Model complexity and model choice for animal movement models

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- 1 Florida panthers
- 2 Hidden Markov models
- 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

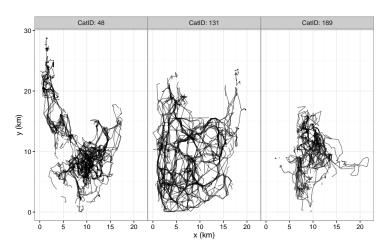
- endangered subspecies,
 Puma concolor coryi
- movement variation by sex and life history stage (juvenile, adult, mom with kittens . . .)
- threats
- predicting the effects of changes in habitat, etc.





panther movement tracks

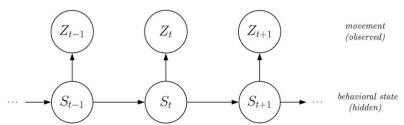
18 GPS-collared animals, 3200 panther days; 49000 locations (hourly); 1-15K observations per animal



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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)

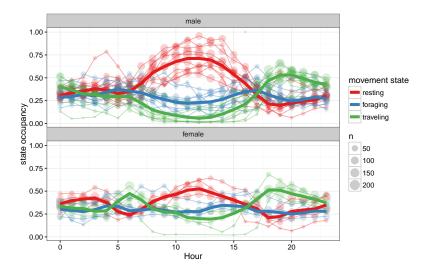


Hidden Markov models in practice

- 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
- ullet dwell distributions approximately geometric (HSMM ightarrow 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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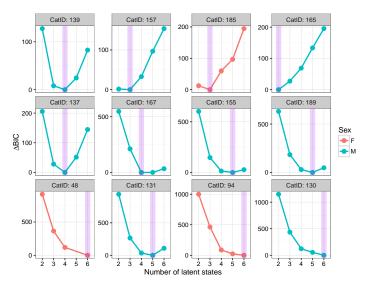
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Model complexity (bad news)

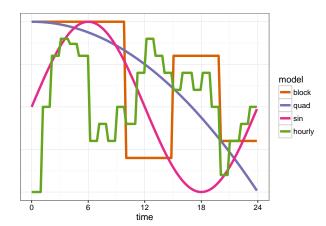


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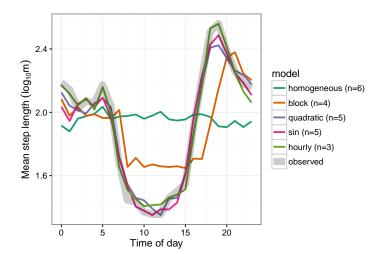
Expanding the model

- allow for diurnal variation: time-varying transition parameters
- (also try finite mixture models with time-varying occupancy)

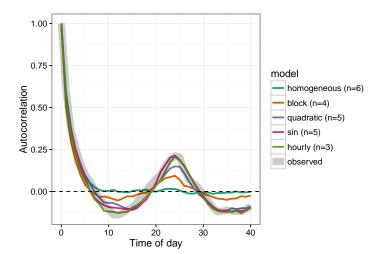
Temporal models



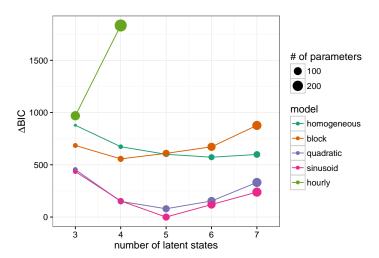
Temporal patterns (step length)



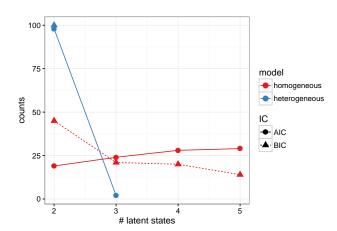
Temporal patterns (autocorrelation)



Goodness of fit/model complexity



Model complexity: simulation (2-state heterogeneous)



Diurnal model: conclusions

- diurnal structure greatly improves fit ($\Delta {\rm BIC} \approx 500$)
- slightly improves latent-state issue ($n = 6 \rightarrow 5$)
- 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)



http://tinyurl.com/panthermoves2

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Diurnal model

Broader issues/outlook

References

Panthers

extras

HMM

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Basic analysis

Hidden Markov models (cont.)

state:

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

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

emission:

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

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?

