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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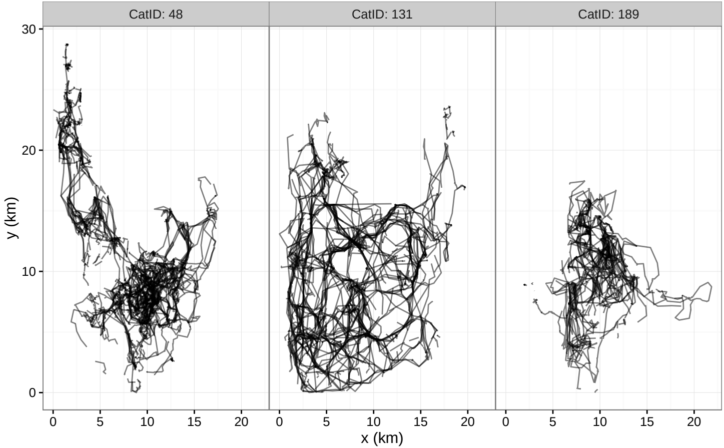
Florida panther movement

- endangered subspecies, *Puma concolor coryi*
- movement variation by sex and life history stage (juvenile, adult, mom with kittens . . .)
- 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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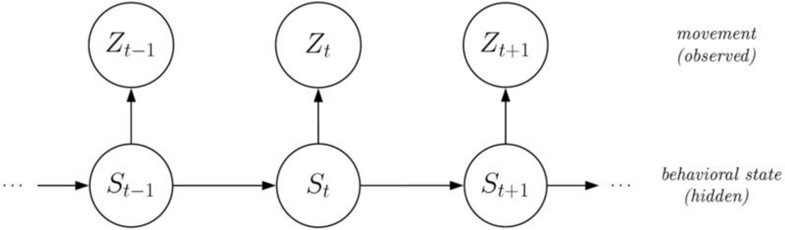
Hidden Markov models

- 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 (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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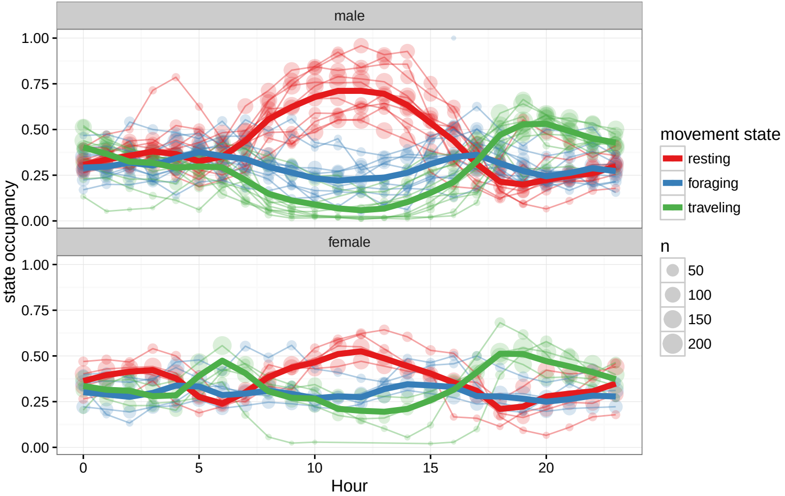
Diurnal variation: Viterbi results



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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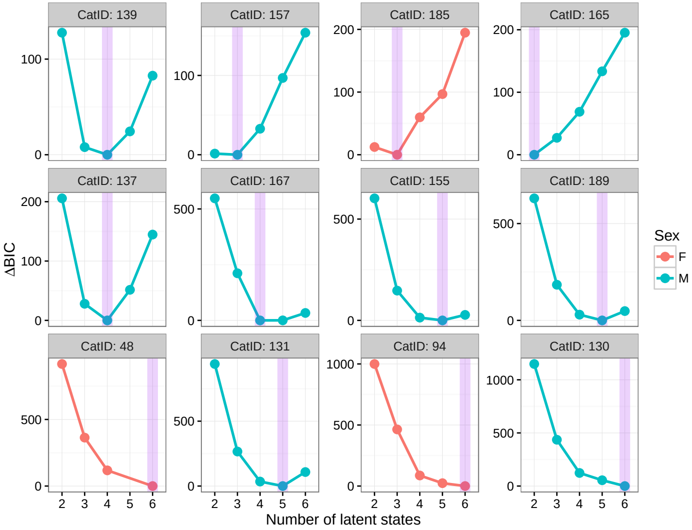
Model complexity (bad news)



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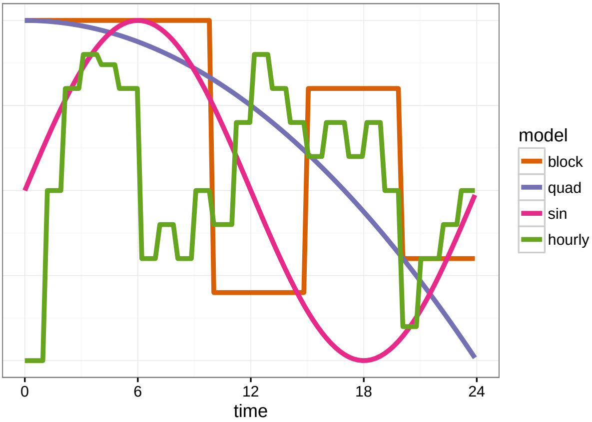
Expanding the model

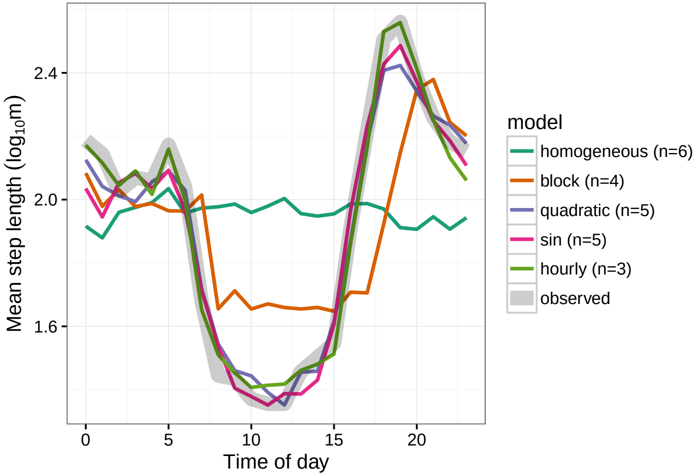
Attempting to fix these problems:

- allow for diurnal variation
    - simplify model (log-Normal step length only)
    - time-varying transition parameters
    - also try *finite mixture models*
      (independent occupancy)

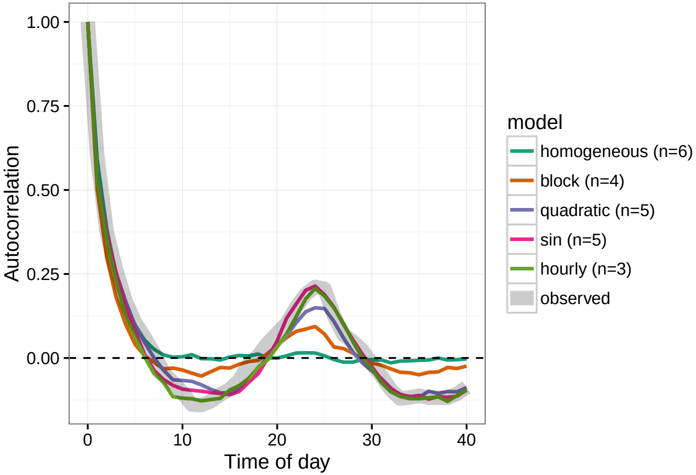
Temporal models



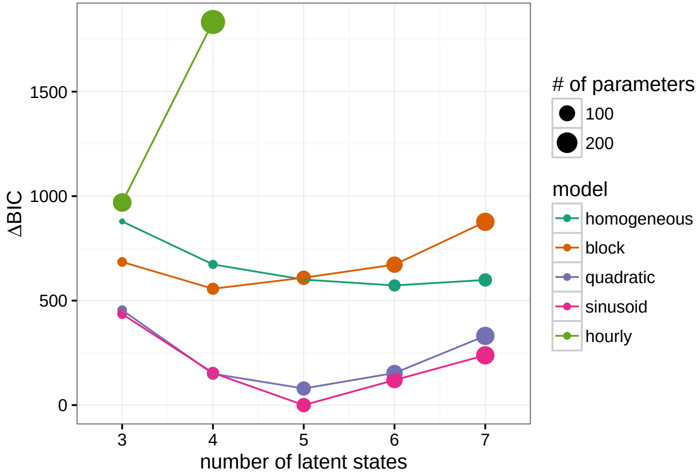
Temporal patterns (step length)



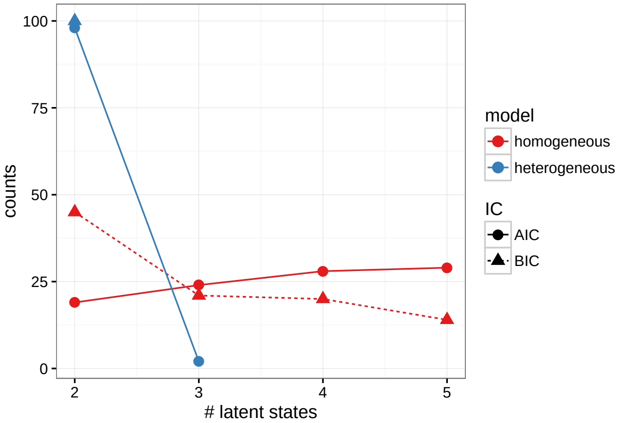
Temporal patterns (autocorrelation)



Goodness of fit/model complexity



Model complexity: simulation (2-state heterogeneous)



Diurnal model: conclusions

- diurnal structure greatly improves fit ($\Delta\mathrm{BIC} \approx 500$)
- slightly improves latent-state issue ($n = 6 \to 5$)
- be careful using Viterbi to assess model fit (double-dipping)
- 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 +
  large data →
  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.*

  . . . i.e. should add *appropriate* complexity to soak up variation

Tools needed

- convenient tools for model checking:
  graphical & quantitative (Potts et al., 2014)
- cross-validation (Wenger and Olden, 2012) ?
- flexible computational frameworks
  (ecologists can't afford consultants/
  there are too many species)

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extras

Hidden Markov models (cont.)

state:

$$S_t \sim \mathrm{Multinomial}(S_{t-1}, \mu_{S,t})$$
$$\mu_{S,t} = \mathrm{multi\text{-}logistic}(\mathbf{X}_{S,t}\boldsymbol{\beta}_S)$$

emission:

$$\mathbf{Z}_t \sim \{\mathrm{Dist}_1(\mu_{Z_1,S_t}), \ldots, \mathrm{Dist}_n(\mu_{Z_n,S_t})\}$$
$$\mu_{Z_i,S_t} = g^{-1}\left(\mathbf{X}_{Z_i,t}\boldsymbol{\beta}_{Z_i,S_t}\right)$$

An aside on AIC vs BIC

- "should I use AIC or BIC? I heard that AIC is inconsistent ..."
- complexity penalty = 2 (AIC) vs $\log(n)$ (BIC)
- best prediction vs. model identification (Yang, 2005)
- *effect size spectrum*: tapering or discrete?