SmartFly: Exploratory Analysis For Scheduled Flight Data

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Assuming that scheduled flight data and historic flight data have the same variables, I load these variable names and types of historic data (prepared in an additional csv file):

```
nameTypeDataFile  <- "../01_exploratory_data_analysis/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 scheduled data into R. As I did for the historic data I set empty strings to `NA` (here because of variable `tail_number`).

```
scheduledDataFile <- "../../data/smartfly_scheduled.csv"
predictDataTyped <- read.csv(scheduledDataFile, header=FALSE, stringsAsFactors=FALSE,
                             col.names=variableNames$name, colClasses=variableNames$type,
                             na.strings=c("NA",""))
```

Checkout data content:

```r
str(predictDataTyped)

## 'data.frame': 566376 obs. of  20 variables:
##  $ id                       : chr  "4972683369271453960" "4755622236989466036" "1092083446069765248" "
##  $ year                     : Factor w/ 1 level "2015": 1 1 1 1 1 1 1 1 1 1 ...
##  $ month                    : Factor w/ 1 level "1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ day_of_month             : Factor w/ 31 levels "1","10","11",..: 4 5 6 7 8 9 11 13 14 15 ...
##  $ day_of_week              : Factor w/ 7 levels "1","2","3","4",..: 1 2 3 4 5 6 1 2 3 4 ...
##  $ scheduled_departure_time: Factor w/ 1086 levels "0","10","100",..: 877 877 877 877 877 877 877 87
##  $ scheduled_arrival_time  : Factor w/ 1250 levels "1","10","100",..: 1206 1206 1206 1206 1206 1206 1
##  $ airline                  : Factor w/ 19 levels "AA","AS","B6",..: 16 16 16 16 16 16 16 16 16 16 ..
##  $ flight_number            : Factor w/ 7321 levels "1","10","100",..: 3913 3913 3913 3913 3913 3913 3
##  $ tail_number              : Factor w/ 4687 levels "0","N050AA","N051AA",..: 3904 4092 1887 3998 4013
##  $ plane_model              : Factor w/ 6 levels "737","747","757",..: 2 2 1 3 5 6 2 3 3 2 ...
##  $ seat_configuration       : Factor w/ 6 levels "Standard","Three Class",..: 6 2 4 4 2 4 4 4 6 4 ...
##  $ departure_delay          : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ origin_airport           : Factor w/ 274 levels "ABE","ABI","ABQ",..: 196 196 196 196 196 196 196 1
##  $ destination_airport      : Factor w/ 274 levels "ABE","ABI","ABQ",..: 60 60 60 60 60 60 60 60 60 60
##  $ distance_travelled       : num  599 599 599 599 599 599 599 599 599 599 ...
##  $ taxi_time_in             : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ taxi_time_out            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ cancelled                : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ cancellation_code        : Factor w/ 0 levels: NA NA NA NA NA NA NA NA NA NA ...
```

As I did for the historic data the variables `scheduled_departure_time` and `scheduled_arrival_time` are first reformatted and then truncated to the hour.

```r
dep_time_number <- as.numeric(as.character(predictDataTyped$scheduled_departure_time))
predictDataTyped$scheduled_departure_time <- as.factor(sprintf("%04i", dep_time_number))

arr_time_number <- as.numeric(as.character(predictDataTyped$scheduled_arrival_time))
predictDataTyped$scheduled_arrival_time <- as.factor(sprintf("%04i", arr_time_number))

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

# remainin levels are:
levels(predictDataTyped$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"

levels(predictDataTyped$scheduled_arrival_time)

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

I also again reformat the variables `day_of_month` and `month`:

```
predictDataTyped$month <- as.factor(
  sprintf("%02i", as.numeric(as.character(predictDataTyped$month))))
predictDataTyped$day_of_month <- as.factor(
  sprintf("%02i", as.numeric(as.character(predictDataTyped$day_of_month))))
```

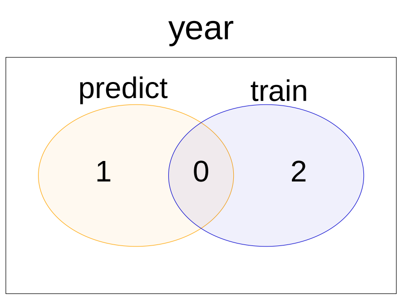
Comparing factor levels of training and prediction data is important because if I train a model on data with levels that don't exist in the prediction data the prediction phase might fail.

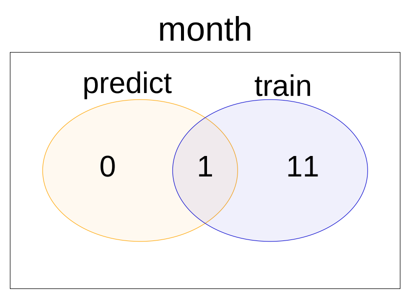
Find levels that exist in the historic fligh data set but are missing in the scheduled flight data set:

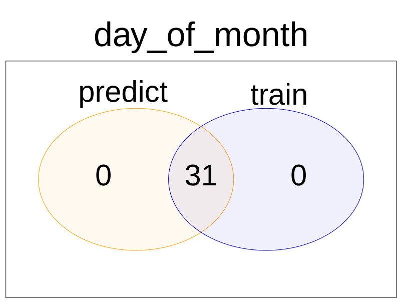
```
pMissingLevels <- lapply(factorNames,
                         FUN=function(list1, list2, x) { setdiff(list1[[x]], list2[[x]]) },
                         list1=tFactorLevels, list2=pFactorLevels)
names(pMissingLevels) <- factorNames
```

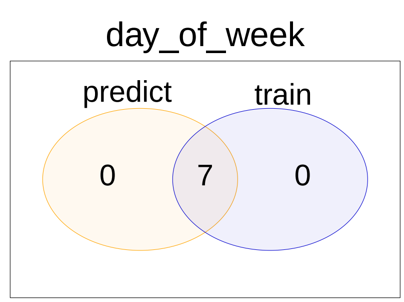
Find levels that don't exist in the historic fligh data set but do exist in the scheduled flight data set:

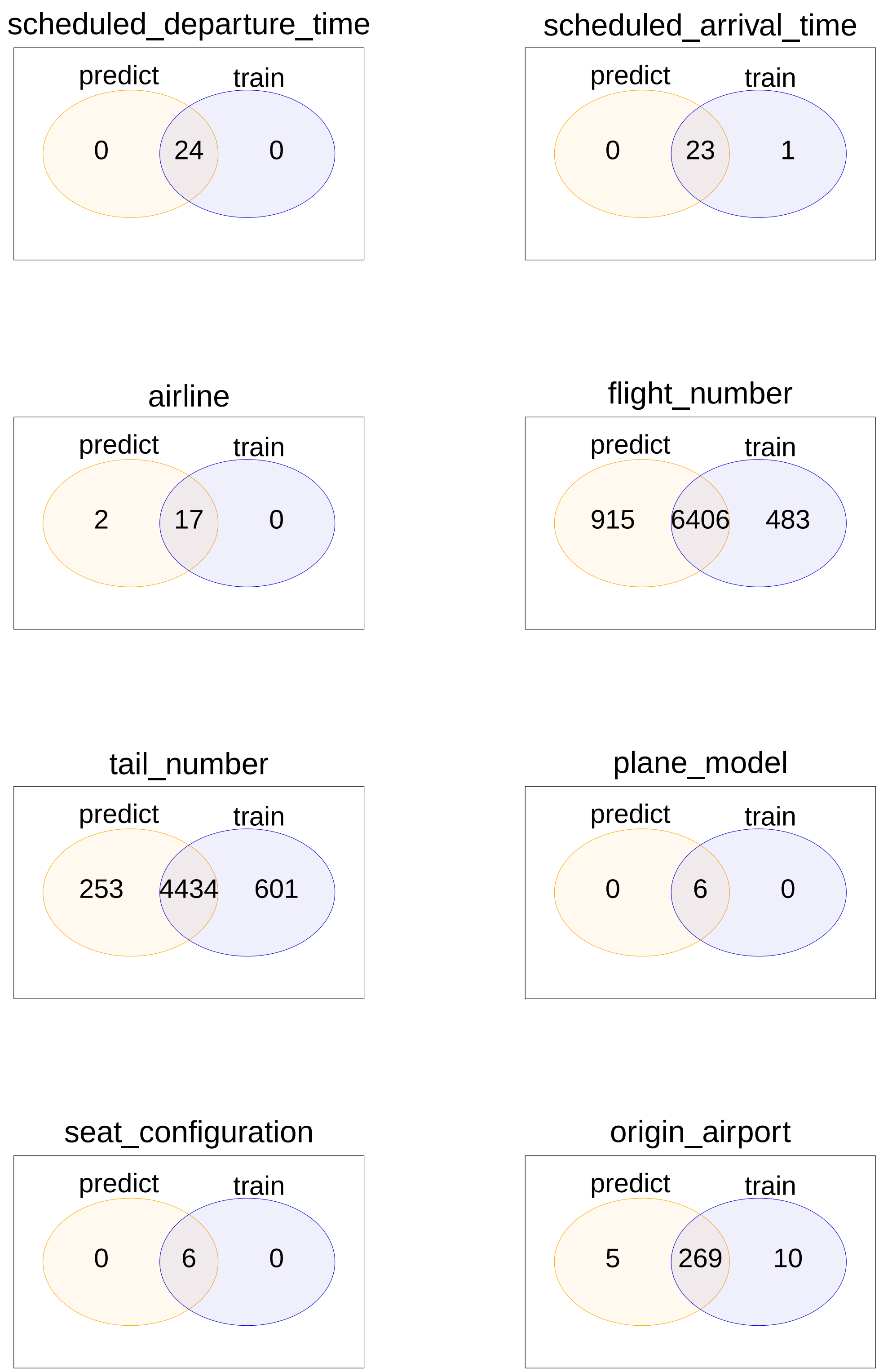
```
tMissingLevels <- lapply(factorNames,
                         FUN=function(list1, list2, x) { setdiff(list1[[x]], list2[[x]]) },
                         list1=pFactorLevels, list2=tFactorLevels)
names(tMissingLevels) <- factorNames
```

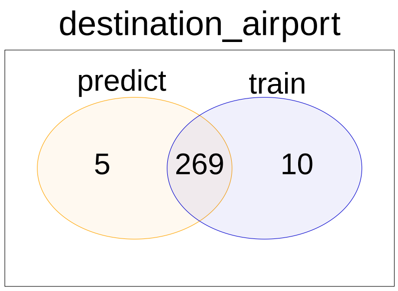


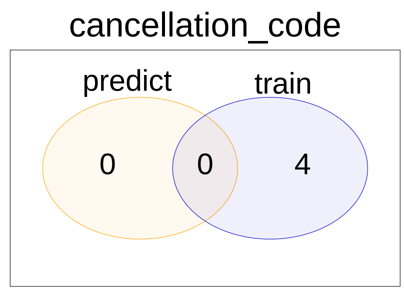







scheduled_departure_time
predict
train
0
24
0
scheduled_arrival_time
predict
train
0
23
1
airline
predict
train
2
17
0
flight_number
predict
train
915
6406
483
tail_number
predict
train
253
4434
601
plane_model
predict
train
0
6
0
seat_configuration
predict
train
0
6
0
origin_airport
predict
train
5
269
10






```
##                    year                    month             day_of_month
##                       2                       12                       31
##             day_of_week scheduled_departure_time   scheduled_arrival_time
##                       7                       24                       24
##                 airline            flight_number              tail_number
##                      17                     6889                     5035
##             plane_model       seat_configuration           origin_airport
##                       6                        6                      279
##     destination_airport        cancellation_code
##                     279                        4
## [1] "year"                    "month"                 "scheduled_arrival_time"
## [4] "airline"                 "origin_airport"        "destination_airport"
## [7] "cancellation_code"
## $year
##      onlyInPredict onlyInTrain
## [1,] "2015"        "2013"
## [2,] NA            "2014"
##
## $month
##       onlyInPredict onlyInTrain
##  [1,] NA            "02"
##  [2,] NA            "03"
##  [3,] NA            "04"
##  [4,] NA            "05"
##  [5,] NA            "06"
##  [6,] NA            "07"
##  [7,] NA            "08"
##  [8,] NA            "09"
##  [9,] NA            "10"
## [10,] NA            "11"
## [11,] NA            "12"
##
## $scheduled_arrival_time
##      onlyInPredict onlyInTrain
## [1,] NA            "03"
##
## $airline
```

```
##      onlyInPredict onlyInTrain
## [1,] "HA"          NA
## [2,] "OH"          NA
##
## $origin_airport
##       onlyInPredict onlyInTrain
##  [1,] "CKB"         "ACK"
##  [2,] "ERI"         "BFF"
##  [3,] "ITO"         "CYS"
##  [4,] "LNY"         "FMN"
##  [5,] "MKK"         "GST"
##  [6,] NA            "LWB"
##  [7,] NA            "OGD"
##  [8,] NA            "ORH"
##  [9,] NA            "SUX"
## [10,] NA            "WYS"
##
## $destination_airport
##       onlyInPredict onlyInTrain
##  [1,] "CKB"         "ACK"
##  [2,] "ERI"         "BFF"
##  [3,] "ITO"         "CYS"
##  [4,] "LNY"         "FMN"
##  [5,] "MKK"         "GST"
##  [6,] NA            "LWB"
##  [7,] NA            "ORH"
##  [8,] NA            "PUB"
##  [9,] NA            "SUX"
## [10,] NA            "WYS"
##
## $cancellation_code
##      onlyInPredict onlyInTrain
## [1,] NA            "A"
## [2,] NA            "B"
## [3,] NA            "C"
## [4,] NA            "D"
```

See summary of descriptive statistics of the scheduled data:

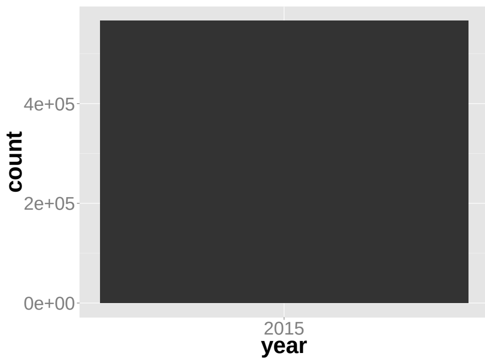
```r
summary(predictDataTyped)
```

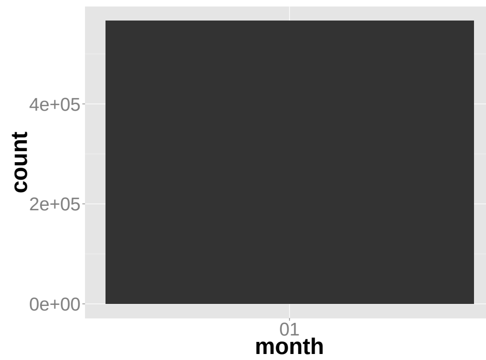
```
##       id                year          month         day_of_month    day_of_week
##  Length:566376      2015:566376   01:566376   22     : 19395   1:75237
##  Class :character                             19     : 19347   2:73819
##  Mode  :character                             16     : 19286   3:74482
##                                               30     : 19268   4:93432
##                                               12     : 19210   5:95177
##                                               05     : 19206   6:82832
##                                               (Other):450664   7:71397
##  scheduled_departure_time scheduled_arrival_time    airline       flight_number
##  17     : 41179           16     : 41124          WN     : 79417   524    :   440
##  08     : 40947           19     : 39394          AA     : 58593   186    :   439
##  09     : 38285           14     : 37482          DL     : 55480   238    :   439
##  13     : 37904           10     : 37170          UA     : 44792   273    :   437
##  15     : 37474           12     : 36938          NW     : 40149   417    :   428
##  11     : 37030           18     : 36871          MQ     : 35795   217    :   416
##  (Other):333557           (Other):337397          (Other):252150   (Other):563777
##   tail_number     plane_model     seat_configuration departure_delay  origin_airport
##  N478HA :   339   737 :179931   Standard    :162109   Min.   : NA      ATL    : 33615
##  N481HA :   339   747 :123049   Three Class: 60695    1st Qu.: NA      ORD    : 30168
##  N484HA :   334   757 : 75092   Two Class  : 60174    Median : NA      DFW    : 28801
##  N183UW :   314   777 : 46719   V1          :109484   Mean   :NaN      LAX    : 18899
##  N487HA :   310   787 : 46837   V2          : 84879   3rd Qu.: NA      CVG    : 16747
##  N95    :   309   A320: 94748   V3          : 89035   Max.   : NA      IAH    : 16169
##  (Other):564431                                       NA's   :566376   (Other):421977
##  destination_airport distance_travelled  taxi_time_in    taxi_time_out
##  ATL    : 33533      Min.   :  11.0     Min.   : NA      Min.   : NA
##  ORD    : 30063      1st Qu.: 305.0     1st Qu.: NA      1st Qu.: NA
##  DFW    : 28743      Median : 547.0     Median : NA      Median : NA
##  LAX    : 18889      Mean   : 712.9     Mean   :NaN      Mean   :NaN
##  CVG    : 16583      3rd Qu.: 944.0     3rd Qu.: NA      3rd Qu.: NA
##  IAH    : 16148      Max.   :4962.0     Max.   : NA      Max.   : NA
##  (Other):422417                         NA's   :566376   NA's   :566376
##    cancelled       cancellation_code
##  Min.   : NA      NA's:566376
##  1st Qu.: NA
##  Median : NA
##  Mean   :NaN
##  3rd Qu.: NA
##  Max.   : NA
##  NA's   :566376
```

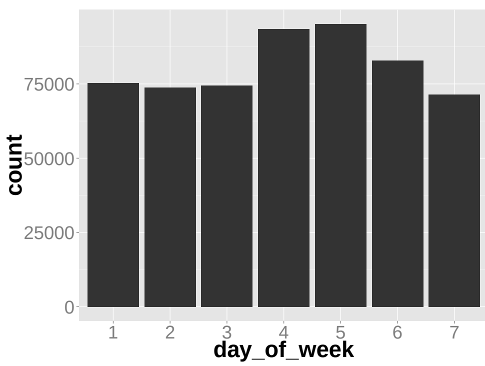
Save data frame for next step:

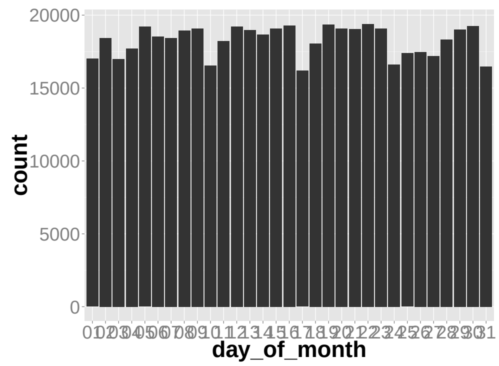
```r
save(predictDataTyped, file="predictDataTyped.RData")
```

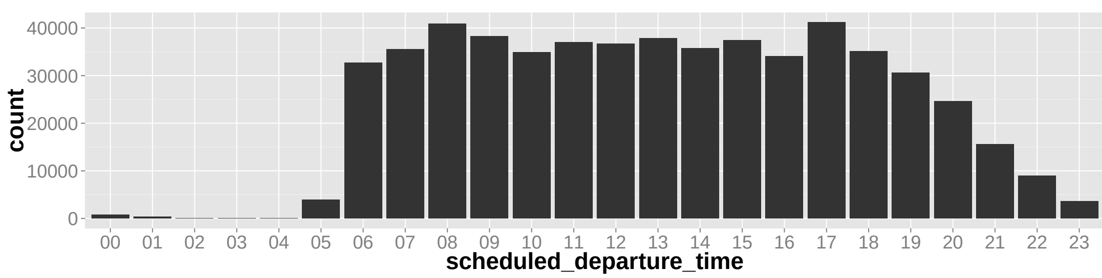
Plot the data independently of delay, cancellation and taxi time (since these variables are not available for prediction):

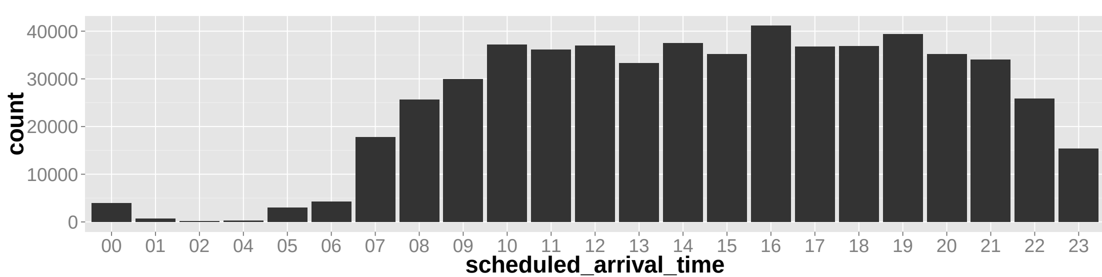

count
4e+05
2e+05
0e+00
2015
year

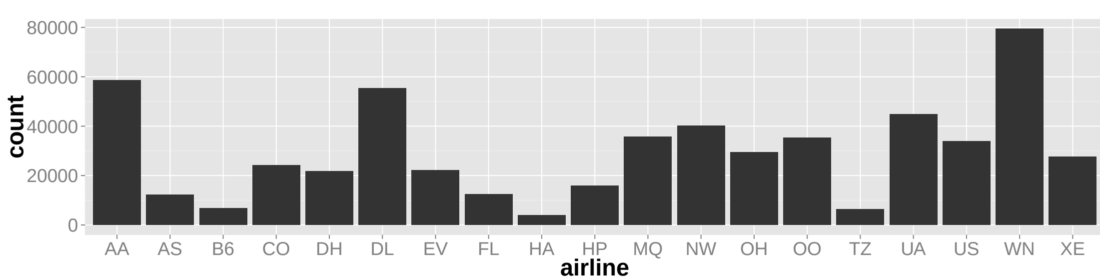

count
4e+05
2e+05
0e+00
01
month

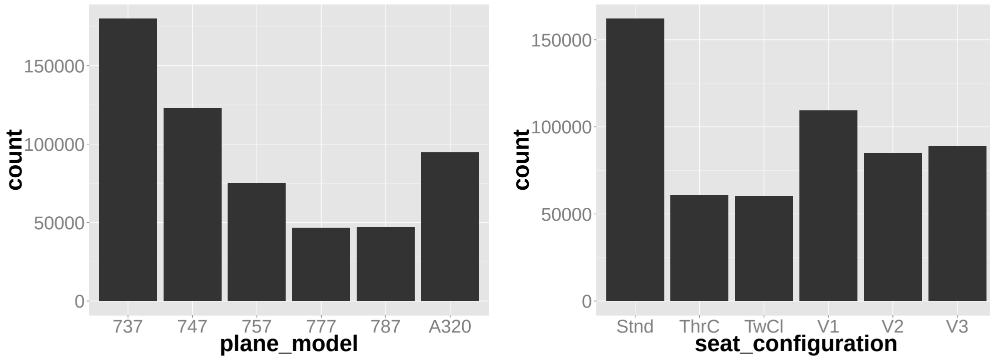

count
75000
50000
25000
0
1 2 3 4 5 6 7
day_of_week


count
20000
15000
10000
5000
0
day_of_month

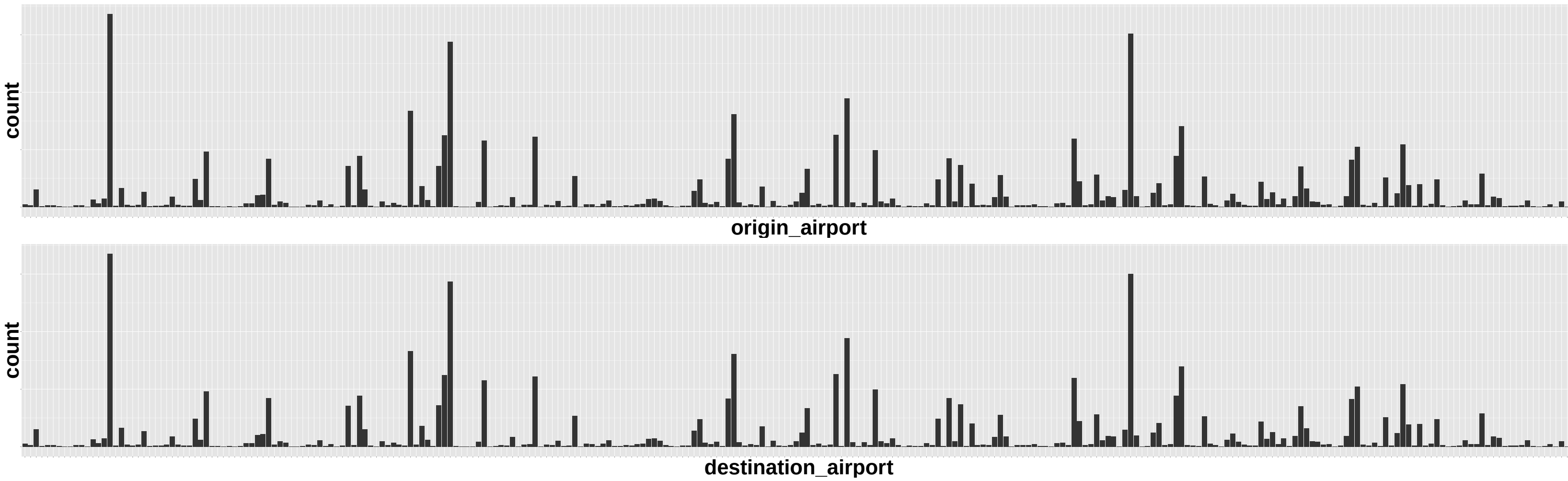

count
40000
30000
20000
10000
0
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23
scheduled_departure_time

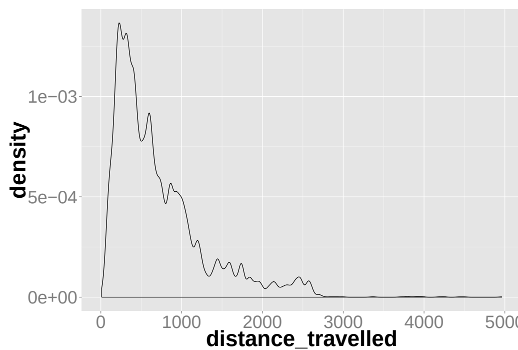

count
40000
30000
20000
10000
0
00 01 02 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23
scheduled_arrival_time


count
80000
60000
40000
20000
0
AA AS B6 CO DH DL EV FL HA HP MQ NW OH 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


density
1e−03
5e−04
0e+00
0
1000
2000
3000
4000
5000
distance_travelled