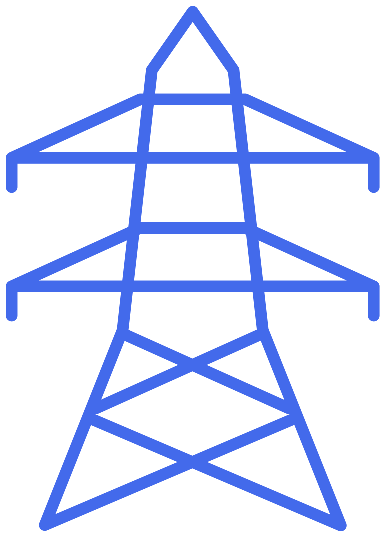


Krafthack 2022

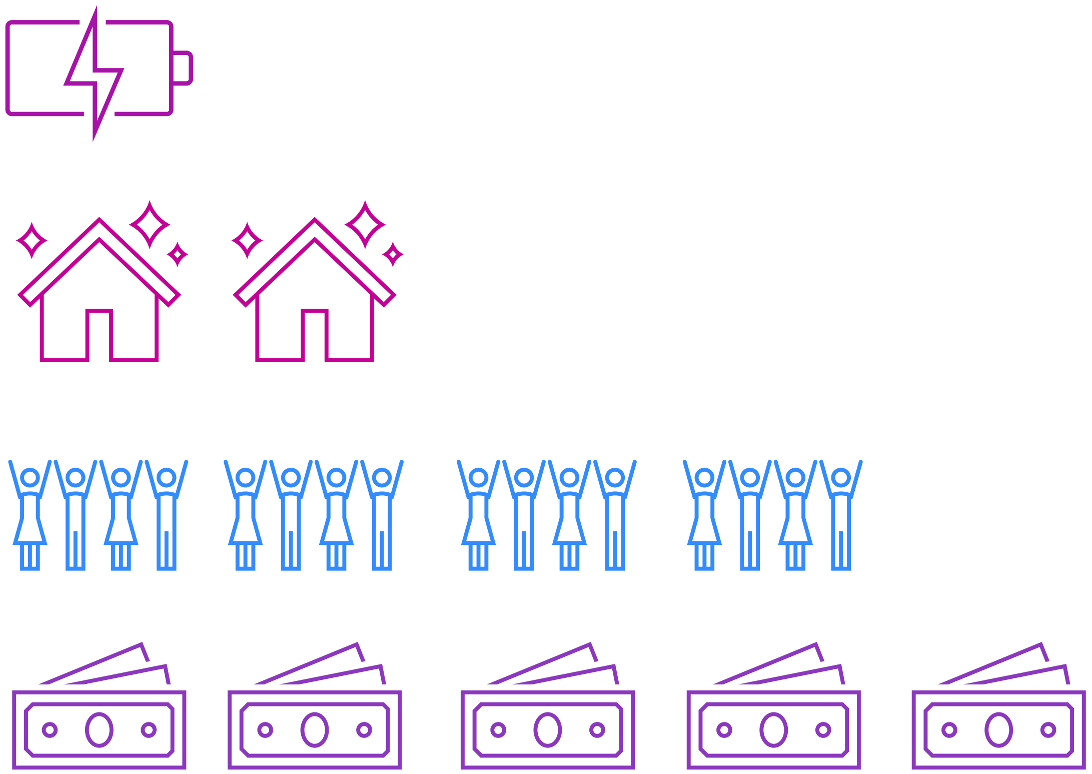
Team Knowit

Challenge Backdrop

- Predict tensil in bolts
- Understand normal movement in steel construction and foresee change

...Why is this important?

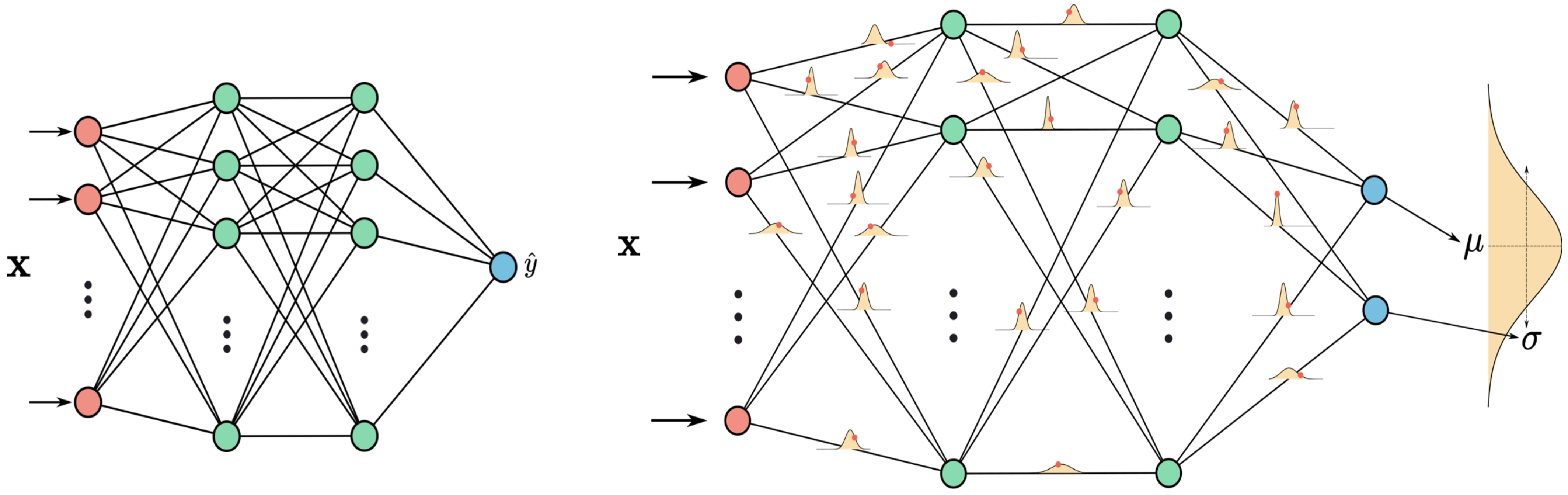
- Production: 3132 GWh/year:
- Households covered: 194 738 /year
- Persons covered: 414 793 /year
- Revenue lost: 5,92 BNOK



Our Approach

- Approximate **Bayesian Neural Network** by use of **Monte Carlo dropout.**
- Involves using the regularization technique, dropout. Not only during training but during inference as well.
- Let's us estimate the epistemic uncertainty. This is the uncertainty that tells us whether the model is familiar with the data passed in during inference.
- A model trained on one power plant could potentially be used on another as it will **flag the cases that are different** (by yielding high uncertainty).

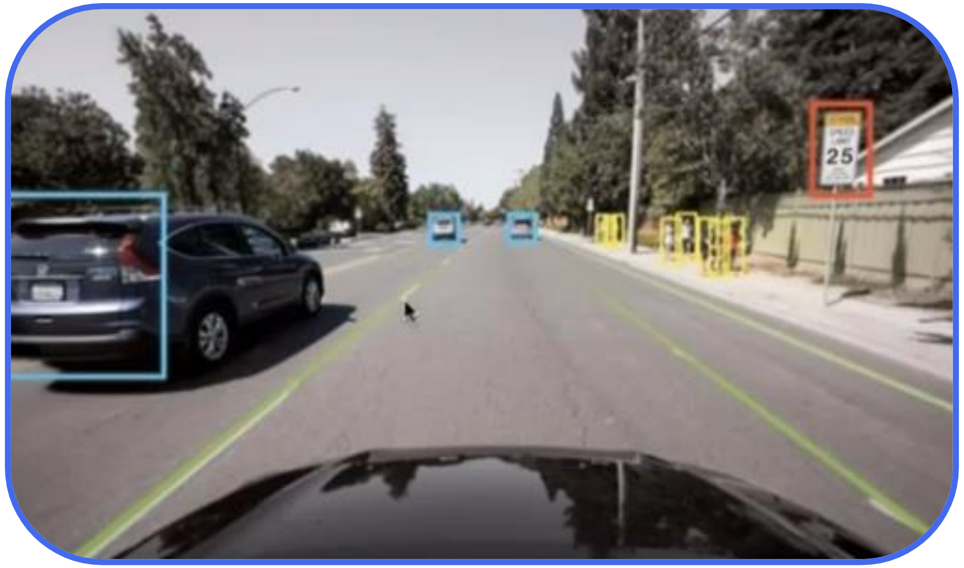
Neural Network vs Bayesian Neural Network

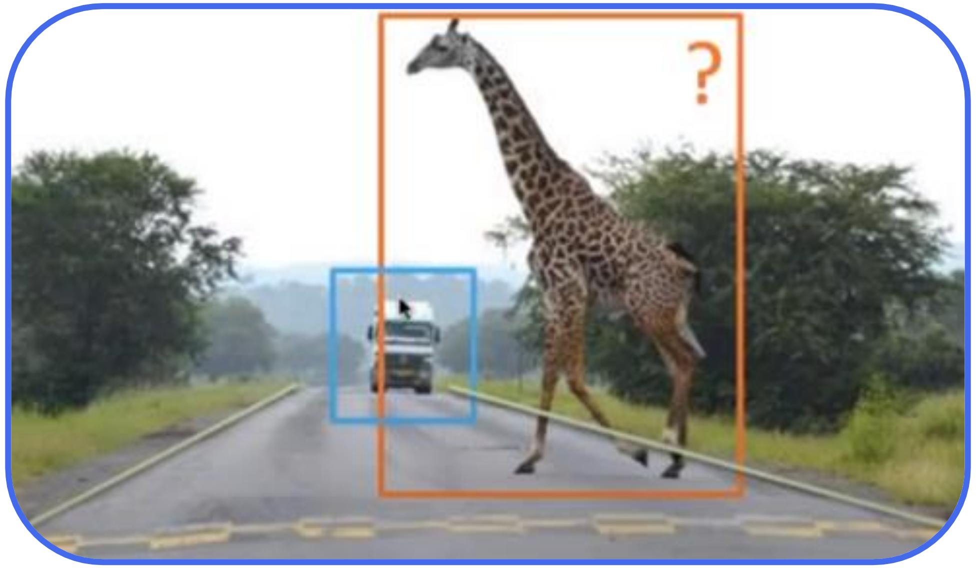


How do we scale this?

- Kvilldal use Francis Turbine (as most Norwegian power plant) – “similar” and transferrable model
- Using the insights from the pilot project we can generalize this knowledge to other powerplants
- Machine learning models are very sensitive to adversarial attacks
- Small differences (or big) can be decisive for the success (or failure) of a machine learning model

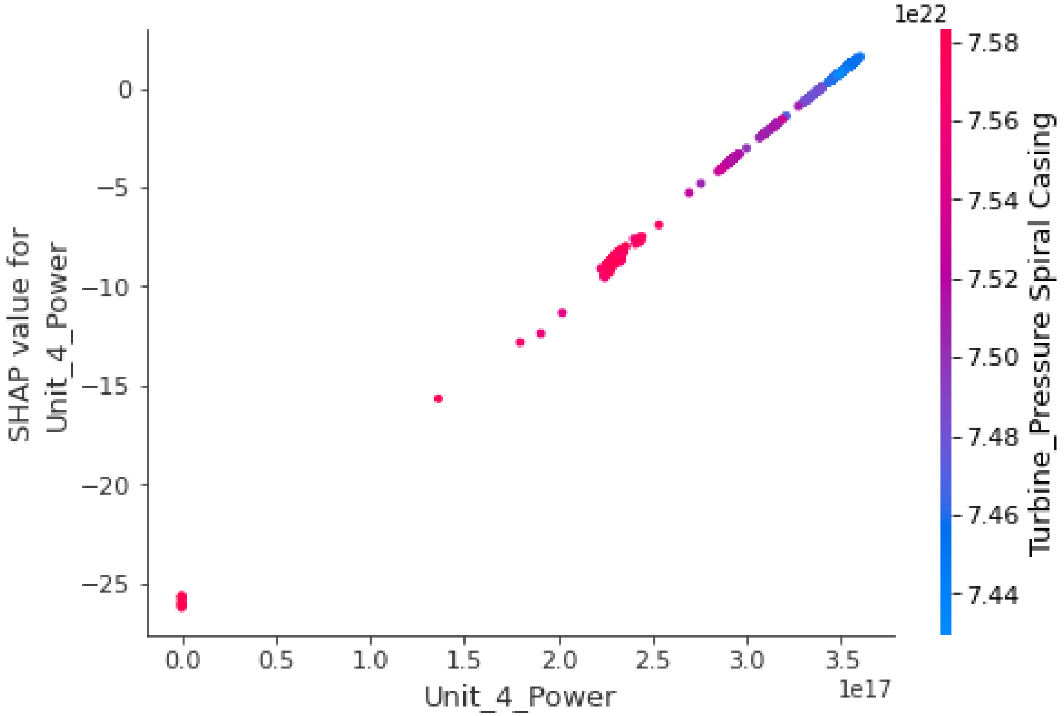
Quantify Uncertainty!

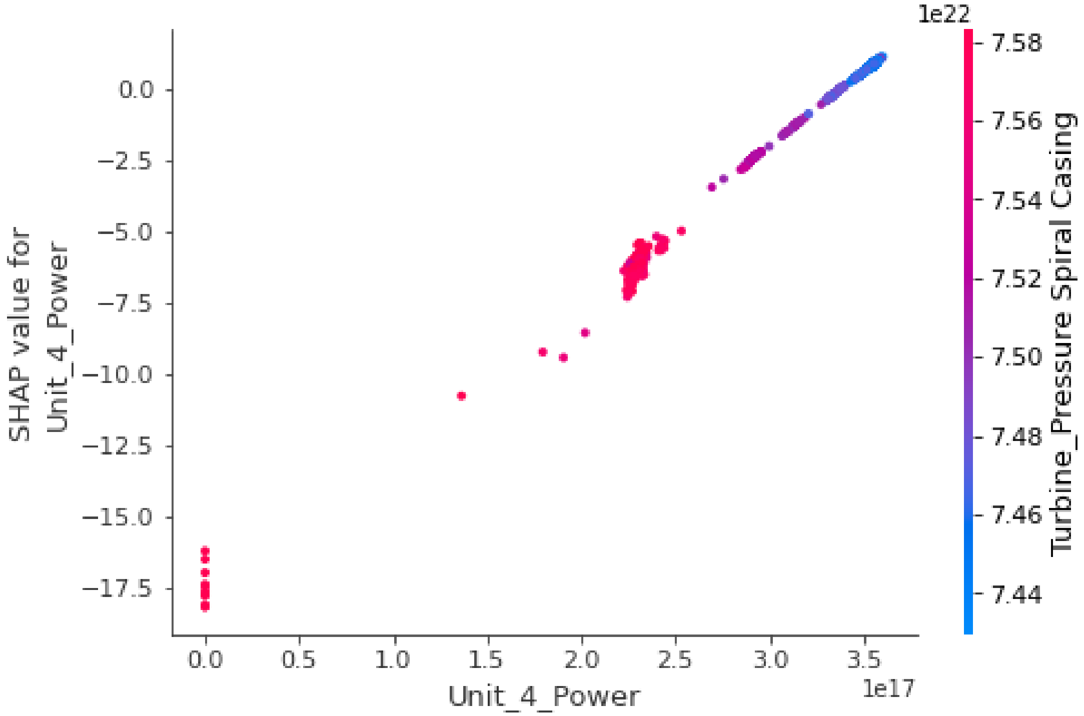




Explaining the «black box»

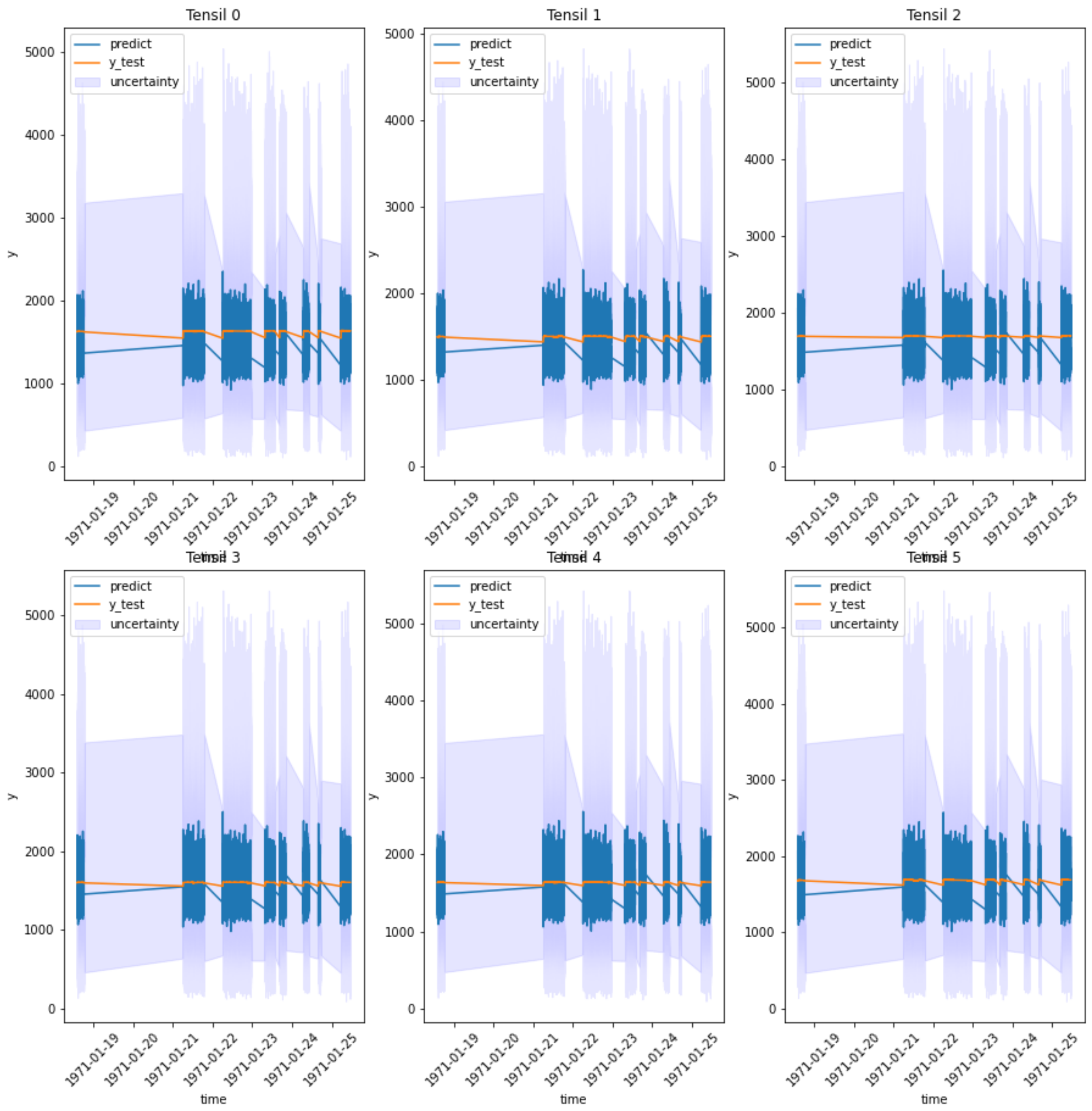
- One can use SHAPLEY values to understand what goes on in the black box
- In this case we see how probability (log-odds) for high tensile values increase with Power, and that turbine pressure reduces concurrently. Note, the units on the axes are off here (scaling error).





Uncertainty

- Here we have a bad model that hasnt trained sufficiently.
- As can be seen from the blue line the prediction behaves eratically
- The uncertainty peaks when it is eratic



Future improvements

- We wanted to create two auxiliary models in which the first one is a generative model that fits a distribution to the data. This can be done a simple fashion with a Gaussian Mixture Model or in a more advanced way with a conditional variational autoencoder. From this distribution we would sample new, “fake” data with an added noise component.

  We would now intermingle noisy, fake data that the Bayesian Neural Network had not been trained on, with a true validation set.

  Next, we would create a second model which would learn to discriminate between data that the model is familiar with (the true validation set) and the fake data, by only using the uncertainty.

  This way we would not only have uncertainties, but also get an idea of what level of uncertainty would make a model trained on Kvilldal data invalid/valid on other power plants.
- More time spent on hyperparameter tuning - this would take at least a week

Thank you!

Appendix – Business Case calculations

Base data:

Kvilldal yearly power supply: 3131,2 GWh (Statkraft)

Power consumption avg. Norwegian household: 16,079 kWh (SSB)

Persons in avg. Household: 2,13 persons (SSB)

Avg. Yearly price electric power (Oslo): 0,94 NOK/khW (Los)

Calculations:

Households covered by Kvilldal/year: 3131,2*10^6 /16 079 = 194 734,5

Persons covered by Kvillda/year: 194 734,5 * 2,13 = 414 793 (persons)

Loss of Revenue with 2 years downtime: 2 years * 0,94 NOK/kWh * 3131,2*10^6 kWh/year = 5 921,9 MNOK