Exercise 3

Arindam Chatterjee (UT EID - AC83995)

2023-05-19

1) What causes what?

1-1 Why can't I just get data from a few different cities and run the regression of "Crime" on "Police" to understand how more cops in the streets affect crime? ("Crime" refers to some measure of crime rate and "Police" measures the number of cops in a city.)

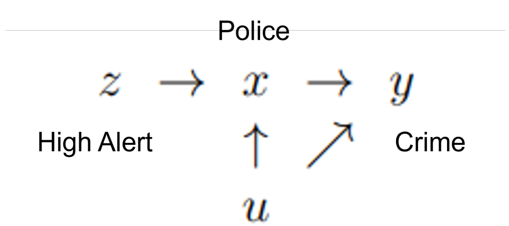
Because we can't understand the causal effect between crime and police. At first we learn as the podcast said and also according to the author of the book that there could be a way of establishing a causal relationship between - at least in Washington, D.C.A lot of extra police officers are hired even if the crime rate is low because of some terrorism alert. Now, when you have extra police there for terrorism-related reasons, they're on the streets, they make the streets safer, and things like murder, robbery, assault go down as in there was less victimes on the street. But when this hypothesis was checked by looking at ridership levels on the Metro system, and they actually were not diminished on high-terror days, so it was suggested and confirmed that the number of victims was largely unchanged. Therefore, if we regress crime on police from a few different cities like D.C., we will probably misunderstand the effect as it's tough to establish the causality. So, we can't do this.

1-2 How were the researchers from UPenn able to isolate this effect? Briefly describe their approach and discuss their result in the "Table 2" below, from the researchers' paper.

They found that when the terror alert level goes up, extra police are put on the mall in other parts of Washington to protect against terrorists has nothing to do with street crime. Also then, the streets were safer(the number of murder, robbery, assault goes down).

To show this causality, they regressed the crime on the High Alert, and got the result of the Table 2, i.e. one unit increase in high alert causes the crime rate to go down by 7.316 unit. This background of the regression is as follow:

At first, they thought this structure, where the outcome y is crime, a variable that want to show the causality x, and a instrument variable z is the High Alert.



Because of the endogeneity, they cannot direct regress y on x, but they selected the High Alert as an instrument, z that is positive correlated with x. And then they used regress y on z with reduced form like:

$$y_{crime} = \gamma_0 + \gamma_1 z_{\{High\ Alert\}} + \varepsilon$$

where $\beta_1\pi_1$ and $x_{police} = \pi_0 + \pi_1 z_{\{High\ Alert\}} + v$. Since the x and z are positive correlated, the coefficient of the High Alert on Table 2 shows $\beta_1 < 0$. This means that on the high-alert days, total crimes decrease by an average of seven crimes per day, or approximately 6.6 percent. Also, it means that the more police causes the less crime.

1-3 Why did they have to control for Metro ridership? What was that trying to capture?

According to their talks, they concerned about the possibility that tourist were less likely to visit Washington D.C. if the High Alert was announced, and what tourist were less likely to visit caused less crime. To check this hypothesis, they added a variable of the scaled Metro Ridership into the regression model.

And then, they found that the coefficient of the High Alert is still negative even if they added its variable. Therefore, they concluded that the number of victims was largely unchanged. Thus we will probably misunderstand the effect as it's tough to establish the causality.

1-4 Below I am showing you "Table 4" from the researchers' paper. Just focus on the first column of the table. Can you describe the model being estimated here? What is the conclusion?

This model is Difference In Difference model, which control group is other district and treatment group is District 1.

Firstly, a clustering approach has been used to cluster by district. And then, the difference between the High Alert × District One and the High Alert × Other Districts coefficients represents the effect of District 1 on the crime under the setting that controls for all common factors between the districts. The most of the increased police attention falls on District 1 because of the presence in that district of the White House, Congress, Supreme Court, and so forth. It is revealing to take this argument one step further and assume that all of the increased protection falls on District 1. In this case, the difference between the High Alert # District One and the High Alert # Other Districts coefficients is a difference- in-difference estimator that controls for all common factors between the districts. The difference-in-difference estimator controls for any factors such as weather, tourism, or other events that affect the districts similarly. Even after controlling for all such factors and recognizing that our assumption is too strong, we still find that crime decreases in District 1 during high-alert periods by some two crimes per day or more than 12 percent.

2) Tree modeling:dengue cases

1. Overview

- Our goal is to use CART, random forests, and gradient-boosted trees to predict dengue cases. From the best predictive model, we need to make three partial dependence plots on specific_humidity, precipitation_amt & one variable of our choice.

2. Data and Model

2-1 Data

- dengue.csv
- The detailed explanations of each variables are in the prompt We did not take logarithm of the total cases because we dont need to scale the number of dengue cases. The cases of dengue range from 0 to 329. We can not take logarithm of 0. So it does not make sense to take logarithm of the cases. Note: we did not take log for total cases because we thought total cases did not look like it had any trend term as follows:

2-2 Model

We took CART, random forests, and gradient-boosted trees to predict dengue cases as follow:

$$total\ cases = city + season + specific\ humidity + tdtr\ k + precipitation\ amt$$

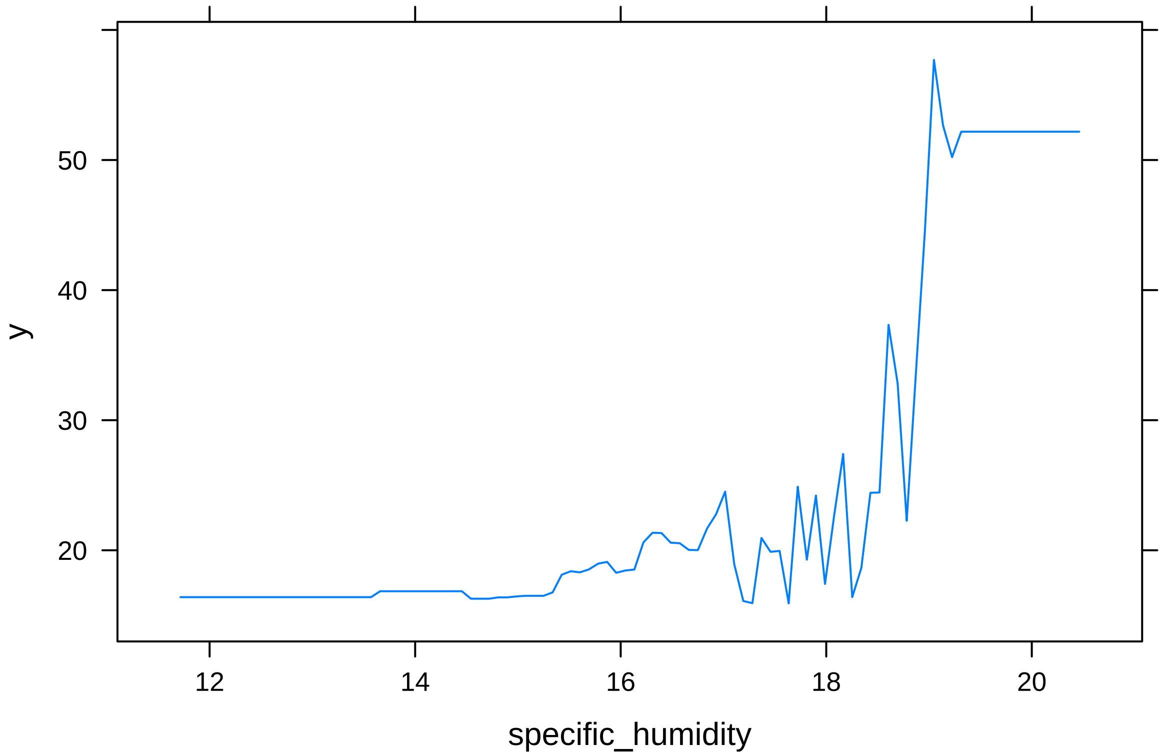
3. Results We have used CART, random forests, and gradient-boosted tree models to predict the dengue cases below.

From the result, these rmse of there models are

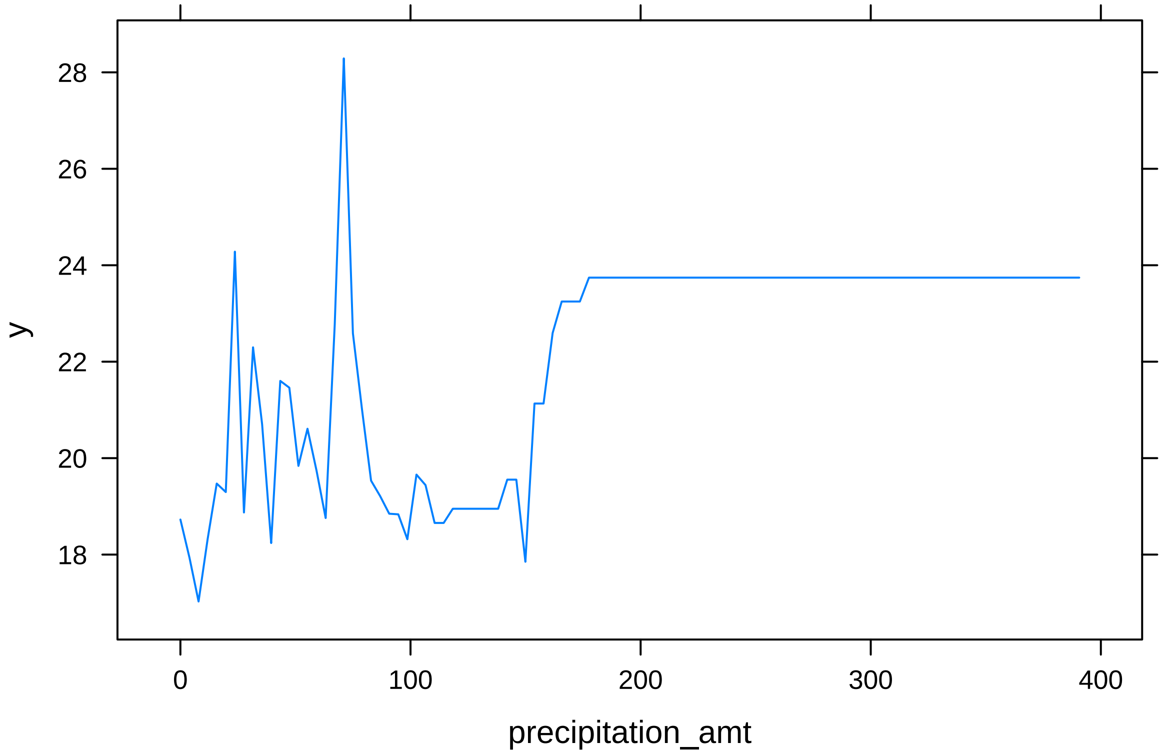
cart	forest	boost
24.83	22.42	18.53

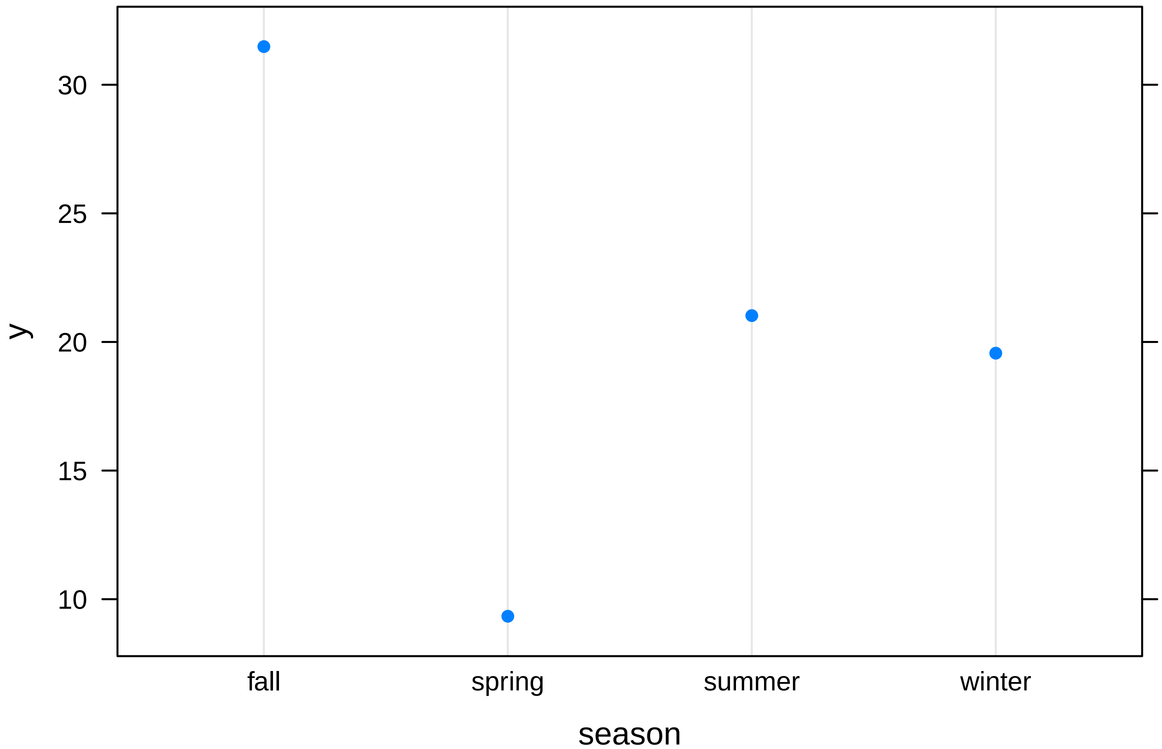
Based on the out of sample RMSE, the Gaussian Booster model seems to have the best prediction power.

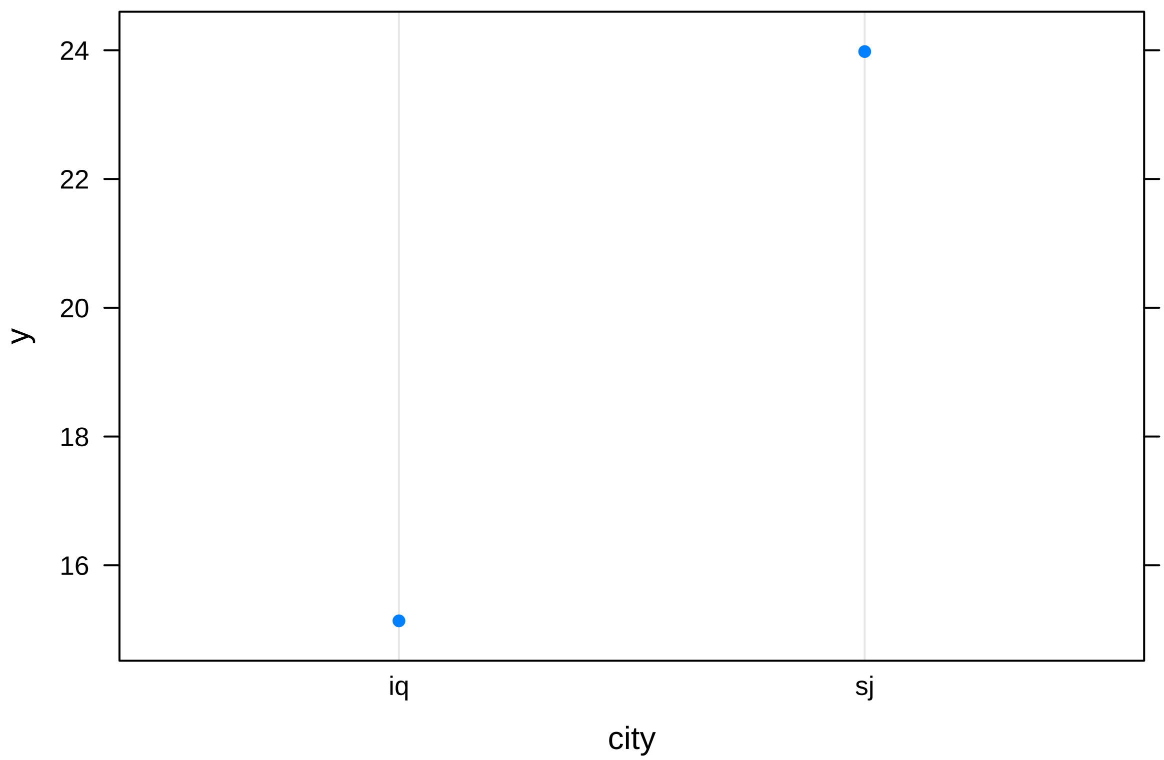
Now we plot the partial dependence of 4 variables.



50
40
30
20
y
12
14
16
18
20
specific_humidity


28
26
24
22
20
18
y
0
100
200
300
400
precipitation_amt


30
25
20
15
10
y
fall
spring
summer
winter
season



The graphs above show the partial dependence (marginal effects) of the chosen variables on total cases of dengue based on the Gaussian boosting model.From the partial dependence plot, we see that the specific humidity shows an interesting pattern on predicted dengue cases. When humidity level is more than 15 gram of water per kg of air, the humidity level increases the dengue cases.From 18 gram to 19 gram of humidity level, the dengue cases increases exponentially with the level of humidity. However, the dengue cases slows down and plateau after 20 gram level. Dengue cases shows fluctuating pattern with respect to the Amount of rainfall per week. The dengue cases reach peak when rainfall is at 75 milimeters. At a rainfall level more than 200 milimeter, the dengue cases plateau. The dengue cases are severe during the Fall season and least severe during spring season.

Finally, between the two cities, the dengue cases are more prevalent in San Juan, puerto rico.

I have included all 4 variables since all of them seems interesting, especially with the high difference between the two cities, and the Fall season with the other seasons.

##Conclusion For predicting dengue cases, we have found that the best model is gradient boosted tree. This model outperforms both the CART & random forest models as the rmse is the minimum for this model among all other models. Using the gradient-boosted model we evaluated the partial dependence/marginal effects of 'specific_humidity','precipitation_amt','season' and 'city' on dengue cases. We saw that at humidity levels between 18 gram & 19 gram of water per kg air, the dengue cases increase exponentially with humidity. Moreover, Dengue cases show fluctuating pattern with respect to the Amount of rainfall per week. The effect of rainfall on Dangue disease is maximum at 75 milimeters of rainfall level but the Dengue cases plateau at a rainfall level more than 200 milimeter. The partial dependence plot also shows that The dengue cases are severe during the Fall season and least severe during spring season.Finally, of the two cities the dengue desease is more prevalent in San Juan, puerto rico.

3) Predictive model building: green certification

1. Overview

The goal of this exercise is predict the revenue per square foot per calender year of about 8,000 commercial rental properties across the US. In addition, some of those properties are green certified which means they got green certification from either LEED or Energystar. Another question we want to answer is whether being green certified will raise total rental revenue or not.

2. Data and Model

2-1 Data

- We have used the dataset of Green buildings in greenbuildings.csv (7894 commercial rental properties from across United States)
- Of these, 685 properties have been awarded either LEED or EnergyStar certification as a green building
- In this model "revenue per square foot per claendar year"(RPS), will be dependent variable, which is the product of rent and leasing_rate in the data.

2-2 Methods

First of all, we have mutated a new column to calculate the revenue per square foot per calender year based on the original data. In order to do that, we took the product of rent and leasing_rate. We need to do that to get unbiased prediction results since the occupancy or the rent_rate alone won't reflect the revenue.Here, "revenue per square foot per claendar year"(RPS), will be our dependent variable. We have excluded CS_PropertyID variable as this is nothing but an ID number for the buildings. We have also excluded Rent & Lease rate from the list of independent variables as we used these two variables to find my dependent variable of ""revenue per square foot per claendar year"(RPS). We collapsed LEED & EnergyStar into 'Green.rating' variable.

Next, We needed to make sure that some of the variables are dummy variables, so we used the factor command on the 0/1 variables. Then, we started working on the model by splitting the data to training set (80%) and testing set (20%). We trained the data to predict revenue using random forest model & gradient boosting model.

We used three random forest models, and one gradient boosting model to measure the efficiency of the predictions.

2-2-1 Model Selection

We have used total 4 models.In my base model & in all other 3 models, my dependend variable is "revenue per square foot per calender year"

We have used a random forest model with all variables as our base model. We have already excluded Rent, Lease Rate, CS_PropertyID , LEED & Energystar variables because of the reasons mentioned above. So, after our base model, the 2nd model is also a random forest including 6 variables (City_Market_Rent , Electricity_Costs , size , stories , age & green_rating) with different importance level for each one of them. The 3rd random forest model had 9 variables with many more less important variables(City_Market_Rent , Electricity_Costs , size , stories , age , green_rating,hd_total07 , total_dd_07 & total_dd_07) . I worried that it is going to overfit the model, so now we got to check the rmse for each one of them and compare it with what we got in the base model. since we are looking for the best predictive model, it is going to be worth it to try to model using gradient boosting model with all variables. Here we have used k fold cross validation for each model.

3. Results

Now let's move on the methodology used to predict the revenue. At first, We have defined the variables& go for train & test split.

Now we use 3 different random forest models & 1 gradient boost model for prediction.

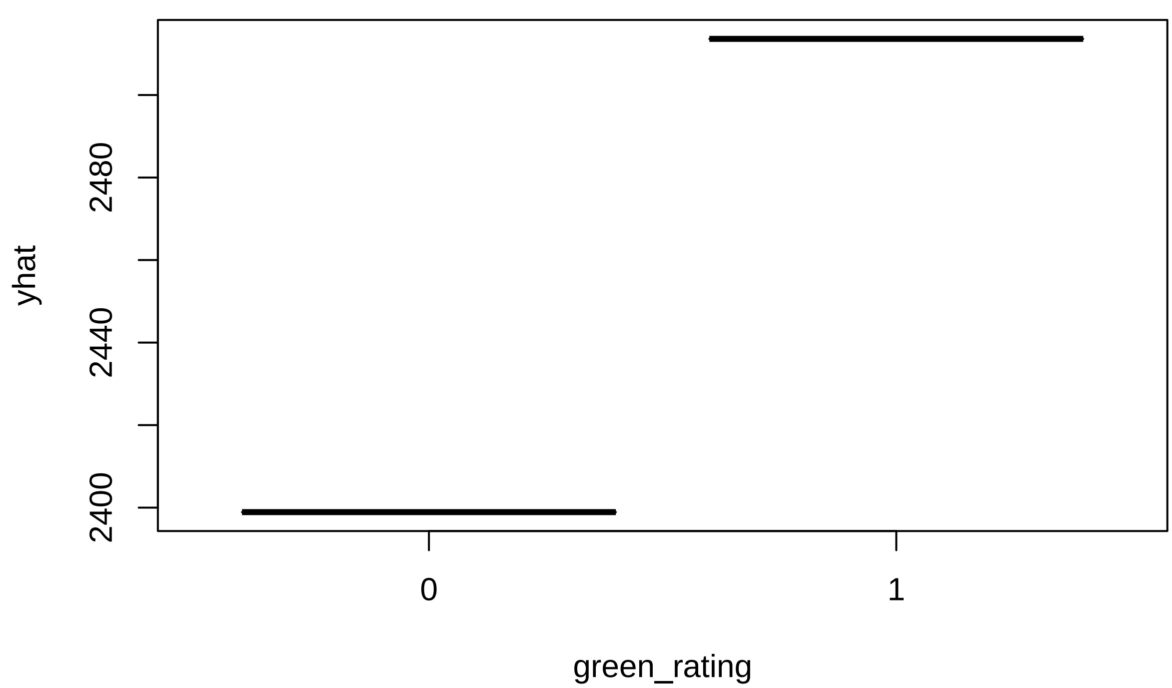
```
## Distribution not specified, assuming gaussian ...
## Distribution not specified, assuming gaussian ...
## Distribution not specified, assuming gaussian ...
## Distribution not specified, assuming gaussian ...
## Distribution not specified, assuming gaussian ...
```

From the results, we got the rmse of 3 random forest & 1 Boost model. It shows that the minimum RMSE is obtained from Random Forest model 2.

rmse_forest_cv1	rmse_forest_cv2	rmse_forest_cv3	rmse_boost_cv4
499.65	493.18	588.5868	924.77

We got partial dependence for 'green rating' below of the random forest model 2 that had the lowest rmse to interpret our model.

```
##   green_rating     yhat
## 1            0 2398.914
## 2            1 2513.602
```



The partial dependence graph shows that the green certified buildings generate greater rental income per square foot.

Conclusion:

Using 4 different predictive modelswith K crossfold validation method , we observe that the 2nd Random Forest model with 6 independent variables(City_Market_Rent, Electricity_Costs , size , stories , age & green_rating) outperformed the other 3 models as it had the best predictive power with minimum RMSE value of 493.18. So We would recommend to use the 2nd Random Forest model with 6 important independent variables to predict the revenue per squared foot per calender year. We predicted the average value for both certified and certified, and as we can see, the green certification has higher partial effects i.e such certifications brings more predicted revenue for the housing properties. So, Green certification is very important for generating superior rental income for the property owners.

Problem 4

Predictive model building: California housing

1. Overview

- My goal is to build the best predictive model you can for medianHouseValue

2. Data and Model

2-1 Data

- CAhousing.csv

2-2 Model

We took 3 steps to get the best predictive model as follow: we have used machine learning tools to provide with reliable predictions. So, we have used the random forest model, which utilizes the interaction effects of the variables. 1. I mutated to new columns to standardized the total rooms and total bedrooms by dividing each variable by households variable. Then, I split the data into 80% training set and 20% testing set and regress medianHousevalue on all the variables to test for the importance of each variables afterward. 2. we did two other specification models with different variables based on the results of the variables importance.

$$
\begin{aligned}
&Model1: \quad medianHouseValue = \beta[all\ data + const.] \\
&Model2: \quad medianHouseValue = \beta[medianIncome + longitude + latitude + totalRooms_{st} + const.] \\
&Model3: \quad medianHouseValue = \beta[medianIncome + longitude + latitude + totalRooms_{st} + population + housingMedian
\end{aligned}
$$

- totalRooms_st = totalRooms/households

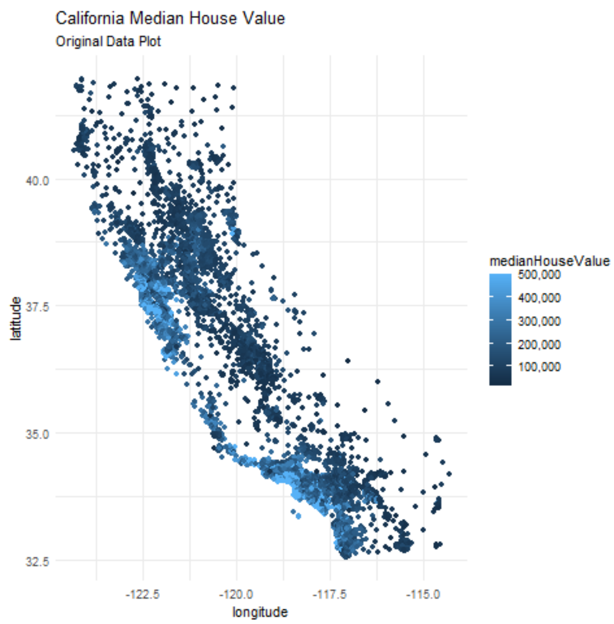
3. model has the lowest root mean squared error which equals to 47,989. In order to check for room of improvements, we ran a gradient boosting model with many different shrinkage rates, but we could not have a lower rmse value than that found using the selected random forest model.
4. Plot we decided to continue with the results of the optimal random forest model and predict the median housing values based on the testing set. Then we plottod the original observation which has the shape of California State, the predicted values based on the testing set, and the estimated residuals which is the difference between the two.

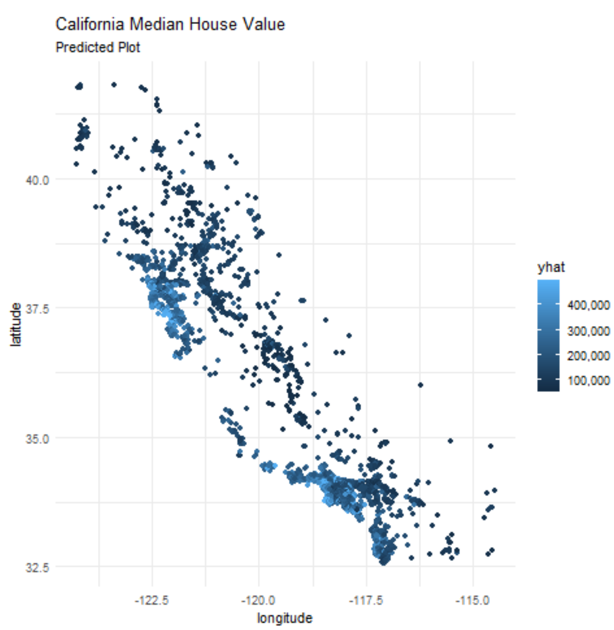
3. Results

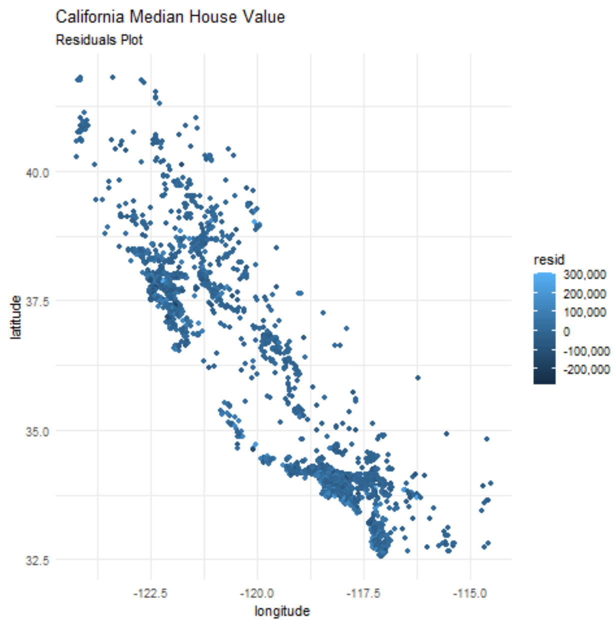
The overall out-of-sample accuracy of our proposed model is

CA_RFM1_rmse	CA_RFM2_rmse	CA_RFM3_rmse	CA_Boost_rmse
48630.96	48572.76	47998.16	51663.24

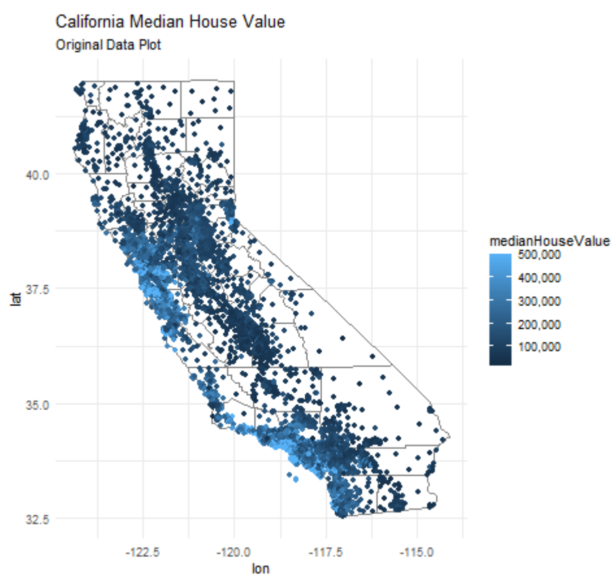
Three figures(row) that required to be plotted (1)a plot of the original data, (2)a plot of your model's predictions of medianHouseValue, (3)a plot of your model's errors/residuals are:

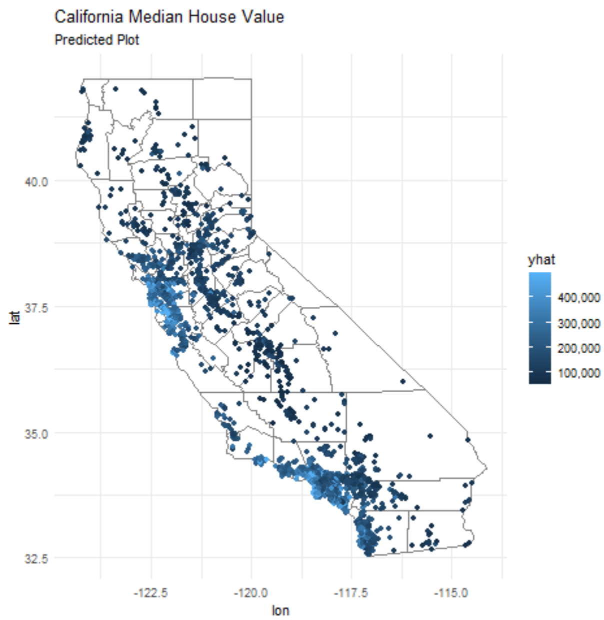


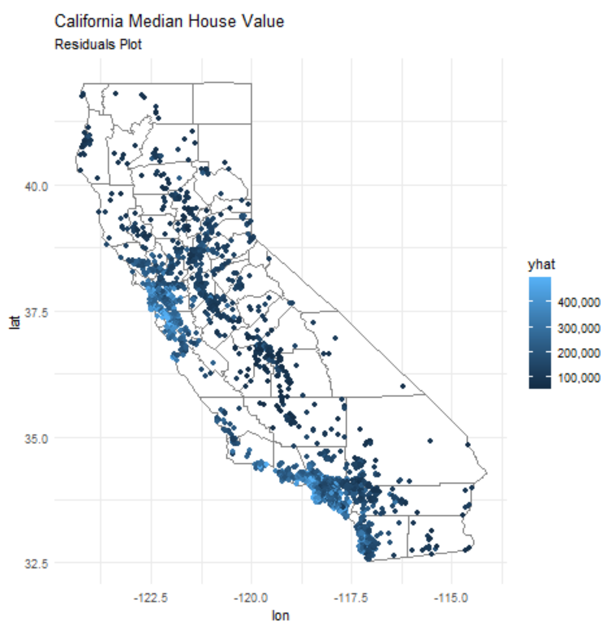




Also, these fugures in the real california map are







4. Conclusion

From the result, median House value in the area of San Francisco bay area and Los Angels are higher than other areas in the real data and predicted data. Also, the area of lower median house value in the prediction looks like the same as that in the real. Therefore, our prediction model shows good performance visually to predict median house values.