

# Estimating Power without Measuring it: a Machine Learning Approach

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## ① Introduction

Context

State-of-the-art

## ② Methods

## ③ Experiments

Materials

Hyper-parameters

## ④ Results

Performance

Zoom-in

Summary

Post-analysis

## ⑤ Future work

# Introduction

## Context

### Problematic

Estimate power from heterogeneous data sensor

### Saris PowerTap PowerCal

- ▶ Low-cost power-meter based on heart-rate
- ✓ Low-cost device
- ✗ Not suitable to track small power changes

### Strava

- ▶ Large amount of data
- ▶ Mathematical model based on mechanic

# Introduction

## State-of-the-art

### Mathematical model based on mechanics

$$P_{meca} = (0.5\rho S C_x V_a^2 + C_r m g \cos \alpha + m g \sin \alpha) V_d . \quad (1)$$

### Model parameters

Name	Symbol	Unit
Air density	$\rho$	$\text{kg m}^{-3}$
Frontal surface	$S$	$\text{m}^2$
Drag coefficient	$C_x$	NA
Air speed	$V_a$	$\text{m s}^{-1}$
Rolling coefficient	$C_r$	NA
Mass of rider and bike	$m$	kg
Gravitational constant	$g$	$\text{m s}^{-2}$
Slope	$\alpha$	rad
Rider speed	$V_d$	$\text{m s}^{-1}$

# Power estimation using machine learning

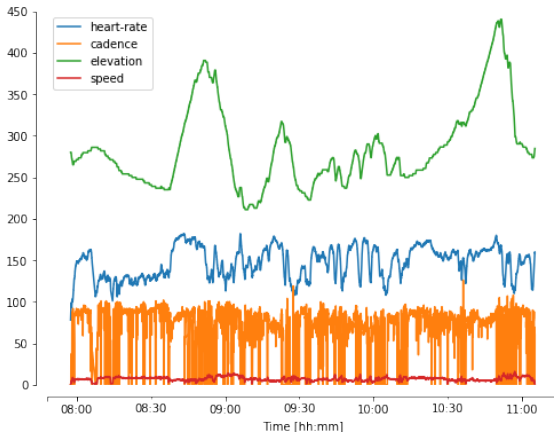


Figure: Original data

# Power estimation using machine learning

## Feature engineering

- ▶ Compute gradient for some data (acceleration, elevation, heart-rate)
- ▶ Compute derivative with different time periods (1 s — 5 s)
- ▶ Total of 48 features

## Regressor

- ▶ Gradient boosting machine

## Experiments Setup

### Data set

- ▶ 5 riders
- ▶ 4 power meters: Saris PowerTap, Rotor Power LT, Power2Max, and SRM
- ▶ 417 rides

### Model validation

- ▶ Group  $k$ -fold cross-validation with  $k = 3$

### Model evaluation

- ▶ Coefficient of determination  $R^2$
- ▶ Median absolute error (MAE)

# Experiments

## Model hyper-parameters

### Mathematical model

Parameter	Value
Rider weight	Specific
Bike weight	6.8 kg
Rolling coefficient $C_r$	0.0045
Atmospheric pressure	1013 hPa
$SC_x$	0.32 m <sup>2</sup>
Temperature	15 °C

### Machine learning model

Parameter	Value
Number of decision tree	200
Depth of each decision tree	8

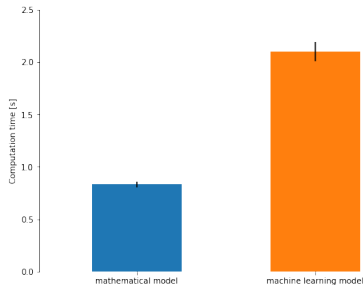


# Results

## Quantitative results

### $R^2$ and MAE scores

Metric	Math	ML
$R^2$	-0.55	0.76
MAE	61.09	21.95



**Figure:** Computation time for estimation around 1 million samples

# Results

## Zoom-in

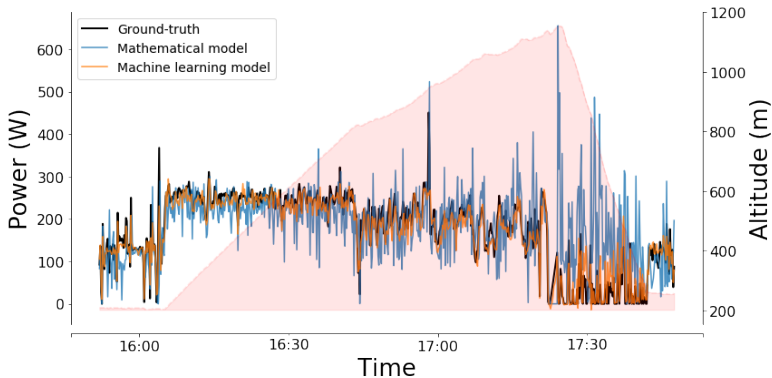


Figure: Power estimation for uphill and downhill

# Results

## Zoom-in

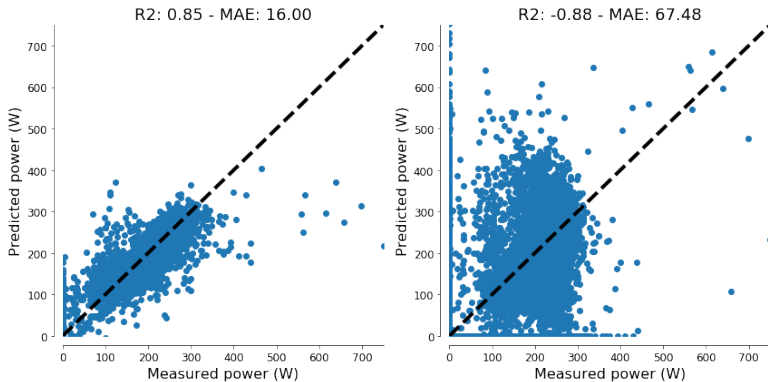


Figure: Left: Machine learning model — right: mathematical model

# Results

## Zoom-in

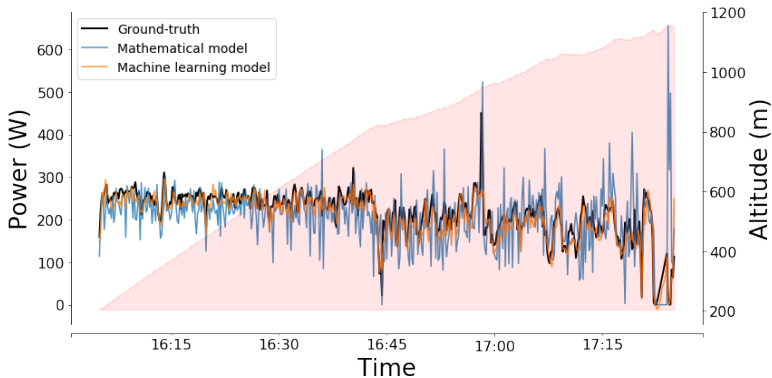


Figure: Power estimation for uphill

# Results

## Zoom-in

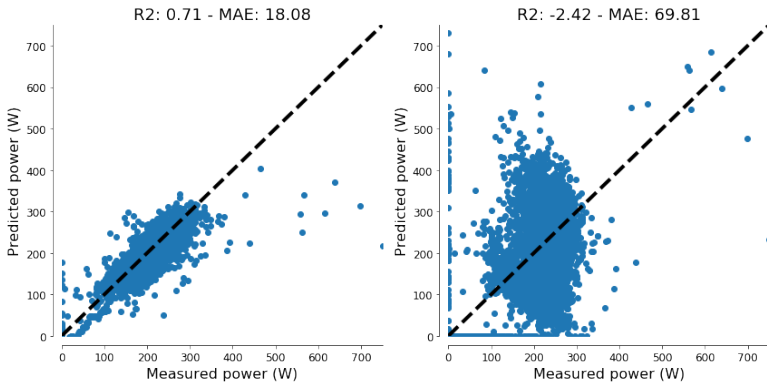


Figure: Left: Machine learning model — right: mathematical model

## Results Summary

### Mathematical model

- ✓ Fast prediction
- ✗ Too much unknown parameters
- ✗ Too much variation in the estimation

### Machine learning model

- ✓ Fast prediction
- ✓ Better prediction
- ✗ Difficulty to predict short power peak

# Results

## Analysis of the machine learning model

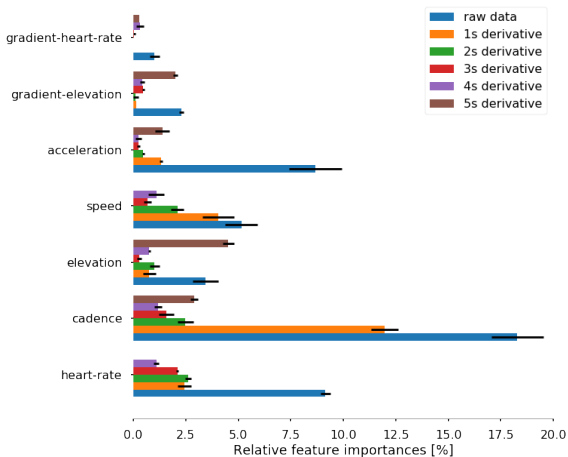


Figure: Feature importances of the different features used in the model

## Future work

### Extension of the current work

- ✓ Convolutional neural-network
- ✗ Larger data set

### Open-source initiative via GoldenCheetah

- ▶ OpenData collection
- ▶ Development of `scikit-sports`

### Purpose

- ✓ Reproducibility of analysis and methods
- ✓ Use data science tools to solve different problematic in cycling performance