A Deep Learning Approach to Anomaly Detection in Nuclear Reactors

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CORTEX
Core monitoring techniques and experimental validation and demonstration

mlearn

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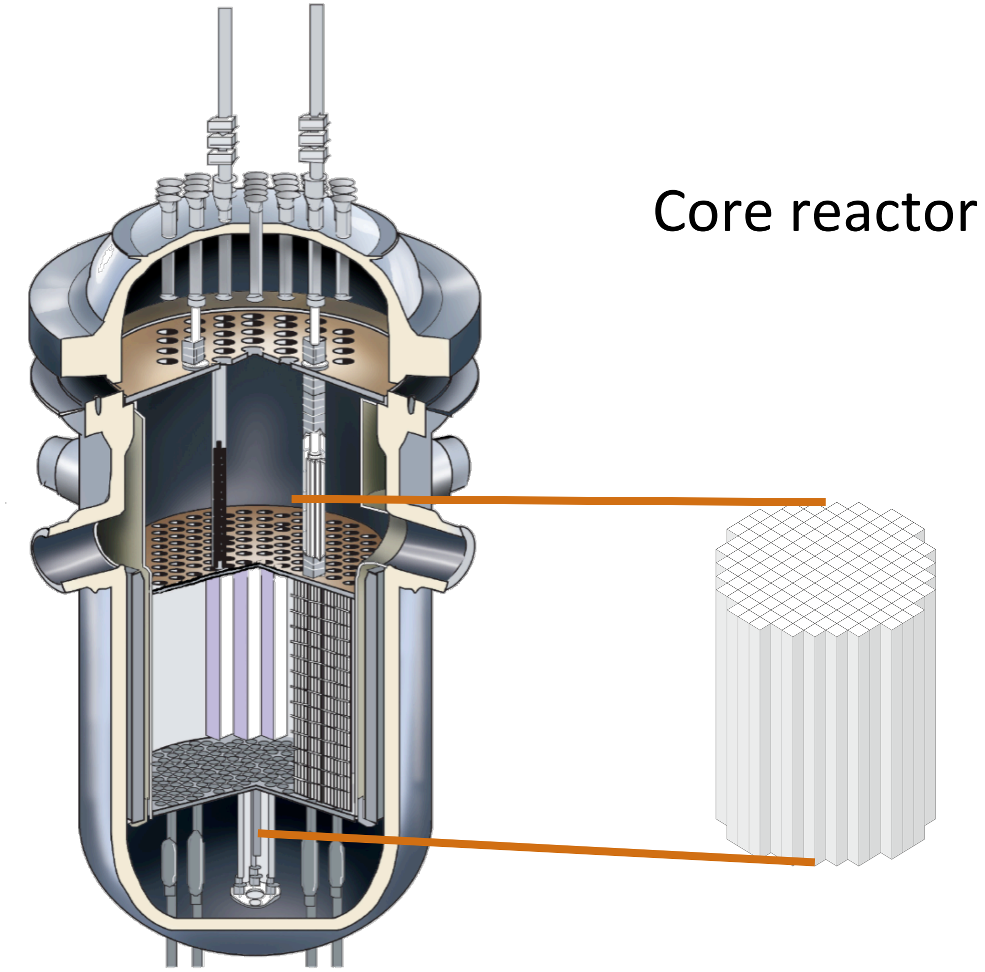
Agenda

- Introduction
- The problem
- Our Approach
- Experimental Study
- Conclusions and Final remarks

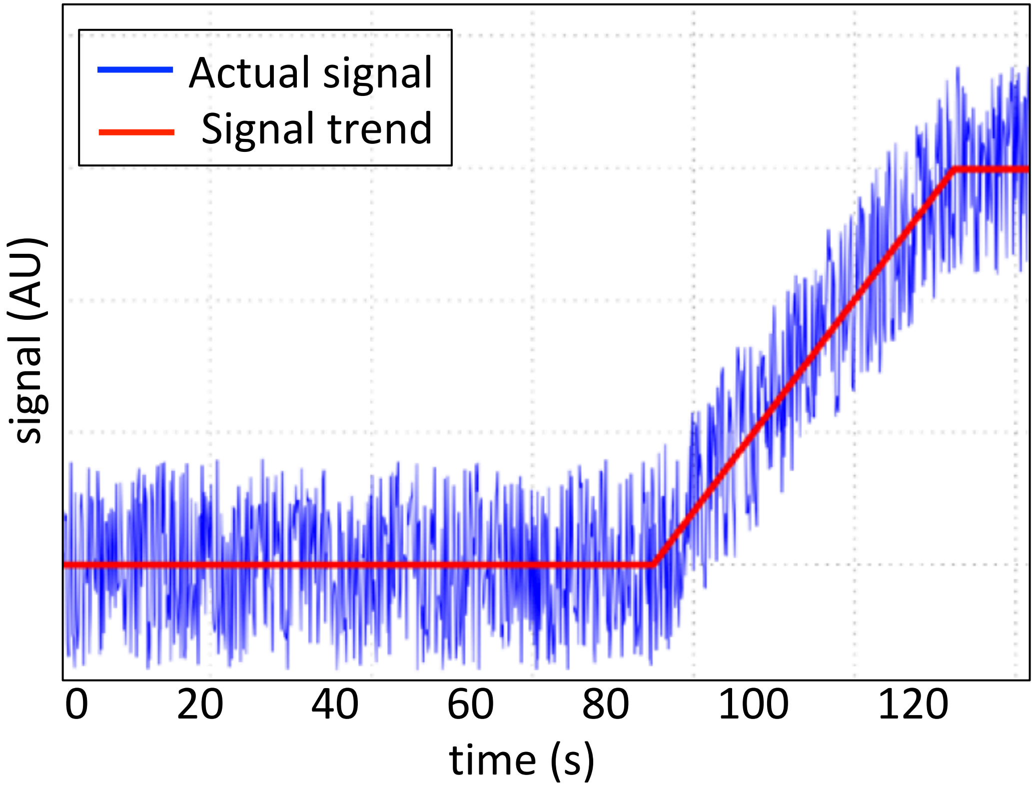
Introduction

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



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

Induced perturbations in the reactor core cause fluctuations of the neutron flux.

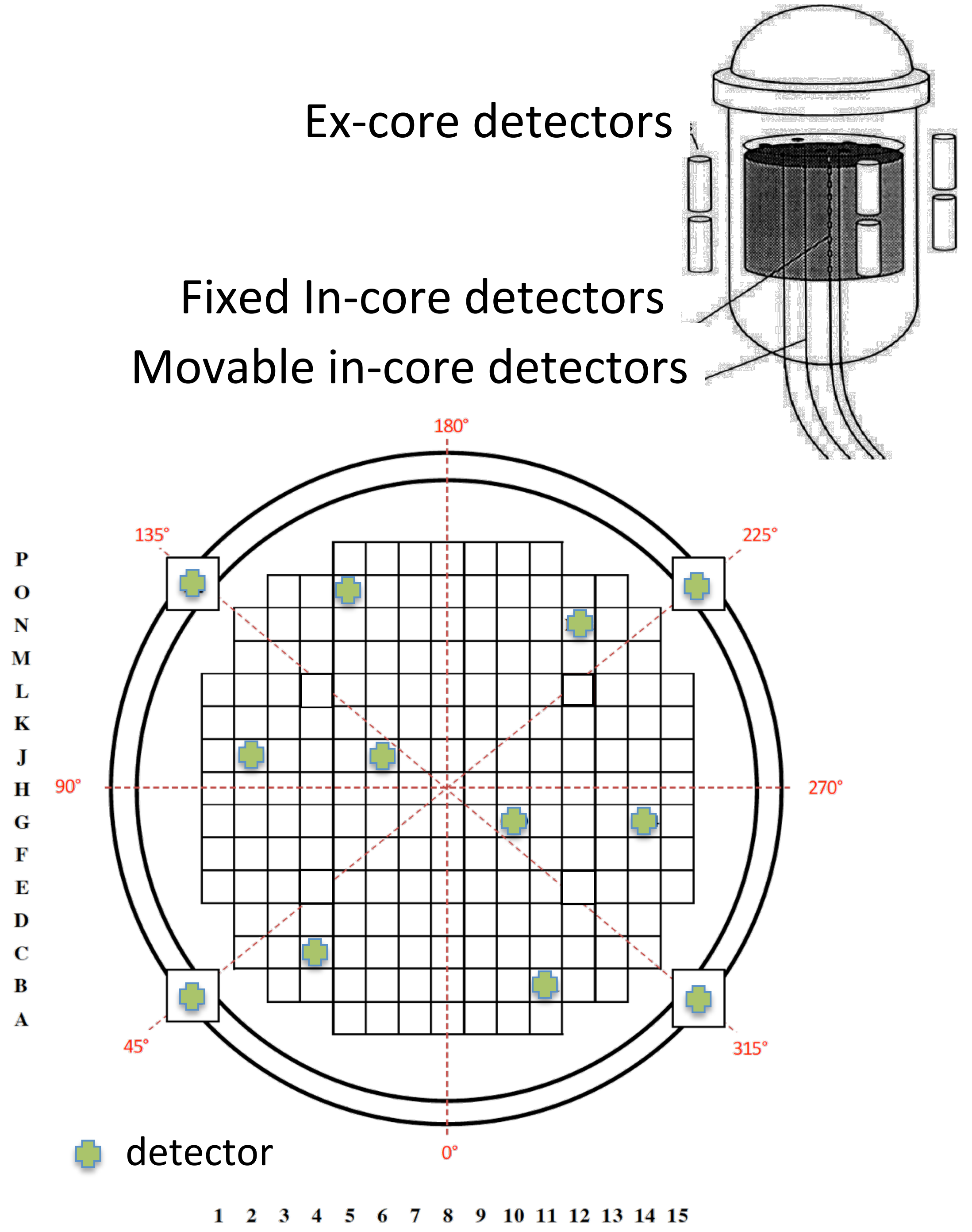


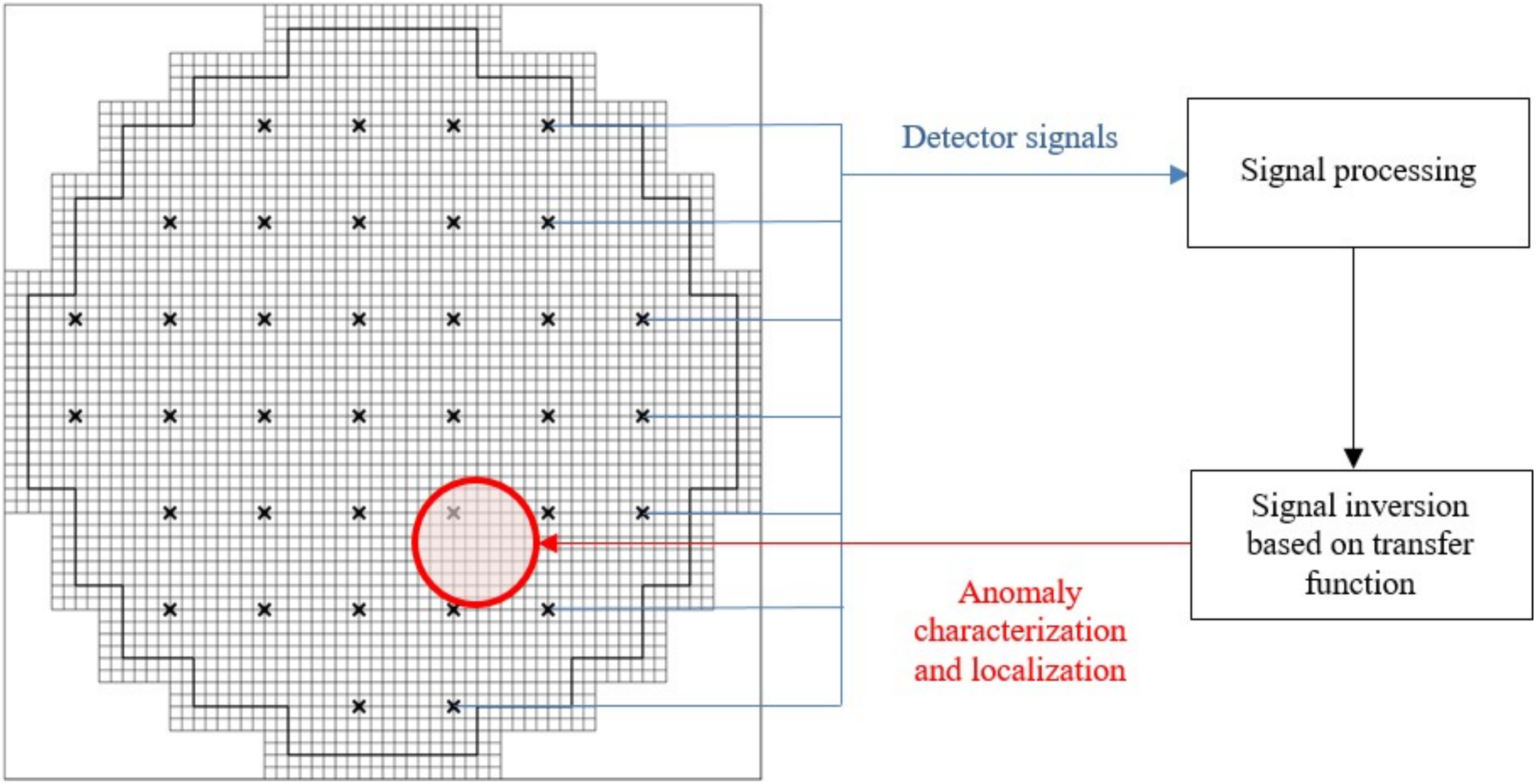
$$X(\mathbf{r},t) = X_0(\mathbf{r},t) + \partial x(\mathbf{r},t)$$

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

Induced perturbations in the reactor core cause fluctuations of the neutron flux.

Anomalies in nuclear reactors can be detected by analysing neutron flux data.

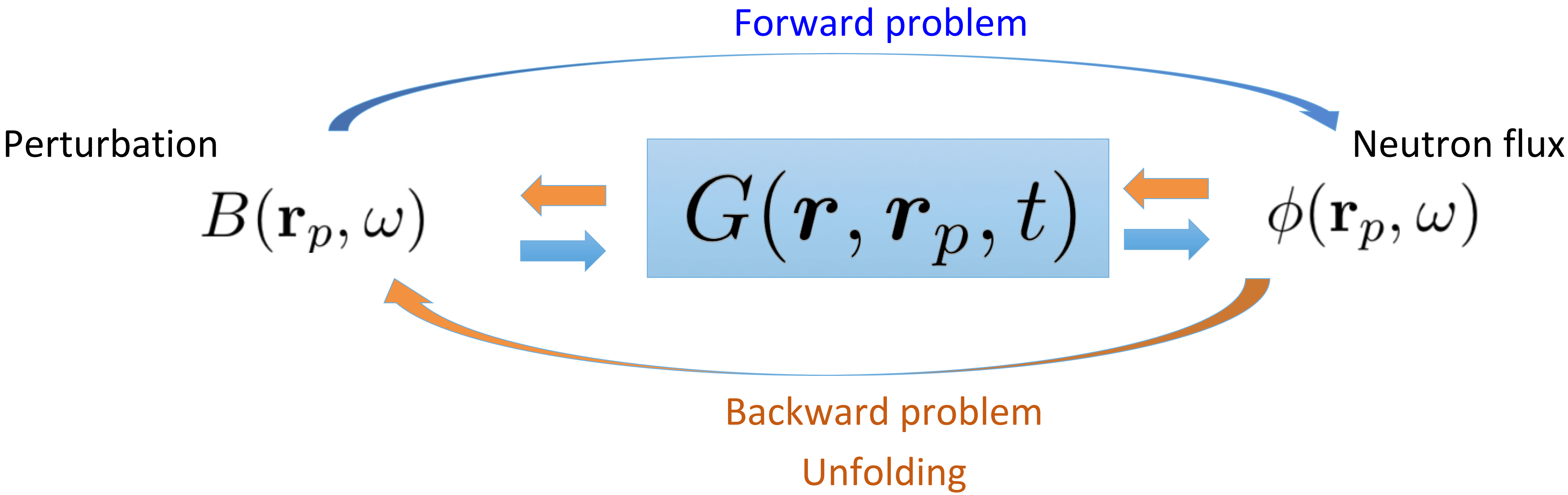



Detector signals
Signal processing
Signal inversion based on transfer function
Anomaly characterization and localization

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



The Problem

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

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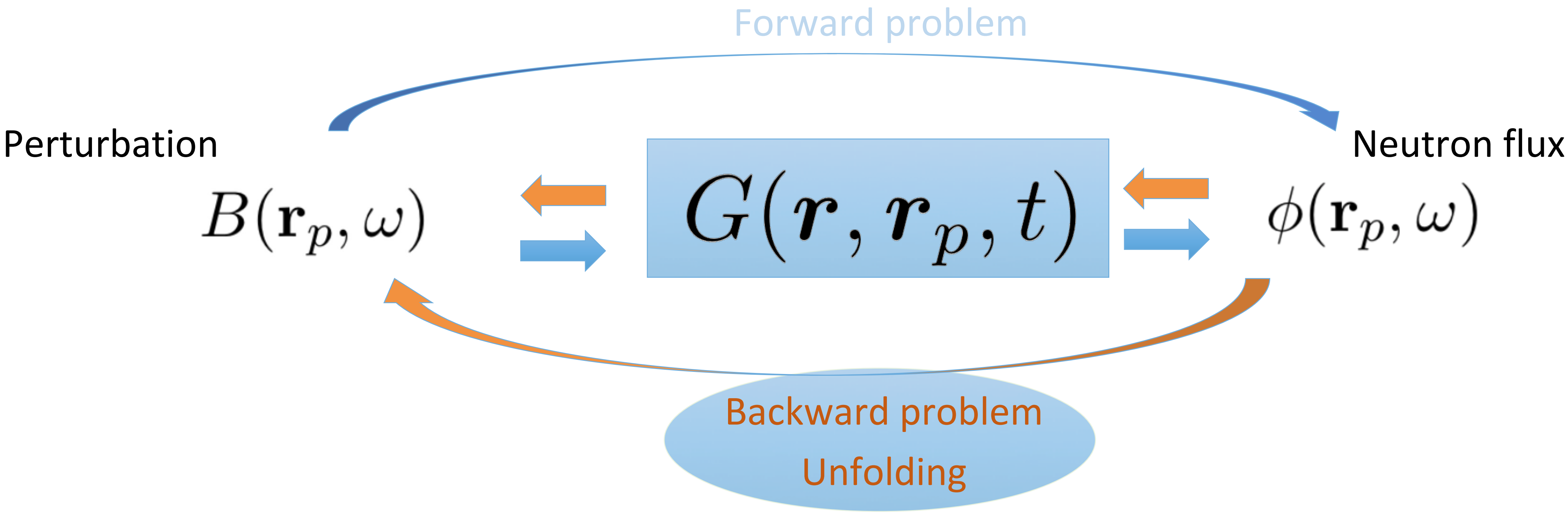
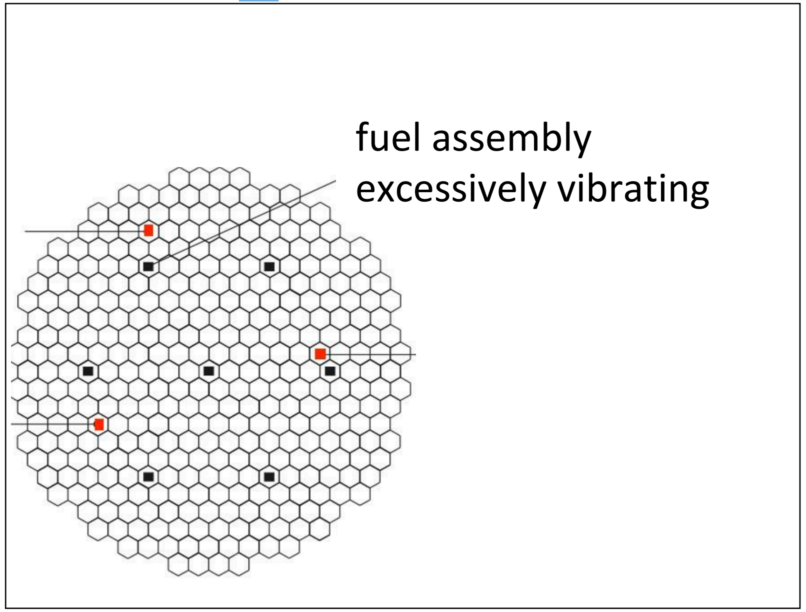
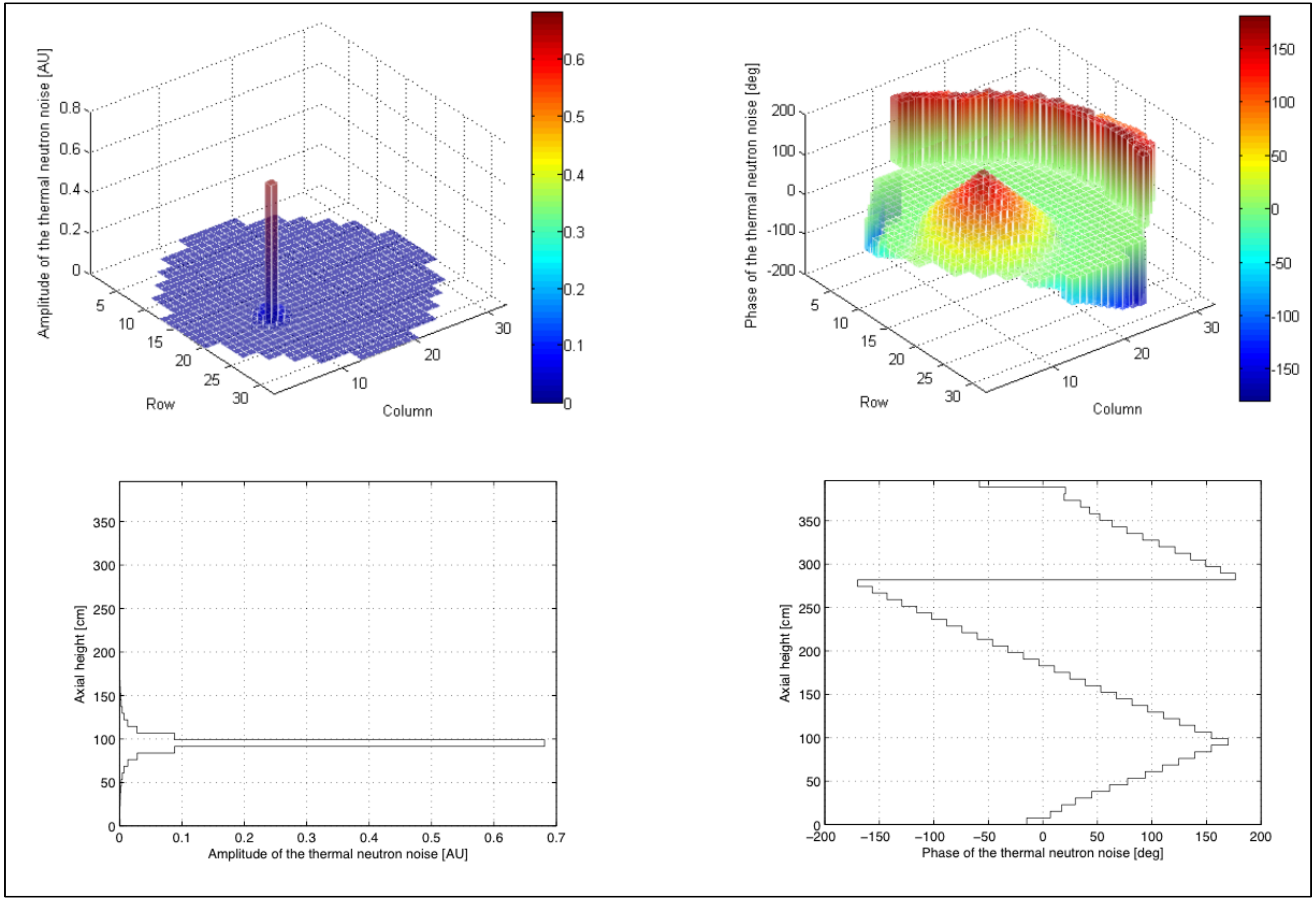


Forward Problem





Unfolding

Our Contributions

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

A *k*-means and k-means 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.

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

Analysed data

- Data simulated by Chalmers University using CORE SIM tool.
- Pressurised Water Reactor (PWR) with:

  Radial core 15×15 fuel assemblies.

  Volumetric mesh of dimension 32×32×26.

  Dirac's like perturbation generated at 0.1 Hz, 1 Hz and 10 Hz.

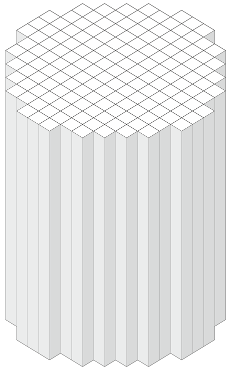
  Green's function as the reactor transfer function.

- CORE SIM output:

  Fast and Thermal neutron response to the applied perturbation.

  The signal is complex and it is distributed in a three-dimensional array of size 32×32×26.

Core reactor



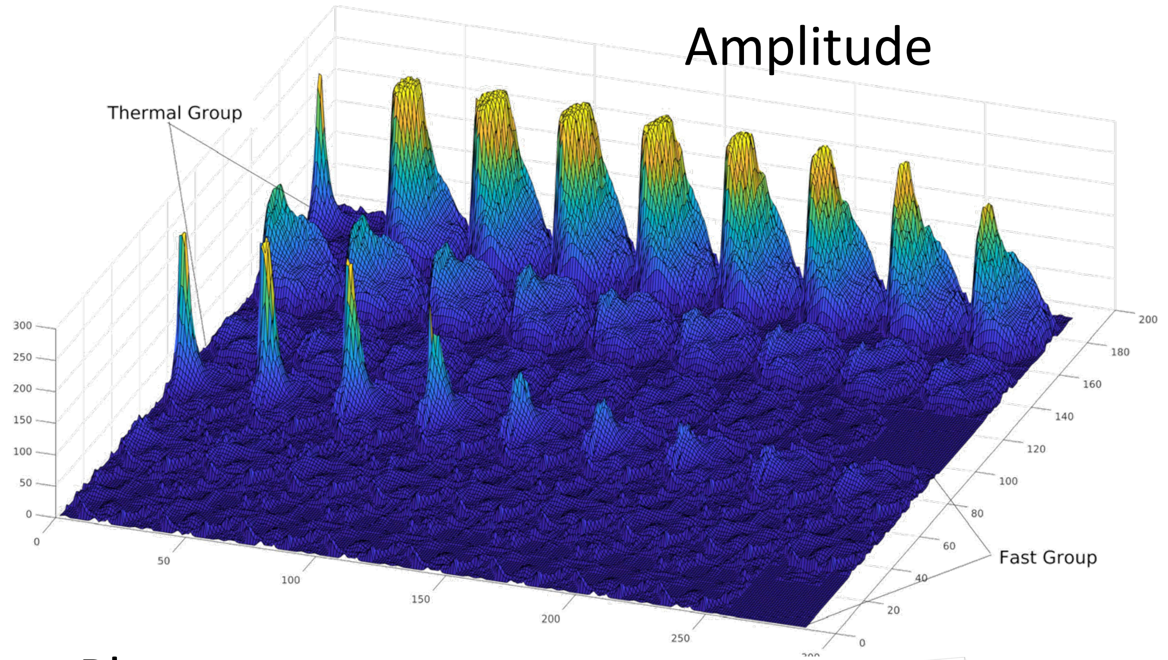
Demazière, C. (2011). CORE SIM: A multi-purpose neutronic tool for research and education. *Annals of Nuclear Energy*, *38* (12), 2698-2718

Data pre-processing

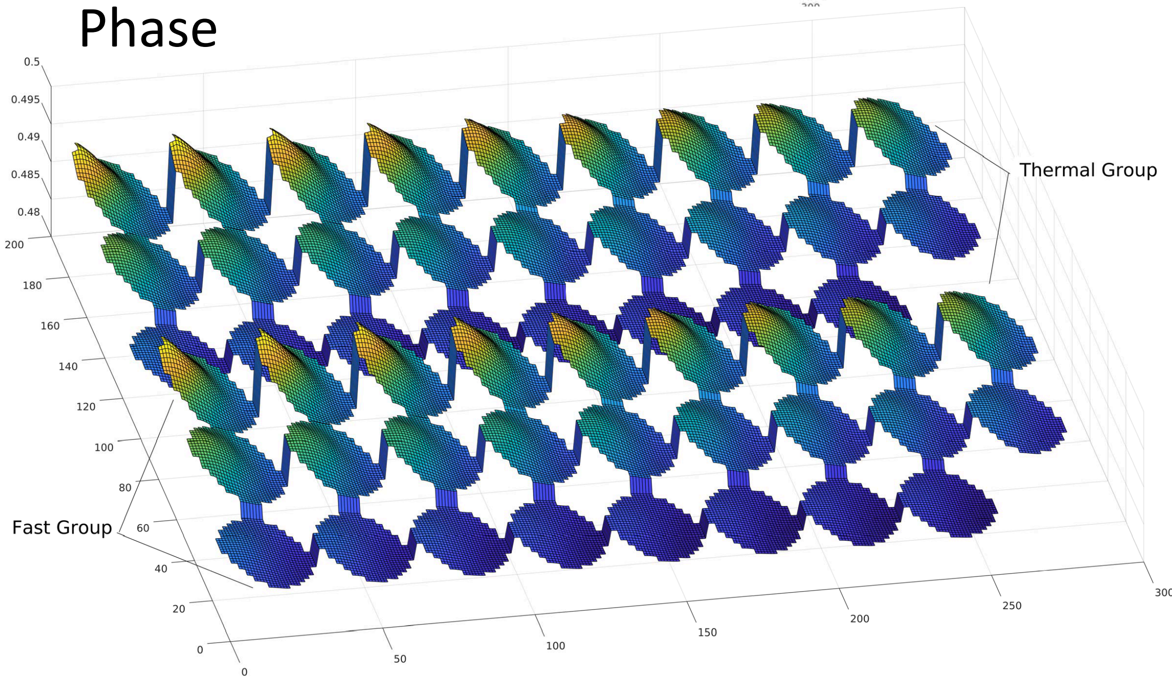
The 3-D information (both amplitude and phase of the thermal and fast group responses) was unrolled into two dimensional forms, and the values rescaled between 0 and 255.

1st ch: Amplitudes of the groups
2nd ch: Amplitudes of the groups
3rd ch: Phase of the groups.

Amplitude



Phase



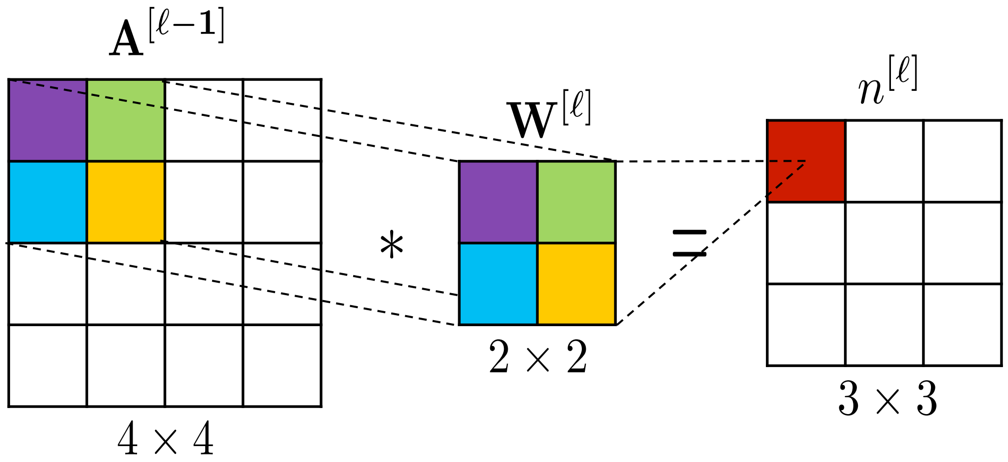
Recap: Convolutional Neural Networks

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

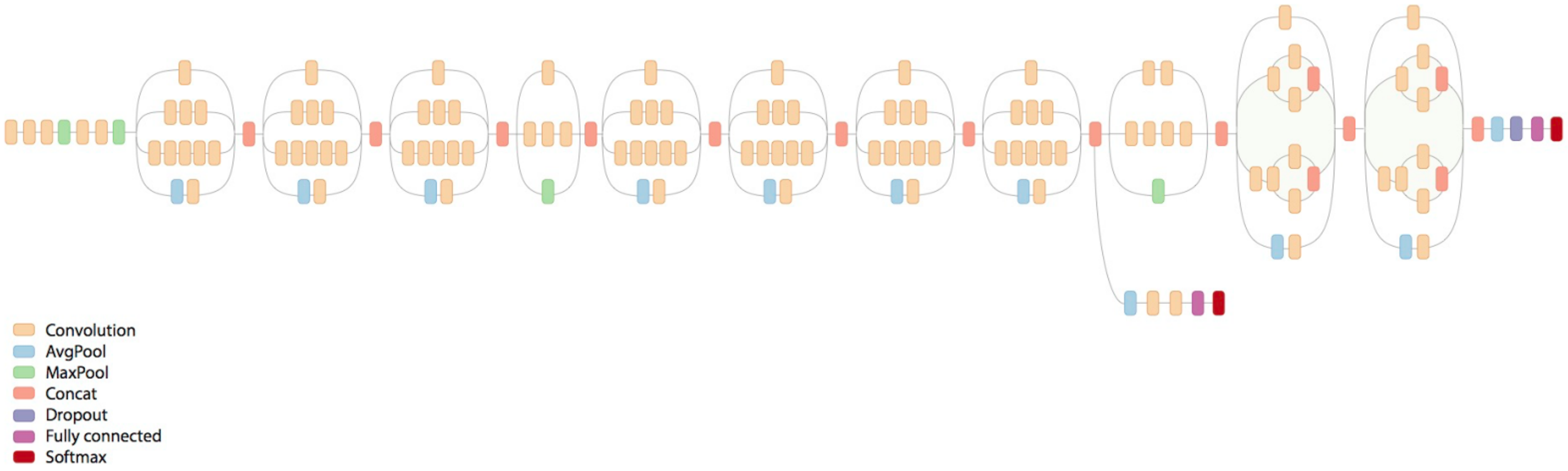
  i.e. classification, object detection, segmentation etc.

- Made up of stacks of Convolutional and Pooling layers

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



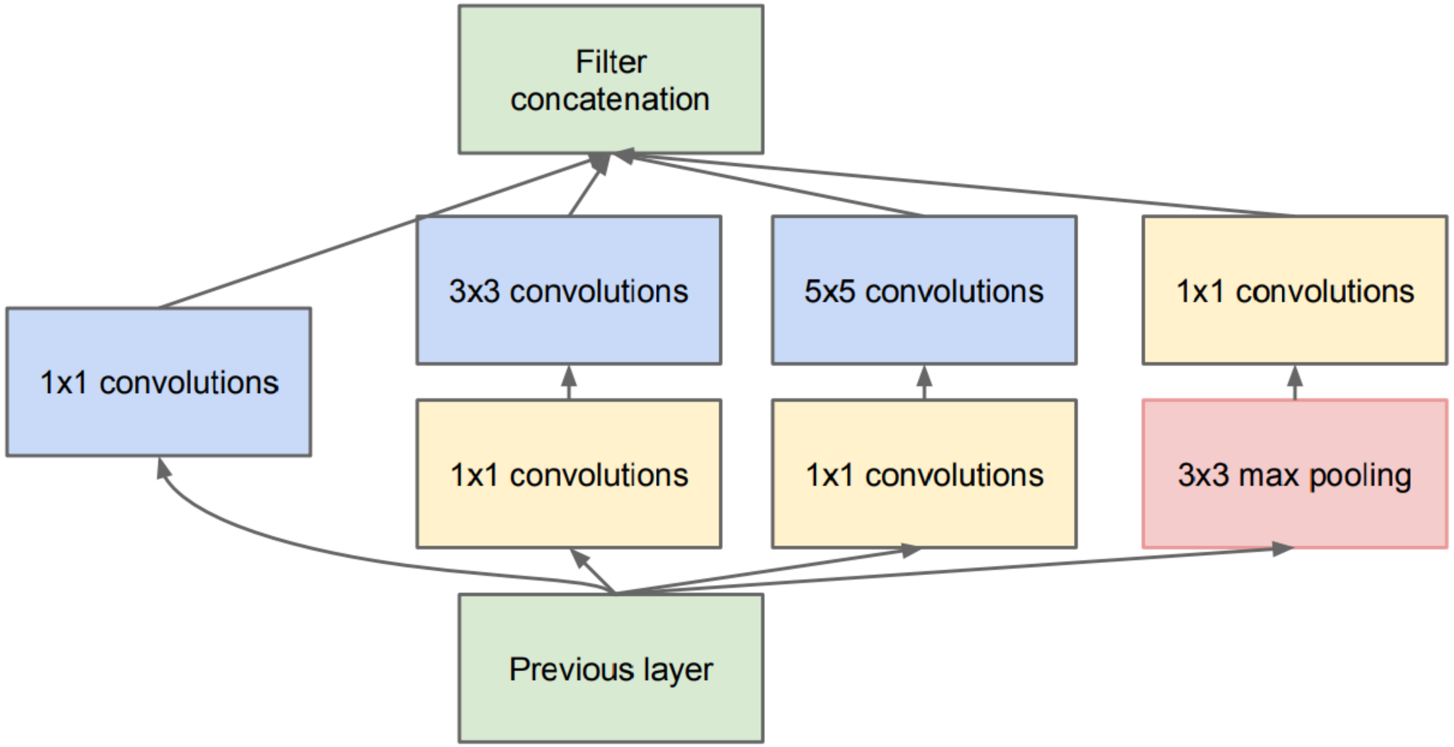
Recap: Inception Architecture



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

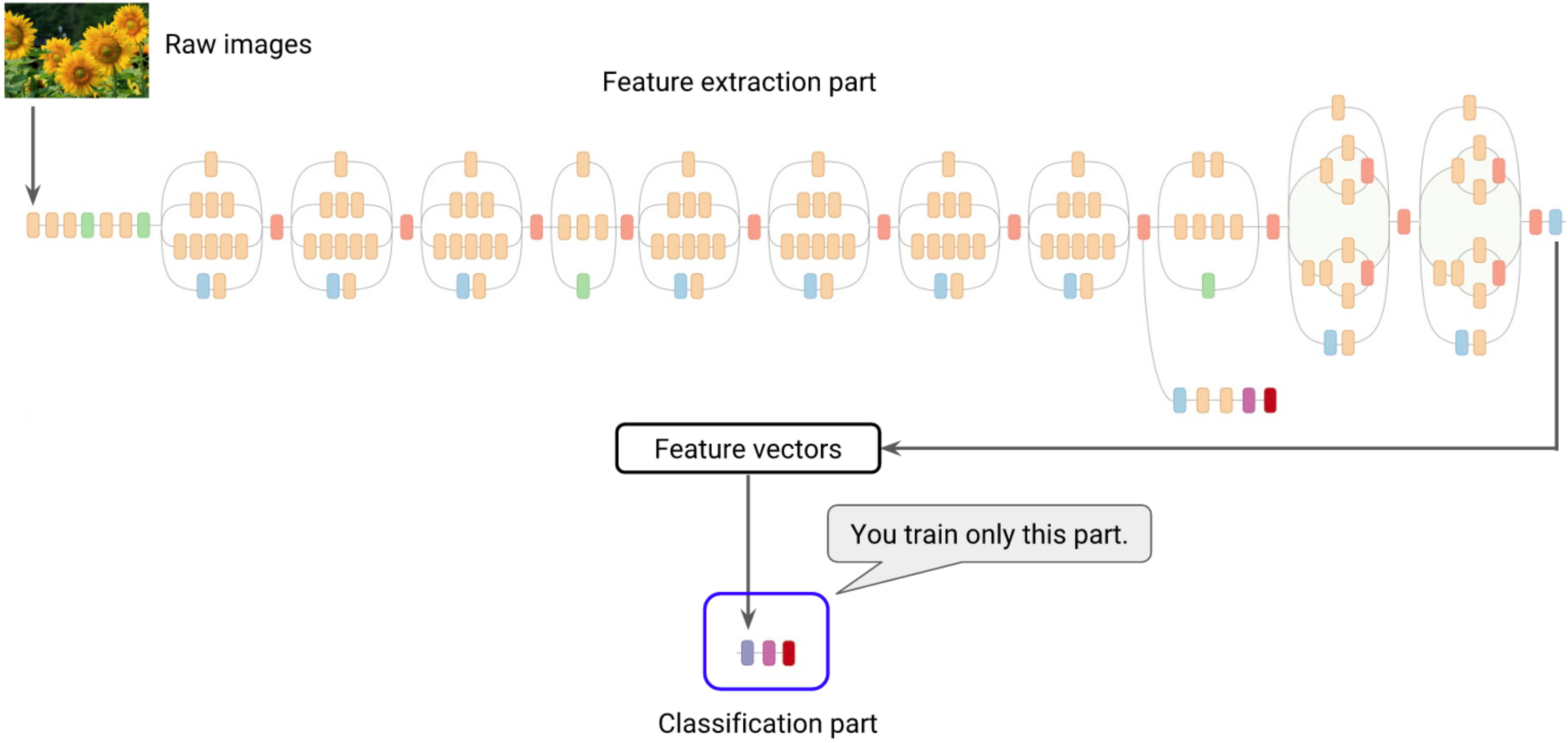
Recap: Inception Module

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



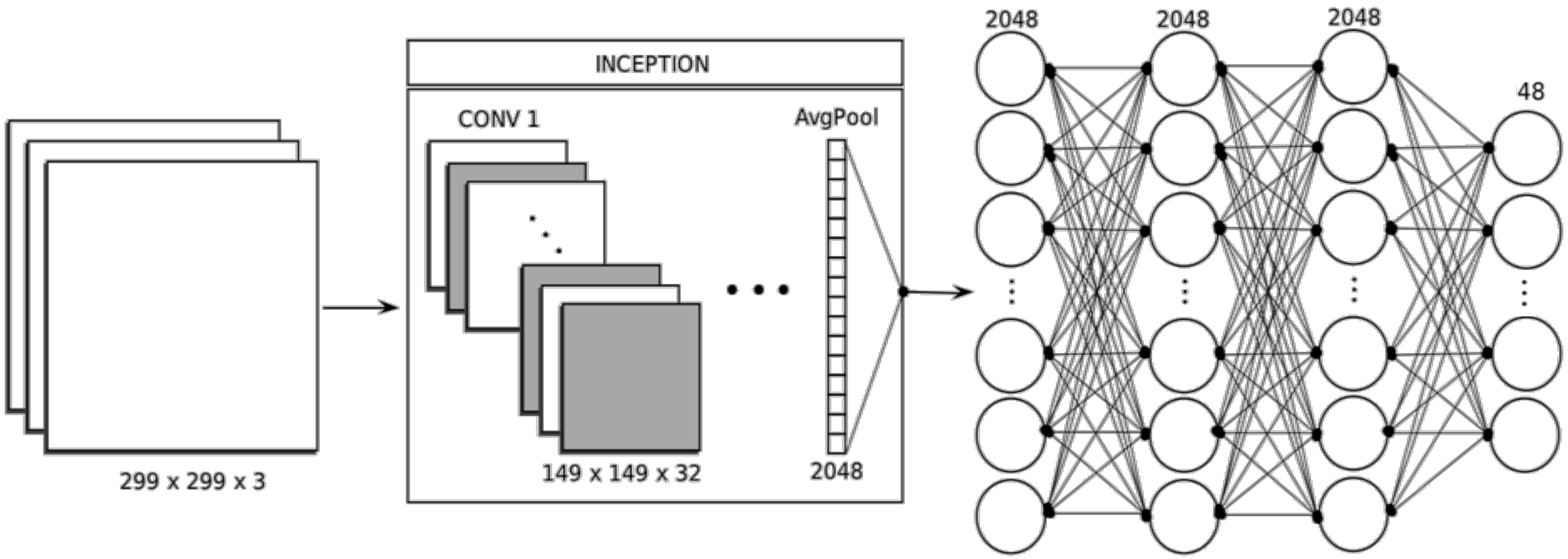
Szegedy, C., et al. “Going deeper with convolutions”. Proceedings of the IEEE CVPR 2016

Recap: Inception Transfer Learning



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

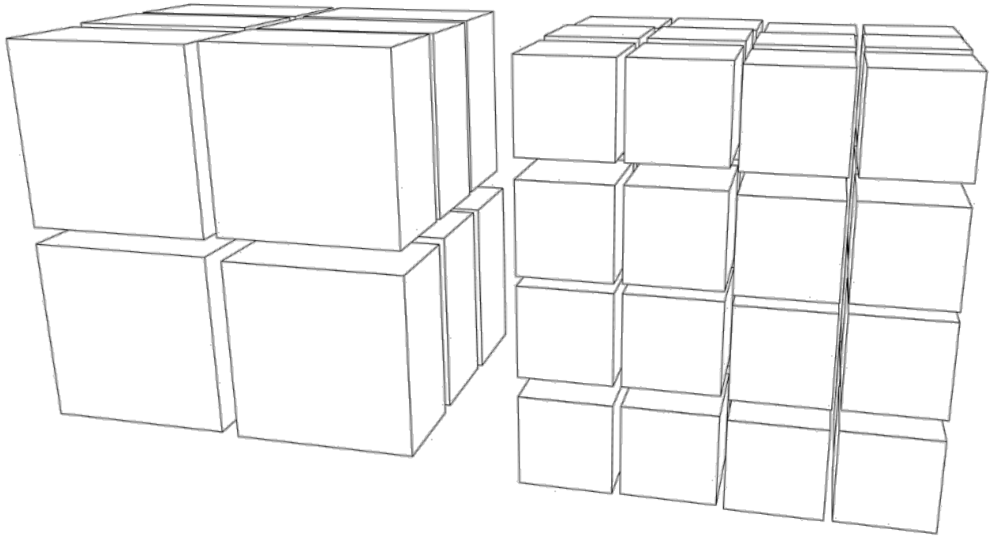
The proposed approach: Deep Convolutional Neural networks (CNN)



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

1st Experiment - Unfolding to 12 - 48 source locations

CNN was used to localise the source of the applied noise within 12and 48 volumetric subsections of the original.



The initial 3D array of size 32 x 32 x 26 was compartmentalised into 12 and 48 subsections, by a factor 2 x 2 x 3 and 4 x 4 x 3 respectively.

1st Experiment - Unfolding to 12 - 48 source locations

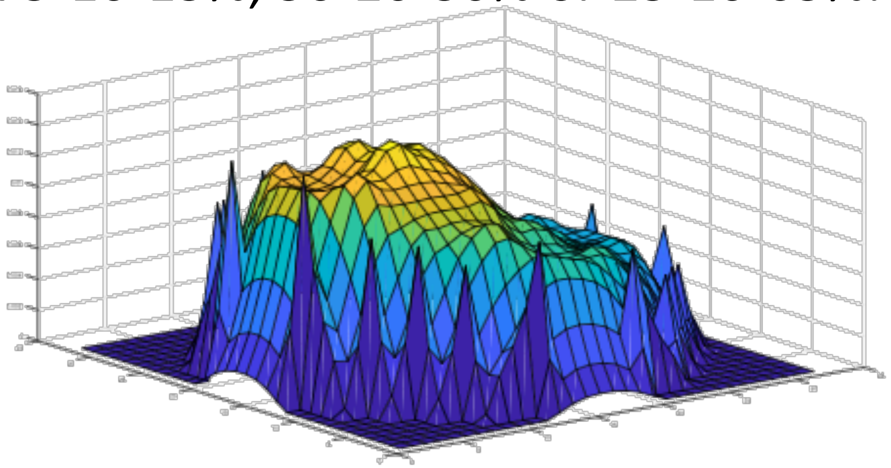
Two sets of experiments were conducted:

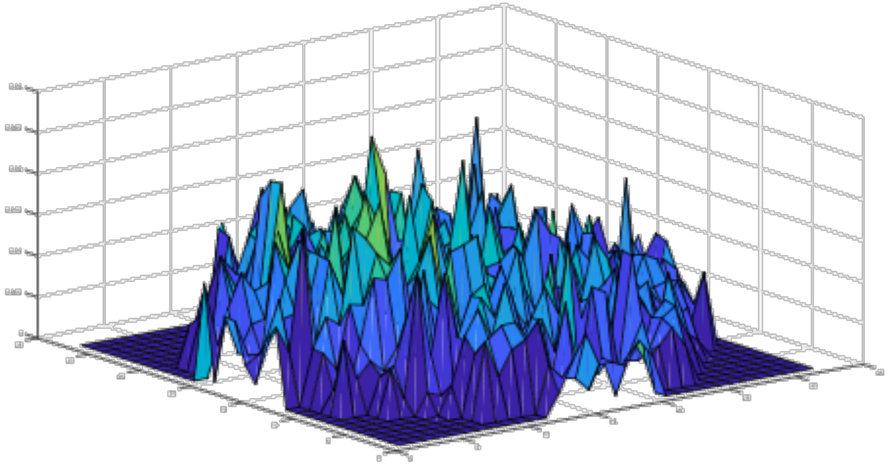
- with pretrained ImageNet weights and partly re-trained.
- with weights re-trained from scratch.

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%.





1st Experiment - Unfolding to 12 - 48 source locations - RESULTS

CNN Unfolding

Classes	Sensors (%)	Signal	Train/Dev /Test (%)	Accuracy Pre-trained	Accuracy 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

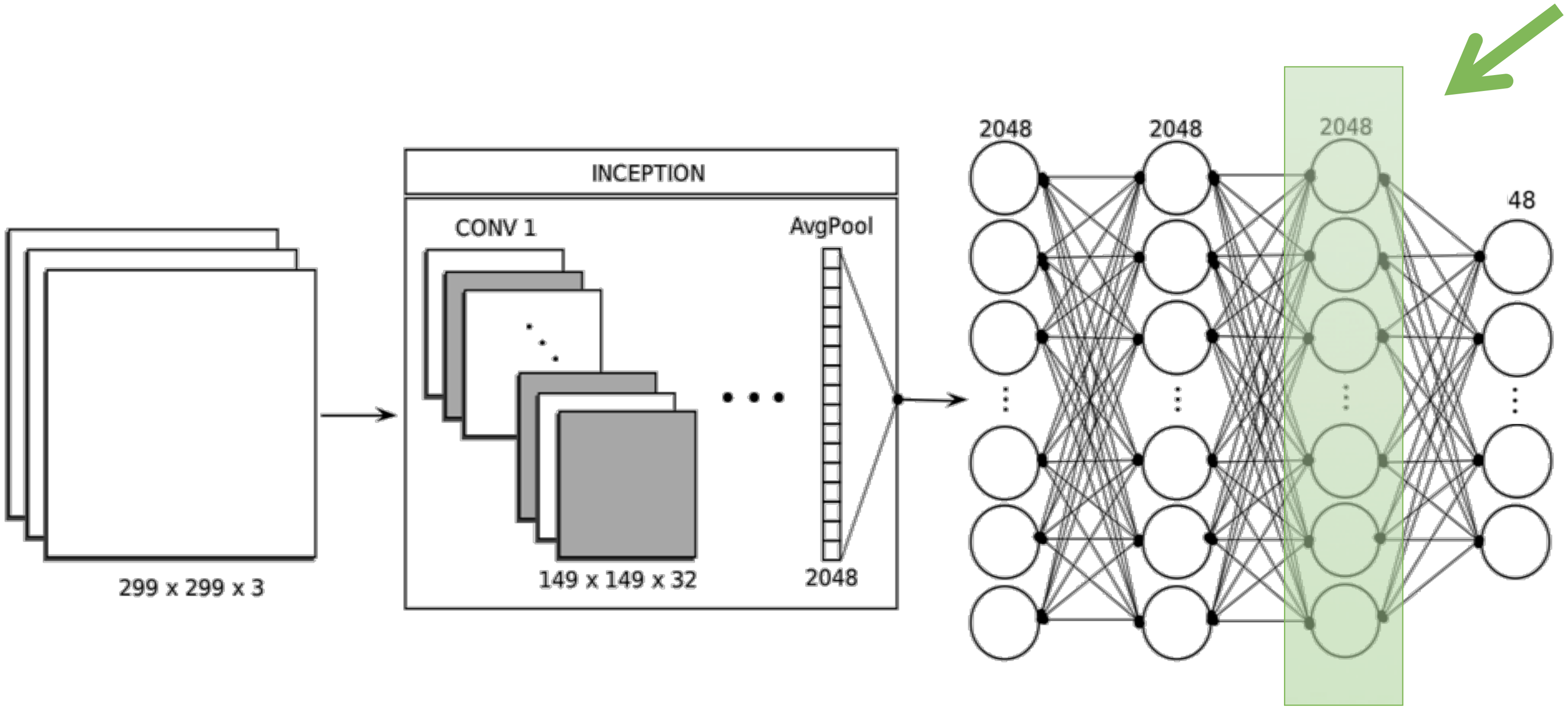
Classes	Sensors (%)	Signal	Train/Dev /Test (%)	Accuracy Pre Trained	Accuracy Scratch
48	100	clean	75-10-25	92.3	99.9
	100	SNR=1	75-10-15	72.9	92.5
	25	clean	50-20-30	90.3	97.8
	25	clean	25-15-60	85.1	91.1
	25	SNR=1	50-20-30	65.2	82.3

MAX

MIN

2nd Experiment - Unfolding from 12 to 48 source locations - RESULTS

A *k*-means clustering approach was devised to cluster the activations from the last fully-connected layer of the trained CNN.



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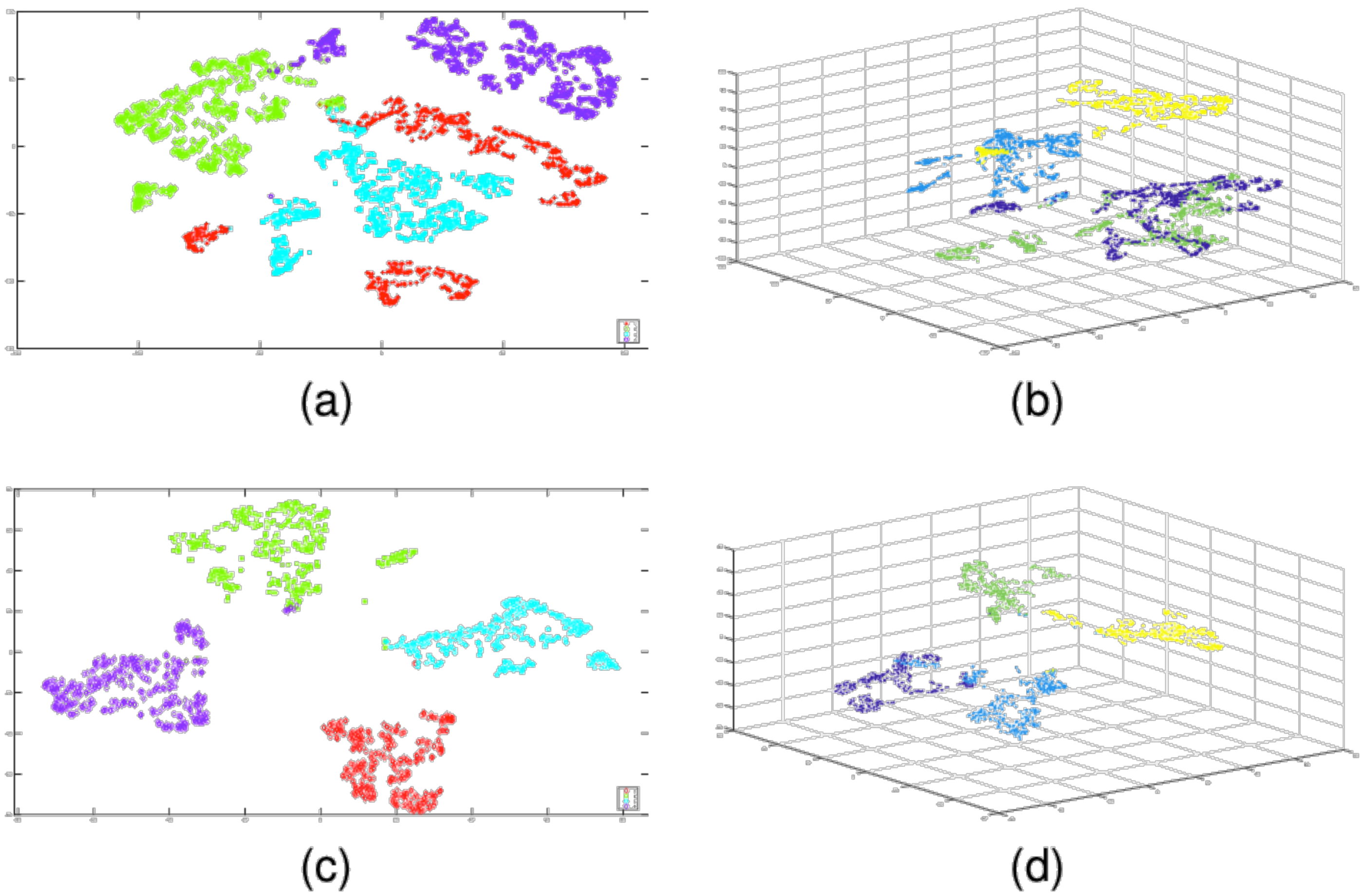


(a) (b) (c) (d)

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

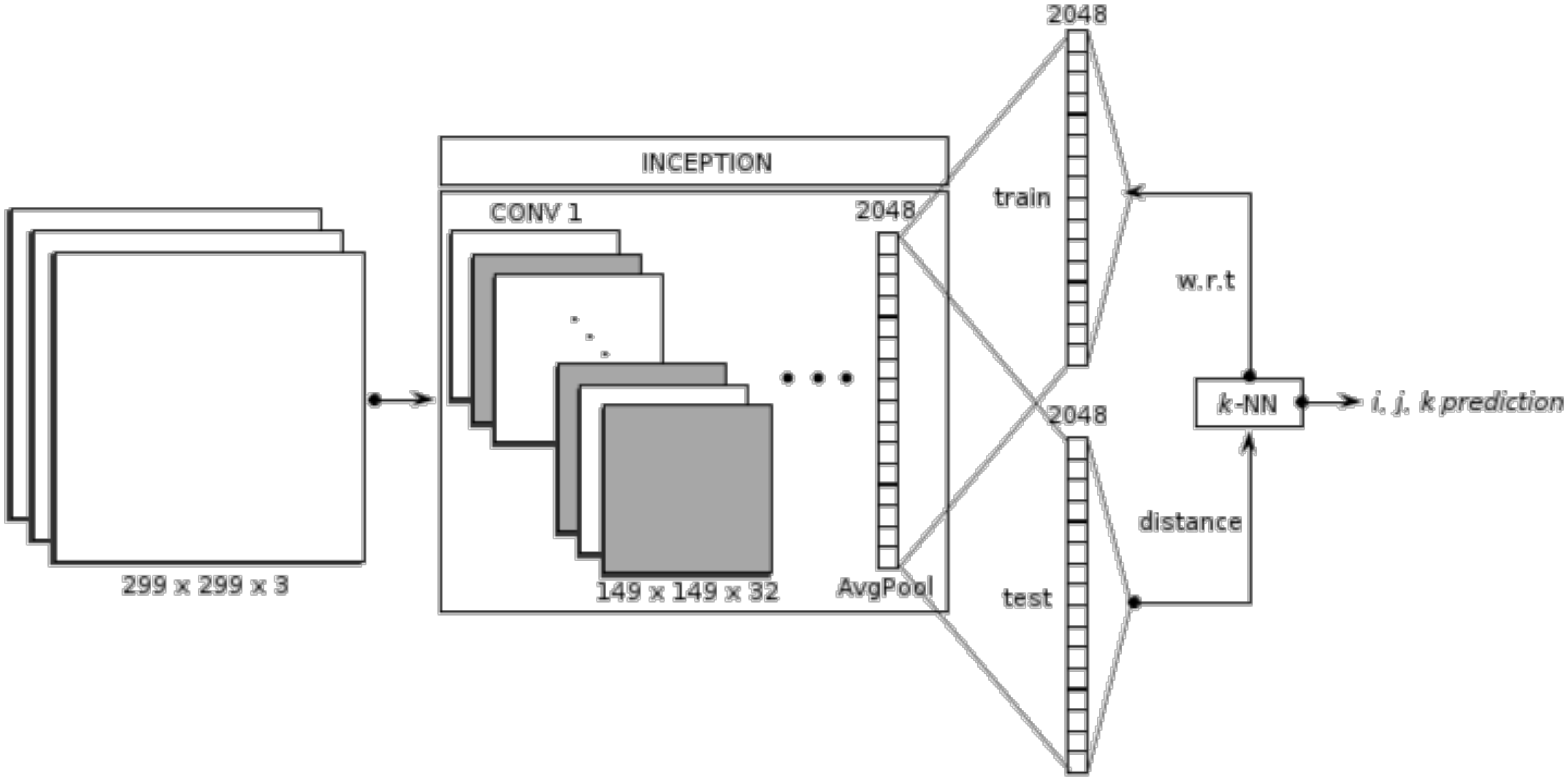
a-b: training set clusters.

c-d: test set predictions.

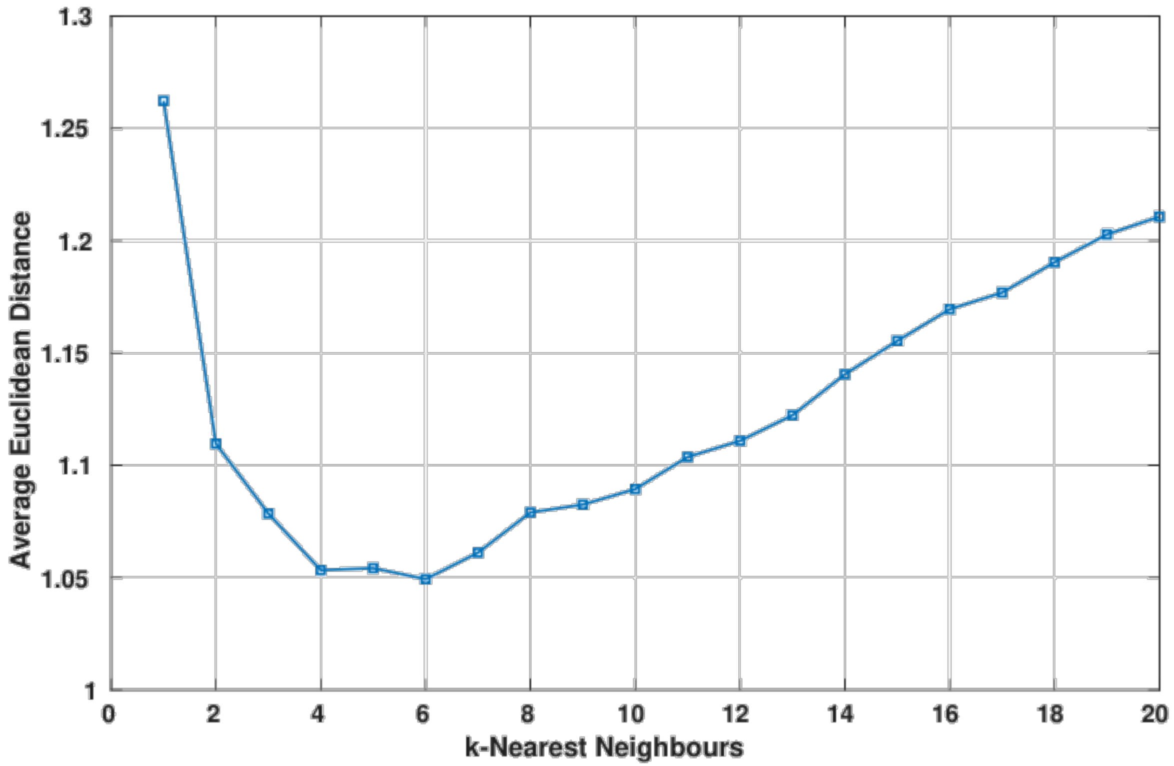
Each point is a lower dimensional projection of 2048 dimensional vector representations of signal.

Each colour indicates a different cluster.

3rd Experiment - Unfolding up to Signal's Original Resolution



3rd Experiment - Unfolding up to Signal's Original Resolution - RESULTS

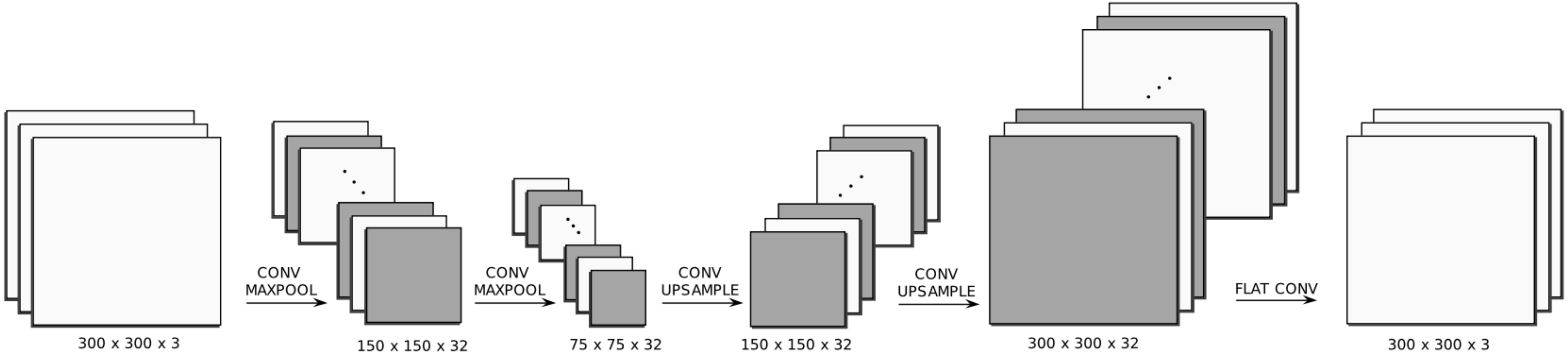


For various values of *k*-, starting from a resolution of twelve blocks it is possible to estimate the source location at the original signal's resolution of 32x32x26.

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

4th Experiment - 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:

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

4th Experiment - Signal denoising and reconstruction - RESULTS

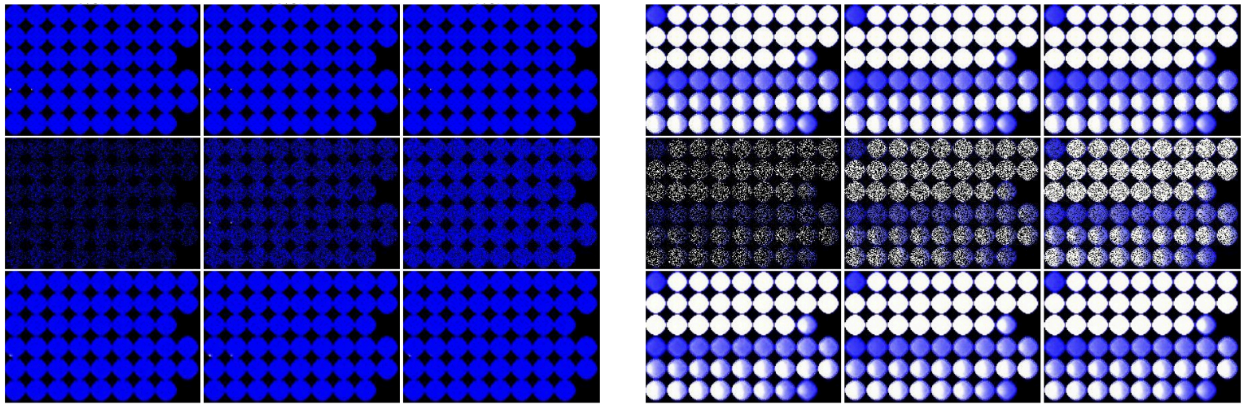
The reconstruction was measured by the **normalised cross correlation** (ncc) metric.

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

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

Sensors' information

25% 50% 75% 25% 50% 75%



Deep-CNN Autoencoder				
			Normalised Cross Correlation	
Sensors	Signal	Train/Test	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

Conclusion and Future developments

We have proposed:

- A Deep Neural-Network approach to unfold the induced neutron noise - to 12 and 48 subvolumes source location.
- A combination of CNN and its internal representation clustering to unfold the signal up to the original signal resolution 32 x 32 x 26.
- A Denoising Autoencoder able to denoise and reconstruct noisy signals - up to SNR =1 - and obscured signals - using up to 25% of the sensors' information. The reconstructed signals were very close approximations to the original ones and were, thereafter used for the unfolding of the noisy and obscured data.
- The experimental study will be extended to other types of perturbations and simulated signals generated in either the frequency or the time domain.

Acknowledgement

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Thank you, any questions?