# Hot Ear - A Machine Hearing Application

Degree programme : MAS | Specialisation : MAS Data Science

The aim of this work is to provide intelligence to a small IoT device that literally listens to a central oil heating system of a building, gets used to its sound and develops the ability to recognise if the heating device works fine or not. The system detects early signs of disfunction, like increasing flame ignition retries, or heater shutdowns. And it alerts for human intervention to restart, or for triggering preventive maintenance.

## Context
Oil heating devices are autonomously running systems, installed in dedicated rooms, and operate during weeks or months without human intervention. They are an ideal use case for supervision based on audible signal analysis. The installation of such supervision system shall be a no-brainer: no sensor, no cabling, no compatibility issues with the heating device. Ideal for monitoring legacy heating devices.

## Strategy
The supervision system records audible sound continuously via an integrated microphone. With the help of machine learning algorithms it shall self-learn the habits of the heating device, being smart enough to interpret the audio signal, and deducing the following:
- **heater operation characteristics** (cycle timings, cycle statistics, relative heating power)
- **heater sanity** (fire ignition retry trend and statistics, heater shutdowns)
- **anomalies** (strange device sounds, unexpected human visits or interventions)

## Analysis
The audio processing works in repeated time-windows of one second duration each. The main features extracted are the magnitude of the frequency spectrum and for some tasks the average audio volume. The task of **heater state recognition** must identify whether the heating device is in one of its states: off, warmup or on. This is repeated on each second. Having this information in an accurate way, allows to derive most of the required results. Several approaches have been explored:
- classification (k-nearest neighbour, convolutional neural network)
- pre-trained clustering (k-means, gaussian mixture)
- self-learning, clustering, sliding window based model, collected during runtime

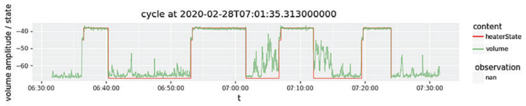


**Figure 1: Heater state recognition: Audio volume time series input superposed with (vertically adjusted) heater state**

The models have been trained and tested based on a data set of independent one-second audio clips. In addition, long-duration tests in a real environment allowed to perform time-series-based metrics.

**Anomaly detection** has been explored with different approaches of using neural network auto- encoders:
- frequency spectrum as input
- audio volume time series as input

Anomaly detection task is more challenging, and the results are mitigated. In answer to this, anomaly information can be used in an unsharp smoothed way, just to give a hint of confidence level for the parallel running heater state recognition.

## Conclusion
The best performance for heater state recognition was reached with the gaussian mixture based self- learner, in a sliding window based model with data samples collected stochastically during runtime. Accuracy around 99.9% could be achieved. This architecture has also proven to work on foreign and never seen before heating devices, validated during field tests. Thousands of heater cycles have been interpreted correctly.

Anomaly detection is not yet there, but the potential to integrate it in a self-learning process is given. It must be ensured, that this learns slowly enough, to avoid adapting to anomalies and interpret them as "normal".

Generally there is a huge potential to use this concepts cost-effectively for a large palette of different supervision applications, on machines and plants, in the domain of automation, industry, transportation and home.

Olivier Gäumann
078 741 92 85
olivier.gaeumann@gmx.ch