Final Project

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Problem 1

let X = X2 and Y = Y2 that is

```
X <- c(7.4, 6.4, 8.5, 9.5, 11.8, 8.8, 8.4, 5.1, 11.4, 15.1, 12.6, 8.0, 10.3, 10.4,
       9.5, 9.5, 15.1, 6.6, 15.4, 8.2)

Y <- c(20.8, 14.6, 18.0, 7.3, 19.4, 13.5, 14.7, 15.3, 12.6, 13.0, 13.1, 10.3, 14.9,
       14.8, 16.2, 15.7, 16.3, 11.5, 12.2, 11.8)
```

a) $P(X > x|Y > y)$ where x and y are the 3rd quartile and 1st quartile of x and y respectively.

- First find the 1st quantile of Y and $P(Y > y)$

```
x_3q <- quantile(X,.75)
y_1q <- quantile(Y,.25)
c(x_3q, y_1q)
```

```
##  75%  25%
## 11.5 12.5
```

```
p_ge_y <- length(Y[Y > y_1q]) / length(Y) # P(Y > y)
p_ge_y
```

```
## [1] 0.75
```

- $P(X > x|Y > y) = P(X > x \cap Y > y)/P(Y > y)$ the numerator is the probability that both X and Y are above their respective quartiles.
- We see that $P(Y > y) = 0.75$ from above and using the intersect() function we can see how many values both operators in the intersection have in common:

```
x <- X[X > x_3q]
y <- Y[Y > y_1q]
p_x_and_y <- intersect(x, y)
p_x_and_y
```

```
## [1] 12.6
```

- only one value of out 20 (value of 12.6) so $P(X > x \cap Y > y) = 1/20$
- Finally computing the conditional probability gives $P(X > x|Y > y) =$

```r
(length(p_x_and_y)/20) / p_ge_y
```

```
## [1] 0.06666667
```

b) $P(X > x, Y > y)$ this is the joint probability or the intersection

- This was calculated in a) and was denoted as 1/20

c) $P(X < x)|Y > y)$ that is what is $P(X < x)$ given $P(Y > y)$

- $P(X < x)|Y > y) = P(X < x \cap Y > y)/P(Y > y)$ we found $P(Y > y) = 0.75$ earlier, now let's find the numerator.

```r
x <- X[X < x_3q]
p_x_and_y <- intersect(x, y)
p_x_and_y
```

```
## numeric(0)
```

- Thus $P(X > x, Y > y) = 0$
- In addition, make a table of counts as shown below:

```
##
## | x/y    | <=3rd quartile     | > 3rd quartile    | Total   |
## |--------|--------------------|-------------------|---------|
## | <=1st  |                    |                   |         |
## |quartile|                    |                   |         |
## |--------|--------------------|-------------------|---------|
## | > 1st  |                    |                   |         |
## |quartile|                    |                   |         |
## |--------|--------------------|-------------------|---------|
## | Total  |                    |                   |         |
## |--------|--------------------|-------------------|---------|
```

- For this we compute the joint probabilities for each of the 4 boxes and add them up

```r
x_1q <- quantile(X,.25)
y_3q <- quantile(Y,.75)

x1 <- X[X <= x_1q]
x2 <- X[X > x_1q]

y1 <- Y[Y <= y_3q]
y2 <- Y[Y > y_3q]

p_leq_x_leq_y <- intersect(x1, y1) # P(X <= 1st quartile, Y <= 3rd quartile)
p_leq_x_ge_y <- intersect(x1, y2) # P(X <= 1st quartile, Y > 3rd quartile)
p_ge_x_leq_y <- intersect(x2,y1) # P(X > 1st quartile, Y <= 3rd quartile)
p_ge_x_ge_y <- intersect(x2,y2) # P(X > 1st quartile, Y > 3rd quartile)

p_leq_x_leq_y
```

```
## numeric(0)
```

```r
p_leq_x_ge_y
```

```
## numeric(0)
```

```r
p_ge_x_leq_y
```

```
## [1] 11.8 12.6 10.3
```

```r
p_ge_x_ge_y
```

```
## numeric(0)
```

- Populating the table gives

x/y	<=3rd quartile	> 3rd quartile	Total
<=1st quartile	0	0	0
> 1st quartile	3	0	3
Total	3	0	3

- Does splitting the training data in this fashion make them independent? Let A be the new variable counting those observations above the 1st quartile for X, and let B be the new variable counting those observations above the 1st quartile for Y. Does $P(AB) = P(A)P(B)$? Check mathematically, and then evaluate by running a Chi Square test for association

```r
c(x_1q,y_1q) # 1st quartiles of X and Y
```

```
##   25%   25%
##  8.15 12.50
```

```r
p_A <- length(X[X > x_1q]) / length(X)
p_B <- length(Y[Y > y_1q]) / length(Y)
p_AB <- length(intersect(X[X > x_1q], Y[Y > y_1q])) / 20
p_AB
```

```
## [1] 0.05
```

```r
p_A * p_B
```

```
## [1] 0.5625
```

```
p_AB == (p_A * p_B) # P(A)P(B)
```

```
## [1] FALSE
```

- We see that the variables are not independent by looking the values and equality above.
- Now using a Chi Squared test to test

```
dat <- data.frame(X,Y)
chisq <- chisq.test(dat)
chisq
```

```
##
##  Pearson's Chi-squared test
##
## data:  dat
## X-squared = 15.213, df = 19, p-value = 0.709
```

- Using the chi squared test, we see that the p-value is about 0.7. This means that the variables X and Y are not stastically significantly associated.

Problem 2

- You are to register for Kaggle.com (free) and compete in the House Prices: Advanced Regression Techniques competition. https://www.kaggle.com/c/house-prices-advanced-regression-techniques . I want you to do the following.
- 5 points. Descriptive and Inferential Statistics. Provide univariate descriptive statistics and appropriate plots for the training data set. Provide a scatterplot matrix for at least two of the independent variables and the dependent variable. Derive a correlation matrix for any THREE quantitative variables in the dataset. Test the hypotheses that the correlations between each pairwise set of variables is 0 and provide a 80% confidence interval. Discuss the meaning of your analysis. Would you be worried about familywise error? Why or why not?
- 5 points. Linear Algebra and Correlation. Invert your 3 x 3 correlation matrix from above. (This is known as the precision matrix and contains variance inflation factors on the diagonal.) Multiply the correlation matrix by the precision matrix, and then multiply the precision matrix by the correlation matrix. Conduct LU decomposition on the matrix.
- 5 points. Calculus-Based Probability & Statistics. Many times, it makes sense to fit a closed form distribution to data. Select a variable in the Kaggle.com training dataset that is skewed to the right, shift it so that the minimum value is absolutely above zero if necessary. Then load the MASS package and run fitdistr to fit an exponential probability density function. (See https://stat.ethz.ch/R-manual/R-devel/library/MASS/html/fitdistr.html). Find the optimal value of λ for this distribution, and then take 1000 samples from this exponential distribution using this value (e.g., rexp(1000,λ)). Plot a histrogram and compare it with a histogram of your original variable. Using the exponential pdf, find the 5th and 95th percentiles using the cumulative distribution function (CDF). Also generate a 95% confidence interval from the empirical data, assuming normality. Finally, provide the empirical 5th percentile and 95th percentile of the data. Discuss.
- 10 points. Modeling. Build some type of multiple regression model and submit your model to the competition board. Provide your complete model summary and results with analysis. Report your Kaggle.com user name and score.

Load the data and examine it

```
household <- read.csv("all/train.csv")
dim(household)
```

```
## [1] 1460   81
```

```
summary(household)
```

```
##        Id           MSSubClass       MSZoning     LotFrontage
##  Min.   :   1.0   Min.   : 20.0   C (all):  10   Min.   : 21.00
##  1st Qu.: 365.8   1st Qu.: 20.0   FV     :  65   1st Qu.: 59.00
##  Median : 730.5   Median : 50.0   RH     :  16   Median : 69.00
##  Mean   : 730.5   Mean   : 56.9   RL     :1151   Mean   : 70.05
##  3rd Qu.:1095.2   3rd Qu.: 70.0   RM     : 218   3rd Qu.: 80.00
##  Max.   :1460.0   Max.   :190.0                  Max.   :313.00
##                                                  NA's   :259
##     LotArea        Street      Alley      LotShape  LandContour
##  Min.   :  1300   Grvl:   6   Grvl:  50   IR1:484   Bnk:  63
##  1st Qu.:  7554   Pave:1454   Pave:  41   IR2: 41   HLS:  50
##  Median :  9478               NA's:1369   IR3: 10   Low:  36
##  Mean   : 10517                           Reg:925   Lvl:1311
##  3rd Qu.: 11602
##  Max.   :215245
##
##   Utilities      LotConfig    LandSlope   Neighborhood   Condition1
##  AllPub:1459   Corner : 263   Gtl:1382   NAmes  :225   Norm   :1260
##  NoSeWa:   1   CulDSac:  94   Mod:  65   CollgCr:150   Feedr  :  81
##                FR2    :  47   Sev:  13   OldTown:113   Artery :  48
##                FR3    :   4              Edwards:100   RRAn   :  26
##                Inside :1052              Somerst: 86   PosN   :  19
##                                          Gilbert: 79   RRAe   :  11
##                                          (Other):707   (Other):  15
##   Condition2     BldgType      HouseStyle   OverallQual
##  Norm   :1445   1Fam  :1220   1Story :726   Min.   : 1.000
##  Feedr  :   6   2fmCon:  31   2Story :445   1st Qu.: 5.000
##  Artery :   2   Duplex:  52   1.5Fin :154   Median : 6.000
##  PosN   :   2   Twnhs :  43   SLvl   : 65   Mean   : 6.099
##  RRNn   :   2   TwnhsE: 114   SFoyer : 37   3rd Qu.: 7.000
##  PosA   :   1                 1.5Unf : 14   Max.   :10.000
##  (Other):   2                 (Other): 19
##   OverallCond      YearBuilt     YearRemodAdd    RoofStyle
##  Min.   :1.000   Min.   :1872   Min.   :1950   Flat   :  13
##  1st Qu.:5.000   1st Qu.:1954   1st Qu.:1967   Gable  :1141
##  Median :5.000   Median :1973   Median :1994   Gambrel:  11
##  Mean   :5.575   Mean   :1971   Mean   :1985   Hip    : 286
##  3rd Qu.:6.000   3rd Qu.:2000   3rd Qu.:2004   Mansard:   7
##  Max.   :9.000   Max.   :2010   Max.   :2010   Shed   :   2
##
##     RoofMatl     Exterior1st   Exterior2nd    MasVnrType    MasVnrArea
##  CompShg:1434   VinylSd:515   VinylSd:504   BrkCmn : 15   Min.   :   0.0
##  Tar&Grv:  11   HdBoard:222   MetalSd:214   BrkFace:445   1st Qu.:   0.0
```

```
##  WdShngl:   6   MetalSd:220   HdBoard:207   None   :864   Median :   0.0
##  WdShake:   5   Wd Sdng:206   Wd Sdng:197   Stone  :128   Mean   : 103.7
##  ClyTile:   1   Plywood:108   Plywood:142   NA's   :  8   3rd Qu.: 166.0
##  Membran:   1   CemntBd: 61   CmentBd: 60                 Max.   :1600.0
##  (Other):   2   (Other):128   (Other):136                 NA's   :8
##  ExterQual ExterCond  Foundation  BsmtQual   BsmtCond    BsmtExposure
##  Ex: 52    Ex:   3   BrkTil:146   Ex  :121   Fa  :  45   Av  :221
##  Fa: 14    Fa:  28   CBlock:634   Fa  : 35   Gd  :  65   Gd  :134
##  Gd:488    Gd: 146   PConc :647   Gd  :618   Po  :   2   Mn  :114
##  TA:906    Po:   1   Slab  : 24   TA  :649   TA  :1311   No  :953
##            TA:1282   Stone :  6   NA's: 37   NA's:  37   NA's: 38
##                      Wood  :  3
##
##  BsmtFinType1   BsmtFinSF1     BsmtFinType2   BsmtFinSF2
##  ALQ :220     Min.   :   0.0   ALQ :  19    Min.   :   0.00
##  BLQ :148     1st Qu.:   0.0   BLQ :  33    1st Qu.:   0.00
##  GLQ :418     Median : 383.5   GLQ :  14    Median :   0.00
##  LwQ : 74     Mean   : 443.6   LwQ :  46    Mean   :  46.55
##  Rec :133     3rd Qu.: 712.2   Rec :  54    3rd Qu.:   0.00
##  Unf :430     Max.   :5644.0   Unf :1256    Max.   :1474.00
##  NA's: 37                      NA's:  38
##    BsmtUnfSF       TotalBsmtSF      Heating     HeatingQC CentralAir
##  Min.   :   0.0   Min.   :   0.0   Floor:   1   Ex:741    N:  95
##  1st Qu.: 223.0   1st Qu.: 795.8   GasA :1428   Fa: 49    Y:1365
##  Median : 477.5   Median : 991.5   GasW :  18   Gd:241
##  Mean   : 567.2   Mean   :1057.4   Grav :   7   Po:  1
##  3rd Qu.: 808.0   3rd Qu.:1298.2   OthW :   2   TA:428
##  Max.   :2336.0   Max.   :6110.0   Wall :   4
##
##  Electrical     X1stFlrSF      X2ndFlrSF     LowQualFinSF
##  FuseA:  94   Min.   : 334   Min.   :   0   Min.   :  0.000
##  FuseF:  27   1st Qu.: 882   1st Qu.:   0   1st Qu.:  0.000
##  FuseP:   3   Median :1087   Median :   0   Median :  0.000
##  Mix  :   1   Mean   :1163   Mean   : 347   Mean   :  5.845
##  SBrkr:1334   3rd Qu.:1391   3rd Qu.: 728   3rd Qu.:  0.000
##  NA's :   1   Max.   :4692   Max.   :2065   Max.   :572.000
##
##    GrLivArea     BsmtFullBath     BsmtHalfBath       FullBath
##  Min.   : 334   Min.   :0.0000   Min.   :0.00000   Min.   :0.000
##  1st Qu.:1130   1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:1.000
##  Median :1464   Median :0.0000   Median :0.00000   Median :2.000
##  Mean   :1515   Mean   :0.4253   Mean   :0.05753   Mean   :1.565
##  3rd Qu.:1777   3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:2.000
##  Max.   :5642   Max.   :3.0000   Max.   :2.00000   Max.   :3.000
##
##     HalfBath       BedroomAbvGr    KitchenAbvGr   KitchenQual
##  Min.   :0.0000   Min.   :0.000   Min.   :0.000   Ex:100
##  1st Qu.:0.0000   1st Qu.:2.000   1st Qu.:1.000   Fa: 39
##  Median :0.0000   Median :3.000   Median :1.000   Gd:586
##  Mean   :0.3829   Mean   :2.866   Mean   :1.047   TA:735
##  3rd Qu.:1.0000   3rd Qu.:3.000   3rd Qu.:1.000
##  Max.   :2.0000   Max.   :8.000   Max.   :3.000
##
##   TotRmsAbvGrd    Functional    Fireplaces    FireplaceQu   GarageType
```

```
##  Min.   : 2.000   Maj1:  14   Min.   :0.000   Ex  : 24    2Types :  6
##  1st Qu.: 5.000   Maj2:   5   1st Qu.:0.000   Fa  : 33    Attchd :870
##  Median : 6.000   Min1:  31   Median :1.000   Gd  :380    Basment: 19
##  Mean   : 6.518   Min2:  34   Mean   :0.613   Po  : 20    BuiltIn: 88
##  3rd Qu.: 7.000   Mod :  15   3rd Qu.:1.000   TA  :313    CarPort:  9
##  Max.   :14.000   Sev :   1   Max.   :3.000   NA's:690    Detchd :387
##                   Typ :1360                               NA's   : 81
##   GarageYrBlt   GarageFinish  GarageCars      GarageArea     GarageQual
##  Min.   :1900   Fin :352     Min.   :0.000   Min.   :   0.0   Ex  :   3
##  1st Qu.:1961   RFn :422     1st Qu.:1.000   1st Qu.: 334.5   Fa  :  48
##  Median :1980   Unf :605     Median :2.000   Median : 480.0   Gd  :  14
##  Mean   :1979   NA's: 81     Mean   :1.767   Mean   : 473.0   Po  :   3
##  3rd Qu.:2002                3rd Qu.:2.000   3rd Qu.: 576.0   TA  :1311
##  Max.   :2010                Max.   :4.000   Max.   :1418.0   NA's:  81
##  NA's   :81
##  GarageCond  PavedDrive   WoodDeckSF      OpenPorchSF     EnclosedPorch
##  Ex  :   2   N:  90     Min.   :  0.00   Min.   :  0.00   Min.   :  0.00
##  Fa  :  35   P:  30     1st Qu.:  0.00   1st Qu.:  0.00   1st Qu.:  0.00
##  Gd  :   9   Y:1340     Median :  0.00   Median : 25.00   Median :  0.00
##  Po  :   7              Mean   : 94.24   Mean   : 46.66   Mean   : 21.95
##  TA  :1326              3rd Qu.:168.00   3rd Qu.: 68.00   3rd Qu.:  0.00
##  NA's:  81              Max.   :857.00   Max.   :547.00   Max.   :552.00
##
##    X3SsnPorch      ScreenPorch       PoolArea        PoolQC
##  Min.   :  0.00   Min.   :  0.00   Min.   :  0.000   Ex  :   2
##  1st Qu.:  0.00   1st Qu.:  0.00   1st Qu.:  0.000   Fa  :   2
##  Median :  0.00   Median :  0.00   Median :  0.000   Gd  :   3
##  Mean   :  3.41   Mean   : 15.06   Mean   :  2.759   NA's:1453
##  3rd Qu.:  0.00   3rd Qu.:  0.00   3rd Qu.:  0.000
##  Max.   :508.00   Max.   :480.00   Max.   :738.000
##
##    Fence      MiscFeature    MiscVal           MoSold
##  GdPrv:  59   Gar2:   2   Min.   :    0.00   Min.   : 1.000
##  GdWo :  54   Othr:   2   1st Qu.:    0.00   1st Qu.: 5.000
##  MnPrv: 157   Shed:  49   Median :    0.00   Median : 6.000
##  MnWw :  11   TenC:   1   Mean   :   43.49   Mean   : 6.322
##  NA's :1179   NA's:1406   3rd Qu.:    0.00   3rd Qu.: 8.000
##                           Max.   :15500.00   Max.   :12.000
##
##      YrSold        SaleType    SaleCondition    SalePrice
##  Min.   :2006   WD     :1267   Abnorml: 101   Min.   : 34900
##  1st Qu.:2007   New    : 122   AdjLand:   4   1st Qu.:129975
##  Median :2008   COD    :  43   Alloca :  12   Median :163000
##  Mean   :2008   ConLD  :   9   Family :  20   Mean   :180921
##  3rd Qu.:2009   ConLI  :   5   Normal :1198   3rd Qu.:214000
##  Max.   :2010   ConLw  :   5   Partial: 125   Max.   :755000
##                 (Other):   9
```

```r
str(household)
```

```
## 'data.frame':    1460 obs. of  81 variables:
##  $ Id           : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ MSSubClass   : int  60 20 60 70 60 50 20 60 50 190 ...
##  $ MSZoning     : Factor w/ 5 levels "C (all)","FV",..: 4 4 4 4 4 4 4 4 5 4 ...
```

```
##  $ LotFrontage  : int  65 80 68 60 84 85 75 NA 51 50 ...
##  $ LotArea      : int  8450 9600 11250 9550 14260 14115 10084 10382 6120 7420 ...
##  $ Street       : Factor w/ 2 levels "Grvl","Pave": 2 2 2 2 2 2 2 2 2 2 ...
##  $ Alley        : Factor w/ 2 levels "Grvl","Pave": NA NA NA NA NA NA NA NA NA NA ...
##  $ LotShape     : Factor w/ 4 levels "IR1","IR2","IR3",..: 4 4 1 1 1 1 4 1 4 4 ...
##  $ LandContour  : Factor w/ 4 levels "Bnk","HLS","Low",..: 4 4 4 4 4 4 4 4 4 4 ...
##  $ Utilities    : Factor w/ 2 levels "AllPub","NoSeWa": 1 1 1 1 1 1 1 1 1 1 ...
##  $ LotConfig    : Factor w/ 5 levels "Corner","CulDSac",..: 5 3 5 1 3 5 5 1 5 1 ...
##  $ LandSlope    : Factor w/ 3 levels "Gtl","Mod","Sev": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Neighborhood : Factor w/ 25 levels "Blmngtn","Blueste",..: 6 25 6 7 14 12 21 17 18 4 ...
##  $ Condition1   : Factor w/ 9 levels "Artery","Feedr",..: 3 2 3 3 3 3 3 5 1 1 ...
##  $ Condition2   : Factor w/ 8 levels "Artery","Feedr",..: 3 3 3 3 3 3 3 3 3 1 ...
##  $ BldgType     : Factor w/ 5 levels "1Fam","2fmCon",..: 1 1 1 1 1 1 1 1 1 2 ...
##  $ HouseStyle   : Factor w/ 8 levels "1.5Fin","1.5Unf",..: 6 3 6 6 6 1 3 6 1 2 ...
##  $ OverallQual  : int  7 6 7 7 8 5 8 7 7 5 ...
##  $ OverallCond  : int  5 8 5 5 5 5 5 6 5 6 ...
##  $ YearBuilt    : int  2003 1976 2001 1915 2000 1993 2004 1973 1931 1939 ...
##  $ YearRemodAdd : int  2003 1976 2002 1970 2000 1995 2005 1973 1950 1950 ...
##  $ RoofStyle    : Factor w/ 6 levels "Flat","Gable",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ RoofMatl     : Factor w/ 8 levels "ClyTile","CompShg",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ Exterior1st  : Factor w/ 15 levels "AsbShng","AsphShn",..: 13 9 13 14 13 13 13 7 4 9 ...
##  $ Exterior2nd  : Factor w/ 16 levels "AsbShng","AsphShn",..: 14 9 14 16 14 14 14 7 16 9 ...
##  $ MasVnrType   : Factor w/ 4 levels "BrkCmn","BrkFace",..: 2 3 2 3 2 3 4 4 3 3 ...
##  $ MasVnrArea   : int  196 0 162 0 350 0 186 240 0 0 ...
##  $ ExterQual    : Factor w/ 4 levels "Ex","Fa","Gd",..: 3 4 3 4 3 4 3 4 4 4 ...
##  $ ExterCond    : Factor w/ 5 levels "Ex","Fa","Gd",..: 5 5 5 5 5 5 5 5 5 5 ...
##  $ Foundation   : Factor w/ 6 levels "BrkTil","CBlock",..: 3 2 3 1 3 6 3 2 1 1 ...
##  $ BsmtQual     : Factor w/ 4 levels "Ex","Fa","Gd",..: 3 3 3 4 3 3 1 3 4 4 ...
##  $ BsmtCond     : Factor w/ 4 levels "Fa","Gd","Po",..: 4 4 4 2 4 4 4 4 4 4 ...
##  $ BsmtExposure : Factor w/ 4 levels "Av","Gd","Mn",..: 4 2 3 4 1 4 1 3 4 4 ...
##  $ BsmtFinType1 : Factor w/ 6 levels "ALQ","BLQ","GLQ",..: 3 1 3 1 3 3 3 1 6 3 ...
##  $ BsmtFinSF1   : int  706 978 486 216 655 732 1369 859 0 851 ...
##  $ BsmtFinType2 : Factor w/ 6 levels "ALQ","BLQ","GLQ",..: 6 6 6 6 6 6 6 2 6 6 ...
##  $ BsmtFinSF2   : int  0 0 0 0 0 0 0 32 0 0 ...
##  $ BsmtUnfSF    : int  150 284 434 540 490 64 317 216 952 140 ...
##  $ TotalBsmtSF  : int  856 1262 920 756 1145 796 1686 1107 952 991 ...
##  $ Heating      : Factor w/ 6 levels "Floor","GasA",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ HeatingQC    : Factor w/ 5 levels "Ex","Fa","Gd",..: 1 1 1 3 1 1 1 1 3 1 ...
##  $ CentralAir   : Factor w/ 2 levels "N","Y": 2 2 2 2 2 2 2 2 2 2 ...
##  $ Electrical   : Factor w/ 5 levels "FuseA","FuseF",..: 5 5 5 5 5 5 5 5 2 5 ...
##  $ X1stFlrSF    : int  856 1262 920 961 1145 796 1694 1107 1022 1077 ...
##  $ X2ndFlrSF    : int  854 0 866 756 1053 566 0 983 752 0 ...
##  $ LowQualFinSF : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ GrLivArea    : int  1710 1262 1786 1717 2198 1362 1694 2090 1774 1077 ...
##  $ BsmtFullBath : int  1 0 1 1 1 1 1 1 0 1 ...
##  $ BsmtHalfBath : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ FullBath     : int  2 2 2 1 2 1 2 2 2 1 ...
##  $ HalfBath     : int  1 0 1 0 1 1 0 1 0 0 ...
##  $ BedroomAbvGr : int  3 3 3 3 4 1 3 3 2 2 ...
##  $ KitchenAbvGr : int  1 1 1 1 1 1 1 1 2 2 ...
##  $ KitchenQual  : Factor w/ 4 levels "Ex","Fa","Gd",..: 3 4 3 3 3 4 3 4 4 4 ...
##  $ TotRmsAbvGrd : int  8 6 6 7 9 5 7 7 8 5 ...
##  $ Functional   : Factor w/ 7 levels "Maj1","Maj2",..: 7 7 7 7 7 7 7 7 3 7 ...
##  $ Fireplaces   : int  0 1 1 1 0 1 2 2 2 ...
```

```
##  $ FireplaceQu  : Factor w/ 5 levels "Ex","Fa","Gd",..: NA 5 5 3 5 NA 3 5 5 5 ...
##  $ GarageType   : Factor w/ 6 levels "2Types","Attchd",..: 2 2 2 6 2 2 2 2 6 2 ...
##  $ GarageYrBlt  : int  2003 1976 2001 1998 2000 1993 2004 1973 1931 1939 ...
##  $ GarageFinish : Factor w/ 3 levels "Fin","RFn","Unf": 2 2 2 3 2 3 2 2 3 2 ...
##  $ GarageCars   : int  2 2 2 3 3 2 2 2 2 1 ...
##  $ GarageArea   : int  548 460 608 642 836 480 636 484 468 205 ...
##  $ GarageQual   : Factor w/ 5 levels "Ex","Fa","Gd",..: 5 5 5 5 5 5 5 5 2 3 ...
##  $ GarageCond   : Factor w/ 5 levels "Ex","Fa","Gd",..: 5 5 5 5 5 5 5 5 5 5 ...
##  $ PavedDrive   : Factor w/ 3 levels "N","P","Y": 3 3 3 3 3 3 3 3 3 3 ...
##  $ WoodDeckSF   : int  0 298 0 0 192 40 255 235 90 0 ...
##  $ OpenPorchSF  : int  61 0 42 35 84 30 57 204 0 4 ...
##  $ EnclosedPorch: int  0 0 0 272 0 0 0 228 205 0 ...
##  $ X3SsnPorch   : int  0 0 0 0 0 320 0 0 0 0 ...
##  $ ScreenPorch  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ PoolArea     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ PoolQC       : Factor w/ 3 levels "Ex","Fa","Gd": NA NA NA NA NA NA NA NA NA NA ...
##  $ Fence        : Factor w/ 4 levels "GdPrv","GdWo",..: NA NA NA NA NA 3 NA NA NA NA ...
##  $ MiscFeature  : Factor w/ 4 levels "Gar2","Othr",..: NA NA NA NA NA 3 NA 3 NA NA ...
##  $ MiscVal      : int  0 0 0 0 0 700 0 350 0 0 ...
##  $ MoSold       : int  2 5 9 2 12 10 8 11 4 1 ...
##  $ YrSold       : int  2008 2007 2008 2006 2008 2009 2007 2009 2008 2008 ...
##  $ SaleType     : Factor w/ 9 levels "COD","Con","ConLD",..: 9 9 9 9 9 9 9 9 9 9 ...
##  $ SaleCondition: Factor w/ 6 levels "Abnorml","AdjLand",..: 5 5 5 1 5 5 5 5 1 5 ...
##  $ SalePrice    : int  208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...
```

```r
head(household)
```

```
##   Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape
## 1  1         60       RL          65    8450   Pave  <NA>      Reg
## 2  2         20       RL          80    9600   Pave  <NA>      Reg
## 3  3         60       RL          68   11250   Pave  <NA>      IR1
## 4  4         70       RL          60    9550   Pave  <NA>      IR1
## 5  5         60       RL          84   14260   Pave  <NA>      IR1
## 6  6         50       RL          85   14115   Pave  <NA>      IR1
##   LandContour Utilities LotConfig LandSlope Neighborhood Condition1
## 1         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
## 2         Lvl    AllPub       FR2       Gtl      Veenker      Feedr
## 3         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
## 4         Lvl    AllPub    Corner       Gtl      Crawfor       Norm
## 5         Lvl    AllPub       FR2       Gtl      NoRidge       Norm
## 6         Lvl    AllPub    Inside       Gtl      Mitchel       Norm
##   Condition2 BldgType HouseStyle OverallQual OverallCond YearBuilt
## 1       Norm     1Fam     2Story           7           5      2003
## 2       Norm     1Fam     1Story           6           8      1976
## 3       Norm     1Fam     2Story           7           5      2001
## 4       Norm     1Fam     2Story           7           5      1915
## 5       Norm     1Fam     2Story           8           5      2000
## 6       Norm     1Fam     1.5Fin           5           5      1993
##   YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType
## 1         2003     Gable  CompShg     VinylSd     VinylSd    BrkFace
## 2         1976     Gable  CompShg     MetalSd     MetalSd       None
## 3         2002     Gable  CompShg     VinylSd     VinylSd    BrkFace
## 4         1970     Gable  CompShg     Wd Sdng     Wd Shng       None
## 5         2000     Gable  CompShg     VinylSd     VinylSd    BrkFace
```

```
## 6         1995     Gable  CompShg     VinylSd     VinylSd       None
##   MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure
## 1        196        Gd        TA      PConc       Gd       TA           No
## 2          0        TA        TA     CBlock       Gd       TA           Gd
## 3        162        Gd        TA      PConc       Gd       TA           Mn
## 4          0        TA        TA     BrkTil       TA       Gd           No
## 5        350        Gd        TA      PConc       Gd       TA           Av
## 6          0        TA        TA       Wood       Gd       TA           No
##   BsmtFinType1 BsmtFinSF1 BsmtFinType2 BsmtFinSF2 BsmtUnfSF TotalBsmtSF
## 1          GLQ        706          Unf          0       150         856
## 2          ALQ        978          Unf          0       284        1262
## 3          GLQ        486          Unf          0       434         920
## 4          ALQ        216          Unf          0       540         756
## 5          GLQ        655          Unf          0       490        1145
## 6          GLQ        732          Unf          0        64         796
##   Heating HeatingQC CentralAir Electrical X1stFlrSF X2ndFlrSF LowQualFinSF
## 1    GasA        Ex          Y      SBrkr       856       854            0
## 2    GasA        Ex          Y      SBrkr      1262         0            0
## 3    GasA        Ex          Y      SBrkr       920       866            0
## 4    GasA        Gd          Y      SBrkr       961       756            0
## 5    GasA        Ex          Y      SBrkr      1145      1053            0
## 6    GasA        Ex          Y      SBrkr       796       566            0
##   GrLivArea BsmtFullBath BsmtHalfBath FullBath HalfBath BedroomAbvGr
## 1      1710            1            0        2        1            3
## 2      1262            0            1        2        0            3
## 3      1786            1            0        2        1            3
## 4      1717            1            0        1        0            3
## 5      2198            1            0        2        1            4
## 6      1362            1            0        1        1            1
##   KitchenAbvGr KitchenQual TotRmsAbvGrd Functional Fireplaces FireplaceQu
## 1            1          Gd            8        Typ          0        <NA>
## 2            1          TA            6        Typ          1          TA
## 3            1          Gd            6        Typ          1          TA
## 4            1          Gd            7        Typ          1          Gd
## 5            1          Gd            9        Typ          1          TA
## 6            1          TA            5        Typ          0        <NA>
##   GarageType GarageYrBlt GarageFinish GarageCars GarageArea GarageQual
## 1     Attchd        2003          RFn          2        548         TA
## 2     Attchd        1976          RFn          2        460         TA
## 3     Attchd        2001          RFn          2        608         TA
## 4     Detchd        1998          Unf          3        642         TA
## 5     Attchd        2000          RFn          3        836         TA
## 6     Attchd        1993          Unf          2        480         TA
##   GarageCond PavedDrive WoodDeckSF OpenPorchSF EnclosedPorch X3SsnPorch
## 1         TA          Y          0          61             0          0
## 2         TA          Y        298           0             0          0
## 3         TA          Y          0          42             0          0
## 4         TA          Y          0          35           272          0
## 5         TA          Y        192          84             0          0
## 6         TA          Y         40          30             0        320
##   ScreenPorch PoolArea PoolQC Fence MiscFeature MiscVal MoSold YrSold
## 1           0        0   <NA>  <NA>        <NA>       0      2   2008
## 2           0        0   <NA>  <NA>        <NA>       0      5   2007
## 3           0        0   <NA>  <NA>        <NA>       0      9   2008
```

```
## 4           0        0   <NA>  <NA>        <NA>       0      2   2006
## 5           0        0   <NA>  <NA>        <NA>       0     12   2008
## 6           0        0   <NA> MnPrv        Shed     700     10   2009
##   SaleType SaleCondition SalePrice
## 1       WD        Normal    208500
## 2       WD        Normal    181500
## 3       WD        Normal    223500
## 4       WD       Abnorml    140000
## 5       WD        Normal    250000
## 6       WD        Normal    143000
```

Descripitive Statistics

- Let's look at some plots and see the trend of the data more closely. We'll start with plotting and visualizing the quantative variables such as LotArea, LotFrontage, MasVnrArea, and SalePrice to see how the data behave.
- Note the dependant variable is the SalePrice a continous numerical variable.

```r
library(ggplot2)
library(gridExtra)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following object is masked from 'package:gridExtra':
##
##     combine

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(glmnet)
```

```
## Loading required package: Matrix

## Loading required package: foreach

## Loaded glmnet 2.0-16
```

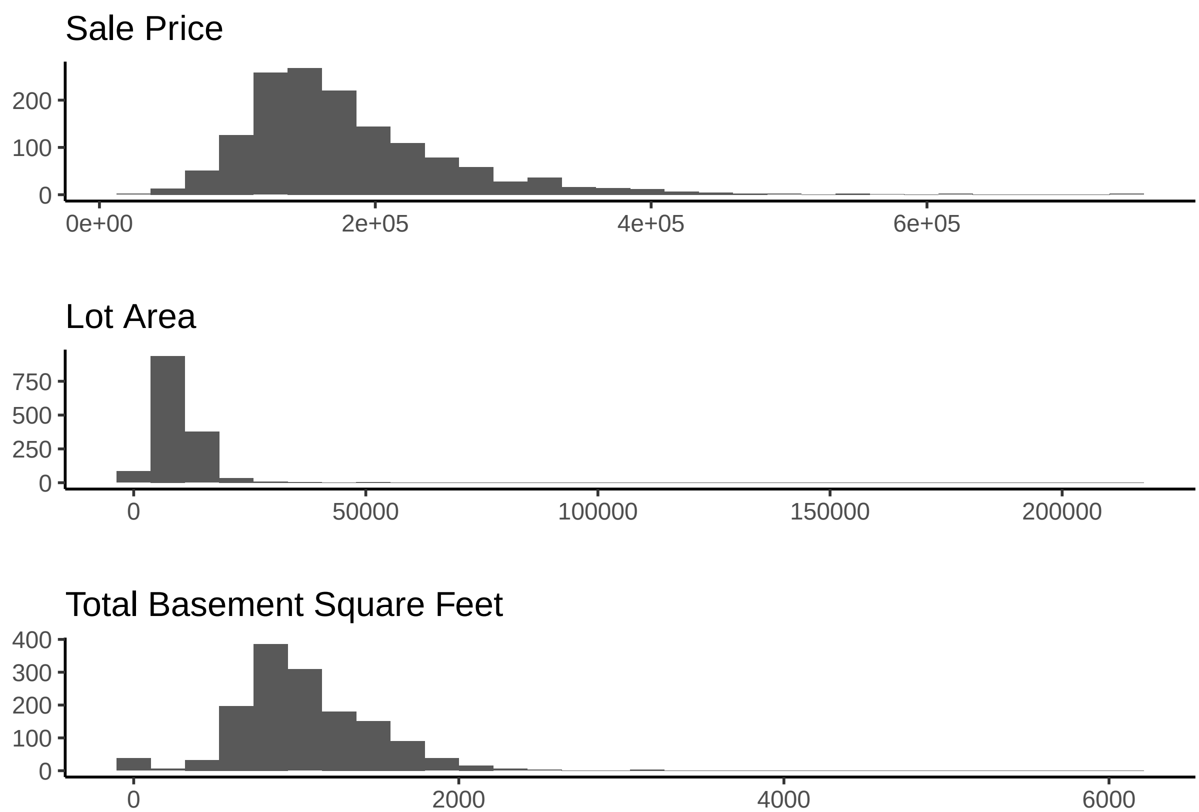
```r
library(FeatureHashing)
```

```r
max(household$SalePrice)
```

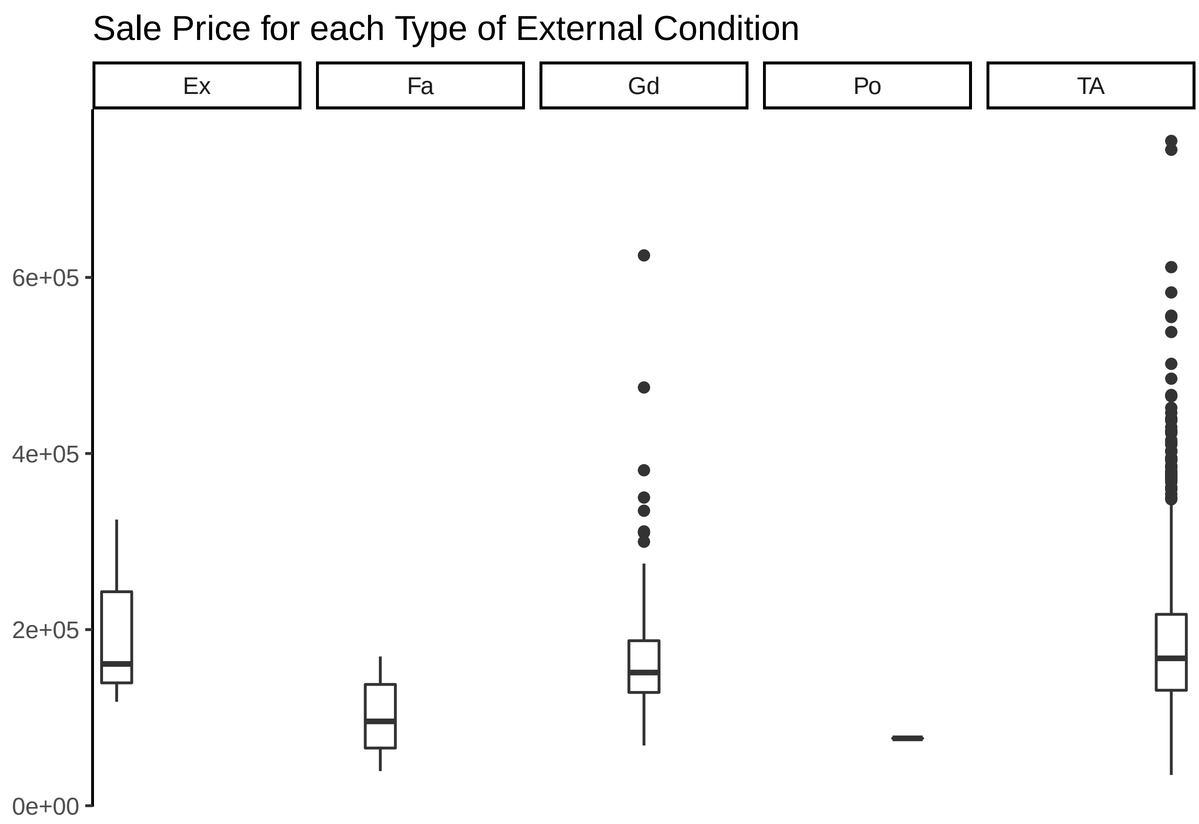
```
## [1] 755000
```

```r
# quantative variable plots

saleprice_plot <- ggplot(household, aes(SalePrice)) +
  geom_histogram() +
  ggtitle("Sale Price") +
  xlab("") + ylab("") +
  theme_bw() +
  theme_classic()

lotarea_plot <- ggplot(household, aes(LotArea)) +
  geom_histogram() +
  ggtitle("Lot Area") +
  xlab("") + ylab("") +
  theme_bw() +
  theme_classic()

totalbsmtsf_plot <- ggplot(household, aes(TotalBsmtSF)) +
  geom_histogram() +
  ggtitle("Total Basement Square Feet") +
  xlab("") + ylab("") +
  theme_bw() +
  theme_classic()

grid.arrange(saleprice_plot, lotarea_plot,totalbsmtsf_plot)
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

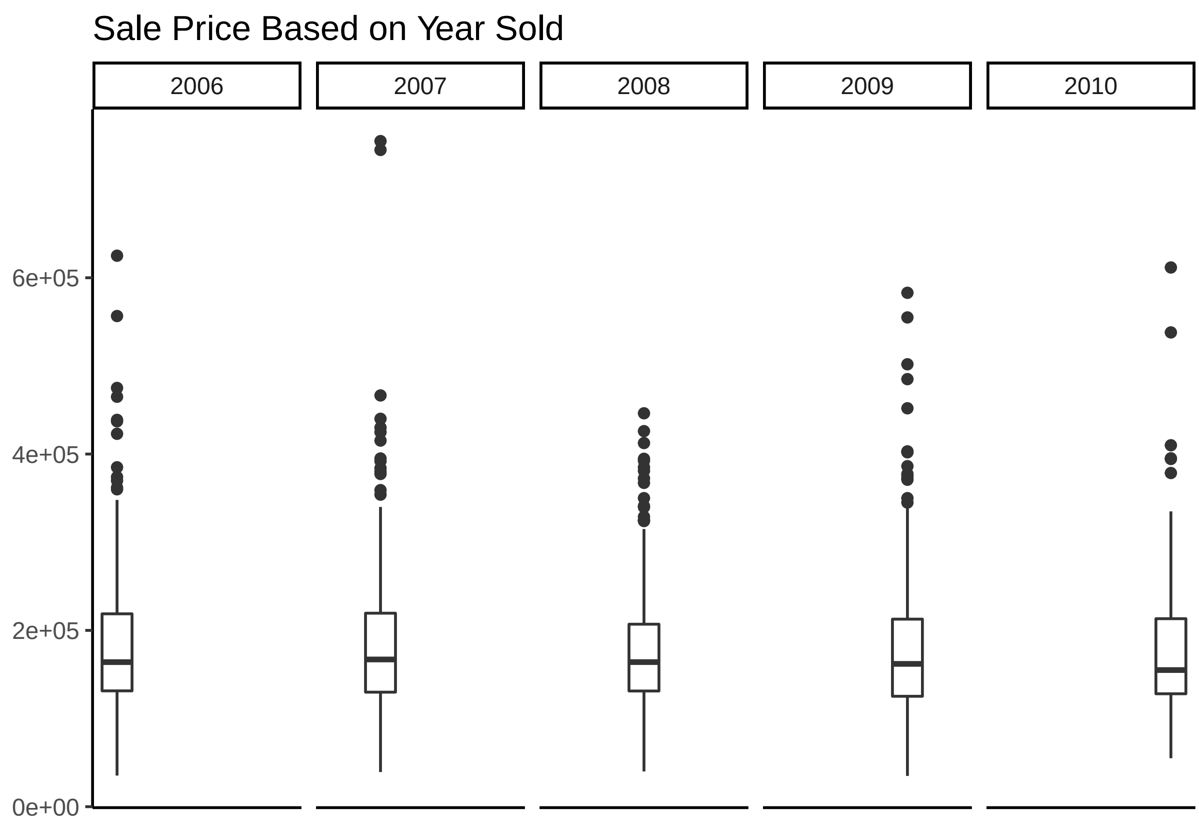



```
ggplot(household, aes(ExterCond,SalePrice)) +
  geom_boxplot() +
  facet_grid(.~ ExterCond) +
  ggtitle("Sale Price for each Type of External Condition ") +
  xlab("") + ylab("") +
  theme_bw() +
  theme_classic() +
  theme(axis.ticks.x=element_blank(),
        axis.text.x = element_blank(),
        axis.line.x = element_blank())
```

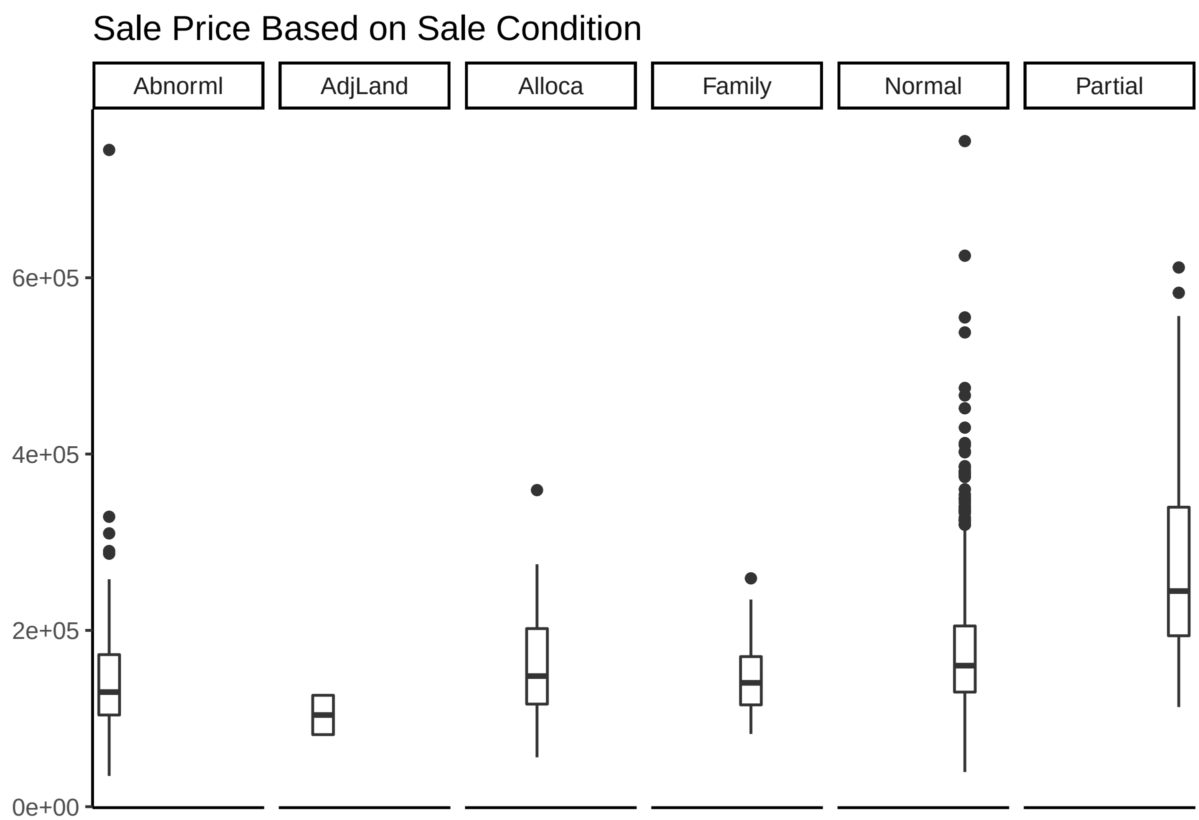



```r
ggplot(household, aes(YrSold,SalePrice)) +
  geom_boxplot() +
  facet_grid(.~ YrSold) +
  ggtitle("Sale Price Based on Year Sold") +
  xlab("") + ylab("") +
  theme_bw() +
  theme_classic() +
  theme(axis.ticks.x=element_blank(),
        axis.text.x = element_blank())
```

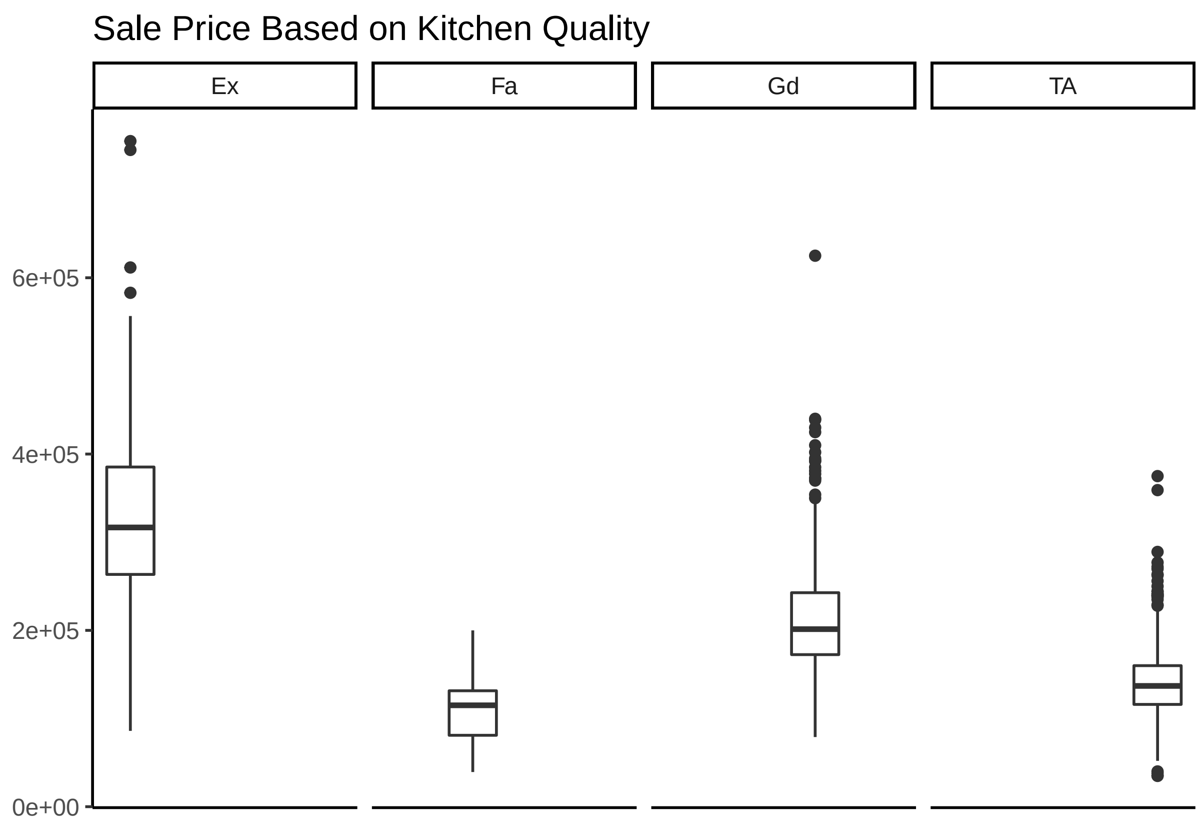
```
## Warning: Continuous x aesthetic -- did you forget aes(group=...)?
```




```r
ggplot(household, aes(SaleCondition,SalePrice)) +
  geom_boxplot() +
  facet_grid(.~ SaleCondition) +
  ggtitle("Sale Price Based on Sale Condition") +
  xlab("") + ylab("") +
  theme_bw() +
  theme_classic() +
  theme(axis.ticks.x=element_blank(),
        axis.text.x = element_blank())
```

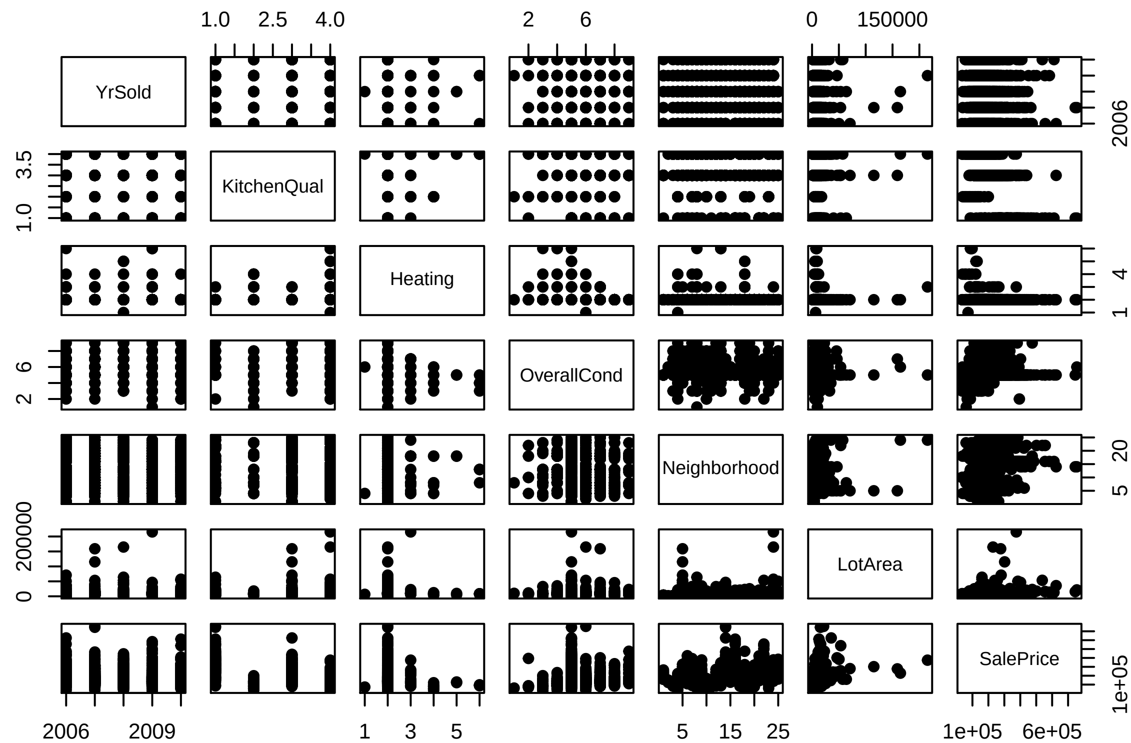



```r
ggplot(household, aes(KitchenQual,SalePrice)) +
  geom_boxplot() +
  facet_grid(.~ KitchenQual) +
  ggtitle("Sale Price Based on Kitchen Quality") +
  xlab("") + ylab("") +
  theme_bw() +
  theme_classic() +
  theme(axis.ticks.x=element_blank(),
        axis.text.x = element_blank())
```



- Plots show that the Sale price is quite left skewed and the lot area is heavily left-skewed; good for analysis later.
- We also see that the median price of sold homes is about the same for each year. For normal sale conditions, there are heavy outliers and that could make a influence in our model and analysis. The same goes for fairly decent homes in okay external condition.
- Let's create a scatterplot matrix using the pairs() function and see the visualization. I will look at the most common things I feel are most important in looking for a place to call home such as Year sold, kitchen quality, heating, overall condition, neighborhood, lot area, and sale price.

```
columns_scatterplotmatrix <- c("YrSold", "KitchenQual", "Heating", "OverallCond", "Neighborhood",
                               "LotArea", "SalePrice")

pairs(household[, columns_scatterplotmatrix], pch = 19)
```



- Let's also examine the correlation matrix as well for 3 quantative variables:

a) Sale Price: Continous

b) Garage Area: Continous

c) Lot Area: Continous

```
cor_matrix <- cor(as.matrix(household[, c("SalePrice", "LotArea", "GarageArea")]))
cor_matrix
```

```
##            SalePrice   LotArea GarageArea
## SalePrice  1.0000000 0.2638434  0.6234314
## LotArea    0.2638434 1.0000000  0.1804028
## GarageArea 0.6234314 0.1804028  1.0000000
```

- With our 3x3 matrix, let's do a 80% confidence interval using the hypothesis below:

a) Null hypothesis: $cor(x, y) = 0$ that is there is not correlation between the two variables in question

b) Alternative hypothesis: $cor(x, y) \neq 0$ that is there is some correlation big or small between the two variables.

```r
cor.test(household$SalePrice, household$LotArea, method = "pearson", conf.level = 0.8)
```

```
##
##  Pearson's product-moment correlation
##
## data:  household$SalePrice and household$LotArea
## t = 10.445, df = 1458, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  0.2323391 0.2947946
## sample estimates:
##       cor
## 0.2638434
```

```r
cor.test(household$LotArea, household$GarageArea, method = "pearson", conf.level = 0.8)
```

```
##
##  Pearson's product-moment correlation
##
## data:  household$LotArea and household$GarageArea
## t = 7.0034, df = 1458, p-value = 3.803e-12
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  0.1477356 0.2126767
## sample estimates:
##       cor
## 0.1804028
```

```r
cor.test(household$SalePrice, household$GarageArea, method = "pearson", conf.level = 0.8)
```

```
##
##  Pearson's product-moment correlation
##
## data:  household$SalePrice and household$GarageArea
## t = 30.446, df = 1458, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  0.6024756 0.6435283
## sample estimates:
##       cor
## 0.6234314
```

- Based on these correlation tests, we can see that we can reject the null hypothesis and favor the alternative that is $cor(x, y) \neq 0$ for the variables chosen.
- There is a quite strong positive correlation between SalePrice (dependent variable) and GarageArea (independent variable). This makes sense as if one is buying a home, the sale price changes based on the area of the garage.
- Lot area doesn't have strong correlation with regards to sale price which it could be lot area may not have much impact on sale price. Same also goes for lot area and garage area.
- We are 80% confident the true correlation is within the intervals above for the specified variables.

- Familywise error is defined as $FWE \leq 1-(1-\alpha_{IT})^c$ and is the probability of coming to at least one false conclusion in a series of hypothesis tests. α_{IT} is the alpha level for an individual test (in this case 0.2) and c is the number of comparisions. c = 3 test and computing the familywise error gives
- $FWE \leq 1-(1-\alpha_{IT})^c = 1-(1-0.2)^3 = 0.488$ which is quite high considering only 3 tests were made and something that would have to be concern of getting a type 1 error.

Linear Algebra and Correlation

- Per the description of this section, let's invert our 3x3 matrix from above that is

```
inv_cor_matrix <- solve(cor_matrix) # precision matrix
inv_cor_matrix
```

```
##              SalePrice     LotArea  GarageArea
## SalePrice    1.7016986 -0.26625940 -1.01285847
## LotArea     -0.2662594  1.07530074 -0.02799273
## GarageArea -1.0128585 -0.02799273  1.63649778
```

- Now multiply the precision matrix by the correlation matrix and do the other way around, then do LU Decomposition

```
# precision matrix x correlation matrix
inv_cor_matrix %*% cor_matrix
```

```
##                SalePrice       LotArea   GarageArea
## SalePrice  1.000000e+00 -5.551115e-17 0.000000e+00
## LotArea    7.979728e-17  1.000000e+00 6.591949e-17
## GarageArea 0.000000e+00  0.000000e+00 1.000000e+00
```

```
cor_matrix %*% inv_cor_matrix
```

```
##             SalePrice      LotArea GarageArea
## SalePrice           1 2.428613e-17          0
## LotArea             0 1.000000e+00          0
## GarageArea          0 3.469447e-17          1
```

```
library(matrixcalc) # lU Decomposition
lu.decomposition(cor_matrix %*% inv_cor_matrix)
```

```
## $L
##      [,1]         [,2] [,3]
## [1,]    1 0.000000e+00    0
## [2,]    0 1.000000e+00    0
## [3,]    0 3.469447e-17    1
##
## $U
##      [,1]         [,2] [,3]
## [1,]    1 2.428613e-17    0
## [2,]    0 1.000000e+00    0
## [3,]    0 0.000000e+00    1
```

```r
lu.decomposition(inv_cor_matrix %*% cor_matrix) # they're not communitative
```

```
## $L
##              [,1] [,2] [,3]
## [1,] 1.000000e+00    0    0
## [2,] 7.979728e-17    1    0
## [3,] 0.000000e+00    0    1
##
## $U
##      [,1]          [,2]         [,3]
## [1,]    1 -5.551115e-17 0.000000e+00
## [2,]    0  1.000000e+00 6.591949e-17
## [3,]    0  0.000000e+00 1.000000e+00
```

```r
min(household$TotalBsmtSF)
```

```
## [1] 0
```

Calculus Based Probability & Statistics

- For this, we will choose the total basement square feet or TotalBsmtSF variable.

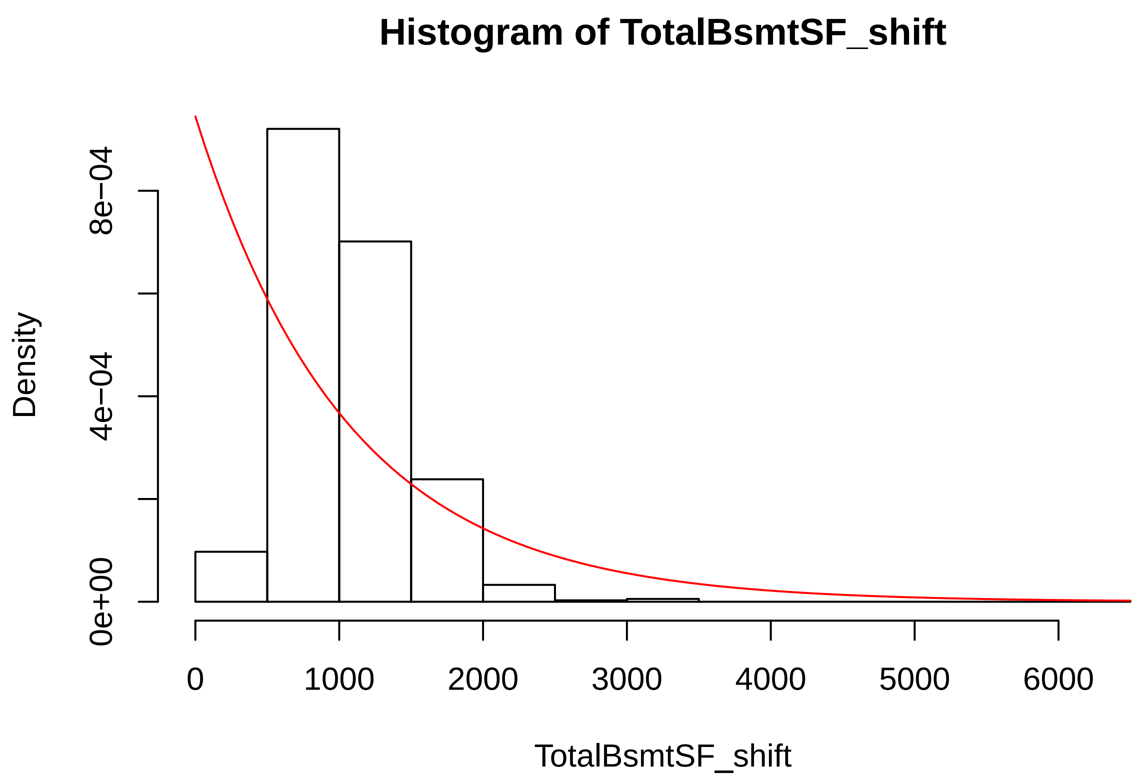
```r
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select
```

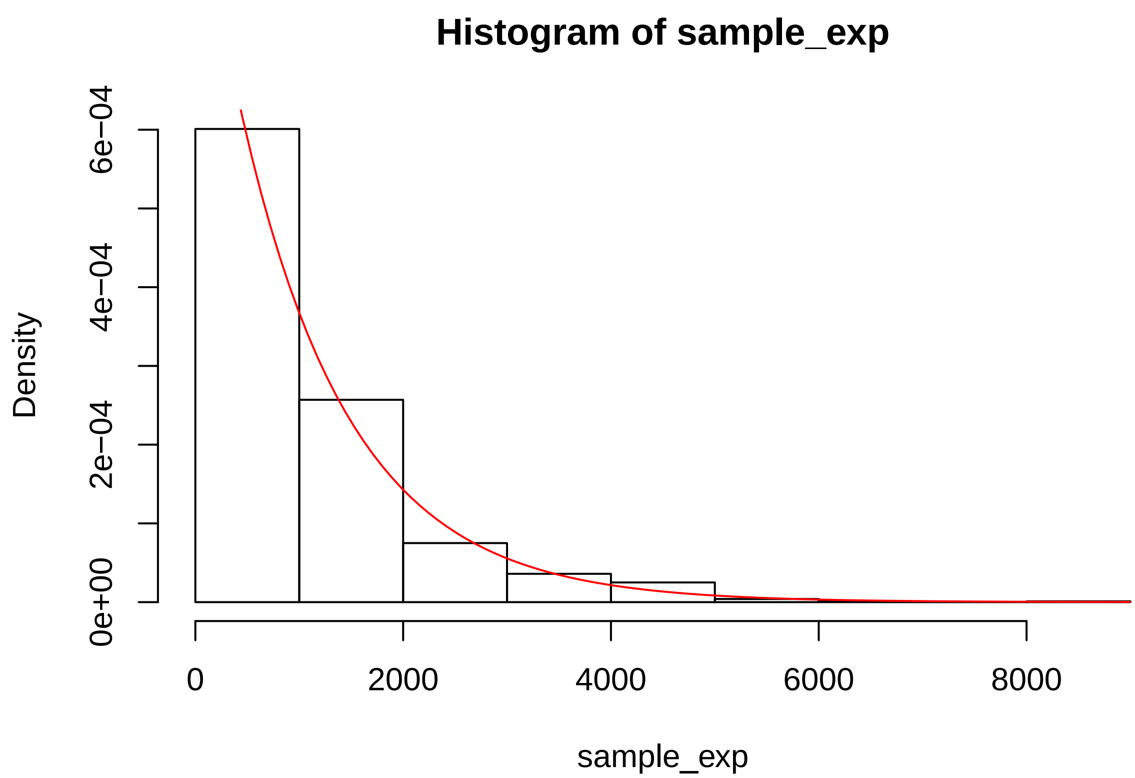
```r
# shift TotalBsmtSF variable so min > 0
TotalBsmtSF_shift <- household$TotalBsmtSF + 1.0
TotalBsmtSF_fit <- fitdistr(TotalBsmtSF_shift, "exponential")
TotalBsmtSF_fit$estimate # optimal value of the rate parameter lambda
```

```
##         rate
## 0.0009447961
```

```r
par(mfrow=c(1,1))
hist(TotalBsmtSF_shift, pch = 20, prob=TRUE)
curve(dexp(x, TotalBsmtSF_fit$estimate), col="red", add=T)
```




```r
# take 1000 random samples from a exponential distribution
sample_exp <- rexp(1000, rate=TotalBsmtSF_fit$estimate)
hist(sample_exp, pch = 20, prob=TRUE)
curve(dexp(x, TotalBsmtSF_fit$estimate), col="red", add=T)
```




```r
# use the cdf that is 1 - exp(-lambda*x)
CDF_sample_exp <- 1 - exp(-TotalBsmtSF_fit$estimate*household$TotalBsmtSF)
# 5% and 95% percentiles
quantile(CDF_sample_exp, .05)
```

```
##        5%
## 0.3877585
```

```r
quantile(CDF_sample_exp, .95)
```

```
##       95%
## 0.8091424
```

```r
# 95% confidence interval assuming normality (mean and sd are the same for a exponential that is 1/lamb

mean_exp <- 1/TotalBsmtSF_fit$estimate
sd_exp <- mean_exp

# standard error
sd_error <- qnorm(0.95)* (sd_exp / sqrt(length(household$TotalBsmtSF)))
left_ci <- mean_exp - sd_error
right_ci <- mean_exp + sd_error
# confidence interval
c(left_ci, right_ci)
```

```
##     rate     rate
## 1012.866 1103.992
```

```
# quantile of empricial data
emp_data <- ecdf(household$TotalBsmtSF)
emp_data(5)
```

```
## [1] 0.02534247
```

```
emp_data(95)
```

```
## [1] 0.02534247
```

- Assuming normality for a exponential distribution is a good idea as our best fit rate $1/\lambda$ is within our 95% confidence interval so we are 95% confident the true value of $1/\lambda$ falls within (1012.866, 1103.992).

Modeling

- Let's use feaature selection such as LASSO to select parameters for our multiple regression model and submit our scores to kaggle. I will also use the technique of feature hashing when dealing with categorical variables and then use the glmnet library and it's function cv.glmnet() to come up with a model and then predict the Sale Prices of the test dataset.
- Feature hashing example: http://amunategui.github.io/feature-hashing/
- LASSO (Least absolute shrinkage and selection operator) is used to to avoid overfitting by penalizing large coefficients and it can shrink some coefficients of the feautres so in turn it also does feature selection.
- LASSO introduction: http://ricardoscr.github.io/how-to-use-ridge-and-lasso-in-r.html
- Let's fill up the NA's of each column using the median for numerical variables and the most popular or frequent for categorical variables

```
features <- setdiff(names(household), "SalePrice")
objtrain_hashed <- hashed.model.matrix(~., data=household[, features], hash.size = 2^12, transpose = FA
objtrain_hashed <- as(objtrain_hashed, "dgCMatrix")

cv.fit <- cv.glmnet(x=objtrain_hashed, y=household$SalePrice, type.measure = "mse")
```

- So after replacing our NA values and doing a LASSO regression, we see that the algorithm based on the plot has the lambda minimum value of about 136 variables and using a lambda value larger gives less factors about 56 variables. The higher lambda is considered (1 standard error from the minimum lambda value).
- Finally let's use this model to predict the Saleprice in the test dataset and submit it to kaggle.

```
household_test <- read.csv("all/test.csv")
objtest_hashed <- hashed.model.matrix(~., data=household_test[, features], hash.size =2^12, transpose =
objtest_hashed <- as(objtest_hashed, "dgCMatrix")
household_predict <- predict(cv.fit, objtest_hashed, s="lambda.min")
```

```r
# append the ID to the predictions
household_predict <- data.frame(Id=household_test$Id, SalePrice=household_predict)
colnames(household_predict) <- c("Id", "SalePrice")
write.csv(household_predict, file = "all/household_predictions.csv",
          row.names = FALSE)
```