



# Predicting Affordability of Houses in Ames, Iowa

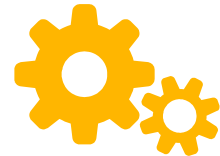
**STATS 101C - LEC 2: KAT**

**Albert Na, Kathy Fu, Tiffaney Pi**



# Overview

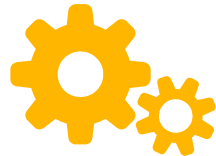
- ❖ Data Cleaning
  - Type Conversion
  - Handling NAs - Imputation, Zero, 'None'
  - Correlation
  - Creation + Deletion of Variables
- ❖ Methodology
- ❖ Results/Interpretation



# The data frame

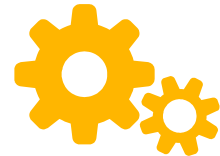
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- ❖ Clean training and testing datasets together in a new data frame  
alldata
  - `rbind()`
- ❖ Remove the 2 observations with an NA value in the affordability column



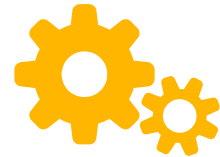
# Type Conversion

- ❖ Use `mutate_if` to save any variables with character types into factors if they weren't already
- ❖ Convert categorical variables with a numeric class type into factors based on their descriptions
  - `MSSubClass`, `OverallCond`, `OverallQual`,  
`BedroomAbvGr`, `KitchenAbvGr`, `TotRmsAbvGrd`  
`Fireplaces`, `GarageCars`, `MoSold`, `YrSold`



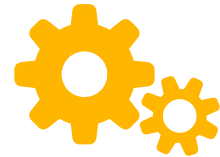
# NA values - Imputation

- ❖ **Median** → numerical variables (low variance)
  - LotFrontage
- ❖ **Mode** → categorical variables
  - MSZoning, Exterior1st/2nd, Electrical, KitchenQual, Functional, SaleType,
- ❖ **Zero** → If the variable had an NA, reasonably assumed this meant the variable did not have the observation at all
  - MasVnrArea, BsmtFinSF1/2, BsmtUnfSF, TotalBsmtSF, BsmtFullBath, BsmtHalfBath, GarageArea, GarageCars
  - Ex: If NA value for MasVnrArea, assumed that there was no Masonry Veneer Type (level was 'None') to begin with.



# NA values → Flagging as “None”

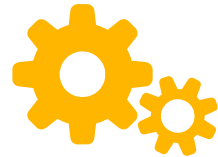
- ❖ If NA means ‘None’, **create factor level ‘None’**.
  - i.e.: PoolQC: NA means ‘No pool’
- ❖ Alley, MasVnrType, BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1/2, FireplaceQu, GarageType, GarageYrBlt, GarageFinish, GarageQual, GarageCond, PoolQC, Fence, MiscFeature



# Correlation

- ❖ Check for highly **correlated** variables ( $r > 0.8$  or  $r < -0.8$ )
  - Remove `TotRmsAbvGrd`, correlated with `GrLivArea`
  - Remove `GarageCars`, correlated with `GarageArea`
  - Remove `GarageYrBlt`, correlated with `YearBuilt`

\*Keep variables that are numerical



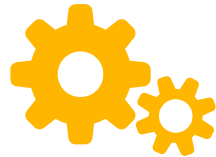
# Interpreting the Data:

## *Combining + Creating New Variables*

- ❖ Create a new variable **AgeofHouse**
  - `AgeofHouse = YearRemodAdd - YrBuilt`
- ❖ Create new variable **BsmtBath**
  - `BsmtBath = BsmtFullBath + .5*BsmtHalfBath`
- ❖ Create new variable **Bath**
  - `Bath = FullBath + .5*HalfBath`

\*Remove old variables and convert new variables into factor type





# Interpreting the Data:

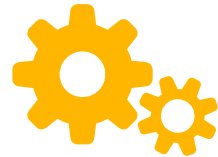
## *Deleting Repetitive Variables*

```
library(caret)
```

- ❖ Apply function `nearZeroVar()` on testing and training

- ❖ Removed all 24 variables:

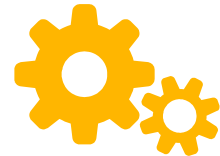
Street, Alley, LandContour, Utilities, LandSlope, Condition2, RoofMatl, MasVnrArea, BsmtCond, BsmtFinType2, BsmtFinSF2, Heating, LowQualFinSF, KitchenAbvGr, Functional, WoodDeckSF, OpenPorchSF, EnclosedPorch, ThreeSsnPorch, ScreenPorch, PoolArea, PoolQC, MiscFeature, MiscVal



# Interpreting the Data:

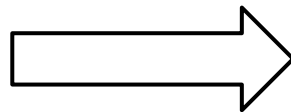
## *Deleting Other Variables*

- ❖ Remove numerical variables:
  - `Obs` - not actually a predictor
  - Use `geom_density()` on remaining numerical variables
    - Remove `LotFrontage` and `LotArea`
- ❖ Remove categorical variables:
  - `Neighborhood` - too many levels
  - Table these variables, remove ones with infrequent levels of around <1000 occurrences
    - Remove `BldgType`, `RoofStyle`, `CentralAir`, `Electrical`, `GarageQual`, `GarageCond`, `PavedDrive`, `Fence`



# Attempting different Methods

- 1) Logistic Regression
- 2) Lasso, Ridge Regression
- 3) SVM
- 4) Xgboost
- 5) Tree



**Random  
Forest**

# Random Forest

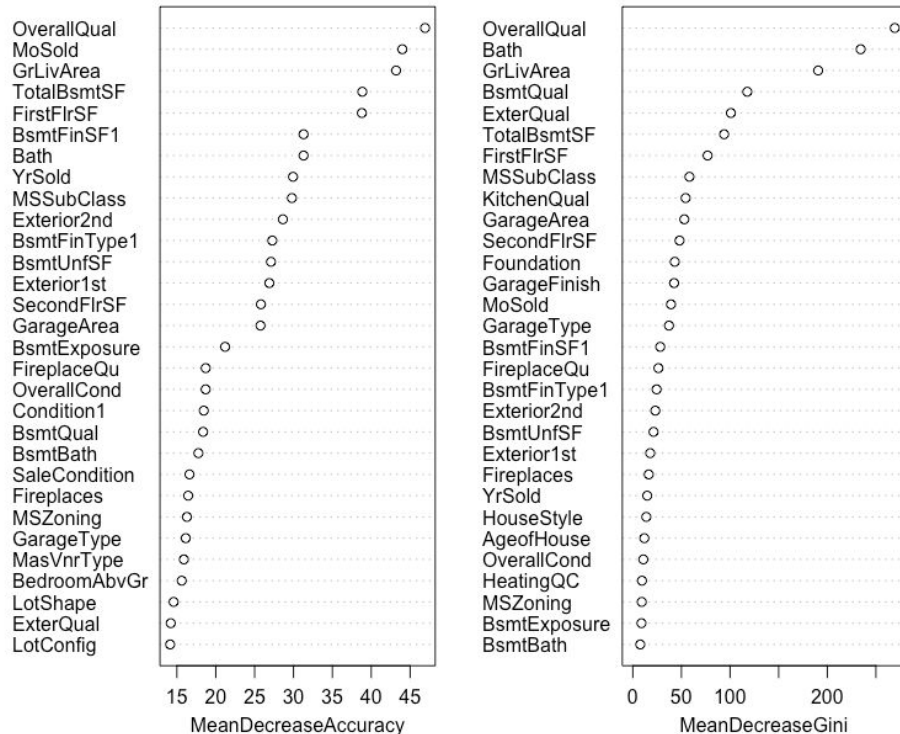


- ❖ Final dimensions of training data: **3498 x 39** (Originally 3500 x 81)
- ❖ mtry=9

Confusion Matrix

	Affordable	Unaffordable
Affordable	1701	38
Unaffordable	35	1724

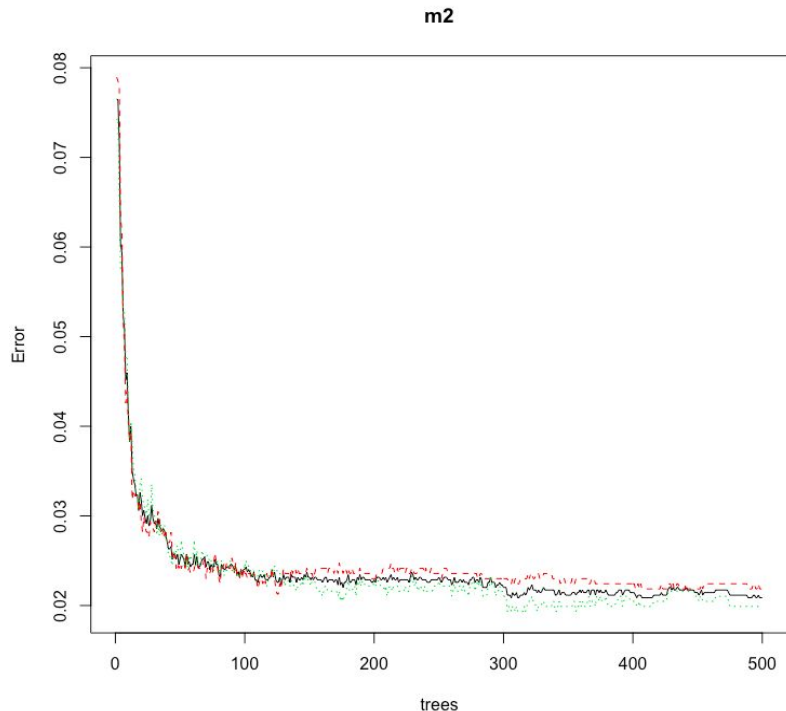
# Variable Importance



- ❖ Most significant predictors at the top.
- ❖ Model contained all predictors



# Classification error



- ❖ Sufficient number of trees ~ 100
- ❖ **OOB** = "Out of Bag" error ~ 2.09%
  - running unbiased estimate of the classification error as trees are added to the **forest**
- ❖ "Affordable" error rate: 2.185%
- ❖ "Unaffordable" error rate: 1.99%



**Final Accuracy: 98.89%**

**Private leaderboard: 97.90%**



# Limitations & Recommendations

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- ❖ Public leaderboard not representative of private leaderboard
- ❖ Overfitting
- ❖ Sample size
- ❖ With more time, perform deeper analysis on each variable and consider using outside data. Possibly combine infrequent levels together into "Other" category.





**Thank you!**

Figure 2:

Figure 3:

Figure 1:

Figure 4:

Figure 5:

Figure 6:

Figure 8:

Figure 7:

	Affordable	Unaffordable
Affordable	1705	34
Unaffordable	40	1719