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DIII-D
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Machine learning models for real-time inference of plasma dynamics using BES signals

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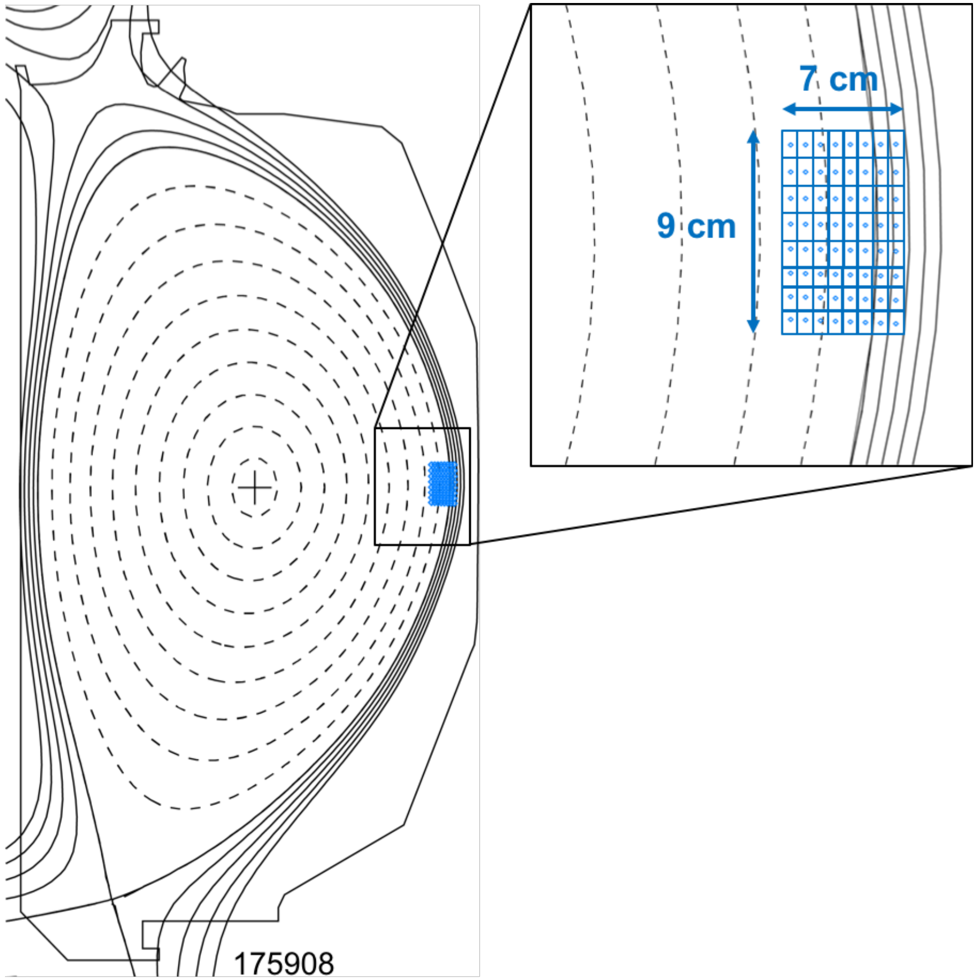
Real-time analysis and control with the high-bandwidth BES data stream

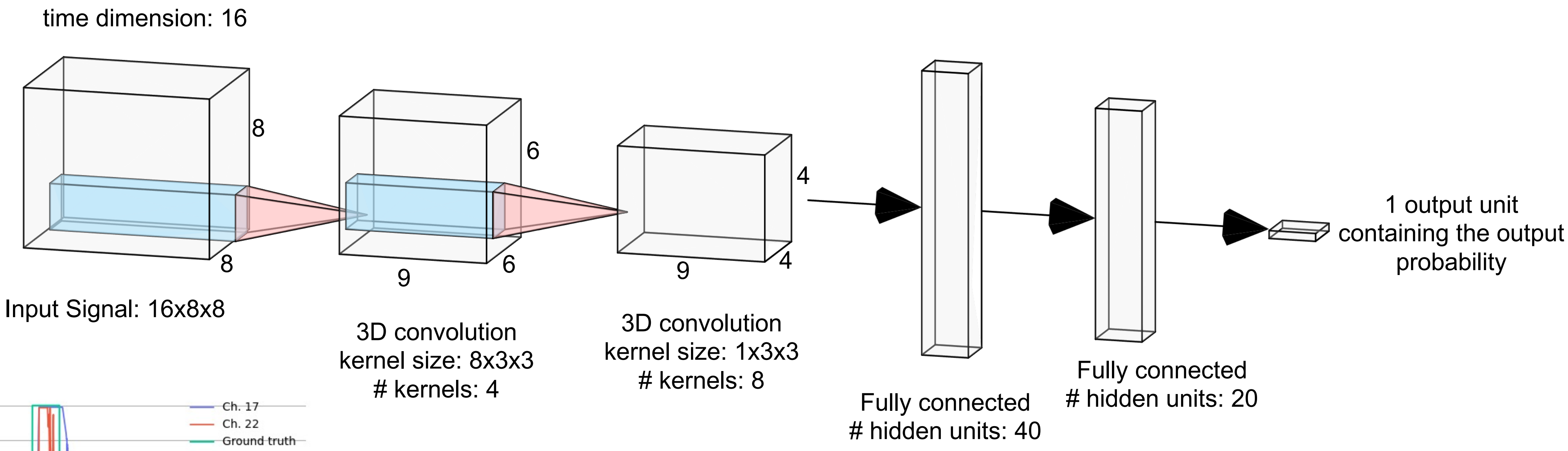
- 2D BES contains 8x8 grid of 64 channels
- BES captures ion-scale turbulence and instabilities at μs-scale time resolution
- Edge localized modes are the periodic bursts of the plasma resulting from growing density and temperature gradients
- Real-time prediction of ELM onset from BES data stream
- Real-time turbulence classifier that will identify the confinement states
  - L-mode, H-mode, and enhanced confinement regimes like the wide-pedestal quiescent H-mode
- Outputs for real-time prediction and classification tasks derived from the high-bandwidth BES data stream provide a new class of signals for downstream control systems

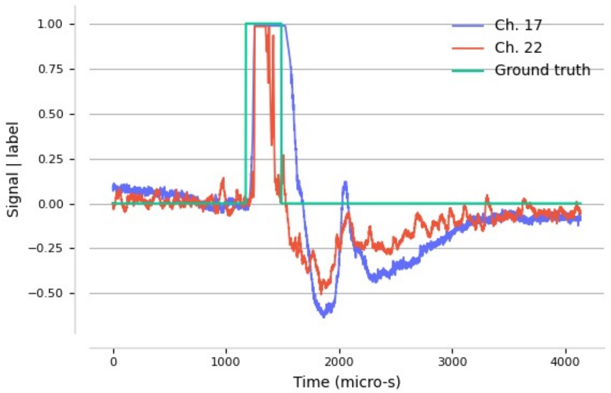
2D BES at DIII-D



Example CNN architecture for ELM onset prediction

Convolutional Neural Network with 3D convolutions

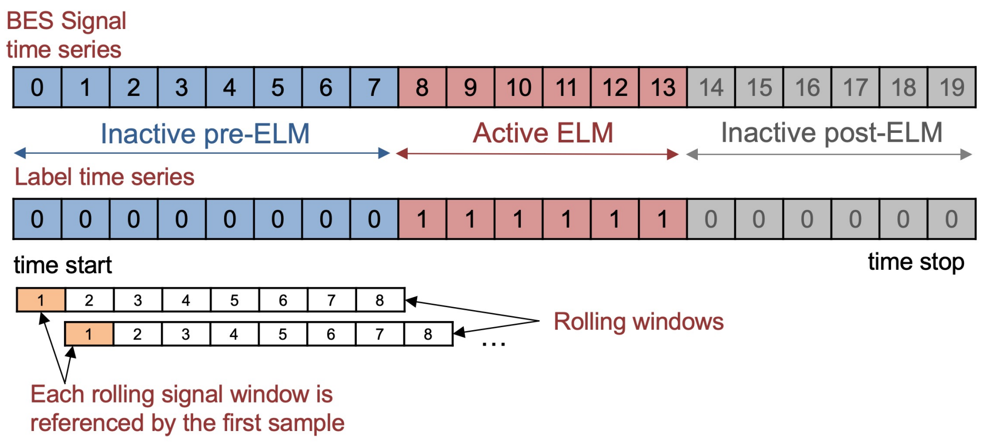


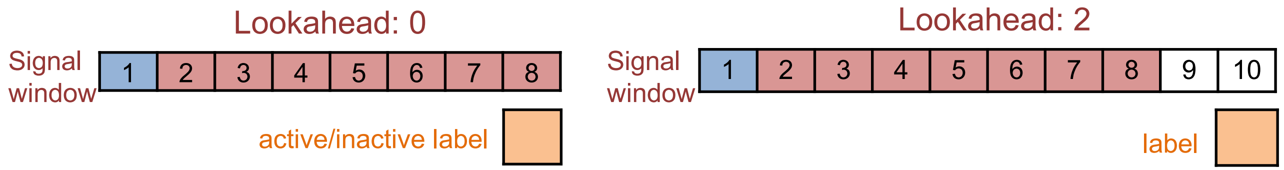


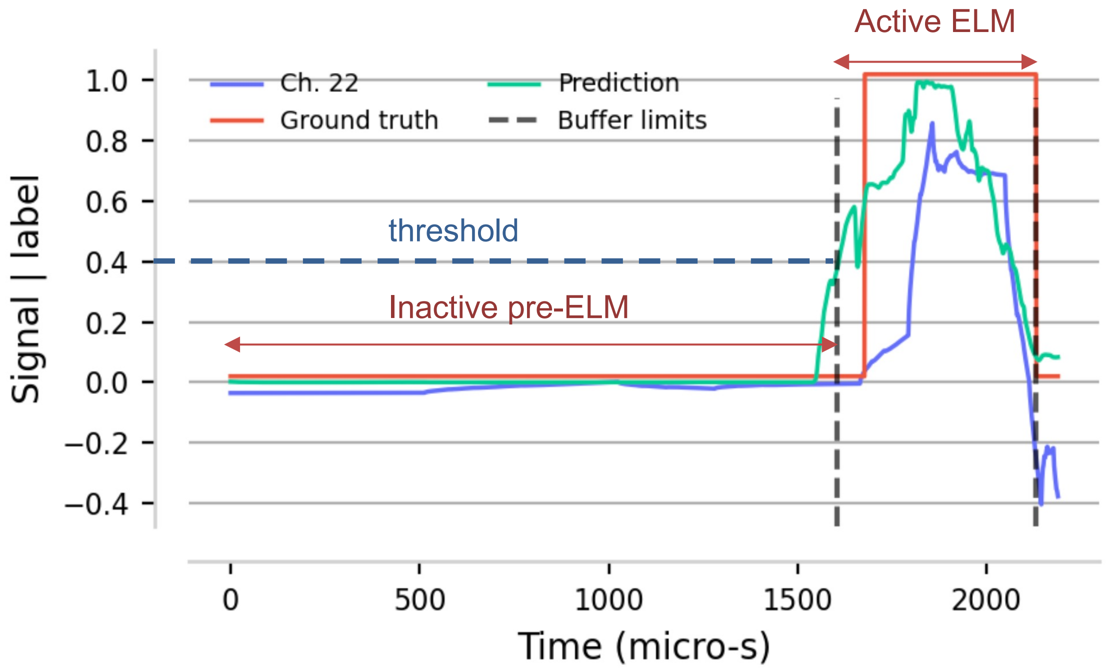
http://alexlenail.me/NN-SVG/AlexNet.html

Model captures inactive pre-ELM and active ELM phases

- Model looks at 8-128 micro-s windows of data and predicts active/inactive ELM up to about 200 or 300 micro-s (lookahead) in the future
- Model performance is assessed in two different ways:
  - Micro predictions – metrics calculated for each point in the time series
  - Macro predictions – metrics aggregated over the regions of inactive pre-ELM and active ELM
- Performance metrics are calculated for both micro and macro predictions
- Repeat these analysis steps for different values of label lookaheads



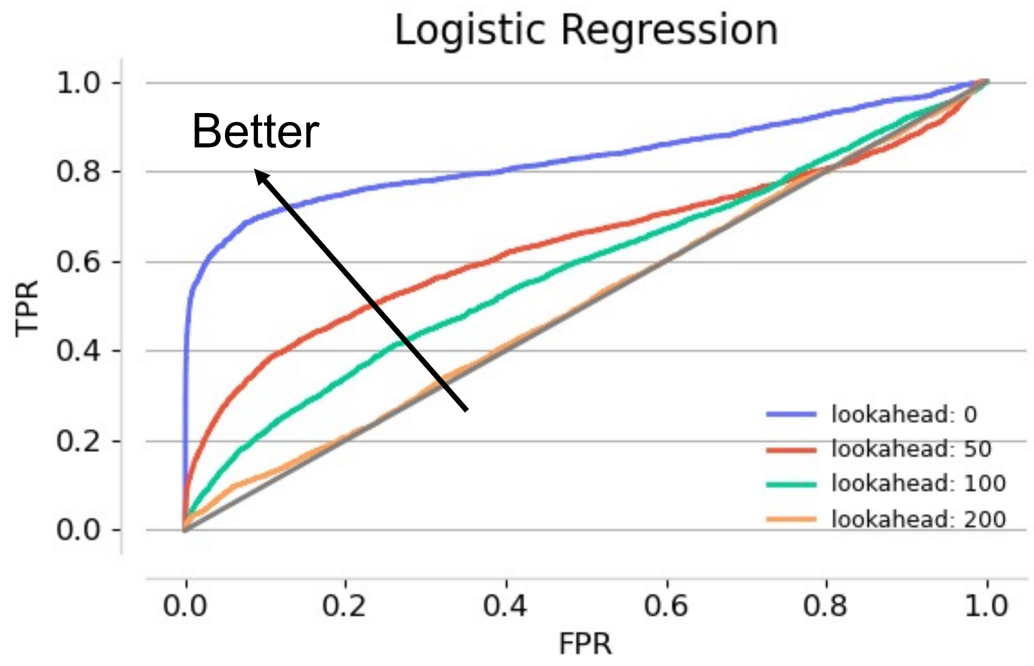


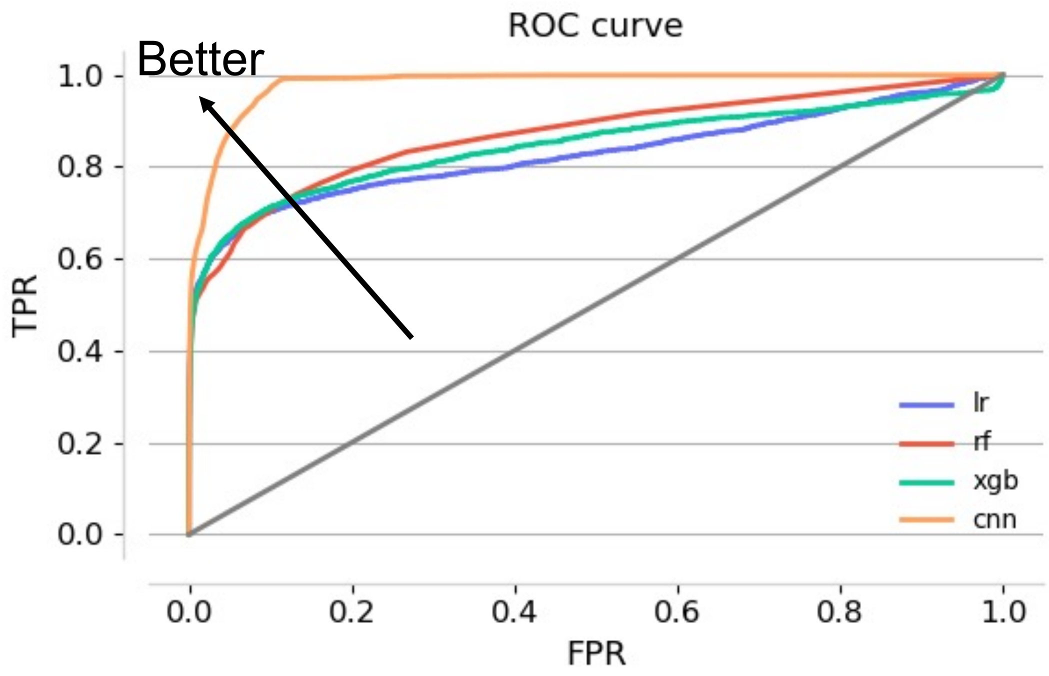


Correct prediction of ELM onset has prediction below a certain threshold for entire time in the inactive pre-ELM region and at least one prediction above the threshold in the active ELM region

Deep neural networks outperform regression and classical ML models

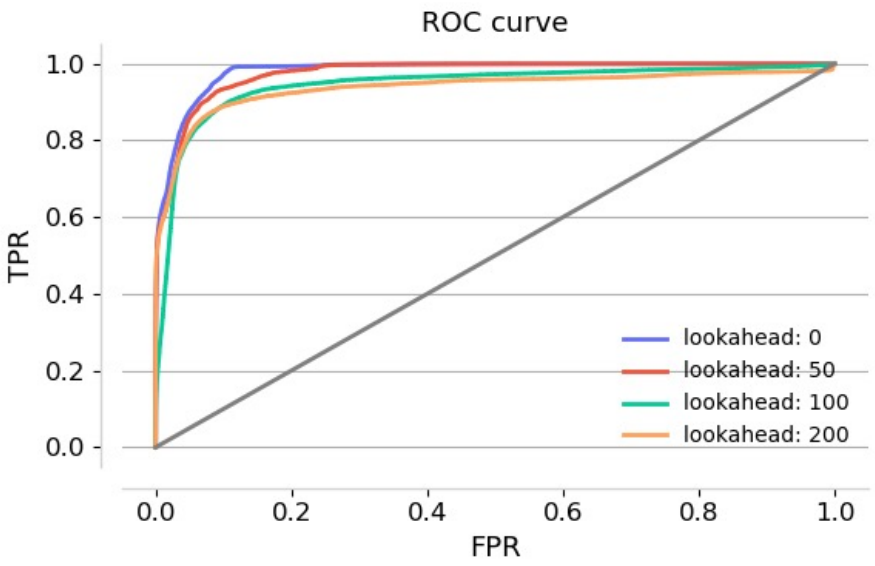
Baseline performance

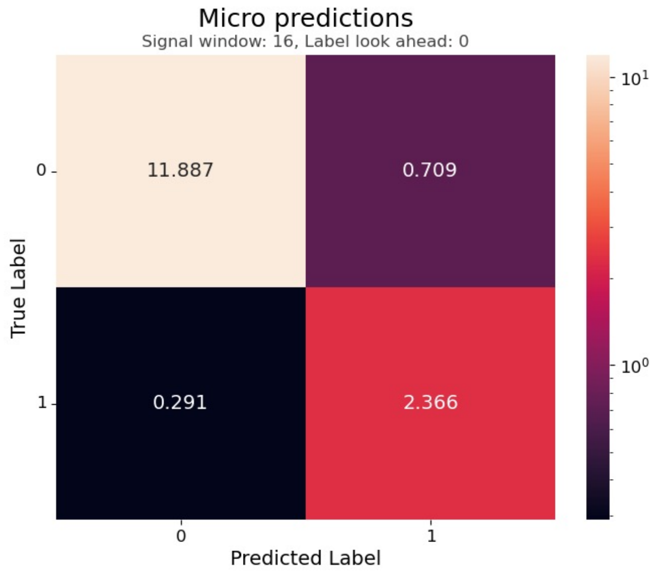


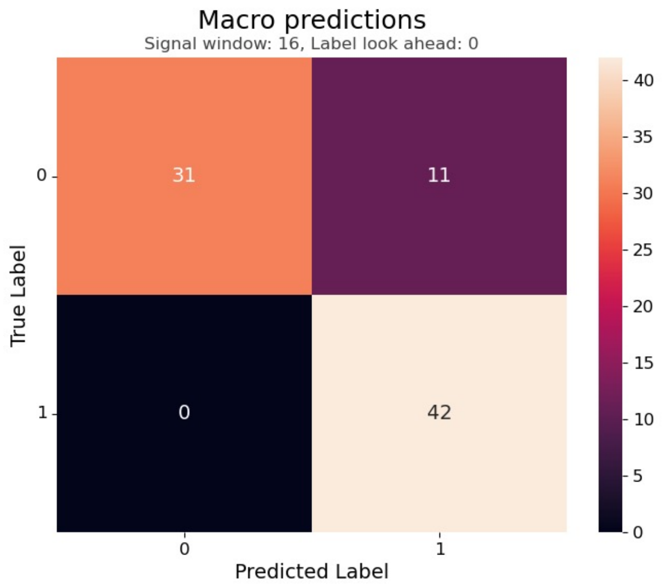


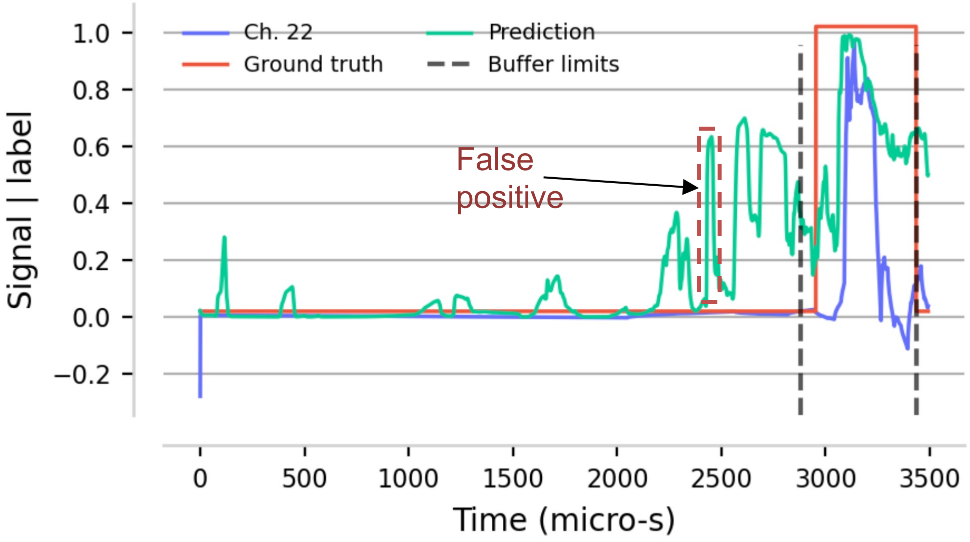
Deep neural networks outperform regression and classical ML models (contd.)

- As compared to the baseline ROC-AUC score of 0.82, convolutional neural networks scored about 0.94 for a lookahead of 0 μs
- Micro predictions show significantly more false positives as compared to false negatives
- Macro predictions have zero false negatives



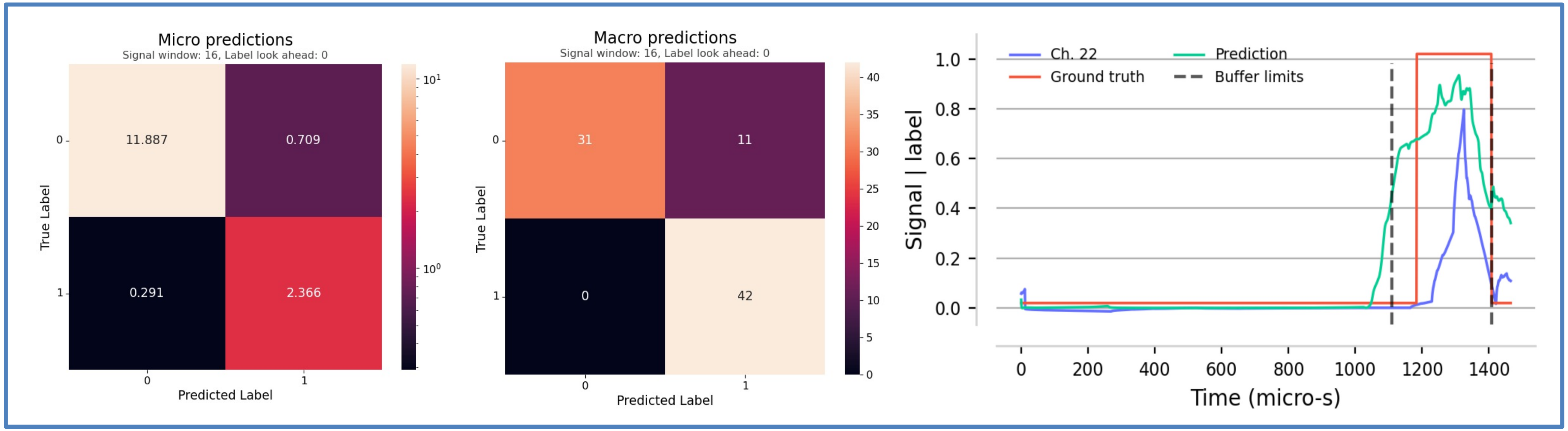




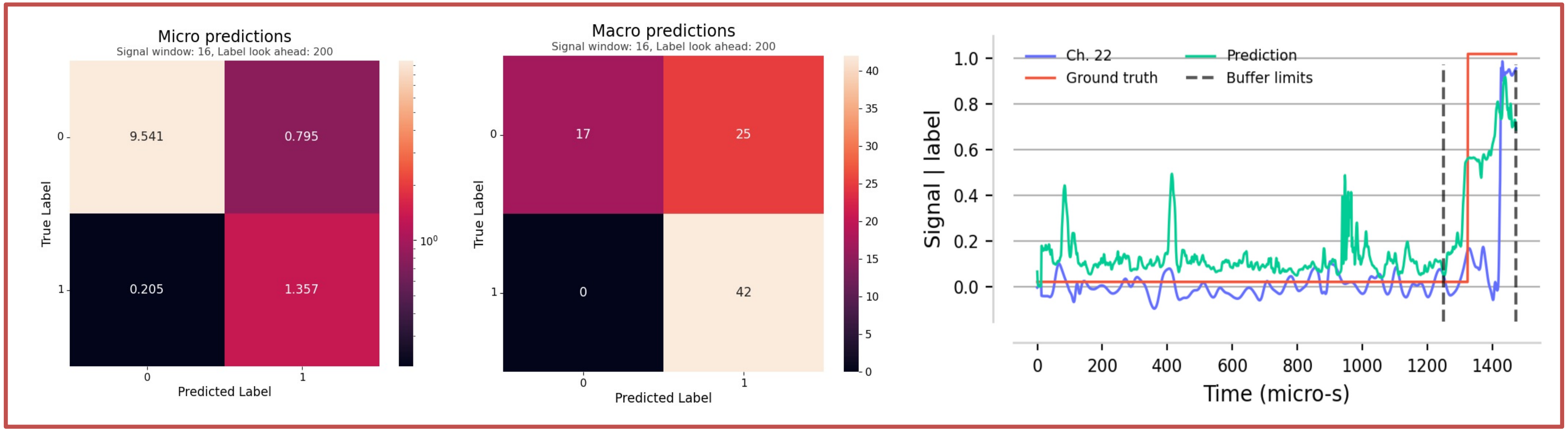


Model performance comparison for different label lookaheads

Lookahead: 0 µs

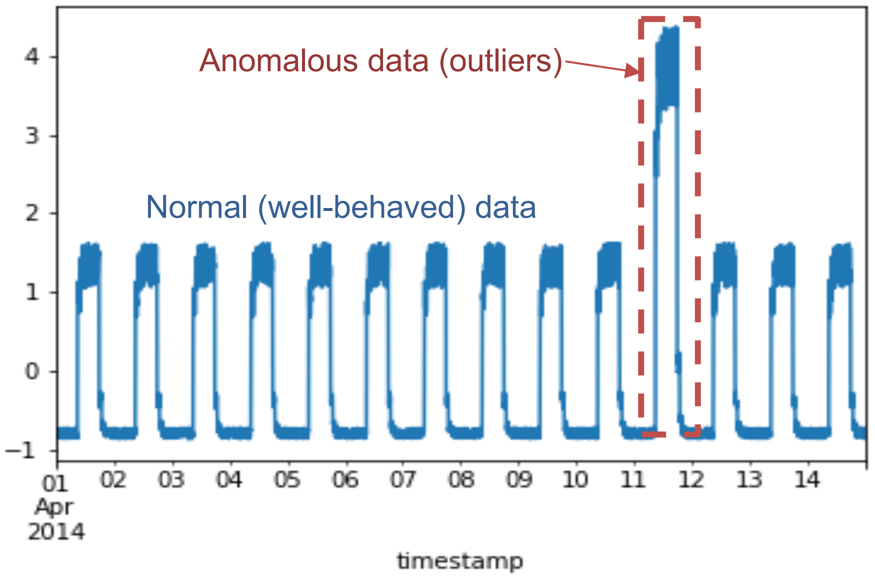


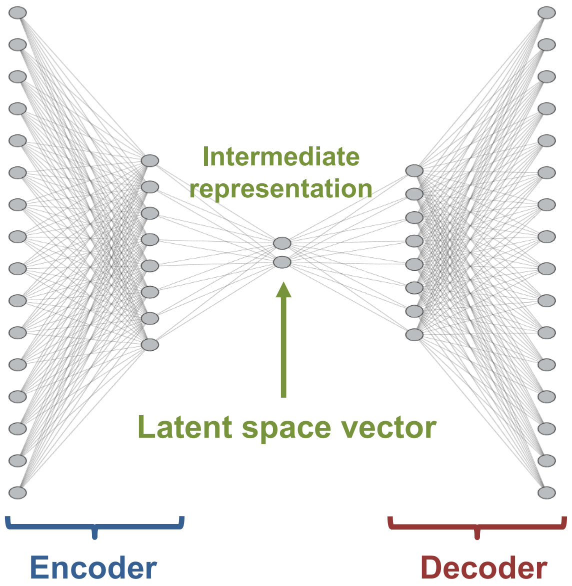
Lookahead: 200 µs



Treating ELM onset prediction as time series anomaly detection

- Another approach to predict ELM onset and task of classifying ELM and no-ELM
- Takes advantage of huge class imbalance (lot more no-ELM events than active ELM)
- Train an autoencoder neural network on majority class and treat minority class as outliers
- Compress the input to a low-dimensional "latent space" and reconstruct the output from these latent space features
- Low reconstruction error on the majority class and high reconstruction error on anomalies (majority class)
- Set a threshold to classify a given training example as an anomaly based on the reconstruction error

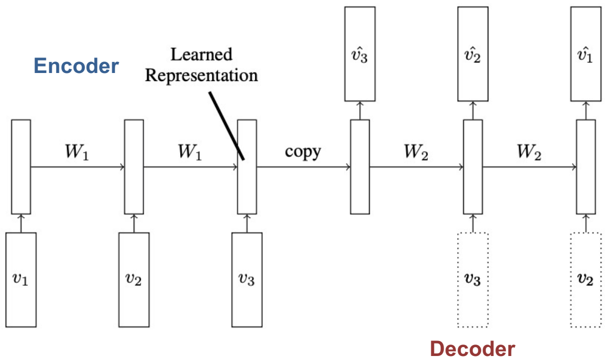


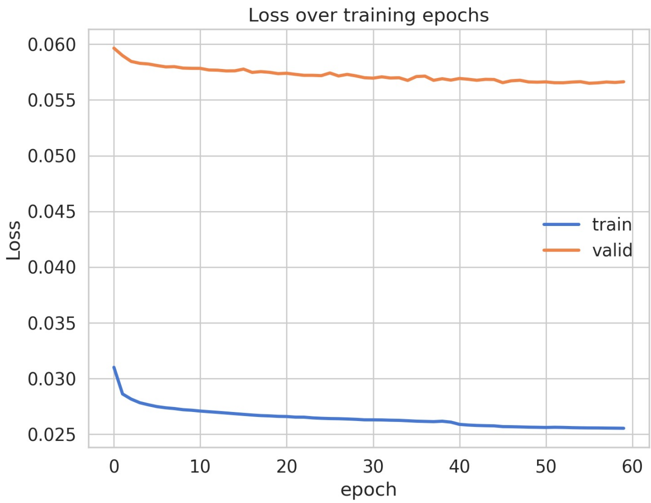


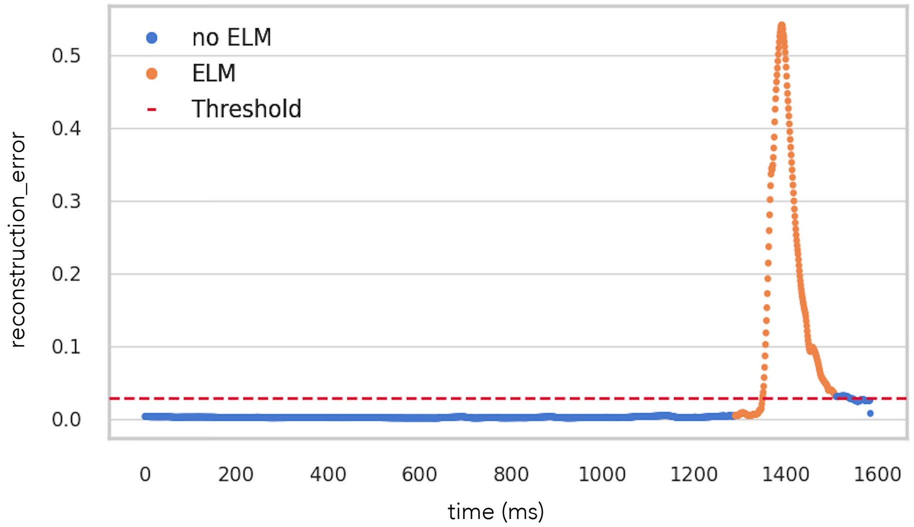
https://www.tensorflow.org/tutorials/generative/autoencoder

LSTM Autoencoders work better with time-series data

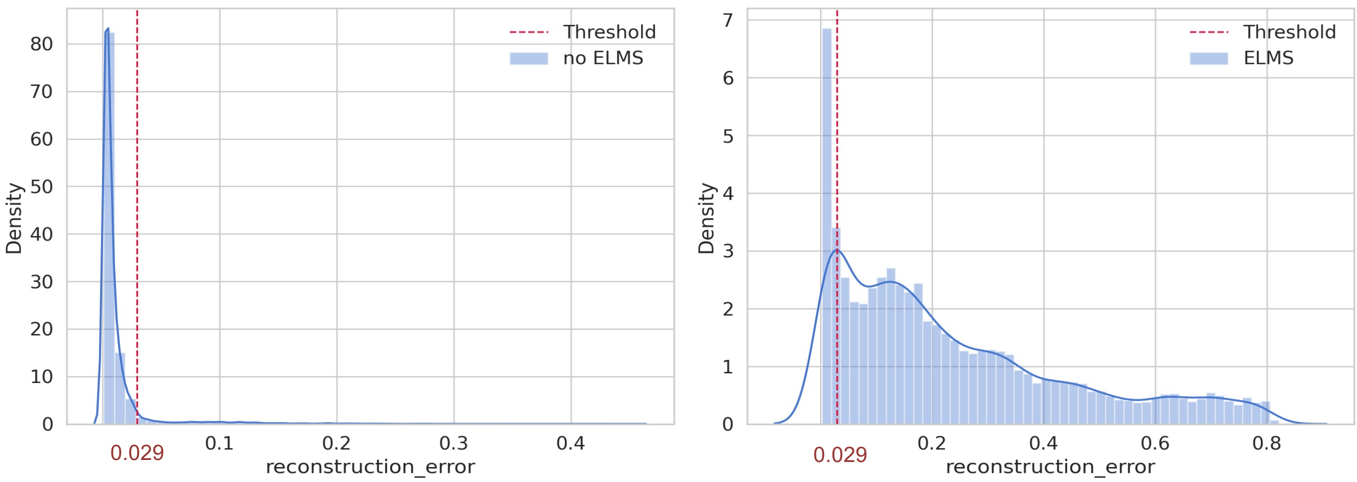
- Implementation of the autoencoders for time-series data using LSTM neural networks as encoder and decoder
- Extract features (learned representation) from the sequenced data while retaining the time ordering of the input sequence
- Learned representation can be used for other supervised learning approaches like multiple classification tasks







Comparison of reconstruction Error



Summary and outlook

- Initial deep learning models can predict ELM onset as far ahead as 200 μs using BES data windows as small as 16 μs
  - Exploring strategies to extend the prediction horizon to a few ms
- Develop models for the real-time identification of the confinement state
  - L-mode, H-mode, QH-mode, wide pedestal QH-mode
- Ideally, we would like the ELM onset and confinement tasks to utilize the same feature space to facilitate concurrent execution/inference