Predicting House Prices

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Capstone Two Presentation

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House prices

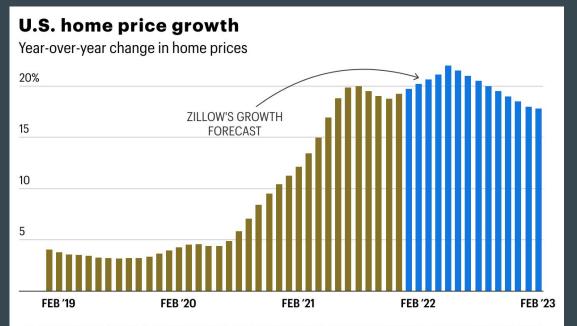
- Always changing
- Reasons
 - Supply and demand, interest rates, recessions, high levels of federal debt, etc
- Stakeholders
 - Homeowner, potential buyer, investor, landlord, real estate agent, broker







United States housing prices



GOLD REPRESENTS ACTUAL 12-MONTH GROWTH AS MEASURED BY THE S&P CASE-SHILLER U.S. HOME PRICE INDEX. BLUE REPRESENTS ZILLOW'S 12-MONTH HOME PRICE FORECAST.

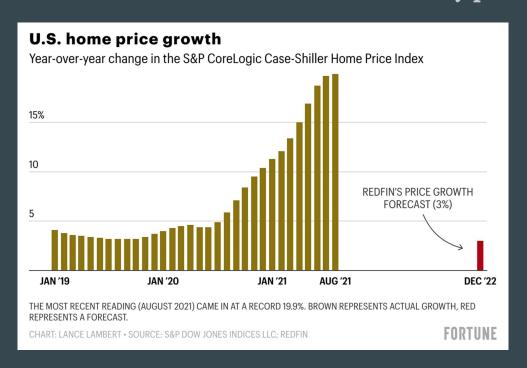
CHART: LANCE LAMBERT • SOURCE: S&P DOW JONES INDICES LLC; ZILLOW

FORTUNE

- Increases over time
- Forecasting
- Fluctuates
 - o Economy
 - o Pandemic
 - Natural disasters

Project goal

Goal: Create a model that can accurately predict housing prices



- House amenities
 - Size
 - Upgrades
 - House features
 - Quality of house

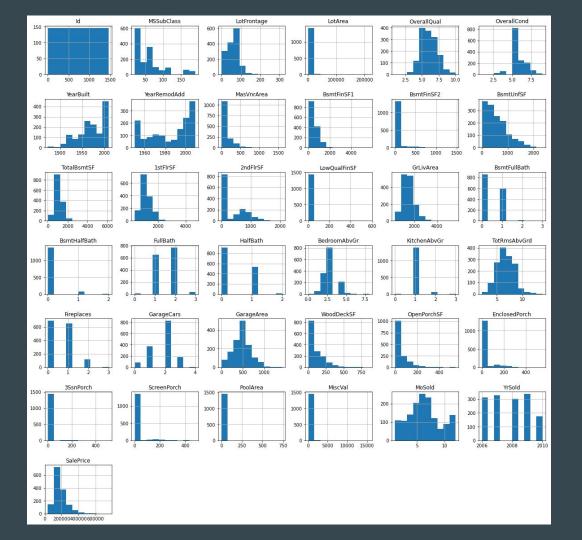
Data



- Ames, Iowa house price data set
- 79 explanatory variables
 - o 58 categorical
 - House style, lot type, type of electrical system
 - o 21 continuous
 - Number of bedrooms, basement size (sq ft), garage size (sq ft)

Data Wrangling

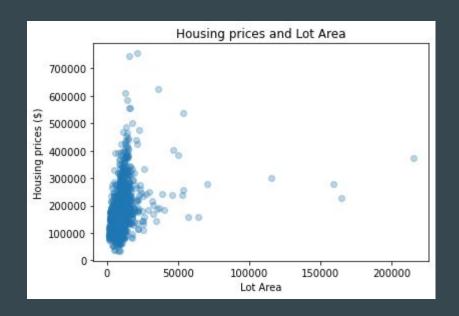
- Categorical: 'None'
 - o Alley, garage
- Continuous: '0'
 - Lot area, lot frontage
- Generated histogram



Data Exploration

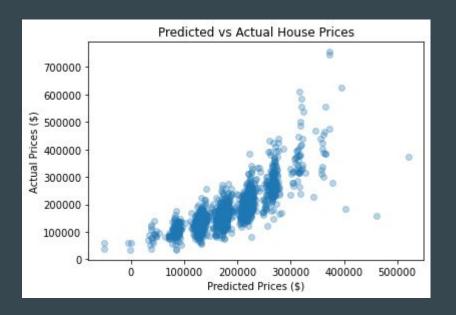
- Goal
 - Explore relationship between first 4 variables and sale price
 - o Linear regression model
- Variables
 - o ID
 - Lot area
 - Lot frontage
 - Overall quality

Linear Regression model





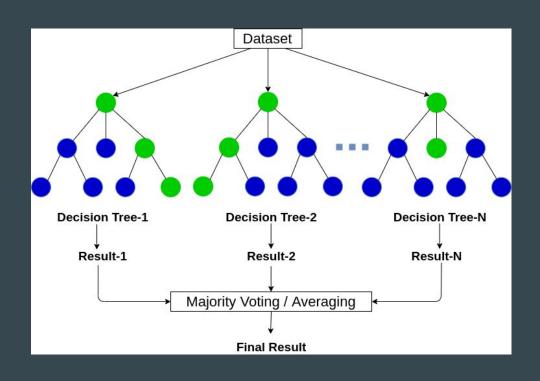
Exploratory data analysis: Actual vs predicted



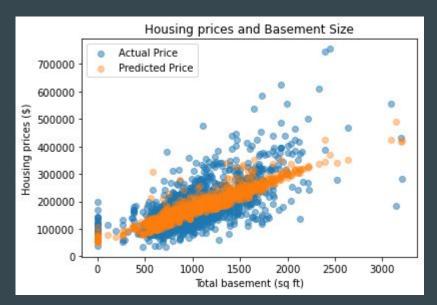
 Hypothesis: Lot area, lot frontage, and overall quality might be good variables at predicting housing prices

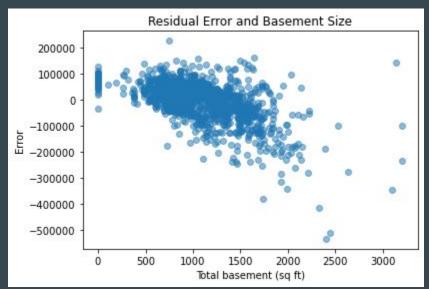
Scikit-learn's models

- Linear Regression
 - Continuous variables
- Random Forest Classifier
 - Continuous and categorical variables
 - Ensemble method, decision trees
- Variables
 - Adjusted thresholds
- Model
 - Tuned hyperparameters



Basement adjusted threshold





• Threshold: < 2,000 sq ft

Hyperparameter tuning: Random Forest Classifier

```
param_dist = {'n_estimators': randint(50,500),
              'max_depth': randint(1,20)}
# Create a random forest classifier
rf = RandomForestClassifier()
# Use random search to find the best hyperparameters
rand_search = RandomizedSearchCV(rf,
                                 param_distributions = param_dist,
                                 n_iter=5,
                                 cv=5)
# Fit the random search object to the data
rand_search.fit(X_train, y_train)
# Create a variable for the best model
best_rf = rand_search.best_estimator_
# Print the best hyperparameters
print('Best hyperparameters:', rand_search.best_params_)
```

- **n_estimator** (# of trees)
- max_depth (# of splits/tree)

Models

	RMSE	RMSEtest	featurenames	model	params
0	76546.713815	79919.058600	LotArea	LinearRegression	NaN
1	73569.131484	83162.654656	LotArea_LotArea_squared	LinearRegression	NaN
2	73139.716444	84373.200915	LotArea_LotArea_squared,LotArea_lt_50000	LinearRegression	NaN
3	72169.128354	85650.352243	LotArea_LotArea_squared,LotArea_lt_50000,LotFrontage	LinearRegression	NaN
4	71470.438467	86435.185894	LotArea_LotArea_squared,LotArea_It_50000,LotFrontage,LotFrontage_gt_0	LinearRegression	NaN
5	71469.968406	86432.358822	LotArea_IcotArea_squared,LotArea_it_50000,LotFrontage_lotFrontage_gt_0,LotFrontage_it_150	LinearRegression	NaN
6	20834.005665	111315.356683	LotArea_IotArea_it_50000,LotFrontage_lotFrontage_gt_0,LotFrontage_it_150	RandomForestClassifier	NaN
7	58099.385054	95527.341760	LotArea_LotArea_squared,LotArea_lt_50000,LotFrontage_gt_0,LotFrontage_lt_150,TotalBsmtSF	LinearRegression	NaN
8	57641.957486	95437.131745	$LotArea_totArea_tt_50000, LotFrontage_t_0, LotFrontage_it_150, TotalBsmtSF_it_2000, LotFrontage_gt_0, LotFrontage_it_150, TotalBsmtSF_it_2000, LotFrontage_it_150, LotFront$	LinearRegression	NaN
9	51832.535131	98242.764980	$LotArea_squared, LotArea_it_50000, LotFrontage_gt_0, LotFrontage_lt_150, TotalBsmtSF, TotalBsmtSF_lt_2000, YearBuiltEndown to the property of the property o$	LinearRegression	NaN
10	48741.063518	100165.073309	$Lot Area_squared, Lot Area_it_50000, Lot Frontage_lot Frontage_gt_0, Lot Frontage_it_150, TotalBsmtSF_it_2000, Year Built_it_1990, Lot Frontage_gt_0, Lot Frontage_gt_0, Lot Frontage_it_150, TotalBsmtSF_it_2000, Year Built_it_1990, Lot Frontage_gt_0, Lot Fron$	LinearRegression	NaN
11	39450.203717	105058.330597	$LotArea_LotArea_squared, LotArea_lt_50000, LotFrontage_LotFrontage_gt_0, LotFrontage_lt_150, TotalBsmtSF_TotalBsmtSF_lt_2000, YearBuilt_tl_1990, OverallQuallege and the property of the pro$	LinearRegression	NaN
12	37801.397783	106568.816990	$LotArea_LotArea_squared, LotArea_lt_50000, LotFrontage_gt_0, LotFrontage_it_150, TotalBsmtSF_it_2000, YearBuilt_t1990, OverallQual_OverallQual_it_9000, TotalBsmtSF_it_2000, YearBuilt_t1990, OverallQual_it_1990, Overal$	LinearRegression	NaN
13	1364.061580	109548.059839	LotArea,LotArea_squared,LotArea_it_50000,LotFrontage,LotFrontage_gt_0,LotFrontage_it_150,TotalBsmtSF,TotalBsmtSF_it_2000,YearBuilt_YearBuilt_It_1990,OverallQual_OverallQual_t_9	RandomForestClassifier	(n_estimators=276, max_depth=14)

Best model: Random Forest Classifier (n_estimators = 276, max_depth = 14)

Conclusions and Future work

- Train error ~\$1,600
- Test error > \$100,000
- Risk of undervaluing houses
- Large potential loss
- Future work:
 - Reduce bias variance problem
 - Add thresholds
 - More/different data
 - Different models

