Automatizing the search for mass resonances using **BumpNet**

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Motivation

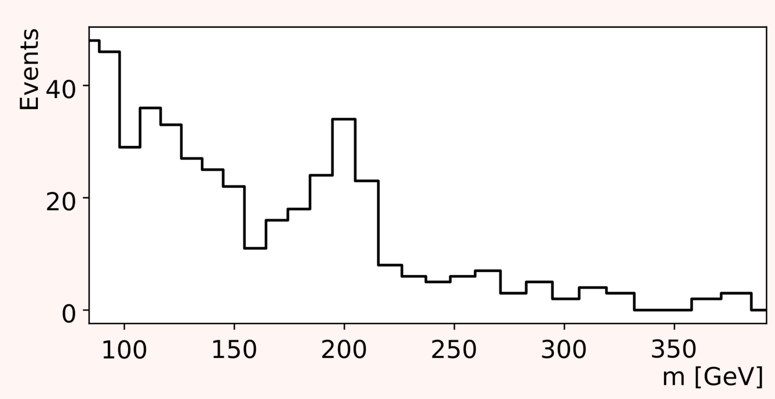
What? Train a neural network to **identify mass bumps in real data** without the need of simulation or analytical fit to estimate the background

Why? Exploit the **discovery potential of the data**
- Impossible to check all possible searches with the traditional analysis
- Many possible resonances in unexplored final states

Overview

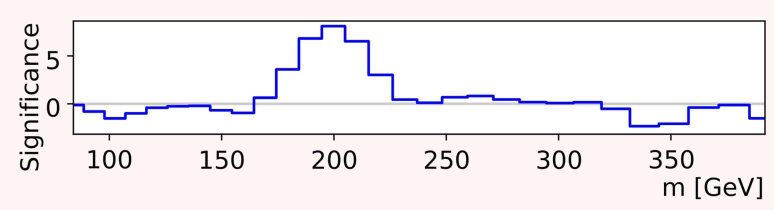
BumpNet [1] is a *fully supervised* neural network (NN) trained to map smoothly falling histogram data to z-significance values.

Training



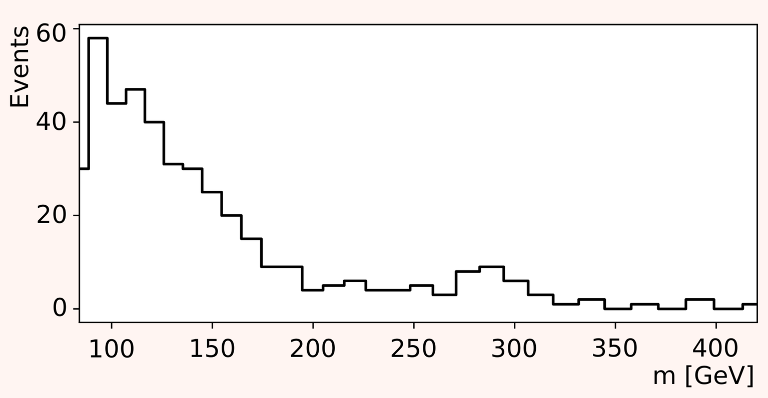
- **Input**: bin entries (from *known* background)

+



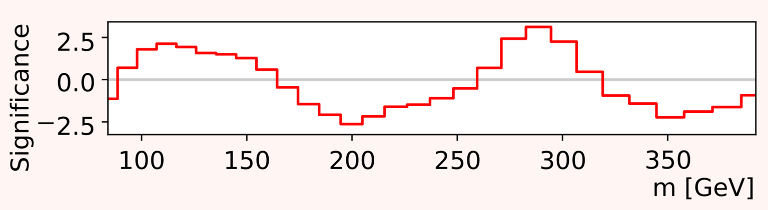
- **Label**: *perfect* statistical significance in each bin

Application



- **Input**: bin entries

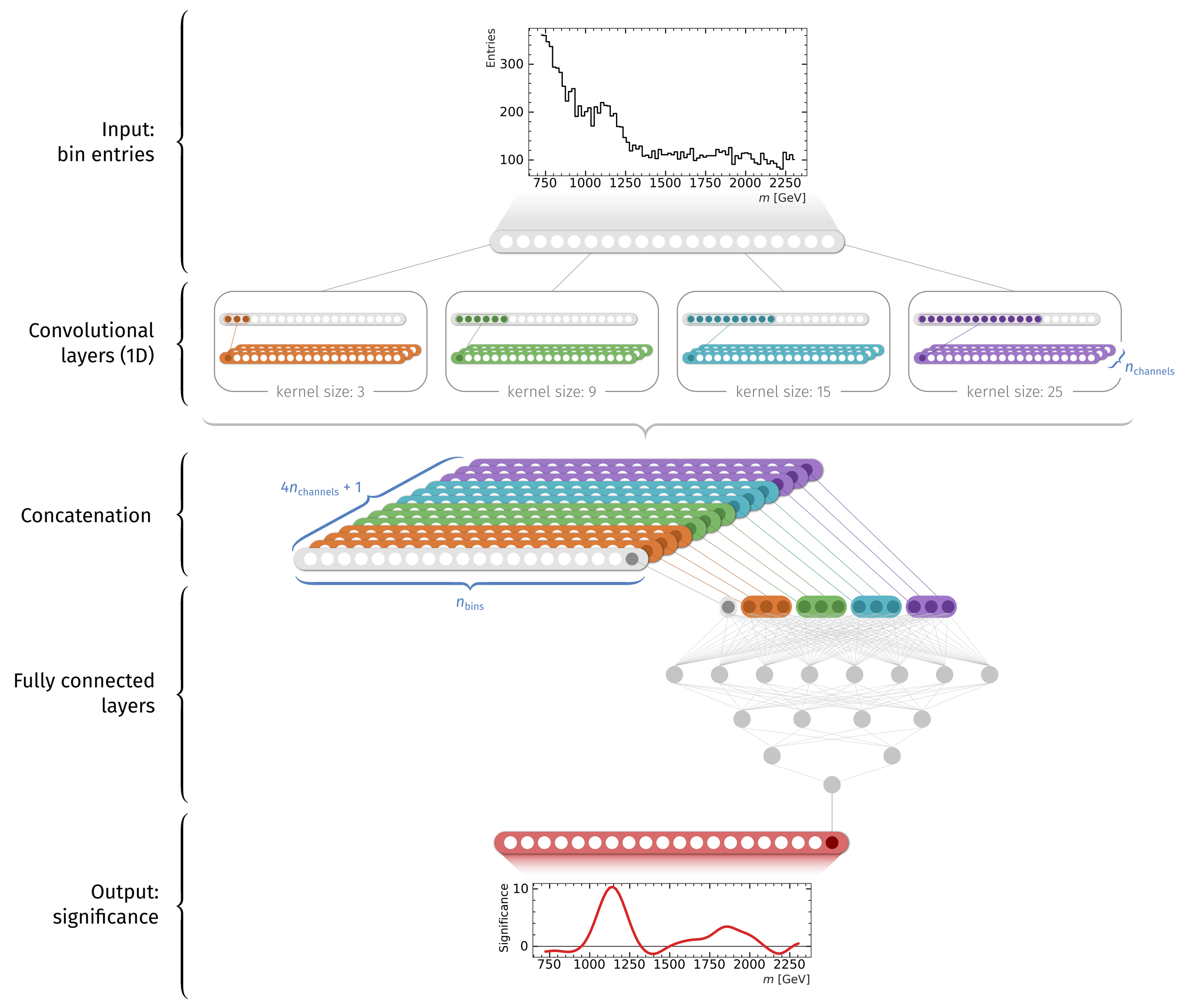
↓



- **Output**: *predicted* statistical significance in each bin

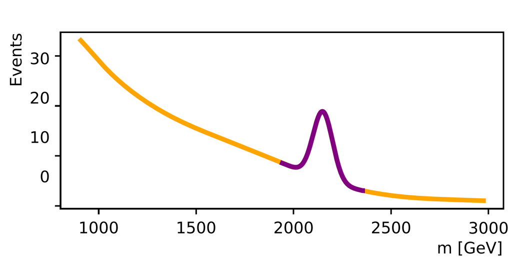
Architecture

$4 \times$ 1-D **convolutional layers** followed by a dense layer.
Intuitive and **agnostic to the number of bins** in the histogram.



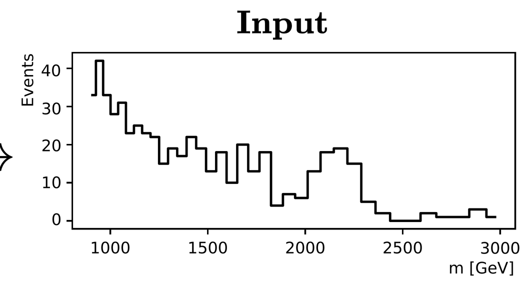
Training

Smoothly falling curve (from analytical functions and GPR) + **gaussian signal** → **Poisson fluctuate** (*training data*) → calculate **local significance** in each bin (*label*) [2]



→

Input



→ **Label**

$$z_i = \sqrt{-2\ln\frac{L(0)}{L(\hat{\mu})}}$$

Acknowledgements

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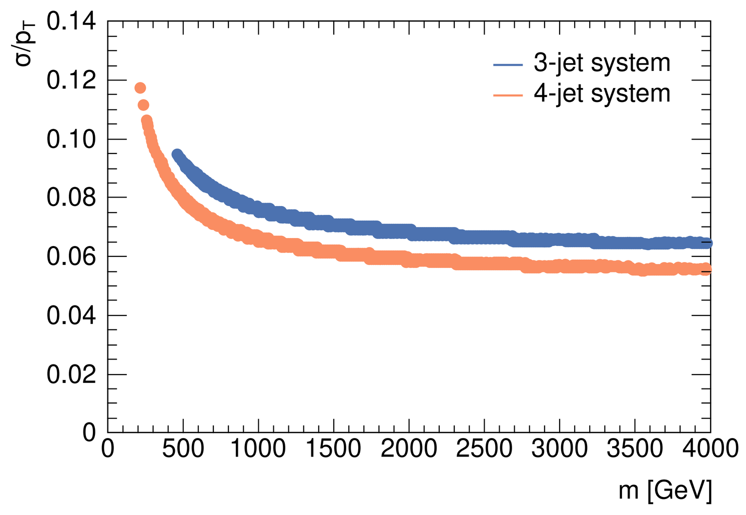
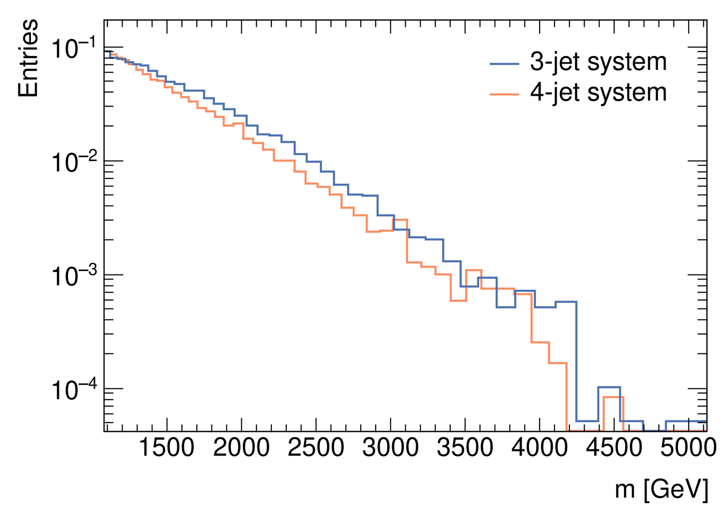
Histogram Processing + Calibration

- Train + evaluate using the **Dark Machines** dataset [3]
  - Designed to test anomaly detection techniques
  - Equivalent to 10 fb^{-1} with highest cross-section processes at the LHC
- **Final states** made from all possible combinations of the following objects:

e	γ	Reconstructed leptonic Z	Boosted t
μ	Jet (j)	Boosted hadronic W/Z	High mass jet ($m > 200$ GeV)

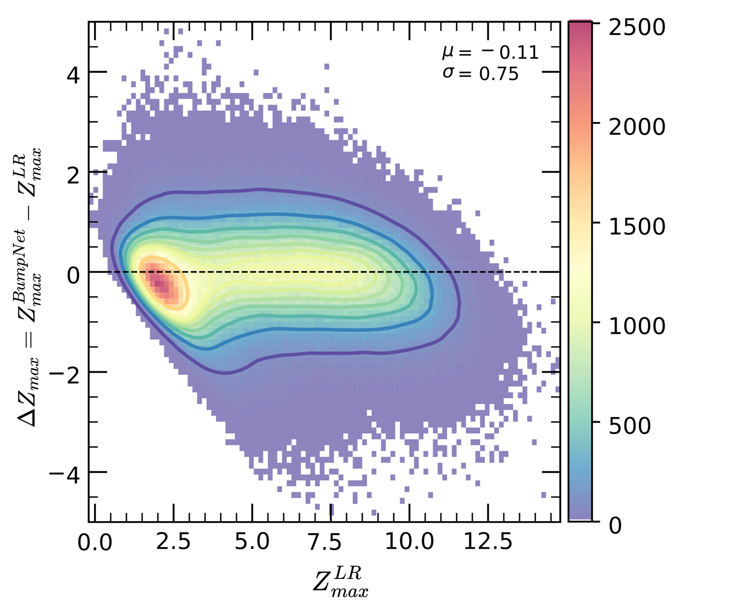
- **30,000 mass histograms** created from all combinations of objects in each final state (e.g. $1e + 2j \rightarrow m(e, j_1), m(e, j_2), m(j_1, j_2), m(e, j_1, j_2)$)
- Rebinning reflects **detector resolution**

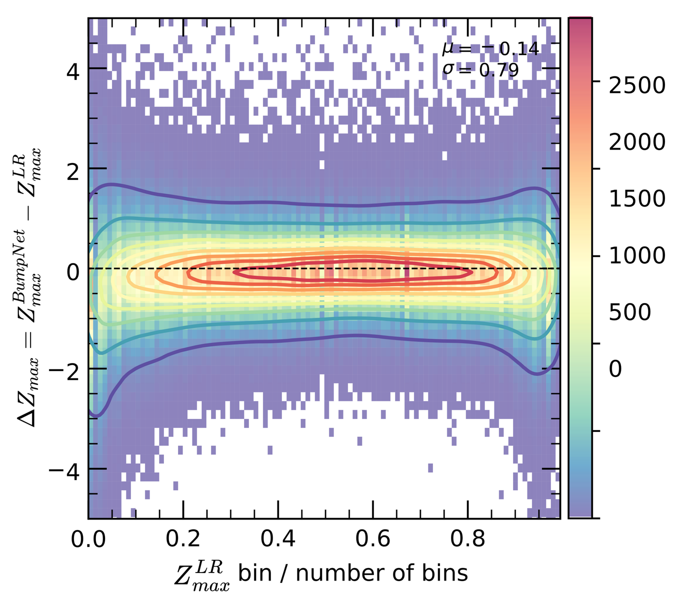




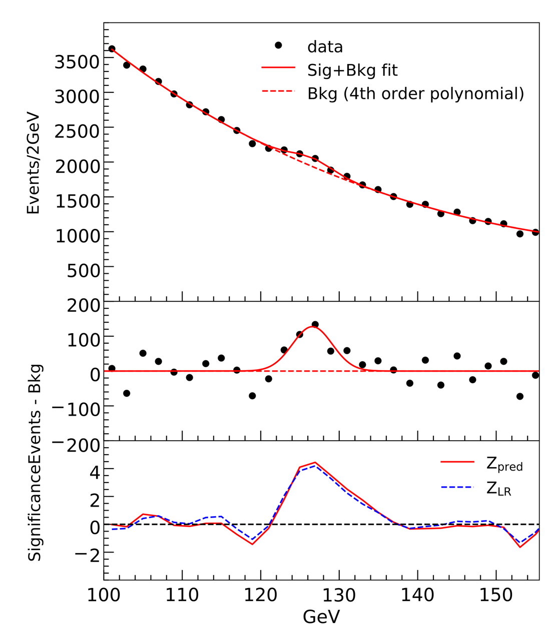
Performance

- **Unbiased agreement** between Z_{max}^{LR} and $Z_{max}^{BumpNet}$

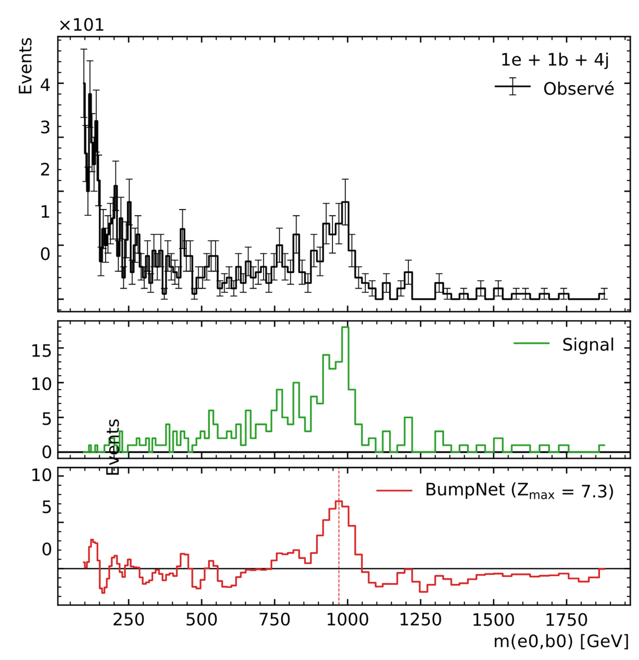




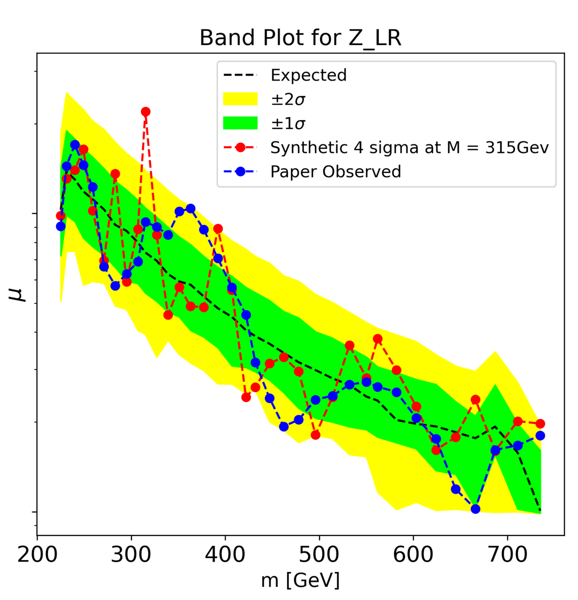
- Promising results when finding the **Higgs bump**; predicted significance is 4.6σ whereas Z_{LR} yields 4.2σ

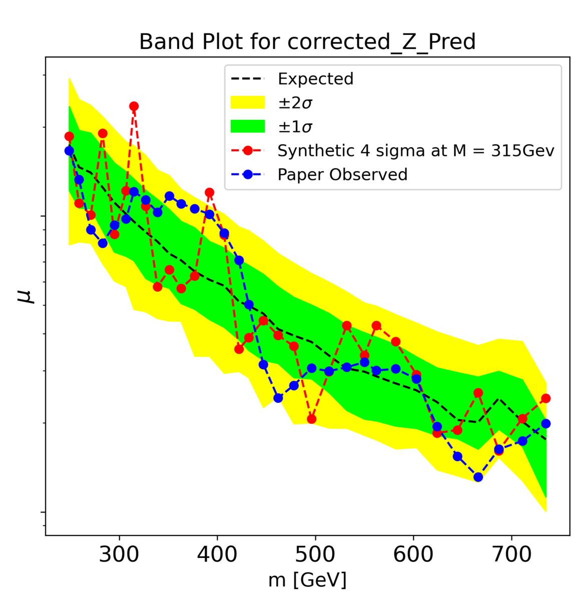


- Sensitive to **BSM signals** (example below: *stop* → *be*)



- **Limits** on the number of signal entries derived from $Z_{BumpNet}$ **closely match** those from Z_{LR}





References

1 Arguin, J.F. et al. (2025). J. High Energ. Phys. 2025, 122 (2025). https://doi.org/10.1007/JHEP02(2025)122
2 Cowan, G., Cranmer, K., Gross, E., & Vitells, O. (2011). European Physical Journal C, 71(2), 1554. https://doi.org/10.1140/epjc/s10052-011-1554-0
3 Aarrestad, T. et al. (2022). SciPost Phys. 12, 043 doi:10.21468/SciPostPhys.12.1.043