

NEURAL NETWORK MODEL PERFORMANCE ANALYSIS

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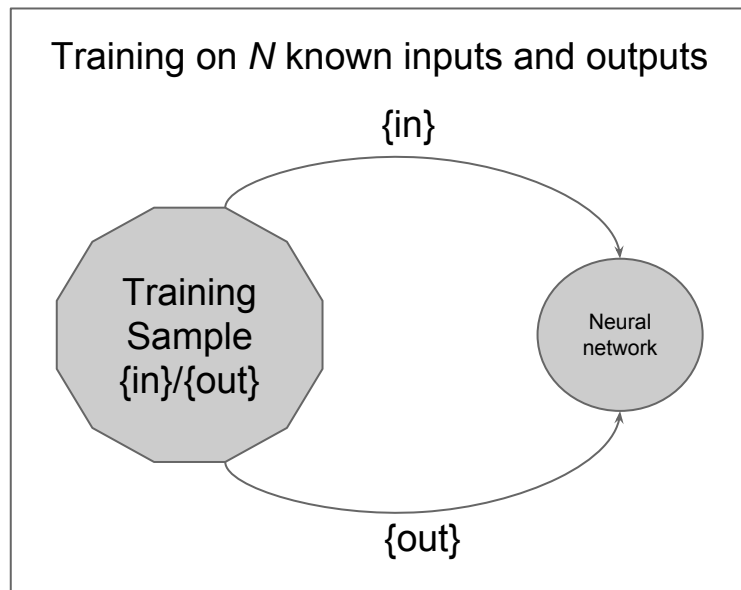
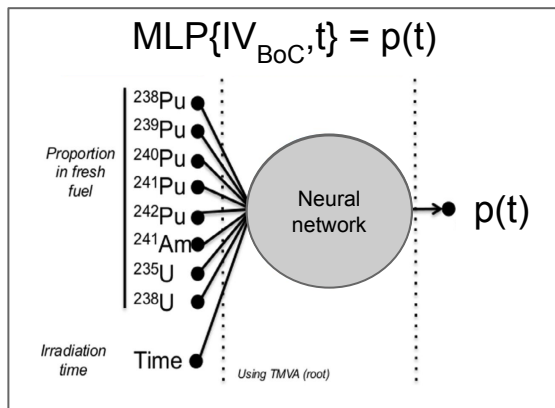


TECHNICAL WORKSHOP ON FUEL CYCLE SIMULATION
2017/07





- Prediction of neutronics metrics evolution during irradiation:
 - Cross section (*fission, capture (n,2n)*)
 - Neutron multiplication factor





PWR:

- MOX-Pu

B. Leniau, et al., "A neural network approach for burn-up calculation and its application to the dynamic fuel cycle code CLASS," Annals of Nuclear Energy, 81, (2015).

- MOX-Pu/Am

A.-A. Zakari-Issoufou, et al., "Americium mono-recycling in PWR: A step towards transmutation" Annals of Nuclear Energy, 102, (2016).

- MOX-Pu/LEU

F. Courtin, et al., "Neutronic predictors for PWR fuelled with multi-recycled plutonium and applications with the fuel cycle simulation tool CLASS" Progress in Nuclear Energy, 100, (2017)

SFR

- MOX-Pu

B. Leniau, et al., "Generation of FBR-Na physics models for the nuclear fuel cycle code CLASS", PHYSOR 2016, USA



Depletion with predicted cross sections



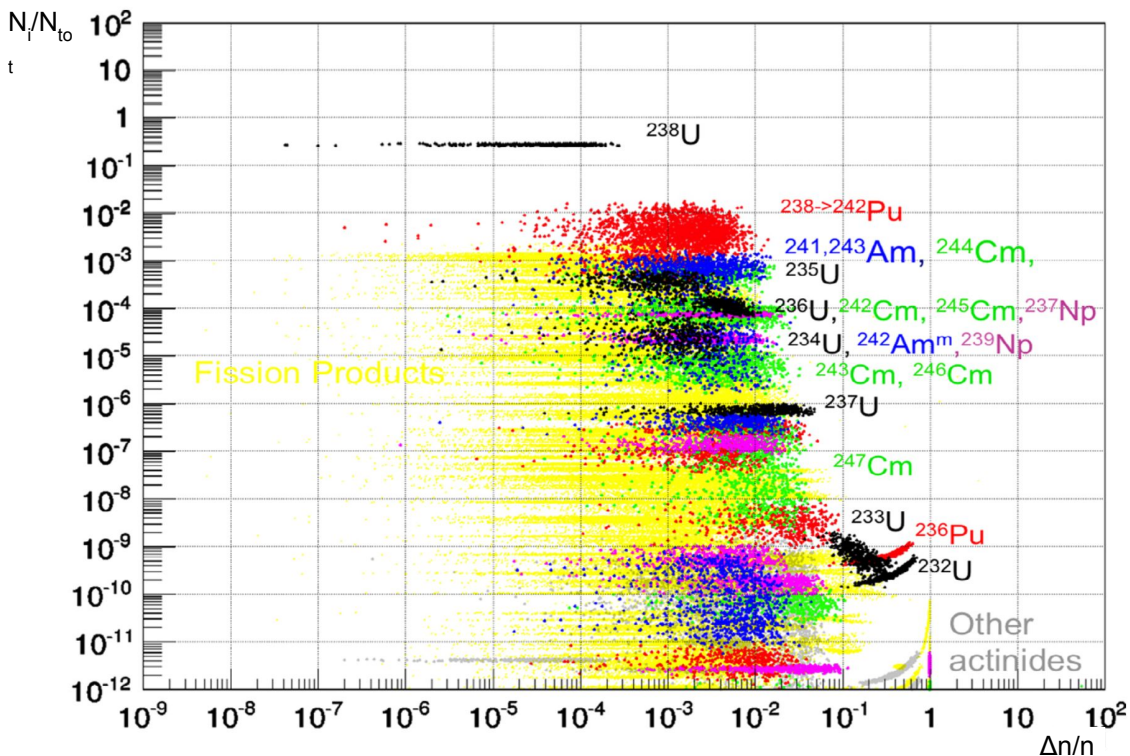
Predicted cross sections:

- fission
- capture
- (n,2n)

reference: MURE (all reactions)

From B. Leniau, et al., "A neural network approach for burn-up calculation and its application to the dynamic fuel cycle code CLASS," *Annals of Nuclear Energy*, 81, (2015).

Relative differences on EoF composition
computed using JEFF-3.1.1 and predicted cross sections





MOX-TRU required for some Fuel cycle study with CYCLUS (see Model vs Recipe presentation):

- Training depletions calculations: N=10, 100, 1000, 5000, 10000,
- Assembly calculation: 1/10 of an assembly with mirror boundary condition^[1],
- Depletion tool: MURE,
- Data base: JEFF 3.1.1,
- Initial composition sampled on a Latin Hypercube, 239Pu as filler



Param	235U	TRU frac	Pu236	238Pu	240Pu	241(Pu+Am)	241Pu/ 241(Pu+Am)	242Pu	237Np	242Am*	243Am	242Cm	243Cm	244Cm	245Cm	246Cm
min	0	0.03	0.0	0	0	0	0	0	0	0	0	0	0	0	0	0
max	0.02	0.2	0.01	0.02	0.2	0.04	1	0.01	0.06	0.001	0.001	0.001	0.001	0.001	0.001	0.001

- Neural Network : TMVA [2]
- Hidden layer : 18,21,9
- Regression: Broyden-Fletcher-Goldfarb-Shannon method (back propagation). [2]
- Testing: 1000 depletion calculations inside sample space & 500 depletion calculations outside.

[1] N. Thiolliere, private communication. Subatch (2017).

[2] Hoecker, A., Speckmayer, P., Stelzer, J., Therhaag, J., von Toerne, E., Voss, H., 2007. TMVA: Toolkit for Multivariate Data Analysis, PoS ACAT, p. 040.



Overtraining: N=10

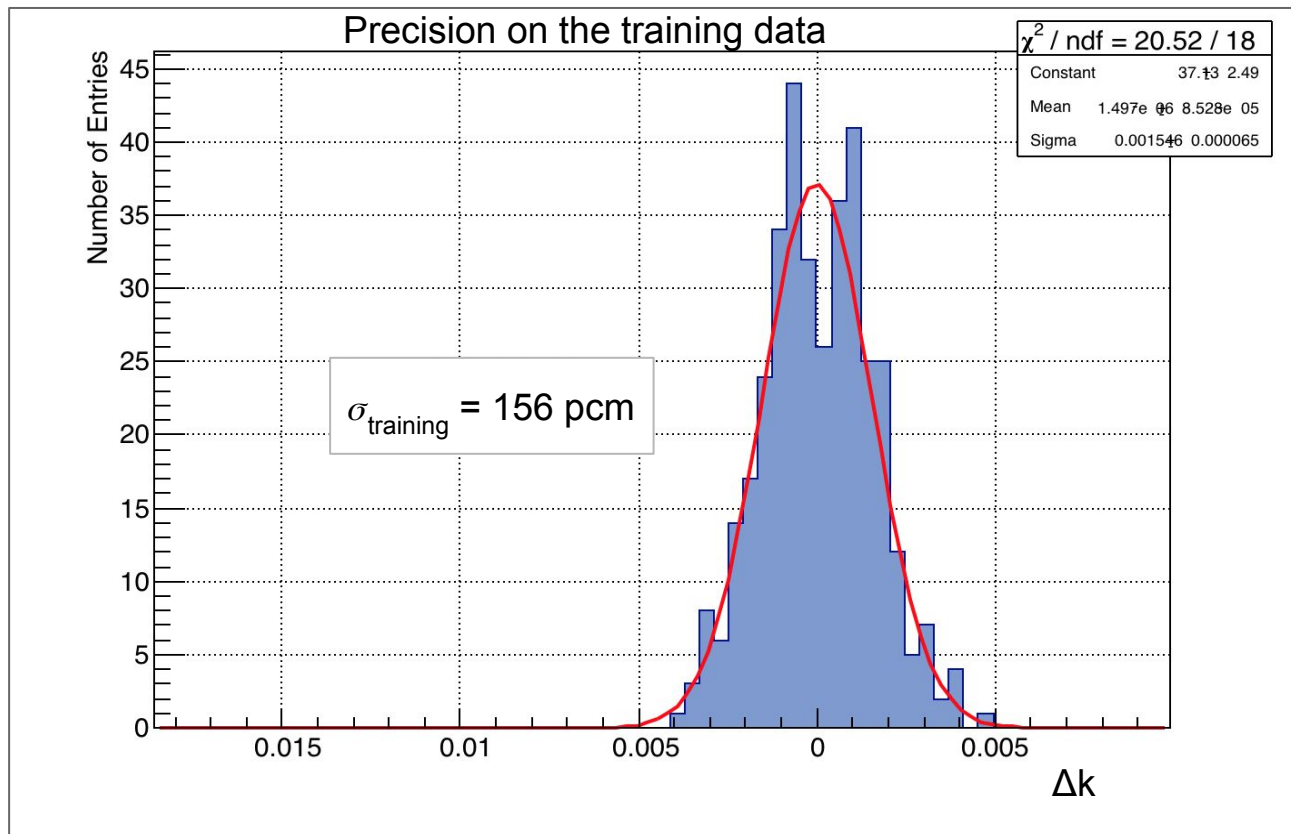


$$\sigma_{\text{MCNP}} = 120 \text{ pcm}$$

$$\sigma_{\text{training}} = 156 \text{ pcm}$$

Measure of the σ on 1000 independent simulations

$$\langle \sigma_{\text{real}} \rangle = 11576 \text{ pcm}$$





Training sample density



Precision improve with the density!

Reach the precision of the MC:

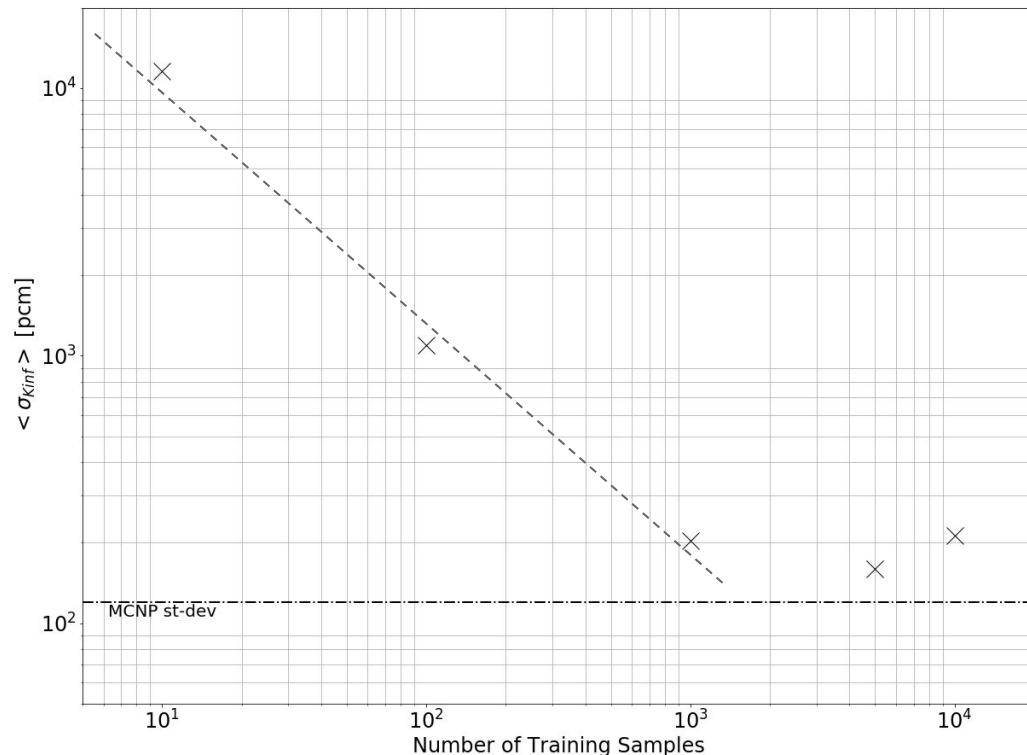
$$\sigma_{\text{MCNP}} = 120 \text{ pcm}$$

1000-2000 samples probably enough !

Prob. with the 10 000 samples:

Not enough training cycles !?
Decrease of the NN quality ?

Evaluation of the prediction on 1000 independent calculations





Precision Map: N=10, “inside” test data



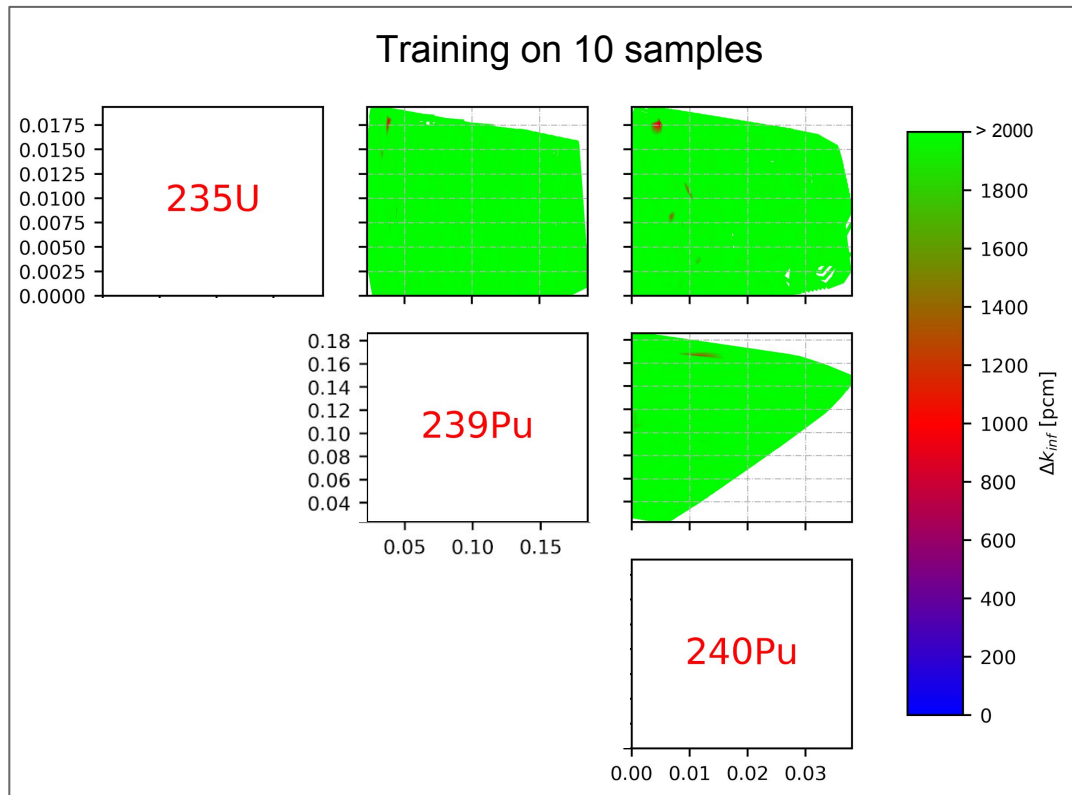
Precision improve with the density

Reach the precision of the MC:

$$\sigma_{\text{MCNP}} = 120 \text{ pcm}$$

Precision:

- 10 : $\sigma > 1200 \text{ pcm}$ | $\langle \sigma \rangle = 11e3 \text{ pcm}$





Precision Map: N=100, “inside” test data



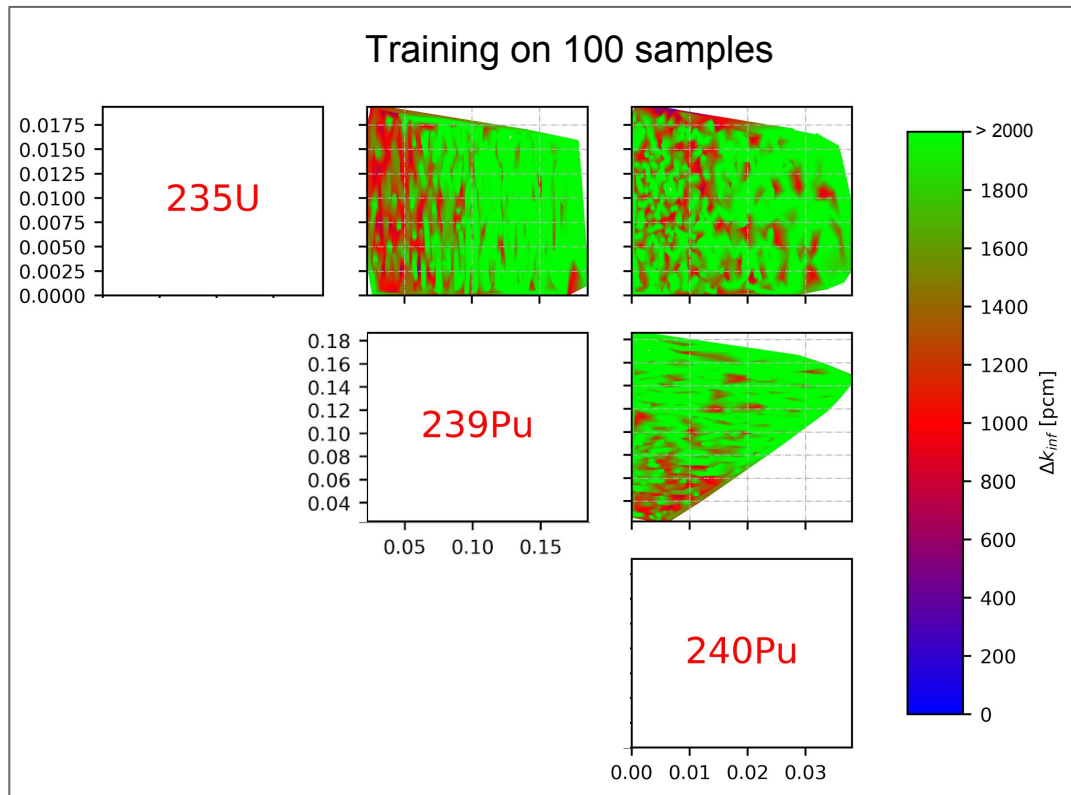
Precision improve with the density

Reach the precision of the MC:

$$\sigma_{\text{MCNP}} = 120 \text{ pcm}$$

Precision:

- 10 : $\sigma > 1200 \text{ pcm}$ | $\langle \sigma \rangle = 11\text{e}3 \text{ pcm}$
- 100 : $\sigma > 800 \text{ pcm}$ | $\langle \sigma \rangle = 1\text{e}3 \text{ pcm}$





Precision Map: N=1000, “inside” test data



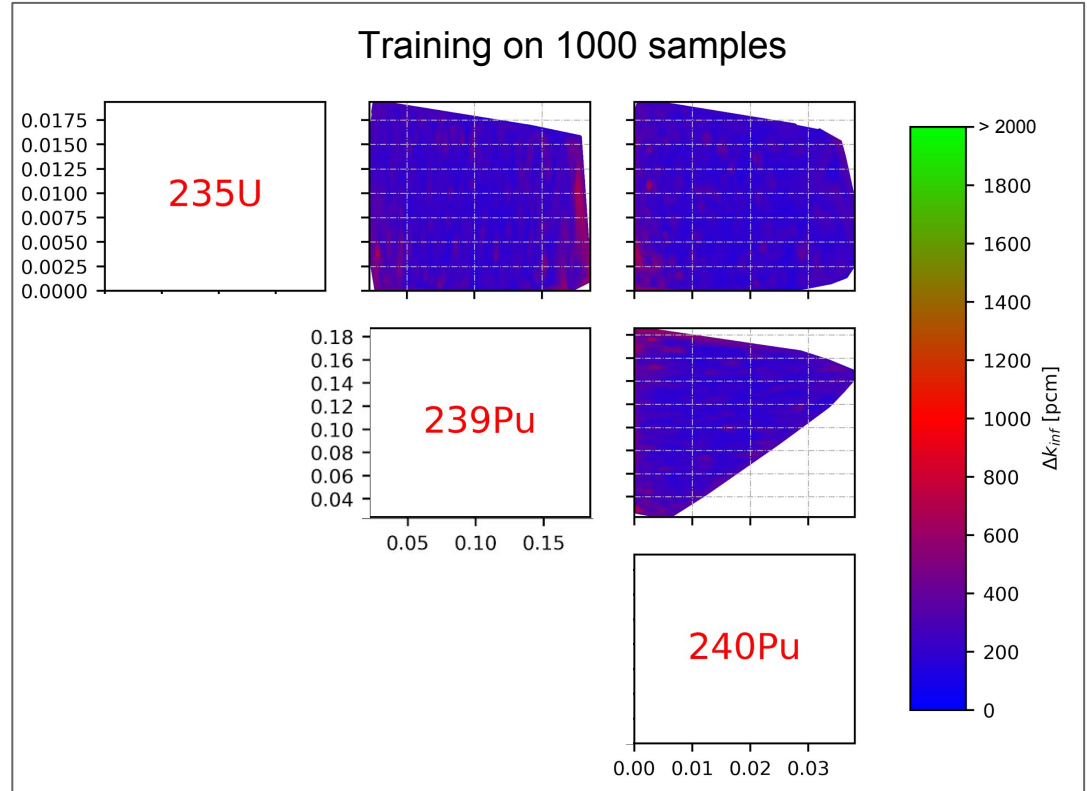
Precision improve with the density

Reach the precision of the MC:

$$\sigma_{\text{MCNP}} = 120 \text{ pcm}$$

Precision:

- 10 : $\sigma > 1200 \text{ pcm}$ | $\langle \sigma \rangle = 11\text{e}3 \text{ pcm}$
- 100 : $\sigma > 800 \text{ pcm}$ | $\langle \sigma \rangle = 1\text{e}3 \text{ pcm}$
- 1000: $\sigma < 800 \text{ pcm}$ | $\langle \sigma \rangle = 200 \text{ pcm}$





Precision Map: N=5000, “inside” test data



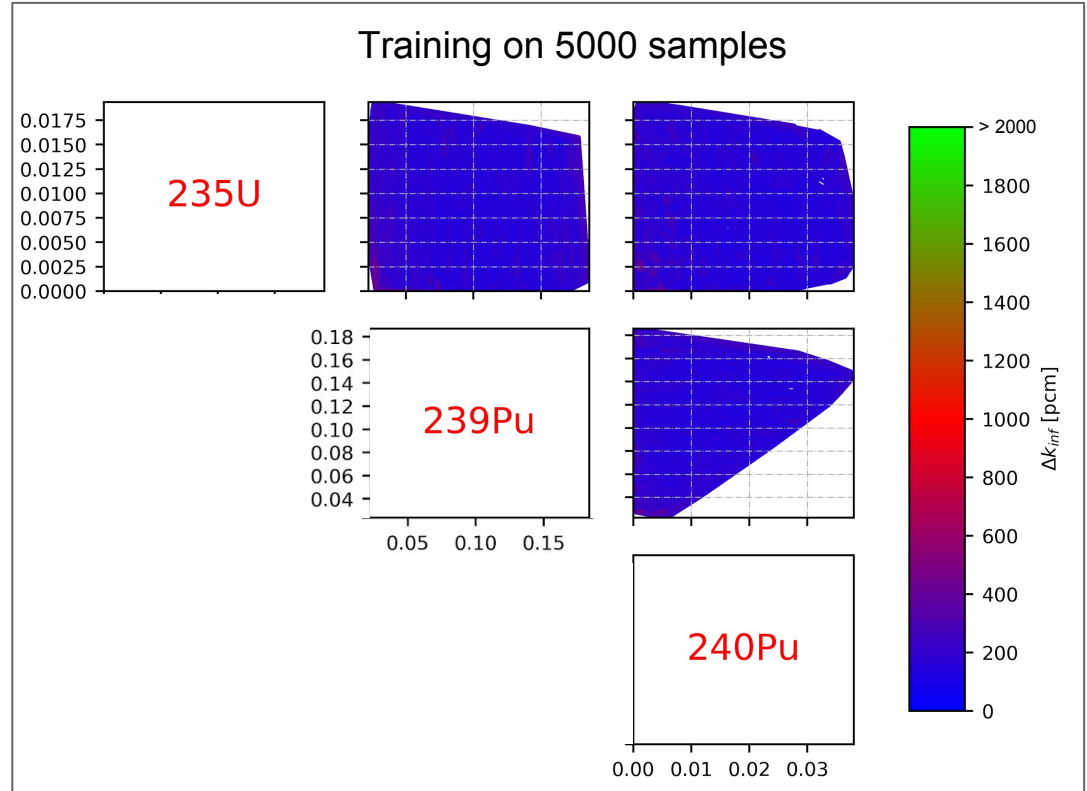
Precision improve with the density

Reach the precision of the MC:

$$\sigma_{\text{MCNP}} = 120 \text{ pcm}$$

Precision:

- 10 : $\sigma > 1200 \text{ pcm}$ | $\langle \sigma \rangle = 11\text{e}3 \text{ pcm}$
- 100 : $\sigma > 800 \text{ pcm}$ | $\langle \sigma \rangle = 1\text{e}3 \text{ pcm}$
- 1000: $\sigma < 800 \text{ pcm}$ | $\langle \sigma \rangle = 200 \text{ pcm}$
- 5000: $\sigma < 300 \text{ pcm}$ | $\langle \sigma \rangle = 160 \text{ pcm}$





Precision Map: N=5000, “outside” test data



Precision improve with the density

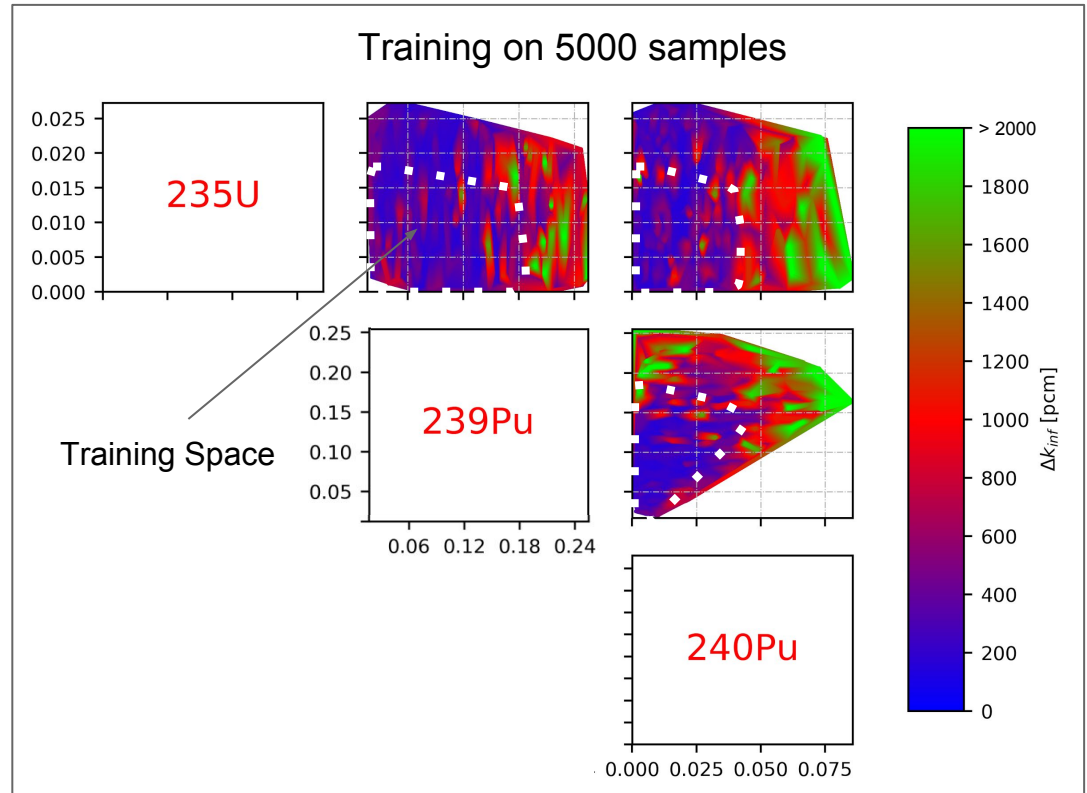
Reach the precision of the MC:

$$\sigma_{\text{MCNP}} = 120 \text{ pcm}$$

Precision:

- 10 : $\sigma > 1200 \text{ pcm}$ | $\langle \sigma \rangle = 11e3 \text{ pcm}$
- 100 : $\sigma > 800 \text{ pcm}$ | $\langle \sigma \rangle = 1e3 \text{ pcm}$
- 1000: $\sigma < 800 \text{ pcm}$ | $\langle \sigma \rangle = 200 \text{ pcm}$

σ grows outside of the training space !





Predicting other metrics:



- Prediction of neutronics metrics evolution during irradiation:
 - Cross section
 - Neutron multiplication factor
- Extension to fuel composition ?



Predicting other metrics?



- Prediction of neutronics metrics evolution during irradiation:
 - Cross section
 - Neutron multiplication factor
- Extension to fuel composition ?

Neural Network train on 5000 training sample,
without topology optimisation

Prediction of the ^{239}Pu content with a non optimised:

$$\sigma = 4.2\text{e-}3$$

Direct prediction of the composition !?

