Overview

The Project is to build a model to improve the Zestimate residual error.

logerror=log(Zestimate)−log(SalePrice)

“Zestimates” are Zillow's estimated home values. The model is to predict the difference between the Zillow's estimated home value, Zestimate, and the actual sale price.

Client

The client could be Zillow. Zillow can improve its algorithm with the model which would predict where zestimates will do good or bad. When we want to improve existing model, modeling errors can be a good way to find areas to improve the existing model.

Data

The data used in the project has been provided from Zillow through Kaggle.com.

The following files were used in the project. We will use data in 2016 as a train data and 2017 data as a test data. Data have 60 columns which have features for homes.

- Train Data: Two dataset where one dataset contains explanary variable and the other dataset has target variable, log error are merged to produce a train data

  1. **properties_2016.csv**: a full list of real estate properties in three counties (Los Angeles, Orange and Ventura, California) data in 2016.
  2. **train_2016.csv**: all the transactions before October 15, 2016, plus some of the transactions after October 15, 2016. It contains parcel ID , transaction date and calculated log error .

- Test Data:

  3. **properties_2017.csv**: a full list of real estate properties in three counties (Los Angeles, Orange and Ventura, California) data in 2017.
  4. **train_2017.csv**: all the transactions from Jan 1, 2017 to Sep 25, 2017. It can be used as a test dataset.

Approach to solving this problem

First of all, find out any variables which relate to the target variable, logerror. Then, apply regression model or any statistical model which can be applicable.

Deliverables

This would include code and a report.

Data Wrangling

Data Cleaning

- Duplication : I explored training data. 125 duplicated data for 2016 and 199 duplicated data for 2017 data were found. However, it meant they were trasacted for more than twice for a year. So, I didn't delete any duplication.

- Negative values: Also, I checked if there were any negative numbers for each column. Two columns, logerror and longitude, have negative values which are reasonable to have for them.

- Unusual Object : We have 5 columns which are objective type. Each column does not have unusual values, for example "?" , "$"

Missing Values

Let's check how many missing value each column has. I found that 47 columns out of 60 columns have missing values and 18 columns among them have more than 95% of missing values.

Let's explore how missing values were treated.

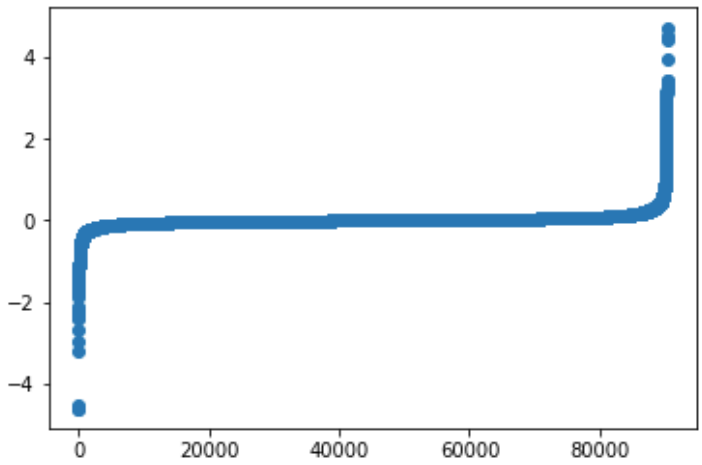
	Column name	Describtion	Missing	Missing Values
1	buildingclasstypeid	The building framing type	99.98%	Deleted the column because only 16 cells out of 90275 cells are not missing and all with the same value 4. Rest of data, 90259 are missing for random.
2	finishedsquarefeet13	Perimeter living area	99.96%	Delete the column because every build must have living area and most of them are missing.
3	basementsqft	Finished living area below ground level	99.95%	Filled with 0 because every building does not have living area below ground leve, missing could mean building does not have partial living room.
4	storytypeid	Type of floors in a multi-story house	99.95%	Deleted the column because every building should have a type of floor and most of them are missing .
5	yardbuildingsqft26	Storage shed/building in yard	99.89%	Filled with 0 because missing value can mean it doesn't have storage in yard
6	fireplaceflag	Is a fireplace present in this home	99.75%	Filled with False because missing value means it does not have a fireplace.
7	architecturalstyletypeid	Architectural style of the home	99.71%	Deleted the column because every buildling has its architectural style and most of them are missing.
8	typeconstructiontypeid	type of construction used to construct the home	99.67%	Deleted the column because every building has its type of construction material and most of them are missing
9	finishedsquarefeet6	Base unfinished and finished area	99.53%	Deleted the column because everyg home should have base area and most of them are missing
10	decktypeid	Type of deck present on parcel	99.27%	Deleted the column because non-missing cells have the same value, 66 and most of them are missing

11	poolsizesum	Total square footage of all pools on property	98.93%	Deleted the column because it is missing randomly and most of them are missing
12	pooltypeid10	Spa or Hot Tub	98.71%	Deleted the column because it is missing randomly and most of them are missing
13	pooltypeid2	Pool with Spa/Hot Tub	98.67%	Deleted the column because it is missing randomly and most of them are missing
14	taxdelinquencyflag	Property taxes for this parcel are past due as of 2015	98.02%	Filled with Y because all non-missing values are "N"
15	taxdelinquencyyear	Year for which the unpaid propert taxes were due	98.02%	Filled with 0 because the missing cells are the same as the previoius column.
16	hashottuborspa	Does the home have a hot tub or spa	97.38%	Filled with False because all non-missing cells are "True"
17	yardbuildingsqft17	Patio in yard	97.07%	Filled with 0 because not every building has a patio in yard.
18	finishedsquarefeet15	Total area	96.05%	Deleted the column because every place should have total area and most of them are missing
19	finishedfloor1squarefeet	Size of the finished living area on the first floor of the home	92.41%	Deleted the column because most place has living area and most of cells are missing
20	finishedsquarefeet50	Size of the finished living area on the first floor of the home	92.41%	Deleted the column because it is the repeat of the previous column.
21	fireplacecnt	Number of fireplaces in a home (if any)	89.36%	Filled with 0 because not every building has fireplace.
22	threequarterbathnbr	Number of 3/4 bathrooms in house (shower + sink + toilet)	86.70%	Filed with 0 because no all home has 3/4 bathrooms
23	pooltypeid7	Pool without hot tub	81.50%	Deleted the column because not every home has a pool and most of them are missing.
24	poolcnt	Number of pools on the lot (if any)	80.17%	Filled with 0 because no every home has pool.
25	numberofstories	Number of stories or levels the home has	77.21%	Deleted the column because every home should have a number of levels and most of them are missing.
26	airconditioningtypeid	Type of cooling system present in the home (if any)	68.12%	Filled with 0 because not all home have a cooling system.
27	garagetotalsqft	Total number of square feet of all garages on lot including an attached garage	66.84%	Deleted the column. Missing might mean no garage, but there are non-missing cells with 0.
28	garagecarcnt	Total number of garages on the lot including an attached garage	66.84%	Deleted the column with the same reason with the previous.
29	regionidneighborhood	Neighborhood in which the property is located	60.11%	Deleted the column because it is missing randoly.
30	heatingorsystemtypeid	Type of home heating system	37.88%	Filed with 0 because not all home have heating system.
31	buildingqualitytypeid	Overall assessment of condition of the building	36.46%	Filled with mean because all home have overall assessment.
32	propertyzoningdesc	Description of the allowed land uses (zoning) for that property	35.41%	Filled with "Missing" to treat missing values as another class
33	unitcnt	Number of units the structure is built	35.36%	Filled with 1 because 1 is the most frequent value.
34	lotsizesquarefeet	Area of the lot in square feet	11.24%	Filled with mean because all home has are of the lot.
35	finishedsquarefeet12	Finished living area	5.18%	Filled with mean because all home has living area.
36	regionidcity	City in which the property is located (if any)	2.00%	Filled with the most frequent value because all home is located in city.
37	fullbathcnt	Number of full bathrooms present in home	1.31%	Filed with 0 because missing might mean home does not have full bathroom.
38	calculatedbathnbr	Number of bathrooms in home including fractional bathroom	1.31%	Filed with 0 because missing might mean home does not have full bathroom.

39	yearbuilt	The Year the principal residence was built	0.84%	Filled with mean because all home have the year built in.
40	calculatedfinishedsquarefeet	Calculated total finished living area of the home	0.73%	Filled with mean because most home have living room
41	censustractandblock	Census tract and block ID combined	0.67%	Filled with most frequent value because every home has it's value
42	structuretaxvaluedollarcnt	The assessed value of the built structure on the parcel	0.42%	Filled with mean because every home has the assessed value
43	regionidzip	Zip code in which the property is located	0.04%	Filled with the most frequent value because every home has zip code.
44	taxamount	The total property tax assessed for that assessment year	0.01%	Filed with mean because every home has property tax.
45	taxvaluedollarcnt	The total tax assessed value of the parcel	0.00%	Filed with mean because every home has property tax.
46	landtaxvaluedollarcnt	The assessed value of the land area of the parcel	0.00%	Filled with mean because every home have assesed value.
47	propertycountylandusecode	County land use code i.e. it's zoning at the county level	0.00%	Filled with the most frequent value.

Outliers

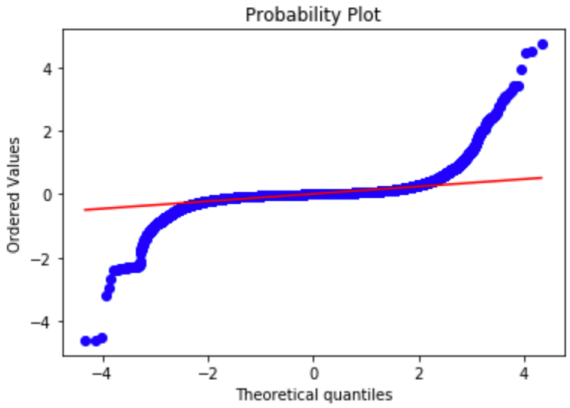
Let's draw a scatter plot on "logerror", then we can find that there are some outliers at the end of both sides.
Our task in the project is to find where the zillow algorithm fails. These outliers means where the zillow algorithm fails the most. Thus, I will leave outliers just like that.

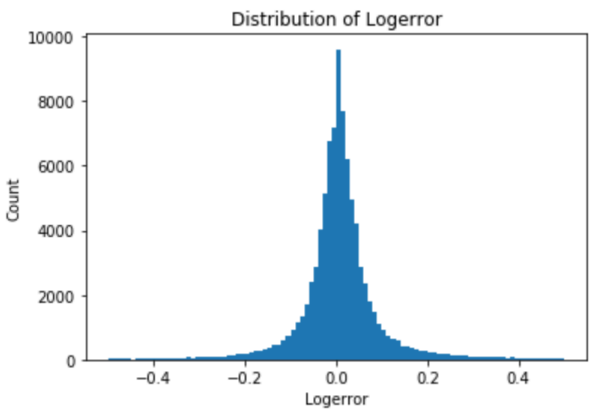


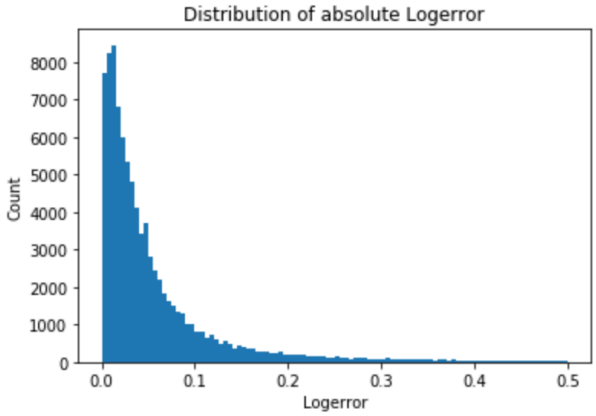
Data Storytelling

Distribution of Logerror

We would check both logerror and absolute value of logerror. Logerror indicates wheather estimated house values has been underestimated or overestimated while absolute logerror tells us that how estimated house value is close to an actual house value. It seems like the distribution of logerror follows a normal distribution by checking QQ plot.

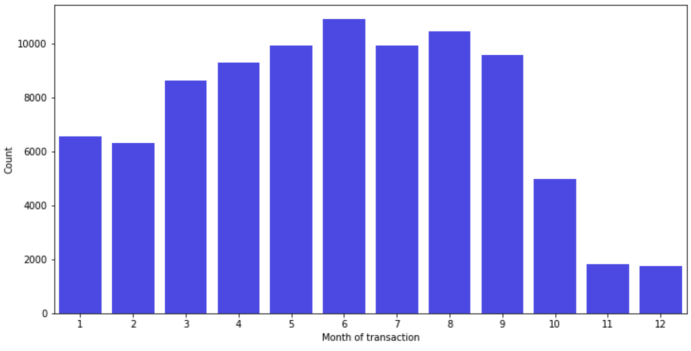




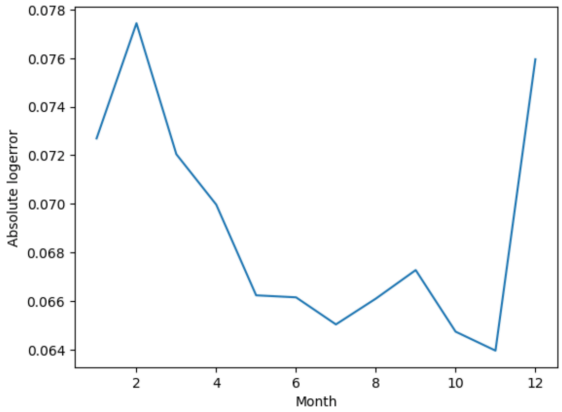


Transaction Dates

Let's check the distribution of transaction dates, there are fewer transactions after October

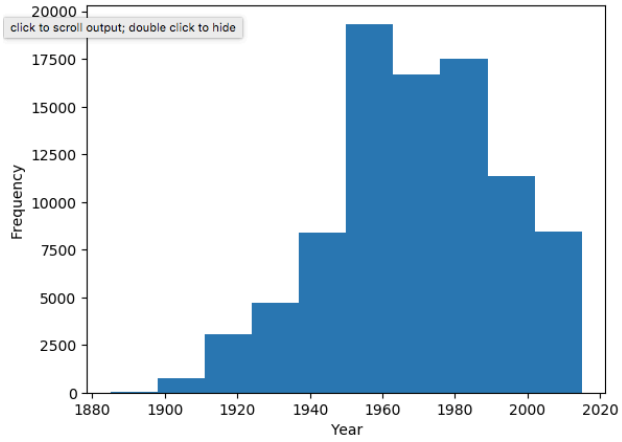


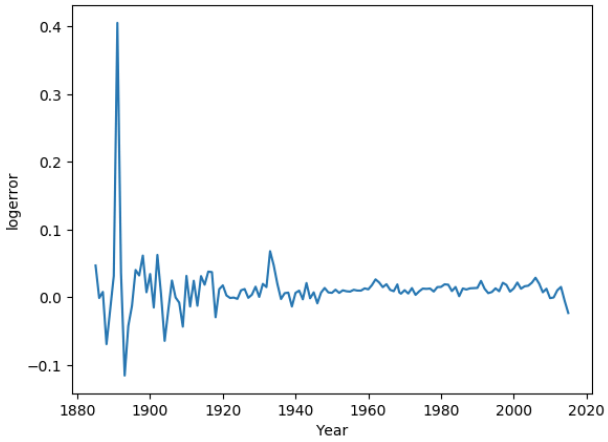
Let's see how absolute logerror change over time. We can see that logerror is getting better over time. The large logerror on December is because there were few transaction at that time. Small quantity of data leaded to large mean of logerror.



Built year

After observing plot for density of built year, we can find that most houses, 59.37%, are built between 1950 and 1990. Logerror is getting smaller with newer houses. Zestimate predicts home value with newer homes.





Inferential Statistics

Let's check correlations of each variables to "logerror" to see how variables are related.

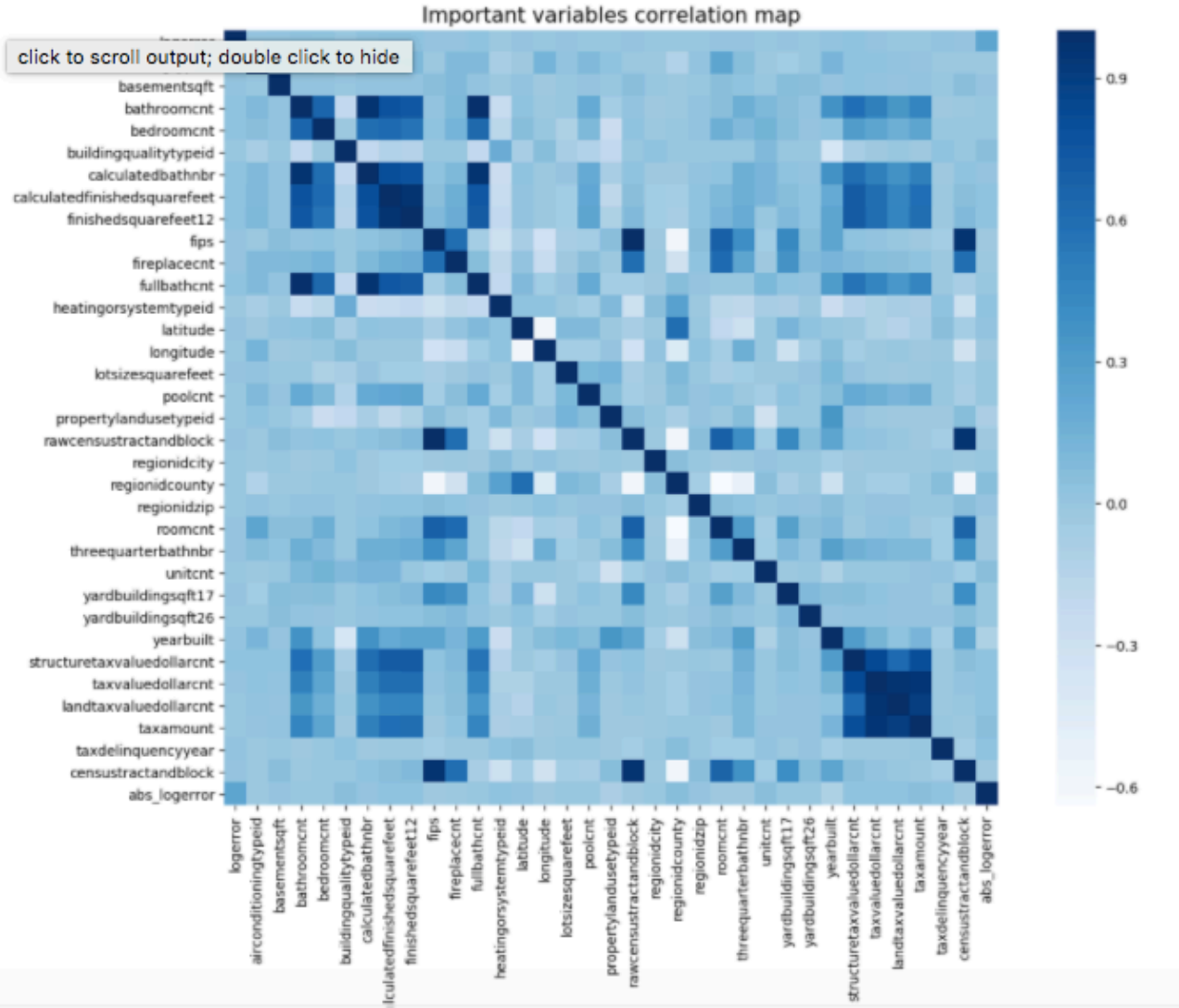
Correlation between target variable, logerror, and dependent variables are all weak. They are between 0.237380 and -0.018009.

Name	Coeff
abs_logerror	0.23738
finishedsquarefeet12	0.039248

calculatedfinishedsquarefeet	0.038341
calculatedbathnbr	0.028788
bathroomcnt	0.027889
fullbathcnt	0.027571
bedroomcnt	0.025467
structuretaxvaluedollarcnt	0.021935
taxdelinquencyyear	0.018107
yearbuilt	0.017089
basementsqft	0.009019
rawcensustractandblock	0.008376
fips	0.008363
fireplacecnt	0.007746
taxvaluedollarcnt	0.006508
roomcnt	0.00576
threequarterbathnbr	0.00549
airconditioningtypeid	0.005404
latitude	0.004915
lotsizesquarefeet	0.004612
censustractandblock	0.004495
yardbuildingsqft17	0.002497
propertylandusetypeid	0.001003
regionidcounty	0.000341
yardbuildingsqft26	-0.000846
regionidcity	-0.002342
landtaxvaluedollarcnt	-0.003051
longitude	-0.003432
unitcnt	-0.003447
regionidzip	-0.006487
taxamount	-0.006671
buildingqualitytypeid	-0.00788
poolcnt	-0.008983
heatingorsystemtypeid	-0.018009

Let's check correlations between pairs of independent variables. We can find that there are 2 clusters on the heat map below. The first cluster on the top left shows that variables about sizes of houses such as bathroom size or bedroom size and total square feets are stronly related. The second cluster on the bottom right tells us that variables about taxes are related to each other. Alse, we can observe from the right top cluster that variables about sizes of houses are weakly related to variables about taxes. It is reasonable because the bigger a house is, the more expensive the property is resulting the more taxes. However, the price of house is not only resulted from the size of house. So correlation is not strong among them.

There are not variables which can be particularly significant in terms of predicting logerror based on correlation. Also, there are strong multicollinearity between dependent variables. Therefore, a linear regression is not suitable for the model because of multicollinearity.



Machine Learning

Random Forest

As we see on the above, a linear regression is not a good choice for a model because of multicollinearity. I first tried a random forest as multicolinearity is not important factor for random forest.

To find the best fitted randome forest model, grid search is used. possible combination of options were applied to find the better model. From grid search, the model with max_depth of 5, min_samples_spli of 20 and n_estimators of 30 was selected.

The RSME for the model was 0.0011. So random forest is a good to predict logerror.

Lasso

Let's try Lasso. To find the alpha for Lasso try many possible variables, 0,0.0001,0.001, 0.01,0.1,0.5,1,2,3,4 for alpha, then choose the suitable variables. Also, R squared is too low.

Alpha	RMSE	R squared
0	0.0258	0.0063
0.0001	0.0258	0.0062
0.001	0.0258	0.0055
0.01	0.0258	0.0047
0.1	0.0258	0.0046
0.5	0.0258	0.0045
1	0.0258	0.0044
2	0.0258	0.0040
3	0.0259	0.0034
4	0.0259	0.0029

11 variables were chosen for Lasso, but coefficients for each chosen variables are low. Therefore Lasso is not a good model to predict logerror

coeff	name
7.13E-08	taxvaluedollarcnt
4.43E-08	rawcensustractandblock
4.46E-09	lotsizesquarefeet
3.76E-09	latitude
1.29E-09	longitude
-4.12E-14	censustractandblock
-4.78E-09	regionidcity
-1.34E-08	regionidzip
-1.40E-08	structuretaxvaluedollarcnt
-5.63E-08	landtaxvaluedollarcnt
-2.22E-06	taxamount

Support Vector Machines

Support Vector Machine is not significant for a model.