NON-PARAMETRIC BAYESIAN MODELS FOR MOVEMENT ECOLOGY

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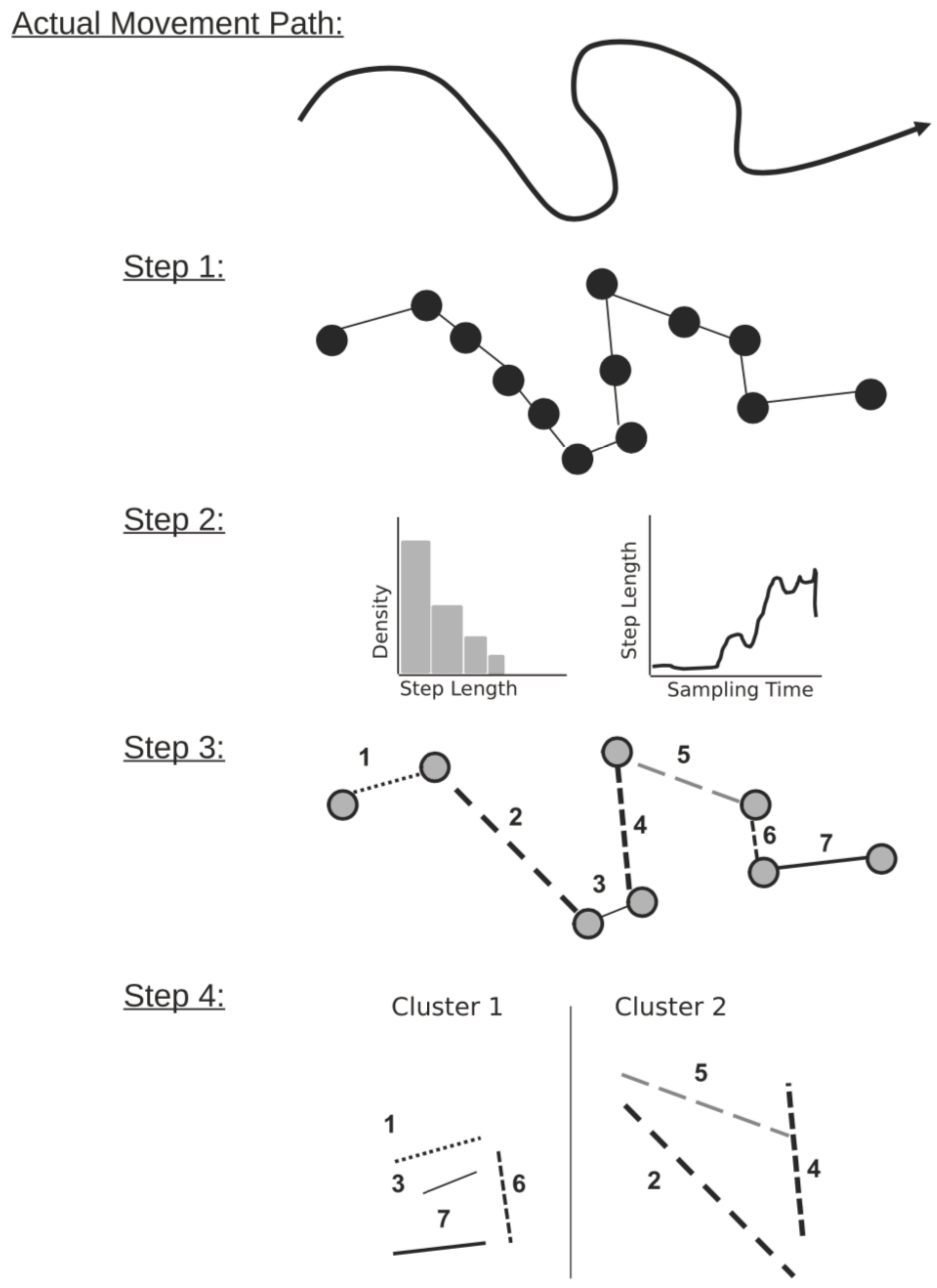
September 8, 2022

What are non-parametric Bayesian movement models?

Table 1. Summary table of four broad categories of behavioural movement analysis methods. The four methods implemented in this paper and the most directly relevant references are bold faced. All of the entries in the last category can be considered multistate random walks, hidden Markov models or state space models

Category	Method	References
Metric-based	Fractal analysis	Fritz, Said & Weimerskirch (2003), Laidre *et al.* (2004) Nams & Bourgeois (2004); Tremblay, Roberts & Costa (2007)
	Tortuosity measures	Bovet & Benhamou (1988); Benhamou (2004)
	First passage time (FPT)	**Fauchald & Tveraa (2003)**
	Residence time (RT)	Barraquand & Benhamou (2008)
Classification and segmentation	Penalized contrasts	Lavielle (2005), Calenge (2006)
	Bayesian partitioning (BPMM)	**Calenge (2006)**
	k-clustering	van Moorter *et al.* (2010)
	RT (segmentation step)	Barraquand & Benhamou (2008)
Phenomenological time-series analysis	Autocorrelation functions	Boyce *et al.* (2010)
	Change point analysis (BCPA)	**Gurarie, Andrews & Laidre (2009), Gurarie (2013)** Kranstauber *et al.* (2012)
	Wavelet	Polansky *et al.* (2010)
Mechanistic movement modelling	**Multistate random walk (MRW)**	***Morales et al.* (2004)**
	Ignoring location error	Forester *et al.* (2007), Langrock *et al.* (2012) Patterson *et al.* (2008), McClintock *et al.* (2012)
	Accounting for error	Jonsen *et al.* (2013), Breed *et al.* (2012)

Gurarie et al., 2016



Edelhoff et al., 2016

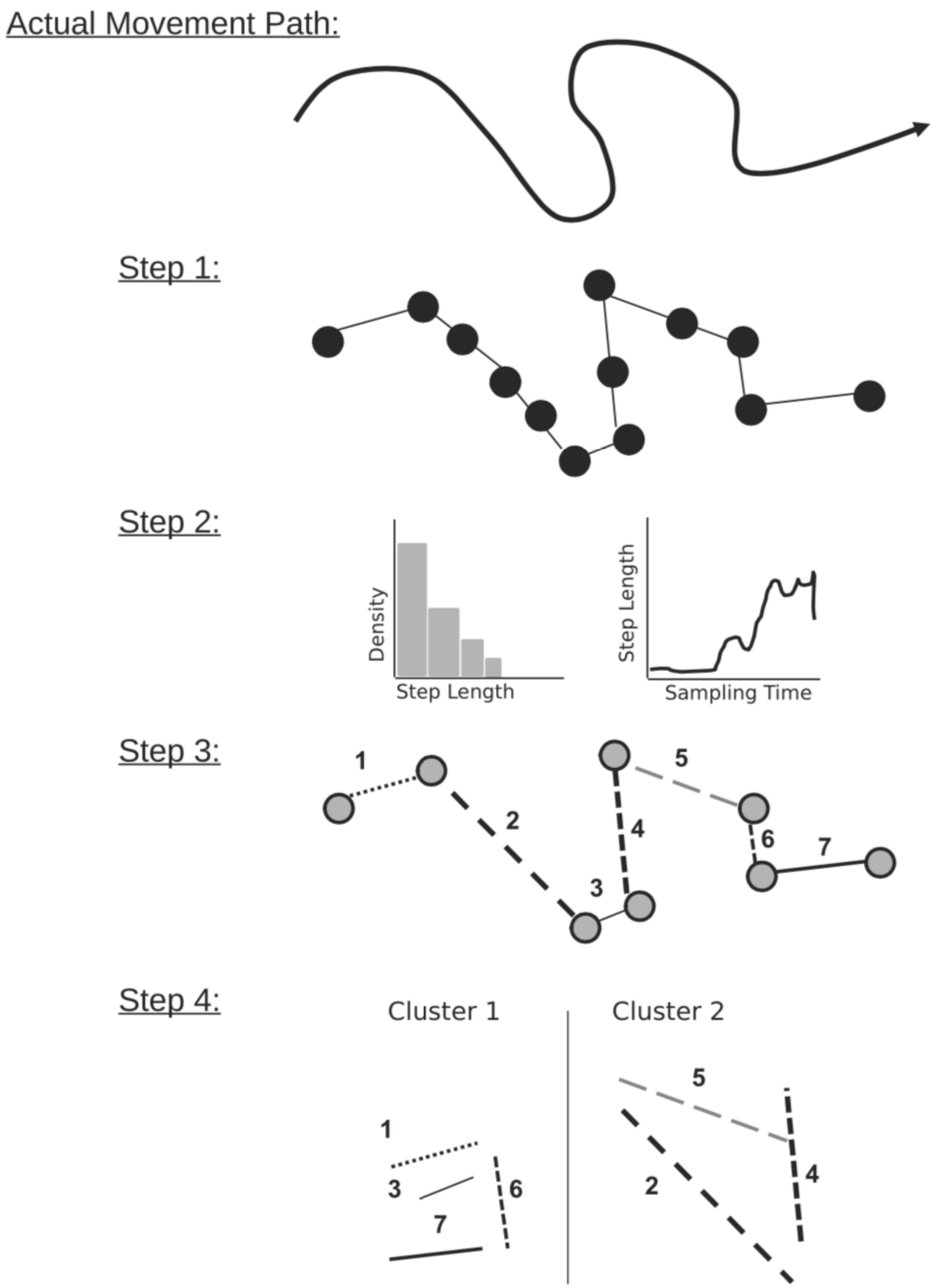
What are non-parametric Bayesian movement models?

<u>2 main types</u>

1. Mixture model for movement (M3[?])

2. Mixed-membership method for movement (M4)

- Both models:
  a) Accommodate multiple movement variables
  b) Don't assume movement variables are well characterized by standard PDFs
  c) Estimate the likely number of behavioral states



Edelhoff et al., 2016

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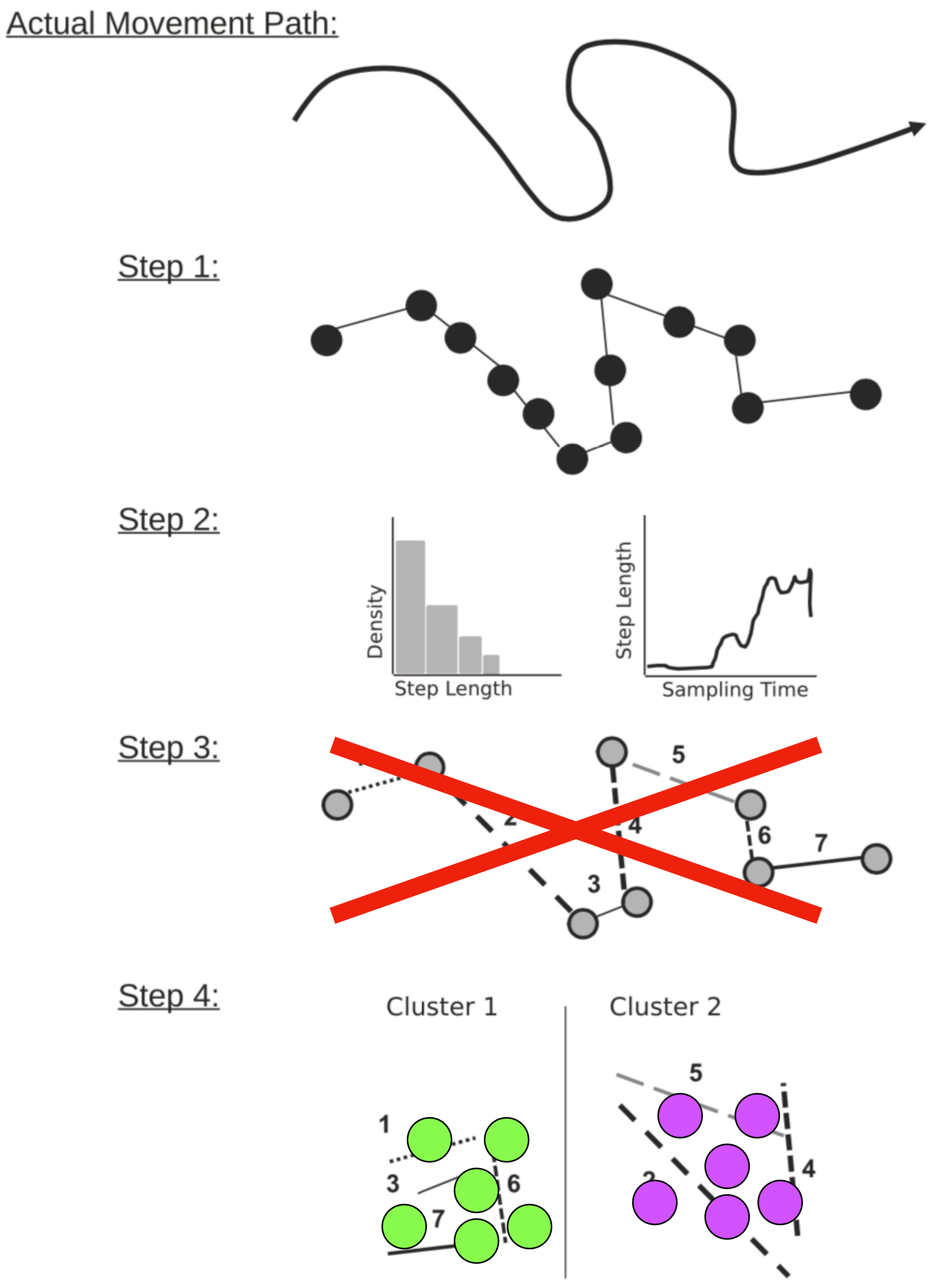

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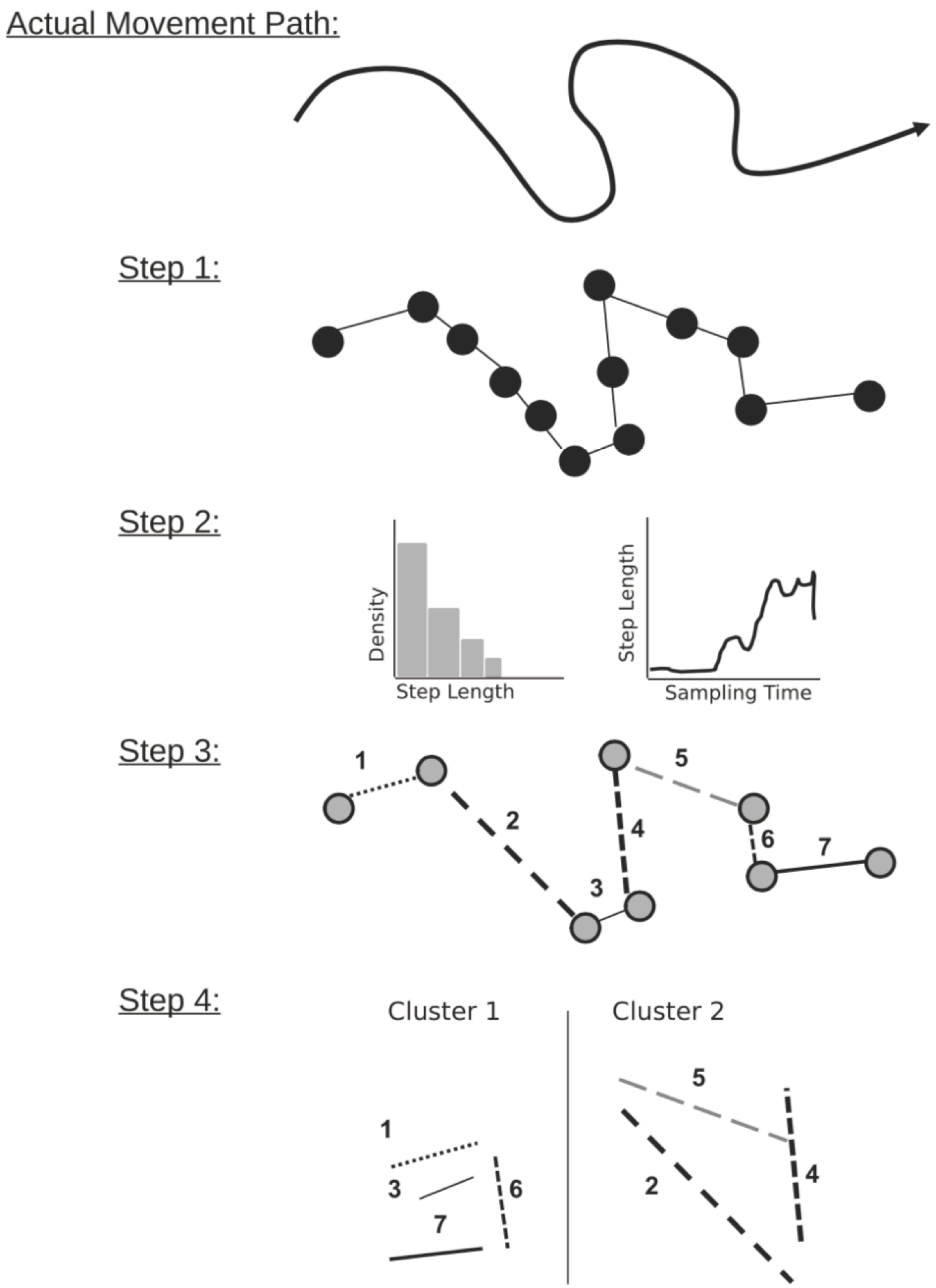
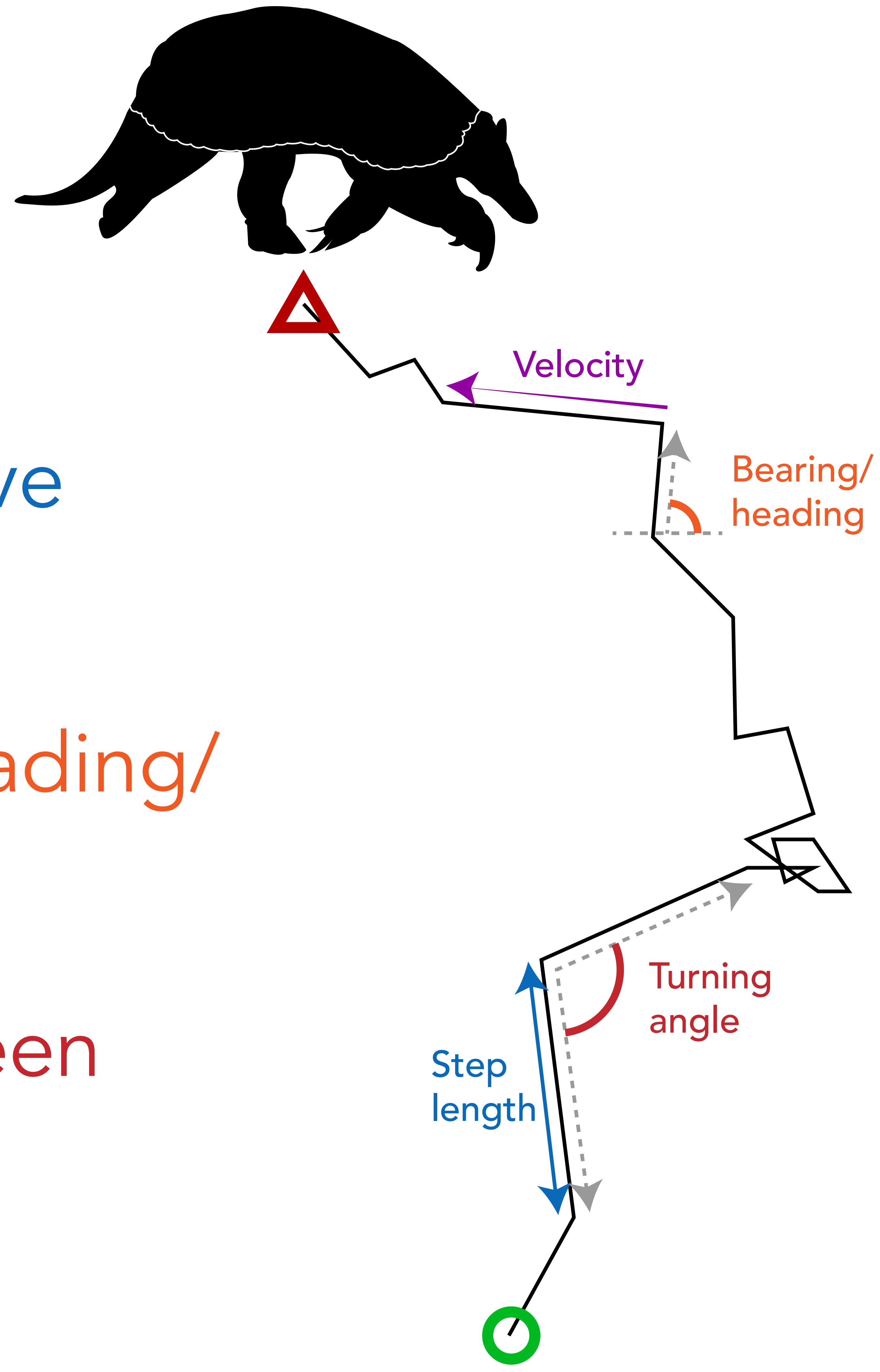


Edelhoff et al., 2016

Movement metrics analyzed by M3/M4

- Bivariate positions or their increments
- Distance between successive observations
- Compass direction (i.e., heading/ bearing)
- Changes in direction between successive relocations



Patterson et al. 2017

- Distance to nearest feature of interest
- Displacement from initial location
- Accelerometer data
- Ancillary environmental data
- Much more!

Framework for M3

Cluster observations directly

- Similar to HMMs, this model:

  1) Estimates discrete behavioral states

  2) Doesn’t account for location error

- Unlike HMMs, this model:

  1) Is not a mechanistic movement model

  2) Doesn’t include a Markovian assumption

  3) Doesn’t use parametric PDFs for movement variables

  4) Estimates the likely number of behavioral states

Framework for M3

Cluster observations directly

Observed movement variable 1 at time i (e.g., step length)

Latent state indicator variable at time i

$$y_i^{(1)} \mid z_i = k \sim \mathrm{Cat}(\boldsymbol{\phi}_{\mathbf{k1}})$$

State-dependent distributions

$$y_i^{(2)} \mid z_i = k \sim \mathrm{Cat}(\boldsymbol{\phi}_{\mathbf{k2}})$$

Observed movement variable 2 at time i (e.g., turning angle)

One of K possible latent states

Where:

<u>Time</u> $1 \leq i \leq N$ Max # of observations

<u>State</u> $k \in 1, \ldots, K$ Max # of states

Vector of probabilities for each state k

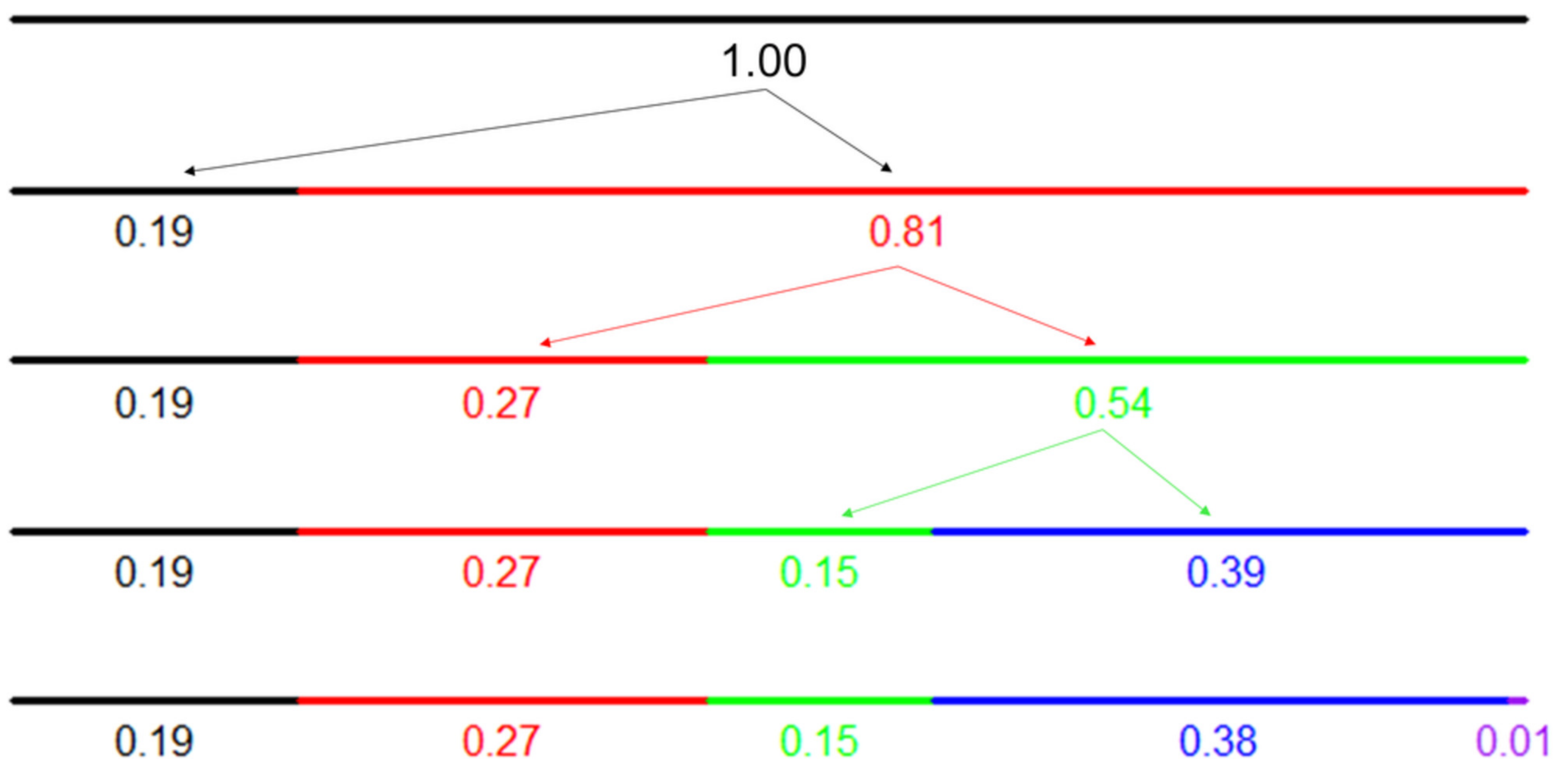
$$z_i \sim \mathrm{Cat}(\boldsymbol{\theta})$$

$$\sum_{k=1}^{K} \theta_k = 1$$ Probabilities must sum to 1

Hyperparameter to define each probability θ_k

$$\boldsymbol{\theta} \sim \mathrm{TSB}(\gamma)$$

<u>Truncated stick-breaking prior (TSB)</u>



Valle et al. 2022

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One of K possible latent states

Where:

Time $1 \le i \le N$ — Max # of observations

State $k \in 1, \ldots, K$ — Max # of states

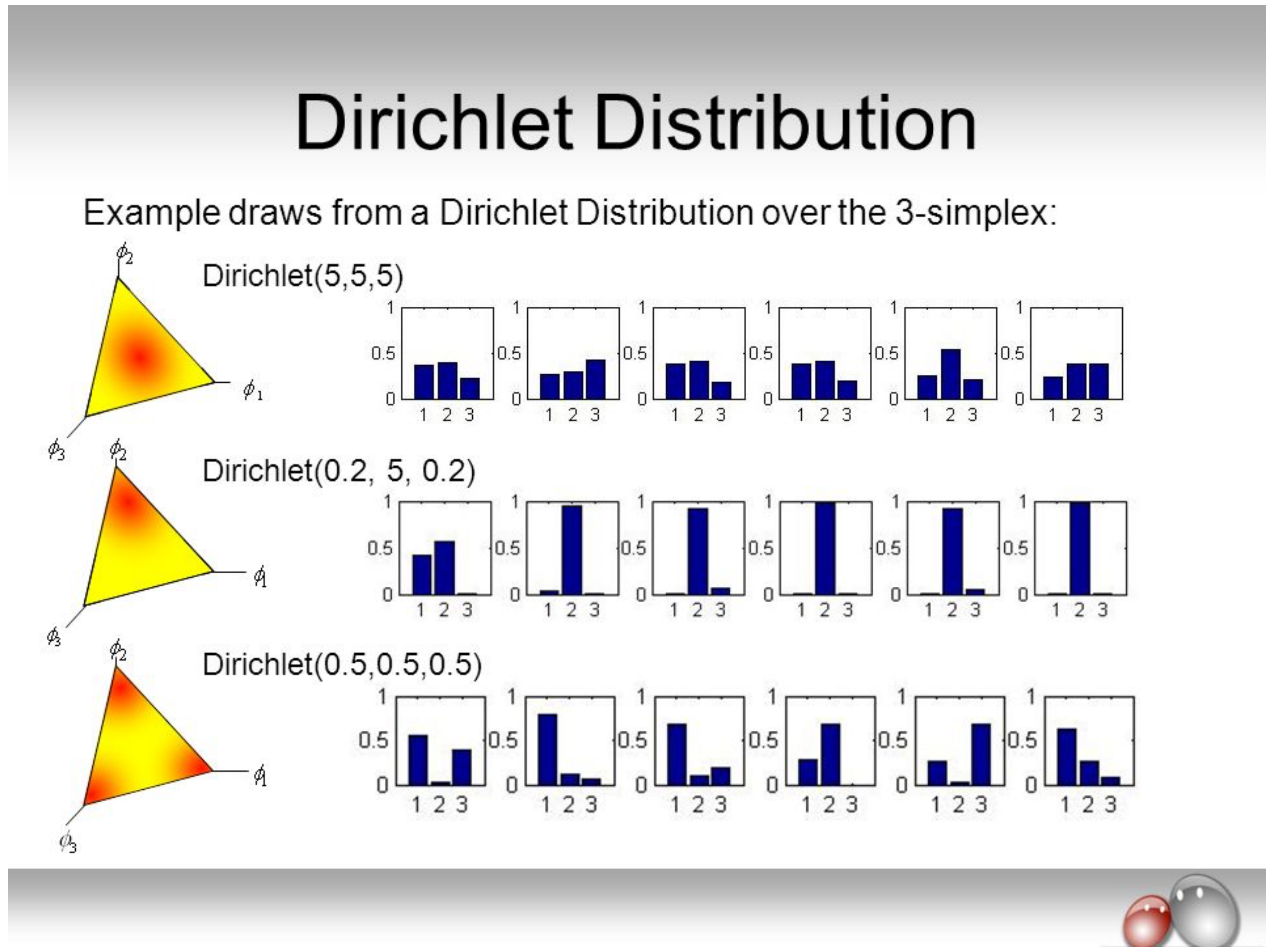
State-dependent distributions for step length

$$\boldsymbol{\phi}_{\mathbf{k1}} \sim \mathrm{Dirichlet}(a)$$

$$\boldsymbol{\phi}_{\mathbf{k2}} \sim \mathrm{Dirichlet}(a)$$

Hyperparameter to define the probability of each bin of the discretized variable

State-dependent distributions for turning angle



Nigel Crook 2009

Framework for M3

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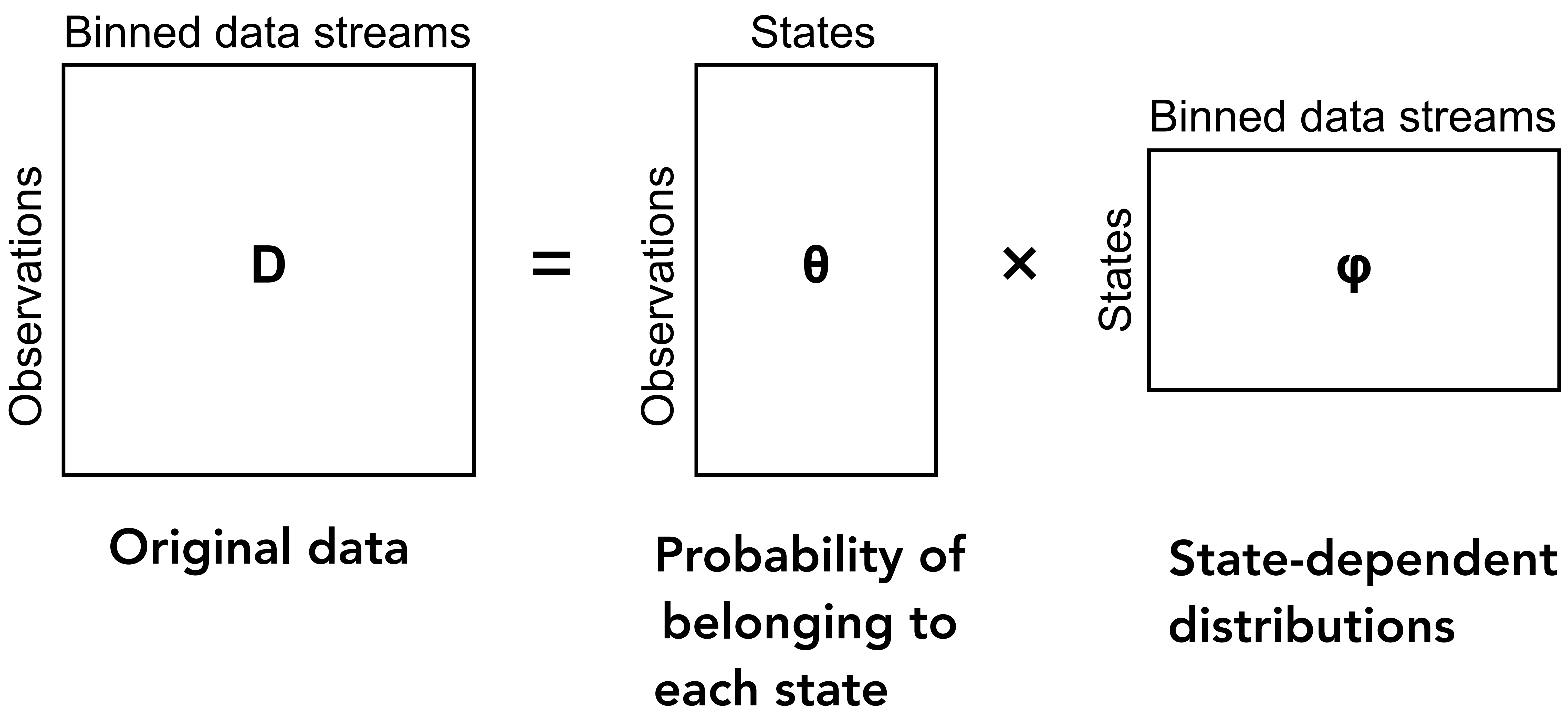


Framework for M4

Segment tracks, then cluster segments

- Similar to HMMs, this model:
  1) Estimates discrete behavioral states
  2) Doesn't account for location error
  3) Accounts for temporal autocorrelation

- Unlike HMMs, this model:
  1) Is not a mechanistic movement model
  2) Doesn't include a Markovian assumption
  3) Doesn't use parametric PDFs for movement variables
  4) Estimates segment-level behavioral state probabilities
  5) Estimates the likely number of behavioral states

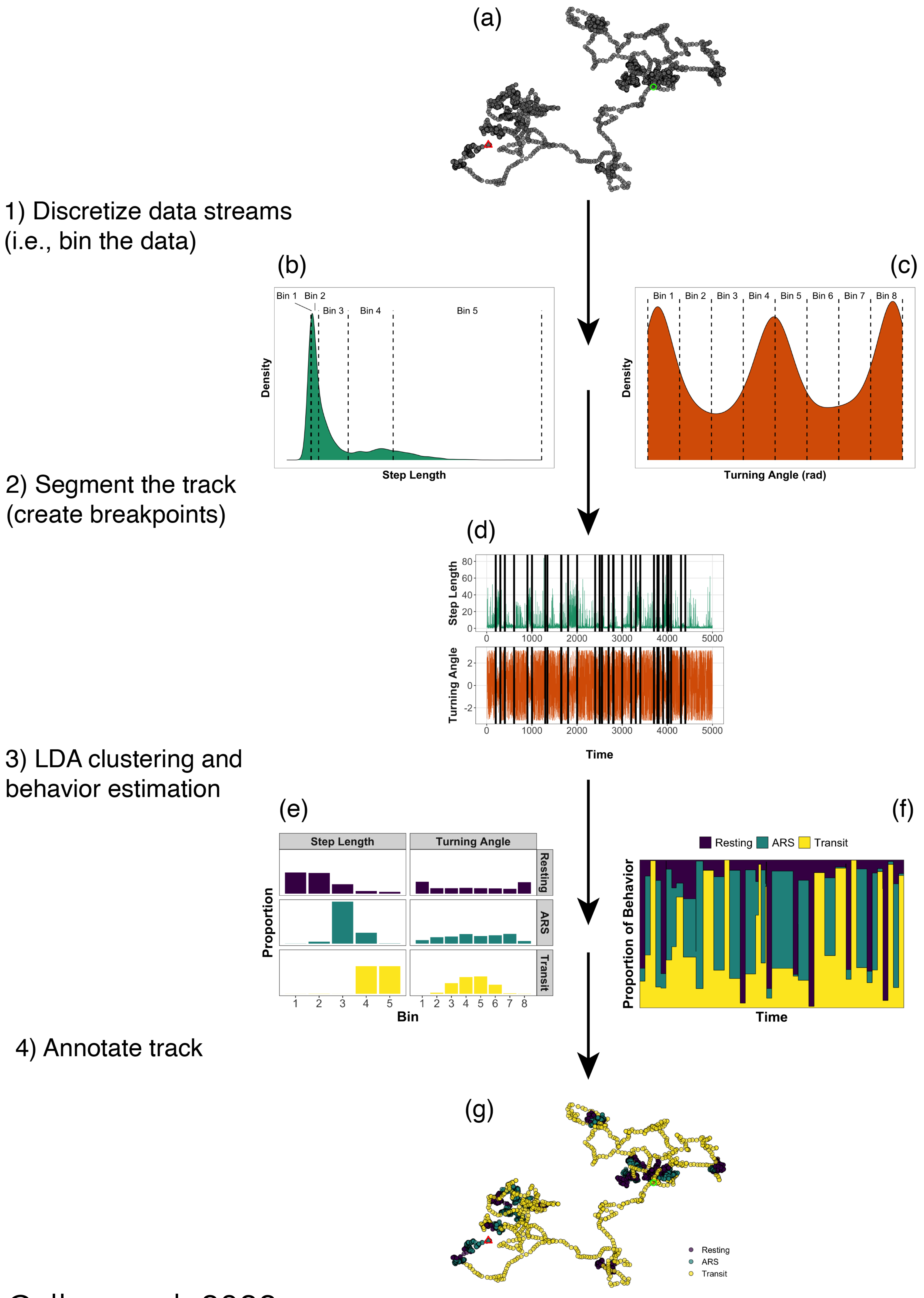
Framework for M4

Segment tracks, then cluster segments

<u>**2-stage model**</u>

1. Estimate breakpoints to segment the tracks
   - Using Bayesian reversible-jump Markov chain Monte Carlo (RJMCMC) algorithm

2. Cluster the segments into states
   - Using Bayesian Latent Dirichlet Allocation (LDA) model



Cullen et al. 2022

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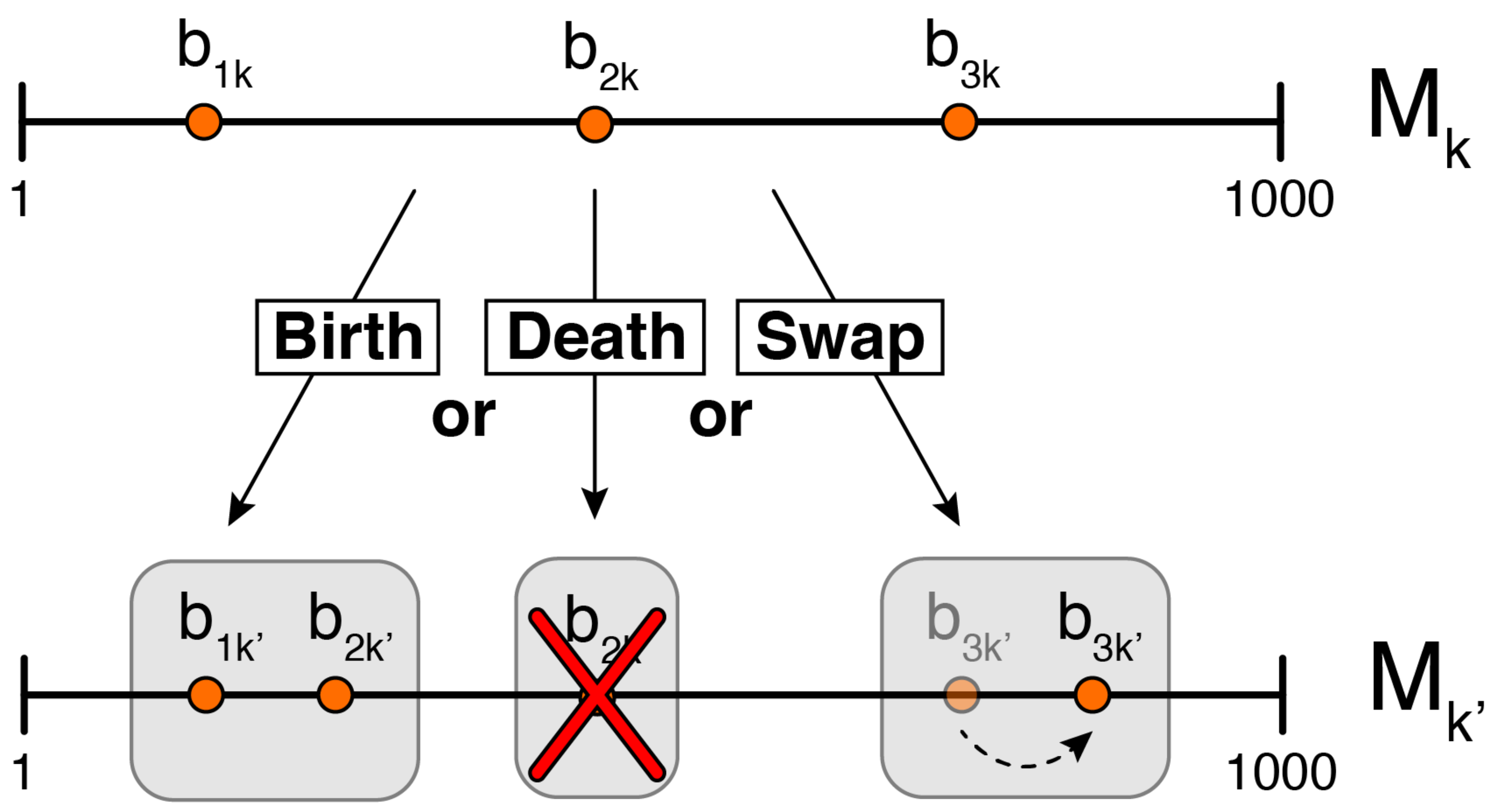
Reversible-jump MCMC




```
if (M_k' / M_k > runif(1)) accept proposal
else reject proposal
```

Framework for M4

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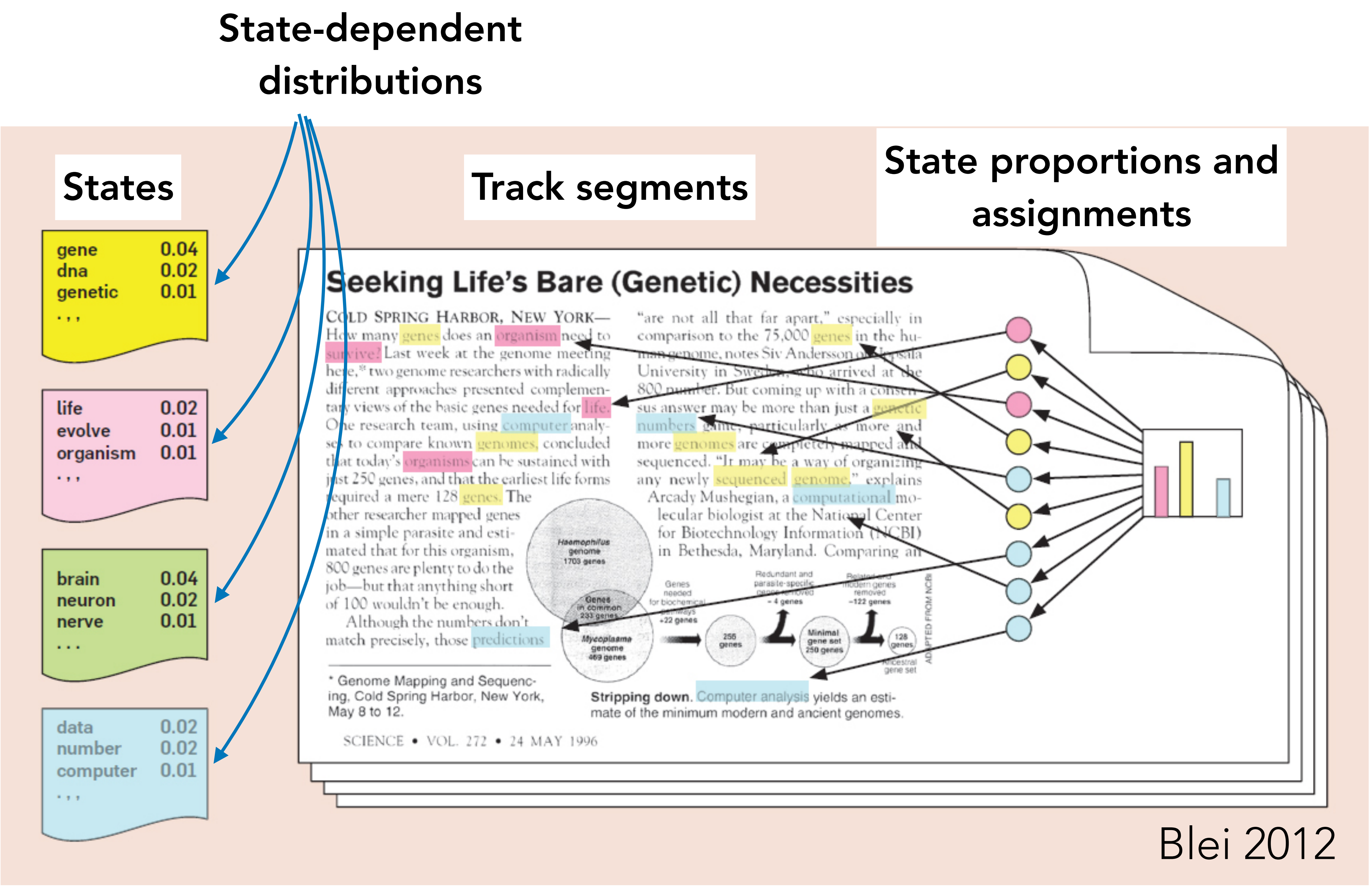

Framework for M4

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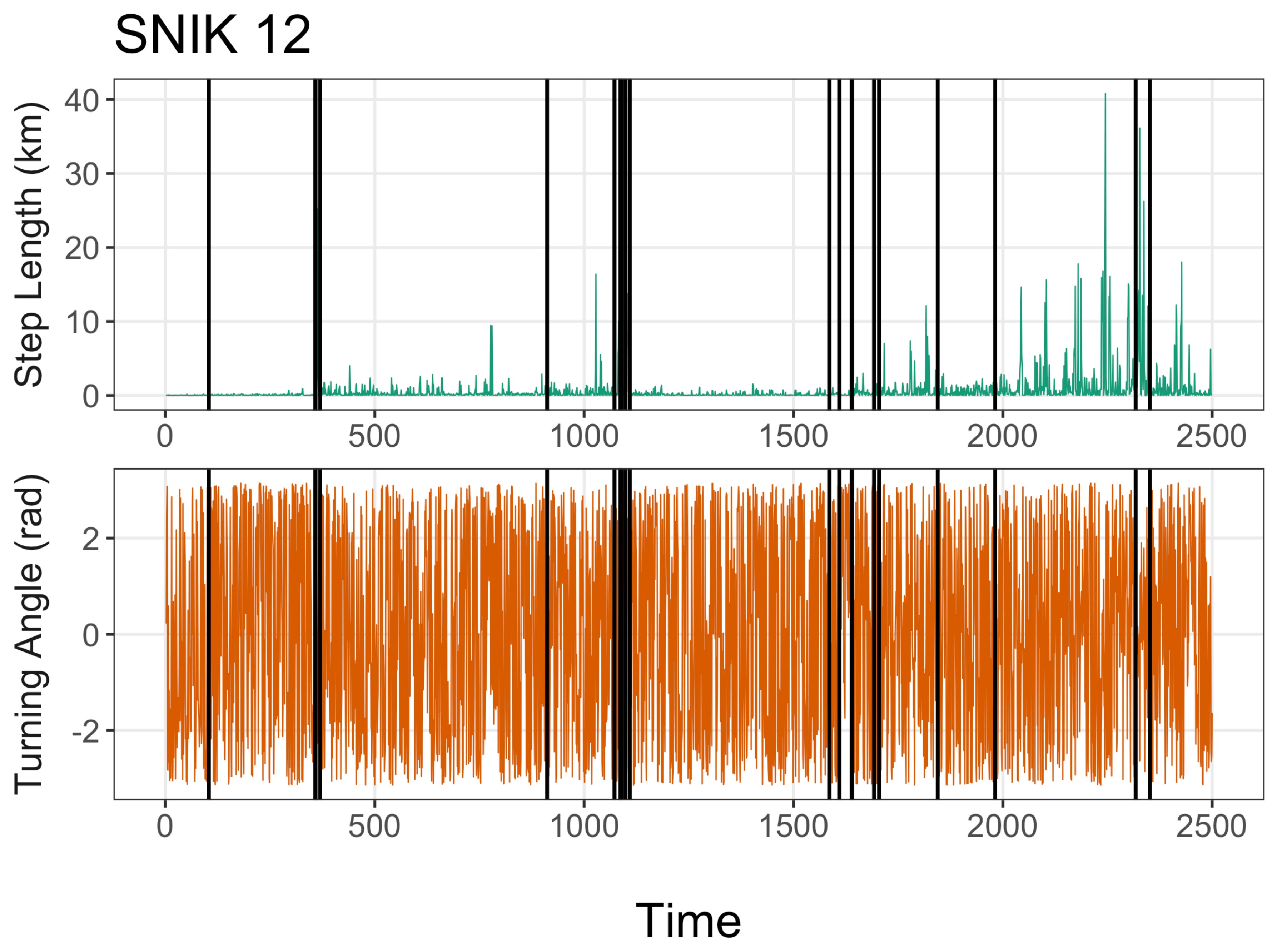


Cullen et al. 2022

$$M_k = \{b_{1k}, \ldots, b_{Pk}\}$$

Last breakpoint (P) of model k

Model k, where is the iteration # of the RJMCMC

Breakpoint 1 of model k

Bin label

$$x_{itj} \sim Cat(\theta_{cj})$$

Probabilities that observations in track segment c are assigned to one of the bins

Hyperparameter to define the probability of each bin of the discretized variable

$$\theta_{cj} \sim Dirichlet(\alpha)$$

i = individual

j = data stream

c = track segment

t = time

- We perform unsupervised segmentation on each individual track
- Model is seeking breakpoints that define relatively homogeneous track segments

Framework for M4

Segment tracks, then cluster segments

2. Cluster the segments into states

i = individual
j = data stream
c = track segment
t = time

One of K possible latent states

Hyperparameter to define the probability of each bin of the discretized variable

$$y_{ijct} \mid \{z_{ijct} = k\} \sim Cat(\phi_{kj}) \qquad \phi_{kj} \sim Dirichlet(\alpha)$$

Bin label

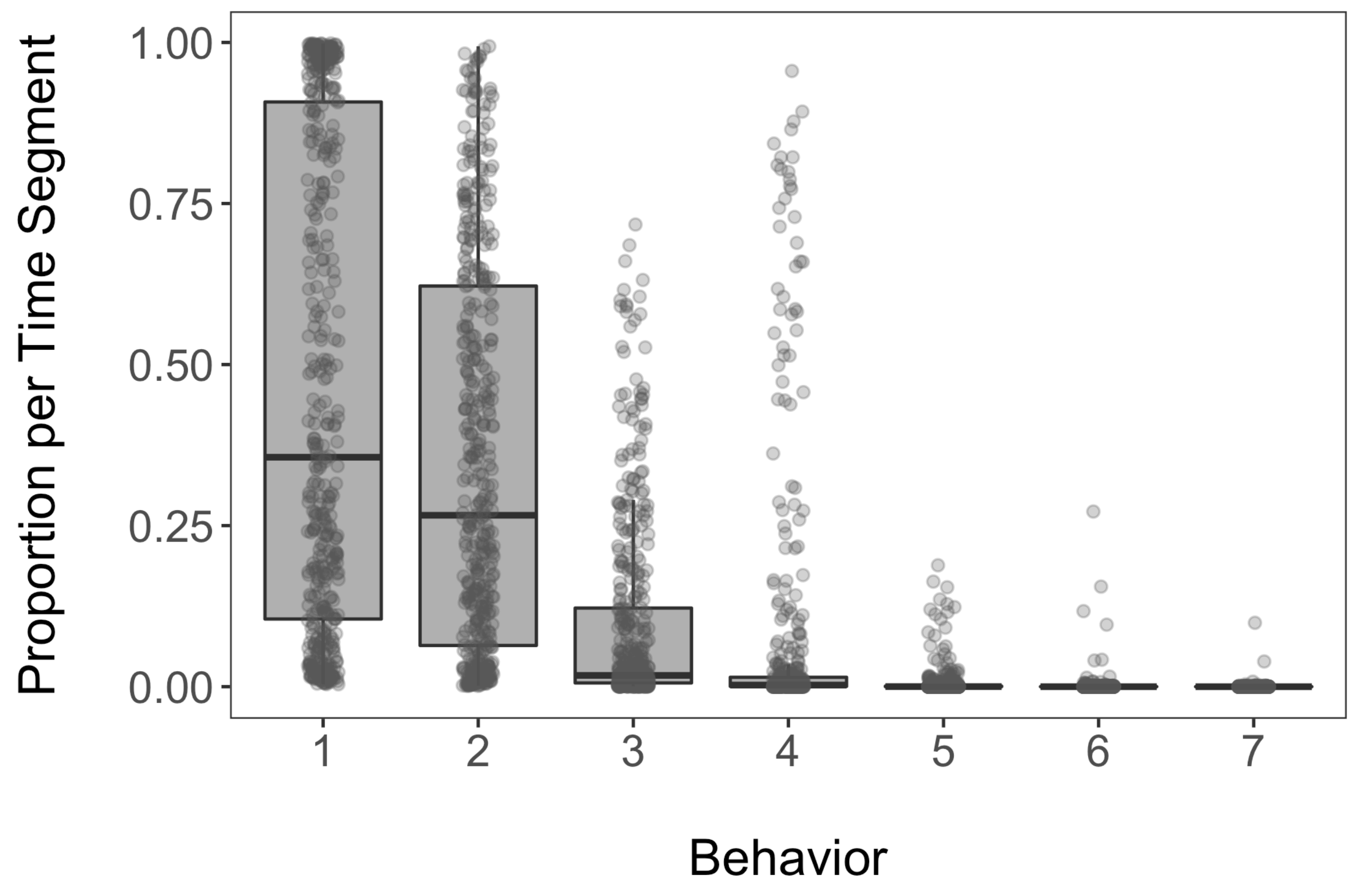
Latent state indicator

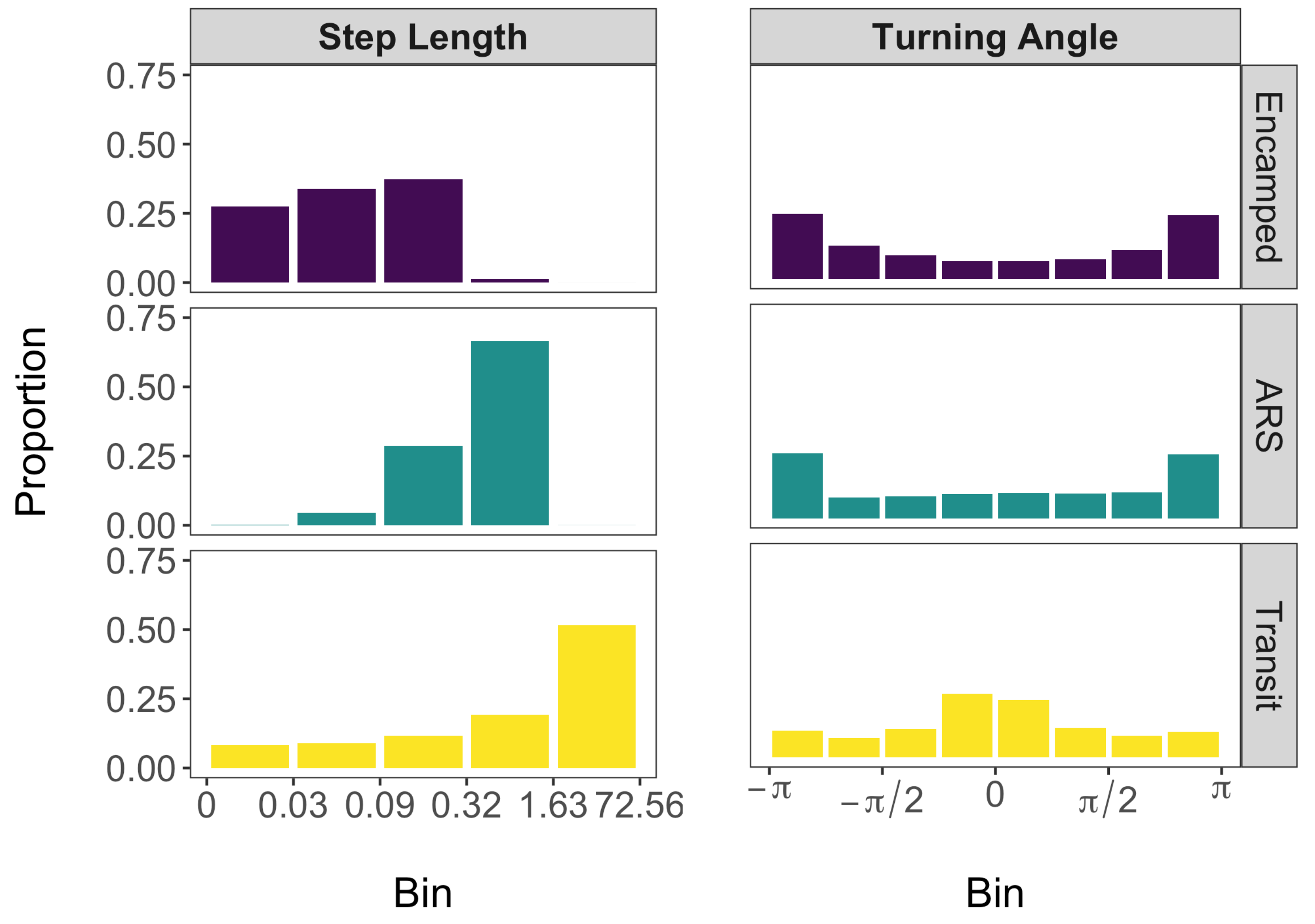
State-dependent distribution

Hyperparameter to define each probability

$$z_{ijct} \sim Cat(\theta_{ic}) \qquad \theta_{ic} \sim TSB(\gamma)$$

Probabilities of assigning observations in segment c to behavioral state k





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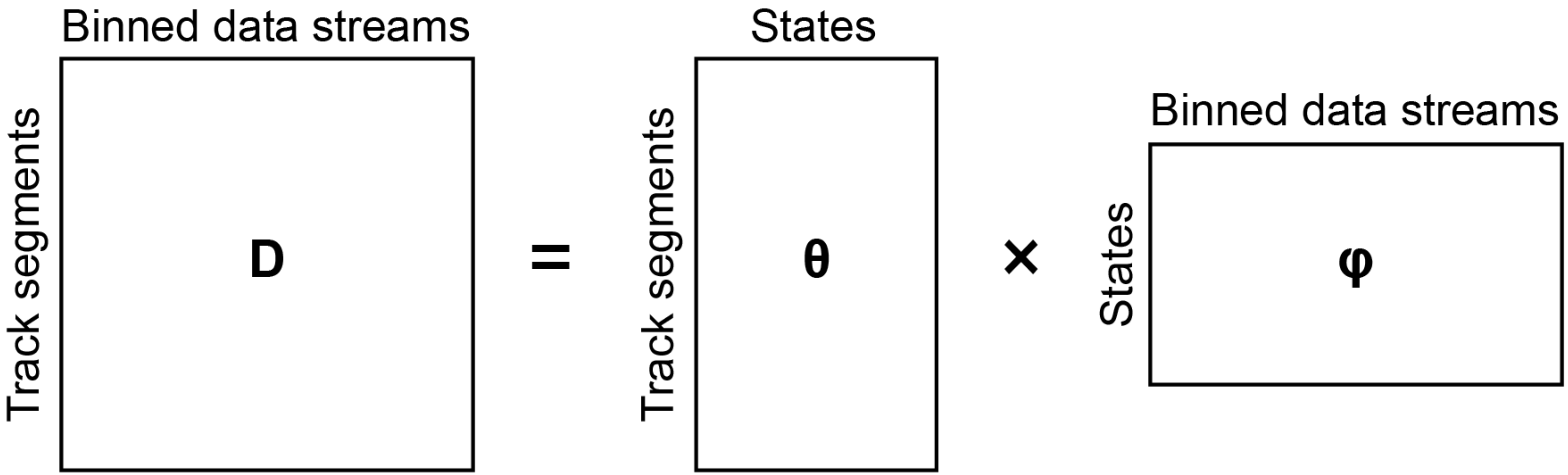
- Track segments can be comprised of multiple behavioral states (as determined by model)

Framework for M4

Segment tracks, then cluster segments



Original data

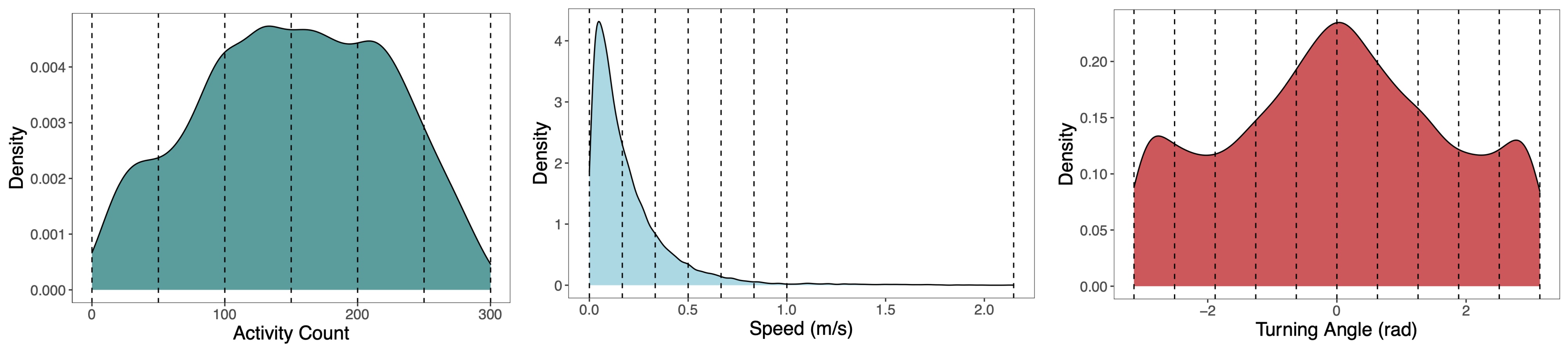
Probability of belonging to each state

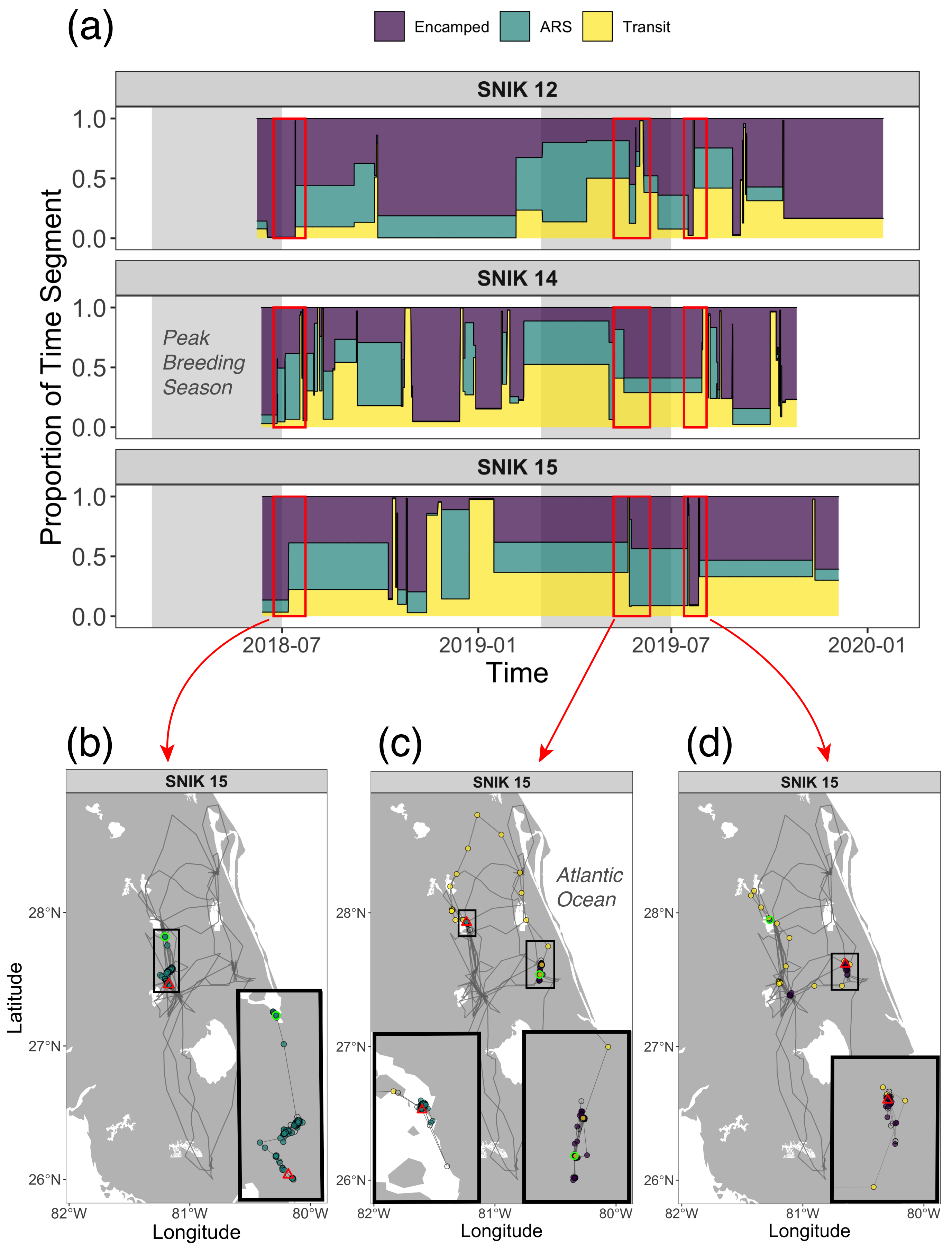
State-dependent distributions

Methods to fit M3/M4

- Since using Bayesian non-parametric approach, only available in Bayesian implementation
- Readily available functions to fit models using the `bayesmove` R package
- If interested in further details or information, please refer to Cullen et al. (2022) for M4 and Valle et al. (2022) for M3

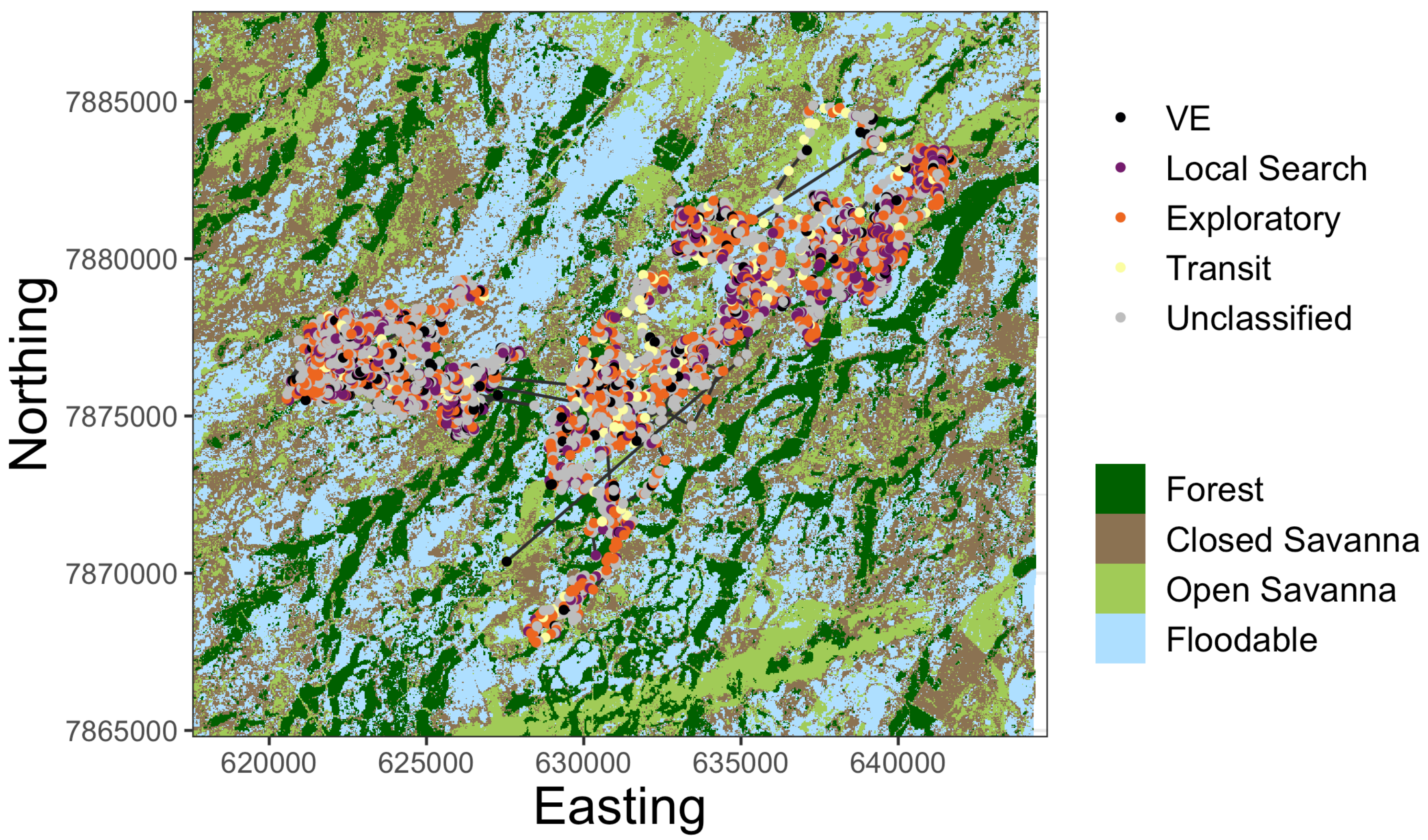
Motivating examples

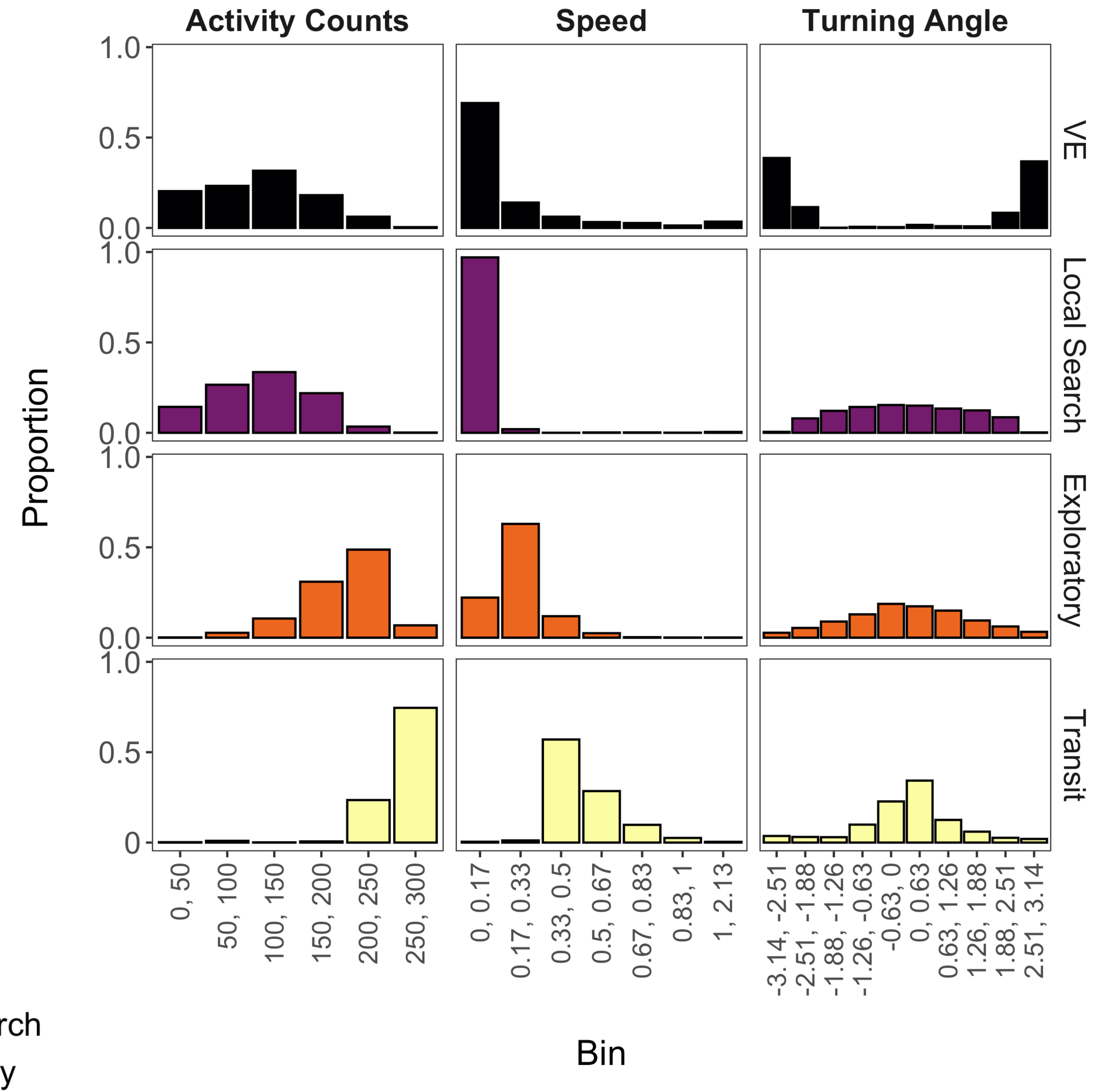




Cullen et al. 2022

Cullen et al. in review





Cullen et al. in review

Let’s do some modeling!

References

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