# Predicting Credit Defaults

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## Exploratory Analysis

### Missing Values (Part I)

The goal of this section is to identify features that are eligible for feature wise deletion in order to make the data set easier to navigate. Part II will discuss how to handle any remaining missing values.

```
anyNA(data) # to see if there are any missing values in the dataset
```

```
## [1] TRUE
```

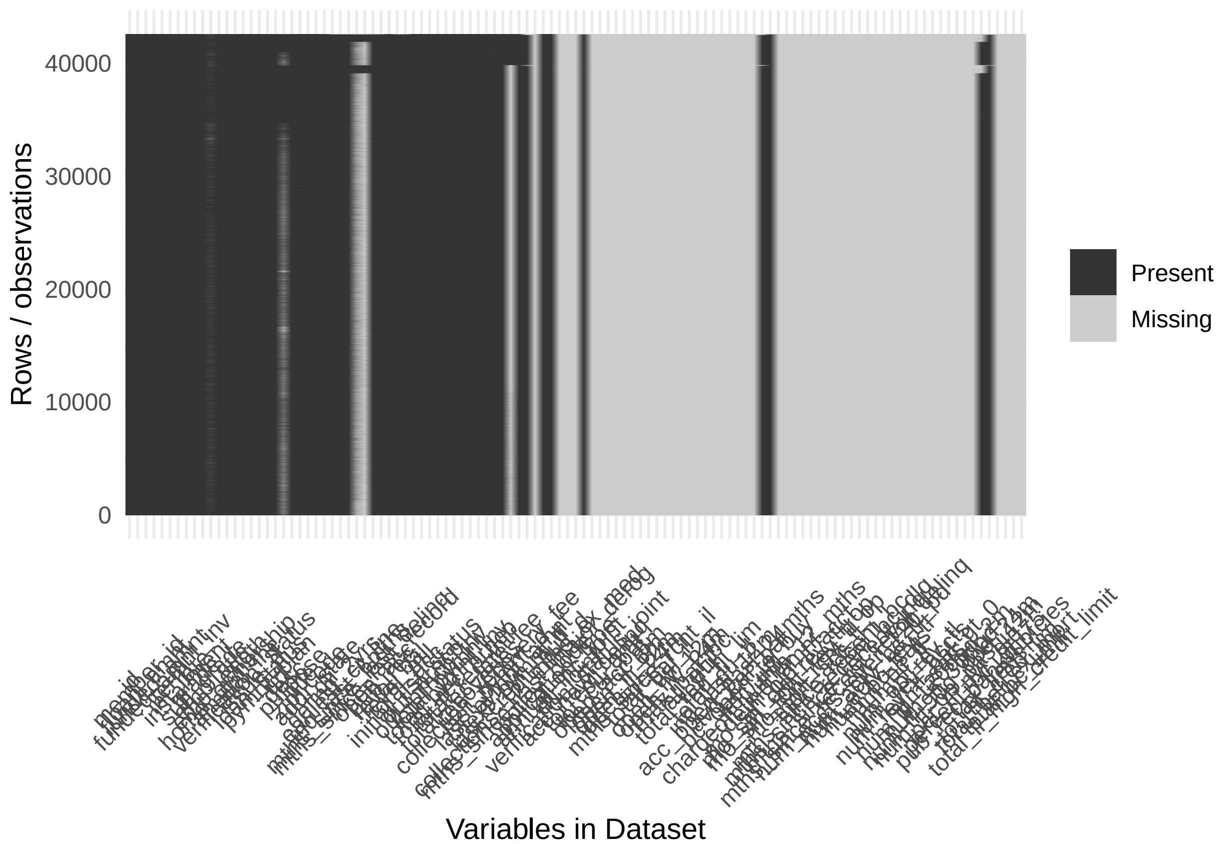
```
dim(data) # number of observations and features
```

```
## [1] 42537   111
```

```
ggplot_missing(data) # visualize missing data
```

```
## Loading required package: reshape2
```

```
## Warning: package 'reshape2' was built under R version 4.0.3
```




The missingness plot indicates that a large amount of features consists of a high percentage of missing values. The following output shows the exact percentages per feature.

```
round(colMeans(is.na(data))*100,3)
```

```
##                                id                        member_id
##                             0.005                            0.005
##                         loan_amnt                      funded_amnt
##                             0.005                            0.005
##                   funded_amnt_inv                             term
##                             0.005                            0.005
##                          int_rate                      installment
##                             0.005                            0.005
##                             grade                        sub_grade
##                             0.005                            0.005
##                         emp_title                       emp_length
##                             6.159                            0.005
##                    home_ownership                       annual_inc
##                             0.005                            0.014
##               verification_status                          issue_d
##                             0.005                            0.005
##                       loan_status                       pymnt_plan
##                             0.005                            0.005
##                               url                             desc
##                             0.005                           31.782
##                           purpose                            title
```

```
##                        0.005                        0.031
##                     zip_code                   addr_state
##                        0.005                        0.005
##                          dti                  delinq_2yrs
##                        0.005                        0.073
##             earliest_cr_line               inq_last_6mths
##                        0.073                        0.073
##       mths_since_last_delinq       mths_since_last_record
##                       63.305                       91.417
##                     open_acc                      pub_rec
##                        0.073                        0.073
##                    revol_bal                   revol_util
##                        0.005                        0.216
##                    total_acc          initial_list_status
##                        0.073                        0.005
##                    out_prncp                out_prncp_inv
##                        0.005                        0.005
##                  total_pymnt              total_pymnt_inv
##                        0.005                        0.005
##              total_rec_prncp                total_rec_int
##                        0.005                        0.005
##           total_rec_late_fee                   recoveries
##                        0.005                        0.005
##      collection_recovery_fee                 last_pymnt_d
##                        0.005                        0.200
##              last_pymnt_amnt                 next_pymnt_d
##                        0.005                       91.581
##           last_credit_pull_d   collections_12_mths_ex_med
##                        0.014                        0.346
##  mths_since_last_major_derog                  policy_code
##                      100.000                        0.005
##             application_type             annual_inc_joint
##                        0.005                      100.000
##                    dti_joint    verification_status_joint
##                      100.000                      100.000
##                 acc_now_delinq                tot_coll_amt
##                        0.073                      100.000
##                  tot_cur_bal                  open_acc_6m
##                      100.000                      100.000
##                   open_il_6m                  open_il_12m
##                      100.000                      100.000
##                  open_il_24m           mths_since_rcnt_il
##                      100.000                      100.000
##                 total_bal_il                      il_util
##                      100.000                      100.000
##                  open_rv_12m                  open_rv_24m
##                      100.000                      100.000
##                   max_bal_bc                     all_util
##                      100.000                      100.000
##             total_rev_hi_lim                       inq_fi
##                      100.000                      100.000
##                  total_cu_tl                  inq_last_12m
##                      100.000                      100.000
##         acc_open_past_24mths                  avg_cur_bal
```

```
##                              100.000                          100.000
##                       bc_open_to_buy                          bc_util
##                              100.000                          100.000
##           chargeoff_within_12_mths                      delinq_amnt
##                                0.346                            0.073
##                   mo_sin_old_il_acct             mo_sin_old_rev_tl_op
##                              100.000                          100.000
##                mo_sin_rcnt_rev_tl_op                    mo_sin_rcnt_tl
##                              100.000                          100.000
##                             mort_acc             mths_since_recent_bc
##                              100.000                          100.000
##            mths_since_recent_bc_dlq            mths_since_recent_inq
##                              100.000                          100.000
## mths_since_recent_revol_delinq            num_accts_ever_120_pd
##                              100.000                          100.000
##                       num_actv_bc_tl                  num_actv_rev_tl
##                              100.000                          100.000
##                          num_bc_sats                        num_bc_tl
##                              100.000                          100.000
##                            num_il_tl                    num_op_rev_tl
##                              100.000                          100.000
##                        num_rev_accts             num_rev_tl_bal_gt_0
##                              100.000                          100.000
##                             num_sats                num_tl_120dpd_2m
##                              100.000                          100.000
##                         num_tl_30dpd               num_tl_90g_dpd_24m
##                              100.000                          100.000
##                   num_tl_op_past_12m                 pct_tl_nvr_dlq
##                              100.000                          100.000
##                     percent_bc_gt_75             pub_rec_bankruptcies
##                              100.000                            3.214
##                            tax_liens                  tot_hi_cred_lim
##                                0.252                          100.000
##                    total_bal_ex_mort                   total_bc_limit
##                              100.000                          100.000
##          total_il_high_credit_limit
##                              100.000
```

Thus, it makes sense to delete features with a large percentage of missing values, say 33% or more.

```r
data = data %>% select_if(~mean(is.na(.))<=0.33) # drop features with a lot of NAs
dim(data) # dimensions of altered dataset
```

```
## [1] 42537    54
```

## Data structures

The following section of code explores the data structures in order to identify any qualitative features that might be coded as quantitative features and vice versa.

```r
table(sapply(data[1,],class)) # number of features per data type
```

```
##
## character   logical   numeric
##        22         1        31
```

```r
str(data) # overview of data types
```

```
## tibble [42,537 x 54] (S3: tbl_df/tbl/data.frame)
##  $ id                        : num [1:42537] 1077501 1077430 1077175 1076863 1075358 ...
##  $ member_id                 : num [1:42537] 1296599 1314167 1313524 1277178 1311748 ...
##  $ loan_amnt                 : num [1:42537] 5000 2500 2400 10000 3000 ...
##  $ funded_amnt               : num [1:42537] 5000 2500 2400 10000 3000 ...
##  $ funded_amnt_inv           : num [1:42537] 4975 2500 2400 10000 3000 ...
##  $ term                      : chr [1:42537] "36 months" "60 months" "36 months" "36 months" ...
##  $ int_rate                  : chr [1:42537] "10.65%" "15.27%" "15.96%" "13.49%" ...
##  $ installment               : num [1:42537] 162.9 59.8 84.3 339.3 67.8 ...
##  $ grade                     : chr [1:42537] "B" "C" "C" "C" ...
##  $ sub_grade                 : chr [1:42537] "B2" "C4" "C5" "C1" ...
##  $ emp_title                 : chr [1:42537] NA "Ryder" NA "AIR RESOURCES BOARD" ...
##  $ emp_length                : chr [1:42537] "10+ years" "< 1 year" "10+ years" "10+ years" ...
##  $ home_ownership            : chr [1:42537] "RENT" "RENT" "RENT" "RENT" ...
##  $ annual_inc                : num [1:42537] 24000 30000 12252 49200 80000 ...
##  $ verification_status       : chr [1:42537] "Verified" "Source Verified" "Not Verified" "Source Ver
##  $ issue_d                   : chr [1:42537] "Dec-11" "Dec-11" "Dec-11" "Dec-11" ...
##  $ loan_status               : chr [1:42537] "Fully Paid" "Charged Off" "Fully Paid" "Fully Paid" ..
##  $ pymnt_plan                : chr [1:42537] "n" "n" "n" "n" ...
##  $ url                       : chr [1:42537] "https://lendingclub.com/browse/loanDetail.action?loan_
##  $ desc                      : chr [1:42537] "Borrower added on 12/22/11 > I need to upgrade my busi
##  $ purpose                   : chr [1:42537] "credit_card" "car" "small_business" "other" ...
##  $ title                     : chr [1:42537] "Computer" "bike" "real estate business" "personel" ...
##  $ zip_code                  : chr [1:42537] "860xx" "309xx" "606xx" "917xx" ...
##  $ addr_state                : chr [1:42537] "AZ" "GA" "IL" "CA" ...
##  $ dti                       : num [1:42537] 27.65 1 8.72 20 17.94 ...
##  $ delinq_2yrs               : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  $ earliest_cr_line          : chr [1:42537] "Jan-85" "Apr-99" "Nov-01" "Feb-96" ...
##  $ inq_last_6mths            : num [1:42537] 1 5 2 1 0 3 1 2 2 0 ...
##  $ open_acc                  : num [1:42537] 3 3 2 10 15 9 7 4 11 2 ...
##  $ pub_rec                   : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  $ revol_bal                 : num [1:42537] 13648 1687 2956 5598 27783 ...
##  $ revol_util                : chr [1:42537] "83.70%" "9.40%" "98.50%" "21%" ...
##  $ total_acc                 : num [1:42537] 9 4 10 37 38 12 11 4 13 3 ...
##  $ initial_list_status       : logi [1:42537] FALSE FALSE FALSE FALSE FALSE FALSE ...
##  $ out_prncp                 : num [1:42537] 0 0 0 0 335 ...
##  $ out_prncp_inv             : num [1:42537] 0 0 0 0 335 ...
##  $ total_pymnt               : num [1:42537] 5863 1009 3006 12232 3717 ...
##  $ total_pymnt_inv           : num [1:42537] 5834 1009 3006 12232 3717 ...
##  $ total_rec_prncp           : num [1:42537] 5000 456 2400 10000 2665 ...
##  $ total_rec_int             : num [1:42537] 863 435 606 2215 1052 ...
##  $ total_rec_late_fee        : num [1:42537] 0 0 0 17 0 ...
##  $ recoveries                : num [1:42537] 0 117 0 0 0 ...
##  $ collection_recovery_fee   : num [1:42537] 0 1.11 0 0 0 0 0 0 2.09 2.52 ...
##  $ last_pymnt_d              : chr [1:42537] "Jan-15" "Apr-13" "Jun-14" "Jan-15" ...
##  $ last_pymnt_amnt           : num [1:42537] 171.6 119.7 649.9 357.5 67.8 ...
##  $ last_credit_pull_d        : chr [1:42537] "Jul-16" "Sep-13" "Jul-16" "Apr-16" ...
##  $ collections_12_mths_ex_med: num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
```

```
##  $ policy_code               : num [1:42537] 1 1 1 1 1 1 1 1 1 1 ...
##  $ application_type          : chr [1:42537] "INDIVIDUAL" "INDIVIDUAL" "INDIVIDUAL" "INDIVIDUAL" ...
##  $ acc_now_delinq            : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  $ chargeoff_within_12_mths  : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  $ delinq_amnt               : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  $ pub_rec_bankruptcies      : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  $ tax_liens                 : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  - attr(*, "problems")= tibble [1 x 5] (S3: tbl_df/tbl/data.frame)
##   ..$ row     : int 39788
##   ..$ col     : chr "id"
##   ..$ expected: chr "a double"
##   ..$ actual  : chr "Loans that do not meet the credit policy"
##   ..$ file    : chr "'Data/LoanStats3a.csv'"
```

```r
sapply(data,function(x){ length(unique(x))})
```

```
##                          id                   member_id
##                       42536                       42536
##                   loan_amnt                 funded_amnt
##                         899                        1052
##             funded_amnt_inv                        term
##                        9242                           3
##                    int_rate                 installment
##                         395                       16460
##                       grade                   sub_grade
##                           8                          36
##                   emp_title                  emp_length
##                       30449                          13
##              home_ownership                  annual_inc
##                           6                        5598
##         verification_status                     issue_d
##                           4                          56
##                 loan_status                  pymnt_plan
##                          10                           3
##                         url                        desc
##                       42536                       28951
##                     purpose                       title
##                          15                       20965
##                    zip_code                  addr_state
##                         838                          51
##                         dti                 delinq_2yrs
##                        2895                          13
##            earliest_cr_line              inq_last_6mths
##                         531                          29
##                    open_acc                     pub_rec
##                          45                           7
##                   revol_bal                  revol_util
##                       22710                        1120
##                   total_acc         initial_list_status
##                          84                           2
##                   out_prncp               out_prncp_inv
##                         831                         833
##                 total_pymnt             total_pymnt_inv
##                       40610                       40118
```

```
##           total_rec_prncp              total_rec_int
##                      8471                      37582
##        total_rec_late_fee                 recoveries
##                      1562                       4518
##   collection_recovery_fee               last_pymnt_d
##                      2843                        106
##           last_pymnt_amnt         last_credit_pull_d
##                     37080                        111
## collections_12_mths_ex_med               policy_code
##                         2                          2
##          application_type             acc_now_delinq
##                         2                          3
##   chargeoff_within_12_mths                delinq_amnt
##                         2                          4
##      pub_rec_bankruptcies                  tax_liens
##                         4                          3
```

There are some qualitative features, some coded as character and some as numeric, that need to be converted to factors. Furthermore, it seems like some features only have one value (besides NA) and should therefore be dropped.

```
# NOTE

##### Dates converted to factors for now

#issue_d: date
#last_pymnt_d: date
#last_credit_pull_d: date
#earliest_cr_line: date

#####

# features with only one value:
#     collections_12_mths_ex_med,
#     application_type,
#     policy_code,
#     chargeoff_within_12_mths

# END NOTE

# get rid of percent signs and convert to numeric
data$revol_util = as.numeric(sub("%","",data$revol_util))
data$int_rate = as.numeric(sub("%","",data$int_rate))

#convert data types
dataQual = data %>% select(c(term,grade,sub_grade,home_ownership,verification_status,loan_status,pymnt_p
                         purpose, initial_list_status, addr_state, zip_code, id, member_id, emp_title,ti
                         last_credit_pull_d,earliest_cr_line, emp_length, url, desc)) %>% mutate_all(fac
dataQuan = data %>% select(-c(names(dataQual),collections_12_mths_ex_med,application_type,policy_code,ch

#final result
str(dataQual)
```

```
## tibble [42,537 x 22] (S3: tbl_df/tbl/data.frame)
```

```
##  $ term                : Factor w/ 2 levels "36 months","60 months": 1 2 1 1 2 1 2 1 2 2 ...
##  $ grade               : Factor w/ 7 levels "A","B","C","D",..: 2 3 3 3 2 1 3 5 6 2 ...
##  $ sub_grade           : Factor w/ 35 levels "A1","A2","A3",..: 7 14 15 11 10 4 15 21 27 10 ...
##  $ home_ownership      : Factor w/ 5 levels "MORTGAGE","NONE",..: 5 5 5 5 5 5 5 5 4 5 ...
##  $ verification_status: Factor w/ 3 levels "Not Verified",..: 3 2 1 2 2 2 1 2 2 3 ...
##  $ loan_status         : Factor w/ 9 levels "Charged Off",..: 6 1 6 6 2 6 6 6 1 1 ...
##  $ pymnt_plan          : Factor w/ 2 levels "n","y": 1 1 1 1 1 1 1 1 1 1 ...
##  $ purpose             : Factor w/ 14 levels "car","credit_card",..: 2 1 12 10 10 14 3 1 12 10 ...
##  $ initial_list_status: Factor w/ 1 level "FALSE": 1 1 1 1 1 1 1 1 1 1 ...
##  $ addr_state          : Factor w/ 50 levels "AK","AL","AR",..: 4 11 15 5 37 4 28 5 5 43 ...
##  $ zip_code            : Factor w/ 837 levels "007xx","010xx",..: 727 281 513 764 813 721 252 749 802
##  $ id                  : Factor w/ 42535 levels "54734","55521",..: 42535 42534 42533 42532 42531 4253
##  $ member_id           : Factor w/ 42535 levels "70473","70626",..: 42206 42535 42534 40932 42533 4253
##  $ emp_title           : Factor w/ 30448 levels "$260M '06 vintage technology venture capital firm",.
##  $ title               : Factor w/ 20964 levels "'08 & '09 Roth IRA Investments",..: 3614 1817 16941 
##  $ issue_d             : Factor w/ 55 levels "Apr-08","Apr-09",..: 14 14 14 14 14 14 14 14 14 14 ...
##  $ last_pymnt_d        : Factor w/ 105 levels "Apr-08","Apr-09",..: 44 6 61 44 18 44 81 44 5 86 ...
##  $ last_credit_pull_d : Factor w/ 110 levels "Apr-09","Apr-10",..: 55 108 55 8 55 45 84 26 14 71 ...
##  $ earliest_cr_line    : Factor w/ 530 levels "Apr-00","Apr-01",..: 202 44 390 171 213 393 222 182 5 
##  $ emp_length          : Factor w/ 12 levels "< 1 year","1 year",..: 3 1 3 3 2 5 10 11 6 1 ...
##  $ url                 : Factor w/ 42535 levels "https://lendingclub.com/browse/loanDetail.action?loan
##  $ desc                : Factor w/ 28950 levels "- Pay off Dell Financial: $ 1300.00 - Pay off IRS for
##  - attr(*, "problems")= tibble [1 x 5] (S3: tbl_df/tbl/data.frame)
##   ..$ row     : int 39788
##   ..$ col     : chr "id"
##   ..$ expected: chr "a double"
##   ..$ actual  : chr "Loans that do not meet the credit policy"
##   ..$ file    : chr "'Data/LoanStats3a.csv'"
```

```r
str(dataQuan)
```

```
## tibble [42,537 x 28] (S3: tbl_df/tbl/data.frame)
##  $ loan_amnt           : num [1:42537] 5000 2500 2400 10000 3000 ...
##  $ funded_amnt         : num [1:42537] 5000 2500 2400 10000 3000 ...
##  $ funded_amnt_inv     : num [1:42537] 4975 2500 2400 10000 3000 ...
##  $ int_rate            : num [1:42537] 10.6 15.3 16 13.5 12.7 ...
##  $ installment         : num [1:42537] 162.9 59.8 84.3 339.3 67.8 ...
##  $ annual_inc          : num [1:42537] 24000 30000 12252 49200 80000 ...
##  $ dti                 : num [1:42537] 27.65 1 8.72 20 17.94 ...
##  $ delinq_2yrs         : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  $ inq_last_6mths      : num [1:42537] 1 5 2 1 0 3 1 2 2 0 ...
##  $ open_acc            : num [1:42537] 3 3 2 10 15 9 7 4 11 2 ...
##  $ pub_rec             : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
##  $ revol_bal           : num [1:42537] 13648 1687 2956 5598 27783 ...
##  $ revol_util          : num [1:42537] 83.7 9.4 98.5 21 53.9 28.3 85.6 87.5 32.6 36.5 ...
##  $ total_acc           : num [1:42537] 9 4 10 37 38 12 11 4 13 3 ...
##  $ out_prncp           : num [1:42537] 0 0 0 0 335 ...
##  $ out_prncp_inv       : num [1:42537] 0 0 0 0 335 ...
##  $ total_pymnt         : num [1:42537] 5863 1009 3006 12232 3717 ...
##  $ total_pymnt_inv     : num [1:42537] 5834 1009 3006 12232 3717 ...
##  $ total_rec_prncp     : num [1:42537] 5000 456 2400 10000 2665 ...
##  $ total_rec_int       : num [1:42537] 863 435 606 2215 1052 ...
##  $ total_rec_late_fee  : num [1:42537] 0 0 0 17 0 ...
##  $ recoveries          : num [1:42537] 0 117 0 0 0 ...
```

```
## $ collection_recovery_fee: num [1:42537] 0 1.11 0 0 0 0 0 0 2.09 2.52 ...
## $ last_pymnt_amnt        : num [1:42537] 171.6 119.7 649.9 357.5 67.8 ...
## $ acc_now_delinq         : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
## $ delinq_amnt            : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
## $ pub_rec_bankruptcies   : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
## $ tax_liens              : num [1:42537] 0 0 0 0 0 0 0 0 0 0 ...
## - attr(*, "problems")= tibble [1 x 5] (S3: tbl_df/tbl/data.frame)
##   ..$ row     : int 39788
##   ..$ col     : chr "id"
##   ..$ expected: chr "a double"
##   ..$ actual  : chr "Loans that do not meet the credit policy"
##   ..$ file    : chr "'Data/LoanStats3a.csv'"
```

## Missing Values (Part II)

Before using any kind of imputation method the data is split into a training and test set. Imputation is only performed on the features of the training set.

```
set.seed(123)
Y = select(dataQual,loan_status) %>% unlist() %>% as.vector()
dataQual = select(dataQual,-loan_status)

# NOTE: Might want to consider stratified train test split because of unequal proportions in the superv

trainIndex = createDataPartition(Y, p=.75, list= FALSE) %>% as.vector()
Y = as.data.frame(Y)

XQualTrain = dataQual[trainIndex,] # split train features into qual and quan for imputation
XQuanTrain = dataQuan[trainIndex,]
Ytrain     = Y[trainIndex,]
Xtest      = cbind(dataQual[-trainIndex,],dataQuan[-trainIndex,]) #combine qual. and quan. features
Ytest      = Y[-trainIndex,]
```

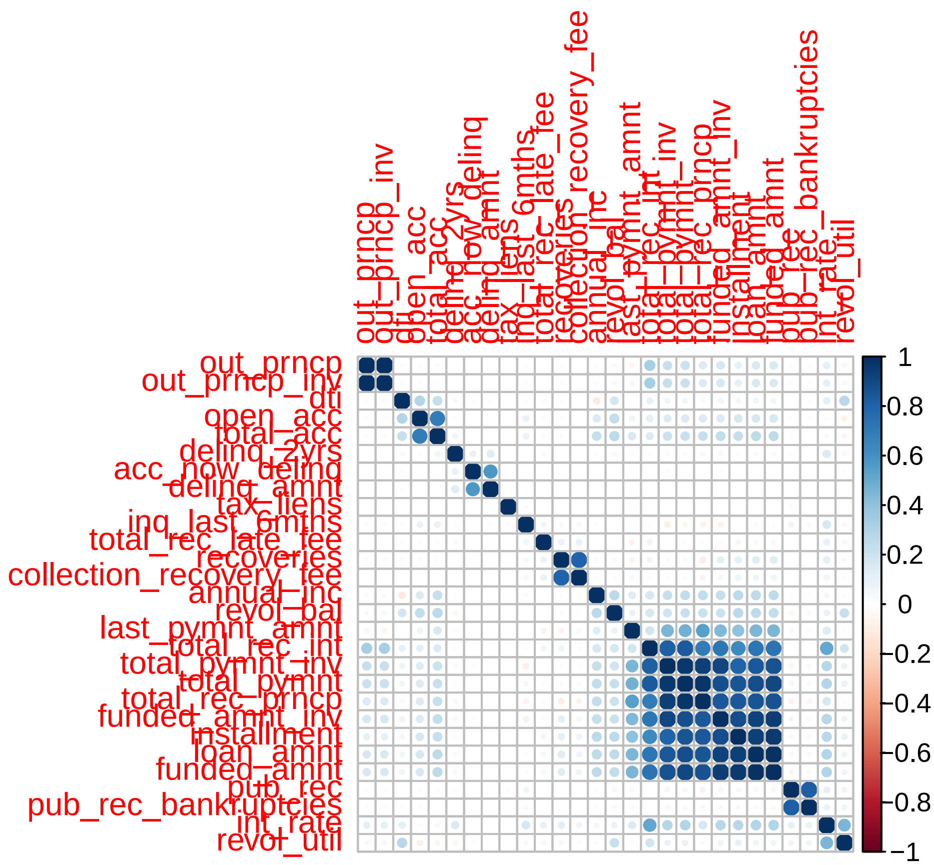
Mode imputation is used for qualitative features, and median imputation is used for quantitative features.

```
modeImpute = function(Xqual){
  tbl = table(Xqual)
  Xqual[is.na(Xqual)] = names(tbl)[which.max(tbl)]
  return(Xqual)
}

XQuanTrain = XQuanTrain %>%
  preProcess(method = 'medianImpute')%>%
  predict(newdata = XQuanTrain)

XQualTrain = XQualTrain %>% mutate(across(.cols=everything(), modeImpute))
```

## Removing correlated variables

Quantitative features with high correlation (p>0.85) are problematic, and will be removed.

```r
datacorr = cor(XQuanTrain)
corrplot(datacorr, order= 'hclust', t1.cex= .35)
```




```r
highCorr = findCorrelation(datacorr, .85, verbose=T, names=T)
```

```
## Compare row 2  and column  17 with corr  0.901
##   Means:  0.326 vs 0.14 so flagging column 2
## Compare row 17  and column  1 with corr  0.885
##   Means:  0.301 vs 0.127 so flagging column 17
## Compare row 1  and column  3 with corr  0.929
##   Means:  0.273 vs 0.114 so flagging column 1
## Compare row 3  and column  18 with corr  0.915
##   Means:  0.244 vs 0.101 so flagging column 3
## Compare row 18  and column  19 with corr  0.933
##   Means:  0.215 vs 0.09 so flagging column 18
## Compare row 15  and column  16 with corr  1
##   Means:  0.091 vs 0.084 so flagging column 15
## All correlations <= 0.85
```

```r
XQuanTrain= select(all_of(XQuanTrain), -any_of((highCorr)))
dim(XQuanTrain)
```

```
## [1] 31905    22
```

### Extreme observations and skewness

Assuming that acceptable values of skewness fall between -1,5 and 1.5, features with values for skewness outside of this range will be transformed.

```
(skewed= apply(XQuanTrain, 2, skewness))
```

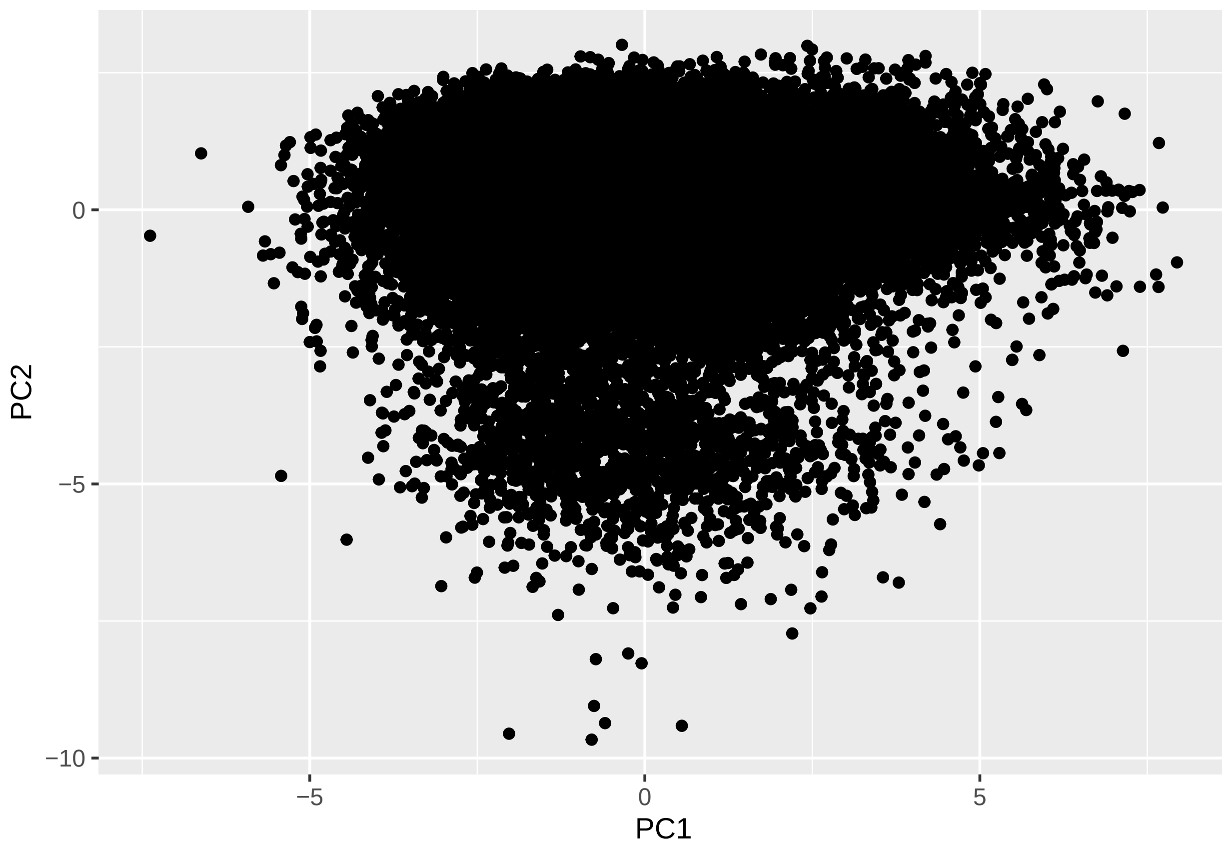
```
##                 int_rate              installment               annual_inc
##               0.24065189               1.11623591              31.53005134
##                      dti              delinq_2yrs           inq_last_6mths
##              -0.02745610               5.42464730               3.45877497
##                 open_acc                  pub_rec                revol_bal
##               1.04893038               4.64001772              12.34338382
##               revol_util                total_acc            out_prncp_inv
##              -0.04429014               0.82179933              11.24336948
##          total_rec_prncp            total_rec_int       total_rec_late_fee
##               1.12028248               2.67310936               8.15606079
##               recoveries collection_recovery_fee          last_pymnt_amnt
##              16.14170323              21.68657176               2.75802790
##             acc_now_delinq              delinq_amnt     pub_rec_bankruptcies
##             103.10674278             178.59759782               4.48878276
##                tax_liens
##             178.60291265
```

The output indicates that some features are heavily skewed.

```
# NOTE: didn't work

XQuanTrain = XQuanTrain %>%
  select_if(abs(skewed) > 1.5) %>%
  preProcess(method = 'YeoJohnson') %>%
  predict(newdata = XQuanTrain)
```

Extreme observations can be identified via PCA.

```
pcaOut = prcomp(XQuanTrain,scale=TRUE,center=TRUE)
XQuanTrainScores = data.frame(pcaOut$x)
ggplot(data = XQuanTrainScores) +
geom_point(aes(x = PC1, y = PC2))
```




No immediate extreme observations apparent.

## Modeling

### Fitting logistic elastic net

```
Xtrain = cbind(XQualTrain, XQuanTrain)
# K            = 5
# trainControl = trainControl(method = "cv", number = K)
# tuneGrid     = expand.grid('alpha'=c(.5, 1),'lambda' = seq(0.0001, .01, length.out = 10))
#
# elasticOut   = train(x= Xtrain, y= Ytrain,
#                       method = "glmnet",
#                       trControl = trainControl,
#                       tuneGrid = tuneGrid) #### Answer 1.1
#
# elasticOut$bestTune
#
# glmnetOut         = glmnet(x = XtrainMat, y = relevel(Ytrain, ref = 'X8'),
#                             alpha = elasticOut$bestTune$alpha, family = 'binomial')
# probHatTestGlmnet = predict(glmnetOut, XtestMat, s=elasticOut$bestTune$lambda, type = 'response')
# YhatTestGlmnet    = ifelse(probHatTestGlmnet>0.5, 'X1', 'X2')# check with roc curve
```

## Validation