

Machine-learning the likelihoods

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in collaboration with:

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SmodelS meeting

Reinterpretation

NEUTRINO MODELS

COMPOSITENESS

LR-SYMMETRY

LEPTOQUARK SUPERSYMMETRY

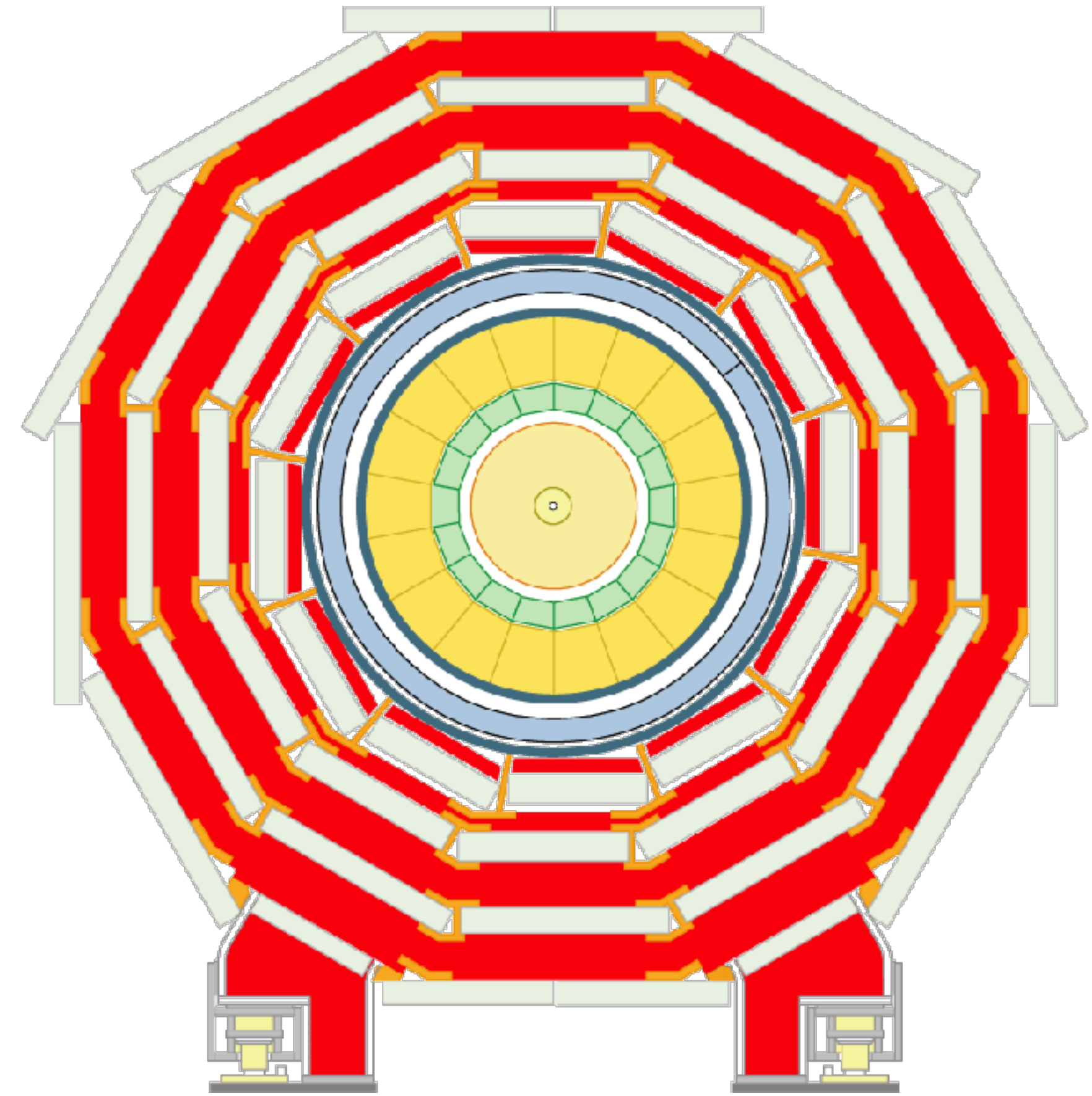
TWO HIGGS DOUBLET

AXIONS WIMPs

EXTRA DIMENSIONS

MILICHARGED PARTICLES

DARK SECTOR



Reinterpretation

Goal: Enhance and unify the statistical analysis step

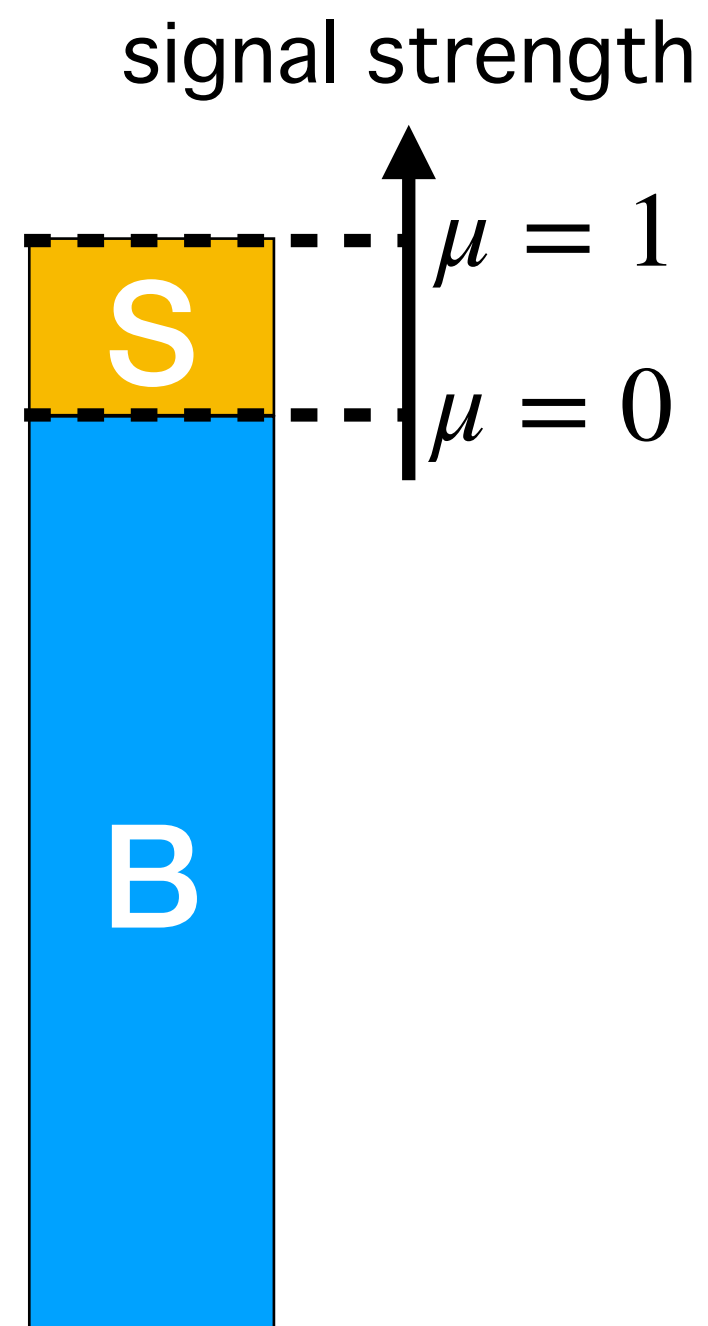
- CHAMOIS MODELS
- COMPLEXTOP
- LR-SYMMETRY
- LEPTOQUARK SUPERSTRAPEZOIDAL
- TWO HIGGS DOUBLETS
- AXIONS WIMPs
- EXTRA DIMENSIONS
- MILICHARGED PARTICLES
- DARK SECTOR



Likelihood template — simple

Let's consider a simple experiment. We have a single channel with multiple bins, one signal and background contribution, and no systematics based on the discriminating variable x .

What is the probability model for obtaining n events in data where the discriminating variable for event e has value x_e ?

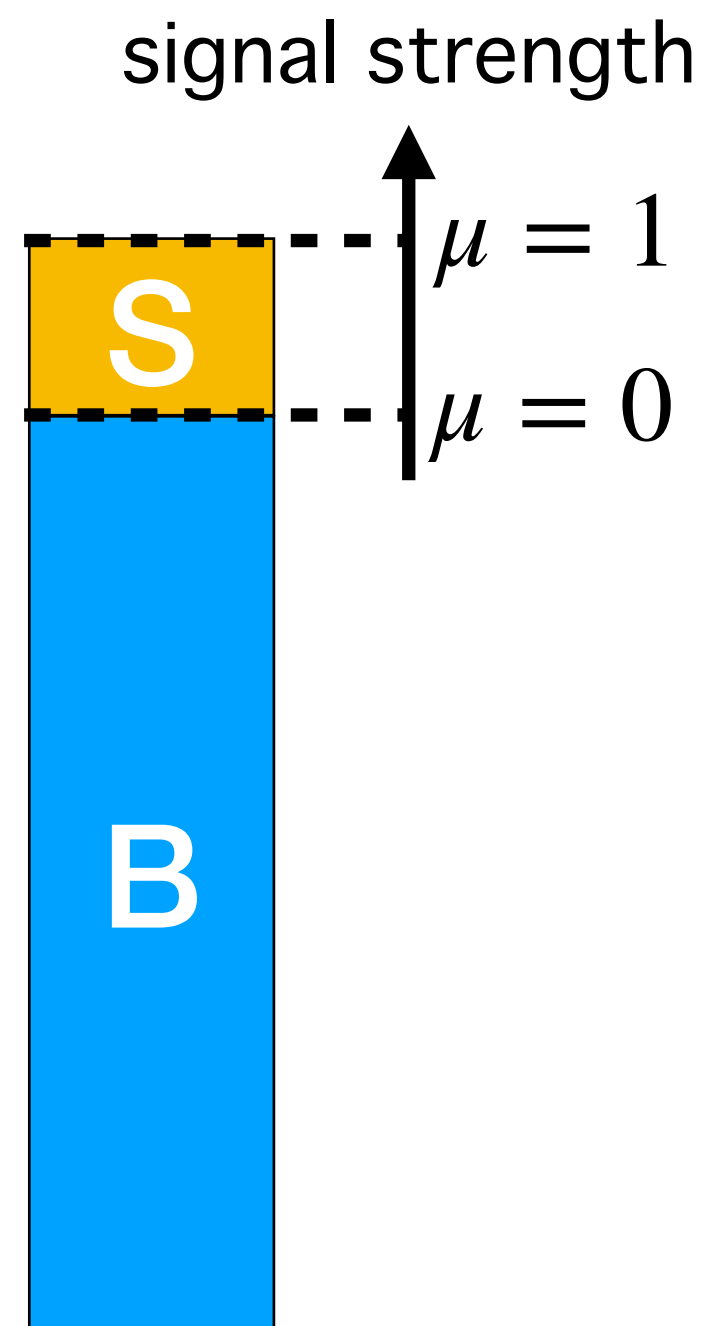


$$L(\mu) = p(\{x_1, \dots, x_n\} | \mu) = ?$$

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$$L(\mu) = p(\{x_1, \dots, x_n\} | \mu) = \text{Pois}(n | \mu S + B) \left[\prod_{e=1}^n \frac{\mu S \cdot f_S(x_e) + B \cdot f_B(x_e)}{\mu S + B} \right]$$

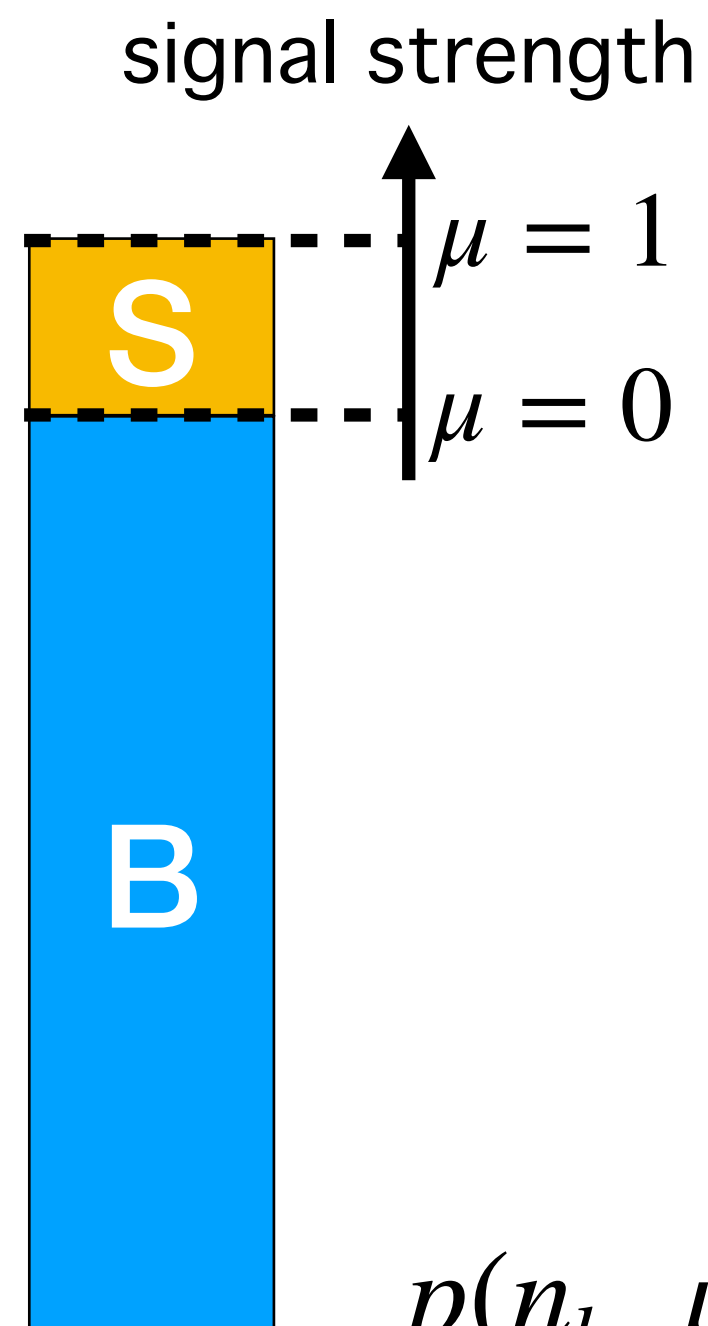
probability to observe n events
given $\mu S + B$ expectation

probability density of obtaining x_e based
on the relative mixture of $f_S(x)$ and $f_B(x)$

Likelihood template — simple

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$$L(\mu) = p(\{x_1, \dots, x_n\} | \mu) = \text{Pois}(n | \mu S + B) \left[\prod_{e=1}^n \frac{\mu S \cdot f_S(x_e) + B \cdot f_B(x_e)}{\mu S + B} \right]$$

In the binned case:

$$f_S(x_e) = \frac{\nu_{b_e}^{\text{sig}}}{S \Delta_{b_e}}$$

$$f_B(x_e) = \frac{\nu_{b_e}^{\text{bkg}}}{B \Delta_{b_e}}$$

$$S = \sum_b \nu_b^{\text{sig}}$$

$$B = \sum_b \nu_b^{\text{bkg}}$$

nominal yields

$$p(n_b | \mu) = \text{Pois}(n_b | \mu S + B) \left[\prod_{b \in \text{bins}} \frac{\mu \nu_b^{\text{sig}} + \nu_b^{\text{bkg}}}{\mu S + B} \right] = \mathcal{N}_{\text{comb}} \prod_{b \in \text{bins}} \text{Pois}(n_b | \mu \nu_b^{\text{sig}} + \nu_b^{\text{bkg}})$$

counts per bin

Likelihood template — HistFactory statistical models

We want to generalise our model to:

- combine multiple channels and correlate the parameters across the various channels
- include unconstrained scaling of the normalization of any sample
- parametrize variation in the normalization of any sample due to some systematic effect
- parameterize variations in the shape of any sample due to some systematic effect
- include bin-by-bin statistical uncertainty on the normalization of any sample
- incorporate an arbitrary contribution where each bin's content is parametrized individually
- use the combination infrastructure to incorporate control samples for datadriven background estimation techniques
- reparametrize the model

$$L(n, a, \mu, \theta) = \prod_c^{\text{channels}} \prod_b^{\text{bins}_c} \text{Pois}(n_{cb} | \nu_{cb}(\mu, \theta)) \prod_\theta c_\theta(a_\theta | \theta)$$

Likelihood template — HistFactory statistical models

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channel data → n auxiliary data → a
free parameters → μ constrained parameters → θ

channels \prod_c bins_c \prod_{bins_c} $\text{Pois}(n_{cb} | \nu_{cb}(\mu, \theta))$ \prod_{θ} $c_{\theta}(a_{\theta} | \theta)$

simultaneous measurement of multiple channels (under the first part)
constraint terms for "auxiliary measurements" (under the second part)

Likelihood template — HistFactory statistical models

channel data auxiliary data

$$L(n, a, \mu, \theta) = \prod_c \prod_{b \in \text{bins}_c} \text{Pois}(n_{cb}, \nu_{cb}(\mu, \theta)) \prod_{\theta} c_{\theta}(a_{\theta}, \theta)$$

free parameters constrained parameters

simultaneous measurement of multiple channels constraint terms for "auxiliary measurements"

$$\nu_{cb}(\mu, \theta) = \sum_s^{\text{samples}} \nu_{scb}(\mu, \theta) = \sum_s^{\text{samples}} \left(\prod_{\kappa} \kappa_{scb}(\mu, \theta) \right) \left(\underbrace{\nu_{scb}^0(\mu, \theta)}_{\text{const. nominal rate}} + \underbrace{\sum_{\Delta} \Delta_{scb}(\mu, \theta)}_{\text{additive modifiers}} \right)$$

multiplicative modifiers const. nominal rate additive modifiers

Likelihood template — implementation

- ⊛ Full statistical models by ATLAS are available on HEPData
- ⊛ They are provided as JSON files
- ⊛ There are background files and signal patches
- ⊛ Each patch corresponds to some signal point and contains modifiers to the background files
- ⊛ There can be hundreds of modifiers
- ⊛ Spey/PyHF can load and process these files

```
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      ],  
      "modifiers": [  
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          "type": "lumi"  
        },  
        {  
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          ],  
          "name": "staterior_QCR1cut_cuts",  
          "type": "staterior"  
        },  
        {  
          "data": {  
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            "lo": 0.911403  
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          "name": "PRW_DATASF",  
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  },  
  {  
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            "hi": 1.06675,  
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          },  
          "name": "PRW_DATASF",  
          "type": "normsys"  
        }  
      ]  
    }  
  }  
]
```

Likelihood ratio test statistic

In the absence of the nuisance parameters, the optimal test statistic (according to Neyman-Pearson lemma) is q :

$$q = -2 \ln \frac{L(\mu = 1)}{L(\mu = 0)}$$

In the more general case, for upper limits we use:

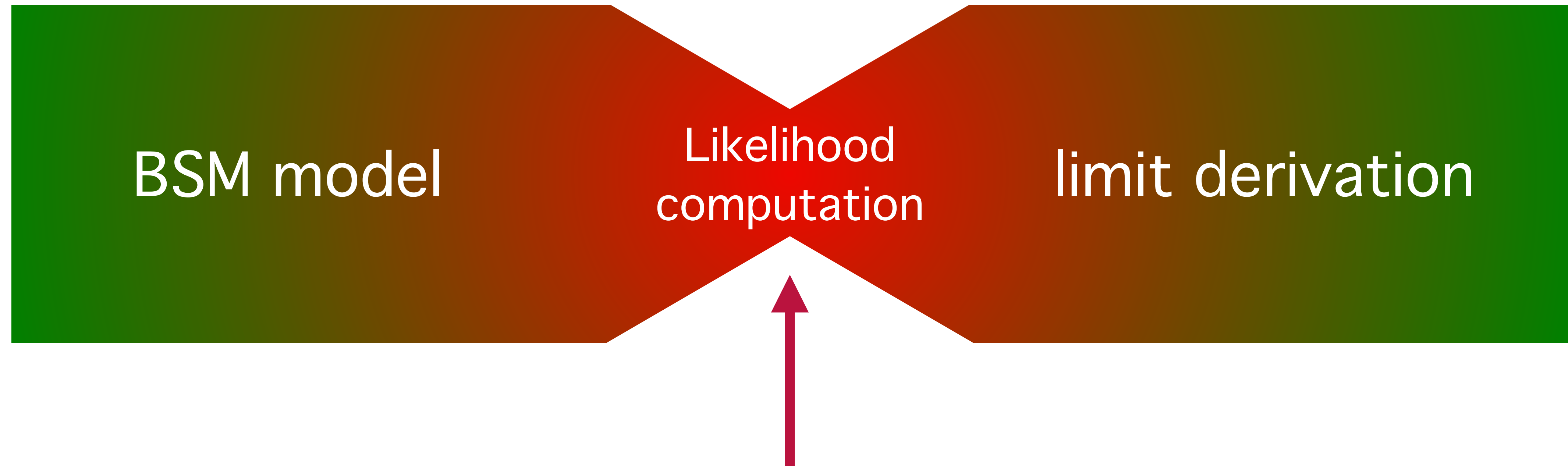
$$\tilde{q}_\mu = \begin{cases} 0, & \mu < \hat{\mu} \\ -2 \ln \frac{L(\mu, \hat{\theta}(\mu))}{L(\hat{\mu}, \hat{\theta})}, & 0 \leq \hat{\mu} \leq \mu, \\ -2 \ln \frac{L(\mu, \hat{\theta}(\mu))}{L(0, \hat{\theta}(0))}, & \hat{\mu} < 0, \end{cases}$$

$\hat{\mu}, \hat{\theta}$ — unconditional ML estimators
 $\hat{\theta}(\mu)$ — ML estimator conditioned on μ .

$$P_{\mu, \text{obs}} = \int_{\tilde{q}_{\mu, \text{obs}}}^{\infty} f(\tilde{q}_\mu, \mu') d\tilde{q}_\mu$$

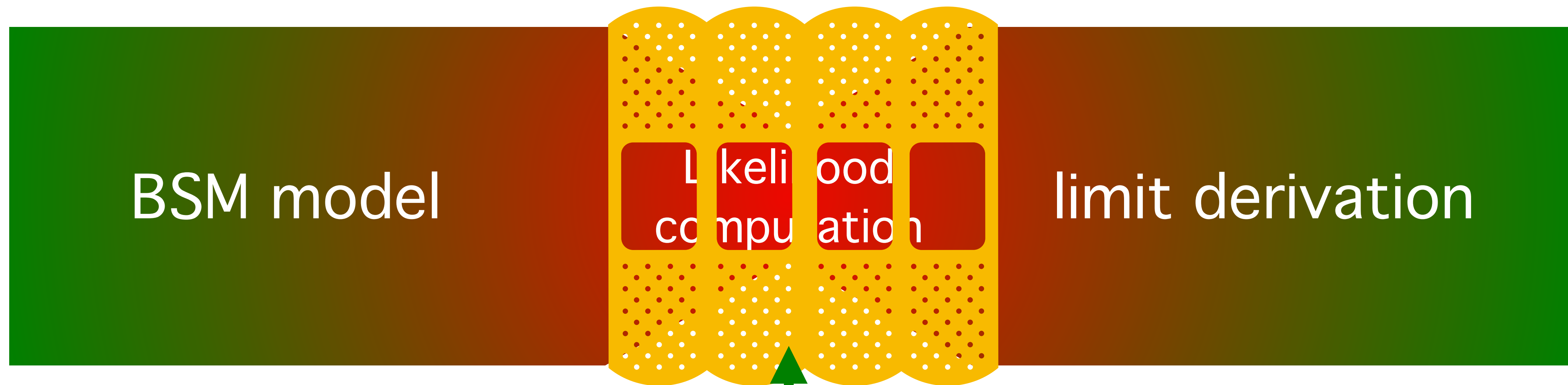
f — PDF of \tilde{q}_μ

Computational bottleneck



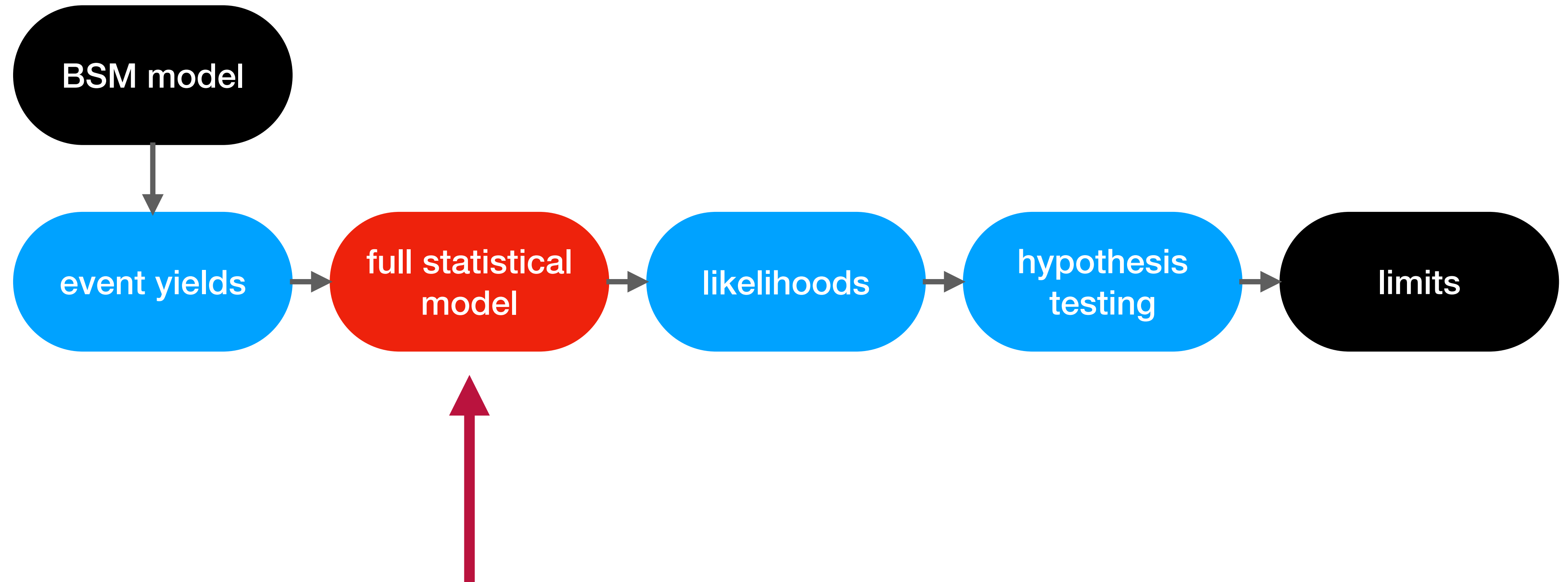
Full statistical model calculations enter here

Fixing the problem



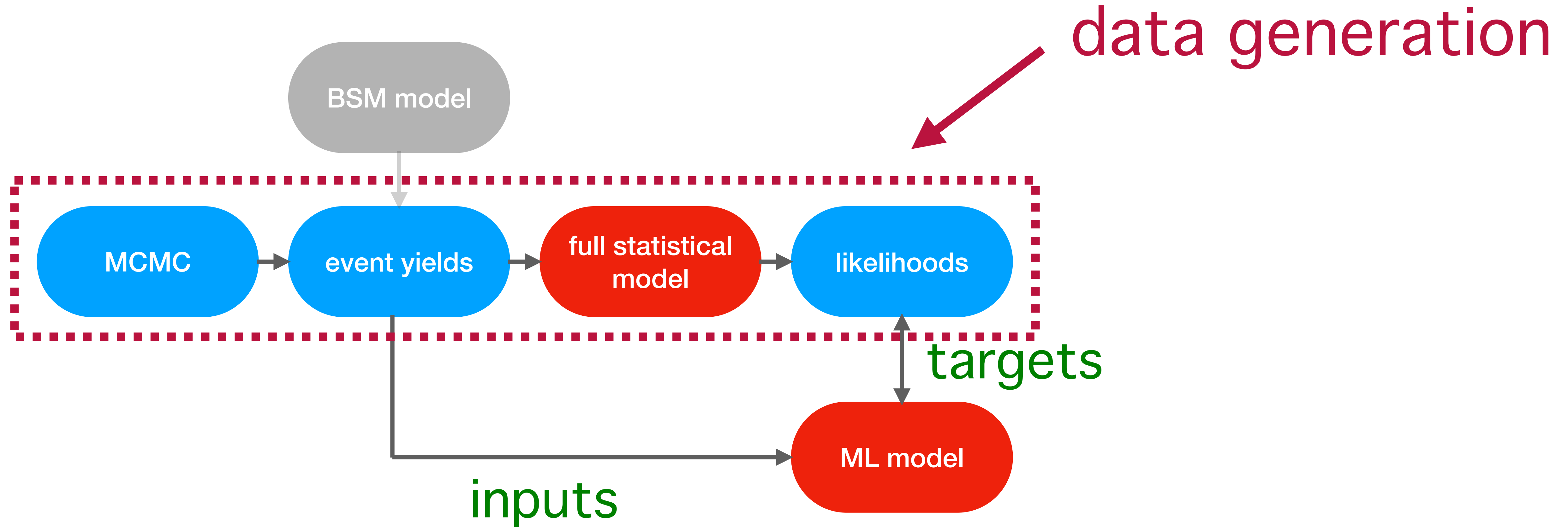
Machine Learning enters here

Old approach

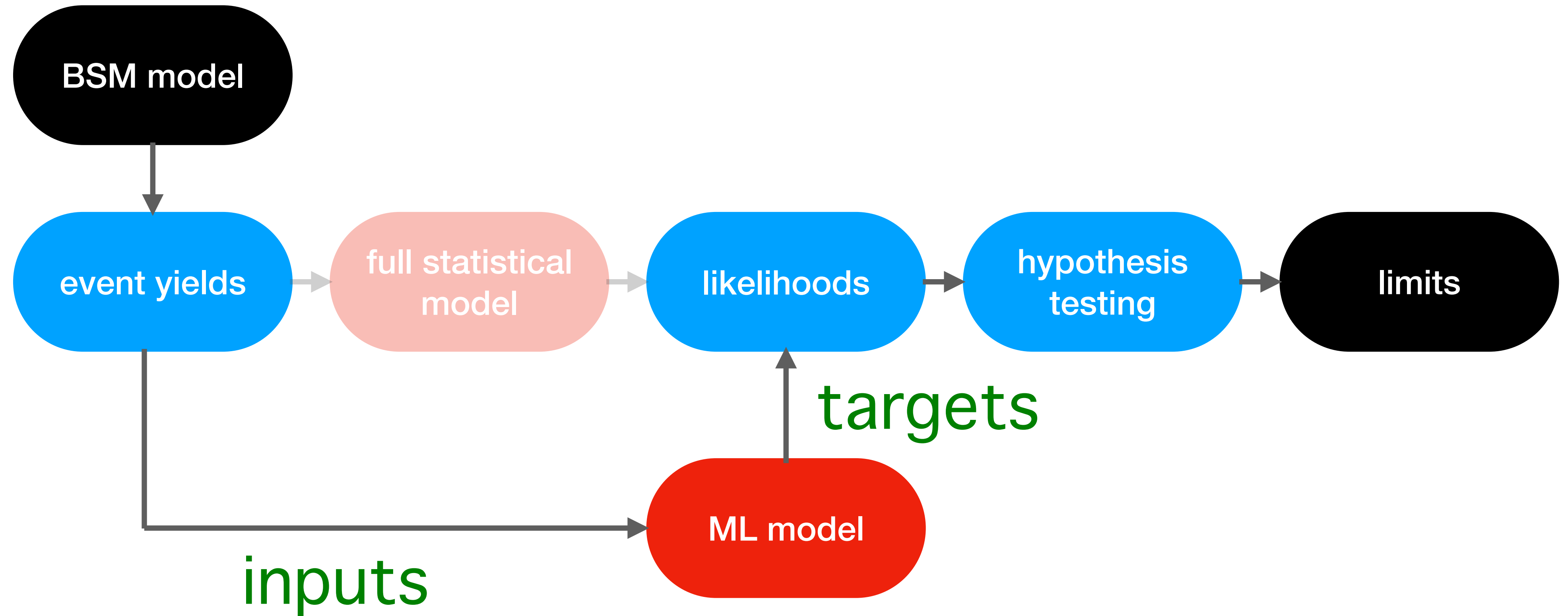


computational bottleneck

Training

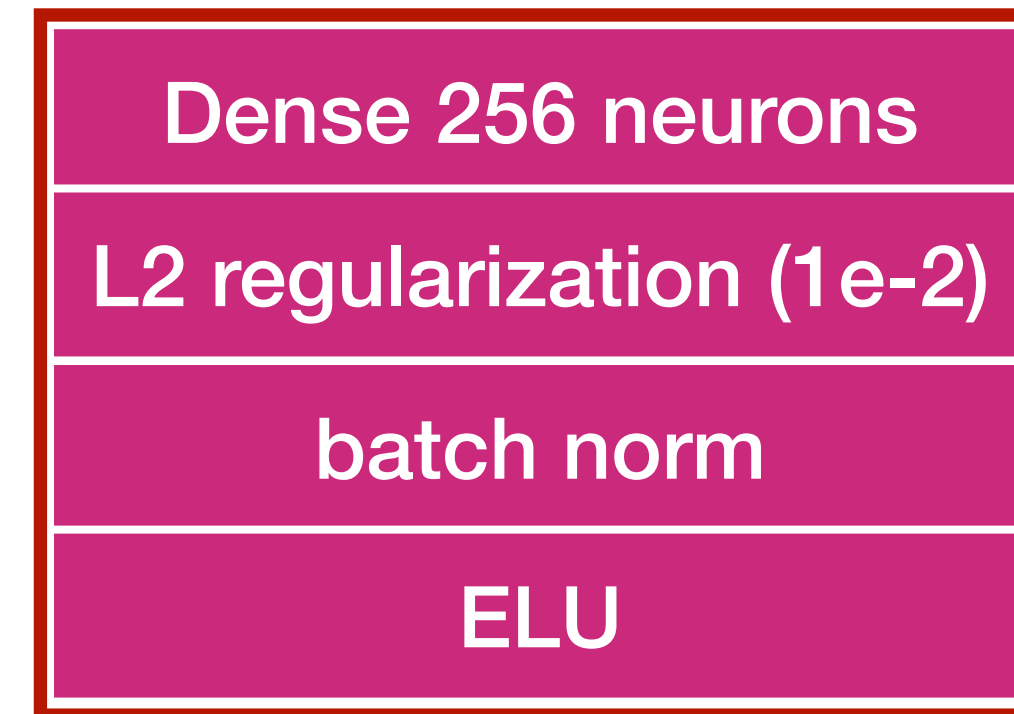
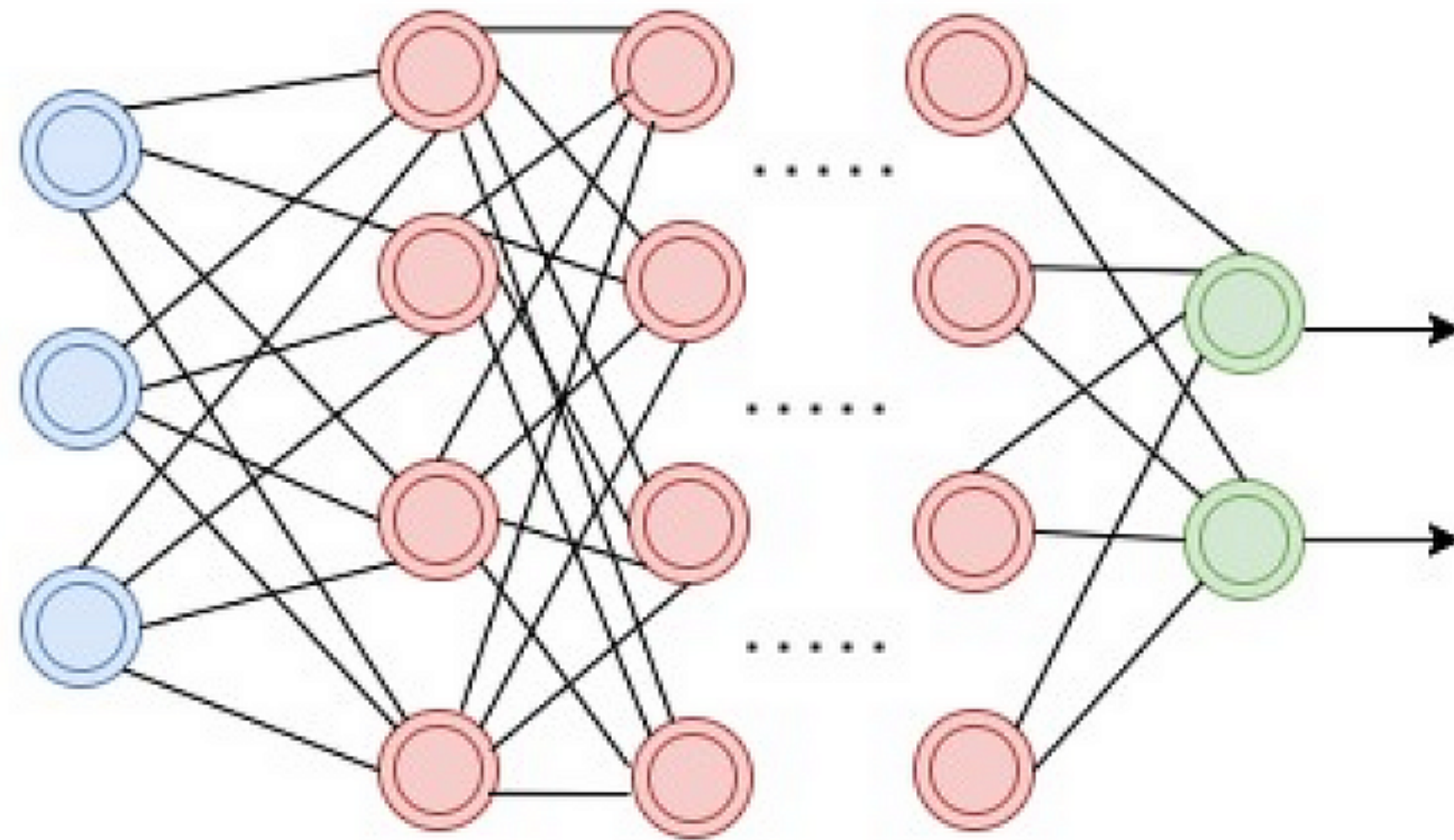


Inference



huge speed up!

ML model



x5

INPUTS: event yields in all bins and channels (including CRs)

OUTPUTS: negative log likelihoods (for $\mu=0$ and $\mu=1$), for expected and observed data

LOSS FUNCTION: MSE but others tested

OPTIMIZER: ADAM

SCHEDULER: Cosine Decay with warmup

Preliminary results

⊗ **ATLAS-SUSY-2018-04** [[arXiv: 1911.06660](#)]

- ⊗ Search for direct stau production in events with two hadronic τ -leptons in $\sqrt{s}=13$ TeV pp collisions with the ATLAS detector
- ⊗ 2 signal bins, 3 control bins

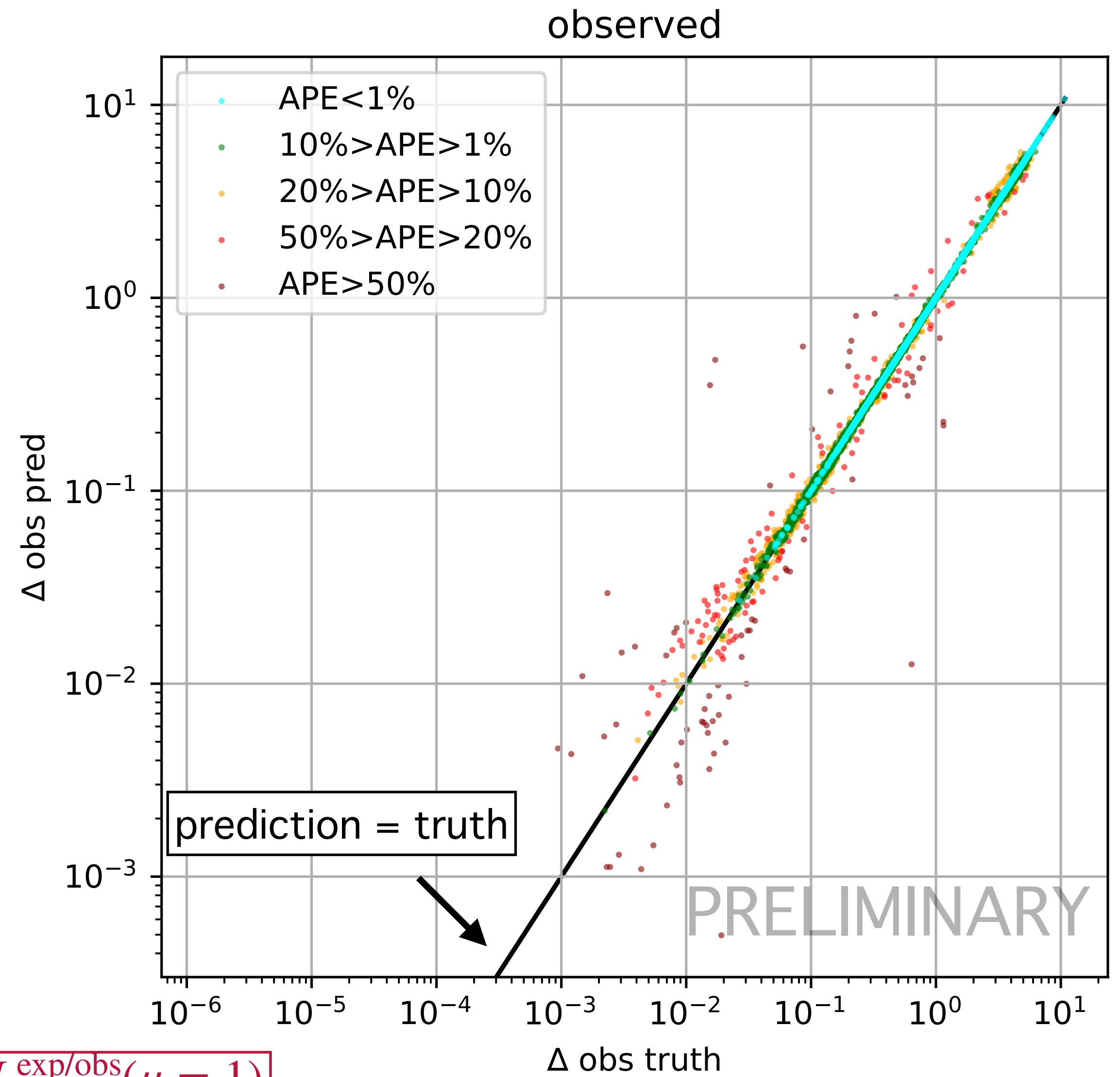
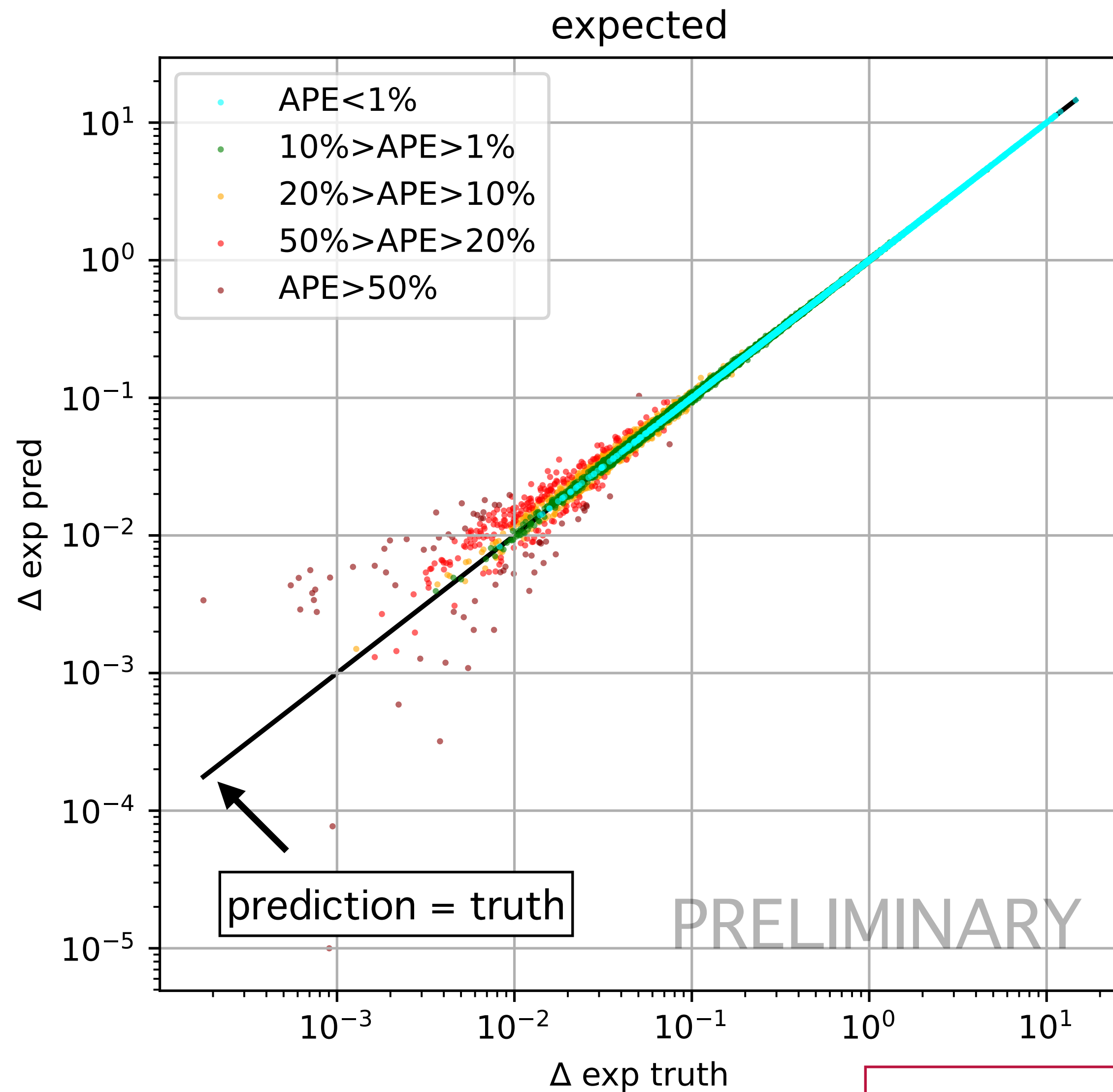
⊗ **ATLAS-CONF-2019-031** [[arXiv: 1909.09226](#)]

- ⊗ Search for direct production of electroweakinos in final states with one lepton, missing transverse momentum and a Higgs boson decaying into two b-jets in pp collisions at $\sqrt{s}=13$ TeV with the ATLAS detector
- ⊗ 9 signal bins, 5 control bins

⊗ **ATLAS-SUSY-2018-16** [[arXiv:1911.12606](#)]

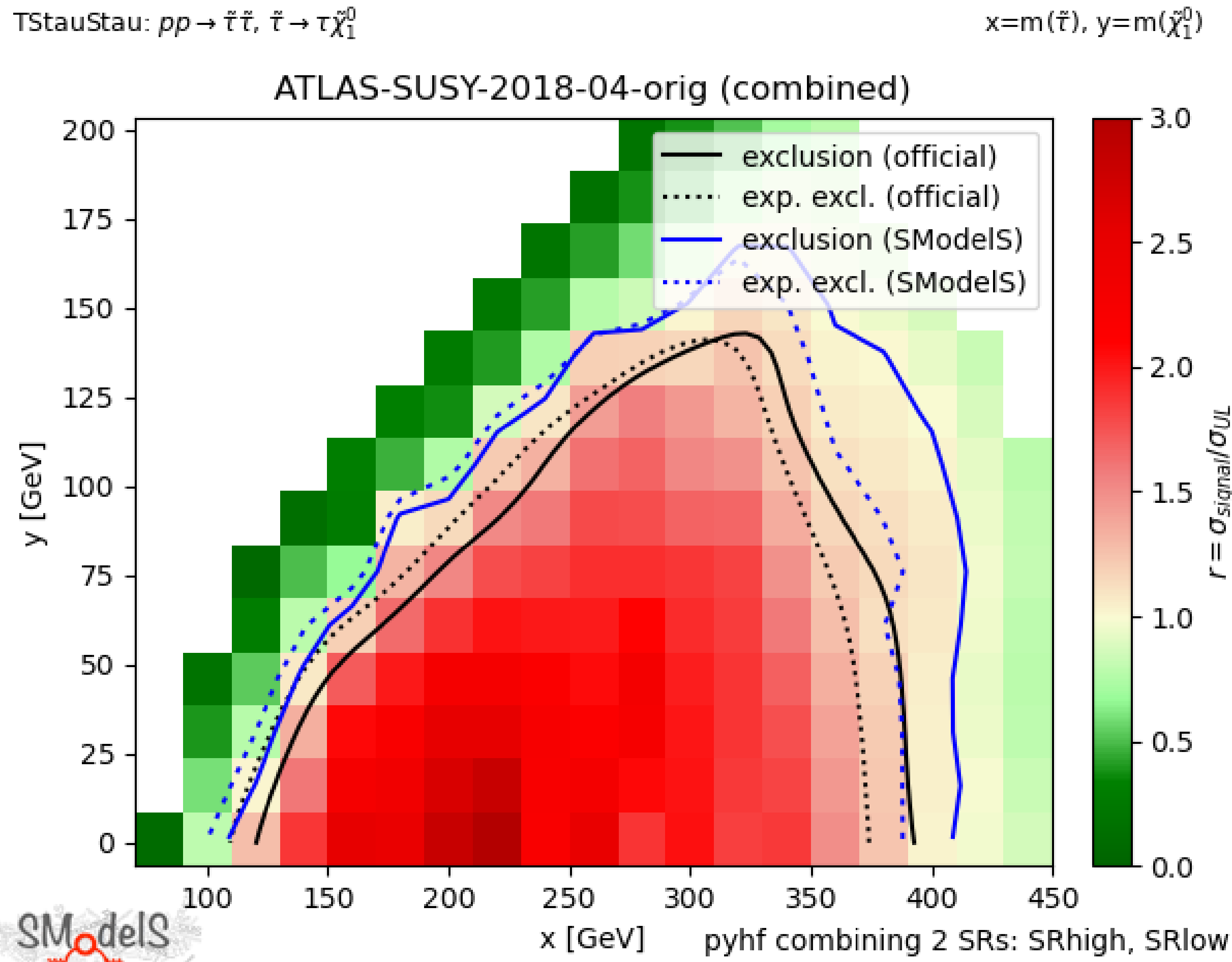
- ⊗ This paper presents results of searches for electroweak production of supersymmetric particles in models with compressed mass spectra
- ⊗ EWKinos: 44 signal bins, 6 control bins
- ⊗ Selectrons: 16 signal bins, 6 control bins
- ⊗ Smuons: 16 signal bins, 6 control bins
- ⊗ Sleptons: 32 signal bins, 6 control bins

Search for direct stau production in events with two hadronic τ -leptons in $\sqrt{s} = 13$ TeV pp collisions with the ATLAS detector



$$\Delta^{\text{exp/obs}} = \ln \frac{L^{\text{exp/obs}}(\mu = 1)}{L^{\text{exp/obs}}(\mu = 0)}$$

Search for direct stau production in events with two hadronic τ -leptons in $\sqrt{s} = 13$ TeV pp collisions with the ATLAS detector



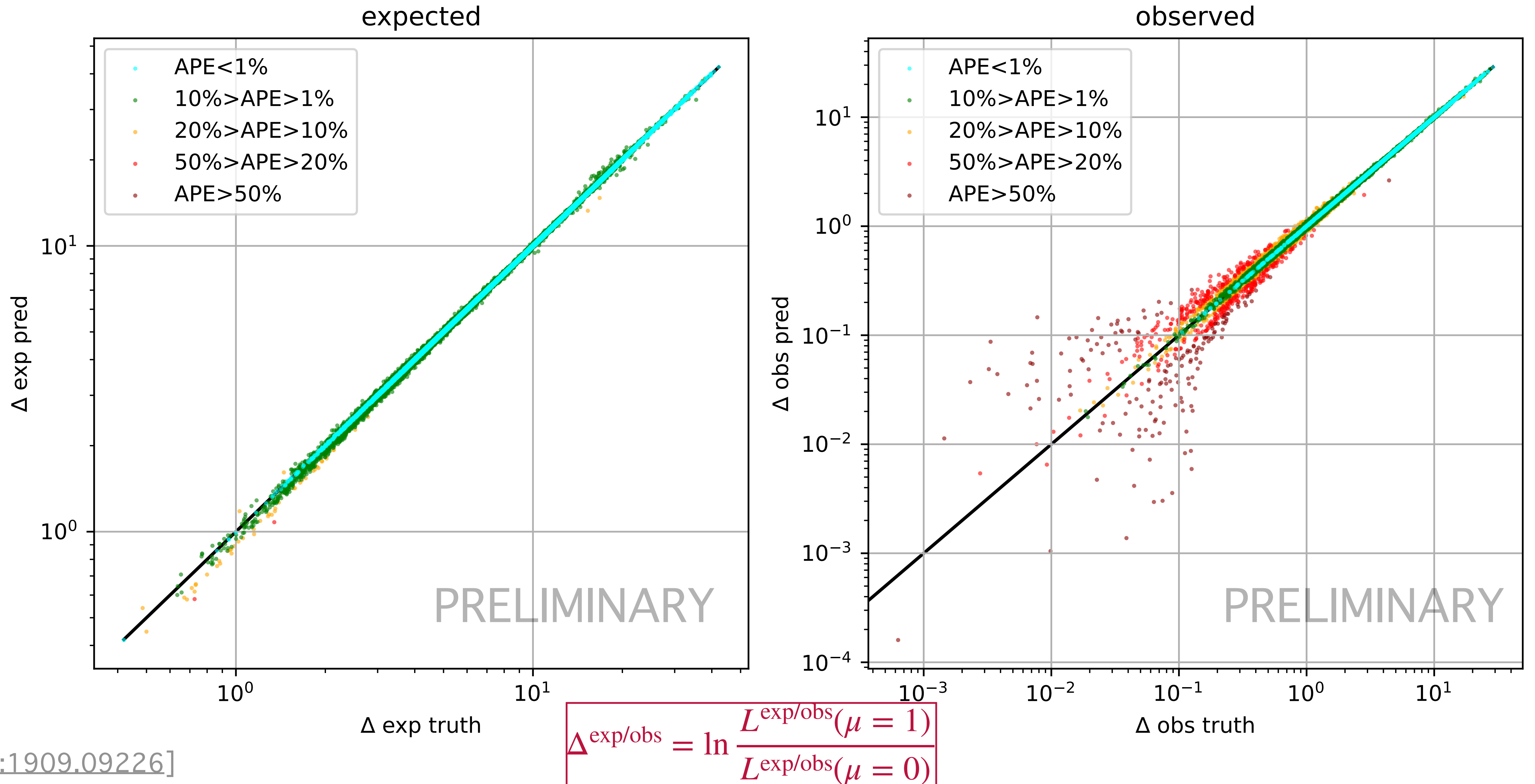
The reproduced limit is very off from the official one because in our fit we include CRs but apparently experimentalists don't.

->

Need for CRs removal option in the ML setup.

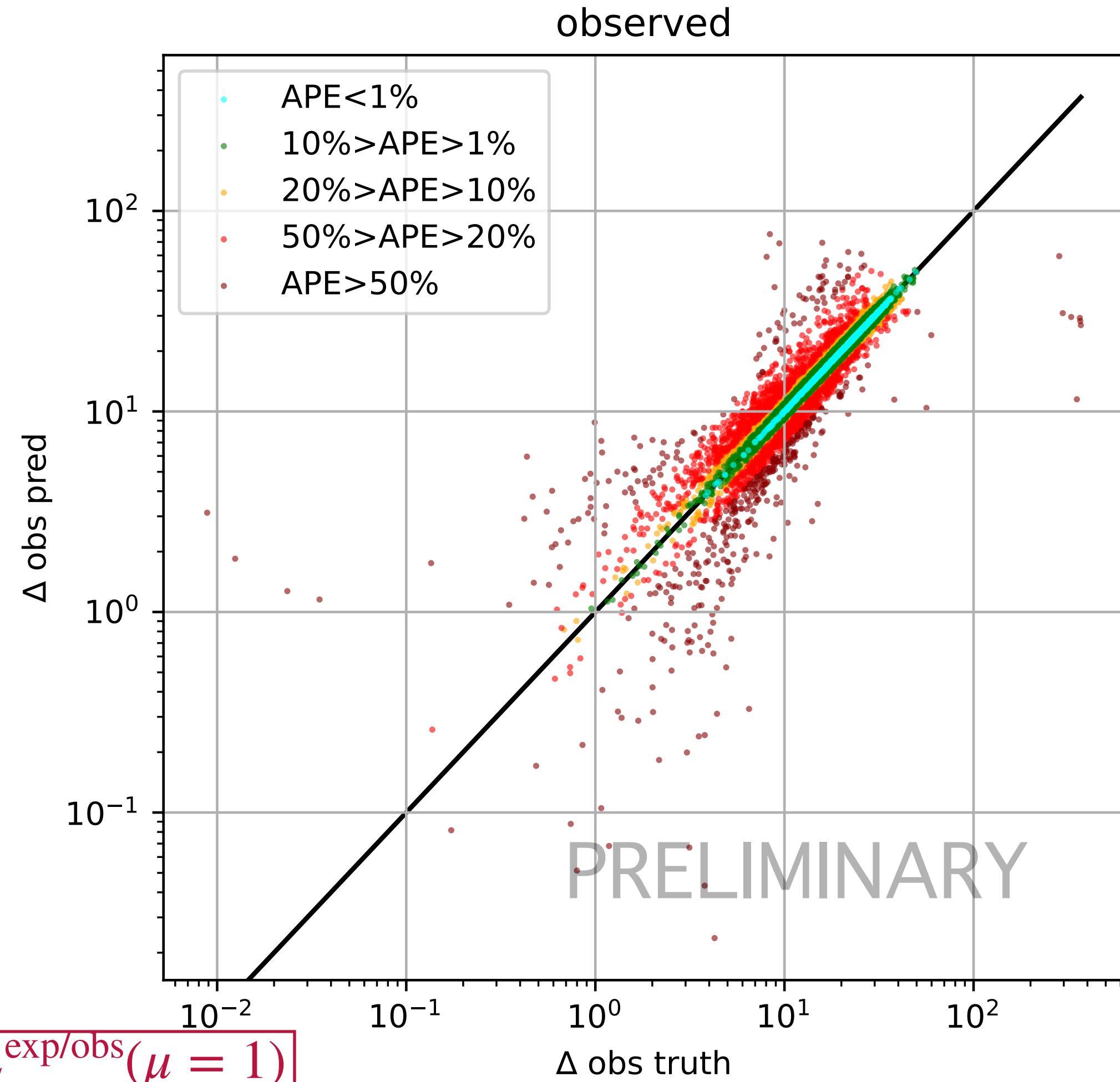
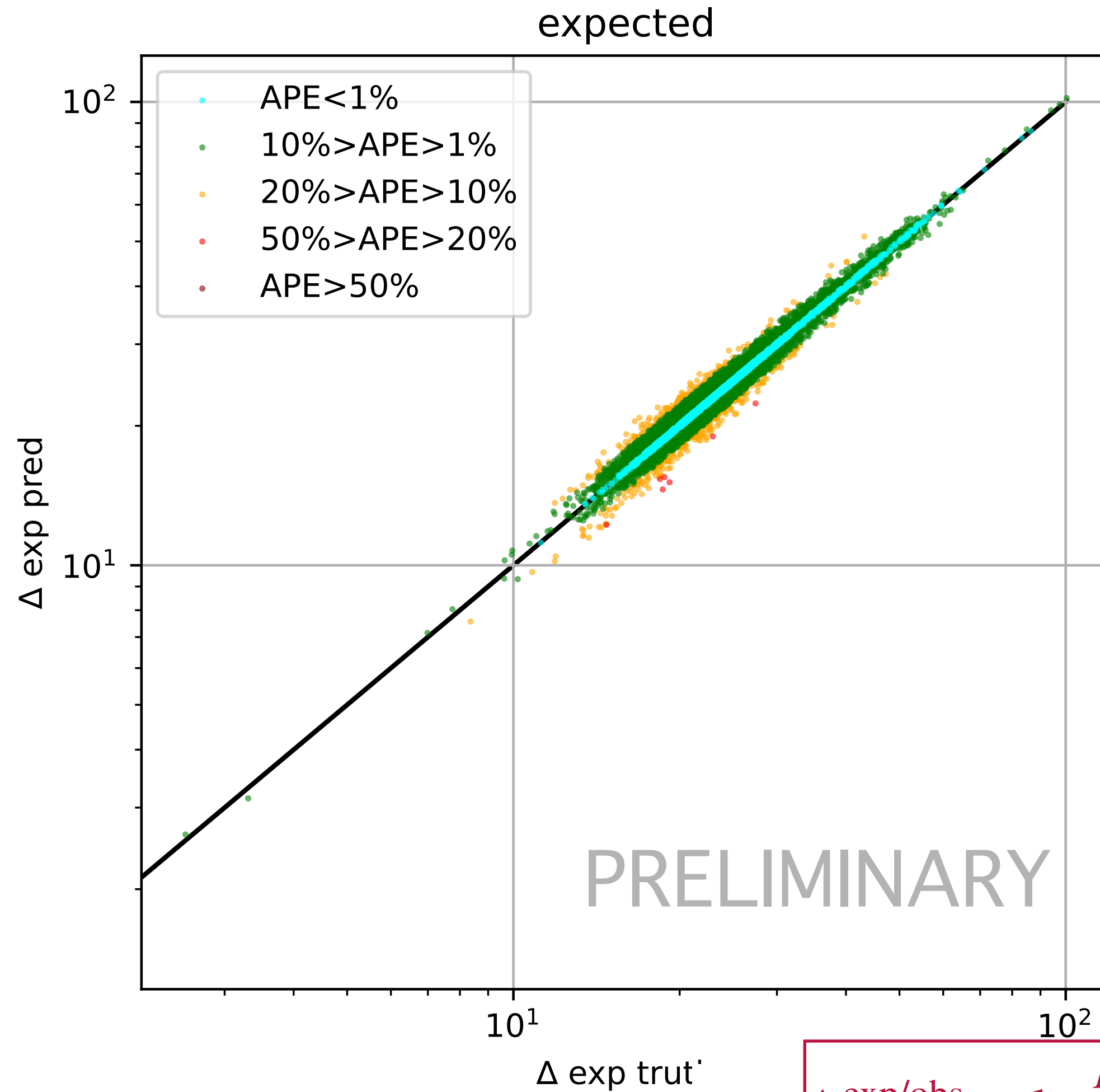
Full Likelihood Model

Search for direct production of electroweakinos in final states with one lepton, missing transverse momentum and a Higgs boson decaying into two b-jets in pp collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector



This paper presents results of searches for electroweak production of supersymmetric particles in models with compressed mass spectra. The searches use 139 fb^{-1} of $\sqrt{s} = 13 \text{ TeV}$ proton-proton collision data collected by the ATLAS experiment at the Large Hadron Collider. Events with missing transverse momentum and two same-flavor, oppositely charged, low transverse momentum leptons are selected, and are further categorized by the presence of hadronic activity from initial-state radiation or a topology compatible with vector-boson fusion processes. The data are found to be consistent with predictions from the Standard Model. The results are interpreted using simplified models of \mathbf{R} -parity-conserving supersymmetry in which the lightest supersymmetric partner is a neutralino with a mass similar to the lightest chargino, the second-to-lightest neutralino or the slepton. Lower limits on the masses of charginos in different simplified models range from 193 GeV to 240 GeV for moderate mass splittings, and extend down to mass splittings of 1.5 GeV to 2.4 GeV at the LEP chargino bounds (92.4 GeV). Similar lower limits on degenerate light-flavor sleptons extend up to masses of 251 GeV and down to mass splittings of 550 MeV. Constraints on vector-boson fusion production of electroweak SUSY states are also presented.

EWKino model



$$\Delta^{\text{exp/obs}} = \ln \frac{L^{\text{exp/obs}}(\mu = 1)}{L^{\text{exp/obs}}(\mu = 0)}$$

Recent updates


- ⊛ Wolfgang implemented new validation
- ⊛ Discrepancy between nLL without signal and nLL with signal and $\mu=0$
- ⊛ Automatic removal of CRs -> **1911.06660** (spey bug found and fixed)
- ⊛ Possibility to remove arbitrary channels -> **1911.12606**
- ⊛ Asimov likelihoods are now also calculated -> first scan for **1909.09226** -> **problem with background estimation with spey**
- ⊛ Maximal likelihoods are calculated and stored in metadata -> **problems with optimisation for normal likelihoods**
- ⊛ Main branch of the repository corresponds to current version of the project.
- ⊛ Need to add more descriptive metadata and clean up the repository.



Thank you for attention!

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Dolina Chochołowska, Poland
photo by Piotr Kałuża

 **ATLAS-CONF-2019-031** [[arXiv: 1909.09226](https://arxiv.org/abs/1909.09226)]

BIN	SR	BKG	Δ BKG	OBS
SRHMEM_mct2-0	True	4.2	1.6	6.0
SRHMEM_mct2-1	True	2.9	2.2	5.0
SRHMEM_mct2-2	True	1.0	1.9	3.0
SRLMEM_mct2-0	True	11.0	7.5	16.0
SRLMEM_mct2-1	True	10.3	7.6	11.0
SRLMEM_mct2-2	True	6.9	5.1	7.0
SRMMEM_mct2-0	True	5.4	4.0	4.0
SRMMEM_mct2-1	True	2.8	3.6	7.0
SRMMEM_mct2-2	True	1.4	1.2	2.0
STCREM_cuts-0	False	178.4	68.0	155.0
TRHMEM_cuts-0	False	680.5	329.6	641.0
TRLMEM_cuts-0	False	717.5	408.6	657.0
TRMMEM_cuts-0	False	474.4	279.2	491.0
WREM_cuts-0	False	130.1	53.4	144.0

BIN	MIN	MAX
SRHMEM_mct2-0	1.6	14.1
SRHMEM_mct2-1	2.2	16.1
SRHMEM_mct2-2	0.0	12.3
SRLMEM_mct2-0	7.5	53.7
SRLMEM_mct2-1	7.6	48.8
SRLMEM_mct2-2	5.1	32.3
SRMMEM_mct2-0	4.0	24.1
SRMMEM_mct2-1	0.0	25.1
SRMMEM_mct2-2	1.2	8.0
STCREM_cuts-0	139.5	170.5
TRHMEM_cuts-0	576.9	705.1
TRLMEM_cuts-0	591.3	722.7
TRMMEM_cuts-0	441.9	540.1
WREM_cuts-0	129.6	158.4

Search for direct stau production in events with two hadronic τ -leptons in $\sqrt{s} = 13$ TeV pp collisions with the ATLAS detector

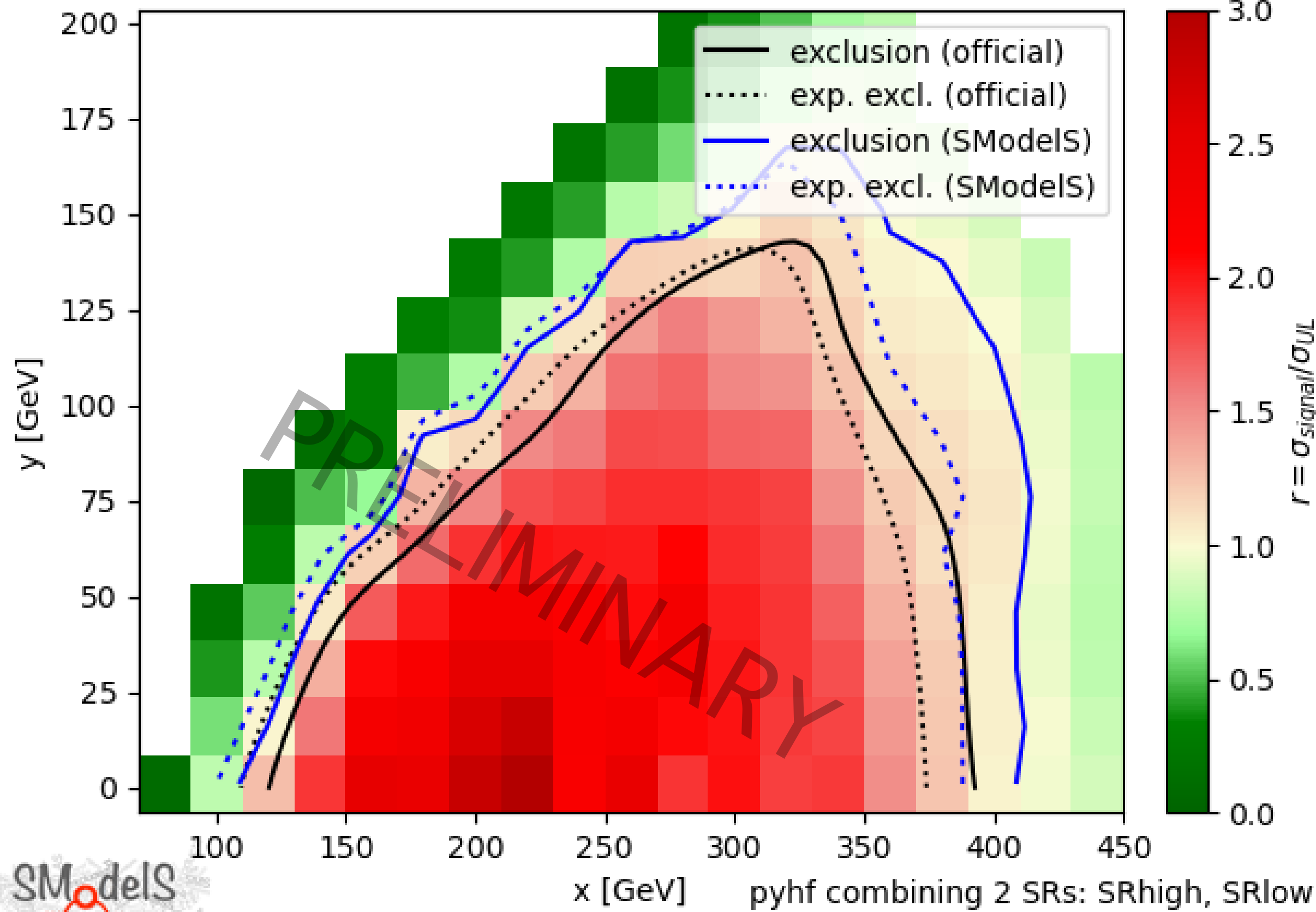
TStauStau: $pp \rightarrow \tilde{t}\tilde{t}, \tilde{t} \rightarrow \tau\tilde{\chi}_1^0$

$x=m(\tilde{t}), y=m(\tilde{\chi}_1^0)$

TStauStau: $pp \rightarrow \tilde{t}\tilde{t}, \tilde{t} \rightarrow \tau\tilde{\chi}_1^0$

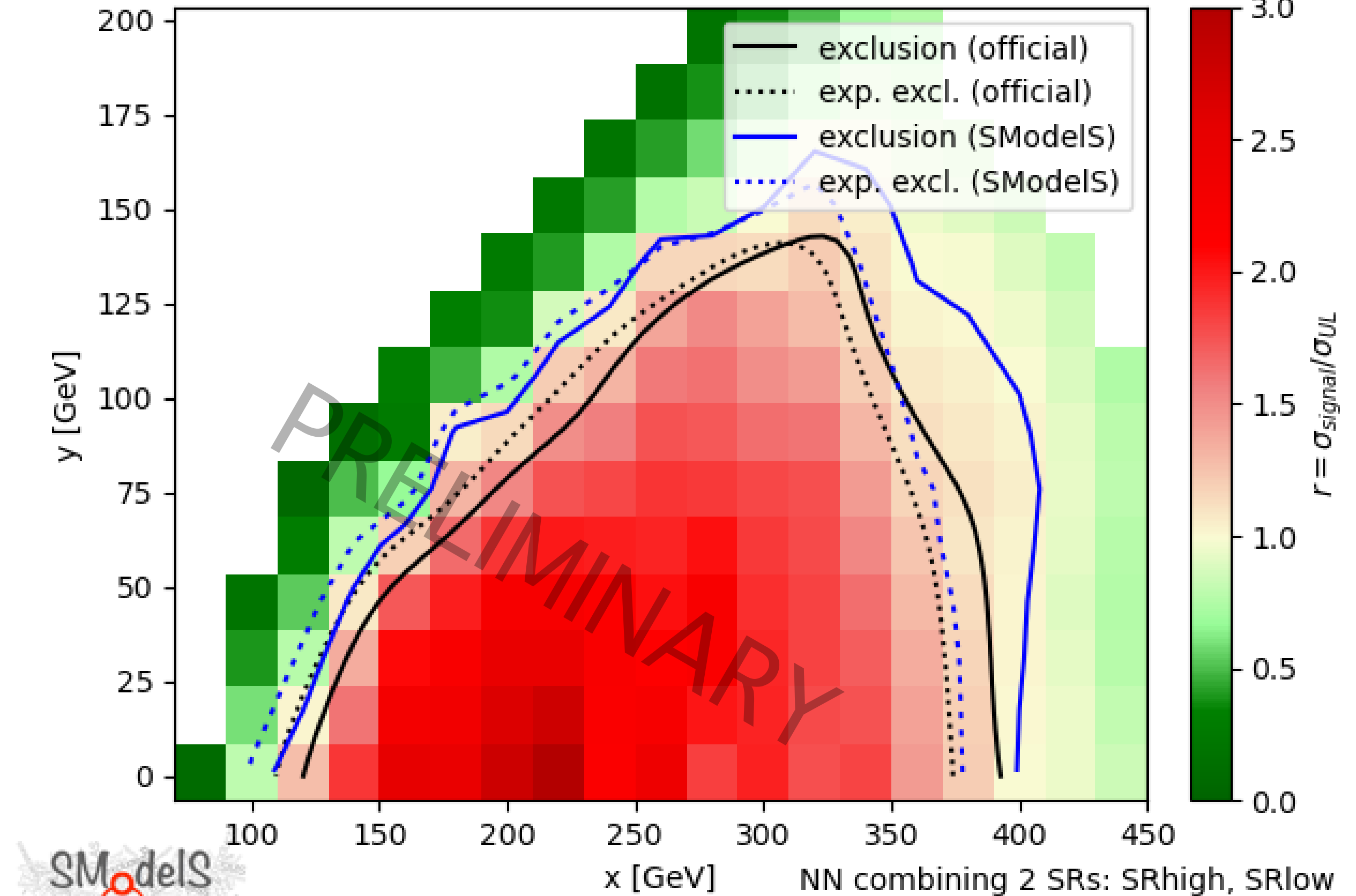
$x=m(\tilde{t}), y=m(\tilde{\chi}_1^0)$

ATLAS-SUSY-2018-04-orig (combined)



Full Likelihood Model

ATLAS-SUSY-2018-04 (combined)



ML SURROGATE

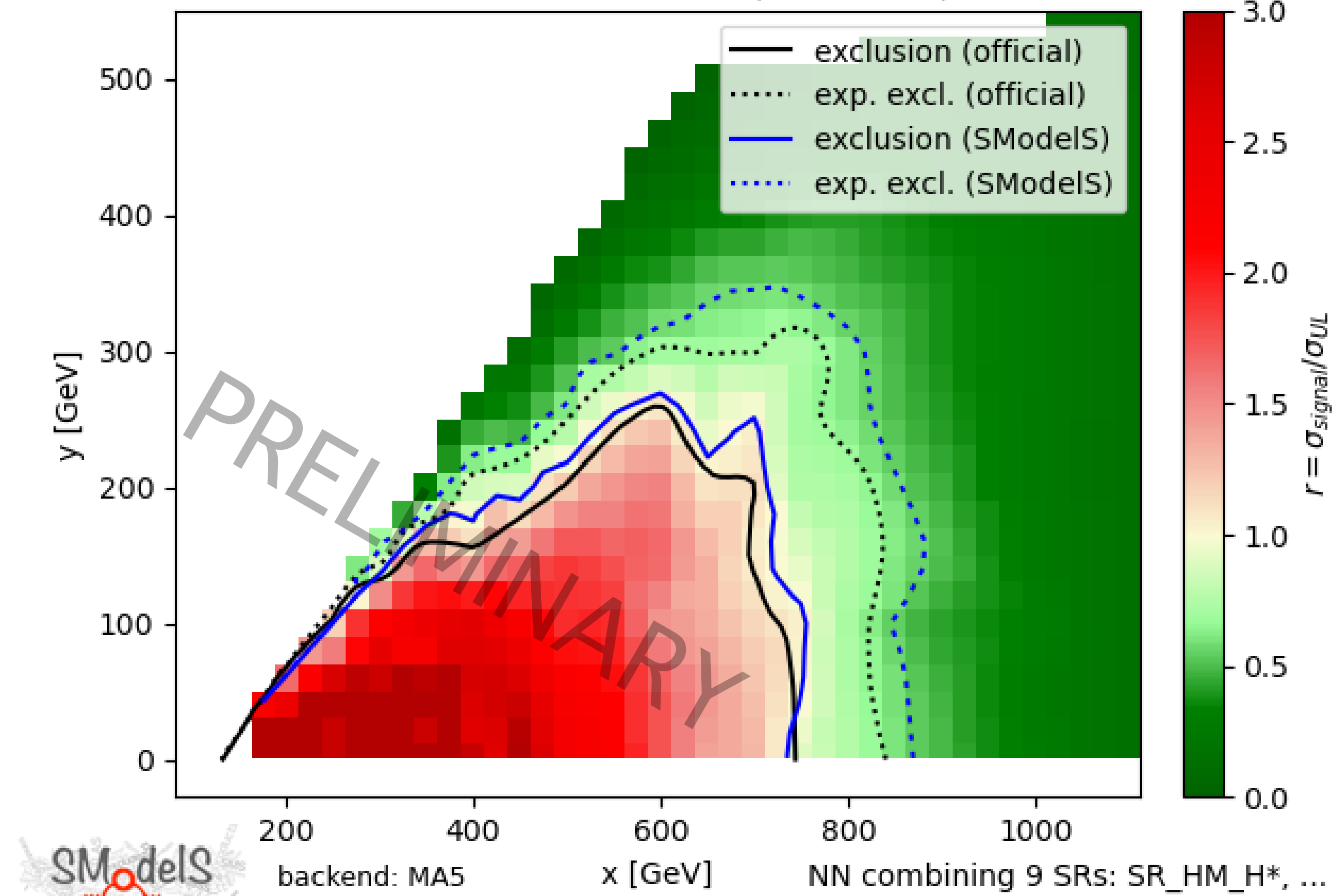
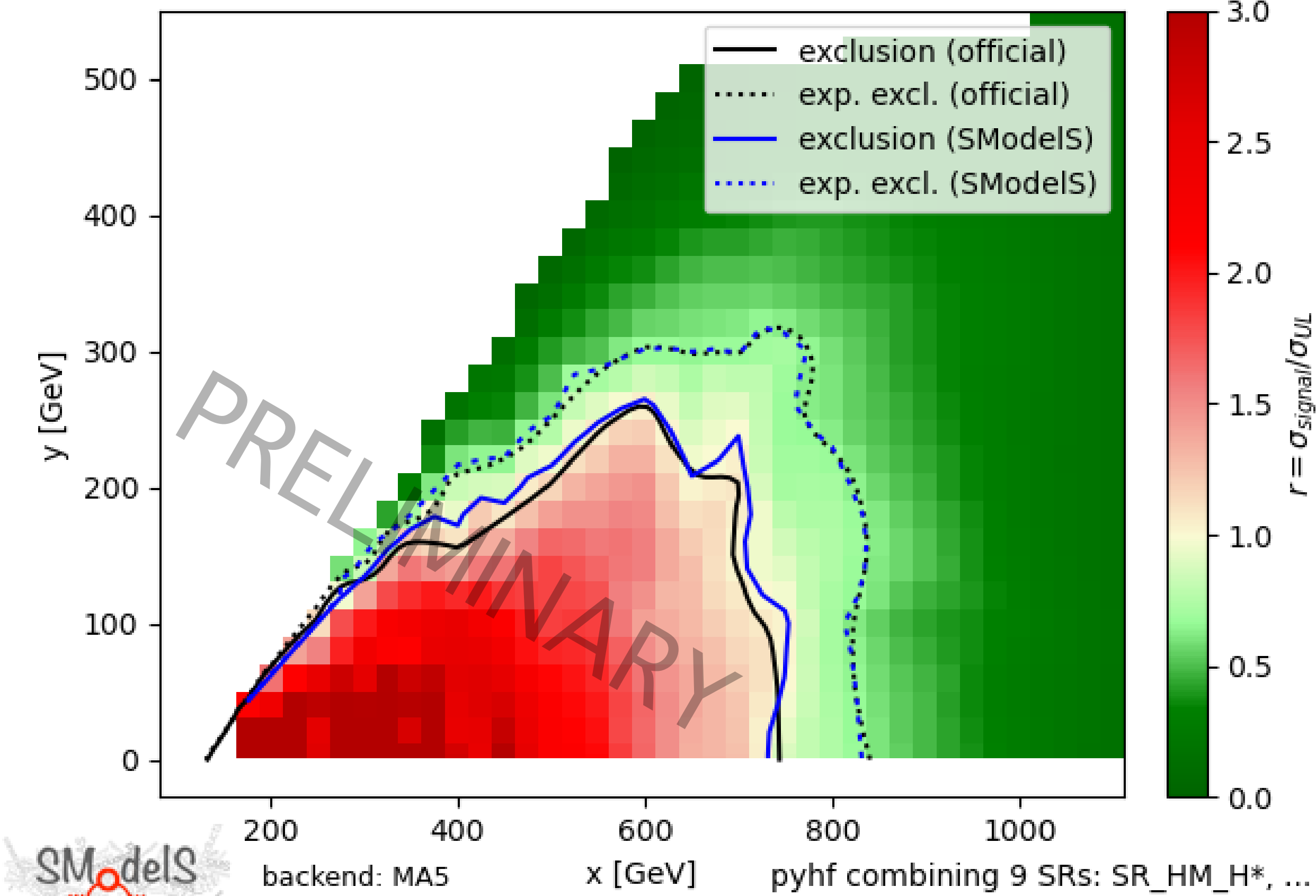
Search for direct production of electroweakinos in final states with one lepton, missing transverse momentum and a Higgs boson decaying into two b-jets in pp collisions at $\sqrt{s} = 13$ TeV with the ATLAS detector

TChiWH: $pp \rightarrow \tilde{\chi}_2^0 \tilde{\chi}_1^\pm, \tilde{\chi}_2^0 \tilde{\chi}_1^\pm \rightarrow HW \tilde{\chi}_1^0 \tilde{\chi}_1^0$ $x=m(\tilde{\chi}_1^\pm, \tilde{\chi}_2^0), y=m(\tilde{\chi}_1^0)$

TChiWH: $pp \rightarrow \tilde{\chi}_2^0 \tilde{\chi}_1^\pm, \tilde{\chi}_2^0 \tilde{\chi}_1^\pm \rightarrow HW \tilde{\chi}_1^0 \tilde{\chi}_1^0$ $x=m(\tilde{\chi}_1^\pm, \tilde{\chi}_2^0), y=m(\tilde{\chi}_1^0)$

ATLAS-SUSY-2019-08-orig (combined)

ATLAS-SUSY-2019-08 (combined)



Full Likelihood Model

ML SURROGATE