Florida’s Residential Single Family Home Re-sales Review

Predicting outcome of the single-family residential home same year re-sales  **By Ruslan Dubas**

**Introduction**

From 2009 to 2020, in Florida, there were on average 135,000 residential homes sales per year. This wealth of the information comes from the Florida Department of Revenue. The research into the data will be focusing on the single residential home sales (SFR) which were bought and sold again within same year. Will the investment create a loss or make a profit? The ability to accurately estimate positive or negative outcome, prior to investment, is an important task for all real estate market participants and stakeholders.

Analysis will be focusing on building explainable (“White-Box”) binary classification models. The two classes which study will attempt to classify: Loss or Profit. Features importance will be measured by applying Logistic Regression, Decision Tree, and Random Forest algorithms.

**Data Source: Florida Department of Revenue (FDOR) Assessment Rolls from 2009 to 2020**

The following is the excerpt from the FDOR’s website: “The Department of Revenue publishes assessment rolls in compliance with chapter 119, Florida Statutes. The files publicly available through the Department and county property appraisers do not contain confidential records, such as social security numbers and the records of property owners exempt from public records disclosure under section 119.071, Florida Statutes.”

**Brief Descriptions of the Data Source**

FDOR publishes the NAL (*“Name, Address and Legal”*) files as comma-delimited files (with the file extension .csv) with field names in the header row. Each file contains 161 columns, detailed descriptions can be reviewed in the Appendix 1 – 2022 User’s Guide. Each row represents a single real estate property parcel. 68 files for each year, from 2009 to 2020, were combined into one SQL Server Database Table for the analysis.

**Gathering the Data**

FDOR upon request provided the link to the NAL files. The main difficulty was to combine all 680 files (68 counties for each year from 2009 to 2020) into one and import it into SQL Server as one Database Table. The importance of such vast data gathering cannot be understated – once all the data has been combined the analysis of the complete population can be performed. Complete population, in this case, pertains to the Single Family Residential (SFR) home same year re-sales.

All SFR homes labeled as ‘001’ in the Use Code field. The nature of the transaction captured in the *Sales Qualification Code* Field. Multi-parcel (‘05’), corrective deed (‘11’) and transfer between relatives (‘30’) sales were removed from the data set. Detailed descriptions of all fields could be found in the Appendix 1 - 2022 User’s Guide.

**Graphing All Florida SFR Home Sales from 2009 to 2020**

The graph below shows counts of all Florida SFR home sales from 2009 to 2020. There were on average - 135,000 SFR homes sales per year. Tampa Bay region (including Hillsborough, Pasco, Pinellas, Manatee, Sarasota, and Charlotte counties) has been chosen as ad-hock check on the data quality and graphed along the Florida SFR home sales. It is evident that Tampa Bay region follows overall Florida trend. Please, note the sharp drop in sales from 2019 to 2020 for both Florida and Tampa Bay Region.

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**Figure 1 - Florida SFR Home Sales from 2009 to 2020**

**Zeroing in on SFR Home Same Year Re-sales**

FDOR NAL files contain information on SFR home re-sales – each record has *Sale Year/Month One* and *Sale Year /Month Two*. To eliminate the scenario where land parcel sales and new home gets built and sells again in the same year, the data were filtered in the following way: *Sale Year One* not equal to *Actual Year Built*. To determine if the SFR sales with profit or loss – *Sale Price One (last sale)* was subtracted from the *Sale Price Two (previous sale)*. Time between *Sale 1* and *Sale 2* measured in months andwas calculated by subtracting *Sale Month One (last sale)* from *Sale Month Two (previous sale).* Detailed descriptions of all fields could be found in the Appendix 1 - 2022 User’s Guide.

**NOTE:** *The SFR homes bought and sold again, which crossed year boundary, were removed from the study.*

**Graphing Florida SFR Home Same Year Re-Sales from 2009 to 2020**

The graph below shows counts of Florida SFR home same year re-sales from 2009 to 2020. There were on average – 35,500 SFR homes re-sales per year. Tampa Bay region (Hillsborough, Pasco, Pinellas, Manatee, Sarasota, and Charlotte counties) has been chosen as an ad-hock check on the data quality and graphed along the Florida SFR home re-sales. It is evident that Tampa Bay region follows overall Florida trend. Please, note the sharp drop in re-sales from 2019 to 2020 for both Florida and Tampa Bay Region.

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**Figure 2 - Florida SFR Home Sales from 2009 to 2020**

Diagram

Description automatically generated**General Machine Learning Process**

**Question: Will Single Family Residential Home re-sell for loss or make a profit in the same year?**

**Data: Florida Department of Revenue Assessment Roll files from 2009 to 2020**

The study will be following steps of the General Machine Learning process diagramed on the left in the figure 3.

Logistic Regression, Decision Tree and Random Forest algorithms will be used to create explainable (“White-Box”) models.

**Figure 3 - Matt Harrison, Machine Learning Pocket Reference Working With Structured Data in Python, 2019**

**Target Variable – Loss or Profit**

Graph below shows counts of outcome of SFR home same year re-sale from 2009 to 2020. Loss was at 89,245 or 22% and Profit – 312,478 or 78%. In cases where *Sale Price One (last sale)* was equal to  *Sale Price Two (previous sale),* the outcome was labeled as *Loss.* The rationale was because of the additional expenses associated with the *Cost of Sale,* break-even would still mean money lost.

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**Figure 4 - Outcome of All SFR home same year re-sale in Florida from 2009 to 2020**

**Target Variable – Loss or Profit (continued)**

It is instructive to look at the target variable broken by individual year. Please notice, SFR home re-sale Losses picked in 2013 prior to the highest Profit Year of 2014. The data is uniformly distributed throughout the years with exception for the 2009 and 2020 years.

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**Figure 5 – Outcome of SFR home same year re-sale by year**

**NOTE:** *The SFR homes bought and sold again, which crossed year boundary, were removed from the study.*

**Measuring Imbalance of the Data Set**

The Imbalance Ratio formula, size of minority class divided by the size of the majority class, was used to measure the extent of the imbalance of the data set. In our case, imbalance ratio was 29% and could be interpreted as for each Loss outcome there are three Profit outcomes. It can be visually seen on the graph above – Figure 5. Upon reviewing Imbalance Ratio, we can conclude - no significant imbalance issue present in the data.

**Baseline Accuracy – 78%**

Baseline Accuracy has been calculated by dividing counts of Florida SFR home same year resales with outcome of Profit (majority class) by total counts of Loss and Profit outcomes, which equals to 78%. In another words, if we make prediction of Profit 100% of the time, we would be 78% correct. Machine Learning algorithms (Logistic Regression, Decision Tree, Support Vector Machine) will attempt to make predictions with accuracy higher than the baseline of 78%

**Predictor Table**

It is good practice to attempt pick input variables based on domain knowledge and logical reasoning prior to building models. Following table attempts to estimate positive or negative effect on the Profit or Loss outcome of the SFR home same year re-sale. More detailed descriptions of input variables can be found in the Appendix 1 – 2022 User’s Guide

|  |  |  |
| --- | --- | --- |
| Predictor | Effect | Rationale |
| LND\_SQFOOT | + | Larger land usually sells for a higher price |
| EFF\_YR\_BLT | + | Effective Year Built helps homes which are maintained to sell for a higher price |
| ACT\_YR\_BLT | -/+ | Actual Year Built can positively or negatively effect profit or loss and uncover effects of renovations |
| TOT\_LVG\_AREA | + | Larger homes usually sell for a higher price |
| S\_LEGAL | + | Subdivisions within neighborhoods could be more desirable than others |
| JV | -/+ | Just Value could affect investor’s decision |
| IMP\_QUAL | + | Higher quality homes usually sell for a higher price |
| LND\_VAL | -/+ | Higher land value could affect investor’s decision |
| NO\_BULDNG | + | Higher number of buildings usually sell for a higher price |
| CONST\_CLASS | + | Higher class of construction usually sell for a higher price |
| NCONST\_VAL | + | New Construction value added for renovations positive effect re-sale |
| DEL\_VAL | - | Cost of demolition negatively effects profit |
| SPEC\_FEAT\_VAL | + | Value of Special Features such as yard items, pool etc. increases the profit |
| MONTH\_DIFF | - | Number of months between Sale 1 and Sale 2 decrease profit |
| SALE\_PRC1 | -/+ | Sale price of the last sale could help uncover the effect on the profit or loss based on the price point for a particular segment of the SFR homes |

**Figure 6 – Predictor Table**

**Feature Engineering**

Actual Year and Effective Year Built categorical columns were transformed to numeric columns – Actual and Effective Age. Actual Year Built was subtracted from current year, 2022, for new Actual Age variable. In the similar way, Effective Year Built was transformed into Effective Age column. Actual Age is the number of years from the actual year built and may or may not reflect actual condition of the SFR home. Effective Age column considers maintenance and renovations for the SFR home which were completed over the years.

**Data Preparation**

Prior to Data Preparation steps, data set’s dimensions were 16 columns (including target variable – 0 for Profit and 1 for Loss) and 401,723 rows.

For Logistic Regression, Decision Tree and Random Forest algorithms, inputs were processed in the following way: numerical columns were standardized, and missing values replaced with median for each column; categorical columns were “one hot encoded” - for each unique categorical label new binary (1,0) column were created and missing values were ignored. Models were created with programing language *Python* using *Jupyter Notebooks* and *Scikit-Learn* module.

Processed data set’s dimensions were 100,785 columns and 401,723 rows. For each model, processed data was split into Training and Test subsets –70% (100,785 columns, 281,206 rows) and (100,785 columns, 120,517 rows) 30%

**Descriptions of Input Variables**

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| --- | --- | --- |
| **Predictor** | **Data Type** | **Description** |
| EFF\_AGE | Numeric | Effective Age |
| ACT\_AGE | Numeric | Actual Age |
| LND\_SQFOOT | Numeric | Land Square Footage |
| TOT\_LVG\_AREA | Numeric | Total Living or Usable Area |
| S\_LEGAL | Categorical | Short Legal Description (Name of the Subdivision) |
| CONST\_CLASS | Categorical | Construction Class |
| IMP\_QUAL | Categorical | Improvement Quality |
| JV | Numeric | Just Value (Assessment Value) |
| LND\_VAL | Numeric | Land Value |
| NO\_BULDNG | Numeric | Number of Buildings |
| NCONST\_VAL | Numeric | New Construction Value |
| DEL\_VAL | Numeric | Deletion Value |
| SPEC\_FEAT\_VAL | Numeric | Special Feature Value |
| MONTH\_DIFF | Numeric | Month Difference between Sale 1 and Sale 2 |
| SALE\_PRC1 | Numeric | Sale Price – Sale 1 |
| TARGET\_VAR | int64 | Profit - 0 or Loss – 1 |

**Figure 7 – Descriptions of Input Variables**

**MODEL I: Logistic Regression**

For the Logistic Regression algorithm’s training data set, baseline accuracy was calculated at 78% For the Training Data set model made predictions with 82% accuracy. For the Test Data set model made predictions with 80% accuracy. One percent difference between Training and Test data sets accuracy measures suggested no model underfitting or overfitting issues.

**Classification Matrix for the Test data set**

|  |  |  |
| --- | --- | --- |
|  | Predicted Class | |
| Actual Class | ***Profit*** | ***Loss*** |
| *Profit* | **90,423** | **3,409** |
| *Loss* | **20,693** | **5,992** |

Looking at the Classification Matrix above, 3,409 observations model predicted as Loss when they were Profit outcomes. 20,693 model incorrectly classified as Loss outcomes when they were in fact – Profit.

Based on the 80% accuracy and error analysis we can conclude that the Logistic Regression algorithm performed favorably compared with the baseline accuracy of 78% and derived formula can be applied to the new data to make predictions.

**Feature Importance**

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| |  |  |  | | --- | --- | --- | | **Predictor Variable** | **Coefficient** | **Proportion of the Loss Outcomes** | | S\_LEGAL | 2.423 | 0.919 | | EFF\_AGE | 0.211 | 0.553 | | TOT\_LVG\_AREA | 0.168 | 0.542 | | CONST\_CLASS | 0.074 | 0.518 | | NO\_BULDNG | 0.032 | 0.508 | | LND\_VAL | 0.021 | 0.505 | | LND\_SQFOOT | -0.008 | 0.498 | | SALE\_PRC1 | -0.017 | 0.496 | | IMP\_QUAL | -0.023 | 0.494 | | JV | -0.027 | 0.493 | | SPEC\_FEAT\_VAL | -0.082 | 0.479 | | ACT\_AGE | -0.173 | 0.457 | | MONTH\_DIFF | -0.215 | 0.446 | | NCONST\_VAL | -0.61 | 0.352 | | DEL\_VAL | -16.754 | 0 | |  |  |  |  |

Proportion of the Loss Outcomes was calculated with the inverse logit of the coefficients.

Upon inspection of the coefficients, we can conclude that location plays the most important role in the determining Loss outcome. S\_LEGAL variable was the Short Legal Description of the Subdivision where SFR home located and coefficient was 2.423 with proportion of the Loss outcomes – 0.919

If DEL\_VAL (Deletion Value) goes up then there little chance of Loss outcome. (Possible during renovations to combine bedrooms, expand living room etc.)

**Figure 8 – MODEL I: Logistic Regression, Feature Importance**

**MODEL II: Decision Tree**

For the Decision Tree algorithm’s training data set, baseline accuracy was calculated at 78% In another words, if we make a prediction of “Profit” for every observation we would be 78% accurate. For the Training Data set model made predictions with 83% accuracy. For the Test Data set model made predictions with 82% accuracy. One percent difference between Training and Test data sets accuracy measures suggested no model underfitting or overfitting issues.

**Classification Matrix for the Test data set**

|  |  |  |
| --- | --- | --- |
|  | Predicted Class | |
| Actual Class | ***Profit*** | ***Loss*** |
| *Profit* | **87,921** | **5,911** |
| *Loss* | **15,273** | **11,412** |

Looking at the Classification Matrix above, 5,911 observations model predicted as Loss when they were Profit outcomes of the SFR home same year re-sale. 15,273 model incorrectly classified as Loss outcomes when they were in fact – Profit.

Based on the 82% accuracy and error analysis we can conclude that the Decision Tree algorithm performed favorably compared with baseline accuracy of 78% and derived formula can be applied to the new data to make predictions.

**Feature Importance**

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| Chart  Description automatically generated |

Feature Importance function of *Scikit-Learn* module were applied following training. Chart on the left, shows top 10 variables with importance scores from 0 to 1.

Per *Scikit-Learn* module documentation, higher importance means that there is higher error when the variable removed from the model.

Top 5 importance scores were for the *MONTH\_DIFF, SALE\_PRC1,* *JV,* *ACT\_AGE, CONST\_CLASS* variables – 0.74, 0.15, 0.06, 0.02, and 0.02

**NOTE:** *Chart in the Figure 9, derived using random sample of 30% from the processed data set*

**Figure 9 – MODEL II: Decision Tree, Feature Importance**

**MODEL III: Random Forest**

For the Random Forest algorithm’s training data set, baseline accuracy was calculated at 78 For the Training Data set model made predictions with 99% accuracy. For the Test Data set model made predictions with 84% accuracy. Fifteen percent difference between Training and Test data sets accuracy measures suggested model overfitting issues. However, the Random Forest made less errors on the test data set compared to Logistic Regression and Decision Tree algorithms and can be considered the best model.

**Classification Matrix for the Test data set**

|  |  |  |
| --- | --- | --- |
|  | Predicted Class | |
| Actual Class | ***Profit*** | ***Loss*** |
| *Profit* | **90,508** | **3,324** |
| *Loss* | **15,614** | **11,071** |

Looking at the Classification Matrix above, 2,542 observations model predicted as Loss when they were Profit outcomes. 14,750 model incorrectly classified as Loss outcomes when they were in fact – Profit.

Based on the 86% accuracy and error analysis we can conclude that the Random Forest algorithm performed favorably compared with the baseline accuracy of 78% and derived formula can be applied to the new data to make predictions.

**Feature Importance**

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Feature Importance function of *Scikit-Learn* module were applied following training. Chart on the left, shows top 10 variables with importance scores from 0 to 1.

Per *Scikit-Learn* module documentation, higher importance means that there is higher error when the variable removed from the model.

Top 5 importance scores were for the *MONTH\_DIFF, SALE\_PRC1,* *JV,* *TOT\_LVG\_AREA, LND\_VAL* variables – 0.133, 0.090, 0.052, 0.045, and 0.042

**NOTE:** *Chart in the Figure 10, derived using random sample of 30% from the processed data set*

**Figure 10 – MODEL III: Random Forest, Feature Importance**

**Discussion**

**Conclusion**

**Lessons Learned**