# AMES HOUSING ANALYSIS



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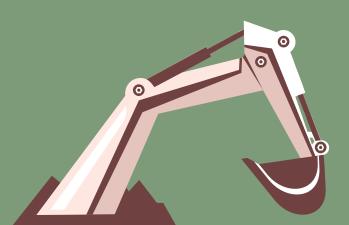
**WORKFLOW** 

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RECOMMENDATIONS

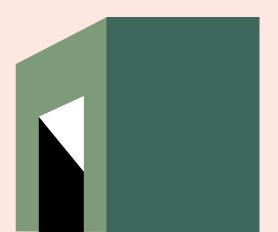
#### **PROBLEM**

Iowa's housing market is seeing a slow down. Appropriately priced houses get sold faster, but the process of getting a property valuation is long and tedious



#### GOAL

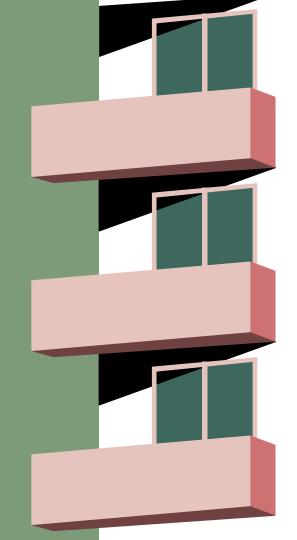
To automate pricing of houses through machine learning to expedite valuation and sale of houses for those looking to sell their property





## WORKFLOW

Data cleaning, feature engineering and selection



#### PROCESS BEFORE MODELLING

Null values i) Absence of features ii) Impute based on most common Check data types

**CLEANING** 

Feature creation (unification)
Convert ordinal, nominal (OHE)
Scaling, polynomial features
Feature selection based on coefficients

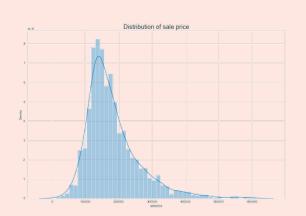
**FEATURE ENGINEERING** 

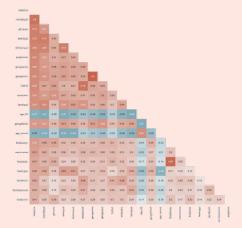
**EDA** 

Sale price - right skewed Heatmap - correlation with target Scatterplots of price vs living area to select features **MODEL PREPARATION** 

Train, test split (20% test) Find optimal alphas

#### **EDA OBSERVATIONS**







#### **SALE PRICE**

Right skewed, not normally distributed

#### **TOP 20 HEAT MAP**

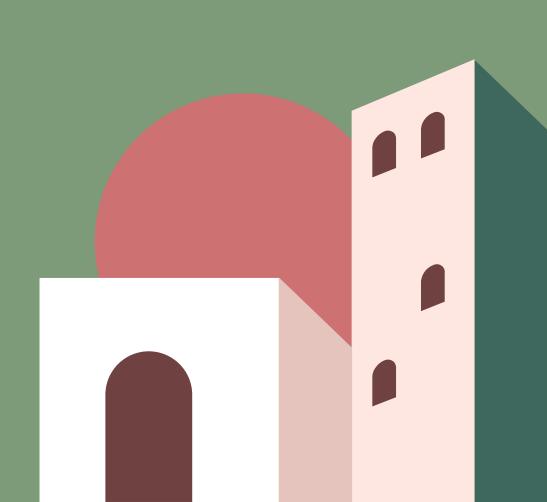
Overall quality, living area, external quality, kitchen quality are amongst the top

#### **BOX PLOTS**

Various neighborhoods showed significant differences in mean prices 03

## MODELLING

Summary and final model chosen



#### **SUMMARY**

# Features

**Training score** 

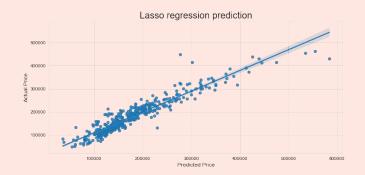
**Testing Score** 

**RMSE** 

BASELINE	LINEAR (OVERFIT)	LASSO (W POLYFIT)	LASSO (Drop Collinear)
92	92	30	26
0 %	90.5 %	89.7%	89.4%
0 %	89.8 %	89.1%	88.4%
80,473	25,746	26,562	27,000

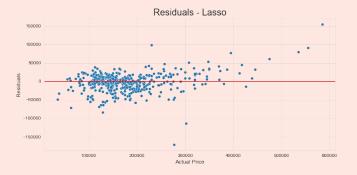


#### **MODEL EVALUATION**



#### **ACTUAL VS PRED**

Line of best fit goes through most points, except at higher sale prices (>300K) but this is only 8% of data



#### **RESIDUALS**

The inequality in variance is especially prominent at the extreme ends of prices

04

### RECOMMENDATIONS

Limitations and improvements

#### RECOMMENDATIONS

# FOR VALUATION

- Model is able to explain 88.7% of variation in price
- For better negotiation power, add 27K USD on top of predicted valuation
- If property is high value (>300K), it is best to get a realtor to do a physical valuation instead

#### **FOR INVESTMENT**

BONUS! Here are some things to consider for best returns:

- Properties in Northridge Heights
- Stone masonry veneer type houses
- Ensure garages are not attached
- Houses with a porch
- Newer houses
- Foundation made from poured concrete
- Central air conditioning

#### LIMITATIONS

- Many null values imputed based on highest value counts, might not be representative of true data
- Model would be more accurate with more features, but this would make it less interpretable to home owners

# FUTURE IMPROVEMENTS

- Consider a separate model dropping the prices above 300K, and examine the features important to this group of properties
- Take into account inflation as these prices were collected over a few years