Machine Learning in Reservoir Production Simulation and Forecast

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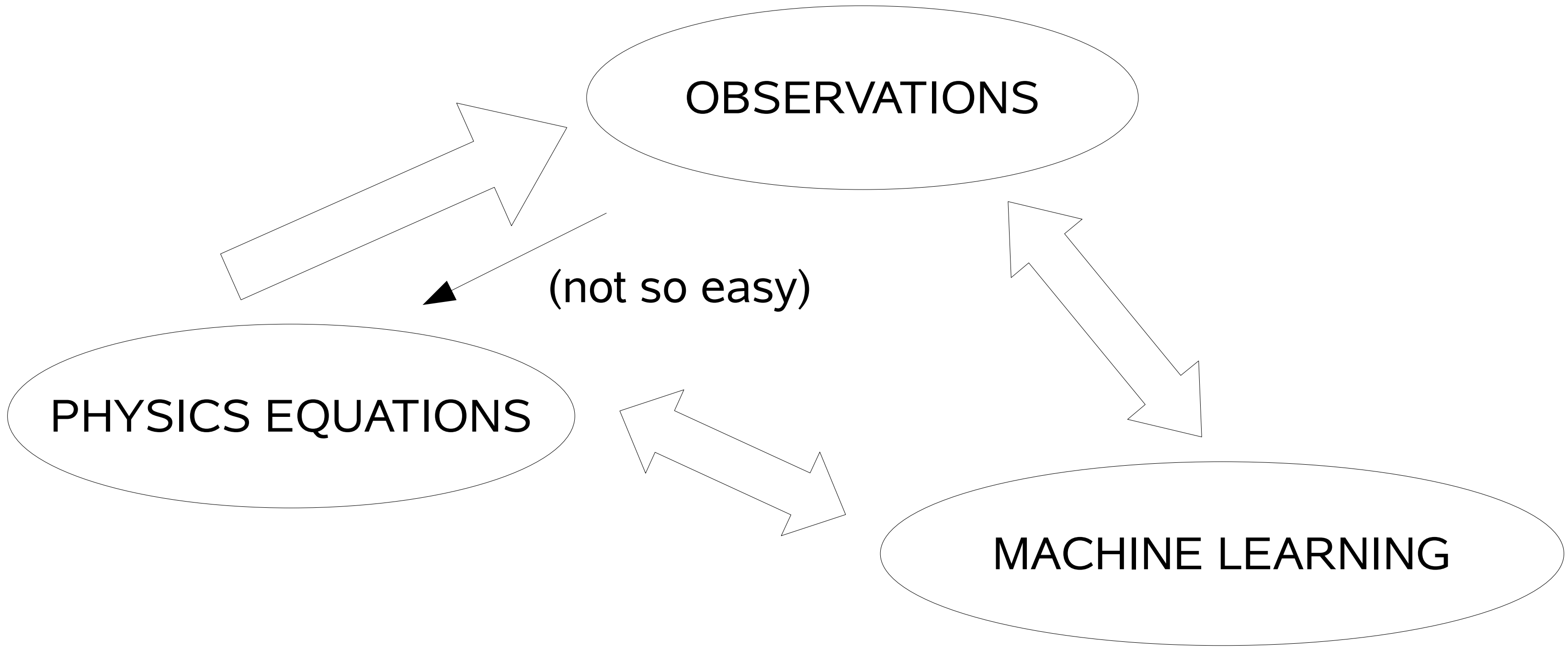
Topics and Goals

- Goals
  - Look at one of topmost levels of model upscaling – dependencies between solution functionals
  - Consider Machine Learning (ML) as possible relevant technology for these levels
- Topics covered
  - Basic problem formulations in ML context
  - Illustrative applications and benefits

To the top of upscaling hierarchy

- Can we upscale original problem of reservoir simulation to the level of functional dependence between observed outputs (e.g. production rates) and controlled inputs (e.g. wells regimes)?
- Is this the only way to do this from original equations?
  - Possibly, alternatives exist: functional and probabilistic dependencies can be simulated by Machine Learning algorithms (neural networks and others)



- PE are the best for direct problems
- PE give useful hints to ML
  - Critical scale factors
  - Conservation laws
  - Constrains
  - Feasibility tests
- ML algorithms are naturally utilize observations, and suitable both for direct and inverse problems
- ML feedbacks to PE
  - Factors influence
  - Optimal factor values

Models for what?

- Modelling for synthetic description of many simulator runs and experimental observations
  - “What-if” tools
  - inverse problems
- Modelling for prediction
  - Prolongation of system trajectory in time
  - Future responses to changing controls
- Machine Learning can serve for both

Formulations of ML tasks

- Requested application problem is described in terms of input variables (controlled and uncontrolled) and outputs. Later directly represent variables to be estimated.
- Datasets are collected from simulations and/or observations in the form of pairs of input-output vectors.
- Machine Learning algorithm provides the IO dependence.
  - Functional view – provide approximation of unknown function
  - Probabilistic view – estimate most probable response to a given input (whole probability distribution is preferable)

Types of ML tasks

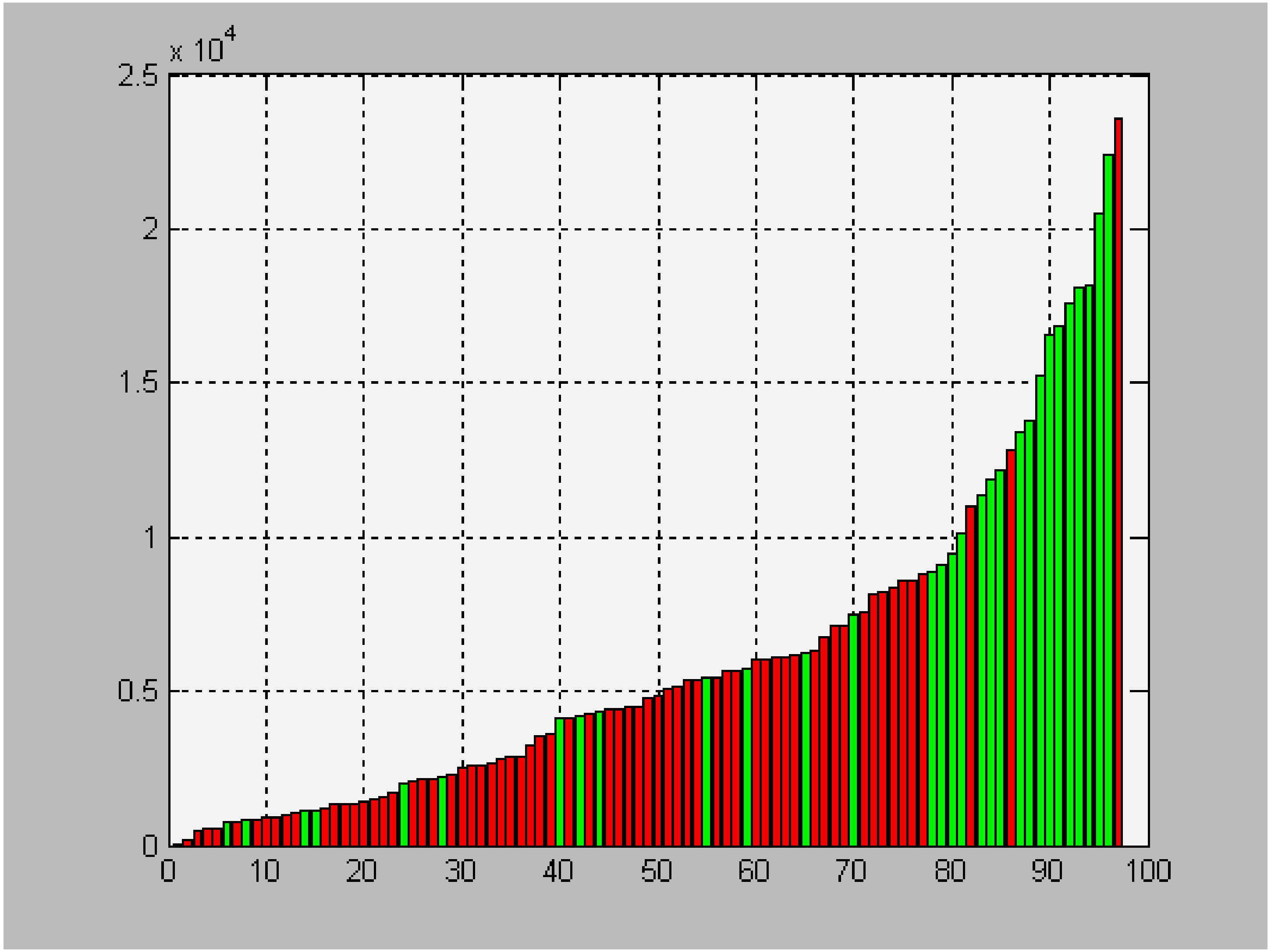
- Classification problem
  - Output variable(s) represents two ore more descriptive alternatives (*classes*). Current input vector belongs to one of them.
- Regression problem and conditional probability estimation
  - Output(s) is typically real-valued.
- Other (less frequent) problems
  - Clustering (unsupervised, no predefined classes and class labels
  - Reinforcement learning (rewards or punishments are given instead of known output values.

Classification example

- Problem: Hydraulic fracturing is one of successful methods of production intensification. Fracturing efficiency *for the particular well* is quite uncertain and strongly depends on many factors (used as inputs):
  - Proppant parameters, pumping rate, perforation, watercut, surround media structure, well “history”, etc.
- Approach: consider classification of wells into two classes (“high” and “low” expected efficiency).
- Solution: neural classifier trained on known examples of previous fractures can predict the outcome.
  - Candidate wells are ordered so that most perspective wells for future fracturing planning are identified

Results: 30 wells of 100

Multiple efficiency is over 90%

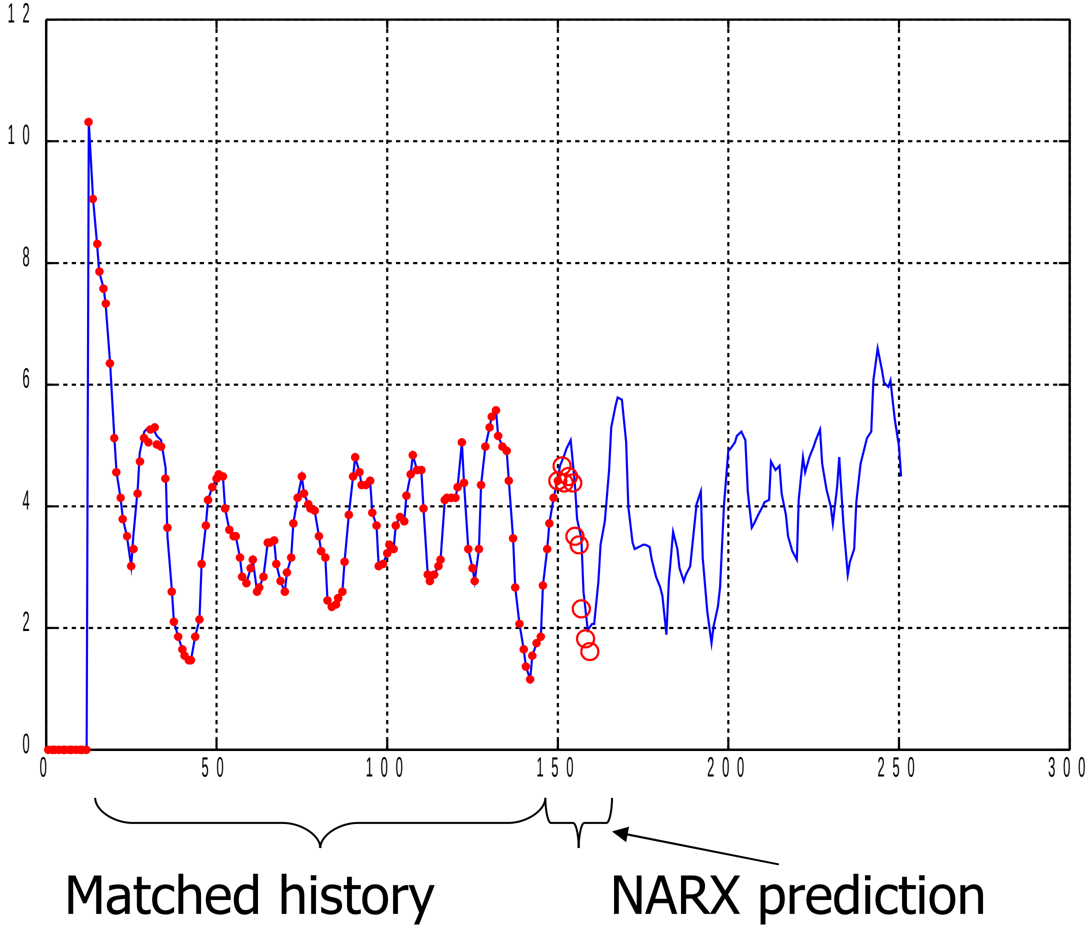


Sorted by actual output, 30 best forecasted are in green

Regression example

- Forecast of future scenario of well production (product and watering) from the production history and areal pumping.
- Regression model uses embedded delayed time series as inputs and estimates both expectation and variance of future production.
- Model can be used in control applications and field planning

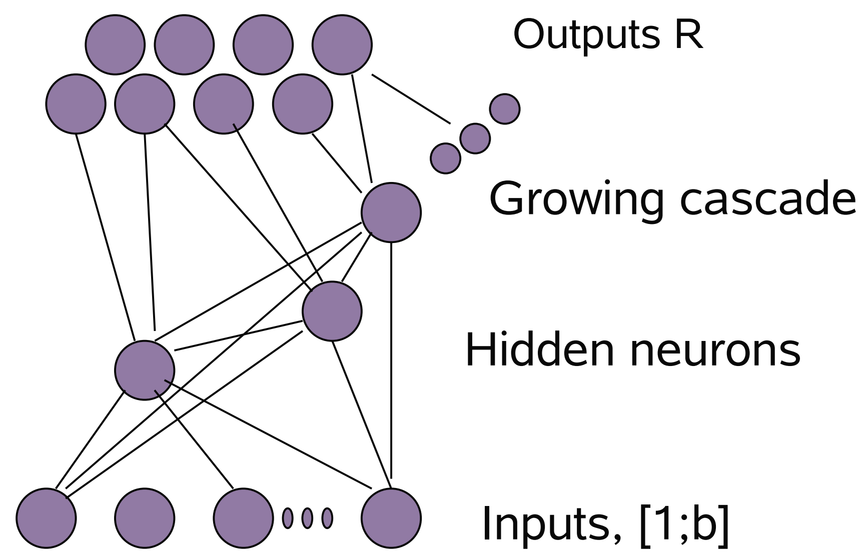
Quality of 1-year forecast



Machine Learning tools

- Neural Networks
- Probabilistic and clustering trees
- SVM
- Kohonen maps
- GA and other optimization

Example: Cascade Neural Network
Gaussian likelihood optimization with CG



Conclusions and benefits

- Machine Learning methods can fruitfully enforce mathematical modelling at topmost level of upscaling.
- Trained models can serve as surrogates for optimization tasks and inverse formulations
- Both simulated and observed data can be aggregated in one predictive model
- Broad area of applications in energy industry

- Thank You!

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