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*, 1998

A. Krizhevsky et al., *ImageNet Classification with Deep Convolutional Neural Networks*, 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, 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
  - PSNR: 35.4 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: \( p_{rd} \geq 0.85 \) \( \land \) \( t_{td} \leq 1.5 \)
    • TP: 11.7%  \( (16.8\% \text{ disruptive pulses in the test set}) \)
    • TN: 77.9%  \( (83.2\% \text{ non-disruptive pulses in the test set}) \)
    • 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*, 2016
Conclusion

• Several opportunities for deep learning
  • CNNs for image processing (e.g. plasma tomography)
  • RNNs for time series analysis (e.g. disruption prediction)

• From single to multiple diagnostics
  • use (bolometer data) + (magnetic equilibrium) as input to CNN
  • use (bolometer data) + (plasma parameters) as input RNN

• From JET to other devices
  • CNN applied to JET and COMPASS (*)
  • RNN applied to JET and DIII-D (**)

(*) 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, 2019