AMES HOUSING PRICE CALCULATOR

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ROLES

WE ARE DATA ANALYSTS

OUR AUDIENCE CONSISTS OF HOUSING AGENTS IN AMES

AGENDA

01 WHAT PROBLEM ARE WE SOLVING

02 OBSERVATIONS OF THE AMES HOUSING MARKET

03 METHODOLOGY

04 FINAL PRICING MODEL AND WHY IT IS GOOD

05 CONCLUSION AND RECOMMENDATIONS

WHAT IS THE PROBLEM

Housing agents face many enquiries on housing prices

Option 1: Respond fast with the mean housing price in Ames

✗ highly inaccurate

How about Option 3, where agents can use a front-end calculator tool that can estimate the housing price from a few key features?

Option 2: Dig into database and try to find the most similar latest transaction

✗ takes too long

✗ might not be able to find exact match: agents are not sure how to adjust for the differences to better advise clients

Our Objective

Help housing agents to better advise potential home buyers and sellers, by developing a tool to estimate housing prices in Ames more quickly and accurately based on a few key features of the house

WHAT WE ARE AIMING FOR

GOOD ESTIMATE

Our model does not have to be perfect, but should hit 80-90% accuracy, and must minimally be better than just using mean housing price in Ames

EASE OF USE

Able to identify a few key features that drive the model, to be implemented as key input on the “front-end calculator” for the agents

INTUITIVE

The key input fields should make intuitive sense to the housing agents

RELEVANCE TO AMES

The key input fields used should have relevance to Ames

FUN FACTS ON AMES

-10°C/29°C

Lowest/Highest Temp

25,538

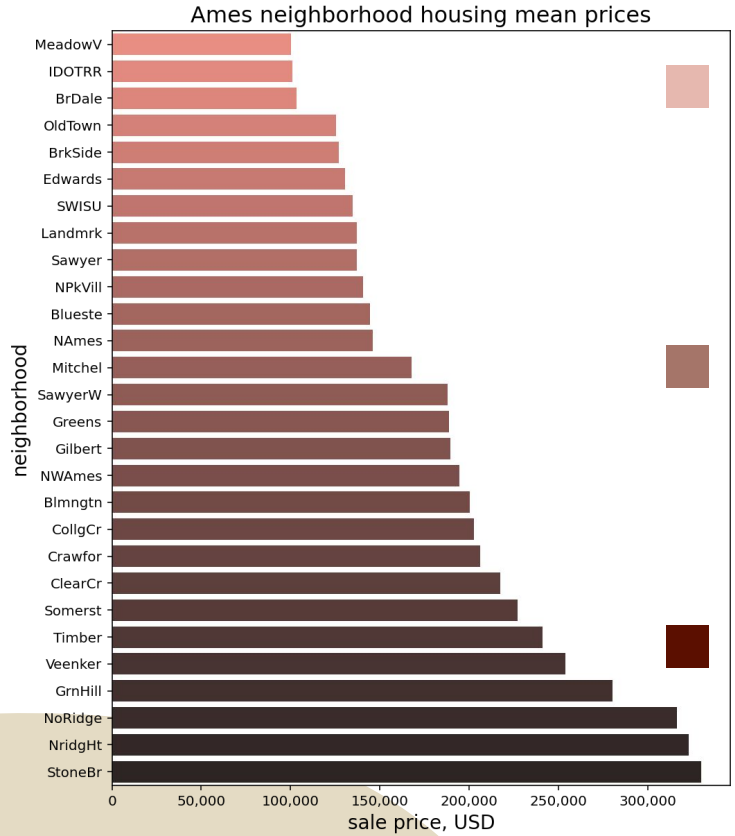
Households

2 CARS

Average number of cars per household

Source: US Census, Weatherspark.com

AMES HOUSING NEIGHBORHOODS



LEAST COSTLY

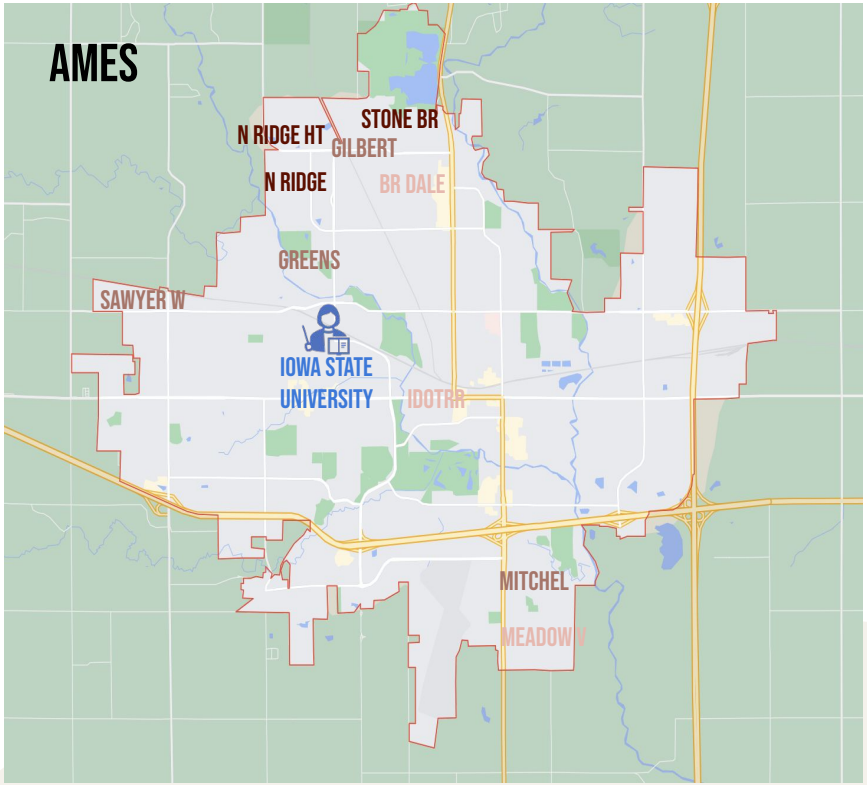
Meadow V
IDOTRR
(Iowa DOT and Rail Rd)
Br Dale

AVERAGE

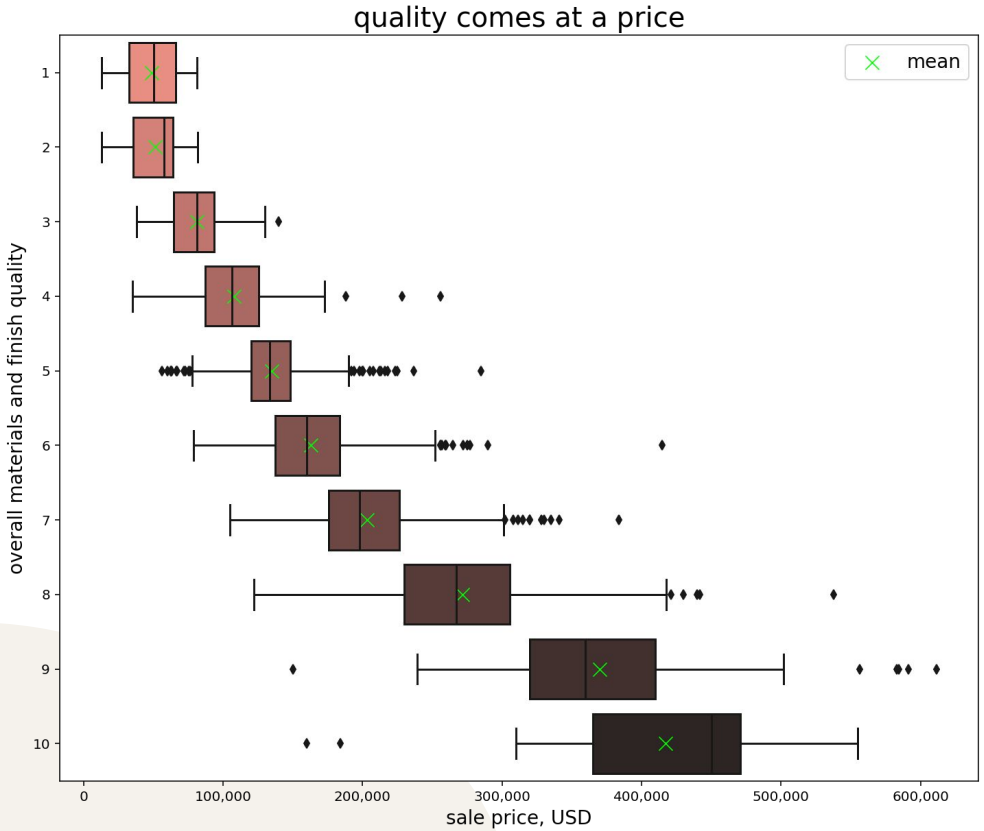
Mitchel
Sawyer W
Greens
Gilbert

MOST COSTLY

Stone Bridge
North Ridge Ht
North Ridge



QUALITY COMES AT A PRICE



LOW QUALITY (1-2)

~50k$ for a house if all you need is just a shelter over your head

AVERAGE QUALITY (5-6)

~150k$ for an average house with average quality materials and finishing

HIGH QUALITY (9-10)

~380k$ for a premium house with the highest quality materials and finishing

BIGGER HOUSE, HIGHER PRICE

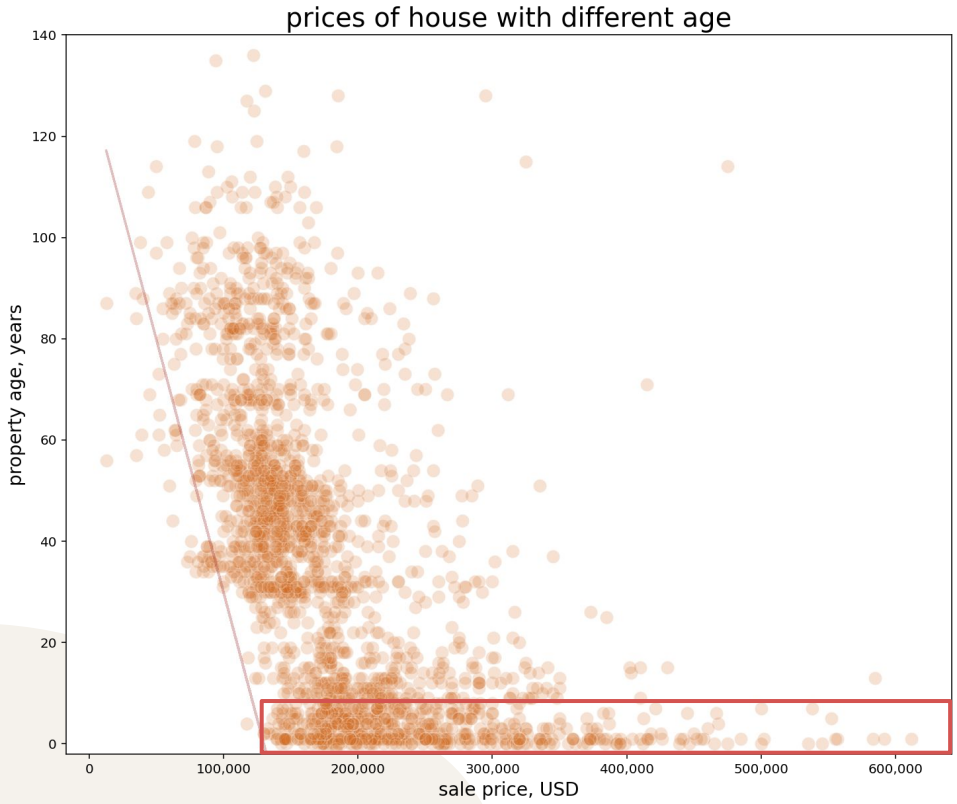
SIZE DOES MATTER

Big house naturally commands high price
Size has a premium

MARKET FLOOR PRICE MECHANISM

There is a minimum price you can expect for a given house size

HOUSE PRICES DO NOT AGE WELL



OLD IS NOT GOLD

House prices decay with age
While they are cheaper, older houses tend to be more costly to maintain

NEW BUILD PREMIUM

You pay top dollar for something new and unused

NOT ALL BASEMENTS ARE EQUAL

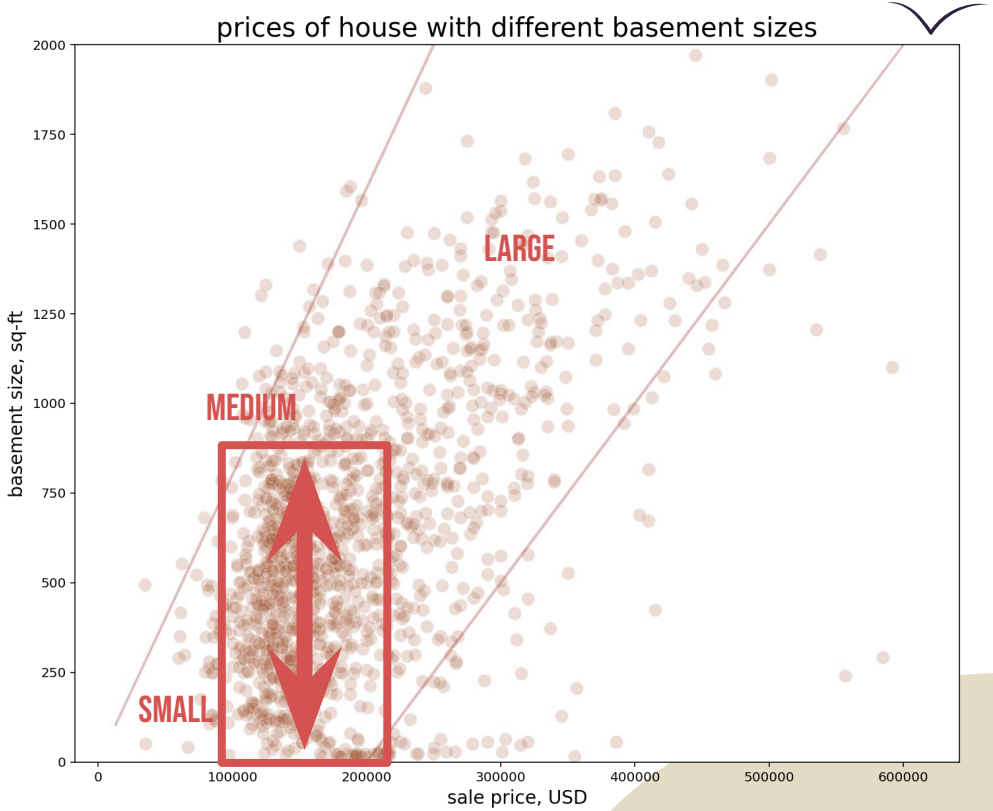
SOME ARE MORE EQUAL THAN OTHER$

SMALL AND MEDIUM

Houses with small and medium basements seems to have similar prices

LARGE MOVES THE NEEDLE

Large basements command a premium over medium and small



RECAP OF OUR AIM

GOOD ESTIMATE

Our model does not have to be perfect, but should hit 80-90% accuracy, and must minimally be better than just using mean housing price in Ames

EASE OF USE

Able to identify a few key features that drive the model, to be implemented as key input on the “front-end calculator” for the agents

INTUITIVE

The key input fields should make intuitive sense to the housing agents

RELEVANCE TO AMES

The key input fields used should have relevance to Ames

METHODOLOGY

Keeping in mind the need for ease of use and intuitiveness, we have done the following steps:

- Make sense of and group similar data fields together, out of the many many (79!!) data columns we have

- Inputs to the model should be easily interpretable, e.g. rather than input year that the house was built, we transformed the data to age of the house, so that it is immediately understandable and makes sense when used in future predictions

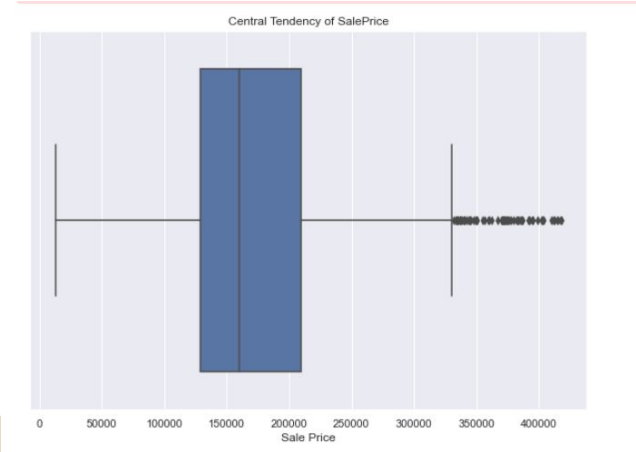
- Get rid of data columns that are a derivation of or closely related to other columns

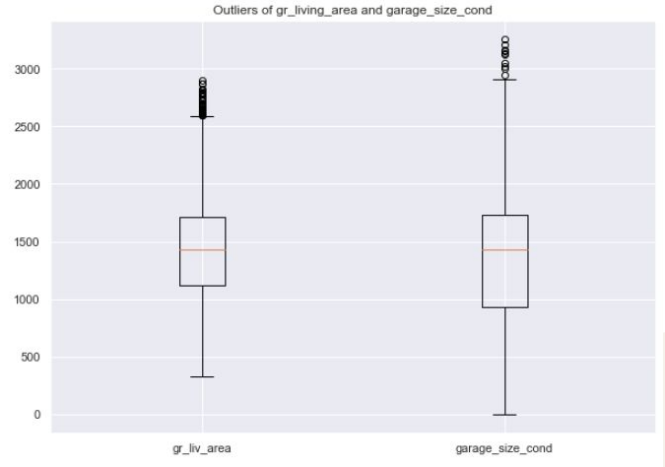
METHODOLOGY

Keeping in mind the need for a good estimate, we have done the following steps:

- Remove outliers in sale price that might distort our model and not give good estimates for the bulk of houses

- Remove outliers for the top 5 features that have strong correlation with saleprice





METHODOLOGY

Keeping in mind the need for features relevant to Ames, we have done the following steps:

- Looked at the garage features in more detail and think of different combinations that house owners might be concerned about (e.g. just a big garage alone will not be attractive, house owners want garages that are both big and have good quality).

- This is because Ames' households have 2 cars each on average, hence garage will be important to them

FINDINGS OF DATA

- Data provided consist of total 79 features with different data types
- Columns belongs to a similar feature group
- There are features with more than 50% null values!
- Missed out useful and interpretable features in the data such as property age, remodel age

```
garage_type
garage_yr_blt
garage_finish
garage_cars
garage_area
garage_qual
garage_cond
```

DATA CLEAN UP INITIAL STEPS

1. **Check all the null values in the data**

    a. Those columns that is integer and float type, assume it means there is no such feature and replace to 0

    b. Those that are in object type, check in data dictionary

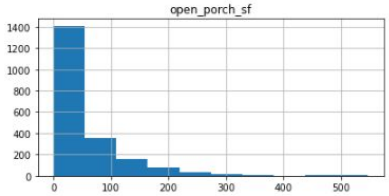
        i. If there is an existing “None” value for that column ,assume null means does not have that feature and replace to None

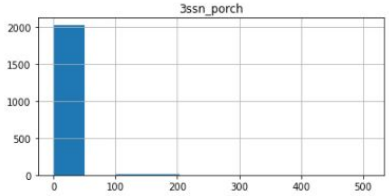
        ii. If there “None” value doesn’t exist , check the number of null values. If more than 5% remove, else replace with mode.

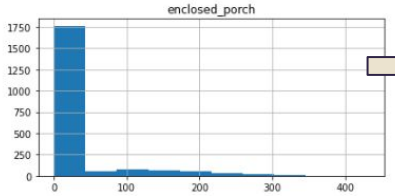
DIGGING DEEPER...

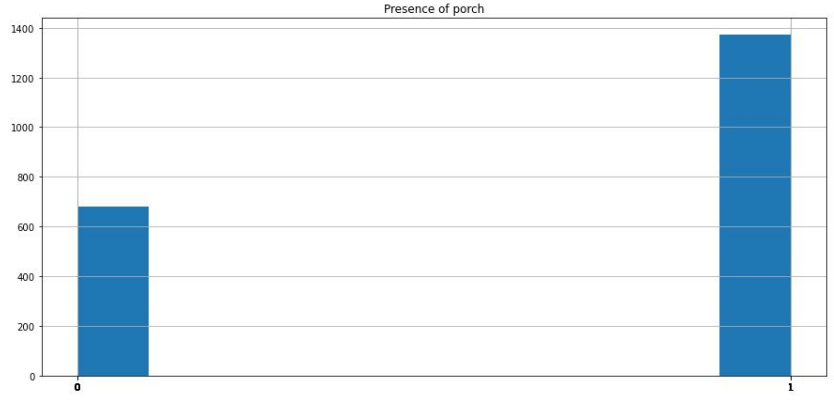
Porch

- There are 3 porch features. Most values are 0 sq. Instead of having 3 porch features, changing it to 1 porch feature to indicate whether there is a porch or not. Categorize them to indicate if they have a porch instead









DIGGING DEEPER...

Garage Year built & Year Built

- Generally, garage built the same year of the property. True enough, 76% of the garage built in the data is equivalent to year built
- Remove garage year built as one of the feature

Garage Area and Garage Condition

- Buyers usually look at the size and garage condition. Putting them together as one feature

Remodel age and Property age

- To better interpret the data:
  Calculate property age and remodel age and include as additional features

DIGGING DEEPER...

1st floor square foot, 2nd floor square foot, Ground Living Area

- There are houses that exist where there is not even a second floor
- Those houses that do not have a 2nd floor, 1st floor and ground area living area will likely be the same values
- Buyers generally look at total size of house above ground
    - 58% with houses have 0% square feet 2nd floor
    - 57.3% 1st floor = ground living area
- Remove 1st floor as a feature and change values in 2nd floor to indicate where there is it is a single storey houses or not

DIGGING DEEPER...

High collinearity of features

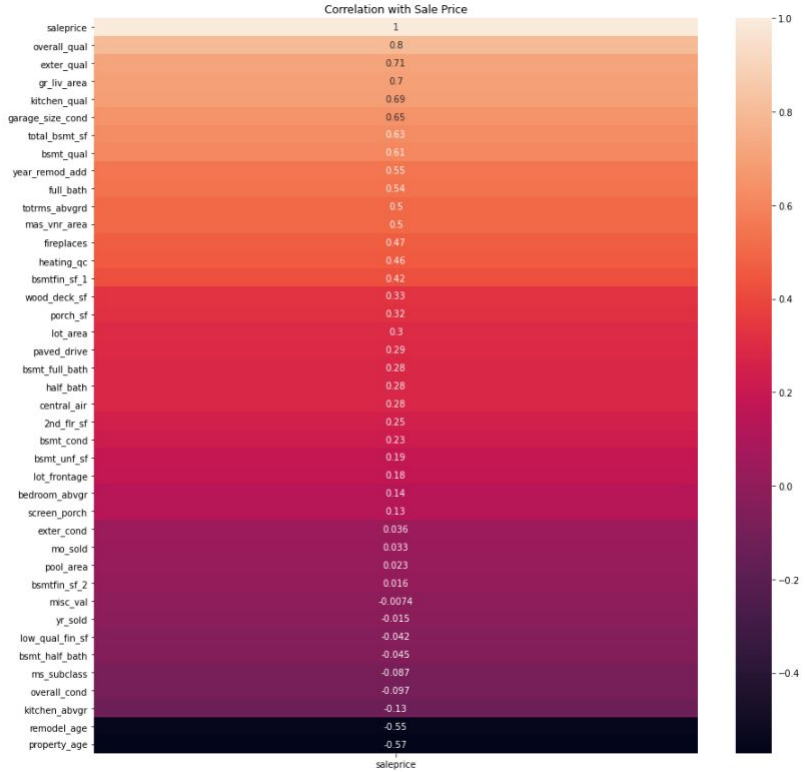
A few features that have very high collinearity(> 80%)

- Garage condition vs garage quality
- Garage cars vs garage area
- Pool quality vs pool area
- Remove one of the feature in each.

Remodel year and Year built

- 65% collinearity
- But more than 50% where remodel year = year built
- Remove year built as a feature

CORRELATION OF FEATURES WITH SALE PRICE



Top 5 features positive correlated: overall quality, external quality, ground living area, kitchen quality, garage size condition

Feature that is most negatively correlated: **Property age!**

CURRENT MODEL

Mean Price Model

Uses the average price of houses in the market to predict the price of a house

ISSUES WITH CURRENT MODEL

INACCURATE

High Root Mean Square Error (US$67,981.3)

DOES NOT PREDICT

All results are based on just the mean price of houses

IGNORES HOUSE FEATURES

No features of the house is considered

OUR NEW MODEL

Supervised Learning

Machine Learning Algorithm trained on a set of current data

Features Considered

Takes into account of features in the house

Uses Regression Models

Creates Regression Models for a more accurate prediction

BENEFITS OF OUR MODEL

Accurate and Precise

Our model can predict House prices with accuracy and precision

Scalable to New Data

Our model can use even new real-world data to expand its learning

Adaptable

Our model is able to adapt to features

Takes Features into Account

Features are always considered

OUR FINAL PRICING MODEL: LASSO REGRESSION

WHY LASSO REGRESSION

Highest Cross Validation Score 91.7%

With a score of 91.7%, Lasso model scored the highest of the 3 models we tested

Highest Degree of Accuracy

Lasso Model scored the highest R2 Score at 91.0% on our test score

Lowest Root Mean Square Error (RMSE)

Low RMSE means sales price predictions are more precise

COMPARING BETWEEN OTHER REGRESSION MODELS

Evaluation Metrics	Linear	Lasso	Ridge
Cross Value Mean	-3.88	0.917	0.913
Train R-square	0.942	0.936	0.942
Test R-square	-8.39	0.910	0.900
RMSE	16187.615	20787.274	21916.231

COMPARING THE OLD AND THE NEW

More Precise

Our model has an RMSE of US$20,787 vs US$67,981 on the old model

Takes features from housing data into account

Our model accepts features of the house, the old model does not

Able to scale with current and new data

Our model can scale with more data, the old model cannot

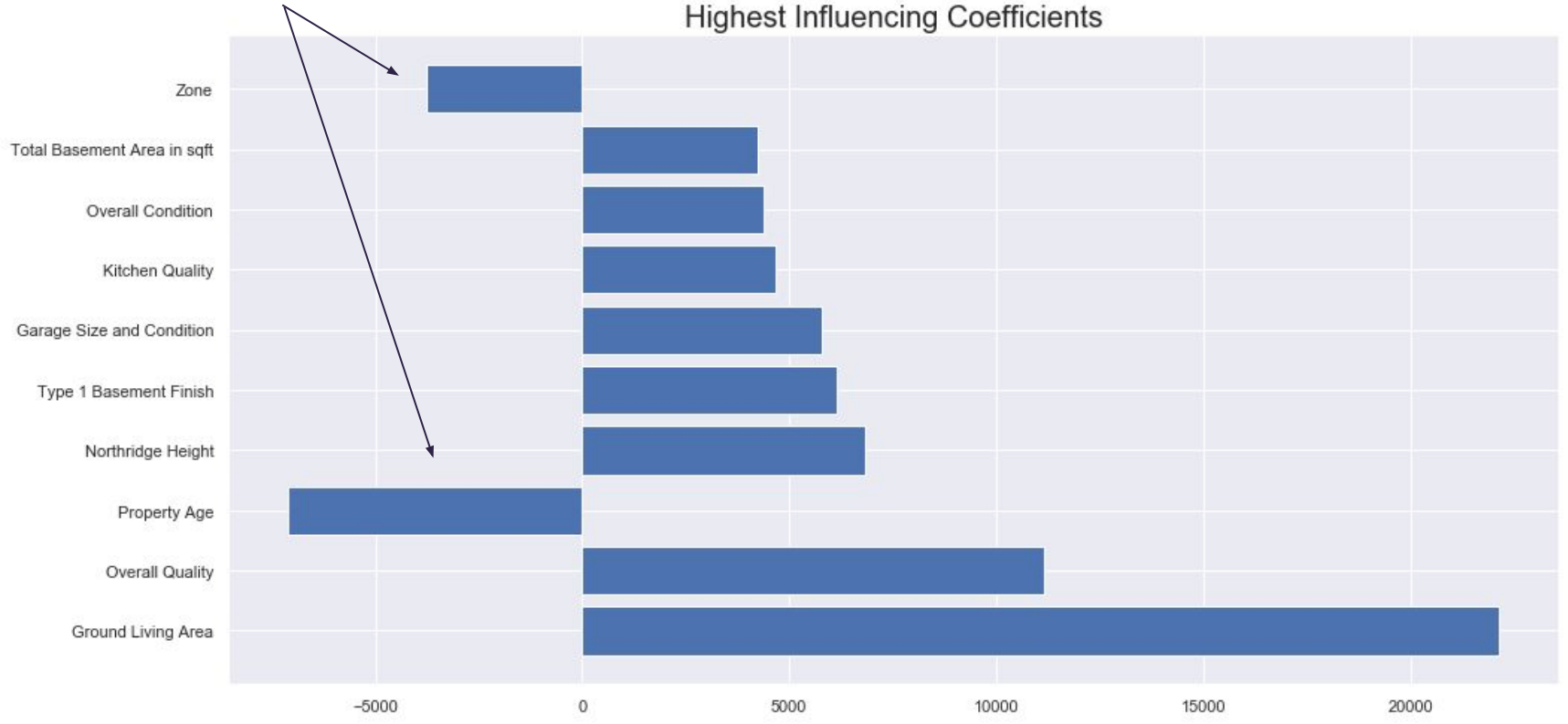

Residuals for best model(lasso)
Horizontal Precision Line
Closer dots are to the line means better model
75000
50000
25000
0
−25000
−50000
−75000
−100000
50000
100000
150000
200000
250000
300000
350000

INTERESTING FINDINGS FROM OUR MODEL

Biggest influencing factors to House Sale Prices are:

- Ground Living Area
- Overall quality
- Property Age
- Proximity to Northridge area
- Type 1 finish basement
- Garage size and condition
- Kitchen quality
- Overall condition
- Total basement area
- House Zone

These are negatives



MODEL VALIDATION FROM KNOWN FACTS

Northridge is one of the more expensive areas

Ames is also an Agricultural Area

Property Price depreciate with Age

Size Does Matter!

Verified with our data as well

CONCLUSION

- Our model is 91% accurate in estimating housing prices
- 5 features identified as top sale price predictors
- Pros: quick, simple, more accurate
- Cons: oversimplified, subjective rating of feature quality

Features	
1	Size of living area (above ground)
2	Overall quality
3	Property age
4	Neighborhood
5	Rating of basement finished area

RECOMMENDATION

Create a tool in the form of a mobile app that accepts top 5 features as inputs, that housing agents can access anytime and anywhere to estimate sale prices

- Advise home sellers on realistic listing prices
- Advise home buyers on reasonable prices to pay

BACK-UP

TRANSFORMATION FROM STANDARD SCALE (BACK-UP)

$$z = \frac{x - \mu}{\sigma}$$

eqn:

$$y = az_1 + bz_2 + k$$

$$y = a\left(\frac{x_1 - \mu_1}{\sigma_1}\right) + b\left(\frac{x_2 - \mu_2}{\sigma_2}\right) + k$$

$$y = \frac{a}{\sigma_1}x_1 - \frac{a\mu_1}{\sigma_1} + \frac{b}{\sigma_2}x_2 - \frac{b\mu_2}{\sigma_2} + k$$

$$y = \left(\frac{a}{\sigma_1}\right)x_1 + \left(\frac{b}{\sigma_2}\right)x_2 + \left(k - \frac{a\mu_1}{\sigma_1} - \frac{b\mu_2}{\sigma_2}\right)$$

Model coefficient interpretation:

'a' is the coefficient from regression post standard scaling

To get the coefficient based on original scale, we divide it by the sigma of the train dataset which was used to fit the standardscaler
i.e. 'a / sigma'

MODEL COEFFICIENT ILLUSTRATION (BACK-UP)

	REFERENCE: HOUSE A	HOUSE B	HOUSE C	HOUSE D
Overall quality	6	7	6	6
Above grade living area (sq-ft)	2000	2000	2100	2000
Property age	50	50	50	90
Delta value vs. A	-	+$9,702	+$4,813	-$3,305
Sale price	**$250,000**	**$259,702**	**$254,813**	**$253,305**