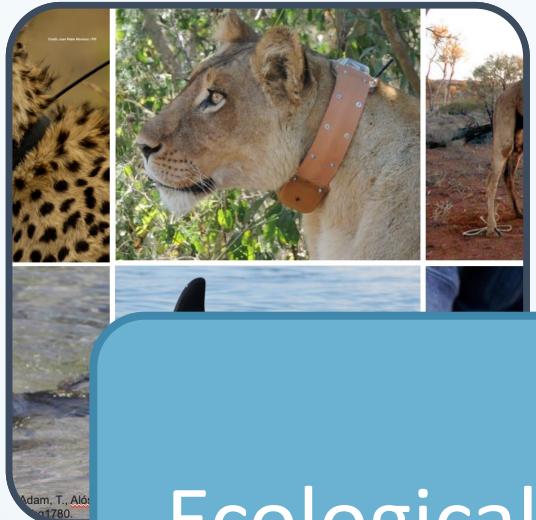


HMM FOR ANIMAL MOVEMENT TUTORIAL

Marie Auger-Méthé and Fanny Dupont



HMM OUTLINE



Ecological motivation



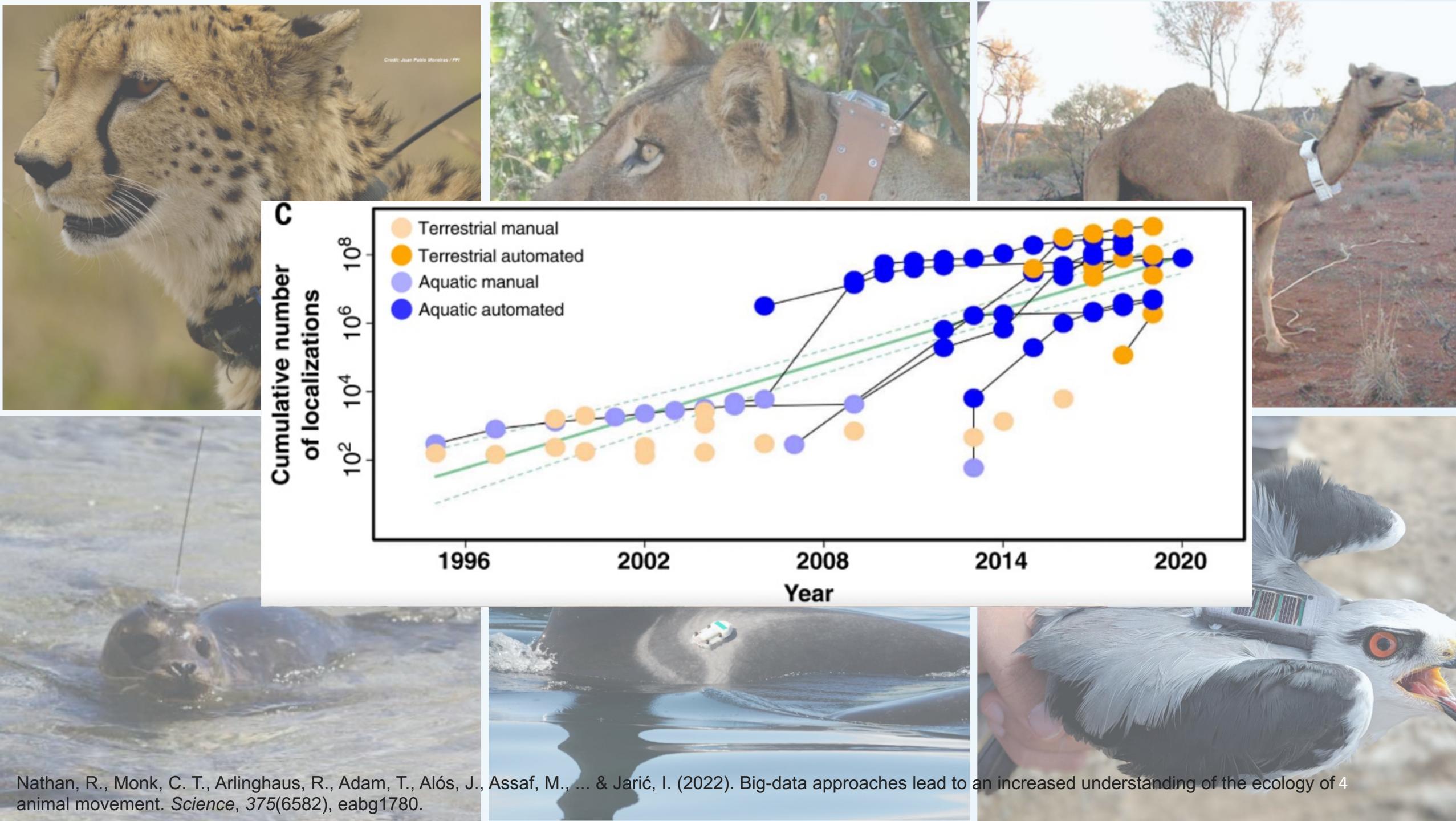
Statistical framework

- CRWs
- HMMs



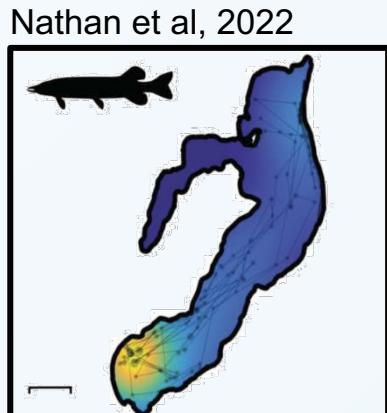
Narwhal case study

MOTIVATION

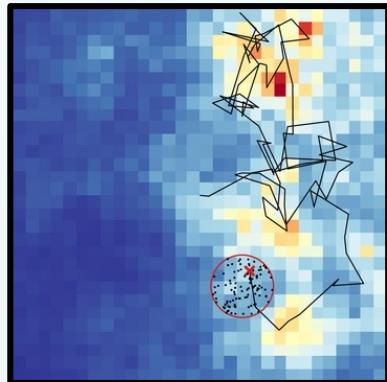


Movement modelling

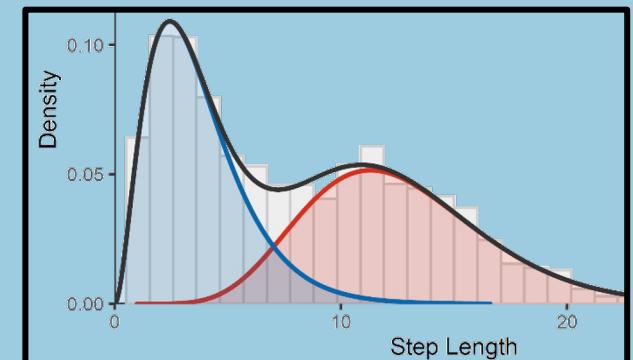
Home range estimation



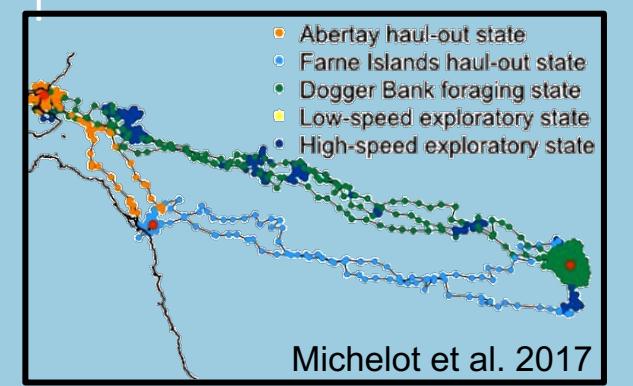
Habitat & resource selection



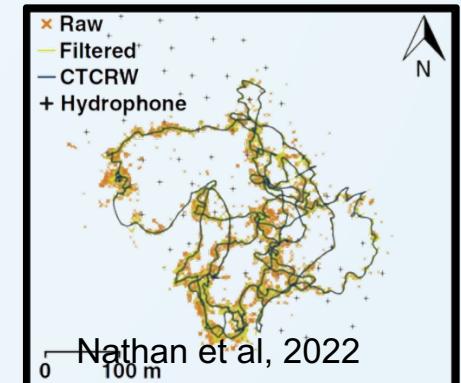
Movement parameter estimation



Behaviour segmentation



Path reconstruction



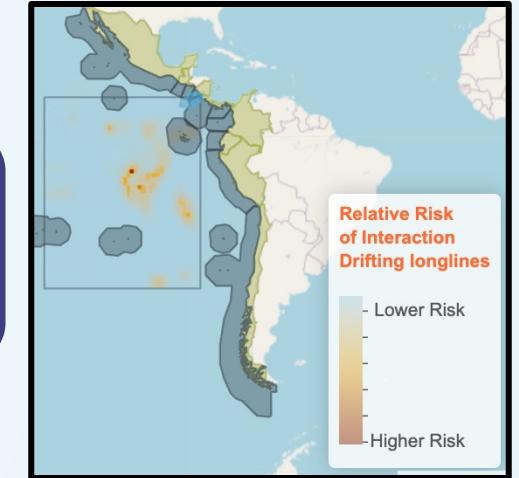
Why behaviour ?

Energy
Expenditure



McRae et al. 2024

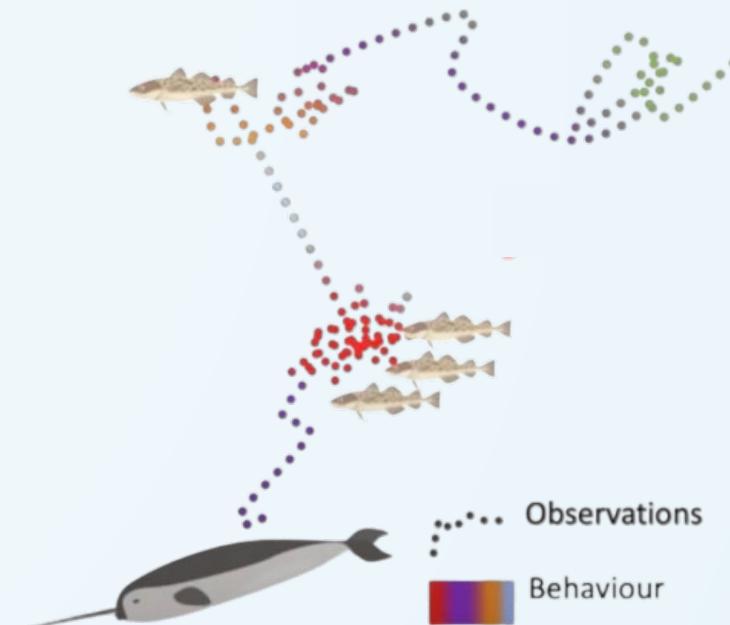
Conservation
studies



Barbour et al. 2022

Hidden Markov models: motivations

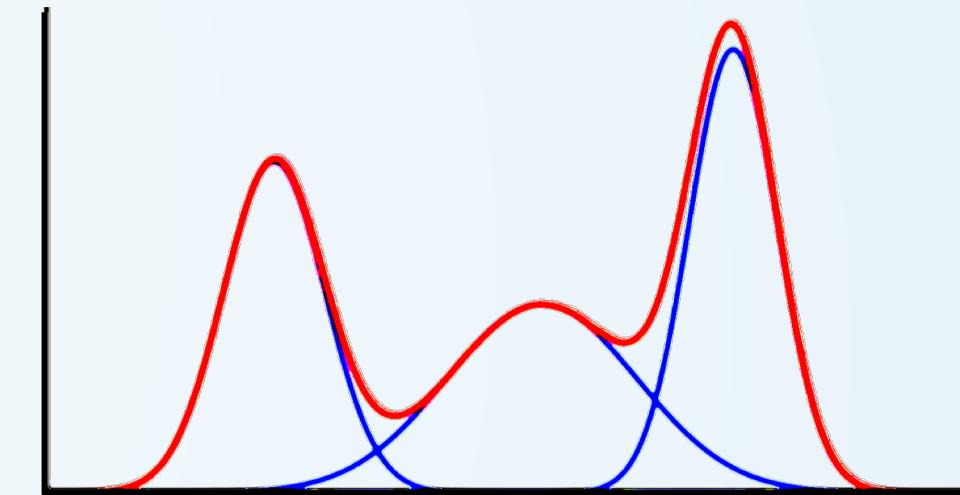
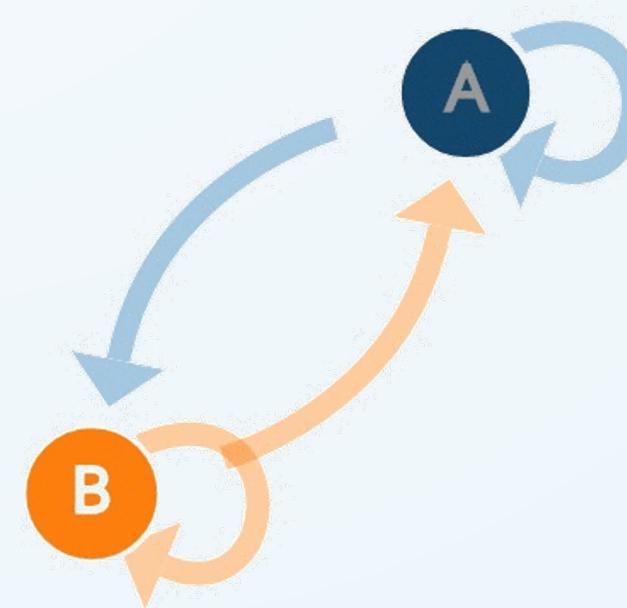
- Underlying biological process is hidden
 - Observation is conditional on latent process
 - Behaviour state vs location data



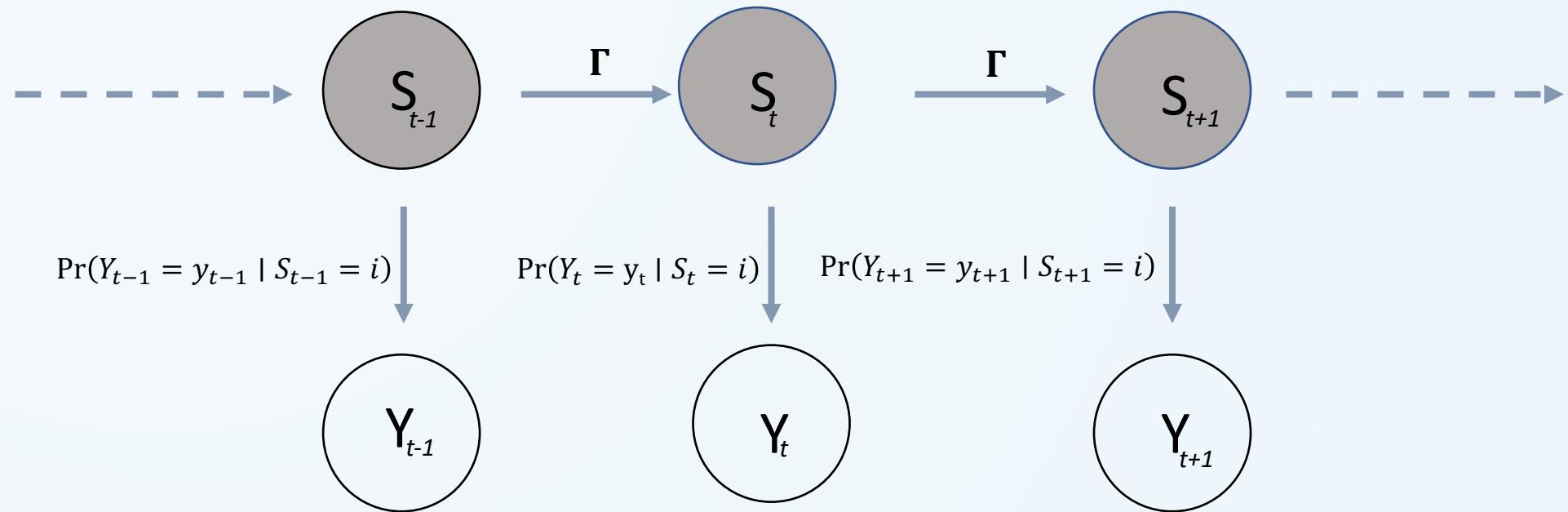
HIDDEN MARKOV MODELS

Hidden Markov models - Solution

- Underlying biological process is hidden
 - Finite mixture model
- Latent process is autocorrelated
 - Markov chain

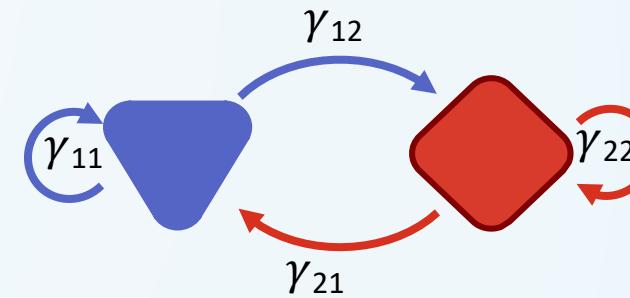
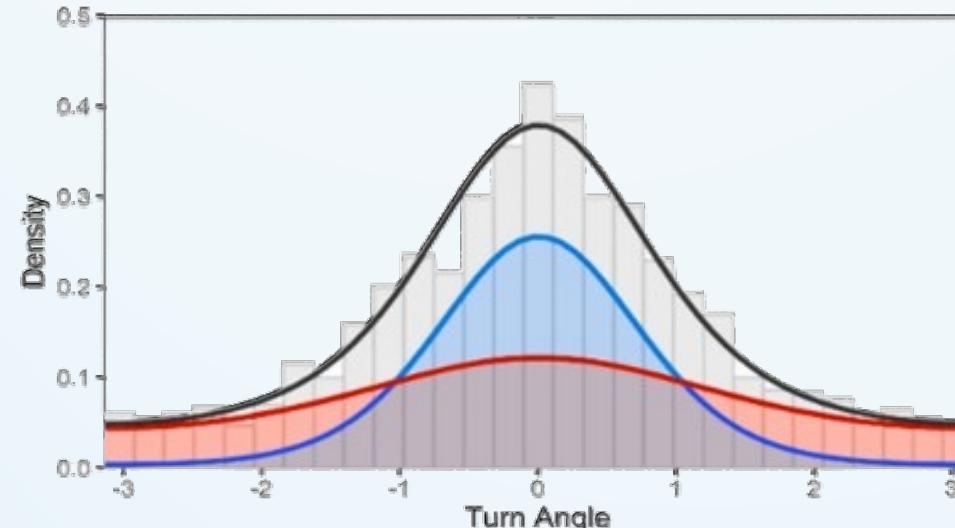
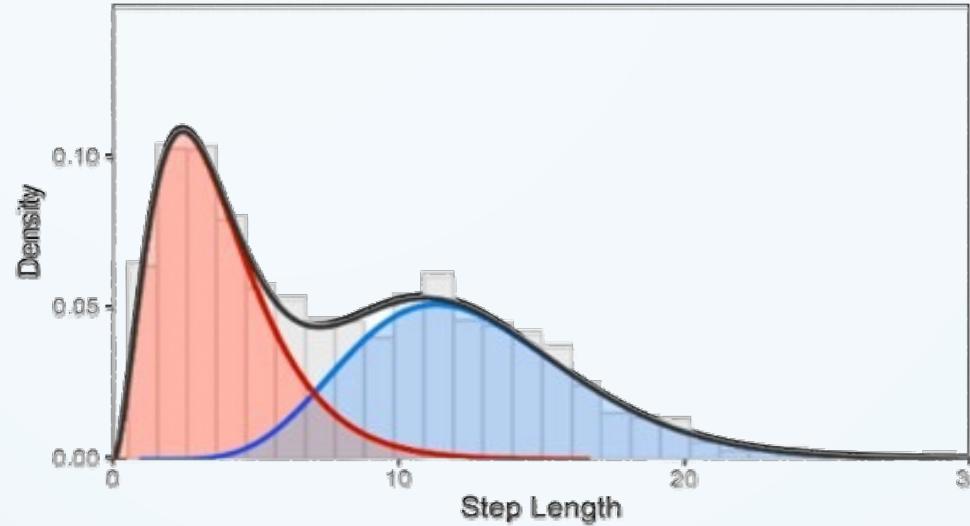


Hidden Markov models – Framework



$$\boldsymbol{\Gamma} = \begin{bmatrix} \gamma_{1,1} & \dots & \gamma_{1,m} \\ \vdots & \ddots & \vdots \\ \gamma_{m,1} & \dots & \gamma_{m,m} \end{bmatrix}$$

Hidden Markov models – 2 states



HMM: Key parameters

- Number of states: m
- State probability: $\Pr(S_t \mid S_{t-1})$
- State dependent distribution: $\Pr(Y_t = y_t \mid S_t = i) = p_i(y_t)$
 - $\mathbf{P}(y_t) = \begin{bmatrix} p_1(y_t) & \dots & 0 \\ \dots & \ddots & \dots \\ 0 & \dots & p_m(y_t) \end{bmatrix}$
- $(\Pr(S_t = 1), \dots, \Pr(S_t = m))$
- $\mathbf{u}_t \mathbf{P}(y) \mathbf{1}' = \Pr(Y_t = y)$

HMM: Likelihood

$$\mathcal{L} = \boldsymbol{\delta} \mathbf{P}(y_1) \Gamma \mathbf{P}(y_2) \dots \Gamma \mathbf{P}(y_T) \mathbf{1}'$$

- $\boldsymbol{\delta}$ is the vector of initial state probabilities

Covariates – hidden process

affect the probability that the animal is in a certain behaviour

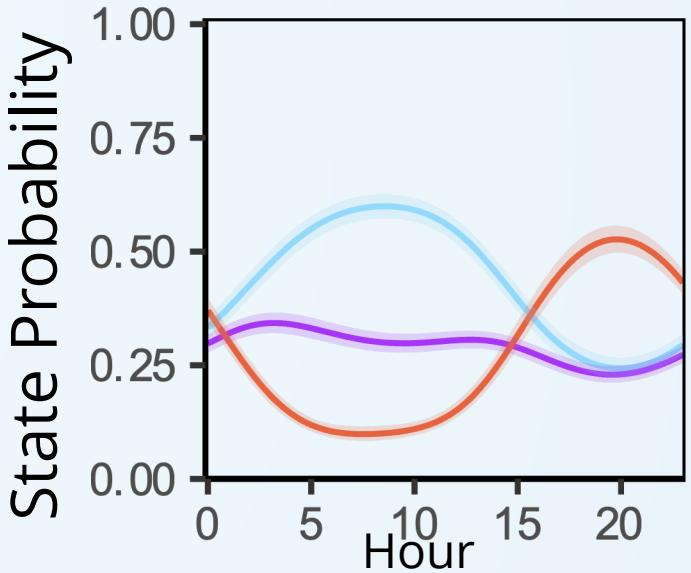


©Jami Tarris

Covariates $(\omega_1^{(t)}, \dots, \omega_p^{(t)})$:

$$\gamma_{ij}^{(t)} = \frac{\exp(\eta_{ij})}{\sum_{k=1}^N \exp(\eta_{ik})},$$

$$\eta_{ij} = \begin{cases} \beta_0^{(ij)} + \sum_{l=1}^p \beta_l^{(ij)} \omega_l^{(t)} & \text{if } i \neq j; \\ 0 & \text{otherwise.} \end{cases}$$



© Theo Allofs

Covariates – observation process

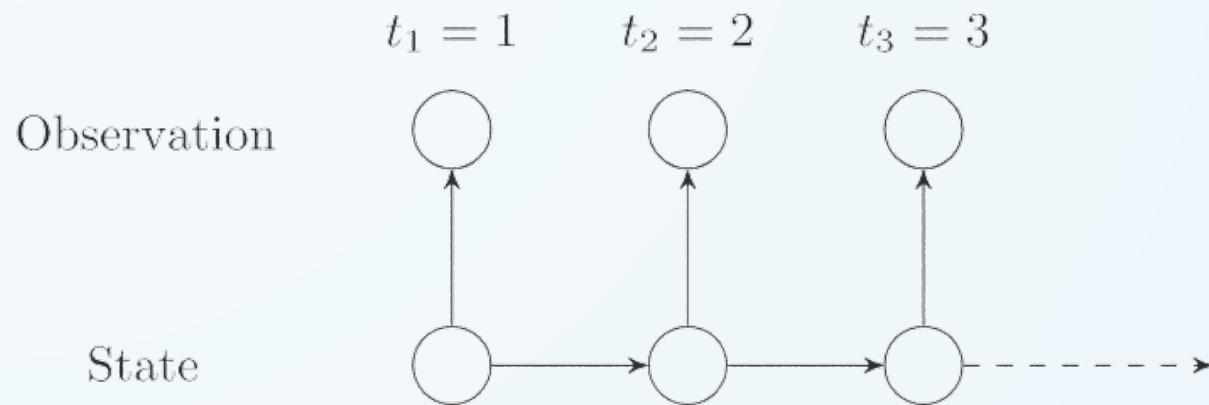
affect the movement

Example: different speed per category of age:

$$\log(\mu_t^{(j)}) = \alpha_0^{(j)} + \alpha_1^{(j)}age_t$$

HMMs – Assumptions

- HMMs assume **regular time intervals** between data row

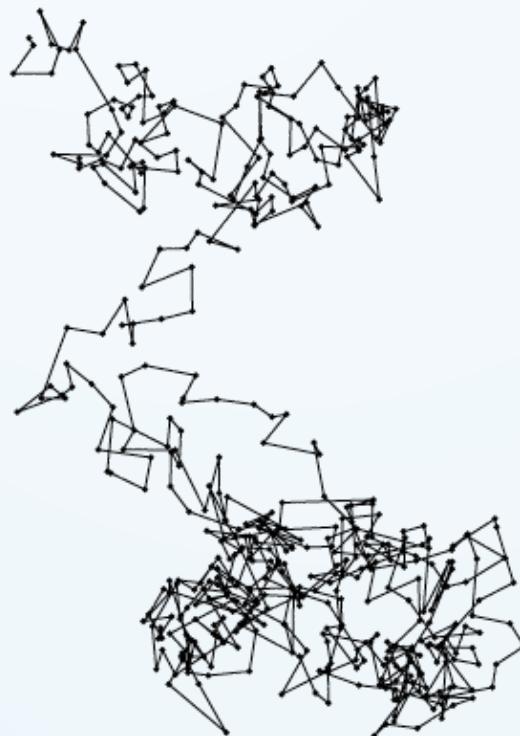


- Auto-correlation in the hidden process **suffices** to characterize the autocorrelation of the movement.

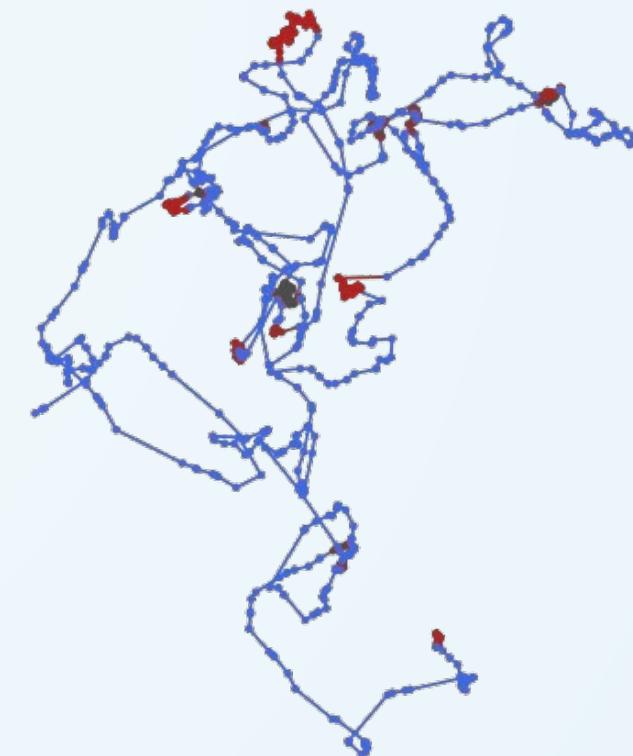
CORRELATED RANDOM WALKS (CRWS)

Persistence in direction: CRWs

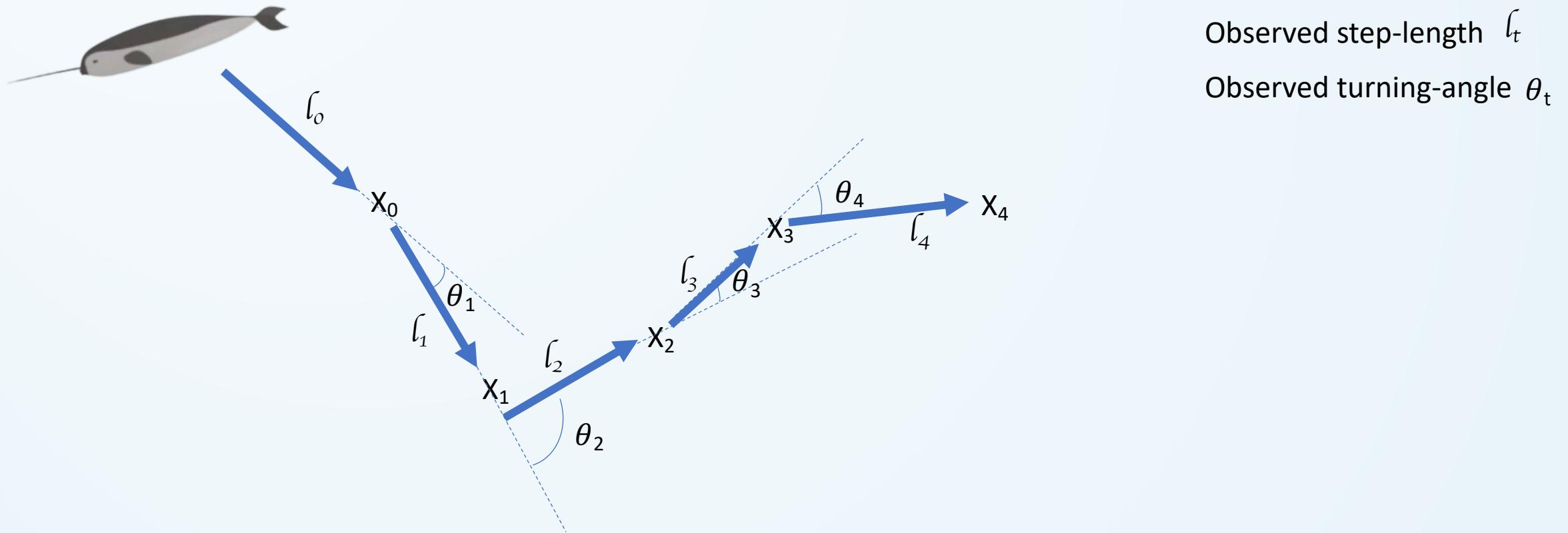
Simple random walk



Multi-state Correlated random walk

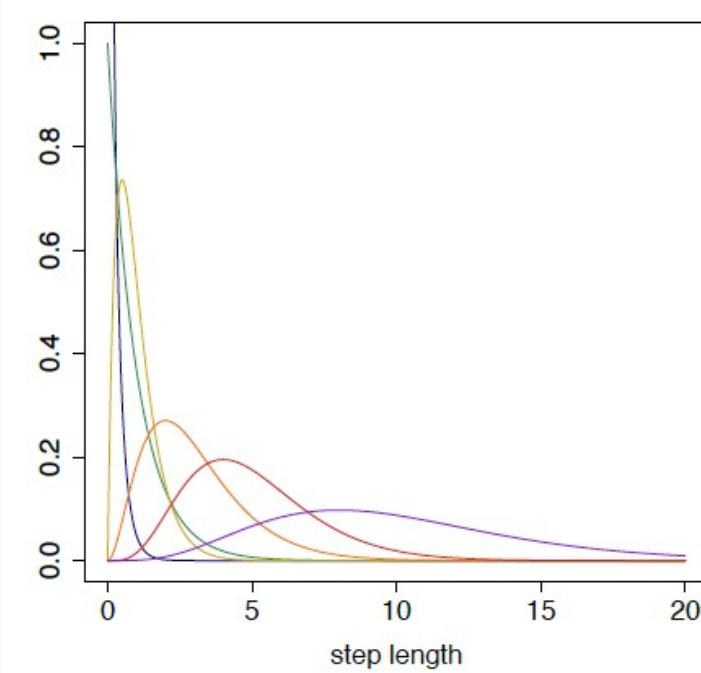


Movement data-streams: step-length and turning angle

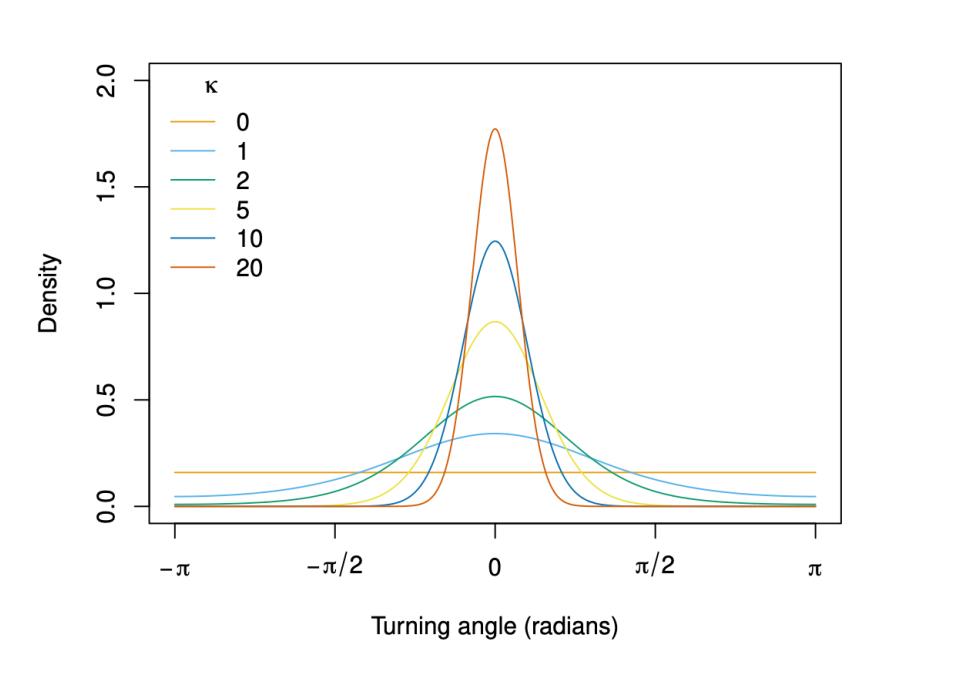


Modelling step-length and turning angle:

gamma distribution



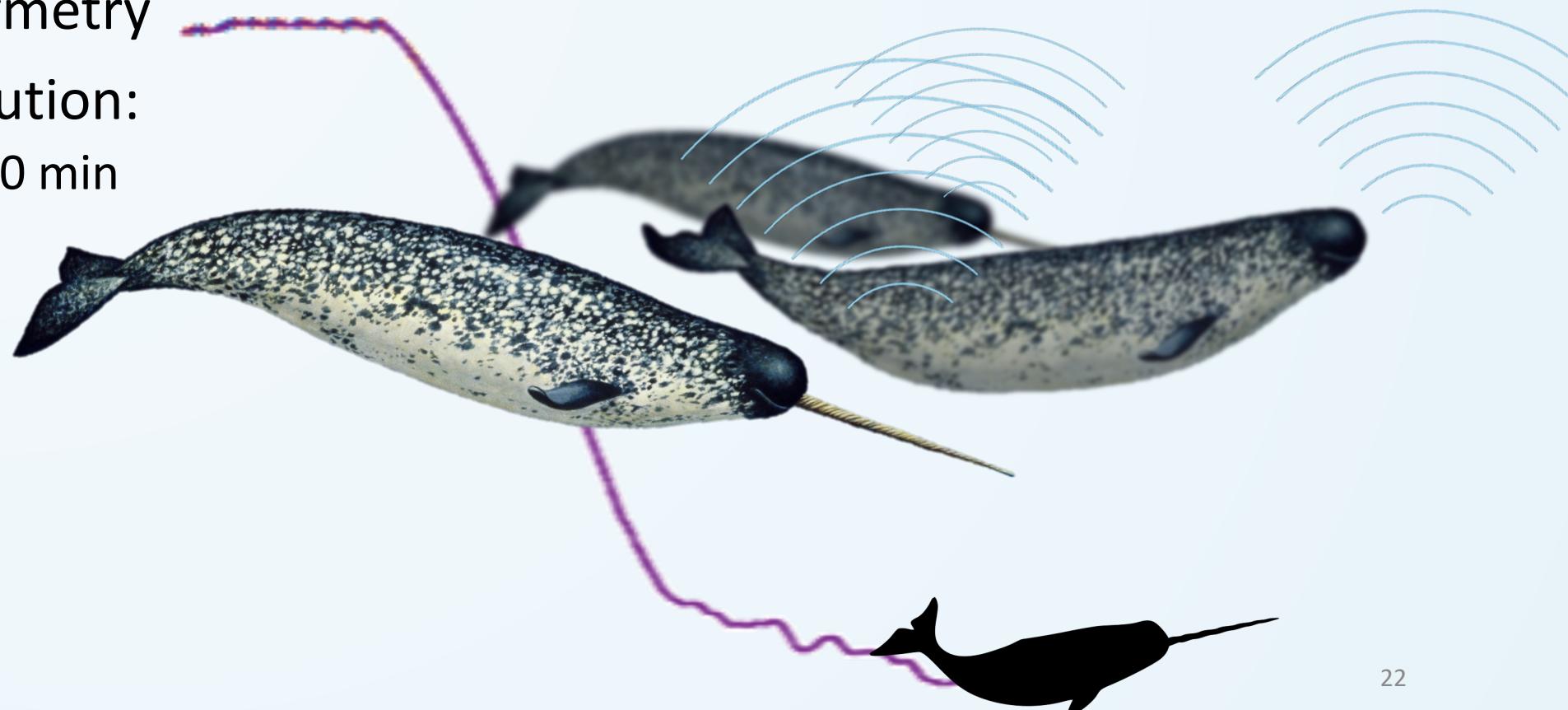
Von Mises distribution



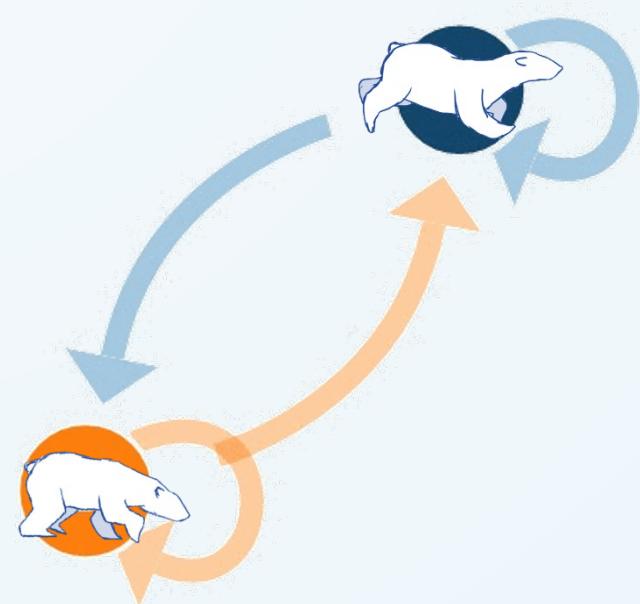
NARWHAL CASE STUDY

1. Narwhal data

- Three Narwhals tagged in Tremblay Sound
- Fastloc GPS location data
- Raster of bathymetry
- Temporal resolution:
 - Fastloc GPS: 10 min



POLAR BEAR EXERCISE



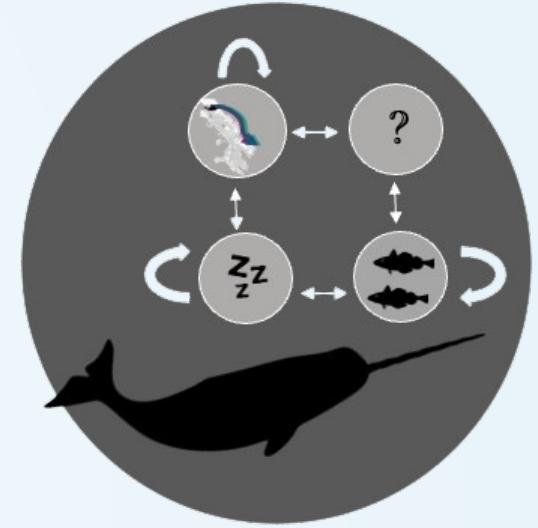
2. Polar bear data

- One polar bear collared in the Beaufort Sea, in April of 2009
- One year GPS locations
- Temporal resolution:
- 1 hour



Tutorial's objectives

1. Fit simple HMMs using momentuHMM
2. Checking model fit
3. Incorporating and interpreting covariates on behaviour transition probabilities
4. Incorporating covariates in the observation model
5. (Bonus)
 - a) Select an appropriate resolution for the data
 - b) Handle missing data



1. Fitting HMM with `momentuHMM`

- Package by Brett McClintock and Théo Michelot, based on `moveHMM`
- Key functions
 - `prepData` – prepare tracking data for fitting HMM
 - Extract environmental data
 - Calculate step length and turning angle
 - Calculate circular covariates (e.g., angle relative to ocean currents)
 - `fitHMM` – Define HMM structure and fit it to model
 - Number of states
 - Distribution associated with each state
 - Starting parameters
 - Covariates

```
prepData(data, type = "LL", coordNames = c("lon", "lat"))
```

Minimum arguments:

- Data (e.g., data = sealreg)
- Type - coordinate reference system ("UTM" if not lat/long)
- coordNames - names of coordinate columns (if not c("x", "y"))

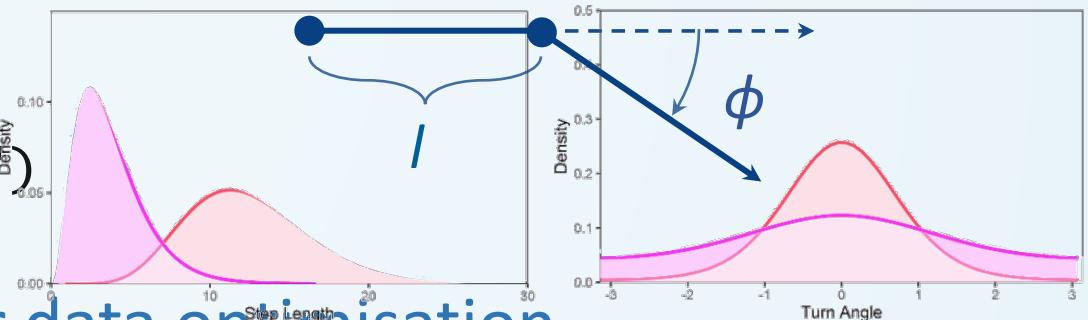
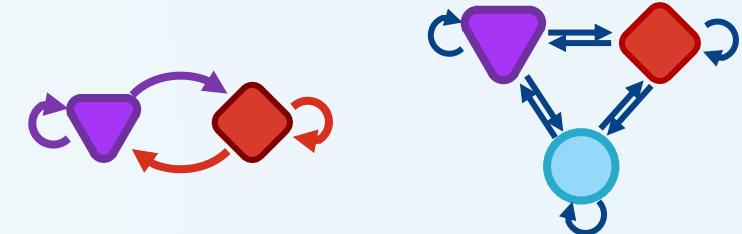
Optional arguments:

- covNames – names of covariates (fills in missing data with nearest value)
- spatialCovs – raster object from which to extract covariate data
- angleCovs – name of angular covariate for which to calculate the relative angle (e.g., turn angle relative to wind)

`fitHMM(data, ...)`

Minimum arguments:

- **nbState** – number of behavioural states
- **Dist** – named list distribution associated with each data stream
 - E.g., gamma for step length and von Mises for turning angle
 - `dist=list(step="gamma", angle="vm")`
- **Par0** – named list initial parameters for data optimisation
 - E.g., step length $l \sim \text{gamma}(\mu_i, \sigma_i)$, define μ and σ for each state
 - `Par0 = list(step=c(mu0, sigma0), angle=kappa0)`
 - `Par0 = list(step=c(c(200, 500), c(100, 250)), angle=c(0.5, 0.8))`



`fitHMM(data, ...)`

Optional arguments:

- **Formula** – effects of covariates on transition probability
 - E.g., `formula= ~bathy`
- **estAngleMean** – Whether to estimate mean turning angle (default=F)
- **circularAngleMean** – Whether to use a circular-circular distribution for turn angle (use if examining bias relative to multiple factors or if expect non-linear relationship; default = circular-linear)
- **stateNames** – names associated with each behavioural state
- **retryFits** – number of times to attempt to fit the model
- **DM, workBounds, betaCons, fixPar, ...**

