

Model complexity and model choice for animal movement models

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Outline

- 1 Florida panthers
- 2 Hidden Markov models
- 3 Basic analysis (van de Kerk et al., 2015)
- 4 Incorporating diurnal variation (Li, 2015)
- 5 Broader issues/outlook

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biologists

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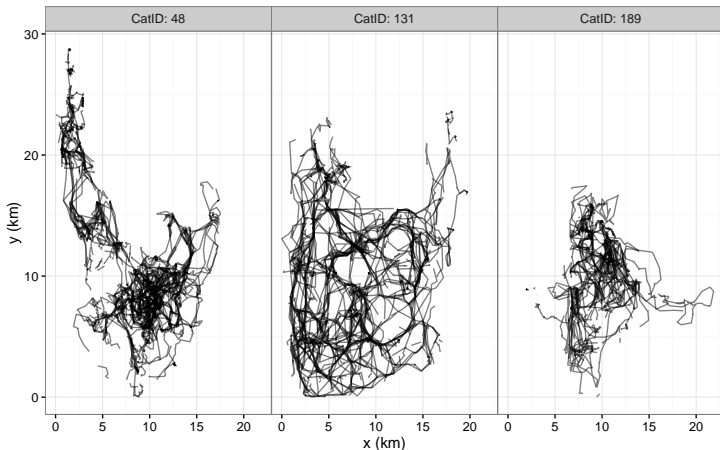
Florida panther movement

- endangered subspecies, *Puma concolor coryi*
- movement variation by sex and life history stage (juvenile, adult, mom with kittens . . .)
- effects of movement on threats
- predicting the effects of changes in habitat, etc.



panther movement tracks

18 GPS-collared animals, 3200 panther days;
49000 locations (hourly); 1-15K observations per animal

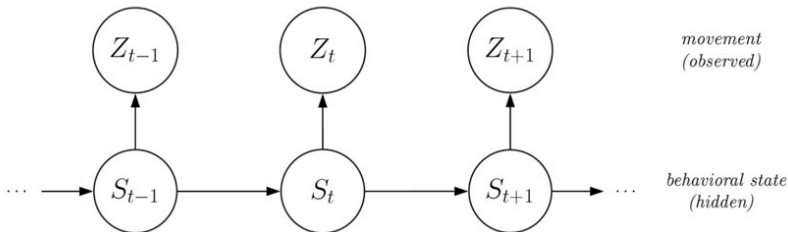


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Hidden Markov models

- finite mixture model with temporal dependence
- discrete time steps
- discrete latent state; *transition matrix*
- observations from *emission distributions*
(continuous or discrete, univariate or multivariate)
- **multiphasic movement** (Fryxell et al., 2008; Langrock et al., 2012)



Hidden Markov models (cont.)

state:

$$S_t \sim \text{Multinomial}(S_{t-1}, \mu_{S,t})$$

$$\mu_{S,t} = \text{multi-logistic}(\mathbf{X}_{S,t} \boldsymbol{\beta}_S)$$

emission:

$$\mathbf{Z}_t \sim \{\text{Dist}_1(\mu_{Z_1,S_t}), \dots, \text{Dist}_n(\mu_{Z_n,S_t})\}$$

$$\mu_{Z_i,S_t} = g^{-1}(\mathbf{X}_{Z_i,t} \boldsymbol{\beta}_{Z_i,S_t})$$

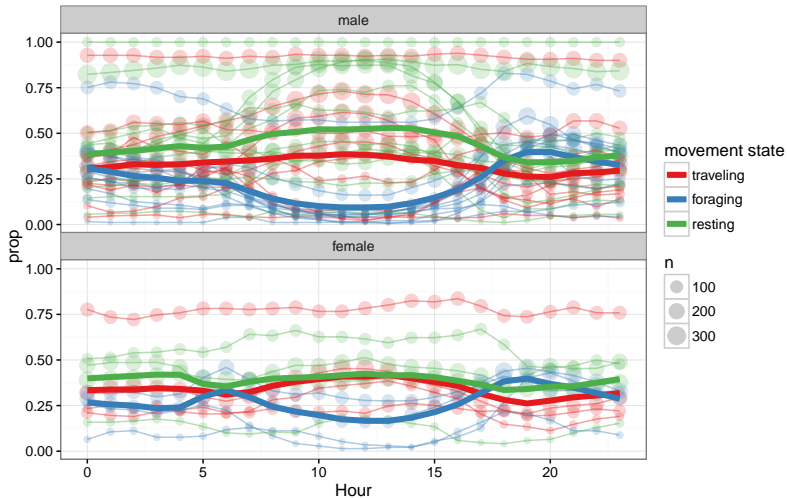
Hidden Markov models (part 3)

- *forward-backward algorithm* for estimating parameters
- *Viterbi algorithm* for estimating most probable state sequences
- depmixS4 package (Visser and Speekenbrink, 2010) (also moveHMM (Michelot et al., 2016))
- hidden *semi-Markov* models: allow for non-geometric *dwell time distributions* (Langrock, 2011; Augustine, 2016): `move.HMM`

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Diurnal variation



what can we conclude so far?

good news

- basic biology: males move faster, farther
- three states are identifiable, sensible
- dwell distributions approximately geometric (HSMM \rightarrow HMM)

bad news

- diurnal variation in Viterbi results - but it's not in the model!
- estimates of model complexity are too high

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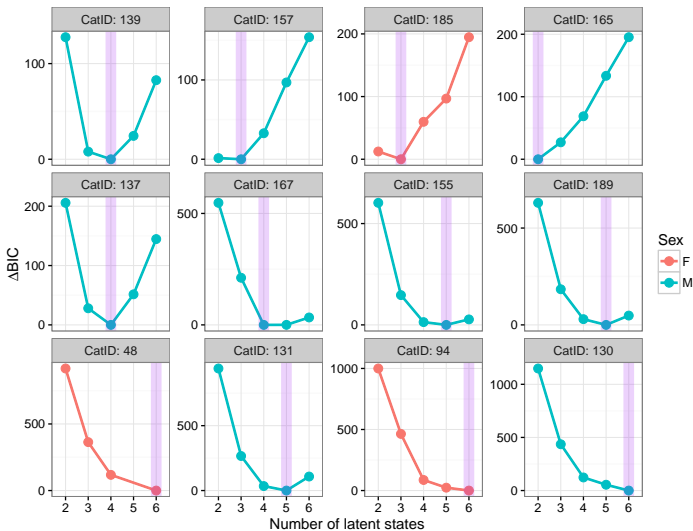
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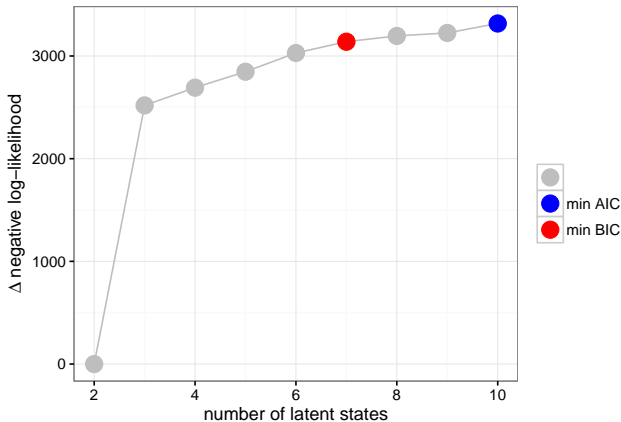
bad news

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Model complexity (bad news)



Model complexity (Manx shearwaters, Dean et al. (2013))



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Expanding the model

Attempting to fix these problems:

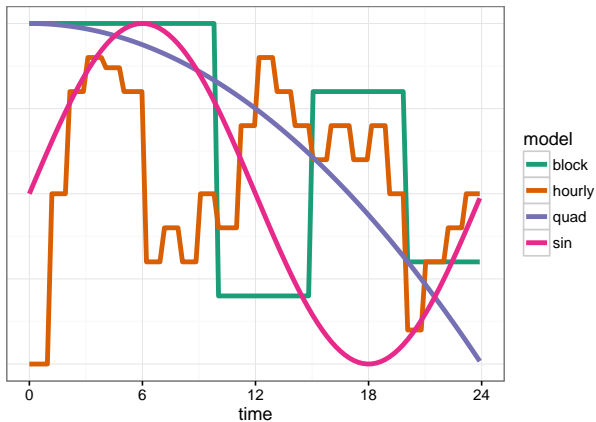
- extend the model to allow covariates
- specifically, allow for diurnal variation
 - simplify model (log-Normal step length only)
 - *fixed* state-specific emissions parameters (step length mean and std dev)
 - time-varying transition parameters
 - also try *finite mixture models* (independent occupancy)
- how much does this help?

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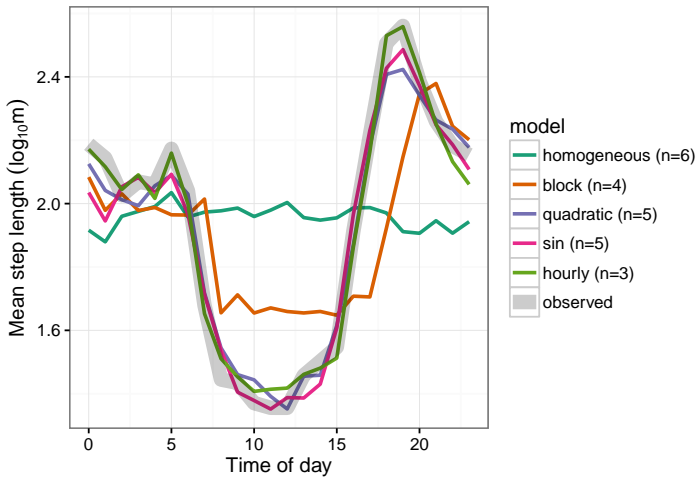
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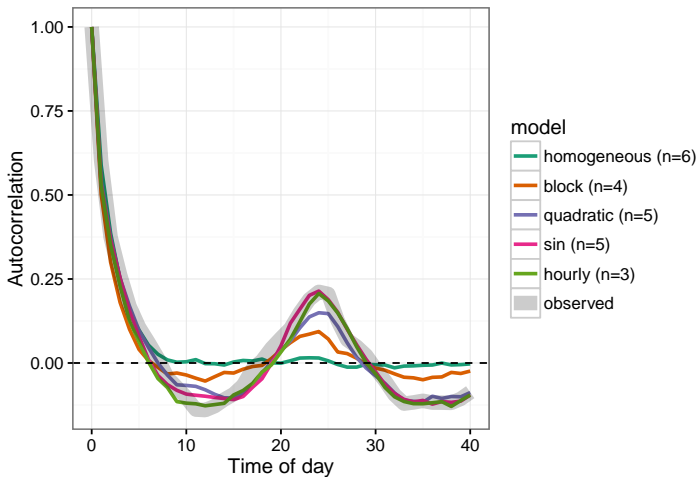
Temporal models



Temporal patterns (step length)

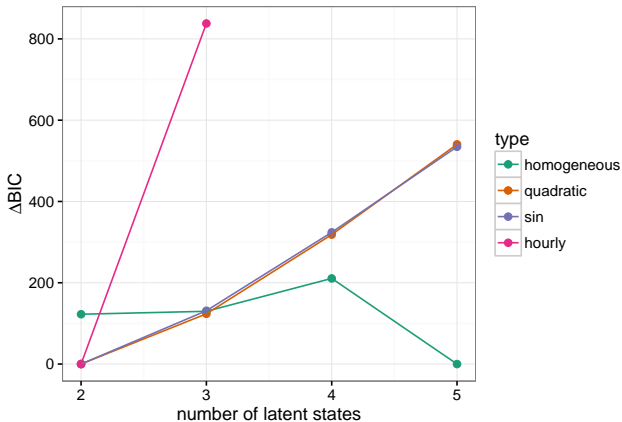


Temporal patterns (autocorrelation)



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Model complexity: simulation



Diurnal model: conclusions

- diurnal structure greatly improves fit ($\Delta\text{BIC} \approx 500$)
- slightly improves latent-state issue ($n = 6 \rightarrow 5$)
- lots left to do!
 - seasonal variation
 - incorporate habitat, home range behaviour
 - etc. etc. etc.

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Big data and small models

- simple model families +
model misspecification →
overparameterization

- Gelman: “Sample sizes are never large”: ([blog post](#))

N is never enough because if it were “enough” you’d already be on to the next problem for which you need more data.

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Tools needed

- cross-validation (Wenger and Olden, 2012)
- protocols and tools for model checking (Potts et al., 2014);
score tests?
- flexible computational frameworks
(ecologists can't afford consultants/
there are too many species out there)



