Using nonlinear state space models for robust shortterm forecasting of milk yield

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Overall modeling aim our SmartFarm project

- A lot prior work in PLF focuses on detection of individual problems: lameness, mastitis, ketosis
 - Requires a substantial dataset for supervised learning: hard to collect for rare conditions
 - Different problems can cause a similar response
- We decided to model normal behavior and yield of dairy cows using measured data combined with relevant system model
 - Short term forecast of what is expected to happen -> alert on anomalies
 - Give alarms on abnormal events.
- Pilot user interface to show alerts









State space models

- State space models are used widely in animal science for state estimation of physiological and behavioural measurements.
- They provide a powerful tool to combine biological knowledge in the state equation combined with statistical methods for parameter estimation.
- In many applications the state equation can be nonlinear and the error distribution of observations can be non-Gaussian



Data sources and system models

Variable	Possible system model						
Milk yield	Wilmink function						
Daily lying time	Maselyne et al. 2017 + herd average						
Daily feeding time	Wilmink function + herd average						
Behavioral frequencis Feeding times / 24h Lying time / 24h	Constant mean model (Poisson distribution) + herd average						



Particle filters

- Sequential Monte Carlo (SMC) method to estimate state space models that can't be estimated using traditional linear or linearized approaches.
 - Name particle first appeared in Kitagawa 1996
 - Work on parameter estimation more recent e.g. PMMH algorithm Andreiu et al (2010)
 - Used increasingly e.g. in economics and biology
- Requires more computational power than linear gaussian models and other non-linear methods such as EKF and UKF
 - A large number of particles can be needed to get repeatable results
 - Not necessarily an issue with current computers



Step 1: Model milk yield and make a short term prediction

- Use Particle filters for modeling individual time series
 and estimate probability of "abnormal" values
- Short term forecasting 1-14 days forecasts and comparison to measured data





Basic idea of particle filtering

- Simulation is used to estimate the parameters of a state space model
- Estimated parameters are represented by a "particles" -> data points
- "Particle Swarm" i.e. a group of datapoints represent different possible values for the parameters. e.g. 1000 particles can be used for estimation
- Particles are initialized at some value using prior distribution
 - Particle values are updated to time t+1 using system equation and added simulation noise
 - Simulated values are compared to measured values -> calculate weights for each particle
 - State estimate are calculated as the weighted mean of particles
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Particle filtering of milk yield data

System model: $\mu_t = \mu_{t-1} + eta_1 \Delta t + eta_2 e^{kt\cdot\Delta t}$





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Estimation and dataset

- Developed a Julia library for particle filtering
- Estimated model parameters: standard deviation of yield and model parameters using global optimizers in models with data from 800 lactations.
- Repeatable results obtained
 with 8000 particles

- Test 2 methods:
 - Maximum likelihood 1 step ahead filtering (ML textbook approach)
 - Minimize prediction error on 7 days ahead forecasting (MSE7)
- Test prediction on 530 lactations:



Results on optimization

- Average MSE for prediction: 31.5 ML and 28.17 MSE7
- The best method depends on the forecast horizon
- For disease detection it's probably better to use separate model for acute and slowly developing conditions



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Real time alerts from the model

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Discussion

- The estimated model was very simple, but particle filtering allows much more complex models e.g. nonlinear predictors
 - We are not limited by not being able to estimate a specific model
 - You can directly interpret the parameters
- Computational cost is mainly an issue when optimizing the parameters (e.g. 48 CPU hours to optimize the Wilmink model -> 2hrs on 24 core task on a cluster (CSC It center for science)
- Anomaly detection approach can be used when we have sensor data without reference data.
 - Requires assumptions/decisions on alert level
 - Needs data for validating alarm performance. We are working on it!









Leverage from theE 2014-2020



Interested in Open Science and alternatives to the current publication system in animal science?

See poster 61.09 by Rafael Muñoz-Tamayo