CHANGE-POINT DETECTION IN HUMAN BEHAVIOR WITH APPLICATION TO PSYCHIATRY

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Introduction

- Psychiatric patients with mental disorders may suffer abrupt transitions in their behavior.
- We consider it as a change-point detection problem.
- Data is structured as multidimensional time-series.
- We explore Bayesian online models for change-point detection (personalized and real-time monitoring).
- We use latent variable models for reducing dimensionality of time-series.
- Results provide new insights in the detection of anomalous behaviour in mental health patients.

Human Behavior in Psychiatry

- Mental disorders with high prevalence: schizophrenia and affective disorders (i.e. depressive and bipolar).
- Chronic conditions and apparition of relapses.
- There exists a lack of real-time monitoring out of ambulatory domains.
- Anomalous behavior of patients is a critical symptom of future relapses.
- Detection of behavioral changes implies detection of relapses.

Data

- We collected all the data through electronic devices (smartphones and wearables).
- Sensory systems perform robust real-time monitoring of multiple actions of its users.
- All together, recorded information represents an accurate measure of the user’s behavior:
  - Location traces (latitude-longitude data points)
  - Metrics from physical activity (number of steps, distance walked)
  - Physiological signals (heart rate)
  - Communication registers (messages sent, number of calls)

Average, Peak and Lowest HR - (BPM)

Conclusions

- We illustrate a reliable procedure to perform change-point detection in behavioral high dimensional data with BOCPD algorithm. Particularly, we have shown how this data is characterized by redundancy and useless correlations.
- Unsupervised linear methods for dimensionality reduction (PPCA as the most relevant) provide an improved way to perform change-point detection in such class of multidimensional time-series.
- We show how automatic monitoring of mental health patients can be improved out of medical centers. Our solution opens new possible applications for ambulatory assessment of diseases in psychiatry, psychology and neurology.

Environments

- Bayesian Online Change-Point Detection algorithm (BOCPD) implements a simple message-passing structure (Adams & MacKay, 2007).
- Calculates the posterior distribution $p(r|x_1)$ iteratively.
- A thread of inference is created with every new observation or time step. The run length $r_t$ indicates the number of time steps since the last segmentation point.

Three key points:
1. Probability of change $p(r_t|x_1)$
2. Underlying predictive model $p(x_t|r_{t-1}, x_{t-1}^{(r_{t-1})})$
3. Conjugate-Exponential models

Posterior computations:

$p(r_t=r_{t-1}+1, x_{t+1}) = p(r_{t-1}, x_{t-1}) p(x_{t+1}^{(r_{t-1})}(1-H(r_{t-1}))$

$p(r_t=0, x_{t+1}) = \sum_{r_{t-1}} p(r_{t-1}, x_{t-1}) p(x_{t+1}^{(r_{t-1})}(1-H(r_{t-1}))$

BOCPD Algorithm

GOAL $\rightarrow p(r_t|x_{1:t}) = p(r_{t-1}, x_{1:t-1})/p(x_{t-1})$

Experiments

Dimensionality Reduction

- We analyze the performance of three dimensionality reduction methods: PCA, SVD and CCA.

Synthetic Change-Points

- Due to CPs are not labeled on real data, we test their detection with synthetic points of transition.
- Two degrees of abruptness: smooth swaps morning-evening and huge changes night-day.

Identifying Different Behaviors

- We collected data from four different individuals. Our goal is to determine in real-time if our solution detects the moment in which observations doesn’t belong to the previous seen person.

Time Frames

- Every human is conditioned to day-night cycles (circadian rhythm). We organize our D-dimensional observations $x_t$ in time frames.
- $D=2$ means each observation $x_t$ at day $t$ would be composed by: $x_{i,t} =$observation: 00:00-11:59 and $x_{i,t} =$observation: 12:00-23:59. Similar for $D=4, 6, 12, 24$. Can be considered a precision factor.