Modelling property prices in King County

Georg F.K. Höhn

Ironhack

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Overview

Introduction

EDA

Implementation aspects

Model comparison

Over $650k

Conclusion/outlook

Introduction

Introduction

- dataset from property sales in King County, Seattle, WA, USA
- timeframe: between May 2014 and May 2015
- source: https://www.kaggle.com/datasets/minasameh55/king-country-houses-aa

Aims

- predict sales prices based on dataset
- (closer look at subset of data with `price` $\geq$ \$650k)

EDA

Overview

- 21 613 datarows
- 21 columns
- descriptions in meta-data, but some clarifications
  - grade up to 13 (instead of 11)
  - views 0–4 (instead of binary)
  - id identifies properties not transactions
- target variable `price`
  - range: 75k–7700k
  - mean: 540088,14
  - median: 450k
  - right-skewed

Pre-processing and feature engineering

- no missing values‘
- duplicates for `id` explained by multiple sales of same property
  - created new column `prev_sale_within_year`
- extracted month and day (as `ints`) from `date`
- later:
  - drop zipcode
  - drop day

Transforming data

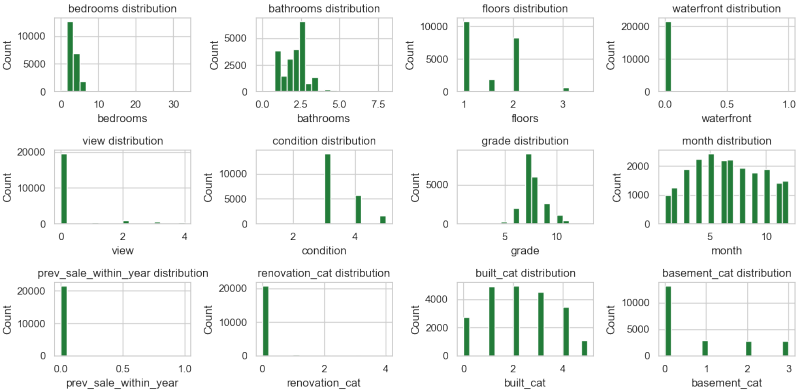
- transformed following data into categorial:
  - `yr_renovated`
  - `yr_built`
  - `sqft_basement`
- two variants:
  - labels
  - one-hot-encoding

Scaling

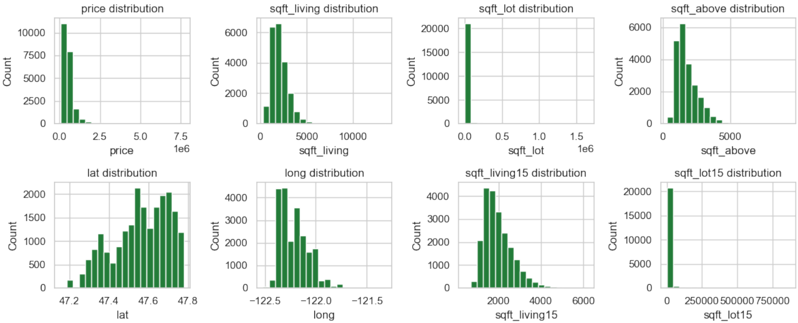
- kept a version of unscaled data
- scaling using `sklearn.compose.ColumnTransformer`
  - apply StandardScaler to continuous columns
  - pass through categorial variables unchanged

Distributions

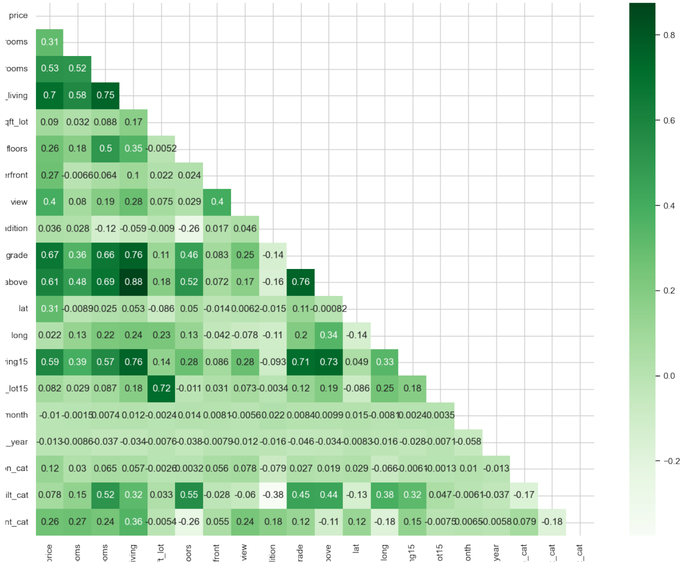
Barplots for categorial data



Histograms for continuous data



Correlation matrix



Implementation aspects

Helper functions

- `mk_histplots`: generate histplots for a (subset of a) dataframe, optionally saving output
- `mk_barplots`: generate countplots for a (subset of a) dataframe, optionally saving output
- `mk_boxplots`: generate barplots for a (subset of a) dataframe, optionally saving output
- `plot_corrmatrix`: plot a correlation matrix for a dataframe, optionally saving output
- evaluation function
- function for plotting coefficients in linear models

Model comparison

Overall approach

- running different models including some hyper-feature tuning
  - Linear Regression Models
  - KNN
  - GradientBoost
  - RandomForests
  - XGBRegressor
- evaluation function printing for training and test sets:
  - r^2-score
  - adjusted r^2-score (penalising models with more features)
  - mean-squared-errors
  - mean-absolute-errors
  - ratio of MAE to maximum target value
- evaluation function returns adj. r^2 and MAE for training and test for collection in dataframes

Data collection

- lists for each model family transformed into DataFrame
- sorted by adj. r^2 and MAE for test sets
- top 3 for each family included in an overall list

Results

type	scaled	r^2-a-train	r^2-a-test	mae-train	mae-test
XGBoost	False	0.975	0.913	40600.868	65516.939
XGBoost	False	0.975	0.913	40600.871	65516.938
XGBoost	False	0.975	0.913	40600.864	65516.941
GradientBoost	True	0.998	0.908	3511.192	64412.386
GradientBoost	True	0.996	0.906	5168.707	64658.581
GradientBoost	True	0.993	0.905	10322.906	63306.014
RandomForests	True	0.980	0.879	30229.928	71517.825
RandomForests	True	0.980	0.879	30229.928	71517.825
RandomForests	True	0.980	0.877	30653.158	72256.111
knn	True	0.818	0.787	86150.484	95555.056
knn	True	0.829	0.783	84326.308	97208.734
knn	True	0.838	0.782	82691.138	97932.769
lm-lasso	True	0.704	0.684	125477.227	126751.772
lm-lasso	True	0.704	0.684	125477.227	126751.772
lm-lasso	True	0.704	0.684	125477.226	126751.891

Hyperparameters of best performing model

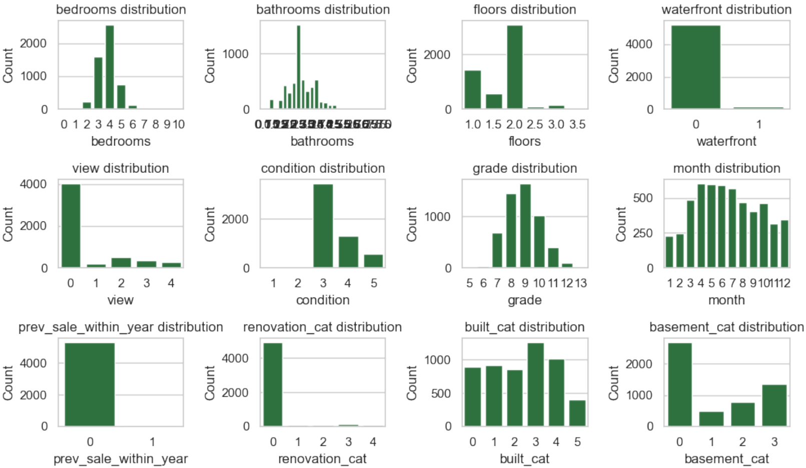
XGBoost

- estimators: 1.0
- booster: gbtree
- subsample: 1
- `dart_nominalized_type`: TREE
- `min_child_weight`: 1.0
- `max_depth`: 6.0
- `reg_alpha`: 0.3
- `reg_lambda`: 1.0
- learning rate: 0.3
- `max_iterations`: 20.0

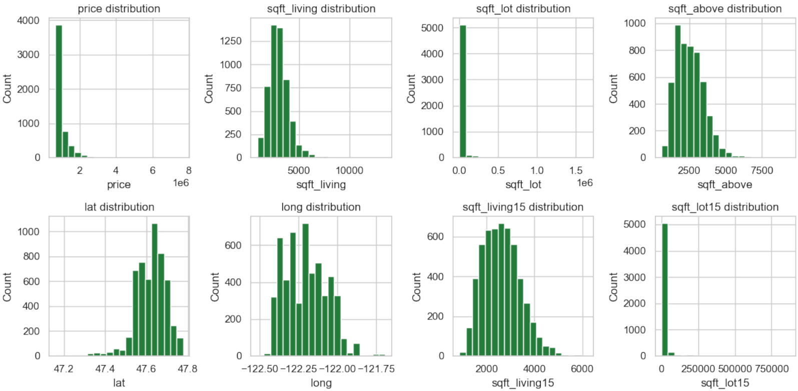
Over $650k

- much smaller dataset (5324 datapoints)

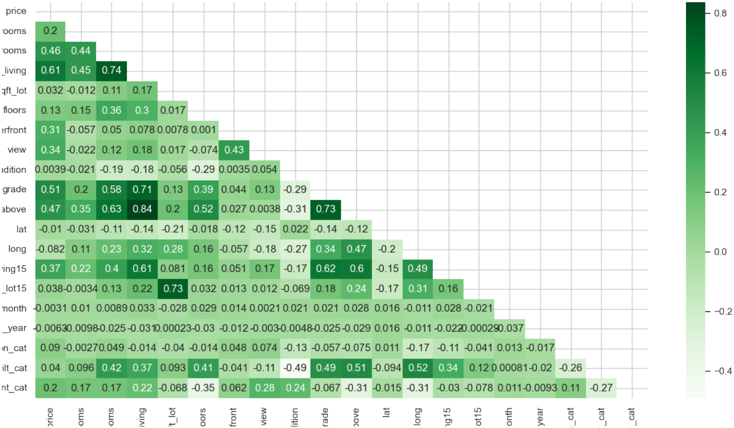
Barplots for categorial data



Histograms for continuous data



Correlation matrix



Model fitting

- fit XGBoost on unscaled data using label encoding with a range of hyperparameters
- best result:
  - r^2-adjusted (train): 0.990268
  - r^2-adjusted (test): 0.761220
  - MAE (train): 33374.973380
  - MAE (test): 132851.792547
- strong overfitting

Conclusion/outlook

- more cleanup
- visualising results would be nice
- using RFE (?) to consider rank of features
- GridSearchCV instead of manual looping?
- idea for lat/long:
    - calculate distance matrix
    - dimensional scaling to 1 or 2 dimensions
    - provides small metric of relative distance for each datapoint (might help to model that house price is also influenced by spatially defined neighbourhoods)

Thanks for your attention!