ETC5512: Wild Caught Data

Week 10

US flights and databases

Lecturer: *Dianne Cook*

Department of Econometrics and Business Statistics

ETC5512.Clayton-x@monash.edu

Image source: https://commons.wikimedia.org/wiki/File:Another_Airplane!_(4676723312).jpg

Motivation

American Statistical Association Statistical Graphics and Computing Sections 2009 Data Expo provided all of the commercial flight records for airtravel in the USA from October 1987 to April 2008.

Questions provided

- When is the best time of day/day of week/time of year to fly to minimise delays?
- Do older planes suffer more delays?
- How does the number of people flying between different locations change over time?
- How well does weather predict plane delays?
- Can you detect cascading failures as delays in one airport create delays in others? Are there critical links in the system?

but participants could also decide for themselves what to analyse.

About the data

- nearly 120 million records
- 1.6 gigabytes of space compressed
- 12 gigabytes when uncompressed

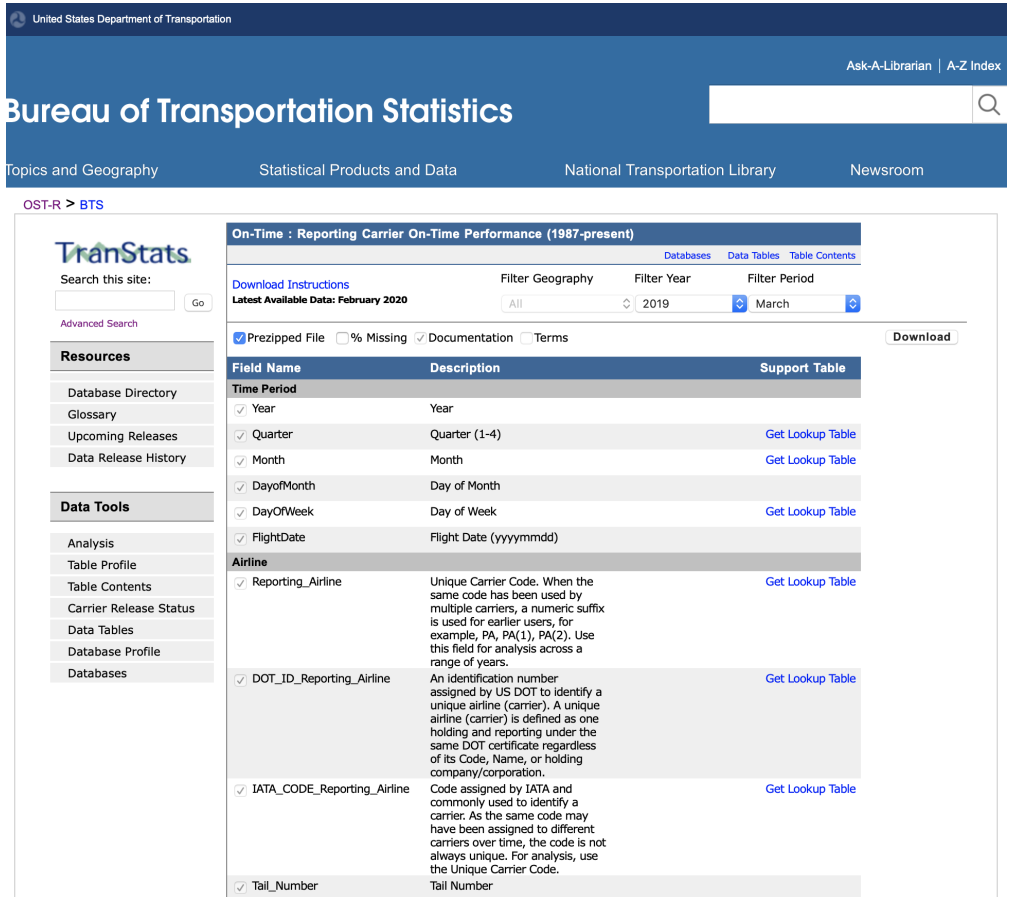
Organisers provided instructions on how to set up an **sqlite database**, and access from R.

Read about accessing databases from R at

This RStudio site https://db.rstudio.com/databases/sqlite/ is a good starting place to read about working with a sqlite database.

The original data source

TranStats



- You can find the most current data at https://www.transtats.bts.gov/DataIndex.asp
- Look at the "On-Time Performance 1987-present" table.

- You can download data a month at a time
- Its about a month lag in records
- Explanations of the variables

Accessing the data

- Data expo files: the data for the competition is still available 🤸
- Navigating the BTS web interface
  - What data is available
  - How do you download
  - Explanations of the records and variables
- R package NYCflight13: provides a small domesticated data set.🐨 This is a good way to *dip your toes in the water* with the airline data - try this if working with the full data is too scary.

What did others do? First prize 🏆

CONGESTION IN THE SKY ✈ Visualizing Domestic Airline Traffic with SAS® Software

Rick Wicklin, SAS Institute
Robert Allison, SAS Institute

THE DATA

Twenty years of data (120 million observations) on commercial domestic flights in the United States.

Variables

- *Dates:* day of week, date, month, year
- *Arrival and departure times:* actual and scheduled
- *Flight times:* actual and scheduled
- *Origin and destination:* airport code, latitude, longitude
- *Carrier:* American, Aloha Air, ..., United, US Air

Data are from the Research and Innovative Technology Administration (RITA) which coordinates the U.S. Department of Transportation research programs

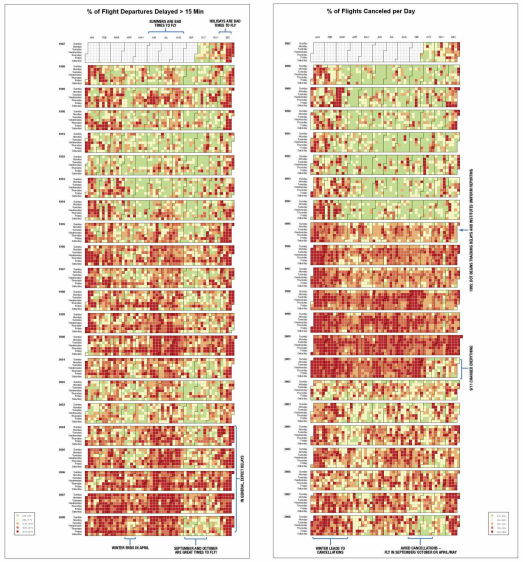
GOALS

- **Summarize data by time periods, airport, and carrier**
- **Temporal effects**
  - Are some time periods more prone to delays than others?
  - Relationships between delays and
    Seasonal factors: winter, summer, holidays
    Weather factors: blizzards and severe weather
    Daily factors: time of day, day of week
- **Spatial effects**
  - Are some airports more prone to delays than others?
  - Are there differences between flying into an airport and flying out?
- **Carrier effects**
  - Are some carriers more prone to delays than others?

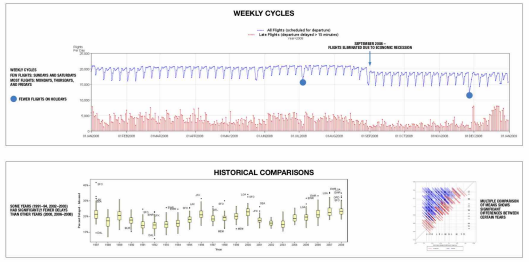
LESSONS LEARNED: TIPS FOR TRAVELERS

- Avoid flying during holidays and summer
- Fly in April, May, and September
- Watch the weather!
- Avoid airports (Newark, JFK, Chicago,...) with consistent delays
- Use carriers (Aloha, Hawaiian, Southwest,...) with superior on-time performance
- Fly early in the day
- Avoid flights that depart between 5 and 7 p.m.

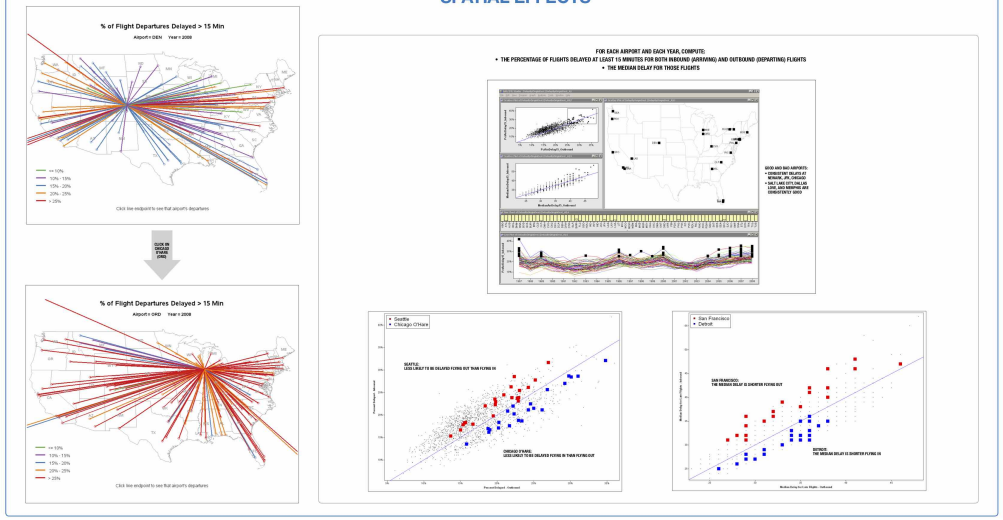
OVERVIEW



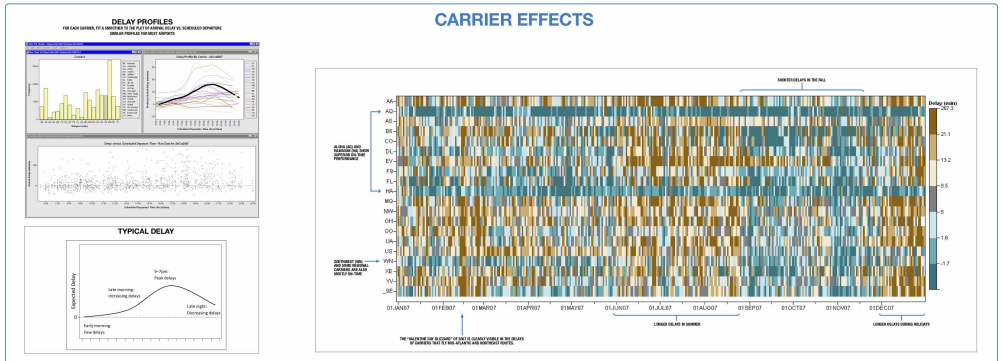
TEMPORAL EFFECTS



SPATIAL EFFECTS



CARRIER EFFECTS



Overview

Its good practice to show a useful view of entire data, to get a rough sense of major patterns.

Temporal trend

A major component of this data is traffic patterns over time.

Highlights

Carriers

Are some carriers operating more widely, or more efficiently?

Spatial pattern

Airports are distributed across the country, explore how the traffic operates relative to this geography

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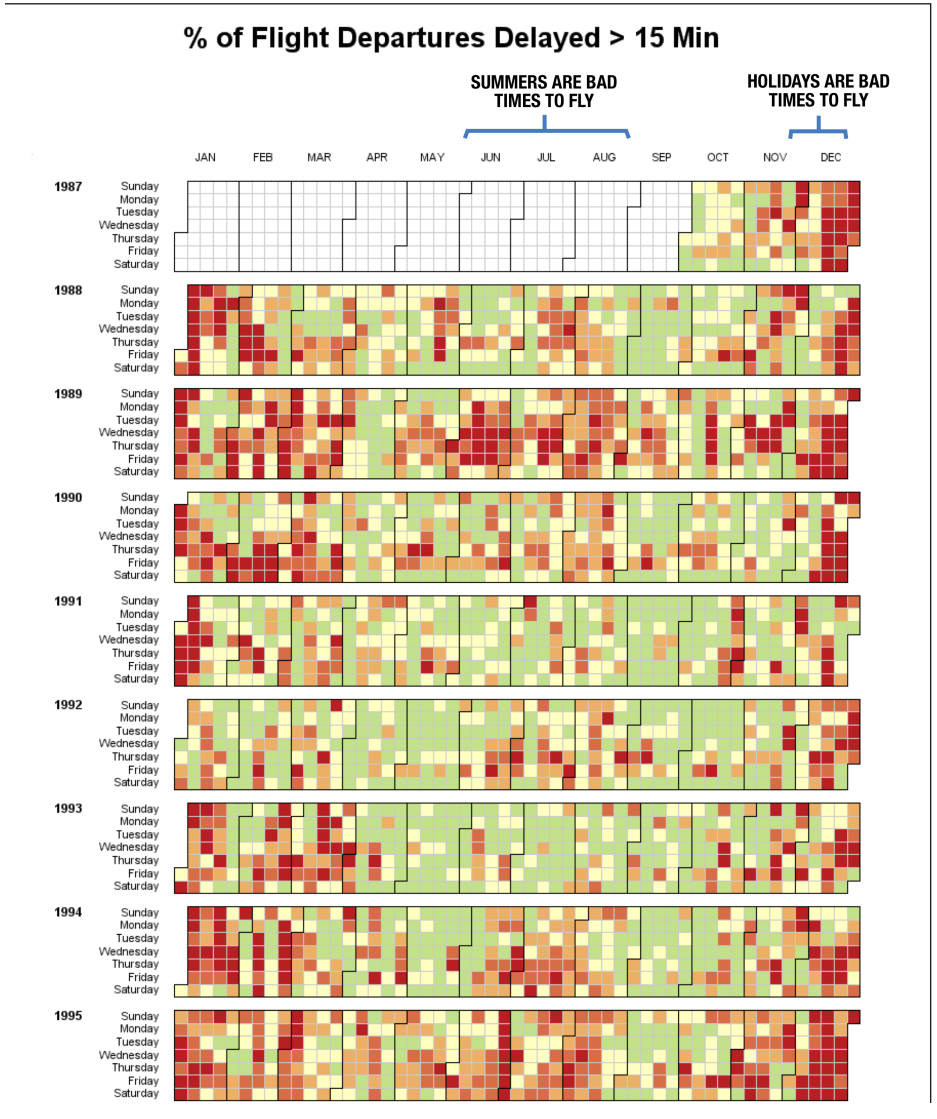
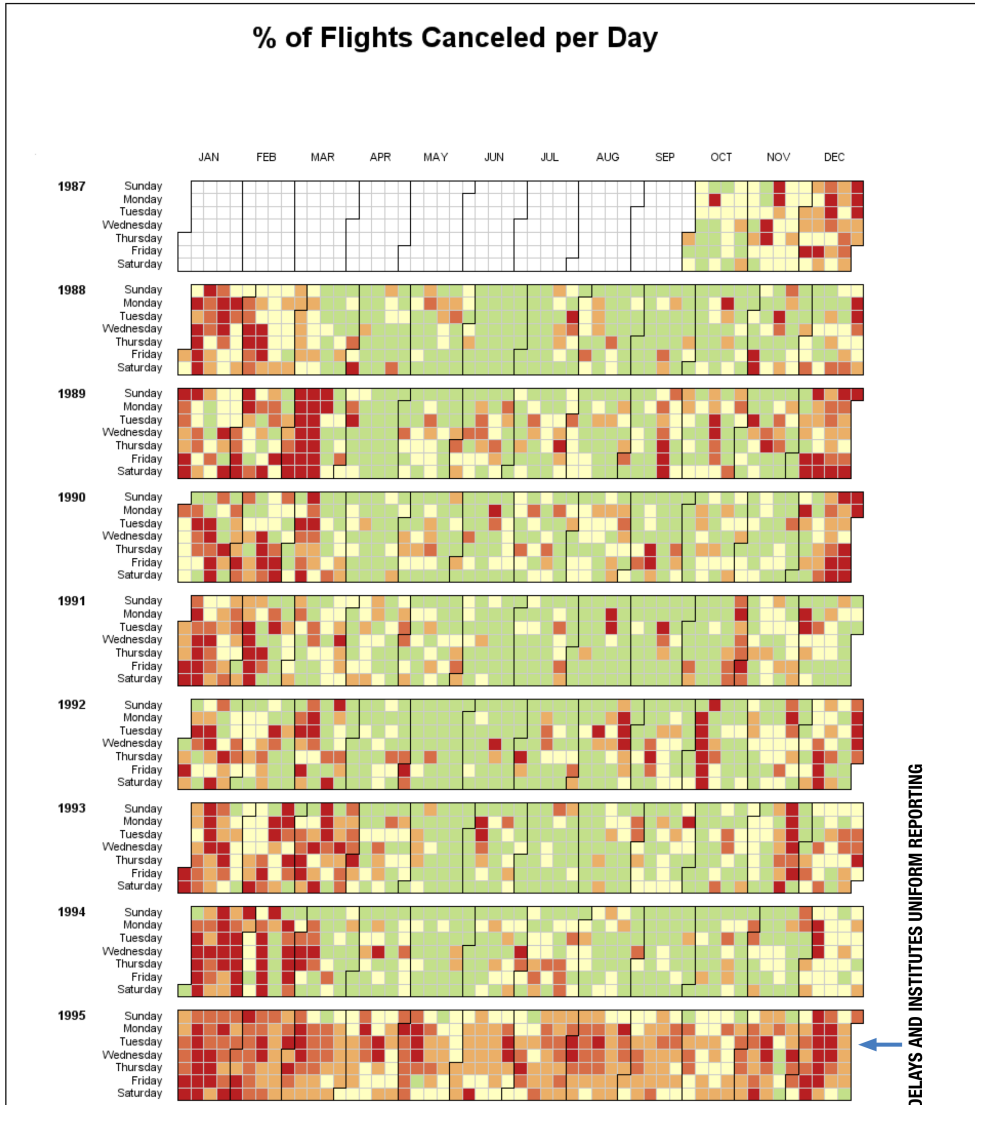
Overview


% of Flight Departures Delayed > 15 Min
SUMMERS ARE BAD TIMES TO FLY
HOLIDAYS ARE BAD TIMES TO FLY
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
1987 1988 1989 1990 1991 1992 1993 1994 1995
Sunday Monday Tuesday Wednesday Thursday Friday Saturday

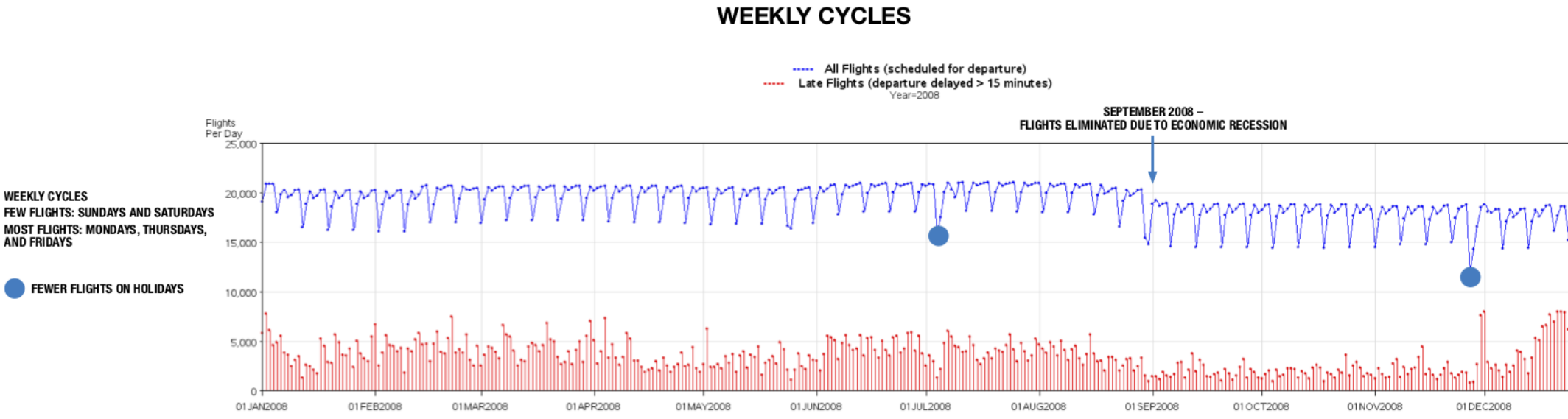

% of Flights Canceled per Day
JAN FEB MAR APR MAY JUN JUL AUG SEP OCT NOV DEC
1987 1988 1989 1990 1991 1992 1993 1994 1995
Sunday Monday Tuesday Wednesday Thursday Friday Saturday
DELAYS AND INSTITUTES UNIFORM REPORTING

Think about it 🤔

Delay was used in providing an overview.

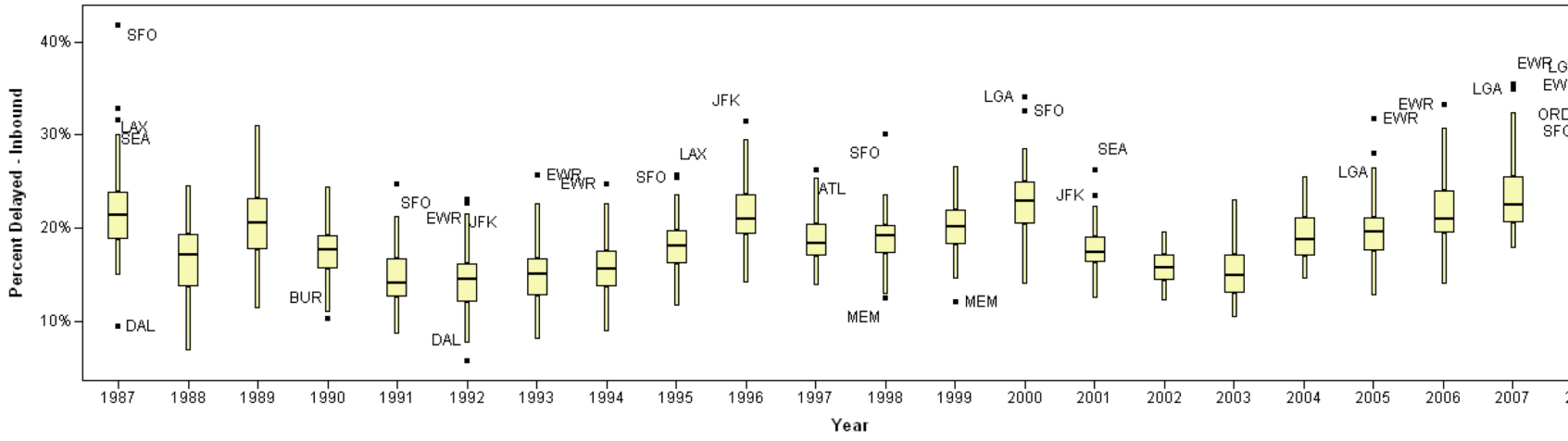
- What other aggregates could have been used?
- Why was delay chosen?

Temporal trend

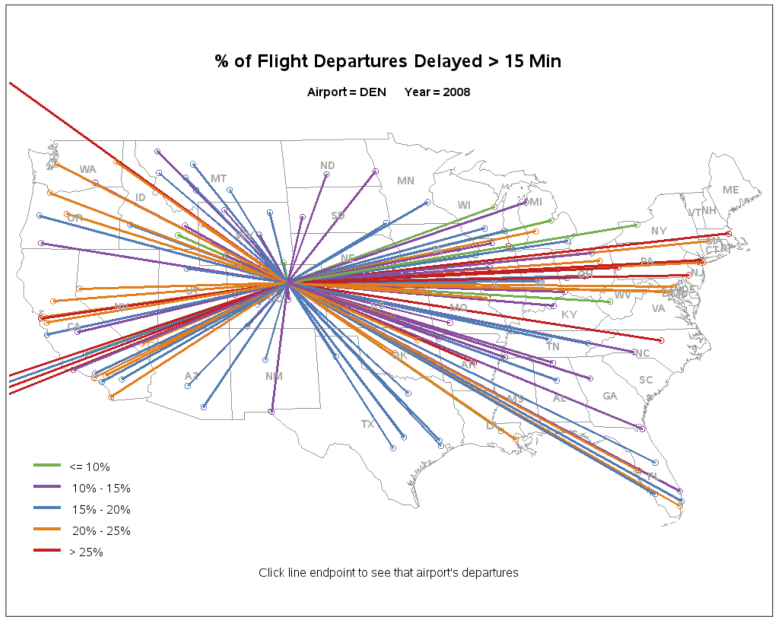


Temporal trend

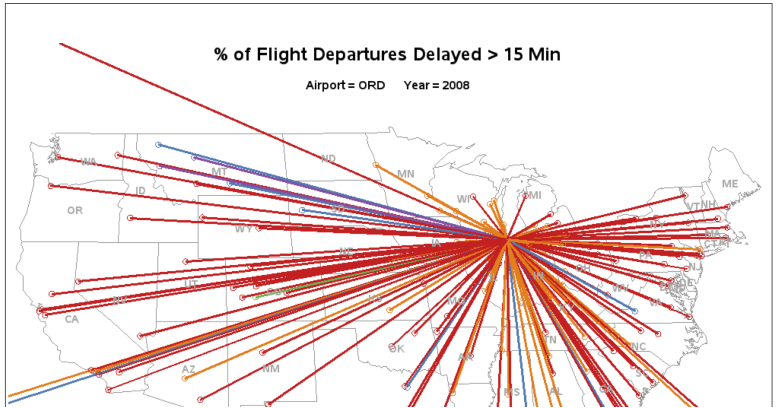
SOME YEARS (1991–94, 2002–2003) HAD SIGNIFICANTLY FEWER DELAYS THAN OTHER YEARS (2000, 2006–2008)



Spatial

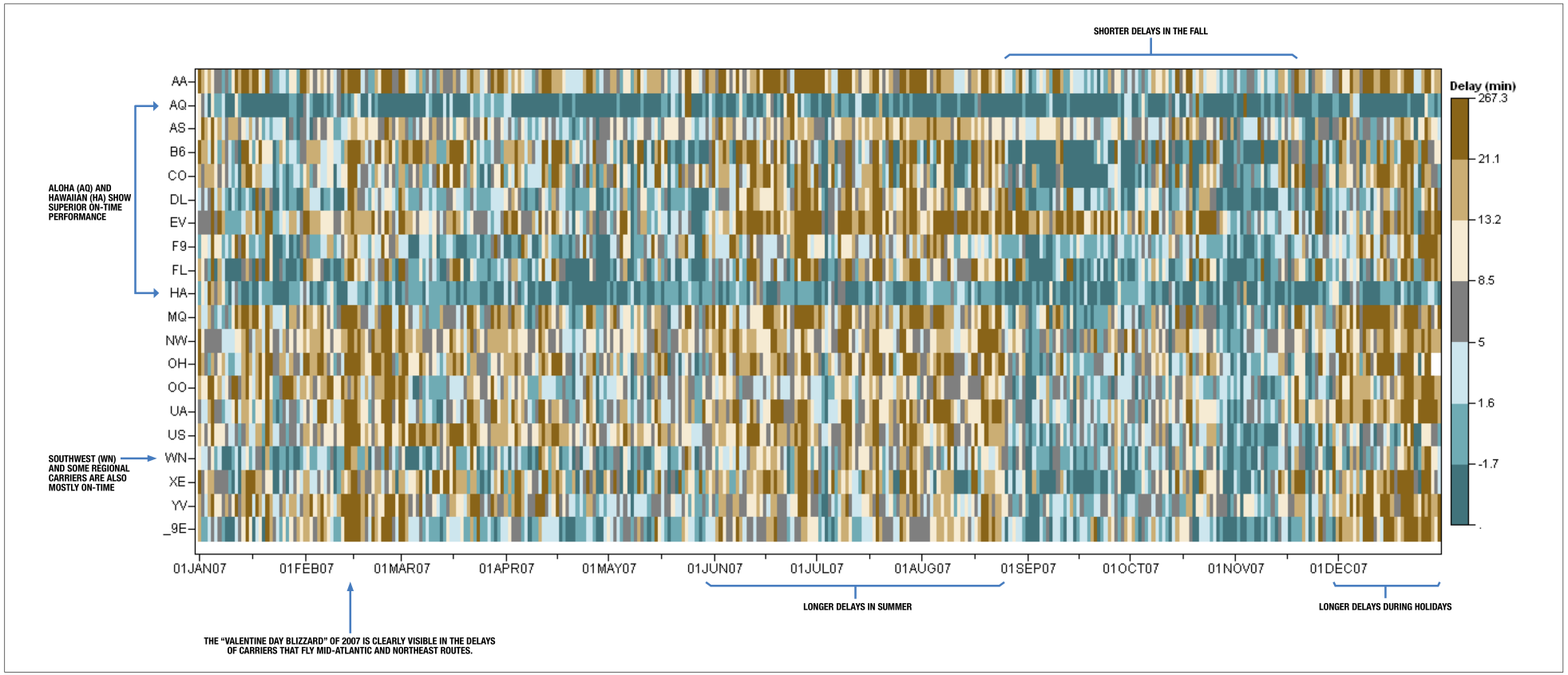


CLICK ON CHICAGO O'HARE (ORD)



Carrier

CARRIER EFFECTS



LESSONS LEARNED: TIPS FOR TRAVELERS

- Avoid flying during holidays and summer
- Fly in April, May, and September
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- Avoid airports (Newark, JFK, Chicago,…) with consistent delays
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- Fly early in the day
- Avoid flights that depart between 5 and 7 p.m.

What did others do? Second prize

Delayed, Cancelled, On Time, Boarding, ... Flying in the USA

Heike Hofmann, Di Cook, Chris Kielion, Barret Schloerke, Jon Hobbs, Adam Loy, Lawrence Mosley, David Rockoff, Yuanyuan Sun, Danielle Wrolstad, Tengfei Yin
Department of Statistics, Iowa State University

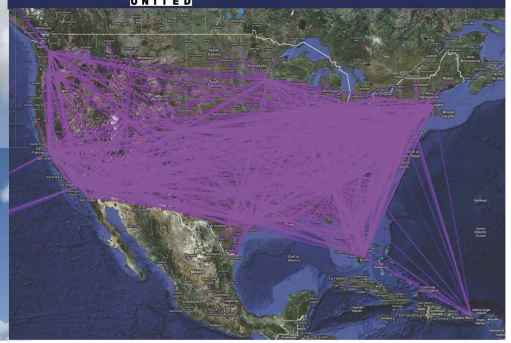
Data

The data are provided by Research and Innovative Technology Administration (RITA) and Bureau of Transportation Statistics (BTS). Arrival and departure details for 123 million commercial flights throughout the United States are recorded between October 1987 and December 2008, representing 29 commercial airlines and 3,376 airports. About 2.3 million flights were cancelled, 25 million flights were at least 15 minutes late.

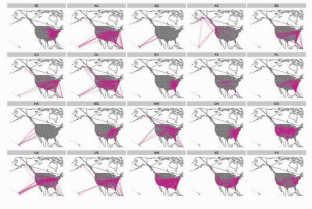
Additional Sources

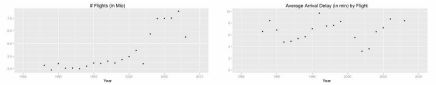
Additional BTS Data:
* Monthy fuel cost and consumption data by carrier
* Fleet information by carrier

Hourly weather details for each airport from Weather Underground at http://www.wunderground.com

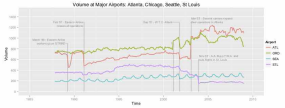


FLIGHTS OF '07
The maps above and below show all flights from 2007. Southwest Airlines (WN) operates without a hub system, the other airlines' hubs are prominent. Small carriers tend to operate locally.



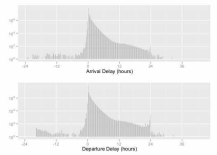


Flight volume is on the increase - dramatically so since 2000. Structural shifts (below) in the flight load for airports lead to minimal average delays (above, right) in '02 and '03. Delays have been on the increase since.

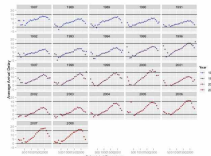


Large changes in airports' daily flight volume are triggered by different events, including strikes, FAA order, and seasonal fluctuations,

Delays

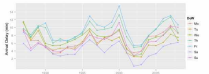


ARRIVAL & DEPARTURE
Most flights have 0 delay, with fewer and fewer flights having increasing delays. A secondary peak occurs at 24 hours suggests a limit of 24 hours delay is used by some carriers. Some data is likely incorrect, eg flights arriving 24 hours early.

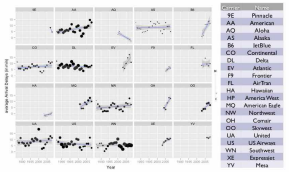


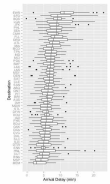
BY SCHEDULED DEPARTURE TIME & YEAR
Delays increase as day progresses. In 2001 they show an overall decrease, likely to be structural change, maybe FAA policy. Delays deteriorated again after 2003.

BY DAY OF WEEK
Best days to travel and avoid delays are Saturdays, and Tuesdays or Wednesdays. Fridays are bad for delays.



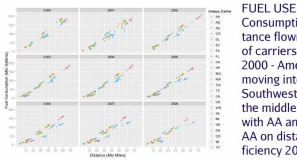
DELAYS BY CARRIER, YEAR
Increasing delays for small carriers, except for Aloha. Delta and US Airways are improving.



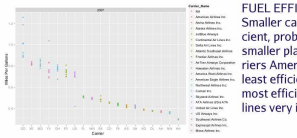


BY AIRPORT
EWR (Newark) is the worst. ORD (Chicago O'Hare) is not good, but also has high volume. DFW (Dallas-Fort Worth) is relatively good - high traffic but relatively small delay. Weather plays a huge role in delays - any kind of preciptation, high winds, or reduced visibility increases delays (scatterplots above)

Fuel Efficiency



FUEL USE
Consumption versus distance flown. Three groups of carriers are operating in 2000 - American Airlines is moving into the lead, Southwest is moving out of the middle group, closing up with AA and has overtaken AA on distance flown and efficiency 2007-8.



FUEL EFFICIENCY
Smaller carriers more efficient, probably due to use of smaller planes. Larger carriers American is one of the least efficient, Southwest is most efficient. Hawaiian Airlines very inefficient.

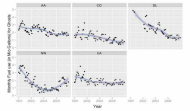
Ghosts of Flights

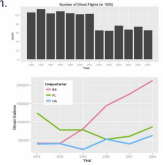
CAN WE SEE WHAT IS NOT THERE?
Planes have, for reasons such as maintenance, weather, or schedule fly empty between airports as so-called *Ghosts*. By tracking individual planes, we reveal their paths, including situations, where a plane lands in a different airport than where it takes off later, i.e. a ghost:

Example: US Airways Aircraft N-881 - Ghostflight from PIT to RIC (222 miles)

Year	Month	Day	DepTime	ArrTime	Origin	Dest	Diverted
1995	3	8	1102	1256	PIT	CVG	0
1995	3	8	1311	NA	CVG	PIT	1
1995	3	8	1913	2050	RIC	PIT	0
1995	3	8	2134	2300	PIT	MSY	0

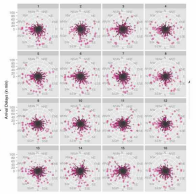
Ghost Flight Totals: over 1 million flights since 1995, with an average distance between airports of 1000 miles, corresponding to about 1.5 million gallons of fuel. Since 2001 the number of ghost flights is cut, with major airlines also decreasing the fuel consumption. Smaller carriers are facing increasing costs from ghost flights.





Crosswinds

All three runways in Phoenix are oriented East-West (see above). Do crosswinds affect air traffic?
On the right, arrival delays are plotted against permutations of wind direction (null plots). One plot shows the real data of the observed wind directions.



Can you spot which one?
If you can differentiate the true plot from the null plots, we can reject the null hypothesis of crosswinds being unrelated to arrival delays with a p-value of less than 0.0625 (= 1/16).

Believe it or not??

Racing Balloons?

Three of American Airlines' registered vehicles in the database are RAVEN hot air balloons. Based on the data, they cruise at an impressive average speed of 430 miles an hour. Fasten those hats!

I'm sorry, Sir, but your flight left 12h early'

According to the data, this was said to all passengers of 247 flights. Another 165 flights left at least 2h early.

"Within-City Hoppers"- if you're in a real time crunch

A total of 232,809 flights cover a distance of less than 50 miles. The shortest commercial flights occur between the New York airports La Guardia (LGA) and John F. Kennedy (JFK). The distance is 11 miles, which according to google.maps can be covered in 18 min by car, and according to data, takes 14 min of air time.

Tools

mySQL database on fast server (thanks to Ted Peterson)

R and packages
- ggplot2 (Hadley Wickham)
- DBI, RMySQL (David James, Jeff Horner)

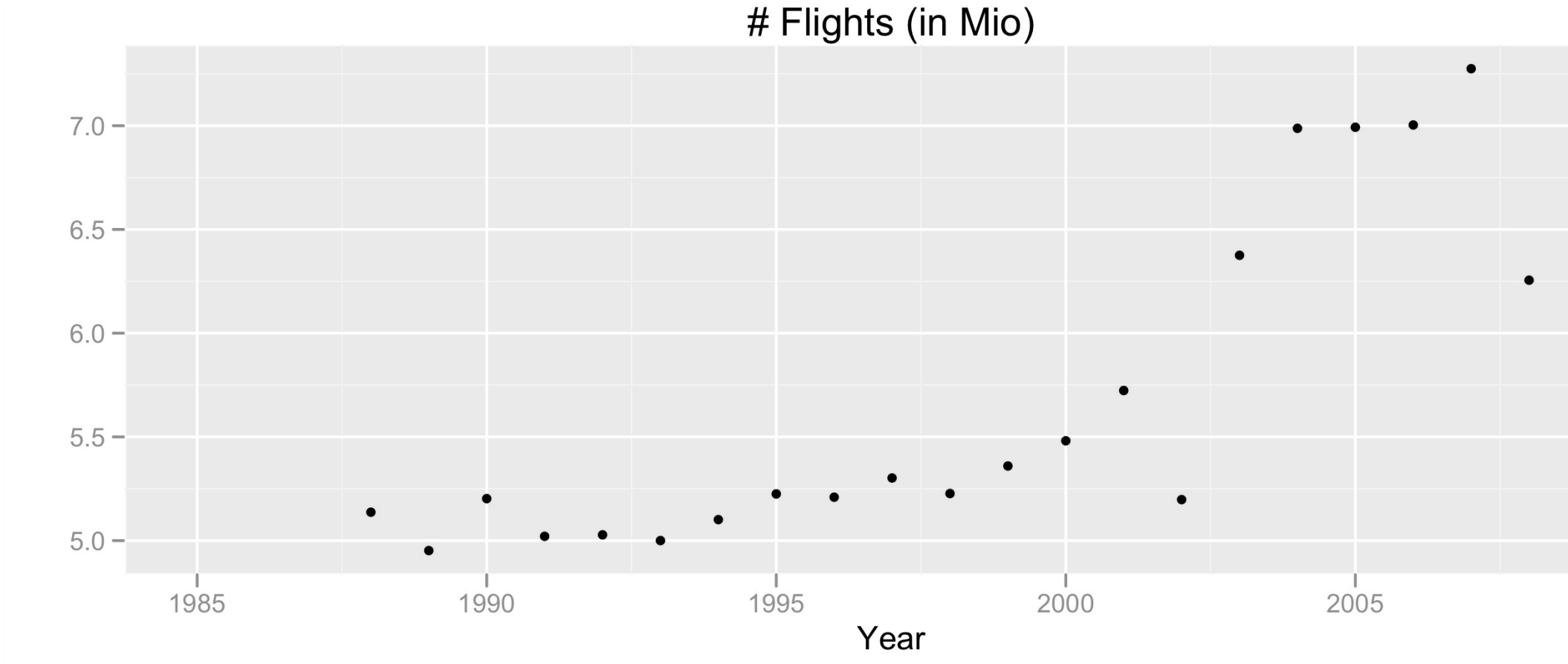
Google Earth

supported by NSF grant # 0706949

Analysis overview

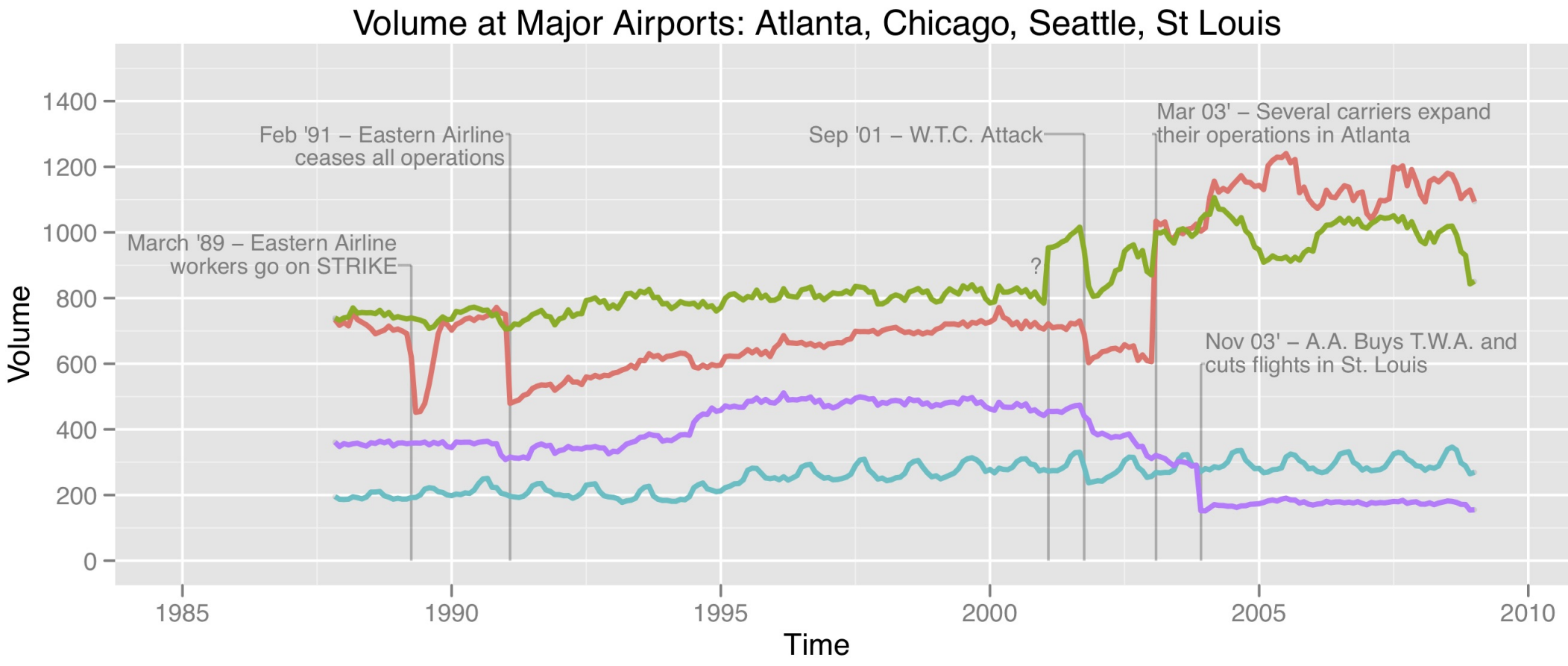
- Traffic patterns over time
- Delays
- Ghost flights
- Mapping traffic

Traffic patterns over time



Number of flights in millions per year: steadily increasing volume until 2001, with a big drop in 2002. Volume recovered in 2003, and flattens 2004-7, with another drop in 2008. What happened in 2001? What was happening in 2008?

Traffic patterns at selected airports

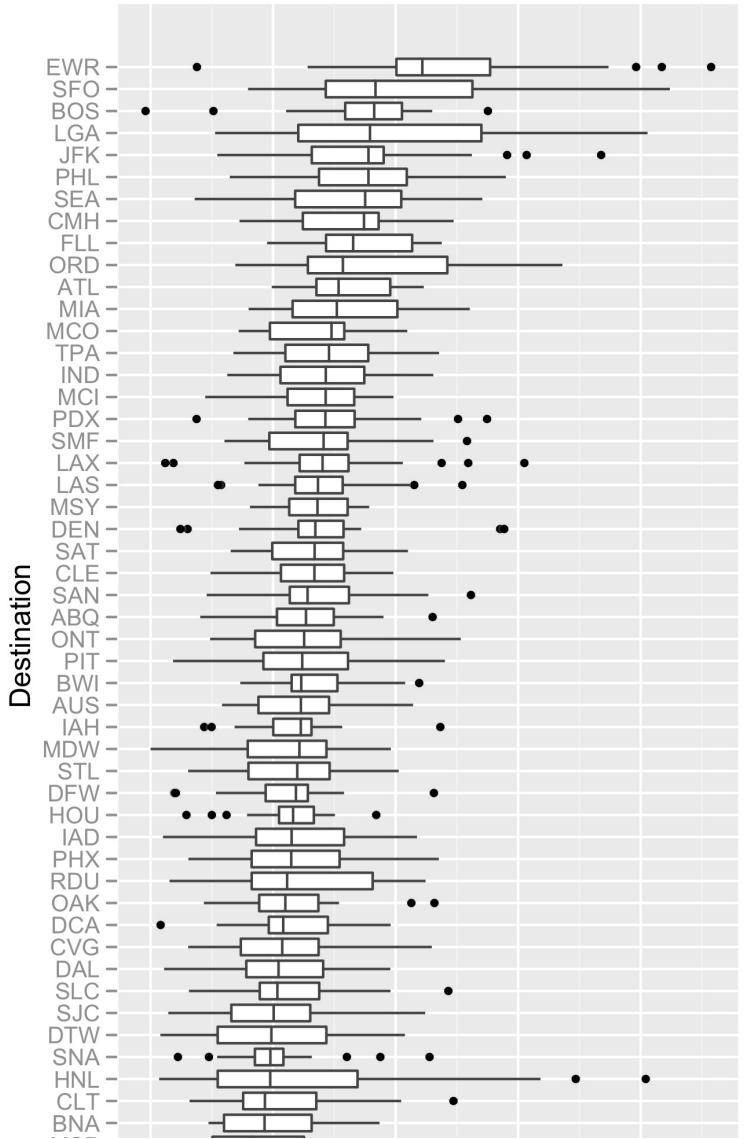


Delays

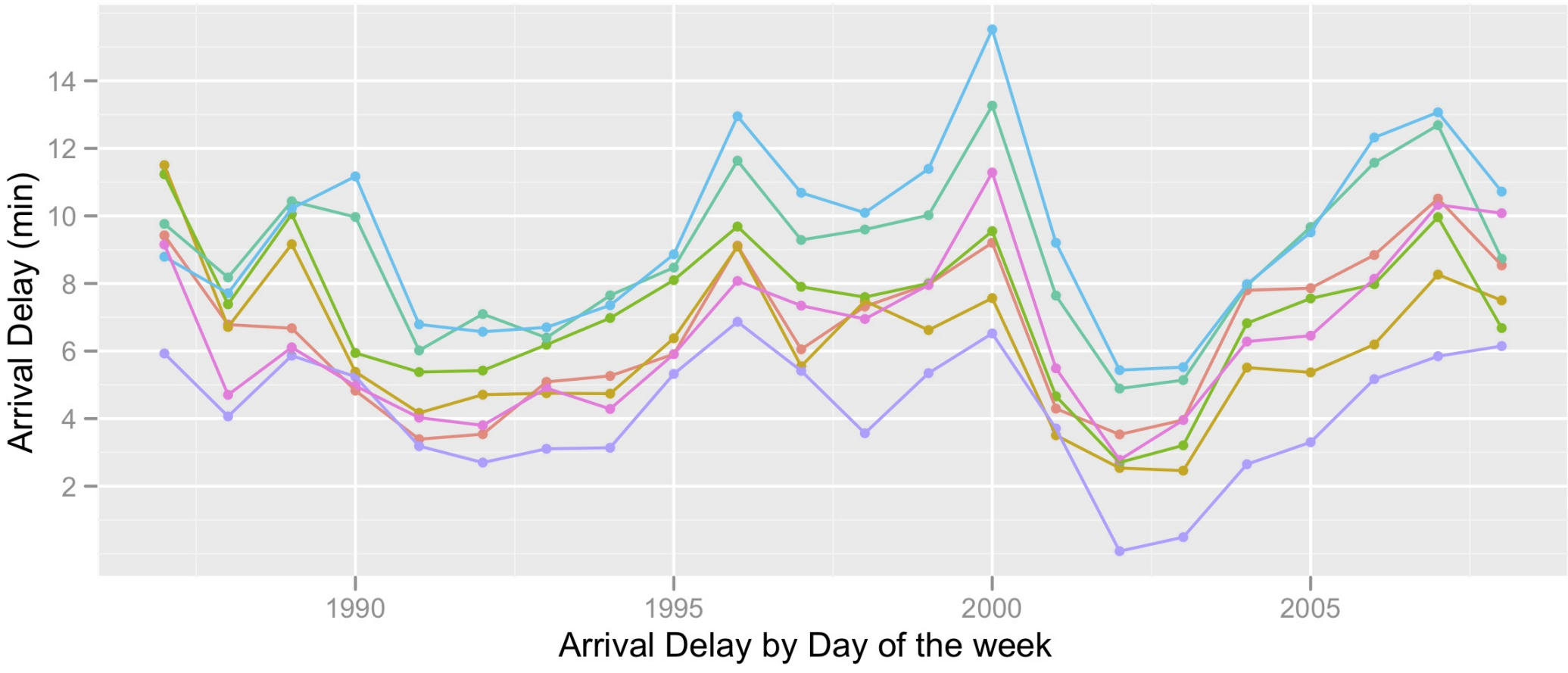
Delays, by year

Delays, by carrier

Delays, by airport



Delays, by day



Fuel use by carrier

Fuel efficiency

Ghost flights

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Ghost flights, wasted fuel

What tools were used and why

A subset of the analysis materials including data and code can be downloaded from the paper site

- sqlite database: Inspired by the guidelines provided by the organisers we created a `mysql` database, on a central server that all team members could access with a password. Each person accessed the data through R.
- R packages: `RMySQL`, `DBI`, `ggplot2`

A brief introduction to working with databases

Working from these notes

https://db.rstudio.com/databases/sqlite/

Why should I use a database?

- The data is too large to load into memory, ie work directly with it in R
- Database can make more efficient calculations
- Only load the data needed for specific analysis tasks

Connecting to an existing database

The packages `DBI`, `RMySQL`, `RPostgreSQL`, `RSQLite`, `bigrquery`, `odbc` enable connection to many different types of databases. The package `dbplyr` enables tidy style access to the databases.

Set up connection

Download the supplementary material for Hofmann et al (2012) and you will find:

```
library(RMySQL)
m <- dbDriver("MySQL")
co <- dbConnect(m, user="2009Expo",
                password="R R0cks",
                port=3306,
                dbname="data_expo_2009",
                host="headnode.stat.iastate.edu")
```

✋ Stop, read the Securing Credentials documentation

SQL

```
dtime <- dbGetQuery(co, "select Year,
avg(CRSArrTime), avg(ArrTime),
count(*) as count,avg(ArrDelay) from
ontime group by Year, (CRSArrTime div 100)")
```

```
qplot(`avg(CRSArrTime)`, `avg(ArrDelay)`,
      geom="point",
      data=subset(dtime, Year > 1998),
      xlab="Scheduled Arrival",
      ylab="Average Arrival Delay (in mins)") +
  facet_wrap(facets=~Year, ncol=5) +
  geom_hline(yintercept=c(0,15))
```

Set up connection, using SQLite

```
# Set up connection
library(DBI)
library(RSQLite)
con <- dbConnect(RSQLite::SQLite(), ":flights:")
```

This creates the link between R and the database.

Suppose we want to set up a database

One month of air traffic data is quite manageable in an R session. We can use this to get started.

To populate our SQLite database with airlines data, you need

```
copy_to(con, d, "flights",
  temporary = FALSE,
  indexes = list(
    c("FlightDate",
    "Reporting_Airline",
    "Tail_Number",
    "Origin",
    "Dest"
  )
))
```

Setting up the indexes makes it faster to process data on the database.

Alternative approach using DBI database functions

```
dbWriteTable(con, "flights", d)
dbListTables(con)
```

and check it

```
flights_db <- tbl(con, "flights")
flights_db
```

```
feb1 <- flights_db  %>%
  filter(DayofMonth==1) %>%
  select(DayofMonth, Origin, Dest) %>%
  collect()
feb1
```

or with SQL

```
dbListFields(con, "flights")
res <- dbSendQuery(con, "SELECT * FROM
                   flights WHERE DayofMonth=1")
firstday <- dbFetch(res)
```

Add a table on airport details

Information about airport location and details is found in a different table at the BTS site: https://www.transtats.bts.gov/Fields.asp?Table_ID=288 . We will download this and add to our database to use for plotting flights on a map.

```
airports <- read_csv("data/402312038_T_MASTER_CORD.csv") %>%
  select(-X29)
copy_to(con, airports, "airports",
  temporary = FALSE
  )
dbListTables(con)
```

Its easy to forget what variables are in the table

You can check this with

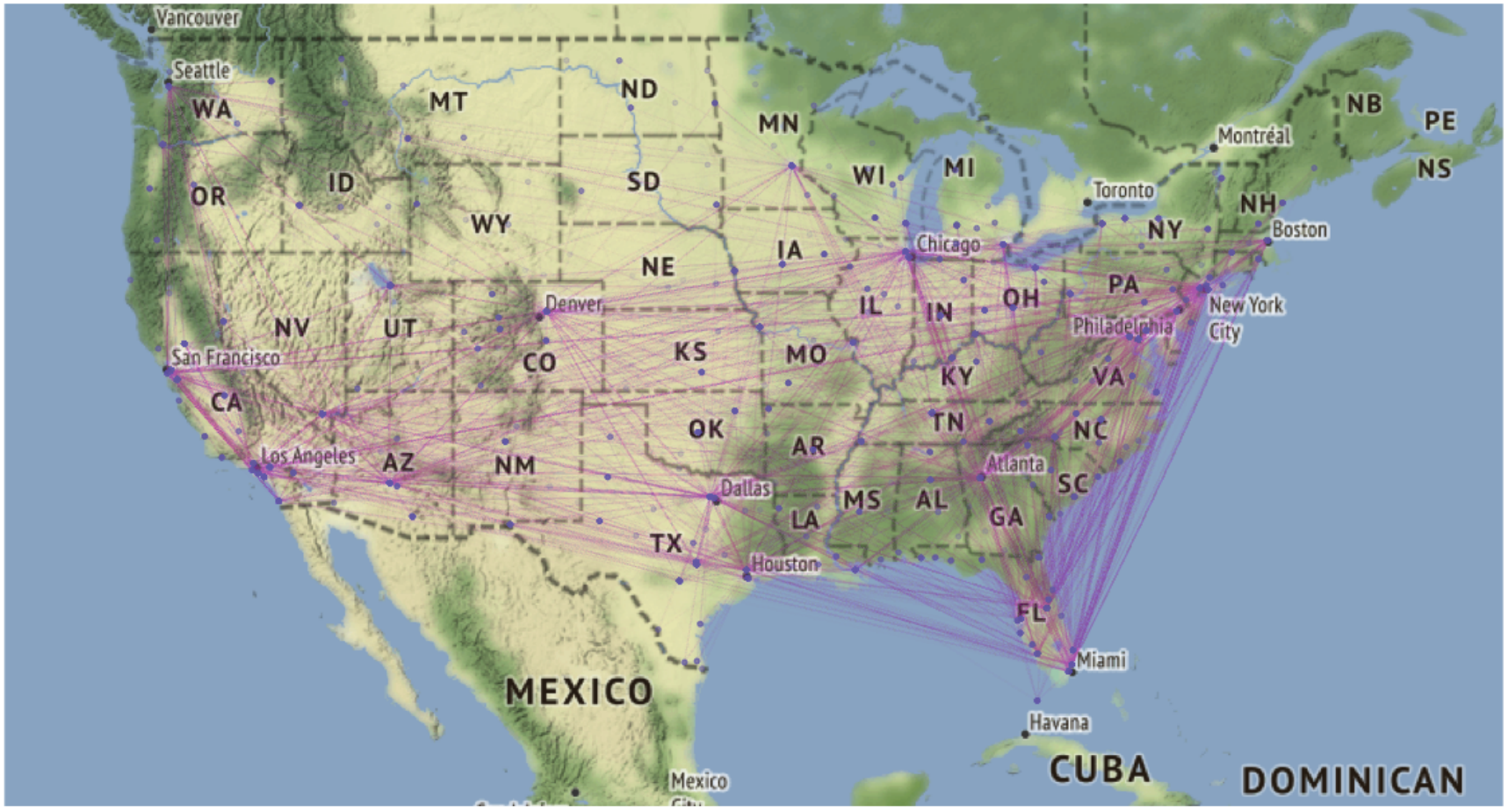
```
dbListFields(con, "airports")
```

Make a map of flights for Feb 1

```
airport_locations <- tbl(con, "airports") %>%
  filter(AIRPORT_IS_LATEST == 1, AIRPORT_COUNTRY_CODE_ISO == "US") %>%
  select(AIRPORT, DISPLAY_AIRPORT_NAME, LONGITUDE, LATITUDE) %>%
  collect()
feb1_flights <- feb1 %>%
  left_join(airport_locations, by=c("Origin" = "AIRPORT")) %>%
  rename(Origin_lon = LONGITUDE, Origin_lat = LATITUDE,
         Origin_name = DISPLAY_AIRPORT_NAME) %>%
  left_join(airport_locations, by=c("Dest" = "AIRPORT")) %>%
  rename(Dest_lon = LONGITUDE, Dest_lat = LATITUDE,
         Dest_name = DISPLAY_AIRPORT_NAME)
```

```r
library(ggmap)
usa_bbox <- c(-130, # min long
              20, # min lat
              -60, # max long
              50) # max lat
usa_map <- get_map(location = usa_bbox, source = "osm")
ggmap(usa_map)
```

```
library(ggthemes)
ggmap(usa_map) + geom_segment(data=feb1_flights,
                      aes(x=Origin_lon,
                          xend=Dest_lon,
                          y=Origin_lat,
                          yend=Dest_lat),
                      colour="#9651A0", alpha=0.01) +
  geom_point(data=feb1_flights, aes(x=Origin_lon, Origin_lat),
             colour="#746FB2", alpha=0.1, size=1) +
  theme_map()
```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That's it!

Lecturer: Dianne Cook

Department of Econometrics and Business Statistics

ETC5512.Clayton-x@monash.edu