# Change point detection in mobile advertising

Nina Golyandina, Kliment Merzlyakov

Saint Petersburg State University Mathematical faculty Applied statistics department

> Saint Petersburg 2018



#### Content

- Change point detection
  - What is change point detection?
  - Real world examples of change point detection
  - Reasons to detect change points
- Change point detection techniques
- Airpush cases
  - Fraud elimination
  - Trend extraction
  - Smart alerts

Change point detection Change point detection techniques Airpush cases

Change point detection

## What is change point detection?

- Change point point in time series where some significant change occurred
- Change point detection group of methods to find change points in time series
- Change points can be two types:
  - Local one time change
  - Global change of time series structure

## What is change point detection?

Let's formalize change point detection problem:

- Suppose  $X = (x_1, ..., x_N)$  time series of length N
- $\mathbf{t} = \{t_1, t_2, ...\} \subset \{1, ..., K\}$  set of change points indexes
- ullet K-1 amount of changes in time series, which can be either known or unknown
- Change point detection problem is a problem of searching such set of indexes, which would be the closest to real set of change point indexes:  $\hat{\mathbf{t}} = \{\hat{t_1}, \hat{t_2}, ...\}$
- To estimate change point detection algorithm quality we need tagged time series with known indexes  $\hat{\mathbf{t}} = \{\hat{t_1}, \hat{t_2}, ...\}$
- Quality can be estimated as sum of distance between real indexes and estimated indexes normalized by length of time series:

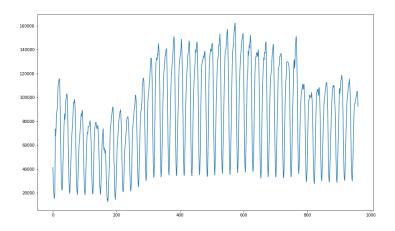
$$\sum_{i=1}^{K} \frac{|\widehat{t_i} - t_i|}{N}$$



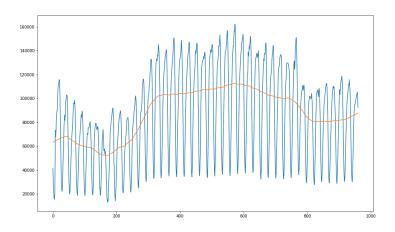
## Types of change points

- Trend change
- Mean change
- Variance change
- Single point change
- Period change
- Structure change

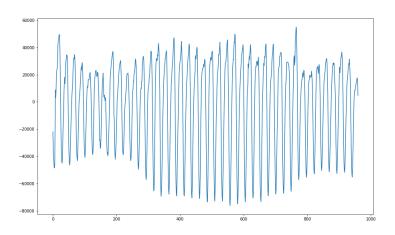
#### Common graph



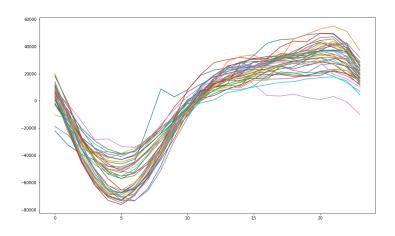
#### Common graph with trend



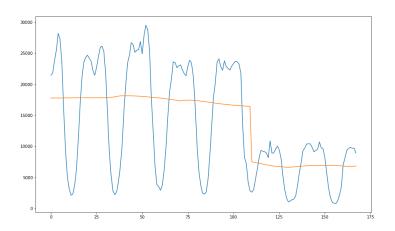
#### Common graph without trend



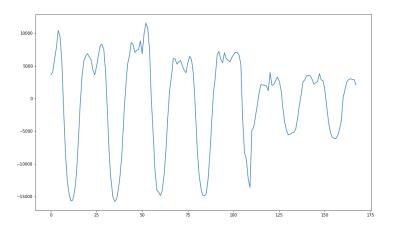
#### Common graph periodic frequency



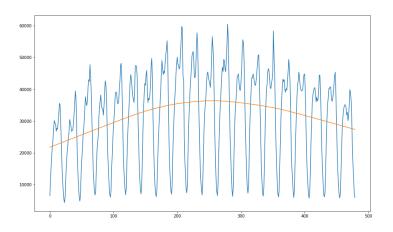
#### Mean change



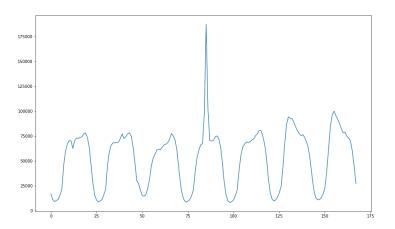
#### Variance change



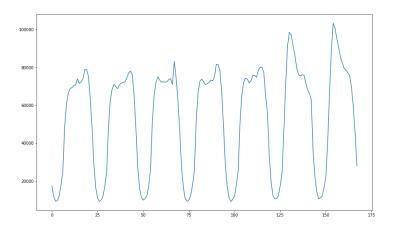
## Trend change



## Point change



#### Structure change



## Reasons to detect change points

- Searching issues in historical data
- Reacting on changes quickly
- Extracting trend more accurately

Change point detection
Change point detection techniques
Airpush cases

Change point detection techniques

## SSA for change point detection

Singular spectrum analysis (SSA) method can be used to allocate change points. Let  $x_1,x_2,...$  be a time series and N,L,l,p,q be fixed integers so that  $0 \le l < L \le N/2$  and  $0 \le p < q$ . The SSA change point detection algorithm is as follows. For each n=0,1,... we compute:

- the base matrix  $\mathbb{X}^{(n)}$ ,
- the lag-covariance matrix  $\mathbb{R}_n = \mathbb{X}^{(n)}(\mathbb{X}^{(n)})^{\top}$ ,
- the SVD of  $\mathbb{R}_n$ ,
- $\nu_{n,I,p,q}$ , the sum of the squared Euclidean distances between the vectors  $\mathbb{X}_{j}^{(n)}(j=p+1,...,q)$  and the I-dimensional subspace  $L_{n,I}$ , and
- $S_n$ , the normalized squared distance.

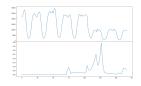
Large values of  $S_n$  indicate a change in the time series.

This method has the following parameters:

- $\bullet$  N window size for base matrix
- $\bullet$  L, I SSA window and number of eigenvectors
- p, q window size for test matrix
- threshold

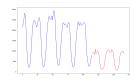
## SSA in action. Mean change

Let's try to apply SSA algorithm to real time series mentioned above. With manually settled parameters.



#### Mean change

Detection 
$$N = 48$$
,  $L = 24$ ,  $I = 5$ , p

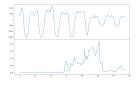


$$= 49$$
,  $q = L$ , threshold  $= 0.15$ 

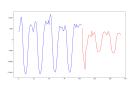
Works good for mean change



## SSA in action. Variance change



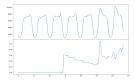
$$N = 48$$
,  $L = 24$ ,  $I = 5$ ,  $p = 49$ ,  $q = L$ , threshold



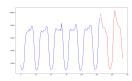
= 0.15

Works good for variance change

## SSA in action. Period change



$$N = 48$$
,  $L = 24$ ,  $I = 5$ ,  $p = 49$ ,  $q = L$ , threshold



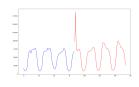
= 0.1

Works well for period change

## SSA in action. Point change



$$N = 48$$
,  $L = 24$ ,  $I = 5$ ,  $p = 49$ ,  $q = L$ , threshold

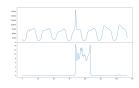


Doesn't work for point change. The reason is that we always move window from left to the right.

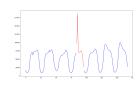
= 0.1

## SSA in action. Point change

Let's try to reverse the time series each time we find change point.



$$N = 48$$
,  $L = 24$ ,  $I = 5$ ,  $p = 49$ ,  $q = L$ , threshold

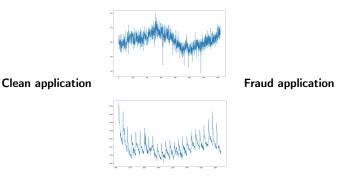


Using this upgrade we make SSA algorithm working for point change as well

= 0.1

# Airpush cases

- Apps minutely requests data
- Red flag: strong pattern.
- Can be a automated bots behind pattern

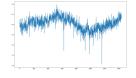


- Goal: to be able to find such apps automatically
- We can reach this goal using frequency analysis

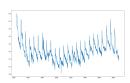
The framework can be described as follows:

- Apply logarithm to time series to stabilyze amplitude
- Remove trend (low frequent part) from time series
- Apply Fourier transform to time series
- Estimate the distribution of periodogram values
- Ompare distributions of each application with a distribution of white noise (which is exponential) using Kullback-Leibler divergence
- If divergence > threshold, then application is marked as suspicious

# Airpush cases. Fraud elimination 1. Apply logarithm

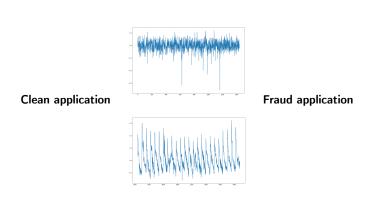


#### Clean application



Fraud application

2. Remove trend



3. Apply Fourier transform

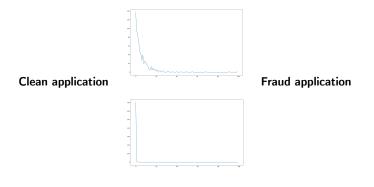


#### Clean application



## Fraud application

4. Estimate the distribution of periodogram values



5. Compare distributions

• Clean app score: 0.09

• Fraud app score: 1.87