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Repositories

All source code, as well as the powertrain anomaly time series benchmark (PATH) dataset, are published under the MIT license. The source code can be found in GitHub repository under `github.com/lcs-crr/Thesis`. The PATH dataset in its various forms can be found in the Zenodo repository under `zenodo.org/records/13255120`.

List of Abbreviations

BiLSTM	bidirectional long short-term memory
DQS	dissimilarity-based query strategy
DTW	dynamic time warping
ELBO	evidence lower bound
EM	electric motor
FEV	full electric vehicle
FS	feedback strategy
GAN	generative adversarial network
GRU	gated recurrent unit
GutenTAG	good time series anomaly generator
HVB	high-voltage battery
LSTM	long short-term memory
LW-VAE	lightweight LSTM-VAE
MA	multi-head attention
MP	matrix profile
MS	multi-head self-attention
MSE	mean-squared error
MSL	Mars Science Laboratory
OA	OmniAnomaly
PATH	powertrain anomaly time series benchmark
PdM	predictive maintenance
PM	preventative maintenance
QS	query strategy
RNN	recurrent reural retworks
RQS	random-based query strategy

RTF	run to failure
RWM	reverse-window method
SISVAE	smoothness-inducing sequential VAE
SMAP	soil moisture active passive
SMD	server machine dataset
SoC	state of charge
SWaT	secure water treatment
TCN-AE	temporal convolutional autoencoder
TeVAE	temporal VAE
TQS	top-based query strategy
TSADIS	time series anomaly detection through incremental search
UQS	uncertainty-based query strategy
VAE	variational autoencoder
VASP	VAE-based selective prediction
VS	variational self-attention
VS-VAE	variational self-attention VAE
WADI	water distribution