A study of foundation models for event classification in collider physics

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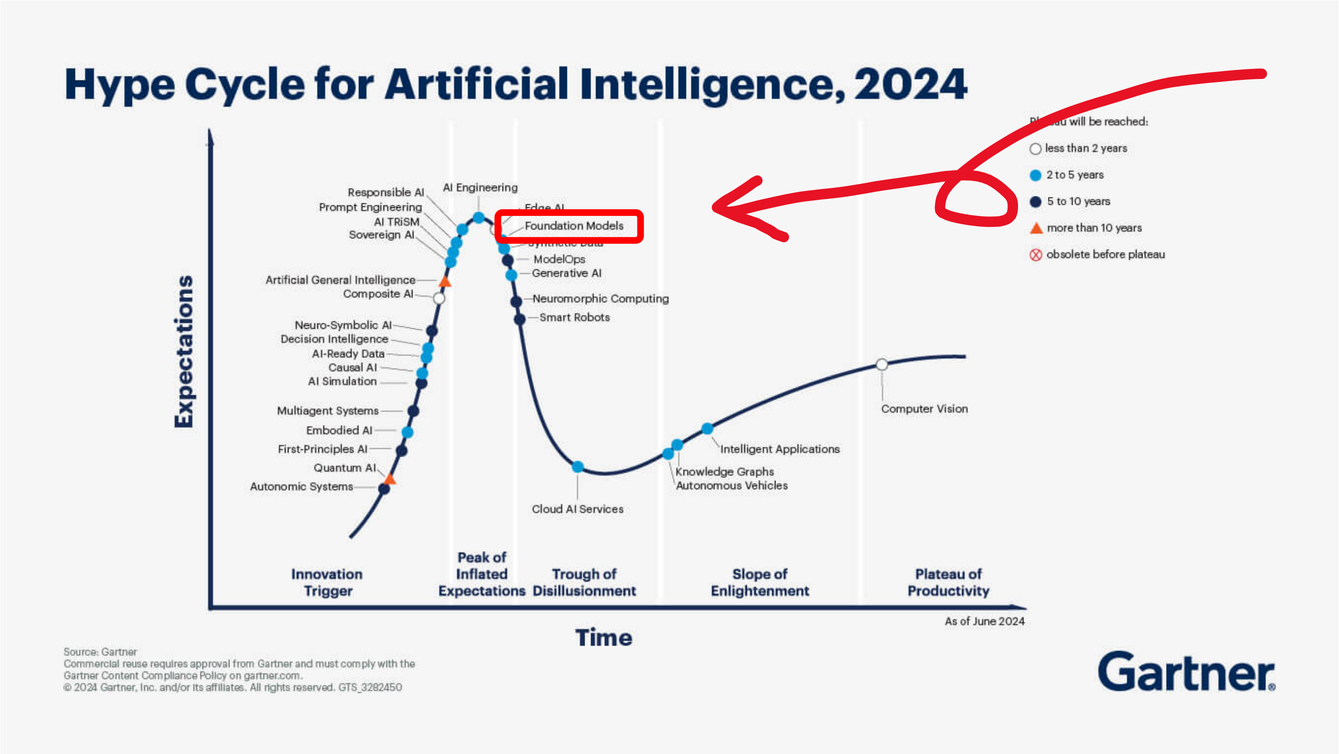
My recent activities

- KEKCC migration
  - The new system including Grid is running well
  - (Some grid services are still running on RHEL7 with ELS…)
- Open Access projects
  - Procured Lenovo DE4000H (2PB) for open data access
  - Evaluating how to integrate with GakuninRDM
- Deep learning for physics analysis in collider physics

Introduction



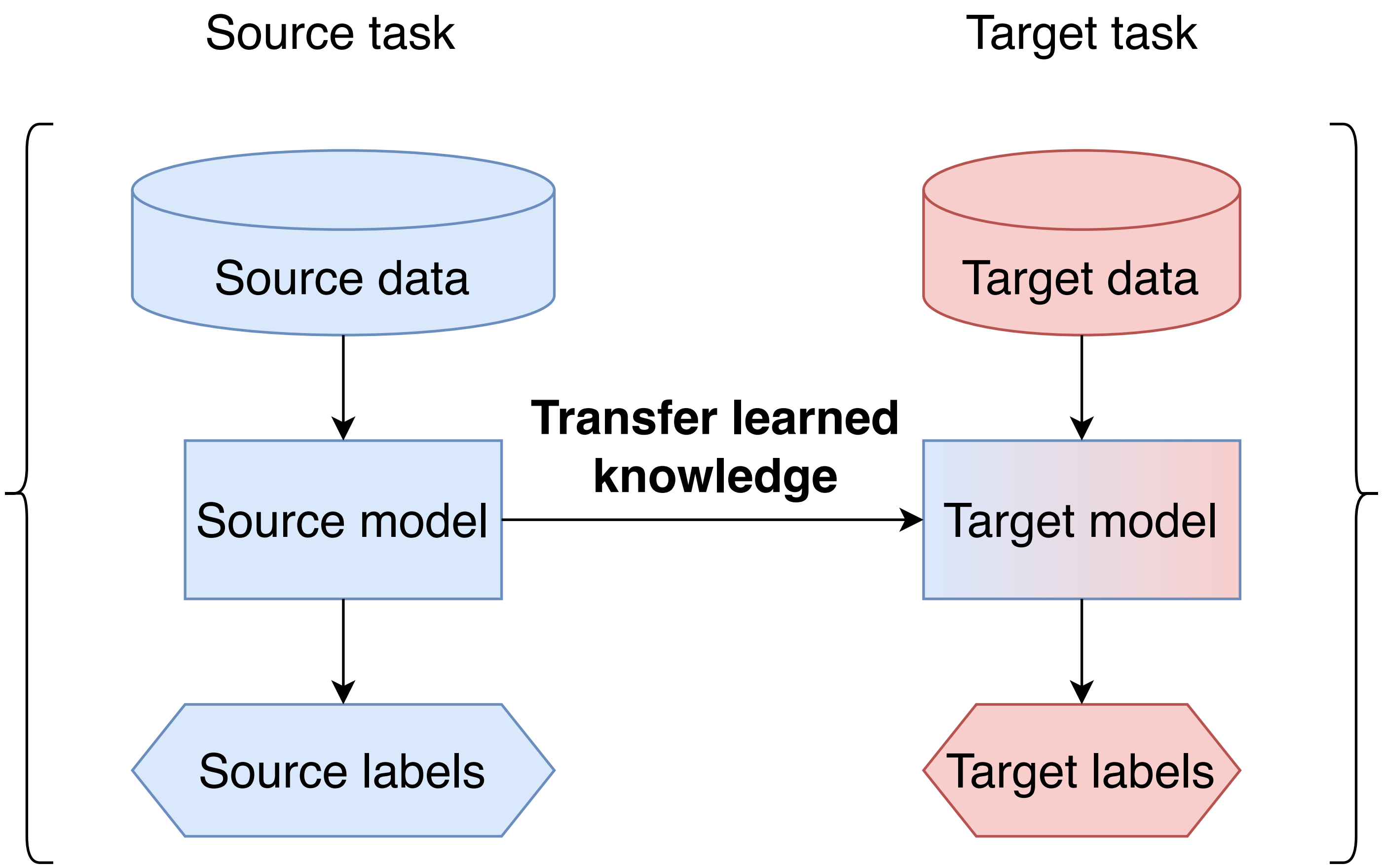
Gartner.com

- "Foundation models" is one of the keywords for AI
  - Pre-training using a large amount of "unlabeled" data
  - Fine-tuning for a target application (transfer learning)

→ Q: Is the concept of foundation models beneficial to collider physics

Transfer learning

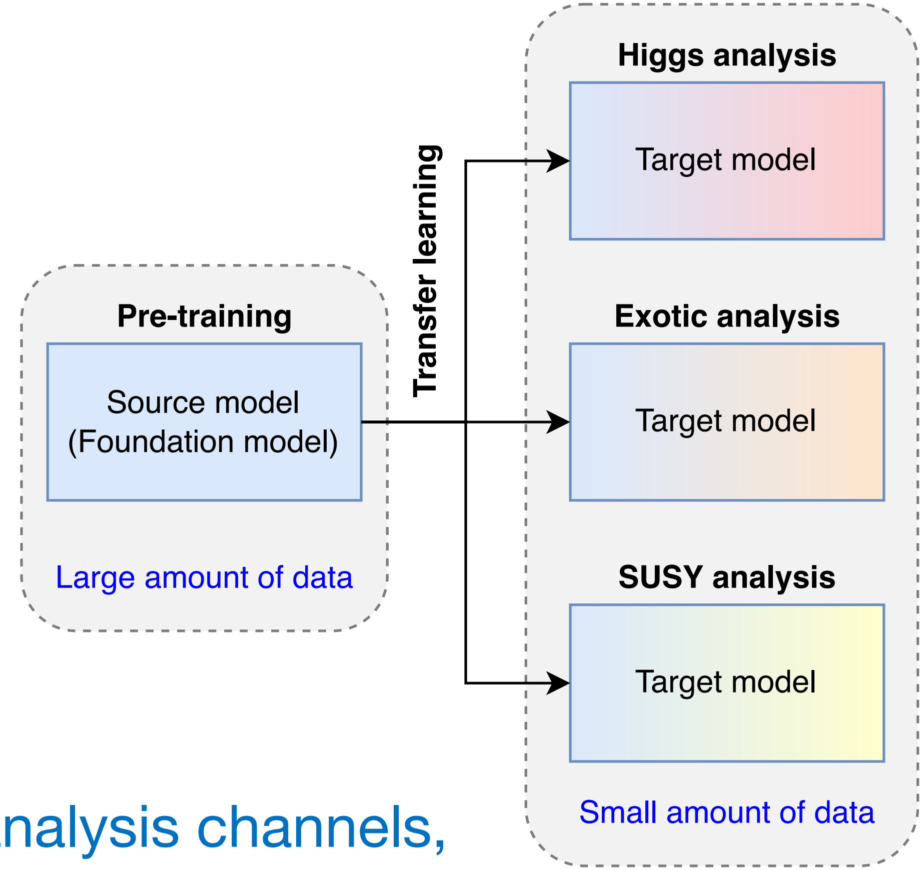
Large amount of data/labels



Small amount of data/labels

Use case of physics analysis

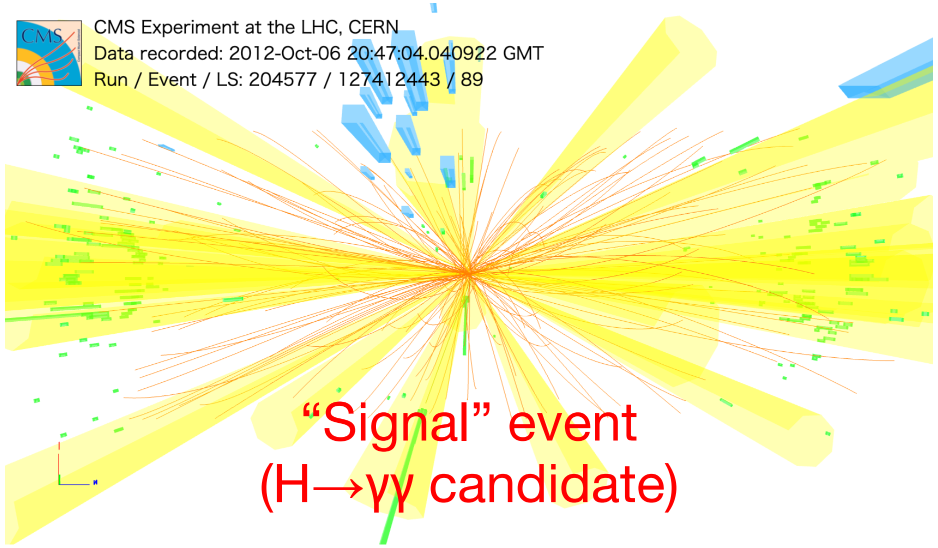
- Many analysis channels in collider physics
  - Higgs, Exotic, SUSY, etc
  - Currently, dedicated DL models are trained from scratch for each channel ← Large amount of training data (MC) for each channel

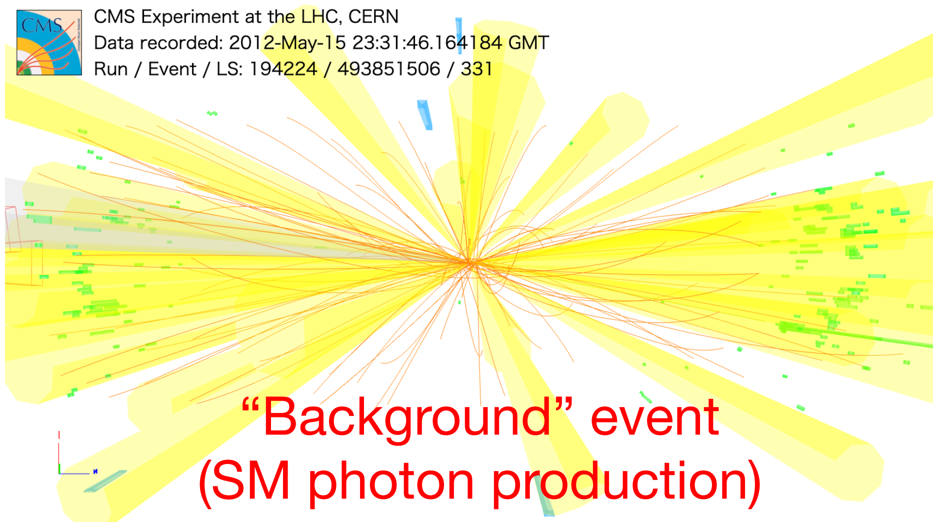


→ If transfer learning can be applied to different analysis channels, computing resources for MC simulations and DL training are saved

Event classification

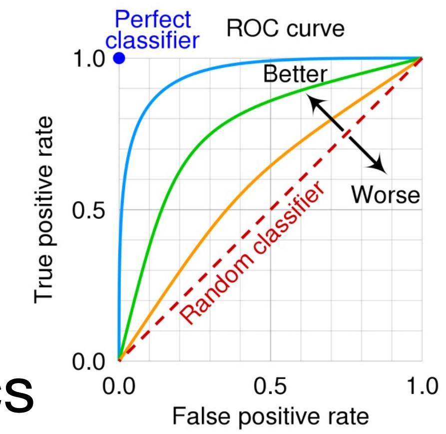
- The concept is examined using “event classification” problem
  - A typical problem in HEP, signal event vs. background event



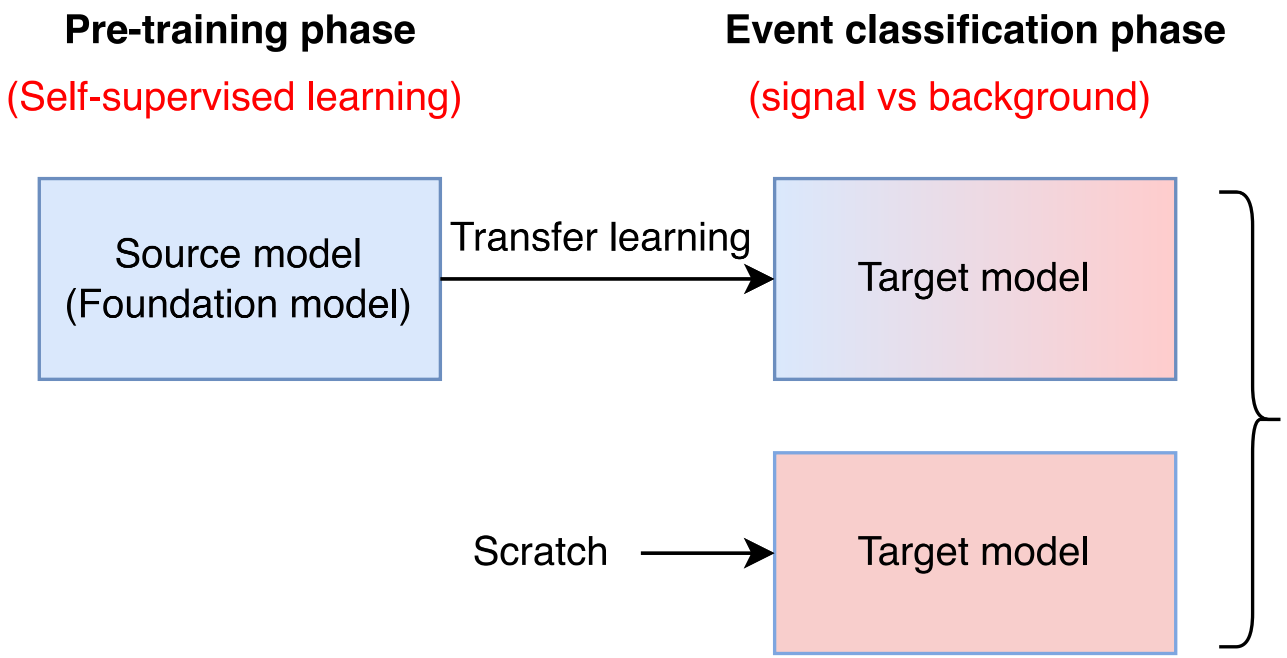


→ Reconstructed particles (objects) are the basic information for the classification

AUC metric



- Event classification performances are evaluated with AUC metrics



→ AUC values of event classifications are compared with and without a foundation model

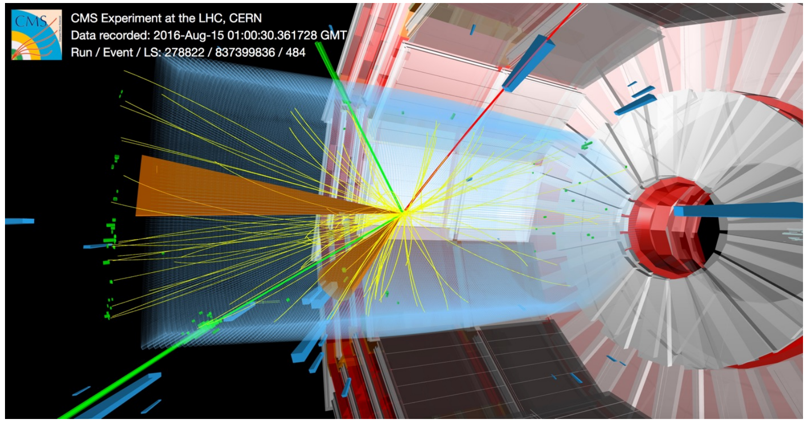
Updates form pervious study

- A preliminary study was showed in the previous FJPPN workshop
  - https://indico.in2p3.fr/event/31887/
- Fully adapted to the CMS open data
  - No hand-made MC simulations (Madgraph+Pythia+Delphes)
- Four types of event classification are evaluated to discuss generalization
- Data augmentation technique is introduced based on our physics knowledge

CMS open data

- CMS released new open data in 2024
  - 70 TB of 13 TeV collision data in 2016 and 830 TB of MC simulations
  - 16.4 fb^{-1} collision data (the Higgs discovery required 10.4 fb^{-1})
  - Nano AOD format
    - Possible to analyse by pure ROOT (and RDataFrame) 😀
    - (Previous open data requires the CMS software…)

→ This study should be reproducible



A candidate event in which a top quark is produced in association with a Z boson.

Datasets

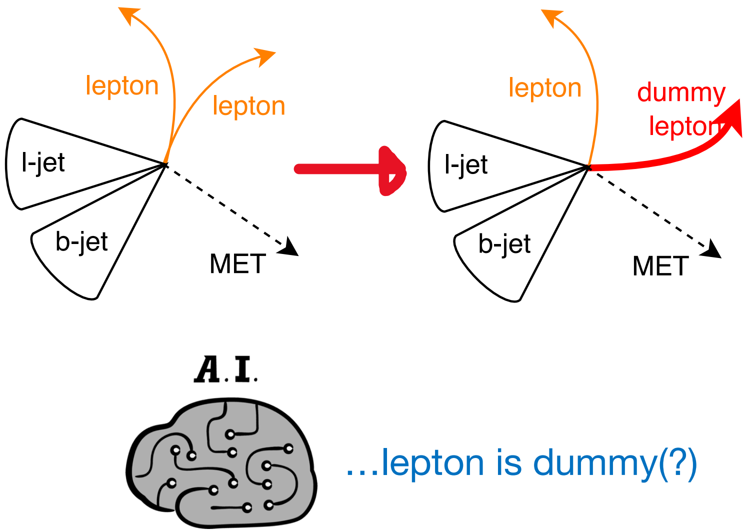
		Selections	# of events
Pre-training →	Collision data	lepton ≥ 1 + jets ≥ 2 + bjets ≥ 1	~10^6
Event classification	H^+tb[ref.] vs ttbar+jets	lepton ≥ 1 + jets ≥ 4 + bjets ≥ 1	~10^6
	H^+HW[ref.] vs ttbar+jets	lepton ≥ 1 + tau≥ 1 + jets ≥ 3 + bjets ≥ 1	~10^6
	ttH[ref.] vs ttbar+jets	lepton ≥ 1 + jets ≥ 4 + bjets ≥ 2	~10^6
	ttH[ref.] vs ttbar+jets	lepton ≥ 2 + jets ≥ 2 + bjets ≥ 1	~10^6

- Pre-training is performed using collision data (unlabelled data) based on the foundation model concept
  - ~10^7 events are available after the selection, but only ~10^6 events are used
  - NVIDIA A100: ~10^4 events/sec (10^7 events /10^4 x 500 epochs = 138 hours)

Pre-training strategy

- Only low-level features of each object (4-vector + charge) are used as inputs
- Self-supervised learning is employed to handle the unlabeled collision data

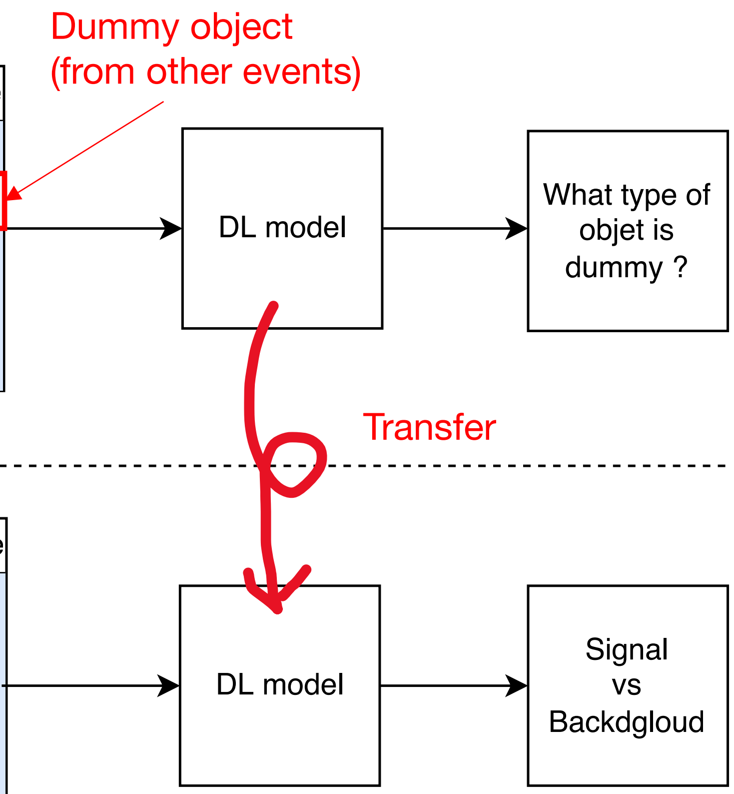
- Strategy:
  - An object (lepton, tau, b-jet, light-jet, or MET) is randomly replaced with a dummy object when preparing a mini-batch
    → DL model is trained to predict what type of object was replaced



Pre-training strategy

Pre-training phase

	pT	η	ϕ	E	charge
lep1	x1	y1	z1	i1	j1
lep2	x0	y0	z0	i0	j0
l-jet1	x3	y3	z3	i3	j3
b-jet1	x4	y4	z4	i4	j4
MET	x5	y5	z5	i5	j5



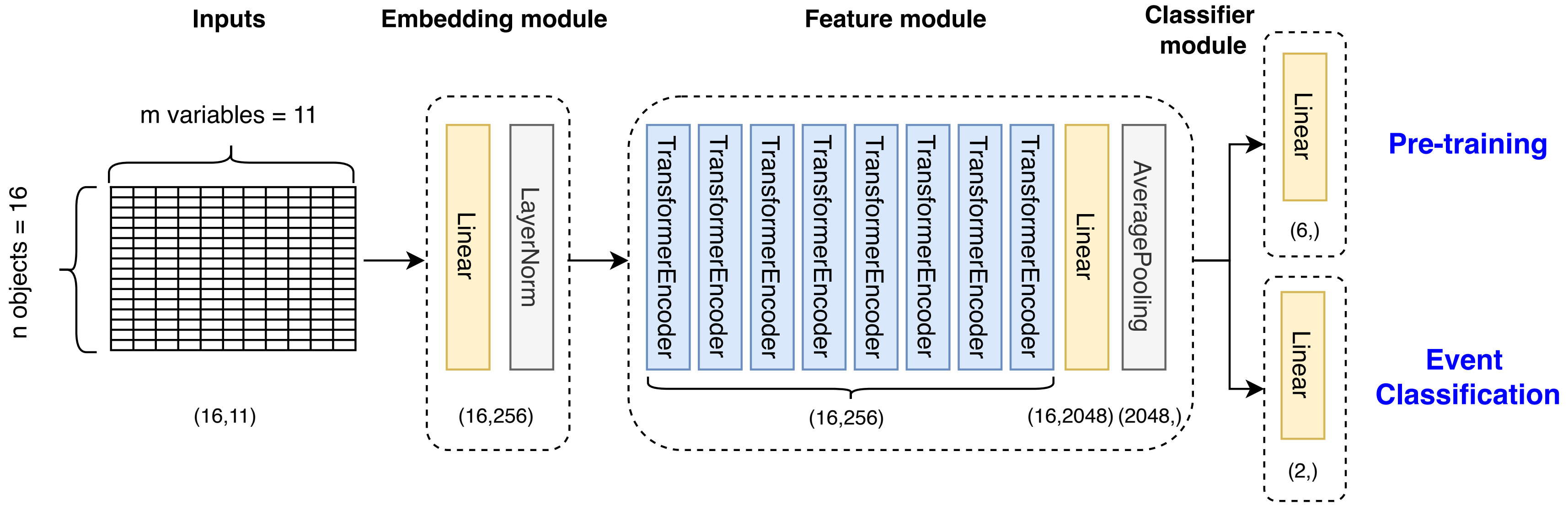
Event classification phase

	pT	η	ϕ	E	charge
lep1	x1	y1	z1	i1	j1
lep2	x2	y2	z2	i2	j2
l-jet1	x3	y3	z3	i3	j3
b-jet1	x4	y4	z4	i4	j4
MET	x5	y5	z5	i5	j5

→ Random masks increase prediction pattern (data augmentation)

DL model

- Transformer encoder is employed:
  - ~11M trainable parameters

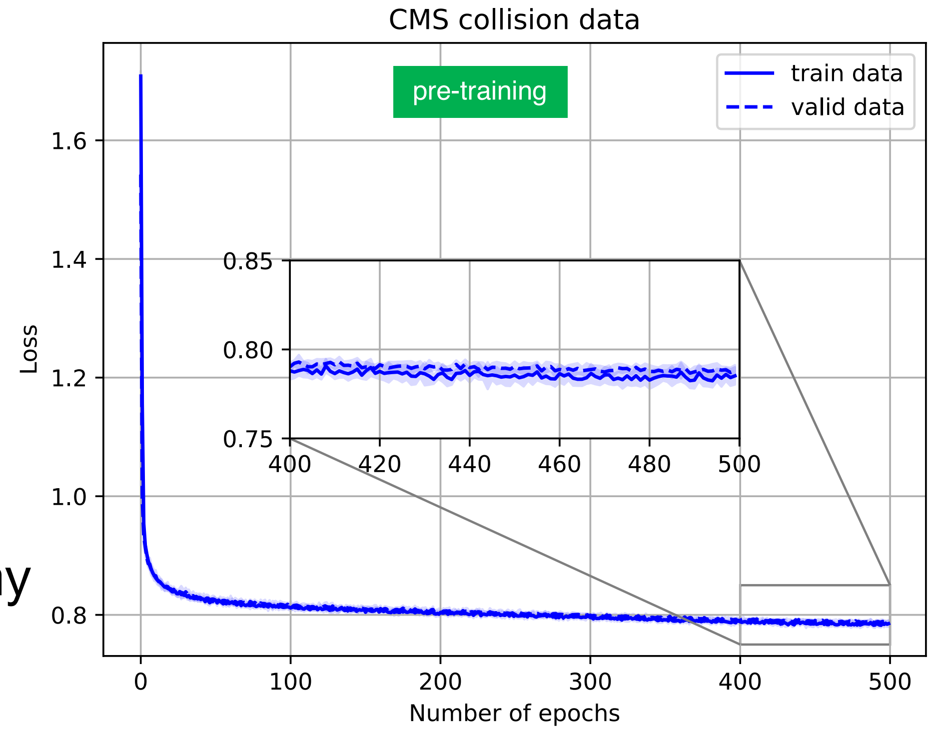


→ Weight parameters of embedding and feature modules are transferred and fine-tuned

→ Classifier module is always trained from scratch

Training details

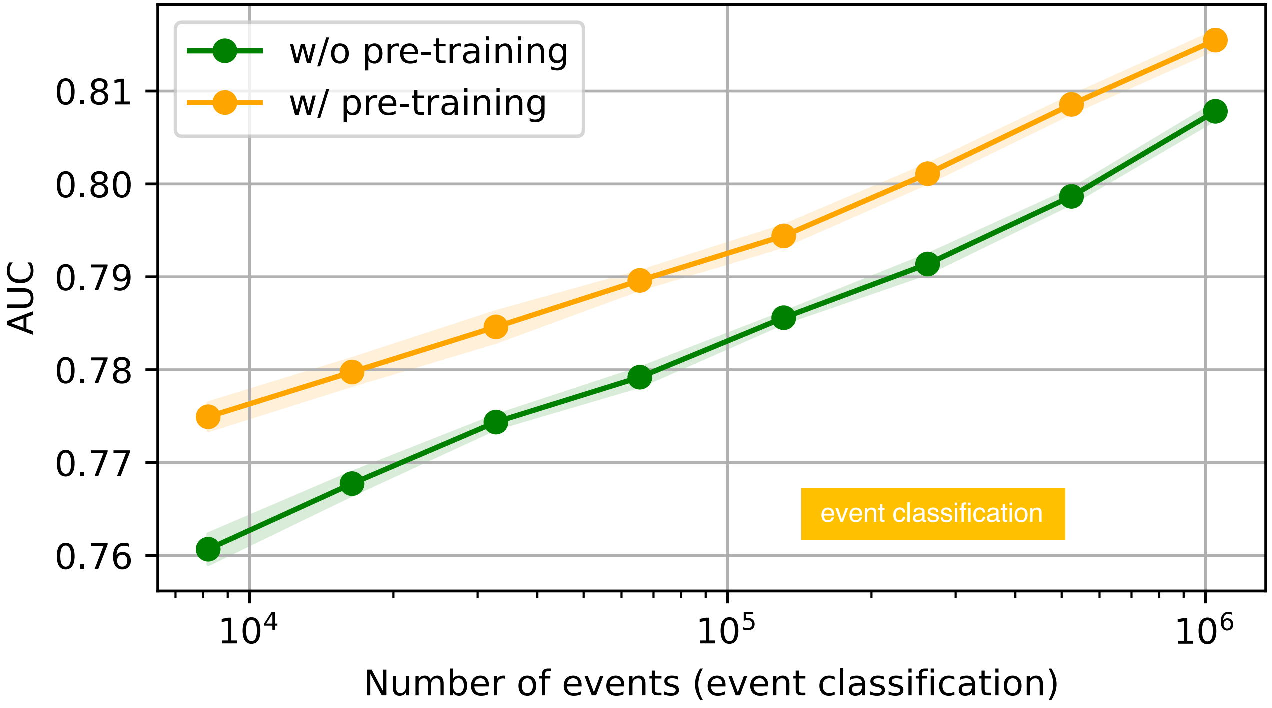
- Basically, the same setting between the pre-training and event classification phases:
  - SGD optimizer:
    - Learning rate: 10^{-2}-10^{-4} (CosineAnnealingLR)
  - Batch size: 512, Epochs: 500
  - Cross entropy loss:
    - Pre-training: lepton, b-jet, l-jet, MET, or No dummy
    - Event classification: signal or background
- NVIDIA A100: ~20 batches/s
  - ~13 hours for one training



~1M events used

AUC of event classification

H+tb signal



small data

large data

- Significant improvements by introducing the pre-training
- Future work: need to check if the performances converge when more data (>10^6) are added

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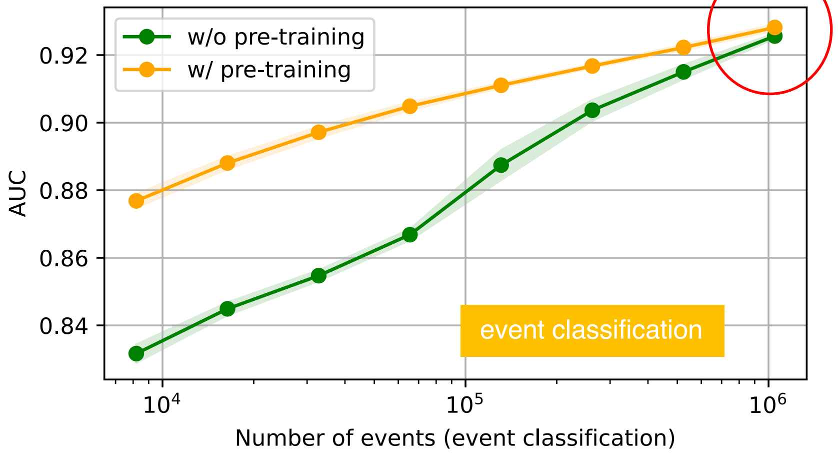
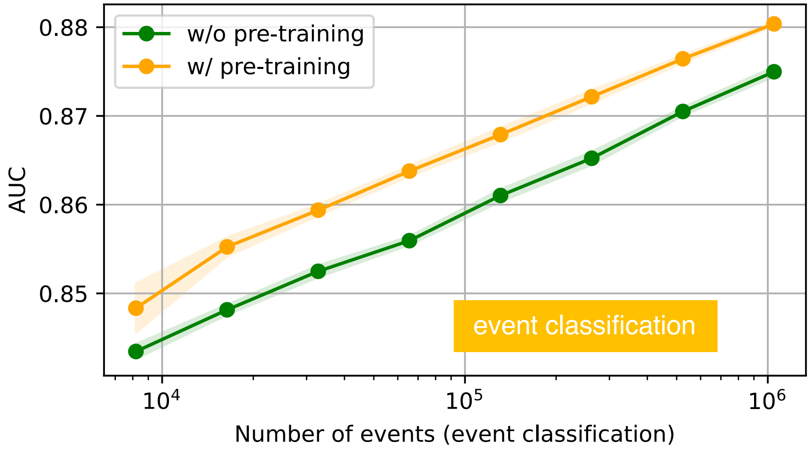
AUC of event classification

H⁺HW signal



ttH (1lep) signal



ttH (2lep) signal

- The improvements are confirmed for all signal events

  → The pre-trained model (foundation model) is well generalized

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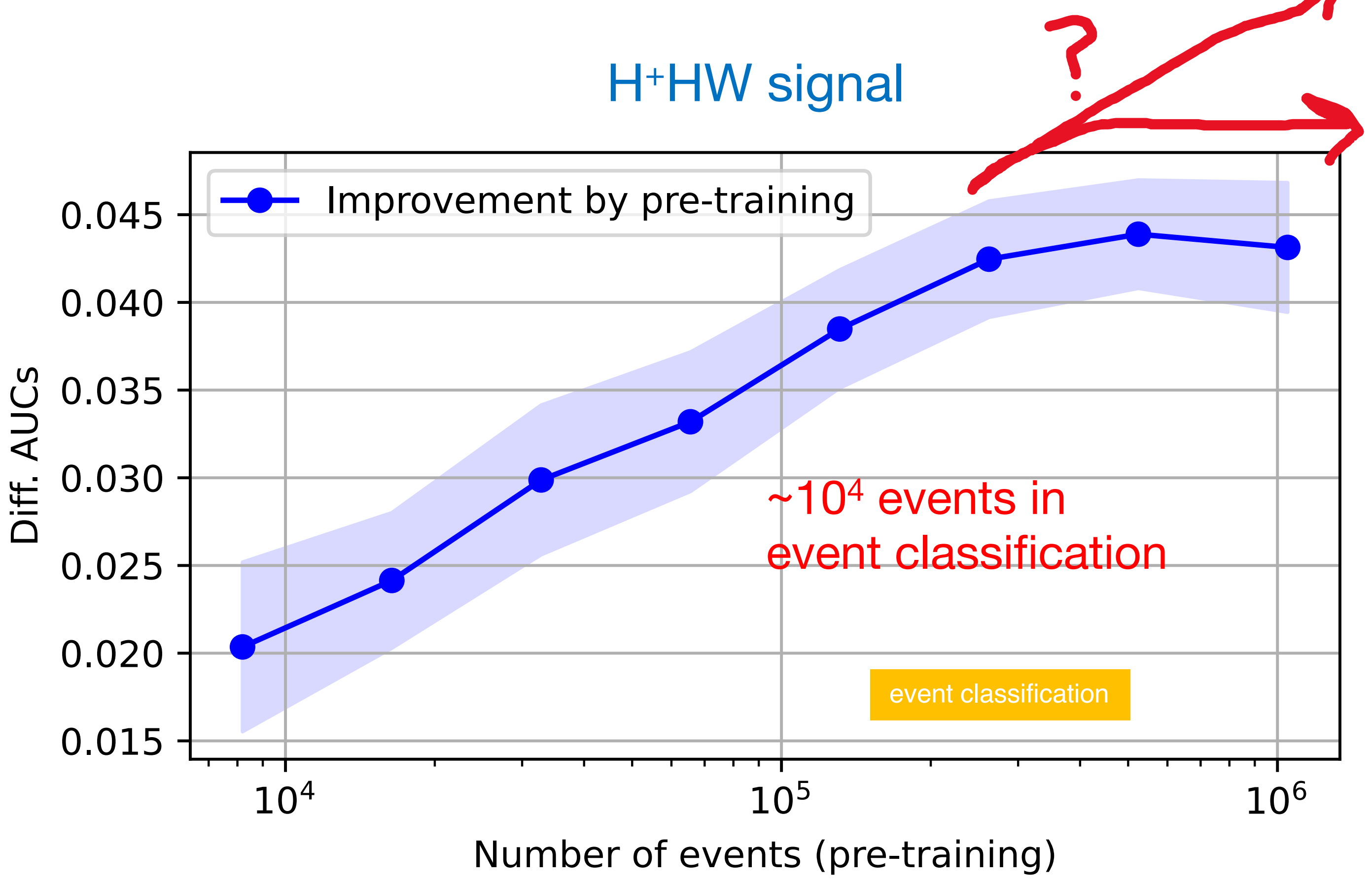
Scaling raw



- The scaling behavior encourages a pre-training with a larger data
  - However, the number of events in the CMS open data itself and computing resources are limited

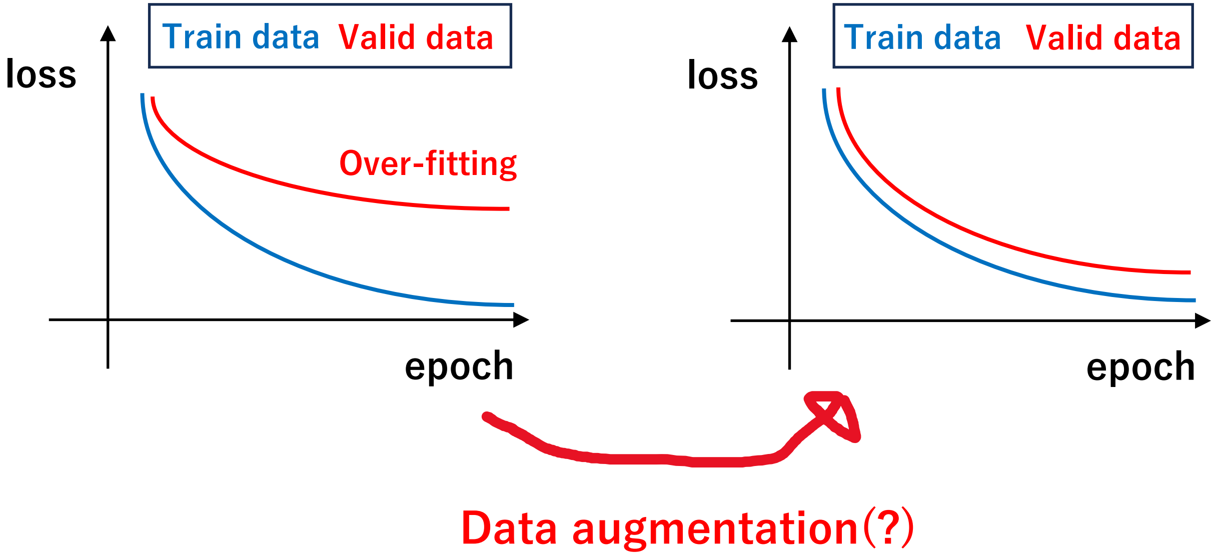
→ Data augmentation is examined

Data augmentation

➢ Data augmentation is well established technique in computer vision field

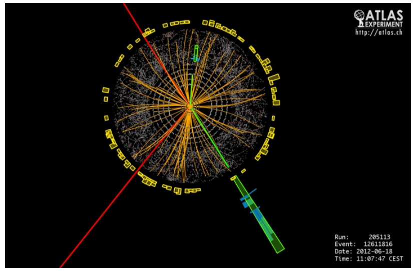
[albumentations]()

→ Easy to increase data with low computing cost, and effective to suppress over-fitting

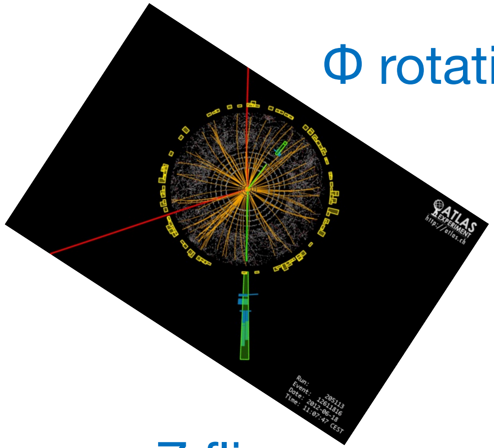


Lorentz transformation

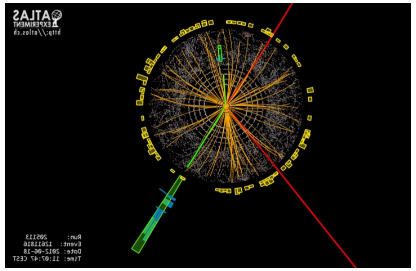
Original event
(Higgs candidate)



Φ rotation



Z flip



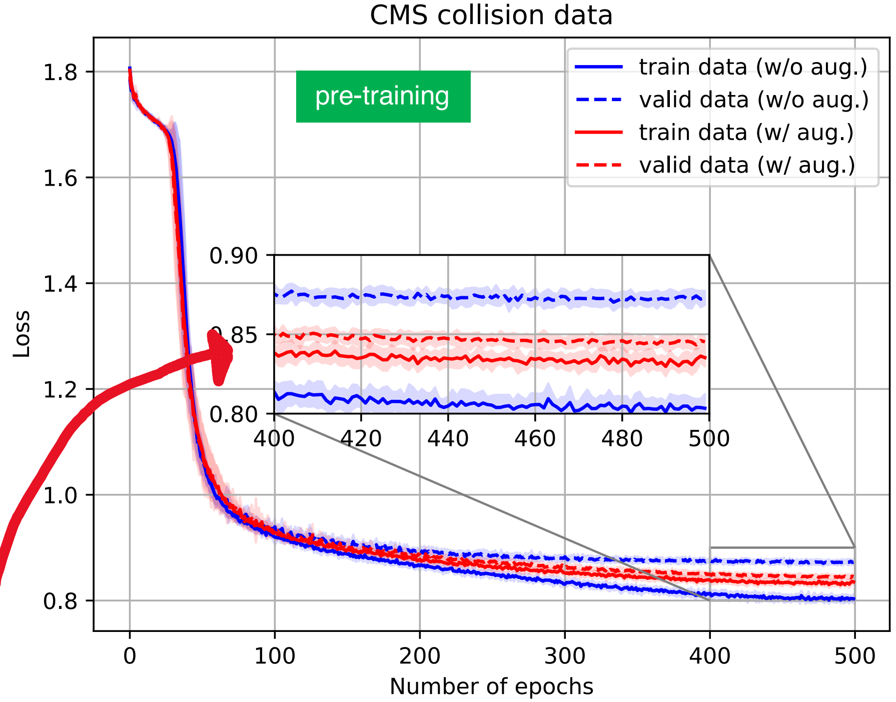
Lorentz boost
(z direction)

← This data is still a Higgs candidate, and should occur with the same probability as the original event

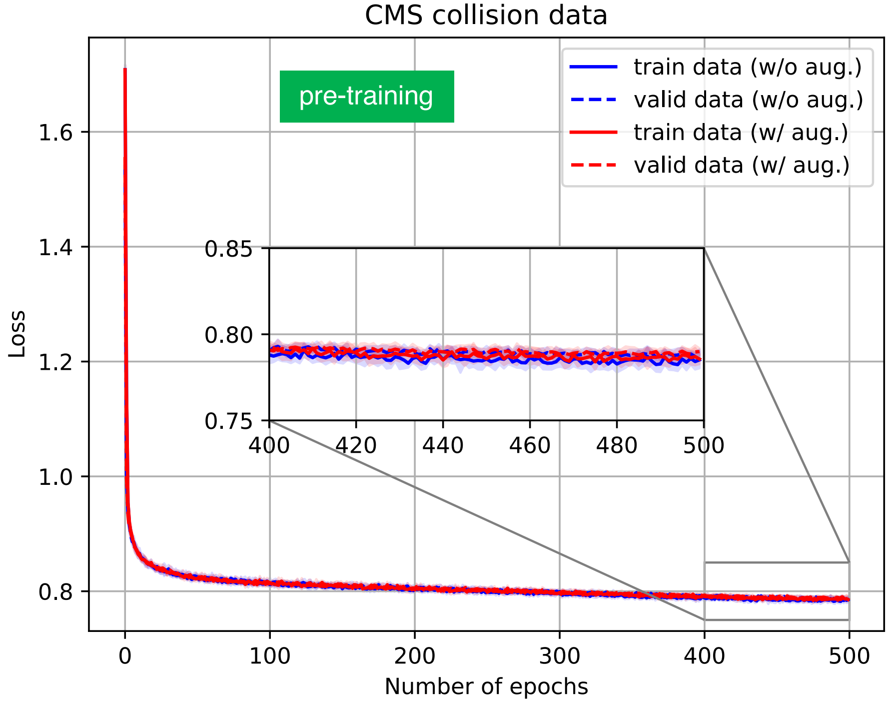
- These transformations are applied randomly before being fed into the DL model (pre-training phase)

DA (pre-training phase)

~10^4 events used



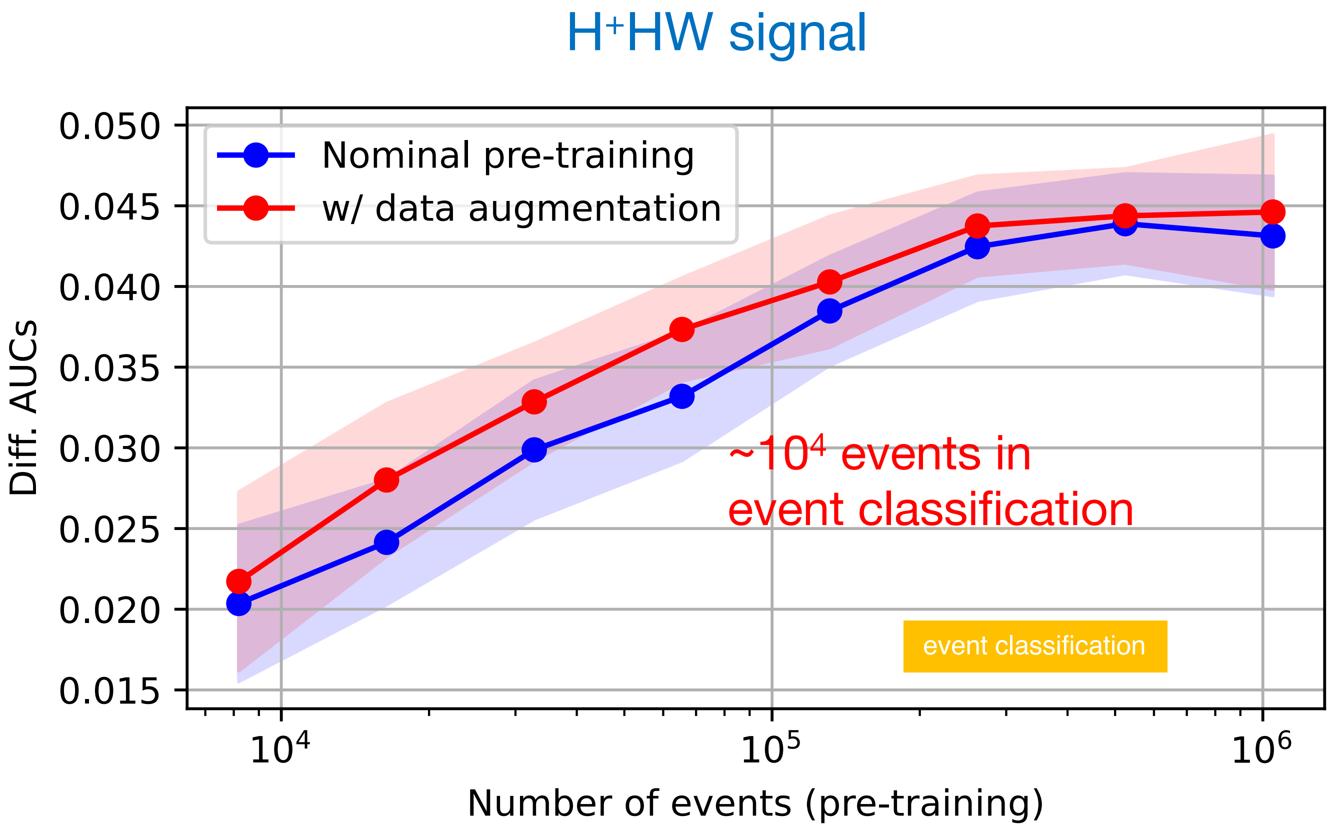
~10^6 events used



No effect(?)

→ Over-fitting is suppressed by the data augmentation if the number of events is small

Improvements for event classification



- ➢ Improvements for the downstream event classification are not so visible (within the standard deviation)

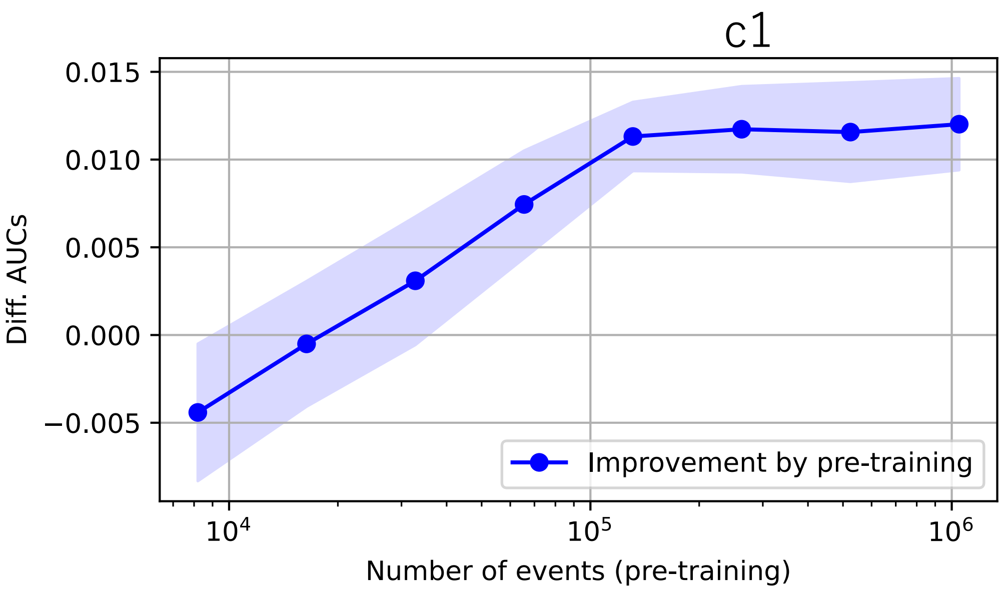
→ Do you have any other data augmentation ideas?

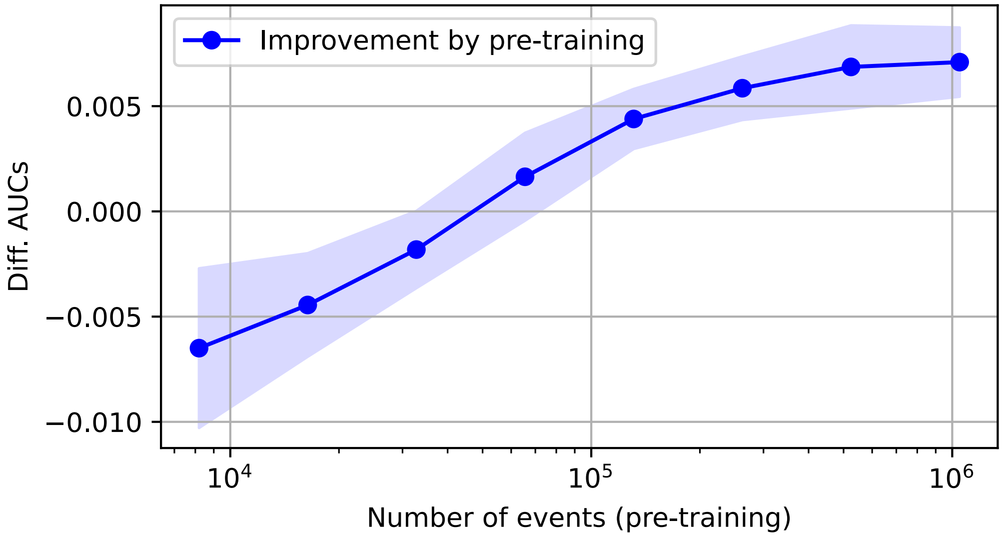
Summary

- Focusing on foundation models (transfer learning) and studying their applications to collider physics
  - Motivated by reduction of computing resources for future experiments
- Developed a self-supervised learning using real data in pre-training
  - The pre-trained model provides significant improvements in event classification when the # of events is small
  - The scaling behavior encourages pre-training with a larger data
    → Data augmentation technique in our physics data was discussed
  - (Need to check the scalability with larger models and larger data)

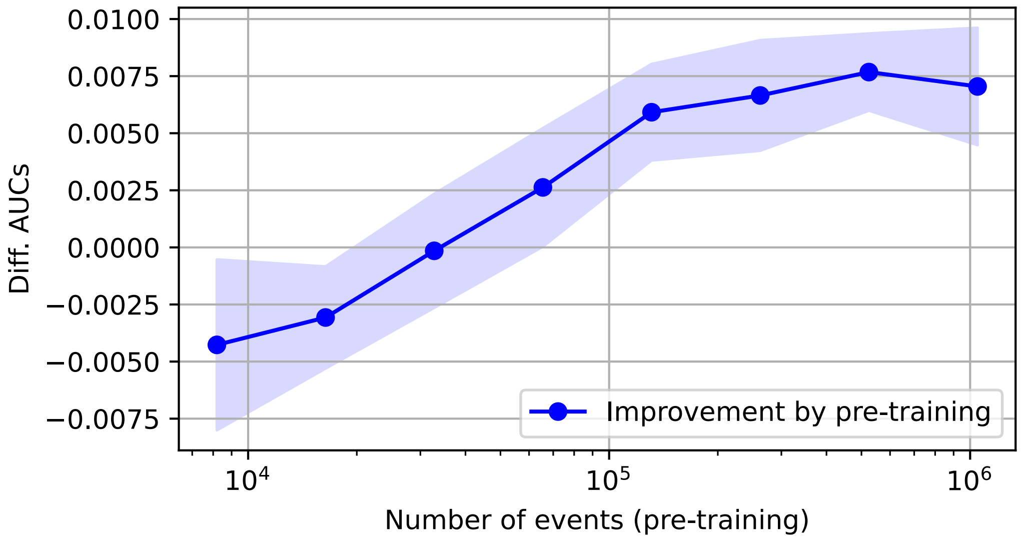
Backup

Scaling raw





c3



c4

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