

Boston Houses Pricing

Predictive Model using Linear Regression

Machine Learning I

Professor: Concepción Diaz

Camilla Perotti | Hector Marmol | Lucia Sarobe | Tomás Silva | Vedant Agrawal

Agenda



Problem Statement
Slide 3

Exploratory Data Analysis
Slide 4-5

Data Model
Slide 6 - 7

Model Deployment (Streamlit App)

Slide 8

Boston residents' face multiple challenges when navigating through housing options



Some of the features in the dataset:



- N° rooms tailored to meet your specific requirements
- Crime rate per capita providing insights into neighborhood safety
- Pollution levels helping you evaluate the environmental quality
- Pupil-teacher ratio supporting decisions for families with children
- Tax rate and industrial proportion offering economic perspectives



This user-friendly platform simplifies the journey of house hunting by allowing users to input their preferences, visualize data trends, and instantly receive a price estimate tailored to their dream home.

Boston Housing Predictor → Value Proposition

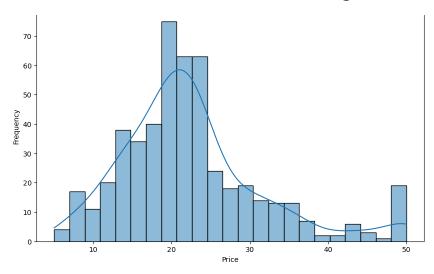


Transparency, simplicity and confidence to the housing market, empowering residents to find homes that meet their needs and align with their budgets

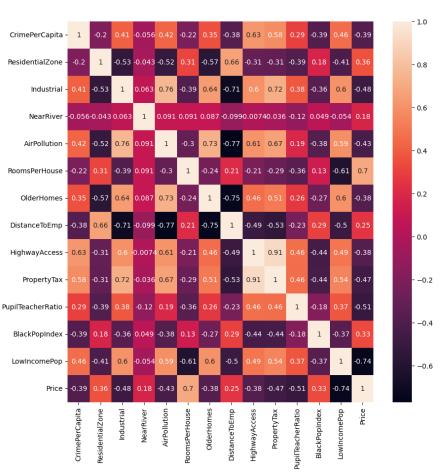
All the features are seemingly correlated with the dependent variable



Distribution of House Pricing



Correlation Heatmap



Key Takeaways

Distribution of House Pricing:

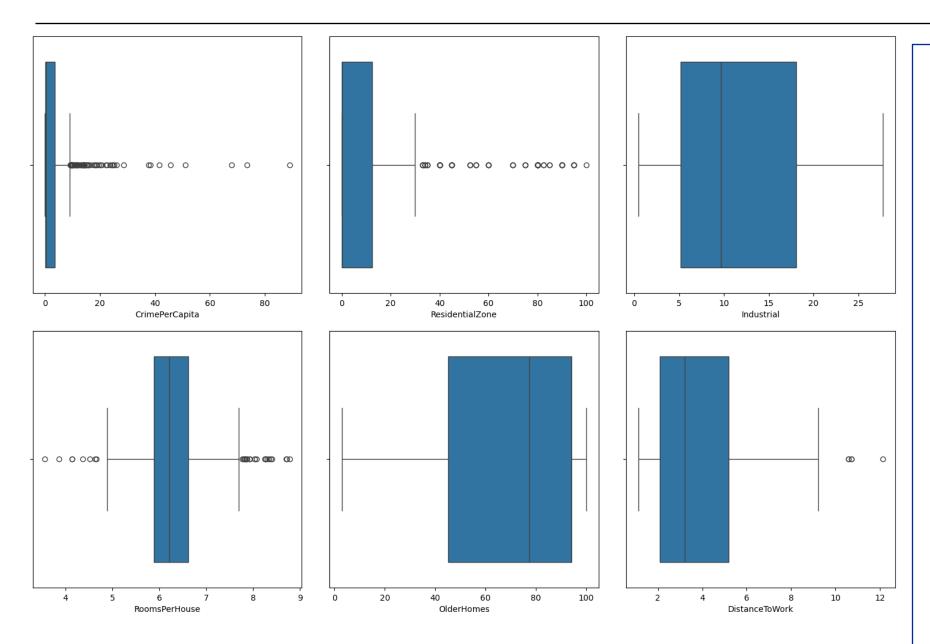
 Most houses are priced between 14K and 26K, although there is a considerable amount in the 50 thousands' (right-heavy tail)

Correlation Heatmap:

- We will use the features with a correlation above 0.4 (absolute value)
- PropertyTax and HighwayAccess are highly correlated (0.91)
 between each other, which would possibly lead to multicollinearity, if they were variable of the same type

No outliers were detected





Key Takeaways

Boxplots for Outlier Detection:

- Example: 6 Charts
- Machine Learning's outliers are considered differently than Statistics
- Charts that have plenty of circles outside the IQR means that the dataset has a wide distribution, hence are not considered outliers
- DistanceToWork required further investigation but lead to be considered as no outlier
- No outliers detected

3 models were trained: df – every feature contemplated; dfl – correlation threshold of 0.4; df2 – correlation threshold of 0.2



Macro Process for a Linear Regression Model

Understand the problem and have a clear value proposition



Dependent variable: Price

Test proportion: 10%



Scale the features:

Fit and transform for training
Transform for test



Elastic Net model for regularization

Cross Validation through Grid Search

df14 featuresdf18 featuresdf212 features

Model I (df) every feature

Parameter Grid Definition – 210 fits

Best hyperparameters: alpha = 0.1; l1_ratio = 0.7

Model II (dfl) >0.4 correlation

Parameter Grid Definition – 210 fits

Best hyperparameters: alpha = 0.1; l1_ratio = 0.5

Model III (df2) >0.2 correlation

Parameter Grid Definition - 210 fits

Best hyperparameters: alpha = 0.1;

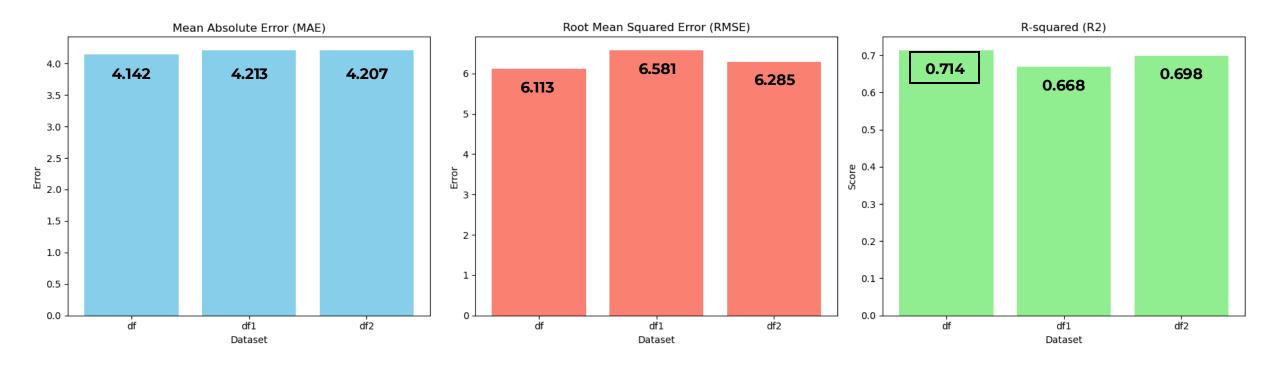


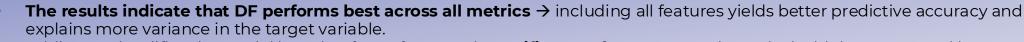


but better than dfl

The 'best' model is the one with all the features with a R-square of 0.714. We should use a more complex model (Neural Networks e.g.) to improve results





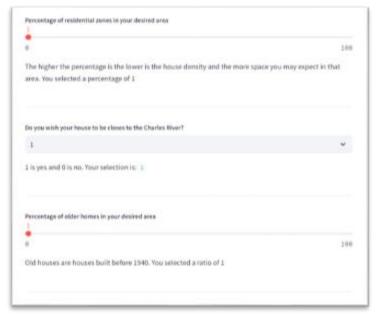


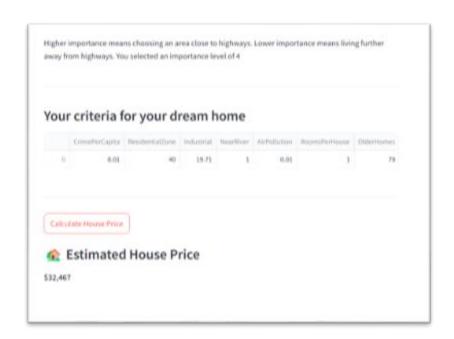
- While **DF1** simplifies the model by using fewer features, it **sacrifices performance**, as shown by its higher RMSE and lower R-squared.
- **DF2 balances feature reduction and performance** but still underperforms compared to DF.
- Conclusion: **Linear regression not suitable as ML model**, opt to use a more complex model, e.g. neural network

The following app in *Streamlit* predicts the house price (in Boston) based on user preferences









Application interface

Check your dream house price here!

