Deep Learning for Plasma Tomography and Disruption Prediction

D. R. Ferreira, P. J. Carvalho, H. Fernandes, and JET Contributors
IPFN / IST, University of Lisbon, Portugal
Deep Learning

- Convolutional Neural Networks (CNNs)


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
  - ...

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
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: \( prd \geq 0.85 \) \& \( ttd \leq 1.5 \)
    • 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: \( \frac{TP}{TP+FP} = 69.0\% \)
    • recall: \( \frac{TP}{TP+FN} = 69.4\% \)

• 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. $q_{95}$ plasma safety factor
2. $\beta$: 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. $\frac{dE_{int}}{dt}$: time derivative of internal energy
10. $P_{in}$: input power

### TABLE I

<table>
<thead>
<tr>
<th>Signal Description</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plasma current error fraction, $(I_p - I_{\text{prog}})/I_p$</td>
<td>$ip_{-error_frac}$</td>
</tr>
<tr>
<td>Poloidal beta, $\beta_p$</td>
<td>betap</td>
</tr>
<tr>
<td>Greenwald density fraction, $n/n_G$</td>
<td>n/nG</td>
</tr>
<tr>
<td>Safety factor at 95% of minor radius, $q_{95}$</td>
<td>$q_{95}$</td>
</tr>
<tr>
<td>Plasma internal inductance, $l_i$</td>
<td>li</td>
</tr>
<tr>
<td>Radiated power fraction, $P_{rad}/P_{\text{input}}$</td>
<td>$prad_frac$</td>
</tr>
<tr>
<td>Electron temperature profile width (m)</td>
<td>Te_HWHM</td>
</tr>
<tr>
<td>Locked mode amplitude (T)</td>
<td>$nlamp$</td>
</tr>
<tr>
<td>Loop voltage, $V_{loop}$ (V)</td>
<td>$V_{loop}$</td>
</tr>
<tr>
<td>Stored energy time derivative, $dW_{th}/dt$ (J/s)</td>
<td>$dWmhd_dt$</td>
</tr>
</tbody>
</table>

A. Svyatkovskiy et al., *Training distributed deep recurrent neural networks with mixed precision on GPU clusters*, MLHPC'17, 2017
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