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
```

```
factor_idx <- which(variableNames$type=="factor")
```

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 ...
##  $ 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))
```

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)))
```

[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.

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
##
```

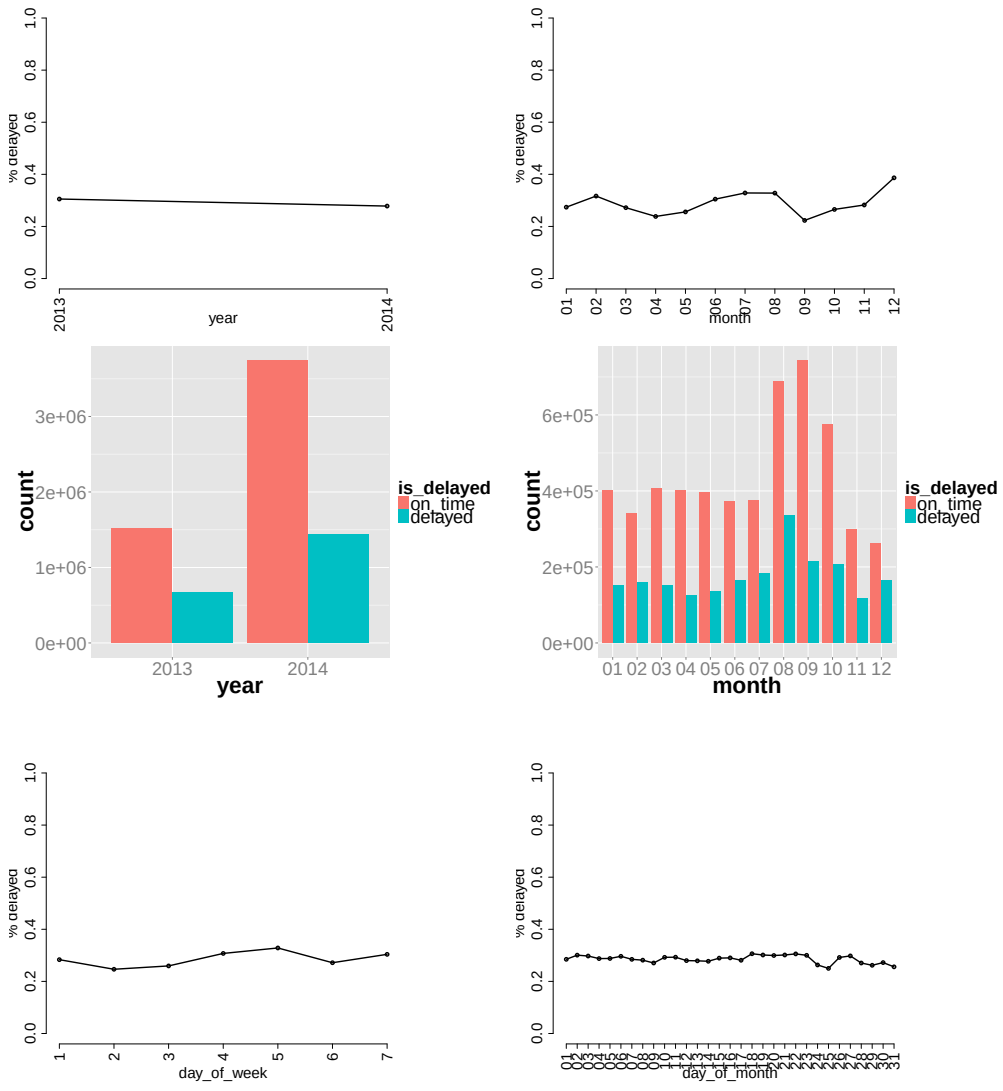
Save data frame for next step:

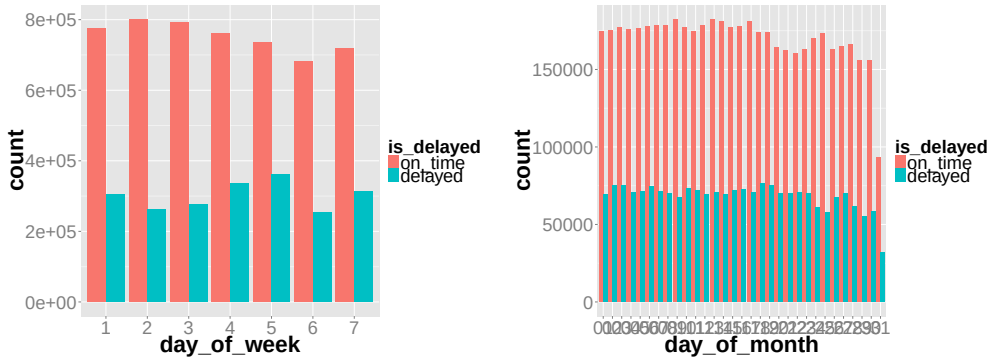
```
save(trainDataTyped, file="trainDataTyped.Rdata")
```

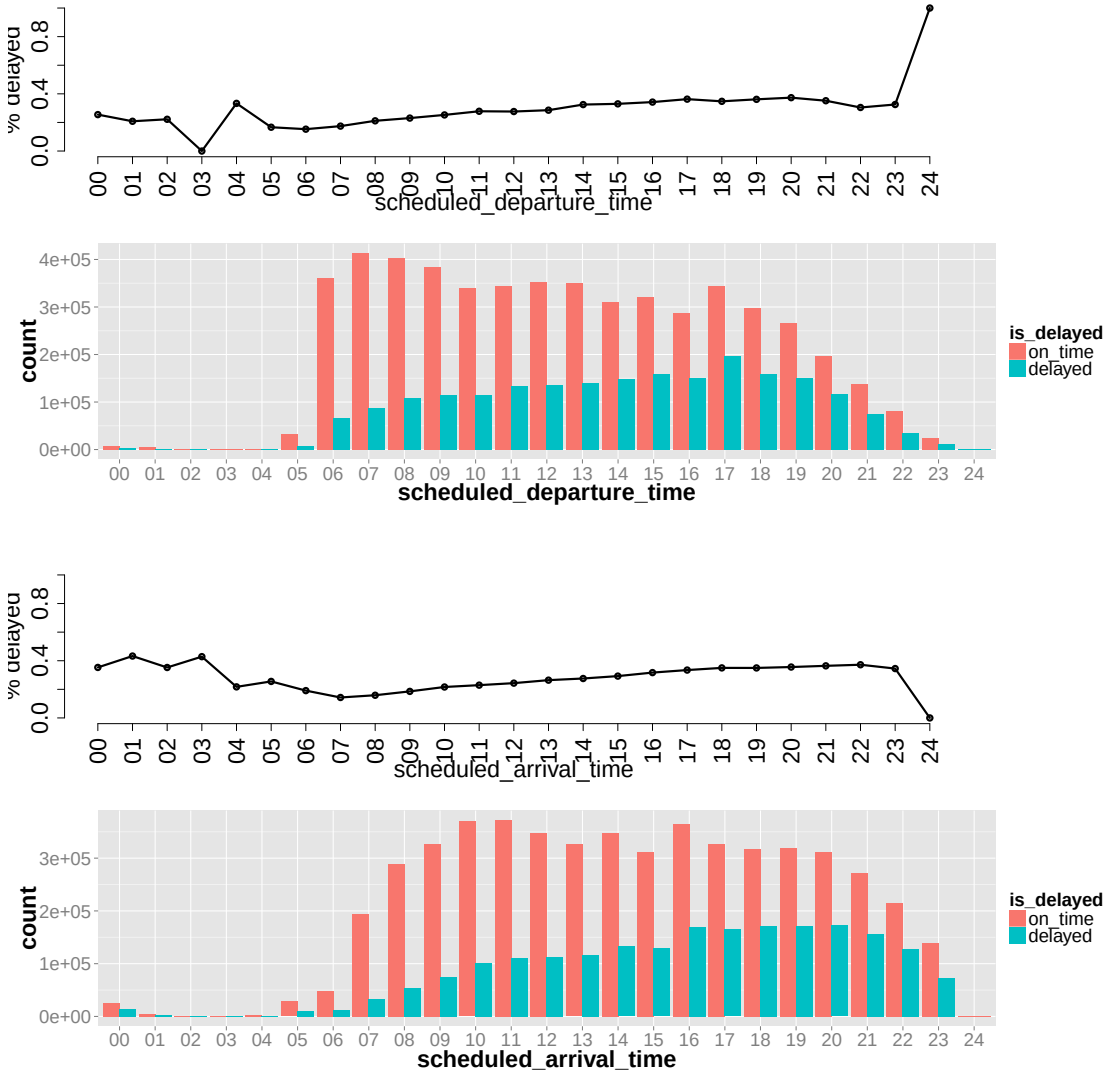
Since I want to predict whether a flight is delayed or not I create a specific variable `is_delayed` based on `departure_delay` using the definition that only positive delay and non-cancelled flights count as "delayed":

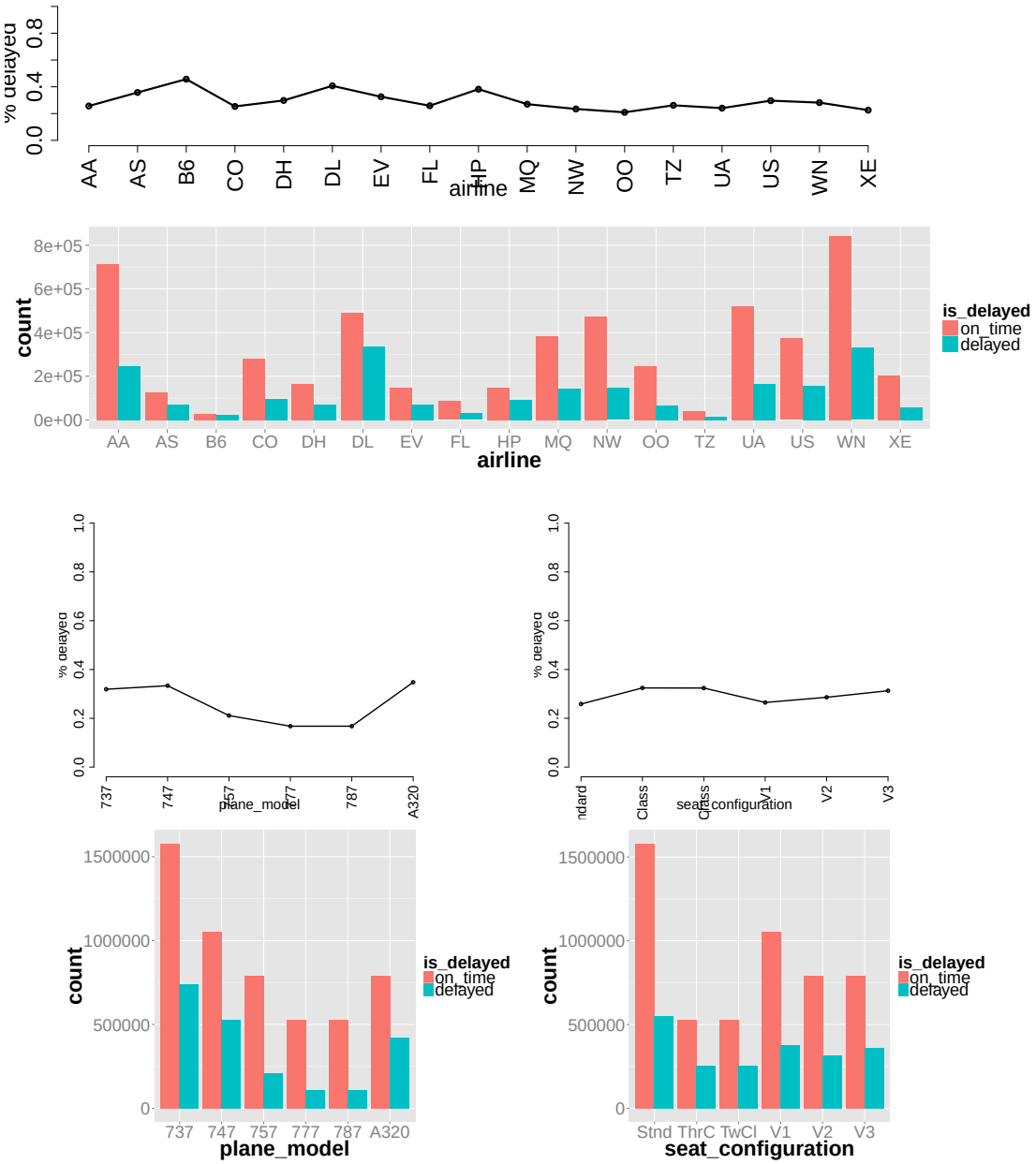
```
trainDataTyped$is_delayed <- factor(trainDataTyped$departure_delay > 0
                                    & trainDataTyped$cancelled==FALSE,
                                    labels= c("on_time", "delayed"))
summary(trainDataTyped$is_delayed)

## on_time delayed
## 5263866 2110499

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

##  on_time  delayed
## 0.713806 0.286194
```

Plot the data:

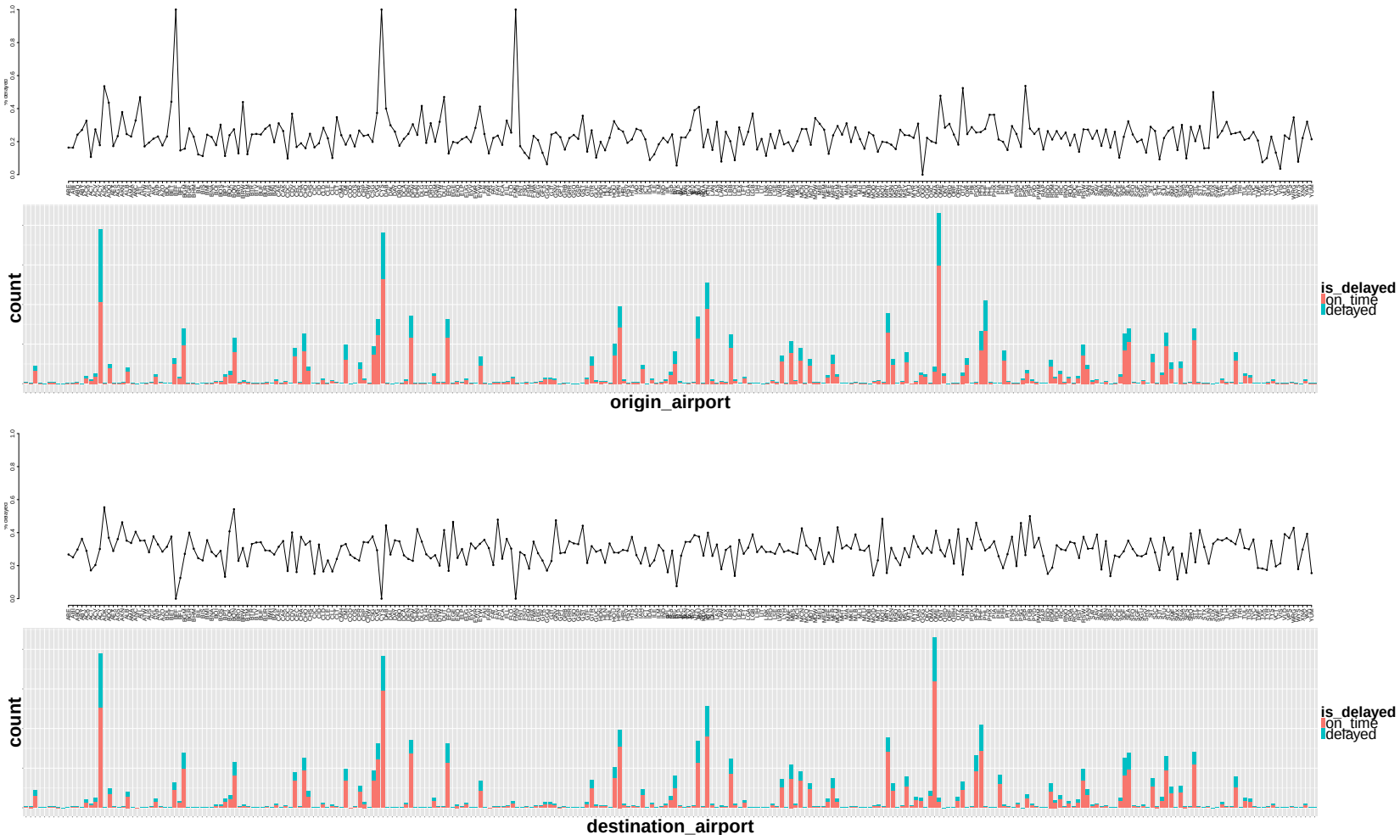


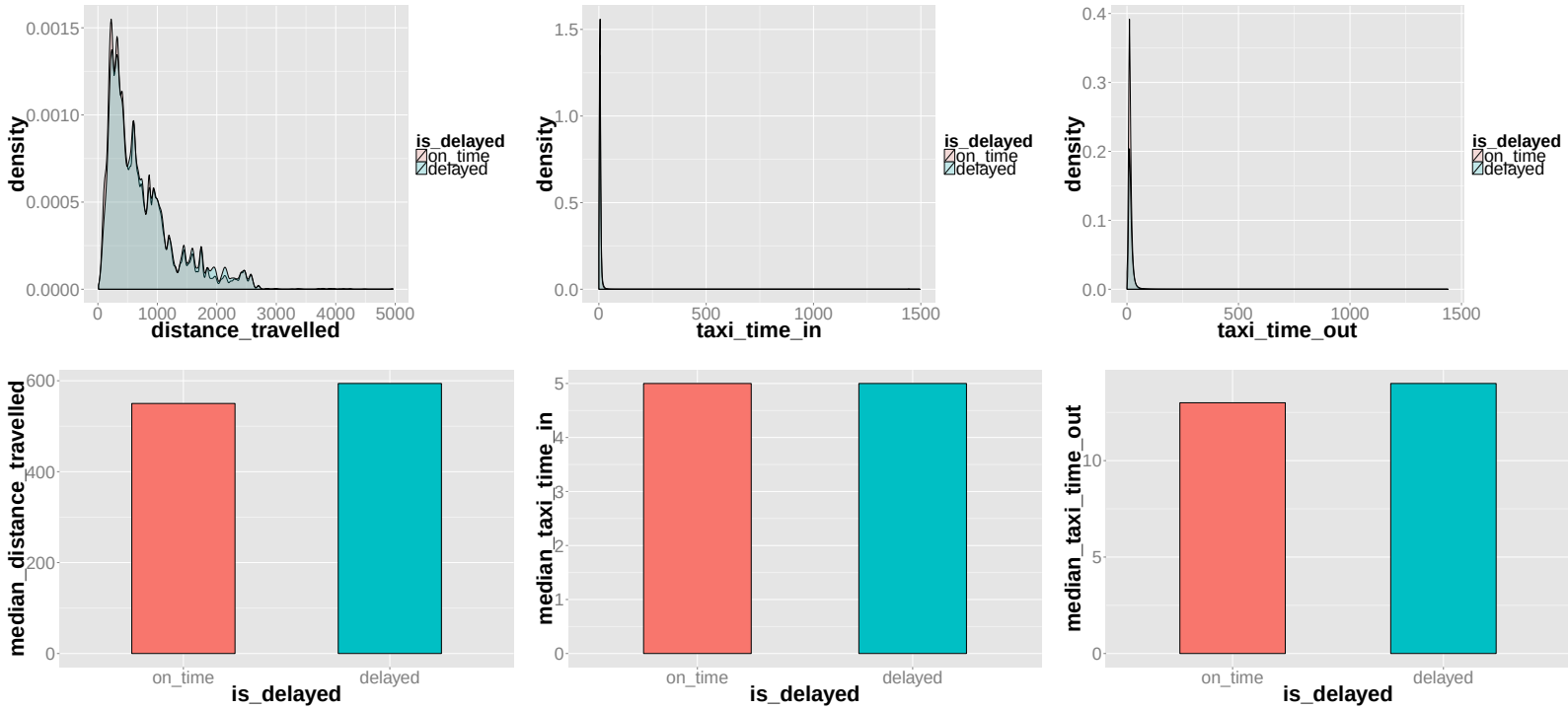

count
8e+05
6e+05
4e+05
2e+05
0e+00
1 2 3 4 5 6 7
day_of_week
is_delayed
on_time
delayed
150000
100000
50000
0
day_of_month


% delayed
0.0 0.4 0.8
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
scheduled_departure_time
count
4e+05
3e+05
2e+05
1e+05
0e+00
is_delayed
on_time
delayed
scheduled_departure_time
% delayed
0.0 0.4 0.8
scheduled_arrival_time
count
3e+05
2e+05
1e+05
0e+00
is_delayed
on_time
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
origin_airport
is_delayed
on_time
delayed
% delayed
count
destination_airport
is_delayed
on_time
delayed


density
distance_travelled
0.0015
0.0010
0.0005
0.0000
0
1000
2000
3000
4000
5000
is_delayed
on_time
delayed
density
taxi_time_in
1.5
1.0
0.5
0.0
0
500
1000
1500
is_delayed
on_time
delayed
density
taxi_time_out
0.4
0.3
0.2
0.1
0.0
0
500
1000
1500
is_delayed
on_time
delayed
median_distance_travelled
600
400
200
0
on_time
delayed
is_delayed
median_taxi_time_in
5
4
3
2
1
0
on_time
delayed
is_delayed
median_taxi_time_out
10
5
0
on_time
delayed
is_delayed

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):

```
dependent_with_target

##               year              month        day_of_week            airline
##               TRUE               TRUE               TRUE               TRUE
##        plane_model seat_configuration  cancellation_code
##               TRUE               TRUE              FALSE
```