IRN TERASCALE (Strasbourg)

Towards a reconstruction of the lightest up-type squark flavour structure

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Summary

I/ INTRODUCTION

II/ A DIRECT RECONSTRUCTION METHOD

III/ LIKELIHOOD INFERENCE

IV/ MULTIVARIATE ANALYSIS (MVA)

IV/ CONCLUSION

MSSM

Supersymmetry (SUSY)

- For each degree of freedom → super-partner (same mass)

\+ Standard model (SM) + A second higgs doublet

\+ Softs terms : break SUSY !

MSSM

Particle content

- 6 quarks + 12 squarks
- 6 leptons + 12 sleptons
- Usual gauge & higgs bosons + 4 neutralinos & 2 charginos
- 8 gluons + 8 gluinos

In favor

- A simple viable SUSY model
- A good UV completion & coupling unification
- A dark matter candidate

Disfavor

- Experimental bounds
- A large number of parameters

→ *We aim to study flavor in up type squark sector*

Squark sector

The Lagrangian mass term for the up type squarks in the super-CKM basis :

$$\mathcal{L}_{m^2_{\tilde{u}}} = \bar{\tilde{u}} \begin{pmatrix} V_{CKM} M^2_{\tilde{Q}} V^{\dagger}_{CKM} + m^2_u + D_{\tilde{u},L} & \frac{v_u}{\sqrt{2}} T^{\dagger}_u - m_u \frac{\mu}{\tan\beta} \\ \frac{v_u}{\sqrt{2}} T_u - m_u \frac{\mu^*}{\tan\beta} & M^2_{\tilde{U}} + m^2_u + D_{\tilde{u},R} \end{pmatrix} \tilde{u}$$

$\tilde{u} = (\tilde{u}_L, \tilde{c}_L, \tilde{t}_L, \tilde{u}_R, \tilde{c}_R, \tilde{t}_R)$

Rotation matrix $R^{\tilde{u}}$ → Physical states $(\tilde{u}_1, \tilde{u}_2, \tilde{u}_3, \tilde{u}_4, \tilde{u}_5, \tilde{u}_6)$

Soft terms $M^2_{\tilde{Q}}$, $M^2_{\tilde{U}}$ and T_u

diagonal → Minimal Flavor Violation (MFV)

- No generation mixing
- Only flavor violation source : CKM
- No FCNC

non-diagonal → Non Minimal Flavor Violation (NMFV)

- Generation mixing
- FCNC possible

For this study we neglect mixing
with the first generation

Problem

We consider NMFV framework with $\tilde{c}/\tilde{t}$ mixing.

→ $\tilde{u}_1 \rightarrow t\tilde{\chi}_1^0$ and $\tilde{u}_1 \rightarrow c\tilde{\chi}_1^0$ Possible at tree level !

Problematic : How can we reconstruct the flavour structure of the lightest up-type squark ?

I.e Estimate the following quantities :

$(R^{\tilde{u}})_{12}$ → Scharm left

$(R^{\tilde{u}})_{13}$ → Stop left

$(R^{\tilde{u}})_{15}$ → Scharm right

$(R^{\tilde{u}})_{16}$ → Stop right

Direct reconstruction method

The idea : Solve a system involving different quantities

Observables

- $R_{c/t} = N(\tilde{u}_1 \to c\tilde{\chi}_1^0)/N(\tilde{u}_1 \to t\tilde{\chi}_1^0)$
- $R_{b/t} = N(\tilde{u}_1 \to b\tilde{\chi}_1^+)/N(\tilde{u}_1 \to t\tilde{\chi}_1^0)$
- $P_t(\tilde{u} \to t\tilde{\chi}_1^0)$ Top polarization from squark decay
- $m_{\tilde{u}_1}, m_{\tilde{\chi}_1^0}, m_{\tilde{\chi}_1^+}$

Variables

- $\tilde{\chi}_1^\pm, \tilde{\chi}_1^0$ composition
- $\tan(\beta)$

$\Rightarrow$

$$\begin{cases} (R_{12}^{\tilde{u}}), (R_{13}^{\tilde{u}}), (R_{15}^{\tilde{u}}), (R_{16}^{\tilde{u}}) \\ (R_{13}^{\tilde{u}}), (R_{16}^{\tilde{u}}) \\ (R_{13}^{\tilde{u}}), (R_{16}^{\tilde{u}}) \\ \text{+ Unitarity : } (R_{12}^{\tilde{u}})^2 + (R_{13}^{\tilde{u}})^2 + (R_{15}^{\tilde{u}})^2 + (R_{16}^{\tilde{u}})^2 = 1 \end{cases}$$

Advantages

- Direct evaluation of $R^{\tilde{u}}$

Disadvantages

- Requires good precision
- Requires a lot of observables
- Does not converge all the time

Likelihood estimation

New variable : $x_{\tilde{t}} = (R^{\tilde{u}})^2_{13} + (R^{\tilde{u}})^2_{16}$

New data

Data base (Simplified scan)

Likelihood $\mathcal{L}$

Averaging the likelihood by bin of stop composition

Inference by fitting a gaussian likelihood

<u>Variables</u>

- $R_{c/t} = N(\tilde{u}_1 \to c\tilde{\chi}_1^0)/N(\tilde{u}_1 \to t\tilde{\chi}_1^0)$
- $R_{b/t} = N(\tilde{u}_1 \to b\tilde{\chi}_1^+)/N(\tilde{u}_1 \to t\tilde{\chi}_1^0)$
- $m_{\tilde{u}_1}, m_{\tilde{\chi}_1^0}, m_{\tilde{\chi}_1^+}$

A simplified scan

In order to test other methods → Simplified scan

Setup

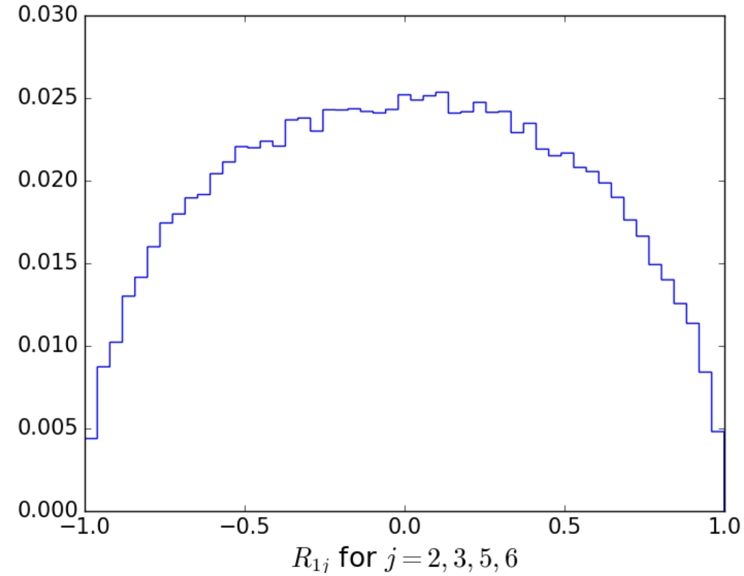
Uniform: $x_{\tilde{t}}$ $\theta_{\tilde{t}}$ $\theta_{\tilde{c}}$ M_1 M_2 μ $m_{\tilde{u}_1}$

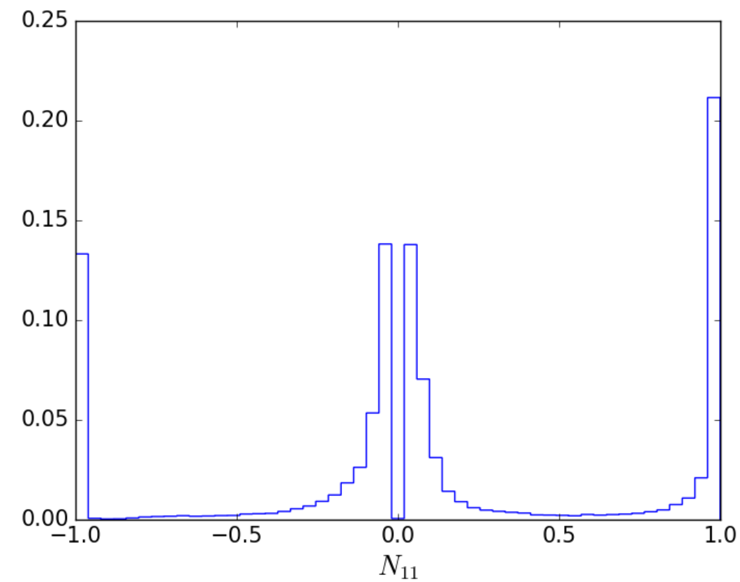
$x_{\tilde{t}}, \theta_{\tilde{t}}, \theta_{\tilde{c}} \rightarrow (R^{\tilde{u}})_{1j}$

$M_1, M_2, \mu \rightarrow (N^{\tilde{\chi}})_{1j}$, $(U)_{1j}$, $(V)_{1j}$, m_{χ^0}, m_{χ^+}

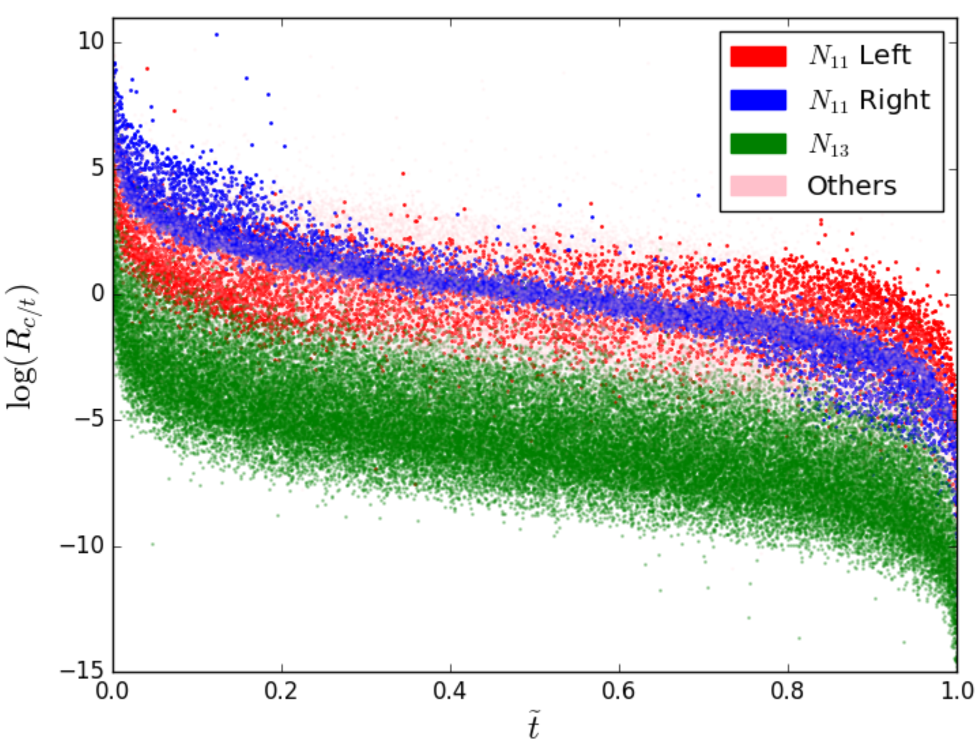
↓

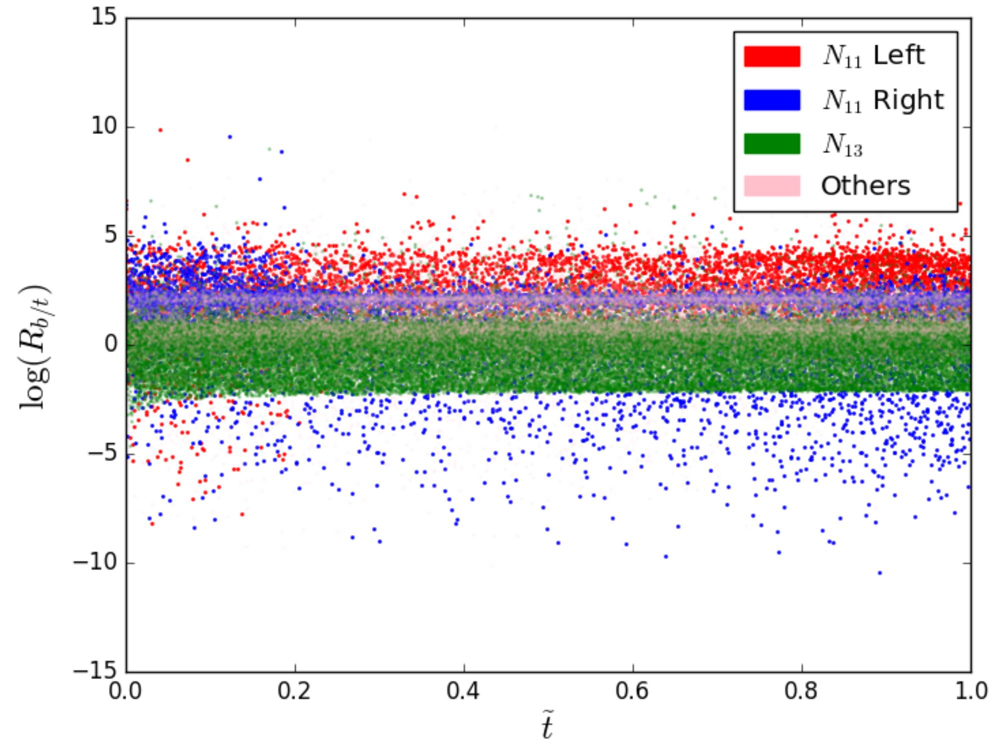
$R_{c/t}$ $R_{b/t}$





A simplified scan



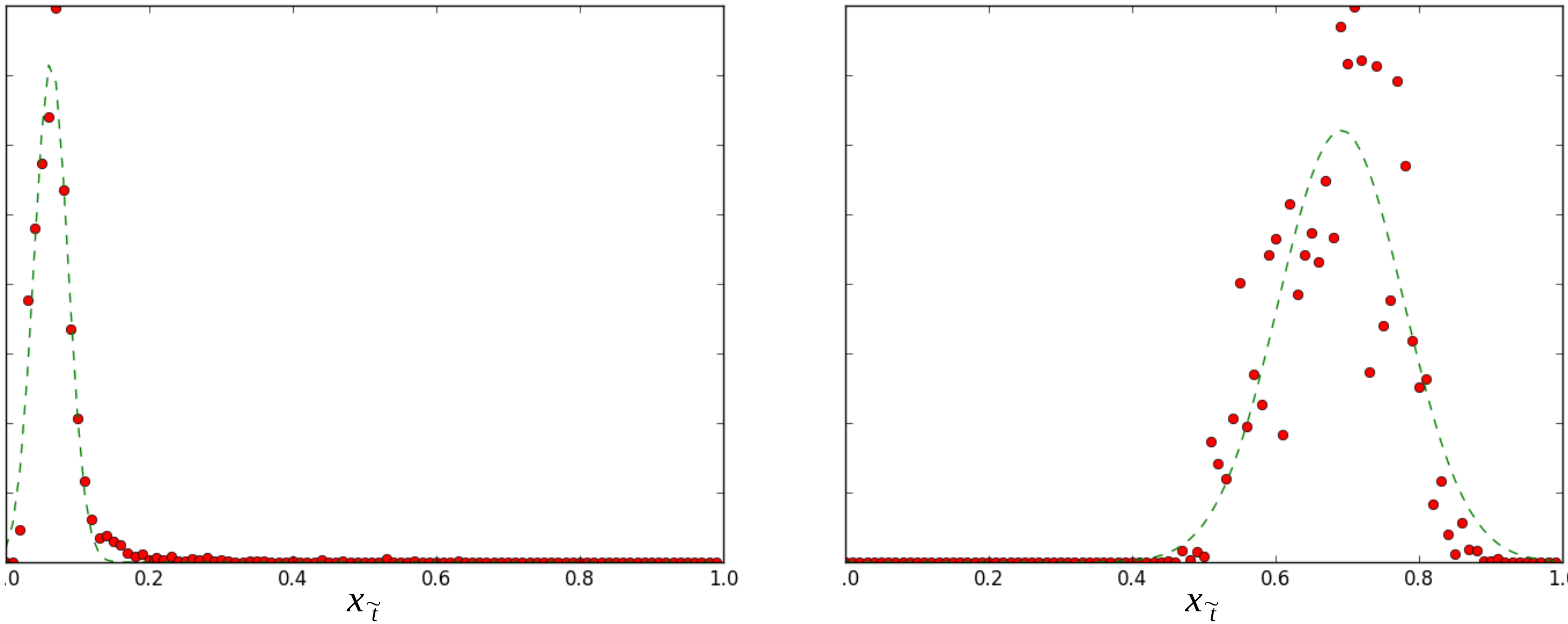


Some analytical asymptotic case:

$$(N^{\tilde{\chi}})_{1j} \rightarrow (N^{\tilde{\chi}})_{13} \text{ and } m_{\tilde{u}_1} \gg m_{\chi^0} : \; R_{c/t} = \alpha \frac{1 - x_{\tilde{t}}}{x_{\tilde{t}}}$$

$$(N^{\tilde{\chi}})_{1j} \rightarrow (N^{\tilde{\chi}})_{11} \text{ and } m_{\tilde{u}_1} \gg m_{\chi^0} : \; R_{c/t} = \beta \frac{1 - x_{\tilde{t}} + \kappa_c (R^{\tilde{u}})^2_{15}}{x_{\tilde{t}} + \kappa_t (R^{\tilde{u}})^2_{16}}$$

Selected results ★



Test 1

- Real stop composition : 0.08
- Inferred one : 0.06
- $\sigma = 0.03$

Test 2

- Real stop composition : 0.70
- Inferred one : 0.68
- $\sigma = 0.12$

★ *Here, for convenience we fixed χ composition*

Transition

A simpler problem : One can try to identify different categories.

In our case we choose to use the following ones, defined by their stop composition :

Categories names	***Stop composition***
MFV scharm	0% - 5%
NMFV scharm	5% - 50%
NMFV stop	50% - 95%
MFV stop	95% - 100%

In the case of categories, one can try to recognize some observables patterns and thus to statistically classify different configurations.

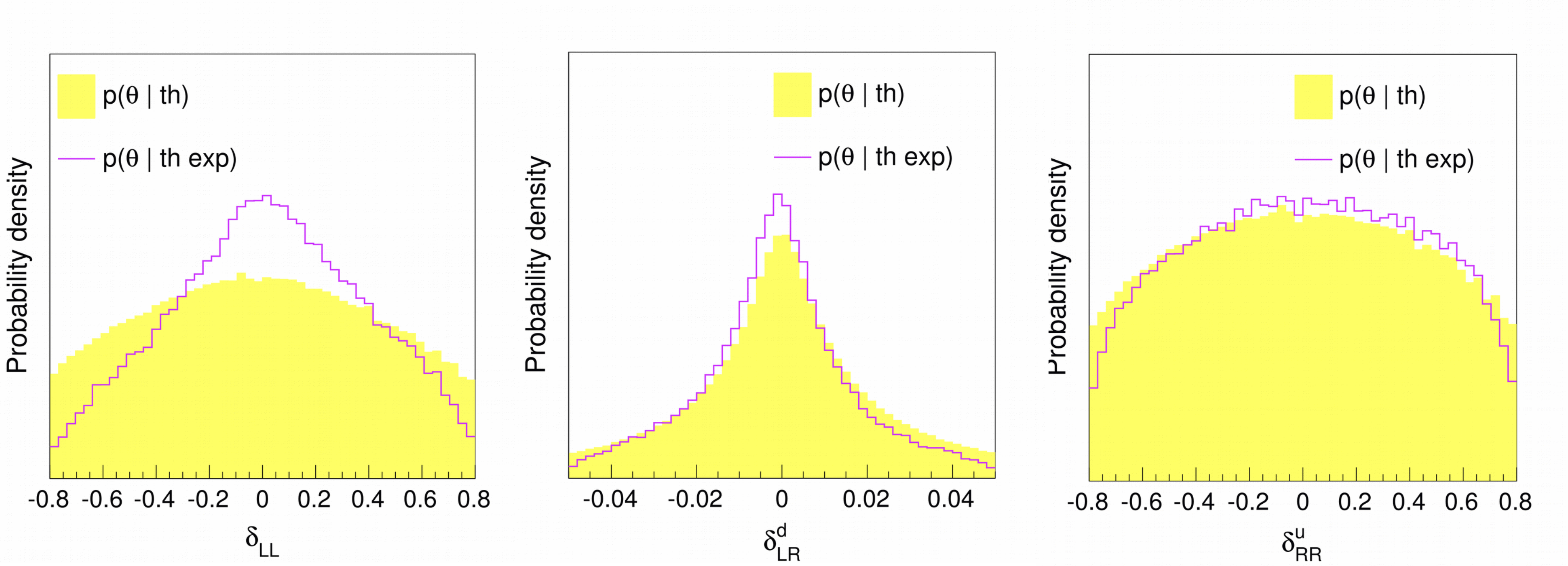
→ We need a database of scenarios

Previous study

We will use the results of the following analysis :

"General squark flavour mixing: constraints, phenomenology and benchmarks",
Karen De Causmaecker et. al. *(2015)* arxiv : [1510.01159]

Selected results :



NB : The masses of charginos and neutralinos are highly correlated because they stem a GUT-inspired relation to reduce the number of parameters.

The last method : MVA classifier

Variables

- $R_{c/t} = N(\tilde{u}_1 \to c\tilde{\chi}_1^0)/N(\tilde{u}_1 \to t\tilde{\chi}_1^0)$
- $R_{b/t} = N(\tilde{u}_1 \to b\tilde{\chi}_1^+)/N(\tilde{u}_1 \to t\tilde{\chi}_1^0)$
- $m_{\tilde{u}_1}, m_{\tilde{\chi}_1^0}, m_{\tilde{\chi}_1^+}$

Disadvantage

- Difficult to “really” interpret

Training data

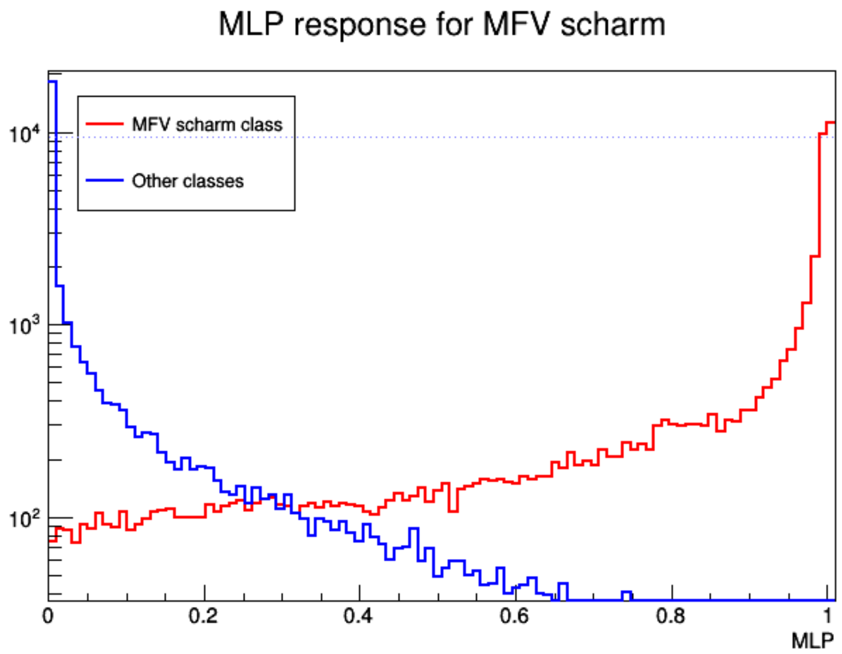
Classifier : MLP (neural network)

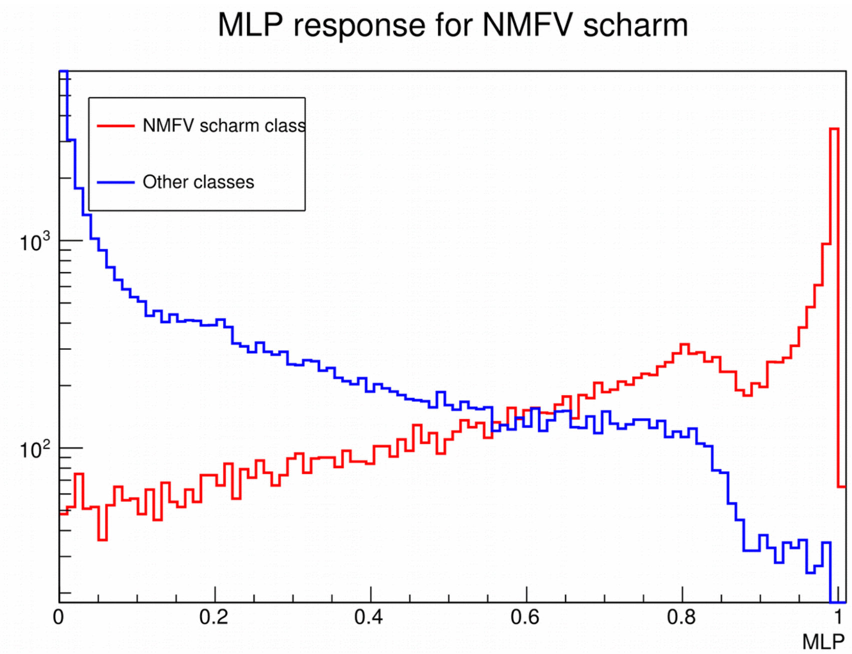
MLP from *Root TMVA*

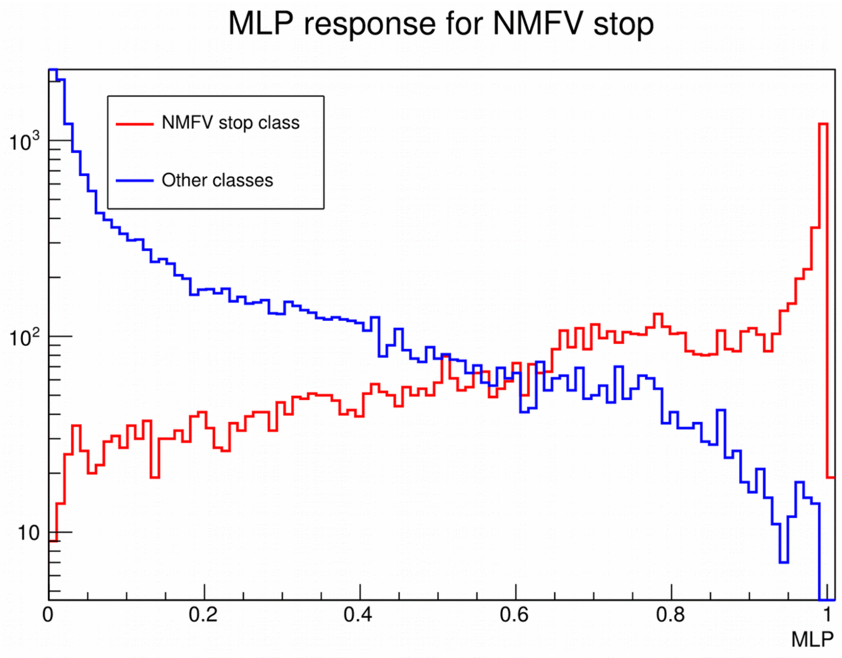
One “super” variable to classify our data

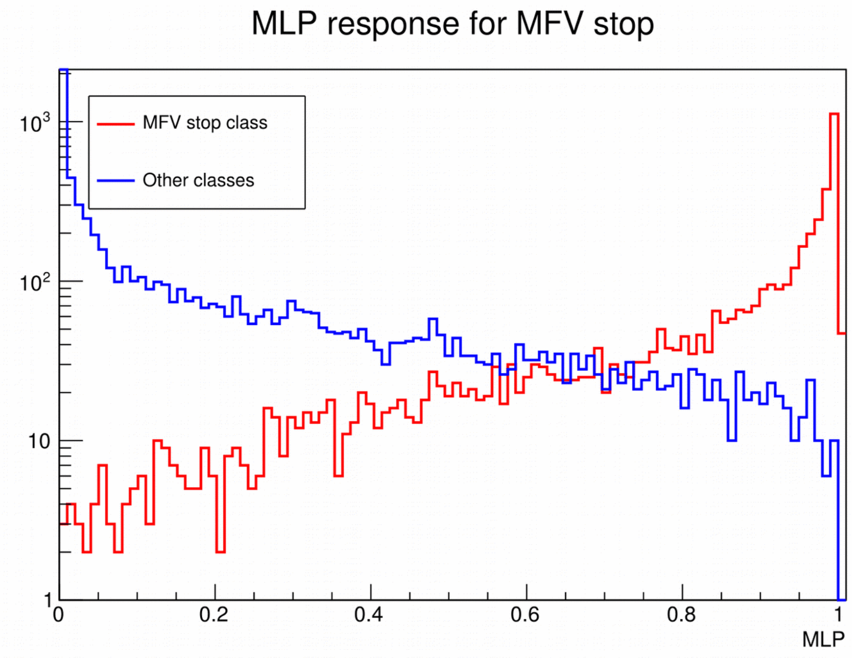
$\tilde{c} - \mathrm{MFV}$ | $\tilde{c} - \mathrm{NMFV}$ | $\tilde{t} - \mathrm{NMFV}$ | $\tilde{t} - \mathrm{MFV}$

Selected results

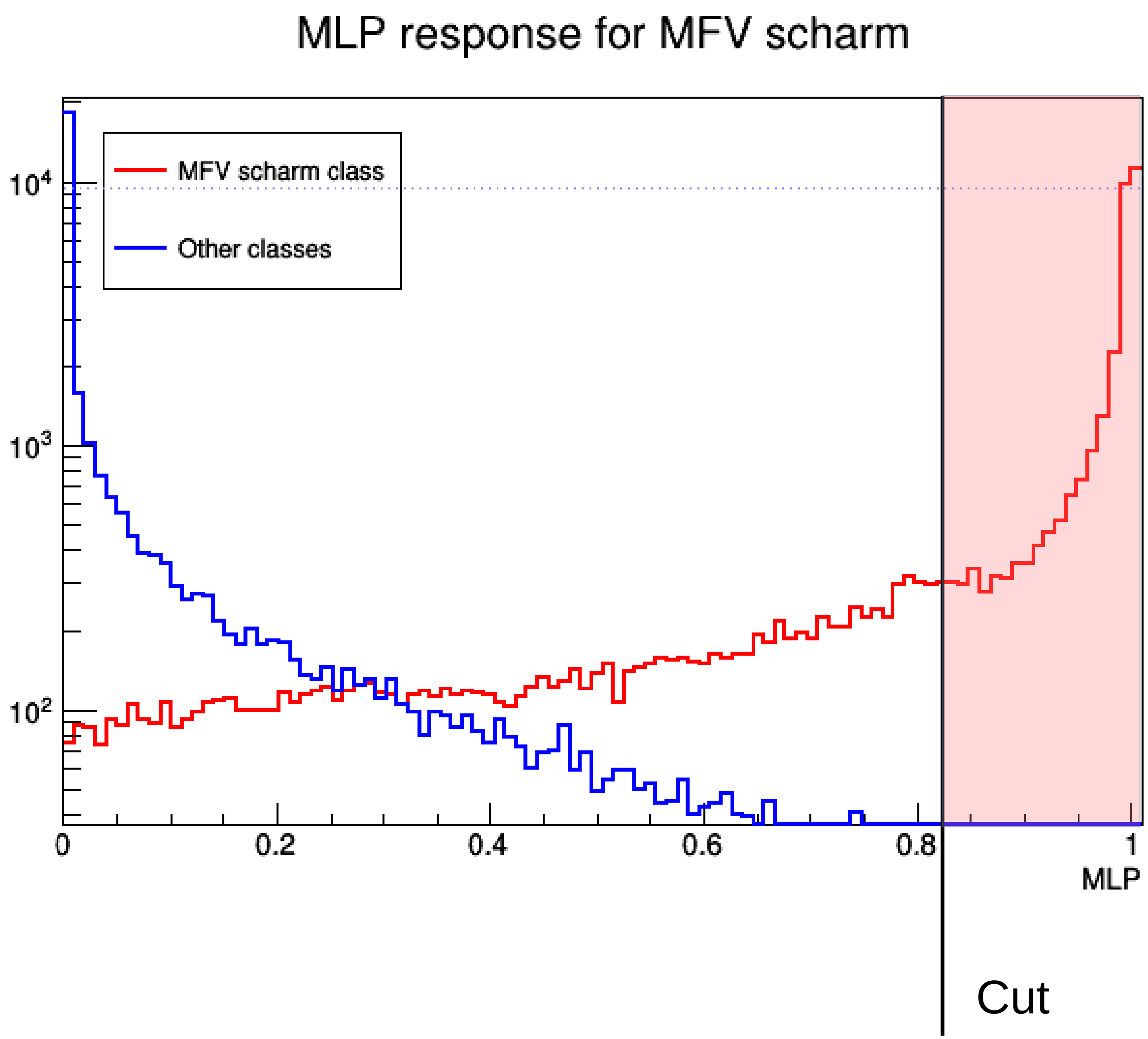








Selected results

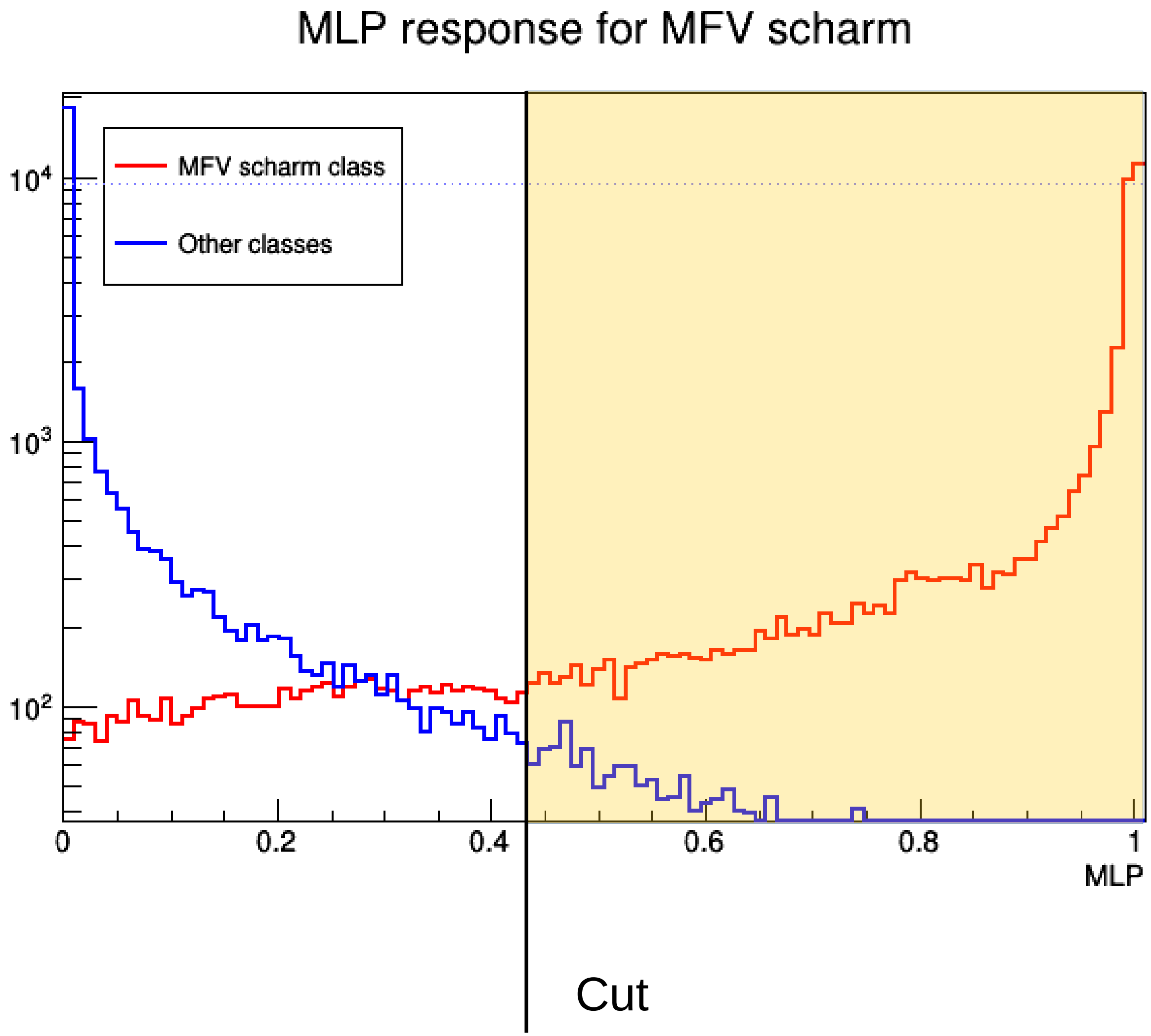


Classification characteristics

Misidentification rate = 1 %

Efficiency = 72 %

Selected results

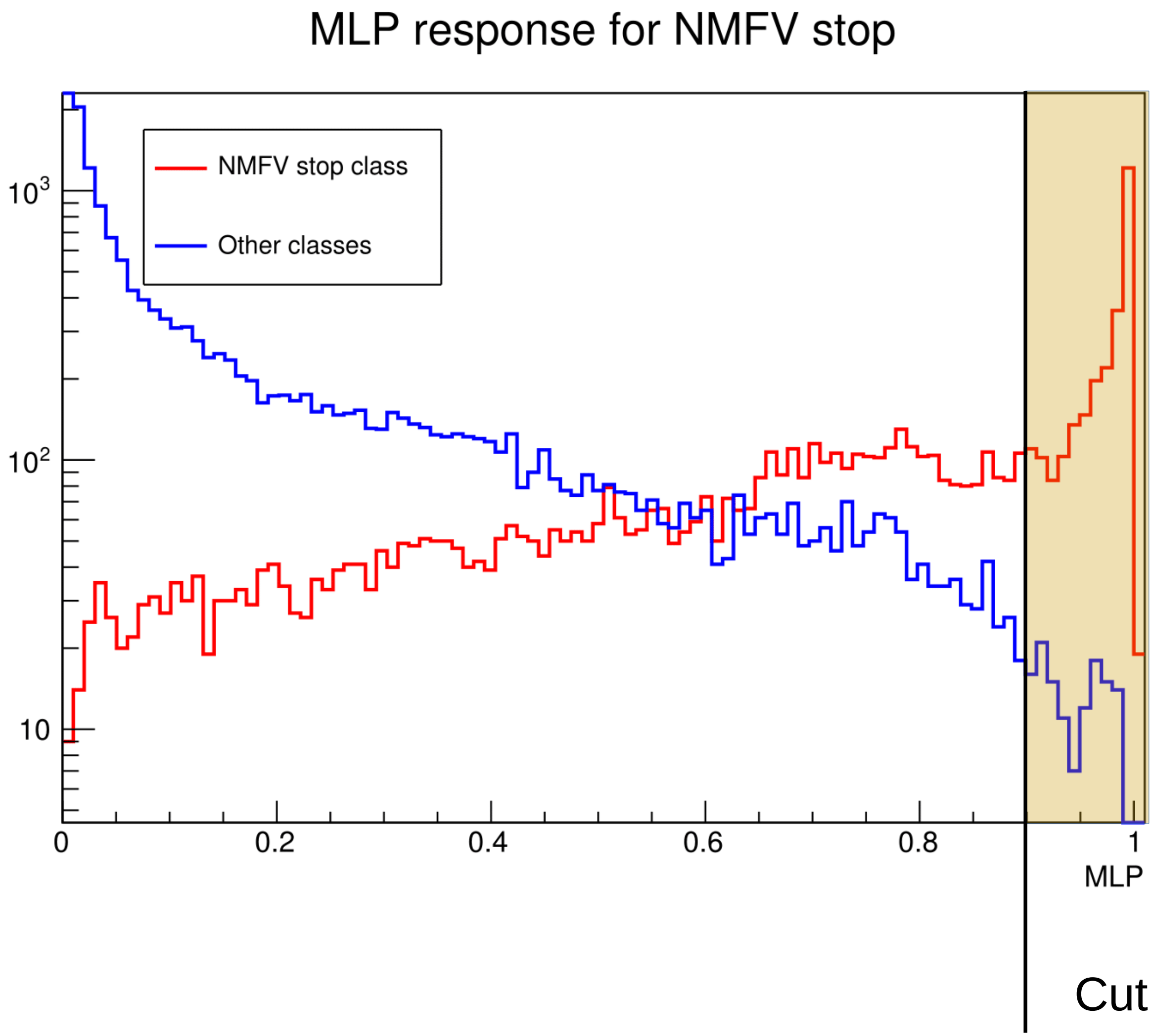


Classification characteristics

Misidentification rate = 5 %

Efficiency = 89 %

Selected results

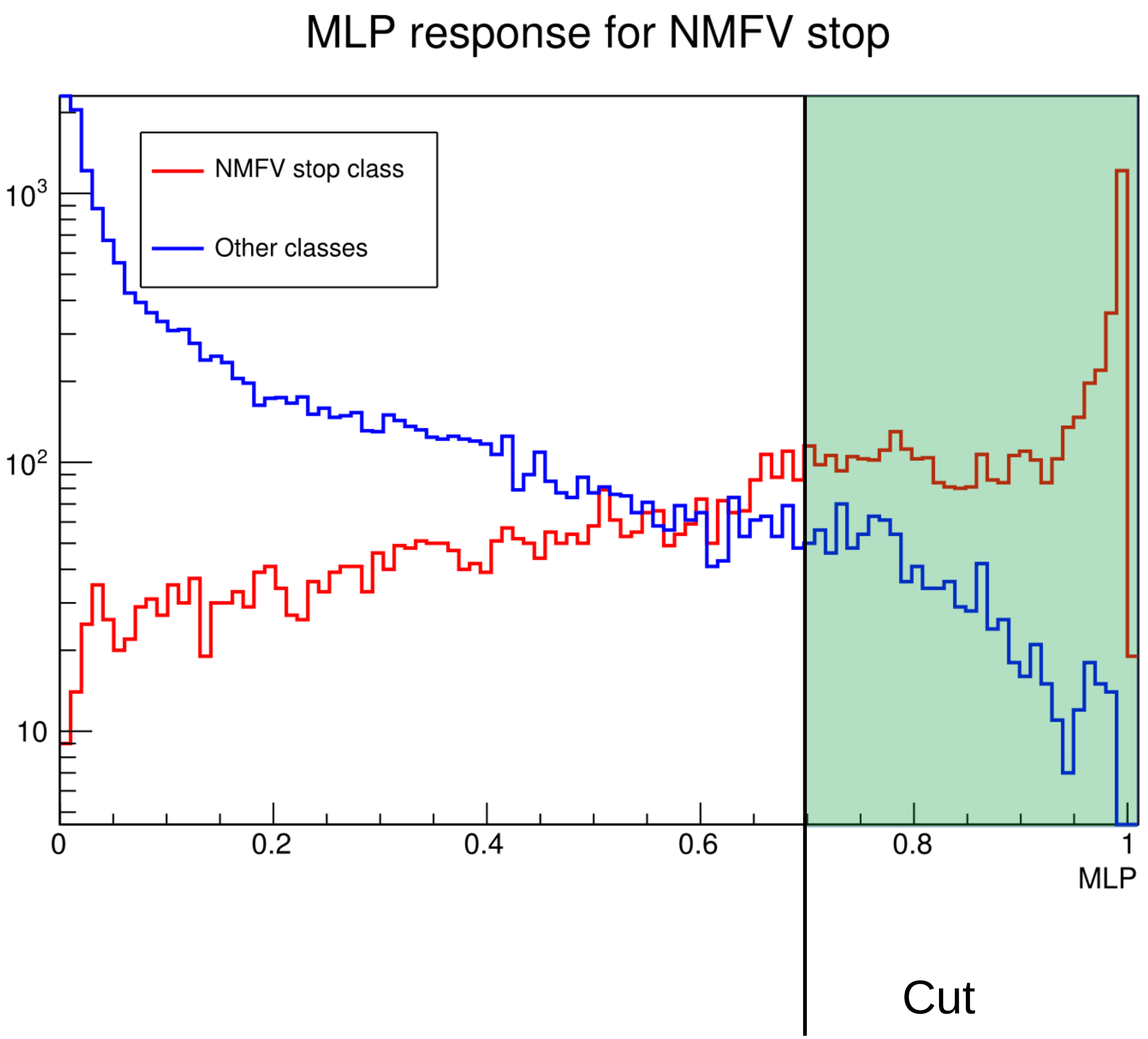


Classification characteristics

Misidentification rate = 5 %

Efficiency = 34 %

Selected results

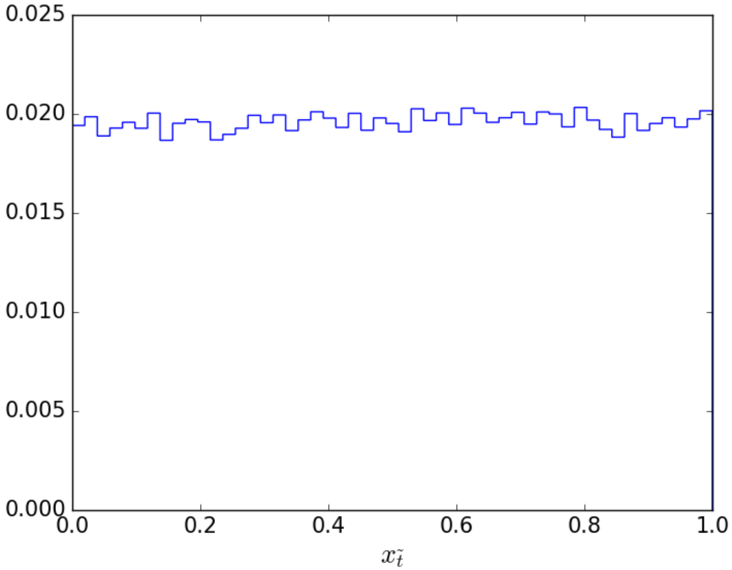


Classification characteristics

Misidentification rate = 20 %

Efficiency = 57 %

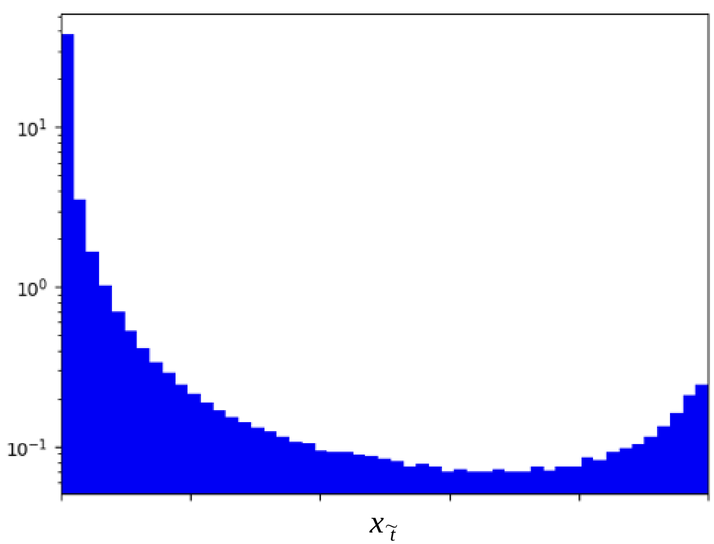
Comparison of methods on the samples



Simplified Scan

Likelihood inference :
Works well !

MLP :
Works but less efficient



MCMC Data base

Likelihood inference :
Doesn’t work ?

MLP :
Works pretty well

Conclusion

It might be difficult to reconstruct the flavour structure of squarks at LHC … We investigated 3 different methods :

Direct reconstruction

- Gives good results

BUT

- Needs a lot of observables
- Needs a too good precision

Likelihood inference

Interesting but not adequate for the present MCMC database

MVA

- Gives results
- Does not need so many information

BUT

- Difficult to handle uncertainties
- Difficult to understand the physics

→ The most appealing ?

We are still investigating this and a lot of things can/should be done :

Better understand behaviour, try new priors, new observables, custom algorithms, test with different categories etc.