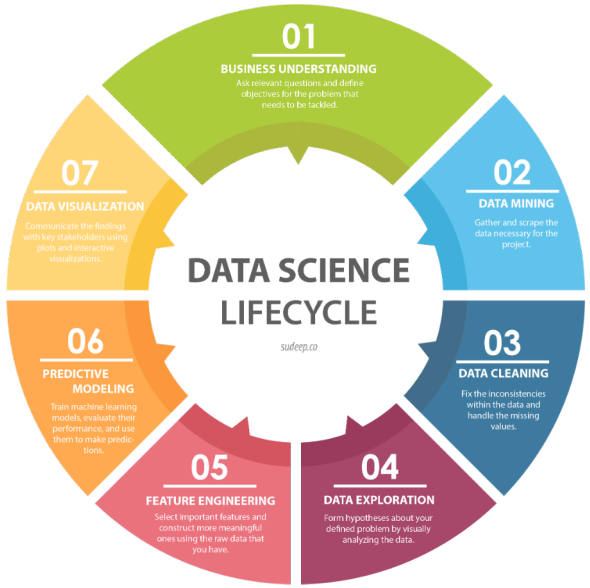
Ames Housing Project:
Advanced Regression Techniques for Predictive Model

DSI – path to become a data scientist
Mori Esam – Jan 2020



Build a model that :

Predict the price of a house at sale

Target : Real estate agencies, mortgage brokers, …

Test key amenities/features that influence house's value

Target : Group 1 + Architects, interior/exterior designers, contractors

Request from Data Governance : Data Audit and Data Capture Solutions

Overview

Identify key metrics that actually matter

Neighborhood | Location	
Nominal	neighborhood
	ms_subclass
	ms_zonning
	pid

Home Size | Usable Space	
Discrete	full_bath
	bedroom_abvgr
	kitchen_abvgr
	totrms_abvgrd
	garage_cars
Continuous	bsmtfin_sf_1
	bsmtfin_sf_2
	bsmt_unf_sf
	total_bsmt_sf
	1st_flr_sf
	2nd_flr_sf
	gr_liv_area
	garage_area
	wood_deck_sf
	open_porch_sf
	lot_area
	lot_frontage
	mas_vnr_area

Features	
Nominal	bldg_type
	house_style
	foundation
	functional
	land_countour
	lot_config
	roof_style
	roof_matl
	mas_vnr_type
	exterior_1st
	exterior_2nd
	Fence
	heating
	utilities
	central_air
	garage_type

Age | Condition	
Discrete	year_built
	year_remod/add
	mo_sold
	yr_sold
	garage_yr_blt
Ordinal	overall_qual
	exter_qual
	exter_cond
	bsmt_qual
	bsmt_cond
	fireplace_qu
	garage_qual
	kitchen_qual
	heating_qc
Nominal	condition_1
	sale_type

Implementation Process

Data Cleaning

- Consistency
- Missing Data
- Categorical Data

Renaming

Null → No Features
Null → Mode or Median

Conversion to numeric dummies
NO - *use directional attributes*

EDA

- Identify relevant var(s)
- Linear Relationship
- Normalize Distribution

Outline Strategy : meaningful data

Attributes with > 0.5 linear corr.

Log Transform SalePrice

Outliers
Do not drop - *avoid forcing model to appear less variable than it is in reality.*

Preprocessing Modeling

- Set up matrix & target
- Choose the best model
- Instantiate I Fit I Cross Validation
  > *Feature engineering*
- Generate Prediction
- Evaluate

MLR > LASSO > Ridge

Interaction term improved $R2$

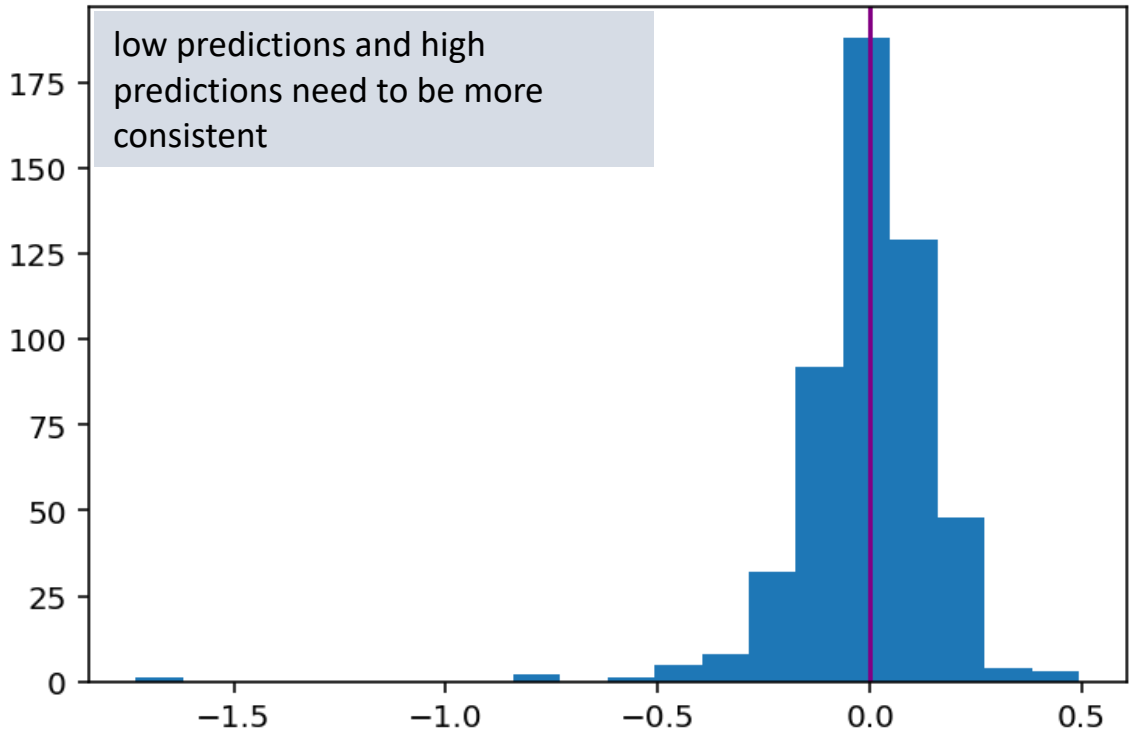
Goal
test R2 ~ 0.9
MAE ~ 0
MSE ~ 0
RMSE ~$10K

Result : MLR Model

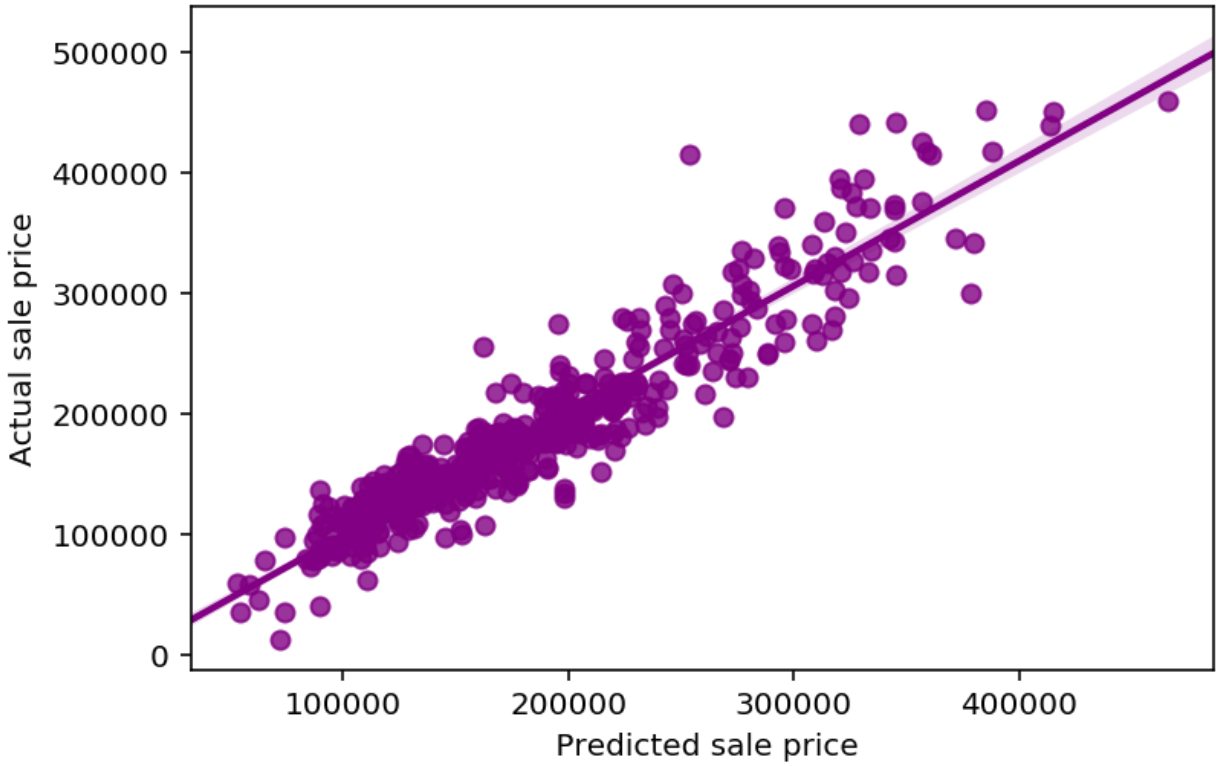
Regression Metrics

$R2$ Score : 0.853
MAE : 0.107
MSE : 0.008
RMSE : $27K

Residual (sale price – actual vs predicted)



Predicted vs actual price



Conclusion and Recommendations:

As of now **85.3%** of the variability in sale price can be explained by this model, indicating that the model is just right. In other words, model can generalize from train/test data to predict the house value, with **+/-$27K** price error. Nevertheless, this model can be used for the following purposes:

Prediction -
This model can be used for any dataset that includes similar attributes on house features to predict the property's selling price .

Inference -
This model can be used to outline and test some of the most important factors/features that influence house's value.

Optimize for accuracy -
Improve model by by leveraging feature engineering to include interesting features like Neighborhood, house style and materials.