**Predicting Real Estate Prices**

Lincoln Brown and James Mulvihill

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Bellevue University

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Professor Hua

**Predicting Real Estate Prices**

Owning a home is a dream that many people have throughout the world. Understanding what a house is worth is an important aspect of attaining that dream. Using predictive analytics, we hope to help people looking for a home in Melbourne Australia determine the estimated value for prospective houses or what their current home’s value may be.

There are a number of important questions that can be investigated when working with real estate data. These include:

* What features contribute to a house’s price?
* What are good predictors of housing market bubbles?
* How might a home appraiser estimate how much a home is worth?

The first of these questions will be a primary focus of our project. Ultimately, our goal is to produce a model designed to predict the sale price of a house.

**The Data**

In 2017, Melbourne, Australia was voted for the seventh year in a row the world’s most liveable city. [[1]](#footnote-0) While it hasn’t done as well since then (mainly because of COVID), we will be looking at data from the housing market as it was in 2017. The data we will be using comes from Kaggle[[2]](#footnote-1) uploaded by user Tony Pino. The dataset has over 13,580 records and 21 features that include the suburb the house is in, number of rooms, size, year built and the all important target variable - price.

**The Models**

We plan on tackling this problem through the production and evaluation of several different models. We will create a baseline model, a linear regression model, decision tree, and random forest. Each of these models has a specific benefit to the analysis of the problem at hand and will contribute to our evaluation of which model has the best performance.

Initially, we will create a baseline model using a median dummy regressor. This will create a baseline model for which we can compare the accuracy of the more complex models. The next model we will create is a linear regression, which will help us identify any potential linear relationships between the target variable (sale price) and the other features. The data may not contain linear relationships, so it will likely be necessary to investigate the dataset further through the use of a decision tree. Since our dataset contains a moderate amount of features, there is a potential for overfitting when using a decision tree. We will use a random forest ensemble to help mitigate the chances of overfitting and potentially improve the predictive capabilities of the model.

**Why are these Models Used?**

* Baseline Model - The baseline model is created as a benchmark that we can use to compare the other models. This baseline will provide us with a simple reference point by which we can evaluate the performance of the other models. We will use a median to establish the baseline as it is more robust to outliers. If a model is not outperforming the baseline, it is likely an indication that the model is not capturing any relevant information or may be overfitting the data.
* Linear Regression - Linear regression is a simple model that can illustrate the relationships between the target variable and the other features in the dataset. This can be helpful for determining which features are the most correlated with the sale price. Correlation can be measured in both strength and direction. Positively correlated variables will trend in the same direction as the target variable, whereas negatively correlated variables will trend in the opposite direction as the target variable.
* Decision Tree - Decision trees are easy to interpret, which make them an excellent candidate for understanding the decision-making process. We will be able to look at the features that are the most important to the performance of the model. Decision trees are robust to non-linear relationships between features making them a good candidate for complex datasets that might not have clear linear relationships.
* Random Forest - Random forests are an ensemble method that aggregate the predictions of multiple decision trees to improve predictive performance and are robust against overfitting. Using a random forest model is an excellent way to help mitigate the potential impact of overfitting in a decision tree model. Like a decision tree, we can view the features most important to the performance of the model.

**Plan of Evaluation**

Model evaluation will consist of measuring several different metrics including, Root Mean Squared Error (RMSE), R2 score, and Mean Absolute Average (MAE). Used in combination, these metrics provide a well balanced assessment of model performance.

* Root Mean Squared Error (RMSE) - Mean Squared Error (MSE) is the metric that measures the average of the squared differences between the predicted and actual sale price.[[3]](#footnote-2) RMSE is the square root of MAE. RMSE penalizes large errors, which makes it sensitive to outliers in the data. Lower RMSE values indicate better performance. RMSE values are interpreted in the context of the dependent variable.
* R2 Score - The R2 score or Coefficient of Determination is a measure of goodness of fit. The R2 score explains how much of the proportion of variance in the dependent variable is predictable from the independent variables.[[4]](#footnote-3) R2 scores are measured between 0 and 1, with 1 indicating a perfect fit. Perfect R2 scores are a strong indication of overfitting.
* Mean Absolute Error (MAE) - This metric is a measure of the average absolute difference between the predicted values and the actual values in a dataset.[[5]](#footnote-4) MAE values are measured in the same context as the dependent variable, making them easy to interpret. In the case of sale prices, the MAE represents the average absolute difference between the predicted sale price and the actual sale price.

Each of these metrics are individually important for evaluation, but when communicating with our stakeholders, we will primarily use MAE because it can be easily interpreted as the average absolute dollar amount that the prediction deviates from the actual sale price.

**What We Hope to Learn**

The goal is to find a model for predicting house price given the features of the dataset. Additional questions that we will investigate are:

* Which features have the most significant impact on house prices?
* Are there any differences in price for different neighborhoods?
* Which model performs the best?
* Which features were most important for the model performance?

**Risks and Ethical Consequences**

One risk is that bad data could skew our results. Inside the dataset, there are a few houses that have huge square meterage. This is unlikely to be the case, especially if the price is around average. The data will need to be carefully cleaned to make sure rows like this do not skew our results. Another risk would be that the data does not contain important factors that would influence house price. Most notably, the quality of the house is not stated in the dataset. While year built might be correlated with this, we don’t have a clear way of knowing if the house is in disrepair.

The data is collected from an open source repository on Kaggle, so there are no ethical concerns with how the data was obtained. If there are any other ethical concerns that emerge we’ll seek guidance at that time.

**Plan for the Unexpected**

It’s possible that we might need to use a different dataset. This could happen if there is confusion about what some of the columns in the Melbourne dataset signify. For example, one column is titled “Rooms”, which might just be bedrooms, but, coming from Australia, might mean something else. As a backup, we will use the Ames Housing Dataset found on Kaggle.[[6]](#footnote-5)

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