Supervised HSMM to study the behavioral sequences of wildlife in nature from accelerometer data.

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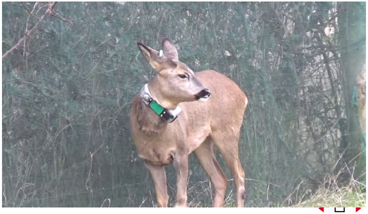
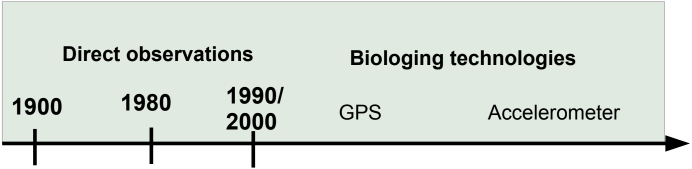


Behavioral ecology

How animals behave to satisfy their fundamental needs



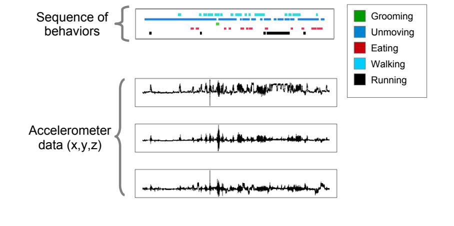



Amount of data	weak	good	very good
Precision of information on behavior	very good	gross	very fine scale but limited methods

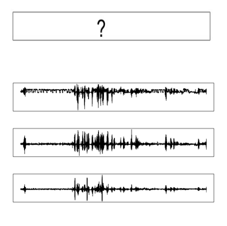
Supervised framework

- Captive animals : videos $\sim$ 10 minutes + accelerometer (32hz)
- Wild animals : accelerometer $\sim$ months

Observed animals



Unobserved animals



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$\hookrightarrow$ To evaluate the model : train/test set

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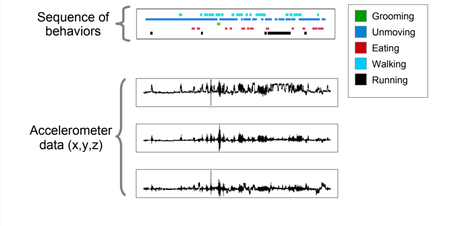

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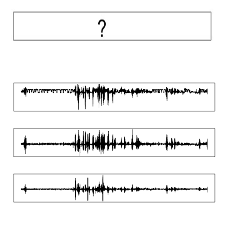

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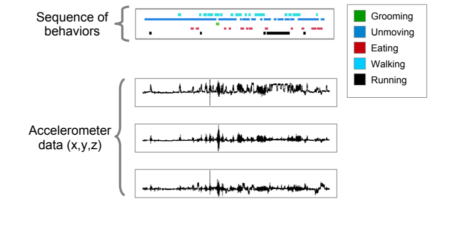

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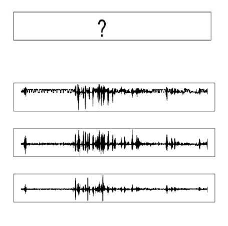
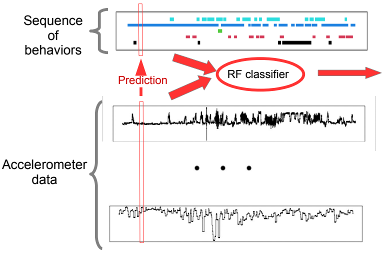


Classic method : Time-by-time classification

Observed animals



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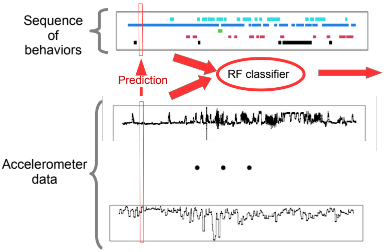

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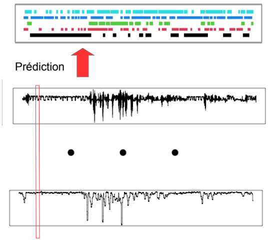

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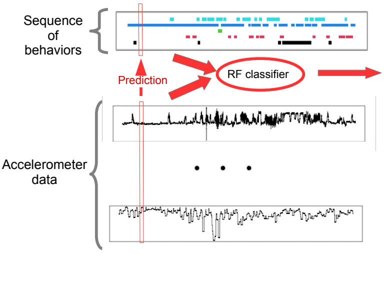

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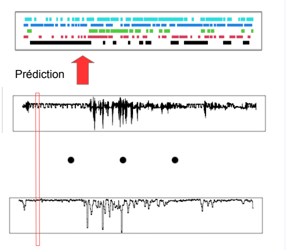
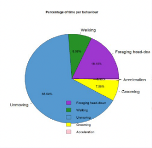
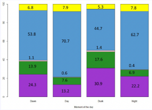


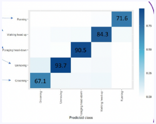
Output

Time budget

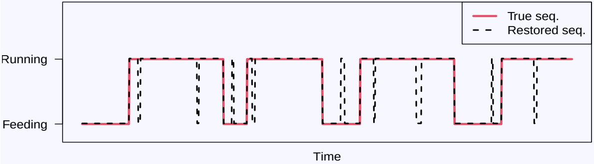




Model evaluation = accuracy

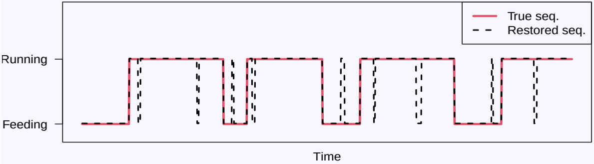


Good accuracy $\neq$ good sequence restoration



- Accuracy : 0.95
- Wrong transitions
- Wrong very short durations

Good accuracy ≠ good sequence restoration



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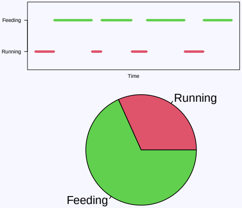
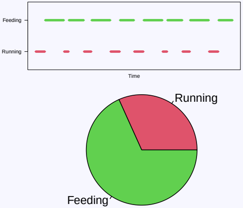
Why sequence analysis?

Forest landscape



Open landscape



- Different dynamics
- Same time budget

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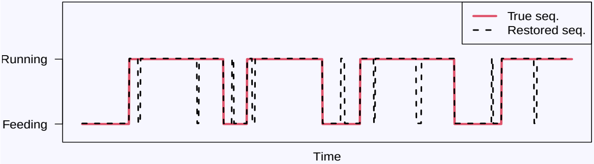

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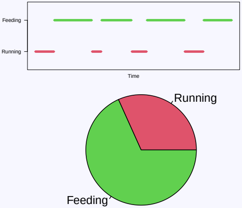

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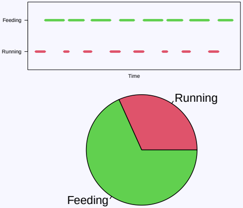

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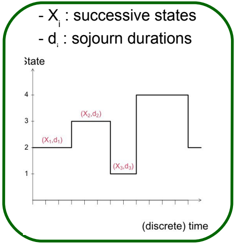
- Same time budget

$\Rightarrow$ HSMM : account for behavior durations and transitions

Hidden Semi-Markov Models

SMM



$$\mathbb{P}[(X_{i+1}, d_{i+1})|(X_i, d_i), \cancel{(X_{i-1}, d_{i-1})}, \ldots, \cancel{(X_1, d_1)}] \overset{\text{ED}}{=} \mathbb{P}[d_{i+1}|X_{i+1}]\mathbb{P}[X_{i+1}|X_i]$$

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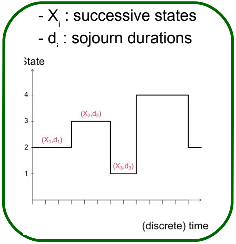
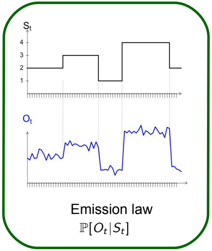


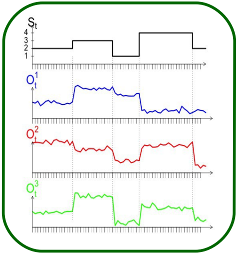
HSMM

Semi-Markov process

Observed process



multiresponse HSMM



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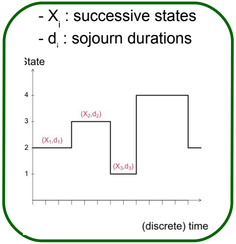
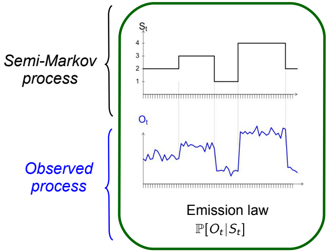


HSMM



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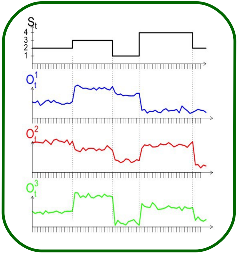

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Parameters (Explicit Duration)

- Emission $\mathbb{P}_\Theta[O_t|S_t]$
- Sojourn duration $\mathbb{P}_\Theta[d_i|X_i]$
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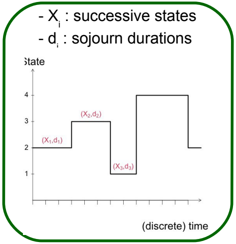

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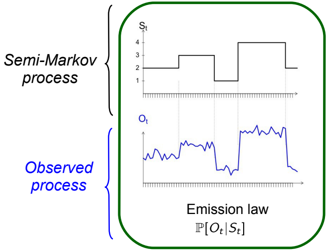

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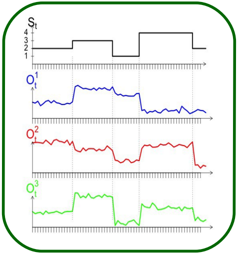

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Issues

- Parameter estimation Θ
- Restoration of hidden sequence, e.g. Viterbi

$$\arg\max_{(S_t)_{t\geq 1}} \mathbb{P}[(S_t)_{t\geq 1}|(O_t)_{t\geq 1},\Theta]$$

H(S)MM for accelerometer data

- In literature
  - HMM more frequent than HSMM

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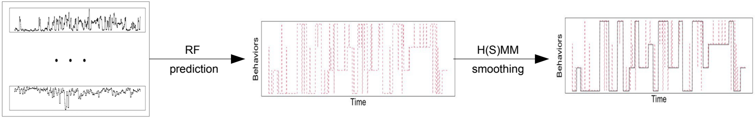
  - Observed variables : two strategies
    - ★ A/few selected feature(s) function of accelerometer (x,y,z)
    - ★ H(S)MM for smoothing RF predictions



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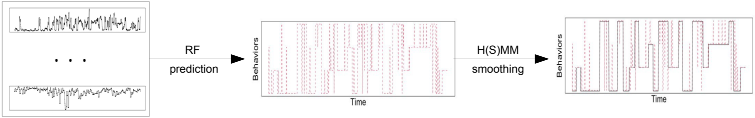

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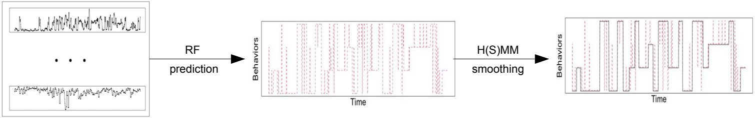
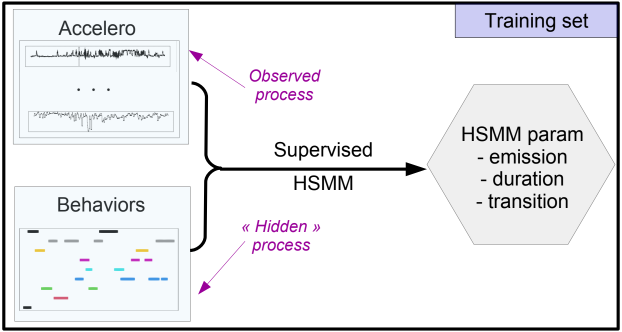


  - Output = time budget/ accuracy /classification $\neq$ sequence analysis
  - A few alternative works
    - Koslik *et al* (2025) : Inhomogeneous Markov models with interest on sojourn time distribution

General statistical framework



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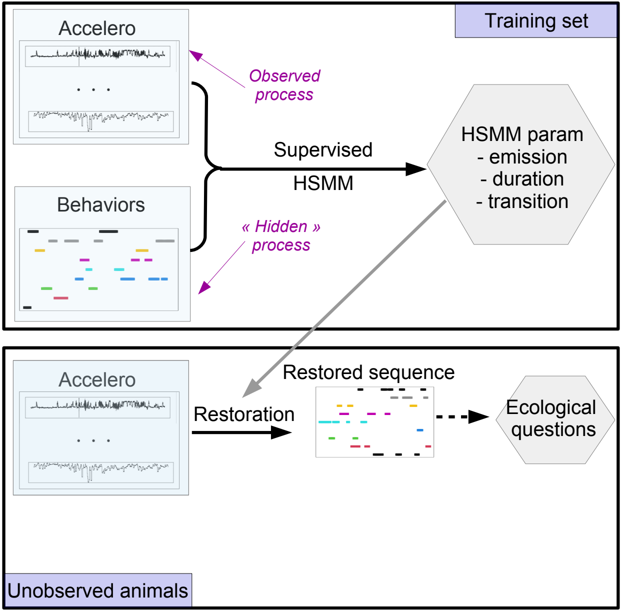
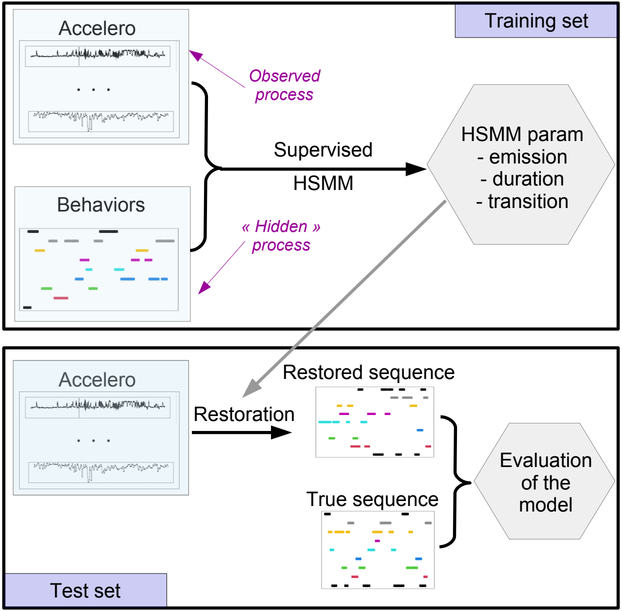
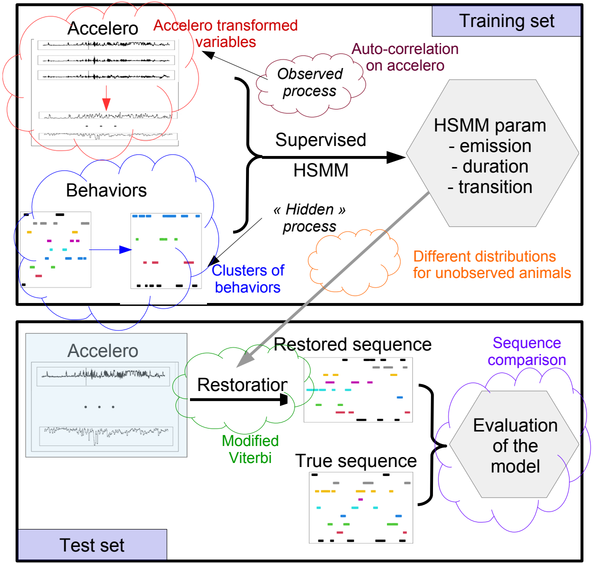


General statistical framework



Various issues



- Which accelerometer features
- Level of details of behaviors
- Autoregressive model for accelerometer data
- Modified Viterbi
- Metric for sequence similarity
- Robustness/transferability

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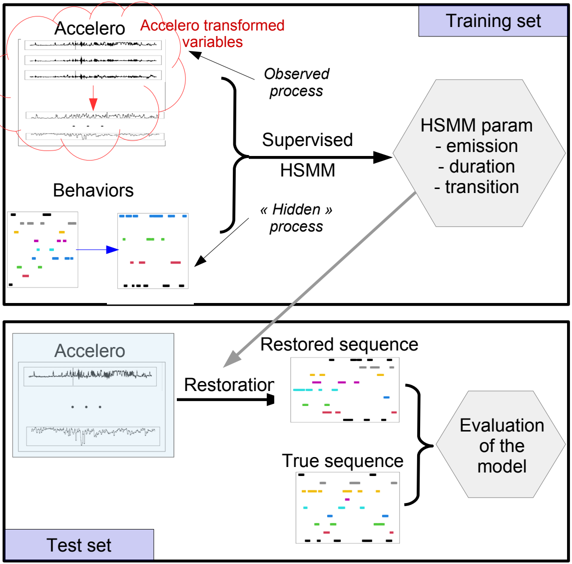

- Which accelerometer features
  - Balance complexity and discriminative power
- Level of details of behaviors
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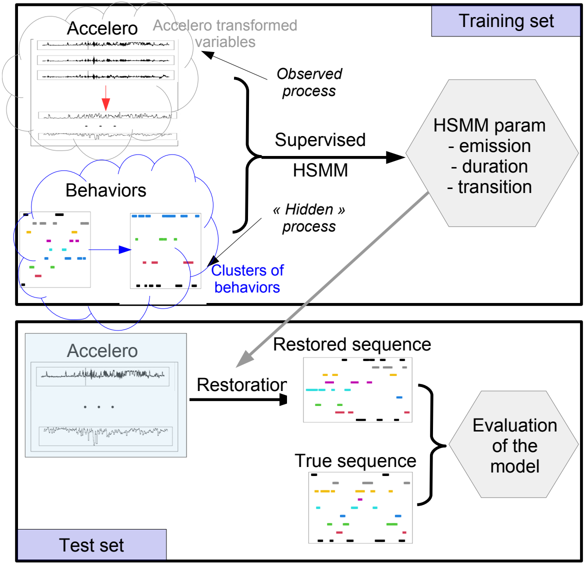
Various issues



- Which accelerometer features
- Level of details of behaviors
  - distinguishable
  - interpretable
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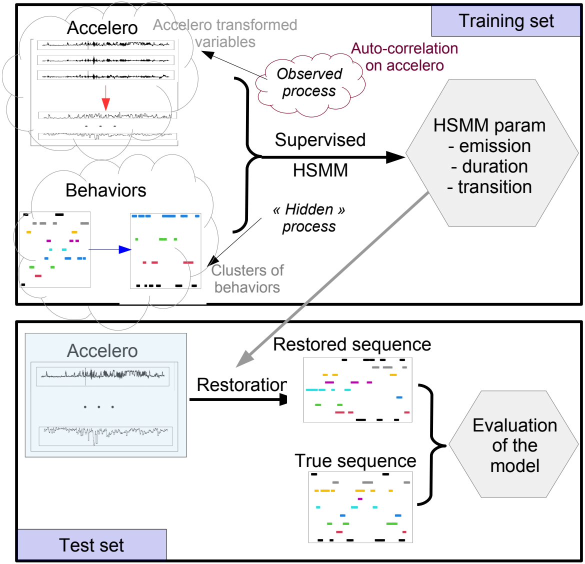
Various issues



- Which accelerometer features
- Level of details of behaviors
- Autoregressive model for accelerometer data
  - Independent observations: unrealistic
  - HSMM-AR
- Modified Viterbi
- Metric for sequence similarity
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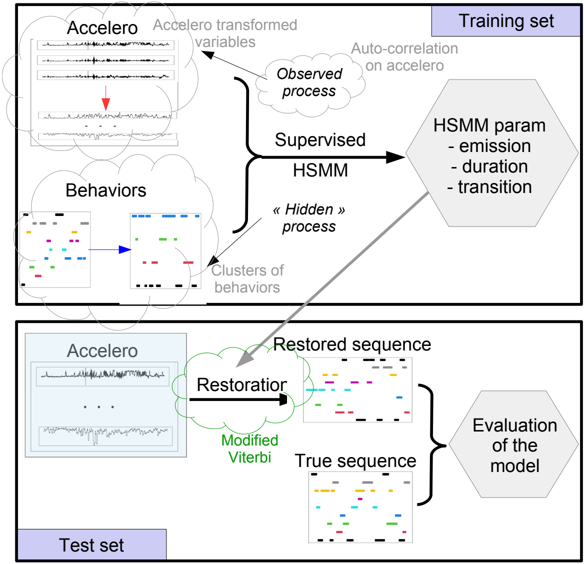
Various issues



- Which accelerometer features?
- Level of details of behaviors
- Autoregressive model for accelerometer data
- Modified Viterbi
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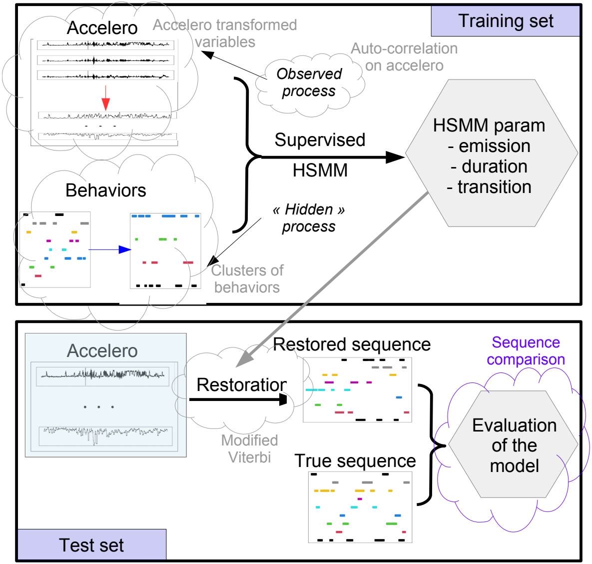
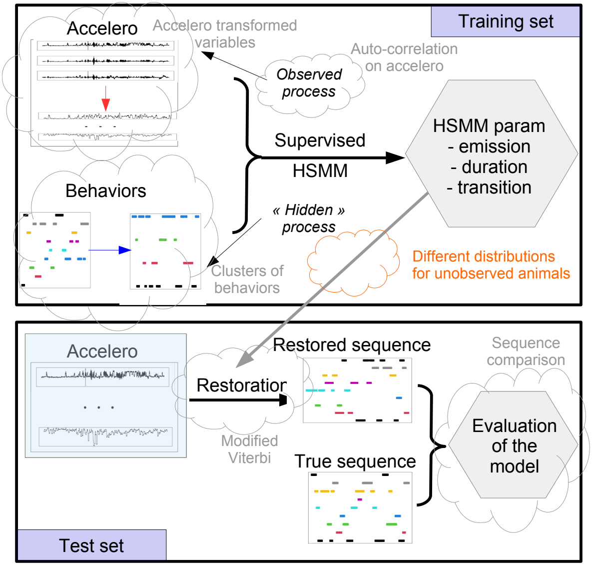
Various issues



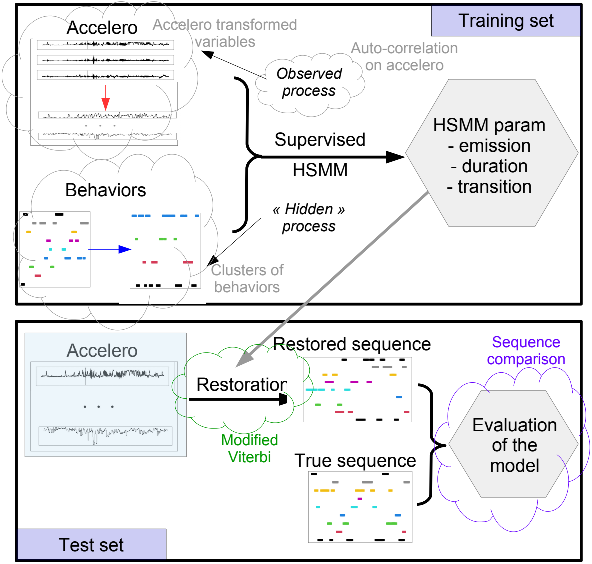
- Which accelerometer features
- Level of details of behaviors
- Autoregressive model for accelerometer data
- Modified Viterbi
- Metric for sequence similarity
  - What is a good restoration?
  - Also for hyperparameter calibration by CV
- Robustness/transferability

Various issues



- Which accelerometer features
- Level of details of behaviors
- Autoregressive model for accelerometer data
- Modified Viterbi
- Metric for sequence similarity
- Robustness/transferability
  - difference of behavior captive/wild animals

Various issues



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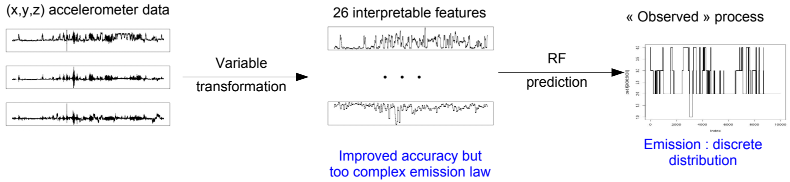
Model choices

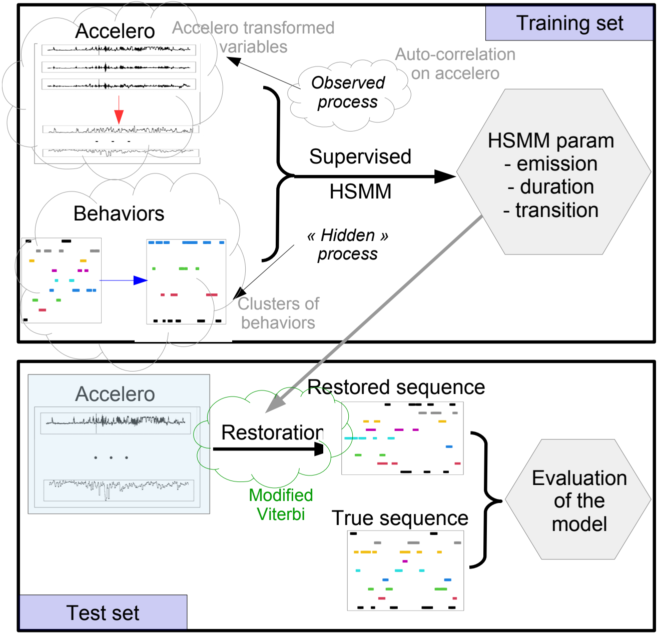
- "Observed" process = RF prediction



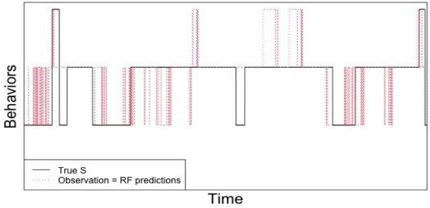
- 4 states $\leftrightarrow$ 4 clusters of behaviors
- Independent accelerometer observations
- Restoration by a modified version of Viterbi

Results

- Unsufficient quality of restoration for sequence-by-sequence analysis
  - Limits of the model but also of the information contained in the data
- Alternative goal : comparison between conditions (e.g. day/night)
  - Not done yet

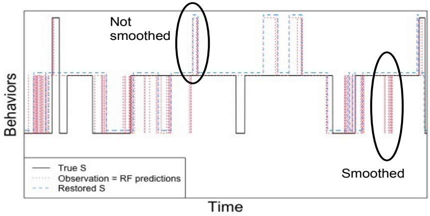

Training set
Accelero
Accelero transformed variables
Auto-correlation on accelero
Observed process
Supervised
HSMM
HSMM param
- emission
- duration
- transition
Behaviors
« Hidden » process
Clusters of behaviors
Accelero
Restored sequence
Restoration
Modified Viterbi
True sequence
Evaluation of the model
Test set

Restored sequences by Viterbi



- RF : many wrong transitions and brief sojourns

Restored sequences by Viterbi



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- HSMM : partially smooth

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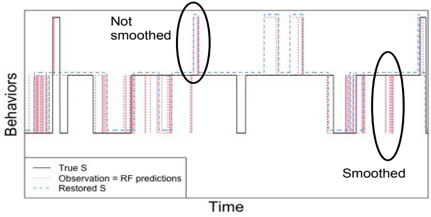

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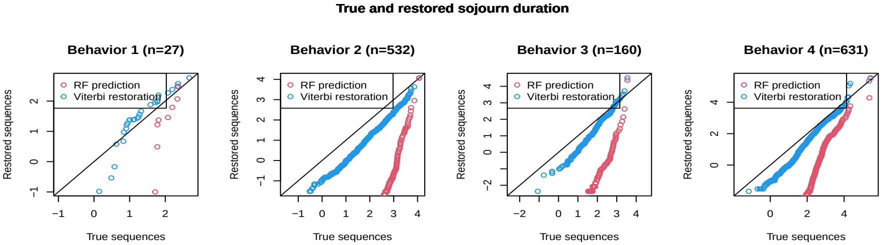

- Over-representation of brief sojourn durations in restored sequences
- Brief sojourn durations unlikely given SMM parameters

  ⇒ Too much adequation to the observed process

Adequation to the model and to the observations

- Viterbi algorithm targets the most probable hidden sequence

$$\arg\max_S \log \mathbb{P}_\Theta[S|O] = \arg\max_S \{ \underbrace{\log \mathbb{P}_\Theta[O|S]}_{\substack{\textit{adequation}\\ \textit{to observations}}} + \underbrace{\log \mathbb{P}_\Theta[S]}_{\substack{\textit{adequation}\\ \textit{to model}}} + \cancel{\log \mathbb{P}_\Theta[O]} \}$$

Adequation to the model and to the observations

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- Select λ by cross-validation on the training set : which λ leads to the best restoration?
  - Metric for sequence comparison

(Digressive) remark: impact of sampling frequency on Viterbi

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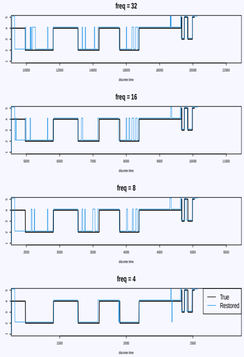
Undersampling accelerometer data



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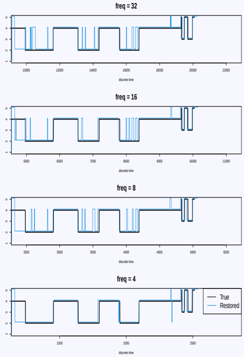

$\Rightarrow$ Modified Viterbi is not only an artefact, it may also compensate the arbitrary choice of sampling frequency

Similarity metric between sequences

$$\begin{cases} S = (S_t)_{t=1:T} & = \quad \text{true behaviour sequence} \\ \hat{S} = (\hat{S}_t)_{t=1:T} & = \quad \text{restored behaviour sequence} \end{cases}$$

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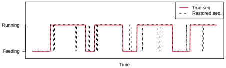

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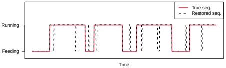

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  - Define acceptable transformations. Example

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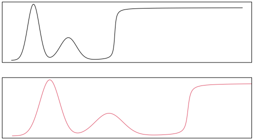
Dilatation (finance)



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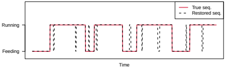

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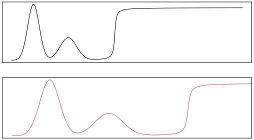
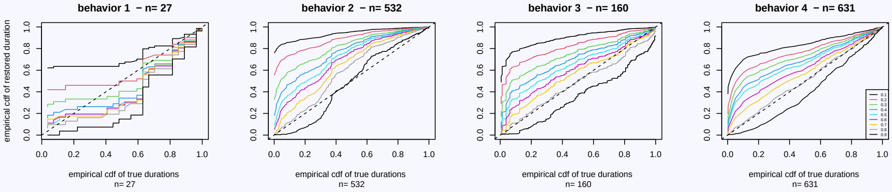


  - Tractable algorithm
- Similarity adapted to behavior sequence analysis?
  - Up to now : no lead for a sequence-by-sequence comparison
  - Compare duration and transitions **distributions**.

Choice of λ in modified Viterbi

- Average distance between empirical cdf of sojourn duration
- weight : number of occurence of this behavior in true sequences



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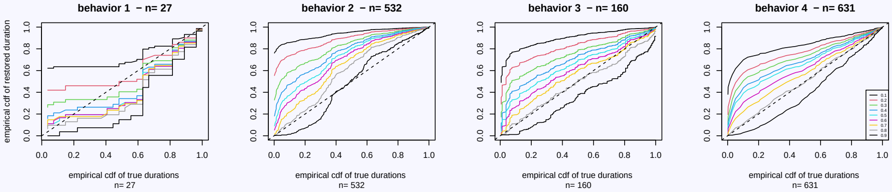

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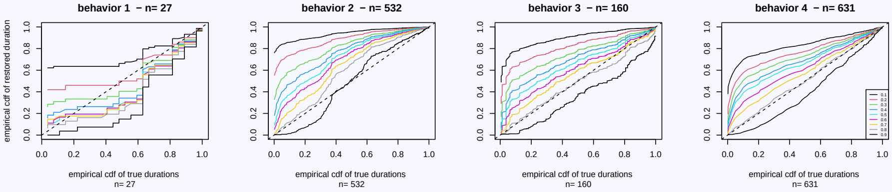

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Leads

- Metric adapted to a given ecological question (e.g. duration of a specific behavior) ?
- More generally : issue to be discussed with ecologists

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- Some issues at the interface of ecology and statistics