

THEORY-INFORMED NEURAL NETWORKS FOR PARTICLE PHYSICS

BMD, M. Spannowsky - [arXiv:2507.13447](#) (IOP MLST)

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INTRODUCTION

Aim

Use reinforcement learning for event reconstruction, mapping final-state particles to matrix-element level partons using the matrix element itself to provide the training signal.

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Disclaimer

This is a proof-of-principle for the method, so:

- Parton-level events.
- Tree-level matrix elements.
- Known process hypothesis and known topology.
- Four-momenta only.
- No b -tagging, showering, hadronisation, or detector simulation.

THE ASSIGNMENT PROBLEM

For a given process hypothesis we have a set of final-state four-momenta.

We need to decide which object matches with which slot in the matrix element.

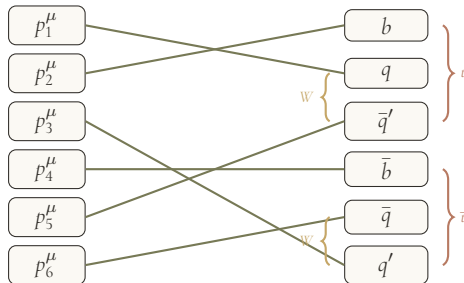
Task

Find the particle-parton assignment favoured by the matrix element.

This is not always the same as the generator truth assignment.

observed
momenta

parton slots
in $\mathcal{M}$



THE ASSIGNMENT PROBLEM

$t\bar{t}$

$$6! = 720$$

$t\bar{t}W$

$$\sim 4 \times 10^4$$

$t\bar{t}t\bar{t}$

$$\sim 4 \times 10^8$$

A brute-force matrix-element search becomes expensive fast.

But the assignment space has structure.

A bad assignment can often be improved by a small number of swaps.

Build a neural network to learn which swaps are worth trying next.

Other tools in the literature

- **Matrix-element methods:**
sum over latent assignments.
- **SPANet:** [A. Shmakov et al., SciPost Phys. 12, 178 (2022)]
attention with assignment symmetries.
- **Topograph:** [L. Ehrke et al., Phys. Rev. D 107, 116019 (2023)]
graph model for decay structure.
- **HyPER:** [C. Birch-Sykes et al., Phys. Rev. D 111, 032004 (2025)]
hypergraphs for multi-object relations.
- **TIGER:** [N. Soybelman et al., Phys. Rev. D 113, 012014 (2026)]
flexible learned reconstruction.

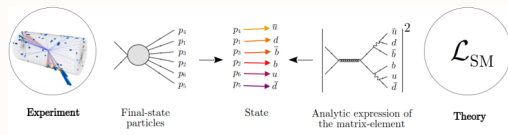
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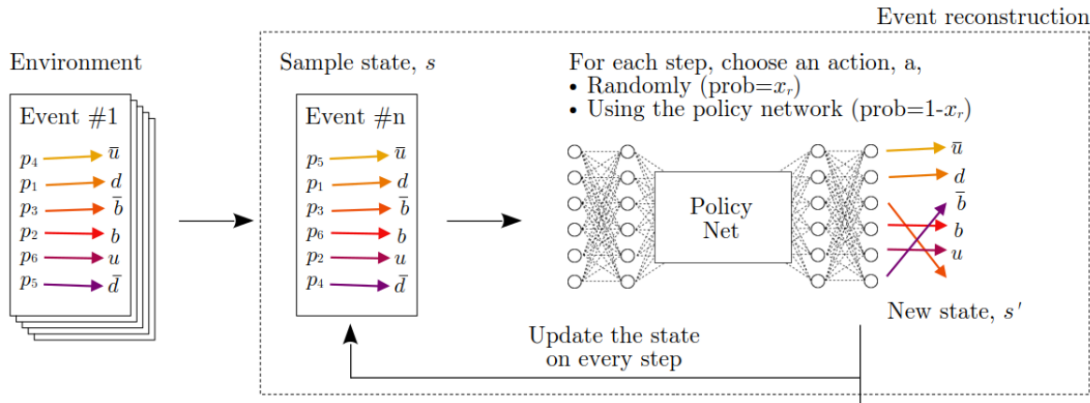
Our work

- Doesn't use assignment truth labels.
- The matrix-element from theory is used as the reward.
- Let the network learn the search policy.



DEEP Q-LEARNING

Deep Q-learning is a reinforcement learning method where an agent learns, from trial and error, which actions lead to the greatest long-term reward.



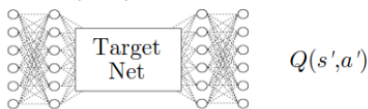
Network training

Sample N tuples from buffer, for each tuple:

- 1) Compute $Q(s,a)$ from the Policy Net



- 2) Compute $Q(s',a')$ from the Target Net

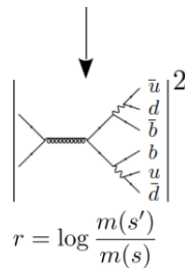


- 3) Compute Loss & update Policy Net

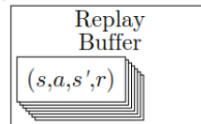
$$L = (Q(s,a) - (r + \gamma Q(s',a')))^2$$

Every n_{target} episodes, update weights of Target Net with the weights of Policy Net.

Compute the
reward, r

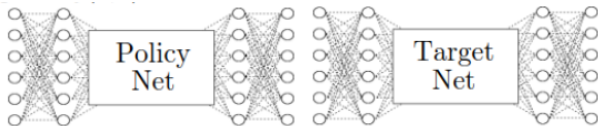


Add the state,
action, new state,
and reward to the
Replay Buffer



NETWORKS AND TRAINING

- Policy and target nets have the same architecture
- (Lorentz-equivariant) Transformer
- Each parton input = p_μ & external node ID
- Separate 128d linear embeddings for p_μ & external node ID
- Transformer head: $128 \rightarrow 128 \rightarrow d_A$
- Lorentz-equivariance $\Rightarrow$ much faster convergence & smaller networks needed



hyperparameter	value
training events	10^4
episodes	2.5×10^6
γ	0.01 to 0.5
buffer size	10^4
batch size	10^3
optimiser	Adam
learning rate	10^{-5}
d_{model}	128
layers, heads	4, 4
dropout	0.1

RECONSTRUCTION EFFICIENCY

- Efficiencies count whether the decay structure is recovered
- But we don't require that every quark label is ordered correctly

$$\text{Efficiency} = \frac{\text{number of correctly reconstructed } X \text{ objects}}{\text{number of generated } X \text{ objects}}.$$

W efficiency

The two daughter quarks must be grouped together.
The up/down order is ignored.

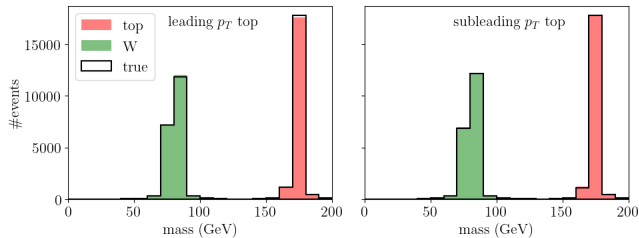
Top efficiency

The correct W candidate must be paired with the correct b quark.

Total efficiency

All W bosons and all top quarks in the event must be reconstructed properly.

RECONSTRUCTION EFFICIENCY



Efficiencies

W reconstruction	0.903
Top reconstruction	0.980
Total event	0.816

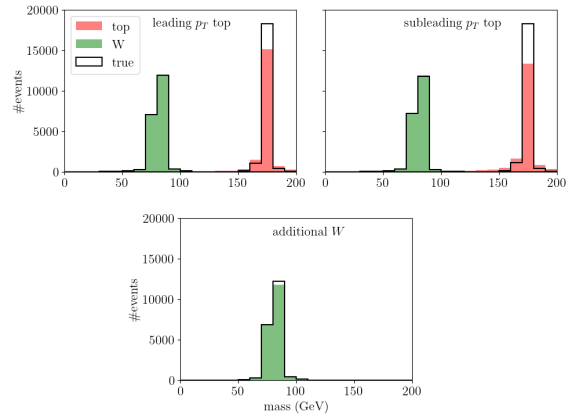
Fully hadronic $t\bar{t}$ has six final-state partons.
Good agreement in reconstructed mass peaks.

Robustness to smearing

σ_{smear}	W eff.	top eff.	total eff.
0.00	0.903	0.980	0.816
0.02	0.891	0.971	0.796
0.05	0.856	0.953	0.737
0.08	0.798	0.911	0.645

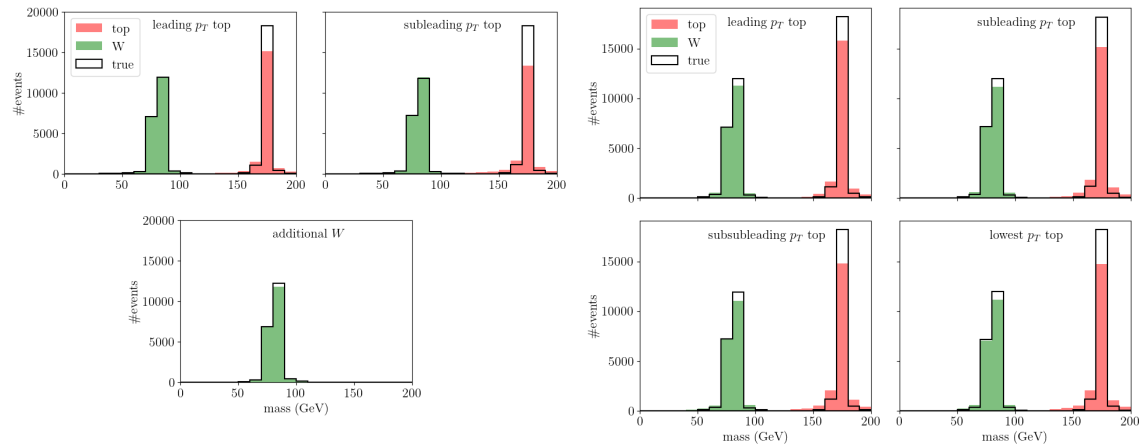
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Efficiencies and reconstruction drop for $t\bar{t}W$ and $t\bar{t}t\bar{t}$ due to larger multiplicities.



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HYPOTHESIS TESTING

With the RL assignments we can construct a likelihood-ratio using the matrix elements, and use it for classification.

- For the demonstration we consider VBF-like production

$$uu \rightarrow W^+ W^- uu.$$

- With hadronic W decays can't distinguish the final state quarks in

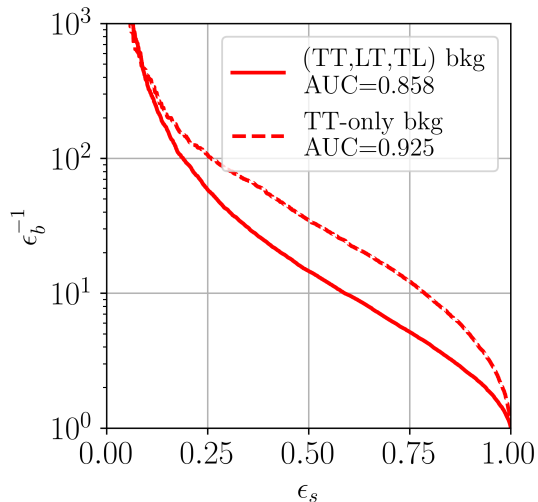
$$W^+ \rightarrow u\bar{d}, \quad W^- \rightarrow \bar{u}d.$$

- We have a state assignment problem that we can solve with our approach

- Dataset: unpolarised $uu \rightarrow W^+ W^- uu$ sample
- Train the DQN to reconstruct the events as best as possible
- Use assignments to compute the polarised matrix elements:
 $m_{LL}(\tilde{x}), m_{LT}(\tilde{x}), m_{TL}(\tilde{x}), m_{TT}(\tilde{x})$
- Now we can evaluate

$$L(\tilde{x}) = \frac{m_{LL}(\tilde{x})}{m_{LT}(\tilde{x}) + m_{TL}(\tilde{x}) + m_{TT}(\tilde{x})}.$$

HYPOTHESIS TESTING



AUC with RL assignment

LL vs TT, LT, TL	0.858
LL vs TT	0.925

With truth assignments, the corresponding AUCs are about 0.925 and 0.965.

ANOMALY DETECTION

With the RL assignments we can compute how likely an event is under a background hypothesis, $m_{\text{BG}}(\tilde{x})$, and use this as an anomaly score.

- Here the proof-of-principle test is:

- background: $t\bar{t}$
- signal: W^+W^-uu

- Again assume hadronic decays:

$$t\bar{t} \rightarrow bW^+ \bar{b}W^- \rightarrow b u \bar{d} \bar{b} \bar{u} d$$

$$uu \rightarrow W^+W^-uu \rightarrow (u\bar{d})(\bar{u}d)uu$$

→ this is not realistic, it's just to demonstrate the idea.

- Train the DQN to make the correct assignments for just the background $t\bar{t}$ events
- we evaluate on both $t\bar{t}$ and W^+W^-uu events

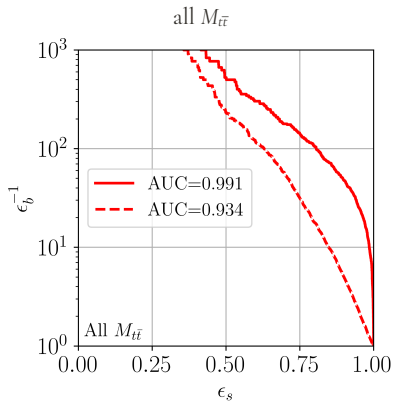
Anomaly score

$$\rho(\tilde{x}) = \frac{1}{m_{\text{BG}}(\tilde{x})}.$$

Events are anomalous if they cannot be arranged into a high-weight background configuration.

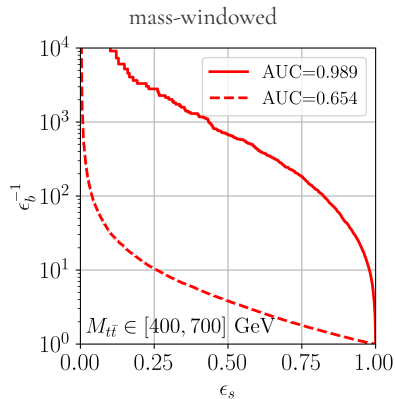
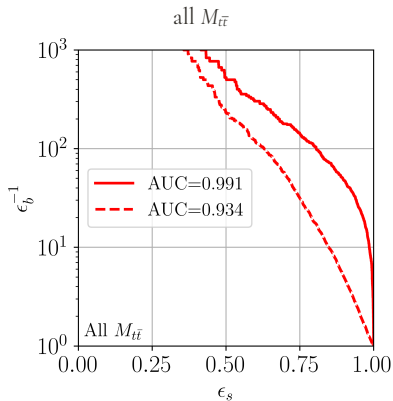
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Solid line shows performance with $\rho(\tilde{x})$ using the RL assignments.
Dashed line shows the autoencoder result.



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Restricting the mass-window to $400 \text{ GeV} < m_{\text{event}} < 700 \text{ GeV}$ prevents the AE (dashed) from relying on the large invariant-mass tail.

CONCLUSIONS

So far...

- Theory-informed event reconstruction using the matrix-element directly.
- RL navigates the particle–parton assignment space.
- Lorentz-equivariant transformers for speed and efficiency.
- The assignment can be reused for interpretable & explainable physics inference.

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- Detector-level reconstruction.
- Higher-order effects.
- Showering + hadronisation.
- Jet substructure.
- Application on realistic analysis tasks.

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Thank you!