

B3M38DIT1

Fault detection of sensors with machine learning using LSTM neural networks

Vít Zeman

09.01.2023

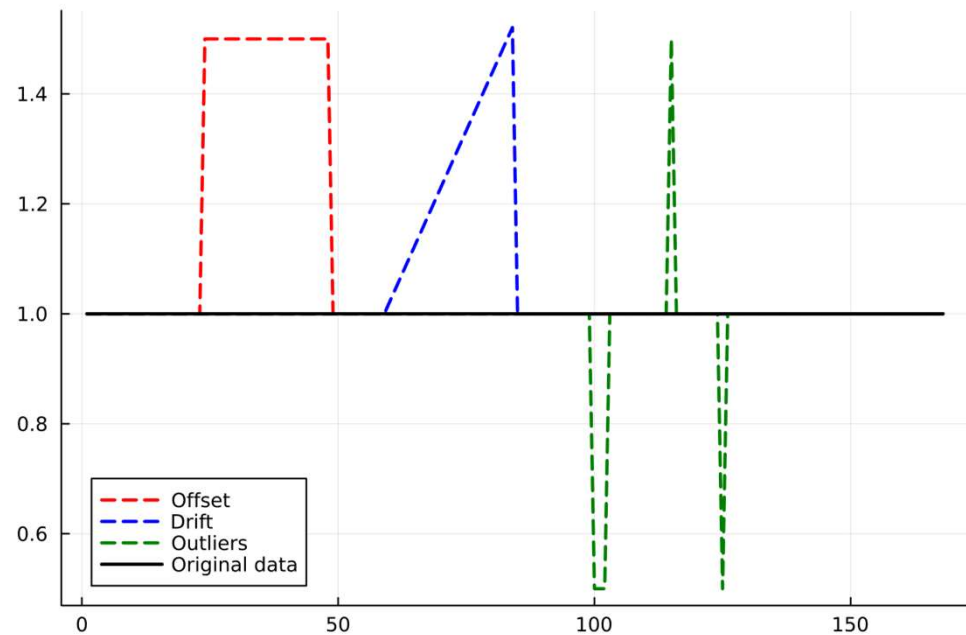
1/9

Task

- Fault detection on temperature sensor
- Long-term time series data from multiple sensors
- Using Long short-term memory (LSTM) neural network

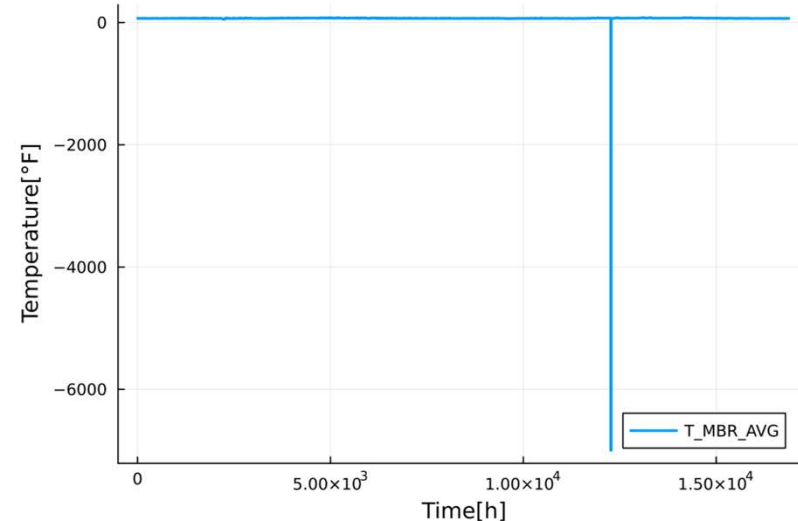
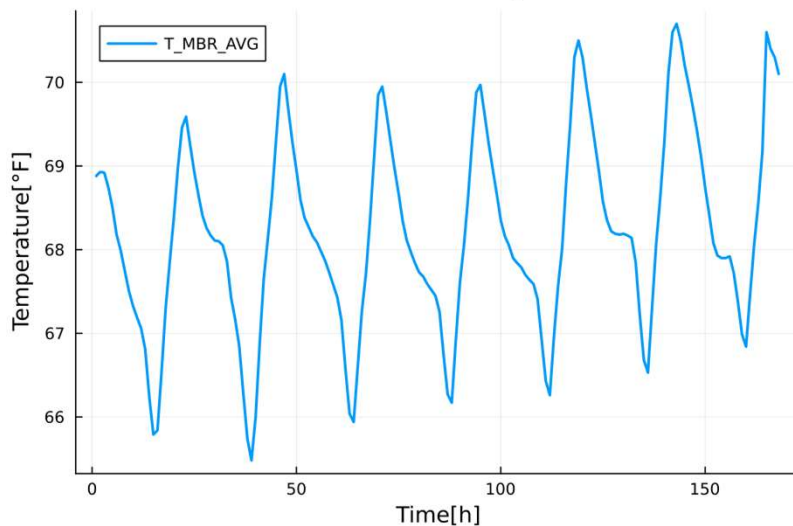
Faults

- Three types of faults:
- Drift:
 - Linear
 - $[0.75; 1.25]$ kelvins every 5 days
- Offset:
 - Shift in temperature values
 - $\pm [0.5; 5]$ Kelvin
- Outliers:
 - Sudden big jump in value
 - $\pm [10; 30]$ Kelvin from average



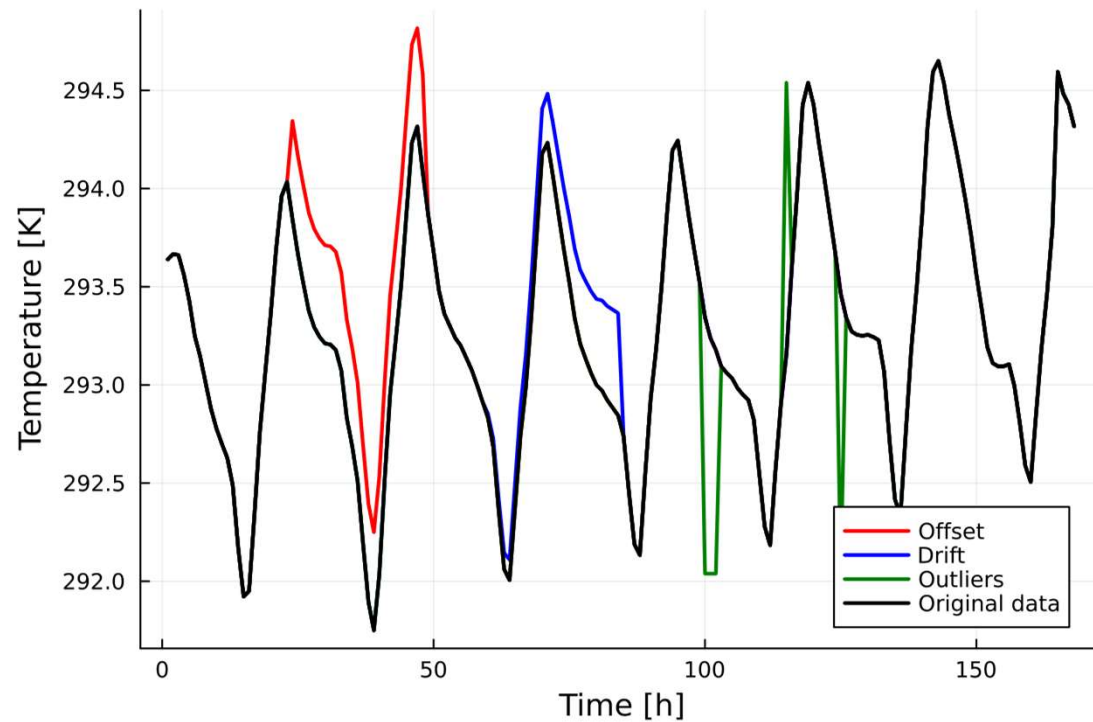
Data

- Temperature, relative humidity, energy consumption and generation
- Approx. 704 days of continuous measurements
- Average over hour
- Inconsistencies (-6999 °F, missing data)



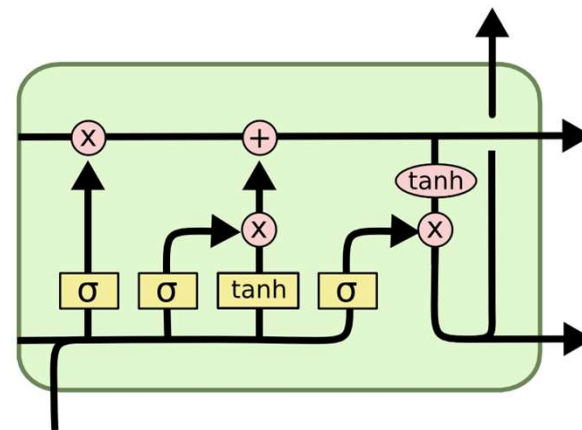
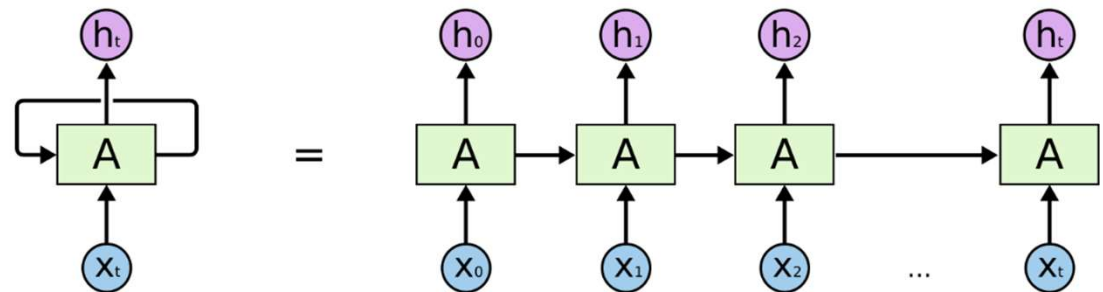
Dataset generation

- Conversion to Kelvins
- Random location and duration
- 4 classes
 - Faultless
 - Drift
 - Offset
 - Outlier
- Distribution of [0.4, 0.2, 0.2, 0.2]



RNNs and LSTMs

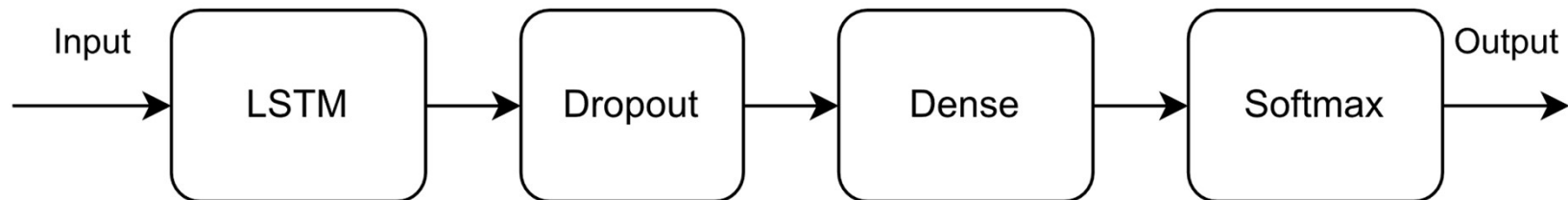
- Memory: Previous input/output impacts current case
- RNNs
 - Only short memory
 - Vanishing or exploding gradient
- LSTMs
 - Added long term memory
 - Used for classification and prediction



Images: <https://colah.github.io/posts/2015-08-Understanding-LSTMs/>

Proposed model

- Idea use LSTM to extract features
- Use Dense layers to classify outputs



- Metrics
 - Accuracy
 - Confusion matrix

Results

- Accuracy 64%

| Ground truth | Faultless | 1315 | 498 | 147 | 118 |
|--------------|-----------|-----------|-------|--------|---------|
| | Drift | 132 | 703 | 195 | 187 |
| | Offset | 73 | 27 | 281 | 32 |
| | Outlier | 53 | 95 | 95 | 657 |
| | | Faultless | Drift | Offset | Outlier |
| Predicted | | | | | |

References

- [1] S. Hochreiter and J. Schmidhuber. Long short-term memory. *Neural computation*, 9:1735–80, 12 1997.
- [2] R. C. Staudemeyer and E. R. Morris. Understanding lstm-a tutorial into long short-term memory recurrent neural networks. 2019.