

Playing with domestic airline performance data

Kirill

September 04, 2019

Introduction

I found this rather interesting data set at data.gov.au, Domestic Airlines - On Time Performance and I decided to investigate it a bit closer.

First thing first is to download it. Note that `read_csv` from `readr` package can “read” directly from url, but I wasn’t sure if everytime I compile html it would re-download the file or use chached version. The data is *Creative Commons Attribution 3.0 Australia* and so no problem in downloading and using the data.

Loading libraries

We are going to use

```
library(tidyverse)
library(knitr)
```

Downloading the data

We are going to use `tidyverse` library that includes several other useful libraries, such as:

- `readr`
- `tidyr`
- `dplyr`
- `ggplot2`

to name a few

Note that we are doing conditional download here, obviously don’t want to re-download if we already have the file.

```
fn_data <- "domestic_airline_performance.csv"
fn_notes <- "domestic_airline_performance_notes.txt"
if(!file.exists(fn_data)) {
  url_data <- "https://data.gov.au/data/dataset/29128ebd-dbaa-4ff5-8b86-d9f30de56452/resource/cf663ed1-
  url_notes <- "https://data.gov.au/data/dataset/29128ebd-dbaa-4ff5-8b86-d9f30de56452/resource/69e214b9-
  download.file(url_data, fn_data)
  download.file(url_notes, fn_notes)
}
df <- read_csv(fn_data, quote = "")
df
```

```
## # A tibble: 80,615 x 14
```

```
##   Route Departing_Port Arriving_Port Airline Month Sectors_Schedul~
##   <chr> <chr>          <chr>      <chr>   <dbl>          <dbl>
## 1 Adel~ Adelaide      Brisbane All Ai~ 37987          155
## 2 Adel~ Adelaide      Canberra All Ai~ 37987           75
## 3 Adel~ Adelaide      Gold Coast All Ai~ 37987           40
## 4 Adel~ Adelaide      Melbourne All Ai~ 37987          550
## 5 Adel~ Adelaide      Perth    All Ai~ 37987          191
```

```
## 6 Adel~ Adelaide Sydney All Ai~ 37987 486
## 7 Albu~ Albury Sydney All Ai~ 37987 168
## 8 Alic~ Alice Springs Sydney All Ai~ 37987 63
## 9 All ~ All Ports All Ports All Ai~ 37987 31913
## 10 Bris~ Brisbane Adelaide All Ai~ 37987 155
## # ... with 80,605 more rows, and 8 more variables: Sectors_Flown <dbl>,
## # Cancellations <dbl>, Departures_On_Time <dbl>, Arrivals_On_Time <dbl>,
## # Departures_Delayed <dbl>, Arrivals_Delayed <dbl>, Year <dbl>,
## # Month_Num <dbl>
```

Exploring the data

Now that we've got the data lets explore it. It always helps if we can find more information about the data set, particular what information each column might have.

Working with data

Great, the information above gives us some starting material. However it wasn't that explicit what each column meant and how man columns are there. Let's quickly take a pick

```
d <- df %>% dim
```

total number of observation 80615 and total number of variables 14

There are many ways you can explore this data, but i just want to have a look at the types of Airlines there are.

```
df %>%
  select(Airline) %>%
  distinct() %>%
  arrange(Airline)
```

```
## # A tibble: 13 x 1
##   Airline
##   <chr>
## 1 All Airlines
## 2 Jetstar
## 3 Macair
## 4 MacAir
## 5 Ozjet
## 6 Qantas
## 7 QantasLink
## 8 Regional Express
## 9 Skywest
## 10 Tigerair Australia
## 11 Virgin Australia
## 12 Virgin Australia - ATR/F100 Operations
## 13 Virgin Australia Regional Airlines
```

Cleaning up

I've noticed that there "All Airlines" name in the Airline column that appears to have the most number of occurrences in the data

```
df %>%
  group_by(Airline) %>%
  summarise(n = n()) %>%
  arrange(-n)
```

```
## # A tibble: 13 x 2
##   Airline      n
##   <chr>    <int>
## 1 All Airlines 21010
## 2 Virgin Australia 18252
## 3 Jetstar    11294
## 4 Qantas     11107
## 5 QantasLink  9622
## 6 Tigerair Australia 3982
## 7 Regional Express 2599
## 8 Virgin Australia Regional Airlines 1655
## 9 Skywest    752
## 10 Virgin Australia - ATR/F100 Operations 290
## 11 Macair    40
## 12 Ozjet     9
## 13 MacAir    3
```

Also there one of the routes is All Ports-All Ports. Googling for that name didn't reveal any places in Australia by that name.

```
df %>%
  group_by(Route) %>%
  summarise(n = n()) %>%
  arrange(-n)
```

```
## # A tibble: 149 x 2
##   Route      n
##   <chr>    <int>
## 1 All Ports-All Ports 1505
## 2 Cairns-Brisbane    908
## 3 Brisbane-Cairns    907
## 4 Broome-Perth       907
## 5 Perth-Broome       907
## 6 Hobart-Melbourne   900
## 7 Melbourne-Hobart   900
## 8 Adelaide-Sydney    872
## 9 Sydney-Adelaide    872
## 10 Adelaide-Melbourne 871
## # ... with 139 more rows
```

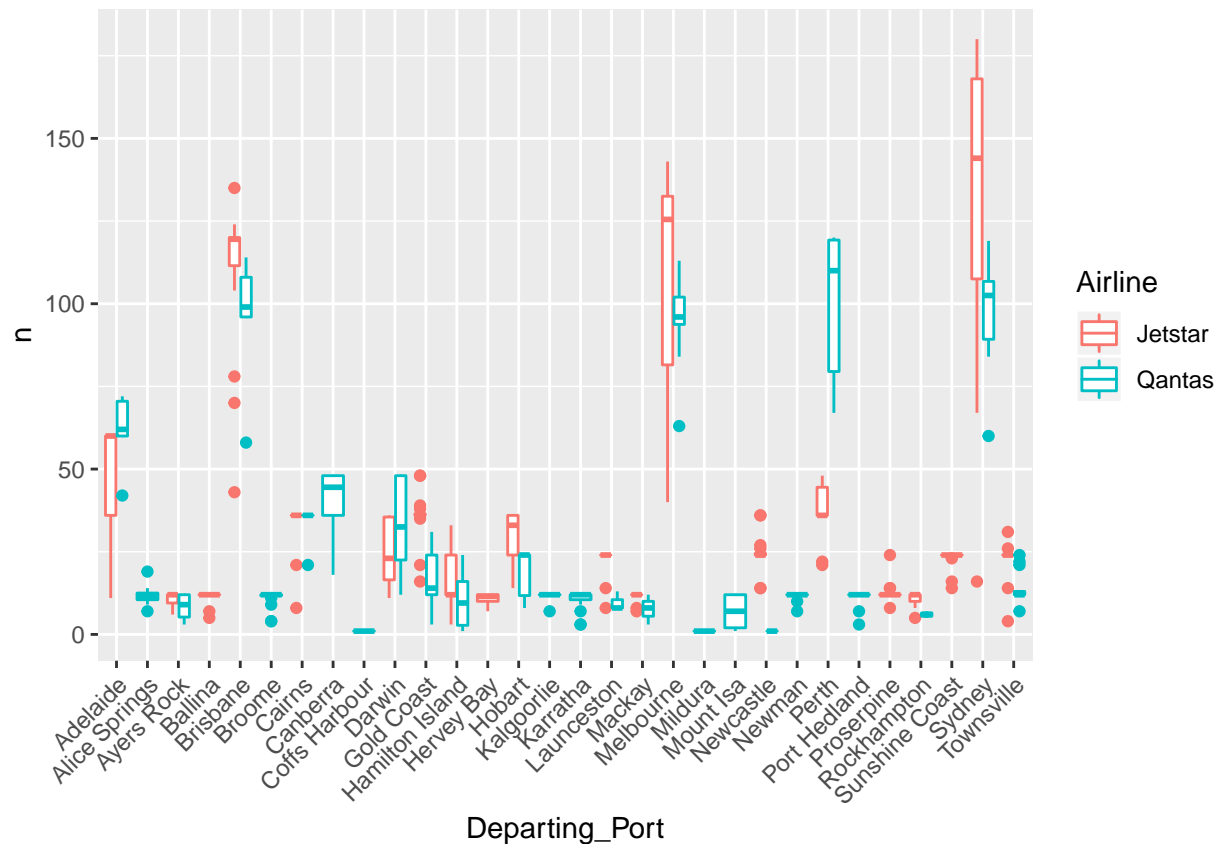
I decide going forward to drop those data points.

```
df2 <- df %>%
  filter(Airline != "All Airlines",
         Route != "All Ports-All Ports")
```

Visualising the data

Here we are summarising so that we have an idea of how many times a particular location had be use per airline per year and we are only going to look at two airlines, Jetstar and Qantas.

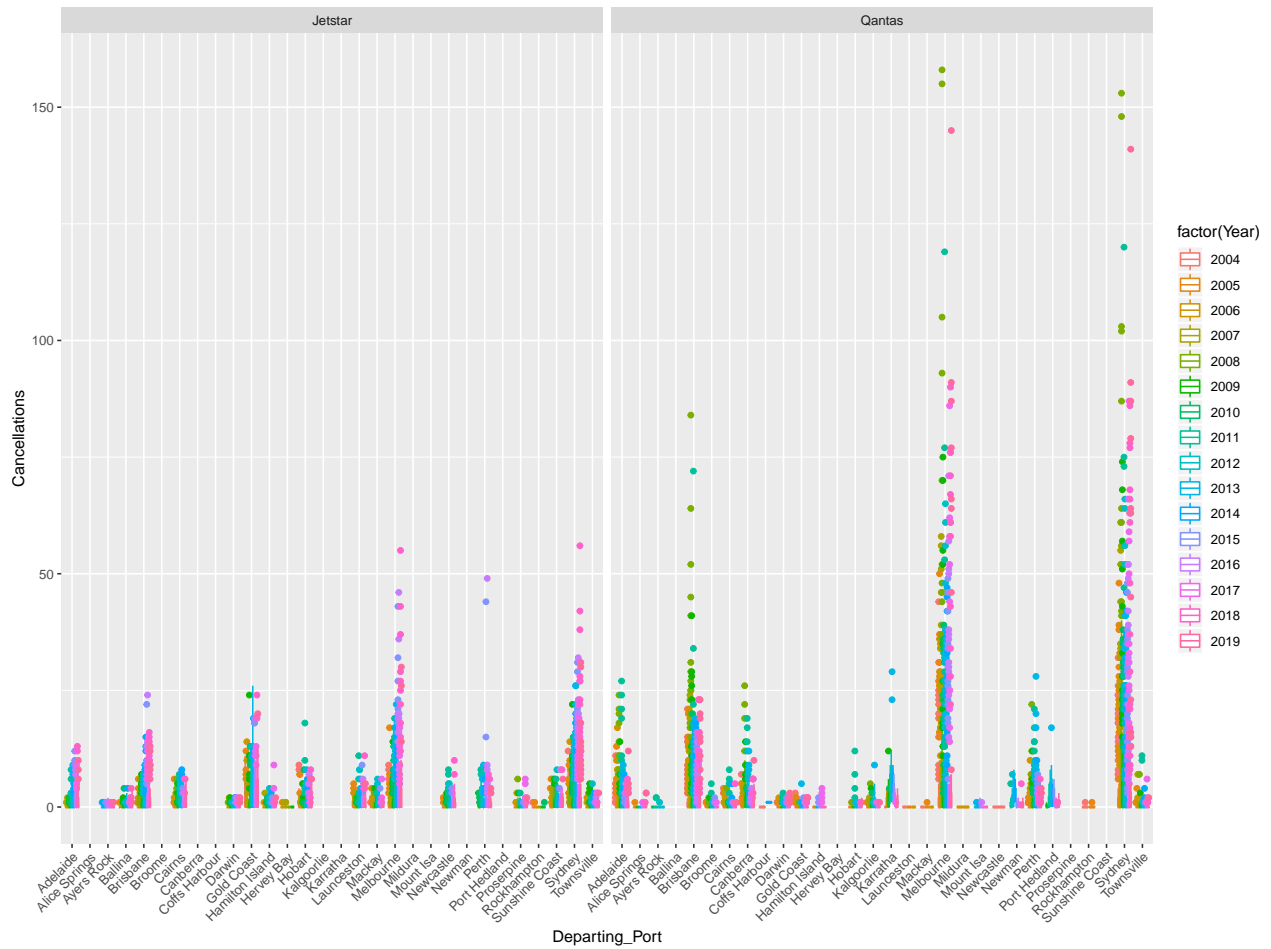
```
p2 <- df2 %>%
  group_by(Airline, Year, Departing_Port) %>%
  summarise(n = n()) %>%
  ungroup %>%
  filter(Airline == "Jetstar" | Airline == "Qantas") %>%
  ggplot(aes(Departing_Port, n, color = Airline)) +
    geom_boxplot() +
    theme(axis.text.x=element_text(angle=45, hjust=1))
p2
```



In any given year what is the distribution of cancellation

```
p3 <- df2 %>%
  filter(Airline == "Jetstar" | Airline == "Qantas") %>%
  select(Airline, Departing_Port, Cancellations, Year) %>%
  ggplot(aes(Departing_Port, Cancellations, color = factor(Year))) +
    geom_boxplot() +
    facet_wrap(~Airline) +
    theme(axis.text.x=element_text(angle= 45, hjust=1))
p3
```

Warning: Removed 219 rows containing non-finite values (stat_boxplot).



References

- themes