Update on Kinematic Fits

C. Sander

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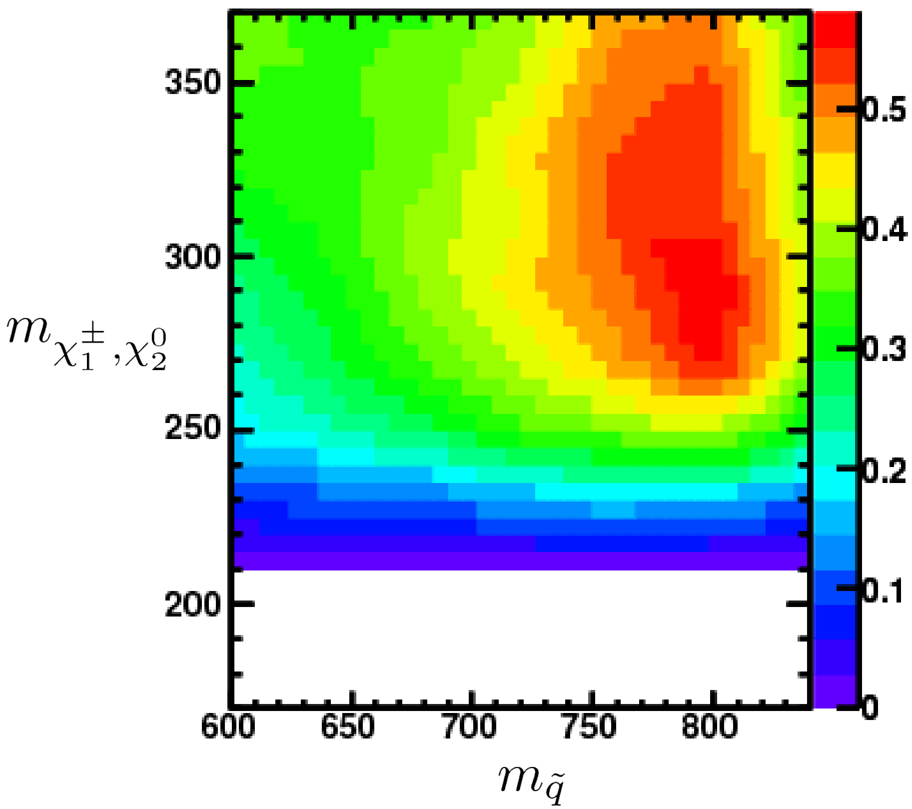
Some Definitions

- N_{tot}: Total number of fitted events (= 87)
- p_i: kinematic fit probability (mass and momentum balance constraints only)
- p_{cut}: probability cut (definition of convergence) (=0.01)
- $Np_{\text{converged}}$: Number of events with $p > p_{\text{cut}}$
- L_i: combined likelihood $p \times LR$ with $LR = \prod_{i=1}^{N} \frac{\mathcal{L}_{\text{sig}}(\cos\theta_i^*)}{\mathcal{L}_{\text{sig}}(\cos\theta_i^*) + \mathcal{L}_{\text{bg}}(\cos\theta_i^*)}$
- L_{cut}: Likelihood cut (definition of convergence) (=0.001)
- $NL_{\text{converged}}$: Number of events with $L > L_{\text{cut}}$

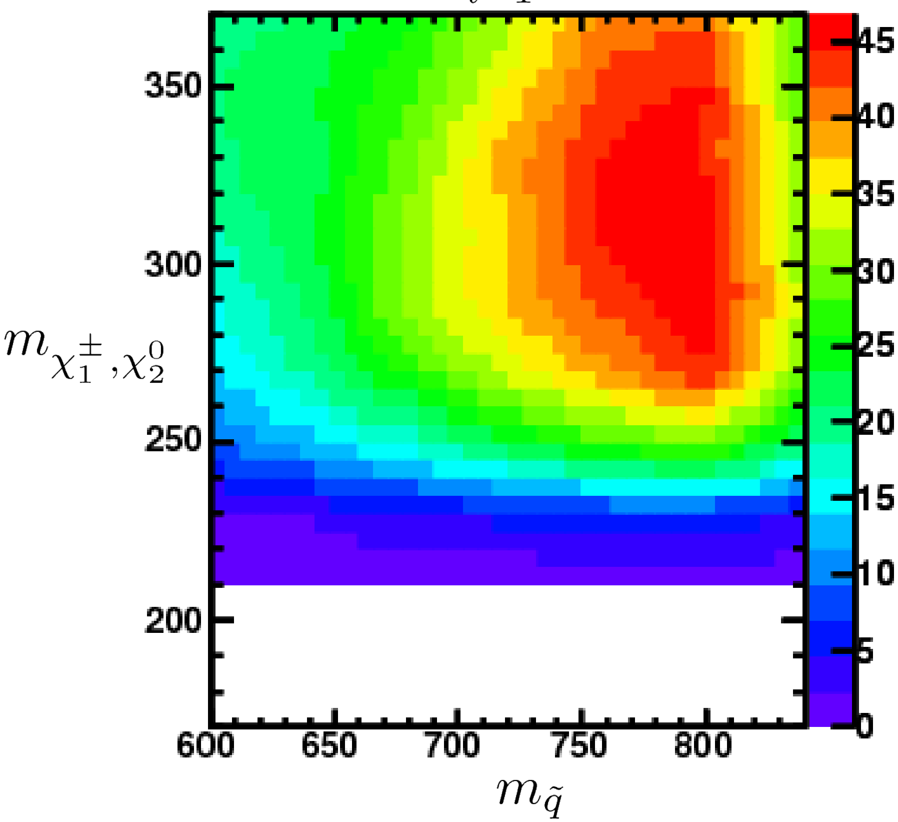
Here:

- Signal events (LM5) contain only Ws
- Full combinatorics
- Angular distributions of squarks and charginos for calculation of LR

$$\frac{1}{Np_{\mathrm{converged}}} \sum_{i=1}^{Np_{\mathrm{converged}}} p_i$$



$$\sum_{i=1}^{Np_{\mathrm{converged}}} p_i$$



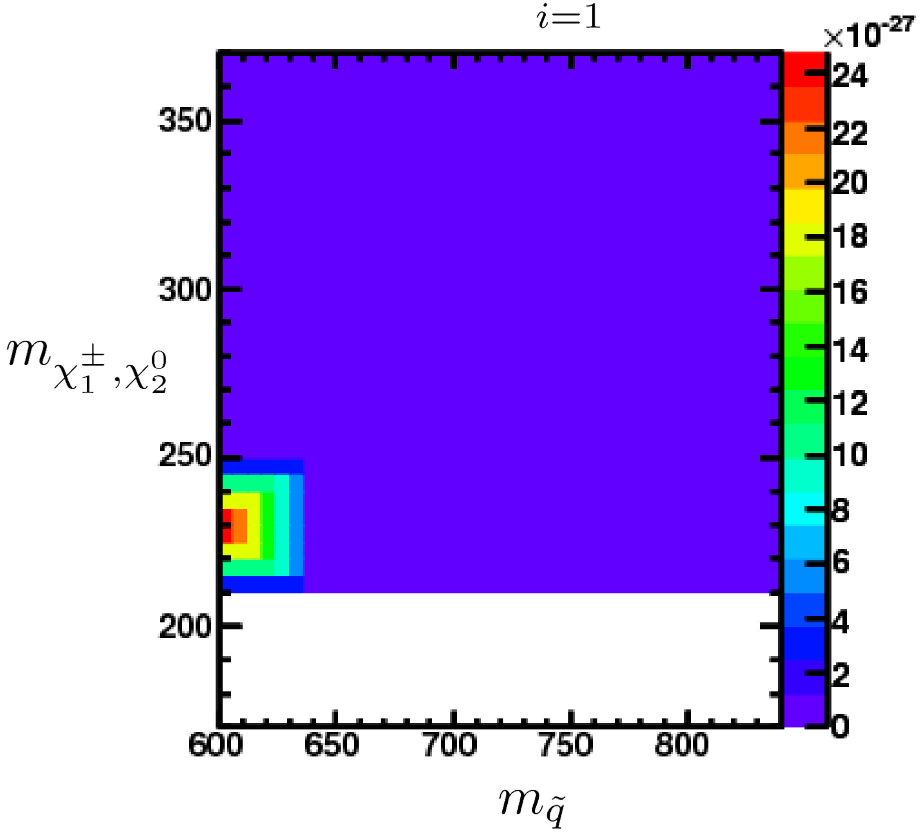
Average fit probability:

- Normalized
- Sensitive to singe accidentally good fits

Frational event count:

- Sensitive to number of converged events
- Peaks where most good events

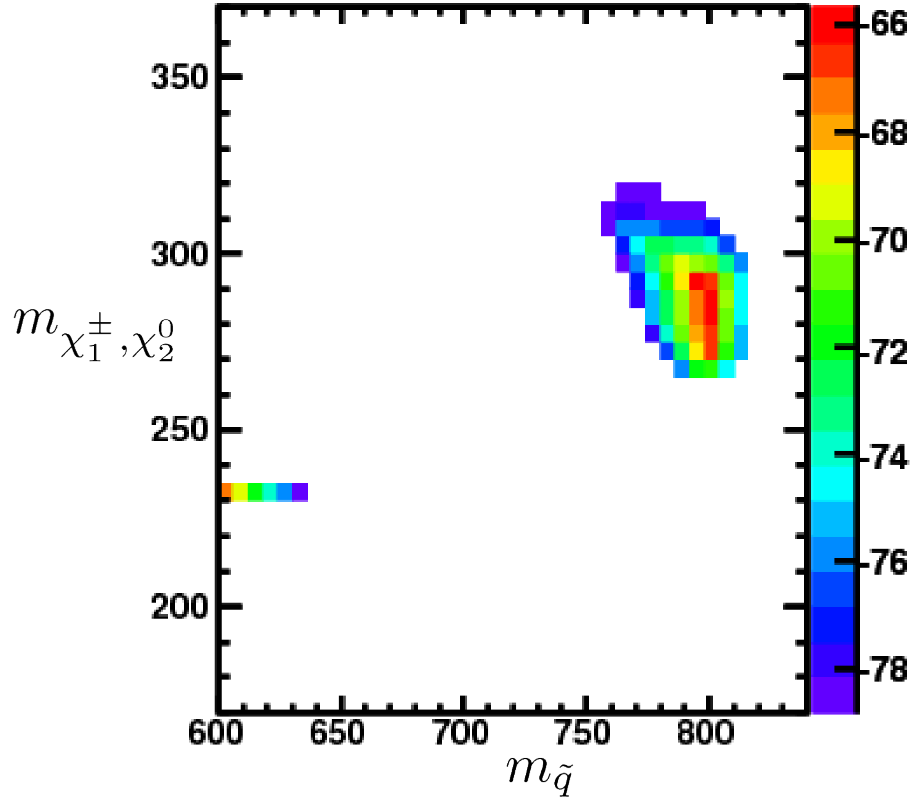
$$P = \prod_{i=1}^{Np_{\text{converged}}} p_i$$



Total probability of event sample:

- Sensitive to number of converged events

$$\sum_{i=1}^{Np_{\text{converged}}} \log p_i$$

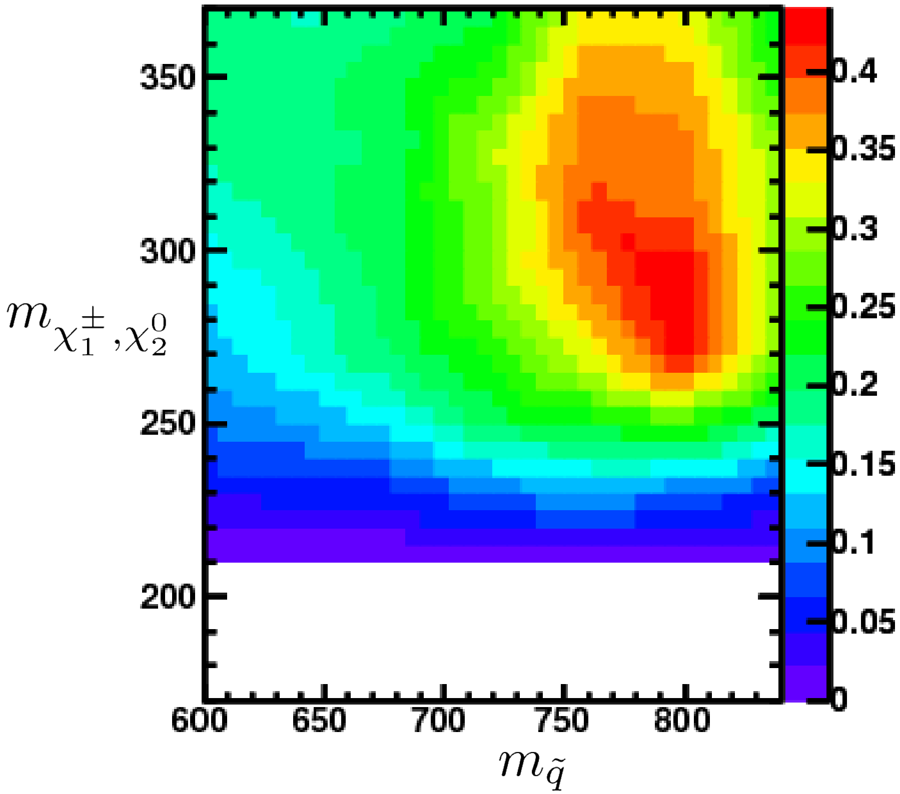


Logarithm of total probability:

- Sensitive to number of converged events
- More stable

Discriminators III

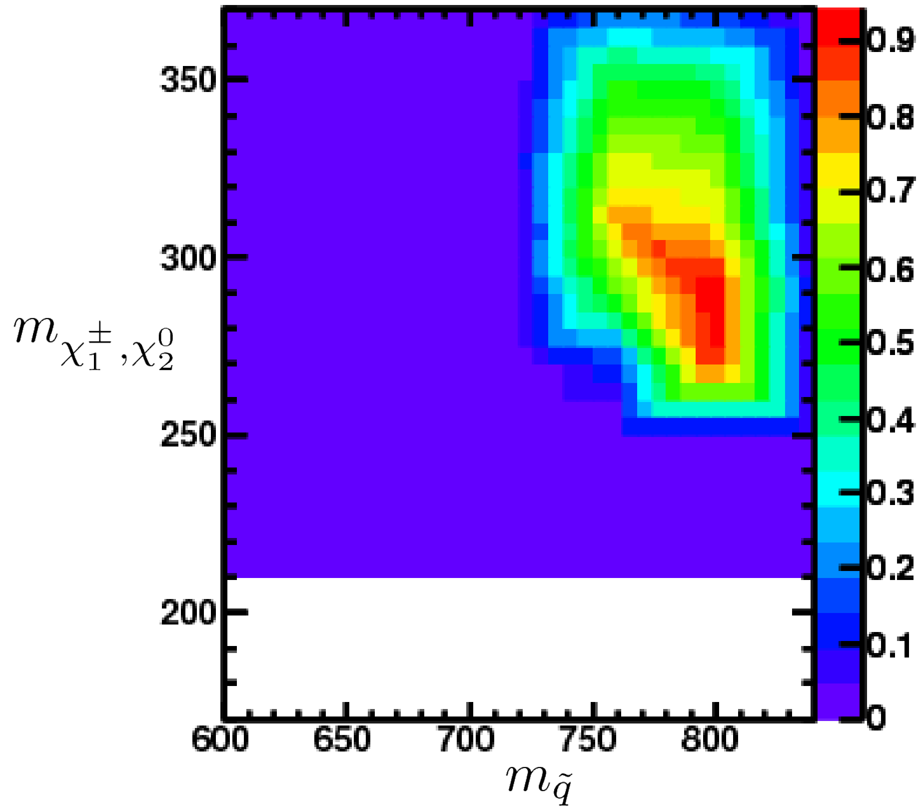
$$P^{\frac{1}{Np_{\text{converged}}}}$$



Normalized total fit probability:

- Normalized
- Sensitive to singe accidentally good fits

$$Q = P \cdot \sum_{k=0}^{Np_{\text{converged}}-1} \frac{(-\log P)^k}{k!}$$

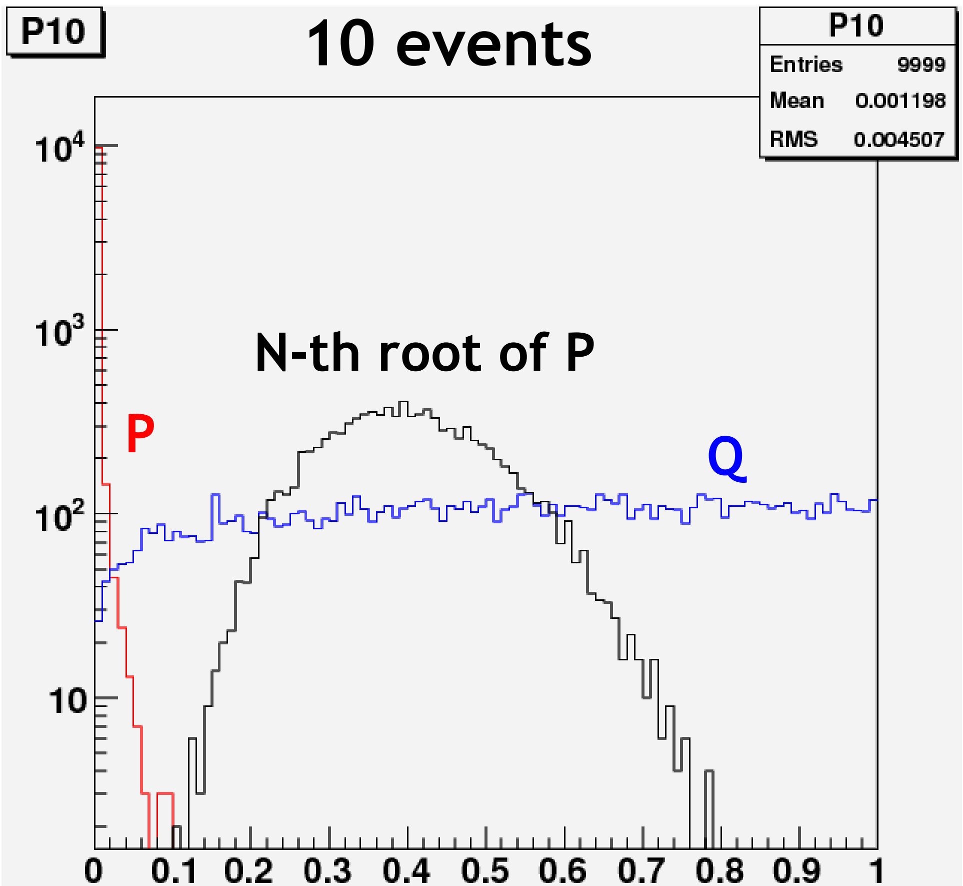


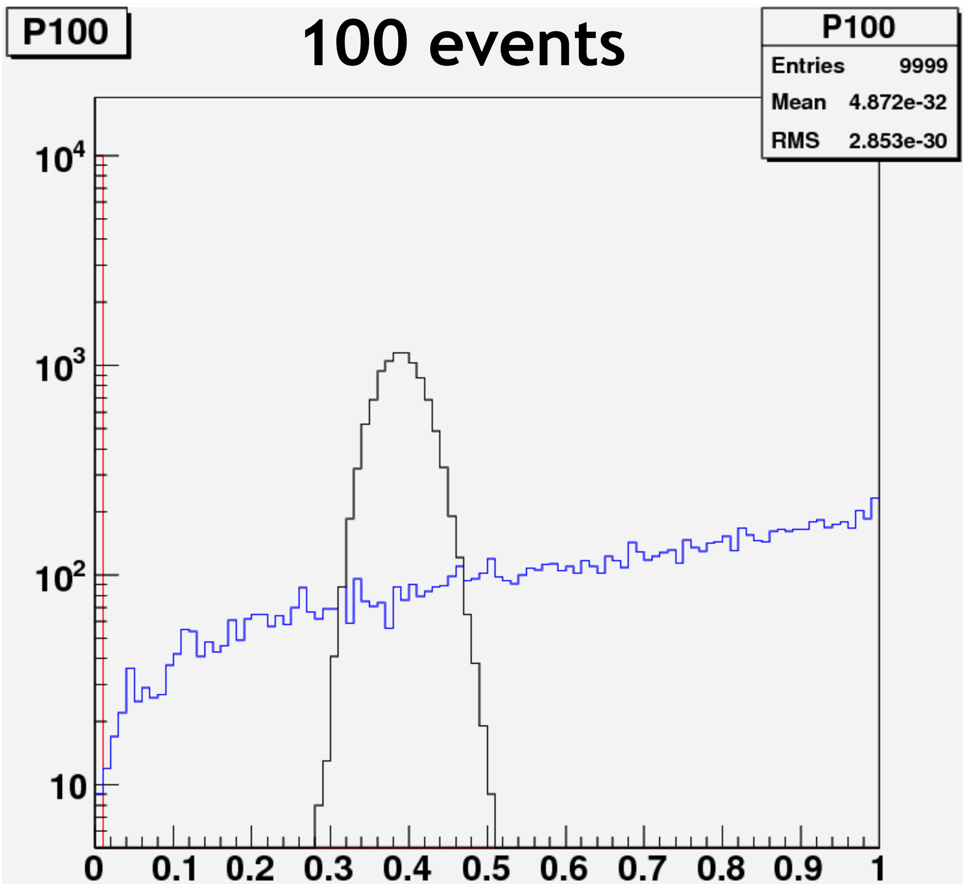
Given N equally distributed variables, Q is also equally distributed:

- Normalized
- Sensitive to singe accidentally good fits

Q

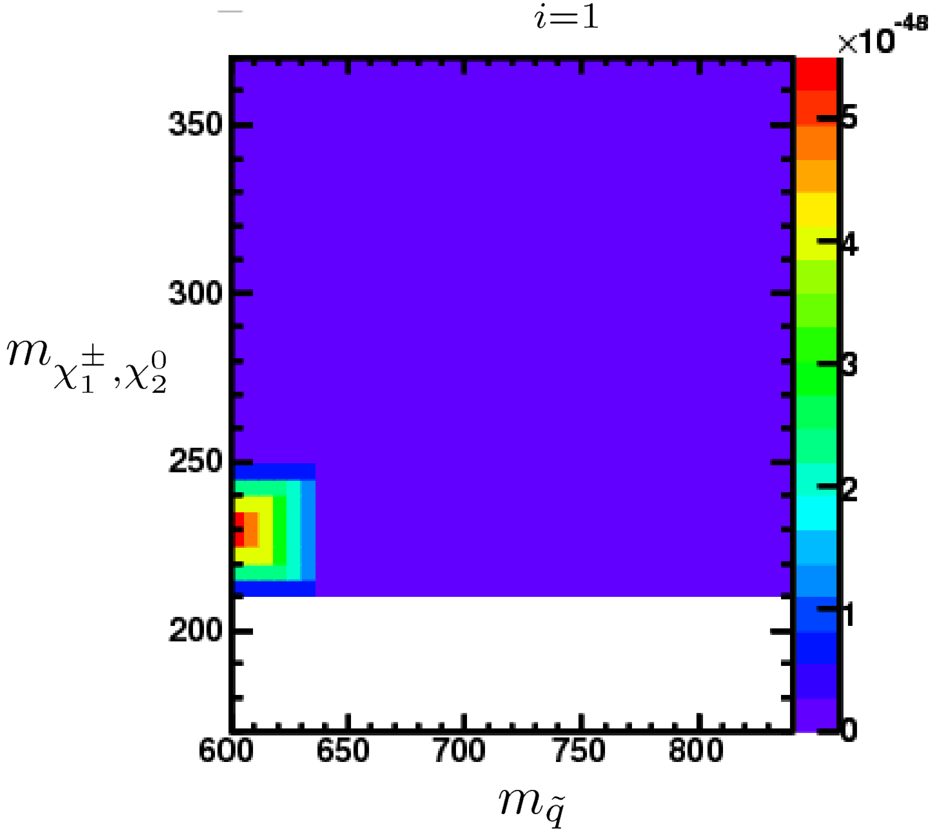
$$Q = P \cdot \sum_{k=0}^{Np_{\text{converged}}-1} \frac{(-\log P)^k}{k!}$$





- Pcut = 0.01 (Q deviates from flat distribution, can be modelled)

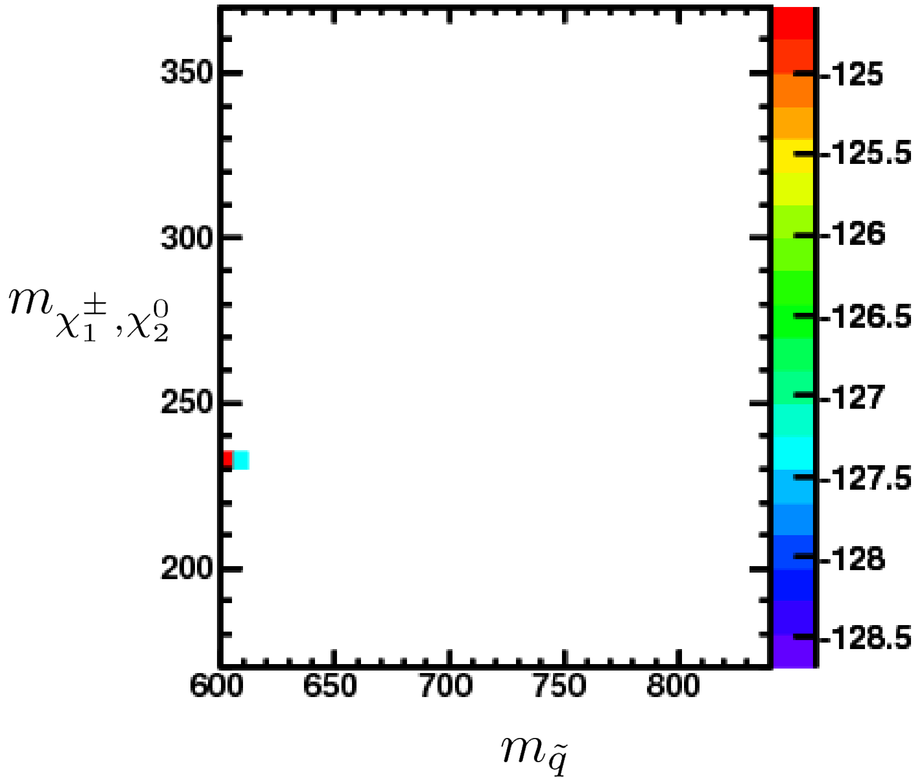
$$L = \prod_{i=1}^{NL_{\text{converged}}} L_i$$



Total combined likelihood of event sample:

- Sensitive to number of converged events

$$\sum_{i=1}^{NL_{\text{converged}}} \log L_i$$

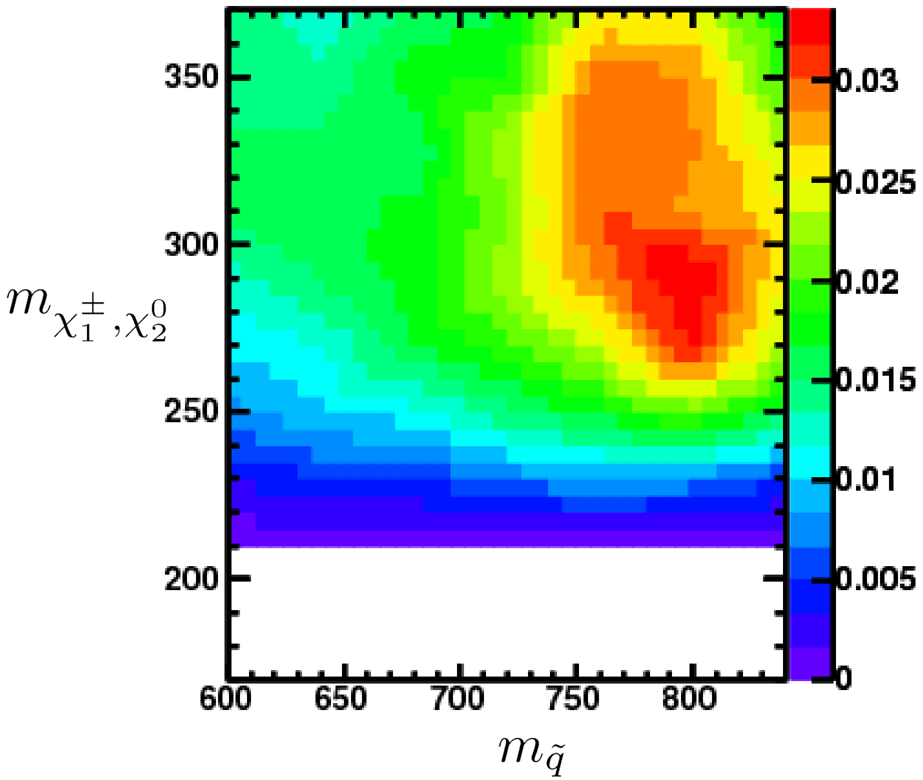


Logarithm of total combined likelihood of event sample:

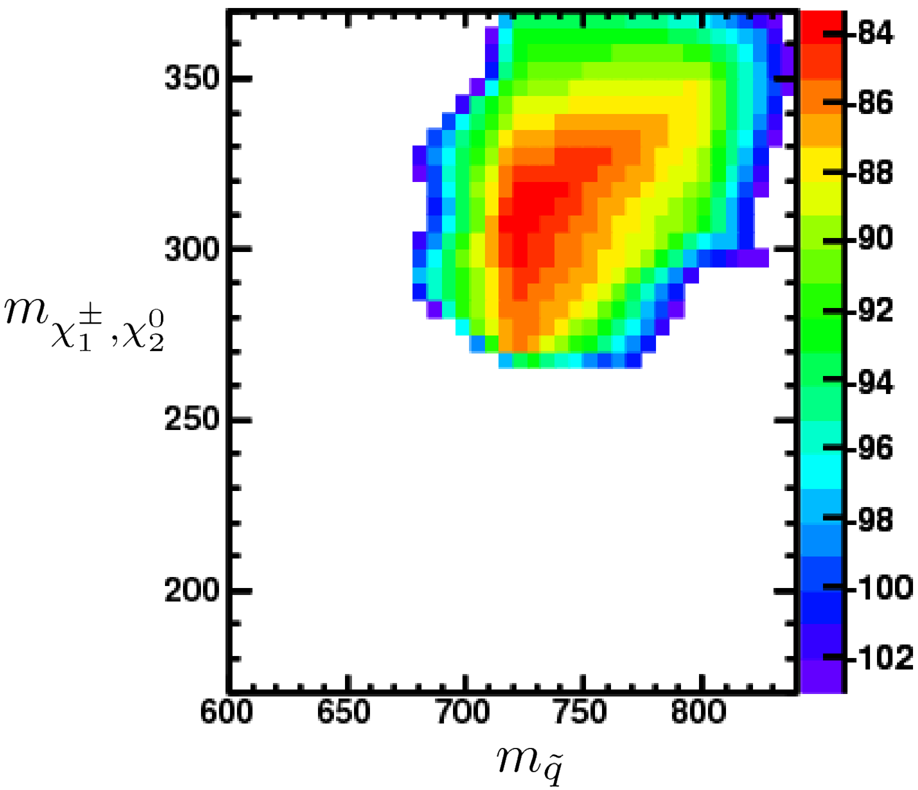
- Sensitive to number of converged events
- More stable

Discriminators V

$$L^{\frac{1}{NL_{\text{converged}}}}$$



$$\mathcal{L} = \sum_{k=0}^{N_{\text{bins}}} \frac{\exp(H_k) \cdot H_k^{D_k}}{D_k!}$$



Normalized total combined likelihood:

- Normalized
- Sensitive to singe accidentally good fits

Binned likelihood of fit probability:

- Contains information of whole distribution as well as proper normalization

Conclusion

- Many possible choices of discriminator!
- Which one is the best?