# Describing Patterns and **Disruptions** in Large Scale Mobile App Usage Data

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*Work carried out as part of Steven Canneyt internship at Yahoo London

# This work

- Why is it important to understand patterns of app usage?
- What is known about patterns of app usage?

- What we did
  - Disruption of app usage behaviour through major sport (Euro 2016), political (Brexit) and social (new year day)

# Why is it important to understand patterns of app usage?

- Increasing usage of mobile devices and mobile applications (apps)
- Emergence of online marketplaces and APIs → developers, market intermediaries & consumers develop, disseminate, and use apps

  - Advertising industry wants to improve targeting and experience with apps
  - Marketplace operators want to identify popular or problematic apps → provide effective app recommender systems
  - Developers want to understand why their apps are liked or disliked → improve app design
  - ***Insights for Yahoo London Ad Sales***

YAHOO!

# What is known about patterns of app usage?

- Relationship between demographics and app usage
- Identify distinct types of users based on their app usage (e.g. evening learners, screen checkers, game addicts)

- Simple features

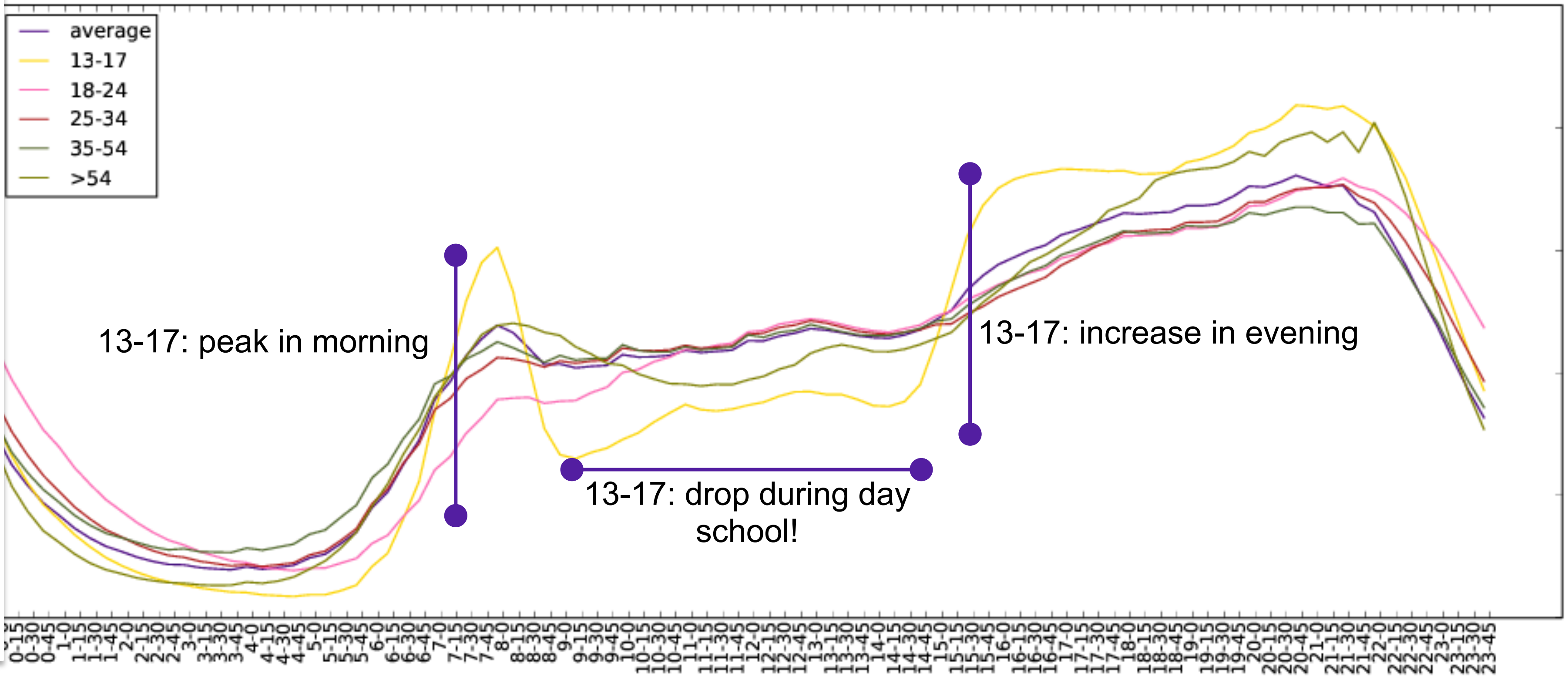
  app category, time of day, workday versus weekend

(Malmi & Weber, 2016; Zhao etal, 2016)

# Teenager app usage (UK)

Weekday

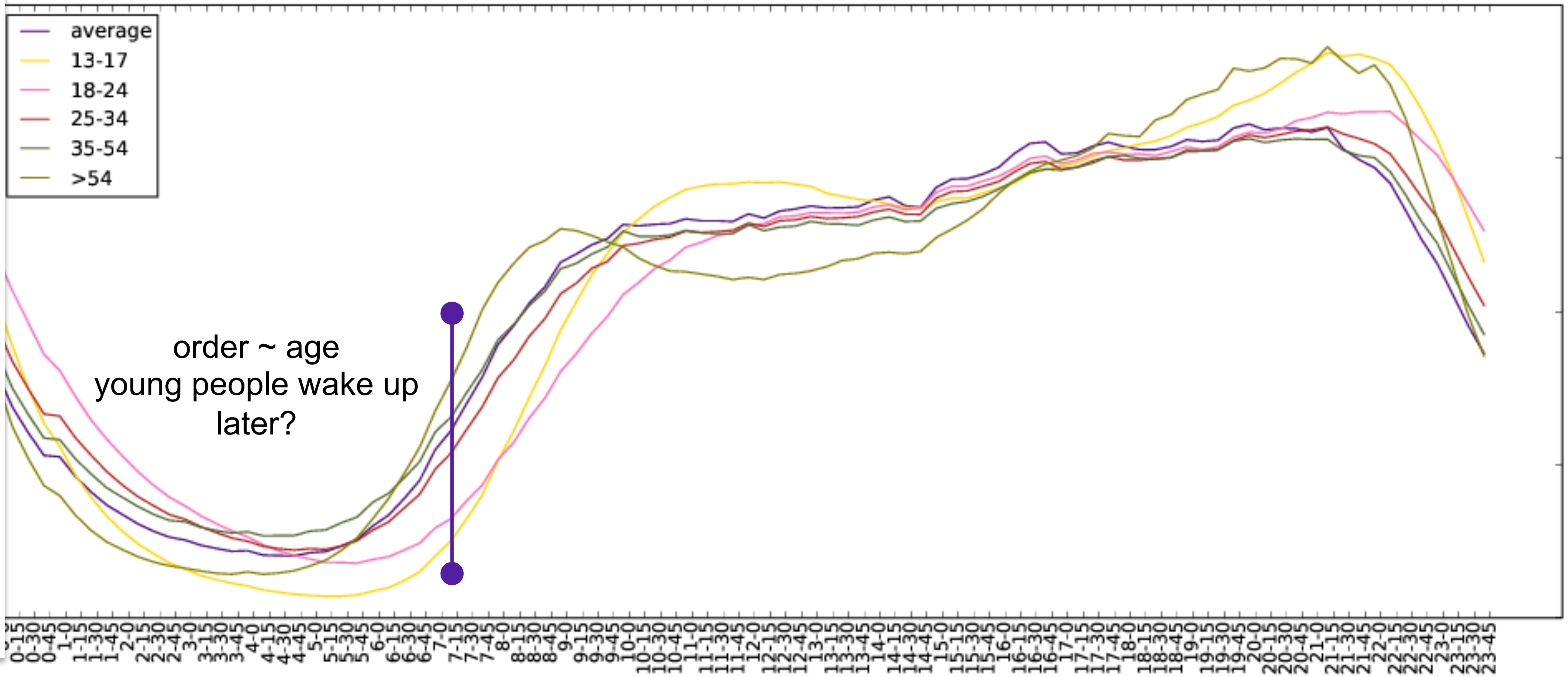
Percentage of app sessions per 15-minute window by age



# Teenager app usage (UK)

Weekend

Percentage of app sessions per 15-minute window by age



# General patterns of app usage

- Average number of visited app per week and per user is 7 with 5 app categories within a day

  social network > search > e-commerce

- Users interact between 10 to 200 times a day on average with session length between 10-250 seconds
- Mostly short sessions with 80% of apps used ≤ 2 minutes

- Overwhelmingly only one app per session
- App usage often focused at specific time (news app in morning)

(Yang etal, 2015; Falaki etal, 2010)

YAHOO!

# Diurnal patterns

- Different diurnal patterns for different categories of apps
  - News apps in early morning
  - Sports apps in evening
  - Games apps peak after standard work hours

- App usage varies during the day
  - grow from 6am to first peak around 11am, then declining slightly between 11am to 12pm
  - 32% of app usage performed during 7pm to 11pm, reaching maximum around 9pm, then decline reaching minimum around 5am → consistent with human habit

(Xu etal, 2013; Li etal, 2015)

## What is known about patterns of mobile app usage?

- App usage follows regular patterns, in terms of which app, and when during the day or the weekday they are mostly used

- **So what about cases when these patterns are disrupted?**

YAHOO!

# Data: Flurry Analytics

# Flurry

**Library that mobile developers to integrate in their apps to measure app usage and allow in-app advertising**

- default app events triggered by user actions (app start event)
- custom-based events

| device feature | %session | %apps | %users | user feature | %session | %users |
|---|---|---|---|---|---|---|
| OS: android | 78% | 38% | 67% | gender: female | 54% | 55% |
| OS: iOS | 21% | 59% | 32% | gender: male | 46% | 45% |
| Make: Samsung | 36% | 32% | 31% | age: 13-17 | 9% | 7% |
| Make: Apple | 21% | 59% | 32% | age: 18-24 | 18% | 17% |
| Make: LG | 6% | 17% | 4% | age: 25-34 | 19% | 17% |
| Make: Sony | 3% | 16% | 3% | age: 35-54 | 47% | 46% |
| Make: Motorola | 3% | 14% | 3% | age: 55+ | 6% | 12% |

Table 1: Coverage statistics of device (left) and demographics (right) information.

## Sample data

- May 2016
- 230K mobile apps
- 600M daily unique users
- US and UK

## Popularity based engagement metric

- number of sessions a user has with an app based on the app start event

https://developer.yahoo.com/analytics/

# App categories

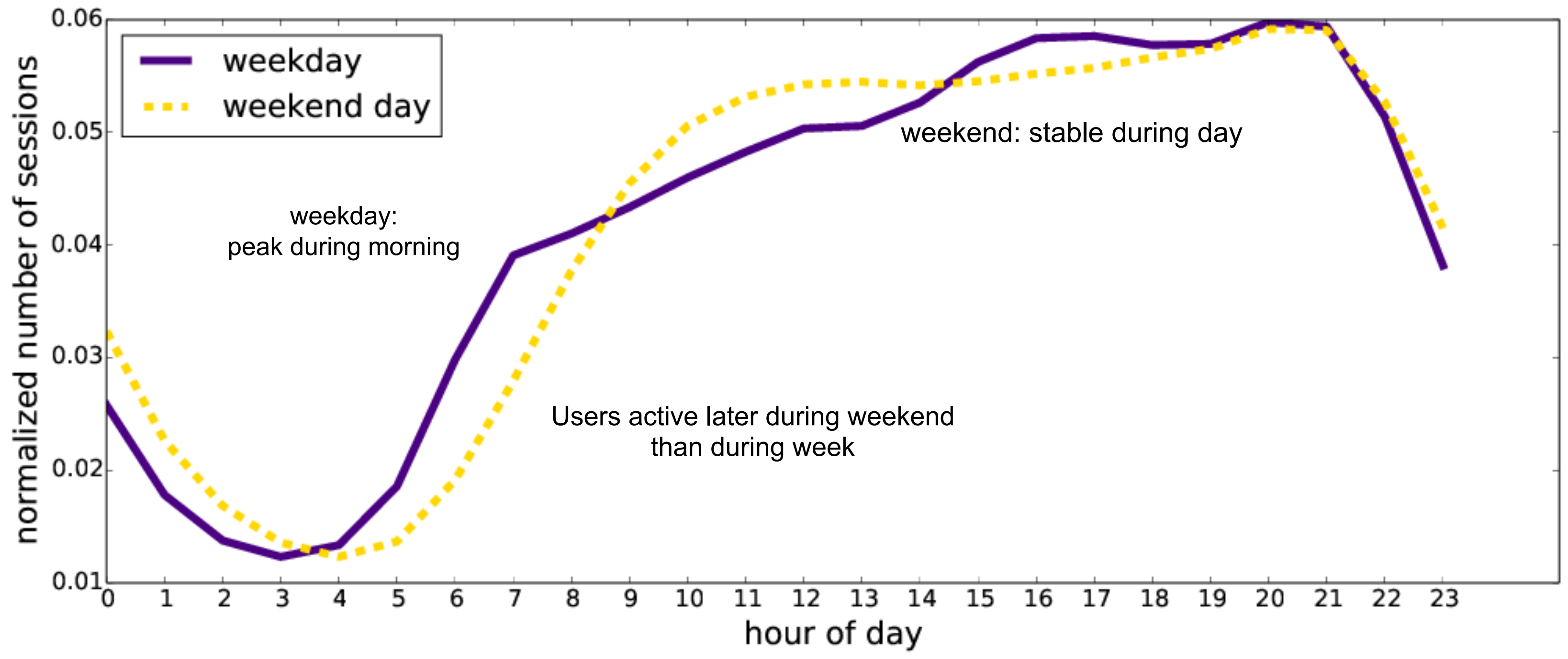
27 categories ranging from work related (productivity) to leisure (games) and other popular categories (news)

| %session | | %apps | | %users | | avg. session length | |
|---|---|---|---|---|---|---|---|
| 1. Utilities | 23% | Games | 33% | Games | 25% | E-readers | 7m |
| 2. Social | 16% | Entertainment | 8% | Utilities | 22% | Health & Fitness | 6m |
| 3. Games | 12% | Lifestyle | 6% | Social | 17% | Games | 6m |
| 4. Productivity | 11% | Productivity | 6% | Productivity | 13% | Entertainment | 5m |
| 5. Personalization | 9% | Education | 5% | Photography | 7% | News | 5m |

Table 2: Coverage statistics for top 5 app categories.

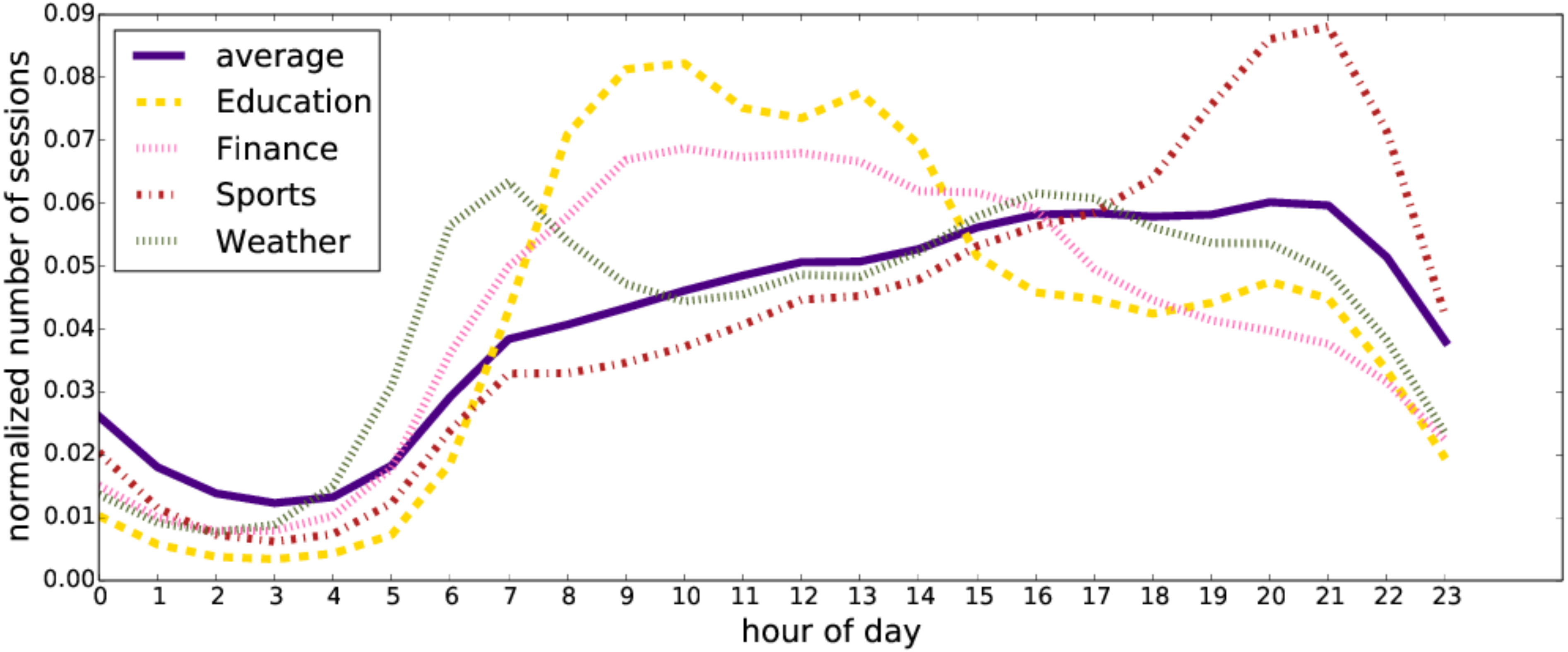
# Engagement patterns in app usage

# General daily engagement patterns (US)




Similar patterns reported in other studies → no or little bias from Flurry inventory

# Daily engagement patterns by category (US)

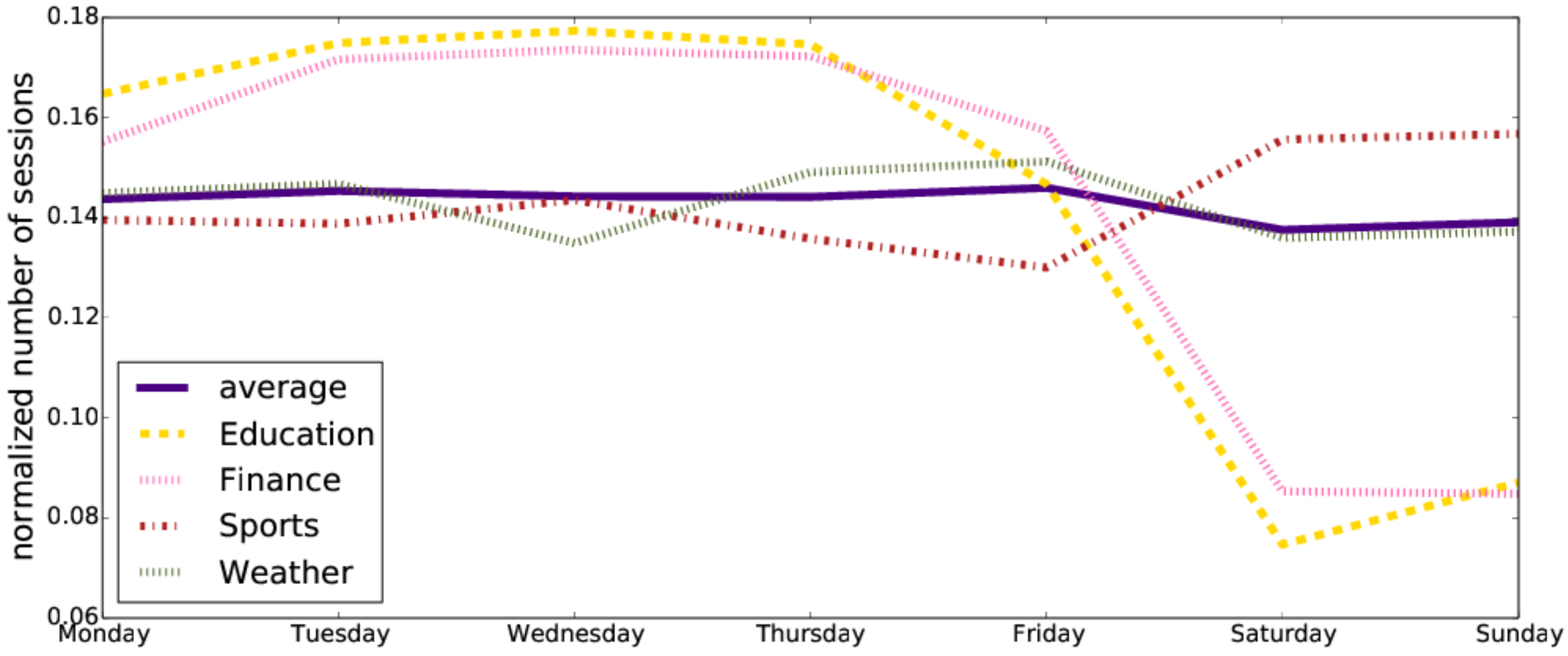



Similar patterns reported in other studies → no or little bias from Flurry inventory

YAHOO!

# App engagement patterns per day of the week and category (US)

Week: productivity
Weekend: sports, entertainment
Fridays and Saturdays: shopping

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YAHOO!

# Disruptions in engagement patterns in app usage in major **UPCOMING KNOWN** events

SPORT: EURO 2016
POLITICAL: BREXIT
SOCIAL: NEW YEAR DAY

# Data processing and measurement

- Target day and reference days
  - If target event occurs on Saturday then take a number of Saturdays before event
- Remove outliers from reference days (outage, new app release, other major event)
  - number of start session events either ≤ 1st quartile – 1.5 or ≥ 3rd quartile + 1.5

- Day divided into time segments (e.g., 15 minutes) and normalize
- **$avg_t$**: expected number of sessions per time segment t estimated by averaging normalized number of sessions for reference days
- **$std_t$**: standard deviation for reference days

- **Behaviour "significantly" disrupted:** normalized number of sessions during target period $\geq avg_t + 2 \cdot std_t$ or $\leq avg_t - 2 \cdot std_t$

# Case study 1: EURO 2016

# Euro 2016: The Data (UK)

16M viewers (25% of UK population) watched Portugal beat France in the final on BBC 1

| **time** | **countries** |
|---|---|
| Sat. June 11, 2016 20:00 GMT | England 1 - 1 Russia |
| Thu. June 16, 2016 14:00 GMT | England 2 - 1 Wales |
| Mon. June 20, 2016 20:00 GMT | Slovakia 0 - 0 England |
| Sun. July 10, 2016 20:00 GMT | Portugal 1 - 0 France |

Table 3: Considered games in Euro 2016.

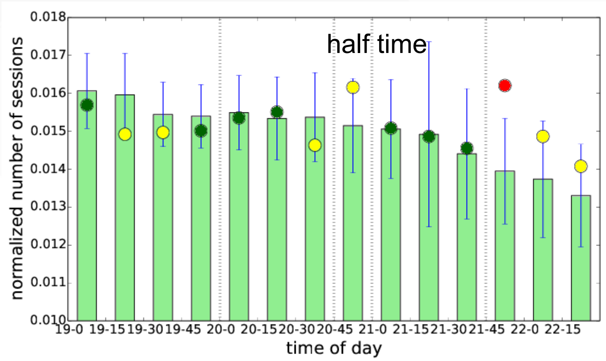
Typical mobile engagement for match played on Saturday as average engagement of all Saturdays between November 2015 & June 2016

Same process used to model typical app engagement on reference days counterpart to each of the match days

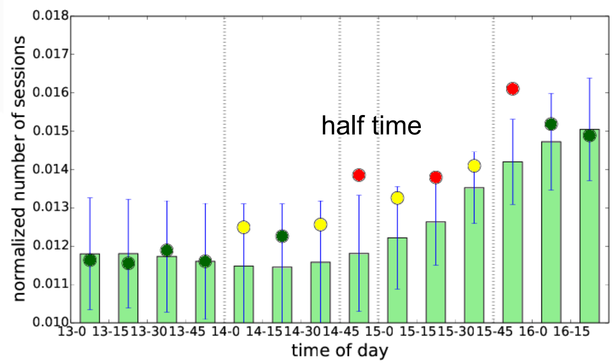
Each event day has 30 reference days

# Number of sessions during games (UK)

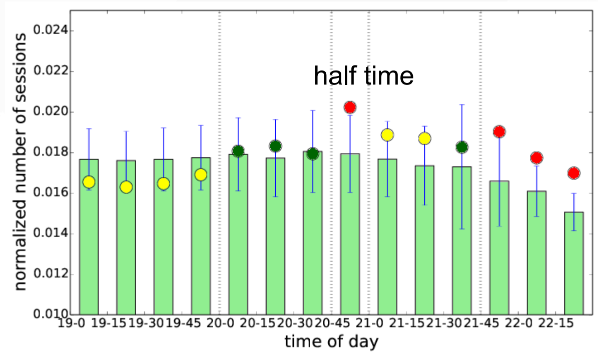
England 1 – 1 Russia 20:00



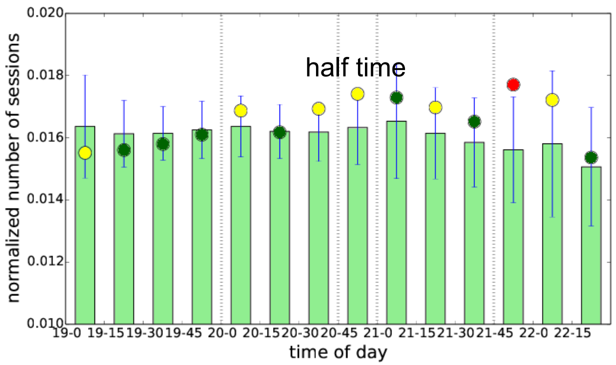

England 2 – 1 Wales 14:00




Slovakia 0 – 0 England 20:00




Portugal 1 – 0 France 20:00




- Green bars: average same weekday based on 30 weeks before EURO 2016
- Blue lines: 2 x std
- Green dots: similar as average
- Yellow dots: < avg - std or > avg + std
- **Red dots: < avg - 2x std or > avg + 2 x std**

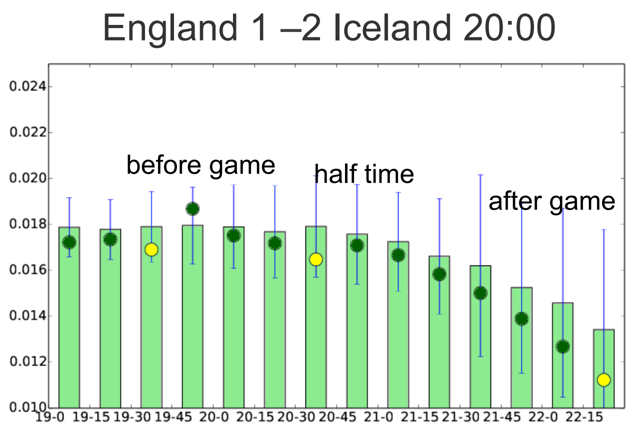
**Sports apps: x3.7!**

YAHOO!

# App engagement during Euro 2016 games

- app engagement during games **not lower** than during same time on an average day for any of the matches
- during half-time app engagement is significantly higher than during same time on an average day for England – Wales and England – Slovakia games

BUT:

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# Case study 2: BREXIT

# BREXIT (UK)

European Union membership referendum – Brexit – took place on Thursday June 23, 2016 in the UK to gauge support for the country's continued membership of the European Union

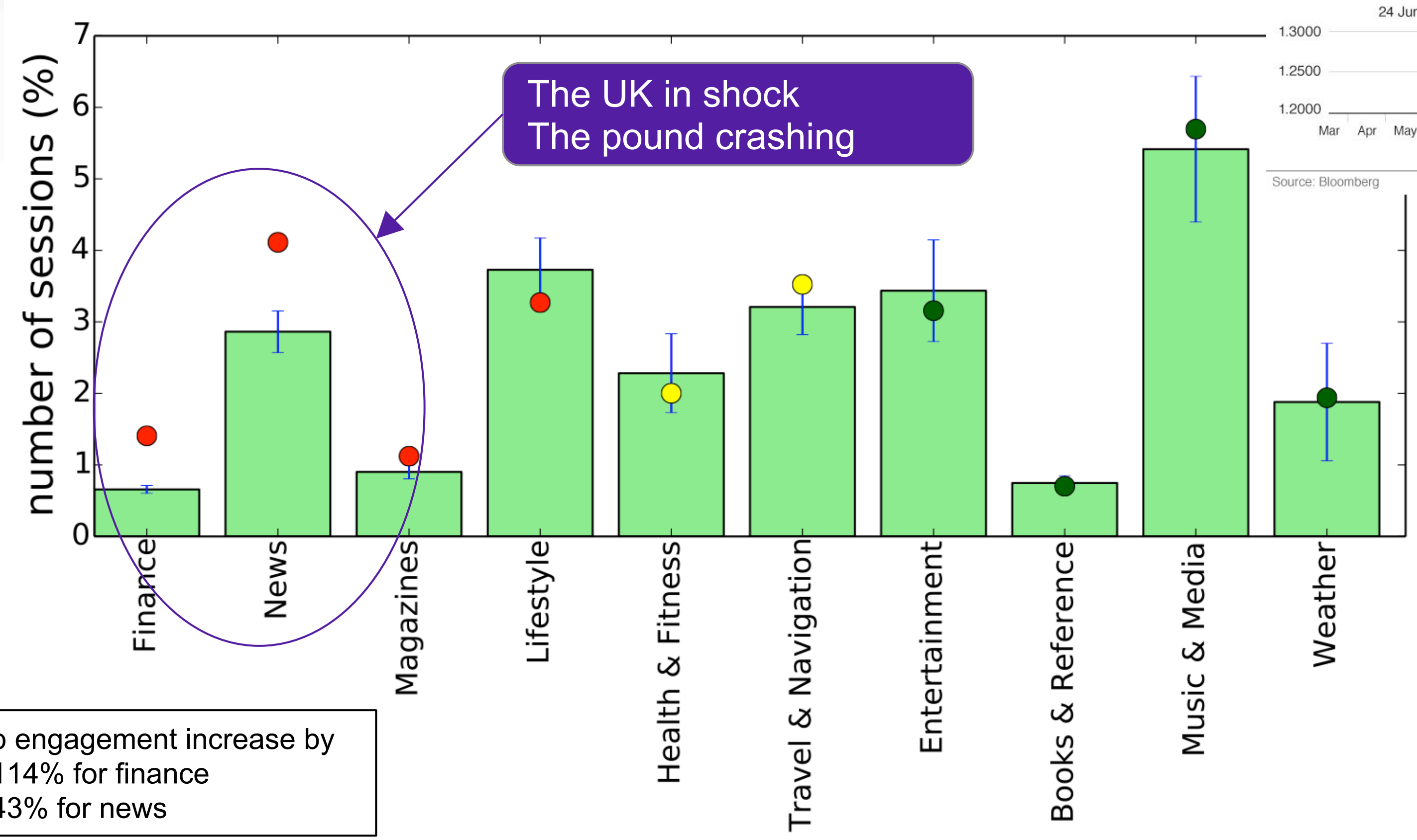

Result was announced in early morning of June 24, 2016:

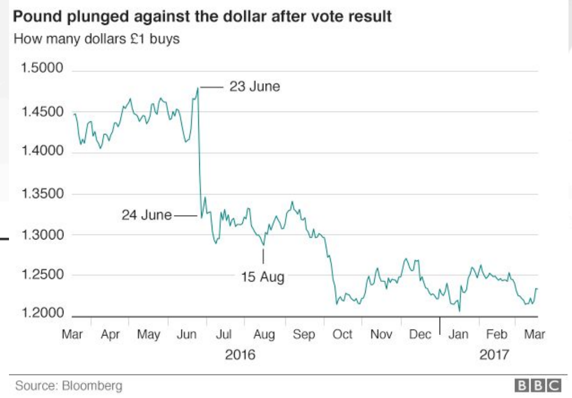
overall vote to leave the EU by 51.9% on a national turnout of 72%

unstability in financial markets & turmoil in UK political landscape

- Study whether outcome coincides with disruptions in app usage
- Reference days are all weekdays in June before June 24
- Top 10 app categories with largest percentage change in session volume compared to average usage

# Day of the referendum result 24 June, 2016 (UK)

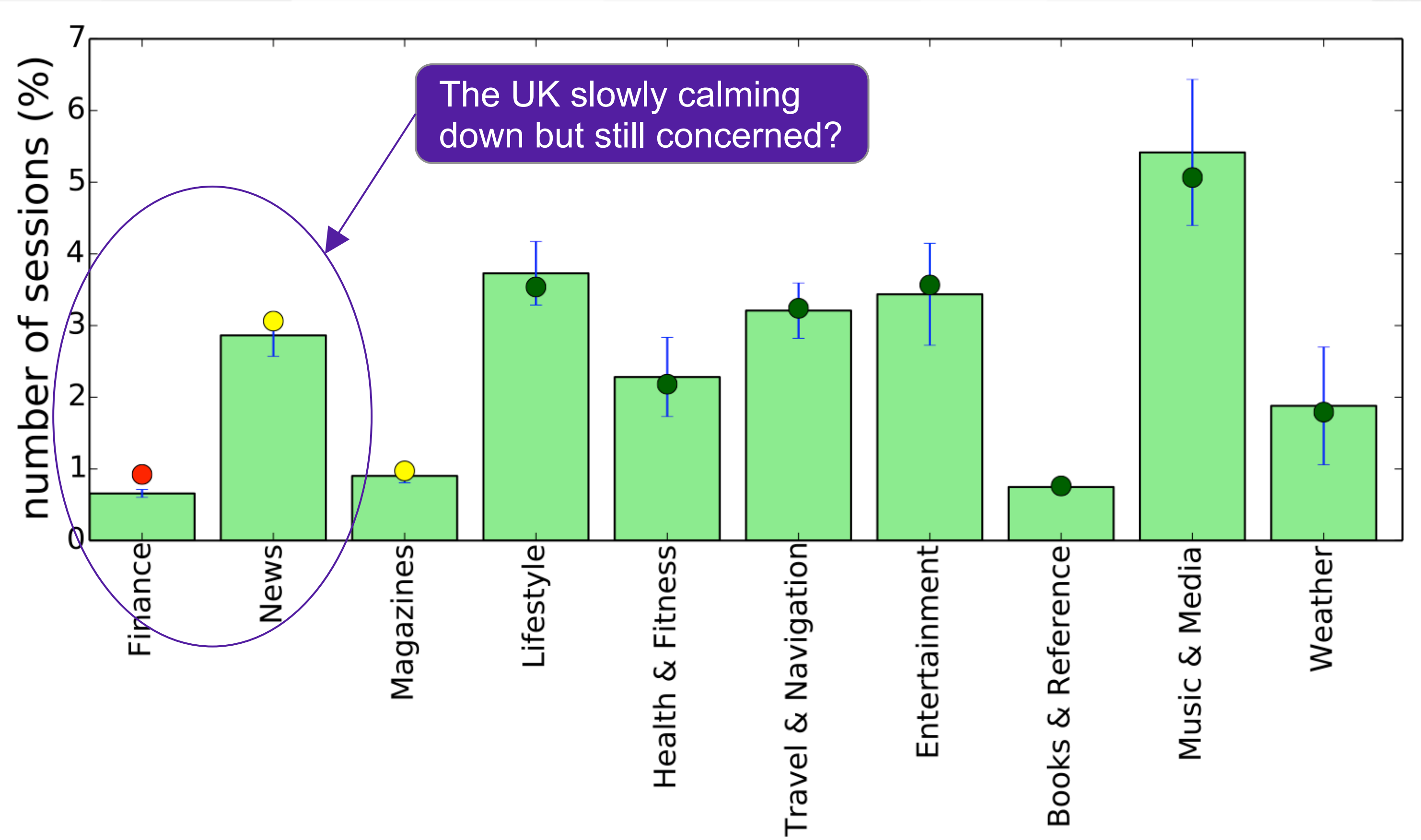



app engagement increase by
114% for finance
43% for news

YAHOO!

# First week after the referendum result (UK)

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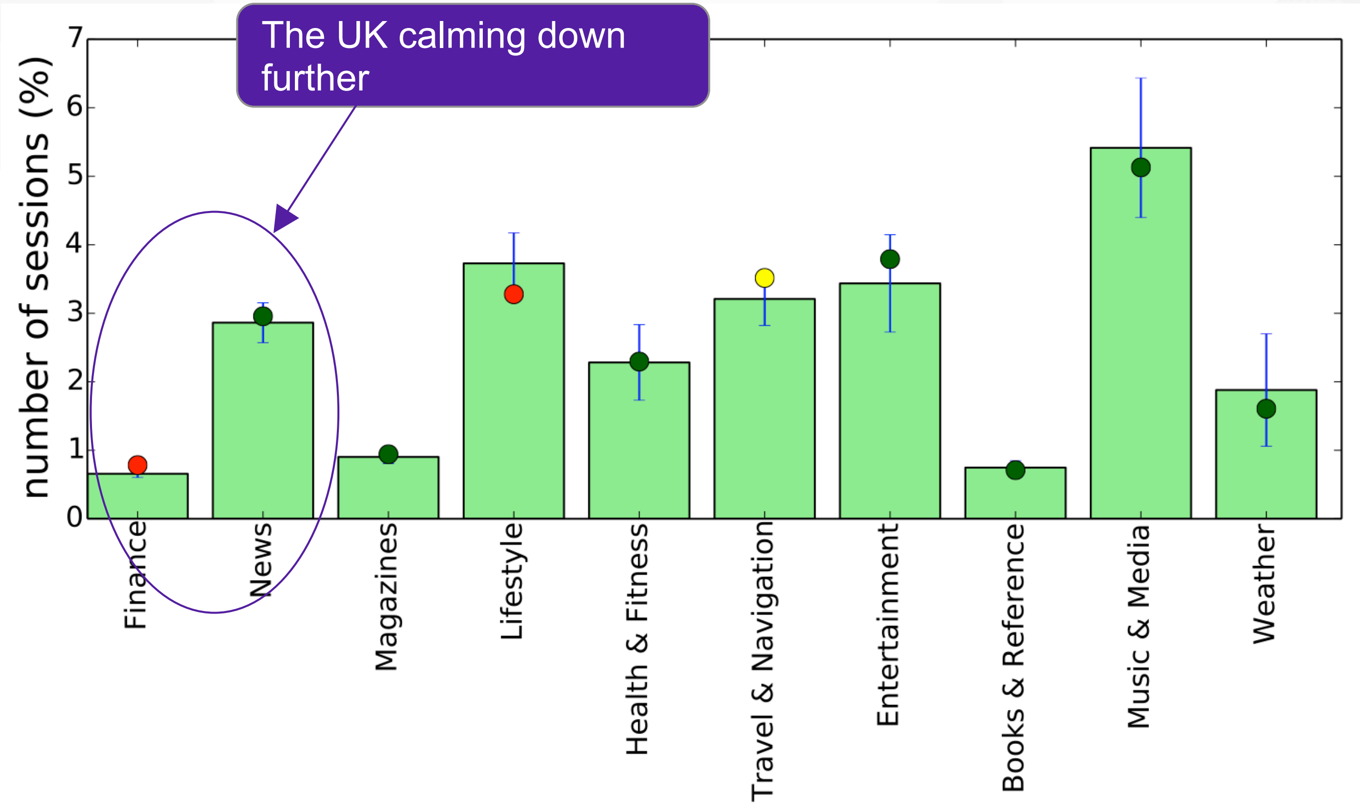
# Second week after the referendum result (UK)

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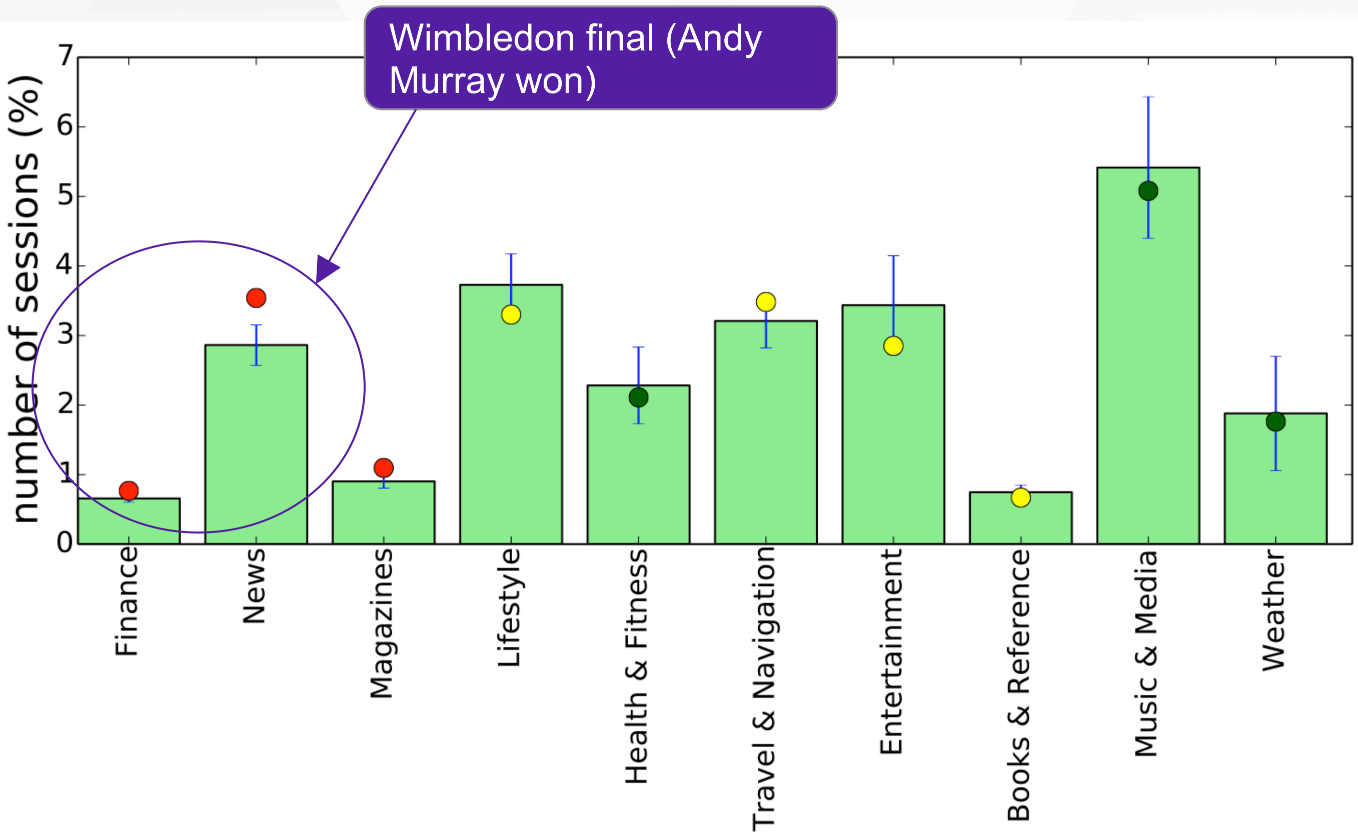
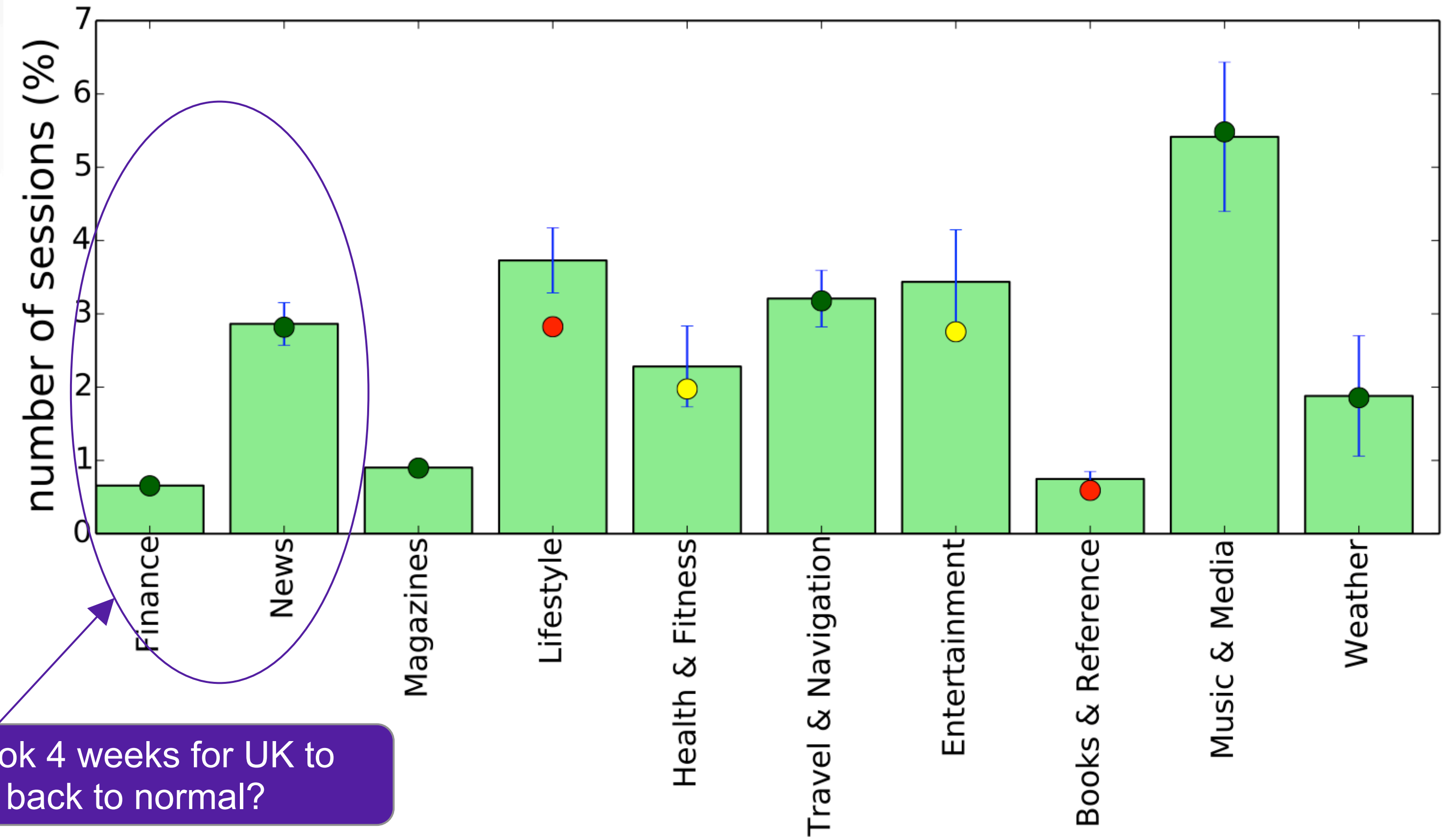
# Third week after the referendum result (UK)



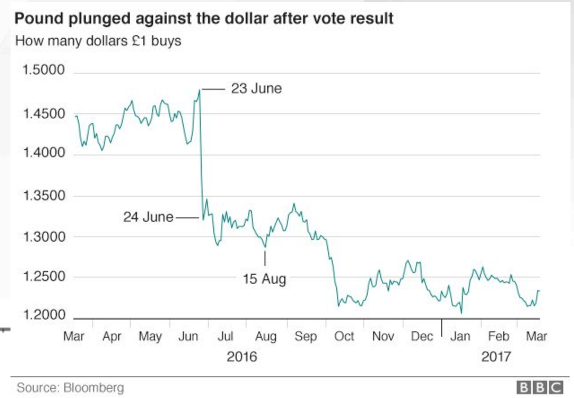

# Fourth week after the referendum (UK)

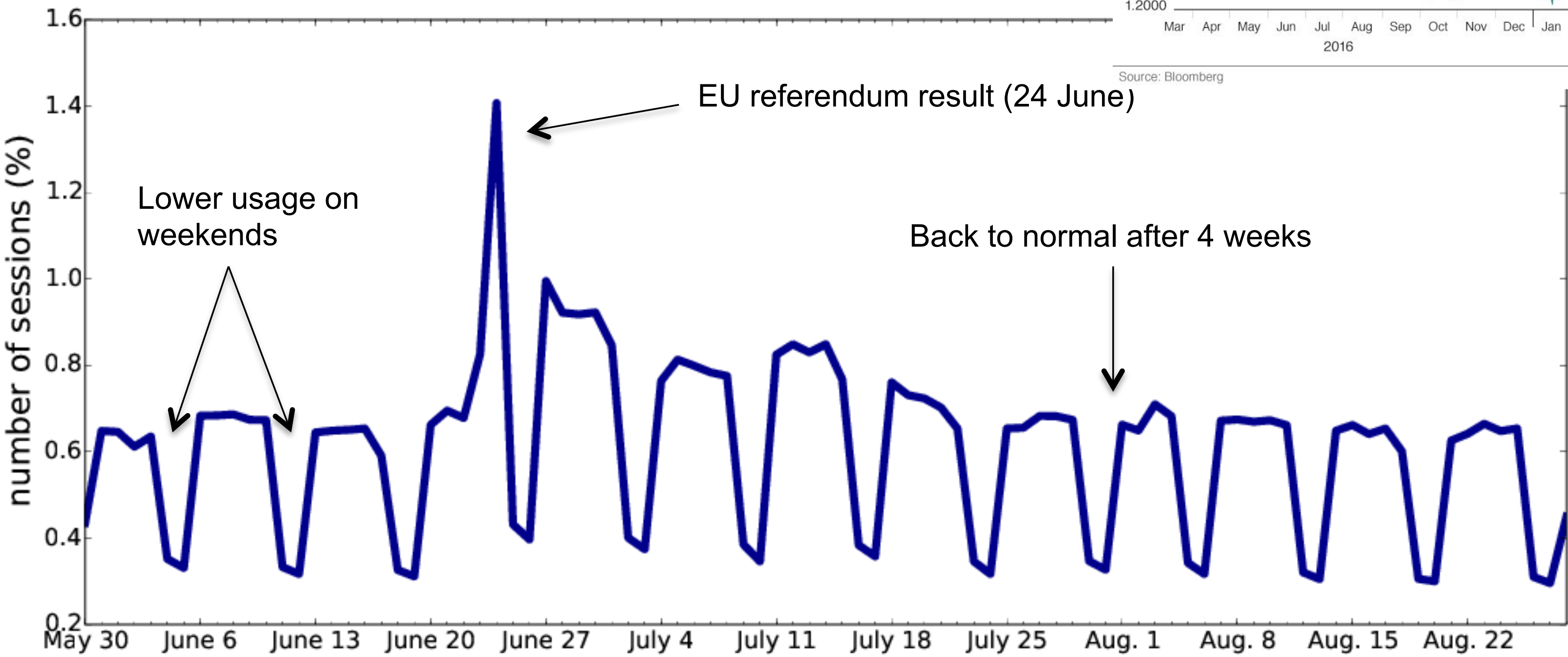



Took 4 weeks for UK to be back to normal?

YAHOO!

# Percentage of UK sessions of finance apps during June- August 2016




YAHOO!

# Case study 3: New year's day

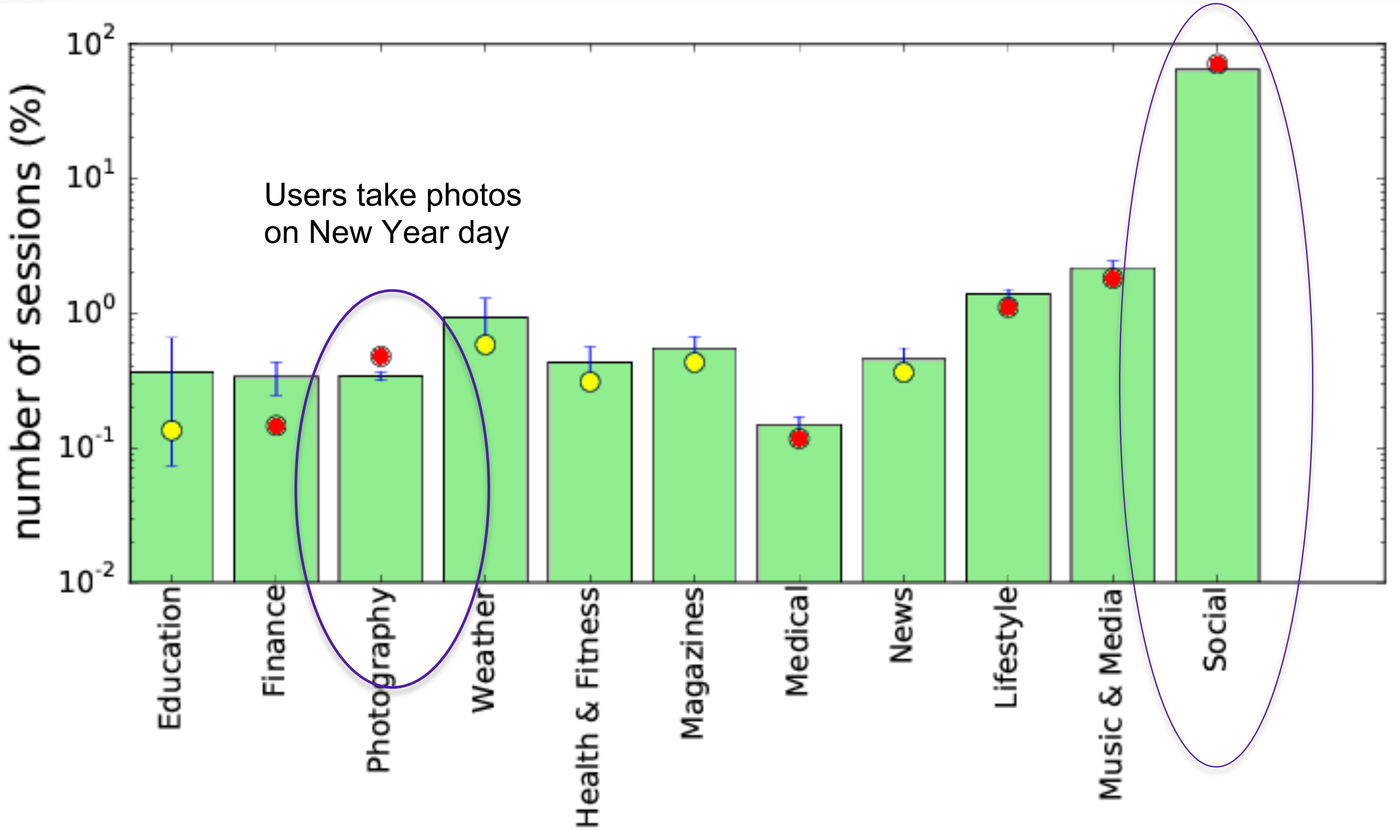
# New year day (US)

- New Year Day, first day of the new year, observed in most Western countries on January 1.
- Common traditions include attending parties, making resolutions for the new year, watching fireworks displays and calling friends and family

Examine whether New Year Day coincides with disruptions in app usage patterns

Week days between December 15, 2015 & January 15, 2016, without January 1, used as reference days

# Percentage of sessions for the 10 categories with the largest percentage change in app engagement




Increased use of social media

YAHOO!

# Conclusions and what next

# Some final thoughts

- We are able to detect disruption of app engagement patterns
- A tool to judge people habit, mood, interest, concern, etc

What next

- We want to look at country difference
- Automatically detect events based on disruptions
- Profile users based on disruptions
- Study of “mobile addiction”