Deep Learning for Plasma Tomography and Disruption Prediction

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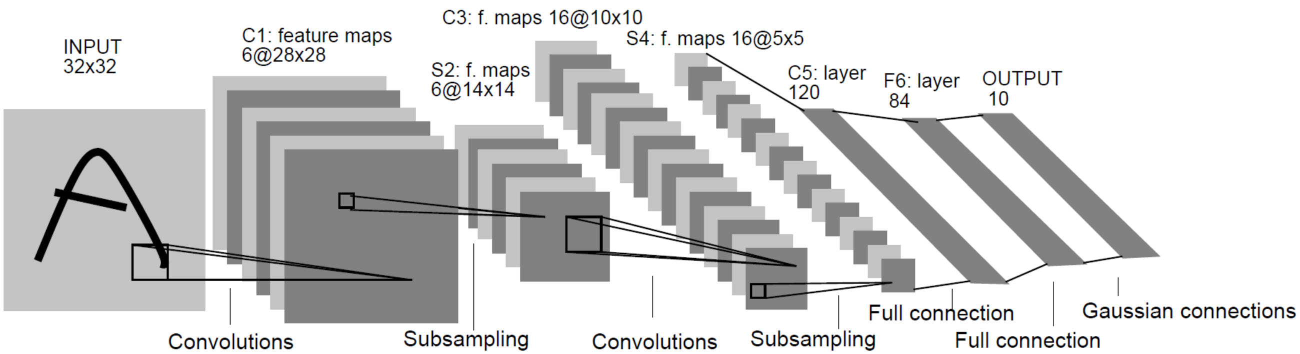
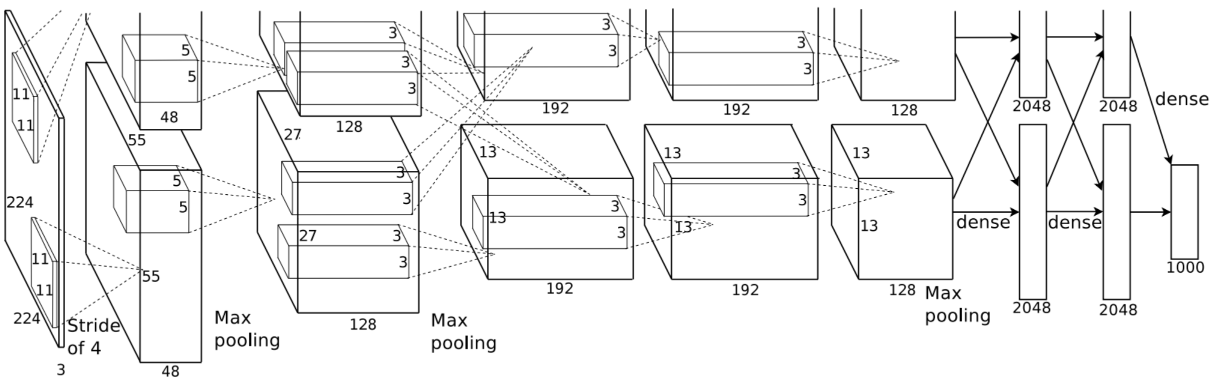
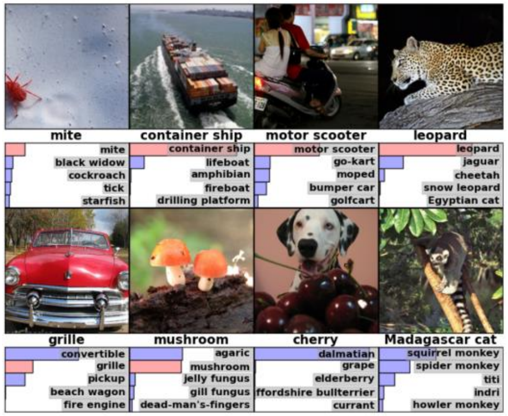
Deep Learning

- Convolutional Neural Networks (CNNs)



Y. Lecun et al., *Gradient-based learning applied to document recognition*, Proc. IEEE, 1998



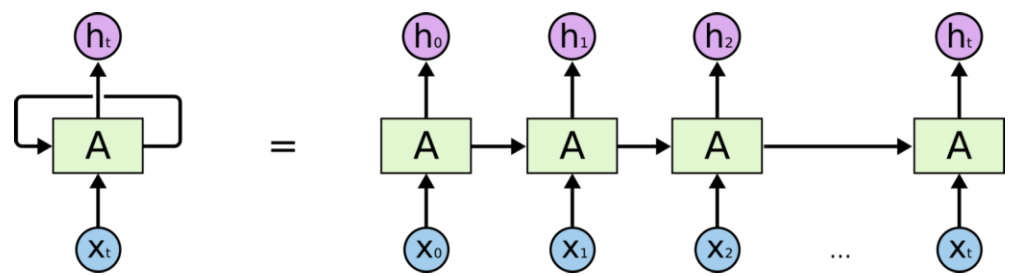


A. Krizhevsky et al., *ImageNet Classification with Deep Convolutional Neural Networks*, NIPS 2012

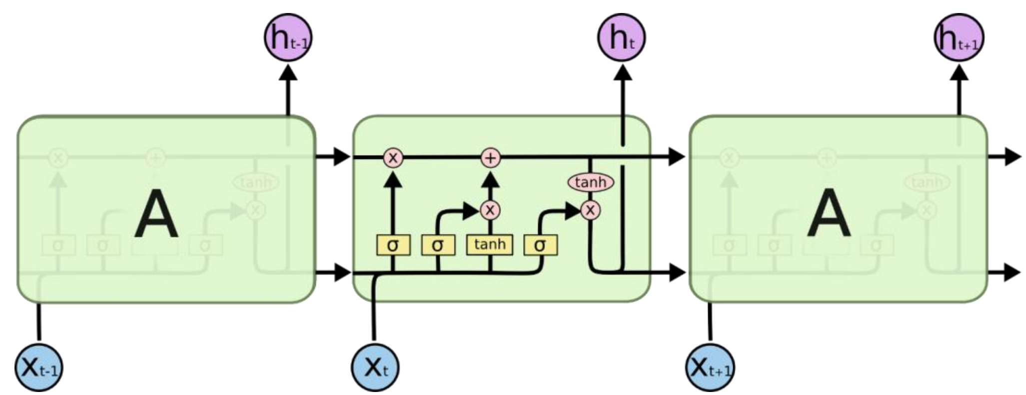
Deep Learning

- Recurrent Neural Networks (RNNs)
  - speech recognition
  - language modeling
  - machine translation
  - time series
  - …

Simple RNN



LSTM
(Long short-term memory)



C. Olah, *Understanding LSTM Networks*, 2015

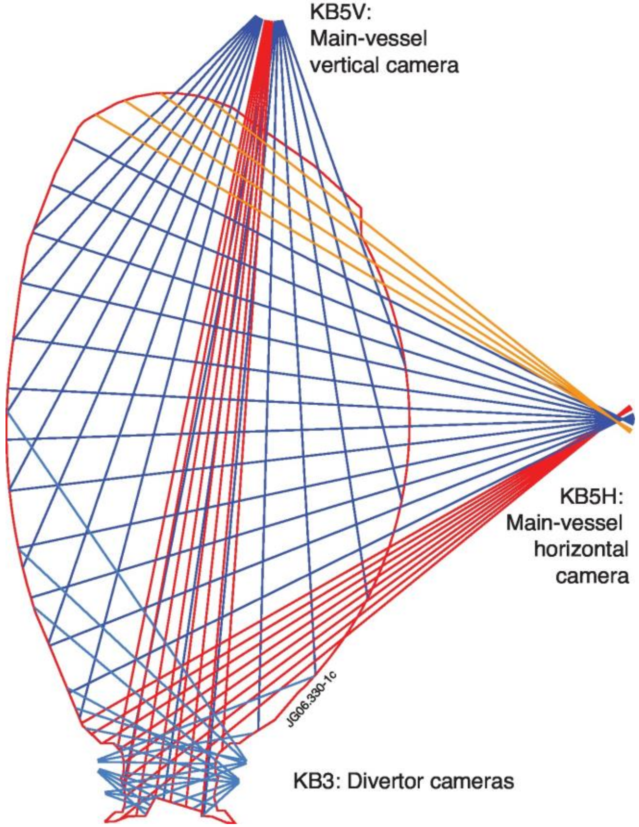
Deep Learning

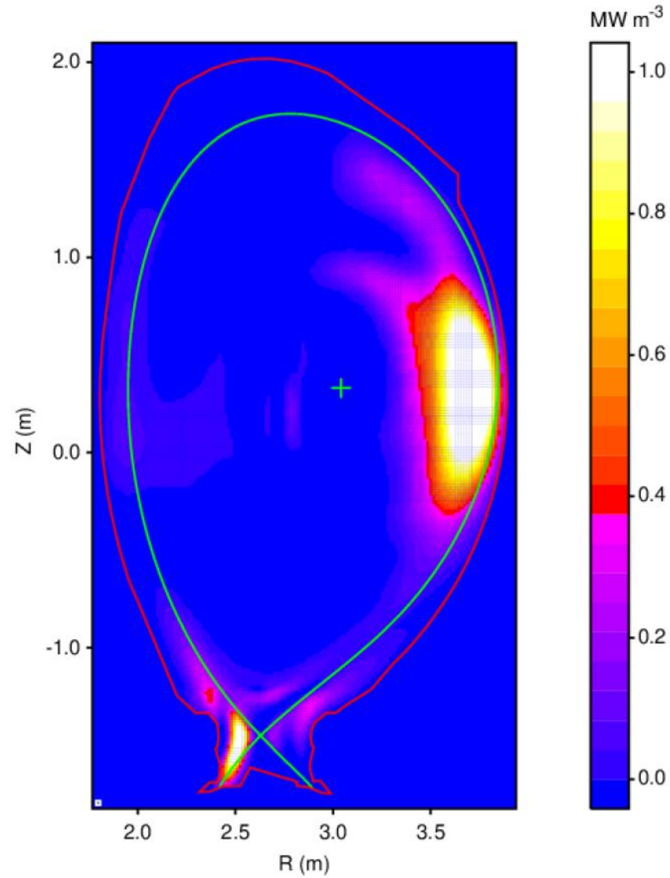
- Convolutional Neural Networks (CNNs)
  - image processing
    - e.g. plasma tomography

- Recurrent Neural Networks (RNNs)
  - time series analysis
    - e.g. disruption prediction

Plasma Tomography

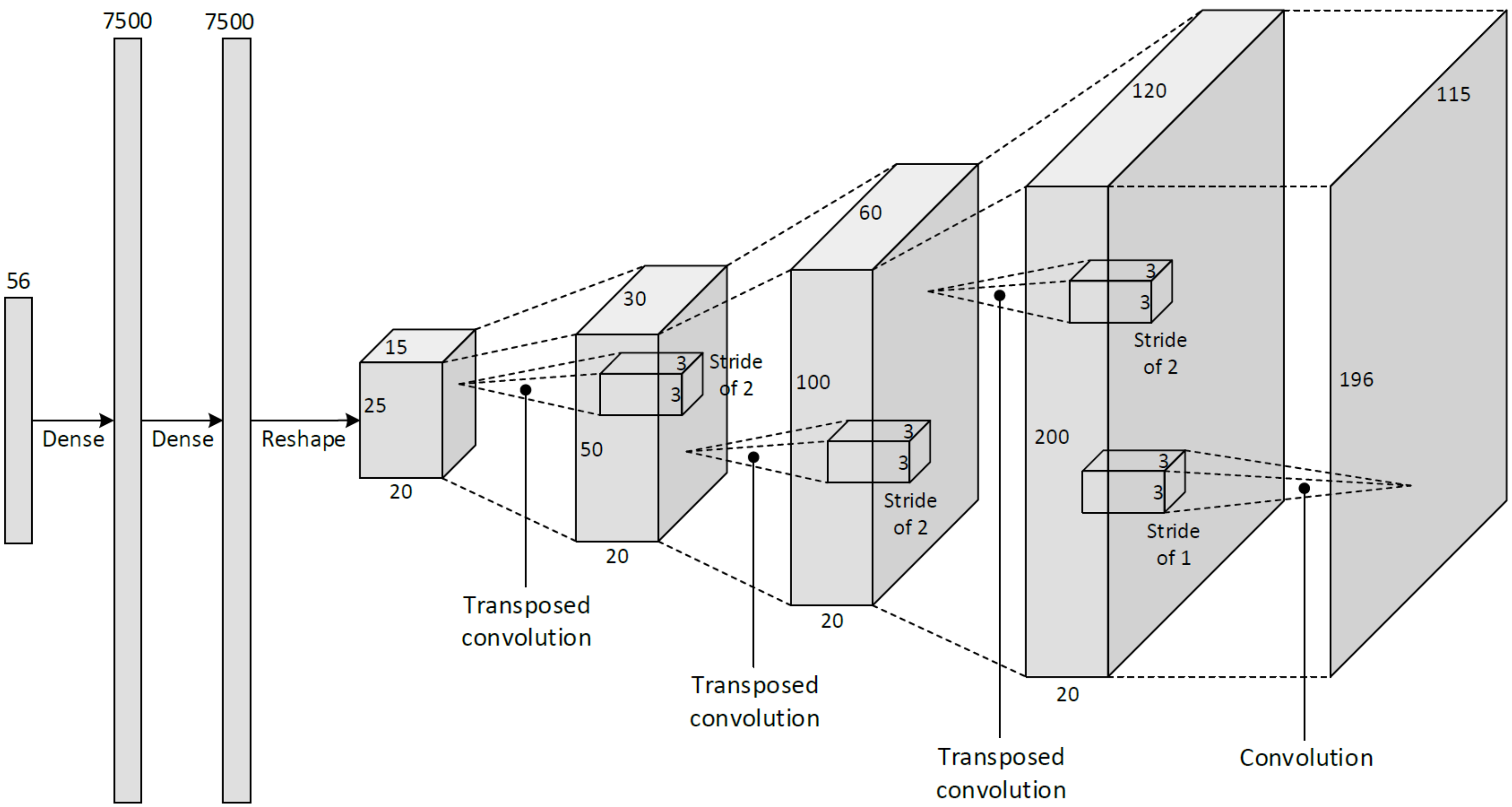
- Reconstruction of the 2D plasma radiation profile





Plasma Tomography

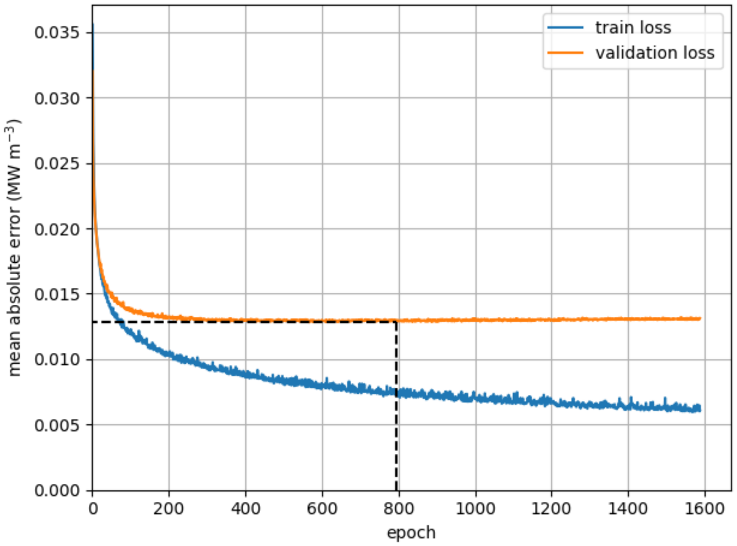
- “Deconvolutional” neural network



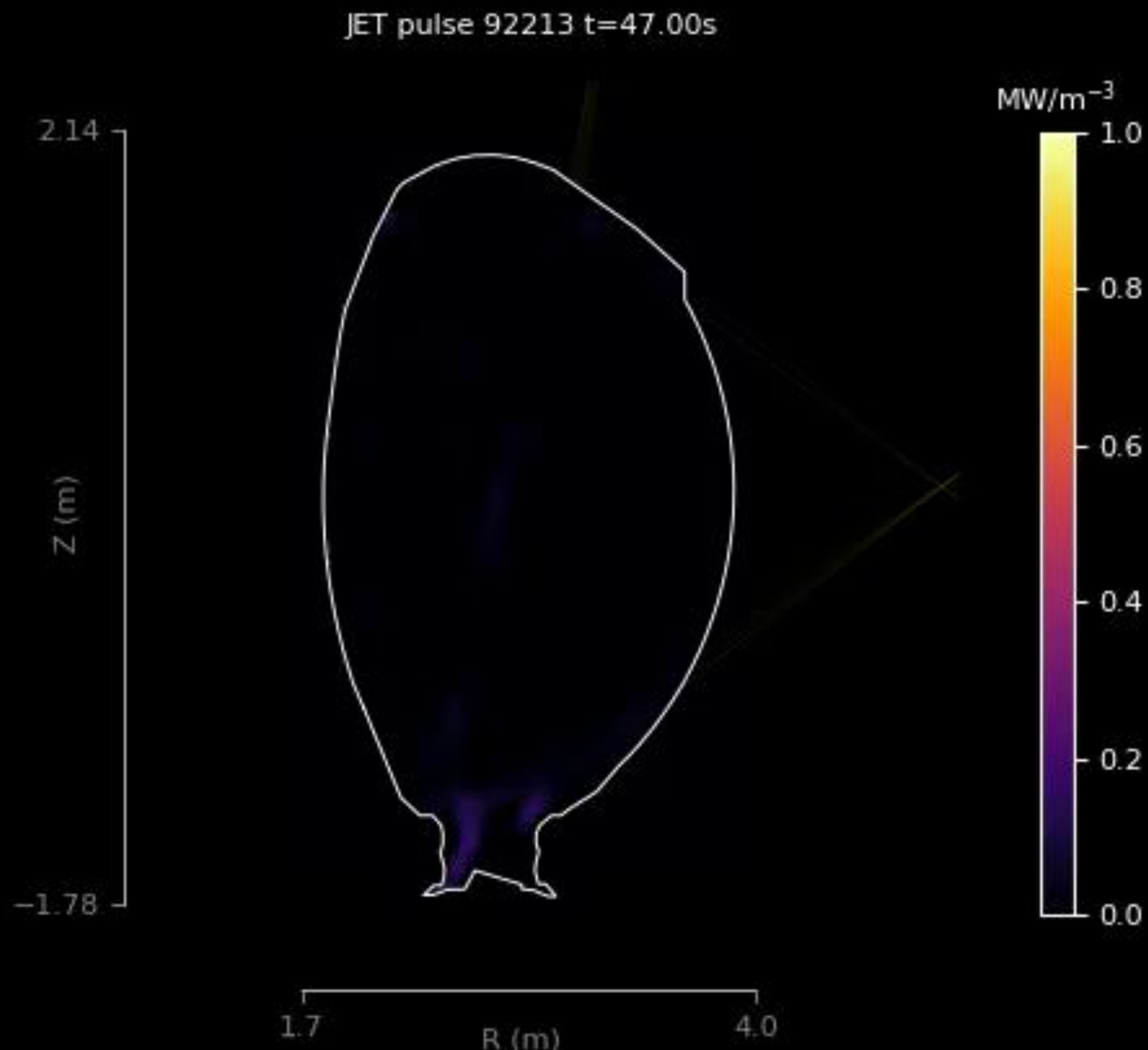
D. R. Ferreira et al., *Full-pulse Tomographic Reconstruction with Deep Neural Networks,* Fusion Sci. Technol., 2018

Plasma Tomography

- Dataset
  - JET ILW pulses 80128–92504
  - ~28K sample reconstructions
  - 80% training, 10% validation, 10% test
- Training
  - loss function: mean absolute error
  - min. validation loss: 0.0128 MW m^{-3}
- Test set
  - loss: 0.0147 MW m^{-3}
  - SSIM: 0.936 ± 0.061
  - PSNR: 35.4 ± 7.2 dB



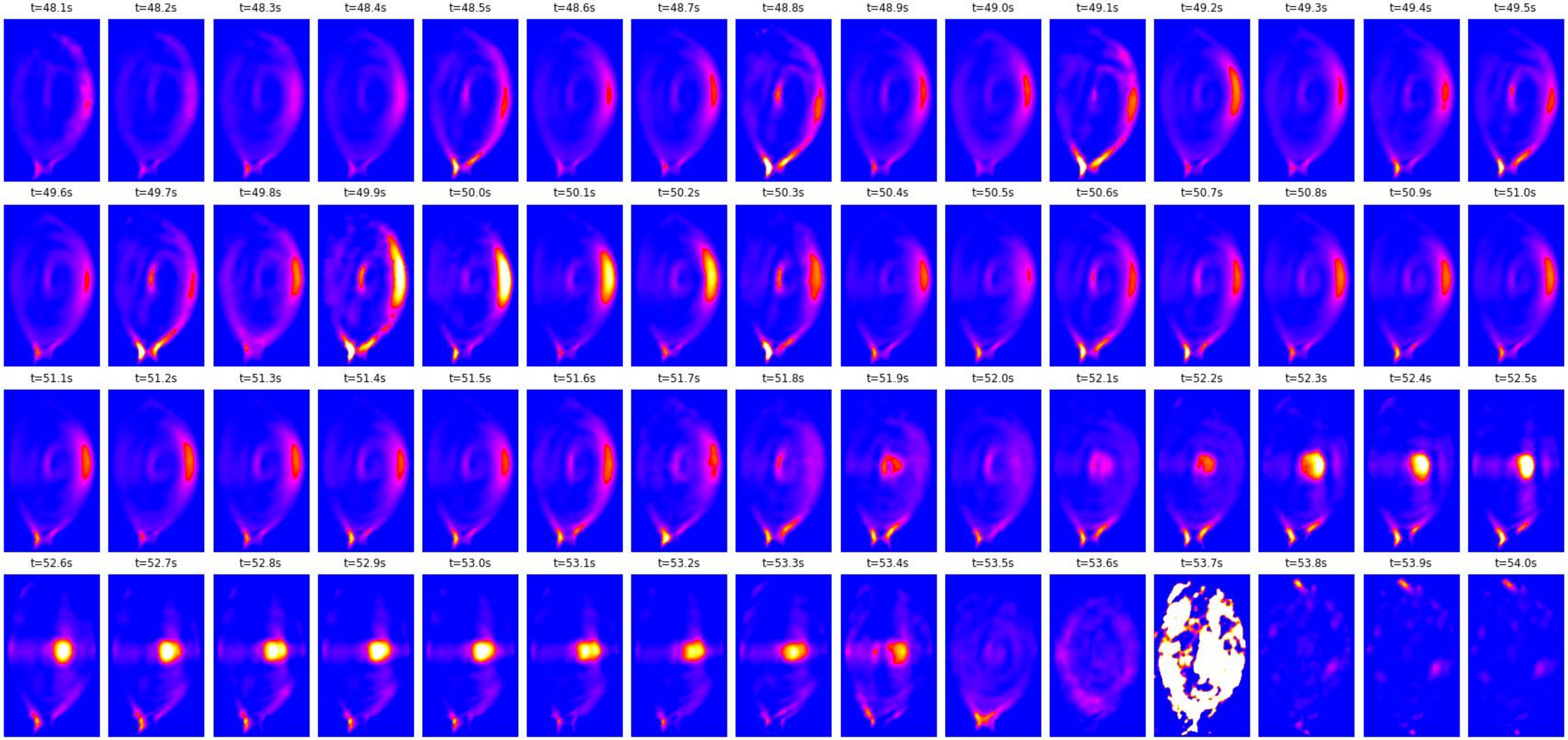
Keras TensorFlow NVIDIA



D. D. Carvalho et al., *Deep Neural Networks for Plasma Tomography with Applications to JET and COMPASS,* ECPD 2019

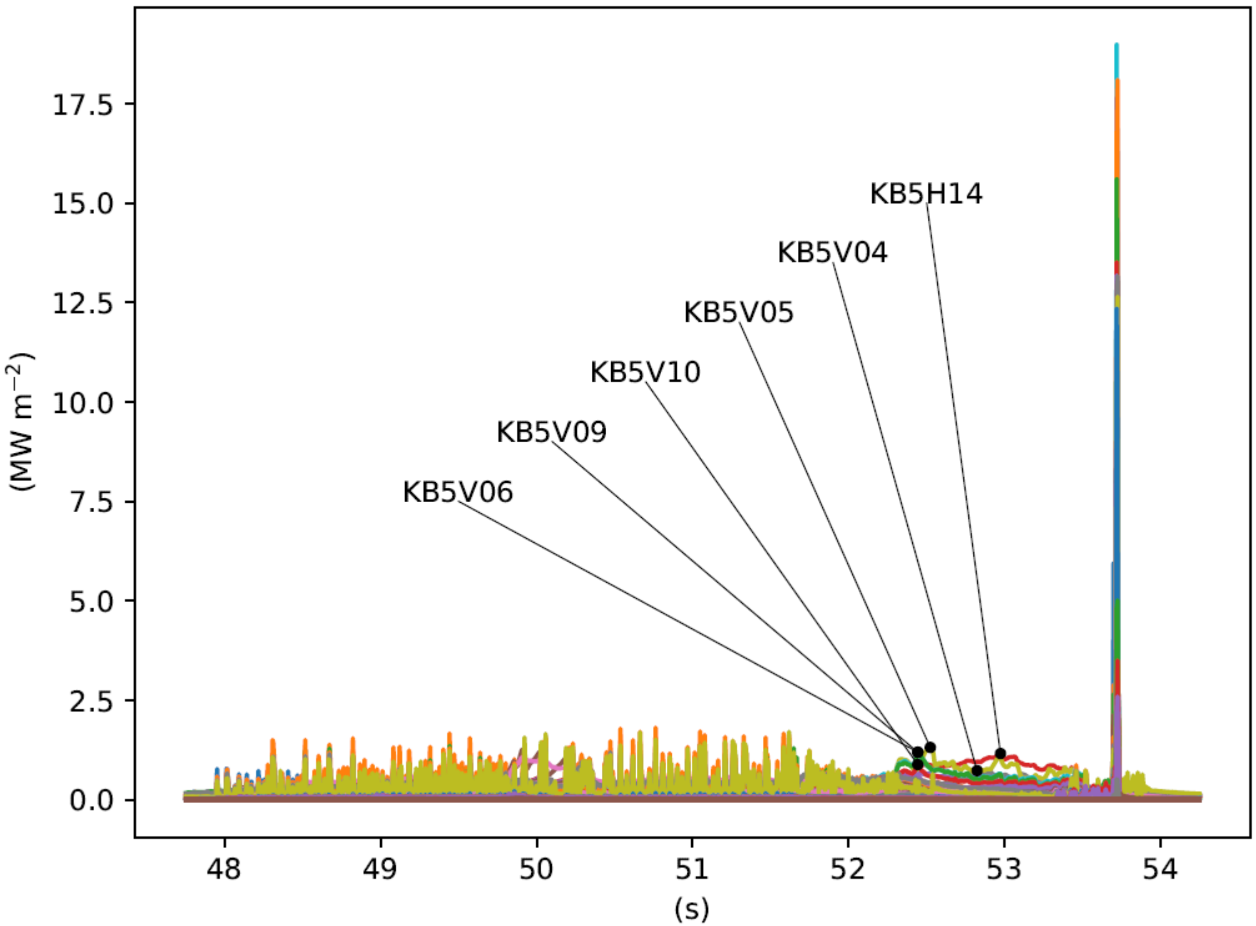
Plasma Tomography

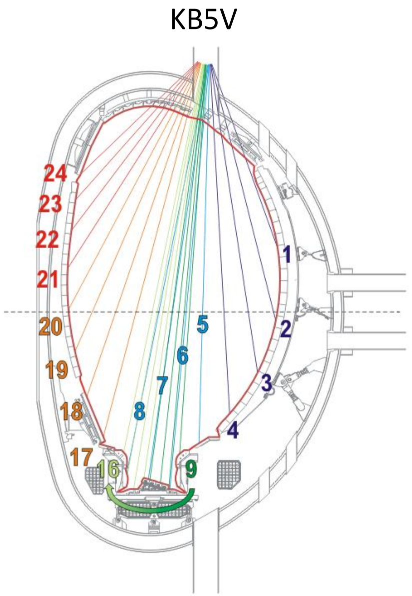
- Full-pulse reconstruction (92213)

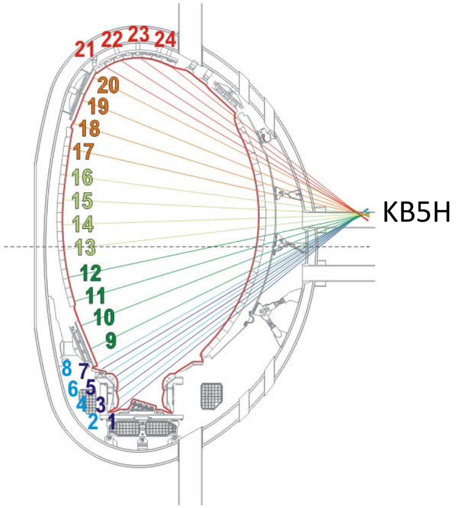


Disruption Prediction

- Bolometer signals (92213)

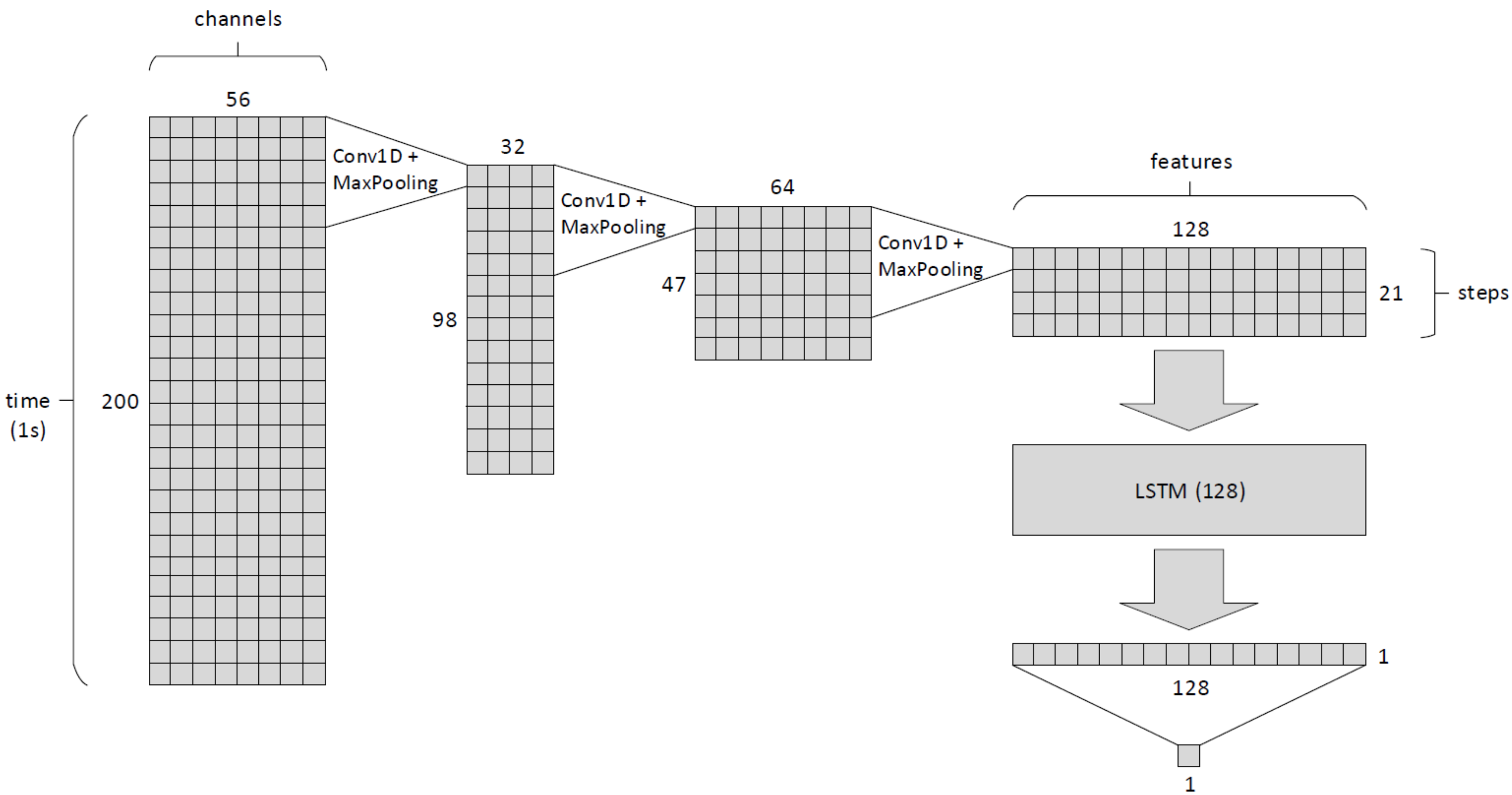






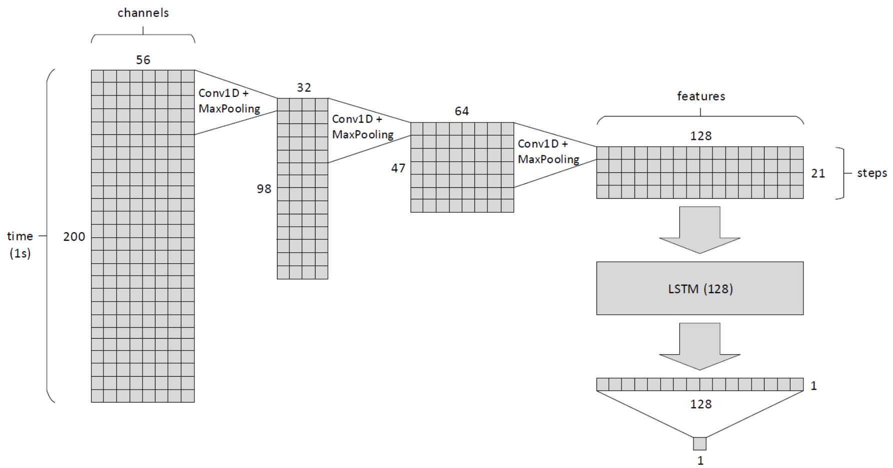
Disruption Prediction

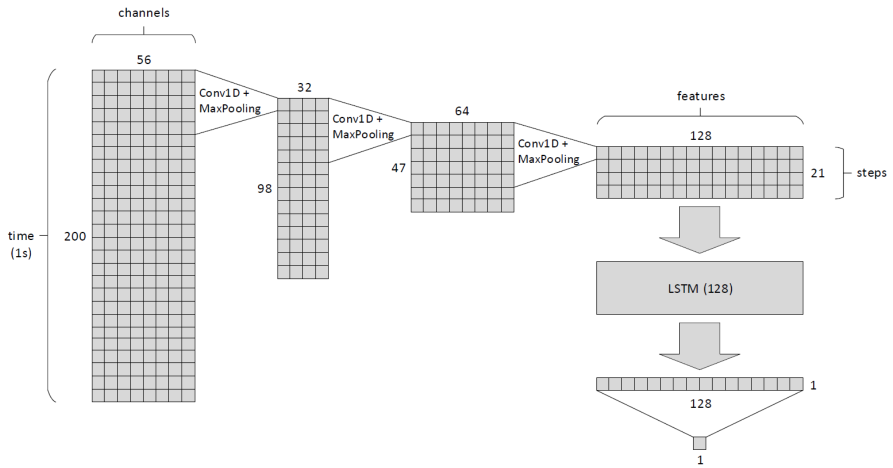
- Recurrent Neural Network



Disruption Prediction

- Two variants



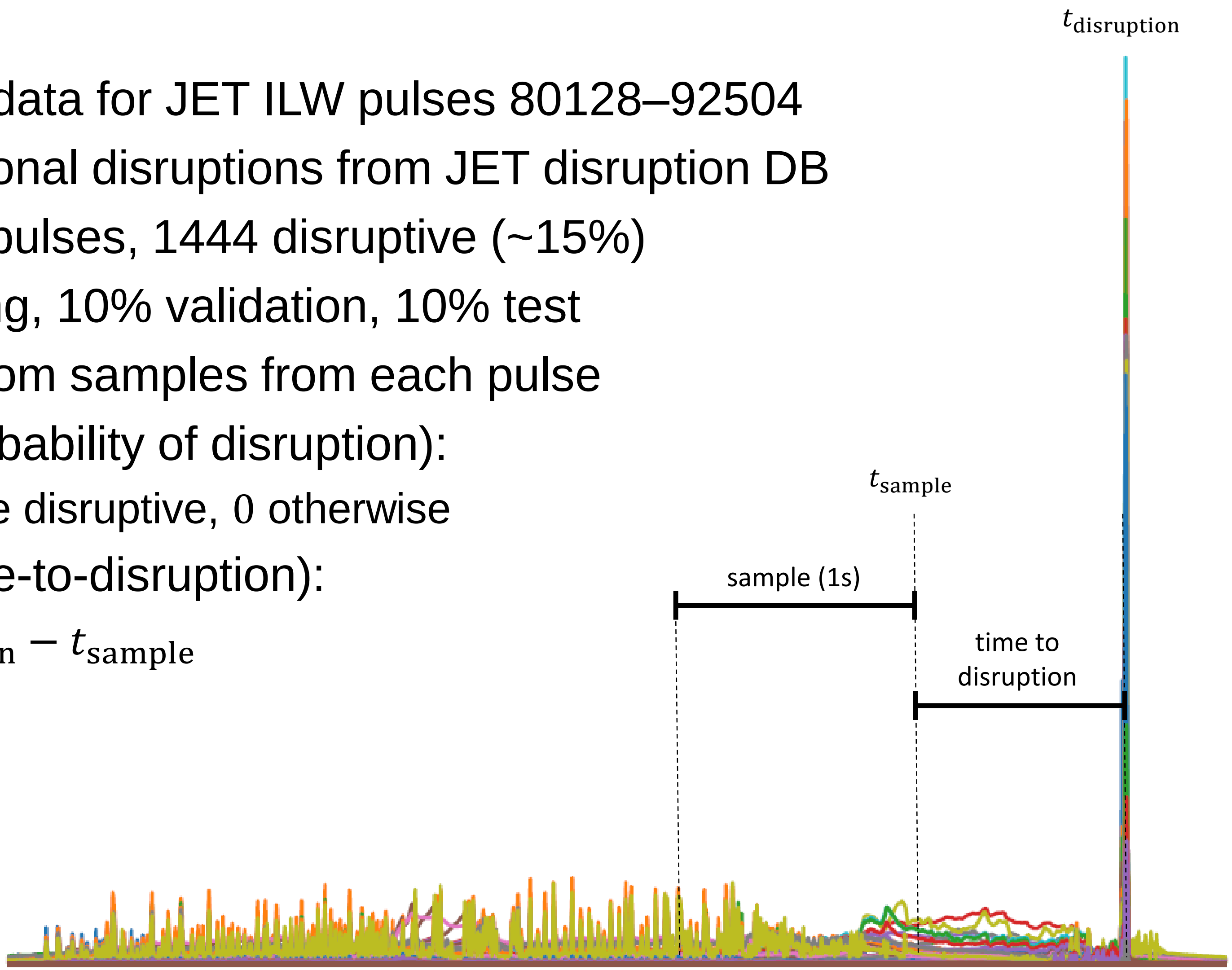


- probability of disruption (*classification*)
  - output: **sigmoid activation**
  - loss: **binary cross-entropy**
  - training: **disruptive** and **non-disruptive** pulses

- time-to-disruption (*regression*)
  - output: **no activation**
  - loss: **mean absolute error**
  - training: **disruptive** pulses only

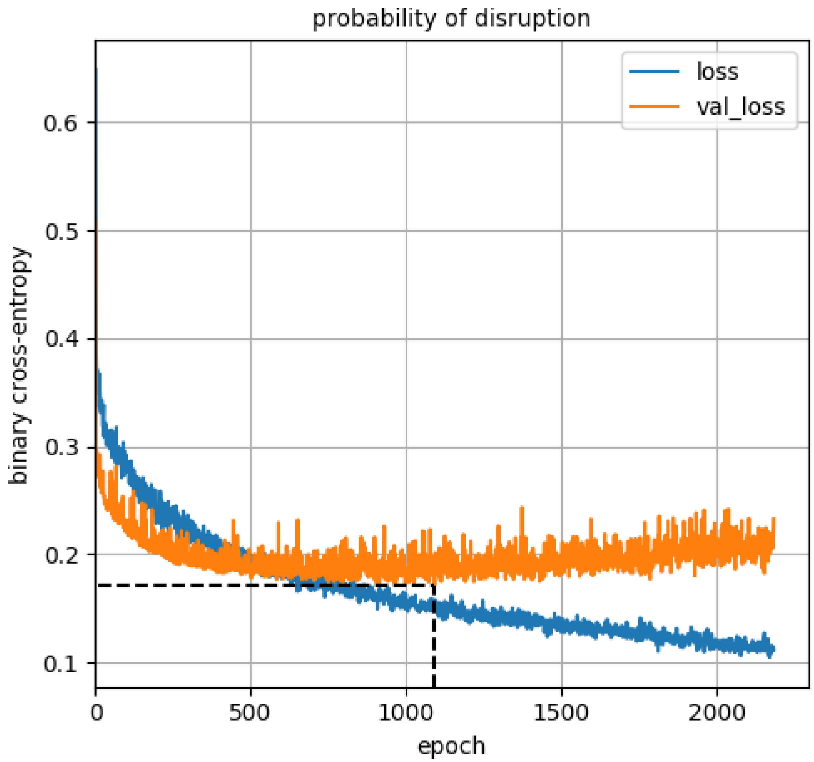
Disruption Prediction

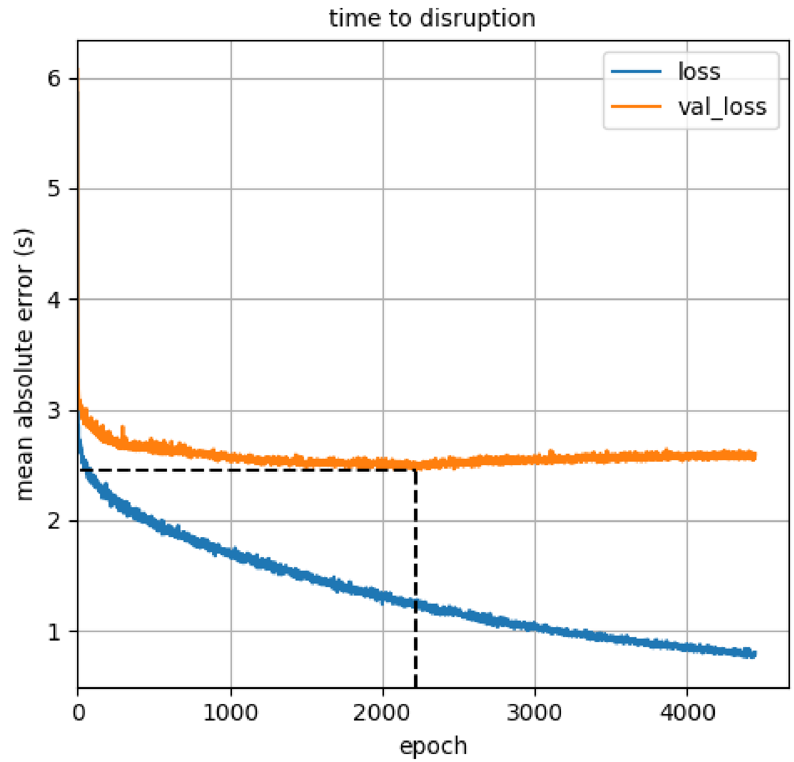
- Dataset
  - bolometer data for JET ILW pulses 80128–92504
  - non-intentional disruptions from JET disruption DB
  - total 9323 pulses, 1444 disruptive (~15%)
  - 80% training, 10% validation, 10% test
  - input: random samples from each pulse
  - output (probability of disruption):
    - 1 if pulse disruptive, 0 otherwise
  - output (time-to-disruption):
    - $t_{\text{disruption}} - t_{\text{sample}}$



Disruption Prediction

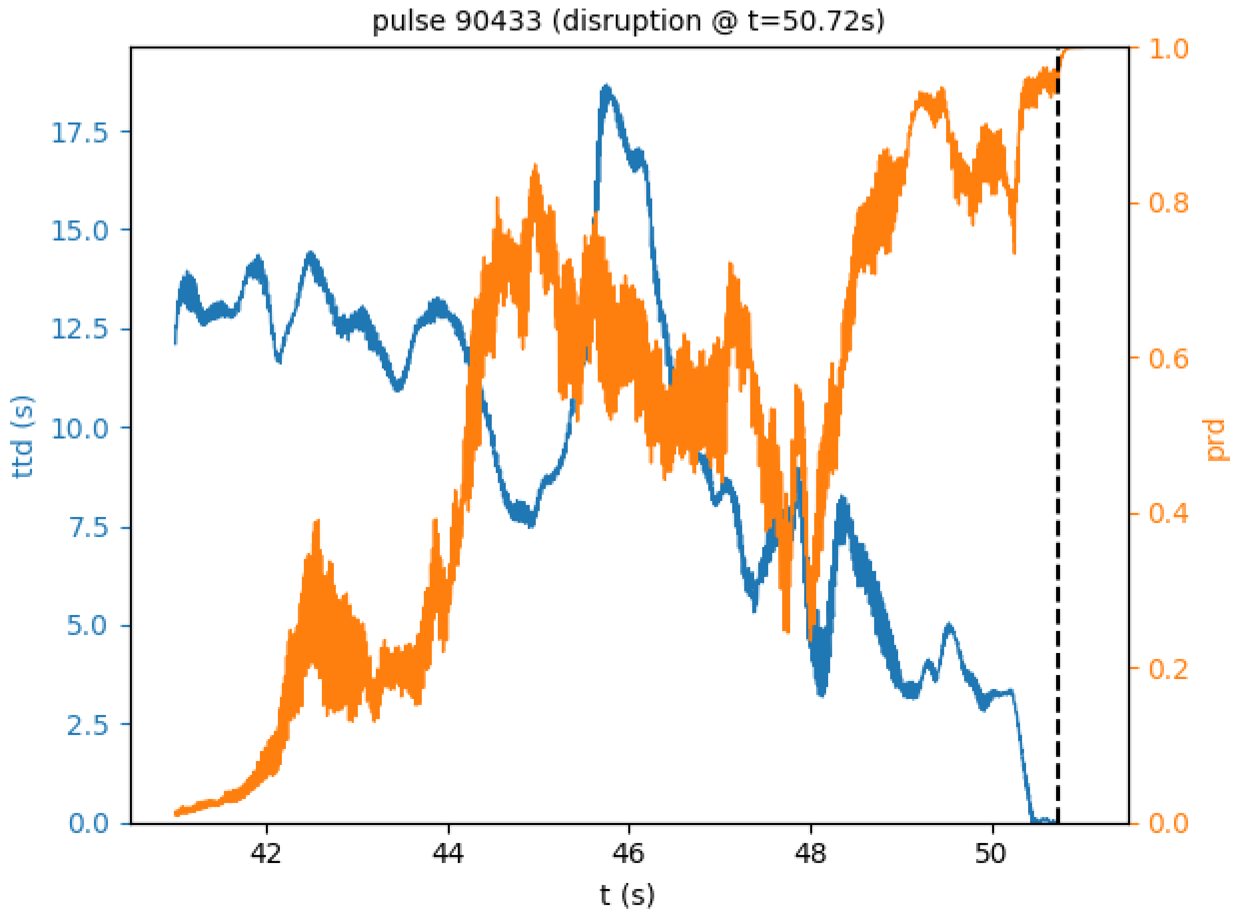
- Training
  - min. validation loss
    - probability of disruption: 0.172 (binary cross-entropy)
    - time-to-disruption: 2.45s (mean absolute error)





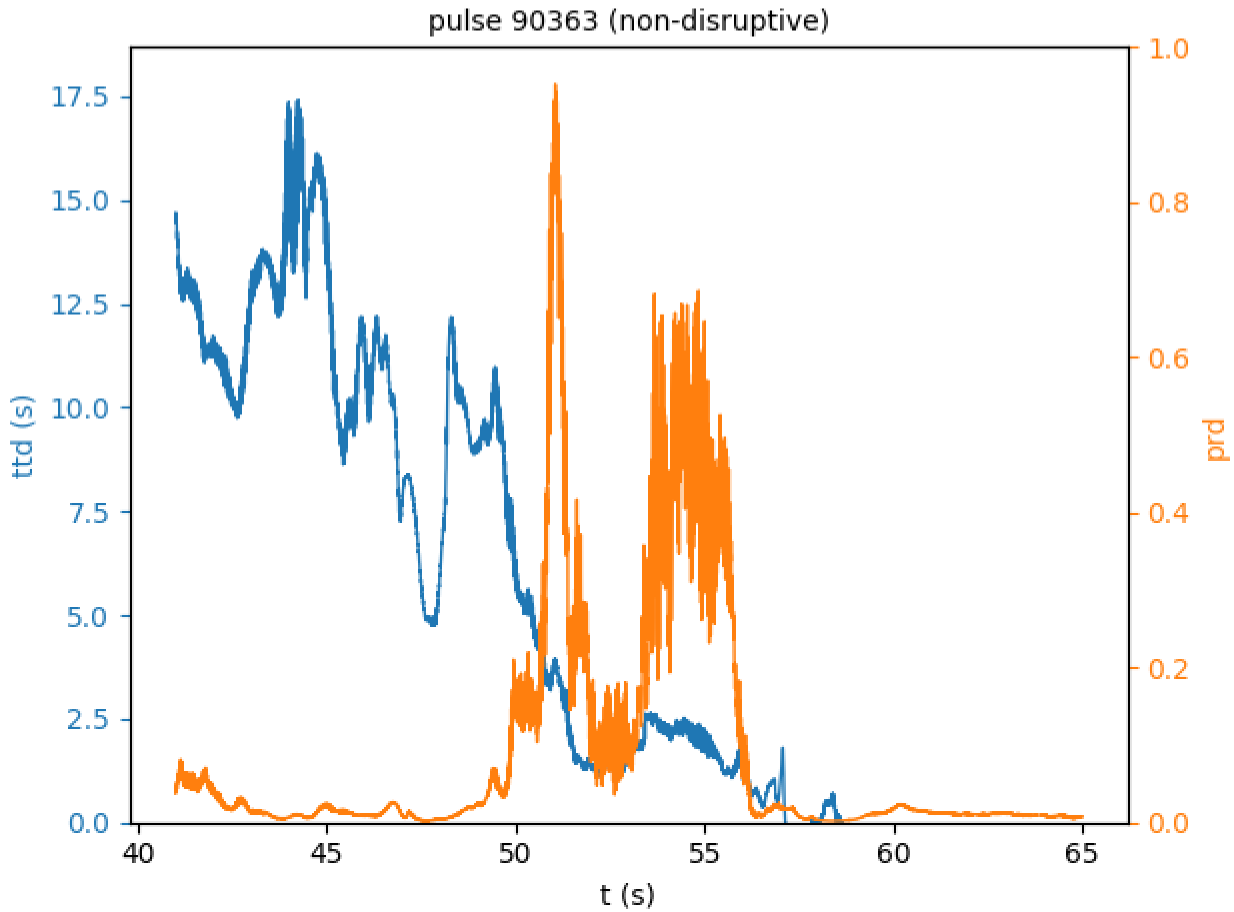
Disruption Prediction

- Full-pulse prediction (90433)



Disruption Prediction

- Full-pulse prediction (90363)



Disruption Prediction

- Alarm-triggering thresholds
  - example: $(prd \geq 0.85) \wedge (ttd \leq 1.5)$
    - TP: 11.7% (16.8% disruptive pulses in the test set)
    - TN: 77.9% (83.2% non-disruptive pulses in the test set)
    - FP: 5.3% (false alarms)
    - FN: 5.1% (missed alarms)
    - precision: TP/(TP+FP) = 69.0%
    - recall: TP/(TP+FN) = 69.4%
  - comparison: APODIS*
    - recall: 85.4%
    - FP: 2.5% (false alarms)

* Moreno et al., *Disruption prediction on JET during the ILW experimental campaigns*, Fusion Sci. Technol., 2016

Disruption Prediction

- Other recent works on disruption prediction

A.1 JET

We present a summary of the JET dataset [15] used throughout this paper. JET is the largest tokamak fusion experiment operating today and is situated in the UK. Plasma discharges ("shots") range in length from ~ 1 to ~ 40 seconds and are sampled at a rate of 1 ms. Thus, there are $O(10^3)$ to $O(10^4)$ timesteps per shot. Each shot consists of a scalar floating point value for each of the following measured plasma parameters for each timestep:

(1) $q95$ plasma safety factor
(2) β: plasma beta
(3) I_p: plasma current
(4) l_i: plasma internal inductance
(5) n: plasma number density
(6) MLA: amplitude of the locked mode signal
(7) P_{rad}: radiated power
(8) E_{int}: internal energy
(9) $\frac{\partial E_{int}}{\partial t}$: time derivative of internal energy
(10) P_{in}: input power

TABLE I

List of Signals and Relative Units Considered for Machine Learning Applications

Signal Description	Name
Plasma current error fraction, $(I_p - I_{prog})/I_p$	ip_error_frac
Poloidal beta, β_p	betap
Greenwald density fraction, n/n_G	n/nG
Safety factor at 95% of minor radius, q_{95}	q95
Plasma internal inductance, l_i	li
Radiated power fraction, P_{rad}/P_{input}	prad_frac
Electron temperature profile width (m)	Te_HWHM
Locked mode amplitude (T)	n1amp
Loop voltage, V_{loop} (V)	Vloop
Stored energy time derivative, dW_{th}/dt (J/s)	dWmhd_dt

A. Svyatkovskiy et al., *Training distributed deep recurrent neural networks with mixed precision on GPU clusters*, MLHPC'17, 2017
C. Rea et al., *Exploratory Machine Learning Studies for Disruption Prediction Using Large Databases on DIII-D*, Fusion Sci. Technol., 74:1-2, 2018

Conclusion

- Several opportunities for deep learning
  - e.g. CNNs for image processing (plasma tomography)
  - e.g. RNNs for time series analysis (disruption prediction)
- From single to multiple diagnostics
  - e.g. use (bolometer data) + (magnetic equilibrium) as input to CNN
  - e.g. use (bolometer data) + (plasma parameters) as input RNN
- From JET to other devices
  - e.g. CNN applied to JET and COMPASS*
  - e.g. RNN applied to JET and DIII-D**
    - and random forests applied to DIII-D and Alcator C-Mod***

* D. D. Carvalho et al., *Deep Neural Networks for Plasma Tomography with Applications to JET and COMPASS,* ECPD 2019
** J. Kates-Harbeck et al., *Predicting disruptive instabilities in controlled fusion plasmas through deep learning,* Nature 568, 2019
*** C. Rea et al., *Disruption prediction investigations using Machine Learning tools on DIII-D and Alcator C-Mod*, Plasma Phys. Control. Fusion 60, 2018