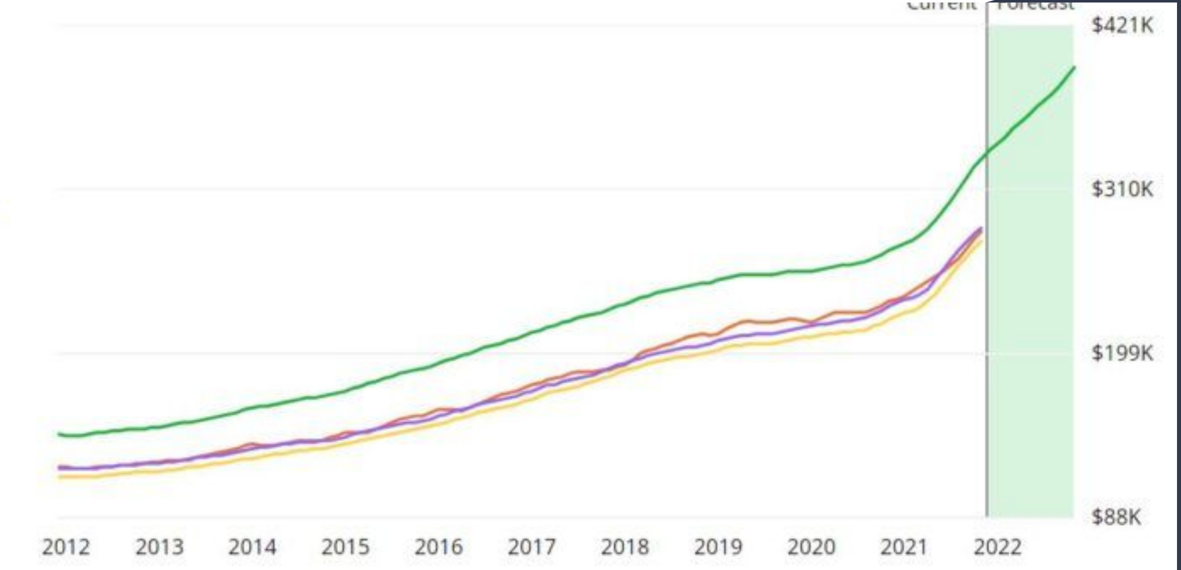
Housing Sales Price Prediction in North Dallas 2021



https://www.noradarealestate.com/blog/dallas-real-estate-market/

Project Background

- The housing market in North Dallas has been growing rapidly over the last few years and even more so in the last 6 months.
  - Several large corporations are relocating their headquarters to the area and moving large numbers of employees with them which is driving the market upward.
- The goal of the project is to solve the problem of optimal housing pricing by using machine learning to estimate a sale price of homes in a small section of North Dallas suburbs.
- This project will use a small subset of the available data as a case study to prove effectiveness of the methodology. If the models show that a home could be sold higher this results in more money for the home sellers, a larger fee for the realty company, and a larger commission for the realtor.
- If the model shows that homes are overpriced then it can be suggested to lower the price if it is needed to move the home quickly.

Data Wrangling

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9117 entries, 0 to 2613
Data columns (total 140 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   APN/PIN/Tax 1                 8527 non-null   object
 1   APN/PIN/Tax 2                 8527 non-null   object
 2   APN/PIN/Tax 3                 3774 non-null   object
 3   FIPS                          9117 non-null   int64
 4   Census Tract                  9006 non-null   float64
 5   Property Address              9103 non-null   object
 6   House Number                  9069 non-null   object
 7   Pre Direction                 198 non-null    object
 8   Street                        9103 non-null   object
 9   Street Suffix                 8968 non-null   object
 10  Post Direction                9 non-null      object
 11  Unit Type                     450 non-null    object
 12  Unit Number                   450 non-null    object
 13  City                          9103 non-null   object
 14  State                         9117 non-null   object
 15  ZIP 5                         9094 non-null   float64
 16  ZIP 4                         9028 non-null   float64
 17  Mailing Address               9101 non-null   object
 18  Mailing House Number          8925 non-null   object
 19  Mailing Pre Direction         384 non-null    object
 20  Mailing Street                9101 non-null   object
 21  Mailing Street Suffix         8724 non-null   object
 22  Mailing Post Direction        57 non-null     object
 23  Mailing Unit Type             899 non-null    object
 24  Mailing Unit Number           889 non-null    object
 25  Mailing City                  9085 non-null   object
 26  Mailing State                 9074 non-null   object
 27  Mailing ZIP 5                 9073 non-null   object
 28  Mailing ZIP 4                 8944 non-null   float64
 29  MLS ID                        9117 non-null   int64
 30  Listing Type                  9117 non-null   object
 31  Status                        9117 non-null   object
 32  List Price                    9117 non-null   int64
 33  Days on Market                9115 non-null   float64
 34  Contract Status Change Date   9117 non-null   object
 35  Township Name                 9114 non-null   object
 36  Subdivision Code              1115 non-null   object
 37  Subdivision                   9114 non-null   object
 38  Current Year Tax              9117 non-null   int64
 39  Tax Amount                    9110 non-null   float64
 40  Tax Rate Code Area            5444 non-null   object
 41  Current Year Assessment       9117 non-null   float64
 42  Total Assessed Value          9117 non-null   int64
 43  Assessed Land                 9117 non-null   int64
 44  Assessed Improvement          9117 non-null   int64
 45  Total Market Value            9117 non-null   int64
 46  Market Value Land             9117 non-null   int64
 47  Market Value Improvement      9117 non-null   int64
 48  Estimated Value               8819 non-null   float64
 49  Absentee Status               9117 non-null   object
 50  Exemption-Veterans            9117 non-null   bool
 51  Exemption-Disabled            9117 non-null   bool
 52  Exemption-Senior              9117 non-null   bool
 53  Exemption-Widow               9117 non-null   bool
 54  Exemption-Homestead           9117 non-null   bool
 55  Block #                       8816 non-null   object
 56  Lot #                         9008 non-null   object
 57  Section #                     0 non-null      float64
 58  County Use Code               9113 non-null   object
 59  Universal Land Use            9117 non-null   object
 60  State Land Use Code           0 non-null      float64
 61  Zoning                        2318 non-null   object
 62  Plat Map Reference            3730 non-null   object
 63  Lot Acres                     9117 non-null   float64
 64  Lot SQFT                      9117 non-null   float64
 65  New Construction              8847 non-null   object
 66  Beds                          9013 non-null   float64
 67  Baths                         9117 non-null   float64
 68  Total Building Area           9117 non-null   int64
 69  Living Area SQFT              9041 non-null   float64
 70  Gross Area SQFT               355 non-null    float64
 71  Basement SQFT                 7 non-null      float64
 72  Garage SQFT                   8301 non-null   float64
 73  Basement                      1551 non-null   object
 74  Flooring Cover                2968 non-null   object
 75  Stories                       8915 non-null   object
 76  Style                         1086 non-null   object
 77  Year Built                    8847 non-null   float64
 78  Air conditioning              8311 non-null   object
 79  Heat Type                     8174 non-null   object
 80  Fireplace indicator           9117 non-null   bool
 81  Construction Type             4996 non-null   object
 82  Exterior Wall                 8312 non-null   object
 83  Roof Material Type            6676 non-null   object
 84  Porch Type                    5825 non-null   object
 85  Has Pool                      1631 non-null   object
 86  Parking spaces                9117 non-null   int64
 87  Parking Type                  8436 non-null   object
 88  Total Units                   9117 non-null   int64
 89  Sell Score                    0 non-null      float64
 90  Distressed Indicator          1 non-null      object
 91  Distressed Recording Date     191 non-null    object
 92  Distressed Case Number        3 non-null      object
 93  Auction Date                  84 non-null     object
 94  Default Date                  0 non-null      float64
 95  Recording Date                8945 non-null   object
 96  Document Type                 8789 non-null   object
 97  Sales Price                   6153 non-null   float64
 98  Equity                        8819 non-null   float64
 99  Equity Percentage             8956 non-null   object
 100 Number Of Mortgages           9117 non-null   int64
 101 Mortgage Loan Balance         9117 non-null   float64
 102 Mortgage 1 Lender Name        6647 non-null   object
 103 Mortgage 1 Loan Type          6647 non-null   object
 104 Mortgage 1 Amount             6647 non-null   float64
 105 Mortgage 1 Loan Date          6635 non-null   object
 106 Mortgage 1 Rate               6647 non-null   object
 107 Estimated Rate                6647 non-null   object
 108 Estimated Rate.1              6647 non-null   object
 109 Mortgage 1 Age                6635 non-null   object
 110 Mortgage 2 Lender Name        260 non-null    object
 111 Mortgage 2 Loan Type          260 non-null    object
 112 Mortgage 2 Amount             231 non-null    float64
 113 Mortgage 2 Loan Date          259 non-null    object
 114 Mortgage 2 Rate               260 non-null    object
 115 Mortgage 2 Age                259 non-null    object
 116 Mortgage 3 Lender Name        3 non-null      object
 117 Mortgage 3 Loan Type          3 non-null      object
 118 Mortgage 3 Amount             1 non-null      float64
 119 Mortgage 3 Loan Date          3 non-null      object
 120 Mortgage 3 Rate               3 non-null      object
 121 Mortgage 3 Age                3 non-null      object
 122 Mortgage 4 Lender Name        2 non-null      object
 123 Mortgage 4 Loan Type          2 non-null      object
 124 Mortgage 4 Amount             0 non-null      float64
 125 Mortgage 4 Loan Date          2 non-null      object
 126 Mortgage 4 Rate               2 non-null      object
 127 Mortgage 4 Age                2 non-null      object
 128 Owner 1 First Name            8122 non-null   object
 129 Owner 1 Middle Name           4869 non-null   object
 130 Owner 1 Last Name             8123 non-null   object
 131 Owner 1 Full Name             9117 non-null   object
 132 Owner 1 Email Addresses       2578 non-null   object
 133 Owner 1 Phone Numbers         2349 non-null   object
 134 Owner 2 First Name            4809 non-null   object
 135 Owner 2 Middle Name           2683 non-null   object
 136 Owner 2 Last Name             4809 non-null   object
 137 Owner 2 Full Name             4953 non-null   object
 138 Owner 2 Email Addresses       690 non-null    object
 139 Owner 2 Phone Numbers         635 non-null    object
dtypes: bool(6), float64(28), int64(14), object(92)
```

List of Features in Raw Dataset

- Goal of Data Wrangling
  - Remove unnecessary features
  - Investigate and fix null values
  - Each row for each feature has a relevant value
  - Each feature is the correct Dtype for analysis
- The list of features and data types of the raw data can be seen to the left
  - It is clear that there is a lot of work to be done removing features
    - Before even looking at values, features that include personal information were removed
      - Owner names
      - Mortgage information
      - Tax information
      - Contact information

Data Wrangling

- This was a very well populated data set so all of the numerical values were populated
- The categorical values needed some work to make sure each row had a value for each feature
- Since the values of some of the categorical features were either ‘Yes’ or 0 it was assumed that 0 was a no, so they were filled as such
    - Has pool
    - Basement
    - Porch Type
- Other features were the opposite so were filled with ‘No’
    - Heat Type
    - Air conditioning

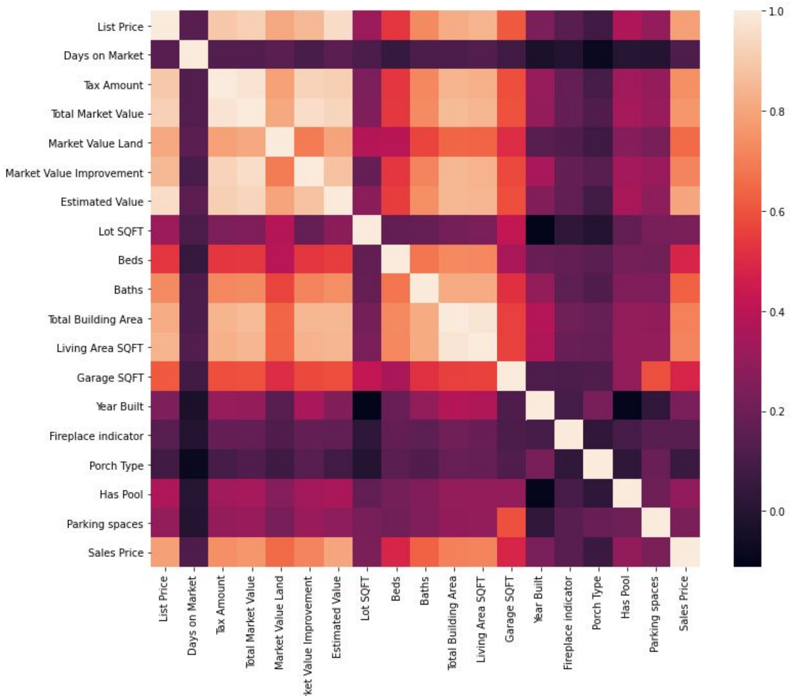
```
cleaning['Has Pool'].fillna('None', inplace = True)
cleaning['Basement'].fillna('No Basement', inplace = True)
cleaning['Porch Type'].fillna('None', inplace = True)
cleaning['Heat Type'].fillna('Yes', inplace = True)
cleaning['Roof Material Type'].fillna('Composition Shingle', inplace = True)
cleaning['Air conditioning'].fillna('Yes', inplace = True)
cleaning = cleaning.drop(['Basement SQFT', 'Total Assessed Value', 'Assessed Land', 'Assessed Improvement', 'State', 'Status', '
```

Code Snippet Showing Filling Null Categorical Data

```
City                            object
ZIP 5                          float64
ZIP 4                          float64
List Price                       int64
Township Name                   object
Subdivision                     object
Tax Amount                     float64
Total Market Value               int64
Market Value Land                int64
Market Value Improvement         int64
Estimated Value                float64
County Use Code                 object
Lot SQFT                       float64
New Construction                object
Beds                           float64
Baths                          float64
Total Building Area              int64
Living Area SQFT               float64
Garage SQFT                    float64
Basement                        object
Stories                         object
Year Built                     float64
Air conditioning                object
Heat Type                       object
Fireplace indicator               bool
Porch Type                      object
Has Pool                        object
Parking spaces                   int64
Sales Price                    float64
dtype: object
```

Final List of Features and Type

Exploratory Data Analysis

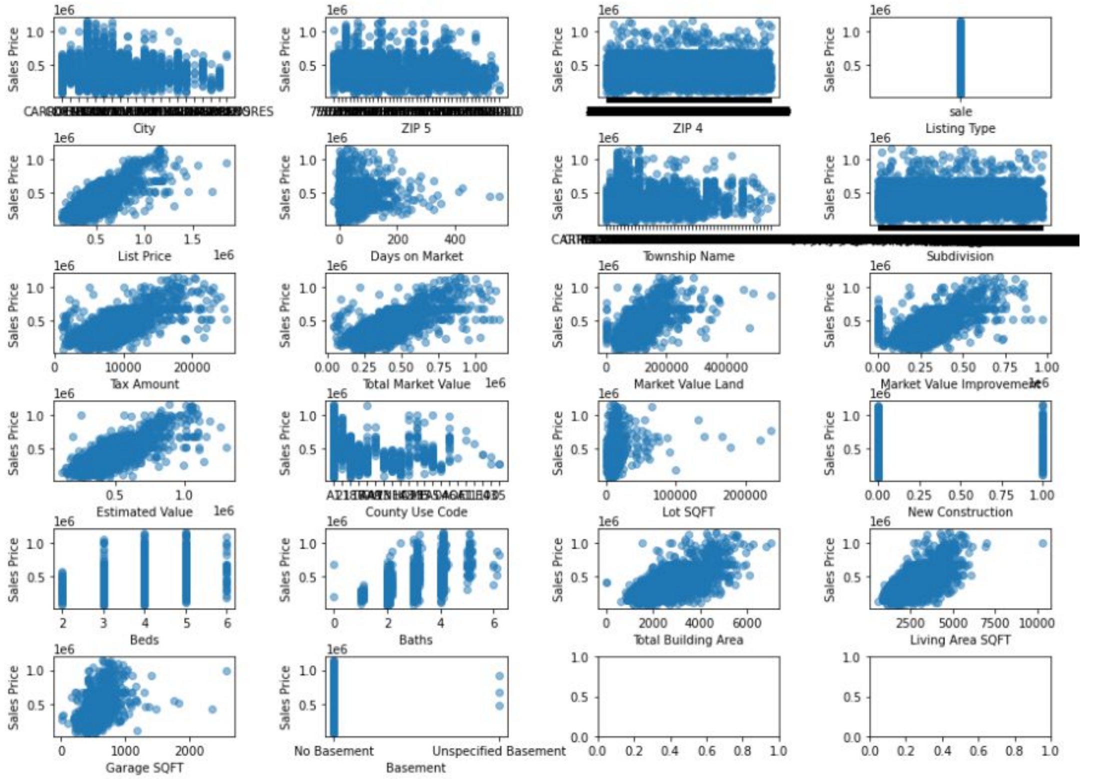


Pearson Correlation Heatmap

- Exploratory data analysis is an important part of getting to know your data before you move on to modeling
  - Summarize and visualize important features
  - Identify patterns
  - Identify correlations
- To the left you can see the Pearson correlation heatmap
  - This is a quick way to view correlations of all of your features
- Another useful library is Pandas Profiling
  - Histograms of each feature
  - Number of null values remaining
  - Identify outliers
- After viewing histograms and outliers you can circle back to your data wrangling to fix any features that are still problematic

Exploratory Data Analysis

- Another way to visualize the correlations is to scatter plot each of the features vs the target variable
- After looking through all of the variables it seems a little unfair to use some of them due to collinearity. The features that may be removed are Tax Amount, Total Market Value, Market Value Land, Market Value Improvement, and Estimated Value
    - In a future update to the project I would use t-SNE with different thresholds to see how many of the correlated features would be removed



Preprocessing

- One Hot encoding variables
  - Massively expanded the number of features, 29-5893
  - Looked into some of the encoded features more and found the 4 digit ZIP codes had very few duplicates
  - These were removed to prevent over complication
- Different X/Y datasets for modeling
  - Tried different combinations of features for modeling
  - Just house features vs including location or price estimates
- Create new features for modeling
  - It was determined that the predicted sales price had the largest effect on the actual sales price
  - I tested creating new features by multiplying the predicted price by 90%-110% to see how it would change the actual sales price
- Split into train/test subsets

Modeling

```python
start = time.time()

steps = [('scaler', StandardScaler()), ('xgbr', XGBRegressor())]
pipe = Pipeline(steps)

n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]
max_depth = [1,2,3,4,5,6,7,8,9,10]
eta = [.001,.005,.01,.025,.05,.1,.2,.3]
subsample = [.25,.5,.75,1]
colsample_bytree = [.25,.5,.75,1]

random_grid = {'xgbr__n_estimators': n_estimators,
               'xgbr__max_depth': max_depth,
               'xgbr__eta': eta,
               'xgbr__subsample': subsample,
               'xgbr__colsample_bytree': colsample_bytree}

xgboost = RandomizedSearchCV(
        estimator=pipe,
        param_distributions = random_grid, n_iter = 100, cv = 5, verbose=2, random_state=42, n_jobs = -1)

grid_result = xgboost.fit(X_big_train, y_big_train)
best_params = xgboost.best_params_
print(best_params)

y_pred_xgboost = xgboost.predict(X_big_test)
y_tr_pred_xgboost = xgboost.predict(X_big_train)



print('It takes %s minutes' % ((time.time() - start)/60))
median_mae_xgboost = mean_absolute_error(y_big_train, y_tr_pred_xgboost), mean_absolute_error(y_big_test, y_pred_xgboost)
median_mae_xgboost

print(median_mae_xgboost)


r2_score(y_big_train, y_tr_pred_xgboost), r2_score(y_big_test, y_pred_xgboost)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
{'xgbr__subsample': 0.5, 'xgbr__n_estimators': 1800, 'xgbr__max_depth': 2, 'xgbr__eta': 0.005, 'xgbr__colsample_bytree': 0.75}
It takes 75.25825051069259 minutes
(60930.19888094893, 64929.436901653615)
```

Code Snippet of Best Performing Model Tuning - XGBoost

- When I got to the modeling phase I planned to test a wide variety of model types in order to compare results
    - Support Vector Regression
    - Random Forest Regression
    - Lasso Regression
    - Ridge Regression
    - XGBoost Regression
- For each of the models I used GridSearchCV for hyperparameter optimization and cross validation in order to find the best combination of parameters
- Metrics Used
    - R2
    - Mean Average Error
    - Both metrics were used to assess the training and test datasets to see how well the model learned the training data and how well it generalized to the testing data

Modeling Results

Model	Train MAE ($)	Test MAE ($)
Support Vector Regression	116,322	109,472
Random Forest Regression	67,369	74,960
Lasso Regression	64,532	66,370
Ridge Regression	64,574	66,138
XGBoost Regression	60,930	64,929

- It is plain to see the XGBoost model had the lowest error and would be the recommended model to use for production.
- All of the models seem to generalize well to the testing data and did not overfit on the training data.
- The five most important features used by the model can be seen here

Feature	Importance
Estimated Value	0.181957
Total Market Value	0.107437
List Price	0.079475
Tax Amount	0.029974
Market Value Improvement	0.023867

Conclusions

- This project was a good overview of the entire data science sequence with practise in each phase
  - Data manipulation/wrangling
  - Exploratory Data Analysis
  - Preprocessing
  - Modeling
- Future work or changes to process
  - As a continuation of the process I would include more in the feature selection/extraction process
    - t-SNE for feature selection
    - Principal component analysis for feature extraction
  - For a different direction for modeling I would try a neural network to see if better results can be achieved