Assignment 2 CDA

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1 Familiarization with the data

The dataset contains a total of 44 signals, with some being static values, other being sinusoid signals, and others being partially discrete (as in, they can rise or drop at certain points). L-signals tend to be more sinusoidal, F-signals tend to be "partially discrete", and S-signals are all binary signals.

All the signals together seem to have little correlation. Some combinations of signals are reasonably correlated: e.g. L_T3 and P_J302 have a 0.42 correlation coefficient. Moreover, the signal P_J302 in figure 1 looks cyclic. A cyclic signal like this is much easier to predict than a 'random' signal, since there is a rough base model that it adheres to. This signal's values are within a clear band at about 2-6 on the Y-axis. In such a case it is very easy to come up with a basic anomaly detection technique: if the signal moves outside this band this would be a clear sign of an anomaly. Plotting the mean error we saw for the ARMA prediction on signal L_T1, we saw that there were only 2 cases were the error was greater than three times the standard deviation.

Figure 1: Visualization of some signals. The red and greens signals are partially discrete.

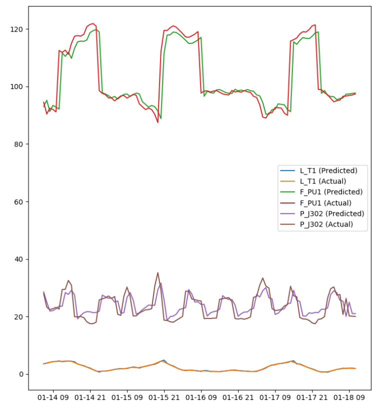

Figure 2: ARMA predictions on some signals. The predictions work better on signals.with less variance

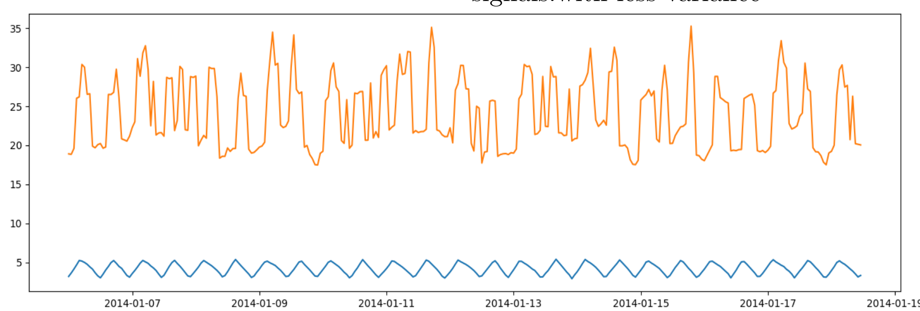

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Figure 3: Signals L_T3 and P_J302. The peaks are roughly aligned.

2 ARMA

The script `ARMA.py` learns a ARMA model for any particular sensor. The parameters for the model are determined by testing out different p's and q's and then looking at the AIC value of the fitted model. A lower AIC means a better fit.

3 Discrete models

4 PCA

5 Comparison