



# Artificial Intelligence methods in computer modeling and recognition of emotions and humanization of computer systems

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**AGH**



**Discipline:**  
Information and communication technology



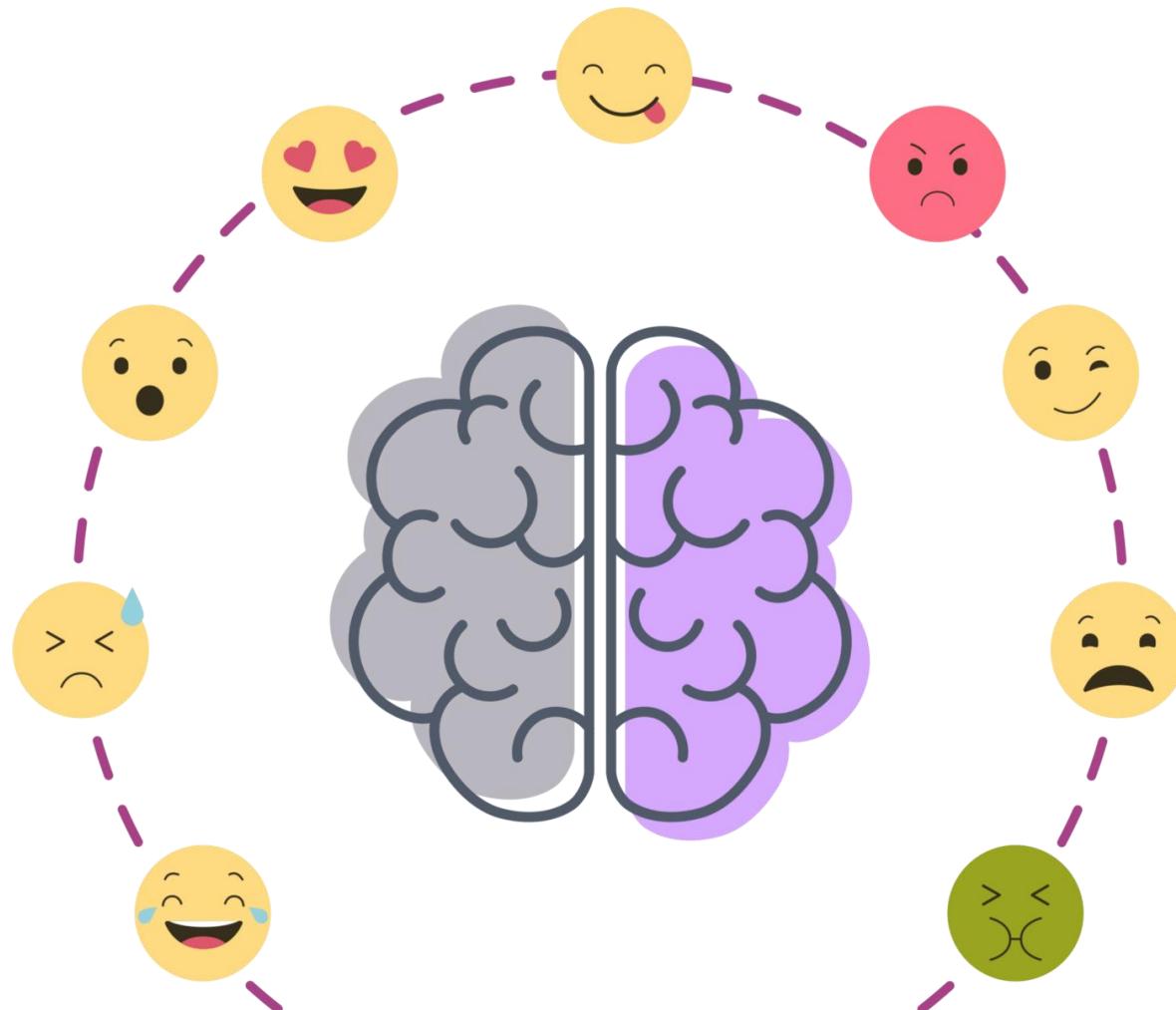
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# Theory of emotions

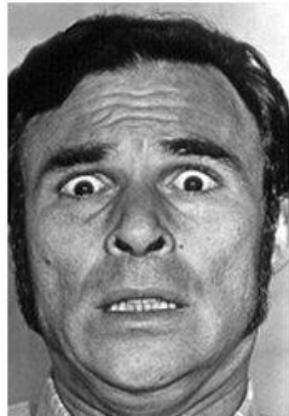


# Emotion sources

- » Human words
- » Tone of the voice
- » Facial expression
- » Body language
- » Physiological data (Heart rate variability, skin conductivity, brain activity etc.)



# Types of emotions



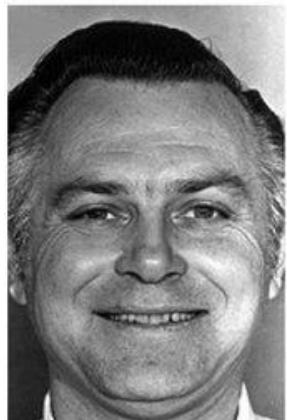
Fearful



Angry



Sad



Happy

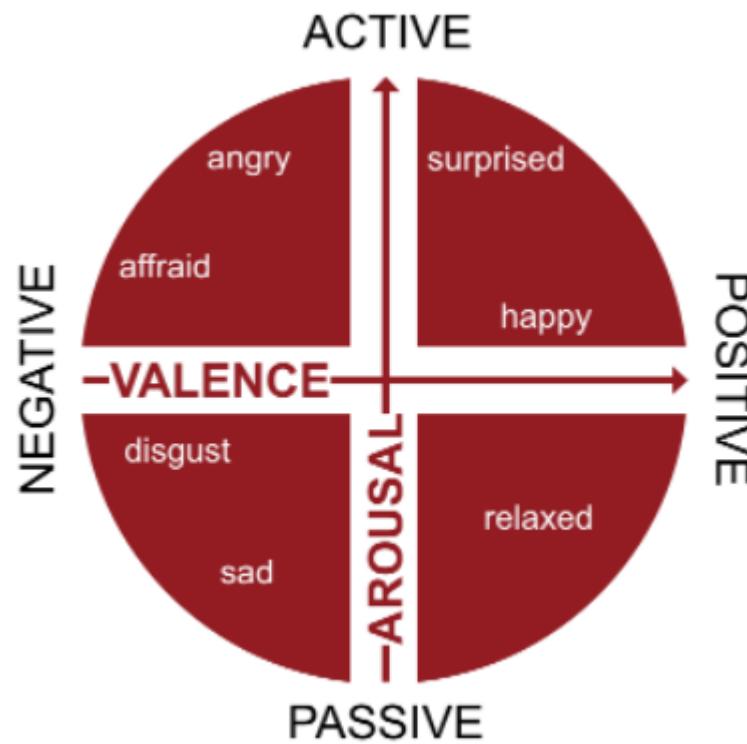


Disgusted



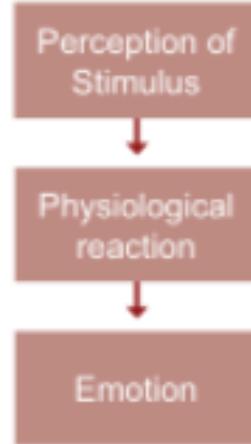
Surprised

# Emotion classification

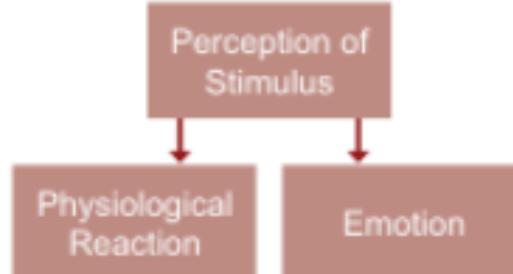


# Origin and nature of emotions

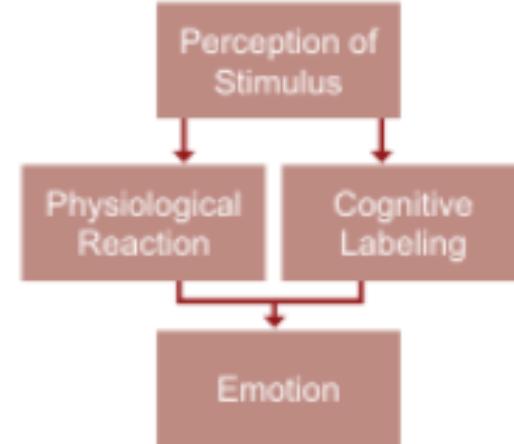
A James-Lange Theory



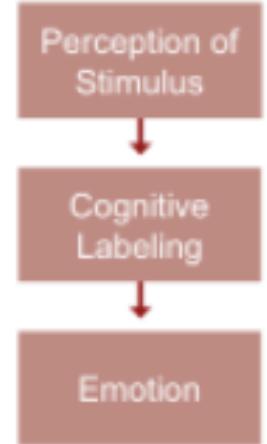
B Cannon-Bard Theory



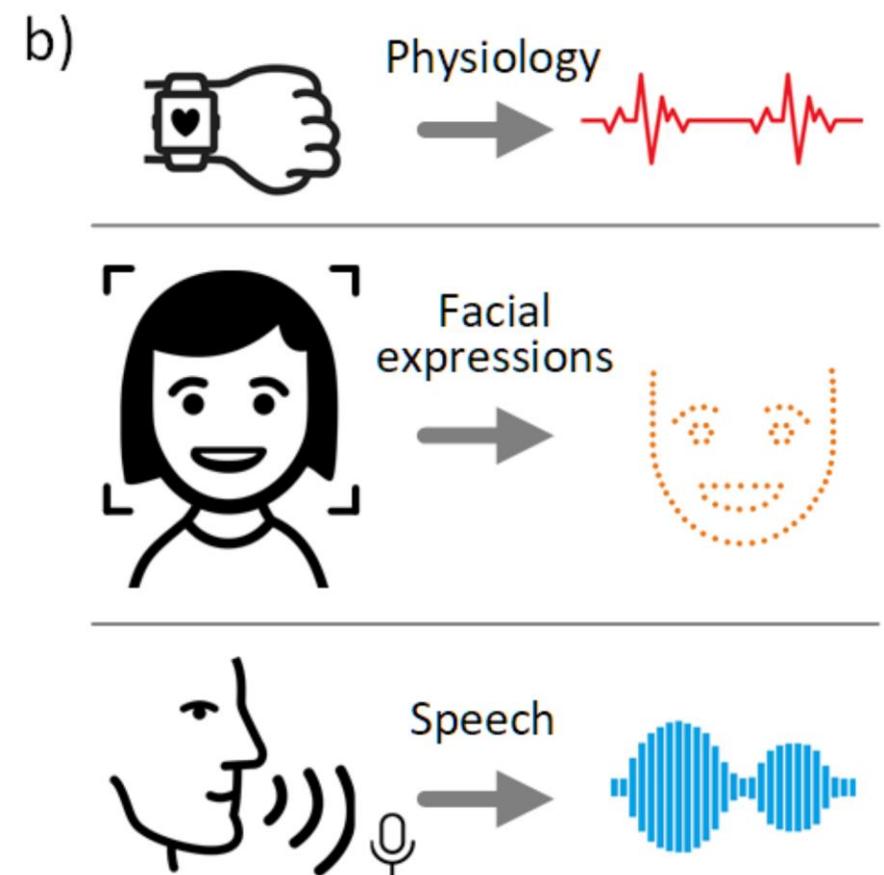
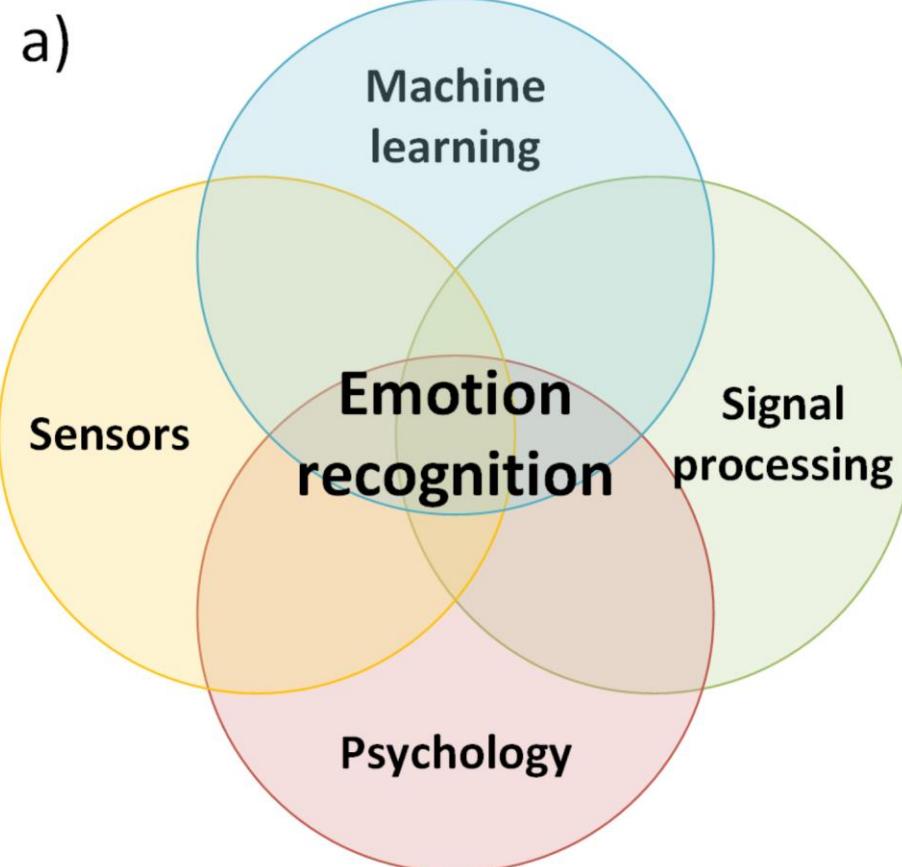
C Schachter's Two-Factor Theory



D Cognitive Appraisal Theory



# Emotion recognition 1/3

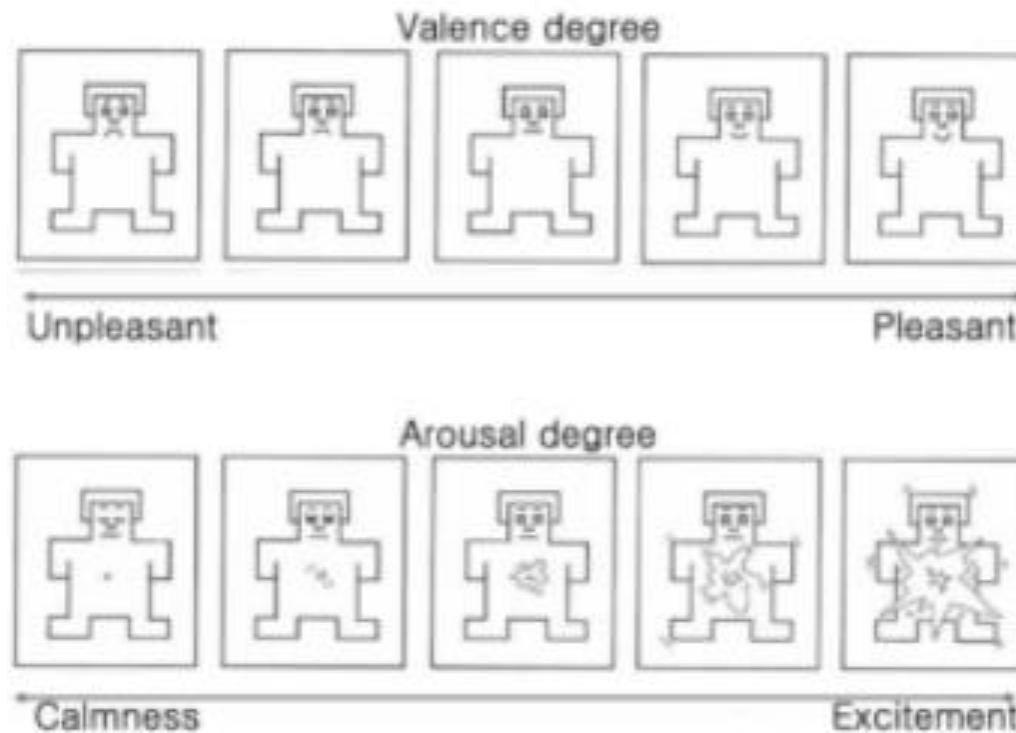


# Emotion recognition 2/3

- » Support Vector Machines (SVM)
- » Artificial Neural Networks (ANN)
- » K-Nearest Neighbor (KNN)



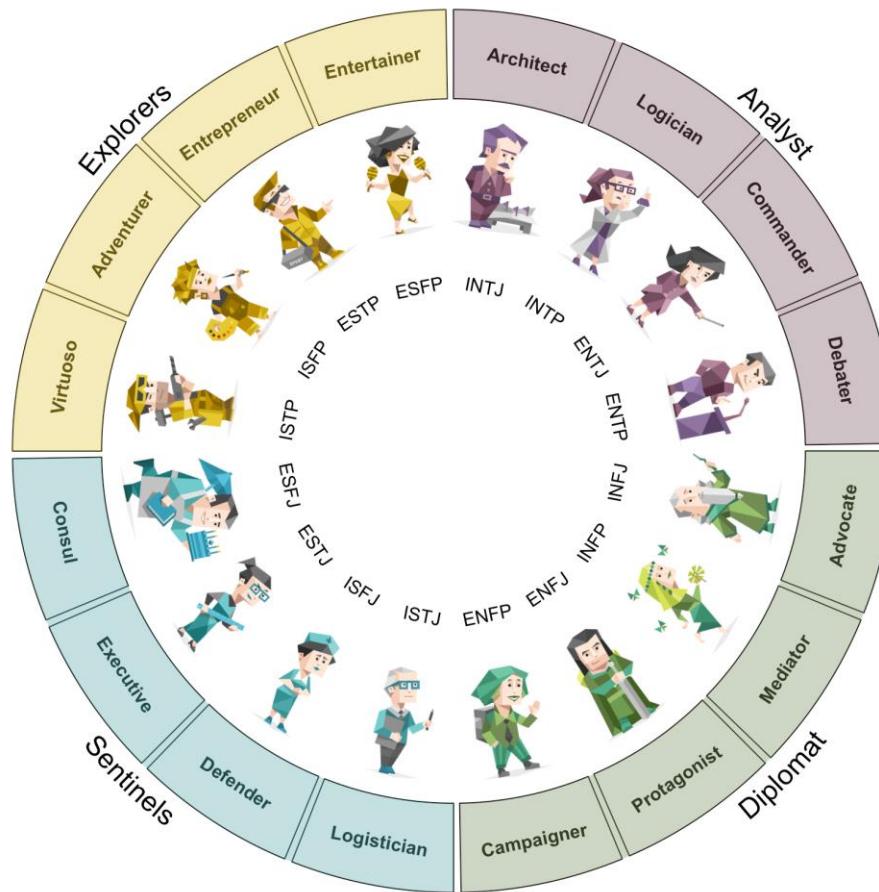
# Emotions recognition 3/3



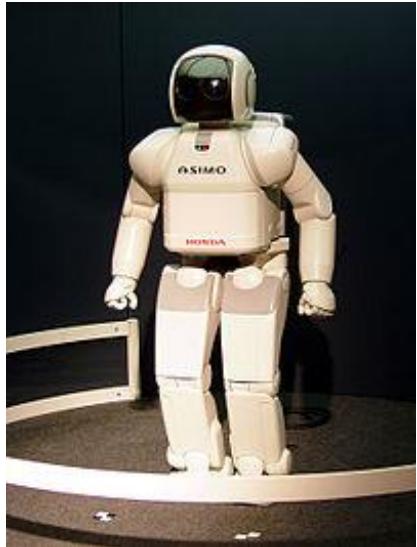
# Problems with emotion recognition

- » Differences (cultural, age, sex)
- » Conscious emotion manipulation
- » Emotions personalize
- » Experiment information
- » Lab environment
- » User dependency or independence

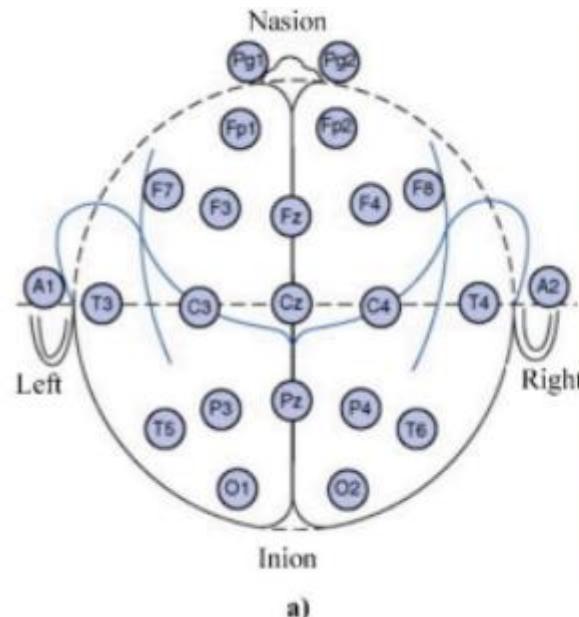
# Model personalization



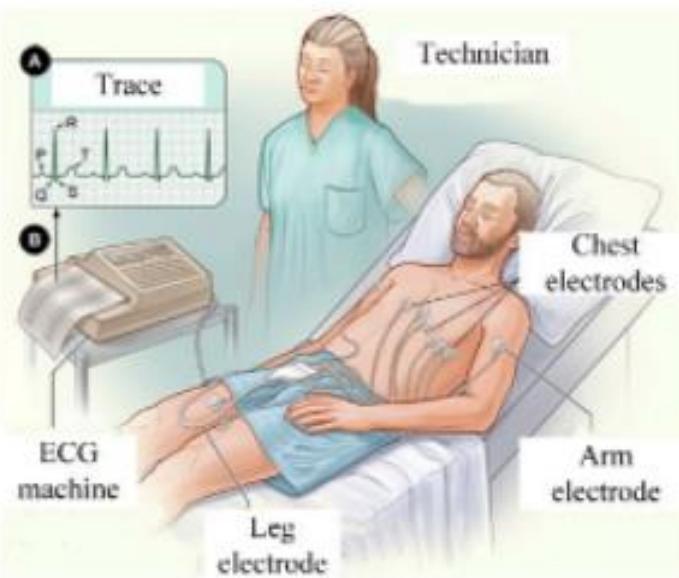
# Application areas



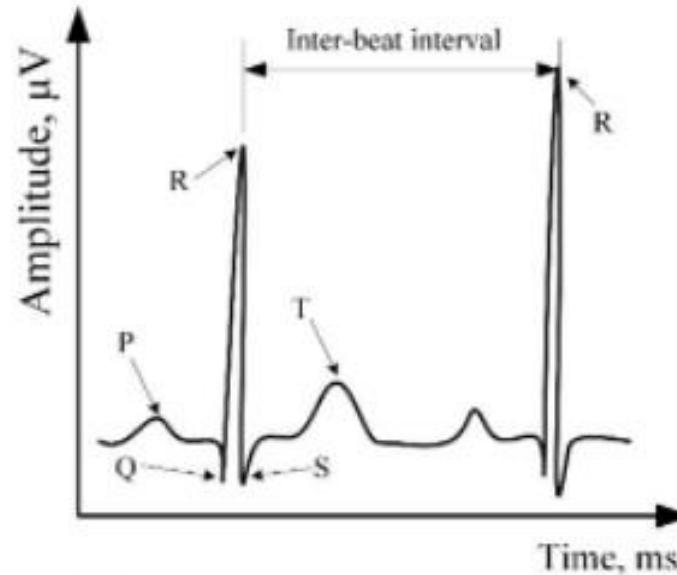
# Methods of acquiring physiological signals: EEG



# Methods of acquiring physiological signals: ECG

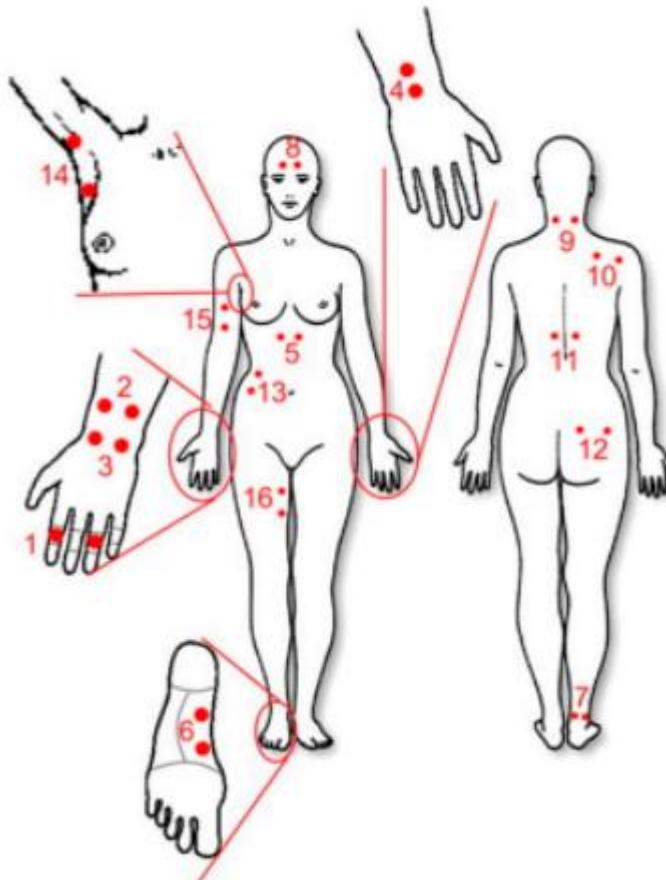


a)

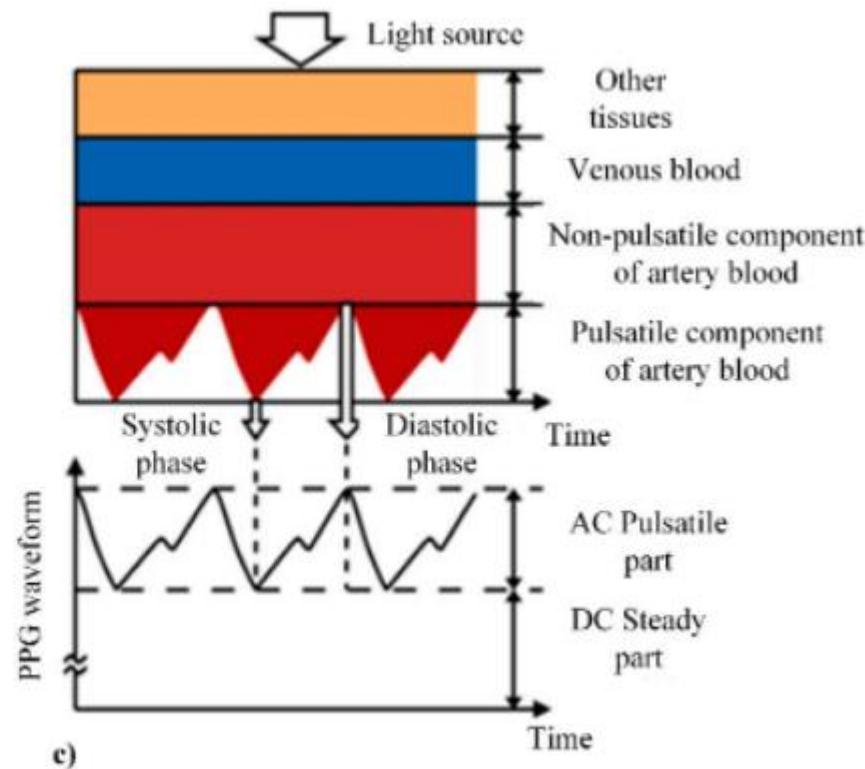
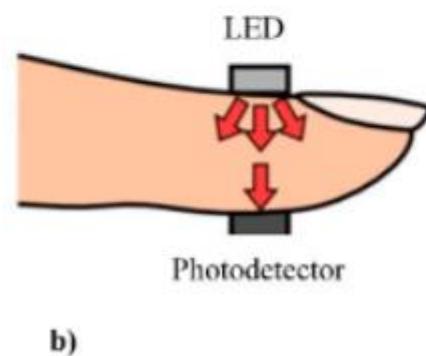
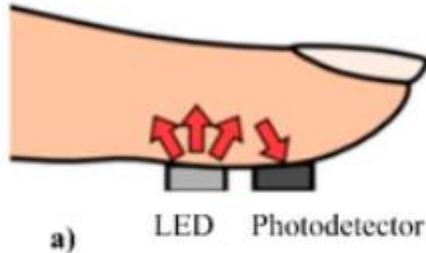


b)

# Methods of acquiring physiological signals: GSR/EDA



# Methods of acquiring physiological signals: HRV and PPG

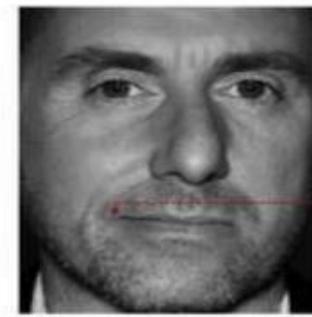


# Emotions recognize from face, body language, gestures



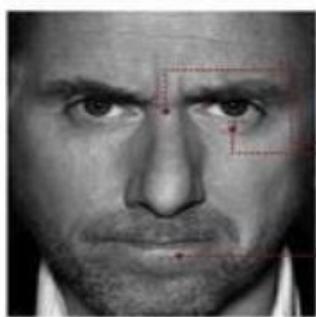
**disgust**

- ① nose wrinkling
- ② upper lip raised



**contempt**

- ① lip corner tightened and raised on only one side of face



**anger**

- ① eyebrows down and together
- ② eyes glare
- ③ narrowing of the lips



**fear**

- ① eyebrows raised and pulled together
- ② raised upper eyelids
- ③ tensed lower eyelids
- ④ lips slightly stretched horizontally back to ears



**surprise**

- Lasts for only one second:
- ① eyebrows raised
- ② eyes widened
- ③ mouth open



**sadness**

- ① drooping upper eyelids
- ② losing focus in eyes
- ③ slight pulling down of lip corners

# Other methods of acquiring data

- » Respiration Rate Analysis (RR)
- » Skin Temperature Measurements (SKT)
- » Electromyogram (EMG)
- » Electrooculography (EOG)



# Methods of acquiring biological data advantages/disadvantages

Method	Advantages	Disadvantages	Application
EEG	Allow to measure patients with intellectual disability	Difficult to use, disruption maintenance	Lab environment
Face Recognition	Contactless, tracking multiple cases in single use	Required camera opposite the face	Lab environment, home, work, public places
ECG	Mobile measurements possible	Disruption possibility in case of mobile measurements	Lab environment, everyday use
EDA	Good factor to detect stress	Arousal measurements only, temperature dependency	Lab environment, everyday use
SKT	Wide possibility to acquire data	Arousal measurements only, reacts slowly to emotional states changes	Lab environment, home, work, public places
EMG	Allow to measure patients with intellectual disability	Valence measurements only, difficult installation	Lab environment

# Face recognition datasets

Name	Emotion types	Dataset type	Number of samples
CMU Facial Expression Database (Cohn-Kanade)	Joy, Surprise, Anger, Fear, Disgust, Sadness	Posed	200 subjects
Extended Cohn-Kanade Dataset (CK+)	Neutral, Sadness, Surprise, Happiness, Fear, Anger, And Disgust	Posed; spontaneous smiles	593 image sequences (327 sequences having discrete emotion labels)
Japanese Female Facial Expressions (JAFFE)	Neutral, Sadness, Surprise, Happiness, Fear, Anger, Disgust	Posed	213 images
FERG (Facial Expression Research Group Database)-DB	Angry, Disgust, Fear, Joy, Neutral, Sad, Surprise	Frontal pose	55767
FER-2013	Neutral, Sadness, Surprise, Happiness, Fear, Anger, And Disgust	-	35887

# FER-2013 Dataset



Surprise  
Happiness



Fear  
Anger



Fear  
Sadness



Sadness  
Fear



Surprise  
Happiness



Anger  
Sadness



Happiness  
Surprise



Anger  
Disgust



Happiness  
Surprise



Fear  
Anger



Neutral  
Sadness



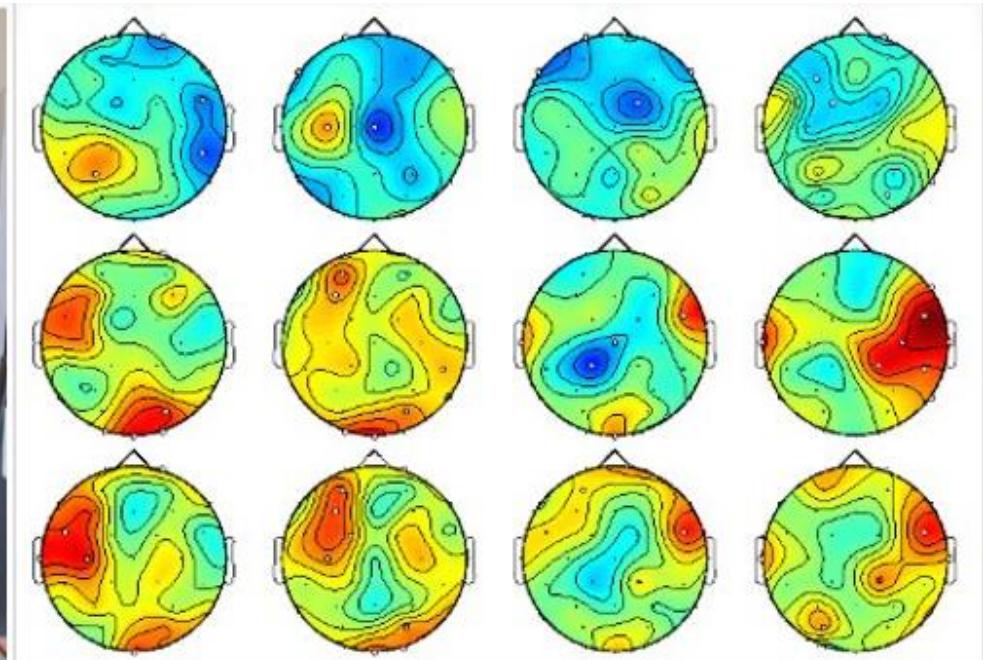
Fear  
Happiness



# Datasets from different physiological signals

Name	Emotion types	Type	Number of samples
MAHNOB	Arousal, Valence, Dominance	EEG, ECG, EDA, GT, RM, FT, ST	27 subjects
DECAF	Arousal, Valence, Dominance	EEG, ECG, MEG, EOG, EMG, FT	30 subjects
DEAP	Arousal, Valence, Dominance	EEG, FT	32 subjects
SEED	Positive, Negative, Neutral	EEG, FT	15 subjects

# DEAP Dataset



# Literature studies

Authors	Model	Dataset	Type	Result
Yang Y. et al (2018)	3DCNN SLC	DEAP	EEG	90.24% (Arousal), 89.45% (Valence)
Salama E. et al (2018)	3DCNN SLC	DEAP	EEG	88.49% (Arousal), 87.44% (Valence)
Tang H. et al (2017)	Bimodal-LSTM + SVM SLC	DEAP	EEG	83.23% (Arousal), 83.82% (Valence)
Koelstra S. et al (2012)	- SLC	DEAP	EEG	62% (Arousal), 57.6% (Valence)

# Literature studies pt.2

Authors	Models	Dataset	Type	Result
Yue Z. et al (2019)	ExpressionNet	FER-2013	FE	68.4%
Kanmani T. et al (2016)	MVFE-LightNet	FER-2013	FE	68%
Arrianga O. et al (2017)	CNN	FER-2013	FE	66%
Tumen V. et al (2017)	CNN	FER-2013	FE	57.1%

# Current progress: Affective Computing literature study

- » Theory of human emotions
- » Emotions sources
- » Emotions classification techniques
- » Process of recognizing emotions in steps
- » Personalization problems



# Current progress: Technology overview

- » Keras: Deep Neural Networks (DNN), Convolutional Neural Networks (CNN)
- » Machine learning: XGB Classifier, Support Vector Machine, K-Nearest Neighbors, Decision Tree Classifier
- » Standardization techniques
- » Preprocessing methods



# Current progress: Existing datasets identification

- » DEAP Dataset (EEG)
- » BIRAFFE2 (Face recognition)
- » YAAD (ECG, GSR)



# Current progress: Overview, early implementation existing models

- » Recognizing emotions from EEG by Continuous Convolutional Neural Network
- » Data preprocessing where I extracted from raw EEG signal
- » Multilabel Class Classification and I archived 82% of accuracy for Low/High Valence and Low/High Arousal

# Current progress: Preparing conference article

- » Machine learning methods in case of recognizing emotions from face
- » BIRAFEE2 dataset with preprocessed photos
- » Have abstract, introduction, and existing model's overview
- » Plan to add information about emotions recognizing process and attach results

# Future: Creating own models with personalization

- » Create personalized models
- » Use XGB Classifier, Support Vector Machine, K-Nearest Neighbors, Decision tree Classifier
- » BIRAFEE2 Dataset
- » BigFive
- » Within article



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- » [SEED Dataset \(sjtu.edu.cn\)](#)
- » [Magnetoencephalography – Wikipedia](#)
- » [Elektrookulogram – Wikipedia, wolna encyklopedia](#)
- » [Electromyography - Wikipedia](#)
- » [DEAP: A Dataset for Emotion Analysis using Physiological and Audiovisual Signals \(qmul.ac.uk\)](#)
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Cooperators welcome

