Property Evaluation in New York City

TEXAS TECH UNIVERSITY
Rawls College *of* Business™

Data Science Capstone

ISQS 5381 Summer II 2019

Professor Fred Davis

August 4, 2019

Prepared by:

Arjuna Menon, Jaimie Capps,

Marcin Grzechowiak, Mikaela Pisani, Rogelio Valdez

Table of Contents

Executive Summary

In this data analysis, “Property Evaluation in New York City,” the intention is to predict the assessed land value (*assessland* variable) and assessed property value (*assesstot* variable, land and buildings) for any given tax lot in New York City. In order to understand the impact of the assessed land and assessed property of the tax lot on its market value, research was conducted to determine the relationship between these variables. Therefore, after predicting the assessed value of the land/property, the market value might be calculated according to the tax class. The prediction models provided in this analysis can be useful as a business service. For example, if a company was looking to expand infrastructure in New York City they could use the information from the predictions to decide if they should buy land and build on it or buy land with a building already on the property. In order to provide this service, a business model in the form of an online platform would be implemented. The online platform will give the user access to filters for multiple variables and receive a visualization about the potential land/property values that align with their preferences.

When considering variables, research was conducted in order to evaluate previous methods of model creation and which variables were chosen for prediction as a reference. One article found titled, “Using machine learning algorithms for housing price prediction: The case of Fairfax County, Virginia housing data,” considered variables such as the number of full bathrooms, fireplaces, garage spaces, bedrooms, and more. While those variables might be important for predicting, at the same time they are very difficult and expensive to gather. In order to find the number of bedrooms a residence has, there comes a need to ask the owner questions about home details and at this point, it is up to the owner if they would like to disclose that information. However, the idea of this project is to predict the value of the property using data which are much easier and cheaper to access, for example, using data that are gathered for tax purposes and that are freely available online. If the model can be built based on that information the business' cost could be significantly reduced, and as a result, the profit would be increased.

This report concentrates on the comparison between different machine learning prediction techniques in order to evaluate which model performs the best. The critical measurement in the analysis is RMSE. The advantages of root mean square error is its interpretability - it gives the error value in the same units as target variables, in dollars. Expressing errors in dollars makes the results easily understandable for people who are not fluent in machine learning analysis.

Business Understanding

Business Objectives and Success Criteria

Imagine a world without Zillow and its “Zestimate” tool. How would you determine what the potential cost of a property should be or what you expect it to be? This research concentrates on analyzing data from New York City to find out what exactly the necessary predictors are when asking this question and how the output can be implemented into an online platform that can be utilized by its users. This analysis requires delving deeper into how we define each variable and what we consider to be influential factors based on the results of tests and modeling we conduct.

The audience, or clientele, are companies and consumers seeking, or selling, property for either business or residential use. The implemented strategy, as mentioned earlier, is to create an online platform where the client can input his or her preferences and the platform will populate with the potential listings corresponding to those preferences. Likewise, there is a need to keep the client’s interests in mind during this process. The expected benefits associated with this analysis, with the seller in mind, is to save time and increase trust in a model to predict the potential value that can be obtained by selling that piece of land or property. For the buyer, the expected benefits include the ability to weigh their options and evaluate whether or not they should buy a certain piece of land or property. The success will be defined by the ability to randomly select a lot and predict the land value or property value associated with that lot.

The evaluation and census data used in this analysis was a result of active data capture. Active data capture is manual data transfer that is initiated by an individual's decision to provide the data. We integrated data fusion into our analysis when we merge the census data and the tax lot data together. Monetization of the data is one of the primary driving factors for creating a dashboard for users. This entire analysis is based on the assumption that the client is risk-averse. This opens up many opportunities for providing a service that in a way, gives the client comfort in their process of deciding where to buy or sell their property. In an effort to evaluate the return on investment, a heatmap tool can be used after the dashboard has been in use for a while to determine the property value across all areas of NYC. Investors can utilize this feature by knowing where in the city they will likely capitalize on the most positive rate of return.

Data Mining Objectives and Success Criteria

Two target variables were defined in the project, *assessland*, and *assesstot*. The first describes the assessed value of the land without any buildings present, while the latter describes the total assessed value of the property. Since those variables are strictly related to the market value, the results of this analysis might be widely used for many business needs. The most important criterion for model evaluation is RMSE. The error allows comparing models in terms of the errors described in dollars. Expressing error in dollars makes model interpretation easy to understand for people who are not fluent in machine learning jargon. Moreover, the results can be easily and quickly transformed into business decisions. Additionally, different visualization techniques are used as well as R-squared value in order to check for overfitting the model. When the histogram of the differences between predicted values and the true values of the test set is significantly different from those of the training set, the model is prone to overfitting. When the value of the R-squared is high for training set but low for the test set, it indicates an overfitting problem. The success criterion is defined by the lowest RMSE in addition to avoiding overfitting the model. The model which best fulfills these criteria will be chosen as the final one.

Data Understanding

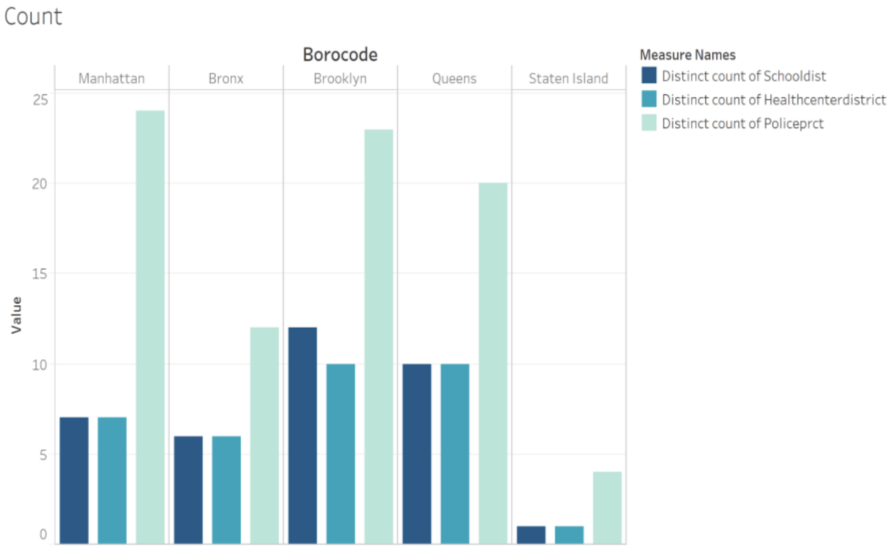
The data from the analysis was found from the City of New York Primary Land Use Tax Lot Output (PLUTO) 2018 and later combined with the 2018 census data by zip code in the same year. The original data set can be found at the website New York City Open Data[1] and the census data can be found on the United States Census Bureau website[2]. A list of all of the variables are located in the appendix of this document. In this location, the defined variables, along with their alias name, datatype, description, issue associated, and the solution can be found.

In order to better understand the data, various views were created and variables were chosen that were most useful for visualizations. Zip code and borough code variables helped plot the data on a map of New York City which became useful combined with different measures of the dataset. Instances of variables for measurement included median income, count of residential units, count of police precincts, count of health center districts and count of school districts per borough.

For visualizations, the application Tableau was chosen. This allowed different inputs such as measures and dimensions in order to plot various graphs. For example, the bar graph figure

[1] https://data.cityofnewyork.us/City-Government/Primary-Land-Use-Tax-Lot-Output-PLUTO-/xuk2-nczf
[2] https://factfinder.census.gov/faces/tables

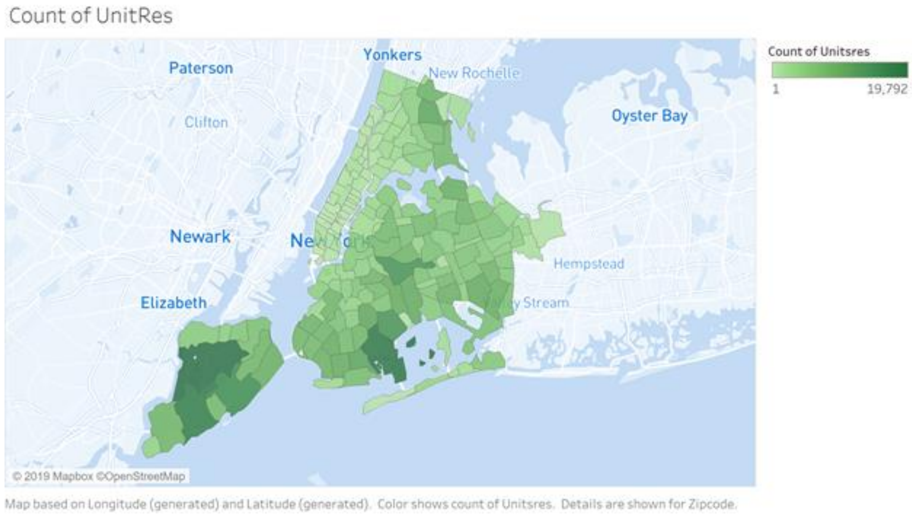
created below, split the data into the five different borough codes in New York City. After grouping data by borough, count function was implemented for variables: *schooldist*, *healthcenterdistrict*, and *policeprct*. Once graphed, it became easier to view the number of police precincts, health center districts, and school districts within each borough. As a result, it can be seen that all of the boroughs contain more police precincts than school districts and health center districts.



Distinct count of Schooldist, distinct count of Healthcenterdistrict and distinct count of Policeprct for each Borocode. Color shows details about distinct count of Schooldist, distinct count of Healthcenterdistrict and distinct count of Policeprct.

Figure 1. Histogram of Measurement for Each District

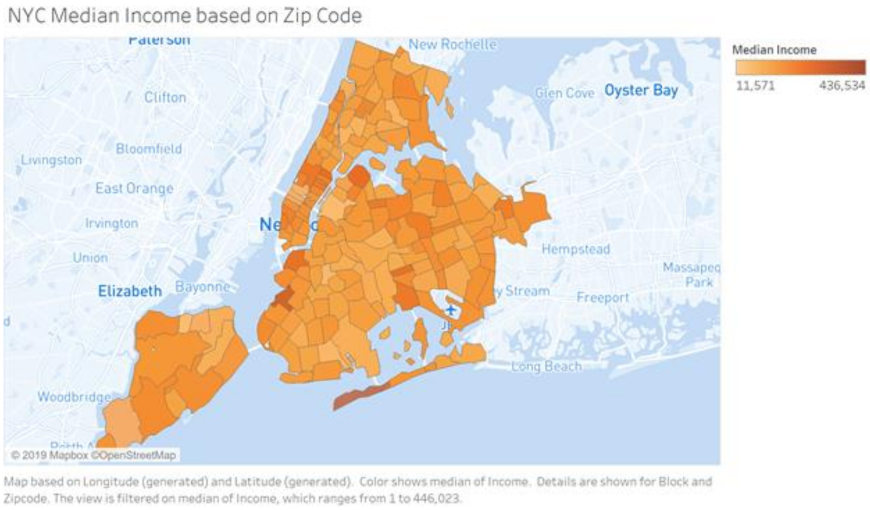
The dataset contained zip codes which were used as a dimension to plot a map graph. From here the measure was created using the count of the variable *unitsres*, which is the sum of residential units in all buildings on the tax lot. The graph provided the results of a map of New York City with darker colors reflecting areas where the number of residential units were the largest. According to the data and referring to the map, it was observed that the largest number of residential units are present in the Staten Island area and the lower East past of Brooklyn.


Count of UnitRes

Map based on Longitude (generated) and Latitude (generated). Color shows count of Unitsres. Details are shown for Zipcode.

Figure 2. Heatmap of the Number of Residential Units in NYC

A similar map as that created above was obtained by using the measure of median income instead of the count of residential units. In this case, the largest median incomes are sporadic with darker areas around Manhattan and closer to the oceanfront around Brooklyn. For these areas, it would make sense that they would have larger median incomes because the cost of living in the most popular US city or an oceanfront property would require a higher income.


NYC Median Income based on Zip Code

Map based on Longitude (generated) and Latitude (generated). Color shows median of Income. Details are shown for Block and Zipcode. The view is filtered on median of Income, which ranges from 1 to 446,023.

Figure 3. Heatmap for Median Income in NYC

In order to get more insights about the data, clustering techniques were conducted based only on numerical data. Two clustering techniques were tried, Model Based Clustering and K-Means Clustering. The only method which performed well with the data was the first one, while K-Means grouped almost all the data into one cluster. In the case of Model Based Clustering, the algorithm distinguished mostly Manhattan from other parts of NYC. It can be concluded that the most distinguishable part of the city is Manhattan, while other parts outside it are more or less similar to each other. This can be seen on the plot below.

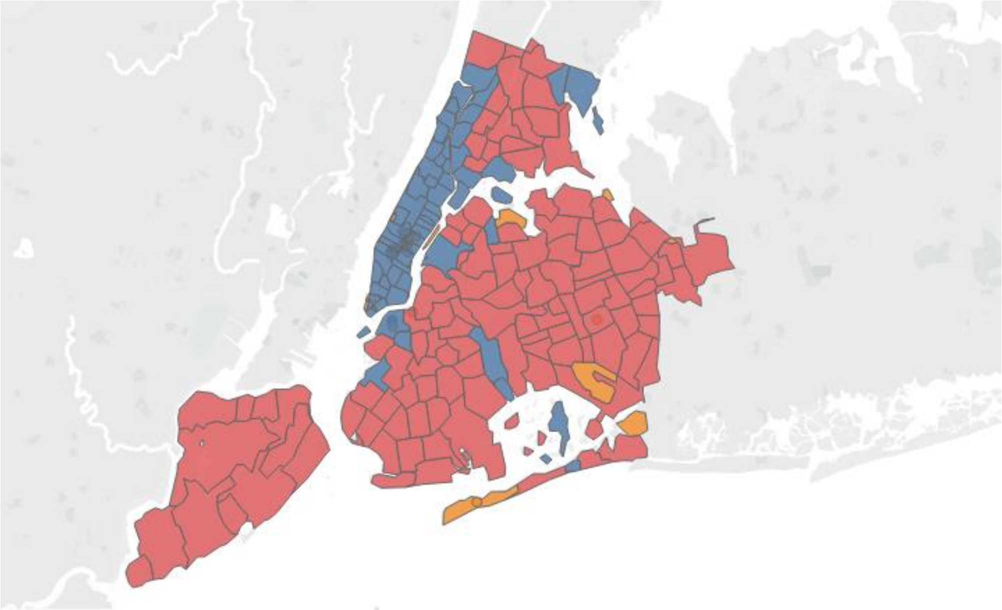


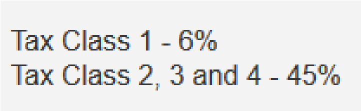
Figure 4. Model-based Clustering based on Numerical Data

Data Preparation

In order to keep the data cleaning process concise and easy to understand, all the steps taken are explained below. Detailed explanations and reasoning for the deletion of variables that would not be useful for prediction are explained in the Appendix. Unless otherwise specified, these steps were carried out using R.

- All variables that have a majority of NA values (mostly greater than 90%) and variables that contained only one value in addition to zeroes, such as *rpaddate* were removed.
- The variables *block* and *lot* were removed since lots are repeated within blocks and blocks are repeated within the borough. Hence, these variables would need to be combined to have unique values and this provides redundant location information present in other variables which would basically act almost like an identifier.
- The missing values of the *zipcode* were assigned values by matching them with a shapefile using Python and QGIS.
- One of the zip codes corresponds to an airport. It was removed because it has an extremely high assesstot value that might affect the prediction. Also, few zip codes were found to be present in the sea and these were removed. These outliers were found via Tableau.
- Variables that must be converted to factors, and later dummies, are identified. Some of these variables have several levels that provide too much detail, and these were transformed into variables with fewer levels.
- For variables containing an acceptable number of NAs, these missing values were replaced with random values of that variable for the corresponding zip code if that variable was non-numeric. For numeric variables, these missing values were replaced with the median value of that variable for the corresponding zip code.
- If a particular zip code contained only NAs for a column, that column’s NA values were replaced with either a random value or the median of that variable for the corresponding borough.
- Outliers that have values more than three standard deviations from the mean in at least one or more of the numerical variables were removed using Python.

- All numeric variables, except for the target variables assessland and assesstot, were scaled and the factors were converted to (n-1) dummies.
- Stratified sampling based on *zipcode* was done on the dataset using Python to obtain a sample that adequately represented the population.
- This sample was used for all models except the neural network. All modelling was done using Python.
- For predicting *assessland*, all building related variables were removed, while for *assesstot* all variables were considered. Since both target variables are highly correlated, for each prediction the other target variable was also removed.
- In the case of the neural network, principal component analysis was performed on the data disregarding building-related variables for predicting *assessland*. 170 principal components were chosen that explained around 93% of the variation in the entire dataset.
- For predicting *assesstot*, all the variables except for *assessland* were considered. 170 principal components were chosen that explained around 95% of the variation in the entire dataset.
- Finally, the market value of *assessland* and *assesstot* can be calculated as follows:



Tax Class 1 - 6%
Tax Class 2, 3 and 4 - 45%

[3]

The tax class is defined by the number of residential units that the lot has. If it has 1,2, or 3 residential units, it is classified as class 1 (6%). Otherwise, the percentage would be 45% (for 0 residential units and above 3 residential units).

[3] https://www1.nyc.gov/site/finance/taxes/definitions-of-property-assessment-terms.page

Merging multiple data sources:

- Merge PLUTO with census data: The census dataset has information about the average income for families and non-families by zip code. This data was merged by *zipcode* with the original dataset.
- Missing values in the mean income for families and non-families were replaced by the median income for families and non-families respectively for the corresponding zip code.
- Any NAs still remaining were replaced by the median value of income for families and non-families of the corresponding borough. This is in the cases of entire zip codes containing only NAs for the mean income for families or non-families.
- In order for a better representation of reality, the mean income was then replaced with values from a triangular distribution with a minimum, maximum and most likely values for each zip code, rather than having a repetition of the same average income value for each zip code.
- Also, income was assigned a value of zero in the case of no building area since the absence of a building should prohibit any income being generated in that tax lot. Furthermore, those tax lots having a land use value greater than 5 were assigned 0 income, since they refer to tax lots that do not contain families residing permanently in these buildings.

Modeling

As stated at the very beginning, the objective of the project is to predict the value of the land as well as the total value of the property. In order to keep this report concise and neat, only the process for predicting assessed land value will be described in detail with plots and descriptions. In the case of assessed value of the property(*assesstot*), the process for the best model is described, and the rest of the plots are presented in Appendix in order to present the process of analysis.

I. Predicting the assessed value of the land (*assessland*)

In order to predict a value for the target variable, *assessland*, five models were used. The process of tuning the models is described below. The used models are as follows:

1) Ridge Regression
2) Lasso Regression
3) KNN
4) Random Forest
5) Neural Network

These models are explained in detail below.

1. Ridge Regression

a) Tuning process

In order to find the best value of the parameter alpha, which describes the penalty level for variables that account for a low prediction power, cross validation was used. The figure below shows that as alpha goes up, the error goes down. This means that the penalty level for predictors should be relatively high and the cross validation yields the best value for alpha equal to 61.

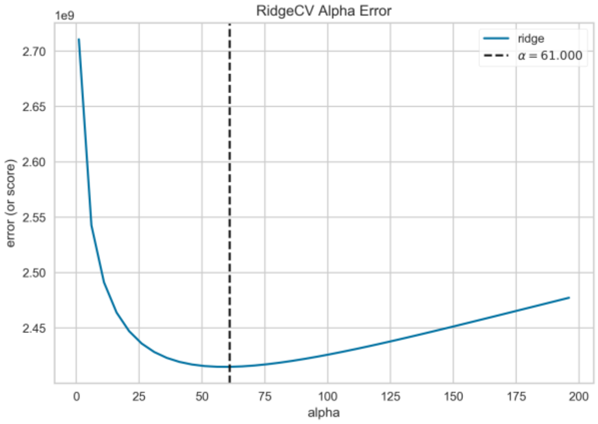


Figure 5. Cross-Validation for Ridge Regression

b) Model performance

In order to better understand the model behavior, several plots and measurements were used, which are presented below:

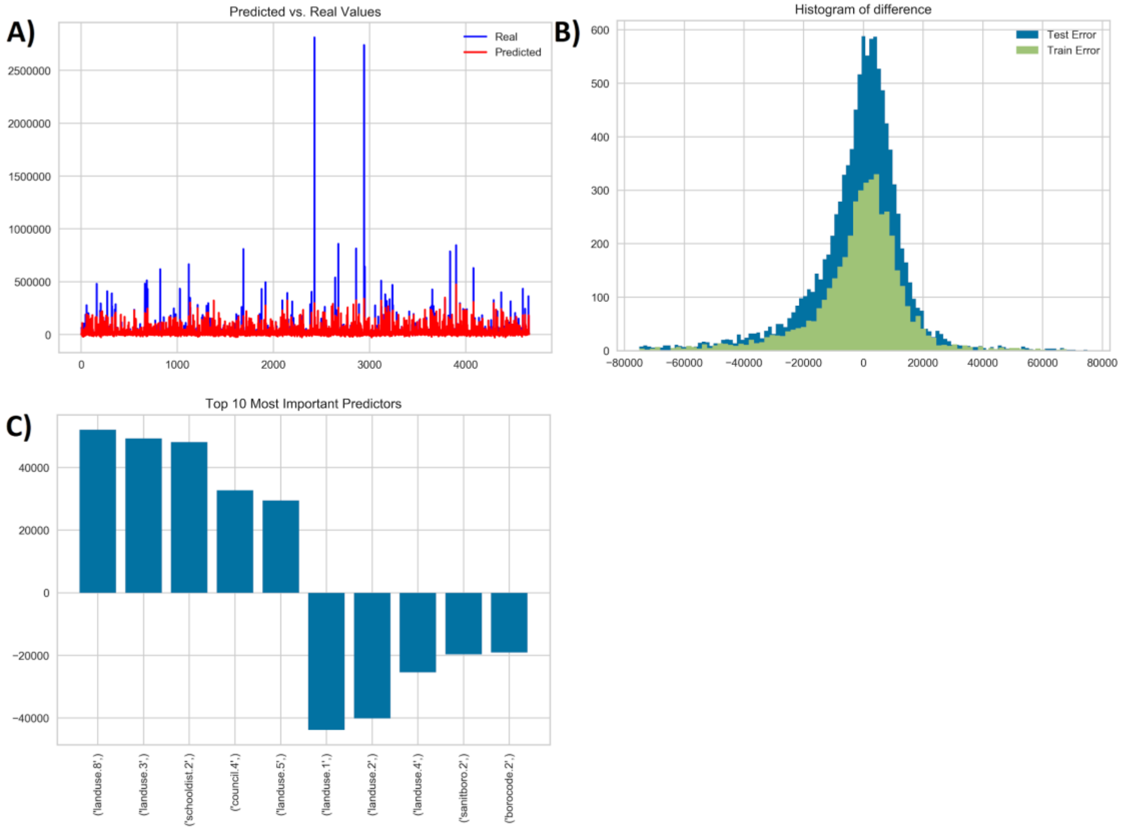


Figure 6. Model Performance for Ridge Regression

The graph (A) compares true values of *assessland* and predicted ones. It can be seen that blue lines represent real values of the land while red lines describe predicted values. The simple regression model performs quite well when it comes to predicting small values of the prices. However, when it comes to higher values in general, Ridge Regression underpredicts the *assessland* value.

Another presented measure is histogram of differences (B). Data for both training and testing sets show the difference between true values and predicted values of *assessland*. The plot tells that on average differences are around zero. Differences, in both training and testing sets, have a similar distribution, which means that there is no overfitting problem in this case. The issue is that, while most of the errors are around zero, in some cases the model makes big mistakes, however they are quite rare.

The advantage of regression is that for each predictor used in the model, it estimates its coefficient. In graph (C), the 10 best predictors, both with positive and negative coefficients are presented. The variables, whose presence increases the price of the land are, for example, *landuse 8*, *3* and *5*. According to the documentation, these refer to lands used for: Public Facilities & Institutions, Multi-Family Elevator Buildings and Commercial & Office Buildings. However, variables whose presence decrease the land value are for example, *landuse 1*, *2* and *4*. These represent lands used for: One- & Two-Family Buildings, Multi-Family Walk-Up Buildings, Mixed Residential & Commercial Buildings. As a result, it can be concluded that lands which are related to public institutions, lands with tall buildings where elevator is needed as well as lands where offices are placed are higher valued.

2. Lasso Regression

The idea of the Lasso Regression is very similar to Ridge Regression. However, Lasso penalizes predictors more harshly. When the variable is not useful as a predictor, its coefficient will be reduced to zero. Because the data presented in this project contains more than thousands of dummy variables, it is reasonable to use Lasso Regression.

a) Tuning process

Similar to the previous Regression problem, the alpha value was determined by cross validation technique. The graph is presented below.

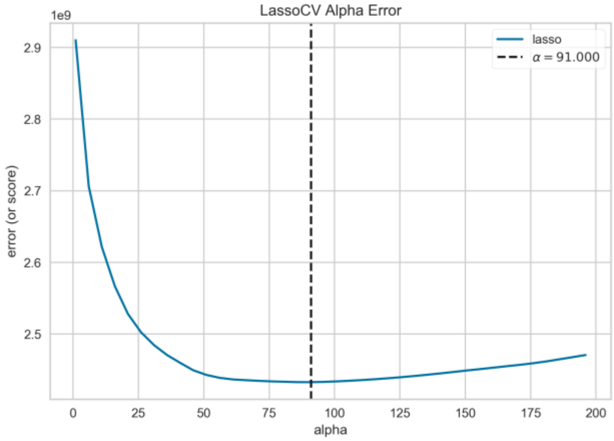


Figure 7. Cross-Validation for Lasso Regression

The process of cross validating the data found the optimal alpha to be 91, and thus this value was utilized in the model.

b) Model performance

While comparing the predictions with real values of *assessland*, the results are very similar to Ridge Regression. The model has difficulties to predict values of the land which are higher than most of the data (A). From the histogram of difference (B) it can be intereferd that the model does not overfit the data and most of the errors are around zero. The coefficients values displayed on plot (C) are very similar to those for Ridge Regression. Additionally, Lasso regression penalized 1027 variables and reduced their coefficients to zero.

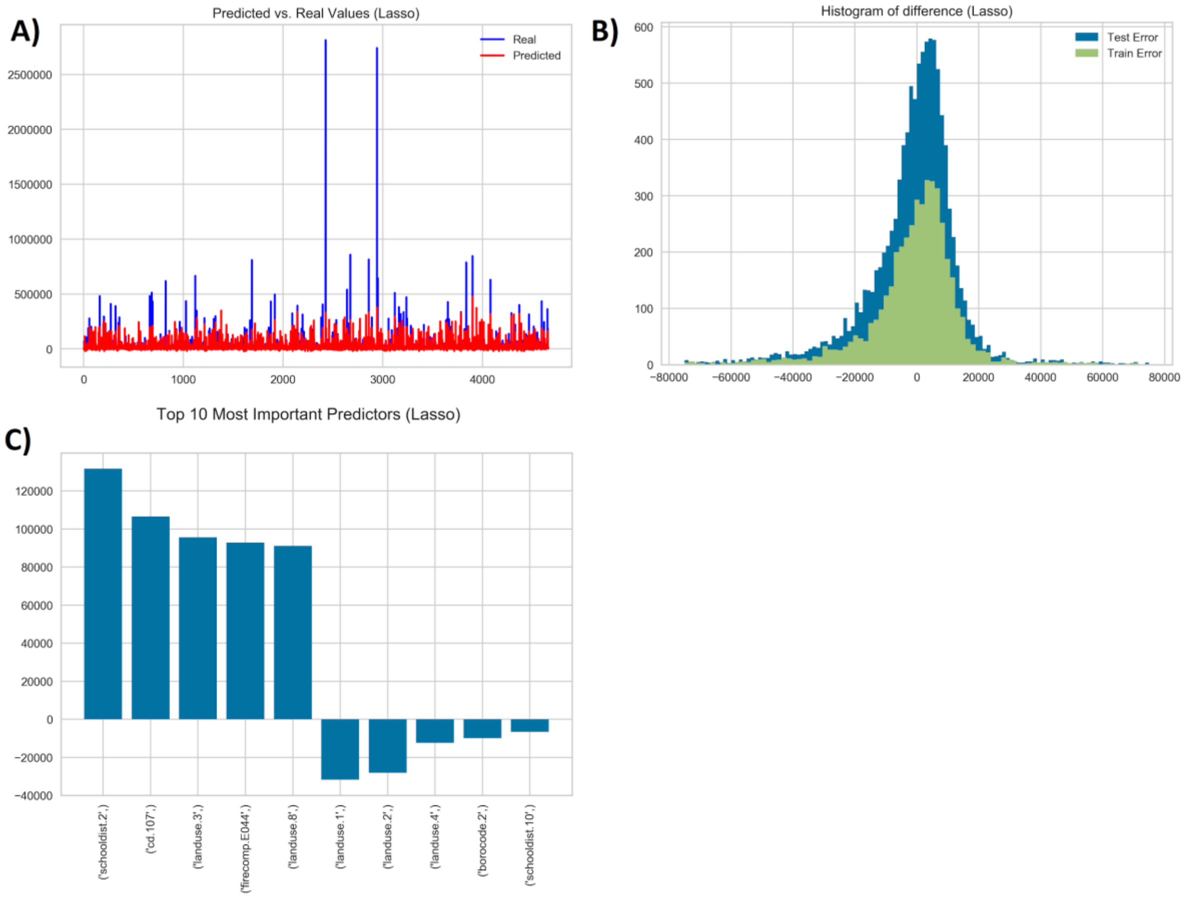


Figure 8. Model Performance for Lasso Regression

3. KNN

a) Model Tuning

This algorithm uses Euclidean distance formula to find the most similar row/rows for prediction. In contrast to previous algorithms, KNN does not have any feature selection processes implemented. Thus, in order to improve the model performance, gradient boosting - XGBoost technique was used to determine the best predictors. Additionally, in order to get the best prediction results, the model was tested on different number of neighbours. Results can be seen below.

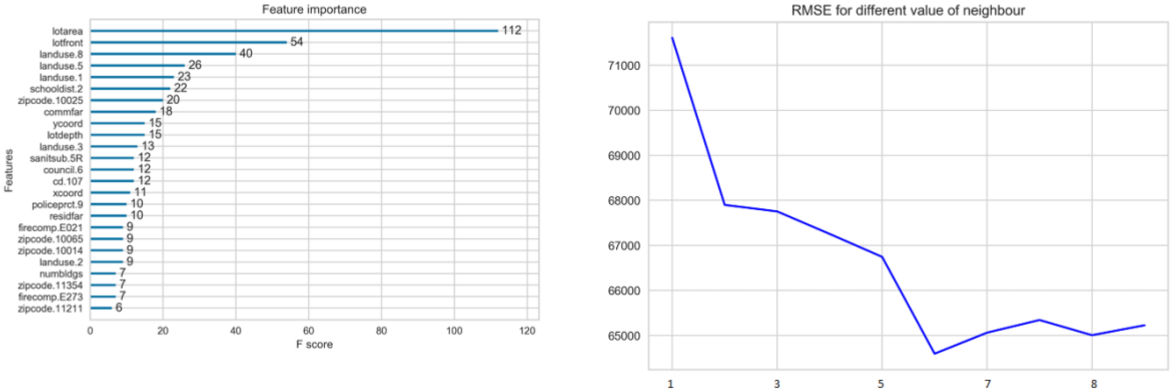


Figure 9. KNN Tuning

The graph on the left shows the top 20 most important variables for prediction used in KNN. As it can be seen, among selected variables are also those which were chosen by Ridge and Lasso regression, for example, *landuse 8*, *5* and *1*. The XGBoost algorithm chooses *lotarea* as the most important variable for predicting assessed value of the land. Graph on the right-hand side shows that the lowest error is presented when number of neighbours is equal to 6.

b) Model performance

Histogram of difference shows that distribution of difference of error for both train and test are very similar. However, the graph on the left shows that predicted values do not align well in the case of higher real values.

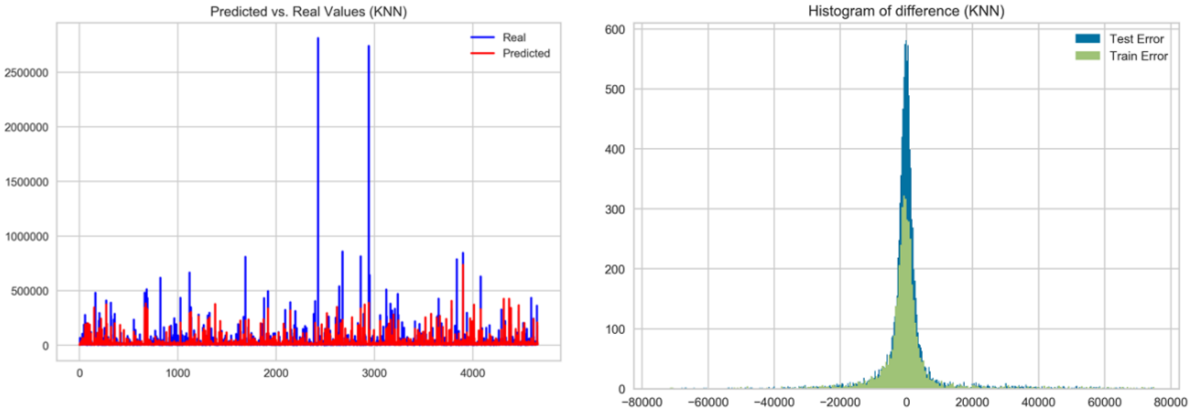
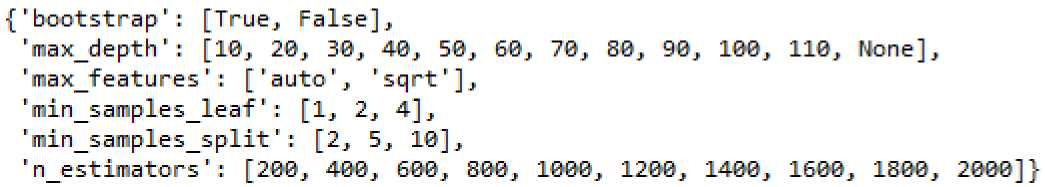


Figure 10. Model Performance for KNN

4. Random Forest

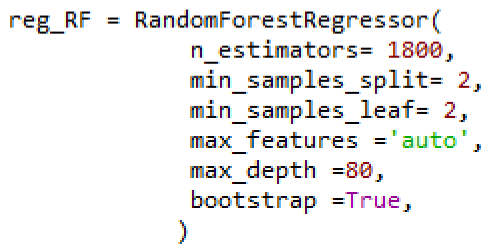
a) Model Tuning

In order to determine the best parameters for Random Forest, cross-validated search over parameter settings were used. Below the list of different settings for each parameter is presented.



```
{'bootstrap': [True, False],
 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None],
 'max_features': ['auto', 'sqrt'],
 'min_samples_leaf': [1, 2, 4],
 'min_samples_split': [2, 5, 10],
 'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000]}
```

It can be seen that there are 32 different parameters to check, so the total number of combinations is equal 1024. However, in order to improve the process, the function RandomizedSearchCV was used. The function does not try all possibilities but randomly chooses the number of specified settings given by the user, in this case 100 different parameters were checked. Best parameters are presented below.



```
reg_RF = RandomForestRegressor(
                    n_estimators= 1800,
                    min_samples_split= 2,
                    min_samples_leaf= 2,
                    max_features ='auto',
                    max_depth =80,
                    bootstrap =True,
                  )
```

b) Model performance

The performance of the model is described by the graphs below. Random Forest still has problems with predicting very big values. However, while comparing histograms across models which were presented before, it can be seen that the histogram for the random forest is very narrow. This means that in general, the difference between predicted values and real values is very close to zero.

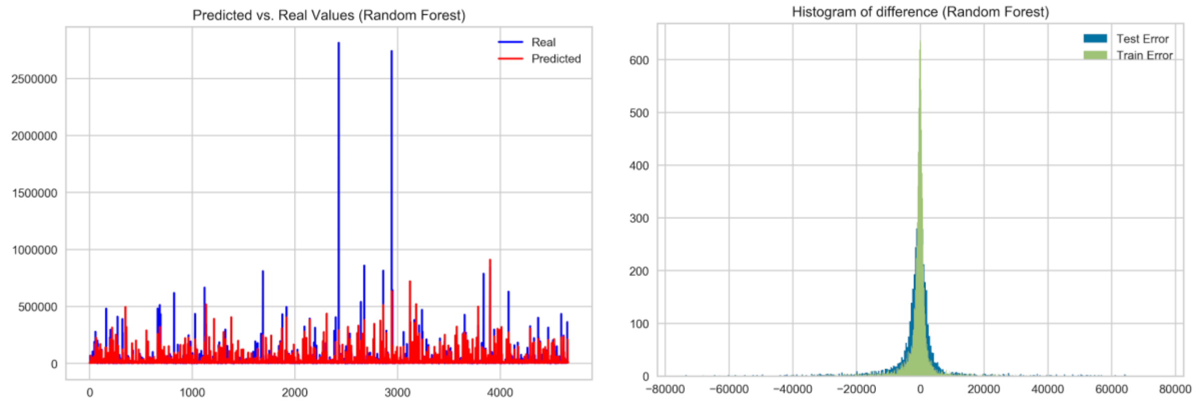


Figure 11. Model Performance for Random Forest

5. Neural Network

a) Model tuning

In order to model a neural network, several parameters should be defined. An automatic test was performed in order to check the performance and choose the best combination of the different parameters discussed below.

Number of layers: With two layers (no hidden layer), the model does not predict well. This might be because the data is complex and it has many variables. Therefore, it was decided to try with three layers, one input layer, one hidden layer, and one output layer. Testing with different amount of nodes for the hidden layer was conducted.

Amount of nodes:

- Input layer: For the input layer the dimension is determined by the amount of predictors
- Hidden layer: In order to determine the number of hidden nodes, a rule of thumb was followed: 1 hidden layer with (Number of inputs + outputs) * (2/3) nodes. Several number of nodes were tried, decreasing the number of nodes in each trial.
- Output layer: The result for the prediction should be only one value, therefore only one node for the output layer is used.

Activation function: With the purpose of introducing non-linearity, a non-linear activation function is used in the hidden layer.

As the problem is prediction, the recommended activation function is relu, which generates an output of 1 if the output value is greater than 0, and an output of 0 otherwise. This makes the activation sparse and efficient. This is recommended when you do not know the nature of the function that is being predicted. This activation function should only be used within hidden layers of a neural network model.

Optimizer: In order to minimize the loss (objective function) during the training process, an optimizer is used during the compile phase. Several optimizers were tried to compare the results obtained. The optimizers used are listed below:

- RMSprop: Root Mean Square Propagation. It utilizes the magnitude of the recent gradient descents to normalize the gradient. This optimizer is usually a good choice for recurrent neural networks. Learning rate gets adjusted automatically, and it is based on division by the average of the exponential decay of squared gradients.
- Adagrad: This optimizer performs larger updates for infrequent parameters and smaller updates for frequent parameters.
- Adam: This parameter can be viewed as a combination of Adagrad, which works well on sparse gradients and RMSprop which works well in online and nonstationary settings.
- AdaDelta: It is an extension of Adagrad and it also tries to reduce the learning rate.

b) Model performance

The following metrics and graphs were used to evaluate the models' performance.

- Learning Curve: The graph compares the performance of the model on the training and testing data over a varying number of training instances. It is based on the loss function, which is the objective function the model is trying to minimize. In each iteration the loss is calculated for the training and the test set. Looking at this plot, it can be determined if the model is overfitting. It is expected that the training error is less than test error, but among the iterations the test error gets closer to that of the training.

- Errors: The metrics MSE, R-square and RMSE errors for each model are provided. Among them, the model that has the maximum R-square and minimum RMSE is chosen. In addition, the actual values versus predicted values are plotted.

Several problems were faced. Firstly, training for a neural network with all the variables as input was performed, this made the model complicated and it took a long time to process. Therefore, it was decided to perform a neural network over the results from Principal Component Analysis (PCA). 170 principal components were chosen that explained 93.4% of the data variation in the data.

In the first attempt, a sample of the data was taken based on the proportion per zip code; applying first PCA and then executing the model over PCA results. A total of twenty models were performed changing the number of nodes for hidden layer. Secondly, the results for the sample case presented a problem, where the error for the testing set was lower than the training. This might be because of several reasons with the way the sample is built, such as the variance of the data or the proportion of the classes in each set. It is difficult to determine the specific reason because of the fact that the data contains many categorical variables. To resolve the issue, PCA was applied to all the data and then the models were performed.

In the case of *assessland* the problem persisted. Although other parameters were configured in order to improve the model, such as batch size, the amount of iterations, regulations functions and the percentage for test set, the problem was not resolved. Thus, further investigation should be done to fit the model.

The twenty models were performed from the result of PCA of the sample, as well as with the full dataset but the issue could not be resolved.

II. Predicting the assessed value of the property (*assesstot*)

In order to keep the report concise, the result of the analysis will be displayed in the Appendix in the form of graphs, where the process of analysis can be tracked by the reader. Only the final model for *assesstot* variable will be described in more detail.

The best model for the prediction of the assessed value of the property is Ridge regression. The results of analysis are presented on the graph below.

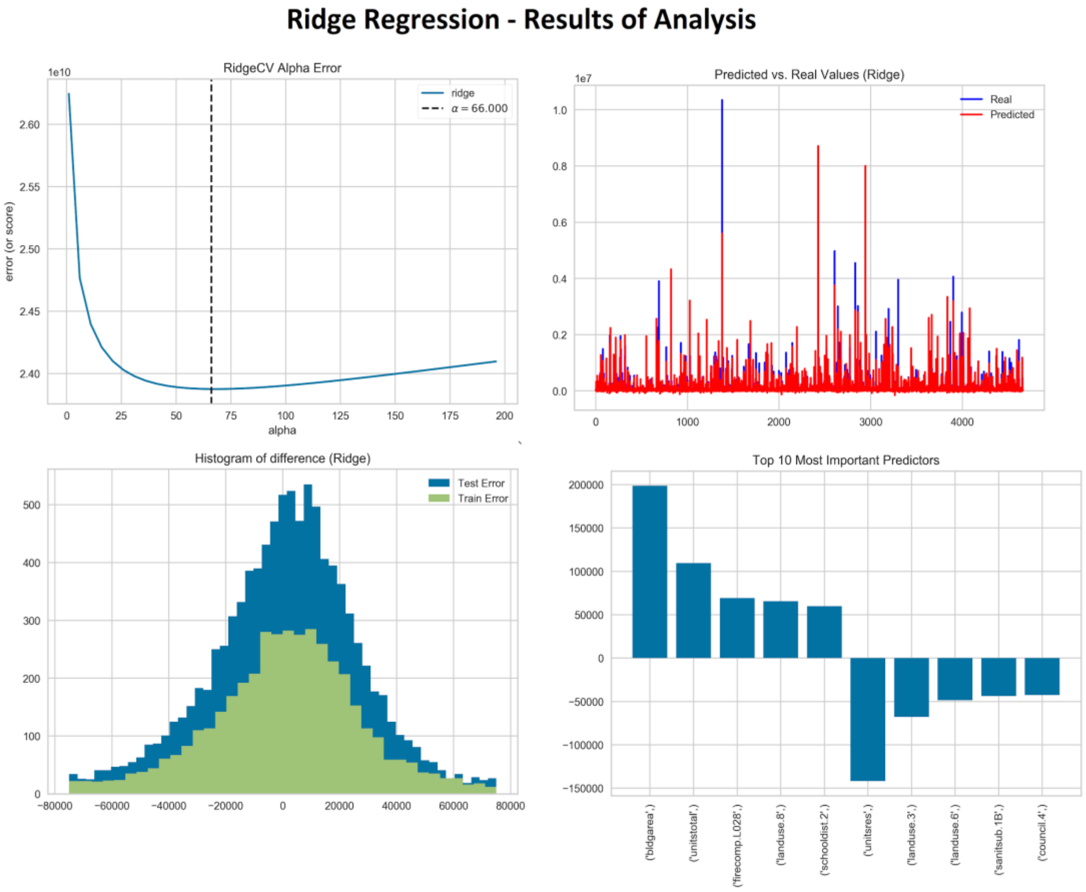


Figure 12. Ridge Regression for assesstot

Applying cross-validation, the best alpha was chosen as 66. Looking at the comparison of predicted against true values it can be seen that it is often similar, although there are few values for which the difference is significant.

In the case of histogram of difference, it can be seen that error ranges from -80,000 to 80,000. That means that model sometimes under-predicts values up to -$80,000 and sometimes over-predicts up to $80,000. However, many of the predicted values are placed around zero, which indicates a small error.

It can be seen that the most important predictors for *assessland* are building area and the number of residential units that the land has. While a bigger building area positively influences the value of the land, the number of residential units negatively influences it. Moreover, *landuse 8*, which specifies land for Public Facilities & Institutions influence the value positively. On the other hand, when the type indicates Multi-Family Elevator Buildings or Mixed Residential & Commercial Buildings, the value goes down. All other variables presented in the graph describe location of tax lot.

Evaluation

The results of all models are presented in the summary table below, where RMSE and R-square measures are compared across models. At first the models for *assessland* will be compared.

Table 1. Model Comparison for assessland

Model for *assessland*	**RMSE train**	**RMSE test**	**R squared (train)**	**R squared (test)**
Ridge Regression	39028	62829	0.57	0.37
Lasso Regression	39508	62622	0.56	0.37
KNN	36621	64593	0.62	0.33
Random Forest	19502	59076	0.89	0.44

It can be seen from the table for predicting the assessed land value that the best performance with the lowest RMSE is for Random Forest. On average, the model is wrong around $59,000 based on the test set. While this value might seem to be very high, it should be kept in mind that values of the lands within New York are very often in hundreds of millions of dollars. Looking from this perspective $59,000 might not look that high.

The second table shows comparison between models regarding *assesstot* value.

Table 2. Model Comparison for assesstot

Model for *assesstot*	**RMSE train**	**RMSE test**	**R squared (train)**	**R squared (test)**
Ridge Regression	141806	155380	0.80	0.80
Lasso Regression	144454	155796	0.79	0.79
KNN	196144	238272	0.63	0.53
Random Forest	77950	184690	0.94	0.71
Neural Network	160423	172456	0.772	0.75

In the case of prediction of assessed value of the property the best performance is shown by the Ridge Regression model. On average, the model is incorrect around $155,380 based on the test set, and it is the best results among all models.

Recommendations

As a result of analysis, it is recommended to use these models for initial evaluation of the property value. Businesses can make use of these models at the beginning of their deciding process in order to consider evaluating among different alternatives. However, it is not recommended to make a final and crucial decision based on the models' predictions. It should be kept in mind that there is a possibility to attach new data for the existing models in order to improve their prediction accuracies.

Additional value can be added by updating the models with data from property's conditions, for instance, if it is ready for business or needs renovations as seen according to the article "Estimating commercial property prices: an application of cokriging with housing prices as ancillary information".

Potential clients might be interested in the results of these predictions to base their decisions, in addition with other sources. Supporting the decisions with models might help to reduce the bias generated by assumptions or gut feelings that buyers and sellers have.

Deployment

Out of the several algorithms that were tested, it was decided from the results that the best choice is the Random Forest Regressor for predicting *assessland* and Ridge Regression for predicting *assesstot*. However, these models give a general idea about the properties in NYC, but it is not enough information to make an important business decision. In order for the models to be accurate and effective, more information would need to be considered instead of just free publicly available data. For deployment it would be noted to include easy update options for the system to account for additional data sources that are not publicly available.

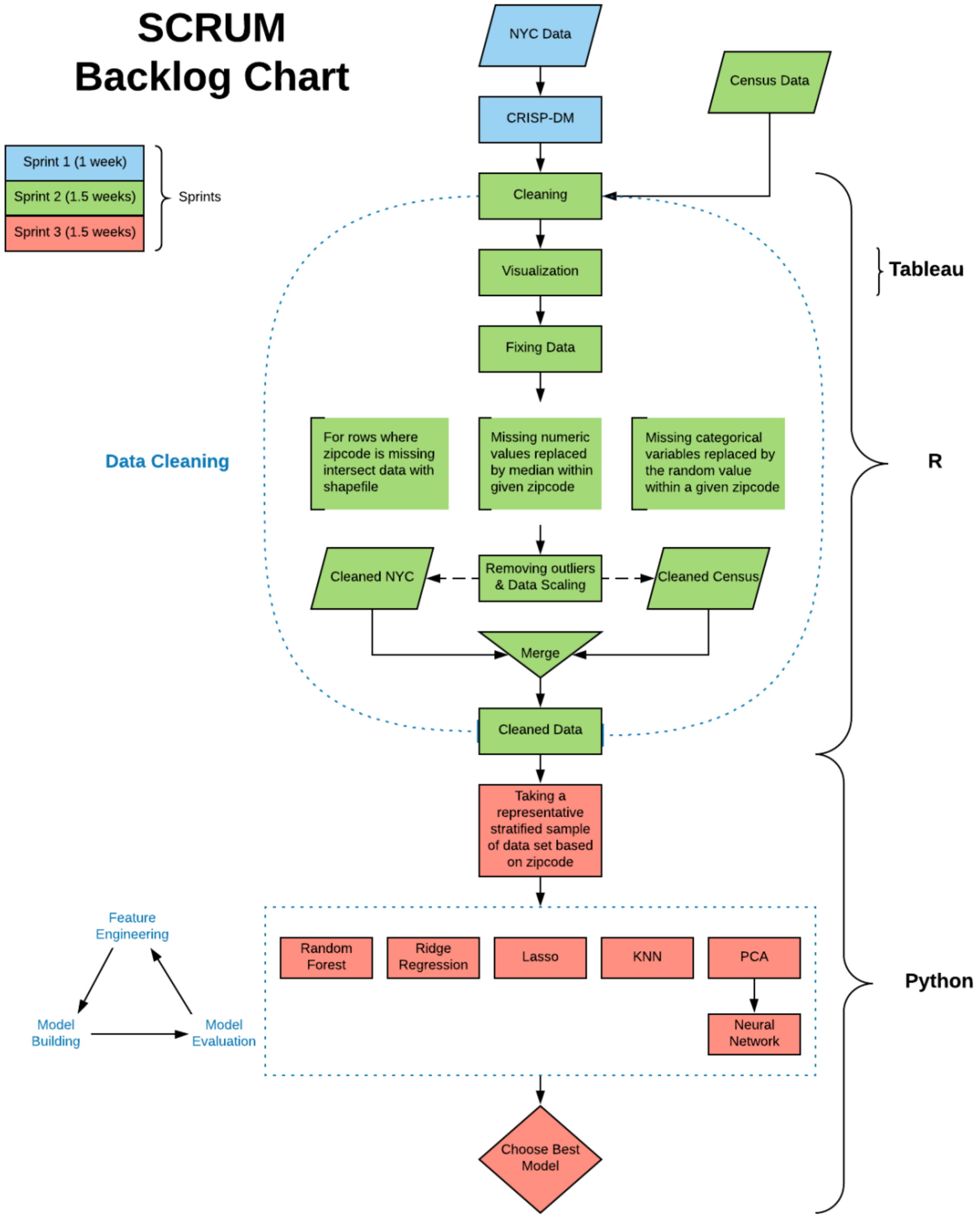
In order to effectively deploy the models, there would need to be necessary guidelines to ensure the project's success. Areas such as storage, documentation, configuration, flexibility, environments, platforms, and ease of use would need to be discussed. Storage infrastructure, or a contract with a cloud computing service like Amazon Web Services, would be crucial to hold the vast amounts of data collected from different sources. When considering between the choices, the decision has to be based on cost, velocity, and volume to have the most effective outcome. In the case of storage infrastructure, it may be more cost effective to outsource to a third-party service like AWS instead of deploying in-house infrastructure. Considering all three, the best strategy is to have enough storage with a large volume and the ability to pull the data quickly. All of the code used for the model should be well documented for the ability to transfer to future developers who need to update or fix the code.

The system should be flexibly configured to change parameters and add predictors in an easy and efficient way. When referring to changing parameters and adding predictors, there would first need to be a managed environment that can account for testing before the actual deployment. Implementing a managed testing environment would allow for mistakes without affecting the model that is already in place. A hosting platform that guarantees high availability and ease of use for the clients would be crucial for the success of the deployment.

SCRUM Backlog/Sprints

This analysis has utilized the SCRUM backlog/sprint process in an attempt to simplify the project tasks. It has been divided into three sprints. The first sprint involves the identification of the data and the CRISP-DM, which gives a layout of what the approach should be throughout the analysis (which have been followed throughout this report). The second sprint involves all of the aspects of cleaning and merging the data. The third and final sprint is dominated by the modeling processes to be considered and evaluated. The visual diagram is shown on the next page.

SCRUM Backlog Chart



Appendix

Table 3. NYC Data description

References	
🟩 *Variables to Keep*	🟥 *Variables Deleted*

Column Alias	Datatype	Column Name	Issue	Description	Solution
🟥 borough	Categorical	Borough	There were some erroneous levels present for this factor.	Borough.	The boroughs of interest are 5, so the rows that have other values were dropped. This column was dropped at the end since we have borocode which has numeric values for each borough, unlike this column which has text.
🟥 block	Categorical	Block	It has 13,968 levels and repeats across boroughs.	Block.	Combining this variable with borocode and lot would make it almost just an identifier. Also, combining it with only borocode would provide too many levels that provide redundant location information that can be gleaned from columns such as firecomp. Hence, this variable was dropped.
🟥 lot	Categorical	Lot	It has 2,521 levels and repeats across blocks.	Lot.	Combining this variable with borocode and lot would make it almost just an identifier. Also, combining it with only block would provide too many levels that provide redundant location information that can be gleaned from columns such as firecomp. Hence, this variable was dropped.
🟩 cd	Categorical	Community District	11 Nas	Community district. It has 76 levels.	Filled NAs with random cd values of the corresponding zip codes.
🟥 ct2010	Categorical	Census Tract	Merged zip code with census data, so this column is not needed.	2010 census tract.	Deleted.
🟥 cb2010	Categorical	Census Block	Merged zip code with census data, so this column is not needed.	2010 census block.	Deleted.
🟩 schooldist	Categorical	School District	78 NAs	School district. It has 32 levels.	NAs filled with random schooldist values of the corresponding zip codes.
🟩 council	Categorical	City Council District	11 NAs	City council district. It has 51 levels.	Filled NAs with random council values within the same zip codes.
🟩 zipcode	Categorical	Zip code	20,535 Nas	Zip code. It has 216 levels.	NAs filled with values after matching them to a shapefile in QGIS.

firecomp	Categorical	Fire Company	102 blank values.	Fire company. It has 348 levels.	Blanks replaced with random firecomp values within the same zip codes.
policeprct	Categorical	Police Precinct	83 NAs	Police precinct. It has 82 levels.	Filled NAs with random policeprct values within the same zip codes.
healtharea	Categorical	Health Area	82 NAs	Health area. It has 228 levels.	NAs filled with random healtharea values of the corresponding zip codes.
sanitboro	Categorical	Sanitation District Boro	259 NAs	Borough of the sanitation district that services that tax lot. It has 5 levels.	Filled NAs with random sanitboro values within the same zip codes.
sanitdist	Categorical	Sanitation District Number	259 NAs	Sanitation district that services that tax lot. It has 27 levels.	Filled NAs with random sanitdistrict values within the same zip codes. When the corresponding zip code had only NAs for sanitdistrict, these NAs were replaced with random sanitdistrict values of the corresponding boroughs.
sanitsub	Categorical	Sanitation Subsection	404 blank values.	Subsection of the sanitation district that services that tax lot. It has 62 levels.	Blanks replaced with random sanitsub values within the same zip codes. When the corresponding zip code had only NAs for sanitsub, these NAs were replaced with random sanitsub values of the corresponding boroughs.
address	Text	Address	Provides redundant location information.	Address.	Deleted.
zonedist1	Categorical	Zoning District 1	967 blank values.	Zoning district classification. It has 5 levels.	Blanks replaced with random zonedist1 values of the corresponding zip codes. Originally had many levels that provided unnecessary details. Replaced with levels R, C, M, MR, and BPC for residential, commercial, manufacturing, mixed-manufacturing and residential, and Battery Park City respectively.
zonedist2	Categorical	Zoning District 2	837565 blanks.	Zoning classification occupying 2nd greatest percentage of the tax lot's area.	Deleted since greater than 90% contains blanks.
zonedist3	Categorical	Zoning District 3	857164 blanks.	Zoning classification occupying 3rd greatest percentage of the tax lot's area.	Deleted since greater than 90% contains b

zonedist4	Categorical	Zoning District 4	857340 blanks.	Zoning classification occupying 4th greatest percentage of the tax lot's area.	Deleted since greater than 90% contains blanks.
overlay1	Categorical	Commercial Overlay 1	782706 blanks.	Commercial overlay.	Deleted since greater than 90% contains blanks.
overlay2	Categorical	Commercial Overlay 2	857191 blanks.	Commercial overlay occupying 2nd greatest percentage of the tax lot's area.	Deleted since greater than 90% contains blanks.
spdist1	Categorical	Special Purpose District 1	756231 blanks.	Special district. It has 2 levels.	Blank means there is no special purpose. Hence, the column is transformed to 1/0 (special purpose/no special purpose).
spdist2	Categorical	Special Purpose District 2	857283 blanks.	Special purpose district occupying 2nd greatest percentage of the tax lot's area.	Deleted since greater than 99% contains blanks.
spdist3	Categorical	Special Purpose District 3	857353 blanks.	Special purpose district occupying 3rd greatest percentage of the tax lot's area.	Deleted since greater than 99% contains blanks.
ltdheight	Numeric	Limited Height District	854317 blanks.	Limited height district.	Blank conveys no height limit and hence, this column is transformed to a binary variable 1/0 (Limit/No limit).
splitzone	Categorical	Split Boundary Indicator	836456 'N' value.	Indicates whether a tax lot is split between multiple zoning features.	Deleted since greater than 97% of the tax lots are not split between zones.
bldgclass	Categorical	Building Class	7943 NAs	Describes major use of structures on the tax lot.	Removed since this information can be inferred from the landuse variable.
landuse	Categorical	Land Use Category	2359 NAs	Land use. It has 12 levels.	NAs replaced with 0 wherein 0 stands for unknown category.

easements	Numeric	Number of Easements	853598 0s	Number of unique easements on the tax lot.	Deleted since greater that 99% of the tax lots have 0 easements.
ownertype	Categorical	Type of Ownership Code	823448 blanks.	Type of ownership.	Deleted since greater than 95% is blank.
ownername	Text	Owner Name	Unnecessary information.	Name of the tax lot owner.	Deleted since it is not useful for prediction here.
lotarea	Numeric	Lot Area	3153 0s and 144 NAs.	Total area.	Zeroes and NAs replaced with the medians for the corresponding zip codes. When the corresponding zip code has only NAs for lotarea, these NAs were replaced with random lotarea values of the corresponding boroughs.
bldgarea	Numeric	Total Building Floor Area	No issues.	Total building floor area.	No issues.
comarea	Numeric	Commercial Floor Area	700290 0s and 47716 NAs.	Area allocated for commercial use.	Deleted since nearly 90% is either 0 or NA.
resarea	Numeric	Residential Floor Area	50940 0s and 47716 NAs.	Area allocated for residential use.	Deleted since it doesn't make sense to replace with the medians in cases where landuse variable might categorize it as non-residential.
officearea	Numeric	Office Floor Area	783667 0s and 47716 NAs.	Area allocated for office use.	Deleted since greater than 95% is either 0 or NA.
retailarea	Numeric	Retail Floor Area	745750 0s and 47716 NAs.	Area allocated for retail use.	Deleted since 90% is either 0 or NA.
garagearea	Numeric	Garage Floor Area	799825 0s and 47716 NAs.	Area allocated for garage use.	Deleted since greater than 98% is either 0 or NA.
strgearea	Numeric	Storage Floor Area	801927 0s and 47716 NAs.	Area allocated for storage use.	Deleted since greater than 99% is either 0 or NA.
factryarea	Numeric	Factory Floor Area	802538 0s and 47716 NAs.	Area allocated for factory, warehouse or loft use.	Deleted since greater than 99% is either 0 or NA.
otherarea	Numeric	Other Floor Area	790856 0s and 47716 NAs.	Area allocated for other uses.	Deleted since greater than 97% is either 0 or NA.
areasource	Categorical	Total Building Floor Area Source Code	Unrequired information.	Methodology used to determine the tax lot's total building floor area.	Deleted since this data is not required for prediction.

numbldgs	Numeric	Number of Buildings	144 NAs	Number of buildings.	Replaced NAs with medians of corresponding zip codes.
numfloors	Numeric	Number of Floors	144 NAs	Number of floors for the tallest building on the tax lot.	Replaced NAs with medians of corresponding zip codes.
unitsres	Numeric	Residential Units	No issues.	Sum of residential units in all buildings on the tax lot.	No issues.
unitstotal	Numeric	Total Units	No issues.	Sum of residential and non-residential units in all buildings on the tax lot.	No issues.
lotfront	Numeric	Lot Frontage	144 NAs	Frontage.	Replaced NAs with medians of corresponding zip codes.
lotdepth	Numeric	Lot Depth	1928 NAs	Depth.	Replaced NAs with medians of corresponding zip codes.
bldgfront	Numeric	Building Frontage	144 NAs	Building frontage along the street.	Replaced NAs with medians of corresponding zip codes.
bldgdepth	Numeric	Building Depth	144 NAs	Building depth.	Replaced NAs with medians of corresponding zip codes.
ext	Categorical	Extension Code	507555 blanks.	Extension on the lot or garage. It has 2 levels.	It originally had 4 levels that were converted to 2 levels. Zeros for blanks (no extensions) and 1 for extensions (E,EG, and G).
proxcode	Categorical	Proximity Code	Too many levels that provide extra details.	Physical relationship of the building to neighboring buildings. It has 3 levels.	Originally had 4 levels. Semi-attached and attached converted to 2 for attached. 1 stands for detached and 0 for unavailable.
irrlotcode	Categorical	Irregular Lot	Blank is a level with no counts.	Irregularly shaped or not.	Blank level dropped.
lottype	Categorical	Lot Type	No issues.	Location in relationship to another tax lot or the water.	No issues.
bsmtcode	Categorical	Basement Type/Grade	Extra information.	Describes building's basement.	Deleted since it provides details that would be hard to use as a meaningful predictor.
assessland	Numeric	Assessed Land Value	3489 0s	Assessed land value.	As this is a target variable, all values equal to 0 were deleted.

assesstot	Numeric	Assessed Total Value	No issues.	Assessed total value.	No issues.
exemptland	Numeric	Exempt Land Value	Extra information.	Exempt land value.	Deleted since tax exemption related to factors other than the location alone (such as the business present, …).
exempttot	Numeric	Exempt Total Value	Extra information.	Exempt total value.	Deleted since tax exemption related to factors other than the location alone (such as the business present, …).
yearbuilt	Numeric	Year Built	39614 0s and 1 value as 2040.	Year construction of the building was completed.	Row containing the year 2040 deleted. 0s replaced by mode value, which is the year 1920.
yearalter1	Numeric	Year Altered 1	763568 0s	If there was only one alteration, this is the date that alteration began. If there were many alterations, this is the date the second most recent alteration began.	If year2 is empty, then take year 1 value. If both are empty, put 0. Here, 0 means there wasn't any modification/renovation. These 2 columns were deleted and instead last_modif was created.
yearalter2	Numeric	Year Altered 2	838572 0s	The year the most recent alteration began. It is 0 if there was only one alteration.	
histdist	Text	Historic District Name	823561 blanks.	Historic district.	Deleted since greater than 96% is blanks.
landmark	Text	Landmark Status	852457 blanks	Indicates whether the tax lot contains an individual landmark building, an interior landmark building, or both.	Deleted since greater than 99% is blanks.
builtfar	Numeric	Built Floor Area Ratio	Extra information since we can calculate this value from other variables.	Total building floor area divided by the tax lot area.	Deleted.

residfar	Numeric	Maximum allowable residential FAR	No issues.	Maximum allowable residential floor area ratio.	No issues.
commfar	Numeric	Maximum allowable commercial FAR	No issues.	Maximum allowable commercial floor area ratio.	No issues.
facilfar	Numeric	Maximum allowable community facility FAR	No issues.	Maximum allowable community facility floor area ratio.	No issues.
borocode	Categorical	Boro Code	No issues.	Borough. It has 5 levels.	No issues.
bbl	Categorical	Borough, Tax Block & Lot	Extra information.	Concatenation of borough code, tax block, and tax lot.	Deleted because it acts nearly similar to an identifier.
condono	Categorical	Condominium Number	845526 0s and 39 NAs	Condominium number assigned to the complex.	Deleted since greater than 99% is 0s or NAs.
tract2010	Categorical	Census Tract 2	Merged zip code with census data, so this column is not needed.	2010 census tract.	Deleted.
xcoord	Numeric	X Coordinate	77 NAs	X coordinate location of the tax lot.	These 77 rows were dropped. Based on X and Y coordinates, the missing values in zip code were found.
ycoord	Numeric	Y Coordinate	No issues.	Y coordinate location of the tax lot.	No issues. Based on X and Y coordinates, the missing values in zip code were found.
zonemap	Categorical	Zoning Map	Extra information.	Department of City Planning Zoning Map Number associated with the tax lot's coordinates.	Deleted since this is not useful for prediction.
zmcode	Categorical	Zoning Map Code	Extra information.	Indicates whether a tax lot is on the border of 2 or more zoning maps.	Deleted since this is not useful for prediction.

sanborn	Categorical	Sanborn Map	Extra information.	Sanborn Map Company number associated with the tax block and lot.	Deleted since this is not useful for prediction.
taxmap	Categorical	Tax Map	Extra information.	Department of Finance paper tax map volume number associated with the tax block and lot.	Deleted since this is not useful for prediction.
edesignum	Categorical	E-Designation Number	Too many levels (105) that provide extra details.	Indicates the presence of an environmental requirement pertaining to potential hazardous materials.	Converted to 2 levels 0 and 1 wherein 0 indicates the absence of potential hazardous materials.
appbbl	Categorical	Apportionment bbl	Extra information.	Originating borough, block, and lot from the apportionment prior to the merge, split, or property's conversion to a condominium.	Deleted since it is not useful for prediction.
appdate	Numeric	Apportionment date	Extra information.	Date of apportionment.	Deleted since it is not useful for prediction.
mappluto_f	Categorical	Map pluto ID	853863 NAs	Map pluto ID.	Deleted since it contains only NAs.
plutomapid	Categorical	Pluto - Dtm Base Map Indicator	Extra information.	Indicates whether the tax lot is in the Pluto file or MapPluto file.	Deleted since it is not useful for prediction.
version	Text	Version Number	Only 1 level, and it is extra information.	Version number for this release of Pluto.	Deleted since it is not useful for prediction.
healthcenterdistrict	Categorical	Health center district	74 NAs	Health center district.	Filled NAs with random healthcenterdistrict values within the same zip codes.
firm07_flag	Categorical	2007 Flood insurance rate map indicator	Old since more recent 2015 data available.	Indicates whether a tax lot falls within the 1% annual chance floodplain.	Deleted.

pfirm15_flag	Categorical	2015 Preliminary flood insurance rate map indicator	789461 NAs	Indicates whether a tax lot falls within the 1% annual chance floodplain.	NAs replaced with 0s wherein 0 means there is no 1% chance of flooding.
rpaddate	Date	Erroneous column not in PDF.	Only 1 date value.	Erroneous column not in PDF.	Deleted.
dcasdate	Date	Erroneous column not in PDF.	Only 1 date value.	Erroneous column not in PDF.	Deleted.
zoningdate	Date	Erroneous column not in PDF.	Only 1 date value.	Erroneous column not in PDF.	Deleted.
landmkdate	Date	Erroneous column not in PDF.	Only 1 date value.	Erroneous column not in PDF.	Deleted.
basempdate	Date	Erroneous column not in PDF.	Only 1 date value.	Erroneous column not in PDF.	Deleted.
masdate	Date	Erroneous column not in PDF.	Only 1 date value.	Erroneous column not in PDF.	Deleted.
polidate	Date	Erroneous column not in PDF.	Only 1 date value.	Erroneous column not in PDF.	Deleted.
edesigdate	Date	Erroneous column not in PDF.	Only 1 date value.	Erroneous column not in PDF.	Deleted.

Transformed Variable:

yearalter	Numeric	Year altered	No issues.	Year the most recent alteration began.	Newly created from columns yearalter1 and yearalter2.

On the next page, are the data types and columns used from census data for 2010 merged to the original dataset by zip code.

Table 4. Census data

Column	Datatype	Description
mean_income_fam	Numeric	Estimate of the mean of the total income of families.
mean_income_non	Numeric	Estimate of the mean of the total income of non-families.
zipcode	Categorical	Zip code.

Process of Analysis for Variable assesstot

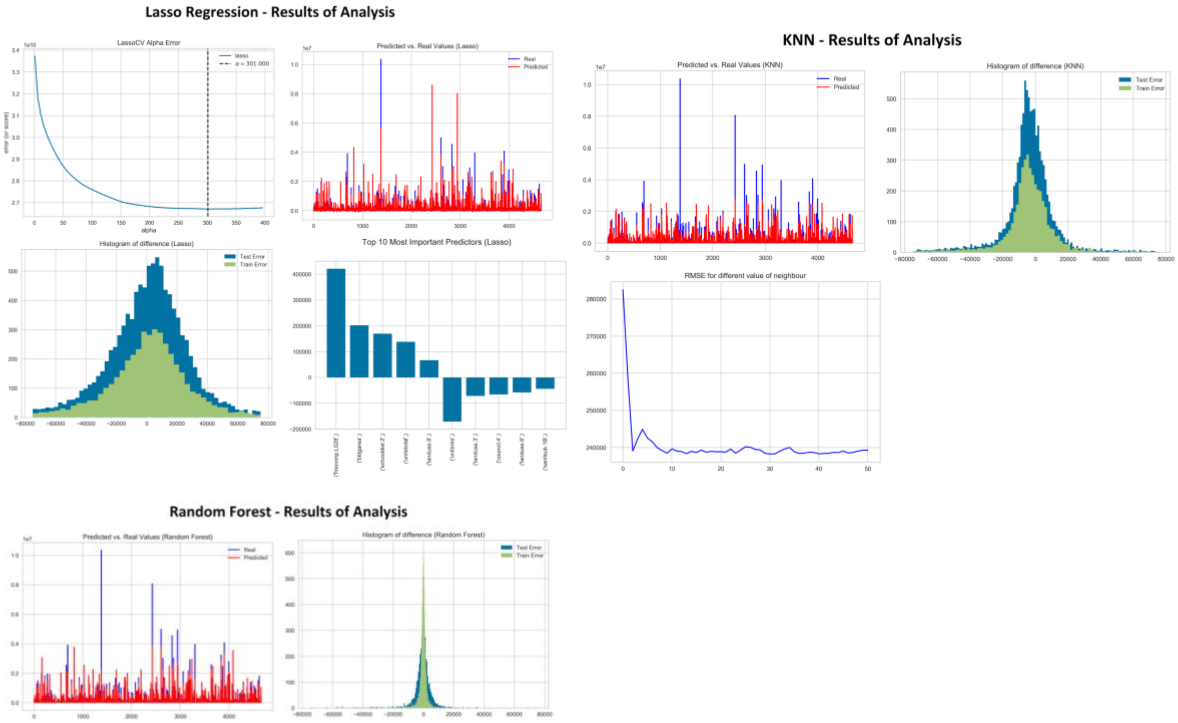
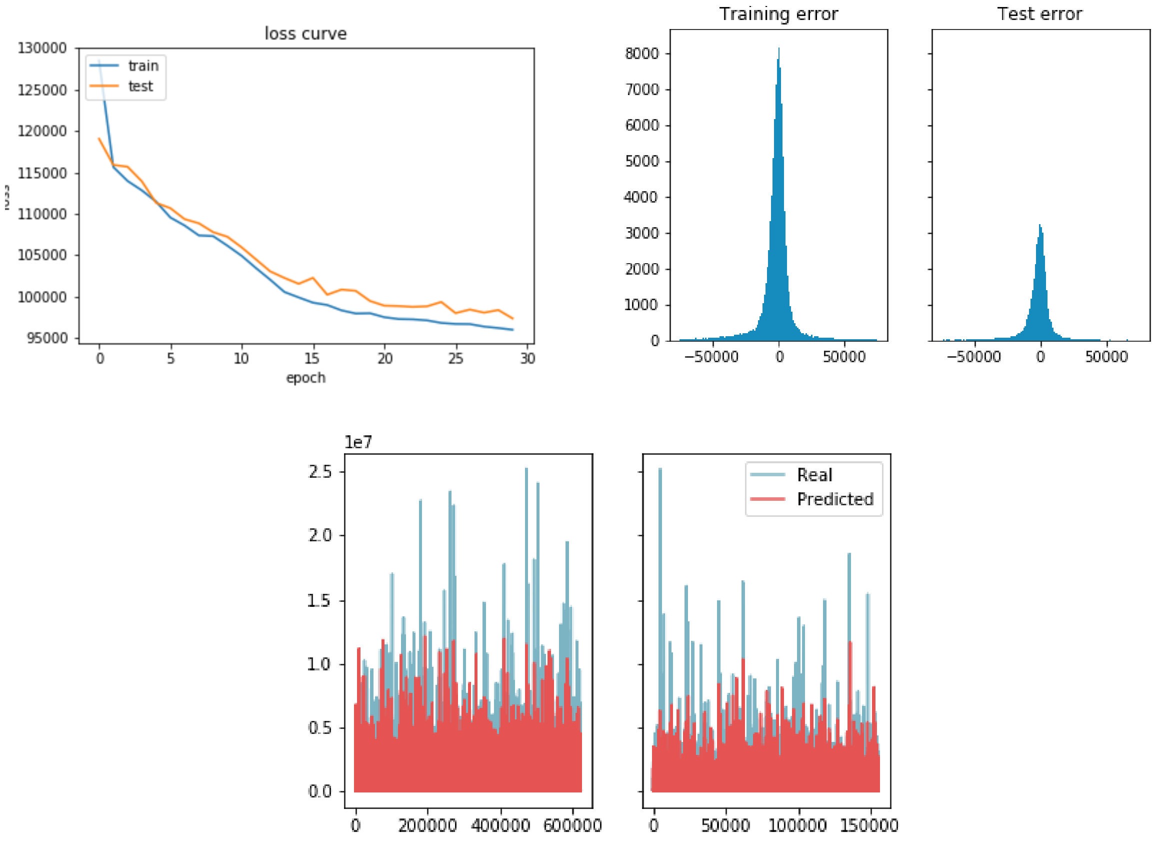


Figure 13. Process of Analysis for Variable assesstot

Neural Network:

The best neural network model for the prediction of the assessed value of the property was one with 170 input nodes, 114 nodes for the hidden layer and adam optimizer with 30 iterations. In this case, the problem about the loss value was present but to a lower level, therefore when performing PCA for the entire dataset the issue could be resolved. As the loss curve shows, the loss for testing is higher than training.



Error	Training	Test
mse	25735610540.596	29741303103.831
RMSE	160423.223	172456.67
R2	0.772	0.75
error	5444.63	5902.59

Figure 14. Model Performance for Neural Network

The overall RMSE error for test is lower than training as well as R-squared is higher for training, as expected. As it can be seen, in the comparison among predicted versus true values, the higher values are not well predicted. Looking at the histograms, it can be concluded that there is no problem of overfitting. The range of errors in training and testing set is very similar.

For code reference, please visit: https://github.com/grzechowiak/Capstone