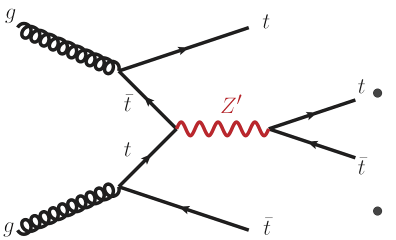
The Search for Beyond Standard Model Top-Philic Resonances via Graph Neural Networks in ATLAS

Sydney Consortium for Particle Physics and Cosmology: June 25, 2022

The Beyond Standard Model Top-Philic Resonance



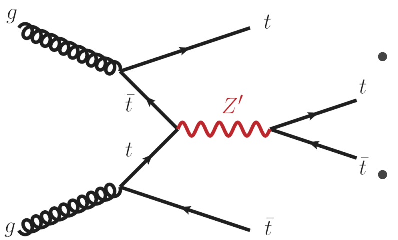
Top-Philic Composite Higgs Resonance Topology.

What is a Top-Philic Resonance and why should we care?

- Various Beyond Standard Model Higgs interpretations attempt to explain mechanisms by which, its observed mass satisfies "naturalness" arguments.
- These are generally satisfied by the introduction of additional mechanisms that counteract radiative corrections, and avoid fine-tuning of parameters.
- The ATLAS BSM 4-tops group I am involved with, is currently exploring a simplified composite Higgs model[a], coupling almost exclusively to top quarks (**Top-philic**), as shown.
- In this topology, tops originating from the Z′ (signal) are expected to be more energetic than the remaining spectator tops.

[a] Jeong Han Kim et al. "Probing TeV scale top-philic resonances with boosted top-tagging at the high luminosity LHC". In: *Physical Review D* 94.3 (2016), p. 035023.

The Beyond Standard Model Top-Philic Resonance



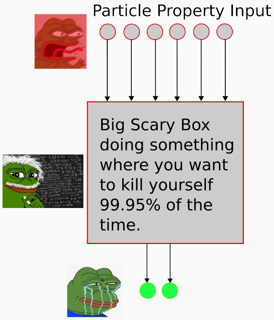
Top-Philic Composite Higgs Resonance Topology.

Why the $t\bar{t}t\bar{t}$ final state?

- Evidence of Standard Model production ($\sigma_{SM}^{t\bar{t}t\bar{t}} = 9.2$ fb)[a] in Same-Sign/Multi-Lepton channels.
- Recommissioning of the LHC at larger energy scales, associated resonance signatures are expected in the top sector, due to the large Higgs field Yukawa coupling.
- Significant collaboration of the Machine Learning and ATLAS coohorts, could boost sensitivity of rare process detection and unveiling of New Physics.

[a] Morad Aaboud et al. "Search for four-top-quark production in the single-lepton and opposite-sign dilepton final states in p p collisions at s= 13 TeV with the ATLAS detector". In: *Physical Review D* 99.5 (2019), p. 052009.

Traditional Neural Networks

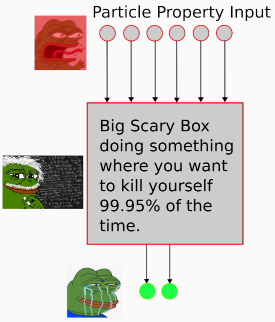


Multi-Layer-Perceptron with Layers Hidden by Scary Box.

What are Multi-Layer-Perceptrons (MLPs)/Neural Networks?

- Fundamentally, Neural Networks (NNs) are derivations of MLPs
- MLPs are **stacked layers (Big Scary Box)** of interconnected fixed inputs and outputs, where the outputs are predictions.
- **Training** MLPs involves quantifying discrepancies, via the **loss-function** (e.g. Mean Square Error), between truth (**only in Monte Carlo!)** and prediction, followed by **updating internal parameters**.
- Ideally, the updating step (**backpropagation**) improves future predictions.

Traditional Neural Networks



Multi-Layer-Perceptron with Layers Hidden by Scary Box.

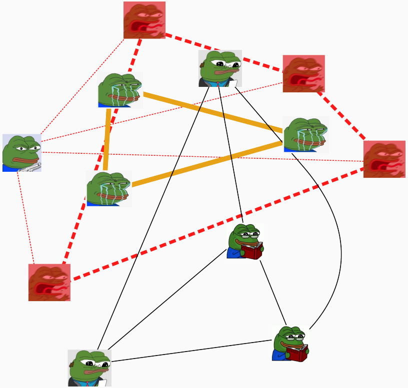
A simple Pepe Particle Example:

- Lets assume we have some particle, which in truth (according to Monte Carlo) is **angry**, and feed its properties into the MLP input (Energy, Charge, etc.)
- Ideally, MLP predicts **Particle** is **angry**, meaning our **loss is zero**, i.e. Tears of joy!
- However, not always the case if MLP was not trained/complex enough, and might predict **happy**, **resulting in higher loss**, i.e. Tears of frustration.

Problems with NN/MLPs:

- Requires consistent and fixed inputs.
- Inputs are permutation variant!
- No consideration of particle relationships in collision event (Event Topology).

Graph Neural Networks



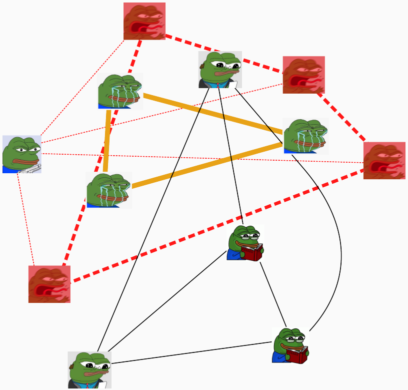
Pepe nodes connected by interest

Graph Neural Networks:

- A manifestation of Graph Theory merging with Machine Learning (specifically Neural Networks)[a].
- In the context of the ATLAS detector, a collision event induces observable **particles**, these are abstracted as **nodes** in the event graph.
- **Nodes** connected by **edges** imply a relationship, as shown in the pepe graph.
- **Pepe particles** with common/similar attributes are **likely to be connected and form clusters** (e.g. reading/professor pepe both have glasses and read).

[a] Jonathan Shlomi, Peter Battaglia, and Jean-Roch Vlimant. "Graph neural networks in particle physics". In: *Machine Learning: Science and Technology* 2.2 (2020), p. 021001.

Graph Neural Networks



Pepe nodes connected by interest

Solving aforementioned problems:

- Fixed input: **Nodes with different attributes are members of mutually exclusive event graphs**.
- Permutation Invariance: Present on a per node basis **but**, not for edges (See Message Passing)!
- Relationships: Infer via particle edges, i.e. Event Topology.

Message Passing Example:

- Lets look at the reading pepe, each have a document but differ in certain attributes, e.g. wearing a tie.
- Using an MLP, we can encode mutual (or exclusive) attributes as **Messages**, and transmit them via edges.
- Nodes receiving messages can **sum** these, and assign weights on each message depending on similarity.

Relevance of GNNs to ATLAS?

- ATLAS is an extremely **interconnected** set of detectors, each with their own problems and uncertainties.
- These properties can be encoded and propagated to event graphs, and make appropriate adjustments (e.g. decides to reject event based on poor quality).
- **Place weighting on important attributes**, for example computation of invariant masses of connected particles (useful for detecting tops).
- More informed decision making when rejecting background processes, e.g. $t\bar{t}$, could improve sensitivity towards New Physics.

Current and Future Work

- Currently exploring and evaluating a multitude of Graph Neural Network architectures.
- Assessing importance of specific attributes to extract from measurements and exploring methods to reduce training time.
- GNNs being applied to HEPP is a rather emerging field and could open up new avenues to explore/contribute to.