Capstone Project

Xiaochuan Yi

Machine Learning Engineer Nanodegree

May 18th, 2018

Domain Background

Long term home price predication is always challenging. But short term home price predication is gaining success in recent years due to quality machine learning research done in this area. Housing data is publicly available including many features of houses and transaction price in market place. This makes home price predication is a suitable area to apply machine learning models. Companies such as Zillow and Redfin have already provided home price estimation services and their price estimation has become more and more valuable to customers, either pricing a home when selling or looking for offer price guidance when buying a home.

The Zestimate home valuation is Zillow's estimated market value, computed using a proprietary formula. It is not an appraisal. It is a starting point in determining a home's value. The Zestimate is calculated from public and user-submitted data, taking into account special features, location, and market conditions.

From my person experience, Zestimate is a very good guide to determine buying and selling price of a home in the metropolitan area where I live. I am curious of how Zestimate is calculated and why its precision is improving over the years. On May 24 2017, Kaggle opened a 1 Million dollar competition predicting short term future house price (Zestimate) residual errors. The participants were asked to develop an algorithm that makes predictions about the future sale prices of homes. At the time when I write the proposal, the competition is already over. However, the dataset of the competition is of high quality. In addition its scoring tool is still available for me to evaluate my solutions.

"Zestimates" are estimated home values based on 7.5 million statistical and machine learning models that analyze hundreds of data points on each property. And, by continually improving the median margin of error (from 14% at the onset to 5% today), Zillow has since become established as one of the largest, most trusted marketplaces for real estate information in the U.S. and a leading example of impactful machine learning.In this project, I created an Android application capable of reading aloud everyday text (e.g. product

Problem Statement

Following the Zillow competition, for each property (unique parcelid) along with it many features, a log error will be predicted for each specified time point. I will be predicting 6 timepoints: October 2016 (201610), November 2016 (201611), December 2016 (201612), October 2017 (201710), November 2017 (201711), and December 2017 (201712). According to the competition, the submission file should contain a header and have the following format:

ParcelId,201610,201611,201612,201710,201711,201712

10754147,0.1234,1.2234,-1.3012,1.4012,0.8642-3.1412

10759547,0,0,0,0,0,0

etc.

Note that the actual log errors are accurate to the 4th decimal places.

The log error is defined as

$logerror=log(Zestimate)-log(SalePrice)$

The Kaggle competition provides real estate data for three counties in and around Los Angeles, CA. Each observation of a property has 56 features; no additional features from outside data sources will be allowed in the analysis.

The data files are

1. 2016 Training data file with ParcelId, actual logerror = log(Zestimate) - log(SalesPrice) and transaction date. The 2016 properties file contains feature information for 90,725 properties. These two data file can be merged(joined) on ParcelId to provide the training data set with all features.
2. Prediction set with only the feature information for 2,985,217 properties.

Submissions will be scored based on the MAE (mean absolute error) across all predictions.

Datasets and Inputs

There are a total of 58 features in the property data file including the property id (parcelid). These data files are loaded into pandas dataframe and each feature data type, distribution and missing value issues are reviewed.

Let's consider drop features with extreme missingness, duplication, and zero variance. Variables with over 90% missingness and no feasible way to determine the correct value were dropped. If variables captured the same information, such as FIPS (Federal Information Processing Standard code) and Zip Code, we only kept one. Finally, variables with the same value across all observations were dropped as they would have had no impact on our model.

Here is the list of all features and their data types:

1. parcelid int64
2. pooltypeid10 float64
3. pooltypeid2 float64
4. pooltypeid7 float64
5. propertylandusetypeid float64
6. rawcensustractandblock float64
7. regionidcity float64
8. regionidcounty float64
9. regionidneighborhood float64
10. regionidzip float64
11. roomcnt float64
12. storytypeid float64
13. threequarterbathnbr float64
14. typeconstructiontypeid float64
15. unitcnt float64
16. yardbuildingsqft17 float64
17. yardbuildingsqft26 float64
18. yearbuilt float64
19. numberofstories float64
20. structuretaxvaluedollarcnt float64
21. taxvaluedollarcnt float64

22. assessmentyear float64
23. landtaxvaluedollarcnt float64
24. taxamount float64
25. taxdelinquencyyear float64
26. poolcnt float64
27. poolsizesum float64
28. longitude float64
29. airconditioningtypeid float64
30. architecturalstyletypeid float64
31. basementsqft float64
32. bathroomcnt float64
33. bedroomcnt float64
34. buildingclasstypeid float64
35. buildingqualitytypeid float64
36. calculatedbathnbr float64
37. decktypeid float64
38. finishedfloor1squarefeet float64
39. calculatedfinishedsquarefeet float64
40. lotsizesquarefeet float64
41. finishedsquarefeet13 float64
42. finishedsquarefeet12 float64
43. finishedsquarefeet50 float64
44. finishedsquarefeet6 float64
45. fips float64
46. fireplacecnt float64
47. fullbathcnt float64
48. garagecarcnt float64
49. garagetotalsqft float64
50. heatingorsystemtypeid float64
51. latitude float64
52. finishedsquarefeet15 float64
53. censustractandblock float64
54. propertyzoningdesc object
55. fireplaceflag object
56. propertycountylandusecode object
57. hashottuborspa object
58. taxdelinquencyflag object

Pandas dataframe data type (int64, float64 and object) only provides limited information about feature variables. Let's look deeper into these features.

We found that there re discrete features with significant ordering semantics, such as numerical identifiers and numerical coding for air condition type, architectural styles, and so on.

- parcelid: Unique identifier for parcels (lots). In other word, unique identification number for each property
- airconditioningtypeid: air conditioning types. It is possilbe certain air conditioning is of higher end than others. So transform the type to ordered numbers will be helpful.

- architecturalstyleid: architectural styles, it is possible one style is more luxurious than other styles. So if we can set ordering that is related to house price, then code the style in ordered number will be helpful.
- buildingclasstypeid: building class type
- buildingqualitytypeid: building quality type
- decktypeid: deck type
- heatingorsystemtypeid: Type of home heating system
- typeconstructiontypeid: What type of construction material was used to construct the home

There are also numerical features that are continuous or fine grain, such as

- basementsqft: basement area in square footage
- finishedfloor1squarefeet: Size of the finished living area on the first (entry) floor of the home
- calculatedfinishedsquarefeet: Calculated total finished living area of the home
- finishedsquarefeet6: Base unfinished and finished area
- finishedsquarefeet12: Finished living area
- finishedsquarefeet13: Perimeter living area
- finishedsquarefeet15: Total area
- finishedsquarefeet50: Size of the finished living area on the first (entry) floor of the home
- garagetotalsqft: Total number of square feet of all garages on lot including an attached garage
- lotsizesquarefeet: Area of the lot in square feet
- yardbuildingsqft17: Patio in yard
- yardbuildingsqft26: Storage shed/building in yard
- poolsizesum: Total square footage of all pools on property
- taxamount: The total property tax assessed for that assessment year
- taxvaluedollarcnt: The total tax assessed value of the parcel
- structuretaxvaluedollarcnt: The assessed value of the built structure on the parcel
- landtaxvaluedollarcnt: The assessed value of the land area of the parcel
- latitude: Latitude of the middle of the parcel multiplied by 10e6, location of the property
- longitude: Longitude of the middle of the parcel multiplied by 10e6, location of the property

There are also numerical features that are discrete with small set of values, and intuitively these features exhibits ordering that is related to property valuation, such as:

- roomcnt: Total number of rooms in the principal residence
- threequarterbathnbr: Number of 3/4 bathrooms in house (shower + sink + toilet)
- bathroomcnt: number of bathrooms
- bedroomcnt: number of bedrooms
- calculatedbathnbr: calculate bath number
- fireplacecnt : number of fireplaces
- fullbathcnt: number of full bathrooms (sink, shower + bathtub, and toilet)
- garagecarcnt: Total number of garages on the lot including an attached garage
- numberofstories: Number of stories or levels the home has
- poolcnt: Number of pools on the lot (if any)

Boolean features are also identified, such as:

- fireplaceflag: is a fireplace present in the house, True or missing(treated as False)
- hashottuborspa: Does the home have a hot tub or spa, true or missing(treated as False)
- taxdelinquencyflag: Property taxes for this parcel are past due as of 2015, Y or missing(treated as N), transformed to True or False

Other features:

fips: Federal Information Processing Standard code, will be not used

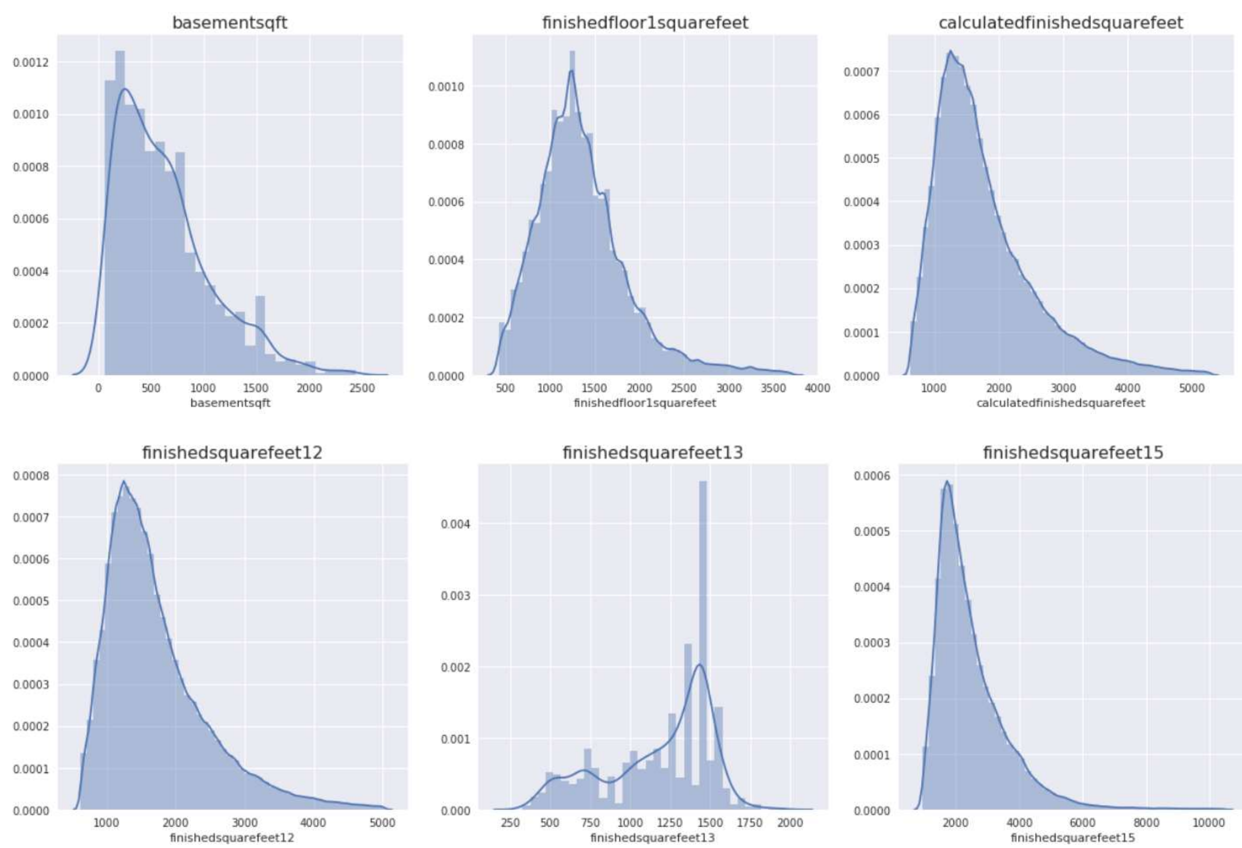
regionidcounty: County in which the property is located

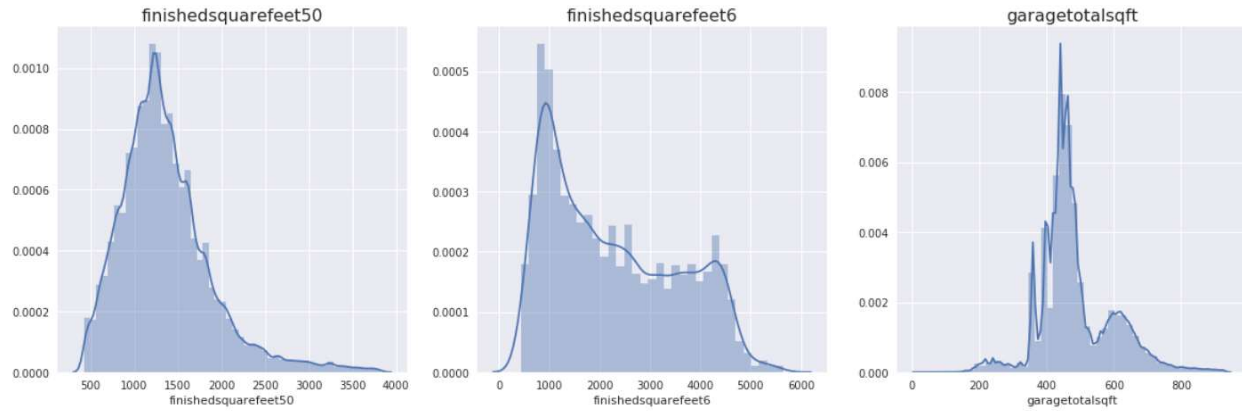
regionidcity: City in which the property is located (if any)

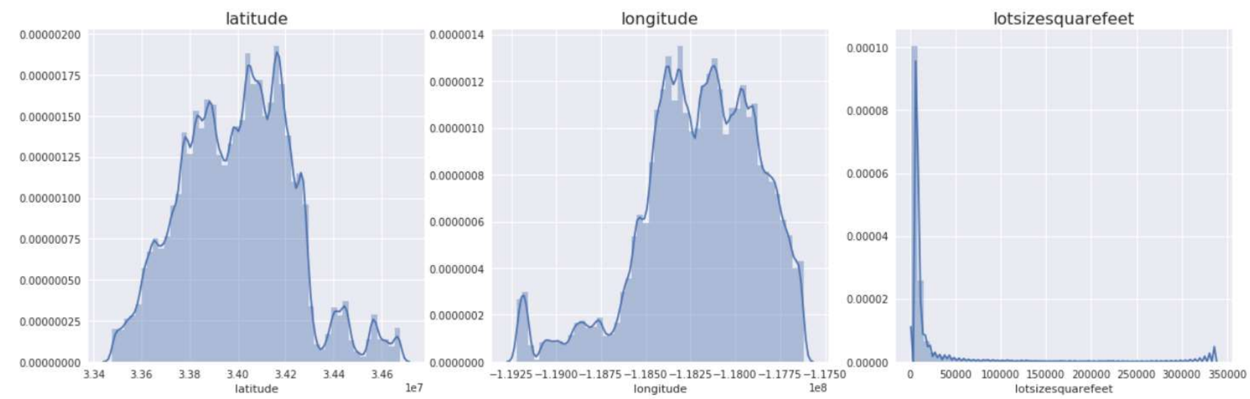
regionidzip: Zip code in which the property is located

regionidneighborhood: Neighborhood in which the property is located

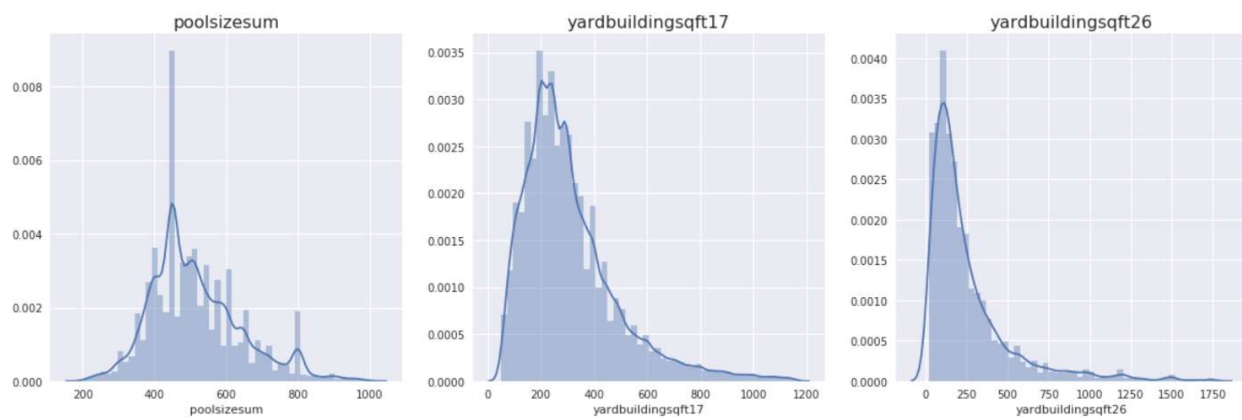
Now let's study the distribution of numerical data features with larger range. numerical_large_range = ['basementsqft', 'finishedfloor1squarefeet', 'calculatedfinishedsquarefeet', 'finishedsquarefeet12', 'finishedsquarefeet13', 'finishedsquarefeet15', 'finishedsquarefeet50', 'finishedsquarefeet6', 'garagetotalsqft', 'latitude', 'longitude', 'lotsizesquarefeet', 'poolsizesum', 'yardbuildingsqft17', 'yardbuildingsqft26', 'yearbuilt', 'structuretaxvaluedollarcnt', 'taxvaluedollarcnt', 'landtaxvaluedollarcnt', 'taxamount']. I have found that most of these features are skewed rather than symmetric or normal distributions. Check the following distribution plots.







poolsizesum yardbuildingsqft17 yardbuildingsqft26



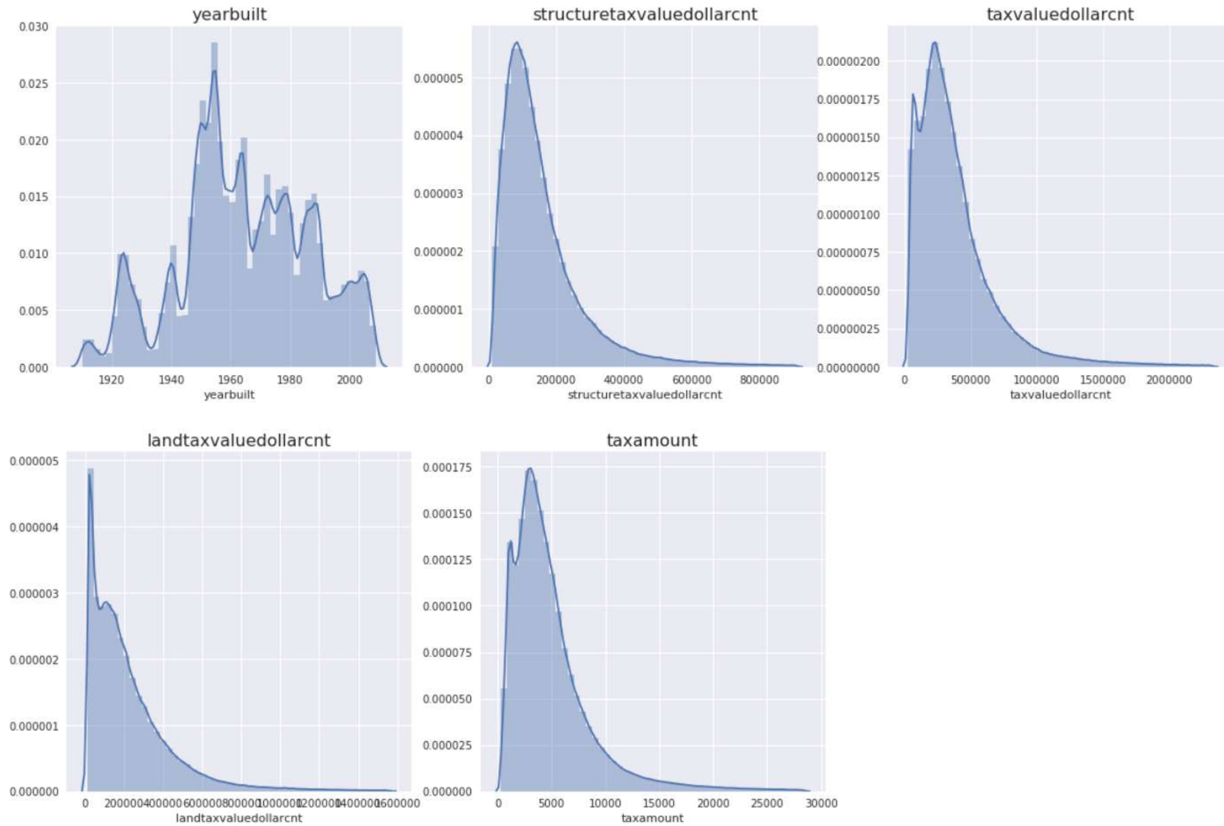
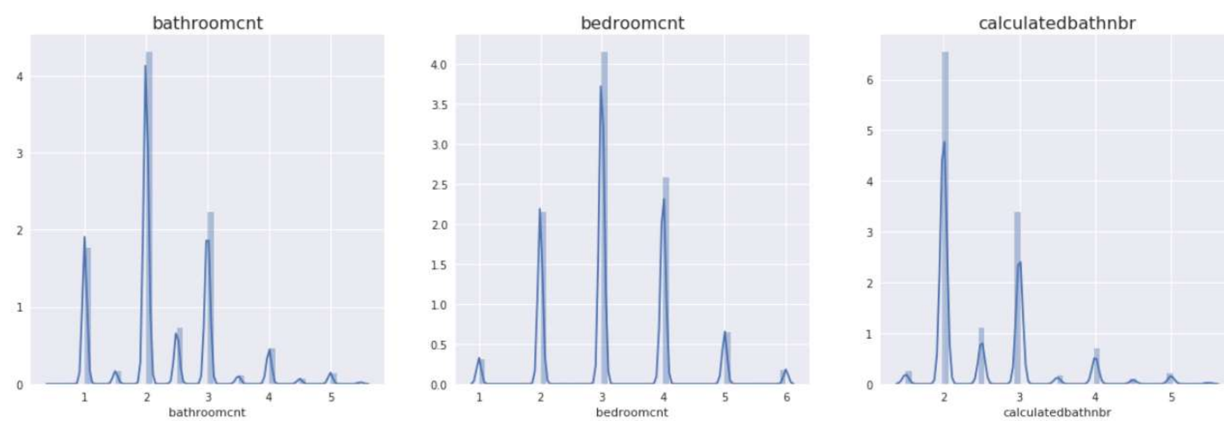
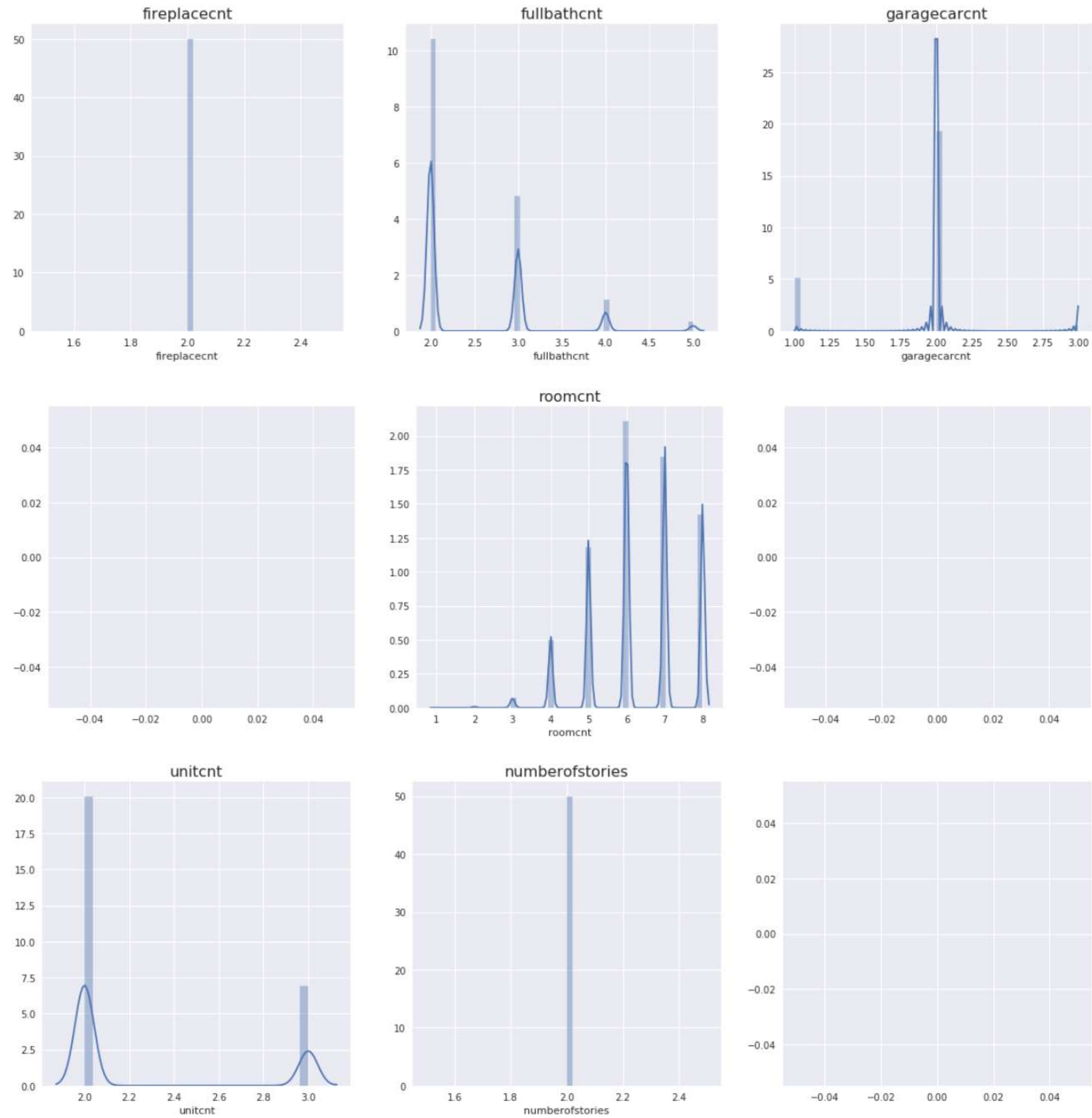


Figure 1. Distribution plots of numerical features that have larger range

Distribution of features that are discrete:




fireplacecnt
fullbathcnt
garagecarcnt
roomcnt
unitcnt
numberofstories

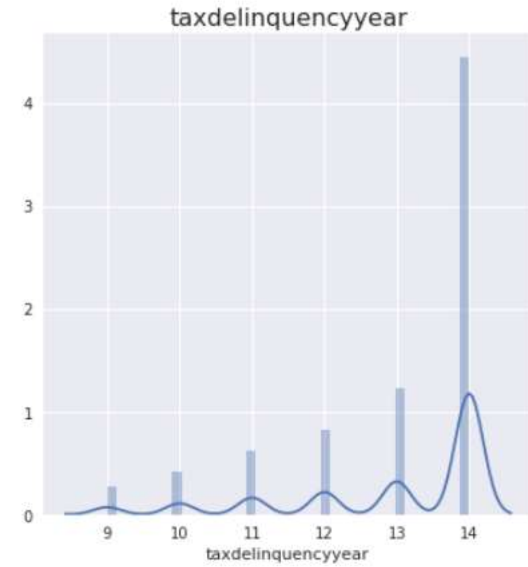


Figure 2. Distribution plots of discrete features

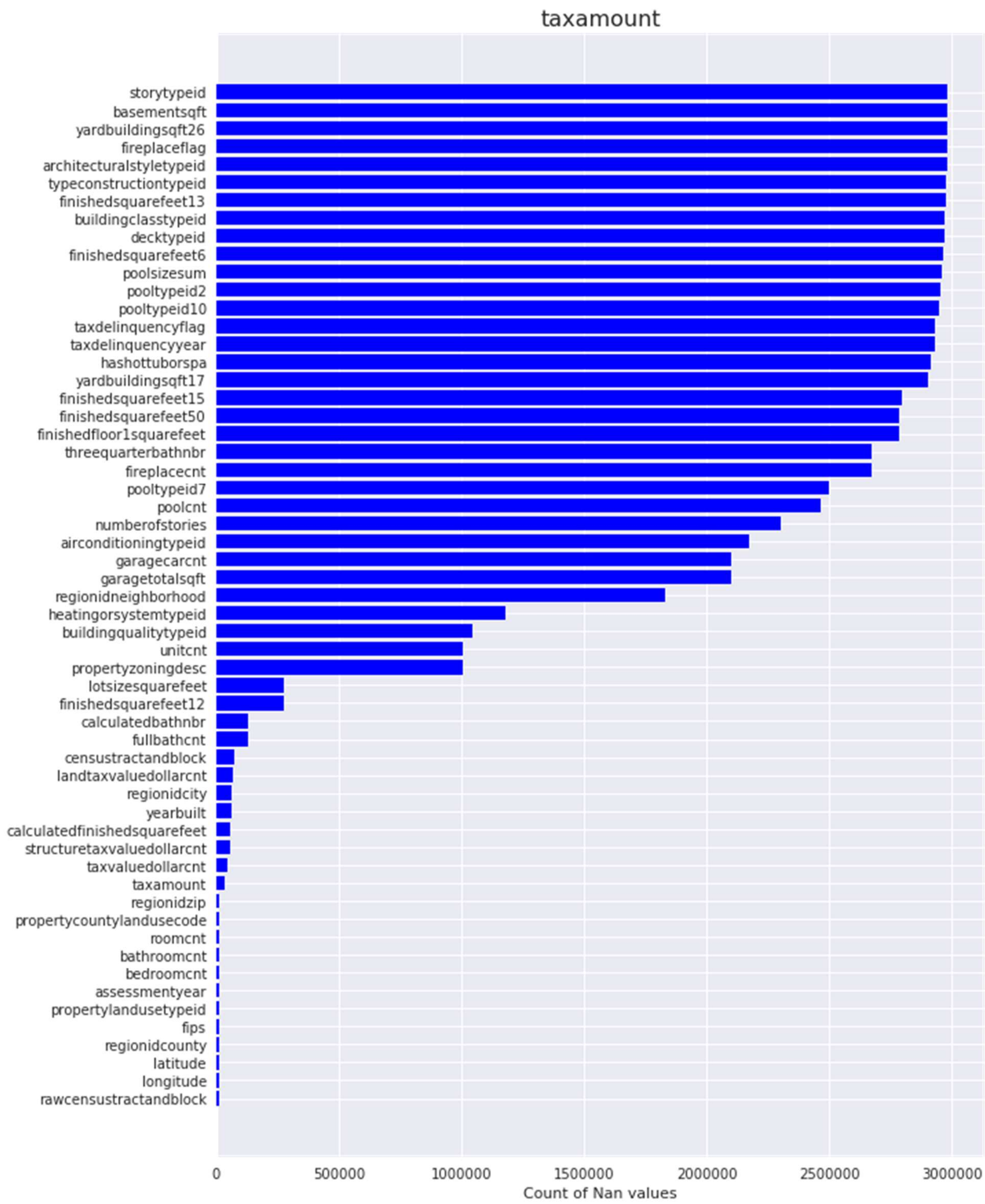


Figure 3. Count of missing values for each property feature.

Lastly, let’s take a look at the target variable. The target variable is legerror, whcih has symmetric distribution with a mean value close to zero. This is not surprising since the log transformation has already been applied to Zestimate and sale price. Log transformation in a commonly used way to reduce the skewness of variables. Check the following distribution plot.

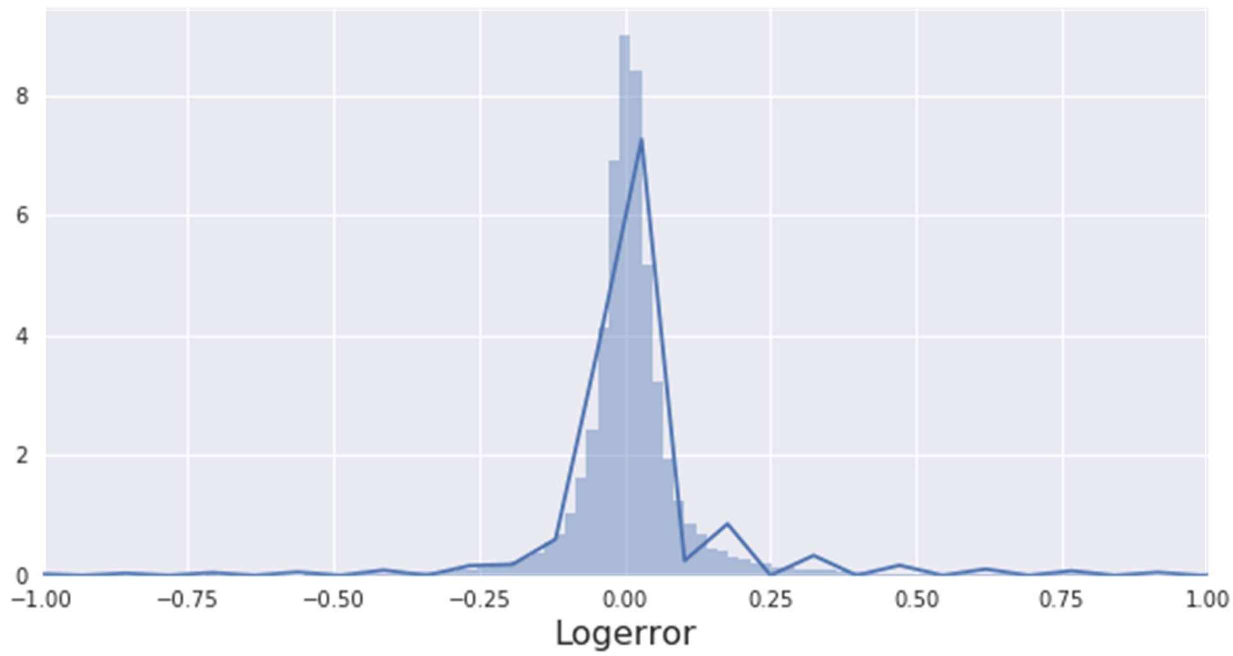


Figure 4. Distribution of target variable logerror

Evaluation metrics and Benchmark

Linear regression can be used as the initial reference models. In Zillow Kaggle competition, various teams apply different models to the data sets such as decision tree based models, support vector machines or neural networks. The competition web site provides a ranking tool and a public leaderboard that I plan to benchmark my results.

Housing price prediction (6 time points future of training data set) will be submitted to the competition web site's ranking tool. With the submission I can get the evaluation on MAE (Mean Absolute Error) score between the predicted log error and the actual log error and also a position in the public leaderboard.

MAE(logerror)

logerror=log(Zestimate)−log(SalePrice)

Project Design and Implementation

After studying the data feature distribution and missing values, rather than use all features, let's select a smaller set of features according to their importance in order to reduce model complexity. In addition to selecting a smaller set of features, another key technique is to remove outliers of selected features. Outliers might have negative impact on machine learning performance.

Let’s do a quick evaluation of feature importance using scikit-learn ensemble ExtraTreeRegressor.

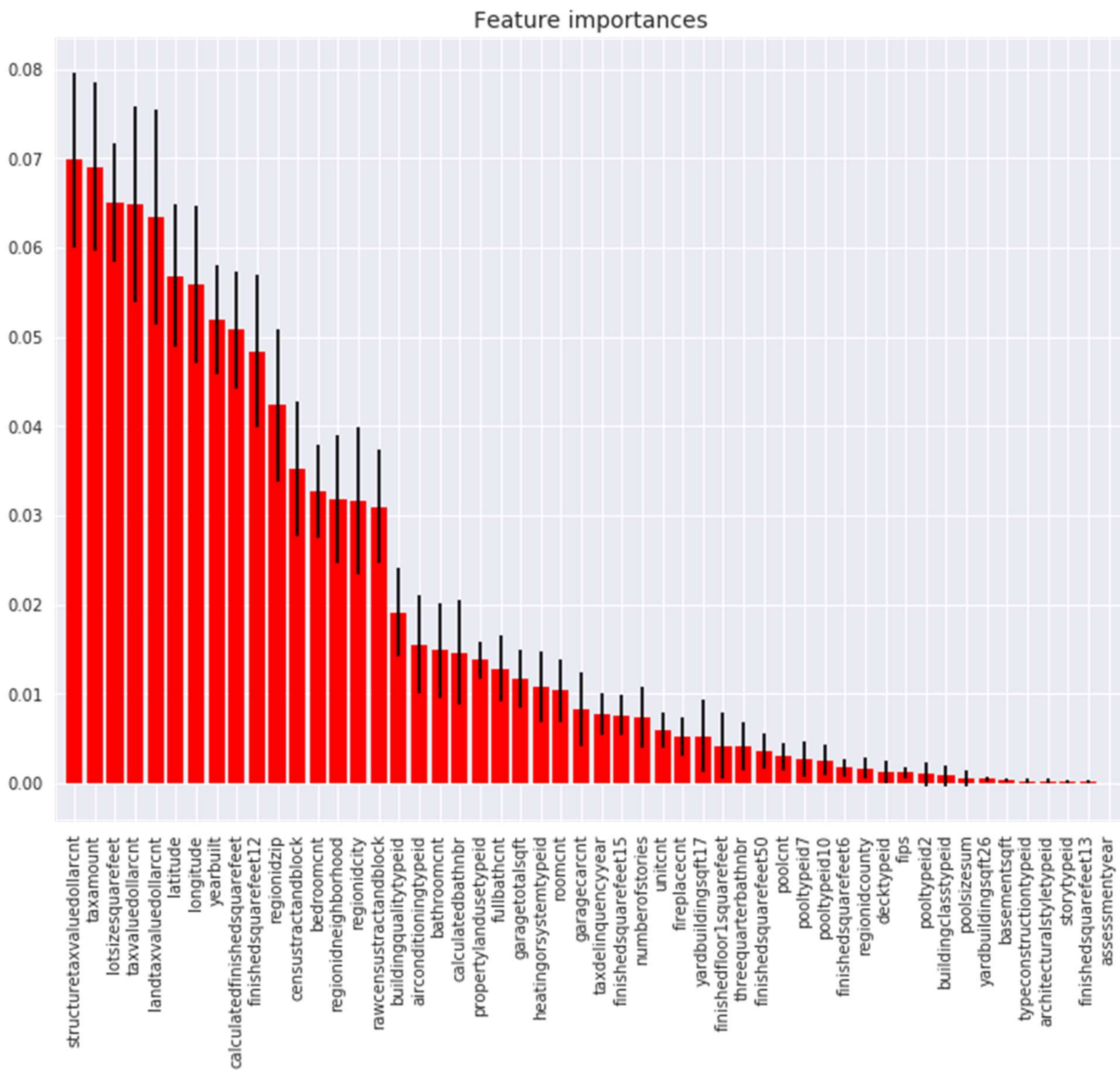


Figure 5. Feature Importance using ensemble.ExtraTreesRegressor

Since the training data set is a mixture of binary, categorical and continuous numerical features, it is suitable to try decision trees at first. Decision trees result in model that can easily be visualized and understood by nonexperts (at least for smaller trees), and the algorithms are completely invariant to scaling of the features. The main downside of decision trees is that even with the use of pre-pruning, they tend to overfit and provide poor generalization performance. Therefore, in most applications, the ensemble methods are used in place of a single decision tree, such as random forest. A random forest is essentially a collection of decision trees, where each tree is slightly different from the others. The idea behind random forests is that each tree might do a relatively good job of predicting, but will likely overfit on part of the data. If we build many trees, all of which work well and overfit in different ways, we can reduce the amount of overfitting by averaging their results. Random forests for regression and classification are currently among the most widely used machine learning methods. They are very powerful, often work well without heavy tuning of the parameters, and don't require scaling of the data.

The gradient boosted regression tree(also called gradient boosting machines) is another ensemble method that combines multiple decision trees to create a more powerful model. Despite the "regression" in the name, these models can be used for regression and classification. In contrast to the random forest approach, gradient boosting works by building trees in a serial manner, where each tree tries to correct the mistakes of the previous one. By default, there is no randomization in gradient boosted regression trees; instead, strong pre-pruning is used. Gradient boosted trees often use very shallow trees, of depth one to five, which makes the model smaller in terms of memory and makes predictions faster. The main idea behind gradient boosting is to combine many simple models (in this context known as weak learners), like shallow trees. Each tree can only provide good predictions on part of the data, and so more and more trees are added to iteratively improve performance. Gradient boosted trees are frequently the winning entries in machine learning competitions, and are widely used in industry. They are generally a bit more sensitive to parameter settings than random forests, but can provide better accuracy if the parameters are set correctly. Gradient boosted decision trees are among the most powerful and widely used models for supervised learning. Their main drawback is that they require careful tuning of the parameters and may take a long time to train. Similarly to other tree-based models, the algorithm works well without scaling and on a mixture of binary and continuous features. As with other tree-based models, it also often does not work well on high-dimensional sparse data[4].

XGBoost (eXtreme Gradient Boosting) is an algorithm that has recently been dominating applied machine learning and Kaggle competitions for structured or tabular data. It was developed by Tianqi Chen and now is part of a wider collection of open-source libraries developed by the Distributed Machine Learning Community (DMLC). XGBoost is a scalable and accurate implementation of gradient boosting machines and it has proven to push the limits of computing power for boosted trees algorithms as it was built and developed for the sole purpose of model performance and computational speed. Because of its computation speed and model performance, it makes parameter tuning easier and improving performance further[5].

Based on proposal reviewer's recommendation of trying faster gradient boosting implementations with CatBoost or LightGBM, I tried LightGBM as follows. LightGBM is a gradient boosting framework that uses tree based learning algorithms. It is designed to be distributed and efficient with the following advantages:

- Faster training speed and higher efficiency
- Lower memory usage
- Better accuracy
- Parallel and GPU learning supported
- Capable of handling large-scale data

LightGBM has been trained for 2 major iteration round. In first iteration, I have dropped the features in cols_to_drop0 = ['parcelid', 'logerror', 'transactiondate', 'propertyzoningdesc','propertycountylandusecode', 'fireplacecnt', 'fireplaceflag']. Missing values are filled with median. The first iteration produces submission_lightgmb.csv.gz with a score of 0.0650229, compared to the best competition score of 0.0631885 . This score ranks 2627th in the public leaderboard of 3779 participants.

In second iteration, I have dropped the features in cols_to_drop1 = ['parcelid', 'logerror', 'transactiondate', 'propertyzoningdesc', 'propertycountylandusecode', 'fireplacecnt', 'fireplaceflag', 'fips','latitude','longitude','poolcnt', 'rawcensustractandblock', 'regionidcounty', 'regionidneighborhood', 'regionidzip'] as fips is federal information standard processing code which is not related to housing valuation, similar to latitude and longitude are numerical values that indicates house location which is already indicated by zipcode. Feature poolcnt is also dropped and pool size is consider more related to house value. Again missing values are filled with median. The second run of LightGBM produces submission_lightgbm2.csv.gz with a score of 0.0647524 (2165th), which is an improvement from using more features in the first major iteration.

Finally XGBoost model has been trained with the feature set that used in the second LightGBM run. It achieves a score of 0.0645364 (rank of 1502nd, getting inside the first half of the learderboard). This is an improvement from previous result using LightGBM. However, LightGBM is faster to train and use less memory and it is very helpful with trying different feature selection and parameter configurations.

References

[1] Working with missing data in machine learning. https://towardsdatascience.com/working-with-missing-data-in-machine-learning-9c0a430df4ce

[2] Data type difference between categorical, ordinal and numerical features. https://stats.stackexchange.com/questions/312437/statistical-data-types-difference-between-categorical-ordinal-and-numerical

[3] https://stackoverflow.com/questions/45515031/how-to-remove-columns-with-too-many-missing-values-in-python

[4] Introduction to Machine Learning with Python: A Guide for Data Scientists

[5] XGBoost: A Scalable Tree Boosting System. https://arxiv.org/abs/1603.02754

[6] Light Gradient Boosting Machine. https://lightgbm.readthedocs.io/en/latest/