Full House price prediction

Housing price prediction challenge from Kaggle

CDIPS Data Science Workshop Aug. 5, 2017

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What are you looking for in a home?

Neighborhood

n BR, *n* bath
n floors
n SQFT
HW FLR
Yard, BSMNT

House Prices: Advanced Regression

kaggle

1460 sale prices 930 witheld
80 features

37 continous
43 categorical

Eames, Iowa housing dataset
De Cock 2011 J. Stat. Educ.

Making *“the best”* predictions

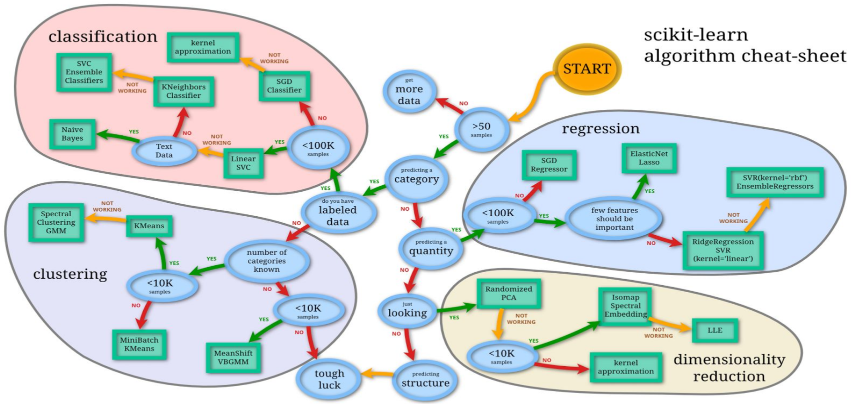
Goals and objectives

Best fit to the data

Appropriate algorithm

Parsimonious ?

Interpretable ?



Feature Engineering

Automagic

Transform skewed

NA filling

pd.getdummies

Manual Intervention…

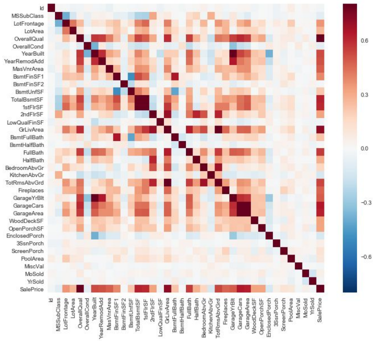
“Manual” feature engineering

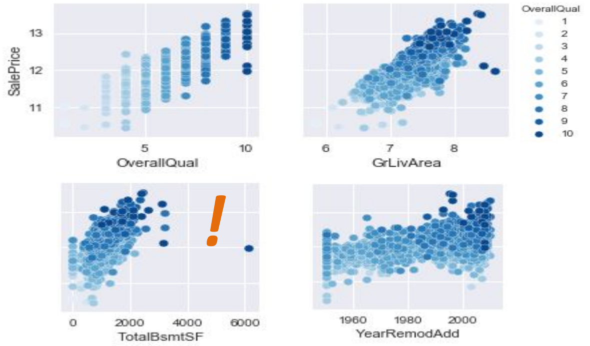
ID important features

Correlation heatmap

Top single features

Co-linear predictors





Recode / combine features

NA ⟶ “none”, 0, mode/average

Ranked cat’s. ⟵ ⟶ num.

Combine related:

- Total: Sqft., Baths
- Quality: Exter, Kitch, Bsmt, Gar.

Total SF=

Machine Learning

Algorithm toolbox

Regression	Linear, Ridge, Lasso, Elastic, NN
Trees	Random Forest, XGBoost
Scoring	RMSE, 10 fold cross-validation

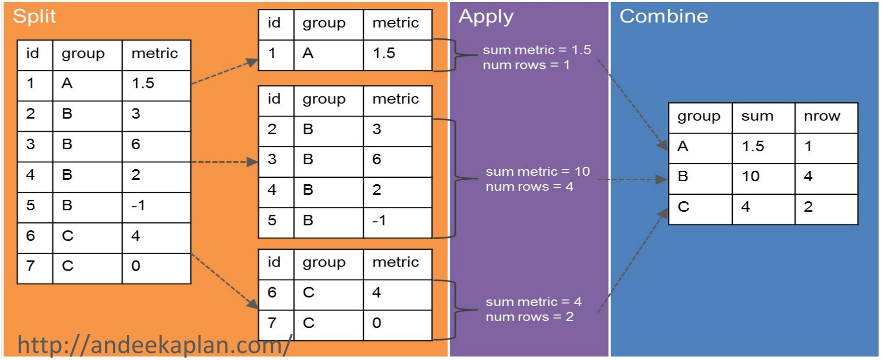
Split datasets

Test / train / witheld

Manual FE only

Continuous only / cat. only

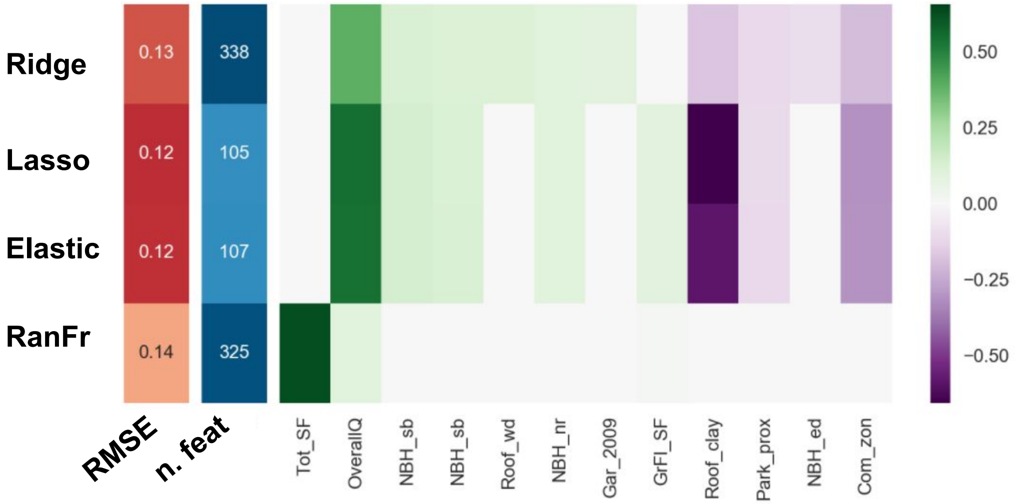
Full data set



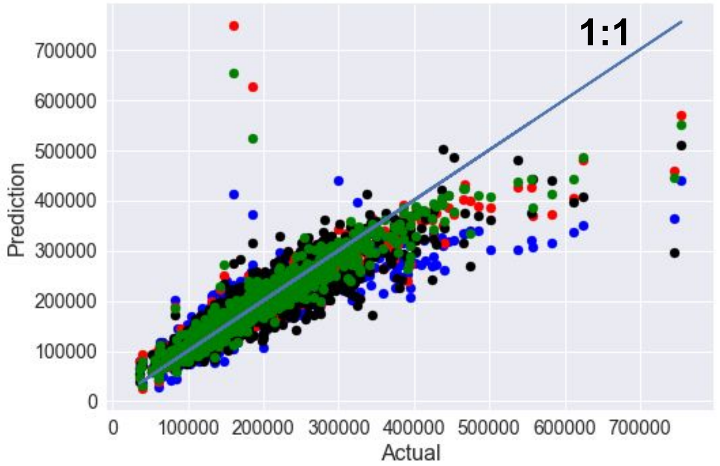
Evaluate models …

Results / Discussion

Algorithm scores, top features



By data subset (Kaggle score)



Subset, K RMSE

- 10_top, K=0.195
- 55_num, K=0.136
- 325_cat, K=0.204
- 380_all, K=0.123

Lessons learned and future development

Outliers are from 2008, economic recession

Piecewise estimation: classification + regression