

Optimal replacement policies for dairy cows based on daily yield measurements

Case example: Markov decision processes

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Biosens II

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- HMDP results
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- Biosens II: Improved monitoring and management of dairy production based on on-farm biosensors
- Goal: Better detection of oestrus and illnesses
- Focus on biomarkers in milk (progesterone, LDH, yield, etc.)
- Commercial partner Lattec I/S (FOSS A/S and DeLaval AB)
- Five year project (2007-2011). Budget ≈5 mill EUR
- Commercial product Herd Navigator™ based on Biosens project (www.herdnavigator.com)

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Project 2.3: Economic value of the dairy cow

Find optimal strategy for each cow w.r.t. replacement, treatment and reproduction (economic point of view).

- Many papers about the dairy cow replacement problem but limited use in practice. Reasons could be:

- Often large and complex models.
- Parameters in the model must be estimated, i.e. data collection frameworks at herd level must exist.
- Stage length: one month up to a year → no assistance when to inseminate, treat or cull the cow in the current month.

- Bio-sensors and cow specific traits/interventions exists in modern dairy herds → parameters can be estimated on a daily basis.

Develop MDP with daily stages based on daily yield measurements.

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Problem, models and results

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Problem

- Assign an economic value to a dairy cow during lactation
- Calculate the optimal replacement strategy based on the economic value
- Assume daily yield measurements available

Models

- Use a state space model (SSM) for predicting daily milk yield
- Use a Markov decision process (MDP) for calculating the optimal strategy with the SSM embedded

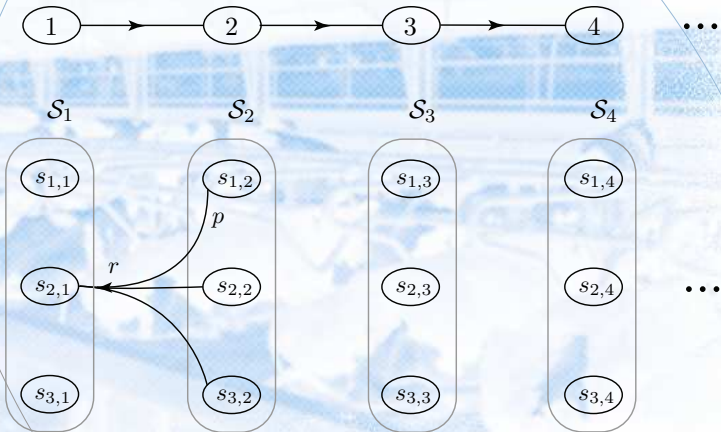
Results

- A strategy saying whether to replace or keep the cow given its current state
- An economic value of the cow and forecast of the yield.

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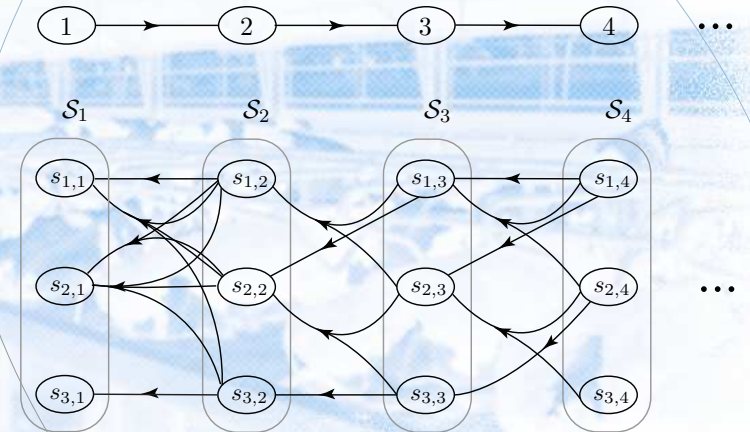
What is an MDP?

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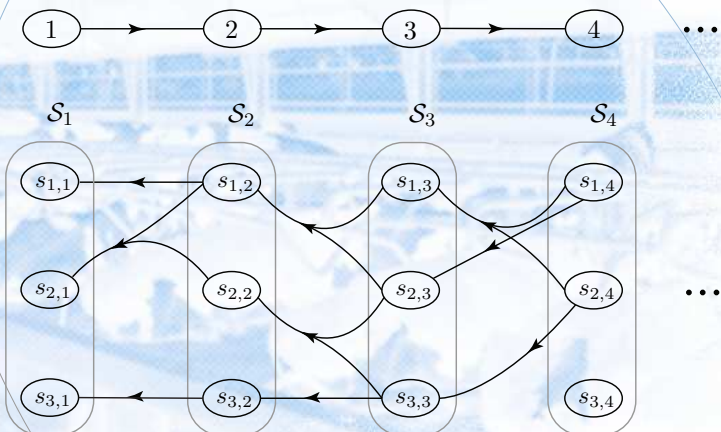
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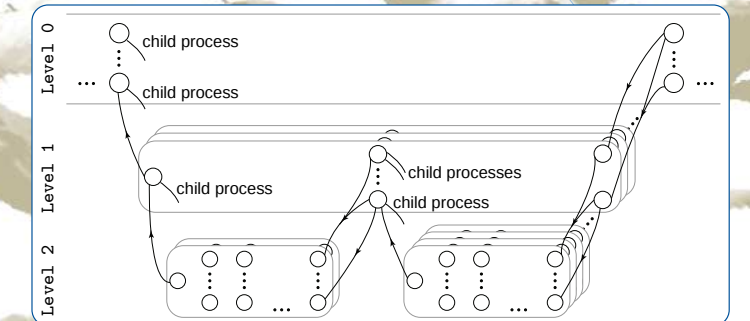
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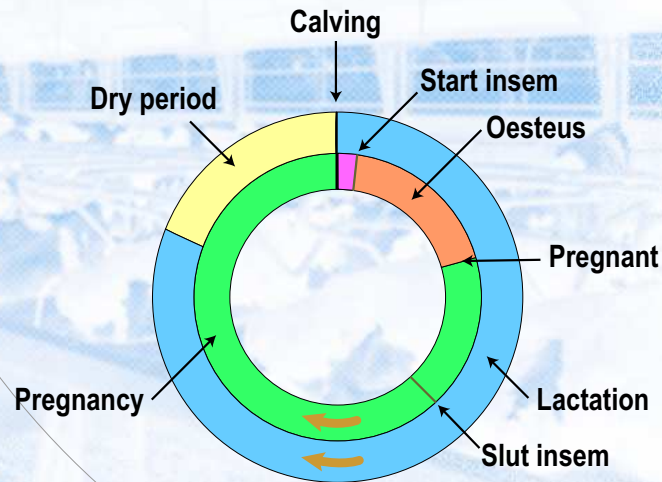
Hierarchical MDP (HMDP)

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Lactation cycle of the cow

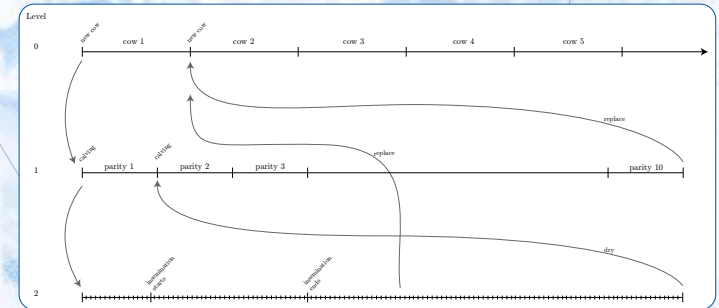
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Dairy model overview

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- ⇒ Formulate a hierarchical MDP (HMDP) based on lactation cycles of the cow.
- ⇒ Infinite time-horizon, Daily stages, 3 levels
- ⇒ Decisions Replace, Keep and Dry
- ⇒ Maximize the discounted net present reward of the cow



Rewards and transition probabilities

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Transition probabilities are found using

- ⇒ The SSM milk yield model
- ⇒ A reproduction model
- ⇒ An IC model

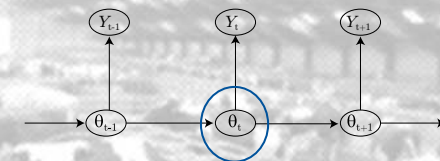
The net reward is a combination of

- ⇒ Milk yield
- ⇒ The calf
- ⇒ Beef
- ⇒ Feeding and treatment costs

SSM models

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- ⇒ ... or dynamic linear models are models of phenomena evolving in time e.g. blood pressure and milk yield.



- ⇒ Latent process evolves as a first order Markov process.

$$\theta_t = G\theta_{t-1} + \omega_t, \quad (\theta_t | \theta_{t-1}) \sim N(G\theta_{t-1}, W)$$

- ⇒ Y_t are observations which we model as a function depending on θ_t .

$$Y_t = F'\theta_t + \nu_t, \quad (Y_t | \theta_t) \sim N(F'\theta_t, V)$$

Milk yield SSM

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→ Yield SSM

→ Kalman filter

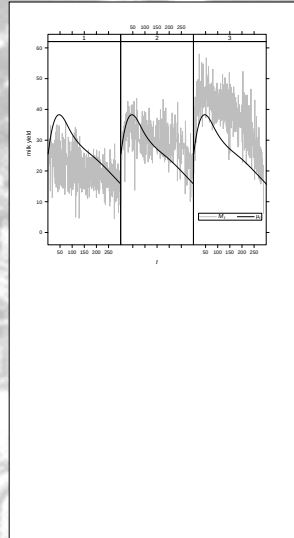
Embedding the SSM

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Observed milk yield intensity

$$M_{tc} = \mu_t + A_c + X_{tc} + \nu_{tc}$$



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Milk yield SSM

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Observed milk yield intensity

$$M_{tc} = \mu_t + A_c + X_{tc} + \nu_{tc}$$

Subtract herd effect (remove index c)

$$Y_t = M_t - \mu_t = F' \theta_t + \nu_t$$

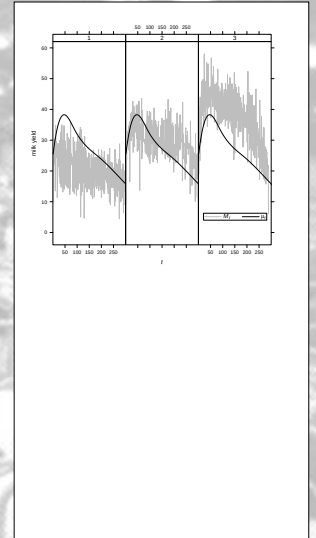
$$= \begin{pmatrix} 1 & 1 \end{pmatrix} \begin{pmatrix} A \\ X_t \end{pmatrix} + \nu_t$$

$$\theta_t = G \theta_{t-1} + \omega_t$$

$$= \begin{pmatrix} 1 & 0 \\ 0 & \rho \end{pmatrix} \begin{pmatrix} A \\ X_{t-1} \end{pmatrix} + \begin{pmatrix} 0 \\ \epsilon_t \end{pmatrix}$$

where

$$(\theta_t | Y_0, \dots, Y_t) \sim N(m_t, C_t)$$



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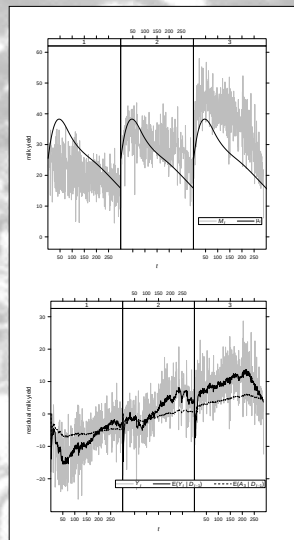
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Applying the Kalman filter

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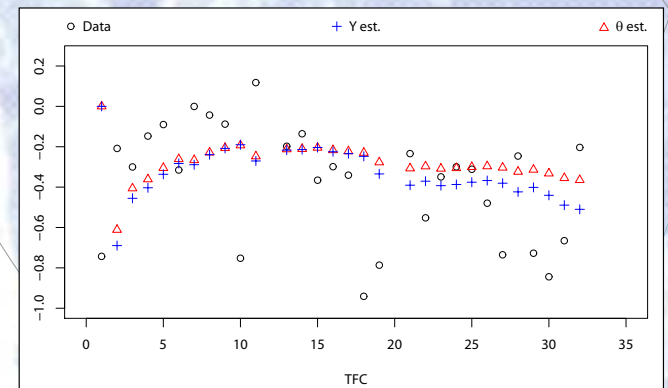
→ Kalman filter

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Status/future work

D_{t-1} : data up to time $t - 1$. Fact:
 $(\theta_{t-1} | D_{t-1}) \sim N(m_{t-1}, C_{t-1})$

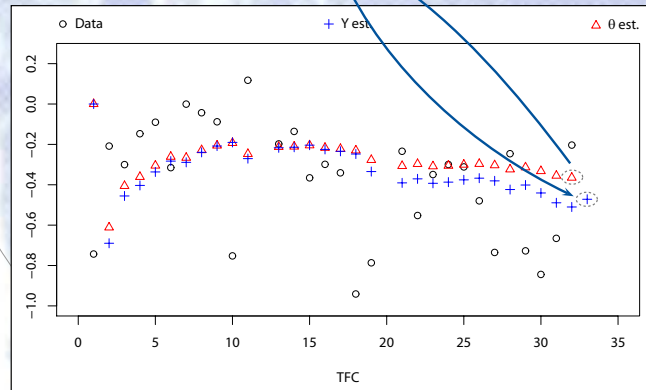


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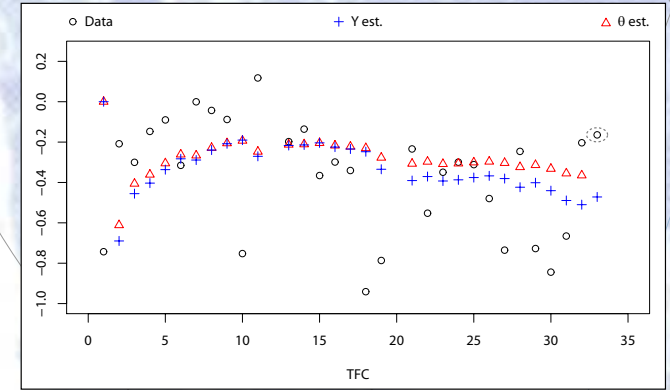
Given $(\theta_{t-1} | D_{t-1}) \sim N(m_{t-1}, C_{t-1})$ we have that
 $(Y_t | D_{t-1}) \sim N(f(m_{t-1}), Q_t)$



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Embedding the SSM into a MDP

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Can find $P(m_{t+1} | m_t)$ if store the mean m_t and variance C_t in each state.

Discrete states → discretize m_t with $\{\tilde{m}^{(1)}, \dots, \tilde{m}^{(q)}\}$ and calculate $P(\tilde{m}_{t+1}^{(i)} | \tilde{m}_t^{(j)})$

Discretization can be done uniform or non-uniform.
 $\mu_t = (E(A_t), E(X_t))$.

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Embedding the SSM into a MDP

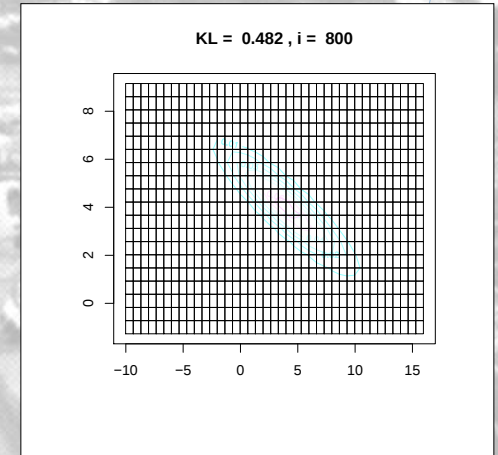
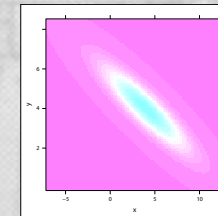
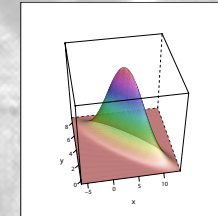
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- Can find $P(m_{t+1} | m_t)$ if store the mean m_t and variance C_t in each state.
- Discrete states $\rightarrow$ discretize m_t with $\{\tilde{m}^{(1)}, \dots, \tilde{m}^{(q)}\}$ and calculate $P(\tilde{m}_{t+1}^{(i)} | \tilde{m}_t^{(j)})$
- Discretization can be done uniform or non-uniform. ($m_t = (E(A_t), E(X_t))$).

Uniform discretization

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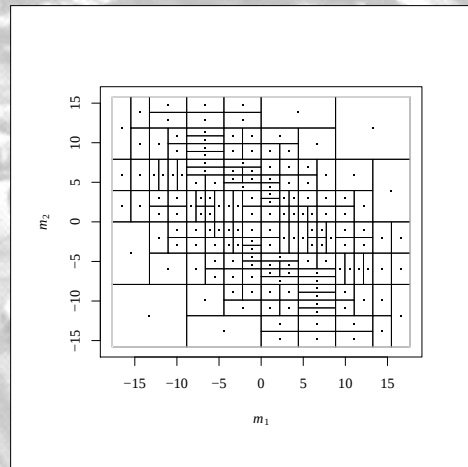
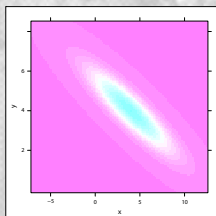
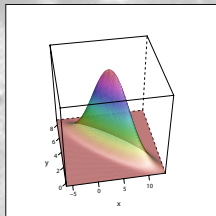
Discretize every variable separately (many states, independent of $\tilde{m}^{(\cdot)}$).



Non-uniform discretization

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Discretize the regions of the density (fewer states, dependent on $\tilde{m}^{(\cdot)}$).



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 - Extensions

- Model running (Linux) using MLHMP Java library.
- Manuscript accepted in JDS.
- Currently working on evaluating different reproduction strategies in the model. Challenge: Number of state variables (complexity)
- Other spinoffs: A MDP and dairy package in R.