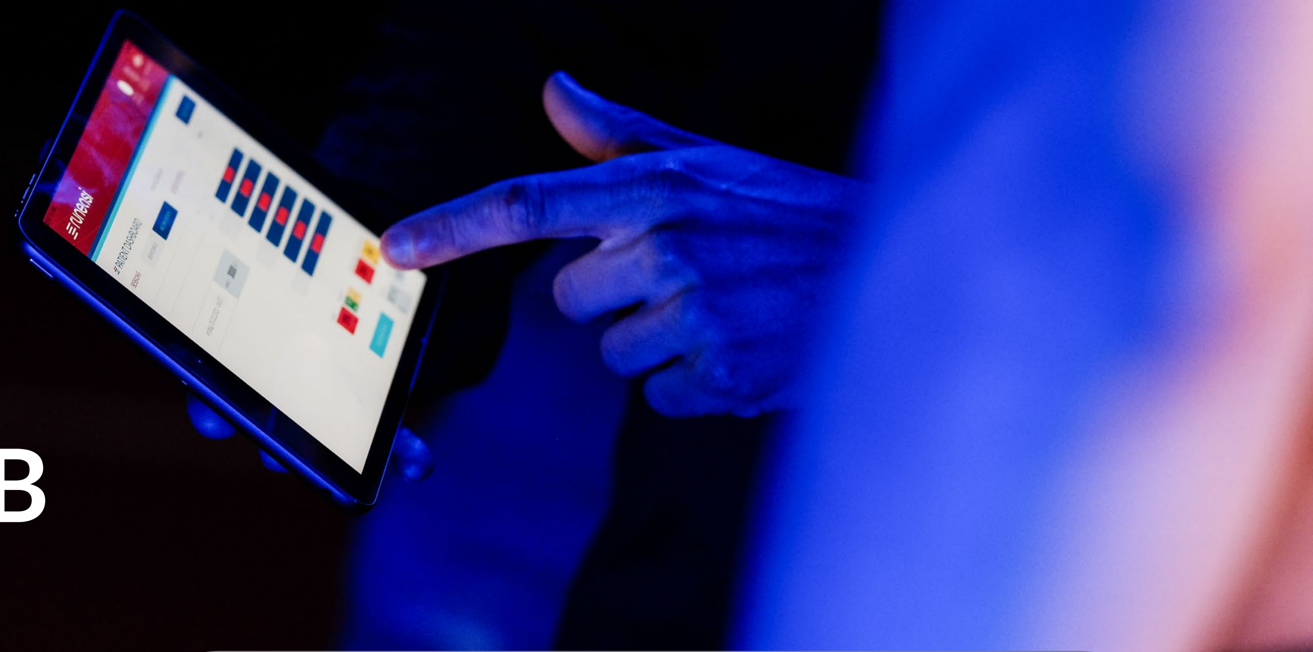
runeasi

THE ENHANCED FUTURE OF PREVENTION & REHAB



StartUs insights

Selected in global top 2 technology for **Performance Analytics**

SPORTS TECHNOLOGY AWARDS 2023

Celebrating 10 Years of Innovation

Shortlisted in worldwide top 6 technology for **Injury Prevention**

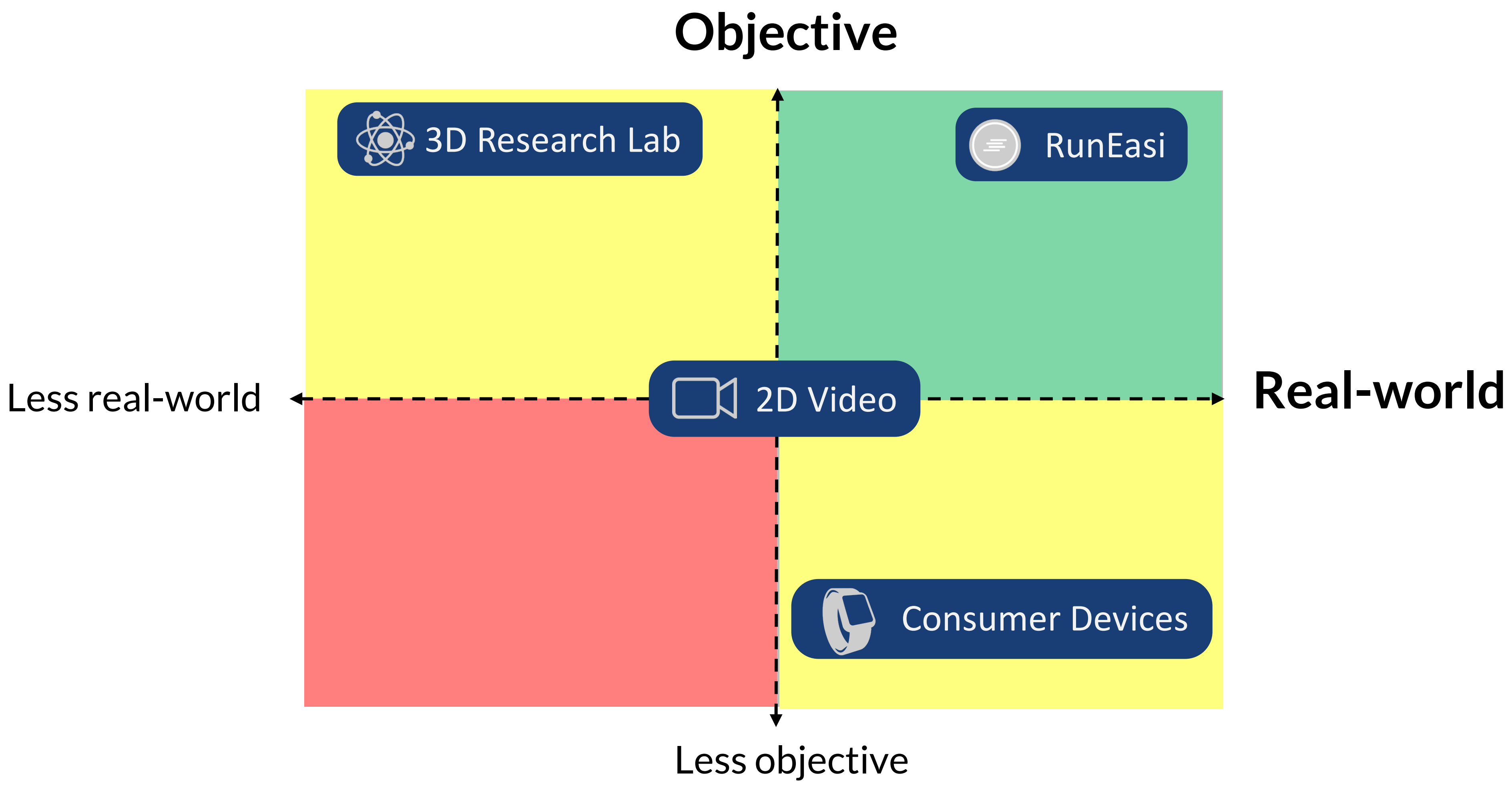
RUNEASI STORY: UNIVERSITY FOUNDED

KU LEUVEN

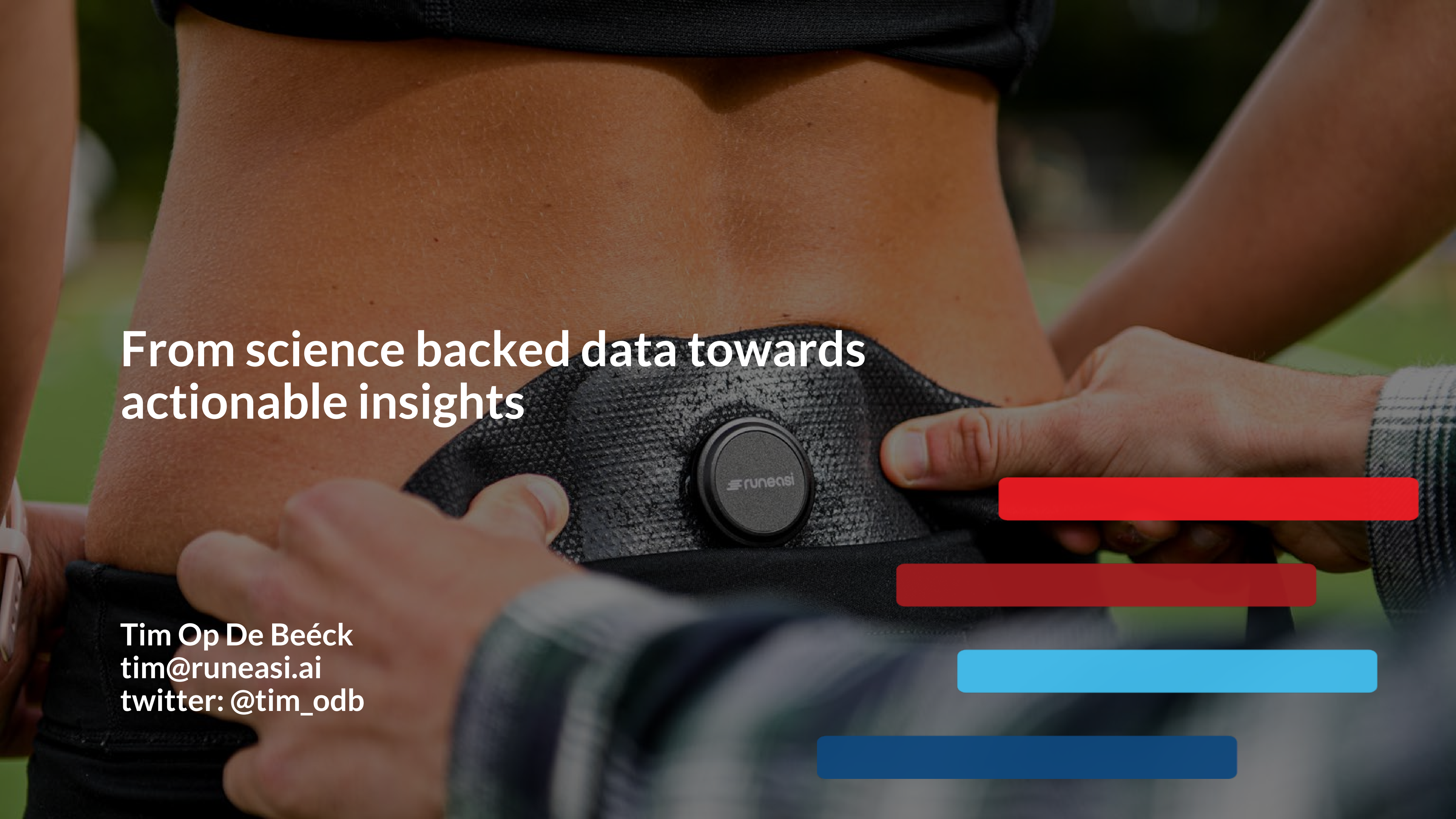
UNIVERSITEIT
iYUNIVESITHI
STELLENBOSCH
UNIVERSITY

runeasi

OBJECTIVE DATA TO REAL-WORLD: NO COMPROMISE



runeasi



From science backed data towards actionable insights

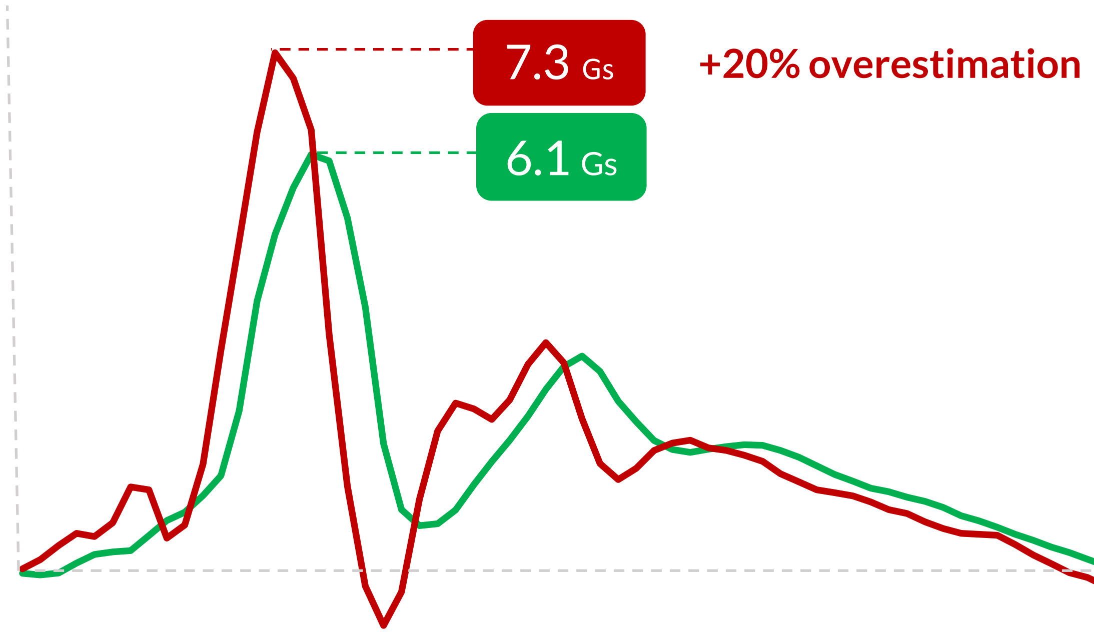
Tim Op De Beéck
tim@runeasi.ai
twitter: @tim_odb

QUALITY OF RAW DATA IS IMPORTANT

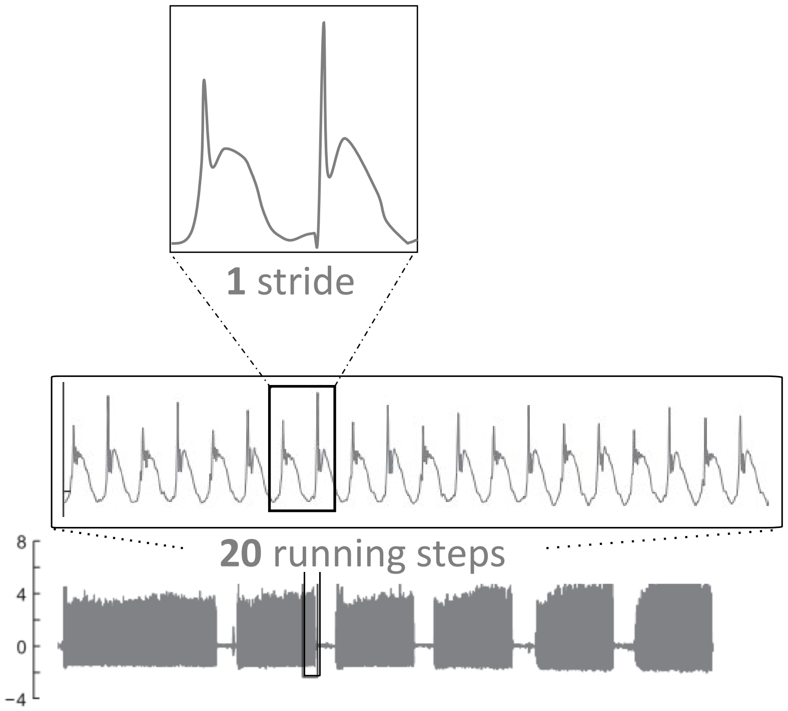
SKIN (BELT)

SHORTS

VERTICAL ACCELERATION (IMPACT)



RAW DATA

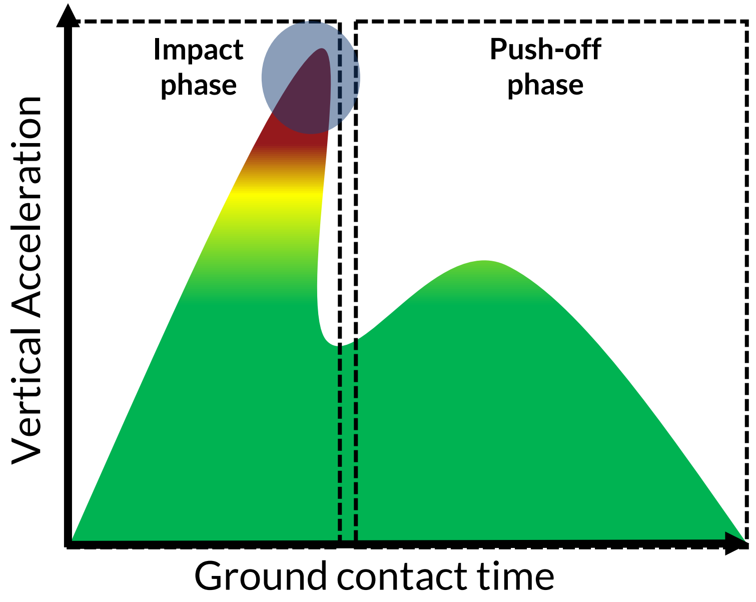


33 minutes of running = **1,98 M** data points

?

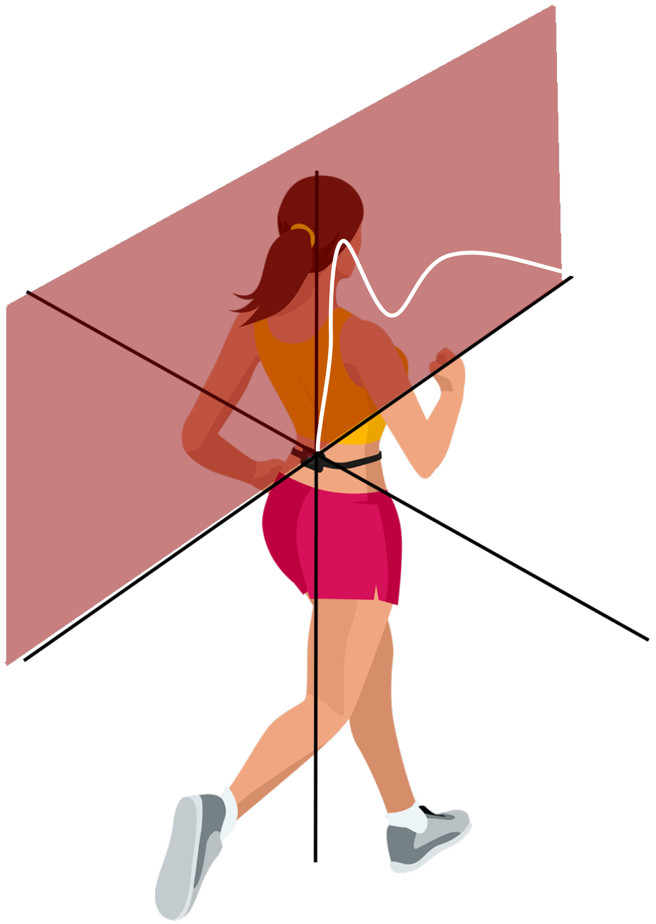
ACTIONABLE INSIGHTS

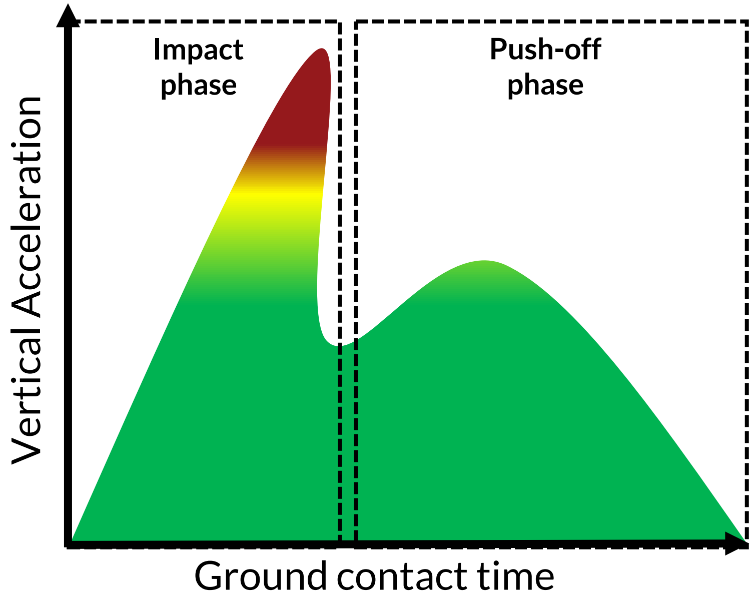
MEANINGFUL METRICS AID INTERPRETABLITY: 3 KEY METRICS



runeasi

#1 KEY METRIC:
IMPACT MAGNITUDE

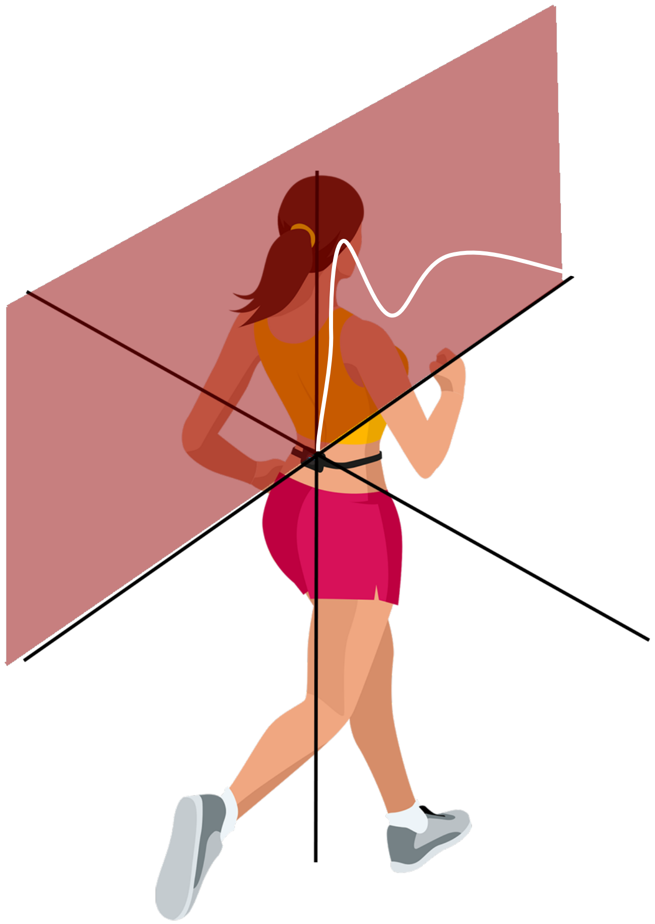


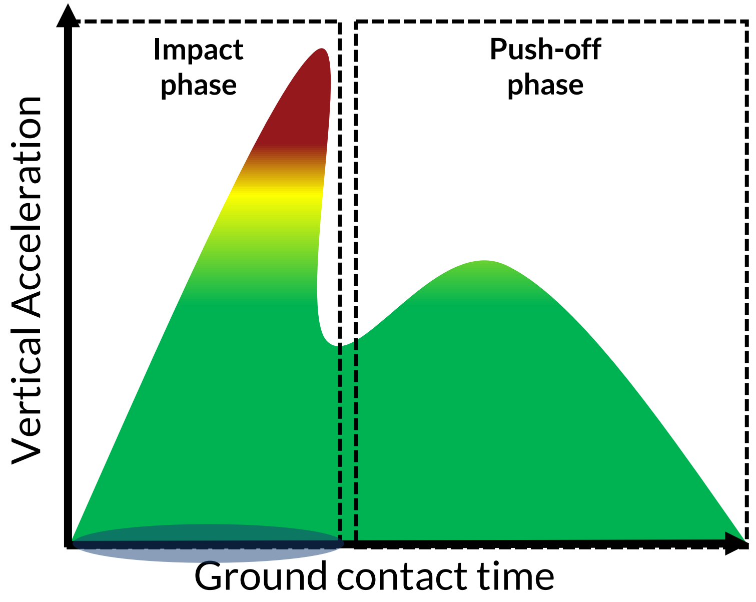


The **peak vertical acceleration** reaching the pelvis
Expressed in Gs (gravitational acceleration)

Linked To: Strength Capacity Of The Legs to absorb impacts

#2 KEY METRIC:
IMPACT DURATION



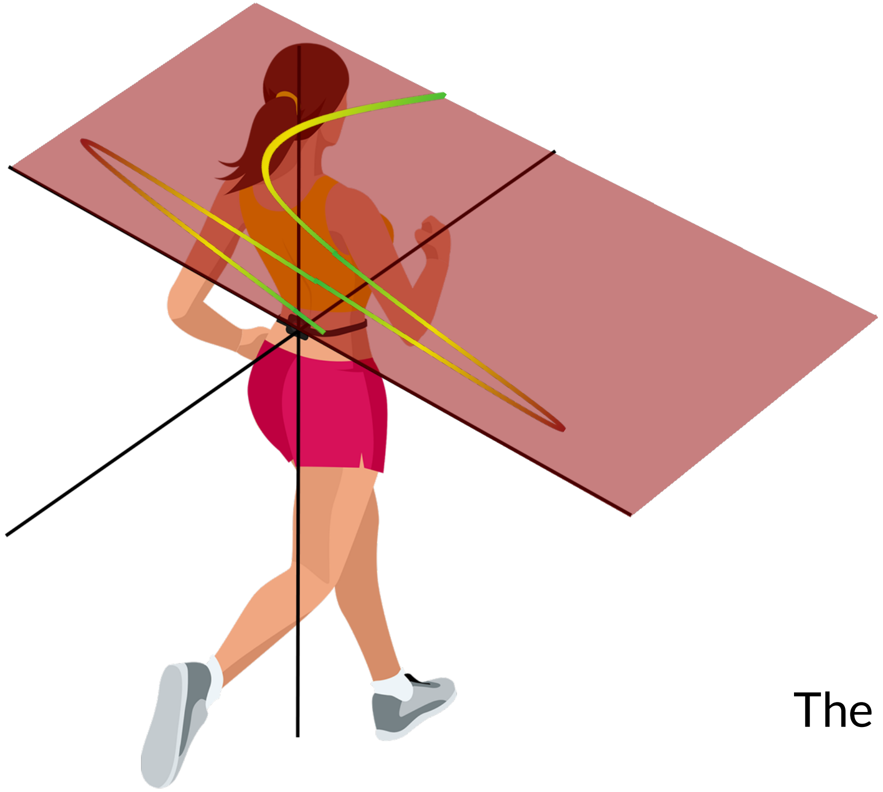


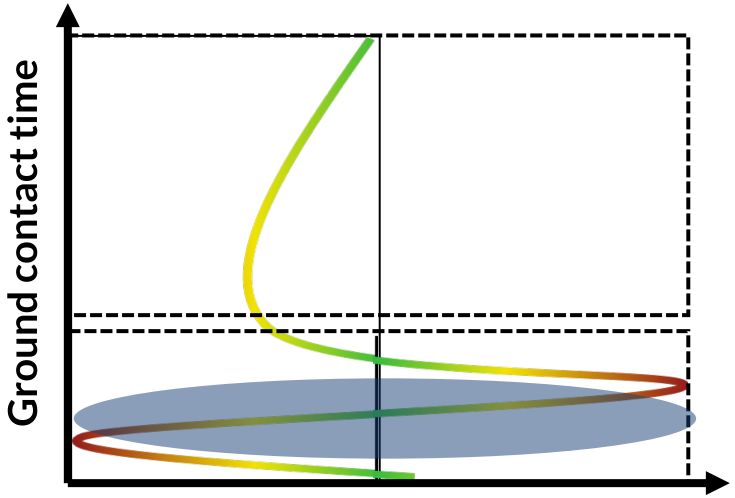
The **timing** between foot strike & reaching the impact peak

Linked To: Efficiency of kinetic chain of the legs to slow down impacts travelling through the legs

runeasi

#3 KEY METRIC:
DYNAMIC INSTABILITY





The **proportion** of **medio-lateral movement** during stance phase

Linked To: Ability of legs to stabilize hips while landing correlated with fatigue and running running efficiency

runeasi

SOLID METRICS CAN PROVIDE INSIGHTS

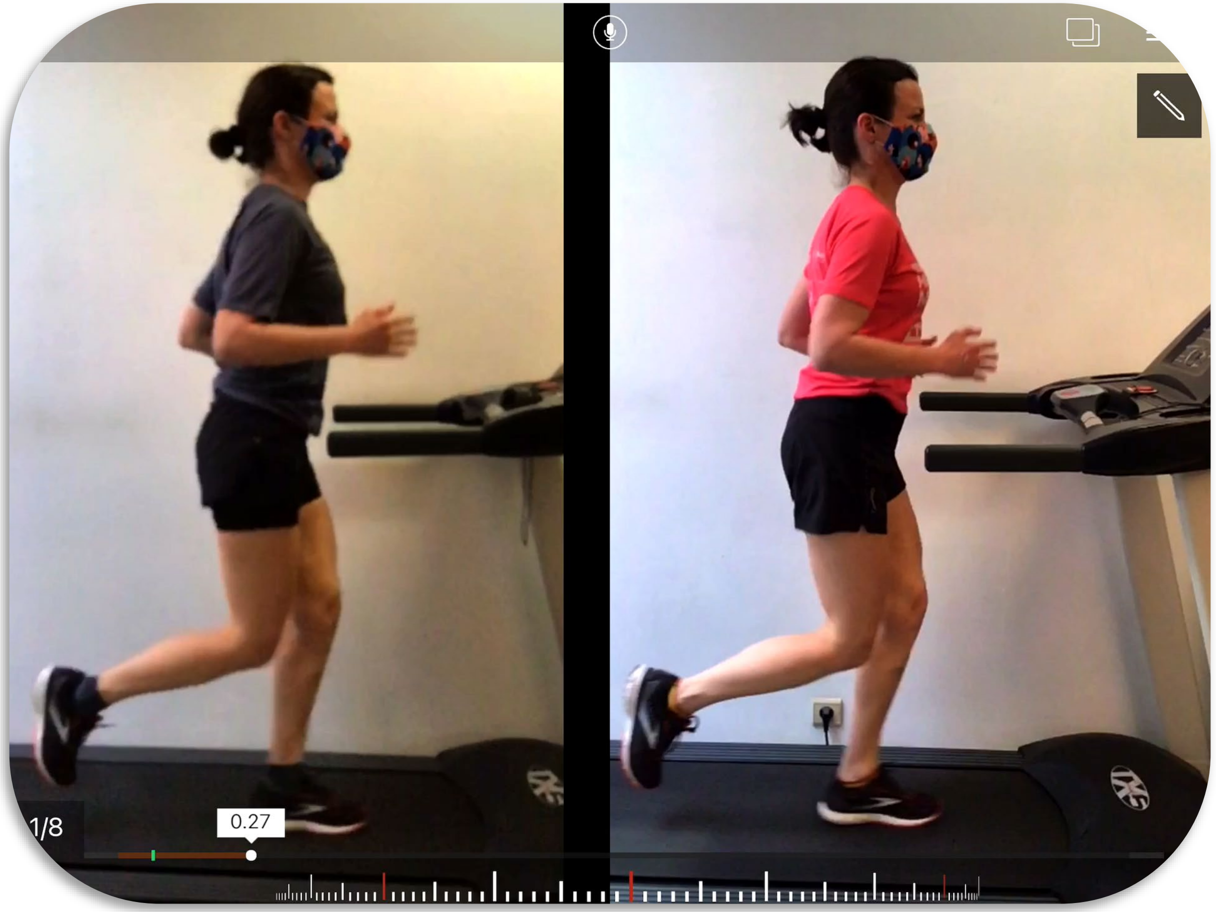
DID MY TRAINING PROGRAM IMPROVE THE SHOCK ABSORPTION OF MY CLIENT?

IMPACT

8,4

Gs

33%
HIGHER



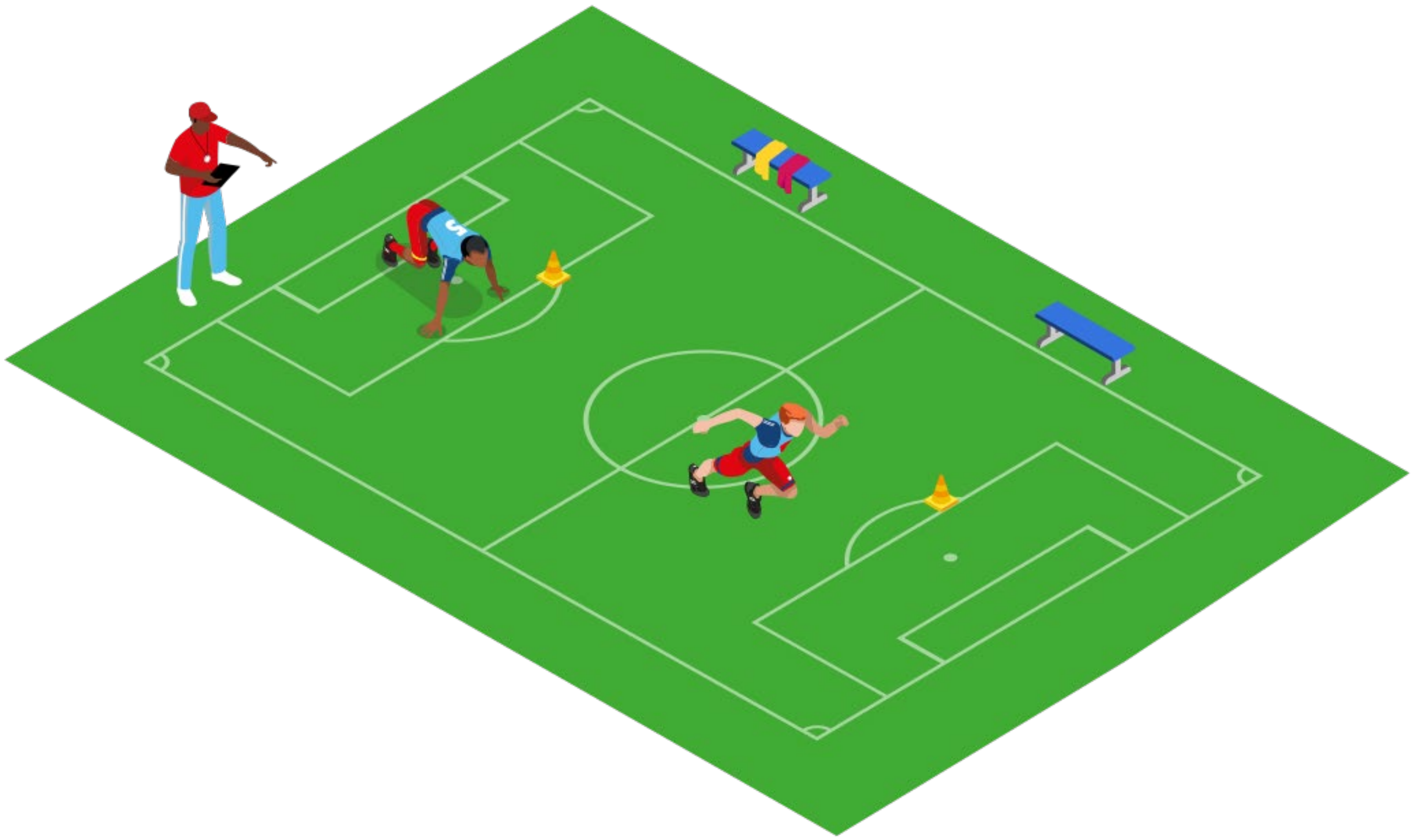
IMPACT

5,8

Gs

runeasi

IS MY PLAYER READY TO RETURN TO PLAY



Easy run

IMPACT

0,9%
right

Fast run

IMPACT

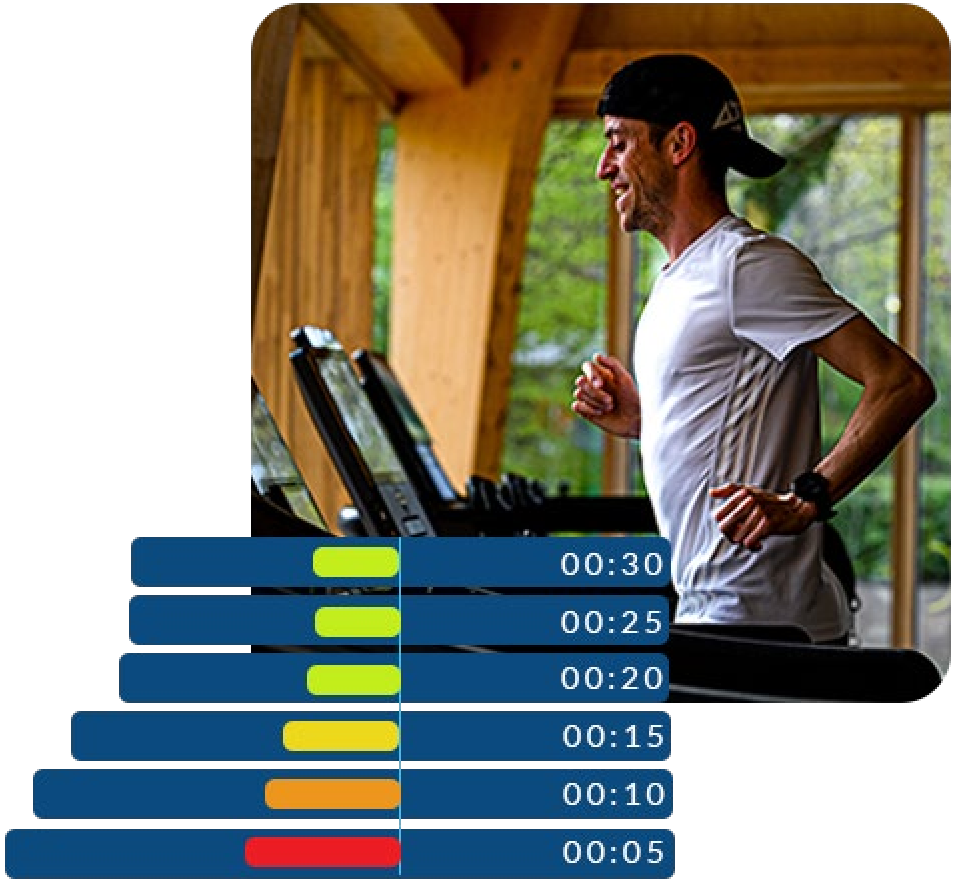
13,7%
right

At risk — Excellent

runeasi

PROBLEM SOLVED?

INDIVIDUAL RESPONSES OF CLIENTS MAKE INTERPRETATION OFTEN NON-TRIVIAL



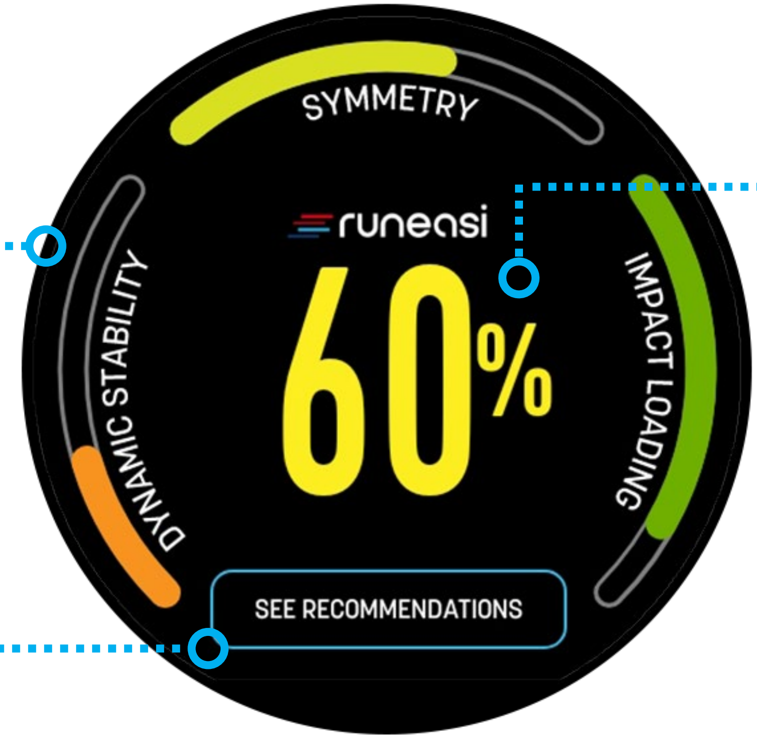
- Real-time feedback to experiment with different cues
- Test and re-test efficiently
- Colored benchmarks for absolute and relative values to speed up interpretation of the metrics

HOW TO INTERPRET MULTIPLE METRICS TOGETHER?

RUNNING QUALITY VISUALIZATION:
THE SCORE RUNNERS LOVE TO IMPROVE

WEAKEST LINK DETECTION

To know what to work on first with your runner

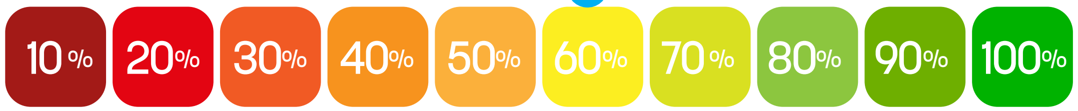


ONE GLOBAL SCORE

To help your runner's reach their fullest potential. Based on 3 main sub-components

INDIVIDUALIZED TRAINING RECOMMENDATIONS

To know how to utilize the data in re/prehab



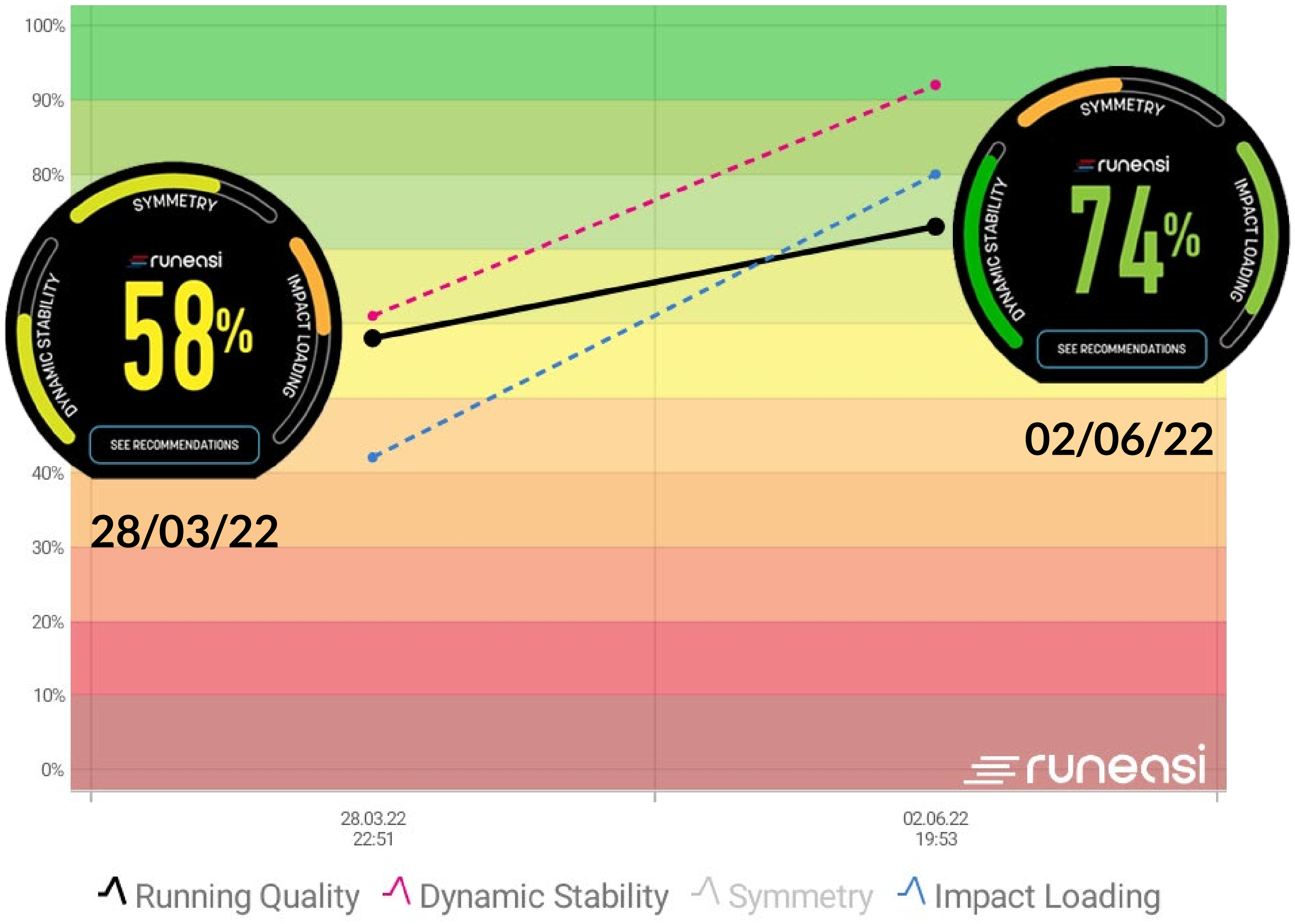
BENCHMARK DATA

To be data-informed based on healthy norms

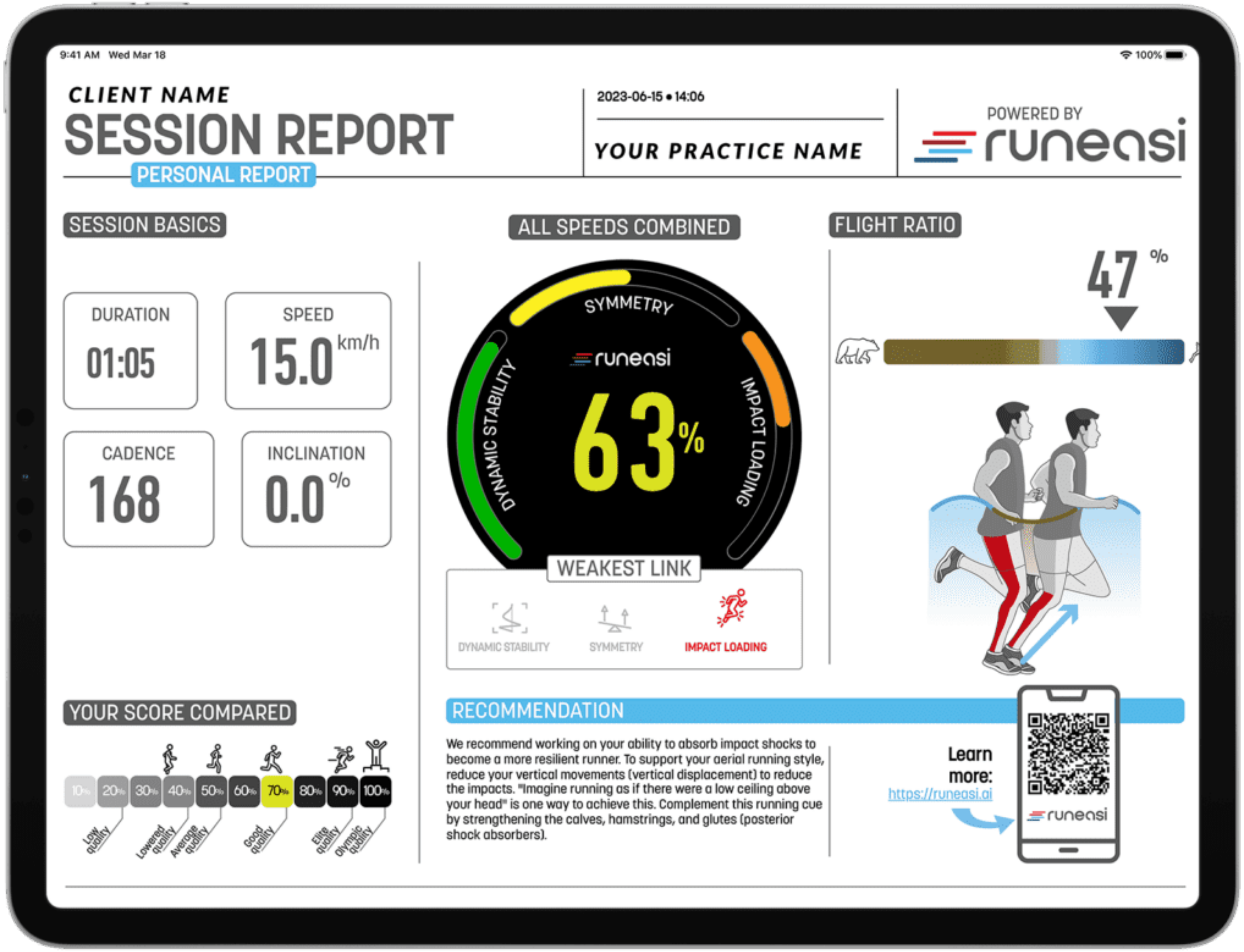
runeasi

PERSONALIZED EXERCISES CAN IMPROVE **RUNNING QUALITY**

Case of 2 months plyometrics & COD training

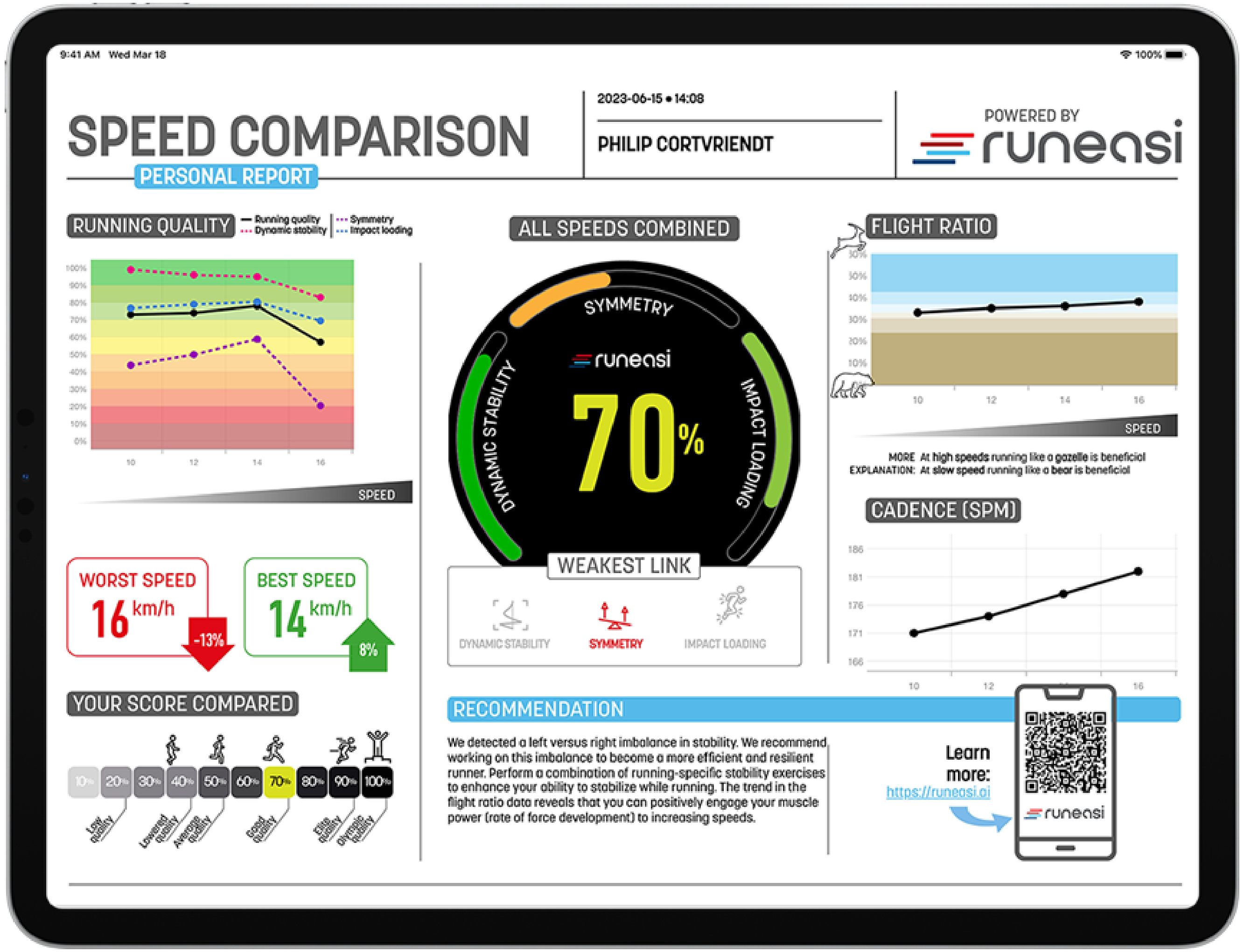


INDIVIDUALIZED TRAINING RECOMMENDATIONS



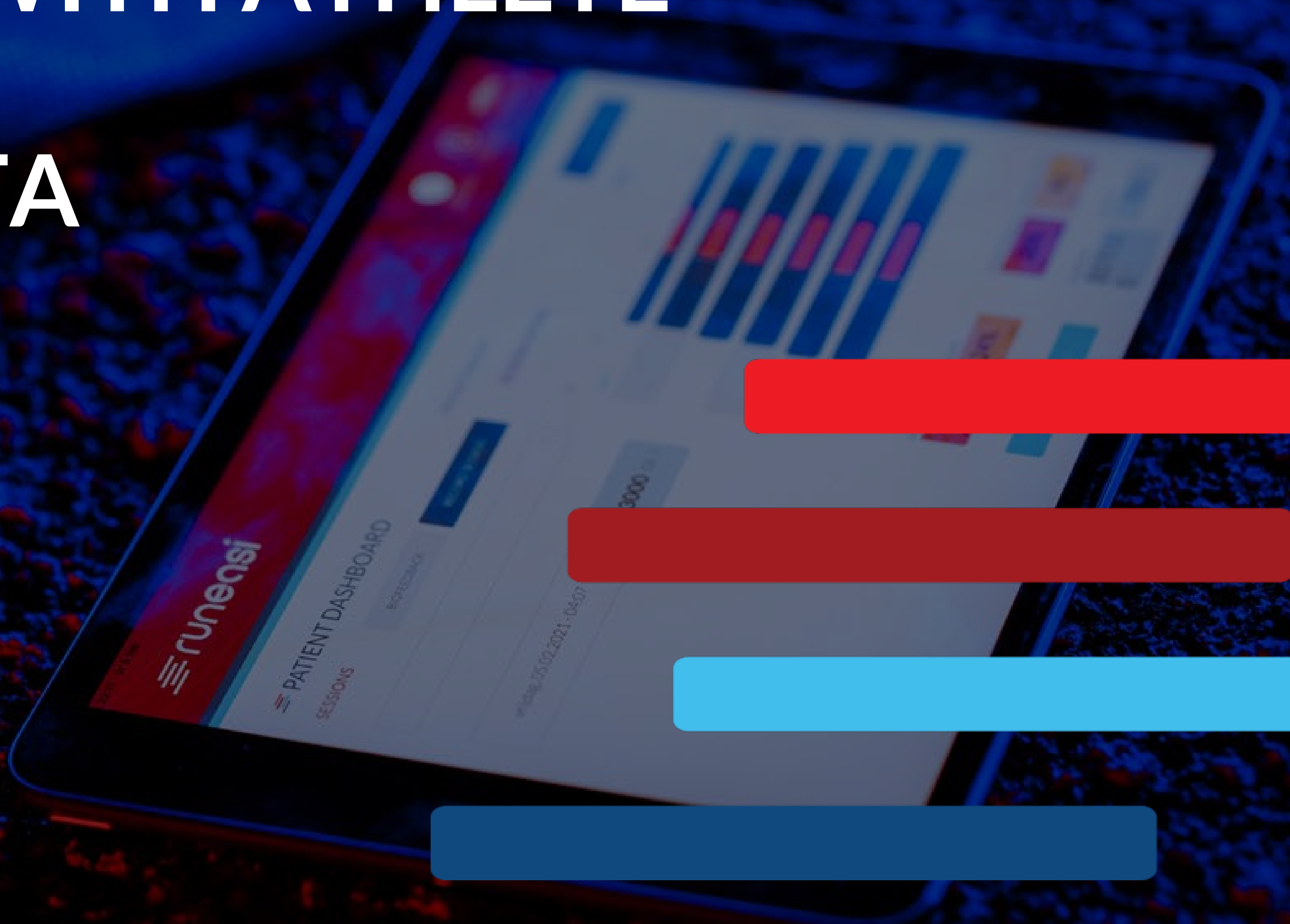
runeasi

INDIVIDUALIZED TRAINING RECOMMENDATIONS



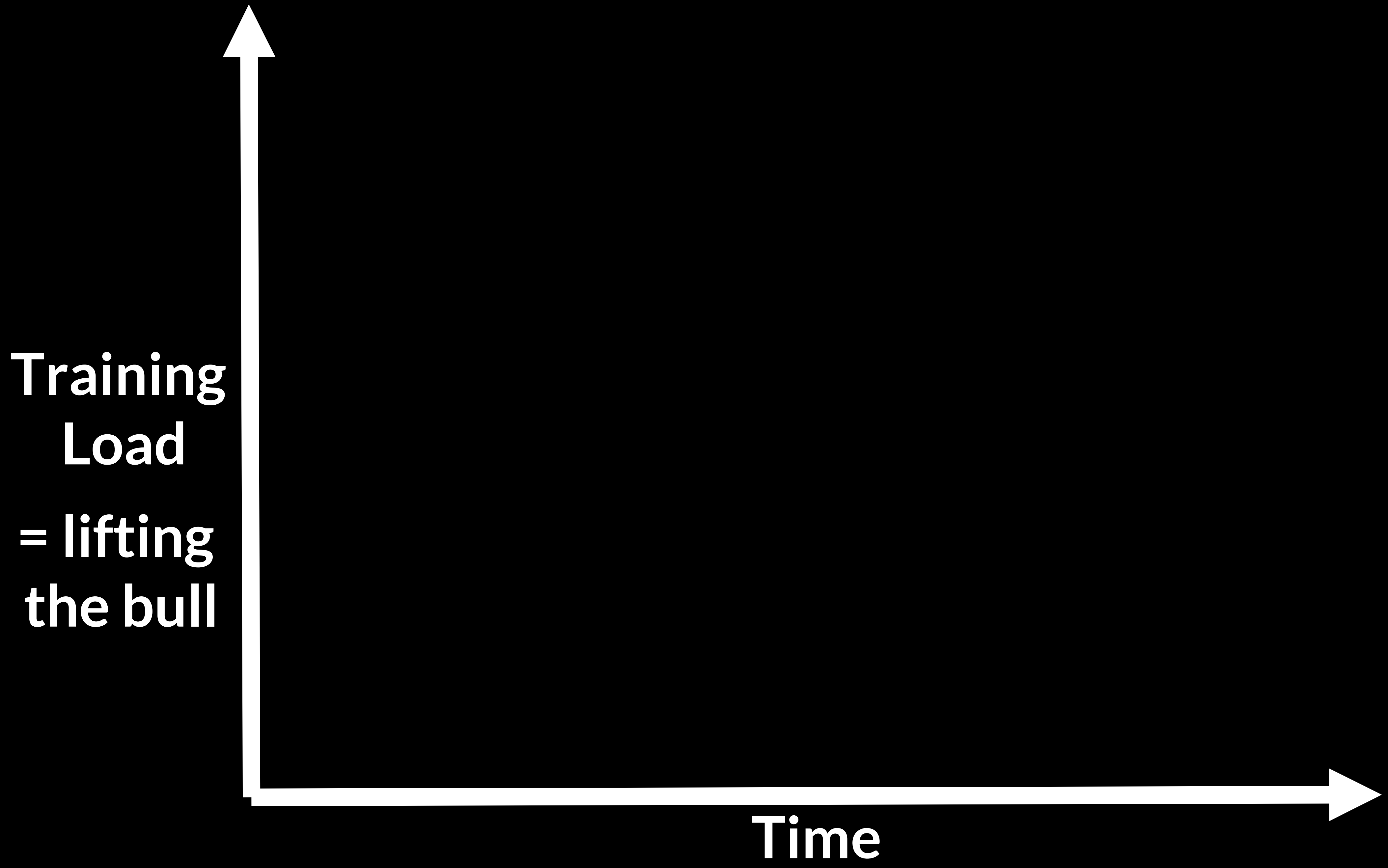
runeasi

DATA SCIENCE CHALLENGES WHEN WORKING WITH ATHLETE MONITORING DATA



More training?
More recovery?

Monitoring training load and load capacity is key.


Training
Load
= lifting
the bull
Time

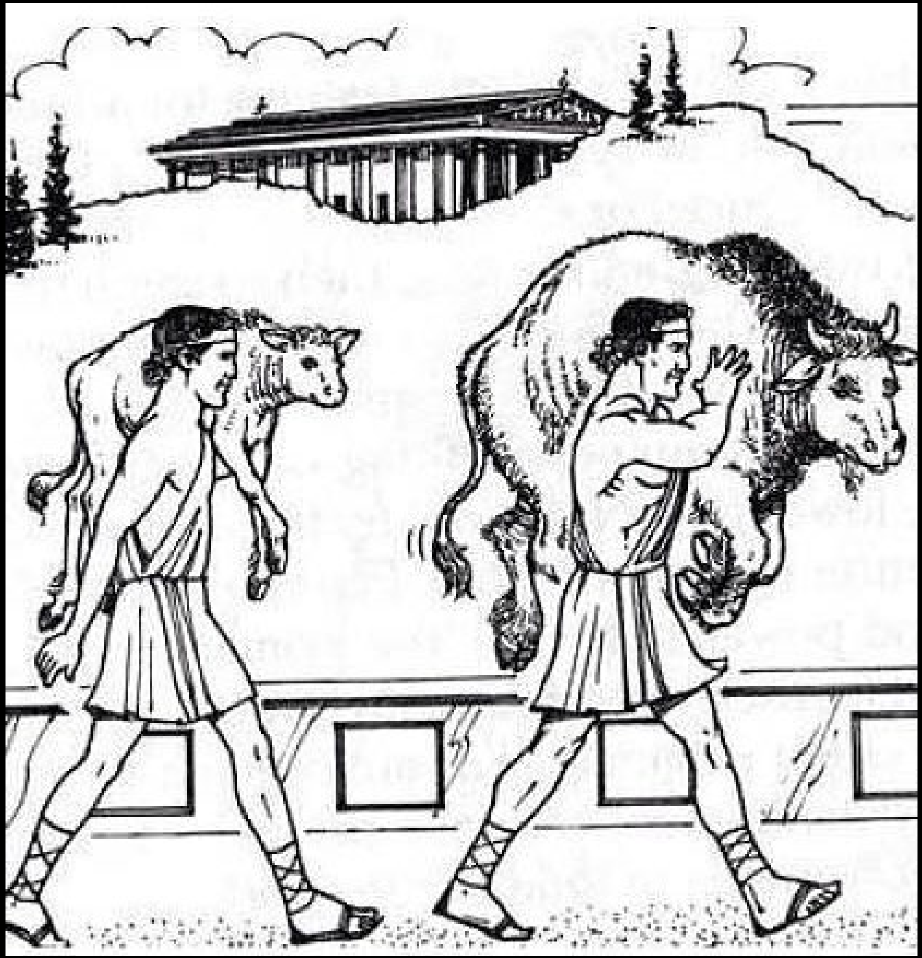
Training Load

= lifting the bull

Time

Training Load

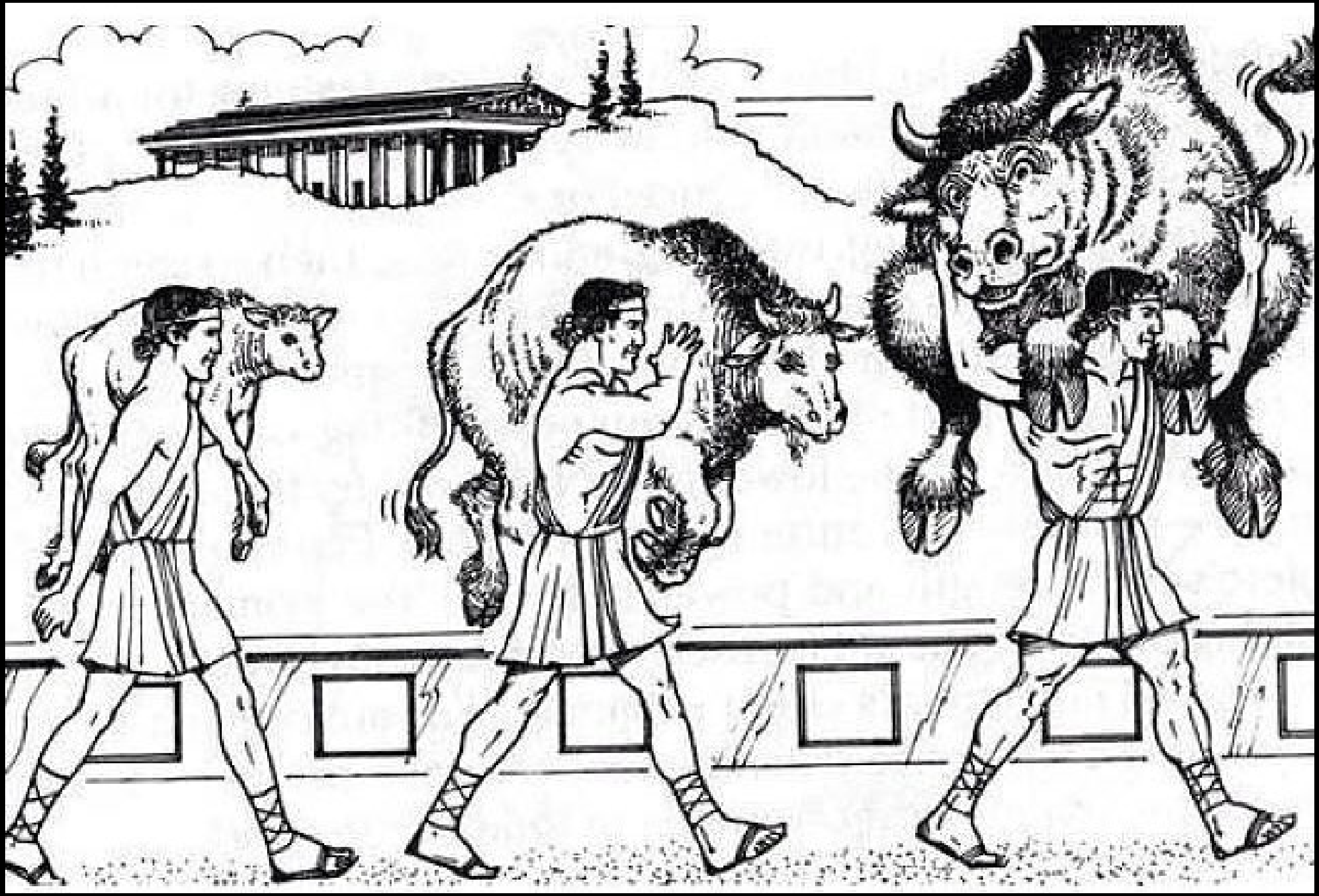
= lifting the bull



Time

Training Load

= lifting the bull

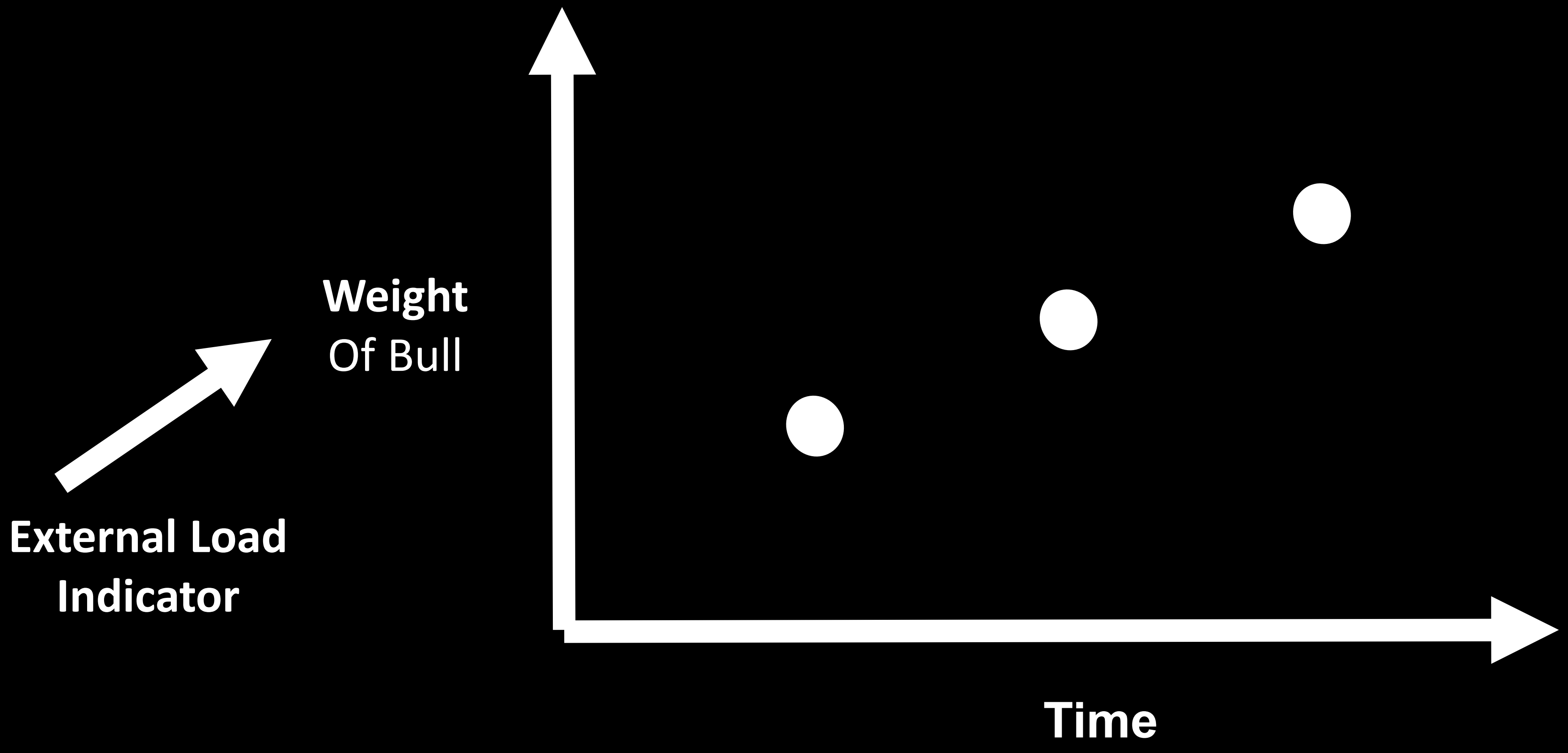


Time

LOAD CAPACITY

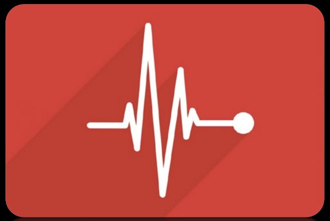
JEFF HIMLER | TRIBUNE-REVIEW

External load



Internal load

Heart Rate



Rating of Perceived Exertion (RPE)

Borg CR10 Scale® (2010)[20]

0	Nothing at all	
0.3		
0.5	Extremely weak	Just noticeable
0.7		
1	Very weak	
1.5		
2	Weak	Light
2.5		
3	Moderate	
4		
5	Strong	Heavy
6		
7	Very strong	
8		
9		
10	Extremely strong	"Maximal"
11		
∫		
•	Absolute maximum	Highest possible

Wellness Questionnaires

	1	2	3	4	5
FATIGUE	Always tired	More tired than normal	Normal	Fresh	Very fresh
SLEEP QUALITY	Insomnia	Restless sleep	Difficulty falling asleep	Good	Very restful
GENERAL MUSCLE SORENESS	Very sore	Increase in soreness/tightness	Normal	Feeling good	Feeling great
STRESS LEVEL	Highly stressed	Feeling stressed	Normal	Relaxed	Very relaxed
MOOD	Highly annoyed/irritable down	Aggravated/short tempered	Less interested in others and/or activities than usual	A generally good mood	Very positive mood


Individual characteristics complicate things…


… and evolve over time

Relationships Between the External and Internal Load in Professional Soccer

Jaspers A. *, Op De Beéck T. *, Brink M., Frencken W., Staes F., Davis J.**, Helsen W.** (2018).
Relationships between the external and internal training load in professional soccer: what can we learn from machine learning?
International journal of sports physiology and performance, 13(5), 625-630.
* Shared First Author
** Shared Last Author

Typical Challenges

- Sport science challenges
  - Many External Load Indicators (ELIs)
  - Multi-collinearity and Non-linear relationships
  - No Normative data
- Data science challenges
  - Limited individual data
  - Noisy data
  - Individual characteristics

Approach: Machine Learning

1. Define features
2. Collect data
3. Learn model
4. Make predictions

Features: Describe problem

Player	Date	Distance > 20 km/h	...	Total Distance	NB of accelerations	RPE
?	?	?	...	?	?	?
?	?	?	...	?	?	?
?	?	?	...	?	?	?
?	?	?	...	?	?	?

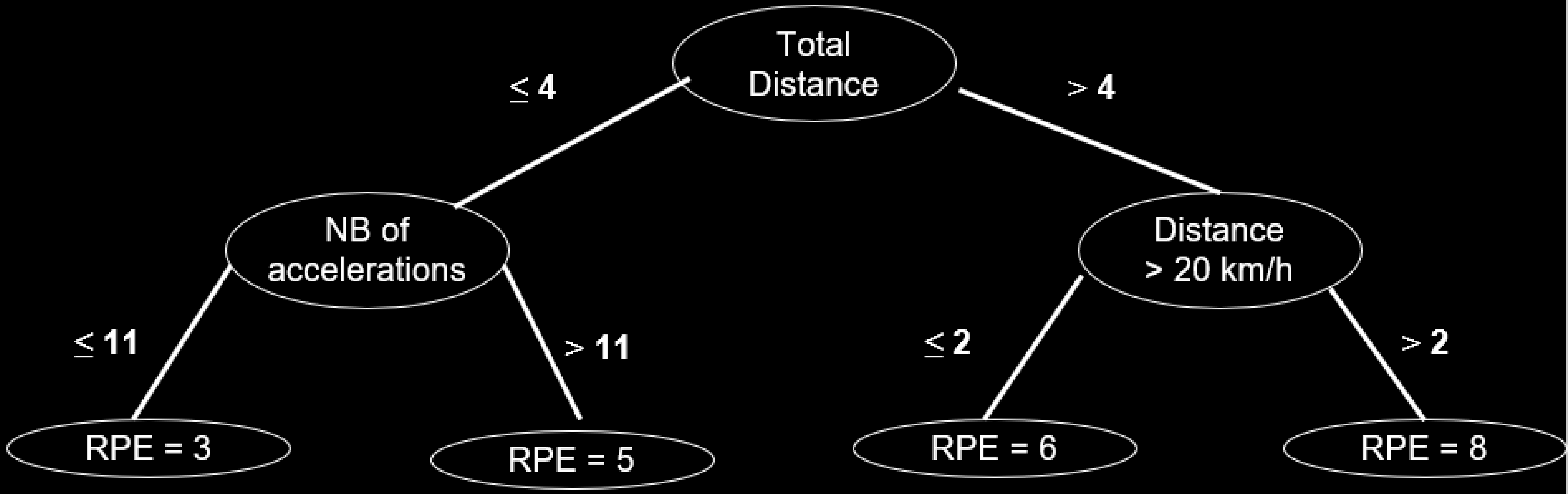
runeasi

Collect data

Player	Date	Distance > 20 km/h	…	Total Distance	NB of accelerations	RPE
1	02/01	0.5	…	3.23	10	4
1	03/01	1.2	…	7.50	54	7
⋮	⋮	⋮	…	⋮	⋮	⋮
21	04/03	1.3	…	6.78	23	5

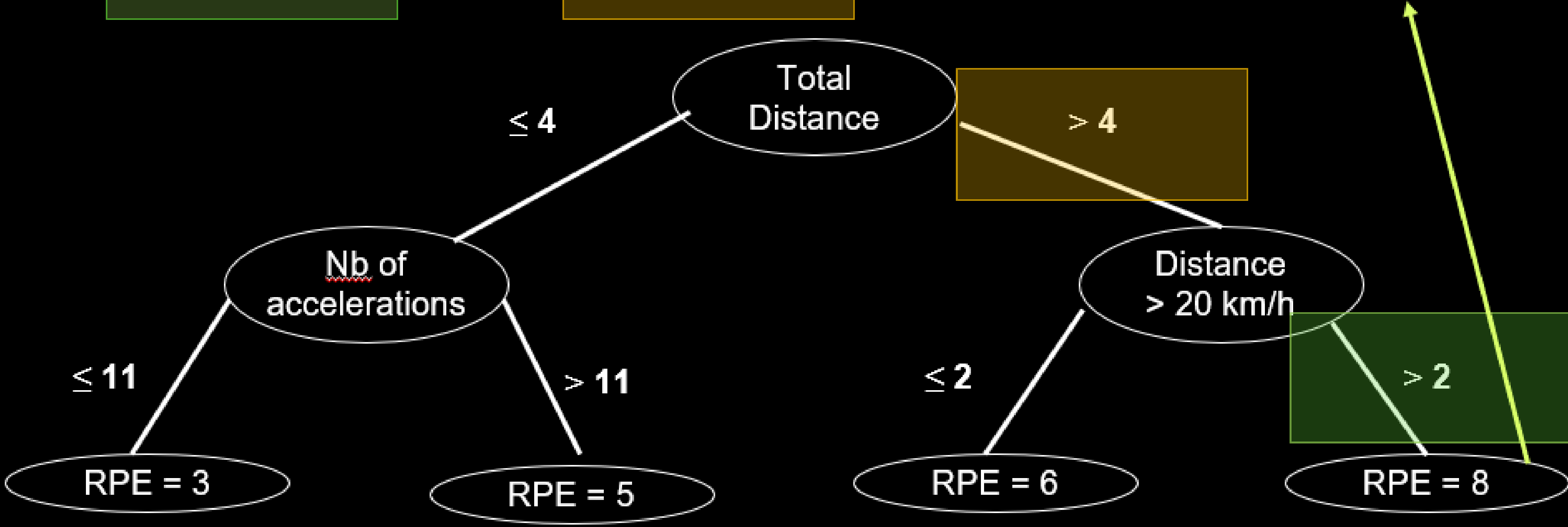
Learn model

Player	Date	Distance > 20 km/h	…	Total Distance	NB of accelerations	RPE
1	02/01	0.5	…	3.23	10	4



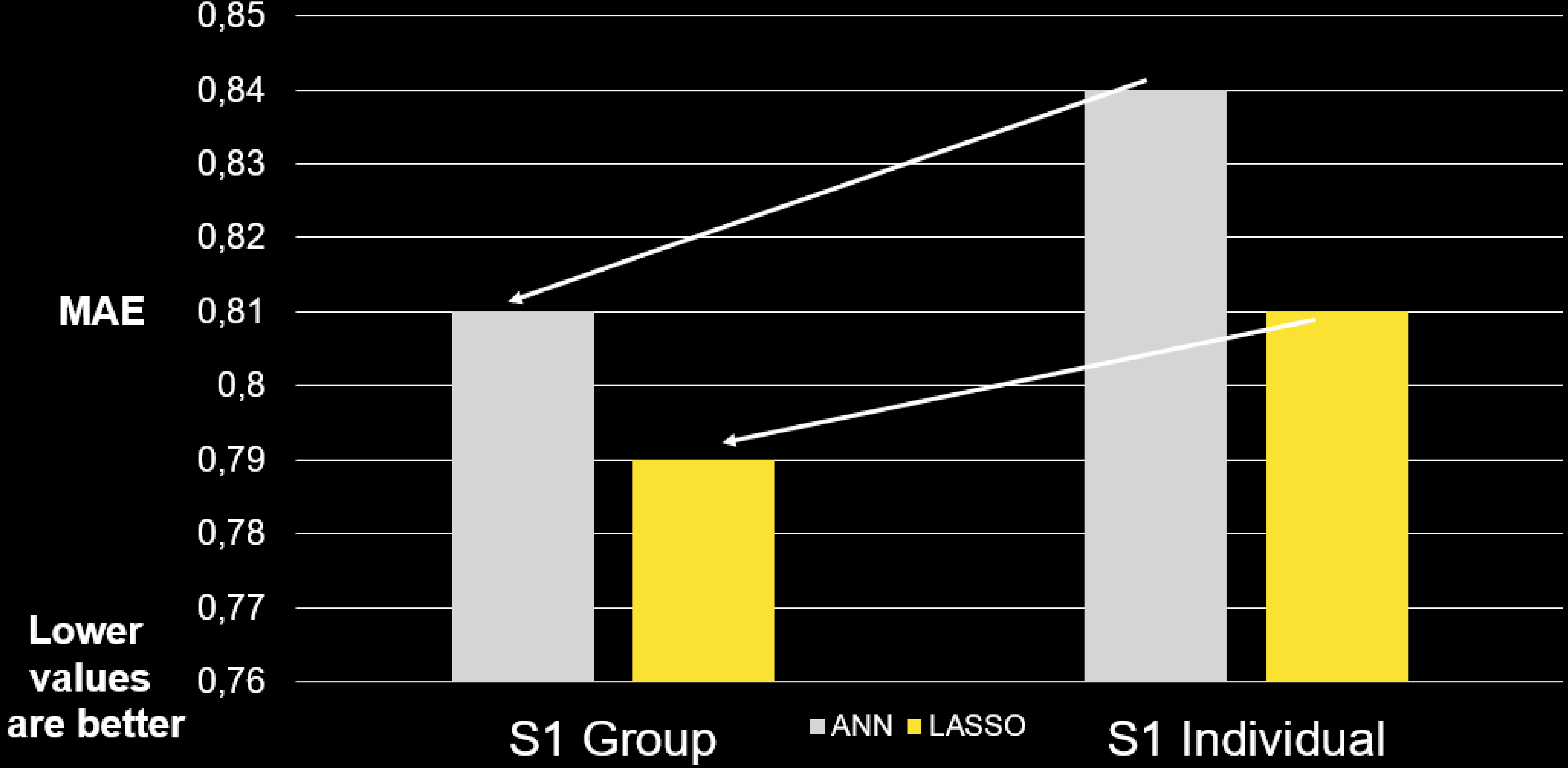
Make predictions

Player	Date	Distance > 20 km/h	…	Total Distance	NB of accelerations	RPE
10	05/05	4	…	5	2	??



Group models or Individual models?

Results Season 1 (23 players, no goalkeepers)



Key Insights

- Group models can be used for individual monitoring of players
- Decelerations are perceived as exerting by players

Fatigue Prediction in Outdoor Runners

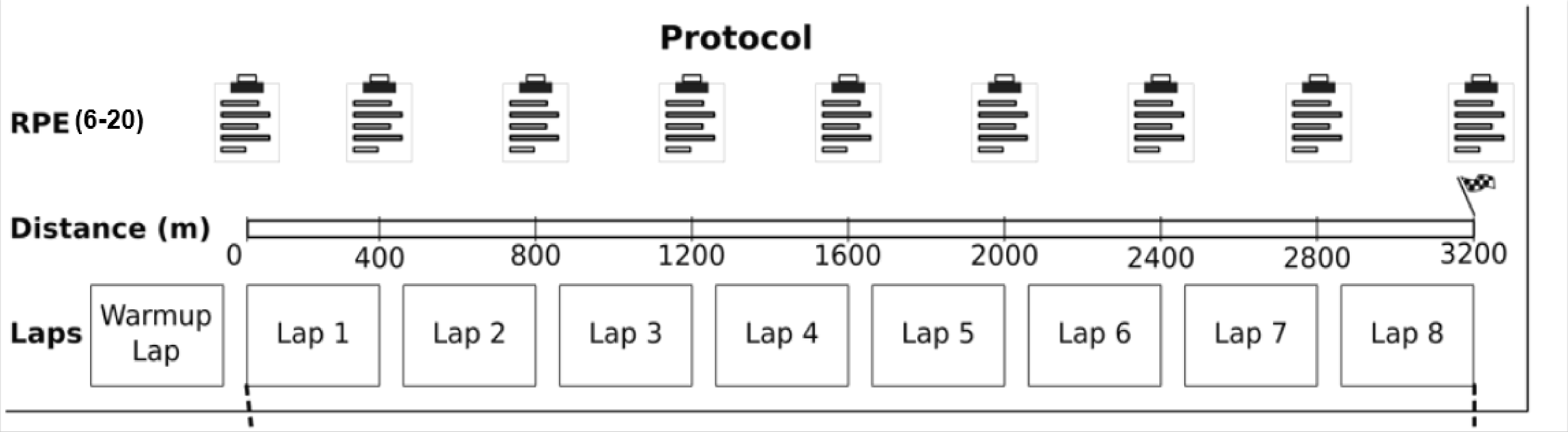
Op De Beéck T., Meert W., Schütte K., Vanwanseele B., Davis J. (2018).
Fatigue Prediction in Outdoor Runners Via Machine Learning and Sensor Fusion.
In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 606-615). ACM.

Task

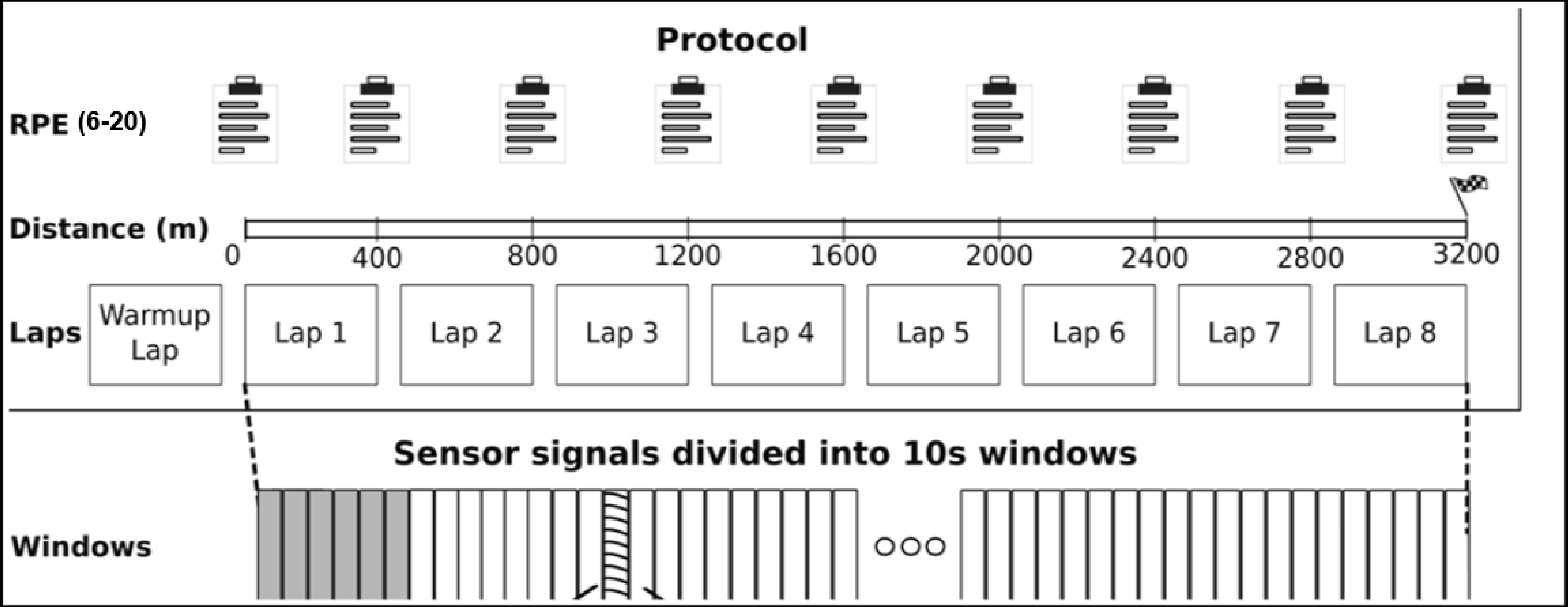
Given: GPS and accelerometer data from a player's training session

Predict: Player's Rate of Perceived Exertion (RPE)

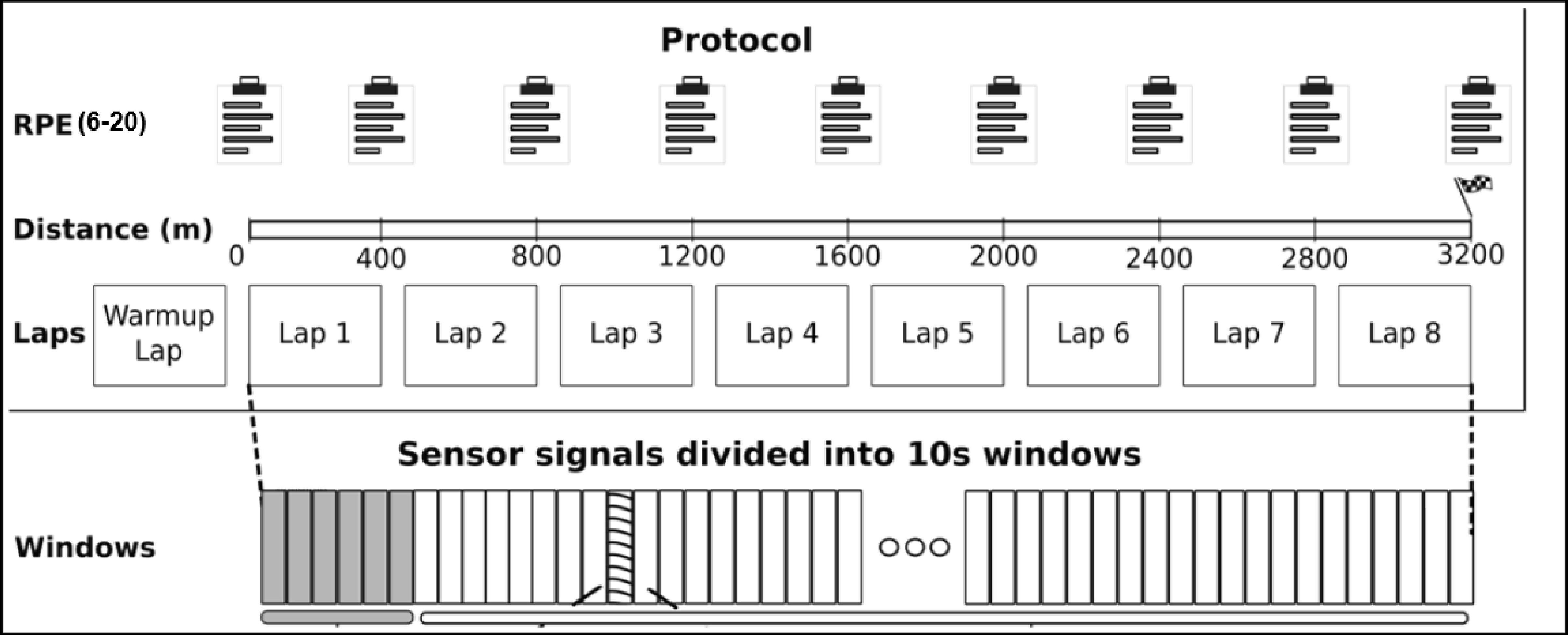
Data


Protocol
RPE (6-20)
Distance (m)
0
400
800
1200
1600
2000
2400
2800
3200
Laps
Warmup Lap
Lap 1
Lap 2
Lap 3
Lap 4
Lap 5
Lap 6
Lap 7
Lap 8

Preprocessing

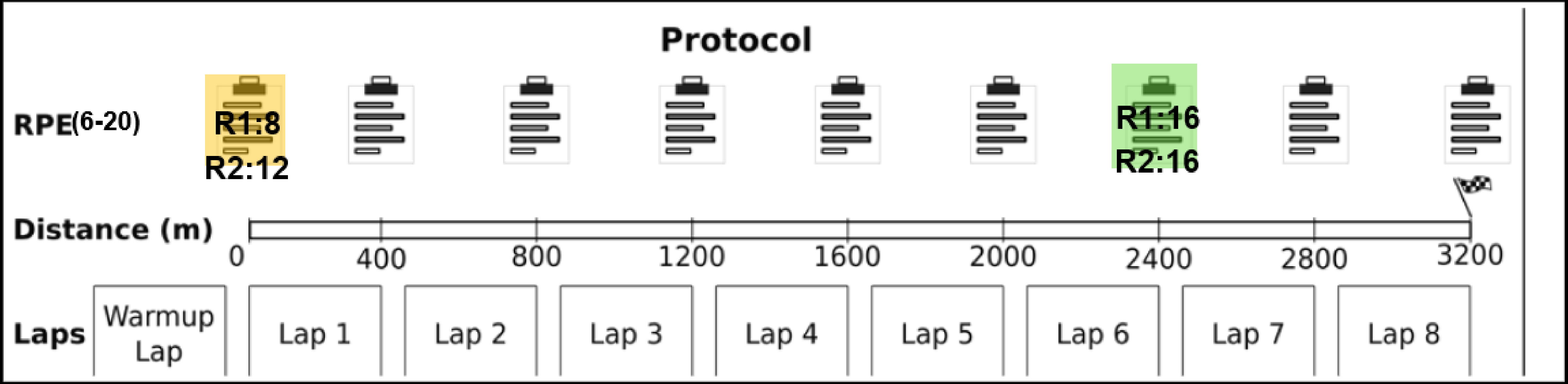


Personalized baseline



Baseline windows

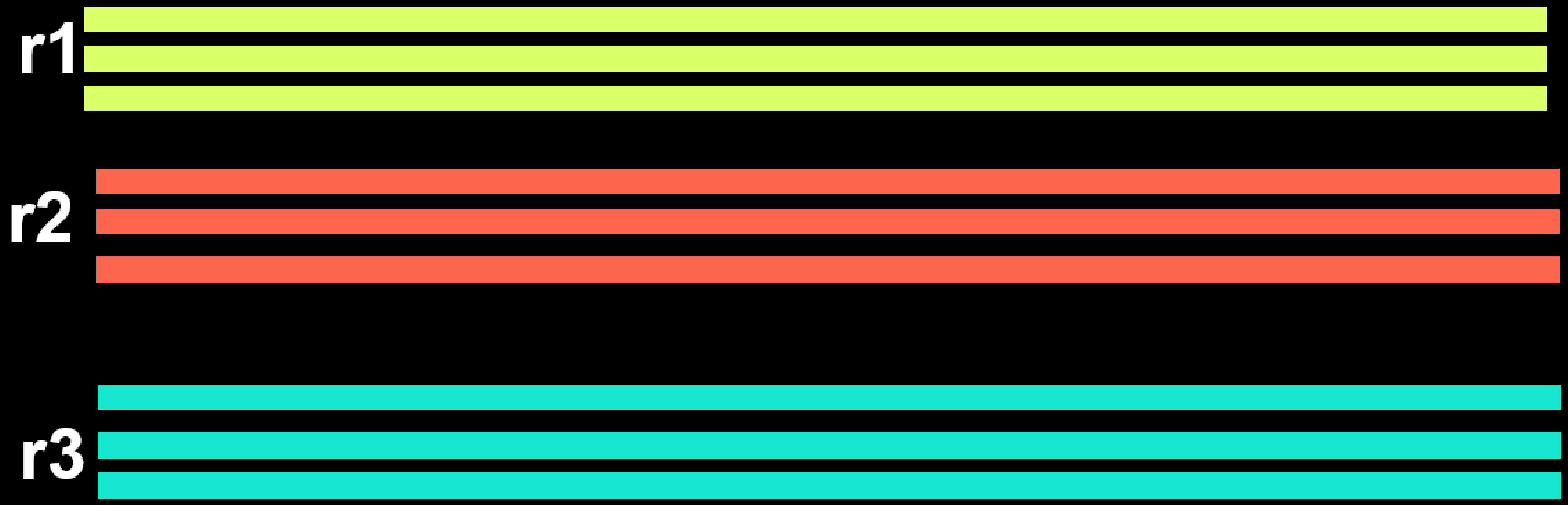
Normalize RPE of runner 2



$$nRPE_{r1} = \frac{(16-8)}{(20-8)} = 0.66$$

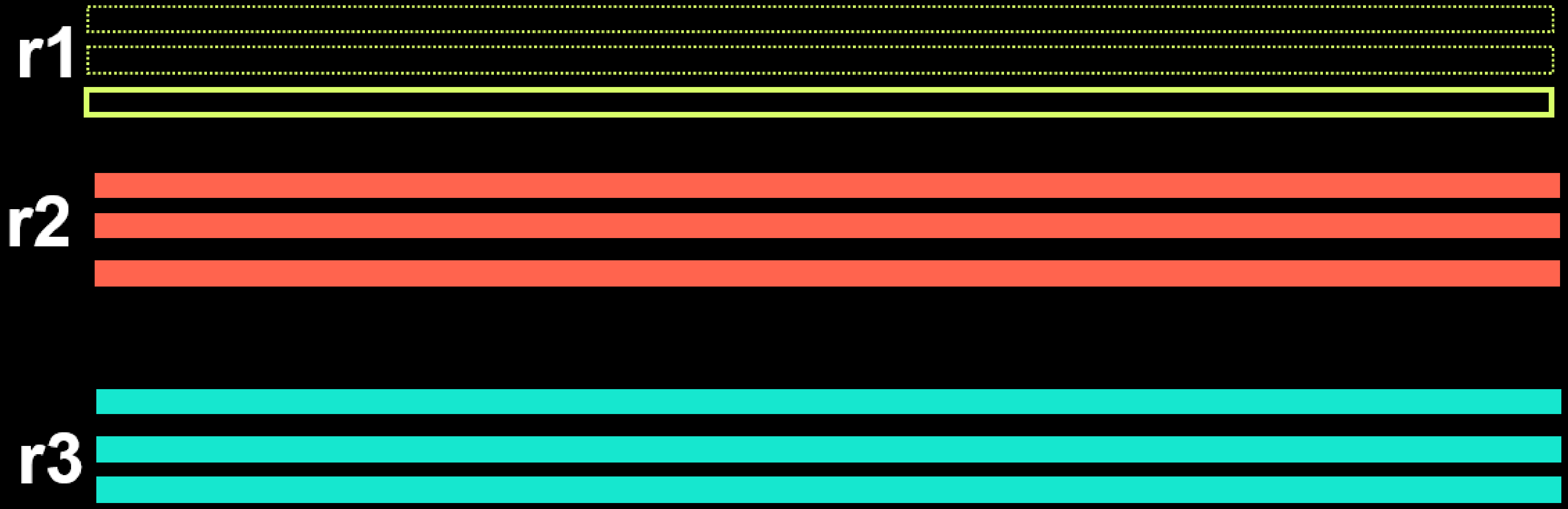
$$nRPE_{r2} = \frac{(16-12)}{(20-12)} = 0.5$$

Database

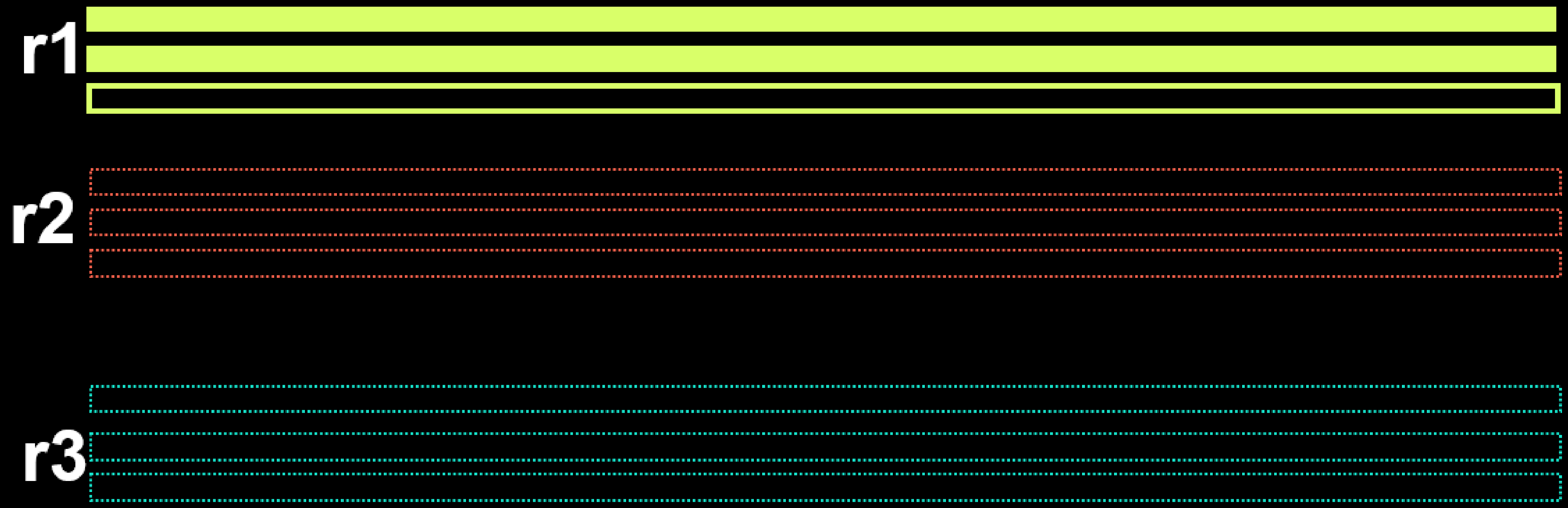


All runners model r1

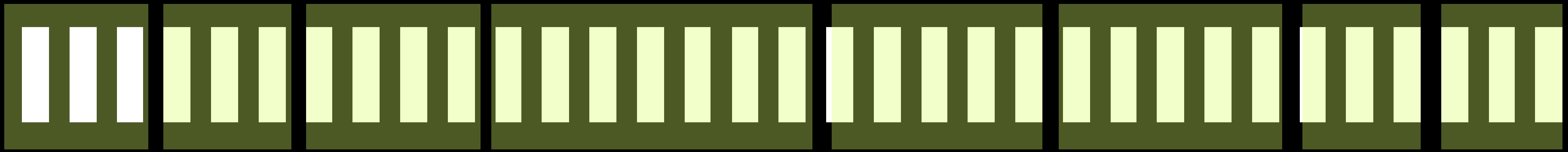
Other runners only model r1



Individual model r1



Variable NB of windows per lap



MAE Lap 1 | MAE Lap 2 | MAE Lap 3 | MAE Lap 4 | MAE Lap 5 | MAE Lap 6 | MAE Lap 7 | MAE Lap 8

MAE
Test 1

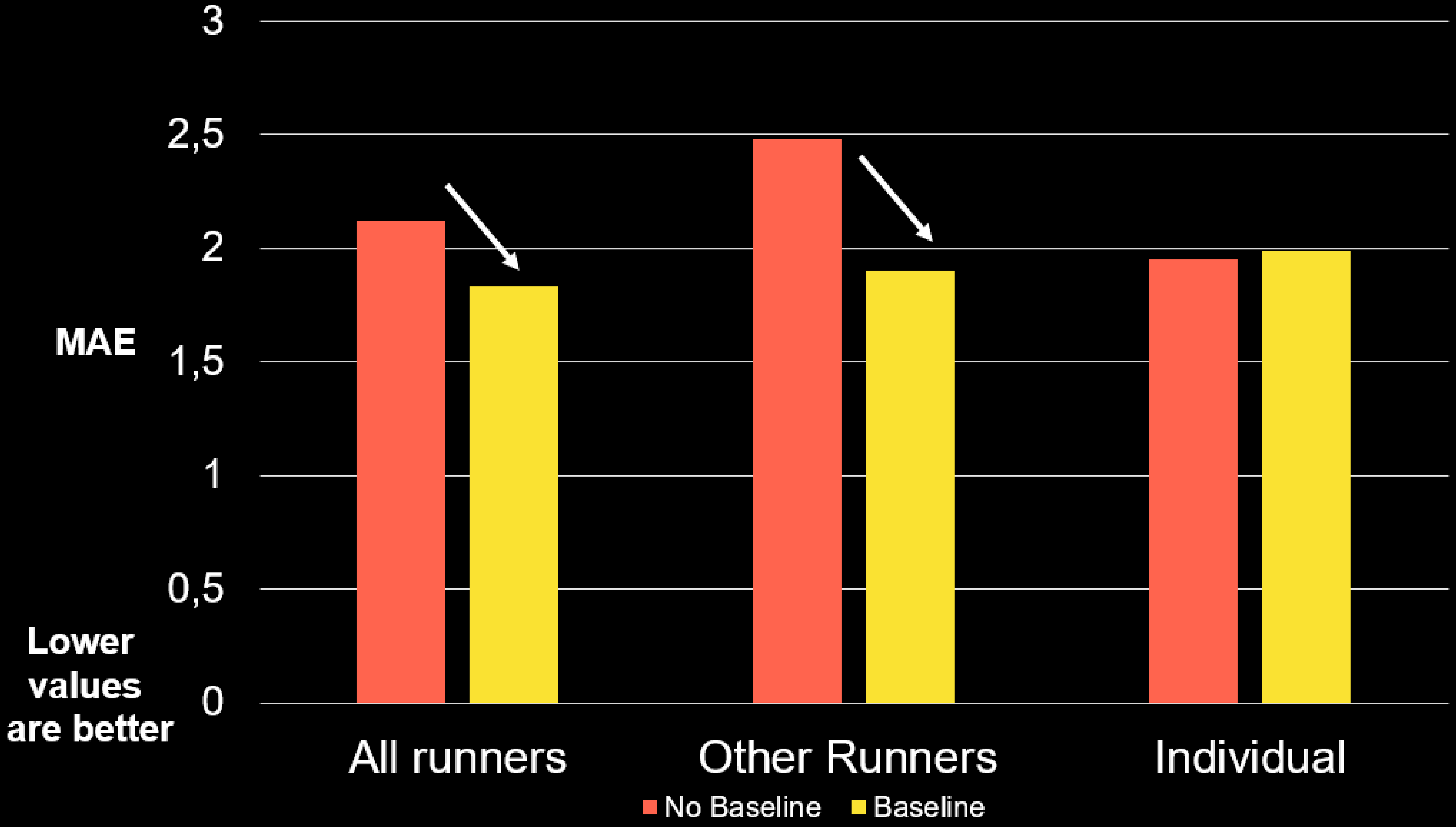
Variable NB of tests per runner

Regression (GBRT + simple statistical features)

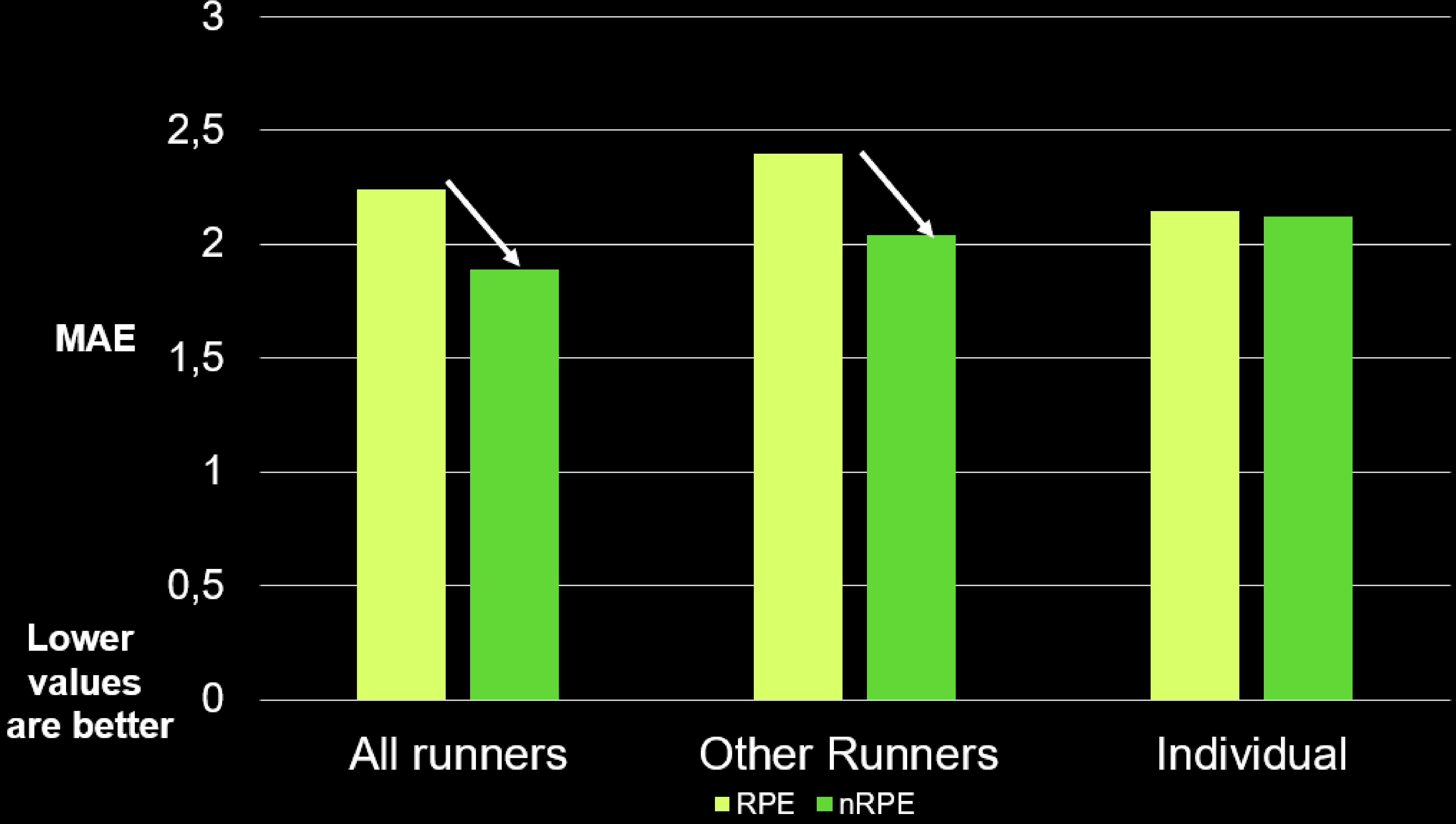
	All runners model	Other runners only model	Individual model
SENSORS	**MAE**	**MAE**	**MAE**
Arm (A)	1.99	2.03	1.98
Wrist (W)	1.89	2.04	2.15
Tibia (T)	1.98	2.08	2.02
T-T-W-A	**1.83**	1.9	1.99

Lower values are better

Impact of personalized baseline



Impact of normalizing RPE values



KEY INSIGHTS

- Simple features of 1 IMU Sensor (attached to the wrist) are sufficient (

- No prior labeled data of the runner is needed

- Our methodology could account for variable running speeds, intra and inter individual differences, and subjectivity of target label

DATA CHALLENGES

AT

RUNEASI

DATA AGGREGATION IS EASY

- =AVERAGE()

- pandas.groupBy(by=‘x’).mean()

SOME CONSTRAINTS WHEN AGGREGATING DATA

- Consistency
- Sensitivity
- Interpretability
- Transparency

THE DEVIL IS IN THE DETAILS

- Session averages: step based vs window based
- Quality score calculations

segment NB	quality	DS	IL	SYM
1	85	89	94	73
2	87	90	96	75
3	87	89	96	76
4	79	88	94	56
5	81	89	95	59
6	85	88	95	70
7	92	92	94	89
8	83	89	94	66
9	72	84	94	38
AVERAGE OF SEGMENTS	**83,44444**	**88,66667**	**94,66667**	**66,88889**

Based on average metrics 90 89 95 87

runeasi

How you aggregate can affect outcome

Left vs Right differences

SEGMENT	DS LEFT	DS RIGHT	LEG	L-R-%
1	19,7	18,6	L	2,9
2	18,8	19	R	0,5
3	19,8	18,5	L	3,4
4	20,3	18,7	L	4,1
5	20	18,4	L	4,2
6	19,7	18,9	L	2,1
7	18,4	18,7	R	0,8
8	19,7	18,7	R	2,6
9	19	21,2		5,5
	19,49	18,97		

1,36 %

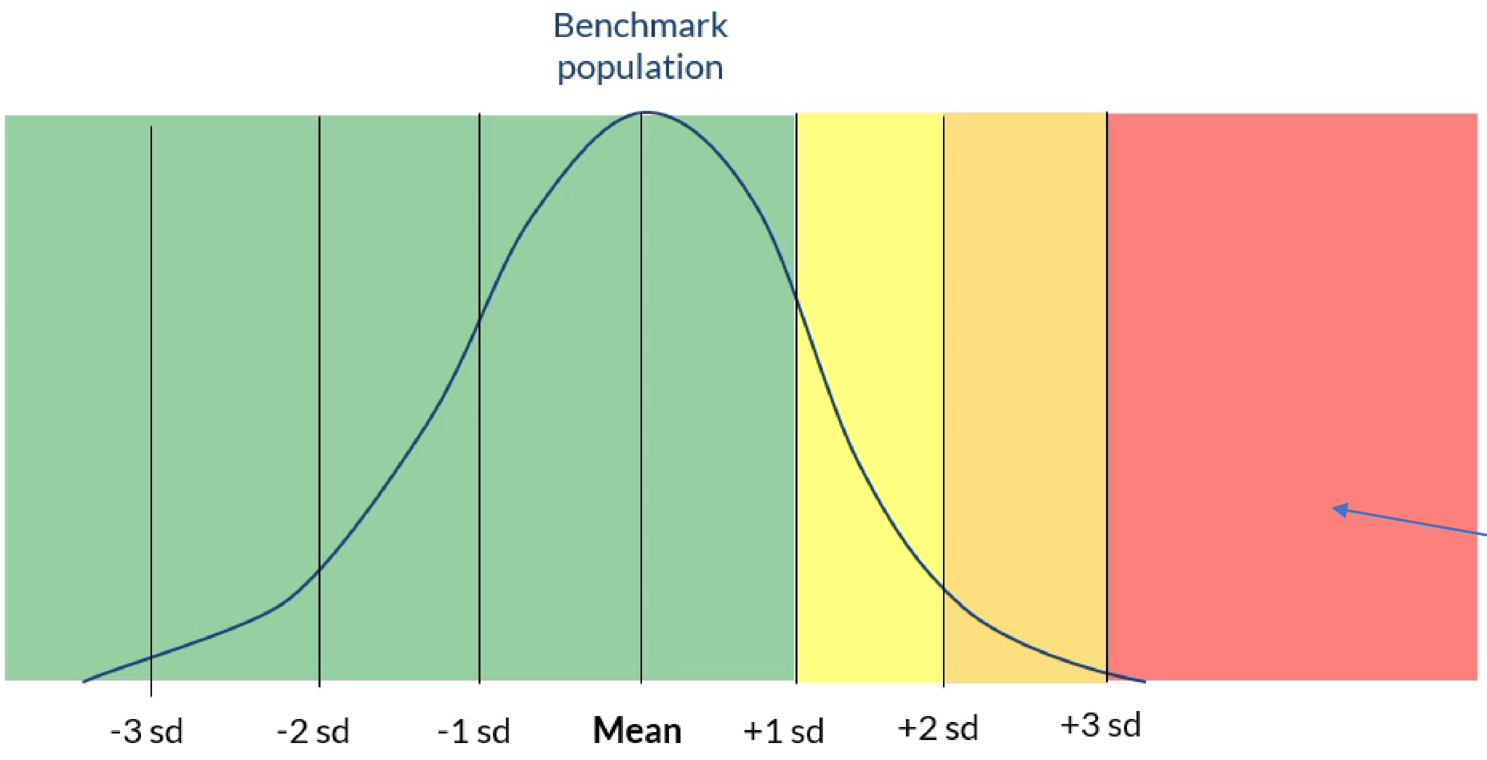
2,89 %

runeasi

COMPUTING BENCHMARKS

- Health e-run study
  - Participants did not have injuries
  - **Variety** in runners (start to run → experienced)
  - **Outdoor data collection** (at least 3 training sessions)

Benchmarks V1



Typical

Mean + 1 standard deviation

Elevated

Mean + 2 standard deviation

High

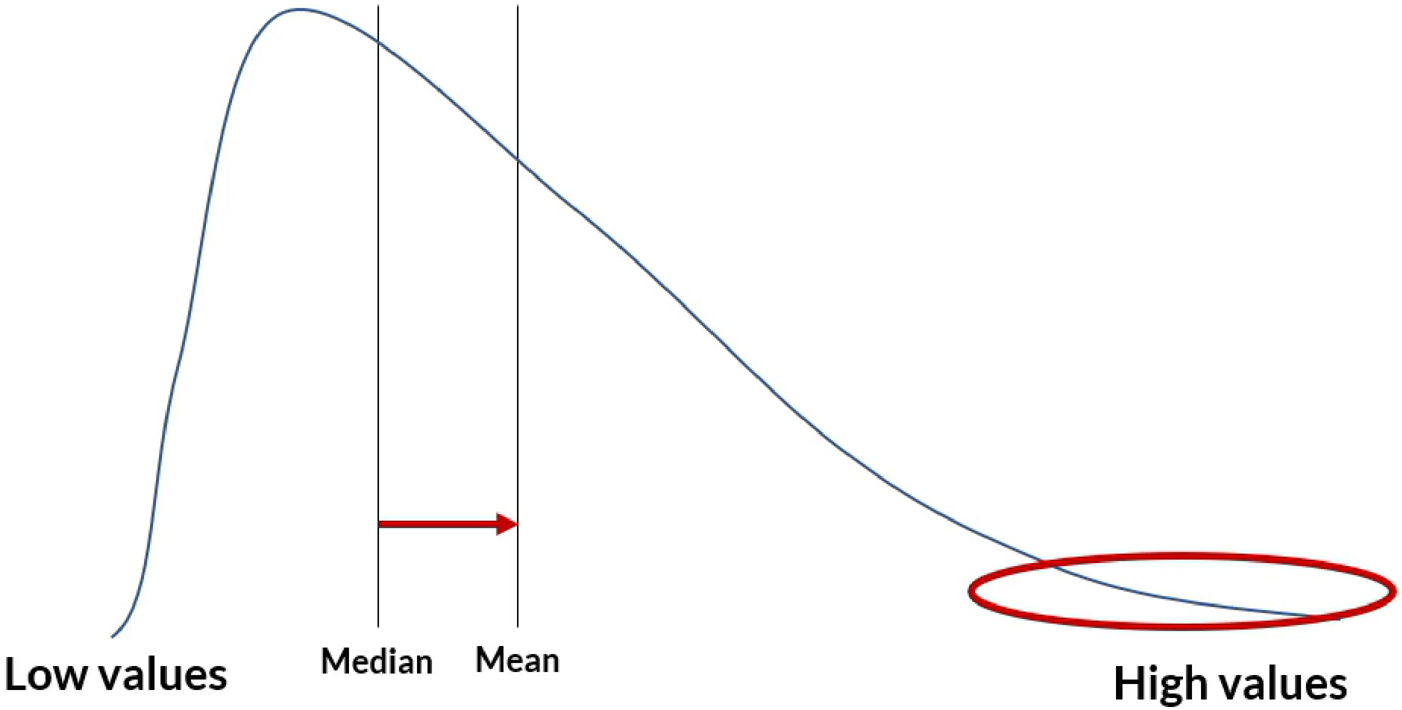
Mean + 3 standard deviation

Very high

Assumption:
Injured people are expected here

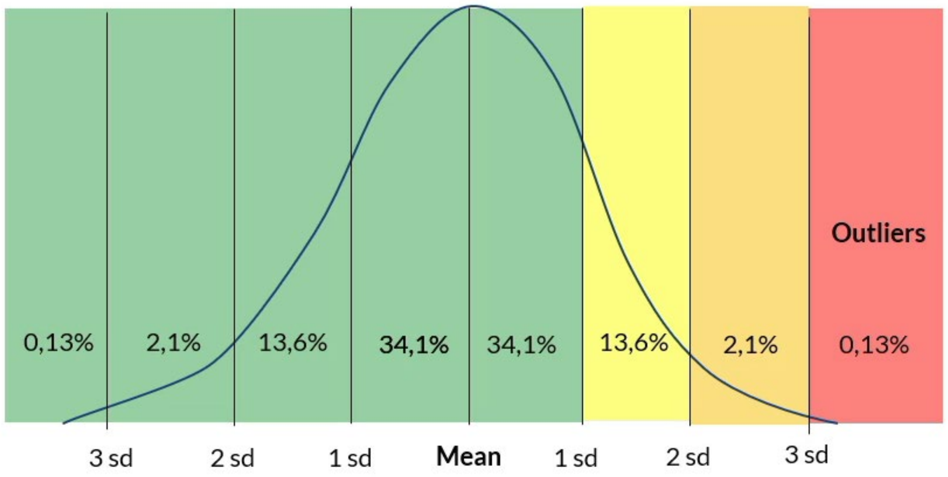
Problem 1

Not always a normal distribution in real-world data

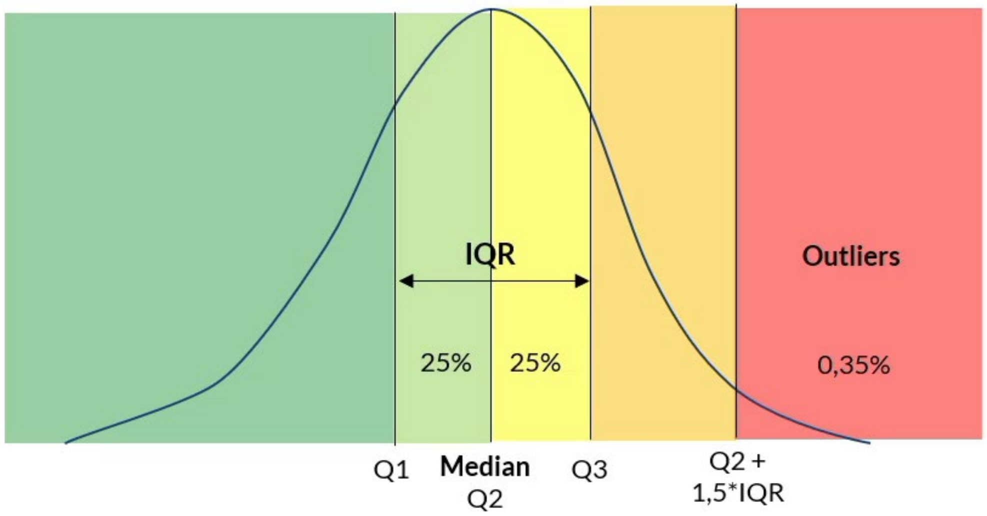


Benchmarks V2

Old way



New way



runeasi

Benchmarks V2 – problem 2

Make sure every runner in the data set contributes equally to the benchmarks

12 (minutes) * 96 (runners) = **1152 min of data**

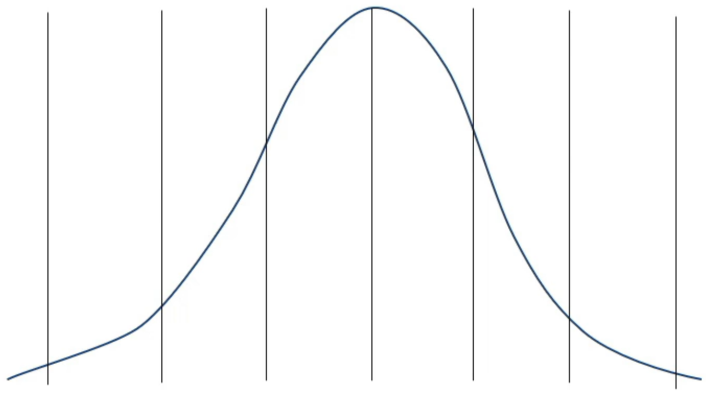
Benchmarks V2 – problem 2

Make sure every runner in the data set contributes equally to the benchmarks

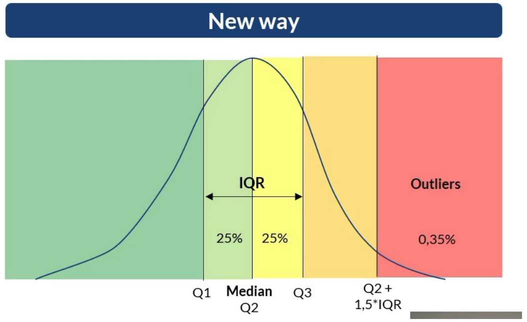
12 (minutes) * 96 (runners) = **1152 min of data**

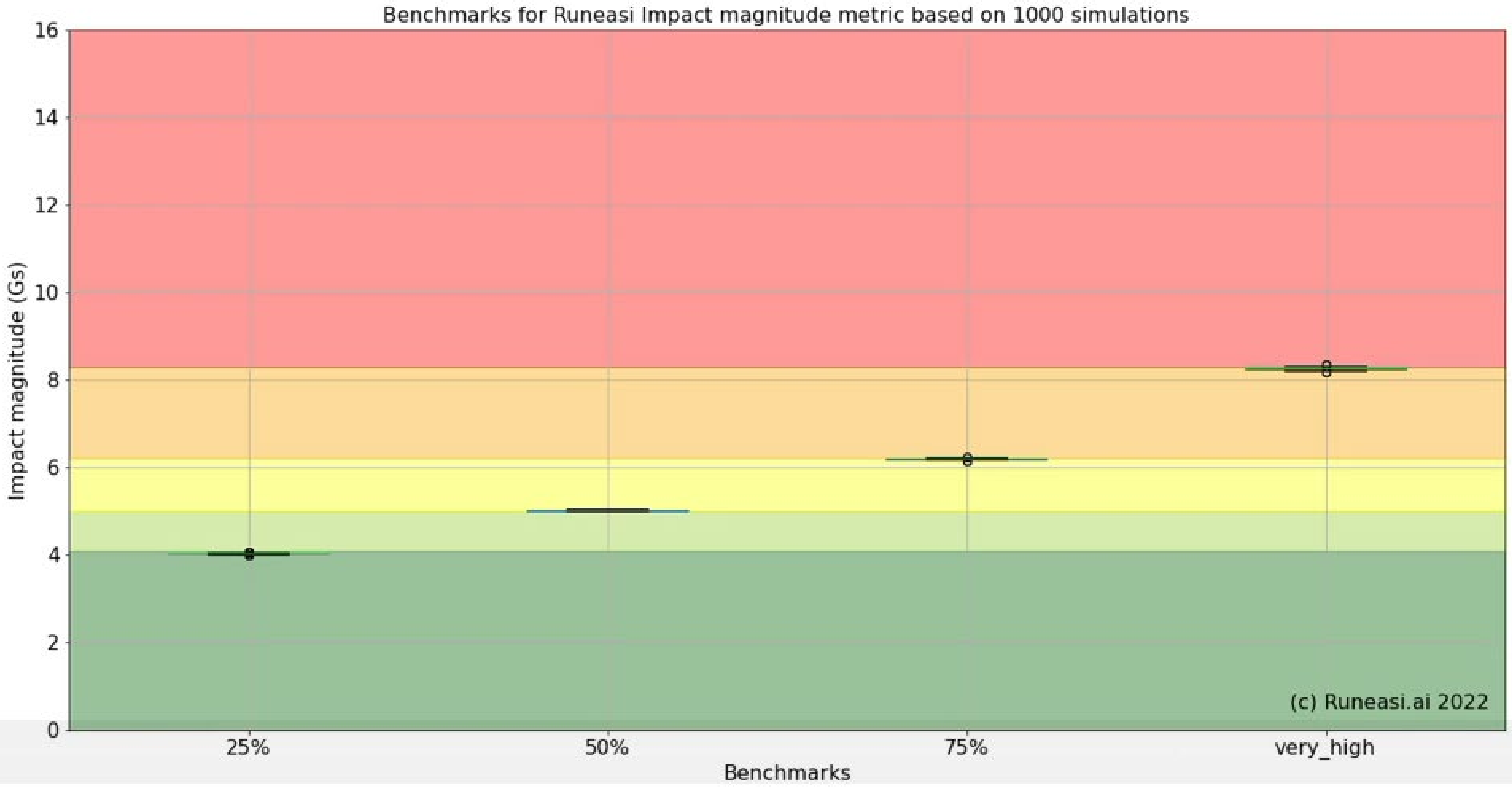
Same values when we repeat it with a different set of 12 minutes?

Normal distribution after 1000 different outcomes



Benchmarks V2 – simulating 1000 outcomes





Conclusion

Data science techniques allow us to **leverage the data of other athletes:**

1. The pipeline should **start from high quality data**

2. **Proper data contextualization** is necessary to make data actionable

3. **Correct methodology** is key to ensure generalizability to the real-world

runeasi

Any questions?

Benedicte

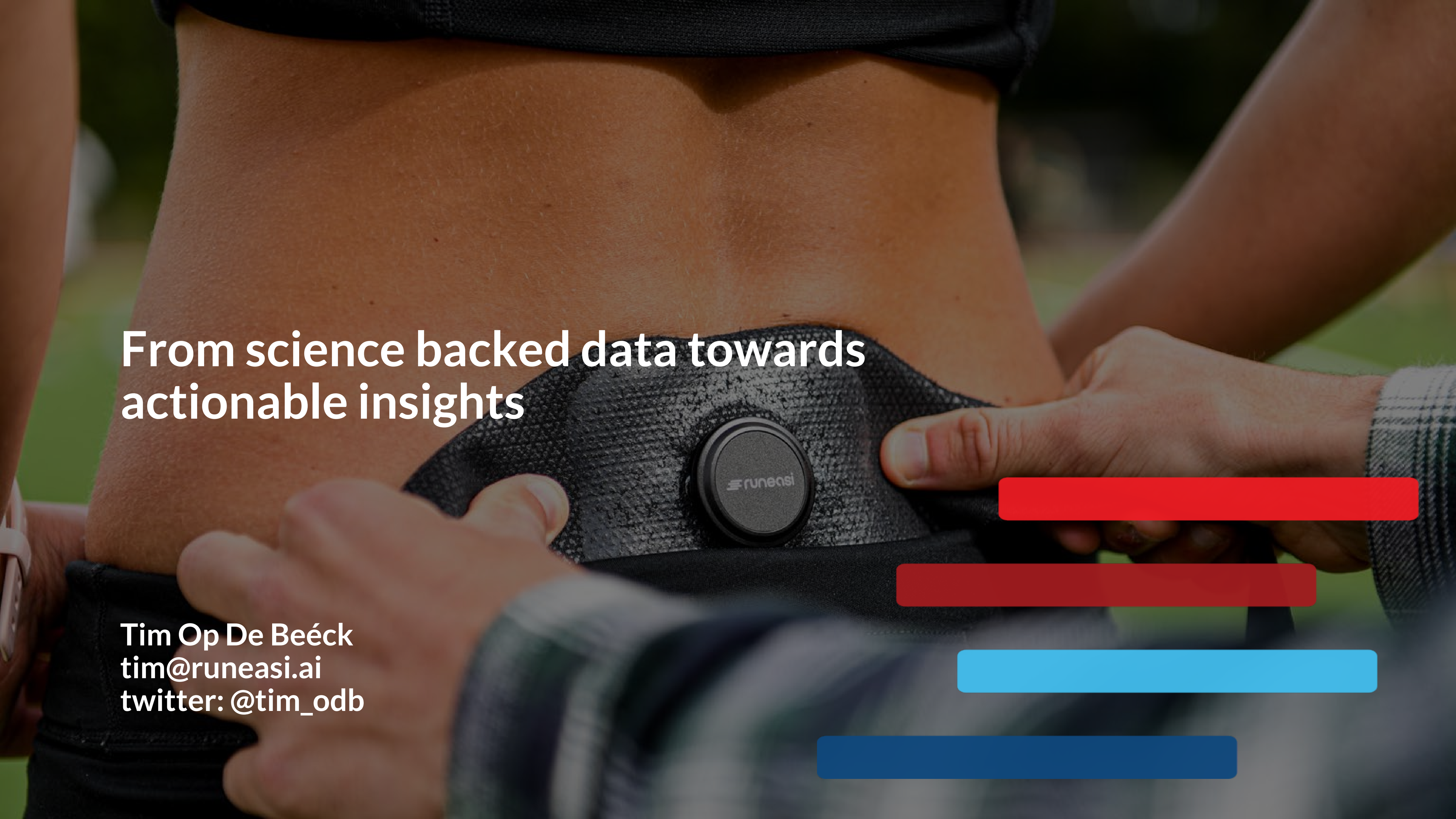
Jesse

Kurt

Tim

Philip

Timothée



From science backed data towards actionable insights

Tim Op De Beéck
tim@runeasi.ai
twitter: @tim_odb