CORTEX

Core monitoring techniques and experimental validation and demonstration

Anomaly detection in nuclear reactors using deep learning

Consultancy meeting on machine learning for nuclear data

Tuesday 8th December 2020 at 16:25 (CET)

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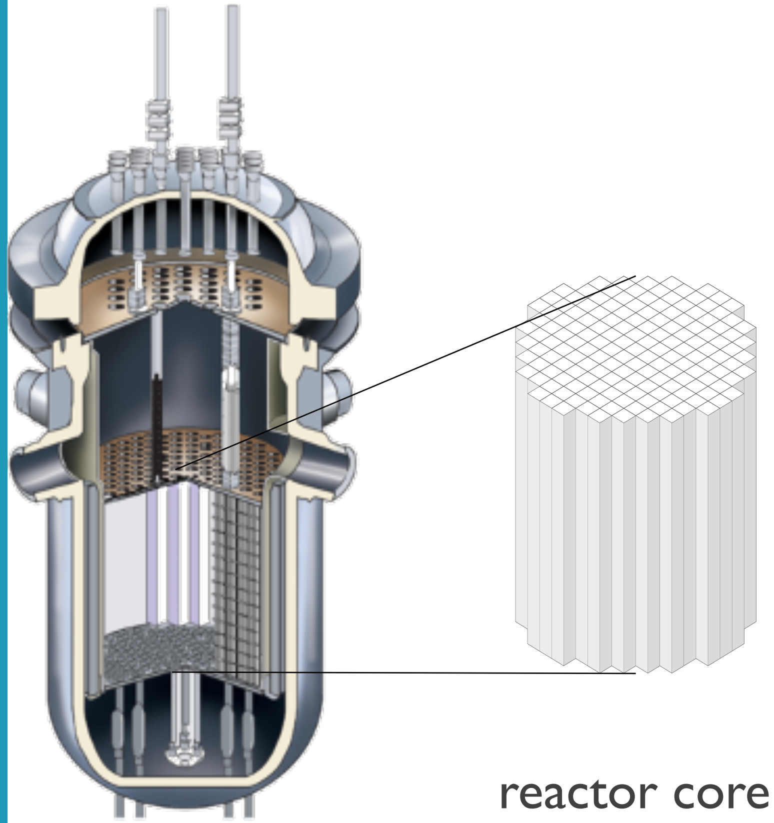
Overview

- On localizing perturbations in nuclear reactors
- Data simulation
- Unfolding perturbations with deep learning
- Experimental study
- Discussion and conclusions
- Final remarks

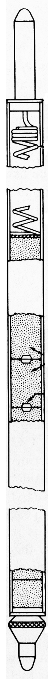
Introduction

Monitoring nuclear reactors working at nominal conditions is fundamental for safety purposes.



reactor core

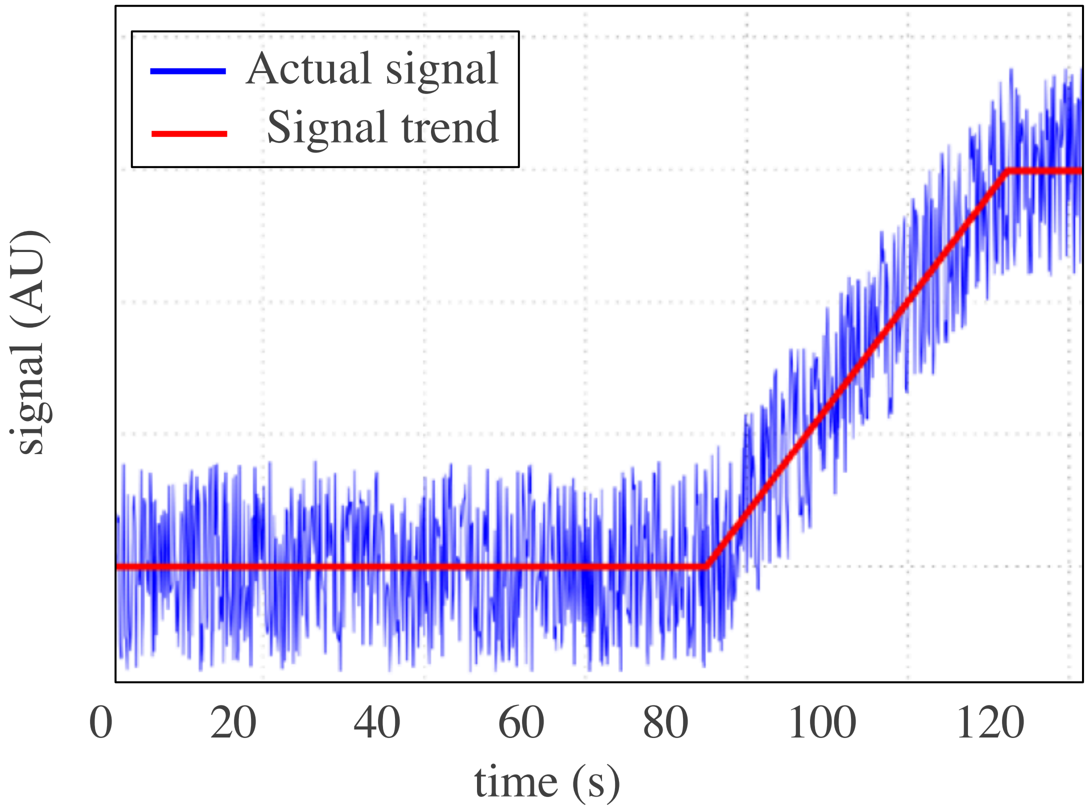
fuel assembly



fuel pin

fuel pellet

Fluctuations always exist in dynamical systems even at steady state-conditions



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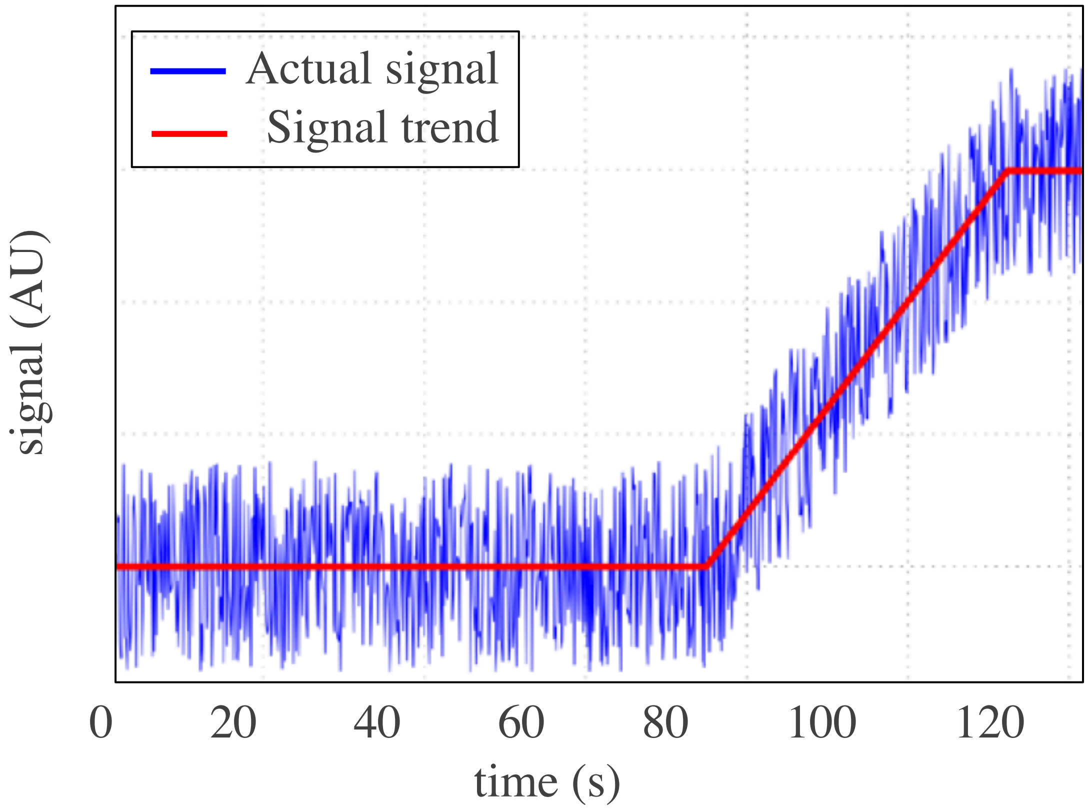

$$\underbrace{X(\mathbf{r},t)}_{\text{actual signal}} = \underbrace{X_0(\mathbf{r},t)}_{\text{signal trend}} + \underbrace{\partial x(\mathbf{r},t)}_{\text{noise}}$$

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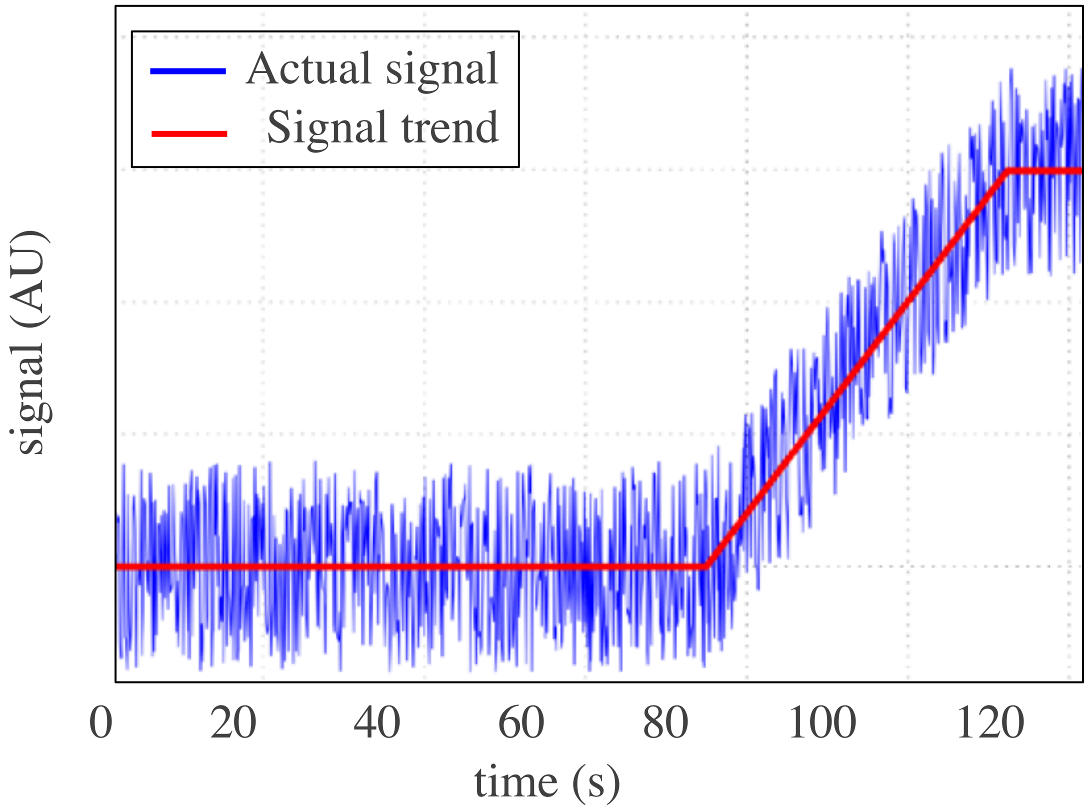

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Fluctuations carry valuable information about the system's dynamics

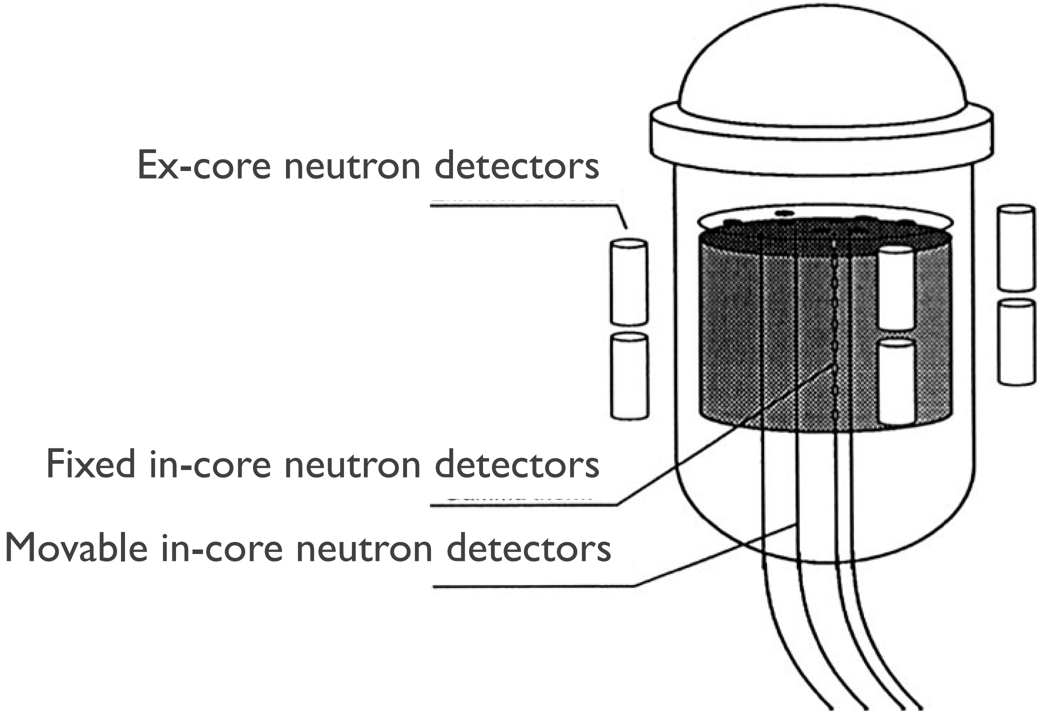
Fluctuations could be used for diagnostics:

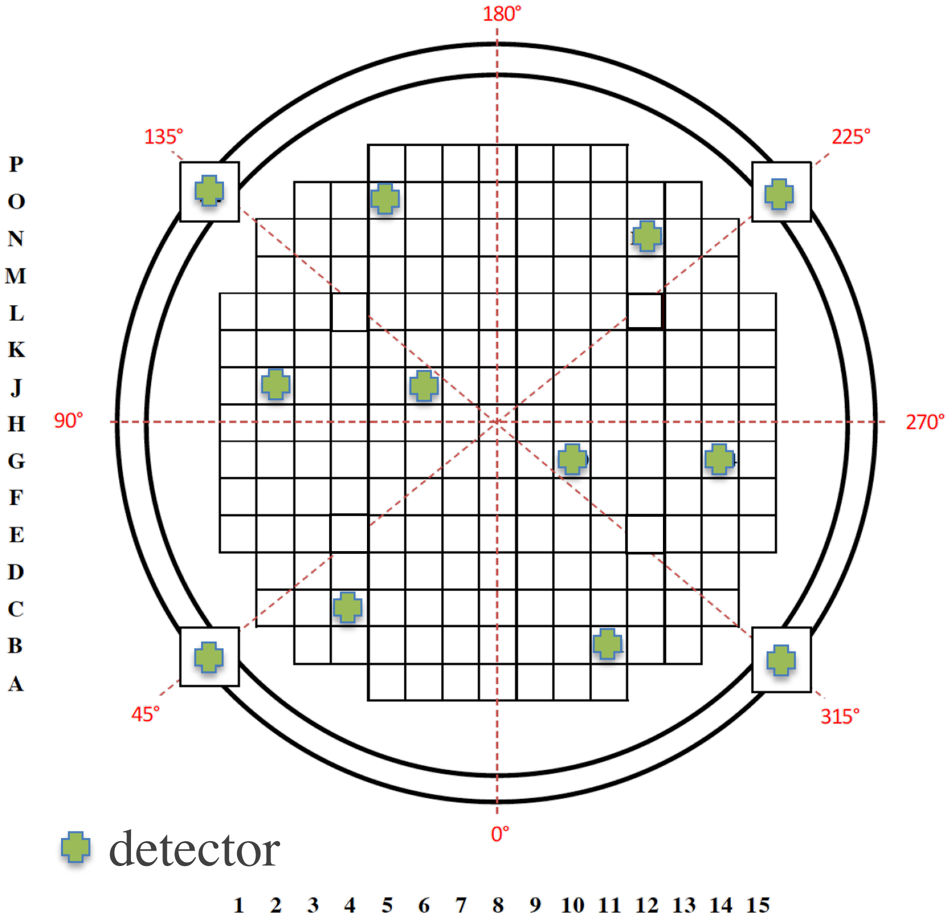
- Early detection of anomalies
- Estimation of dynamical system characteristics

Fluctuations could be used for diagnostics:

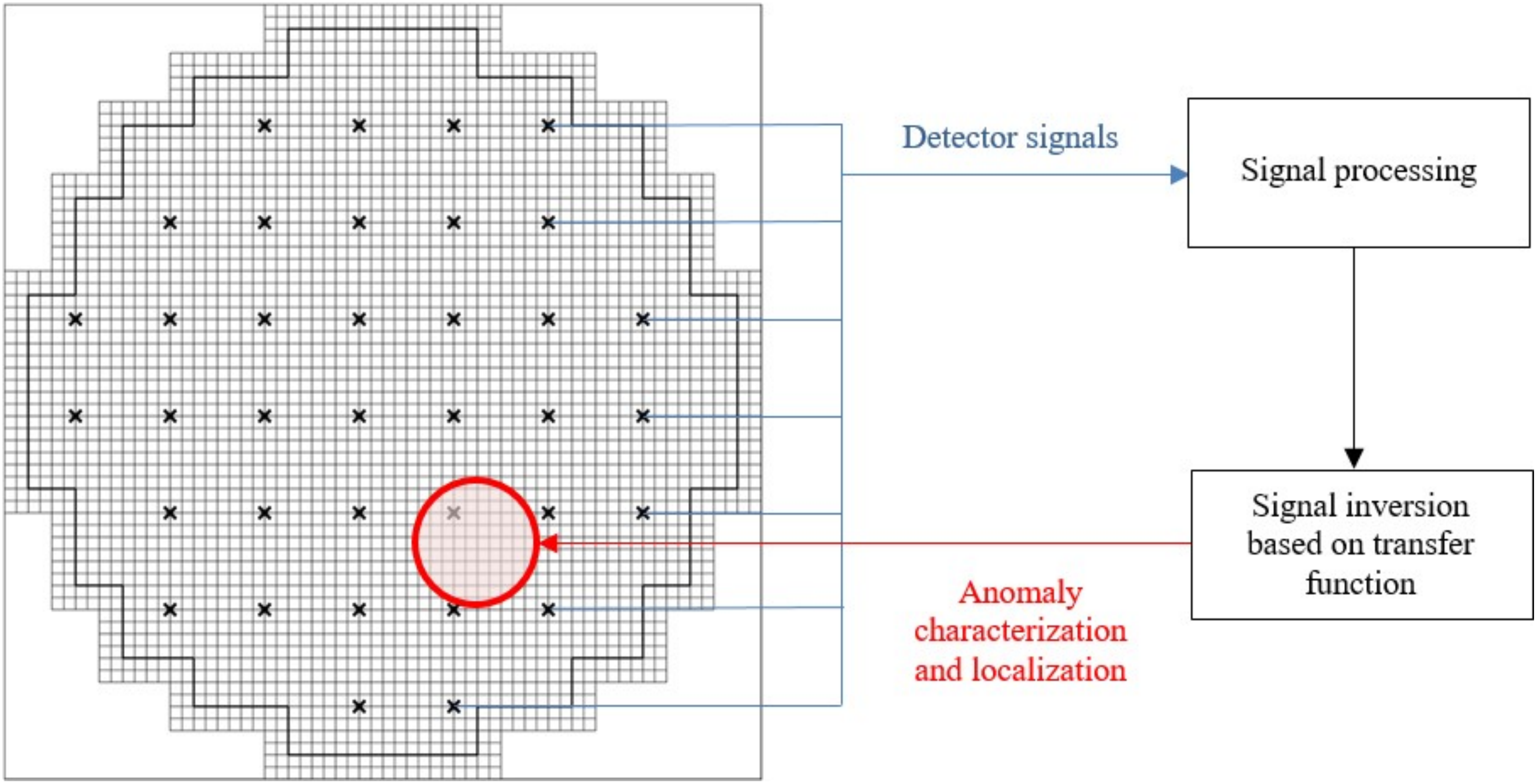
- Early detection of anomalies
- Estimation of dynamical system characteristics
- Perturbations in core reactors can alter the production of neutrons, which in response is seen as a fluctuation in the neutron flux
- Anomalies in nuclear reactors can be detected by analysing neutron flux data.

Neutron detectors present both in-core and ex-core:





- Advantage: "sense" perturbations even far away from the perturbations
- Disadvantage: western-type reactors do not always contain many in-core neutron detectors


Detector signals
Signal processing
Signal inversion based on transfer function
Anomaly characterization and localization

The problem

Signal analysis techniques are insufficient for back-tracking the nature and spatial distribution of possible anomalies

- Need to be able to invert the reactor transfer function

Forward problem

Perturbation

Neutron flux

$$B(\mathbf{r}_p, \omega) \rightleftarrows \boxed{G(\boldsymbol{r}, \boldsymbol{r}_p, t)} \rightleftarrows \phi(\mathbf{r}_p, \omega)$$

Backward problem

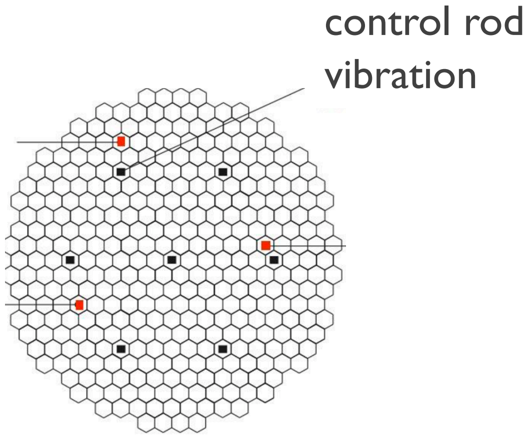
Unfolding

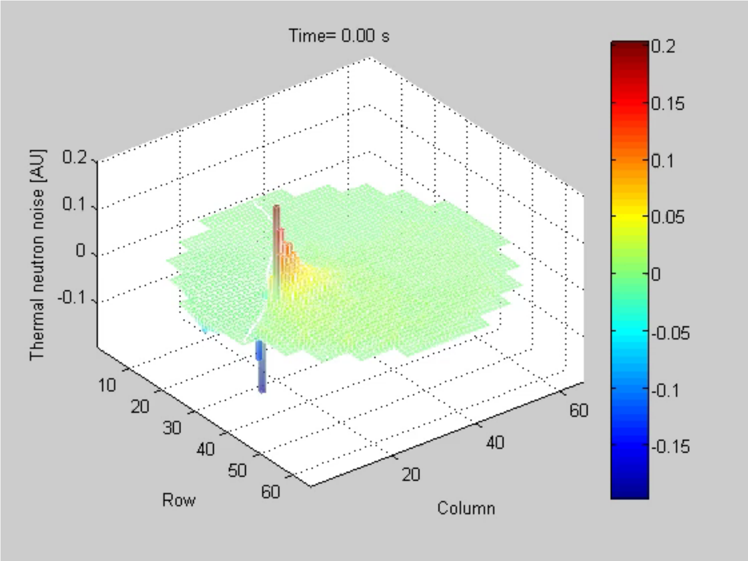
Machine Learning makes it possible to find a mapping between the signal read by the neutron detectors and the perturbation location and type

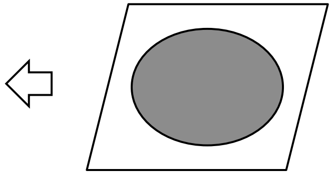
Forward Problem

Example of a vibrating control rod @ 0.2 Hz

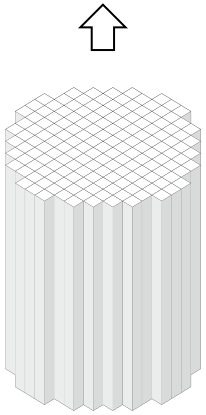
Perturbation of the absorption in the macroscopic cross section







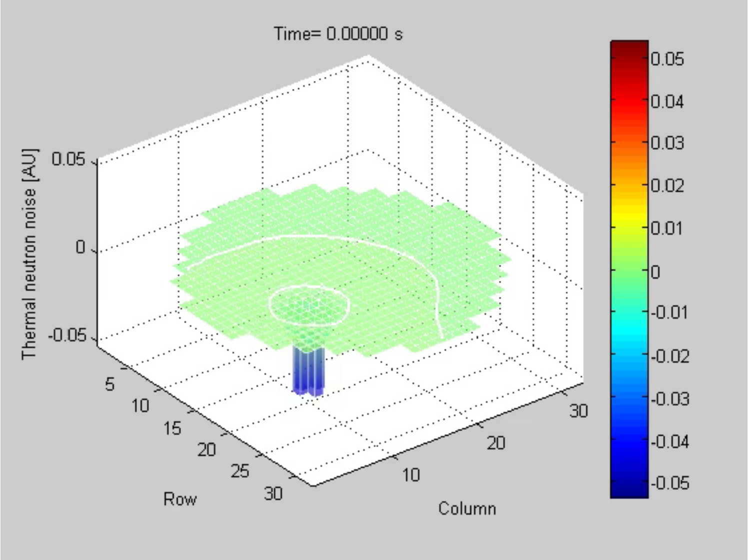
(2-D calculations)

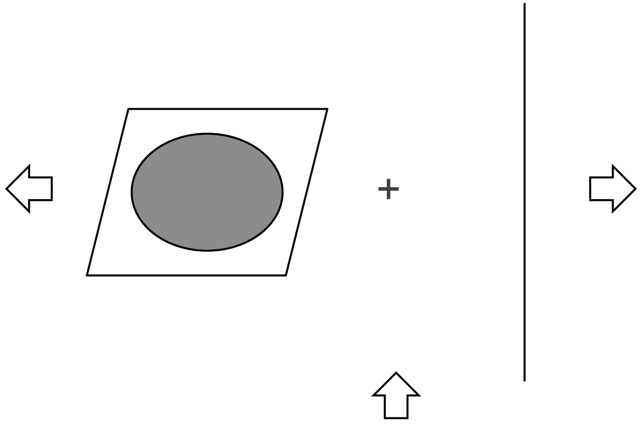


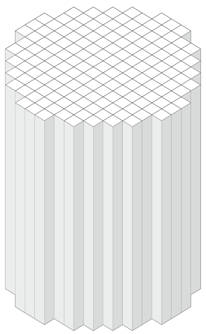
Unfolding

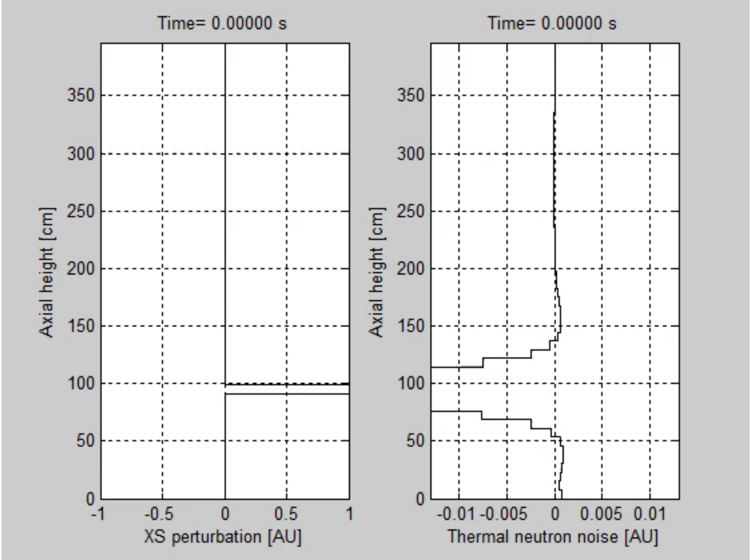
Noise diagnostics in nuclear reactors

- Example of a localized "absorber of variable strength" @ 1kHz









Proposed approach

1. A deep-learning approach to unfold neutron flux signals, and localise perturbations within 12 and 48 regions inside the core reactor

2. A *k*-means and k-NN based coarse-to-fine approach to better localise perturbation sources. Starting from 12 and 48 core regions, the signal is unfold up to the core reactor spatial resolution

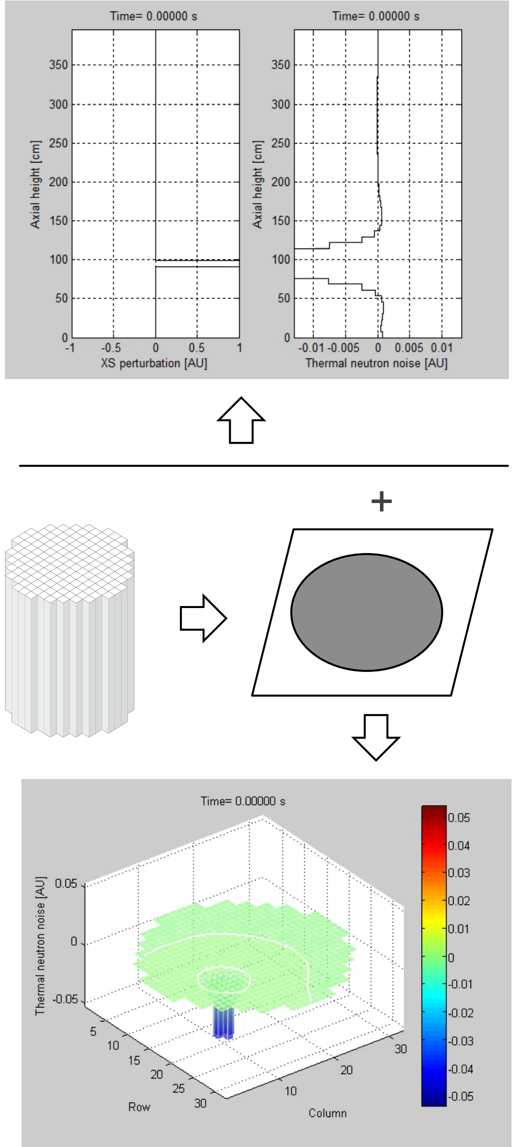
3. A denoising autoencoder to reconstruct part of missing signals and to filter noise out

Dataset

- Data simulated by Chalmers University using CORE SIM tool:
  - 2-energy group formulation - high and low energy spectra
  - first-order approximation of the neutron noise

- Pressurised Water Reactor (PWR) with:
  - Radial core 15×15 fuel assemblies
  - Volumetric mesh of dimension 32×32×26 (Δx=10.75, Δy = 10.75, Δz = 15.24)[cm]
  - Absorber of variable strength
  - Dirac's like perturbation generated at 0.1 Hz, 1 Hz and 10 Hz
  - Green's function as the reactor transfer function

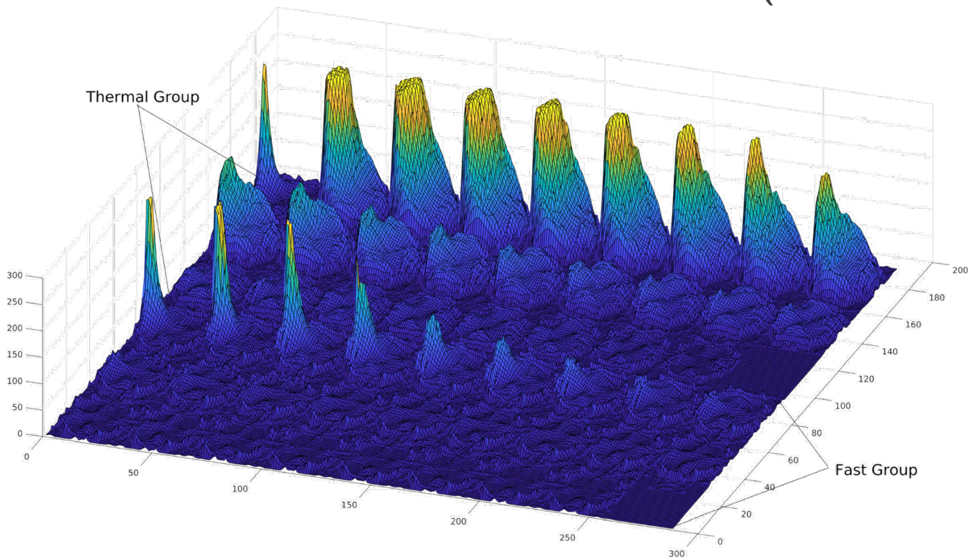
- CORE SIM output:
  - Fast and Thermal neutron response to the applied perturbation
  - The signal is <u>complex</u> and it is distributed in a three-dimensional array of size 32×32×26

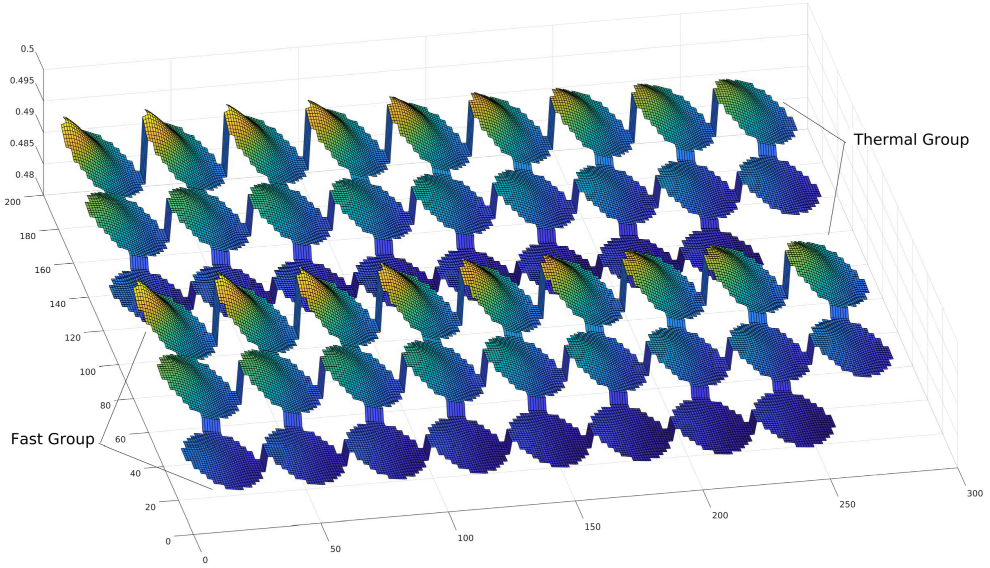


Demazière, C. (2011). CORE SIM: A multi-purpose neutronic tool for research and education. *Annals of Nuclear Energy*, *38* (12), 2698-2718

Data processing

- 19552 responses per frequency (0.1, 1, 10 Hz)
- The 3-D complex information (both amplitude and phase of the thermal and fast group responses) was unrolled into two dimensional forms, and the values rescaled between 0 and 255
  - 1st ch: Amplitudes of the groups
  - 2nd ch: Amplitudes of the groups
  - 3rd ch: Phase of the groups
- Portions of the signal were obscured (25%, 50%, 75%)
- Added White Gaussian Noise (SNR=1, 3)





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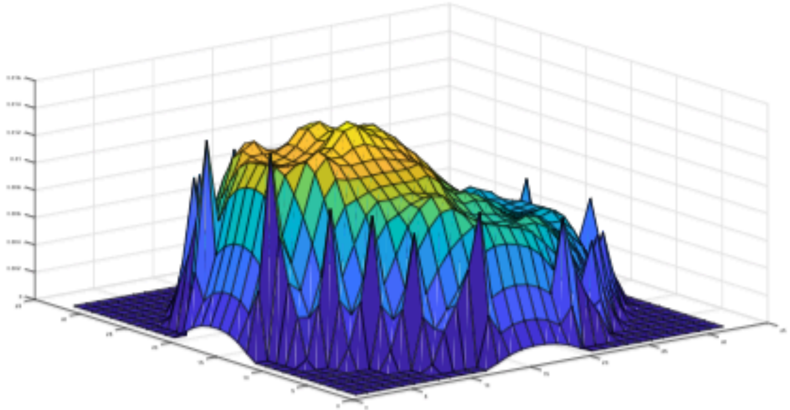
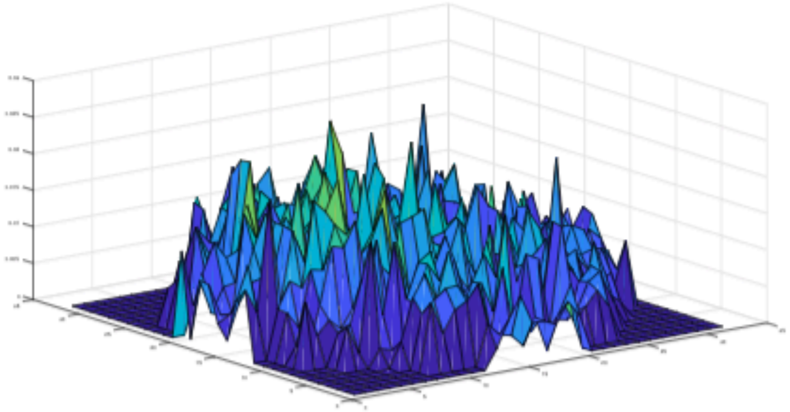


SNR = 1



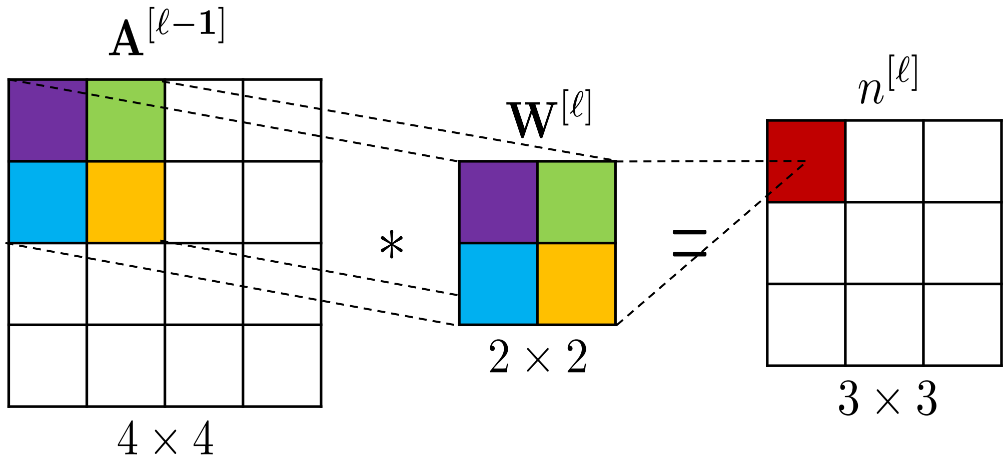
Recap: Convolutional Neural Networks

- State-of-the-art in many Computer Vision tasks

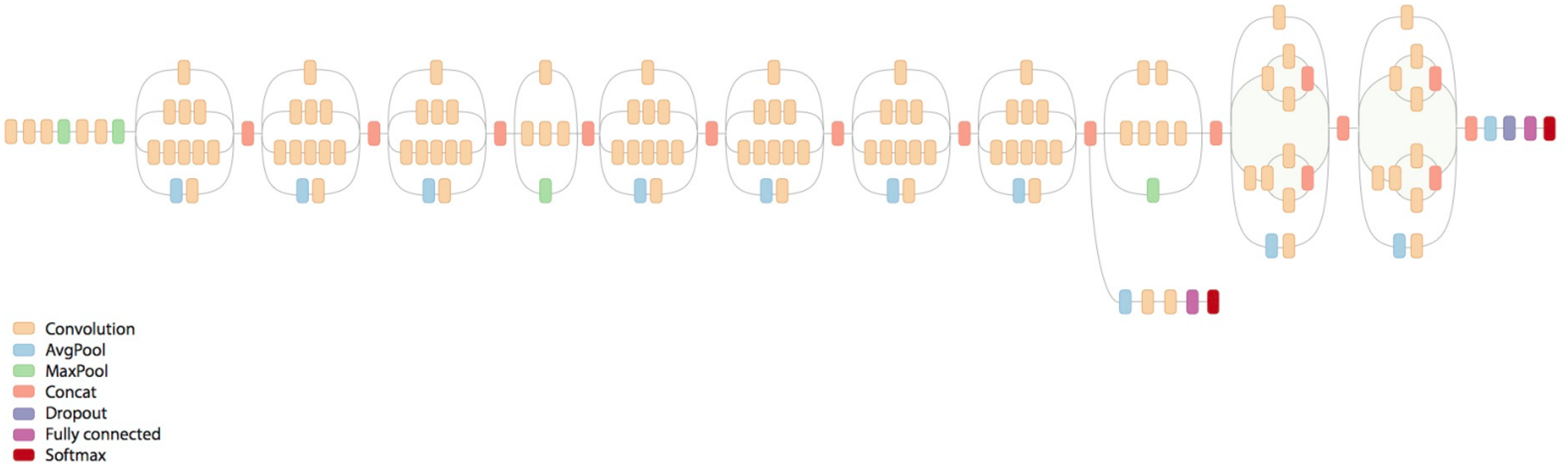
  i.e. classification, object detection, segmentation etc.

- Made up of stacks of Convolutional and Pooling layers

$$n_{i,j}^{[\ell]} = \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} \mathbf{W}_{x,y}^{[\ell]} \mathbf{A}_{i+x,j+y}^{[\ell-1]}$$



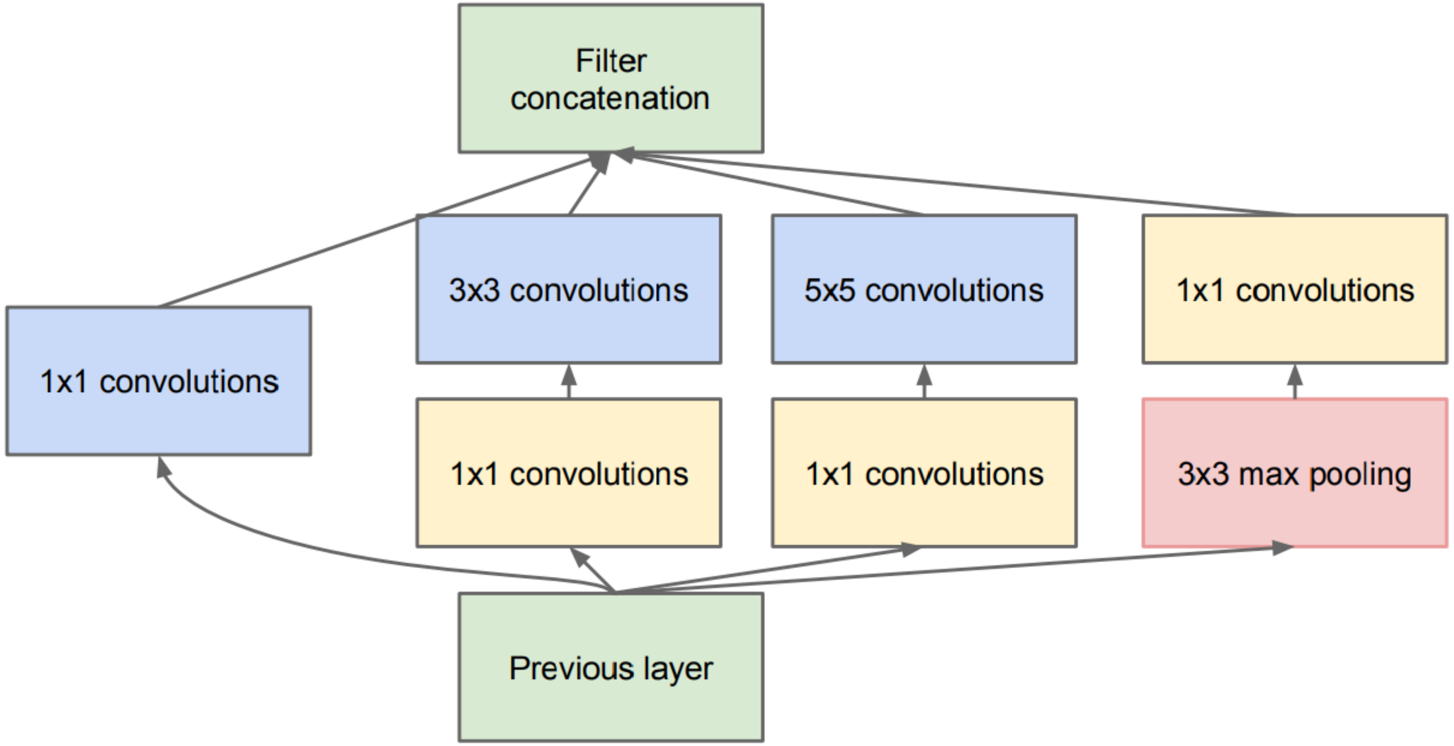
Recap: Inception Architecture



Szegedy, Christian, et al. "Rethinking the inception architecture for computer vision." Proceedings of the IEEE CVPR 2016

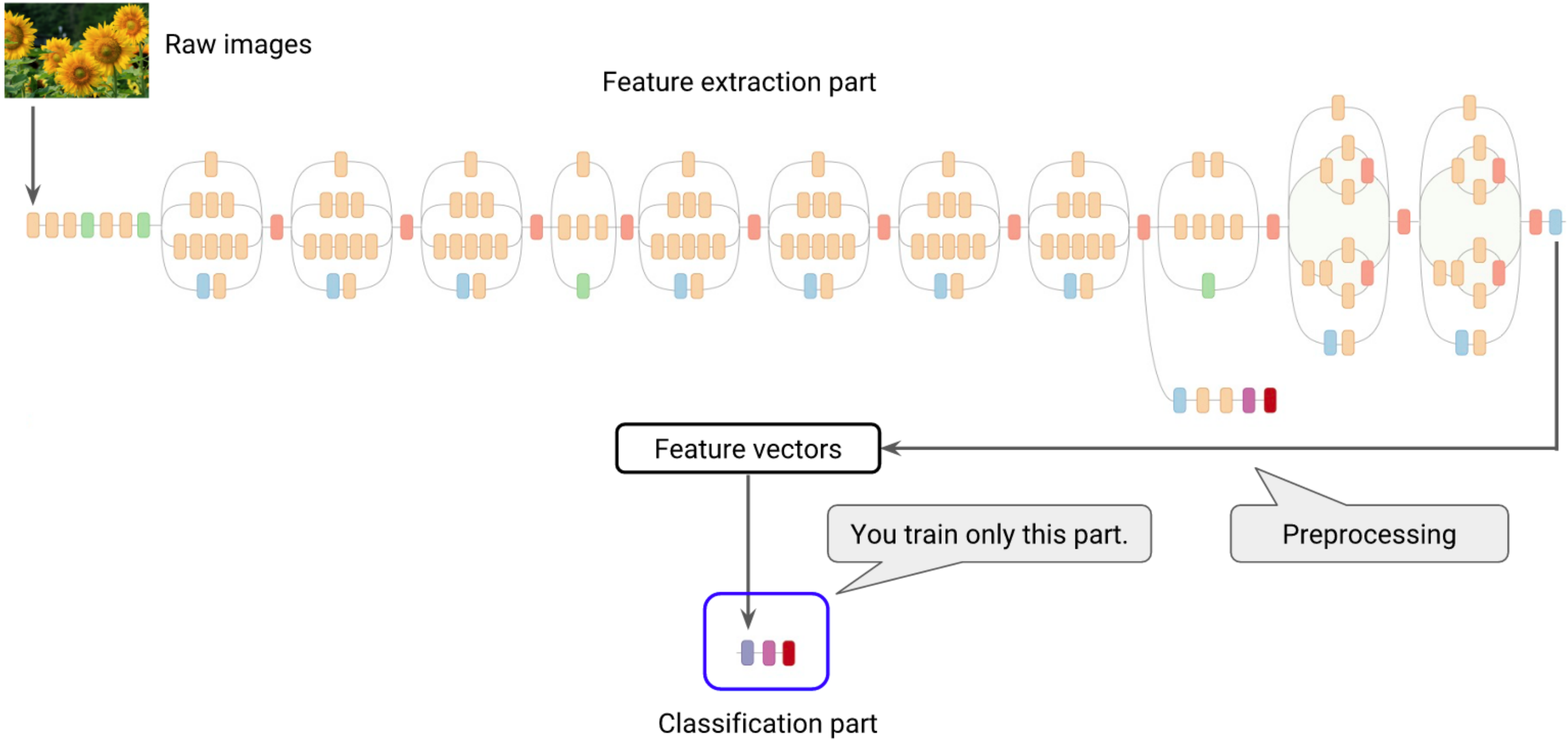
Recap: Inception module

1x1 convolutions reduce number of parameters and add non-linearity (ReLU) to learn more complex functions



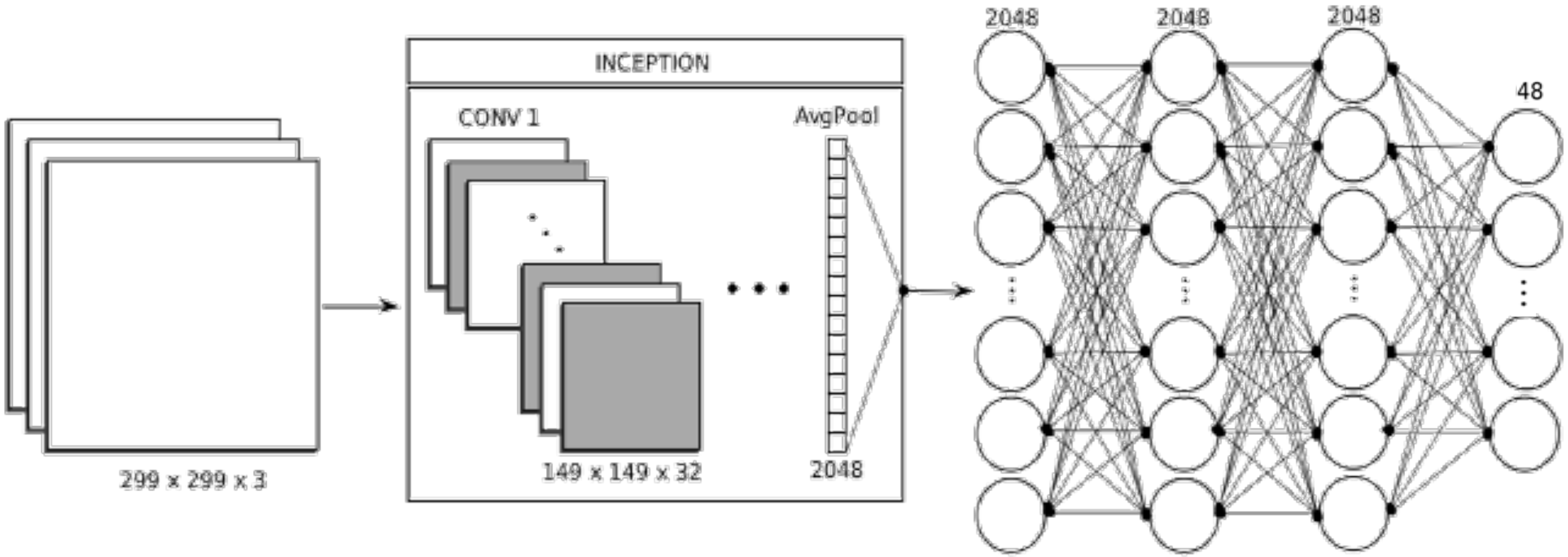
Szegedy, C., et al. "Going deeper with convolutions". Proceedings of the IEEE CVPR 2016

Recap: Inception transfer learning



Codelabs.developers.google.com. (n.d.). Image Classification Transfer Learning with Inception v3.

Proposed approach based on CNN

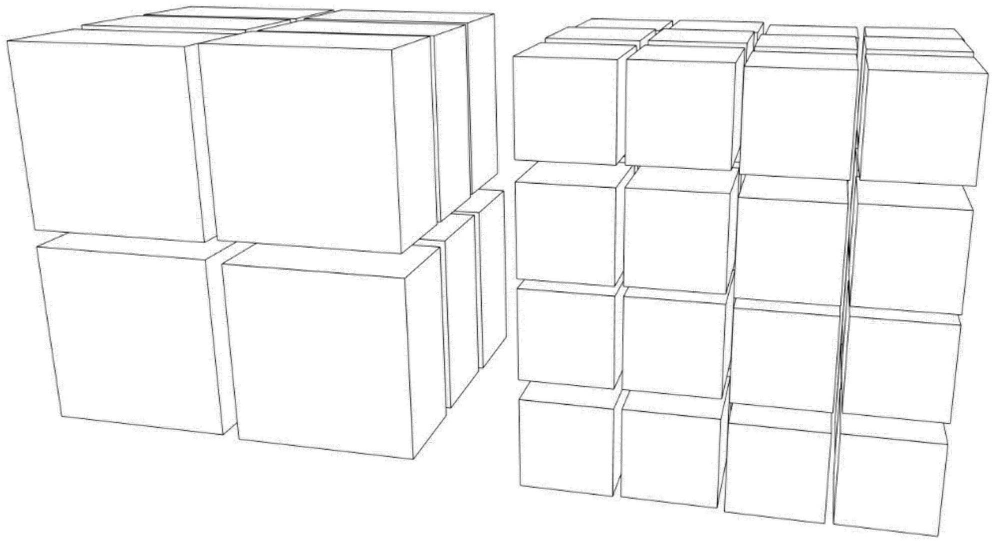


Softmax for Multiclass: $\sigma(\mathbf{x}_j) = \frac{e^{\mathbf{x}_j}}{\sum_{i=1}^{N} e^{\mathbf{x}_i}} \, for\ j = 1, \ldots N$

Weighted categorical cross entropy: $\mathscr{L}(x, \hat{x}) = -\sum_{j=1}^{J} \omega x \log(\hat{x})$

Experiment 1: Unfolding to 12-48 source locations

The initial 3D array of size 32x32x26 was compartmentalised into 12 and 48 subsections, by a factor 2x2x3 and 4x4x3 respectively.



Experiment 1: Unfolding to 12-48 source locations

Two sets of experiments were conducted:

- with pretrained ImageNet weights and partly re-trained
- with weights re-trained from scratch

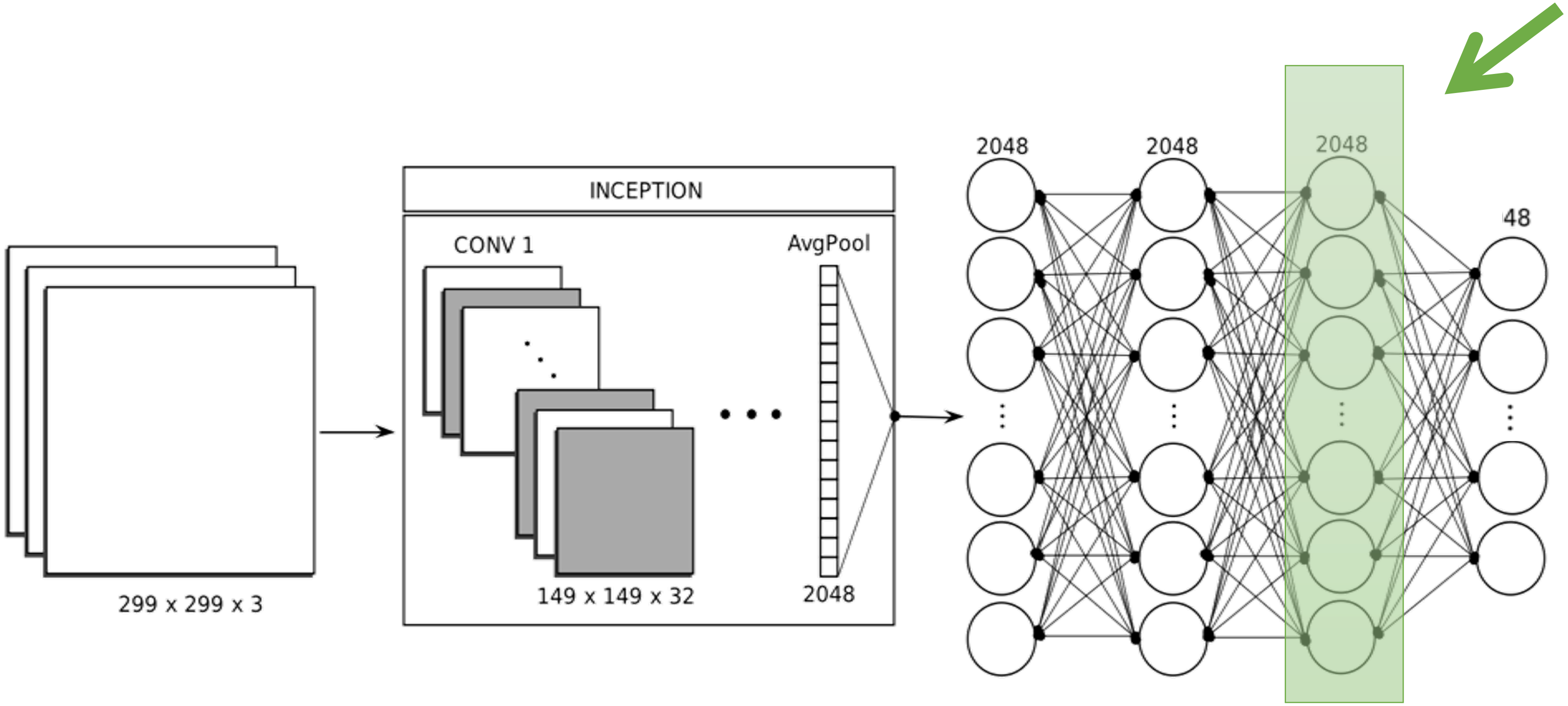
Additionally, to make the problem more difficult, the signal was corrupted by:

- Adding White Gaussian Noise at signal-to-noise-ratio (SNR) equal to 1 or 3
- Obscuring part of the signal (maintaining 25-50-75% of the sensors' information)

- **Using different train - development - test data splits, such as:**

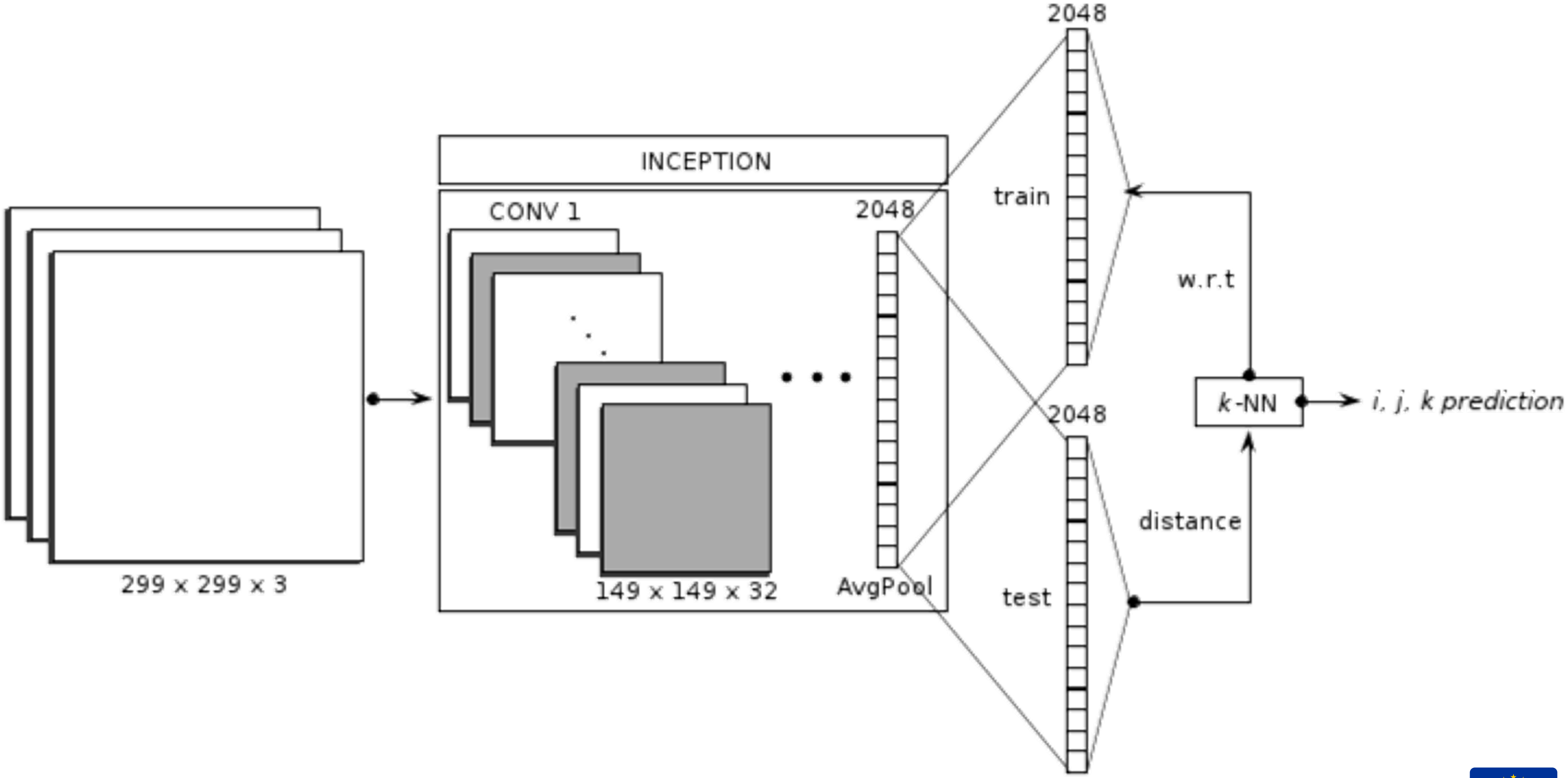
  75-10-15%, 50-20-30% or 25-10-65%

Experiment 2 - Unfolding from 12 to 48 source locations



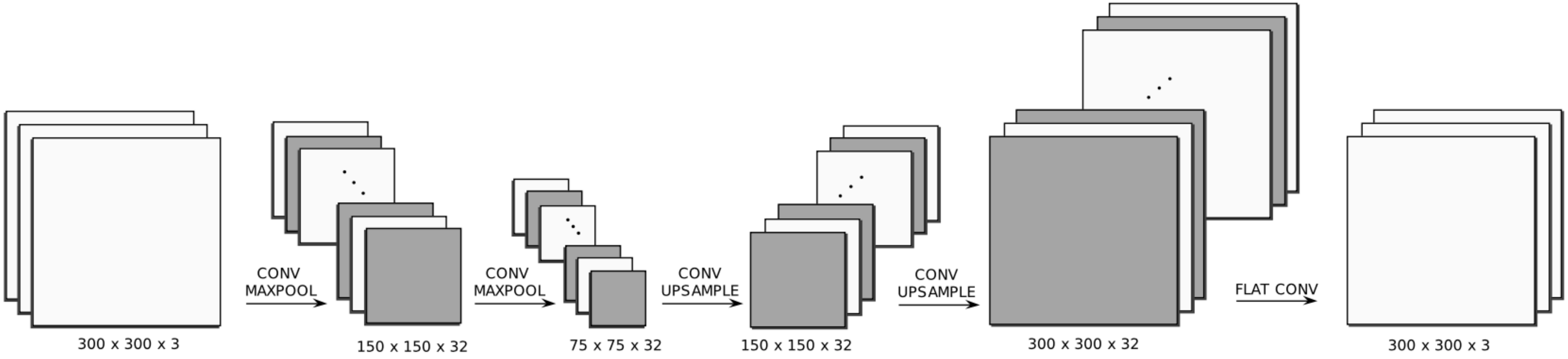
Within cluster L^2 norm: $\arg\min_C \sum_{i=1}^{k} \sum_{\boldsymbol{x} \in C_i} ||\boldsymbol{x} - \boldsymbol{\mu}_i||^2$

Experiment 3 - Unfolding up to signal's original resolution



Experiment 4 – Signal denoising and reconstruction

A denoising autoencoder was trained to reconstruct and filter the partially obscured - using 25—50—75% of the sensors - and noisy - at SNR=1 and SNR=3 – signals.



Mean Squared Error for noise filtering:

$$mse = \frac{1}{n}\sum_{i=1}^{n}(\boldsymbol{x}_i - g(f(\hat{\boldsymbol{x}}_i)))^2$$

Results - Experiment 1 - Unfolding to 12-48 source locations

CNN Unfolding					
Classes	Sensors (%)	Signal	Train/Dev /Test (%)	Accuracy	
				Pre-trained	Scratch
12	100	clean	75-10-25	97	99.9
	100	SNR=3	75-10-15	88.7	99.9
	100	SNR=1	75-10-15	84.2	98
	25	clean	50-20-30	93.7	99.9
	25	clean	25-15-60	93.4	98.4
	25	SNR=1	50-20-30	76.6	94.1

Classes	Sensors (%)	Signal	Train/Dev /Test (%)	Accuracy	
				Pre Trained	Scratch
48	100	clean	75-10-25	92.3	99.9
	100	SNR=1	75-10-15	72.9	92.5
	25	clean	50-20-30	90.3	97.8
	25	clean	25-15-60	85.1	91.1
	25	SNR=1	50-20-30	65.2	82.3

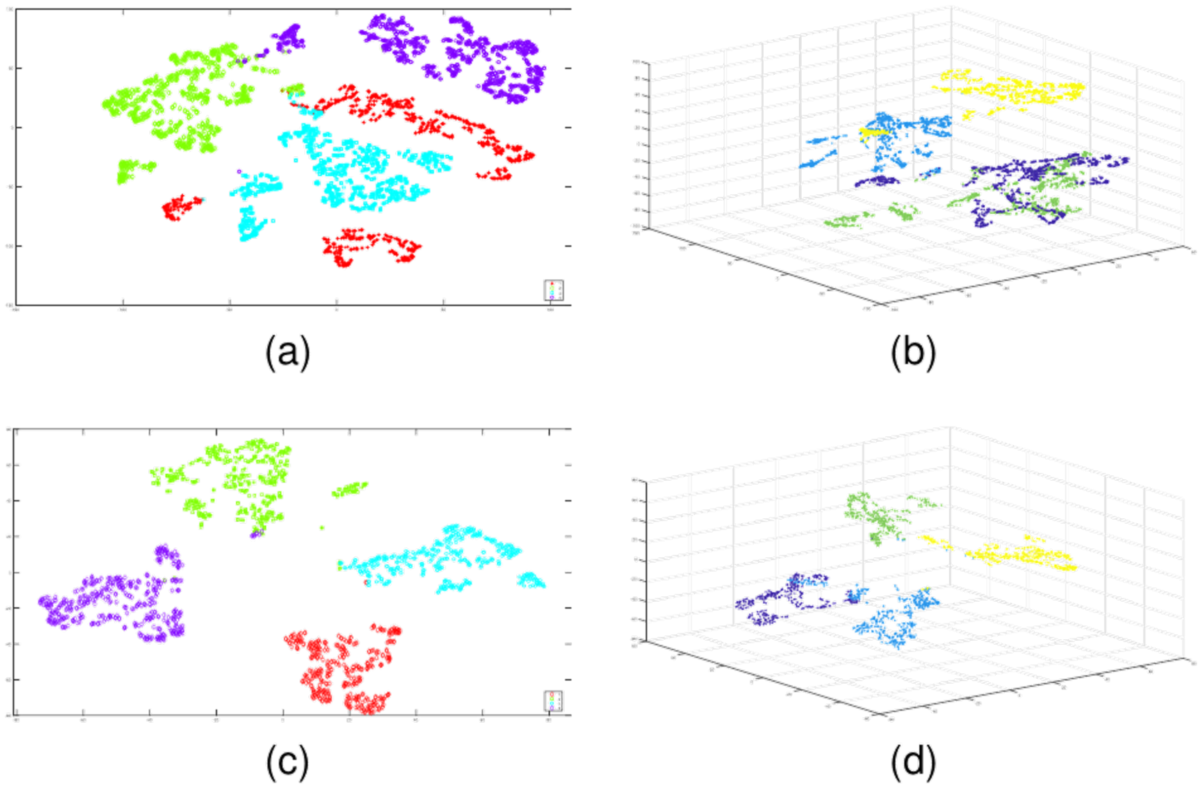
MAX

MIN

Results - Experiment 2 - Unfolding from 12 to 48 source locations

t-Stochastic Neighbour Embedding (t-SNE) representation of *k*-means (*k*=4) of the seventh block.

Each point is a lower dimensional projection of 2048 dimensional vector representations of signal. Each colour indicates a different cluster.

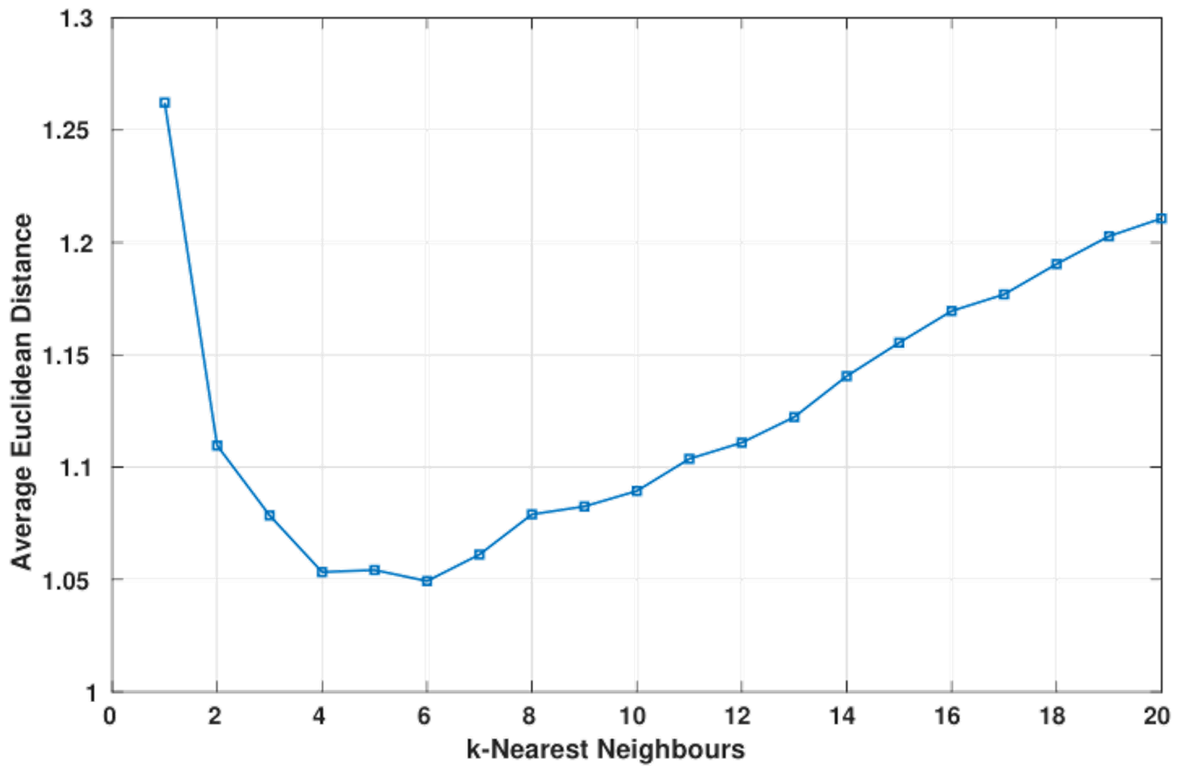


a-b: training set clusters. **c-d:** test set predictions.

Results - Experiment 3 - Unfolding up to signal's original resolution

For various values of *k*-, starting from a resolution of twelve blocks it is possible to estimate the source location at the original signal's resolution of 32x32x26.

The resulting accuracy error was slightly greater than one point in the reactor.

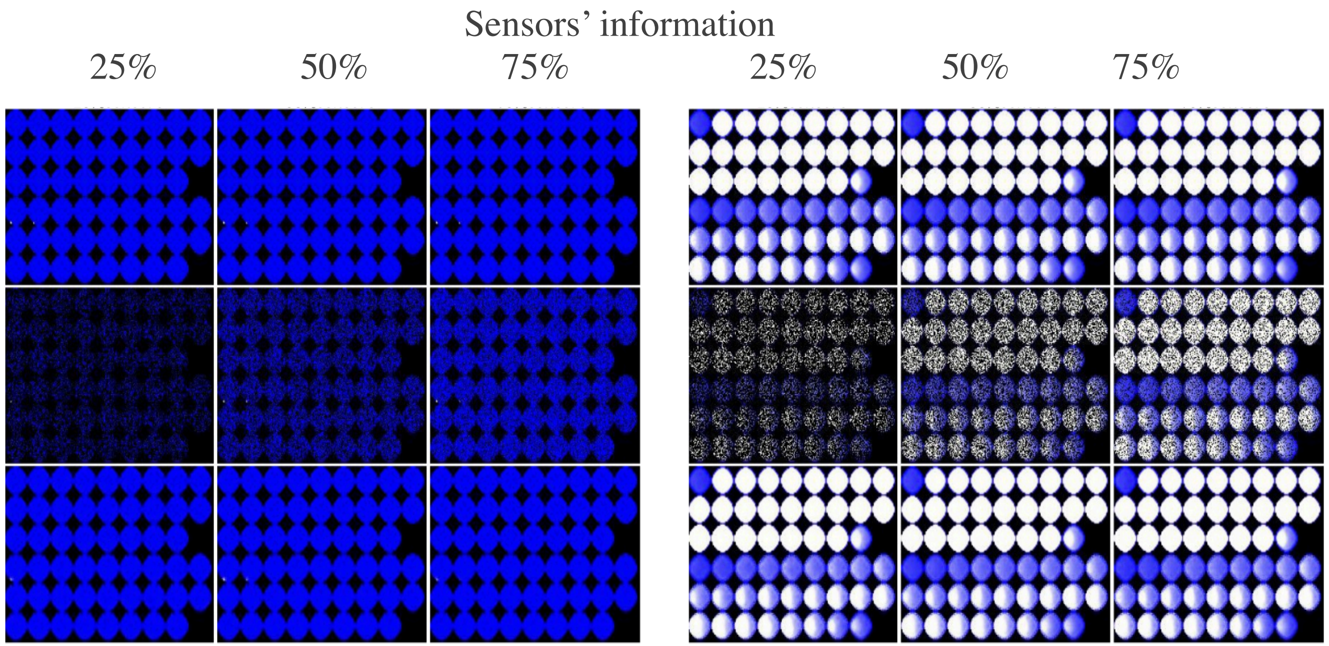


Results - Experiment 4 – Signal denoising and reconstruction

The reconstruction was measured by the **normalised cross correlation** (ncc) metric.

$$ncc = \frac{\sum_{i,j}(a_{i,j} - \mu_{\boldsymbol{A}})(b_{i,j} - \mu_{\boldsymbol{B}})}{[\sum_{i,j}(a_{i,j} - \mu_{\boldsymbol{A}})^2 \sum_{i,j}(b_{i,j} - \mu_{\boldsymbol{B}})^2]^{0.5}}$$

This allows a quantitative comparison of the similarity among two images; ncc ranges between -1 (completely differing) and +1 (perfectly matching).



Deep-CNN Autoencoder				
Sensors	Signal	Train/Test	Normalised Cross Correlation	
			Clean vs Corrupted	Clean vs Reconstructed
75%	clean	25/75%	0.77	0.995
50%	clean	25/75%	0.57	0.995
25%	clean	25/75%	0.37	0.993
25%	SNR=1	25/75%	0.36	0.991

MAX

MIN

Discussion

Goals of CORTEX project:

- Developing high fidelity tools for simulating stationary fluctuations
- Validating those tools against experiments to be performed at research reactors
- Developing advanced signal processing and machine learning techniques (to be combined with the simulation tools)
- Demonstrating the proposed methods for both on-line and off-line core diagnostics and monitoring
- Machine learning able to correctly identify and localize the type of perturbations existing in a nuclear core

Further readings

For further details about the work please refer to:

Caliva, Francesco*, Fabio De Sousa Ribeiro*, et al. "A deep learning approach to anomaly detection in nuclear reactors." ***2018 International joint conference on neural networks (IJCNN).*** **IEEE, 2018.**

Limitations:

- Classification based coarse-to-fine approach
- Only signals in the frequency domain were unfolded
- Only one type of perturbation was simulated

Follow-up work:

- Unfolding of perturbations in the frequency and time domains
- Variety of perturbations were precisely unfolded

Fabio De Sousa Ribeiro*, Francesco Calivà* et al. "Towards a deep unified framework for nuclear reactor perturbation analysis." *2018 IEEE symposium series on computational intelligence (SSCI)*. IEEE, 2018.

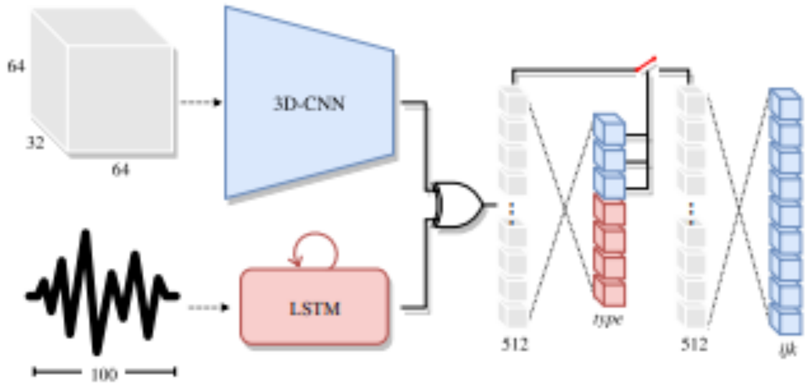


Fig. 1. Unified framework for Time and Frequency domain perturbation type classification and coordinate regression.

Acknowledgements

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Thank you

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