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# Deep learning to estimate power output from breathing


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# Outline

CONTEXT

METHODS

RESULTS

# Motivation

Physical inactivity – a major leading risk factor for non-communicable diseases

Activity tracking – a tool for motivating physical activity and measuring health variables

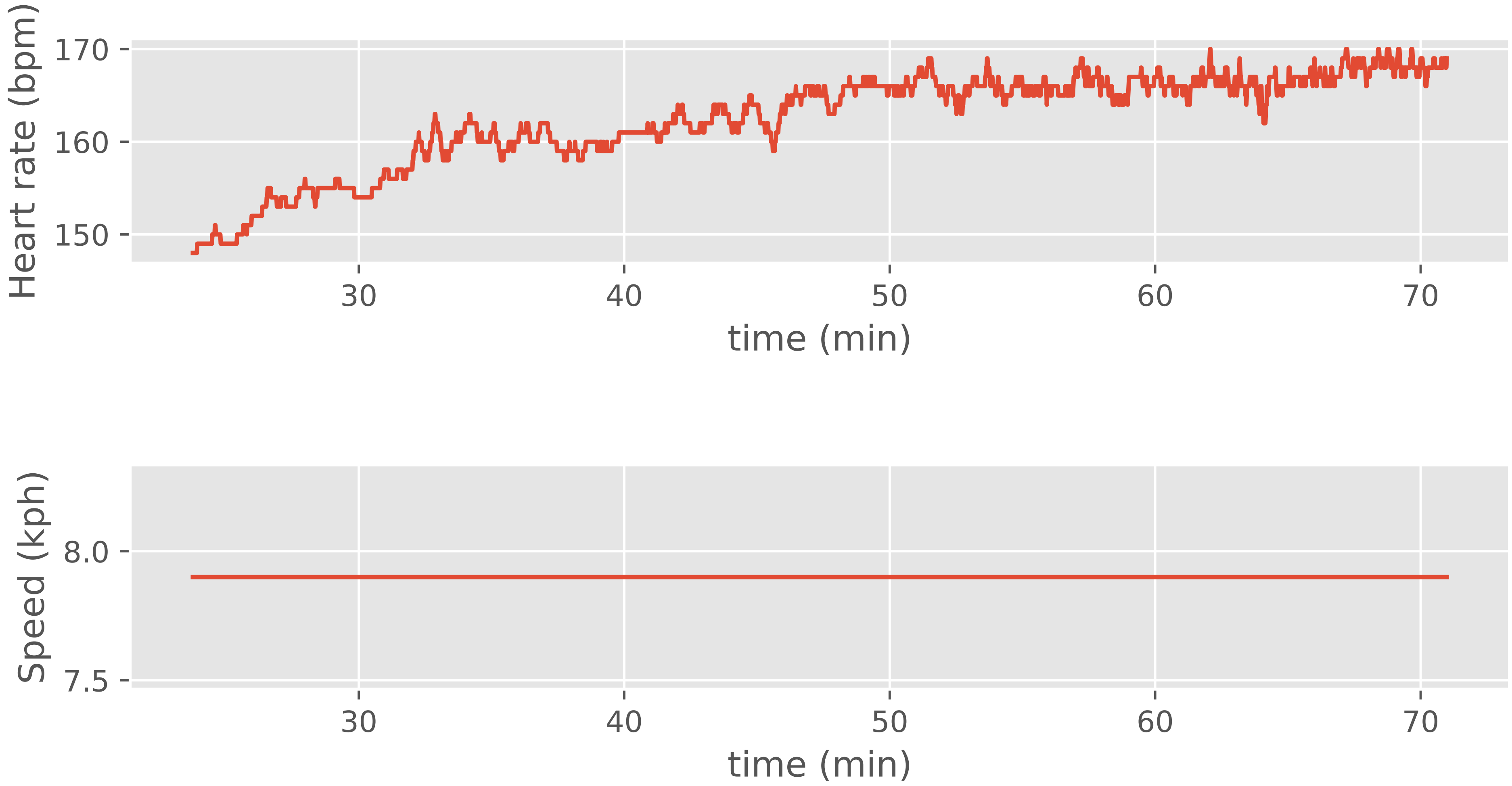
# Activity trackers

Heart rate monitors

Speed measurements

Power meters

# Cardiovascular drift



# Breathing and physical activity

- Increased muscle work leads to increased need for oxygen.
- Reactive to change in exercise intensity.
- Universal metric across various exercise forms.

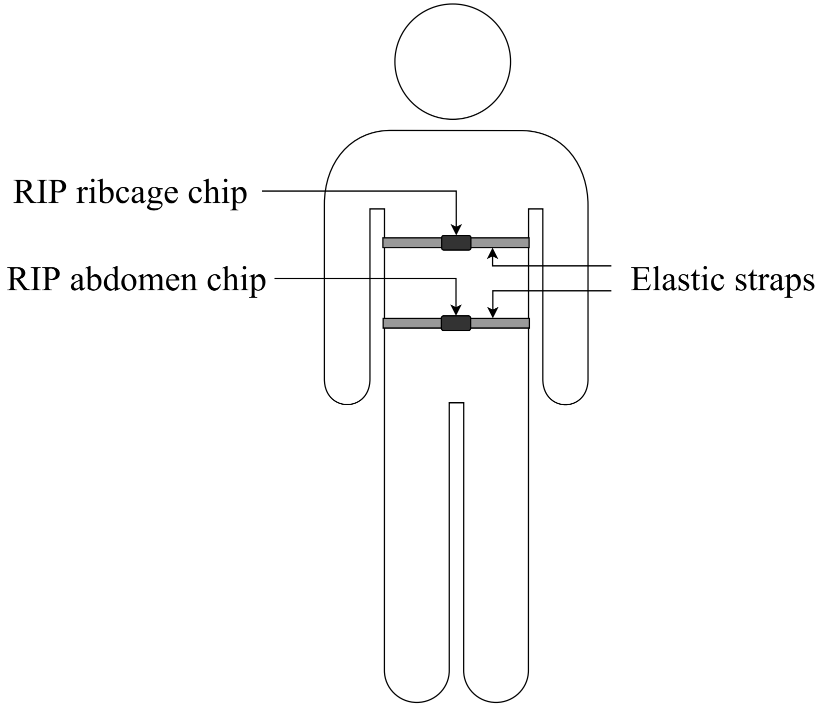
# How to measure breathing?


Exercise spirometer[1]

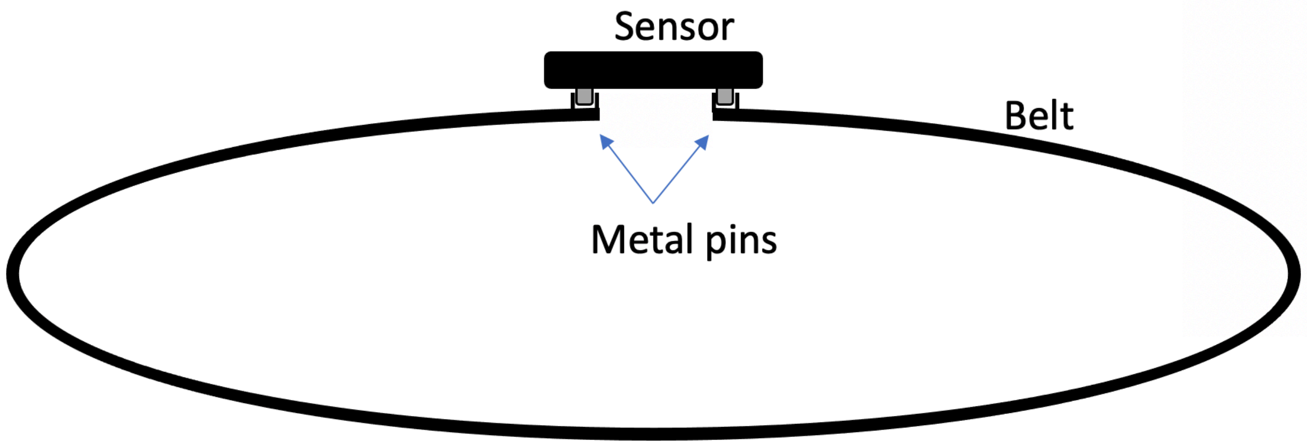
[1] Cosmed. Advanced six minute walk test with ventilation measurement. https://commons.wikimedia.org/wiki/File:Advanced_Six_Minute_Walk_Test_(6MWT).jpg, 2010. [Cropped from original; used under Creative Commons Attribution-Share Alike 3.0 Unported; accessed April 27, 2021].

# How to measure breathing?


Respiratory inductive plethysmography (RIP)



# How to measure breathing?




# Research objective

- Can we use breathing to estimate physical effort?
- Can we use RIP signals to estimate power output?

# How to estimate power output?

INPUT

Respiratory inductive plethysmography (RIP)

↓

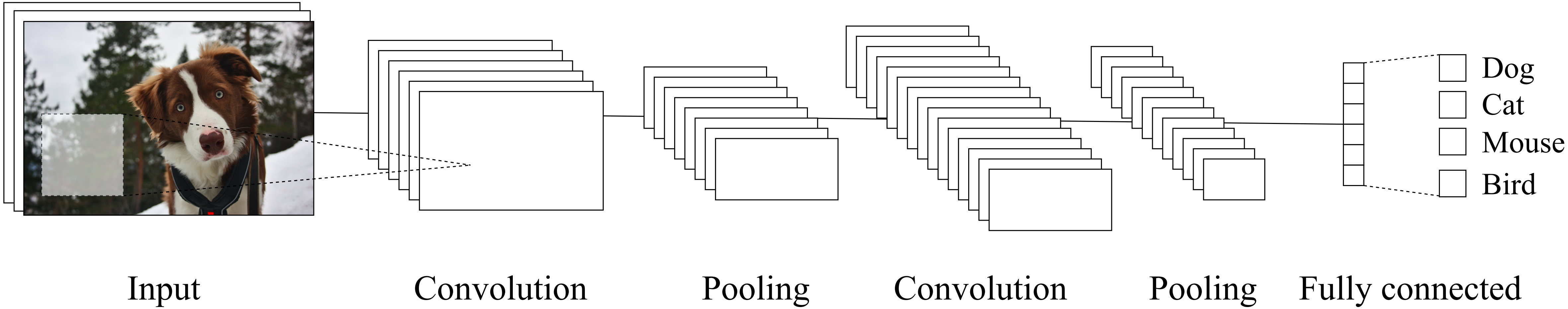
OUTPUT

Power output

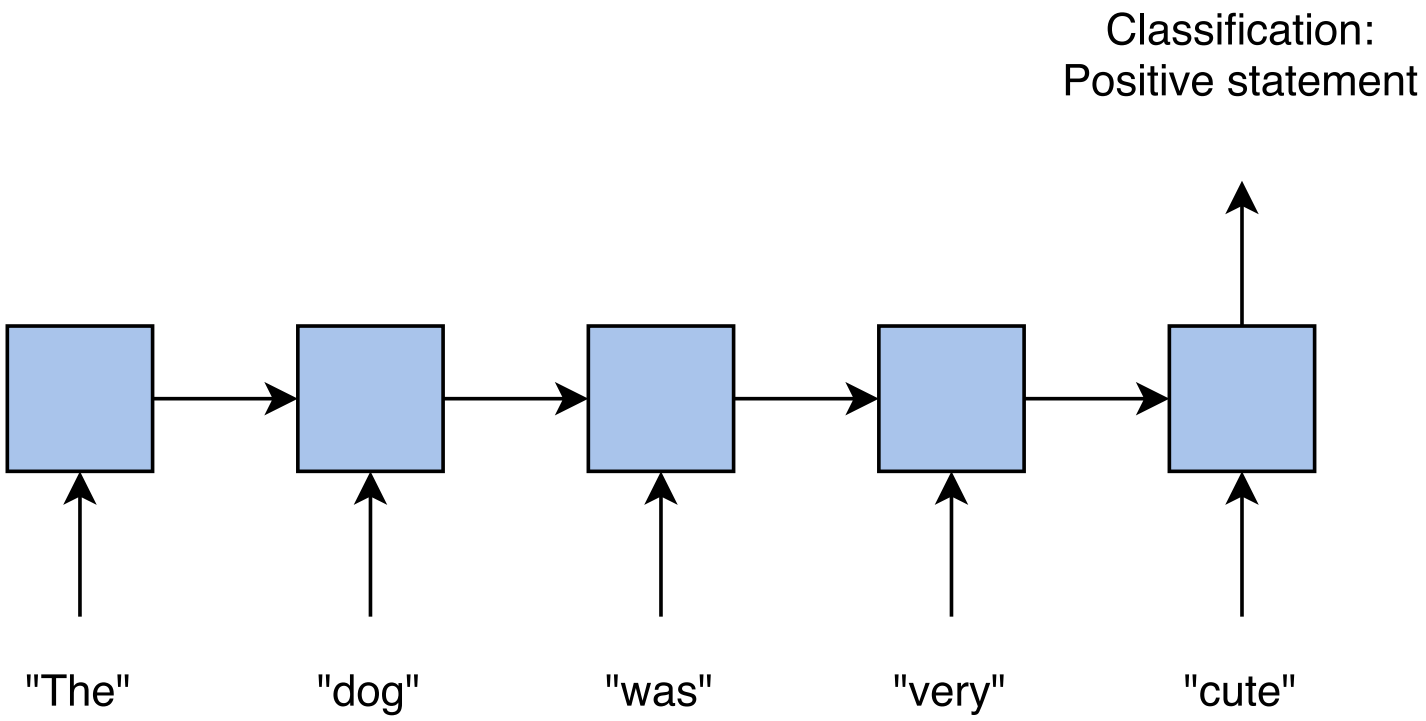
# How to estimate power output?

- Predictive models: Neural neworks
  - Dense neural networks (DNNs)
  - Convolutional neural networks (CNNs)
  - Long short-term memory (LSTM) networks

# CNNs


Dog
Cat
Mouse
Bird
Input
Convolution
Pooling
Convolution
Pooling
Fully connected

# LSTM networks



# Methods

Data acquisition

Preprocessing

Building predictive models

# Data acquisition

**Cycling as activity form**

**N-of-1 study**

**Four sensors**

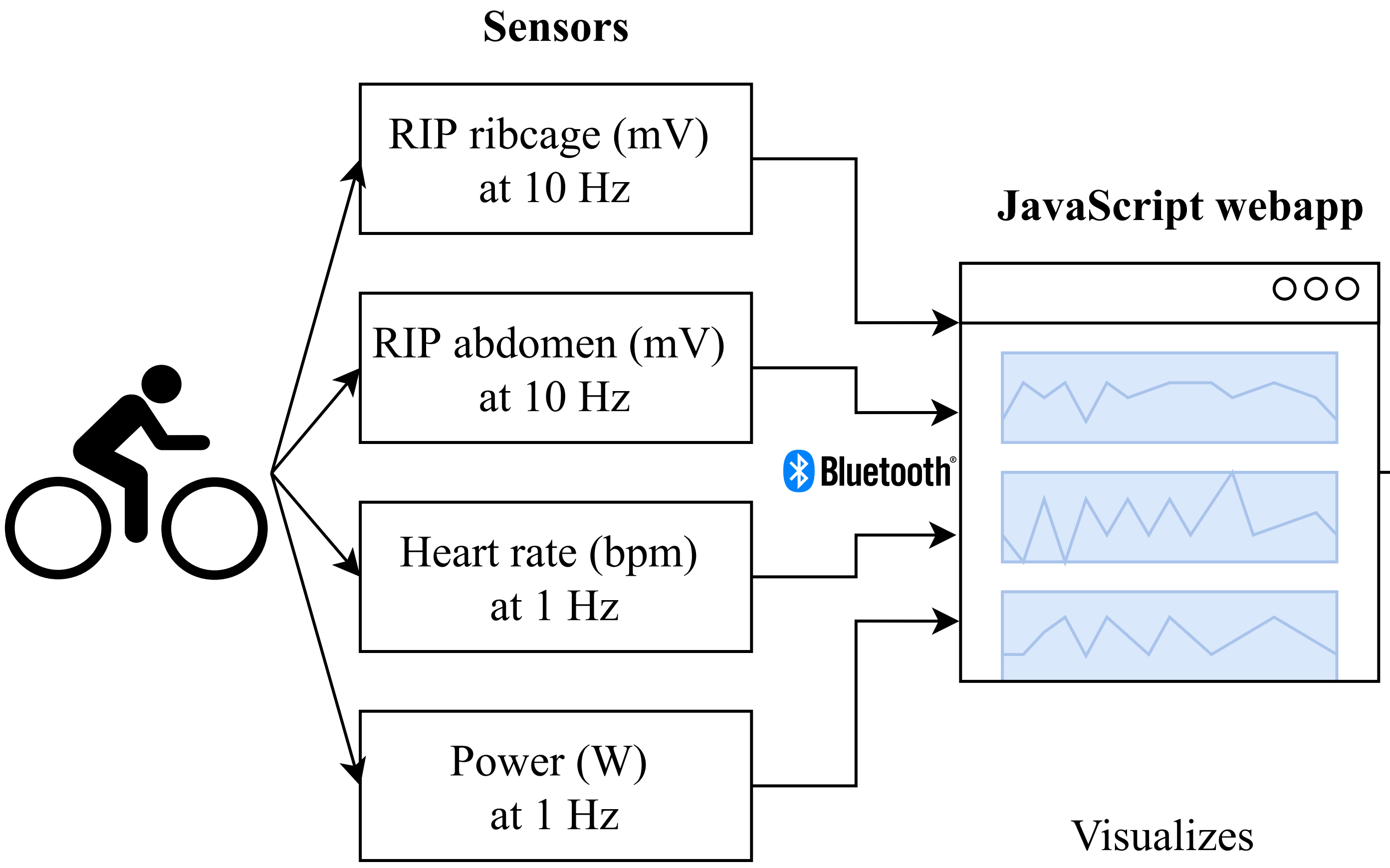
RIP from rib cage

RIP from abdomen

Heart rate

Power output

# Data acquisition software



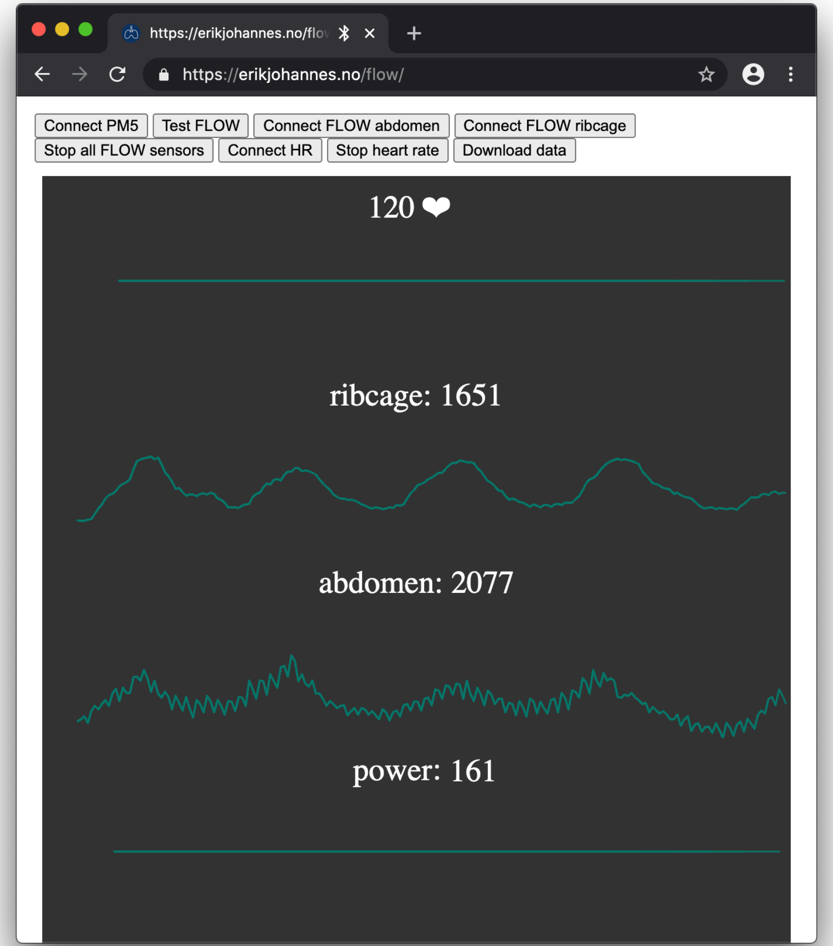

Visualizes real time data

**Array**

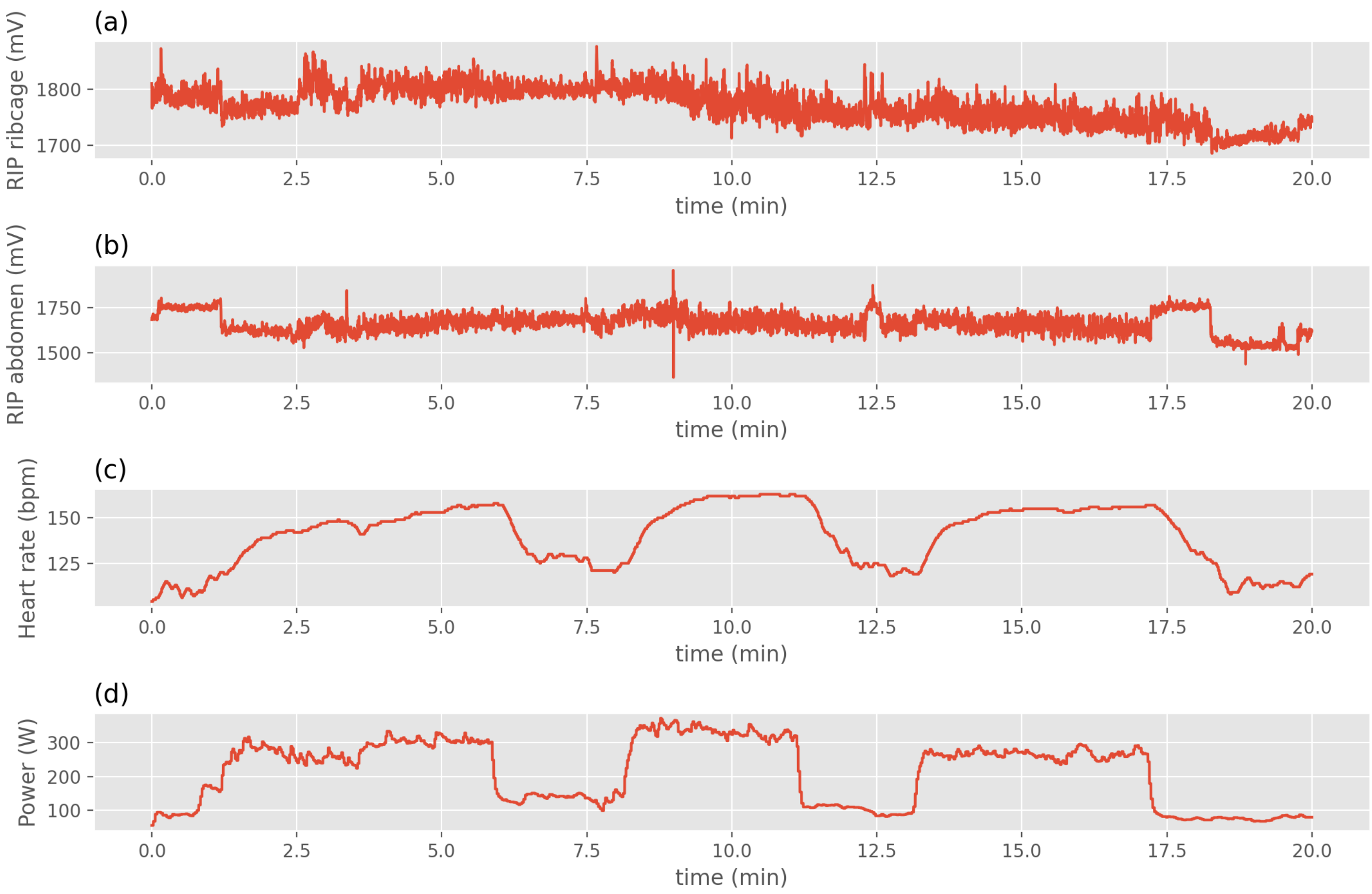
| Timestamp | Type | Value |
|---|---|---|
| 0 | RIP ribcage | 1831 |
| 0 | RIP abdomen | 1683 |
| 0 | Heart rate | 134 |
| 0 | Power | 241 |
| 1 | RIP abdomen | 1920 |
| ... | ... | ... |

Saves all recorded values continuously in array

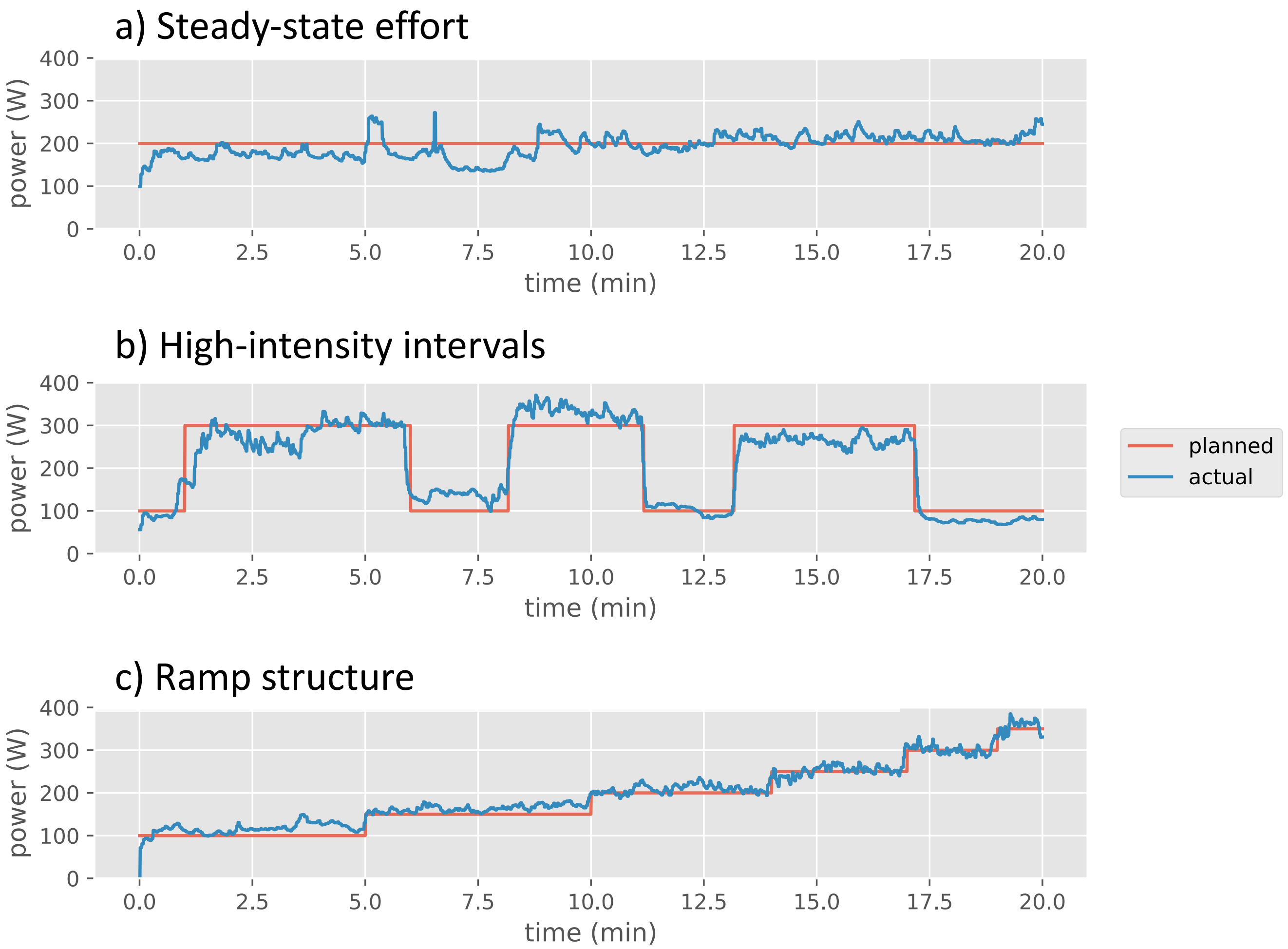
# Experimental setup

# Example of raw data

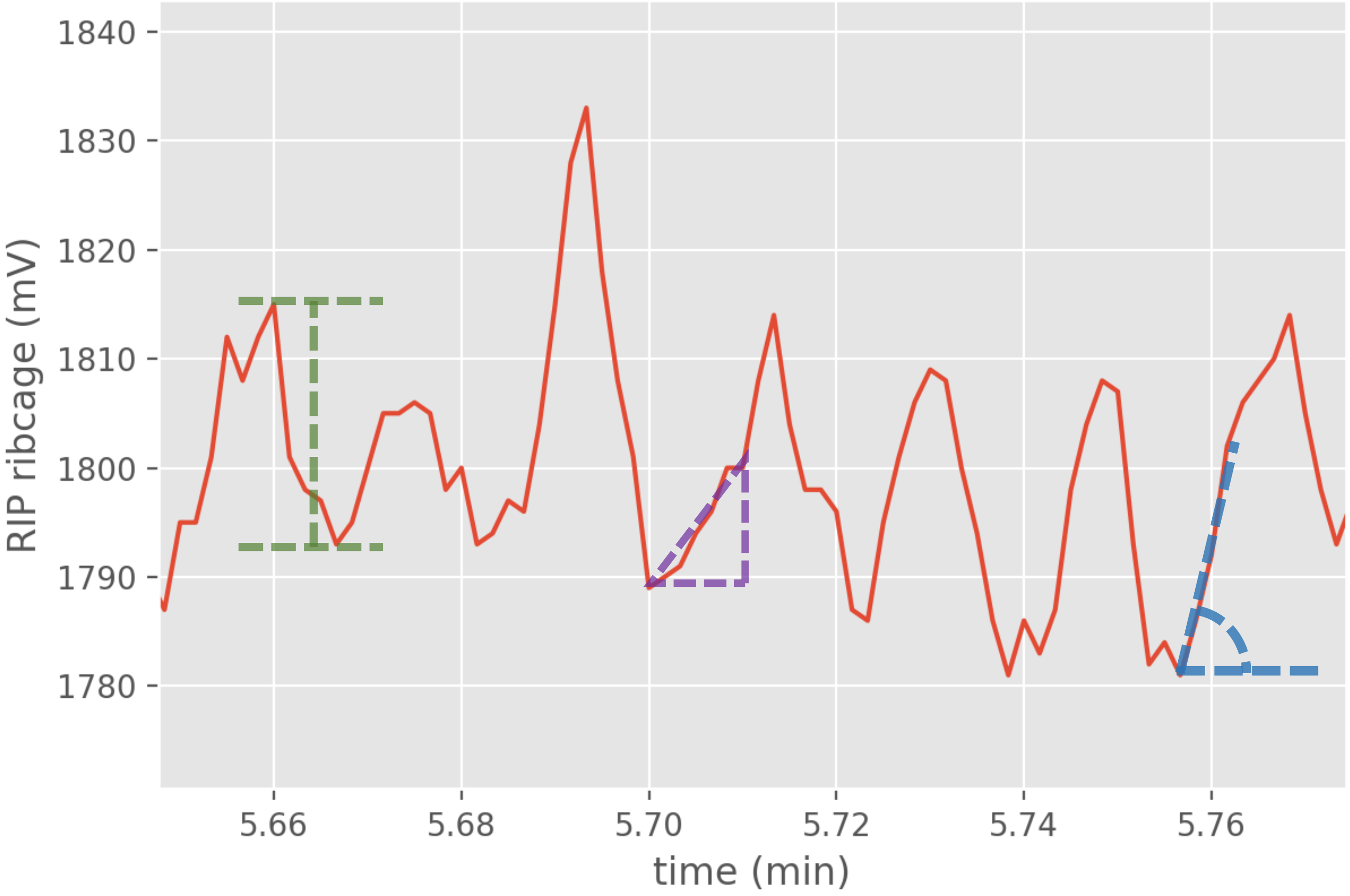


# Workout categories



# Preprocessing: Feature extraction

- RIP range
- RIP gradient
- RIP slope/angle
  - Sine/cosine encoding



# Neural network architectures

- DNN: 3 fully connected layers.
- CNN: 4 convolutional layers, 1 dropout layer, 1 fully connected layer.
- LSTM: 110 hidden units.

# Feature sets

| | RIP rib cage and abdomen | | | | | Heart rate | |
|---|---|---|---|---|---|---|---|
| Feature set no. | Raw | Range | Frequency | Gradient | Slope | Raw | Slope |
| 1 | x | | | | | | |
| 2 | x | | | | | x | |
| 3 | | x | | | | x | |
| 4 | | | x | | | x | |
| 5 | | | | x | x | x | |
| 6 | | | | x | x | x | x |
| 7 | | x | x | x | x | | |
| 8 | | x | x | x | x | x | |
| 9 | | | | x | x | | |
| 10 | | | | | x | | |
| 11 | | | | | | x | |

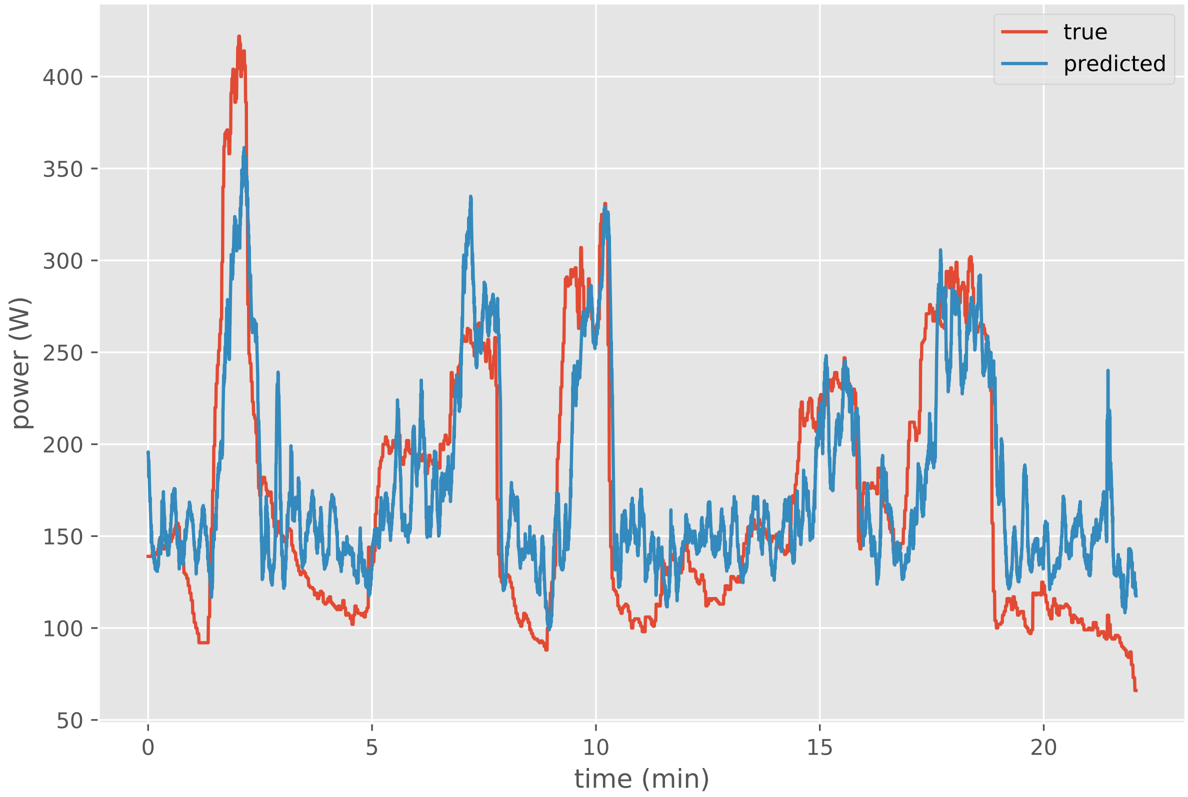
# Feature sets

| Set 3 | Set 6 | Set 10 | Set 11 |
|---|---|---|---|
| RIP range | RIP gradient+slope | RIP slope | HR |
| HR | HR | | |
| | HR slope | | |

# Results

| Type of network | Feature set | $R^2$-score | Mean absolute percentage error (MAPE) |
|---|---|---|---|
| DNN | 3 (combination of RIP and HR) | 0.36 | 0.23 |
| **CNN** | **6 (combination of RIP and HR)** | **0.56** | **0.20** |
| LSTM | 3 (combination of RIP and HR) | 0.35 | 0.22 |
| CNN | 10 (only RIP) | 0.50 | 0.24 |
| DNN | 11 (only HR) | 0.43 | 0.22 |

# Example of power output estimation: CNN



# Example of power output estimation: CNN

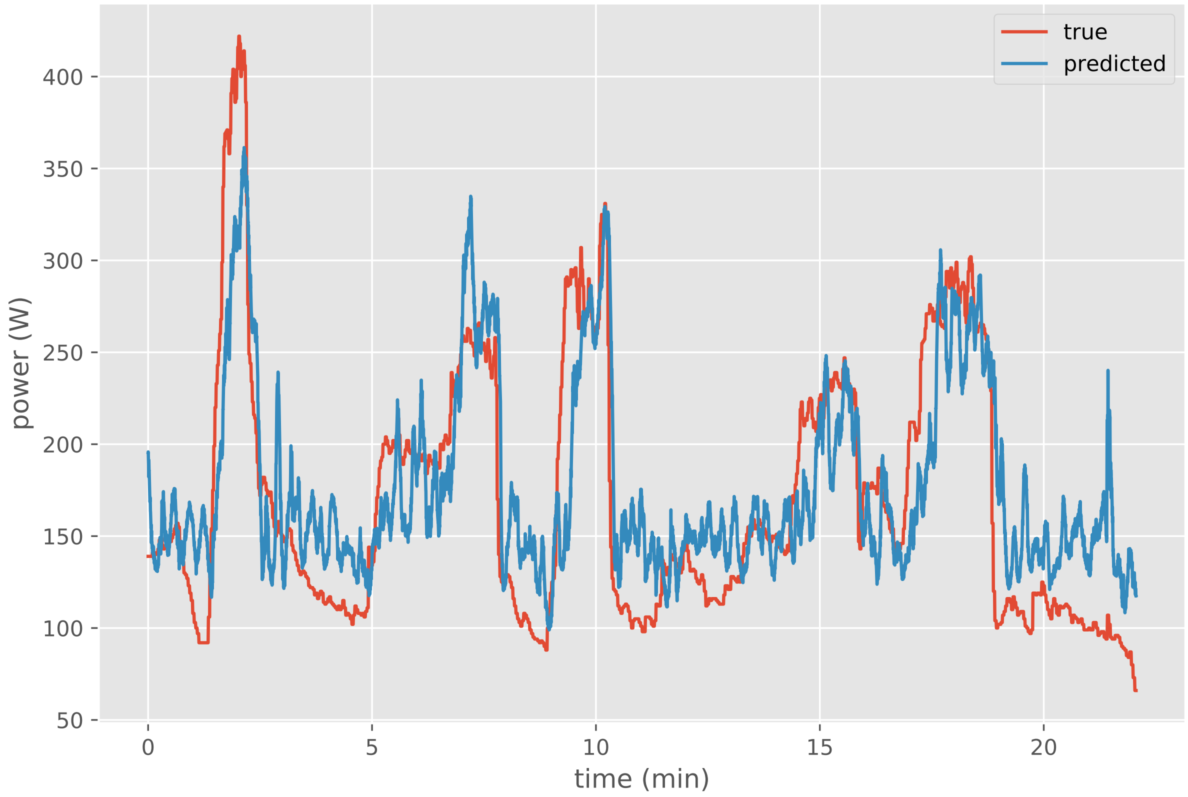



Figure 1: Using feature extraction

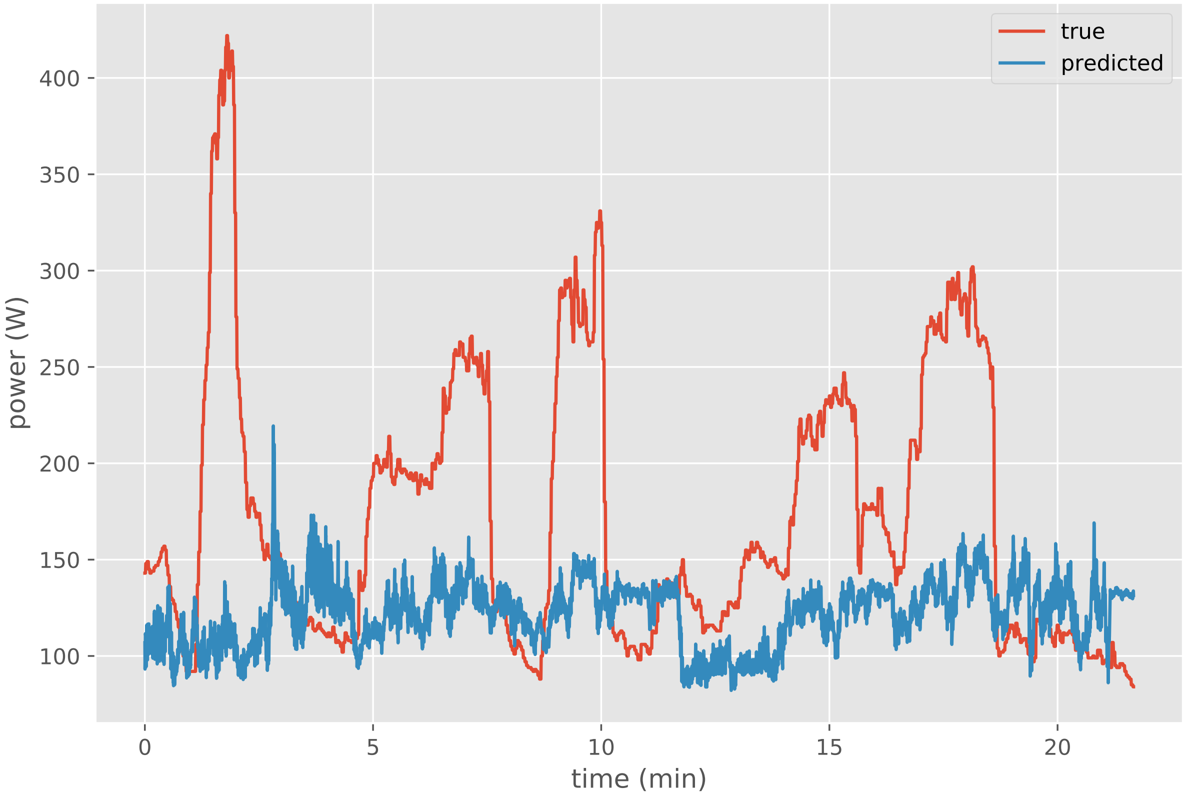



Figure 2: Using raw data

# Conclusion

- Promising results using deep learning to estimate power output from breathing
- Enabling a non-invasive, portable way of estimating physical effort
- Future work:
  - Easily extended to other applications
  - Larger, more diverse data set
- Source code is available at GitHub: https://github.com/ejhusom/DeepPower