A Data Analysis of Parking Meter Transactions in San Diego and an Evaluation of Economic Applications

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Capstone Project
ECON 1660: Big Data
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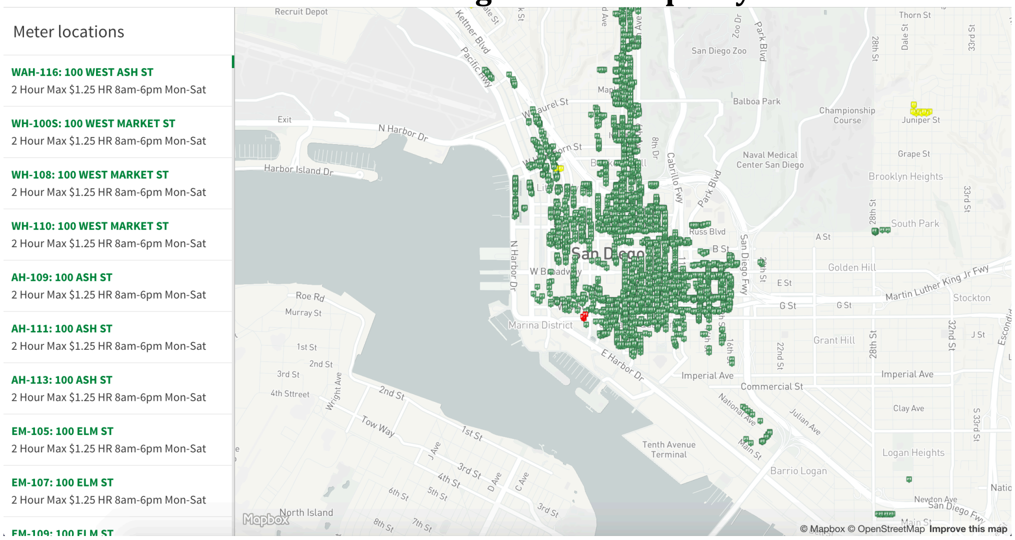
May 5th, 2017

Overview and Motivation:

Visualized Predictions of Parking Meter Occupancy Rate



Even before selection of a dataset, the goal of my project was to extract meaning from a piece of data, specifically to ask some larger question of the data's economic applicability and to discover some tangible statistical significance that is useful in answering that question or at least uncovering its associated challenges. Additionally, I wanted to make use of many of the skills acquired from the Big Data course to the best of my ability.

After failed attempts exploring Foursquare check-in data and urban dictionary + twitter data where I was able to do accomplish the first task but not the second, I settled on analyzing San Diego Parking Meter Transaction data from 2015-2016.

In terms of economic applicability, I anticipated two possible approaches to analyzing the parking meter data. First, to consider what uses the data might have in terms of city planning efforts. More specifically, to determine broadly how well the city has planned its existing meters and to see if the data can express possible ways to do better. Second, to figure out whether the data could be useful to consumers, and whether insights could lead to better consumer outcomes.

Notably, the San Diego Parking Meter Transactions is the first publically available data of its kind with per-transaction, daily aggregate, and monthly aggregate data. In this project, I focused on examining daily aggregate data (2,118,403 observations across 3907 meters), which seemed like the appropriate scope for a prediction model and for answering some of the related economics questions. In my discussion, I will discuss in depth why a decent statistical prediction by my model is useful in theory, but might not be sufficient to practically address the needs of policymakers, businesses, and consumers.

Related Work/Literature:

Donald Shoup, a research professor of urban planning at UCLA, is well known for his extensive work studying the economic impacts of parking meters. In an article entitled “Cruising for Parking”, Shoup suggests parking meters have the potential to “reduce congestion, clean the air, save energy, reduce GHG emission, and improve neighborhoods” (Shoup 22). Specifically, the effectiveness of parking meters, he notes, is extremely sensitive to price and location variables. If the occupancy rate of meters is too high, cars are forced to cruise around to find space. This wastes tens of thousands of cumulative hours for drivers and creates an excess of vehicle miles traveled (VMT) in the scale of thousands in a single city area each weekday (Shoup 19). In this case, the most common cause of excess demand is the underpricing of meters. With regards to an optimal guideline, he suggests an occupancy rate of around 85%, which optimizes meter usage and consumer benefit without any significant impact to revenue generation.

Another interesting analysis of parking meters is offered in the article “Parking Meters Spread Economic Plague”. This article highlights a case in Providence, RI where the presence of parking meters actually had extreme negative impacts as a result of under-demand (Dulgarian). Specifically, inconveniences in payment and prices went far enough to negatively influence the patronization of businesses in the area. Though this project focuses on parking demand, it is important to acknowledge the many unseen effects of meters on the urban ecosystem.

In 2011, a dynamic pricing program for parking meters was actually introduced in San Francisco, built on the findings of Shoup and another urban planning professor Gregory Pierce. The policy aimed to implement a variable pricing model to achieve a block occupancy rate between 60 and 80 percent. After implementation, the city successfully achieved the target occupancy in 62% of blocks, but with no measurement of whether that number actually benefitted consumers or other parties. The research suggested to use seasonally adjusted demand criteria for setting prices and to modify time periods of operation to manage peak parking periods. Notably, the findings also suggested that circumstances on individual blocks vary greatly and that these fine-grained issues make it difficult to make perfectly optimal decisions (Holmes). Accordingly, some of this project will reflect on the points made by this pricing program.

A paper entitled “Determinants of Off-Street Parking Demand in Downtown Eugene, OR" studies parking demand and its applications in city planning, but for off-street garages as opposed to on-street parking and solely using regression methods. They highlight a number of features relevant to predicting daily parking demand as well as a few economic applications of the parking demand data, which inspires some of the analysis in this project[1].

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[1] I didn’t discover this resource until May 7th, and am using it as a sanity checker and for guiding minor points in the discussion. Important to note, I derived all of my features and methods independently from this paper.

Initial Questions:

Given that there are so many aspects of an urban ecosystem influenced by parking meters, one can begin to capture the impacts of parking meters by first analyzing its demand. In particular, as related to demand[2], can we predict revenue and occupancy[3]?

I examine and attempt to predict daily revenue in terms of absolute revenue (a continuous output) and when revenue for a meter is unusually high or greater than the median revenue earned by *all meters* (a binary output of true or false).

Similarly, with occupancy, I attempt to predict daily occupancy rate in terms of the absolute rate (a continuous output) and when there is unusually high demand or when occupancy of a meter is greater than median occupancy *for that meter* (a binary output of true or false). In order to accomplish this, I first needed to address the question of what features might be important to look at, as discussed in the feature preparation section.

Later on, the discussion will look at more interesting questions related to the economic applicability of the information gained from the initial analysis and from the predictions. First, what are some explanations of unexplained variance in meter revenue and occupancy across different meters or across different days? Accordingly, what features were missing that would allow for better predictions, if possible at all? Next, what useful information was gained that could influence people's behavior or help them to make certain decisions? As mentioned, it is not possible to calculate the full opportunity cost of meters, but what else would we need to know and is it possible to get it?

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[2] In my project, I use the word *demand* interchangeably to imply either or both *revenue* and *occupancy*

[3] Not explicitly given in San Diego Parking Meter Transaction data but derived as revenue divided by price per hour, over the daily hours of operation.

Exploratory Analysis:

Before jumping to a prediction model, I conducted an initial assessment of San Diego's parking meters to compare the data against some of the points made in the literature.

Number of Meters by San Diego Neighborhood (Area)

Neighborhood	*Number of Meters*
Bankers Hill	650
Barrio Logan	36
College	5
Core-Columbia	414
Cortez Hill	391
East Village	1096
Five Points	75
Gaslamp	331
Golden Hill	9
Hilllcrest	637
Little Italy	317
Marina	292
Midtown	17
Mission Hills	116
North Park	116
South Park	2
Talmadge	33
University Heights	103

<u>Revenue Information:</u>
Average Yearly Revenue (2015-2016): **$6,596,490.88**
Average Yearly Revenue Per Meter: **$1688.34 per meter**
Cost of Parking Meter Installation[4]: **$737.37 once + $100.32 per year**

Average Yearly Revenue by San Diego Neighborhood (Area)

Neighborhood	*Average Yearly Revenue ($)*
Bankers Hill	437866.550
Barrio Logan	26266.620
College	8632.705
Core-Columbia	753931.570
Cortez Hill	570480.340
East Village	1628906.700
Five Points	125542.090

[4] As estimated from "Purchase and Installation of New Parking Meters - City of Santa Monica."

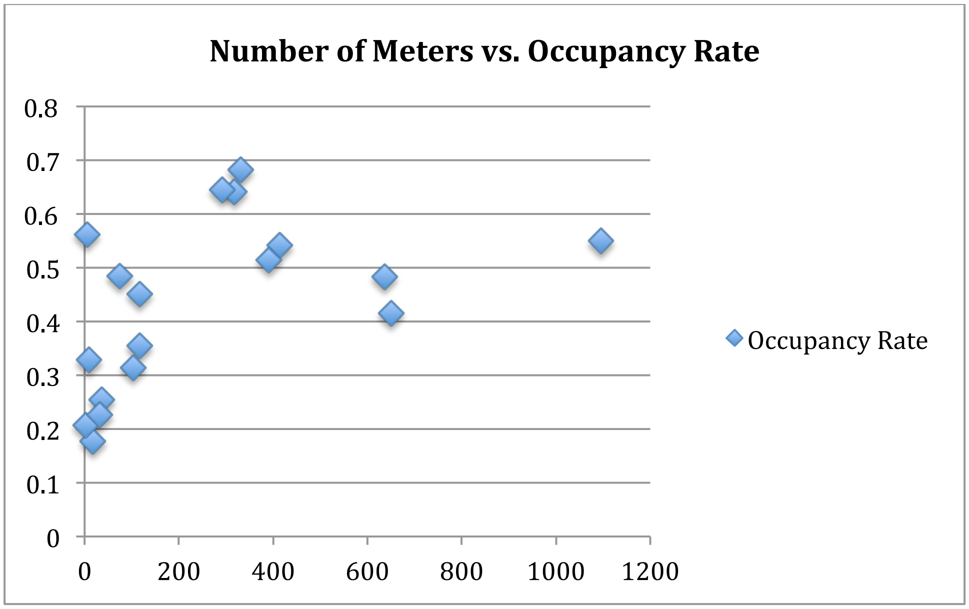
Gaslamp	824882.580
Golden Hill	10162.975
Hilllcrest	535343.515
Little Italy	679476.175
Marina	573521.865
Midtown	3414.395
Mission Hills	174824.380
North Park	128709.415
South Park	1362.895
Talmadge	21915.210
University Heights	91250.900

Comparing *revenue per meter* to *cost of meter*, the earnings of meters in San Diego make up for the costs in just half a year (notably, monetary costs, but perhaps not opportunity costs). However, this notion is merely relative, and does not speak to how well the meters are doing relative to how they would be doing under optimal conditions.

<u>Occupancy:</u>
Average Meter Occupancy (2015-2016):
43.52%

Average Occupancy by San Diego Neighborhood (Area)

Neighborhood	*Occupancy Rate*
Bankers Hill	0.415547
Barrio Logan	0.254907
College	0.561477
Core-Columbia	0.541757
Cortez Hill	0.513865
East Village	0.549727
Five Points	0.484473
Gaslamp	0.682278
Golden Hill	0.328567
Hilllcrest	0.483252
Little Italy	0.642231
Marina	0.645735
Midtown	0.176797
Mission Hills	0.450753
North Park	0.355091
South Park	0.207088
Talmadge	0.225843
University Heights	0.314130



Gaslamp Quarter – City Walk, Children's Museum, San Diego Convention Center, Balboa Theatre, Petco Park

Compared to Shoup's suggestion of 85% occupancy, the Gaslamp neighborhood known for its tourist attractions comes the closest at 68.22% occupancy, but still falls well below the suggested optimal rate. In comparison, the lowest occupancy of 17.68% occurs in Midtown slightly outside the downtown area and near the airport. Returning to a question of whether the meters are doing well, it seems that they are making adequate revenue to make up for the costs, but doing so while there is still an under-demand for meters with an average occupancy of just 43.52%. In other words, the revenue makes up for the meters' monetary costs, but not necessarily the opportunity costs (e.g. a lot of valuable street space is sacrificed to place parking meters). There is a slight positive correlation between the number of meters in a neighborhood and occupancy rate, suggesting that an excess of meters might not be the primary cause of low occupancy. This further warrants an investigation into revenue and occupancy predictions of parking meters.

Feature Preparation:

Returning to the matter of predicting revenue and occupancy, the first step was to prepare the data for prediction.

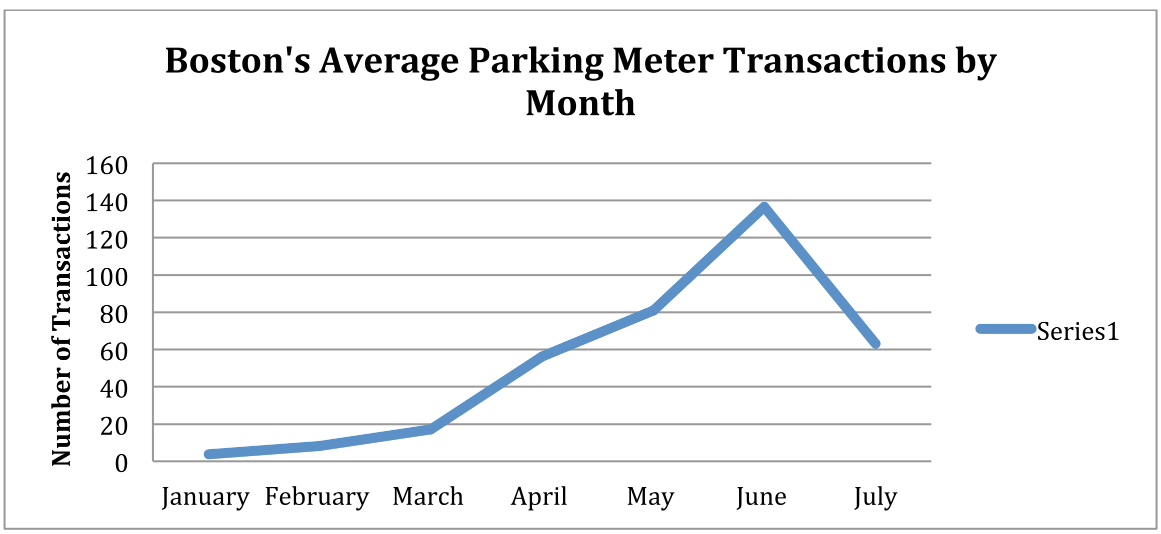
Categorical location information was inherently provided with *zone, area, and sub-area* delineations.

From the original data, there was a need to derive and scrape some features. In terms of meter configuration, I broke down a text description to derive *maximum occupancy hours per patron, price per hour, hours active per day, days active per week*, and whether the meters *allowed payment by mobile phone*. I also derived an *in-vicinity* metric, which counted the number of meters sharing the same street space or a clustering by immediate location.[5]

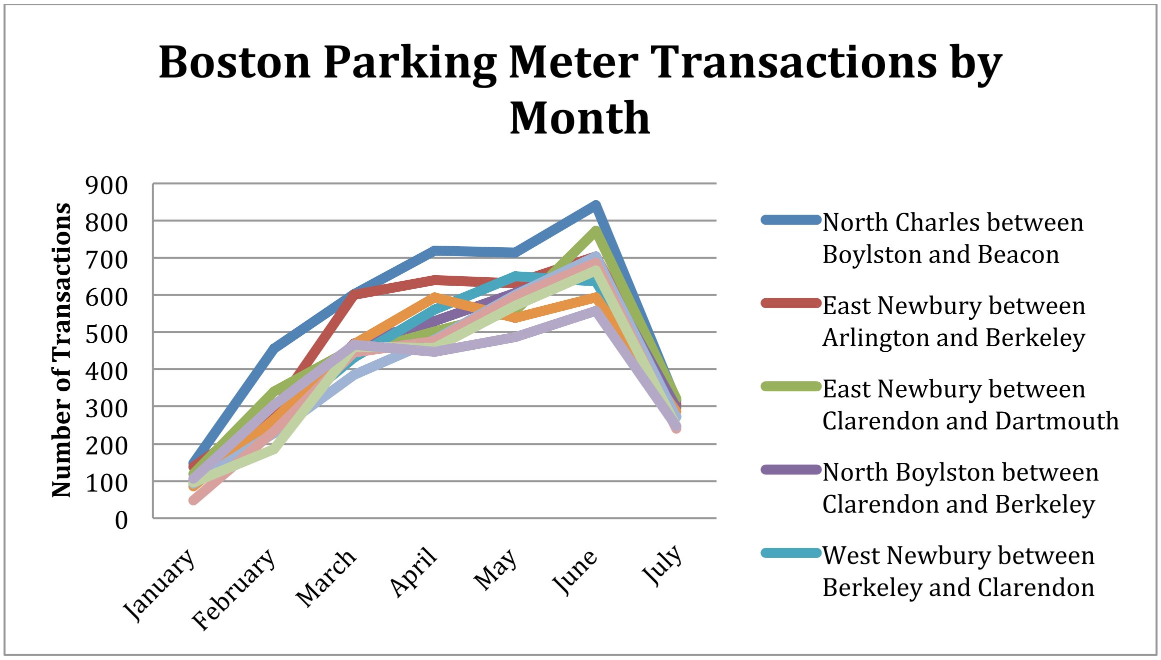
Next, additional features from other datasets were compiled and integrated.

To capture some notion of the effectiveness of the meters' placement, I added a feature indicating each meter's *vincenty distance to the nearest transit stop*.

After examining a separate parking meter dataset in Boston, which recorded pay-by-phone transactions of parking meters over half a year in 2015, I developed the theory that weather might be a useful factor in accounting for the daily variance in occupancy and revenue for parking meters[6].



[5] Because meters were presented in order by group, this did not require a need for running a clustering algorithm.



This data might be slightly misleading as the pay-by-phone program was only adopted in January, so the increase in usage over the first few months might be partially or fully attributable to its introduction. It also appears that July transactions might have not been recorded in full. Nonetheless, there is a distinct incline in usage between March and June, the period when weather conditions generally improve substantially in the Northeast.

Thus, to see if weather truly could be a source of variance in parking meter demand, I compiled *wind speed, temperature, rainfall, temperature, and daylight* features, then ran a normalized regression and random forest prediction of revenue on weather variables and then on *months*. The R^2 with weather was near 0 with the OLS regression, but .07 with the random forest. On the other hand, the R^2 with months was 0 in both the regression and the random forest, demonstrating that weather is perhaps slightly more effective for capturing variance in demand, but not substantially.

Results and Analysis:

Features Revisited:

Controlling for *zone*, I conducted a normalized regression of daily meter revenue and occupancy on the meter configuration features and the added features I thought would be useful in predictions of revenue and occupation. I recorded the coefficient signs that indicate the nature of correlations between the variables and parking meter demand.

Table 0: Coefficients from Regression (Zone variables included not shown)

Feature	Coefficient Sign
Windspeed	-
Rainfall	-
Temperature	+
Humidity	+
Daylight	+
Number of Meters in Vicinity	+
Maximum Occupancy Hours Per Patron	+
Price Per Hour	+
Hours Active per Day	+
Days Active per Week	-
Pay by Phone	+
Distance to Nearest Transit	-

Highlighted above are the unanticipated coefficient signs from the regression.

It was surprising that *humidity* had a positive correlation with parking meter revenue and occupancy, because like *rainfall* and *wind speed*, humidity in the environment might imply that less people are out for activities and less parking is demanded.

Number of meters in vicinity had a positive correlation, with two possible explanations. Originally, I would have expected a negative relationship capturing the idea that meters sharing the same space imply lower demand for each successive meter in that area (crowding-out effect). However, the data may have been imperfectly clustered and doesn't cluster to realize the effect mentioned above. Alternatively, perhaps there is a residual effect of location popularity (i.e. more meters are placed in popular areas) that is not controlled for by regressing on the zone of the meter. On further investigation, after controlling for *zone* and *area,* the coefficient sign did indeed become negative, supporting this hypothesis.

Similarly, locational popularity could justify why there is a positive correlation between *price per hour* and both revenue and occupancy. However, controlling for *area* did not switch the coefficient signs of this feature. I did attempt to control for *sub_area,* but the program took too long to process.

Days active per week had a negative correlation with parking meter revenue, which may be the case because the more days it is active, the more demand is spread out over those days leading to lower revenue per day.

I also tried to get a sense of the relative importance of variables. With a lasso regression[7], the zeroed out variables were exactly the five weather variables and the *maximum hours per patron*. However, running a random-forest, the top-6 feature importances (importance in reducing tree impurity) were *distance to nearest transit stop, humidity, daylight, temperature, wind speed*, and *number of meters in vicinity*. This remained consistent in multiple iterations.

One explanation for why weather was important in the random-forest, but not in the regression is because the relationships between weather variables and parking demand is non-linear and complex. For instance, warm weather is generally preferred to too hot or cold, but it's also unclear whether there is more of an effect of "nice weather" on making people more likely to do activities and need parking or to pursue alternative transportation methods like biking and walking. Generally, I would suspect the former to have a greater effect. Adding a squared term to the regression for certain features is one way this may have been better accounted for.

Classification:

For each of the tables below, the first two rows of each classification are benchmarks to gauge the effectiveness of the predictions. The first benchmark is the classification accuracies given a naïve guess, which are the *mean* for the continuous outputs and the *most commonly occurring label* for the binary outputs. The second benchmark is to use *number of transactions* from the data as a proxy feature, and predict using a regression and random-forest on that feature alone. The justification of this benchmark is that the number of transactions is a fairly good

[7] $\alpha = .01$

indicator of occupancy and revenue even by itself, since there likely isn't too much variance in how long people stay at meters, in the price structures of meters, and the money spent per patron at a meter. Of course, adding other variables would yield an extremely accurate prediction of occupancy and revenue, but the idea here was to get a benchmark of "pretty good" accuracy. Notably, *number of transactions* is not actually useful for predictions because like revenue and occupancy, this factor is calculated after the fact and would not be known until the end of a day. Given these benchmarks, my goal was to achieve a significantly better accuracy than the first benchmark and an equal or better accuracy than the second benchmark.

Table 1: Predictions of Absolute Revenue

Classification Method	MSE	R^2
Benchmark 1 (Mean)	122937.83	N/A
Benchmark 2 (Proxy: Number of Transactions - Regression, RandomForest)	95267.47 (89907.38)	.23 (.27)
OLS Regression	97898.90	.20
Linear SVR	84078.95	.32
Decision Tree	85550.78	.30
Random Forest: 10 Trees	78271.84	.36

Table 2: Predictions of Revenue above Median Meter Revenue

Classification Method	Accuracy
Benchmark 1 (Most common label)	.501
Benchmark 2 (Proxy: Number of Transactions - Regression, RandomForest)	.628 (.636)
OLS Logistic Regression	.733
Decision Tree	.736
Random Forest: 10 Trees	.738

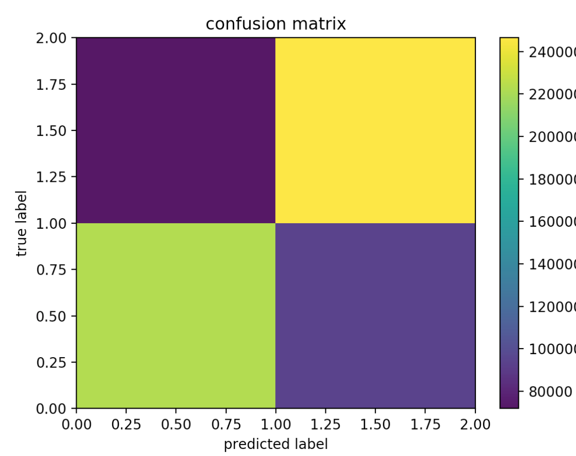
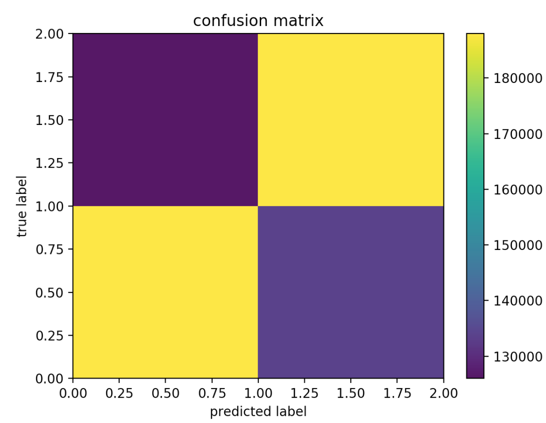


Table 3: Predictions of Absolute Occupancy

Classification Method	MSE	R^2
Benchmark 1 (Mean)	.08	N/A
Benchmark 2 (Proxy: Number of Transactions - Regression, RandomForest)	.07 (.07)	.16 (.19)
OLS Regression	.07	.17
Decision Tree	.06	.32
Random Forest: 10 Trees	.05	.35

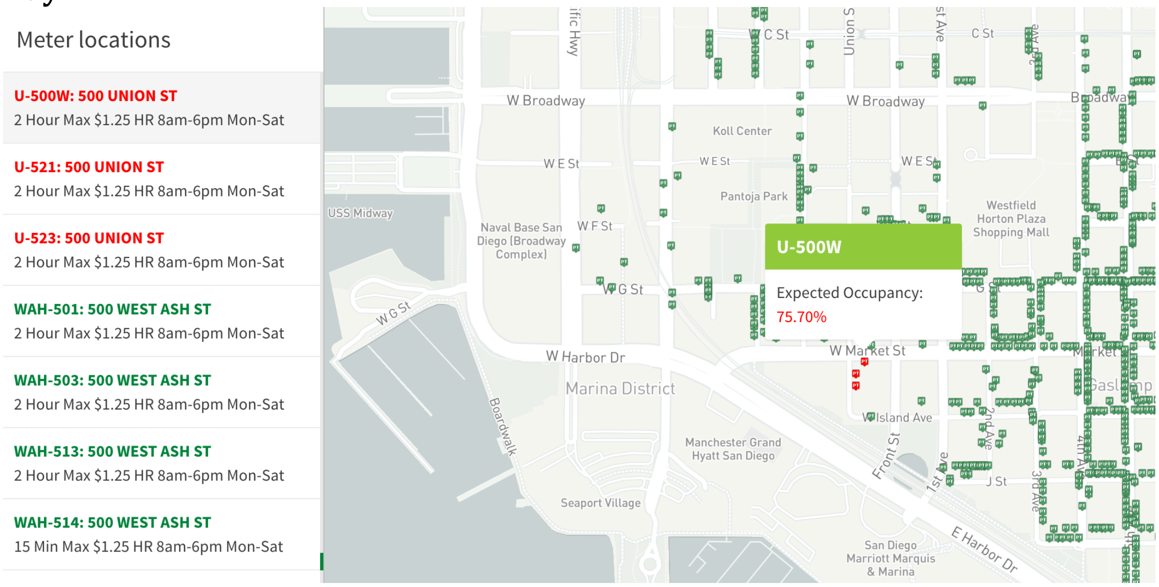
Table 4: Predictions of Occupancy above Median Occupancy of Same Meter

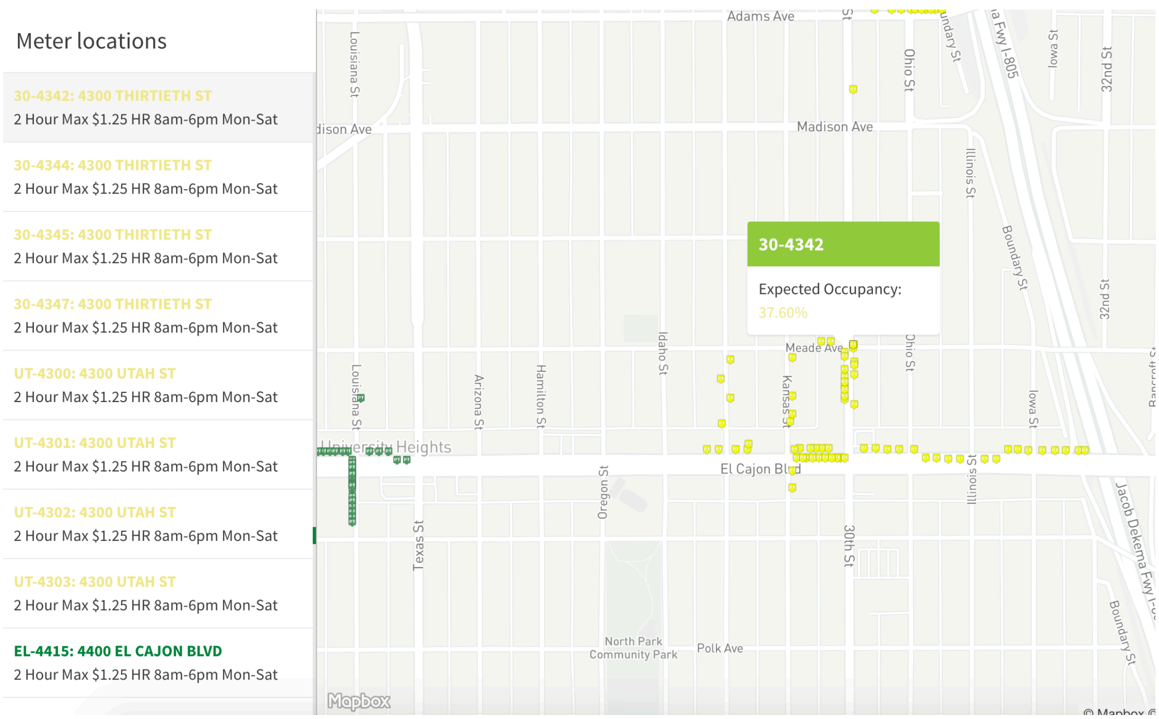
Classification Method	Accuracy
Benchmark 1 (Most common label)	.5063
Benchmark 2 (Proxy: Number of Transactions - Regression, RandomForest)	.5904 (.594)
OLS Logistic Regression	.515
Decision Tree	.5918
Random Forest: 10 Trees	.5915



I generally received the best results by including meter configuration features, weather features, and all three scales of location (*zone, area, sub-area*). In each of the four cases, I was successfully able to beat both benchmarks using random-forest classification.

Interactive Map of Parking Meters with Occupancy Predictions for Current Day





Occupancy Key:

0-33% 33-66% 66-100%

Using the random-forest model predicting absolute occupancy, I created an application that queries current weather data and displays predictions of each meter's occupancy for the current day on an interactive map. This application serves as a proof-of-concept for a website or integration into Google Maps that consumers might reference when attempting to find parking on a certain day.

This application could also be extended the other way for city planners and policy-makers to get an idea of how meters would perform over a year by extrapolating daily estimates of revenue to a full year[8]. Theoretically, the model should also provide revenue estimates with reconfigurations, additions, or removals of meters, and a tool could be added to the application that would allow city planners to interactively assess their choices.

[8] Two methods for predicting yearly revenue include aggregating meter revenue by year and then generating a new model, or taking daily estimates using average weather conditions and summing across 365 daily estimates

Discussion:

What are some explanations of unexplained variance in meter revenue and occupancy?

The prediction models that combine meter configuration features, weather features, and all three scales of location (zone, area, sub-area) do better than the benchmarks, but it appears that they still aren't able to explain a lot of the variance. For the absolute estimations of revenue and occupancy, the R^2 is approximately .35 or that the model accounts for 35% of the variance of the values in the data.

The data strongly indicates that this unexplained variance comes more from meter variance across daily conditions as opposed to across meter configurations/geography. In the model, the weather features are the only features that actually account for variance across daily conditions. San Diego, for one, is known for having fairly constant weather. In other cities where weather varies more widely and frequently, we might expect weather to play a greater importance. Naturally, there are many more features that account for the variance across meter configurations/geography, as they are far more easily identified. Evidence of this is shown by the distinction between "Predictions of Revenue above Median Meter Revenue" and "Predictions of Occupancy above Median Occupancy of Same Meter", where the accuracy of the first (~75%) is far greater than the second (~60%). This is because the second actually aims to address the variance of parking meter demand over days, as the separation in data depends on each unique meter.

What features were missing that would allow for better predictions?

In terms of addressing additional unexplained variance across meter configurations/geography, the underlying matter of concern is making sure to capture the inherent popularity of a meter, especially because the features analysis and coefficient signs on *number of meters in vicinity* and *price-per-hour* indicated that this variable was perhaps not completely controlled for. The *distance to nearest transit stop* was one measure attempting to address this matter. Additionally, one could try to figure out the types of businesses and establishments around the area that might better capture the popularity of a meter (e.g. *number of X places in vicinity* where X is something that influences the popularity of a parking meter). Referring back to the exploratory analysis, the high occupancy rate of the Gaslamp area could be attributed to the many tourist attractions nearby. Another useful feature might be the *availability of free parking or other parking options nearby*. Basically, the idea is to figure out what is going on with the actual street the parking meter is placed on.

It is a far greater challenge to address the unexplained variance across differences in daily conditions, though accounting for this type of variance is probably far more critical in predicting *daily* parking demand. Weather was chosen for the model allowing for an independent increase of approximately .05-0.1 in R^2 for the absolute predictions of revenue and occupancy. This suggests that weather only superficially addressed this issue, if at all (though I suspect it is more an issue that "Sunny" San Diego doesn't have enough variance in weather). Some features that might be more helpful here are *whether special events are occurring near the area of the parking meter, traffic conditions near the parking meter, public transport ridership near parking meters,* and *day of the week*[9]. However, most of these features are difficult to obtain on the fly and the relationship between these features and parking meters might not be straight-forwards.

Further supporting this notion, in a brief auxiliary investigation, I used the year-to-date daily aggregate parking meter data and compiled an *event_occurring_nearby* (true if event within 0.5 miles of meter on date) and *expected_attendees* (expected number of attendees if event within 0.5 miles of meter on date) feature. From both the regression and a random-forest inspection similar to the one conducted on weather, neither was helpful in accounting for any variance in meter revenue (R^2 of 0), perhaps because the feature didn't rightfully capture the implied meaning of special events or a more complex relationship between special events and parking demand.

At the end of my project, I also did conduct an examination of a *day of the week* (dummy). The variance score of the regression on revenue was .04, implying that the day of the week does minorly influence parking meter demand and can help account for day-by-day variance. Thursday and Friday had the greatest demand, while Saturday had the least demand[10]. Accordingly, after rerunning the random-forest model on revenue with this variable included, I obtained a slightly improved R^2 of .38.

In summary, one can imagine the parking meter demand on a day-by-day basis is substantially influenced by an element of intractable randomness, as it comes down to whether some number of people decides they want to visit a certain location on a certain day.

<u>What useful information was gained would influence people's behavior or help them to make certain decisions?</u>

From the perspective of the consumer, they would like to use the interactive application to get accurate estimates of daily occupancy. However, as just discussed, the model mostly captures variance across meter configuration/geography. They can get a sense of how busy a meter is in general, but not how busy it is today compared to other days. A person thus might be better off using his or her own intuition to figure out whether a parking meter of choice might be busy. Only by

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[9] Many of these are inspired by the "Determinants of …Eugene, OR" paper

[10] In contrast to the paper, where Tuesday faced the greatest demand

capturing more of the variance across daily conditions will the prediction information be compelling to use.

For city planners and policymakers, the outlook of this data is slightly more optimistic, because meter configuration/geography is relevant to deciding how existing meters could be modified and where to build new parking meters or to remove existing ones. The prediction model could theoretically be used to simulate changes in meter configurations (e.g. price) that would improve the economic efficiency of the meters (e.g. increasing occupancy as implied by the exploratory analysis). However, the standing regression model would likely give misleading estimates of revenue for an increase in price given the positive correlation. It might also be possible to use the other types of classification models, though in that case the exact relationship between the features and predicted output is less clear[11].

With decisions of how to add, remove, or reconfigure meters, the information might only serve to supplement more in-depth case-by-case analyses, especially because the output (revenue or occupancy) is a fairly one-dimensional metric. If one could get at the opportunity cost of a meter or equivalently the opportunity benefit that takes into account externalities, the forecasted information would be far more compelling. Urban planning often involves choices among a set of alternatives (i.e. parking meters vs. bike lane), and opportunity cost/benefit could provide a means of quantitative comparison across alternatives. From a data analysis perspective, this is a huge and potentially impossible challenge because one must figure out a common "opportunity cost/benefit" metric that is applicable across all the types of alternatives.

In summary, the issue here comes down to complexity and a limitation of big data. A parking meter's demand is sensitive to so many hyper fine-grained details that it appears infeasible to make accurate daily predictions. It might be easier to forecast demand across longer time periods, but nonetheless, the parking meter is always affected by micro factors only relevant to that single parking meter. A better idea might be to reverse the exercise and use parking meter demand as a feature for predictions of other considerations, such as the success of businesses around the area.

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[11] Branch selection and feature influences in random-forest/decision-tree models are conditional on the selections made at higher branches. This allows for better accuracy at the expense of simplicity.

Conclusion:

Initially, it seemed that predictions of parking meter occupancy and revenue could be extremely useful to policymakers, businesses, or consumers and allow them to make more informed decisions leading to the many economic and environmental benefits as outlined by Shoup, especially if the analysis could be rendered in the accessible form of a visualization tool. However, after conducting my analysis, it seems not practical or even feasible to reach an understanding of the urban ecosystem from meter transaction data alone that would be useful to any party. At the very most, policymakers may get a rough idea of how they are doing, but not a compelling idea on how they could do better by changing up the configurations, number, or locations of parking meters. For consumers and businesses, the predictions don't account for enough of the day-by-day variance to be useful for decision-making. Nonetheless, the project has raised many concerns that arise when you attempt to "predict the future" and the limits of big data analysis. Like stocks, you might be dealing with something that has so many moving parts that you can't exactly pinpoint what is going on unless you get down to the hyper fine-grained details of the company or parking meter. Even then, the sensitivity of the to-be-predicted variable to those minor details may be impossible to track or conceptualize in a model.

Visualizer README:

Run Instructions:

1. Extract Visualizer.zip
2. From a terminal, CD into visualizer directory
3. Execute "sudo python3 classifcation_server.py" - a local server should start up from port 2321, using columns.pkl and forest_occupancy.pkl as local resources.

```
~/Desktop/Capstone/Visualizer$ sudo python3 classification_server.py
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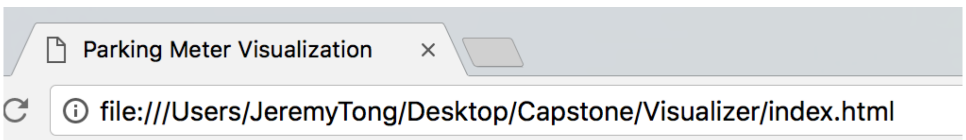
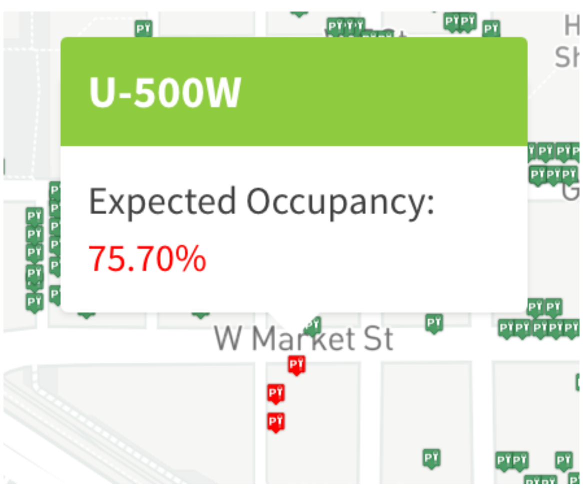
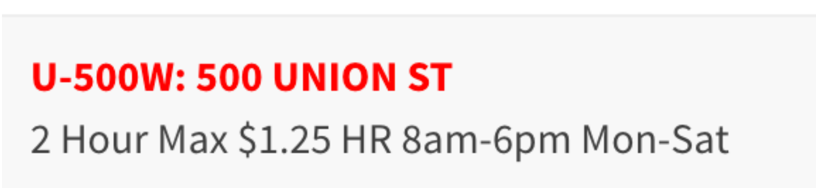
4. Open index.html in a browser, which should query the local server for predictions and render the parking meters.



Operation:

Click on any parking meter on the map to zoom to the meter. The left column will scroll to the meter and display the meter's configurations.





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