

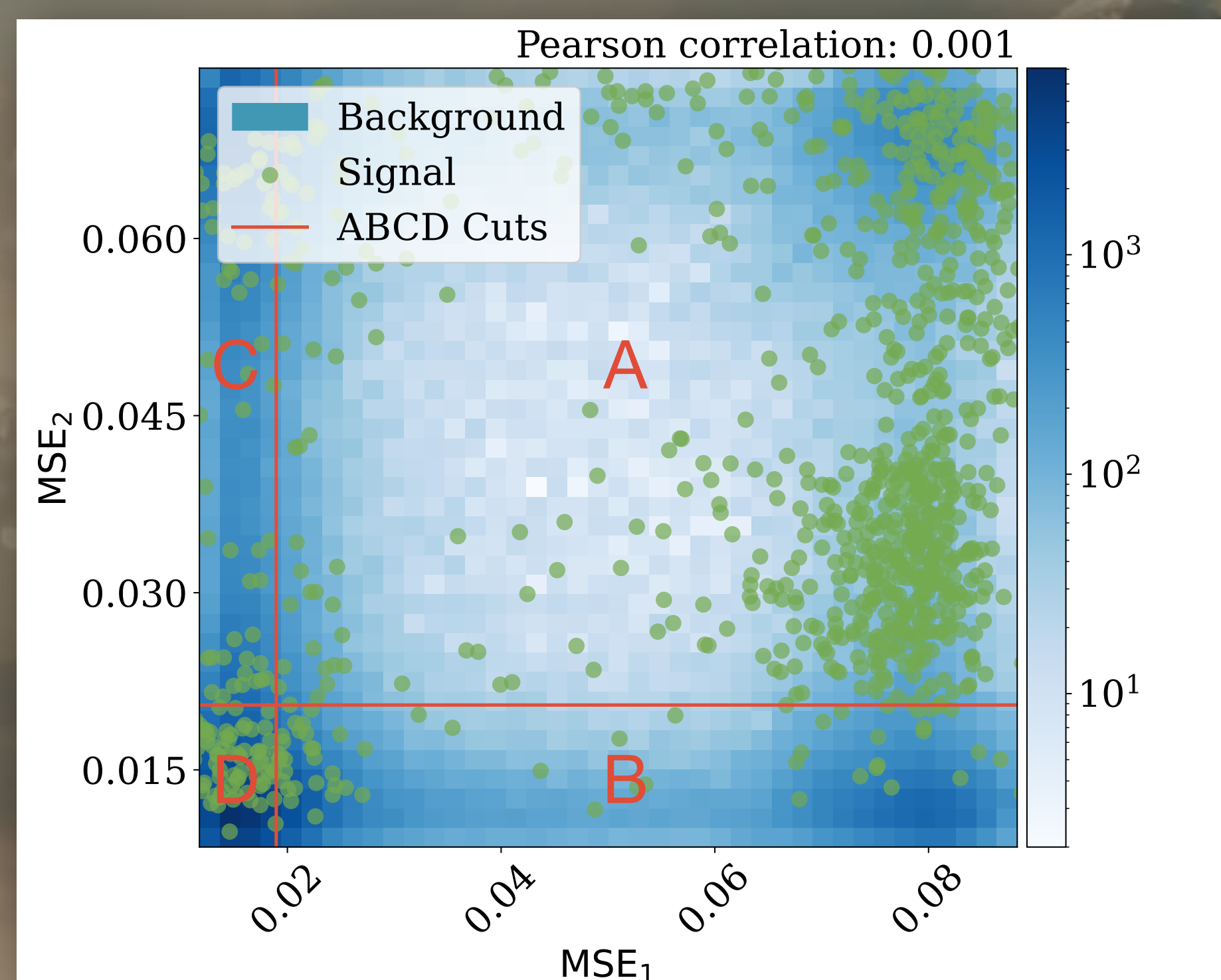
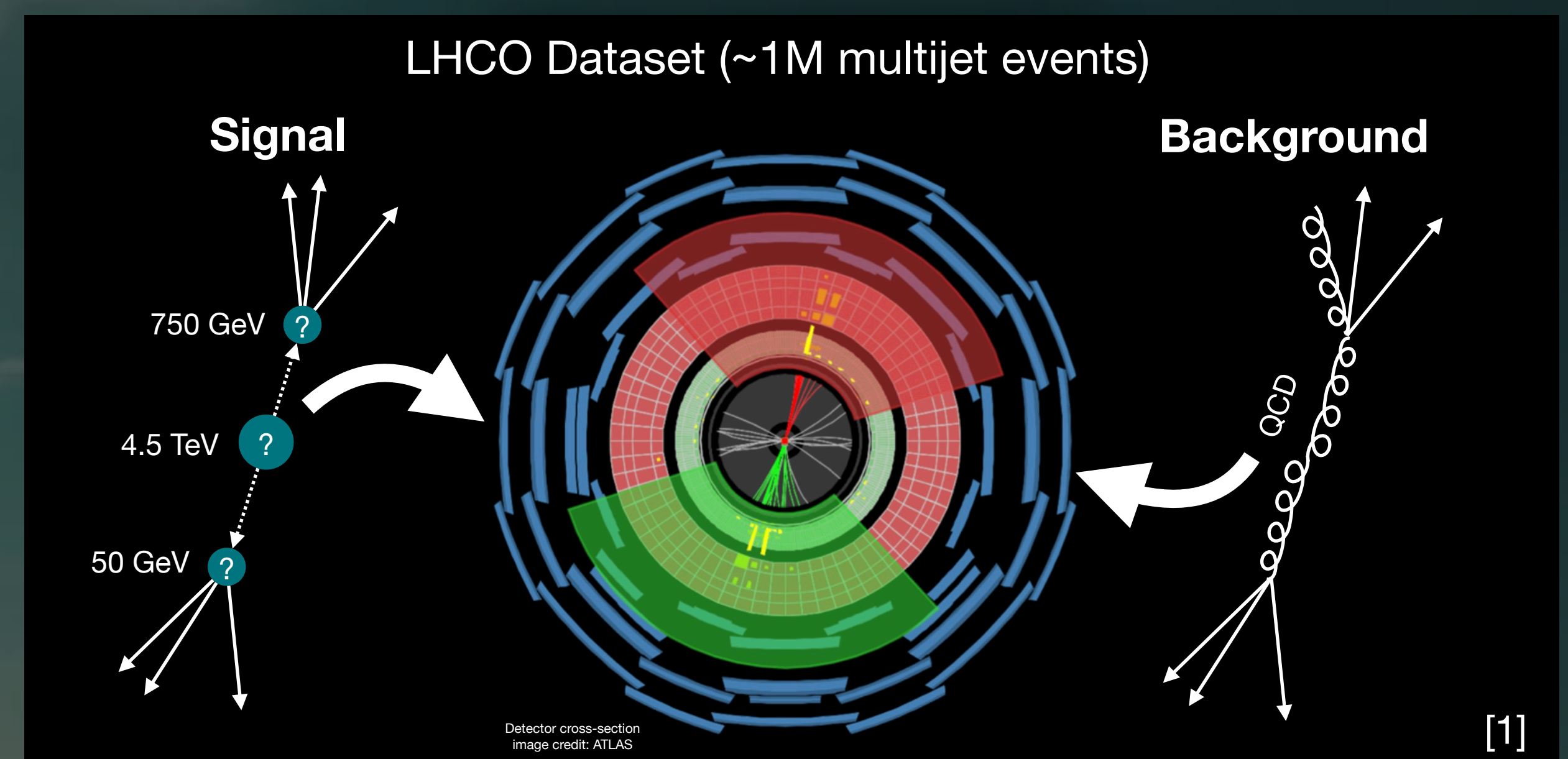
HyLAND

Hybrid Learning for Anomaly Detection

Vinicius Mikuni, Benjamin Nachman, Dennis Noll

Motivation

- Want to find new physics in LHC collider data
- Search for anomalies in agnostic way
- Target resonant and non-resonant anomalies
- Study performed on LHC0 2020 dataset [1]

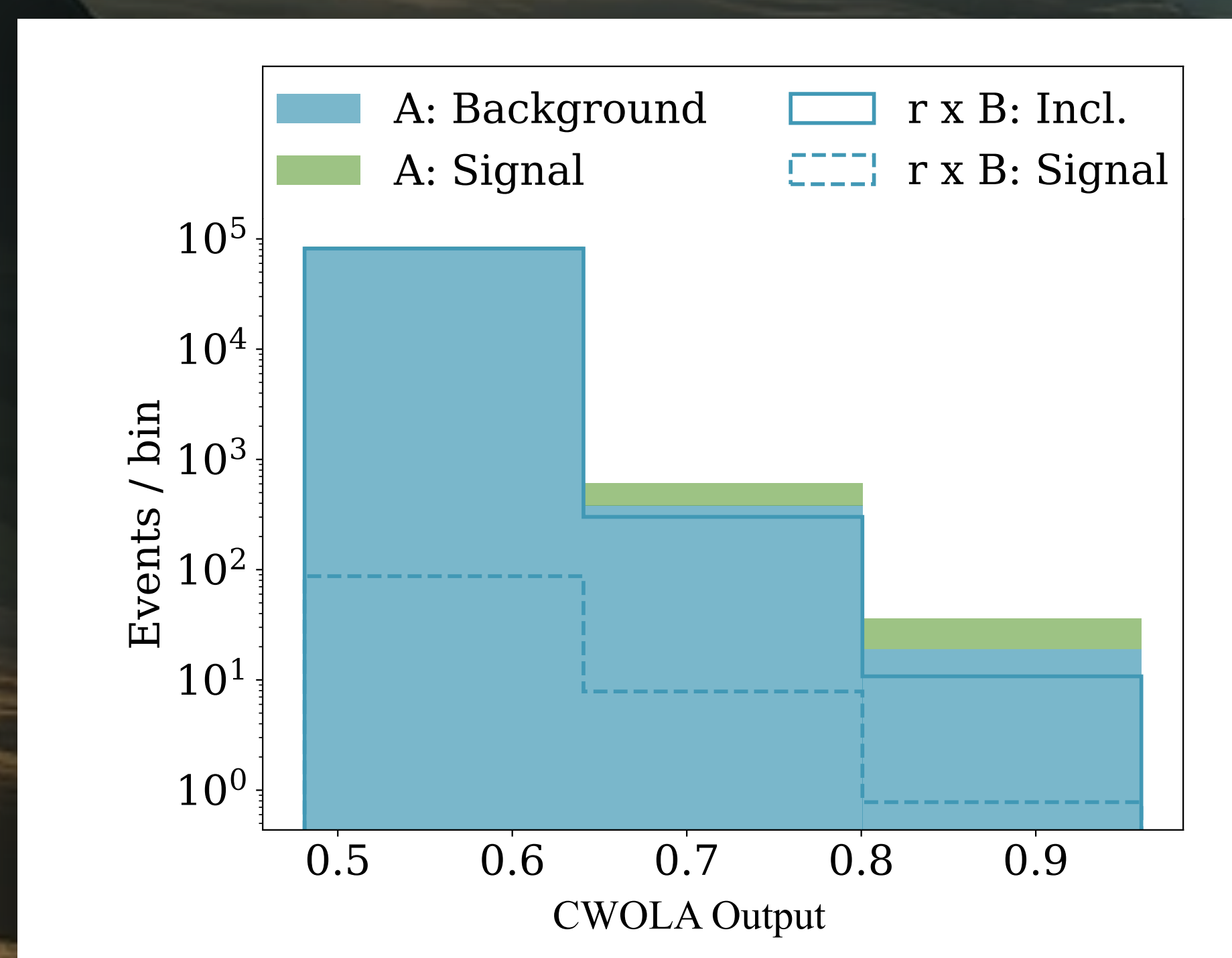
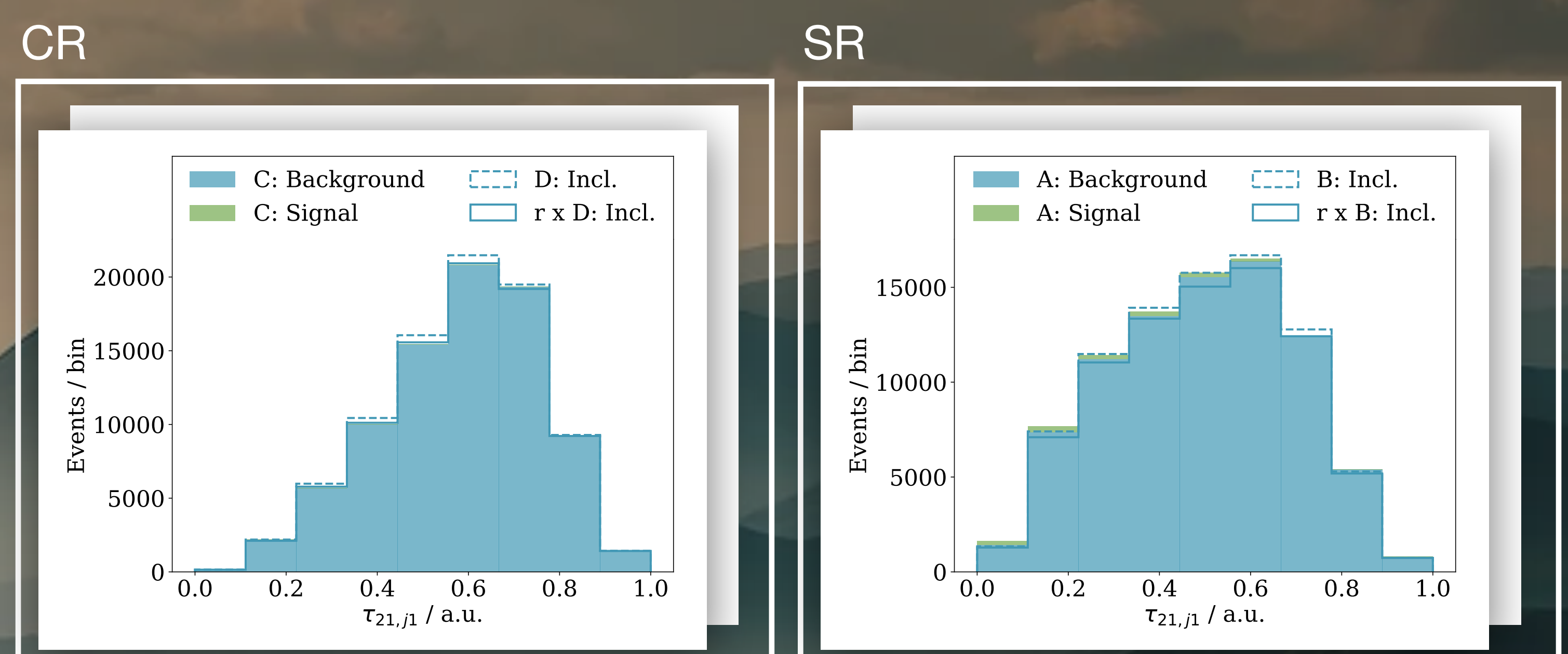


1. Define Signal Region

- Training two decorrelated autoencoders:
 $\mathcal{L} \propto \text{MSE}_1 + \text{MSE}_2 + \text{DisCo}(\text{MSE}_1, \text{MSE}_2)$
- MSE (Reconstruction loss): Finds low densities
- DisCo (Distance Correlation [2]): Decorrelates AEs
- Inputs: Kinematic features ($m_{jj}, m_{j1}, m_{j2}, \dots$)
- **Get**: SR (25% of events with highest MSEs)

2. Estimate Background

- Use ABCD Method [3]: $C / D = A / B$
- Differential transfer (R) via classification:
 - Training in Control Region (CR): $r = C / D$
 - Application in Signal Region (SR): $A = r \times B$
 - Inputs: Substructure features ($\tau_{21,j1}, \tau_{32,j1}, \dots$)
- **Get**: Differential background-only estimate in SR



3. Measure Signal

- Semi-supervised CWOLA [4] in SR:
 - Classification of Data vs Background-estimate
 - Provides optimized discriminant
 - Inputs: Substructure features ($\tau_{21,j1}, \tau_{32,j1}, \dots$)
- **Get** (injected 3σ signal):
 - Highly sensitive signal classifier
 - WIP: further mitigate false positives

Conclusion

- New anomaly detection method for resonant and non-resonant signals
- Hybrid Approach:
 - Unsupervised learning to define signal region and differential bkg. estimate
 - Semi-supervised learning for optimized signal classification
- Can greatly improve signal significance