Predicting Housing Prices in Ames Iowa through Machine Learning Techniques

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Purpose

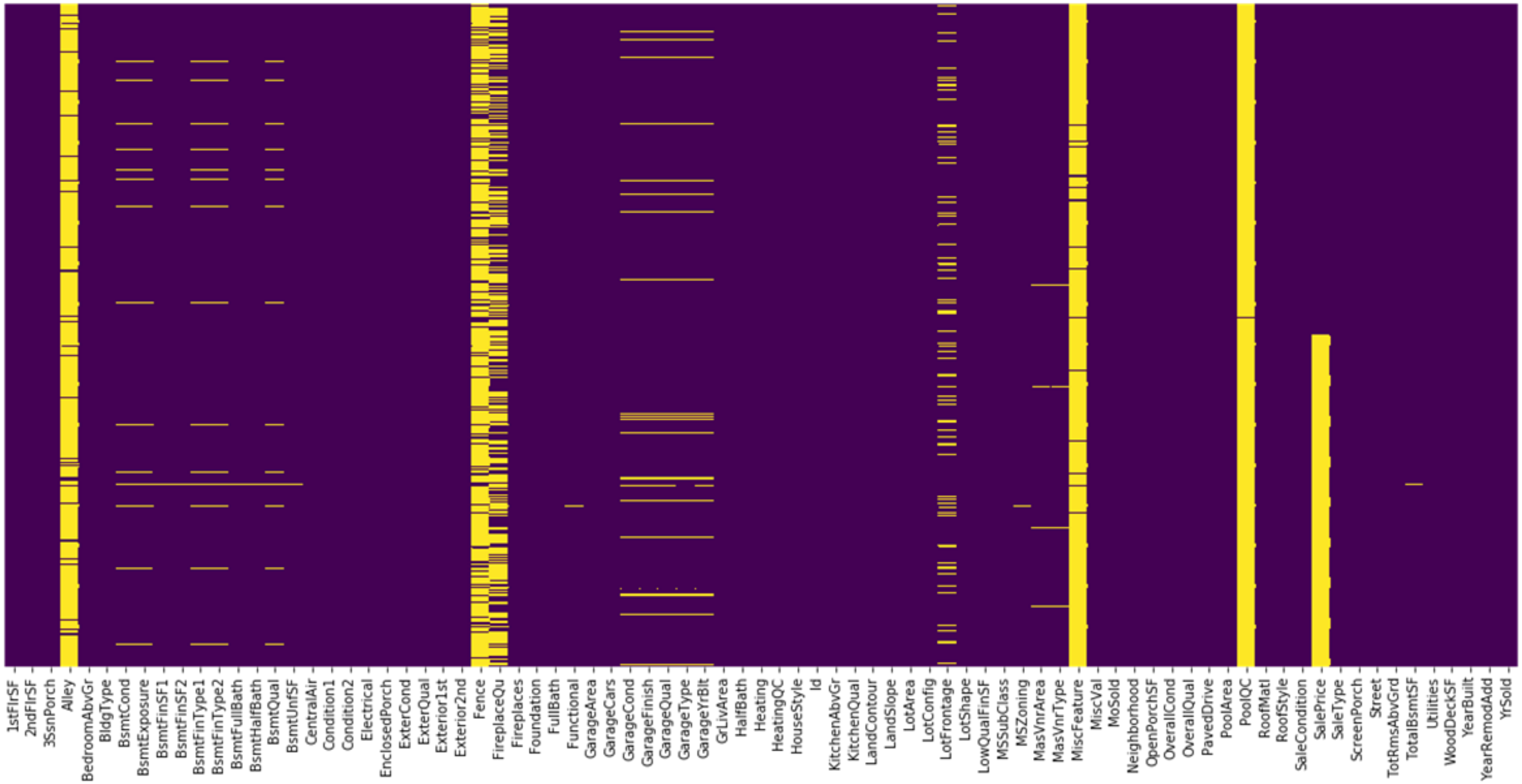
For Industry: Understand which housing aspects are valued by consumers, in order to accurately price assets, and evaluate undervalued/overvalued assets n the market.

For Consumers: Understand how much they might expect to pay for specific features/aspects of a new home.

Presentation Outline:

Visualizing Data
Missing Data
Feature Selection
Data Transformation
Linear Models
Tree Models
KNN

Missingness



Data cleaning

we drop few unwanted columns, which don't have any impact on sale price. Then we change the data type of the ‘MSSubClass’ features from numeric to string.

- Missing Values

- Flagging as 'No':
  BsmtFinType1, BsmtFinType2, GarageType, GarageFinish
  Values are Missing, Because there is no Garage and Basement.

- Impute the Mode:
  Electrical,Exterior1st, GarageCars, MSZoning, KitchenQual, MasVnrType, SaleType

- Impute Zero:
  GarageQual, GarageCond, BsmtCond, BsmtExposure, BsmtQual, FireplaceQu

- Changing categorical ranking into numerical scale values.

- Dummify remaining categorical features.

Features engineering

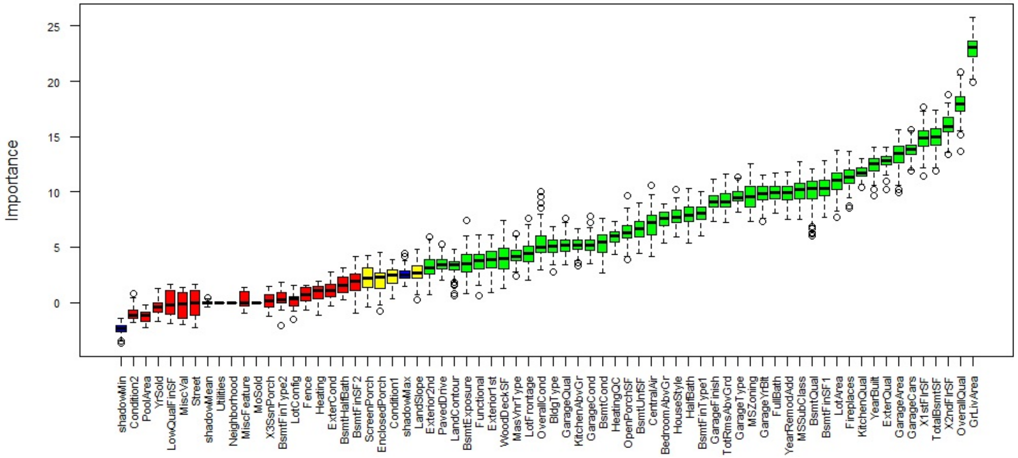
- Derived Features
- Feature:
  - TotalSF = TotalBsmtSF + GrLivArea + all other areas
  - TotalBaths = FullBath + BsmtFullBath + .5(HalfBath + BsmtHalfBath)
  - YearBuilt_Age = 2018 - YearBuilt
- Dropping columns which are repeated:
  - TotalBsmtSF = sum of(BsmtFinSF1, BsmtFinSF2, BsmtUnfSF')
  - GrLivAre = sum of(1stFlrSF, 2ndFlrSF)
- Taking log of ‘SalePrice’

Understanding and visualizing data

- Missing values
- Boruta as starting point
  - Random Forest

```
> missingness
```

Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street
0.00	0.00	0.00	17.74	0.00	0.00
Alley	**LotShape**	**LandContour**	**Utilities**	**LotConfig**	**LandSlope**
93.77	0.00	0.00	0.00	0.00	0.00
Neighborhood	**Condition1**	**Condition2**	**BldgType**	**HouseStyle**	**OverallQual**
0.00	0.00	0.00	0.00	0.00	0.00
OverallCond	**YearBuilt**	**YearRemodAdd**	**RoofStyle**	**RoofMatl**	**Exterior1st**
0.00	0.00	0.00	0.00	0.00	0.00




```
> train.boruta.selected.features.stats
```

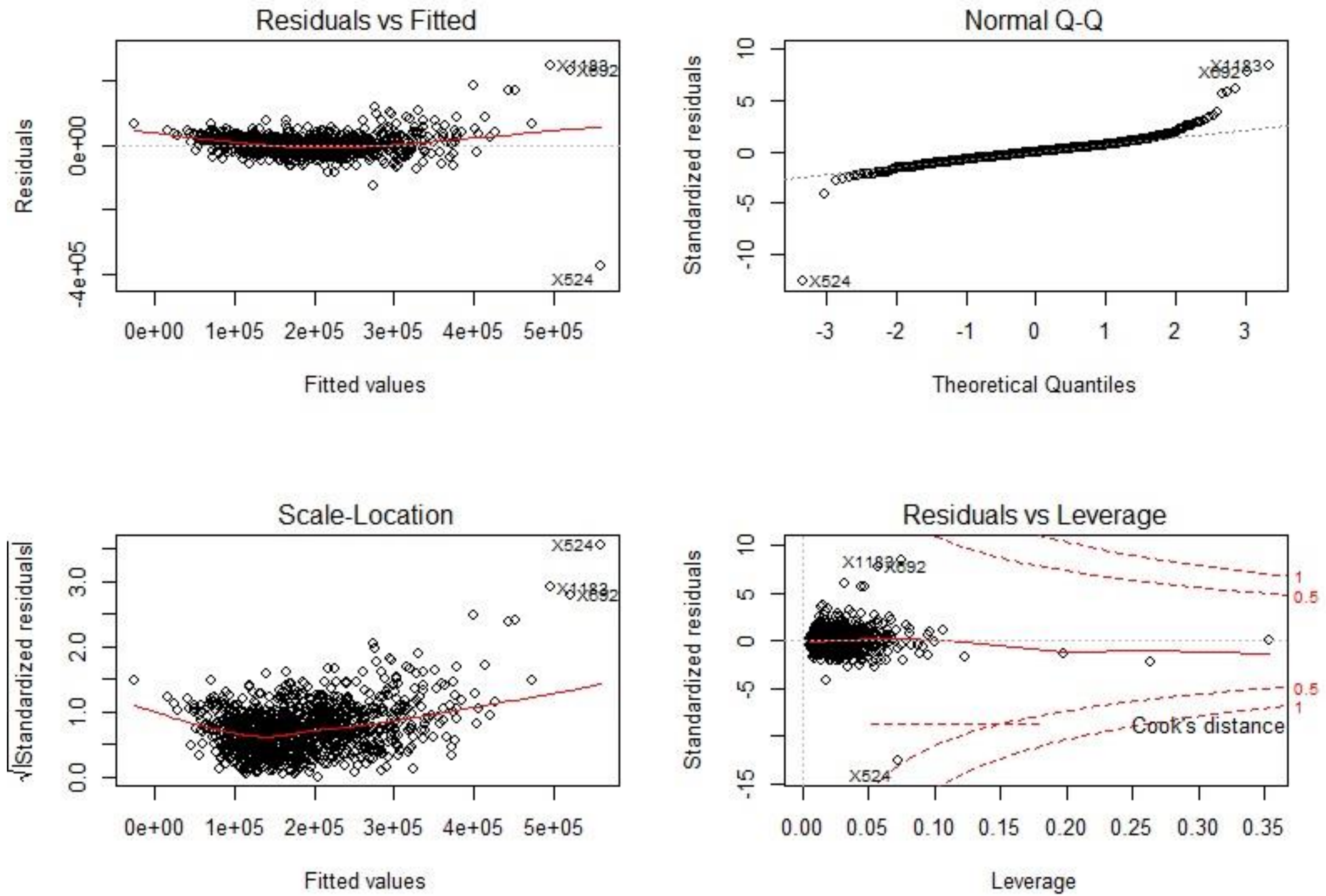
	meanImp	medianImp	minImp	maxImp	normHits	decision
MSSubClass	10.23146182	10.19289121	7.0381690	13.4160559	1.000000000	Confirmed
MSZoning	9.54442241	9.54223872	6.6190851	13.5386744	1.000000000	Confirmed
LotFrontage	4.84000063	4.81041786	1.0591037	8.2433175	0.945891784	Confirmed
LotArea	11.06137068	11.07546492	7.6883059	14.6355573	1.000000000	Confirmed
Street	0.32034836	0.60605652	-2.2139295	1.6233930	0.000000000	Rejected
LandContour	3.29294944	3.33744953	0.8217137	5.0138084	0.825651303	Confirmed
Utilities	0.00000000	0.00000000	0.0000000	0.0000000	0.000000000	Rejected
LotConfig	0.01045448	-0.34702343	-1.6685811	2.2380066	0.000000000	Rejected
LandSlope	2.78879262	2.78509174	-0.1224927	6.3589709	0.597194389	Confirmed
Neighborhood	0.00000000	0.00000000	0.0000000	0.0000000	0.000000000	Rejected
Condition1	2.31997212	2.37257459	-0.7026733	4.6660047	0.452905812	Rejected
Condition2	-1.05018471	-1.39913091	-2.5243537	0.5650928	0.000000000	Rejected
BldgType	5.14919430	5.13505760	2.5850106	7.1341928	0.993987976	Confirmed
HouseStyle	7.80085816	7.90203825	4.2218717	10.1629154	1.000000000	Confirmed
OverallQual	17.83794999	17.97926215	13.8490065	20.3389953	1.000000000	Confirmed
OverallCond	5.19890016	4.97132116	2.8419043	9.9911439	0.993987976	Confirmed
YearBuilt	12.45174947	12.49480428	9.2918448	14.1892539	1.000000000	Confirmed

Linear models

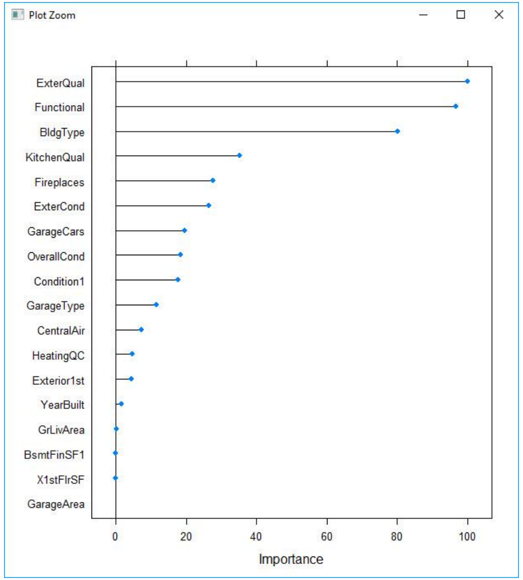
- Individual team models, best “crowdsourced” results selected
- Multivariable linear models
- Ridge
- Lasso
- Elastic

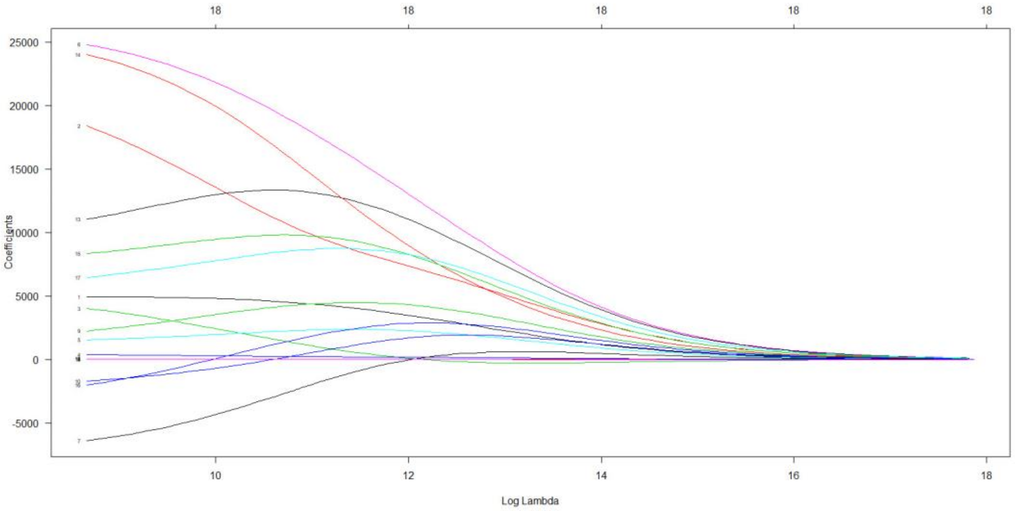
Plot different values for different attempts by different team members for different models

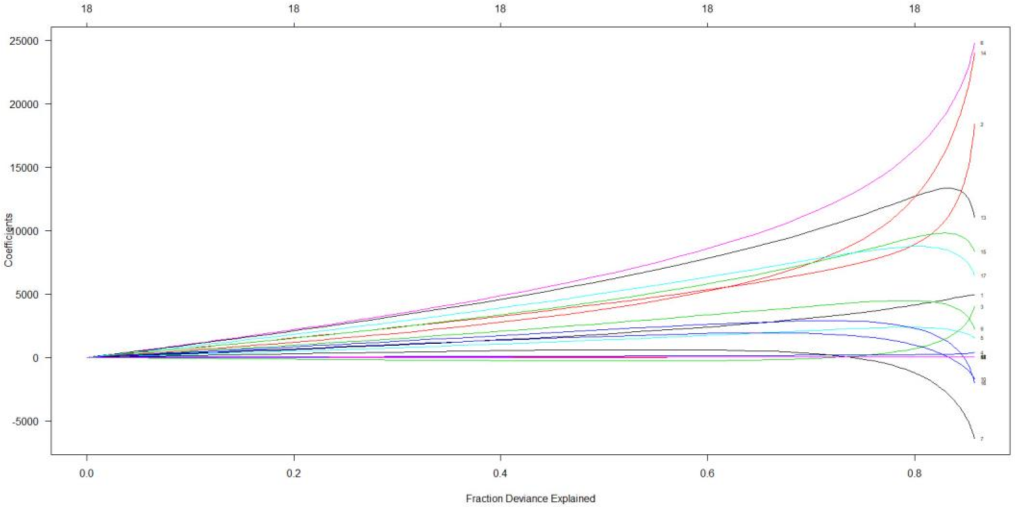
lm


Residuals vs Fitted
Residuals
Fitted values
X1183
X692
X524
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Scale-Location
√|Standardized residuals|
Residuals vs Leverage
Leverage
Cook's distance
0.5
1

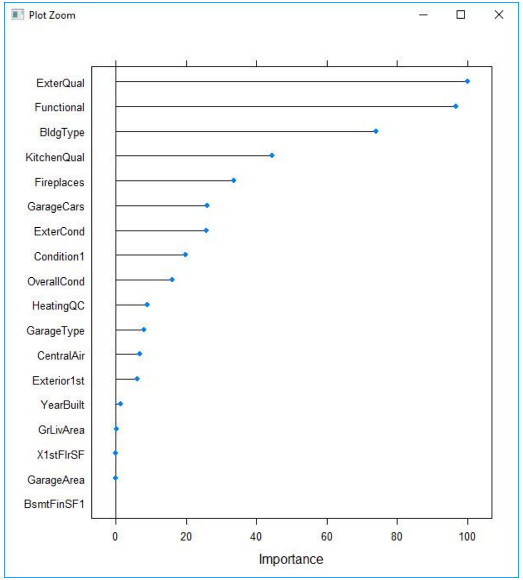
ridge


Plot Zoom
ExterQual
Functional
BldgType
KitchenQual
Fireplaces
ExterCond
GarageCars
OverallCond
Condition1
GarageType
CentralAir
HeatingQC
Exterior1st
YearBuilt
GrLivArea
BsmtFinSF1
X1stFlrSF
GarageArea
0
20
40
60
80
100
Importance


18
18
18
18
18
25000
20000
15000
10000
5000
0
-5000
Coefficients
10
12
14
16
18
Log Lambda


18
18
18
18
18
25000
20000
15000
10000
5000
0
-5000
Coefficients
0.0
0.2
0.4
0.6
0.8
Fraction Deviance Explained

lasso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Fireplaces
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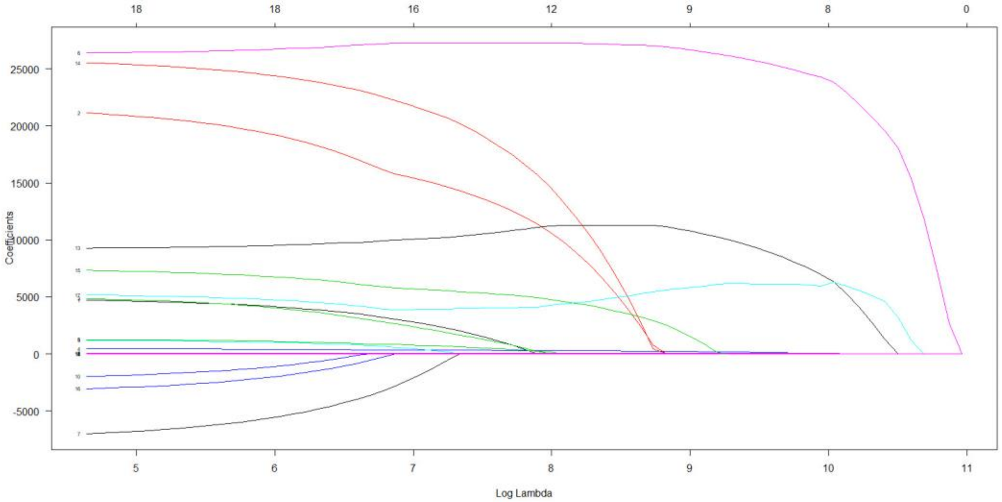
X1stFlrSF
GarageArea
BsmtFinSF1
0
20
40
60
80
100
Importance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Coefficients
25000
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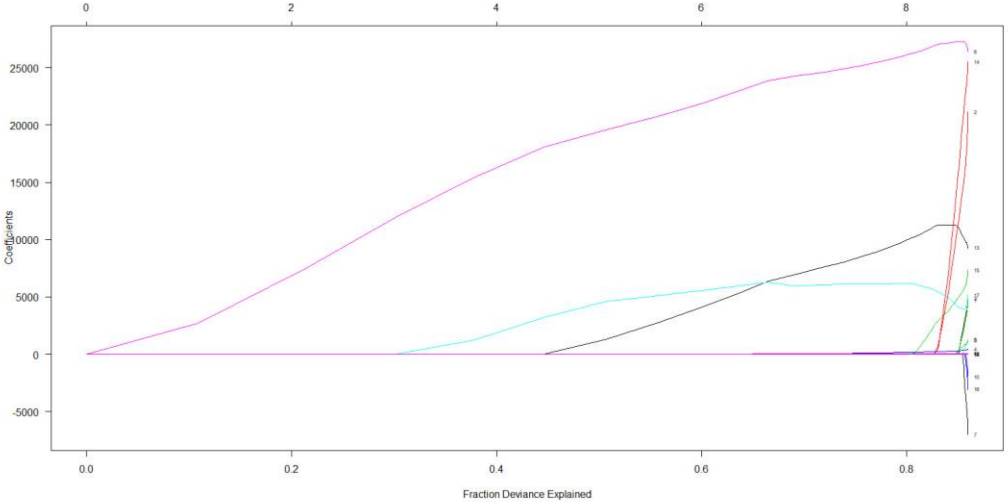
10
11
Log Lambda


0
2
4
6
8
Coefficients
25000
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15000
10000
5000
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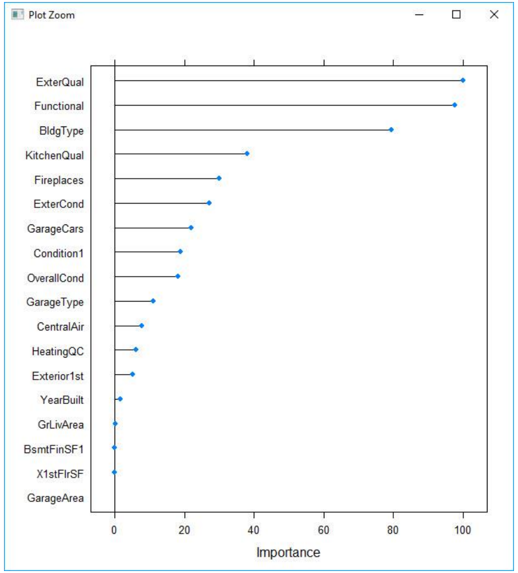
-5000
0.0
0.2
0.4
0.6
0.8
Fraction Deviance Explained

elastic net


Plot Zoom
ExterQual
Functional
BldgType
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GrLivArea
BsmtFinSF1
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GarageArea
0
20
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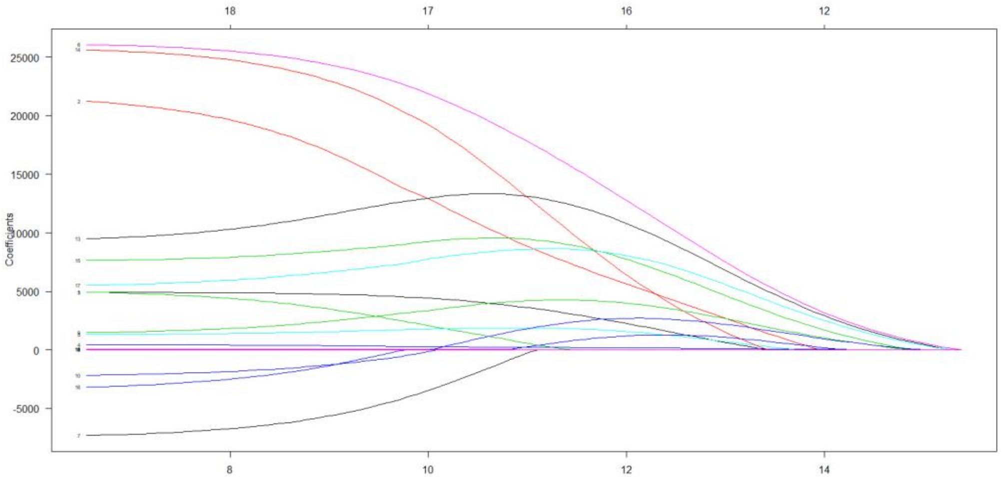
100
Importance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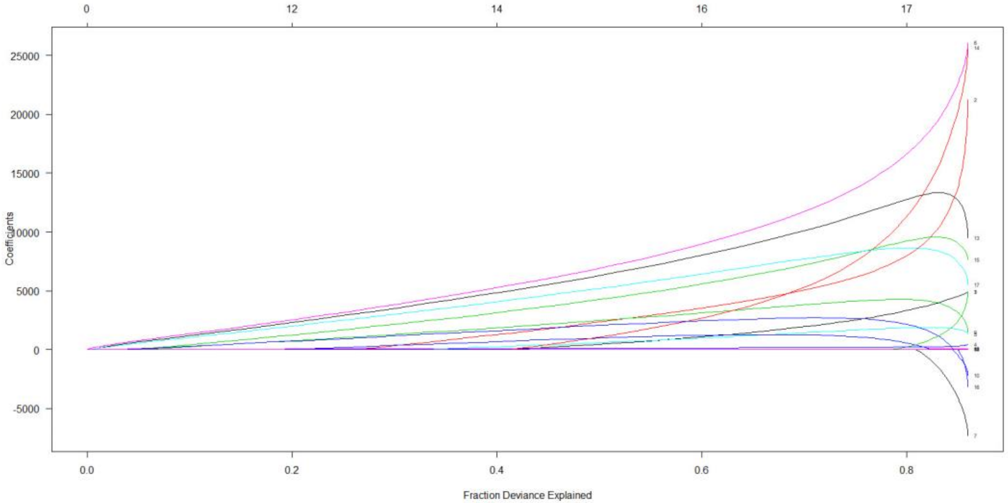
-5000
Coefficients
8
10
12
14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15000
10000
5000
0
-5000
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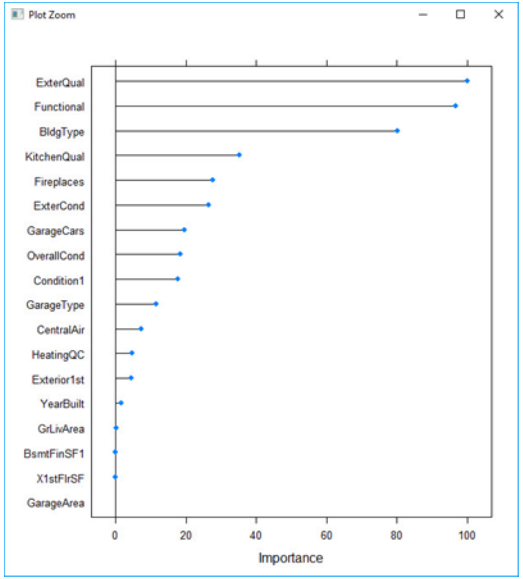
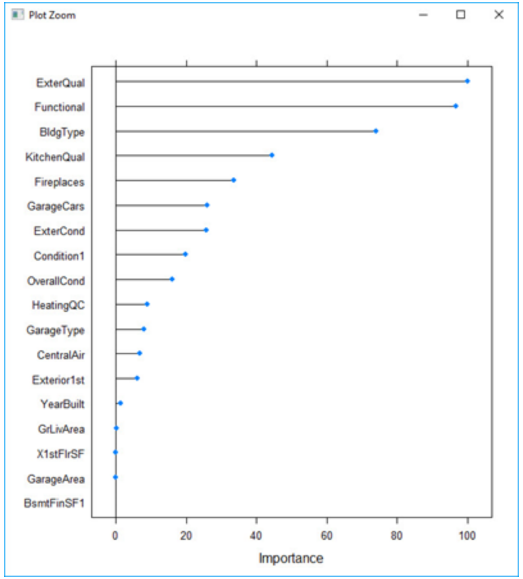
0.6
0.8
Fraction Deviance Explained

Comparing variables importance

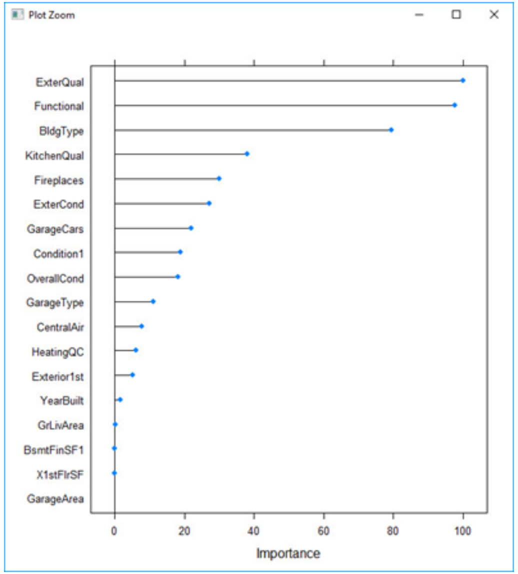
Ridge



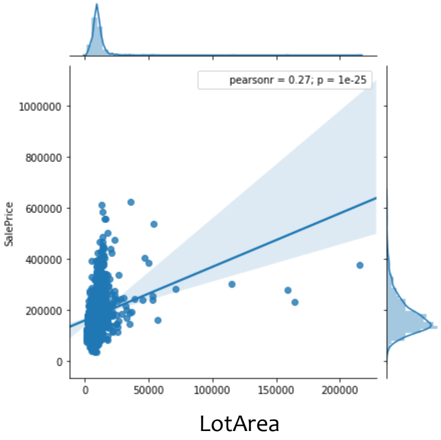
lasso

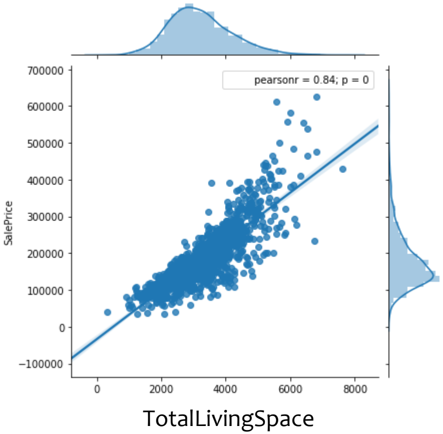


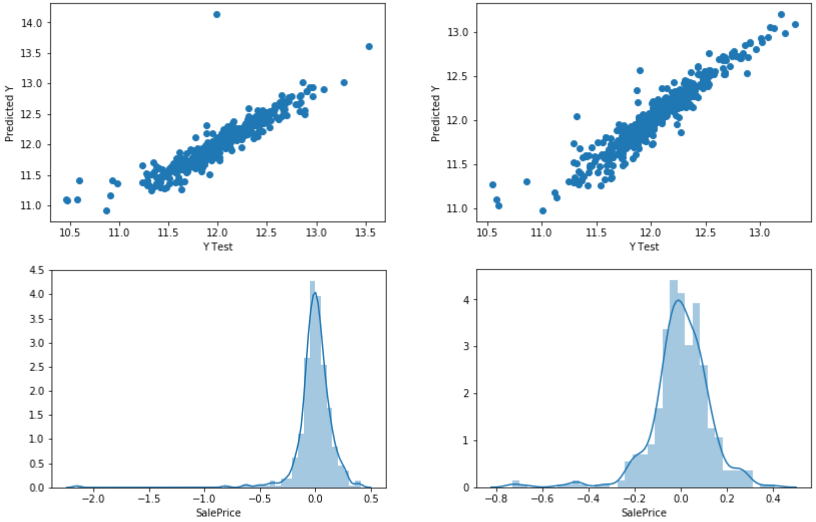
Elastic



Predicting house prices using linear models







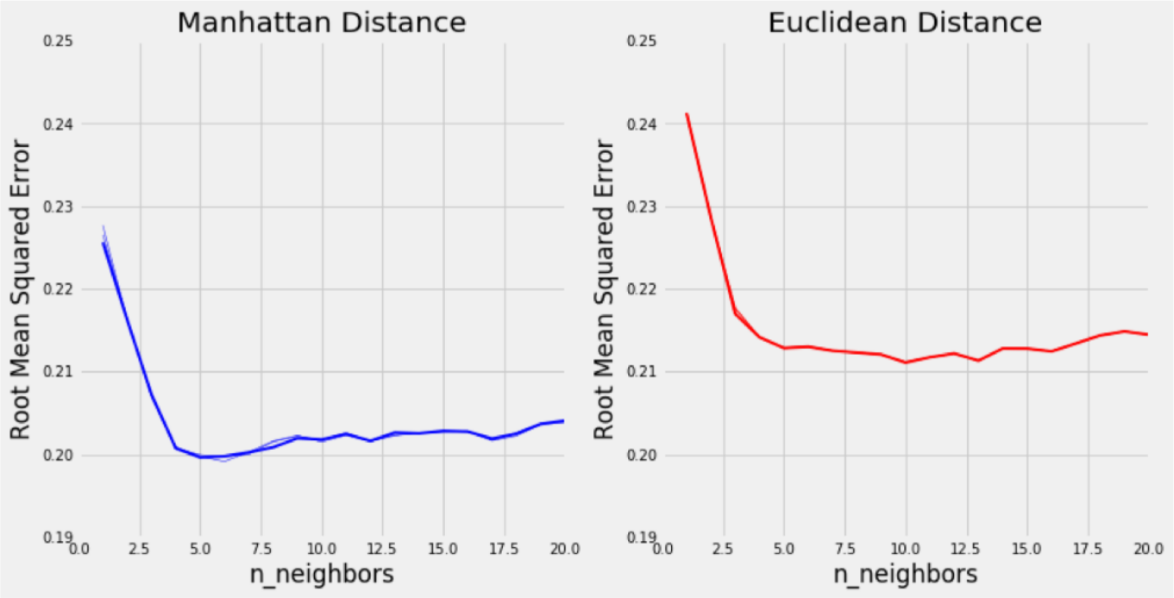
Model	RMSE	Comments
Linear Regression	0.1685	49 features, TotalLivingSpace
Linear Regression	0.1317	Squared # Bedrooms

Predicting house prices using k-nearest neighbors regression

New Features:
TotalLivingSpace instead of **LotArea**
Squared # BedRooms

Normalized the values: 0 - 1

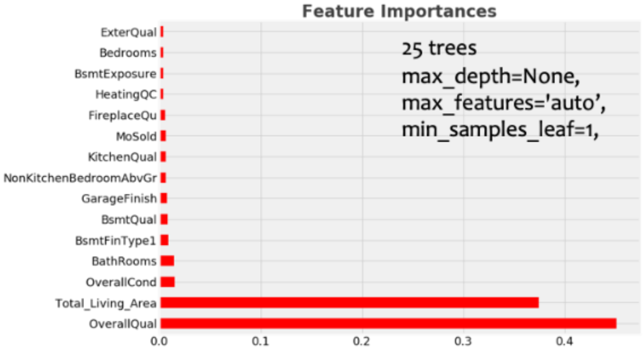
Metrics
Manhattan Distance
Euclidean Distance



Best **RMSE** obtained when K = 5 **0.19915480**

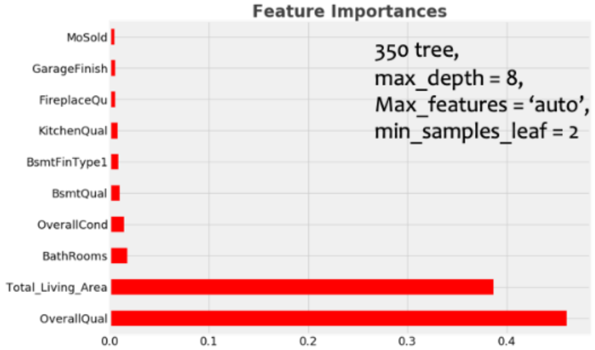
Predicting house prices using Tree-based models

Random Forest



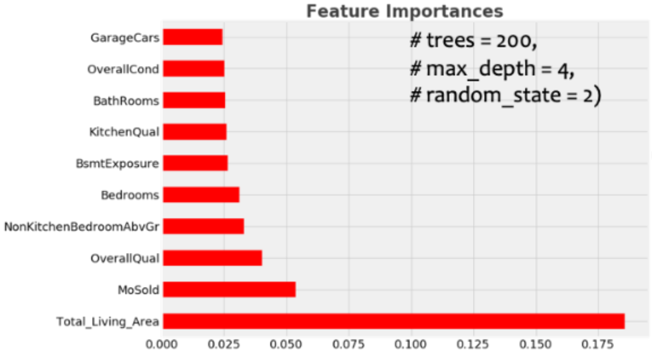
RMSE : 0.14987602771011657

Optimal Random Forest



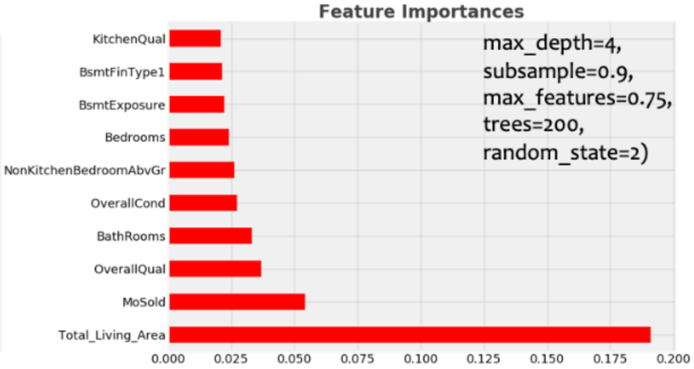
RMSE : 0.136551205992994

Gradient Boosting Regressor



RMSE :0.132472706

Optimal Gradient Boosting Regressor



RMSE: 0.121276024

Decision Tree

0.2383957875036891

Random Forest

0.14987602771011657

0.136551205992994

Boosting Regressor

0.132472706

0.121276024

Stochastic Boosting Regressor

0.13312094

0.122846123

XGBoost Regressor

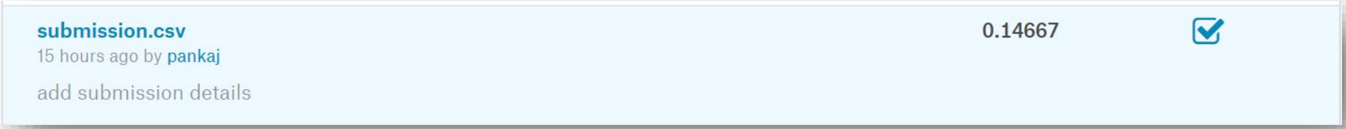
1.963953

0.167252

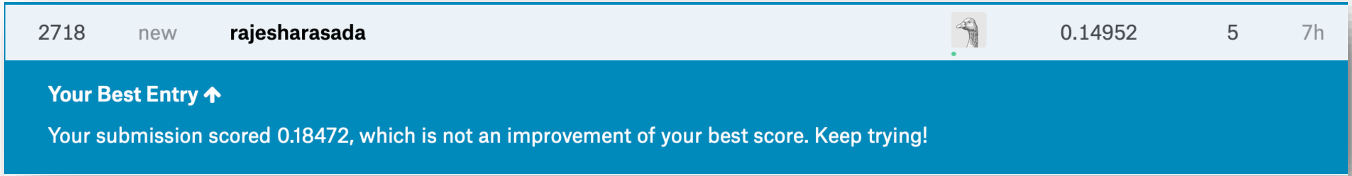
0.1492399

Scores

- Linear mode: 014667



- Tree-based: 014952



Conclusions and lessons learned

- Feature selection is difficult and subjective!
- Heart on common sense, mind on statistics
- The selected features reveal similar results in all regress models.
- The following features appear to have much influence on a house price:
    - Total Living Area
    - Lot Area
    - Month Sold
    - Overall Quality
- For the tree-based models,
    - Total Living Area
    - Month Sold
    - Number of Bathroom
    - Kitchen Quality