Predicting San Jose Home Prices

Aaron Lopez

6/25/2017

Project Description

Affordable housing is a major concern in the Bay Area of California. Many people are priced out of affordable housing options where the median home price has reached $1 million in San Jose, California.[1] This trend impacts low and median income families looking to secure home ownership. Politicians and voters have voiced their concerns and willingness to address this issue by approving new policies at the ballot box. Last November voters passed Measure A allowing the city to issue $950 million in new bonds for affordable housing.[1] The current mayor of San Jose, Sam Liccardo, has said, "San Jose is facing an affordable housing crises."[2] To help address this issue I'd like to take a look at recent median home price trends and also predict how prices will change in the near term. This information will help to keep track of affordability and give insights into the effectiveness of government policy changes.

There are two major client groups. First, the city of San Jose who has made housing affordability a priority as the city continues to grow and city officials create urban planning policy. Politicians have expressed their desire to introduce an impliment policy to make housing more affordable for low and middle income residents. Understanding the trend and where housing prices are headed will help politicians determine what policy may be needed or developed. The second group of clients would be low and median income individuals seeking to find affordable housing and deciding when and if San Jose home price are affordable today or in the near future. This information can help them make an infored decision on when and if to purchase a home in the near future.

To predict near term median home prices I will use three different model approaches, linear regression, time-series (ARIMA), and regression tree. I will then compare each model to actual median home prices from a test data set. Data will be used from the city of San Jose outlined below.

Data Set

The main source of data will be from the City of San Jose http://data.sanjoseca.gov/home. Economic and labor data including unemployment, total jobs, jobs by sector, median home prices, median rental prices will all be utilized along with broader economic data such as average mortgage rates from FRED https://fred.stlouisfed.org/graph/?g=NUh#0. The data set is approximately 6 years of monthly data from 2009-2015 after merging and cleaning up any missing values. There are 6 csv files all under the "Data" file.

apt_rents.csv
home_prices.csv
jobs_by_sector.csv
mortgagerates.csv
total_jobs.csv
unemployment.csv

San Jose provides relatively clean uniform data however it can be a little outdated and incomplete. I would have like to include crime data but this was missing at the time of my analysis and a time frame for requesting the data was uncertain. Including this information may be useful in further analyizing median home price trends.

Data Wrangling

The main steps to cleaning up the data were simplifying the variable names, formatting strings, and converting objects. The city of San Jose has some consistency in their data sets but to combine all the data I had to do some clean up of individual csv files before combining it all into one data frame for analysis.

```r
# Load Data and Libraries

library(dplyr)
library(tidyr)
library(reshape2)
library(plyr)
jobs_by_sector  <- read.csv("Data/jobs_by_sector.csv")
home_prices     <- read.csv("Data/home_prices.csv")
total_jobs      <- read.csv("Data/total_jobs.csv")
unemployment    <- read.csv("Data/unemployment.csv")
apt_rents       <- read.csv("Data/apt_rents.csv")
mortgagerates   <- read.csv("Data/mortgagerates.csv")
jobs_by_sector  <- tbl_df(jobs_by_sector)
total_jobs      <- tbl_df(total_jobs)
unemployment    <- tbl_df(unemployment)
apt_rents       <- tbl_df(apt_rents)
mortgagerates   <- tbl_df(mortgagerates)

# Bring column names (dates) into a unique column so table is in long format
jobs_by_sector <- melt(jobs_by_sector, variable.name = "Sector")

# Rename column to correct variable name
colnames(jobs_by_sector)[2] <- "Date"

# Move sector names into column names moving the table back to wide format
jobs_by_sector <- spread(jobs_by_sector, Sector, value)

# Rename column names to be short and concise
colnames(jobs_by_sector)[3] <- "Education"
colnames(jobs_by_sector)[4] <- "Finance"
colnames(jobs_by_sector)[6] <- "Hospitality"
colnames(jobs_by_sector)[8] <- "Mining"
colnames(jobs_by_sector)[9] <- "Other"
colnames(jobs_by_sector)[10] <- "Business"
colnames(jobs_by_sector)[11] <- "Public"
colnames(jobs_by_sector)[12] <- "Trade"

# Changing dates from string to date format. as.Date returns NA for "Sept"
# abbreviation so first we'll change that to "Sep"
jobs_by_sector$Date <- gsub("Sept", "Sep", jobs_by_sector$Date)
# Adding a day
jobs_by_sector$Date <- paste0("01.", jobs_by_sector$Date)
# Format date
jobs_by_sector$Date <- as.Date(jobs_by_sector$Date, format = "%d.%b.%Y", "%b/%d/%Y")

# Setup column names for gather function to put back into long format
jobs_by_sector <- jobs_by_sector %>%
  gather(Construction, Education, Finance, Information, Hospitality,
         Manufacturing, Mining, Other, Business, Public, Trade, Unclassified,
         key = "JobSector", value = "NumJobs")

# Setting up dates "Sept" replaced with "Sep"
home_prices$Date <- gsub("Sept", "Sep", home_prices$Date)

# Adding a day then format to date
home_prices$Date <- home_prices$Date %>%
    paste("01", sep = " ") %>%
    as.Date(format = "%b %Y %d", "%b/%d/%Y")

# Same steps for total_jobs df
total_jobs$Date <- gsub("Sept", "Sep", total_jobs$Date)
total_jobs$Date <- total_jobs$Date %>%
    paste("01", sep = " ") %>%
    as.Date(format = "%b %Y %d", "%b/%d/%Y")

# Again for unemployment df
unemployment$Date <- gsub("Sept", "Sep", unemployment$Date)
unemployment$Date <- unemployment$Date %>%
    paste("01", sep = " ") %>%
    as.Date(format = "%b %Y %d", "%b/%d/%Y")

# Slightly different strategy for apt_rents df. Dates are in integer format.
# First I added the day then converted to date format.
apt_rents$Date <- paste0("01/", apt_rents$Date)
apt_rents$Date <- apt_rents$Date %>%
    as.Date(format = "%d/%m/%Y", "%b/%d/%Y")

# Cleaninging up mortgage rates with more consies variable names then date format
colnames(mortgagerates)[1] <- "Date"
colnames(mortgagerates)[2] <- "Rates"
mortgagerates$Date <- mortgagerates$Date %>%
    as.Date(format = "%Y-%m-%d", "%b/%d/%Y")

# Combine all data frames by date nd arranging in desending order
clean_df <- join_all(list(jobs_by_sector,apt_rents,home_prices,total_jobs,
                          unemployment, mortgagerates), by="Date", type="left")
clean_df <- arrange(clean_df, desc(Date))

# Cleaning up some formating to convert data types to numeric by removing dollar
# signs and commas
clean_df$Condo.Townhome <- gsub("\\$|,", "", clean_df$Condo.Townhome)
clean_df$Single.Family.Home <- gsub("\\$|,", "", clean_df$Single.Family.Home)
clean_df$X2.bedroom <- gsub("*,", "", clean_df$X2.bedroom)
clean_df$X1.Bedroom <- gsub("*,", "", clean_df$X1.Bedroom)
clean_df$Average <- gsub("*,", "", clean_df$Average)

# Converting integers to numeric across variables
clean_df[3:9] <- lapply(clean_df[3:9], as.numeric)

# Converting job secotrs from characters to factors
clean_df$JobSector <- as.factor(clean_df$JobSector)
```

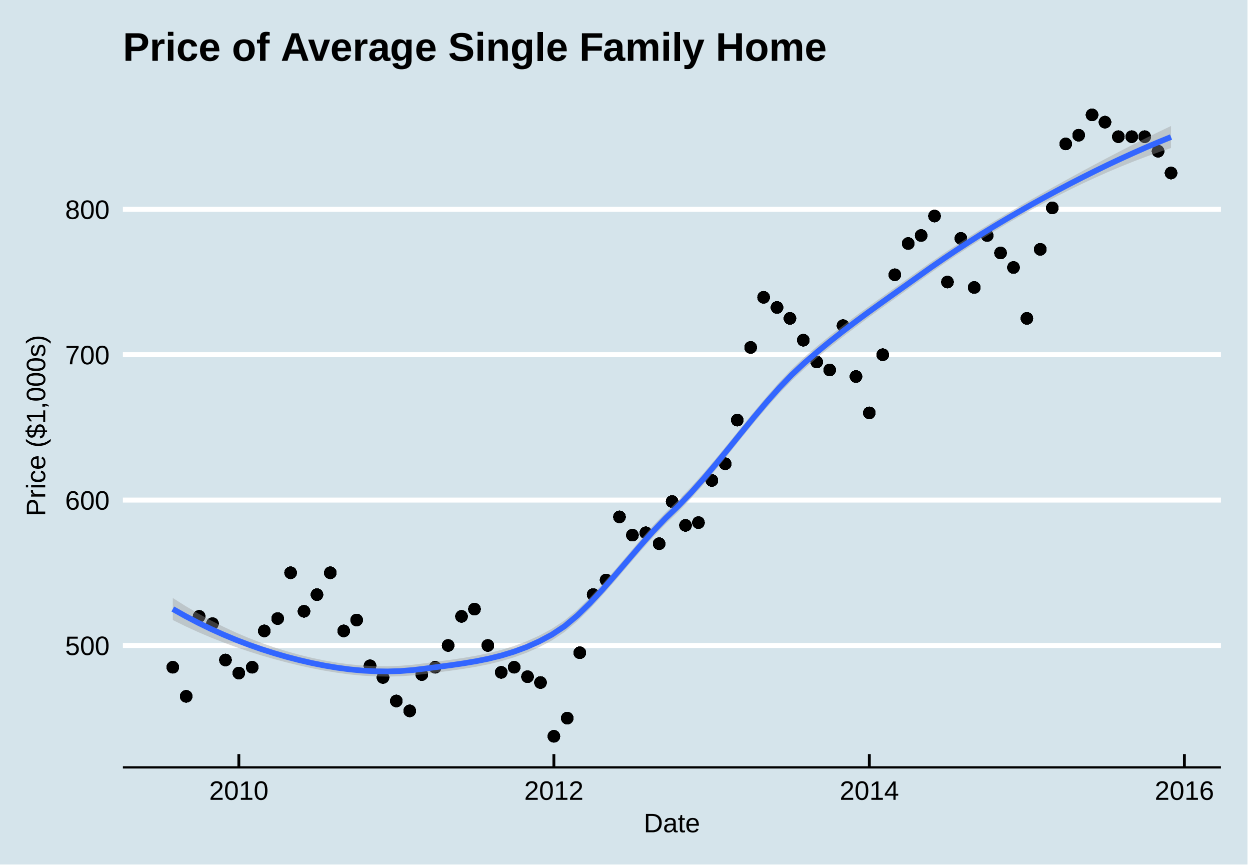
```r
# Renaming variables with more descrptive concise names
colnames(clean_df)[4] <- "AvgAptRent"
colnames(clean_df)[5] <- "Avg1bdAptRent"
colnames(clean_df)[6] <- "Avg2bdAptRent"
colnames(clean_df)[7] <- "AvgPriceHome"
colnames(clean_df)[8] <- "AvgPriceCondo"
colnames(clean_df)[9] <- "TotalJobs"
colnames(clean_df)[10] <- "URateSJ"
colnames(clean_df)[11] <- "URateSJMetro"

# Removing missing data
clean_df <- na.omit(clean_df)

# Adding a month variable for exploritory analyis
month_prices <- c('Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep',
                  'Oct', 'Nov', 'Dec')
clean_df$Month <- factor(format(clean_df$Date, "%b"), levels = month_prices)

# Create final new csv file
write.csv(clean_df, file = "Data/clean_df.csv")

# Summary of the final data frame
str(clean_df)
```

```
## 'data.frame':    924 obs. of  13 variables:
##  $ Date         : Date, format: "2015-12-01" "2015-12-01" ...
##  $ JobSector    : Factor w/ 12 levels "Business","Construction",..: 2 3 4 6 5 7 8 9 1 10 ...
##  $ NumJobs      : num  22886 82406 16574 11972 41518 ...
##  $ AvgAptRent   : num  2791 2791 2791 2791 2791 ...
##  $ Avg1bdAptRent: num  2469 2469 2469 2469 2469 ...
##  $ Avg2bdAptRent: num  3073 3073 3073 3073 3073 ...
##  $ AvgPriceHome : num  825000 825000 825000 825000 825000 825000 825000 825000 825000 825000 ...
##  $ AvgPriceCondo: num  465000 465000 465000 465000 465000 465000 465000 465000 465000 465000 ...
##  $ TotalJobs    : num  403194 403194 403194 403194 403194 ...
##  $ URateSJ      : num  4.2 4.2 4.2 4.2 4.2 4.2 4.2 4.2 4.2 4.2 ...
##  $ URateSJMetro : num  3.9 3.9 3.9 3.9 3.9 3.9 3.9 3.9 3.9 3.9 ...
##  $ Rates        : num  3.96 3.96 3.96 3.96 3.96 3.96 3.96 3.96 3.96 3.96 ...
##  $ Month        : Factor w/ 12 levels "Jan","Feb","Mar",..: 12 12 12 12 12 12 12 12 12 12 ...
##  - attr(*, "na.action")=Class 'omit'  Named int [1:228] 925 926 927 928 929 930 931 932 933 934 ...
##   .. ..- attr(*, "names")= chr [1:228] "925" "926" "927" "928" ...
```

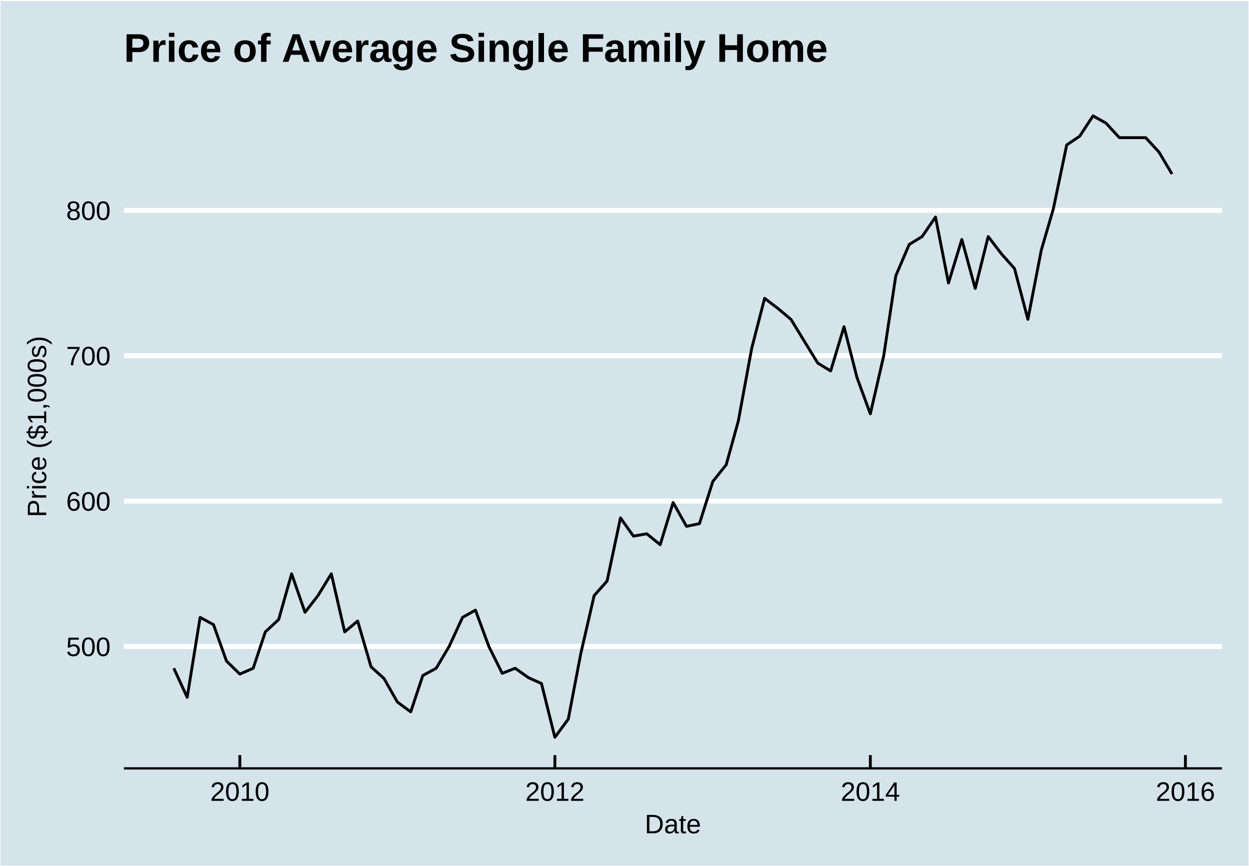
Exploratory Analysis

To start exploring the data set let's look at correlations between the variables. Rental prices, house prices, condo prices, jobs, and umeployment all are highly corrilated either positively or negatively as one would expect. The two variables that are the most interesting are rates and number of jobs. Rates refers to the average 30-year mortgage interest rate and number of jobs is tied to each job sector i.e. construction, business, finance. The positive or negative correlations are what you would expect but not as strong as some of the other variables.

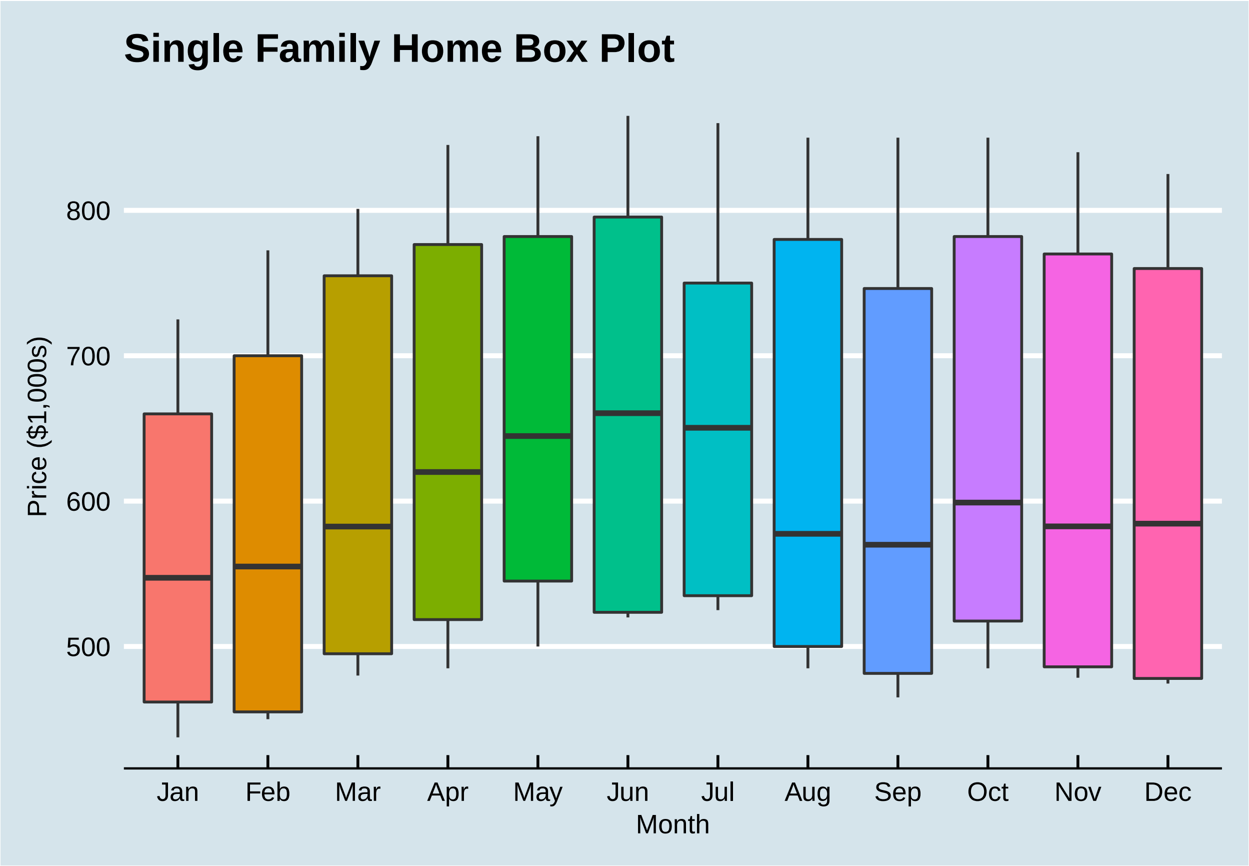
```
##                      NumJobs  AvgAptRent Avg1bdAptRent Avg2bdAptRent
## NumJobs        1.00000000  0.06235937    0.06197694    0.06256243
## AvgAptRent     0.06235937  1.00000000    0.99648134    0.99476460
## Avg1bdAptRent  0.06197694  0.99648134    1.00000000    0.99040318
## Avg2bdAptRent  0.06256243  0.99476460    0.99040318    1.00000000
## AvgPriceHome   0.06188430  0.92368942    0.90848338    0.92613877
## AvgPriceCondo  0.06126985  0.90730429    0.88731460    0.90631008
## TotalJobs      0.06526213  0.95552156    0.94966168    0.95863311
## URateSJ       -0.06362893 -0.96168471   -0.96505948   -0.95925571
## URateSJMetro  -0.06365025 -0.96249251   -0.96531654   -0.95975949
## Rates         -0.03349193 -0.56699496   -0.60168275   -0.53628273
##               AvgPriceHome AvgPriceCondo   TotalJobs     URateSJ
## NumJobs          0.0618843    0.06126985  0.06526213 -0.06362893
## AvgAptRent       0.9236894    0.90730429  0.95552156 -0.96168471
## Avg1bdAptRent    0.9084834    0.88731460  0.94966168 -0.96505948
## Avg2bdAptRent    0.9261388    0.90631008  0.95863311 -0.95925571
## AvgPriceHome     1.0000000    0.97569997  0.94824225 -0.92856164
## AvgPriceCondo    0.9757000    1.00000000  0.93882699 -0.90922165
## TotalJobs        0.9482422    0.93882699  1.00000000 -0.97497483
## URateSJ         -0.9285616   -0.90922165 -0.97497483  1.00000000
## URateSJMetro    -0.9315962   -0.91185750 -0.97530145  0.99977450
## Rates           -0.4376577   -0.41007855 -0.51319093  0.61154583
##               URateSJMetro       Rates
## NumJobs        -0.06365025 -0.03349193
## AvgAptRent     -0.96249251 -0.56699496
## Avg1bdAptRent  -0.96531654 -0.60168275
## Avg2bdAptRent  -0.95975949 -0.53628273
## AvgPriceHome   -0.93159617 -0.43765766
## AvgPriceCondo  -0.91185750 -0.41007855
## TotalJobs      -0.97530145 -0.51319093
## URateSJ         0.99977450  0.61154583
## URateSJMetro    1.00000000  0.61115102
## Rates           0.61115102  1.00000000
```



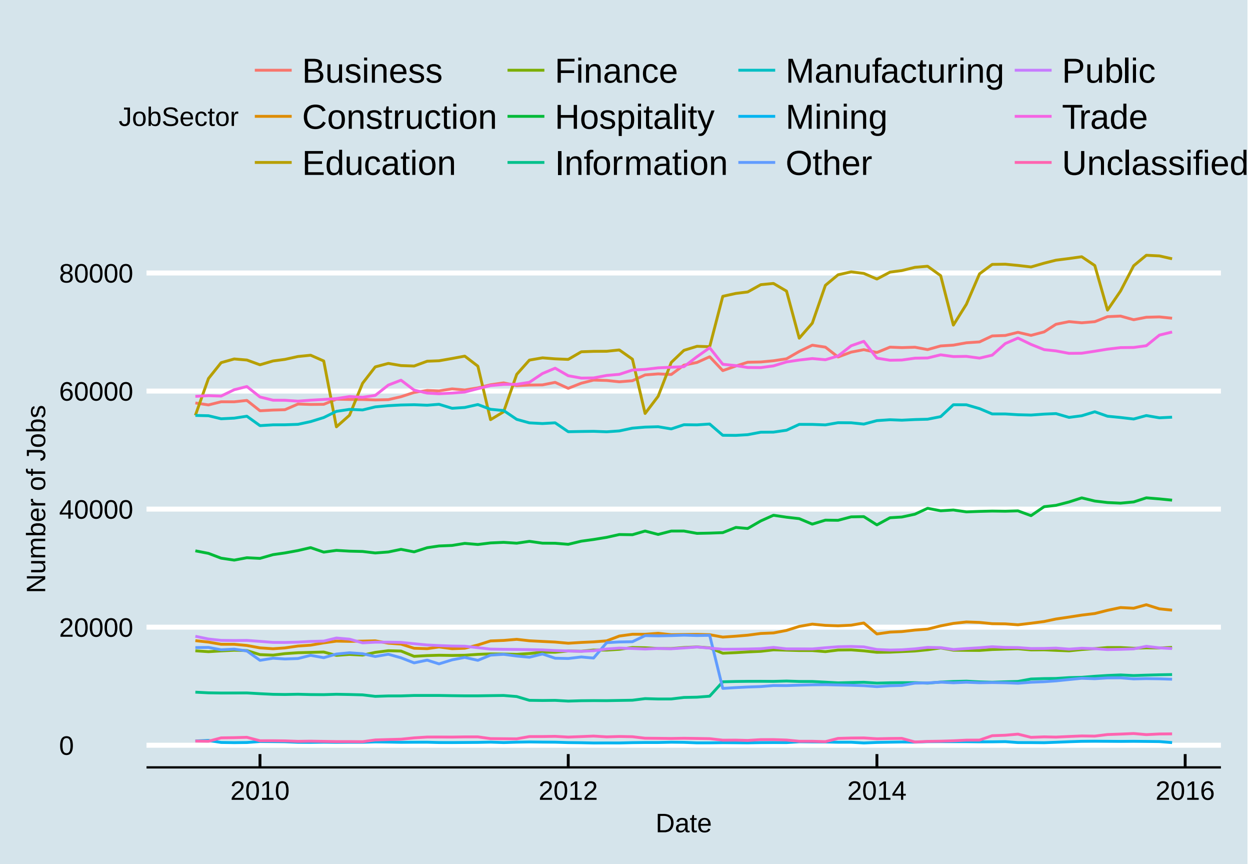
Next let's start visualizing some of the data with a few plots. First, let's look at a time series of home prices. The data starts after the bottom of the financial crises in 2009 and then there is a second drop in prices a few years after with a subsequent rebound in more recent years to pre-recession levels. There seems to be some short term trends or seasonality in housing prices that may be easier to visualize with other plots but overall the data set reflects a time of home price appreciation in San Jose.



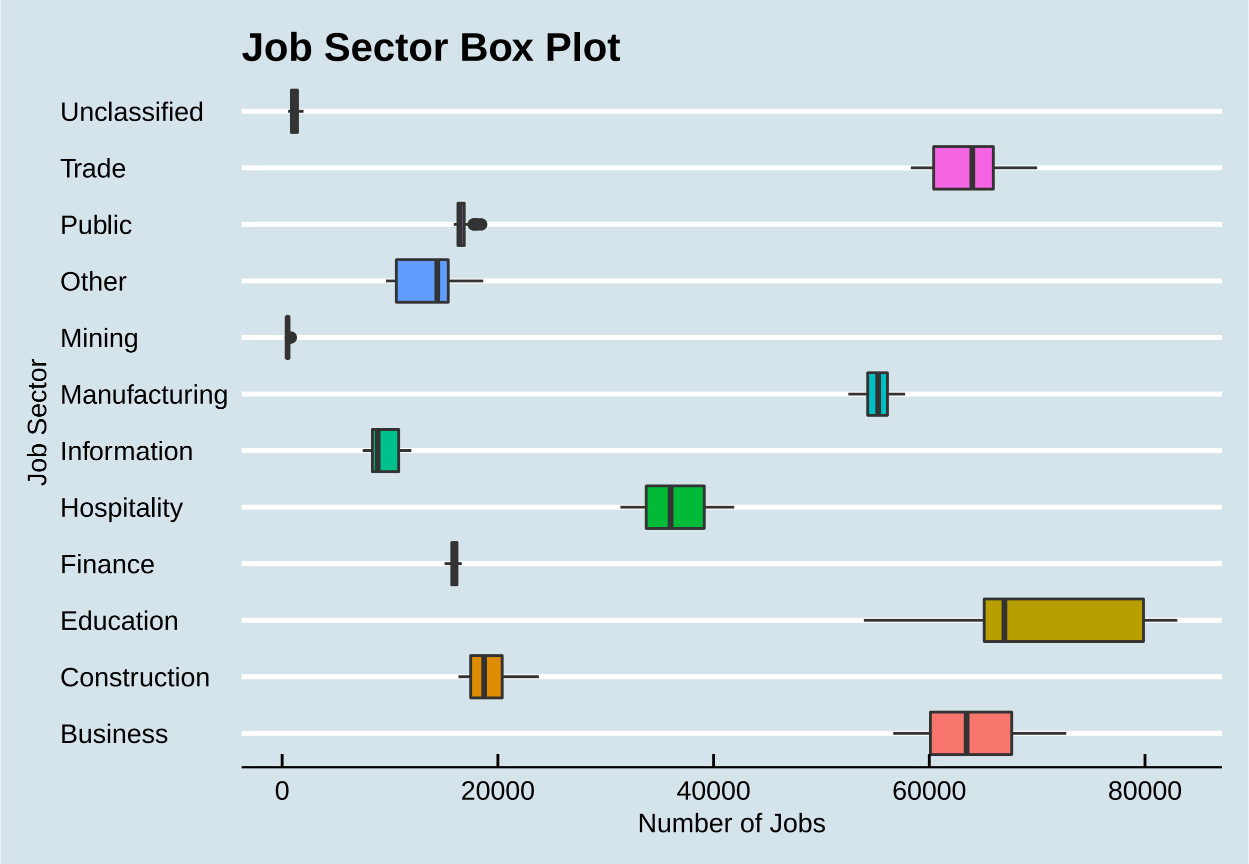
With a time series in a simple line graph its easier to see the up and down movement of home prices that perhaps reveals a seasonal trend. I would expect home prices to rise during the summer buying months when people are perhaps more inclined to go out and look for homes. During the winter months people tend to stay in more although winters are not that harsh in San Jose. A box plot would be useful to analyze this on a monthly basis.



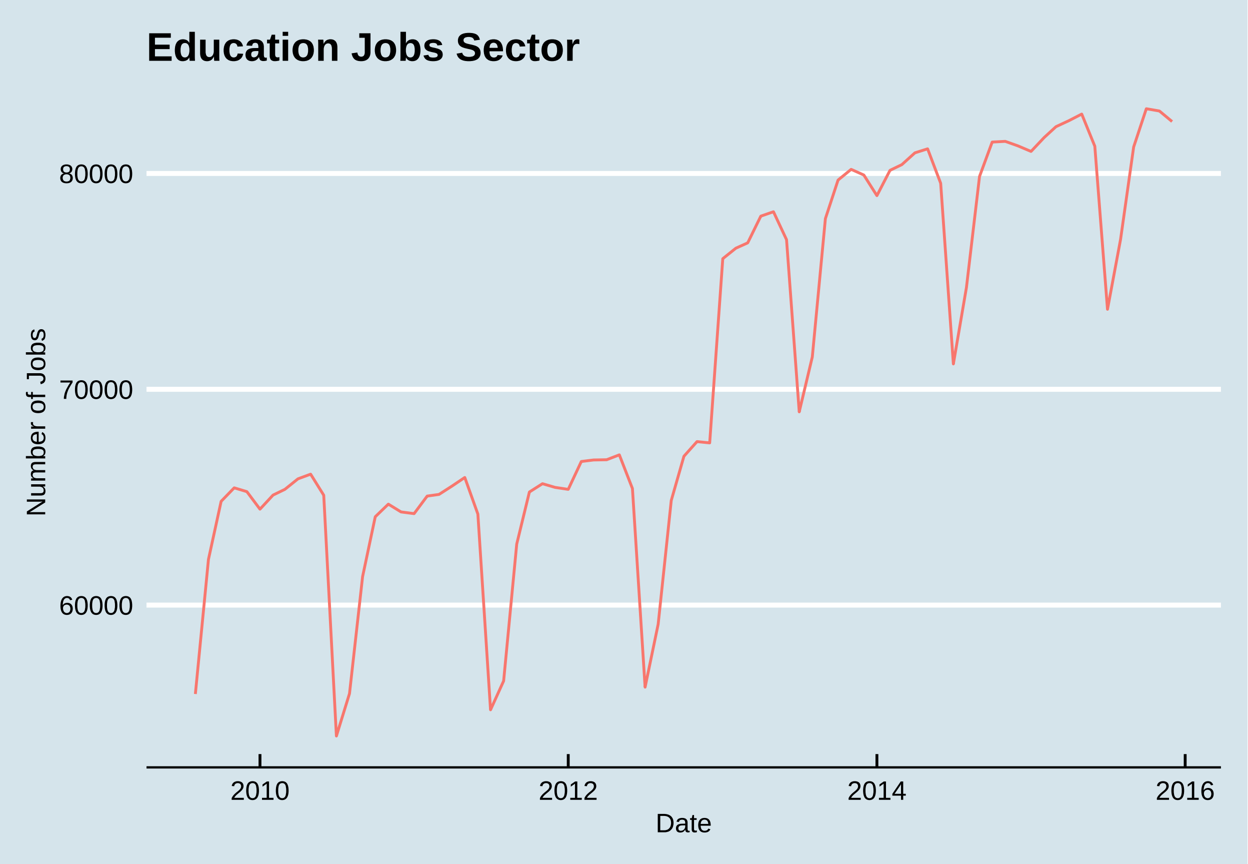
From the box plot above we can see home prices tend to be higher during the summer months of April, May, June, and July then start to come down as the winter months begin. From this data January and February seems to be the best time to buy if you're looking for a new home.



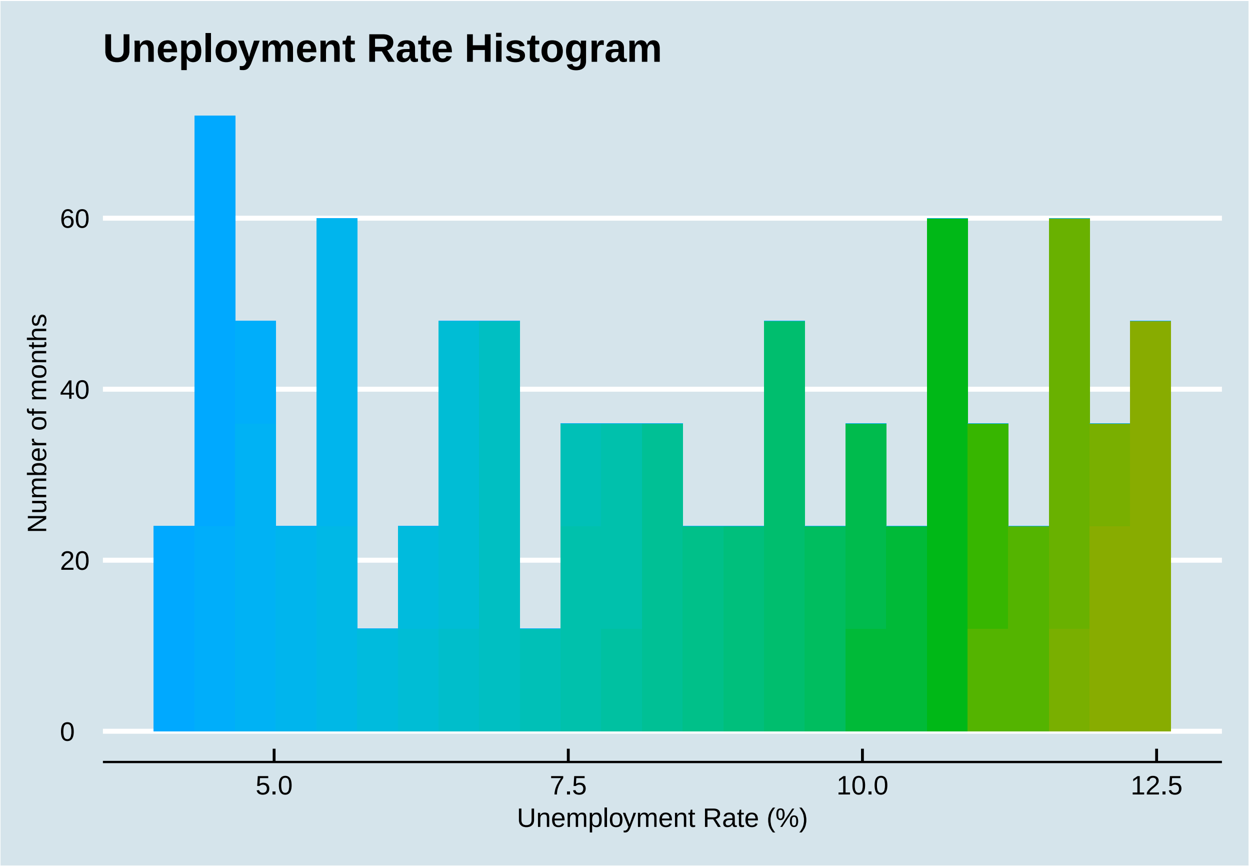
The second set of time series plots shows the total number of jobs by job sector. Education, Business, and Trade are the top sectors in terms of number of jobs. The education sector shows high yearly variation most likely due to teachers getting let go for the summer months when students aren't in school.



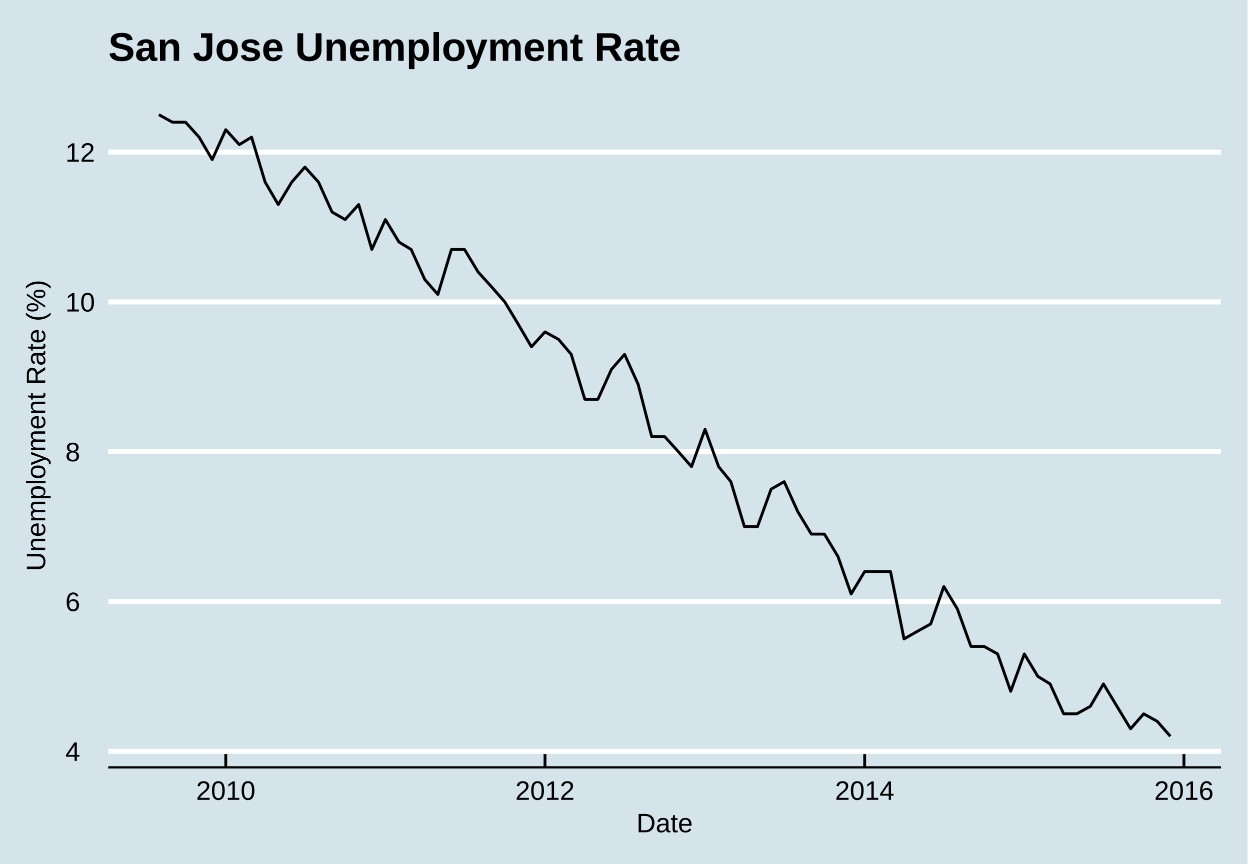
If we look at a box plot the top jobs sectors also have the most variabliility in the number of jobs. Manufacturing is the fourth place sector but shows a lot less variablity when compared to the other top sectors. It's importatnt to consider the data set is mostly in a time of strong economic growth so manufacturing may or may not be more variable through a full business cycle that includes both weak and strong economic growth.



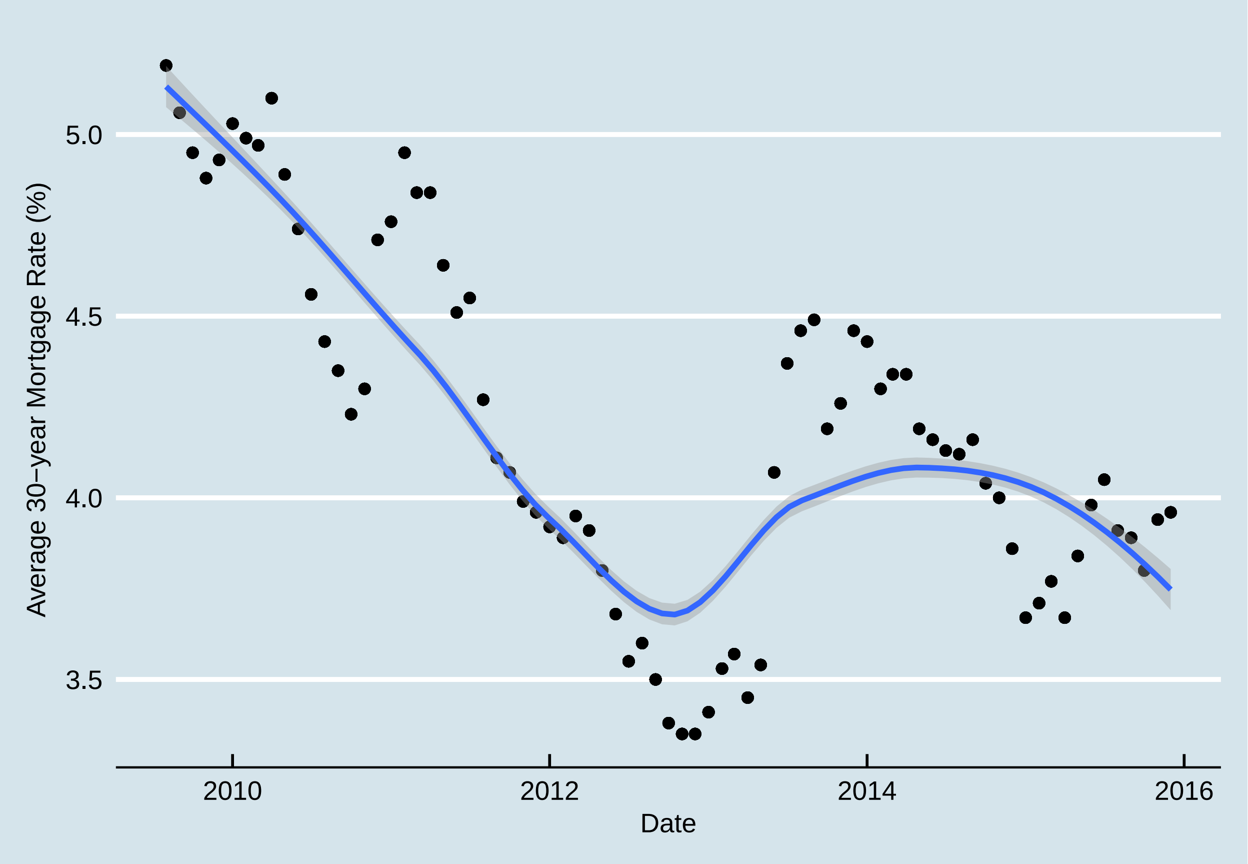
Lastly, I've pulled out the Education sector to show how the number of education jobs drops siginifcantly each year during the summer months as you might expect. It's also interesting how the variation seems to be in the same range from 2009 - 2012 then spikes to a new level in 2013. Perhaps more teachers were hired overall due to a budget increase or the methodogy changed for counting education jobs.



Taking a look at the unemployment rate in our data set I thought a histogram might be intersting to look at. When counting the number of observations for each unemployment rate in a historgram we can see the rate stood the most months at 5.4 and 5.5% and ranged from 4.6 to 12.6%.



The umeployment rate has trended downward over the range of our data set. This would indicate we are looking only at a time when economic conditions were improving and not a full market cycle that would reflect both improving and declining economic conditions.



Lastly, a final time series plotting average 30-year mortgage rates shows a historical fall in rates since 2008 that bottomed in late 2012 and have remained range bound between 3.5 and 4.5% since. This may have helped the rise in average home prices recently as lower rates create a more favorable lending environment for borrowers to purchase homes. Rates started to trend downward due to the financial crises and have remained historically low ever since.

Model Building

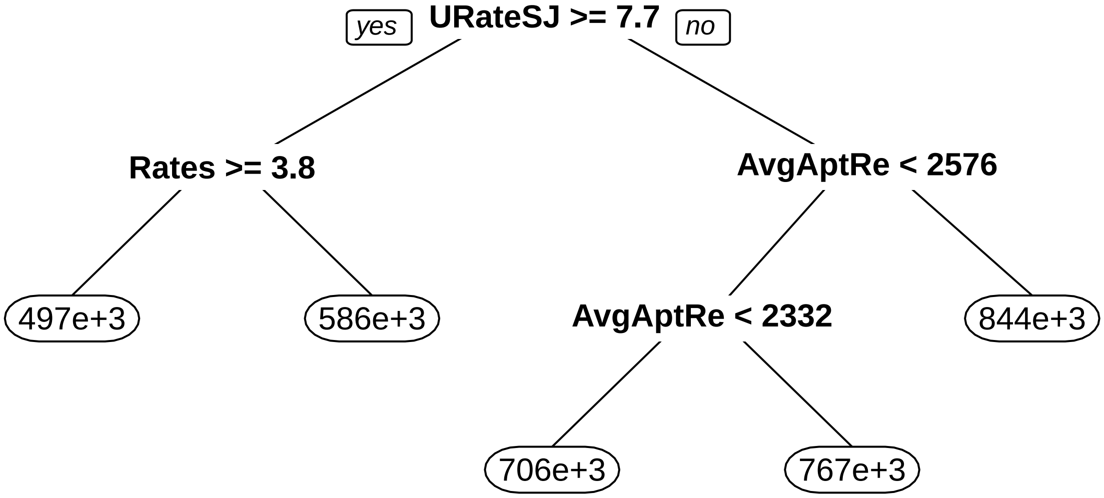
Now that we've taken some time to do some analysis I'm going to look at three different models and determine from test data which one does the best job at predicting average home prices. To compare each model I'll use root-mean-squre error (RMSE) results. RMSE measures the square root mean differences between the values our models predict and the actual values from the test data set. The model with the lowest RMSE corresponds to the model with the best predictive accuacy. To compare each model fairly we will use the test data set from the time-series model since we cannot use randomly selected test data for a time-series model.

Linear Regression

First, I started with a linear regression model. From analyzing our data set and looking at all the variables I chose average apartment rents, uemployment rate, and mortgage rates as the best variables for the model. All variables were highly significant with a high adjusted R-squared of 0.899. To test the model I created a random train and test data set from the original data set. I then made predictions using the test data set to calculate the RMSE using the predicted and real average home prices. For the linear regression model the RMSE was 42673.19. I will compare this result with the tree regression model next.

Tree Regression

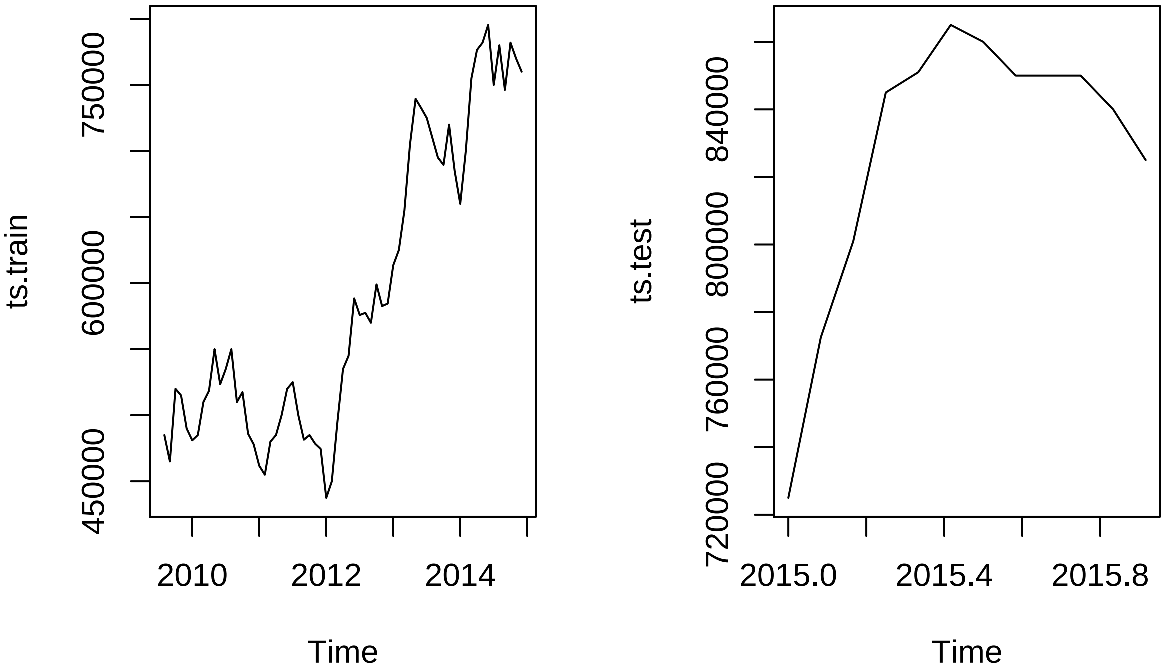
In the first step of the tree regression model I used the same variables as the linear regresssion model. This got an RMSE of 24843.1 which outperformed the linear regression model. To see if I could make imporvements on the tree model I then used cross validation using all the variables in the data set. This improved the RMSE dramatically over both the linear model and the first tree model to 3591.5. The complexity is much greater than the original tree model but the accuracy is signficantly higher, this is the best model so far. Finally, I will compare these results with the time series model.

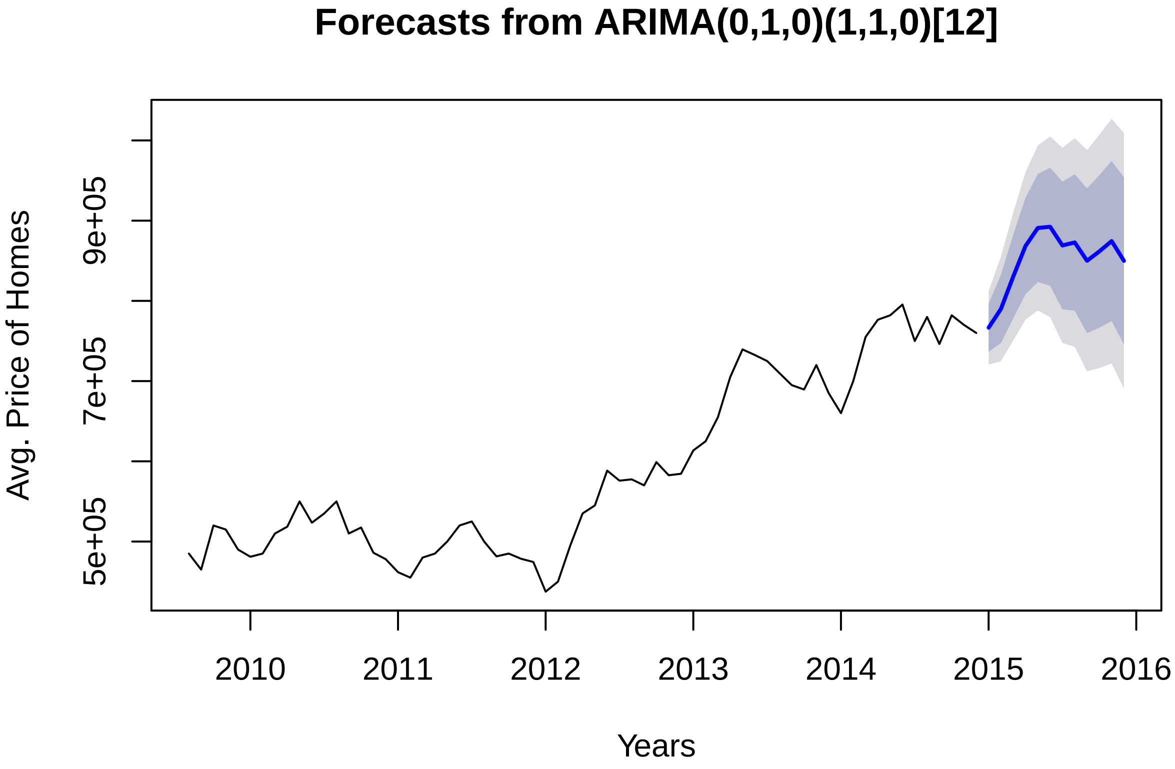


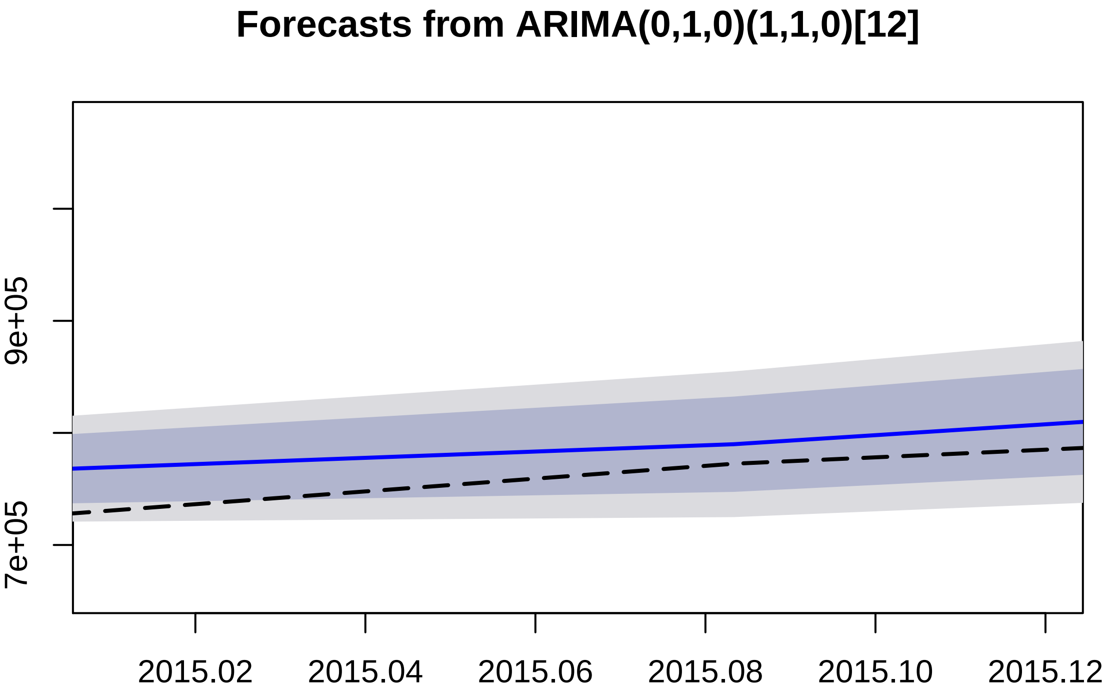
Time Series

For the time series model the train and test data sets cannot be random since we have to structure our time series in a logical order from past to present. The train data will be the oldest data and the most recent data will be used for the test data set. The time series anlysis will be an autoregressive integrated moving average (ARIMA) model. To build the best model we had to be sure to incorporate seasonal trends. As we saw in the explortory analysis average home prices in San Jose would rise in the summer and fall in the winter. This seasonal trend had to be taken into consideration when building the time series model and to try and improve the forecasting we assumed the model to be multiplicative. To make it additive we took the log of the time series data sets and built our model from that. This gave us an RMSE of 0.02252769. To compare this result to the linear and tree regression models I also had to compare the predictions of those models to the log of the time series data sets. The results were calculated manually with the results in the table below. The model with the higest accuarcy according to RMSE is the regression tree model followed by the the linear regression model and finally the time series model which is the least accurate.

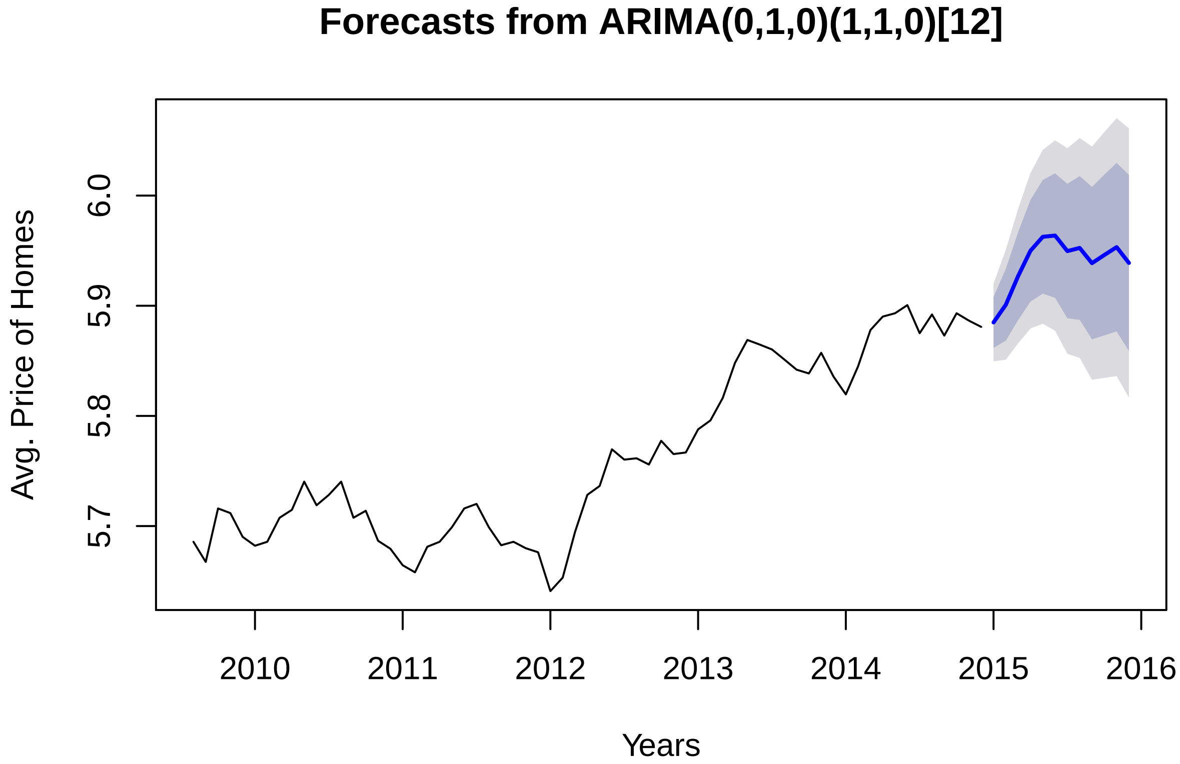
Model	Linear	Tree	Time Series
RMSE	0.012206	0.001140	0.022528

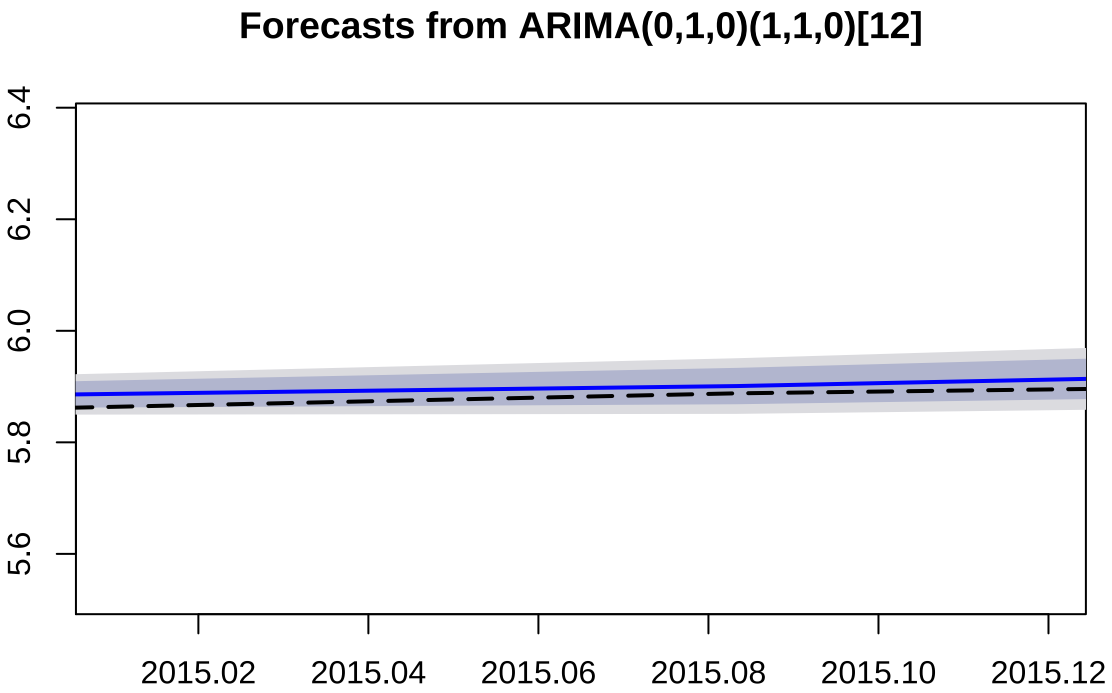

ts.train
450000
600000
750000
2010
2012
2014
Time
ts.test
720000
760000
800000
840000
2015.0
2015.4
2015.8
Time


Forecasts from ARIMA(0,1,0)(1,1,0)[12]
Avg. Price of Homes
5e+05
7e+05
9e+05
2010
2011
2012
2013
2014
2015
2016
Years

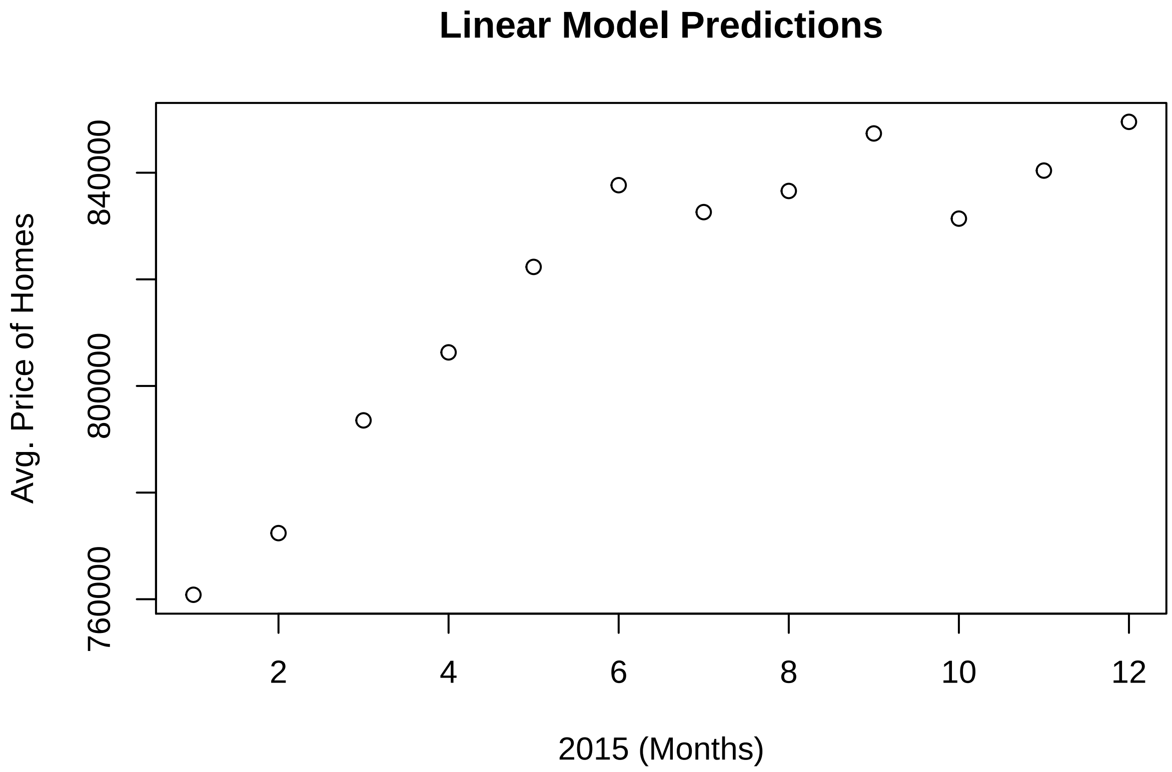


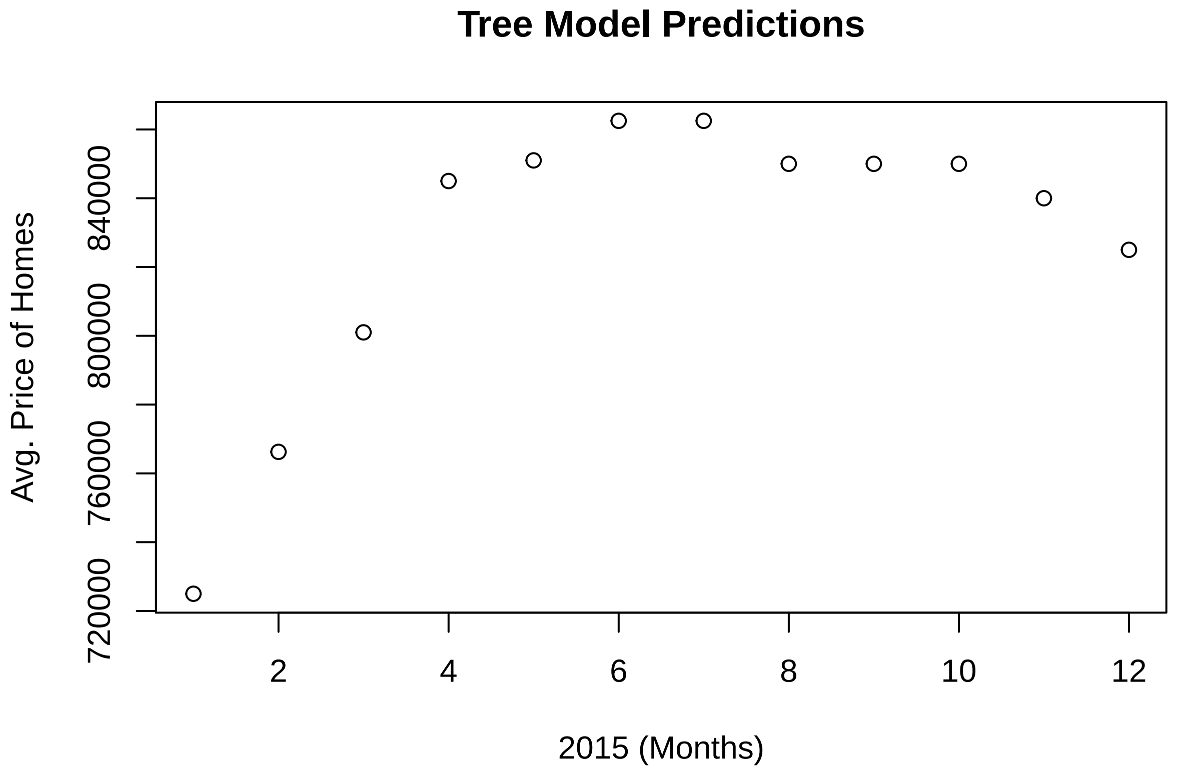
```
##                     ME  RMSE   MAE    MPE MAPE  MASE    ACF1 Theil's U
## Training set    793 20779 15403  0.103 2.57 0.219 -0.1687        NA
## Test set     -23502 26347 23502 -2.877 2.88 0.335  0.0291         1
```





```
##                    ME   RMSE    MAE       MPE  MAPE  MASE    ACF1
## Training set -2.09e-06 0.0159 0.0120 -8.42e-05 0.209 0.234 -0.0945
## Test set     -2.16e-02 0.0225 0.0216 -3.64e-01 0.364 0.419  0.0100
##              Theil's U
## Training set        NA
## Test set          1.77
```





Results and Discussion

After analyzing the data set and working through building our models to predict average home prices for San Jose there are a few takeaways for stakeholders. First, in the near term housing prices will continue to rise. For someone looking to buy a home it may be advantages to wait until prices fall if buying a home isn't a short term necessity. Secondly, when the time comes to purchase a new home it may be more beneficial to buy during the winter months when seasonal trends show prices to be the lowest. This could save buyers a substanical amount of money compared to purchasing a home during the summer months. Lastly, from a governement policy perspective, it seems as though current initiatives to create affordable housing for more people aren't having a significant impact on average home prices. However it is hard to say definitively since this data set is limited and more variables would need to be considered. Further analysis should be done by the city of San Jose to measure the impact of policy initiatives to verify they are working as intended. The subject of affordable home prices will continue to be of interest in cities with limited space and growing populations. San Jose is at the heart of Silicon Valley where innovation and wealth creation thrive making the area a popular place to live and affordable housing hard to come by.

Appendix

References

1. https://www.nar.realtor/sites/default/files/reports/2017/embargoes/2017-q1-metro-home-prices/metro-home-prices-q1-2017-single-family-2017-05-15.pdf
2. http://yesonaffordablehousing.org/
3. http://www.sanjoseca.gov/index.aspx?NID=5256