ARTIFICIAL NEURAL NETWORKS: APPLICATION EXAMPLES

Michele Rossi
rossi@dei.unipd.it

Dept. of Information Engineering
University of Padova, IT

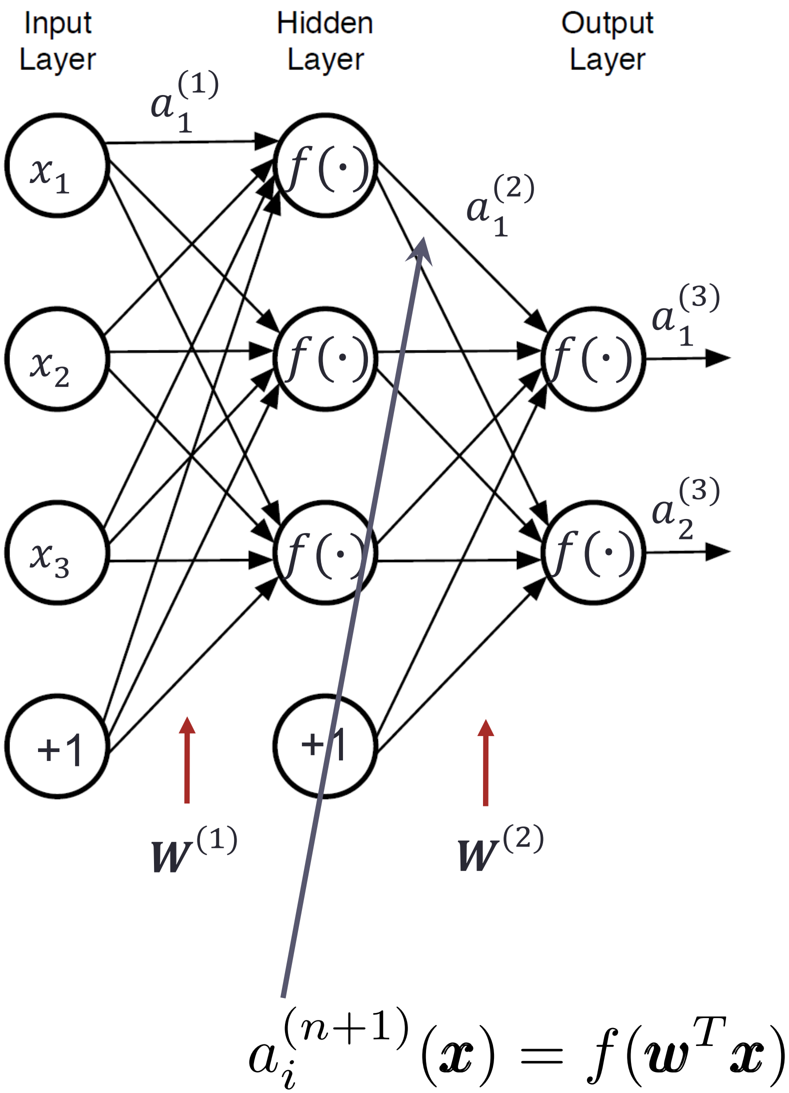
DIPARTIMENTO
DI INGEGNERIA
DELL'INFORMAZIONE

Outline

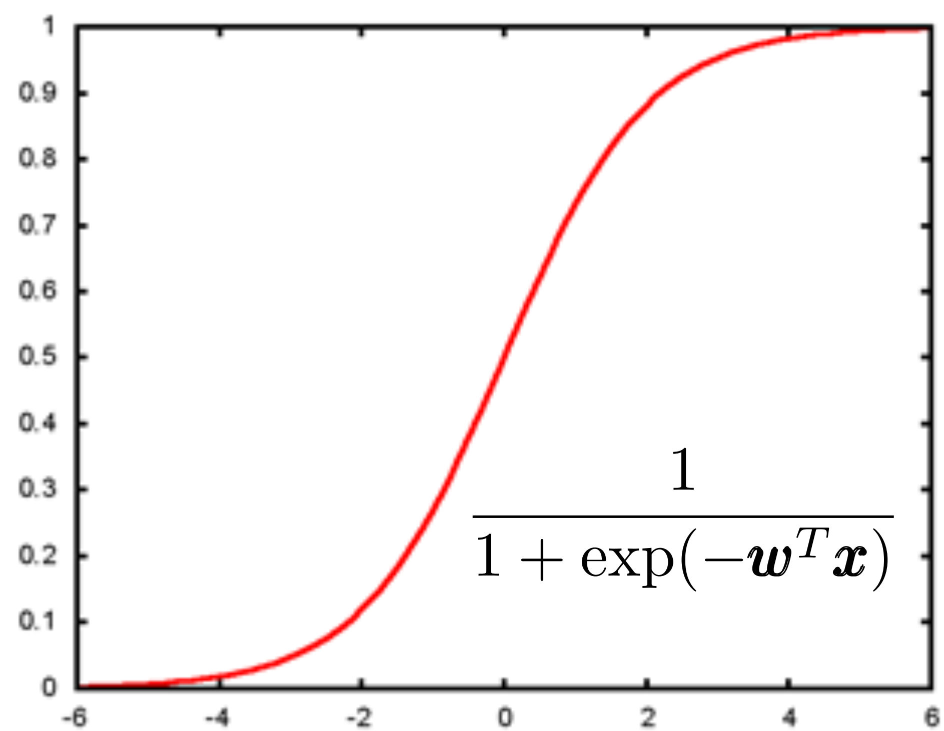
- Vector quantization and compression of ECG
  - Auto-encoder architectures
  - Performance metrics
  - Numerical results
- Analysis of inertial signals
  - System model
  - Data acquisition & preprocessing
  - Coordinate transformation
  - Template based segmentation
  - CNN architecture
  - One-class SVM
  - Sequential decision making
  - Numerical results

VECTOR QUANTIZATION AS AUTOENCODER-BASED COMPRESSION

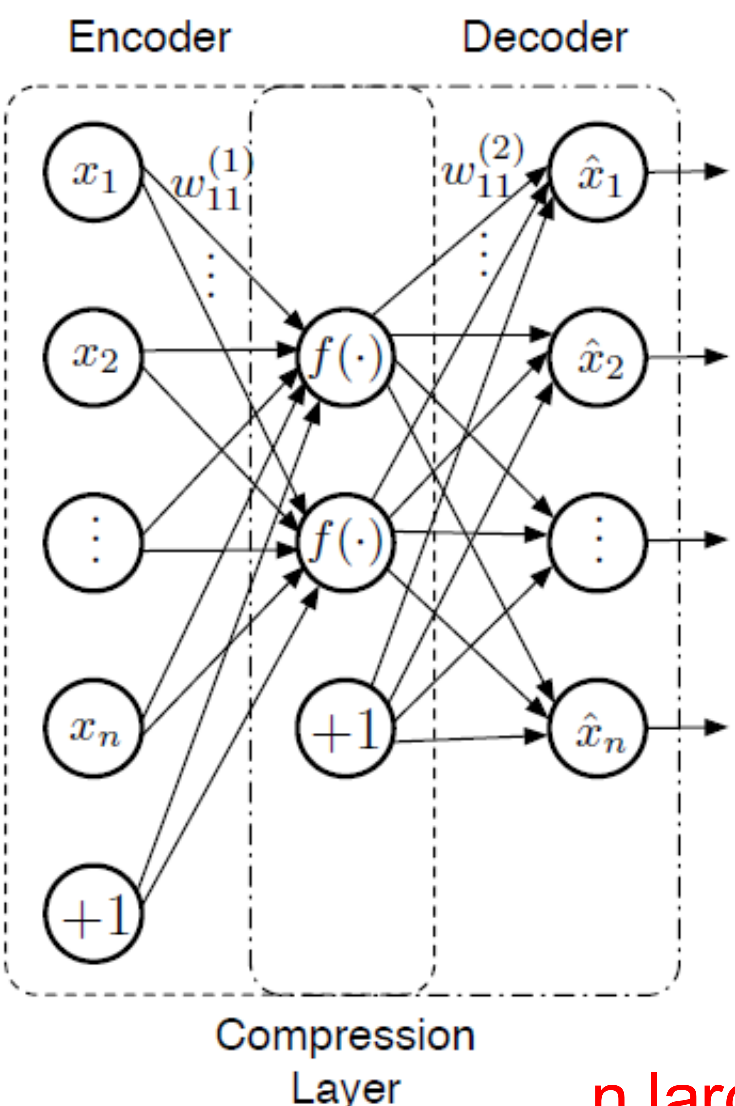
Neural networks



- Feed Forward NN
- Layers of neurons
- Non-linear activation functions
- Set of weights



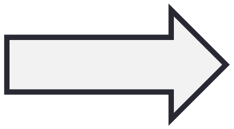
Autoencoders



- Unsupervised learning
- Same no. of input & output neurons
- Target values = input
- Goal: learn the identity function

$\boldsymbol{x} \in \mathbb{R}^n$

mapped onto $\boldsymbol{x}' \in \mathbb{R}^c,\ c < n$

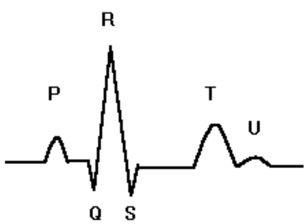


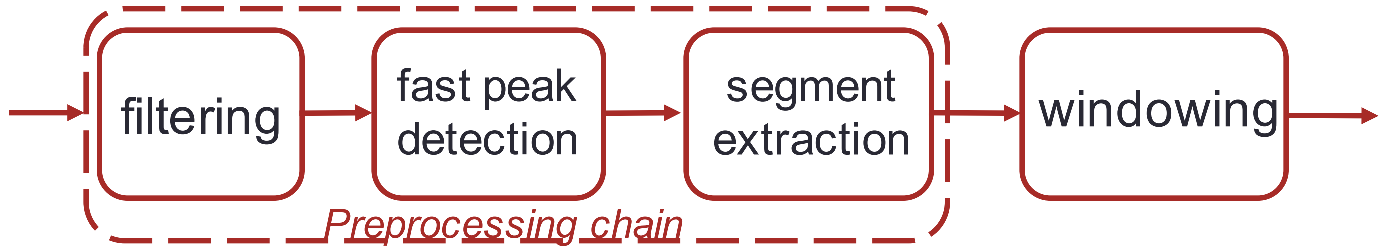
c hidden units

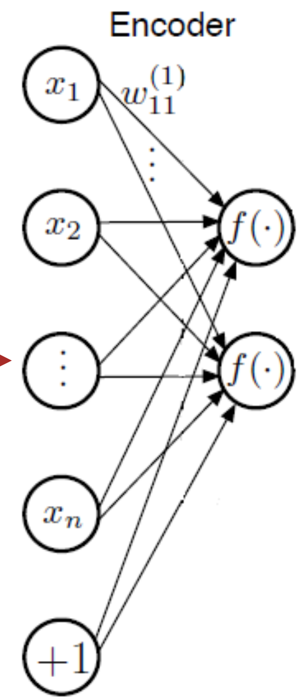
n larger than 250 ECG samples / segment

Compression architecture

Compressor (transmitter)

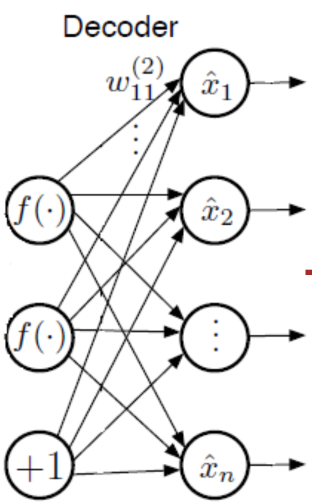


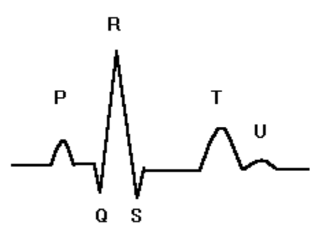




c values TX

Decompressor (receiver)





weight set $\mathbf{W}$
computed offline
(training examples)

Performance metrics (1/2)

E1 - Energy associated with compression

- We count the number of operations (divisions, additions, comparisons)
- Translate them into the corresponding number of clock cycles
- From clock cycles → energy consumption
- MCU: ARM Cortex M4

E2 - Energy associated with transmission / reception

- Consider the compressed data stream
- Compute the energy consumption associated with TX / RX
- Radio: Texas Instruments CC2541 (Bluetooth SoC)

⇒ total energy E1+E2

Performance metrics (2/2)

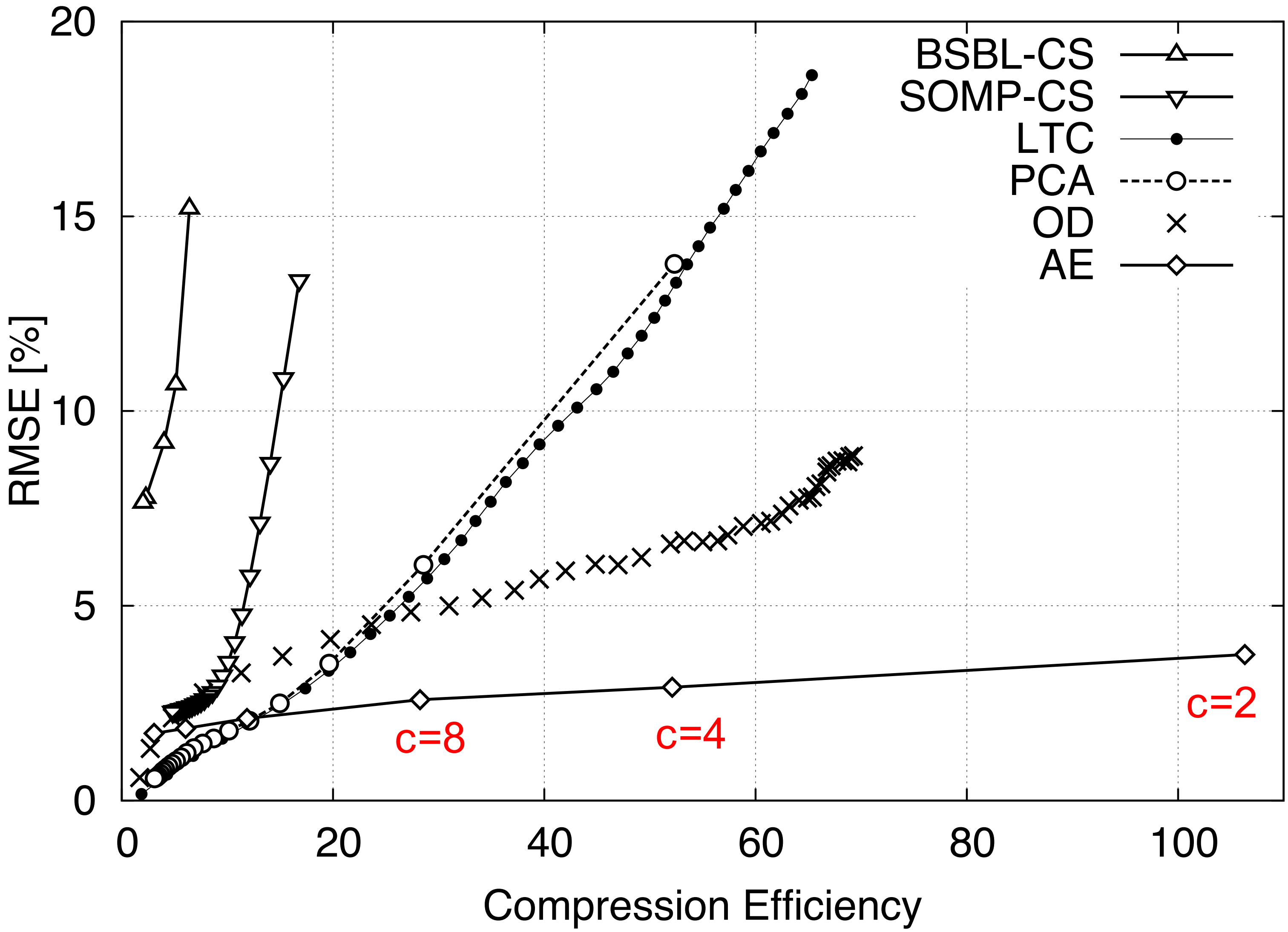
Representation accuracy

- Root Mean Square Error (RMSE)
- Expressed as % of the p2p signal's amplitude

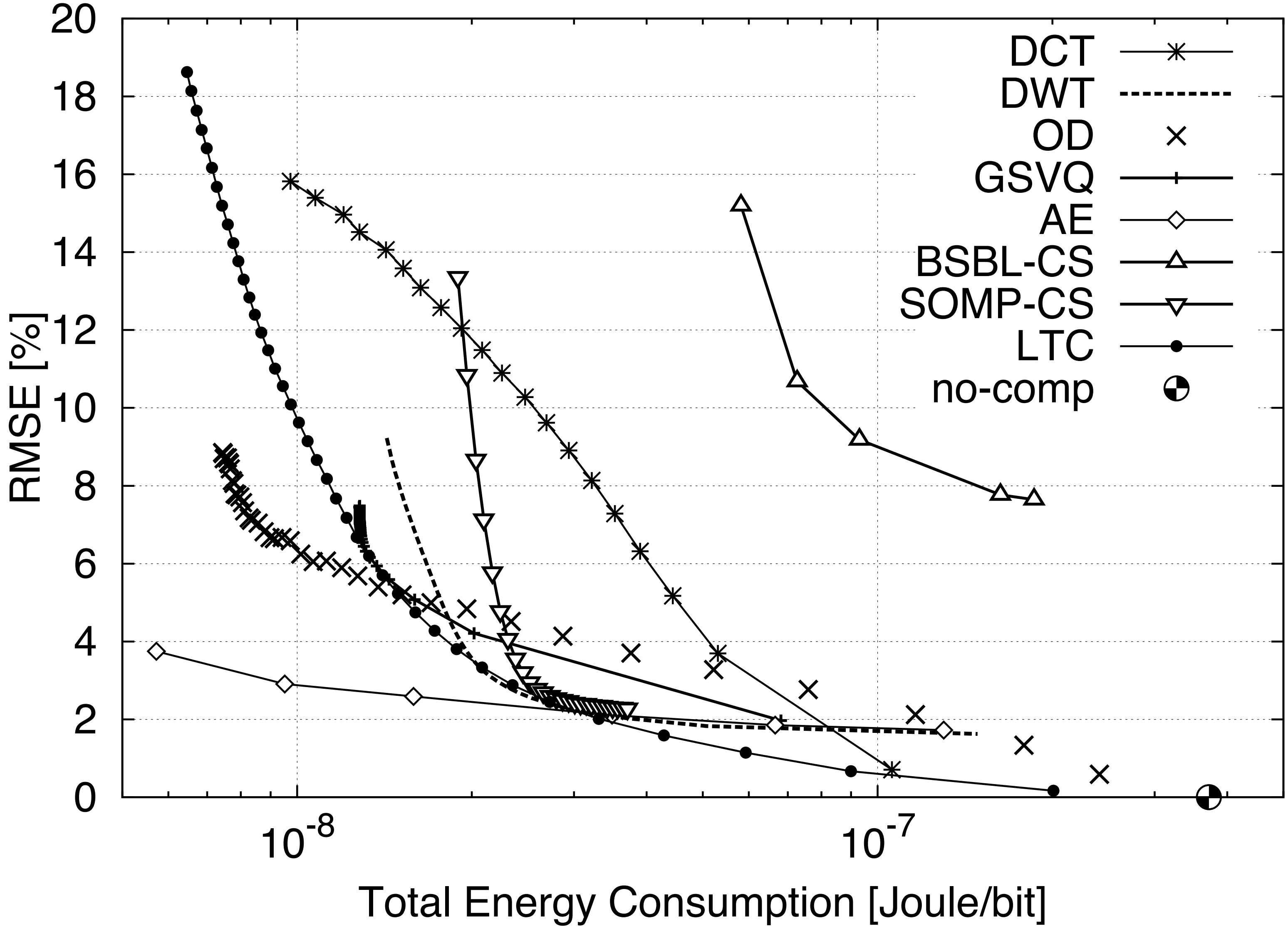
Compression efficiency

$$CE = \frac{\#\text{bits in the original stream}}{\#\text{bits in the compressed stream}}$$

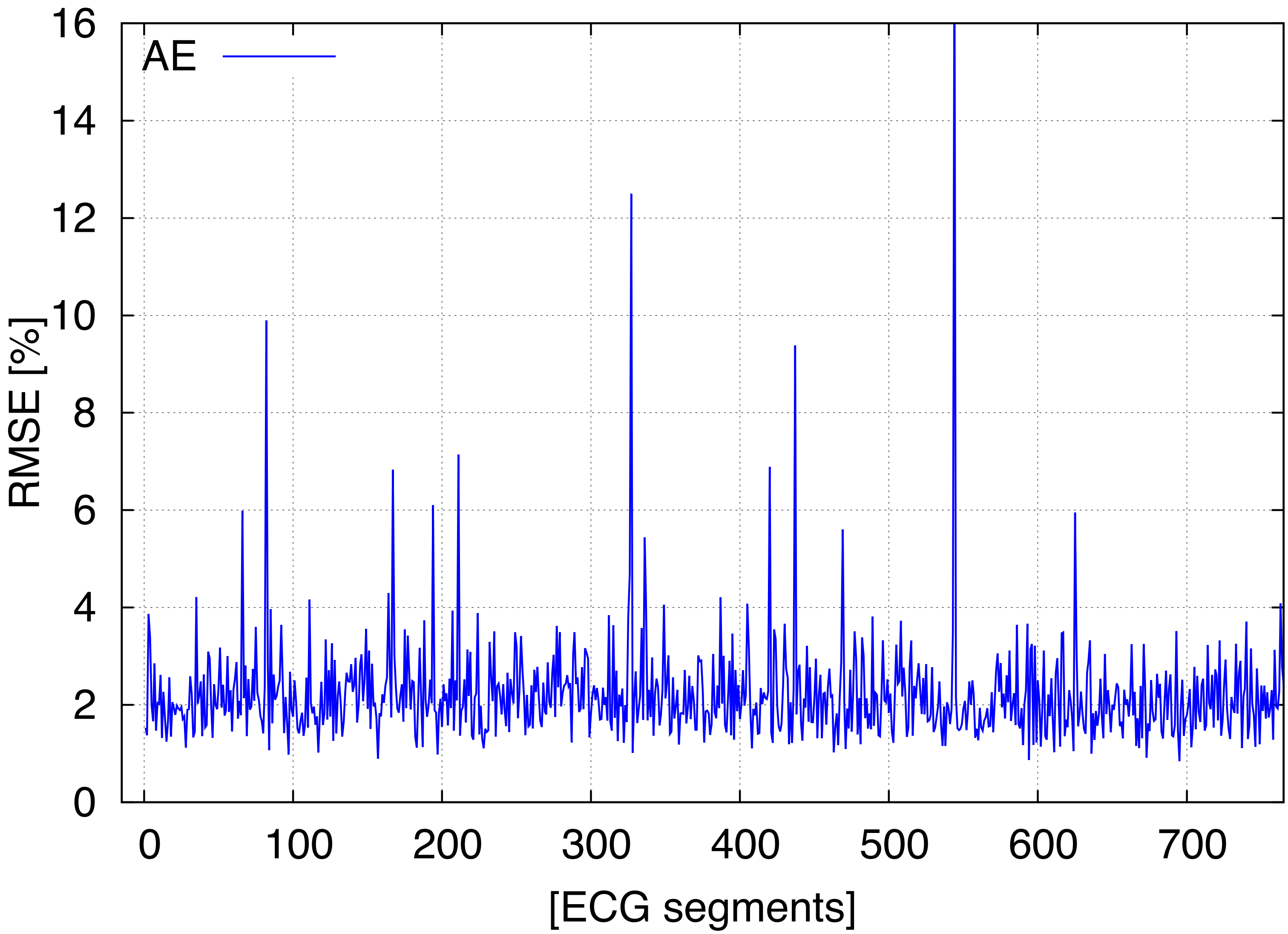
Results: RMSE *vs* CE



Results: RMSE *vs* Energy

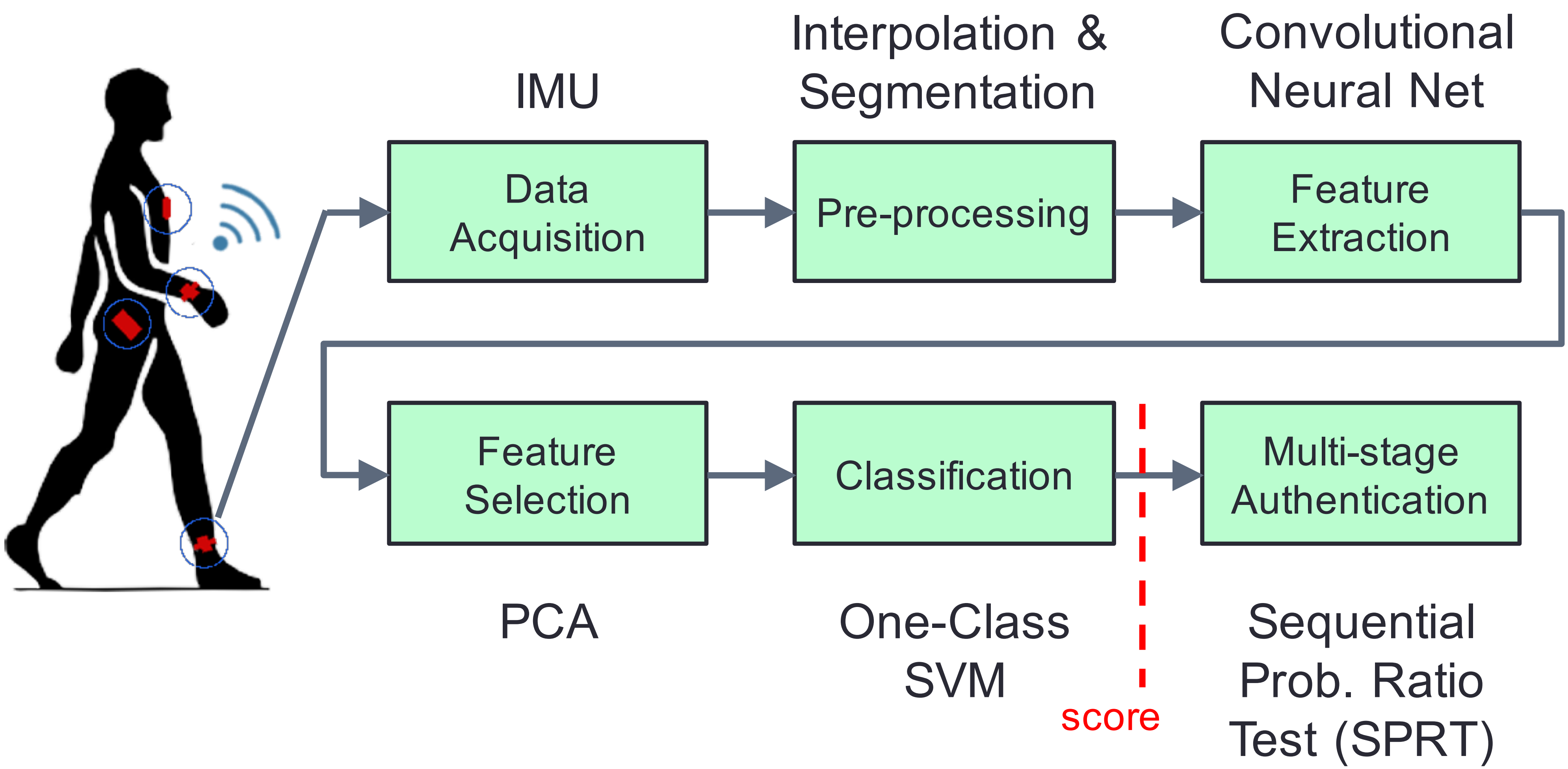


Where AE fails



ANALYSIS OF INERTIAL SIGNALS

System Model



Data Acquisition (1/2)

Inertial Measurement Unit (IMU)

- **Axivity WAX9**
  - **Accelerometer** ±2 / 4 / **8 g** (14 bit resolution)
  - **Gyroscope** ±250 / 500 / **2000 dps** (16 bit resolution)
  - Temperature 0 - 65 °C (0.1˚C resolution)
  - Pressure 30-110 kPA (1Pa resolution)
  - Max. sampling frequency: **400 Hz**
  - Bluetooth LE radio
  - https://axivity.com/downloads/wax9
- Worn on the ankle of the user

Data Acquisition (2/2)

Smartphone

- Measures the 9 axes
- Sampling frequency
  - Fluctuates (non-realtime OS)
  - Some samples may be lost
  - Re-interpolation needed
- Carried in the front pocket

Pre-processing

Interpolation & resampling

- Cope with missing points & variable sample rate

Coordinate system transformation

- Onto rotation invariant system

Template extraction

- Manually done from acc & gyro magnitudes

Segment extraction

- Correlation measure between signal & template

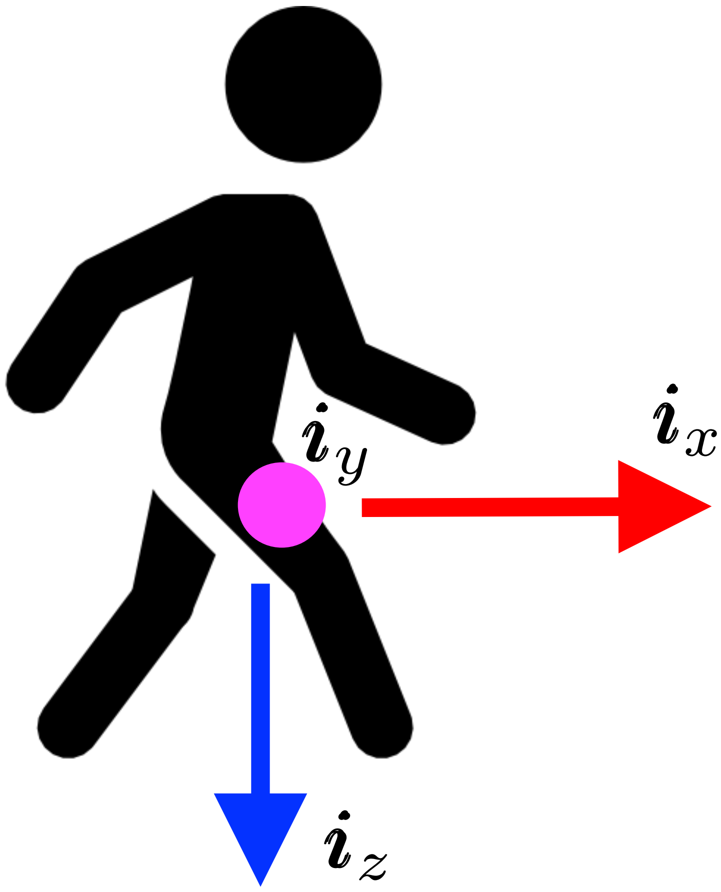
$$\mathrm{corr\_dist} = 2 - \mathrm{corr}(\mathrm{acc}) - \mathrm{corr}(\mathrm{gyro})$$

Tranformation of coordinate system

- Only needed for smartphone system
- Accelerometer and gyroscope
  - Measured in the coordinate system of the smartphone
  - This depends on phone orientation in the pocket
  - Not good
- What we need
  - To measure a trajectory that is independent of the phone orientation
  - Orientation invariant coordinate system
- Solution
  - Move the x, y, z measurements (9 axes)
    - from phone system to orientation invariant coordinate system

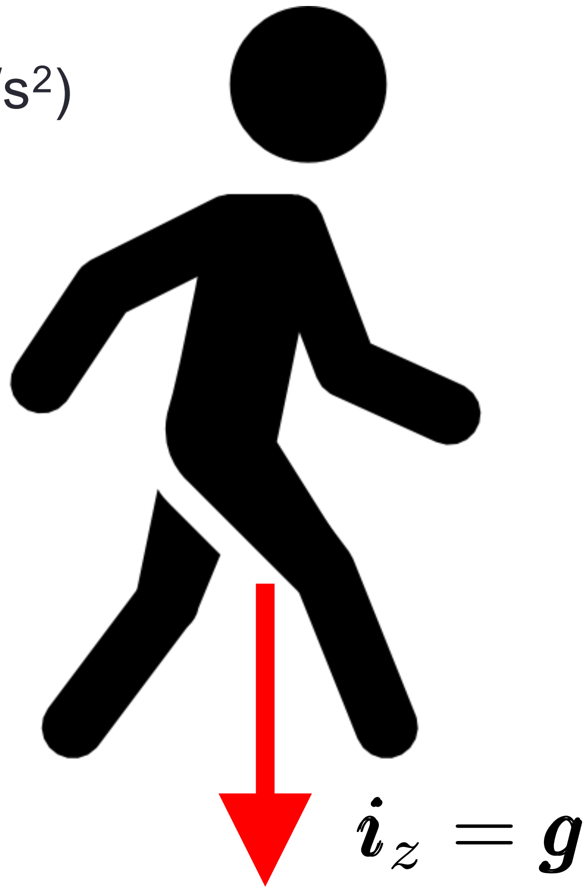
Orientation invariant coordinate system

- 3 orthogonal versors are to be found
- One pointing down
  - Aligned with gravity (and user's torsc
- One pointing forward
  - Aligned with direction of motion
- One tracking lateral movement
  - Orthogonal to the other two versors



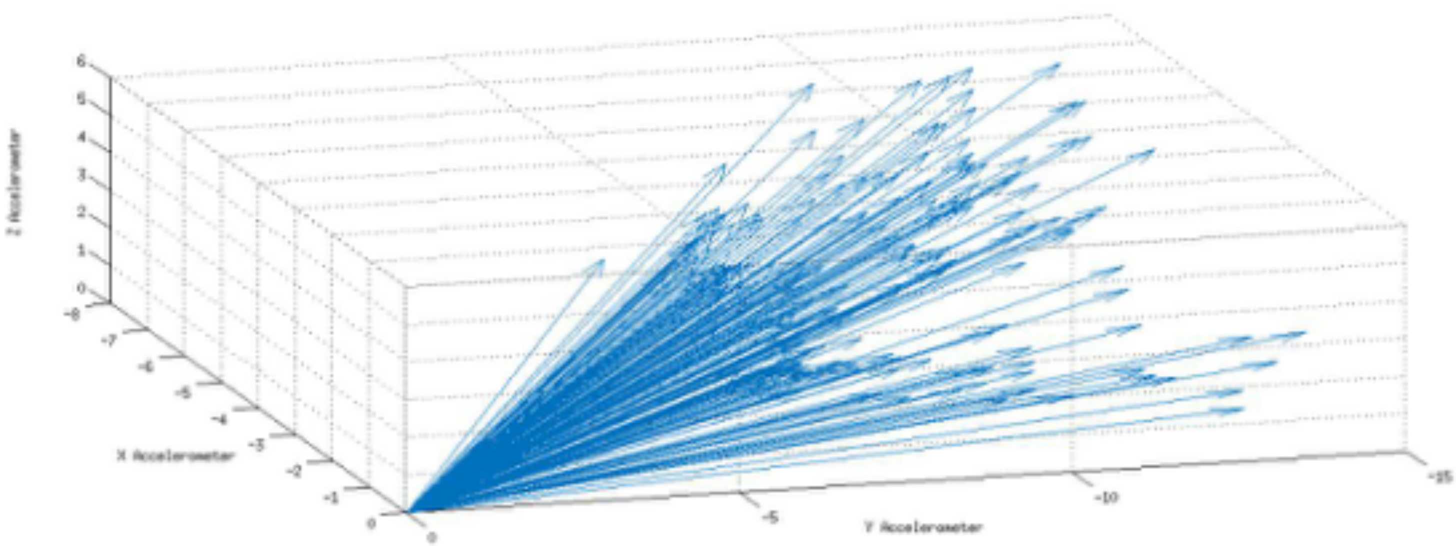
Orientation invariant coordinate system

- Solution
  - Gravity! **g** = (g_x,g_y,g_z)
  - Is a constant acceleration vector
  - We even know its average value (9.81 m/s^2)



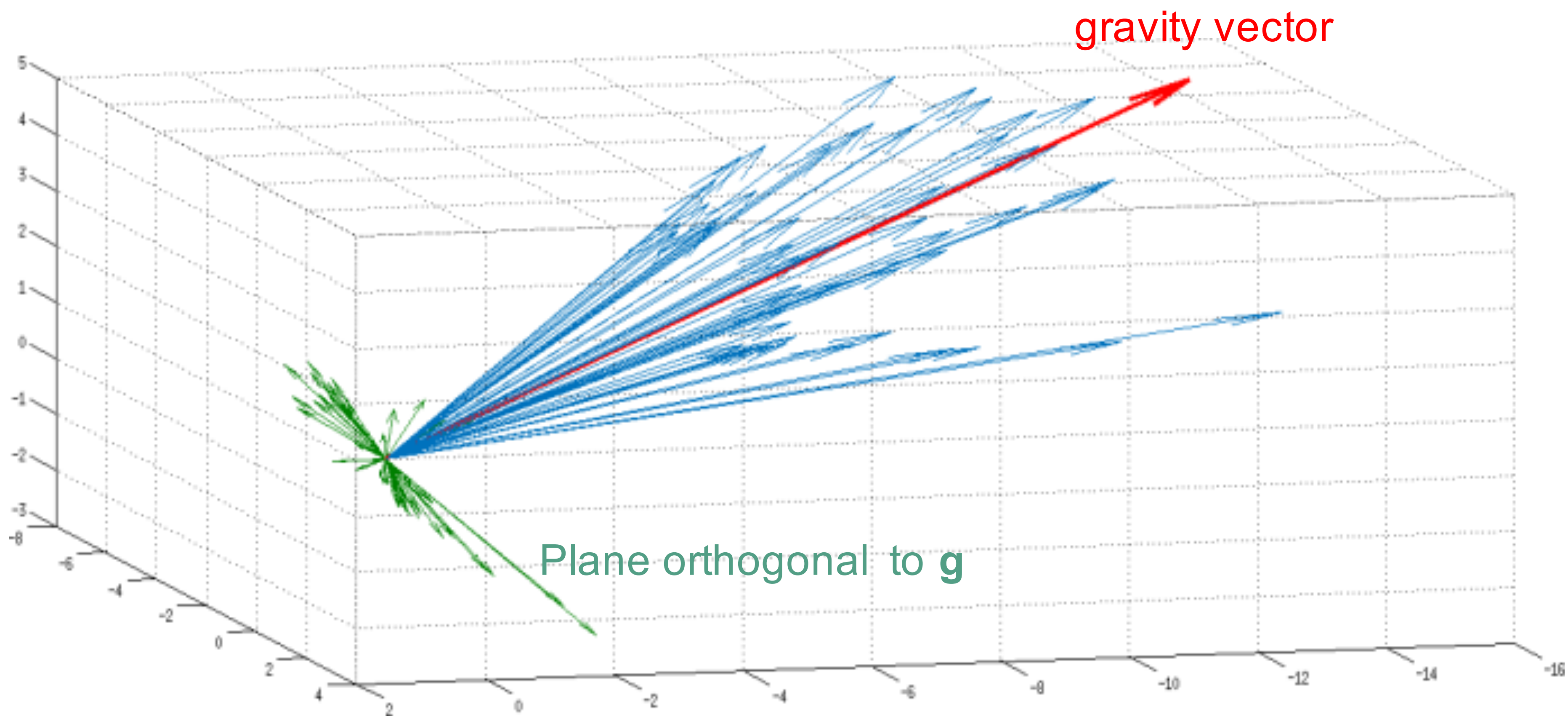
Orientation invariant coordinate system

- Obtaining the new coordinate system
  - Measure accelerometer signal (a_x, a_y, a_z), in the native system
  - Low pass filter to extract constant gravity vector (0 Hz component)
  - This will be aligned with the first versor (pointing down)
  - Below graph
    - 3D acceleration signal
    - There is a main component (gravity)



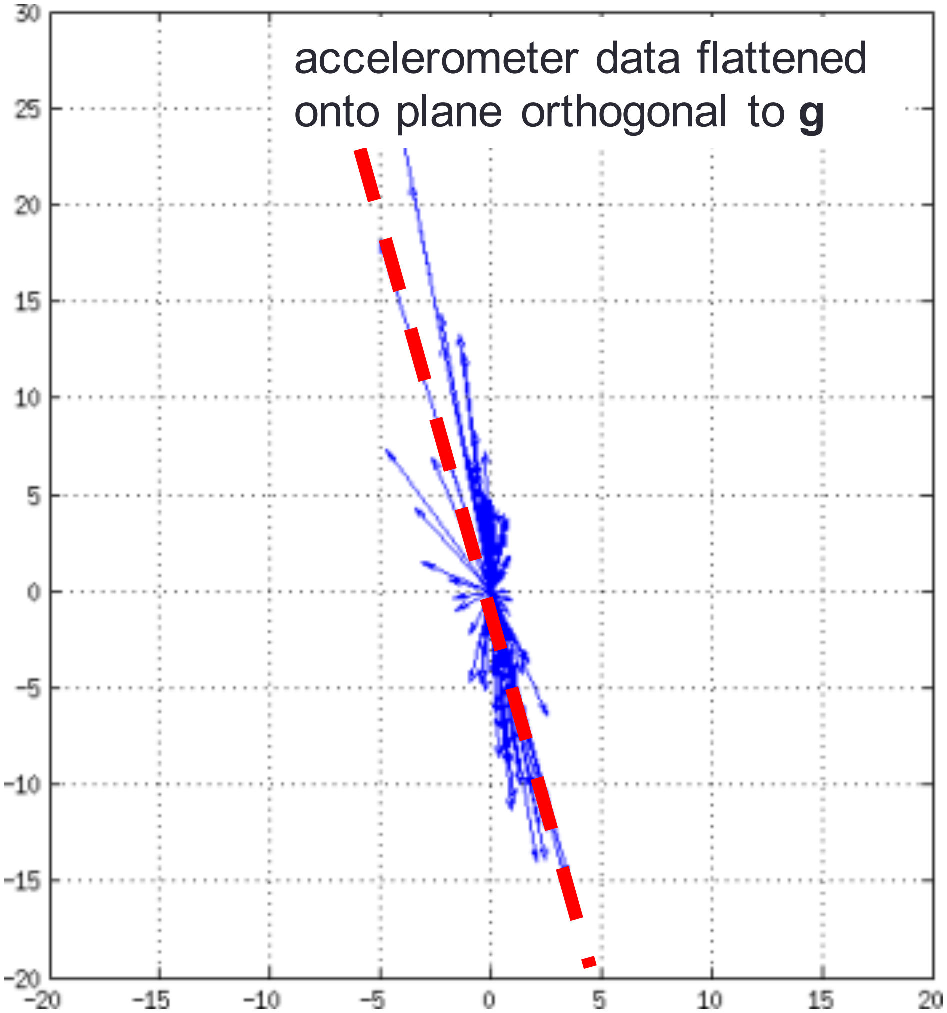
Low filtering and projection

- Low pass filtering to find **g**
- Projection onto orthogonal plane to **g**



Plane orthogonal to **g**

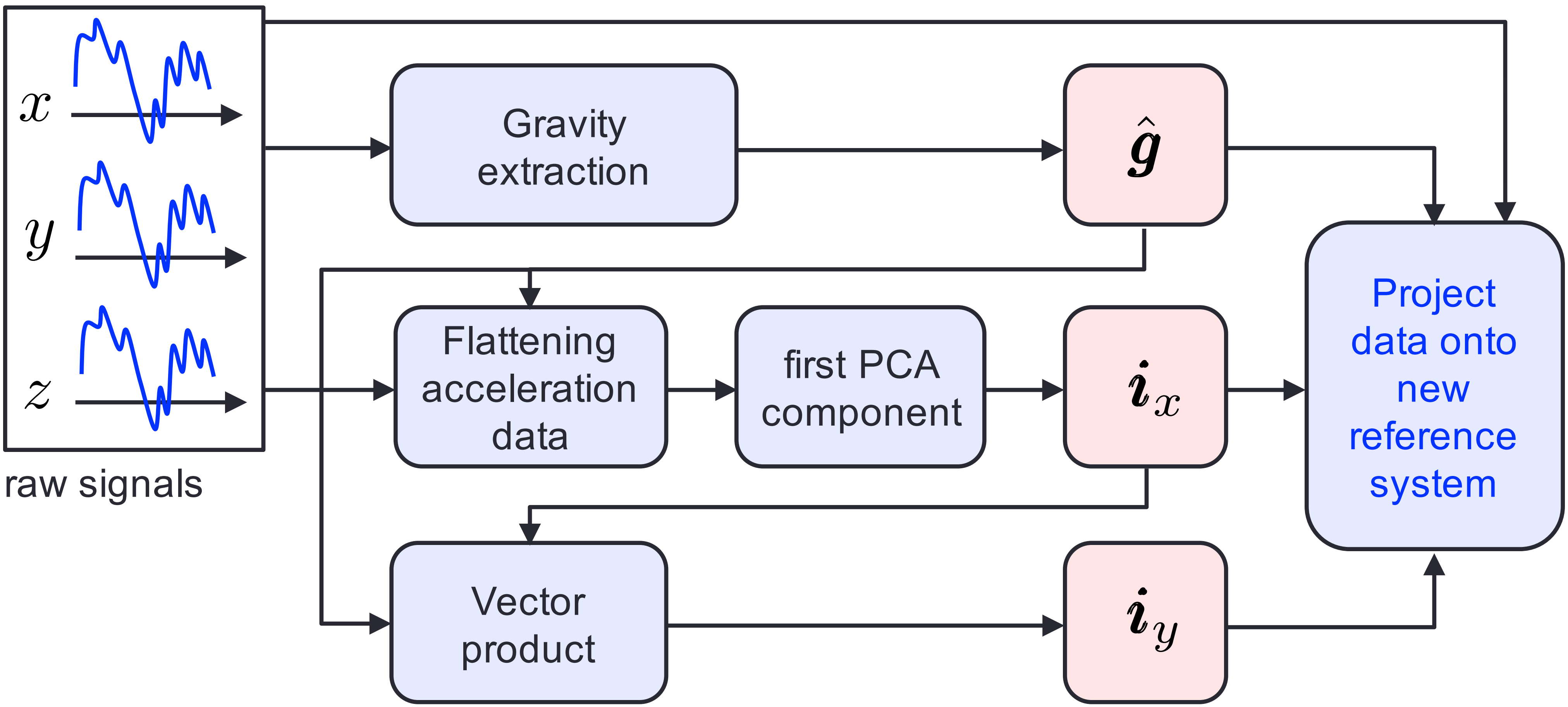
- How to identify the forward direction of motion?
  - Corresponds to dashed line
- Variance of data cloud
  - Is max along direction of motion



maximum variance → PCA!!!

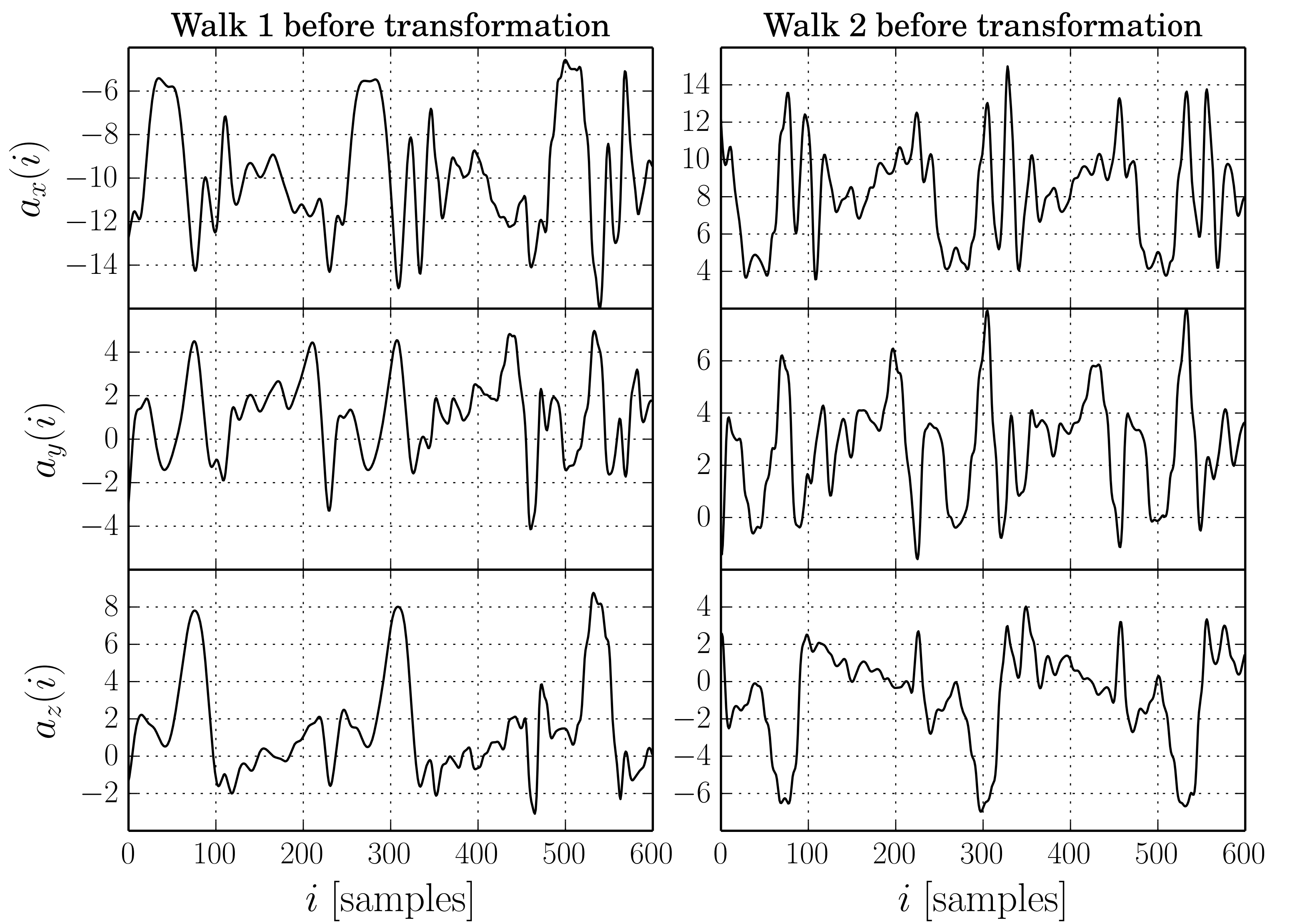
- First PCA component
- Has strongest variance

Reference system transform

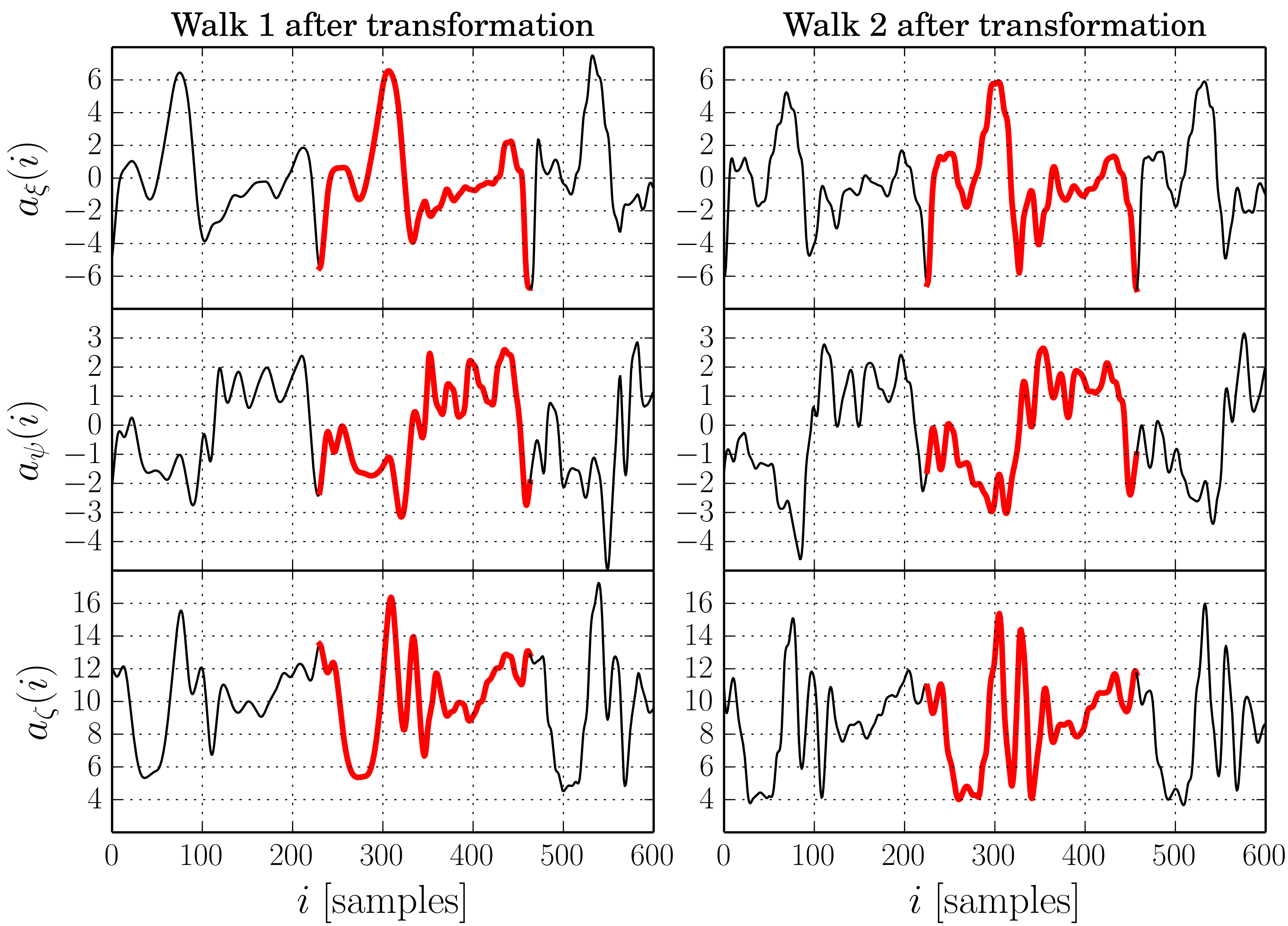


new reference system versors

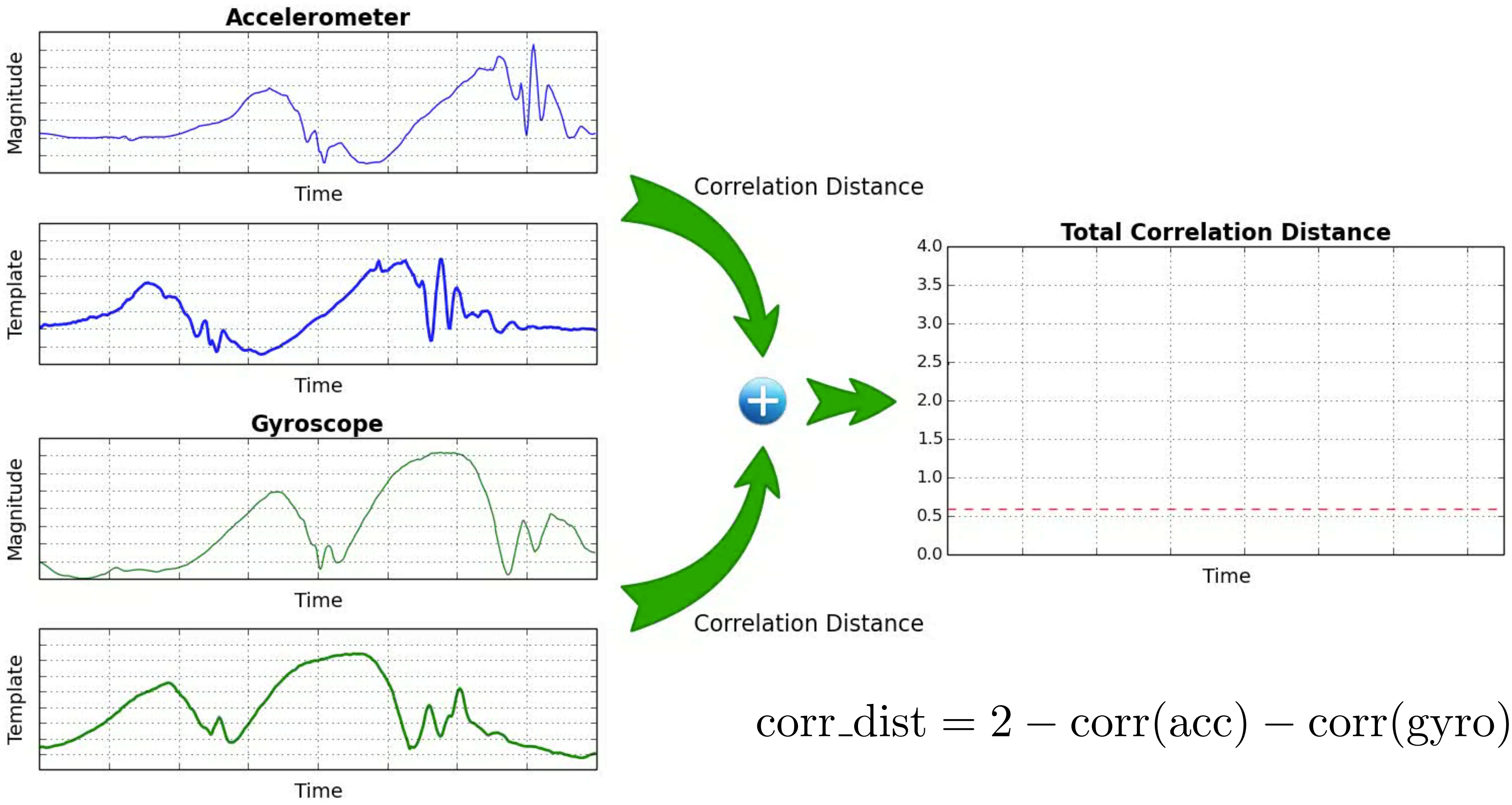
Walking pattern before tranform



Walking pattern after tranform

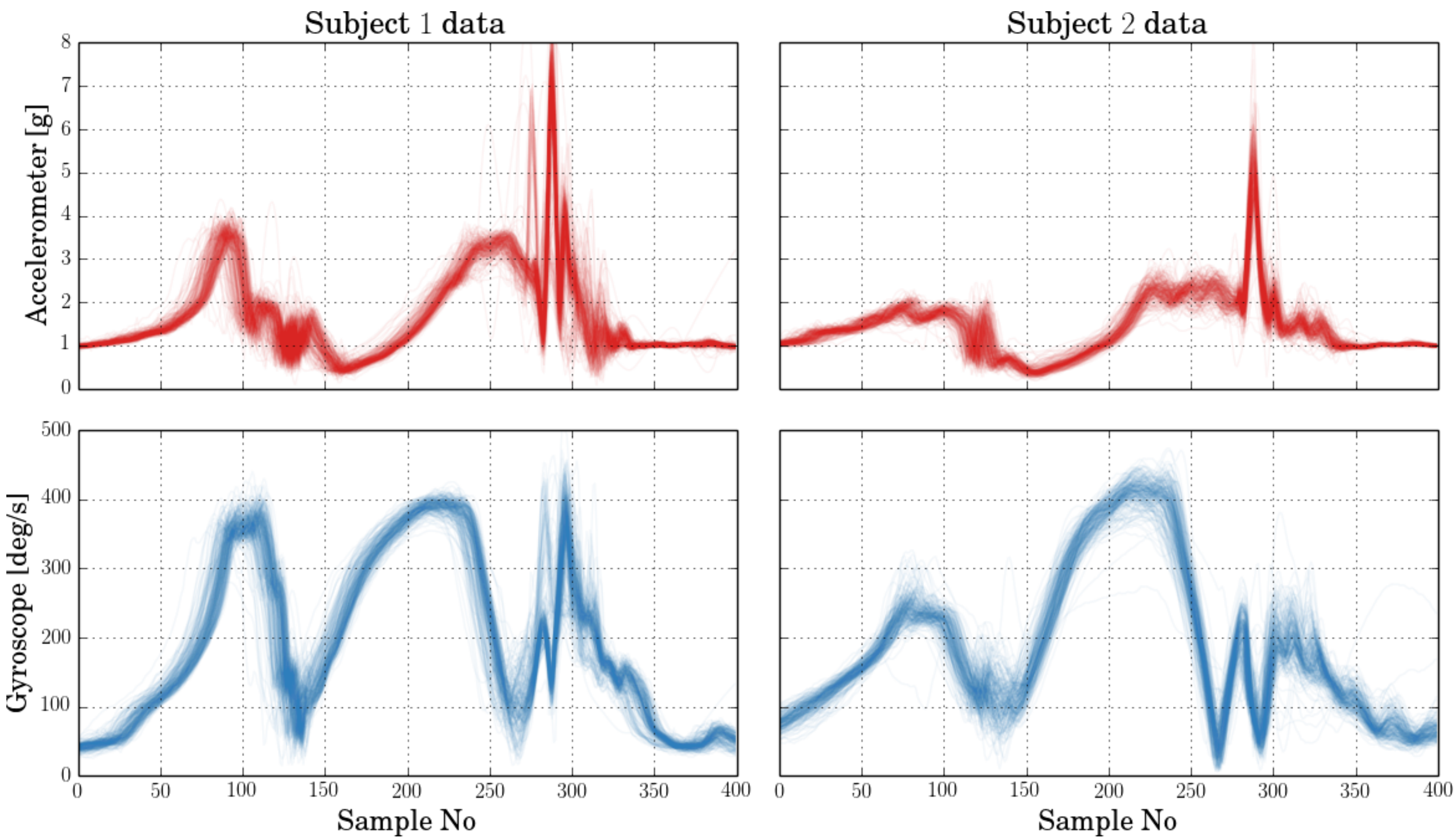


Template-based segmentation



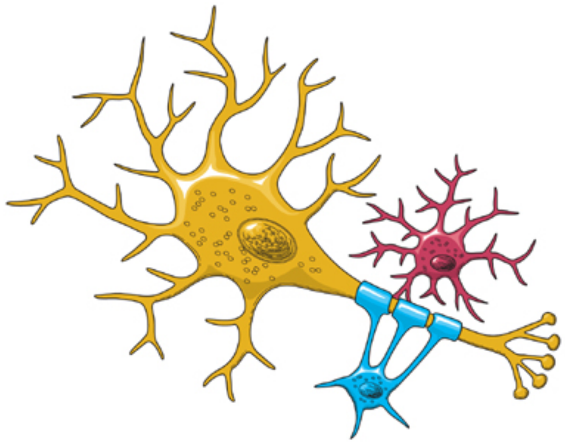
$$\mathrm{corr\_dist} = 2 - \mathrm{corr(acc)} - \mathrm{corr(gyro)}$$

Walking pattern examples: two subjects



Convolutional Neural Network (CNN)

- Supervised training (50 subjects)
  - 10 minutes of walk, at least 2 sessions
  - Smartphones
    - Asus Zenfone 2,
    - Samsung S3 Neo,
    - Samsung S4,
    - LG G2, LG G4,
    - Google Nexus 5



- CNN to extract of relevant features
  - Automatic feature engineering

CNN – conv layer 1

- **CL1** We do not capture any correlation among different accelerometer and gyroscope axes
- 20, 1D kernels of size 1 x 10: processing each input vector separately. For each walking cycle, input vectors are (normalized to fixed lenght):

$$\boldsymbol{a}_x, \boldsymbol{a}_y, \boldsymbol{a}_z, |\boldsymbol{a}|, \mathbf{gyr}_x, \mathbf{gyro}_y, \mathbf{gyro}_z, |\mathbf{gyro}|$$

- Activation functions are linear

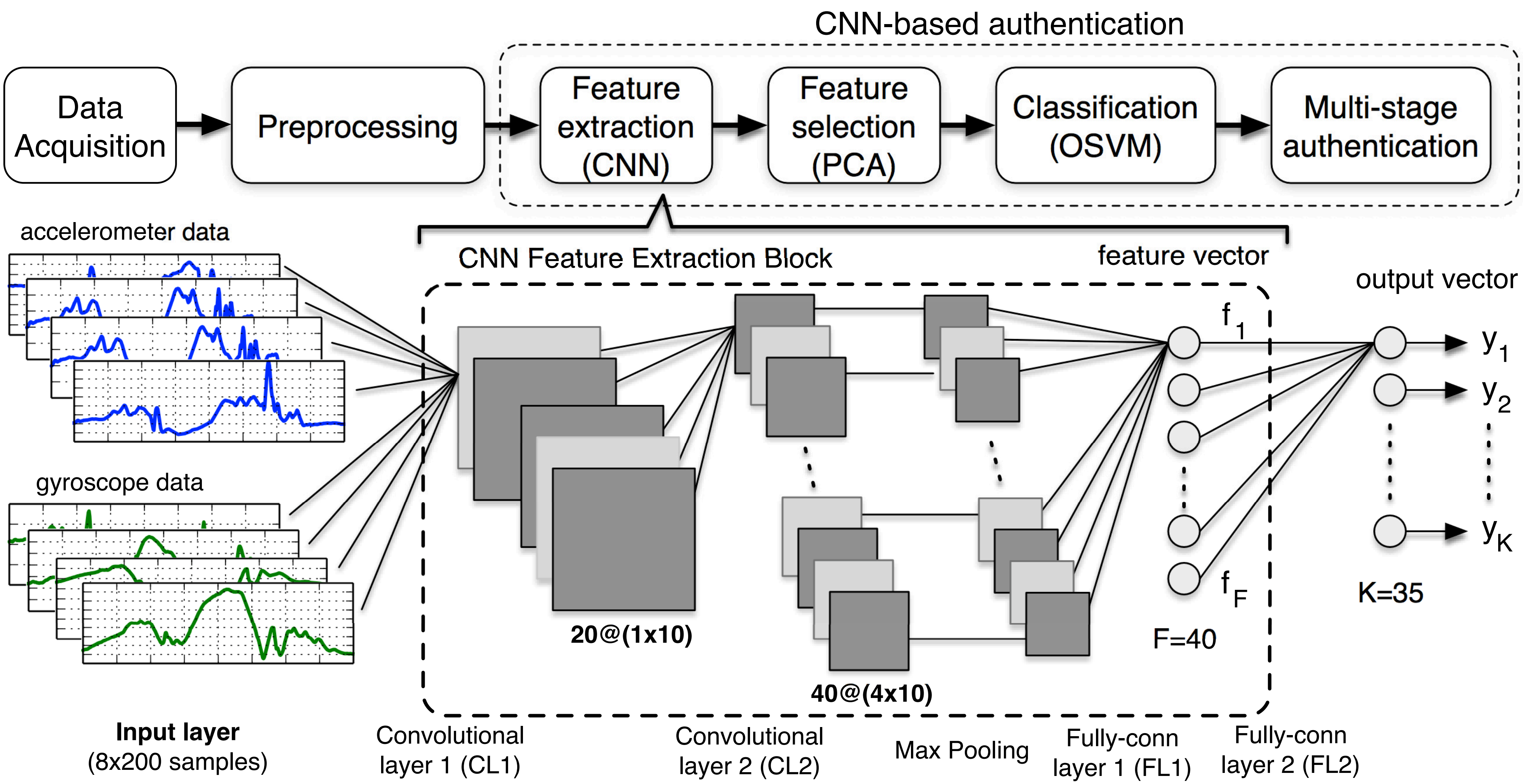
CNN – conv layer 2

- **CL2** With the second convolutional layer we seek discriminant and class-invariant features.
- 40, 2D kernels of size 4 x 10: the cross-correlation among input vectors is considered
- tanh: non-linear activation functions
- Max pooling: applied to
  - reduce the dimensionality and
  - increase spatial invariance

Fully connected layers 2 and 3

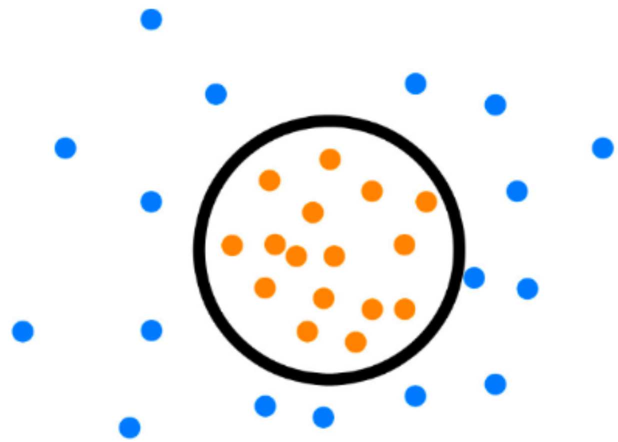
- **FL2** fully connected layer with tanh activations
  - Has F output neurons
  - These are the features extracted by the network
- **FL3** fully connected layer with softmax activations
  - Has K output neurons
  - One for each user in the training dataset

CNN architecture



One-Class SVM [S+00]

- Only target class (orange) data is available
- Training finds the *boundary* (tick circle)
- Classification output: score
  - Distance from the boundary



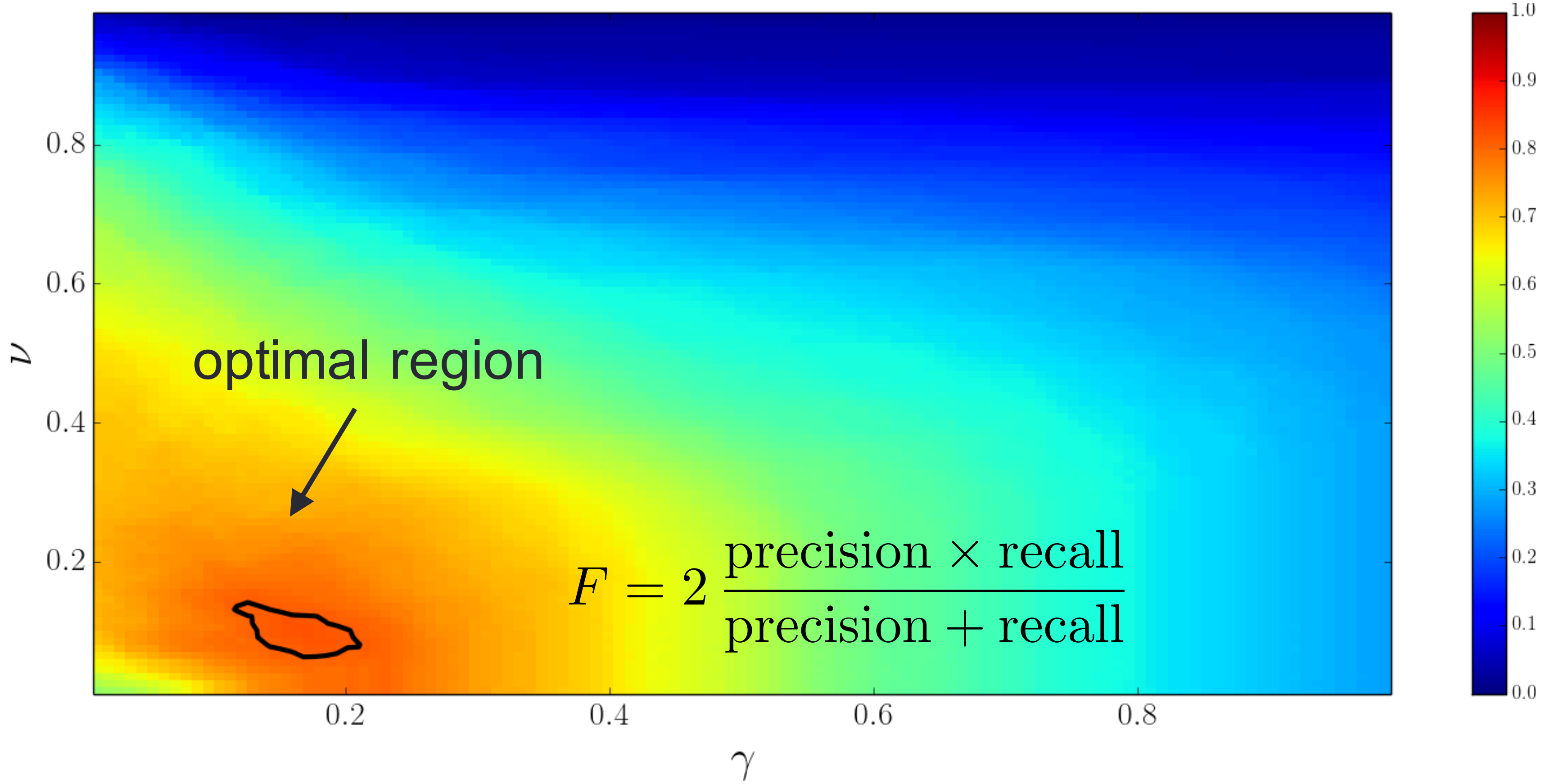
- Training
  - We only used data from target user
- Test
  - Data from the negative class are also used
  - Performance assessment

[S++00] B. Schölkopf, J.C. Plattz, J. Shawe-Taylory, A.J. Smolax, Robert C. Williamson, “Estimating the Support of a High-Dimensional Distribution,” *Neural Computation Journal*, Vol. 13, No. 7, Pages 1443-1471, July 2001.

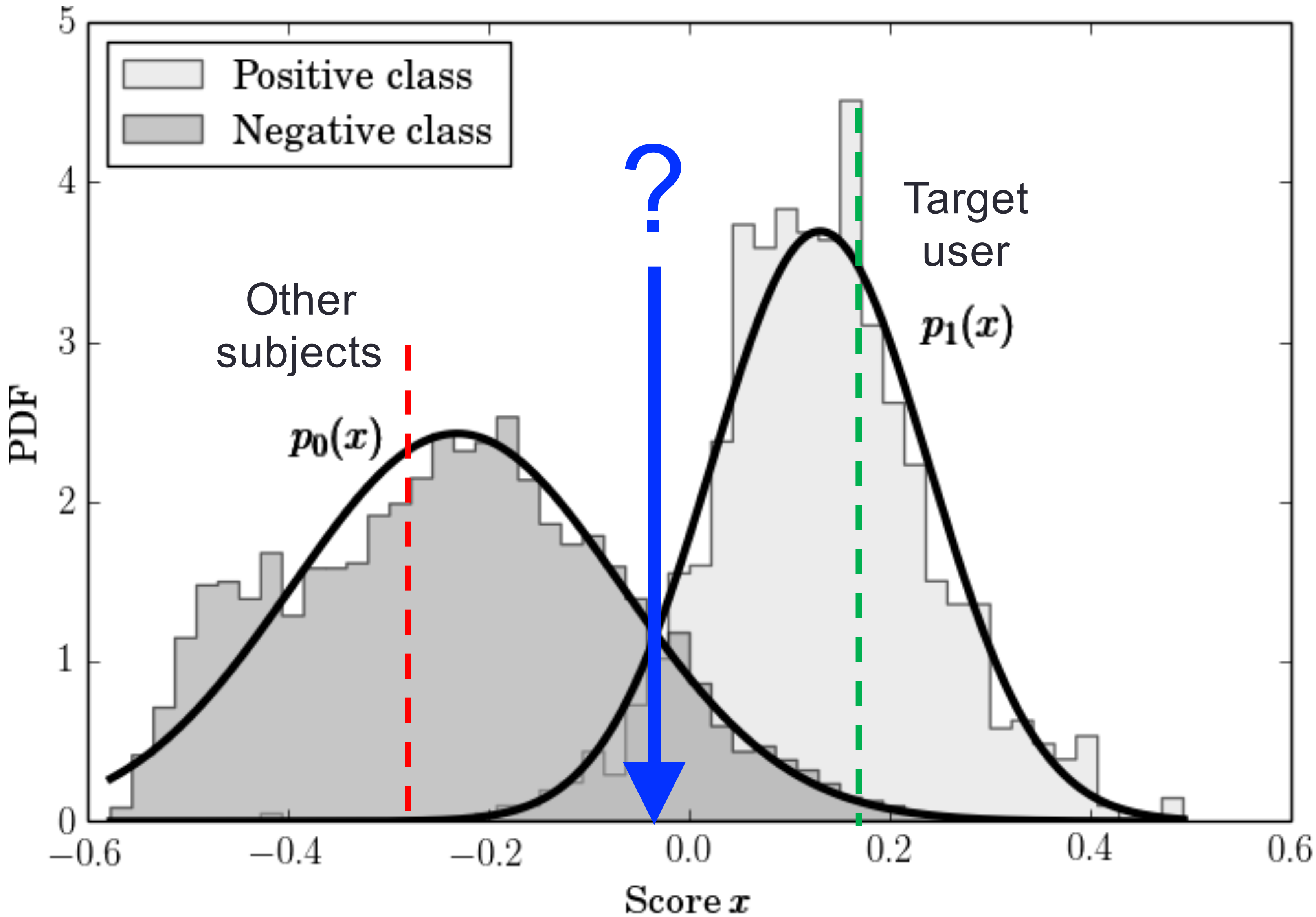
OSVM –parameters setting

Precision: no. of positives classified as positives / tot. number of positives
Recall: no. of positives classified as positives / tot. number of positives

F-measure



One-Class SVM (test output)



“I got the light bulb”

- A single walking cycle
  - Single pass through the network
  - Single SVM score
  - Unclear answer if happens to be in between the two pdfs
- What about observing multiple subsequent scores
  - Will they all fall in the problematic region (where the pdfs intersect)?
  - Probably not ☺
- Accumulating scores from multiple cycles
  - Should increase our likelihood of detecting the user

"I got the light bulb"

- A single walking cycle
  - Single pass through the network
  - Single SVM score
  - Unclear answer if happens to be in between the two pdfs
- What about observing multiple subsequent scores
  - Will they all fall in the problematic region (where the pdfs intersect)?
  - Probably not ☺
- Accumulating scores from multiple cycles
  - Should increase our likelihood of detecting the user

“I got the light bulb”

- A single walking cycle
  - Single pass through the network
  - Single SVM score
  - Unclear answer if happens to be in between the two pdfs
- What about observing multiple subsequent scores
  - Will they all fall in the problematic region (where the pdfs intersect)?
  - Probably not ☺
- Accumulating scores from multiple cycles
  - Should increase our likelihood of detecting the user
  - But, how can we do this?

Abraham Wald

October 31, 1902 –
December 13, 1950

- American mathematician
- Born in Cluj, Romania
- Contributed in
  - decision theory,
  - geometry,
  - econometrics
- Worked @ Columbia University
- Founded the field of statistical sequential analysis

[W47] Abraham Wald, “Sequential analysis,” Dover, New York, NY, US, 1947.

Sequential decision making (1/2)

Sequential Probability Ratio Test (SPRT) [W47]

$$p_0(x) = p(x|H_0) \qquad H_0 \longrightarrow \text{OTHER USERS' CLASS}$$

$$p_1(x) = p(x|H_1) \qquad H_1 \longrightarrow \text{TARGET CLASS}$$

- Samples acquired sequentially, one at a time
  - are of either class H_0 (pdf p_0) or H_1 (pdf p_1)
  - are i.i.d.
- Extension to correlated samples is in [TNB15]

[W47] A. Wald, "Sequential analysis," Dover, New York, NY, US, 1947.
[TNB15] A. Tartakovsky, I. Nikiforov, M. Basseville, "Sequential Analysis Hypothesis Testing and Changepoint Detection," CRC Press, 2015.

Sequential decision making (2/2)

Sequential Probability Ratio Test (SPRT) [W47]

$H_1 \rightarrow p_1(x) = p(x|H_1)$ $\qquad$ $H_0 \rightarrow p_0(x) = p(x|H_0)$

TARGET CLASS

LOG-LIKELIHOOD ratio:

$$S_n = \log\left(\frac{p(x_1,\ldots,x_n|H_1)}{p(x_1,\ldots,x_n|H_0)}\right) = \sum_{i=1}^{n} \log\left(\frac{p_1(x_i)}{p_0(x_i)}\right)$$

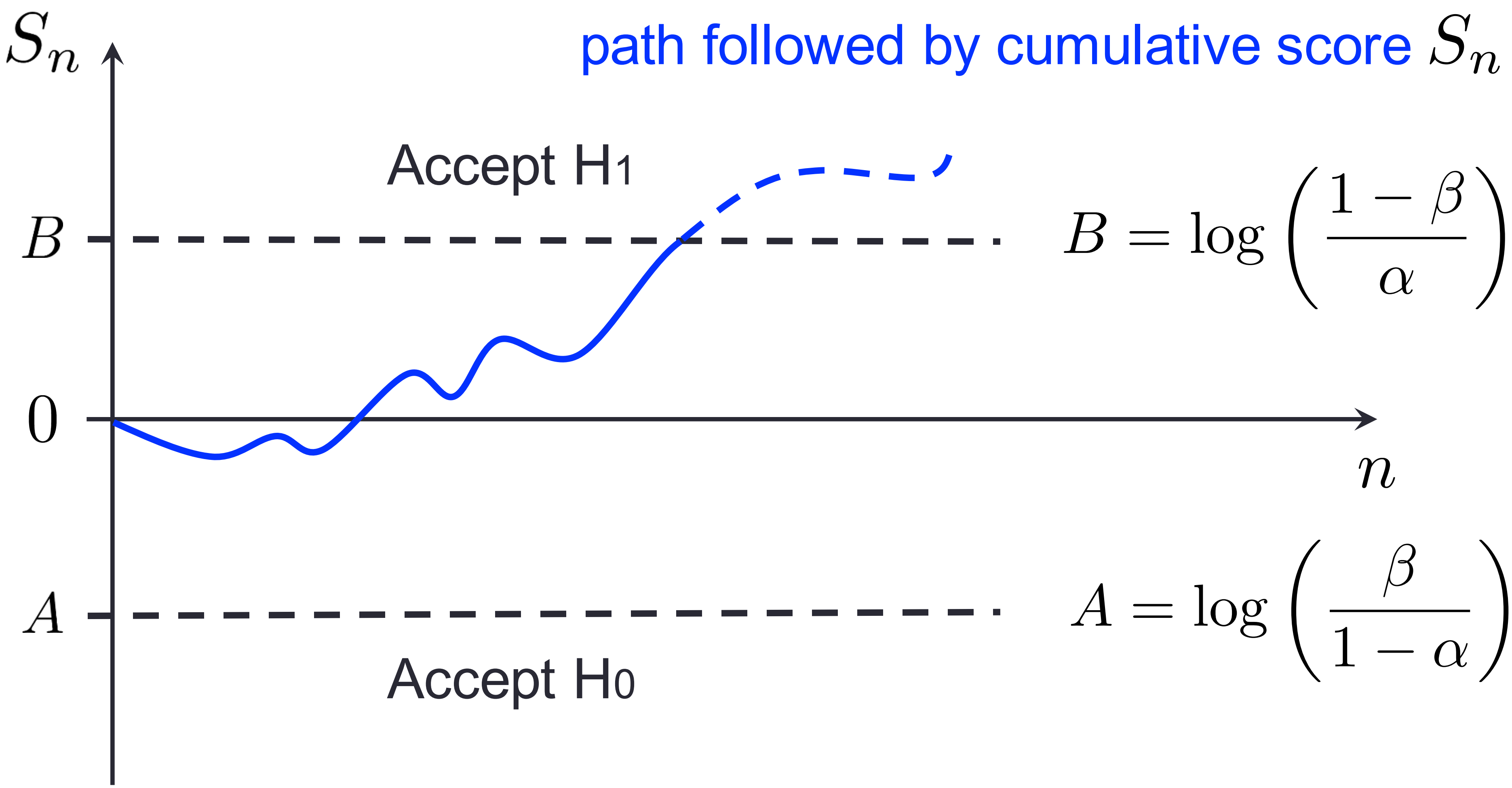
$\beta =$ probability of accepting H0 when H1 is true

$\alpha =$ probability of accepting H1 when H0 is true

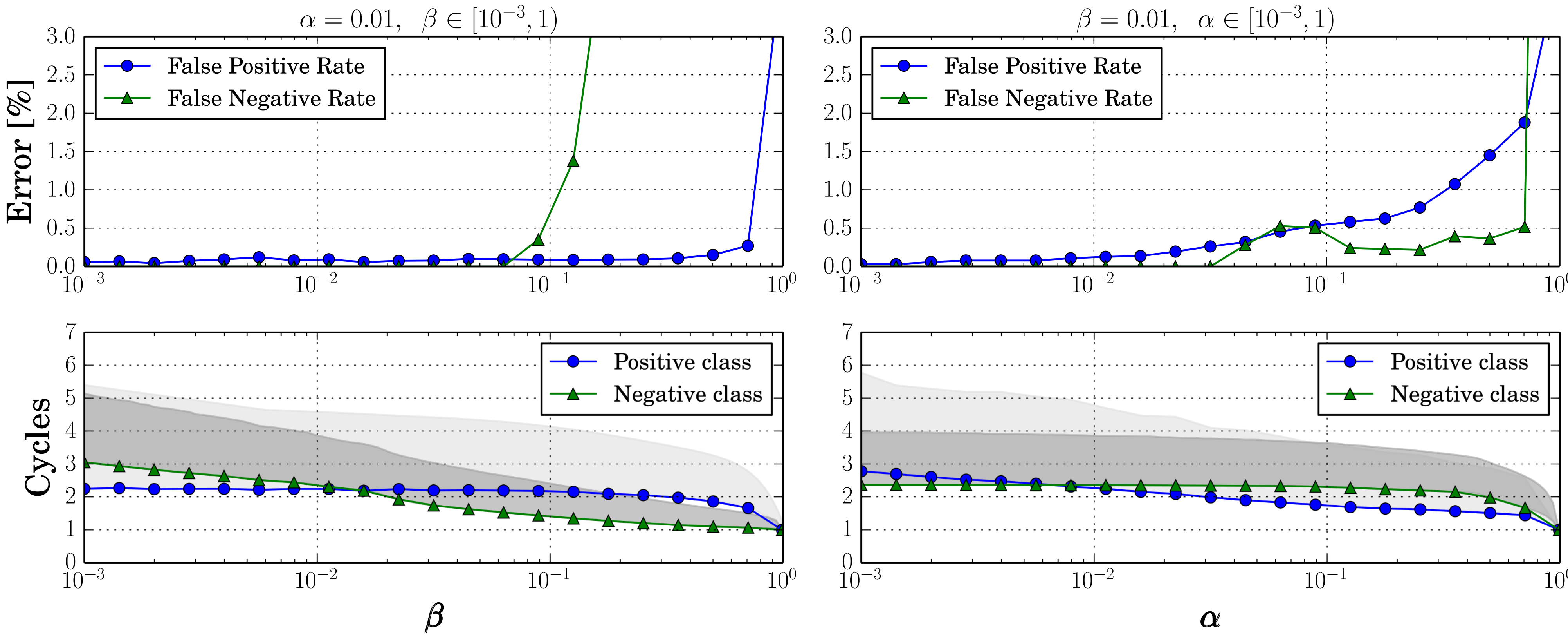
[W47] A. Wald, "Sequential analysis," Dover, New York, NY, US, 1947.

[TNB15] A. Tartakovsky, I. Nikiforov, M. Basseville, "Sequential Analysis Hypothesis Testing and Changepoint Detection," CRC Press, 2015.

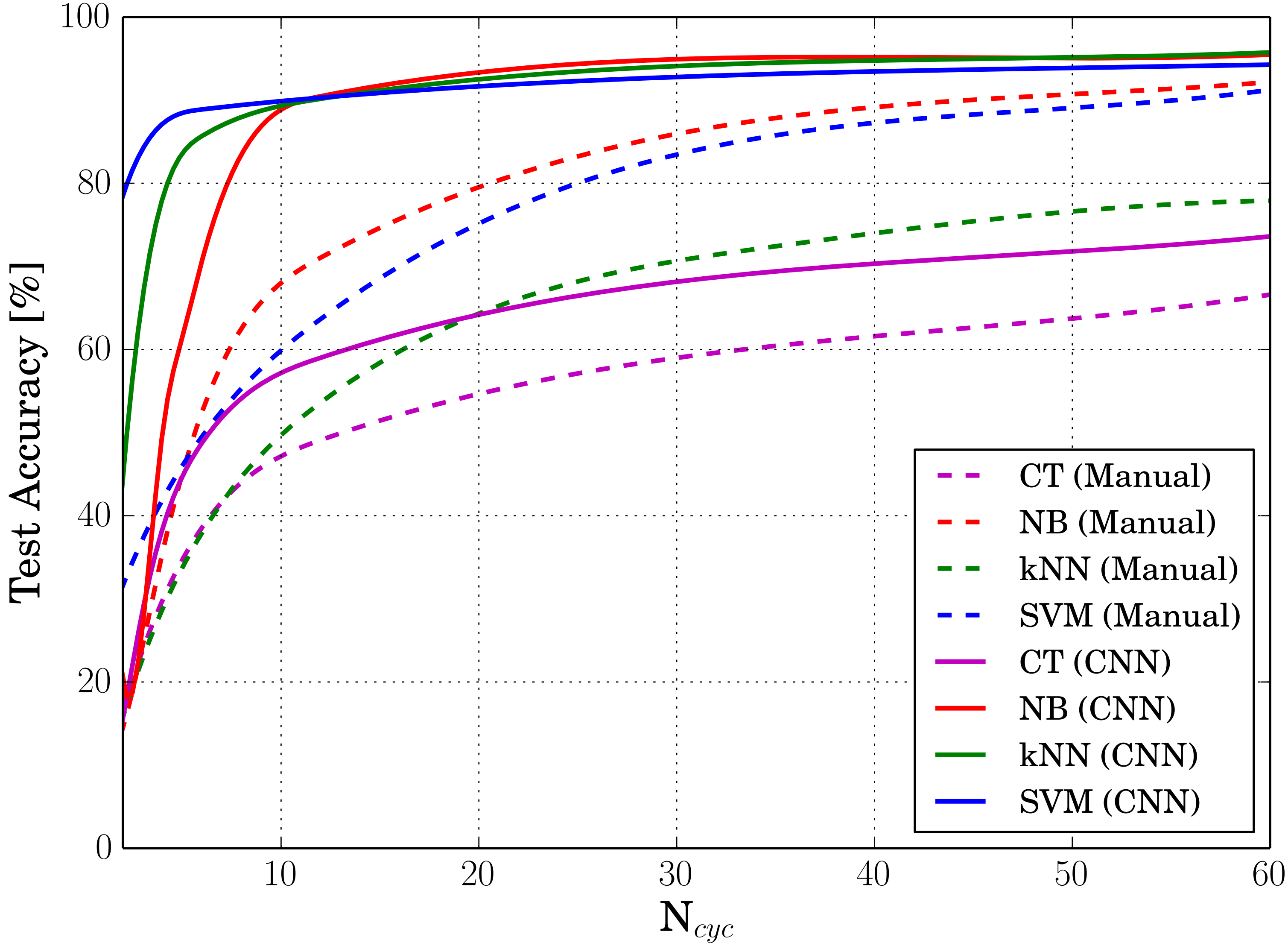
Sequential analysis



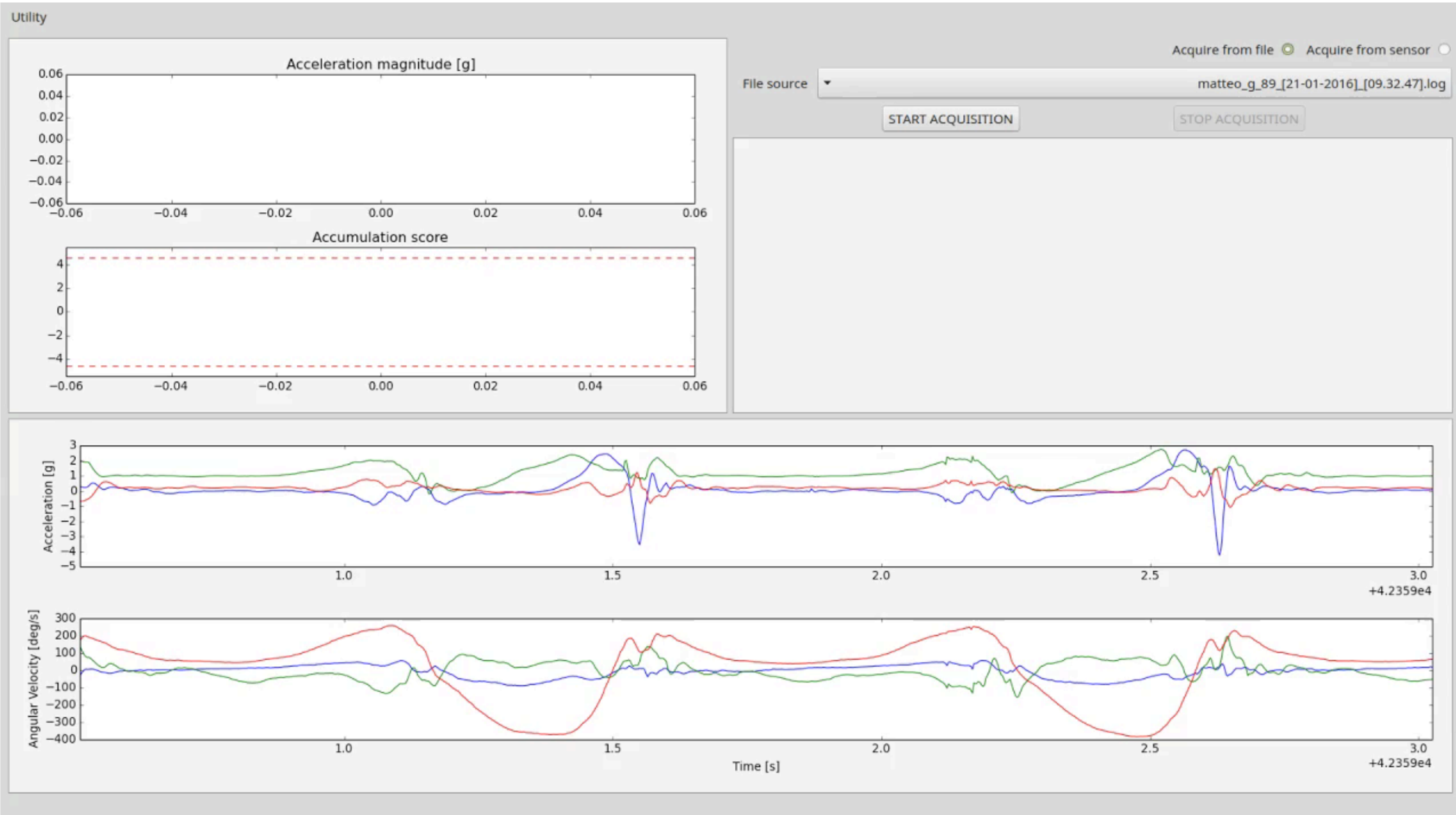
Final results



Feature extraction CNN *vs* SOTA



Demo



Utility
Acceleration magnitude [g]
Accumulation score
Acquire from file
Acquire from sensor
File source
matteo_g_89_[21-01-2016]_[09.32.47].log
START ACQUISITION
STOP ACQUISITION
Acceleration [g]
Angular Velocity [deg/s]
Time [s]
+4.2359e4

Bibliography

- [S++00] B. Schölkopf, J.C. Plattz, J. Shawe-Taylory, A.J. Smolax, Robert C. Williamson, “Estimating the Support of a High-Dimensional Distribution,” *Neural Computation Journal*, Vol. 13, No. 7, Pages 1443-1471, July 2001.
- [W47] A. Wald, “Sequential analysis,” Dover, New York, NY, US, 1947.
- [TNB15] A. Tartakovsky, I. Nikiforov, M. Basseville, “Sequential Analysis Hypothesis Testing and Changepoint Detection,” CRC Press, 2015.
- [TR15] D. Del Testa, M. Rossi, ”Lightweight Lossy Compression of Biometric Patterns via Denoising Autoencoders,” *IEEE Signal Processing Letters*, Vol. 22, No. 12, September 2015.
- [GR18] M. Gadaleta, M. Rossi, ”IDNet: Smartphone-based Gait Recognition with Convolutional Neural Networks,” *Pattern Recognition*, Vol. 74, Pages 25–37, February 2018.

рахмат
danke
謝謝
spas
ngiyabonga
teşekkür ederim
Баярлалаа
mersi
kia ora
barka
welalin
tack
mahalo
tapadh leat
спасибо
faafetai lava
vinaka
спасибі
blagodaram
dank je
misaotra
matondo
paldies
grazzi
gracias
хвала
asante
manana
kiitos
dankie
nanni
nandri
dhanyavad
mauruuru
köszönöm
thank you
bedankt
bayarlalaa
gràçie
hvala
dankon
aciū
akun
obrigada
murakoze
tenki
enkosi
djiere dieuf
tau
mochchakkeram
дякую
mamnun
chokrane
dziękuję
chnorakaloutioun
gratias ago
gràcies
sulpáy
go raibh maith agat
sobodi
dēkuji
sagolun
sukriya
kop khun krap
taiku
obrigado
mèsi
didi madloba
ありがとう
arigatô
takk
dakujem
trugarez
najis tuke
tanemirt
grazie
terima kasih
kam sah hamnida
rahmat
rahmet
ευχαριστώ
diolch
dhanyavadagalu
shukriya
mercè
мерси
감사합니다
xièxie
merci

ARTIFICIAL NEURAL NETWORKS: APPLICATION EXAMPLES

Michele Rossi

rossi@dei.unipd.it

Dept. of Information Engineering

University of Padova, IT

DIPARTIMENTO
DI INGEGNERIA
DELL'INFORMAZIONE