Uncertainty-aware Remaining Useful Life predictors

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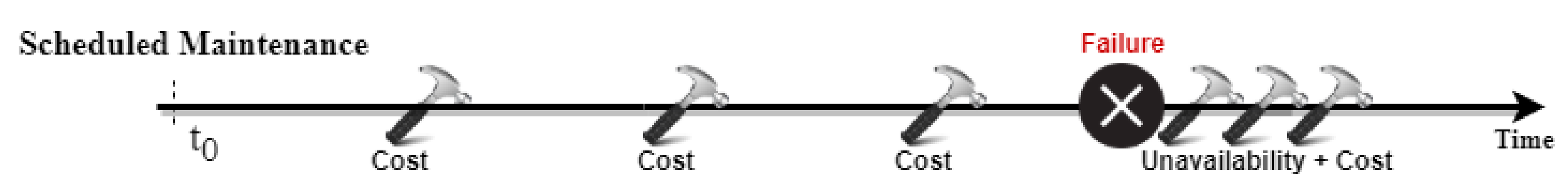
NEURAL INFORMATION PROCESSING SYSTEMS

Predictive Maintenance

- The current most popular maintenance strategy is based on scheduling interventions at fixed time intervals



- **Predictive Maintenance (PM)**, on the other hand, aims at setting maintenance operations based on the information extracted from data describing the health state of the machine

- PM relies on efficient **Remaining Useful Life (RUL) estimation**, i.e. the problem of inferring how long a certain industrial asset is going to operate until a system failure occurs

- In the context of PM, **Uncertainty Quantification (UQ)** is crucial given the potentially catastrophic consequences associated with wrong maintenance decisions

Dataset

- The new C-MAPSS dataset is a synthetic dataset providing the full degradation trajectories of **9 large turbofan engines under real flight conditions**
  - For each unit we have:
    - $X = [x_1, \ldots, x_t, \ldots, x_T]$ where each $x_t \in \mathrm{R}^{41}$ and T is the time series duration
    - $Y = [y_1, \ldots, y_T]$ where each $y_t \in \mathrm{R}$ is the RUL at time step t
- 6 units are used for training (**0.53M samples**), 3 for testing (**0.12M samples**)

Techniques

- Standard Gaussian Processes (GPs) suffer from **2 main limitations**:
  1. Do not scale well with the number of data (cubic cost in the number of data points)
  2. They are limited by the expressiveness of the kernel/covariance function

- We address these limitations by leveraging recent advances in the GP literature, namely
  1. **Stochastic Variational Gaussian Processes (SVGP)** [Hensman et al., 2015]
  2. **Deep Gaussian Processes** [Salimbeni and Deisenroth, 2017]
  3. **Deep Sigma Point Processes** [Jankowiak et al., 2020]

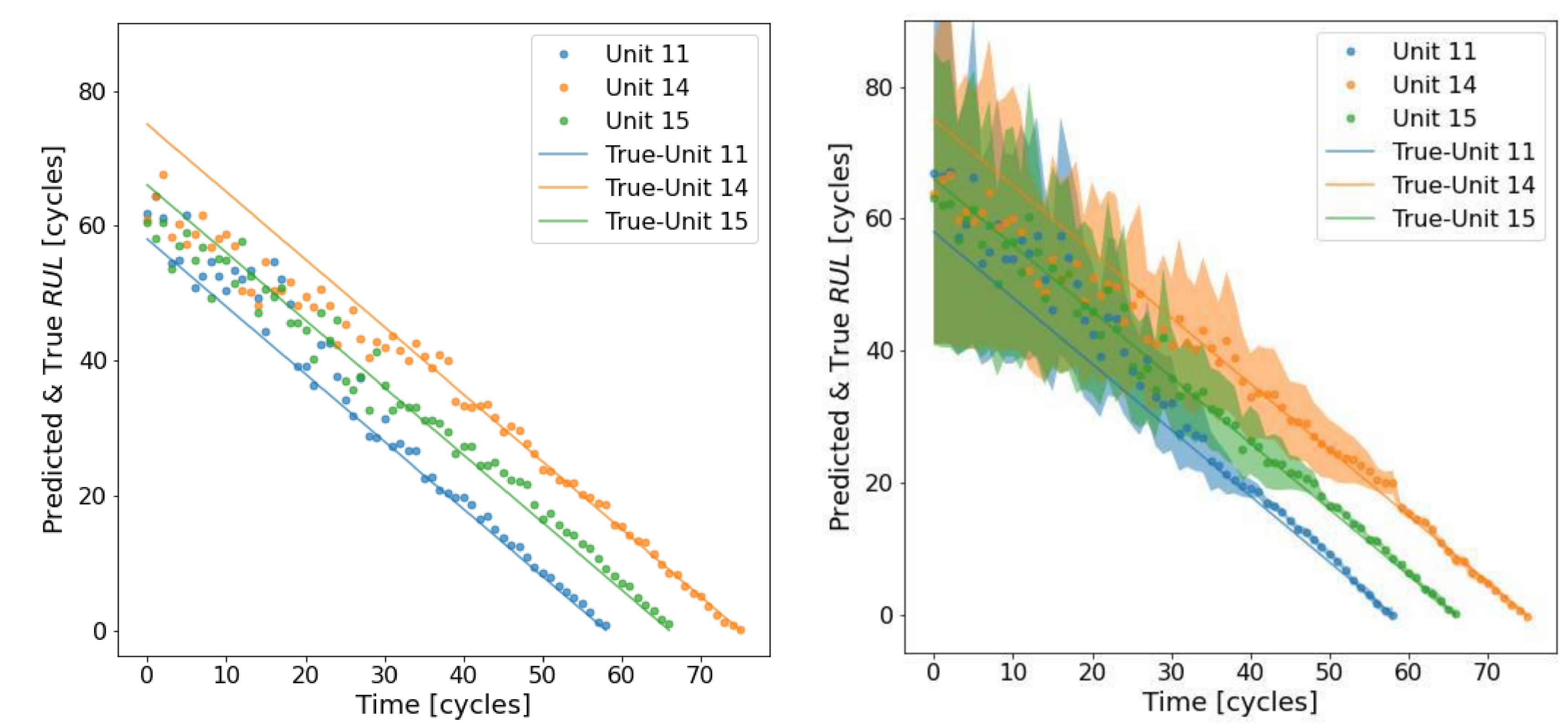
Quantitative Results

- Our experiments show that the application of such techniques to the C-MAPSS dataset results in predictive performances close to or superior than those obtained by two DL baselines: a standard deep feed-forward neural network (FFNN) and a one-dimensional Convolutional Neural Network (1-d CNN).

Gaussian Processes		
Models	**RMSE**	**NLL**
SVGP [Hensman et al., 2015, Jankowiak et al., 2019]	4.90	2.72
DGP [Salimbeni and Deisenroth, 2017, Jankowiak et al., 2019]	4.74	2.57
DSPP [Jankowiak et al., 2020]	**3.97**	**2.46**
Deep Neural Networks		
Models	**RMSE**	**NLL**
FFNN	4.11	-
1d CNN [Arias Chao et al., 2020a]	4.18	-

Visualizations

- As opposed to standard NNs (left), DSPs (right) provide physically meaningful uncertainty estimates alongside their predictions.



Conclusions

- We provide the first evidence that modern GP models can be successfully applied to the domain of PM of industrial assets.
- The application of such techniques to the C-MAPSS dataset results in predictive performances close to or superior than those obtained by two strong DL baselines.
- The proposed GP-models are able to provide physically meaningful uncertainty estimates alongside their RUL estimates.

References

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- M. Jankowiak, G. Pleiss, and J. R. Gardner. Deep sigma point processes.arXiv, pages arXiv–2002,2020.
- H. Salimbeni and M. Deisenroth. Doubly stochastic variational inference for deep gaussian processes.In Advances in Neural Information Processing Systems, pages 4588–4599, 2017.