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# A basic machine learning method for identifying individual biological state and ecological context from movement data

**Timothy Schaerf [a], Andrei Zvezdin [a], Mitchell Welch [a], Alexander Wilson [b] and Ashley Ward [c]**

[a] *School of Science and Technology, University of New England, Armidale, Australia*
[b] *Behavioural and Marine Ecology Laboratory, School of Biological and Marine Sciences, University of Plymouth, United Kingdom*
[c] *Animal Behaviour Lab, School of Life and Environmental Sciences, University of Sydney, Australia*
*Email: tschaerf@une.edu.au*

**Abstract:** Experimental and observational work has demonstrated that the fine time-scale movement behaviour of animals can be affected by both the internal state of the animals, such as their hunger level, and external ecological factors, such as threat of predation or the opportunity to feed. Given that internal state and ecological context have an effect on movement behaviour, from individual to collective level, this leads to the question "can the state and context of an individual be inferred from their movement behaviour"?

In this talk, we will discuss the effectiveness of a basic machine learning method for identifying individuals' internal state and ecological state from the idiosyncrasies of their trajectories (movement signatures). The underlying method, outlined in Figure 1, was described and applied by Stefan Krause in (Herbert-Read et al., 2013), but has not seen widespread use or refinement since then. We will examine the accuracy of the method in identifying model prescribed differences in collective motion simulation data, with a focus on the role of the spatial resolution at which data is translated to integer states. We will then apply the method to experimental data where the ecological context of fish has been manipulated.

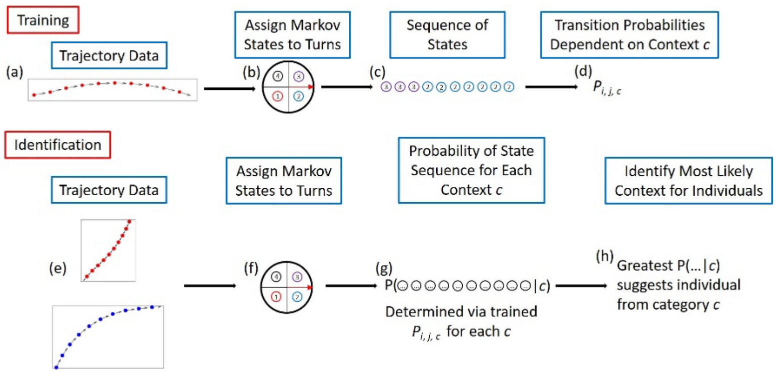


**Figure 1.** Identification of individual biological context via movement signatures and machine learning. Data is divided into independent training data sets, and data for which identification of ecological context, denoted *c*, is required. At the start of the training phase, fundamental measures of locomotion, such as directions of motion (the arrows in (a)) and changes in direction of motion, are derived from individual coordinate data for which the defining ecological context is known. In this example, changes in direction are then translated to discrete Markov states (numerical states), using a discretisation scheme like that in (b) (the red arrow points in the current direction of motion of a focal individual, and the state is determined by the relative direction at the next time step). Entire sequences of numerical states are constructed from each trajectory, (c), and then data is aggregated across all relevant individuals to determine the observed probabilities of transition from one numerical state to another, (d). During identification, trajectory data for which the ecological state is to be inferred is reduced to a sequence of states using the same approach as for (a) to (c) ((e) and (f)). The probability of observing each sequence of states in each possible ecological context is determined at (g) using the conditional probabilities from (d). The most likely ecological context for a given trajectory is then identified as the context, *c*, for which the probability $P(\ldots|c)$ is greatest (h).

## REFERENCES

Herbert-Read, J.E., Krause, S., Morrell, L.J., Schaerf, T.M., Krause, J., Ward, A.J.W., 2013. The role of individuality in collective group movement. Proceedings of the Royal Society B 280 20122564.

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