Hidden Markov models of animal movement and behaviour

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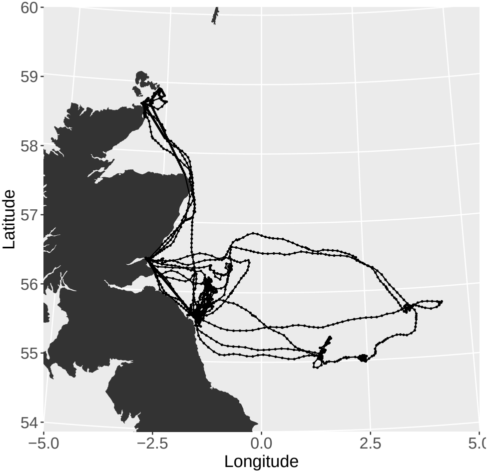
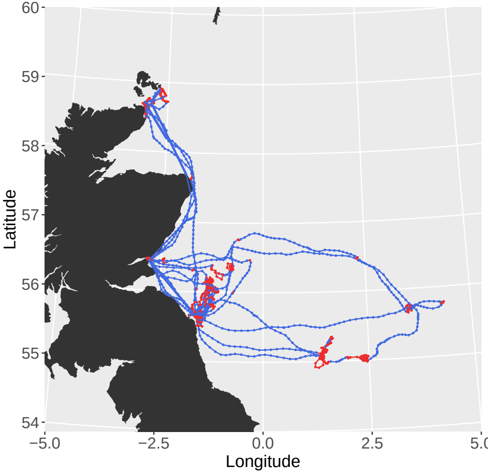
Photo: Theoni Photopoulou



Data from: Russell et al. (2015), "Intrinsic and extrinsic drivers of activity budgets in sympatric grey and harbour seals", *Oikos*, 124(11).



Data from: Russell et al. (2015), “Intrinsic and extrinsic drivers of activity budgets in sympatric grey and harbour seals”, *Oikos*, 124(11).

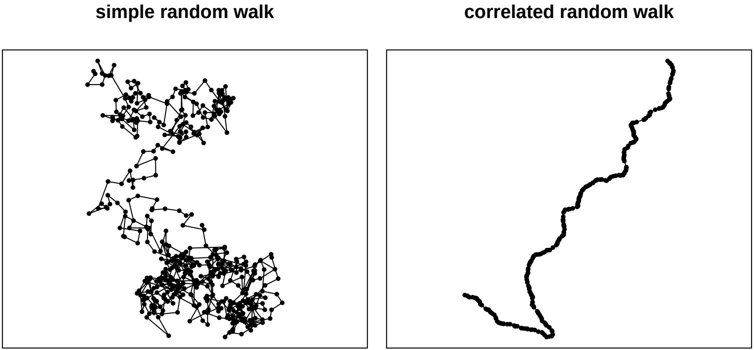
Standard movement HMM

1. Correlated random walks

2. State-switching model

Correlated random walk

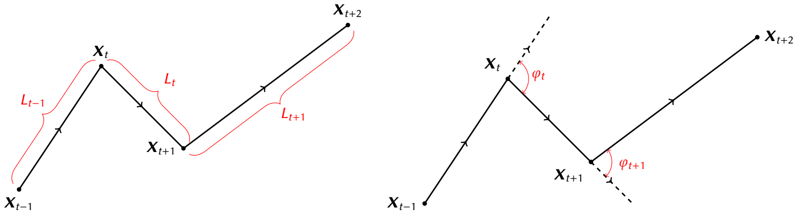
A correlated random walk includes **persistence in direction**.
⟶ Correlation between successive directions.



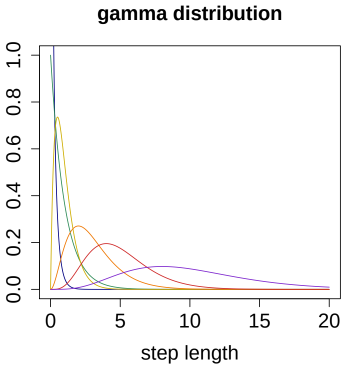
Movement metrics

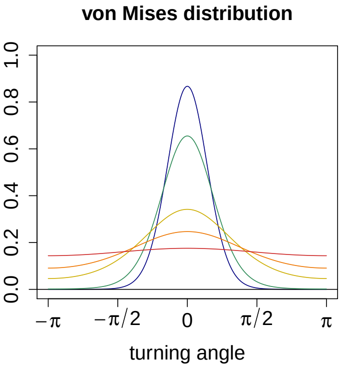
In a correlated random walk, we can model:

- step lengths (L_t);
- turning angles (φ_t).



Modelling the steps and angles





Parameters often of interest:

- Mean of step length distribution (= measure of speed);
- Concentration of turning angle distribution (= measure of directional persistence).

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2. State-switching model

Multistate random walk

Different behaviours lead to different movement patterns.
$\longrightarrow$ Behavioural process = unobserved Markov chain (S_t).

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Example: foraging ("F") and exploring ("E")

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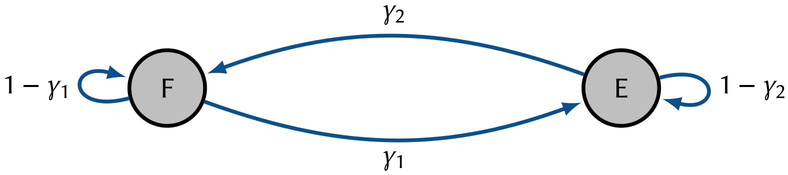
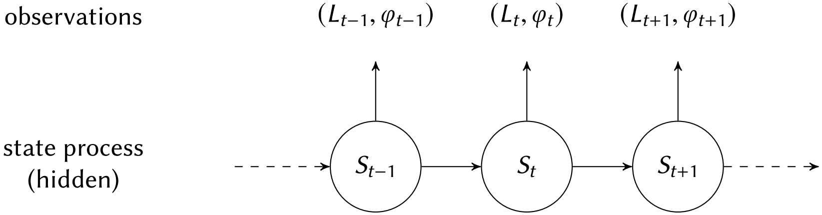


Hidden Markov model for animal movement



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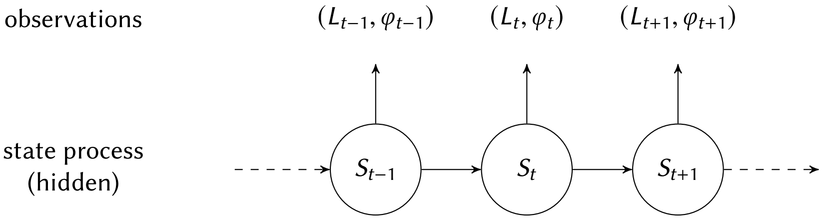


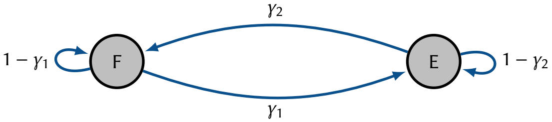
The steps and angles are modelled by state-dependent distributions. For example:

$$L_t | \{S_t = j\} \sim \text{gamma}(\alpha_j, \beta_j)$$
$$\varphi_t | \{S_t = j\} \sim \text{von Mises}(\theta_j, \kappa_j)$$

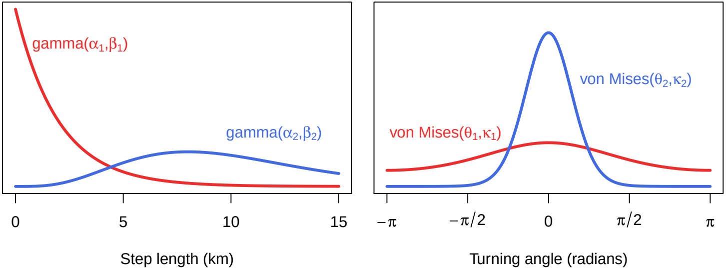
HMM parameters

There are two sets of parameters:

- The transition probabilities $\Pr(S_t = j | S_{t-1} = i)$, e.g.



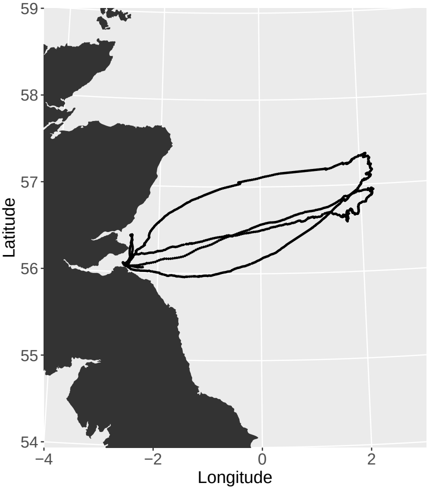
- The state-dependent movement parameters, e.g.



HMM inference

1. Derive step lengths and turning angles from location data.
2. Estimate transition probabilities and movement parameters (using standard statistical methods).
3. Compute the "most likely state sequence" to classify the track into behavioural phases.

Example: Gannet



Data from: Grecian et al. (2018). "Understanding the ontogeny of foraging behaviour: insights from combining marine predator bio-logging with satellite-derived oceanography in hidden Markov models". Journal of the Royal Society Interface.

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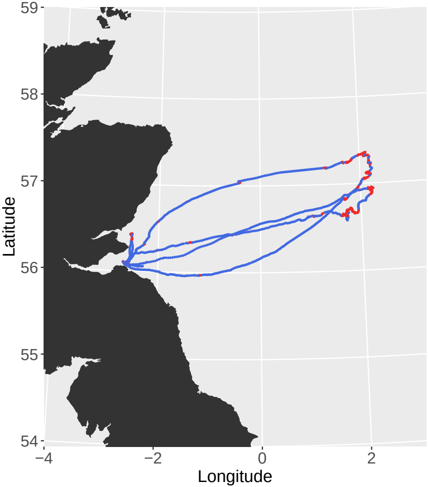

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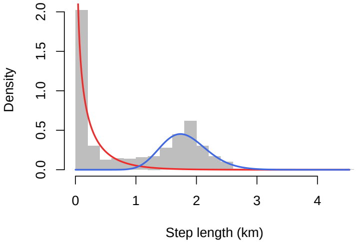
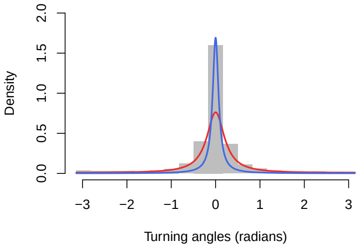
Example: Gannet

Estimated transition probabilities:

$$\Gamma = \begin{array}{c c} & \begin{array}{cc} \text{slow} & \text{fast} \end{array} \\ \begin{array}{c} \text{slow} \\ \text{fast} \end{array} & \begin{bmatrix} 0.96 & 0.04 \\ 0.05 & 0.95 \end{bmatrix} \end{array}$$

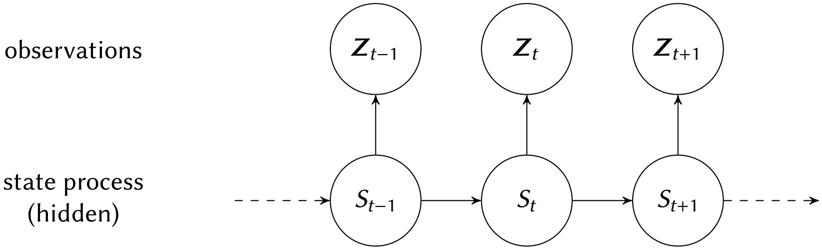
Estimated observation distributions:





General HMM for telemetry data

General dependence structure

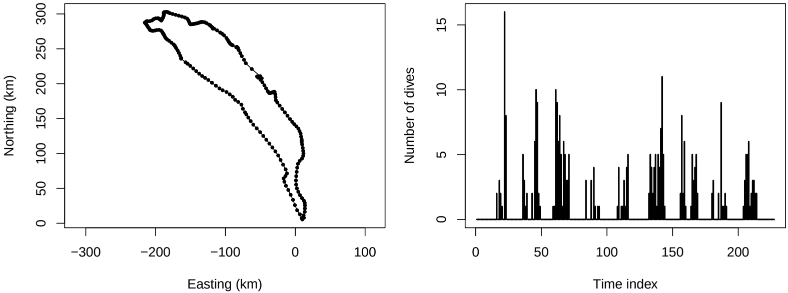


$\boldsymbol{Z}_t$ could be, for example:

- Depth;
- Acceleration;
- Count of dives...

Example: Dive count

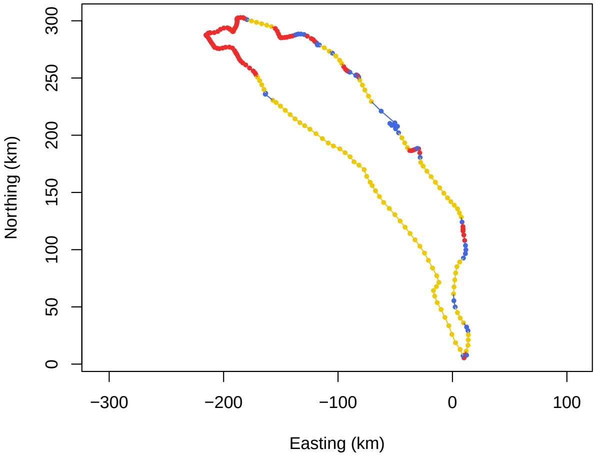
Can we identify foraging activity of this northern fur seal from locations and hourly dive counts?



Data from: McClintock et al. (2014), "When to be discrete: the importance of time formulation in understanding animal movement", Movement Ecology.

Example: Dive count

We fitted a 3-state model:



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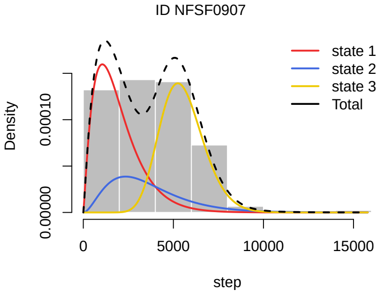
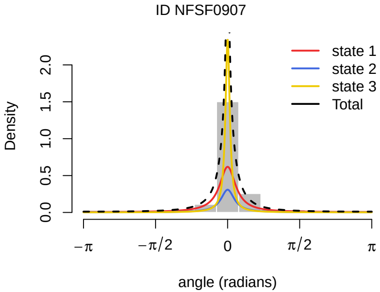
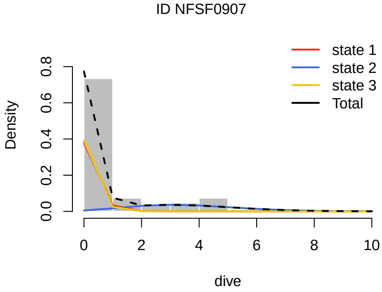






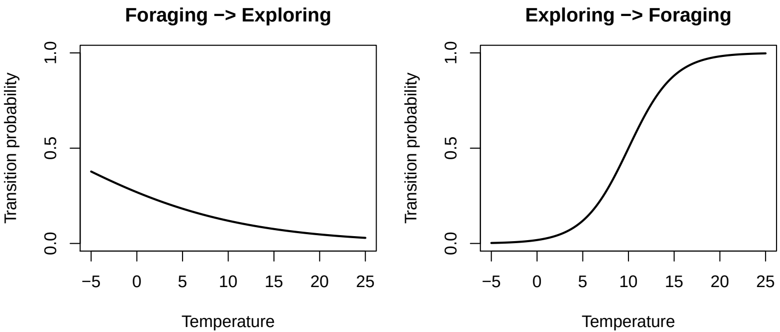
Extensions

1. Covariates in the transition probabilities
2. Covariates in the movement parameters
3. Biased random walks

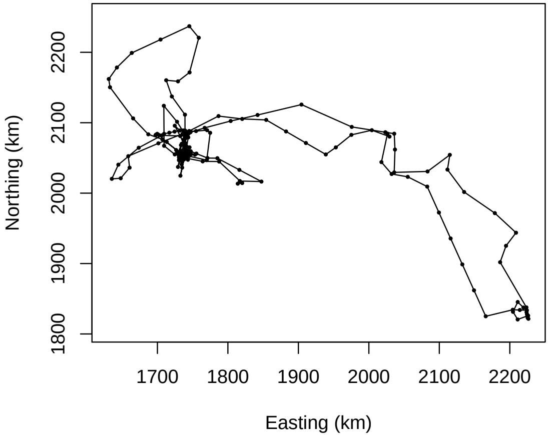
Covariates on the transition probabilities

Question: "Does [*covariate*] have an effect on the probability that the animal is [*behaviour*]?"

⟶ Time-varying transition probabilities.



Example: Triggerfish



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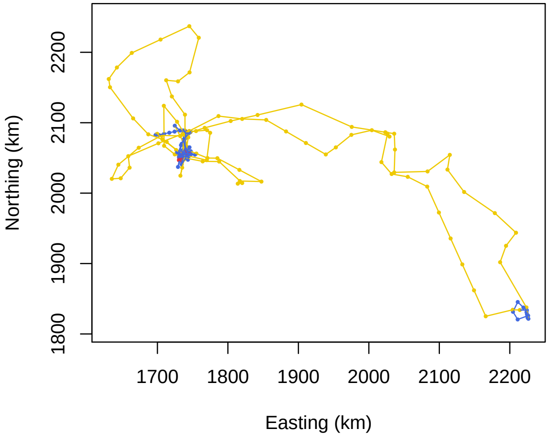

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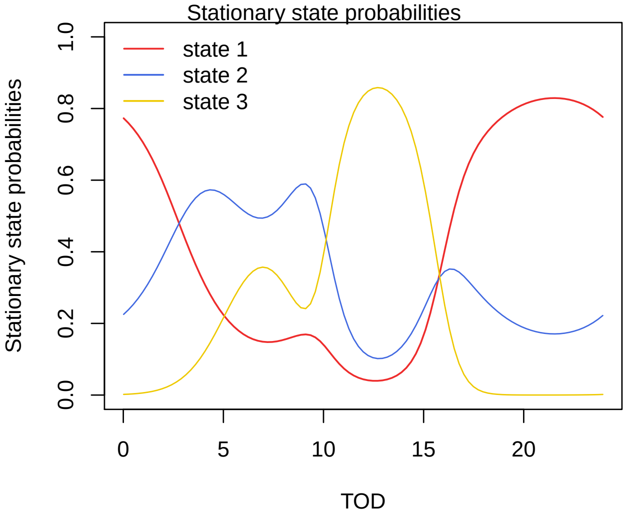

1. Covariates in the transition probabilities
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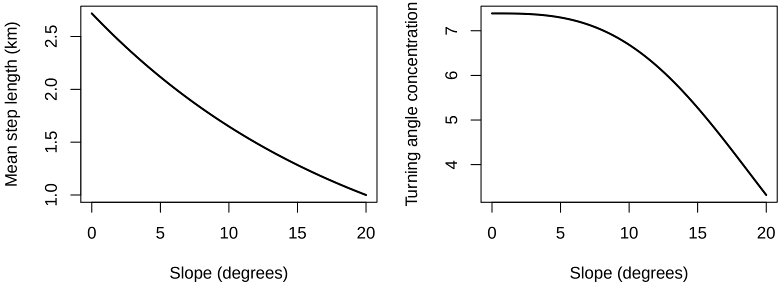
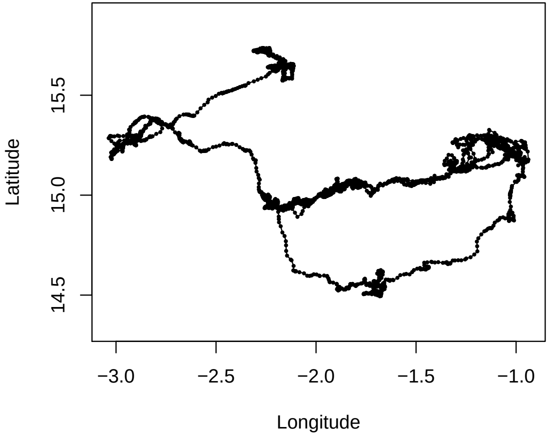
Covariates on the movement parameters

Question: "Does [*movement parameter*] depend on [*covariate*]?"

$\longrightarrow$ Time-varying movement parameters within each state.



Example: Elephant



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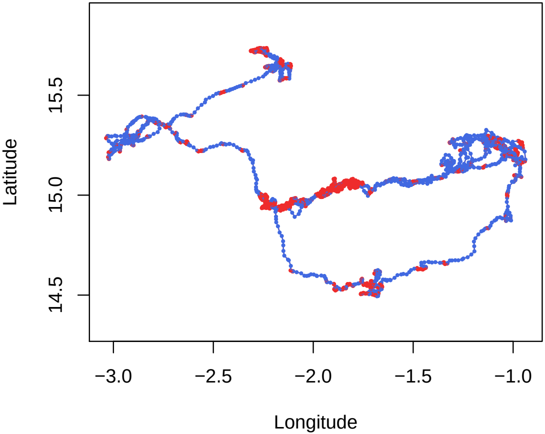

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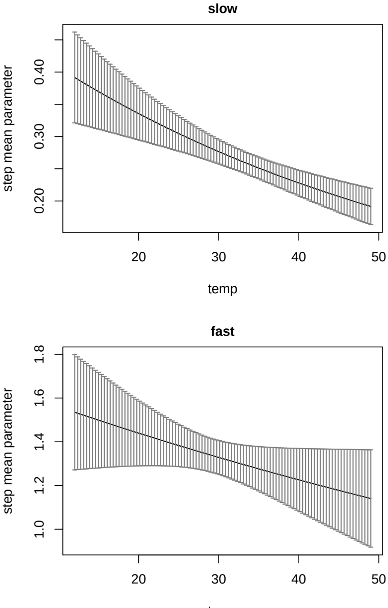

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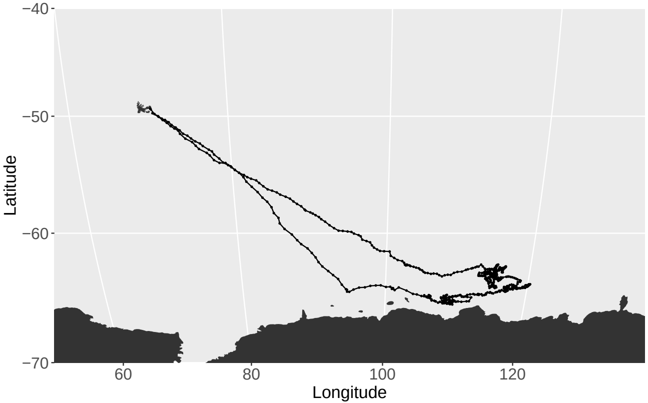
Southern elephant seal



Data from: Michelot et al. (2017). "Estimation and simulation of foraging trips in land-based marine predators". Ecology.

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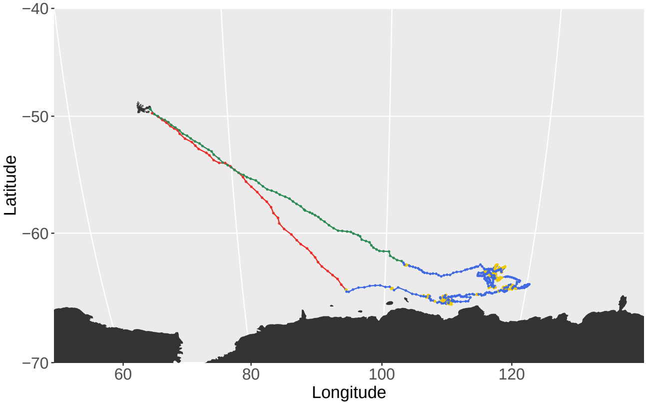

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Limitations and challenges

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- Interpretation of the states as behaviours.

Software

moveHMM

R package to fit hidden Markov models to location data:

```
install.packages("moveHMM")
```

A good place to start is the **package vignette** (background, detailed case study with code, implementation details...), and the **package documentation** (details for each function).

1. Plot the data.
2. Fit model(s). (Fast!)
3. Plot the model:
   ⟶ map of "decoded" tracks;
   ⟶ covariate effects.
4. Plot goodness-of-fit diagnostics ("pseudo-residuals").

Thanks!

- Patterson et al. (2009). “Classifying movement behaviour in relation to environmental conditions using hidden Markov models”. *Journal of Animal Ecology*.
- Langrock et al. (2012). “Flexible and practical modeling of animal telemetry data: hidden Markov models and extensions”. *Ecology*.
- Michelot et al. (2016). “moveHMM: An R package for the statistical modelling of animal movement data using hidden Markov models”. *Methods in Ecology and Evolution*.