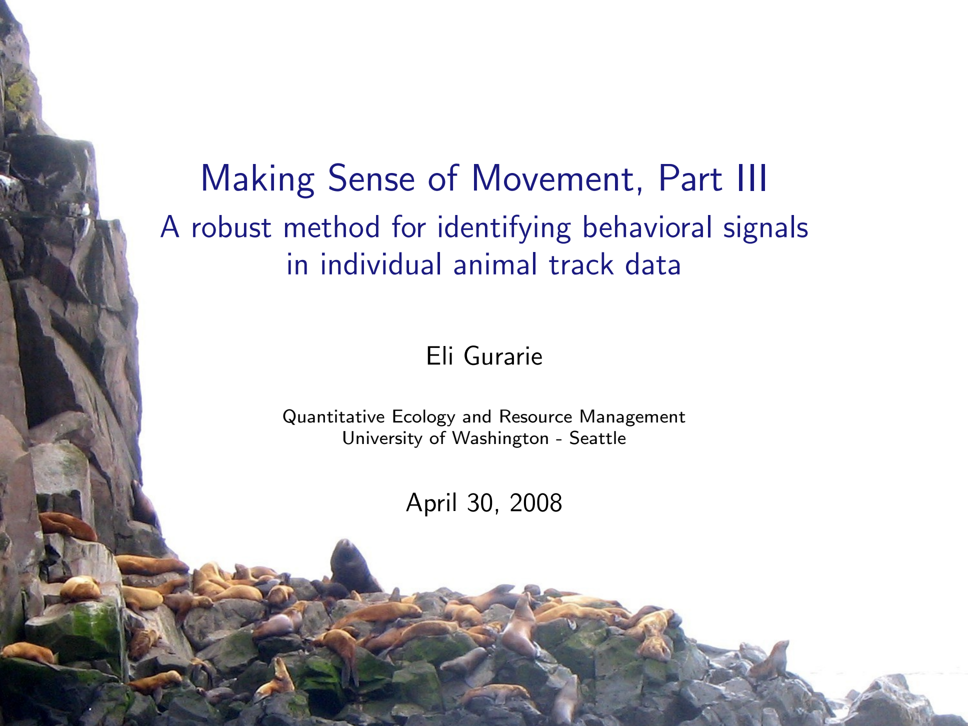

Making Sense of Movement, Part III

A robust method for identifying behavioral signals in individual animal track data

Eli Gurarie

Quantitative Ecology and Resource Management
University of Washington - Seattle

April 30, 2008

Motivation

- Movement is important
- There's lots of data
- There's lots of really interesting questions to ask

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I. Mark-Recapture

II. First-Passage Time

III. Tracks

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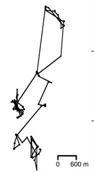

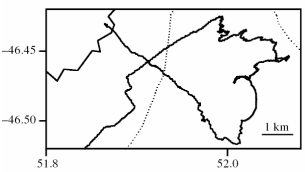

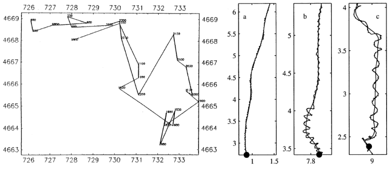

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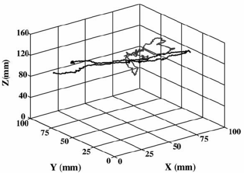

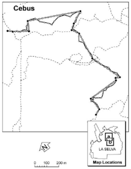

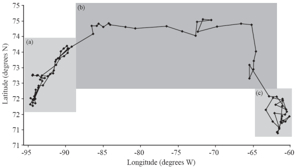

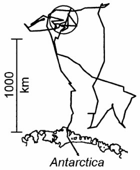

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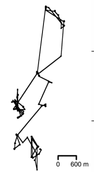

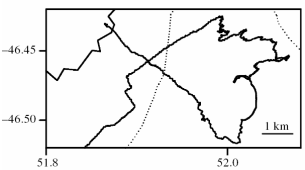

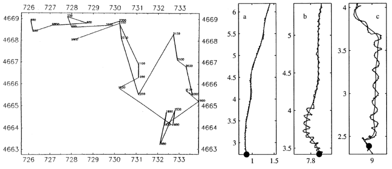

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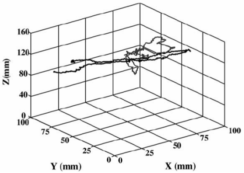

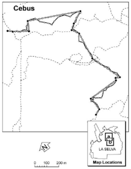

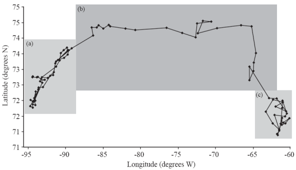

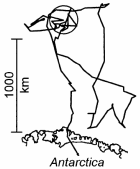

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What kind of information is hiding in this data?

Common and Somewhat Inconvenient Features of Track Data

- Multi-dimensional
- Auto-correlated
- Error-ridden
- Gappy
- Heterogeneous

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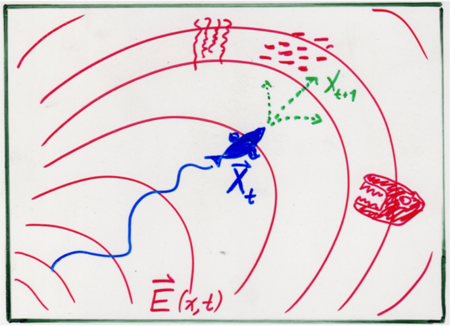
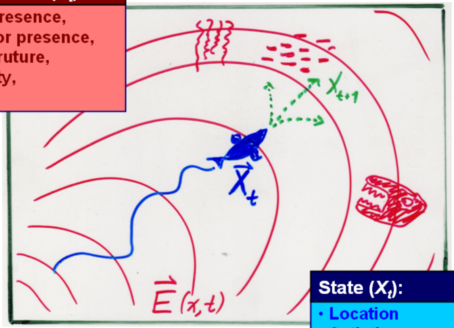
Conceptual model of Behavior



Conceptual model of Behavior

Environment (E_t):

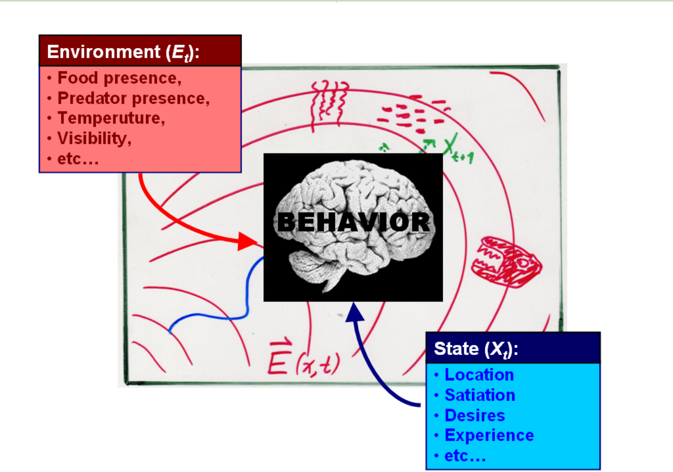
- Food presence,
- Predator presence,
- Temperuture,
- Visibility,
- etc...



State (X_t):

- Location
- Satiation
- Desires
- Experience
- etc...

Conceptual model of Behavior



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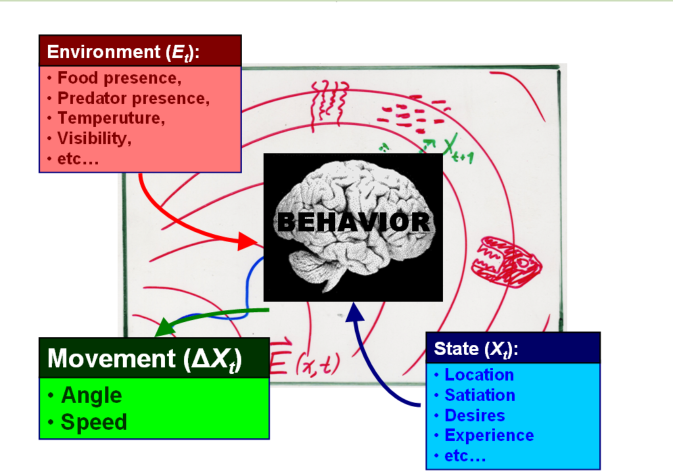

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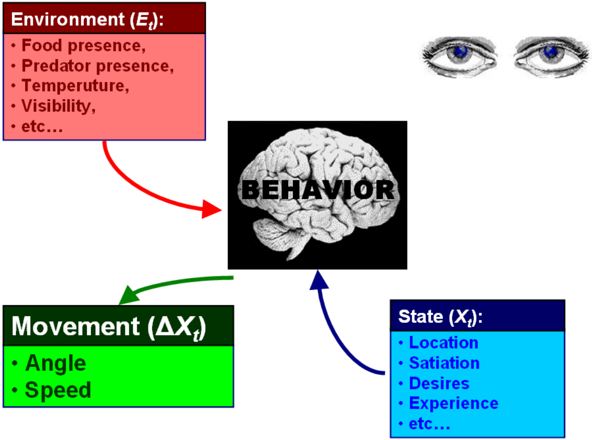

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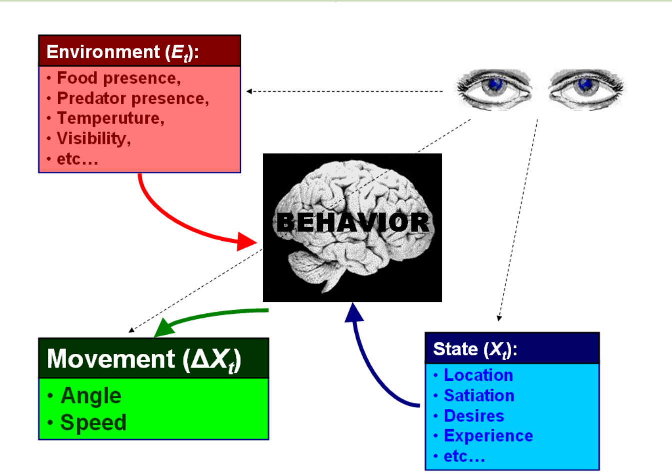

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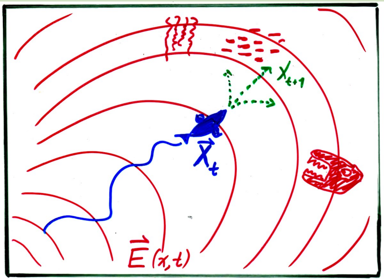
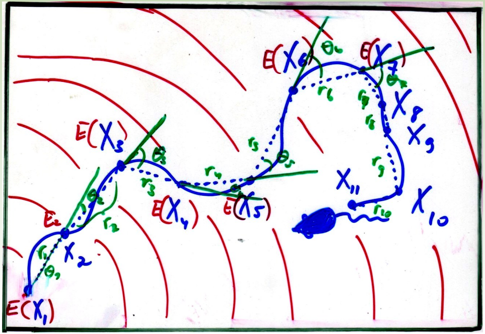


In Math: $\Delta X_t = f(\mathbf{X}_t, \mathbf{E}_t)$

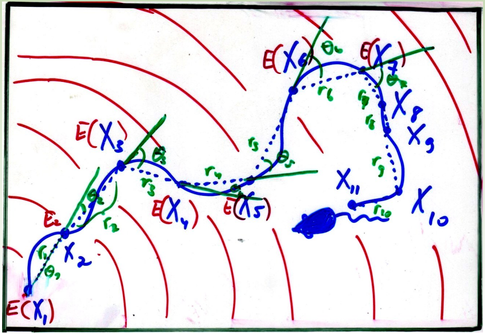
In English: *Behavior* (f) is a process which transforms the state of an organism (X_t) and the the local environment (E_t) into Movement (ΔX_t).

Decomposing Tracks



Strategy:

Decomposing Tracks



Strategy:

- Obtain positions X_t and times of observation T_t

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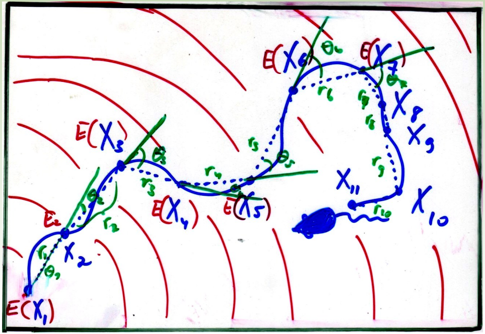

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- Obtain positions X_t and times of observation T_t
- Find series of speeds $V_t = \Delta X / \Delta T$and turning angles θ_t

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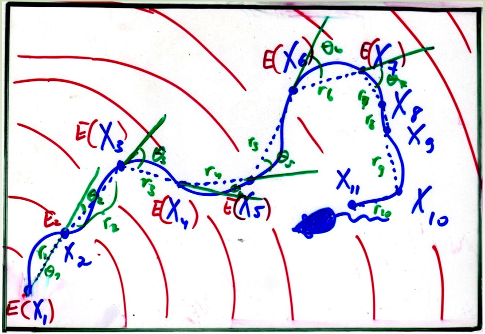

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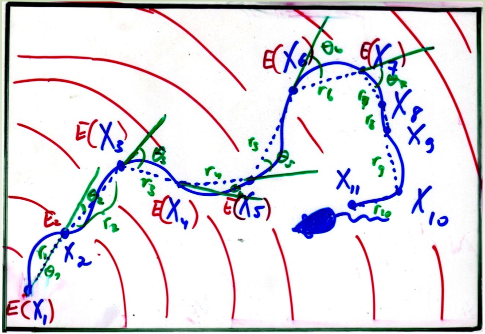

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- Analyze and Interpret!

Correlated Random Walk (CRW) Model

- $\theta_t \sim$ Some Circular Distribution
- $V \sim$ Some Skewed Unimodal Positive Distribution.

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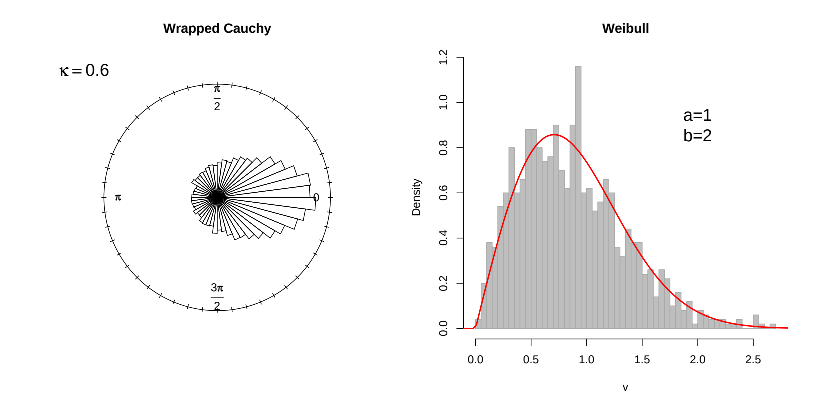

BUT ... these distributions depend on the time interval!

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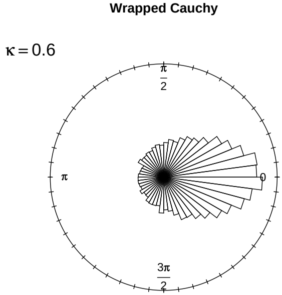
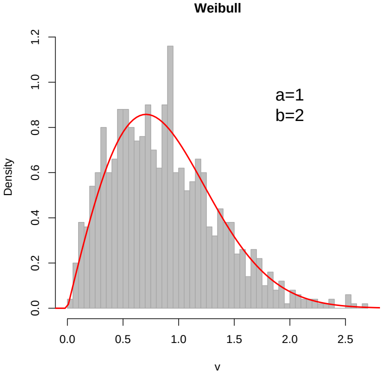
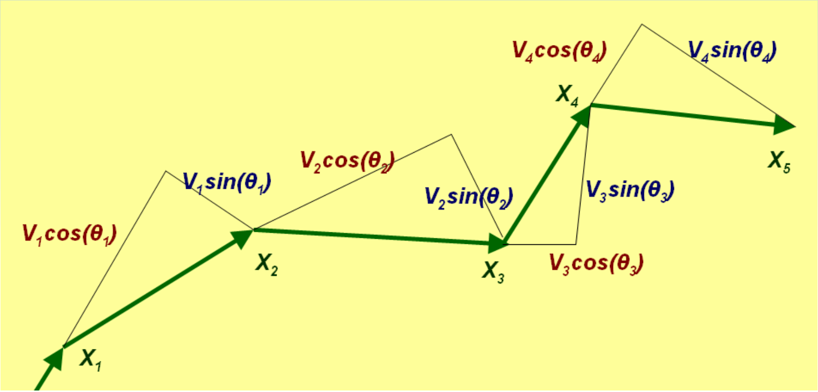




BUT ... these distributions depend on the time interval!
AND ... this is a slightly narrow “rendering” of correlation

Orthogonal decomposition



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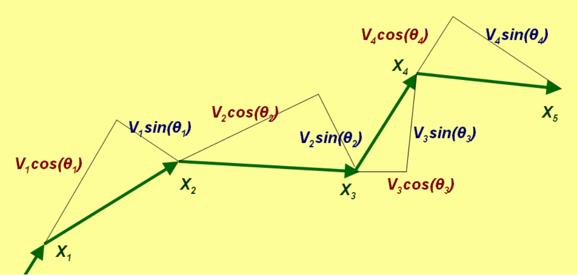
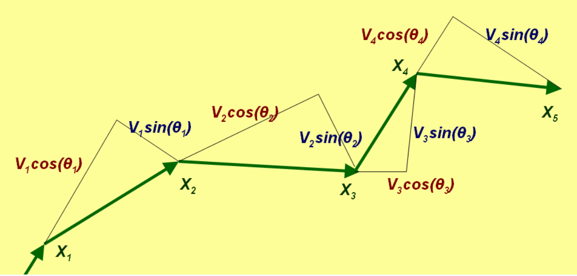


Persistence Velocity Component: $V_p = V\cos(\theta)$

- Captures tendency and speed of persistence:
  - high **mean** indicates speed and consistent orientation
  - high **variance** indicates variable behaviors (stopping and going, slowing down and speeding)
  - high **auto-corellation** indicates behavioral changes occur more slowly than the sampling interval

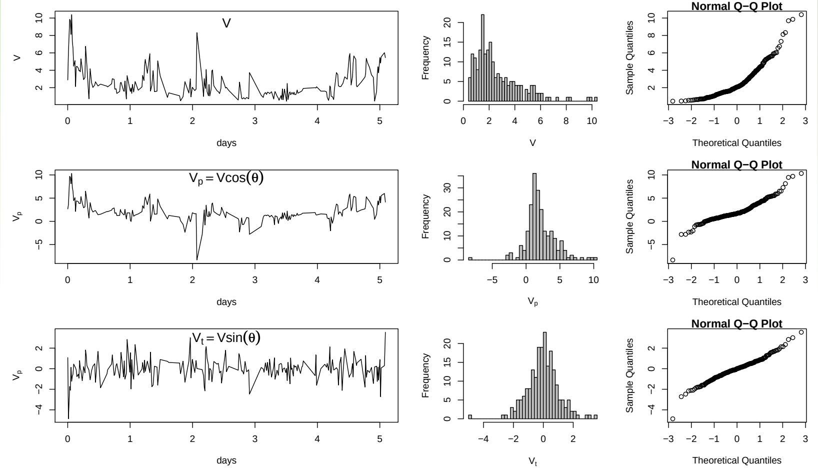
Orthogonal decomposition

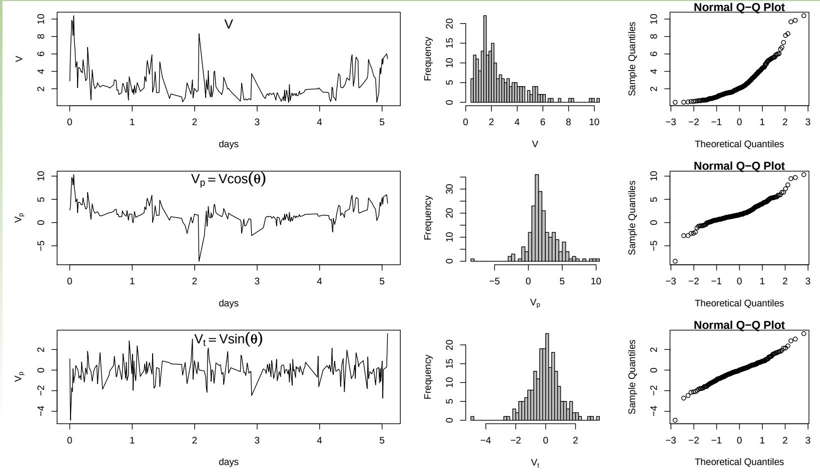


Orthogonal Component of Velocity: $V_t = V\sin(\theta)$

- Captures tendency and speed of turning (displaciement at a perpendicular direction)
  - **mean** can be fixed at zero.
  - high **variance** indicates combination of high speeds and “sharp” turns
  - high **auto-corellation** indicates turning radius larger than the scale of measurement.

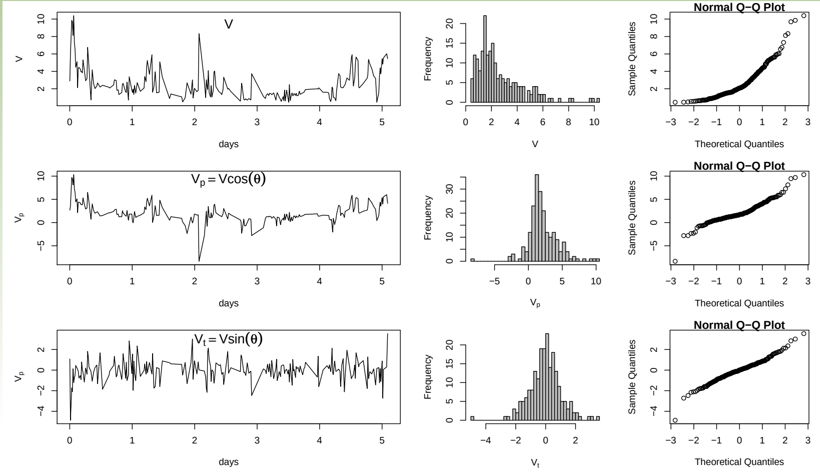
Actual Data Decomposed (northern fur seal)





The real trump card

- Stationary
- Gaussian
- Modellable using standard time-series techniques



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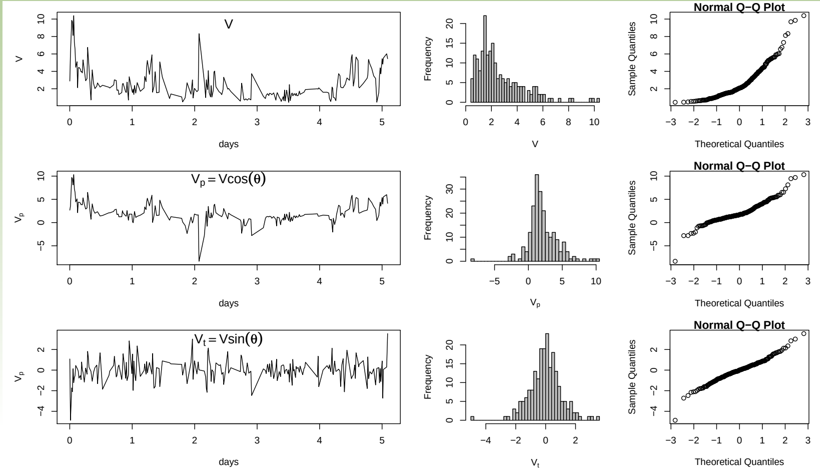

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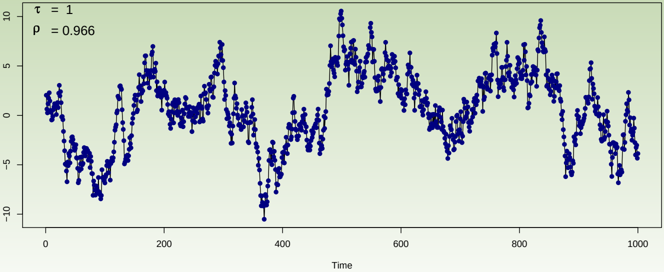
Properties of AR(1) time-series



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\begin{aligned}
X_t &= \rho\left(X_{t-1} - \mu\right) + \mu + \epsilon \\
\epsilon &\sim \mathrm{N}(0, \sigma^2)
\end{aligned}
$$

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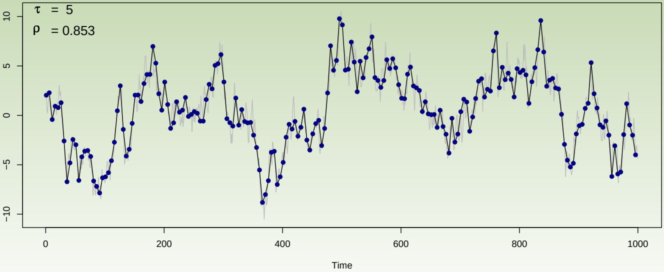

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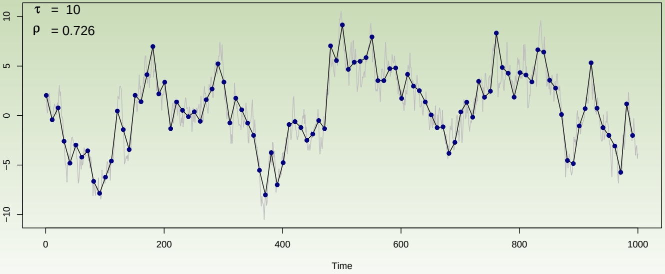

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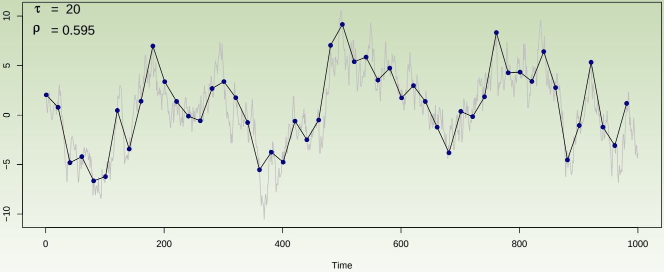

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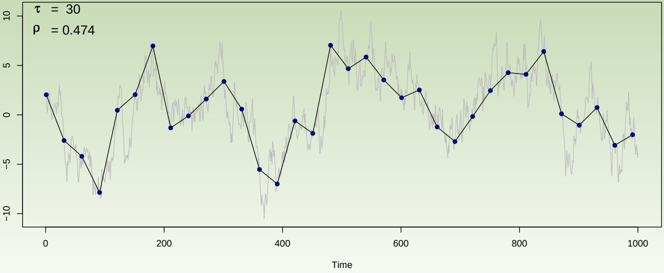

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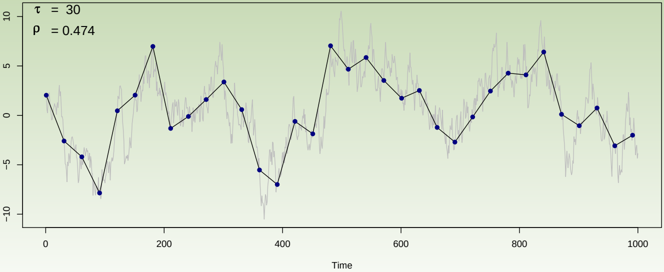
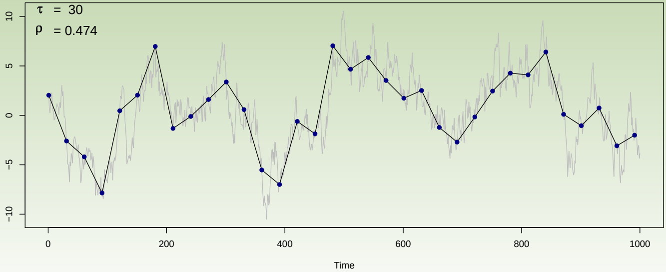


$$
\begin{aligned}
\mathrm{E}\left[X(t)\right] &= \mu \\
\mathrm{Var}\left[X(t)\right] &= \sigma^2 \\
\mathrm{Corr}[X(t), X(t-\tau)] &= \rho^\tau
\end{aligned}
$$

Properties of AR(1) time-series



$$f(X(t)|X(t-\tau)) \sim$$

$$\text{Gaussian}\left[\rho^{\tau}X(t-\tau), \sigma^2(1-\rho^{2\tau})\right]$$

Estimating ρ

Conditional Likelihood:

$$L(\rho|\mathbf{X},\mathbf{T}) = \prod_{i=1}^{n} f(X_i|X_{i-1},\tau_i,\rho),$$

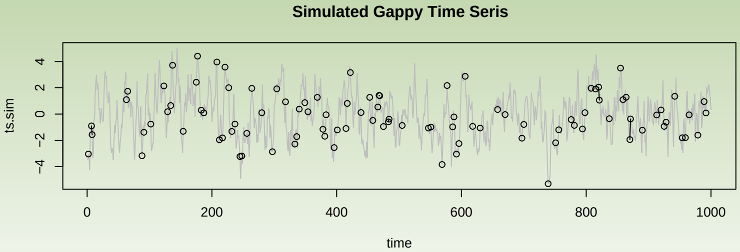
where:

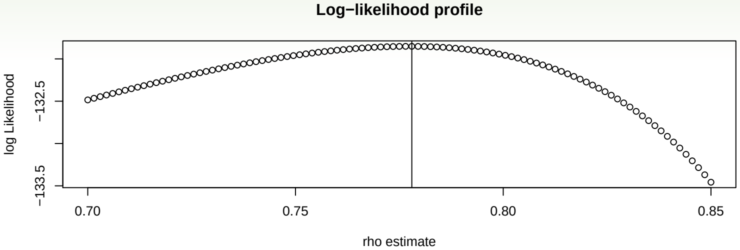
$$f(X_i|X_{i-1}) = \frac{1}{\sigma\sqrt{2\pi(1-\rho^{2\tau_i})}} \exp\left(\frac{(X_i-\rho^{\tau_i}(X_{i-1}-\mu))^2}{2\sigma^2(1-\rho^{2\tau_i})}\right).$$

then:

$$\widehat{\rho} = \underset{\rho}{\operatorname{argmax}}\ L(\rho|\mathbf{X},\mathbf{T})$$

Estimating ρ





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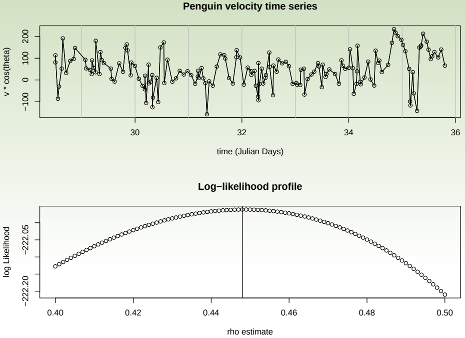
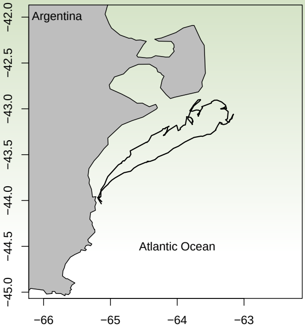




Structural shifts

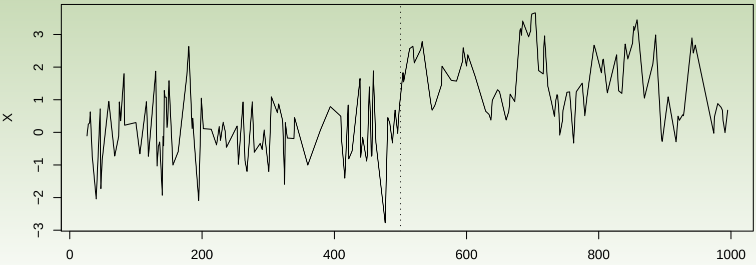
$$\mathbf{\Theta(t)} = \left\{ \begin{array}{lll} \mathbf{\Theta_1} & \text{if} & 0 < t \leq \tau \\ \mathbf{\Theta_2} & \text{if} & \tau < t \leq T \end{array} \right\}$$

$$L(\mathbf{\Theta}|\mathbf{X},\mathbf{T}) = \prod_{i=1}^{n} f(X_i|X_{i-1},\mathbf{\Theta}_1) \prod_{j=n+1}^{N} f(X_j|X_{j-1},\mathbf{\Theta}_2)$$

All estimates:

$$\begin{aligned} \widehat{n} &= \underset{n}{\operatorname{argmax}}\ L(\mathbf{\Theta}|\mathbf{X},\mathbf{T}) \\ \hat{\mu}_j &= \bar{X}_j \\ \hat{\sigma}_j &= S_j \\ \hat{\rho}_j &= \underset{\rho}{\operatorname{argmax}}\ L(\rho|\mathbf{X_j},\mathbf{T_j},\hat{\mu}_j,\hat{\sigma}_j) \end{aligned}$$

Identifying Change Point



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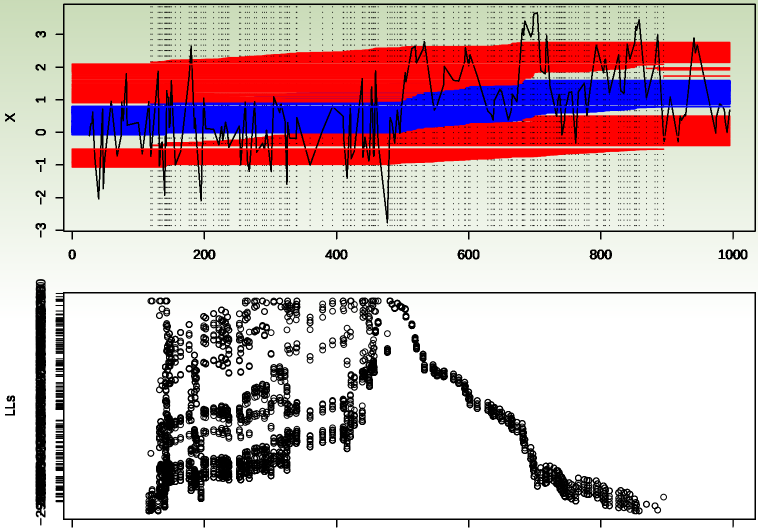

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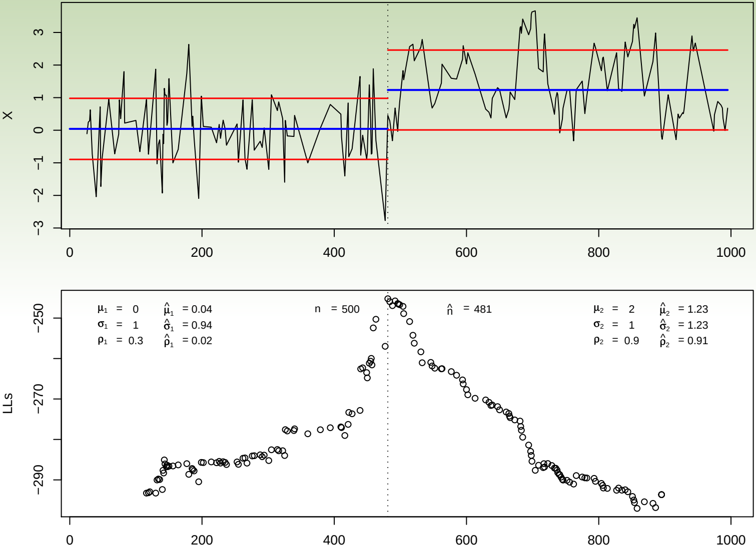
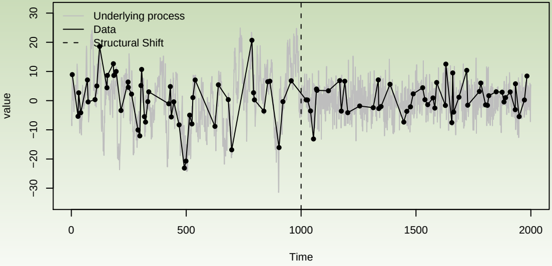
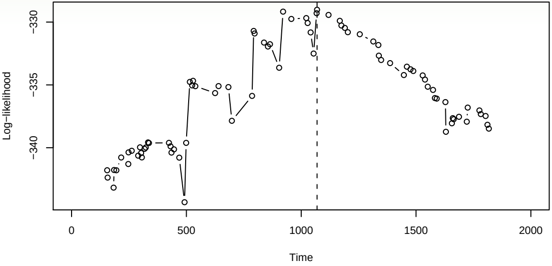
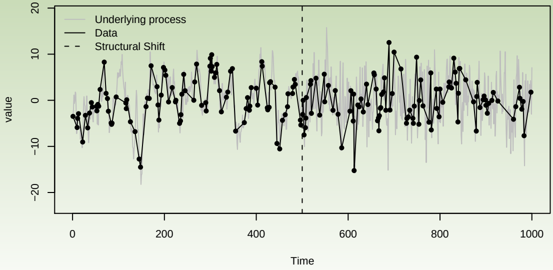


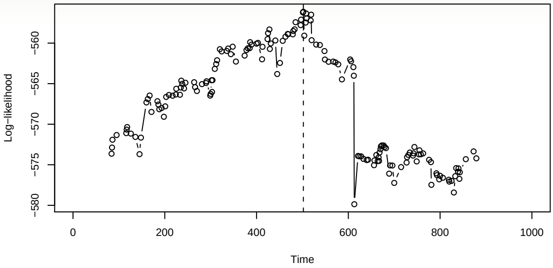
Identifying Change Point, sparce data





Identifying Change Point, different ρ's





Identifying Models

Model 0	$\mu_1 = \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 = \rho_2$
Model 1	$\mu_1 \neq \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 = \rho_2$
Model 2	$\mu_1 = \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 = \rho_2$
Model 3	$\mu_1 = \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 \neq \rho_2$
Model 4	$\mu_1 \neq \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 = \rho_2$
Model 5	$\mu_1 \neq \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 \neq \rho_2$
Model 6	$\mu_1 = \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 \neq \rho_2$
Model 7	$\mu_1 \neq \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 \neq \rho_2$

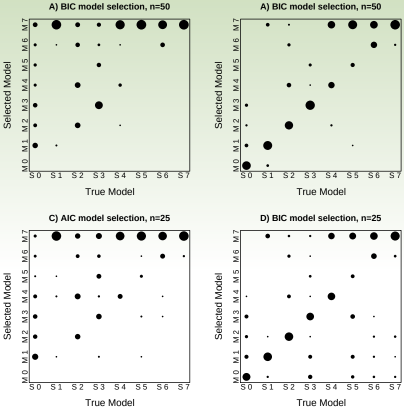
Identifying Models

Model 0	$\mu_1 = \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 = \rho_2$
Model 1	$\mu_1 \neq \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 = \rho_2$
Model 2	$\mu_1 = \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 = \rho_2$
Model 3	$\mu_1 = \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 \neq \rho_2$
Model 4	$\mu_1 \neq \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 = \rho_2$
Model 5	$\mu_1 \neq \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 \neq \rho_2$
Model 6	$\mu_1 = \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 \neq \rho_2$
Model 7	$\mu_1 \neq \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 \neq \rho_2$

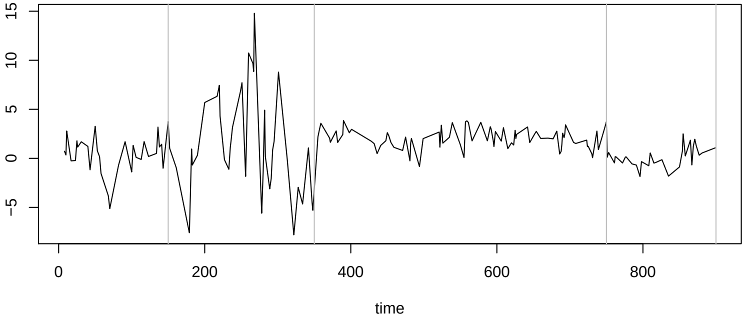
How to choose?

$$
\begin{aligned}
\text{AIC} : I_A(\mathbf{X}, \mathbf{T}) &= -2n \log \left(L(\hat{\theta} | \mathbf{X}, \mathbf{T}) \right) + 2d \\
\text{BIC} : I_B(\mathbf{X}, \mathbf{T}) &= -2n \log \left(L(\hat{\theta} | \mathbf{X}, \mathbf{T}) \right) + d \log(n)
\end{aligned}
$$

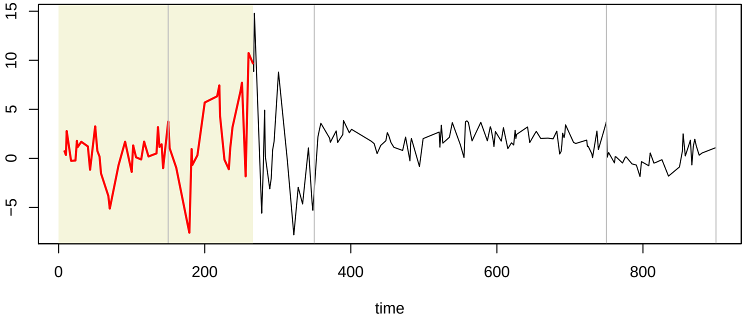
Identifying Models



	μ_1	μ_2	σ_1	σ_2	ρ_1	ρ_2
S0	0	0	1	1	0.5	0.5
S1	**-1**	**1**	1	1	0.5	0.5
S2	0	0	**0.5**	**2**	0.5	0.5
S3	0	0	1	1	**0.2**	**0.9**
S4	**-1**	**1**	**0.5**	**2**	0.5	0.5
S5	**-1**	**1**	1	1	**0.2**	**0.9**
S6	0	0	**0.5**	**2**	**0.2**	**0.9**
S7	**-1**	**1**	**0.5**	**2**	**0.2**	**0.9**

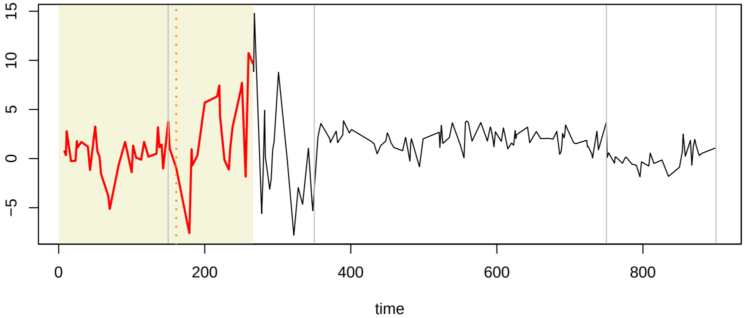


15
10
5
0
−5
0
200
400
600
800
time



Algorithm for Identifying Multiple Changepoints

- Select Window
- Find MLBP
- Identify Model
- Record estimates based on model selected.
- Move window forward and repeat



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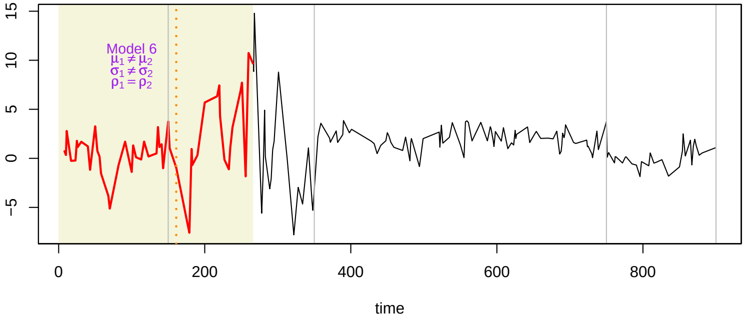

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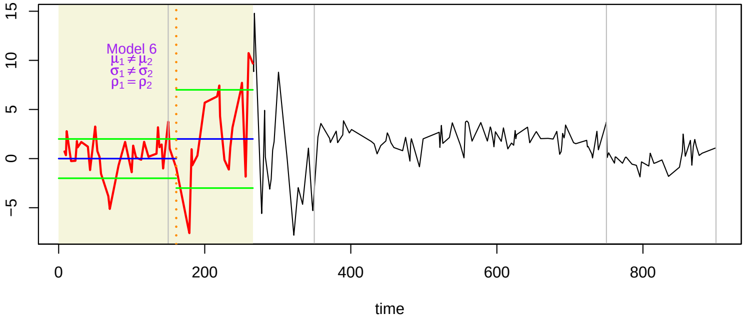

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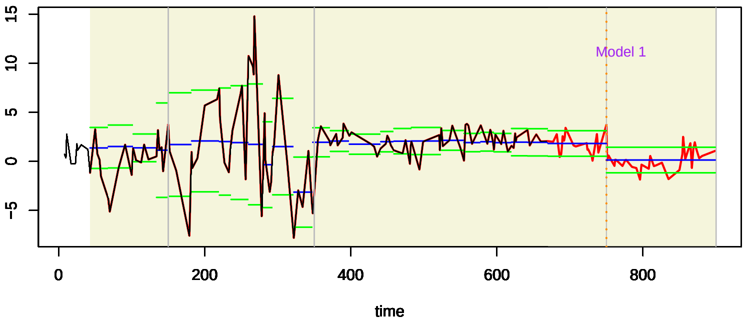

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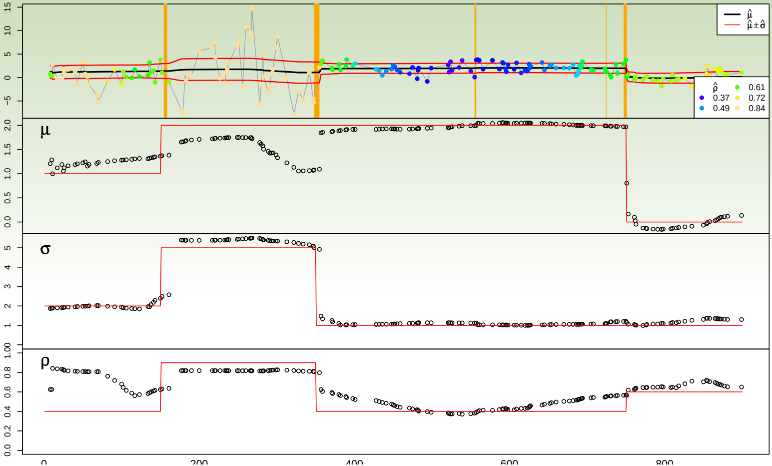
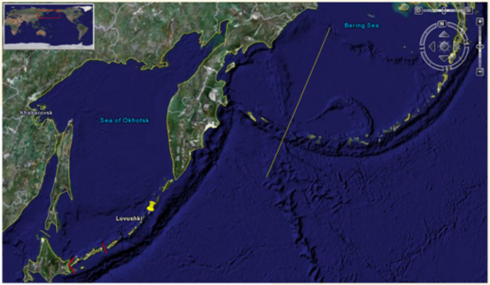
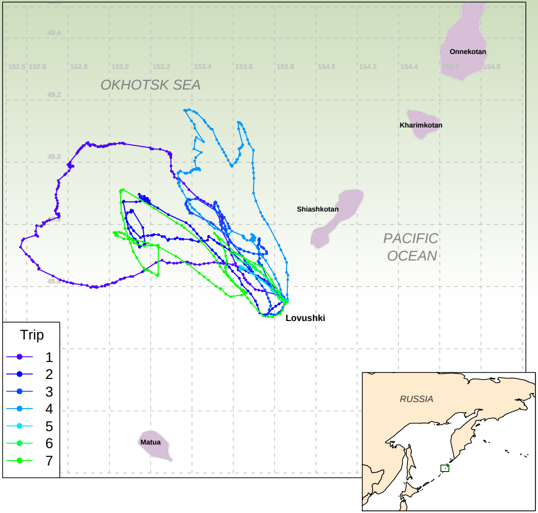
Movement analysis output



Northern Fur Seal (*Callorhinus ursinus*)

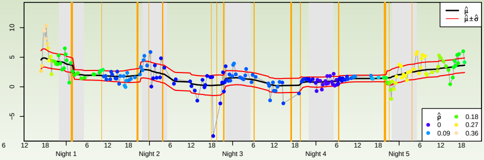


Map of all tracks

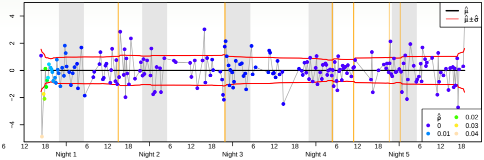


Track Analysis

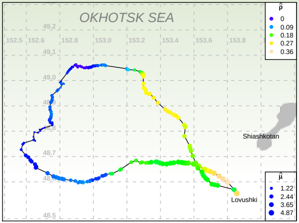
Vcos(θ)



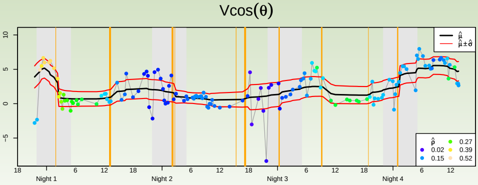
Vsin(θ)

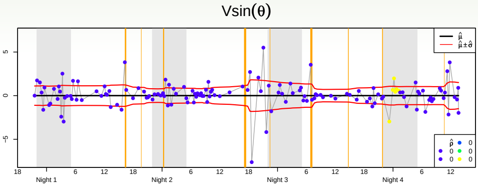


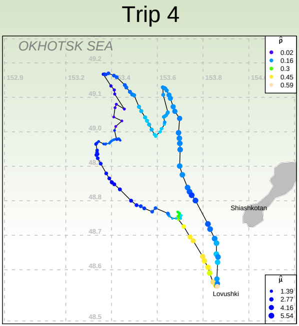
Trip 1



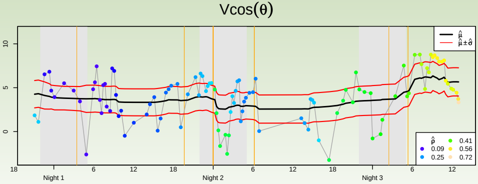
Track Analysis

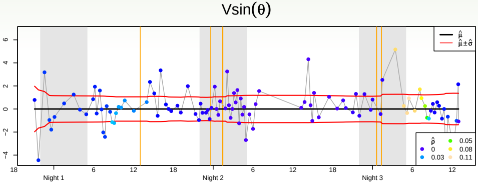


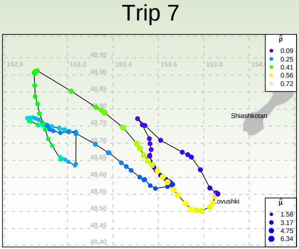




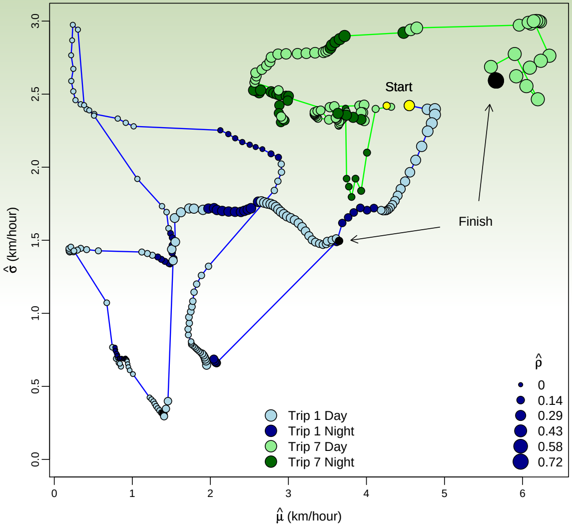
Track Analysis



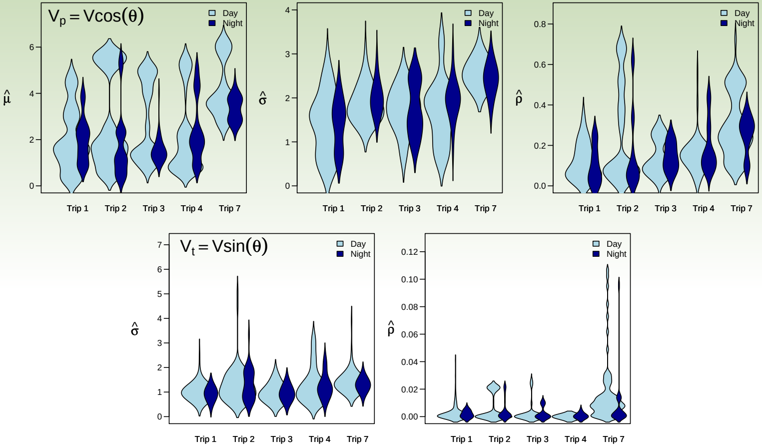




Behavioral Phaseplot



Violin plots



Conclusions:

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- But patterns *can* be robustly picked out of messy data.
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Acknowledgements

Data:

- Fur Seals: R. Andrews, V. Burkanov, Russian Far East Marine Mammal Project
- Penguin: Elizabeth Skewgar, P. Dee Boersma

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