Stat 420 Final Project Proposal

STAT 420, Summer 2022, D. Unger

Modeling California Housing Prices

Introduction

Executive Summary

In this report we will discuss the creation of a linear model to model median house value of a block group in California (CA) in the 1990's based on administrative (Census) data. Given the recent turbulence in the real estate market and associated bidding wars, there is a renewed interest in what the value of a house is. Utilizing methods from STAT 420, we underwent model selection to identify the optimal model that minimized RMSE, met the assumptions of linear modelling, and had the fewest parameters to enhance explainability. The best linear model include the parameters <!TODO: add params from best linear model> and a test RMSE of <!TODO: add test RMSE>. Our model provides utility in explaining the relationship between how features of a California Block Group relate to the median house value of the block group.

The Data

For our project we leveraged a data set from kaggle California Housing Prices. The data contains information from the 1990 California census and pertains to houses found in a given California district. It contains one row per census block group. A block group is the smallest geographical unit for which the U.S. Census Bureau publishes sample data (a block group typically has a population of 600 to 3,000 people).

'California Housing Prices' data set pertains to the houses found in a given California district and some summary stats about them based on the 1990 census data. There are 10 columns and 20,640 rows in the data. The columns are as mentioned below:

Column Name	Description
longitude	Longitudinal location of block group of houses.
latitude	Latitudinal location of block group of houses
housing_median_age	Median age of the houses in the block group
total_rooms	Total rooms in the group of houses
total_bedrooms	Total bedrooms in the block group
population	Total number of people in the block group
households	Households comprised in the block group
median_income	Median income calculated from the individual income of house.
median_house_value	Median house value of a block group.
ocean_proximity	Indicating whether each block group is near the ocean, near the Bay Area, inland or on an island.

Limitations of the Data In order to ensure the reader understands the caveats of working with our data, we will first underscore the differences between census housing data and typical sources of real estate data.

The census data set, unlike scraped real estate data, is gathered by an administrative body, the Census. Since the stakeholder involved in collecting the data is not interested in selling a house, we see different features represented that relate more to geography (Latitude, longitude), population density (population, number of households), and age of the building (median_housing_age).The data set is aggregated at the block level (rather than at the house level). This means our analysis is not directly modelling housing values, but the median housing value of a neighborhood. We believe this will help us better to understand the value of the neighborhood as opposed to the value of the amenities of the individual houses.

Another important limitation of the source of this data is the date range. Since the data were gathered as part of the 1990 Census, we cannot extrapolate to current housing prices or utilize the model to explain what features are important to median house value at any other time period. For this particular reason, we focused our project on modelling rather than prediction. While there are few use cases for a prediction algorithm for median house value of a census block group in the 1990's at the present date, understanding historical features that related to a census block groups' price point provides an opportunity for understanding how median house price varied based on parameters at the time of data collection.

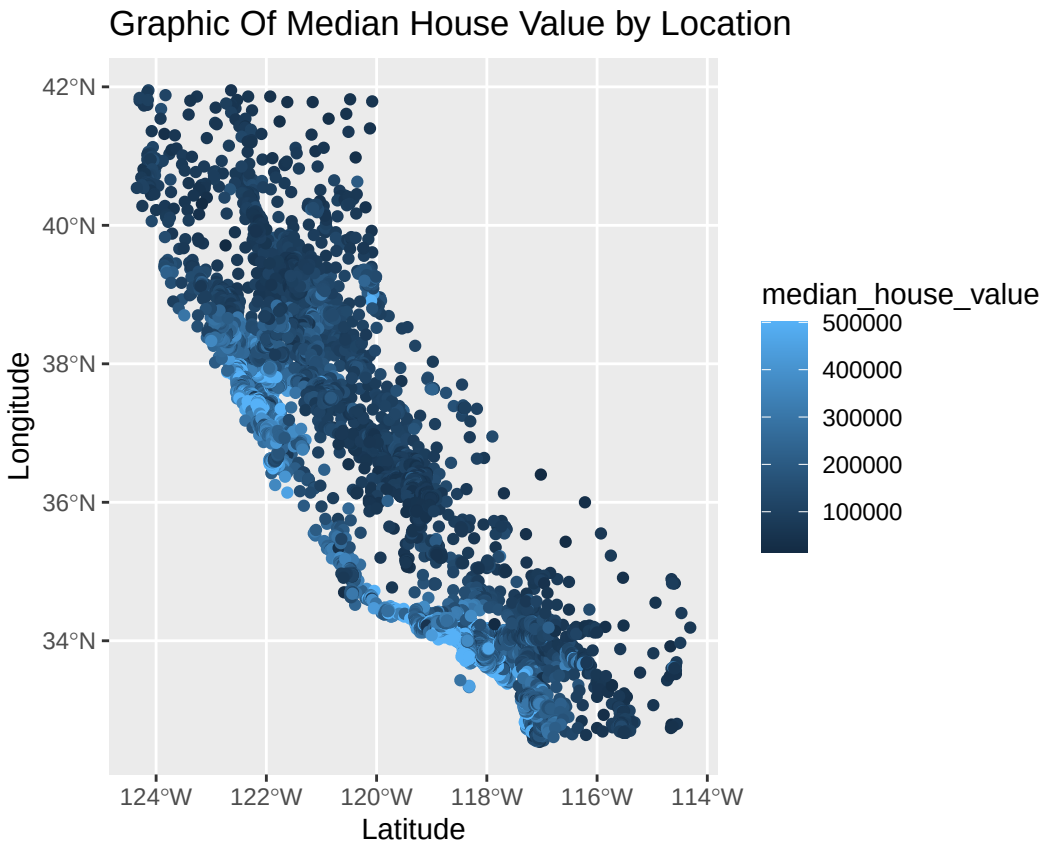
Methods

We will now discuss the steps we used to generate our linear model. We began by conducting exploratory data analysis (EDA). Based on the EDA, we identified steps necessary to clean our data. In order to ensure our model was not overfit, we split the data set into a 70-30 train-test split. Next we underwent model selection process to minimize the RMSE of our model.

Data Cleaning

As part of data cleaning, we plotted the `median_house_value` against latitude and longitude to visualize the locations of the different houses. One of the first things we noticed were two distinct clusters of highly priced houses that appear to correspond to Los Angeles and the San Francisco Bay Area.

```
#read in the data

read_in <- function(){
  ca_housing_data = read.csv('../000_Data/california-housing-prices/housing.csv')
  #turn ocean_proximity to factor

  ca_housing_data
}

ca_housing_data <- read_in()

## Map the data
#Source: https://stackoverflow.com/questions/65233613/plot-a-map-using-lat-and-long-with-r
my_sf <- st_as_sf(ca_housing_data, coords = c('longitude', 'latitude'))
my_sf <- st_set_crs(my_sf, value = 4326)

ggplot(my_sf) +
  geom_sf(aes(color = median_house_value)) +
              labs( y = "Longitude",
                    x = "Latitude",
                    title = "Graphic Of Median House Value by Location")
```



The next thing we we looked at were basic summary statistics and missingness. We found that there were 207 observation missing `total_bedrooms`. We cannot generate a linear model with missing data. However, looking at the colinearity, we will find a solution that allows us to keep these observations.

```
summary(ca_housing_data)
```

```
##    longitude       latitude    housing_median_age  total_rooms
##  Min.   :-124   Min.   :32.5   Min.   : 1.0       Min.   :    2
##  1st Qu.:-122   1st Qu.:33.9   1st Qu.:18.0       1st Qu.: 1448
##  Median :-118   Median :34.3   Median :29.0       Median : 2127
##  Mean   :-120   Mean   :35.6   Mean   :28.6       Mean   : 2636
##  3rd Qu.:-118   3rd Qu.:37.7   3rd Qu.:37.0       3rd Qu.: 3148
##  Max.   :-114   Max.   :42.0   Max.   :52.0       Max.   :39320
##
##  total_bedrooms   population      households   median_income
##  Min.   :   1   Min.   :    3   Min.   :   1   Min.   : 0.50
##  1st Qu.: 296   1st Qu.:  787   1st Qu.: 280   1st Qu.: 2.56
##  Median : 435   Median : 1166   Median : 409   Median : 3.54
##  Mean   : 538   Mean   : 1425   Mean   : 500   Mean   : 3.87
##  3rd Qu.: 647   3rd Qu.: 1725   3rd Qu.: 605   3rd Qu.: 4.74
##  Max.   :6445   Max.   :35682   Max.   :6082   Max.   :15.00
##  NA's   :207
##  median_house_value ocean_proximity
##  Min.   : 14999     Length:20640
##  1st Qu.:119600     Class :character
##  Median :179700     Mode  :character
```

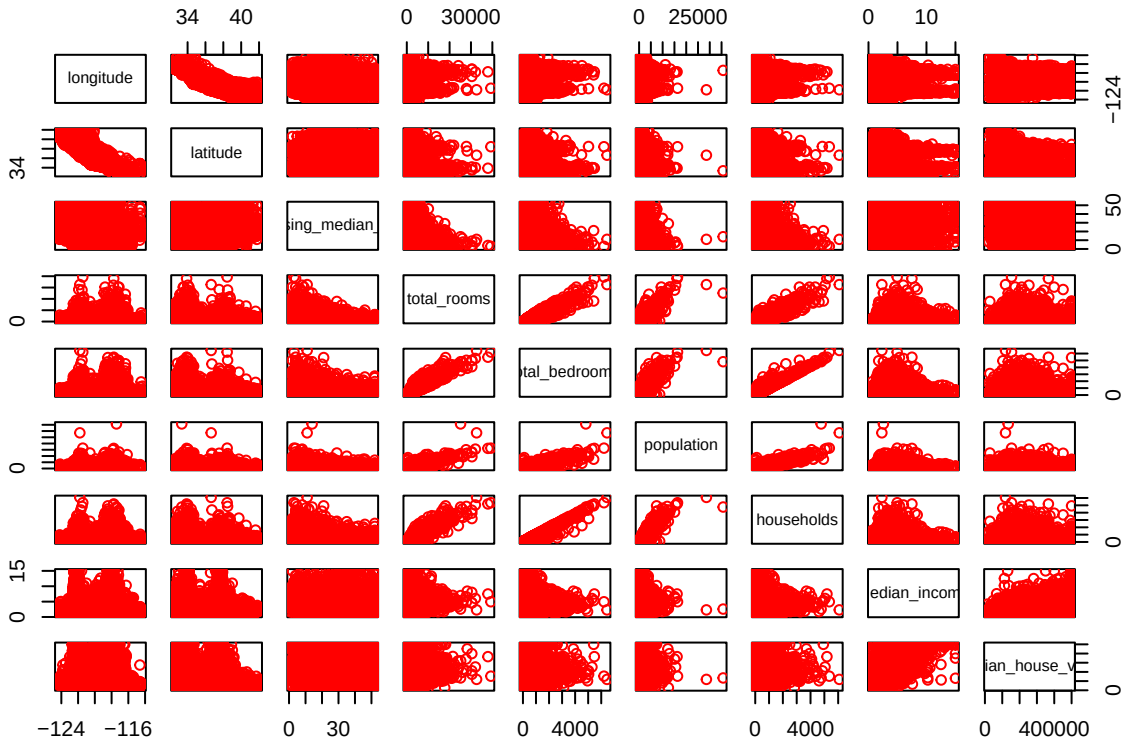
```
##  Mean   :206856
##  3rd Qu.:264725
##  Max.   :500001
##
```

```
#How many missing values do we have?
colSums(is.na(ca_housing_data))
```

```
##           longitude            latitude housing_median_age        total_rooms
##                   0                   0                   0                   0
##     total_bedrooms          population          households       median_income
##                 207                   0                   0                   0
## median_house_value     ocean_proximity
##                   0                   0
```

In addition to looks at graphs and summary statistics, we also began to identify variables with colinearty issues via a correlation matrix and pairwise plot. In the pairwise plot we see that `total_bedrooms` is highly colinear with `total_rooms`, but total_rooms is not missing any values. With this in mind, we can utilize the variable `total_rooms` to preserve the 207 observations.

```
## pairs & Cor matrix
numeric_vals <- unlist(lapply(ca_housing_data, is.numeric), use.names = FALSE)
pairs(ca_housing_data[,numeric_vals], col="red")
```



```
round(cor(ca_housing_data[,numeric_vals]), 2)
```

```
##                     longitude latitude housing_median_age total_rooms
## longitude                1.00    -0.92              -0.11        0.04
## latitude                -0.92     1.00               0.01       -0.04
## housing_median_age      -0.11     0.01               1.00       -0.36
## total_rooms              0.04    -0.04              -0.36        1.00
## total_bedrooms             NA       NA                 NA          NA
## population               0.10    -0.11              -0.30        0.86
## households               0.06    -0.07              -0.30        0.92
## median_income           -0.02    -0.08              -0.12        0.20
## median_house_value      -0.05    -0.14               0.11        0.13
##                     total_bedrooms population households median_income
## longitude                       NA       0.10       0.06         -0.02
## latitude                        NA      -0.11      -0.07         -0.08
## housing_median_age              NA      -0.30      -0.30         -0.12
## total_rooms                     NA       0.86       0.92          0.20
## total_bedrooms                   1         NA         NA            NA
## population                      NA       1.00       0.91          0.00
## households                      NA       0.91       1.00          0.01
## median_income                   NA       0.00       0.01          1.00
## median_house_value              NA      -0.02       0.07          0.69
##                     median_house_value
## longitude                        -0.05
## latitude                         -0.14
## housing_median_age                0.11
## total_rooms                       0.13
## total_bedrooms                      NA
## population                       -0.02
## households                        0.07
## median_income                     0.69
## median_house_value                1.00
```

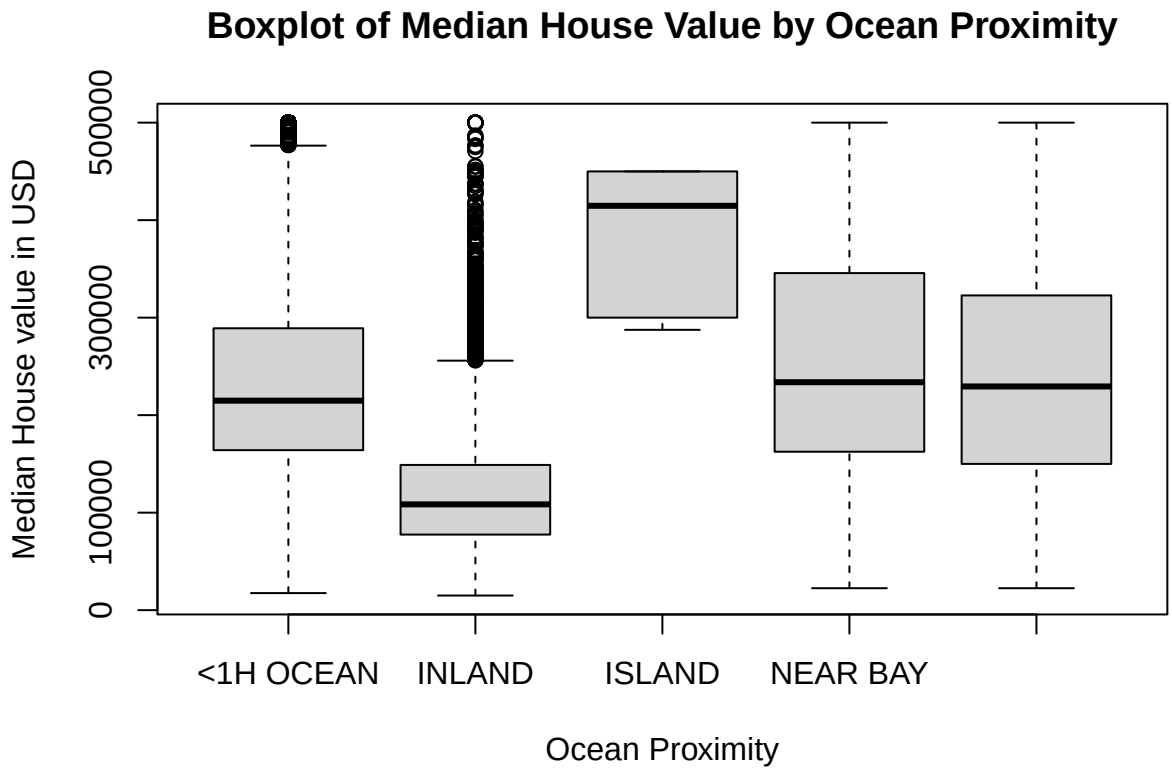
```
#Population and households are colinear
#Population and Total rooms are also colinear
#latitude and longitude are also highly correlated
```

We have another column `ocean_proximity` which is a categorical variable indicating how close the block is from ocean. As can be seen, this column has 5 different categories. The `ISLAND` category has only 5 observations. During initial analysis, our team determined that `ISLAND` has high leverage on the predicting response variable `median_house_value` which is problematic for our purpose. We will be dropping the rows from data set with `ISLAND` category and coercing the predictor `ocean_proximity` to be categorical.

```
#Ocean proximity - only 5 in island, and substantially different. I propose removing from consideration
table(ca_housing_data$ocean_proximity)
```

```
##
##  <1H OCEAN     INLAND     ISLAND   NEAR BAY NEAR OCEAN
##       9136       6551          5       2290       2658
```

```
boxplot(median_house_value ~ ocean_proximity,
        ca_housing_data,
        main = "Boxplot of Median House Value by Ocean Proximity",
        ylab = "Median House value in USD",
        xlab = "Ocean Proximity")
```




```
#Remove the islands rows
ca_housing_data = ca_housing_data[ca_housing_data$ocean_proximity != "ISLAND",]

#Now we turn it into a factor after dropping that level
ca_housing_data$ocean_proximity <- as.factor(ca_housing_data$ocean_proximity)
```

At this point, we have concluded the prerequisite data cleaning and can move onto model selection.

Model Selection Procss

Now that we have data cleaned, we will proceed with building a model. The very first step we will take is to divide data into train and test. Based on total number of observations we've, team has decided to use 70%-30% split for train-test data.

Initialize global variables.

```
# build different models to test the performance
n_models = 7
```

```r
# create a vector list of models to pass to various functions
cahoudta_models = vector("list", length = n_models)
cahoudta_model_names = vector("character", length = n_models)
# Train-Test Split Ration
tr_pct = 0.70
```

Helper Functions

Function : `model_performance_metrics` will generate model performance metrics such as RMSE and R-squared, etc.

Inputs:

models : A list of models to generate the performance metrics

model_names : Names of the models passed to the function

Returns : Returns a data frame with following performance metrics as columns and a row for each model provided in `model_names` as input.

```
R2: R-Squared
ADJR2: Adjusted R-Squared
RMSE: Root Mean Square Error
LOOCV_RMSE: Leave One Out Cross Validated RMSE
Coefs: Total number of coefficients in the model
```

```r
model_performance_metrics = function(models, model_names){
  # Calculate model names and total numbers
  n_mod = length(models)
  # Initialize the data frame to be be built by the function
  perf_metrics_df = data.frame(
    row.names = model_names,
    "R2" = rep(0L, n_mod),
    "ADJR2" = rep(0L, n_mod),
    "RMSE" = rep(0L, n_mod),
    "LOOCV_RMSE" = rep(0L, n_mod),
    "Coefs" = rep(0L, n_mod)
  )

  for (idx in 1:n_mod){
    perf_metrics_df[model_names[idx], "R2"] = summary(models[[idx]])$r.squared
    perf_metrics_df[model_names[idx], "ADJR2"] = summary(models[[idx]])$adj.r.squared
    perf_metrics_df[model_names[idx], "RMSE"] = sqrt(mean(resid(models[[idx]]) ^ 2))
    perf_metrics_df[model_names[idx], "LOOCV_RMSE"] = sqrt(mean((resid(models[[idx]]) /
                                                                  (1 - hatvalues(models[[idx]]))) ^ 2))
    perf_metrics_df[model_names[idx], "Coefs"] = length(coef(models[[idx]]))
  }
  return(perf_metrics_df)
}
```

```r
set.seed(420072022)
# Randomly select train indexes
cahoudta_trn_idx = sample(nrow(ca_housing_data),
                          size = trunc(tr_pct * nrow(ca_housing_data)))
```

```r
# Split into train and test data sets based on the index
ca_housing_data.tr = ca_housing_data[cahoudta_trn_idx, ]
ca_housing_data.te = ca_housing_data[-cahoudta_trn_idx, ]

n_tr_rows = nrow(ca_housing_data.tr)
n_te_rows = nrow(ca_housing_data.te)
```

<!TODO: add more about data cleaning!>

Results

Chosen Model

Discussion

Utility of Model

> section should contain discussion of your results and should frame your results in the context of the data. How is your final model useful?

Future Directions and Lessons Learned

Appendix

Authors

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