Predicting Housing Prices in Austin, Texas

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1 Introduction and Background

For many, buying a house will be their most expensive purchase. Not only that, but it will represent a large share of their assets. As such, it can be vitally important that the house is assessed fairly. Not doing so can lead to people losing tens of thousands of dollars, if not more. A consistent and more objective way of evaluating housing prices could be hugely beneficial to homeowners and buyers, making sure that people get market value for their property.

When it comes to trying to predict housing prices, there are a lot of factors. There are more physical ones like size and location, and then more subtle ones like local school rating and appearance. There are even fluctuations in the economy which can alter the price. While it would be an interesting avenue to explore, economic fluctuations and time-based features are out of the scope of this project. As such, we chose to stick with relatively constant features like the size and location.

This won't allow us to achieve the same accuracy as more sophisticated and inclusive models, but it can still provide valuable information on the relationships between these features and price. Additionally, while the model wouldn't predict how the price changes during an economic event, two houses outputting roughly similar values from our model should have roughly the same value as economic conditions change.

There is no one-size-fits-all model that will work for all problems. Different data has different relationships and a model that performs well on one set might struggle on another. Not only that, but more complex models, while generally capable of being more accurate, can have much greater complexity. For our project, we aim to compare different models and compare their accuracy. With our completed models, we hope to use their results to check for different relationships between housing variables and house price. We can also gain insights into the viability of these models, which can pave the way for future projects which attempt to improve upon these models or test new models.

Our GitHub repository for this project is available at `https://github.com/xychen26/ECS171GroupProject`.

2 Literature Review

Housing price prediction has had its fair share of predictive methods thrown at it in the past decade. In 2008, a paper was released comparing hedonic regression (a popular method of housing price prediction) to artificial neural networks using a dataset from turkey. The results showed improved performance in the neural network compared to hedonic regression (Selim 2008). In 2014, another study was published reviewing data from Fairfield County, Virginia in which they tested several alternative methods from ours, finding error rates around 27% using decision trees and the Ripper algorithm (Park and Bae 2014). Beyond that they note the use of SVM's, a model which was found to outperform ANNs in a 2019 study of Hong Kong housing prices by Abidoye et al., and which had the lowest MSE in a 2014 study by Mu, Wu, and Zhang (Abidoye et al. 2019; Mu, Wu, and Zhang 2014). These results make sense, since a SVM will find the global minimum while ANNs may get stuck at local minima (Abidoye et al. 2019).

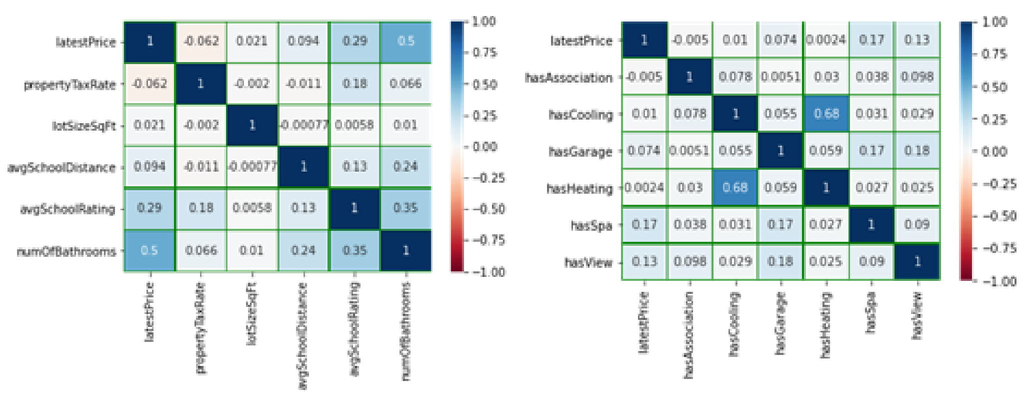
More recently, a conference paper by Mangaleswaran and Vigneshwari carried out a test similar to ours, comparing ANNs, logistic regression, k-means clustering, and linear regression. While they only tried to predict if houses would be above or below the mean price, they still found ANNs to be the most accurate, standing at 85% with logistic regression at 80% (Mangaleswaran and Vigneshwari 2020). This was to be expected since the recommended the semi-logarithmic form is known to produce more accurate results (Selim 2009). Diving specifically into neural networks, a 2021 paper by Kalliola et al. tested hyperparameters for neural networks used in housing price prediction on a Helsinki dataset. They found 6 hidden layers to be ideal with each layer having anywhere from 150 to 950 nodes (Kalliola et al. 2021). While unable to meet this level of complexity in our network, we aim to compare neural network performance to some of the other models when it comes to housing price prediction.

3 Dataset Description and Exploratory Analysis of Dataset

Dataset is from kaggle.com and provided by Eric Pierce.

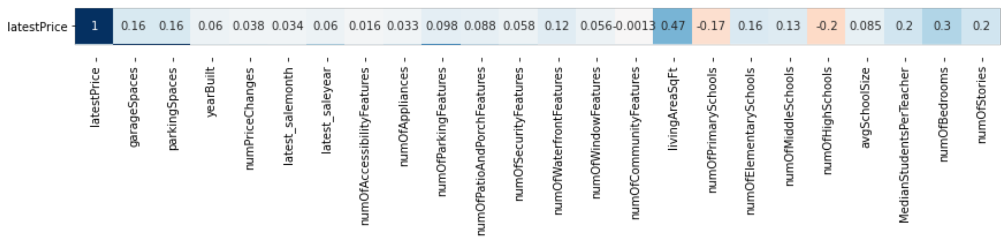
This dataset consists of 2018 to 2021 house transaction records from Austin, TX area. There are total 15,171 samples in the dataset. Each sample has 47 attributes such as: cities, name, zip code, address, built years, amenities info, purchase price, etc. Because some of the attributes are irrelevant or difficult to deal with, we will drop some of them such as 'homeImage', 'description', etc. to make our machine learning models less complex when predicting house price.

The main indicator of relevant data we used was correlation to the latestPrice attribute. When we created a correlation matrix of the integer values, we saw that numOfBathrooms field has the highest correlation with price of 0.5. For the Boolean values, we saw that none of these fields were particularly noteworthy, with hasSpa having the highest correlation of 0.17.



For the floating-point values, we observed that livingAreaSqFt has the highest correlation of 0.47. The other closest correlations are 0.3 for numOfBedrooms, -0.2 for numOfHighSchools, and 0.2 for medianStudentPerTeacher.

The zipcode and hometype categorical attributes were determined to not have relevant correlation with the price, so they were ignored.



4 Proposed Methodology and Data Pre-processing

Since our goal was to predict the housing price, we decided to use Simple Linear Regression, Multiple Linear Regression, Polynomial regression, and Artificial Neural Network (ANN) for this numerical response variables. For regression methods, the output should be continuous numerical values. We figured that regression was the right methodology for our problem statement, considering that the dataset uses continuous values that we would not be surprised to see fit a linear or polynomial regression model. In regression training processes (both linear and polynomial), we did not scale the data except for y data to make MSE values more easily comparable between models. For our application, we kept y values unscaled in regression so that the user could see a human-readable price prediction.

We wanted to see if a neural network could compare, however, so we planned to work on a neural network model once the regression models were finished. For the ANN model, we divided the price to several ranges of intervals to make them classification problems with meaningful predictions. In ANN training processes, scaling data is required because each neuron receives inputs from all attributes. We used a MinMaxScaler to normalize our data to value between [0,1]. Also, since the response variable latestPrice is a numerical continuous variable, this implies that we could have at most N number of different prices as N is the number of samples in the dataset. This would make it difficult to get a useful prediction out of the ANN. Therefore, we divided the price into several ranges of intervals of every \$50,000 from [0 – 600,000), every \$100,000 from [600,000 – 1,000,000), \$500,000 from [1,000,000 – 2,000,000), every \$1,000,000 from [2,000,000 – 10,000,000), and then all that were above $10,000,000 were all in one price bucket. With limited numbers of price ranges as output, the ANN models can predict, with certain values of input attributes, which price range the data point should fall into.

When determining which features to use, we considered the information gained from the exploratory analysis section, which revealed that numOfBathrooms, livingAreaSqFt, numOfBedrooms, avgSchoolRating, MedianStudentsPerTeacher, and numOfHighSchools all had the highest correlation for latestPrice. We saw that number of stories also had high correlation, but we did not include that one. It likely would have contributed mostly to similar information that the numOfBathrooms and numOfBedrooms explained. If we were to have done principle component analysis (PCA), we would likely have included it since the PCA would have handled features that were too similar for us. We used livingAreaSqFt for simple linear regression while all of the other models used all of the viable features.

5 Experimental Results

5.1 Simple Linear Regression

The simple linear regression measures the correlation between the living area square footage and the latest price of the house. According to the linear regression model, the testing MSE was 0.0031034538994231665, while the training MSE was 0.0007533569972620845. Since the testing MSE was much higher than the training MSE, it can be concluded that the simple linear regression showed signs of overfitting. Note that all of the above assumes the outliers have not been removed. When the outliers were removed, the training and testing MSEs were 0.01683046917734069 and 0.017602933835473195, respectively. The regression model no longer showed signs of overfitting but appeared to be much less accurate.

5.2 Multiple Linear Regression

The multiple linear regression used the living area square footage, the number of bathrooms, the average school rating, the number of bedrooms, the number of high schools, and the median number of students per teacher, as the dependent variables. Just like before, the dependent variable was the latest price of the house. Assuming the outliers have not been removed, the training and testing MSEs turned out to be 0.001161543841697301 and 0.002612637208211 7054, which indicates that the model showed signs of overfitting. Once the outliers were removed, the training and testing MSEs became 0.015228611447641035 and 0.016849382441537858, respectively. Just like the simple linear regression model, the multiple linear regression model no longer showed signs of overfitting. The multiple linear regression model seemed to be more accurate than the simple linear regression model, although it remained relatively inaccurate.

5.3 Polynomial Regression

The polynomial regression used the living area square footage, the number of bathrooms, the average school rating, the number of bedrooms, the number of high schools, and the median number of students per teacher, as the dependent variables. Just like before, the dependent variable was the latest price of the house. The data for the polynomial regression is shown below:

	With Outliers		Without Outliers	
Degree	Training MSE	Testing MSE	Training MSE	Testing MSE
2	0.000387109	0.002220175	0.010744637	0.010886175
3	0.000320944	0.002171320	0.010197520	0.010304872
4	0.000266263	0.002670675	0.009781156	0.010232087
5	0.000229394	0.014071381	0.009121448	0.010224790
6	0.000203251	0.743694487	0.008724810	0.012790388
7	0.000175687	15694.16772	0.007842996	0.011763088
8	0.000150009	3302357.643	0.006905841	3.645199721

When the outliers are present, the 3rd-degree polynomial regression appeared to be the most accurate model out of all the polynomial models that were created, with a training MSE of 0.000320944 and a testing MSE of 0.002171320. After the outliers were removed, however, the best polynomial regression model turned out to be the 5th-degree polynomial model, with a training MSE of 0.009121448 and a testing MSE of 0.010224790. Furthermore, the regression model no longer showed signs of overfitting once the outliers were removed. The 5th-degree polynomial regression model appeared to be more accurate than the simple and multiple linear regression models since it had lower training and testing MSEs than the linear regression models once the outliers were removed.

5.4 Artificial Neural Network

The artificial neural network used the living area square footage, the number of bathrooms, the average school rating, the number of bedrooms, the number of high schools, and the median number of students per teacher, as the dependent variables. Just like before, the dependent variable was the latest price of the house. The prices themselves were divided into 22 different ranges. The ANN is based off Keras' sequential model and three hidden dense layers with 100, 80, and 50 nodes and ReLu as their activation functions while the output layer uses the sigmoid function. It uses stochastic-gradient descent as its optimizer and categorical_crossentropy as its loss function. The output layer had 17 nodes since there were 17 different price bucket classes. Unfortunately, it ended up having an accuracy of .26, roughly, which was very undesirable. We tried to make the model more accurate by making the ANN more complex, less complex, and increasing epochs, but those options either led to overfitting or underfitting which reduced our accuracy even further. After exhausting those options, the conclusion was that the ANN was simply not viable for the predictions we were attempting. Perhaps it was the amount of price buckets that we used or the features that we chose that made it very incompatible with our data, but our focus was mainly on the regression models anyway.

5.5 Overall Results and Error Analysis

	With Outliers		Without Outliers	
Model Used	Training MSE	Testing MSE	Training MSE	Testing MSE
Simple Linear Regression (threshold = 2)	0.000753357	0.003103454	0.016830469	0.017602934
Multiple Linear Regression (threshold = 2)	0.001161544	0.002612637	0.015228611	0.016849382
Polynomial Regression (5th degree, threshold = 3)	0.000229394	0.014071381	0.009121448	0.010224790
Neural Network	0.3990	0.4040	N/A	N/A

One possible reason why the models were not as accurate as they could be is the fact that too many samples were removed from the dataset during preprocessing. Removing too many samples reduced the sample size, which made it more difficult to properly train models. The accuracy of these models suffered as a result. Keep in mind that removing outliers from the dataset is supposed to increase the accuracy of the models, not decrease it. The fact that removing the outliers decreased the accuracy of these models indicates that too many legitimate samples were removed from the dataset. A post-experimental analysis of the regression models showed that the percentages of samples that were removed from the dataset was 3.72% for simple linear regression (threshold = 2), 17.26% for multiple linear regression (threshold = 2), and 11.28% for polynomial regression (threshold = 3). The number of actual outliers could be counted with one or two hands with the help of a scatter plot. This means most of the samples removed during preprocessing were not true outliers. To remedy this, the threshold used to remove the outliers needs to be increased so that fewer legitimate samples will be removed from the dataset. Alternately, a manual effort to remove outliers would have probably been more efficient. For now, we will simply refer to the models where outliers were not removed to be our main output of this project.

6 Conclusions and Discussion

We began this project expecting to see that regression models would perform well for our dataset and problem statement, and we were not disappointed. What was surprising to us, however, was how terribly low our neural network accuracy was, especially considering how successful other projects have been with neural networks for housing price prediction. It is clear that either our dataset was not suited well for a neural network, we did not use the right features for our ANN, or the method of classification was not designed well. We believe that the last option is the most likely. If we were to continue this project, we would likely try a different approach for our neural network (use less price buckets, perhaps) or even try an SVM. For positive results, our project was certainly successful in developing regression models. It was interesting to see just how close to the true price our simple linear regression model predictions could get with just the livingAreaSqFt field. Adding the other features to the multiple linear and polynomial regression increased the accuracy of our models the way we expected. Based on the results of our regression models and correlational analysis, it is clear that the size of the housing option and the number of rooms greatly dictates the price in Austin, Texas.

7 Sources

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