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Surrogate Model for Linear Accelerator

LinacNet: A fast Neural Network Approximation of ThomX simulations

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[2]Laboratoire Interdisciplinaire des Sciences du Numérique (LISN)

Monday 12th December 2022

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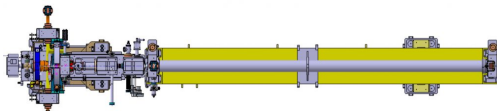
ThomX: A Compact Compton Source

Figure: Linac of ThomX.

ThomX

- X-ray source by Compton backscattering
- Compact Accelerator (70m^2)
- In commissioning at the IJCLab since May 2021

Linac

- Accelerate the electron beam up to 50 MeV

Goal

Use machine learning to tackle the problem of adjusting the Linac parameters to fulfill the beam requirements for the transfer line.

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Accelerator Tuning

$\mathcal{A}$: Controllable Parameters

- 15 controllable parameters
    - Laser position and size
    - Gun and Cavity phase and field
    - Solenoid Fields
    - Steerer Fields
    - Quadrupoles Fields

Accelerator Tuning

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$\mathcal{B}$: Hidden Parameters

- Mechanical Misalignment
- Unknown initial particle distribution
- Slow drift of electromagnetic elements

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$\mathcal{O}$: Observables

- 17 Observables
  - Position and Charge at BPMs
  - Charge at ICTs
  - Position and Size at Screen
  - Charge at Faraday Cup

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F: Objective function

- Quality of the beam
- Function of (A, B)

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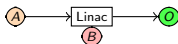 - ▸ Position and Size at Screen
  - ▸ Charge at Faraday Cup

F: Objective function

- Quality of the beam
- Function of (A, B)

Goal

- Optimize A depending on B to get minimal F with the aid of $\mathcal{O}$
- Currently : manual tuning, heavy load on expert

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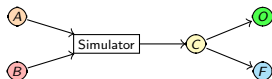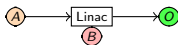## Context: Machine and Simulation Tools

On the Machine

1. B unknown
2. Only partial information with O
3. F not directly measurable

Computation time on the machine

1. Set A and measure O : ~ 1 sec.
2. Estimation of F: ~ 10 min.
3. Collective Schedule

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[1]Pöplau, Van Rienen, and Floettmann, "3D space charge calculations for bunches in the tracking code Astra".

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Context: Machine and Simulation Tools

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1. Set A and measure O : ~ 1 sec.
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3. Collective Schedule

On the Simulator

1. B can be specified (90 parameters)
2. Output of the simulator $C \in \mathbb{R}^{6 \times 17}$
3. F is a function of C

Computation time on the simulator

1. Computation of C: ~ 10min.
2. F and O given by C
3. Individual Schedule, can run in parallel

Simulations performed with Astra[1]

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[1]Pöplau, Van Rienen, and Floettmann, "3D space charge calculations for bunches in the tracking code Astra".

Methods

> ### The exploration-optimization accelerator tuning
>
> 1. Learn $\widehat{F} \simeq F_{\text{simulator}}$
> 2. Learn $\widetilde{F} \simeq F_{Linac}(A, B_{Linac})$
> 3. Estimate $\widehat{B}_{Linac} = \underset{B \in \mathcal{B}}{\arg\min}\, d\left(\widehat{F}(.,B) - \widetilde{F}\right)$
> 4. Adjust A such that $A = \underset{A \in \mathcal{A}}{\arg\min}\, \widehat{F}\left(A, \widehat{B}_{Linac}\right)$

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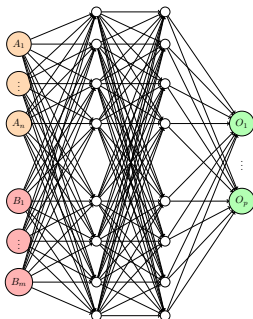Conclusion
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Multi Layer Perceptron: A First Model

Figure: MLP as a surrogate model of a Linac

Multi Layer Perceptron

- Stack all inputs and outputs
- 10k simulations sampling $\mathcal{A}$ and $\mathcal{B}$
- Minimization of the L2 loss

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LinacNet: from a Physical Architecture to a Neural Network Architecture
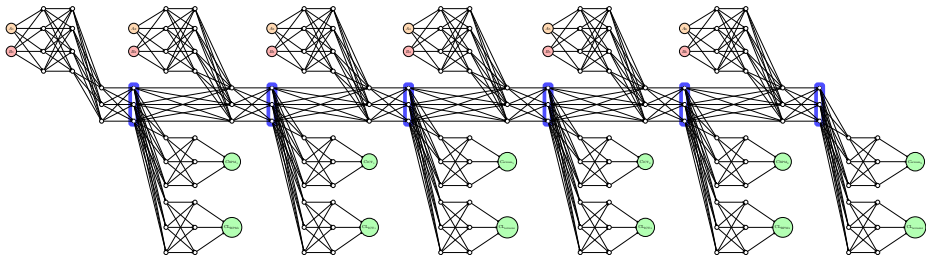

Figure: LinacNet with 6 modules corresponding to 6 diagnostic stations on the Linac

LinacNet

- Split input and output according to their position in the Linac
- Neural Network Architecture reflecting a Linac architecture
- Each Module models one Diagnostic

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LinacNet: from a Physical Architecture to a Neural Network Architecture

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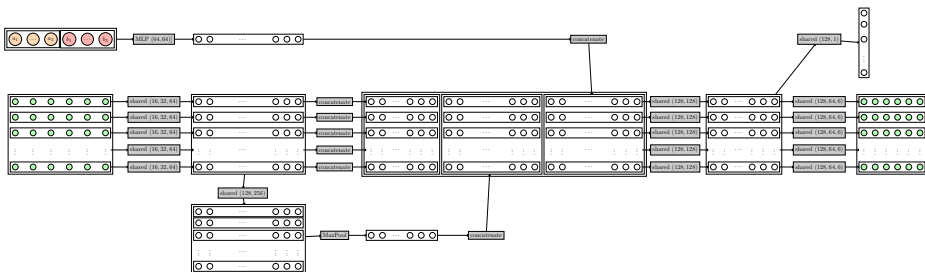## ThomNet: Incorporating the structure of a beam

Figure: One module of ThomNet

ThomNet

- Track the full distribution of particles
- Inspired by Qi et al., "PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation" (CVPR 2017)

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Results: Comparable with accuracy of the diagnostic station

The best model achieves results comparable with the diagnostic station accuracy.

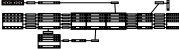| Architecture	BPM	ICT	YAG	ICT	BPM	YAG
FeedForward	776μm	1084μm	1692μm	1106μm	1261μm	1554μm
LinacNet	198μm	254μm	541μm	618μm	719μm	913μm
ThomNet	$\mathbf{178\mu m}$	$\mathbf{134\mu m}$	$\mathbf{247\mu m}$	$\mathbf{224\mu m}$	$\mathbf{258\mu m}$	$\mathbf{336\mu m}$

Table: MAE of the position. The accuracy of the BPM is $\sim 100\mu$m

Architecture	BPM	ICT	YAG	ICT	BPM	YAG
FeedForward	176pC	177pC	167pC	91pC	91pC	91pC
LinacNet	28pC	28pC	29pC	34pC	34pC	35pC
ThomNet	**8pC**	**9pC**	**9pC**	**8pC**	**8pC**	**8pC**

Table: MAE of the charge. The accuracy of the ICT is ~ 10pC

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A boost in execution time

Execution Speed

In 10 min:

- 1 simulation on Astra
- 20000 predictions of the model

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Results

- Reflecting the physical constraints in the neural architecture speed up the training and gives better results
- Precision of the same orders than the diagnostics installed on ThomX

Challenges

- Training of a modular model
- Performance for the optimization task to be tested

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Questions?