

```
knitr::opts_chunk$set(fig.show = 'hide',  
  fig.width = 8.4,  
  fig.height = 7,  
  out.width = "8.4in")
```

```
library(data.table)  
library(dplyr)  
  
##  
## Attaching package: 'dplyr'  
##  
## The following objects are masked from 'package:data.table':  
##  
##   between, last  
##  
## The following objects are masked from 'package:stats':  
##  
##   filter, lag  
##  
## The following objects are masked from 'package:base':  
##  
##   intersect, setdiff, setequal, union  
  
library(magrittr)  
library(ggplot2)  
library(nycflights13) # for airports  
library(fasttime)  
library(grattan)  
  
## Loading required package: devEMF  
##  
## Attaching package: 'grattan'  
##  
## The following object is masked from 'package:datasets':  
##  
##   Orange
```

```
pre2008_flights <-  
  rbindlist(lapply(list.files(path = "../flights/1987-2008/",  
    pattern = "csv$",  
    full.names = TRUE), fread))
```

```

pre2008.names <-
  names(pre2008_flights)

read_and_report <-
  function(filename){
    year <- gsub("^.*(2[0-9]{3}).{3,4}csv$", "\\1", filename)
    if(grepl("1.csv", filename, fixed = TRUE))
      cat(year)
    fread(filename, select = pre2008.names, showProgress = FALSE)
  }

gc(1,1)
post2008_flights <-
  rbindlist(lapply(list.files(path = "../flights", recursive = TRUE, pattern = "2[0-9]{3}
                        full.names = TRUE),
                    read_and_report))

flights <- rbindlist(list(pre2008_flights, post2008_flights), use.names = TRUE)
readr::write_csv(flights, path = "../1987-2015-On-Time-Performance.csv")

```

```

Sys.time()

## [1] "2016-01-03 22:33:43 AEDT"

flights <- fread("../1987-2015-On-Time-Performance.csv")

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Read 165931626 rows and 29 (of 29) columns from 15.111 GB file in 00:04:16

# flights <- readRDS("../1987-2015-On-Time-Performance.rds")

```

```

sample.frac = 0.1
sample.weight.int = as.integer(round(1/sample.frac))
flights <- flights[sample(.N, .N * sample.frac)]

```

```

# First we want a time for each flight. This is more difficult than it might seem.
# We need to concatenate the Year, Month, and DayofMonth fields, but we also need
# to take into account the various time zones of the airports in the database.
integer.cols <- grep("Time$", names(flights))

```

```
Sys.time()
```

```
## [1] "2016-01-03 22:38:20 AEDT"
```

```

for (j in integer.cols){
  set(flights, j = j, value = as.integer(flights[[j]]))
}
Sys.time()

```

```
## [1] "2016-01-03 22:38:20 AEDT"
```

```
# See stackoverflow: links and comments under my question
```

```

create_DepDateTime <- function(DT){
  setkey(DT, Year, Month, DayofMonth, DepTime)
  unique_dates <- unique(DT[,list(Year, Month, DayofMonth, DepTime)])
  unique_dates[,DepDateTime := fastPOSIXct(sprintf("%d-%02d-%02d %s", Year, Month, DayofMonth,
                                                    sub("([0-9]{2})([0-9]{2})", "\\1:\\2:00",
                                                    perl = TRUE)),
                                           tz = "GMT")]

  DT[unique_dates]
}

```

```

create_ArrDateTime <- function(DT){
  setkey(DT, Year, Month, DayofMonth, ArrTime)
  unique_dates <- unique(DT[,list(Year, Month, DayofMonth, ArrTime)])
  unique_dates[,ArrDateTime := fastPOSIXct(sprintf("%d-%02d-%02d %s", Year, Month, DayofMonth,
                                                    sub("([0-9]{2})([0-9]{2})", "\\1:\\2:00",
                                                    perl = TRUE)),
                                                    tz = "GMT")]

  DT[unique_dates]
}
flights <- create_DepDateTime(flights)
flights <- create_ArrDateTime(flights)
#flights[,`:=`(Year = NULL, Month = NULL, DayofMonth = NULL, DepTime = NULL, ArrTime = NULL)]
Sys.time()

## [1] "2016-01-03 22:39:37 AEDT"

```

```

# Now we join it to the airports dataset from nycflights13 to obtain time zone information
Sys.time()

## [1] "2016-01-03 22:39:37 AEDT"

airports <- as.data.table(airports)
airports <- airports[,list(faa, tz)]
gc(1,1)

##           used      (Mb) gc trigger      (Mb) max used      (Mb)
## Ncells    533293    28.5   7974897    426.0    533293    28.5
## Vcells 324371914 2474.8   973788657 7429.5 324371914 2474.8

setnames(airports, old = c("faa", "tz"), new = c("Origin", "tzOrigin"))
setkey(airports, Origin)
setkey(flights, Origin)
flights <- flights[airports]
setnames(airports, old = c("Origin", "tzOrigin"), new = c("Dest", "tzDest"))
setkey(flights, Dest)
flights <- flights[airports]
rm(airports)
gc(1,1)

##           used      (Mb) gc trigger      (Mb) max used      (Mb)
## Ncells    533306    28.5   5103933    272.6    533306    28.5
## Vcells 354325754 2703.3   973788657 7429.5 354325754 2703.3

```



```

# The joins produce NAs when the airports table isn't present in the flights table.
flights <- flights[!is.na(Origin)]
gc(1,1)

##           used      (Mb) gc trigger      (Mb)  max used      (Mb)
## Ncells    533321    28.5   4083146    218.1    533321    28.5
## Vcells 354303746 2703.2  973788657 7429.5 354303746 2703.2

Sys.time()

## [1] "2016-01-03 22:39:56 AEDT"

```

```

Sys.time()

## [1] "2016-01-03 22:39:56 AEDT"

setkey(flights, DepDateTime)
flights[, `:=` (DepDateTimeZulu = DepDateTime - lubridate::hours(tzOrigin),
               ArrDateTimeZulu = ArrDateTime - lubridate::hours(tzDest) )]
Sys.time()

## [1] "2016-01-03 22:41:52 AEDT"

```

```

# Flights typically follow a weekly cycle, so we should obtain the week in the dataset.
# Pretty quick!
Sys.time()

## [1] "2016-01-03 22:41:52 AEDT"

setkey(flights, Year, Month, DayofMonth)
unique_dates <- unique(flights)
unique_dates <- unique_dates[, list(Year, Month, DayofMonth)]
unique_dates[, Week := (Year - 1987L) * 52 + data.table::yday(sprintf("%d-%02d-%02d", Year,
unique_dates[, Week := Week - min(Week)]
flights <- flights[unique_dates]
Sys.time()

## [1] "2016-01-03 22:41:57 AEDT"

```

# **Flights 1987-2015**

Hugh P

January 3, 2016

# 1

There were 164 million flights from 1987-10-01 05:00:00 to 2015-11-01 09:43:00.

## 2 San Francisco

```
SanFran_flights <-  
  flights %>%  
  filter(Origin %in% c("SFO", "OAK") | Dest %in% c("SFO", "OAK"))
```

```
SanFran_flights %>%  
  filter(!(Origin %in% c("SFO", "OAK") & Dest %in% c("SFO", "OAK"))) %>%  
  mutate(SF_airport = ifelse(Origin %in% c("SFO", "OAK"),  
                             Origin,  
                             Dest)) %>%  
  count(Week, SF_airport) %>%  
  mutate(Date = Week,  
         n = n) %>% # sample  
  ggplot(aes(x = Date, y = n, color = SF_airport, group = SF_airport)) +  
  geom_line()  
  stat_smooth(n = 10000, span = 0.01, se = TRUE)
```

```
carriers <- as.data.table(airlines)  
if("carrier" %in% names(carriers))  
  setnames(carriers, old = "carrier", new = "UniqueCarrier")  
  
setkey(carriers, UniqueCarrier)  
set(carriers, j = 1L, value = as.character(carriers[[1L]]))  
set(carriers, j = 2L, value = gsub("^([A-Za-z]+)\\s.*$", "\\1", carriers[[2L]]))  
  
SanFran_flights %>%  
  filter(Origin %in% c("SFO", "OAK")) %>%  
  count(Year, Month, Origin, UniqueCarrier) %>%  
  group_by(UniqueCarrier) %>%  
  filter(sum(n) > (2015 - 1987) * 12 * 30) %>%  
  mutate(Date = Year + (Month - 1)/12) %>%  
  setkey(UniqueCarrier) %>%  
  merge(carriers) %>%  
  ggplot(aes(x = Date, y = n * sample.weight.int, color = name, group = interaction(name,  
  geom_smooth(span = 0.25, se = FALSE) +
```

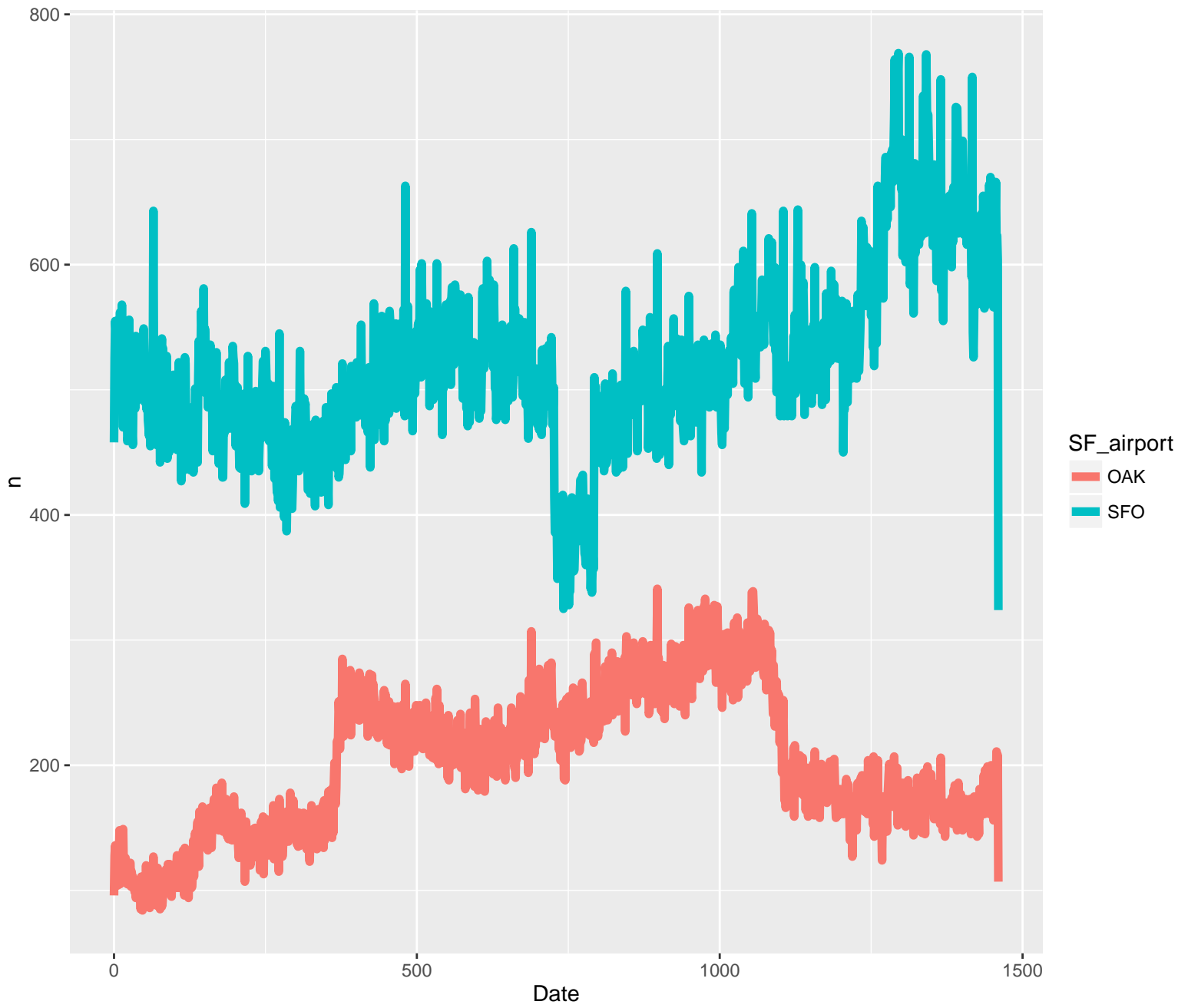


Figure 2.1: Number of depatures over time from Oakland and San Francisco Intl.

```

geom_text(aes(label = ifelse(Date == max(Date),
                             name,
                             NA_character_),
              vjust = ifelse(name == "Southwest" & Origin == "SFO",
                             -0.5,
                             0.5)),
          nudge_x = 0.75,
          size = 5) + theme(legend.position = "none") +
annotate("blank", x = 2019, y = 0) +
facet_grid(Origin ~ .) +
theme(text = element_text(size = 16))

## Warning: Removed 3926 rows containing missing values (geom_text).

```

After September 11, flights from SFO fell, whereas OAK's volume did not. Flights fell more in SFO than they did in OAK because most of OAK's flights are from Southwest, which did not change its flight patterns. Furthermore, United was affected more than most airlines from the aftermath of the attacks.

```

flights %>%
  count(Year)

## Source: local data table [29 x 2]
##
##   Year      n
##   (int) (int)
## 1  1987 129860
## 2  1988 516321
## 3  1989 498605
## 4  1990 521873
## 5  1991 502872
## 6  1992 503344
## 7  1993 501444
## 8  1994 513989
## 9  1995 528486
## 10 1996 530212
## .. ...

```

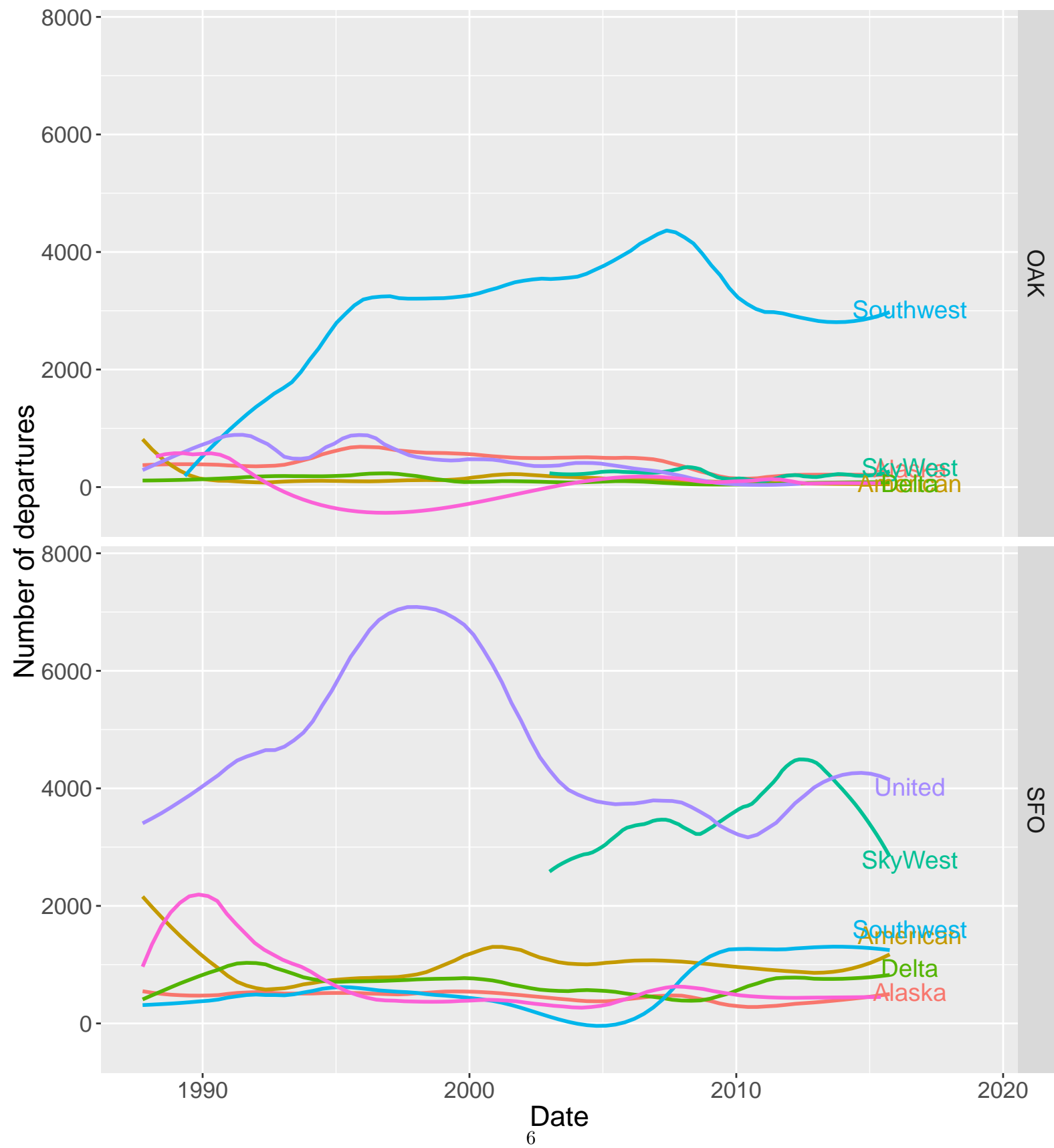


Figure 2.2: Number of depatures over time from Oakland and San Francisco Intl.