

Artificial Intelligence in High Energy Physics : Experiment

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Disclaimer: Artificial Intelligence evolves too fast,
I'm drawing some sketch,
picking up only few items around me

this talk will be short 😊

Ask ChatGPT:



You

please summarize recent trends of AI in the experimental High Energy Physics area



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ChatGPT

As of my last knowledge update in January 2022, I don't have specific information on the most recent trends in AI in experimental High Energy Physics (HEP). However, based on the general trajectory of AI and its applications in scientific research, especially in fields like particle physics, some trends could be anticipated. Keep in mind that the actual developments may have evolved since then. Here's a general outline of potential recent trends:

1. **Advanced Machine Learning Techniques:** Continued exploration and implementation of advanced machine learning techniques, such as deep learning, reinforcement learning, and unsupervised learning, to improve the efficiency and accuracy of data analysis in HEP experiments.
2. **Integration of Generative Models:** Increased use of generative models like GANs for simulating realistic particle interactions and detector responses, aiding in the development of more accurate simulations and facilitating better understanding of experimental conditions.
3. **Explainability and Interpretability:** Growing emphasis on developing AI models that are not only accurate but also interpretable. Ensuring that AI algorithms provide insights into the reasoning behind their decisions is crucial for gaining trust in the HEP community.
4. **Transfer Learning for Experiment Optimization:** The application of transfer learning techniques to optimize experimental setups. Leveraging knowledge gained from one experiment to enhance the efficiency and design of subsequent experiments, particularly in terms of detector configuration and data collection strategies.

5. **Quantum Machine Learning:** Exploration of the potential benefits of quantum machine learning algorithms for certain HEP tasks, taking advantage of quantum computing capabilities to address complex problems more efficiently than classical approaches.
6. **Edge Computing for Real-time Analysis:** Increased use of edge computing to enable real-time data processing and analysis directly at the experiment site. This trend could lead to quicker decision-making and adaptive experiment control based on immediate data insights.
7. **Collaborative Efforts and Open Source Initiatives:** Collaborative projects and open-source initiatives in the HEP community to share AI tools, models, and best practices. This promotes transparency, reproducibility, and the efficient adoption of AI technologies across different experiments.
8. **Robotic Process Automation:** Integration of robotic process automation to automate repetitive tasks in data processing, calibration, and analysis, freeing up researchers to focus on more complex and creative aspects of their work.

Please verify these trends with the latest literature and developments in the field, as the landscape of AI in HEP is dynamic, and new trends may have emerged since my last update in January 2022.

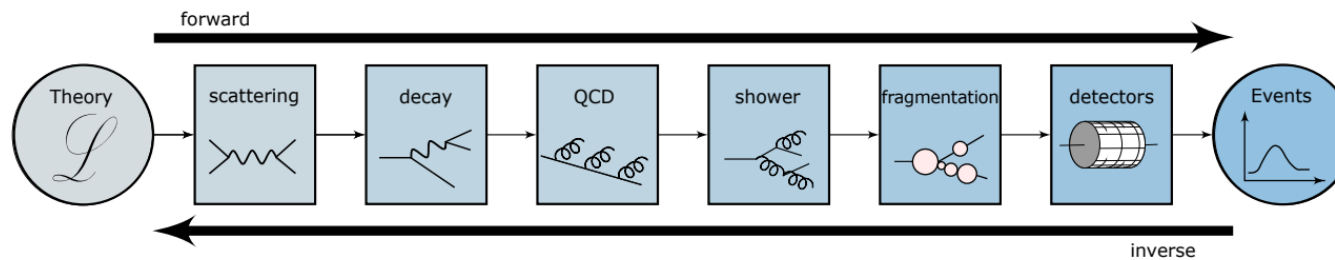
ChatGPT only gives summary text (and sometimes gives fakes)
But I believe we can set our starting point here

Key items from ChatGPT's answer



- Advanced ML to improve the efficiency and accuracy
- Generative Models for more accurate simulation
- Explainability and Interpretability
- Transfer learning to optimize setup
- Quantum Machine Learning
- Edge computing for real-time analysis
- Collaborative Efforts and Open Source Initiatives
- Process Automation

An overall picture



Which part does AI come in?
.. with which shape?

Keywords

- ML to improve the efficiency & accuracy
- Generative Models
for more accurate simulation
- Edge computing for real-time analysis
- Process Automation
- Collaborative Efforts
and Open Source Initiatives
- Transfer learning to optimize setup
- Explainability and Interpretability
- Quantum Machine Learning

Concepts in HEP

- Object tagging
- Event/object reconstruction
- Background rejection
- Fast & accurate Simulation
- ML in Trigger
- Detector monitoring
- ...

Concepts in AI/ML

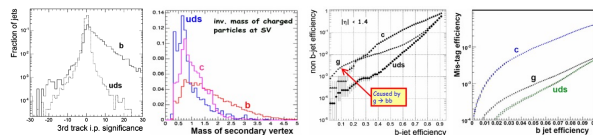
- Classification
- Regression
- Generative models
- Hardware acceleration
- Anomaly detection
- ...

Image: T. Plehn, Modern Machine Learning for LHC Physicists

Event/object classification, tagging

Traditional: Multi-variate analysis
with physics observables

b-tagging with vertex displacement,
track counting, mass, etc



Non-trivial, due to the difficulties in reliability,
computing requirements, software,
physics performance

Initial stage: Software & Algorithms

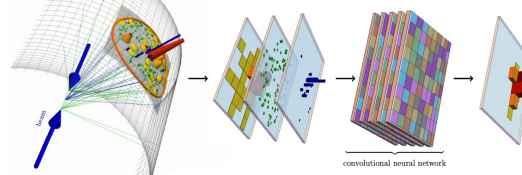
Adopt commercial software developed by
computer science community & industry

Better computing performances - GPUs,
better software design, rapid development
cycle by larger open-source community

DNN allows training many feature variables
with better performance

Deep Learning in Pattern recognition

Early stage: Convolutional Neural Network,
Jet as an image



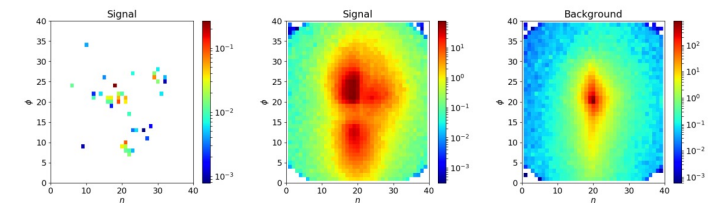
Interpret HEP data from the detector as an
image, put into the ML algorithm designed for
the pattern recognition in images
→ CNN developed for handwriting pattern
recognition could learn patterns in the HEP data
→ Can be scaled up with different pixel sizes,
or higher dimension
→ Multiple detector components / particle
identification as multiple colors / channels

Disadvantages:

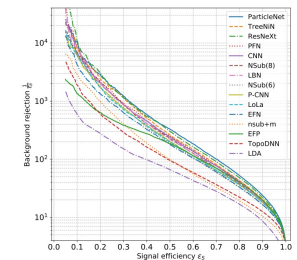
- General HEP detector has irregular shape
- Sparse data in huge number of pixels,
extreme dynamic ranges
- Detector components based on different physics

Application to complicated case:

Multiple objects, boosted topology, or entire event



CNN and variants applied to
top-tagging problem, gives
very good discrimination
power compared to the
traditional methods



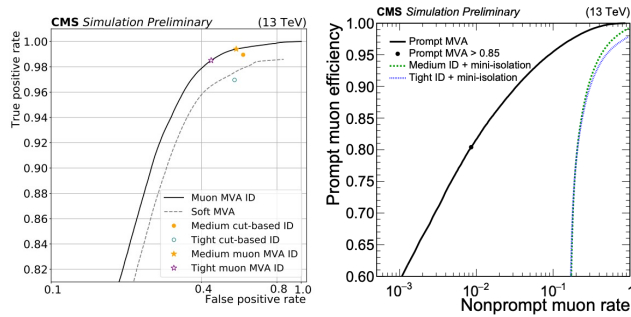
There are advanced DNN models
which can describe the HEP event,
and maybe address physics

Images : 2103.12226 Modern Machine Learning and Particle Physics, 1902.09914v3 The Machine Learning Landscape of Top Taggers

ML for object identification: traditional, image

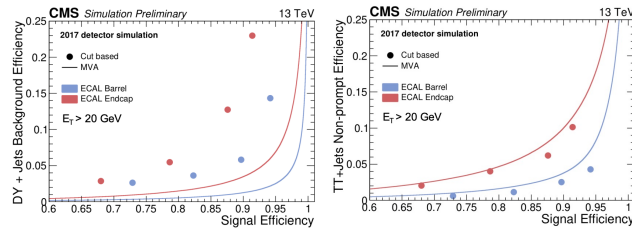
Muon Identification/Isolation

BDT, better performance compared to the traditional cut-based ID



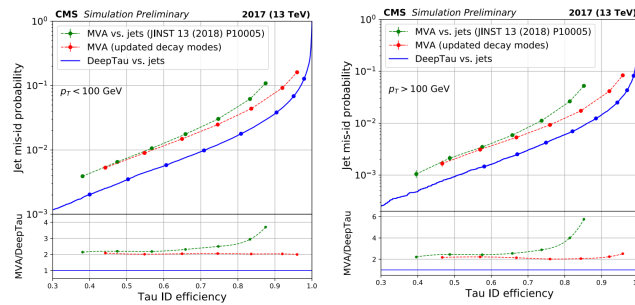
Electron Identification/Isolation

BDT, better performance compared to the traditional cut-based ID in general



DeepTau tagger

CNN + high level feature variables,
Multi-classification tagger against e, mu, jet

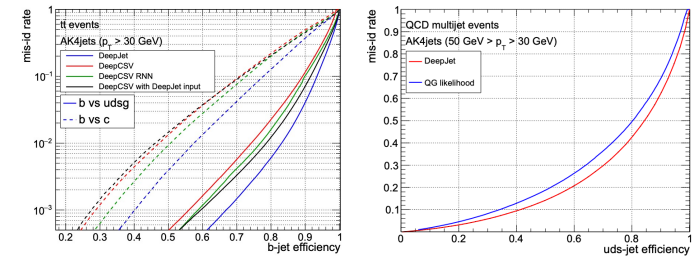


Jet flavour tagging

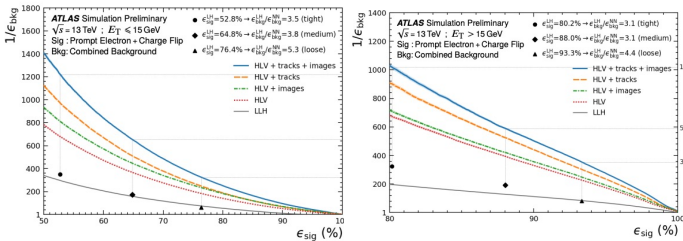
1x1 conv + RNN on feature variables

Multiclassification 6 categories,

Existing algorithms: Shallow NNs, with tracks, or BDT, likelihood
(We already moved to advanced architectures)



CNN + high level feature variables
outperforms the traditional methods

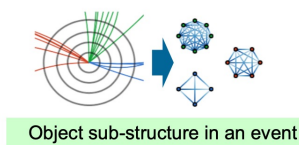
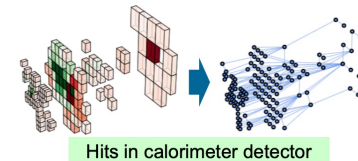
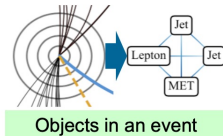
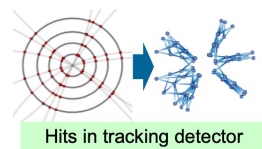


Again, we lose some information with
NN with selected feature variables
or image-based methods,
and maybe not so optimal

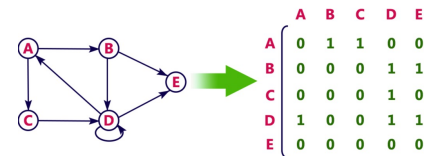
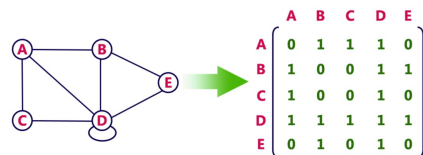
Images : [CMS DP 2019-033](#), [CMS MUO-22-001](#), [CMS DP2018_017](#), [ATL-PHYS-PUB-2023-001](#), [CMS PAS-BTV-15-001](#)

DNN with Geometry

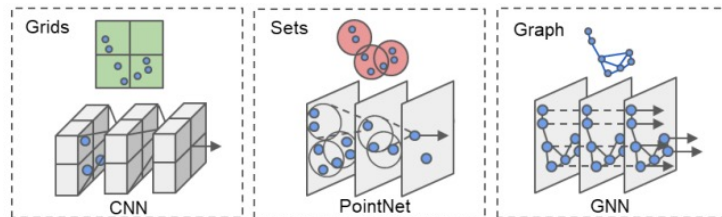
HEP data is not regular image – varying number of particles (or detector cells), with some relations among them
There are DNN architectures which can deal with graphs - Geometric-DNNs or GNNs



Particles => Nodes / Relationships => Edges, Fill into adjacency matrix



GNN can perform convolution in irregular shaped data – position: feature variables of nodes, convolution: adjacency matrix



Are there any existing SW? -> Yes.

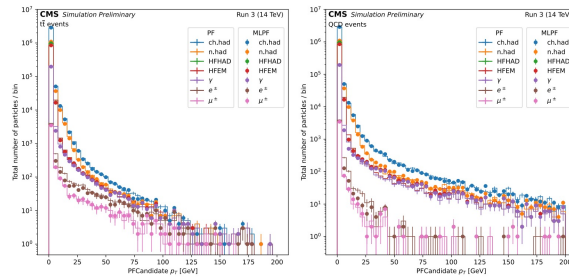
Are there any results in HEP? -> Yes, with papers and codes

Images : [1902.08570](#), http://btechsmartclass.com/data_structures/graph-representations.html, [2003.01251v1](#)

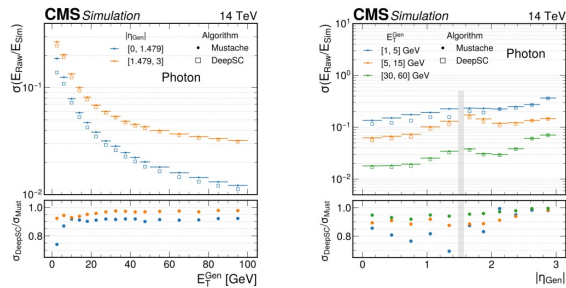
Some working examples of GNN

Sooooo many ideas & results...
I'm picking up some of them in CMS

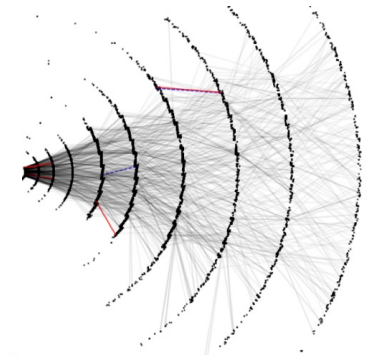
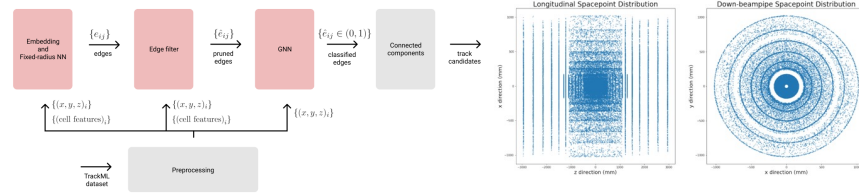
Particle Flow with ML



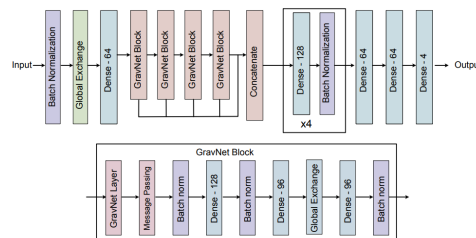
ECal regression (Graph+Attention)



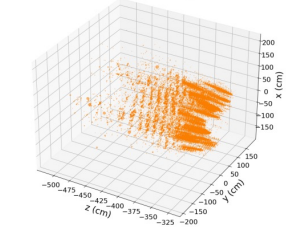
HL-LHC Track reconstruction



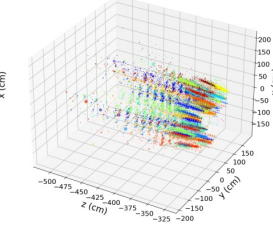
HGCal reconstruction (GravNet)



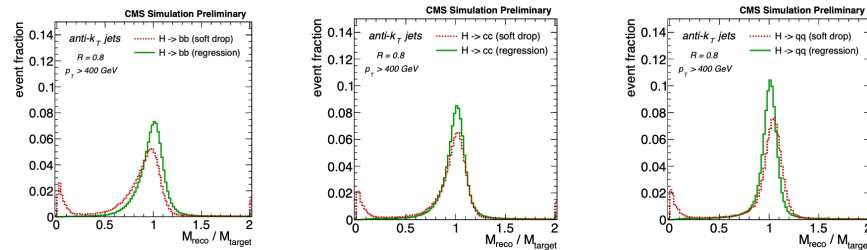
CMS Phase-2 Simulation Preliminary



CMS Phase-2 Simulation Preliminary



Boosted Jet mass regression (ParticleNet)



ParticleNet is
widely used in
reconstruction

Some aspects

- Many improvements in object reconstruction using advanced DNN models such as GNN
- Even more advanced models are available – Attention, Transformer
 - Bottleneck: Data, Computing
- AI evolves too fast, new ideas / architectures appear every day, not sure what will come in the next meeting