Anomaly Detection in Collider Physics via Factorized Observables

Raymond Wynne

Based on work with Eric Metodiev and Jesse Thaler

Preprint and code coming soon!

ML4Jets 2023 - 07 November 2023

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How to Become a FORCE Wielder

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Introduce new method with different assumption: **factorization** [1708.02949, 1802.00008, 2002.12376]

What is factorization?

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Factorization: physics at different energy scales approximately independent

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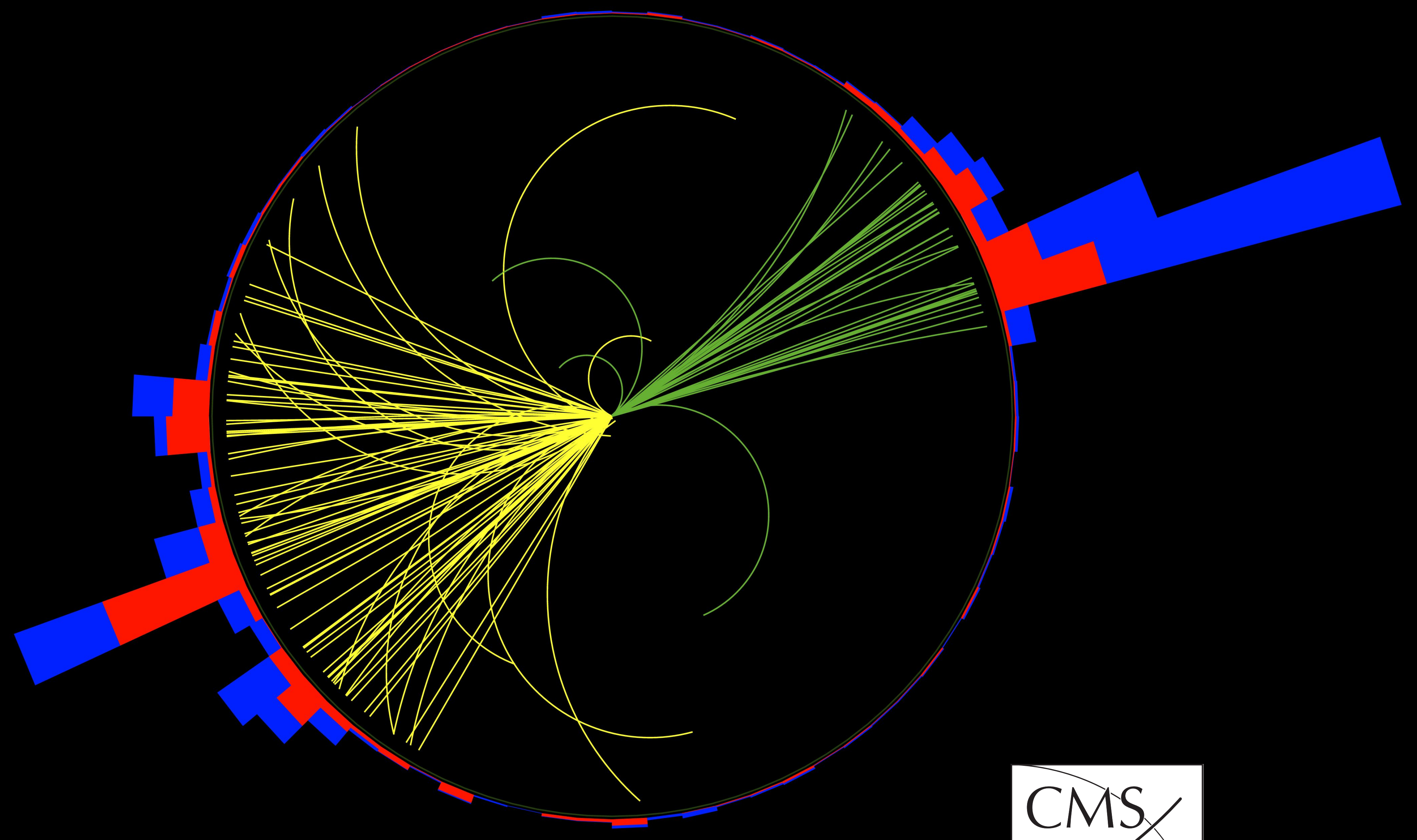
Canonical example: ***jets***



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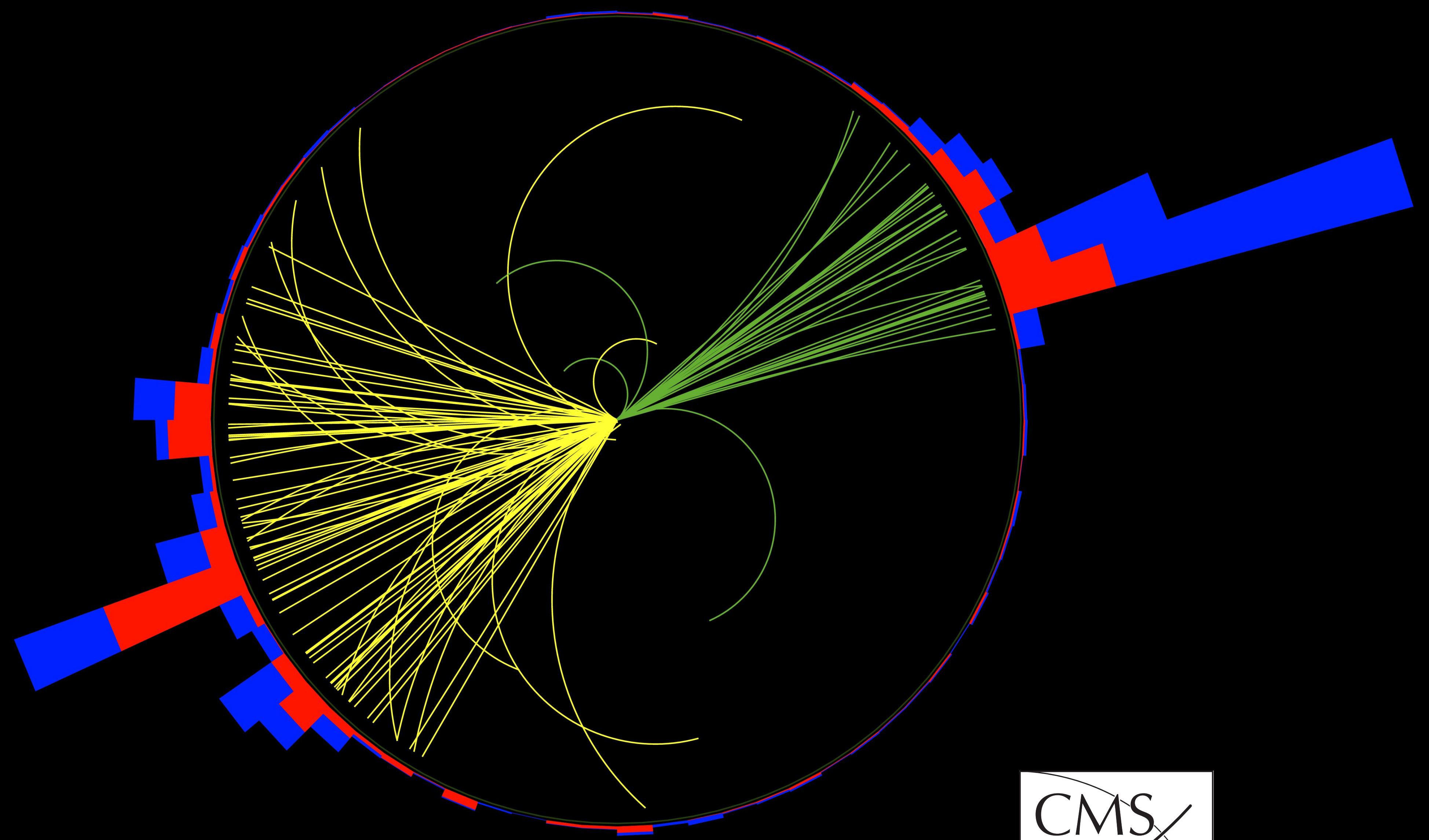

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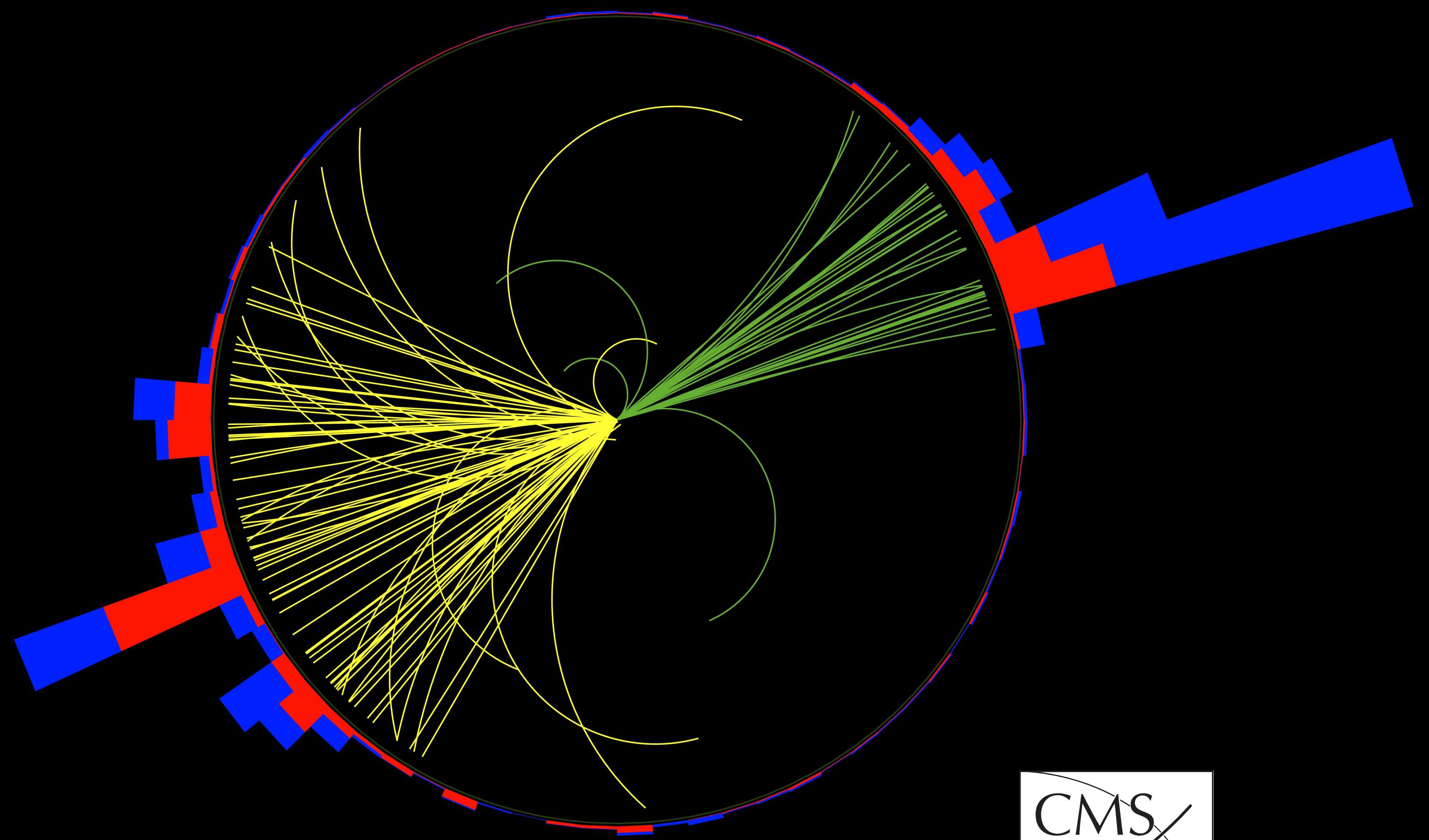

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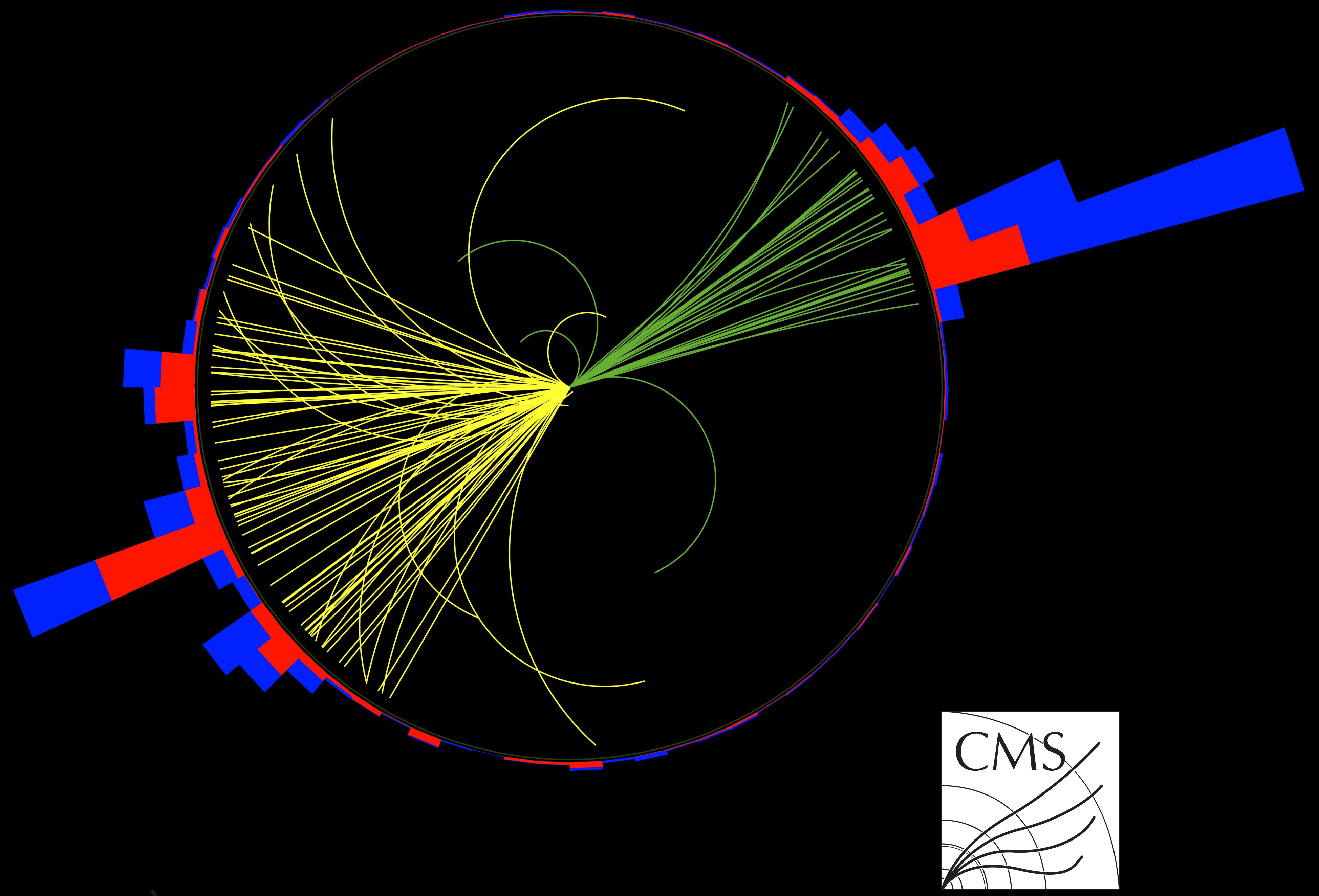

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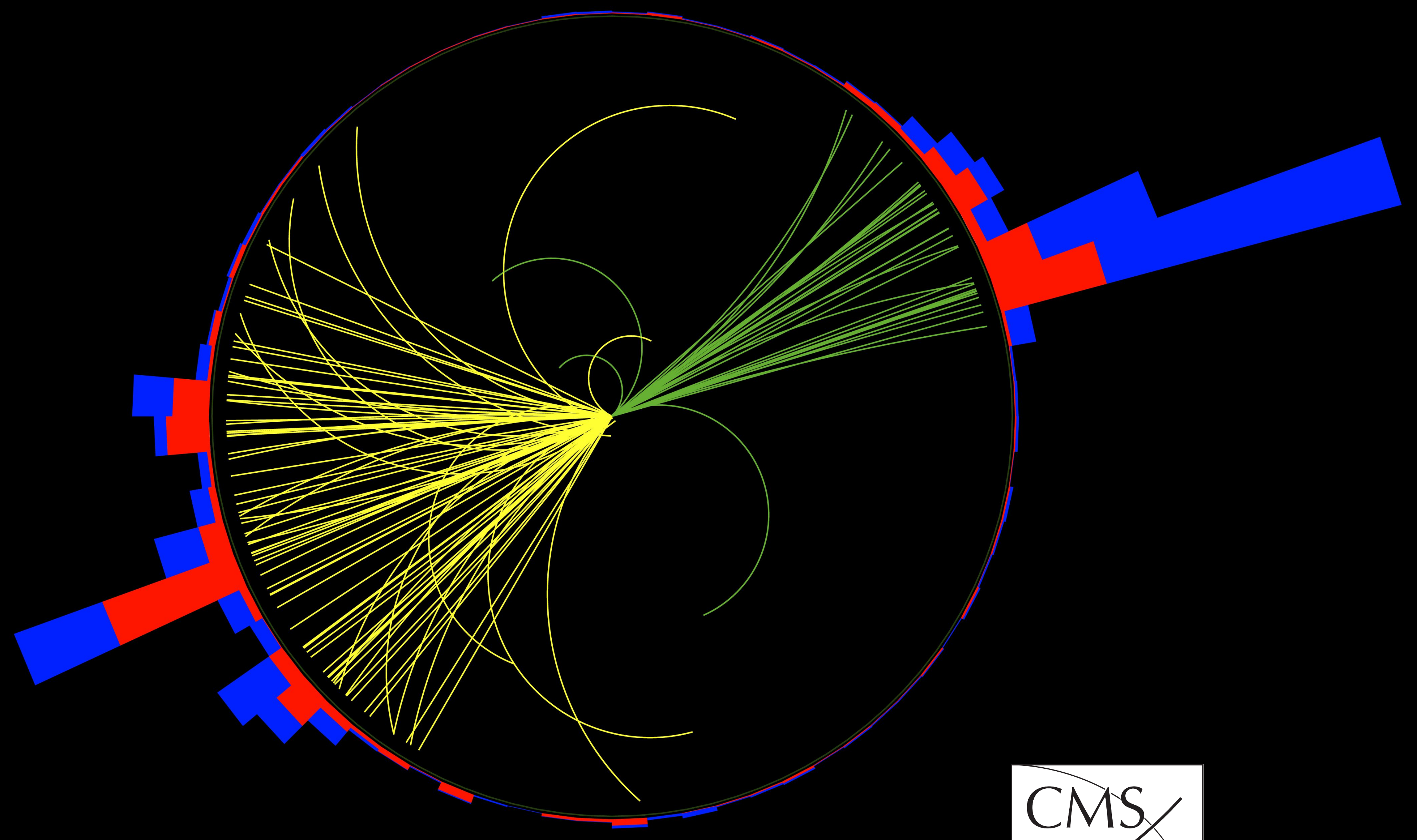

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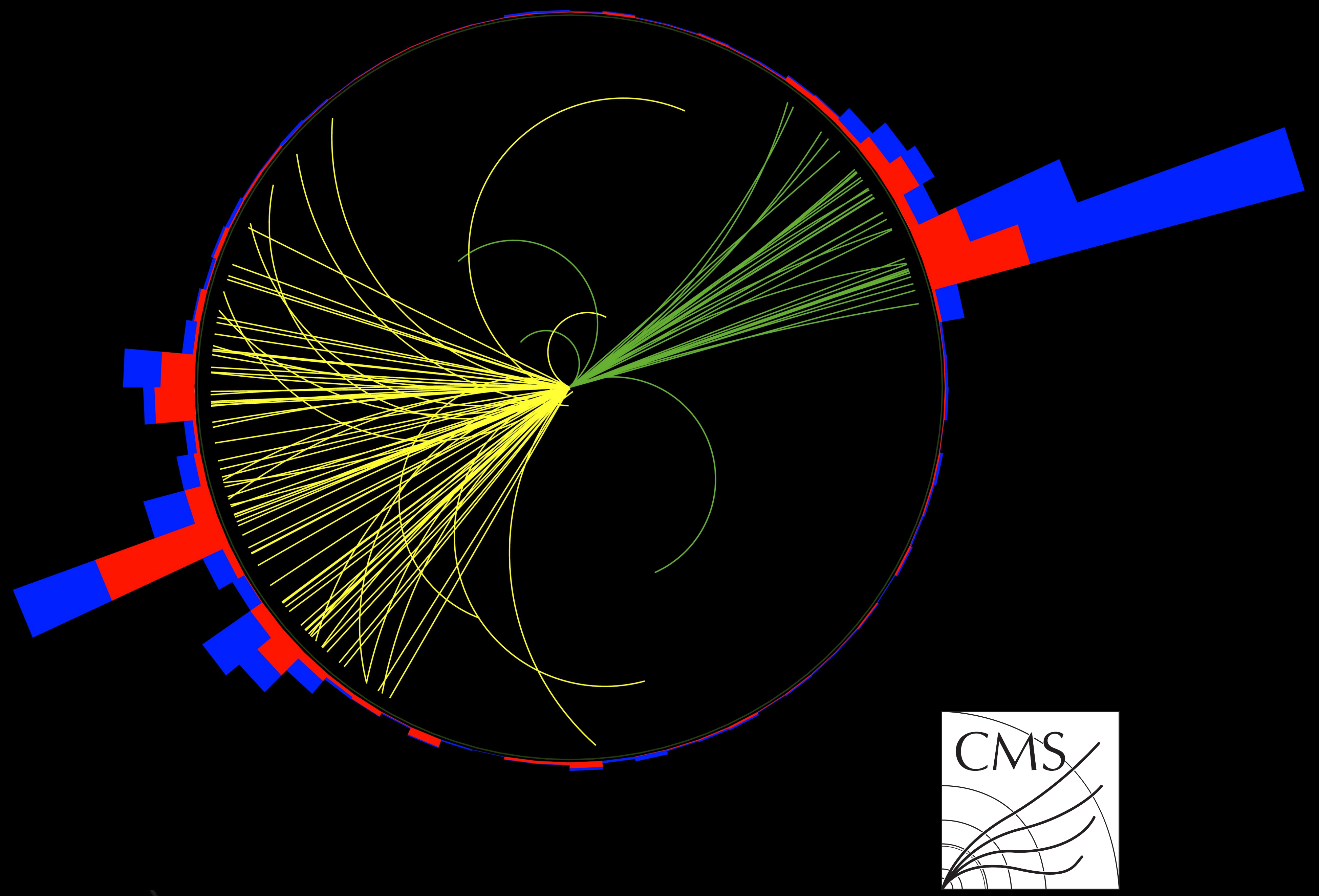

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[1108.2701]

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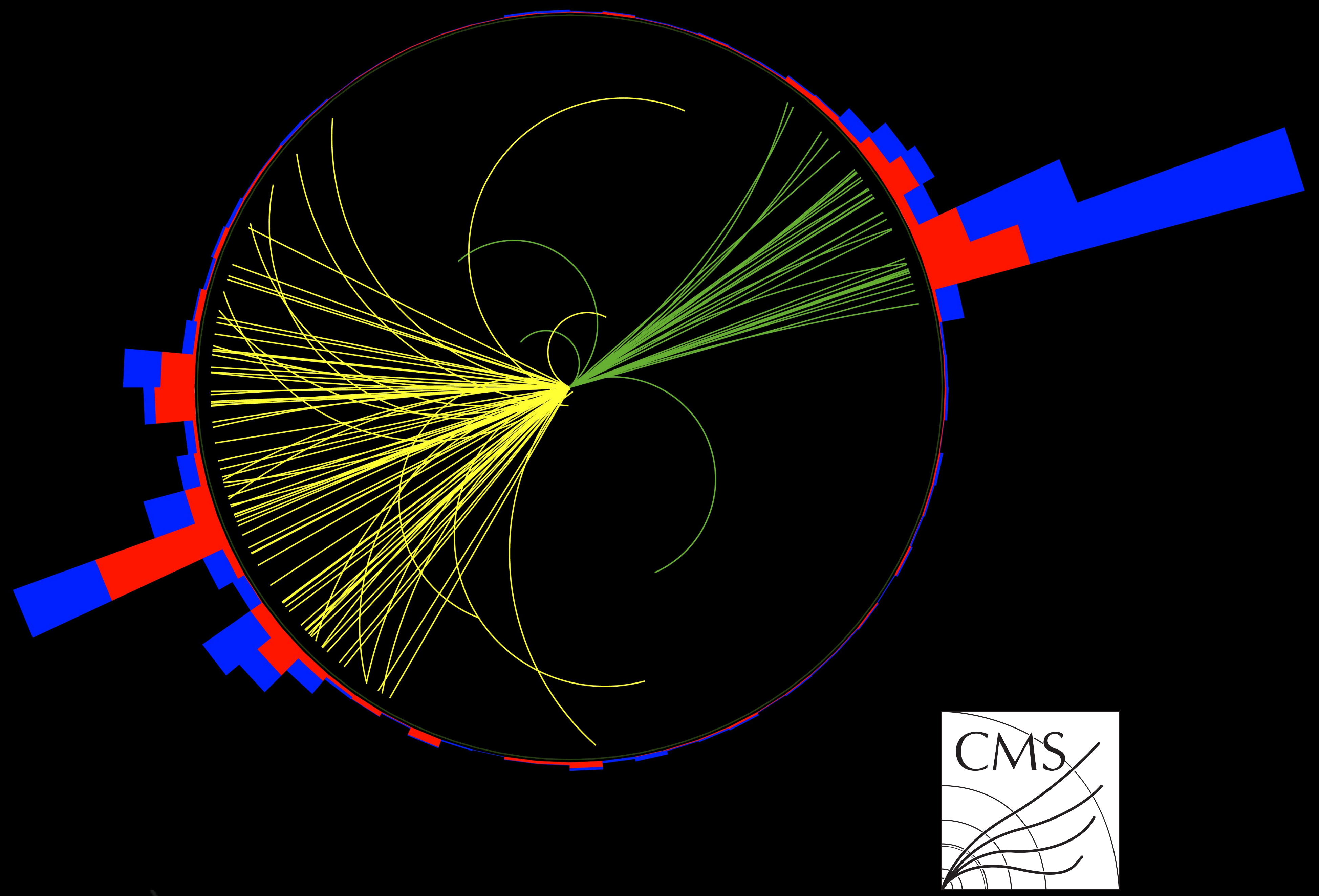

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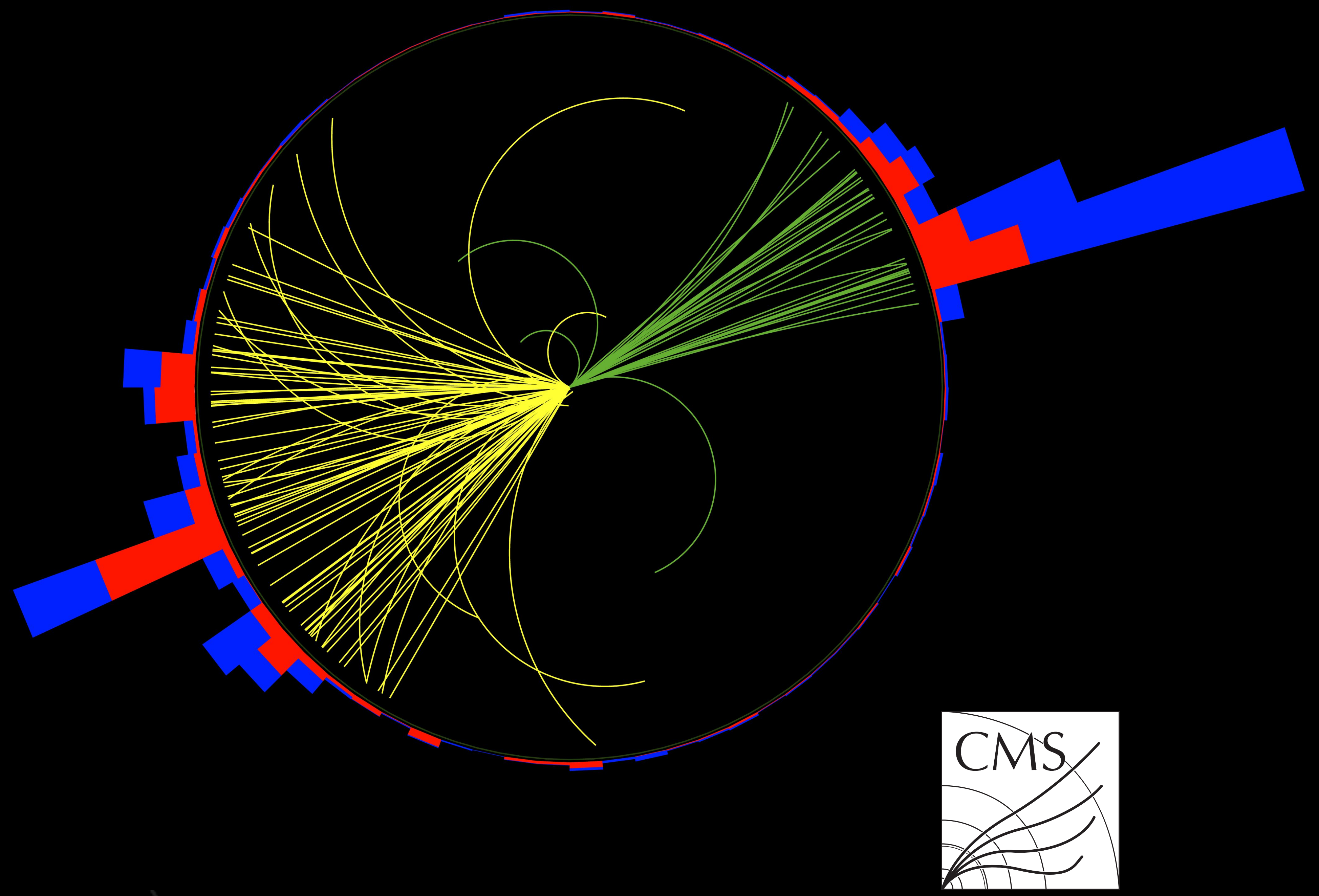

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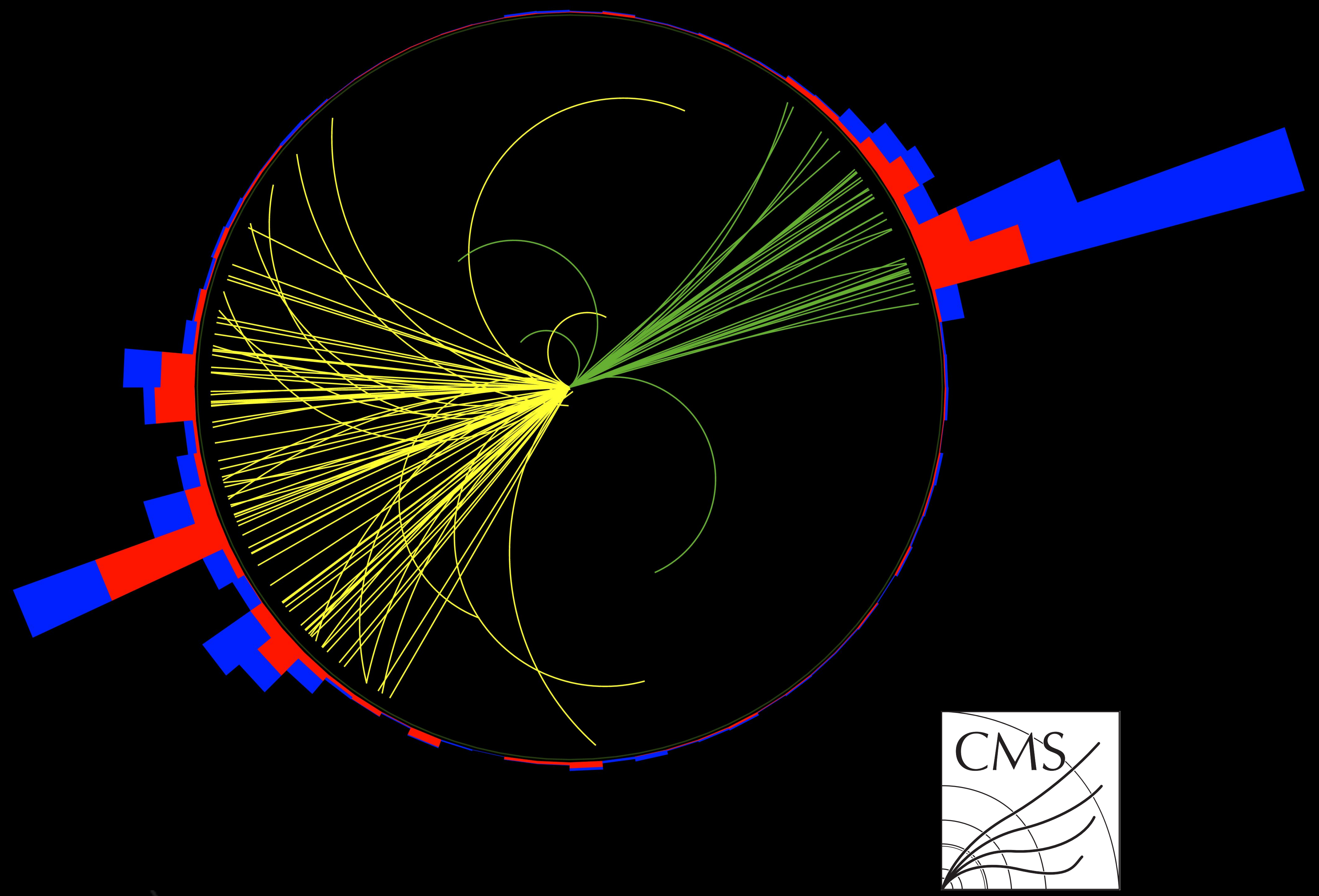

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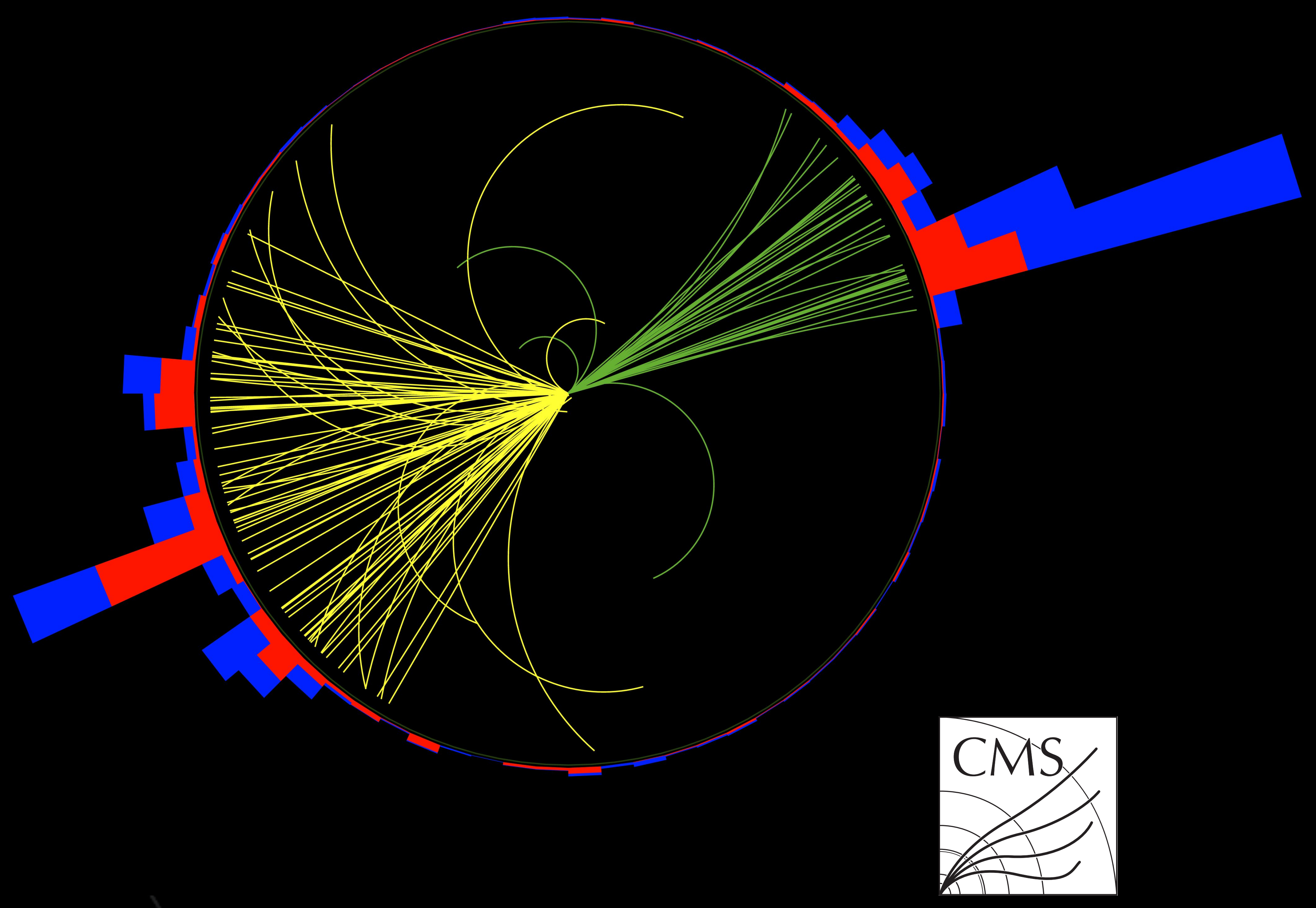

Signal versus Background Factorization

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For $f_S = 0$, we get a random classifier

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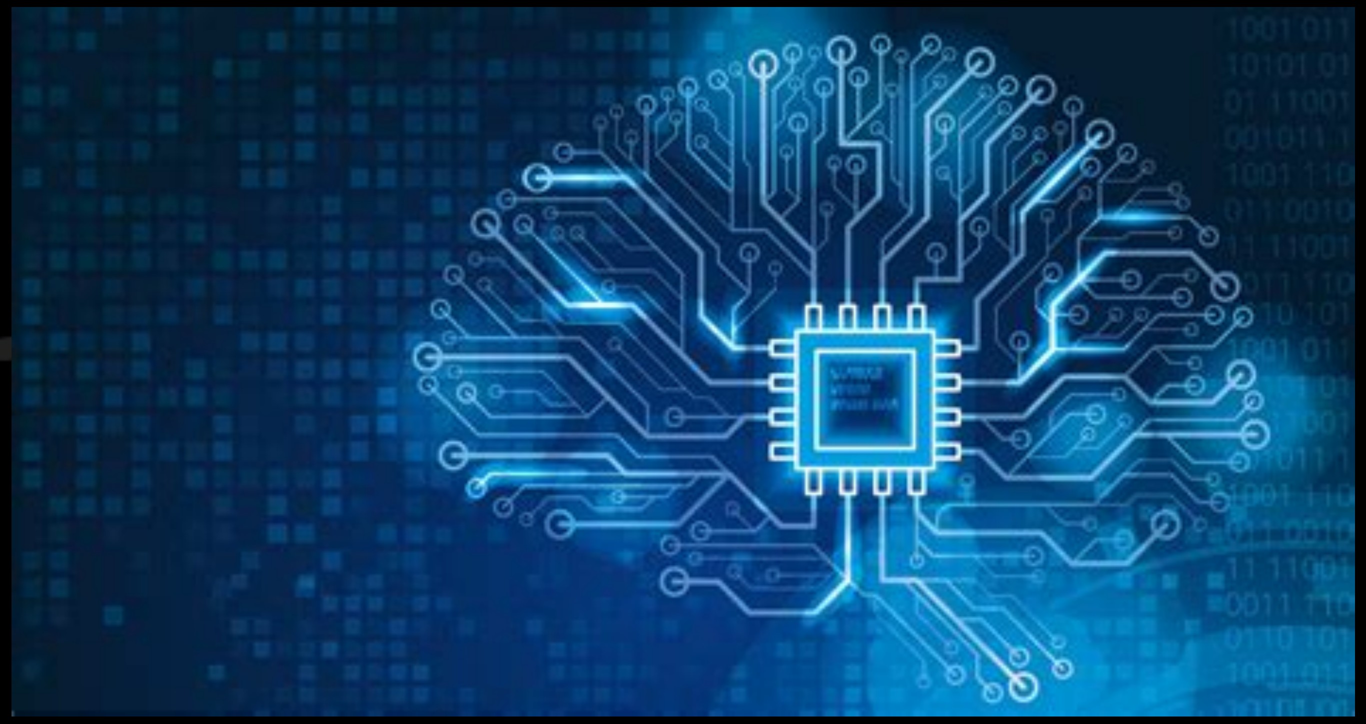

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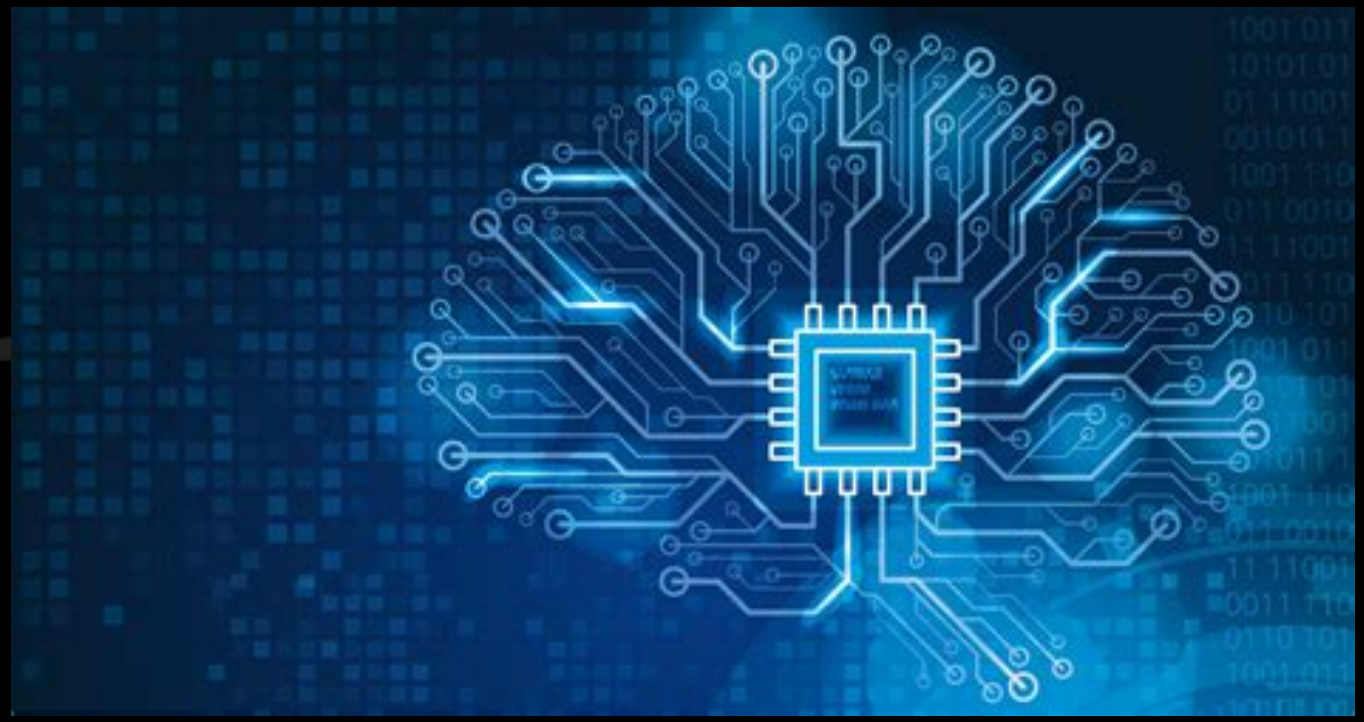

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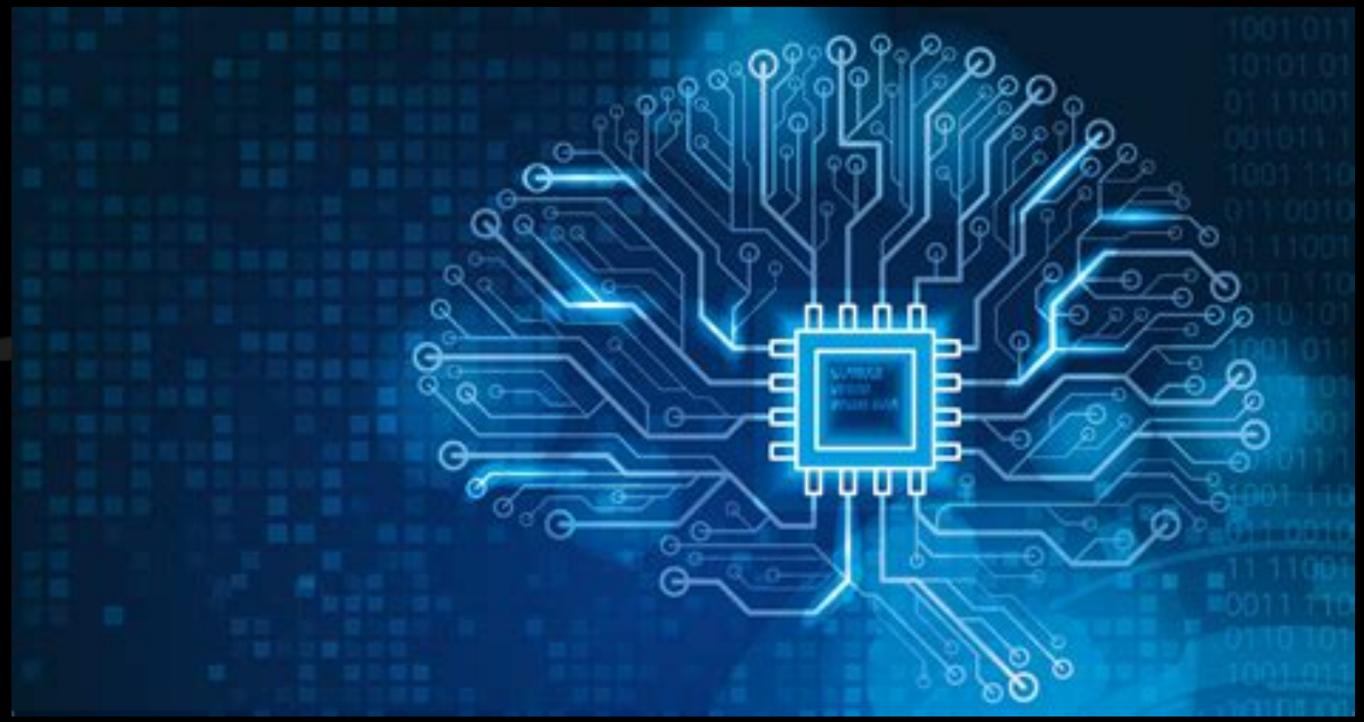

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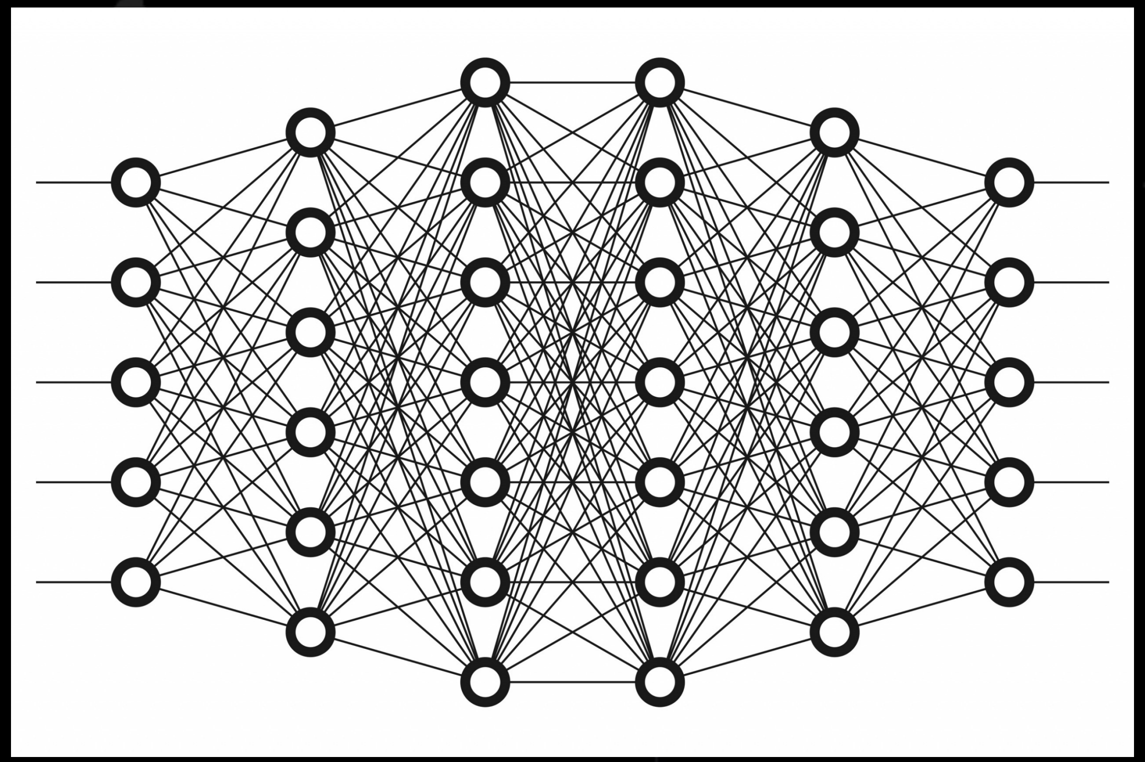

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Factorized Observables for Regressing Conditional Expectation

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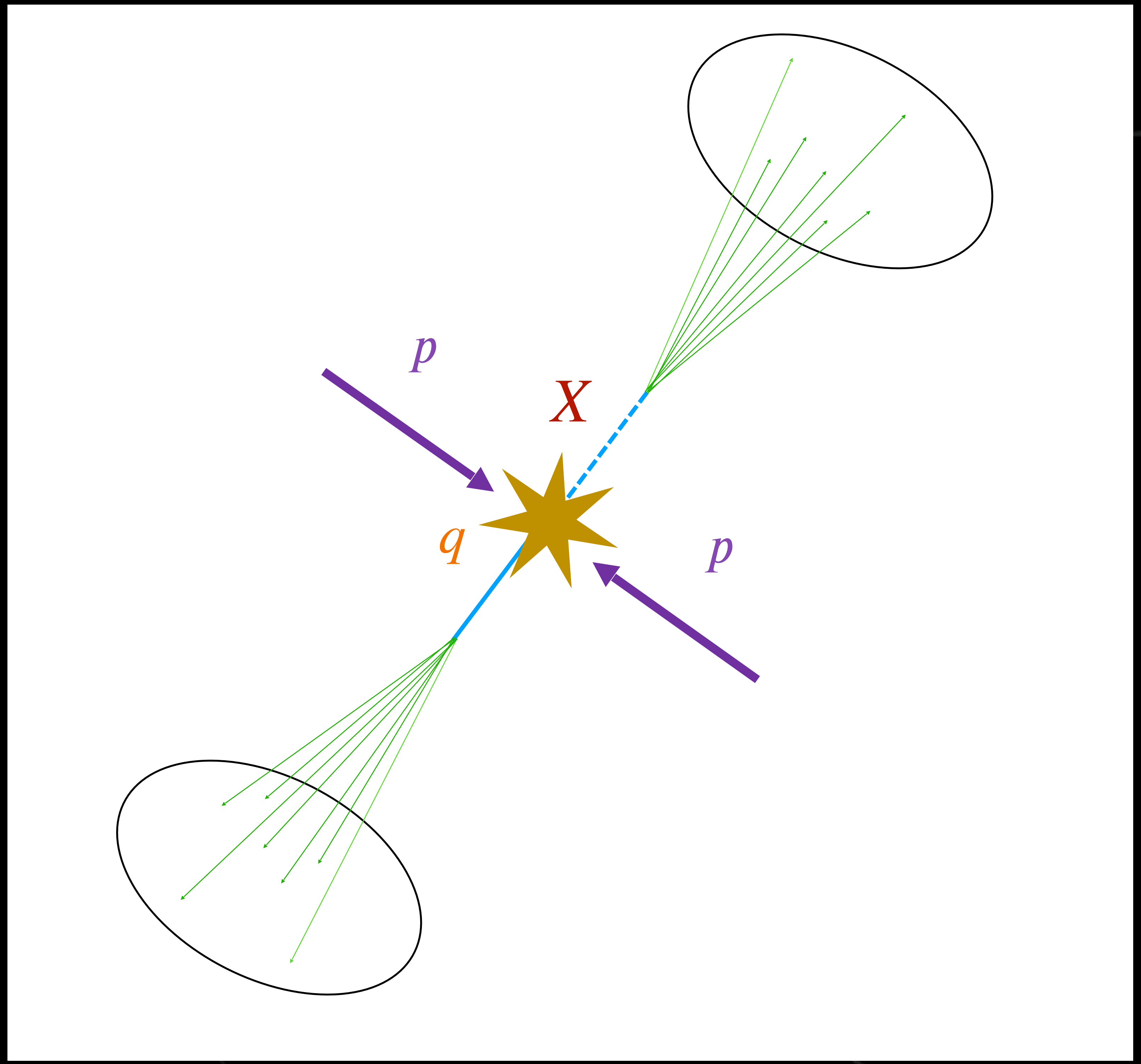

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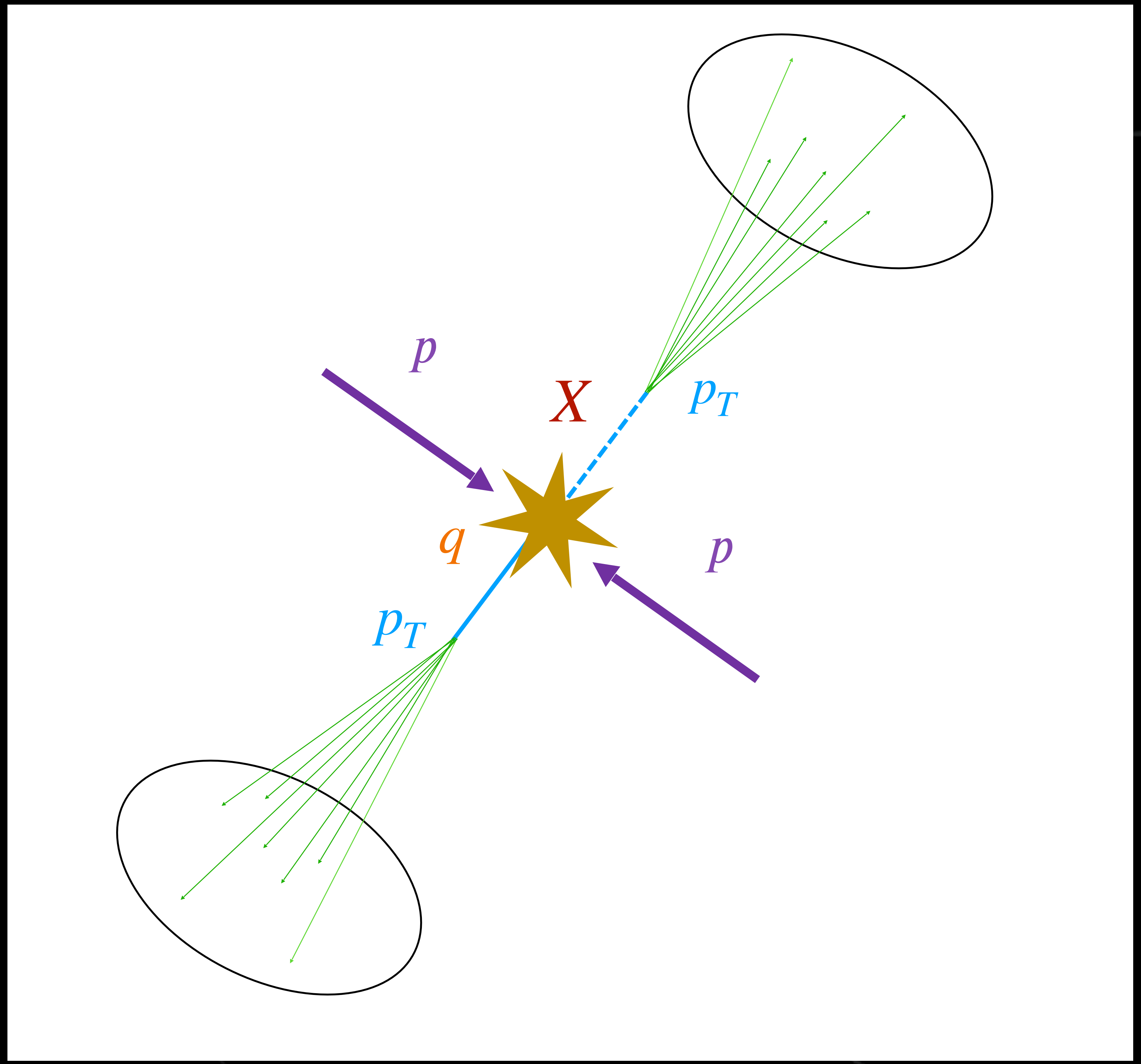

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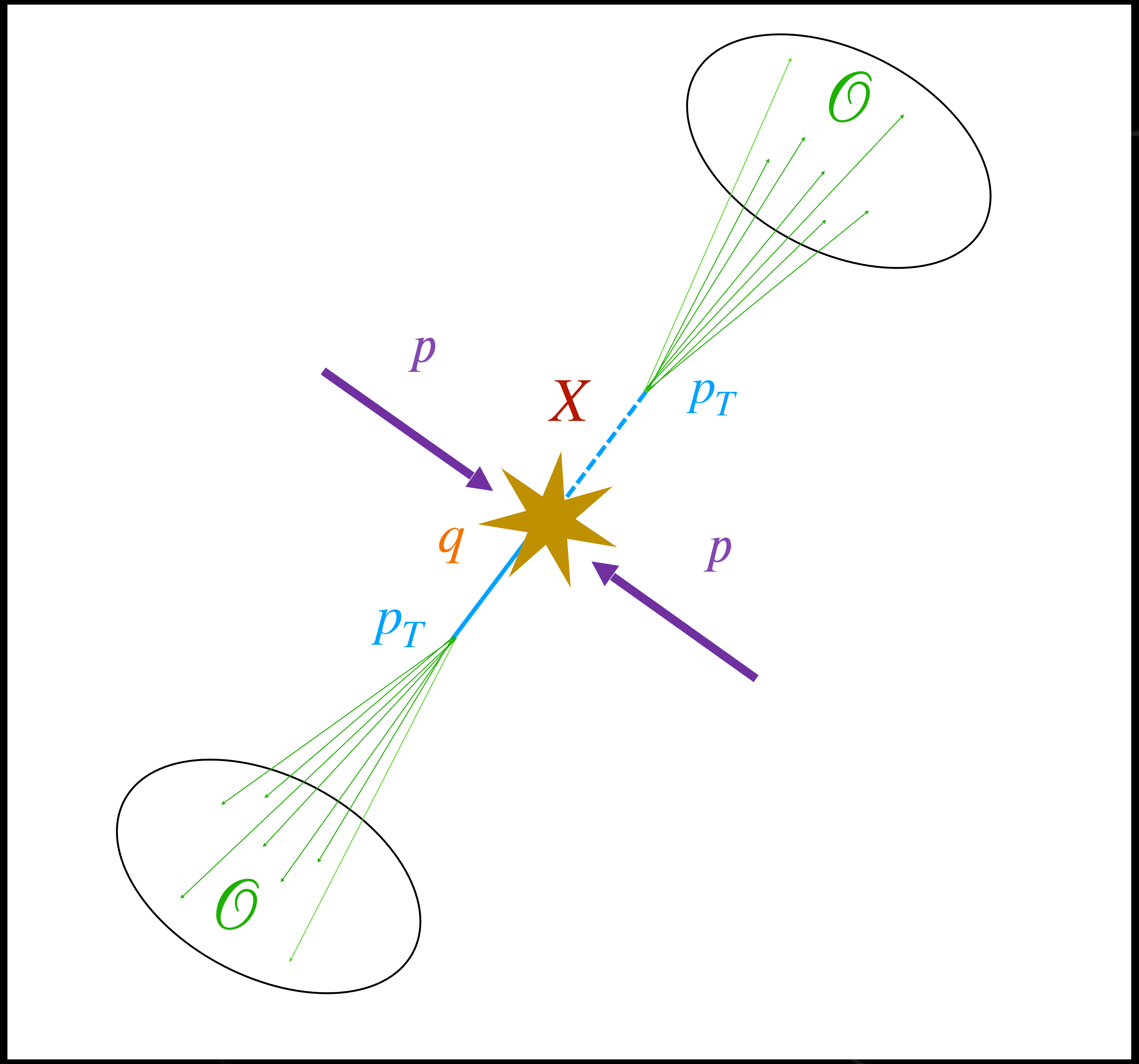

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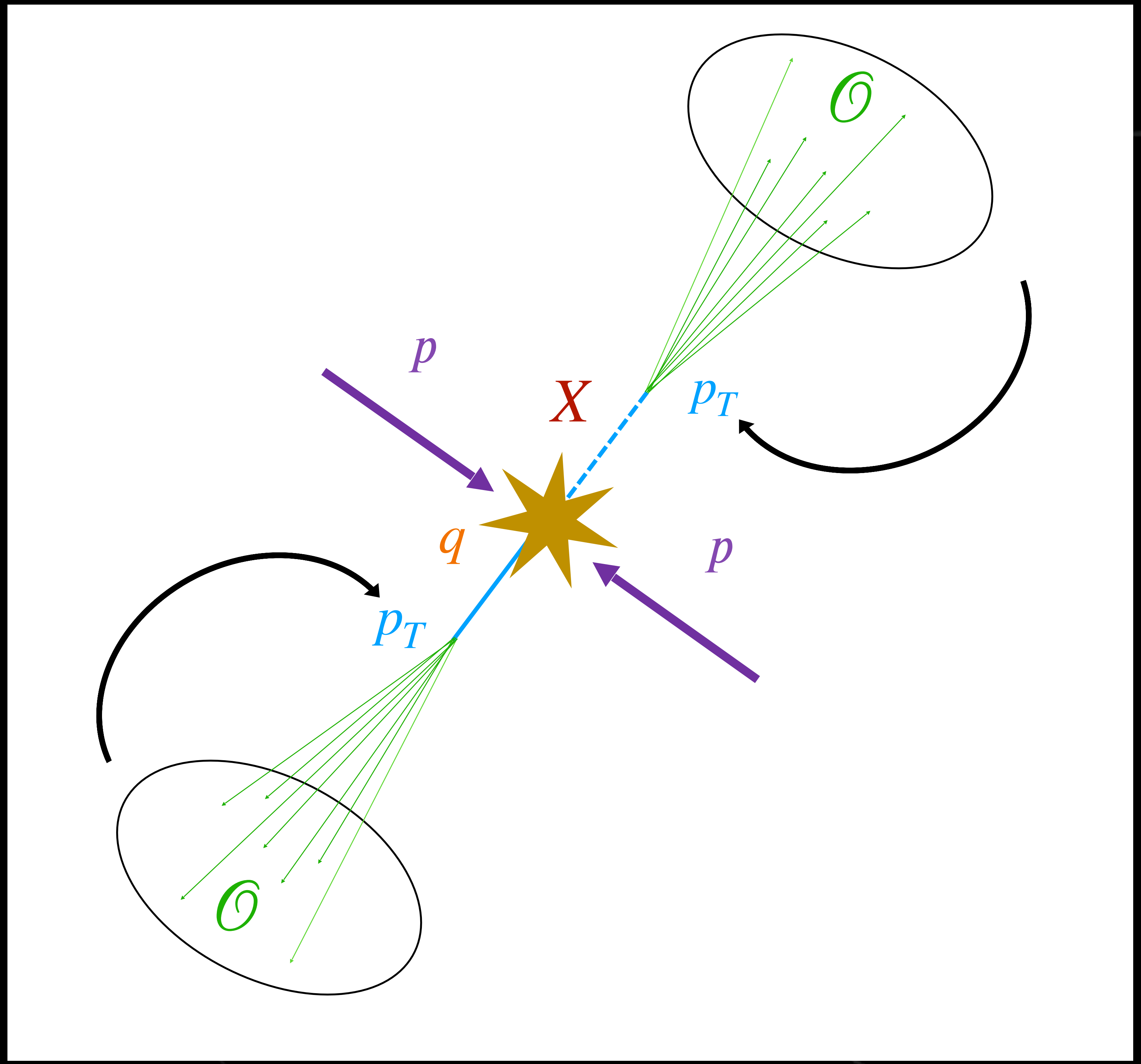

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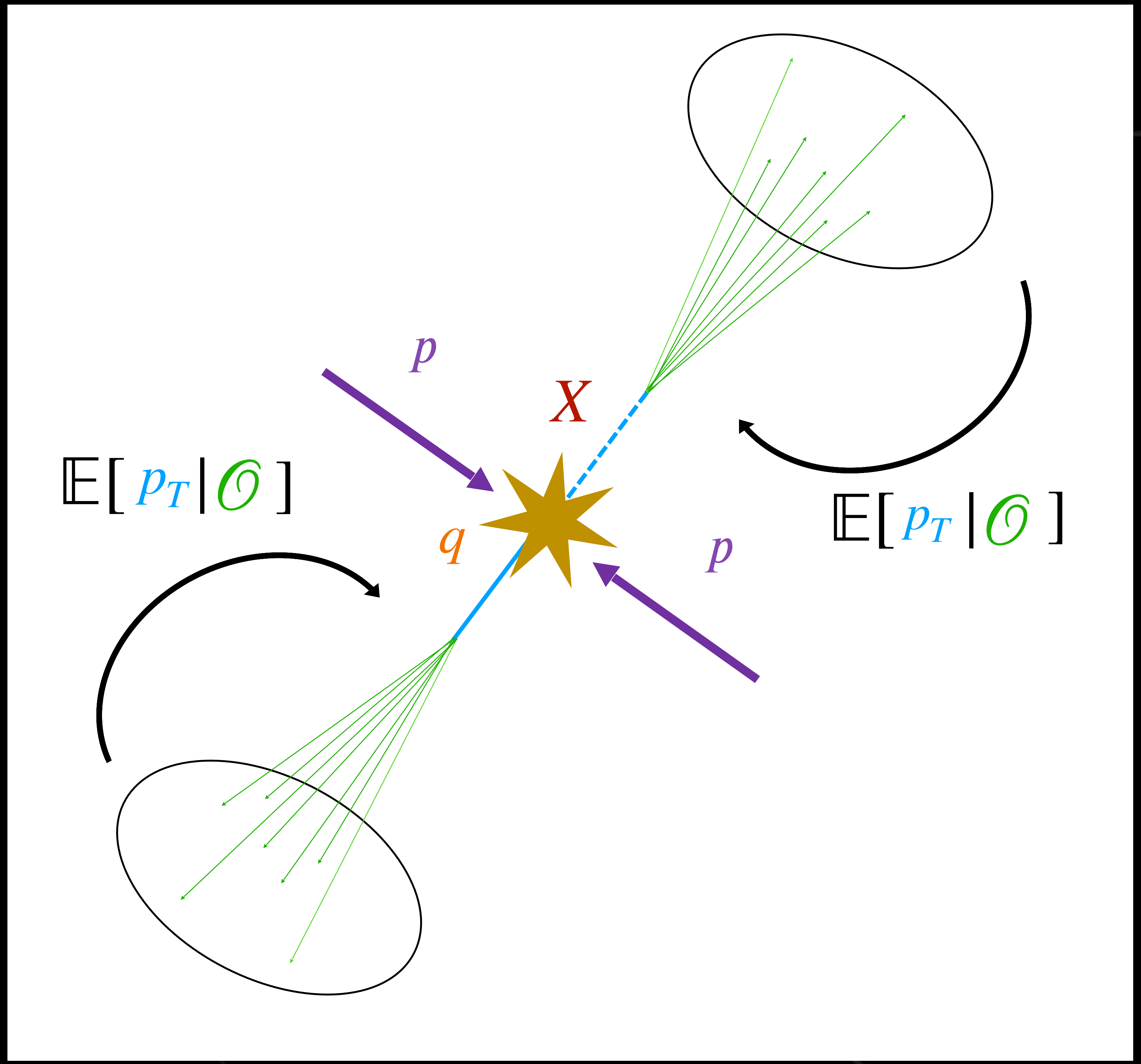

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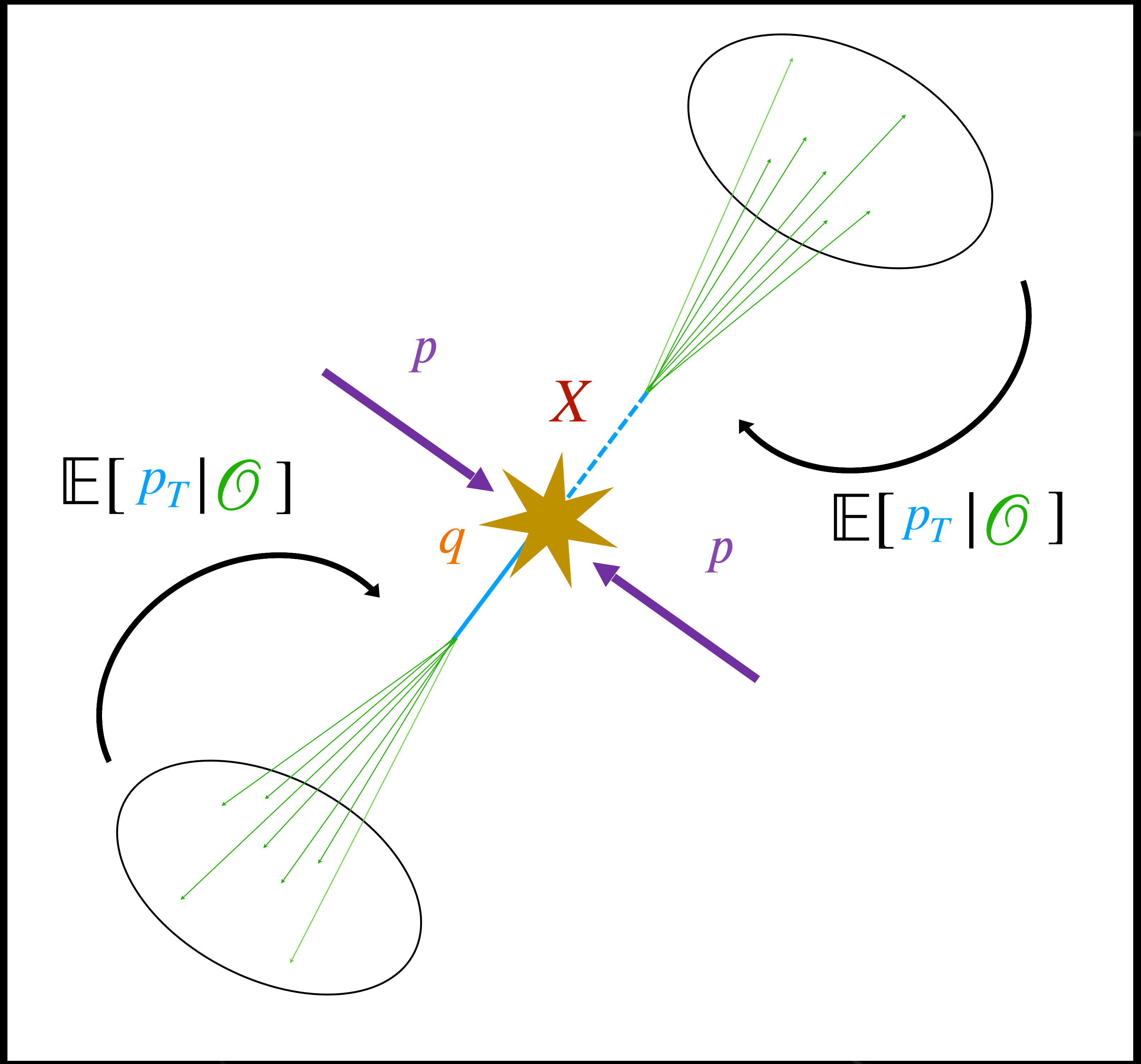

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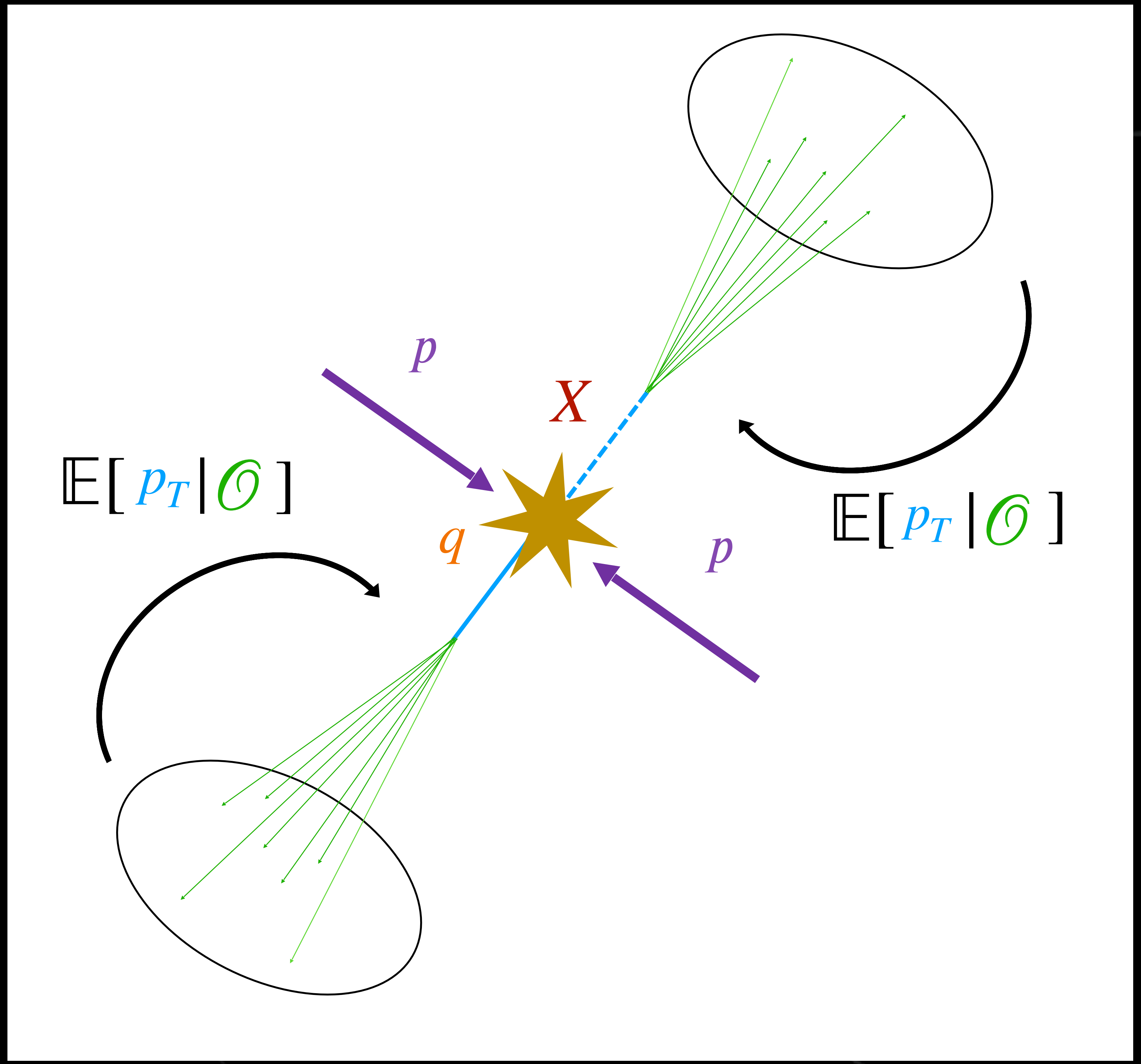

Find anomalies by predicting kinematics from substructure

Use the FORCE Luke

Demonstrations of FORCE:

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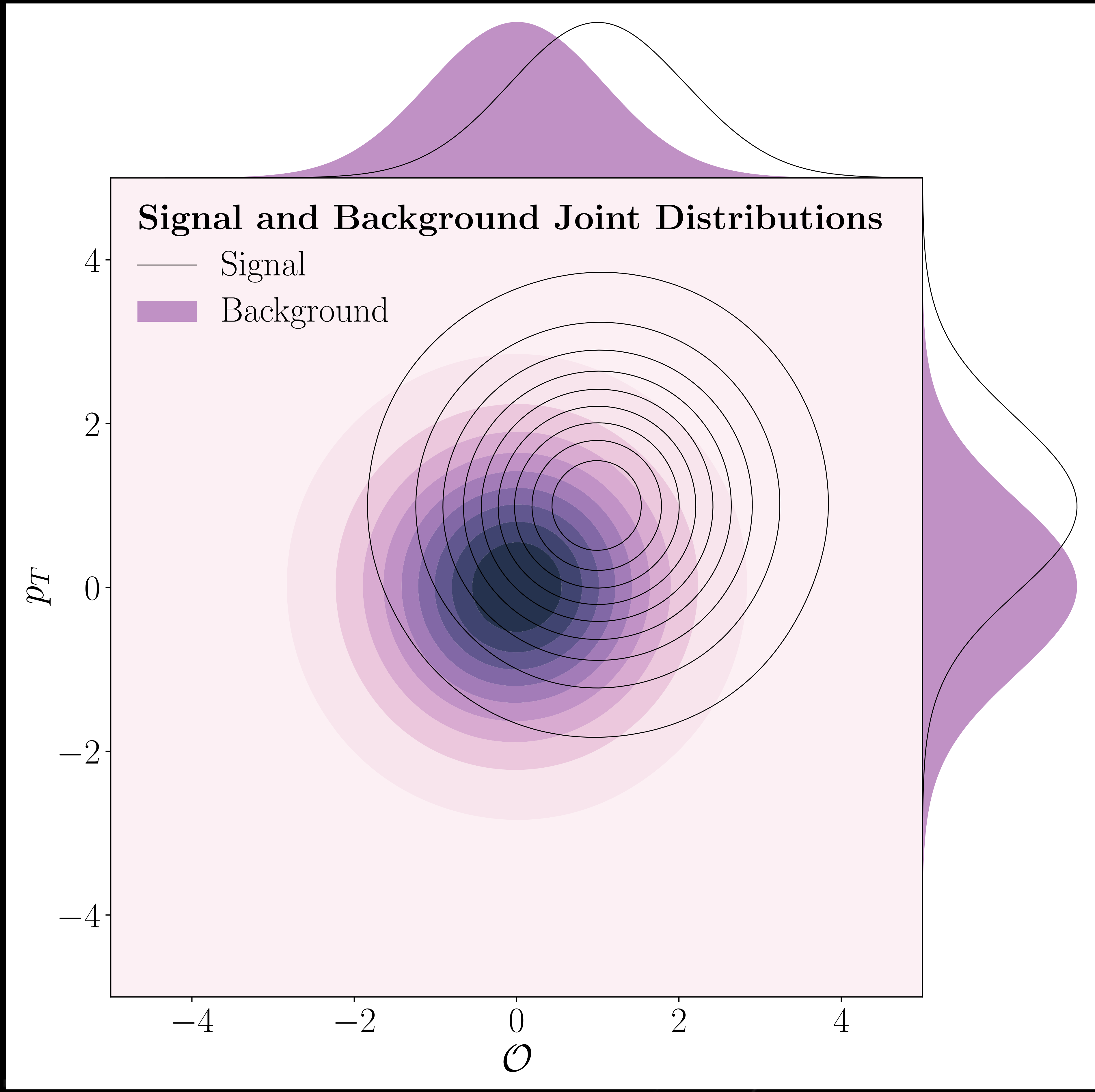
1. Toy Gaussian Dataset

Use the FORCE Luke

Demonstrations of FORCE:

1. Toy Gaussian Dataset
2. LHC Olympics R&D Dataset

Gaussian Simulation



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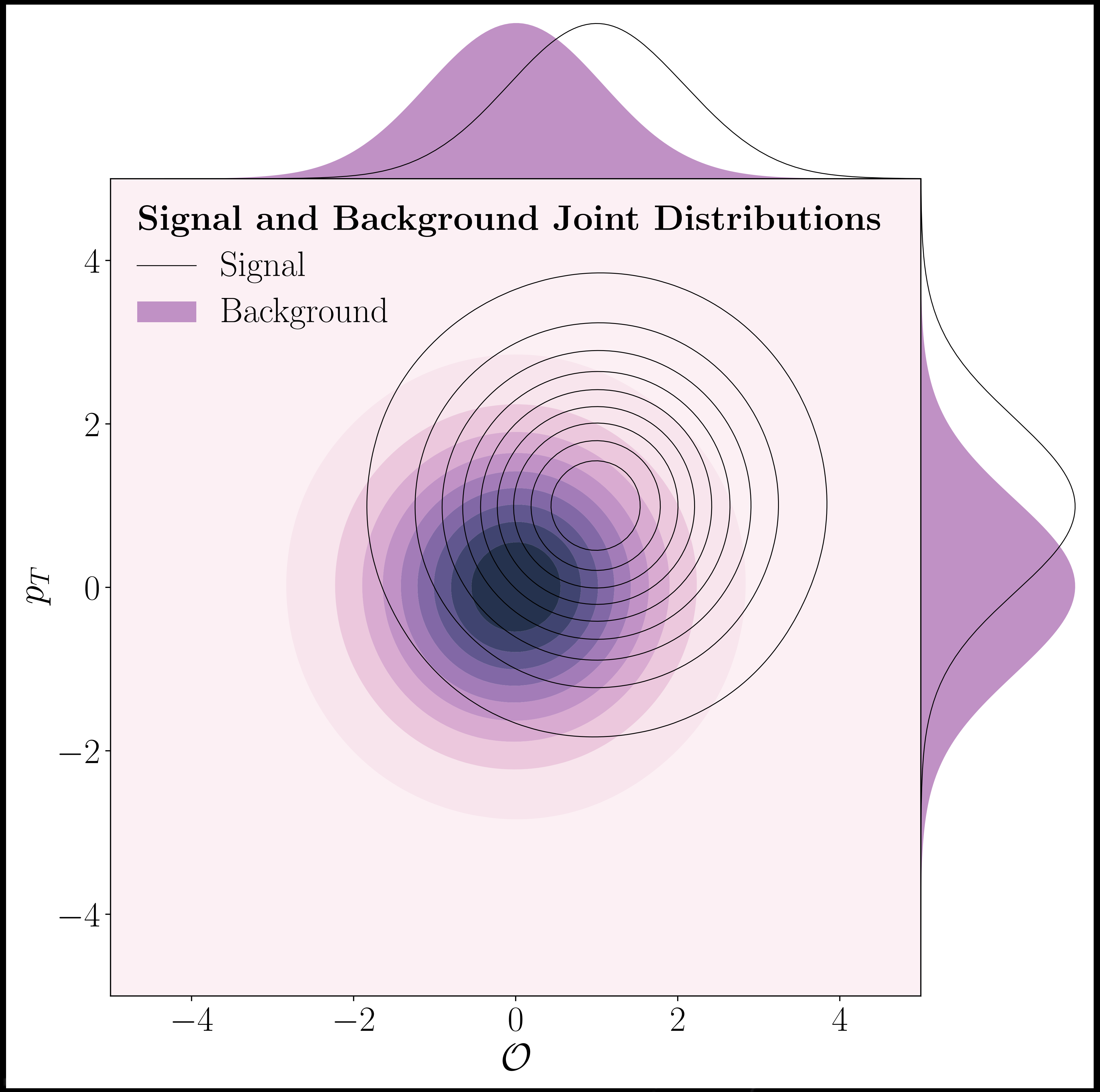

1 kinematic variable, 1 substructure variable

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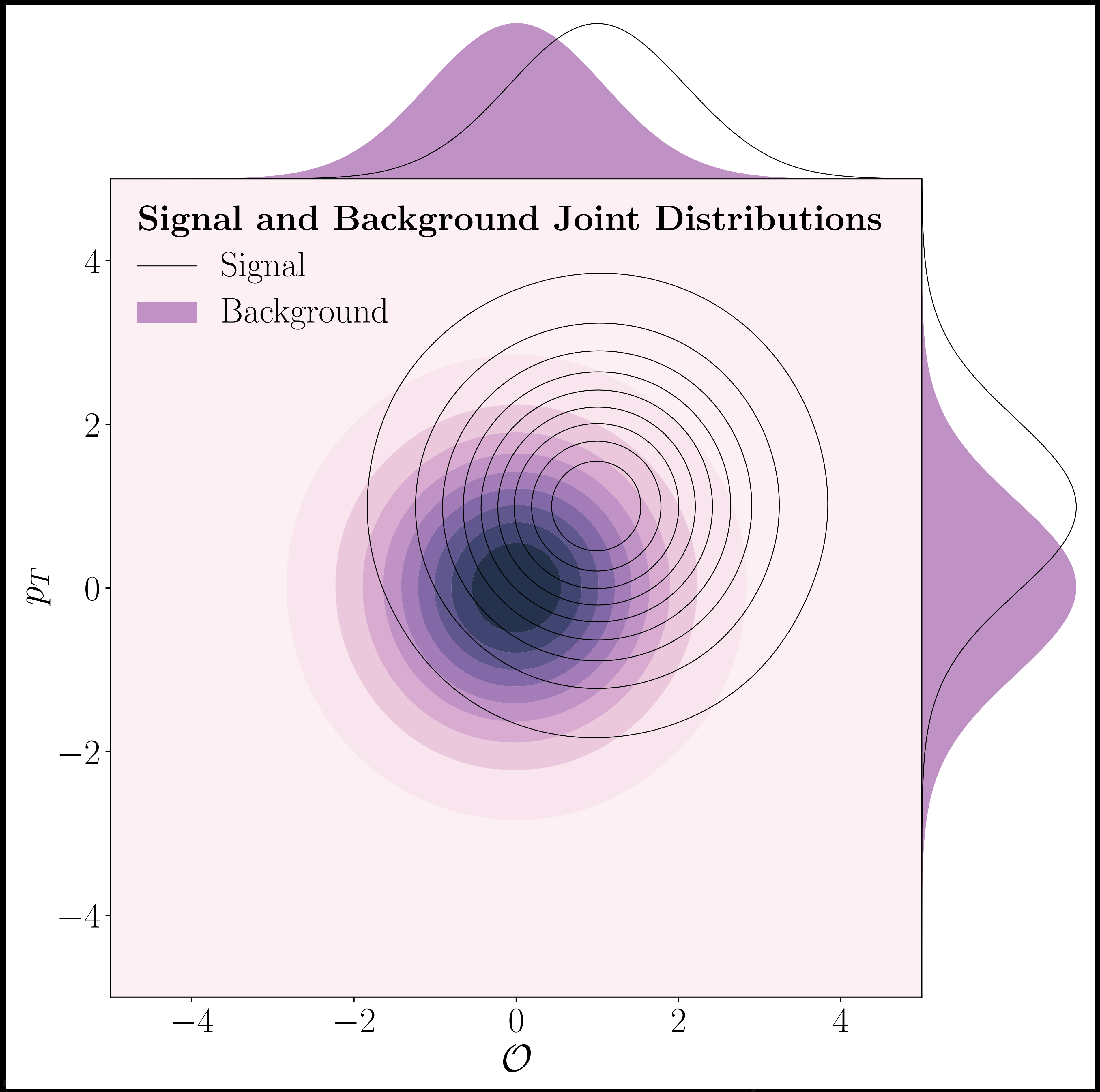

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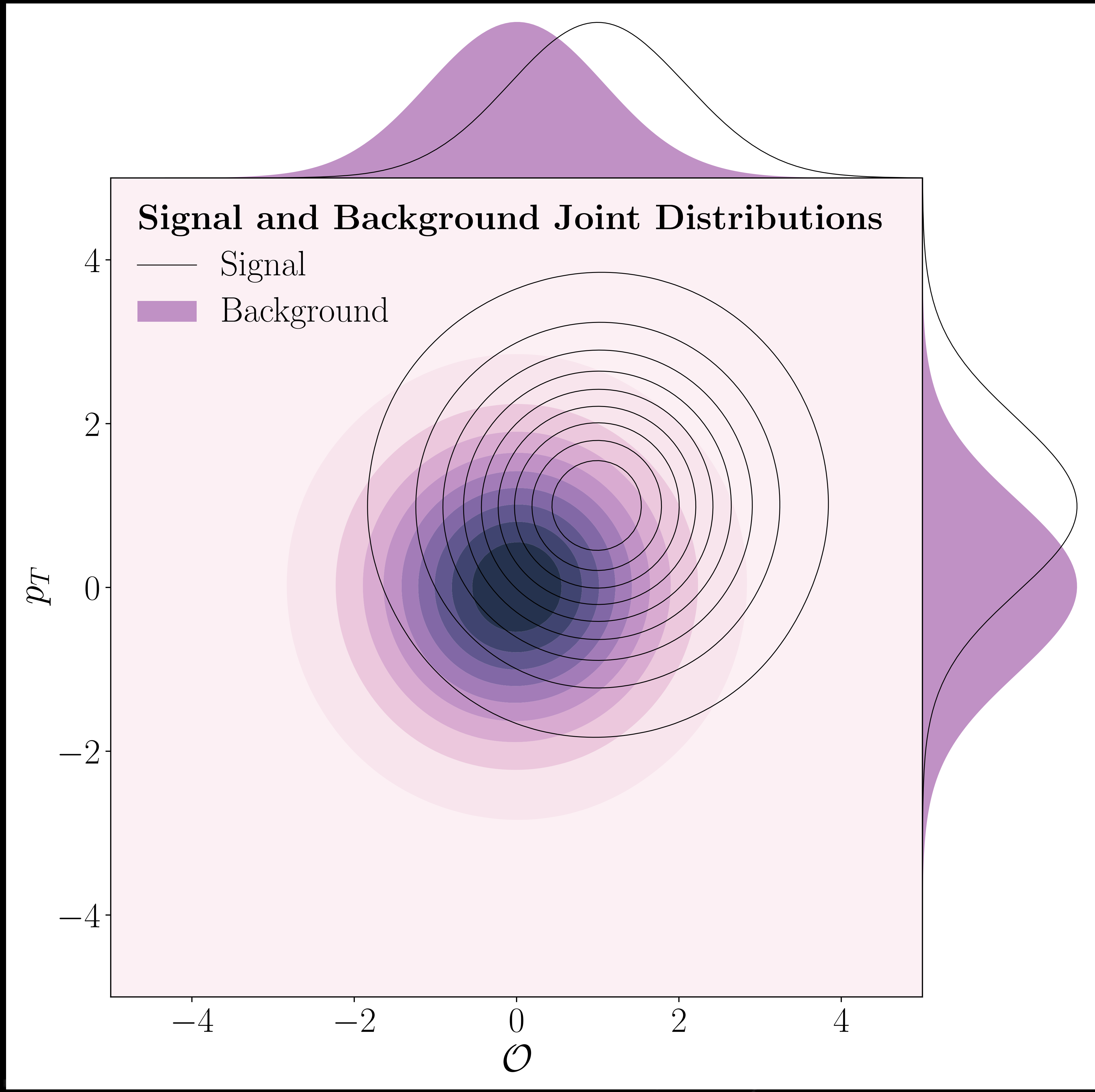

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$f_S \cdot$ 1 million draws from signal model

ROC-AUC for Gaussian Simulation

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- Fully connected network
- 3 layers of 100 nodes
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$\Longrightarrow$

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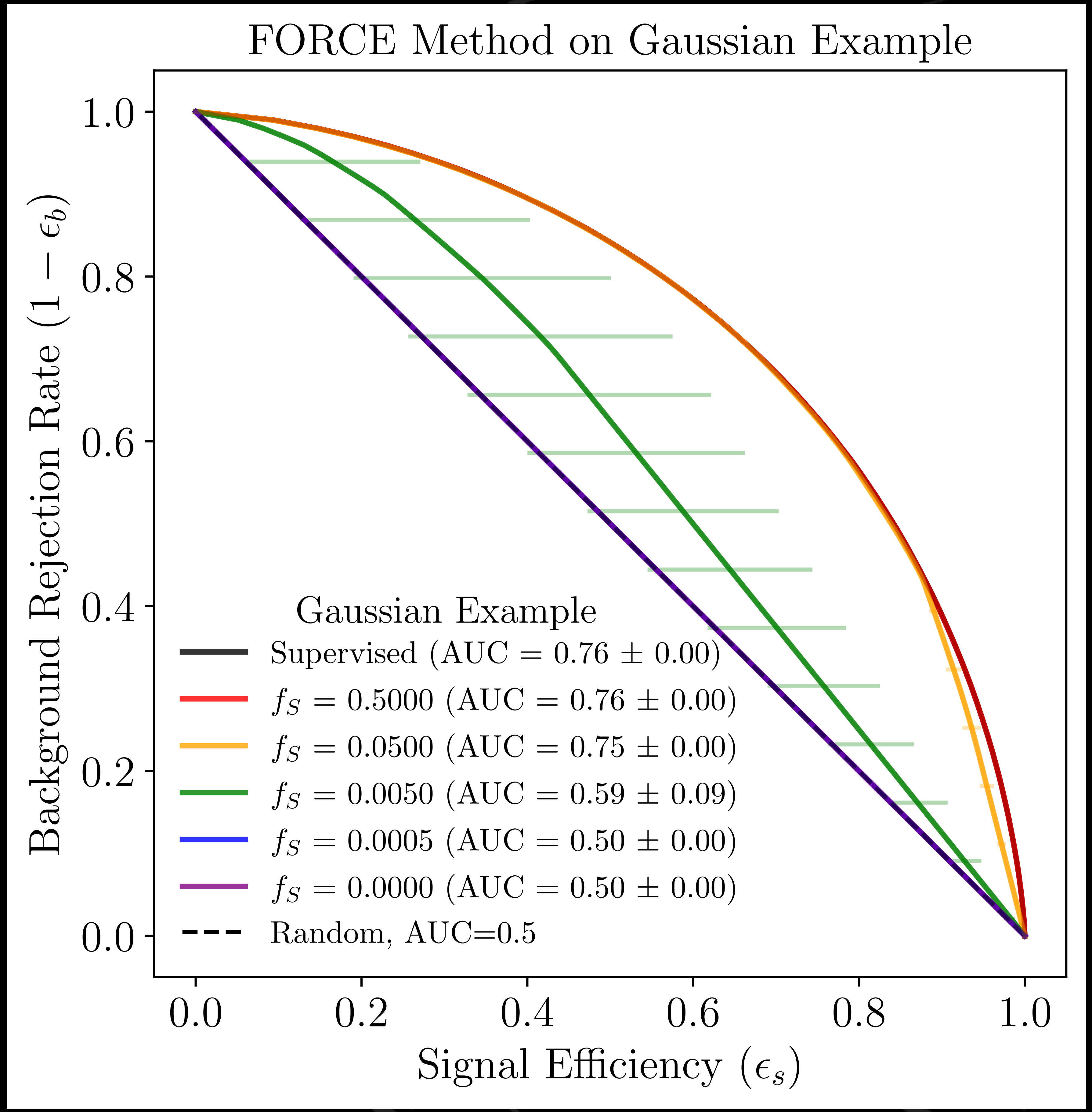

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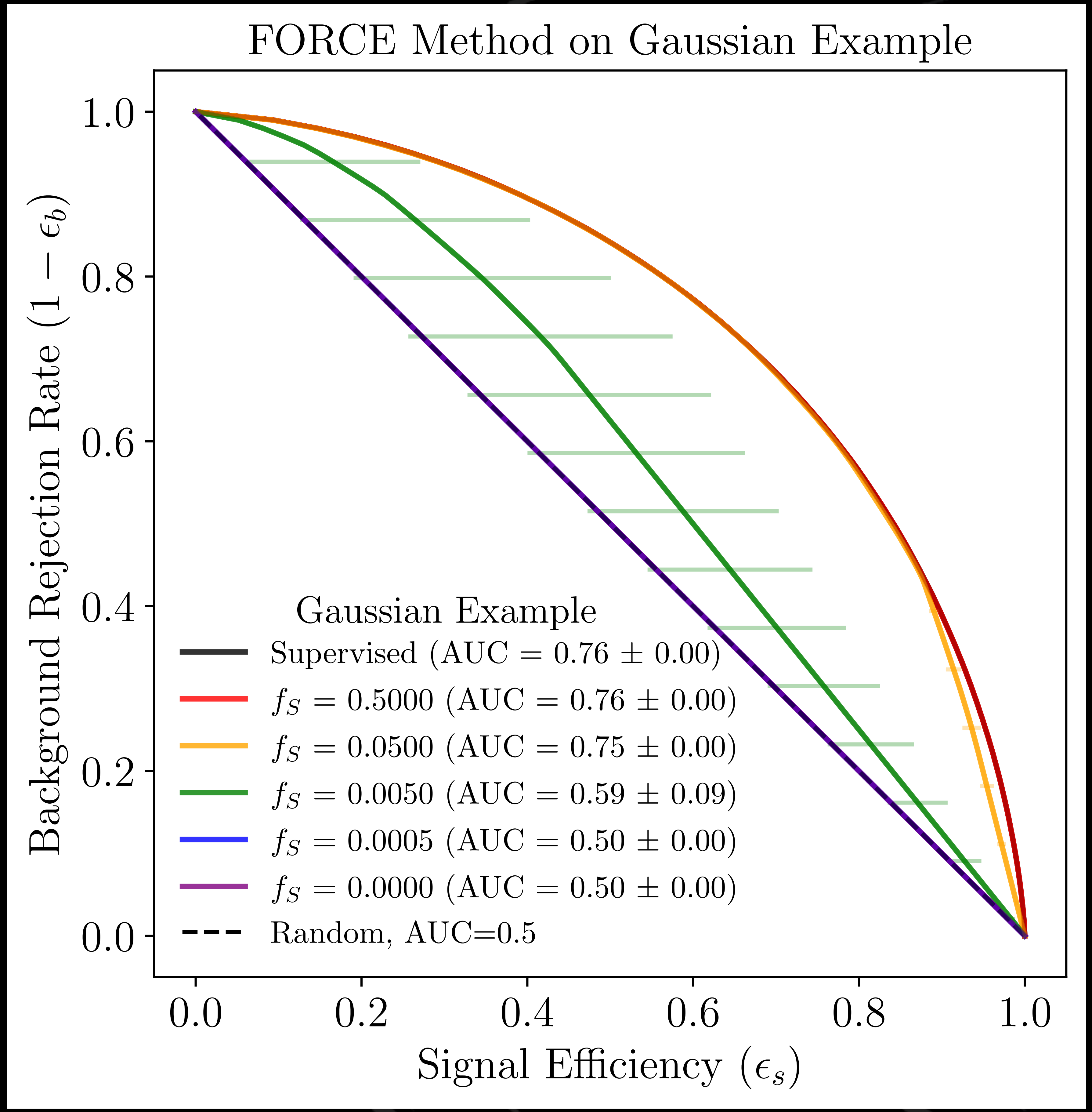

Optimal performance in high signal limit

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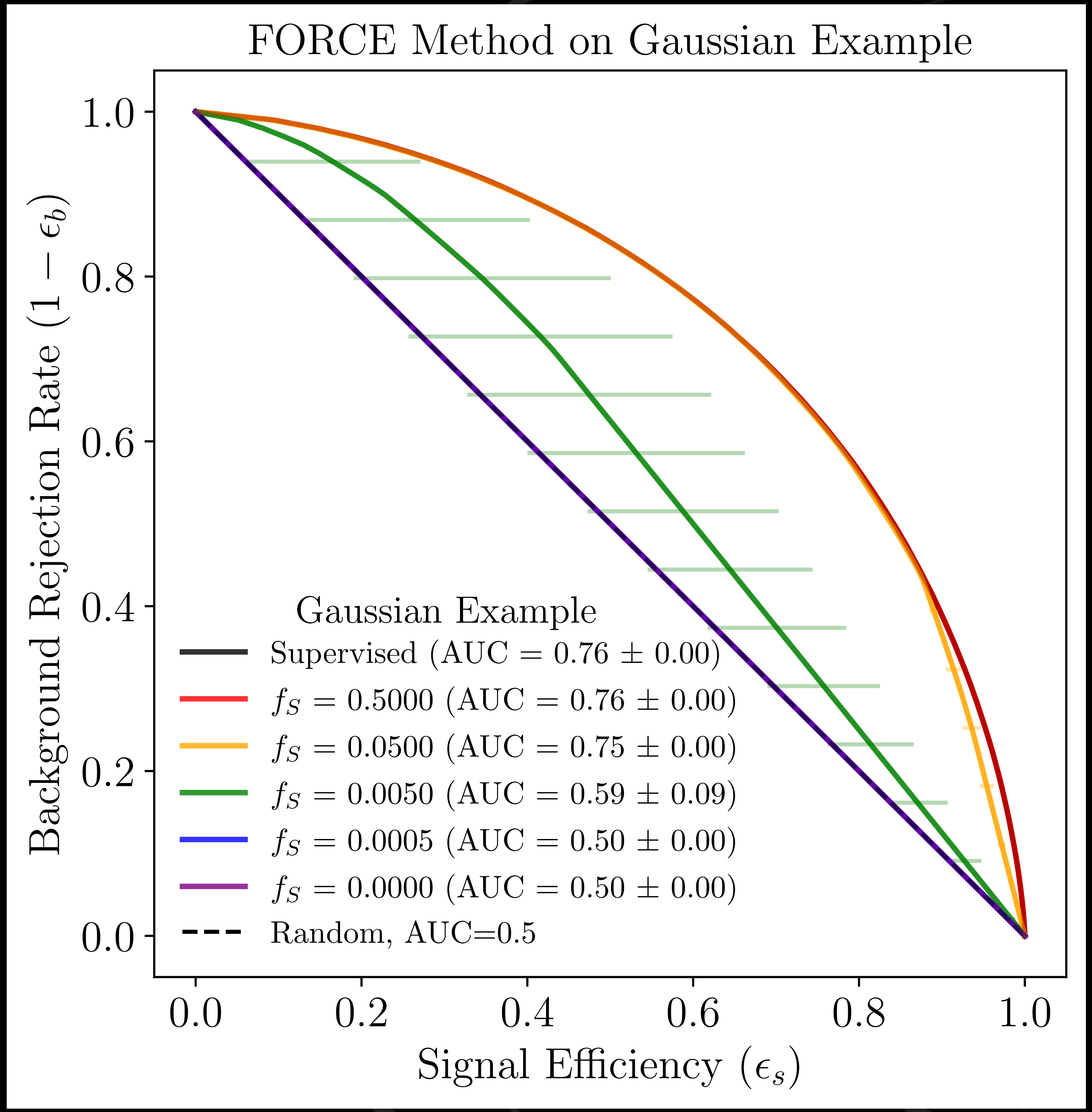
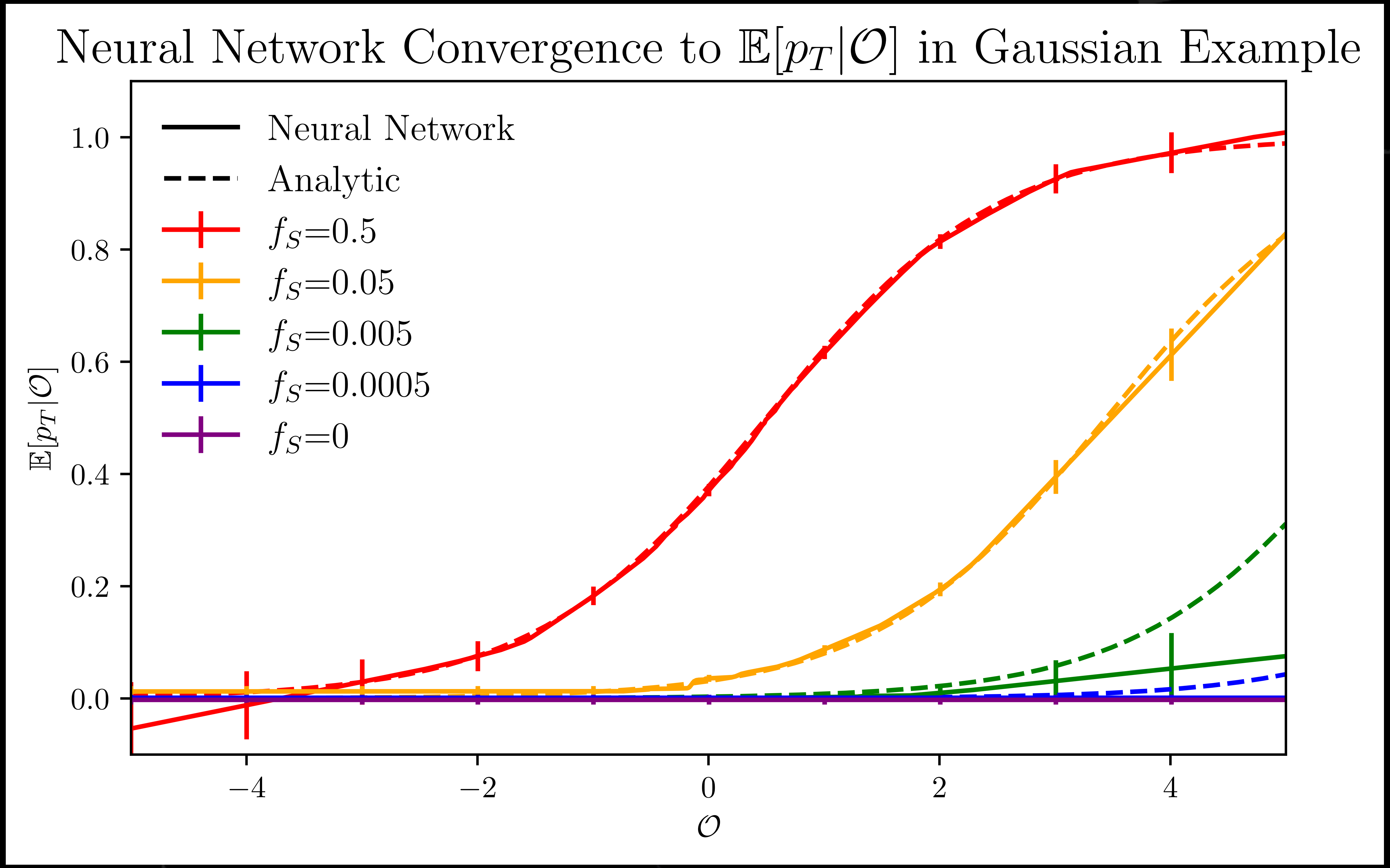


Optimal performance in high signal limit

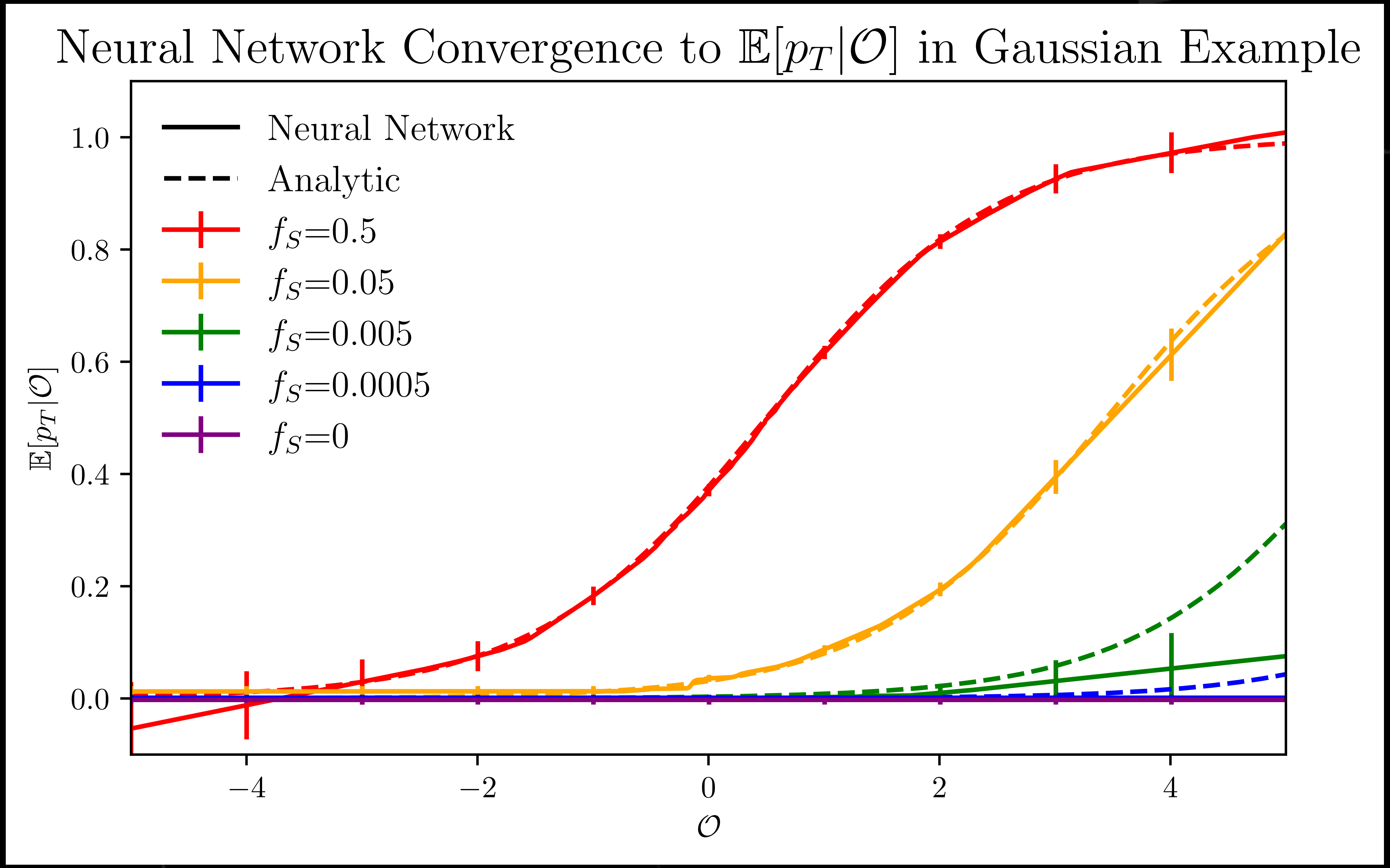
Random classifier in low signal limit

Convergence for Gaussian Simulation



Convergence for Gaussian Simulation

Since we constructed from Gaussians, can compute $\mathbb{E}[p_T \,|\, \mathcal{O}]$ analytically



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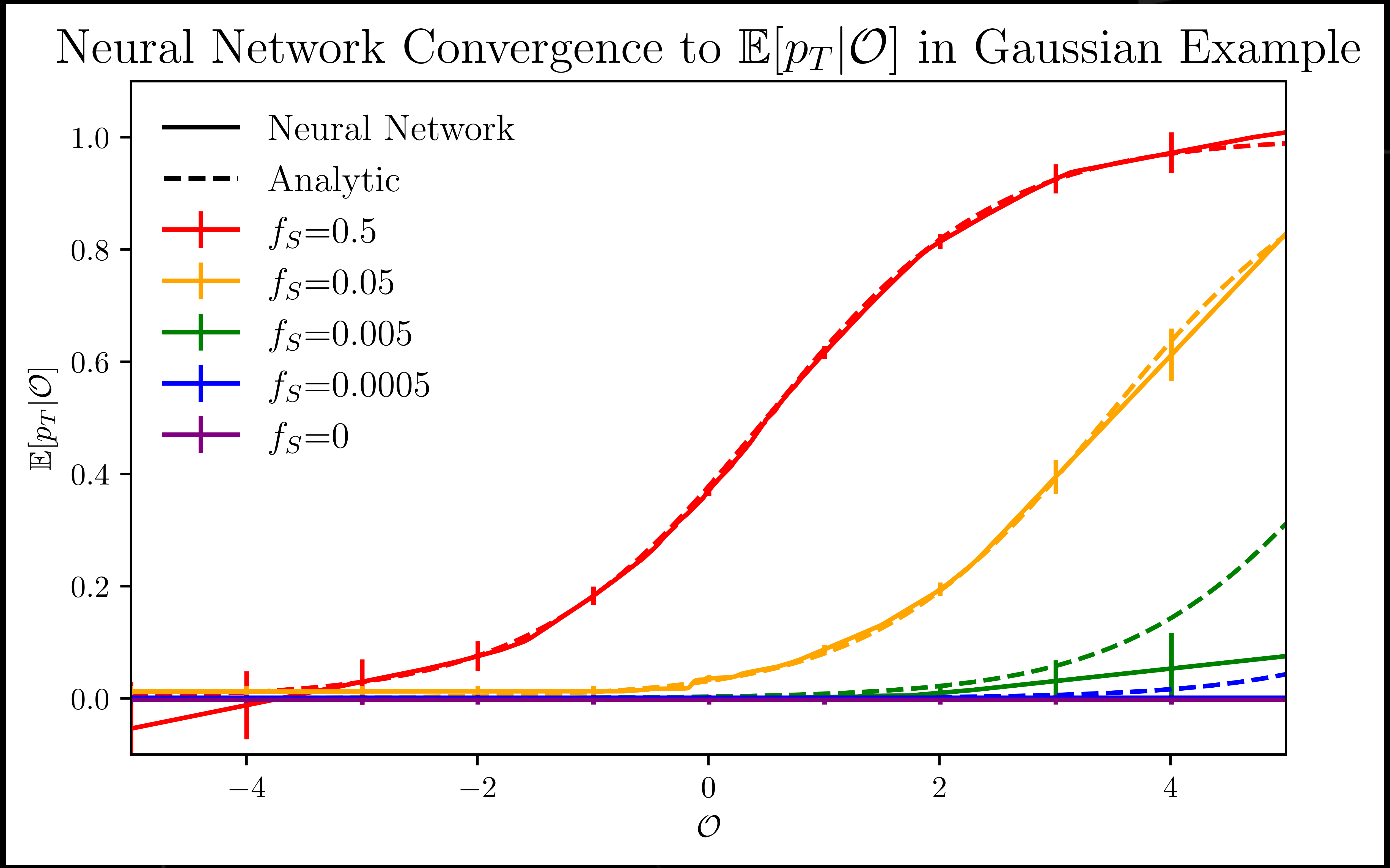
Find solid convergence in large signal limit, with decaying performance as signal fraction decreases



LHC Olympics

R&D Dataset

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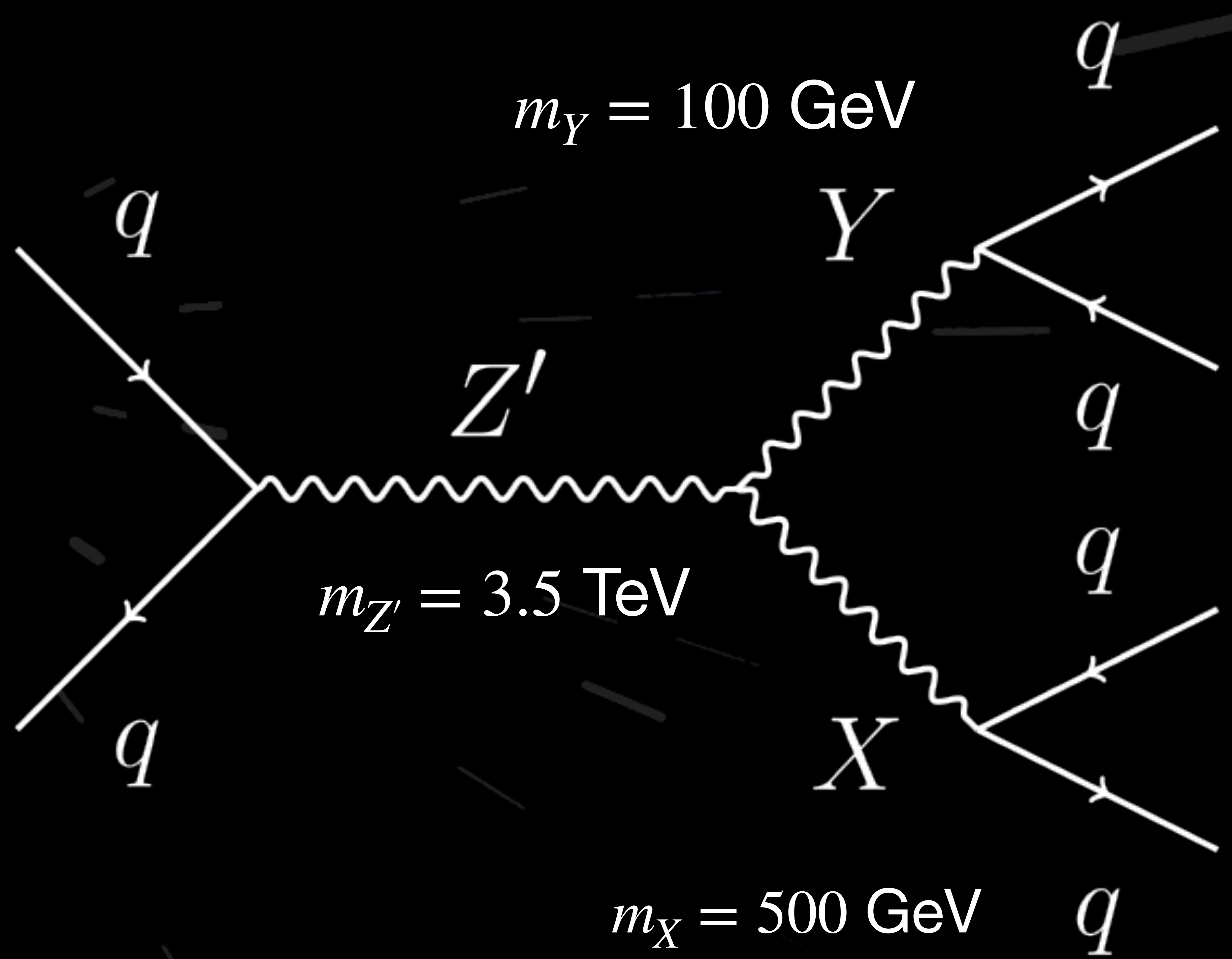
[2101.08320]



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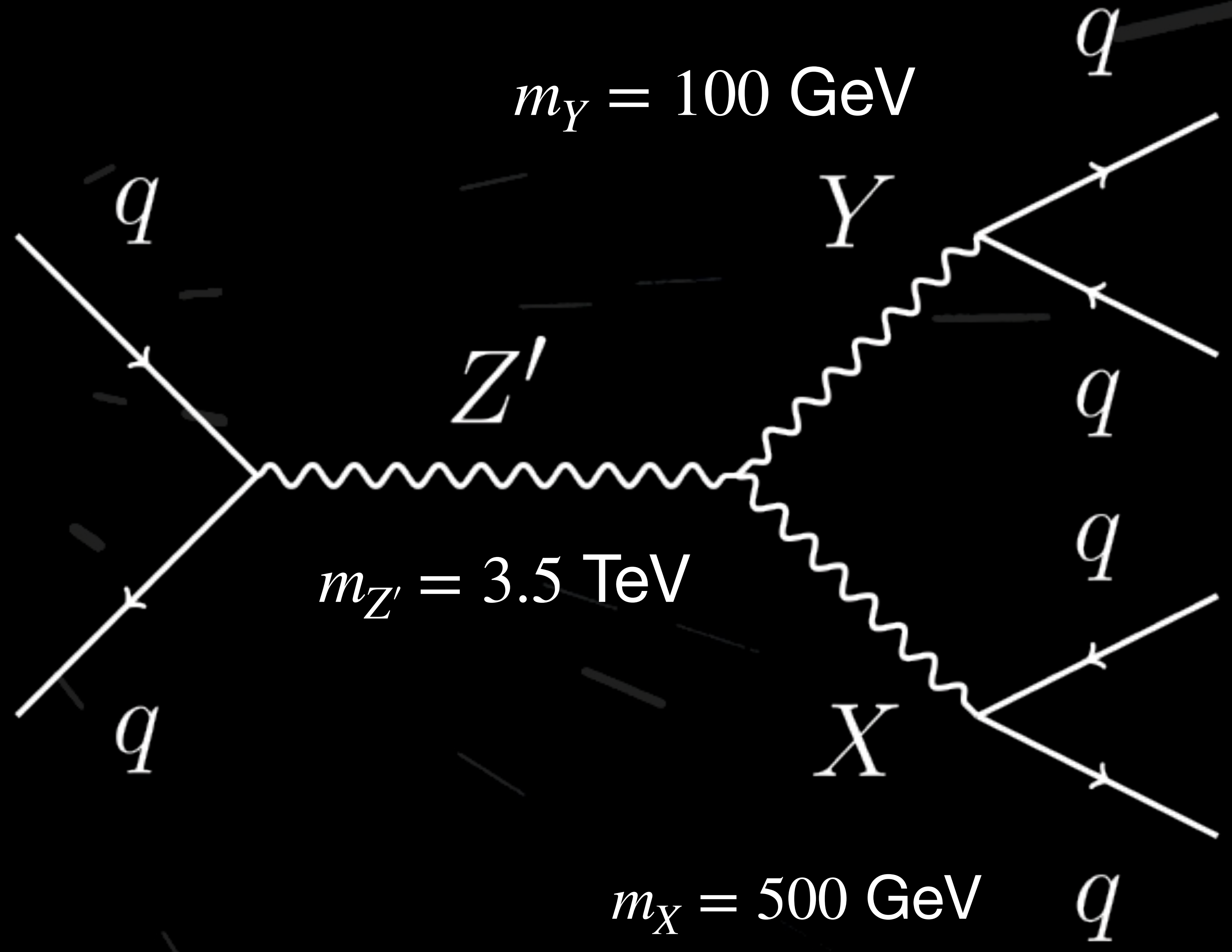

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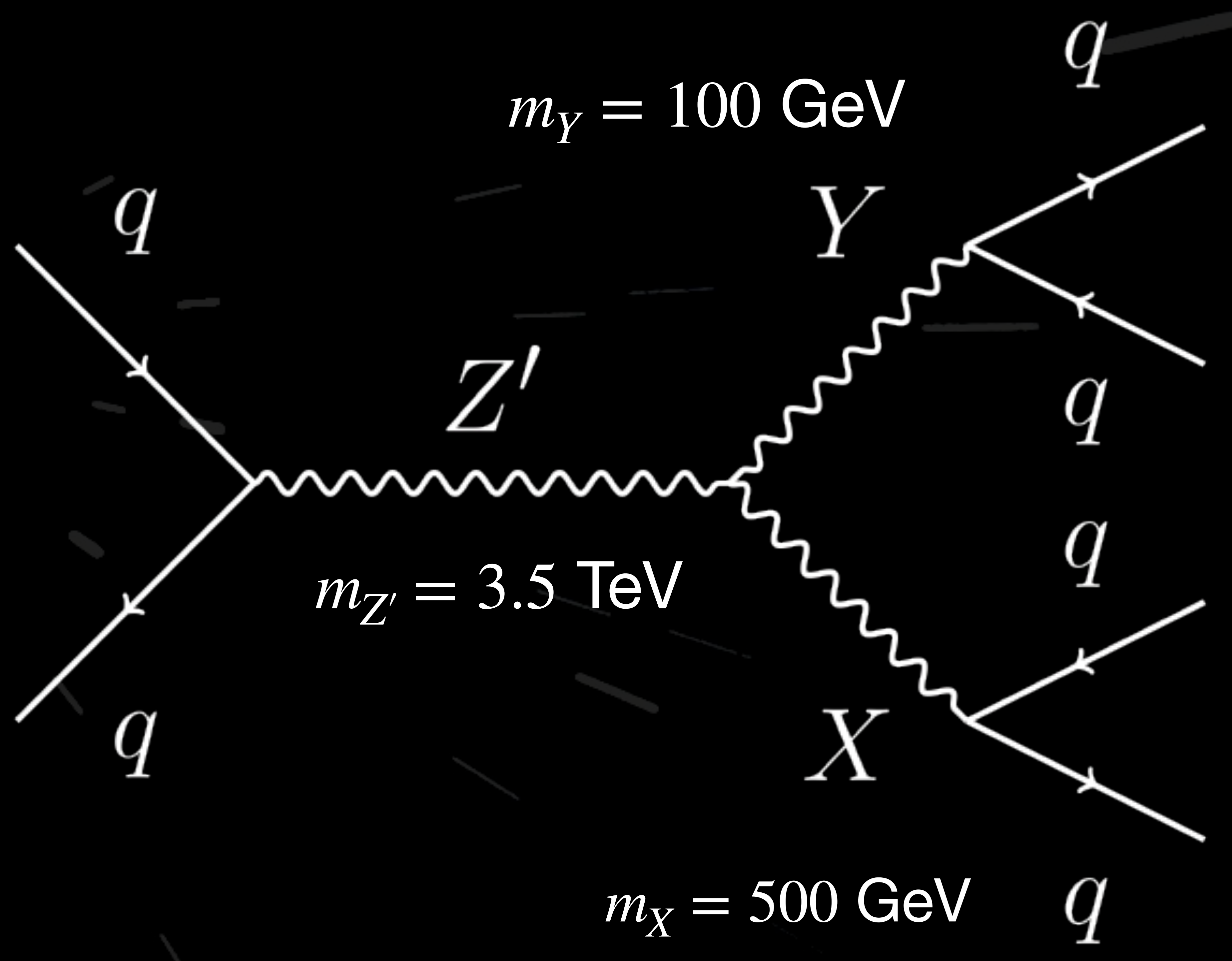

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$\Longrightarrow$ Can combine FORCE with other bump hunting algorithms

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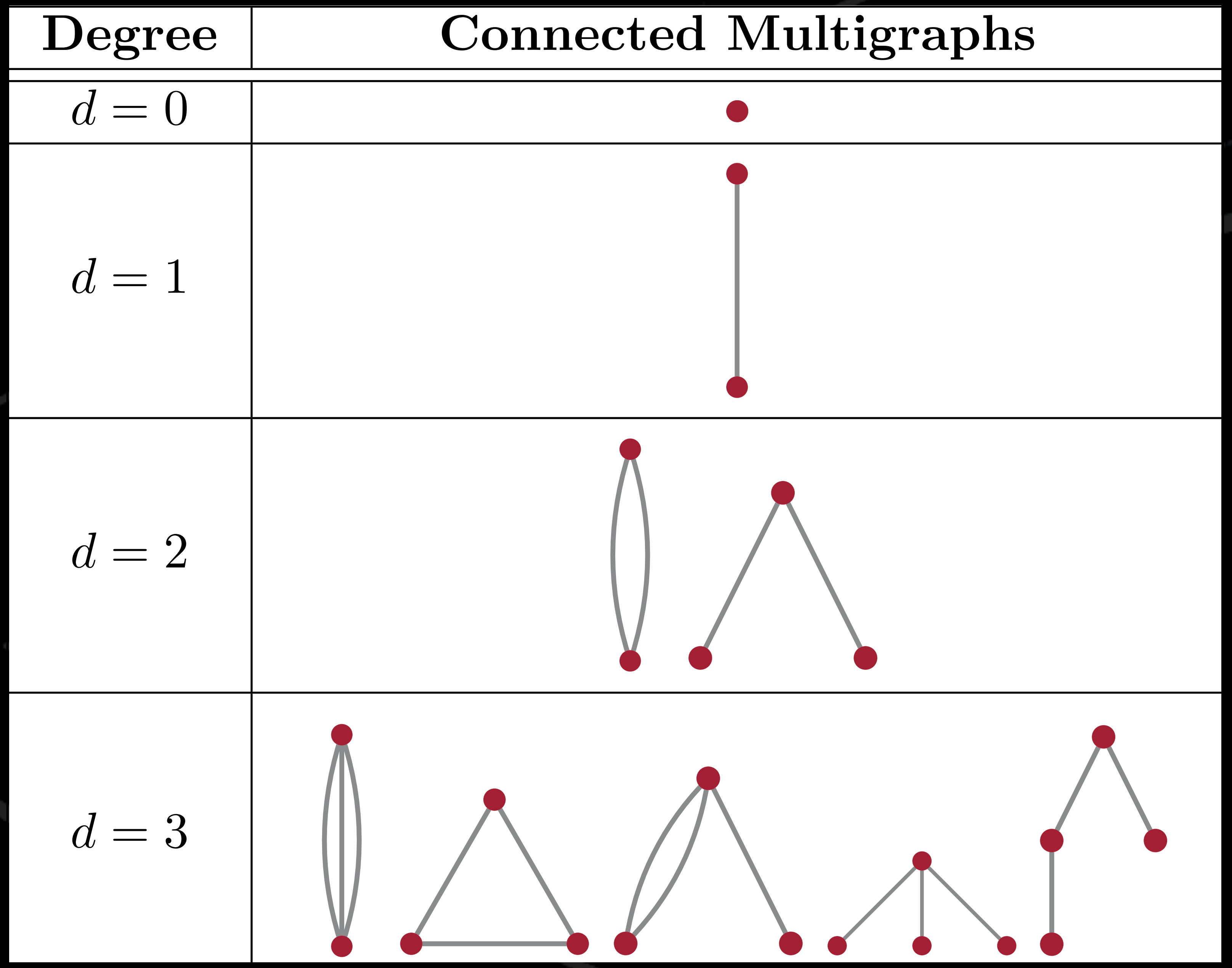

[1712.07124]

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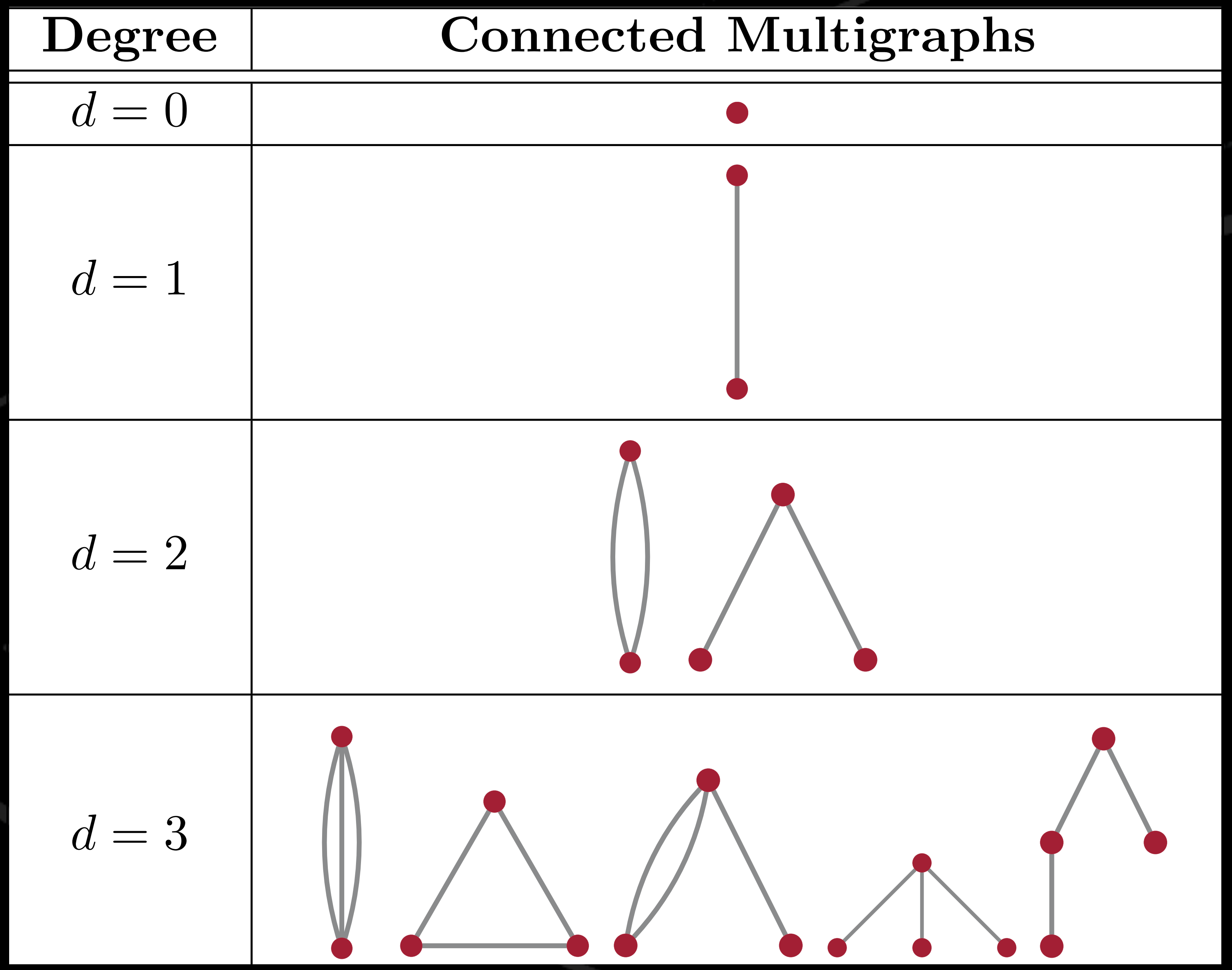
Energy flow polynomials - systematic expansion in energy and angle

Take EFPs $d \leq 3 \implies$ 13 features



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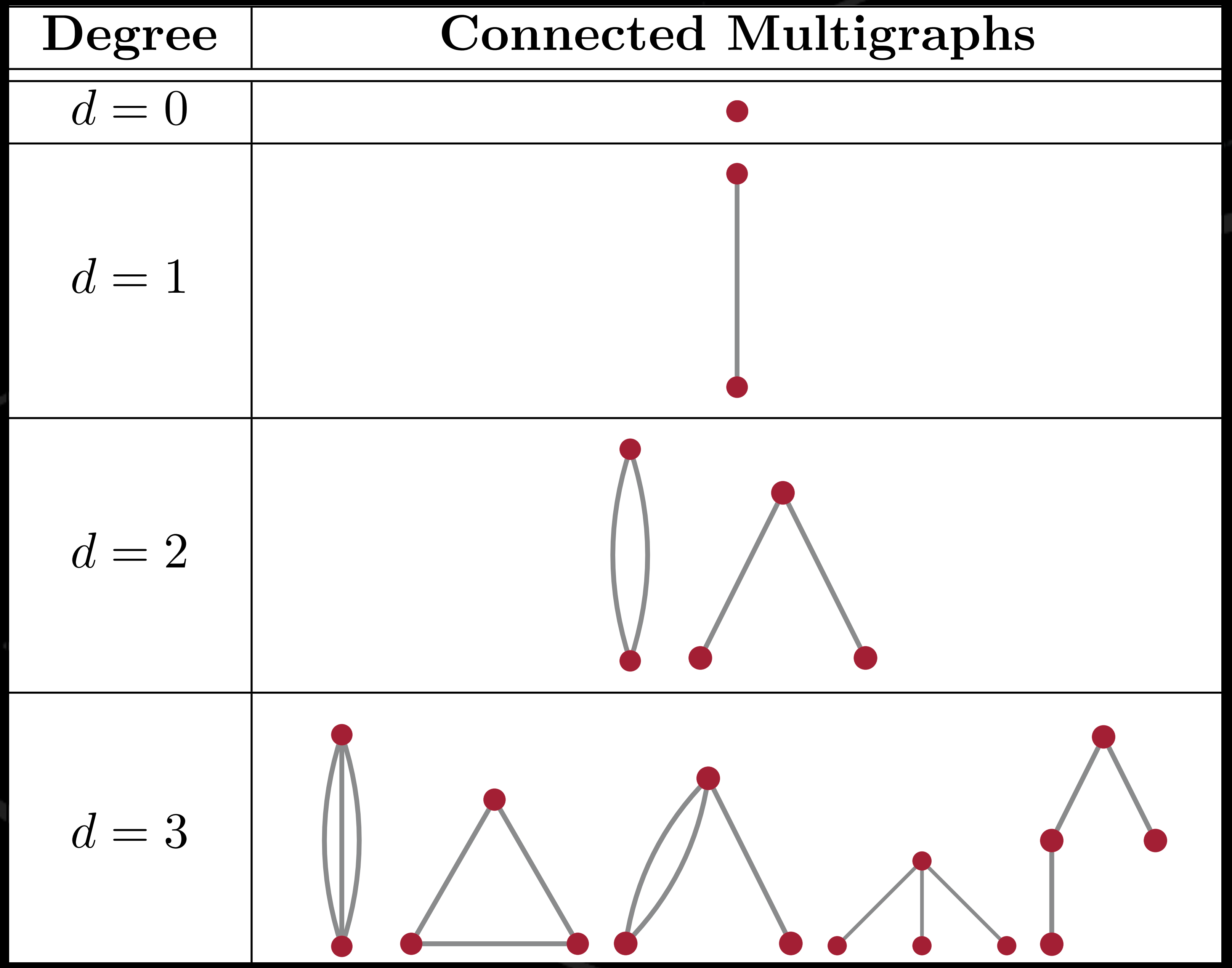
Energy flow polynomials - systematic expansion in energy and angle

Take EFPs $d \leq 3 \implies$ 13 features

Transverse boosts scale



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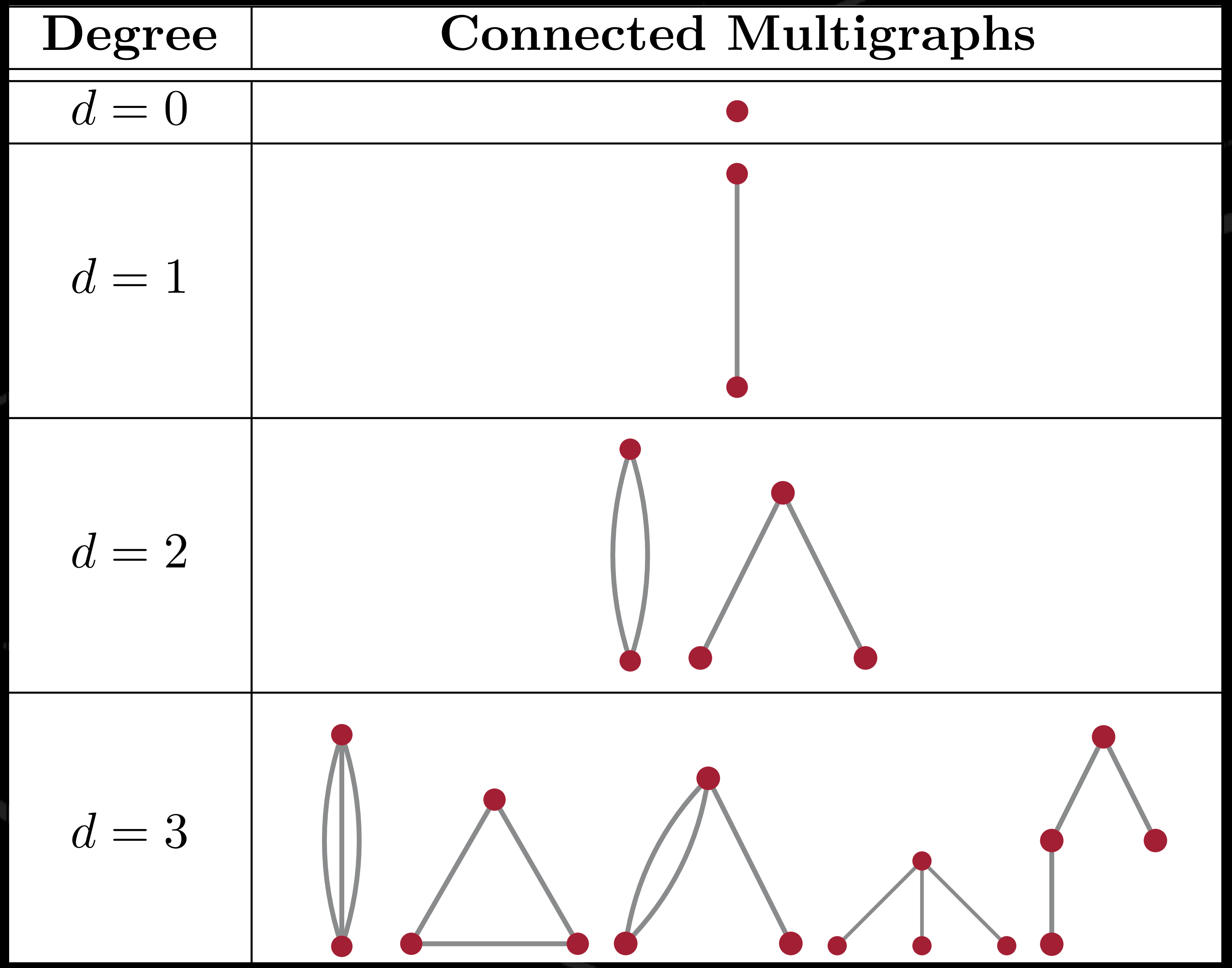

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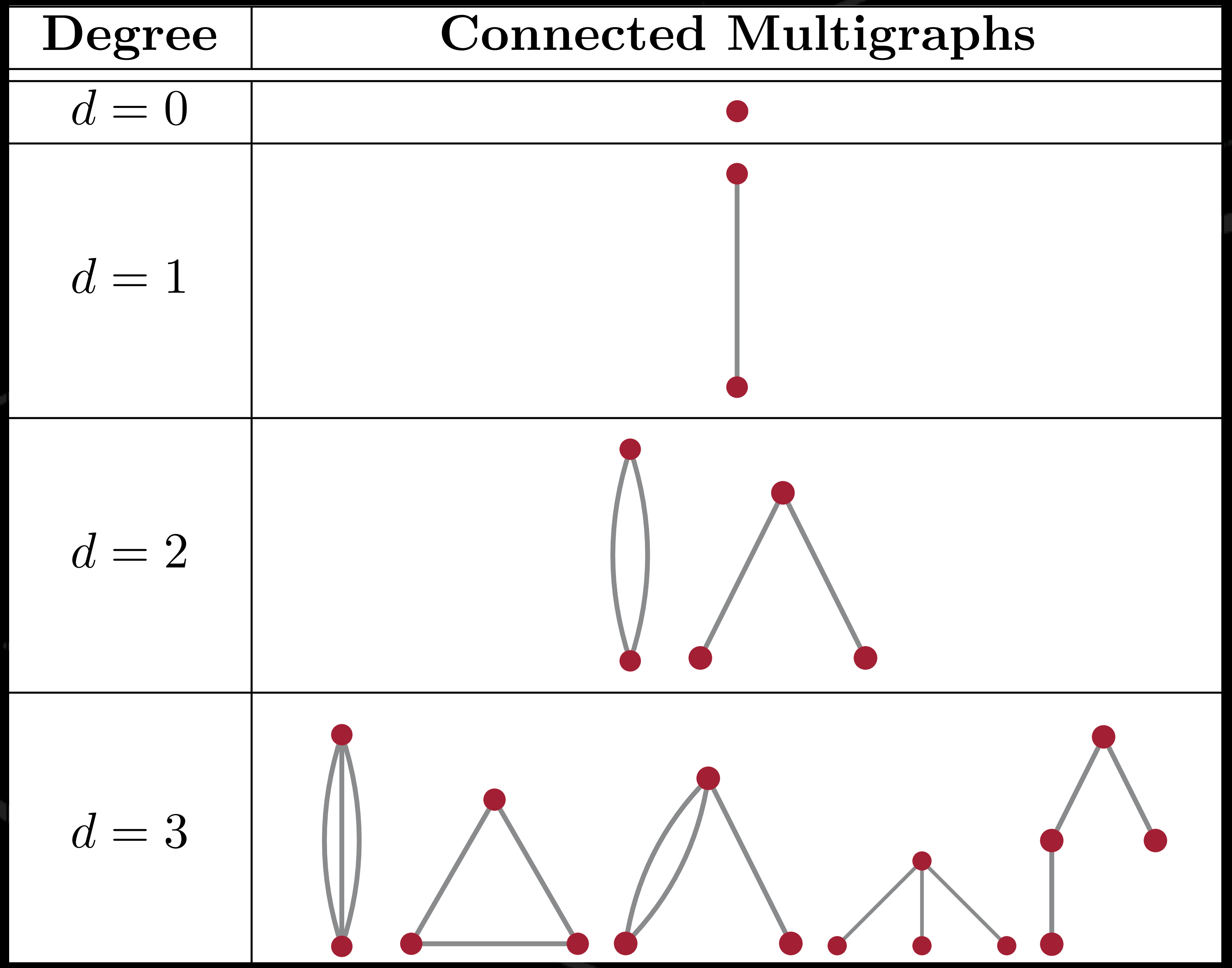

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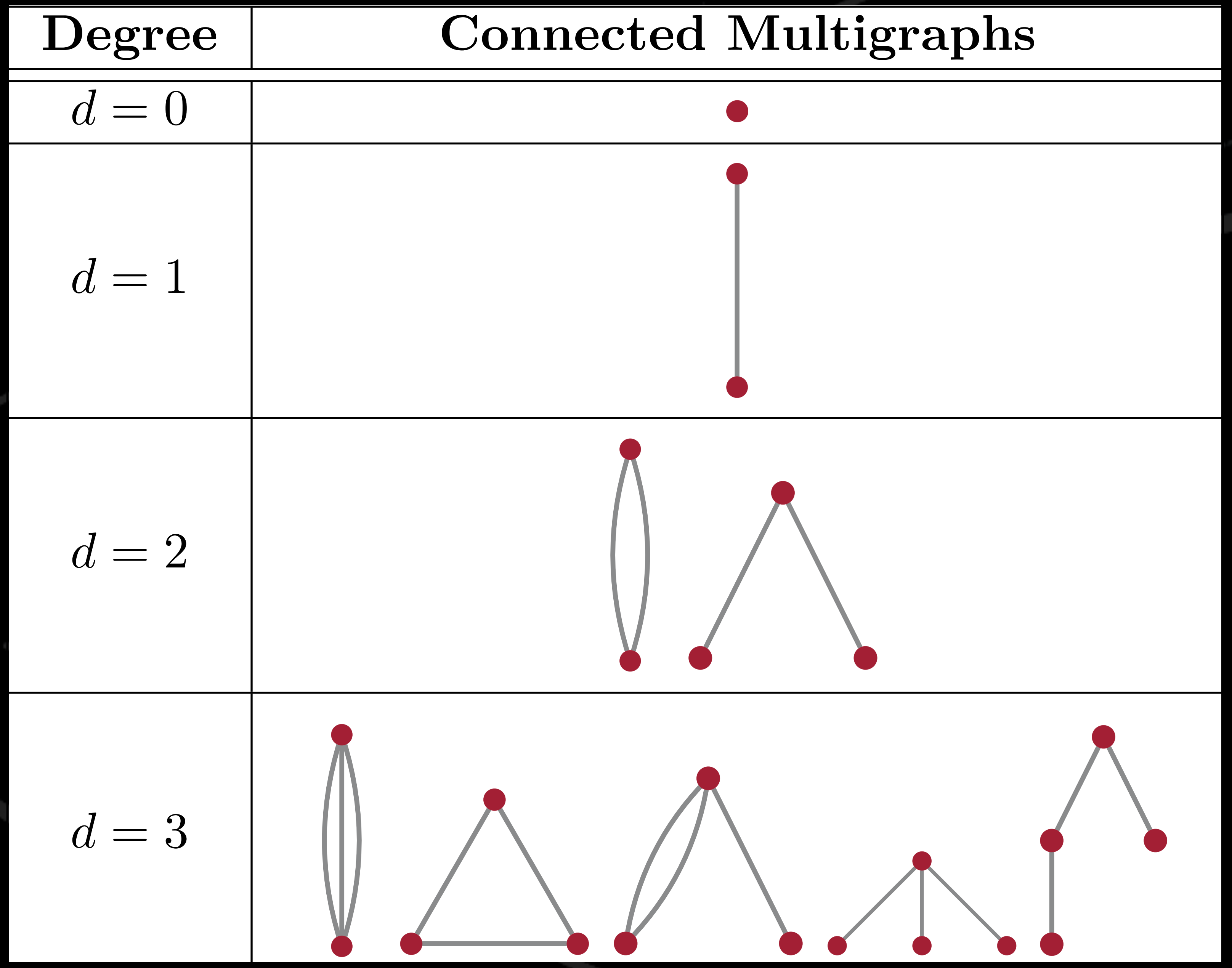

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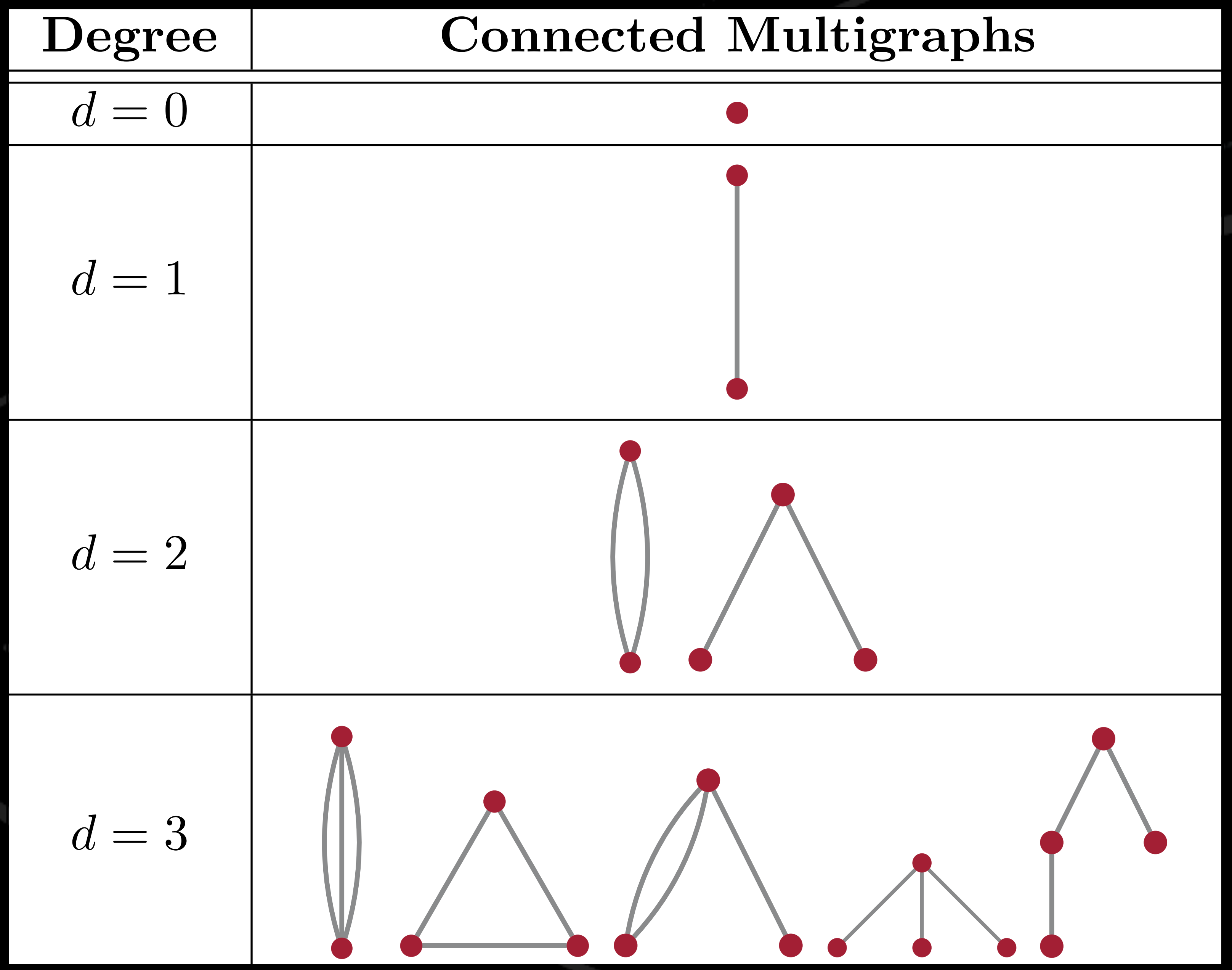

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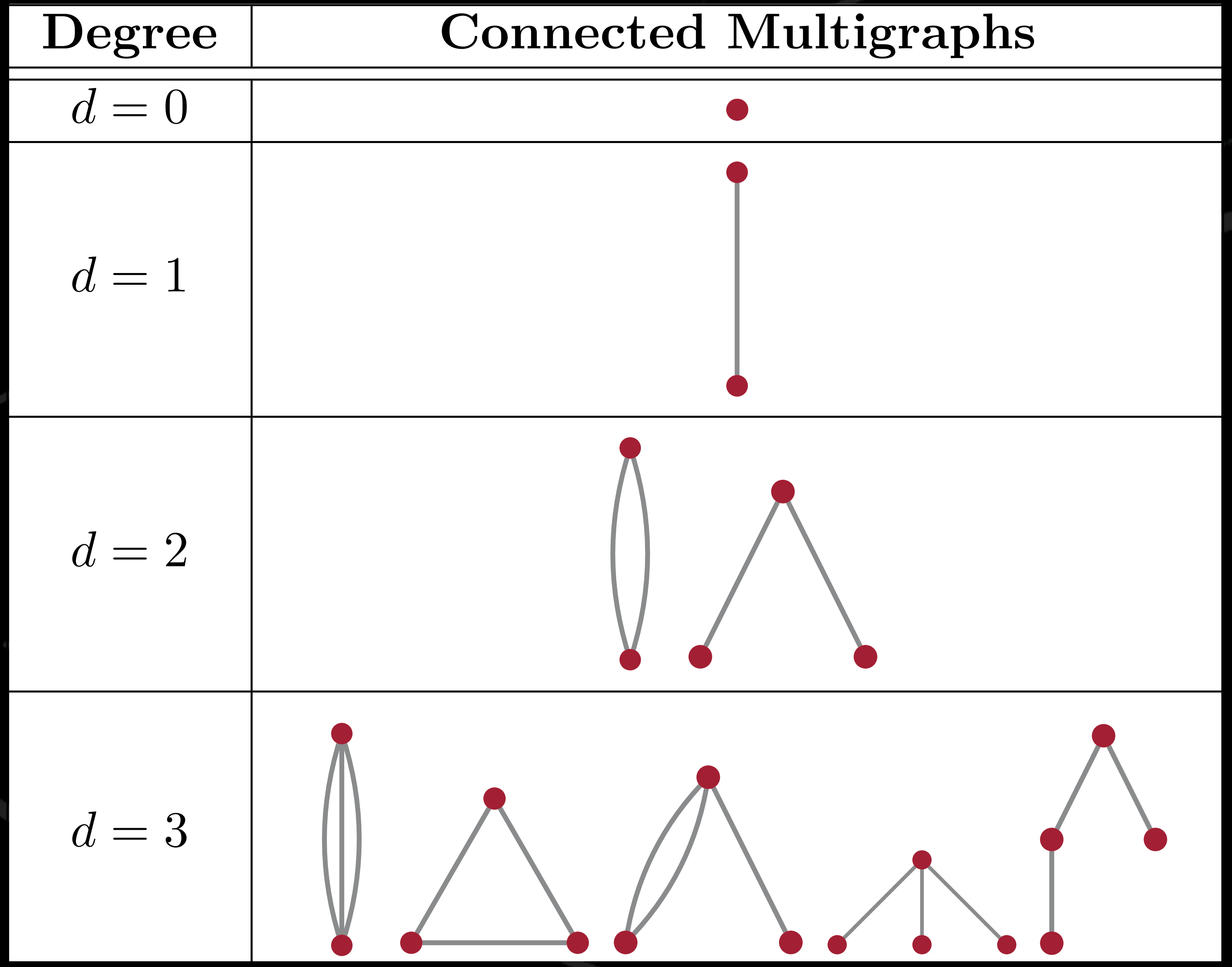

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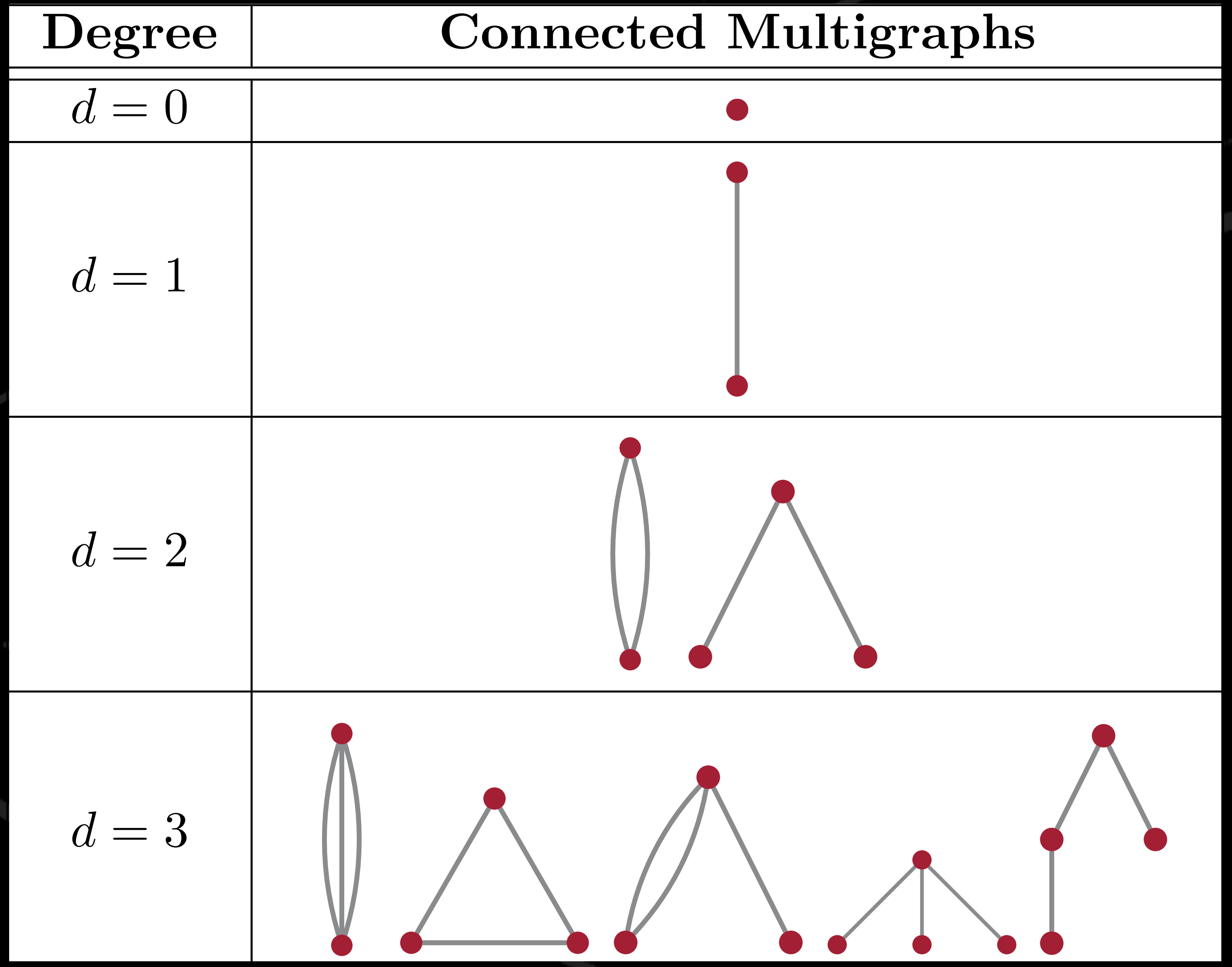
$13 \to 8$ independent observables



[1712.07124]

ROC-AUC for LHCO

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- Fully connected network
- 3 layers of 100 nodes
- ReLU Activation
- Dropout and L2 Regularization
- Mean across 10 models

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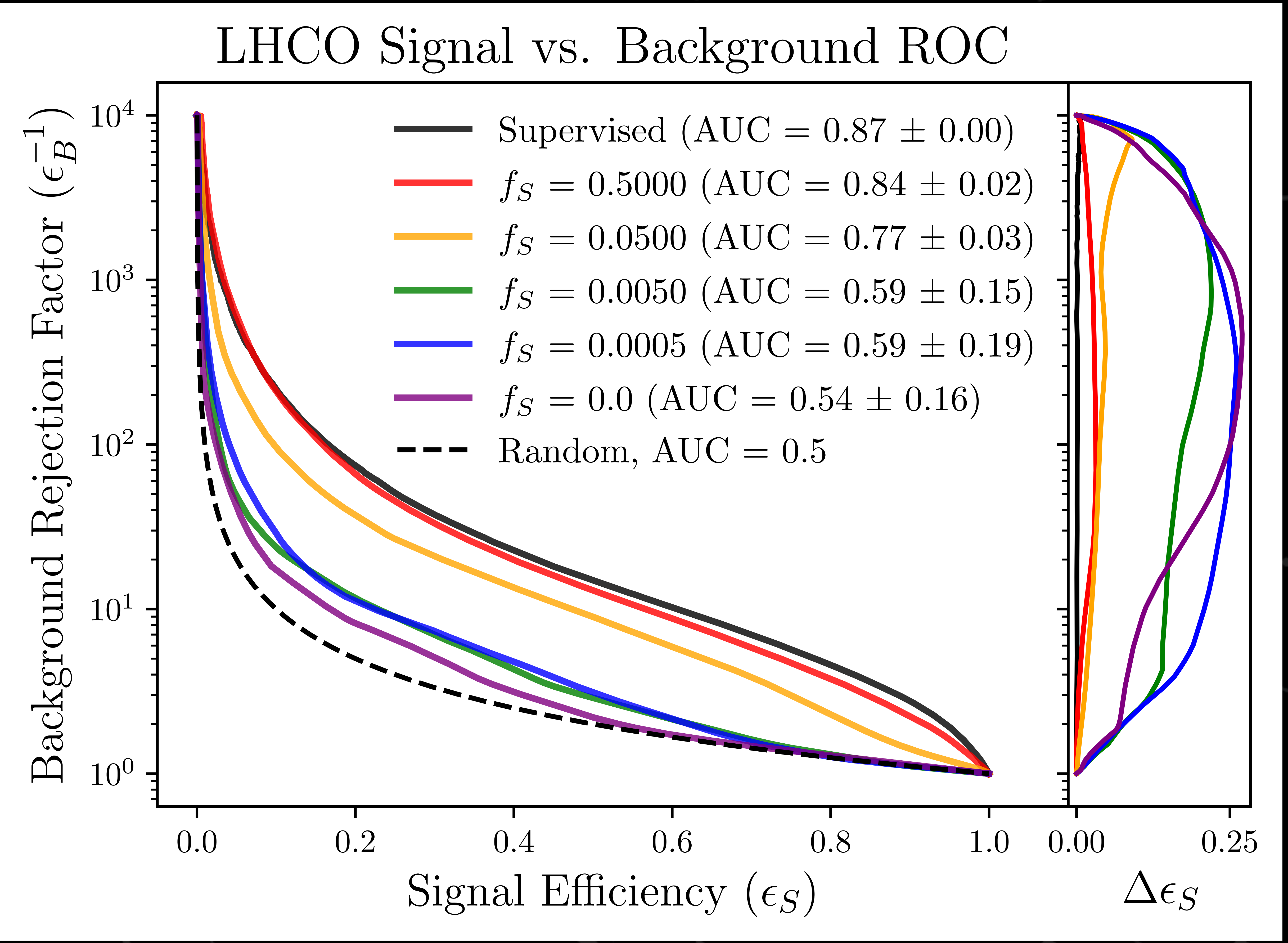

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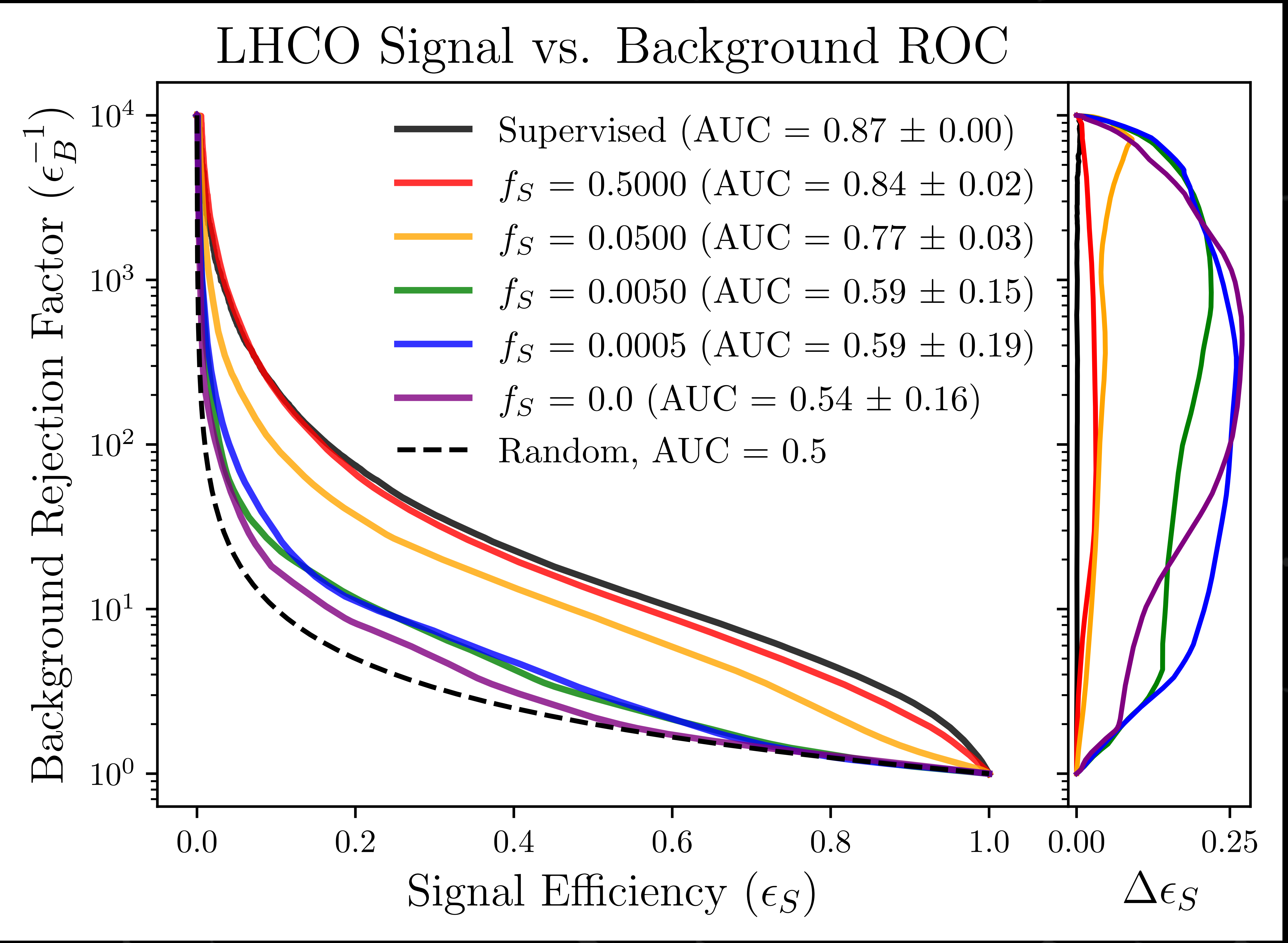

Near optimal in high signal limit

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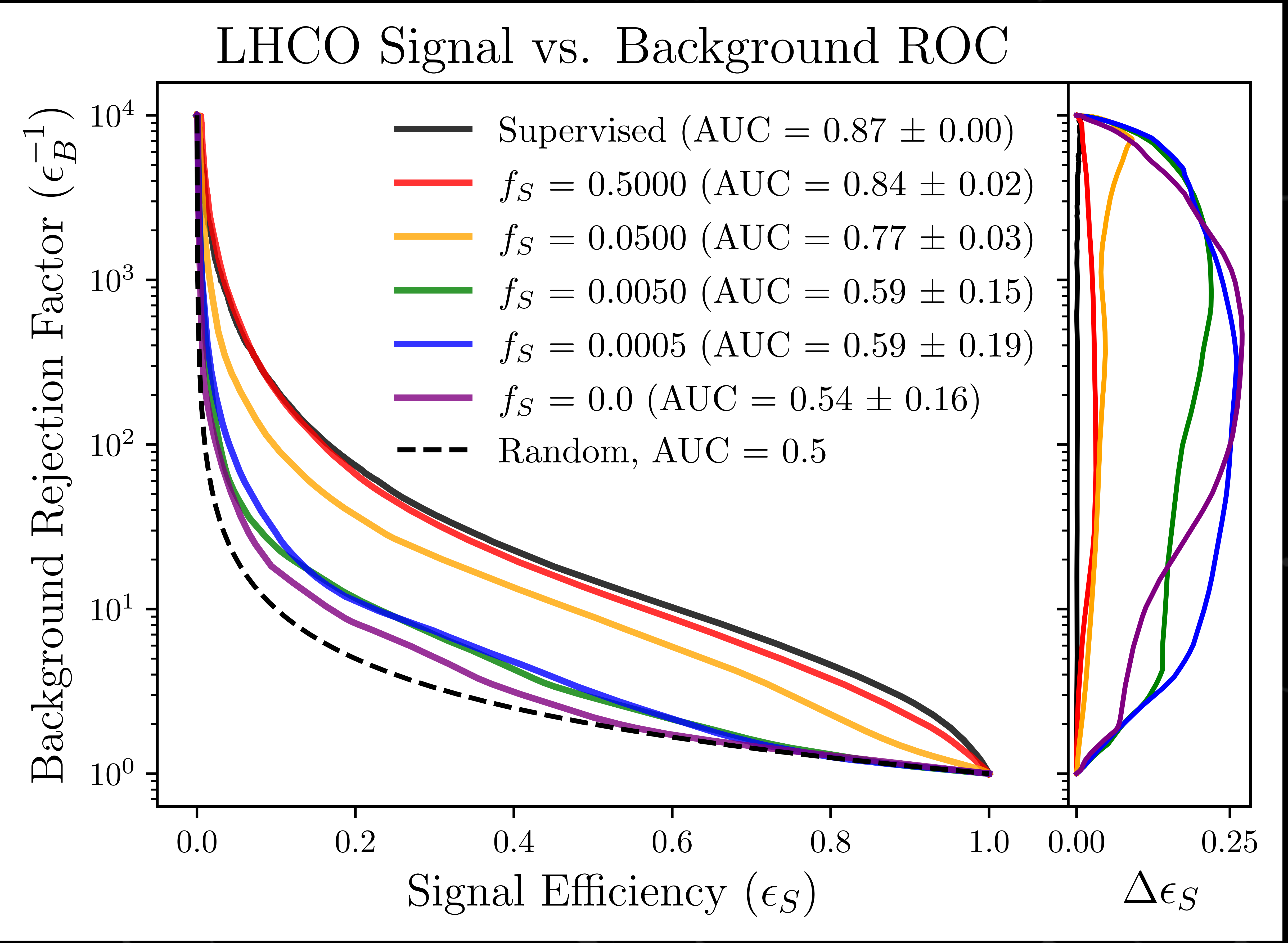

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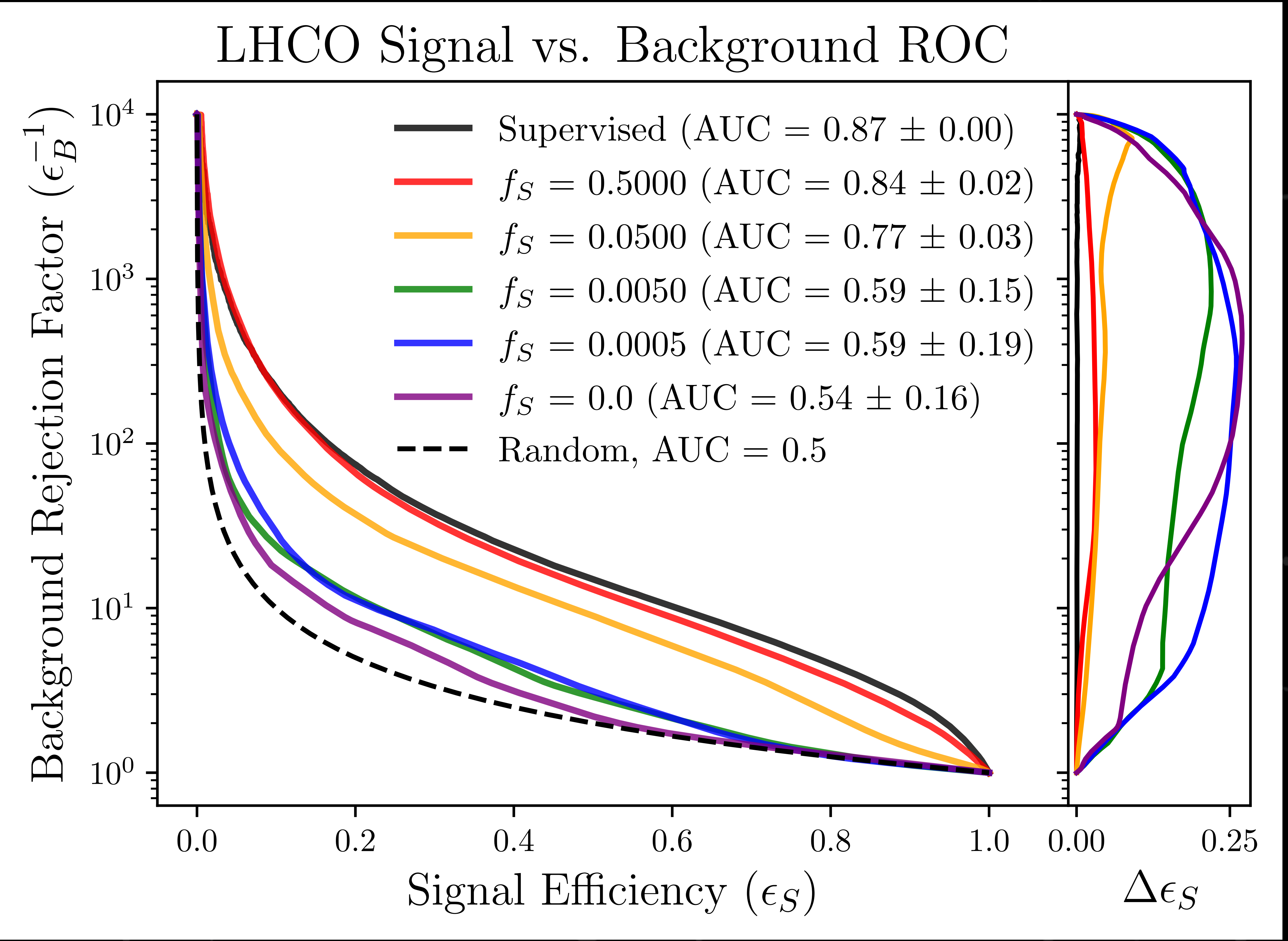

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More on that later

Let's go on a bump hunt!

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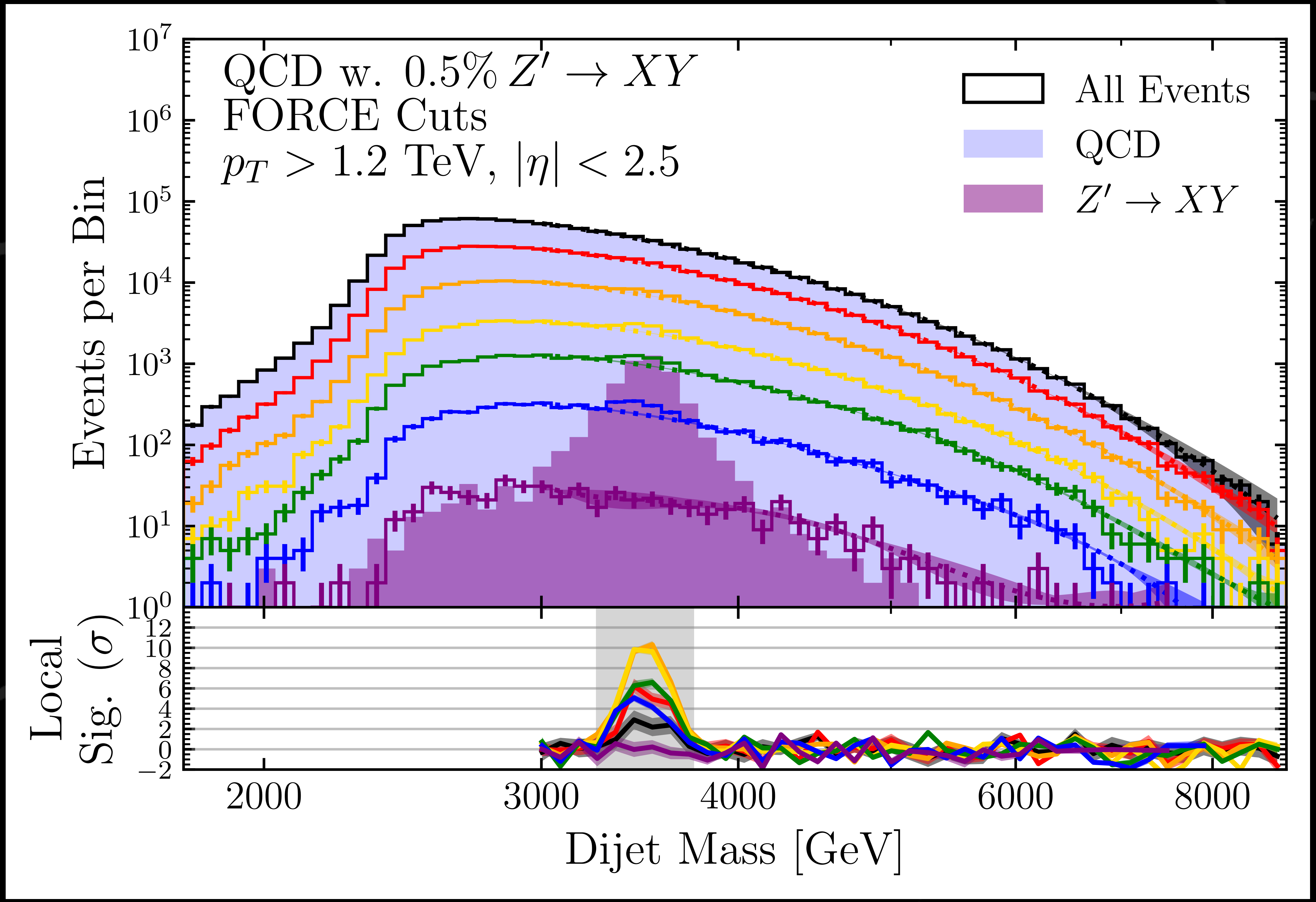
We find the Z'



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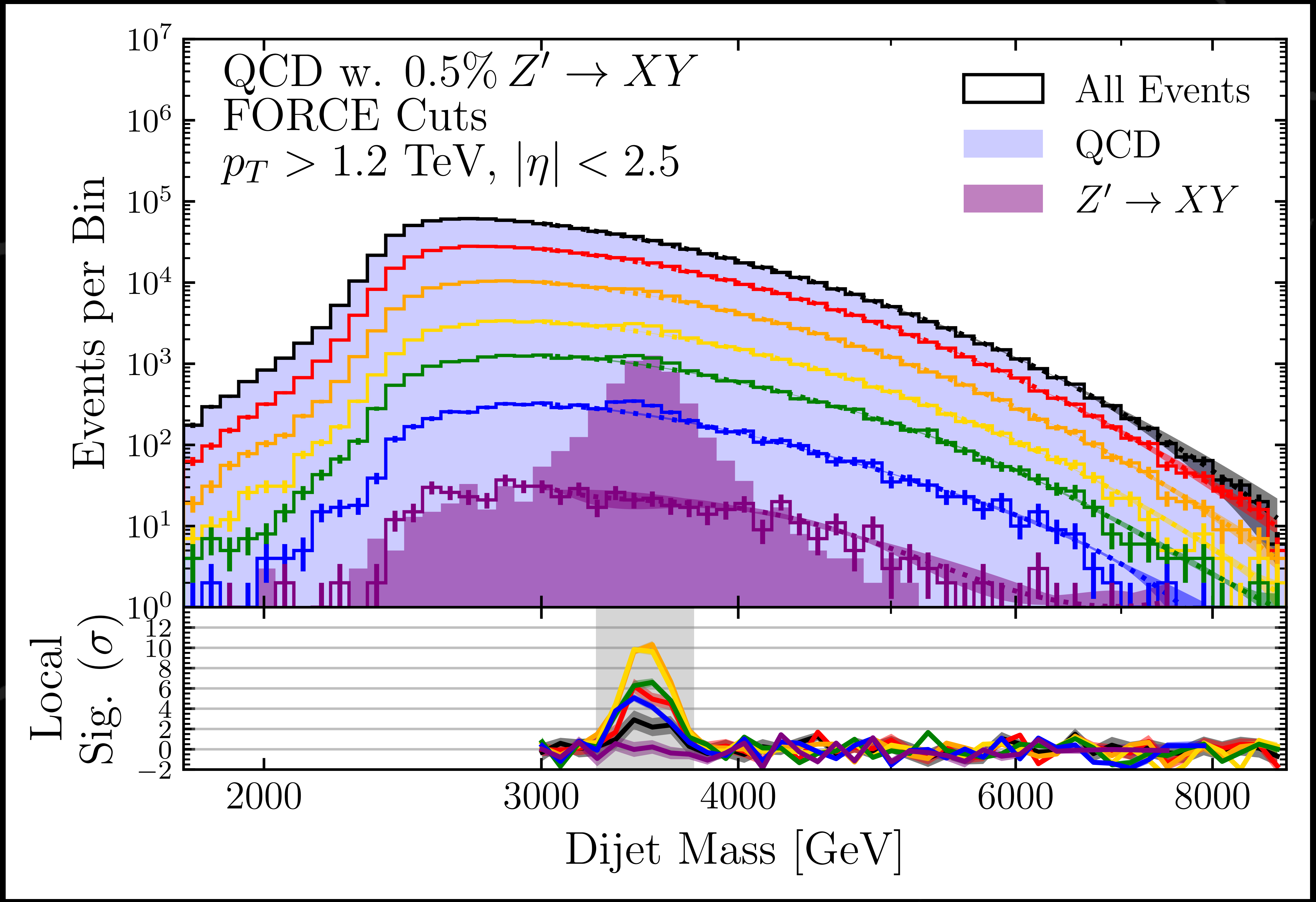
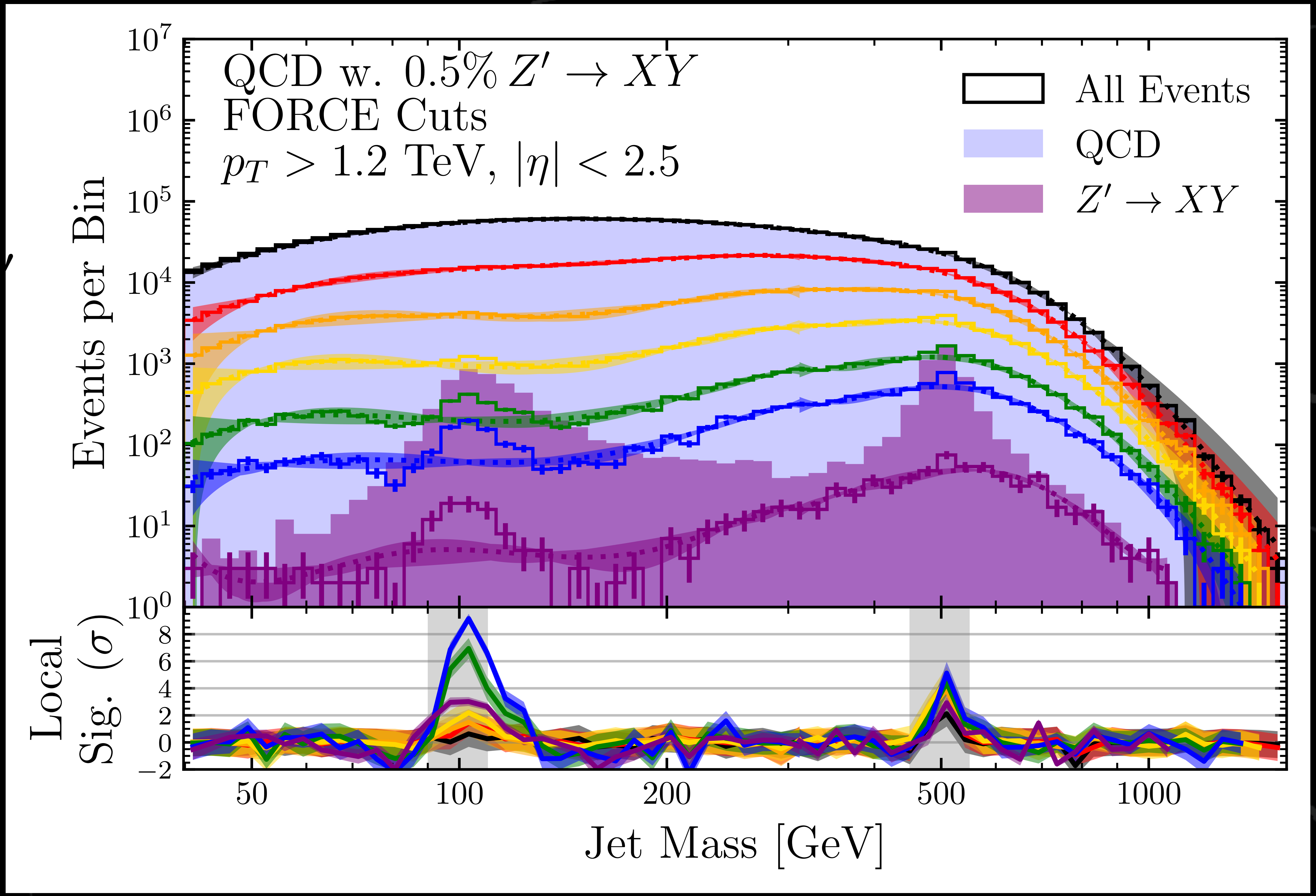


and the X and Y!



FORCE-ing Factorization with Shuffling

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Explicitly construct factorized distribution by separately shuffling signal and background

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FORCE-ing Factorization with Shuffling

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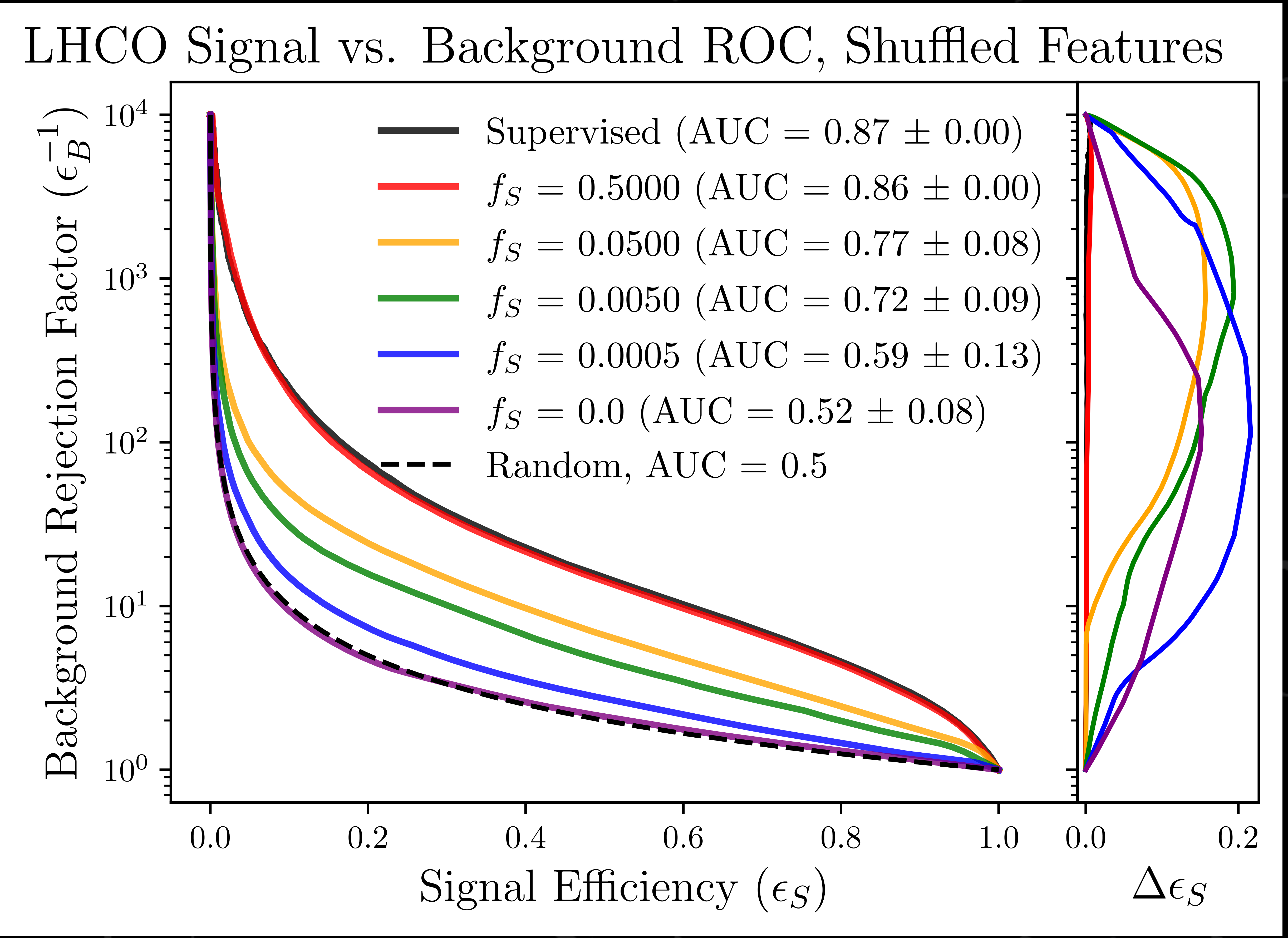

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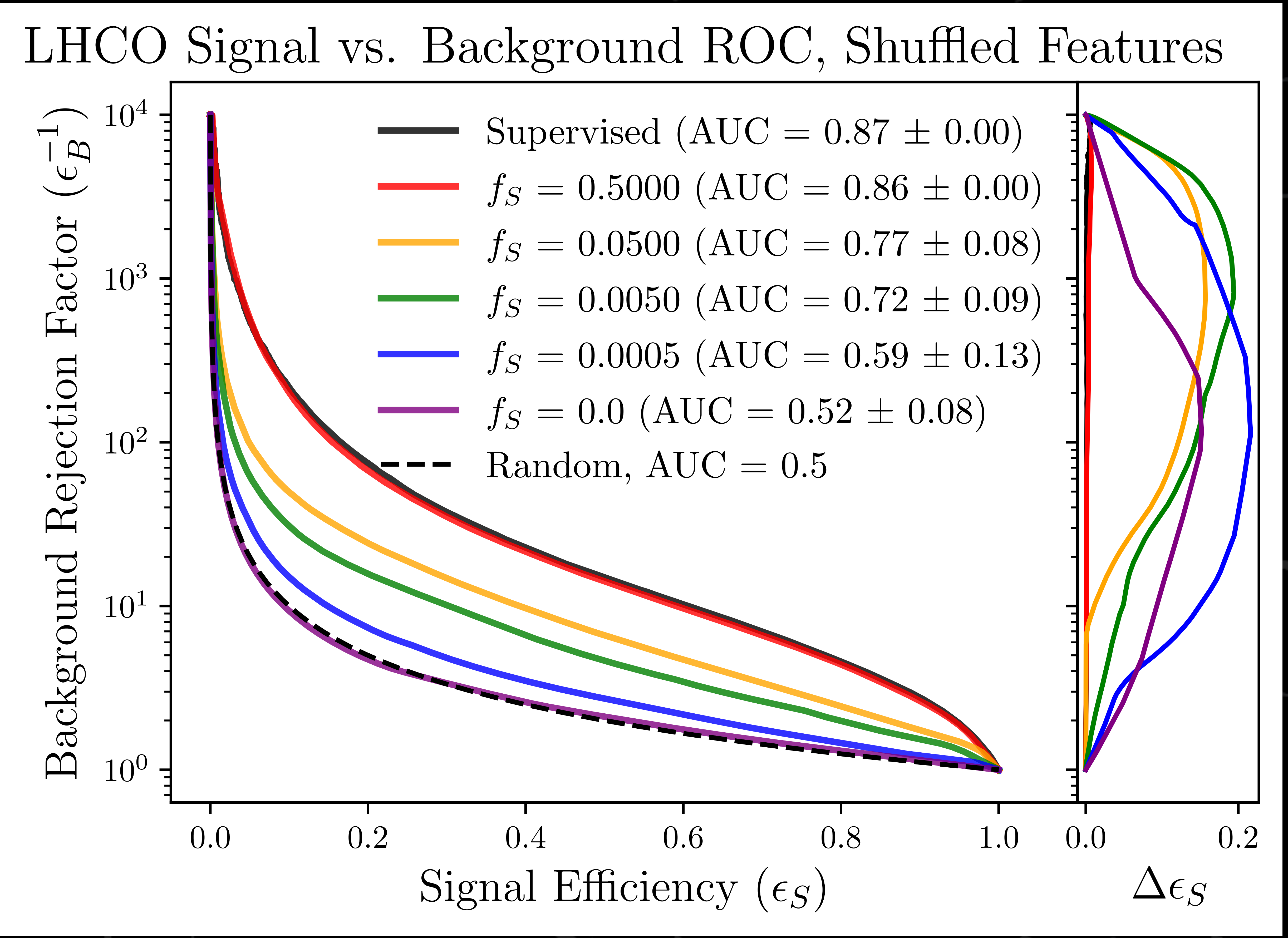
Optimal performance in high signal limit



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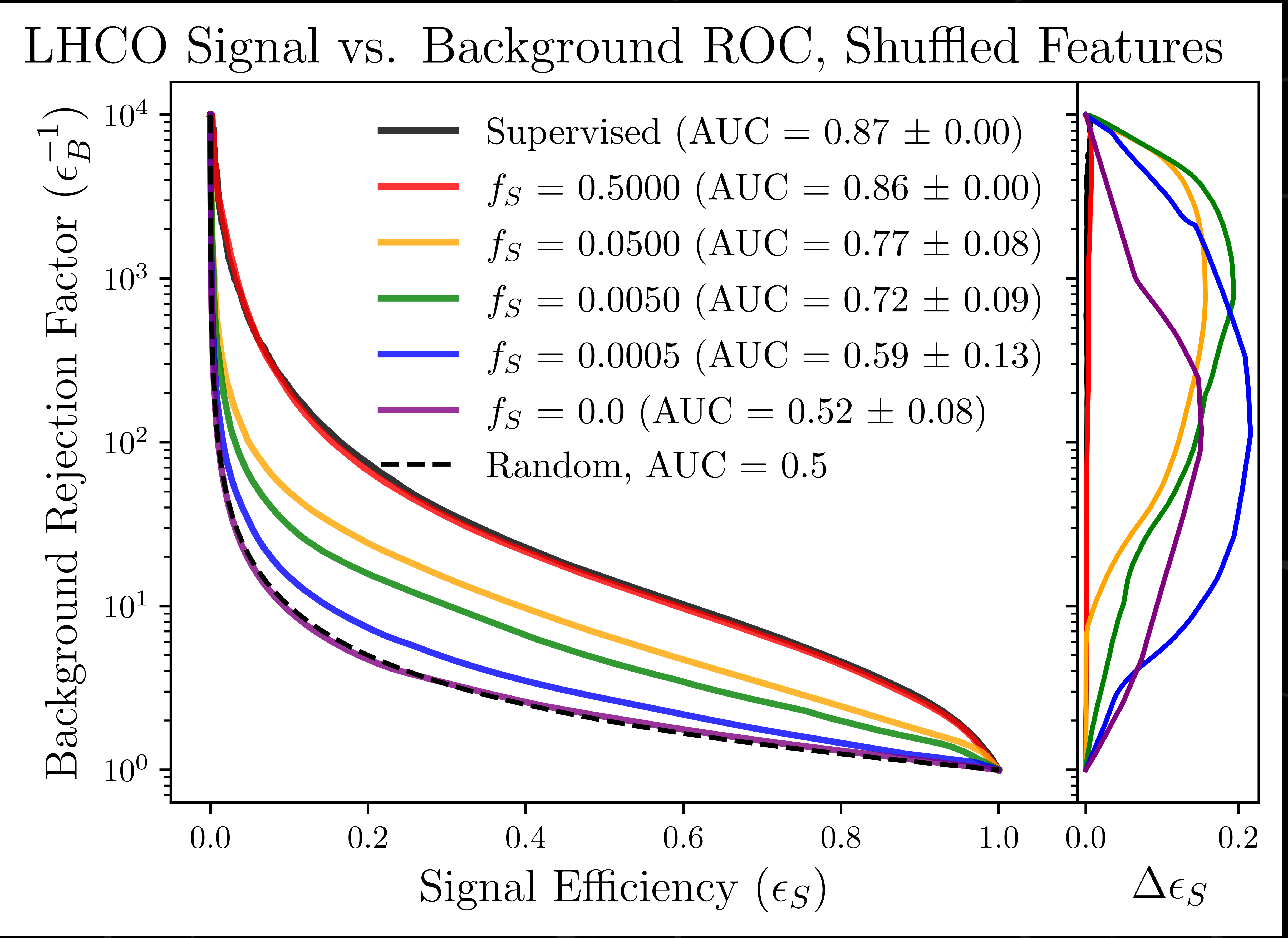

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Smooth decay of statistical power

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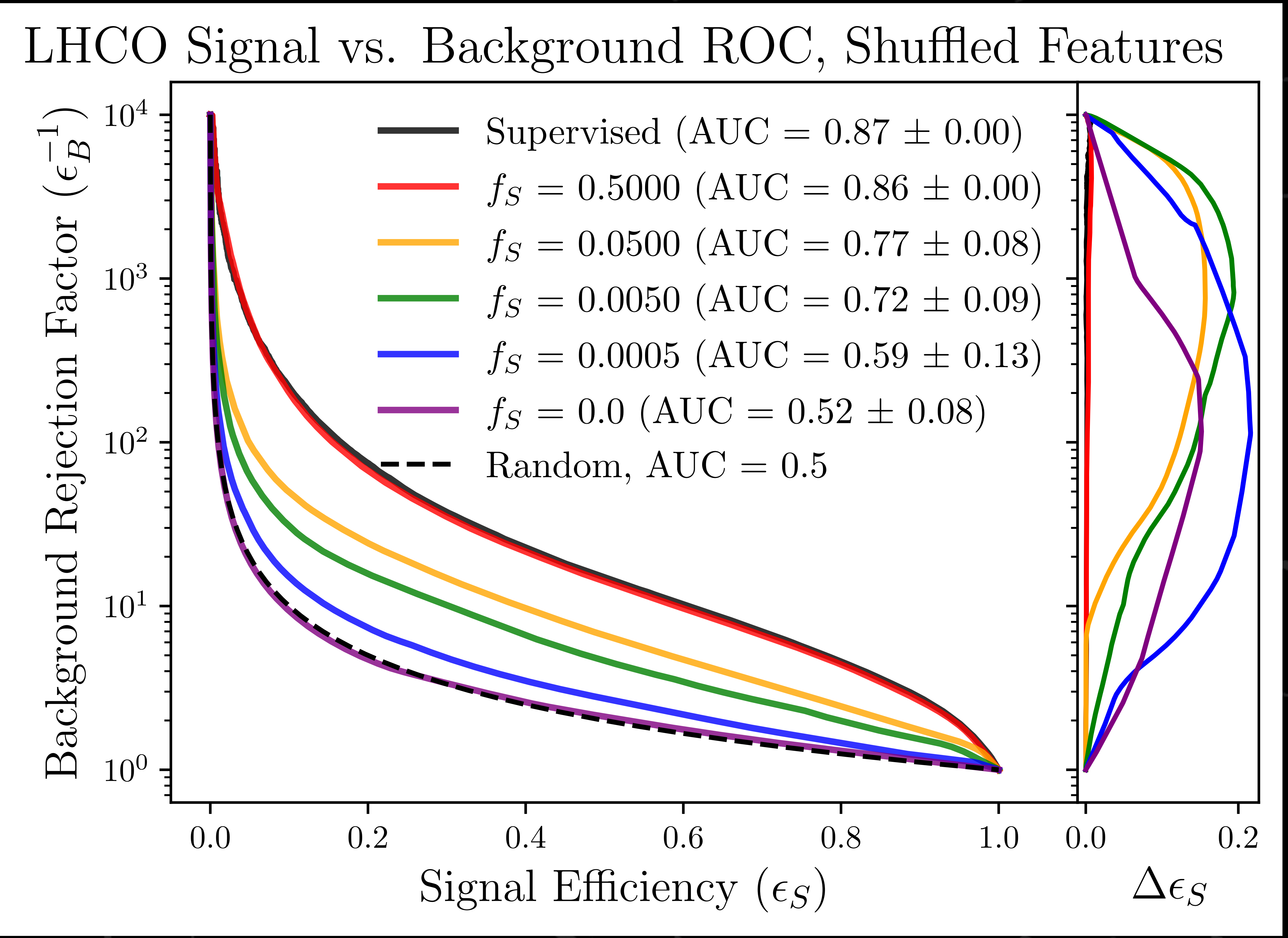
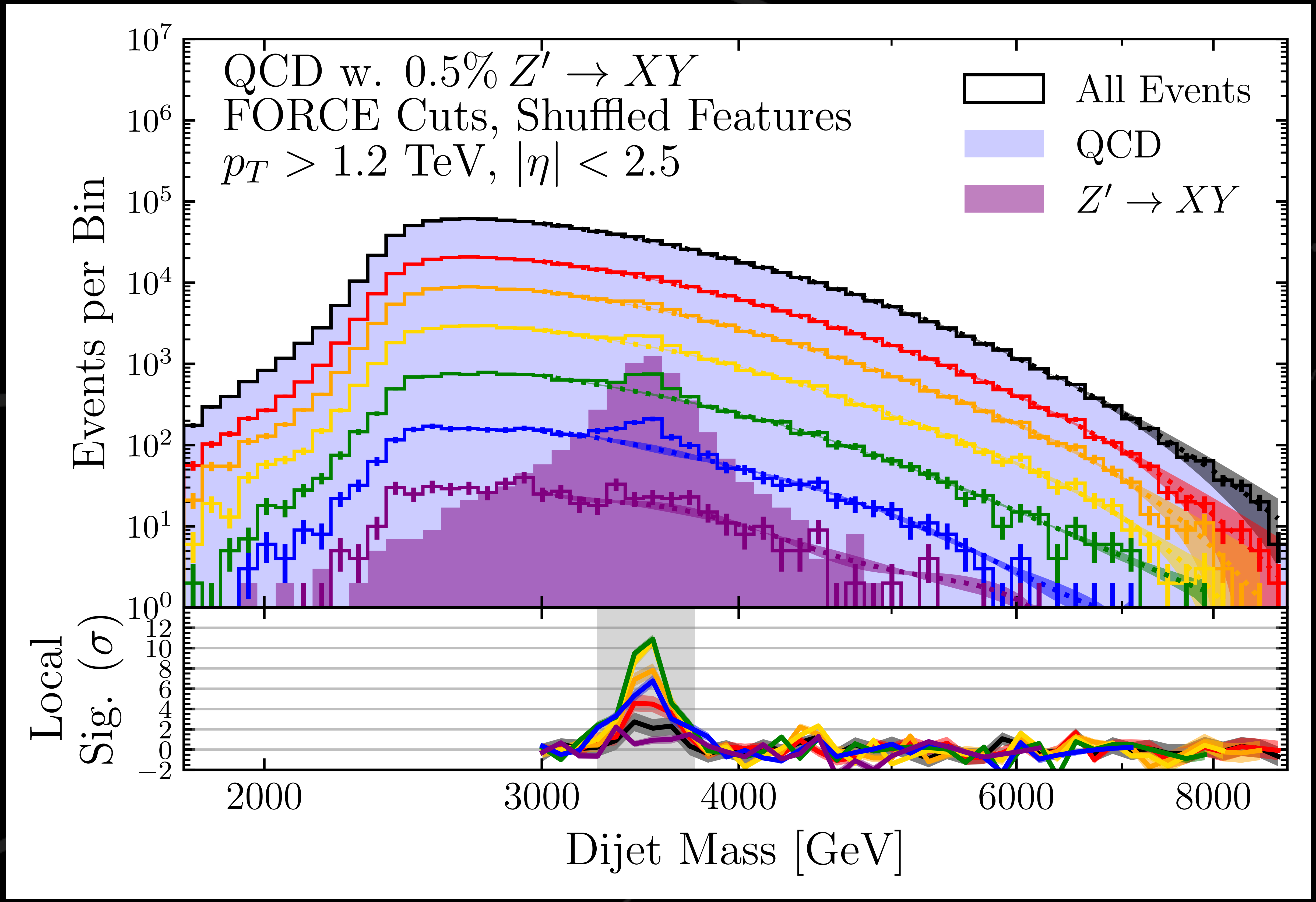


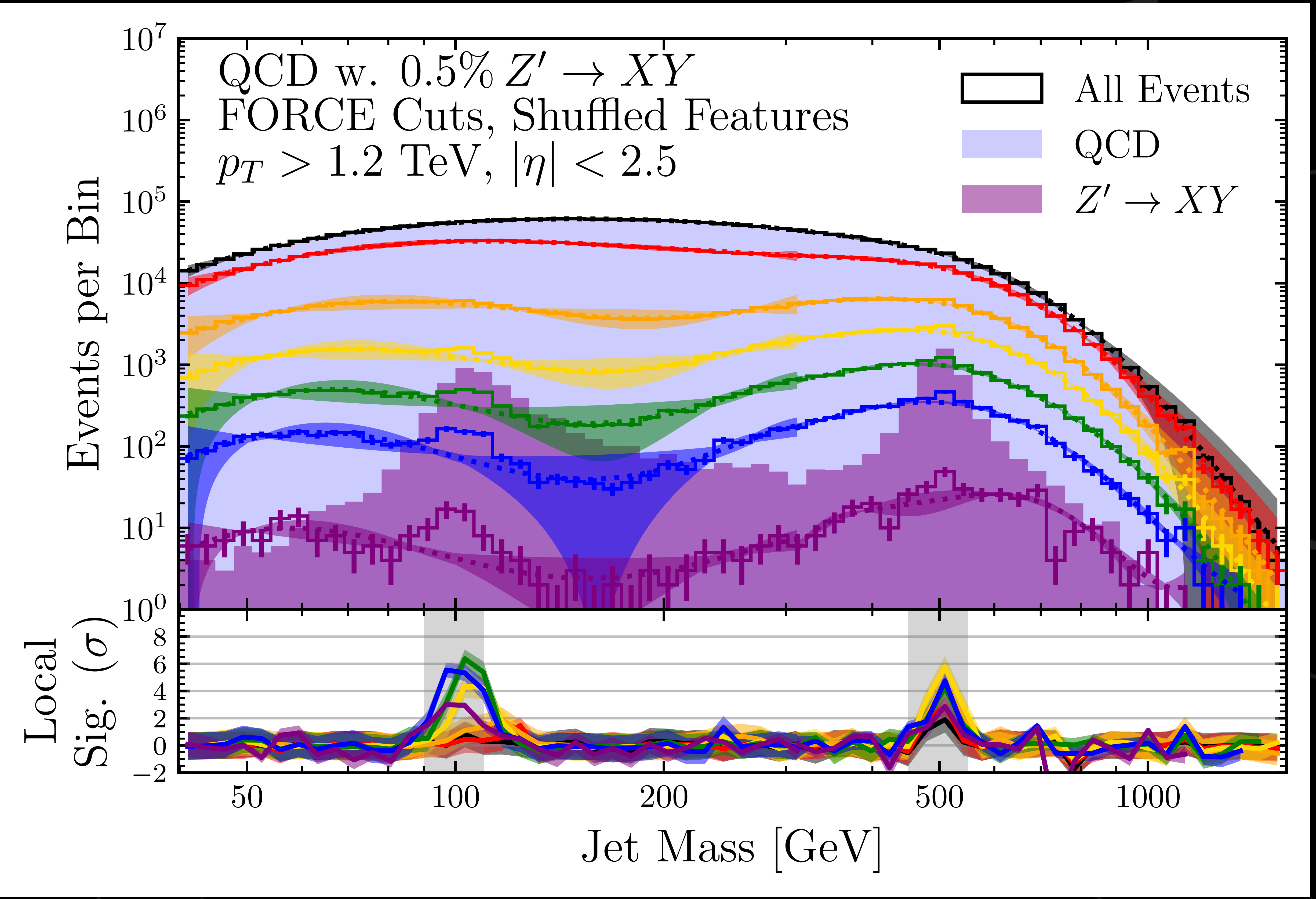
Optimal performance in high signal limit

Smooth decay of statistical power

Random classifier in low signal limit

How does shuffling affect the bump hunt?





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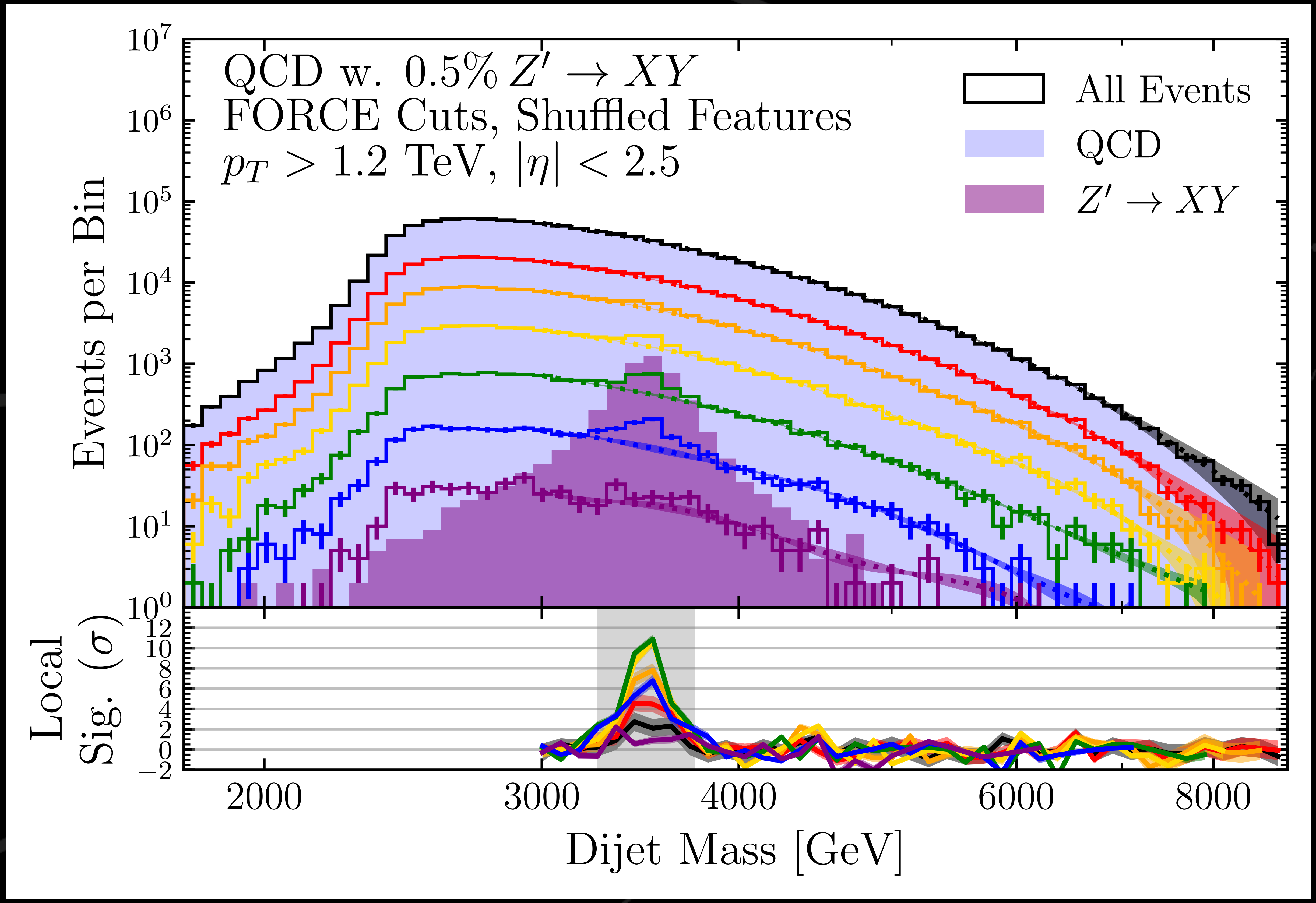

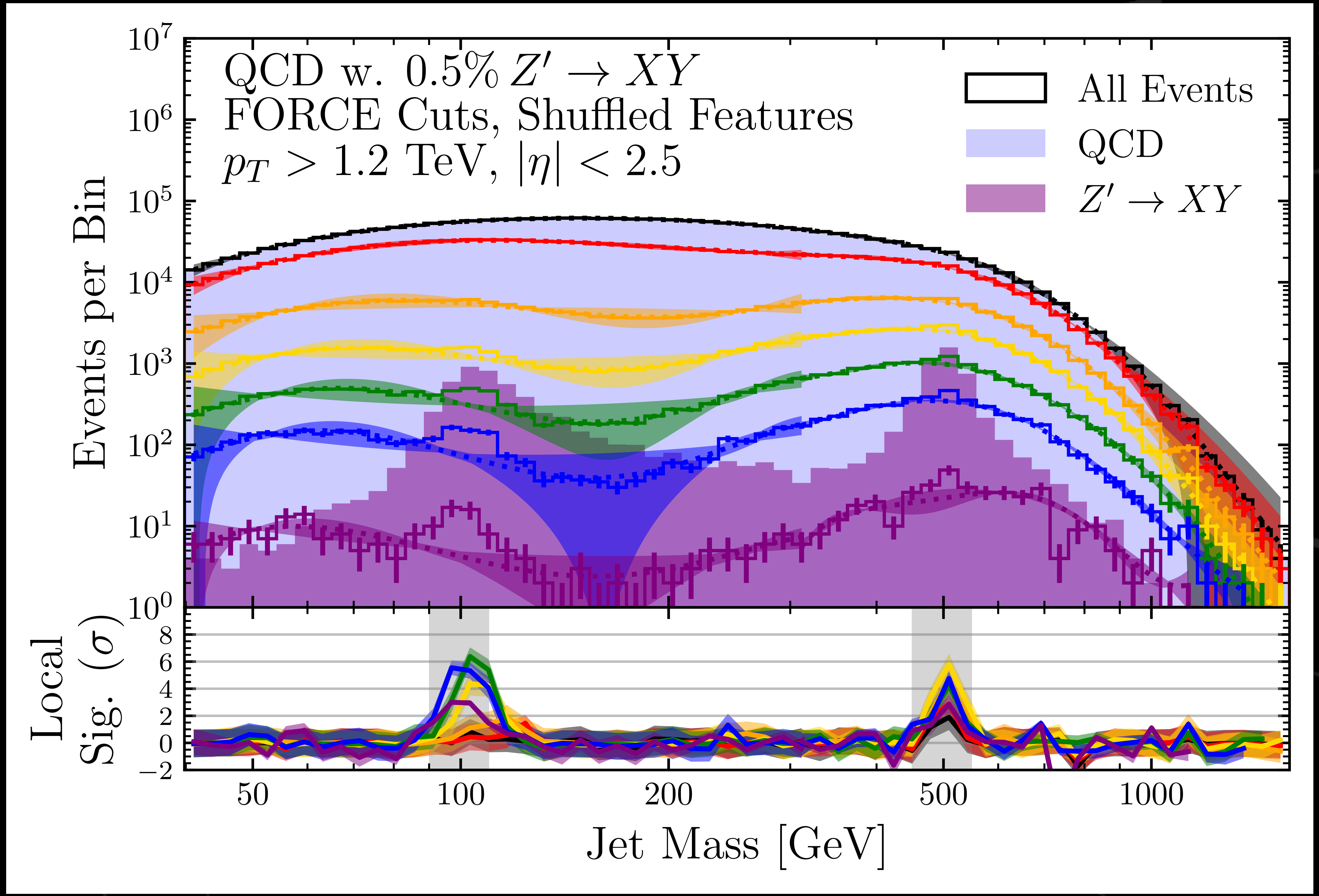

We see comparable results to non-shuffled features, motivating original feature set

Come to the dark side: Future Work

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Integrate with existing anomaly detection methods

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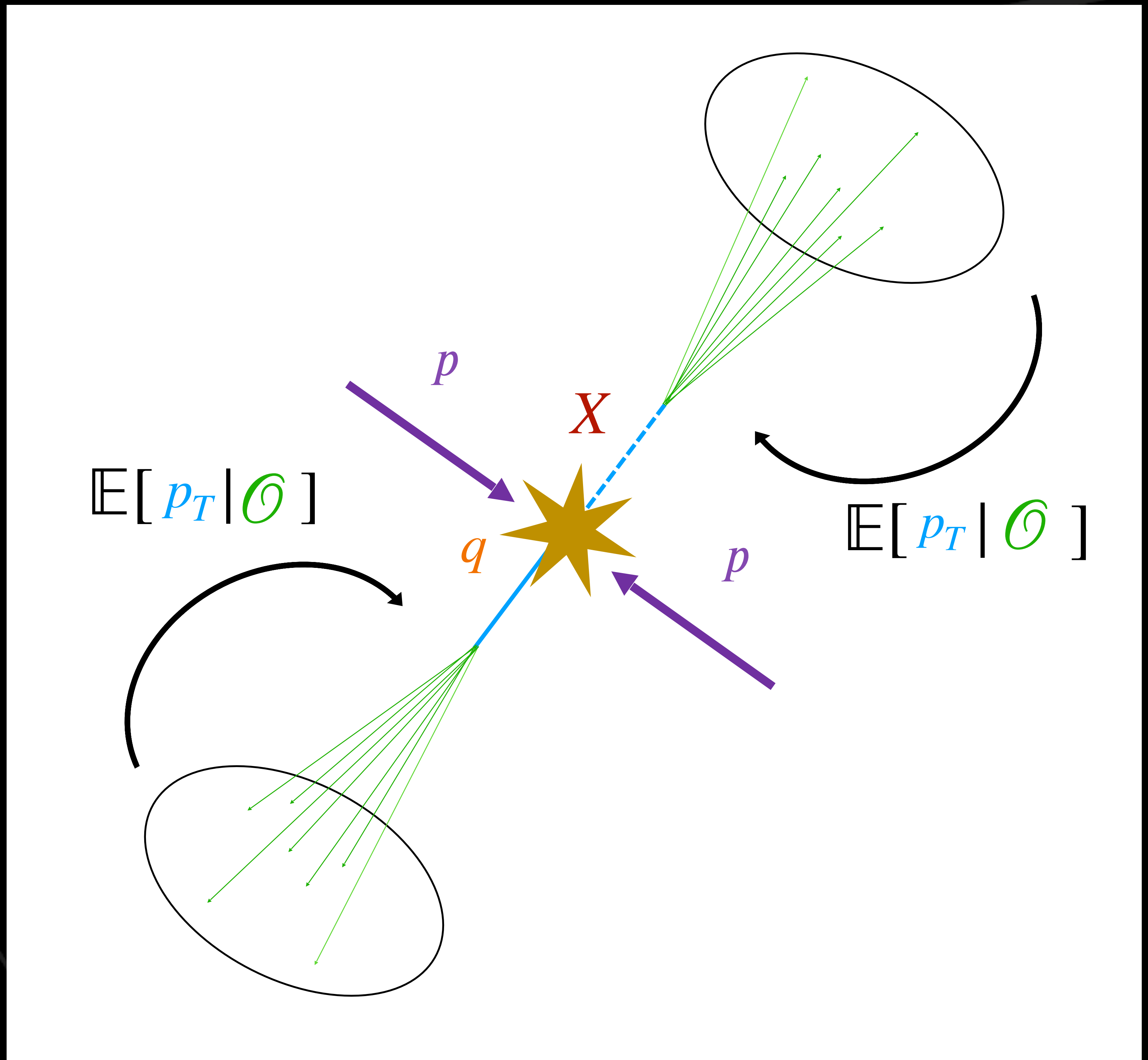
Interrogate conditional expectation to recover f_S, $\langle p_T \rangle_B$, $\langle p_T \rangle_S$, and $L_{S/B}(\mathcal{O})$

Conclusion

Key Takeaways:



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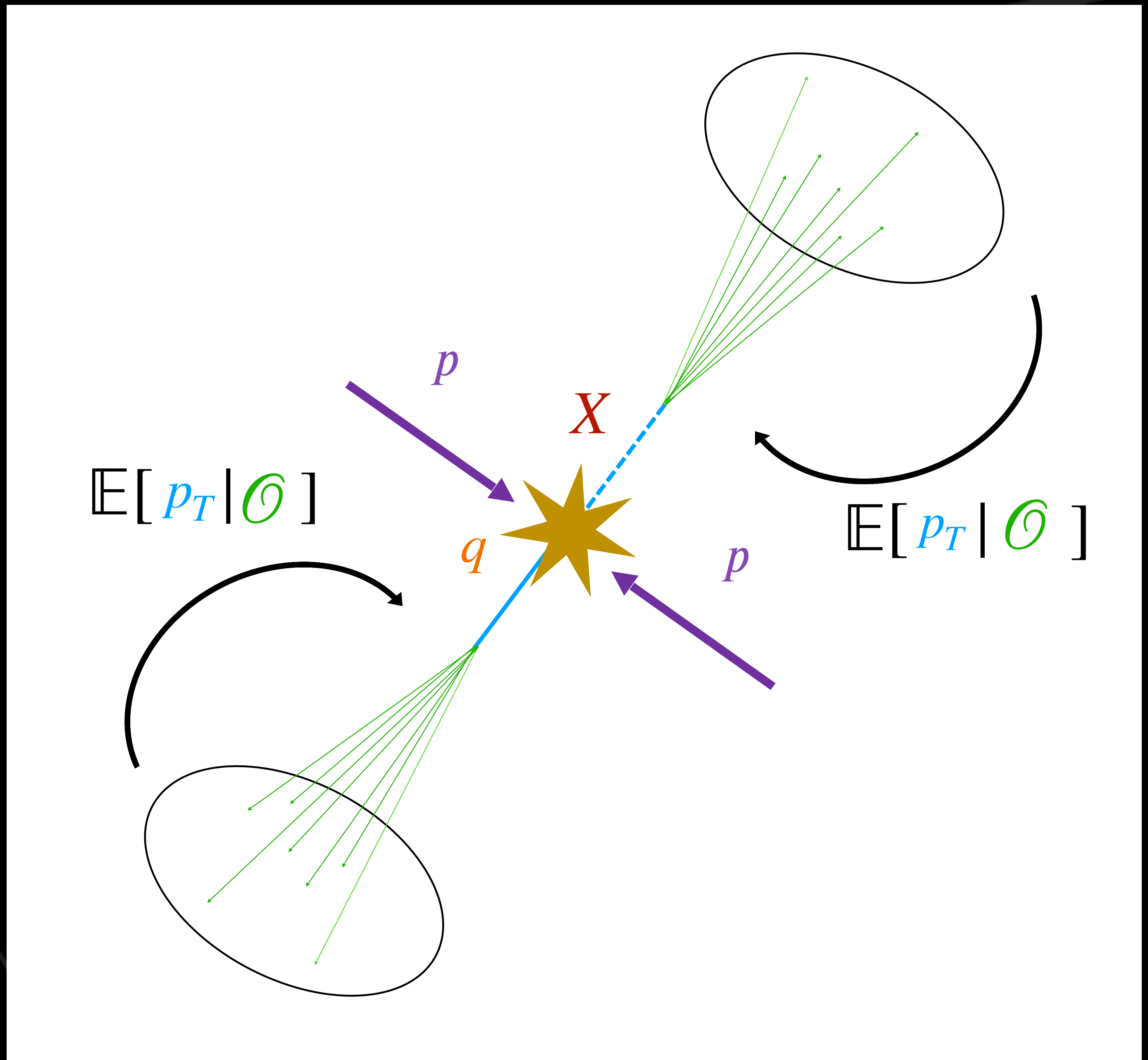
Train ML model to predict kinematics from substructure $\Longrightarrow$ powerful classifier



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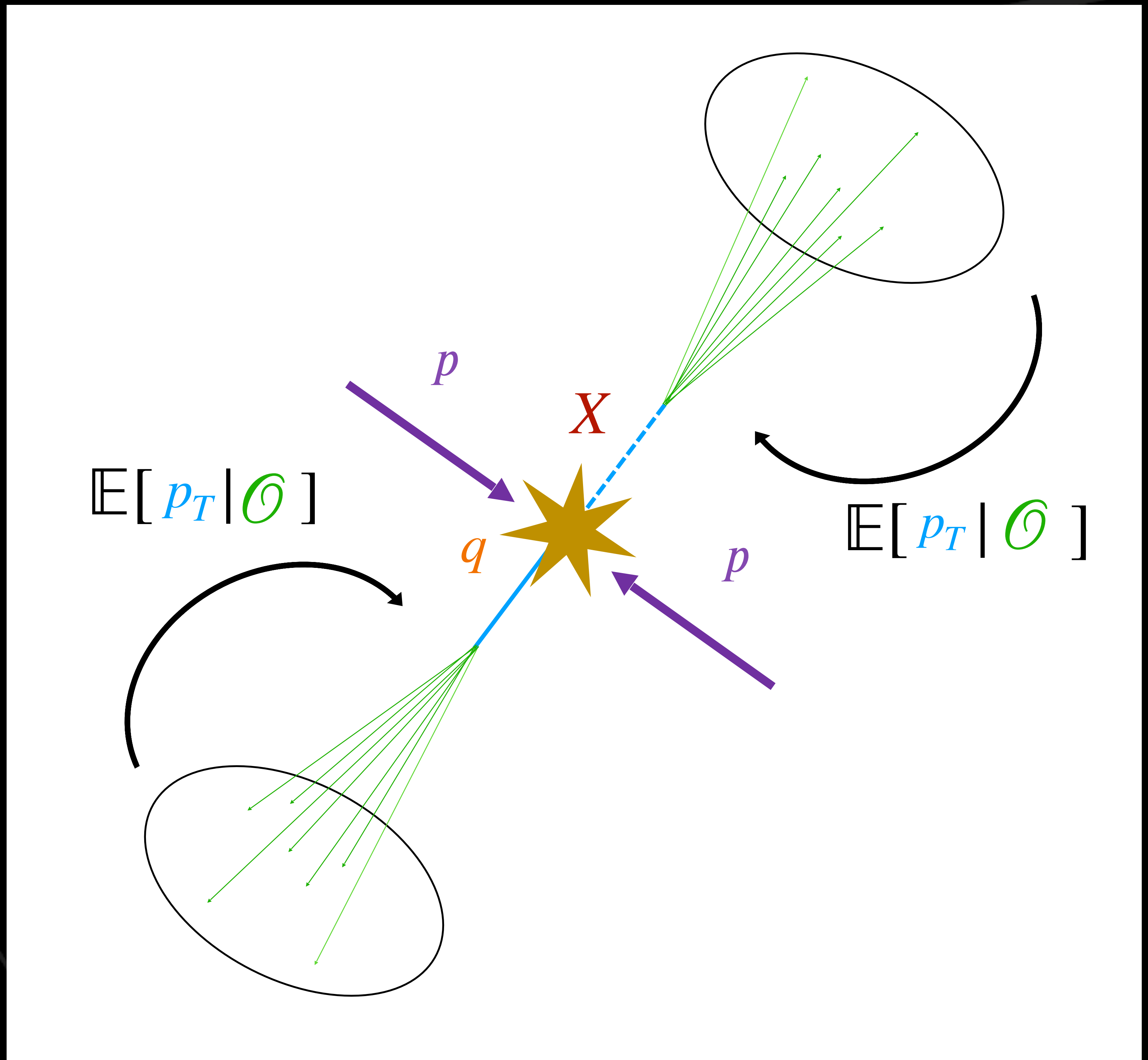

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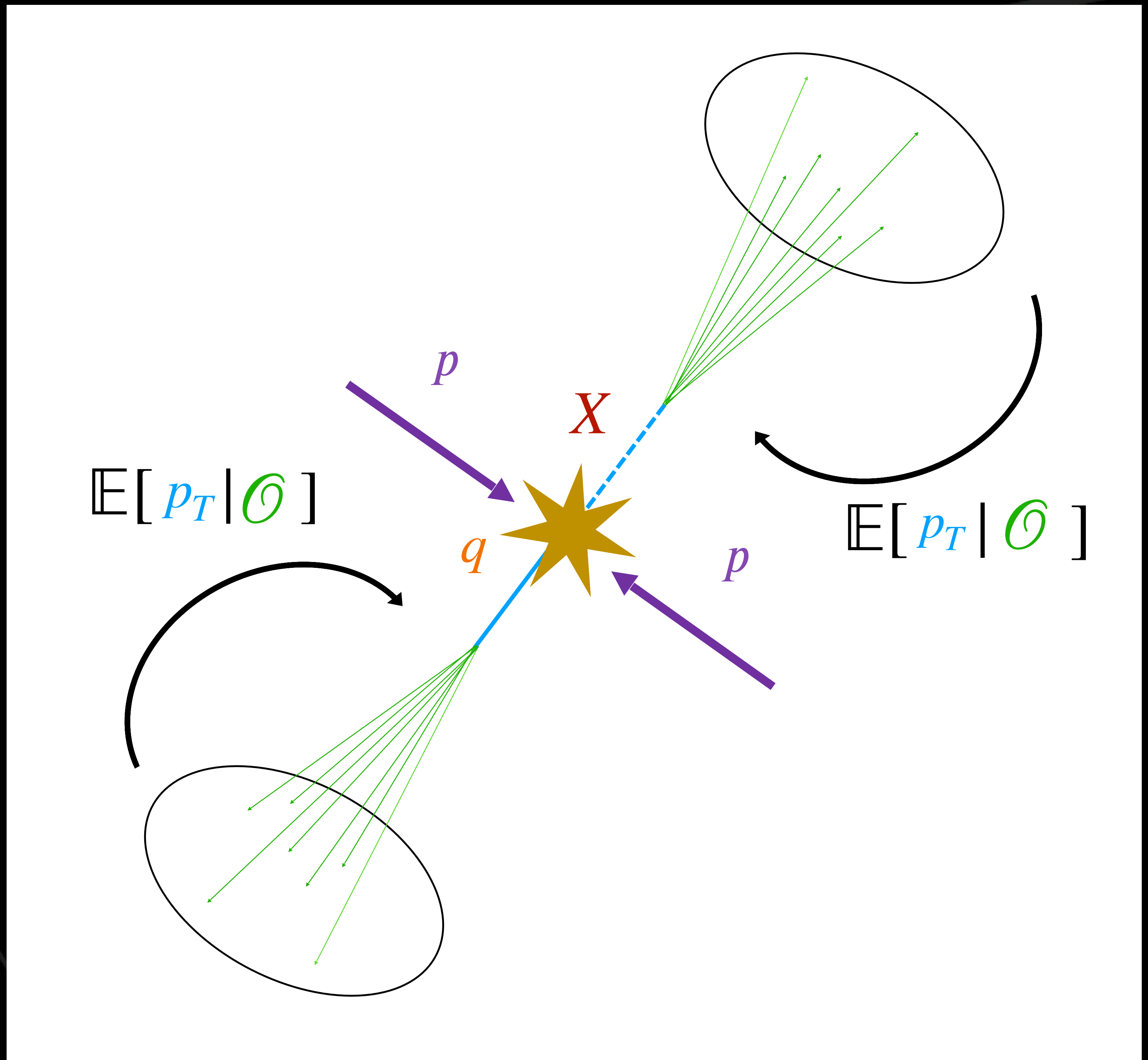
Focused on jets, but works for any factorized objects



Thank you!

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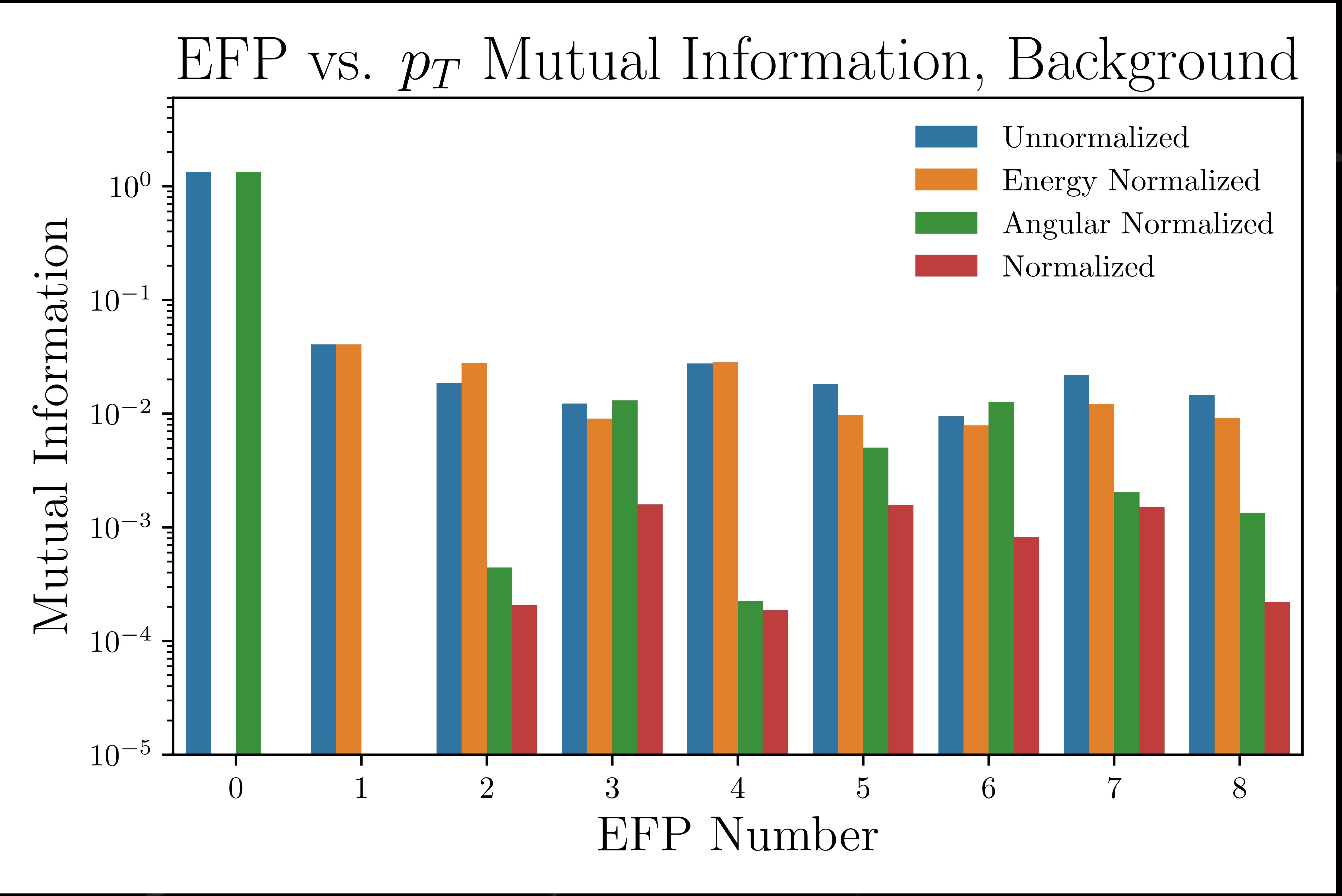
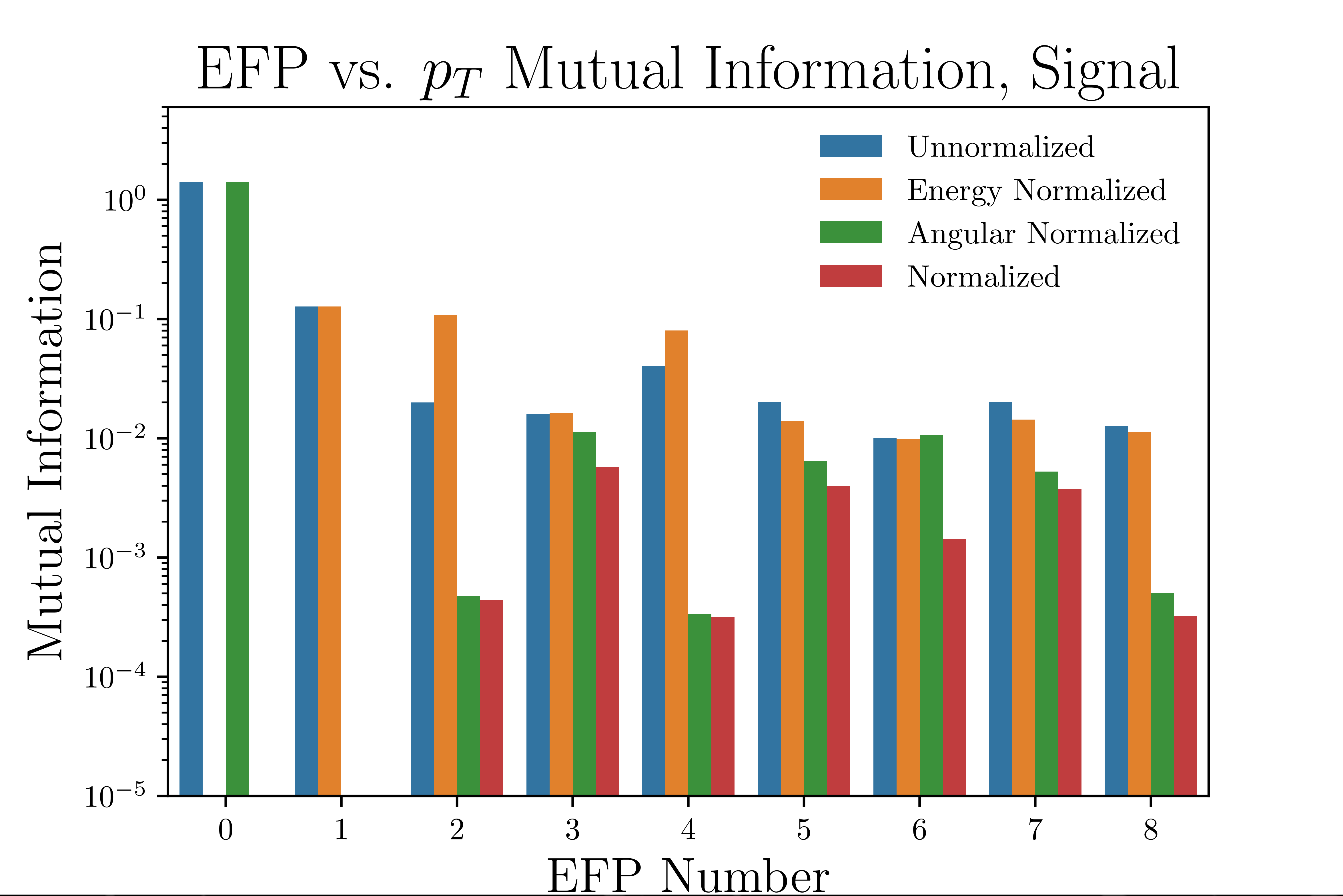
Backup Slides

Interrogating the Normalization

EFPs vs p_T Mutual Information





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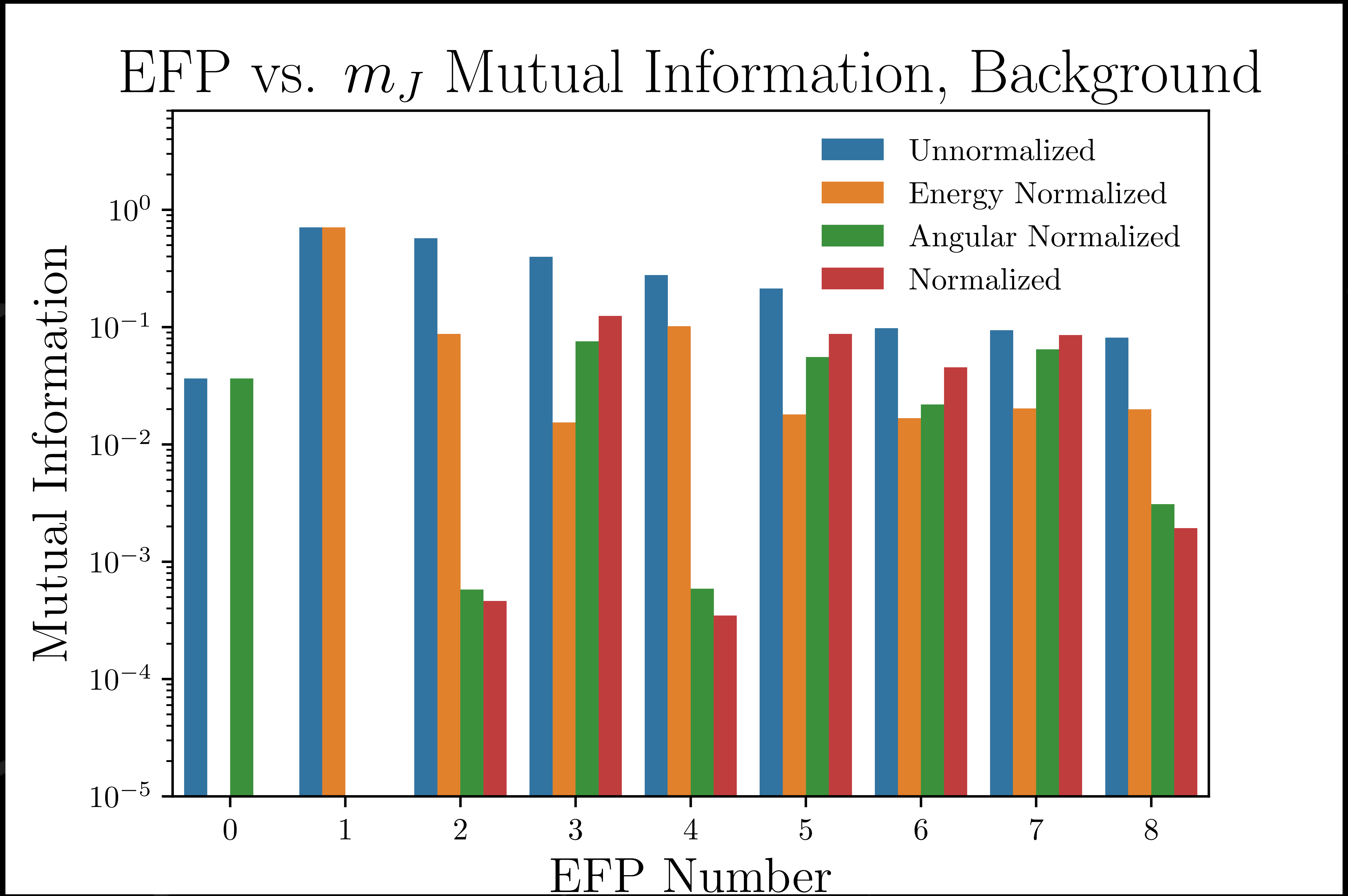
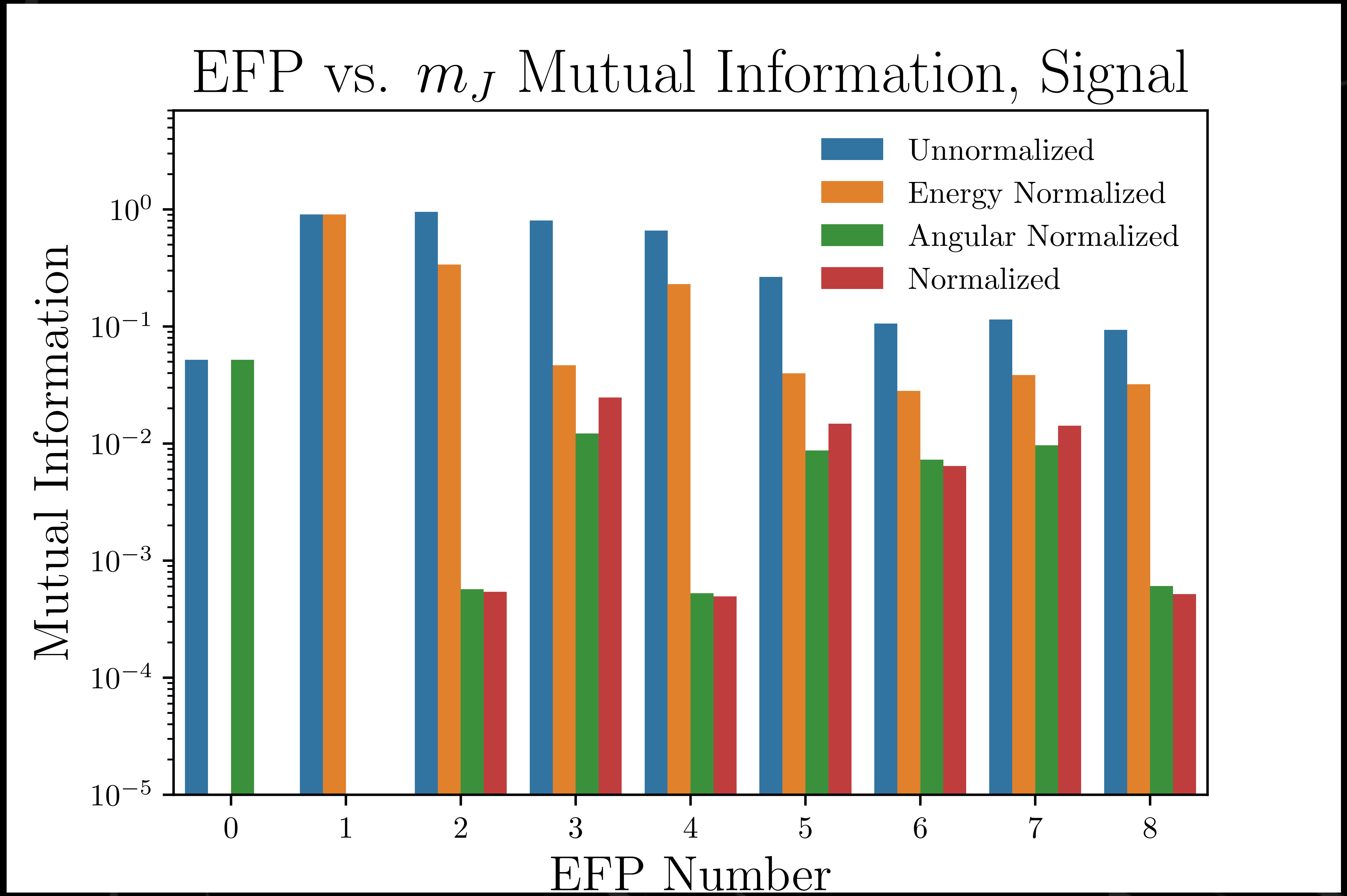
EFPs vs m_J Mutual Information





Bump Hunt w/ $f_S = 0$