min      1Q  Median      3Q     Max
-0.2551 -0.2551 -0.2551 -0.1373  0.8628

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.25512    0.01676  15.219  < 2e-16 ***
streetMM    -0.04083    0.08157  -0.501  0.61679
streetMWD   -0.11786    0.04506  -2.616  0.00905 **
streetTECH  -0.03561    0.04161  -0.856  0.39242
streetUC    -0.07330    0.07542  -0.972  0.33136
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4224 on 916 degrees of freedom
  (1319 observations deleted due to missingness)
Multiple R-squared: 0.008277,     Adjusted R-squared: 0.003946
F-statistic: 1.911 on 4 and 916 DF,  p-value: 0.1065
```

ths shouldn't be happening -- didn't you run the analyses on the cleaned up data after post-survey processing?

```
fit.day=lm(meter~day)
summary(fit.day)

Call:
lm(formula = meter ~ day)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-0.42763 -0.27273 -0.08654 -0.08654  0.91346

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.27273    0.03530   7.727  2.9e-14 ***
dayM         0.05630    0.04803   1.172  0.24139
dayT        -0.18619    0.04211  -4.422  1.1e-05 ***
dayTH       -0.06096    0.04705  -1.296  0.19537
dayW         0.15490    0.04825   3.211  0.00137 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4055 on 916 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.08595, Adjusted R-squared: 0.08196
F-statistic: 21.53 on 4 and 916 DF,  p-value: < 2.2e-16
```

```
fit.time=lm(meter~time)
summary(fit.time)
```

```
Call:
lm(formula = meter ~ time)

Residuals:
    Min      1Q  Median      3Q     Max
-0.3527 -0.3527 -0.1205 -0.1205  0.8795

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.12051    0.01872   6.436 1.98e-10 ***
timePM       0.23217    0.02685   8.648  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4072 on 919 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.07525, Adjusted R-squared: 0.07424
F-statistic: 74.78 on 1 and 919 DF,  p-value: < 2.2e-16
```

```
fit.time.street=lm(meter~time+street)
summary(fit.time.street)
```

```
Call:
lm(formula = meter ~ time + street)

Residuals:
     Min       1Q   Median       3Q      Max
-0.38917 -0.30819 -0.14386  0.02148  1.02148

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.14386    0.02017   7.134 1.99e-12 ***
timePM       0.24531    0.02690   9.121  < 2e-16 ***
streetMM    -0.07851    0.07825  -1.003 0.315948
streetMWD   -0.16534    0.04348  -3.803 0.000153 ***
streetTECH  -0.04601    0.03988  -1.154 0.248968
streetUC    -0.08098    0.07225  -1.121 0.262676
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.4047 on 915 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.09092, Adjusted R-squared: 0.08596
F-statistic:  18.3 on 5 and 915 DF,  p-value: < 2.2e-16

fit.time.day=lm(meter~day+time)
summary(fit.time.day)

Call:
lm(formula = meter ~ time + day)

Residuals:
    Min       1Q   Median       3Q      Max
-0.48038 -0.28409 -0.10590 -0.03628  0.96372

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.18498    0.03711   4.985 7.43e-07 ***
timePM       0.17819    0.02758   6.461 1.69e-10 ***
dayM         0.04403    0.04704   0.936  0.34942
dayT        -0.14870    0.04161  -3.574  0.00037 ***
dayTH       -0.07908    0.04612  -1.715  0.08673 .
dayW         0.11721    0.04757   2.464  0.01392 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3968 on 915 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.1258,   Adjusted R-squared: 0.1211
F-statistic: 26.34 on 5 and 915 DF,  p-value: < 2.2e-16

fit.street.day=lm(meter~street+day)
summary(fit.street.day)

Call:
lm(formula = meter ~ street + day)

Residuals:
    Min       1Q   Median       3Q      Max
-0.45099 -0.29969 -0.10725  0.02606  1.02606

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.29969    0.03672   8.161 1.10e-15 ***
streetMM    -0.04191    0.07809  -0.537  0.59165
streetMWD   -0.13331    0.04317  -3.088  0.00208 **
streetTECH  -0.03519    0.03984  -0.883  0.37733
streetUC    -0.08629    0.07224  -1.194  0.23263
dayM         0.05657    0.04794   1.180  0.23829
dayT        -0.19244    0.04205  -4.577 5.37e-06 ***
dayTH       -0.06348    0.04691  -1.353  0.17633
dayW         0.15130    0.04814   3.143  0.00173 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4041 on 912 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.09645, Adjusted R-squared: 0.08852
F-statistic: 12.17 on 8 and 912 DF,  p-value: < 2.2e-16
```

```
fit.time.street.day=lm(meter~street+day+time)
summary(fit.time.street.day)

Call:
lm(formula = meter ~ street + day + time)

Residuals:
    Min       1Q   Median       3Q      Max
-0.51325 -0.25561 -0.08854  0.03872  1.10866

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.21200    0.03798   5.582 3.13e-08 ***
streetMM    -0.07156    0.07627  -0.938 0.348397
streetMWD   -0.16708    0.04238  -3.943 8.68e-05 ***
streetTECH  -0.04357    0.03887  -1.121 0.262620
streetUC    -0.08862    0.07045  -1.258 0.208724
dayM         0.04361    0.04678   0.932 0.351447
dayT        -0.15358    0.04138  -3.711 0.000219 ***
dayTH       -0.08365    0.04584  -1.825 0.068340 .
dayW         0.10981    0.04733   2.320 0.020543 *
timePM       0.19143    0.02760   6.936 7.67e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.394 on 911 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.1418,   Adjusted R-squared: 0.1333
F-statistic: 16.72 on 9 and 911 DF,  p-value: < 2.2e-16
```

Part C.

```
fit.color=lm(meter~color)
summary(fit.color)

Call:
lm(formula = meter ~ color)

Residuals:
    Min       1Q   Median       3Q      Max
-0.75000 -0.27273 -0.20000 -0.00781  0.99219

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           0.007812   0.036018   0.217 0.828334
color blue           -0.007813   0.409091  -0.019 0.984768
colorbeige            0.355824   0.079557   4.473 8.73e-06 ***
colorbeige            0.492188   0.290390   1.695 0.090441 .
colorblack            0.272188   0.049035   5.551 3.75e-08 ***
colorblack            0.992187   0.290390   3.417 0.000662 ***
colorblack and pink   0.992188   0.409091   2.425 0.015492 *
colorblue             0.220534   0.051038   4.321 1.73e-05 ***
colorblue             0.742187   0.206910   3.587 0.000353 ***
colorbolack          -0.007813   0.409091  -0.019 0.984768
colorbrown            0.349330   0.114711   3.045 0.002393 **
colordark gray       -0.007813   0.409091  -0.019 0.984768
colorgold             0.403952   0.105192   3.840 0.000132 ***
colorgold            -0.007812   0.409091  -0.019 0.984768
colorgray             0.412187   0.067959   6.065 1.95e-09 ***
colorgreeen           0.992188   0.409091   2.425 0.015492 *
```

```
colorgreen         0.167188   0.073816   2.265 0.023757 *
colorgreen         0.992188   0.409091   2.425 0.015492 *
colorgrey         -0.007812   0.409091  -0.019 0.984768
colororange        0.242187   0.206910   1.170 0.242115
colorpolice cmu    0.992188   0.409091   2.425 0.015492 *
colorpurple        0.992188   0.409091   2.425 0.015492 *
colorred           0.248285   0.057641   4.307 1.84e-05 ***
colorsilber       -0.007812   0.409091  -0.019 0.984768
colorsilver        0.192187   0.049035   3.919 9.56e-05 ***
colorSILVER       -0.007813   0.409091  -0.019 0.984768
colorslilver      -0.007812   0.409091  -0.019 0.984768
colorunknown       0.992187   0.409091   2.425 0.015492 *
colorwhite         0.264915   0.054541   4.857 1.41e-06 ***
colorwhite        -0.007813   0.409091  -0.019 0.984768
coloryellow       -0.007812   0.206910  -0.038 0.969889
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4075 on 890 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.1033,   Adjusted R-squared: 0.07303
F-statistic: 3.416 on 30 and 890 DF,  p-value: 3.19e-09

fit.state=lm(meter~state)
summary(fit.state)

Call:
lm(formula = meter ~ state)

Residuals:
   Min      1Q  Median      3Q     Max
-0.6000 -0.2675 -0.2675  0.0000  0.8750

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   -2.718e-15  3.676e-02   0.000 1.000000
state0        1.000e+00  4.126e-01   2.423 0.015573 *
stateca       5.000e-01  1.499e-01   3.336 0.000886 ***
stateco       1.000e+00  4.126e-01   2.423 0.015573 *
statect       5.000e-01  2.929e-01   1.707 0.088194 .
statedc       1.458e-14  4.126e-01   0.000 1.000000
statede       8.283e-15  4.126e-01   0.000 1.000000
statefa       1.598e-14  4.126e-01   0.000 1.000000
statefl       4.000e-01  1.874e-01   2.134 0.033117 *
stateflorida  2.991e-14  4.126e-01   0.000 1.000000
statega       1.102e-14  2.401e-01   0.000 1.000000
stateil       3.750e-01  1.499e-01   2.502 0.012532 *
statema       7.684e-15  1.874e-01   0.000 1.000000
statemaryland 1.918e-14  4.126e-01   0.000 1.000000
statemd       5.000e-01  2.088e-01   2.395 0.016822 *
statemi       1.761e-15  2.401e-01   0.000 1.000000
statemo       2.200e-15  4.126e-01   0.000 1.000000
statenc       5.000e-01  1.718e-01   2.911 0.003694 **
statenj       2.308e-01  1.198e-01   1.927 0.054328 .
statenv       1.000e+00  4.126e-01   2.423 0.015573 *
stateny       2.667e-01  1.123e-01   2.374 0.017785 *
stateoh       2.308e-01  1.198e-01   1.927 0.054328 .
stateor       5.000e-01  2.088e-01   2.395 0.016822 *
statepa       2.675e-01  4.010e-02   6.670 4.49e-11 ***
statepa       1.250e-01  1.091e-01   1.145 0.252328
```

```
statePA       -6.579e-15  2.401e-01   0.000 1.000000
stateps        1.000e+00  4.126e-01   2.423 0.015573 *
stateri        1.000e+00  4.126e-01   2.423 0.015573 *
statesd       -2.219e-15  4.126e-01   0.000 1.000000
statetx       -3.964e-16  2.929e-01   0.000 1.000000
stateunknown   4.013e-15  2.401e-01   0.000 1.000000
stateva        2.500e-01  1.499e-01   1.668 0.095682 .
statewv        6.000e-01  1.874e-01   3.201 0.001418 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.411 on 888 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.08987, Adjusted R-squared: 0.05708
F-statistic:  2.74 on 32 and 888 DF,  p-value: 1.071e-06


fit.make=lm(meter~make)
summary(fit.make)

Call:
lm(formula = meter ~ make)

Residuals:
   Min      1Q  Median      3Q     Max
-0.7500 -0.2439 -0.1964  0.0000  0.9091

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)     9.978e-16  3.560e-02   0.000 1.000000
makeacura       4.375e-01  1.060e-01   4.125 4.07e-05 ***
makeacura       1.000e+00  4.012e-01   2.493 0.012867 *
makeaudi        3.077e-01  1.164e-01   2.643 0.008361 **
makebenz        3.662e-16  4.012e-01   0.000 1.000000
makebmw         3.043e-01  9.061e-02   3.359 0.000817 ***
makebuick       9.091e-02  1.256e-01   0.724 0.469490
makebuivk       1.821e-14  4.012e-01   0.000 1.000000
makecadillac   -5.443e-15  2.334e-01   0.000 1.000000
makechecy       1.000e+00  4.012e-01   2.493 0.012867 *
makechevy       3.137e-01  6.632e-02   4.731 2.62e-06 ***
makechexy      -5.328e-15  4.012e-01   0.000 1.000000
makechryshler   3.614e-14  4.012e-01   0.000 1.000000
makechrysler    2.500e-01  1.207e-01   2.071 0.038667 *
makedodge       2.083e-01  8.899e-02   2.341 0.019465 *
makeDODGE      -7.560e-15  4.012e-01   0.000 1.000000
makedodge       7.099e-15  2.848e-01   0.000 1.000000
makeford        3.962e-01  6.542e-02   6.057 2.09e-09 ***
makeford        1.000e+00  4.012e-01   2.493 0.012867 *
makegeo         1.779e-15  4.012e-01   0.000 1.000000
makegmc         5.000e-01  2.029e-01   2.464 0.013946 *
makegnc        -5.241e-15  4.012e-01   0.000 1.000000
makeharley      1.000e+00  4.012e-01   2.493 0.012867 *
makehaundai     1.979e-15  4.012e-01   0.000 1.000000
makehonda       1.964e-01  5.189e-02   3.785 0.000164 ***
makehonda       2.500e-01  2.029e-01   1.232 0.218330
makehummer      1.000e+00  2.848e-01   3.511 0.000469 ***
makehundai      3.333e-01  2.334e-01   1.428 0.153668
makehyundai     2.857e-01  9.418e-02   3.034 0.002490 **
makehyundai     1.000e+00  4.012e-01   2.493 0.012867 *
makeinfiniti   -1.819e-15  2.848e-01   0.000 1.000000
```

```
makeinfinity     5.000e-01  2.029e-01   2.464 0.013946 *
makeintrigue     1.000e+00  4.012e-01   2.493 0.012867 *
makejeep         3.333e-01  8.899e-02   3.746 0.000192 ***
makejeep        -4.049e-15  2.334e-01   0.000 1.000000
makejonda        1.000e+00  4.012e-01   2.493 0.012867 *
makekia          3.750e-01  1.457e-01   2.574 0.010224 *
makekia          1.000e+00  4.012e-01   2.493 0.012867 *
makeland rover  -2.070e-15  4.012e-01   0.000 1.000000
makelexus        4.545e-01  1.256e-01   3.618 0.000314 ***
makemazda        1.739e-01  9.061e-02   1.919 0.055262 .
makemazda        1.000e+00  4.012e-01   2.493 0.012867 *
makemb          -9.095e-15  2.029e-01   0.000 1.000000
makemecury       1.000e+00  4.012e-01   2.493 0.012867 *
makemercedes     1.250e-01  1.457e-01   0.858 0.391145
makemercury      1.818e-01  1.256e-01   1.447 0.148192
makemini         5.556e-01  1.007e-01   5.518 4.57e-08 ***
makemini         1.000e+00  2.848e-01   3.511 0.000469 ***
makemitsubishi   6.667e-01  2.334e-01   2.856 0.004396 **
makemozda        4.457e-15  4.012e-01   0.000 1.000000
makeniessan      2.952e-16  4.012e-01   0.000 1.000000
makenissan       2.439e-01  7.184e-02   3.395 0.000719 ***
makeNISSAN      -4.950e-16  4.012e-01   0.000 1.000000
makeoldsmobile   7.500e-01  2.029e-01   3.696 0.000233 ***
makepiaggio     -1.272e-15  4.012e-01   0.000 1.000000
makeponitac     -2.638e-15  4.012e-01   0.000 1.000000
makepontiac      2.857e-01  1.552e-01   1.841 0.065924 .
makerange rover  5.743e-15  4.012e-01   0.000 1.000000
makesaab         2.500e-01  2.029e-01   1.232 0.218330
makesaturm      -1.514e-15  4.012e-01   0.000 1.000000
makesaturn      -8.384e-16  1.670e-01   0.000 1.000000
makesaturn       1.000e+00  4.012e-01   2.493 0.012867 *
makescion        6.667e-01  2.334e-01   2.856 0.004396 **
makesubaru       2.500e-01  7.551e-02   3.311 0.000970 ***
makesubaru       1.000e+00  4.012e-01   2.493 0.012867 *
makesubuar      -9.071e-16  1.822e-01   0.000 1.000000
makesuburu       2.500e-01  1.457e-01   1.716 0.086535 .
makesuzuki       2.500e-01  2.029e-01   1.232 0.218330
maketoyota       2.126e-01  5.024e-02   4.231 2.58e-05 ***
maketoyota       2.905e-15  2.848e-01   0.000 1.000000
makevolkswagen  -3.021e-15  9.834e-02   0.000 1.000000
makevolkswagen   1.000e+00  4.012e-01   2.493 0.012867 *
makevoltzwaggon -2.808e-15  2.334e-01   0.000 1.000000
makevolvo        4.000e-01  1.313e-01   3.047 0.002384 **
makevw           3.333e-01  1.207e-01   2.761 0.005883 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3996 on 846 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.1804,   Adjusted R-squared: 0.1087
F-statistic: 2.516 on 74 and 846 DF,  p-value: 3.378e-10
```

```
fit.type=lm(meter~type)
summary(fit.type)
```

```
Call:
lm(formula = meter ~ type)

Residuals:
```

```
  Min      1Q  Median      3Q     Max
-0.3333 -0.2782 -0.2697  0.0000  0.8409

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.756e-16  3.677e-02   0.000   1.0000
type1          2.782e-01  4.077e-02   6.824 1.62e-11 ***
type2          3.333e-01  1.040e-01   3.205   0.0014 **
type3          2.697e-01  4.806e-02   5.611 2.66e-08 ***
type4          1.591e-01  7.228e-02   2.201   0.0280 *
type5         -3.449e-15  2.942e-01   0.000   1.0000
type6         -2.768e-15  4.144e-01   0.000   1.0000
typemotorcycle  1.000e+00  4.144e-01   2.413   0.0160 *
typescooter    -2.452e-15  4.144e-01   0.000   1.0000
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4128 on 912 degrees of freedom
 (1319 observations deleted due to missingness)
Multiple R-squared: 0.05721, Adjusted R-squared: 0.04894
F-statistic: 6.918 on 8 and 912 DF,  p-value: 7.199e-09
```

Part D

```
a<-which(present==1&meter==1)
predict(fit.day,data=parking[a,])

plot(parking[a,]$day,parking[a,]$time,xlab="Day",ylab="Time of Day",main="Unpaid Meters")

plot(Lat,Long,pch=(time==1),
   col=terrain.colors(10)[1+floor(predict(fit.time.day)*20)],
   bg=terrain.colors(10)[1+floor(predict(fit.time.day)*20)],cex=sqrt(predict(fit.time.day)),
   xlab="Longitude",ylab="Latitude",main="Unpaid Meters",
   sub="Circle area proportional to Predicted Unpaid Meters")
legend(x="topleft",legend=.1*(1:10),fill=terrain.colors(10))

> fit.ticket=lm(parking[a,]$ticket~parking[a,]$street)
> summary(fit.ticket)

Call:
lm(formula = parking[a, ]$ticket ~ parking[a, ]$street)

Residuals:
  Min      1Q  Median      3Q     Max
-0.2857 -0.1062 -0.1062 -0.1062  0.8938

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.10625    0.02689   3.951 0.000107 ***
parking[a, ]$streetMM   -0.10625    0.14146  -0.751 0.453429
parking[a, ]$streetMWD   0.17946    0.09481   1.893 0.059760 .
parking[a, ]$streetTECH  0.15301    0.07078   2.162 0.031767 *
parking[a, ]$streetUC    0.06042    0.14146   0.427 0.669743
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3402 on 208 degrees of freedom
```

```
Multiple R-squared: 0.03921, Adjusted R-squared: 0.02073
F-statistic: 2.122 on 4 and 208 DF,  p-value: 0.07927

fit.ticket=lm(parking[a,]$ticket~parking[a,]$street+parking[a,]$day+parking[a,]$time)
summary(fit.ticket)

Call:
lm(formula = parking[a, ]$ticket ~ parking[a, ]$street + parking[a, 
  ]$day + parking[a, ]$time)

Residuals:
   Min       1Q   Median       3Q      Max 
-0.37248 -0.20204 -0.08893 -0.05165  1.05464 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)  
(Intercept)           0.095755   0.072241   1.325   0.1865  
parking[a, ]$streetMM   -0.142505   0.142304  -1.001   0.3178  
parking[a, ]$streetMWD   0.170436   0.094914   1.796   0.0740 .
parking[a, ]$streetTECH  0.141966   0.070212   2.022   0.0445 *
parking[a, ]$streetUC    0.043493   0.142009   0.306   0.7597  
parking[a, ]$dayM        0.002874   0.074303   0.039   0.9692  
parking[a, ]$dayT       -0.113115   0.087520  -1.292   0.1977  
parking[a, ]$dayTH      -0.033867   0.081205  -0.417   0.6771  
parking[a, ]$dayW       -0.150397   0.073298  -2.052   0.0415 *
parking[a, ]$timePM      0.106288   0.055473   1.916   0.0568 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.3363 on 203 degrees of freedom
Multiple R-squared: 0.08367, Adjusted R-squared: 0.04305 
F-statistic:  2.06 on 9 and 203 DF,  p-value: 0.0347

fit.ticket=lm(parking[a,]$ticket~parking[a,]$day)
summary(fit.ticket)

Call:
lm(formula = parking[a, ]$ticket ~ parking[a, ]$day)

Residuals:
   Min       1Q   Median       3Q      Max 
-0.19608 -0.19444 -0.07407 -0.06349  0.93651 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)        0.194444   0.056938   3.415 0.000767 ***
parking[a, ]$dayM   0.001634   0.074367   0.022 0.982491    
parking[a, ]$dayT  -0.120370   0.086975  -1.384 0.167852    
parking[a, ]$dayTH -0.027778   0.080523  -0.345 0.730468    
parking[a, ]$dayW  -0.130952   0.071376  -1.835 0.067981 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 0.3416 on 208 degrees of freedom
Multiple R-squared: 0.03096, Adjusted R-squared: 0.01233 
F-statistic: 1.661 on 4 and 208 DF,  p-value: 0.1602

fit.ticket=lm(parking[a,]$ticket~parking[a,]$time)
summary(fit.ticket)
```

```
Call:
lm(formula = parking[a, ]$ticket ~ parking[a, ]$time)

Residuals:
    Min       1Q   Median       3Q      Max
-0.15385 -0.15385 -0.15385 -0.08772  0.91228

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.08772    0.04547   1.929   0.0551 .
parking[a, ]$timePM  0.06613    0.05313   1.245   0.2147
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3433 on 211 degrees of freedom
Multiple R-squared: 0.007287,     Adjusted R-squared: 0.002582
F-statistic: 1.549 on 1 and 211 DF,  p-value: 0.2147
```

```
summary(parking[a,]$type)
                0          1          2          3          4          5          6 motorcycle    scooter
        0          0        152          6         48          6          0          0          1          0
summary(parking[a,]$color)
                    blue            0          beige          beige          black          black
           0            0            0           12            1           42            2
black and pink          blue          blue         bolack          brown      dark gray           gold
           1           29            3            0            5            0            7
        gold           gray         greeen          green          green           grey     milk truck
           0           20            1            7            1            0            0
      orange     police cmu         purple            red         silber         silver         SILVER
           1            1            1           21            0           30            0
     slilver        unknown          white          white         yellow
           0            1           27            0            0
summary(parking[a,]$make)
              acura      acura        audi       benz        bmw      buick      buivk   cadillac
        0          7          1          4          0          7          1          0          0
     checy      chevy      chexy  chryshler   chrysler      dodge      DODGE      dodge       ford
        1         16          0          0          3          5          0          0         21
      ford        geo        gmc        gnc     harley    haundai      honda      honda     hummer
        1          0          2          0          1          0         22          0          2
    hundai    hyundai    hyundai   infiniti   infinity   intrigue       jeep       jeep      jonda
        1          6          1          0          2          1          8          0          1
       kia        kia land rover      lexus      mazda      mazda         mb     mecury   mercedes
        3          1          0          5          4          1          0          1          1
   mercury       mini       mini mitsubishi      mozda    niessan     nissan     NISSAN oldsmobile
        2         10          2          2          0          0         10          0          3
   piaggio    ponitac    pontiac range rover       saab     saturm     saturn     saturn      scion
        0          0          2          0          1          0          0          1          2
    subaru     subaru     subuar     suburu     suzuki     toyota     toyota volkswagen volkswagen
        9          1          0          2          1         26          0          0          1
voltzwaggon      volvo         vw
        0          4          4
summary(parking[a,]$model)
      cooper        civic      corolla        focus       malibu       accord       sonata
          12           11            8            7            6            4            4
```

x6	camry	is250	legacy	mdx	na	outback
4	3	3	3	3	3	3
sentra	sorento	4runner	a4	alero	camry le	crv
3	3	2	2	2	2	2
elantra	envoy	escape	explorer	f-150	fit	fusion
2	2	2	2	2	2	2
grand cherokee	h2	highlander	impreza	jetta	liberty	lumina
2	2	2	2	2	2	2
new	prius	s10	stratus	tsx	villager	3
2	2	2	2	2	2	1
3.2tl	325xi	328i	5	93	a5	a8
1	1	1	1	1	1	1
accent	altima	altuma	blazer	camery	camty	caravan
1	1	1	1	1	1	1
cavalier	cobalt	cobalt	compass	concord	convertible	cr-v
1	1	1	1	1	1	1
crossfire	cruze	e350	eclipse	element	escort	express
1	1	1	1	1	1	1
fancy	fiesta	fontier	forester	forrester	g6	galant
1	1	1	1	1	1	1
golf	gramd cherokee	grand voyager	gti	gti vr6	i30	integra
1	1	1	1	1	1	1
lesabre	liberty	mariner	matrix	maxima	mazda3	miata
1	1	1	1	1	1	1
monte arlo	mustang	neon	nitro	partriot	prius hybrid	q30
1	1	1	1	1	1	1
rav4	(Other)					
1	25					