SmartFly: Exploratory Analysis For Historic Flight Data

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First load variable names and types of historic data (prepared in an additional csv file):

```
nameTypeDataFile  <- "resources/raw_variables.csv"
variableNames <- read.csv(nameTypeDataFile, header=TRUE, stringsAsFactors=FALSE)
variableNames
```

```
##                         name      type
## 1                         id character
## 2                       year    factor
## 3                      month    factor
## 4               day_of_month    factor
## 5                day_of_week    factor
## 6  scheduled_departure_time    factor
## 7    scheduled_arrival_time    factor
## 8                    airline    factor
## 9             flight_number    factor
## 10              tail_number    factor
## 11              plane_model    factor
## 12       seat_configuration    factor
## 13          departure_delay   numeric
## 14           origin_airport    factor
## 15      destination_airport    factor
## 16       distance_travelled   numeric
## 17             taxi_time_in   numeric
## 18            taxi_time_out   numeric
## 19                cancelled   integer
## 20        cancellation_code    factor
```

```
factorIdx <- which(variableNames$type=="factor")
factorNames <- variableNames$name[factorIdx]
```

Then load historic data into R. I set empty strings to `NA` (since I saw in the first rough analysis of the data on the command line that at least `cancellation_code` contains empty spaces).

```
historicDataFile <- "../../data/smartfly_historic.csv"
# historicDataFile <- "../../data/mod4000.csv"
trainDataTyped <- read.csv(historicDataFile, header=FALSE, stringsAsFactors=FALSE,
                           col.names=variableNames$name, colClasses=variableNames$type,
                           na.strings=c("NA",""))
# convert integer to logical
trainDataTyped$cancelled <- as.logical(trainDataTyped$cancelled)
```

Checkout data content:

```
str(trainDataTyped)
```

```
## 'data.frame': 7374365 obs. of  20 variables:
##  $ id                      : chr  "4982598272866526024" "5074130684343212714" "8872634703988349126" "
##  $ year                    : Factor w/ 2 levels "2013","2014": 1 1 1 1 1 1 1 1 1 1 ...
##  $ month                   : Factor w/ 12 levels "1","10","11",..: 11 11 11 11 11 11 11 11 11 11 ...
##  $ day_of_month            : Factor w/ 31 levels "1","10","11",..: 3 9 10 17 18 25 1 12 23 26 ...
##  $ day_of_week             : Factor w/ 7 levels "1","2","3","4",..: 7 6 7 6 7 6 4 5 6 7 ...
##  $ scheduled_departure_time: Factor w/ 1190 levels "0","10","100",..: 20 20 20 20 20 20 1041 1041 104
##  $ scheduled_arrival_time  : Factor w/ 1323 levels "0","1","10","100",..: 111 111 111 111 111 111 123
##  $ airline                 : Factor w/ 17 levels "AA","AS","B6",..: 15 15 15 15 15 15 15 15 15 15 ..
##  $ flight_number           : Factor w/ 6889 levels "1","10","100",..: 6744 6744 6744 6744 6744 6744 6
##  $ tail_number             : Factor w/ 5035 levels "0","000000","N050AA",..: 3898 3963 3806 3810 4008
##  $ plane_model             : Factor w/ 6 levels "737","747","757",..: 3 3 5 2 5 2 2 3 2 6 ...
##  $ seat_configuration      : Factor w/ 6 levels "Standard","Three Class",..: 2 1 4 5 4 5 2 1 5 2 ...
##  $ departure_delay         : num  -5 5 -4 -6 -3 -8 0 -2 14 -6 ...
##  $ origin_airport          : Factor w/ 279 levels "ABE","ABI","ABQ",..: 46 46 46 46 46 46 133 133 133
##  $ destination_airport     : Factor w/ 279 levels "ABE","ABI","ABQ",..: 61 61 61 61 61 61 61 61 61 61
##  $ distance_travelled      : num  361 361 361 361 361 361 185 185 185 185 ...
##  $ taxi_time_in            : num  9 7 6 15 7 5 9 3 5 5 ...
##  $ taxi_time_out           : num  11 7 9 11 12 15 8 8 16 9 ...
##  $ cancelled               : logi  FALSE FALSE FALSE FALSE FALSE FALSE ...
##  $ cancellation_code       : Factor w/ 4 levels "A","B","C","D": NA NA NA NA NA NA NA NA NA NA ...
```

Specifically note the factor levels for the different variables[1]. I see that `scheduled_departure_time` and `scheduled_arrival_time` need to be reformatted to have for all observations values that are 4 characters long (assuming "100" means "0100" and thus a time of 01h00):

```
trainDataTyped$scheduled_departure_time <- as.factor(
  sprintf("%04s", as.character(trainDataTyped$scheduled_departure_time)))
trainDataTyped$scheduled_arrival_time <- as.factor(
  sprintf("%04s", as.character(trainDataTyped$scheduled_arrival_time)))
```

In addition I truncate the scheduled times to the hour:

```
trainDataTyped$scheduled_departure_time <- as.factor(
  substr(as.character(trainDataTyped$scheduled_departure_time),1,2))
trainDataTyped$scheduled_arrival_time <- as.factor(
  substr(as.character(trainDataTyped$scheduled_arrival_time),1,2))

# remaining levels are:
levels(trainDataTyped$scheduled_departure_time)
```

```
##  [1] "00" "01" "02" "03" "04" "05" "06" "07" "08" "09" "10" "11" "12" "13" "14" "15" "16"
## [18] "17" "18" "19" "20" "21" "22" "23" "24"
```

```
levels(trainDataTyped$scheduled_arrival_time)
```

```
##  [1] "00" "01" "02" "03" "04" "05" "06" "07" "08" "09" "10" "11" "12" "13" "14" "15" "16"
## [18] "17" "18" "19" "20" "21" "22" "23" "24"
```

[1]The number of levels matters if I would want to create a dummy variable for each level. With lots of levels the number of variables would be HUGE and so would be the sparsity of the design matrix.

I notice that there is hour "00" and "24", I consolidate this into "00" (and remove level "24":

```
replace24with00 <- function(column) {
  moveIdx <- which(column=="24")
  column[moveIdx] <- "00"
  removeIdx <- which(levels(column) == "24")
  levels(column)[removeIdx] <- NA
  return(column)
}
trainDataTyped$scheduled_departure_time <- replace24with00(trainDataTyped$scheduled_departure_time)
trainDataTyped$scheduled_arrival_time <- replace24with00(trainDataTyped$scheduled_arrival_time)
```

I also reformat the variables `day_of_month` and `month` (so that they're ordered automatically in graphs):

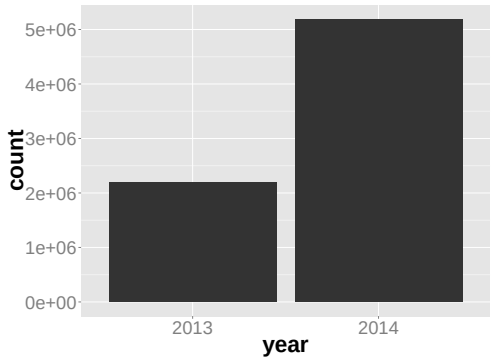
```
trainDataTyped$month <- as.factor(
  sprintf("%02s", as.character(trainDataTyped$month)))
trainDataTyped$day_of_month <- as.factor(
  sprintf("%02s", as.character(trainDataTyped$day_of_month)))
```

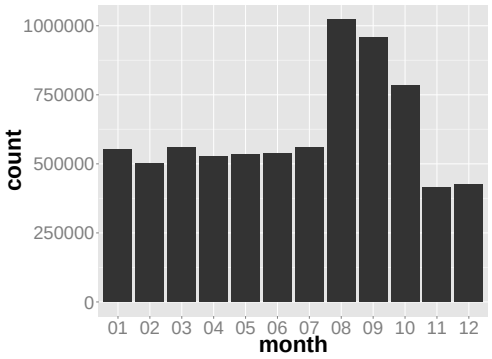
See summary of descriptive statistics of the historic data:

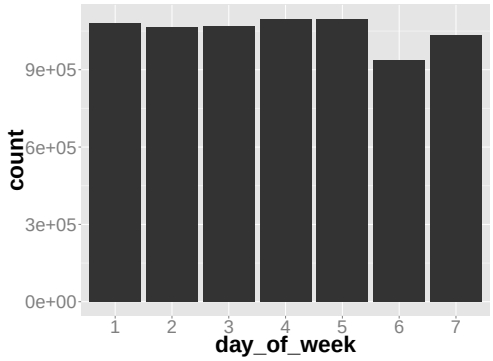
```
summary(trainDataTyped)
```

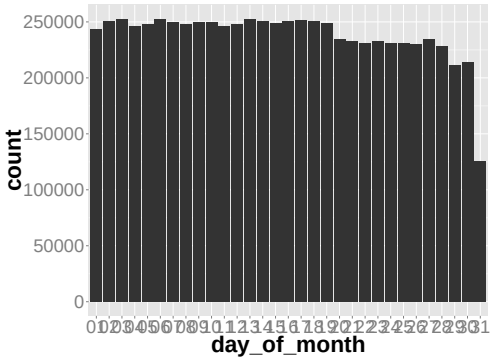
```
##       id              year             month          day_of_month     day_of_week
##  Length:7374365     2013:2185499   08     :1023748   13     : 252615   1:1079862
##  Class :character   2014:5188866   09     : 957710   06     : 252560   2:1063516
##  Mode  :character                  10     : 782952   03     : 252160   3:1069847
##                                    03     : 559342   17     : 251944   4:1096825
##                                    07     : 558568   16     : 250869   5:1096417
##                                    01     : 552109   02     : 250647   6: 935465
##                                    (Other):2939936   (Other):5863570   7:1032433
##  scheduled_departure_time scheduled_arrival_time    airline         flight_number
##  17     : 539987          16     : 534524        WN     :1171236   192    :   5702
##  08     : 511491          17     : 492008        AA     : 960866   64     :   5639
##  09     : 500448          19     : 490631        DL     : 825543   706    :   5409
##  07     : 499763          18     : 488335        UA     : 686409   186    :   5373
##  13     : 490531          20     : 484248        NW     : 619091   751    :   5209
##  12     : 487784          11     : 482204        US     : 529032   340    :   5060
##  (Other):4344361          (Other):4402415        (Other):2582188   (Other):7341973
##   tail_number      plane_model      seat_configuration  departure_delay
##  0      :  17138   737 :2317735   Standard   :2130560   Min.   :-1410.00
##  000000 :  10157   747 :1579936   Three Class: 779700   1st Qu.:   -4.00
##  N183UW :   4694   757 : 999512   Two Class  : 779964   Median :    0.00
##  N80    :   4290   777 : 634170   V1         :1430984   Mean   :    4.87
##  N96    :   4269   787 : 633182   V2         :1105044   3rd Qu.:    2.00
##  (Other):7291604   A320:1209830   V3         :1148113   Max.   : 2119.00
##  NA's   :  42213                                       NA's   :104127
##  origin_airport    destination_airport distance_travelled  taxi_time_in
##  ORD    : 431004   ORD    : 431004     Min.   :  11       Min.   :   0.000
##  ATL    : 389963   ATL    : 389886     1st Qu.: 308       1st Qu.:   4.000
##  DFW    : 382123   DFW    : 382349     Median : 569       Median :   5.000
##  LAX    : 255642   LAX    : 255786     Mean   : 726       Mean   :   6.808
##  PHX    : 209831   PHX    : 209839     3rd Qu.: 964       3rd Qu.:   7.000
##  IAH    : 195923   IAH    : 195926     Max.   :4962       Max.   :1495.000
##  (Other):5509879   (Other):5509575
##  taxi_time_out     cancelled       cancellation_code
##  Min.   :   0.00   Mode :logical   A   :  14587
##  1st Qu.:  10.00   FALSE:7270238   B   :   8072
##  Median :  13.00   TRUE :104127    C   :   8309
##  Mean   :  15.05   NA's :0         D   :    179
##  3rd Qu.:  18.00                   NA's:7343218
##  Max.   :1439.00
##
```

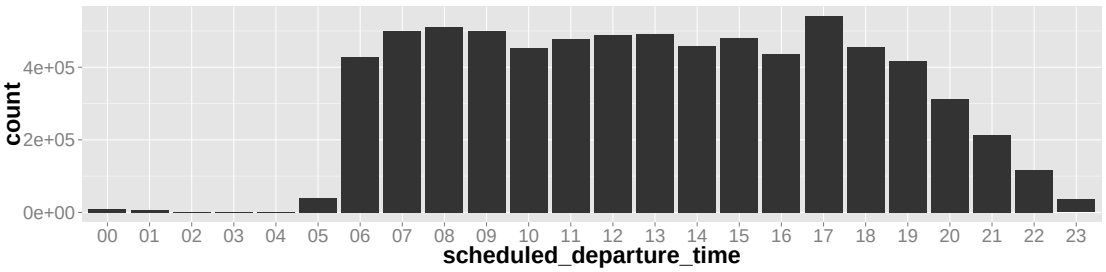
Plot the data independently of delay, cancellation and taxi time (since these variables are not available for prediction):

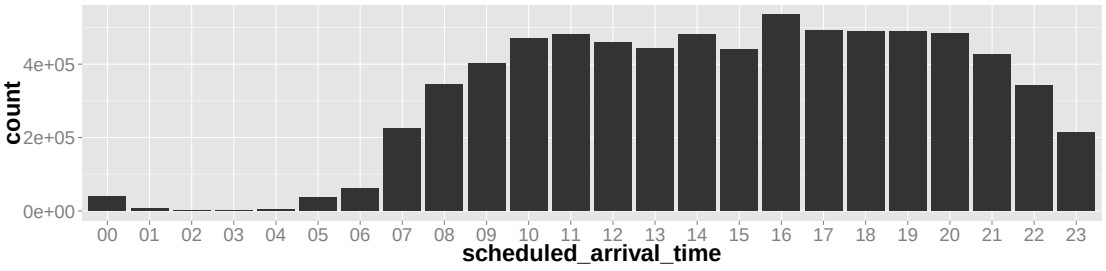

count
5e+06
4e+06
3e+06
2e+06
1e+06
0e+00
2013
2014
year

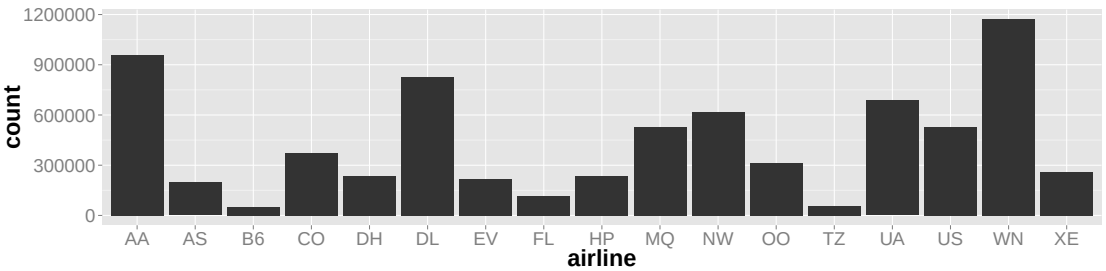

count
1000000
750000
500000
250000
0
01 02 03 04 05 06 07 08 09 10 11 12
month

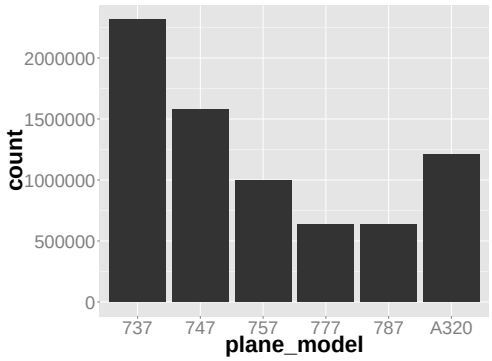

count
9e+05
6e+05
3e+05
0e+00
1 2 3 4 5 6 7
day_of_week

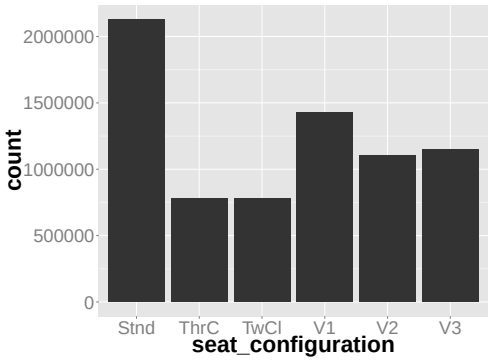

count
250000
200000
150000
100000
50000
0
day_of_month


count
4e+05
2e+05
0e+00
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23
scheduled_departure_time

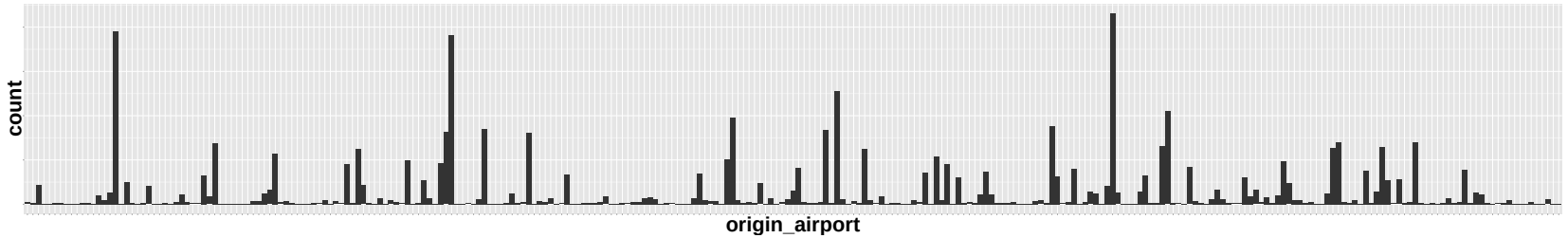

count
4e+05
2e+05
0e+00
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23
scheduled_arrival_time

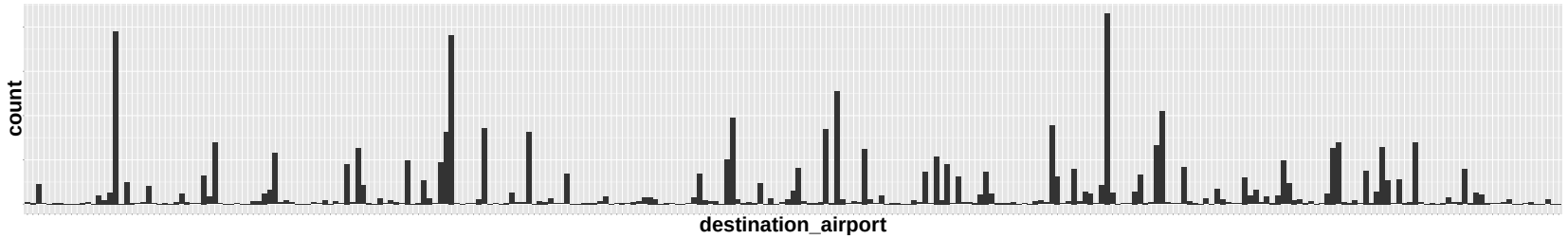

count
1200000
900000
600000
300000
0
AA AS B6 CO DH DL EV FL HP MQ NW OO TZ UA US WN XE
airline

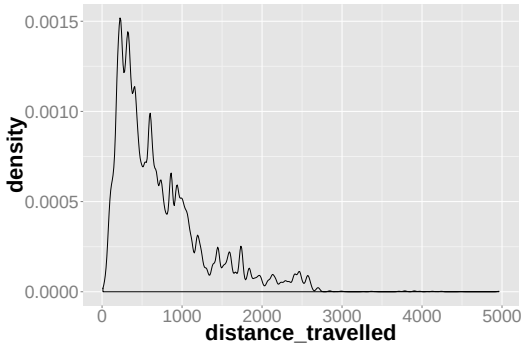




The variables `flight_number` and `tail_number` don't produce any valuable plots due to their large number in levels.


count
origin_airport


count
destination_airport


0.0015
0.0010
0.0005
0.0000
density
0
1000
2000
3000
4000
5000
distance_travelled

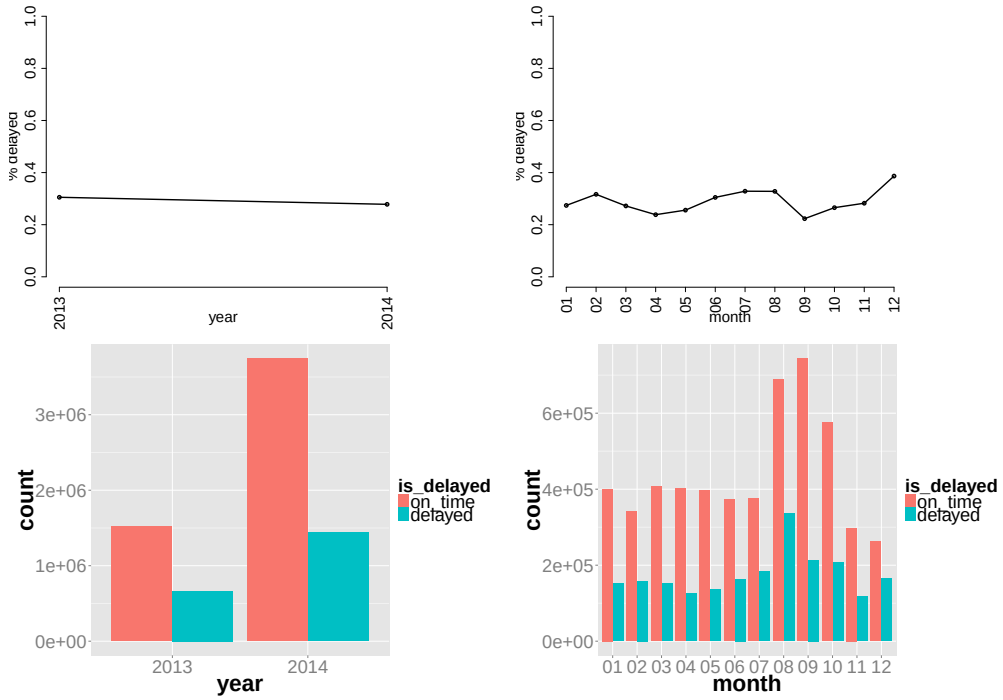
Since I want to predict whether a flight is delayed or not I create a specific variable `is_delayed` based on `departure_delay` using the definition that only positive delay and non-cancelled flights count as "delayed":

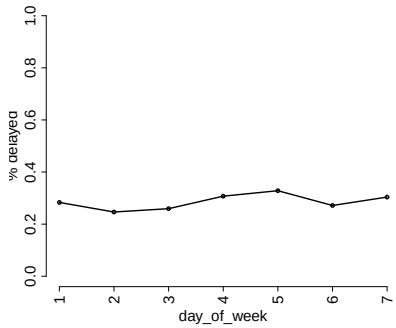
```
trainDataTyped$is_delayed <- factor(trainDataTyped$departure_delay > 0
                                    & trainDataTyped$cancelled==FALSE,
                                    labels= c("on_time", "delayed"))
summary(trainDataTyped$is_delayed)

## on_time delayed
## 5263866 2110499

summary(trainDataTyped$is_delayed) / length(trainDataTyped$is_delayed)

##  on_time  delayed
## 0.713806 0.286194
```

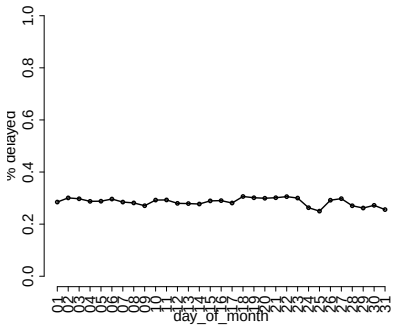
Save data frame for next step:

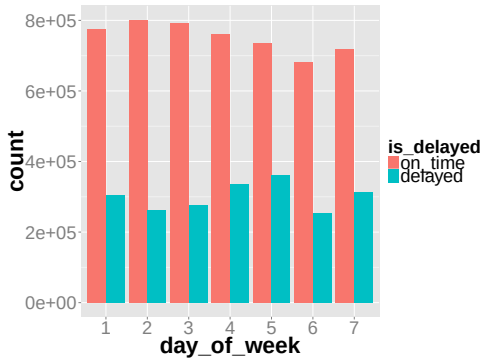
```
factorLevels <- sapply(factorNames, FUN=function(df, x) { levels(df[,x]) }, df=trainDataTyped)
save(trainDataTyped, factorLevels, file="trainDataTyped.Rdata")
```

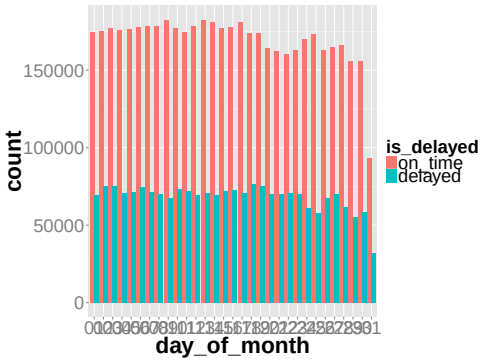
Plot the data:

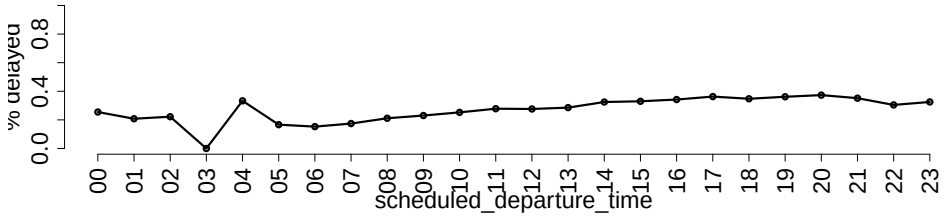


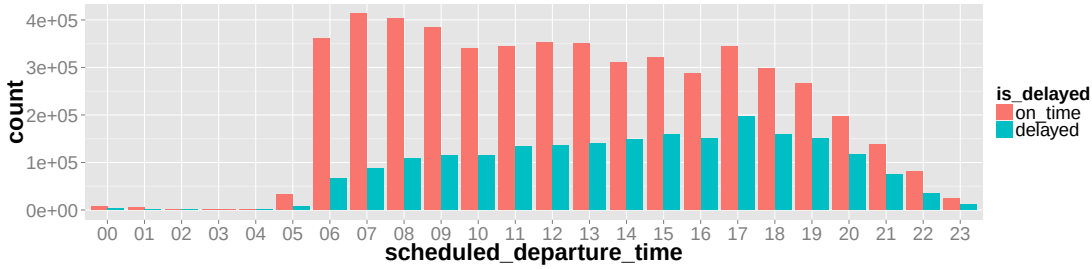

% delayed
day_of_week

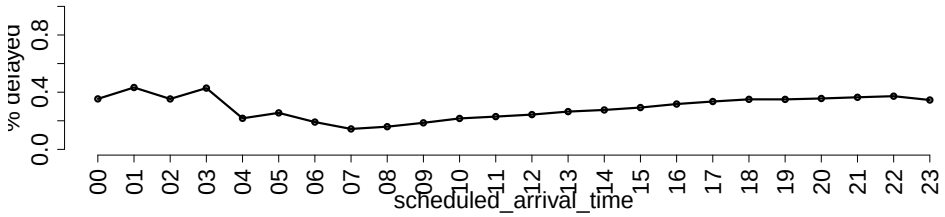

% delayed
day_of_month

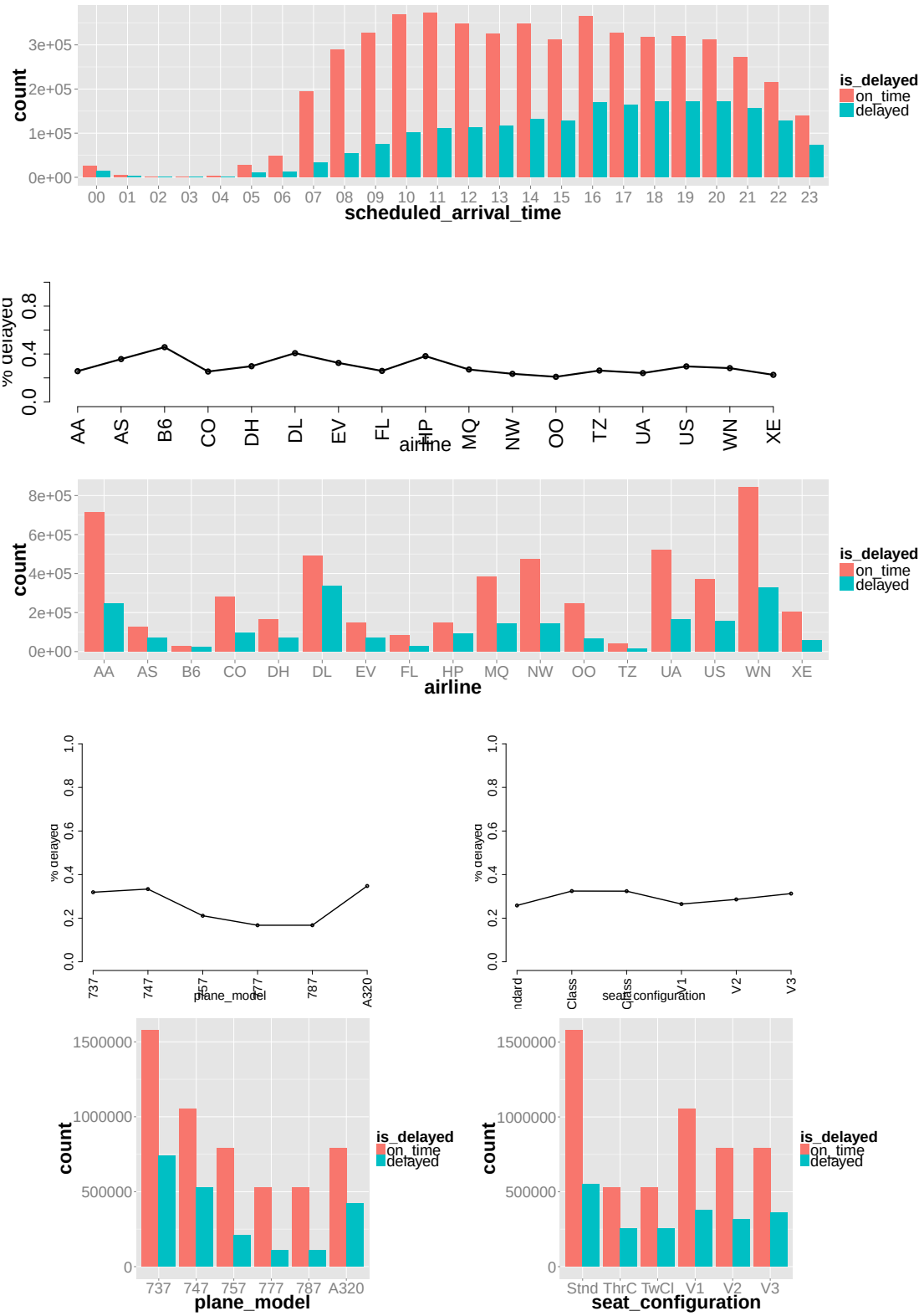

count
day_of_week
is_delayed
on_time
delayed


count
day_of_month
is_delayed
on_time
delayed

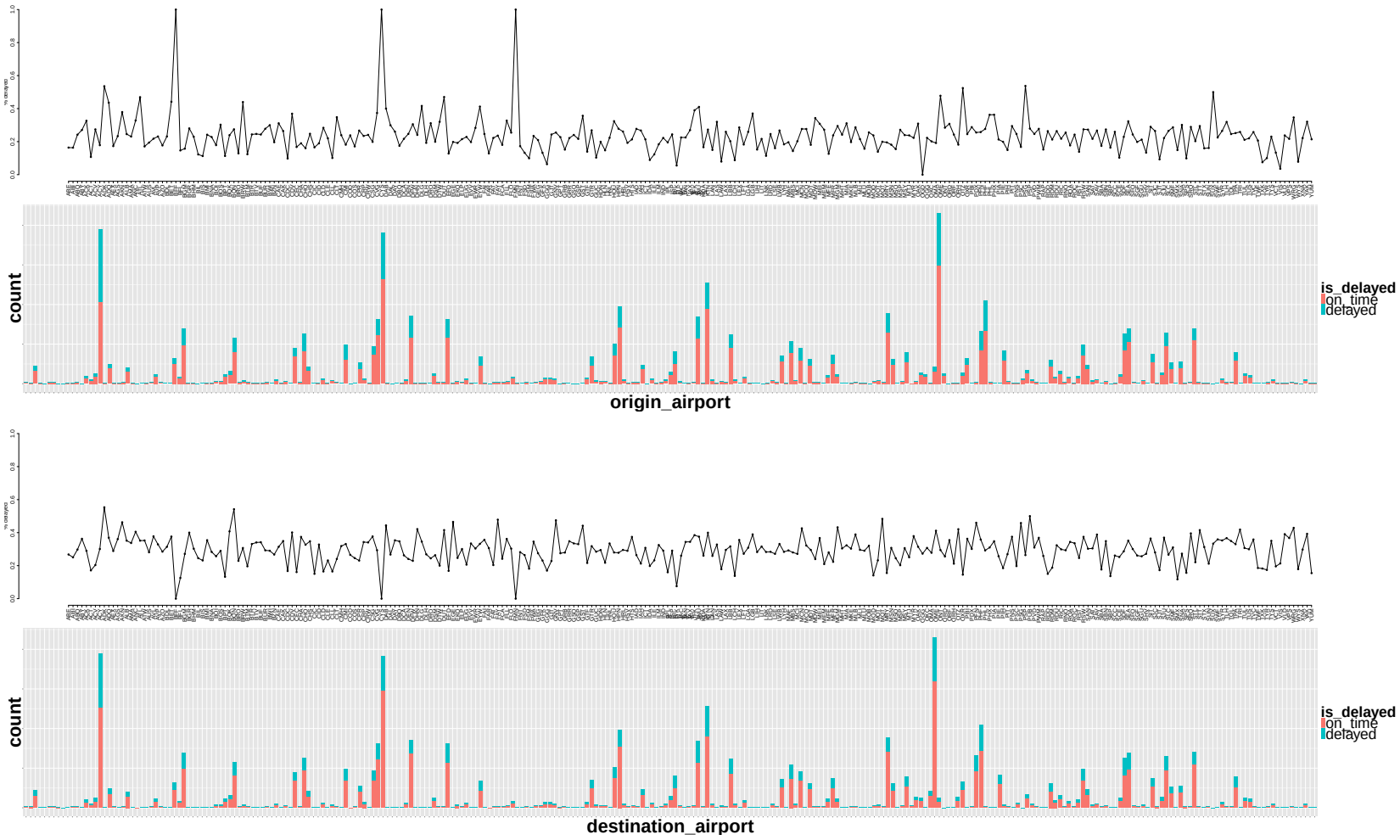

% delayed
scheduled_departure_time

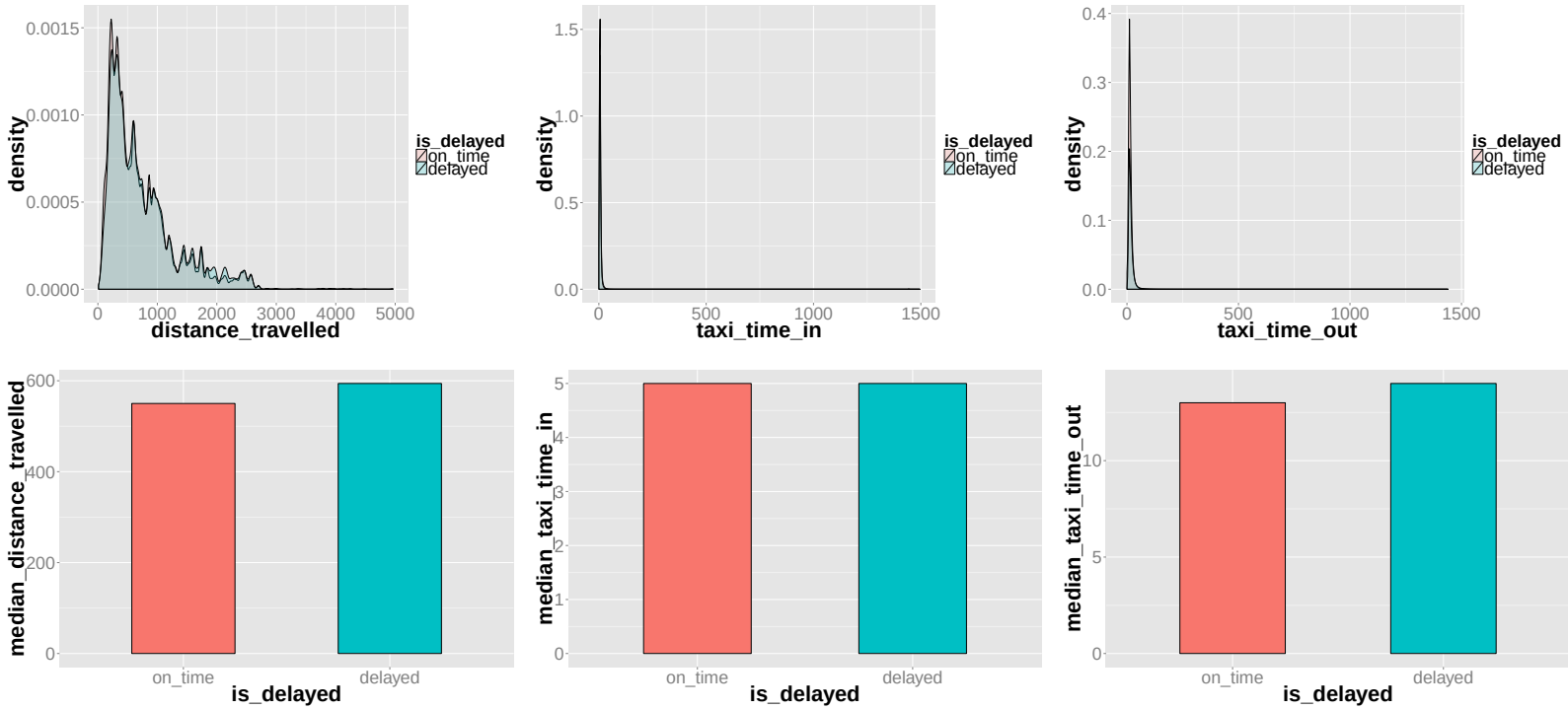

count
scheduled_departure_time
is_delayed
on_time
delayed


% delayed
scheduled_arrival_time



The variables `flight_number` and `tail_number` don't produce any valuable plots due to their large number in levels.


% delayed
count
is_delayed
on_time
delayed
origin_airport
% delayed
count
is_delayed
on_time
delayed
destination_airport


density
distance_travelled
taxi_time_in
taxi_time_out
is_delayed
on_time
delayed
median_distance_travelled
median_taxi_time_in
median_taxi_time_out

Look at correlations between continuous variables:

```
cor(trainDataTyped$departure_delay, trainDataTyped$distance_travelled, use="pairwise.complete.obs")

## [1] -0.0007718446

cor(trainDataTyped$departure_delay, trainDataTyped$taxi_time_in, use="pairwise.complete.obs")

## [1] 0.03345877

cor(trainDataTyped$departure_delay, trainDataTyped$taxi_time_out, use="pairwise.complete.obs")

## [1] 0.06387488
```

Look at some dependency between the binary target variable and other factor variables (with reasonably few levels) using the Chi-Square test of independence. The null hypothesis is that the two variables are independent, which I reject if the p-value is smaller than $\alpha = 0.001$ (chosen so small due to large sample size):

```
dependentWithTarget

##                       id                     year                    month
##                    FALSE                     TRUE                     TRUE
##             day_of_month              day_of_week scheduled_departure_time
##                     TRUE                     TRUE                     TRUE
##   scheduled_arrival_time             tail_number             plane_model
##                     TRUE                     TRUE                     TRUE
##       seat_configuration         departure_delay           origin_airport
##                     TRUE                     TRUE                     TRUE
```