STRESS PATTERN RECOGNITION THROUGH WEARABLE BIOSENSORS IN THE WORKPLACE: EXPERIMENTAL LONGITUDINAL STUDY ON THE ROLE OF MOTION INTENSITY

Vadym Mozgovoy – University of Lausanne

Swiss Graduate School of Public Administration (IDHEAP)

1. OUTLINE

We will discuss how Machine Learning Methods can help to induce stress-related states from physiological and non physiological signals.

We will discuss:

- Background on stress and wearables;
- Research methodology for Stress Pattern Recognition;
- Application of Machine Learning Methods on experimental data in order to induce stress-related states;
- Findings;
- Implications.

2. BACKGROUND: STRESS

- **Stress** is defined as a particular relationship between the person and the environment that is appraised by the person as taxing or exceeding his or her resources and endangering his or her well-being.

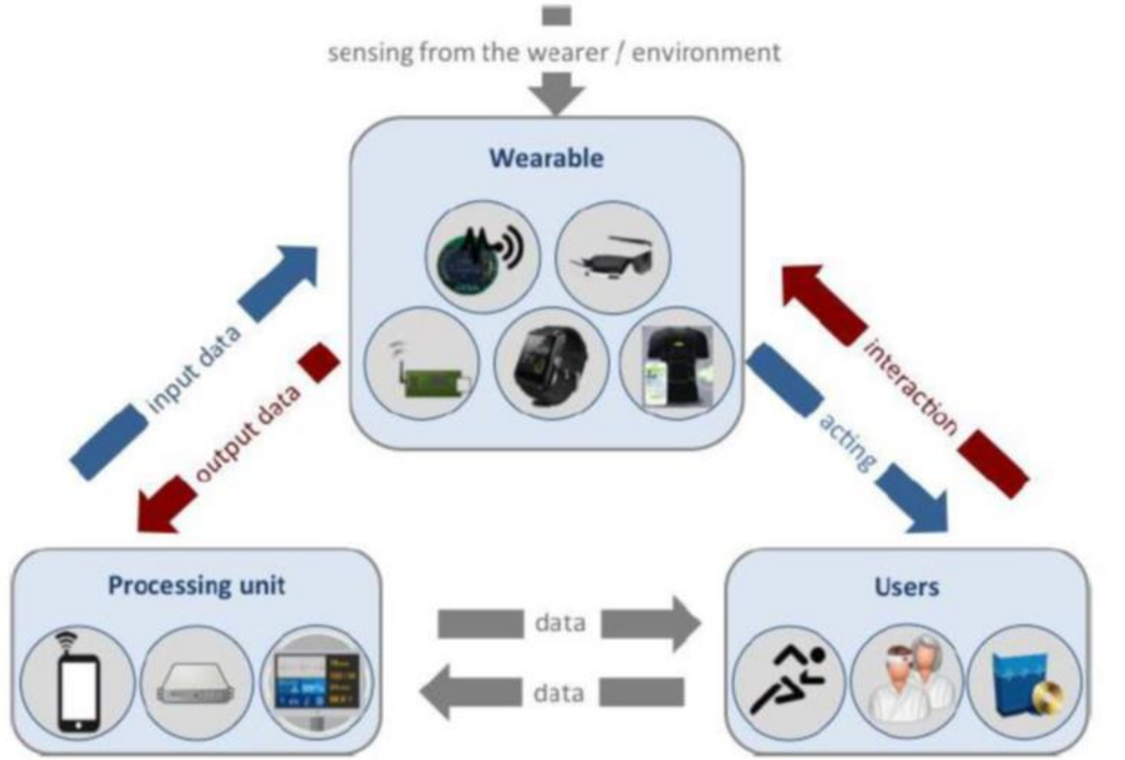
- **Stress in the workplace** is a burning issue in public service organizations. There is a growing pressure on employees according to the research evidence.

- **Stress Management** in the workplace may improve employee well-being by effective Stress Pattern Recognition and Stress Prevention.

- Modern **Information Technologies** and **Machine Learning Methods** for data analysis may support effective **Stress Management** in the workplace.

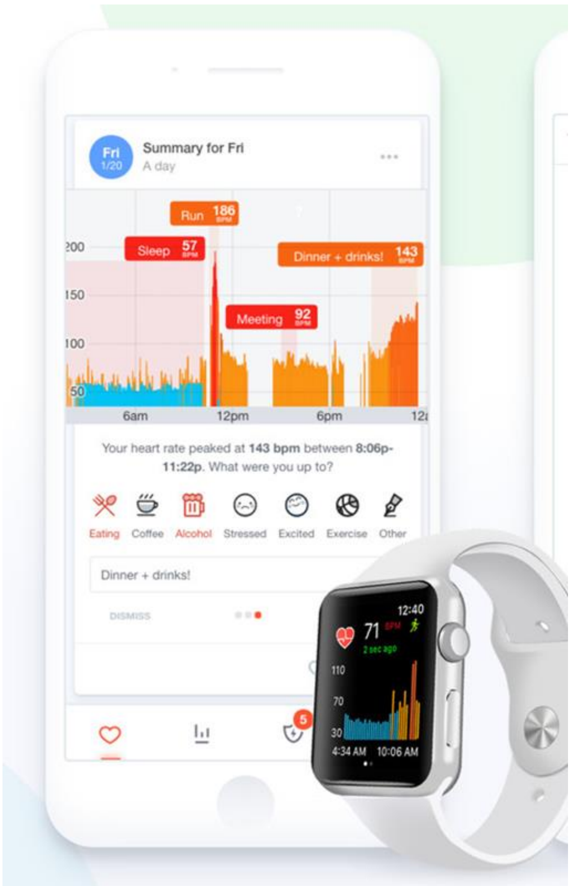
2. BACKGROUND: WEARABLES (1)

- **Wearables** are “body-borne computational and **sensory devices** which can **sense the person** who wears them and/or their environment” (IEC, 2016).
- They facilitate **collection of health-related measures in dynamic environments**.



2. BACKGROUND: WEARABLES (2)

- **Smartwatch**



- **Smartsleeve**

- **Armband with sensor**

2. BACKGROUND: MACHINE LEARNING METHODS

- **Stress** can be manifested by means of **Physiological signals** (ex: Heart Rate, Blood Pressure, Respiration Rate, etc.);

- **Machine Learning Methods** are used for ***stress pattern recognition*** by means of **Physiological signals**.

- The **choice of method for Stress Pattern Recognition** depends on:
  - **The type of environment:**
    - **Restricted environment** facilitate collection of Labeled Data and <u>Supervised Learning</u>;
    - **Open environment** challenges the collection of Labeled Data and facilitate <u>Unsupervised Learning</u>**.**

  - **Type of monitoring:**
    - **Self-monitoring** includes contextual information and demands <u>less variables</u> for pattern recognition;
    - **Remote Stress Monitoring** requires <u>more variables</u>**.**

3. AIM

This research is held in the **context of remote stress monitoring in the workplace.**

This study **aims** to explore how a **non-physiological signal** may enhance the information on physiological signals in order to **recognize stress-related patterns** in this **context**.

Non-physiological signal is **Motion Activity** indicating the users' **Motion Intensity.**

Non-Physiological signals can:

- Provide contextual information about stress;
- Help to control for confounders;
- Help to better distinguish between various stress-related states.

4. EXPERIMENTAL SETTING AND DATA COLLECTION

The experimental study involved **18 public servants** from Municipal Fiscal Administration Office.

The participants included **males and females** of different age groups.

Employees have been using wearable biometric devices in the period from **1 November 2018 to 18 December 2018.**

Most of the users (16 out of 18) have been wearing devices during **working days.** However, some of them (2 out of 18) used devices during the **weekends** as well.

Stress Pattern Recognition was performed in the context of **Remote Workplace Stress Monitoring** relying on the collected data.

5. METHODOLOGY

There is no well established methodology for the context of the remote workplace stress monitoring.

By workplace this study understands the physical place or group of places where employees are located or move during working hours.

Type of environment: Open or Semi-restricted environment

- Favors **Unsupervised Learning**

Type of Monitoring: Remote Stress Monitoring

- Favors including additional **Contextual Variables** charactering users' activities

Finally, we can **induce stress-related states** from the **data** relying on:

1. Physiological and **Non-Physiological** signals (**data**);
2. Clustering Algorithms;
3. Interpretation of Clusters with Theoretic Knowledge;
4. Evaluating Uncertainty.

6. PHYSIOLOGICAL AND NON-PHYSIOLOGICAL SIGNALS

Physiological signals:

- **Heart Rate** reflects the number of heartbeats per unit of time. In this study, it is measured in beats per minute “bpm”. HR may increase during periods of stress;

- **Galvanic Skin Response** refers to electrodermal activity, and associated to emotional arousal. Specifically, emotional arousal may lead to increase in GSR.

Non-physiological signal:

- This signal **Motion Activity** is operationalized as the intensity of user’s motion.

7. CLUSTERING ALGORITHMS

1. K-Means:

- Hard Clustering (Non-overlapping Classes);
- No distributional Assumptions;
- We Minimize objective function:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} \|x_n - \mu_k\|^2$$

2. Gaussian Mixture Model

- Soft Clustering (Overlapping Classes are possible);
- Gaussian distribution is assumed;
- Stress States are viewed as latent variables;
- We Minimize likelihood function with Expectation-Maximization algorithm:

$$ln\ p(X|\pi, \mu, \Sigma) = \sum_{n=1}^{N} \ln\left\{\sum_{k=1}^{K} \pi_k \mathcal{N}(x_n|\mu_k, \Sigma_k)\right\}$$

Data pre-processing and feature extraction are non shown.

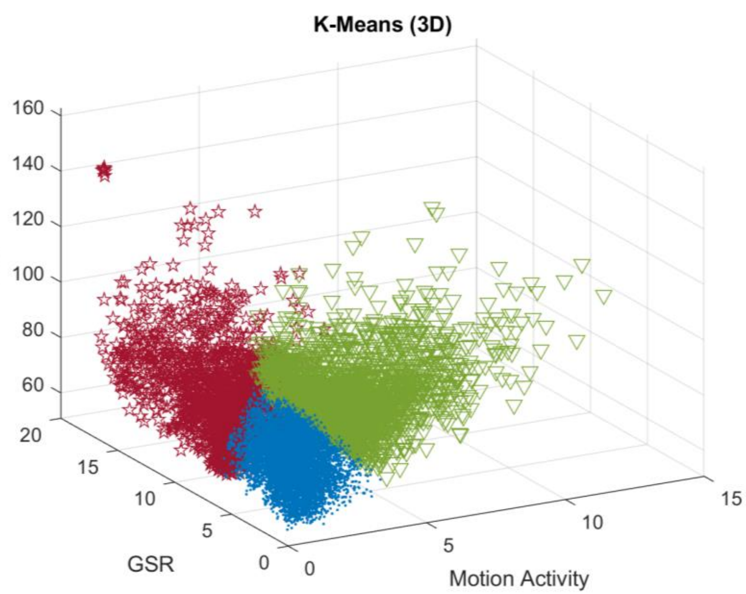
8. CLUSTERING AND INTERPRETATION

Classification from Yerkes-Dodson law of arousal and Catastrophe Theory of arousal:

<table>
<tr><td rowspan="3">1. Underaroused</td><td>2. Optimal Arousal & High Physical Activity</td><td>5. Overarousal & High Physical Activity</td></tr>
<tr><td>3. Optimal Arousal & Medium Physical Activity</td><td>6. Overarousal & Medium Physical Activity</td></tr>
<tr><td>4. Optimal Arousal & Low Physical Activity</td><td>7. Overarousal & Low Physical Activity</td></tr>
<tr><td>Low Range of Arousal - can lead to boredom, inertia, dissatisfaction.</td><td>Middle Range of Arousal - optimizing the performance; it can be thrilling and exciting.</td><td>High Range of Arousal - highly likely leading to STRESS.</td></tr>
</table>

8. CLUSTERING AND INTERPRETATION WITH K-MEANS(1)

Heart Rate



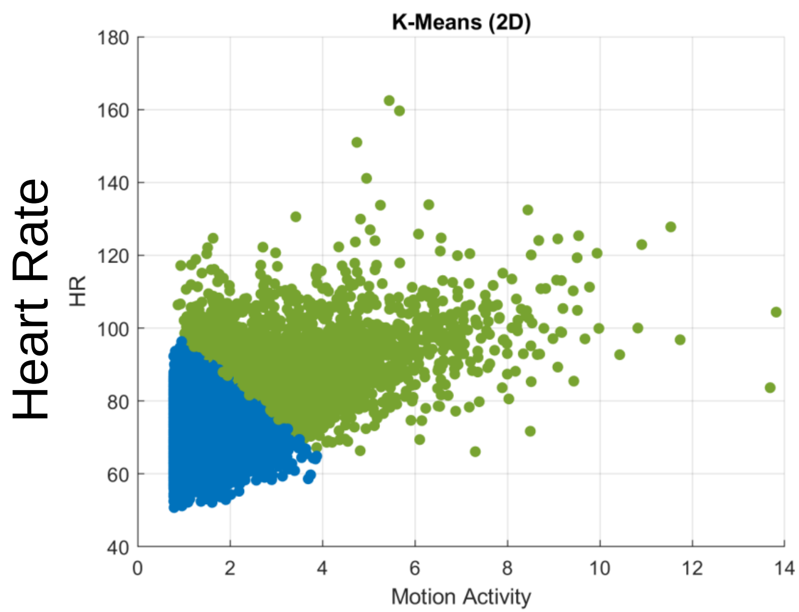
Galvanic Skin Response

Yerkes-Dodson law	Features	Labeling of Clusters
Underaroused	Low GSR	Relaxation
	Low HR	
	Low MA	
Optimal Arousal & Medium Physical Activity	Medium GSR	Arousal
	Medium HR	
	Medium MA	
Overarousal & Low Physical Activity	High GSR	Overarousal
	Medium HR	
	Medium MI	

3 classed are identified. Other classes are non observed but could be found in different environment (for example Optimal Arousal & High Physical Activity).

Red cluster: This state highly likely leading to STRESS or expressing STRESS.

8. CLUSTERING AND INTERPRETATION WITH K-MEANS (2)



In **Green Cluster,** an increase in Motion Activity is followed by increase in HR.

This may be an **normal physiological reaction to the increase of Motion Activity** but not to Overarousal or Stress.

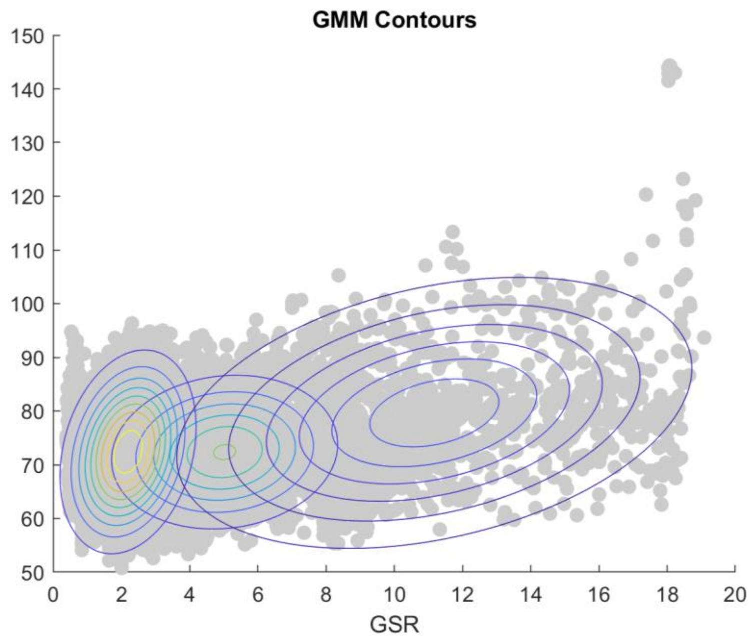
Green Cluster: This state may correspond to optimizing the performance; it can be thrilling and exciting.

8. CLUSTERING AND INTERPRETATION WITH GMM

Observations with high Motion Activity values were deleted.

Labeling according to **Yerkes-Dodson law and Catastrophe Theory:**

Heart Rate



Galvanic Skin Response

1) Left Cluster Relative size 67%. It may be related to the **State of Relaxation - Low Range of Arousal;**

2) Central Cluster Relative size 24 %. It may be related to the **Arousal State – Middle Range of Arousal**;

3) Right Cluster Relative size 8%. It may be related to the **Emotional Overarousal State – High Range of Arousal.**

Weighted likelihood bootstrap confidence Intervals were computed for μ in order to reflect uncertainty of clusters.

9. FINDINGS

- There are distinguishable stress-related patterns characterizing specific work-environments that we can analyze with help of wearables;

- It is possible to build an unsupervised classifier with help of clustering algorithms and theoretic knowledge;

- Motion Activity can be used in stress pattern recognition in order to provide additional insights on stress-related states of the users.

10. IMPLICATIONS

- It may be possible to develop special monitoring programs where users wear the devices outside of the work environment under their consent.

- This study may contribute to the development of new stress-monitoring practices, processes and procedures in the workplace and outside.

11. FURTHER RESEARCH

- Validation of classification with questionnaires;
- Development of stress-related anomaly detection systems;
- Development of meaningful and interpretable stress-related indicators on Individual and Collective levels;
- Development of methodologies incorporating physiological and non-physiological signals for stress pattern recognition;
- And so forth.

12. QUESTIONS

Thank you for your attention!