What is Unique in Individual Gait Patterns?

Understanding and Interpreting Deep Learning in Gait Analysis

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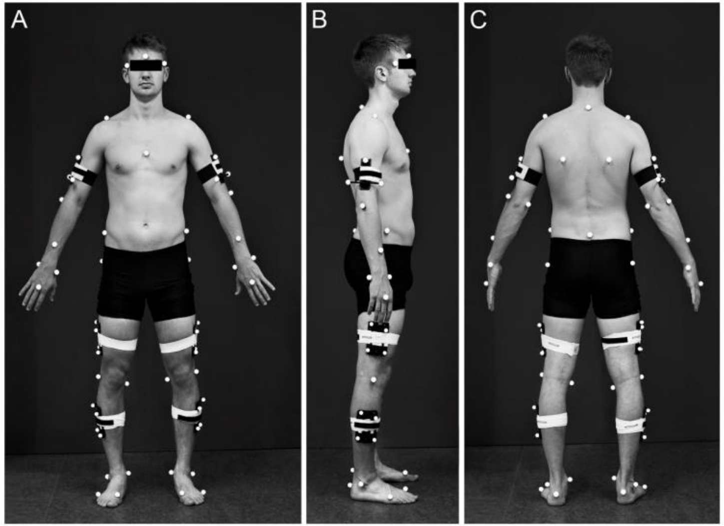
Outline of the talk

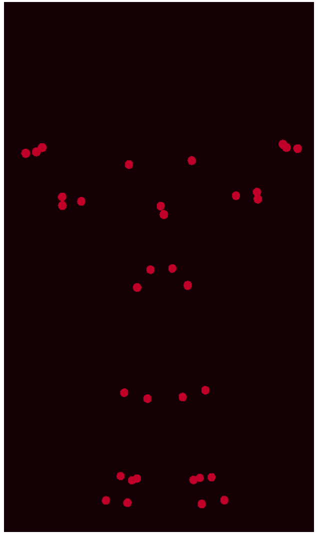
- What is biomechanical gait analysis?
- Why is Machine Learning beneficial in biomechanical gait analysis?
- What we did learn from Machine Learning about human gait?
- **Study:** Explaining unique nature of individual gait patterns using Deep Learning
- Future perspectives for Deep Learning in biomechanical gait analysis

Biomechanical gait analysis - Joint Angles

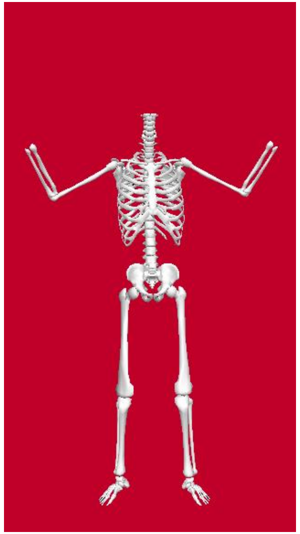
Marker Set-Up



Motion Capturing



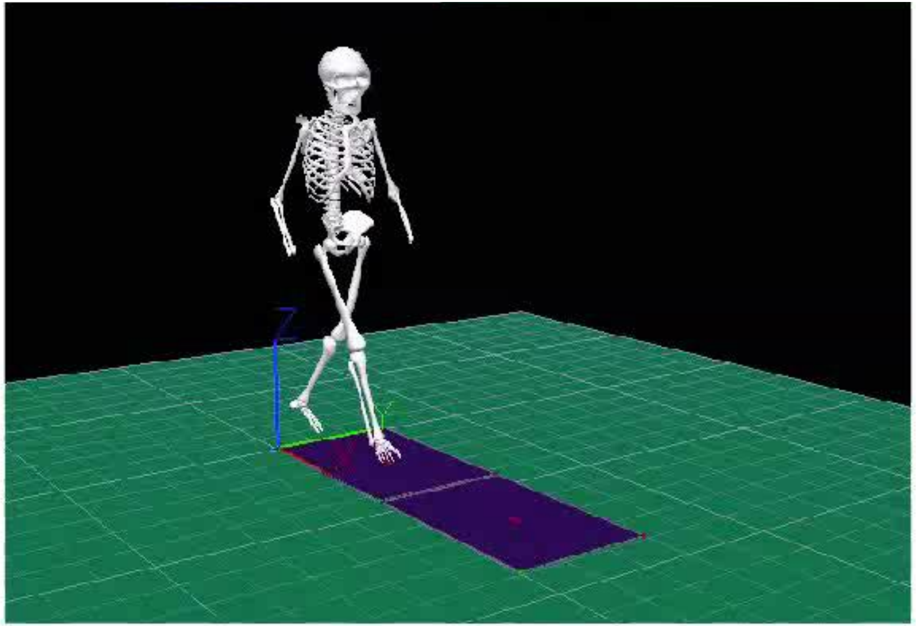
Model-Based Analysis

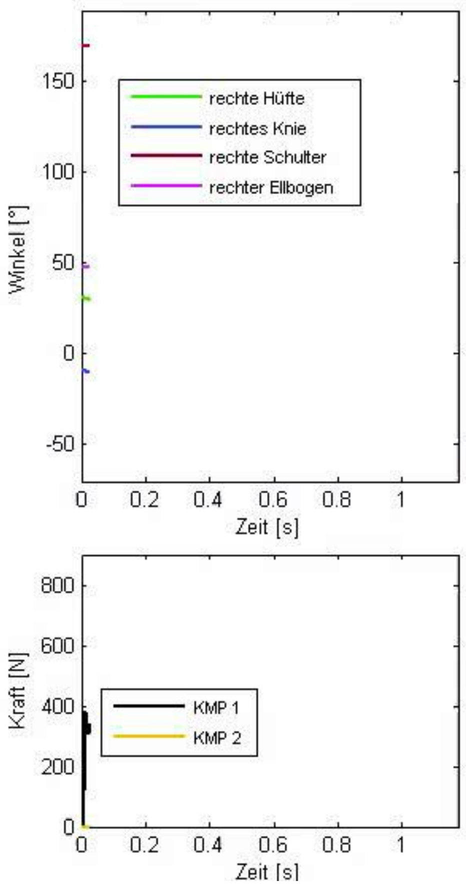


φ ω α

M J

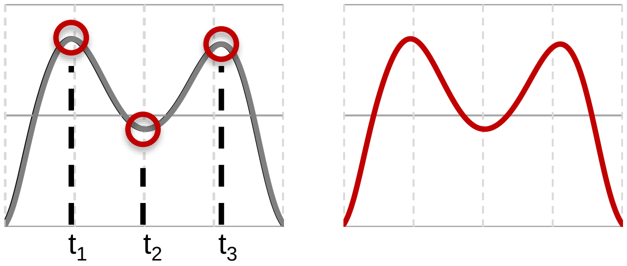
Biomechanical gait analysis





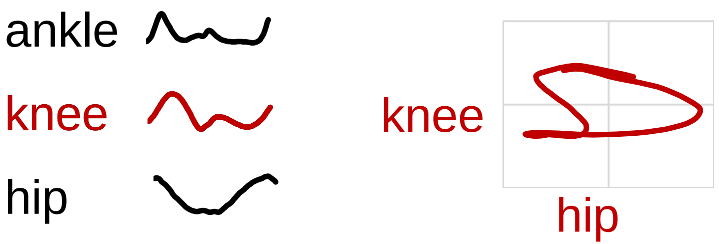
Biomechanical gait analysis

time-discrete vs. time-continuous



[Schöllhorn et al. 2002]

single vs. multiple variables

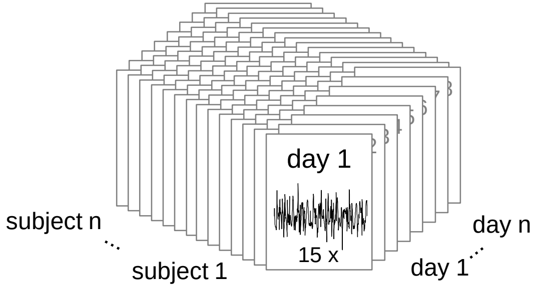


[Schöllhorn et al. 2002]

measurement devices

[Phinyomark et al. 2018]

"large" amount of data



[McKay et al. 2016]

Why is Machine Learning beneficial for biomechanical gait analysis?

Conventional gait analysis

- Single time-discrete variables
- “Subjective” pre-selection
- “Missing” information

Machine Learning

- Multiple time-continuous variables
- Holistic (full-body) analysis

What did we learn from Machine Learning about human gait?

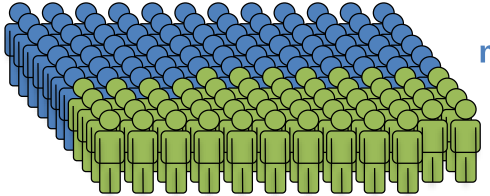
Aim:

Classification of unique gait patterns to individual persons

Horst, F., Mildner, M., & Schöllhorn, W. I. (2017). One-year persistence of individual gait patterns identified in a follow-up study - A call for individualised diagnose and therapy. *Gait & Posture,* 58, 476-480.

Machine Learning in biomechanical gait analysis

Sample



male = 76

female = 52

n = 128 normal subjects (23.8 ± 9.1 years)

Protocol

informed consent

weighting

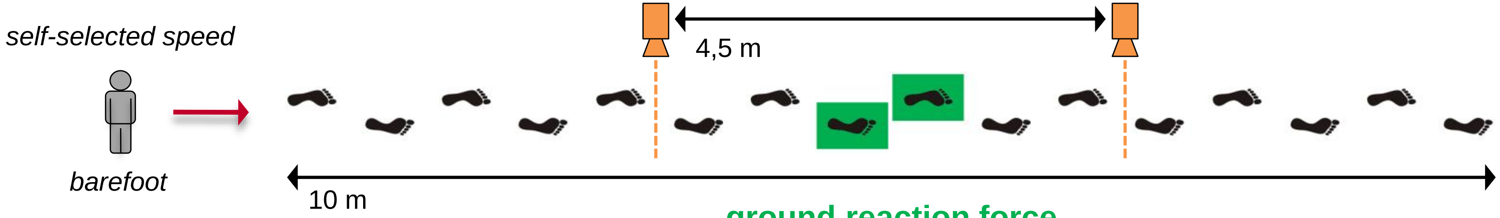
assignment of individual start position

5 test trials

10 analysis trials

Data acquisition

light barriers for speed control



ground reaction force

2 x Kistler force plate (40 x 60 cm ; 1000 Hz)

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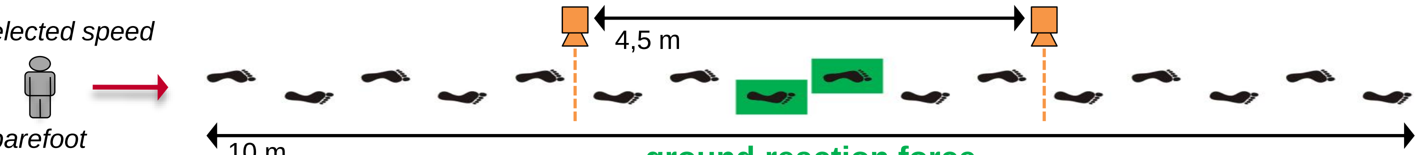
Machine Learning in biomechanical gait analysis

Data acquisition

light barriers for speed control

self-selected speed

barefoot

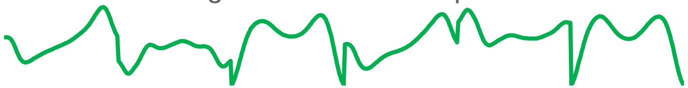


ground reaction force

2 x Kistler force plate (40 x 60 cm ; 1000 Hz)

Data processing

1 x 606 vector of 3D ground reaction force
of right and left stance phase



2. order Butterworth lowpass filter by 30 Hz

normed to body weight

time-normalized to 101 data points

z-transformed and scaled to a range of -1 to 1

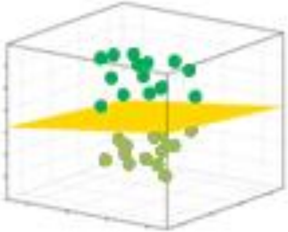
128 subjects x 10 trials

= 1280 gait vectors

Data analysis

Classification:

Support Vector Machines

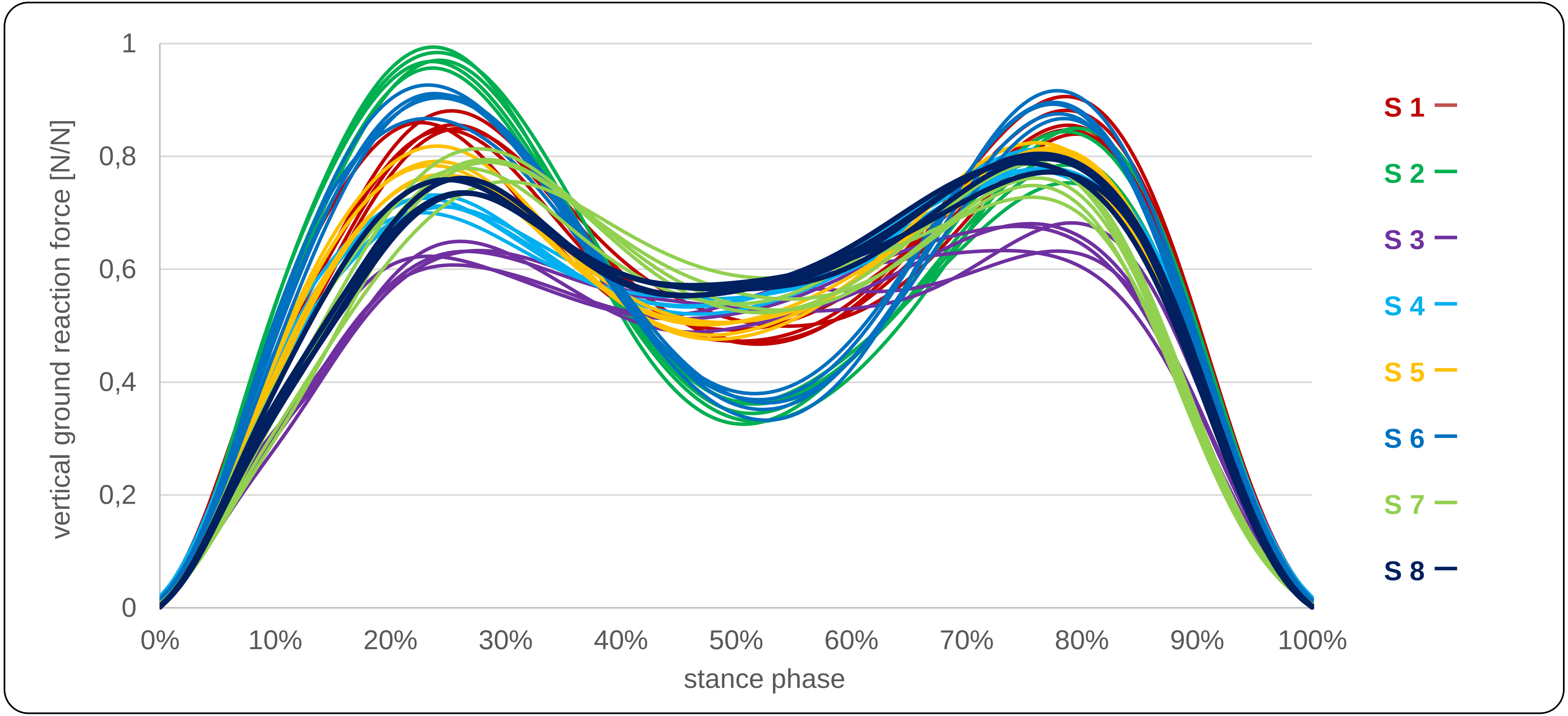


“leave-one-out”

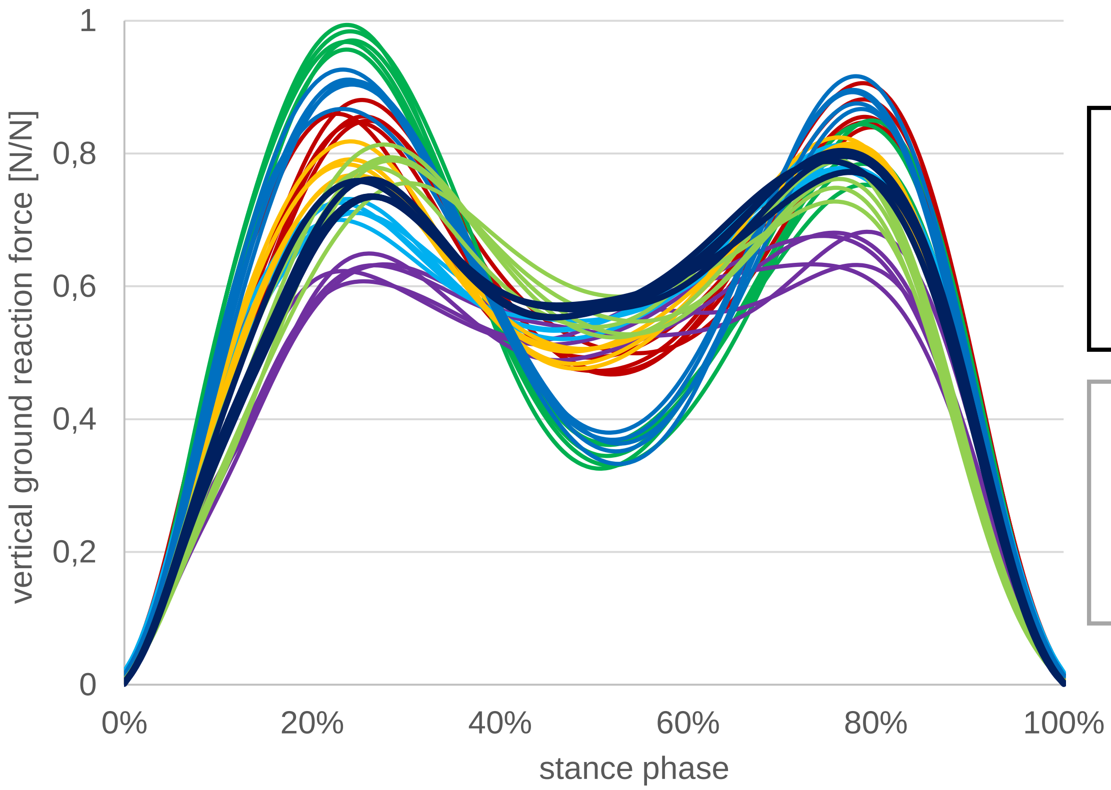
cross-validation

Liblinear Toolbox 1.4 (Fan et al., 2008)

Machine Learning in biomechanical gait analysis



Machine Learning in biomechanical gait analysis



initial observation

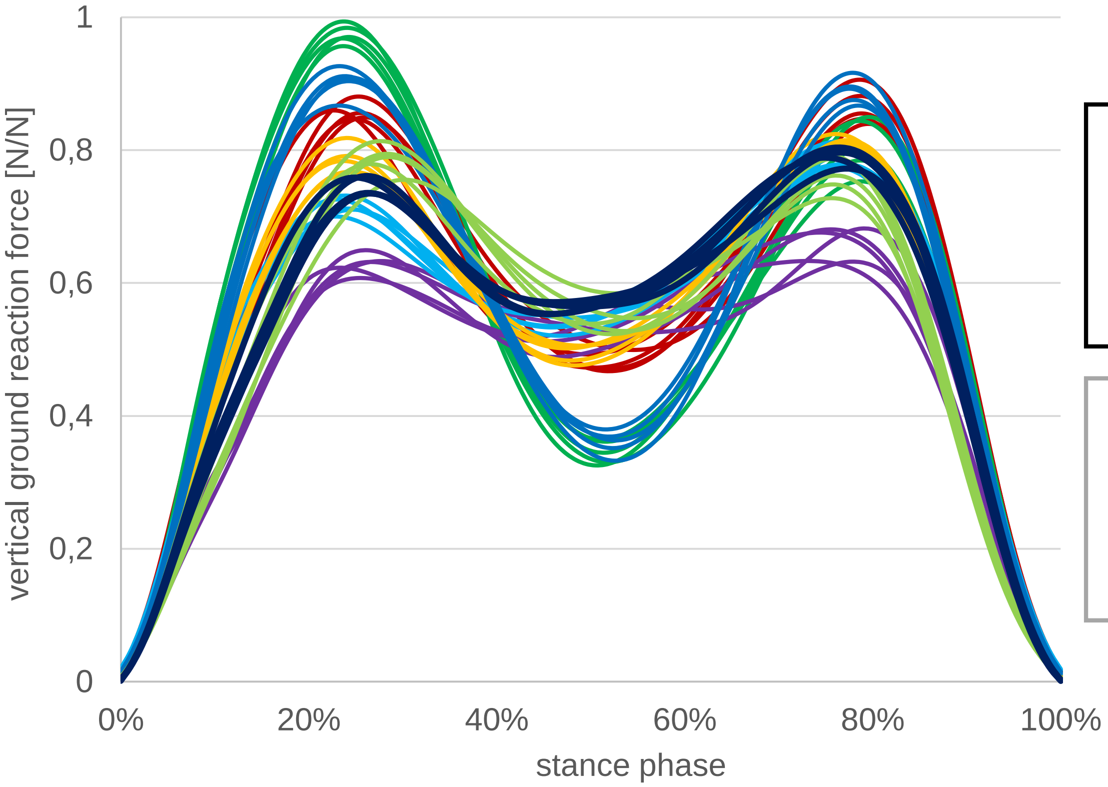
person identification: 99.8%

(1278 of 1280 gait patterns)

chance level: 0.8%

(1 of 128 persons)

Machine Learning in biomechanical gait analysis



follow-up (after 7-16 month)

person identification: 99.4%

(914 of 920 gait patterns)

chance level: 2.2%

(1 of 46 persons)

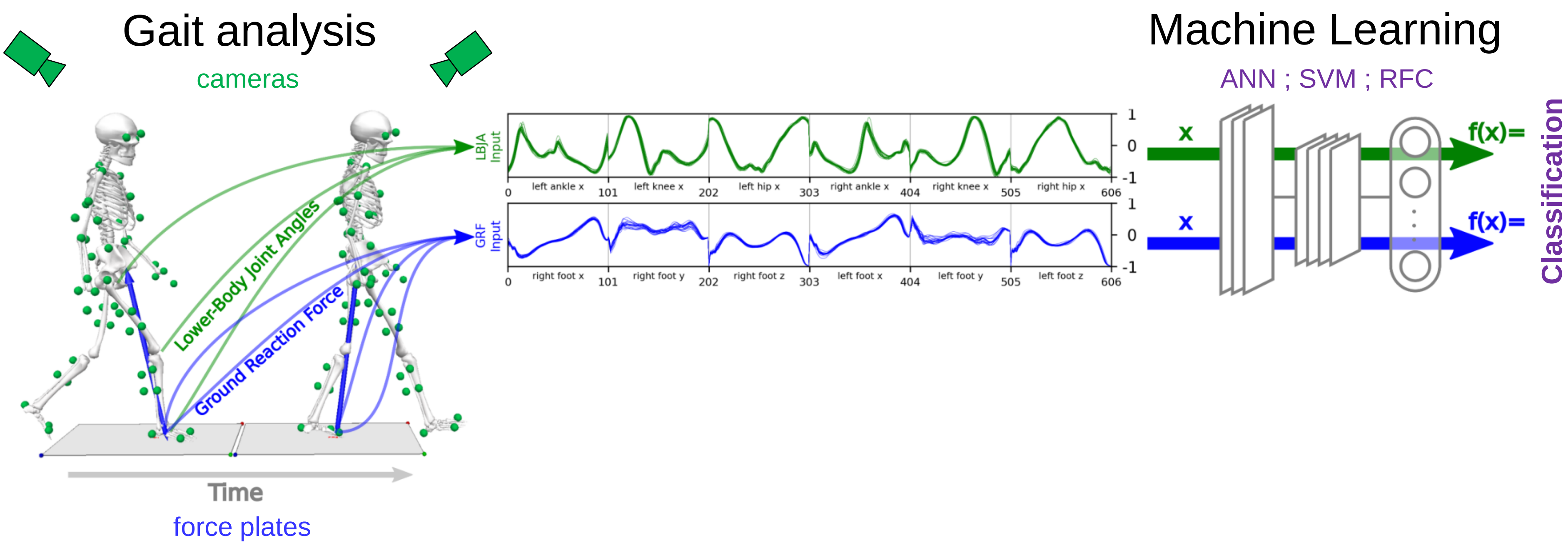
What did we learn from Machine Learning about human gait?

- gait patterns are unique to the individual (similar to other biometrics)
- long-term persistence of individual gait characteristics
- diagnoses [Simonsen & Alkjaer 2012] therapy [Schöllhorn et al. 2002] should respect individual persons rather than focus on stereotypes and normal data

What did we learn from Machine Learning about human gait?

- **Individual** [Schöllhorn et al. 2002; Horst et al. 2017; Costilla Reyes et al. 2018; Connor & Ross 2018]
- **Age** [Fukuchi et al. 2011; Eskofier et al. 2013; Li et al. 2018]
- **Gender** [Begg & Kamruzzaman 2005; Eskofier et al. 2013; Andrade et al. 2013]
- **Fatigue** [Jäger et al. 2003; Janssen et al. 2011]
- **Emotions** [Janssen et al. 2008; Roether et al. 2009; Gross et al. 2012]
- **…**

Machine Learning in biomechanical gait analysis



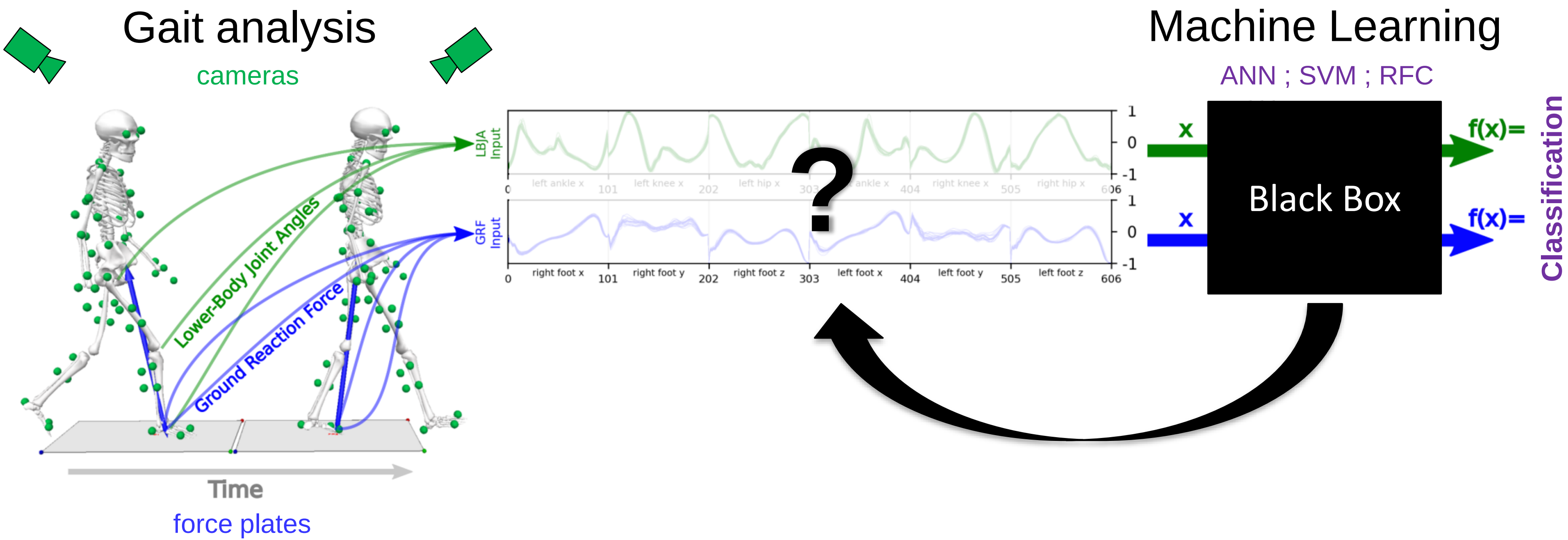
Pathological gait conditions like:

- Lower limb fractures [Holzreiter & Köhle 1993; Figueiredo et al. 2018]
- Anterior cruciate ligament injury [Christian et al. 2016]
- Arthrosis [Lafuente et al. 1997; Wu & Su 2000]
- Hallux valgus [Barton & Lees 1995]

(Neurological) disorders like:

- Cerebral palsy [Barton 1999]
- Parkinson’s disease [Zeng et al. 2016]
- Multiples scleroses [Alaqtash et al. 2011]
- Traumatic brain injuries [Williams et al. 2015]

Machine Learning in biomechanical gait analysis



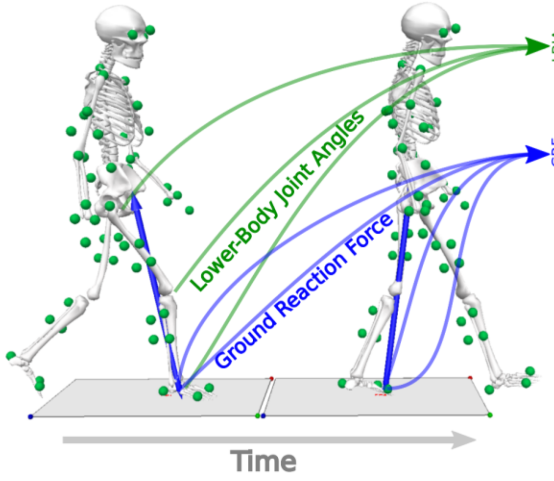
Aim: Understanding und interpreting Deep Learning in gait analysis

Objective: Uniqueness of individual gait patterns

Methods

Gait analysis

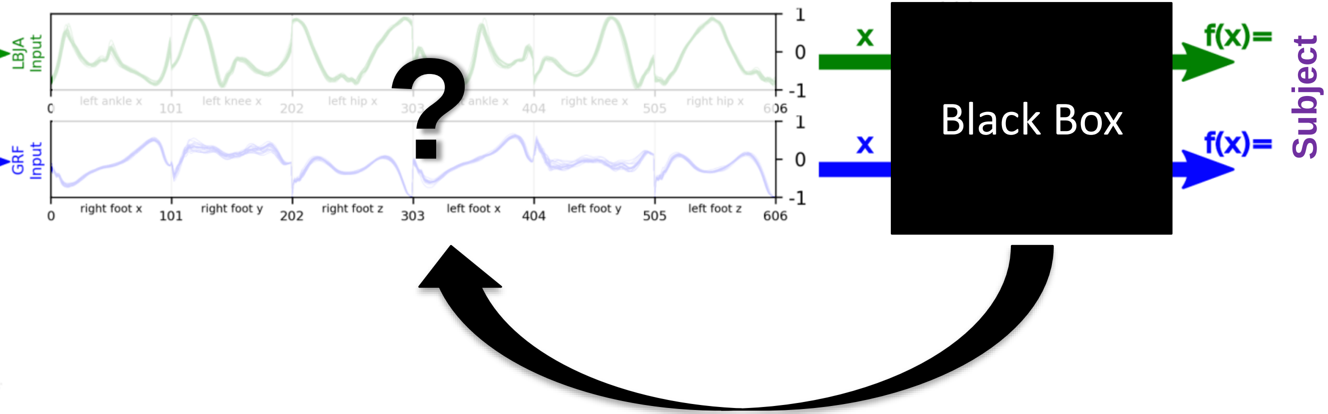
10 x camera (Qualysis, 250 Hz)



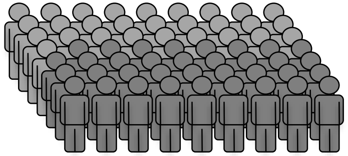
2 x force plate (Kistler, 1000 Hz)

Machine Learning

DNN



Sample



male = 28

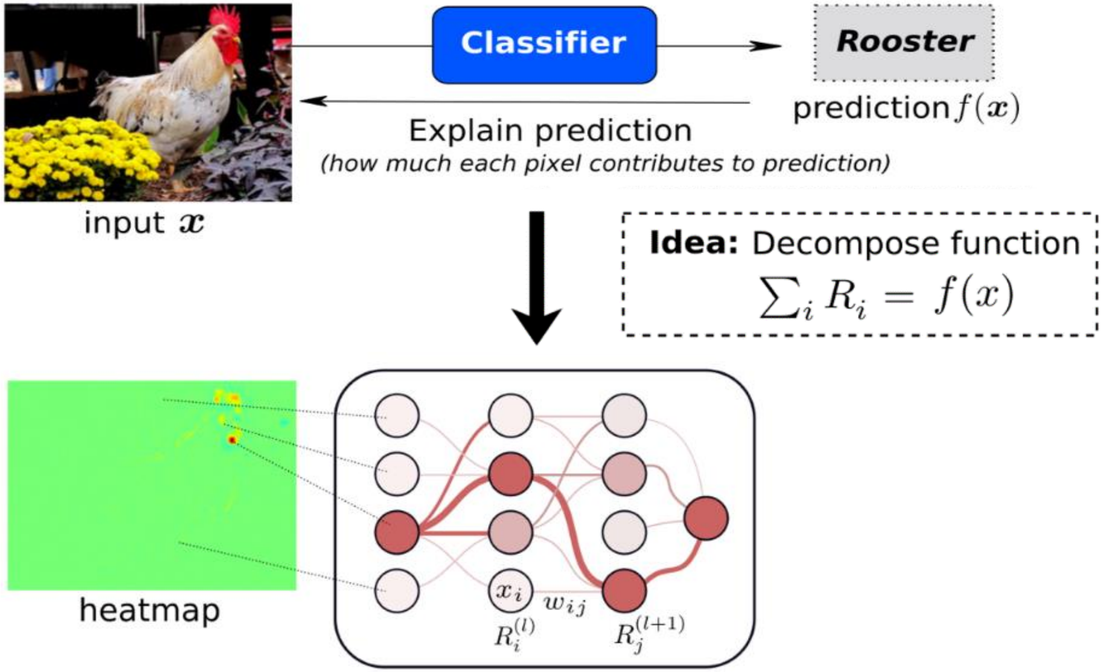
female = 29

n = 57 subjects
(23.1 ± 2.7 years)

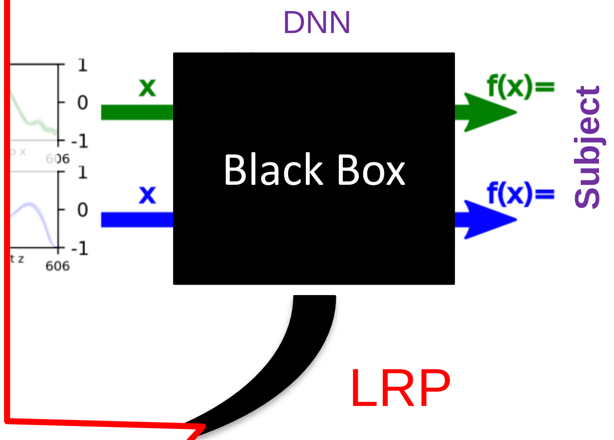
Methods

Layer-Wise Relevance Propagation (LRP)

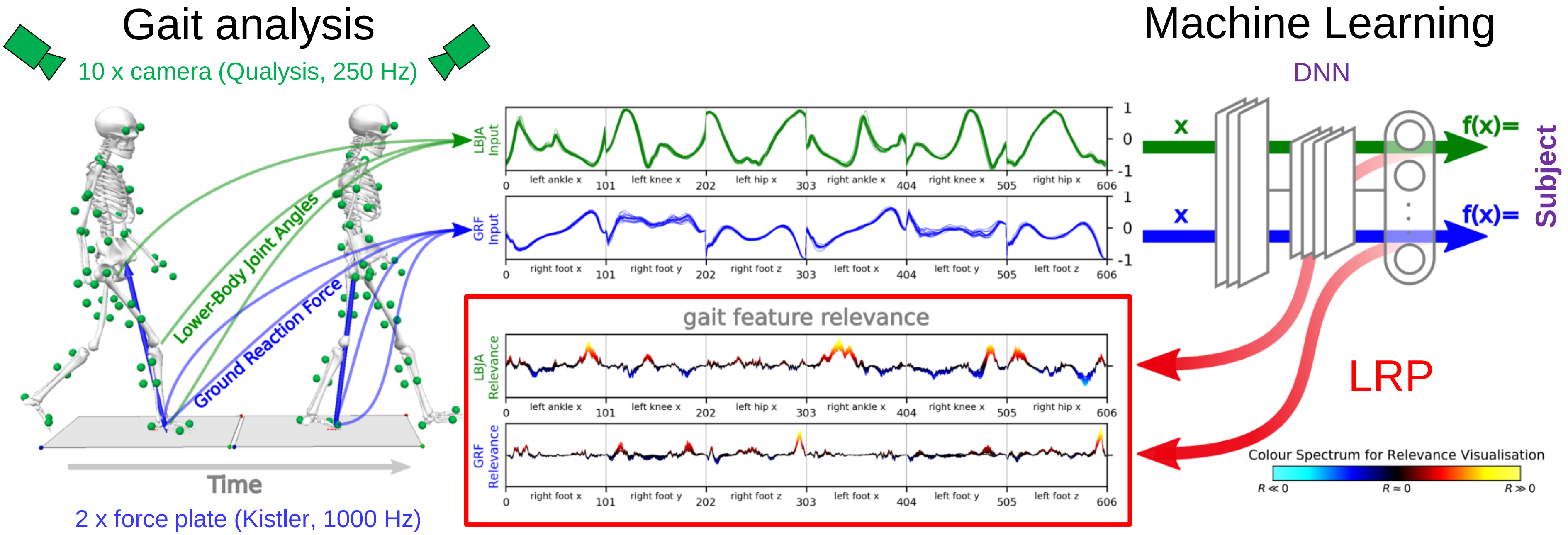
Bach S et al. 2015. PLOS One, 10(7), e0130140.



Machine Learning



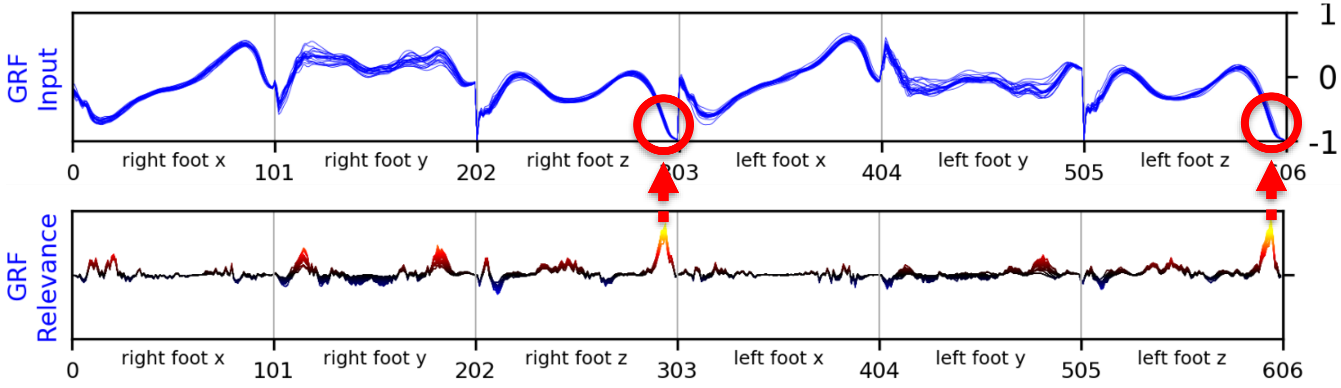
Methods



Gait analysis
10 x camera (Qualysis, 250 Hz)
Lower-Body Joint Angles
Ground Reaction Force
Time
2 x force plate (Kistler, 1000 Hz)
LBJA Input
GRF Input
left ankle x
left knee x
left hip x
right ankle x
right knee x
right hip x
right foot x
right foot y
right foot z
left foot x
left foot y
left foot z
0
101
202
303
404
505
606
1
0
-1
gait feature relevance
LBJA Relevance
GRF Relevance
Machine Learning
DNN
x
f(x)=
Subject
LRP
Colour Spectrum for Relevance Visualisation
R ≪ 0
R ≈ 0
R ≫ 0

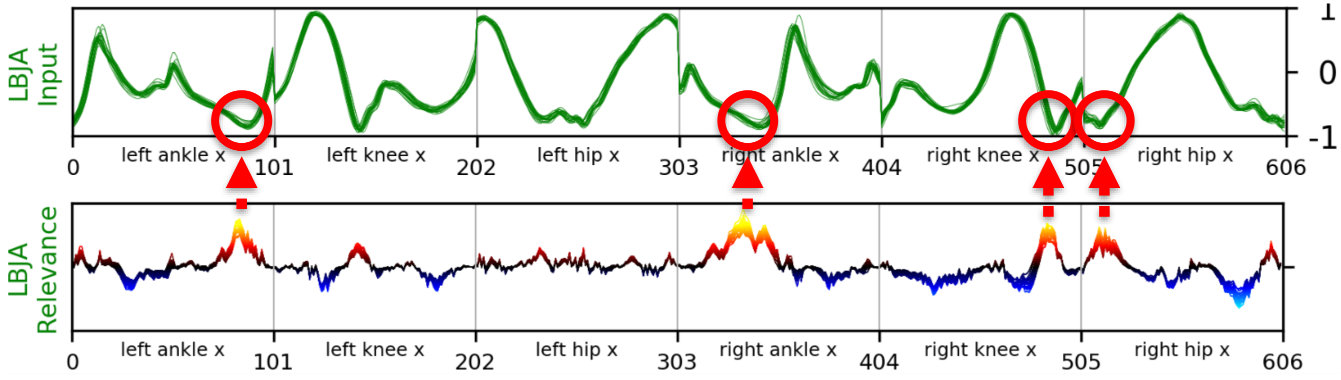
Results

Subject 6



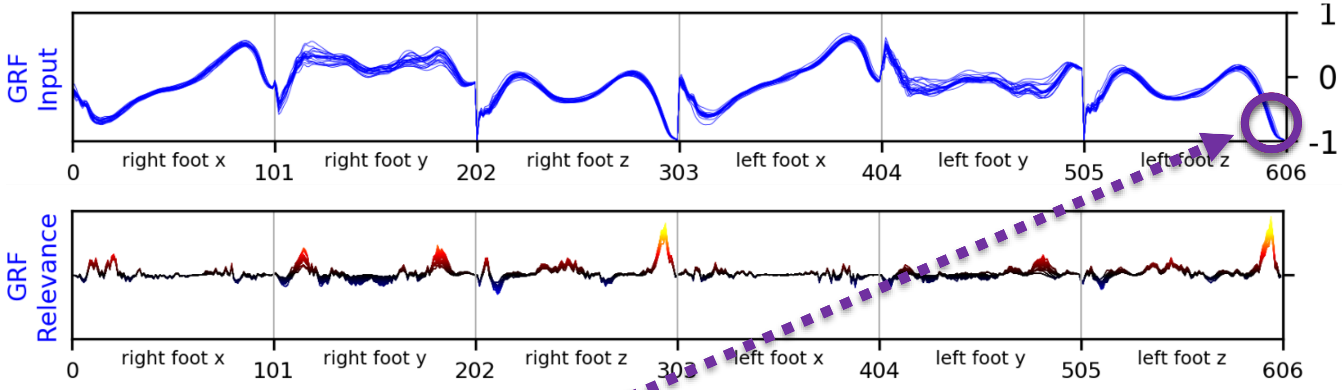
no single variable

Subject 6



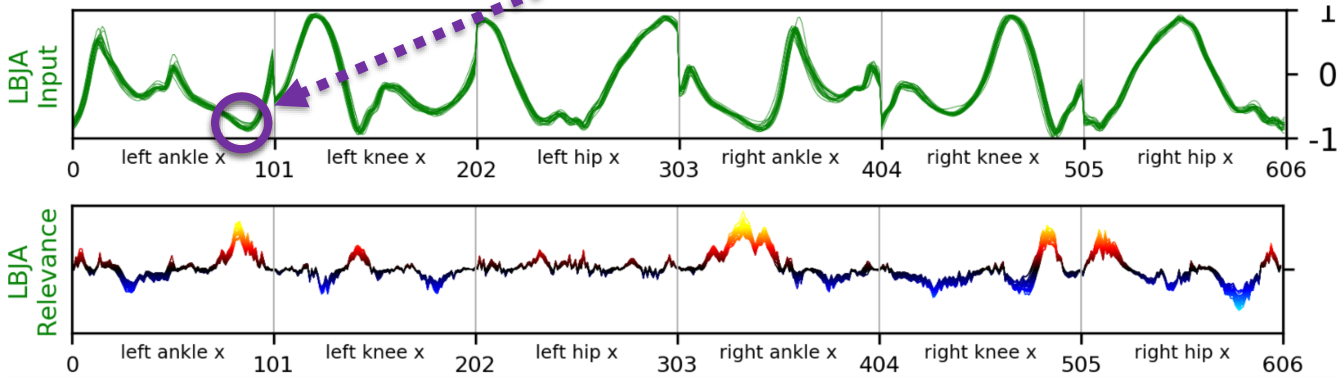
Results

Subject 6



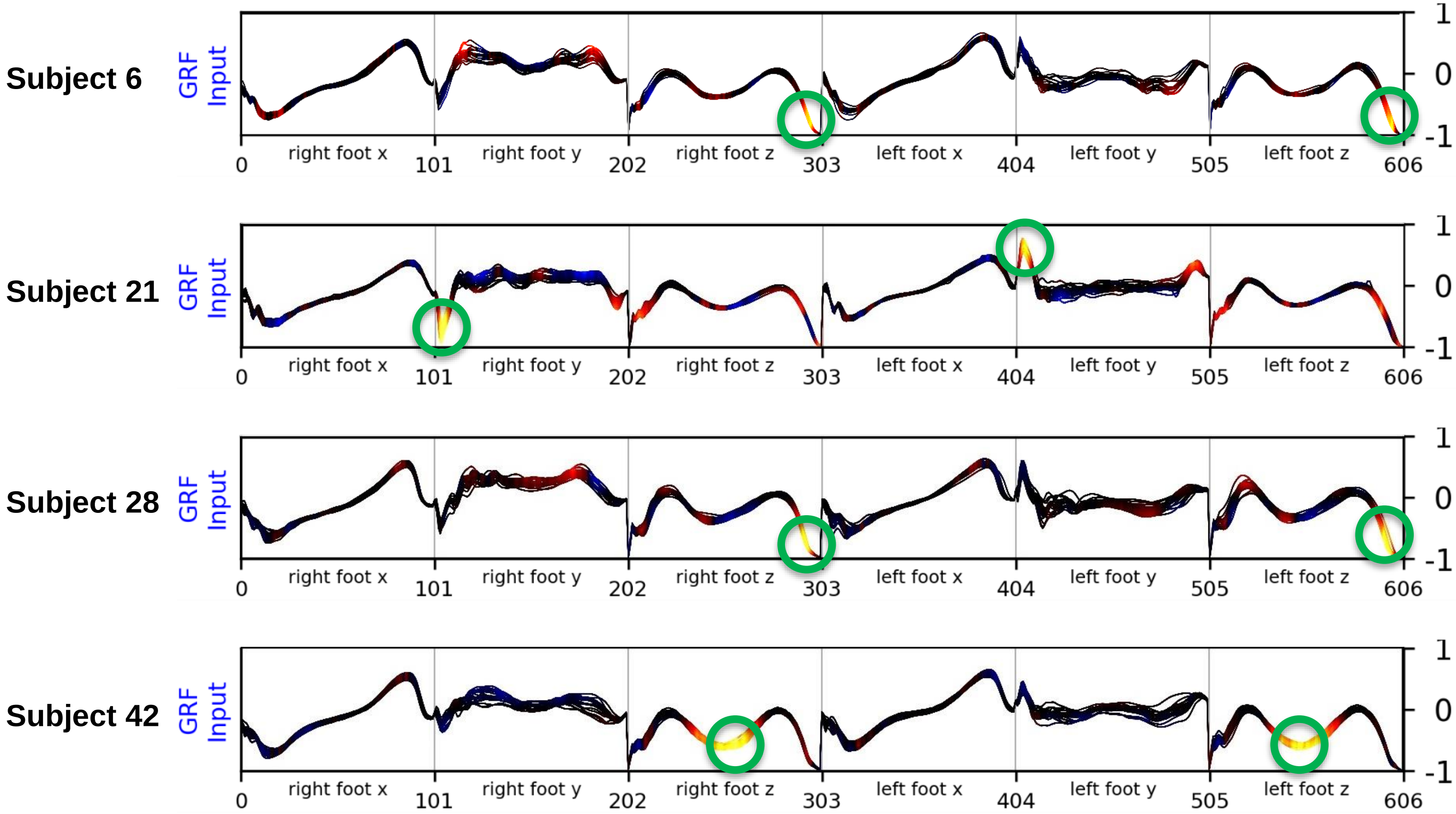
no single variable

Subject 6



plausible features

Results



no single variable

plausible features

left / right symmetries

Future perspectives for Deep Learning in gait analysis

- **Understanding and interpreting** in clinical gait classification

- **Pretrained models for gait patterns**
  - Biomechanical data collection of large, balanced numbers of samples, subjects and classes under standardized conditions is time-consuming

- **Public gait database**
  - Small number of public datasets of biomechanical gait patterns available
  - Heterogeneous experimental protocols, different model variables, different measurement devices and data formats between the individual data sets, which are difficult to combine

Full paper

- Horst, F., Lapuschkin, S., Samek, W., Müller, K.-R., & Schöllhorn, W. I. (2019). Explaining the unique nature of individual gait patterns with deep learning. *Scientific Reports, 9 (1),* 2391. https://doi.org/10.1038/s41598-019-38748-8

Public datasets

- Horst, F., Lapuschkin, S., Samek, W., Müller, K.-R., & Schöllhorn, W. I. (2019). A public dataset of overground walking kinetics and full-body kinematics in healthy individuals. *Mendeley Data*, v2. http://dx.doi.org/10.17632/svx74xcrjr.2

- Horst, F., Kramer, F., Schäfer, B., Eekhoff, A., Hegen, P., Nigg, B. M., & Schöllhorn, W. I. (2019). A public dataset of overground walking kinetics and lower-body kinematics in healthy adult individuals on different days. *Mendeley Data*, v1. http://dx.doi.org/10.17632/8kyv4jm759.1

- Horst, F., Eekhoff, A., Newell, K. M., & Schöllhorn, W. I. (2019). A public dataset of overground walking kinetics and lower-body kinematics in healthy adult individuals on different sessions within one day. *Mendeley Data*, v1. http://dx.doi.org/10.17632/b48n46bfry.1

- Horst, F., Mildner, M., & Schöllhorn, W. I. (2018). A public dataset of overground walking kinetics in healthy individuals. *Mendeley Data*, v1. http://dx.doi.org/10.17632/yrpbd8fhc4.1

GitHub

- Layer-Wise Relevance Propagation Toolbox (https://github.com/sebastian-lapuschkin/lrp_toolbox)
- Interpretable Deep Gait (https://github.com/sebastian-lapuschkin/interpretable-deep-gait)