Measuring the incremental impact of marketing campaigns with geo experiments

My Loan Tong
Marketing Intelligence Data Analyst
December 12, 2019
Düsseldorf

Agenda

1. Advertising Examples
2. What do we measure?
3. Geo Experiments
4. Limitations
5. Q&A

Advertising Examples

Channels

- Out-Of-Home
- TV
- Online Video
- Football Club Sponsorship
- Radio

How can we measure the effectiveness of these campaigns?

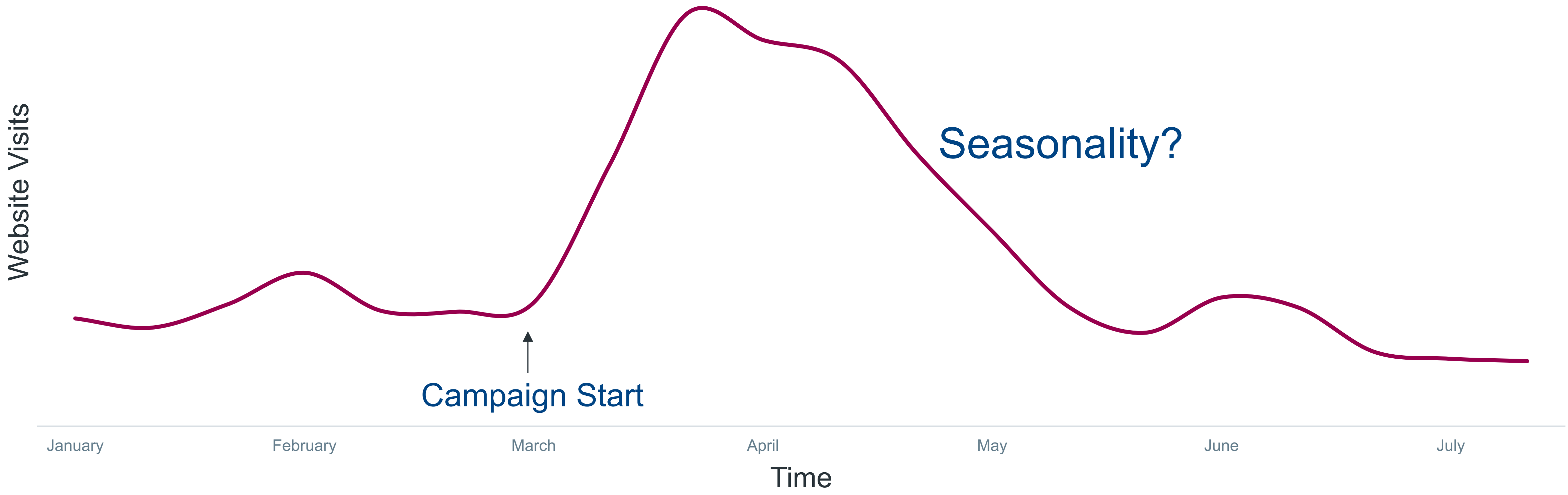
What do we measure?

Example: Number of visits over a period of time

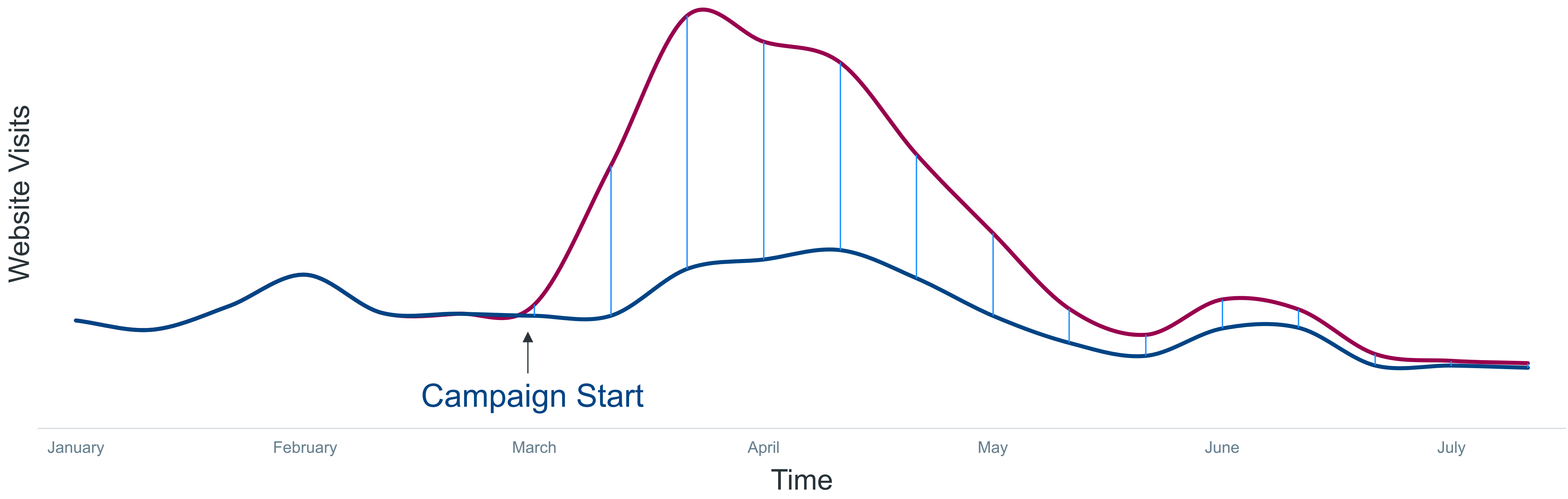
Did the campaign generate additional visits?

Did the campaign generate additional visits?

We don‘t know for certain

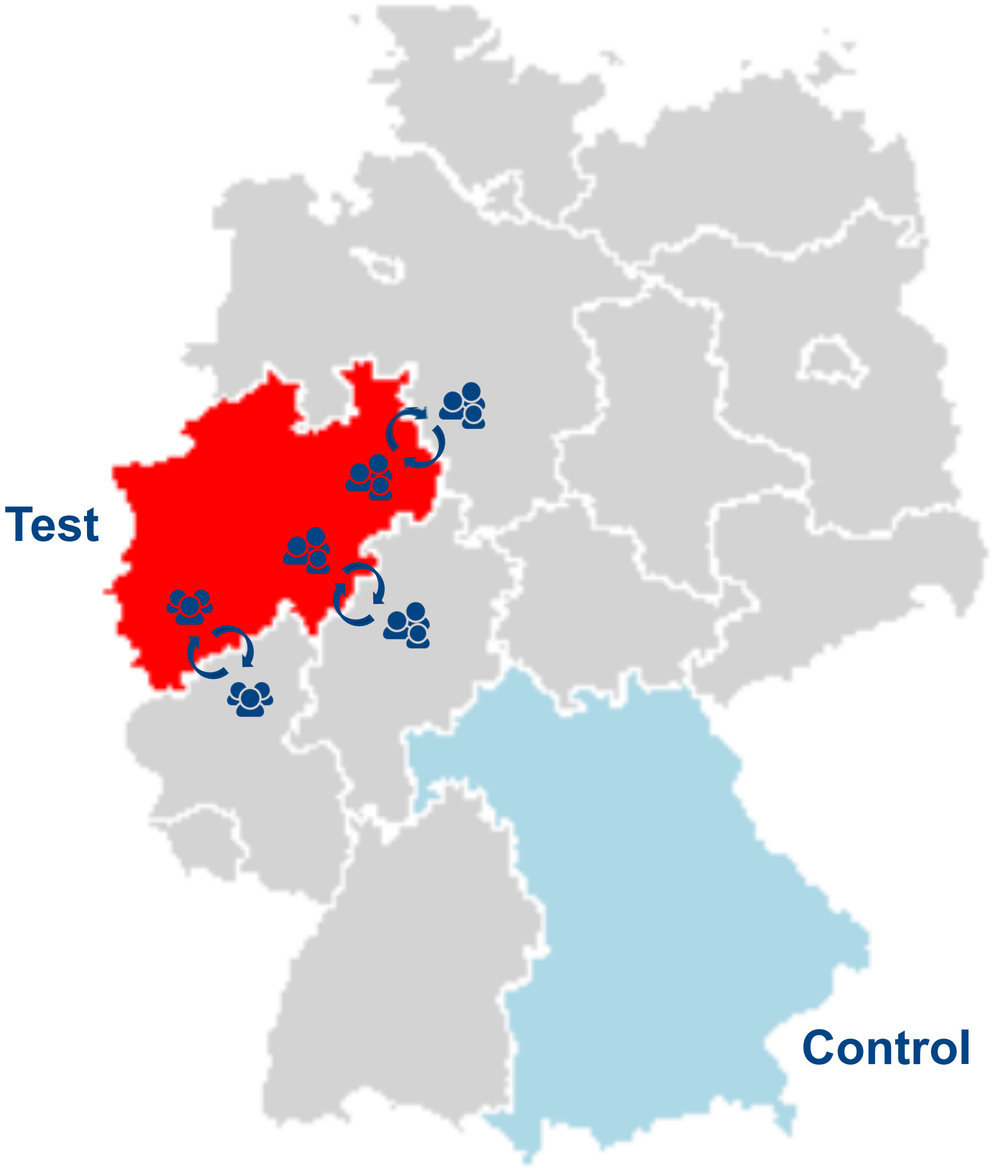


We need a counterfactual to measure the additional visits.



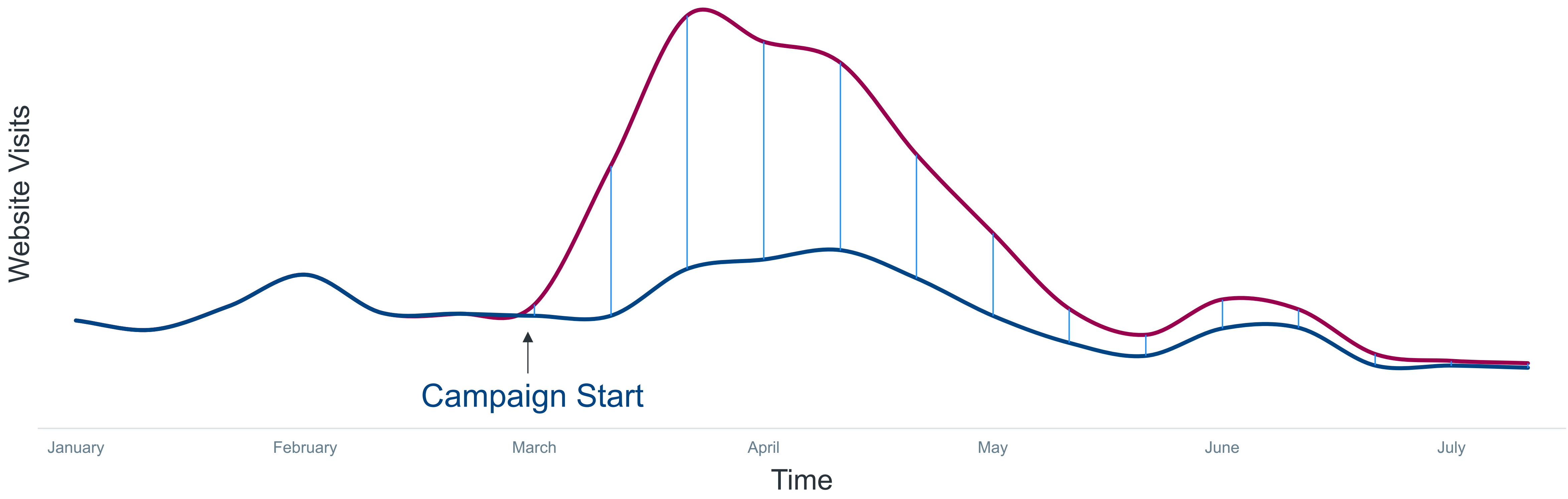
Geo Experiments

How it works



How do we select the regions?

We need a counterfactual to measure the additional visits.



Test and control time series data should be correlated

- Simply measure the correlation and plot
- Hierarchical Clustering using Dynamic Time Warping to measure the distance between two time series
- Spatial data to exclude neighbouring regions

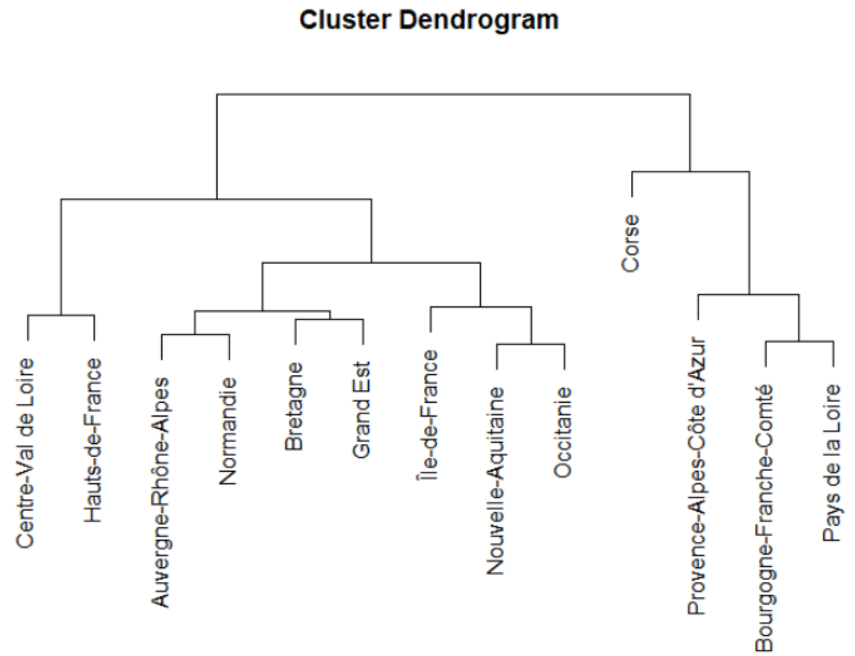
```
library(dtwclust)
```

```
hclust()
```

```
tsclust()
```

```
library(sp)
```

For reading GADM spatial data



Post Campaign Analysis

CausalImpact - An R package for causal inference using Bayesian structural time-series models

Authors: Kay H. Brodersen, Alain Hauser

trivago

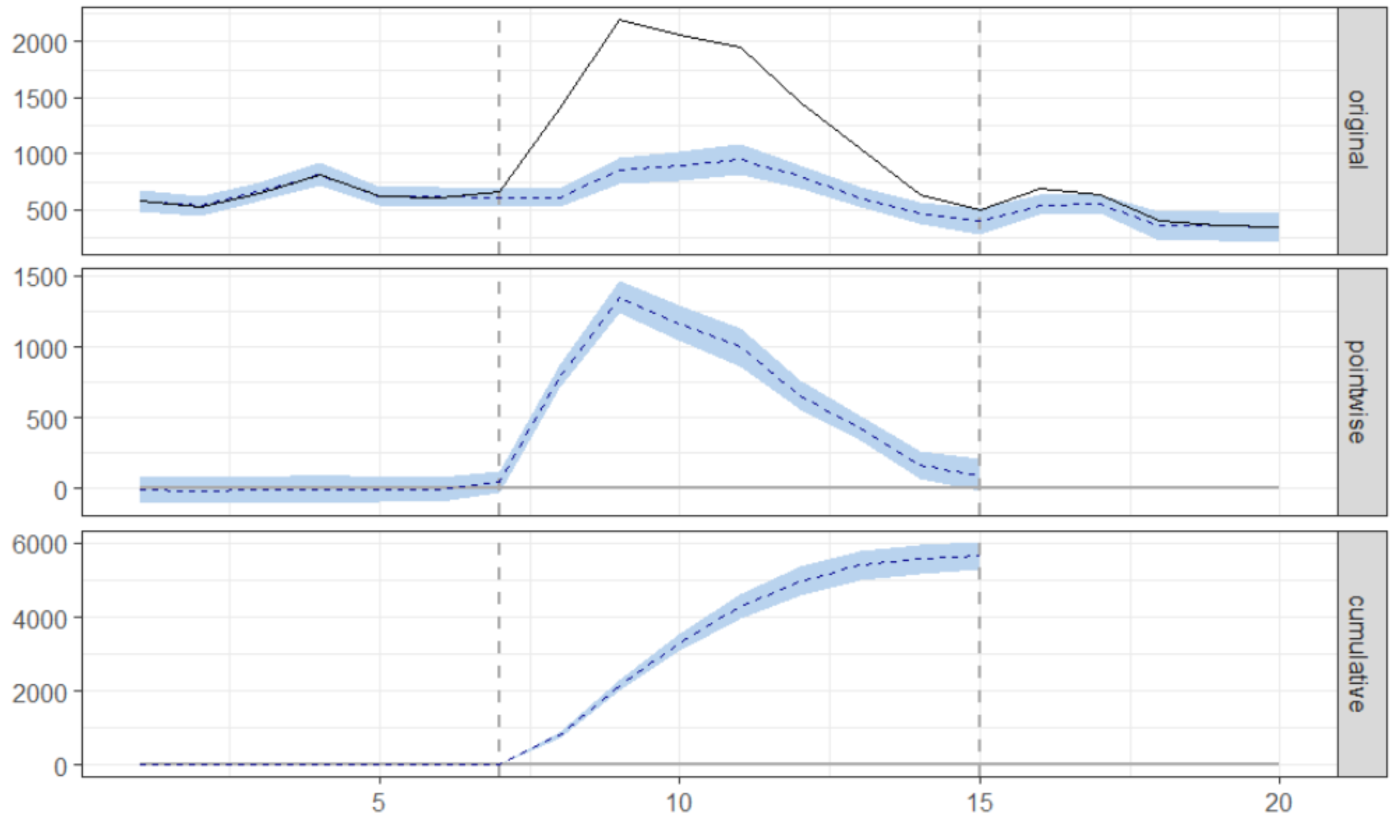
Very easy to use!

```
library(CausalImpact)

pre.period <- c(1, 7)
post.period <- c(8, 15)

impact <- CausalImpact(data,
                       pre.period,
                       post.period)

plot(impact)
summary(impact)
summary(impact, 'report')
```



CausalImpact - An R package for causal inference using Bayesian structural time-series models

Authors: Kay H. Brodersen, Alain Hauser


```r
library(CausalImpact)

pre.period <- c(1, 7)
post.period <- c(8, 15)

impact <- CausalImpact(data,
                       pre.period,
                       post.period)

plot(impact)
summary(impact)
summary(impact, 'report')
```

```
Posterior inference {CausalImpact}

                         Average        Cumulative
Actual                   1406           11247
Prediction (s.d.)        699 (24)       5593 (190)
95% CI                   [650, 743]     [5203, 5942]

Absolute effect (s.d.)   707 (24)       5654 (190)
95% CI                   [663, 755]     [5305, 6044]

Relative effect (s.d.)   101% (3.4%)    101% (3.4%)
95% CI                   [95%, 108%]    [95%, 108%]

Posterior tail-area probability p:   0.001
Posterior prob. of a causal effect:  99.8997%
```

Limitations

- We need to be able to target specific locations – can be costly
- We need to be able to identify these locations also with our data
- We need to have comparable and high correlated regions as well as a big impact campaign for significant results
- There are lots of assumptions
- With real data it is unfortunately we often get insignificant results

Q&A