# Machine Learning

## Some direction for LH BSM 2023

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# Agnostic searches for new physics

We search for a needle in the haystack, knowing (more or less) how the haystack looks like (the SM), but **not knowing** how the needle (BSM) looks like.

Lots of work done, also by many people here.

Two main threads:

**Anomaly detection:**

— define some notion of "rarity" (e.g. autoencoders) or "over-density" (e.g. weak supervision)

— select anomalous events and search for BSM in there

**Goodness of fit:**

— inspect all events searching for statistically significant departures from SM

— can make stronger or weaker assumption on BSM nature and SM knowledge

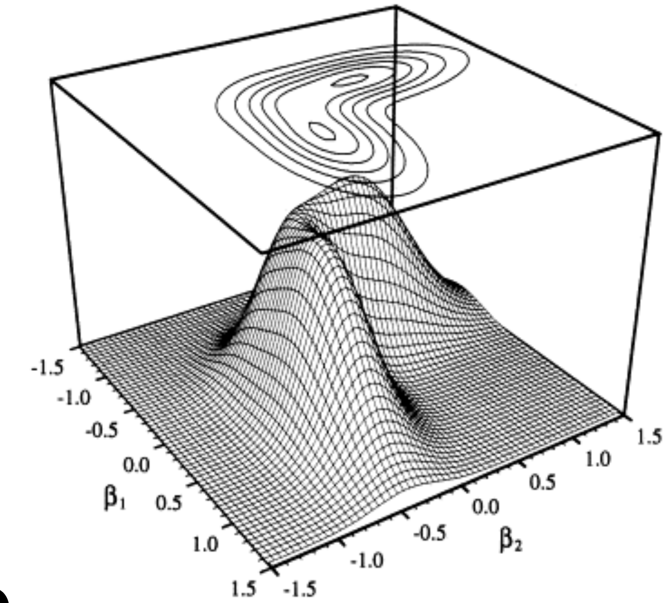
What we could discuss:

**Mapping the space of agnostic searches**: Define Benchmarks**:** having in mind possible real applications; Strategies for assessing coverage beyond individual benchmarks; A unifying view of AD & GOF; Sharing of results

**Use cases Beyond BSM:** e.g., spotting out mistakes/differences in generators; validating generative models; data quality monitoring. Comparison with traditional methods and/or cutting edge advances in other fields; other

# Likelihood Learning

Aiming at “optimal” BSM sensitivity by precision.
The SM EFT at the LHC and HL-LHC as an ideal use case for these ideas.




## Also on this topic, much activity by this group

Several proposals, based on the “likelihood-ratio trick”.

Towards automation, for extensive deployment at LHC

## What we could discuss:

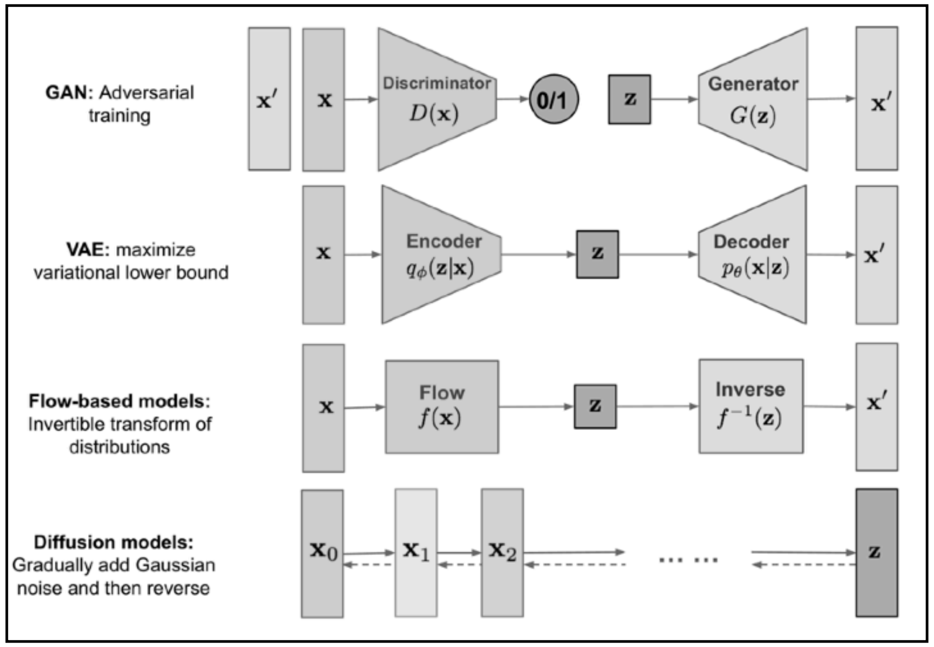
**Comparing performances:** assessing also validation tools, uncertainties, robustness, simplicity, perspective for automation of different proposals.

**Towards real analyses:** one CSM result using these ideas. What is (or should be) coming next? What is missing from the theory side?

**In-situ generative models:** Are there other uses of learning background distributions (either as likelihood or as sample-able generativer model) from data (also related to anomalies)

# Generative Models

Active use of generative models across for e.g. detector simulation and event generation




# What we could discuss:

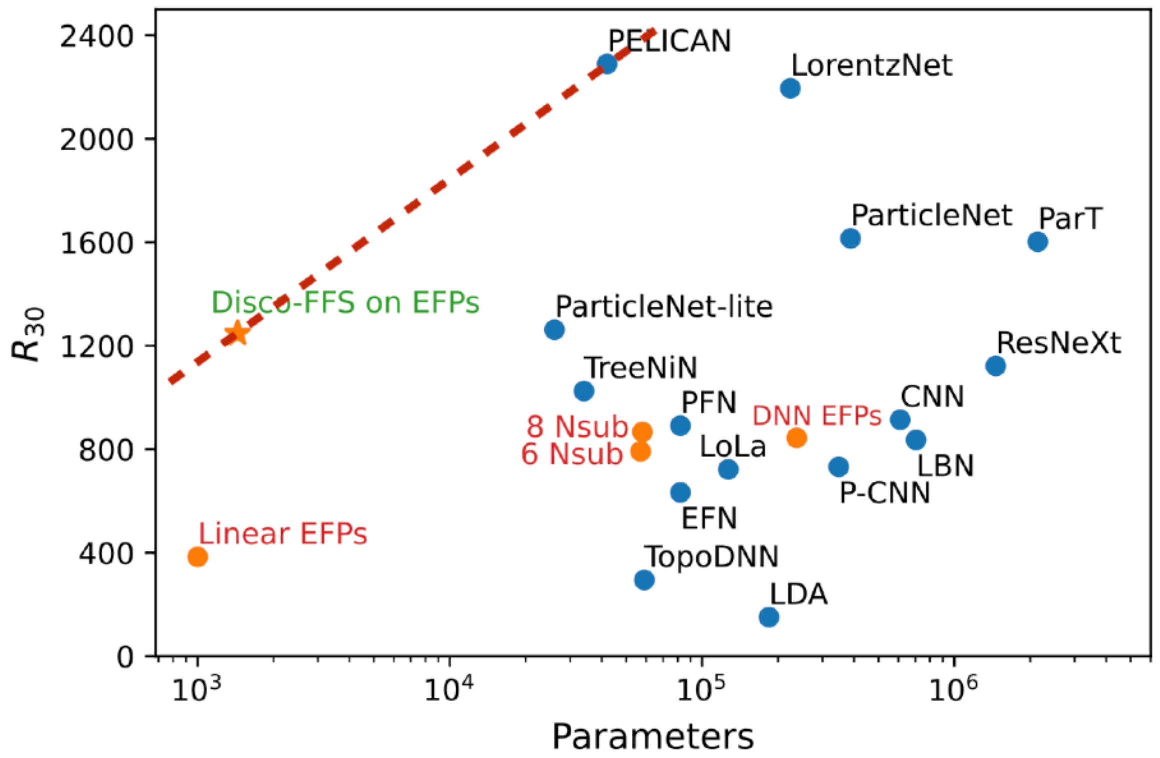
**Other applications of generative models**

**Inclusion of physical symmetries and other constraints in generative architectures**

**Specifically: What can be done with diffusion models?**

# Physical Symmetries

For tagging algorithms, see benefit from including physical symmetries (primarily Lorentz group)




What we could discuss:

**Other ways of including physics information:** decay chains, IRC safety, …

# Exploration of large language models

ChatGPT and similar models
see increased attention in many domains.

Are there serious topics where these methods can be a game-changer in our physics


## What we could discuss:

**Direct LLM research use in fundamental physics**

**Automated text and code generation**

**LLM integration in traditional workflows**

**Symbolic computation**

**Prompt Engineering**