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Generative model approach on TFM data based on variational inference for multi-fidelity data generation

Granados, Gerardo E.¹ - Colombera, Giorgia² - Gatti, Filippo² - Robert, Sébastien¹ - Miorelli, Roberto¹ - Clouteau, Didier²

¹ Université Paris-Saclay, CEA, List, F-91120, Palaiseau, France

² LMPS - Laboratoire de Mécanique Paris-Saclay CNRS



IUTAM DDMech 2022 - Paris

Generative model approach on TFM

1. Introduction

- Industrial context, motivation et applications
- Challenges for UT inspection
- Case of study: TFM data-set

2. Method

- Conditional U-Net as generator architecture

3. Results

- Metrics on test set
- Latent space (looking inside the network)

4. Conclusions and perspectives



Examples of applications in industrial fields

- Nuclear
 - Inspection of welds
 - Characterization of materials
- Metallurgy
 - Inspection of parts during manufacturing process
 - Characterization of materials
- Aeronautics and aerospace
 - Multi-layer structure
 - Composite materials



NDT&E and SHM modelling

- Data generation for diagnostic, life time prediction
- Materials characterization (Advanced Manufacturing)
- Performance demonstration
- Probe optimization
- Defect detection, classification and characterization

Exploitation of fast and reliable models

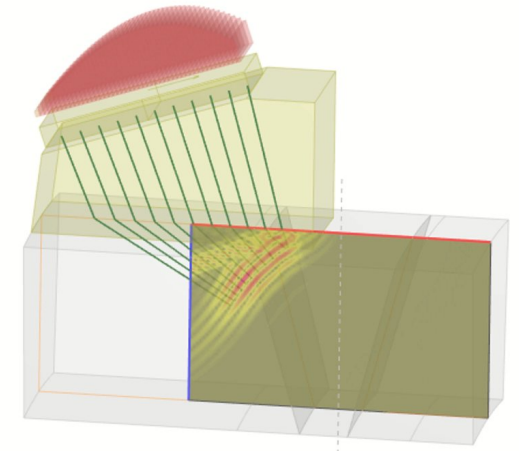
- Dimensioning and defect characterization (form/type/criticality)
- Confidence intervals on estimation (e.g., uncertainties).
- Assessment of the “well-posed” nature of the inverse problem
- Rapid Inversion (Online diagnostic)



On the application of ML to nondestructive testing and evaluation (NDT&E) and in particular in ultrasound testing (UT)

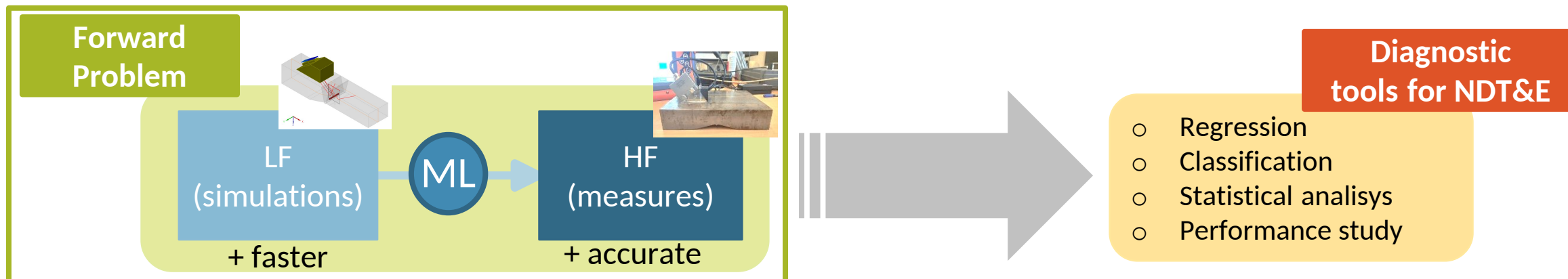
Peculiarity, challenges, and issues of UT inspection problems:

- **Access to reliable simulations** (semi-analytical approaches finite elements models, etc.)
 - ☉ model driven ML approaches are feasible
- **Lack of public realistic datasets** (security and secrecy constraint issues)
 - ☉ data driven ML approaches are very often not feasible
- Operational conditions **may impact** the measurements (from the ML perspective)
 - ☉ non-negligible impact on the acquisitions
- **Lack of knowledge** associated to the inspection scenarios
 - ☉ non-negligible aleatoric uncertainty in the data



Objective: Coupling of reliable simulations and experimental data for enhancing ML performance in view of developing UT inspection and diagnostic tools

Investigated solution: Multi-fidelity deep generative model aiming at combining low fidelity (LF) simulated data and high fidelity (HF) experimental acquisitions for enhancing the performance of automatic diagnosis tools in NDT&E



Industrial context: inspection of complex welded structures via ultrasonic testing (Total Focusing Method -TFM-) imaging



Simulation data

1. Wave emission and propagation (inspected area)
2. Interaction (diffusion) with acoustic discontinuities.
3. Simplified approach for attenuation and structural noise.

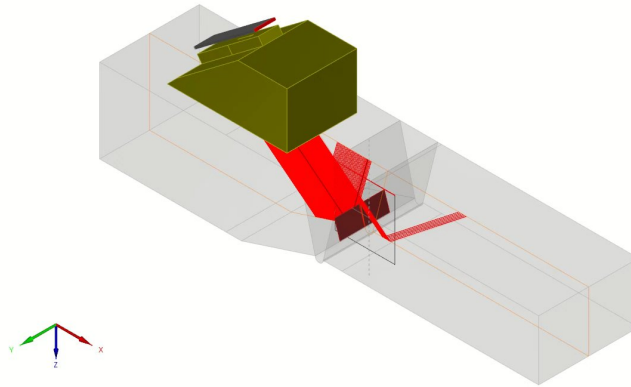
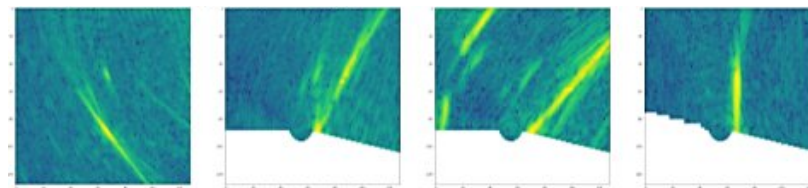
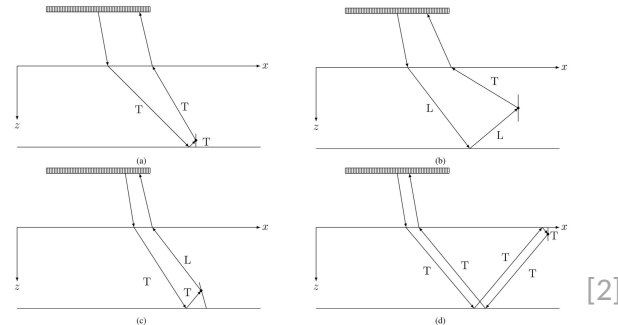
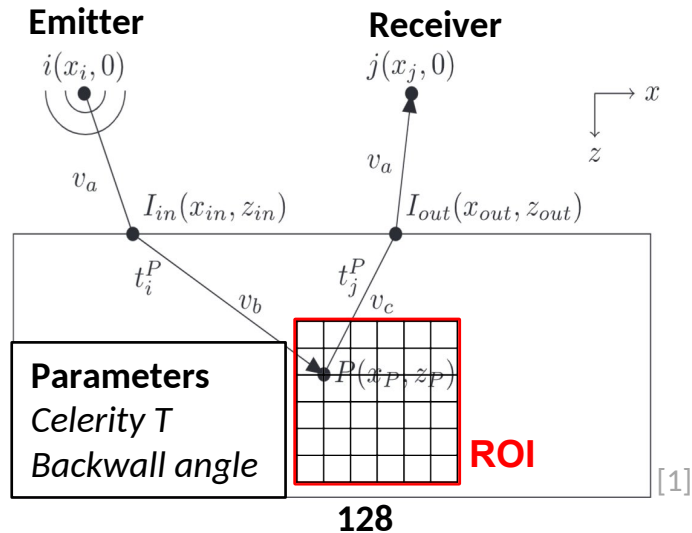
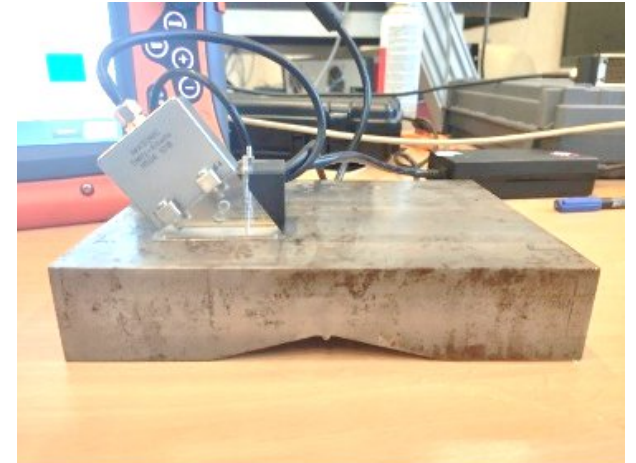


Fig 1 - CIVA configuration for simulated welded structure NDT inspection.

Some background on the generation of TFM dataset images



Experimental acquisitions



Pixel amplitude

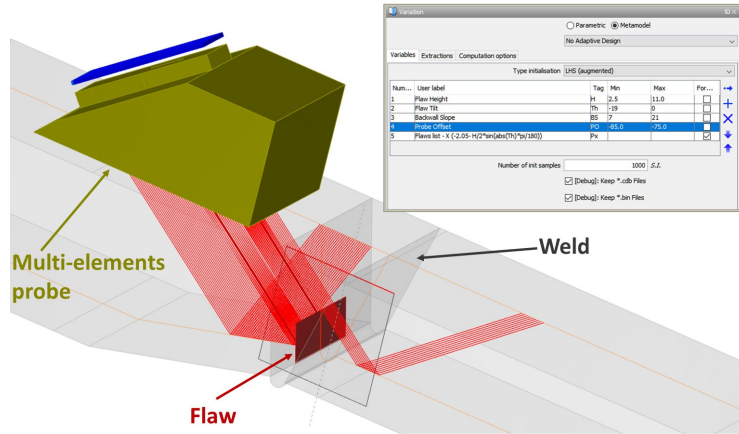
$$s_{ij} = k_{ij}(t) + jH(k_{ij}(t))$$

$$A(P) = \left| \sum_{i=1}^N \sum_{j=1}^N s_{ij}(t_i^P + t_j^P) \right|$$

[1] L. Le Jeune, S. Robert, E.L. Lopez Villaverde, C. Prada, (2016)

[2] L. Merabet, S. Robert, C. Prada (2020)

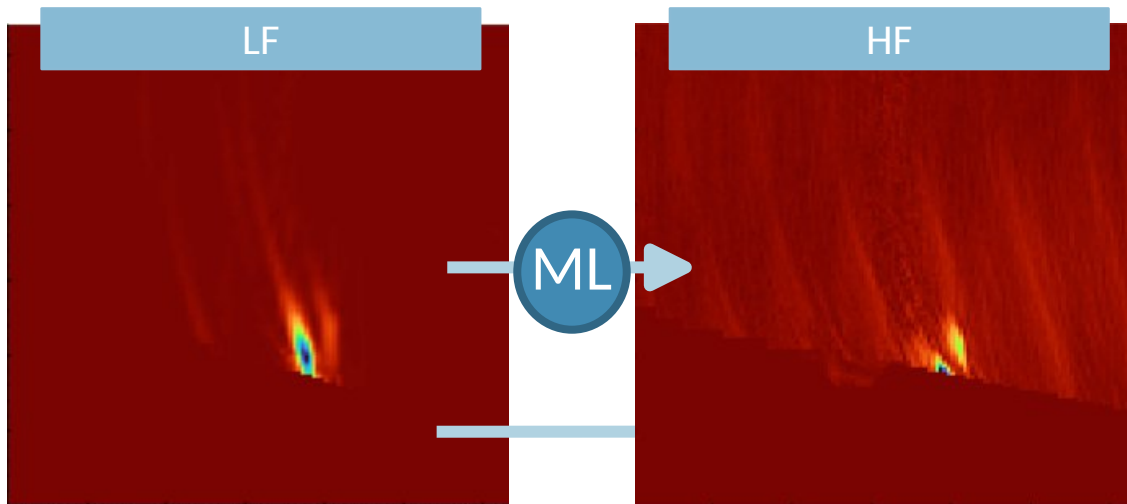
Multi-fidelity deep generative model: mixing mode- & data- driven approaches



| Parameters (labels) | Valeurs |
|---|-------------------|
| Flaw orientation | Vertical ; Tilted |
| Flaw high | 3mm ; 10mm |
| Wave speed T (reconstruction image) | [3080; 3380] |
| Alpha (angle) (reconstruction image) | [10;18] |

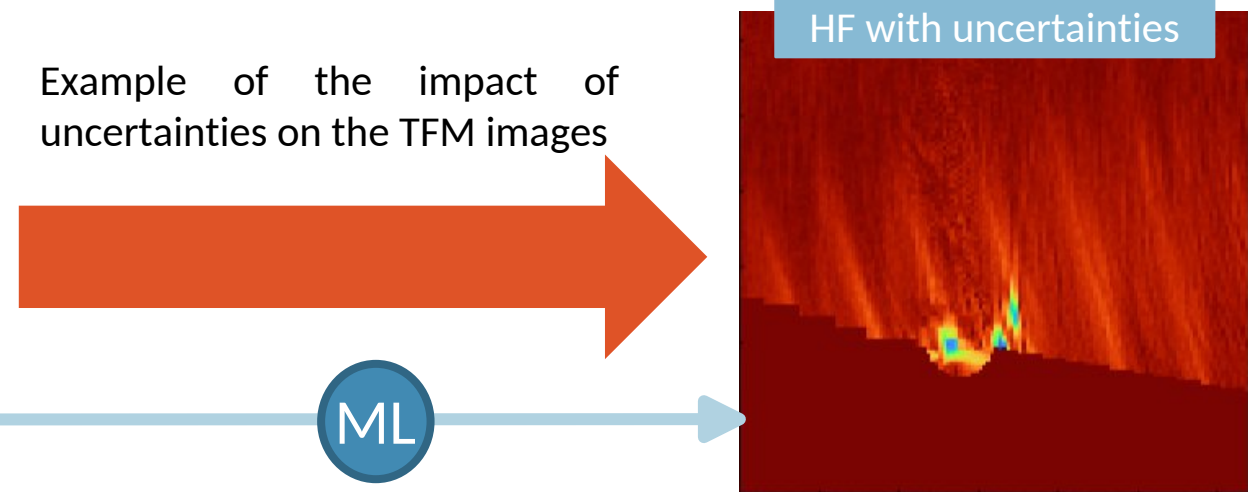
Uncertain parameters

Example of same realisation: **simulation** and **experience** TFM reconstruction parameters without uncertainties

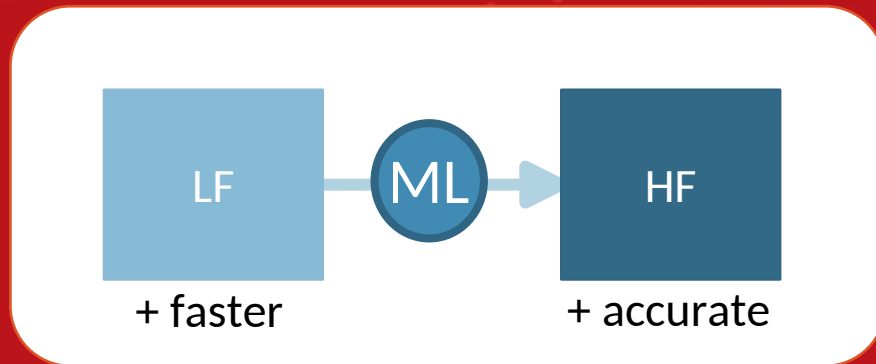


Same experimental realisation with **uncertainties on wave speed** of the piece (same flaw geometry, etc.)

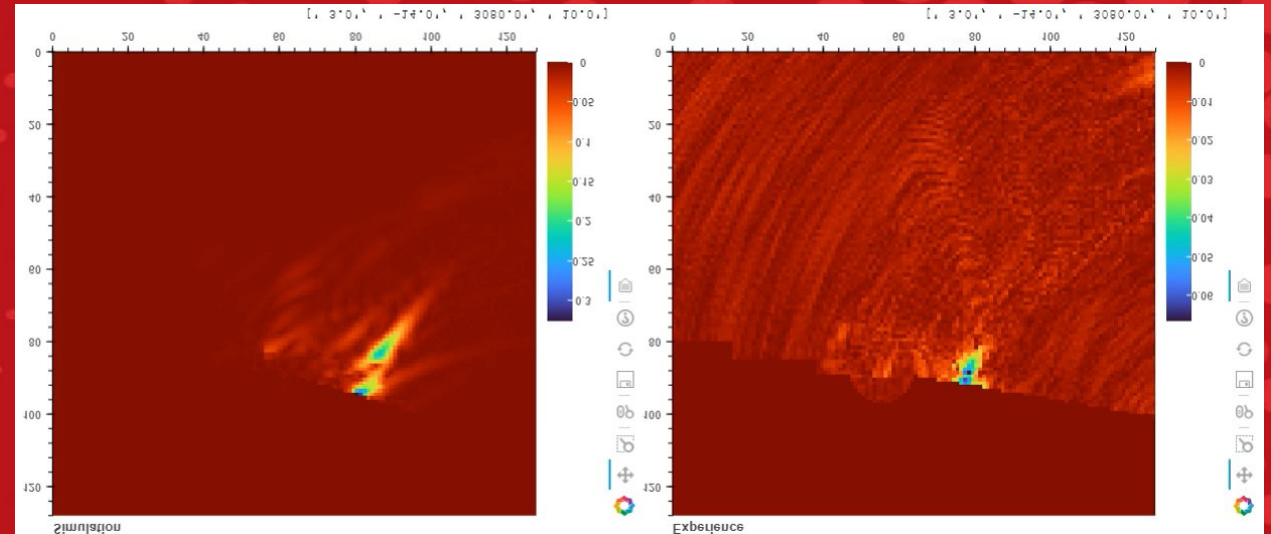
Example of the impact of uncertainties on the TFM images



Meta Model (ML)



Sim. (LF) vs Exp. (HF)



TFM samples: ~3k per class (2 classes)







Approch:

Conditional U-net on ultrasonic testing (UT) TFM images

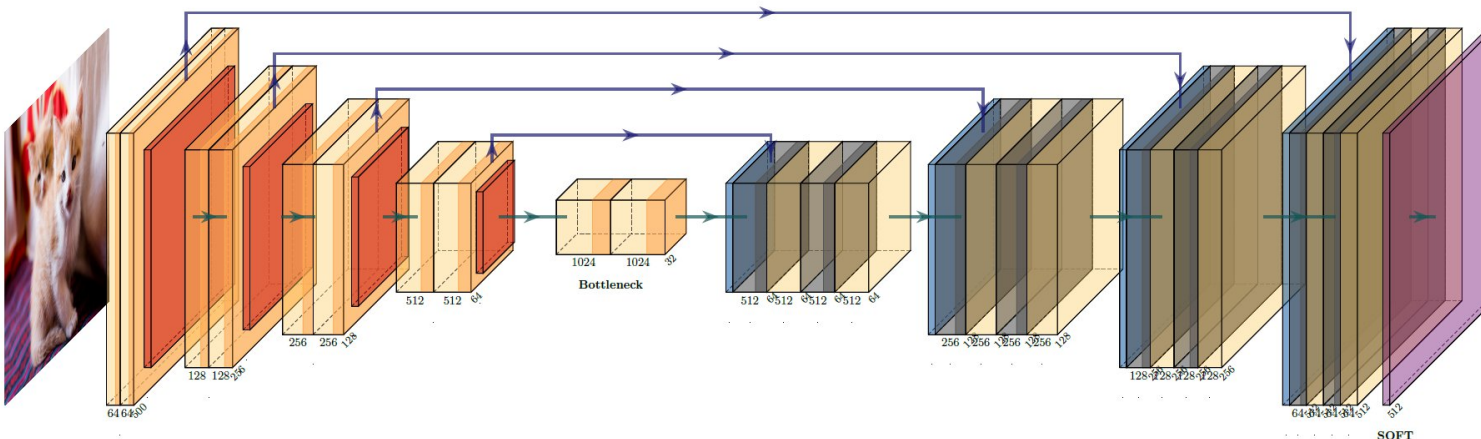
Conditional U-Net as generator on TFM data

Architecture

U-Net common applications

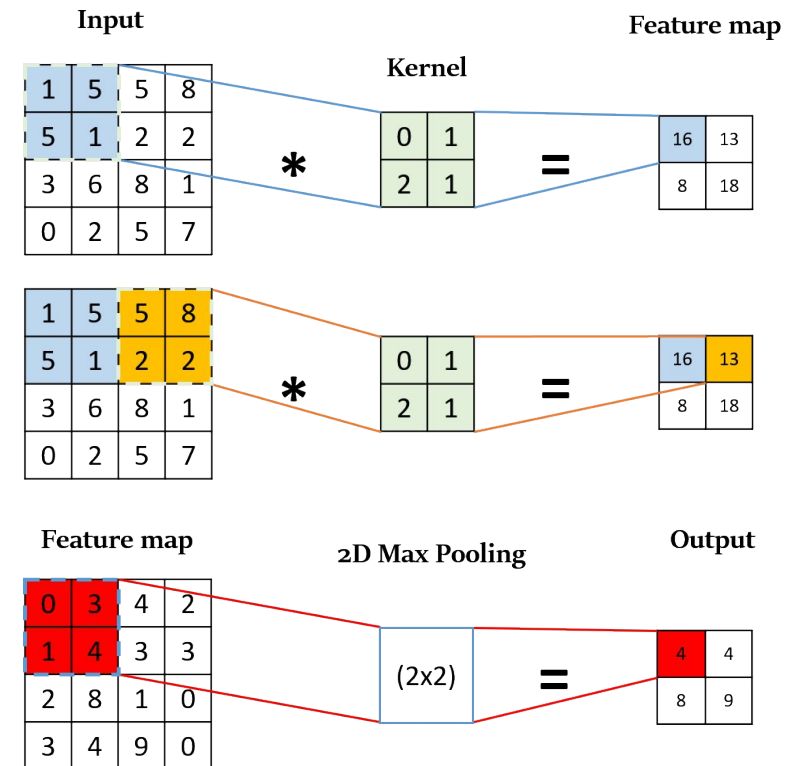
-  Image classification (class distinction)
-  Objects detection (label and localization)
-  Semantic segmentation (label for each pixel)
-  Style transfer
-  Image super-resolution
-  Conditional U-Net for multitask (multi-label and multi-class)




U-Net base architecture ^[3]



[3] Ronneberger, O., Fischer, P., Brox, T. (2015).

Convolution and 2D Max Pooling



-  Spatial features extraction
-  Learns hierarchy on images
-  Less parameters than FC layers

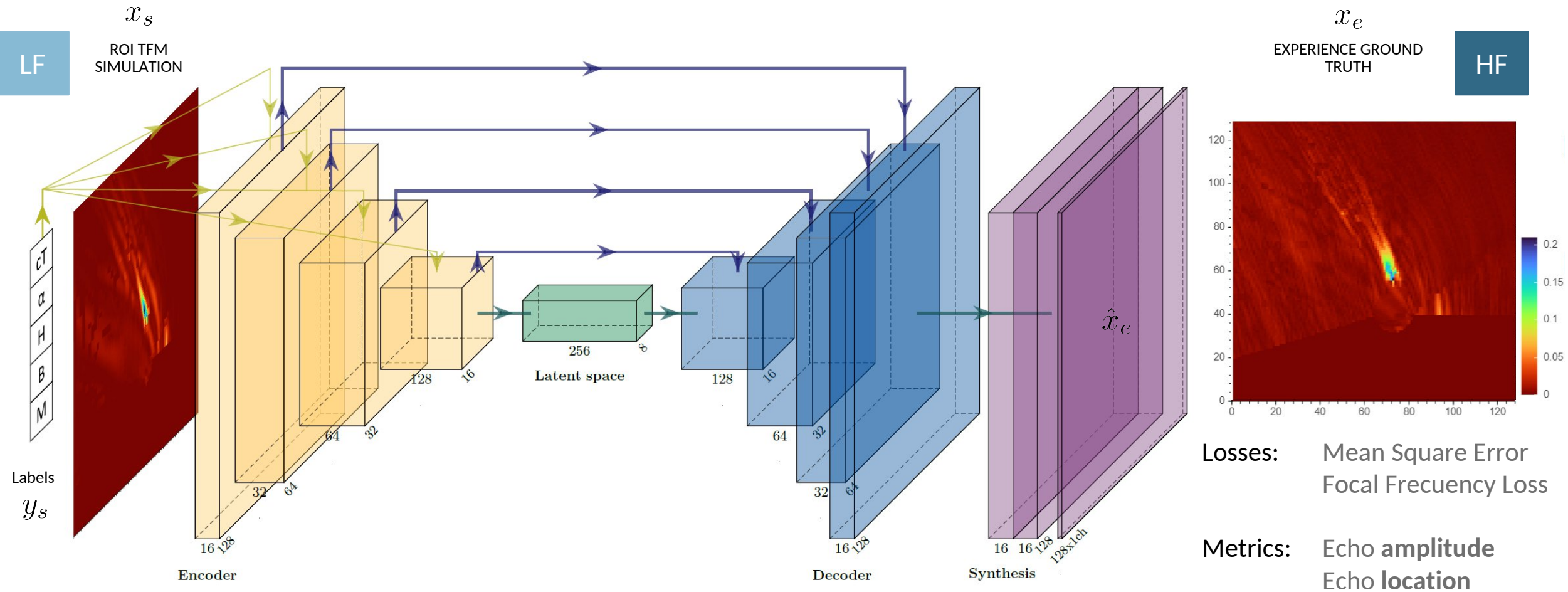
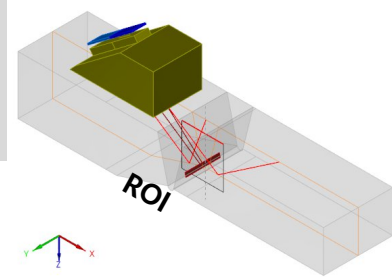
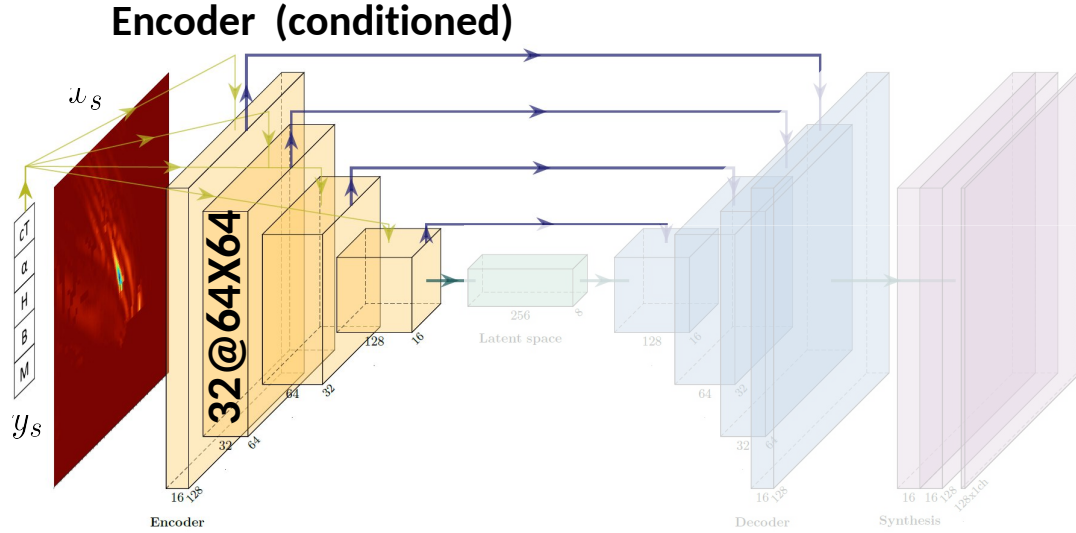


Fig 6 - Conditional CNN U-net architecture for realistic image generation.

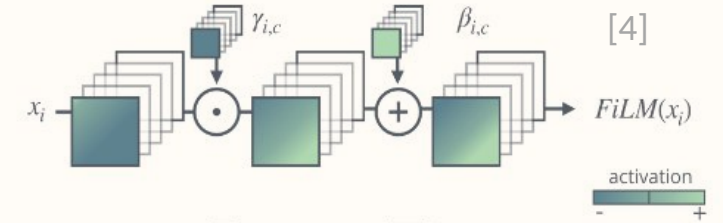


conditioning conditioning

$$FiLM(x_k) = \gamma_k(y_s) \cdot \frac{x_k - E[x_k]}{\sqrt{Var[x_k] + \epsilon}} + \beta_k(y_s) \quad \beta_k \in \mathbb{R}^{n_{ch_k}}$$

$$\gamma_k \in \mathbb{R}^{n_{ch_k}} \quad [4]$$

FiLM complex layer (Co):
independent affine transformations are applied to each feature map c .

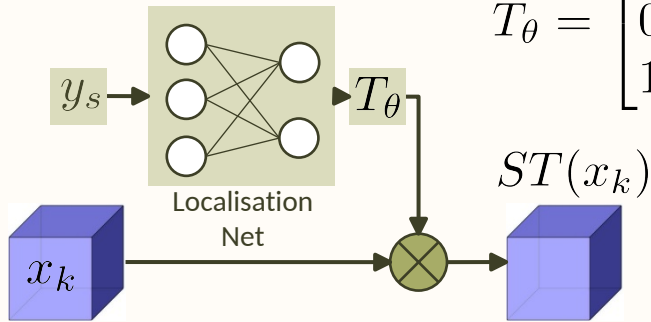


The new per-channel statistics modify the relative importance of features for the subsequent convolution operation.

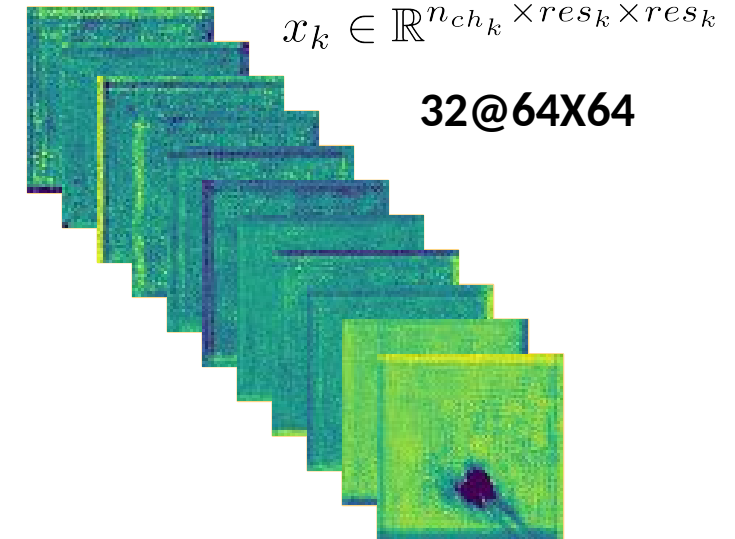
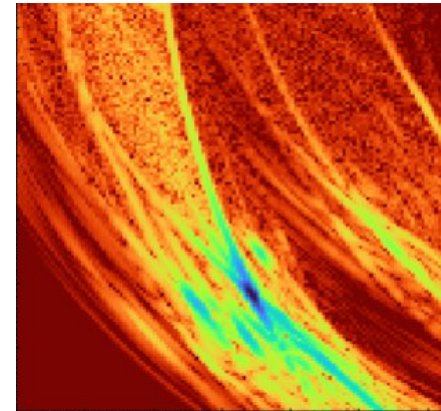
conditioning

$$ST(x_k) = T_\theta(y_s) \cdot x_k \quad T_\theta \in \mathbb{R}^{3 \times 3}$$

$$\theta \in \mathbb{R}^6 \quad T_\theta = \begin{bmatrix} s & 0 & t_x \\ 0 & s & t_y \\ 1 & 1 & 1 \end{bmatrix}$$

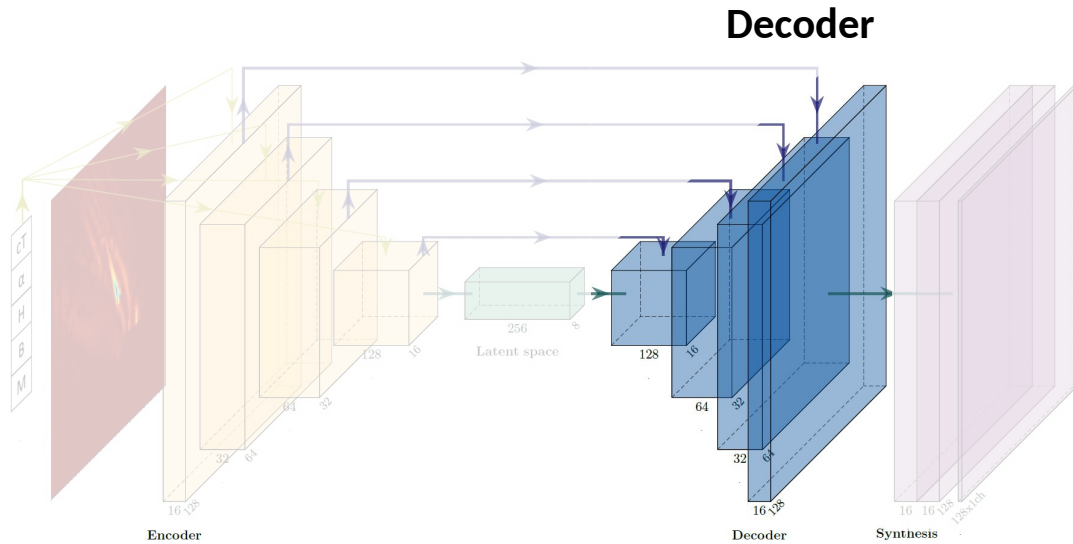


[5]





[5] M. Jaderberg, K. Simonyan, A. Zisserman, and K. Kavukcuoglu (2015).




[4] E. Perez, F. Strub, H. De Vries, V. Dumoulin, and A. Courville (2022)



Principal layers:

-  Convolutional Neural Network
-  Fast stylization through Instance Normalisation

Task:

-  Learns the difference between classes (mse+ffl loss)
-  Take into account uncertainties from experience
-  Generate new experience data (new instances) in a supervised way

Instance Normalisation

$$IN(x_k) = \frac{x_k - E[x_k]}{\sqrt{Var[x_k] + \epsilon}} \times \gamma_k + \beta_k$$

$$\beta_k \in \mathbb{R}^{n_{ch_k}}$$

$$\gamma_k \in \mathbb{R}^{n_{ch_k}}$$

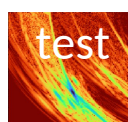
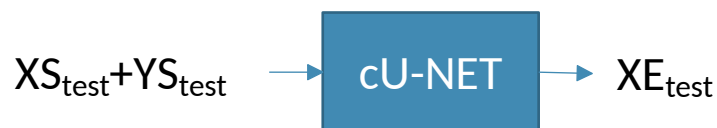
Learned bias
and scale

[6] D. Ulyanov, A. Vedaldi, and V. Lempitsky, "Instance Normalization: The Missing Ingredient for Fast Stylization," Jul. 2016, doi: 10.48550/arxiv.1607.08022.

Conditional U-Net as generator on TFM data

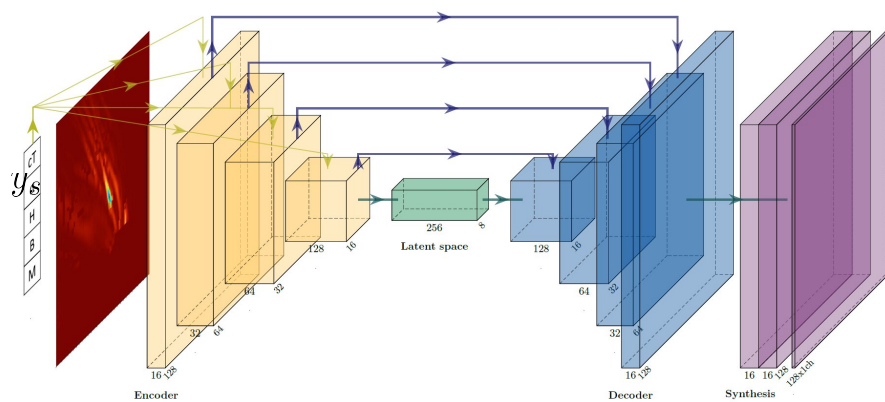
**Results on
Realistic data-set generation
Surrogate model**

Realistic data-set generation



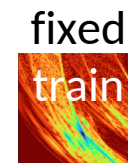
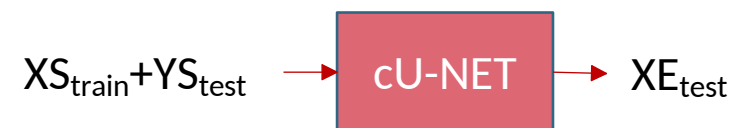
| |
|----------|
| cT |
| α |
| H |
| B |
| M |

Simulations from CIVA

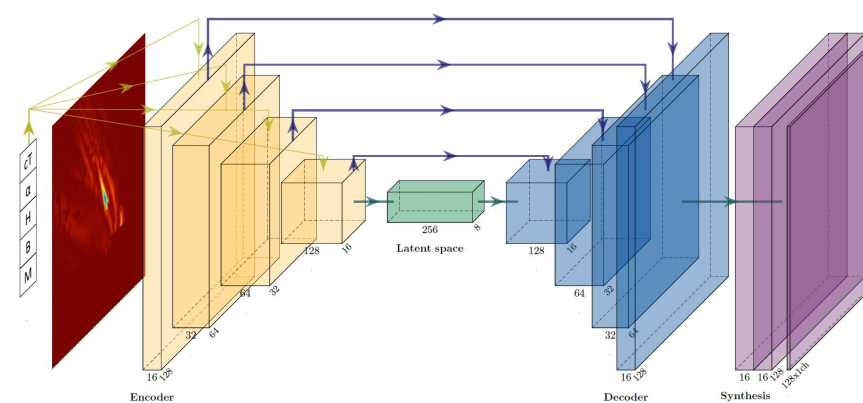


- Generate experience images
- Need new simulations

Surrogate model



| |
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| cT |
| α |
| H |
| B |
| M |

 regression


- Metamodelling just changing parameters
- No new simulation needed

U-Net Generation

- Generative frame on imaging
- Transfer experience to simulation
- Account uncertainties from experience
- Generate new data to train diagnostic tools

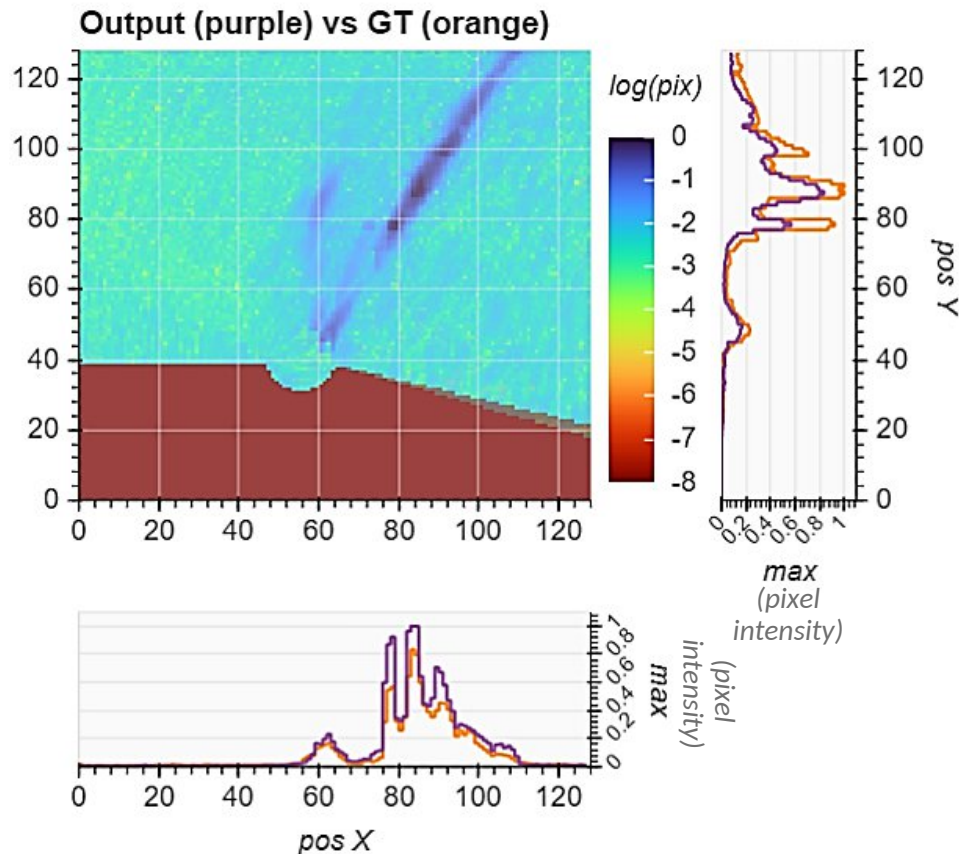
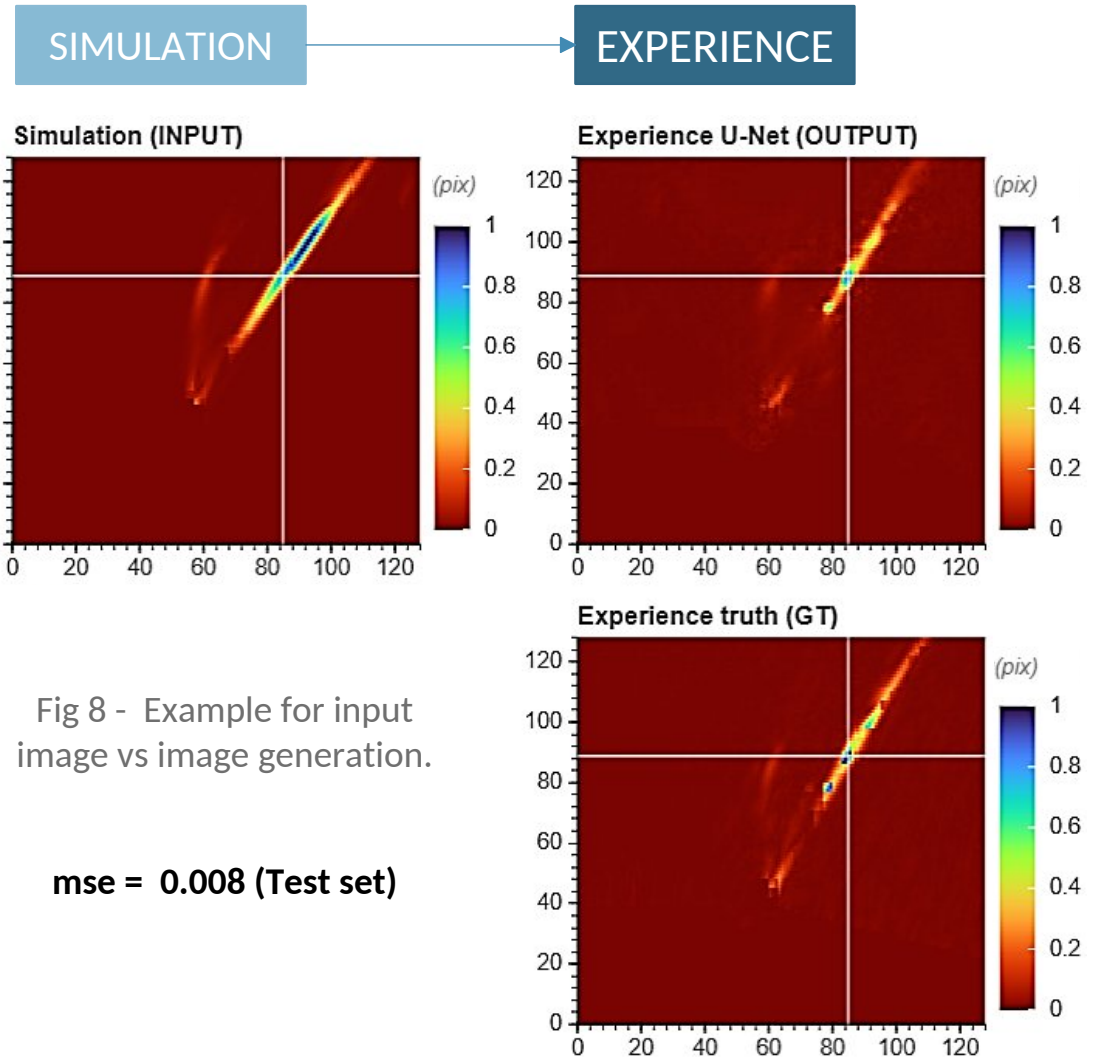


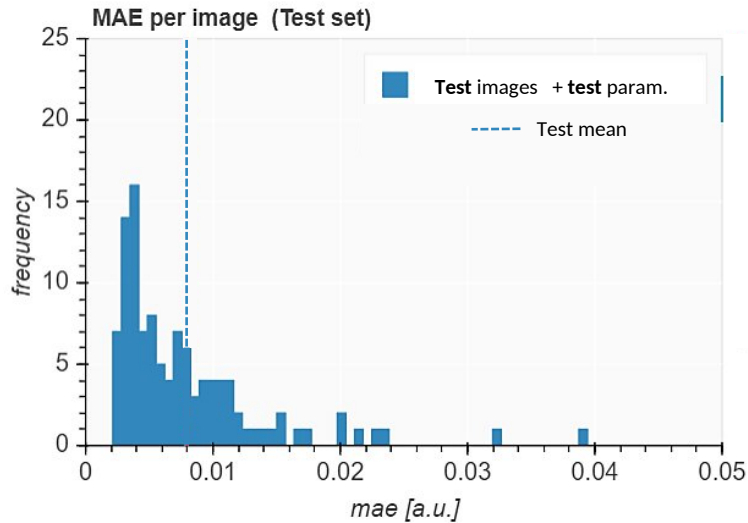
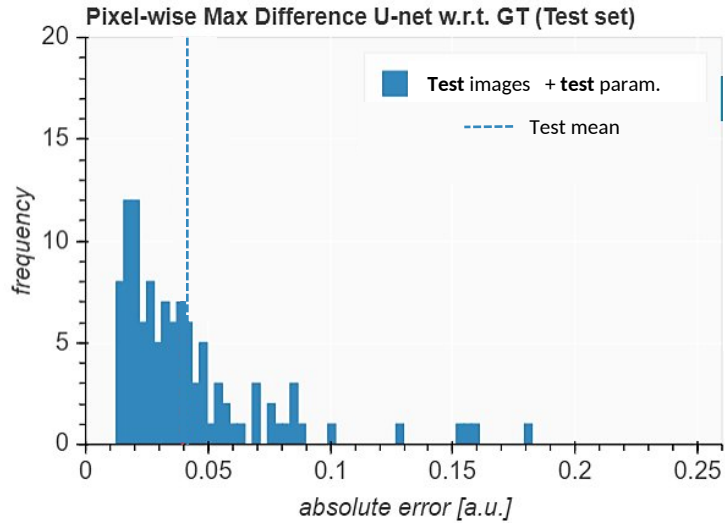
Fig 7 - Example for image generation vs ground truth. Comparison of maximum pixel value and (x,y) position.

$X_{\text{test}} + Y_{\text{test}} \rightarrow \text{cU-NET} \rightarrow X_{\text{e}}_{\text{test}}$



cU-Net as multifidelity generator

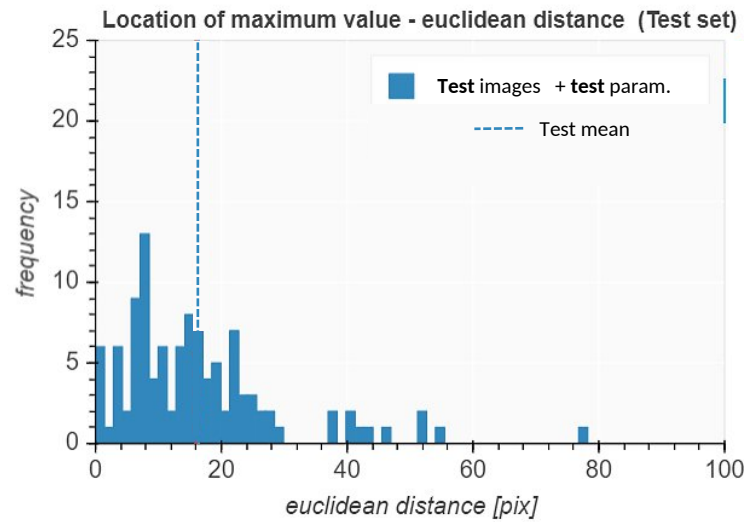
Echo amplitude



SIMULATION

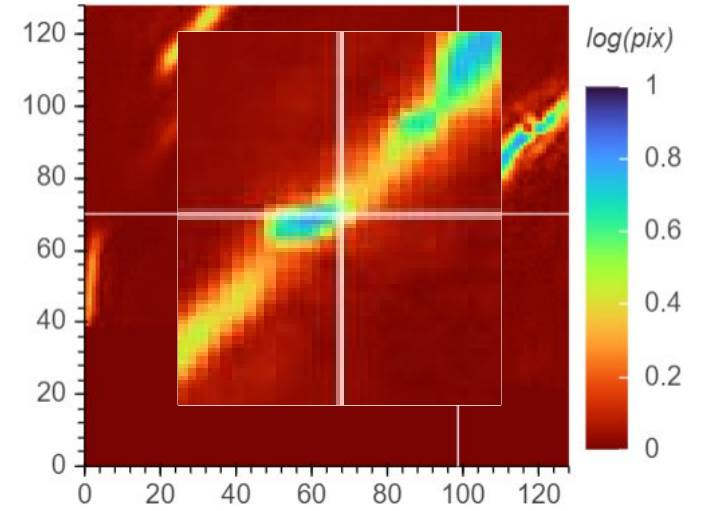
EXPERIENCE

Echo localisation

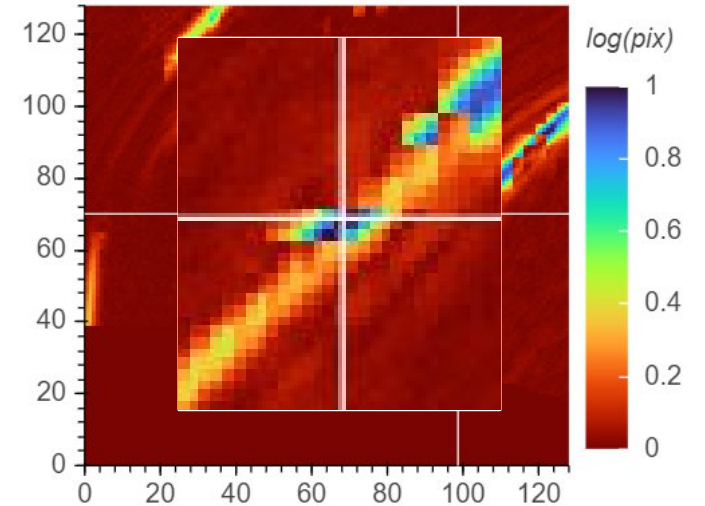


$X_{S_{test}} + Y_{S_{test}}$ → cU-NET → $X_{e_{test}}$

Experience U-Net (OUTPUT)

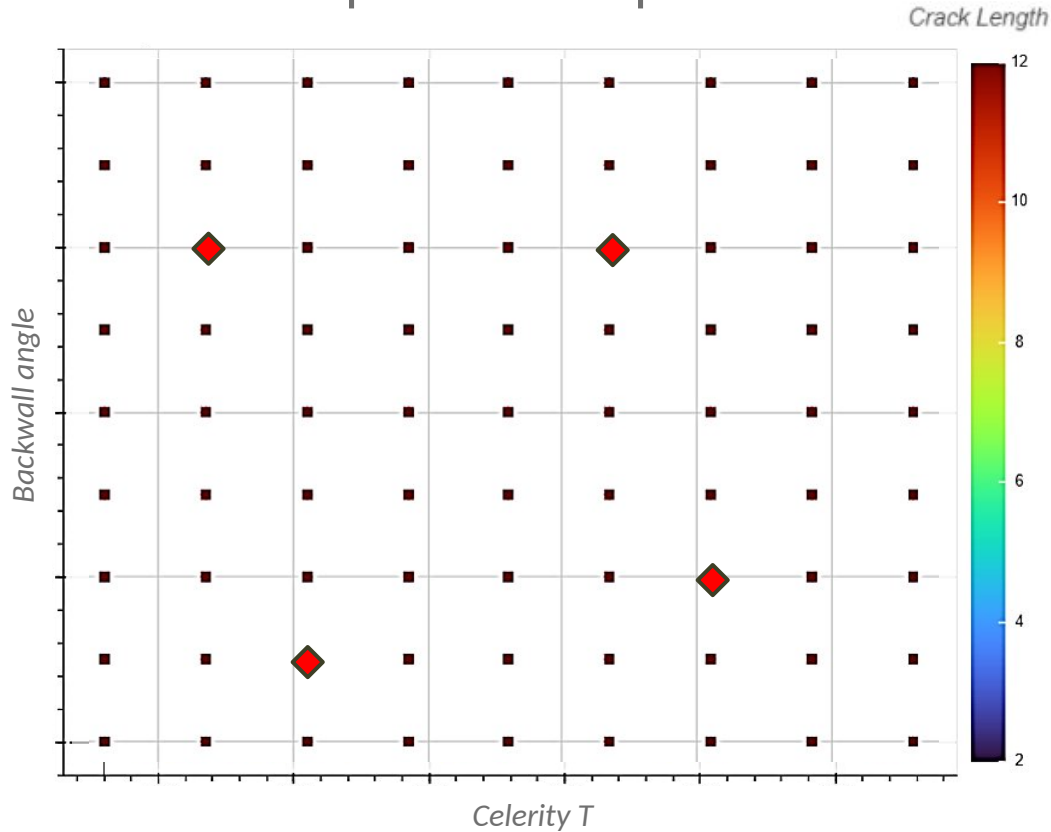


Experience truth (GT)



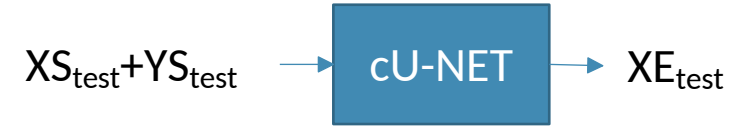
cU-Net as multifidelity generator

Sampling from simulation parameter space

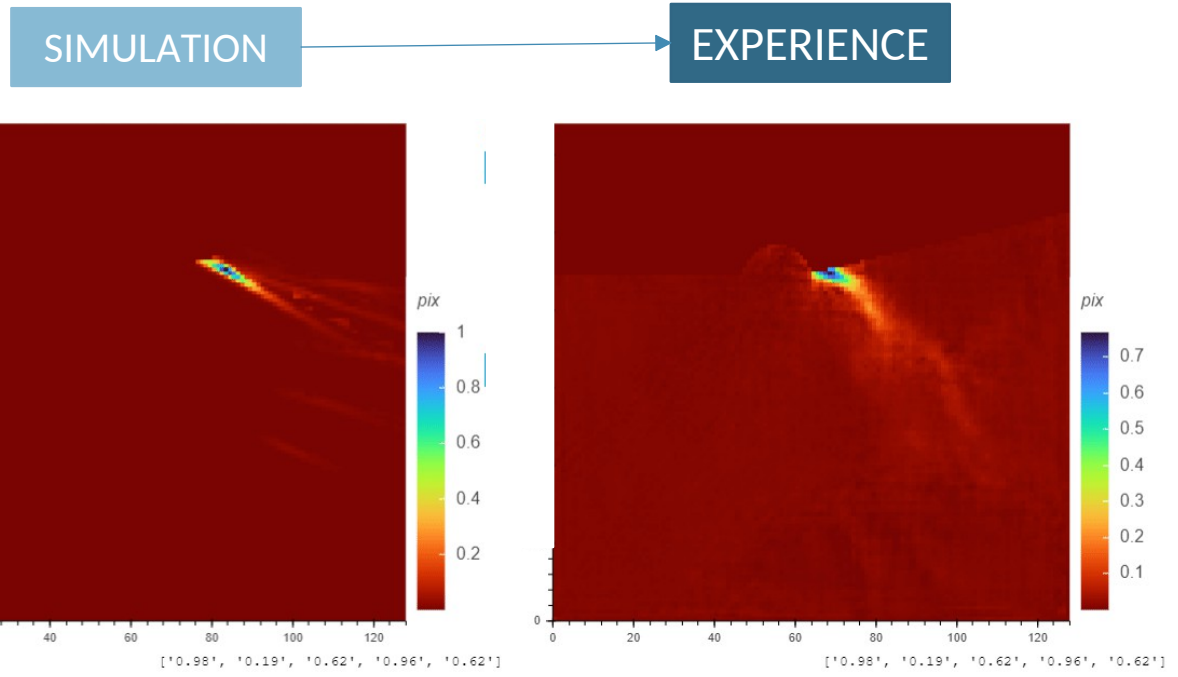


- ◆ Examples of points is **test set**
 - Examples of points is **training set**
- New simulated samples

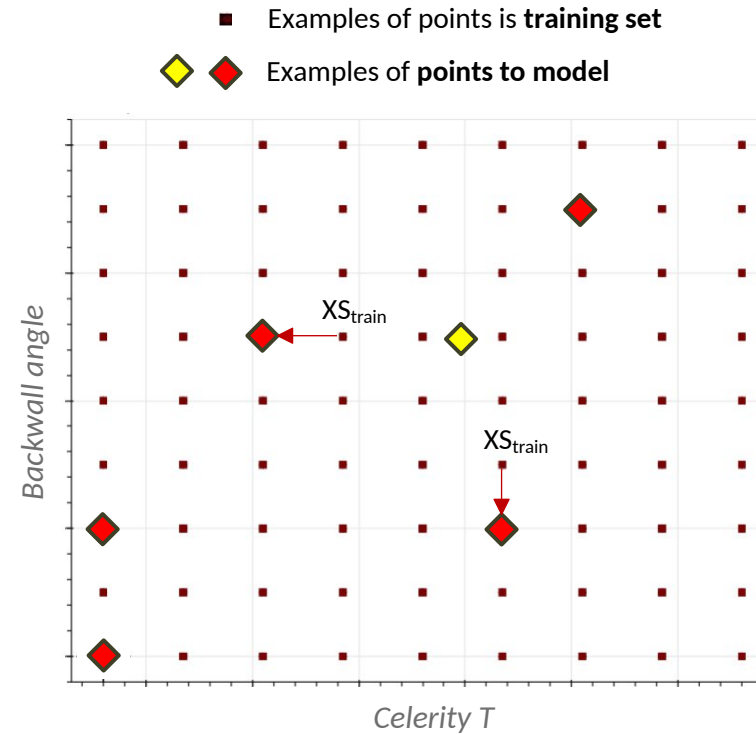
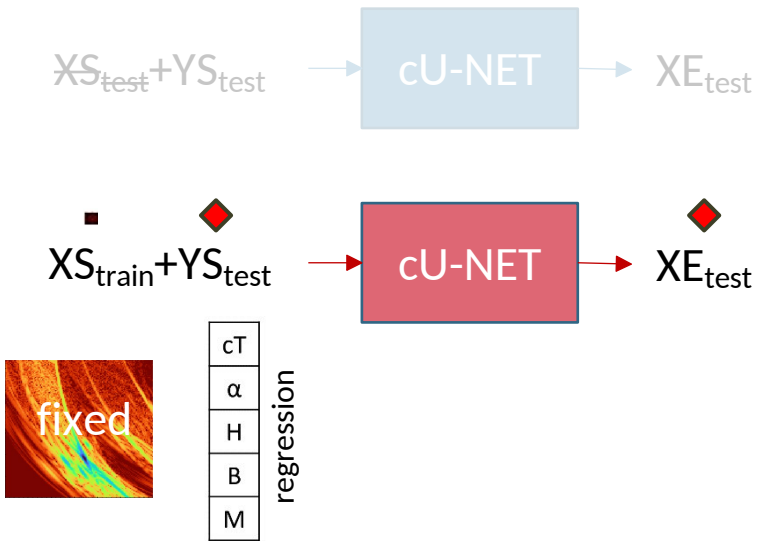
A point represents: simulated image + parameters vector



New generated dataset



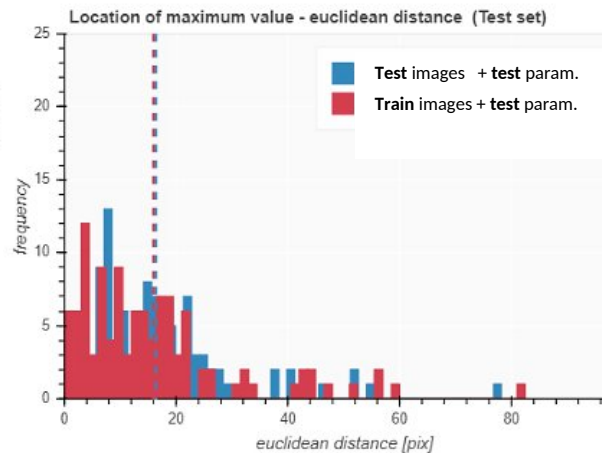
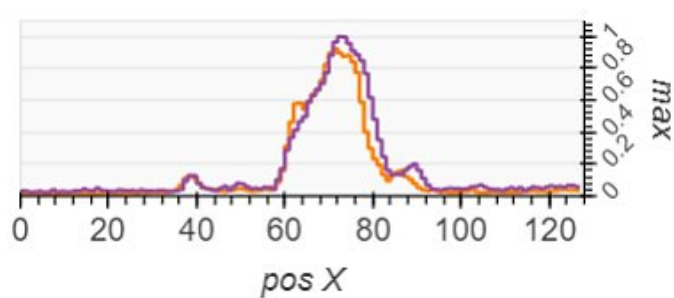
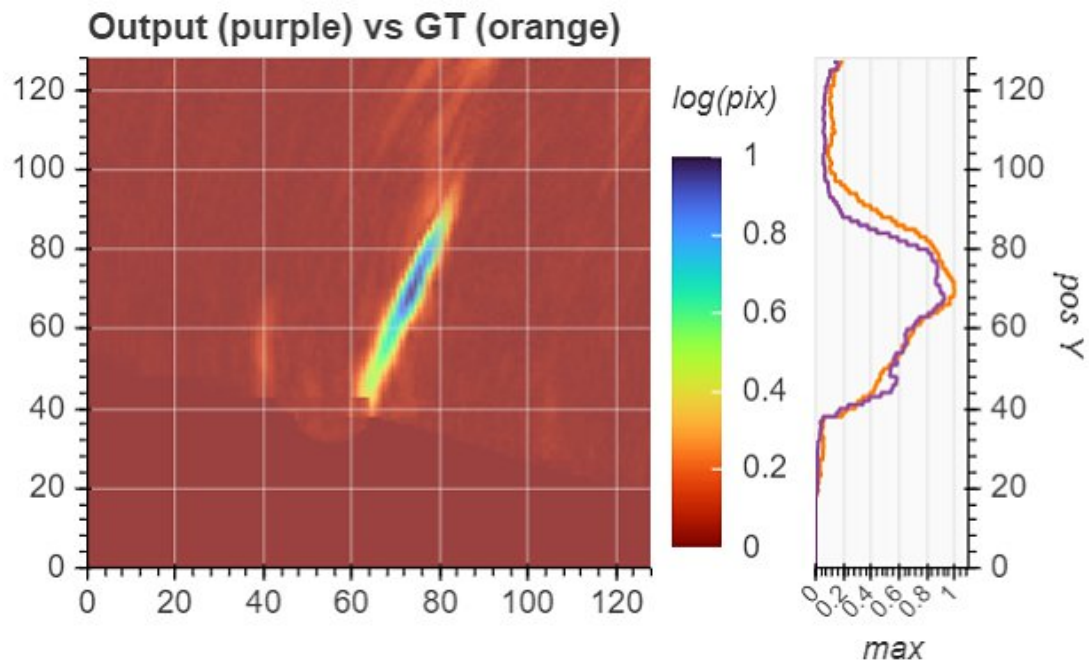
cU-Net surrogate model - *regression in parameter space (labels)*



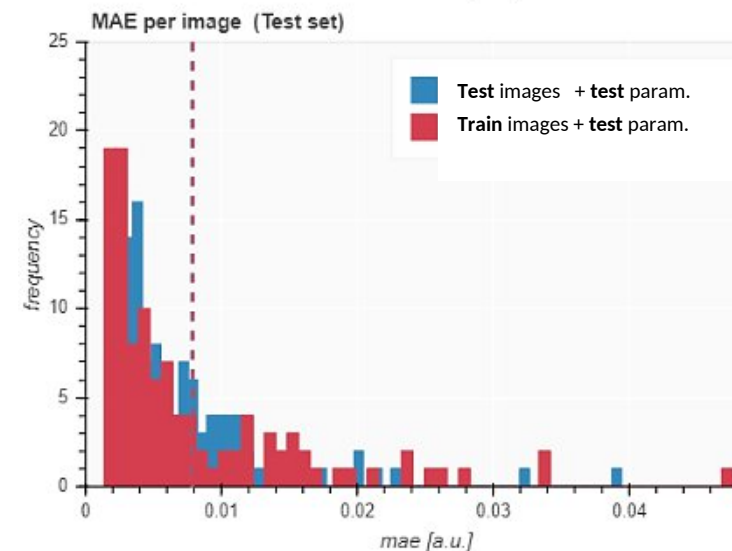
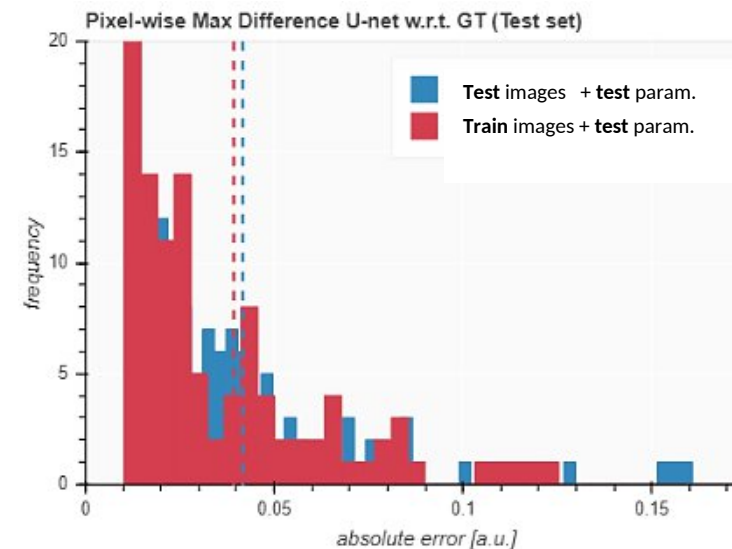
The neural network has a parametric input that modifies the input image in relation to the input parameters.

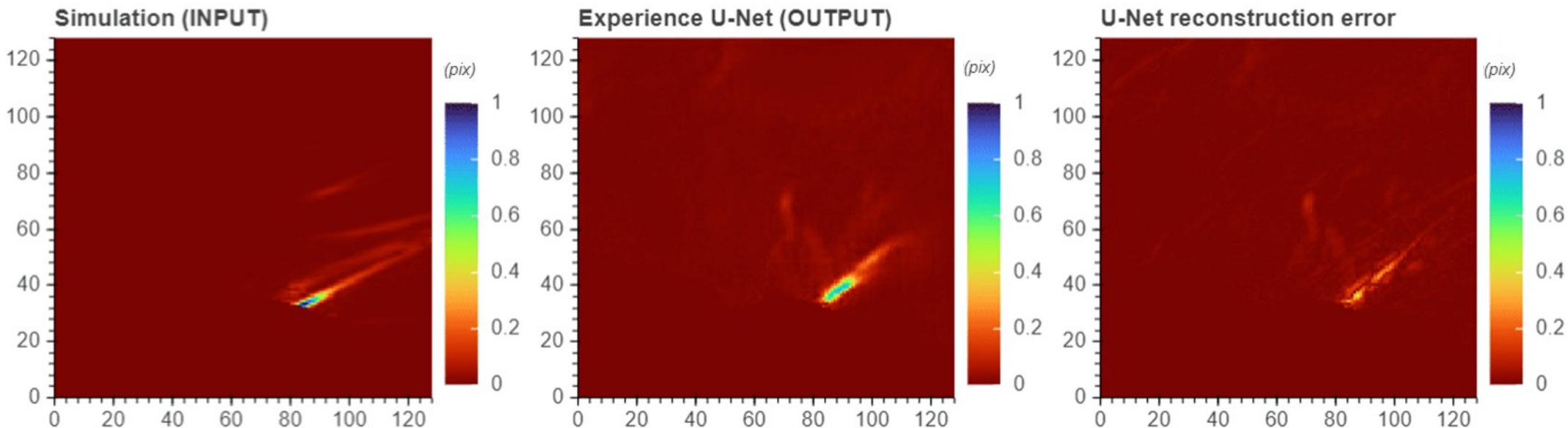
Can we sample the parameter space to generate **new images** related to **new labels**?

Echo localisation

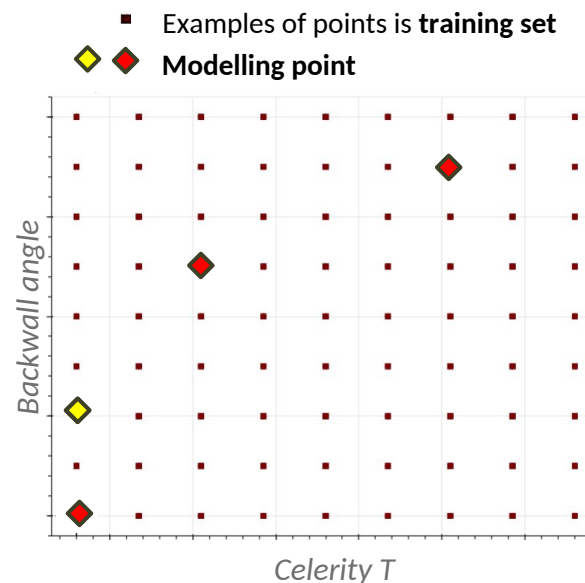
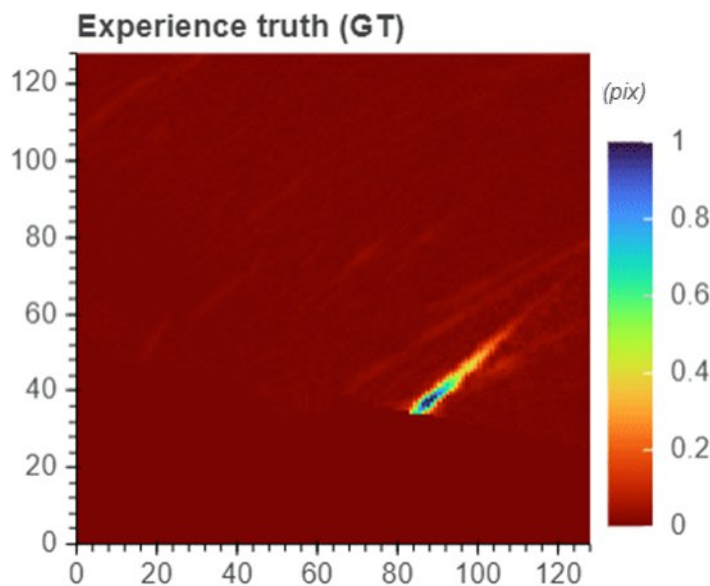


Echo amplitude



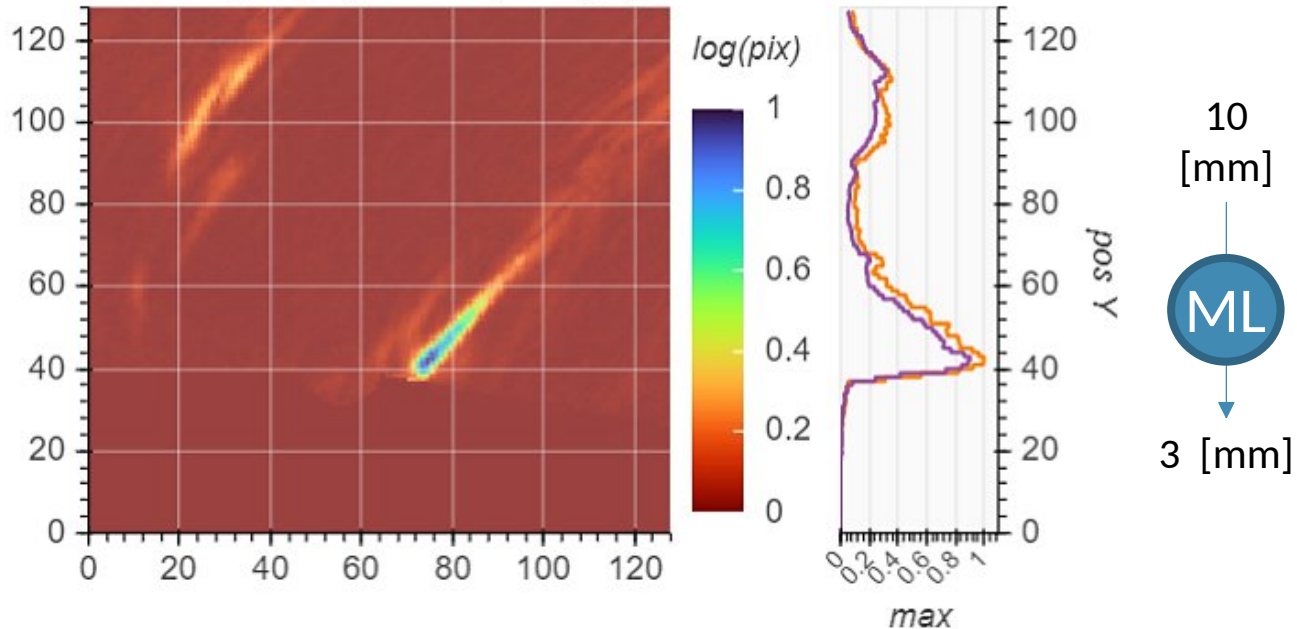


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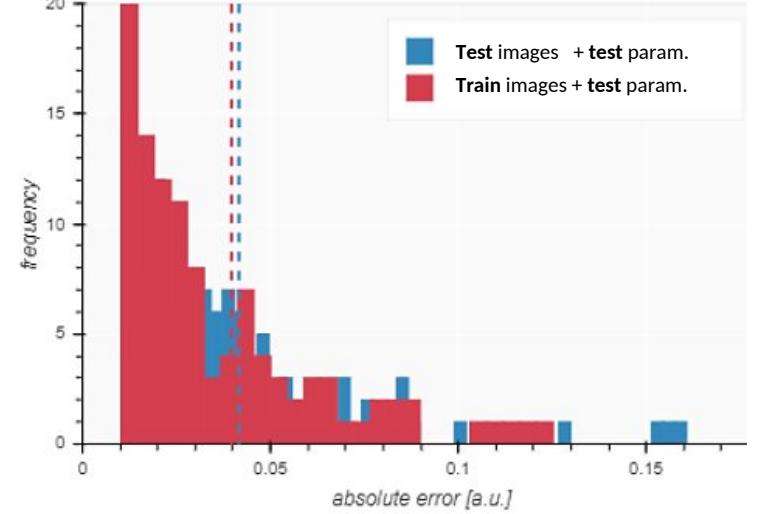
Echo localisation

Output (purple) vs GT (orange)

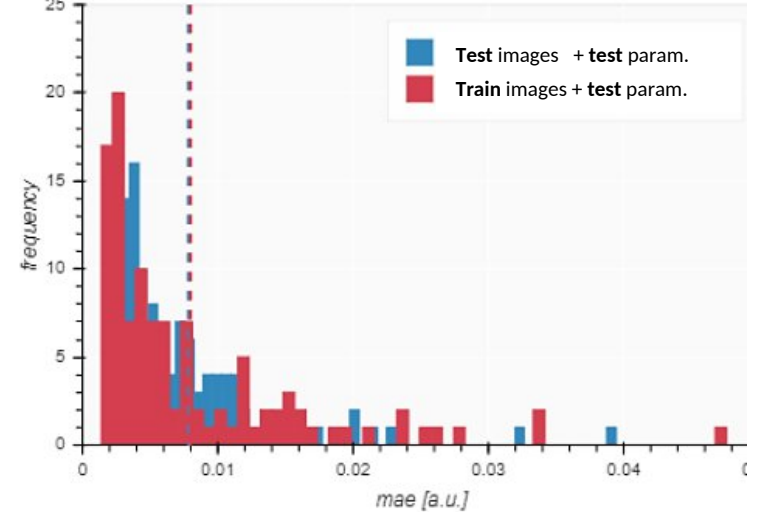


Echo amplitude

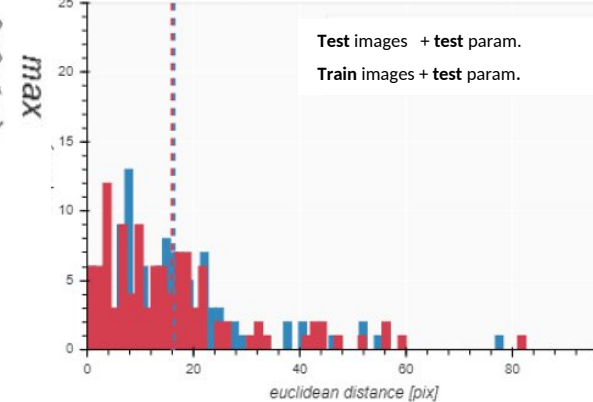
Pixel-wise Max Difference U-net w.r.t. GT (Test set)



MAE per image (Test set)



Location of maximum value - euclidean distance (Test set)

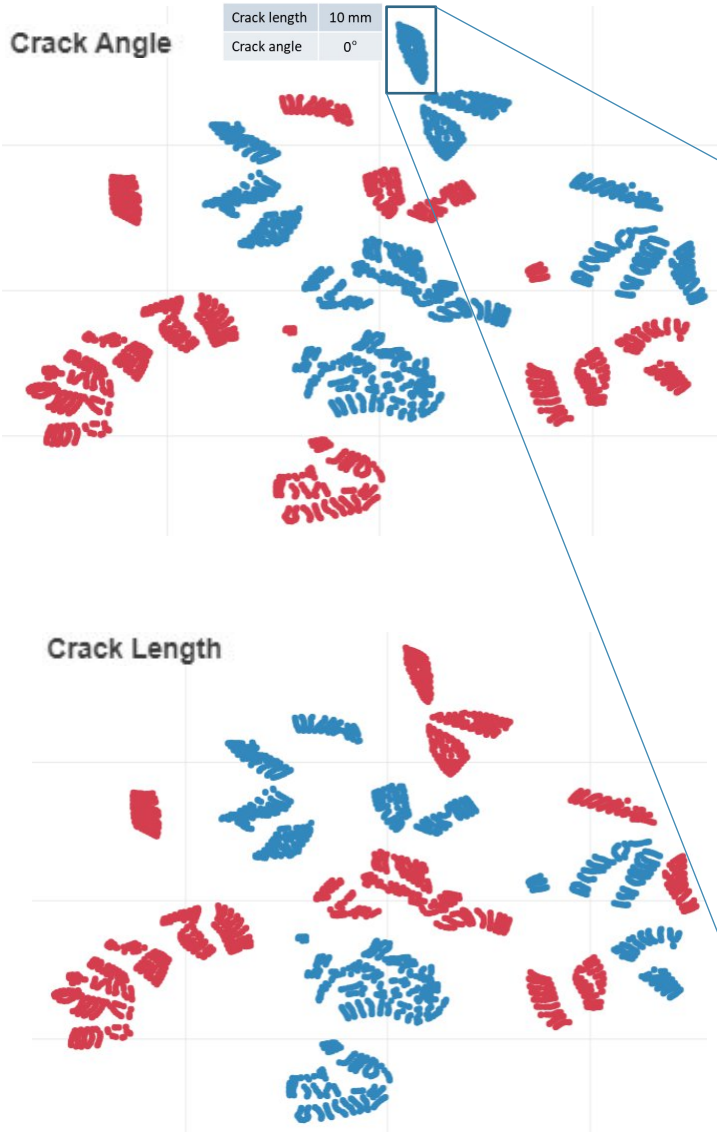
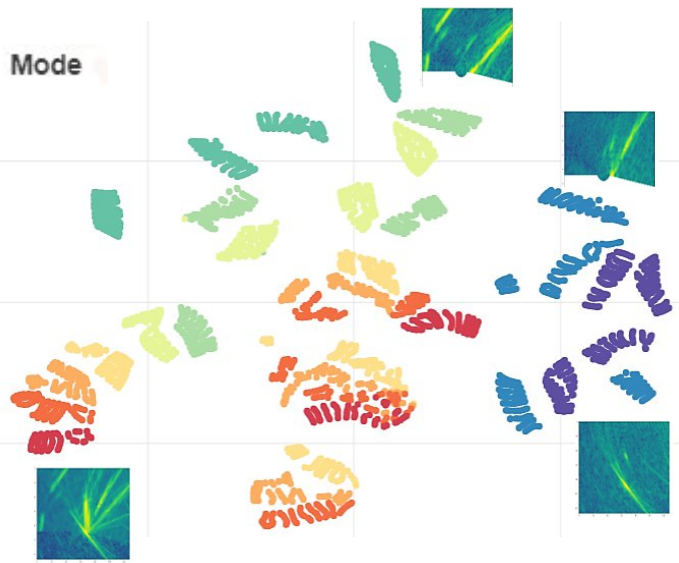
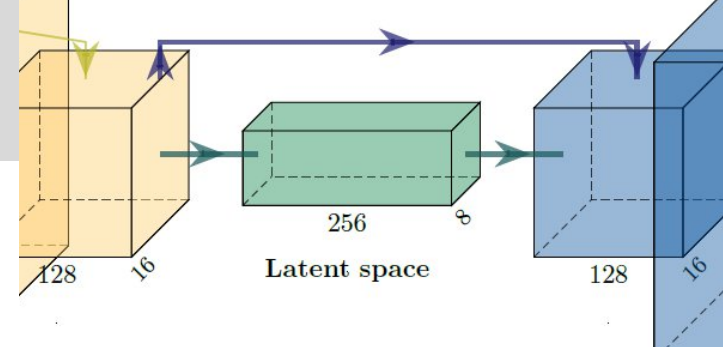


Conditional U-Net as generator on TFM data (supervised)

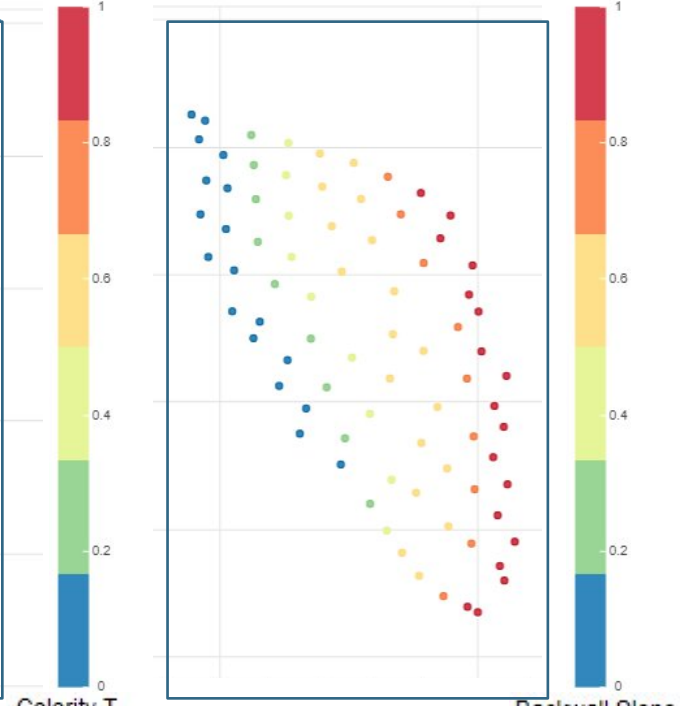
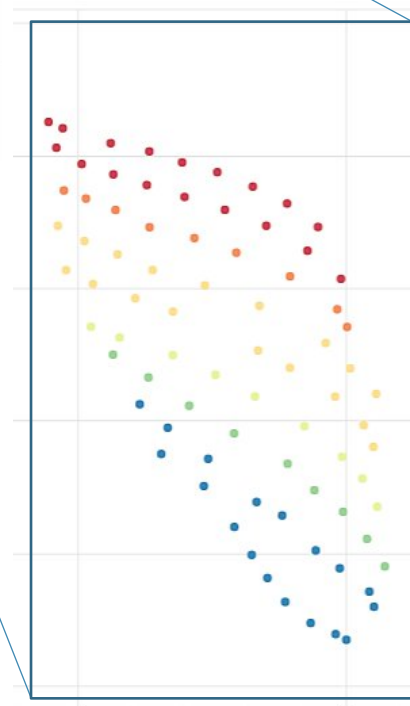
Features exploration

Latent space exploration

U-MAP representation 8x8x256 \hookrightarrow 2D



| | |
|--------------|-------|
| Crack length | 10 mm |
| Crack angle | 0° |



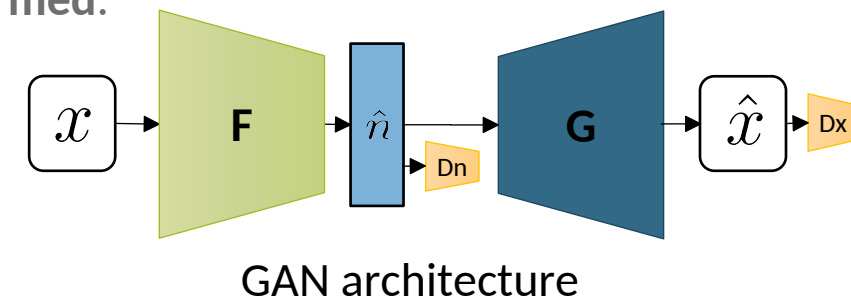
UMAP constructs a high dimensional graph representation of the data then optimizes a low-dimensional graph to be as structurally similar as possible

Conclusion

- 🧑‍🔬 **Multitask neural network**: 9 TFM reconstruction modes are learned. New modes requires DA or new training.
- 🧑‍🔬 The model takes as HF domain the experience. **Different degrees of data fidelity on HF side** can be considered (e.g: FEM).
- 🧑‍🔬 A **novel application of ST and FiLM modules** is presented to learn parametric subrogated model on ML frame.
- 🧑‍🔬 Relation between NDT image features and the simulation parameter are learned by the model.
The architecture is **not limited by the shape of the parameter vector**.
- 🧑‍🔬 Parametric **metamodeling** allows to generate new “**experimental**” instances, even without new simulation instances.
- 🧑‍🔬 Regression on label space provides **direct labelling for new data**.

Perspectives

- 🧑‍🔬 **cU-net as realistic data generator** for data-set creation provides the tool to have enough data to train deeper models:
GAN as variational inference tool to link two fidelity data domains (e.g.: simulation and experience)
- 🧑‍🔬 GAN approach is pertinent when **couples on each fidelity domain are not informed**.





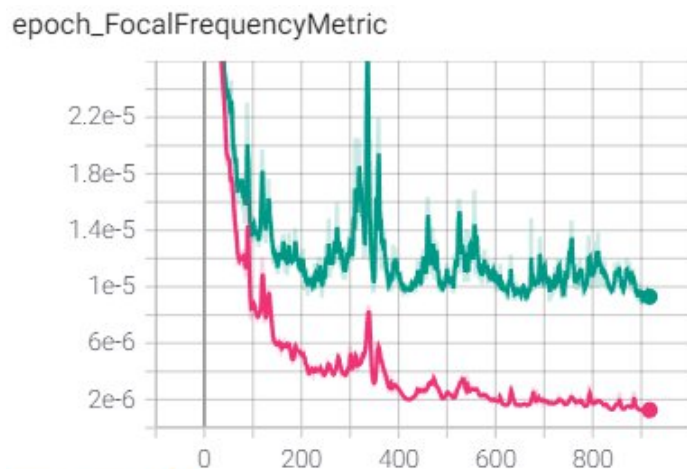
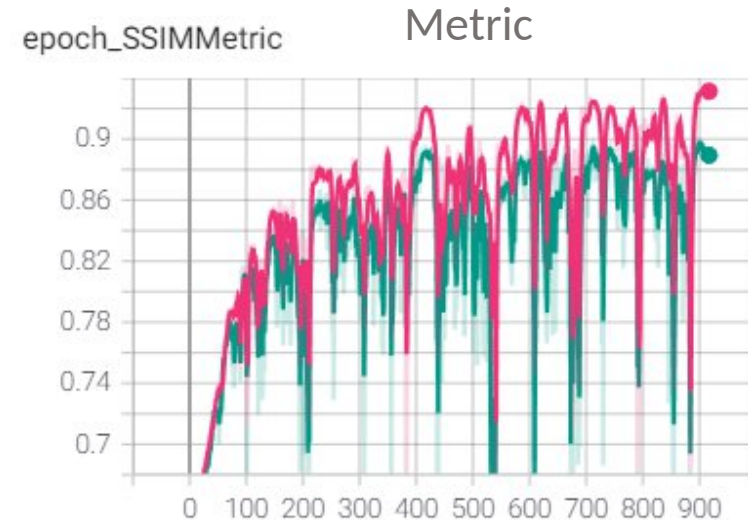
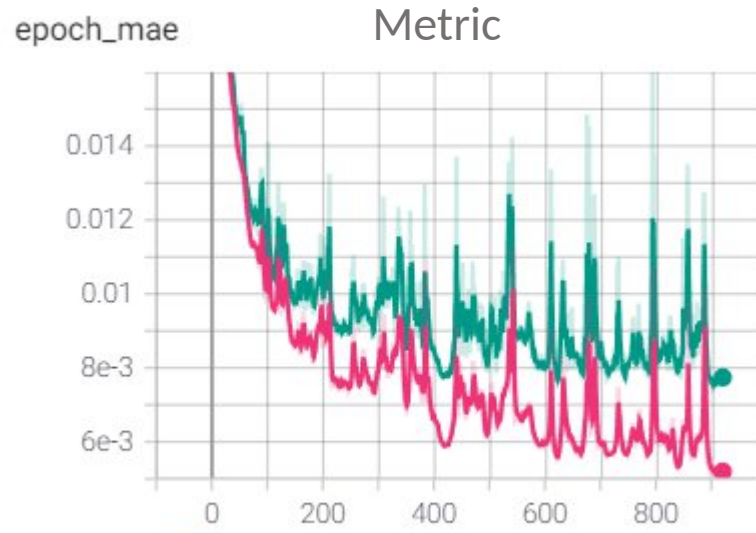
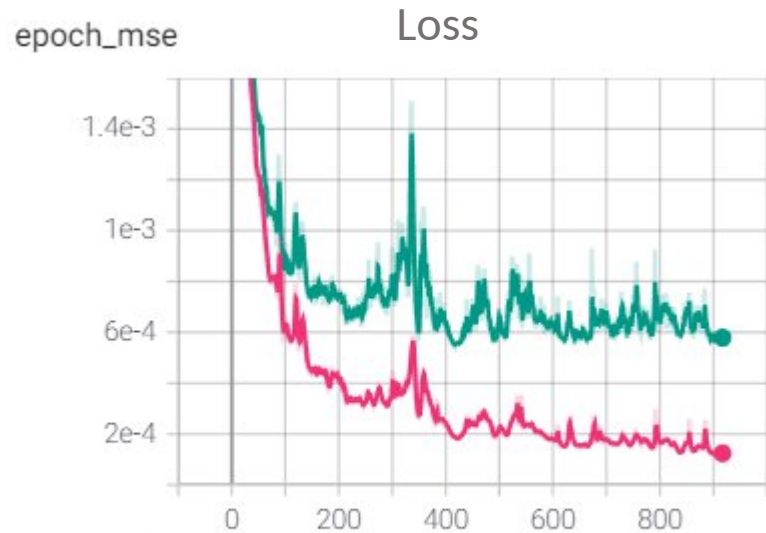
Merci de votre attention

Thanks you for you attention

Gerardo E. Granados

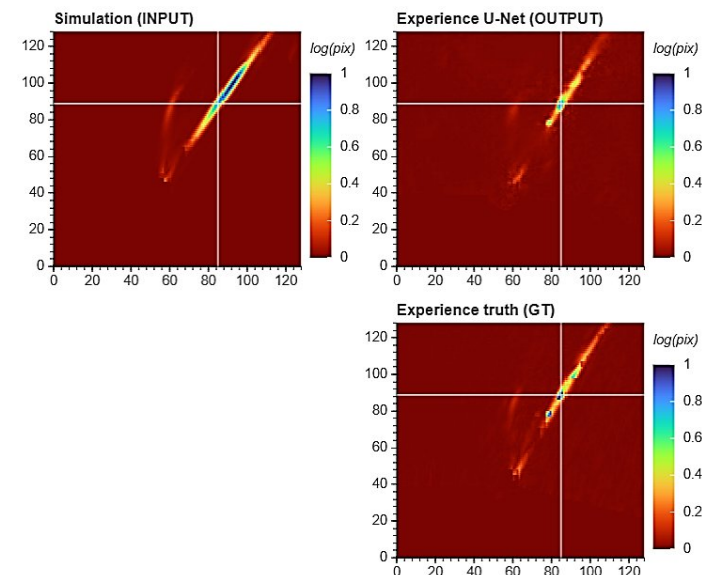
Contact mail:

gerardo.granados@cea.fr



— Training
— Validation

4h sur GPU
NVIDIA Quadro RTX 6000
Batch 128
22 GB on GPU



Loss

