Utilizing Machine Learning in Nuclear Power Plant Lifecycle Management

Herkko Pirkkalainen

The Core Team of Nuclear Experts

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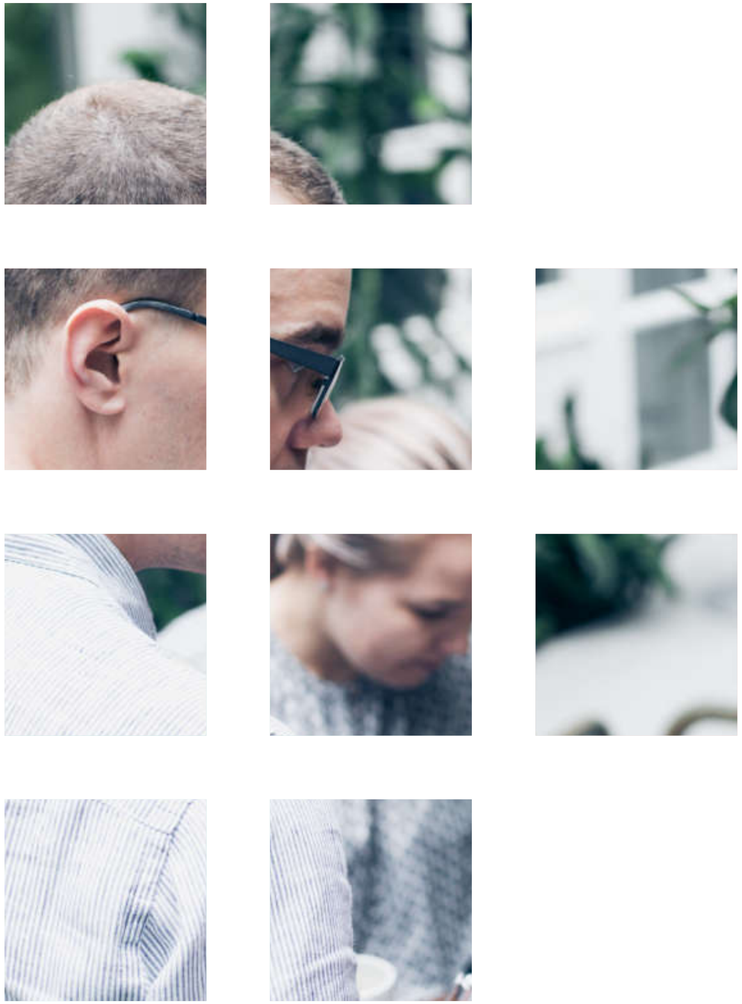

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Presentation agenda

1. Background information about the Master's Thesis
2. The concept of machine learning (ML)
3. The structure of the Thesis
4. The 3 cases that were studied
   - Feedwater pump axle seal leakage
   - RPV water surface level measurements
   - Prioritization of NPP lifecycle management projects
5. Lessons learned & future prospects

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Thesis background information

- The Masters' Thesis was made for Teollisuuden Voima Oyj (TVO), and was examined by TVOs Lifetime Management Manager Matti Vaaheranta and by Plant Life Management Team Leader Joel Maunula from Platom Oy
- Nuclear power plants (NPPs) have thousands of devices for collecting data with both periodic and online measurements of various processes
- Is it possible / reasonable to **utilize machine learning** methods to help with ageing management related issues at Olkiluoto with the data already collected during the ~40 years of operation?
- Author had no previous experience with machine learning, but was experienced in using MATLAB, which has multiple ML-toolboxes

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The concept of machine learning 1

Machine learning is currently very trendy:

- The core concepts have been around from the end of the 17th century
- Modern machine learning started in the 1960s with the development of modern digital computers
- ML has become accessible to a wide audience thanks to toolboxes in popular numerical computation programs (MATLAB, Octave) and free open source ML-libraries (TensorFlow, Theano)
- Modern office laptops are powerful enough to utilize computationally demanding ML methods
- Know-how is needed to make training timeframes reasonable by **selecting the right methods** and **extracting the right features** for each type of dataset

The concept of machine learning 2

Machine learning can be divided into **3 main categories**:

1. Supervised learning
   - Give the machine a data set and the right answers for interpretation, hoping it will learn from example
2. Unsupervised learning
   - Give the machine only the data set, see what it can learn by itself
3. Reinforcement learning
   - The machine starts with unsupervised learning, user starts giving feedback during the process

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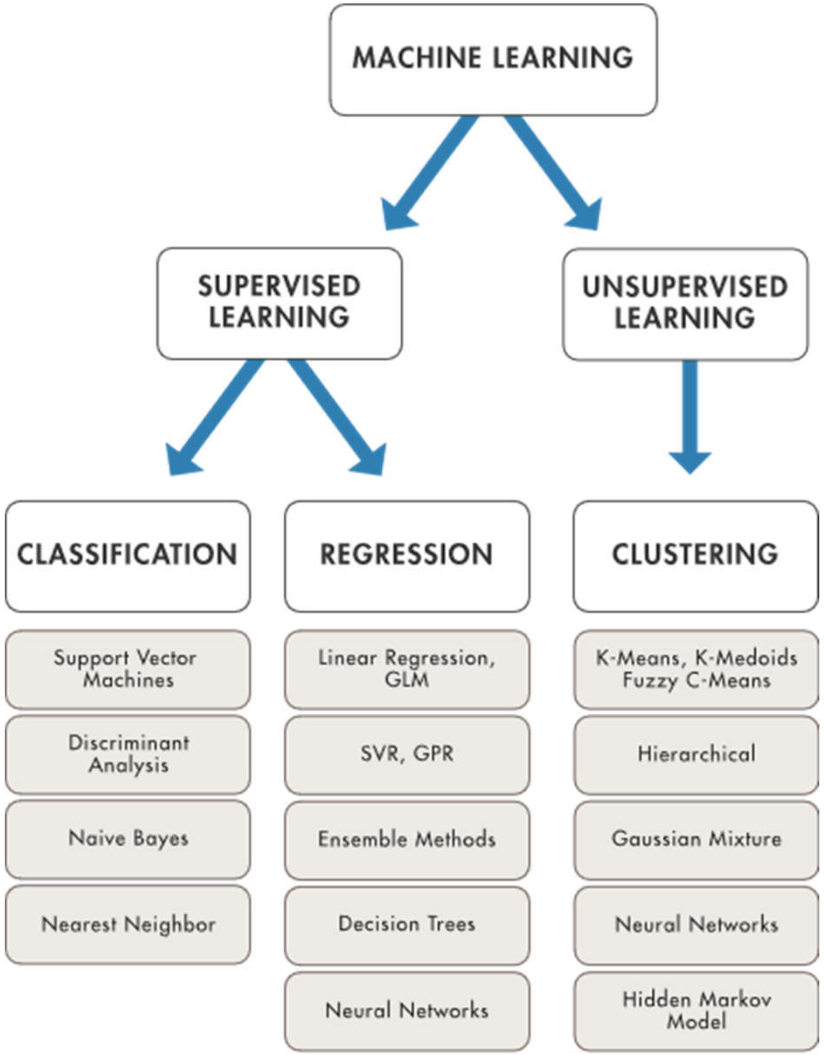
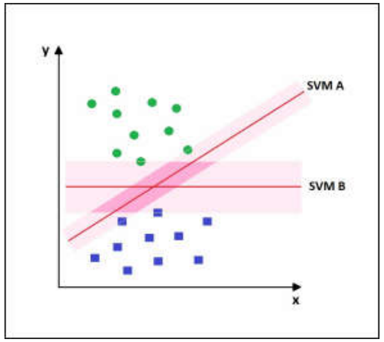
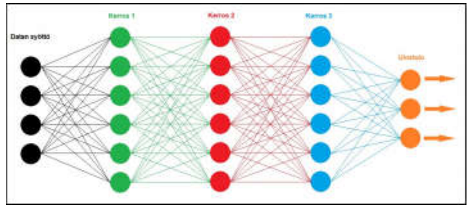
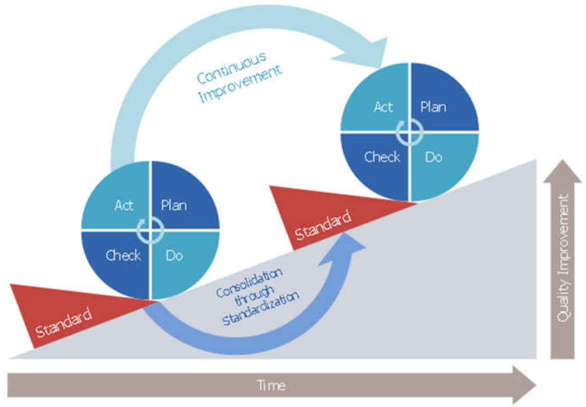


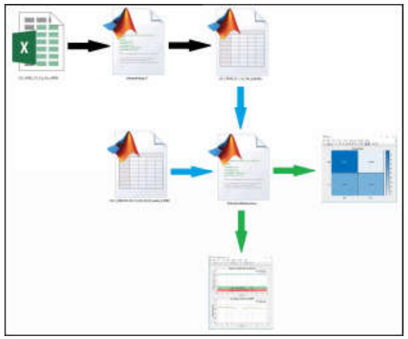
The structure of the Master’s Thesis

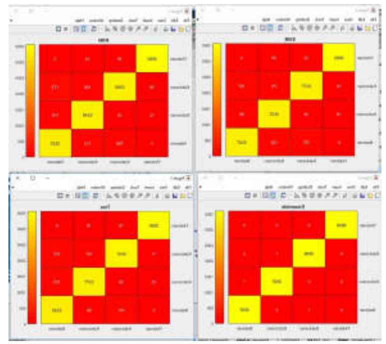




- The first third of the thesis contains an introduction to the history and current state of machine learning and the terminology used. Some of the most common ML-methods and algorithms are showcased.
- One chapter discusses the current state and future plans for ageing management at the Olkiluoto NPP (proactive → predicative)
- The rest of the thesis is about **utilizing ML-methods in three different cases** at OL1 and OL2 plants







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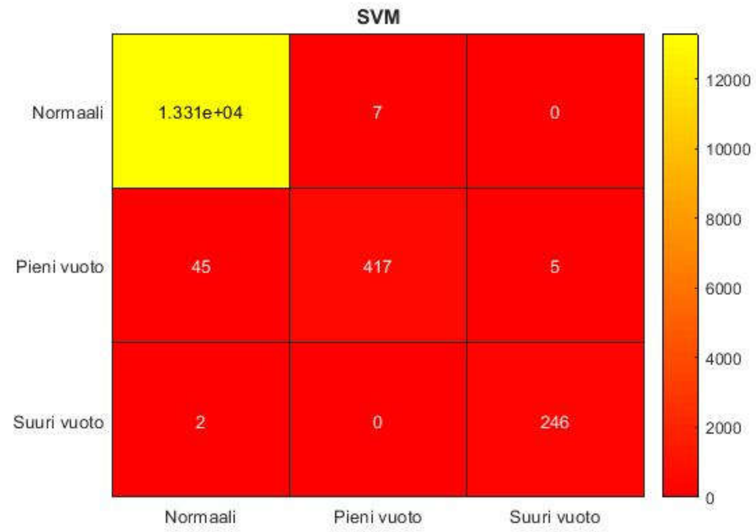
The case of the feedwater pump axle seals 1

- In the past ~3 years there have been a few leaks of the feedwater pump axle seals in both OL1 and OL2 plants. The leaks are detected by the rise in the axle seal water temperature.
- The leaks are usually detected by operating personnel monitoring the temperature rise, but the system itself gives a warning at T = 50 °C.
- Could ML-methods be used to **notice the leaks earlier** than if the plant personnel were continuously monitoring the situation?
- Could ML-methods be used to predict future leaks from plant process data?

The case of the feedwater pump axle seals 2

- Data had to be cleaned up by self made scripts to remove plant downtimes, pump maintenances and sensor malfunctions
- The state of the seals were classified as “normal”, “small leak” and “large leak” from the perspective of plant personnel monitoring the situation
- A new leak happened during the writing of the thesis and was used as the final test data
- Promising results, the overall accuracy was quite good with multiple algorithms, but we need to remember that with the disparity of the training class sizes, **a completely wrong result would still be 95% accurate**



Machine learning algorithm	Success percentage
Classification tree (fine)	98.3 %
SVM (quadratic)	98.1 %
k-NN (fine)	98.6 %
Ensemble (forest)	98.7 %

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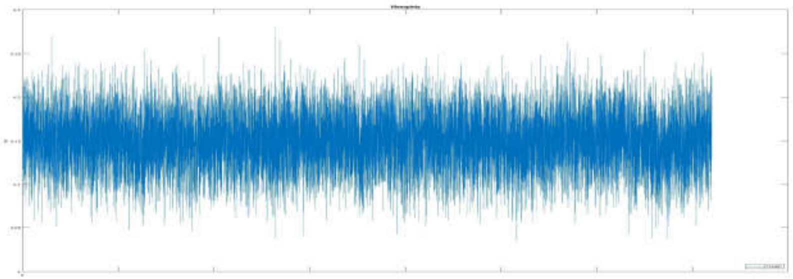
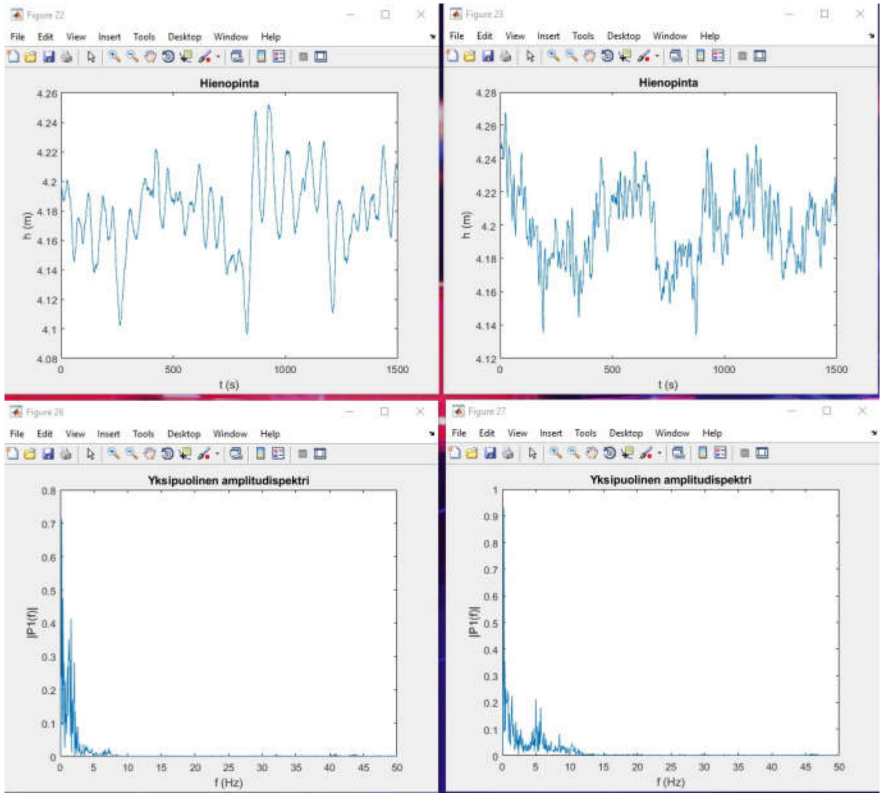
The case of the RPV water surface level measurement 1

Can ML be used to **find and identify differences** in supposedly similar measurement signals?

- 4 identical RPV water surface level measurements
- Components have been replaced and they rarely age identically, so it should be possible to differentiate the signals from each other in a blind test
- Supervised ML methods were used, features were extracted from 50 ms intervals of the signals, training data and test data were from different weeks





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The case of the RPV water surface level measurement 2

- Several trained machines were able to achieve reasonable results
- An ensemble method (forest) was clearly the best at 99,9 % accuracy
- Neural networks were **very dependent on the size of training data**, but achieved good results if there was enough of it

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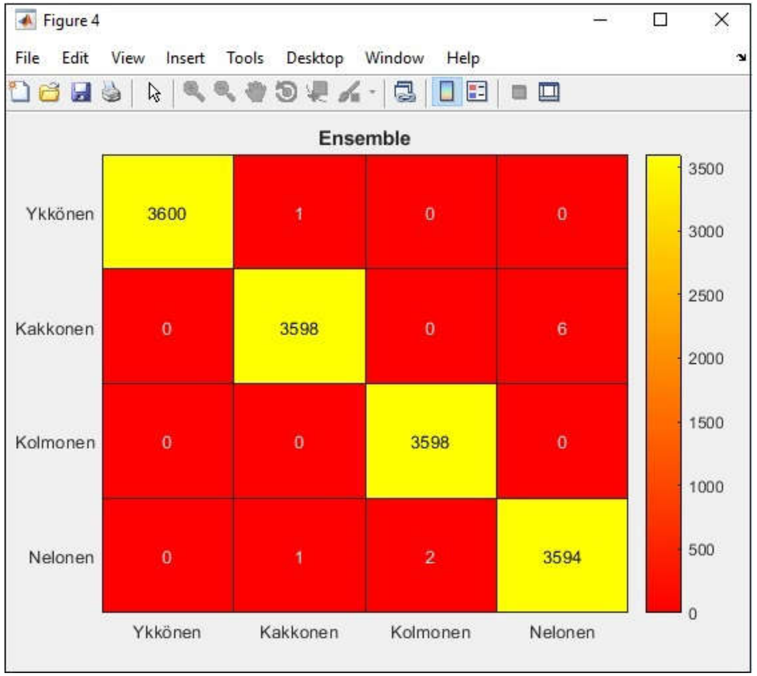

Machine learning algorithm	Success percentage
Classification tree (fine)	94.8 %
SVM (quadratic)	94.9 %
k-NN (fine)	94.6 %
Ensemble (forest)	99.9 %
Neural network	94.7 %

The prioritization of NPP lifecycle management projects 1

- The systems of OL1/OL2 NPP units are classified by **3 lifecycle management metrics**:
  - Importance to safety
  - Importance to plant economics
  - Overall system aging factor
- The metrics are given a numeric value, which is calculated from several hundred underlying metrics
- TVO has a MATLAB script library to calculate the metrics, could ML algorithms be taught to calculate these metrics as well?

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The prioritization of NPP lifecycle management projects 2

The answer: Yes, but **what’s the point?**

- The best ML-algorithm trained (k-NN classifier) achieved a classification accuracy of 99,7 % while taking longer than the current script library
- ML-methods could become relevant, but the amount of underlying metric data would have to be significantly larger and more complex, so that writing a new script library would be too time-consuming

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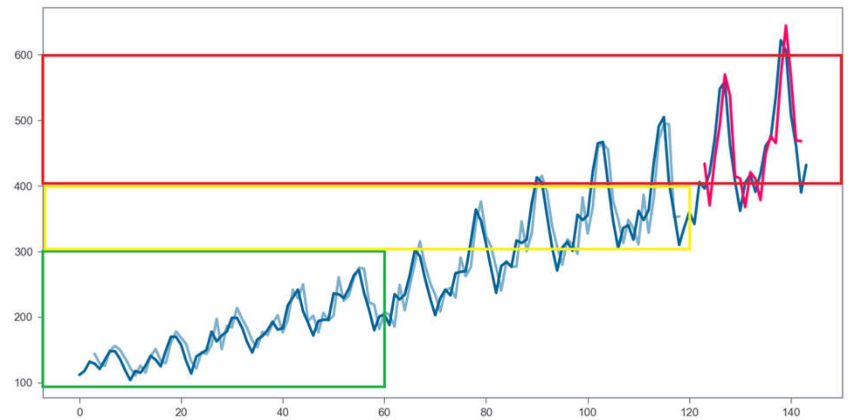
Conclusions and development ideas 1

Feedwater pump axle seal leaks:

- Promising results, the beginning of leaks can now be **detected sooner than before**
- By tweaking ML-algorithm variables and improving the preprocessing of training data, significantly better results are possible
- With further development, a machine could possibly be taught to predict the timing of the next leak based on the state and future trend of the various process variables



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Conclusions and development ideas 2

RPV surface level measurement signals:

- Good results, multiple ML algorithms can **differentiate seemingly similar signals** clearly from each other
- If electronic components in a measurement chain are replaced, there will be a change in the behavior of the output signal that ML-algorithms can detect
- ML-algorithms and knowledge of the maintenance history of components could be used in conjunction to determine which components in other signal chains are showing signs of ageing and need replacement

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Conclusions and development ideas 3

- The idea of combining all of the measured data from the NPP's processes and combining them with the entire maintenance history in order to see what a neural network could figure out about it sounds nice (Big Data)
  - Very labor-intensive to actually do, must start at a much smaller scale

- Many ML-methods can be **used by regular engineers** with some training and the right tools, no degree on the subject needed
  - ML-capable computation software is priced quite reasonably if you know what you want, free tools require a little more training

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Thanks!

Time for your questions

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