Deep Learning and Machine Learning algorithms for disruption prediction and heat-load monitoring in fusion devices

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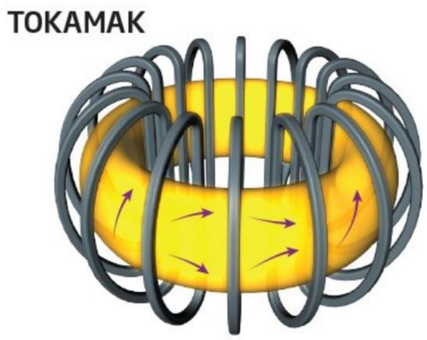
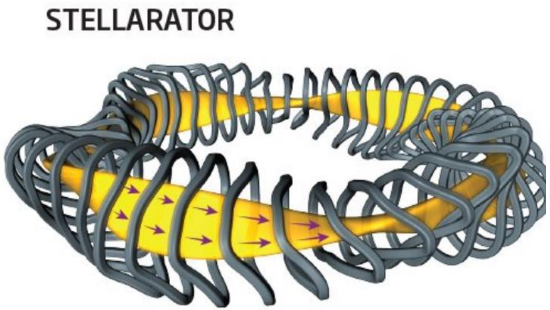
Approaches to magnetic confinement fusion



Axisymmetric
Induced toroidal current
Current driven instabilities

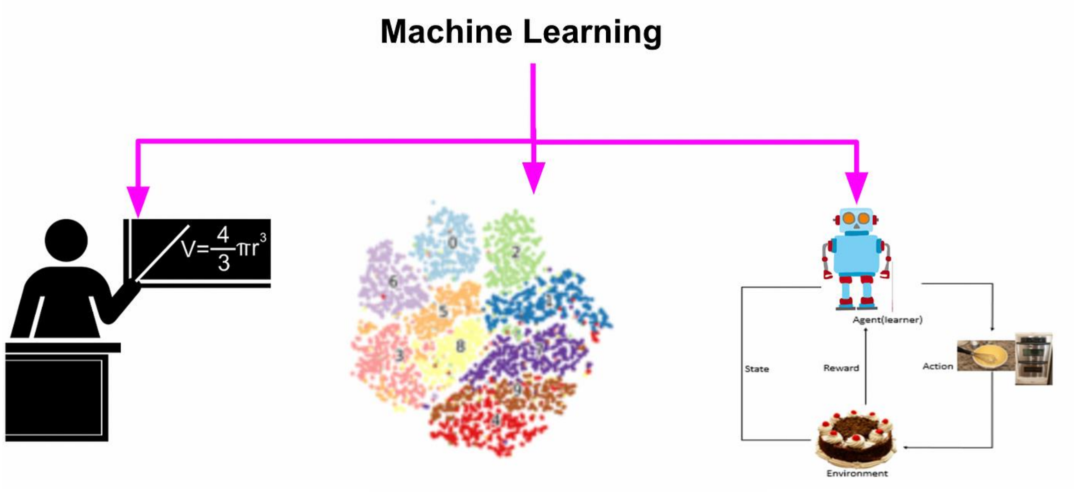
Disruption prediction and avoidance towards real-time control



Not-axisymmetric
No need for inductive toroidal current
No major current driven instabilities
Overload on the first wall

Heat load monitoring for protection of overloads

Machine learning



Supervised learning
- Input data
- Output data (Target)
- LABELED DATA

Unsupervised learning
- Input data
- UNLABELED DATA

Reinforcement learning
- No data
- Agent
- Enviroment
- Goal

Disruption prediction in tokamaks

Instabilities in the tokamak plasma

- rapid loss of the stored thermal and magnetic energy
- high power fluxes and mechanical forces on in-vessel components,

Severe damage to present-day fusion devices and more devastating effects in future devices.

Disruption prediction and avoidance

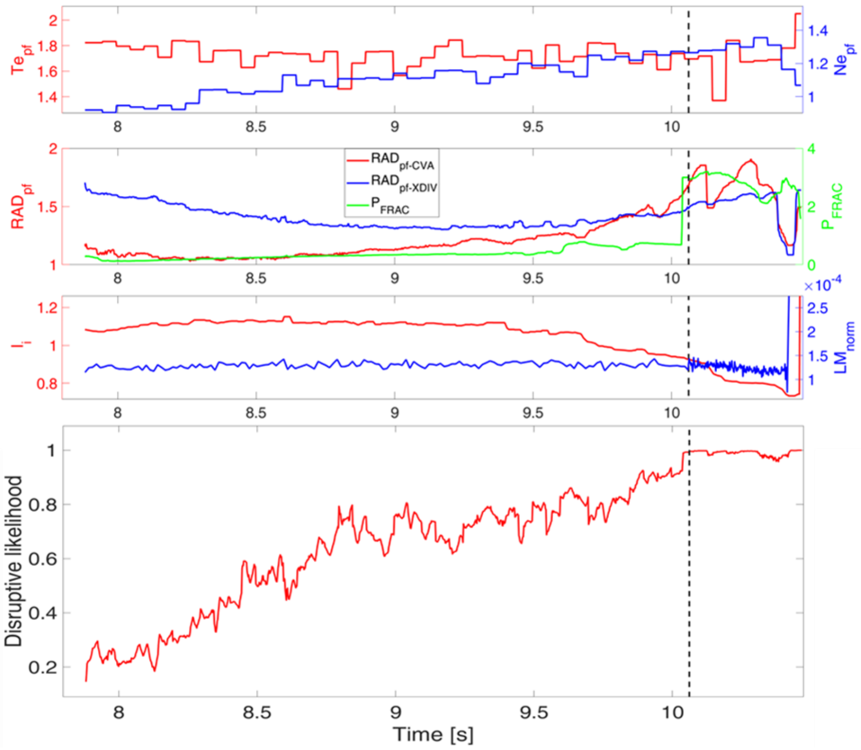
Disruption mitigation

- Theoretical models insufficient to reliably describe all disruption classes

- Empirical models based on machine learning are a common approach for predicting disruptions

Disruption prediction: real time prediction of the thermal quench based on measured plasma parameters

The plasma parameters



The disruption predictor

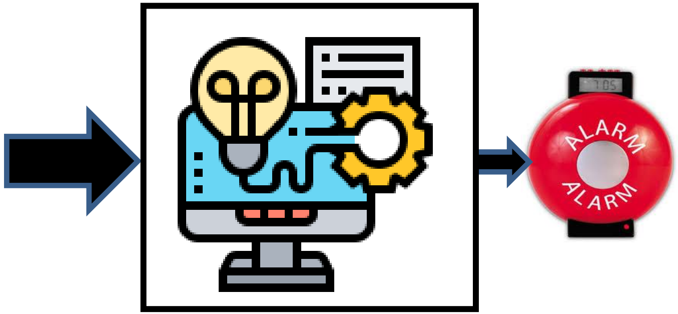
Temperature
(peaking factor)

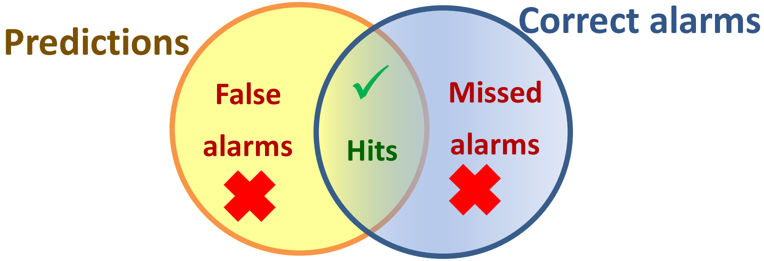
Electron density
(peaking factor)

Radiation
(peaking factors)

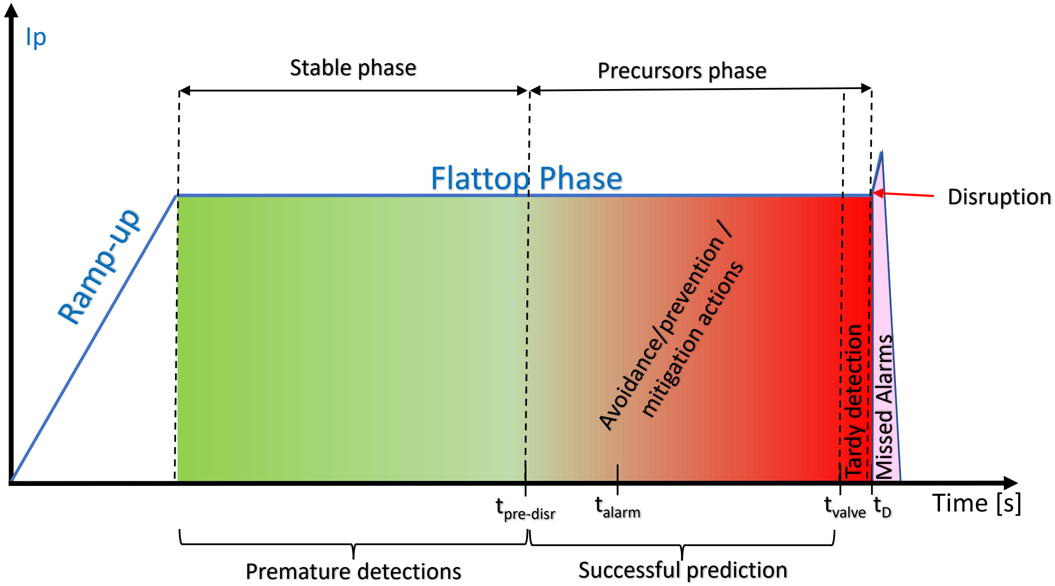
Internal inductance

Locked mode
‘
‘
‘





Metrics



- Missed alarms MA
  (disruption terminated discharges)
- Tardy detections TD
  (disruption terminated discharges)
- False alarms FA
  (regularly terminated discharges)
- Cumulative fraction of predicted disruptions before t*
  (disruption terminated discharges)

Supervised and unsupervised approaches

Task

to learn a function that maps the plasma state in input to the desired output

given the pairs

plasma state / disruption risk

Supervised approach

Need for human labelling to classify the current plasma state is either stable or unstable

plasma state / experiment termination

Unsupervised approach

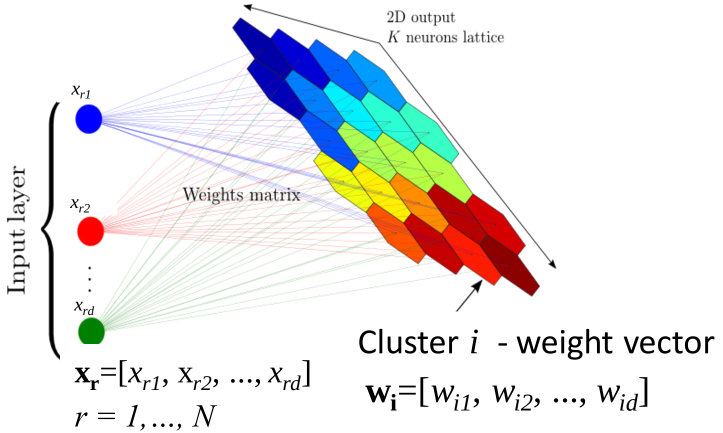
No need for human labelling of different plasma states

Unsupervised approaches: Self Organising Maps

SOMs transform a set of
N d-dimensional input data

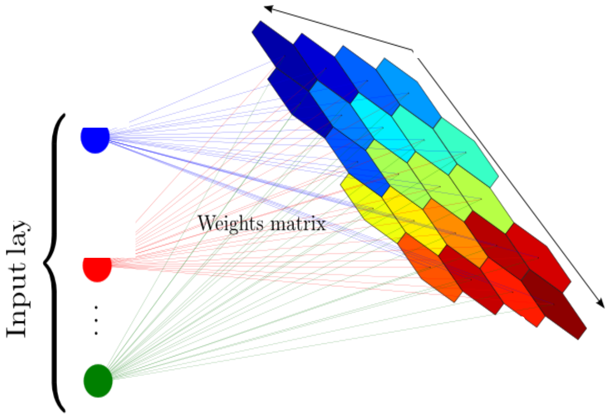
$$\mathbf{x}=[x_1, x_2, \dots, x_d]$$

into a $2D$ **discrete map topologically ordered**



Each input **x** is associated to a cluster of the map characterized by a weight vector **w** (barycenter of the inputs mapped in the node)

How does the SOM algorithm work?



Competition

find the winning neuron, i.e., the closest to each input vector

Cooperation

find the winning neuron's neighbors

Adaptation

update the weights of winning neuron and its neighbors

$\mathbf{w}_j(n+1) = \mathbf{w}_j(n) + \alpha h_{ij}\,[d(\mathbf{x}, \mathbf{w}_j(n))]$

α learning rate

d distance function

h defines the winner neighborood

The Self Organising Map (SOM)

Temperature

(peaking factor)

Electron density

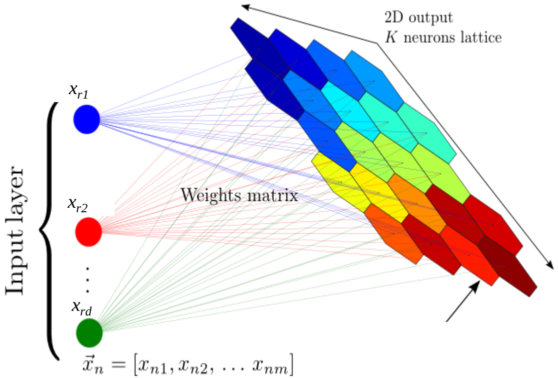
(peaking factor)

Radiation

(two peaking factors)

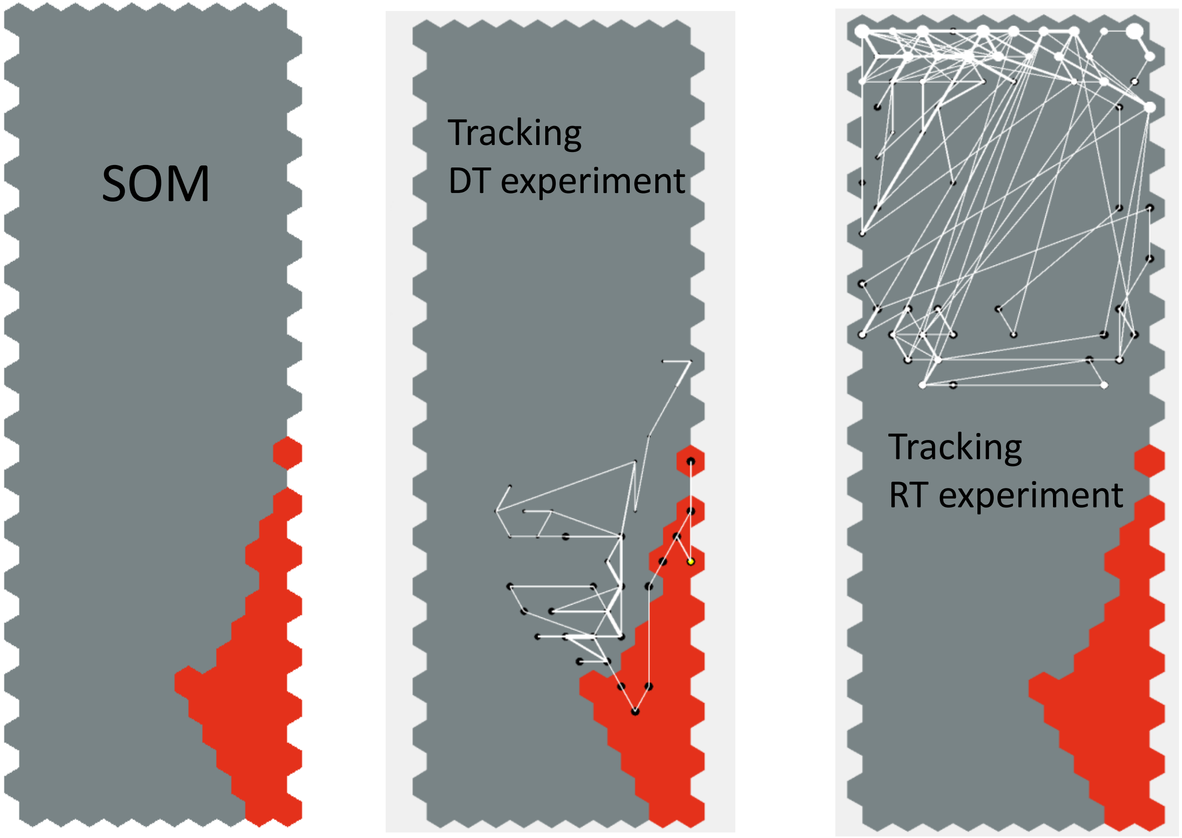
Internal inductance

Locked mode



Each 6D plasma state is associated to a cluster of the map characterized by a weight vector **w** (barycenter of the data mapped in the cluster).

JET SOM of the 6D plasma parameter space

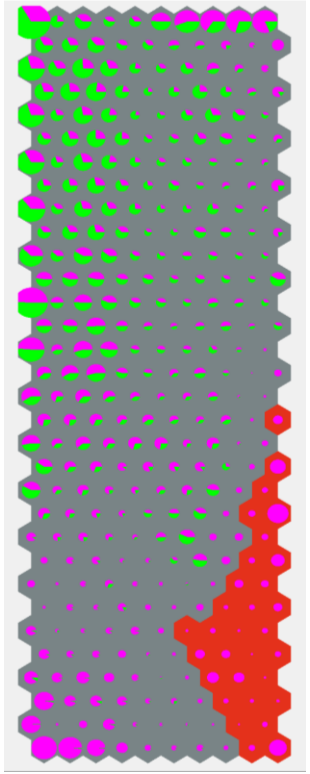


32×10 = 320 clusters

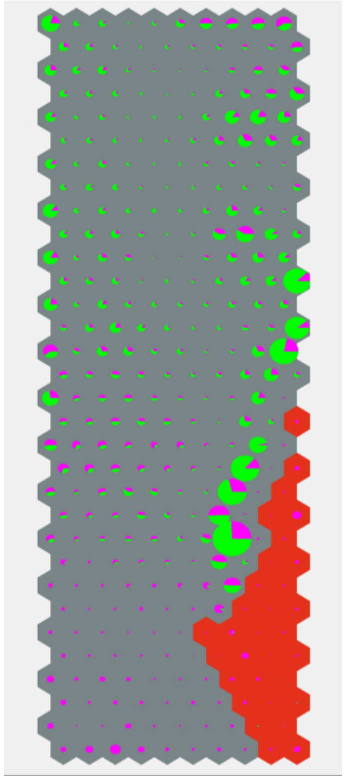
safe clusters samples from Regularly and Disruption terminated experiments

disruptive clusters only samples from disruption terminated experiments

Adding knowledge on training and test set experiments



Training
Experiments
until C30



Test
Experiments
until C38

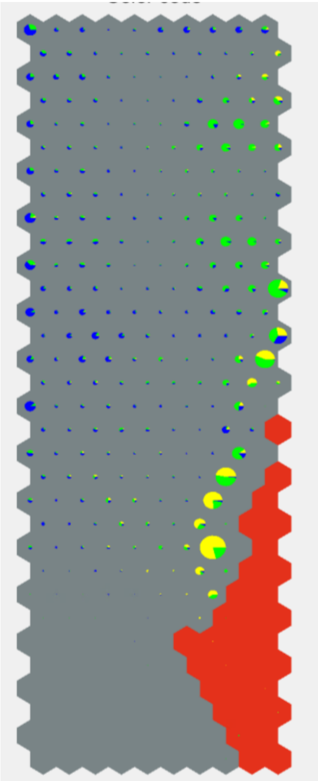
Regularly terminated experiments

Disruptive experiments

Adding knowledge on experimental campaigns

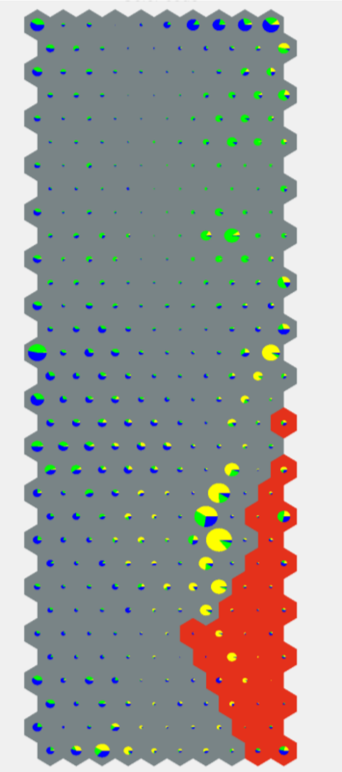
Test
experimental campaigns

Regularly terminated experiments

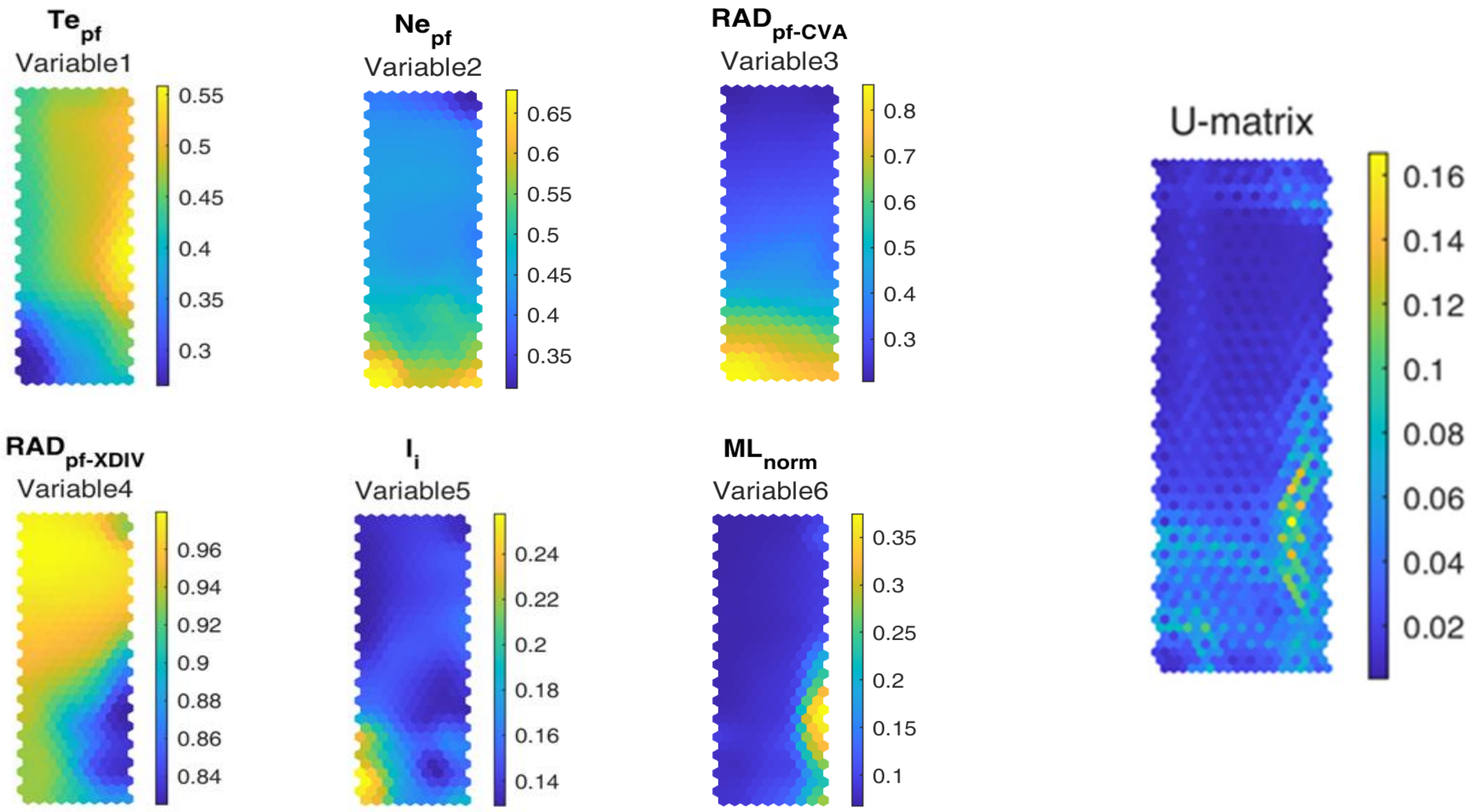


C28-30
C36
C38

Disruption terminated experiments



Get insight on data distribution: the Component Planes

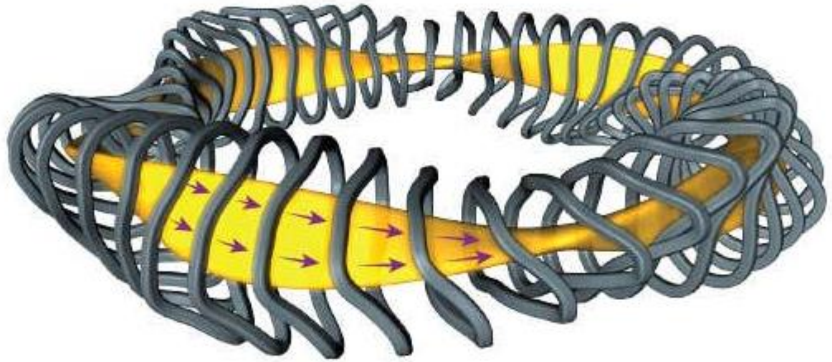


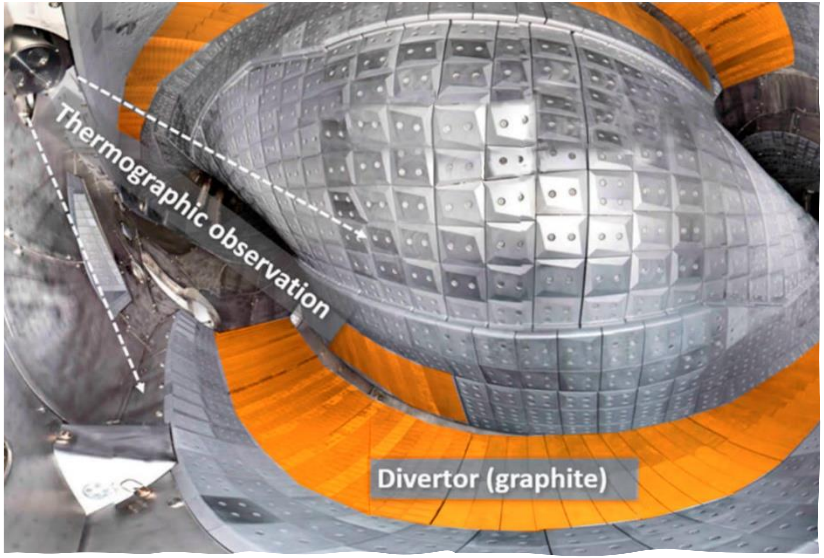
SOM performance

	False alarms	Missed alarms	Tardy detections
Training	0% (0/70)	0% 0/85	1.18% 1/85
Validation	0% (0/70)	0% 0/85	1.18% 1/85
Test	2.01% (3/149)	4.63% 5/108	0% 0/108

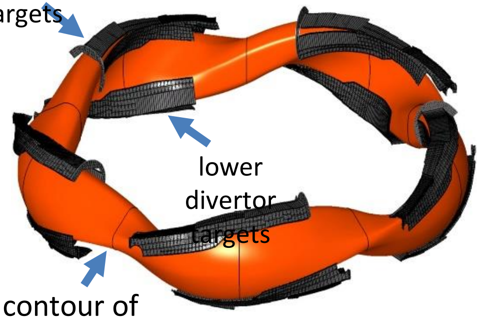
Novelty detection: any alarm if the sample is out of the range of the cluster training data

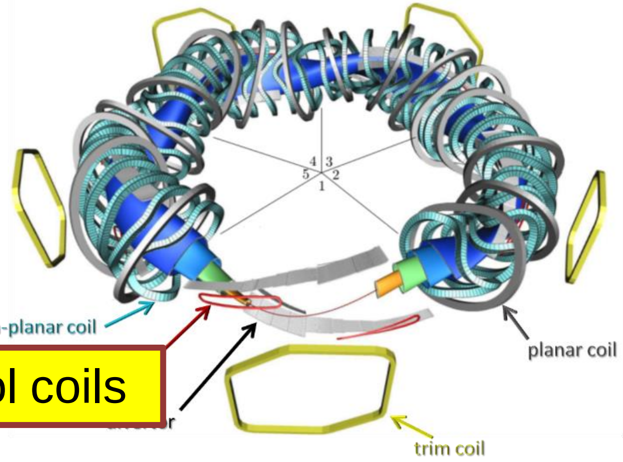
Heat-flux monitoring at W7-X



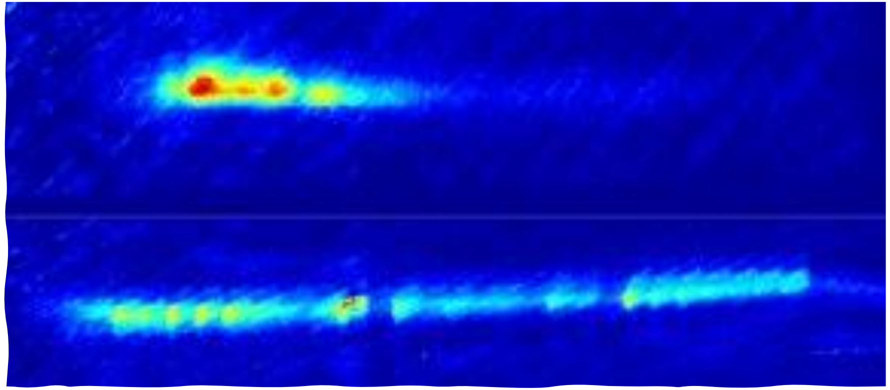


Strike-lines





Strike-line image

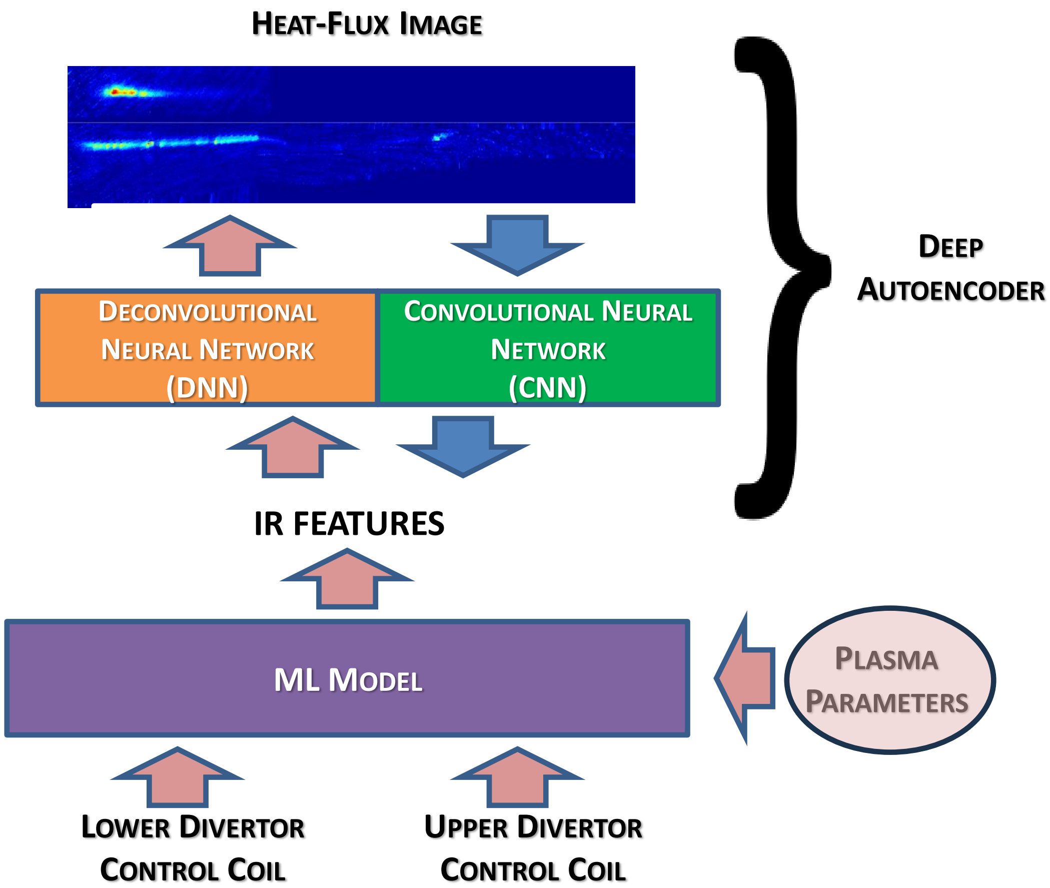


control coils were varied in different ways

- DC ramps
- AC signals

in fixed experimental conditions

From Control Coil Currents to Heat-Flux …



Objective:

Predict a set of features of the the heat-flux distribution on the divertor (strike-line) from the actuators (control coil currents) and plasma parameters.

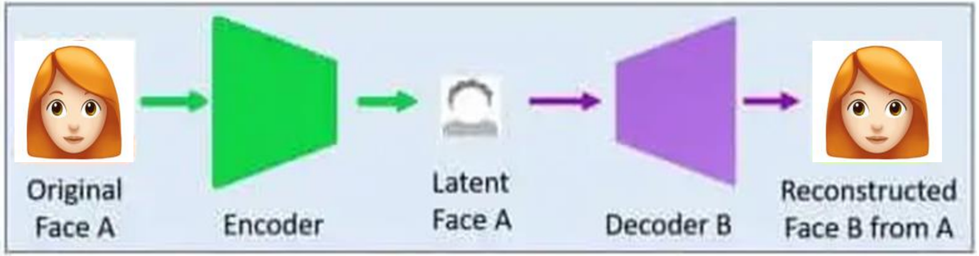
Two tasks:

1. Compress the heat-flux image into a set of IR features, so that IR features can be decoded back to heat-flux image → Deep Autoencoder

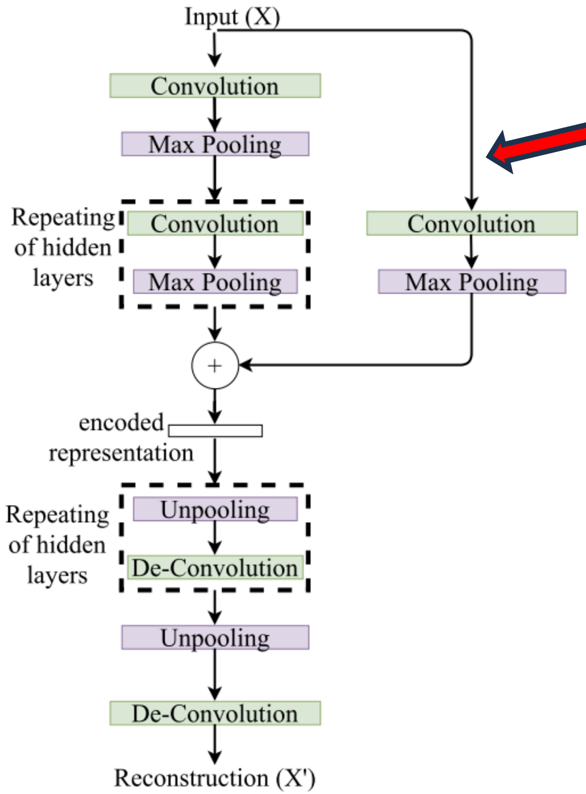
2. Predict IR features from actuators and plasma parameters
   Control purposes

Deep Autoencoder

- Efficient and nonlinear low-dimensional coding of data
- Do not require labeled input data
- *Self-supervised:* generate their own labels



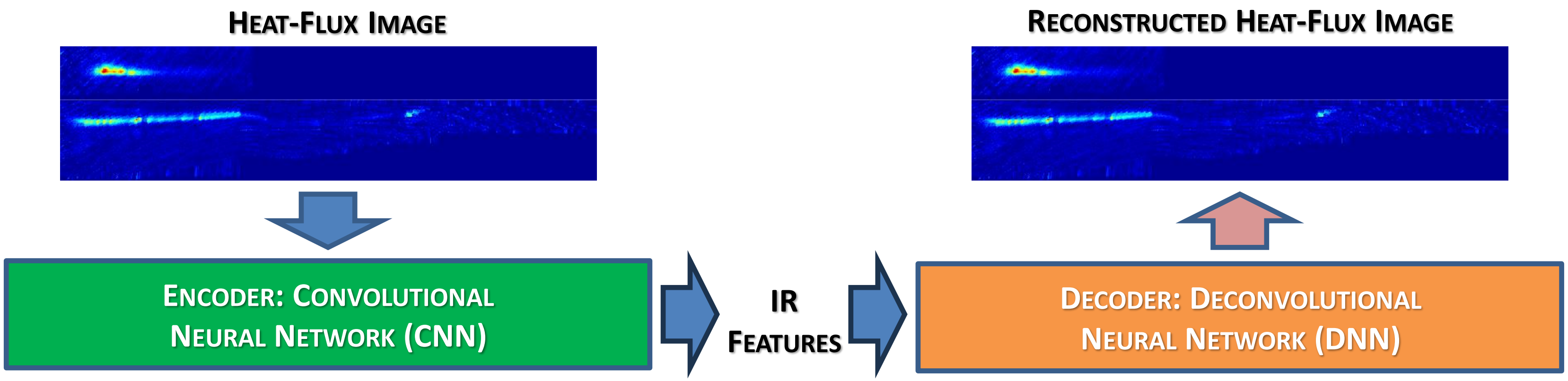
ResNet Autoencoder



Residual connection

C. S. Wickramasinghe et al.: RAEs for Unsupervised Feature Learning From High-Dimensional Data

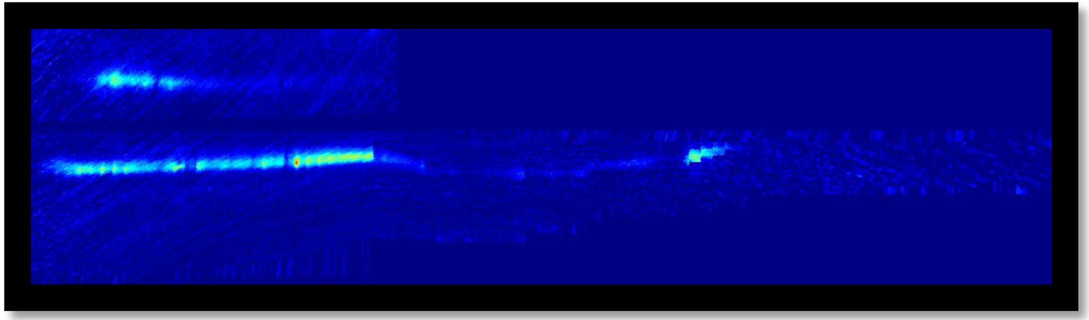
Deep Autoencoder for heat-flux reconstruction

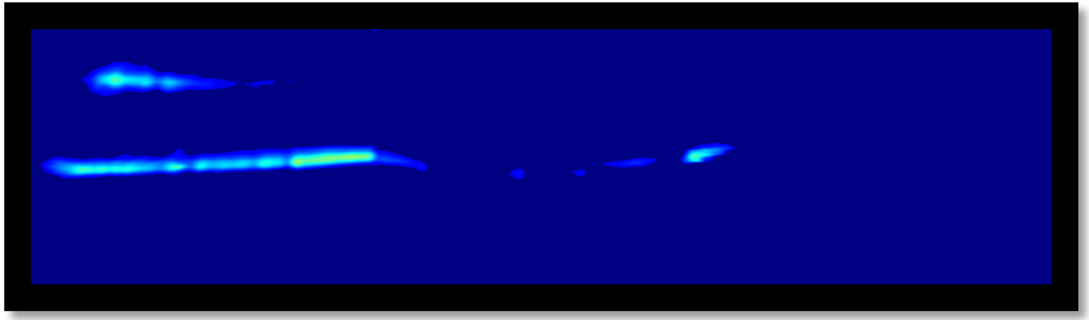


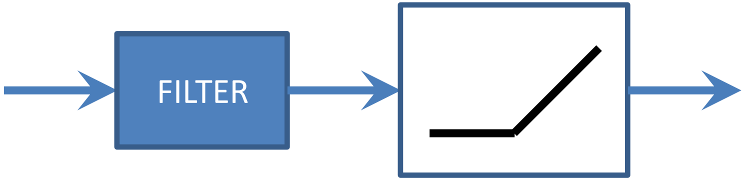
Two actors:

Encoder: compresses the information coming from the heat-flux image into a set of features
Decoder: encodes back the set of features into a reconstructed heat-flux image

Deep Autoencoder Preprocessing







Spatio-temporal filter

- kernel 5x21x21
  (Height x Width x Time)
- $\sigma_H = 1, \sigma_W = \sigma_T = 5$

Thresholding

hf = 0 if $hf < 0.15\mathrm{MW/m^2}$

exception: $hf = 1$ if hole

Performance indices

$RMSE$

Root Mean Squared Error

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Structural similarity index measure (SSIM)

measures the perceived similarity of two images

μ average brightness of the image (luminosity)

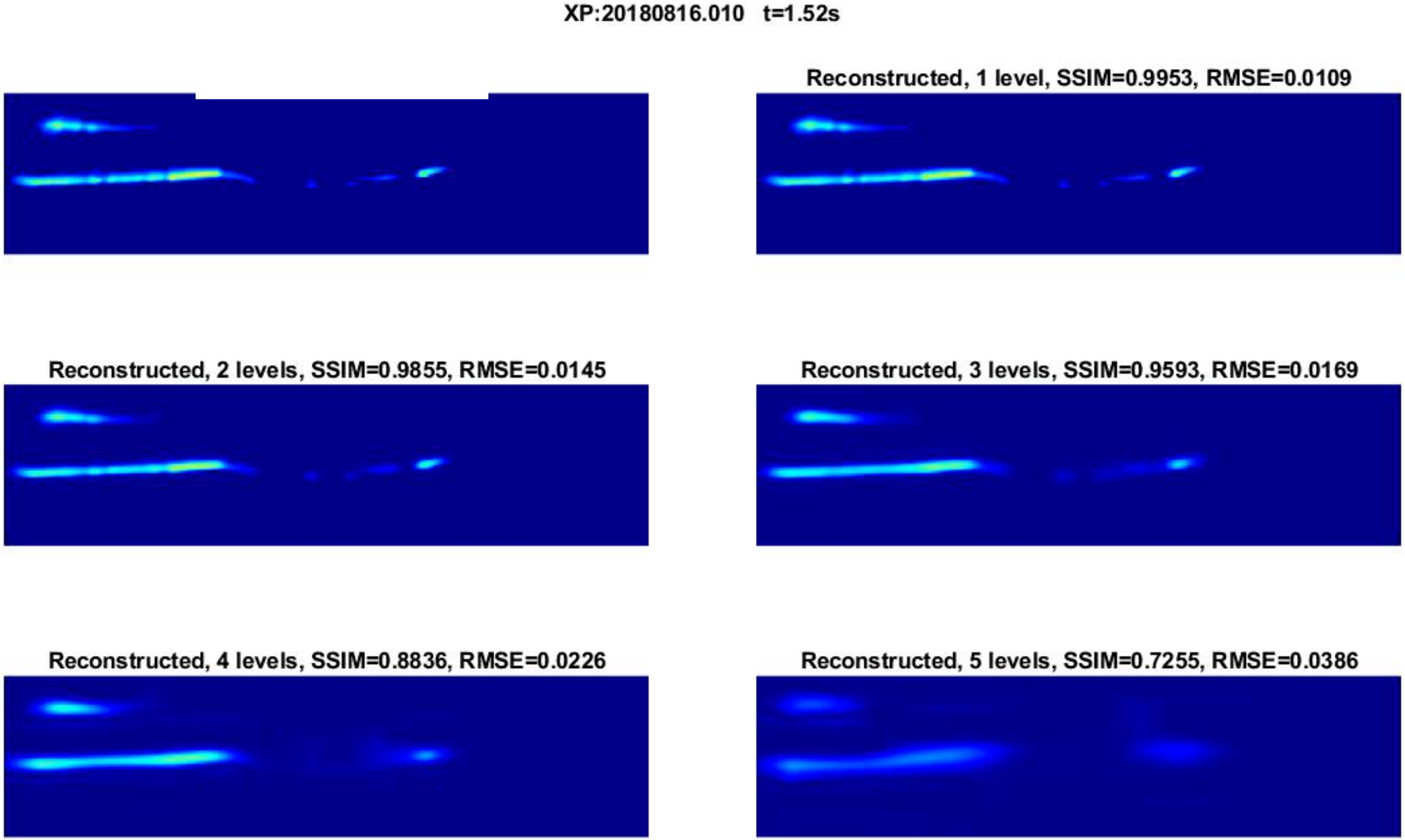
σ standard deviation (contrast)

σ_{xy} covariance (the images deviate in the same direction)

Deep Autoencoder performance

- Training and validation set: experiment with DC ramps control coil currents
- Test set: experiment with AC control coil currents

			Training		Validation		Test	
Levels	Compressed Size	Compression	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM
0	1296x324x1	100.00%	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000
1	648x162x8	200.00%	0.0123	0.9921	0.0126	0.9921	0.0153	0.9875
2	324x81x6	37.50%	0.0150	0.9800	0.0159	0.9800	0.0175	0.9742
3	162x41x6	9.49%	0.0163	0.9563	0.0180	0.9549	0.0174	0.9535
4	81x21x4	1.62%	0.0199	0.9118	0.0212	0.9087	0.0193	0.9201
5	41x11x8	0.86%	0.0313	0.7847	0.0313	0.7849	0.0275	0.8083
6	21x6x2	0.06%	0.0316	0.7852	0.0314	0.7872	0.0280	0.8066
7	11x3x6	0.05%	0.0395	0.6164	0.0394	0.6190	0.0334	0.6879


XP:20180816.010 t=1.52s
Reconstructed, 1 level, SSIM=0.9953, RMSE=0.0109
Reconstructed, 2 levels, SSIM=0.9855, RMSE=0.0145
Reconstructed, 3 levels, SSIM=0.9593, RMSE=0.0169
Reconstructed, 4 levels, SSIM=0.8836, RMSE=0.0226
Reconstructed, 5 levels, SSIM=0.7255, RMSE=0.0386

Conclusions

- ML helps extracting scientific knowledge and bridge gaps between theoretical models and practical implementations

- Unsupervised techniques for machine protection (disruptions and heat-loads)
  - ➢ Do not assume a priori knowledge (SOM and ResNet)
  - ➢ Data visualization (SOM)
  - ➢ Model interpretation: the reasoning behind the predictions is understandable (SOM)
  - ➢ Extrapolation to ITER
    - » acquire a general representation of experimental data that can be used in cross-machine applications

    e.g., identify event chains that lead to disruptions