

# Predicting AirBnB Rental Prices

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# Motivation

- ▶ You are looking for some additional income and decide renting on AirBnB is the best option
- ▶ How much should you rent your extra space for?

# Data

- ▶ In general, AirBnB data is very open and be easily accessed
- ▶ The original dataset is from a past Kaggle competition
  - ▶ Contained over 74,000 individual listings between 2011-2018
- ▶ For sake of time and processing power, we took a random sample of 17,500 from those 74,000 listings
- ▶ They also provided a testing file
- ▶ Since the competition is over, we will compile our final predictions on that file using our best model

# Data

- ▶ Original data consists of 30 variables
- ▶ Variables are about the property, property location, the host and host reviews
- ▶ After cleaning and eliminating variables, our data consisted of 22 variables
- ▶ Property:
  - ▶ property\_type, room\_type, accommodates, bedrooms, beds, bed\_type, bathrooms
- ▶ Location:
  - ▶ latitude, longitude, city
- ▶ Host:
  - ▶ cancellation\_policy, cleaning\_fee, host\_has\_profile\_pic, host\_identify\_verified, etc

# Baseline Regression

```
linear = lm(price ~ ., data = training)
```

```
## [1] "MSE of Testing Set: 0.165"
```

# Regression Splines/Generalized Additive Models

- ▶ 20 Fold Cross-Validation was performed for different degrees of freedom ranging usually between 3 and 6
- ▶ Cross-Validation MSE used to pick degrees of freedom for splines

# Splines

- ▶ Splines fit to variables Accommodates, review\_scores\_rating, bathrooms, and bedrooms
- ▶ Best performing spline based on Cross-Validation MSE was the spline on review\_scores\_rating with degrees of freedom = 4
- ▶ Use these splines with their optimal degrees of freedom in my general additive model

# GAM Model

- ▶ Performed the GAM on the training data set using all of the predictors plus splines on Accommodates, review\_scores\_rating, bathrooms, and bedrooms with their optimal degrees of freedom
- ▶ Not a great fitting model,  $R^2 = 0.6388$
- ▶ Decent MSE when fit on the test data set

```
## [1] "Test MSE of GAM: 0.1612"
```



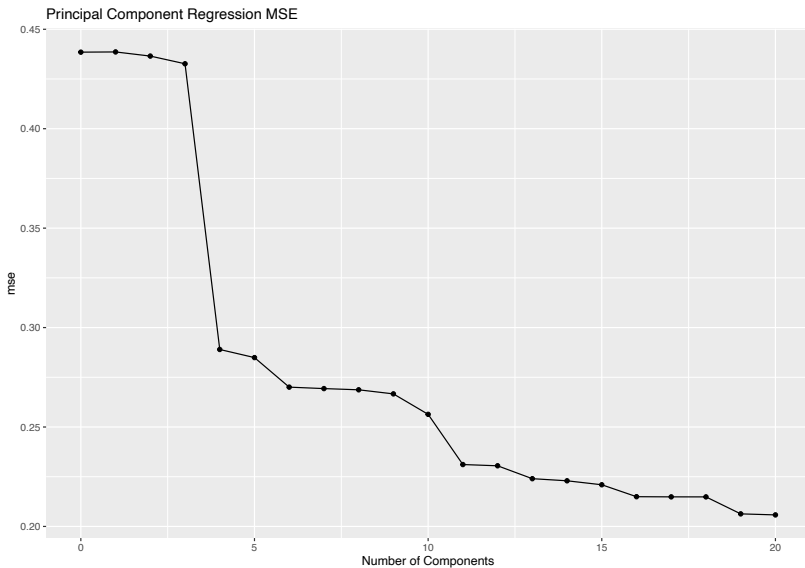
# Future Modeling with Splines

- ▶ Received errors when using degrees of freedom larger than 6 or so
- ▶ Want to look into these errors and figure out if I could try larger degrees of freedom in my splines to get a better model.

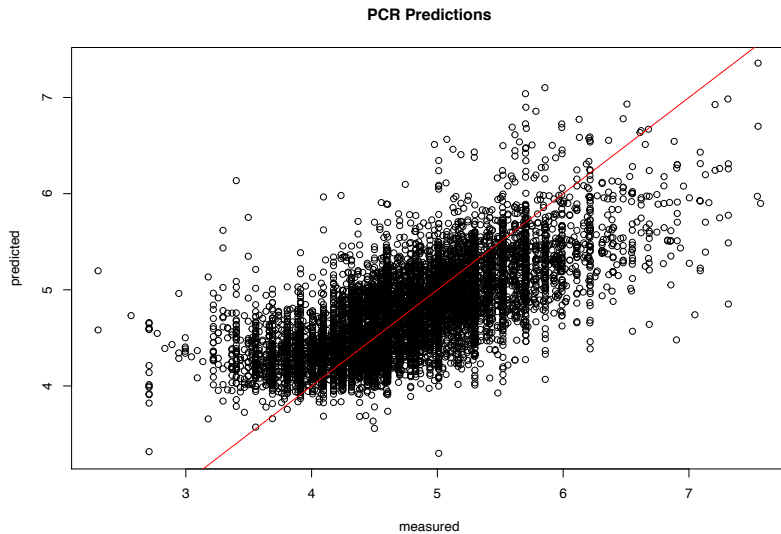
# PCR and PLS

- ▶ 10 Fold Cross-Validation was performed for number of components ranging from 1 to 20.
- ▶ The Cross-Validation MSE was used to pick optimal number of components for both models.

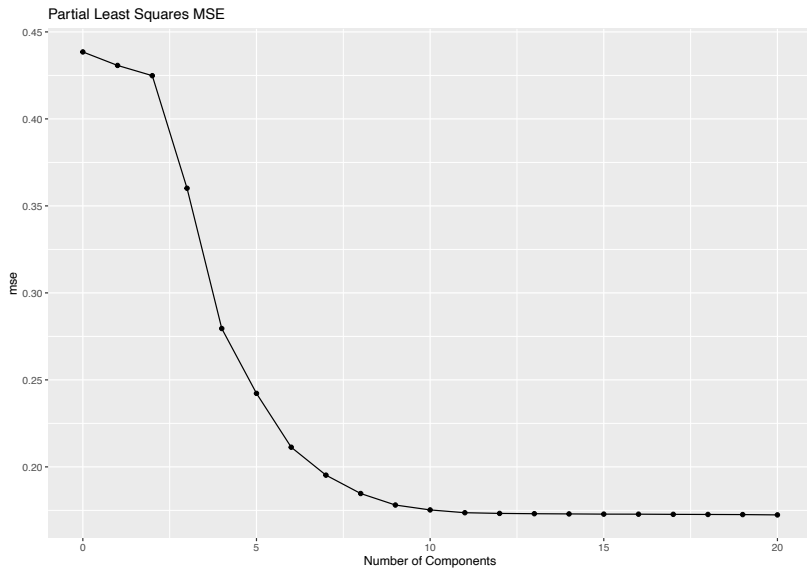
# PCR



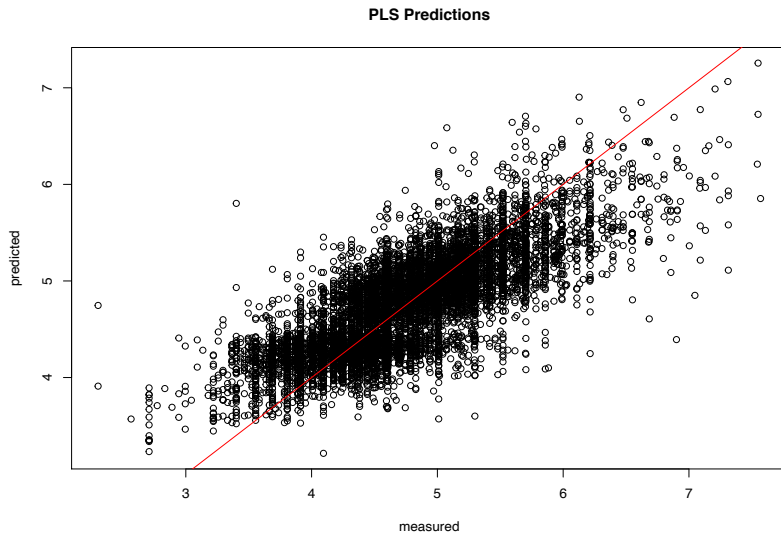
# PCR Predictions



# PLS



# PLS Predictions



## PCR and PLS Summary

| ##                      | PCR     | PLS     |
|-------------------------|---------|---------|
| ## Components           | 15.0000 | 10.0000 |
| ## Test MSE             | 0.1765  | 0.2192  |
| ## % Variance Explained | 99.7000 | 99.9000 |

# Regression Trees

```
##
```

```
## Regression tree:
```

```
## tree(formula = price ~ ., data = training)
```

```
## Variables actually used in tree construction:
```

```
## [1] "room_type" "longitude" "bathrooms" "city"
```

```
"beco
```

```
## Number of terminal nodes: 8
```

```
## Residual mean deviance: 0.1885 = 1695 / 8992
```

```
## Distribution of residuals:
```

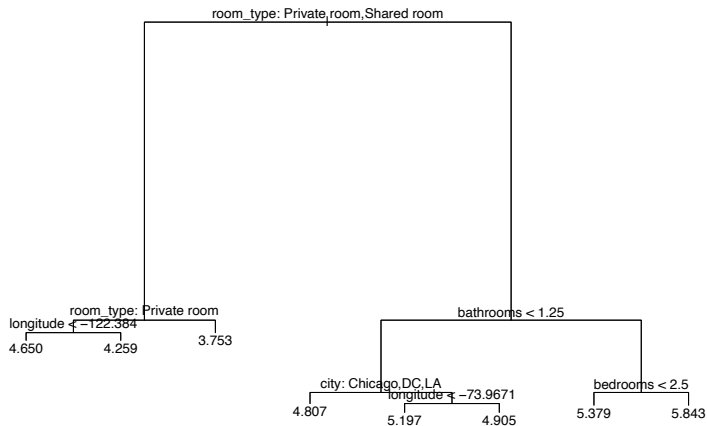
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```

```
## -2.5050 -0.2999 -0.0196  0.0000  0.2558  2.8310
```

```
## [1] "Test MSE of Initial Tree: 0.1926"
```



# Regression Trees

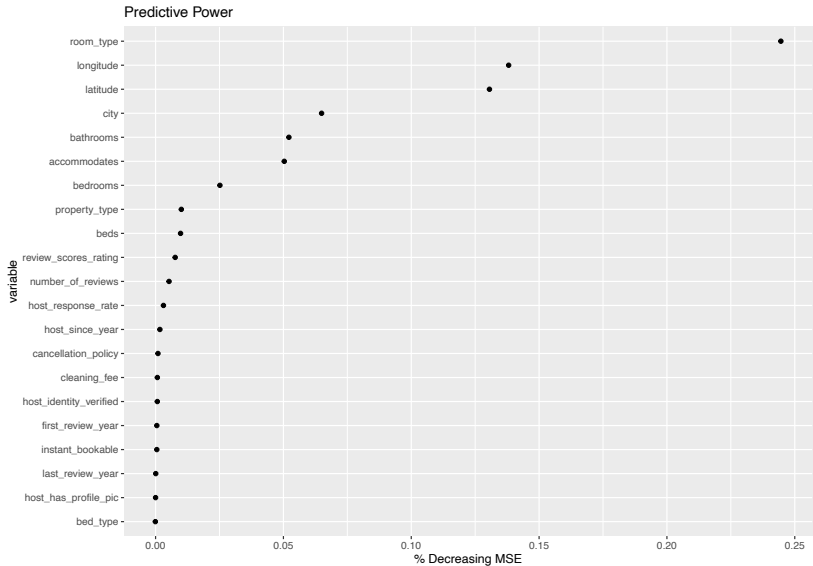


# Bagging

```
bag_fit <- randomForest(price ~ ., data = training, mtry =  
bag_predict = predict(bag_fit, testing, type = "response")  
bag_MSE = round(mean((testing$price - bag_predict)^2), 4)  
print(paste("Test MSE of Bagging: ", bag_MSE))
```

```
## [1] "Test MSE of Bagging: 0.1292"
```

# Bagging

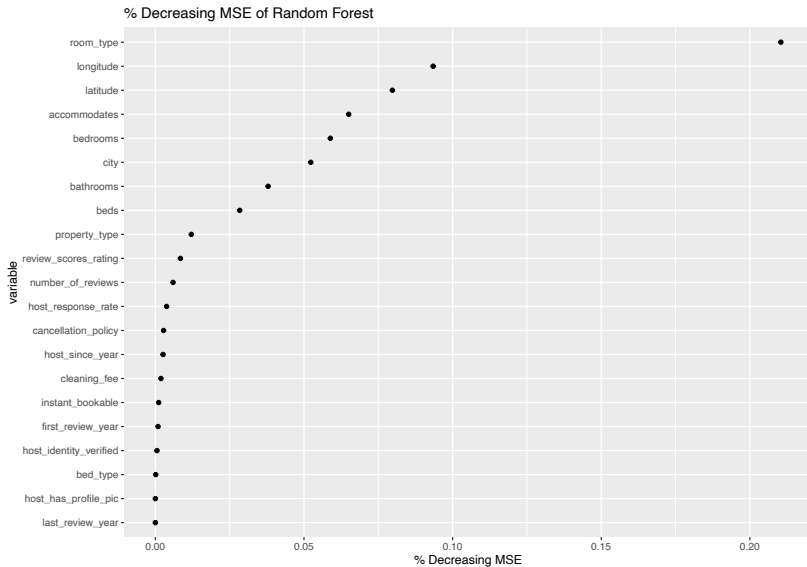


## Random Forests

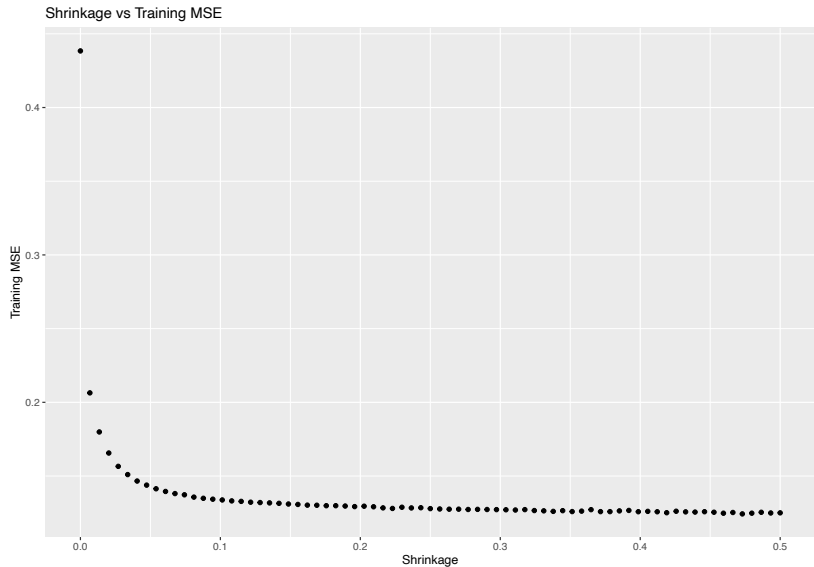
```
rf_fit <- randomForest(price ~ ., data = training, mtry = s
```

```
## [1] "Test MSE of Random Forest: 0.1299"
```

# Random Forests



# Boosting



## Boosting

```
## [1] "Testing MSE for Boosted Model: 0.131"
```

| ##                      |                      | var        | rel.in |
|-------------------------|----------------------|------------|--------|
| ## property_type        | property_type        | 21.8431150 |        |
| ## room_type            | room_type            | 20.4914154 |        |
| ## bedrooms             | bedrooms             | 13.5380988 |        |
| ## bathrooms            | bathrooms            | 9.7906620  |        |
| ## longitude            | longitude            | 8.0095709  |        |
| ## accommodates         | accommodates         | 7.9834933  |        |
| ## latitude             | latitude             | 7.3532396  |        |
| ## beds                 | beds                 | 4.1904587  |        |
| ## review_scores_rating | review_scores_rating | 2.2476044  |        |
| ## city                 | city                 | 2.1601492  |        |
| ## number_of_reviews    | number_of_reviews    | 0.5952030  |        |
| ## host_response_rate   | host_response_rate   | 0.5349262  |        |
| ## bed_type             | bed_type             | 0.3479078  |        |
| ## cancellation_policy  | cancellation_policy  | 0.3113388  |        |
| ## instant_bookable     | instant_bookable     | 0.1584258  |        |

## MSE Table

| ##   | Methods           | MSE    | MSE_Dollars |
|------|-------------------|--------|-------------|
| ## 1 | Linear Regression | 0.1652 | 1.18        |
| ## 2 | PCR               | 0.2192 | 1.25        |
| ## 3 | PLS               | 0.1765 | 1.19        |
| ## 4 | Splines           | 0.4423 | 1.56        |
| ## 5 | GAM               | 0.1612 | 1.17        |
| ## 6 | Trees             | 0.1926 | 1.21        |
| ## 7 | Bagging           | 0.1292 | 1.14        |
| ## 8 | Random Forest     | 0.1299 | 1.14        |
| ## 9 | Boosting          | 0.1310 | 1.14        |



## Going Forward

- ▶ Our data has listings from multiple cities across the country
- ▶ Can we apply this to a certain city and see similar results?
- ▶ Is this accurate enough to help AirBnB hosts in selected cities?
  - ▶ Using current data, can this model help hosts correctly adjust their rates?

Questions?