National Aeronautics and Space Administration

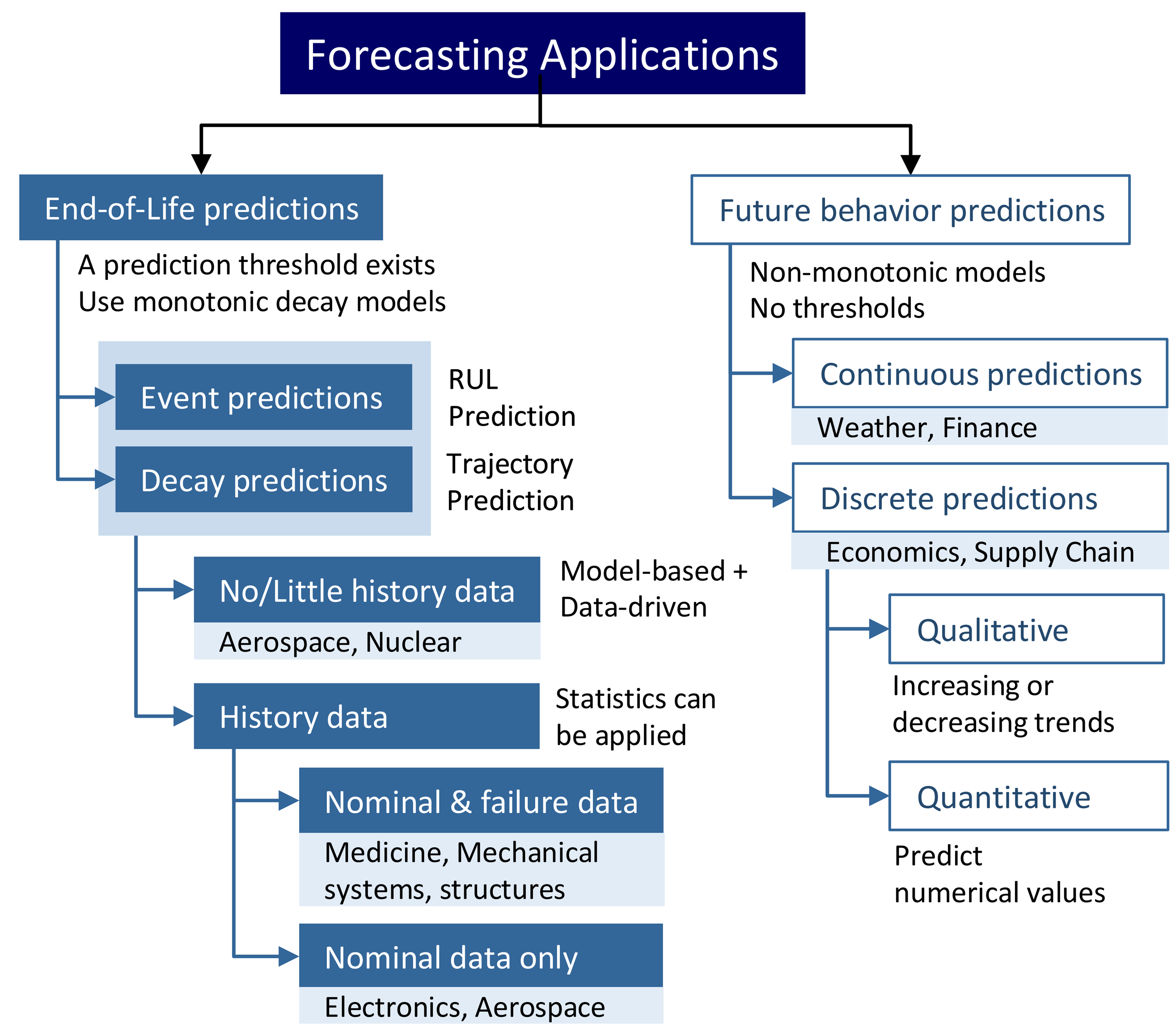
Algorithms for Prognostics

Bhaskar Saha[1], Abhinav Saxena[2], Jose Celaya[2], Sankalita Saha[1], Kai Goebel[3]
[1]Mission Critical Technologies, Inc., [2]Stinger Ghaffarian Technologies, Inc., [3]NASA ARC
Prognostics Center of Excellence, NASA Ames Research Center CA

Motivation

Develop data-driven algorithms for prognostics and demonstrate their applicability on diverse applications to benchmark prognostic performance.

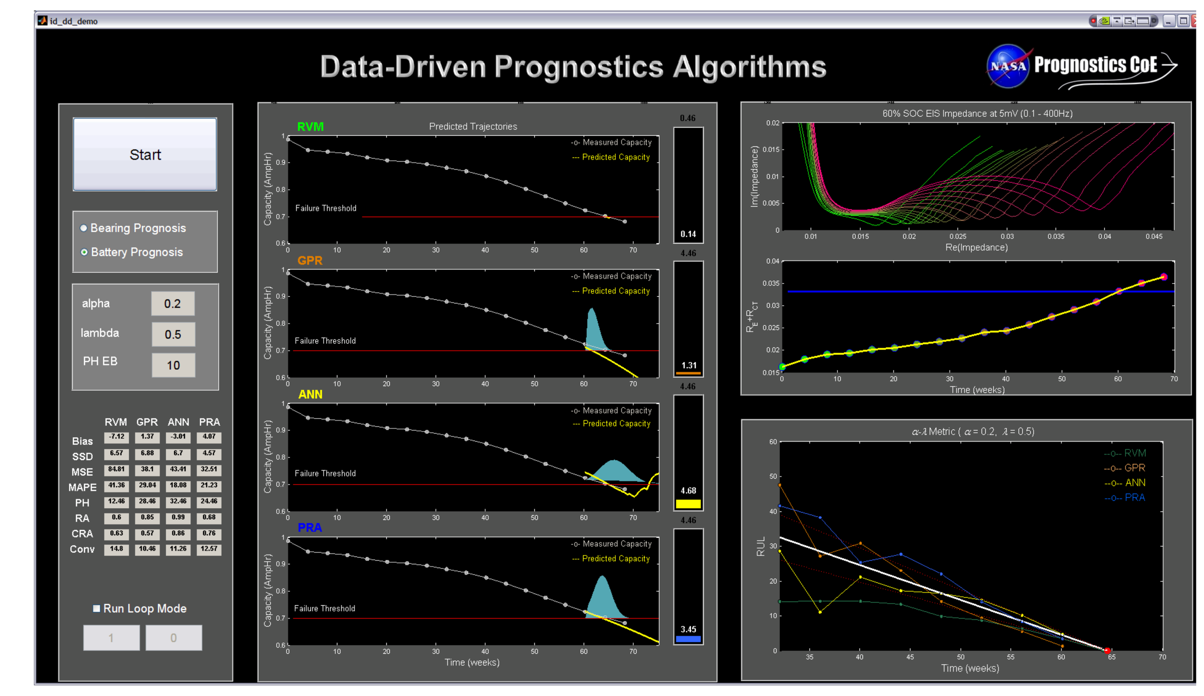
- Evaluate different algorithms for their suitability for various applications
- Assess trade-offs that arise from
  - Amount of data needed
  - Computational complexity
  - Robustness towards input space perturbations
  - Ability to support uncertainty management
  - Accuracy and usability of predictions (prediction horizon)
- Develop performance evaluation metrics for prognostics



Algorithms should be developed to cater to specific prediction tasks

Software Demonstration

- Interactive software environment allows visual assessment in addition to numerical performance tracking.



Features

- Runs multiple prediction algorithms
- Tracks and compares prediction performance simultaneously
- Computes performance

Data-Driven Algorithms

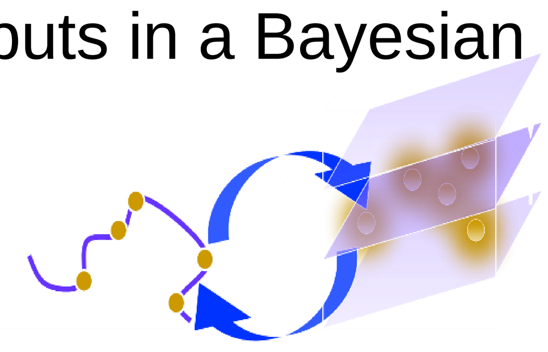
Relevance Vector Machines

- Supervised learning algorithm using expectation maximization
- Stochastic sparse kernel method similar to Support Vector Machines
- Allows probabilistic outputs in a Bayesian framework

–Data

Targets, Observations

$$\mathbf{t}_n = F(\mathbf{x}_n;\mathbf{w}) + \varepsilon_n$$



–Likelihood of the data set

Design matrix (kernel functions)

$$p(\mathbf{t}\mid\mathbf{w},\sigma^2) = (2\pi\sigma^2)^{-N/2}\exp\left\{-\frac{1}{2\sigma^2}\|\mathbf{t}-\Phi\mathbf{w}\|^2\right\}$$

–Predictions for the new observations $\boldsymbol{x}^*$

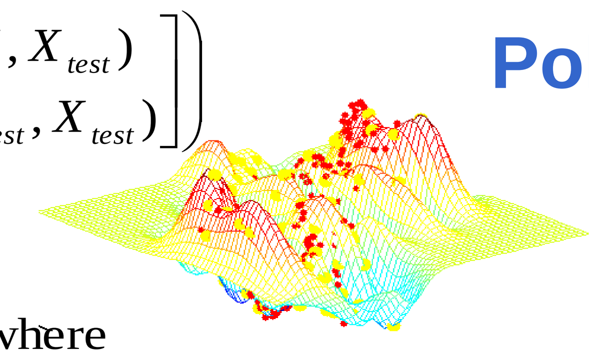
$$p(\mathbf{t}^*\mid\mathbf{t}) = \int p(\mathbf{t}^*\mid\mathbf{w},\sigma^2_{MP})\,p(\mathbf{w}\mid\mathbf{t},\eta_{MP},\sigma^2_{MP})\,d\mathbf{w}.$$

Gaussian Process Regression

- Supervised learning belonging to the family of least squares estimation algorithms
- Bayesian framework to derive posteriors from priors (history data)
- Provides mean and variance estimates for the predictions

–Prior

$$\begin{bmatrix} y \\ f_{test}\end{bmatrix} \sim N\left(0,\begin{bmatrix} K(X,X)+\sigma_n^2 & K(X,X_{test}) \\ K(X_{test},X) & K(X_{test},X_{test})\end{bmatrix}\right)$$



–Posterior

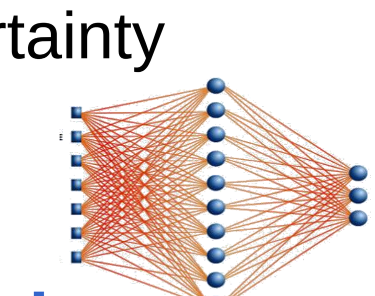
$$f_{test}\mid X,y,X_{test} \sim N(\bar{f}_{test},\operatorname{cov}(f_{test})), \text{ where}$$

$$\bar{f}_{test} \equiv \mathrm{E}[f_{test}\mid X,y,X_{test}] = K(X,X_{test})[K(X,X)+\sigma_n^2 I]^{-1}y,$$

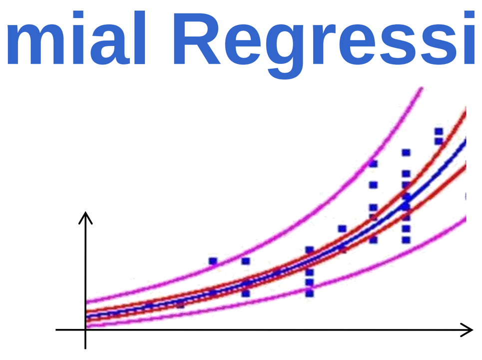
$$\operatorname{cov}(f_{test}) = K(X_{test},X_{test}) - K(X_{test},X)+\sigma_n^2 I]^{-1}K(X,X_{test}).$$

Artificial Neural Networks

- Universal function approximators
- Widely used for data-driven learning, i.e. provide a well represented prognostic technique, e.g. DWNN, CPNN
- Do not incorporate uncertainty management inherently



Polynomial Regression



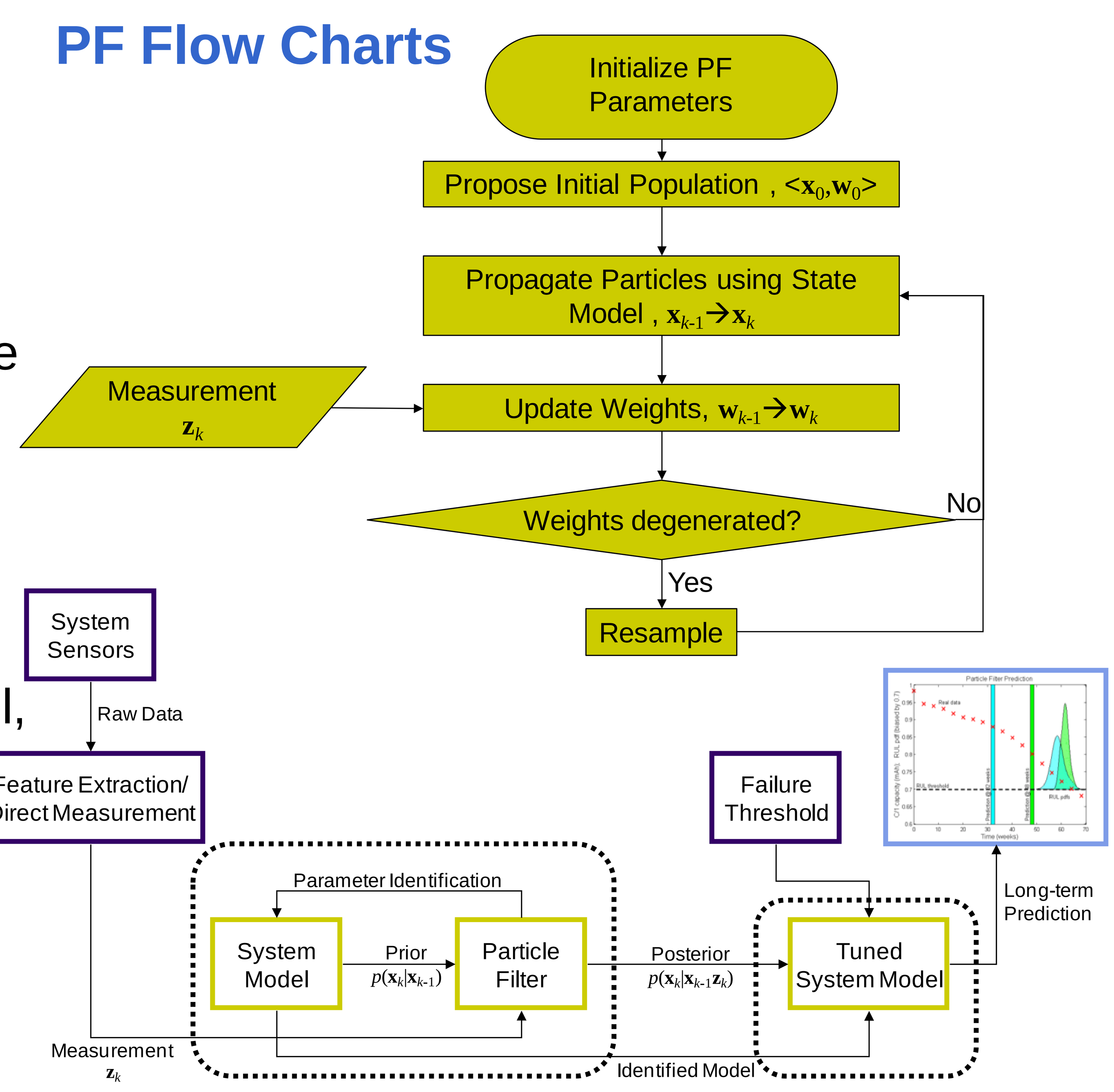
A simple regression approach, here used as baseline for comparisons

Model-Based Algorithms

Particle Filters

- State-of-the-art for nonlinear non-Gaussian state estimation
- Uses model to predict and data to correct prediction
- Performs model adaptation in addition to state estimation, tracking and prediction
- Nice trade-off between the convergence guarantees of Monte-Carlo methods and the computational simplicity of Kalman filters
- Allows explicit representation and management of the uncertainties in the model, the measurements and expected usage
- If only part of the state is non-deterministic, the other part can be treated deterministically in a *Rao-Blackwellized Particle Filter*, thus improving the precision of the prognosis

PF Flow Charts



PF Results