2018 DC R Conference

Anomaly Detection with Time Series

Catherine Zhou

SENIOR DATA SCIENTIST + MANAGER

Anomaly Detection with Time Series

... or how to know when something is terribly wrong 🔥🔥🔥

twitter @catherinezh

#rstats

#rstatsdc

#rladies

#codecademy

About Me_

- Proud New YorkeR
- Currently @ Codecademy
- Formerly @ JetBlue & NY/DC/Boston Sports Clubs

ABSTRACT

With the rise of streaming data and cloud computing, data scientists are often asked to analyze terabytes of data. The sheer amount of data available leads to a lag time in identifying irregularities, resulting in lost time and revenue.

We can pinpoint these outliers through anomaly detection algorithms, which can be repurposed to monitor key metrics, website breakage, and fraudulent activity. I will demonstrate how we can build a system for anomaly detection to uncover blind spots in large datasets and reduce fire drills at work.

Agenda

By the end of this talk you will be able to:

- **Analyze seasonal trends** in time series
- **Plot and visualize anomalies** in *Google Trends* data
- Use *anomalize* to **do this the tidy way**
- Explore different **anomaly detection algorithms**
- Explain **case studies** where outliers can be useful

PART ONE

Time Series_

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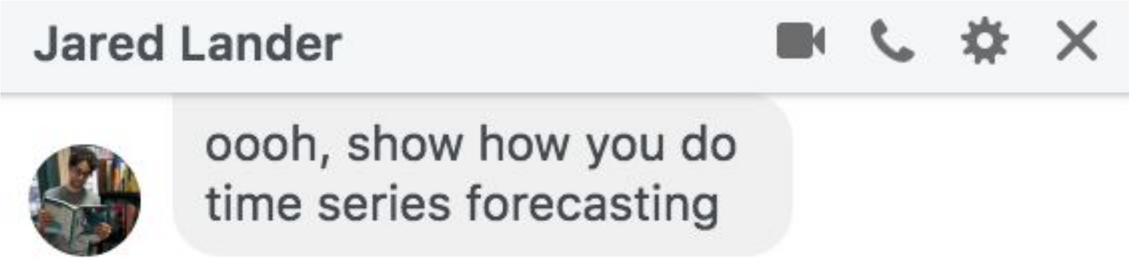
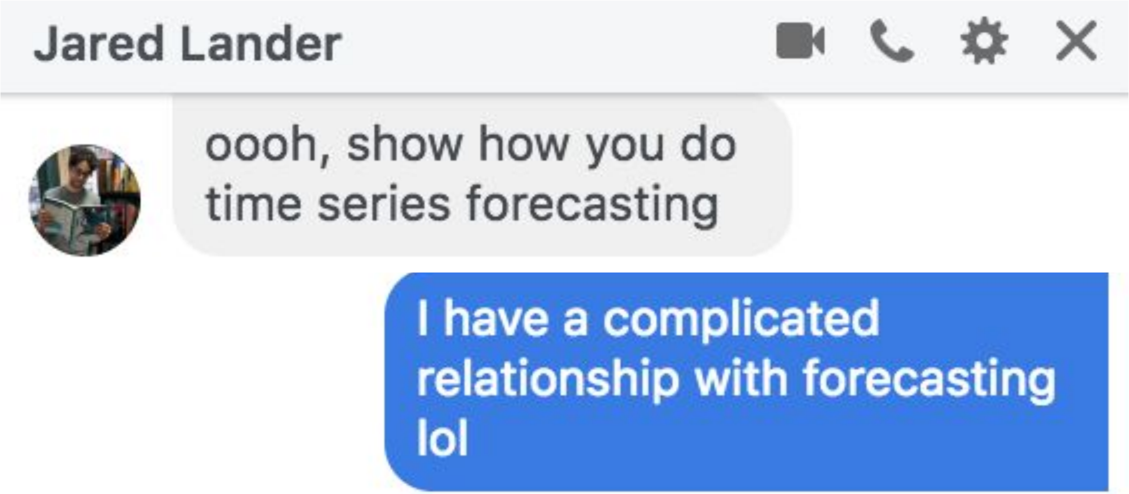


Jared Lander

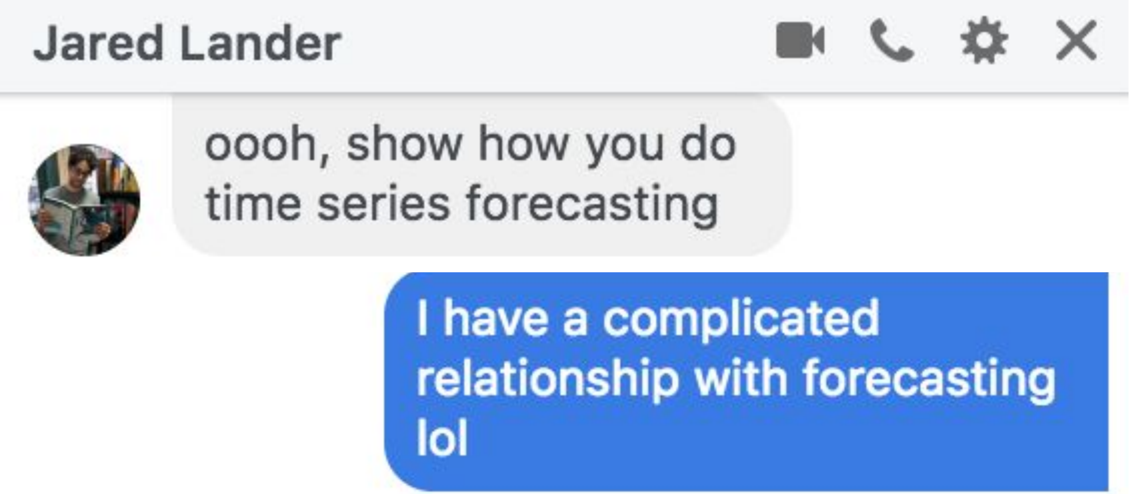
oooh, show how you do time series forecasting



Jared Lander

oooh, show how you do time series forecasting

I have a complicated relationship with forecasting lol



Jared Lander

oooh, show how you do time series forecasting

I have a complicated relationship with forecasting lol

facebook

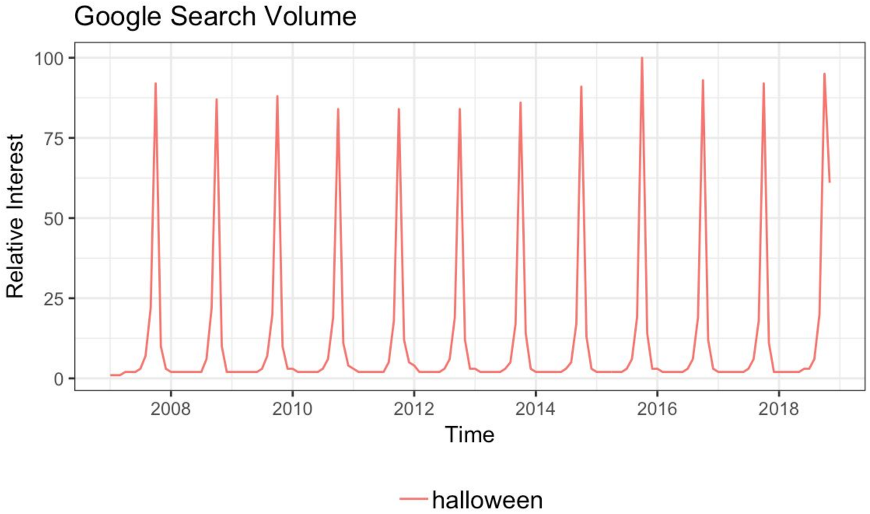
Basic Information

Relationship Status	It's complicated

EXPECTATION

We want to work with data that is:

- Clean and well-organized
- Daily or weekly patterns
- Clear seasonal trends
- Key metrics to monitor
- Actionable insights



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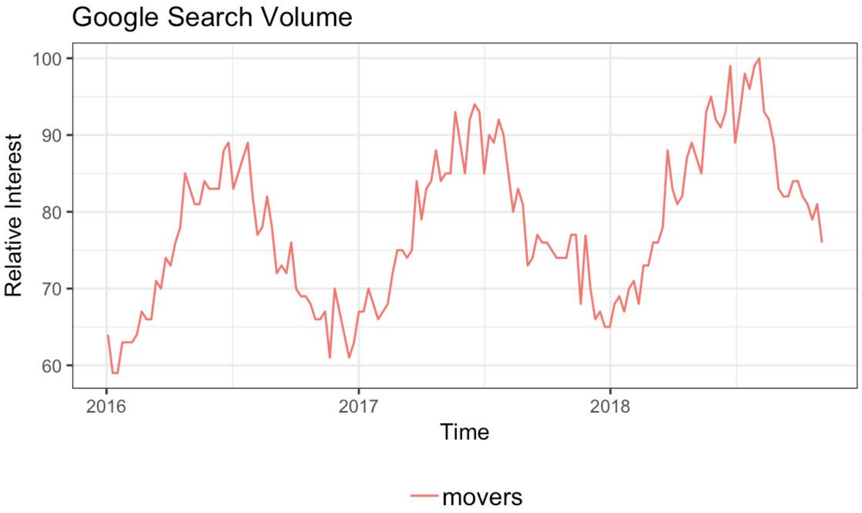

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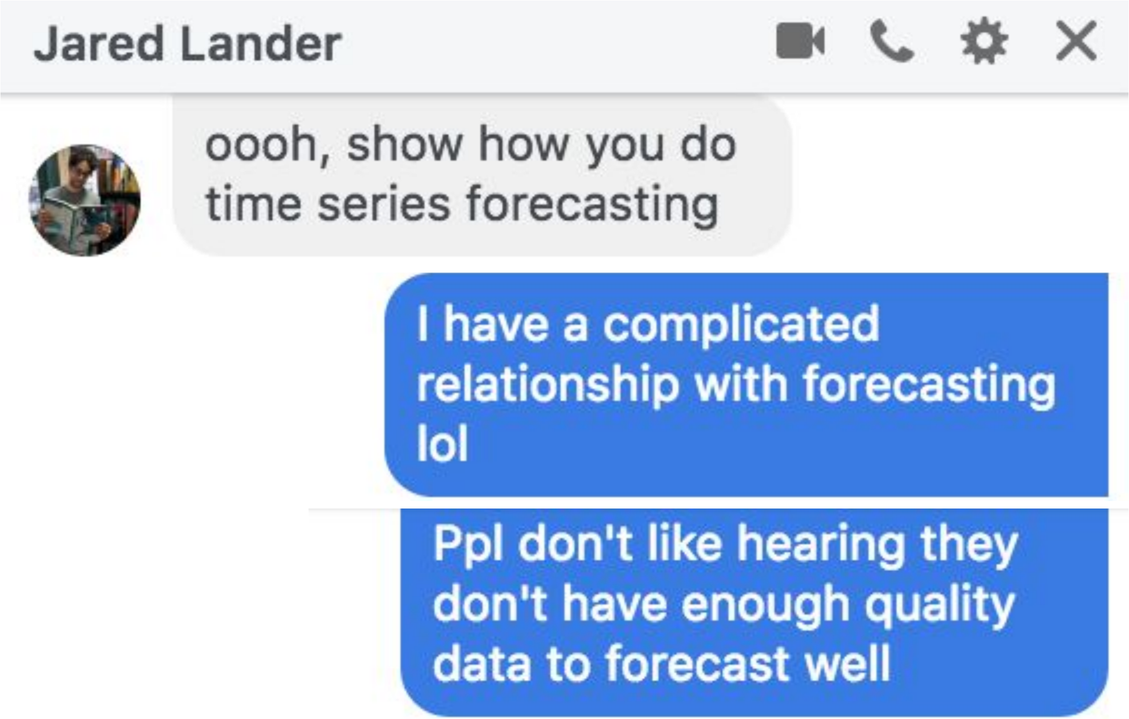

Jared Lander

oooh, show how you do time series forecasting

I have a complicated relationship with forecasting lol

Ppl don't like hearing they don't have enough quality data to forecast well

EXPECTATION

We want to work with data that is:

- Clean and well-organized
- Daily or weekly patterns
- Clear seasonal trends
- Key metrics to monitor
- Actionable insights

VS.

REALITY

We often work with data that has:

- Inconsistent trends and patterns
- Terabytes in size
- Multiple key metrics
  - Difficult to monitor
  - Difficult to interpret

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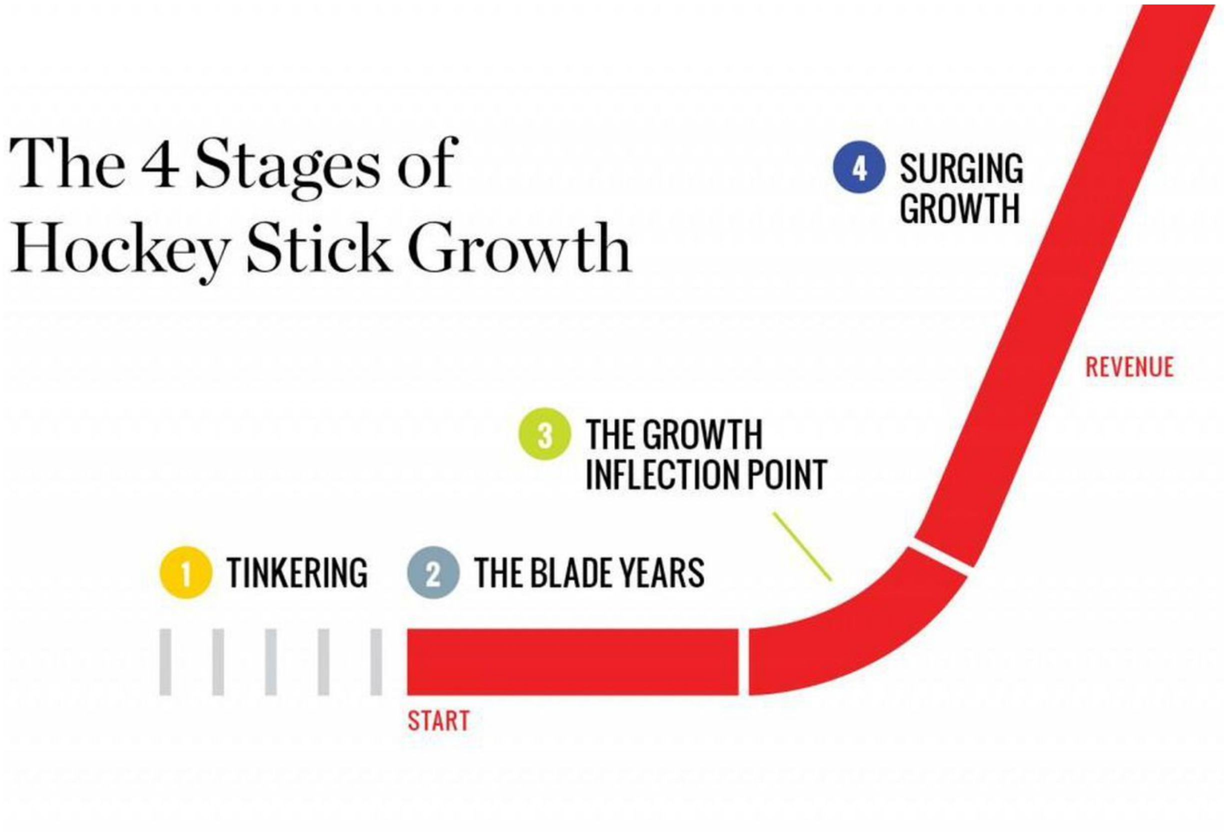
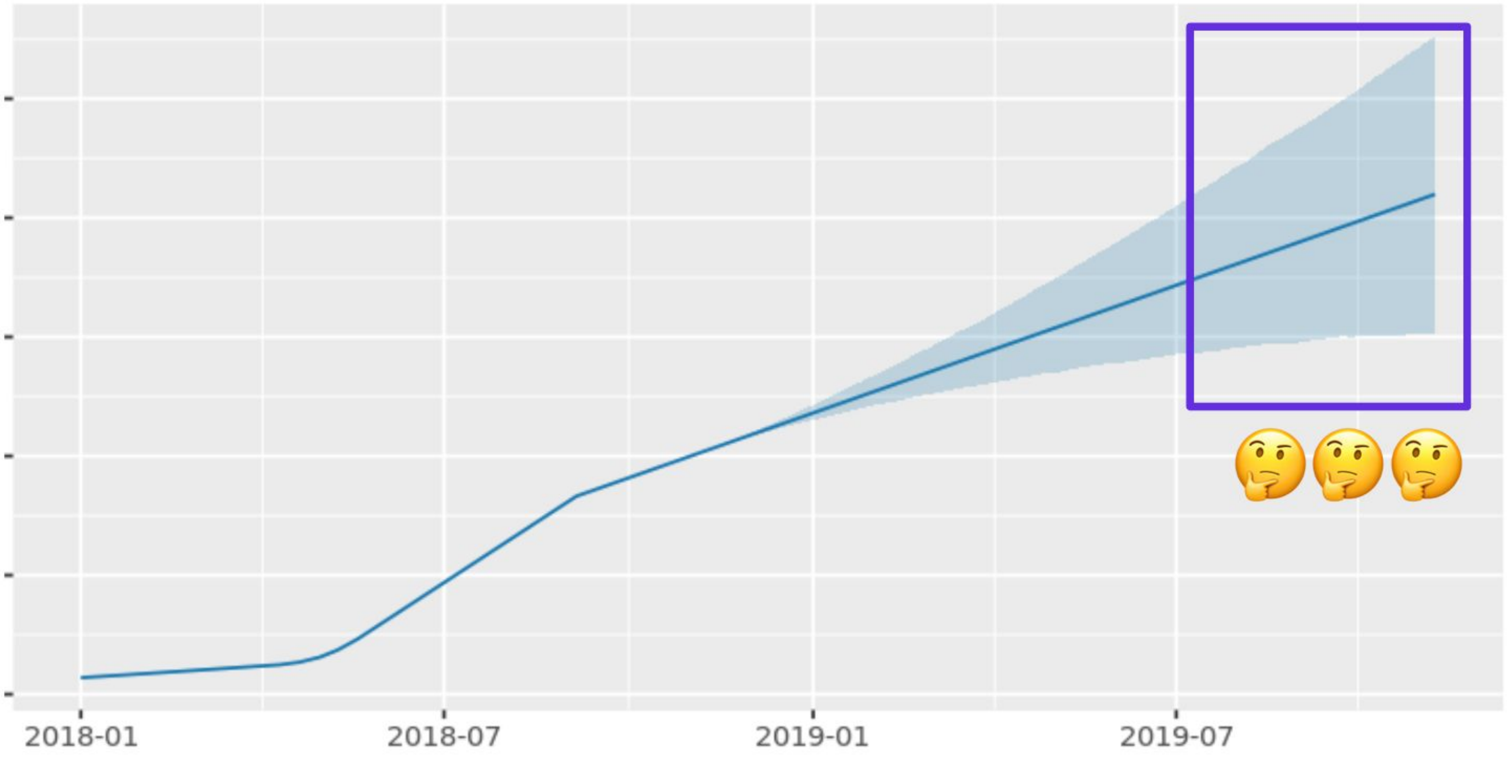
For data scientists in tech, growth is a double-edged sword.



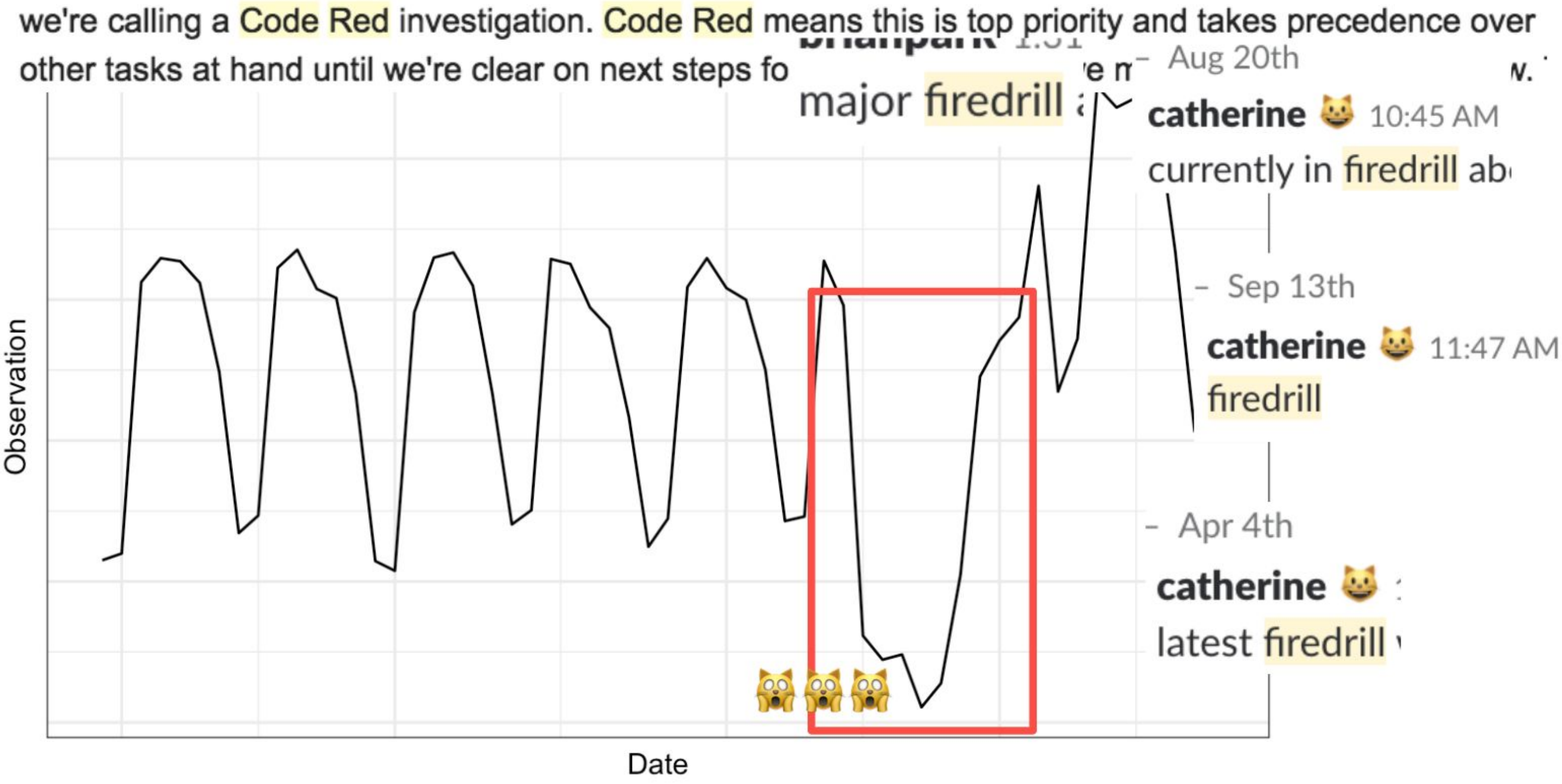
Growth creates uncertainty in time series forecasting.



PART TWO

Dealing with Fire Drills_

something is terribly wrong 🔥🔥🔥



we're calling a Code Red investigation. Code Red means this is top priority and takes precedence over other tasks at hand until we're clear on next steps fo e m w.

brianpark 1:51

major firedrill a

Aug 20th

catherine 😺 10:45 AM

currently in firedrill ab

Sep 13th

catherine 😺 11:47 AM

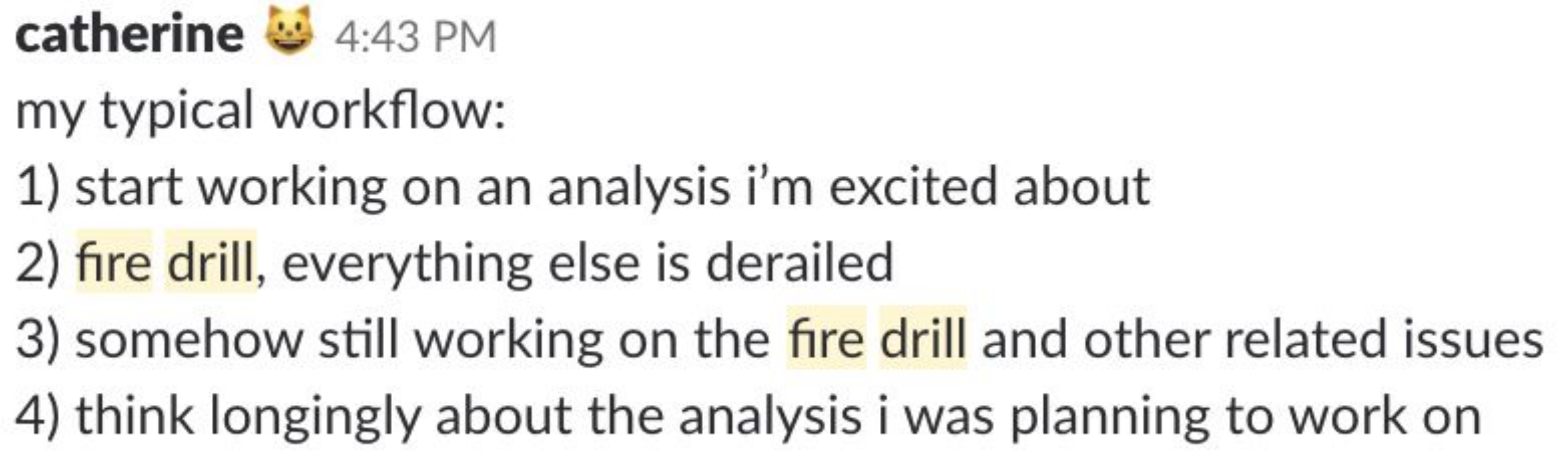
firedrill

Apr 4th

catherine 😺 1

latest firedrill

DATA SCIENCE FIRE DRILLS



catherine 😺 4:43 PM

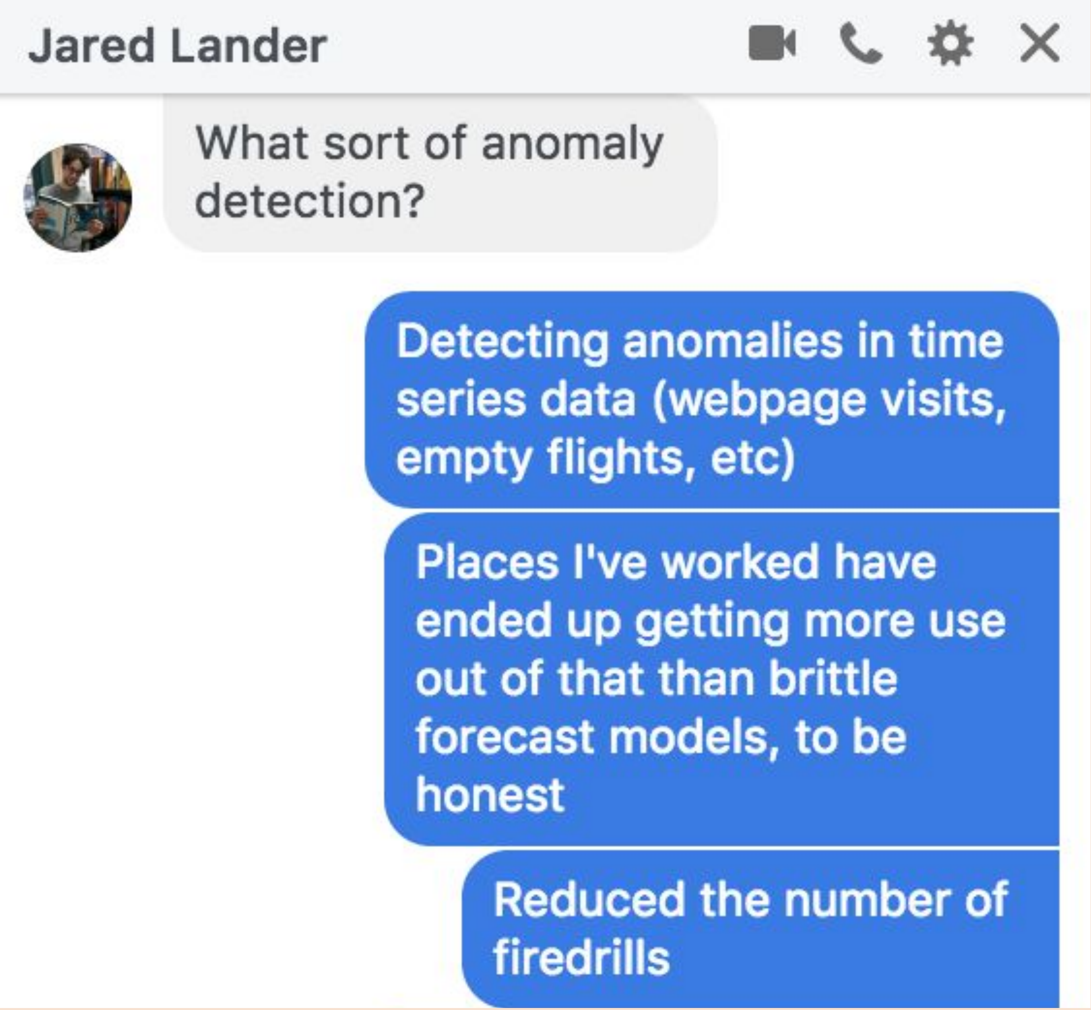
my typical workflow:

1) start working on an analysis i’m excited about

2) fire drill, everything else is derailed

3) somehow still working on the fire drill and other related issues

4) think longingly about the analysis i was planning to work on



Jared Lander

What sort of anomaly detection?

Detecting anomalies in time series data (webpage visits, empty flights, etc)

Places I've worked have ended up getting more use out of that than brittle forecast models, to be honest

Reduced the number of firedrills

Anomaly detection on key metrics can lead to earlier detection of irregularities and reduce the number of fire drills.

We can be proactive instead of reactive.

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Applications of Anomaly Detection_

- Fraud Detection
- KPI Monitoring
- Identify Breakage
- Workforce Planning
- Nature (e.g. weather)
- … and more!

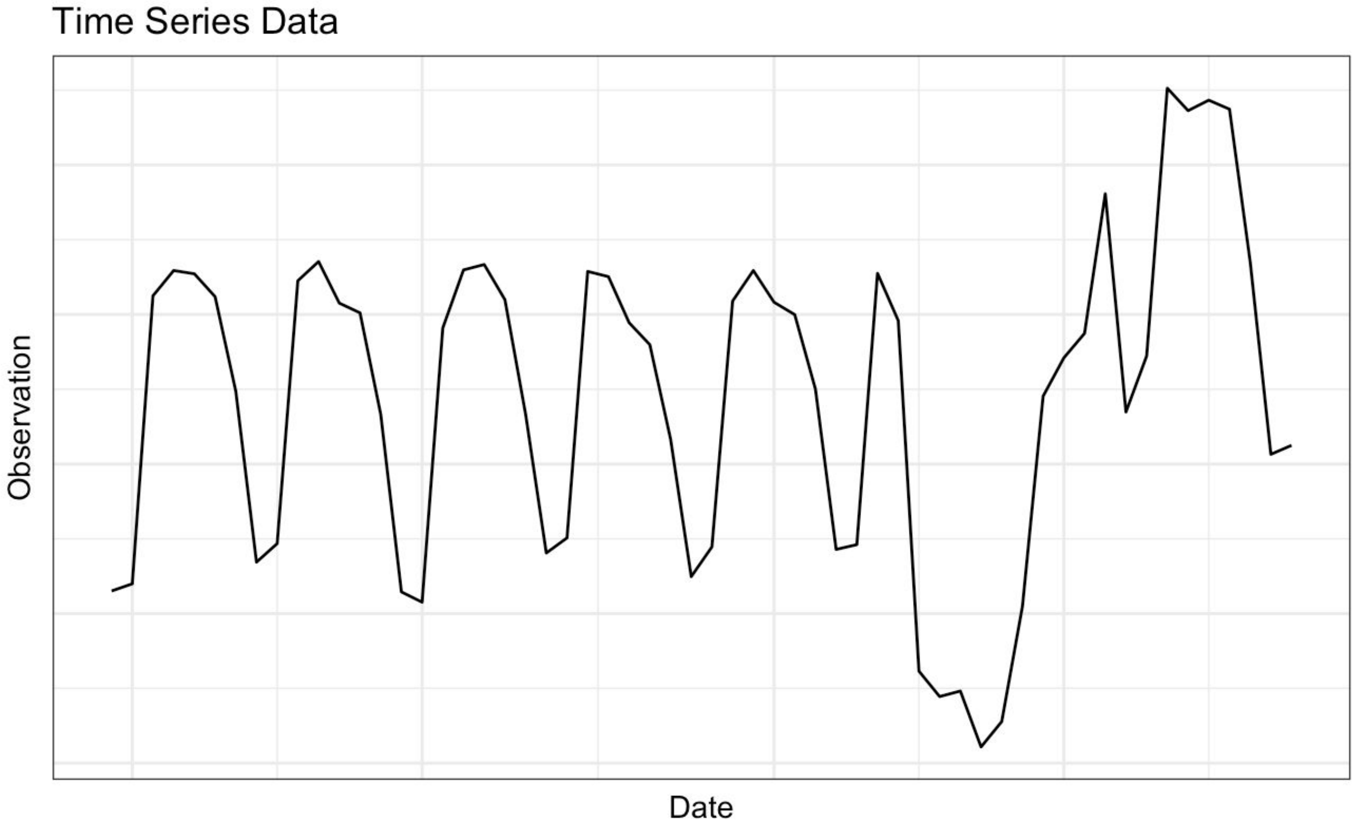
“monitor key metrics, website breakage, and fraudulent activity… we can build a system for anomaly detection to uncover blind spots in large datasets and reduce fire drills at work”

- my DC R promise, stated at the beginning of this talk

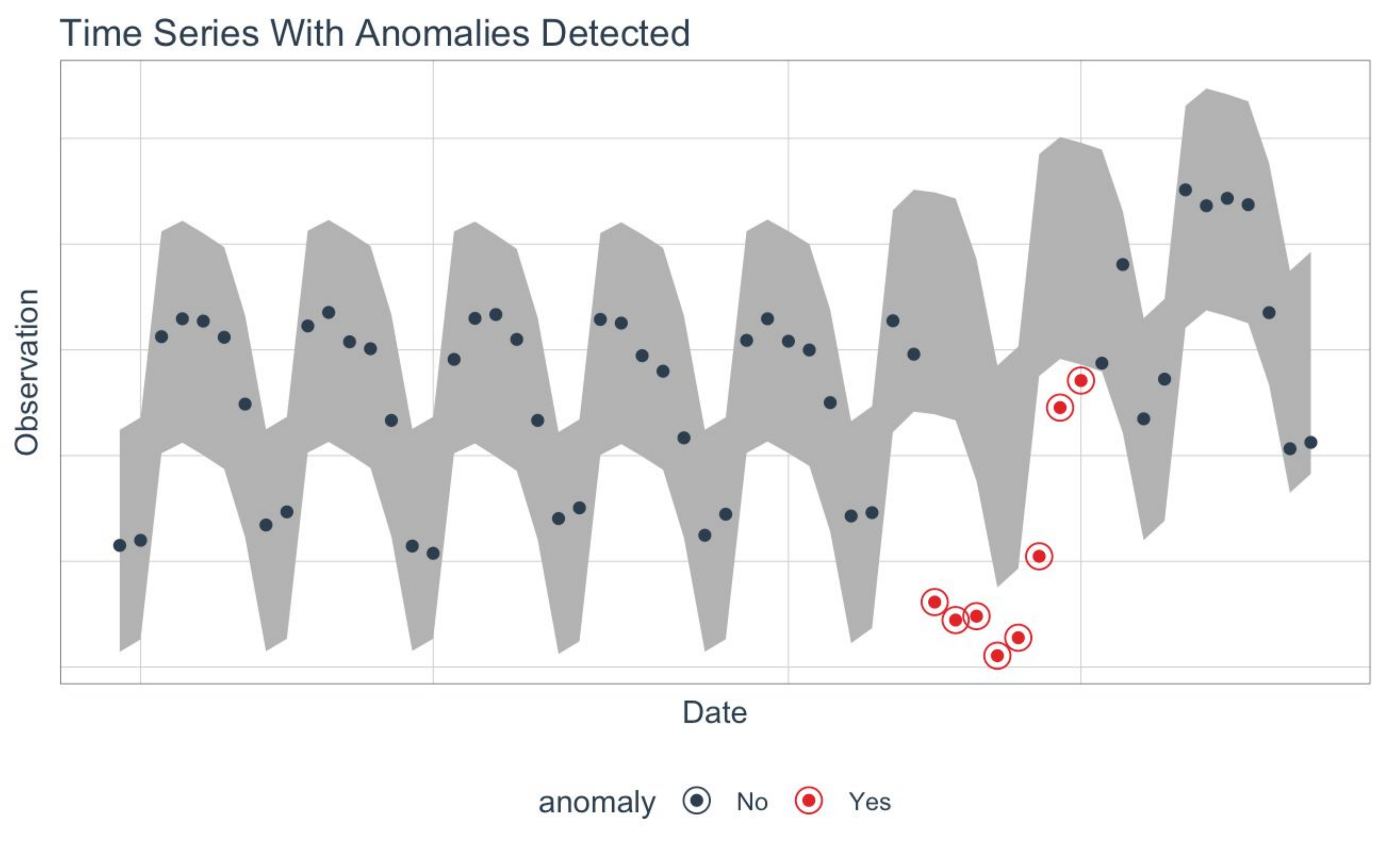
PART THREE

Anomaly Detection_

Before...



AFTER!


Time Series With Anomalies Detected
Observation
Date
anomaly
No
Yes

LIVE CODE SESSION

Let’s get started!

Follow along:

twitter @catherinezh

github @cattystats

https://github.com/cattystats/Anomaly_Detection

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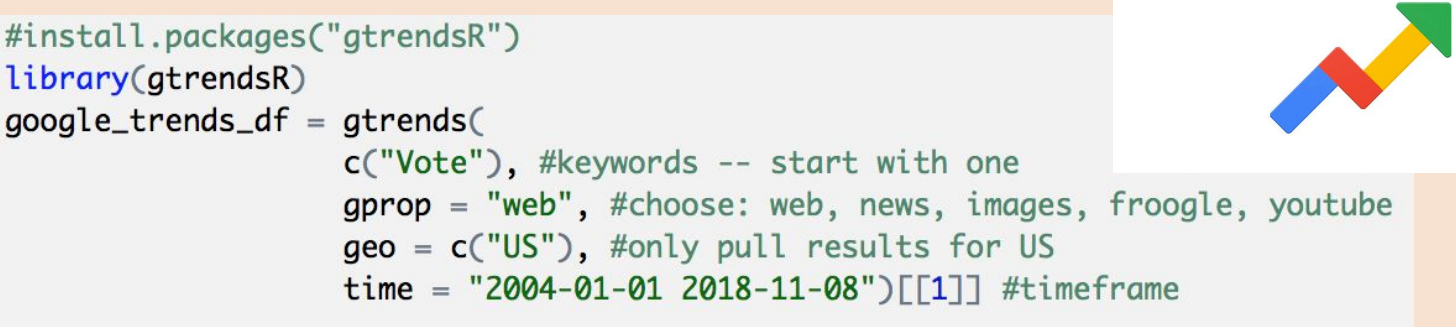
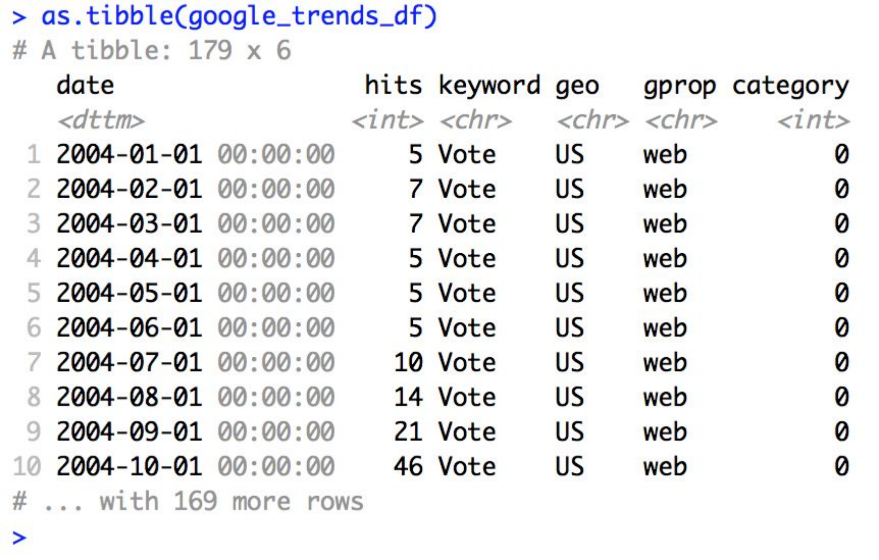
1. CREATE A DATA FRAME



```r
#install.packages("gtrendsR")
library(gtrendsR)
google_trends_df = gtrends(
                    c("Vote"), #keywords -- start with one
                    gprop = "web", #choose: web, news, images, froogle, youtube
                    geo = c("US"), #only pull results for US
                    time = "2004-01-01 2018-11-08")[[1]] #timeframe
```

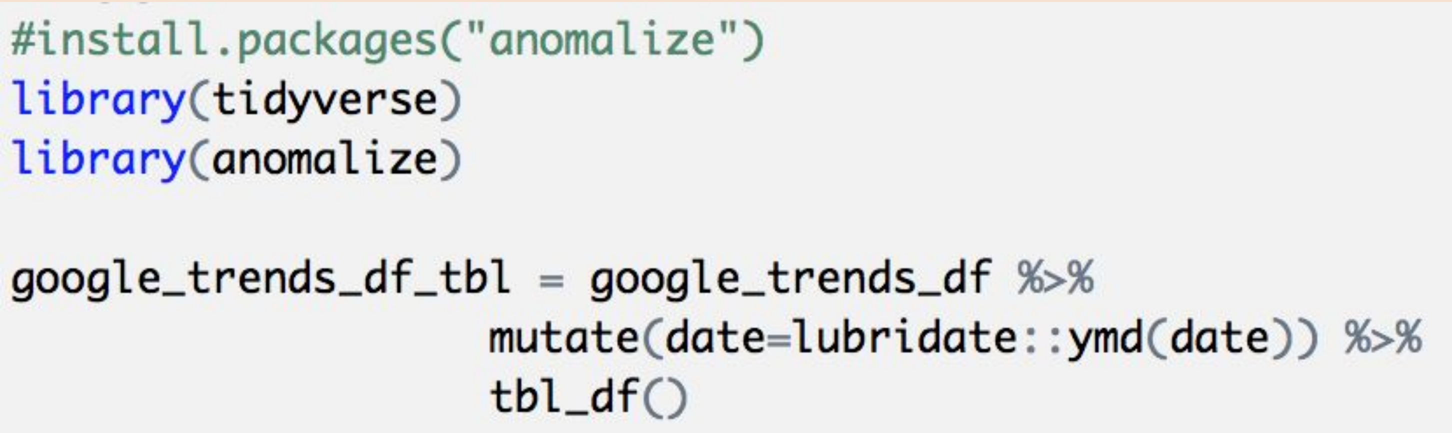


```
> as.tibble(google_trends_df)
# A tibble: 179 x 6
   date                 hits keyword geo   gprop category
   <dttm>              <int> <chr>   <chr> <chr>    <int>
 1 2004-01-01 00:00:00     5 Vote    US    web          0
 2 2004-02-01 00:00:00     7 Vote    US    web          0
 3 2004-03-01 00:00:00     7 Vote    US    web          0
 4 2004-04-01 00:00:00     5 Vote    US    web          0
 5 2004-05-01 00:00:00     5 Vote    US    web          0
 6 2004-06-01 00:00:00     5 Vote    US    web          0
 7 2004-07-01 00:00:00    10 Vote    US    web          0
 8 2004-08-01 00:00:00    14 Vote    US    web          0
 9 2004-09-01 00:00:00    21 Vote    US    web          0
10 2004-10-01 00:00:00    46 Vote    US    web          0
# ... with 169 more rows
>
```

install + load gtrendsR: choose a keyword that interests you

2. PREPARE DATA

install + load tidyverse and anomalize

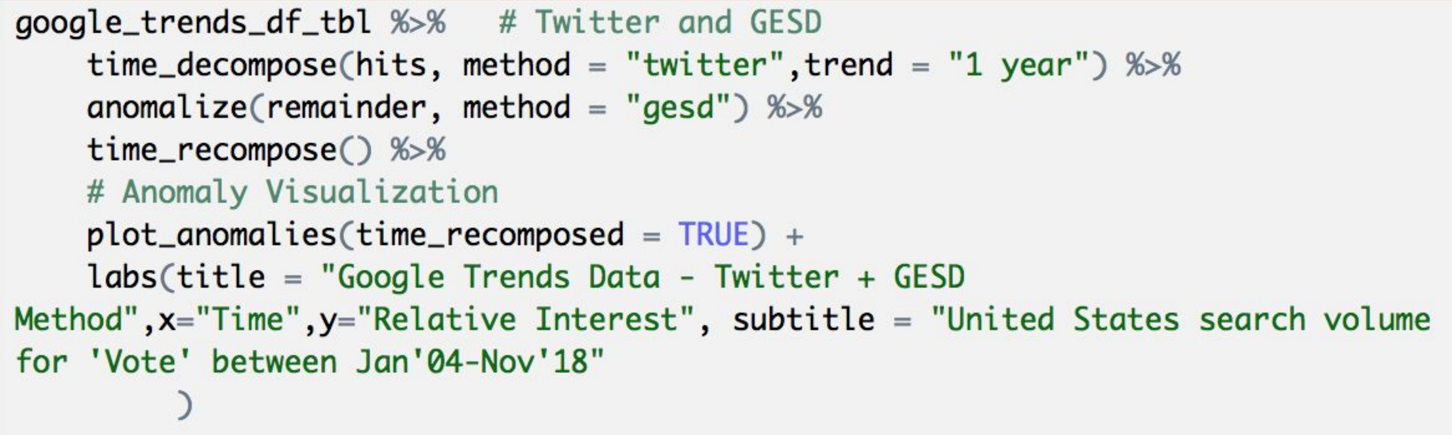


```
#install.packages("anomalize")
library(tidyverse)
library(anomalize)

google_trends_df_tbl = google_trends_df %>%
                 mutate(date=lubridate::ymd(date)) %>%
                 tbl_df()
```

3. ANOMALIZE!

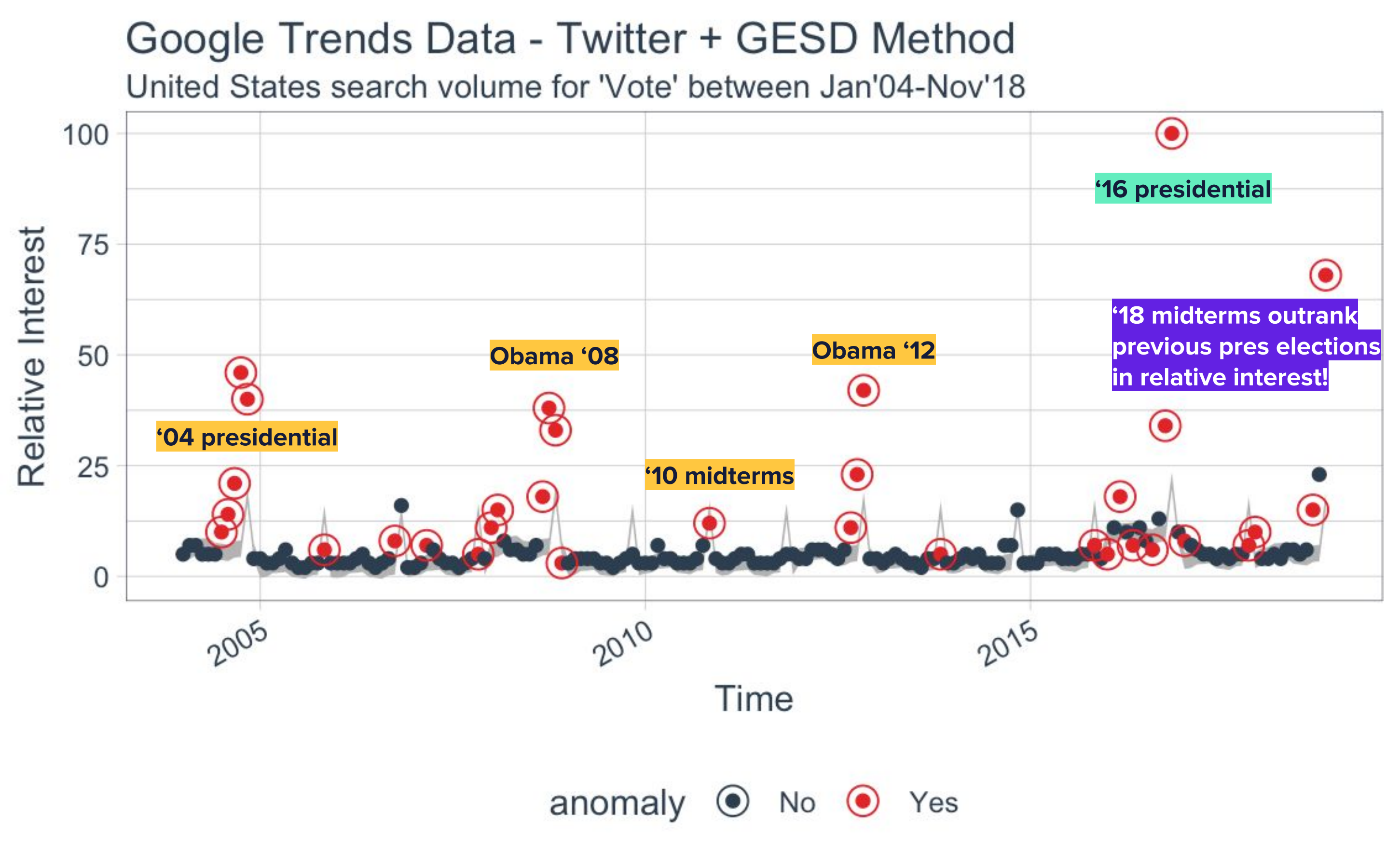
anomalize!



```
google_trends_df_tbl %>%   # Twitter and GESD
    time_decompose(hits, method = "twitter",trend = "1 year") %>%
    anomalize(remainder, method = "gesd") %>%
    time_recompose() %>%
    # Anomaly Visualization
    plot_anomalies(time_recomposed = TRUE) +
    labs(title = "Google Trends Data - Twitter + GESD
Method",x="Time",y="Relative Interest", subtitle = "United States search volume
for 'Vote' between Jan'04-Nov'18"
         )
```

3. ANOMALIZE… TADA!

KEYWORD: VOTE



Google Trends Data - Twitter + GESD Method

United States search volume for 'Vote' between Jan'04-Nov'18

‘04 presidential

Obama ‘08

‘10 midterms

Obama ‘12

‘16 presidential

‘18 midterms outrank previous pres elections in relative interest!

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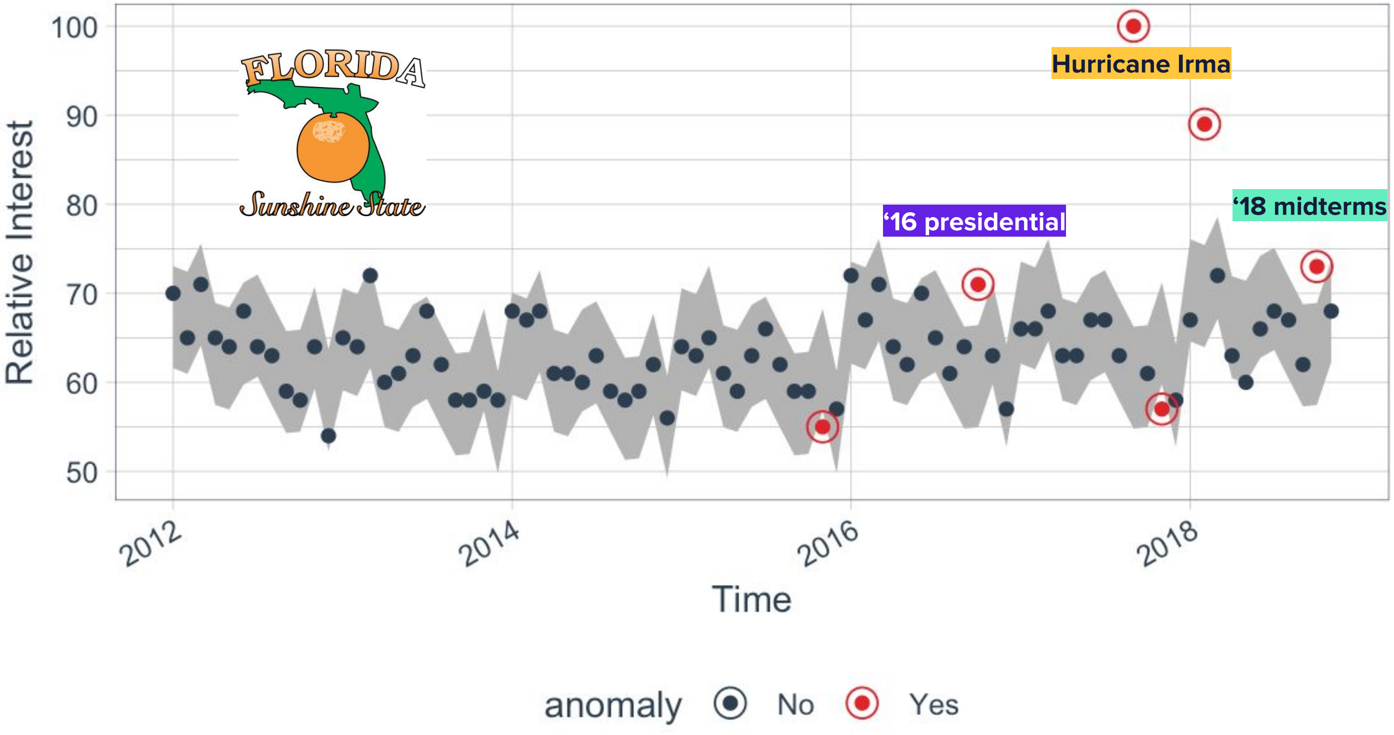
LET'S TRY THIS WITH… KEYWORD: FLORIDA

Google Trends Data - Twitter + GESD Method

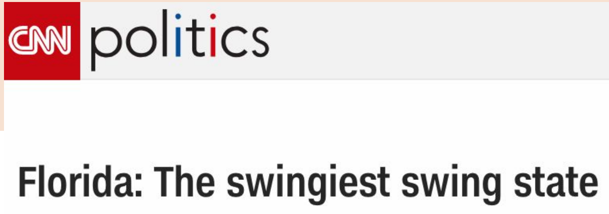
United States search volume for 'Florida' between Jan'12-Nov'18



Hurricane Irma

'16 presidential

'18 midterms



Florida: The swingiest swing state

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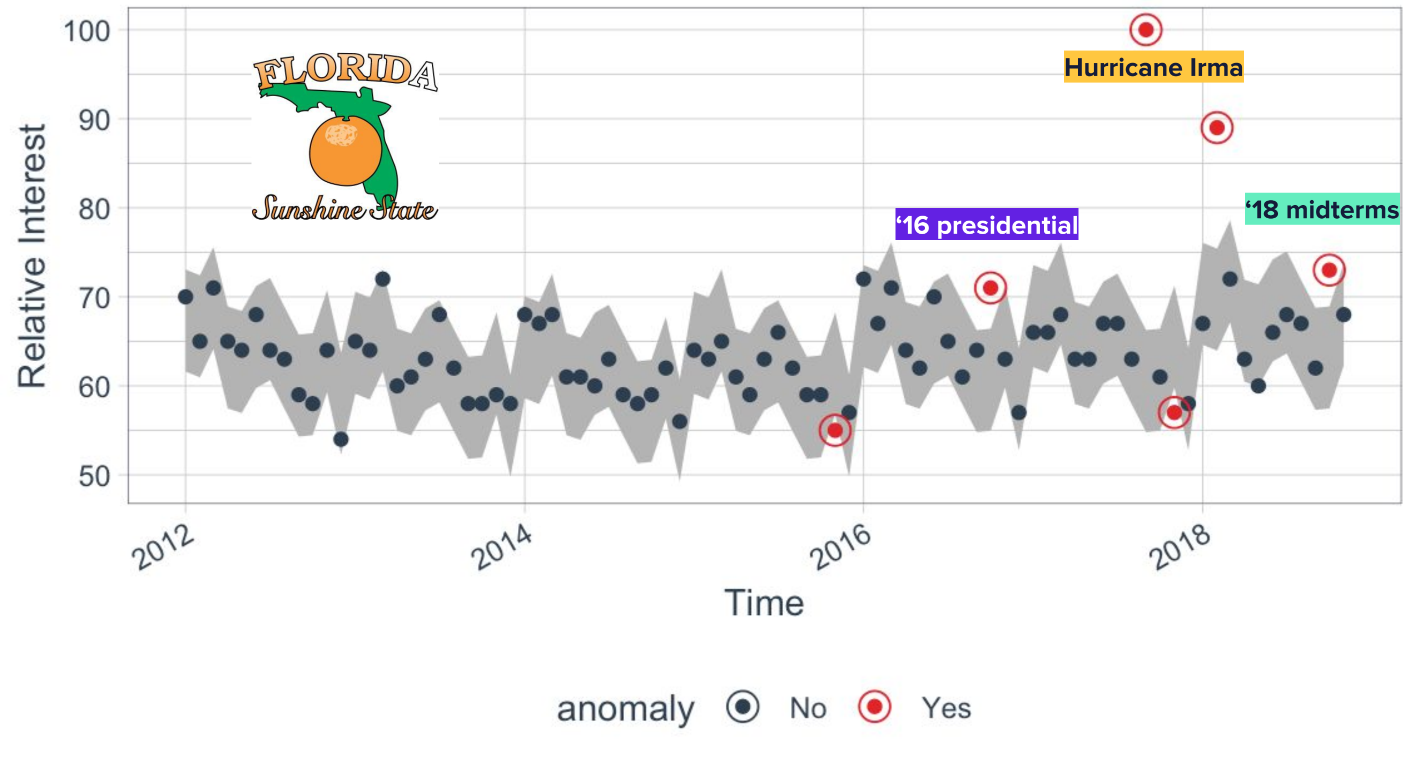
LET’S TRY THIS WITH...

KEYWORD: FLORIDA


Google Trends Data - Twitter + GESD Method

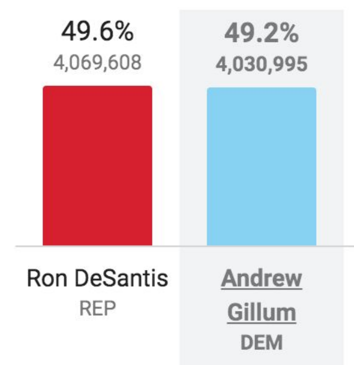
United States search volume for 'Florida' between Jan'12-Nov'18

Hurricane Irma

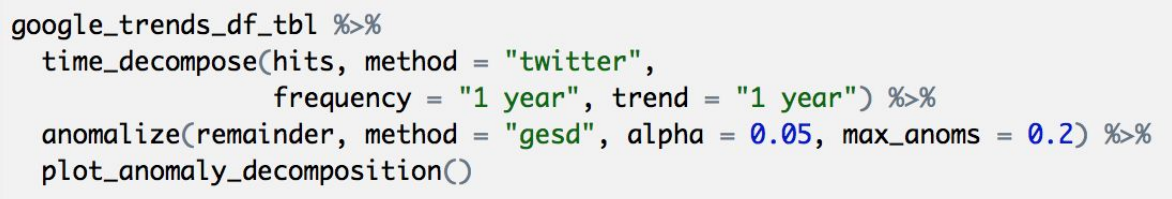
‘16 presidential

‘18 midterms

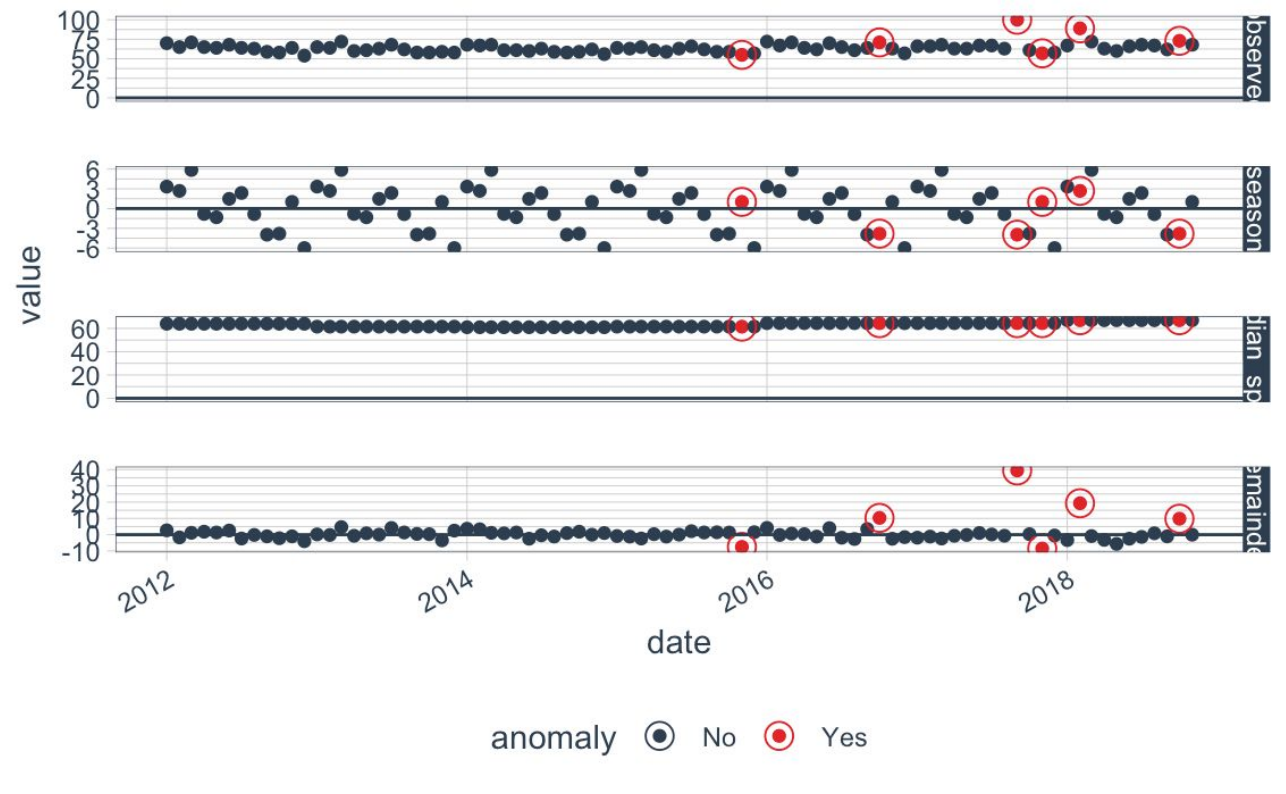
Florida: The swingiest swing state


49.6% 4,069,608	49.2% 4,030,995
Ron DeSantis REP	Andrew Gillum DEM

KEYWORD: FLORIDA



```
google_trends_df_tbl %>%
  time_decompose(hits, method = "twitter",
                         frequency = "1 year", trend = "1 year") %>%
  anomalize(remainder, method = "gesd", alpha = 0.05, max_anoms = 0.2) %>%
  plot_anomaly_decomposition()
```



plot_anomaly_decomposition()

visualize inner workings of how algorithm detects anomalies in the “remainder”

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4. EXPLORE METHODS BASED ON TIME SERIES ATTRIBUTES

anomalize cheat sheet:

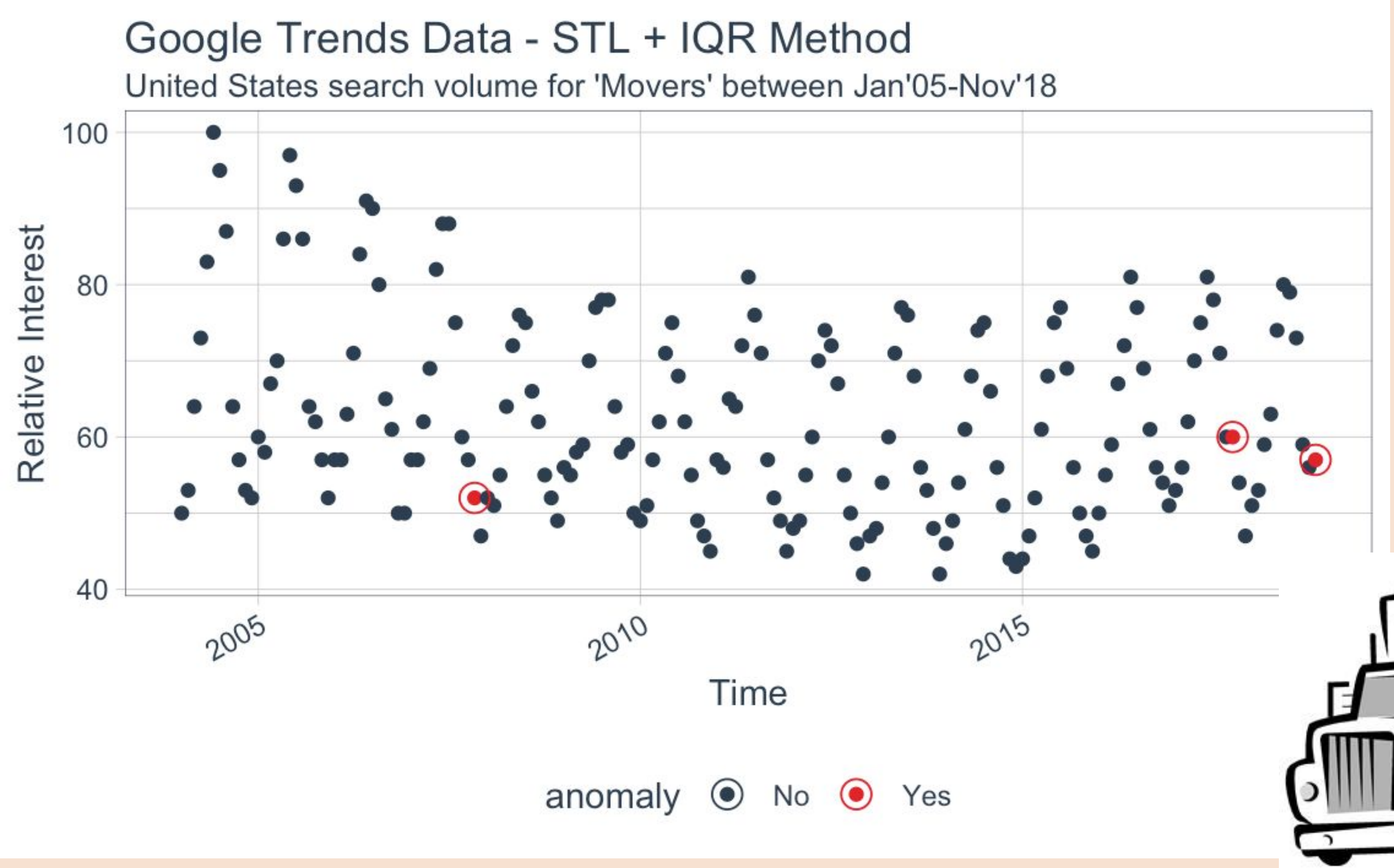
Twitter + GESD better for highly seasonal data

STL + IQR if seasonality is not a major factor

adjust trend period using domain knowledge

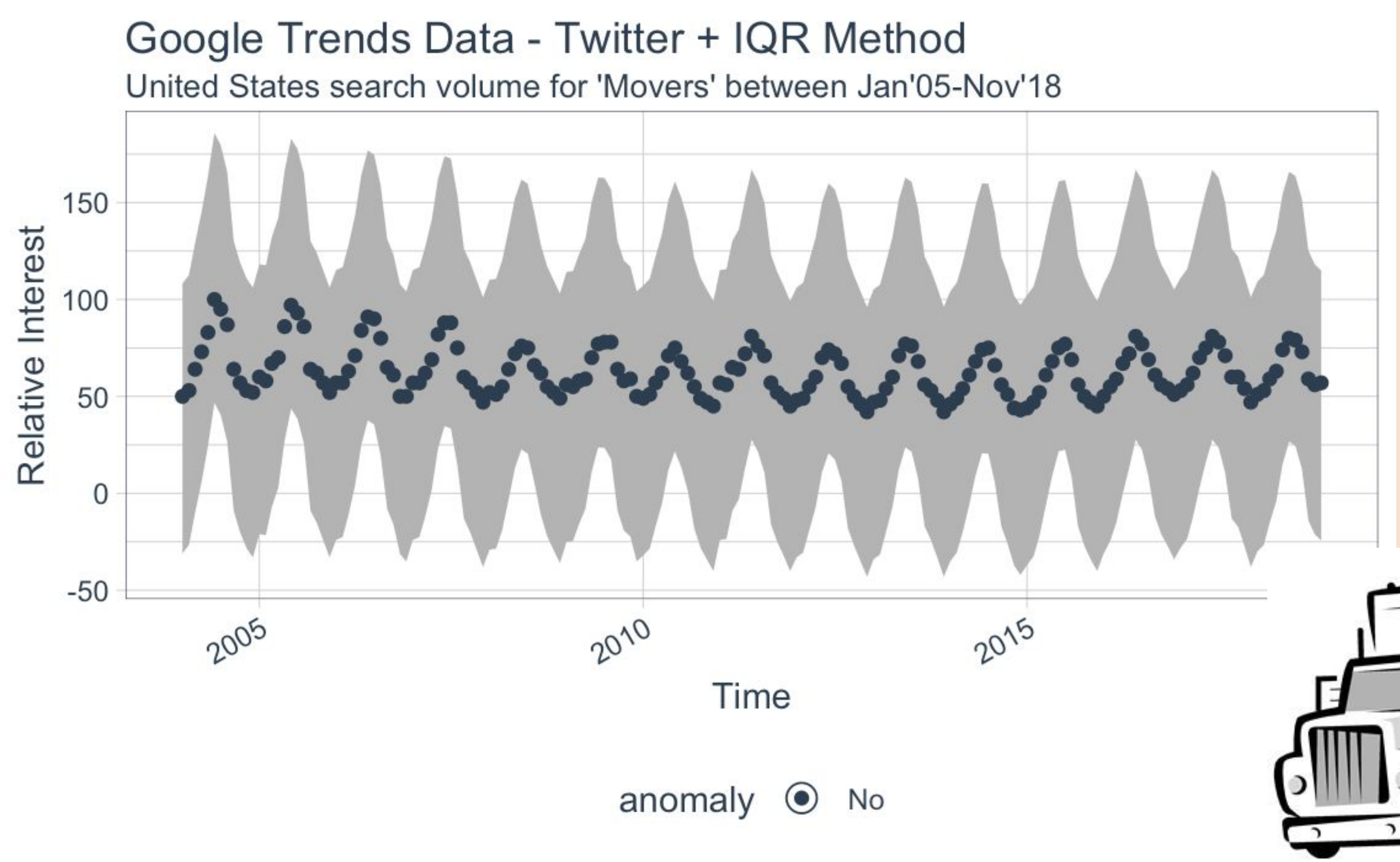
STL + IQR

KEYWORD: MOVERS



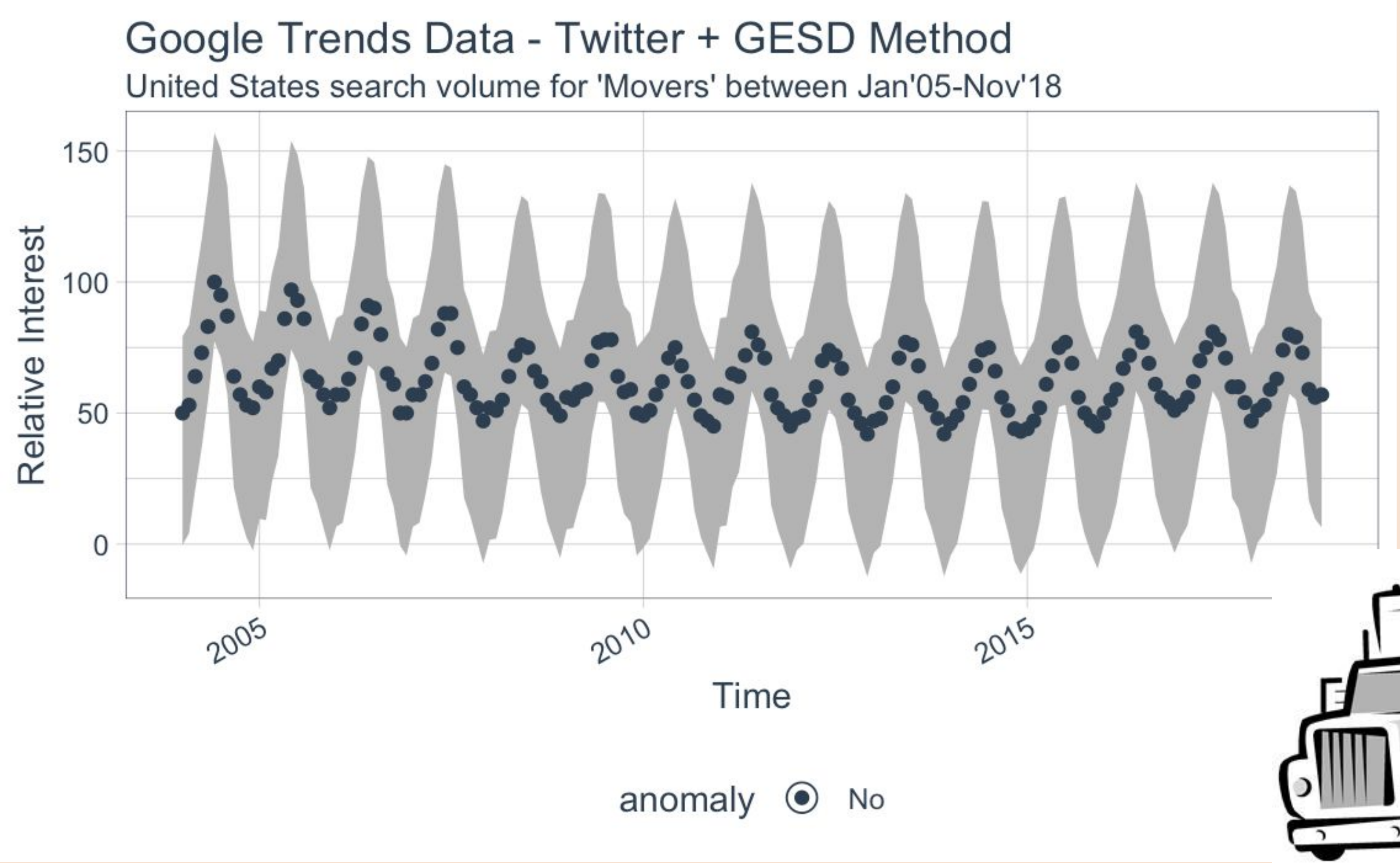
TWITTER DECOMPOSE CONTROLS FOR SEASONALITY

KEYWORD: MOVERS



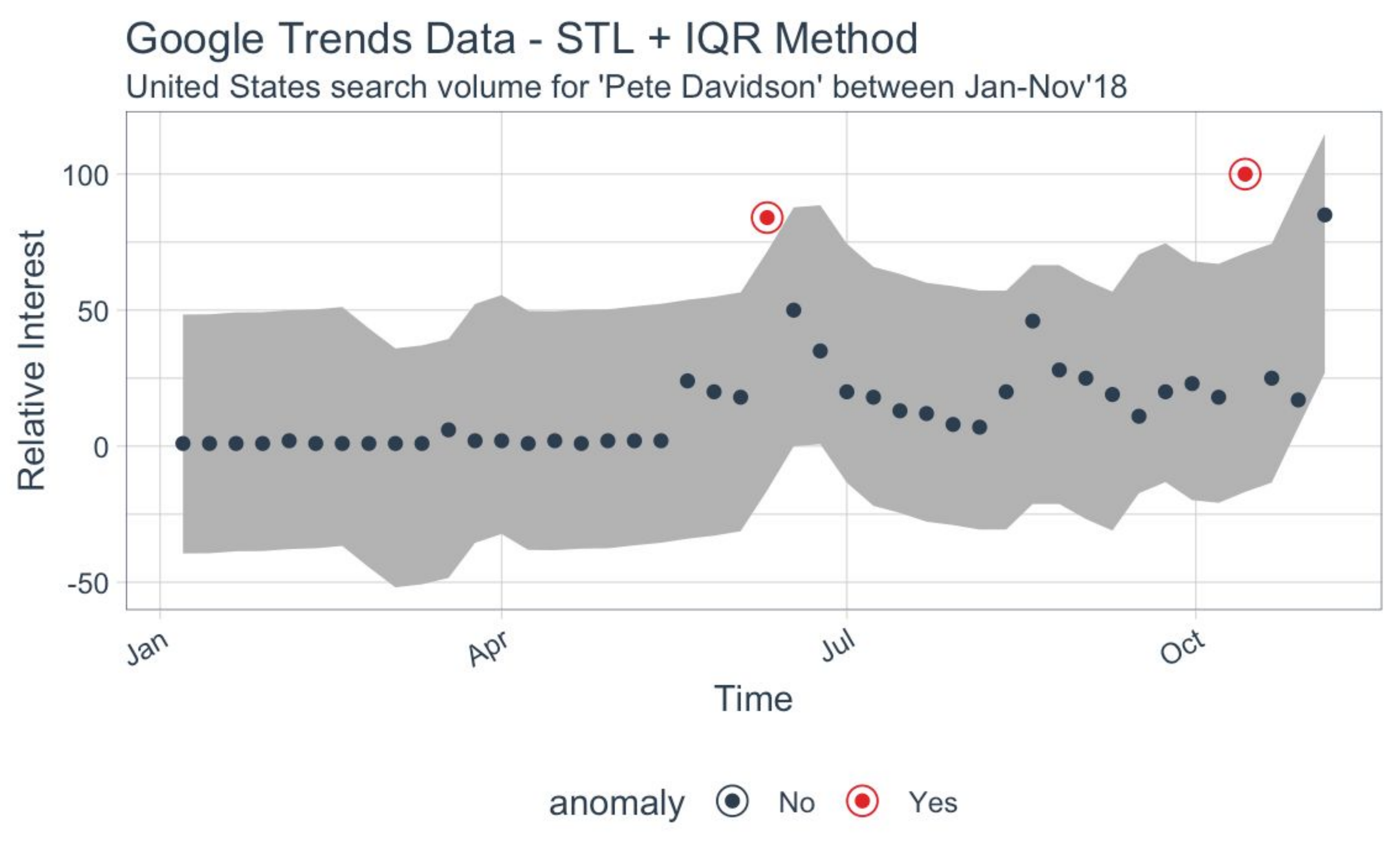
TWITTER + GESD PULLS IN THE MEDIAN/MEAN

KEYWORD: MOVERS



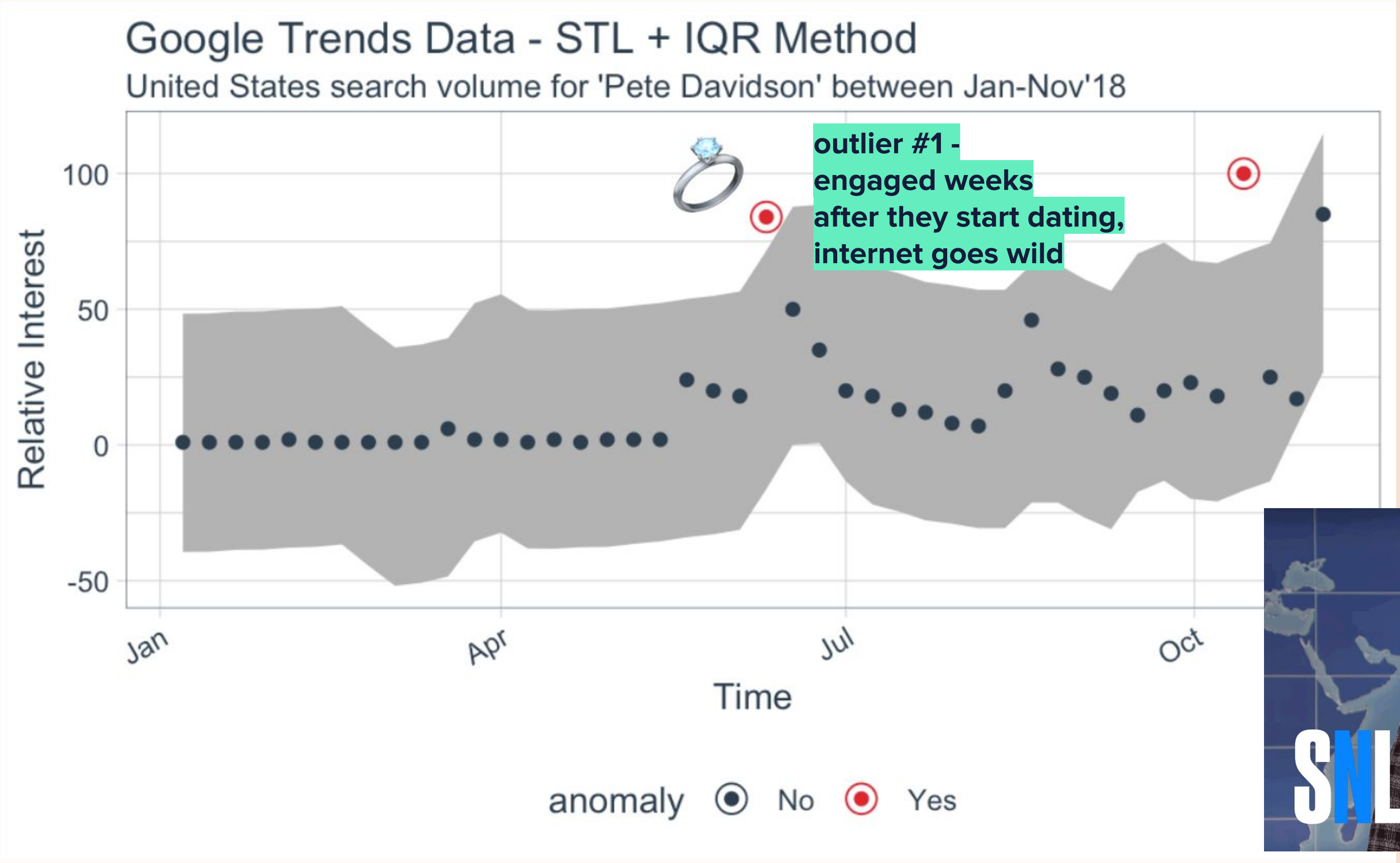
TRY THIS ON DIFFERENT KEYWORDS

PETE DAVIDSON



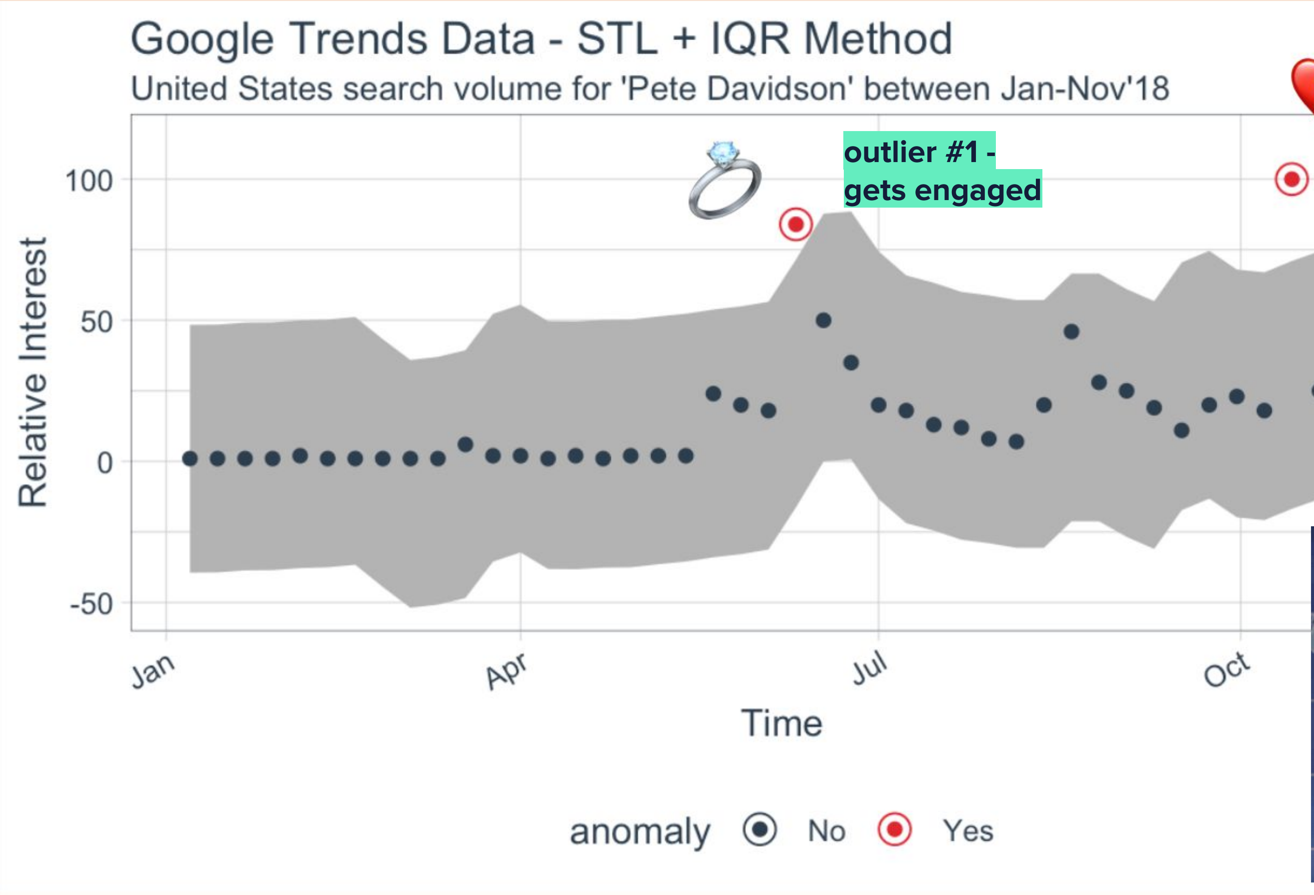
recent news, and 2018 data only -- seasonality is not really a factor, so we go back to using STL + IQR

PETE DAVIDSON



outlier #1 -
engaged weeks
after they start dating,
internet goes wild

PETE DAVIDSON



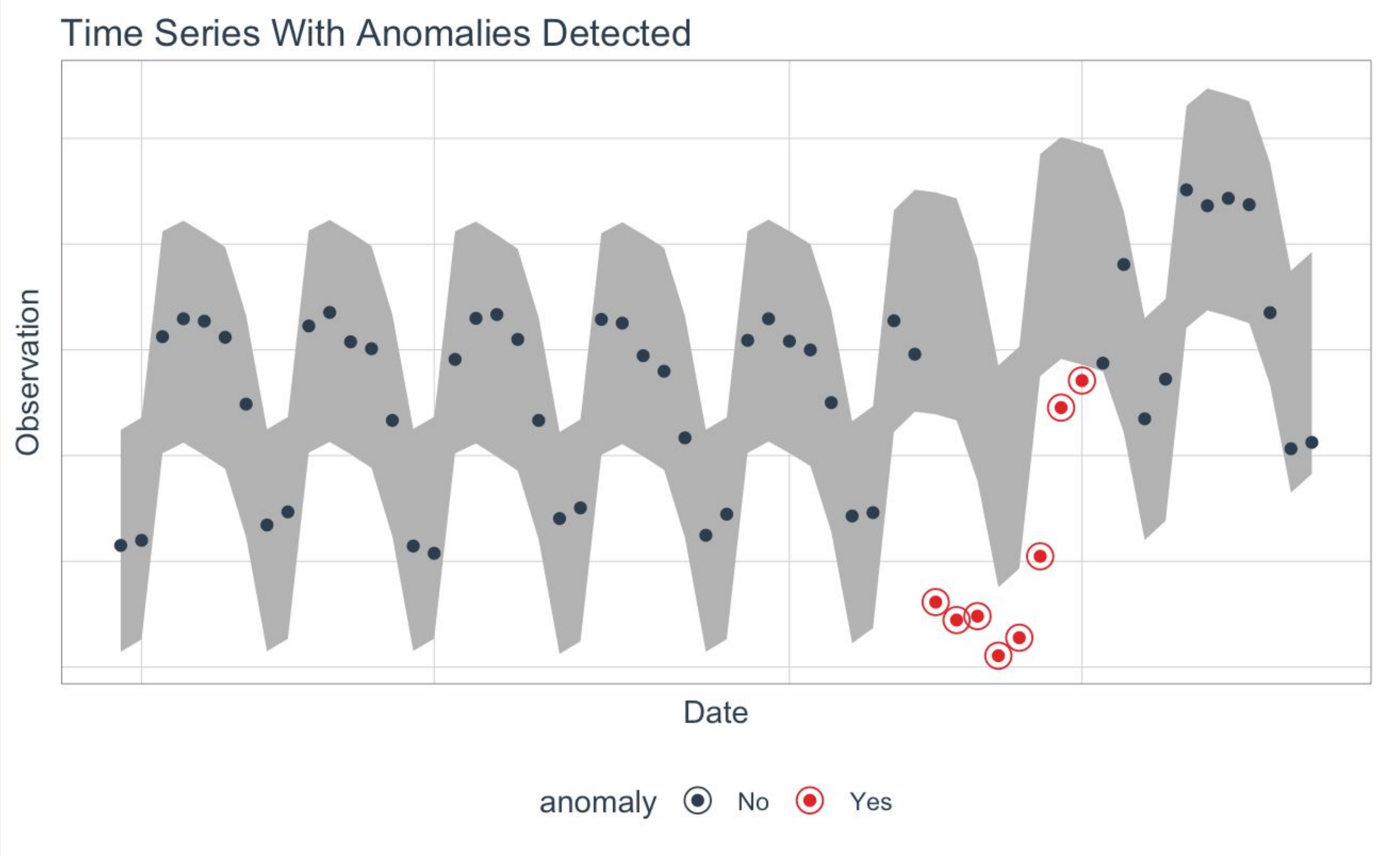
Google Trends Data - STL + IQR Method

United States search volume for 'Pete Davidson' between Jan-Nov'18

💍 outlier #1 - gets engaged

💔 outlier #2 - they call off their engagement, internet breaks again

TRY THIS AT HOME!



Keywords To Try:

- NBA
- Weather
- Politicians
- Elon Musk
- Bitcoin
- Holidays
- Memes
- Events

... and anything else you might think of!

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Additional Resources

- R Code + Notebook
- Introducing Anomalize
- Github: Anomalize
- Codecademy

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GOOD LUCK AND HAVE FUN!

twitter @catherinezh

github @cattystats

#rstats

#rstatsdc

#rladies

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