Assignment 2 By Team 4

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Import data

After downloading the datasets from **here**, we 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 Although it can be missing or outdated[3], we can safely assume that this dataset has not been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 achive 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] "finishedfloor1squarefeet"     "calculatedfinishedsquarefeet"
[15] "finishedsquarefeet12"         "finishedsquarefeet13"
[17] "finishedsquarefeet15"         "finishedsquarefeet50"
[19] "finishedsquarefeet6"          "fips"
[21] "fireplacecnt"                 "fullbathcnt"
[23] "garagecarcnt"                 "garagetotalsqft"
[25] "hashottuborspa"               "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

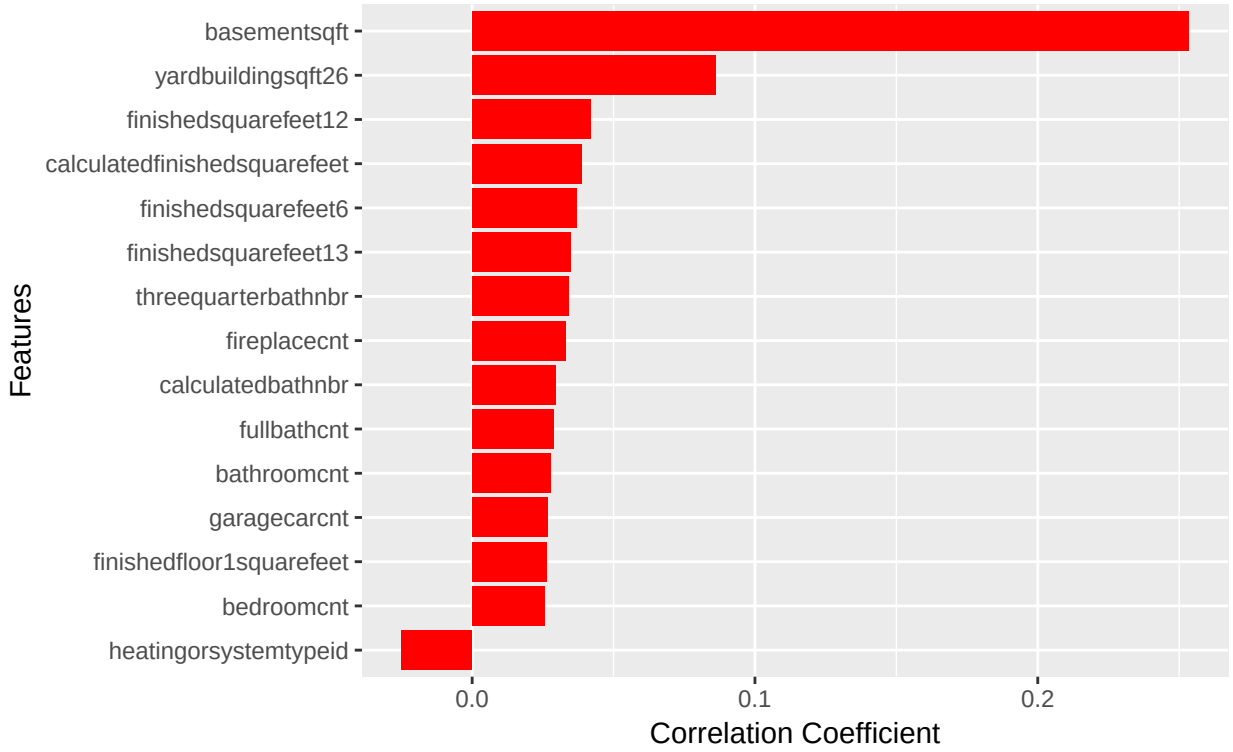
The goal of this data challenge is to predict the *log(error)* value. To select 15 relevant attributes out of 60, we assume that "relevant" means "linearly correlated". Hence, we choose the first 15 attributes with highest absolute correlation coefficients between logerror below.

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

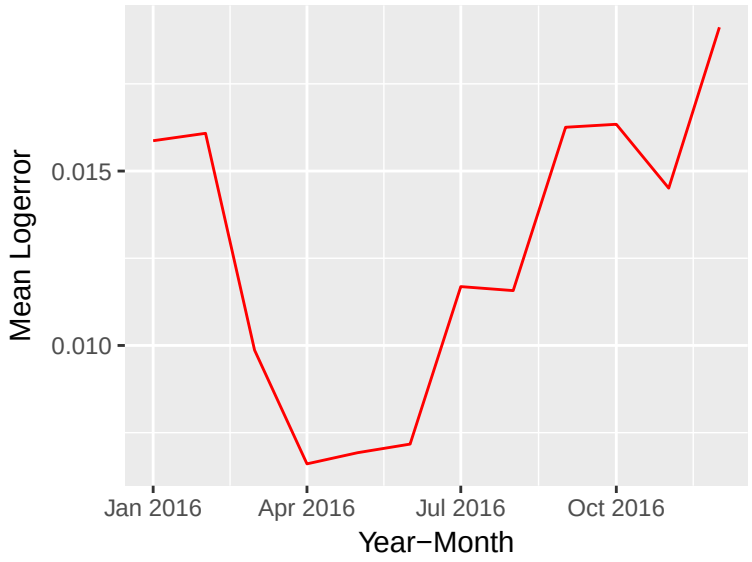
The Zillow home valuation challenge is a supervised learning problem. The target variable namely the *log(error)* is labeled. Hence, we rely on the independent variables to predict a known target.

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
 poolsizesum       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.   :             -1
Class :character   1st Qu.:14.0       1st Qu.: 60374002041015
Mode  :character   Median :14.0       Median : 60375715022011
                   Mean   :13.9       Mean   : 60484312212563
                   3rd Qu.:15.0       3rd Qu.: 60590423191014
                   Max.   :99.0       Max.   :483030105084015
                   NA's   :2928753    NA's   :          75126
```

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 NA values. More missing data can be present in the dataset under other formats.

References

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