Housing Price Prediction

Kaggle Competition

The Avengers:
Andrew Dodd 
Michael Goldman 
Peter Yang 
Roger Ren 

Housing Price Prediction

Main objective:

Develop accurate models for estimating housing price in Ames, Iowa.

Sub-objectives:

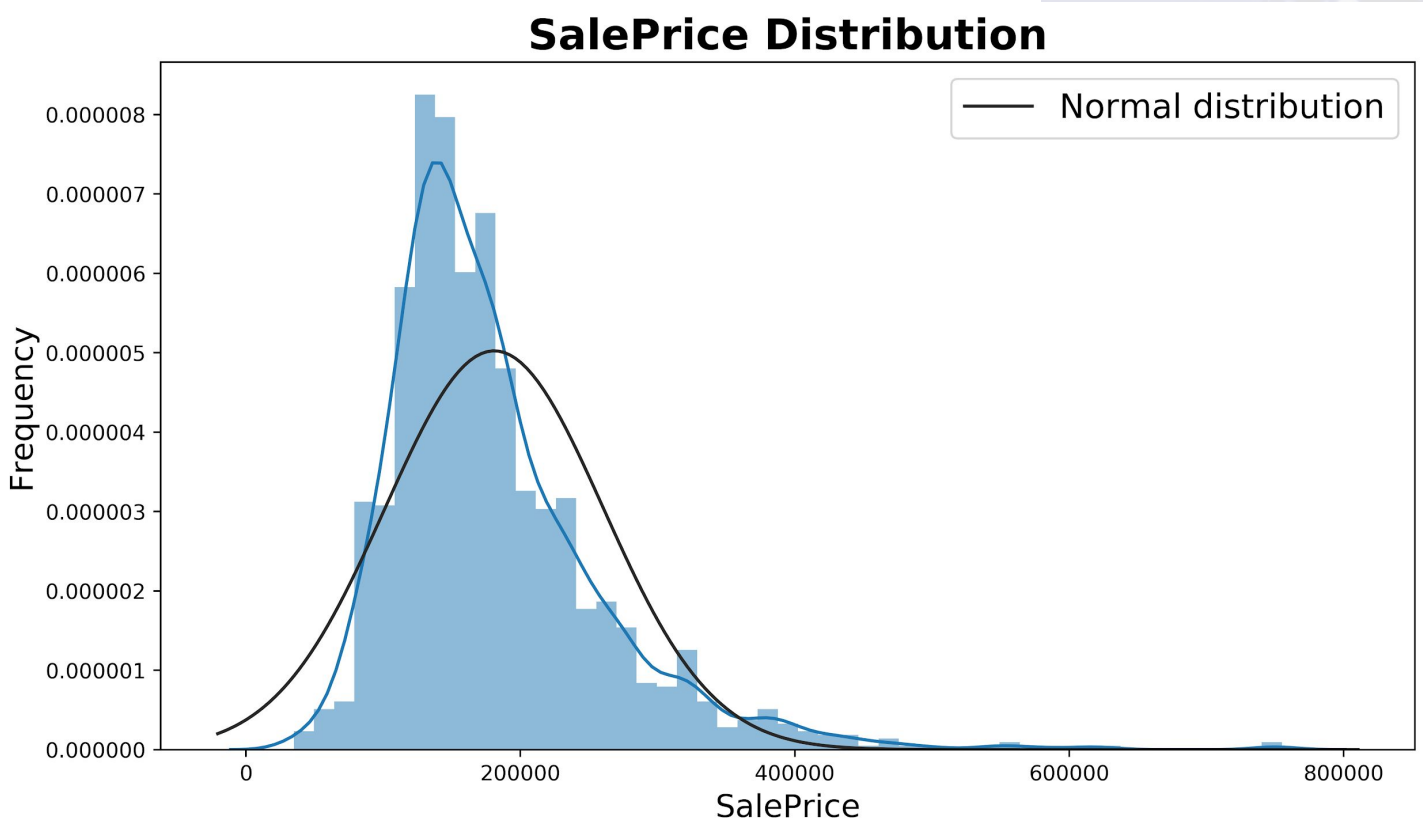
a. Explore dataset, variable distributions, correlations, clean data.
b. Perform feature engineering.
c. Look for outside effects (inflation, seasonality, housing market).
d. Cluster dataset into sub-datasets.
e. Identify which variables significantly impacted sales price.
f. Select and tune models.
g. Create train, validate, and prediction pipeline.

Presentation Overview

1. THE DATA
2. THE MODELS
3. THE PIPELINE
4. THE RESULTS
5. THE FUTURE

1. THE DATA

Dataset Exploration



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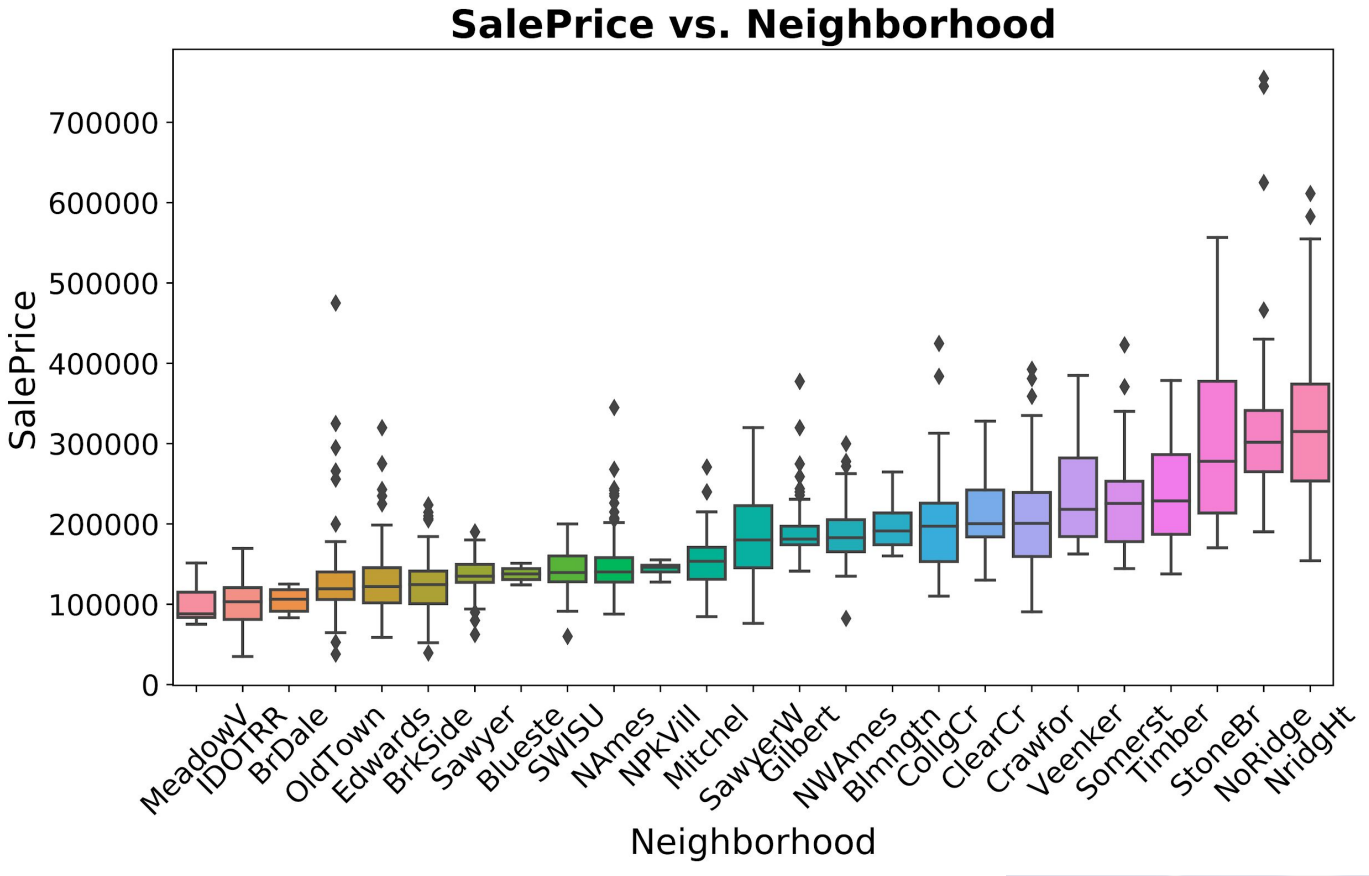

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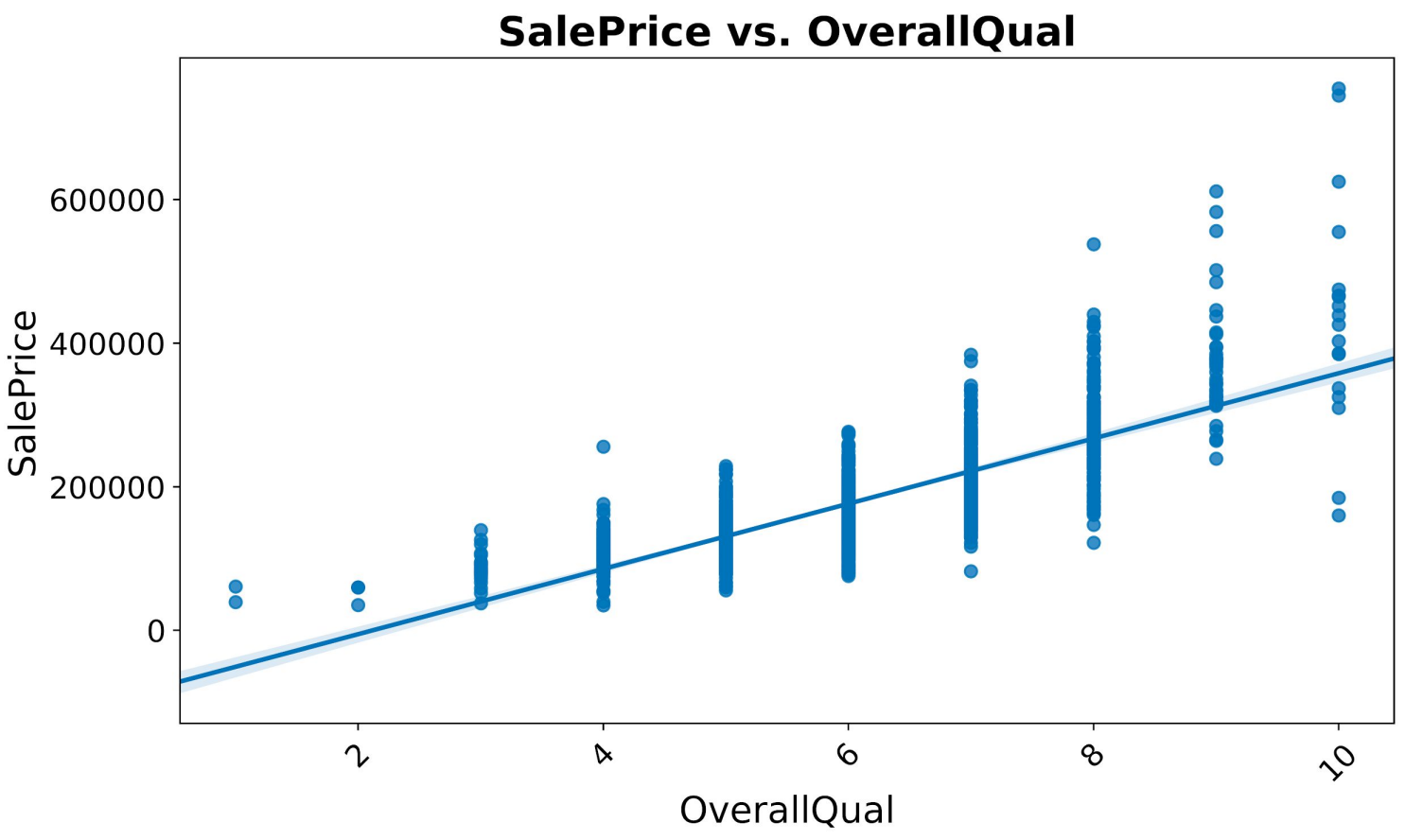

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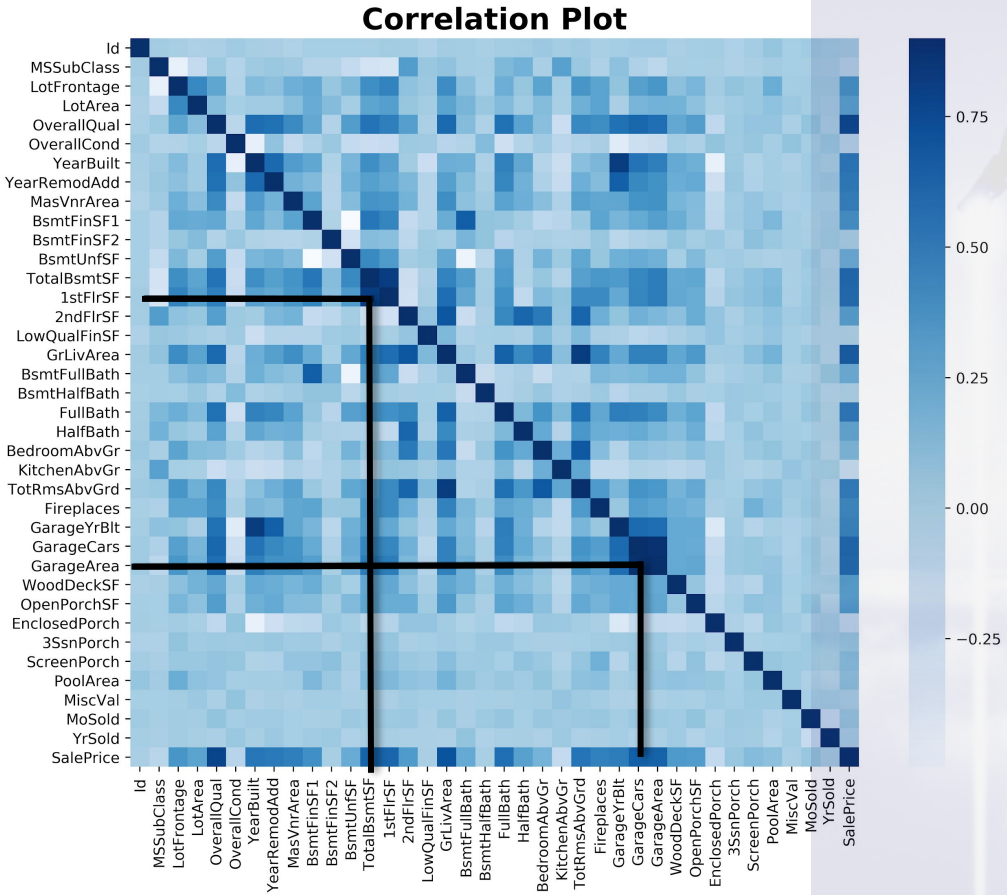
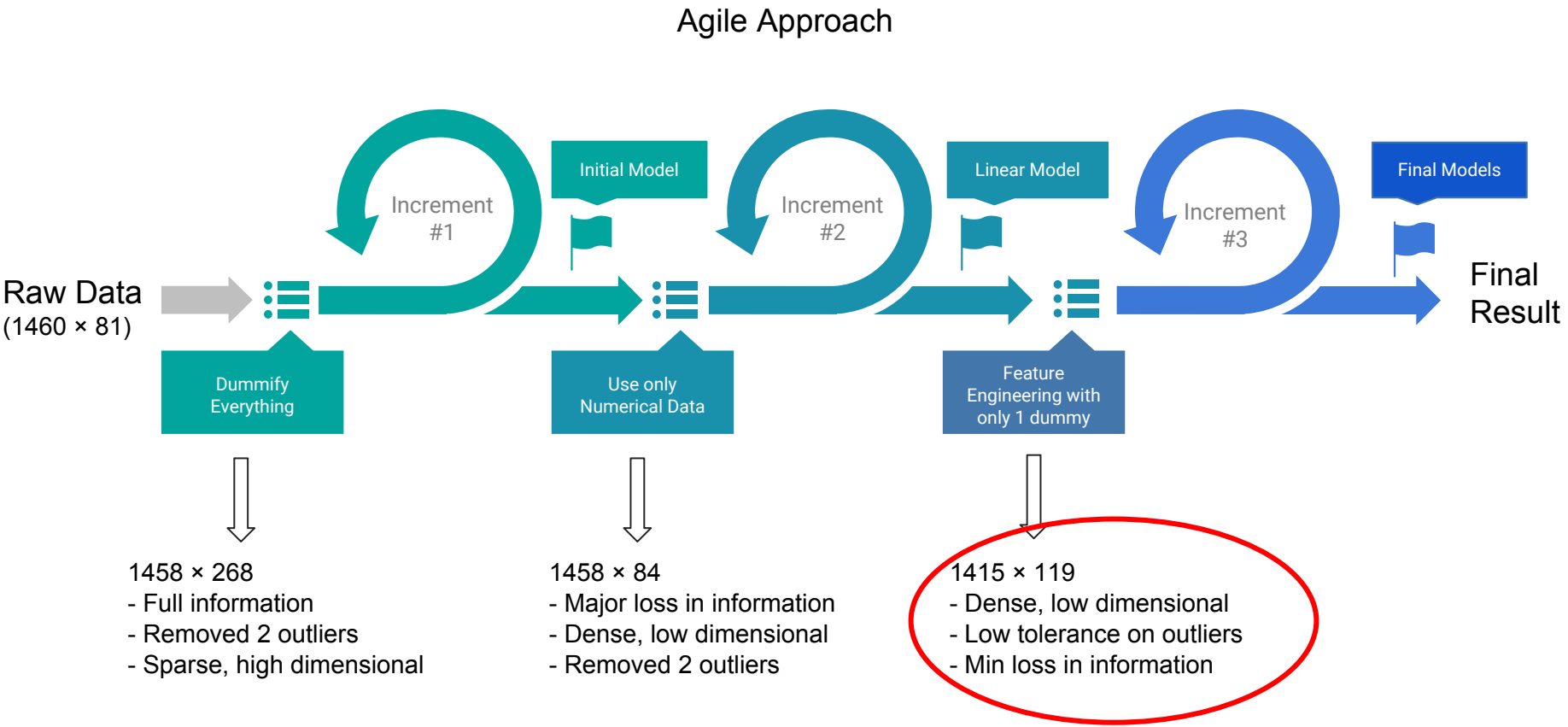
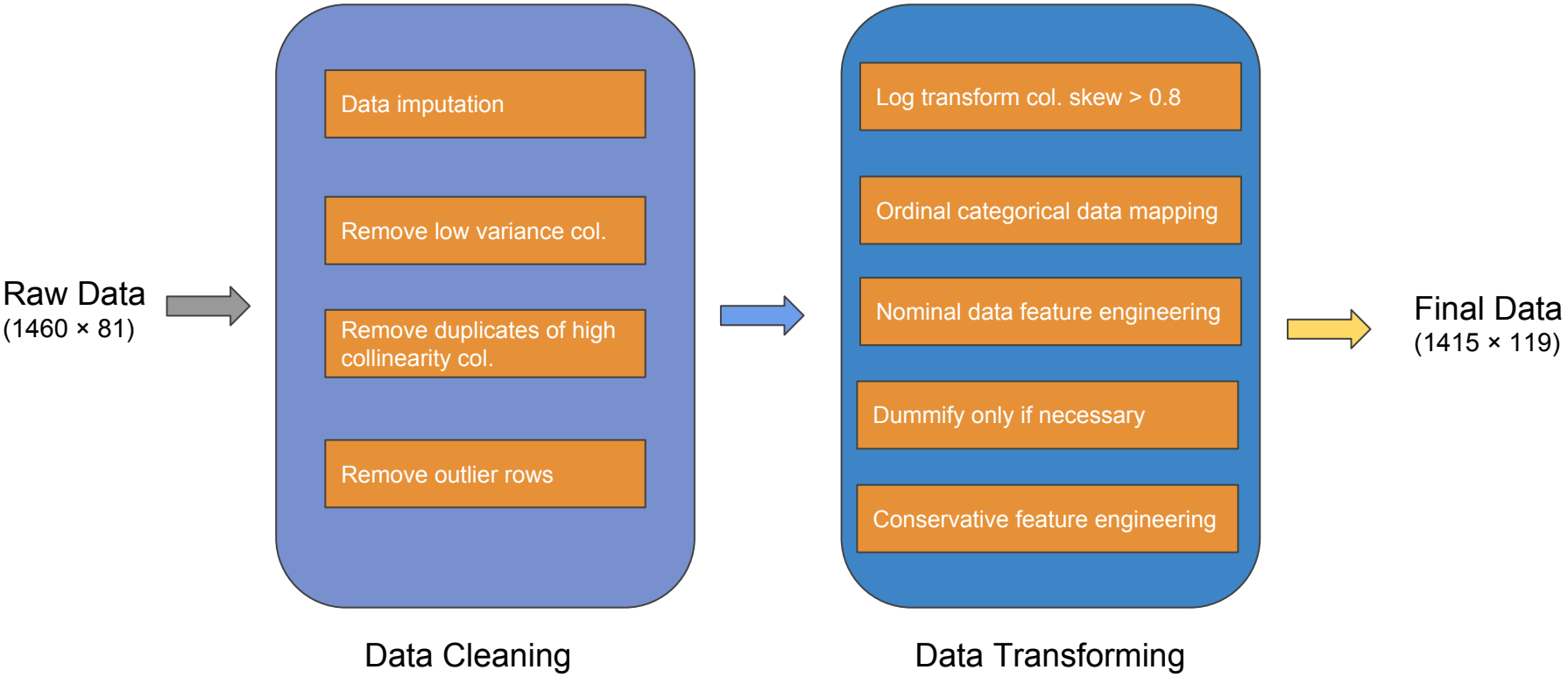


Data Preparation: Overview

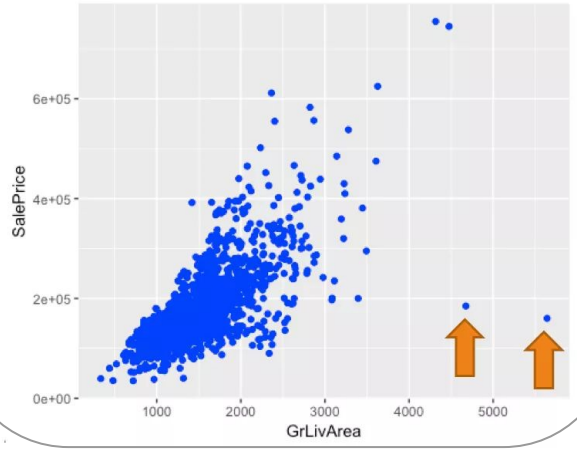


Data Preparation: Pipeline



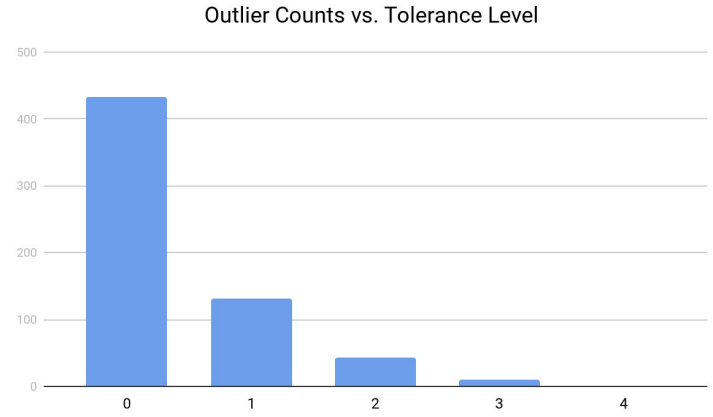
Data Preparation: Outliers Tolerance

- Remove outliers by plotting
- Some obvious ones
- Lack of systemic approach

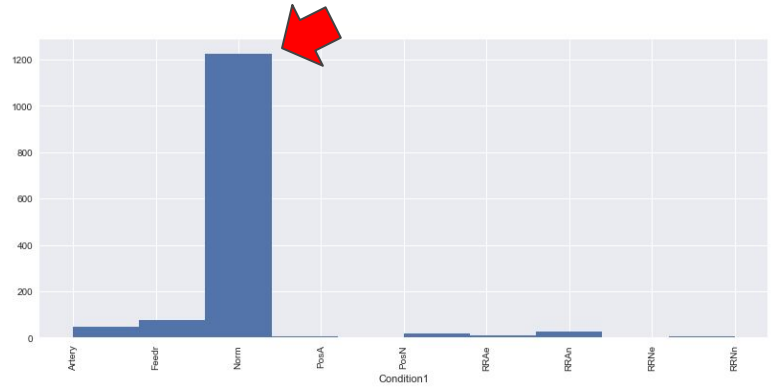


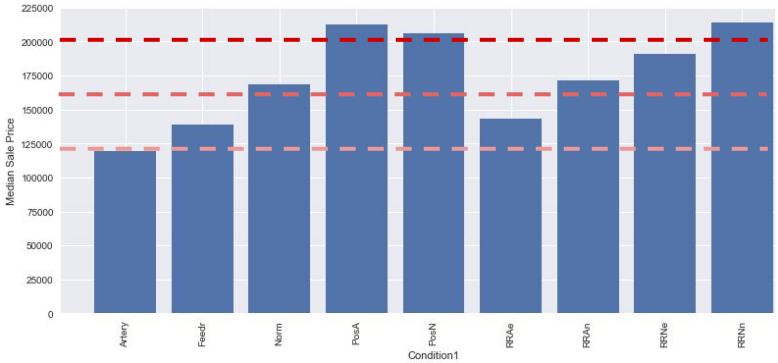
- Remove outliers by +/- 3 std or 1.5 IQR
- Can set ‘tolerance level’

Log transform → Test +/- 3 std → Tolerance Analysis → Masked deletion



Data Preparation: Feature Engineering





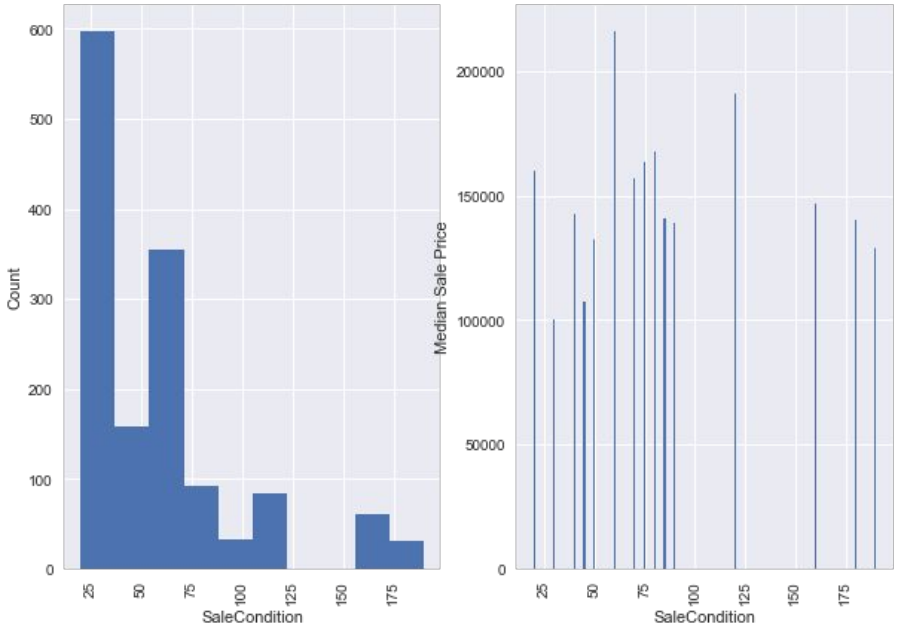
Simple dummify:
- 1 col → 9 col
- Preserve all information
- Data set becomes sparse

Label by frequency:
- Lost information
- Arbitrary assignment

Significant factor:
- Preserve the information of a single / a few dominant factor(s)

Group and label:
- Keeps majority of information between ‘Factor’ and ‘SalePrice’
- Avoid unnecessary cols count increase
- Keeps dataset dense

Data Preparation: Only 1 Dummy

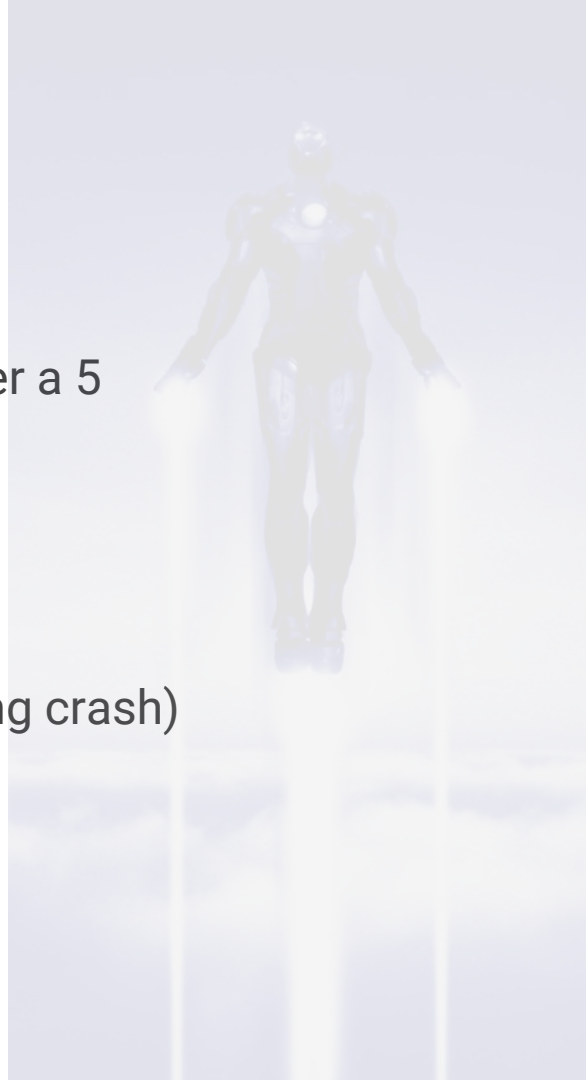


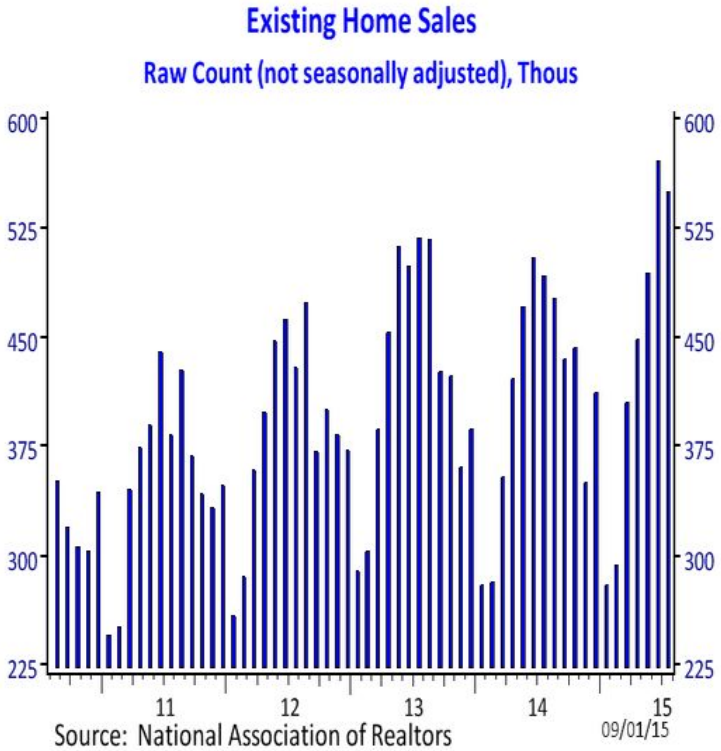
'**MSSubClass**' column:

- Appears to be numerical at first
- It is actually categorical data
- Do not exhibit 'dominant' factor

Time Trends

a. Inflation
   - The US inflation rate is approximately 2%
   - This might lead to a ~10% increase in houses over a 5 year span
b. Seasonality
   - Quantity of sales is higher in middle of year
c. Housing Market
   - Do the changes in the housing market (i.e. housing crash) affect the home prices in Ames, Iowa?

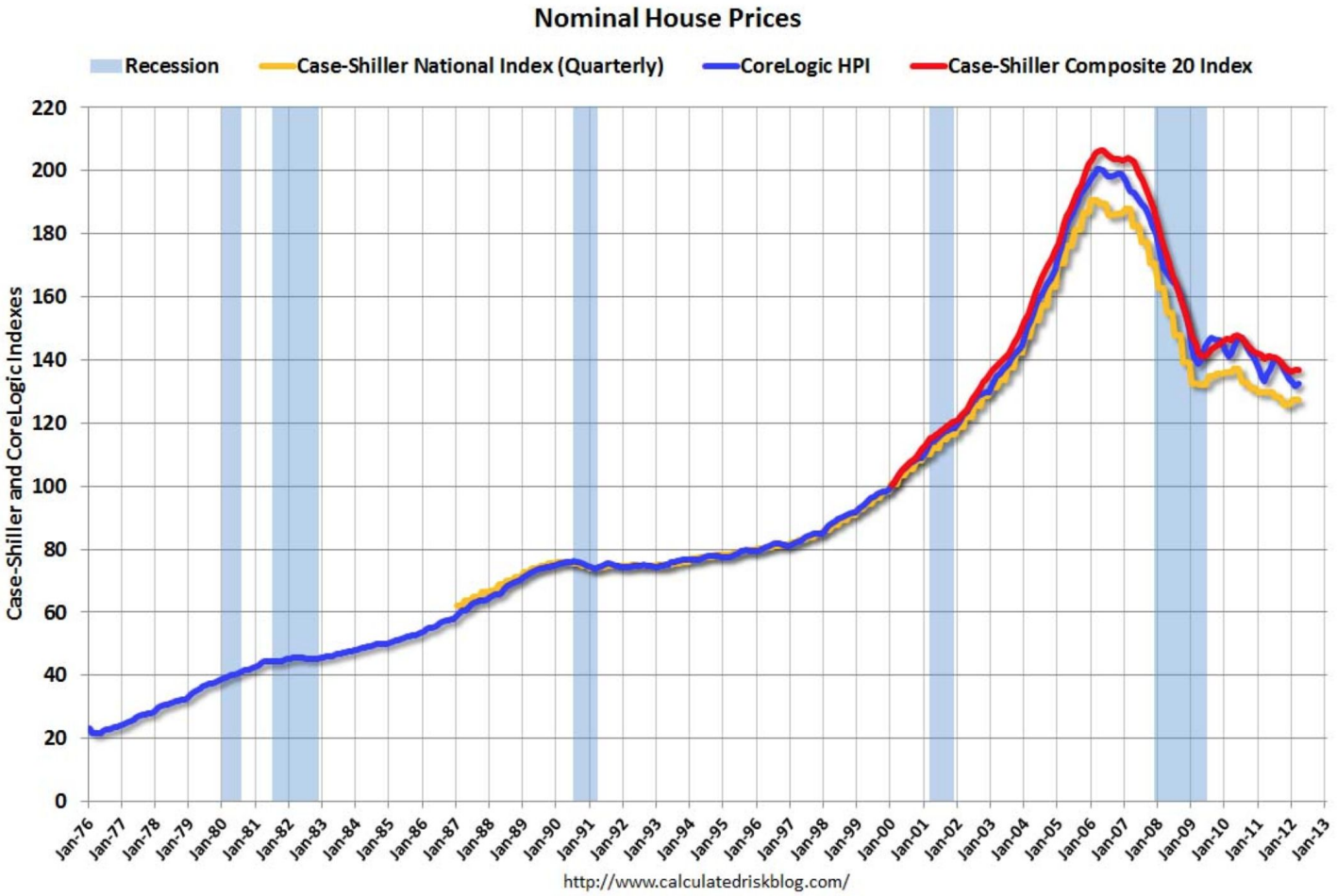




Seasonality changes in number of homes sold

Inflation rate versus year

Do home prices trend strongly with time in the United States?



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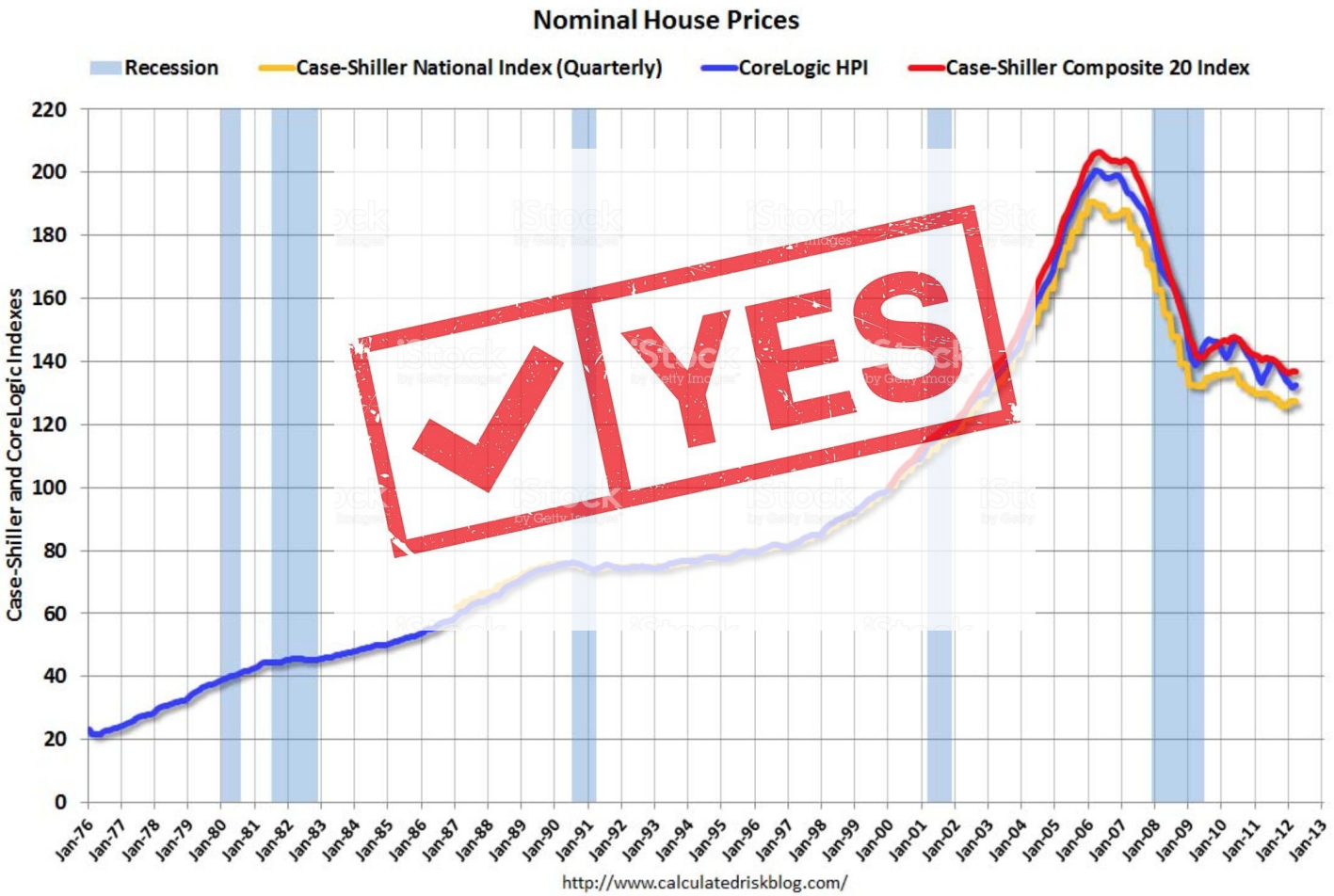

Does there seem to be a reasonable level of price correlation between Des Moines and US National Home Price Index?

Below left: Sales price in Des Moines, Iowa, 37 miles south of Ames.

Below right: US National Home Price index.

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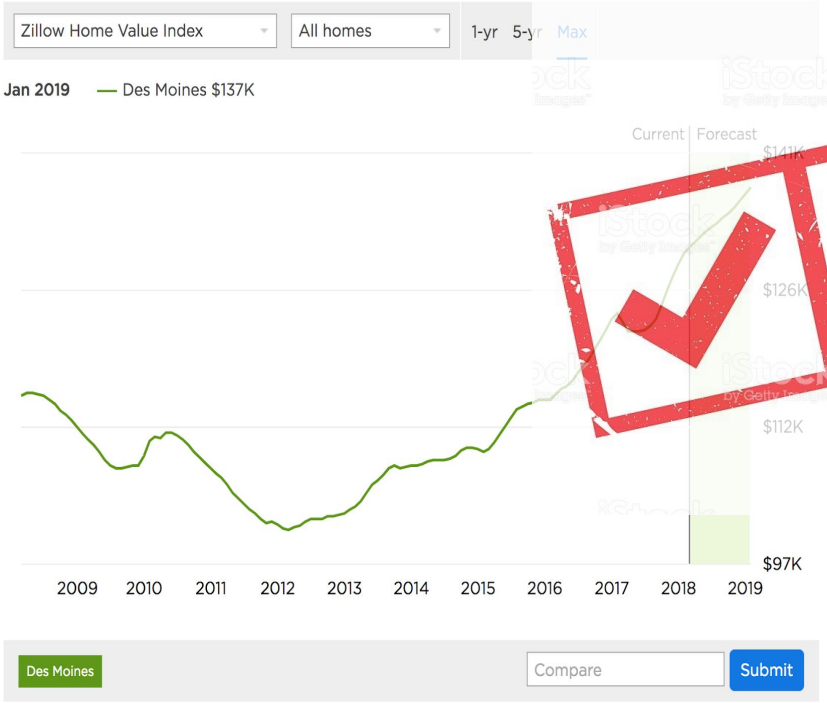


YES

Modeling the effect of time...

- Transform SalePrice column based on scaled inverse of US home index
- Steps:
    1. Create train/test split
    2. Normalize SalePrice column w.r.t. time before fitting model.
    3. Train/fit model using these normalized prices as y_train
    4. Predict with this model
    5. Reverse the transform
    6. Try a variety of time trends and see which trends (if any) decrease the rmsle.

Did this work?

Modeling the effect of time...

- Create transform using home price index to normalize SalesPrice column based on average US sales price
- Steps:
  1. Create train/test split
  2. Normalize SalePrice column w.r.t. time before fitting model.
  3. Train/fit model using these normalized prices as y_train
  4. Predict with this model
  5. Transform predictions back to original time varying world
  6. Try a variety of time trends and see which trends (if any) decrease the rmsle

Did this work?

2. THE MODELS

Models

a. Linear Models
    - Ridge
    - Lasso
    - Elastic Net
b. Random Forest
c. Boosting Models
    - Gradient Boosting
    - XGBoost
    - Light Gradient Boosting

Linear Models

a. Ridge
   - Want to minimize the impact of weak prediction coefficients.

b. Lasso
   - Want to drop unnecessary coefficients.

c. Elastic Net
   - A combination of both Lasso and Ridge.

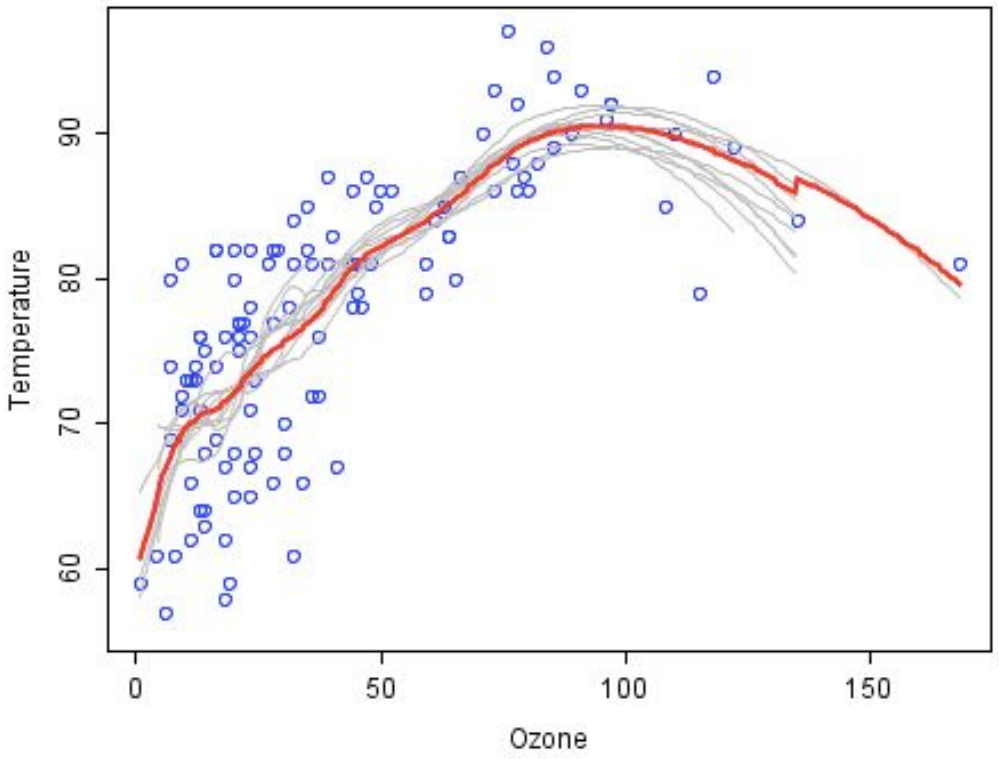
Pros: They provide a good baseline and are relatively easy to implement.

Cons: Assume a linear relationship between variables and sale price. Suffer from multicollinearity.

Random Forest

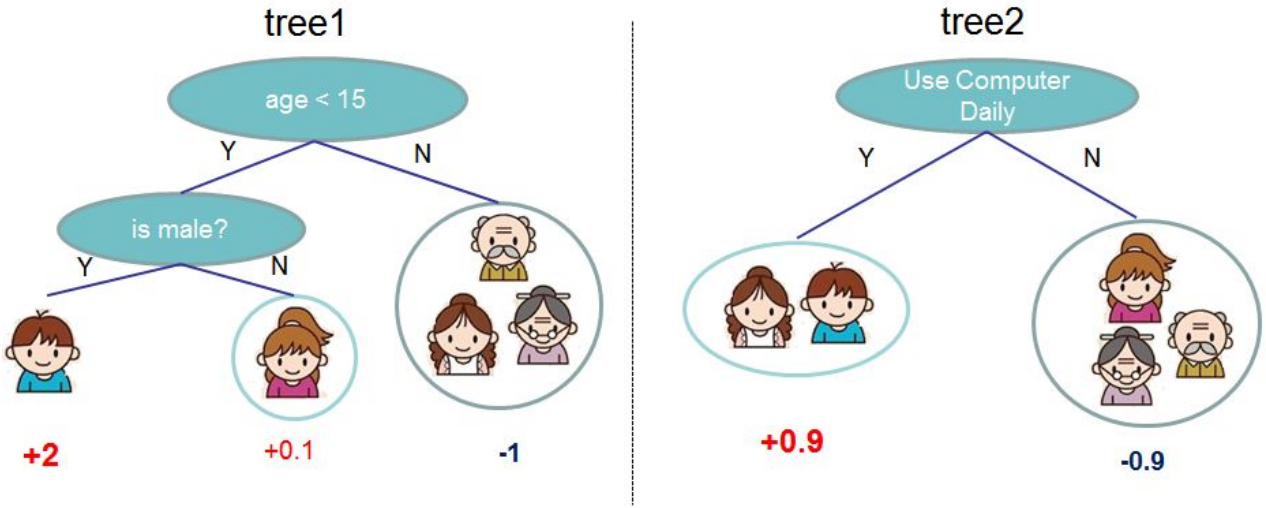
- It is a large number of decision trees randomly selecting a limited number of factors at each split.
  a. Pros:
     - Tends to not overfit when creating a large enough number of trees.
     - This works because all the individual trees are uncorrelated. Weaker predictive trees will average out to a more predictive stronger learner.
  b. Cons:
     - Although it can handle multicollinearity for predictions and feature selection, we cannot be certain that the feature importance for multicollinearity factors is completely accurate.
       - With enough trees, this should be addressed, but can never be certain we have enough trees to address this.
     - Accuracy can suffer when predicting on data it has not seen before.
       - Since there are a maximum number of leaf nodes, there can only be that many different prices predicted.

Random Forest - an example



Boosting Methods

a. We used Gradient Boosting, XGBoost, Light Gradient Boosting
   - Predicting on the residual of a decision tree



f( ) = 2 + 0.9= 2.9 f( )= -1 - 0.9 = -1.9

Boosting Methods

a. Pros:
   - Very accurate. As the number of trees increase, the closer our prediction will be to the true value.
   - A bit faster than random forest.

b. Cons:
   - Susceptible to overfitting the data, since it is predicting on the residual of a pervious tree.

Optimizers Used

a. Grid Search
   - Brute force method.
   - Put in a list of parameters and it generates the model with every combination of the parameters listed.

b. Bayesian Optimization
   - Initialize the regression based on values put into the regression.
   - Explores the model to find the global maximum based on the greatest widths of the confidence interval.
   - Exploits the the max iteratively.

Ran the optimizers twice. First time with a large scope search (eg: .001-10). Second time with a more accurate scope within the more ‘correct area’.

~Now Some Graphs~

TABLE OF CVs

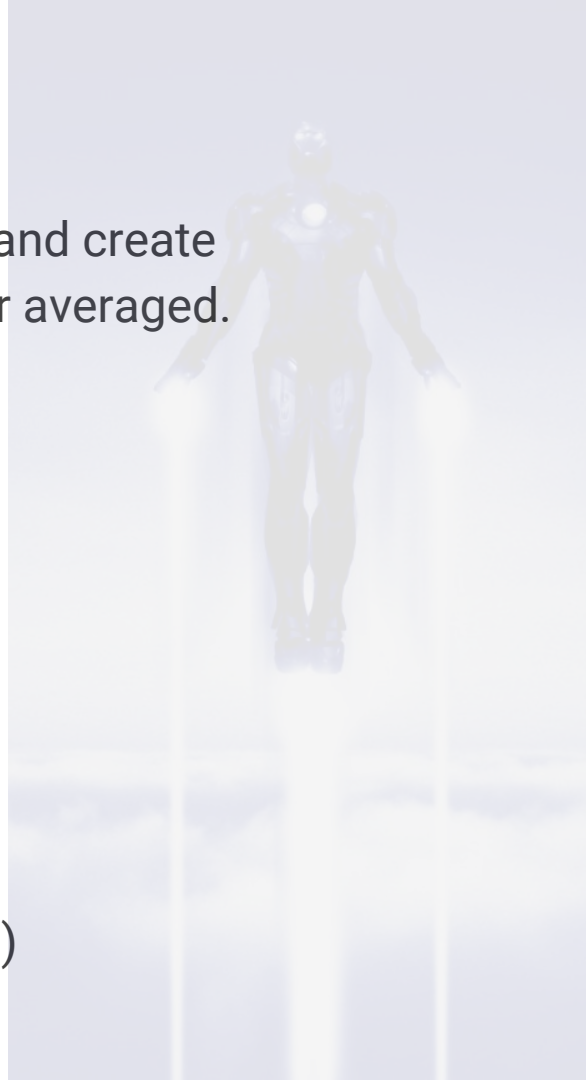
Model	CV Score (approx.)
Lasso regression	.120
Ridge regression	.120
Elastic net regression	.120
Random Forest	.125
XGBoost	.118
GBoost	.118
LightGBM	.118

3. THE PIPELINE

Object oriented modeling

- **Goal:** Create a way to quickly implement, train, validate and create predictions from multiple models that can be stacked or averaged.

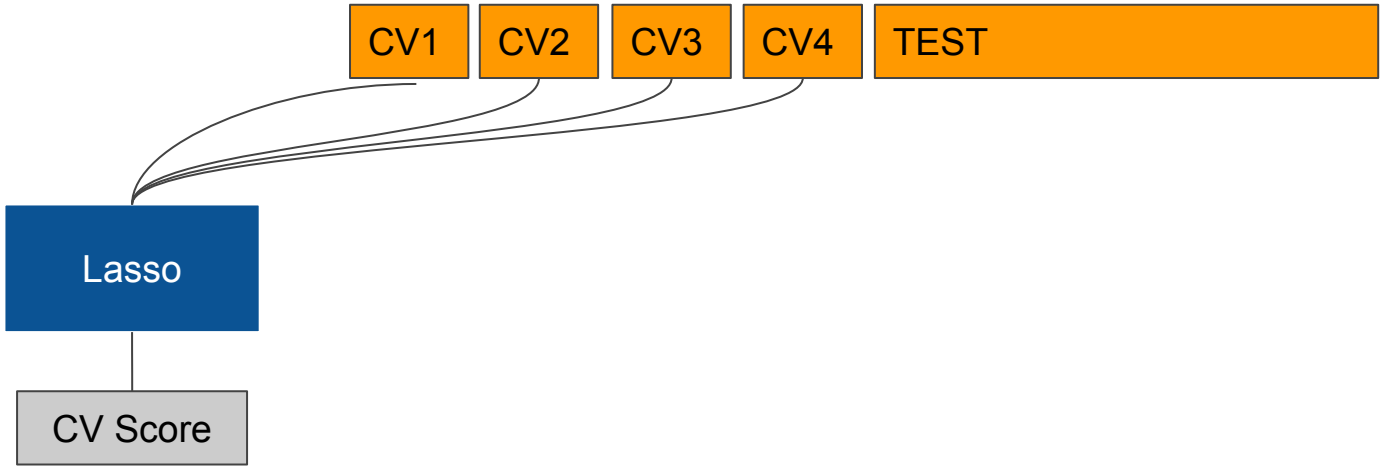
- Model class
  - Functions:
    - init(model_type)
    - train_validate(data)
    - train_predict(data)
- Stacking class
  - Functions:
    - init(metamodel_type)
    - train_validate_predict(base_model_predictions)



Stacking Approach

Lasso

Stacking Approach



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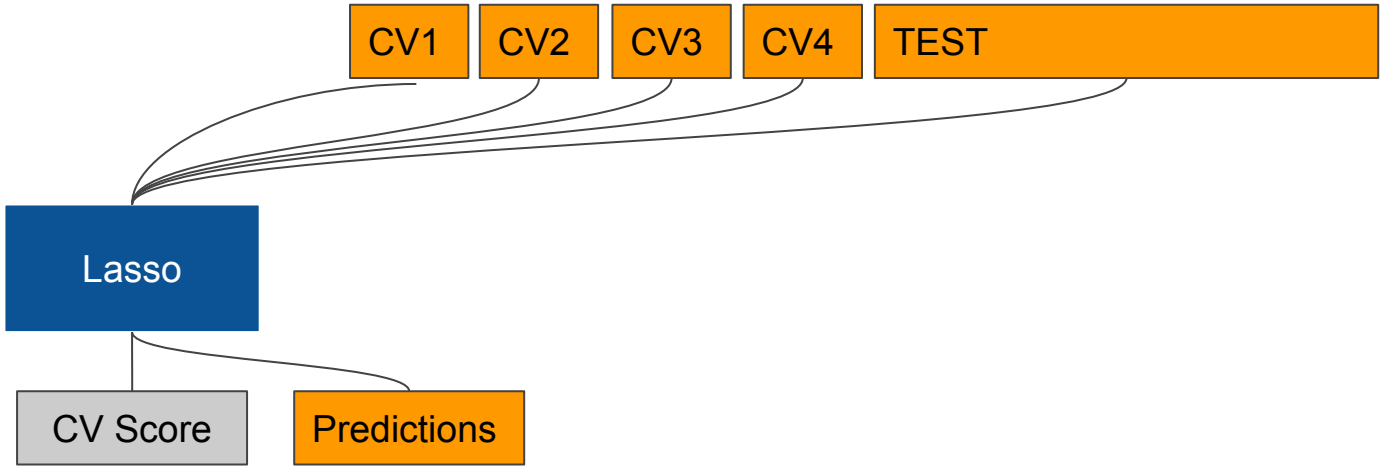
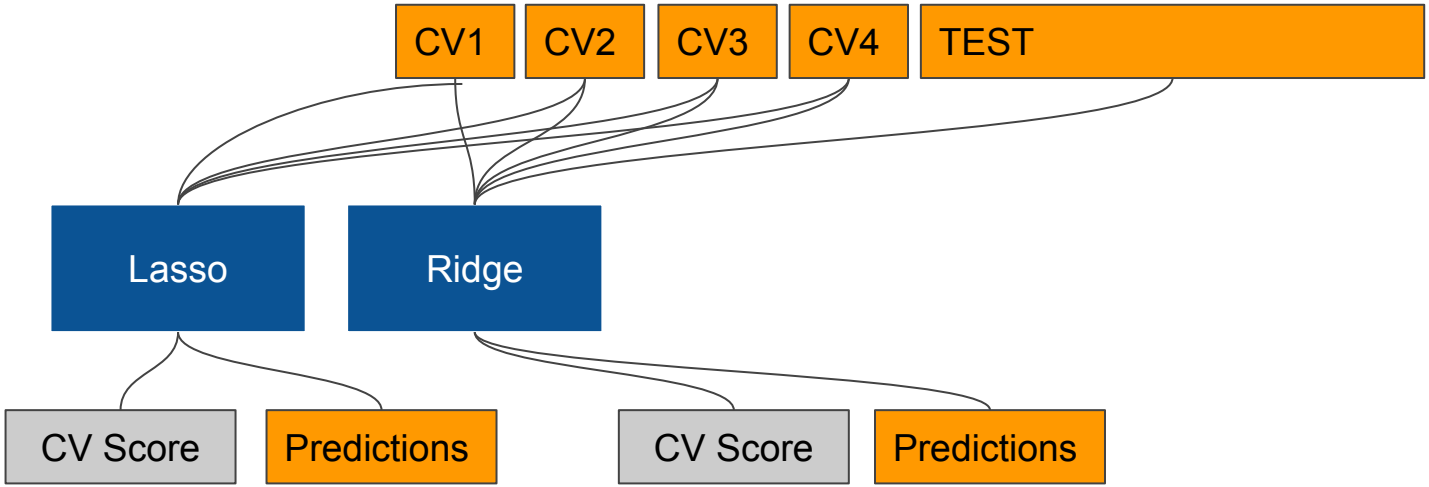


Stacking Approach



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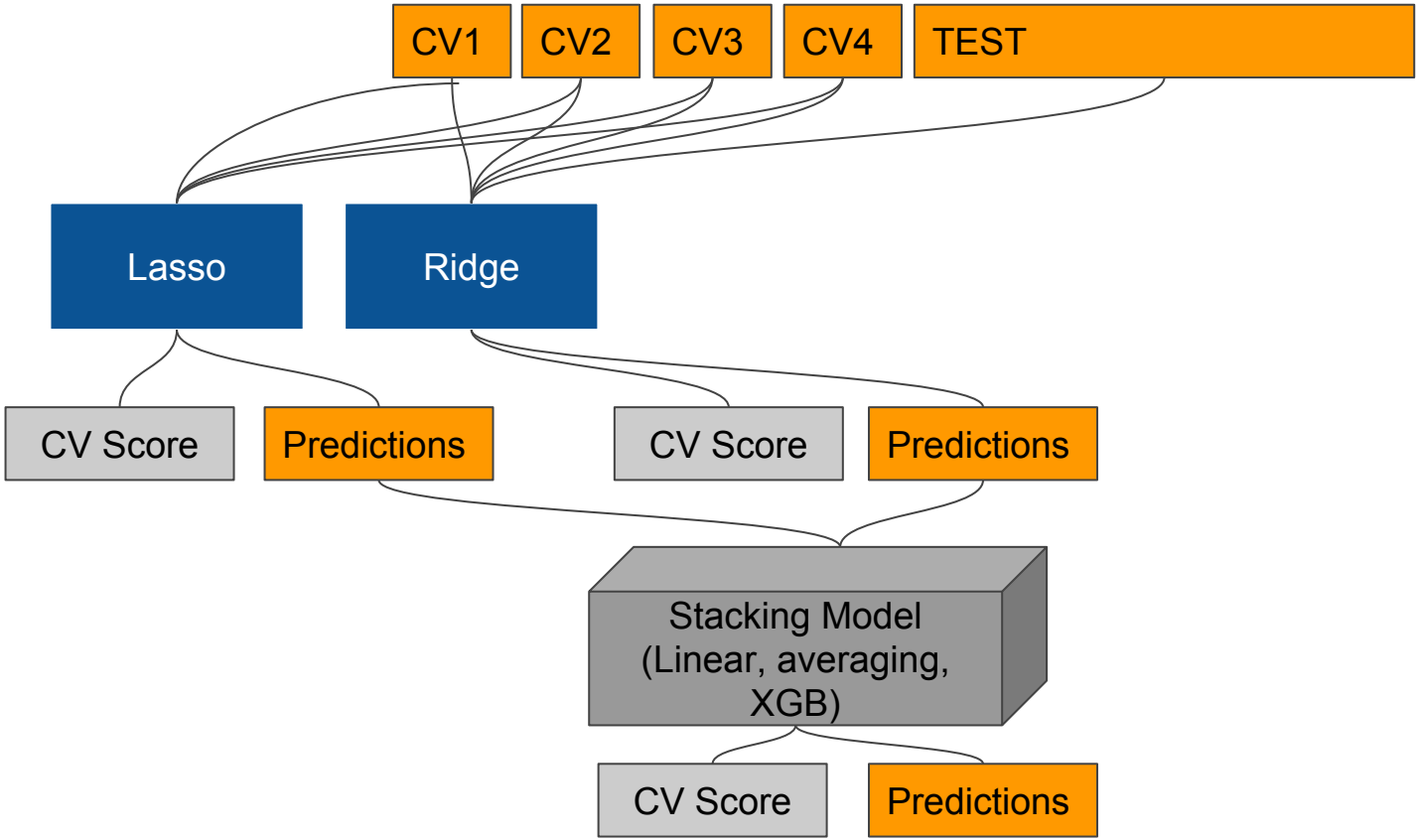

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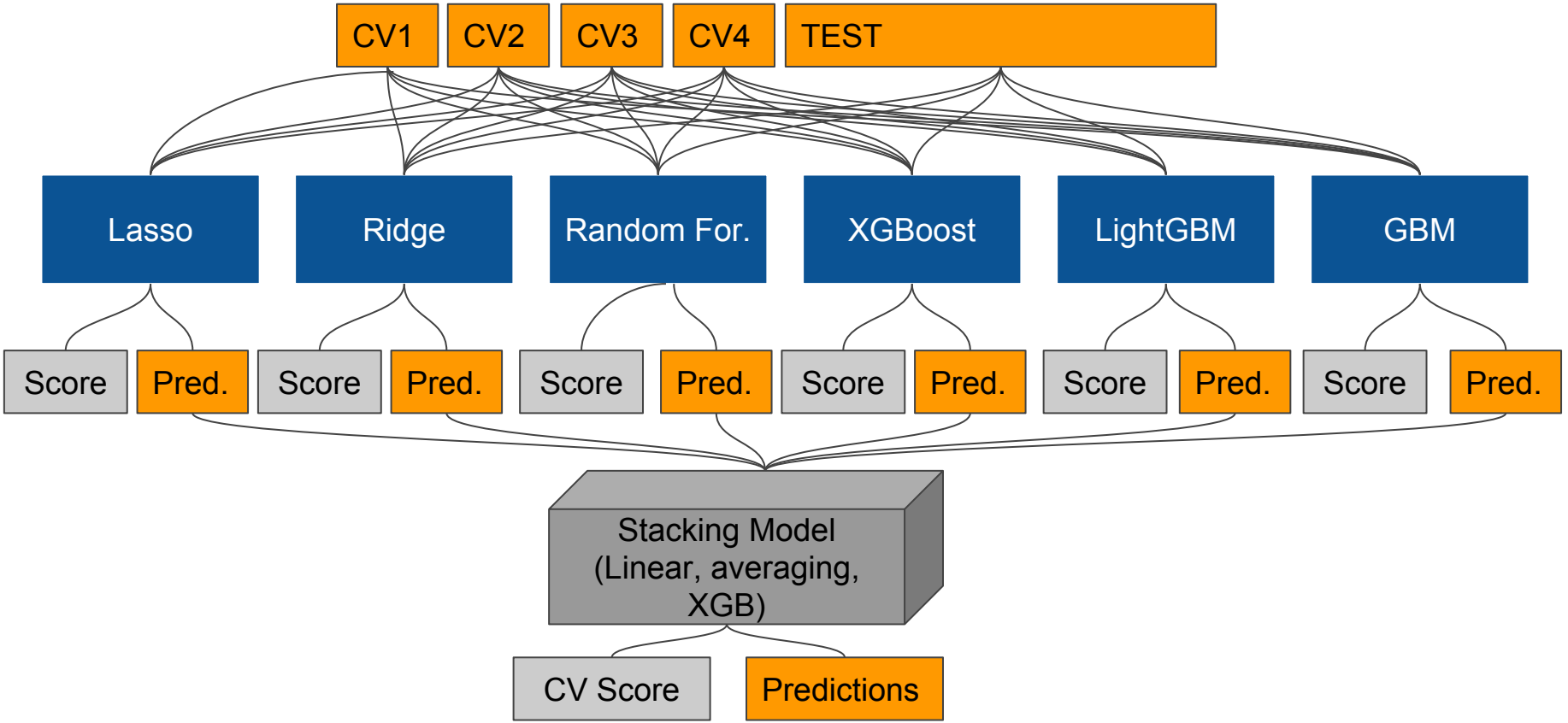
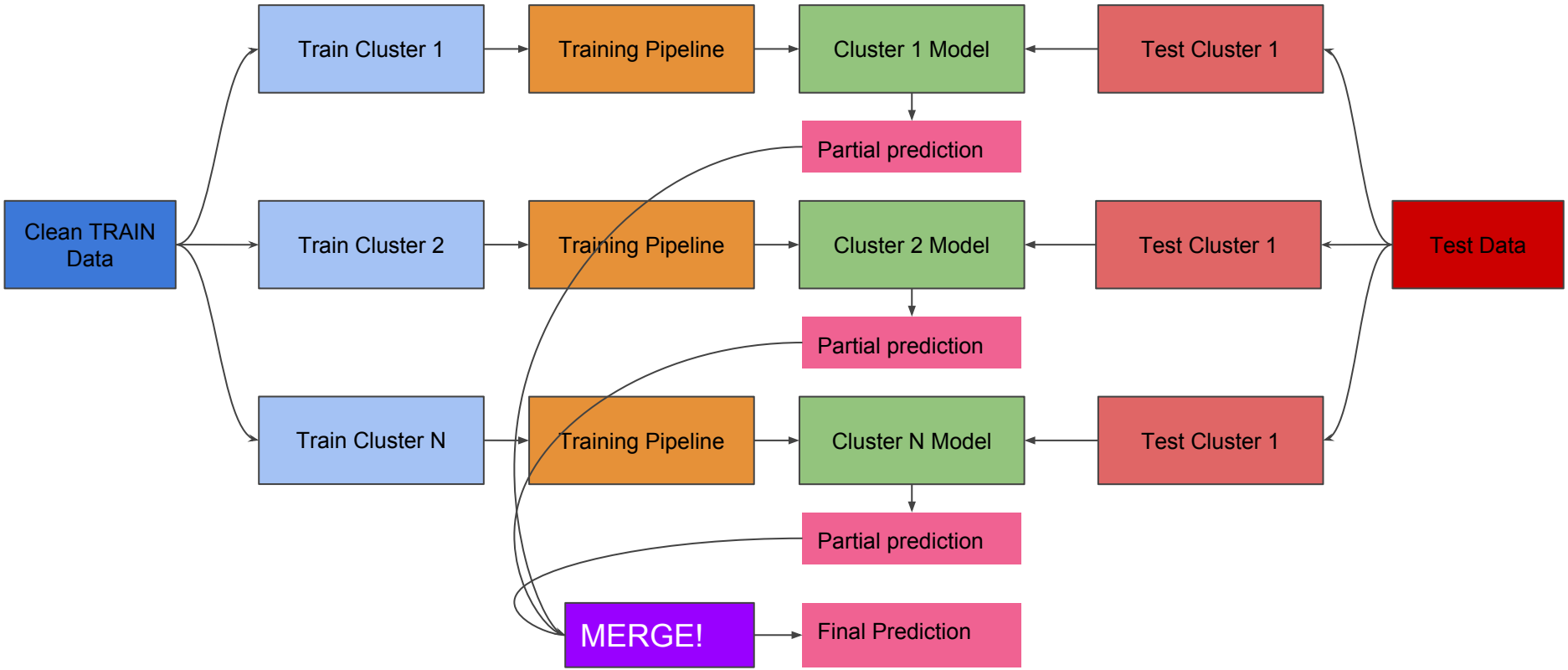


Clustering Exploration: Overview



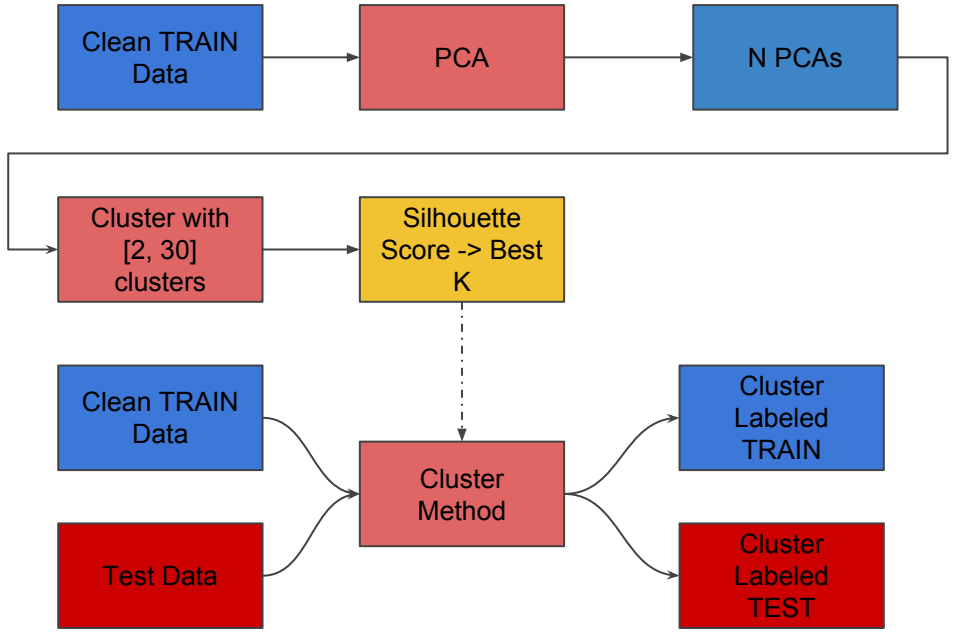
Clustering Exploration: Pipeline

- **Trade off:**
  1. Cluster sample size
  2. Homogeneous cluster

- **High dimension cluster:**
  1. Reduce dimension
  2. Keep AMAP info

- **Cluster algorithms:**
  1. KMeans, Agglomerative, Gaussian Mixture...
  2. Distance metrics:
['cityblock', 'cosine', 'euclidean', 'l1', 'l2', 'manhattan']

- **Feature selection:**
  1. Filtering
  2. Wrapping



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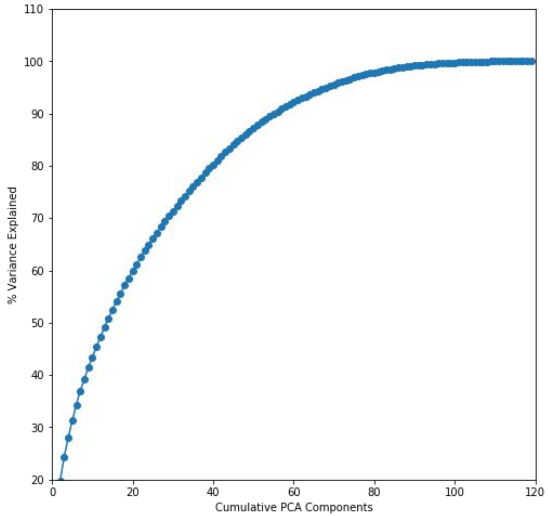
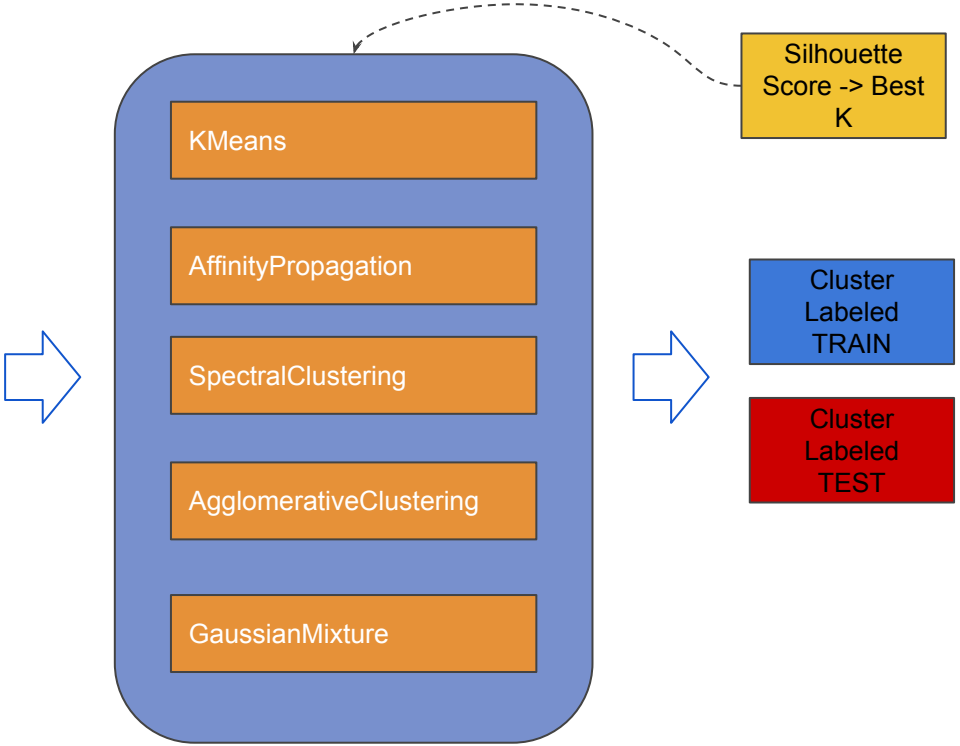
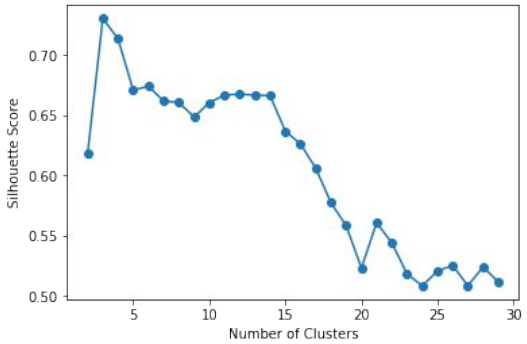


54 PCAs explains 90%

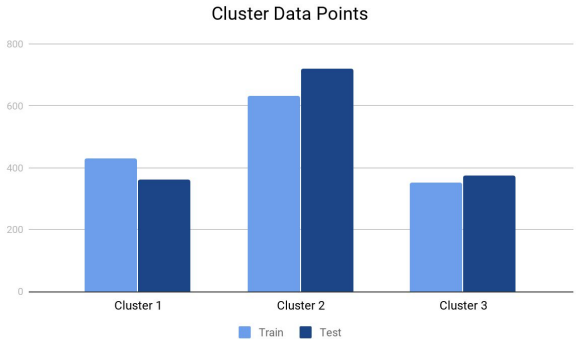


Clustering Exploration: Method and Metric

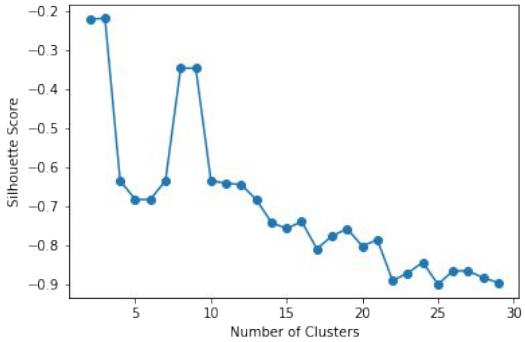
KMeans



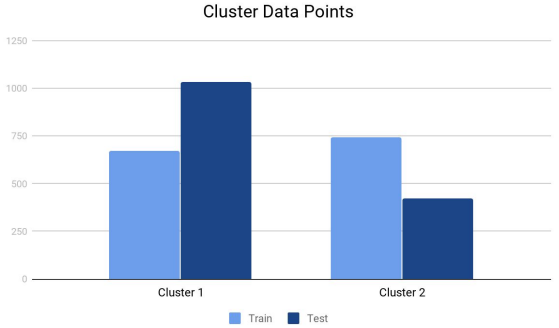
3 Clusters



Agglomerative



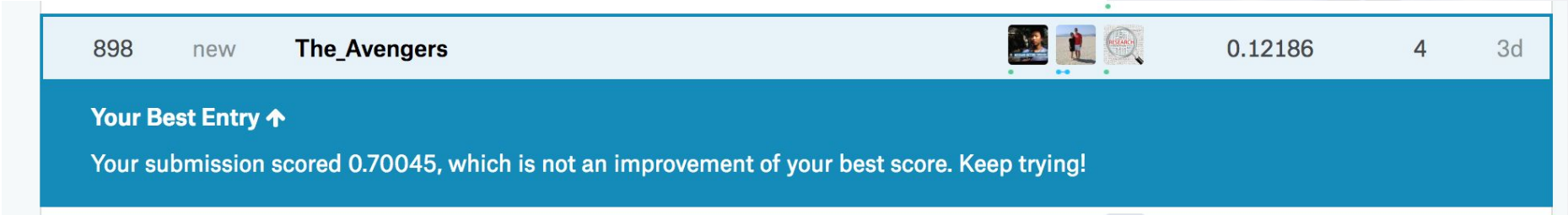
2~3 Clusters



4. THE RESULTS

Results

- Placed 898/4376, with a leaderboard score of .12186
- This means our CV error was not a great match to our real test error

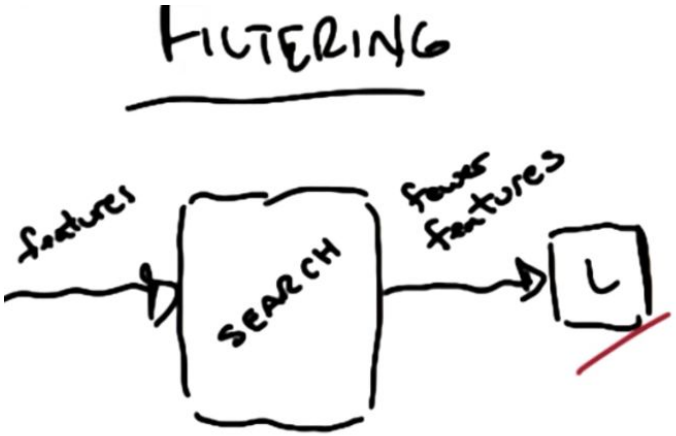


5. THE FUTURE

Future considerations

- Investigate more into effects of time (are we sure there are not trends in housing price with time? Is this possible?)
- Include an OOB error method (maybe put aside 20% of training data as a test set)
- Focus more on an iterative feature engineering process
- Using GitHub more effectively
- Better team workflow (redundant work)

Backup



+ SPEED
- SPEED ⇒ ISOLATED FEATURES

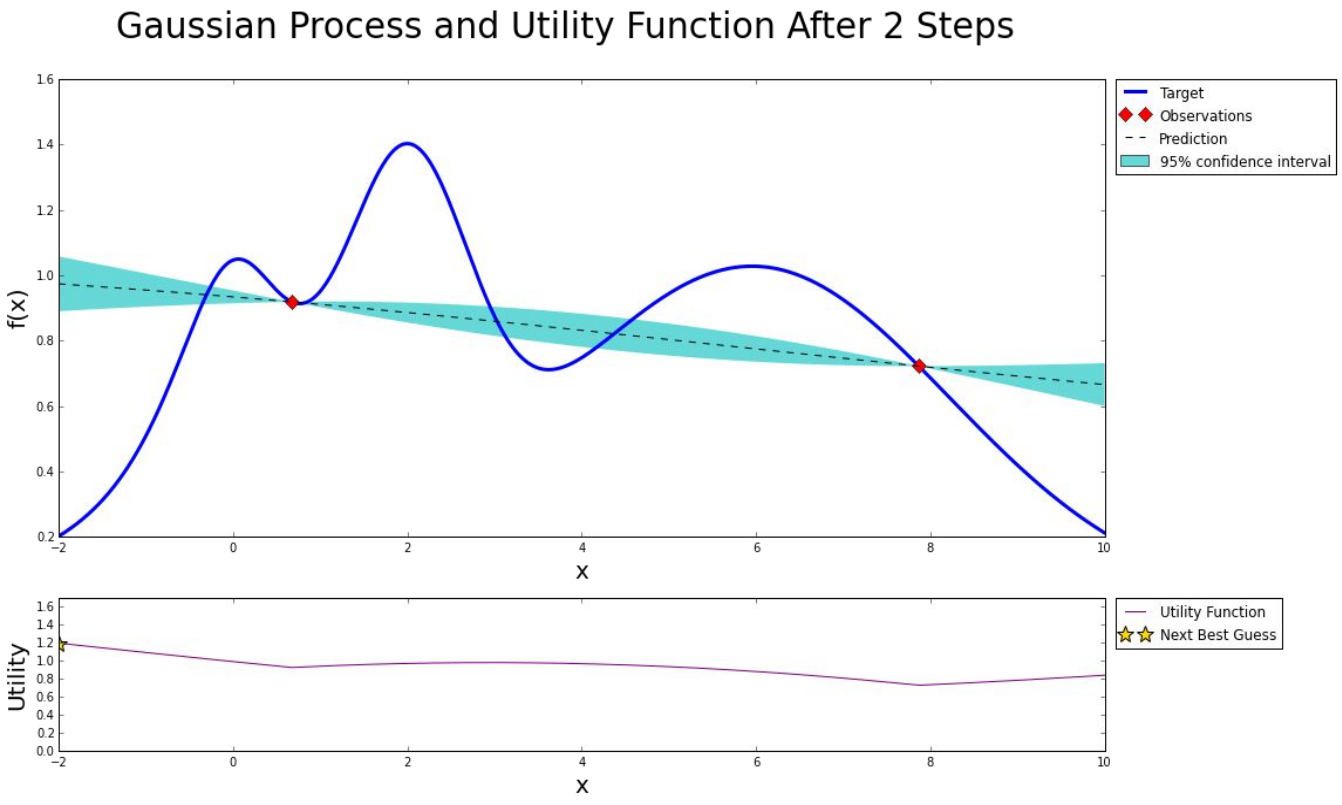
- IGNORES THE LEARNING PROBLEM

+ TAKES INTO ACCOUN
MODEL BIAS
+ ... AND LEARNG

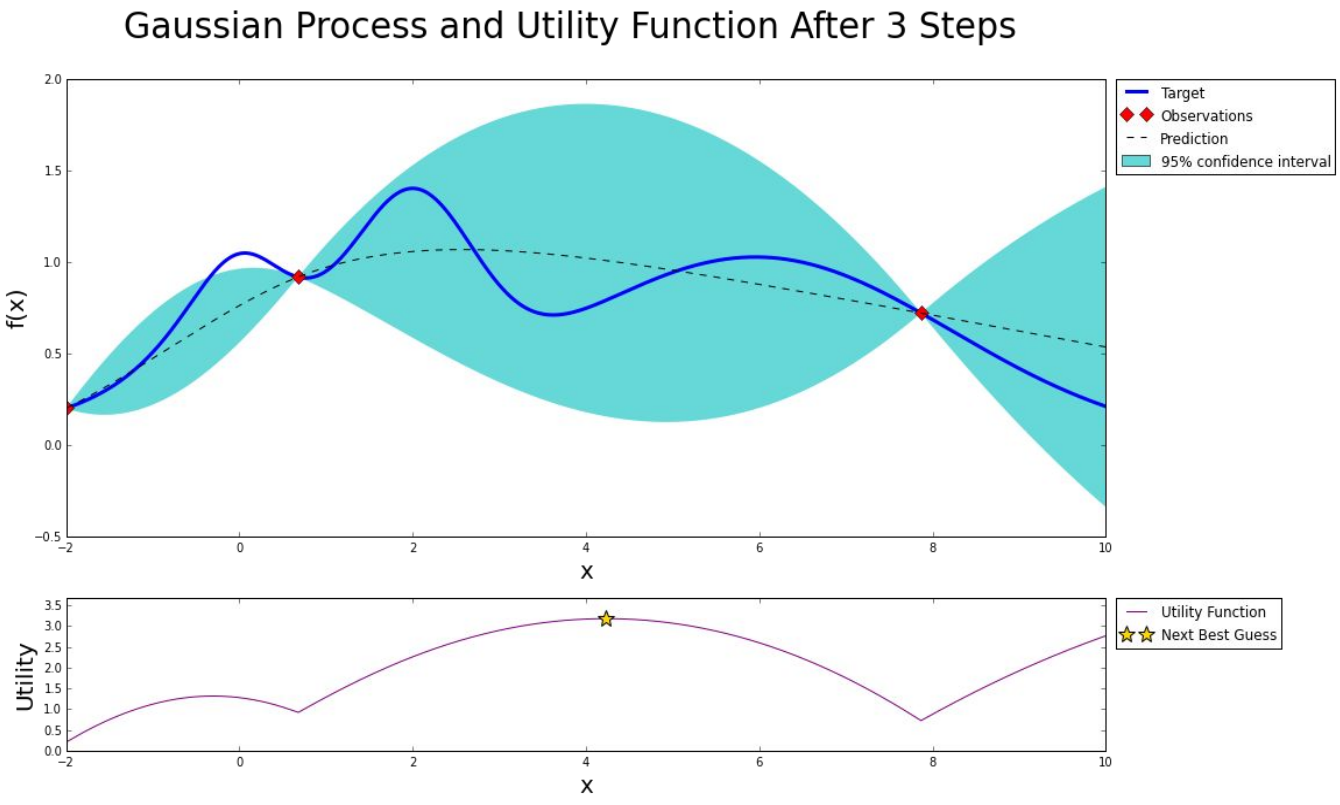
- 3000.000 SLOW

Questions?

Bayesian Optimization



Bayesian Optimization



Bayesian Optimization