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

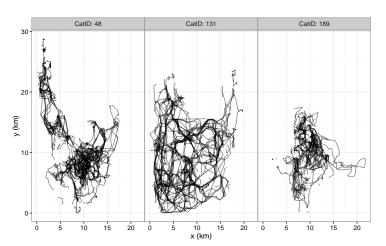
- endangered subspecies, Puma concolor coryi
- movement variation by sex and life history stage (juvenile, adult, mom with kittens . . .)
- effects of movement on threats
- predicting the effects of changes in habitat, etc.





panther movement tracks

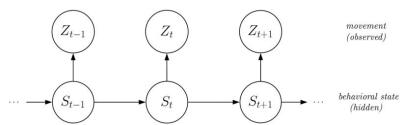
18 GPS-collared animals, 3200 panther days; 49000 locations (hourly); 1-15K observations per animal



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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:

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

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

emission:

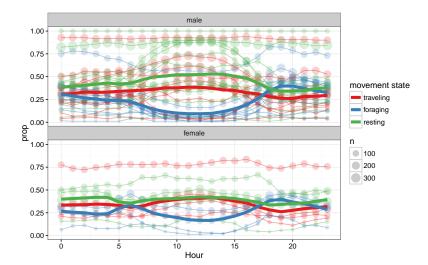
$$\mathbf{Z}_{t} \sim \{ \mathrm{Dist}_{1}(\mu_{Z_{1},S_{t}}), \dots, \mathrm{Dist}_{n}(\mu_{Z_{n},S_{t}}) \}$$
$$\mu_{Z_{i},S_{t}} = g^{-1}(\mathbf{X}_{Z_{i},t}\beta_{Z_{i},S_{t}})$$

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
- 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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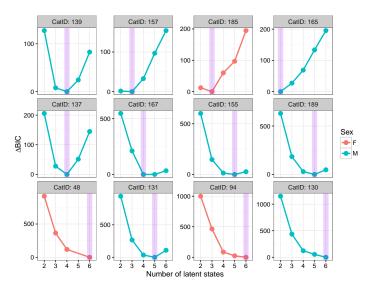
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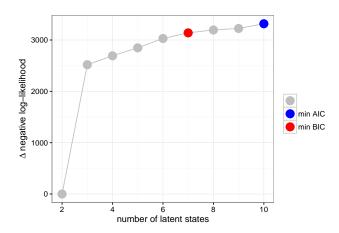
bad news

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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:

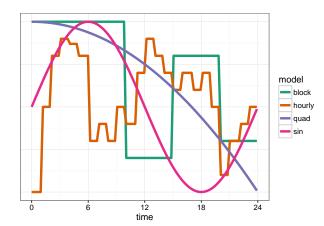
- extend the model to allow covariates
- specifically, allow for diurnal variation
 - simplify model (log-Normal step length only)
 - fixed state-specific emissions parameters (step length mean and std dev)
 - time-varying transition parameters
 - also try finite mixture models (independent occupancy)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

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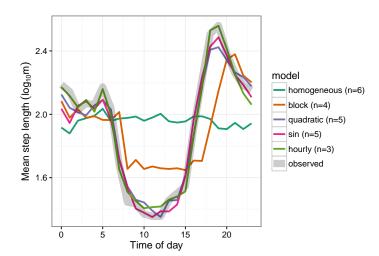
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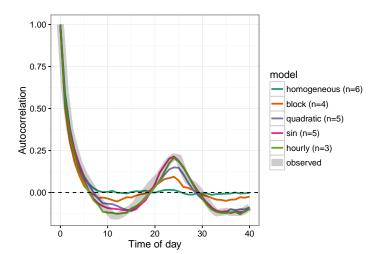
Temporal models



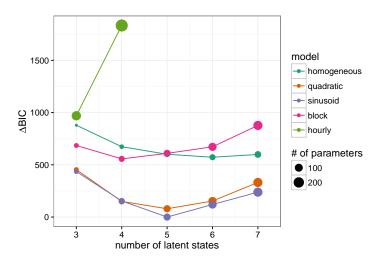
Temporal patterns (step length)



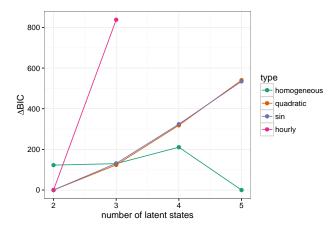
Temporal patterns (autocorrelation)



Goodness of fit/model complexity



Model complexity: simulation



Diurnal model: conclusions

- diurnal structure greatly improves fit ($\Delta {
 m BIC} \approx 500$)
- 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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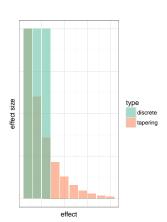
Big data and small models

- 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.

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?



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)



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