Master's degree ICT Internet Multimedia Engineering

ML FOR HUMAN DATA ANALYTICS: A.Y. 24/25

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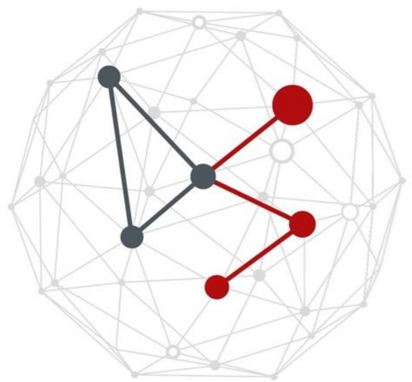


DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

DIPARTIMENTO MATEMATICA

UNIVERSITÀ DEGLI STUDI DI PADOVA

ML4HDA

- A course on Applied ML for Human Sensing Systems
  - Centered around human-generated signals

- Master Degrees
  - Data science (DM)
  - ICT for Internet and Multimedia (DEI)

- Teacher
  - Prof. Michele Rossi - theory & apps
    - https://www.dei.unipd.it/~rossi/

Michele Rossi

Lab. classes

- Lab classes (14 hours)
  - Will be held *in presence*
  - **how-to**:
    - install & use environments

Francesca Meneghello

- Lab. classes for self study
  - Preliminary material 1/2 videos
    + supporting material
  - Advanced Phyton machine learning
    - Deep learning

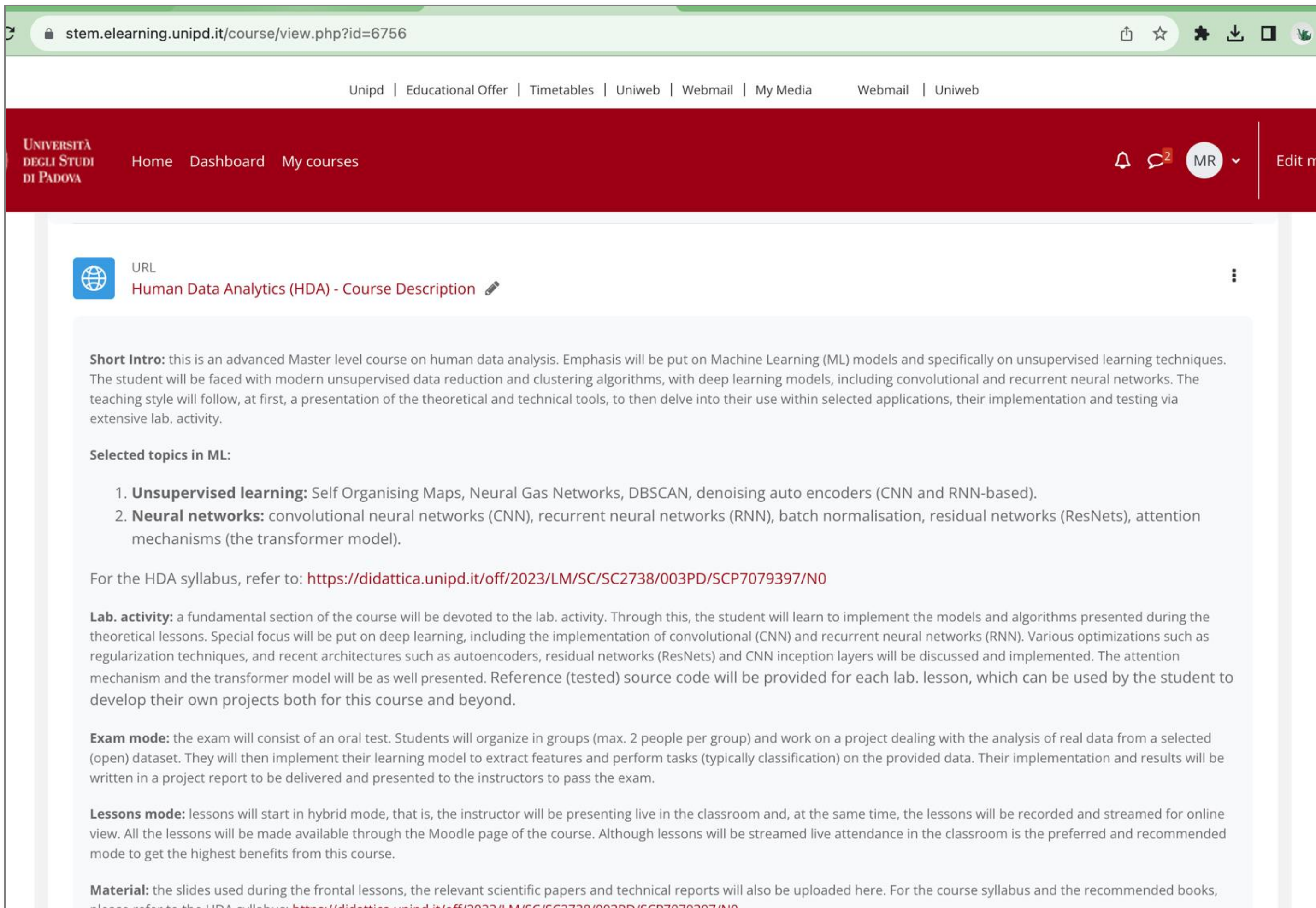
Eleonora Cicciarella

Course material

- Course material
  - ML for HUMAN DATA ANALYTICS 2024/2025
  - Integrated Moodle platform
    - https://stem.elearning.unipd.it/
  - Slides
  - Video lessons (**no videos** for the labs)
  - Lab classes (14 hours)
    - preliminary material
    - videos of assignments
    - software with solutions

https://stem.elearning.unipd.it/course/view.php?id=9864

ML for HUMAN DATA ANALYTICS 2024-2025



Teaching approach

- Teaching mode
  - All the theoretical lessons will be live in the classroom
  - Recorded for online view
    - Posted later for offline view/study
- Lab activity
  - In presence, in the lab
  - Lab experiences
    - will not be recorded
    - will not be streamed
  - Project assignments, software & solutions
    - will be posted for offline use

HDA Selling Points (1/2)

- Unsupervised learning techniques
  - Clustering, classification
  - Seldom studied in MS level courses
  - Very important for applications
  - Will be key to future research/developments

- Neural networks
  - Theoretical lessons (architectures, learning)
  - Lab. activity + hands-on activity
    - Set up and use environments (mainly Phyton, TensorFlow)
    - Learn to code your neural network (CNN, RNN, etc.)
    - Case studies based on real datasets

HDA Selling Points (2/2)

- Usually
  - Focus of basic machine learning courses is on i.i.d. data samples
  - Problems are typically: regression, classification

- This course
  - Is often concerned about modeling complex data sequences
  - Some (spatio-temporal) correlation exists among data points

- Our focus is on (temporal/spatial) <u>pattern analysis</u>
  - For correlated data (space, time)
  - Often such data is generated by sensing applications

Exams (1/2)

- Project based
  - Project assignment from instructors
  - Design/implement a machine learning model
    - Testing it on a public dataset
    - Testing it on own-collected data from wearable sensors
- Outcome
  - Written project report (max. 15 pages)
  - Python implementation of the processing pipeline
  - Power Point presentation (small demo at exam is appreciated)
- Groups
  - Max. 2 students per group

Guidelines about: public database, task to be performed and project report structure will be provided when we start the laboratory activity

Exams (2/2)

Exam dates for a.y. 24/25

- 28-29 January 2025
- 18-19 February 2025
- 18-19 June 2025
- 2-3 July 2025
- 18-19 Sept 2025

Enrolment on an exam

- https://uniweb.unipd.it/

Exam mode

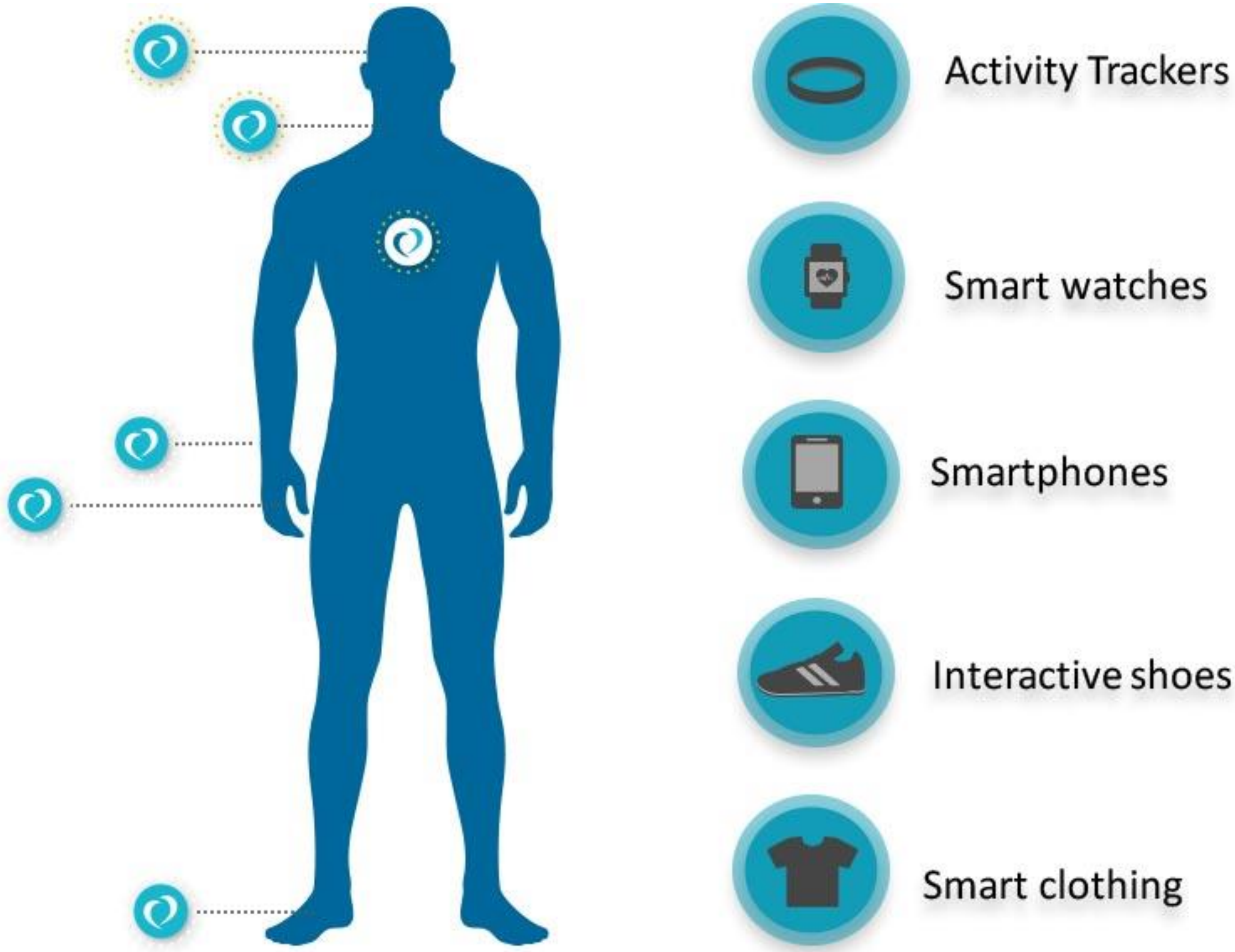
- Upload technical report in pdf (template will be provided)
- Upload your code in advance
- Present your work using slides (20 minutes)

TOPICS

ML4HDA in a nutshell

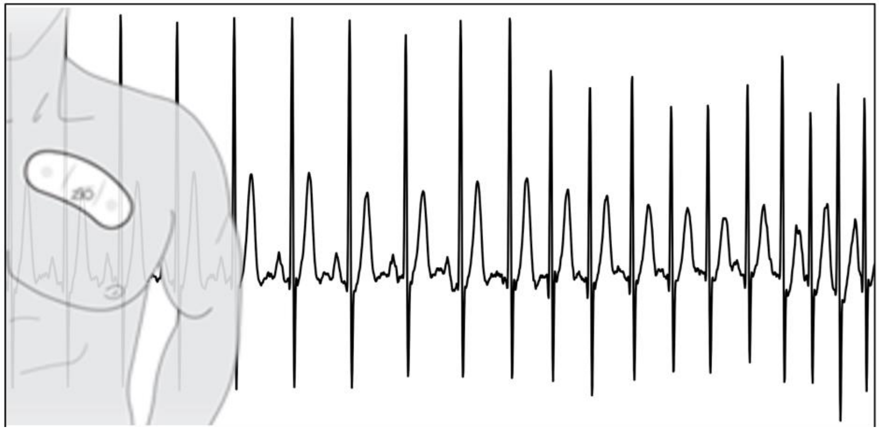
- Tools
  - Dimensionality reduction: PCA
  - Unsupervised Clustering: K-means, SOM, GNG, DB-SCAN
  - Neural networks:
    - Feed Forward (FFNN), Convolutional (CNN),
    - Recurrent Neural Networks (RNN), Autoencoders, Spiking Nets
    - Implementation tricks: batch normalization, dropout, inception layers, attention mechanism, autoencoders
  - Times series analysis: RNN, RNN+attention, transformer model
- Applications
  - ECG signals, pulse oximeter (blood oxygenation), speech analysis
  - Inertial signals (motion analysis)
    - authentication, activity recognition (heterogeneous data)
  - Medical images

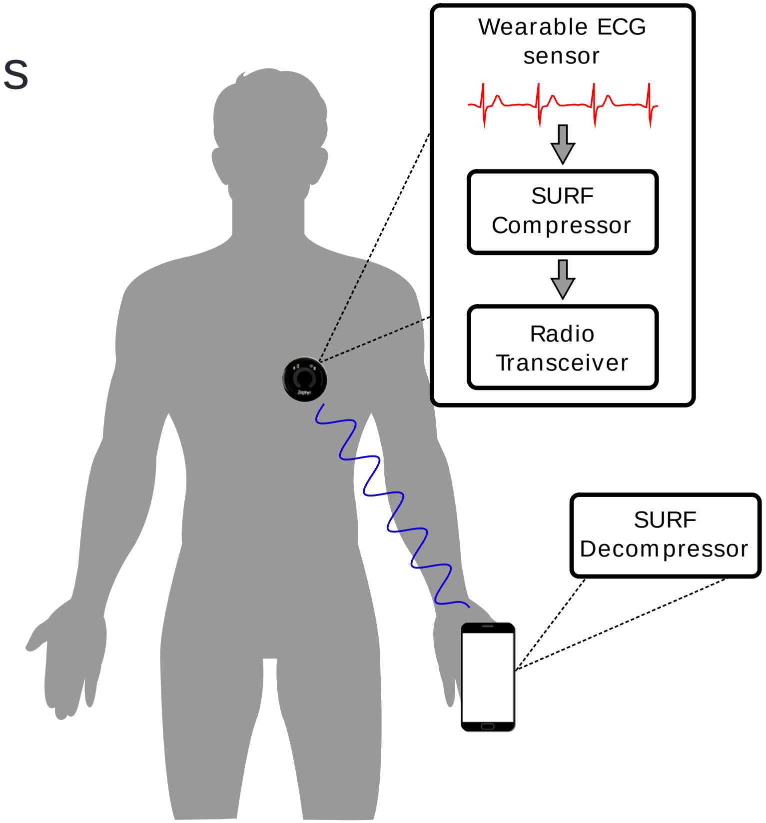
Human sensing



Modeling ECG signals

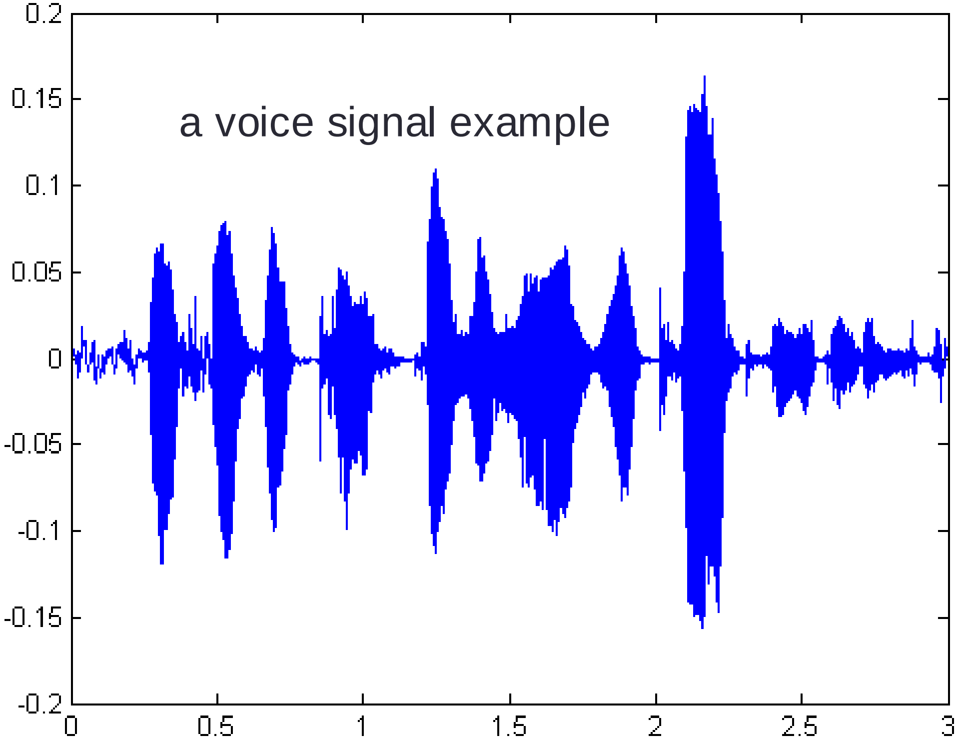
- Useful for many reasons
  - Efficient TX in resource limited systems
  - Automated detection of arrhythmia
  - User identification / authentication





Statistical modeling of time series

- How to reliably decode words and sentences (speech)
  - CNN, RNN, attention mechanism

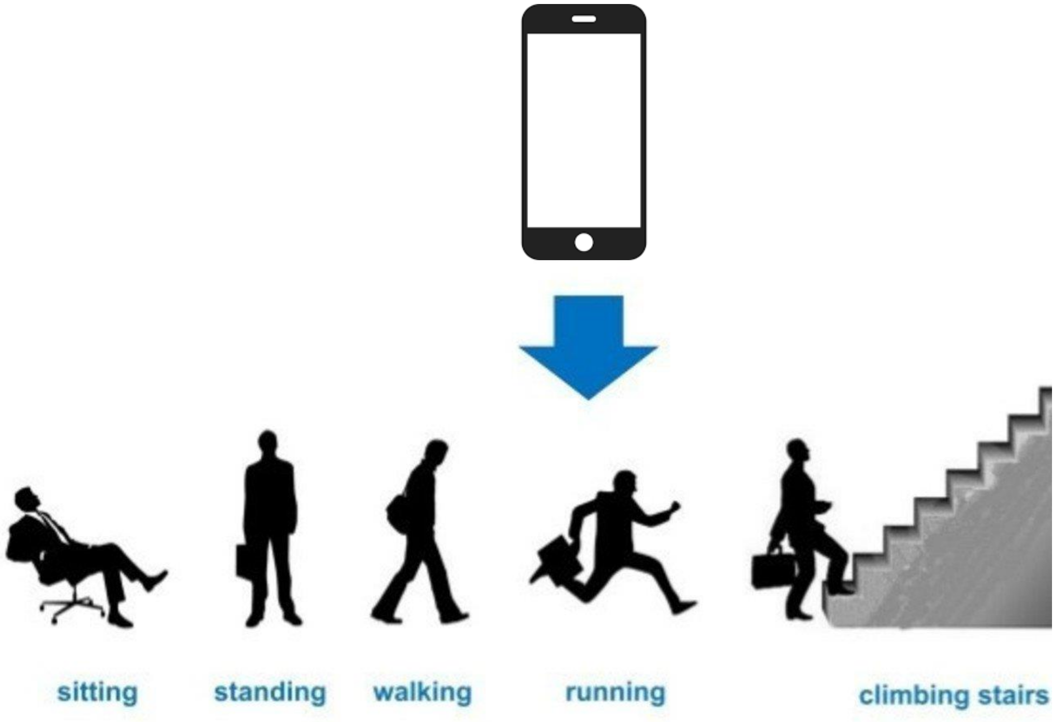


Automatic speech recognition

- How to decode voice
  - Feature extraction
  - Cepstral features
- The tools
  - CNN, RNN
  - Attention mechanism

Inertial signals

- Accelerometer and Gyroscope signals
  - From Inertial Measurement Units (IMU)
    - Chest-band, wrist-band, smart watches, smart phones, etc.
- Applications
  - User authentication
  - Activity recognition



Course structure

1) Tools: dimensionality reduction & clustering

   Apps: Electrocardiography (ECG) signal

2) Tools: Neural networks (CNN, RNN, autoencoders, residual networks, attention mechanism/transformers)

   Apps:
   - ECG signal
   - speech analysis
   - inertial signal (motion analysis)
   - medical images: lymphoma classification

Spiking Neural Networks: Motivations

Deep Learning models are getting bigger and bigger

- Long training times
- Huge requirements in terms of energy consumption
- Implementation on energy-constrained devices is infeasible

- Need for efficient DL architectures

Spiking Neural Networks: Motivations

GPT-3, contains 175 billion learnable parameters, estimated to consume roughly 190,000 kWh to train (12 Million USD$ in energy bills)

Imagine we wanted to train the brain as an ANN:

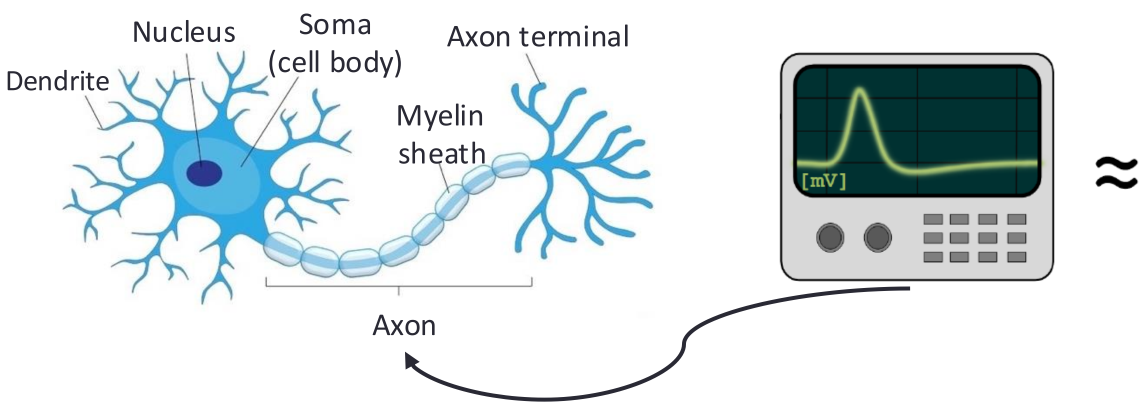
Simon Thorpe, Embedded Systems Research Group 2021

$$\underbrace{8.6^{10}}_{\text{neurons}} \cdot \underbrace{7.0^{3}}_{\text{synapses}} \cdot \underbrace{1.0^{3}}_{\text{time resolution (ms)}} = 600 \text{ PetaFLOPS}$$

- Most powerful existing supercomputer: 442 PetaFLOPS at **30MW**
- Meanwhile, our brains operate within **~12-20 W** of power

Can we take inspiration from the brain?

Spiking Neural Networks



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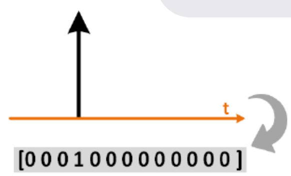


Spikes are modeled as **all-or-nothing event**

- Biological neurons communicate via **action potentials**, or *spikes*
- The form of the action potential does not carry any information
- It is the **number** of spikes and their **timing** which matter
- Event-based processing

LABORATORIES

Lab. Classes

- Will use several tools

python™

NumPy scikit learn Pandas matplotlib

- Guided coding sessions to build machine learning apps
  - Build everything from scratch (simple applications)
  - Use some popular libraries (more complex projects)

TensorFlow jupyter

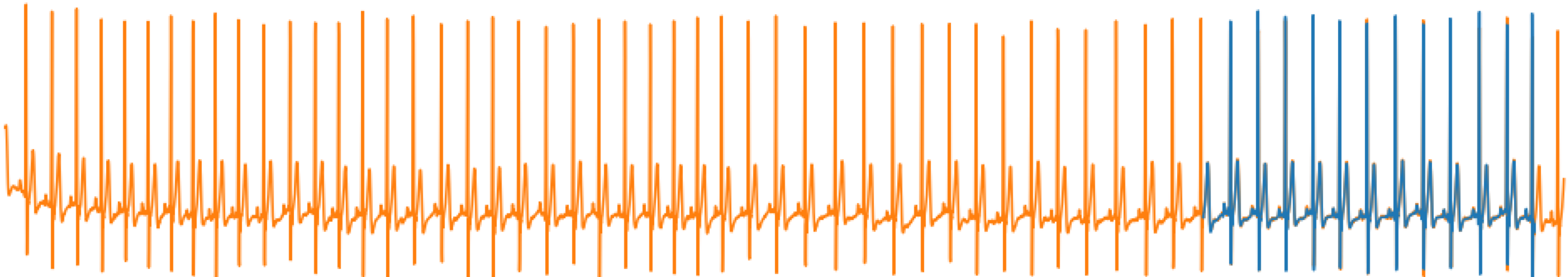
snnTorch

Lab 0 – preparatory material

- For self-study
  - Guided coding sessions to build machine learning apps
  - You will learn to:
    - use Jupyter notebooks and JupyterLab
    - use math and NumPy Python libraries
    - define your own functions in Python

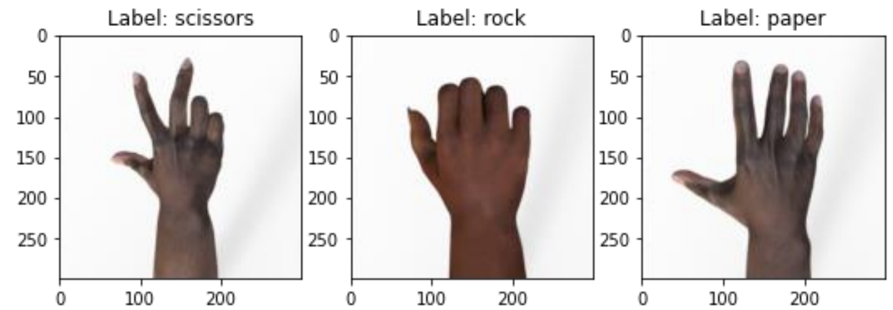
Lab 1 – Oct. 29

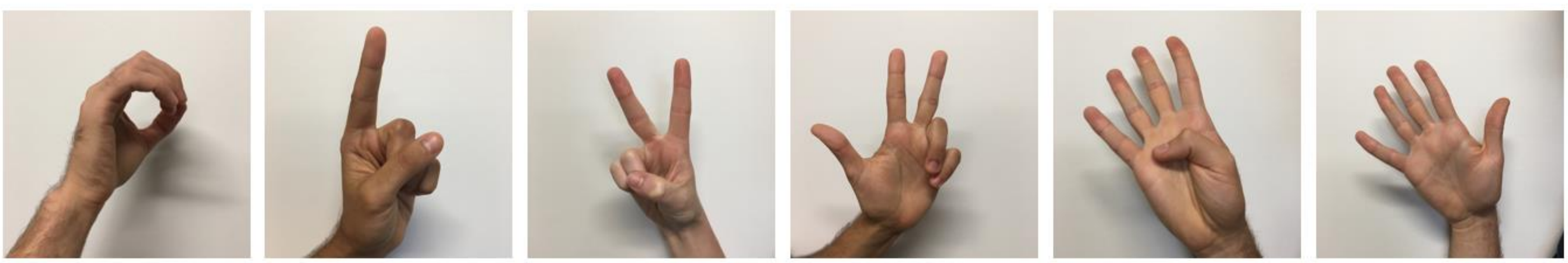
- Machine learning tools for dimensionality reduction: PCA and clustering
  - The challenge:
    - ECG and PPG signals dimensionality reduction
  - You will learn to:
    - implement a dimensionality reduction algorithm based on PCA from sketch and using the implementation from Python libraries
    - implement a dimensionality reduction algorithm based on clustering
    - use Scikit-learn Python library



Lab 2 – Nov. 12

- CNN based classifier
  - The challenge:
    - hand gesture recognition
  - You will learn to:
    - implement a CNN based classifier using TensorFlow
    - train the classifier and test its performance



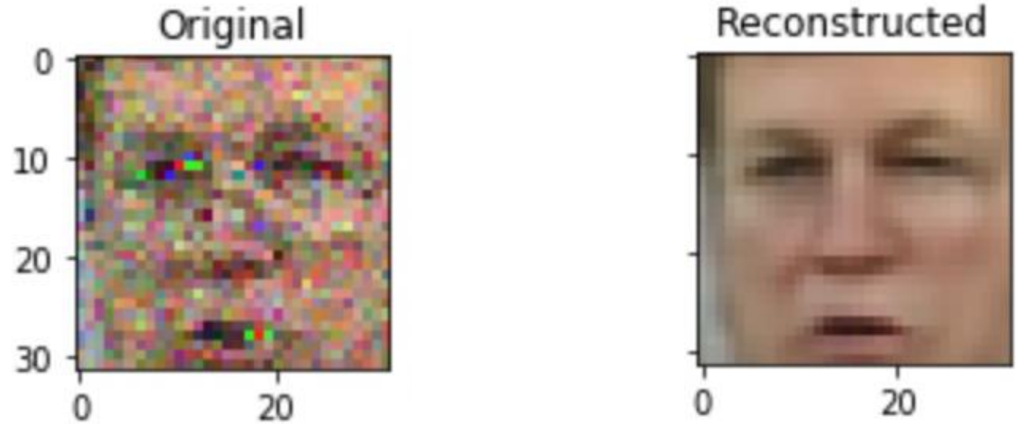


Lab 2a – optional for self study

- FFNN based classifier
  - Step-by-step implementation
  - The challenge:
    - classification of cat images
  - You will learn to:
    - implement a feed forward neural network classifier, defining the model, the forward and backward propagation steps and the update rule – TensorFlow is not used here!
    - train the classifier and test its performance

Lab 3 – Nov. 19

- CNN based autoencoder
  - The challenge:
    - image dimensionality reduction and denoising
  - You will learn to:
    - implement a CNN based autoencoder using TensorFlow
    - use the autoencoder to denoise noisy images

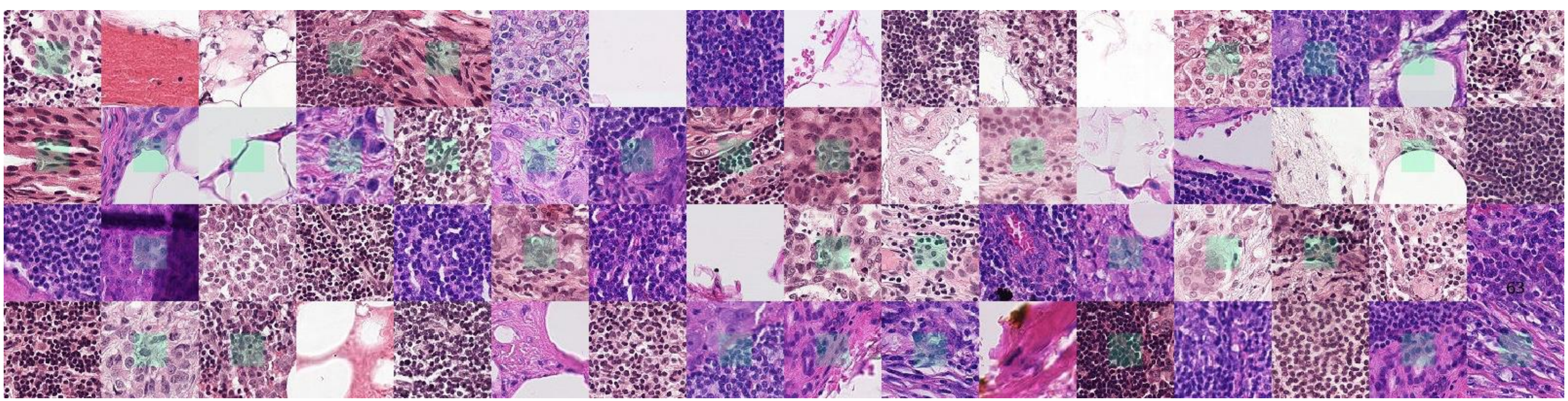


Denoised

Lab 4 – Nov. 27

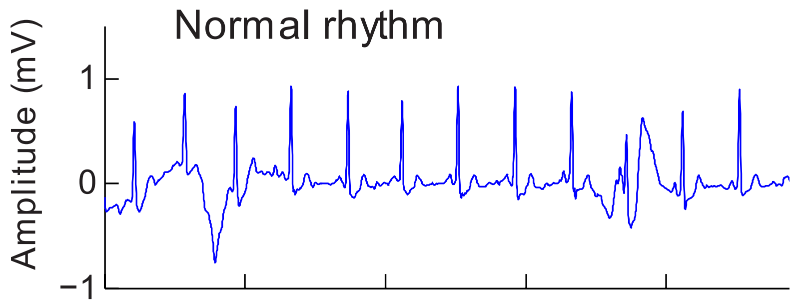
TensorFlow

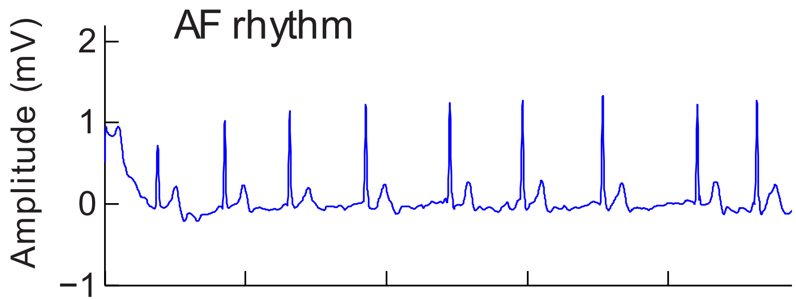
- Inception-V4 network for classification
  - The challenge:
    - metastatic tissue identification
  - You will learn to:
    - implement the basic building blocks of Inception-v4
    - combine them to shape the classifier



Lab 5 – Dec. 4

- CNN-RNN based classifier
  - The challenge:
    - abnormal heart rhythm recognition
  - You will learn to:
    - use Pandas Python library to handle data structures in Python
    - use Scikit-learn and SciPy Python libraries
    - preprocess the input data & implement a caching
    - implement a CNN-RNN based classifier using TensorFlow
    - train the classifier and test its performance using different metrics





Lab 6 – Dec. 11

TensorFlow

- Attention mechanisms & sequence-to-sequence
  - The challenge:
    - neural machine translation
  - You will learn to:
    - integrate attention mechanism into a neural network architecture
    - use attention to create complex deep learning models
    - define custom tf.keras.layer.Layers and tf.keras.Model through the sub-classing strategy.
    - implement the encoder and decoder blocks, integrating an attention mechanism in the decoder part
    - train the model through the teacher-forcing approach on an Italian-English dataset
    - assess the performance of the translator on real sentences

Lab 6a – optional for self study

- Transformers
  - The challenge:
    - neural machine translation
  - You will learn to:
    - focus on the attention mechanism
    - define custom tf.keras.layer.Layers and tf.keras.Model through the sub-classing strategy
    - implement the encoder and decoder blocks, integrating an attention mechanism into the decoder part
    - train the model through the teacher-forcing approach on an Italian-English dataset
    - assess the performance of the translator on real sentences

Lab 7 – Dec. 18

snnTorch

- Spiking neural networks
  - The challenge:
    - classification task
  - You will learn to:
    - implement a spiking neural network in snnTorch
    - assess the performance of the classifier

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