Assignment 2 By Team 4

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Import data

We first downloaded the data sets from **here**, and then we imported and stored them as R 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.

With respect to the 4Vs (Variety, Velocity, Volume and Veracity) dimentions of big data, we would say it is NOT a big data problem. First of all, the data set, unlike videos or images, is already quite strutured. Of course, the data set still has to be cleaned for further analysis. But the time spent on data cleaning of this data set could be less than that of other unstrutured data sets.

Moreover, the data set is static rather than streaming data, and hence it could not be a big data problem in terms of velocity. Third, according to the table below[1], a data set that has less than 10 gigabytes memory may not be considered as a big data problem. After using `pryr::object_size(properties)` in R, one can see that the the memory size of the data set is merely 0.908 GBs, which is far less than 10 GBs.

As can be seen from the **introduction page**, the "Zestimate" is predicted by millions of machine learning models and the error of these model has been improved consistently. In addition, the other attributes, such as size or location, can gernally be measured by objective observation. As a result, we would say that the data set's veracity has reached a certain extent, and may not need to deal with high inaccurary in some big data problems.

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. Why is it an analytics problem?

According to the **definition of analytics in wikipedia**, analytics is to interpret and find valuable pattern in data, and often relies on statistics and computer programming.

In this problem, the goal is to find the smallest *log(error)*, which is defined as *log(Zestimate) - log(SalePrice)*. To this end, one has to interpret the data through data viusalization and data transformation, and to build statistical models for predictions. One often uses programming languages, such as R and Python, to accomplish this task more efficiently and effectively, Therefore, finding the minimal *log(error)* in this problem is a analytics problem.

3. How many data attributes are there?

As can be seen from the result of `colnames(joined_df)`, the whole data set contains 60 attributes. Also, properties contains 58 attributes and transaction contains 3 attributes.

```
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

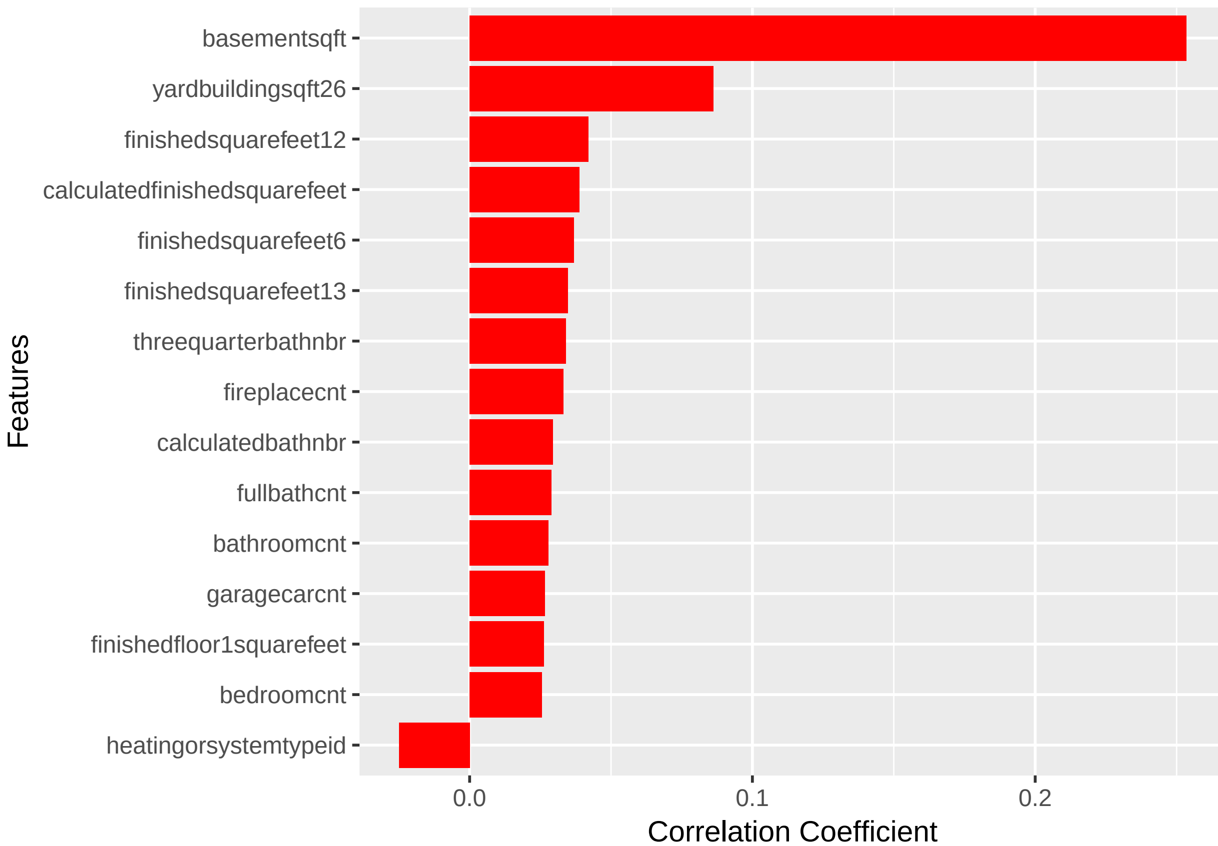
Since the goal of this problem is to find minimal *log(error)*, and we assume that "relevant" means "linearly correlated". We show the first 15 attributes that has highest absolute correlation coefficients between logerror below.

Firstly, we pickcd those features that are numeric, and then used `Hmisc::rcorr()` to get the correlation coefficient matrix. At last we sorted the correlation coefficients between logerror decreasingly, and chose the first 15 items. The result is shown as the barplot.

```r
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

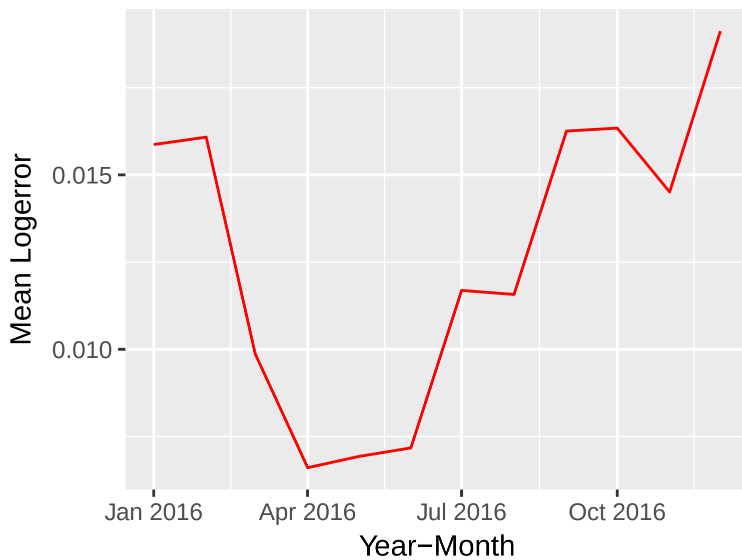
This should be a supervised learning proplem, according to the **definition of supervised learning in wikipedia**. Given that we have to predict *log(error)* variable in this problem, so *log(error)* is the labeled or desired variable in a supervised problem. Therefore, it is a supervised learning proplem.

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

In order to find the optimal logerror, a standard analysis algorithm that can be used is the regression analysis. Regression analysis is for estimation the relationship among variables. for this task, one can build regression models to find the relationship between logerror and other variables.

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

We summarised transaction by ploting its trend. One can see an uprising trend of the average logerror of each month.



Also, we used `summary()` in R to summarise properties. One can see a noticeable number of missing values (NAs) in many of the features, and we would carry out a deeper analysis of these missing values in the next question.

```r
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
```

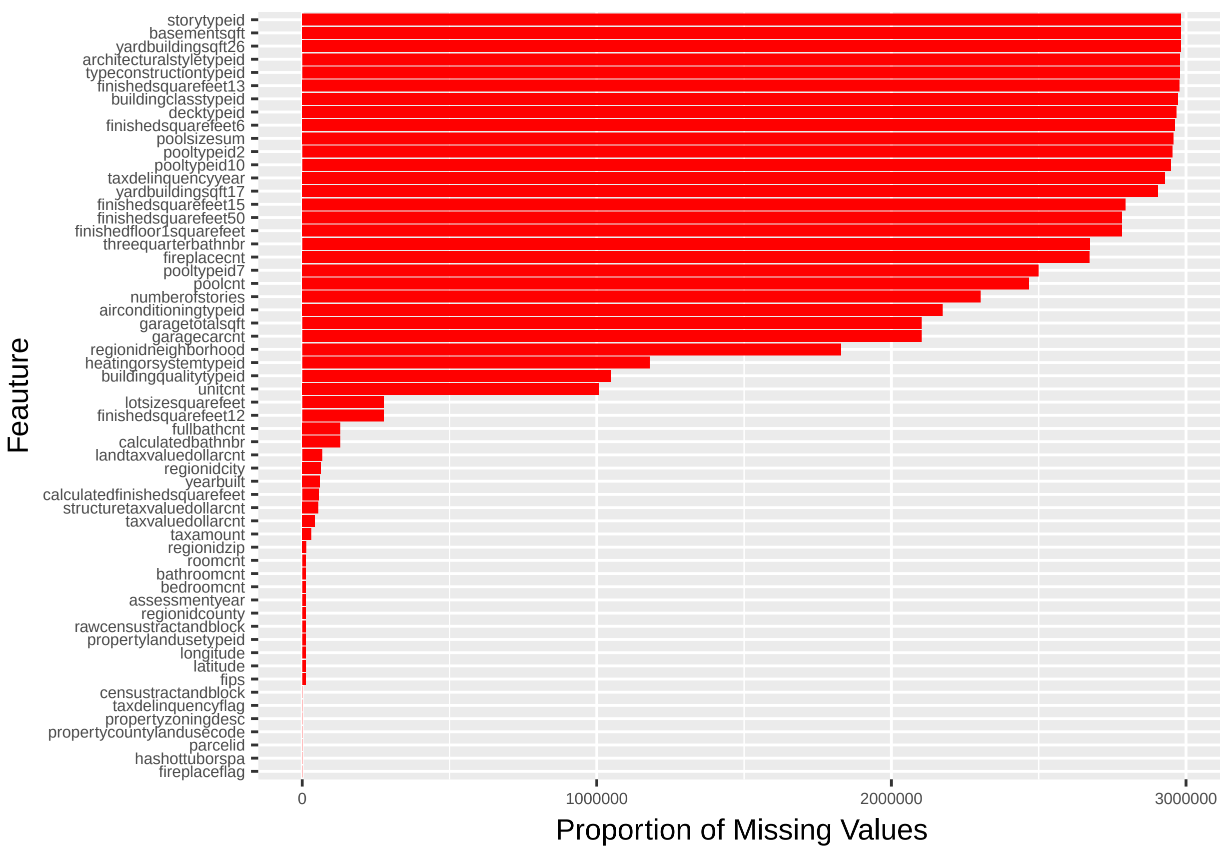
```
finishedfloor1squarefeet calculatedfinishedsquarefeet
Min.   :    3           Min.   :     1
1st Qu.: 1012           1st Qu.:  1213
Median : 1283           Median :  1572
Mean   : 1381           Mean   :  1827
3rd Qu.: 1615           3rd Qu.:  2136
Max.   :31303           Max.   :952576
NA's   :2782500         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.   :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?

As can be seen from question 7, there exist a great amount of missing values in many features of properties. The plot below shows the counts of missing values of each feature and how they distribute. One can see that at least a half of the features have more than one million missing values.



References

[1] Adalbert F.X. Wilhelm (2017), The Big Data Challenge: Topics, Applications, Perspectives [Powerpoint

slides]