Master thesis presentation – 17th June 2021

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

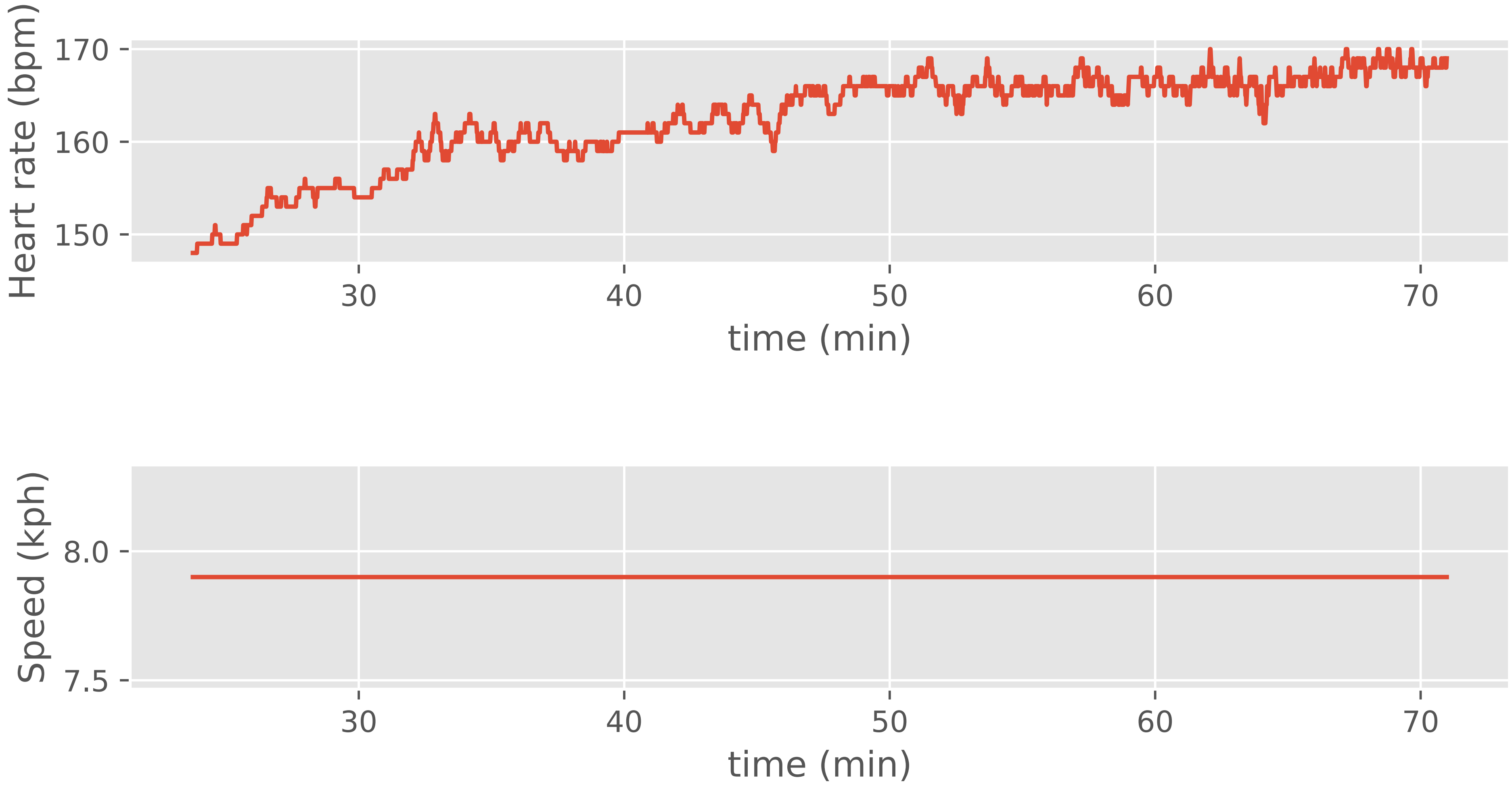
Activity trackers

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.

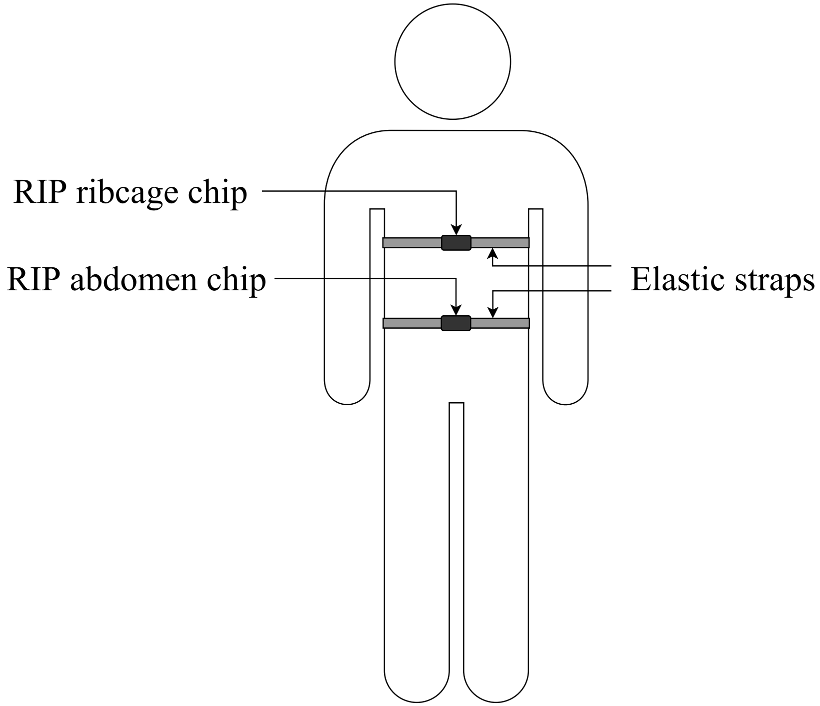
How to measure breathing?

Exercise spirometer[1]

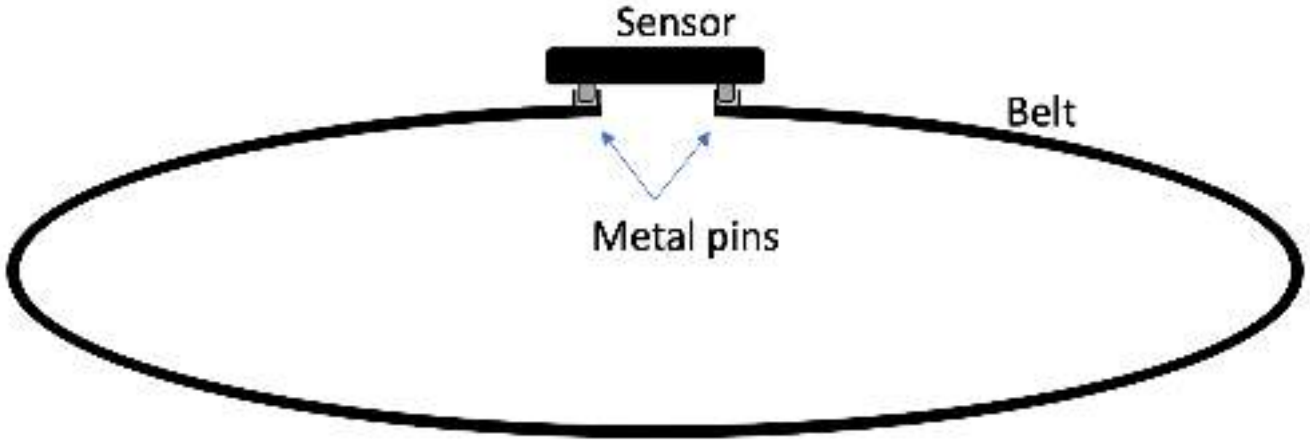
[1] Cosmed. Advanced six minute walk test with ventilation measurement. https://commons.wikimedia.org/wiki/File:Advanced_Six_Minute_Walk_Test_(6MWT).jpg, 2010. [Cropped from original; used under Creative Commons Attribution-Share Alike 3.0 Unported; accessed April 27, 2021].

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)

↓

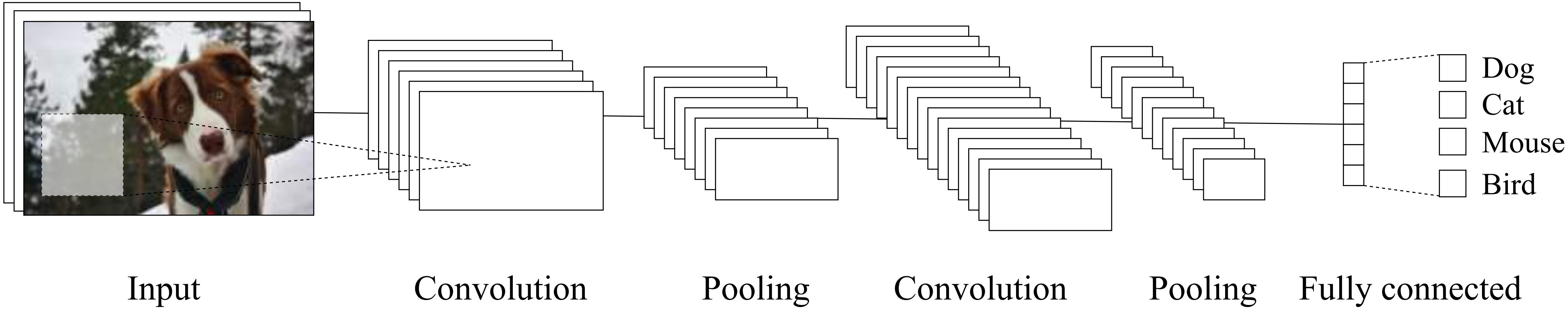
OUTPUT

Power output

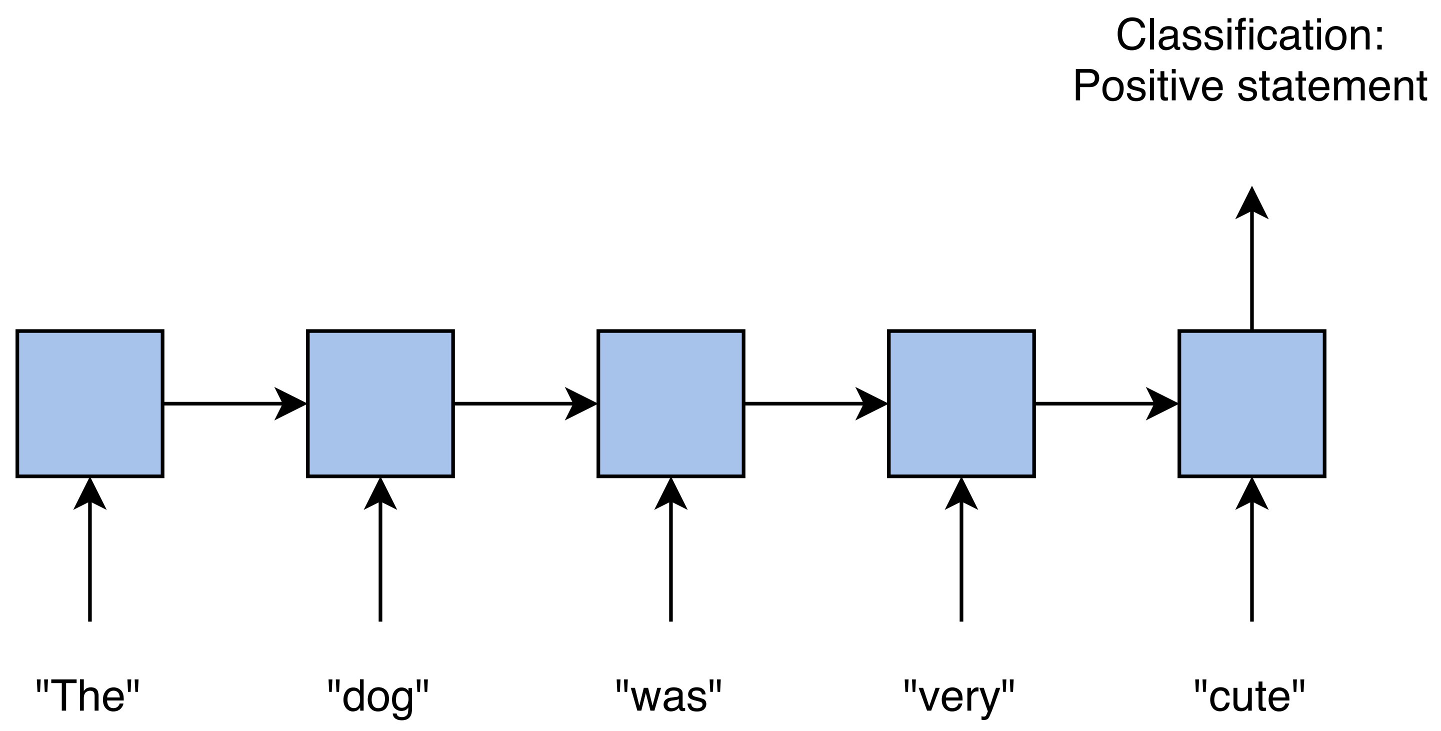
How to estimate power output?

- 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

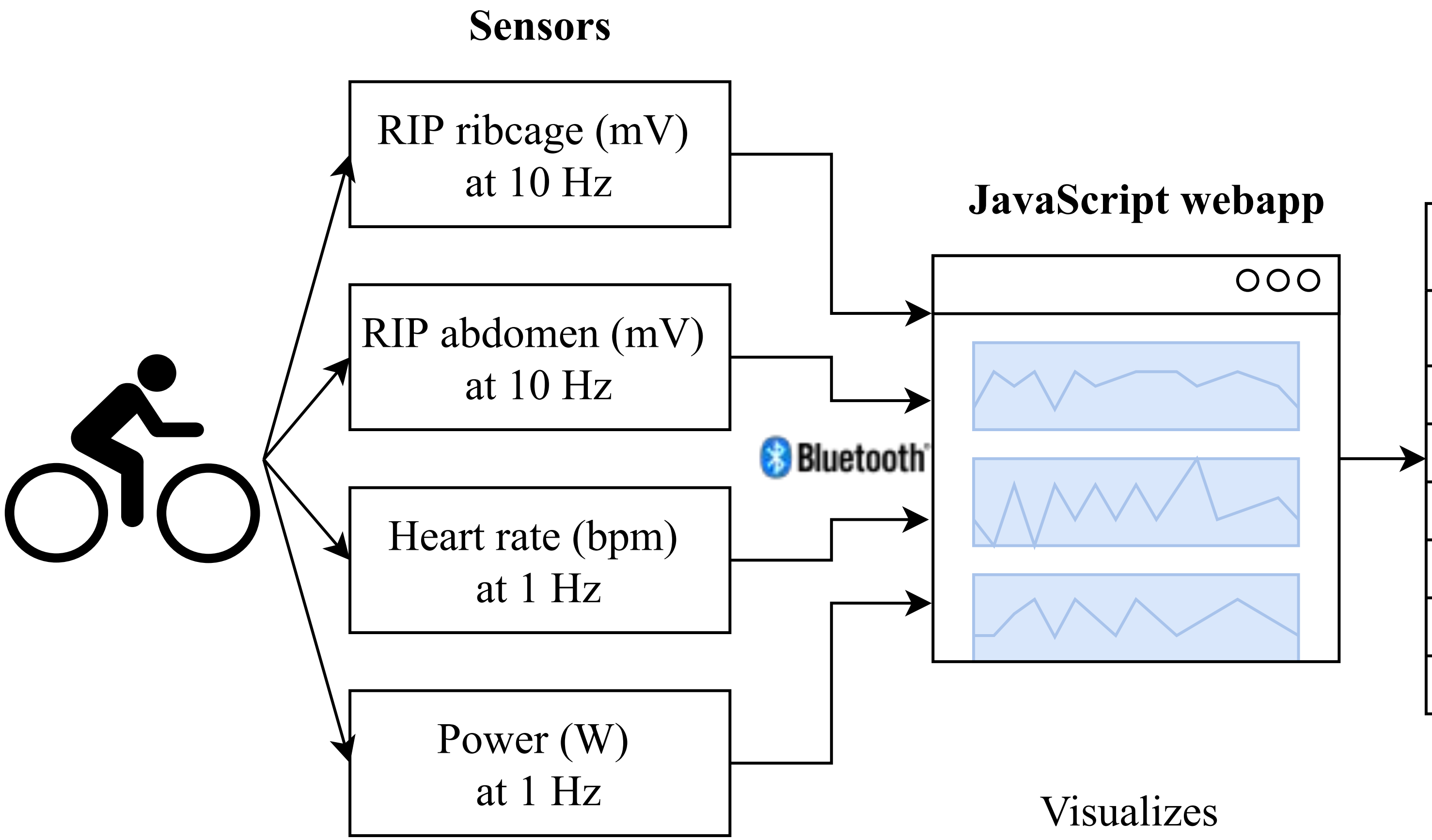
RIP from rib cage

RIP from abdomen

Heart rate

Power output

Data acquisition software



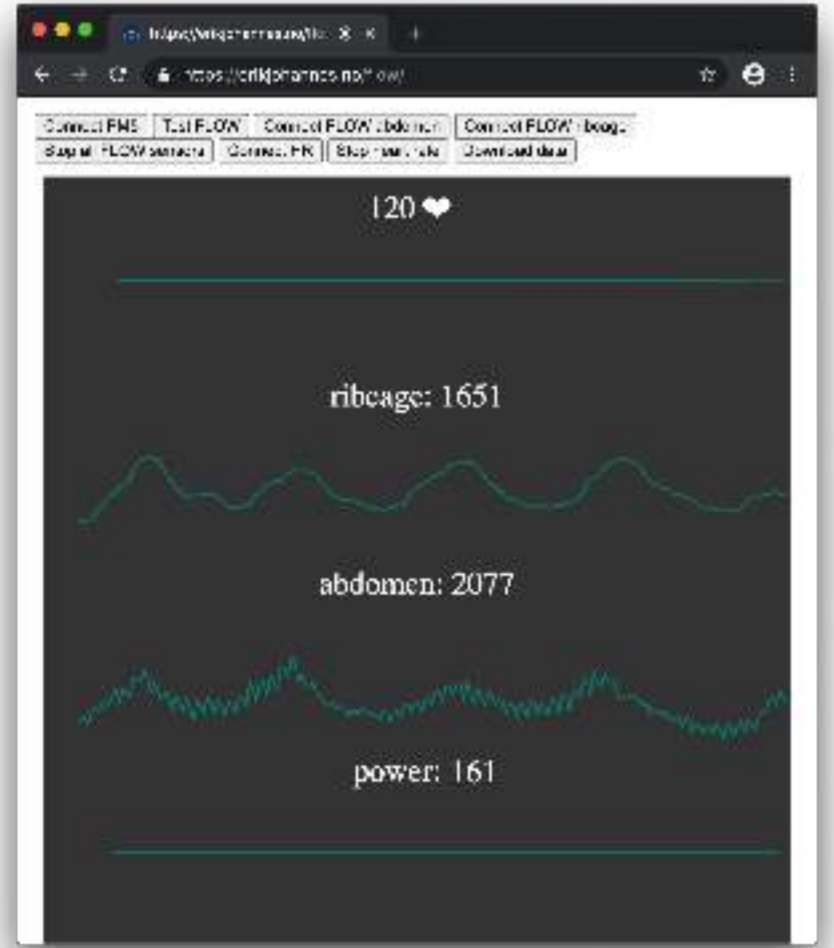
Visualizes
real time data

Array

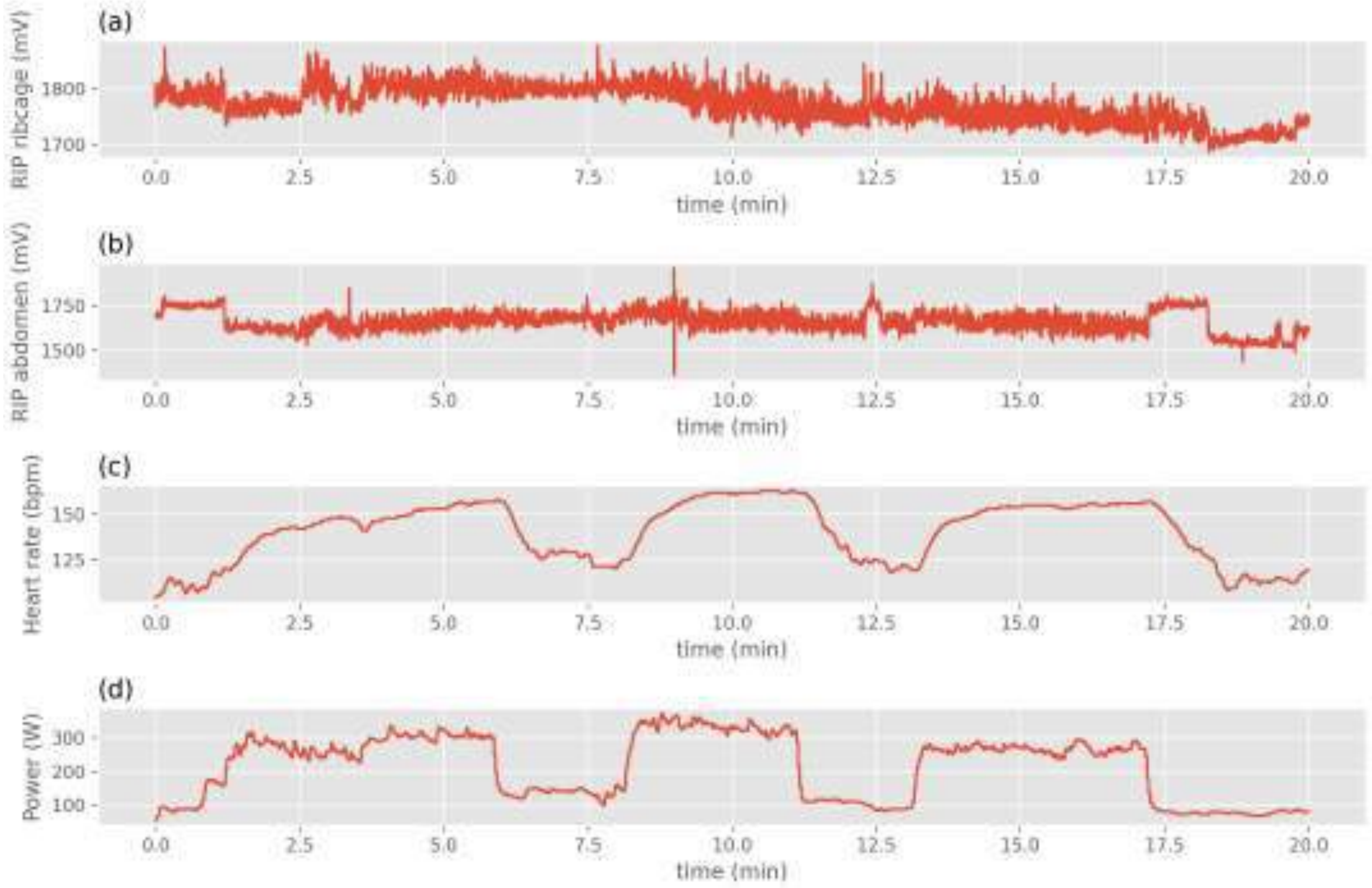
Timestamp	Type	Value
0	RIP ribcage	1831
0	RIP abdomen	1683
0	Heart rate	134
0	Power	241
1	RIP abdomen	1920
...	...	...

Saves all recorded values
continuously in array

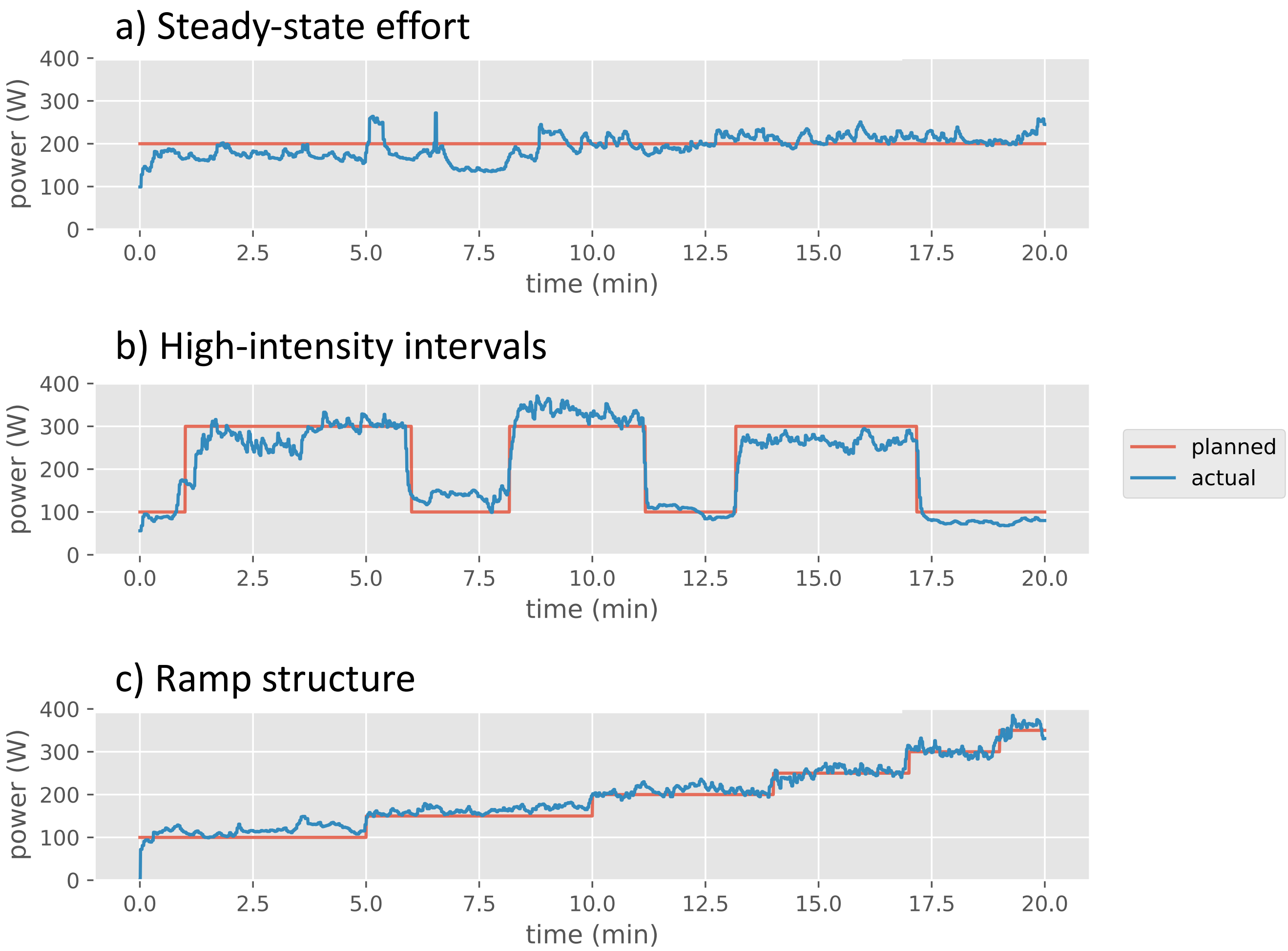
Experimental setup



Example of raw data

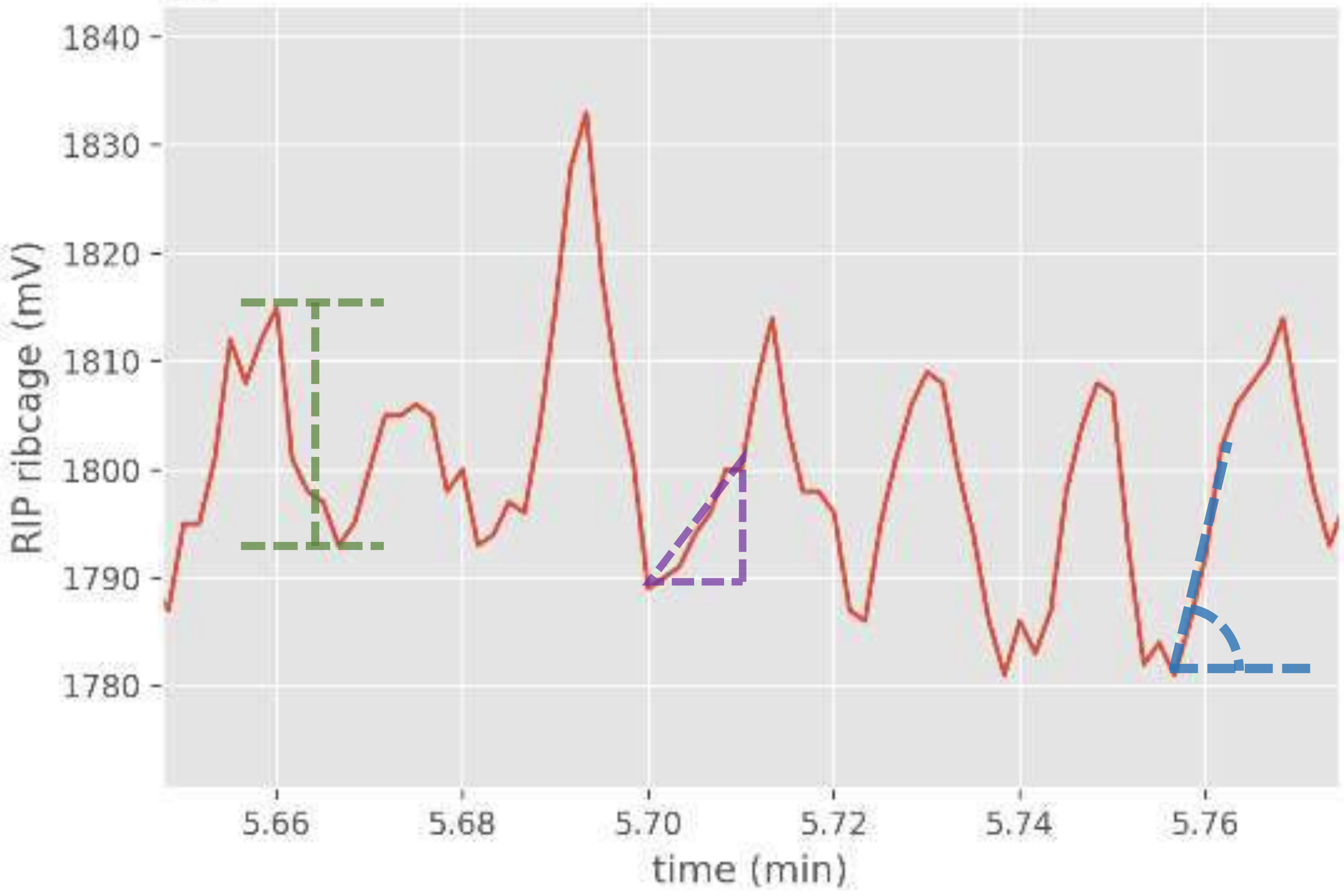


Workout categories



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	

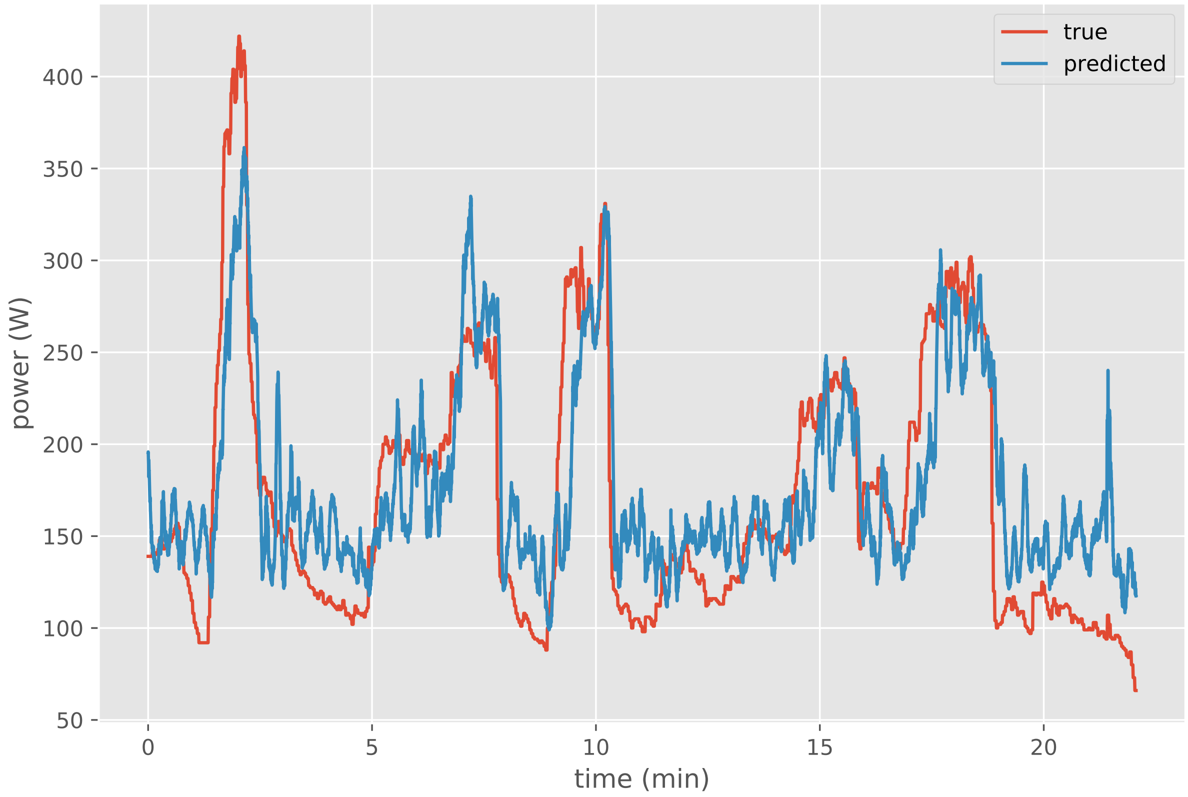
Feature sets

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

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

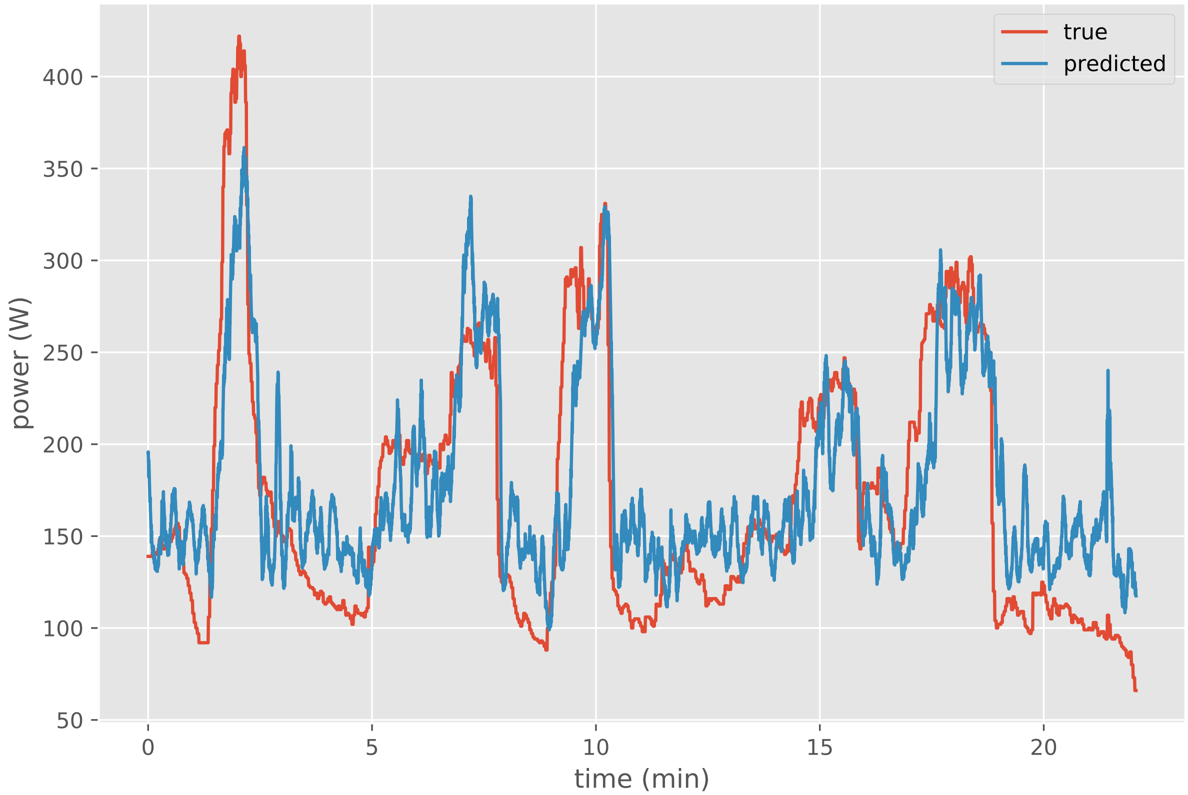


Figure 1: Using feature extraction

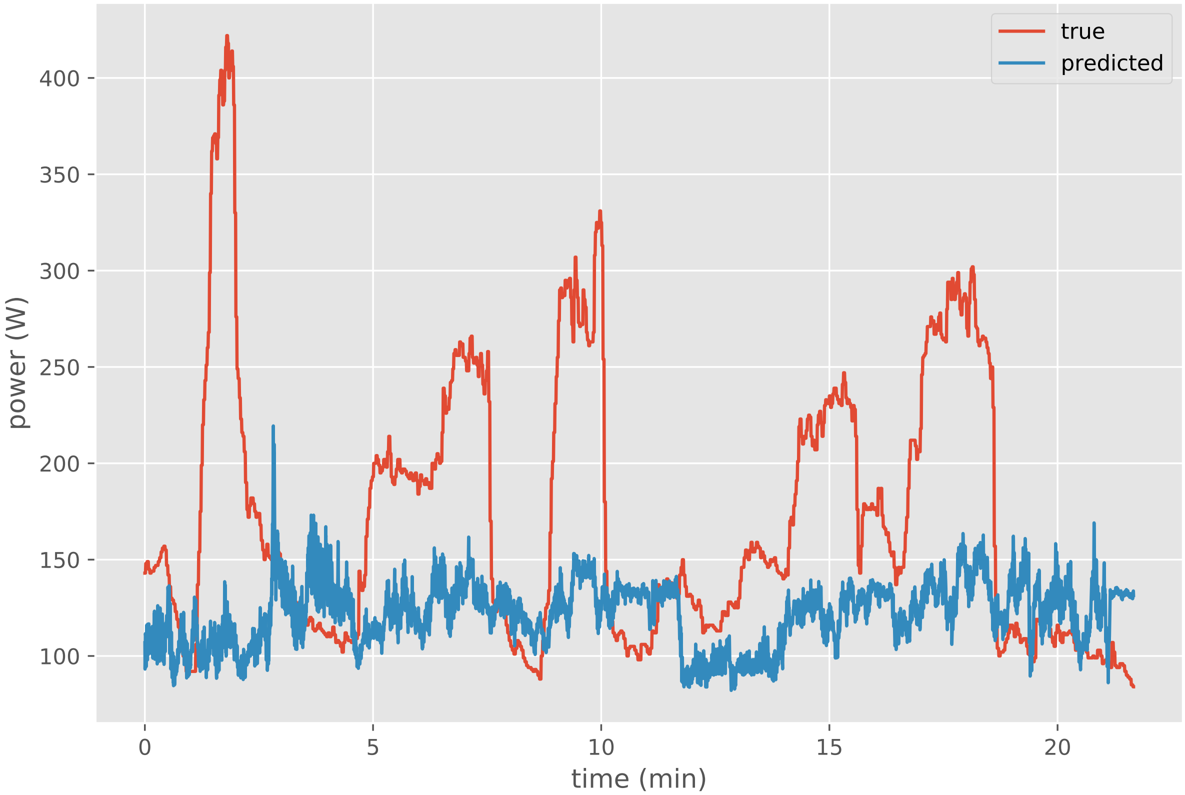


Figure 2: Using raw data

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