Revealing the Hidden Lives of Cryptic Carnivores with Machine Learning and AI

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Department of STATISTICS

CENTER FOR EcosystemSentinels

Botswana Predator Conservation

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Washington Research FOUNDATION

BOTSWANA PREDATOR CONSERVATION

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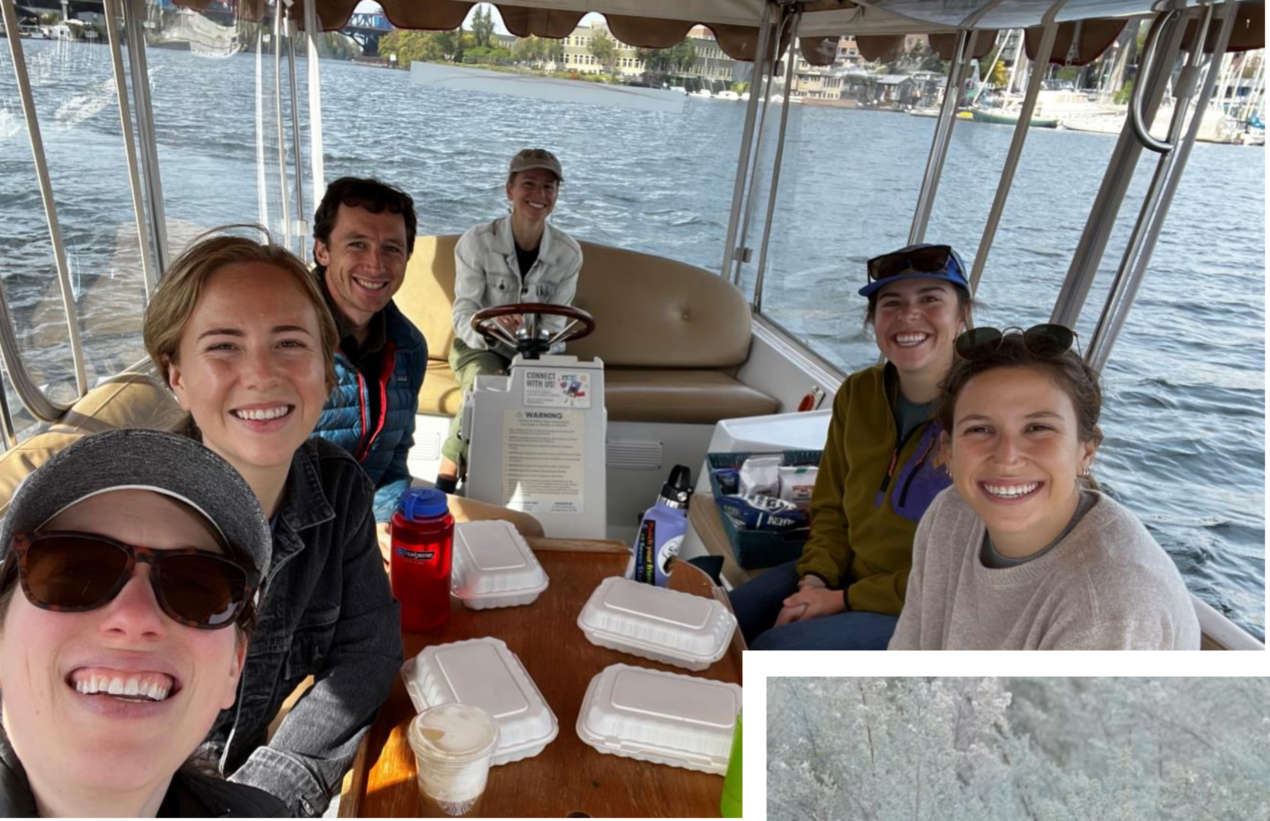
Video credit: D.Bessenhoffer



BOTSWANA PREDATOR CONSERVATION

eScience Institute

Environment & Climate

Movement

Mate acquisition

Disease transmission

Ecosystem services

Survival & Fitness

Ecosystem dynamics

Environment & Climate

Movement

Hunger

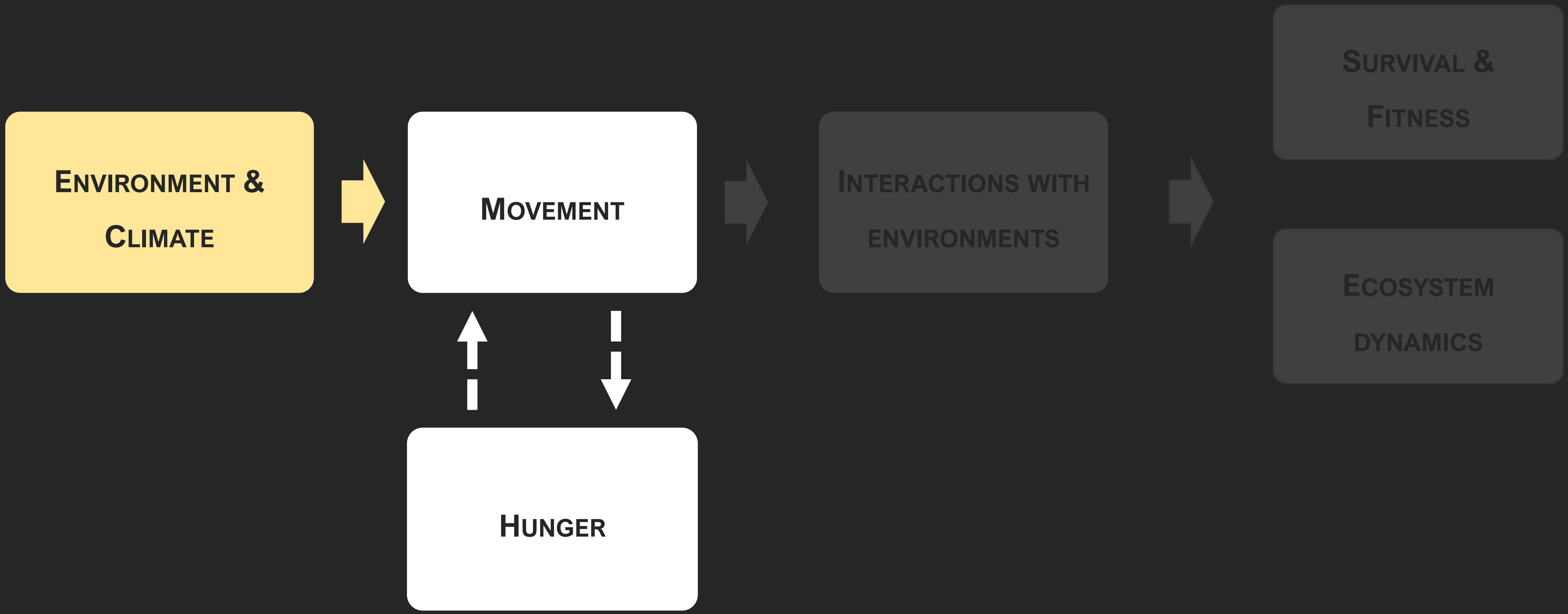
Mate acquisition

Disease transmission

Ecosystem services

Survival & Fitness

Ecosystem dynamics

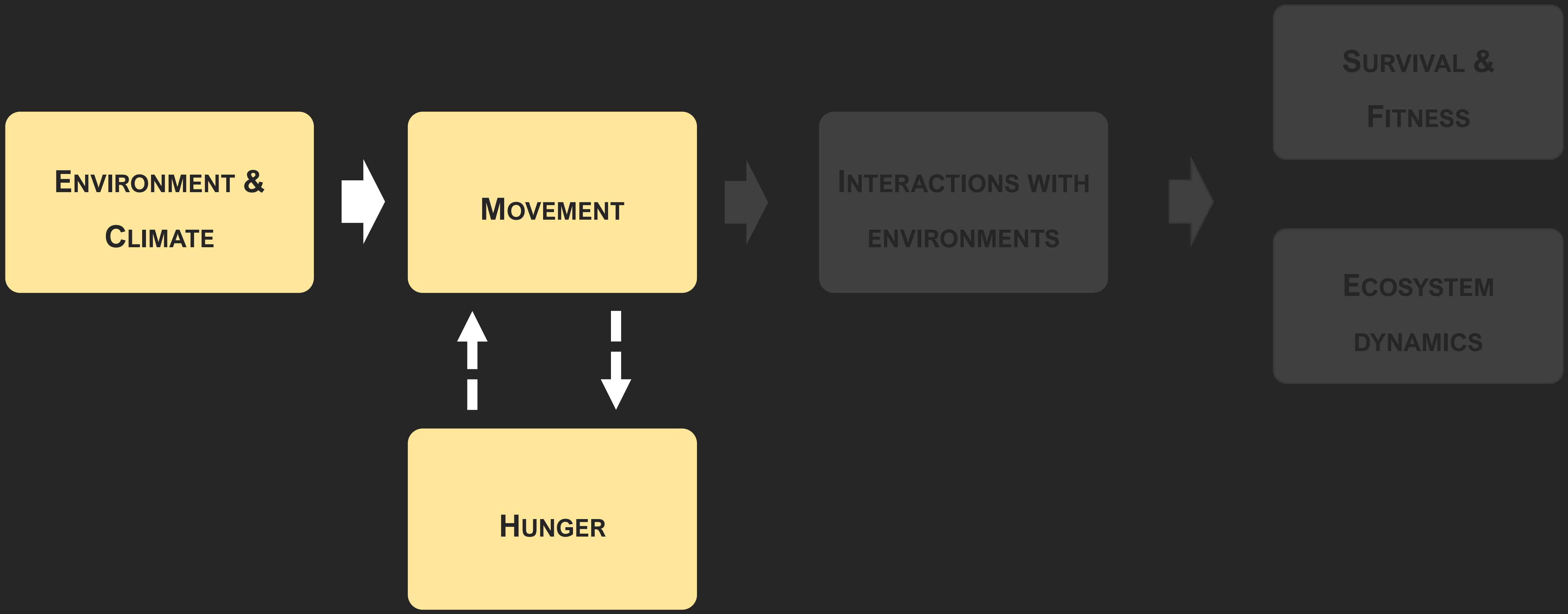

Environment & Climate
Movement
Hunger
Interactions with environments
Survival & Fitness
Ecosystem dynamics

Endangered
one of Africa's most endangered large carnivores

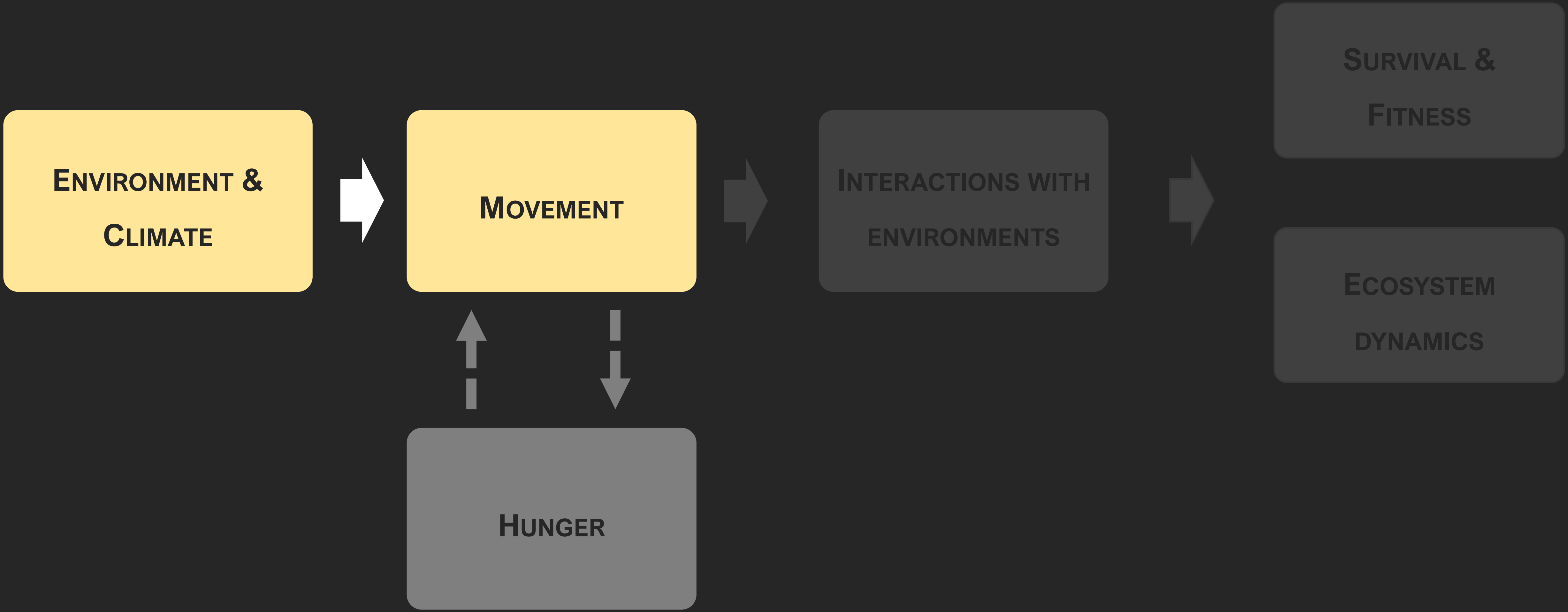
Keystone species
playing crucial roles in the ecosystem

Vulnerable to climate
through unknown mechanisms

How does climate impact the movement of predators, and how is this mediated by hunger?



How does climate impact the movement of predators, and how is this mediated by hunger?



Google Earth

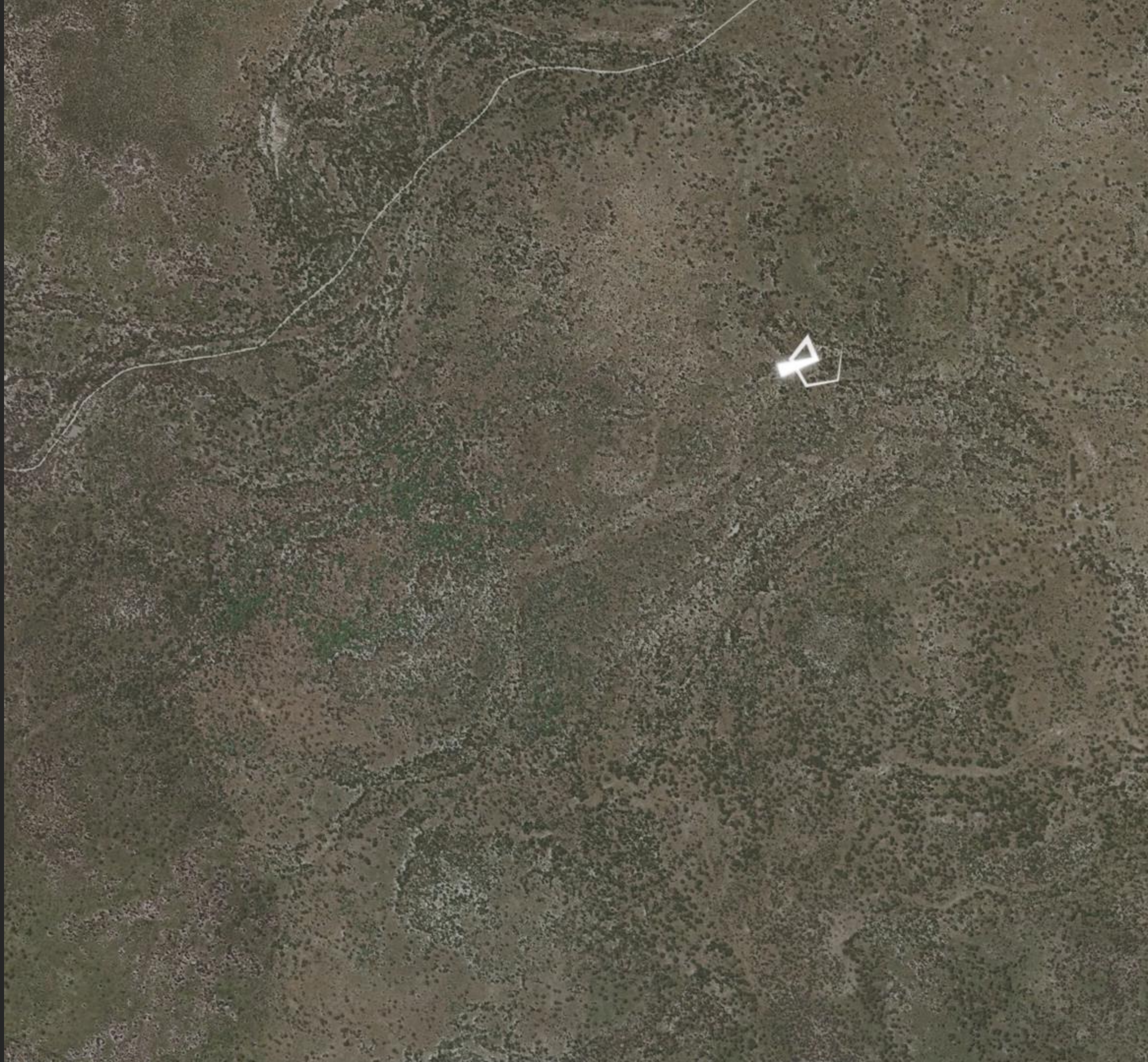

Wild Entrust
RESEARCH | PLAY | COEXIST
Video credit: D.Bessenhoffer

Background

What we have

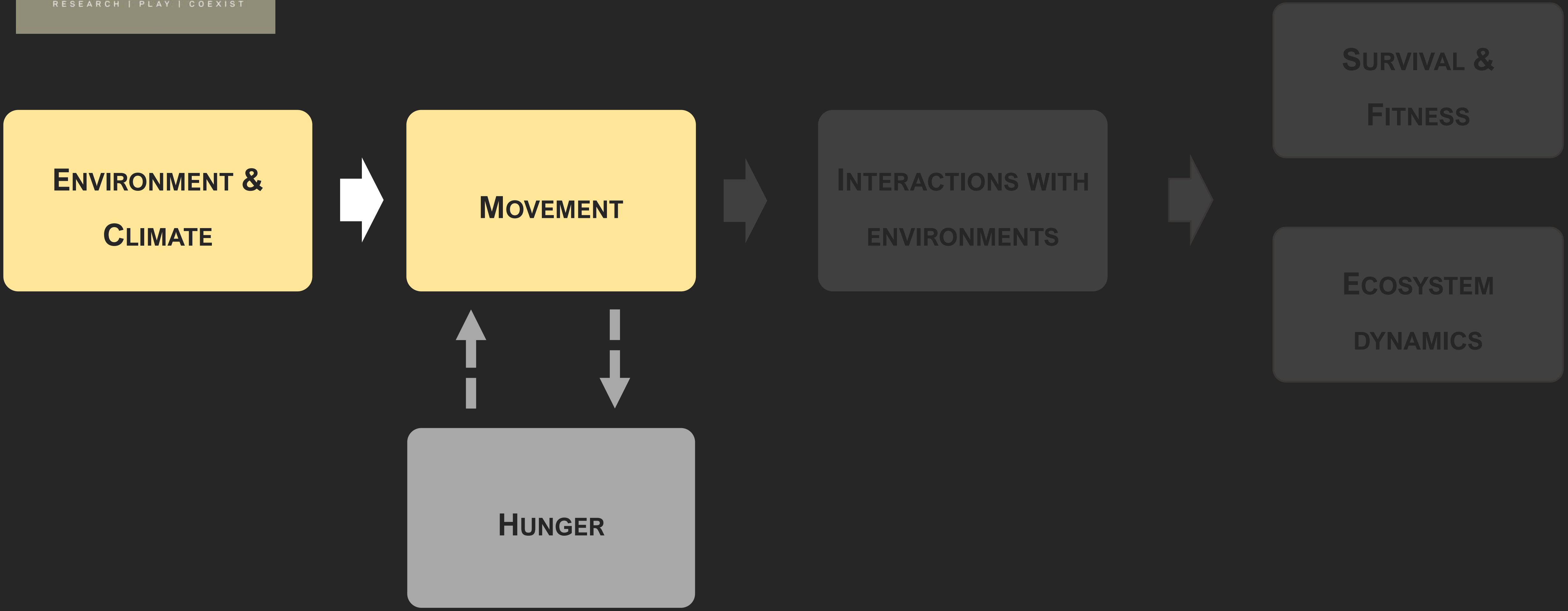
2010 - 2024

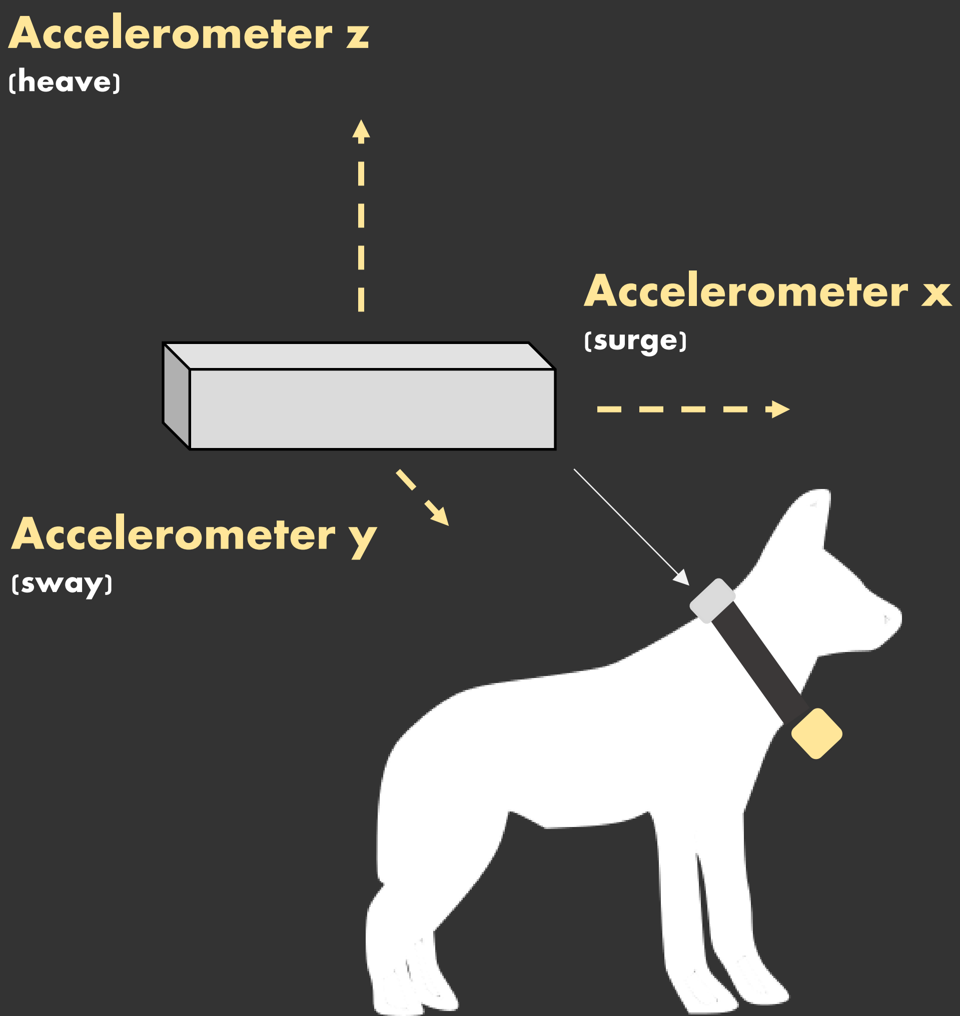
- **GPS collar data**
  30 + deployed collars
- **Environmental data**
  habitat, temperature, precipitation
- **Accelerometer data**
  largely unused

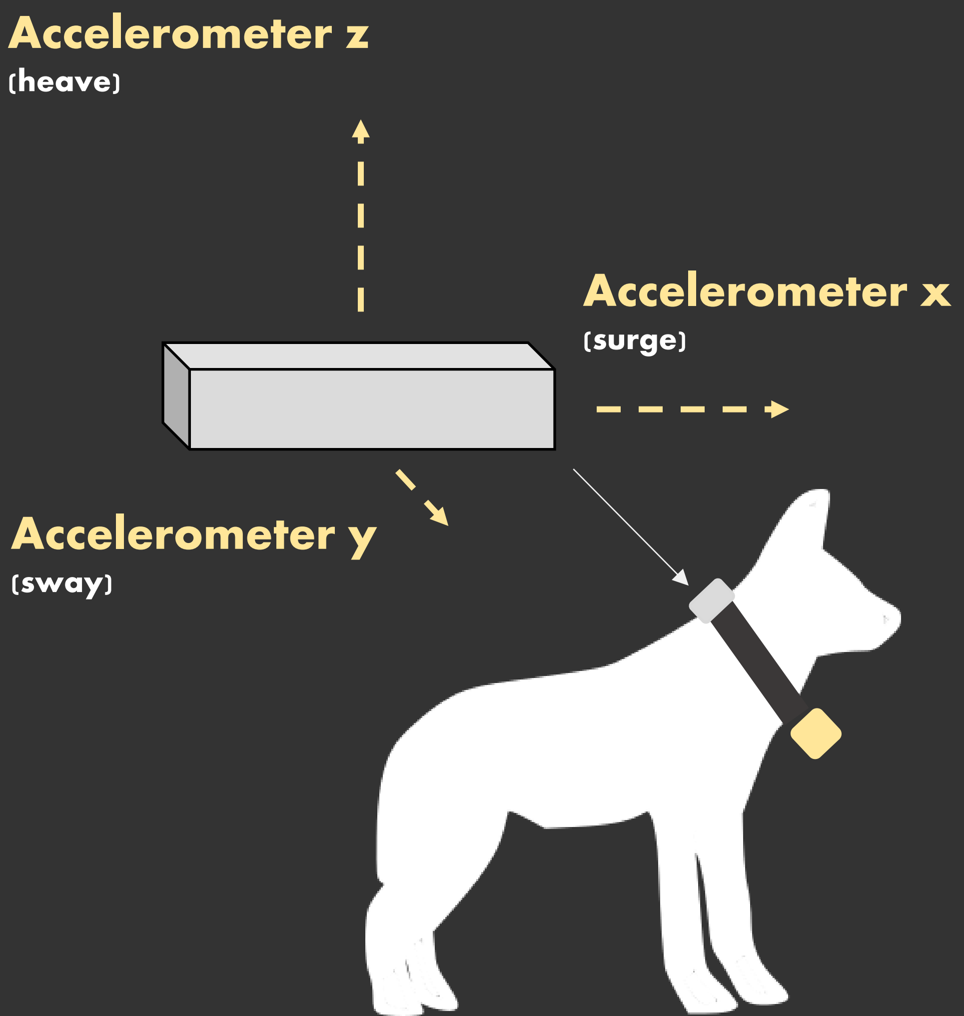


Wild Entrust
RESEARCH | PLAY | COEXIST

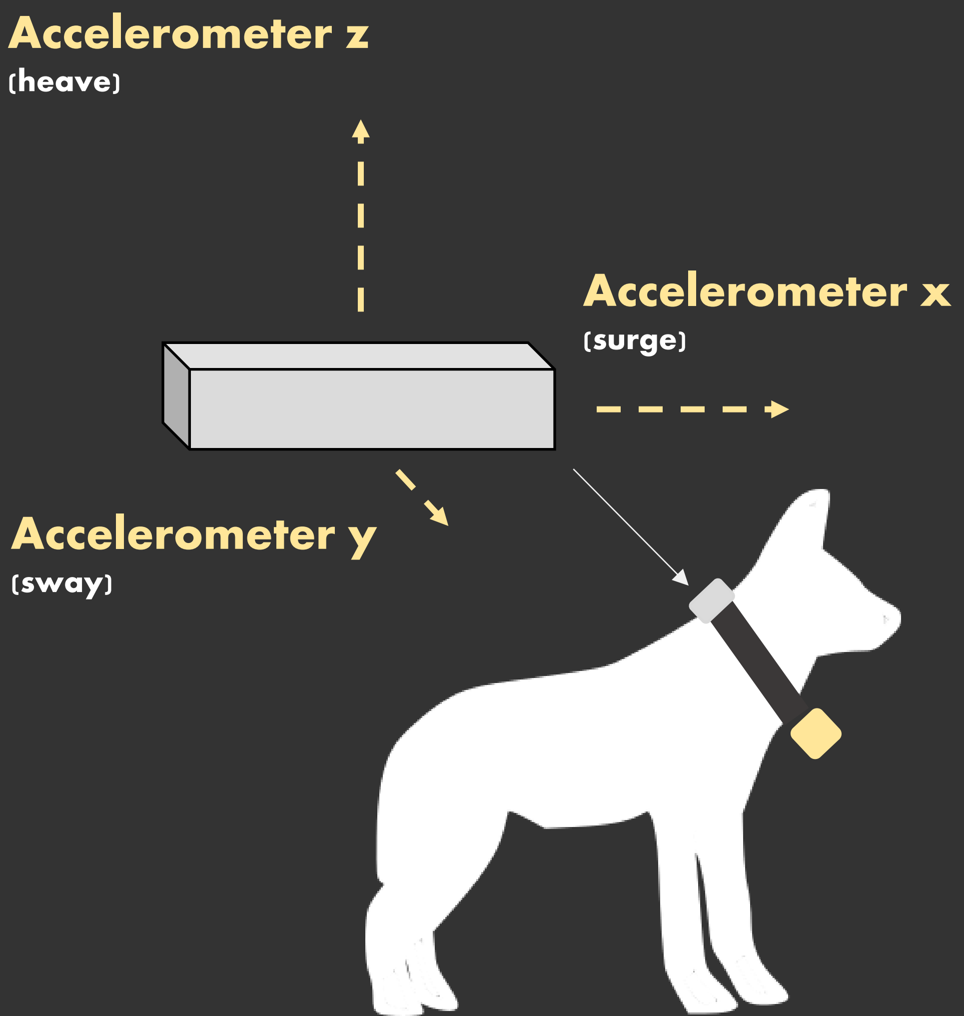
- **Predator movements**
  > 30 predators over 15 years
- **Environmental data**
  habitat type, rainfall, temperature




Accelerometer z
(heave)
Accelerometer x
(surge)
Accelerometer y
(sway)



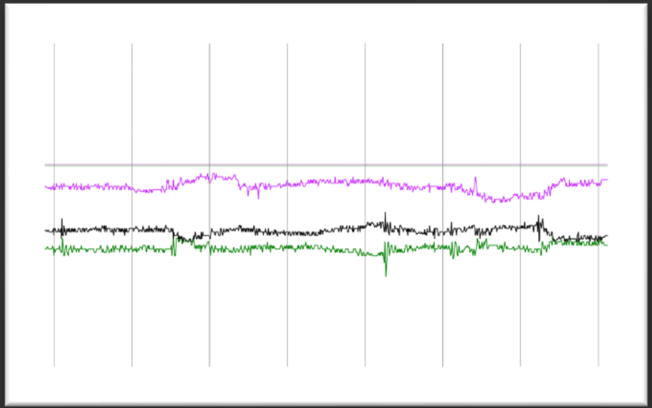
Estimate energy output

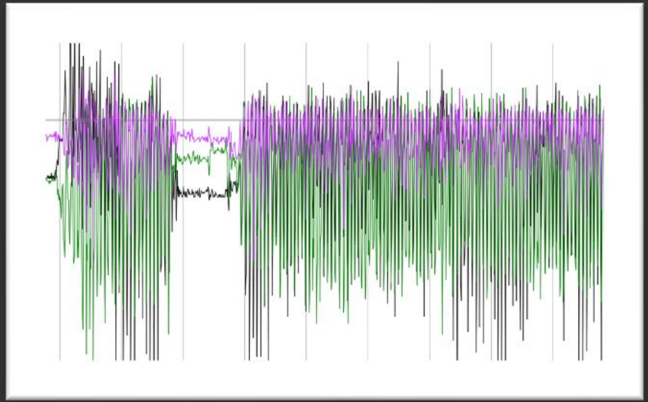


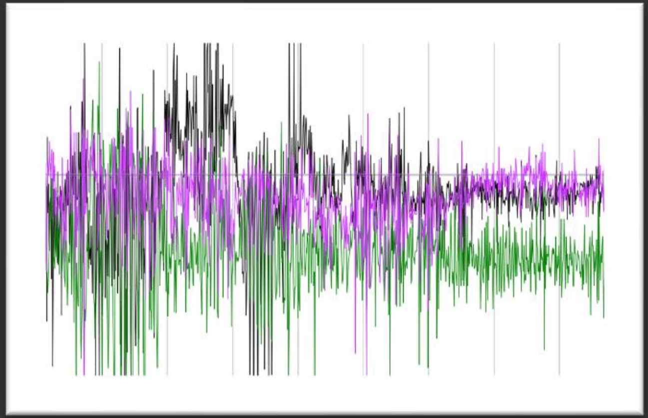
Estimate energy intake

Different behaviours have different data signatures

But you need to learn what these look like



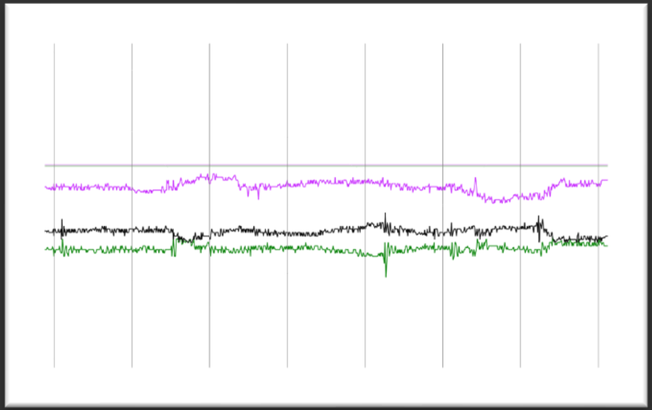


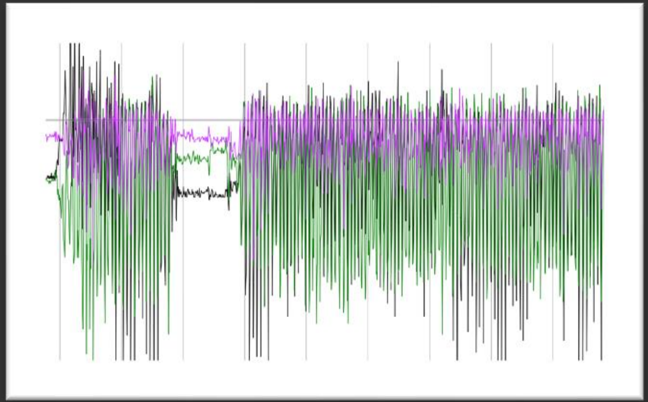


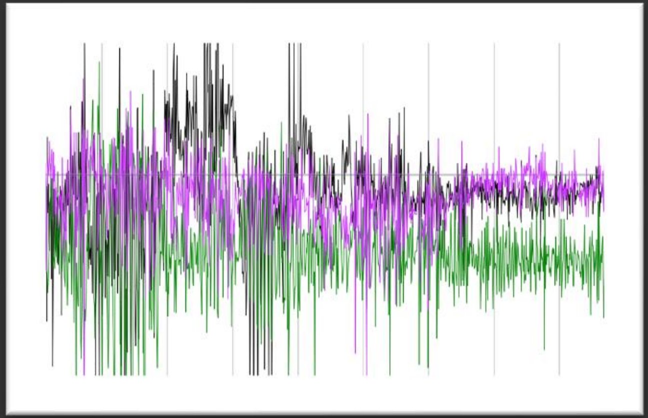
1. Label acceleration data with known behaviours
2. Repeat
3. Train AI models

Different behaviours have different data signatures

But you need to learn what these look like







Collected data for training models

Audio recordings

> 900 hours

Video footage

> 200 hours

Four big challenges

1. Class imbalance

Four big challenges

1. Class imbalance

2. Quantifying uncertainty

Four big challenges

1. Class imbalance

2. Quantifying uncertainty

3. Distribution shift

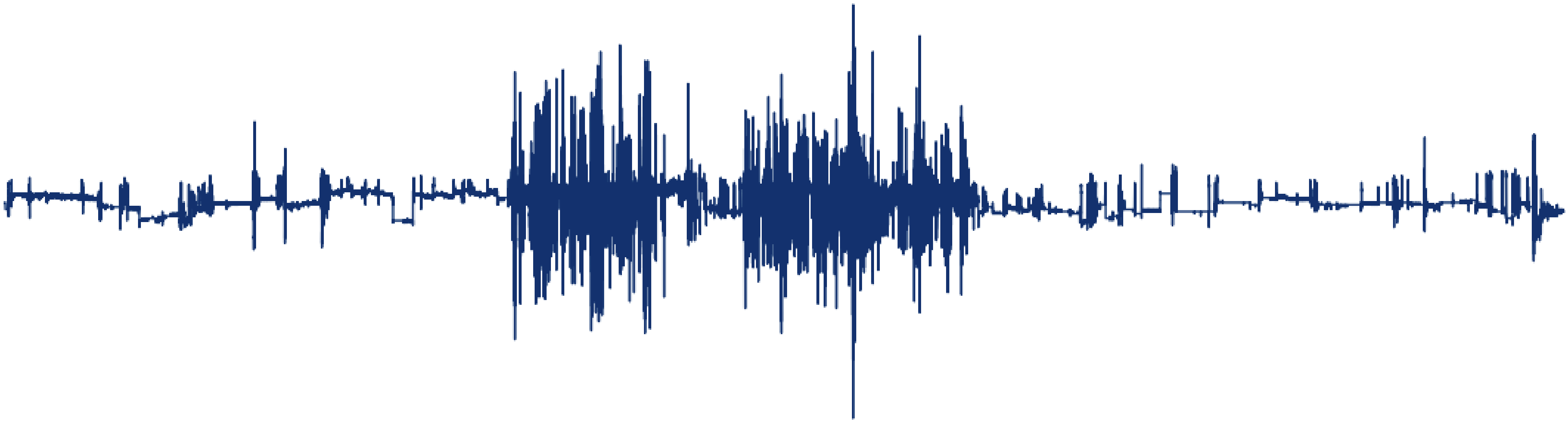
Four big challenges

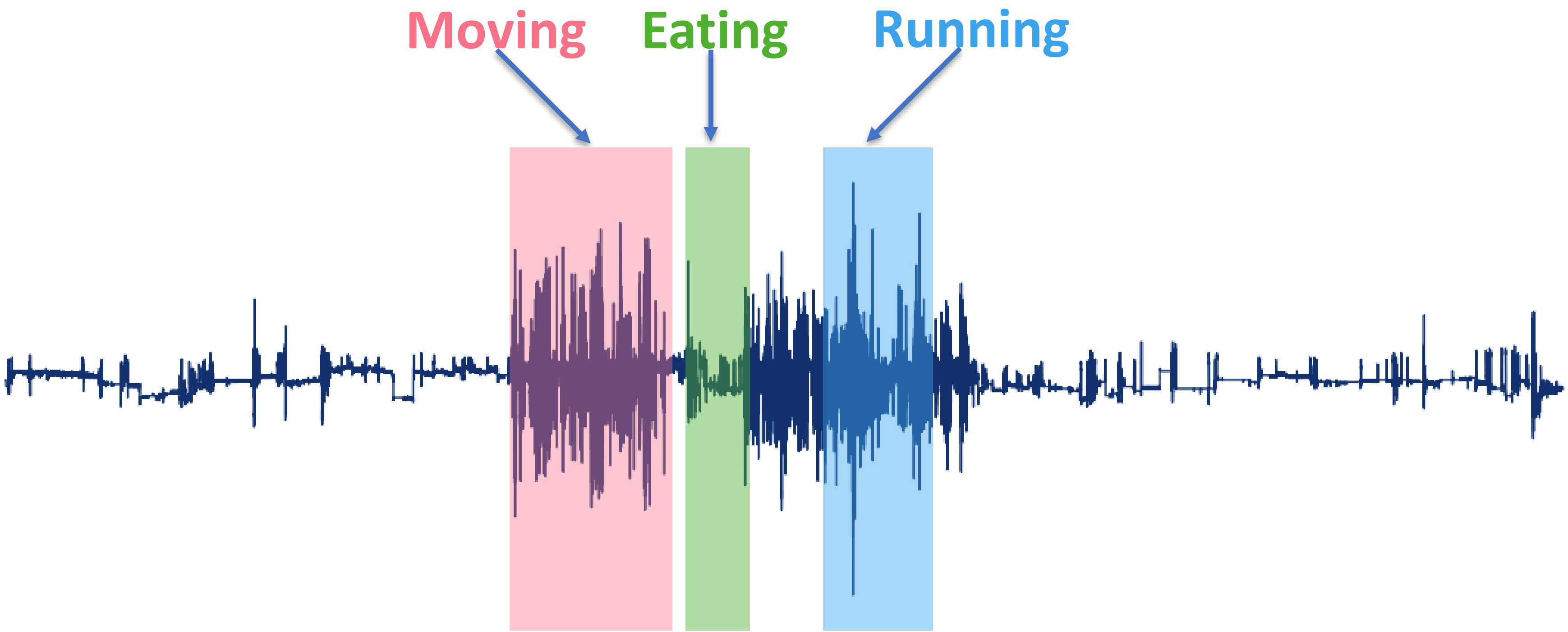
1. Class imbalance
2. Quantifying uncertainty
3. Distribution shift
4. Temporal context

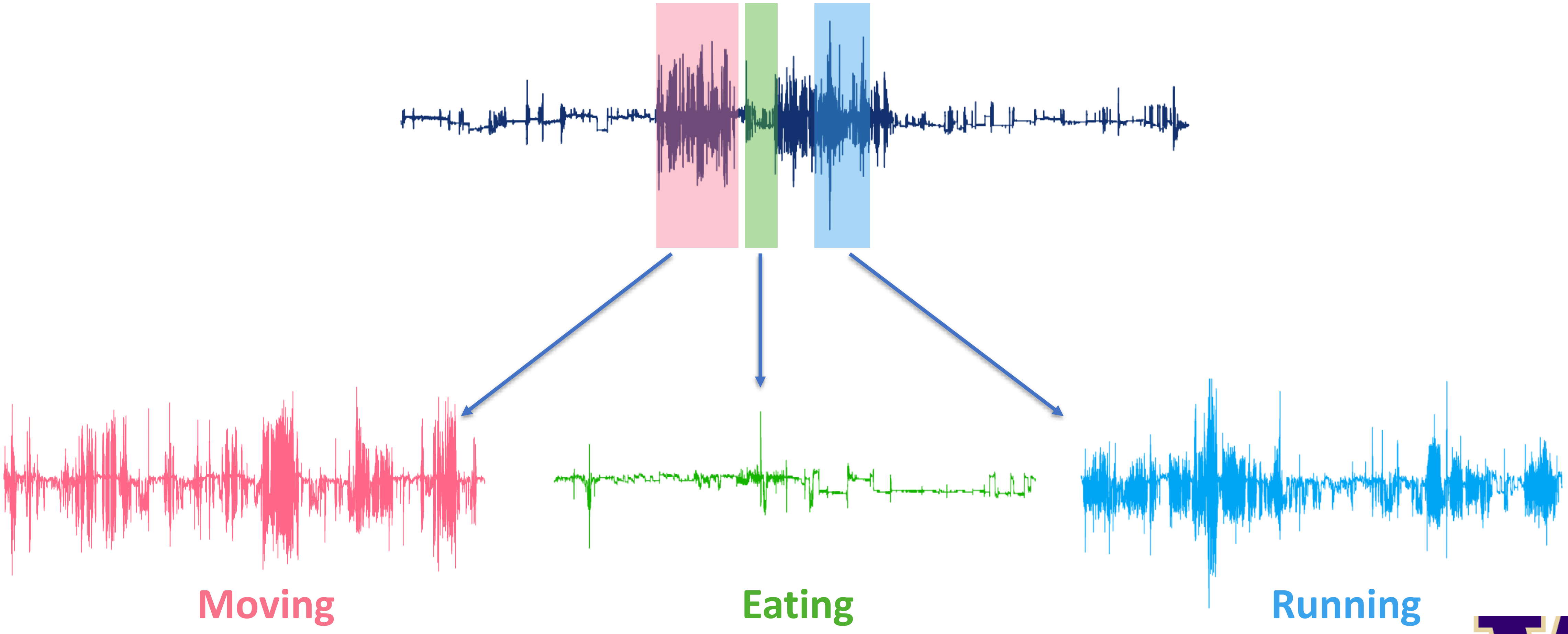
Data Preparation & Class Imbalance

Class Rebalancing

X Axis Accelerometry Signal

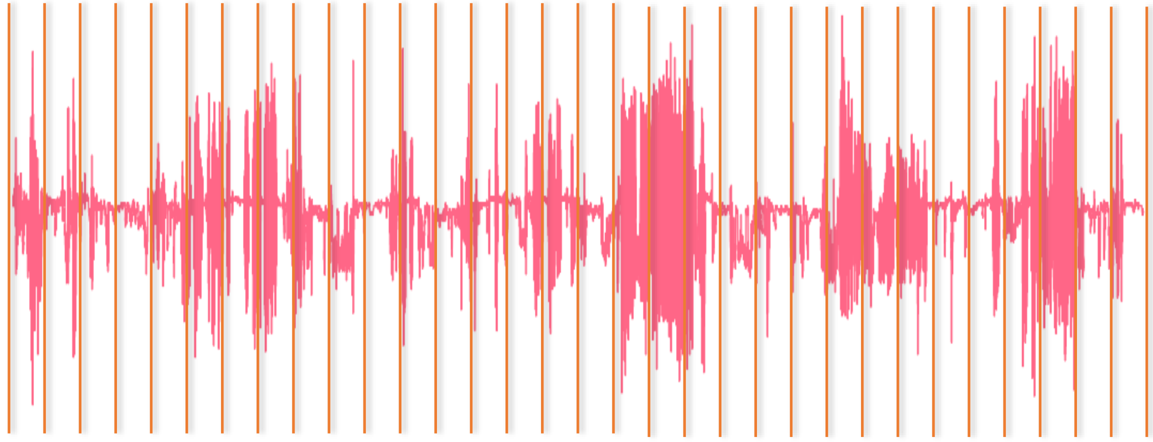


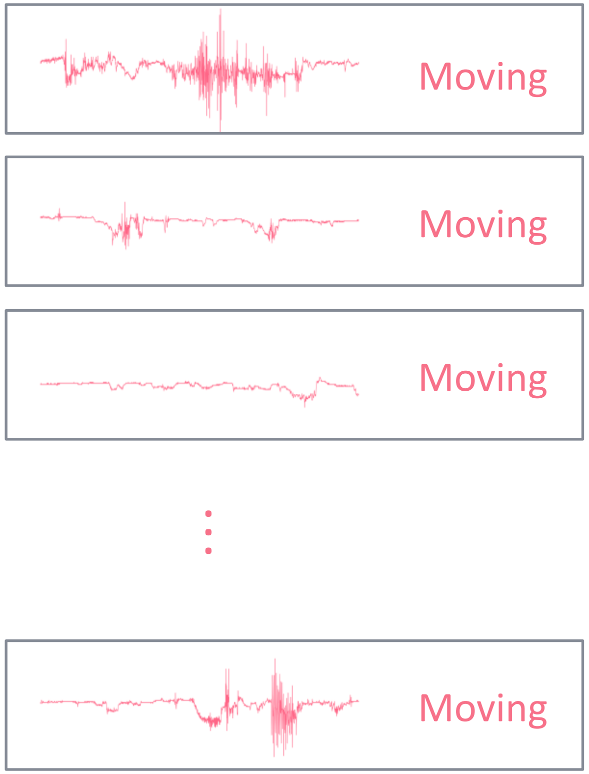

Moving
Eating
Running



Moving
Eating
Running

Fixed duration acceleration-behavior pairs

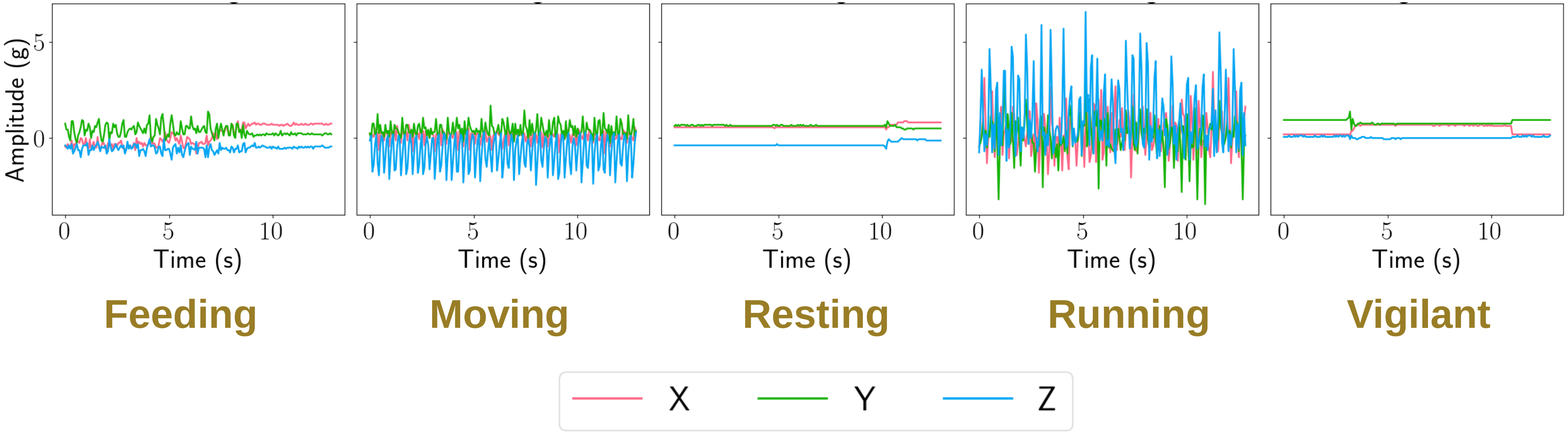




12 seconds windows

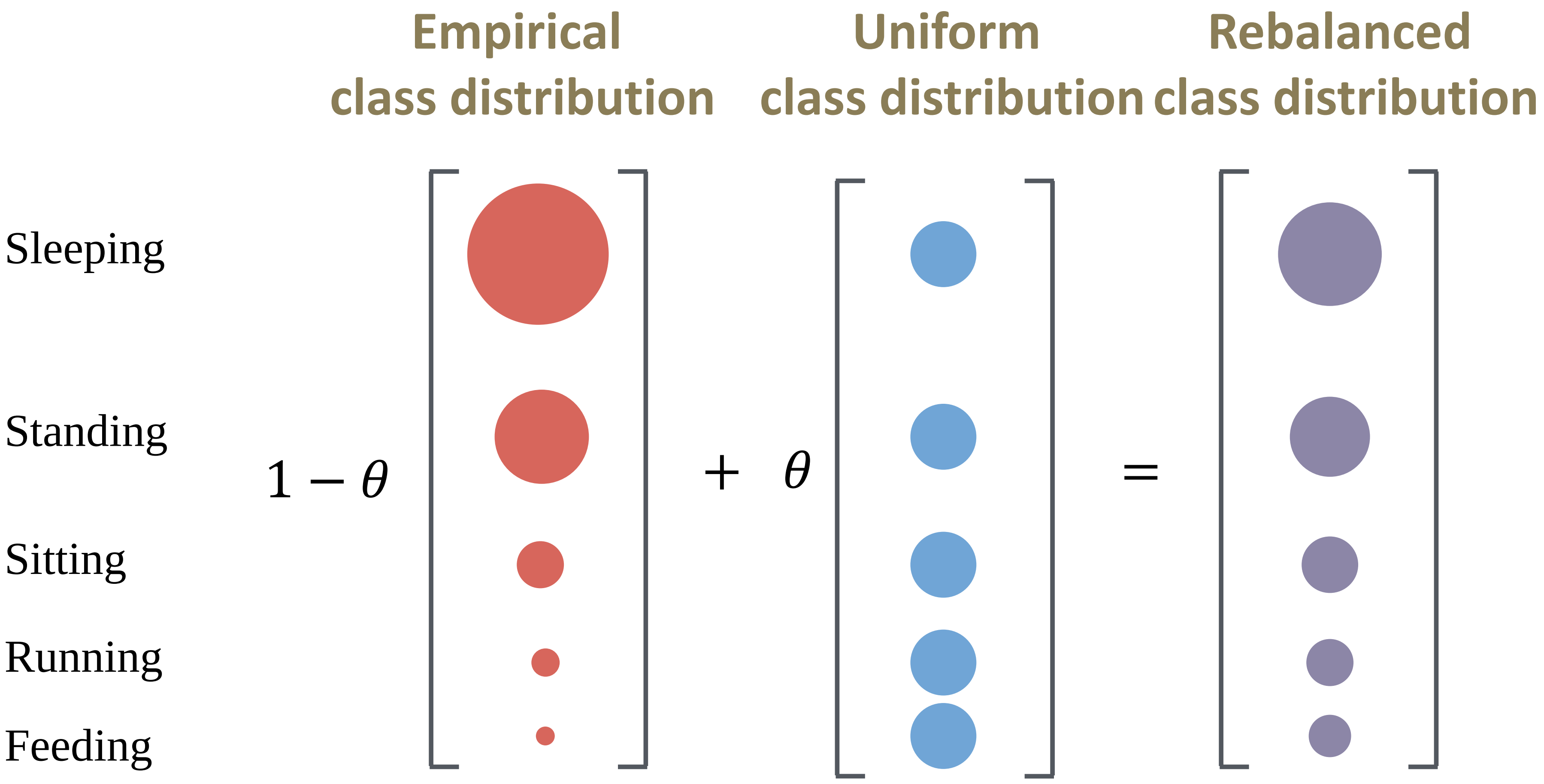
Accelerometry Data Windows and Behavior Labels

23,368 pairs of matched signal windows and behavior labels



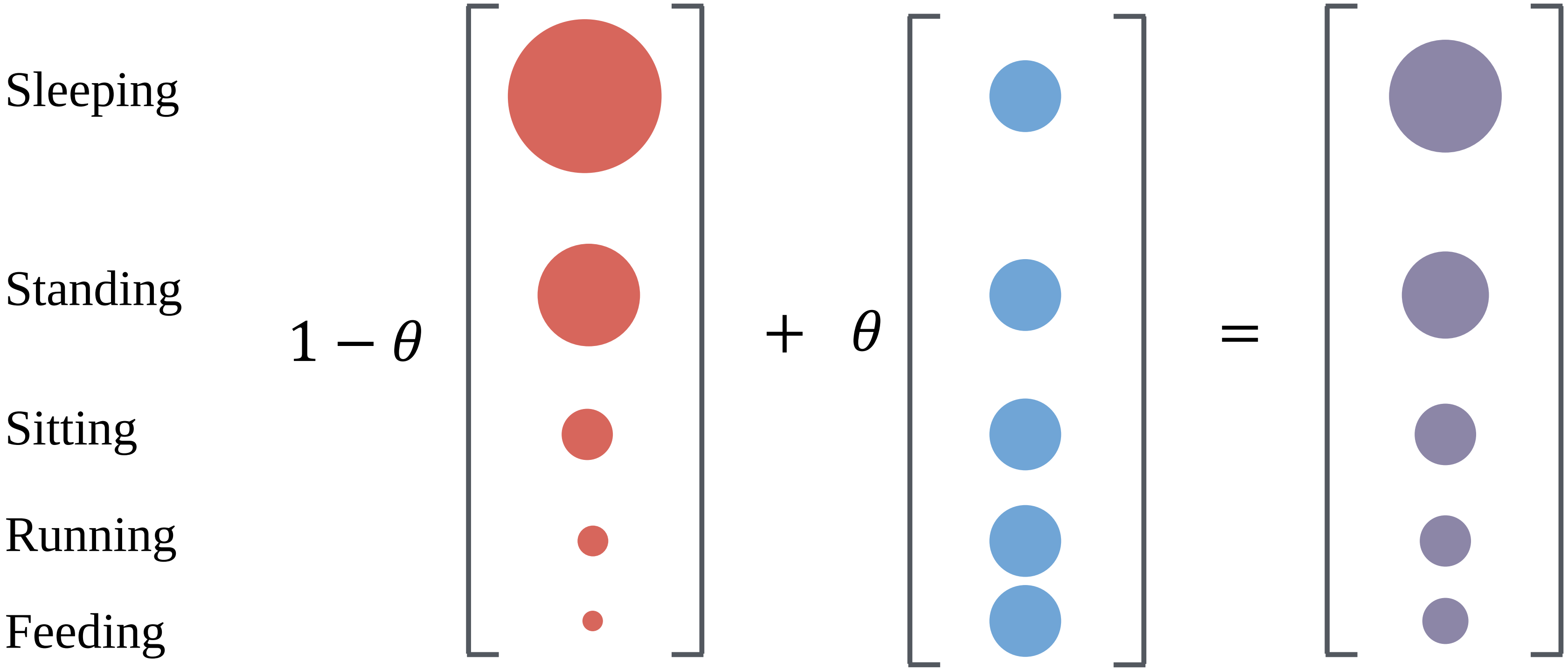
Class Imbalance

Behavior	Video labels duration [h]	Audio labels duration [h]
Feeding	1.32	0.20
Moving	1.67	0.39
Resting	51.57	0.00
Running	0.09	0.48
Vigilant	16.45	0.05



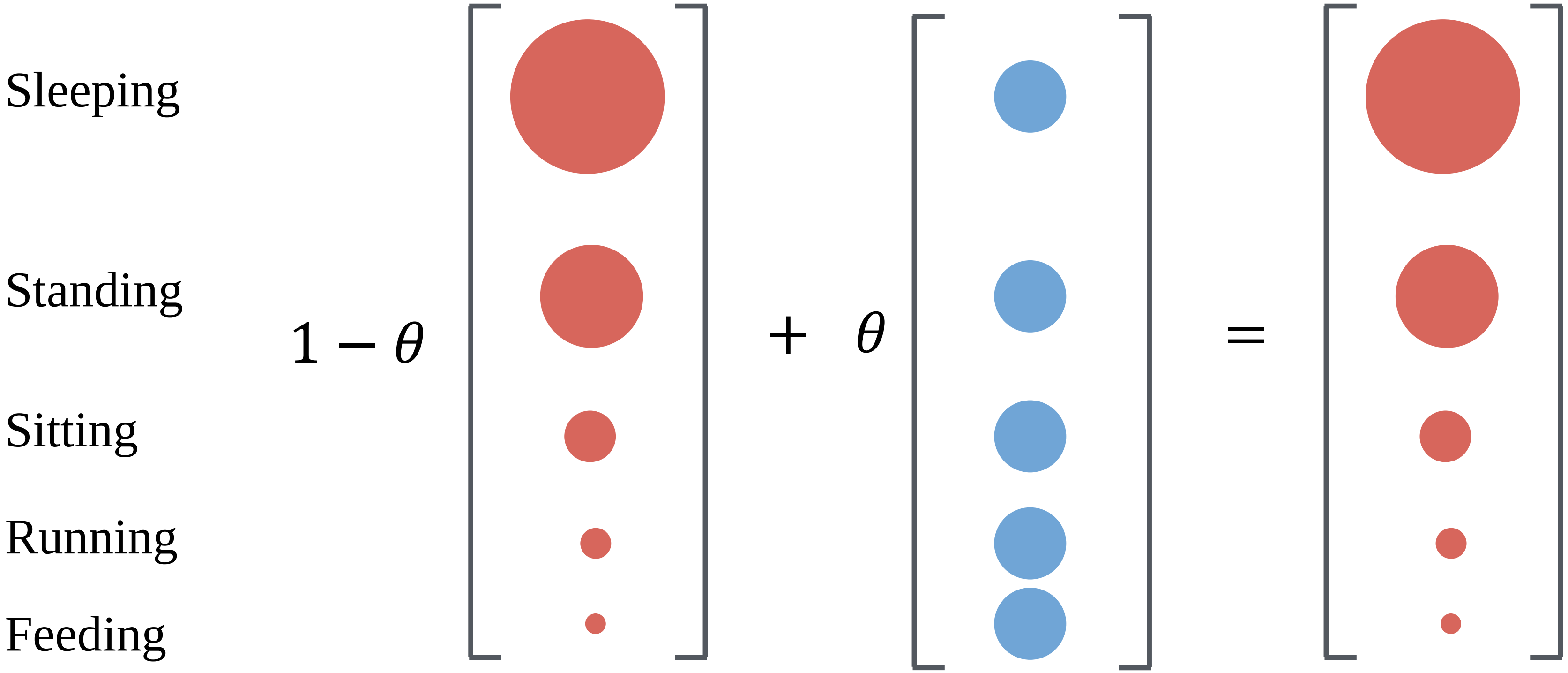
θ =rebalancing parameter

Class Rebalancing, $\theta = 0.7$



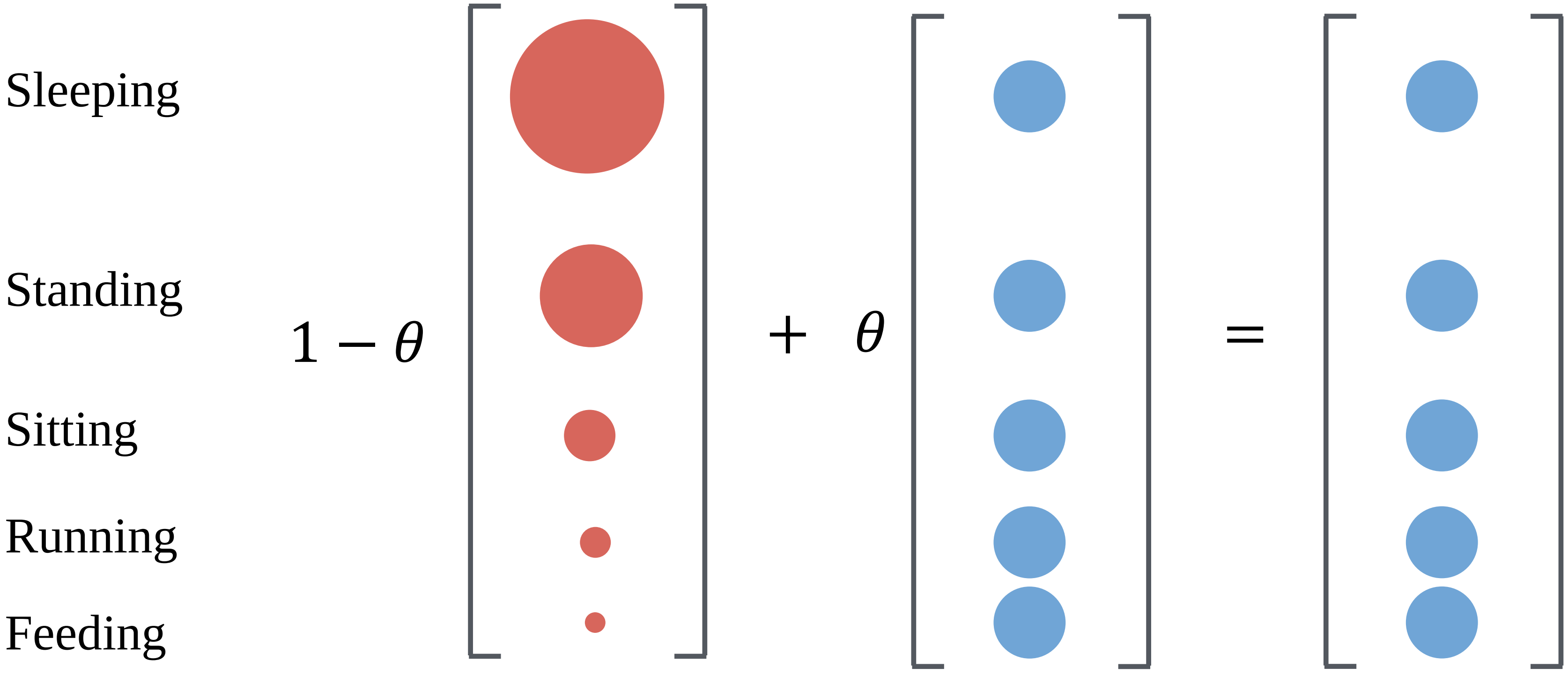
Partial rebalancing

Class Rebalancing, $\theta = 0.0$



No rebalancing

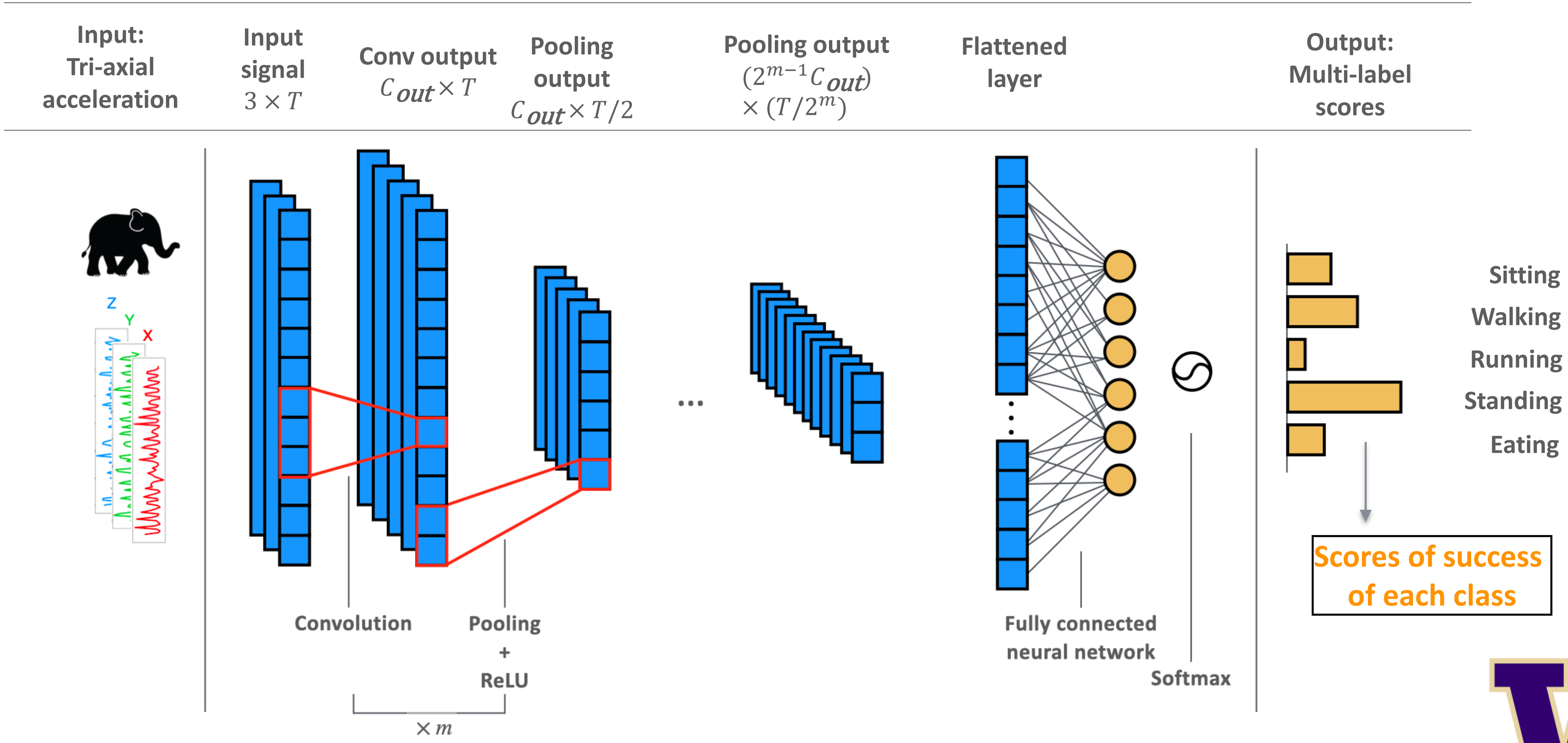
Class Rebalancing, $\theta = 1.0$



Complete rebalancing

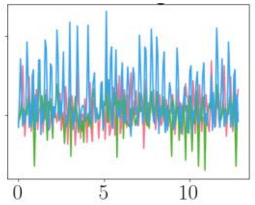
Model Architecture & Uncertainty Quantification

Model Architecture



Uncertainty Quantification - Prediction Sets

A set of predictions that provably contains the true class label with a pre-specified probability, for example 90%.

$P(Y \in$  $| X =$ 

$) \geq 0.9$

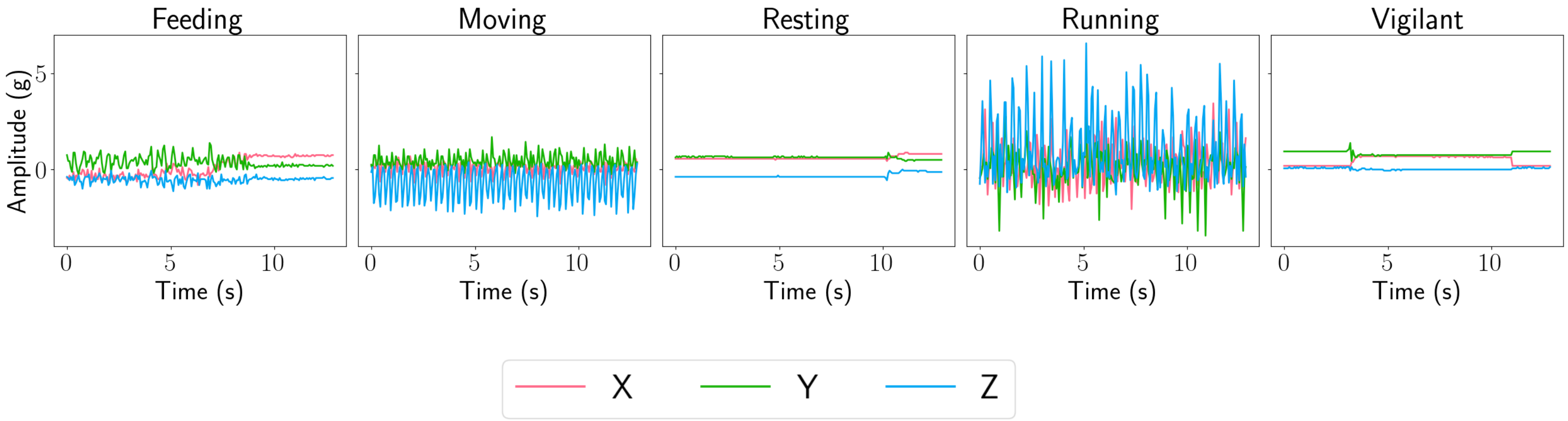
Label

Prediction set

Covariate

We use regularized adaptive prediction sets (RAPS) calibrated on a held-out set.

Uncertainty Quantification - Example

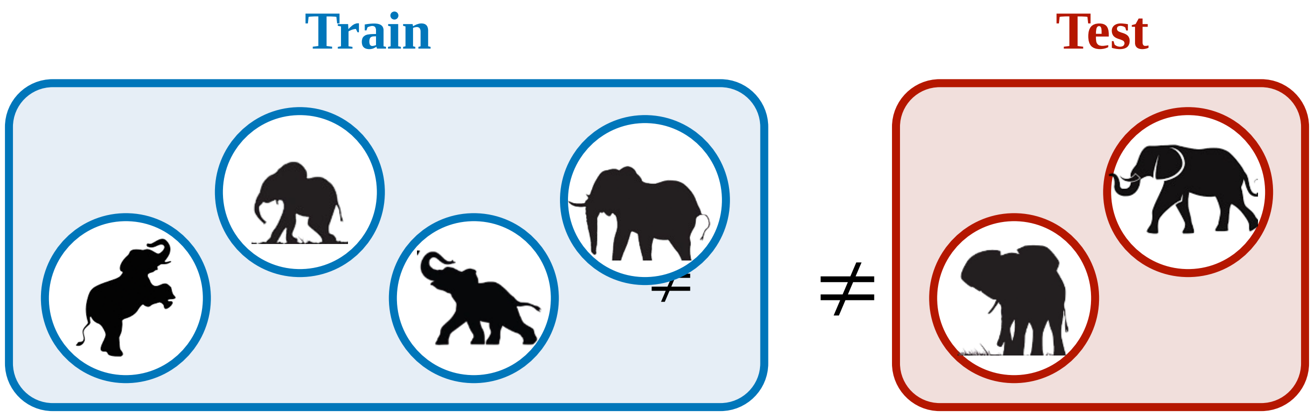


{ Feeding 0.3343 Vigilant 0.2422 } { Moving 0.4034 } { Resting 0.3484 Vigilant 0.1839 } { Running 0.4016 } { Vigilant 0.3094 Resting 0.2110 }

Distribution Shift

Testing Model Robustness

Distribution Shift



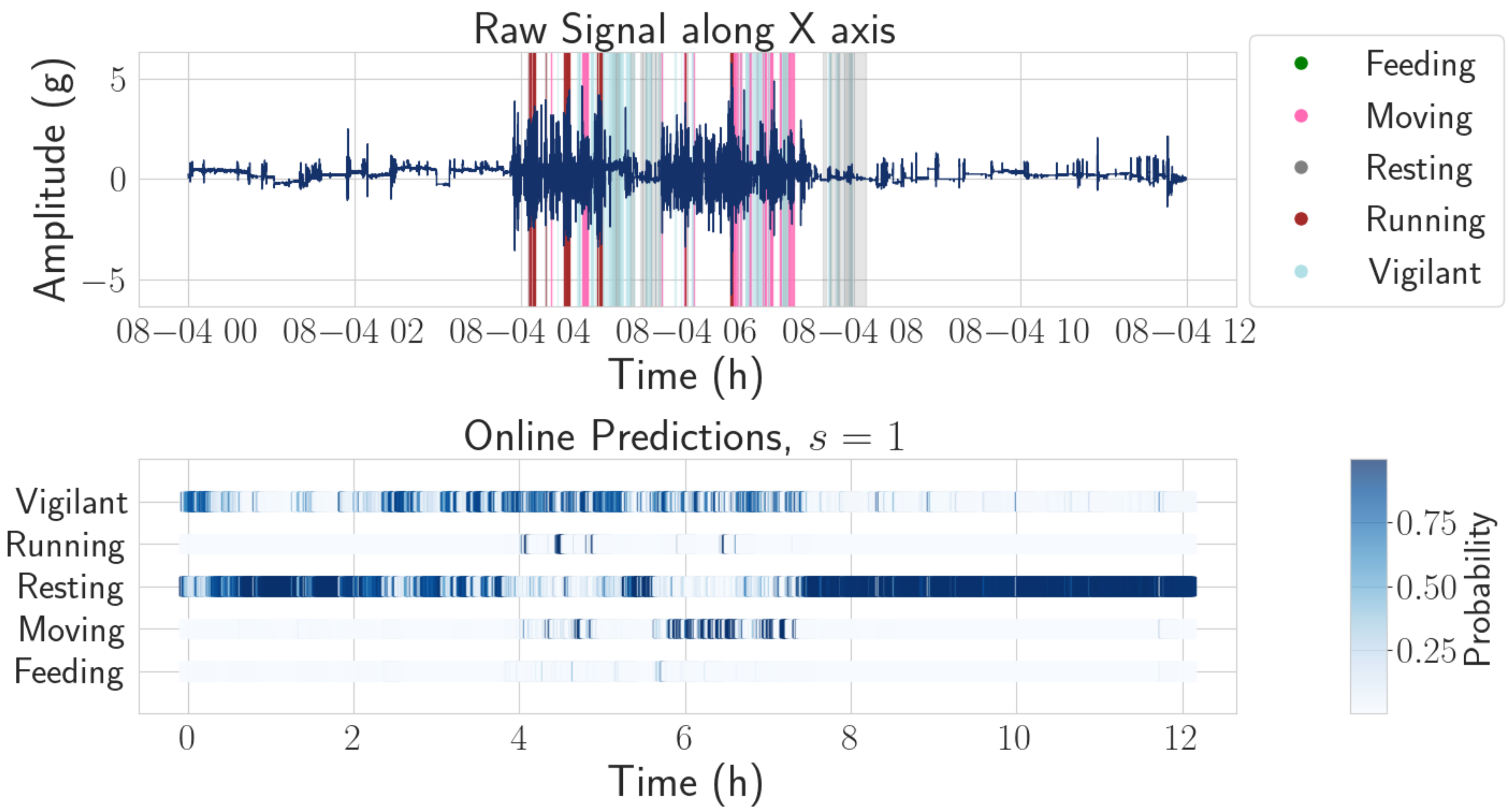
Model performance can decline due to distribution shift, where he characteristics of the training data differ those of dataset used for model implementation.

Potential Distribution Shift in Data

Temporal Context

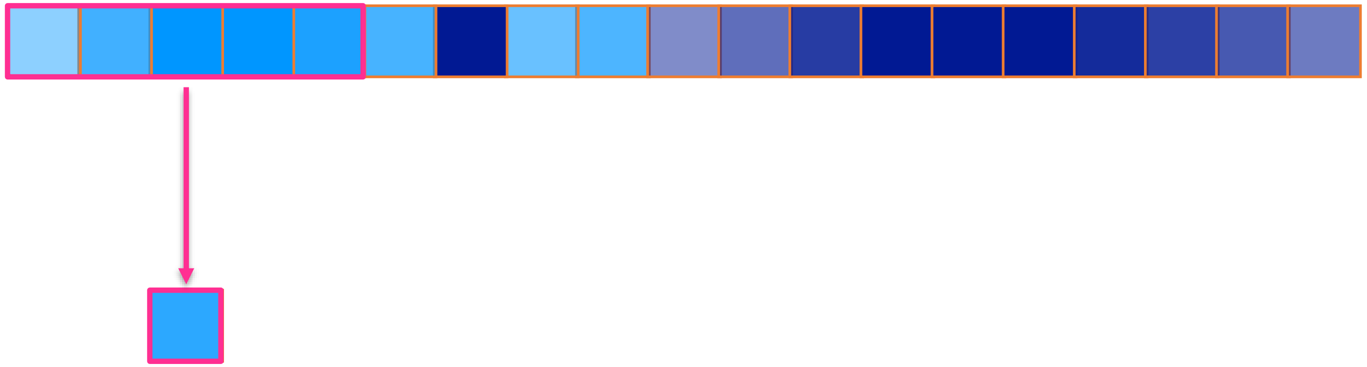
Temporally Smoothed Classification

Behavior classification on signal can be abrupt…



Temporally Smoothed Classification

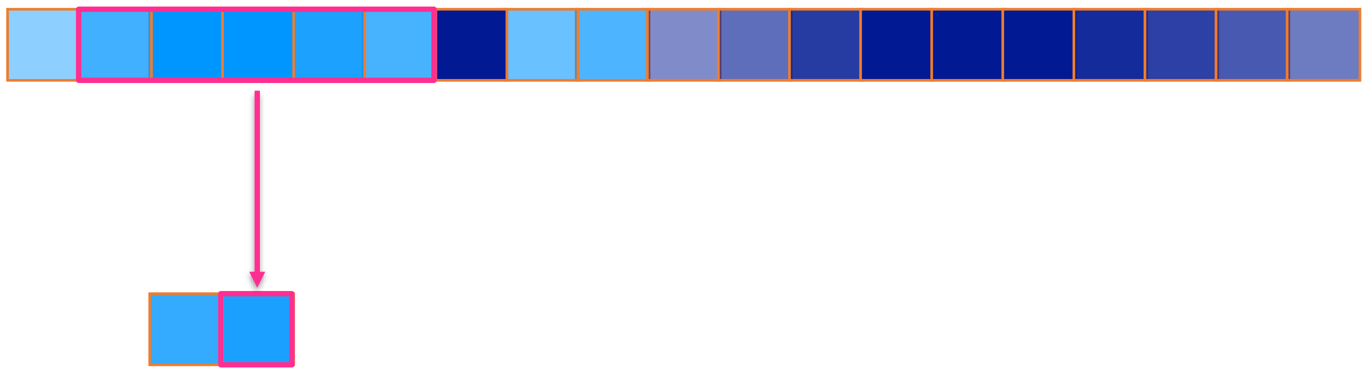
Moving scores



Smoothed moving scores

Temporally Smoothed Classification

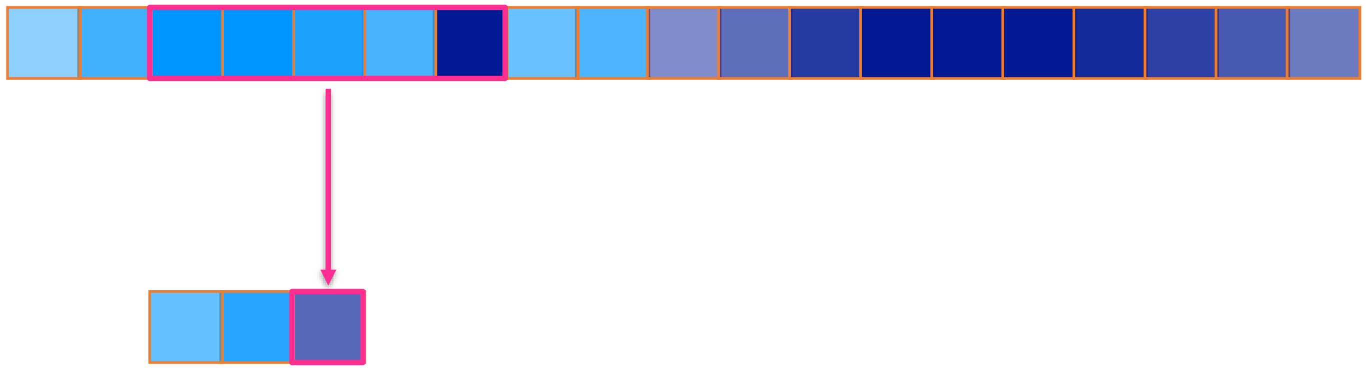
Moving scores



Smoothed moving scores

Temporally Smoothed Classification

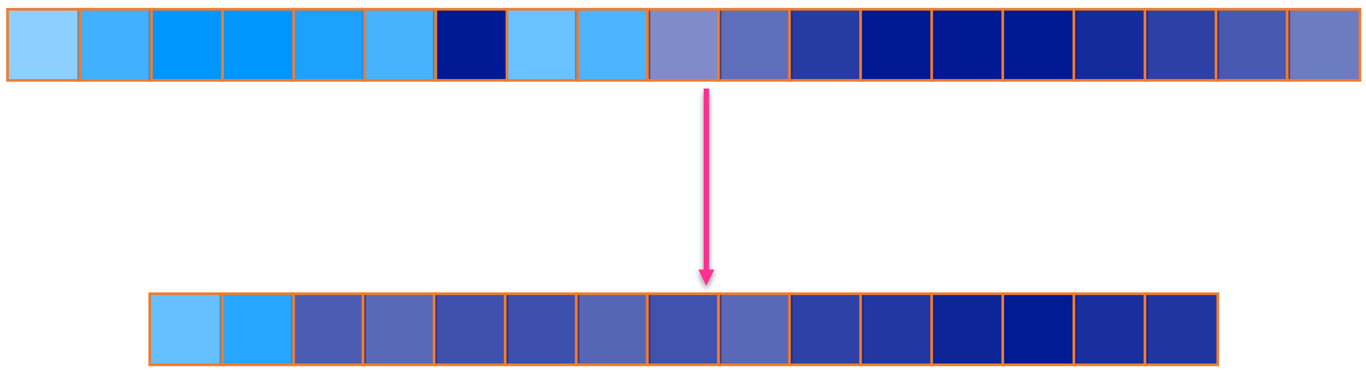
Moving scores



Smoothed moving scores

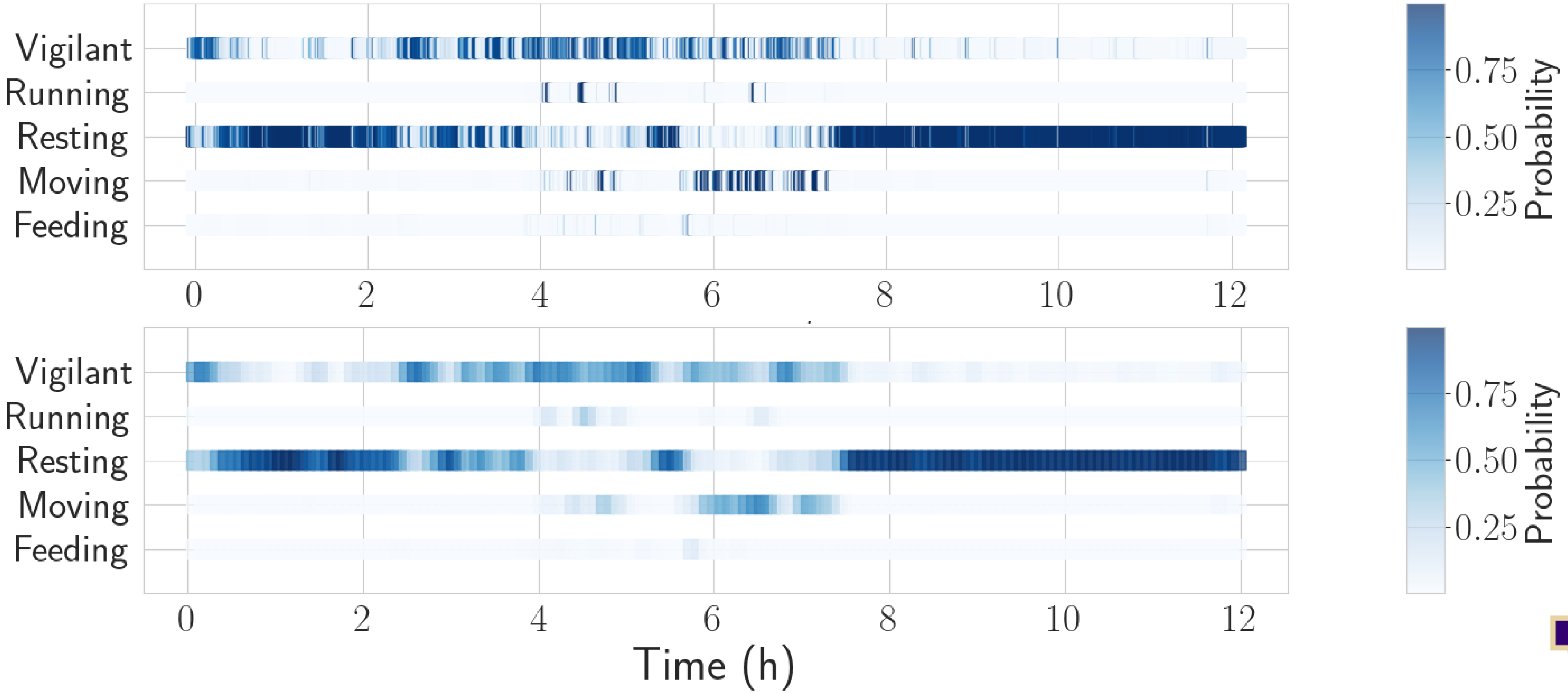
Temporally Smoothed Classification

Moving scores



Smoothed moving scores

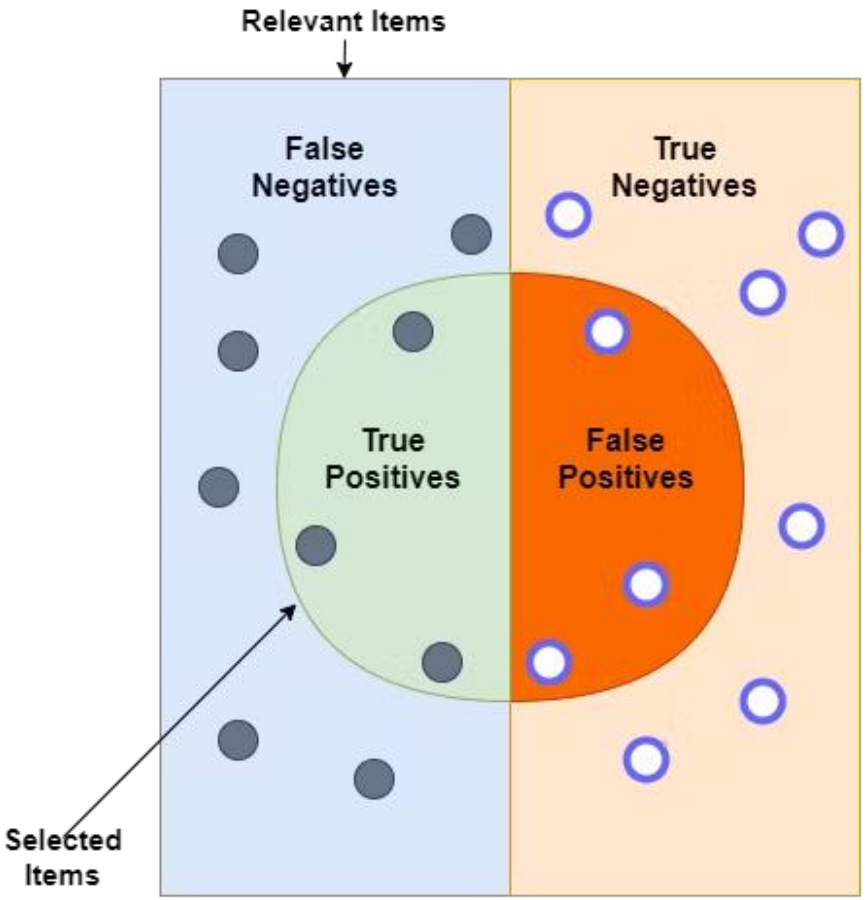
Temporally Smoothed Classification

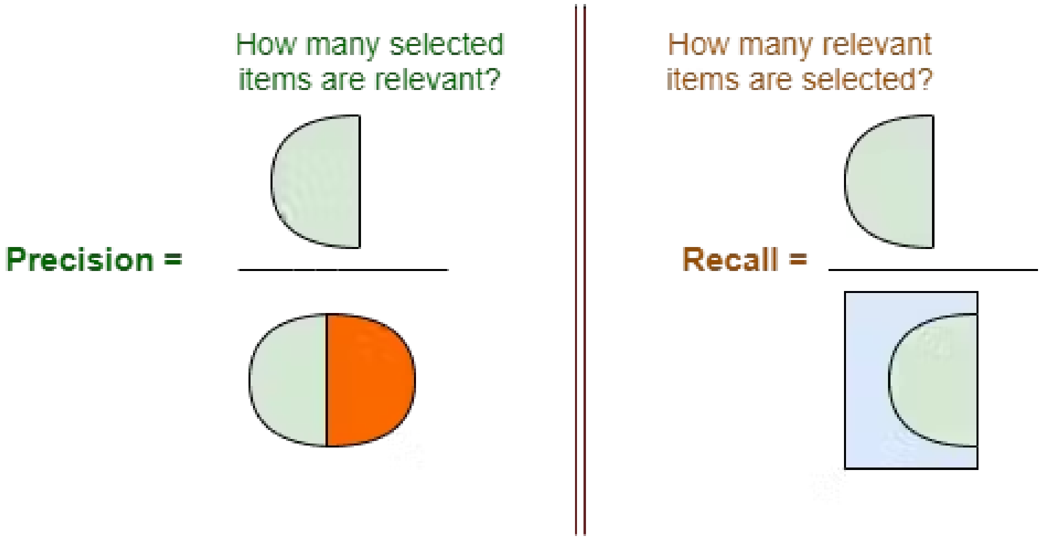


Results

Evaluation Metrics

for most likely predictions…





$$\text{F1 score} = \frac{2\ \text{Precision} \times \text{Recall}}{2\ \text{Precision} + \text{Recall}}$$

Evaluation Metrics

for prediction sets…

Coverage:

Proportion of instances for which correct label is included in the prediction set.

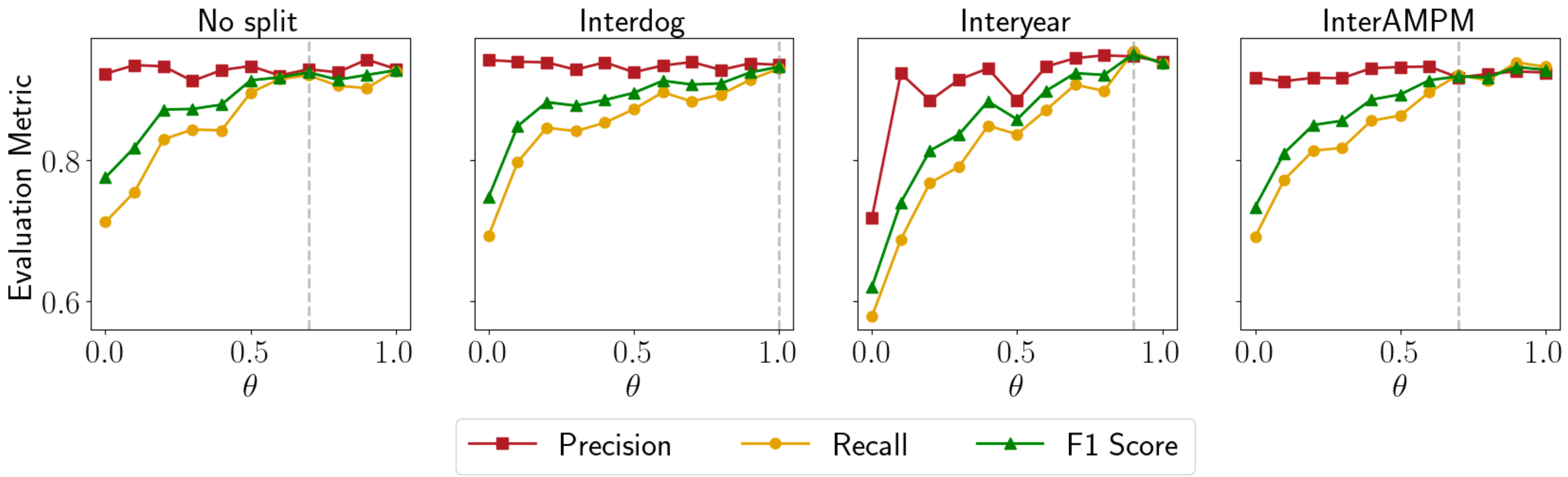
More is better.

Average RAPS Size:

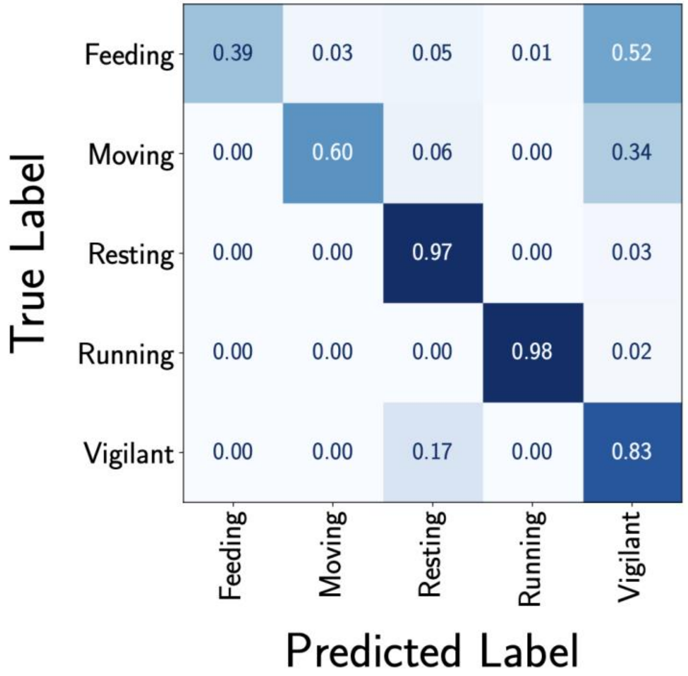
Average size of the reduction sets. Ranges between one to number of classes.

Less is better.

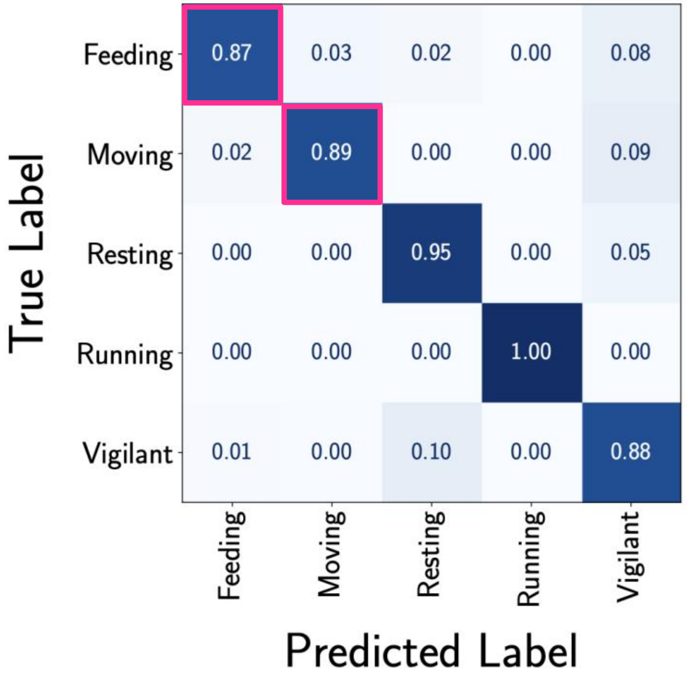
Tuning the rebalancing parameter θ



No-split experiment - most likely predictions



$\theta = 0.0$



$\theta = 0.7$

All experiments - all evaluation metrics

Evaluation Metric	No split	Interdog	Interyear	InterAMPM
Train set size	14978	13104	9528	13712
Validation set size	3745	3277	2382	3429
Test set size	4645	6987	11458	6227
Precision (val, test)	(0.93, 0.92)	(0.94, 0.86)	(0.92, 0.84)	(0.91, 0.88)
Recall (val, test)	(0.92, 0.92)	(0.93, 0.90)	(0.89, 0.84)	(0.90. 0.88)
F1 score (val, test)	(0.92, 0.92)	(0.93, 0.88)	(0.91, 0.83)	(0.90, 0.88)
Accuracy (val, test)	(0.93, 0.93)	(0.93, 0.91)	(0.89, 0.80)	(0.87, 0.85)
Top-1 coverage (val, test)	(0.88, 0.86)	(0.89, 0.79)	(0.90, 0.80)	(0.88, 0.83)
RAPS coverage (val, test)	(0.95, 0.93)	(0.95, 0.89)	(0.92, 0.83)	(0.94, 0.90)
RAPS avg size (val, test)	(1.32, 1.32)	(1.21, 1.30)	(1.05, 1.06)	(1.21, 1.23)

Future Directions

Integrate other data modalities

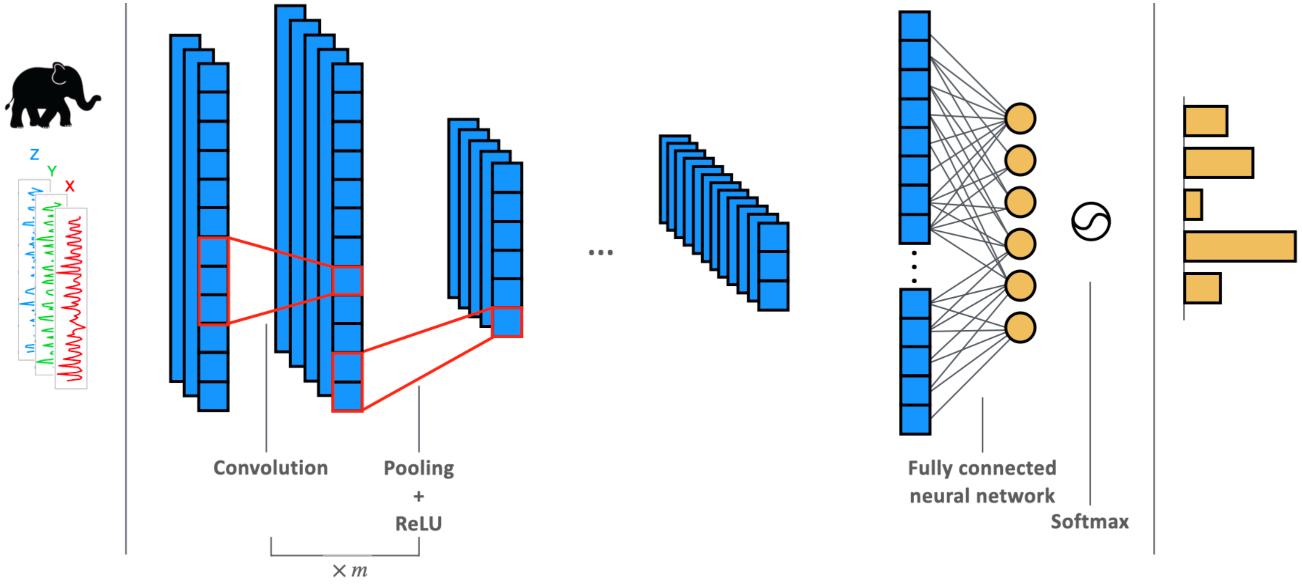
Running

Lying down

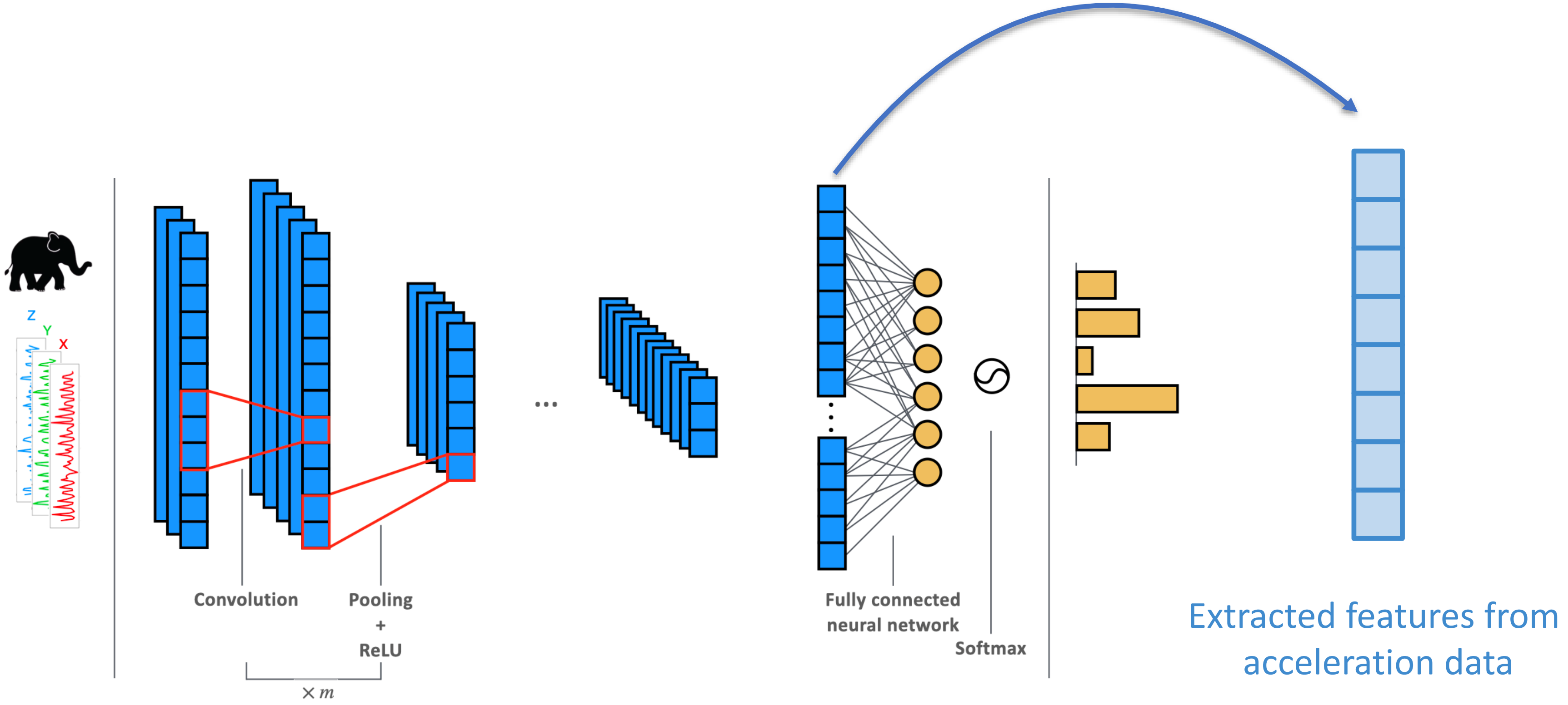
Stationary

Eating

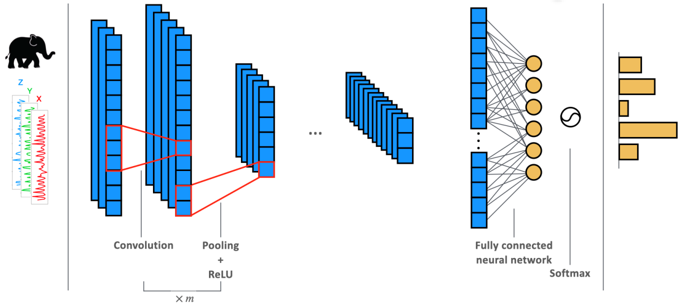
Integrate other data modalities



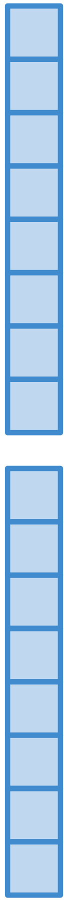
Integrate other data modalities

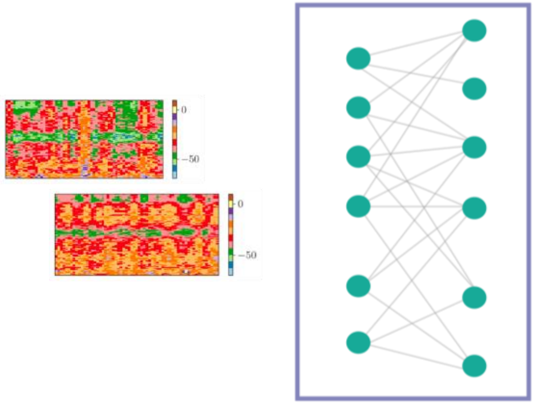


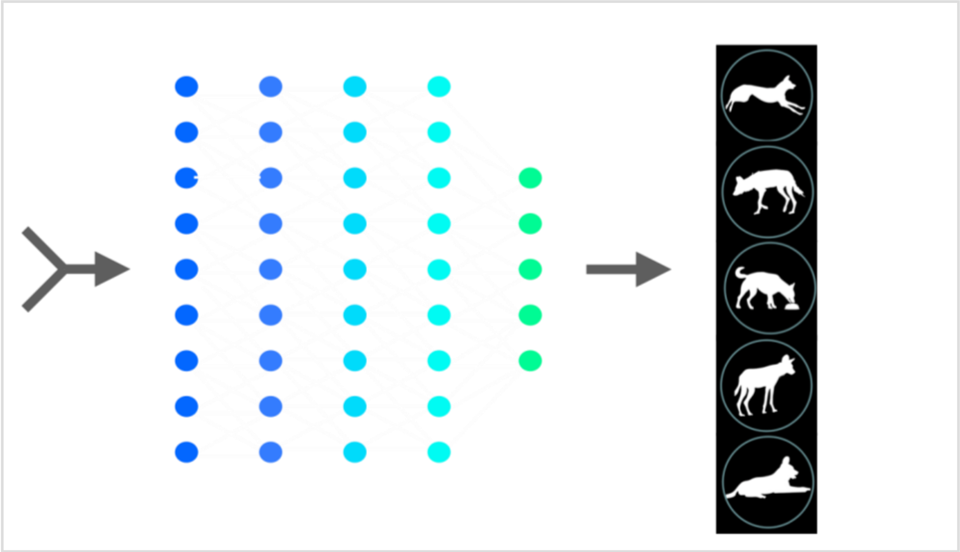
Integrate other data modalities



Extracted features from acceleration data





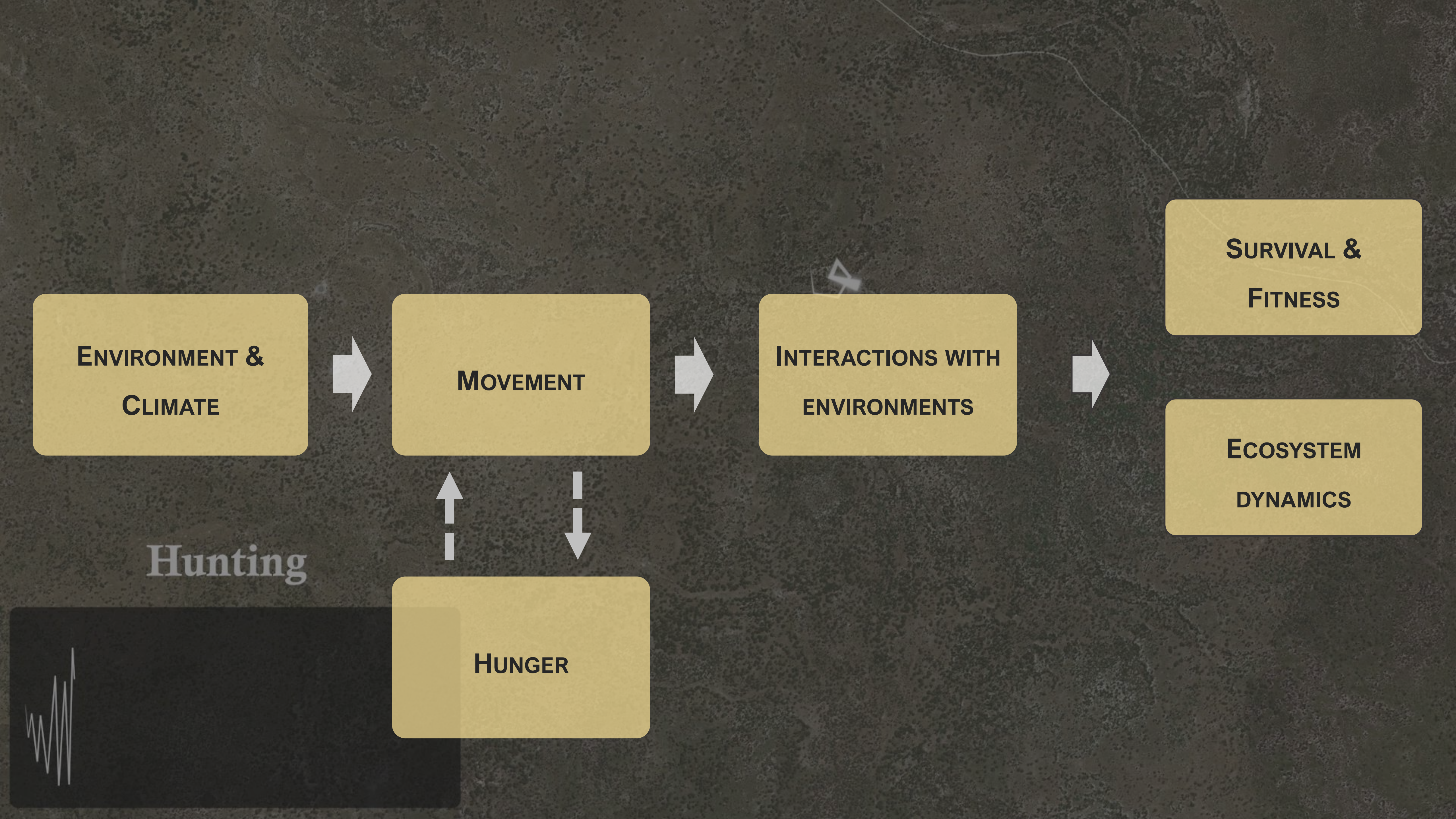


Extracted features from audio data

UNIVERSITY of WASHINGTON

NSF

Botswana Predator Conservation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Ecosystem dynamics
Hunger
Hunting

GPS collar data
30 + deployed collars

Environmental data
habitat, temperature, precipitation

Accelerometer data
largely unused

Audio recordings
> 900 hours

Species demographics
survival, morphometrics

Herbivore data
bi-annual surveys

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Earthsounds @ Apple TV

Thank you

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