

Assignment 2 By Team 4

Salma Bouzid, Shun-Lung Chang, Savitha Singh

Import data

We first downloaded the datasets from [here](#), then imported them into R as dataframes (**properties** and **transaction** for “properties_2016.csv” and “train_2016.csv” respectively). In addition, the two dataframes were joined as a new dataframe, **joined_df**.

```
properties <- fread("./data/properties_2016.csv")
transaction <- fread("./data/train_2016.csv")
joined_df <- merge(transaction, properties, all.x = TRUE)
```

1. Explain why it is or why it is not a big data problem.

We can safely conclude that analyzing this dataset is not a big data problem, since it fails to satisfy the volume, variety, velocity. It only satisfies the veracity criterion.

A closer look at the 4 Vs of big data[2] will enable us to better understand this problem:

1. The dataset is not voluminous

After using `pryr::object_size(properties)` in R, we know that properties’s memory is merely 0.908 GBs. According to the table below[1], we know that handling this data set can be done on a consumer PC and does not require extra cores or machines.

Big	Can't fit in memory on one computer: >1 TB
Medium	Fits in memory on a server: 10 GB-1 TB
Small	Fits in memory on a laptop: <10 GB

Big	Many machines, many cores
Medium	Many cores
Small	One core

2. The dataset is structured

The dataset is well-defined in labeled rows and columns. In fact, the dataset comes with a dictionary that clearly explains the 58 attributes in the properties data.

3. The dataset is static

Most of the datasets’ attributes come from government agencies that publish yearly or bi-monthly statistics. Moreover, this dataset does not include the newly user generated input, although users can update their housing information on Zillow’s portal anytime to reflect changes in their home characteristics[3].

4. We can trust the data

The dataset’s observations come from public records regarding location and property characteristics. Although it can be missing or outdated[3], we can safely assume that this dataset has not been

manipulated to reflect bias that favors one housing area or similar fraudulent behaviors. Therefore, the uncertainty of this problem does not achieve the level of big data problems.

2. Why is it an analytics problem?

Analytics aims to derive actionable insights from data. To address an analytics issue, we define the problem. Second, statistical models and computing algorithms are used to solve the issue[4]. We will rely on this definition to answer this question.

1. Problem definition

Buyers and sellers are not equally informed about the value of houses. In fact, some players, such as real estate agents, have information advantage. They are more informed about future gentrification and demographic patterns that impact future house prices[5].

2. How does the Zillow fight information asymmetry through data analytics?

The Zestimate - Zillow's star index estimates future house prices by analyzing user inputted data and public records. The target feature in this challenge aims to measure the log difference between Zillow's proprietary estimates and the actual prices in the house market[6].

Zillow launched this challenge in order to improve its housing valuation algorithm by learning from the best performing models submitted by Kaggle users.

3. How many data attributes are there?

After merging the two datasets we obtain 60 attributes in total. The initial properties dataframe contained 58 attributes while the transaction dataframe contained 3 attributes including the transaction date and target variable.

```
colnames(joined_df)
```

[1] "parcelid"	"logerror"
[3] "transactiondate"	"airconditioningtypeid"
[5] "architecturalstyletypeid"	"basementsqft"
[7] "bathroomcnt"	"bedroomcnt"
[9] "buildingclasstypeid"	"buildingqualitytypeid"
[11] "calculatedbathnbr"	"decktypeid"
[13] "finishedfloorisquarefeet"	"calculatedfinishedsquarefeet"
[15] "finishedsquarefeet12"	"finishedsquarefeet13"
[17] "finishedsquarefeet15"	"finishedsquarefeet50"
[19] "finishedsquarefeet6"	"fips"
[21] "fireplacecnt"	"fullbathcnt"
[23] "garagecarcnt"	"garagetotalsqft"
[25] "has hottuborspa"	"heatingorsystemtypeid"
[27] "latitude"	"longitude"
[29] "lotsizesquarefeet"	"poolcnt"
[31] "poolsizesum"	"pooltypeid10"
[33] "pooltypeid2"	"pooltypeid7"
[35] "propertycountylandusecode"	"propertylandusetypeid"
[37] "propertyzoningdesc"	"rawcensustractandblock"
[39] "regionidcity"	"regionidcounty"
[41] "regionidneighborhood"	"regionidzip"
[43] "roomcnt"	"storytypeid"
[45] "threequarterbathnbr"	"typeconstructiontypeid"

```

[47] "unitcnt"                "yardbuildingsqft17"
[49] "yardbuildingsqft26"    "yearbuilt"
[51] "numberofstories"       "fireplaceflag"
[53] "structuretaxvaluedollarcnt" "taxvaluedollarcnt"
[55] "assessmentyear"        "landtaxvaluedollarcnt"
[57] "taxamount"             "taxdelinquencyflag"
[59] "taxdelinquencyyear"    "censustractandblock"

```

4. Identify the type of the 15 attributes you find most relevant in this context

The goal of this data challenge is to predict the $\log(\text{error})$ value. To select 15 relevant attributes out of 60, we assume that “relevant” means “linearly correlated”. Hence, we choose the first 15 attributes with highest absolute correlation coefficients between logerror below.

To do so, we pick numeric features, use `Hmisc::rcorr()` to get the correlation coefficient matrix, sort the correlation coefficients between logerror decreasingly, and choose the first 15 items. The below barplot showcases the final result.

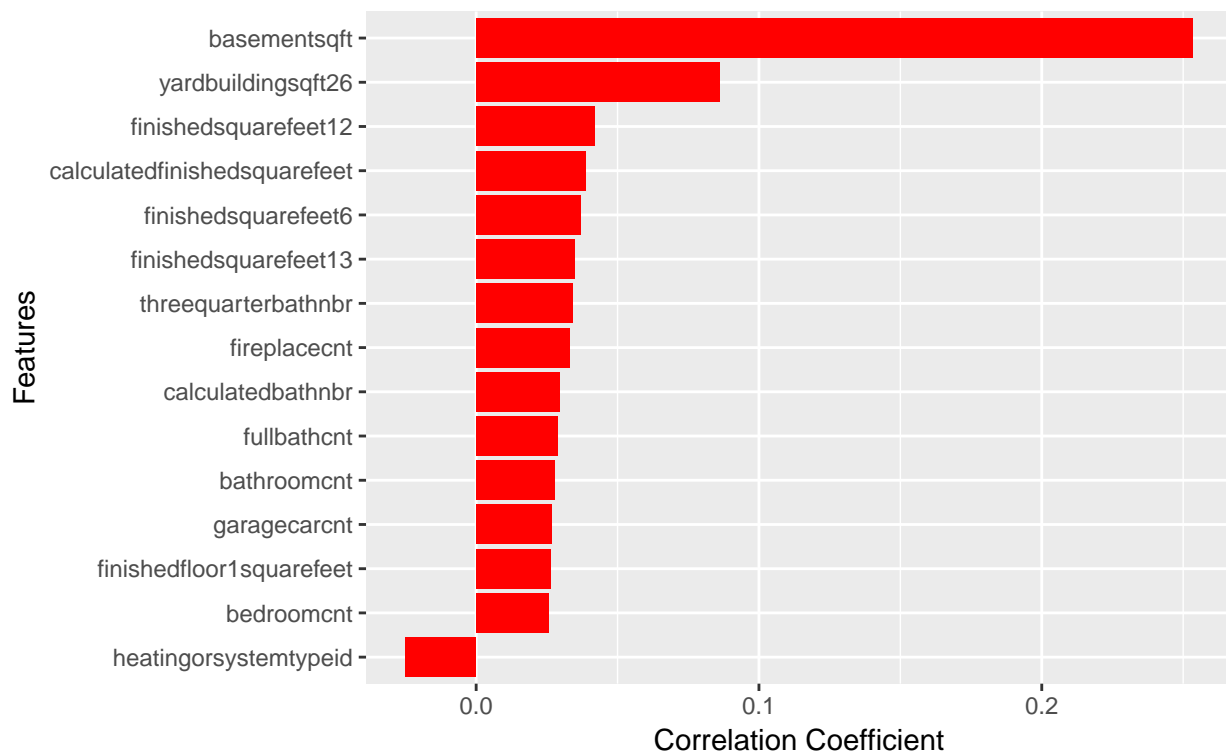
```

numeric_df <- joined_df[, sapply(joined_df, is.numeric), with = FALSE]

corr_mat <- Hmisc::rcorr(as.matrix(numeric_df))

top15 <- abs(corr_mat$r[2, ]) %>%
  sort(decreasing = TRUE) %>%
  .[2:16] %>%
  names()

```



5. Determine whether the task refers to a supervised or unsupervised learning problem

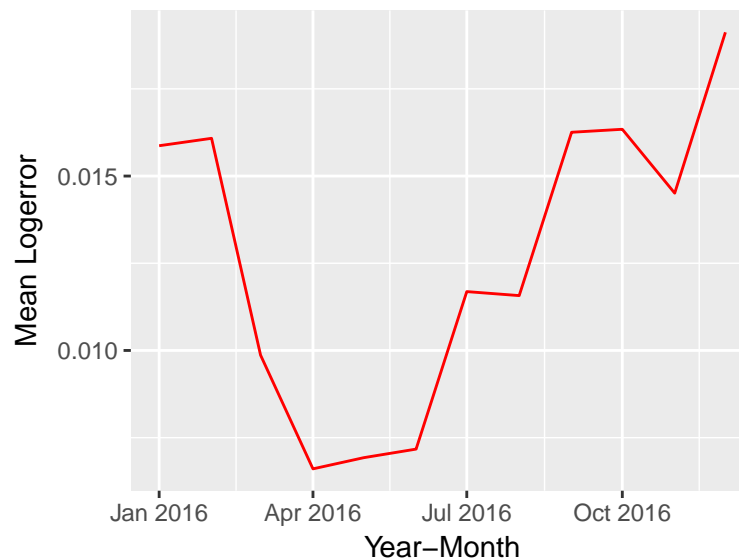
The Zillow home valuation challenge is a supervised learning problem. The target variable namely the $\log(\text{error})$ is labeled. Hence, we rely on the independent variables to predict a known target.

6. Find out what the standard analysis algorithms are for this analytics problem

The Zillow Home Value Kaggle challenge is a **supervised learning** task that deals with a regression problem since the output value is a **real number**. Hence, the standard algorithms used in this task are regression models.

7. Download the data and provide descriptive summaries of the sample data

To summarize the data, we visually display the target variable between January and October 2016, then use the `summary()` function in R to get the minimum, maximum, 1st and 3rd quartile, mean and median and number of missing values for each independent variable.



```
summary(properties)
```

parcelid	airconditioningtypeid	architecturalstyletypeid	
Min. : 10711725	Min. : 1.0	Min. : 2.0	
1st Qu.: 11643707	1st Qu.: 1.0	1st Qu.: 7.0	
Median : 12545094	Median : 1.0	Median : 7.0	
Mean : 13325858	Mean : 1.9	Mean : 7.2	
3rd Qu.: 14097122	3rd Qu.: 1.0	3rd Qu.: 7.0	
Max. : 169601949	Max. : 13.0	Max. : 27.0	
	NA's : 2173698	NA's : 2979156	
basementsqft	bathroomcnt	bedroomcnt	buildingclasstypeid
Min. : 20.0	Min. : 0.000	Min. : 0.000	Min. : 1.0

1st Qu.: 272.0	1st Qu.: 2.000	1st Qu.: 2.000	1st Qu.:3.0
Median : 534.0	Median : 2.000	Median : 3.000	Median :4.0
Mean : 646.9	Mean : 2.209	Mean : 3.089	Mean :3.7
3rd Qu.: 847.2	3rd Qu.: 3.000	3rd Qu.: 4.000	3rd Qu.:4.0
Max. :8516.0	Max. :20.000	Max. :20.000	Max. :5.0
NA's :2983589	NA's :11462	NA's :11450	NA's :2972588
buildingqualitytypeid	calculatedbathnbr	decktypeid	
Min. : 1.0	Min. : 1.0	Min. :66	
1st Qu.: 4.0	1st Qu.: 2.0	1st Qu.:66	
Median : 7.0	Median : 2.0	Median :66	
Mean : 5.8	Mean : 2.3	Mean :66	
3rd Qu.: 7.0	3rd Qu.: 3.0	3rd Qu.:66	
Max. :12.0	Max. :20.0	Max. :66	
NA's :1046729	NA's :128912	NA's :2968121	
finishedfloor1squarefeet	calculatedfinishedsquarefeet		
Min. : 3	Min. : 1		
1st Qu.: 1012	1st Qu.: 1213		
Median : 1283	Median : 1572		
Mean : 1381	Mean : 1827		
3rd Qu.: 1615	3rd Qu.: 2136		
Max. :31303	Max. :952576		
NA's :2782500	NA's :55565		
finishedsquarefeet12	finishedsquarefeet13	finishedsquarefeet15	
Min. : 1	Min. : 120	Min. : 112	
1st Qu.: 1196	1st Qu.: 960	1st Qu.: 1694	
Median : 1539	Median :1296	Median : 2172	
Mean : 1760	Mean :1179	Mean : 2739	
3rd Qu.: 2070	3rd Qu.:1440	3rd Qu.: 2976	
Max. :290345	Max. :2688	Max. :820242	
NA's :276033	NA's :2977545	NA's :2794419	
finishedsquarefeet50	finishedsquarefeet6	fips	
Min. : 3	Min. : 117	Min. :6037	
1st Qu.: 1013	1st Qu.: 1079	1st Qu.:6037	
Median : 1284	Median : 1992	Median :6037	
Mean : 1389	Mean : 2414	Mean :6048	
3rd Qu.: 1618	3rd Qu.: 3366	3rd Qu.:6059	
Max. :31303	Max. :952576	Max. :6111	
NA's :2782500	NA's :2963216	NA's :11437	
fireplacecnt	fullbathcnt	garagecarcnt	garagetotalsqft
Min. :1.0	Min. : 1.00	Min. : 0.0	Min. : 0.0
1st Qu.:1.0	1st Qu.: 2.00	1st Qu.: 2.0	1st Qu.: 324.0
Median :1.0	Median : 2.00	Median : 2.0	Median : 441.0
Mean :1.2	Mean : 2.24	Mean : 1.8	Mean : 383.8
3rd Qu.:1.0	3rd Qu.: 3.00	3rd Qu.: 2.0	3rd Qu.: 494.0
Max. :9.0	Max. :20.00	Max. :25.0	Max. :7749.0
NA's :2672580	NA's :128912	NA's :2101950	NA's :2101950
hashottuborspa	heatingorsystemtypeid	latitude	
Length:2985217	Min. : 1	Min. :33324388	
Class :character	1st Qu.: 2	1st Qu.:33827685	
Mode :character	Median : 2	Median :34008249	
	Mean : 4	Mean :34001469	
	3rd Qu.: 7	3rd Qu.:34161860	
	Max. :24	Max. :34819650	
	NA's :1178816	NA's :11437	

longitude	lotsizesquarefeet	poolcnt	
Min. : -119475780	Min. : 100	Min. : 1	
1st Qu.: -118392983	1st Qu.: 5688	1st Qu.: 1	
Median : -118172540	Median : 7000	Median : 1	
Mean : -118201934	Mean : 22823	Mean : 1	
3rd Qu.: -117949468	3rd Qu.: 9898	3rd Qu.: 1	
Max. : -117554316	Max. : 328263808	Max. : 1	
NA's : 11437	NA's : 276099	NA's : 2467683	

poolsize	pooltypeid10	pooltypeid2	pooltypeid7
Min. : 19.0	Min. : 1	Min. : 1	Min. : 1
1st Qu.: 430.0	1st Qu.: 1	1st Qu.: 1	1st Qu.: 1
Median : 495.0	Median : 1	Median : 1	Median : 1
Mean : 519.7	Mean : 1	Mean : 1	Mean : 1
3rd Qu.: 594.0	3rd Qu.: 1	3rd Qu.: 1	3rd Qu.: 1
Max. : 17410.0	Max. : 1	Max. : 1	Max. : 1
NA's : 2957257	NA's : 2948278	NA's : 2953142	NA's : 2499758

propertycountylandusecode	propertylandusetypeid	propertyzoningdesc
Length:2985217	Min. : 31	Length:2985217
Class :character	1st Qu.:261	Class :character
Mode :character	Median :261	Mode :character
	Mean :260	
	3rd Qu.:261	
	Max. :275	
	NA's :11437	

rawcensustractandblock	regionidcity	regionidcounty
Min. : 60371011	Min. : 3491	Min. : 1286
1st Qu.: 60373203	1st Qu.: 12447	1st Qu.: 2061
Median : 60375712	Median : 25218	Median : 3101
Mean : 60483450	Mean : 34993	Mean : 2570
3rd Qu.: 60590423	3rd Qu.: 45457	3rd Qu.: 3101
Max. : 61110091	Max. : 396556	Max. : 3101
NA's : 11437	NA's : 62845	NA's : 11437

regionidneighborhood	regionidzip	roomcnt	storytypeid
Min. : 6952	Min. : 95982	Min. : 0.000	Min. : 7
1st Qu.: 46736	1st Qu.: 96180	1st Qu.: 0.000	1st Qu.: 7
Median : 118920	Median : 96377	Median : 0.000	Median : 7
Mean : 193476	Mean : 96553	Mean : 1.475	Mean : 7
3rd Qu.: 274800	3rd Qu.: 96974	3rd Qu.: 0.000	3rd Qu.: 7
Max. : 764167	Max. : 399675	Max. : 96.000	Max. : 7
NA's : 1828815	NA's : 13980	NA's : 11475	NA's : 2983593

threequarterbathnbr	typeconstructiontypeid	unitcnt
Min. : 1	Min. : 4	Min. : 1.0
1st Qu.: 1	1st Qu.: 6	1st Qu.: 1.0
Median : 1	Median : 6	Median : 1.0
Mean : 1	Mean : 6	Mean : 1.2
3rd Qu.: 1	3rd Qu.: 6	3rd Qu.: 1.0
Max. : 7	Max. : 13	Max. : 997.0
NA's : 2673586	NA's : 2978470	NA's : 1007727

yardbuildingsqft17	yardbuildingsqft26	yearbuilt	numberofstories
Min. : 10.0	Min. : 10.0	Min. : 1801	Min. : 1.0
1st Qu.: 190.0	1st Qu.: 96.0	1st Qu.: 1950	1st Qu.: 1.0
Median : 270.0	Median : 168.0	Median : 1963	Median : 1.0
Mean : 319.8	Mean : 278.3	Mean : 1964	Mean : 1.4
3rd Qu.: 390.0	3rd Qu.: 320.0	3rd Qu.: 1981	3rd Qu.: 2.0

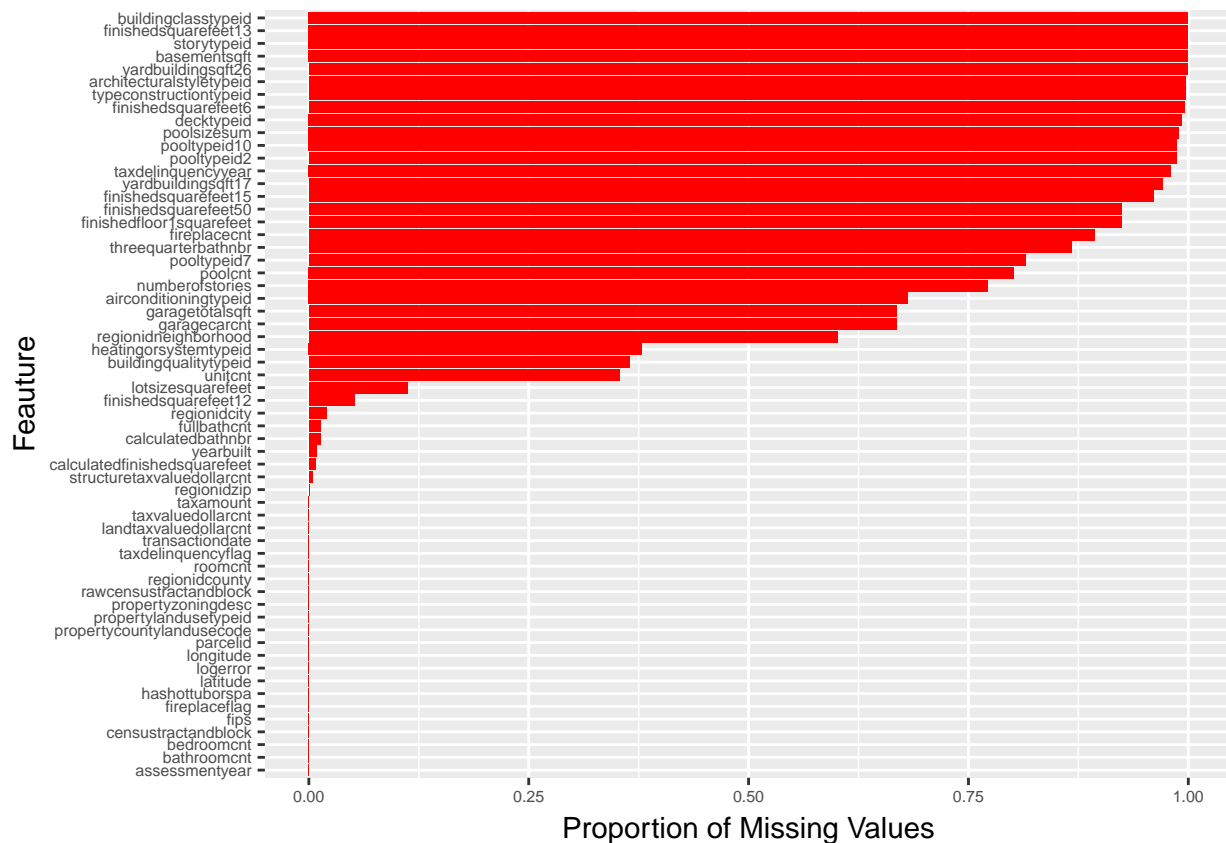
Max. :7983.0	Max. :6141.0	Max. :2015	Max. :41.0
NA's :2904862	NA's :2982570	NA's :59928	NA's :2303148
fireplaceflag	structuretaxvaluedollarcnt	taxvaluedollarcnt	
Length:2985217	Min. : 1	Min. : 1	
Class :character	1st Qu.: 74800	1st Qu.: 179675	
Mode :character	Median : 122590	Median : 306086	
	Mean : 170884	Mean : 420479	
	3rd Qu.: 196889	3rd Qu.: 488000	
	Max. :251486000	Max. :282786000	
	NA's :54982	NA's :42550	
assessmentyear	landtaxvaluedollarcnt	taxamount	
Min. :2000	Min. : 1	Min. : 1	
1st Qu.:2015	1st Qu.: 74836	1st Qu.: 2461	
Median :2015	Median : 167042	Median : 3992	
Mean :2015	Mean : 252478	Mean : 5378	
3rd Qu.:2015	3rd Qu.: 306918	3rd Qu.: 6201	
Max. :2016	Max. :90246219	Max. :3458861	
NA's :11439	NA's :67733	NA's :31250	
taxdelinquencyflag	taxdelinquencyyear	censustractandblock	
Length:2985217	Min. : 0.0	Min. :0	
Class :character	1st Qu.:14.0	1st Qu.:0	
Mode :character	Median :14.0	Median :0	
	Mean :13.9	Mean :0	
	3rd Qu.:15.0	3rd Qu.:0	
	Max. :99.0	Max. :0	
	NA's :2928753	NA's :3	

8. Check for completeness of the data! Are there any missings? How are the missings distributed?

After merging the two datasets, we obtain 90275 observations of which 37.1% are missing. 18 features lack 95% of values. Four features namely 'basementsqft', 'buildingclasstypeid', 'finishedsquarefeet13', 'storytypeid' miss 99.99 % of observations.

However, 13 features have 0 missing values such as geographical and house room attributes. The below horizontal histogram illustrates the distribution of NaN values across the dataset.

Note: It is worth noting that this analysis is incomplete since it only checks for missing values. More missing data can be present in the dataset under other formats.



References

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