CHANGE-POINT DETECTION IN HUMAN BEHAVIOR WITH APPLICATION TO PSYCHIATRY

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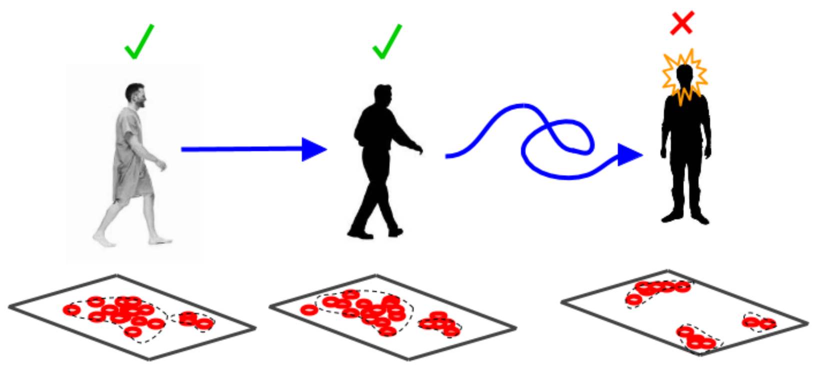
Introduction

- 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**.

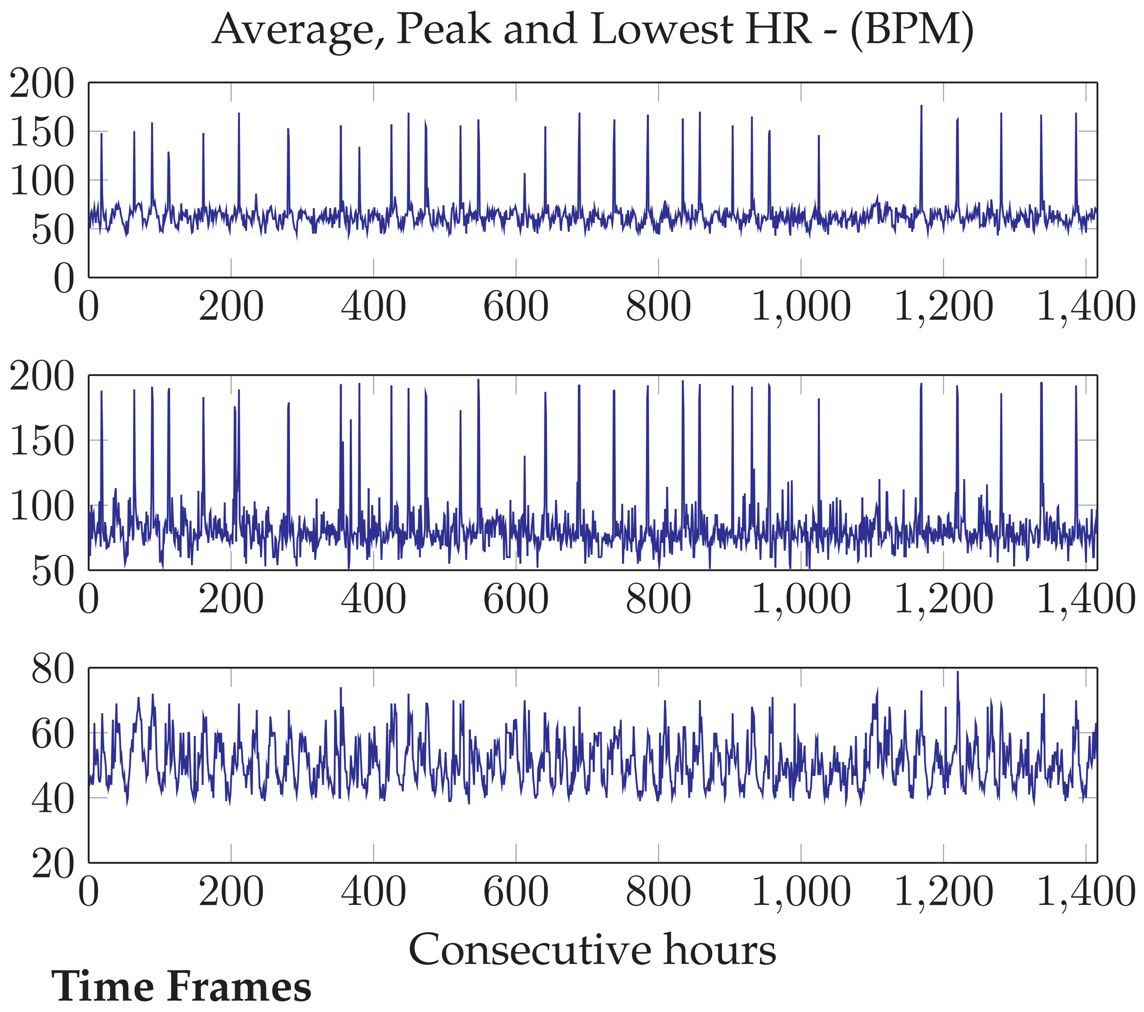


- There exists a lack of real-time monitoring out of ambulatory domains.
- Anomalous behavior of patients is a critical symptom of future relapses.
- Detection of behavioral changes implies detection of relapses.

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 paces, distance walked)
  - Physiological signals (heart rate)
  - Communication registers (messages sent, number of calls)

Average, Peak and Lowest HR - (BPM)



Time Frames

- Every human is conditioned to day-night cycles (circadian rhythm). We organize our D-dimensional observations $\mathbf{x}_t$ in time frames.
- $D = 2$ means each observation $\boldsymbol{x}_t$ at day t would be composed by: $x_{t,1}$ ={observation: 00:00-11:59} and $x_{t,2}$ ={observation: 12:00-23:59}. Similar for $D = 4, 6, 12, 24$. Can be considered a precision factor.

Change-Point Detection

- Sequences of data/ time-series present statistical changes. There are two points of view: **offline** methods and **online** methods.
- **Classical goal**: Exact computations of change-points with offline models (processing the complete signal from beginning to end).
- Patients **cannot wait** two of three years for diagnosis. An online change-point detection setting is required.

BOCPD Algorithm

- **Bayesian Online Change-Point Detection algorithm** (BOCPD) implements a simple message-passing structure (Adams & MacKay, 2007).
- Calculates the *posterior* distribution $p(r_t|\mathbf{x}_{1:t})$ iteratively.

$$r_t = \begin{cases} 0 & \text{if a change point appears} \\ r_{t-1}+1 & \text{otherwise} \end{cases}$$

- 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 $p(r_t|r_{t-1})$
2. Underlying predictive model $p(x_t|r_{t-1}, \mathbf{x}_t^{(r)})$
3. Conjugate-Exponential models

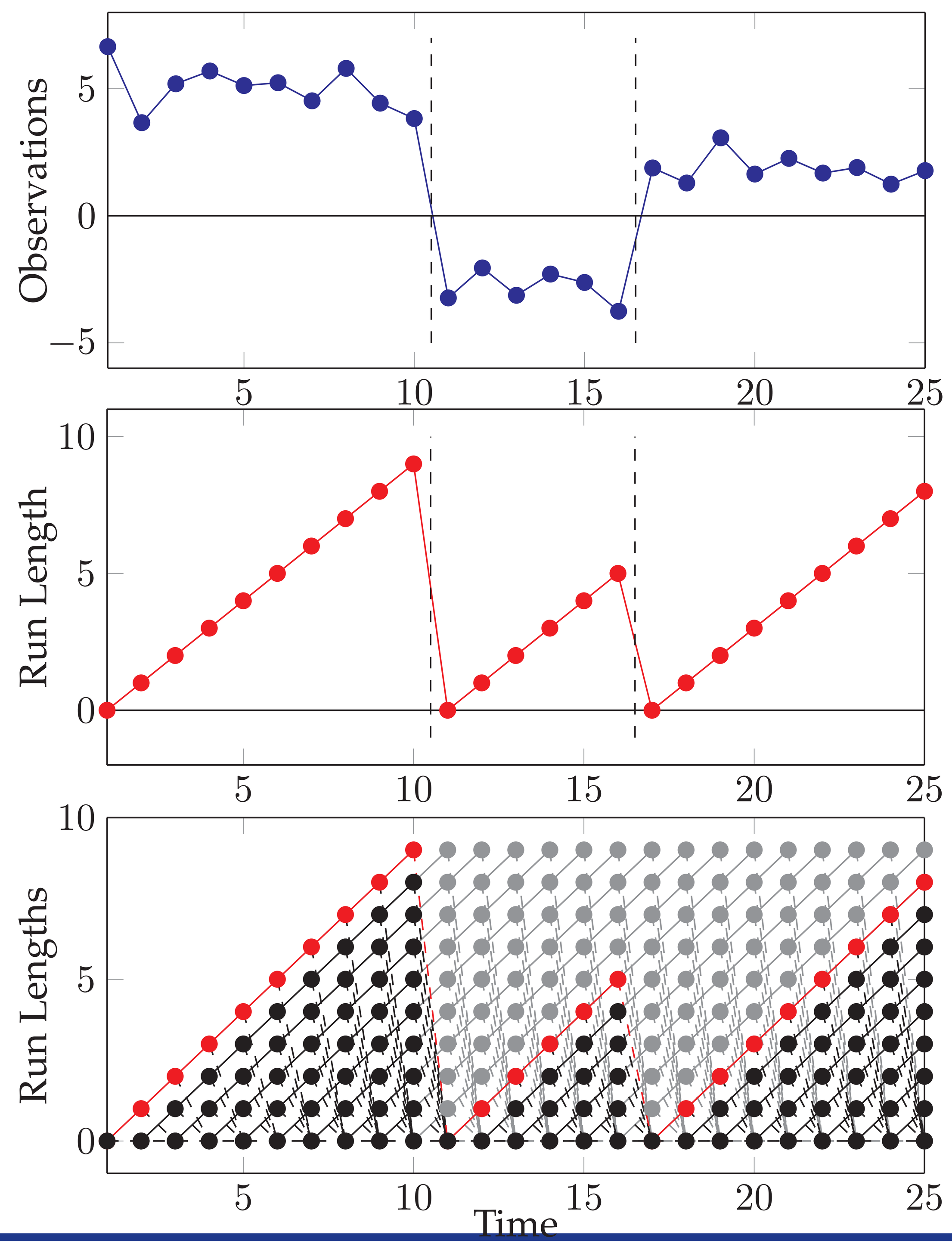
Posterior computations

$$\pi_t^{(r)} = p(x_t|\nu_t^{(r)}, \boldsymbol{\chi}_t^{(r)})$$

$$p(r_t = r_{t-1}+1, \boldsymbol{x}_{1:t}) = p(r_{t-1}, \boldsymbol{x}_{1:t-1})\pi_t^{(r)}(1 - H(r_{t-1}))$$

$$p(r_t = 0, \boldsymbol{x}_{1:t}) = \sum_{r_{t-1}} p(r_{t-1}, \boldsymbol{x}_{1:t-1})\pi_t^{(r)} H(r_{t-1})$$

GOAL → $p(r_t|\boldsymbol{x}_{1:t}) = p(r_t, \boldsymbol{x}_{1:t})/p(\boldsymbol{x}_{1:t})$



Experiments

Dimensionality Reduction

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

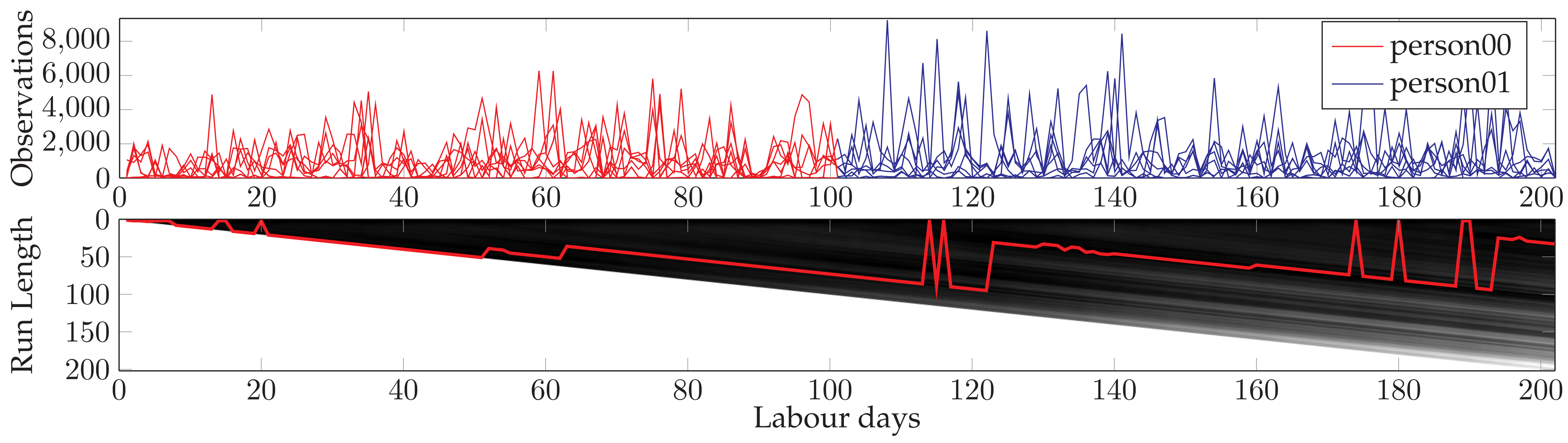
Synthetic Chage-Points

- 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.

Method	Time Frames	M	synth-CPD	CPs	Delay
PCA	**6**	**2**	√	**2**	**Short**
PCA	**6**	**3**	√	**2**	**No**
PCA	6	4	√	3	No
PCA	12	2	×	1	No
PCA	**12**	**3**	√	**2**	**Short**
PCA	**12**	**4**	√	**2**	**Short**
t-SVD	6	2	√	2	Yes
t-SVD	6	3	√	2	Yes
t-SVD	6	4	√	3	Yes
t-SVD	12	2	√	3	Yes
t-SVD	12	3	√	3	Yes
t-SVD	12	4	√	4	Yes
CCA	6	2	√	2	Yes
CCA	6	3	×	4	Yes
CCA	6	4	√	6	Yes
CCA	12	2	√	2	Yes
CCA	12	3	√	2	Yes
CCA	**12**	**4**	√	**2**	**Short**



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.