Deciphering internet traffic patterns

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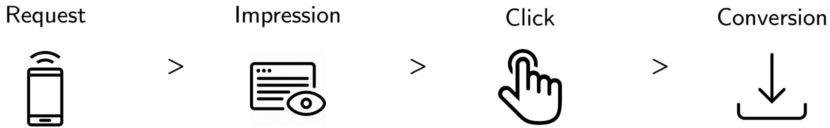
Airpush

Unlock customer lifetime value with advanced statistical techniques
London
17.10.2018

Content

Change point detection. General notes

Changes in data



User side changes

- Application popularity
- Competition
- Applications' marketing activity
- ...

Advertising network side changes

- New features released
- New advertisers onboarded
- New targeting strategy
- ...

Time series

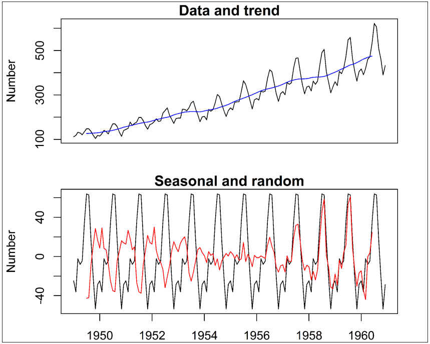
Time series is a series of values of a quantity obtained at successive times, often with equal intervals between them (minute, hour, day, week, etc.)

Time	Data
17-Oct-2018 19:00	435 098
17-Oct-2018 20:00	431 248
17-Oct-2018 21:00	420 329
...	...

Formal notation:
$X = (x_1, x_2, ..., x_{N-1}, x_N)$

Commonly time series can be decomposed $X = T + S + E$

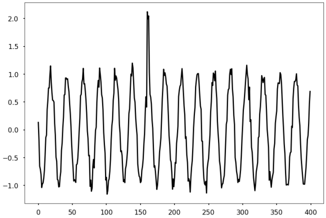
Time series. Decomposition example



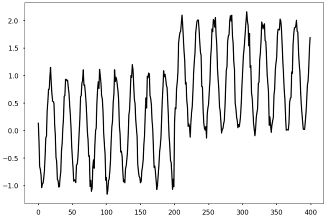
What is change point detection?

- Change point is a point in time series, where some significant change in structure occurred
- Change point detection is a group of methods to find change points in time series
- Change points can be of two types:
  - Local — anomaly or outlier
  - Global — change of time series structure

Local change



Global change

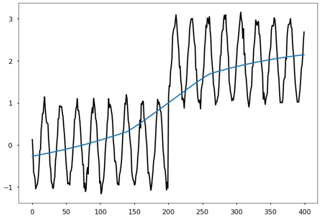


Motivation

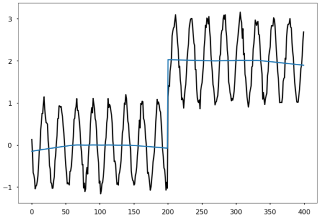
When it helps:

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

Without CP detection



With CP detection

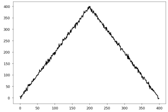


What can we do after change point detection:

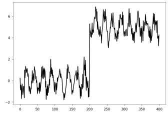
- Remove/change outliers
- Split time series and analyze separately

Types of change points

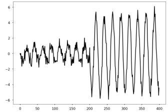
Trend change



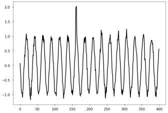
Mean change



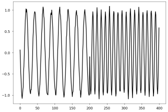
Variance change



Local change



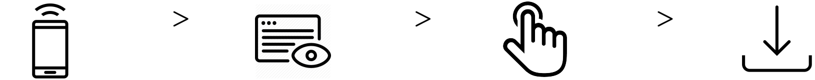
Periodic component change



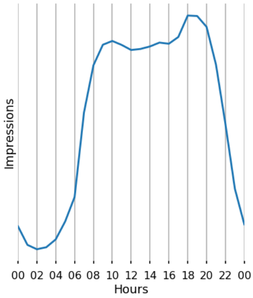
Mobile advertising data

Real data description

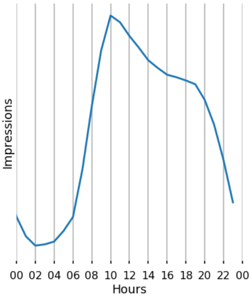
Request > Impression > Click > Conversion



Typical day

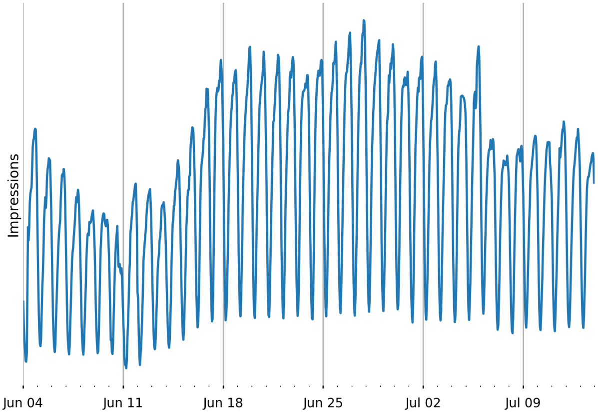


Typical weekend

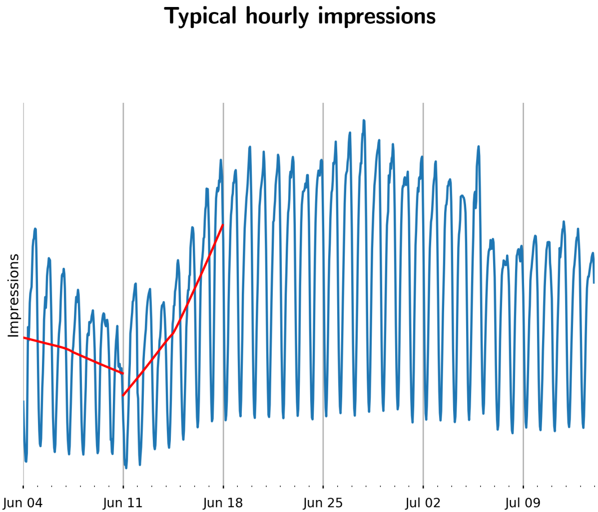


Real data example

Typical hourly impressions



Real data example



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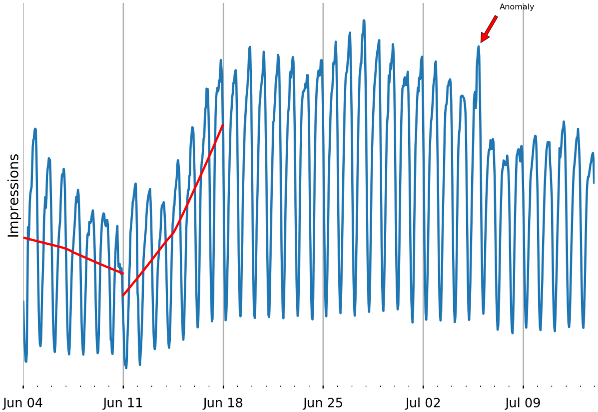
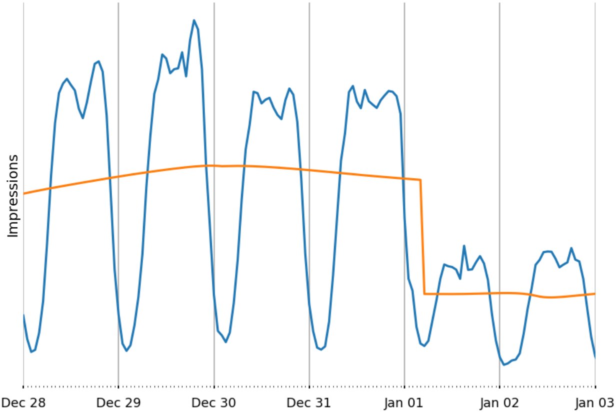
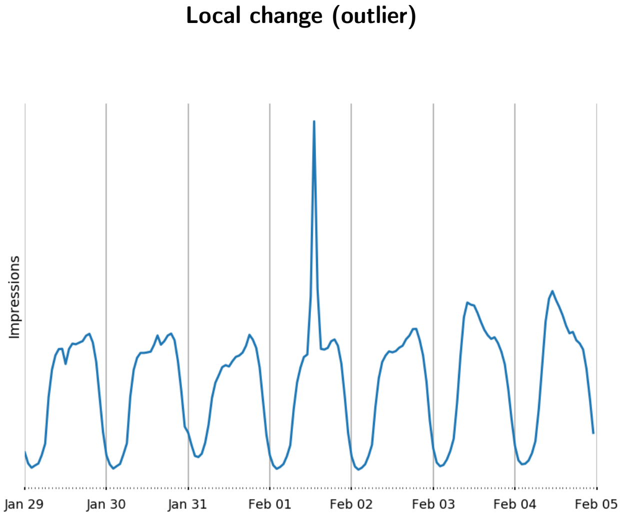


Change point examples

Mean change

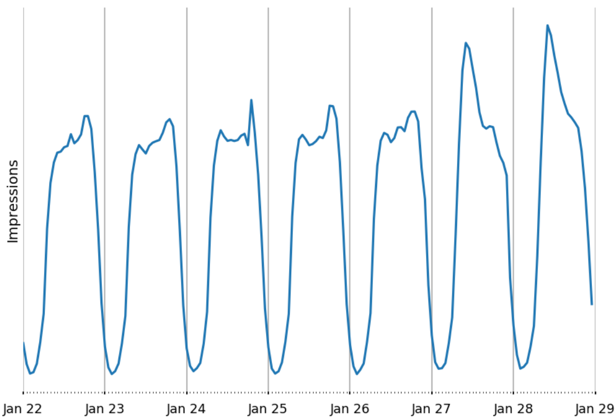


Change point examples



Change point examples

Periodic component change



Change point detection techniques

General framework description

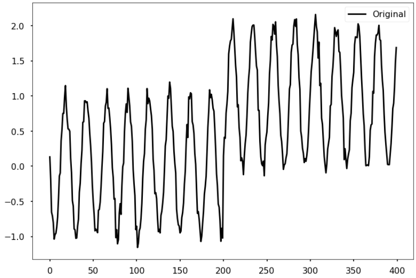
- Preliminaries:
  - Time series has a structure
    (e.g. a constant trend)
  - Structure can be described by a model
    (e.g. the time series is equal to sum of a constant and some oscillations)
  - Structure is abruptly changed; we should detect this change
  - Types of changes are different; therefore, we need different methods to detect
- Approach:
  - Around the change point (CP), model describes time series worse
  - We can calculate this "worseness" using cost function
  - Once cost value more than threshold - algorithm detects change point
- Types of methods:
  - Prediction based
  - Approximation based

Prediction approach

Prediction based approach

- Predict with appropriate model
- Measure difference between prediction and actual data
- Perform this for sliding subseries (windows)
- Construct detection function with difference measures
- Compare with threshold

Example: change in mean; model is a constant trend



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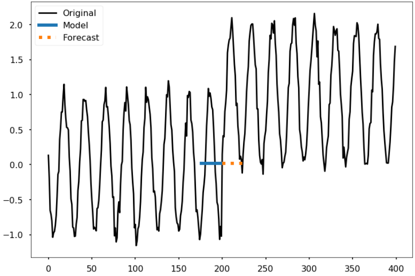

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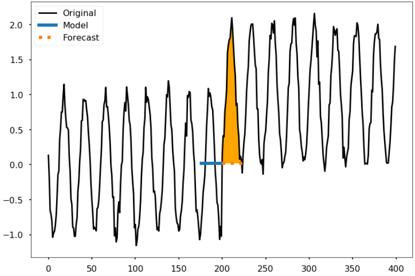

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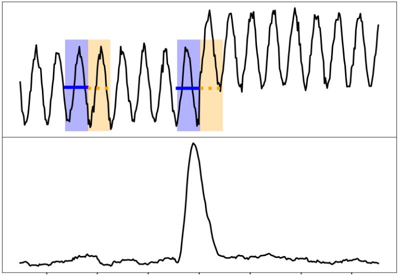

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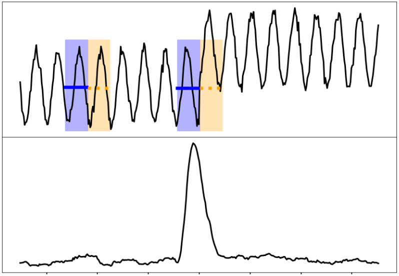

Detection function is synchronized with the last point of window

Approximation approach

Approximation based approach

- Approximate time series with appropriate model
- Measure difference between approximation errors for left and right halves separately and the overall approximation error
- Perform this for sliding subseries (windows)
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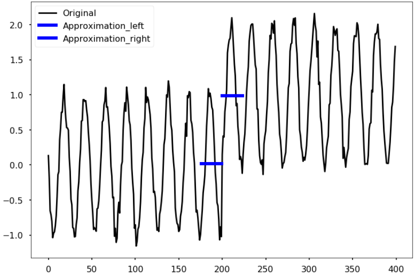

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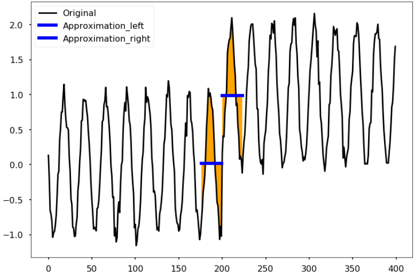

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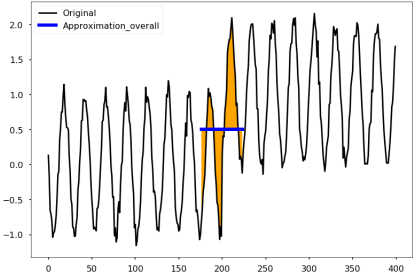

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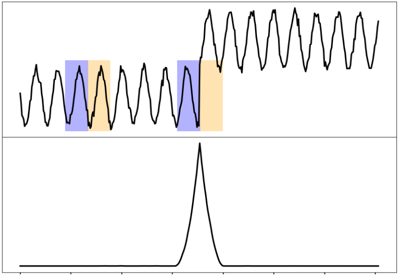

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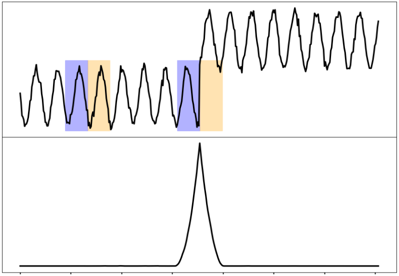


Detection function is synchronized with the last point of window

Things to define

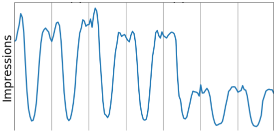
- Model. Based on what changes do you want to find and specifics of your time series
  - Data has a constant trend, we are interested in changes in trend (formal model: in the time (e.g., a hour) with number n, $x_n = \mathrm{const} + \mathrm{residual}_n$).
  - Data has a linear trend, we are interested in changes in trend (formal model: $x_n = an + b + \mathrm{residual}_n$).
  - Data has a constant trend with regular (e.g. daily) fluctuations, we are interested in changes in trend or in fluctuations (formal model: $x_n = \mathrm{const} + A\sin(2\pi n/24 + \phi) + \mathrm{residual}_n$)
  - Others
- Window size. Based on timeframe that is significant to your task. Larger window causes larger delay of detection.
- Threshold. Depends on small or big changes would you like to find.

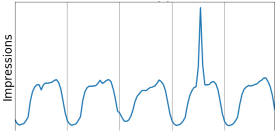
Direction of change point search (forward, backward, both directions) depends on your task.

Applications to real data

Applications to real data

Consider global changes in constant trend and local anomalies





Data structure: constant or slowly varying trend + daily (24-hours) regular oscillations + some noise

Two formal models:

1. Ignore daily oscillations:

$$x_n = \mathrm{const} + \mathrm{residual}_n$$

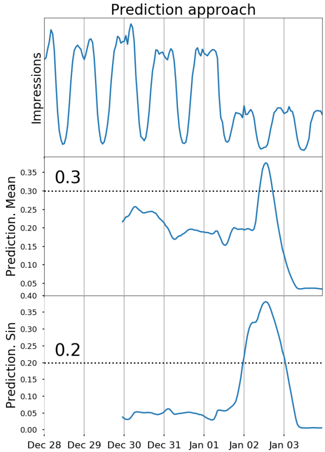
2. Take into consideration daily oscillations:

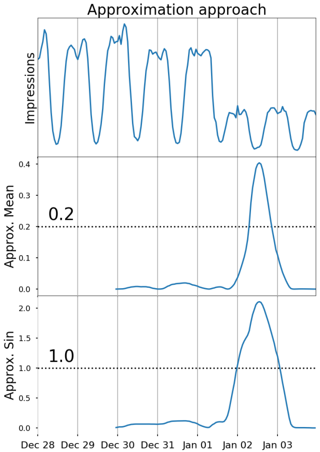
$$x_n = \mathrm{const} + A\sin(2\pi n/24 + \phi) + \mathrm{residual}_n$$

Window size is equal to 2 days; that is, we consider sliding 48-hour subseries.

Two methods: prediction- and approximation- based ones.

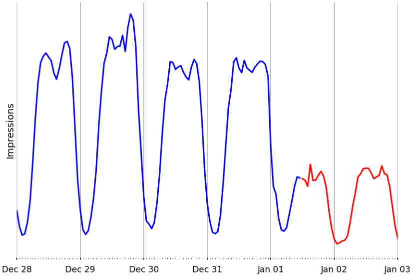
Applications to real data. Mean change





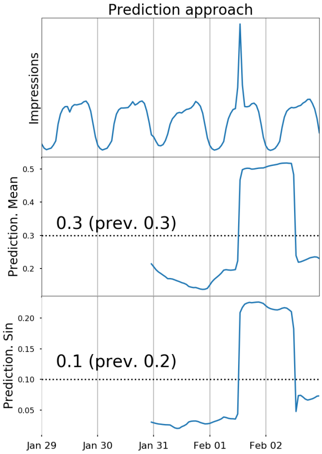
Approximation approach is better

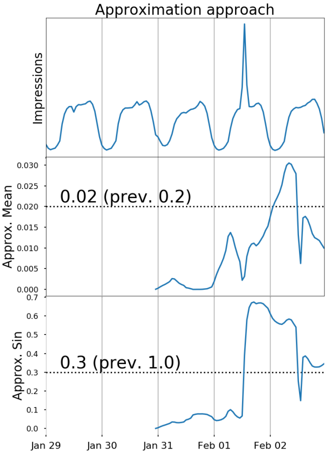
Applications to real data. Mean change



- Approximation-based approach
- Model with constant trend and daily oscillations
- Threshold $= 1$

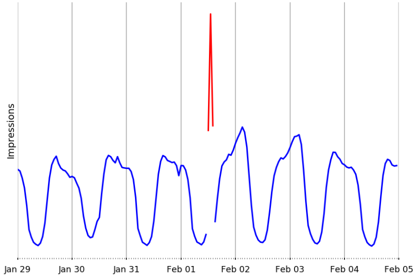
Applications to real data. Outlier





Prediction approach is better

Applications to real data. Outlier



- Prediction-based approach
- Model with constant trend
- Threshold = 0.1

Applications to real data. Discussion

- Different methods should be chosen for different types of change points. Prediction-based approach looks more perspective for outliers prediction, whereas Approximation-based approach is more robust for changes in mean.

- Model with constant trend finds change points well, despite of clear daily oscillations. However, in more complex cases, it is important to choose a proper model. E.g., the model with constant trend is totally inappropriate for the case of linear trends.

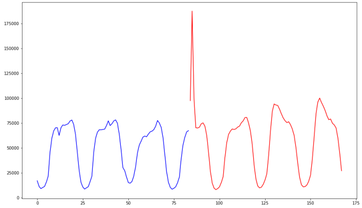
- Choice of thresholds is a big challenge. Moreover, for different types of change points, threshold can be different.

Direction of CP search

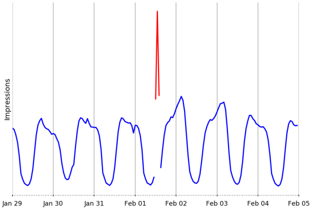
We can search for change points in different directions

- Forward (always from left to right). Good for alerts.
- Backward (always from right to left). Good for forecast.
- Both forward and backward to localize the change interval. Good for analysis of historical data.

Forward method:



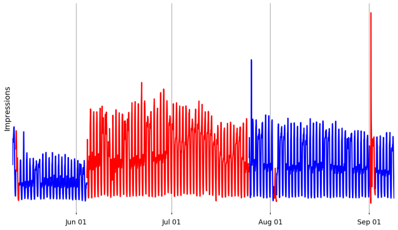
Forward-backward method:

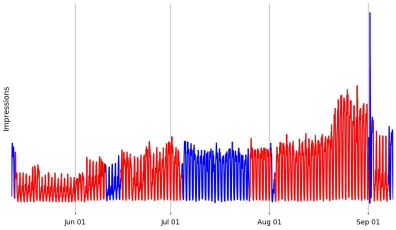


Applications to real data. Long time series

Final model: Approximation-based approach with the model with constant trend, threshold = 0.4 and forward-backward search method.

Two different countries





Approaches to model and threshold choice

1. Theoretical approach based on the model of data. Drawback: usually, real-world data are various and do not fit a model exactly.

2. Supervised machine-learning approach when data are tagged in advance and then learning is performed by comparison of found change points and tagged change points. Drawback: it is a hard task to tag the data in advance.

3. Empirical approach with adaptive adjustment of the threshold. This is a very promising method: each alert is considered by business people from the viewpoint of its importance. If there are too many false alerts, then threshold increases.

Airpush experience

1. Alert system works at two levels:
   - Hourly level model, which detect local changes in mean, variance, daily oscillations and detects anomalies
   - Daily level model, which detect changes in global trend
2. Overall impressions data are splitted by countries, ad formats, applications, since the sources of changes can be specific for these characteristics.
3. Thresholds are adjusted adaptively by monitoring for false alerts.

Next steps

But we can move forward. Instead of plain alerts we can develop smart alert system:
Instead of sending notification on each separate case (which could be a lot of at once), the system aggregates alerts and send you only a summary.

Example:

- Countries: 167 out of 196 had change
- Ad formats: 6 out of 8 had change
- Applications: 1 out of 3000 had change

This example means that something affected almost all countries and almost all ad formats, **but** only one application. That is why most probably real root of change is the application, so we want to be notified only about this application.

Conclusion

- Change point detection system can help us to react on significant change fast.
- The important application is the alert system. However, the scope of applications is much wider.
- The model of time series should be chosen adequately to the data and the changes to detect.
- The problem of threshold choice is sophisticated. However, if the model is chosen adequately, the choice of threshold can be performed adaptively on the base of false alerts.