Data Mining Exercise 3

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What Causes What?

1. Simply running a regression of "Crime" on "Police" doesn't capture a definitively causal relationship. The regression may lead you to asses a causal relationship where there simply may be a correlation. High crime cities have an incentive to hire a lot of police, so you may see a positive relationship between crime and police due to this correlation.
2. Researchers at UPenn isolated this effect by looking at situations where there is a high police presence unrelated to crime. So, the researchers look at data when DC is experiencing an orange (medium) terrorism alert, so there is an increased police presence in the district, unrelated to street crime. This study finds that increased police presence causes less street crime (murder, robbery, assault). As shown in table 2 column (1), on high alert days, meaning days with increased police presence, crime is negatively correlated (an estimated 7 fewer crimes on high alert days). When the authors control for METRO ridership to account for any change in public behaviors due to the high alert, they still find a statistically significant reduction in crime of about 6 fewer crimes on high alert days.
3. The researchers controlled for METRO ridership in case there were fewer people on the streets on high alert days, thus reducign the opportunity and instance of crime. They had to control for this in case the reduction in crime was due to fewer crim opportunities and not police presence.
4. This model is estimating crime in DC based on police presence (via High Alert days) in district 1 versus other districts, controlling for METRO ridership. This regression suggests that the impact of police presence in district 1 is associated with lower crime than police presence in other districts. The interaction terms show that high alert in district 1 reduces crime by ~2.6 crimes while in other districts, high alert only reduces crime by ~0.5 crime. This regression is also controlled for METRO ridership as discussed before.

Predictive Model Building: Green Certification

Commercial real estate owners are looking to understand the value of a LEED or Energystar building certification in order to decide whether or not to invest in the certification. Using a dataset that captures a variety of characteristics of commercial rental properties across the United States, I aim to predict the value of green building certification to yearly rental revenue per square foot.

The dataset contains 7820 observations of 23 variables describing commercial rental properties across the US. These variables include size, age, renovation status, rent, leasing rate, green certification and various other qualities. In order to examine the impact of green certification on yearly revenue per square foot, I use a random forest model. This model is appropriate due to the the number of variables and possible interactions, as well as possible non-linearities. The model will pull in information from variables that are impactful.

In order to run the random forest, I fit the model using all variables in the dataset to predict the yearly revenue per square foot, where yearly-revenue-per-sq-ft = Rent * rental-rate (omitting the Rent, rental-rate and property ID). Fitting this model resulted in the plot below of predicted values (x) versus true yearly revenue values (y). The RMSE on the out-of-sample test set is shown below.

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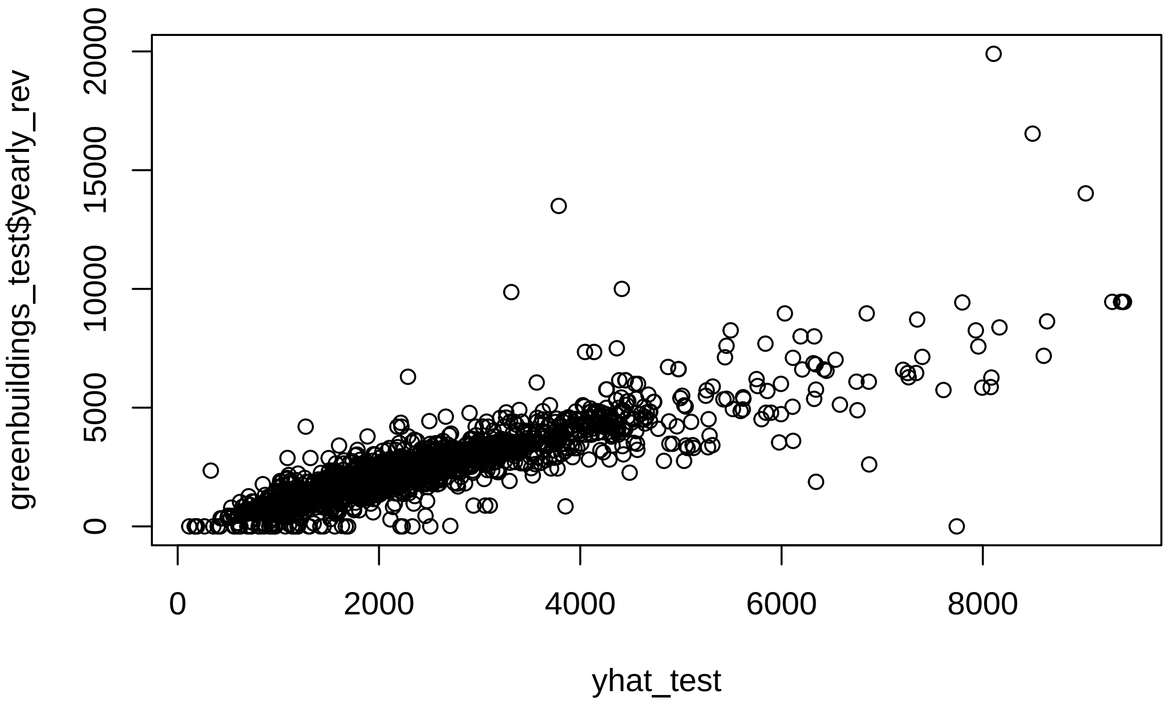
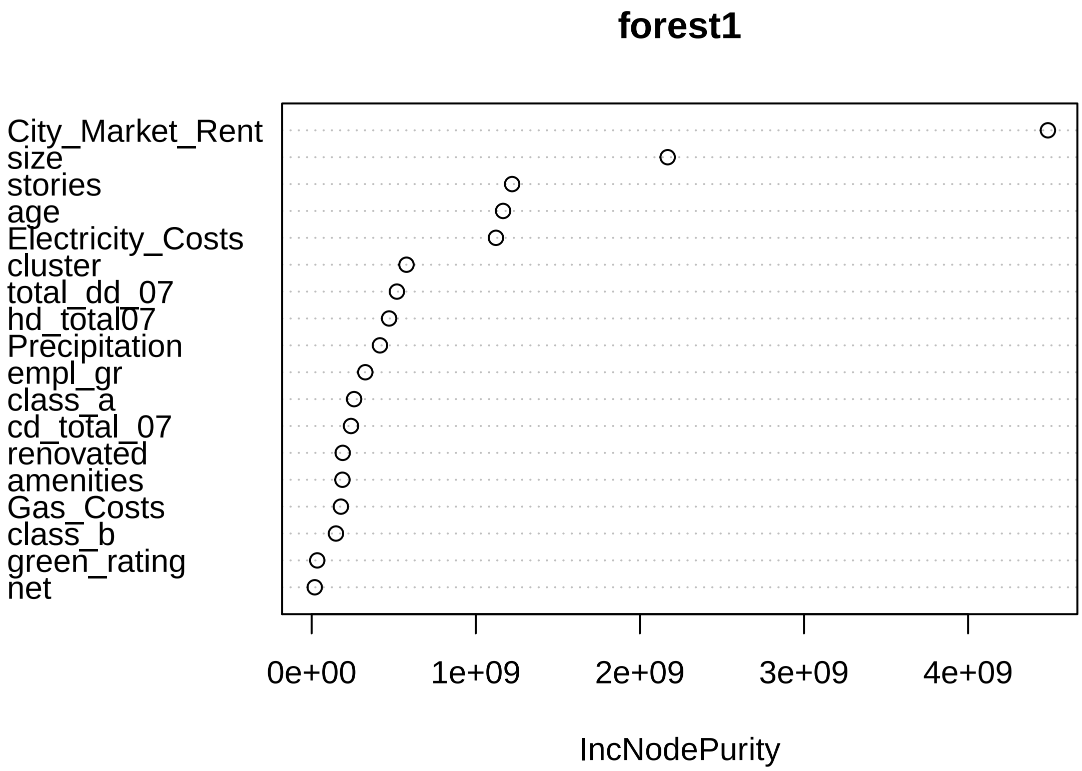
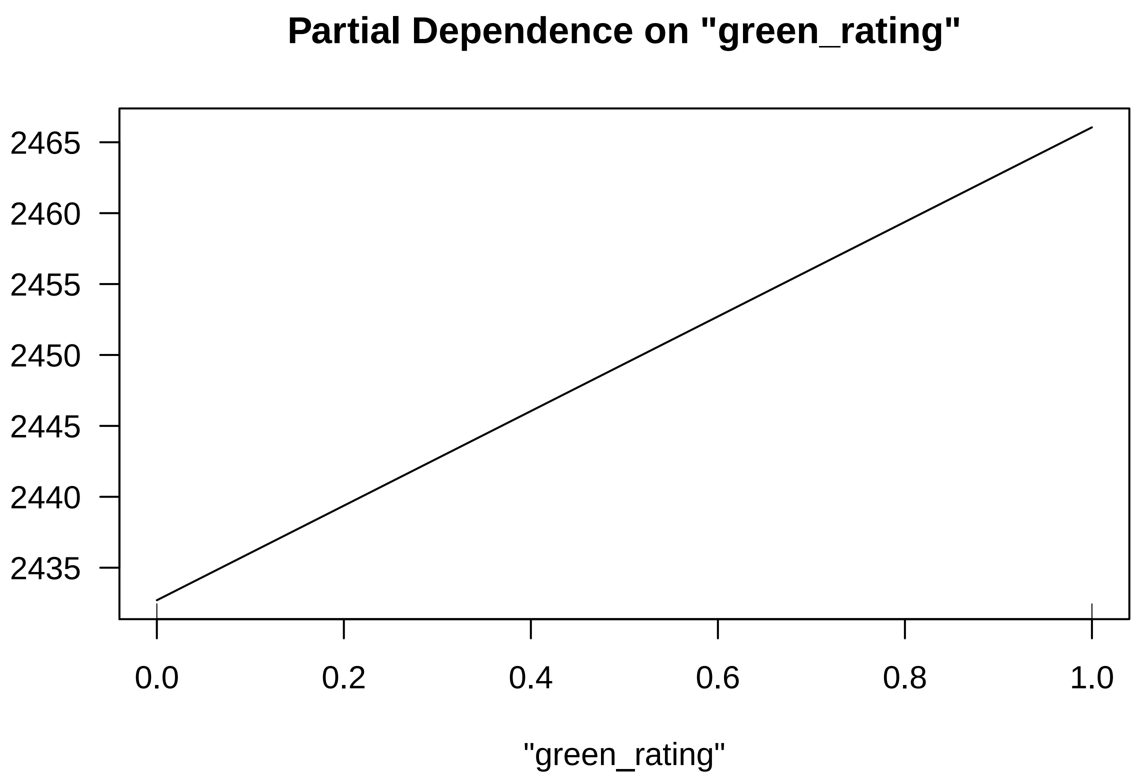
## [1] 774.0547
```

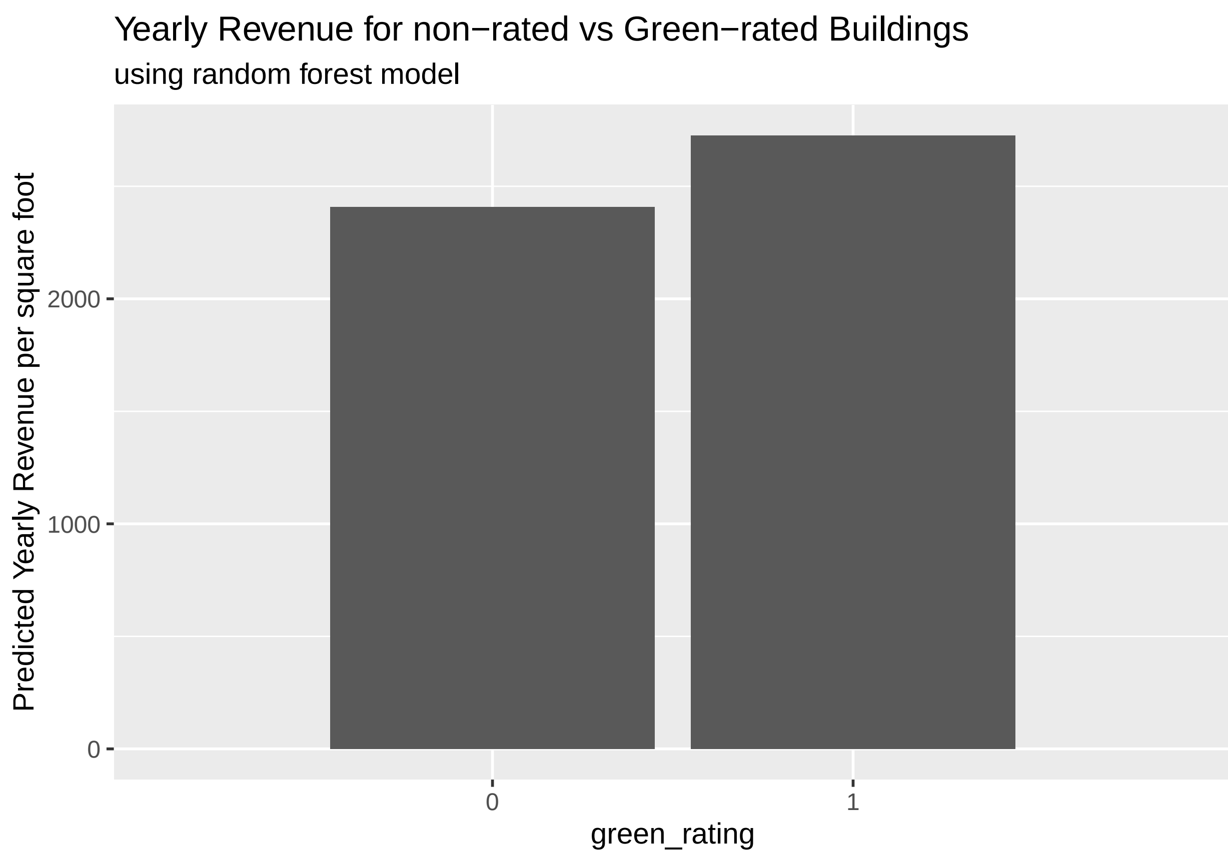


Looking at the variable importance plot below reveals that the most impactful variables in predicting yearly revenue are the city's market rent, the size of the property, number of stories, age, electricity costs, and location-dependent variables such as heating days, cooling days and precipitation. It is clear from the plot below that green certification is not a strong predictor of yearly revenue.



The plot and data below shows the average difference in yearly revenue-per-square-foot for a green certified (either LEED or Energystar, or both) building, versus non-green certified. The partial importance plot below shows the return to yearly revenue for any green rating, holding all else constant. Achieving any sort of green rating returns about 80 dollars /sq.ft. per year, holding all other variables constant. The bar chart and table show that on average, the model predicts that a non-green building will bring in about 400 dollars/ sq.ft. per year less. The 400 dollar difference in the bar chart is likely the result of all other factors correlated with green rating, and not green rating alone. The partial dependence chart shows the true isolated impact of green rating as $80/sq.ft. per year.


Partial Dependence on "green_rating"
2465
2460
2455
2450
2445
2440
2435
0.0
0.2
0.4
0.6
0.8
1.0
"green_rating"


Yearly Revenue for non−rated vs Green−rated Buildings
using random forest model
Predicted Yearly Revenue per square foot
2000
1000
0
0
1
green_rating

```
## # A tibble: 2 x 2
##   green_rating yhat_mean
##          <int>     <dbl>
## 1            0     2408.
## 2            1     2725.
```

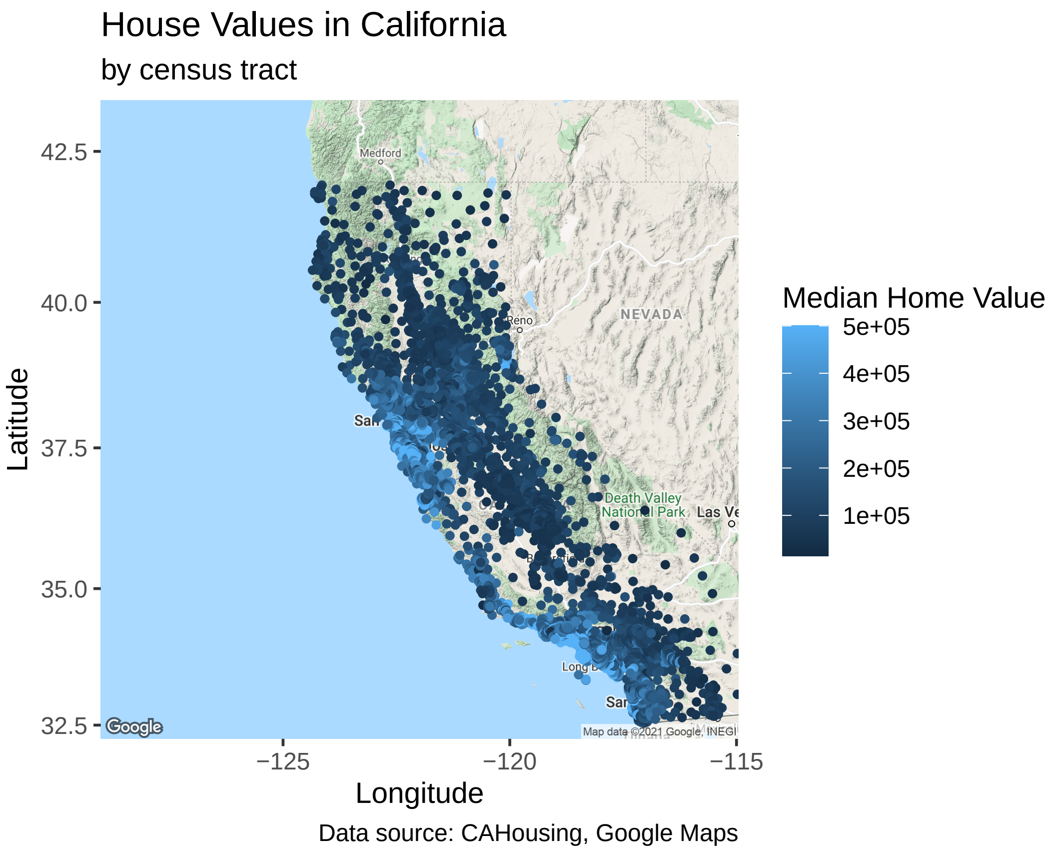
Based on this result, the property owner should weigh the cost of renovation for green certification per square foot versus the predicted return and make their decision on green certification accordingly.

Predictive model building: California housing

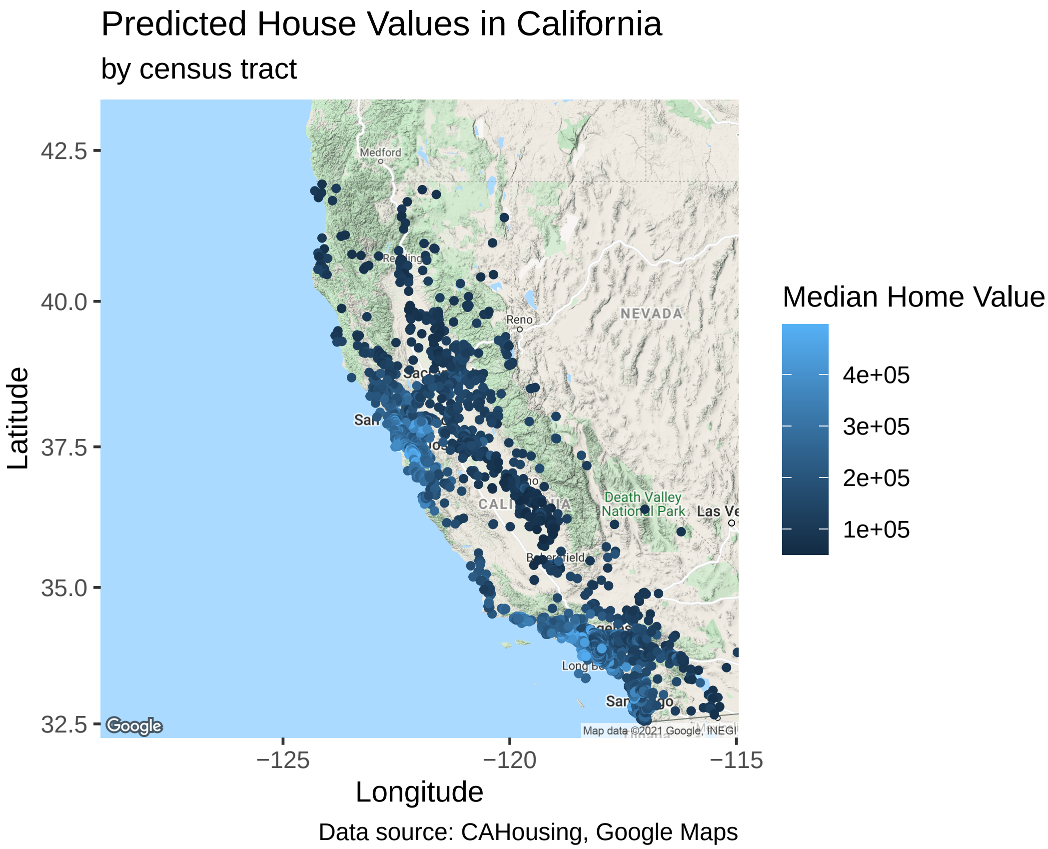
Using data on homes in California, my goal is to fit a model predict house value. The data I am using detail the house location, age, rooms, bedrooms, population of the area, number of homes, as well as median income. I used a random forest model to predict house value based on these variables. The random forest model allows for flexibility and interactions. The model resulted in an out-of-sample error of about $50k.

```
## [1] 51362.96
```

The map below shows the census tracts sampled in the dataset, with the actual median home value of the tract variation shown by color variation. This clearly shows that homes located on the coast, and around San Francisco and Los Angeles have the highest value.



The next map below shows the predicted home values using the prediction model built. This map shows the results using the test data. The model effectively predicts the higher home values around San Francisco and Los Angeles on the coast.



The map below show the error on each of the predictions in the test data shown above. This map shows small error across the entire state, except for the higher error in the high-value locations of San Francisco and Los Angeles. This is a reasonable result as properties in these very high-cost, fast-moving locales tends to be less predictable than more conventional markets.