INSS 2026 Stats Presentation: How To Work As A Group And Basic NLL

July 10th, 2026

INSS Stat Group VI, Santa Barbara, CA

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  A. Do all of the questions by splitting
  B. Focus on each question and have detailed answers even if don’t have time to present all.

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- **n** = number of questions we tackle (out of 5)
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- **I** = individual understanding gained
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Key assumption (fixed total time T and opportunity):

When we spread over more questions, the depth, understanding and audience impact per question are diluted.

We model this as

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Therefore,

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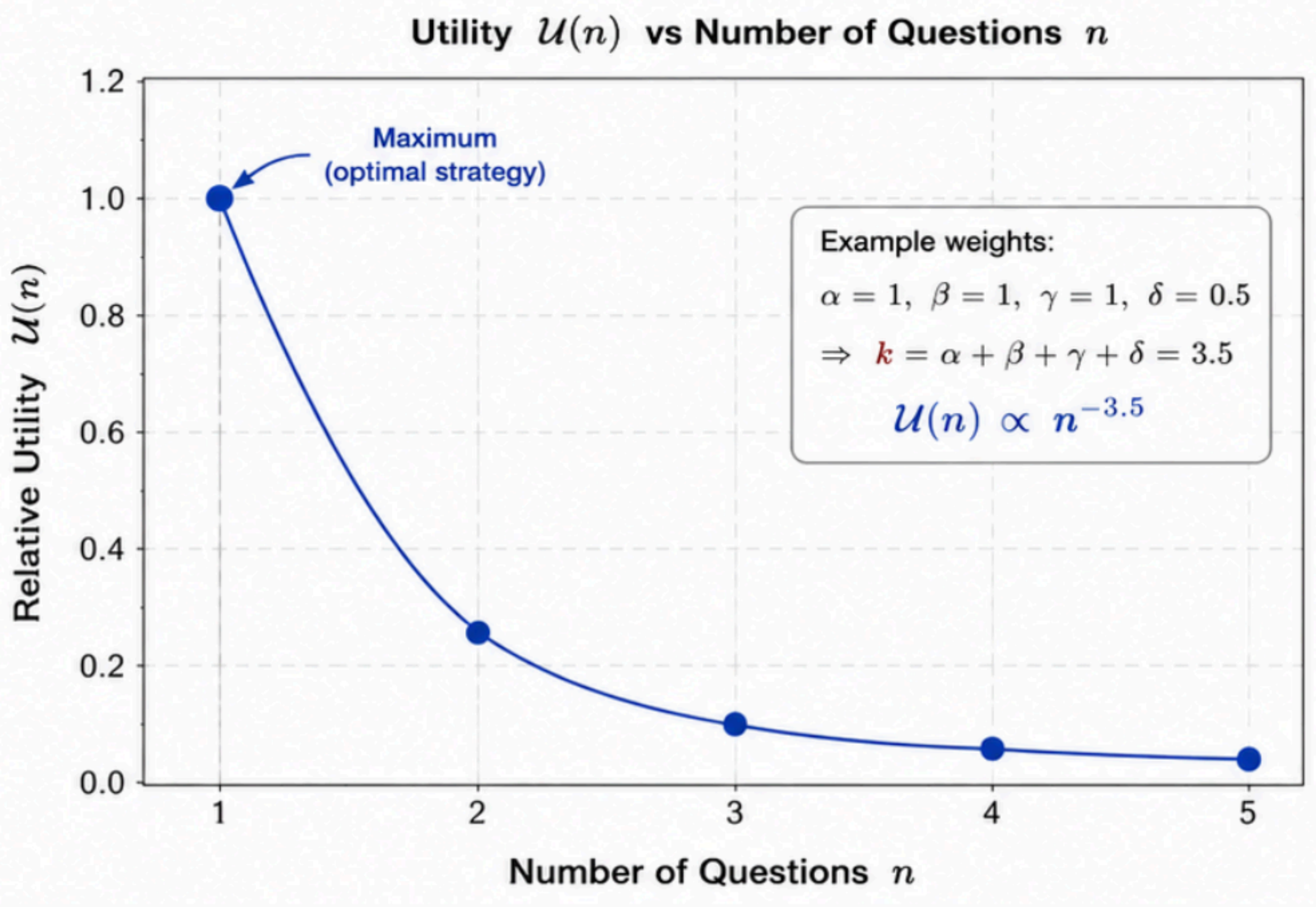

Exercise I

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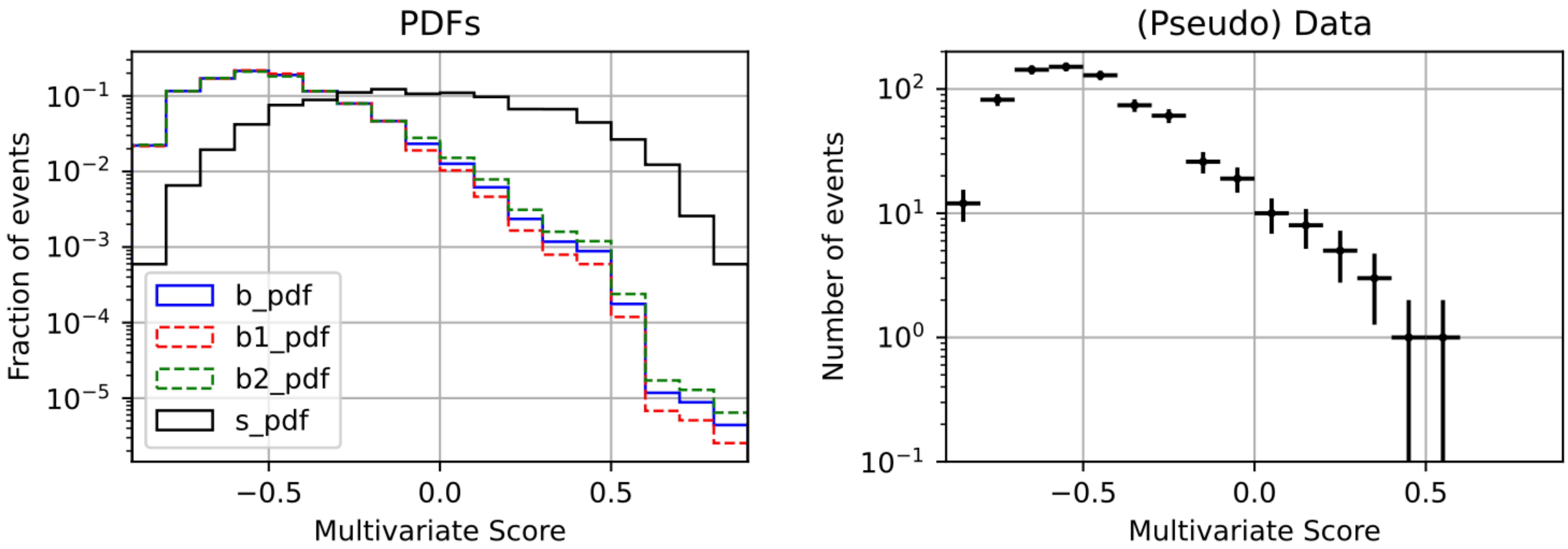
A physics analysis with a large background B seeks the extract a signal S from and extended likelihood $S + B$ fit to a multivariate discriminant. The binned PDFs for signal and background, as well as the data distributions are shown in Fig. 1. The histograms of Fig. 1 can be downloaded in `ROOT` or `npz` format from



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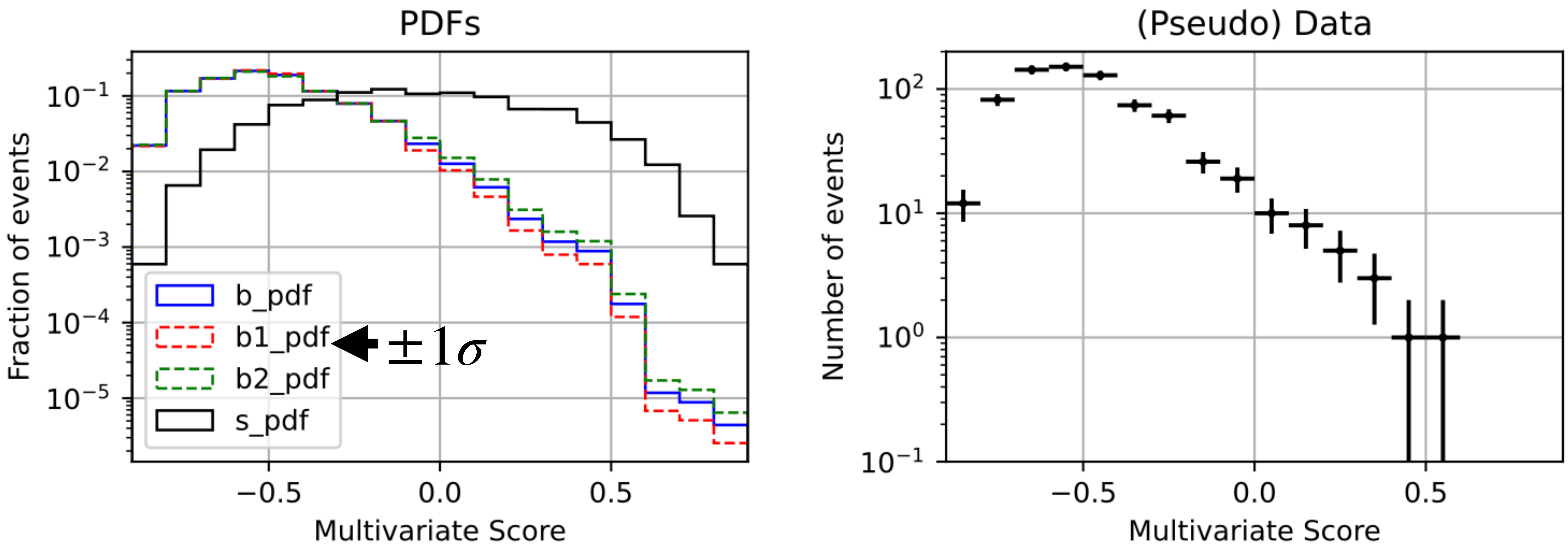

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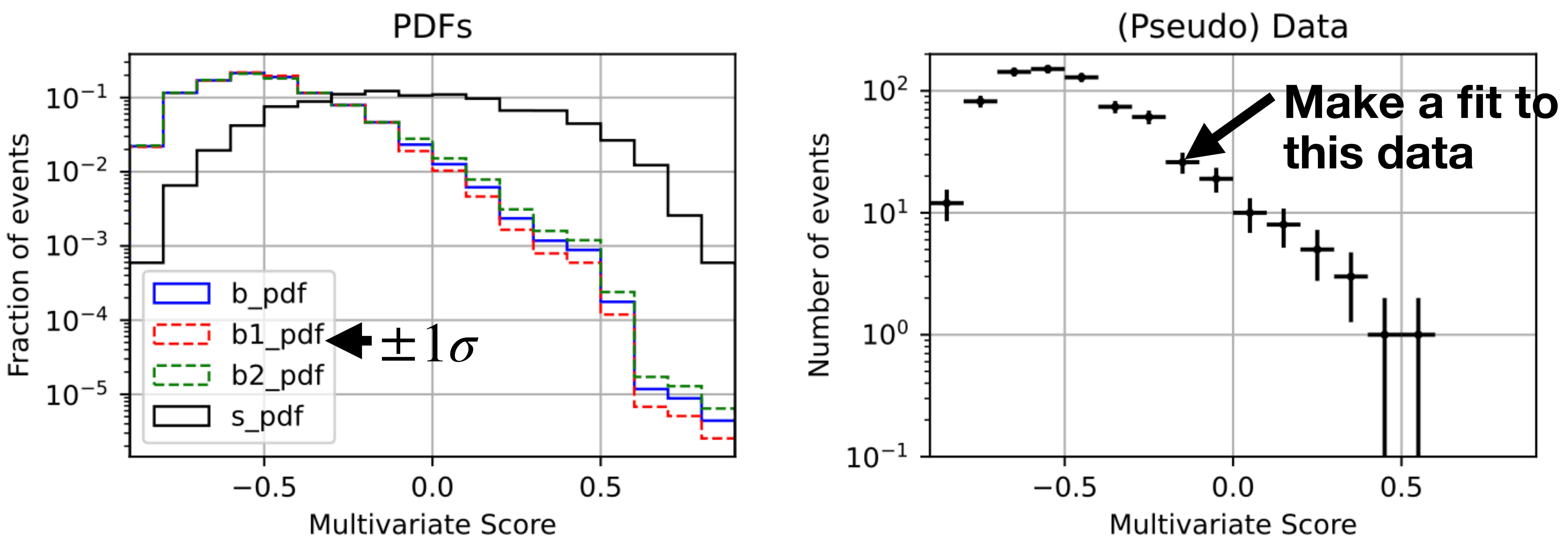

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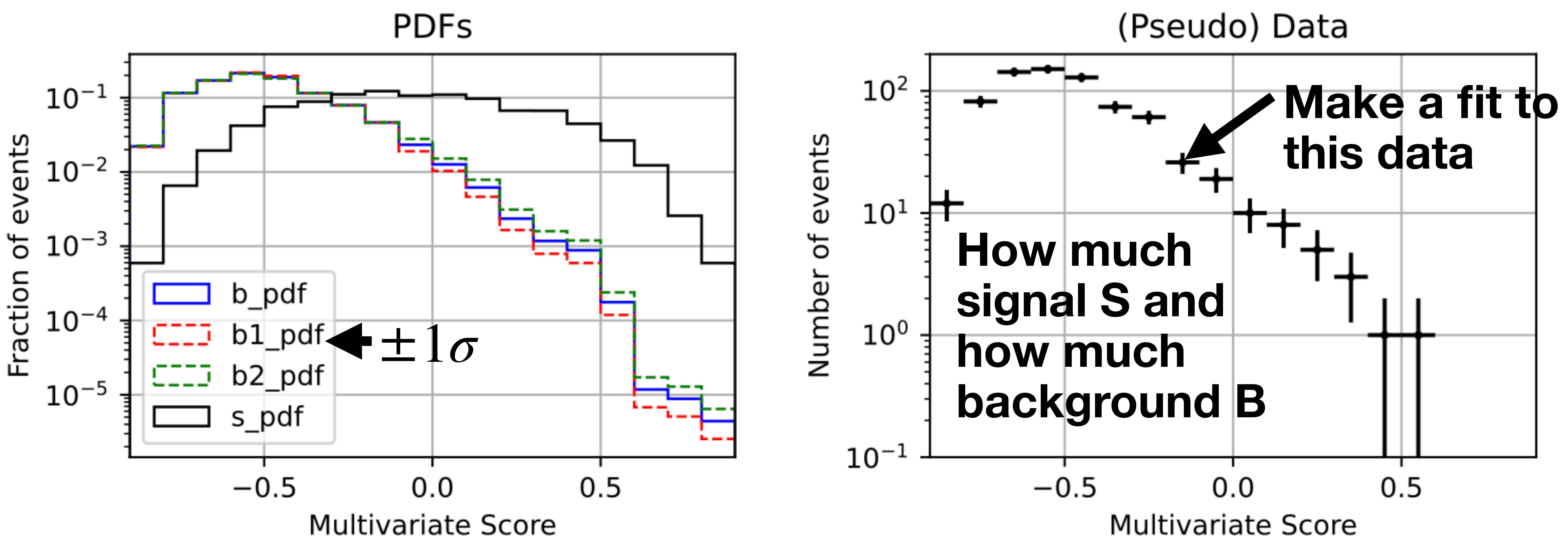

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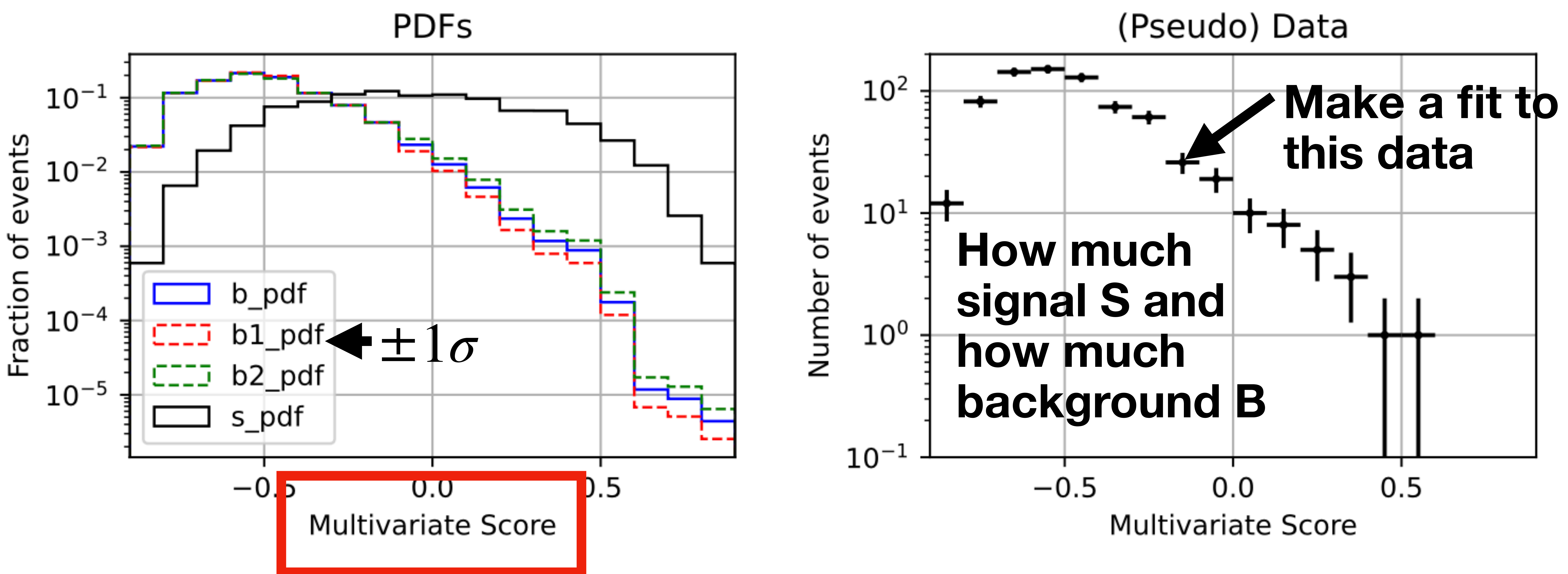

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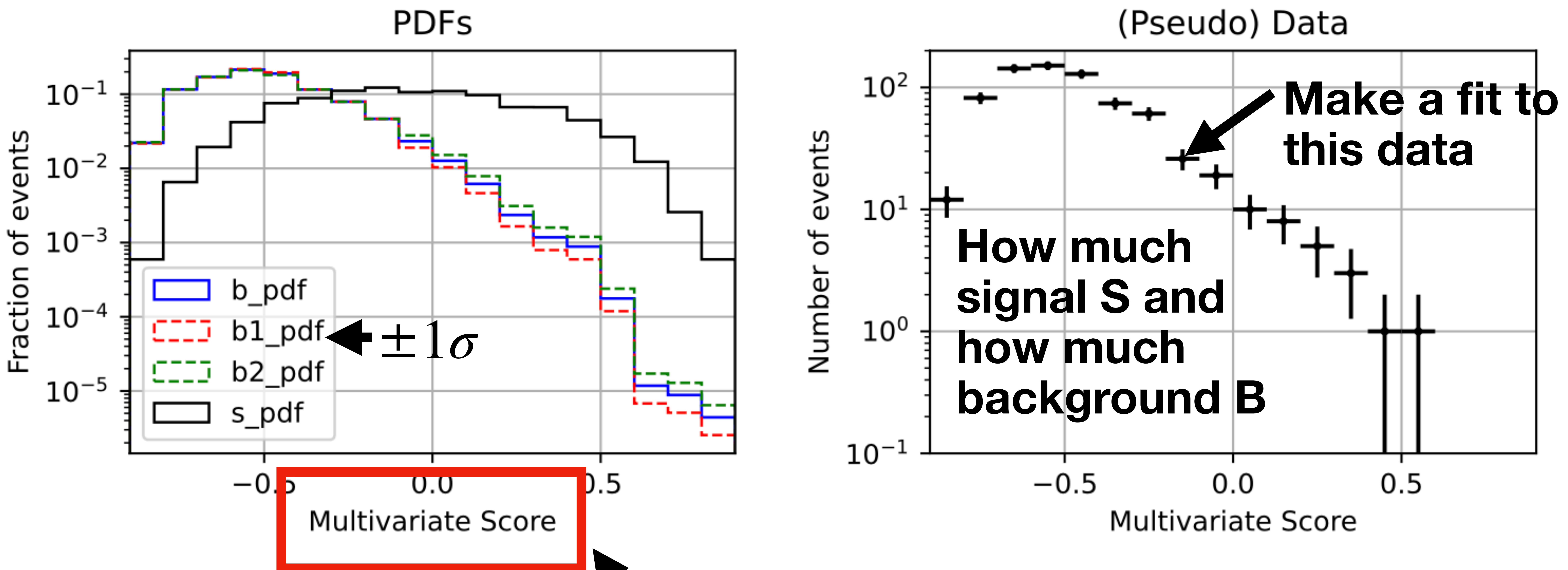

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- **This is the chi square!**

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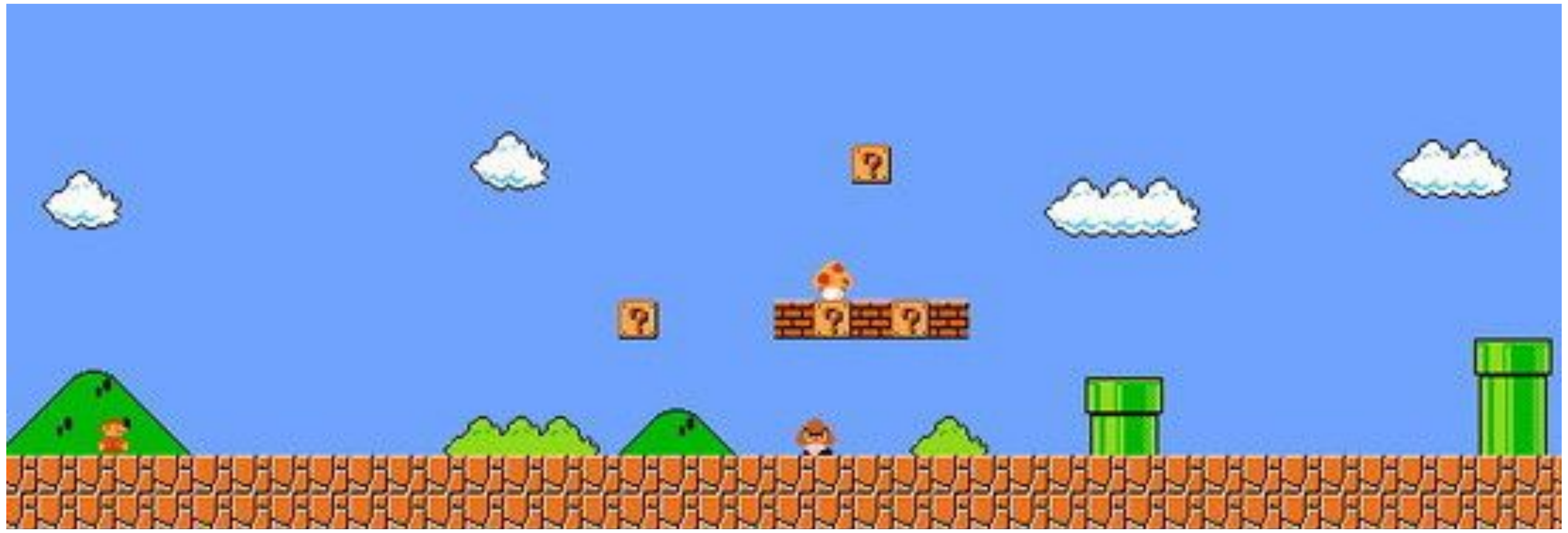

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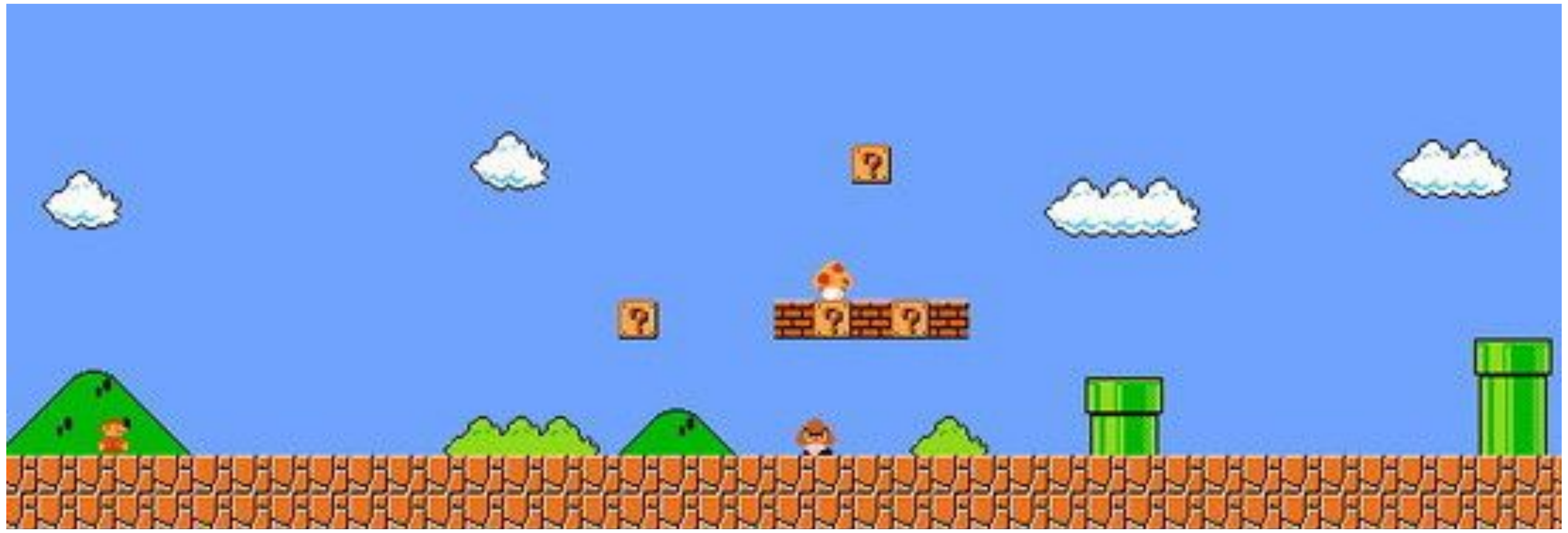

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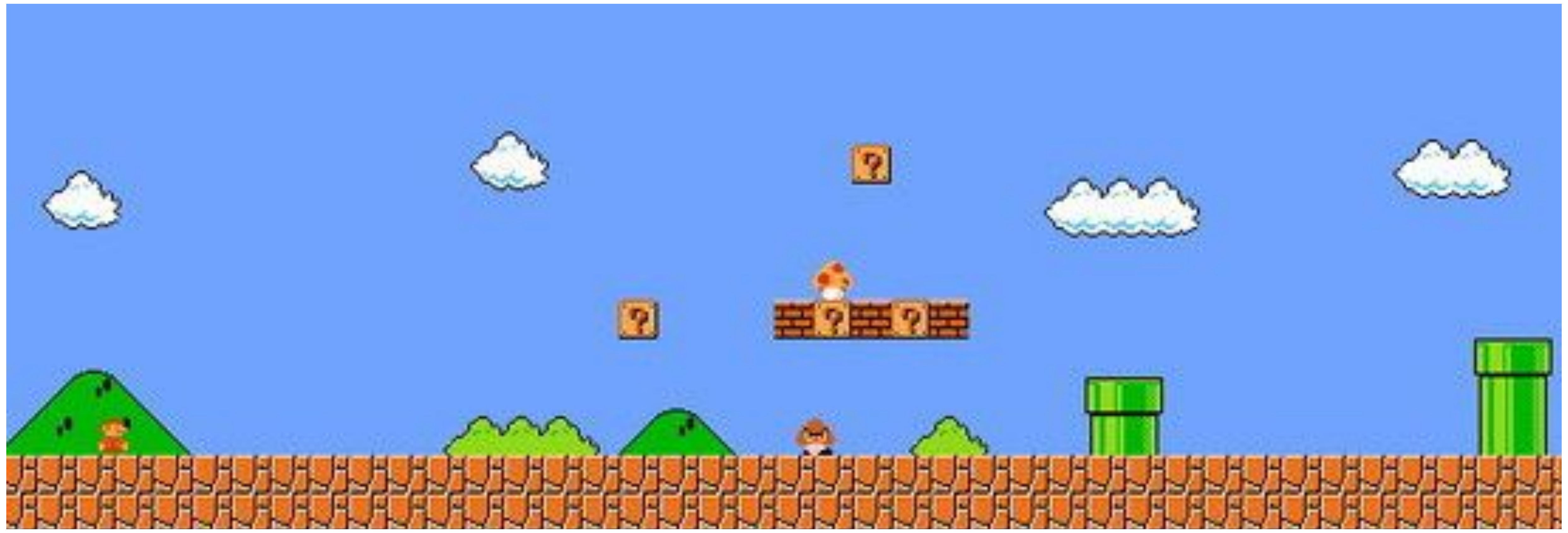

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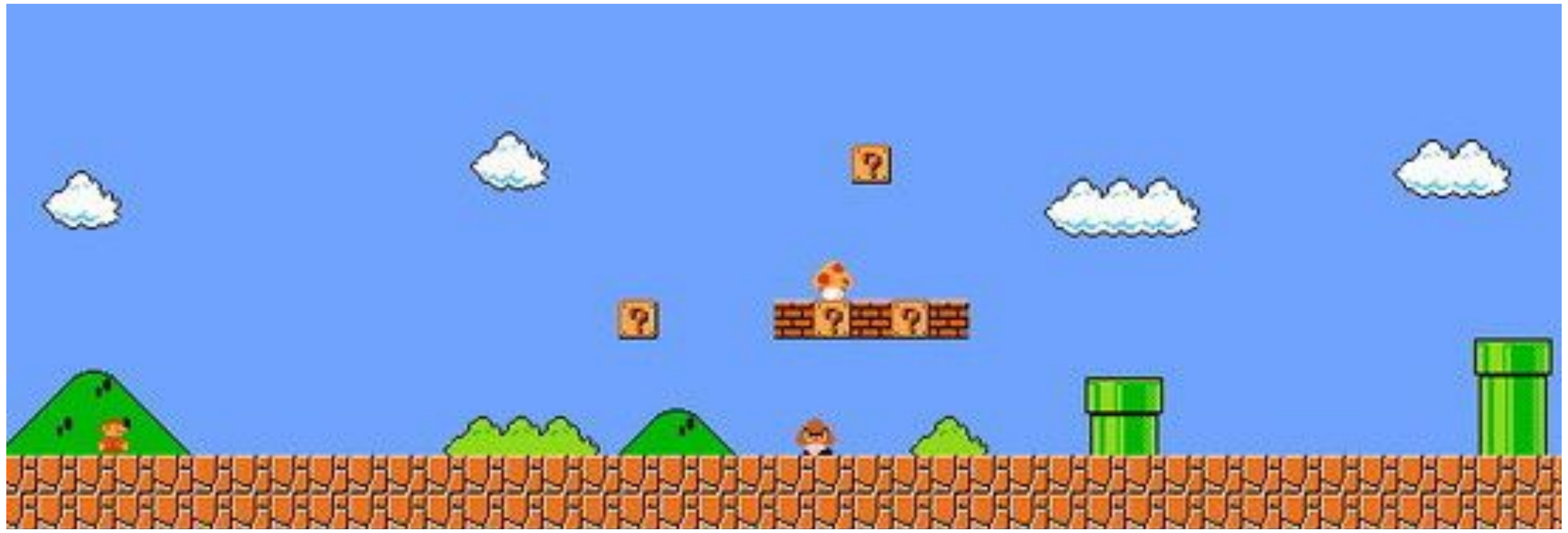

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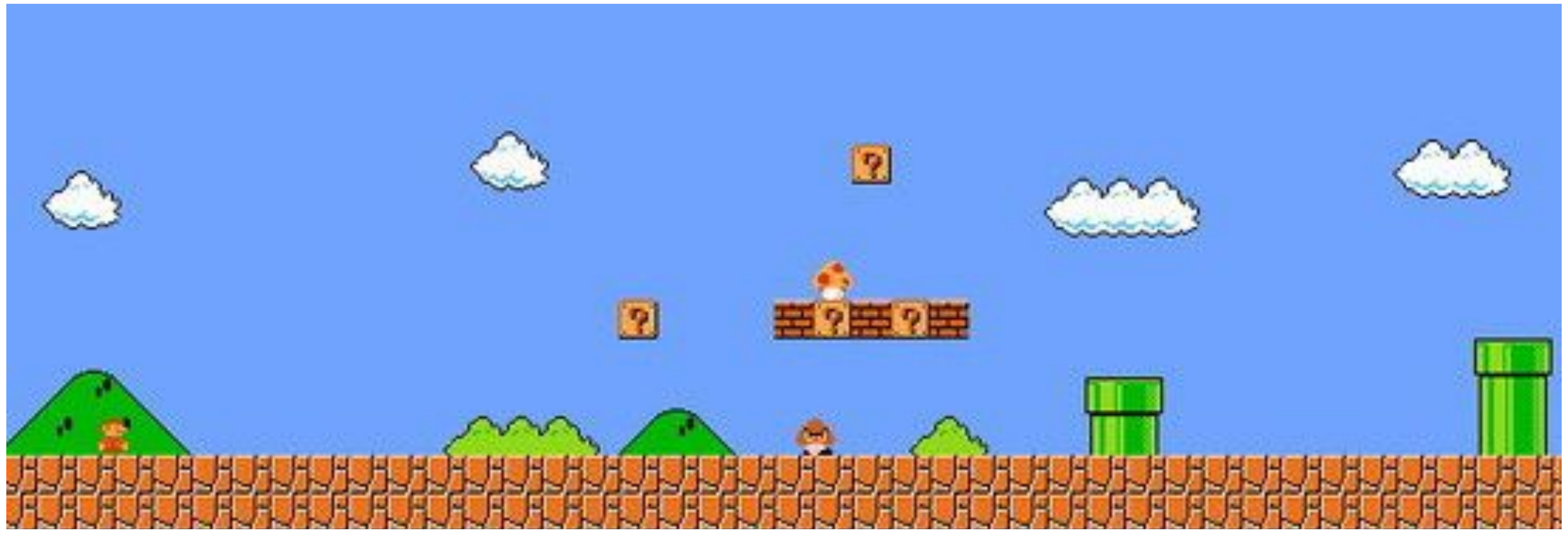

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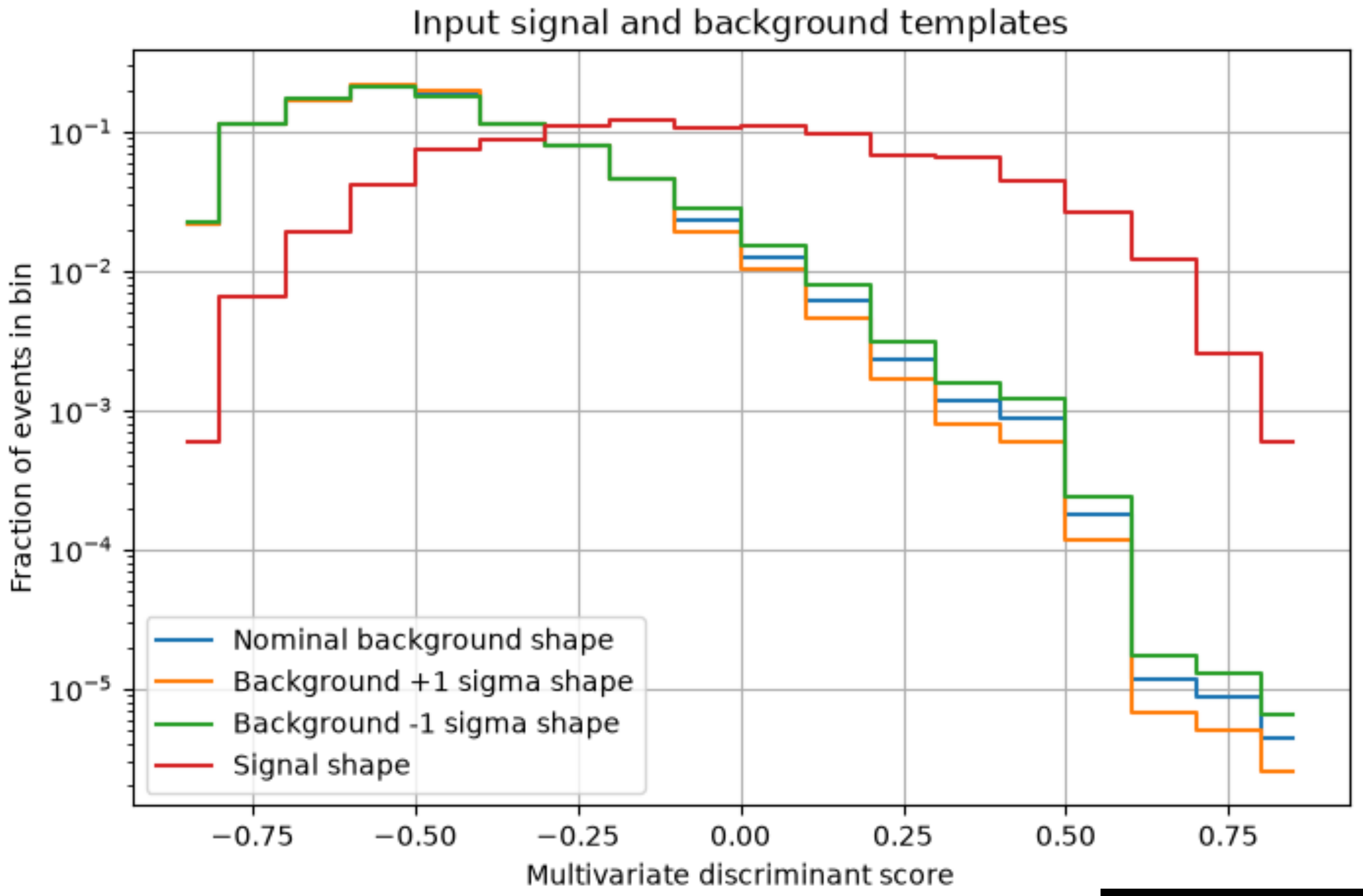

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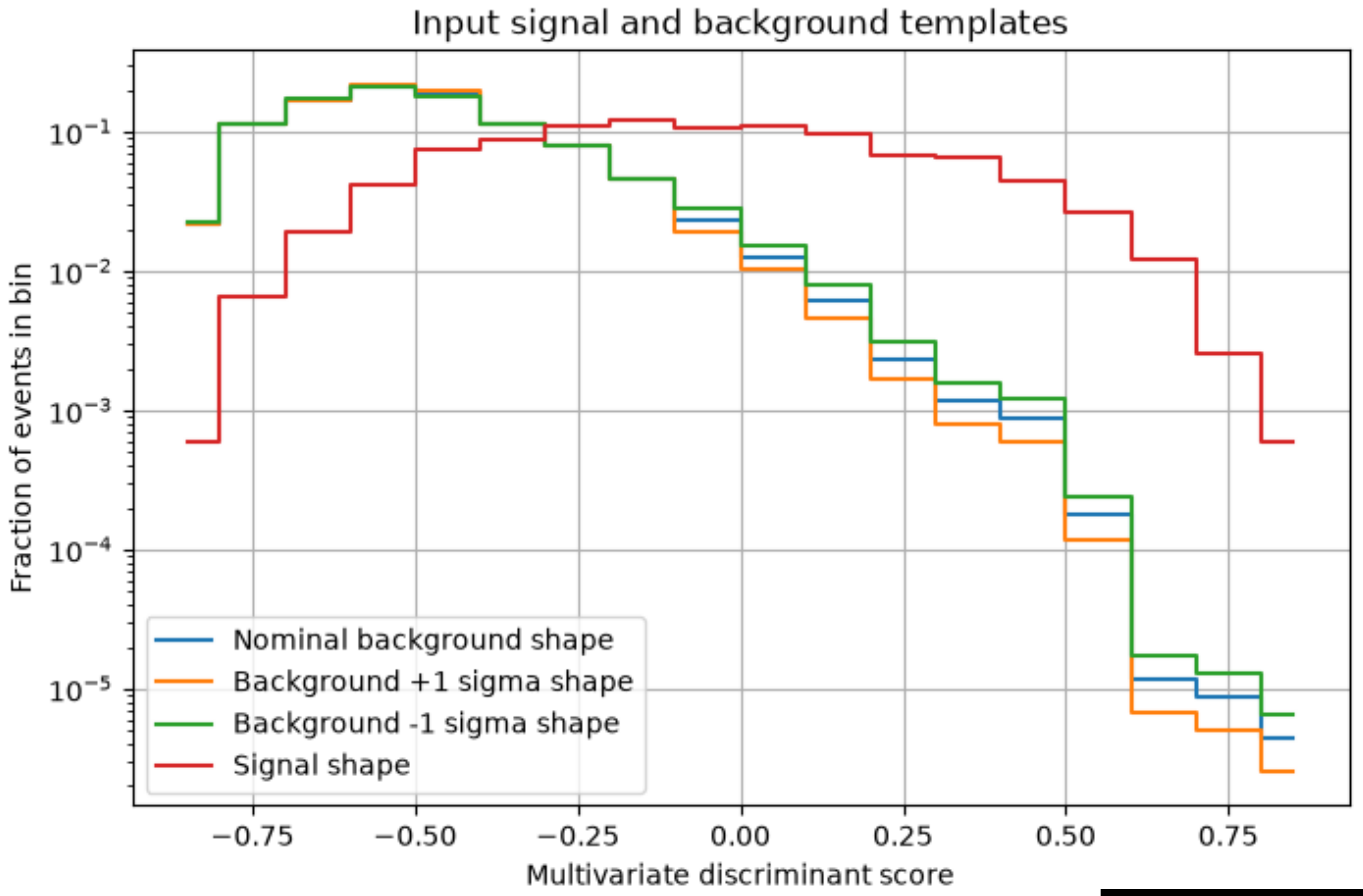

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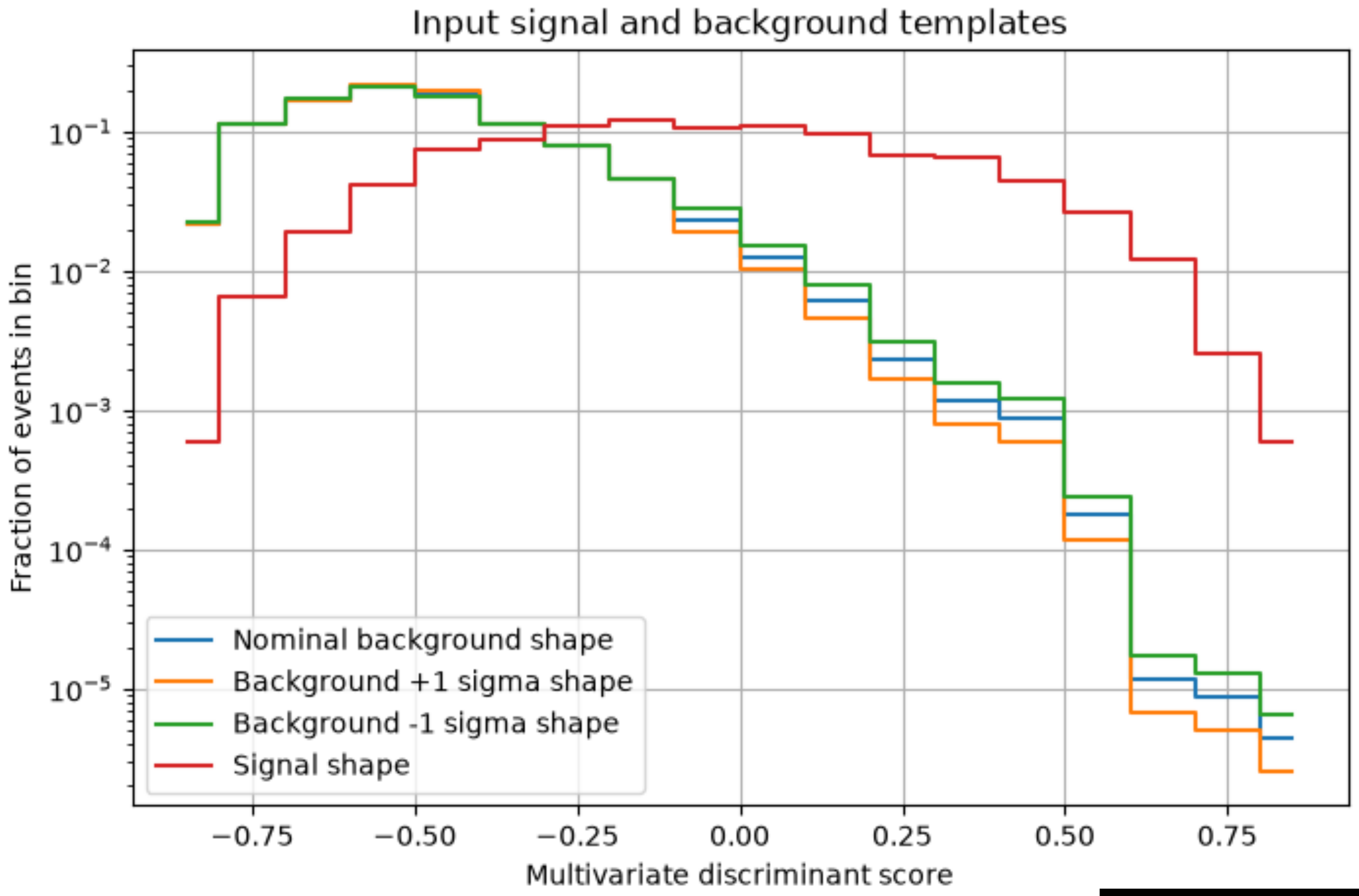

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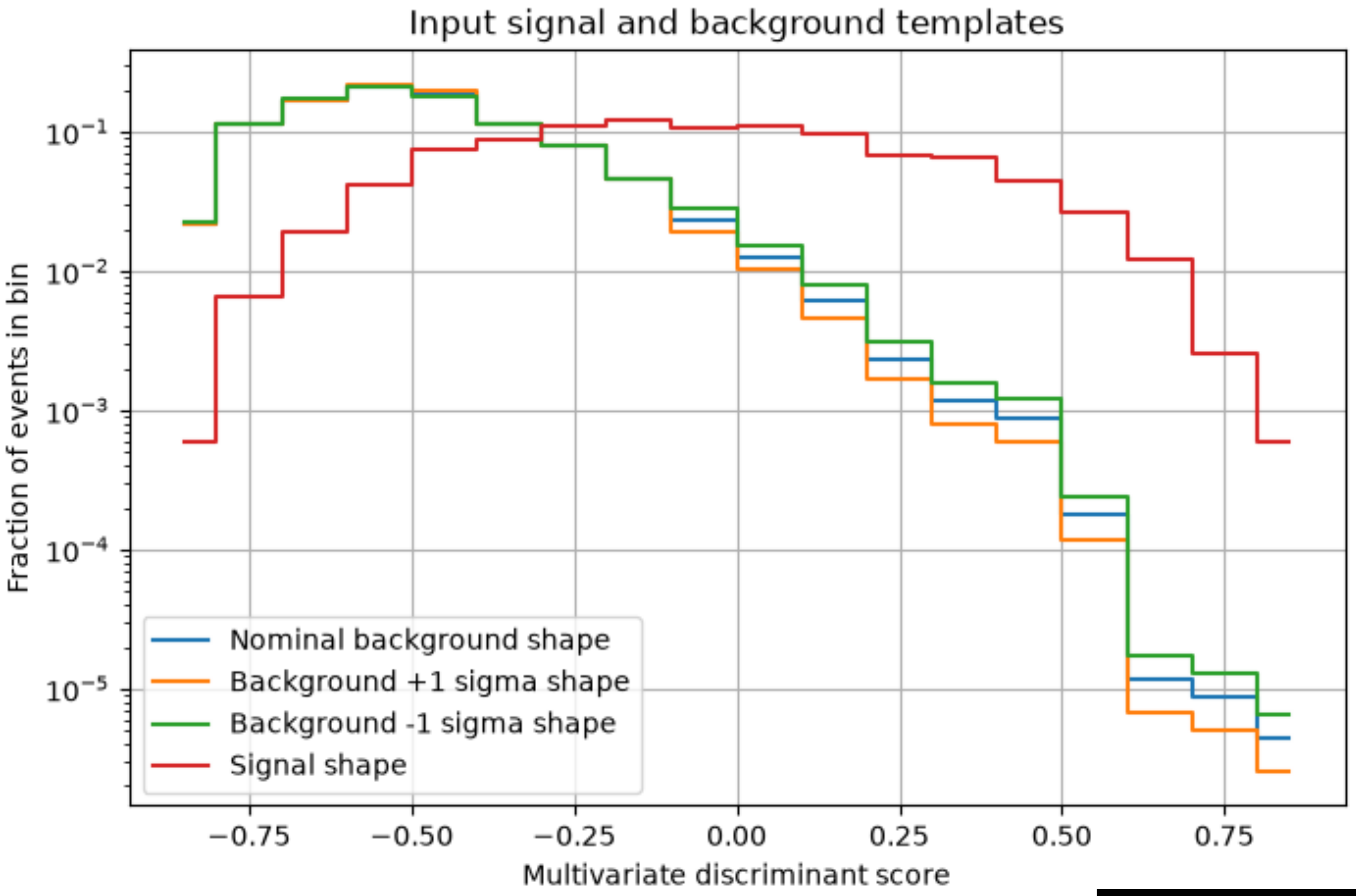

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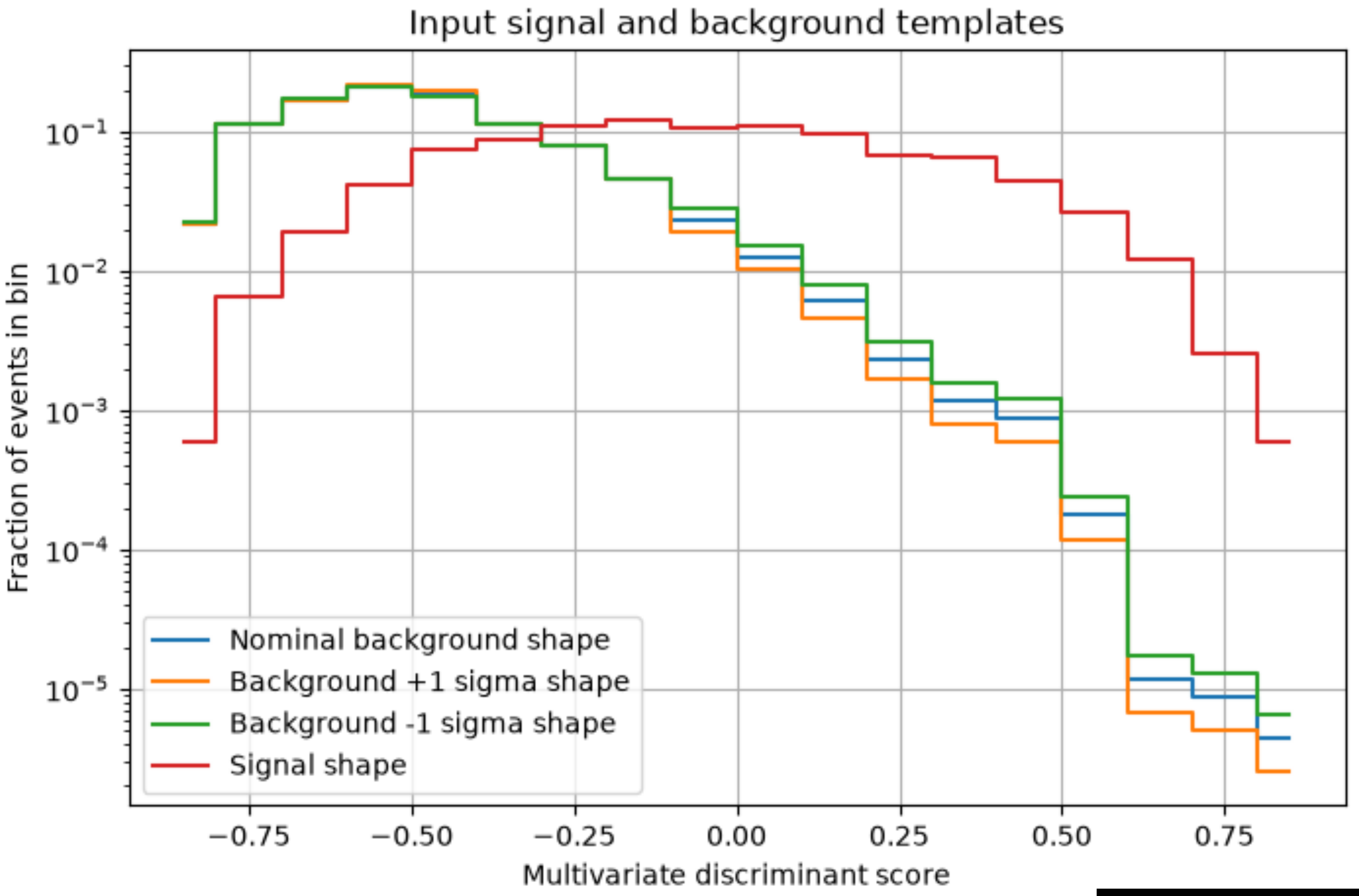

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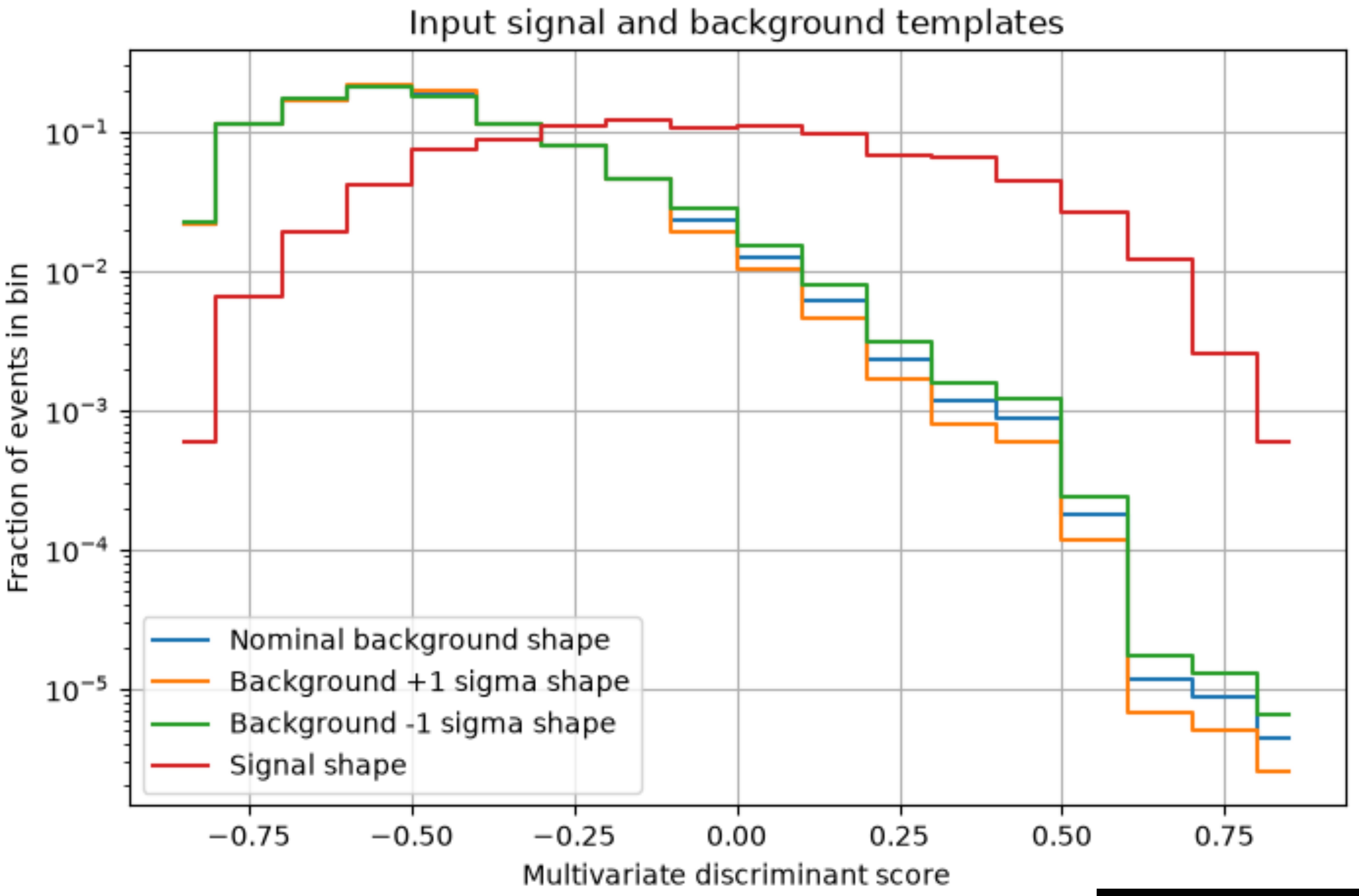

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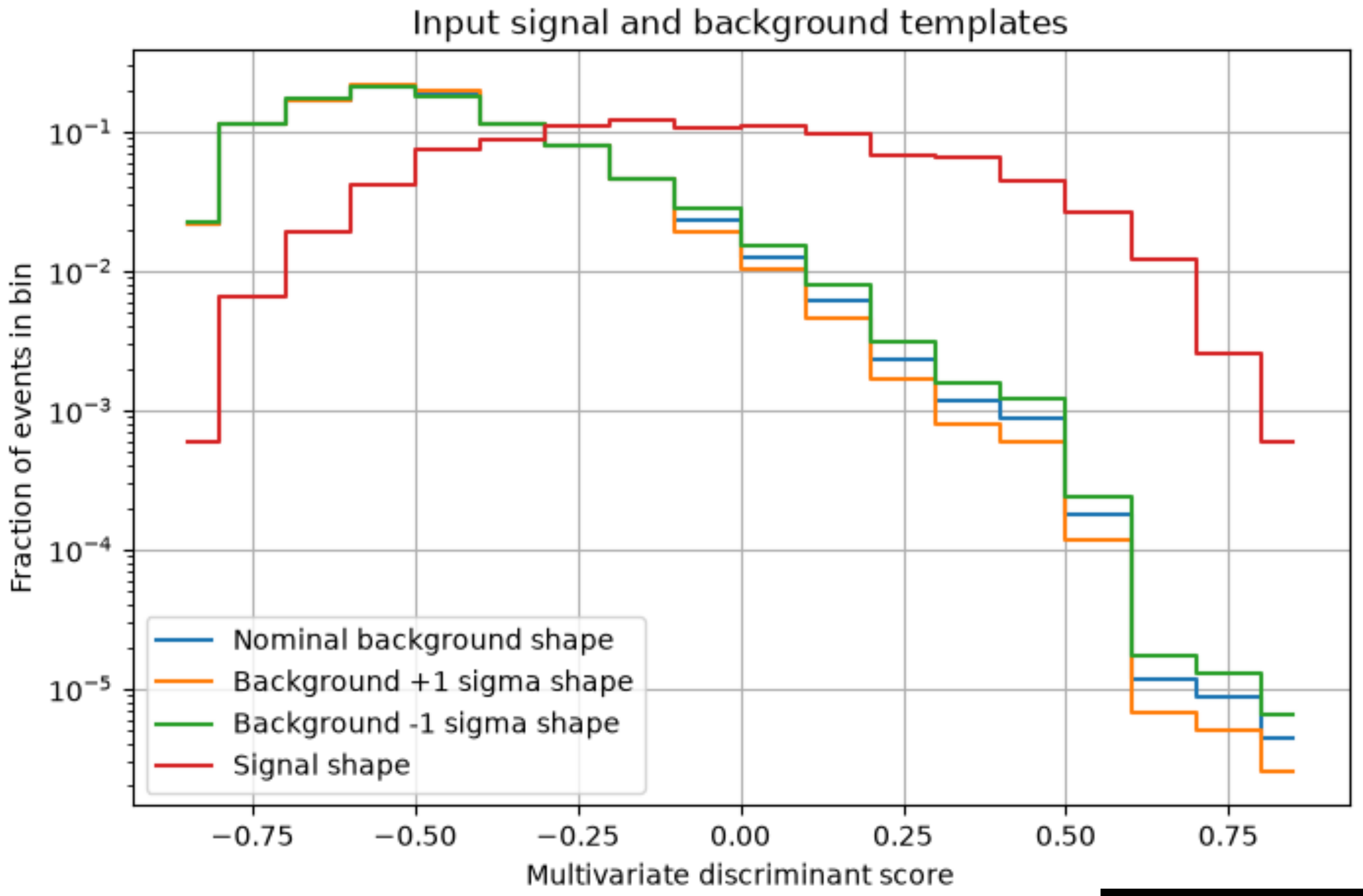

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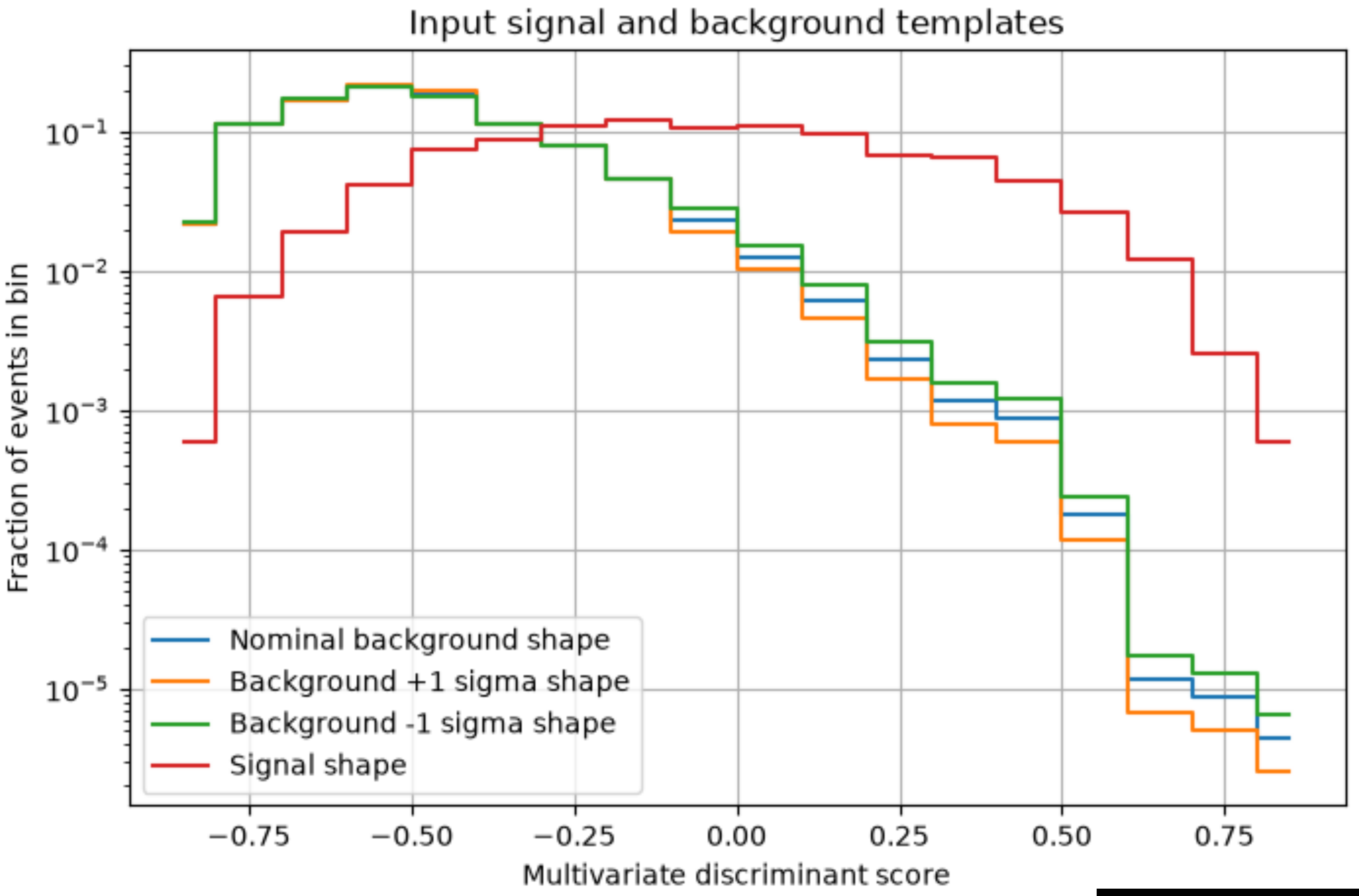

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- The likelihood becomes $L(S, B, \alpha) = \left[\prod_i \frac{\mu_i(S,B)^{d_i} e^{-\mu_i(S,B)}}{d_i!}\right] \cdot e^{-\frac{\alpha^2}{2}}$.

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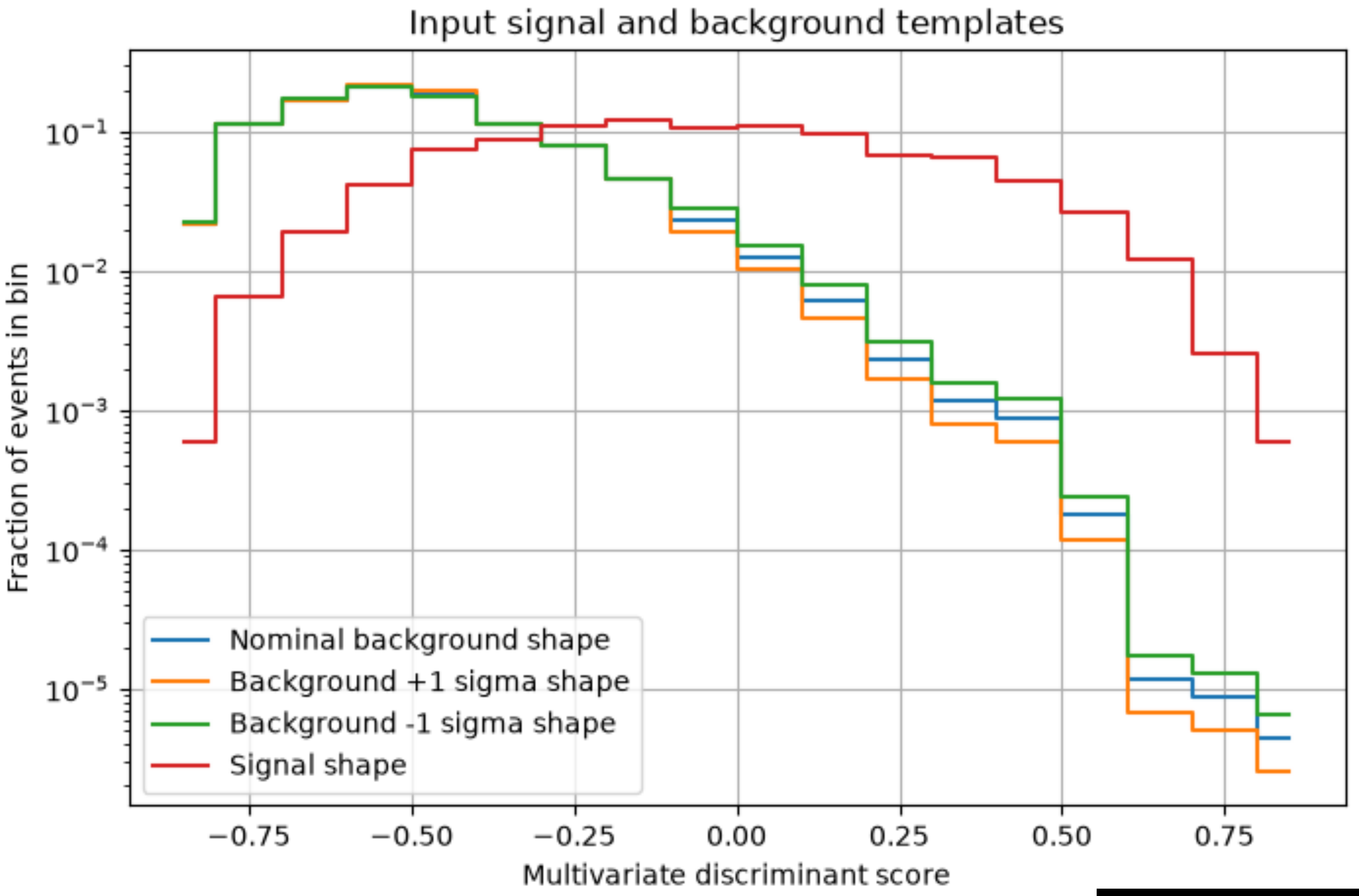

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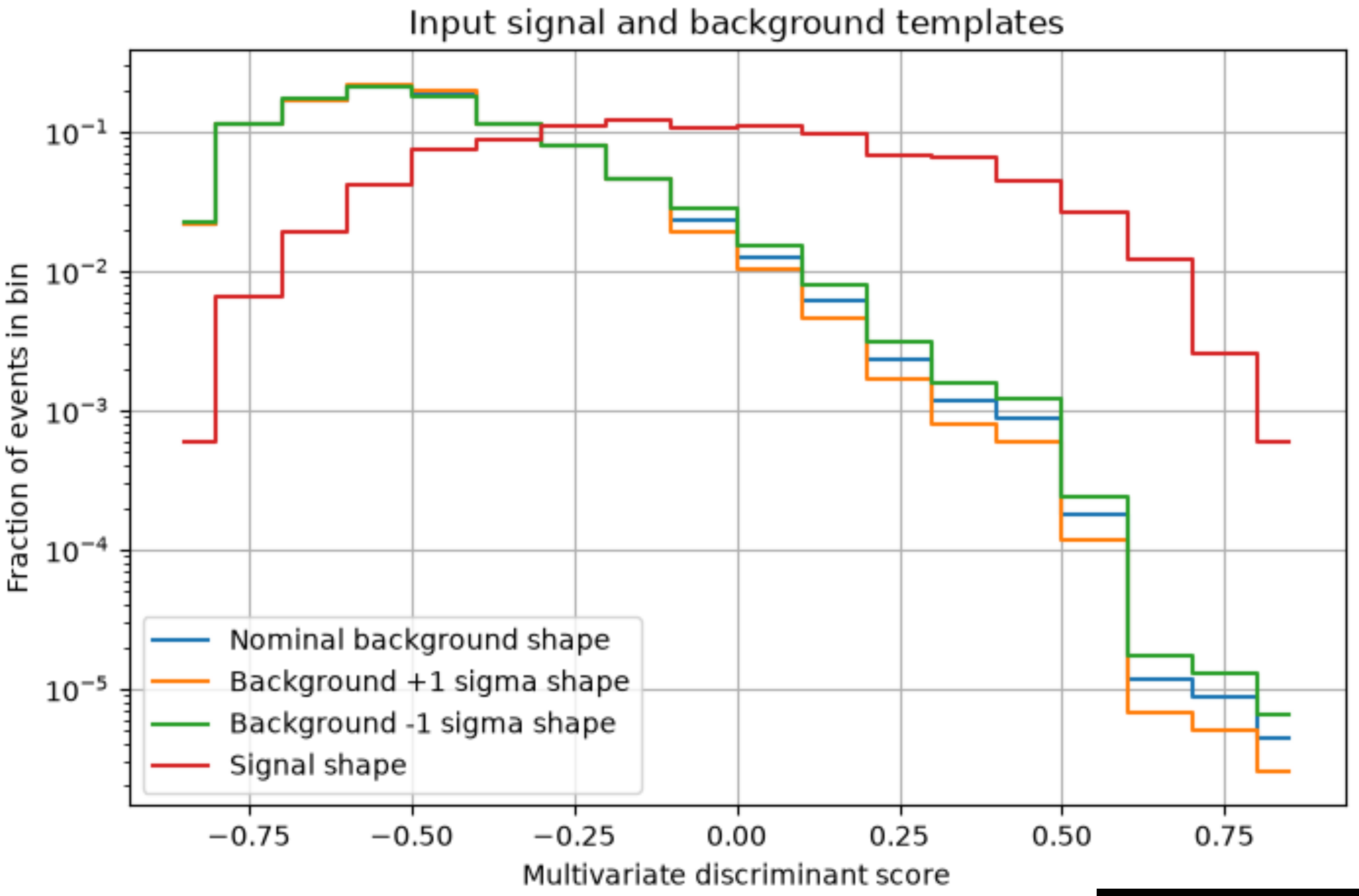

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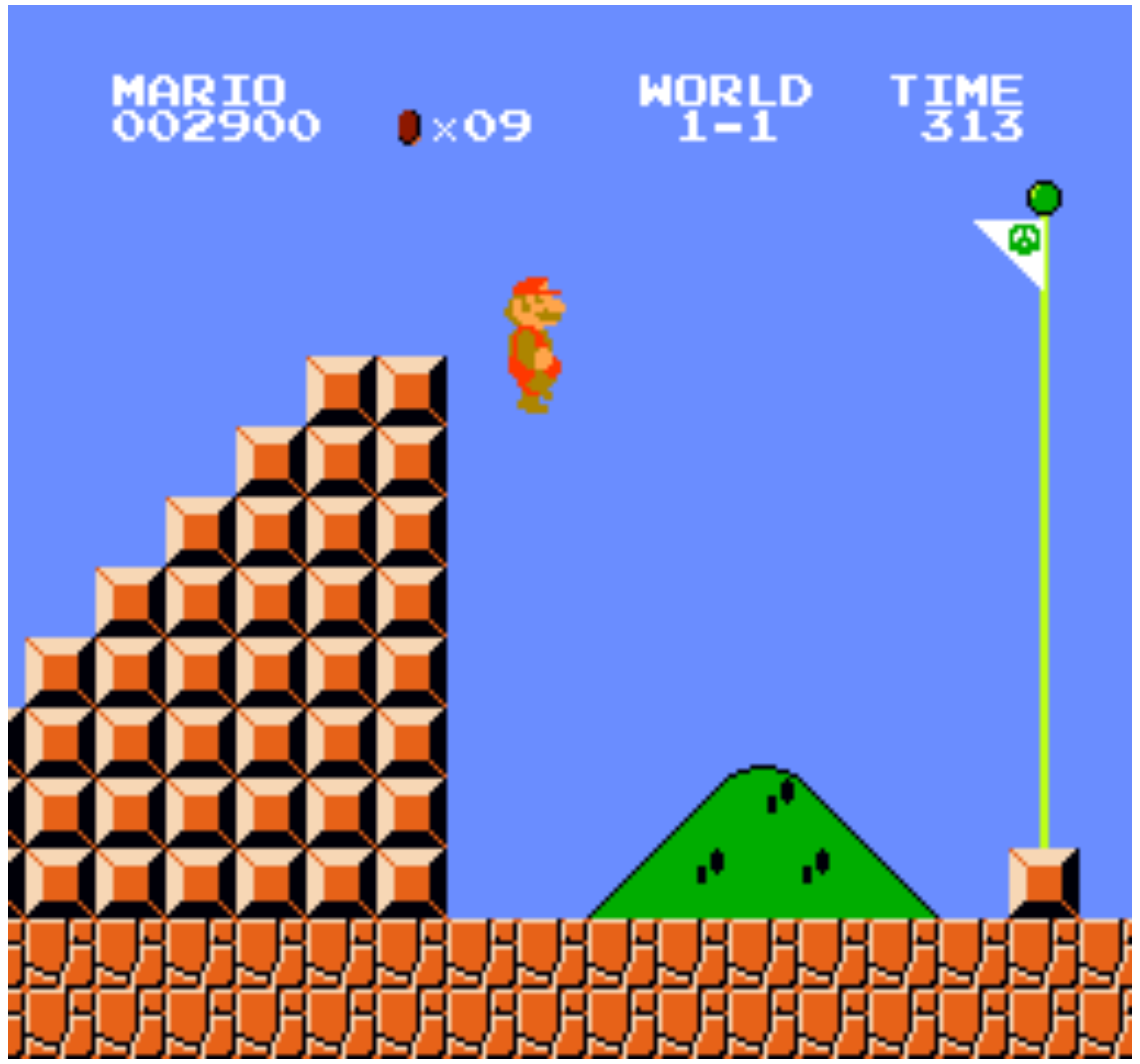

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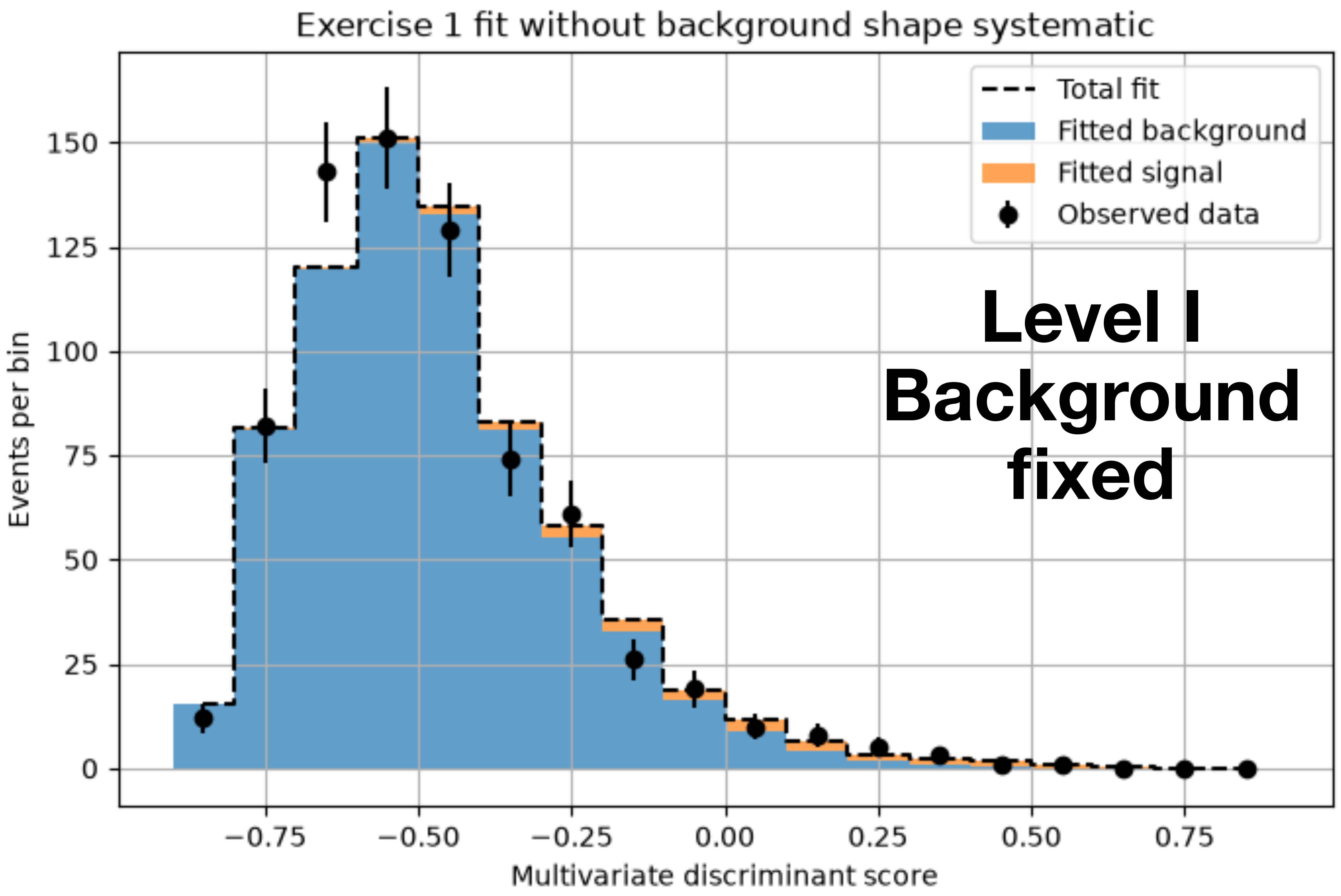

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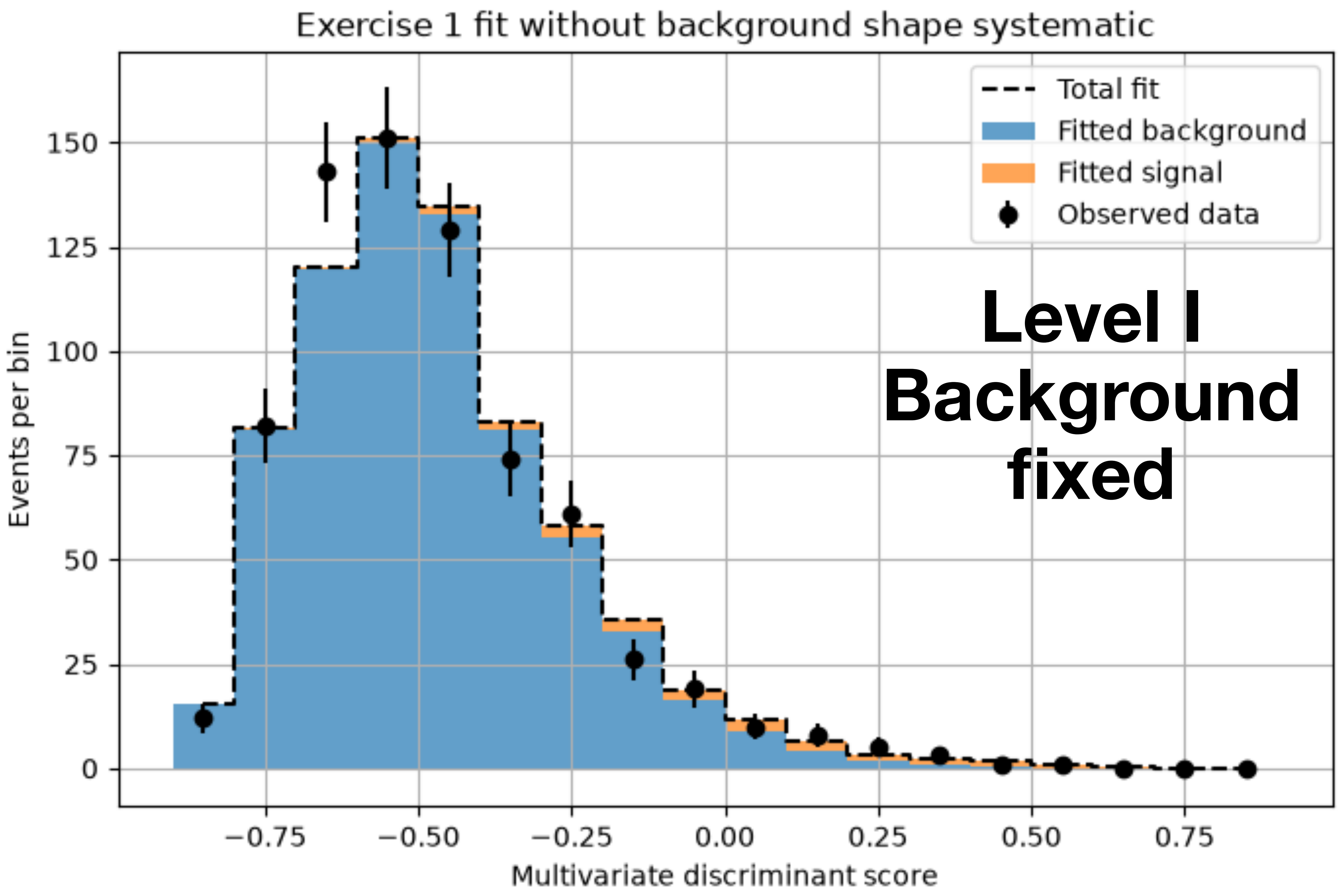

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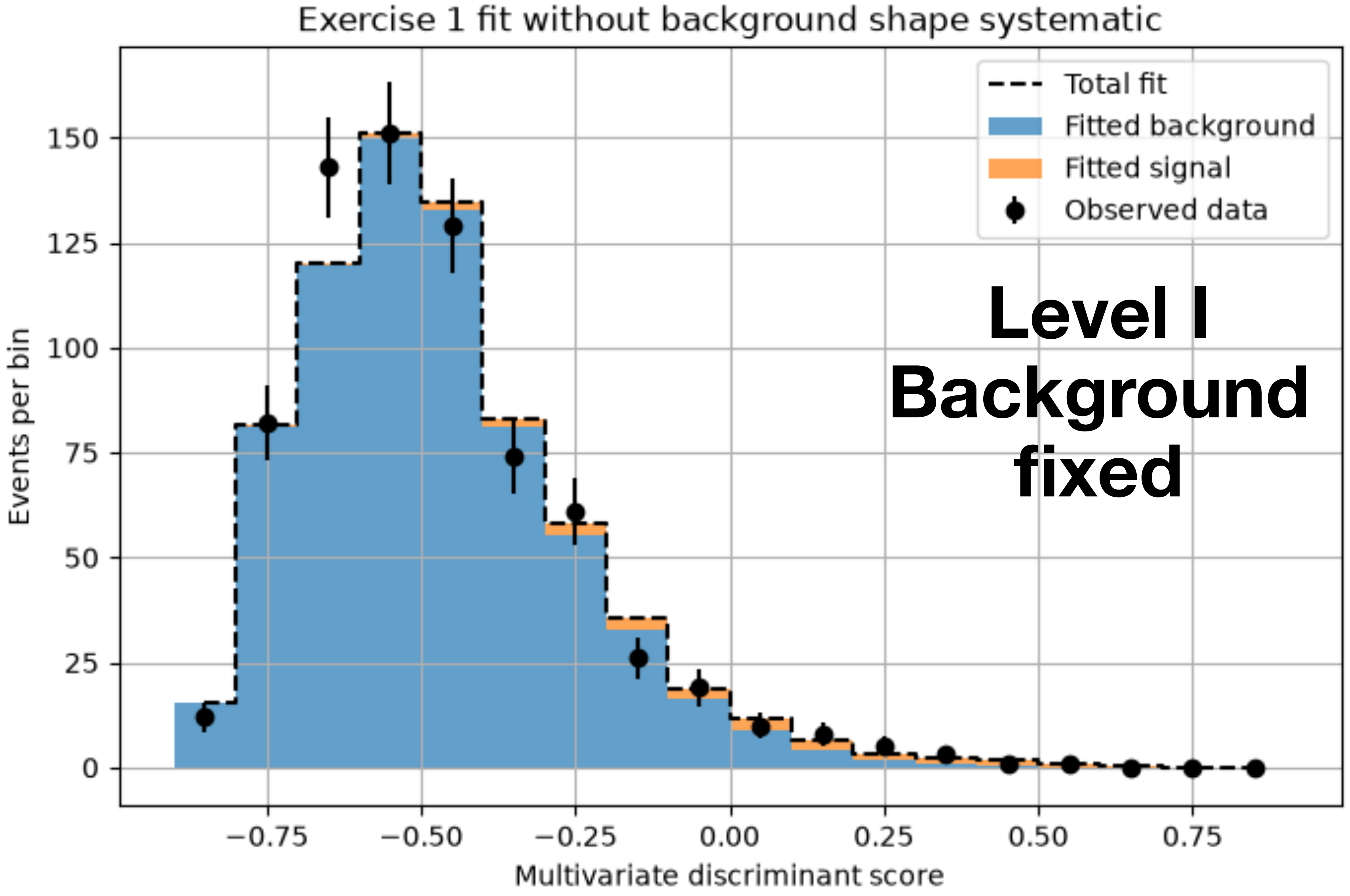

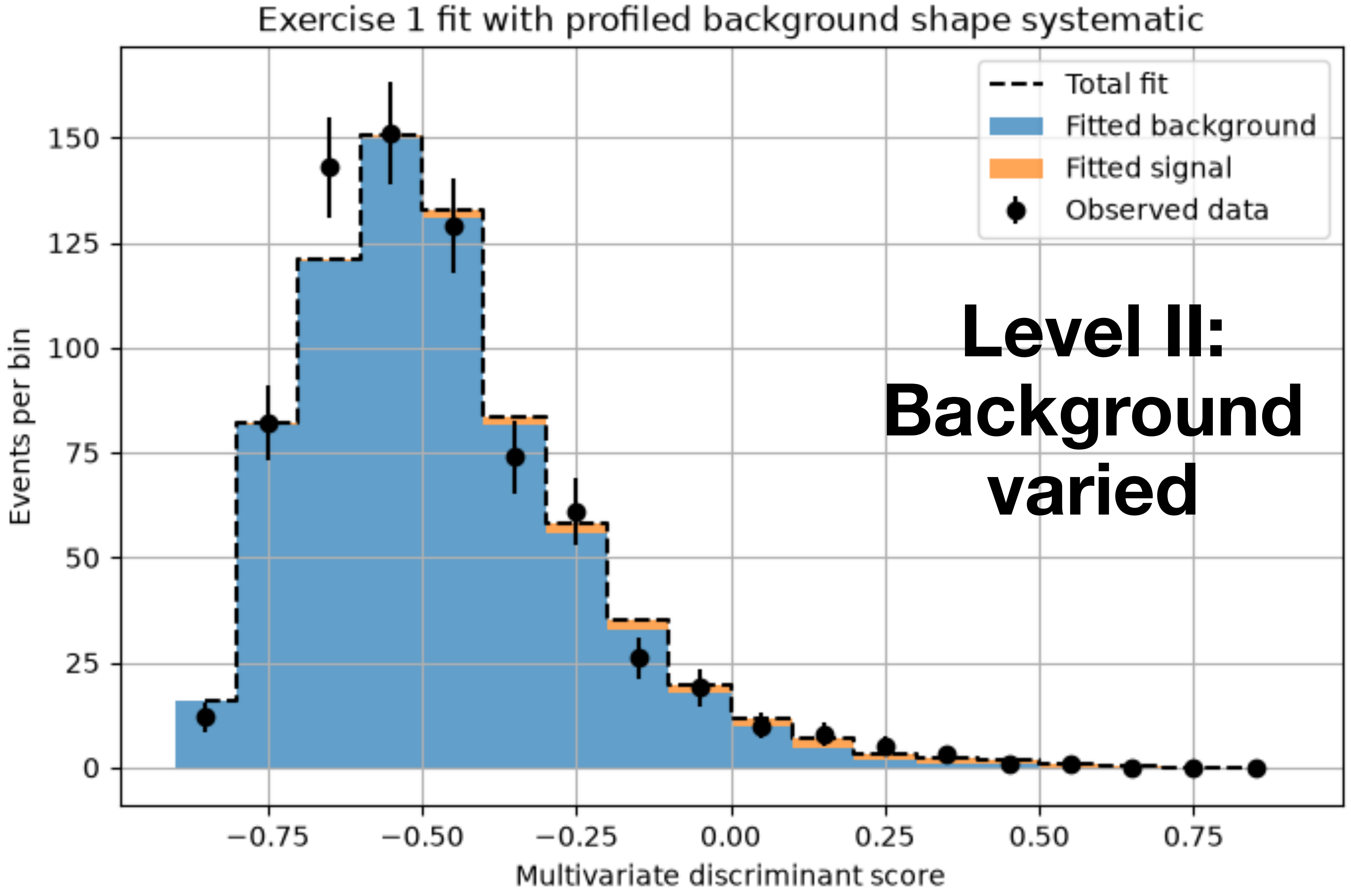

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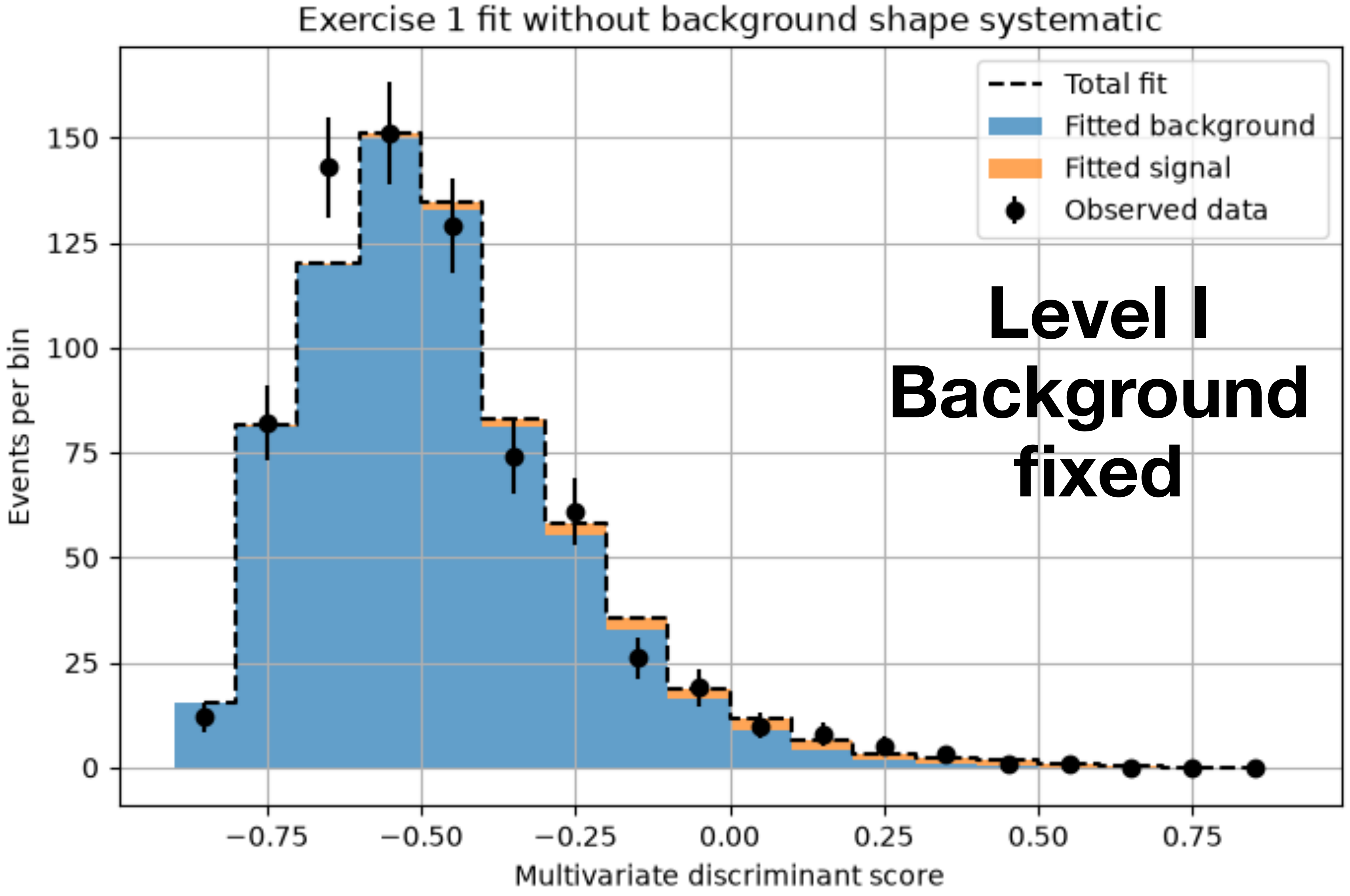

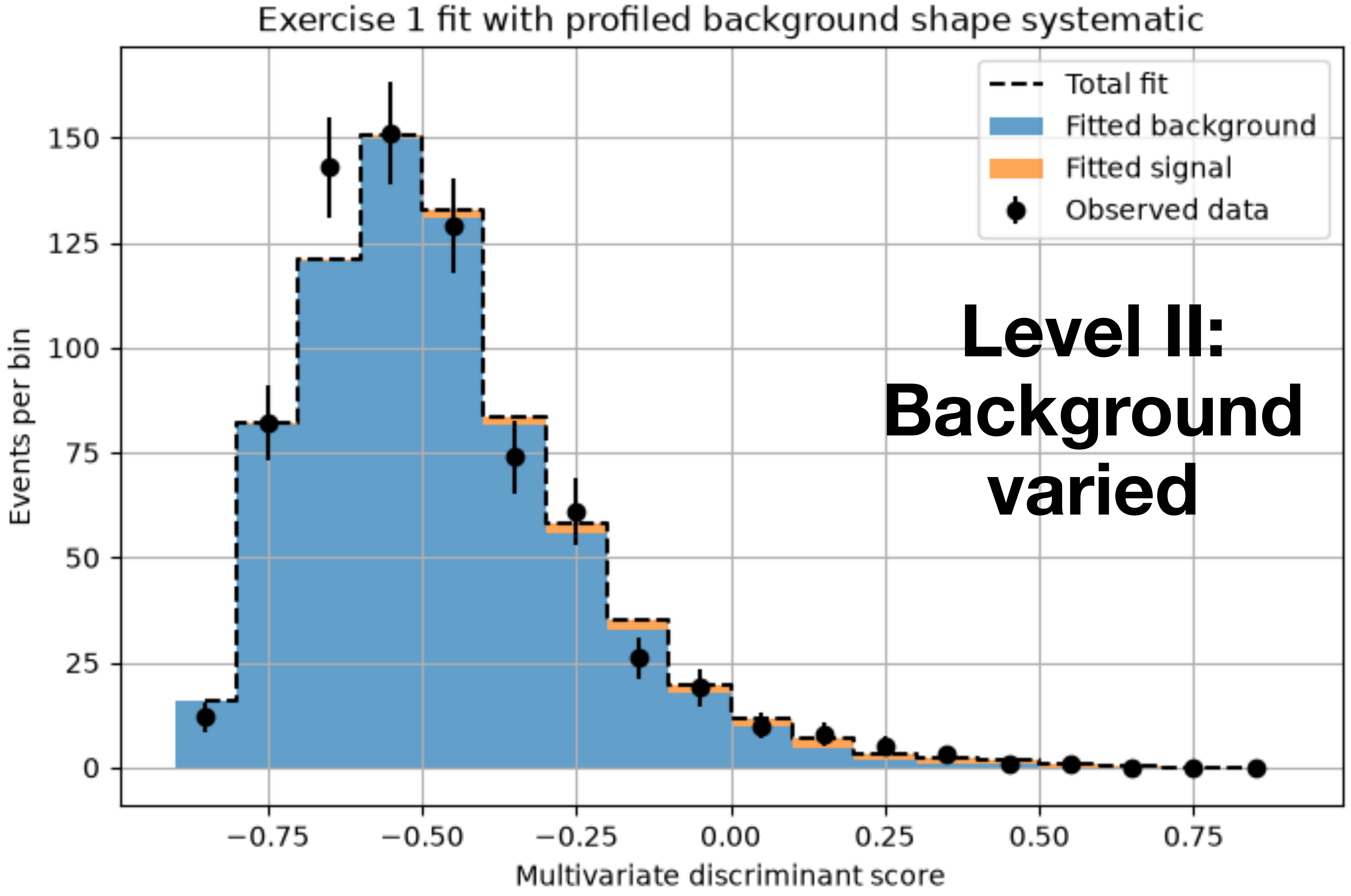

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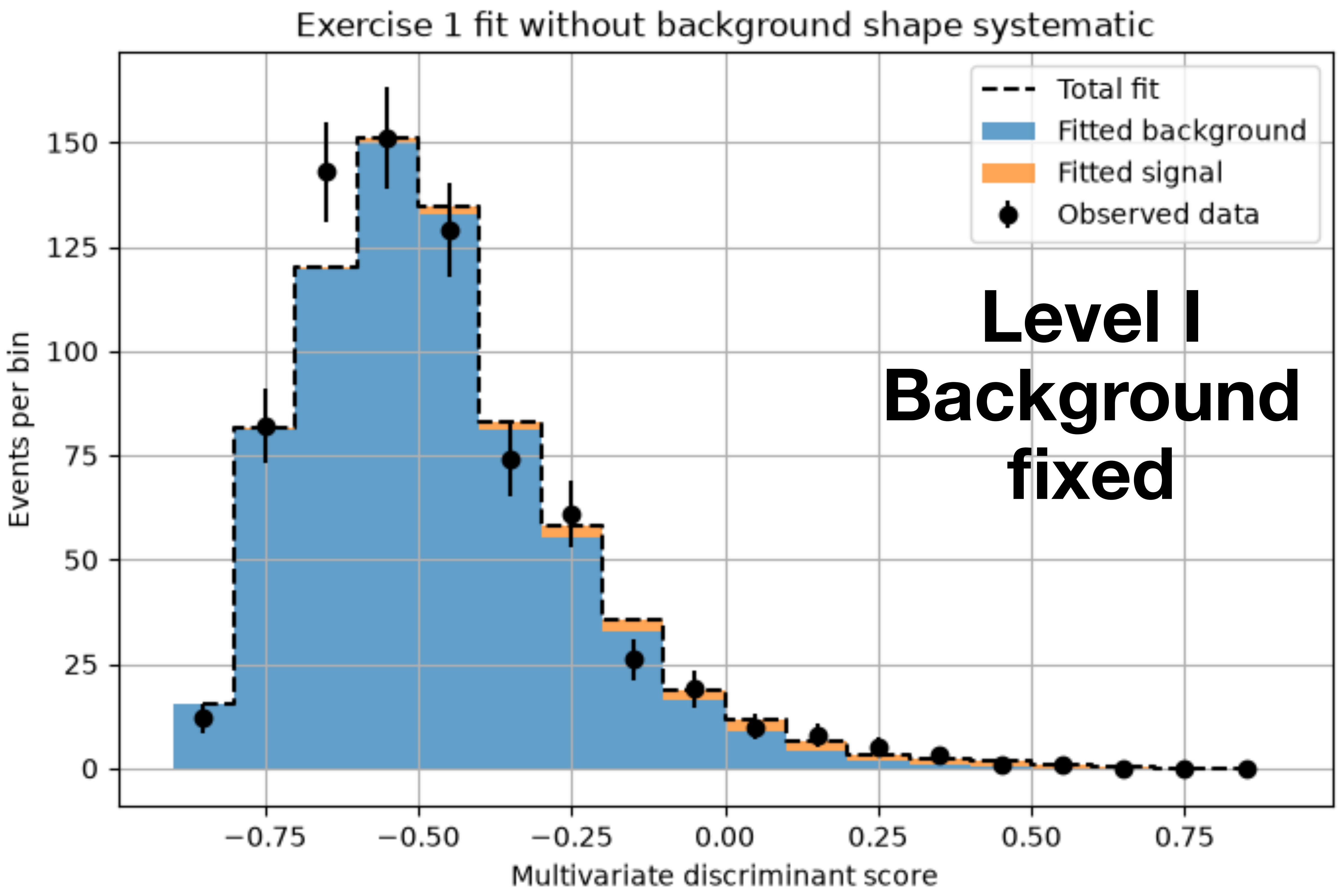

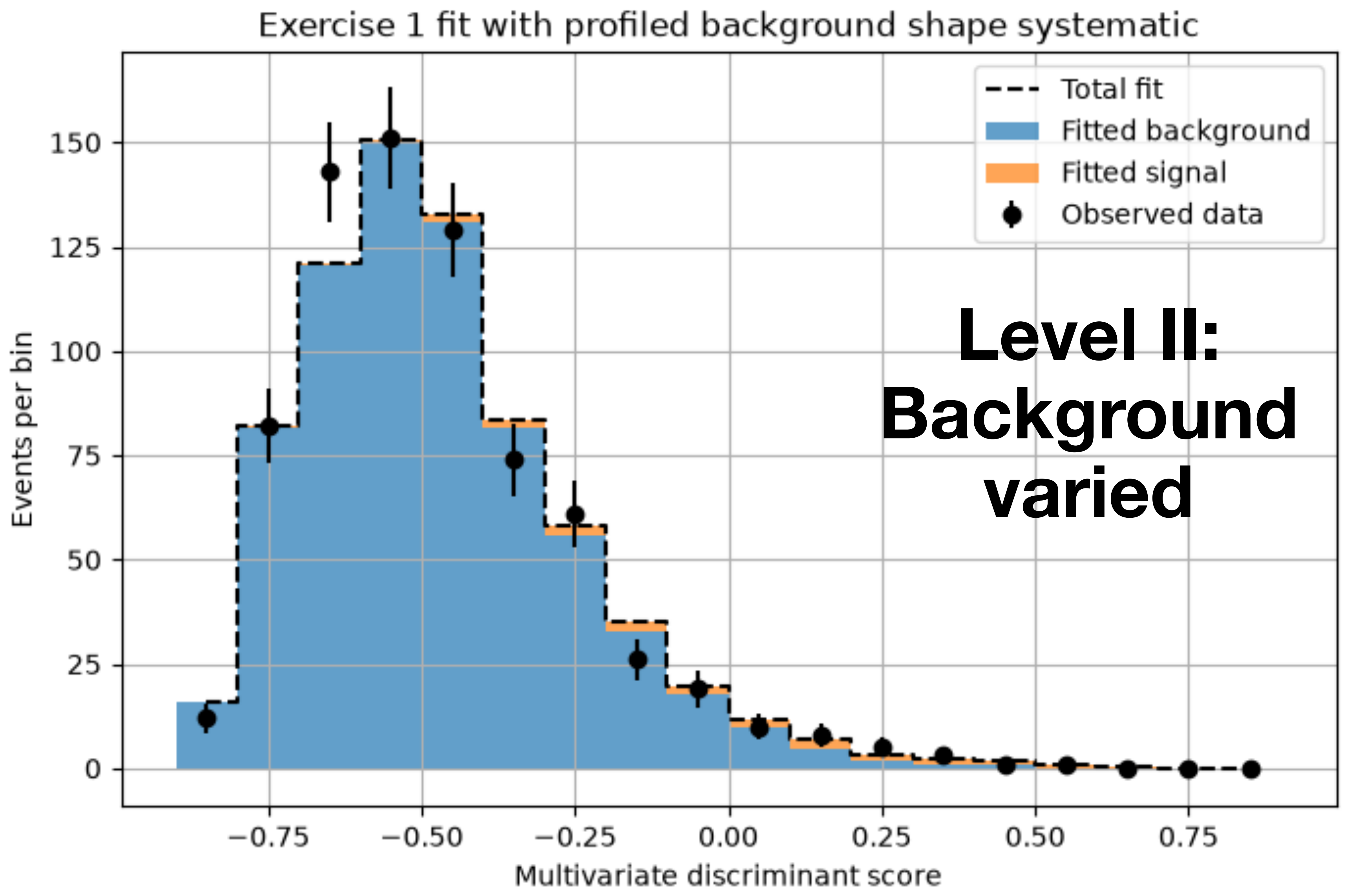

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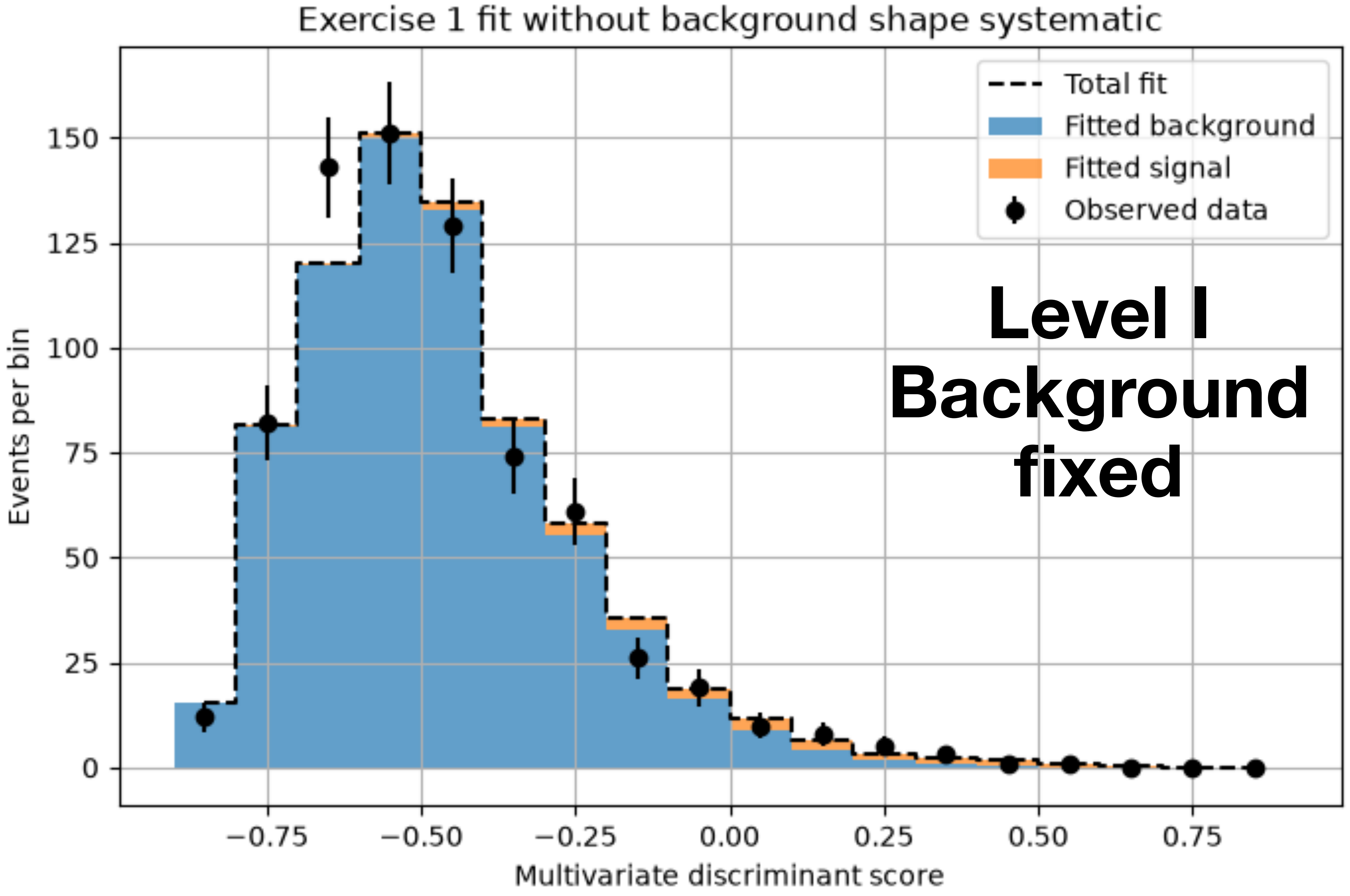

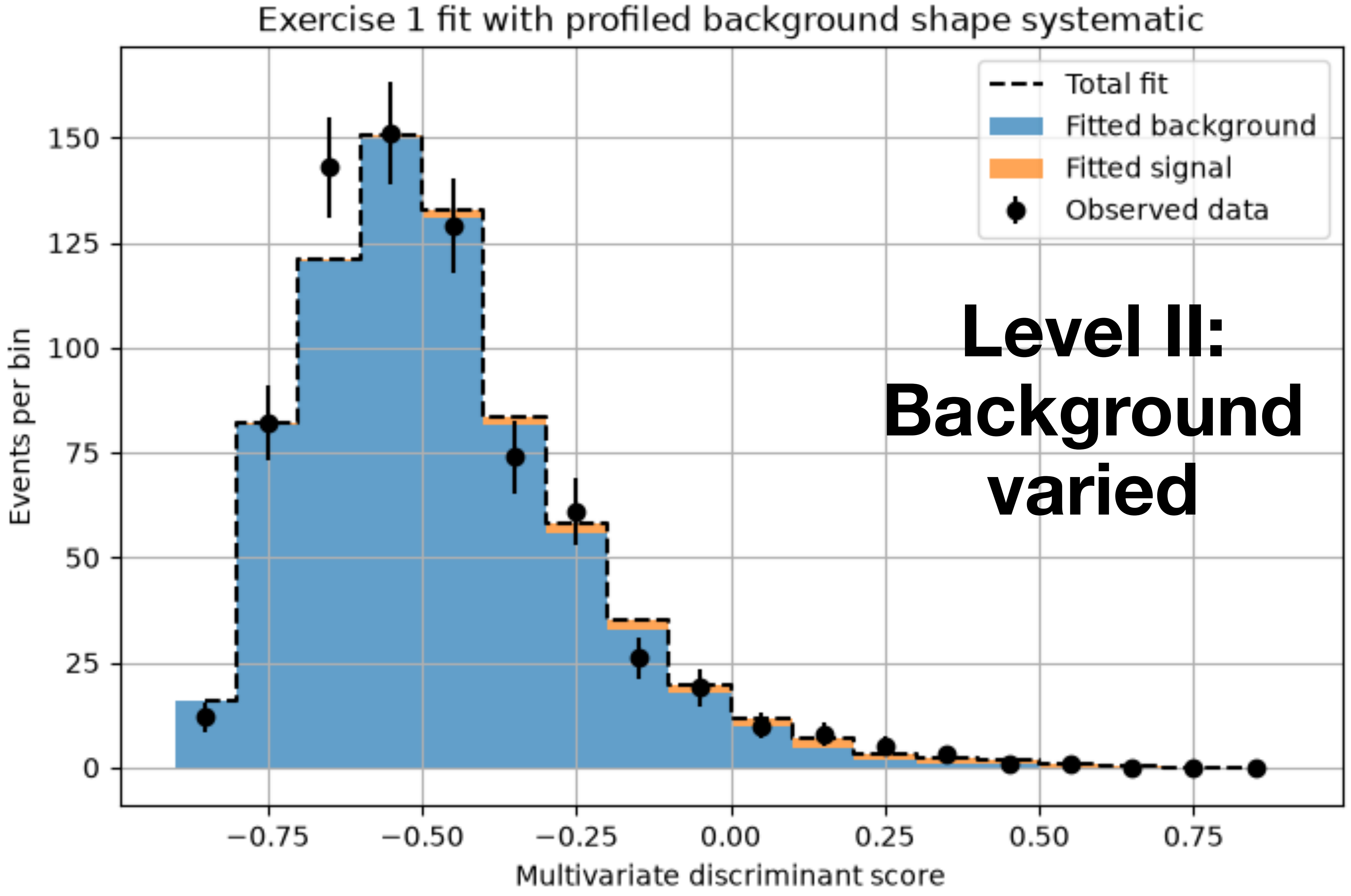

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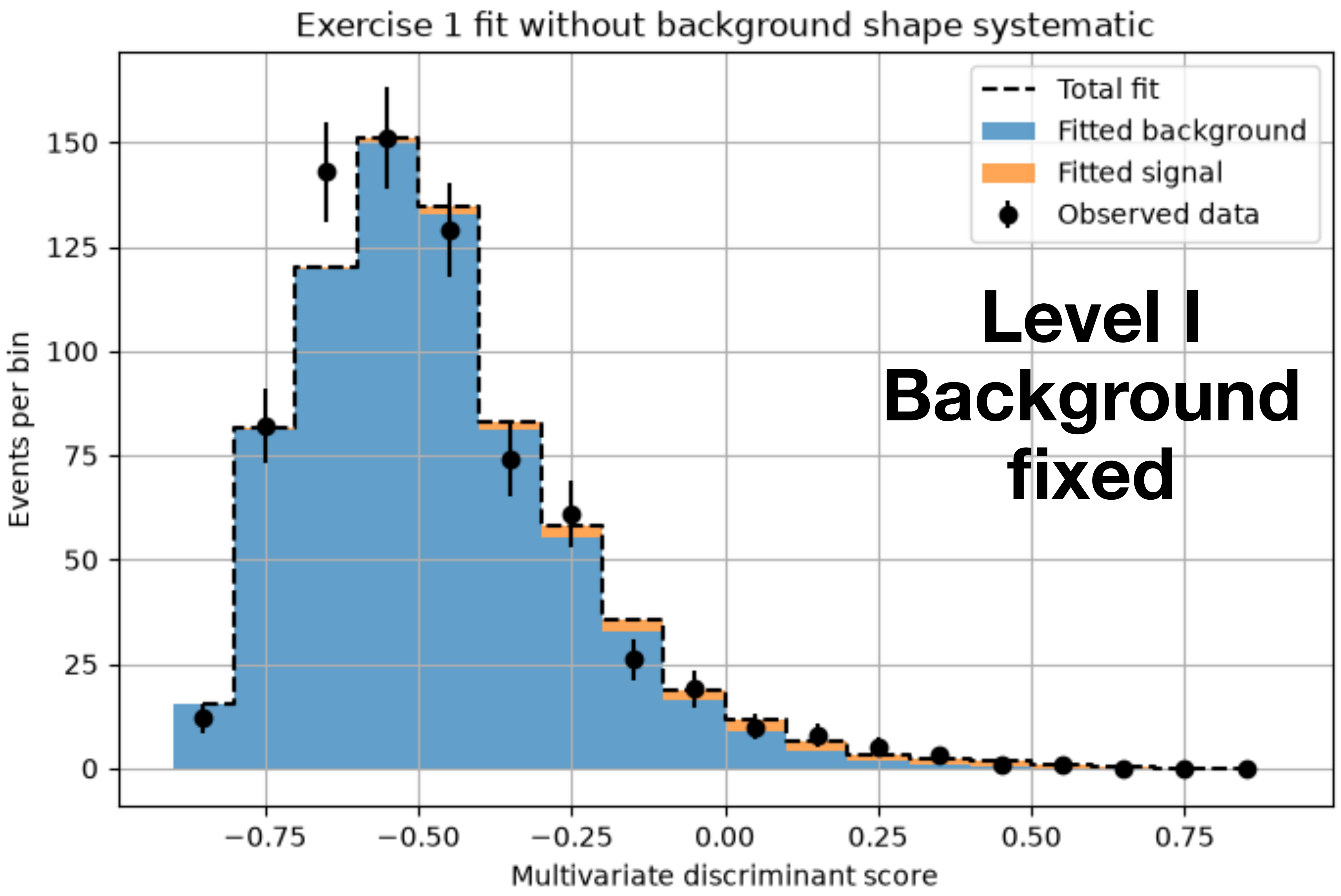

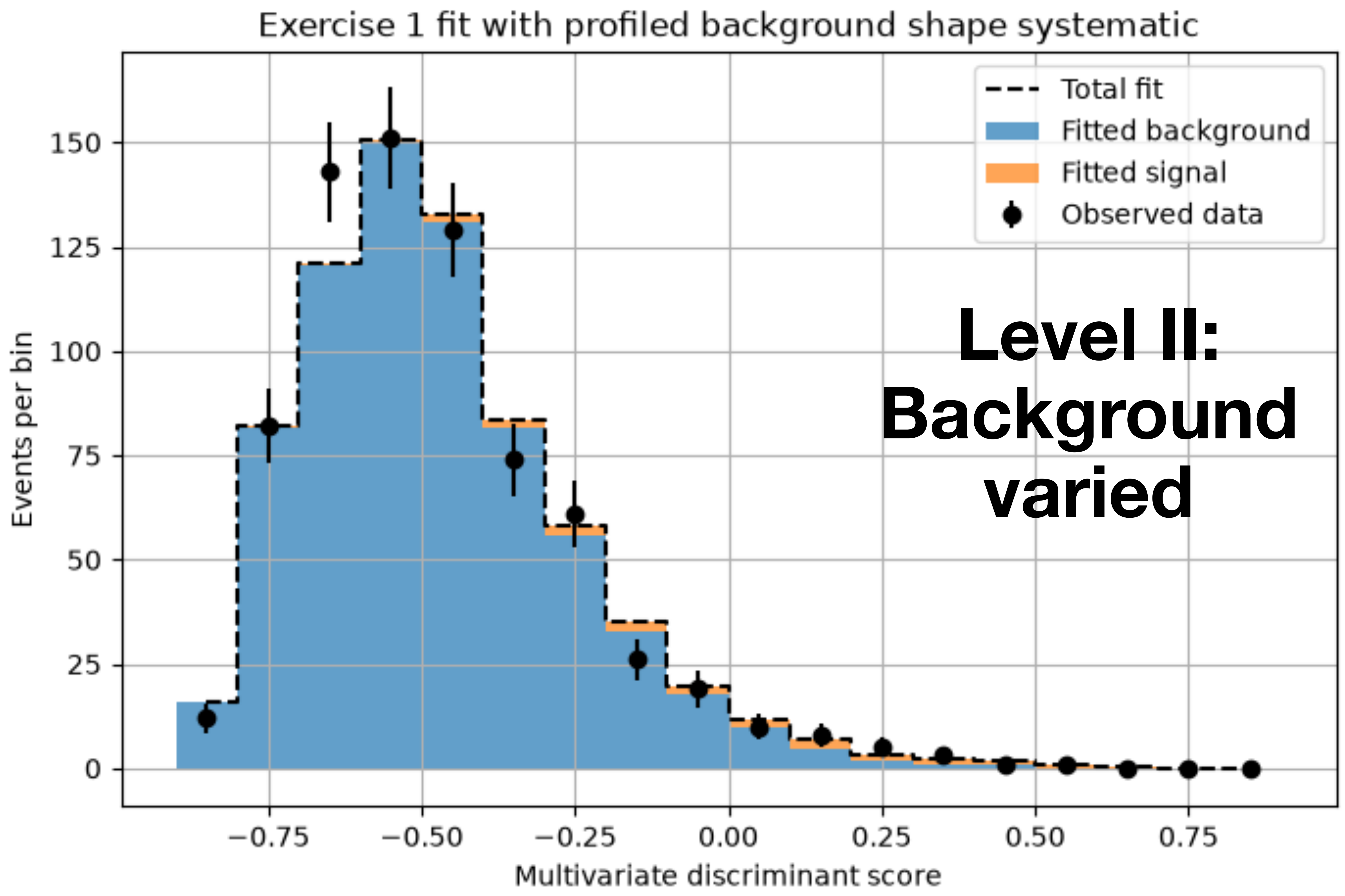

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Wait!! Where are the uncertainties of these values????

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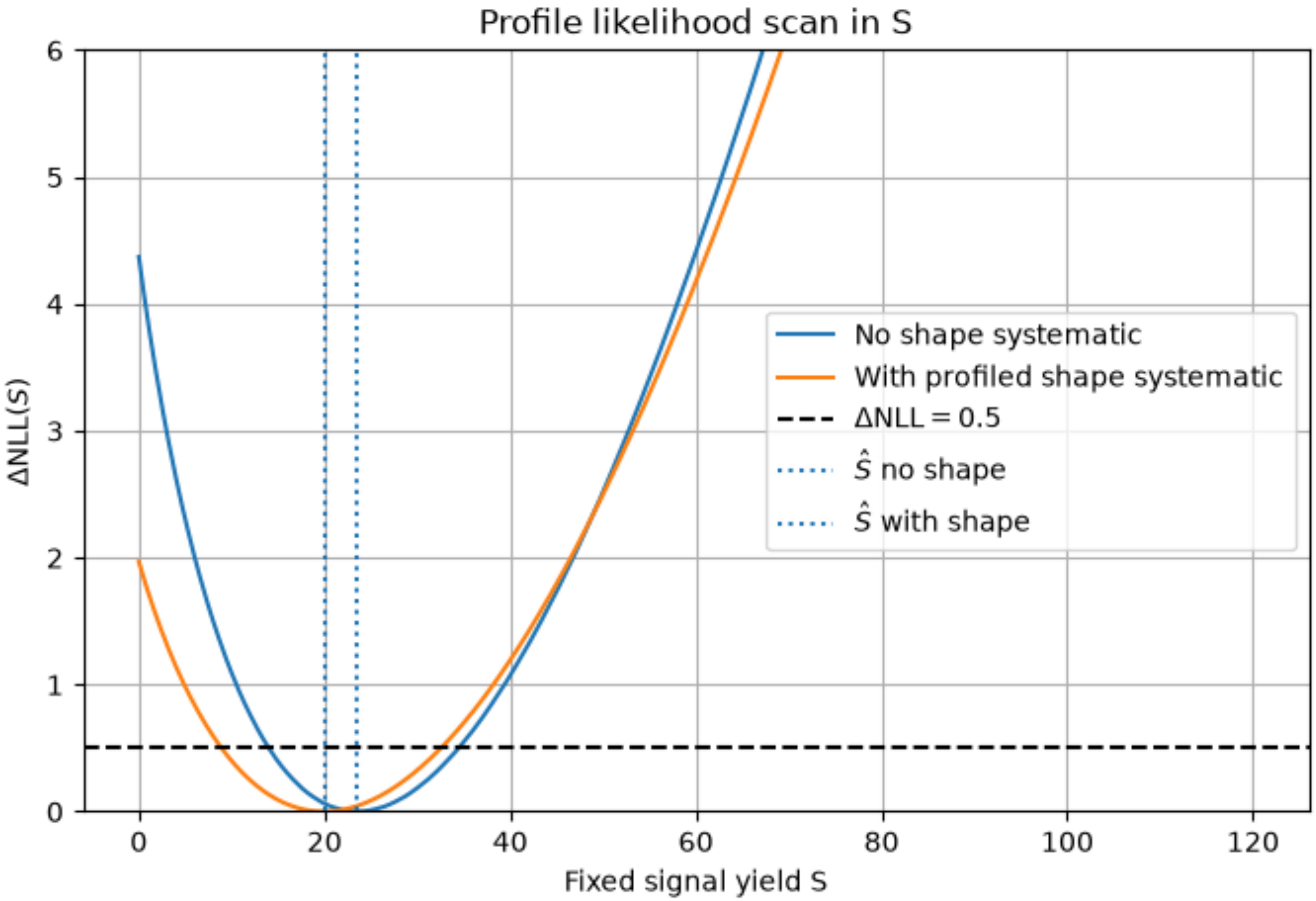

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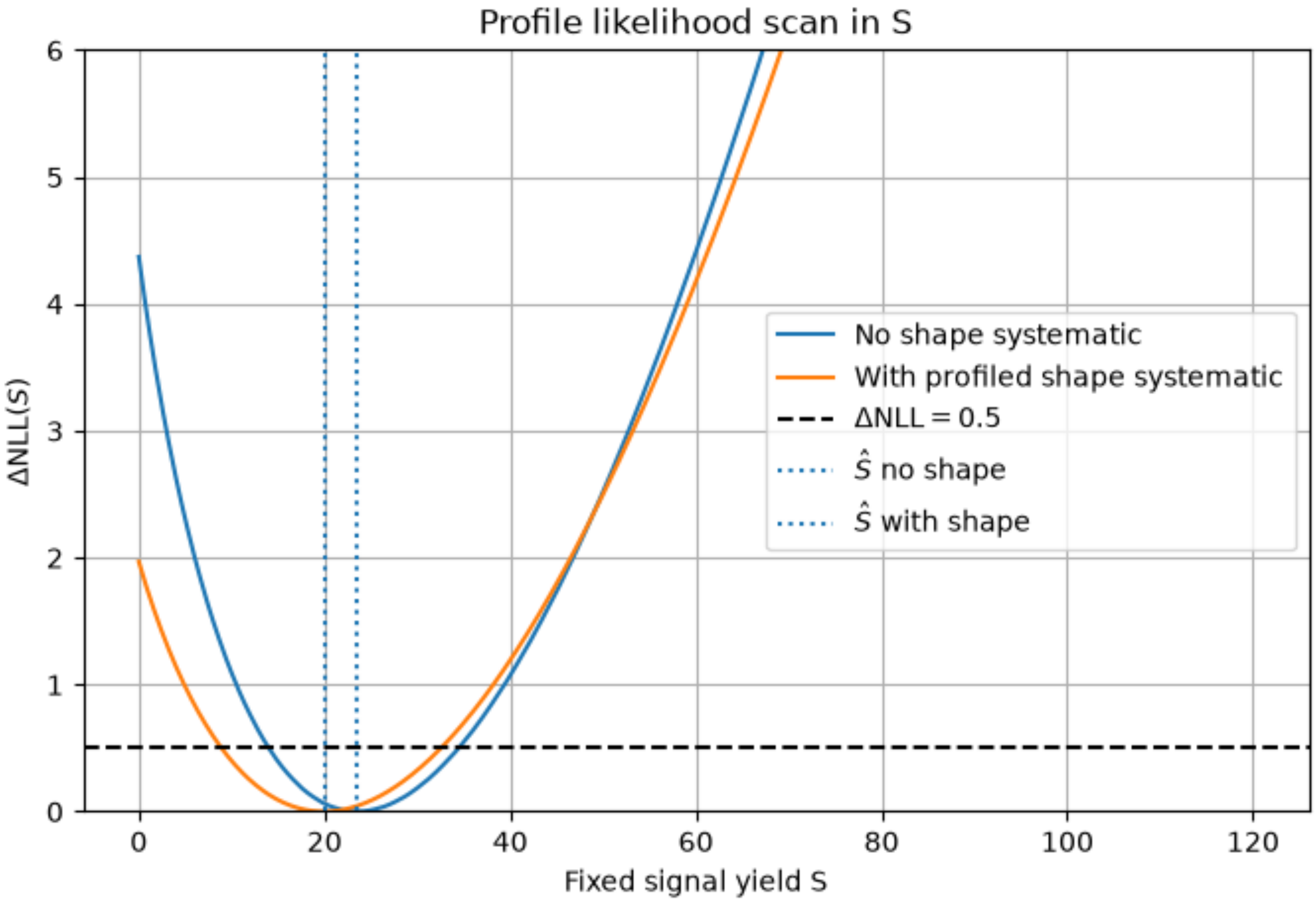

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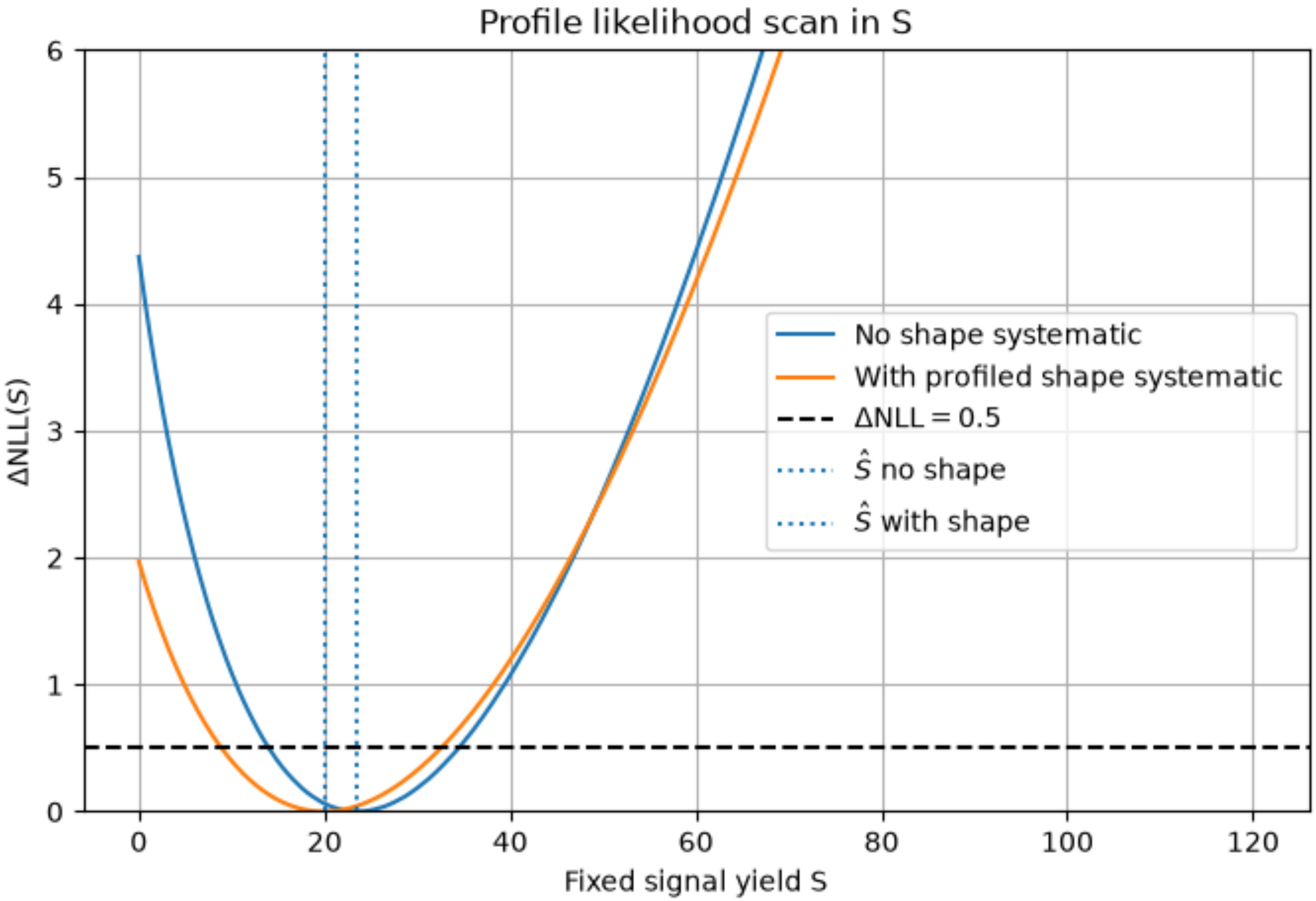

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Thank You For Your Time

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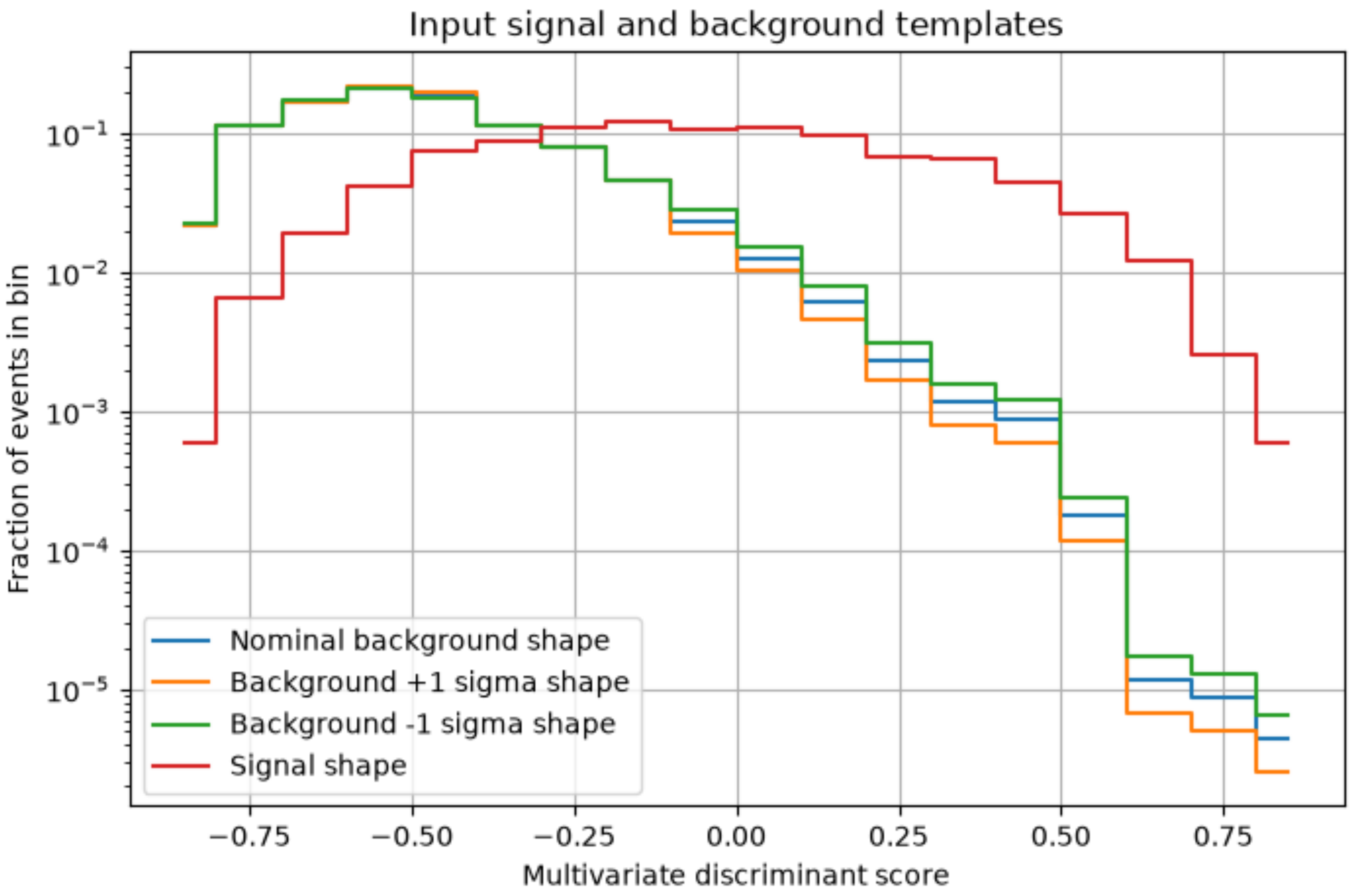

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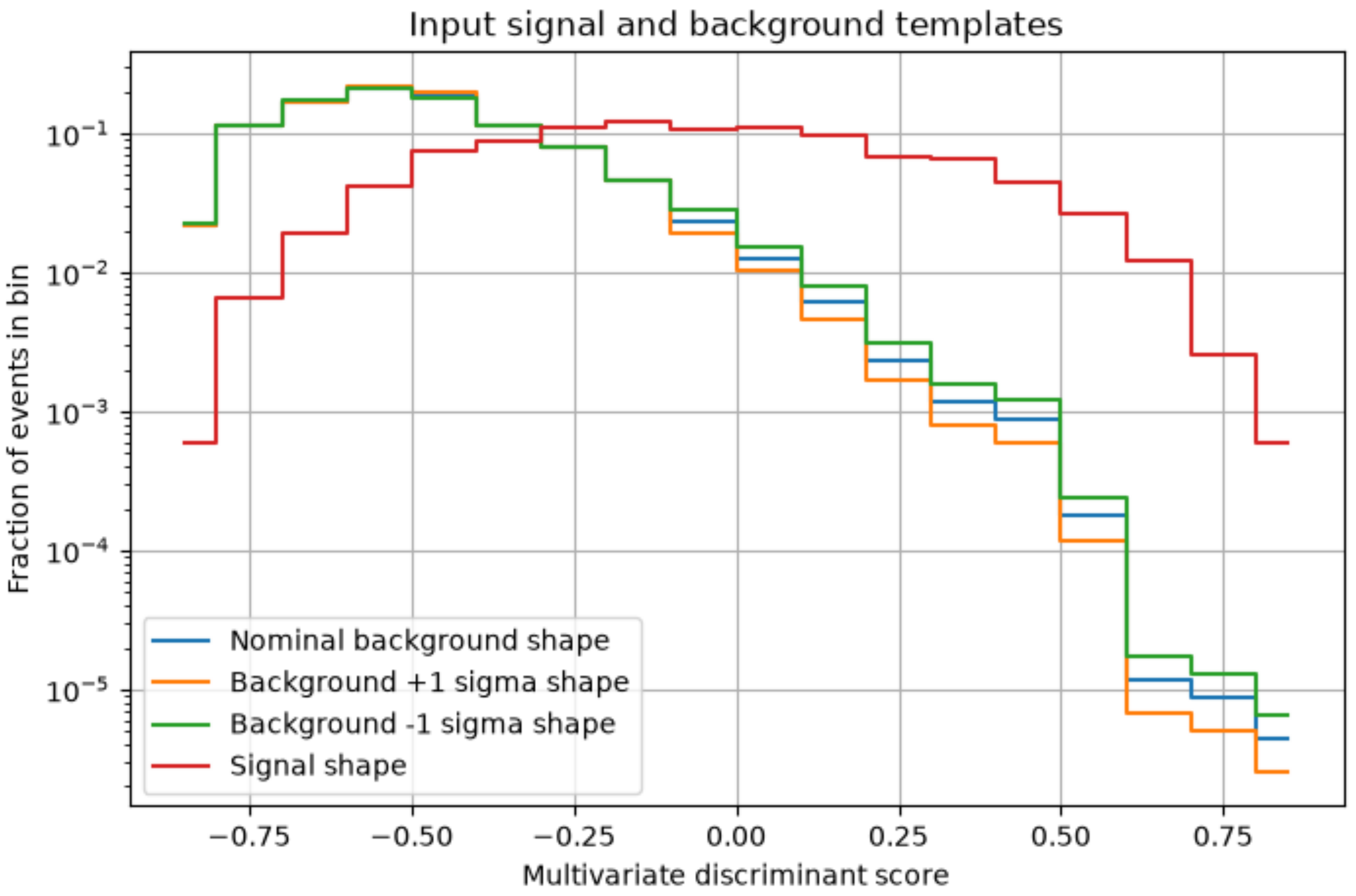

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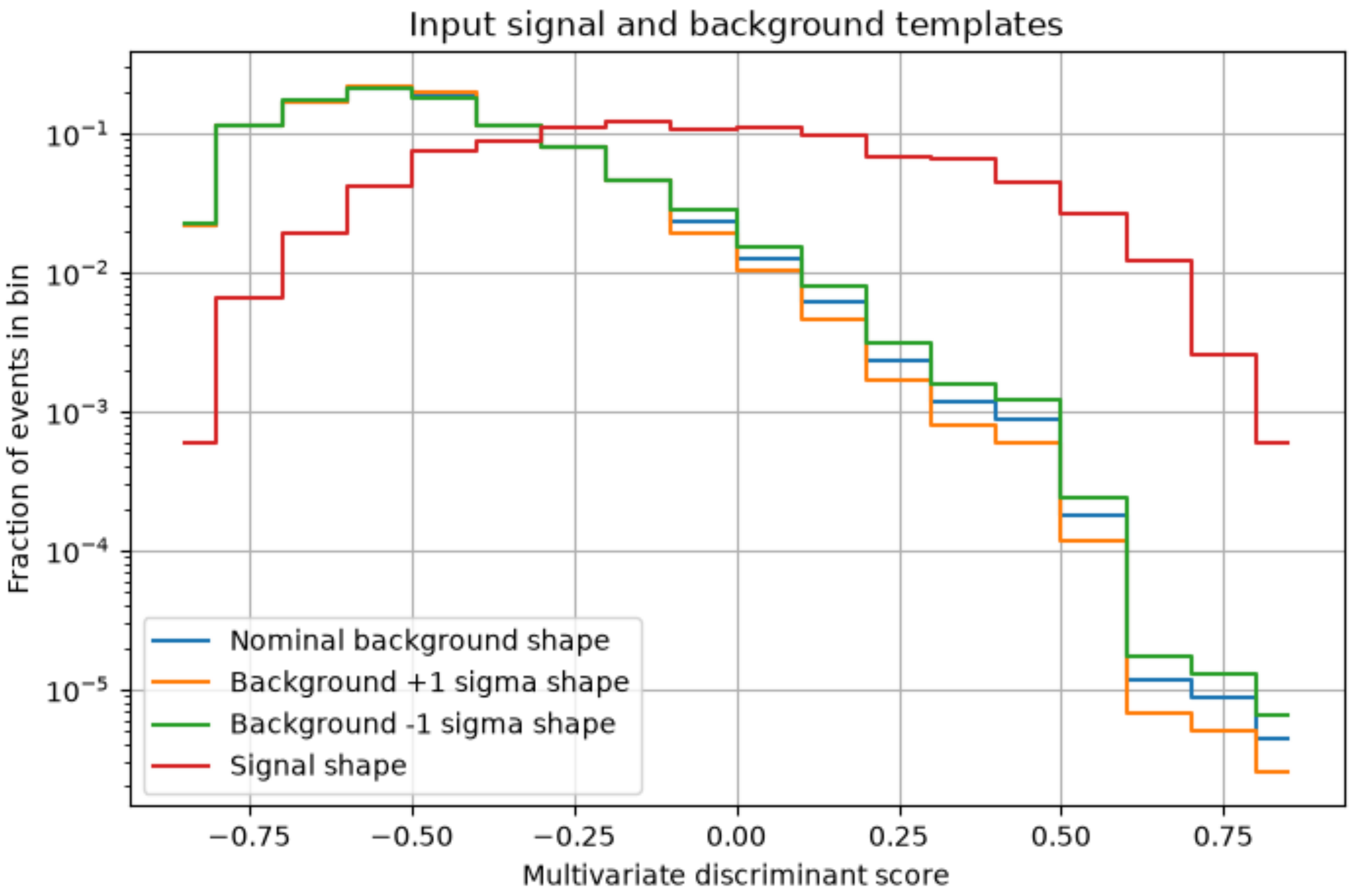

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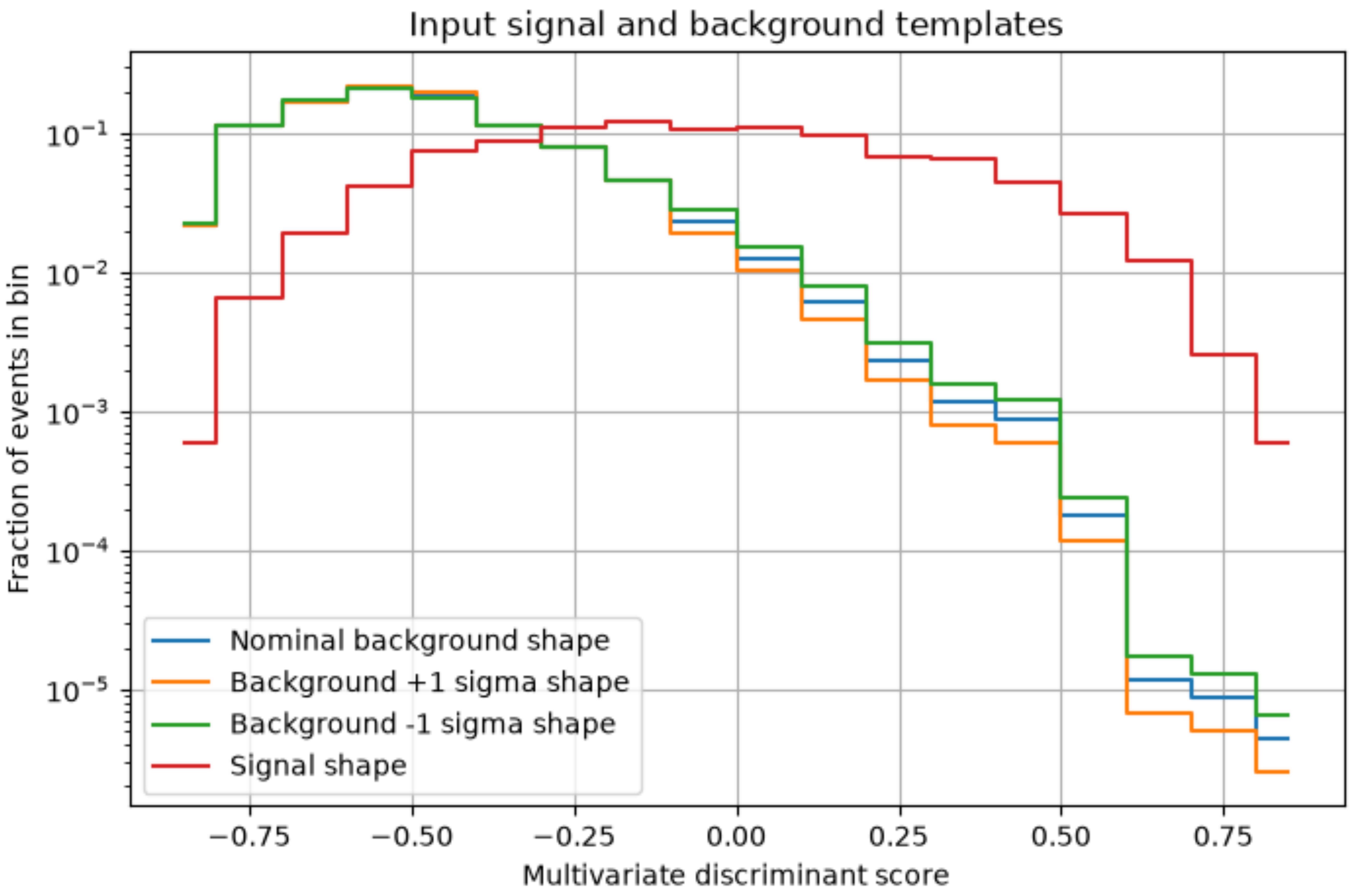

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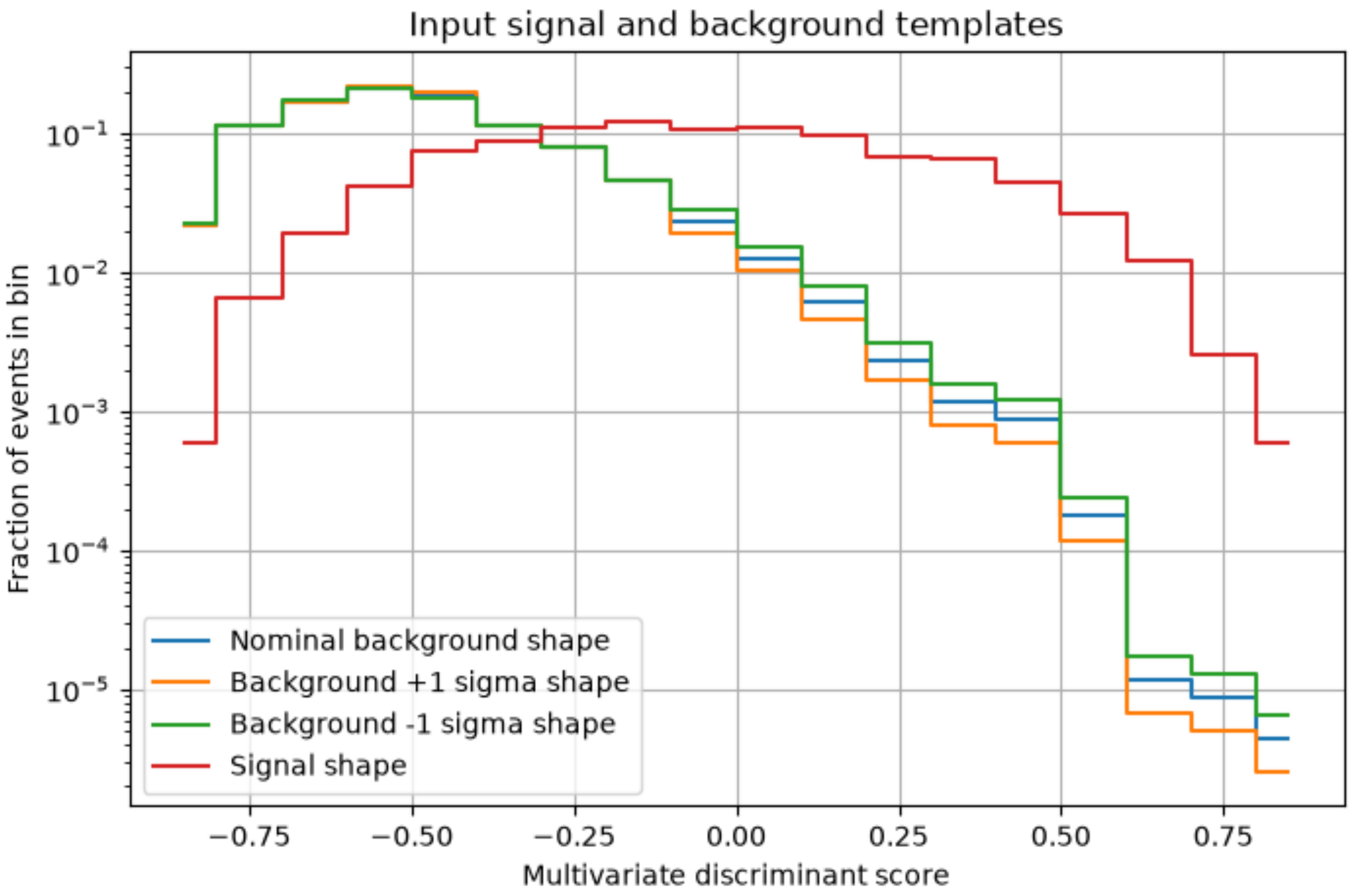

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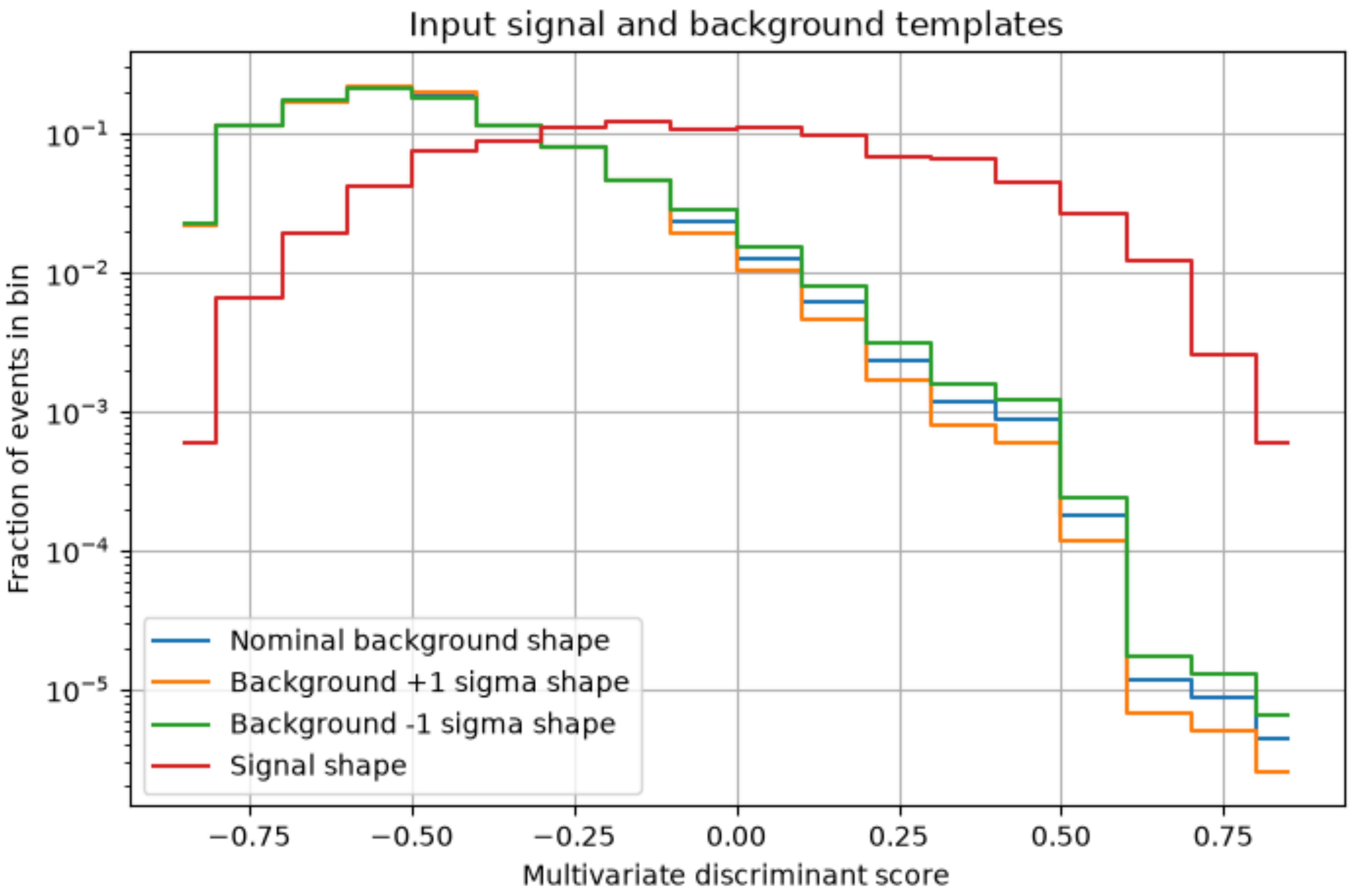

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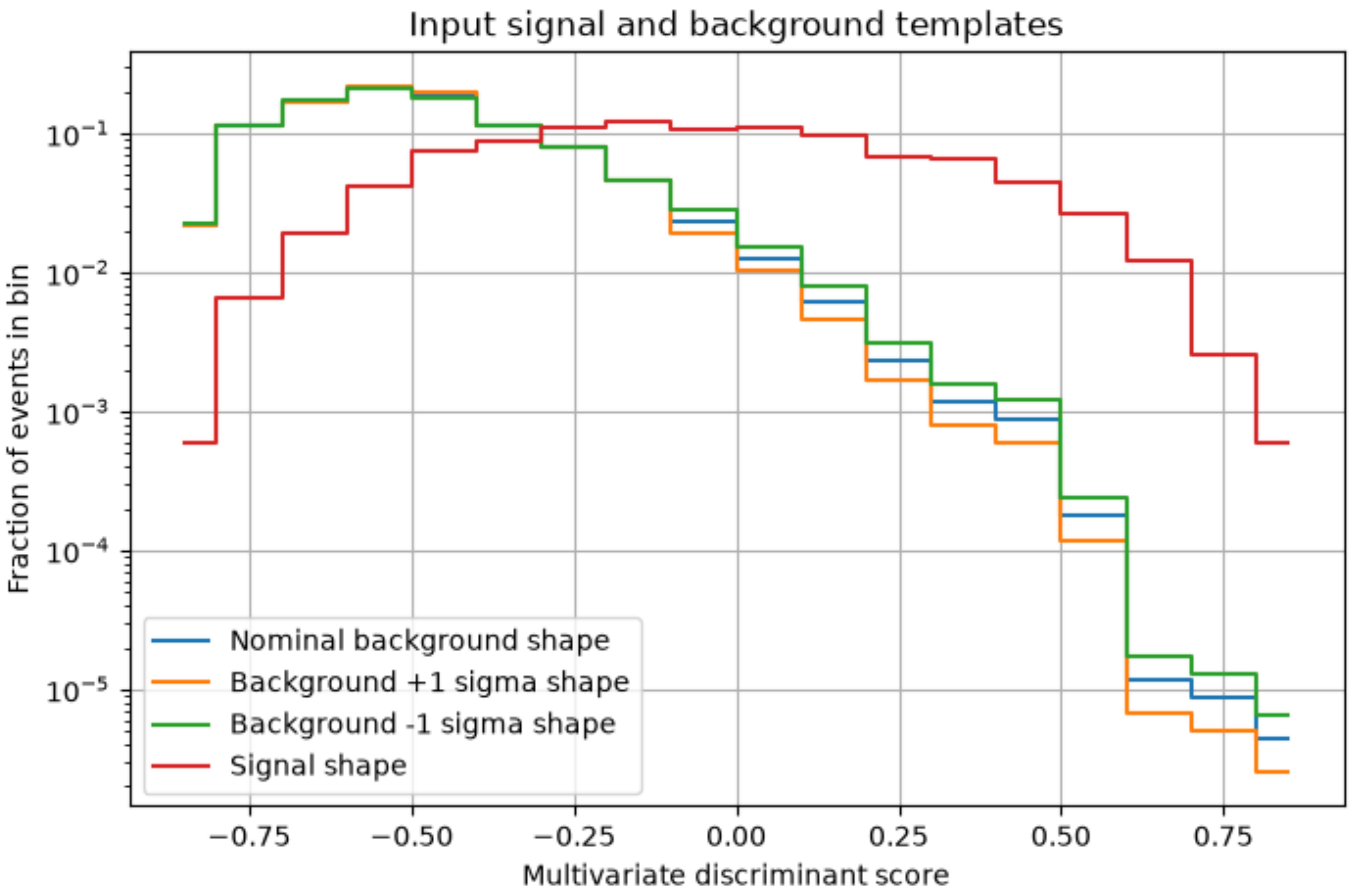

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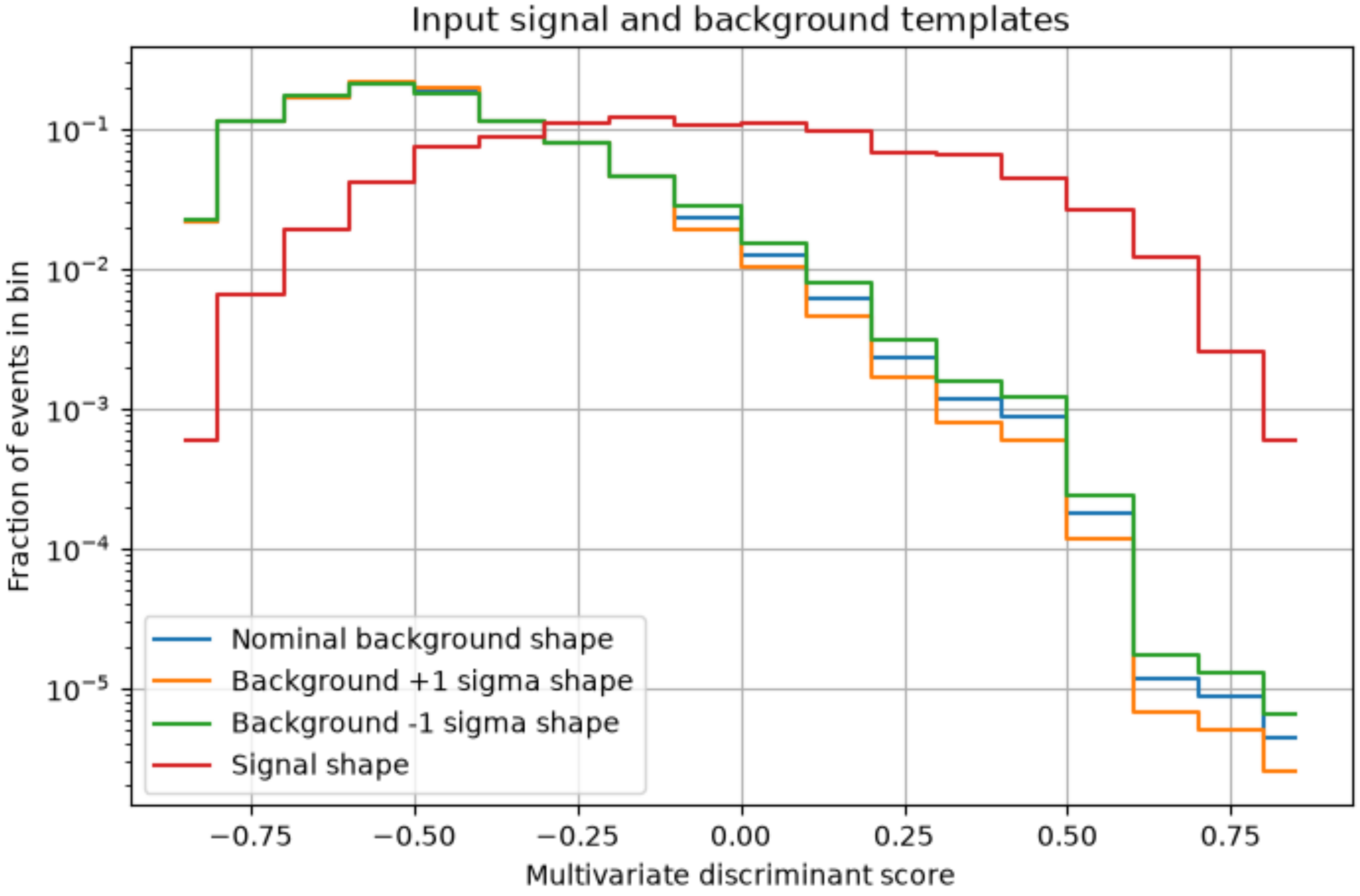

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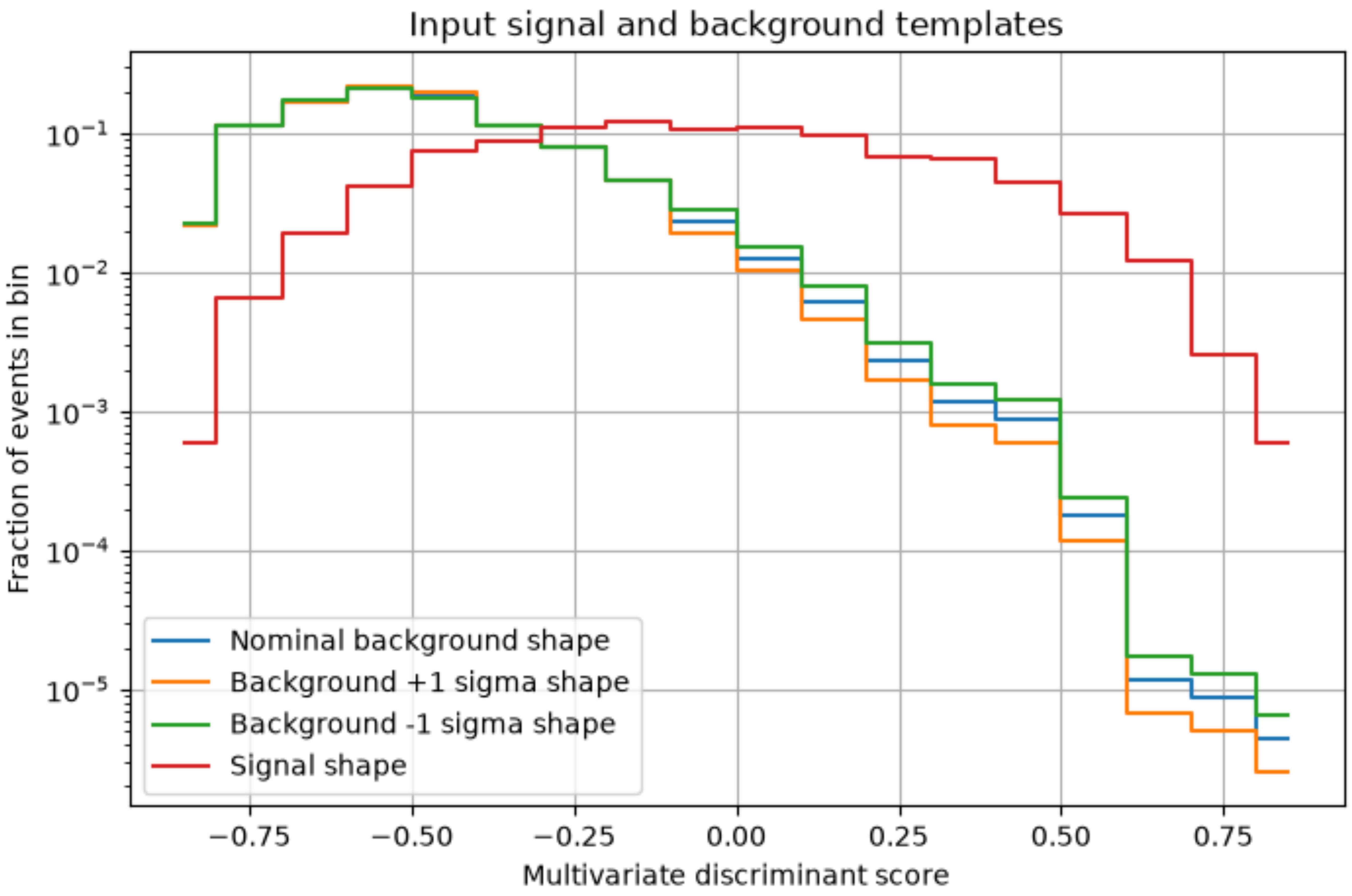

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