# Fairness

Regarding property assessments, there are two primary fairness concerns. The first concern arises because property assessments of unsold and sold homes are usually based off databases that consist only of sold homes. If we expect that there is something about sold homes that makes them intrinsically different from unsold homes, then the resulting assessments may be problematic. For instance, if we think that sold homes are systematically more undesirable than unsold homes (e.g. sold homes may have been put up for sale because they have existing issues such as a leaky roof), then the valuation of unsold homes based on observed sale prices of sold homes would lead to a systematic undervaluation of unsold homes. On the other hand, if we think that sold homes are better on average than unsold homes (e.g. because someone decided to buy the home, it must be an indication that the home is of good quality), then applying the sale prices of sold homes to valuate unsold homes may lead to a systematic overvaluation of the unsold homes. Based on our reasoning, it is difficult to say which of these phenomena is more prevalent in the real world. In addition, it is not possible to observe what someone is willing to pay for an unsold home, so this concern is extremely difficult to address without access to counterfactual data. As such, we do not consider this issue further in this paper.

The second fairness concern is that property assessments tend to undervalue higher-priced homes and overvalue lower-priced homes. [INSERT CITATION] The reason for this is that higher-priced homes tend to have internal features (e.g. a newly remodeled kitchen) that make buyers willing to pay more money for them. However, these features—because they are internal—may not be observable to property assessors. Likewise, a lower-priced home may look identical to a higher-priced home on the outside, but on the inside, the lower-priced home may lack high-end details. Due to the immense number of home features in our dataset (the dataset has 77 features, many of which capture internal home characteristics), we hope that our analysis will better capture the qualitative differences between homes and therefore produce more accurate estimates for homes of all prices.

Both of the above fairness concerns pose policy problems. When a home is under-assessed, the owners of that home will pay less than their fair share of taxes—leaving the government with less money with which to fund critical public programs. On the other hand, when a home is over-assessed, the owners of that home face a disproportionate property tax burden, which is of particular concern if we believe that these over-taxed homeowners belong to an economically-marginalized group. This is the case, for example, when lower-priced homes are over-assessed and owners of those homes—who themselves tend to have lower incomes—are overtaxed. Meanwhile, owners of higher-priced homes—who tend to have higher incomes—have been historically undertaxed. This perpetuates a pre-existing imbalance in society because it causes the poorer to become poorer and the richer to become richer. Due to these concerns, we will consider various fairness metrics when evaluating our models.

To determine which homes are low-priced and which homes are high-priced, we used k-means clustering to divide the homes into three groups based on the similarity of their sale prices. We performed the clustering based on the training set. The resulting three groups represent low-price, medium-priced, and high-prices homes, respectively. The clusters are plotted below. For the purposes of evaluating fairness, we are primarily interested in the low- and high-priced groups. The maximum sale price among the low-priced homes is $174,000, while the minimum price of the high-priced group is $293,077.



For our regression-based models, our target variable is continuous so we cannot use the typical fairness metrics (e.g. precision, recall, etc.) that are used to evaluate classification models. Instead, we will examine the distribution of the predictive error separately for low-priced homes and high-priced homes in our test set. For each low-priced and high-priced home in the test set, we will compute the predictive error. Predictive error for home *i* is defined as:

where is the actual sale price for home *i* and is the predicted sale price for home *i*. To examine the distribution of the predictive error, we will primarily use statistics such as the median, the 25th percentile, and the 75th percentile. We will opt not to use the mean so that outlying errors do not unduly affect our fairness metrics. Based on the statistics we compile, we will check to see if there are any systematic differences in the predictive errors across the high-priced and low-priced groups of homes. In particular, we will be concerned if high-priced homes are systematically under-valued compared to low-priced homes, or if low-priced homes are systematically over-valued compared to high-priced homes.

For our classification models, [INSERT FAIRNESS METRICS + REASONING]

For our clustering models, [INSERT FAIRNESS METRICS + RESONING]