Model-Independent Searches with Background Matrix Elements

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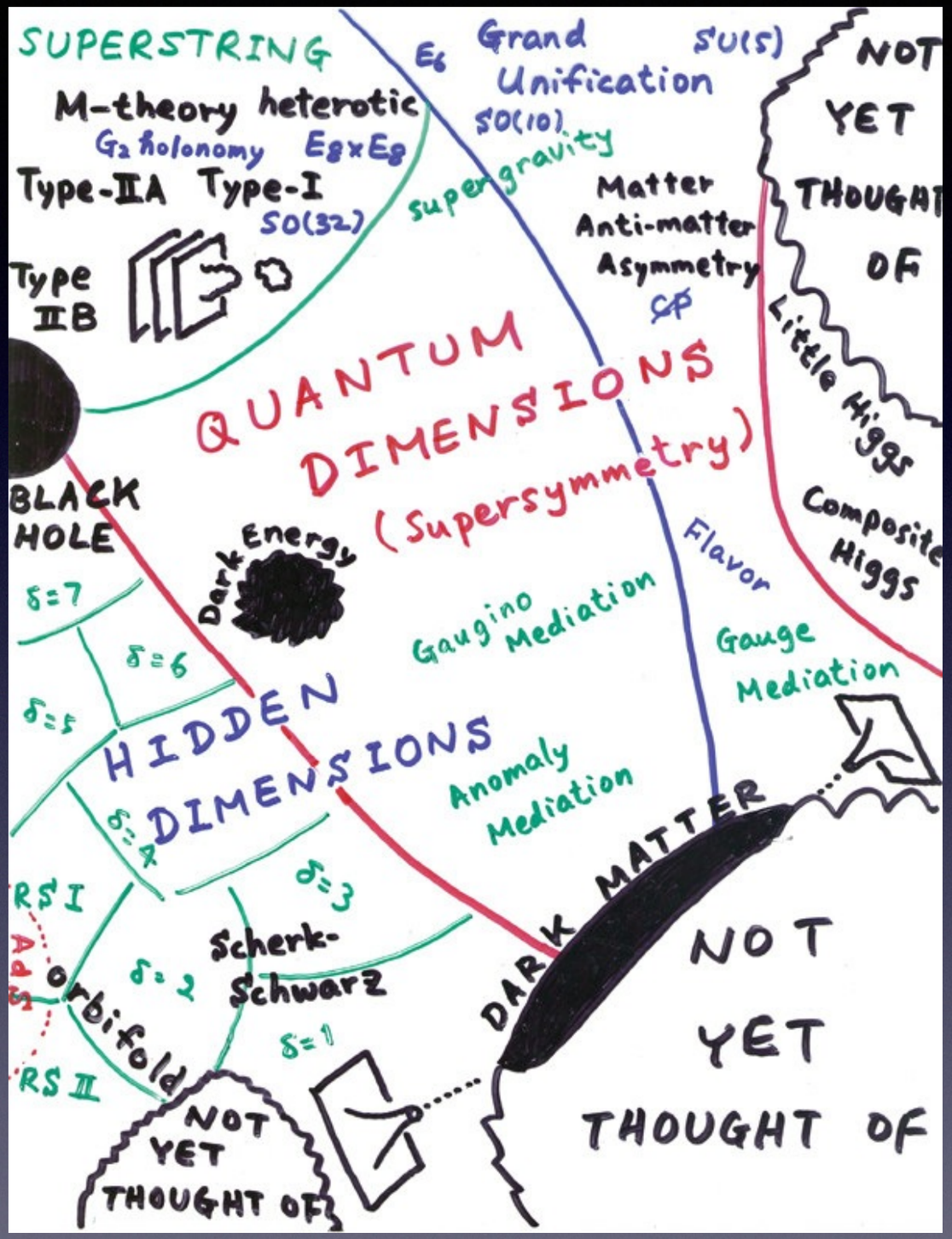
Work by Dipsikha Debnath, JG, Konstantin Matchev
arXiv:1405.5879

LHCP 2014: June 3, 2014

Goal: Discover new physics without a specific signal hypothesis

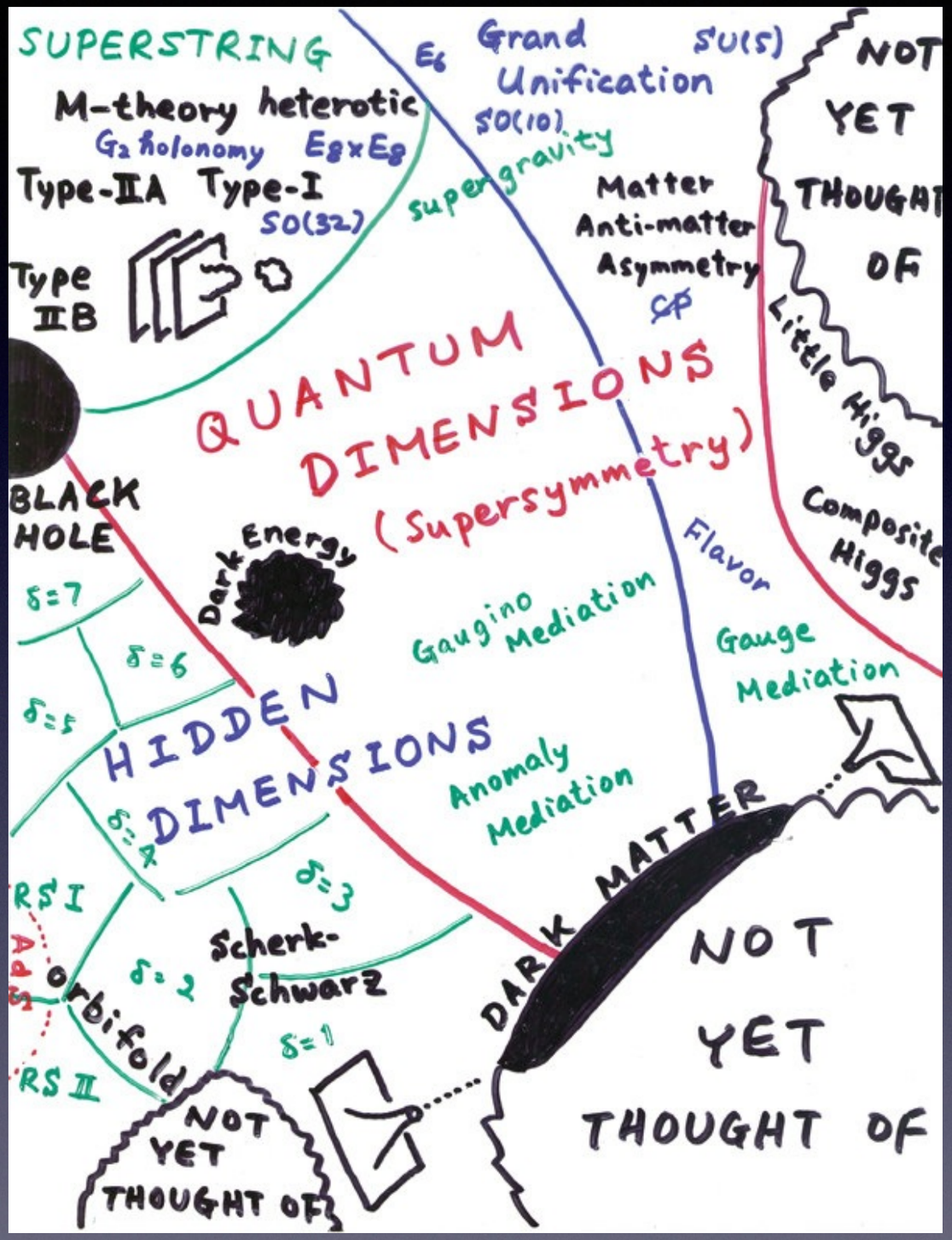
Why?

- Many ideas for physics beyond the Standard Model



(Murayama)

- Many ideas for physics beyond the Standard Model
- So far the LHC has yet to find this new physics.



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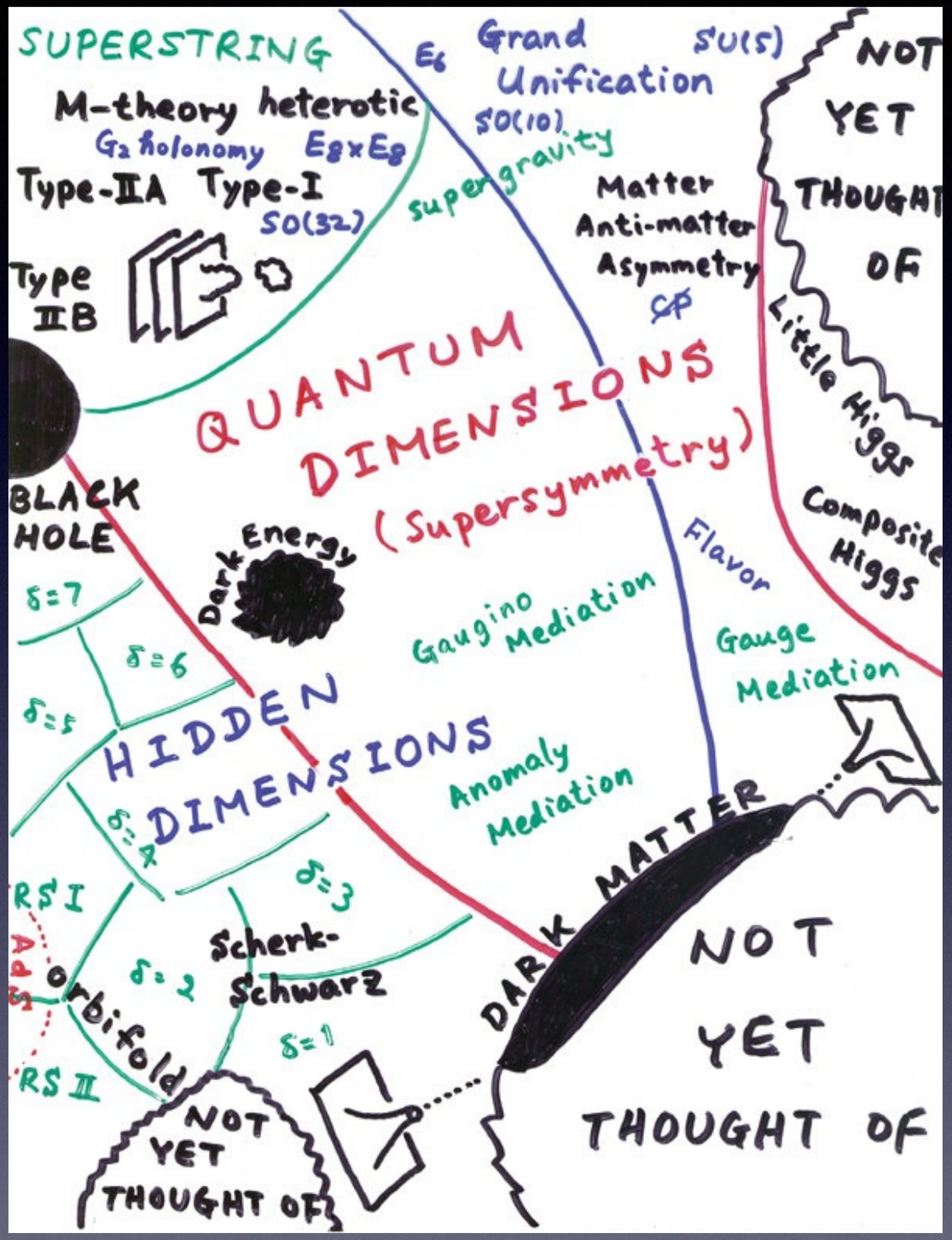
- Most analyses are optimized for a particular model (e.g. mSUGRA).



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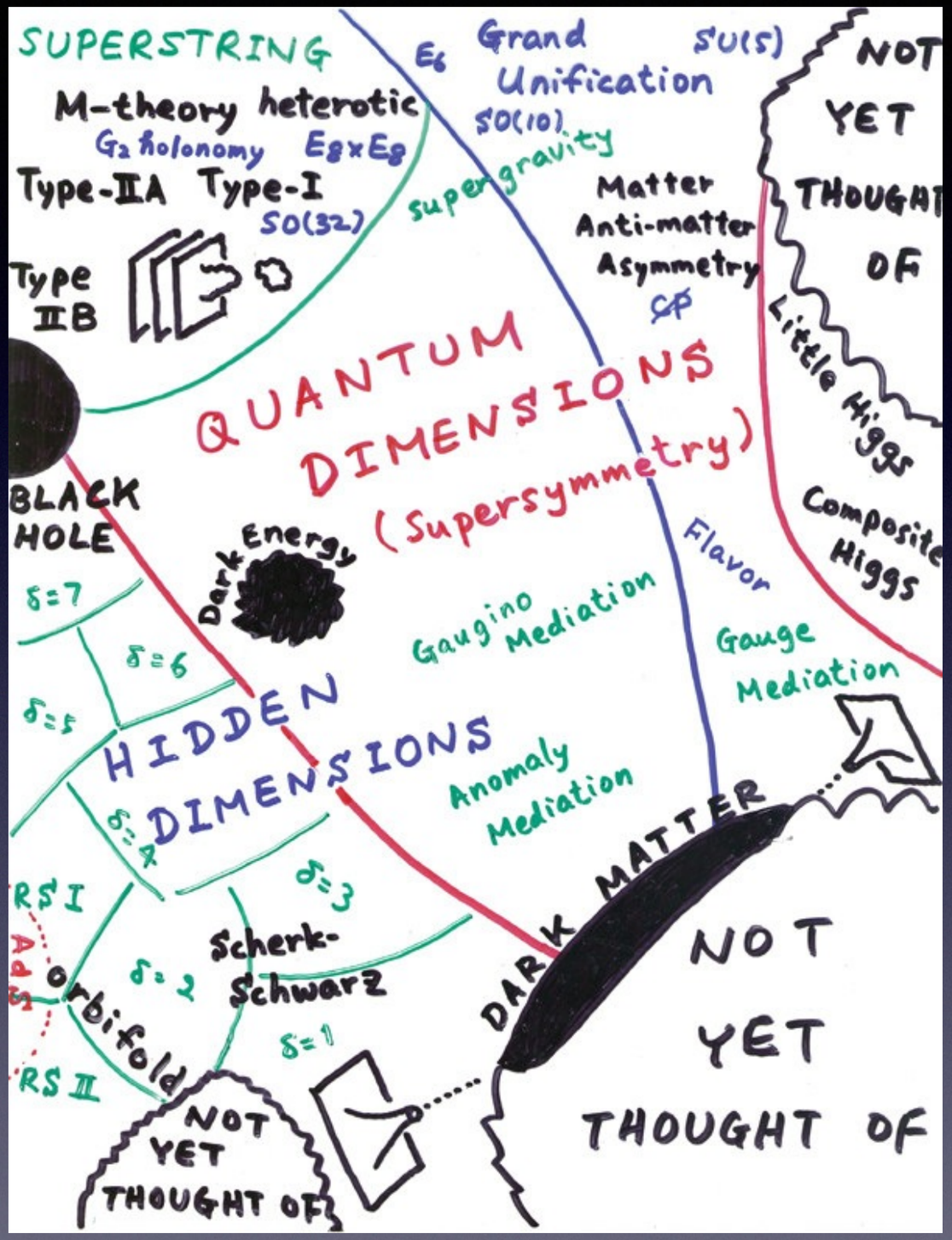
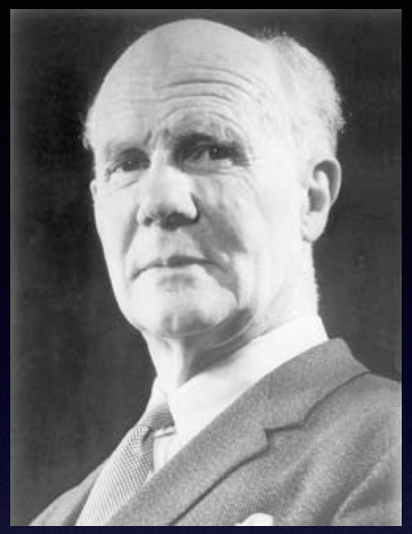


- Can we discover "Not Yet Thought Of" theories?

- We would like to be as sensitive to new physics as possible
- Without optimizing for a particular signal model
- We take our inspiration from the Matrix Element Method.

Neyman-Pearson Lemma



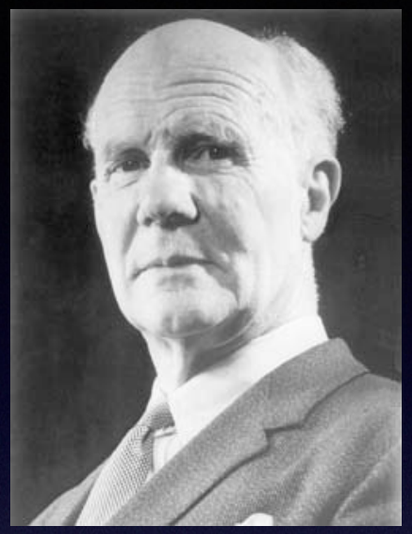
Actually Neyman and Pearson were roughly the same age. Google works in mysterious ways...

In a mathematically well-defined sense, the best choice of test statistic for distinguishing between two hypotheses (like “signal” and “background”) is the likelihood ratio/ discriminant

$$\Lambda(E) = \frac{L(H_1 \mid E)}{L(H_0 \mid E)}$$

where H_0 and H_1 are two alternative hypotheses and E is the data in an experiment

Neyman-Pearson Lemma



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Suggests that the likelihood will be an optimal variable.

Matrix Element Method

- In particle physics, the likelihood/ we use the expression for probability on the right:

$$\mathcal{P}(\boldsymbol{x}_i|A(B)) = \frac{1}{\sigma(A(B))}\sum_{k,l}\int dx_1 dx_2 \frac{f_k(x_1)f_l(x_2)}{2sx_1x_2} \times \left[\prod_{\text{all } j}\int \frac{d^3q_j}{(2\pi)^3 2E_j}\right] \times \left[\prod_{\text{visible } j} T(\{q_j\},\{p_j\})\right] \times |\mathcal{M}_{A(B),kl}(\{q_j\})|^2,$$

- Normalized to the total cross section
- With integrals over transfer functions, invisible momenta, etc.
- Use of this likelihood = "Matrix Element Method"

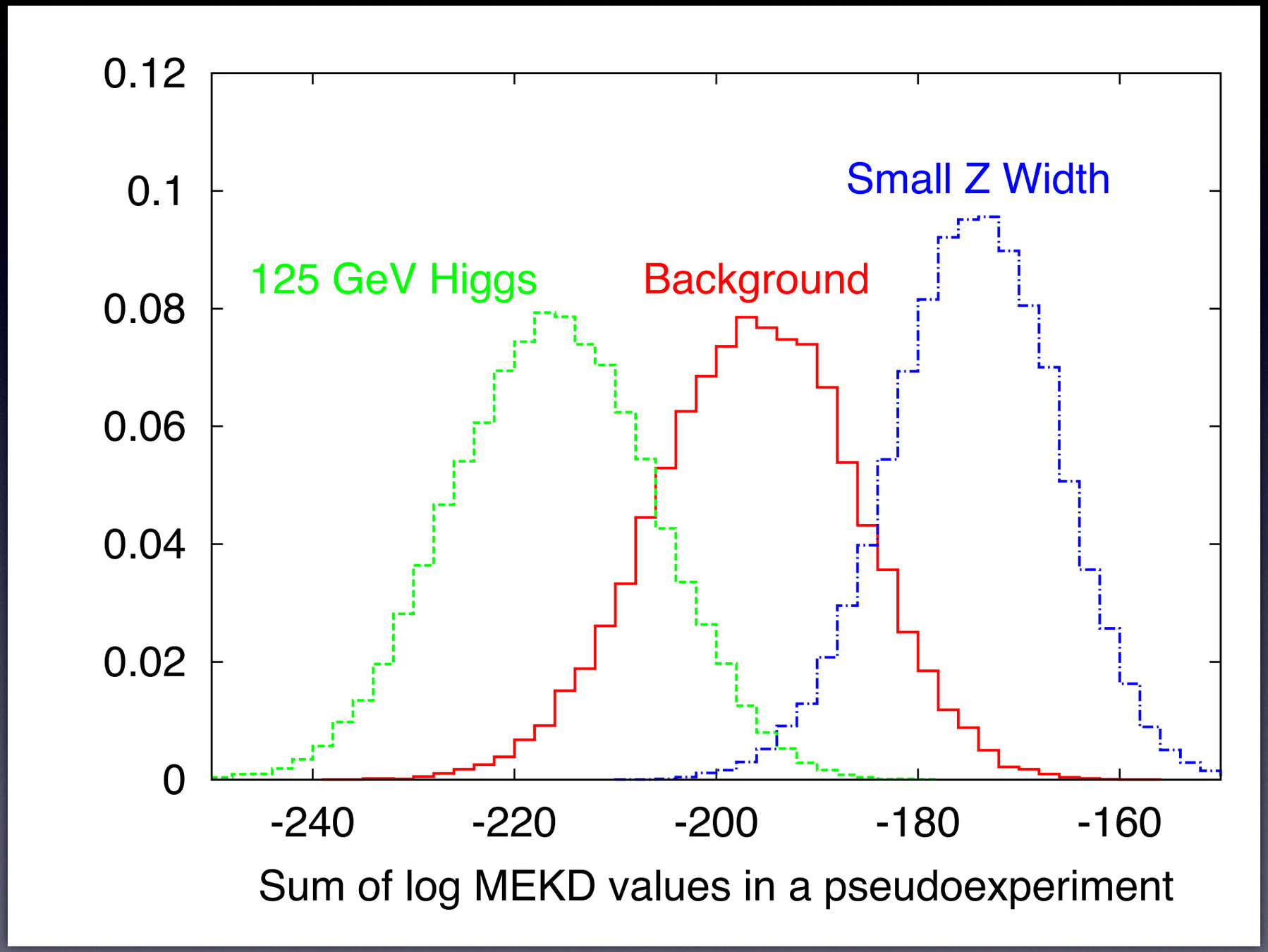
- In the Neyman-Pearson Lemma we needed a likelihood **ratio.**

- Need to know both signal and background likelihood to compute this ratio

- For signal independence, use **background likelihood** as a test statistic.

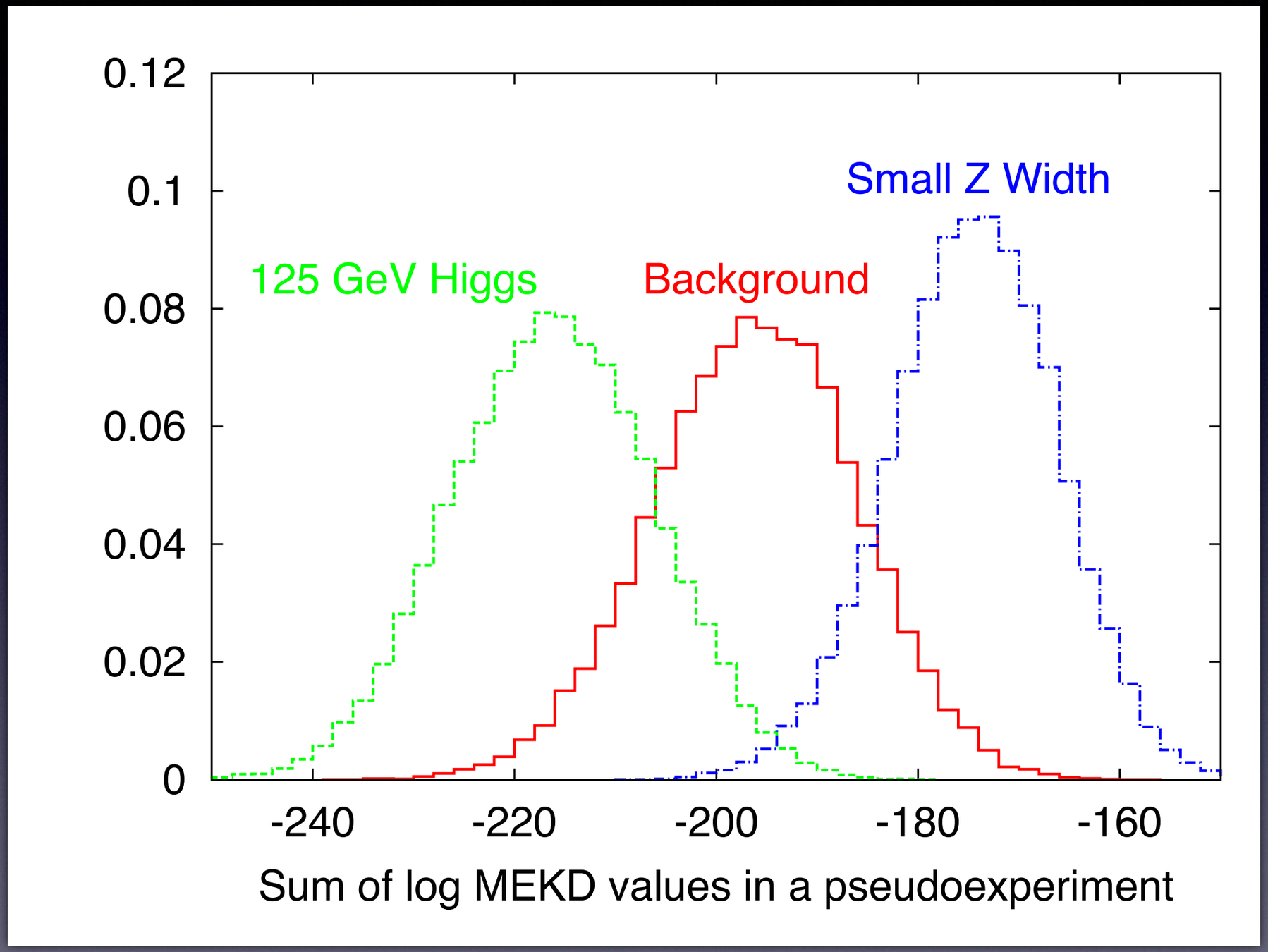
- Matrix element variables still “know a lot” about the background so should be optimal at rejecting background

Background Likelihood



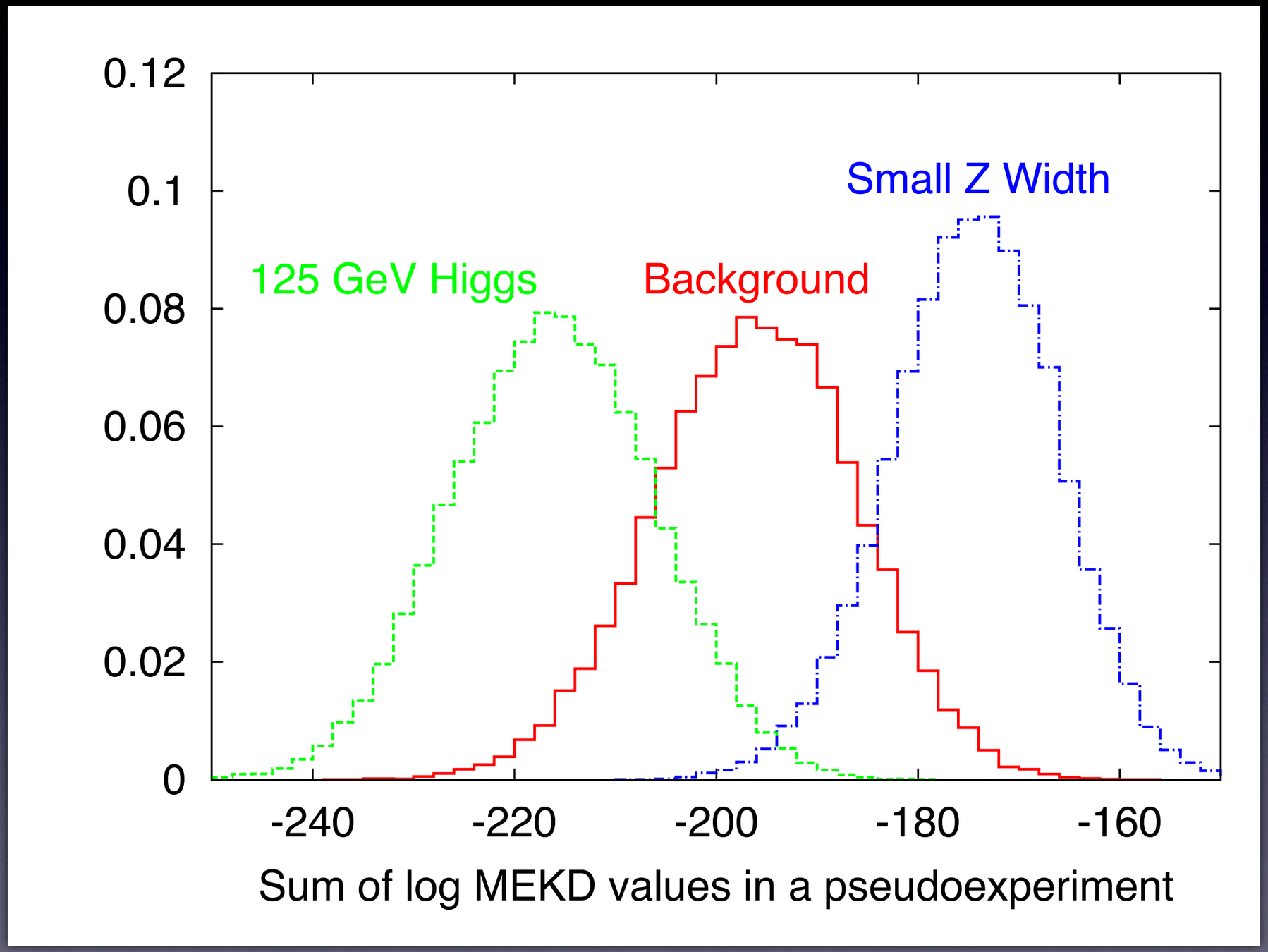
As an example, we consider 20 event pseudoexperiments

Background Likelihood



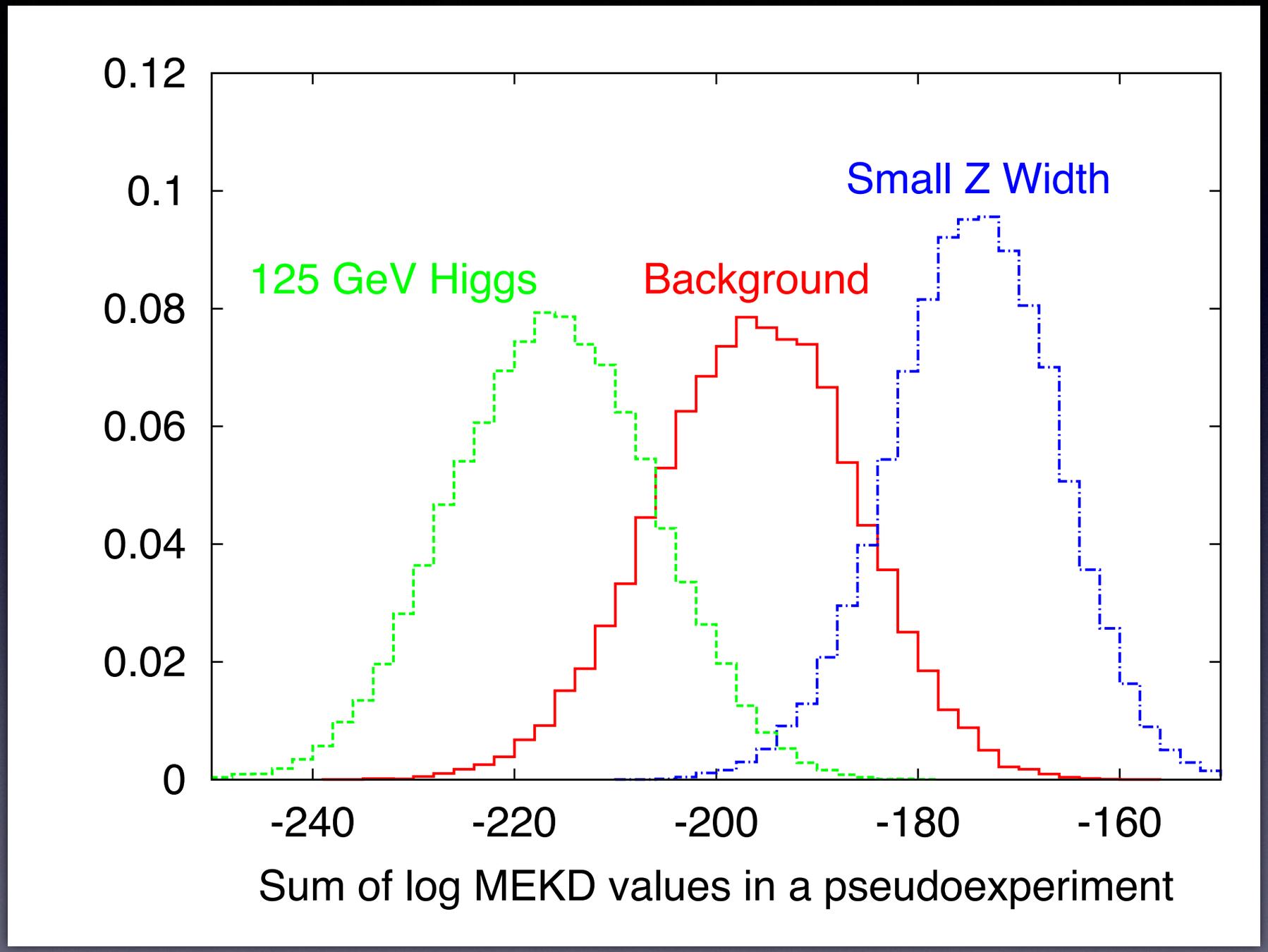
Processes: gluon fusion Higgs → 4ℓ

Background Likelihood



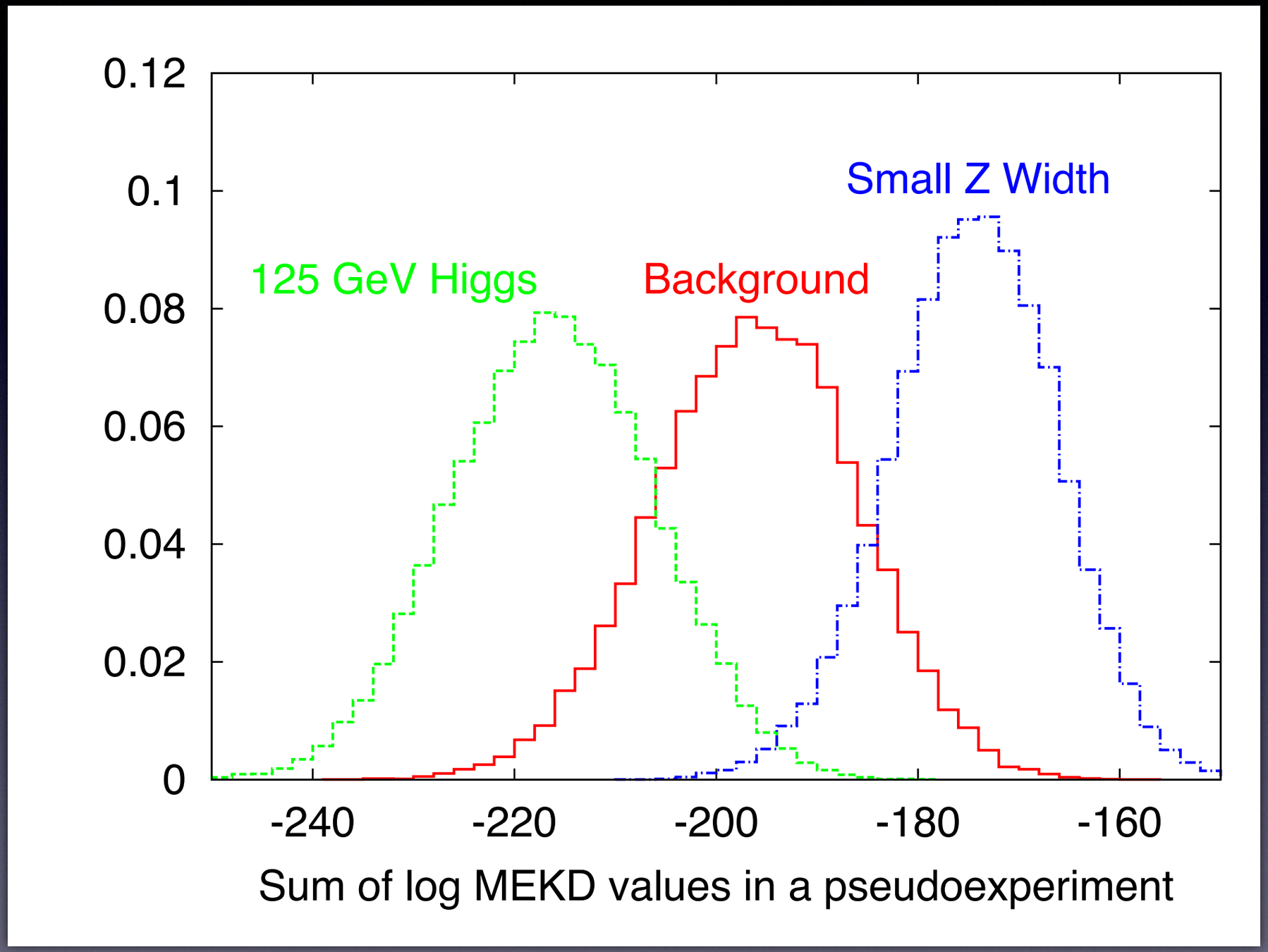
Processes: $q\bar{q} \rightarrow 4\ell$ background

Background Likelihood



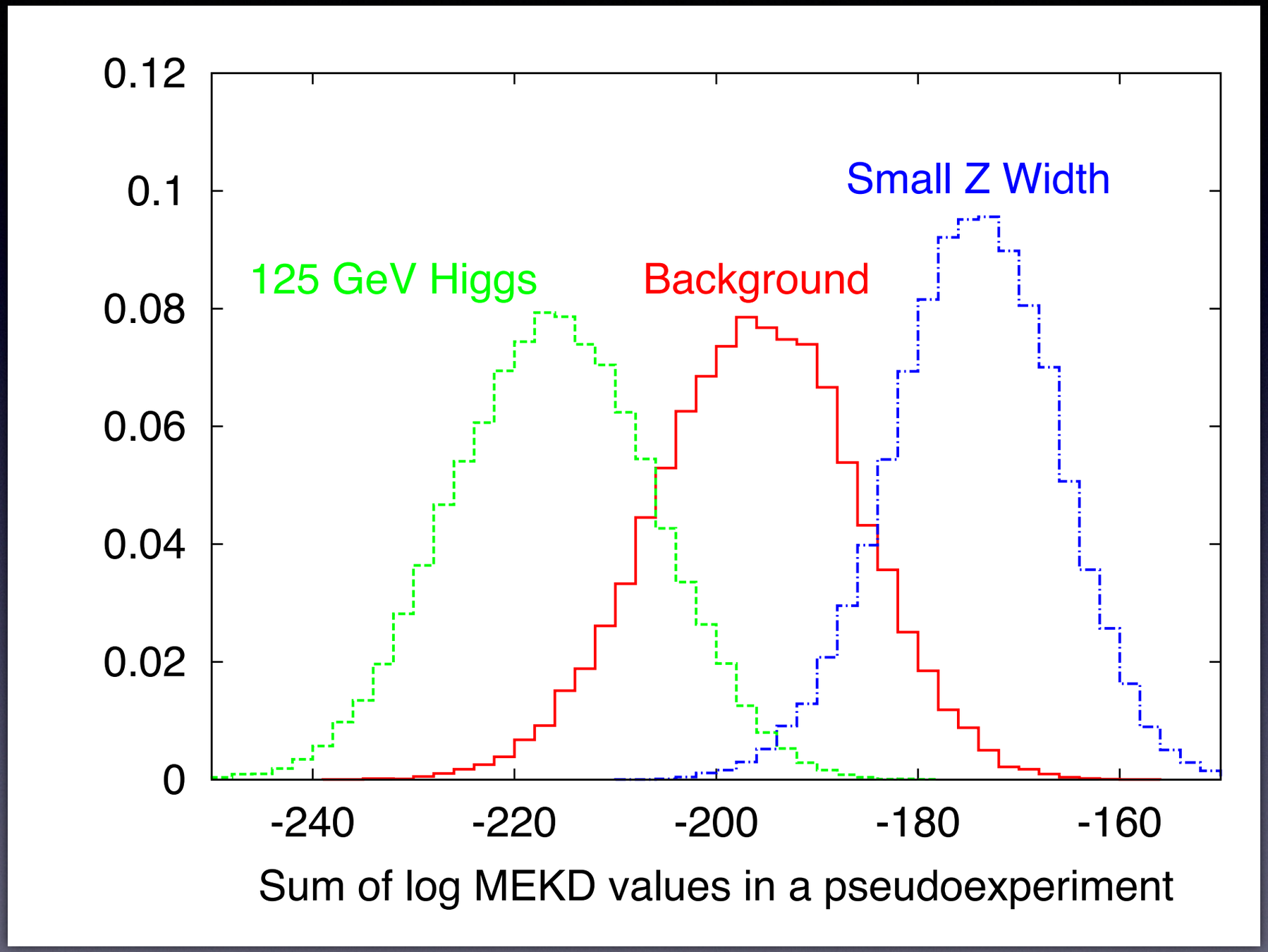
Processes: $q\bar{q} \rightarrow 4\ell$ background, $\Gamma_Z \rightarrow \Gamma_Z/5$

Background Likelihood



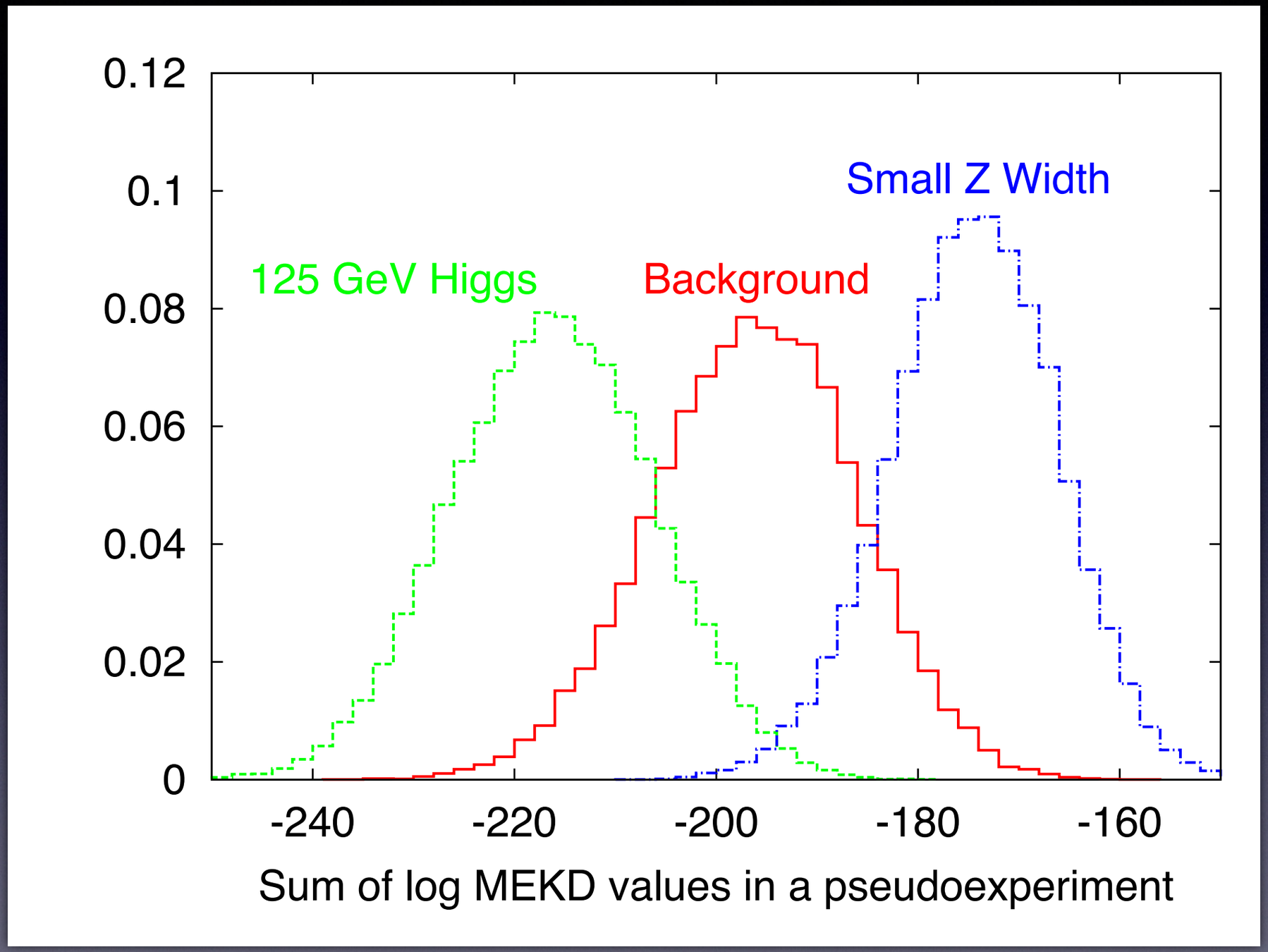
For each 20 event pseudoexperiment, we calculate the sum of the

Background Likelihood



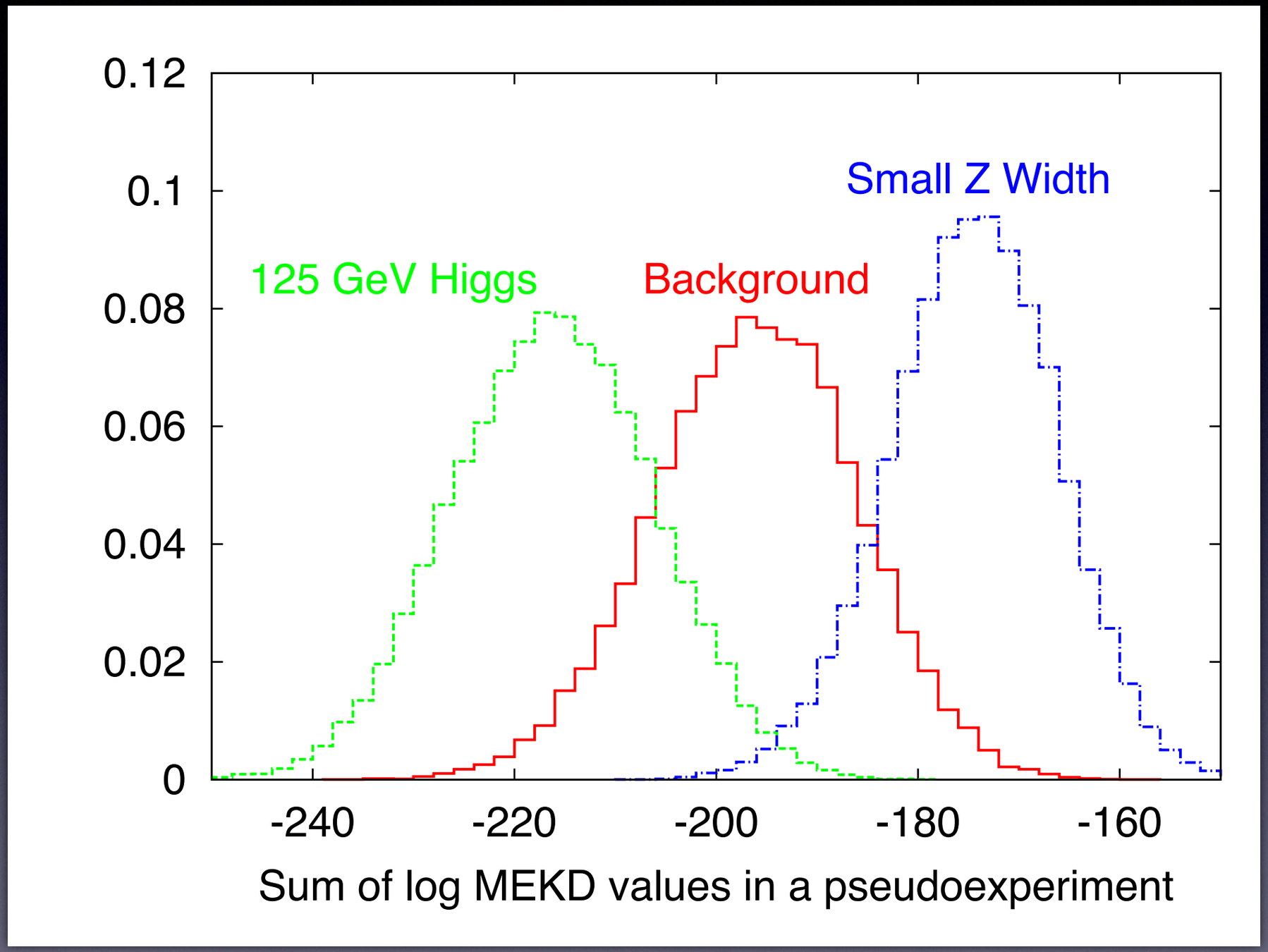
logarithms of background squared matrix elements evaluated for

Background Likelihood



the particular kinematics of the event.

Background Likelihood



We perform this calculation using the MEKD package

Background Likelihood

Avery, Bourilkov, Chen, Cheng, Drozdetskiy, JG, Korytov, Matchev, Milenovic, Mitselmakher, Park, Rinkevicius, and Snowball

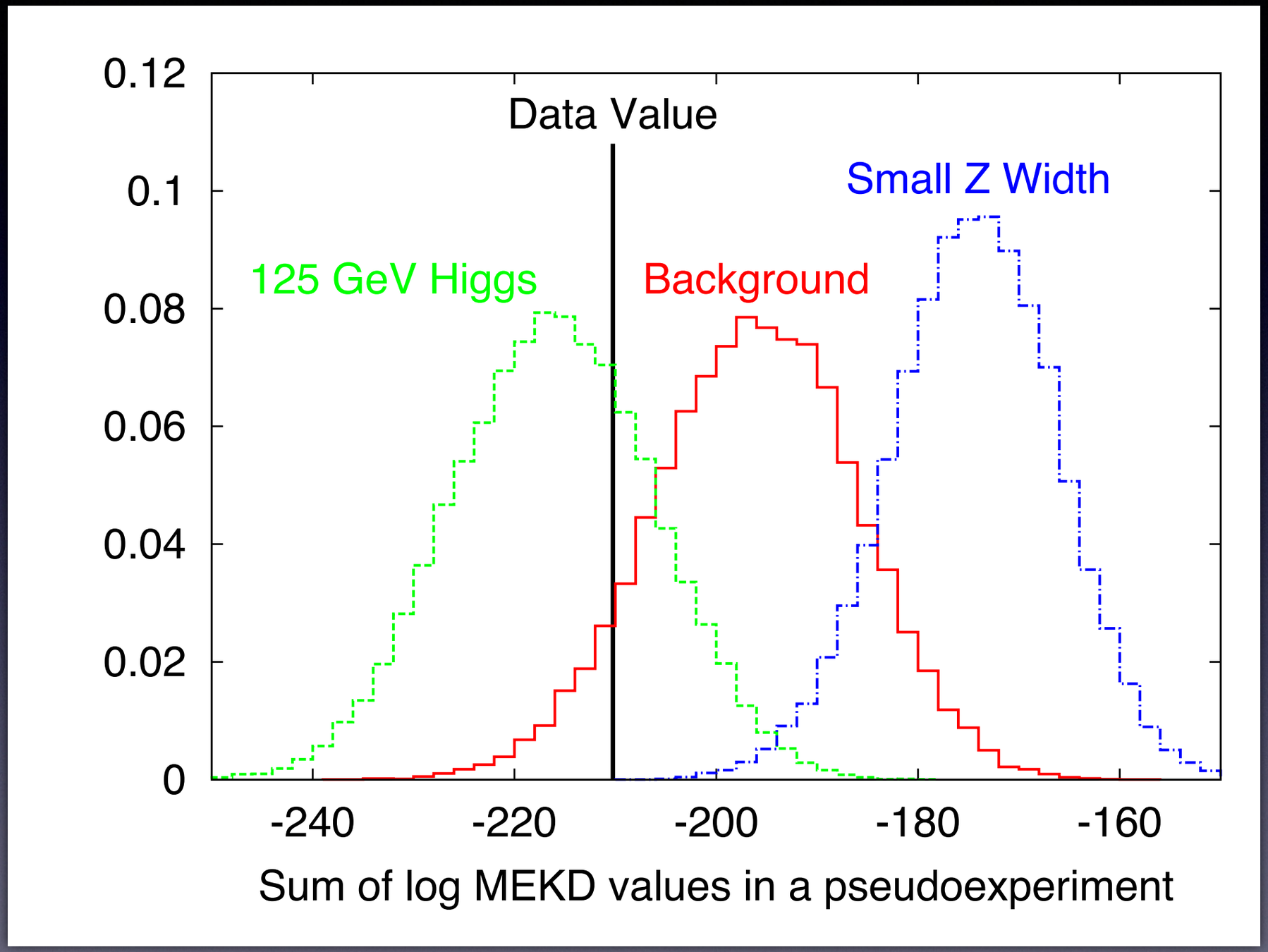
Phys.Rev. D87 (2013) 5, 055006

Chen, Cheng, JG, Korytov, Matchev, Milenovic, Mitselmakher, Park, Rinkevicius, and Snowball

Phys.Rev. D89 (2014) 034002

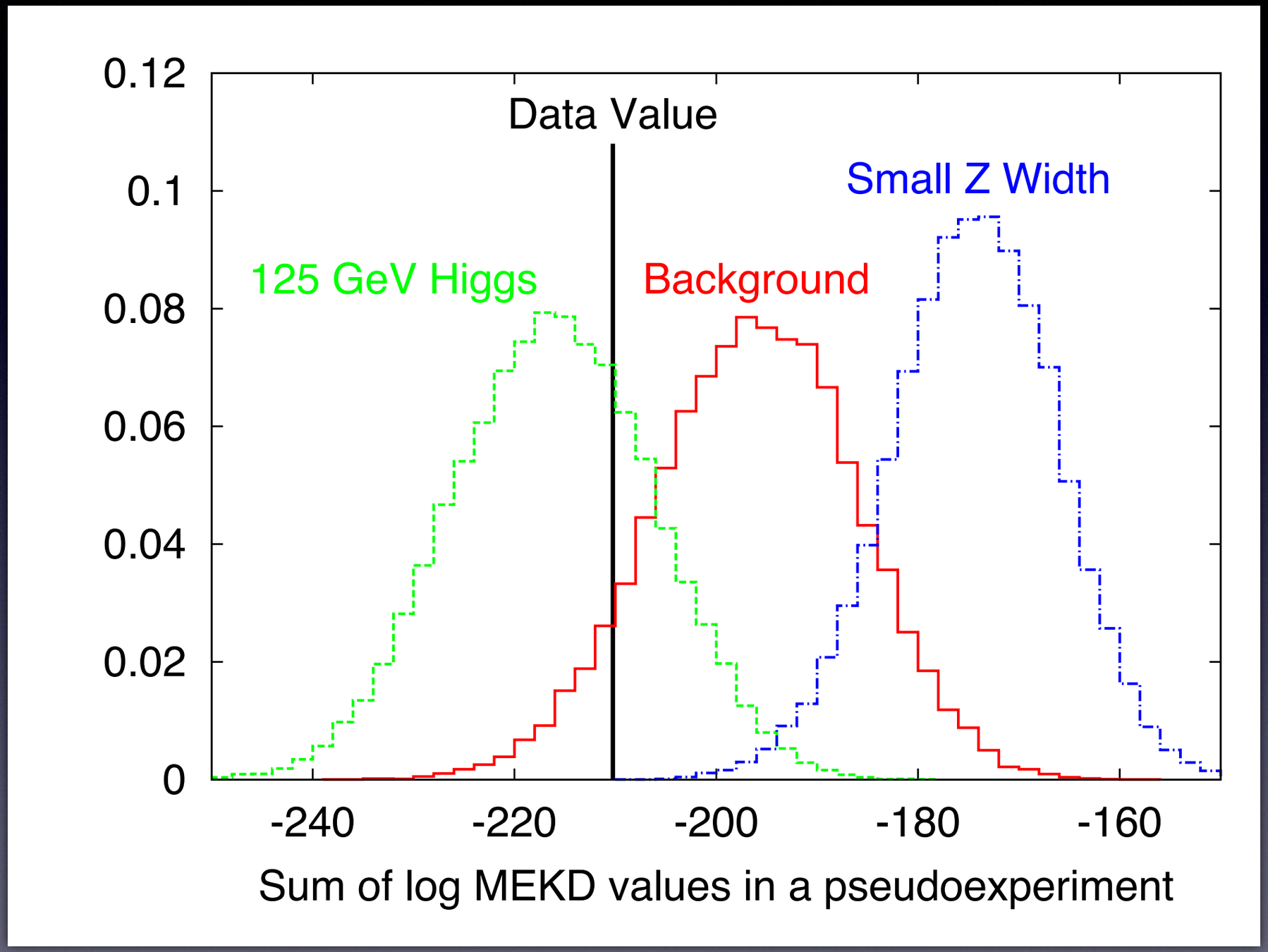
http://mekd.ihepa.ufl.edu

Background Likelihood



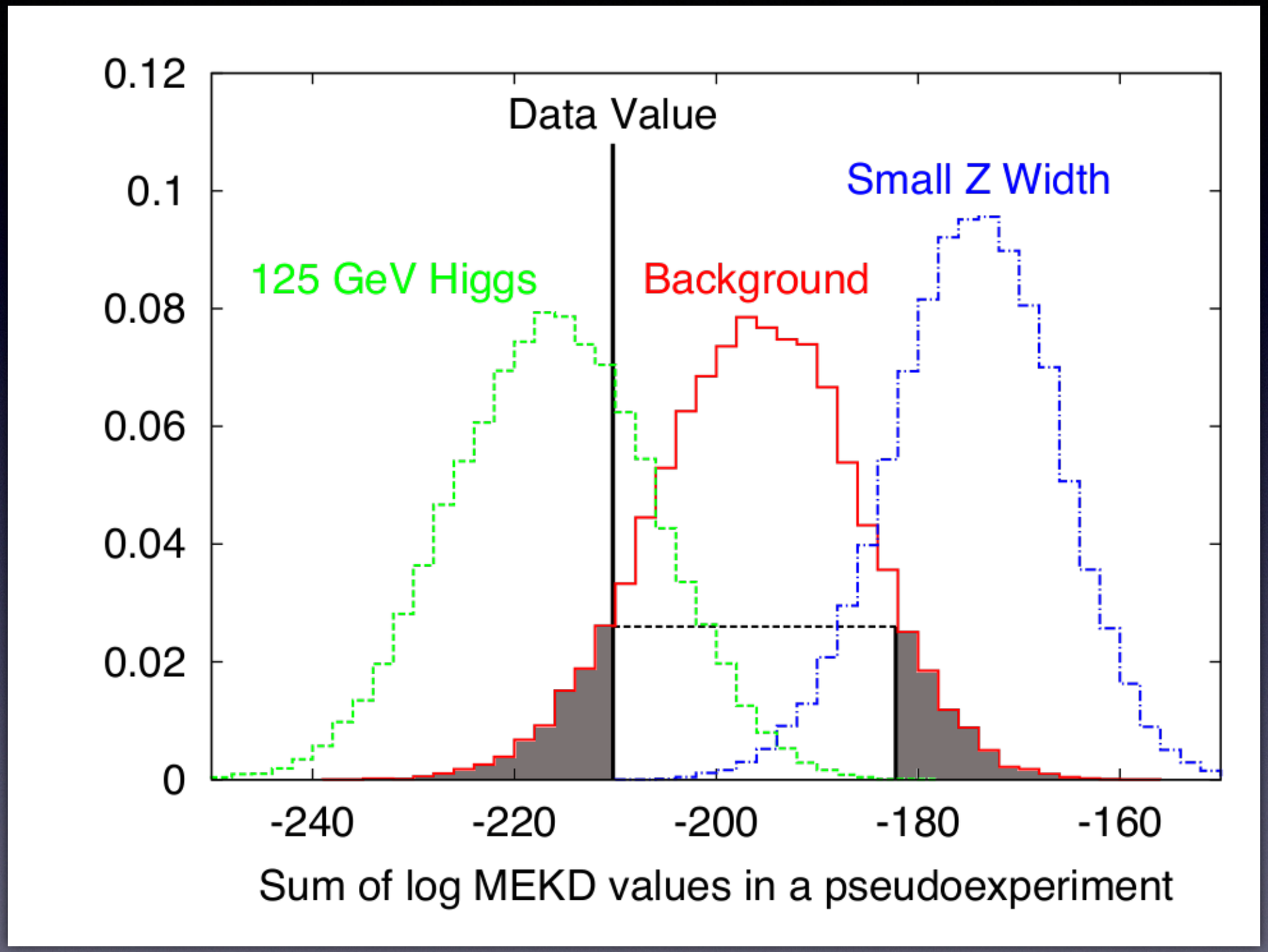
We take our 20 “data” events and evaluate the sum of the logarithms

Background Likelihood



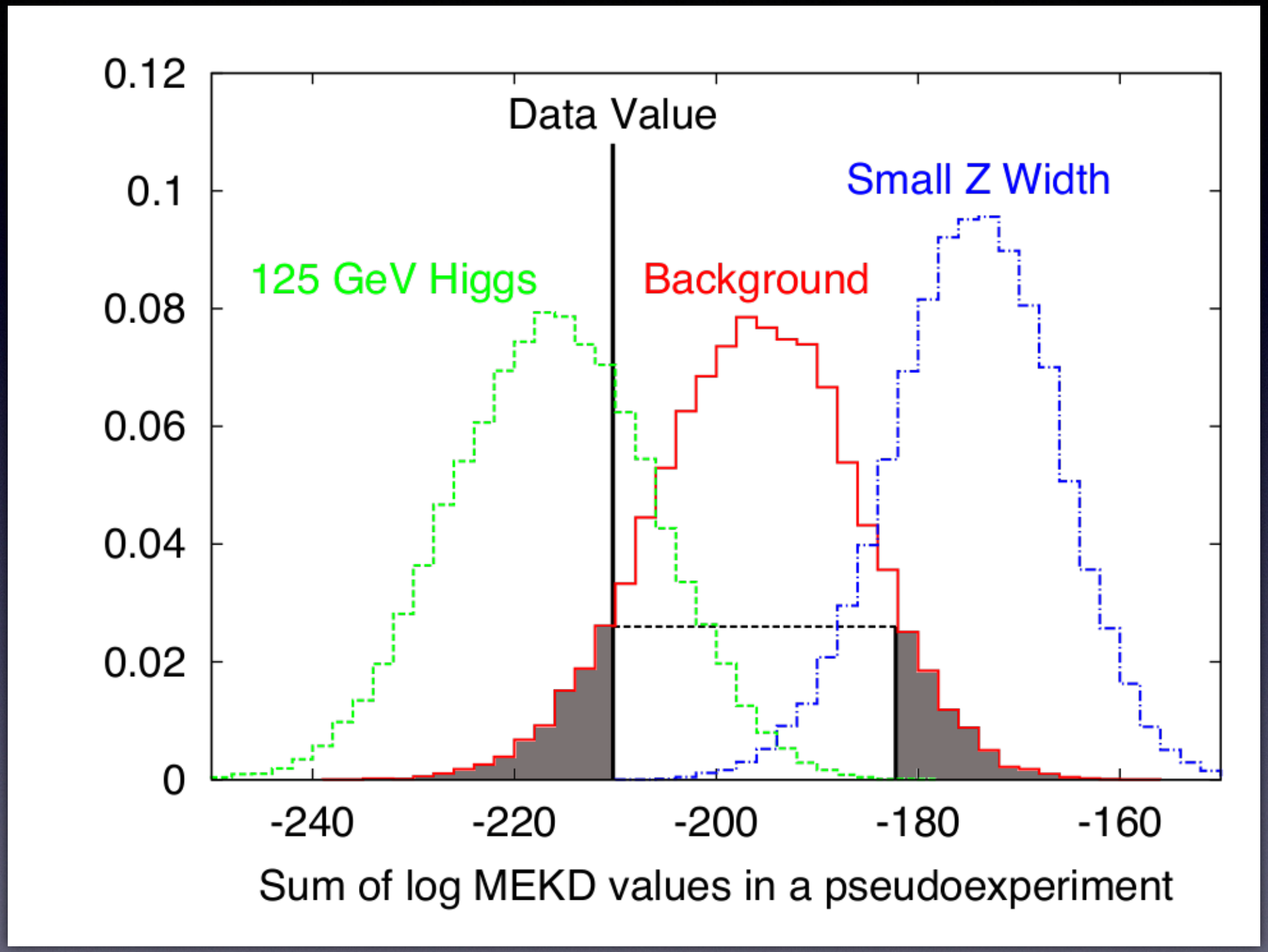
of background squared matrix elements, obtaining “Data Value.”

Background Likelihood



p-value is shaded region: fraction of pseudoexperiments

Background Likelihood



with more extreme values of the test statistic than “Data Value”

- p-value from likelihood distribution calculated from Monte Carlo pseudoexperiments
- so reducible backgrounds, detector effects, NLO (if your MC has it) etc. are included in the test statistic distribution, though not in the calculation of the test statistic

Flattening the Background

- I've argued for using the background matrix element as a "test statistic" for discovering signals in a model-independent way

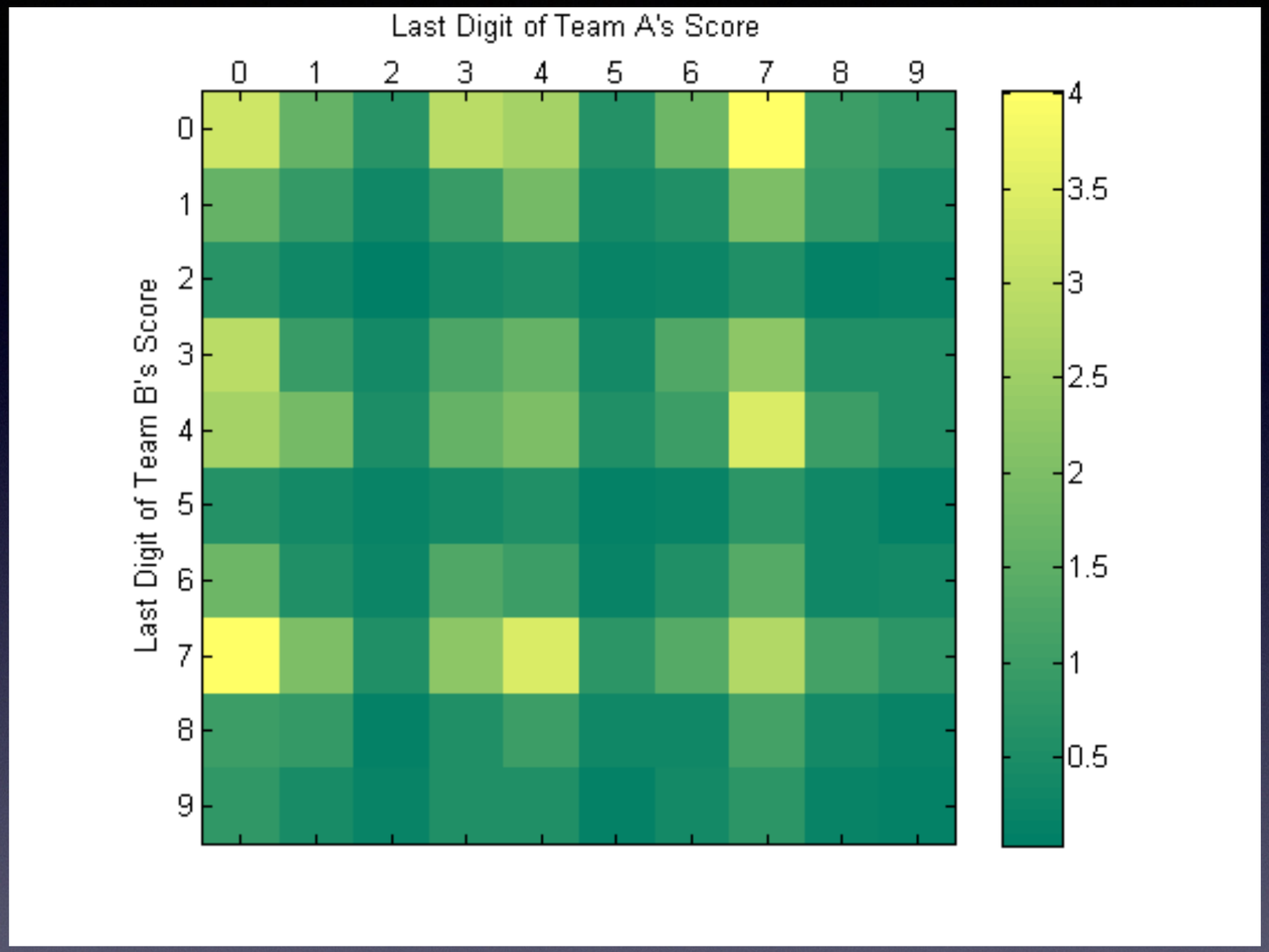
- Now I'm going to present some related ideas in which we use similar tools to obtain flat background distributions

Why?

When your background is flat…

It’s easy to discover an unexpected signal.

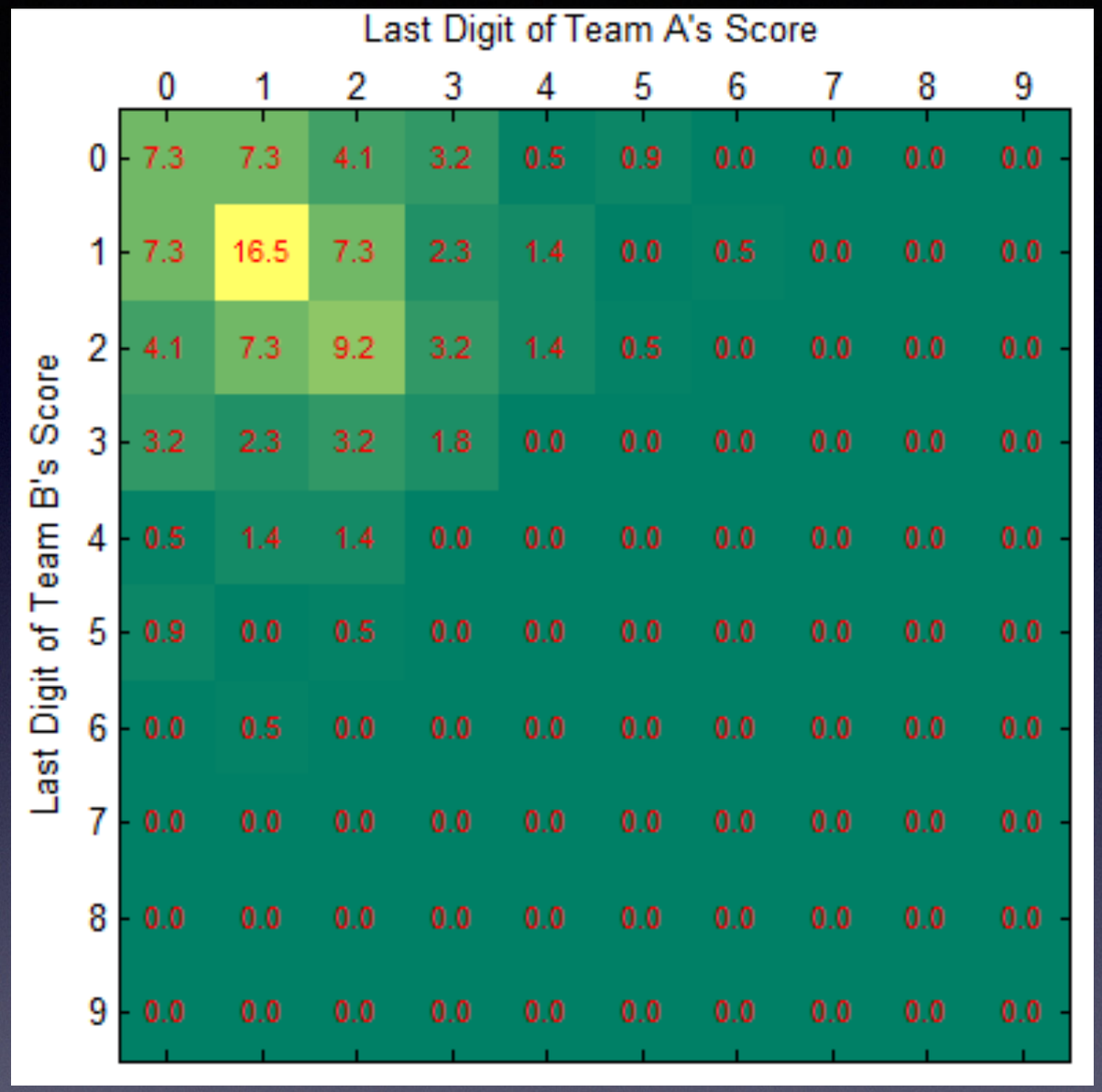
Example: Football Scores



http://blogs.mathworks.com/community/2013/01/07/football-squares-with-matlab/

- Excess in scores that end in “7”, “3”, or “4” evidence that scores are quantized in units of “7” or “3”.

Example: Football Scores



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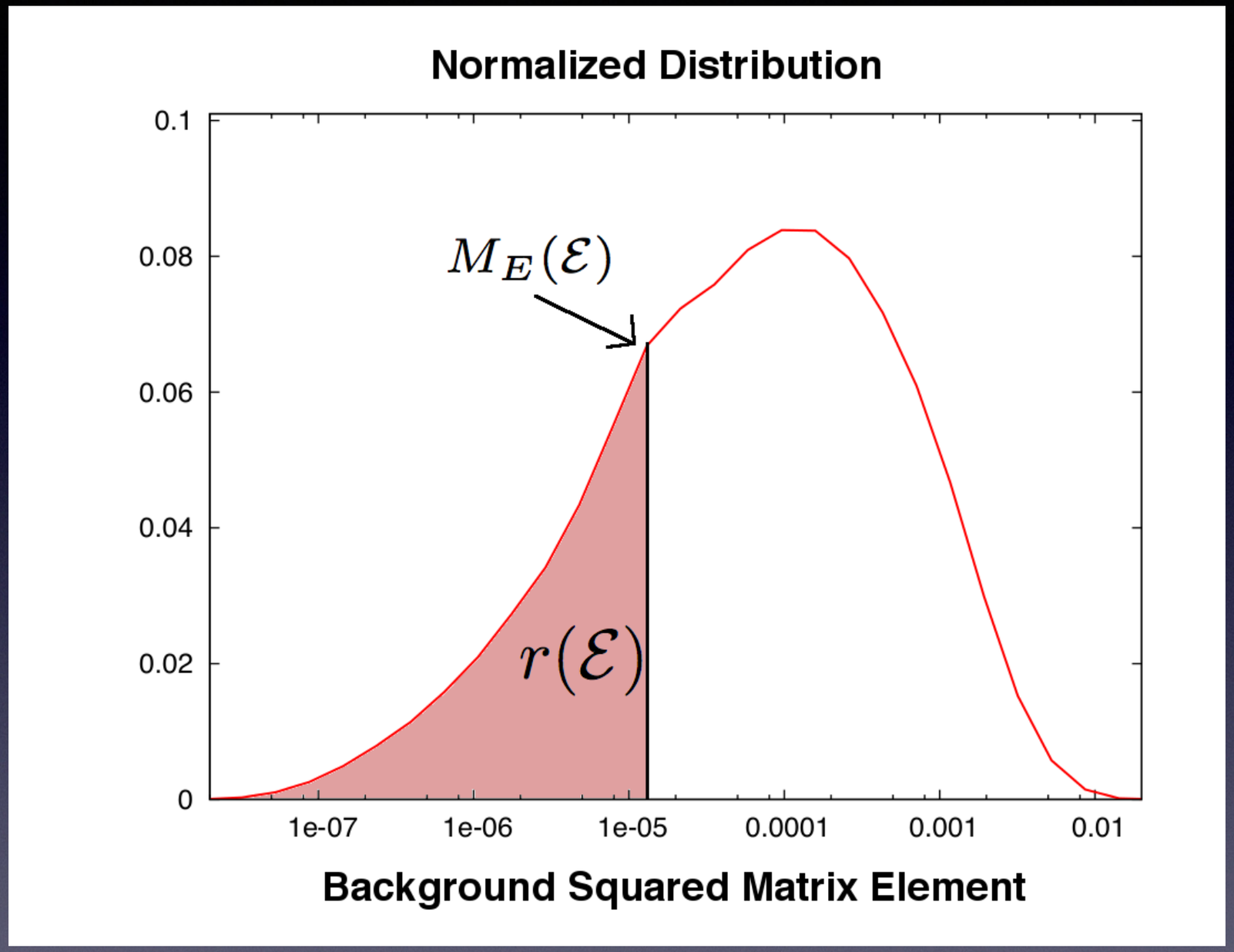
- Broad peak at (1,1). Suggests that scores quantized in units of “1”; not as many scores per game.

- We learned about the structure of football(s) from deviations from flatness in distributions.

- Can we do the same in particle physics?

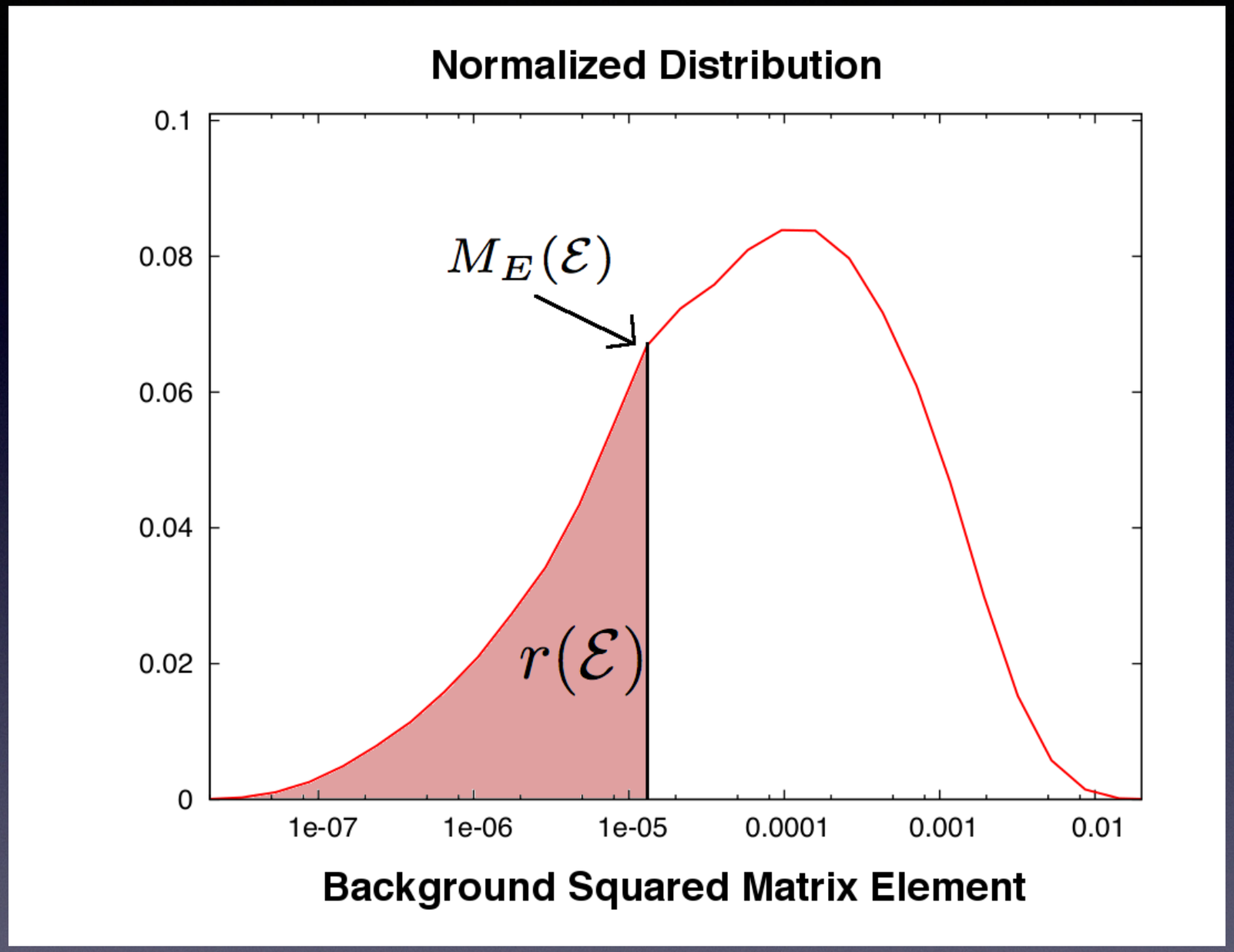
- How do we make background distributions flat?

Background Ranking



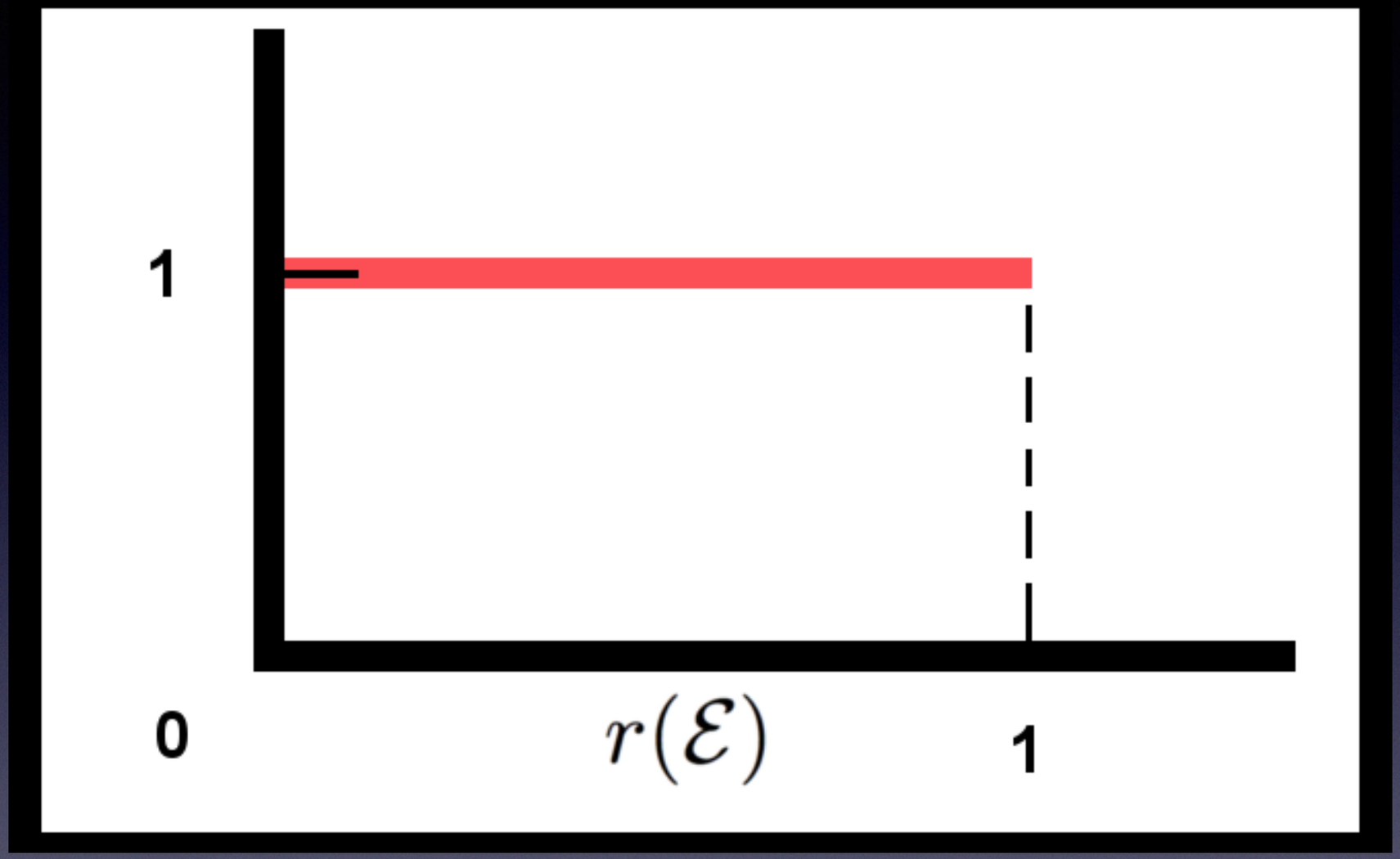
- Want to flatten the background distribution of ME-based variable

Background Ranking



$$r(\mathcal{E}) = \int_0^{M_E(\mathcal{E})} dM_E \frac{dN}{dM_e}$$

Background Ranking



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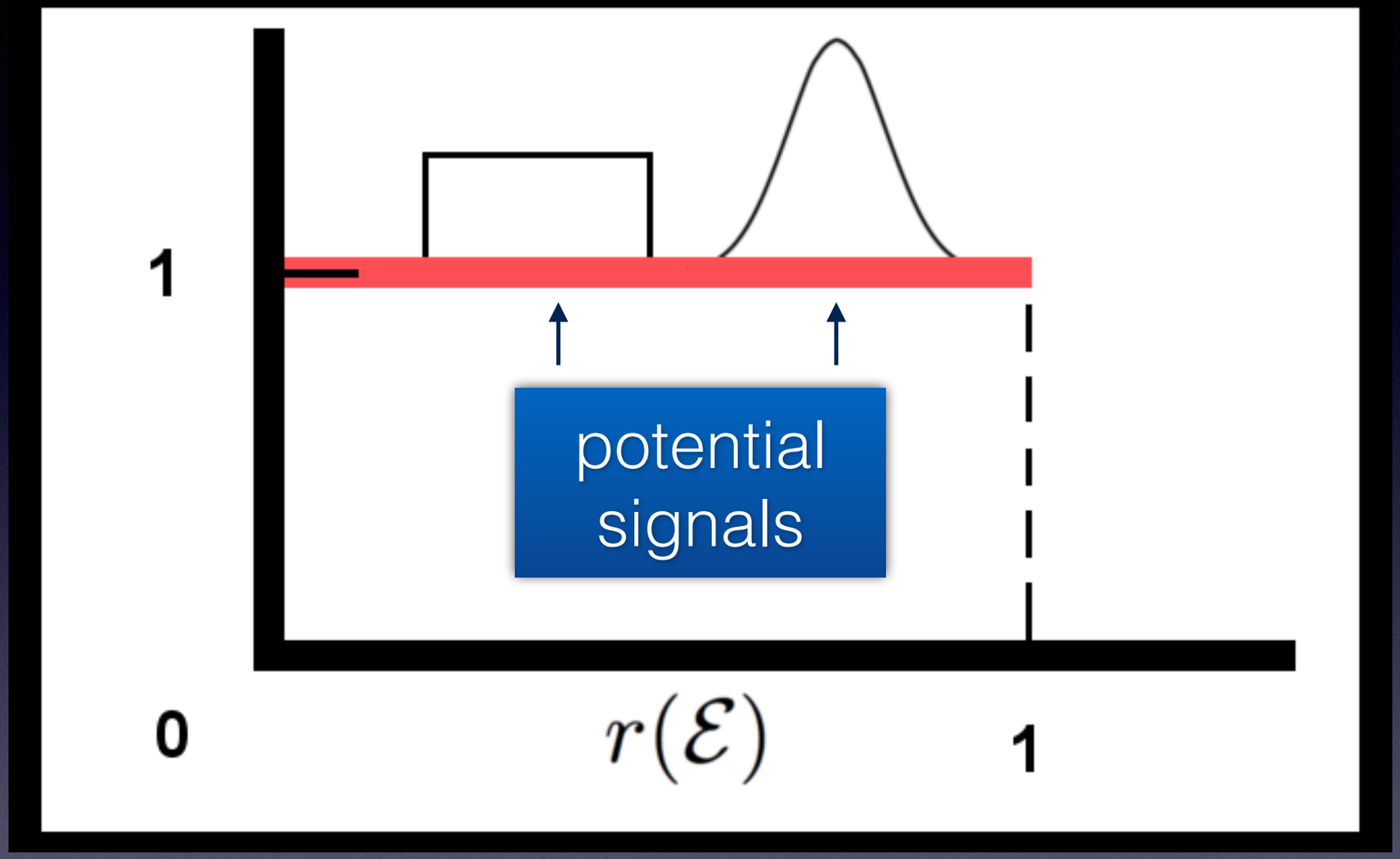

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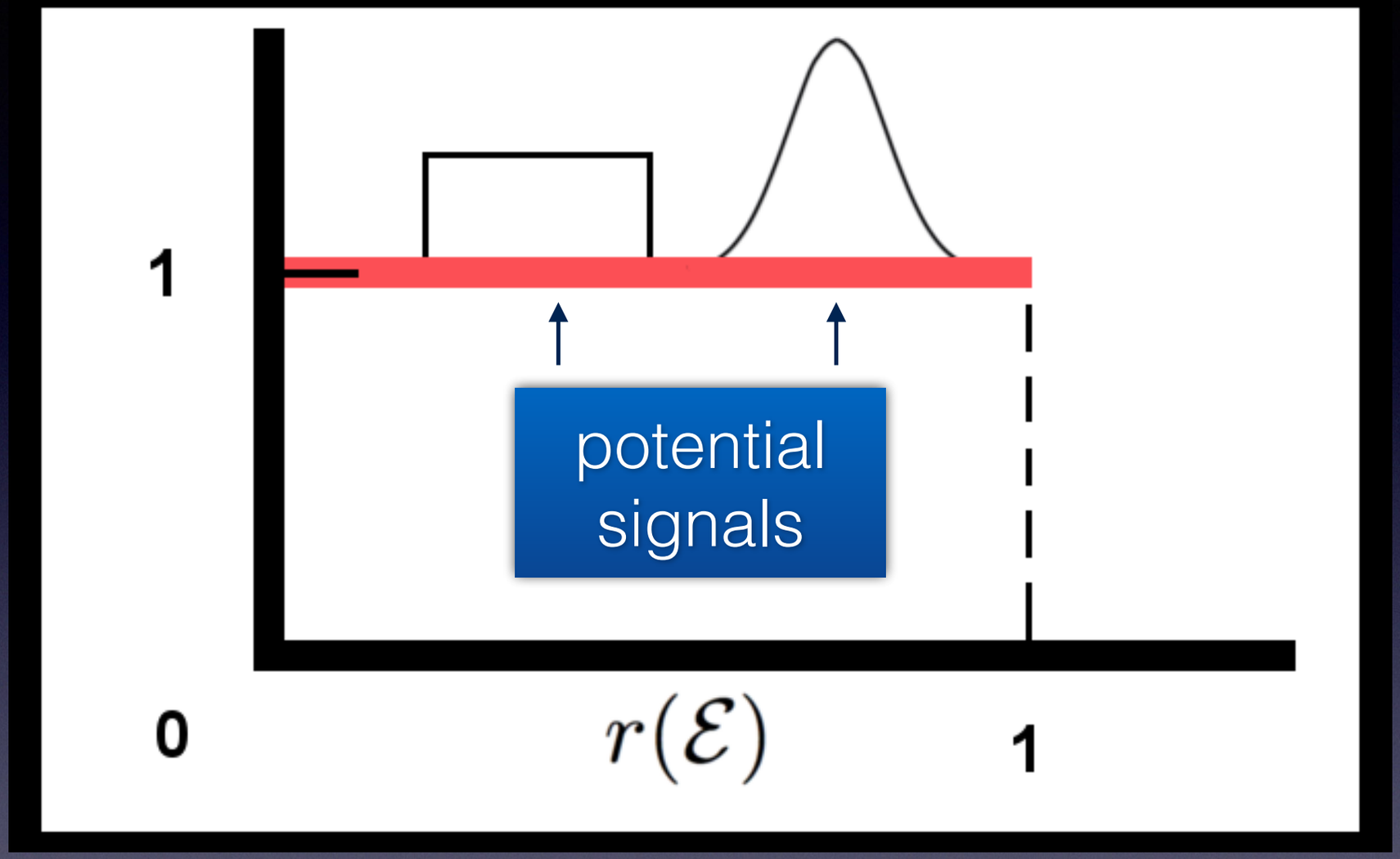
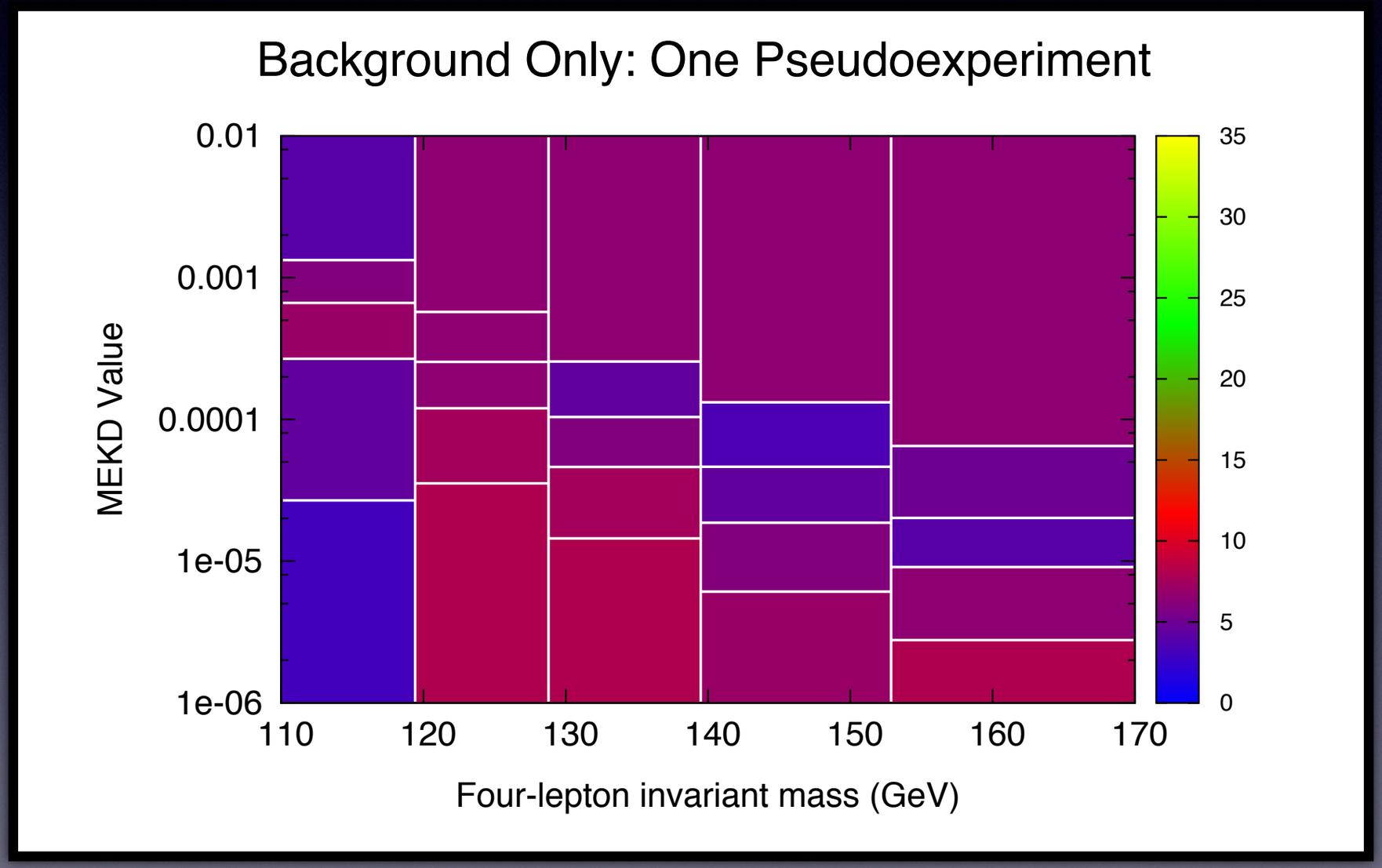


If we take our normalization from data, deficits will also indicate signals.

Simpler Approach: Quantile Bins

- A mini-version of ranking. Make quantile bins in ME(ε) and other variables (here four-lepton invariant mass)



Like the NFL scores example above.

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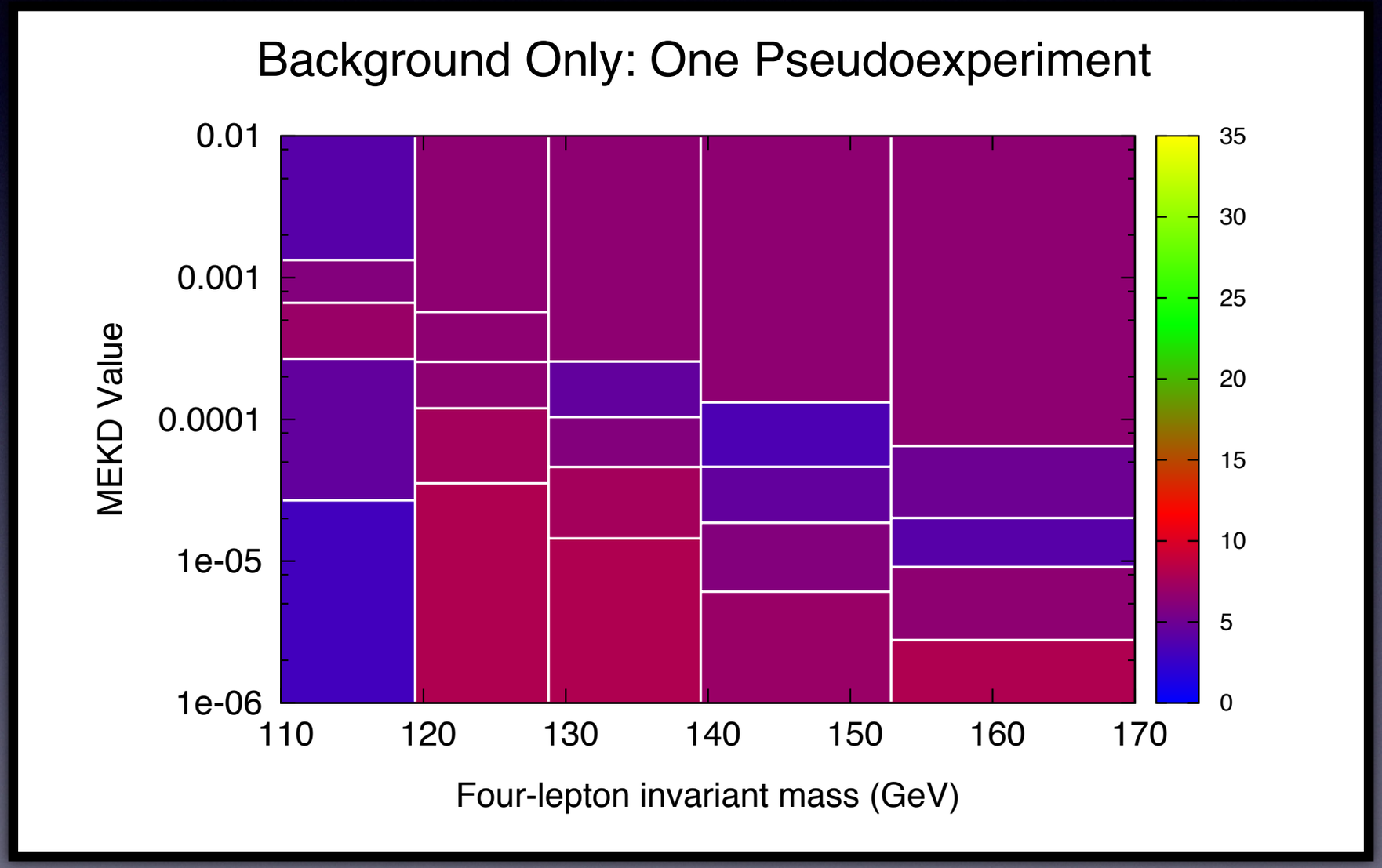

Here we consider 150 BG events.

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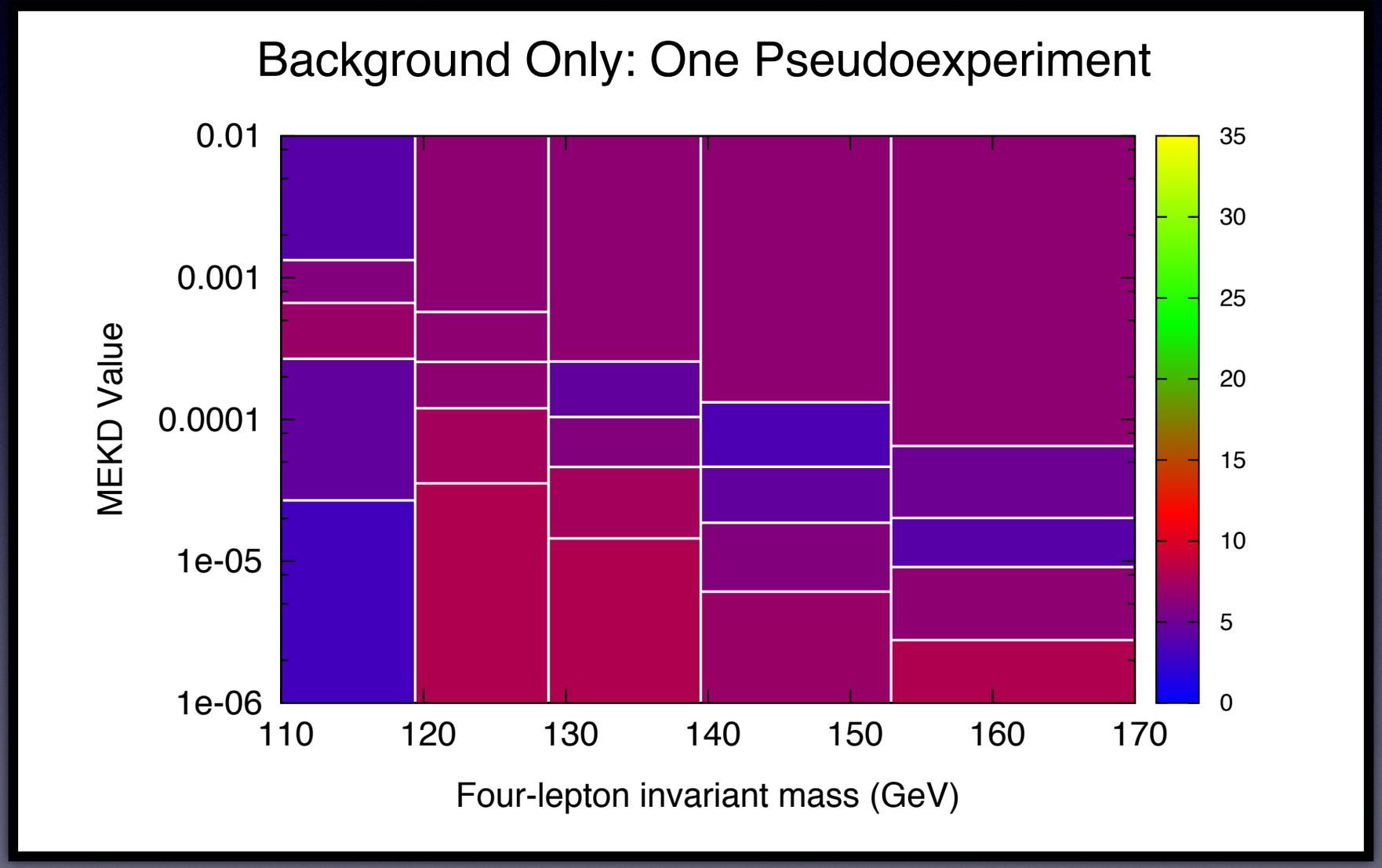

Quantile bins made with large MC set— not the data.

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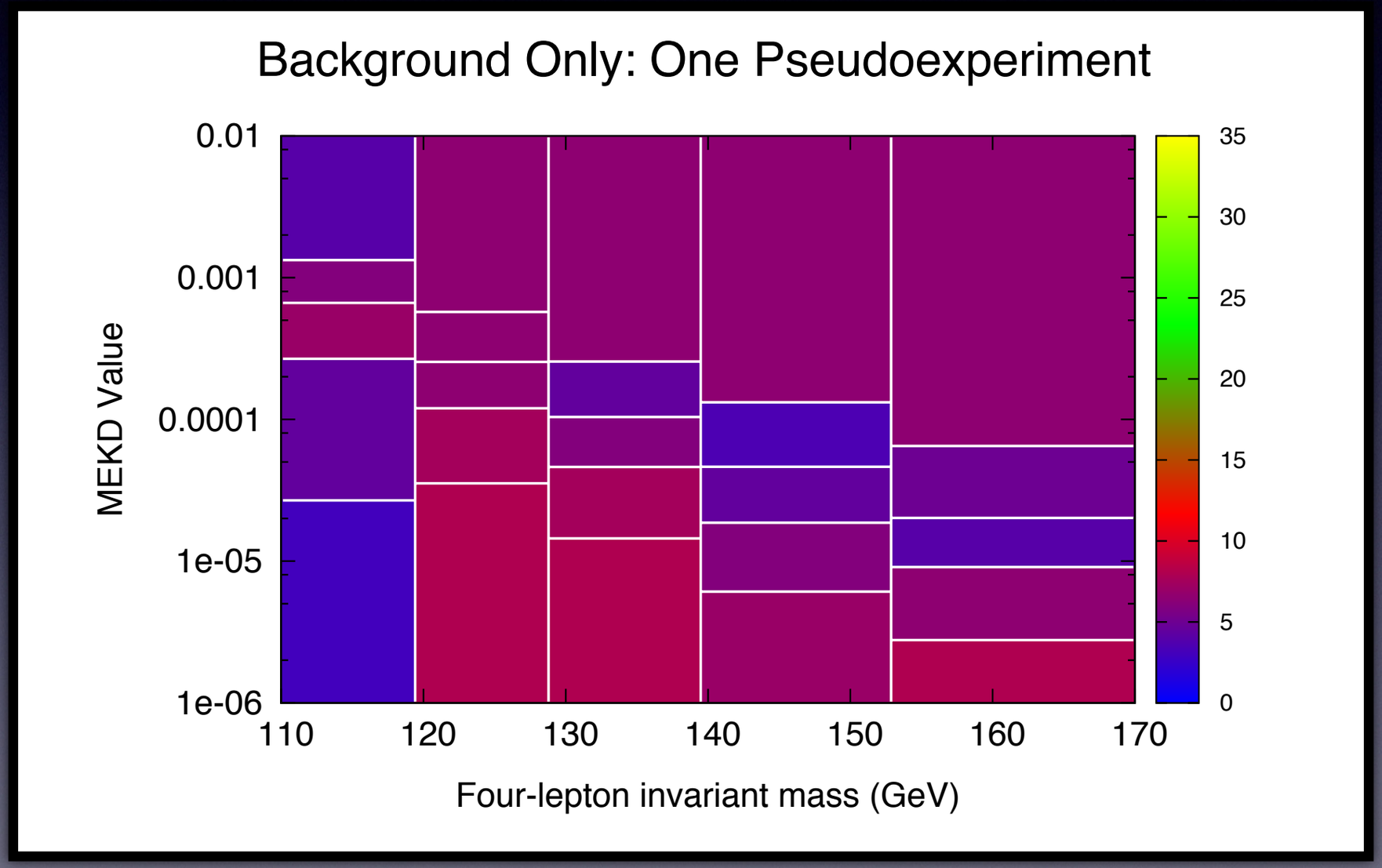

Relatively flat with some fluctuations.

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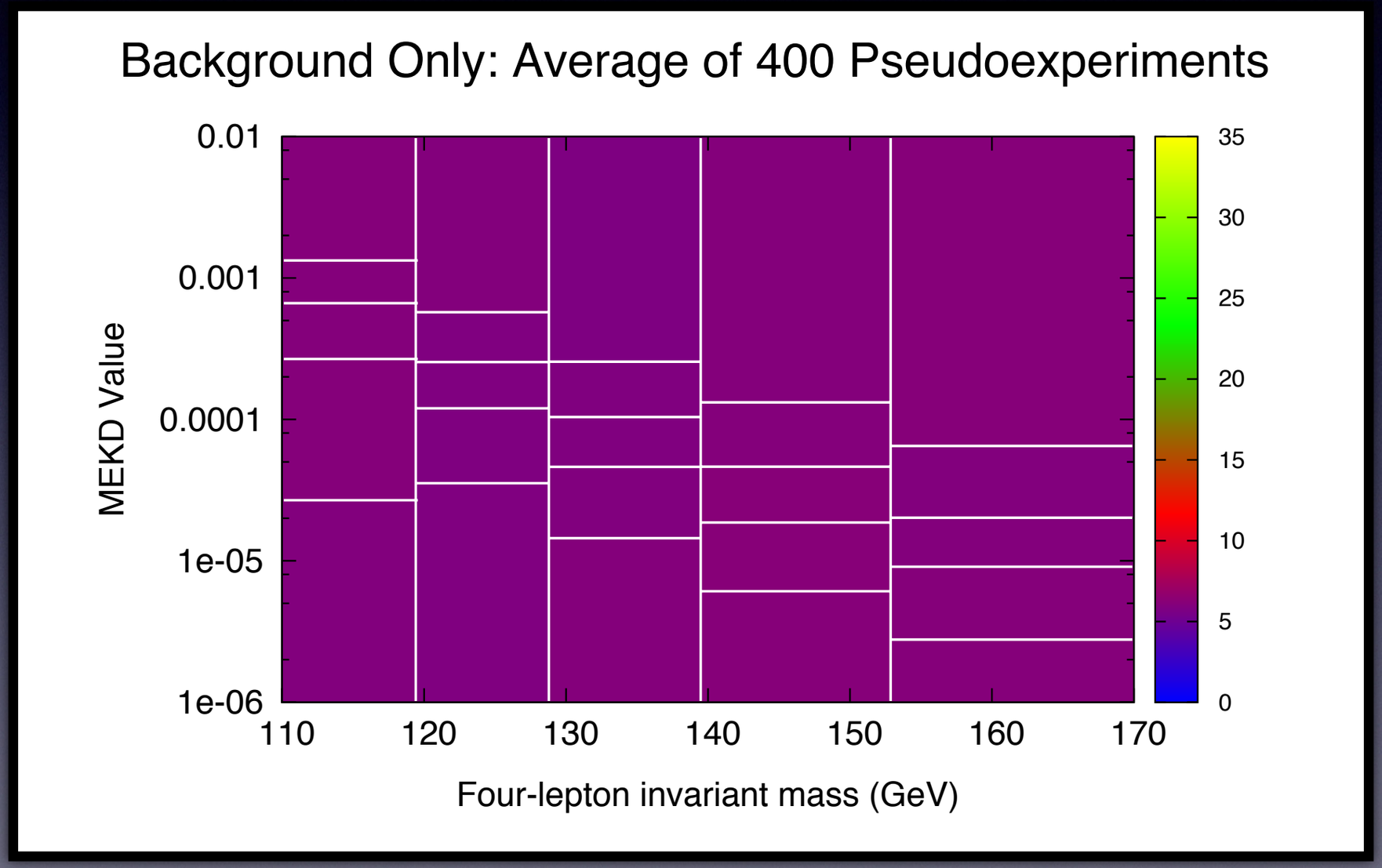

On average, BG is flat (that was our goal!)

Simpler Approach: Quantile Bins

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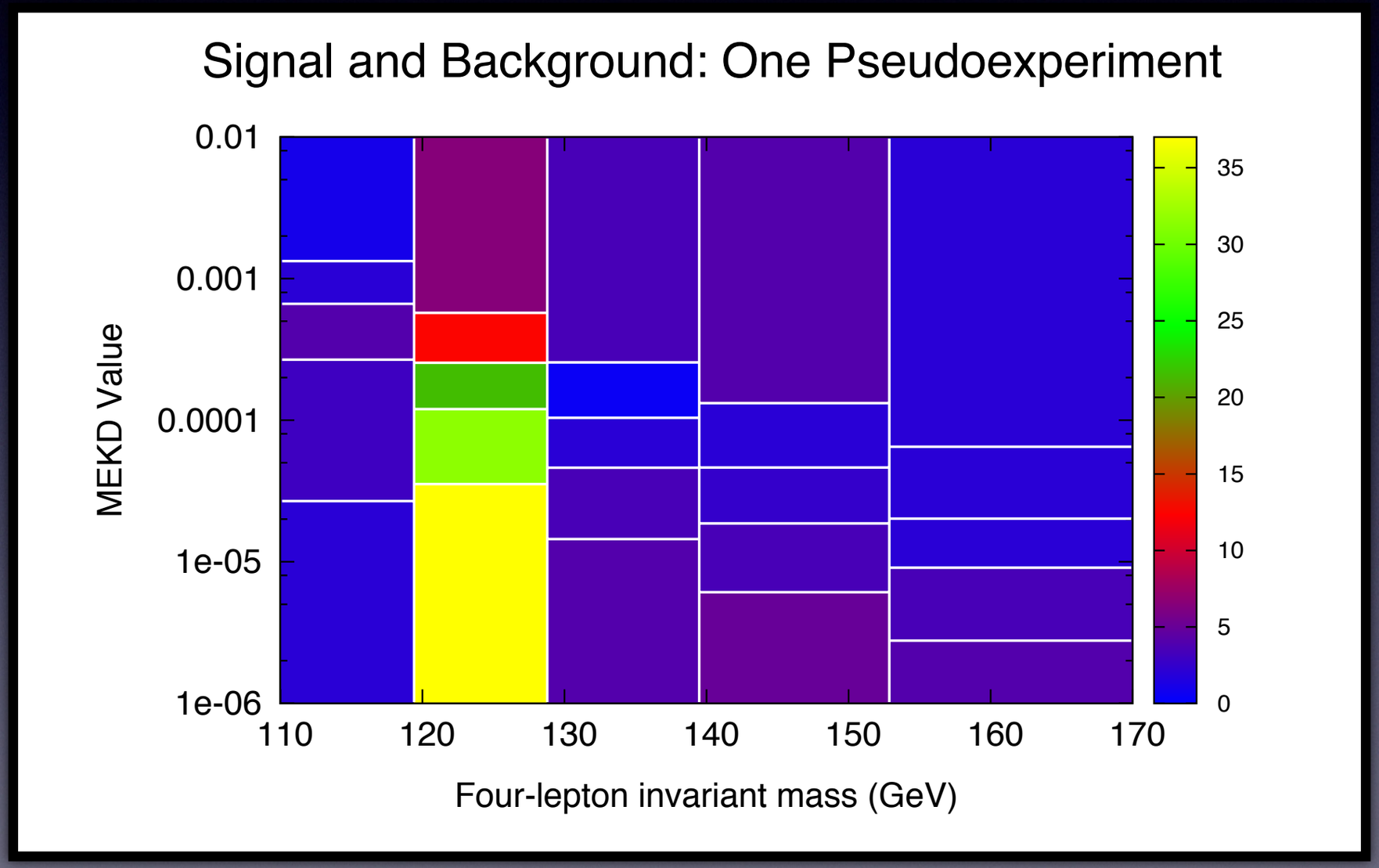

Now we consider 150 events in total, but 60 are signal.

Simpler Approach: Quantile Bins

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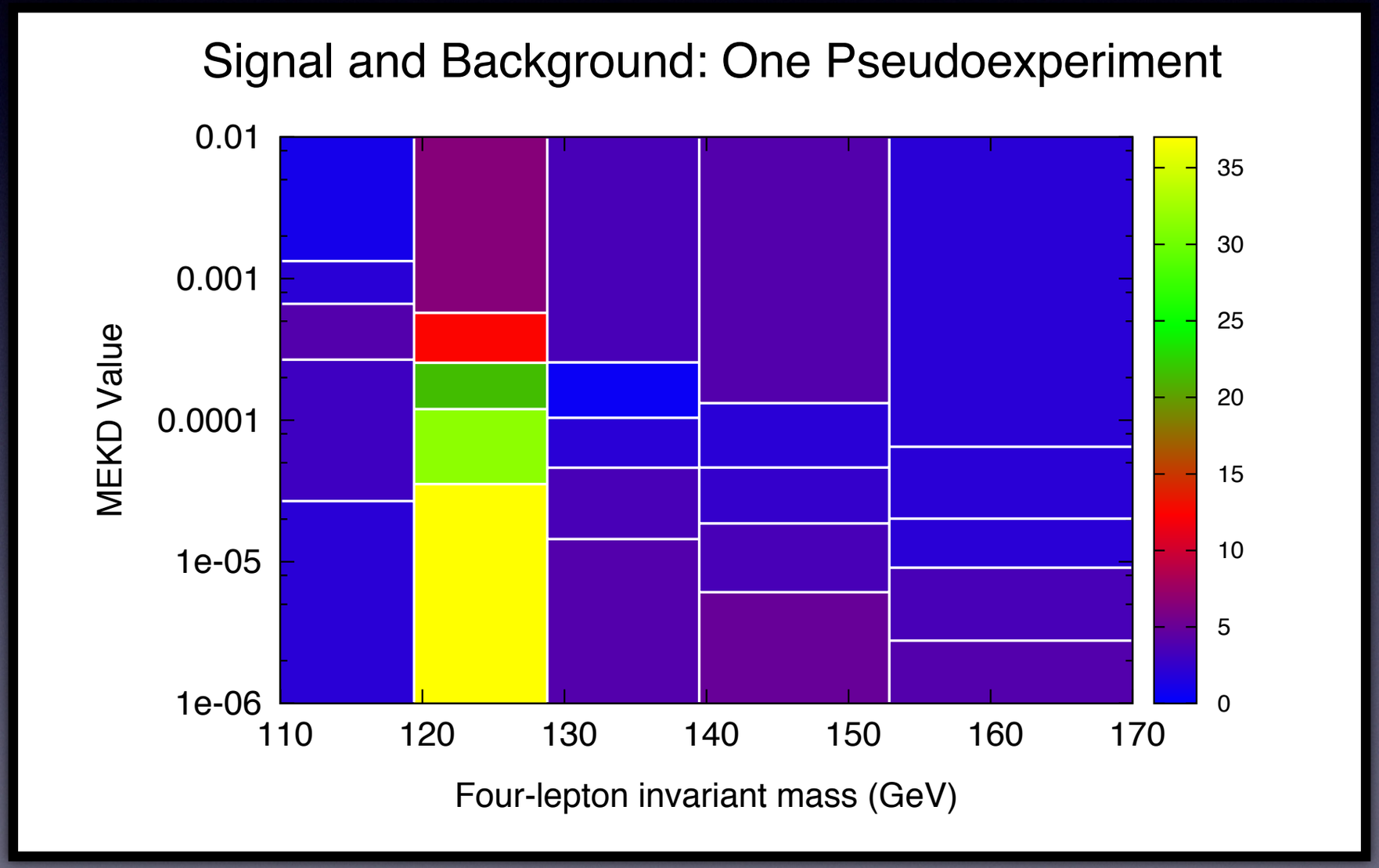

Normalization from data: signal also causes deficits.

Simpler Approach: Quantile Bins

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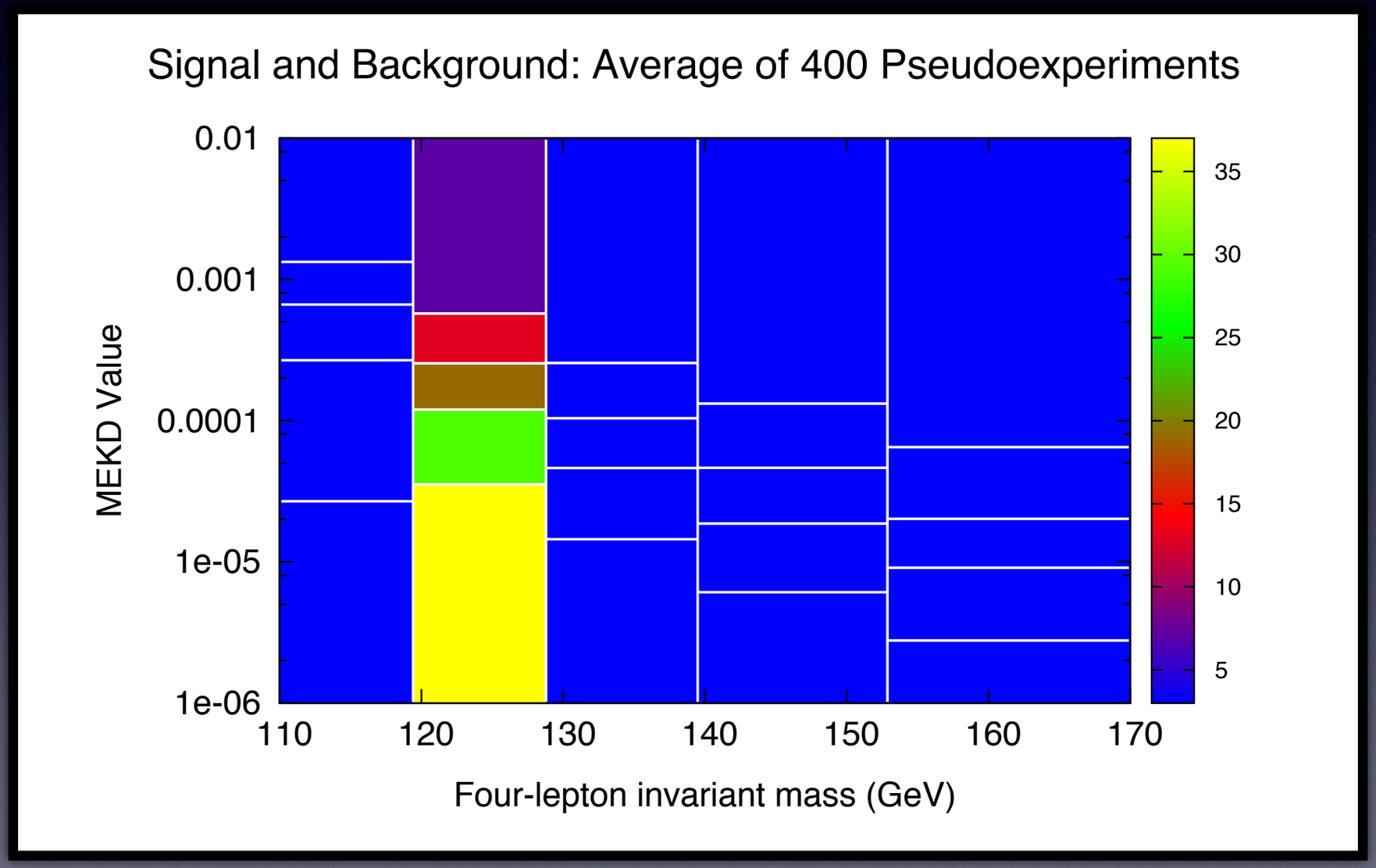
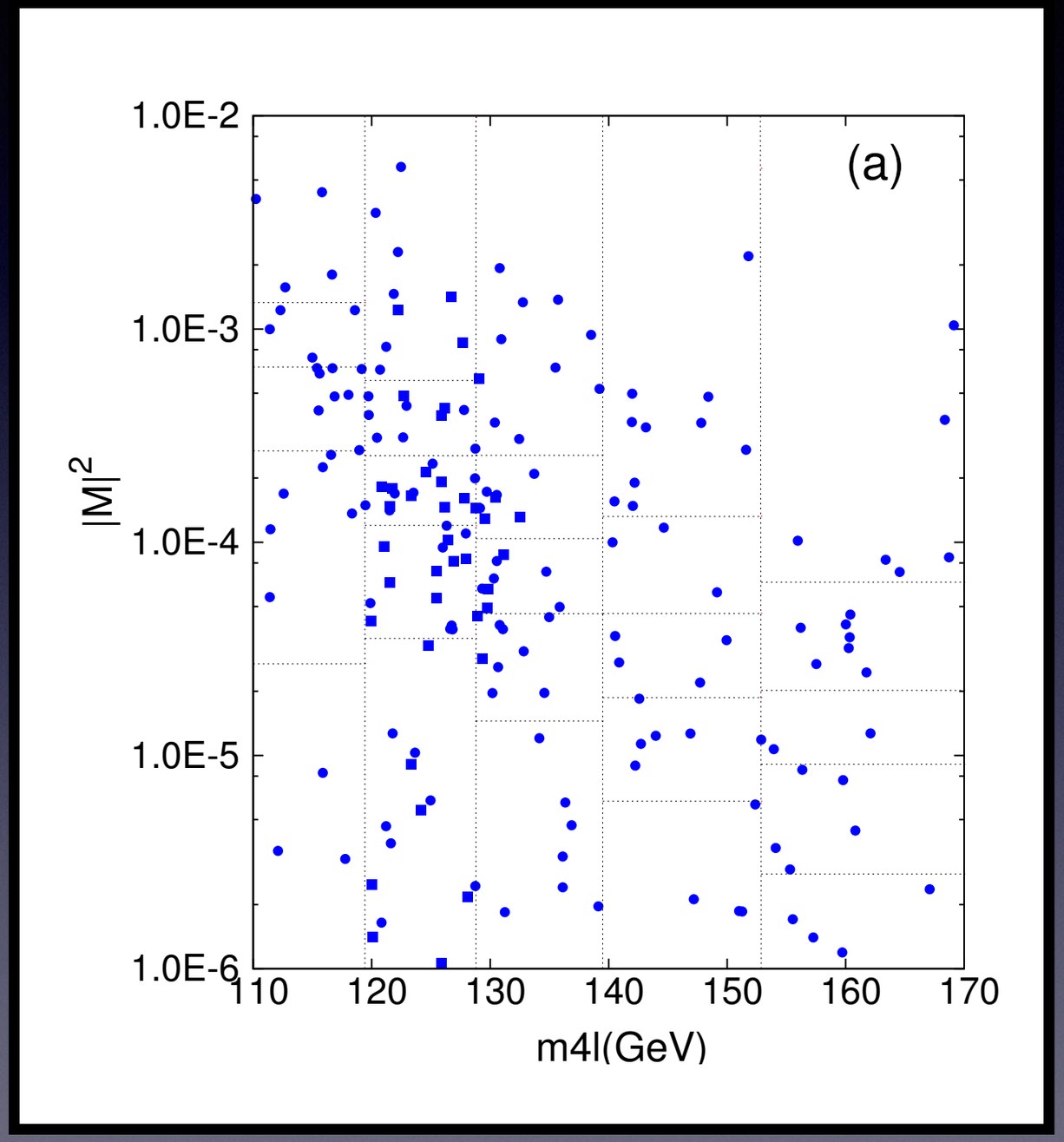


Signal + Background pseudoexperiments averaged.

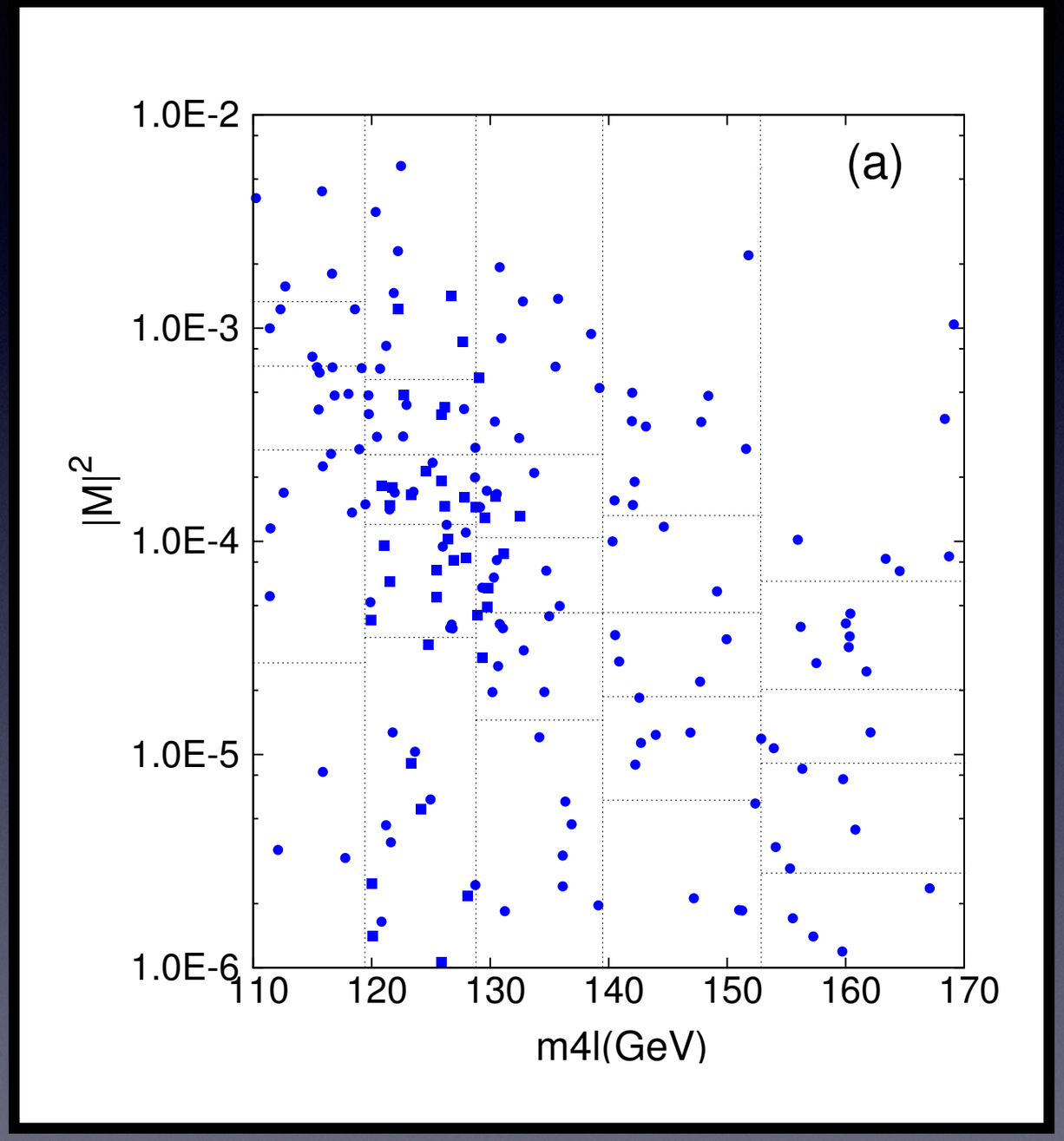
Simpler Approach: Quantile Bins

- To see more concretely how quantile bins help, we consider
- 50 gluon fusion signal four-lepton events
- 150 background ($q\bar{q}$) four-lepton events



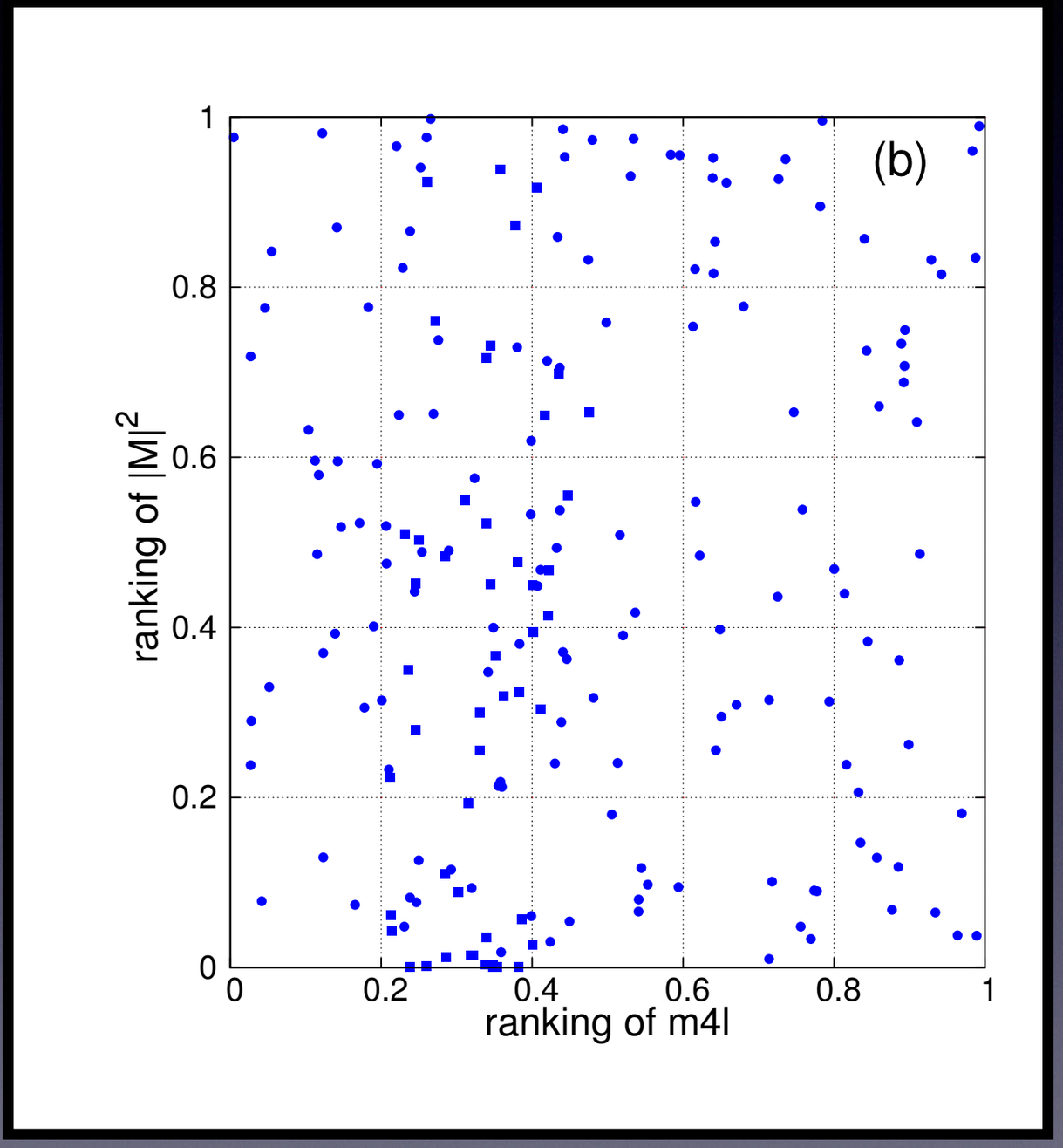
Simpler Approach: Quantile Bins

- "By eye" it seems like there is
- an excess in m4l below ~130 GeV
- a deficit in m4l above ~140 for high $|M|^2$ values



Simpler Approach: Quantile Bins

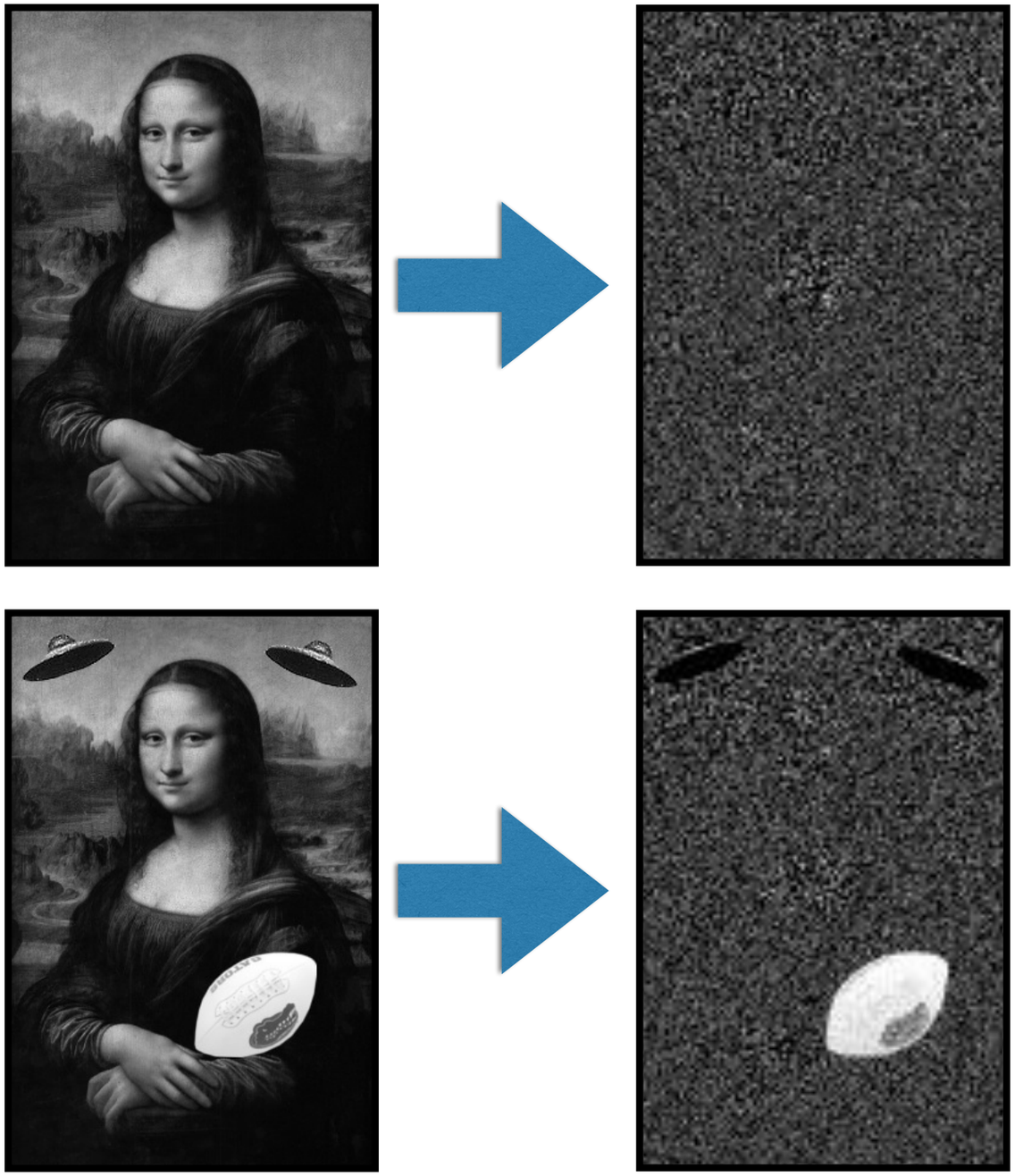
- After quantile binning (according to the background distribution)
- No real deficit in upper right hand corner
- Moderate excess in 2nd m4l column, especially the lower ranked bins.



Analytic Flattening

- Of course we can also obtain flat distributions by weighing contributions to (potentially multivariable) distributions by the inverse of the background PDF

- To explain this, I am going to invoke Leonardo da Vinci and aliens…



Conclusions

- Important to develop model independent ways to search for signal
- This can be done in a straightforward, sensitive way using the background matrix element.
- Related techniques allow backgrounds to be flattened— giving an intuitive and general understanding of the significance of possible signals.
  - Ranking
  - Quantile Binning
  - Reweighting
- Looking forward to the discovery of unexpected signals at the LHC!