CORTEX

Core monitoring techniques and experimental validation and demonstration

Detection and Localisation of Multiple In-Core Perturbations with Neutron Noise-Based Self-Supervised Domain Adaptation

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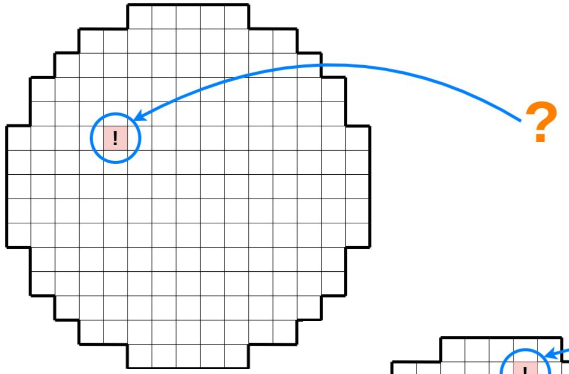
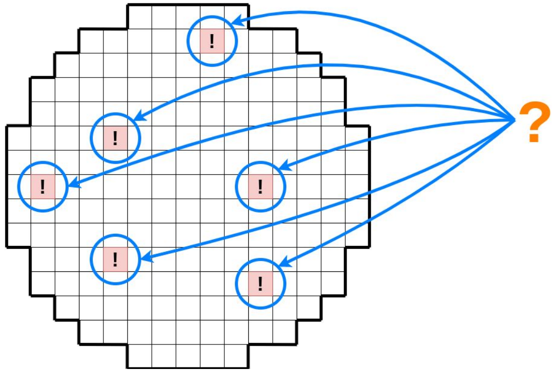
Outline

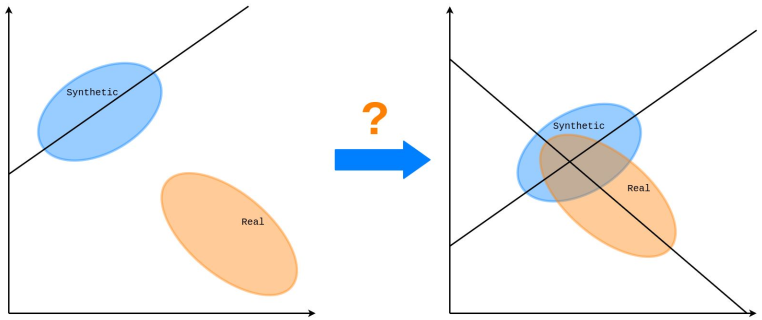
- 1) Background



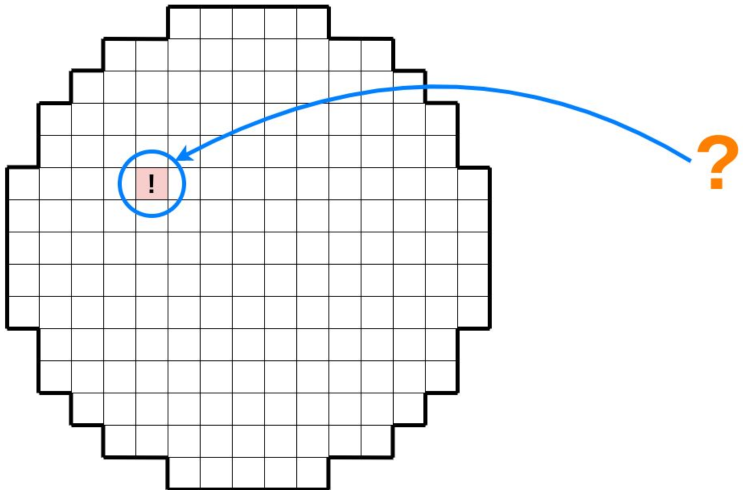
- 2) Classification and Localisation of Multiple Simultaneously Occurring Perturbations



- 3) Leveraging Simulated Data for Applicability with Real Plant Measurements



Background
- Unfolding the Reactor Transfer Function

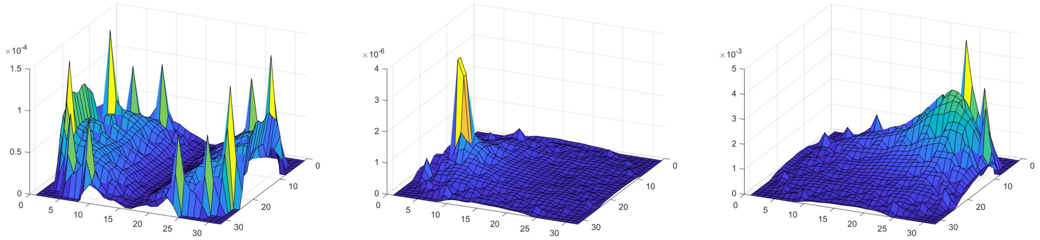


Problem Case

- We aim to unfold reactor transfer function to provide core diagnostics.
  - Derivation of core perturbation characteristics to **classify** and **locate** its origin.
- Yet this is challenging due to the limited number of neutron detectors in western type reactors.
- We ask, *can we use machine learning to successfully approximate the reactor transfer function?*
- However, to effectively train ML algorithms large quantities of data are required.

Data - Acquisition

- We utilise a diffusion-based core simulation tool that is capable of producing any theoretically possible driving perturbation whilst being labelled.
    - CORE SIM + (A. Mylonakis, P. Vinai, and C. Demaziere. “CORE SIM+: A flexible diffusion-based solver for neutron noise simulations.” *Annals of Nuclear Energy*, volume 155, p. 108149 (2021).)



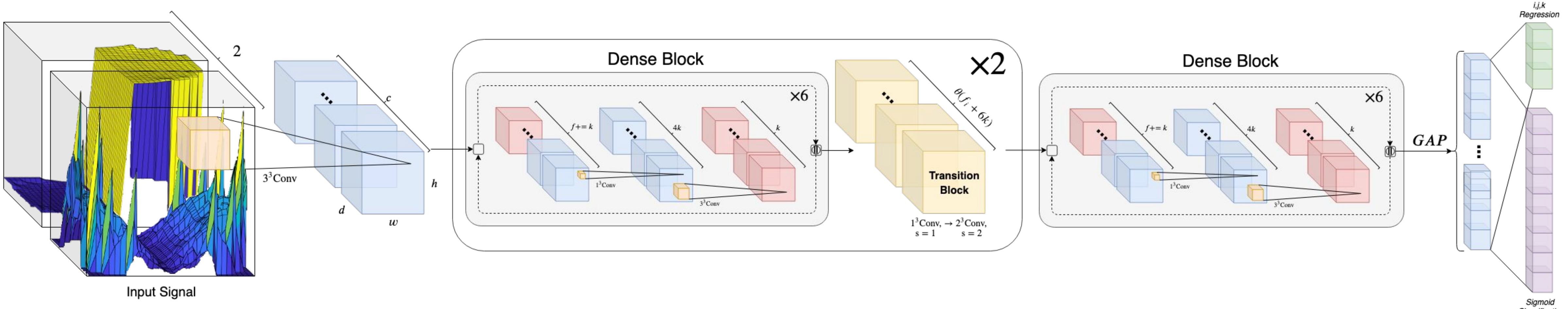
- Only a small number of readings are used corresponding to the neutron detectors of equivalent plant settings.
- We employ the APSD/CPSD of of simulated neutron detector readings as input into our ML network.
- There are 9 different perturbation scenarios, each being simulated for all theoretically possible origins = Terabytes of Data

Data - Perturbation Scenarios

- Generic "absorber of variable strength"
- Axially travelling perturbations at the velocity of the coolant flow
- Fuel assembly vibrations, for which the lateral movement of fuel assemblies is modelled according to the following modes of vibrations:
  - The cantilevered beam mode,
  - The simply supported on both sides mode (with its two first harmonics)
  - The cantilevered beam and simply supported mode (with its two first harmonics).
- Control rod vibrations
- Core barrel vibrations

Previous Work - 3D Densely Connected CNN

- The complexity of the problem and the limited detectors required a deep network to adequately parameterise the problem.
- A 3D extension to DenseNet was proposed.
- 98% classification accuracy, 4cm error in $4m^3$ core volume.

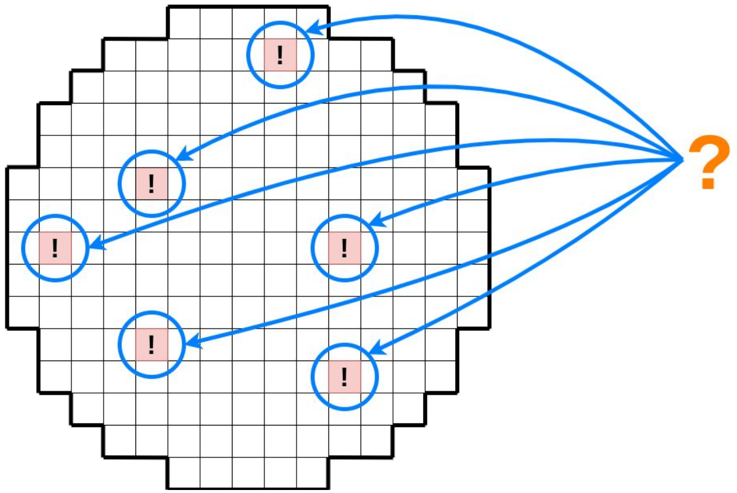


C. Demaziere, A. Mylonakis, P. Vinai, A. Durrant, F. De Sousa Ribeiro, J. Wingate, G. Leontidis, S. Kollias. "Neutron Noise-based Anomaly Classification and Localization using Machine Learning." PHYSOR (2020)

A. Durrant, G. Leontidis, and S. Kollias. "3D convolutional and recurrent neural networks for reactor perturbation unfolding and anomaly detection." EPJ Nuclear Sciences & Technologies (2019).

Semantic Segmentation

- Multiple, Simultaneously Occurring Perturbation Classification and Localisation



Beyond One Perturbation!

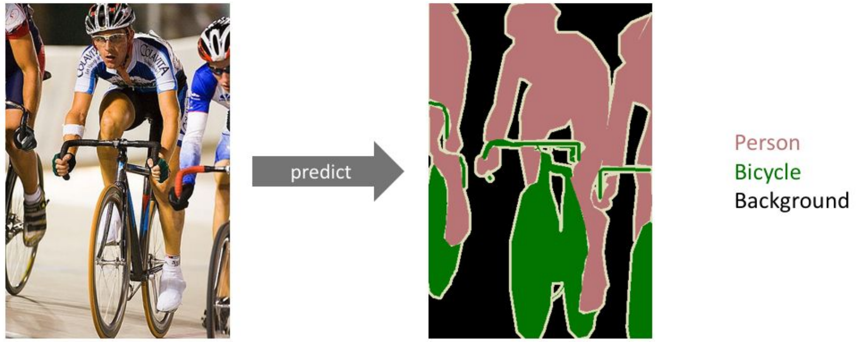
- In reality **perturbations rarely occur in isolation**, instead they are found as multiple perturbations occurring simultaneously.

Therefore we ask?

- Importantly, how can we make an **arbitrary number of predictions** per sample that change between samples?
- How can we develop architectures that are able to effectively process **sparse data input** in an efficient manner?

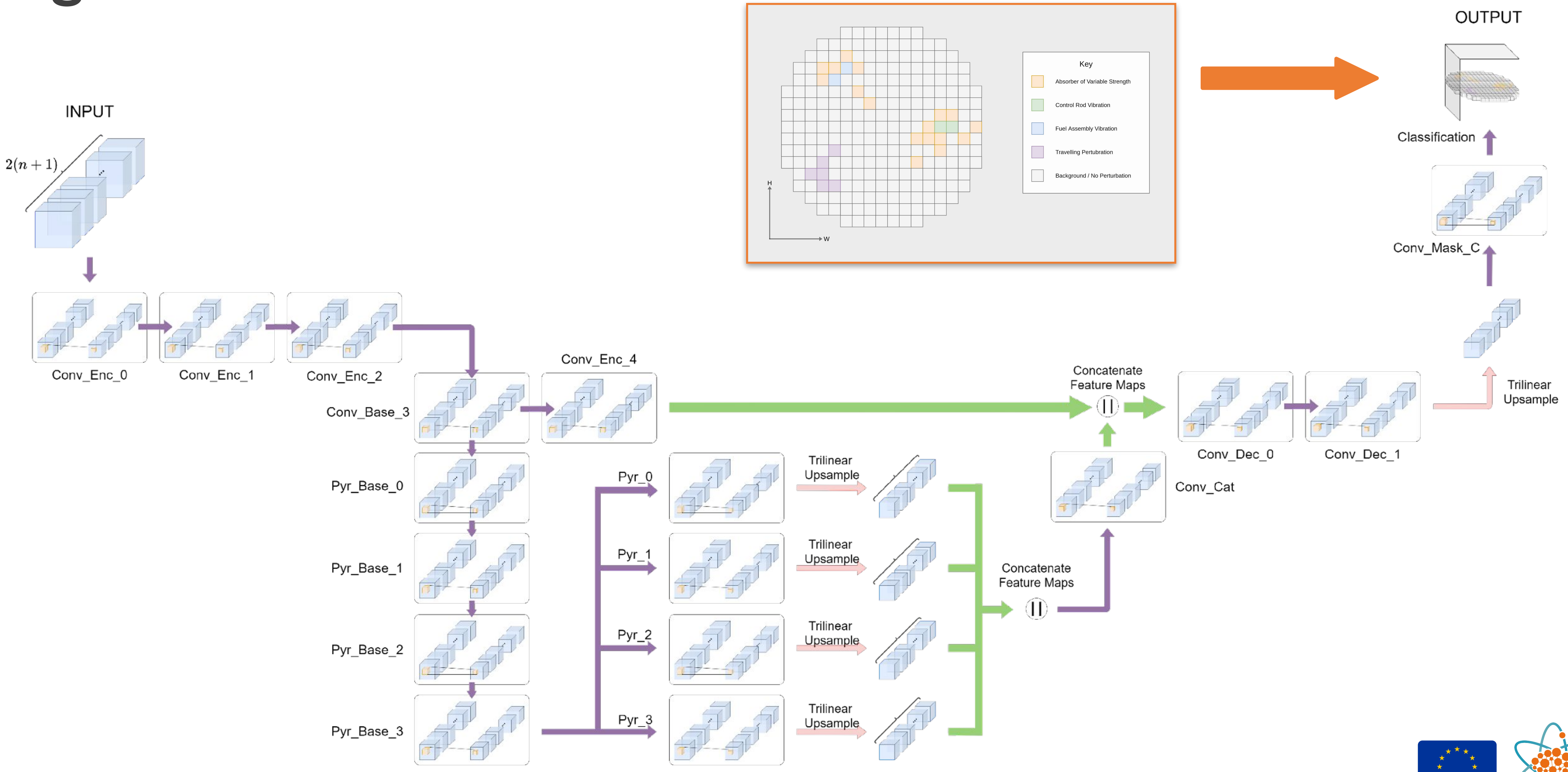
Network Architecture - Semantic Segmentation

- Semantic segmentation is a methodology for the “linking” of each pixel in an input sample to a semantic (class) label.



- Each voxel in the output represents an origin location of a driving perturbation, the classification of a voxel represents that a driving perturbation of the identified scenarios is present.
- We employ an 3D Fully-Convolutional U-net architecture.

Network Architecture - Voxel-Wise Semantic Segmentation



Network Training - Voxel-Wise Semantic Segmentation

- Our major challenge lied with class imbalance, we have a large volume (34^3 voxels) with only a relatively small number of present perturbations.

- Focal loss helps, it gives more weight for “hard-to-classify examples”.

- We train the network to minimise the average categorical focal loss of every voxel in the mask to the ground truth (the true source location of the simulated perturbation).

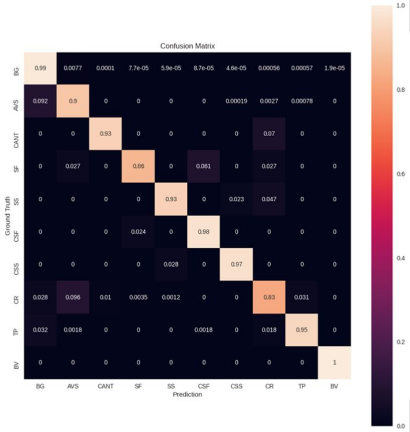
$$FL(y,\hat{y}) = -\frac{\lambda_1}{P}\sum_{p=1}^{P}\left[y_p(\boldsymbol{\alpha}_p(1-\hat{\boldsymbol{y}}_p)^{\gamma}\log(\hat{y}_p)) + (1-y_p)((1-\alpha_p)\hat{y}_p{}^{\gamma}\log(1-\hat{y}_p))\right]$$

- We also utilise a logarithmic class weighting scheme to the focal loss to reduce the impact of perturbation classification imbalance.

Results

- We additively combine a random number of individual driving perturbation samples within a range [1, x]
- We produce 500,000 combined samples per set (15, 30, 45)
- Strong classification of source perturbations at their originating assemblies.
- The majority of erroneous results come from False Positive identification, around the location of the true perturbation.

Per Class Voxel Prediction Accuracies *											
No. Comb	No. Det	Accuracy (%)									
		BG	AVS	CANT	SF	SS	CSF	CSS	CR	TP	BV
15	56	99.08	90.47	92.98	86.49	93.02	97.62	97.22	83.06	94.74	100.00
30	56	99.64	85.97	81.48	90.48	97.37	90.24	95.12	90.21	93.25	100.00
45	56	99.35	82.28	88.00	87.50	89.23	90.00	92.42	88.99	93.20	100.00



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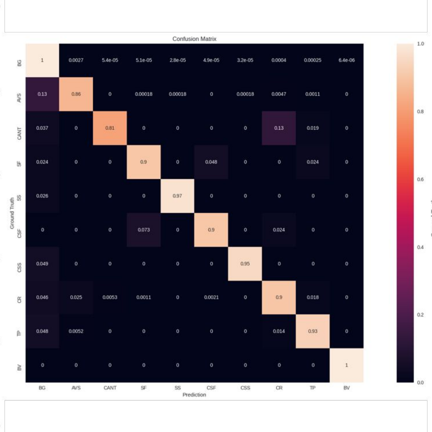

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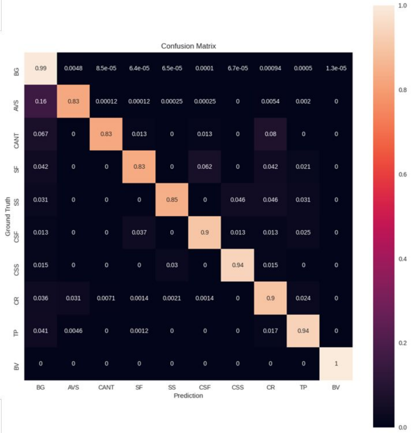
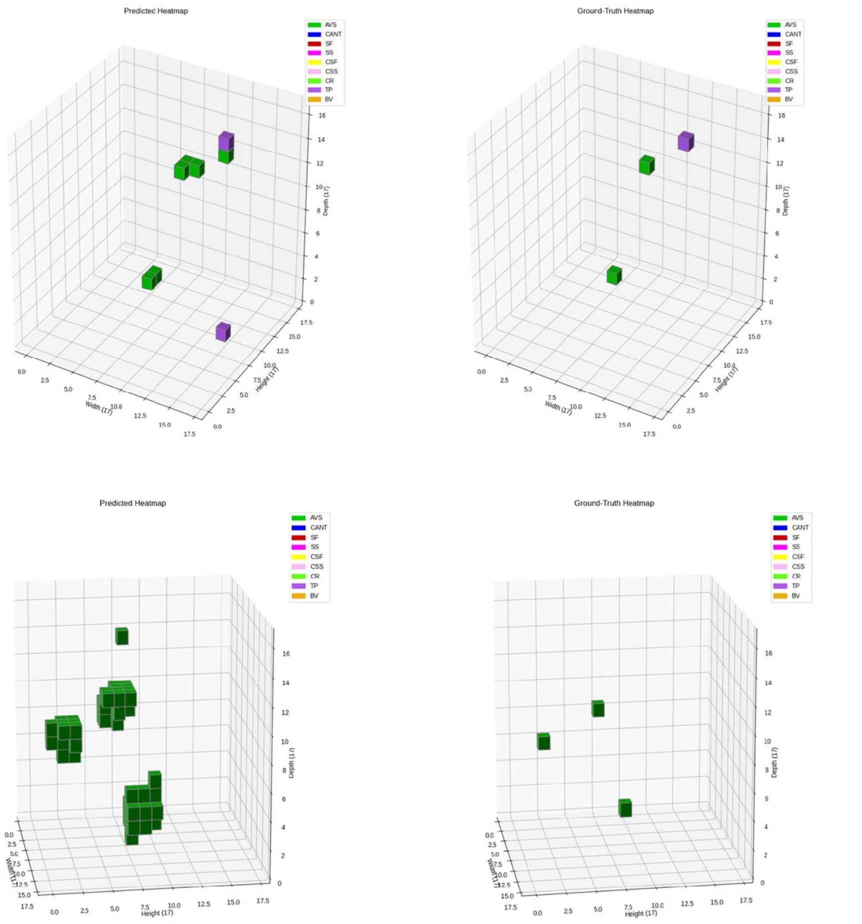
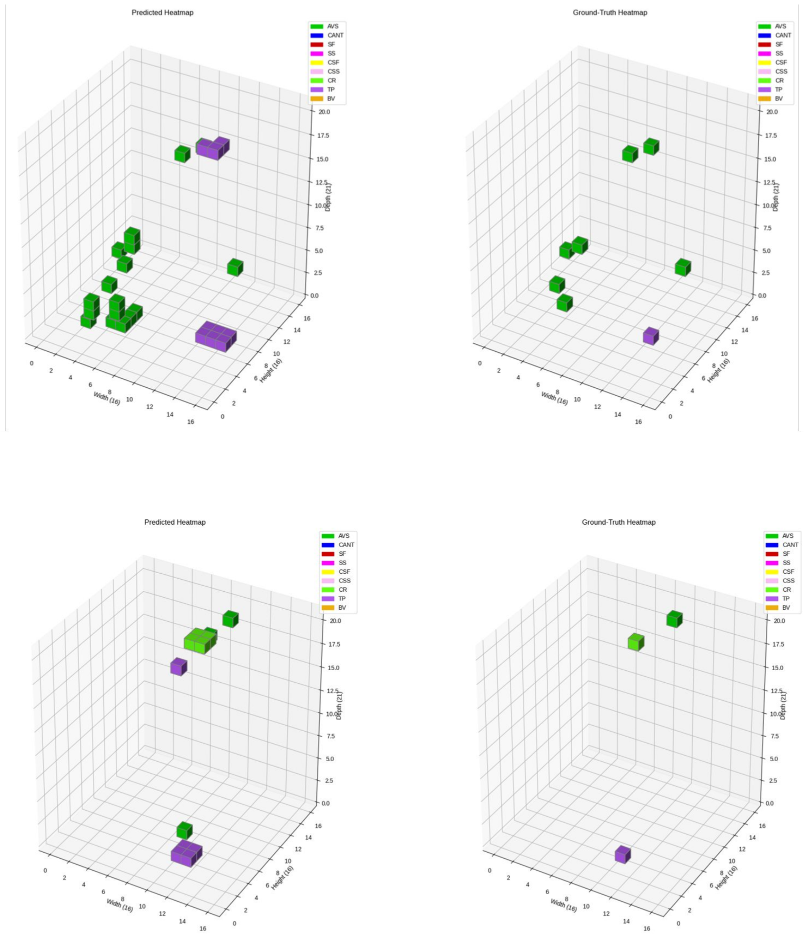


45

Example Prediction Masks



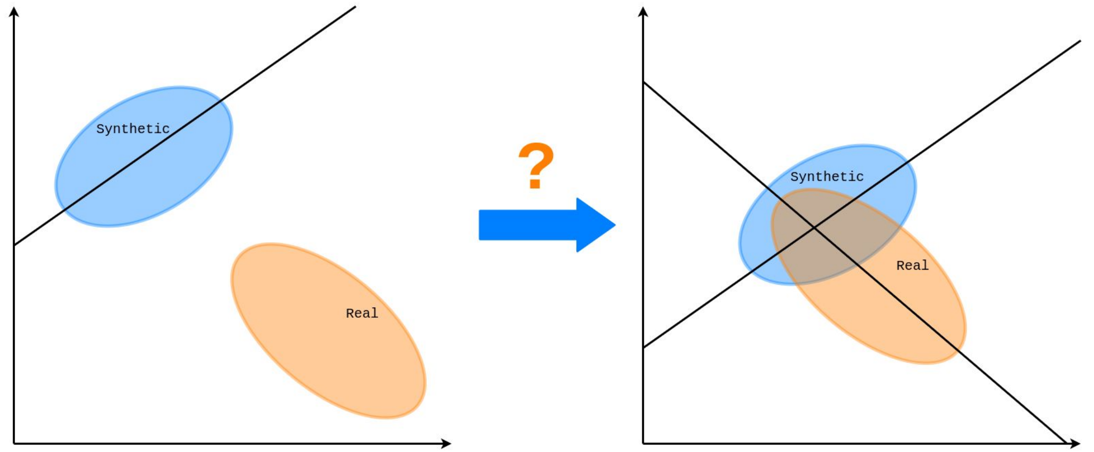
(German pre-KONVOI)



(Swiss pre-KONVOI)

How can we Leverage Synthetic and Real Plant Measurements?

- Self-Supervised Domain Adaptation
- Synthetic to Real Adaptation



Towards Application to Real Measurement

- Can we just make predictions on the real plant measurements from the network trained on simulated data?

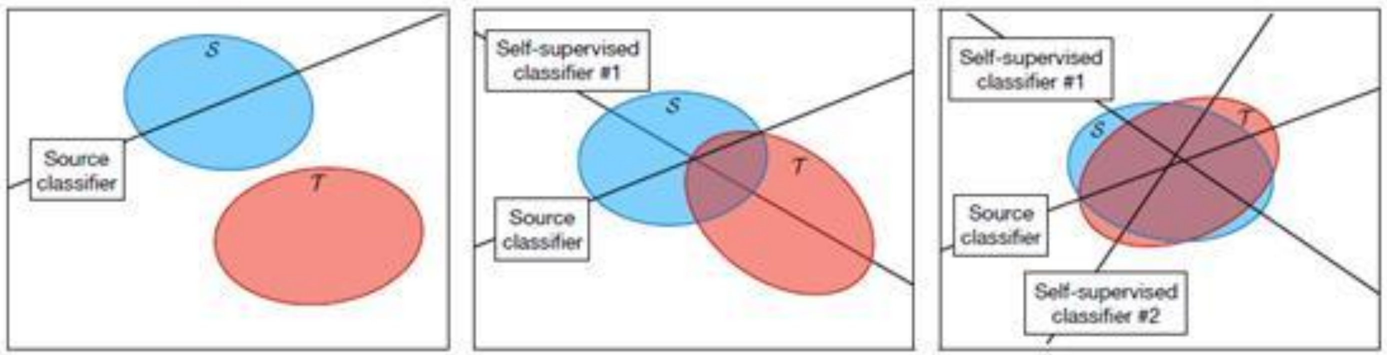
- Real plant data, although modelled by the simulations, **contains some inherent differences to simulated data**, how do we minimise these differences as not to confuse our trained network?
- **Real plant data is not annotated** (unsupervised), how can we leverage the annotated simulated data that is abundant and provides clear perturbations distinctions?

Unsupervised Domain Adaptation

- We aim to learn a discriminative classifier (our voxel-wise semantic segmentation network) for classifying perturbations that is invariant to the presence of a domain shift from simulated to real data.
- We have no annotations in the real plant measurements so we need a method to align these different domains without semantic information rather we need to find common features across domains.
- Therefore, we opt to train our classifier to align the two domains in some shared feature space represented by the discriminative model through the process of solving a common auxiliary task that are constructed from the data itself (self-supervised learning).

Self-Supervised Domain Adaptation (1)

- Auxiliary tasks are constructed from the input, providing feature understanding of structurally relevant info whilst not requiring annotation.
- These tasks encourage alignment between the distribution of features captured in both the simulated (S) and real measurements (T) domains.
- The feature extractor predict identical augmentations for each input, enforcing invariance to the nuances displayed between distributions.



(a) Source classifier only (b) adding a self-supervised task (c) adding more tasks

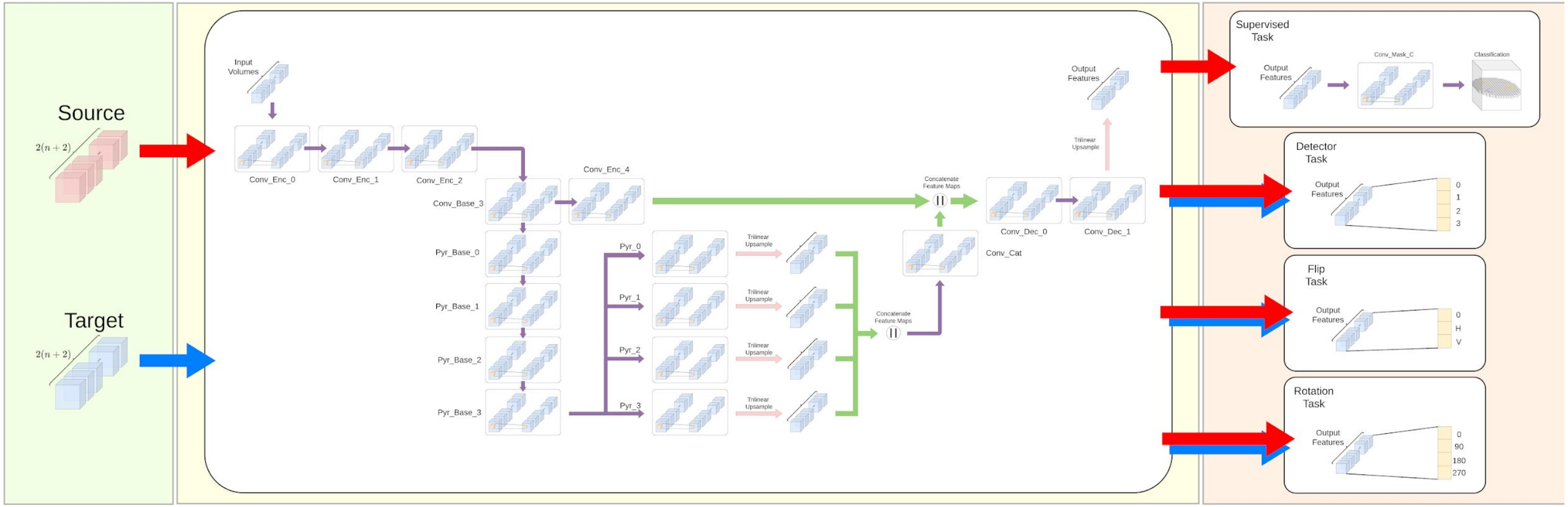
Auxiliary Tasks

These are simple softmax classification tasks that take as input the feature representations from the encoder-decoder network.

- **Rotation:** Identify degree of rotation $\longrightarrow$ [0°, 90°, 180°, 270°]
- **Flip:** Identify axis of flip $\longrightarrow$ [No Flip, Vertical, Horizontal]
- **Missing Detector:** Identify the missing detector $\longrightarrow$ [1, ..., 44]

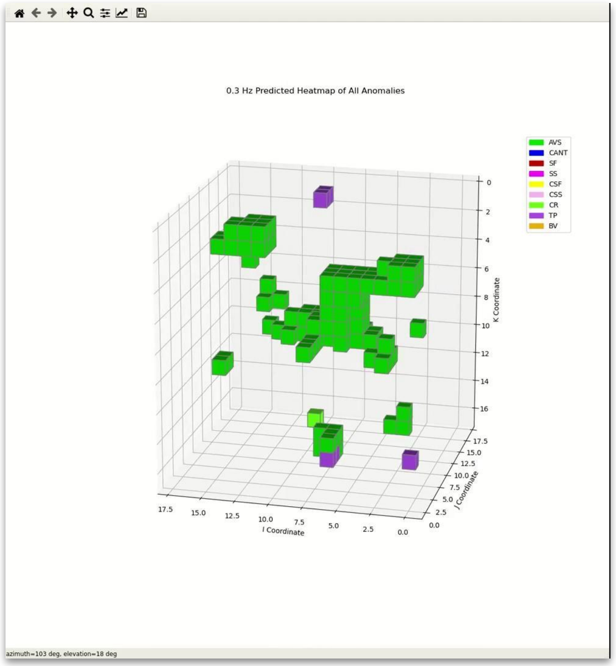
Augmentations are applied identically to both source and target input sample and processed simultaneously by the network.

Self-Supervised Domain Adaptation (2)



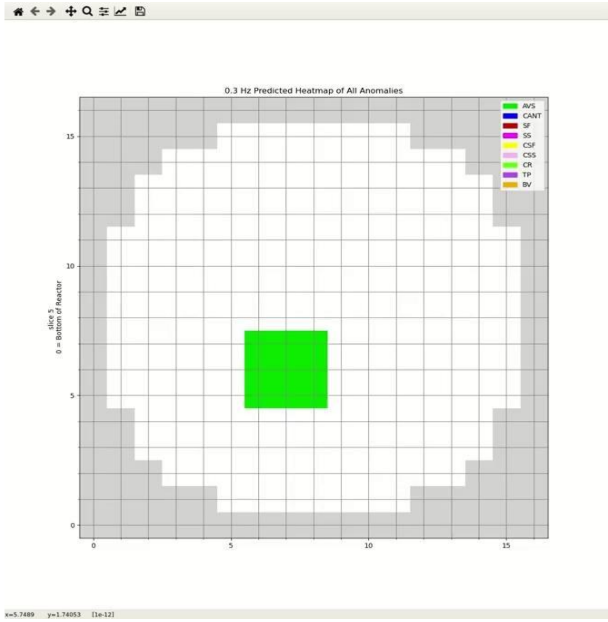
Results

- Very initial results, as we have no assured validation.
- Positively, we identify vertically transporting phenomena which is also identified in signal processing analysis.
- Additionally, we observe a vertical column of AVS inline with this transport phenomena.



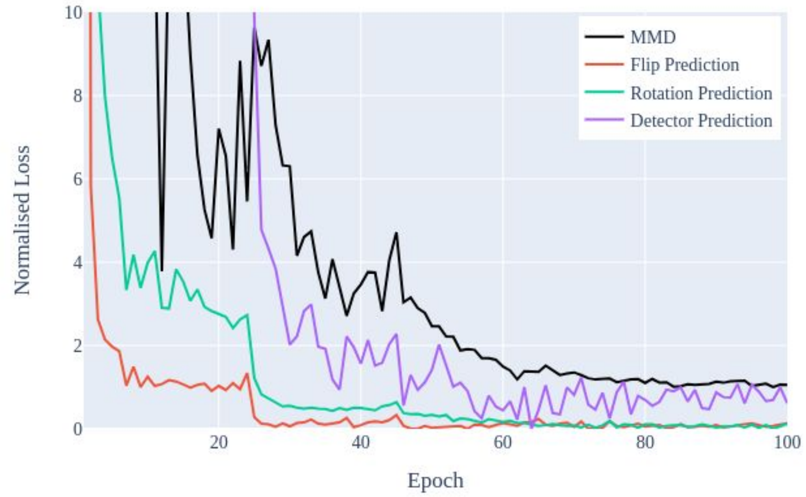
German
4-Loop pre-KONVOI

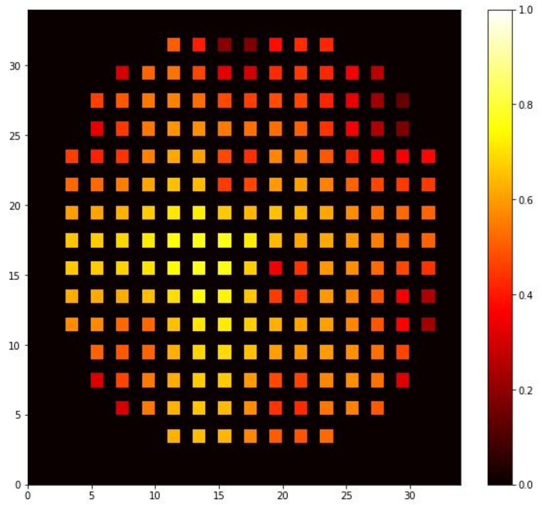
Frequency = 0.3 Hz

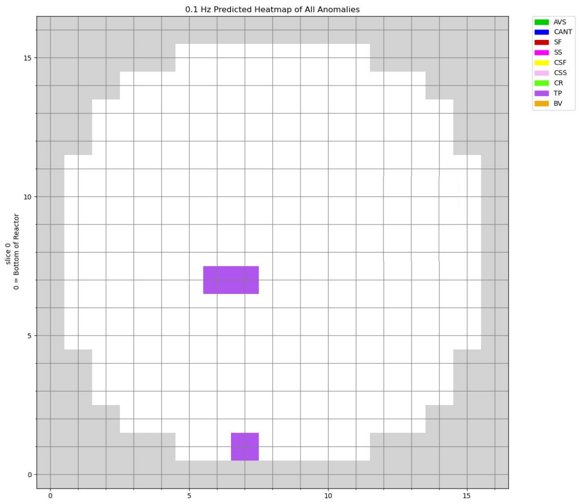


Results

- The MMD between the synthetic and real domains in feature space is reduced during training.
- Such convergence shows the network is reducing the distance between domains in feature space empirically showing alignment.
- Our results are further verified by other works within the project in which an unsupervised approach reports similar phenomena.







G. Ioannou, T. Tasakos, A. Mylonakis, G. Alexandridis, C. Demaziere, P. Vinai, and A. Stafylopatis. “Feature extraction and identification techniques for the alignment of perturbation simulations with power plant measurements.” In International Conference on Mathematics & Computational Methods Applied to Nuclear Science & Engineering (M&C 2021). 2021.)

Conclusions

- We provide a technique to perform the novel task to accurately (*in the simulated case*) classify and subsequently localize many simultaneously occurring perturbations via noise diagnostics.
- Our network requires very little additional reactor information to make these strong predictions.
- We provide a methodology to leverage both domains of data, simulated and real.
- Our model uses structurally relevant information inherent in both domains to find common features.
- This approach does not require extra-human annotation yet can use the large labelled datasets and align to the nuances of real data to get a more accurate result.

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