Klinik für Psychosomatik und Psychotherapie &
Institut für Med. Statistik, Informatik und Datenwissenschaften

# Risk prediction of premature autonomic ageing based on non-invasive cardiovascular measurements

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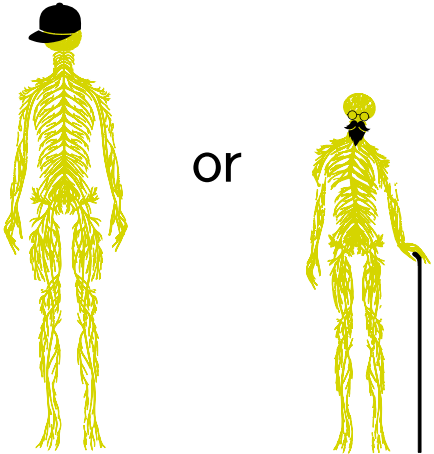
# Motivation

**Goals:**

1. Detect: anomalous autonomic ageing (AAA)
2. Identify characteristics: AAA

**Basis of prediction:**

- ECG lead II
- Continous non-invasive blood pressure




Adapted from brgfx; *Systeme des menschlichen körpers* on Freepik

# Outline

Labelling of data:

- How to define "autonomic age"?
  - Adiposity as proxy for premature autonomic ageing

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Approach:

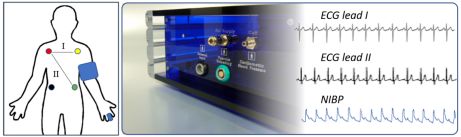
1. Collect cardiovascular and demographic data from healthy individuals
2. Develop model for age prediction on non-obese (BMI $< 30$) persons

Assumption:

- Good model performance: Persons with normal autonomic ageing
- Worse model performance: Persons with AAA
- **Difference between prediction and real age: risk score**

# Origin of Data

System 1: CNSystems Task Force Monitor




System 2: BIOPAC MP150 combined with CNSystems CNAP 500


- Collected at Dept. of Psychosomatic Medicine and Psychotherapy, Jena University Hospital
- $1,121$ healthy volunteers
- Data:
  1. ECG (one or two leads)
  2. Non-invasive continuous blood pressure (NIBP)
  3. Sex $[670$ female, $433$ male, $18$ N/S$]$
  4. Body mass index $[23.7 \pm 4.5]$
  5. Calendar age $[32.5 \pm 14.7]$

# Classic ML approaches

Gaussian process regression

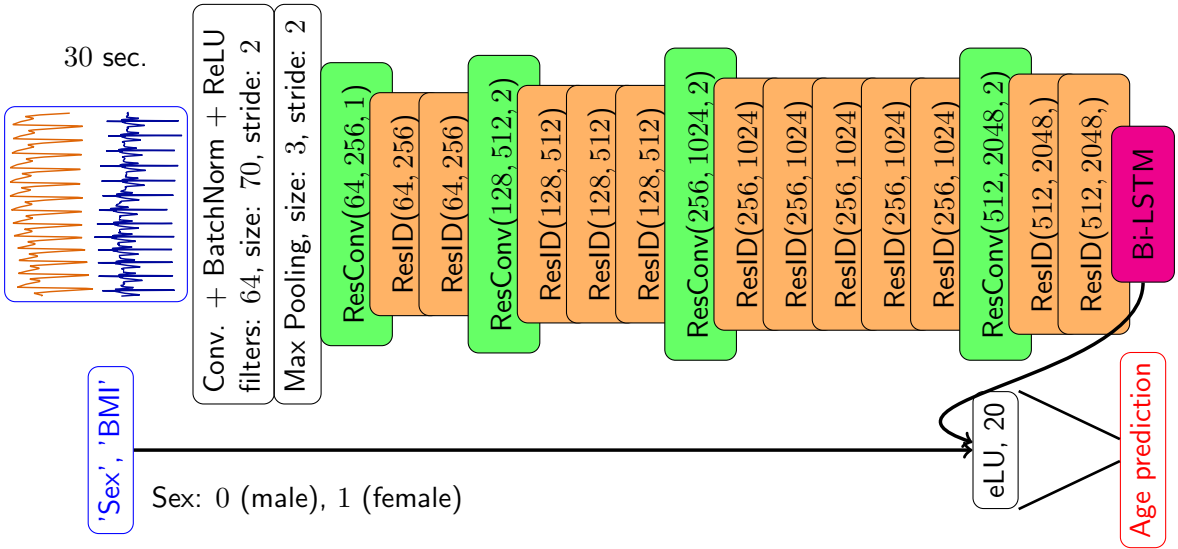
- $29$ cardiovascular indices (heart rate variability, QT characteristic etc.)

$\Rightarrow$ Significantly larger age residues for obese volunteers

# Deep Learning approach

**ResNet 50 + Bi-LSTM**

- Convolutional Layers: Feature Extraction
- Recurrent Layer: Combination of sequential features


30 sec.
Conv. + BatchNorm + ReLU
filters: 64, size: 70, stride: 2
Max Pooling, size: 3, stride: 2
ResConv(64, 256, 1)
ResID(64, 256)
ResID(64, 256)
ResConv(128, 512, 2)
ResID(128, 512)
ResID(128, 512)
ResID(128, 512)
ResConv(256, 1024, 2)
ResID(256, 1024)
ResID(256, 1024)
ResID(256, 1024)
ResID(256, 1024)
ResID(256, 1024)
ResConv(512, 2048, 2)
ResID(512, 2048,)
ResID(512, 2048,)
Bi-LSTM
'Sex', 'BMI'
Sex: 0 (male), 1 (female)
eLU, 20
Age prediction

# Experiments

1. 5-fold Cross Validation (3: training, 1: validation, 1:test)
   - Individuals: 881
   - Mean age: 31.17 ($\sigma = 13.80$)
2. Training/Validation on BMI $< 30$, testing on BMI $\geq 30$
   - 967 individuals with BMI $< 30$
     - mean age: 30.57 ($\sigma = 14.79$)
     - mean BMI: 22.72 ($\sigma = 2.76$)
   - 98 individuals with BMI $\geq 30$
     - mean age: 42.00 ($\sigma = 17.7$)
     - mean BMI: 34.08 ($\sigma = 5.38$)

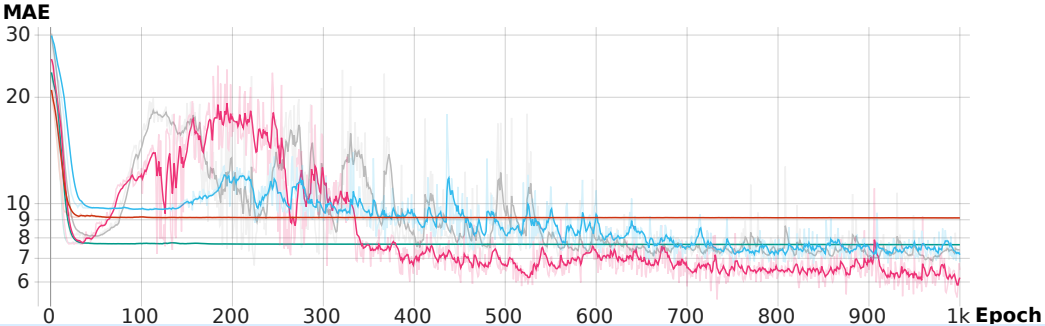
# Results

1) Cross Validation

Mean absolute error: $\mathbf{7.5}$ years

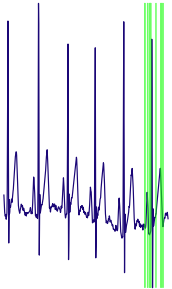
2) Set split according to BMI

MAE (BMI $\geq 30$): $\mathbf{14.66}$ years
MAE (BMI $< 30$): $\mathbf{9.40}$ years



# Analysis of Features - Method

Importance of ECG structures:

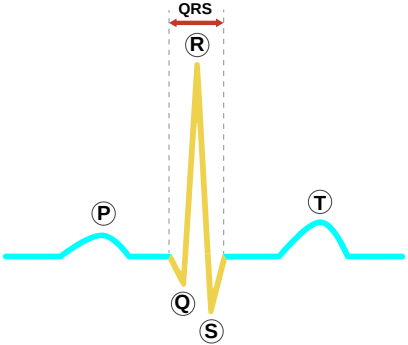


# Analysis of Features - Results

1) Cross Validation

| | QRS | non-QRS |
|---|---|---|
| Avg. absolute importance | $0.006$ | $0.211$ |

Avg. importance of "sex": $-1.12$
Avg. importance of "BMI": $0.87$



# Discussion and Outlook

**Preliminary findings:**

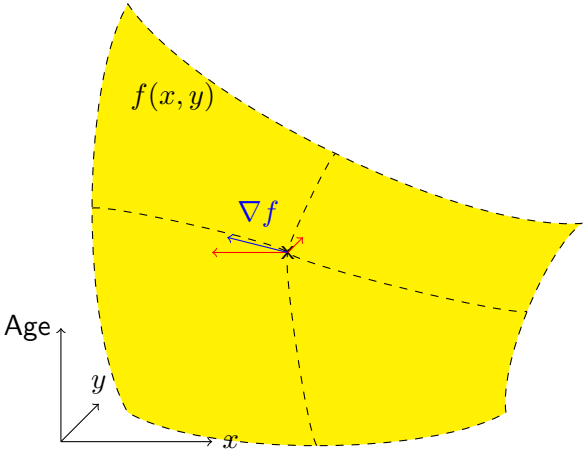
- Model associates higher BMI with higher estimated age
- Age residues: risk score for AAA
- Non-QRS regions contain more information than QRS regions

**Next steps:**

- Combine learned and manually defined features for final regression
- Better definition for AAA
- Understand importances of features for detecting AAA

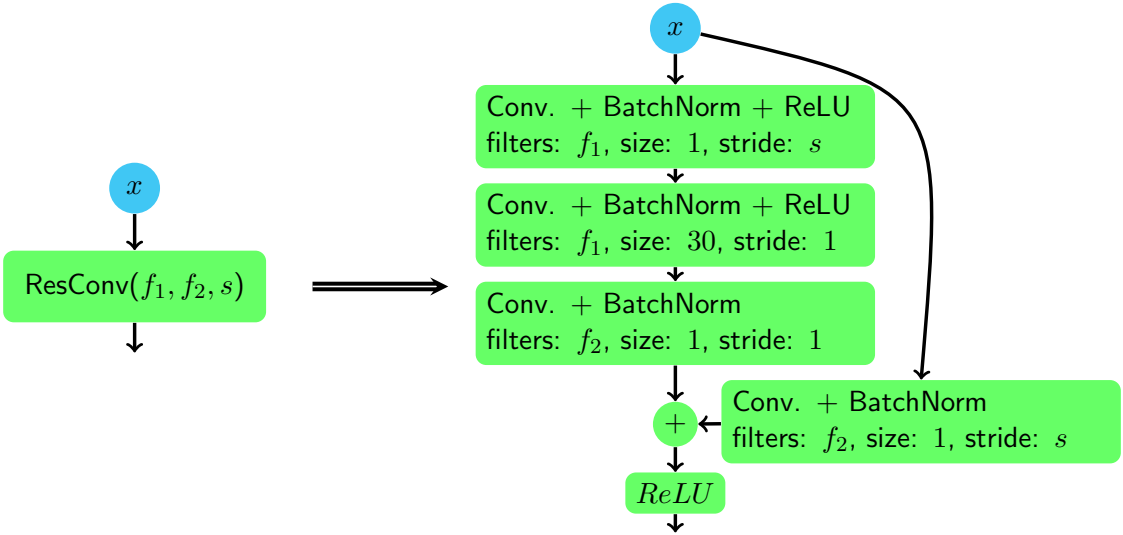
# Appendix

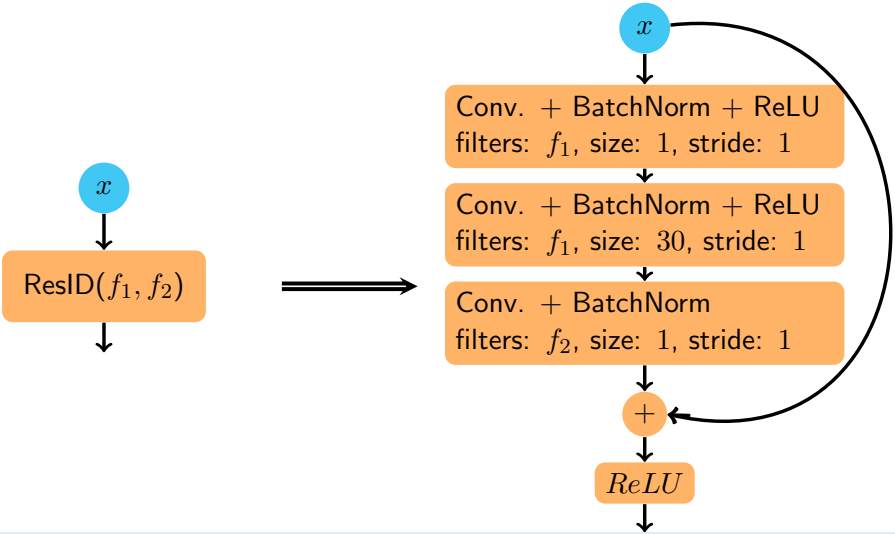
# Analysis of Features - Method

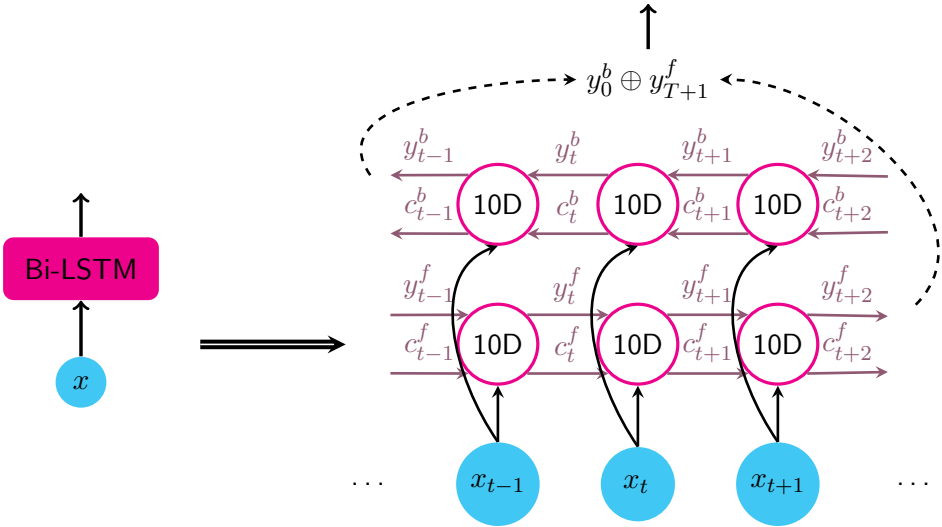



Taylor Approx. (1st) of $f$:

- Slopes in $x$ and $y$ direction
- **Local** estimates for feature importance
- Average slopes over full data set: **Global** importance estimates


$x$
ResConv($f_1, f_2, s$)
$x$
Conv. + BatchNorm + ReLU
filters: $f_1$, size: 1, stride: $s$
Conv. + BatchNorm + ReLU
filters: $f_1$, size: 30, stride: 1
Conv. + BatchNorm
filters: $f_2$, size: 1, stride: 1
Conv. + BatchNorm
filters: $f_2$, size: 1, stride: $s$
+
$ReLU$


$x$
ResID($f_1, f_2$)
$x$
Conv. + BatchNorm + ReLU
filters: $f_1$, size: 1, stride: 1
Conv. + BatchNorm + ReLU
filters: $f_1$, size: 30, stride: 1
Conv. + BatchNorm
filters: $f_2$, size: 1, stride: 1
+
$ReLU$


$y_0^b \oplus y_{T+1}^f$
$y_{t-1}^b$
$y_t^b$
$y_{t+1}^b$
$y_{t+2}^b$
$c_{t-1}^b$
$c_t^b$
$c_{t+1}^b$
$c_{t+2}^b$
10D
10D
10D
$y_{t-1}^f$
$y_t^f$
$y_{t+1}^f$
$y_{t+2}^f$
$c_{t-1}^f$
$c_t^f$
$c_{t+1}^f$
$c_{t+2}^f$
10D
10D
10D
Bi-LSTM
$x$
$x_{t-1}$
$x_t$
$x_{t+1}$
...
...

# Data Collection - Protocol

- Measurements in autonomic laboratory
  - Temperature controlled at 22 °C
  - Quiet and fully shaded environment
  - Constant illumination via an indirect light source
- Session started with an interview / explanation of the study design
- All participants gave informed written consent
- Weight was measured using a person scale (SECA GmbH & Co. KG., Hamburg, GER)
- Height using a stadiometer (Harpenden, Holtain Ltd., Crosswell, UK).
- Participants lay down comfortably on the examination table
- Electrodes and pressure cuffs were placed.
- Participants instructed to avoid movement, yawning or coughing.
- A few min time for participant to calm down, quality check of acquired signals
- In case of insufficient quality, electrodes and cuffs were re-arranged.
- Otherwise, the recording was started and supervised by the instructor (8 - 35 min)

# Data Collection - Exclusion criteria

- any medical conditions
- illegal drugs or medication potentially influencing cardiovascular function
- pathological findings in routine laboratory parameters and ECG recordings