



CHARLES
UNIVERSITY



ATLAS
EXPERIMENT

CERN

School of Computing



Machine Learning Methods in high jet multiplicities

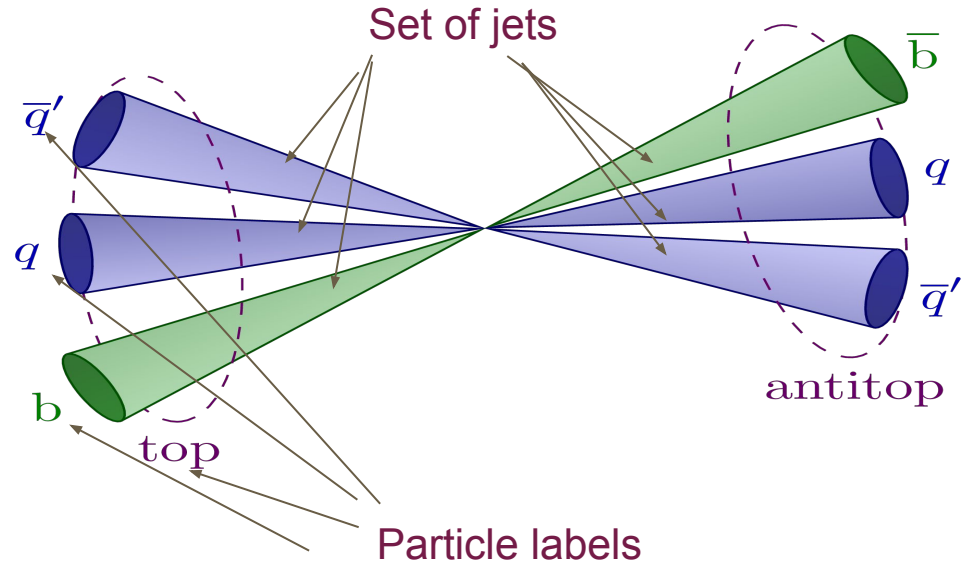
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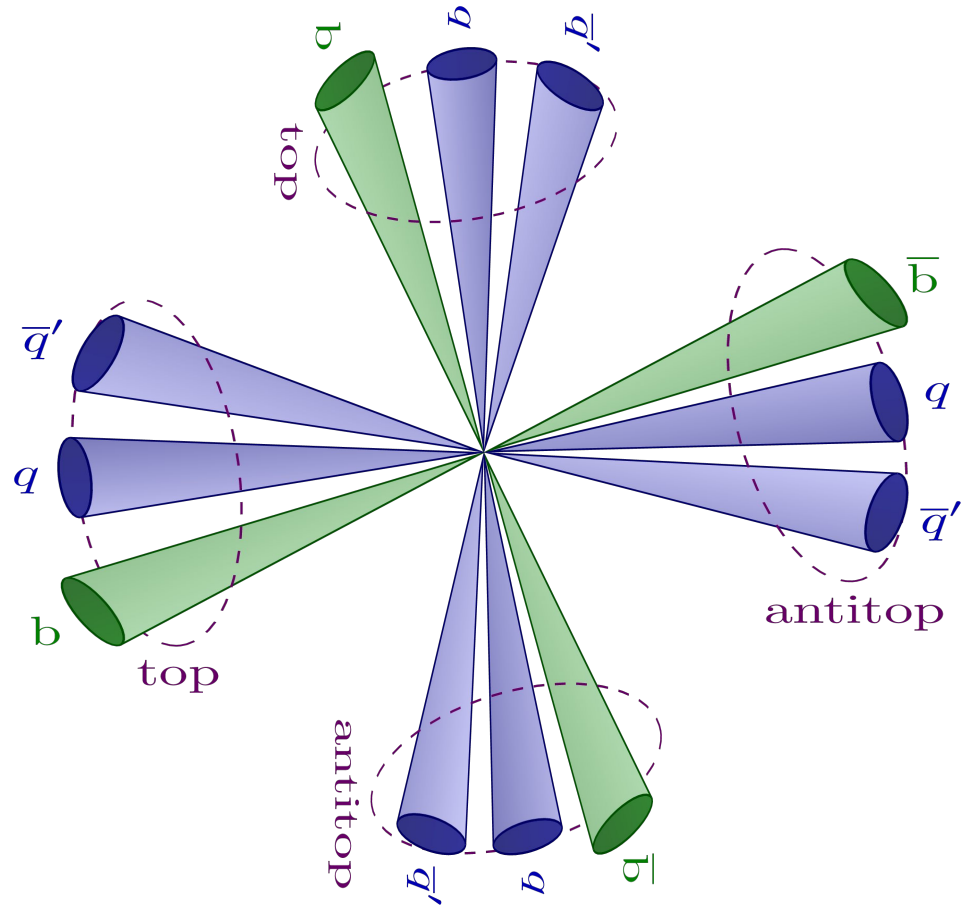
Particle physics objects

- ❖ Jets and leptons are the key detector signatures we observe at the end of particle collisions, helping us to identify what happened during the process
- ❖ A particle assignment to a jet set - i.e. a reconstruction of event - plays a significant role in analyses
- ❖ For low-jet multiplicity processes (pp->tt), signature is 2-6 jets, depending on decay channel
 - 6 jets lead to 90 combinations
- ❖ Pile-up, final state radiation and other underlying processes can increase final number of jets
- ❖ The methods: KLFitter, χ^2 -minimisation, BDT can deal with them



High jet multiplicity process

- ❖ A process like all-hadronic four top quark production has a jet signature of 12, which leads to 1247400 combinations to check using χ^2 -minimisation
 - There is a need for new reconstruction techniques!



- ❖ **Symmetry Preserving Attention Network** ([arxiv:2106.03898](#)) is a transformer based NN
 - SPANet improves run-time performance over baseline permutation methods by avoiding having to construct all valid assignment permutations via special attention head

Training input

```
Source:
[ $\{E_0, \eta_0, \sin \phi_0, \cos \phi_0, b\text{-tag}_0\}$ ,
 $\{E_1, \eta_1, \sin \phi_1, \cos \phi_1, b\text{-tag}_1\}$ , ...
...],
[ $\{E_{\text{miss}_T}^{\text{miss}}, \sin \phi^{\text{miss}}, \cos \phi^{\text{miss}}\}$ ]
Targets:
t1:
    q1: 0 <- Matched using
    q2: -1 <- True level parton
    b: 4 <- kinematics
t2:.....
t3:.....
t4:.....
Symmetries:
[t1,t2,t3,t4], [t1/q1, t1/q2] ,...
```

Prediction results

```
Targets:
t1:
    q1: 0 <- predictions
    q2: 3 <- predictions
    b: 7 <- predictions
    detection Probability
    assignment Probability
    marginal Probability
t2:.....
t3:.....
t4:.....
```

SPANet model - short summary of SPANet article [arxiv:2106.03898](https://arxiv.org/abs/2106.03898)

- ❖ Number of particles - m
- ❖ Each particle - k_p partons/products
- ❖ For each particle (p) model searches for best parton - jet assignment
- ❖ G_p is a permutation group of partons (b , $[q_1, q_2]$ our case). σ are its elements
- ❖ Encoded jet tensor X_p has dimensions: $X_p \in \mathbb{R}^{N \otimes \mathbb{R}^{N \otimes \dots (D\text{-times})}} = \mathbb{R}^{N \otimes D}$
 - N - total number of jets
 - D - hidden dimensions
- ❖ A Symmetric Tensor Attention a rank k_p $\Theta \in \mathbb{R}^{D \otimes k_p}$
- ❖ Due to summation over G_p permutations we have jet-symmetric outputs
- ❖ There is an implemented symmetry of particles via symmetrized loss function, where T_i are true assignments

$$\mathcal{L}_{min} = \min_{\sigma \in G_E} \sum_{i=1}^m CE(\mathcal{P}_i, T_{\sigma(i)})$$

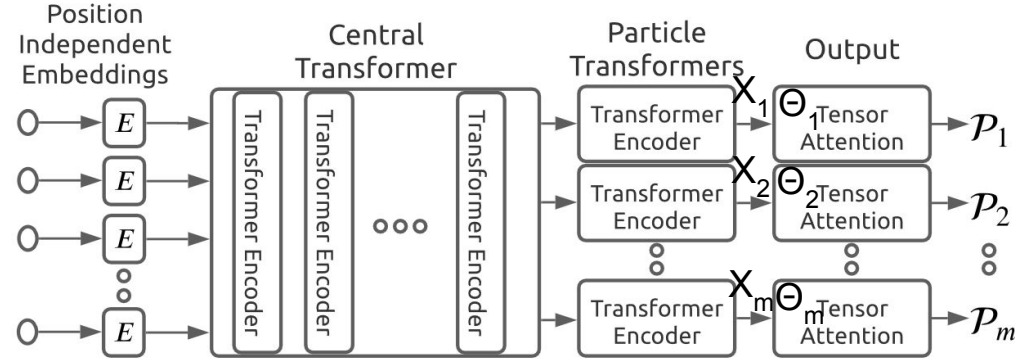


Figure 2: A visualization of the high level structure of SPA-NET.

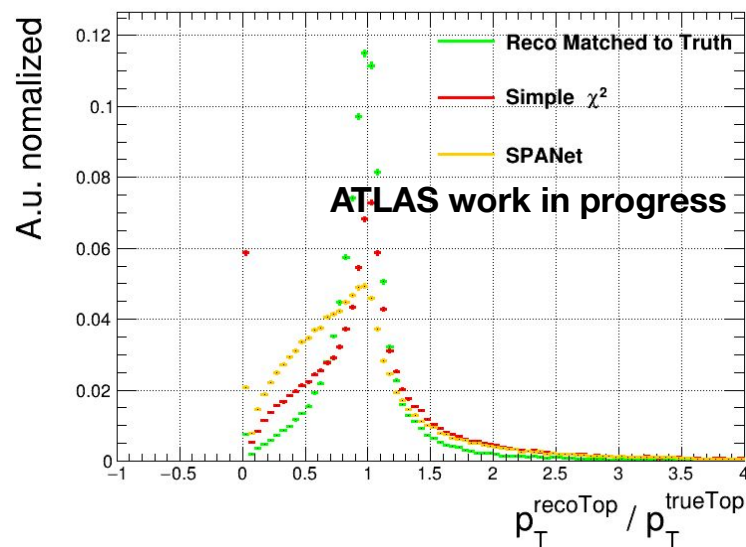
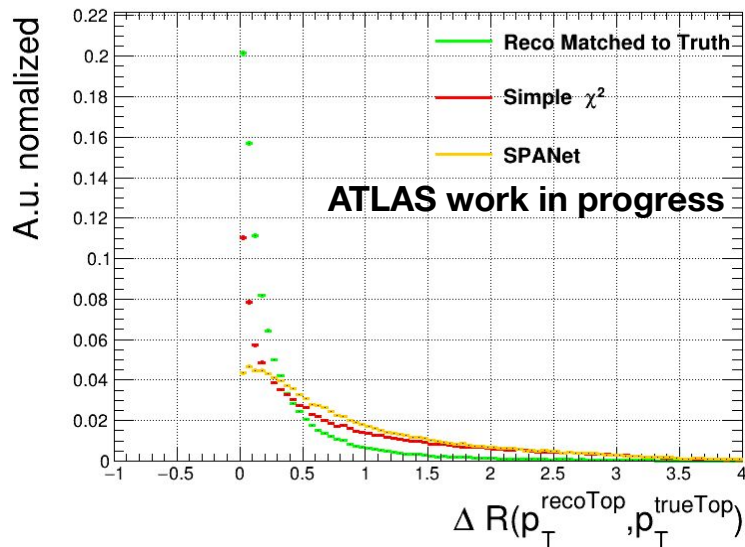
$$\mathcal{S}^{i_1 i_2 \dots i_{k_p}} = \sum_{\sigma \in G_p} \Theta^{i_{\sigma(1)} i_{\sigma(2)} \dots i_{\sigma(k_p)} ,$$

$$\mathcal{O}^{j_1 j_2 \dots j_{k_p}} = X_{i_1}^{j_1} X_{i_2}^{j_2} \dots X_{i_{k_p}}^{j_{k_p}} \mathcal{S}^{i_1 i_2 \dots i_{k_p}} ,$$

$$\mathcal{P}_p^{j_1 j_2 \dots j_{k_p}} = \frac{\exp(\mathcal{O}^{j_1 j_2 \dots j_{k_p}})}{\sum_{j_1, j_2, \dots, j_{k_p}} \exp(\mathcal{O}^{j_1 j_2 \dots j_{k_p}})}$$

SPANet results for tttt sample

- ❖ SPANet was trained using tttt information
- ❖ Trained model can be used on process



- ❖ For each true top reconstructed top was found via smallest Delta R between. Pairwise Delta-R (angular distance) and transverse momenta ratios are shown

Summary

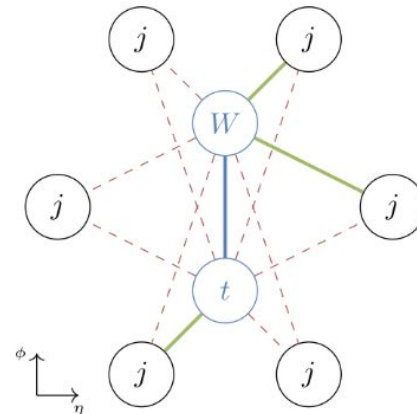
- ❖ High multiplicity processes can help getting extra precision on fundamental interactions
- ❖ Need appropriate tools to deal with combinatorial complexity
- ❖ SPANet provides a symmetry preserving approach
- ❖ SPANet models is also integrated into [TopCPToolkit](#), a framework for producing Monte-Carlo simulations for studies

Backup

Other state of the art approaches

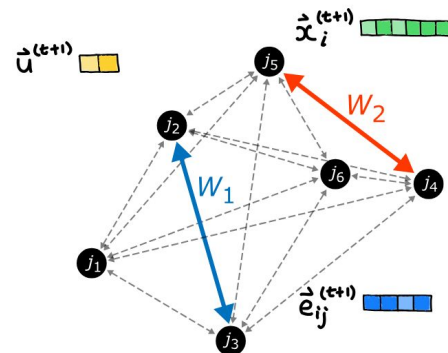
Topograph - a GNN

[arxiv:2303.13937](https://arxiv.org/abs/2303.13937)



HyperGraph - a digraph NN structure

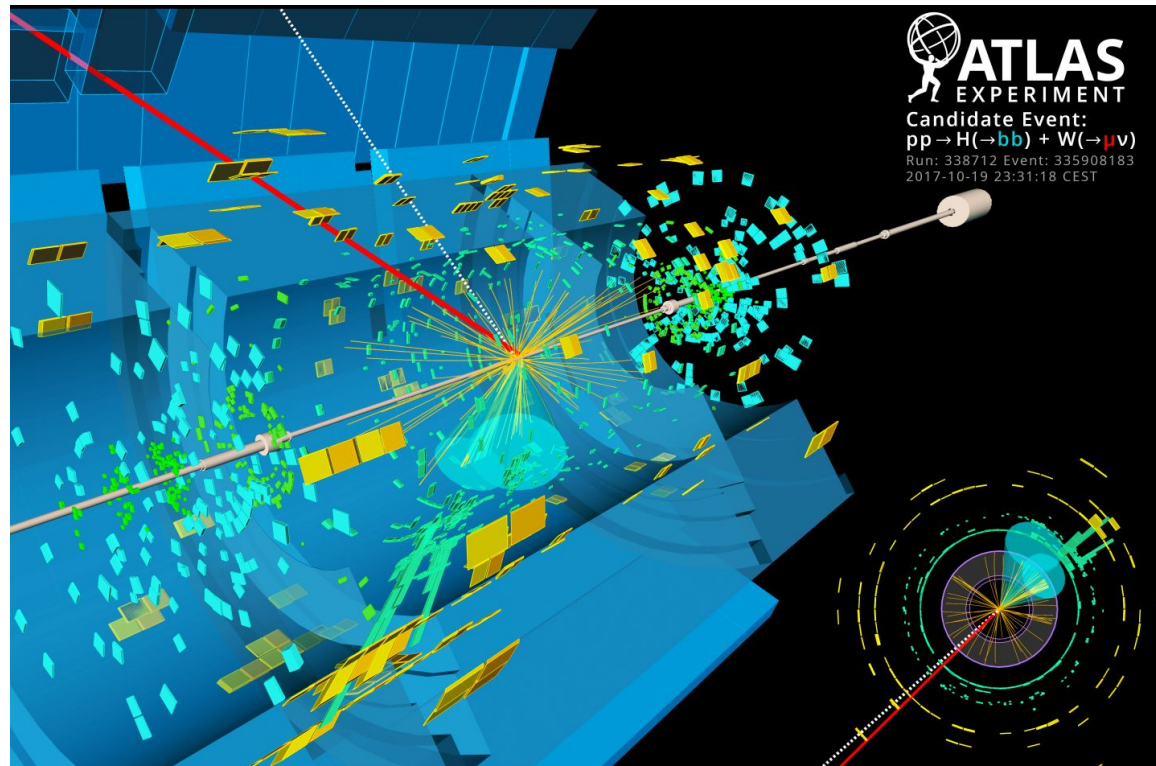
[arxiv:2402.10149](https://arxiv.org/abs/2402.10149)



[HyperGraph presentation](#)

Detector view of jets and leptons

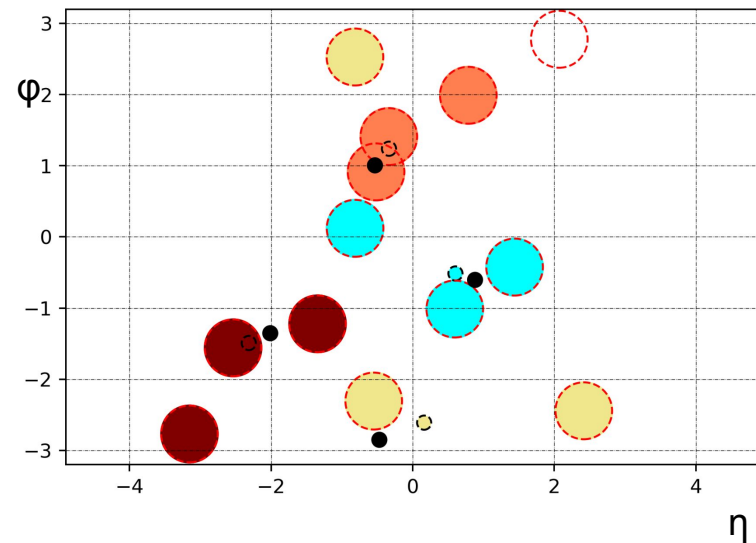
[ATLAS Event Displays]



Simple χ^2 tttt reconstruction

- ❖ Is a very combinatorially complex task due to high jet multiplicity
- ❖ Following objects become top candidates
 - All Large-R jet in event, tagged by Contained Top 50%, become top candidates
 - Each top candidate should have 3 small-R jets
 - Can have less as majority of events have less than 12 jets
- ❖ Candidates must satisfy following conditions
 - Reconstructed top mass should be in [130, 220] GeV mass range
 - If applicable:
 - 2 out of 3 jets should yield mass close to 80 GeV and the third is b-tagged with DL1 WP 77&
- ❖ From candidates, the final reconstructed tttt set is obtained via finding the set with minimum of metric:

$$\chi_{reco}^{2,sum} = \sum_{i=1}^4 \frac{\chi_{t,i}^2}{30} + \frac{\chi_{W,i}^2}{20} + \frac{\chi_{b,i}^2}{10}$$



● - true tops momenta vector position in (η, ϕ) plane

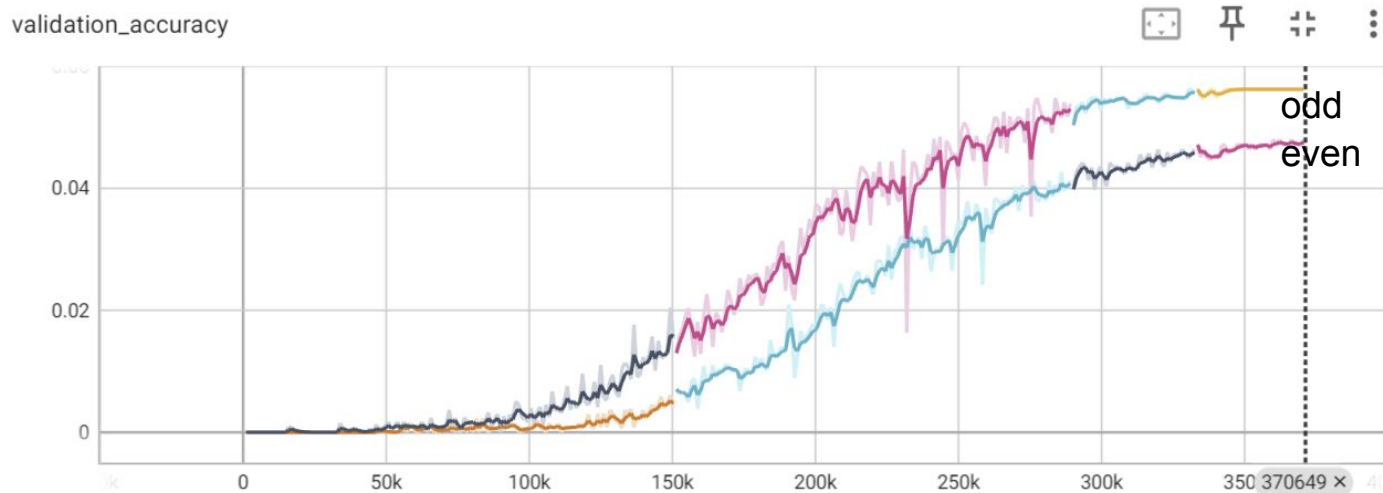
●●●● - detector level jets the make up one group - a reconstructed top

●●●● - reconstructed tops momenta vector

○ - detector level jets that are left out of reconstruction

SPANet training

- ❖ 28 hours on 1 GPU L40 NVIDIA for an even and an odd
- ❖ Batch size 4096
- ❖ Model has 832 K (Input embedder 38.2 K; Jet Encoder 63.3 K; Decoder 730 K) parameters with 4.5 entries per training (1000 step per epoch), 350 epochs
- ❖ Can state that training reached maximum performance for even
- ❖ Learning rate **0.003** for odd **0.0015** for even



SPANet results

- ❖ We can also see some separation in assignment probabilities for signal and background processes

