

UCSB

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*with*

SLAC

**Philip Schuster**

Stanford

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**MARMOSSET @ CMS**



Hep-ph/0703088 (N.Arkani-Hamed et al.)

Talks given at the CMS week 12/12/07

P. Schuster:

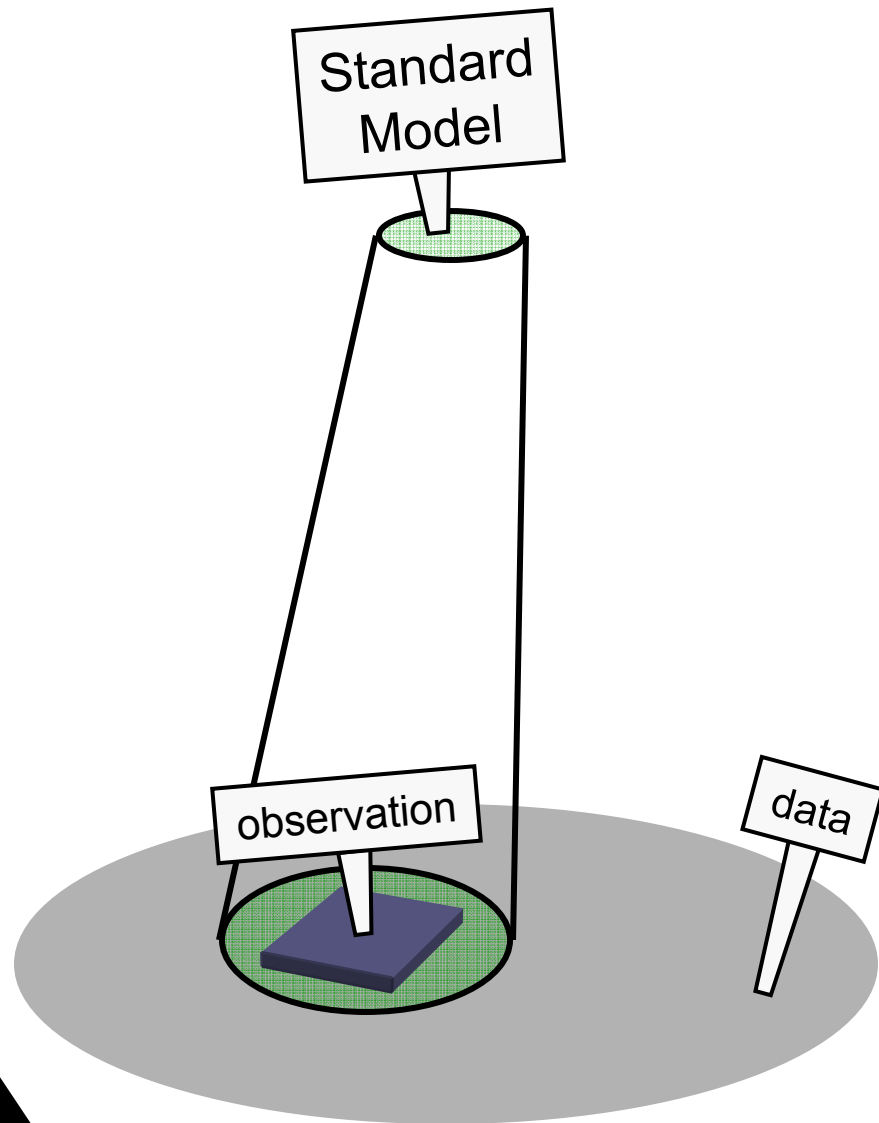
Preparing for new physics at the LHC with On-shell  
Effective Theories

S.A. Koay:

A tale of two particles



# Present History



# of Physics searches

Specific predictions :

(e.g.  $tt \rightarrow bW$   $bW \rightarrow blv$   $blv$  , ...)

- topologies
- kinematics range
- distinguishing features

Analysis (the search)

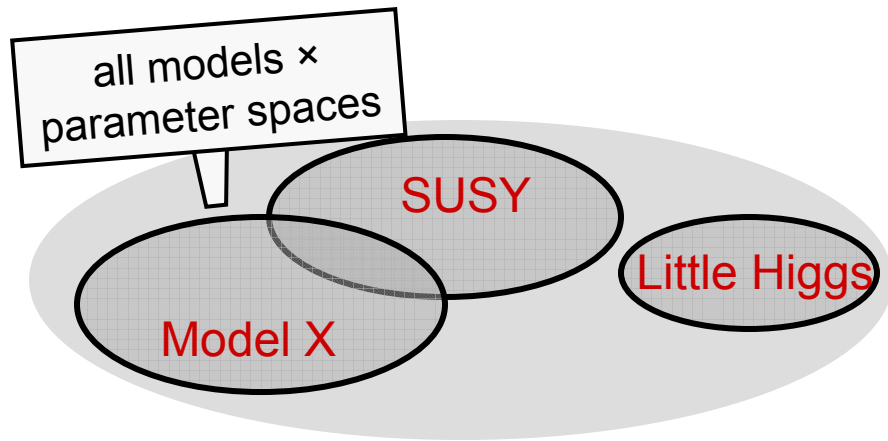
- cross-sections
  - masses
  - ...
- } fit {
- couplings  
...

# New-Physics searches

Interpretation?

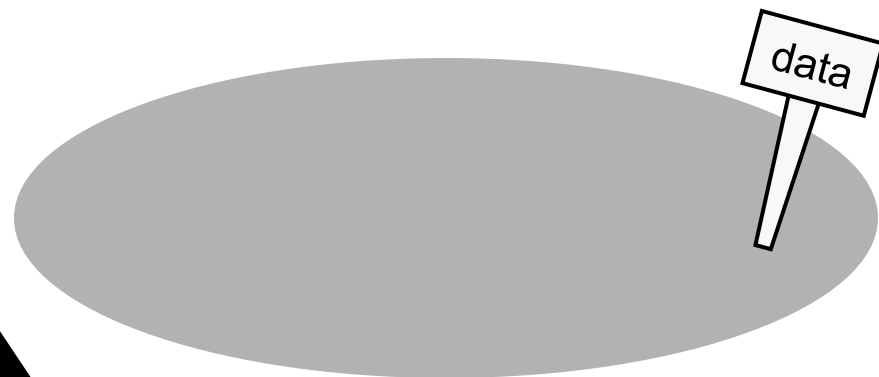
What next?

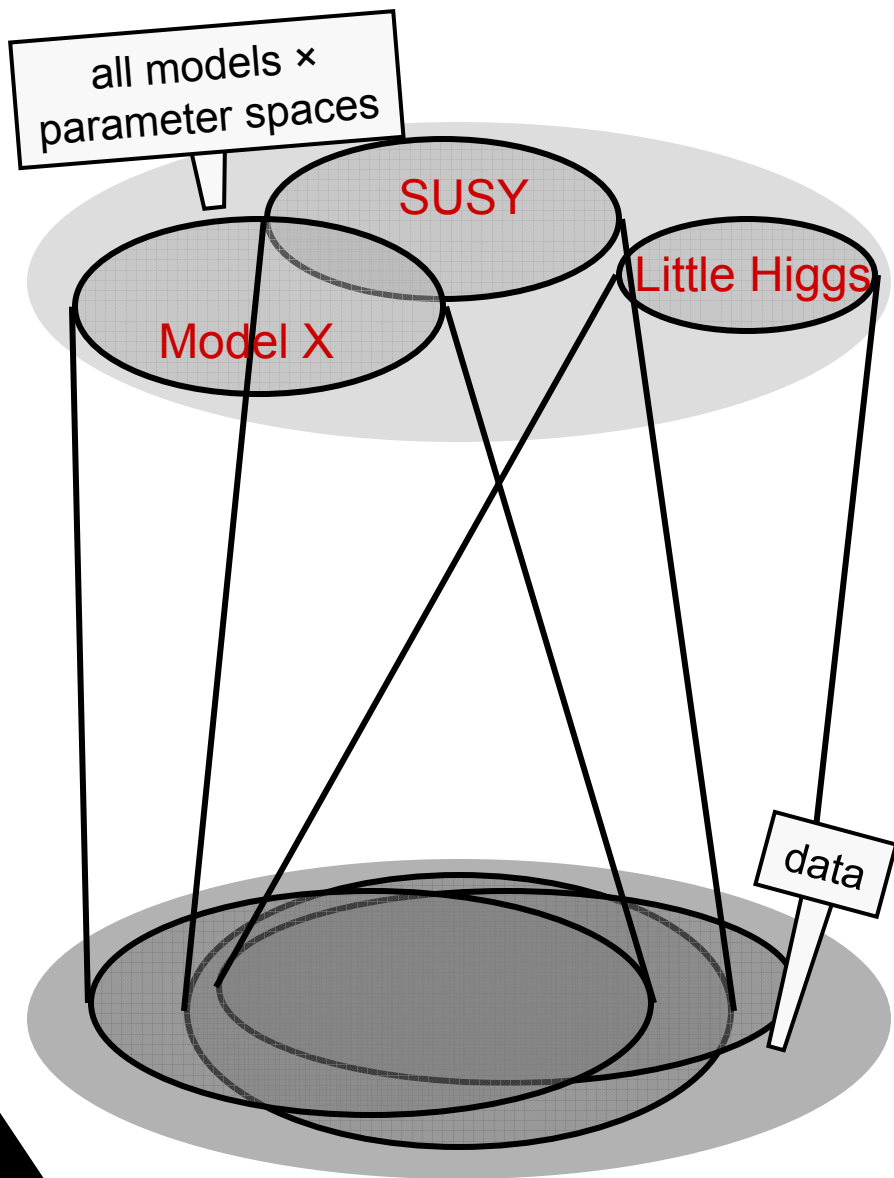




## New-Physics searches

BSM models  $\sim O(\infty)$





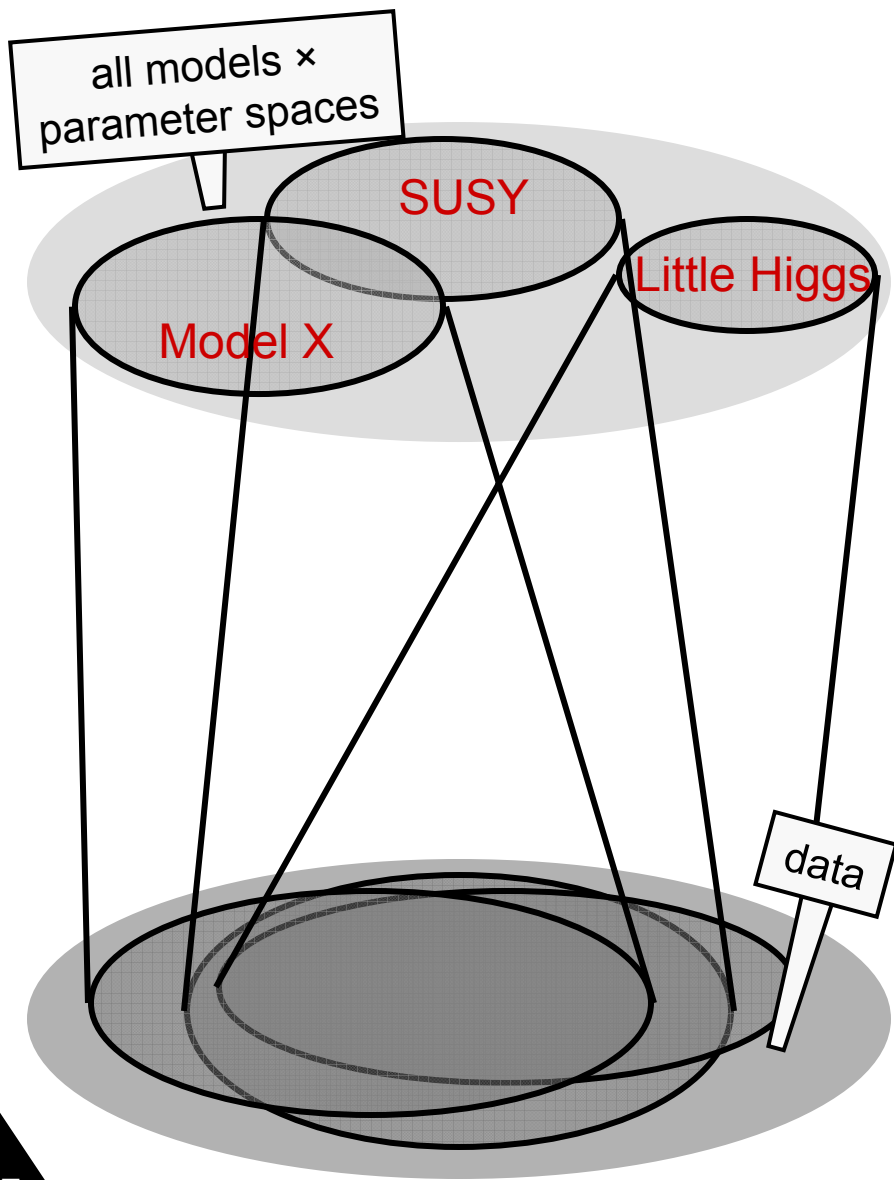
# New-Physics searches

BSM models  $\sim O(\infty)$

within model  
parameter  
space

across  
models

Large degeneracies in  
predictions for the LHC



## New-Physics searches

# Full scan:

BSM models  $\sim O(\infty)$

within model  
parameter  
space

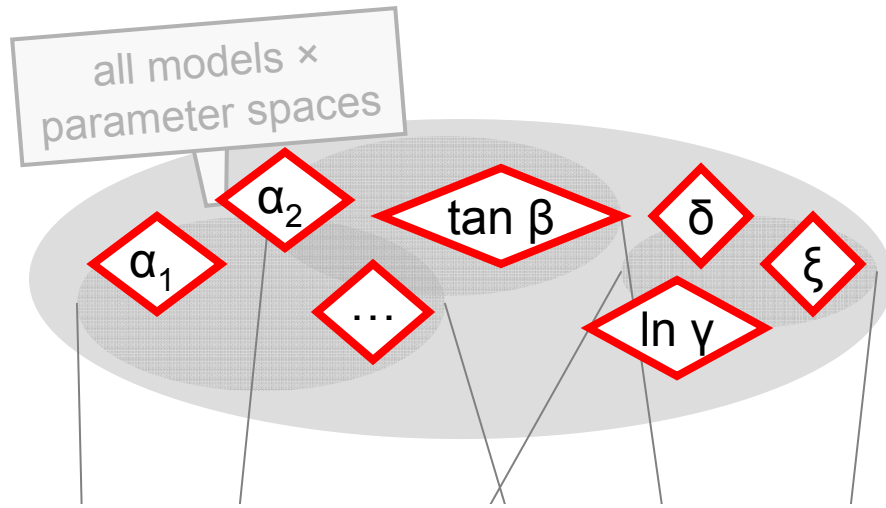
across  
models

predictions for the LHC

# Computationally daunting

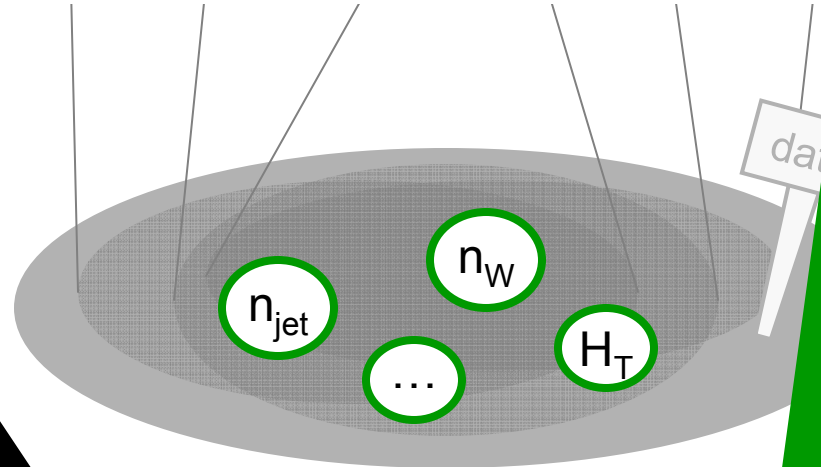
# New-Physics searches

Full Models



Intermediate characterization?

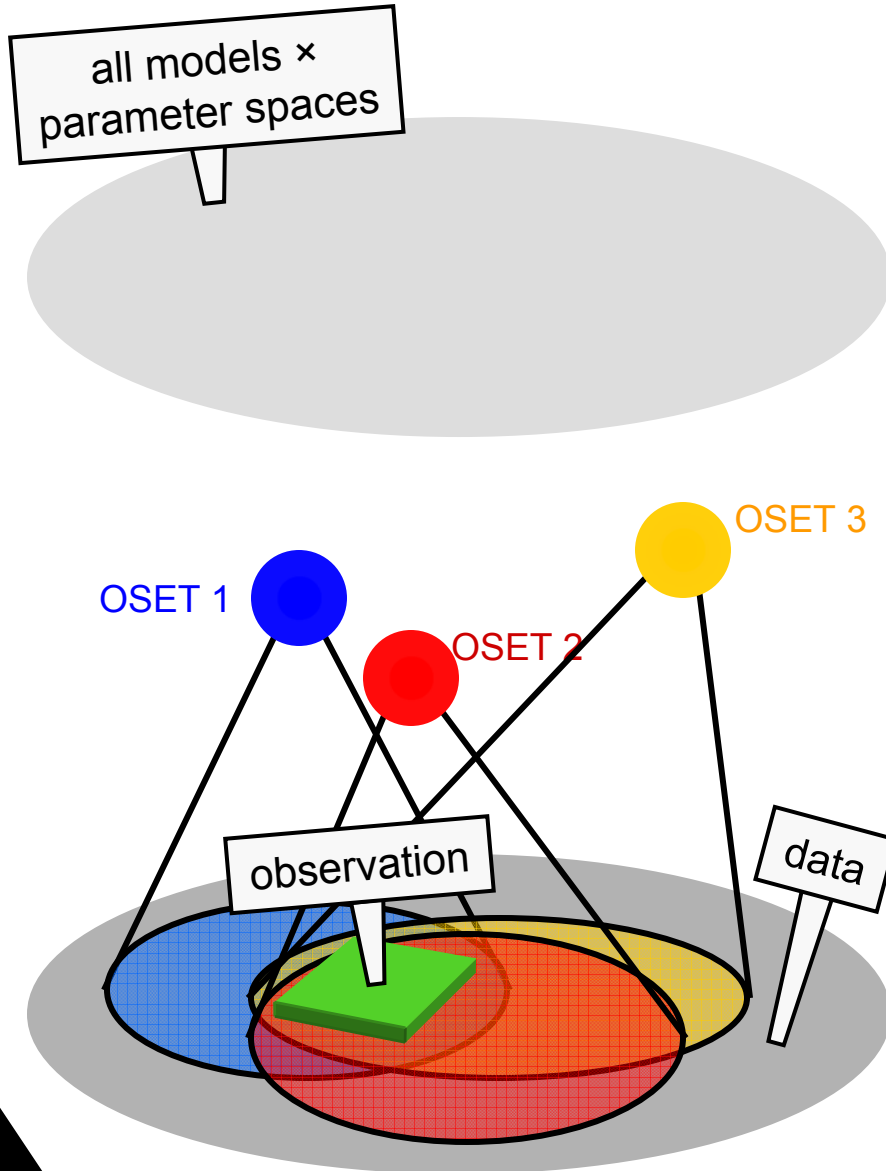
Pure-Experimental Observations





# OSETs

in New-Physics searches

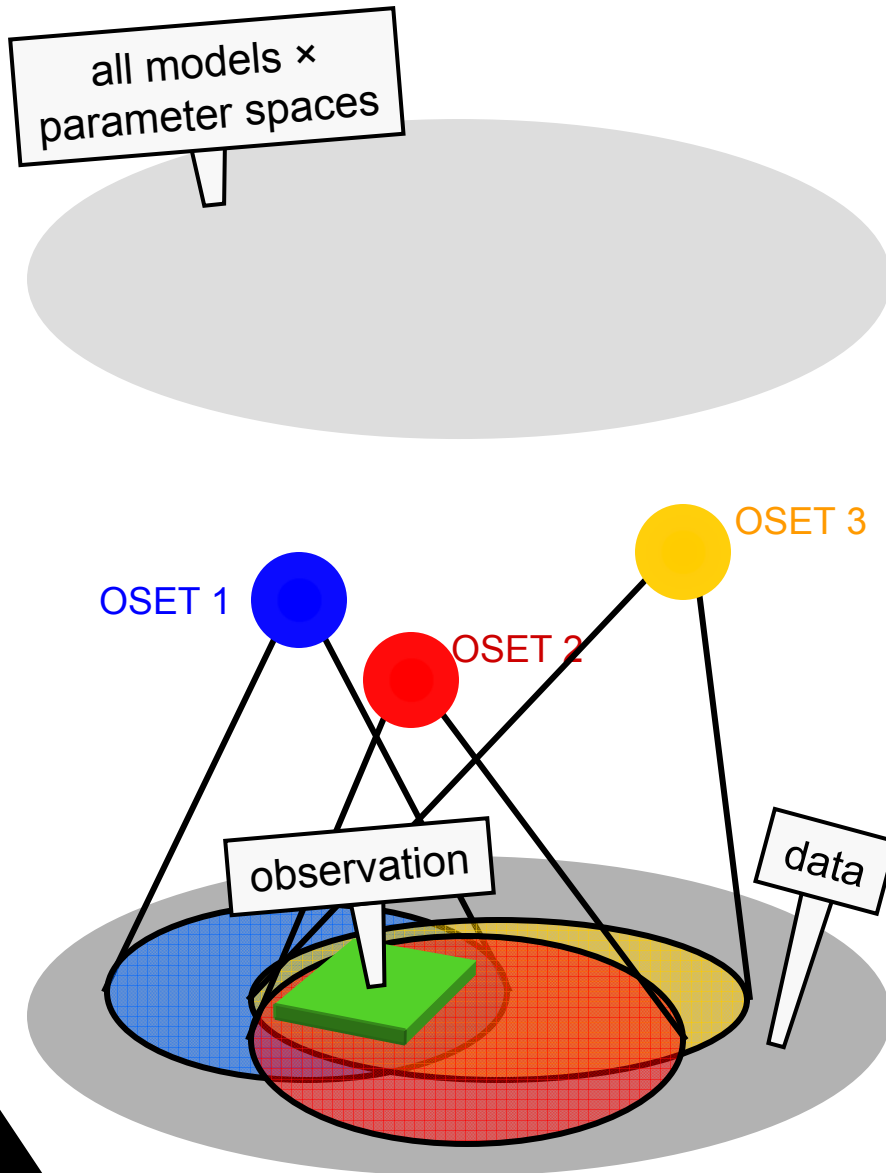


On-shell effective theory

OSETs  $\equiv$  observation-inspired skeleton models

# OSETs

in New-Physics searches



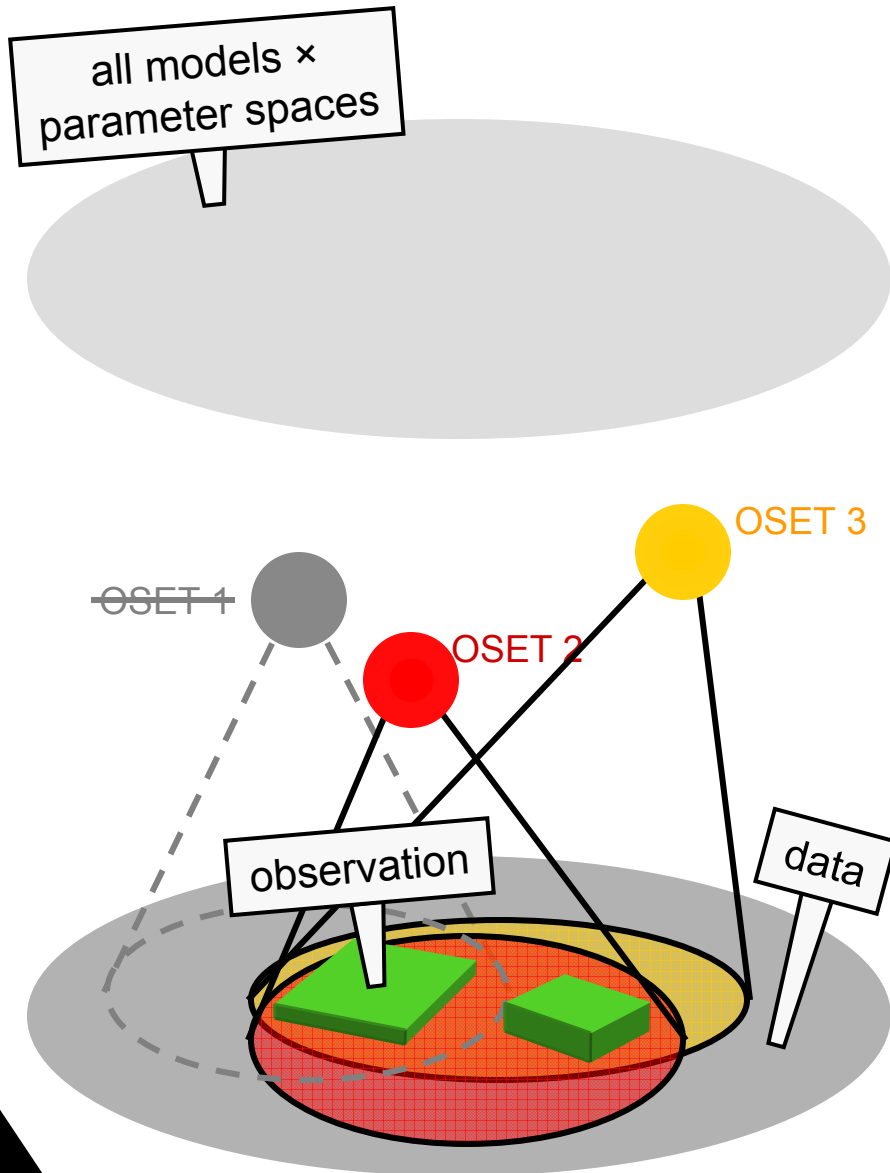
on-shell effective theory

OSETs  $\equiv$  observation-inspired skeleton models

Still with predictive power

# OSETs

in New-Physics searches



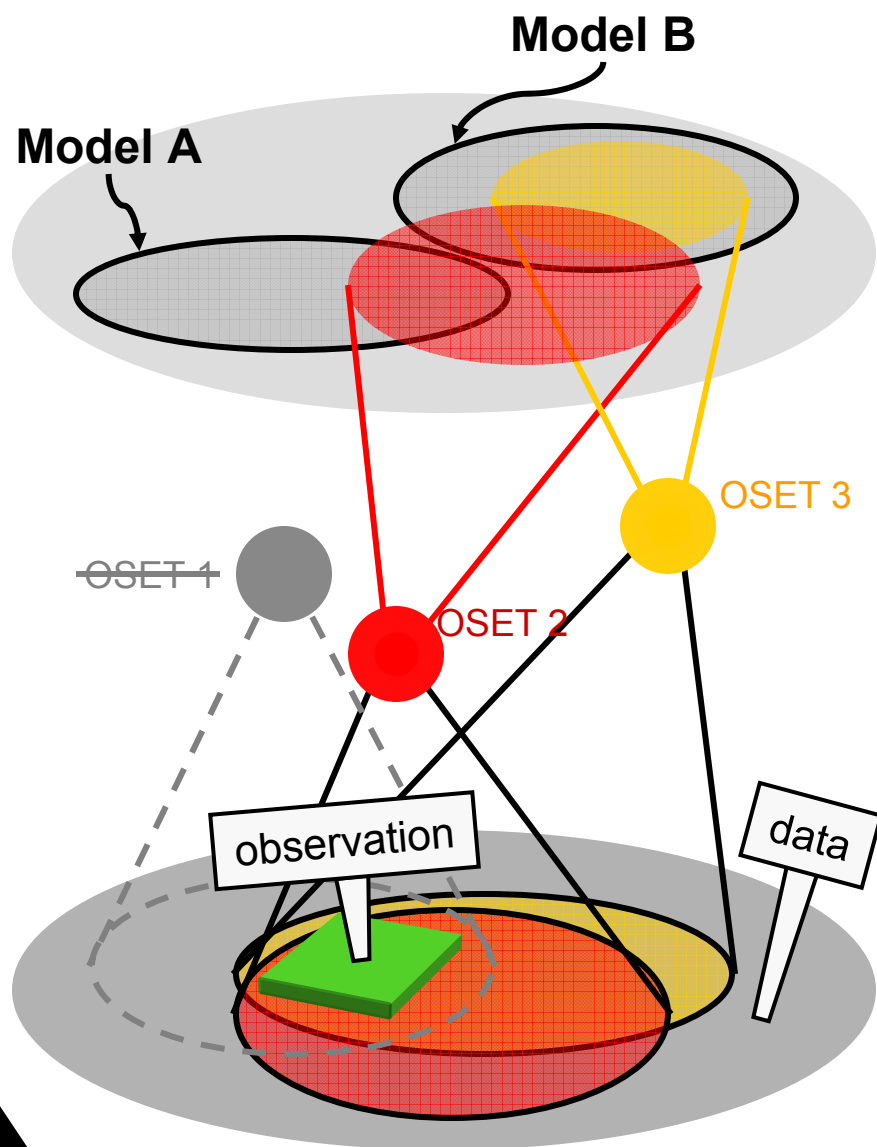
Summaries of  
(part of) full models

*non-hell effective theory*

O S E T s  $\equiv$   
observation-inspired  
skeleton models

Still with predictive power

# OSETs



in New-Physics searches

Summaries of  
(part of) full models

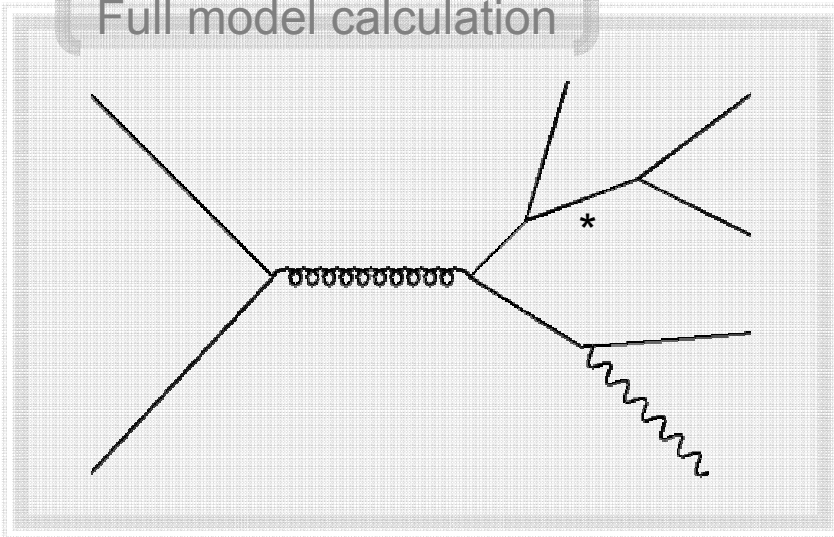
*on-shell effective theory*

OSETs ≡  
observation-inspired  
skeleton models

Still with predictive power

$$\frac{d\sigma}{d\hat{t}} = \int \text{Parton Luminosity} \times \text{Phase Space (Threshold)} \times |\mathcal{M}|^2$$

Full model calculation



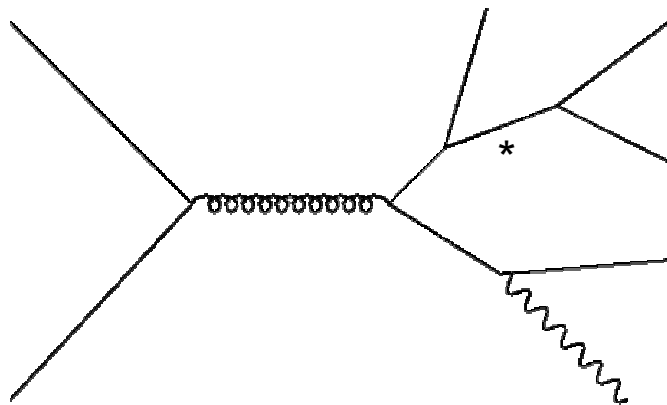
- spins
- couplings
- off-shell states
- ...

# OS Effective Theories

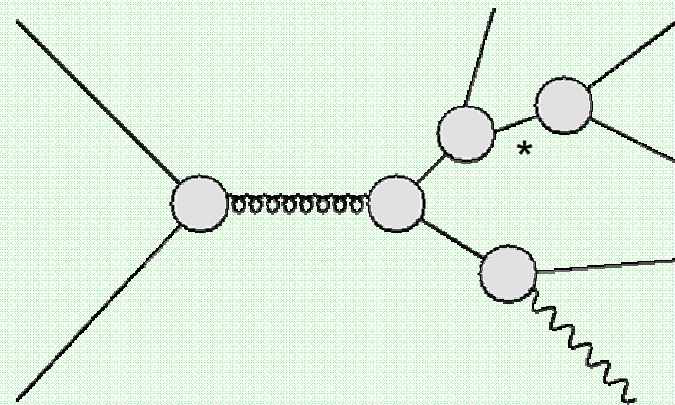
the language

$$\frac{d\sigma}{d\hat{t}} = \int \text{Parton Luminosity} \times \text{Phase Space (Threshold)} \times |\mathcal{M}|^2 \sim \text{constant}$$

Full model calculation



Parameterization



spins  
couplings  
off-shell states  
...

branching ratios

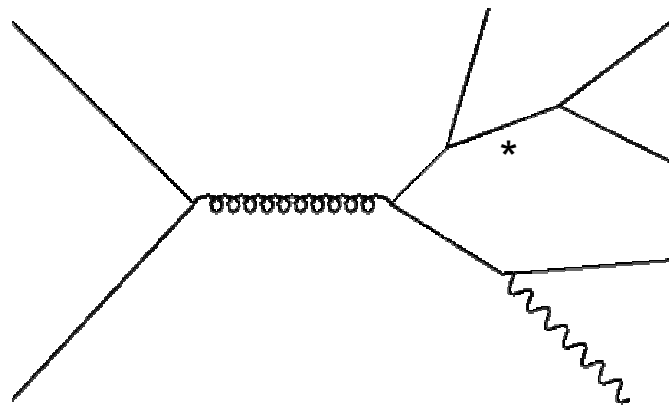
# On-Shell Effective Theories

the language

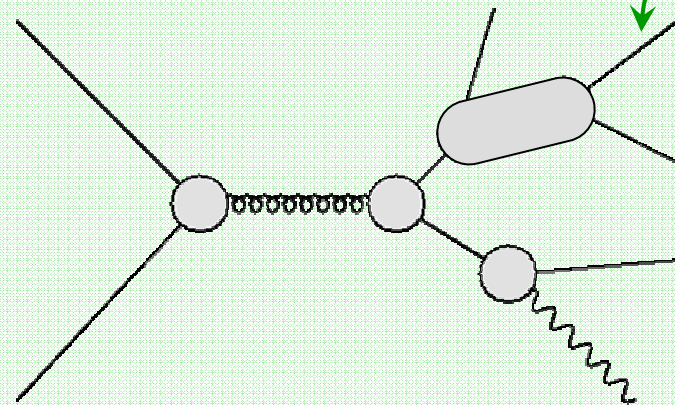
$$\frac{d\sigma}{d\hat{t}} = \int \text{Parton Luminosity} \times \text{Phase Space (Threshold)} \times |\mathcal{M}|^2 \sim \text{constant}$$

all lines on-shell

Full model calculation



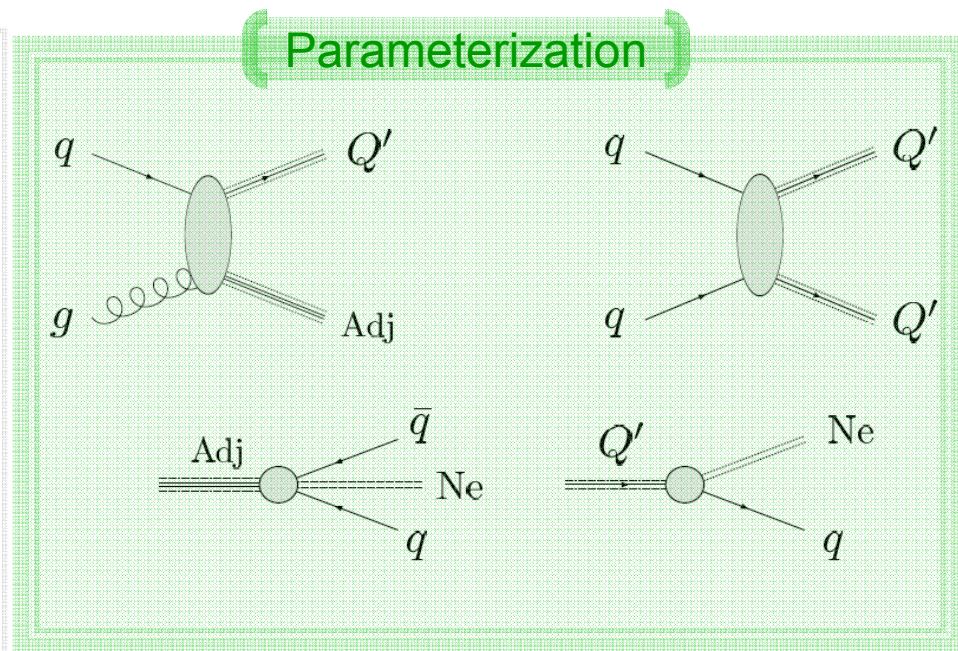
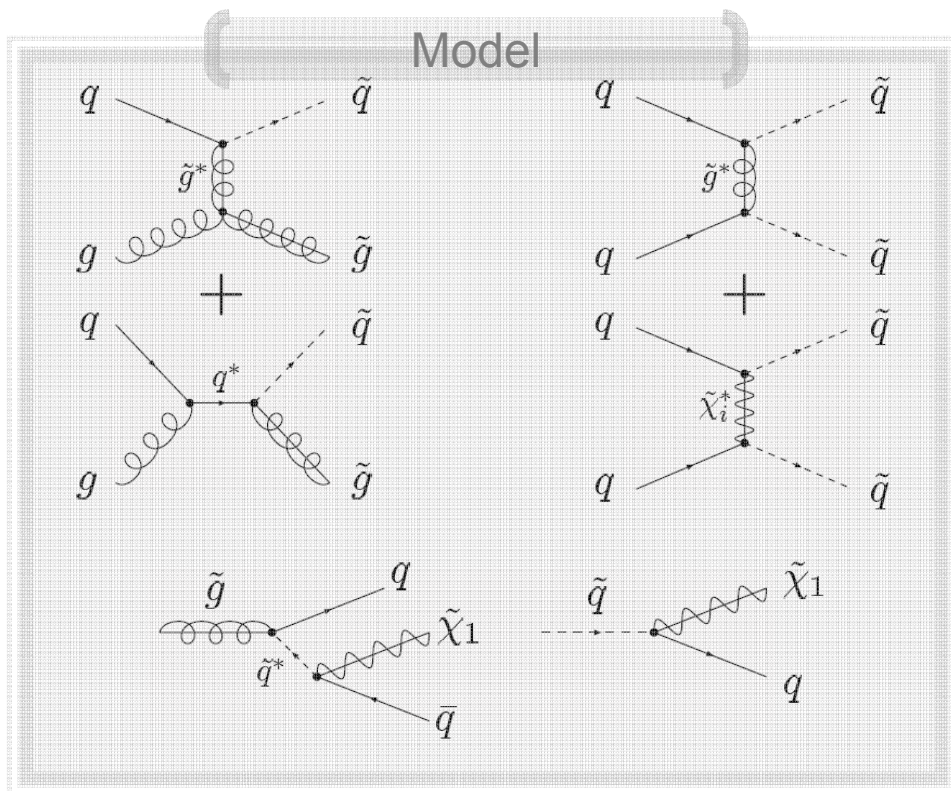
Parameterization



- spins
- couplings
- off-shell states
- ...

branching ratios

# A SUSY example



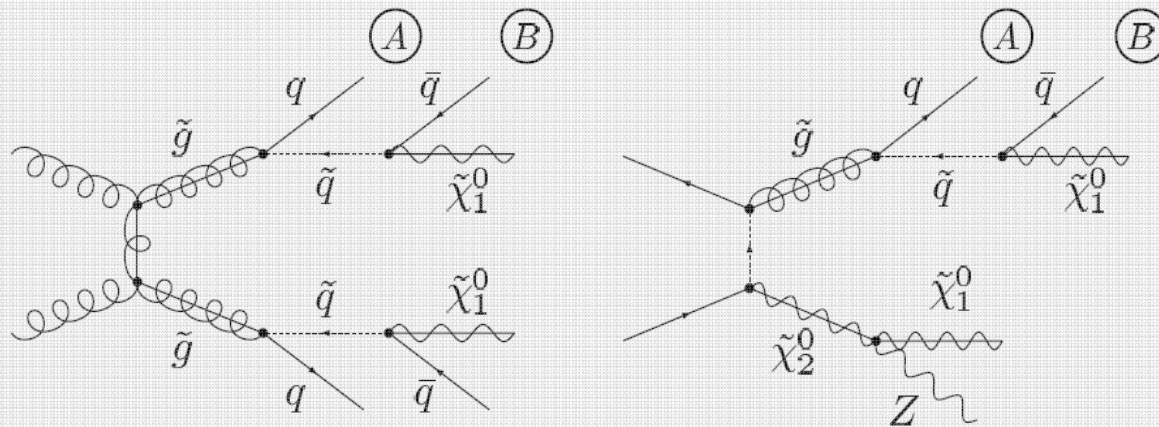
- on- and off-shell masses
- several couplings
- control both kinematics and rates

- Production contributions:  
Associated  $\tilde{q}$ - $\tilde{g}$ : intermediate  $q$  and  $\tilde{g}$   
Same sign  $\tilde{q}$ :  $g$  and 4 neutralinos

- “blobs” represent dynamics that are parameterized by one rate and possibly an additional shape parameter
- Off-shell particles do not appear, their effects are present in the rates
- gauginos do not appear in the OSET



# Another SUSY example



Particle	Mass (GeV)
$\tilde{g}$	992
$\tilde{q}$	700
$\tilde{\chi}_2^0$	197
$\tilde{\chi}_1^0$	89

$$|\mathcal{M}(gg \rightarrow \tilde{g}\tilde{g})|^2 \propto \left(1 - \frac{t_g u_g}{s^2}\right) \left[ \frac{s^2}{t_g u_g} - 2 + 4 \frac{m_{\tilde{g}}^2 s}{t_g u_g} \left(1 - \frac{m_{\tilde{g}}^2 s}{t_g u_g}\right) \right]$$

$$|\mathcal{M}(q\bar{q} \rightarrow \tilde{g}\tilde{g})|^2 \propto \left[ \frac{t_g^2 + m_{\tilde{g}}^2 s}{s^2} + \frac{4t_g^2}{9t_q^2} + \frac{t_g^2 + m_{\tilde{g}}^2 s}{st_q} + \frac{1}{18} \frac{m_{\tilde{g}}^2 s}{t_g u_g} + (t \leftrightarrow u) \right]$$

$$t_g = (p_{g,1} - p_{\tilde{g},1})^2 - m_{\tilde{g}}^2, \quad u_g = (p_{g,1} - p_{\tilde{g},2})^2 - m_{\tilde{g}}^2$$

$$t_q (u_q) = (p_{g,1} - p_{\tilde{g},1(2)})^2 - m_{\tilde{q}}^2$$

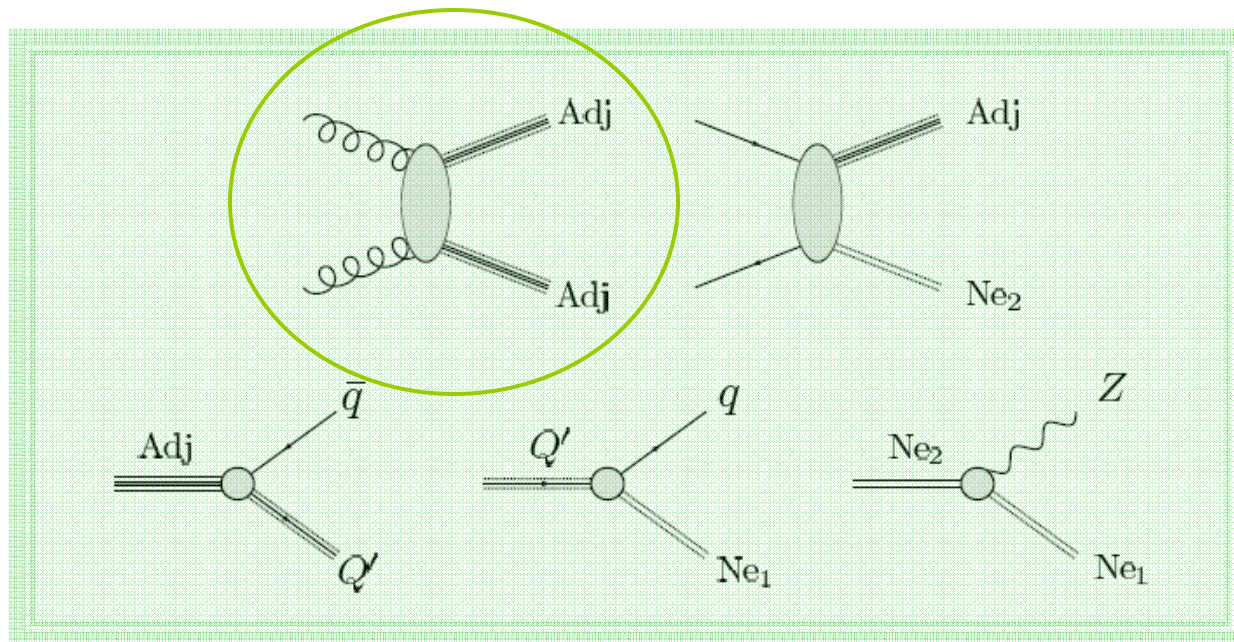
# Another SUSY example

How can we manage to approximate the ME?

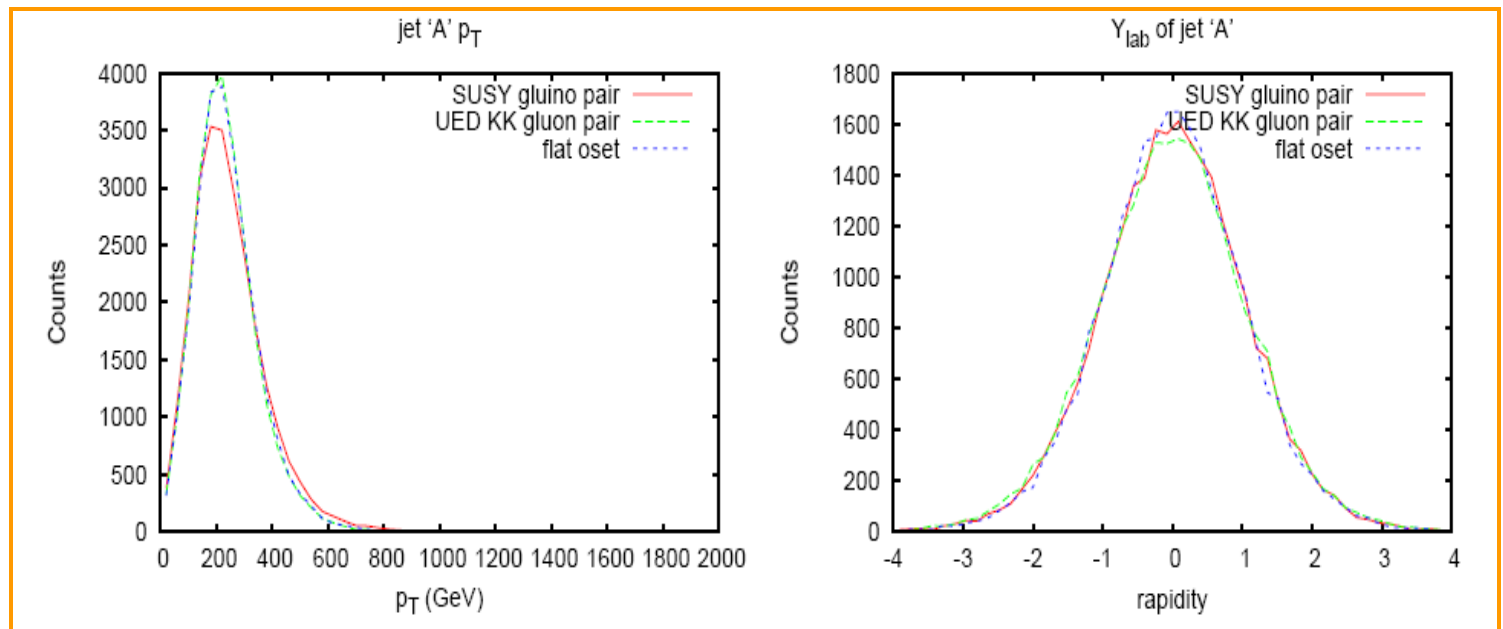
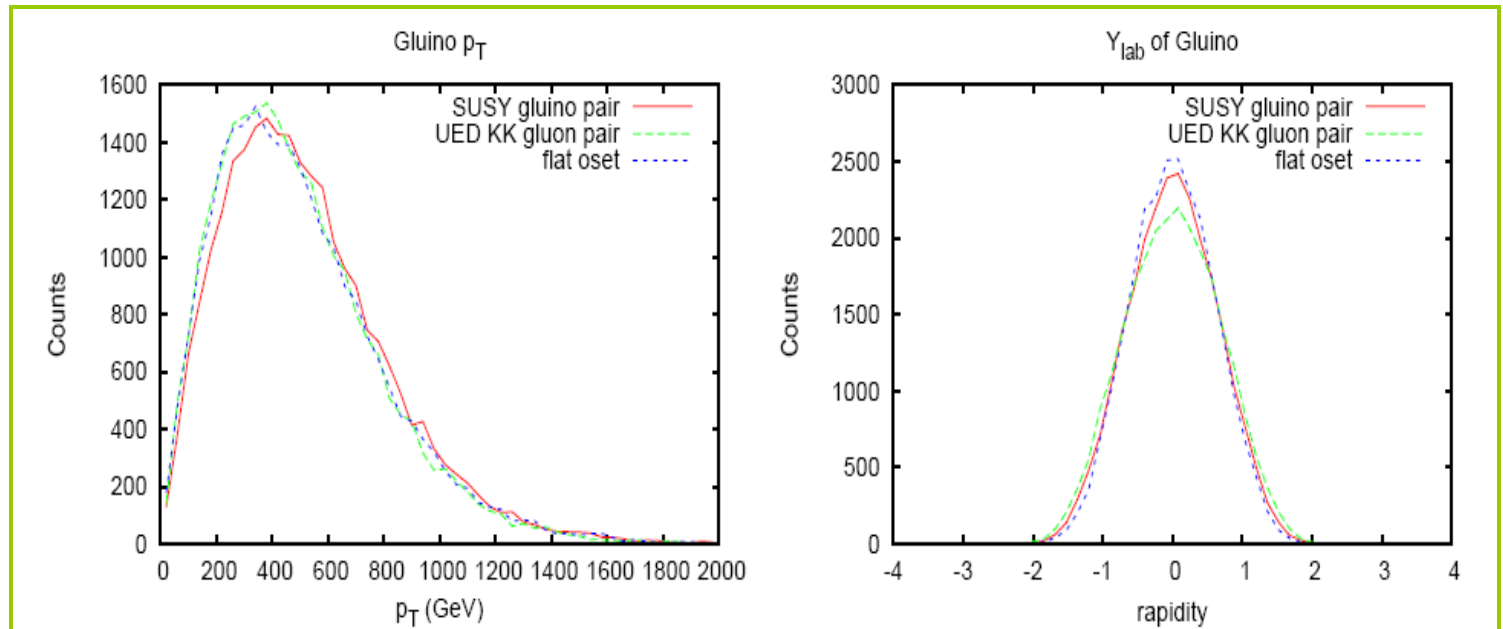
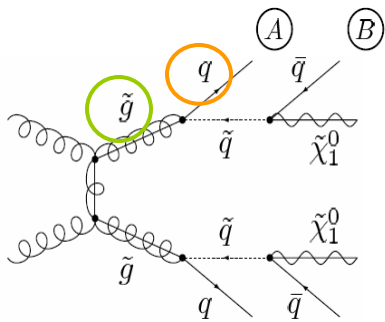
- If the matrix element  $|M|^2$  varies smoothly over energy,
- while parton luminosities fall rapidly about threshold

$$|\mathcal{M}|^2 = \text{constant}$$

reproduces well the kinematics of the hadron production  
This is indeed true for the **gluino** pair-production



# Another SUSY example



# Parametrization scheme

Introduce dimensionless energy and angular variables

$$\begin{aligned} \text{---} \bigcirc & X \equiv \hat{s}/s_0, \\ \text{---} \bigcirc & \xi \equiv \frac{\hat{t} - \hat{u}}{\hat{s}} = \beta_{34} \cos \theta^* \end{aligned}$$

$s_0$  is the minimum possible value of  $\hat{s}$

$b_{34}^2$  is the relative velocity of the products

$\theta^*$  is the scattering angle in the center-of-mass frame.

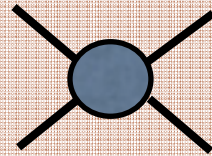
$\xi \propto$  z-component of momentum of the particles in the center-of-mass system

to parameterize corrections to constant  $|M|^2$ :

$$\text{---} \bigcirc \text{---} \sim |M|^2 = \sum_{p,q} C_{pq} X^p \xi^q$$

# Parametrization scheme

Near threshold one term of the expansion dominates:

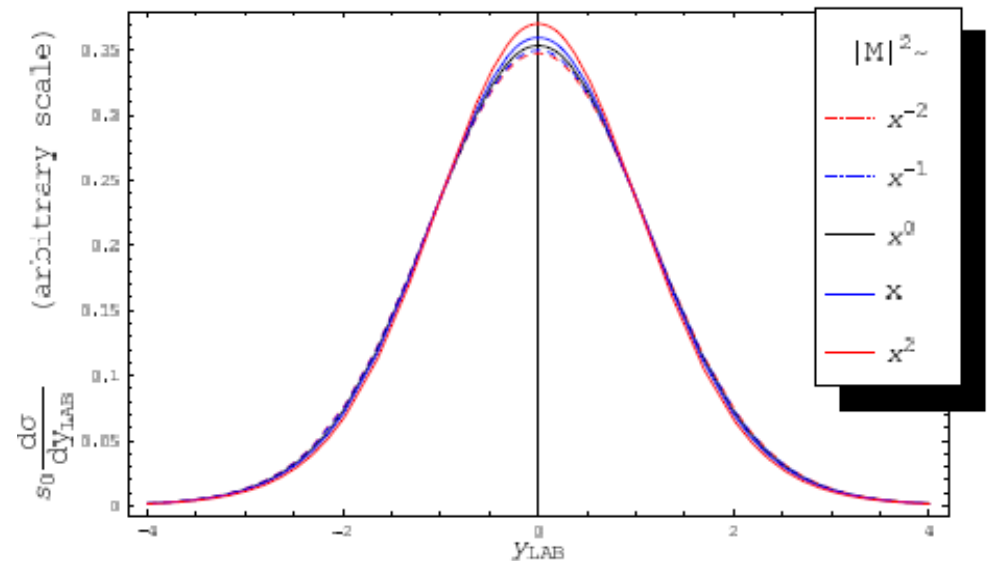
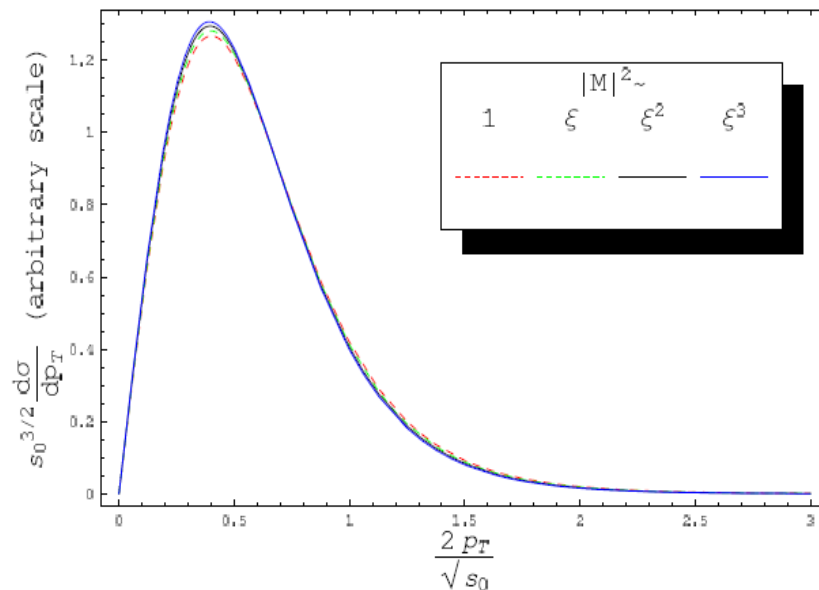


$$\sim |M|^2 \sim X^q \xi^p$$

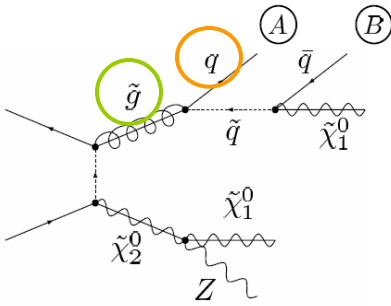
PDF  $E_{cm}$  and  $y_{cm}$   
homogeneity properties

Inclusive  $p_T$  shape invariant  
under  $X^q \xi^p \rightarrow X^q$   
Inclusive  $y_{lab}$  shape invariant  
under  $X^q \xi^p \rightarrow \xi^p$

$p=0$  usually dominates  
Cascade decays wash out dependence

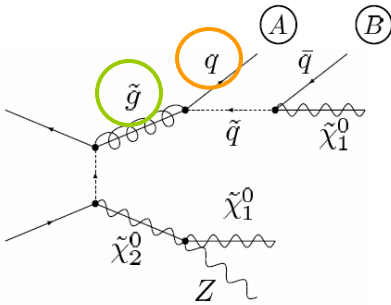
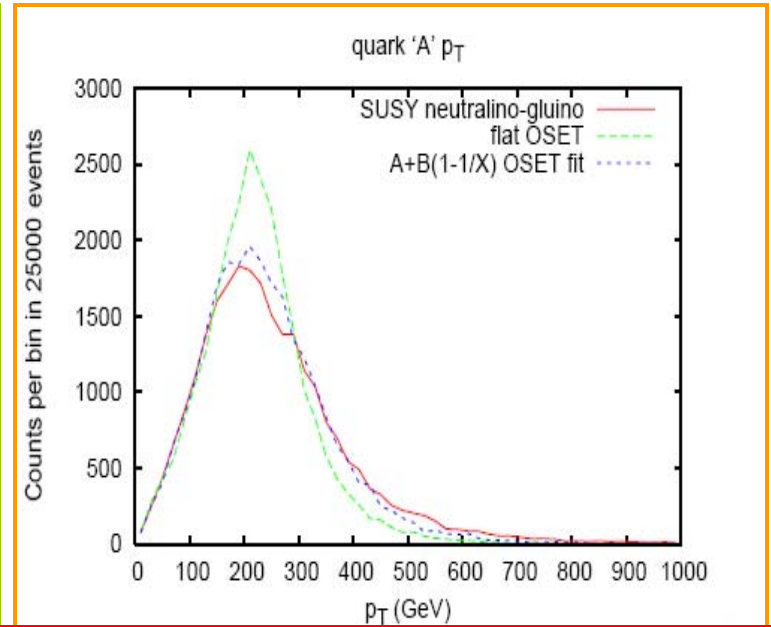
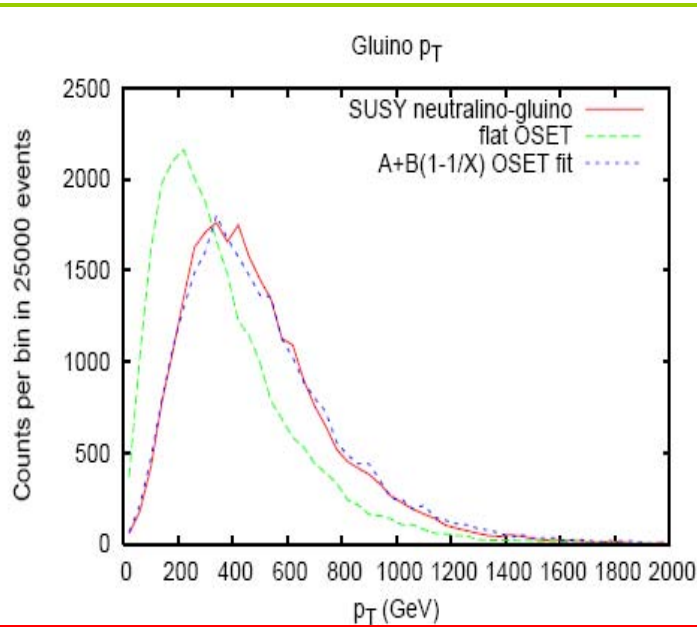


# Parametrization scheme



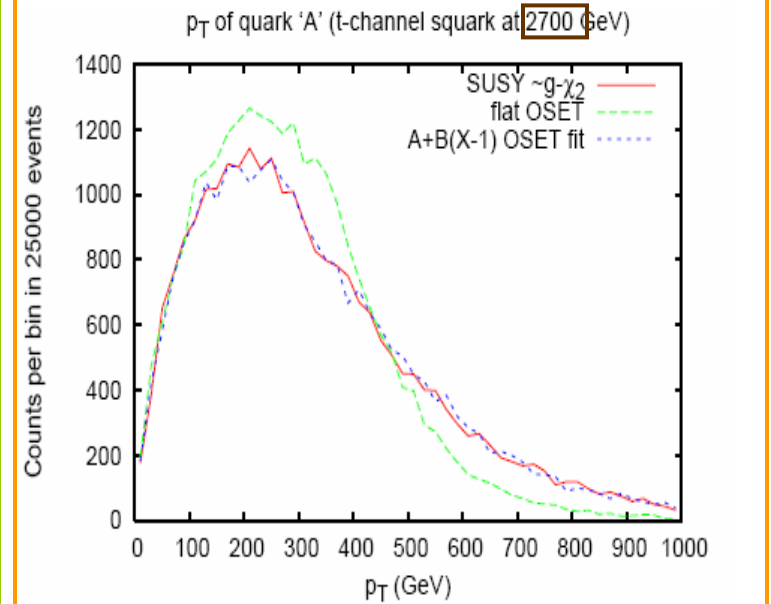
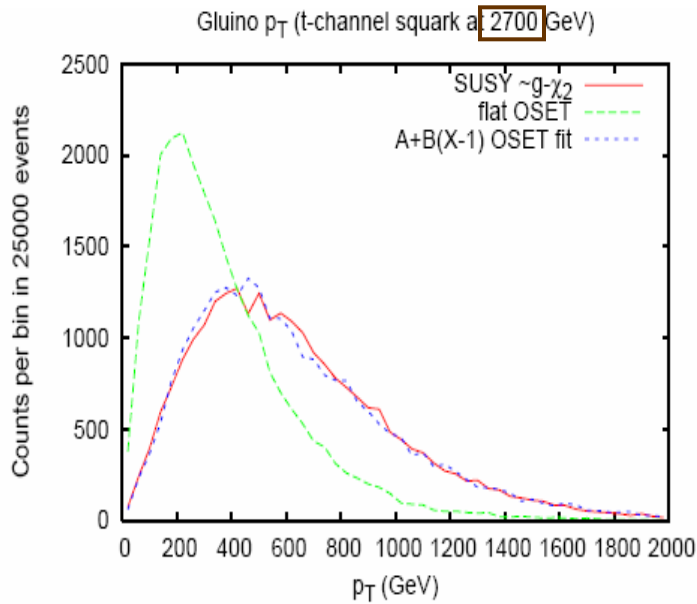
$$|\mathcal{M}|^2 \rightarrow A + B(1 - 1/X)$$

p-wave dominated



$$|\mathcal{M}|^2 \rightarrow A + B(X - 1)$$

Contact interaction



MARMOSSET is a Pythia based Monte Carlo tool which implements the parametrization in  $X$  and  $\xi$  variables

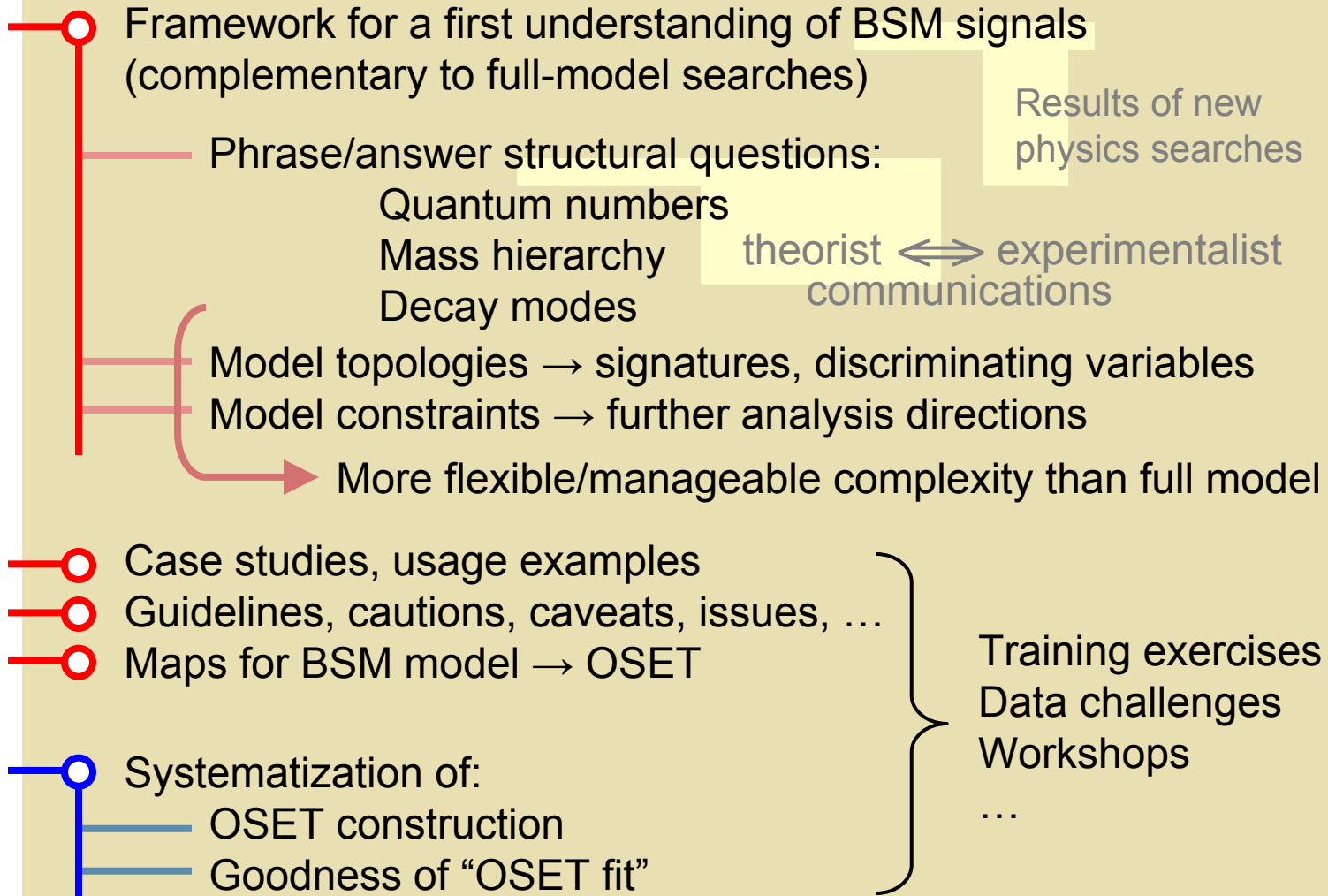
In this framework an OSET is defined by:

- A spectrum of new particles w/ given masses
- The  $U_{EM}(1)$  and  $SU_C(3)$  gauge quantum numbers
- Observable production and decay modes  
In terms of on-shell particles
- A parametrized ME  $|M|^2$  for each vertex

→ BLOBS

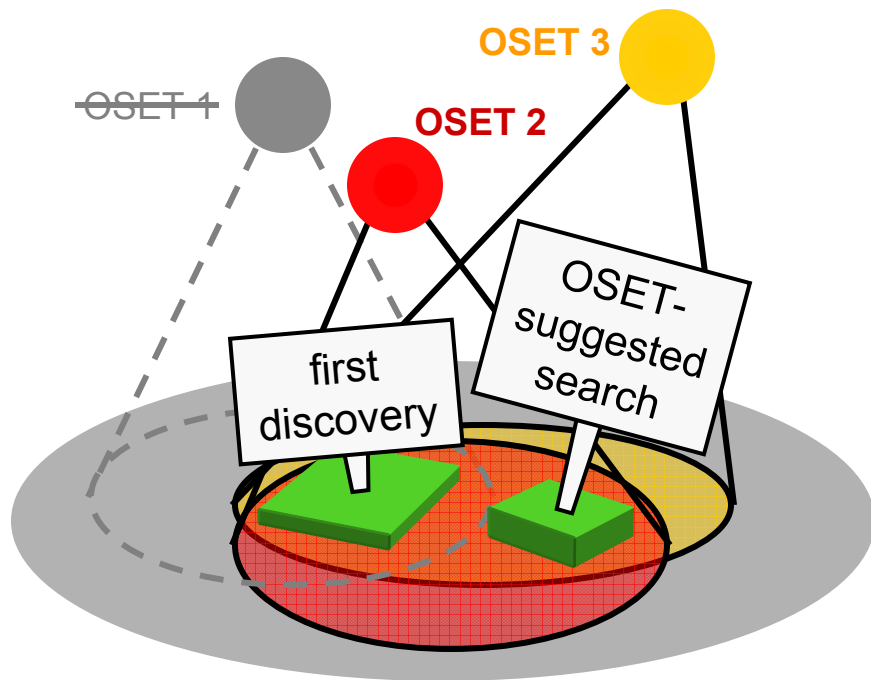
- $2 \rightarrow 1$  Resonant production
- $2 \rightarrow 2$  Pair or associated production
- $2 \rightarrow 3$  Production
- $1 \rightarrow n$  Decay



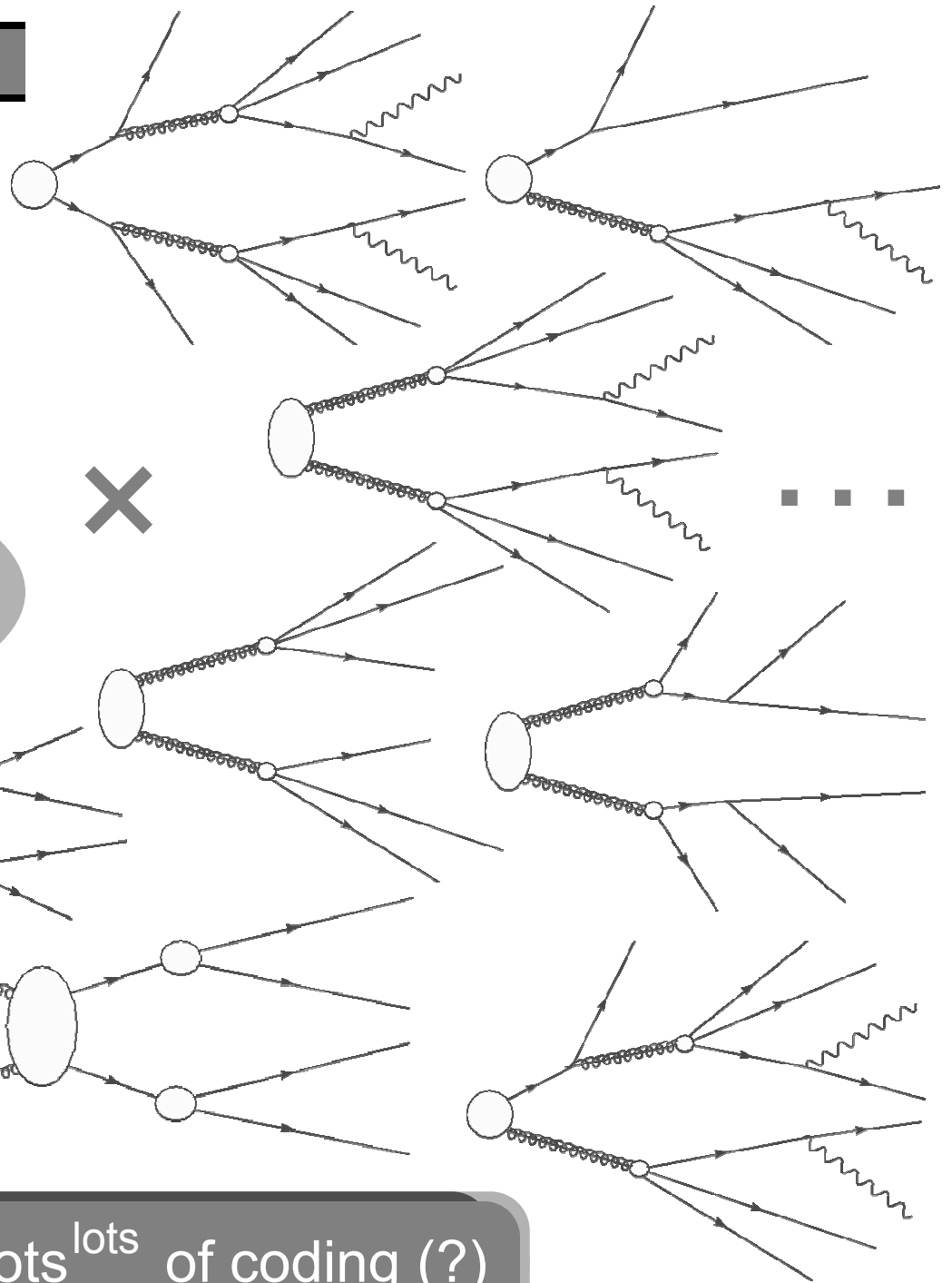
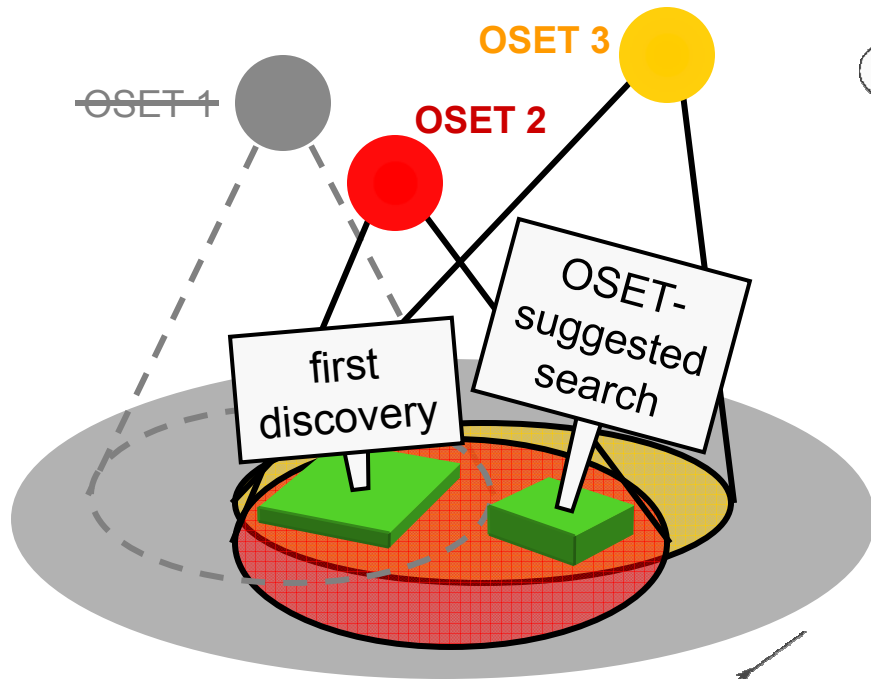




# OSETs in new-physics analyses



# OSETs in new-physics analyses



= lots<sup>lots</sup> of coding (?)

# The Monte-Carlo

“ scripting language ”

Quantum numbers / mass

New particle

```
duplo : charge=0 color=0 mass=800
```

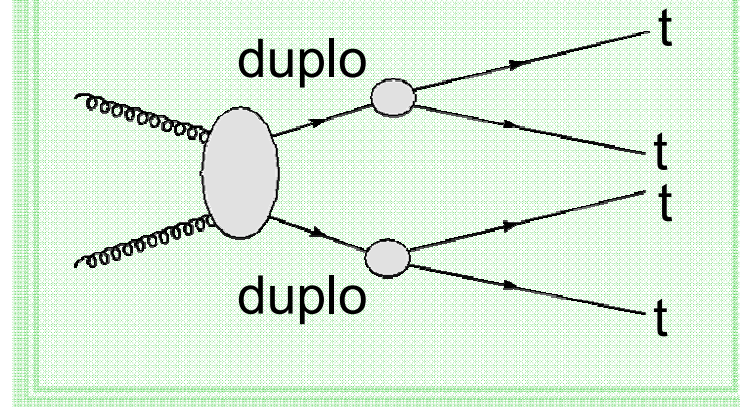
Decay mode

```
duplo > t tbar
```

Production mode

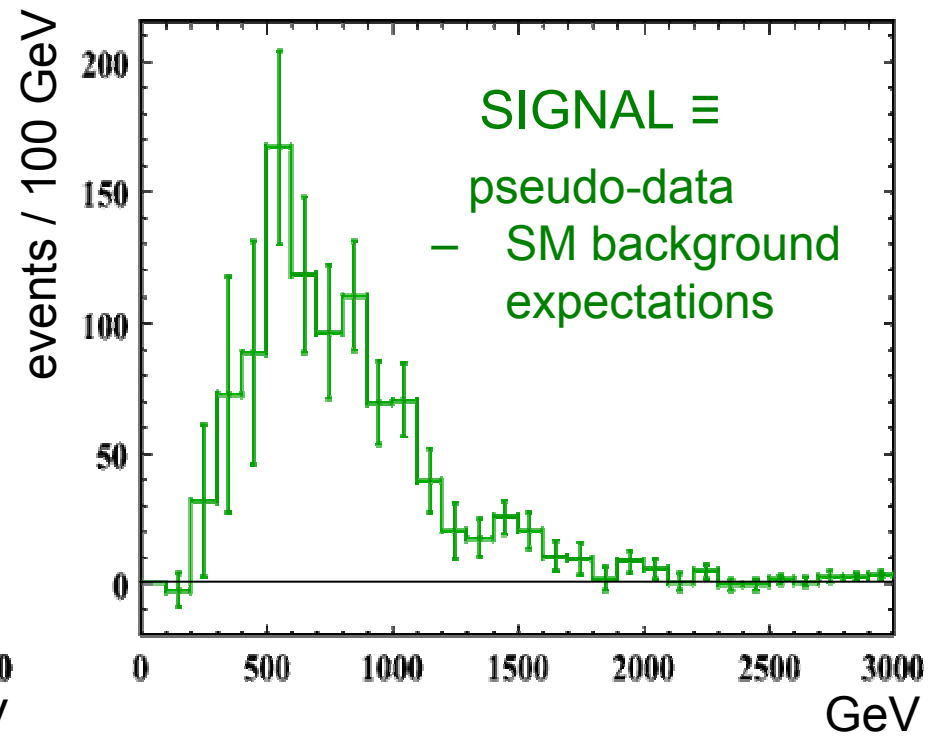
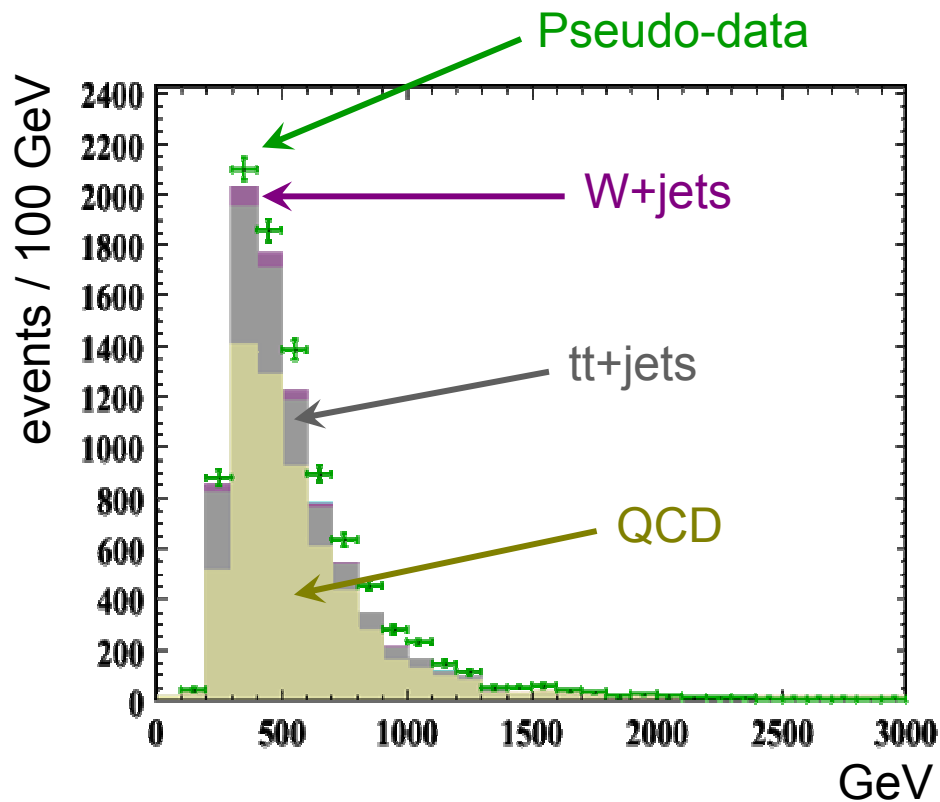
```
g g > duplo duplo : matrix 1
```

OSET hypothesis



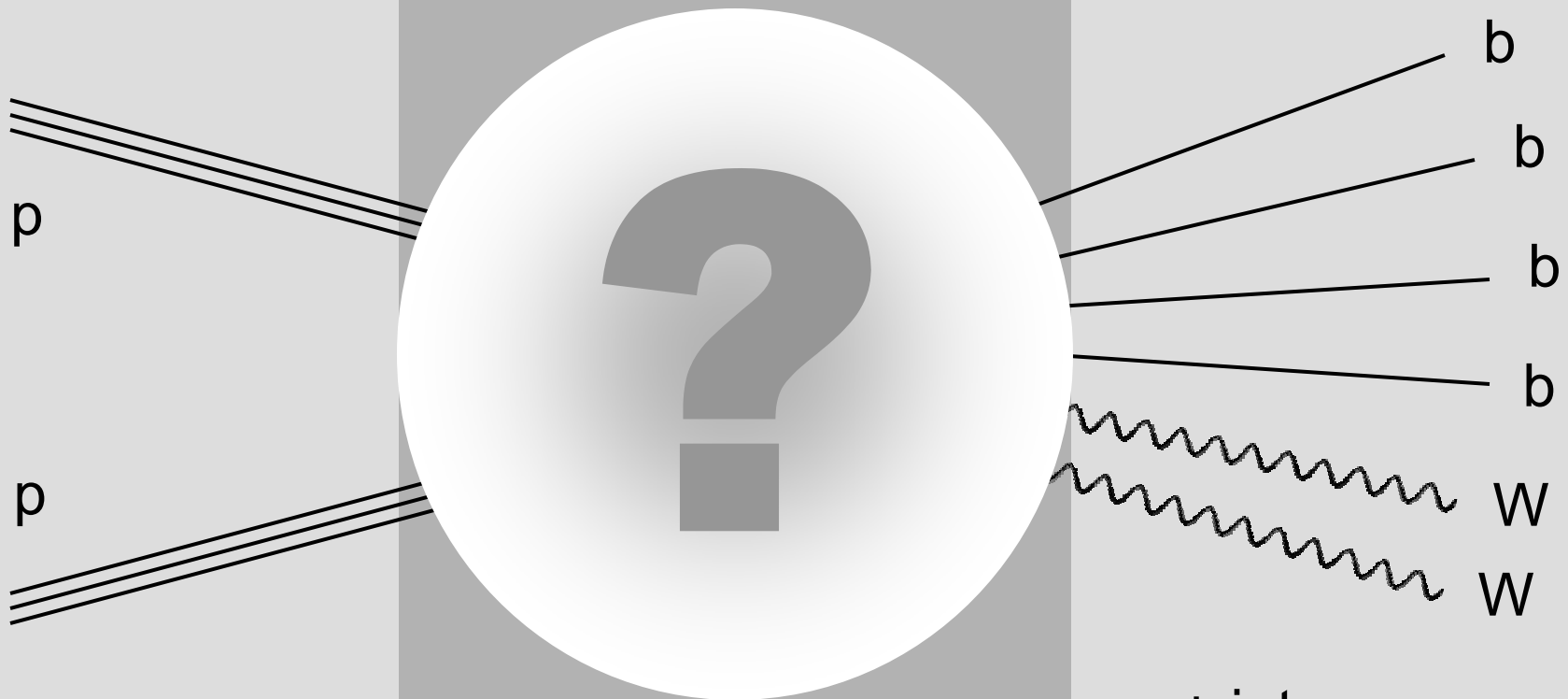
# Case Study: Jets + MET channel

$H_T \equiv \sum \text{scalar } E_T \text{ of electrons, muons, jets}$



Energy scale  $\lesssim 500$  GeV to 1 TeV

# Case Study: Jets + MET channel

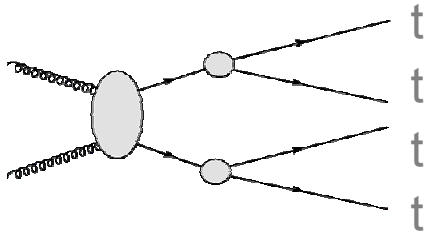


+ jets

+ significant  $\cancel{E}_T$

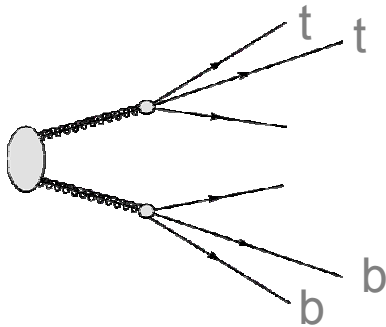
"Most salient" final state

# (Some) Attempted OSETs



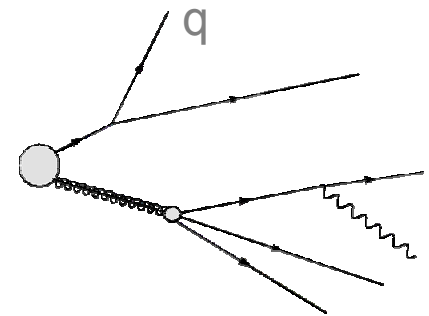
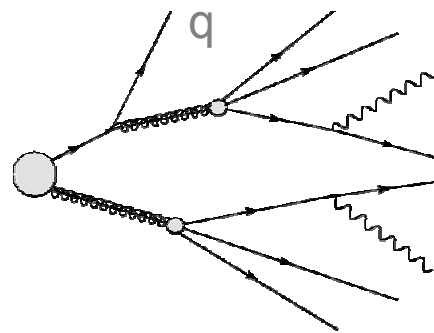
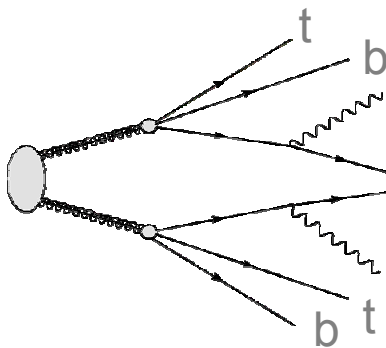
- Too many leptons
- Not enough missing energy

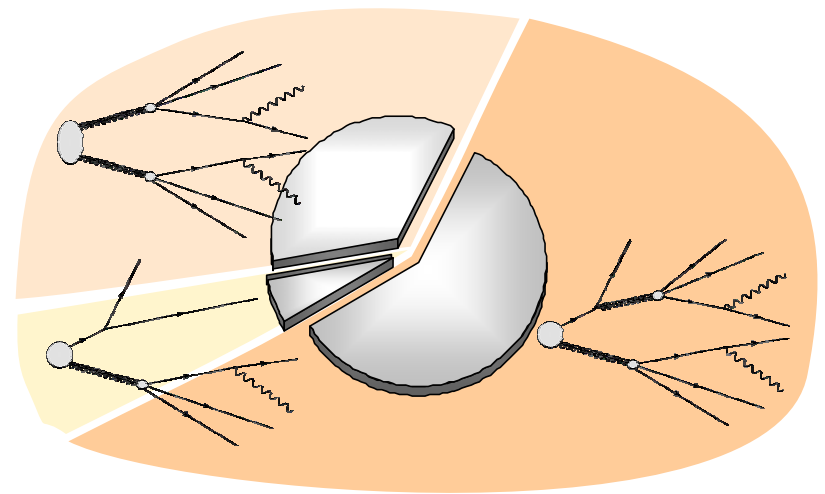
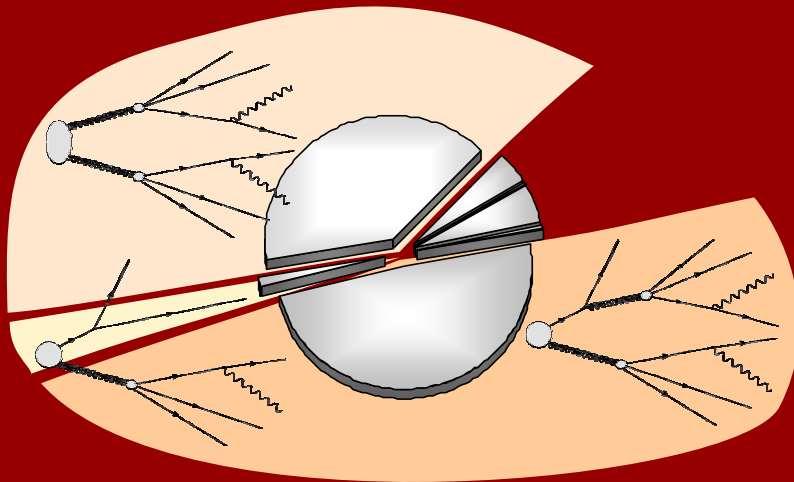
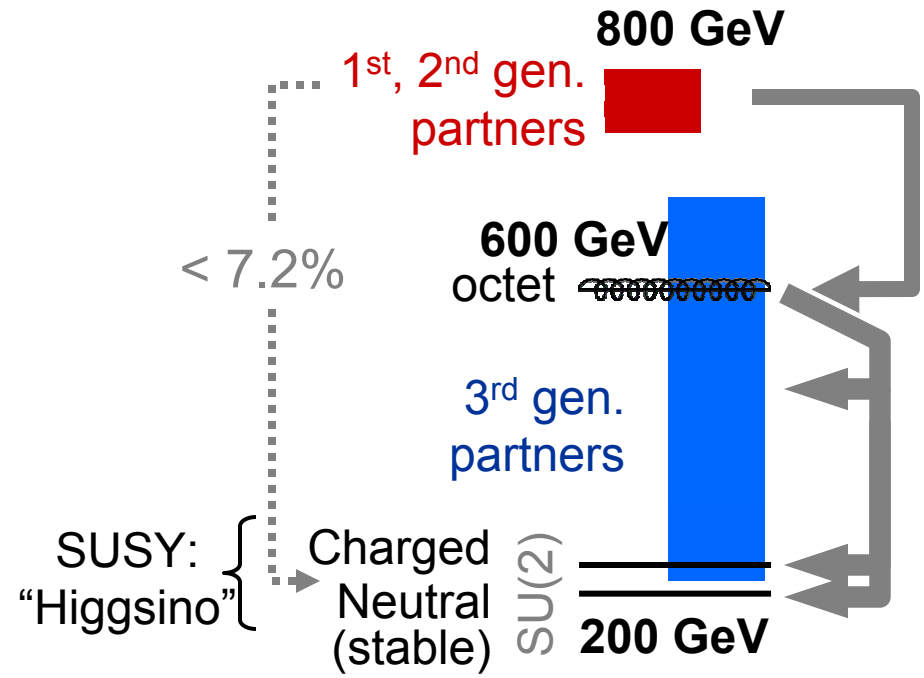
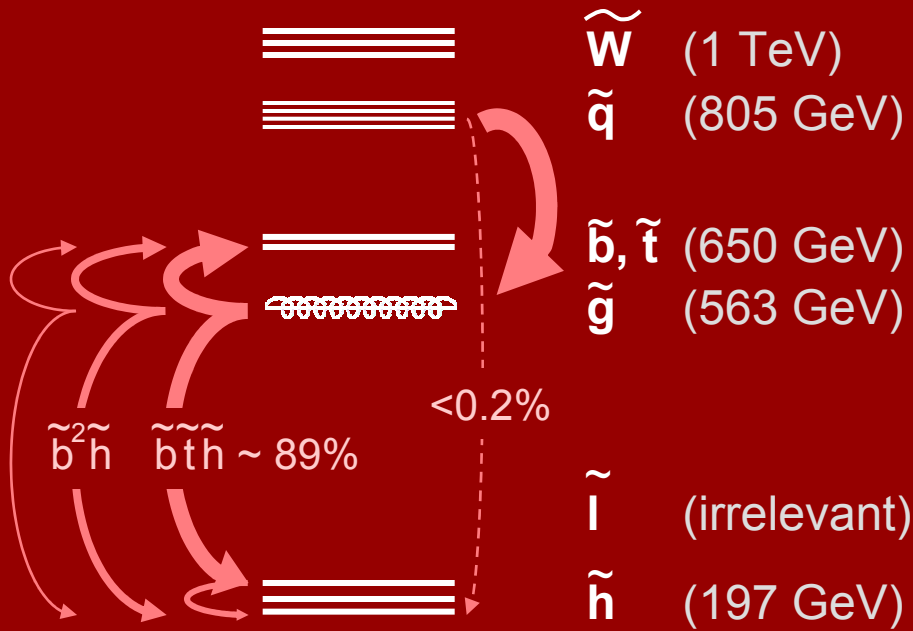
Massive missing energy particle required



- $t^4$  final state has too many leptons

Implied for model consistency

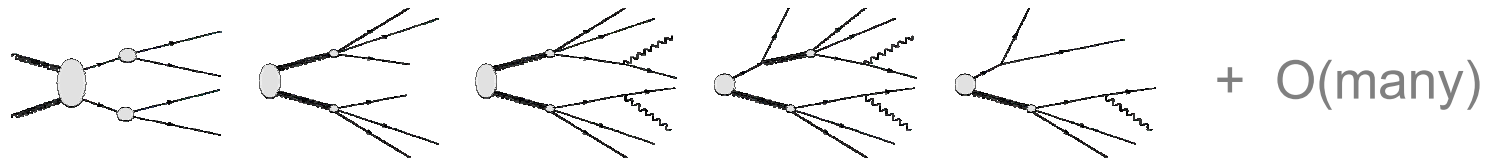




**Actual Model**

**OSET Deduction**

## Where did OSETs come in?



Monte Carlo “scripting” : ~~Wait-less~~ } Effortless } to simulate hypotheses

## What made (quick) model-deduction possible?

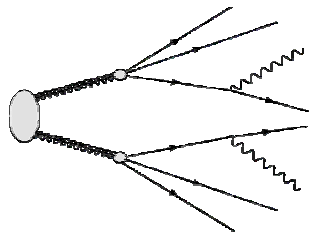
- ✦ Standard Model → BSM constraints (charge conservation, small rate of flavor violation, ...)
- ✦ Minimal addition of new content (a negotiable assumption)
- ✦ Factorization into subsets of salient signatures
- ✦ Hypothesized topologies ⇒ new signatures and searches
- ✦ Number of parameters (masses, branching ratios, ...) ≪ full model

o | o g y @ CMS



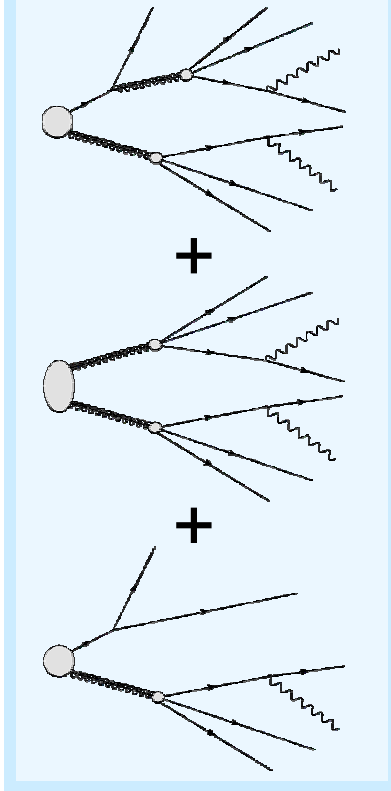
OSET Process

Masses=200,600,...

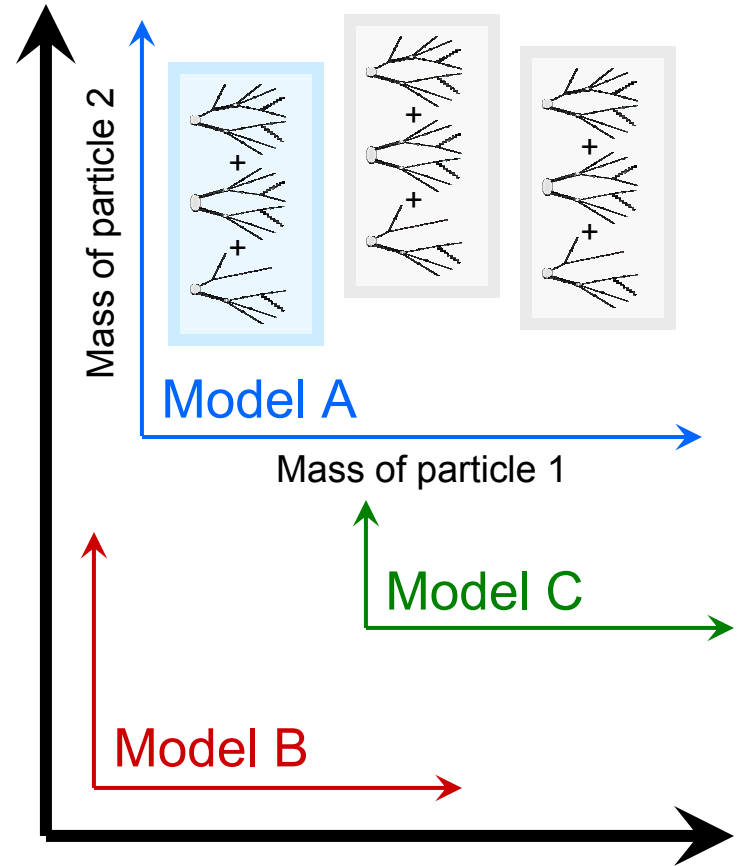


OSET Model

Masses=200,600,...



BSM Physics



Upper-bound:

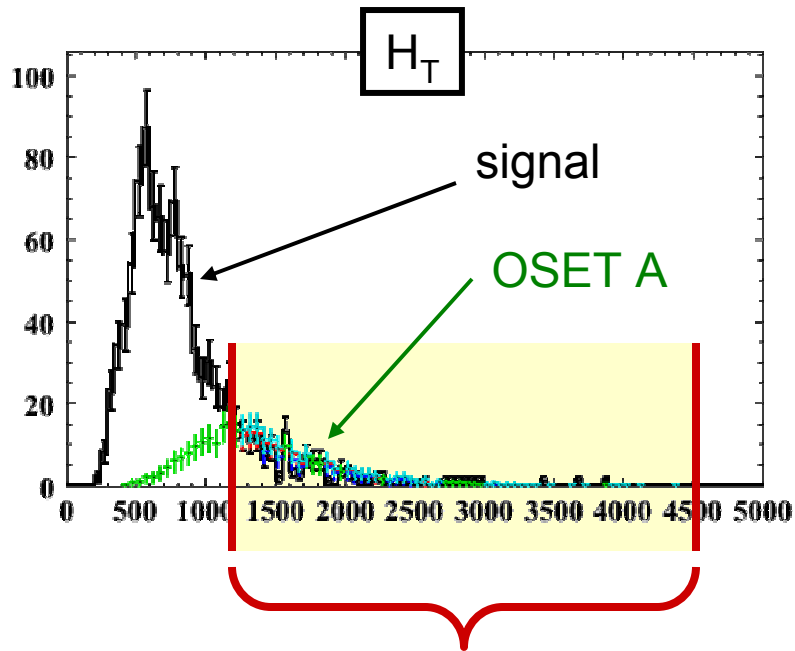
- Determine if a given process is important
- Indicate regions that require contributions from other processes

Fit to signal:

- Extract best-fit model parameters for a given set of mass hypotheses

Goodness-of-fit:

- Compare mass hypotheses to locate most likely spectrum
- Compare distinct models



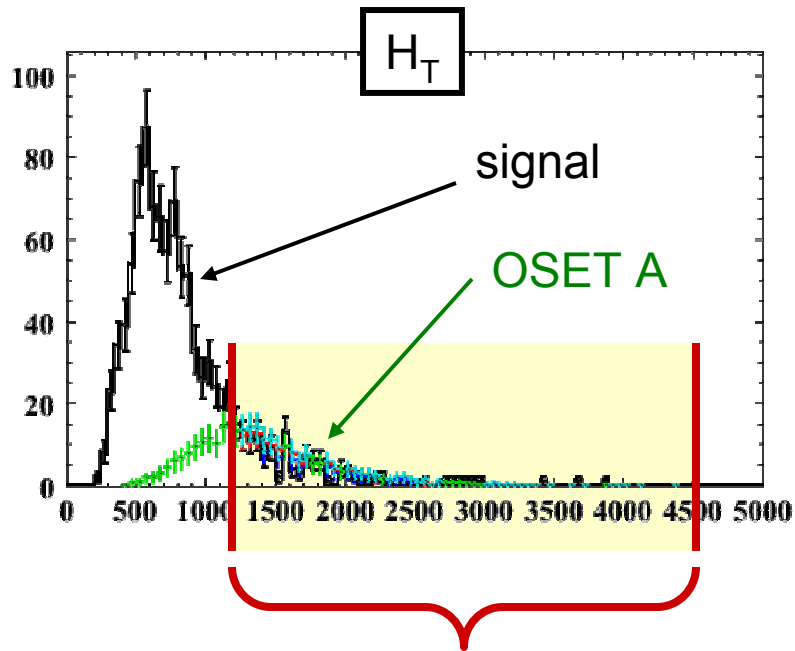
Suppose that we think “signal” consists of 25% events from a model like OSET A.

If we overlay the shapes of the  $H_T$  distribution (OSET A scaled to 25% number of signal events), they would look like this.

Compute a “constrained distance” ( $\chi^2$  or the Poisson equivalent) in only those bins where the OSET A prediction exceeds the number of signal events.

### Upper-bound:

- Determine if a given process is important
- Indicate regions that require contributions from other processes

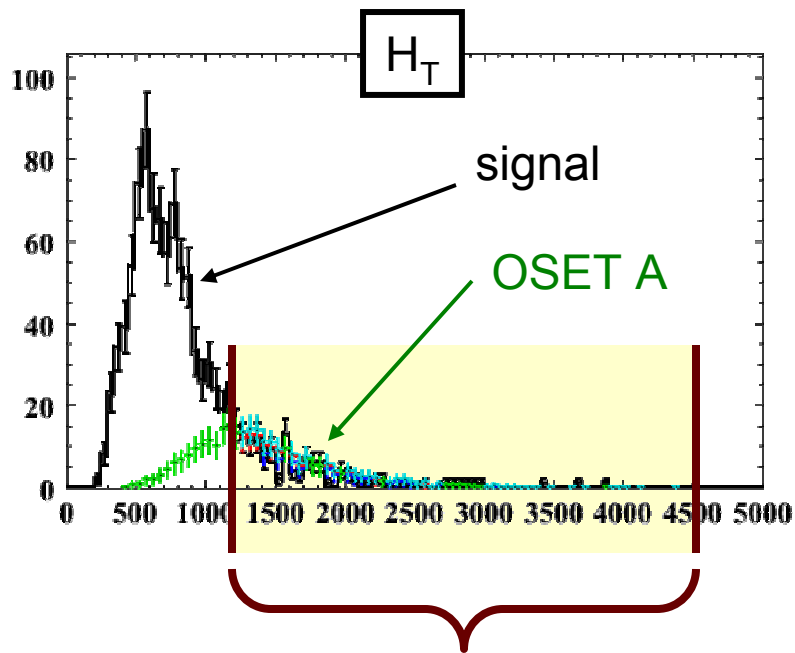


Assuming that OSET A *is* the correct model in this region, how likely are we to measure the “constrained distance” that we measured (in this pseudoexperiment)?

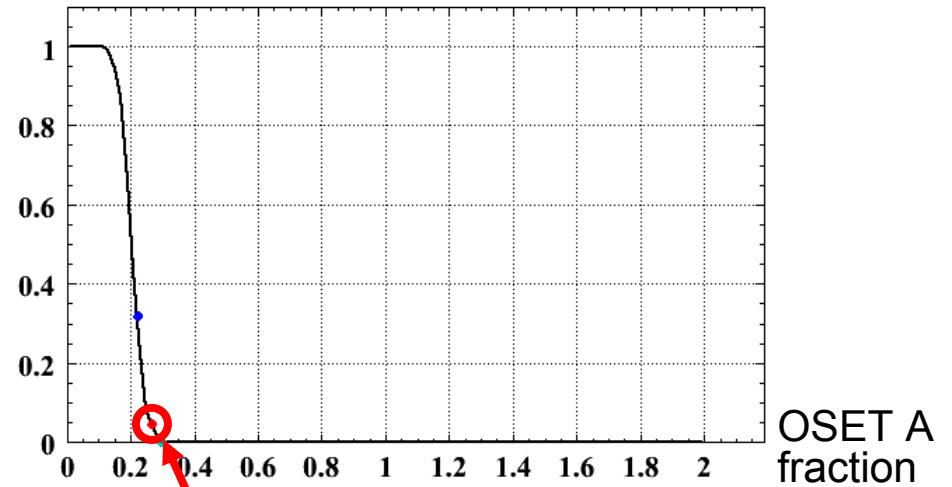
Compute a “constrained distance” ( $\chi^2$  or the Poisson equivalent) in only those bins where the OSET A prediction exceeds the number of signal events.

### Upper-bound:

- Determine if a given process is important
- Indicate regions that require contributions from other processes



$\chi^2$  Probability

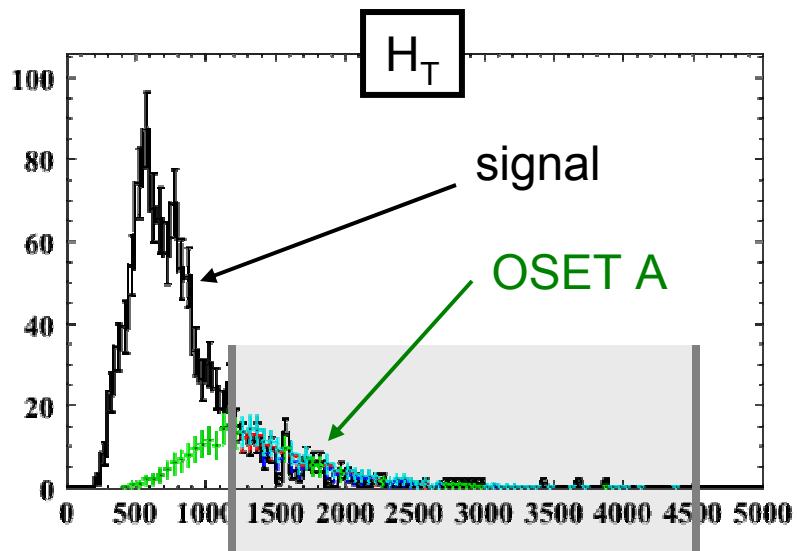


Compute a “constrained distance” ( $\chi^2$  or the Poisson equivalent) in only those bins where the OSET A prediction exceeds the number of signal events.

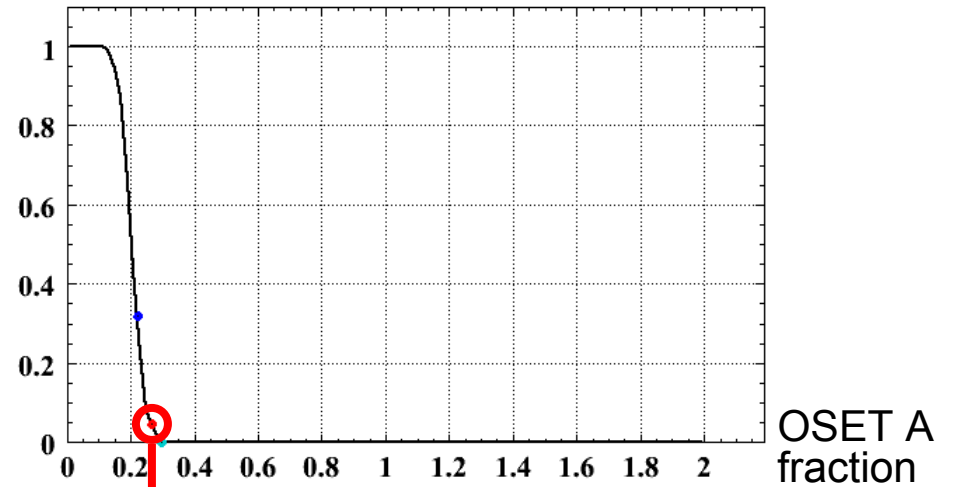
**Upper-bound:**

- Determine if a given process is important
- Indicate regions that require contributions from other processes

the maximal OSET fraction such that it can explain all signal events *in the constraining region*,  
 ... supposing that there was a total downward fluctuation of, say  $2\sigma$ , down from expectation.



$\chi^2$  Probability

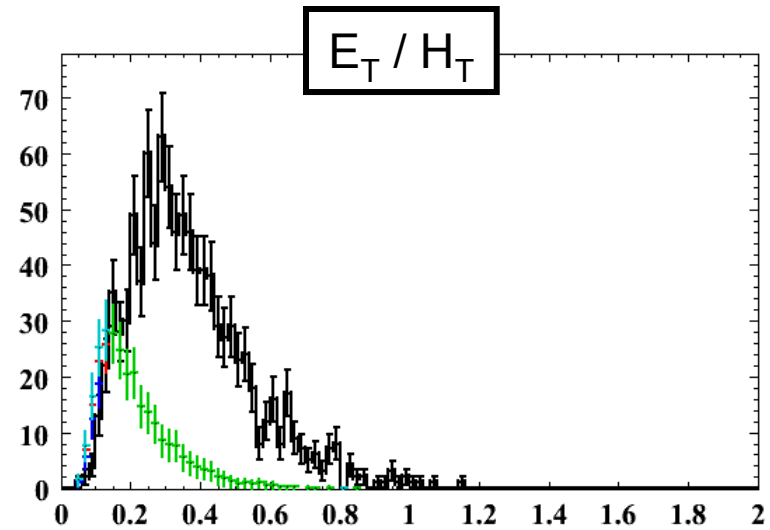
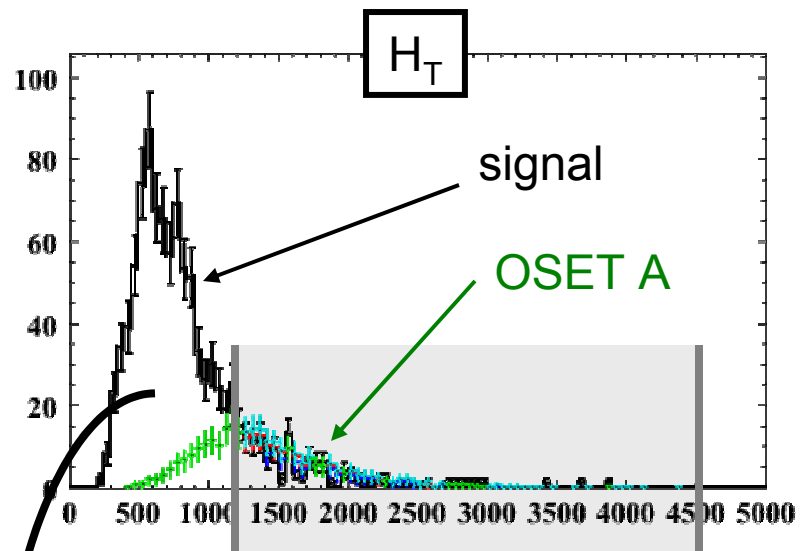


### Upper-bound:

- Determine if a given process is important
- Indicate regions that require contributions from other processes

Typically the upper bound is not very constraining, unless we picked a model that is obviously wrong.

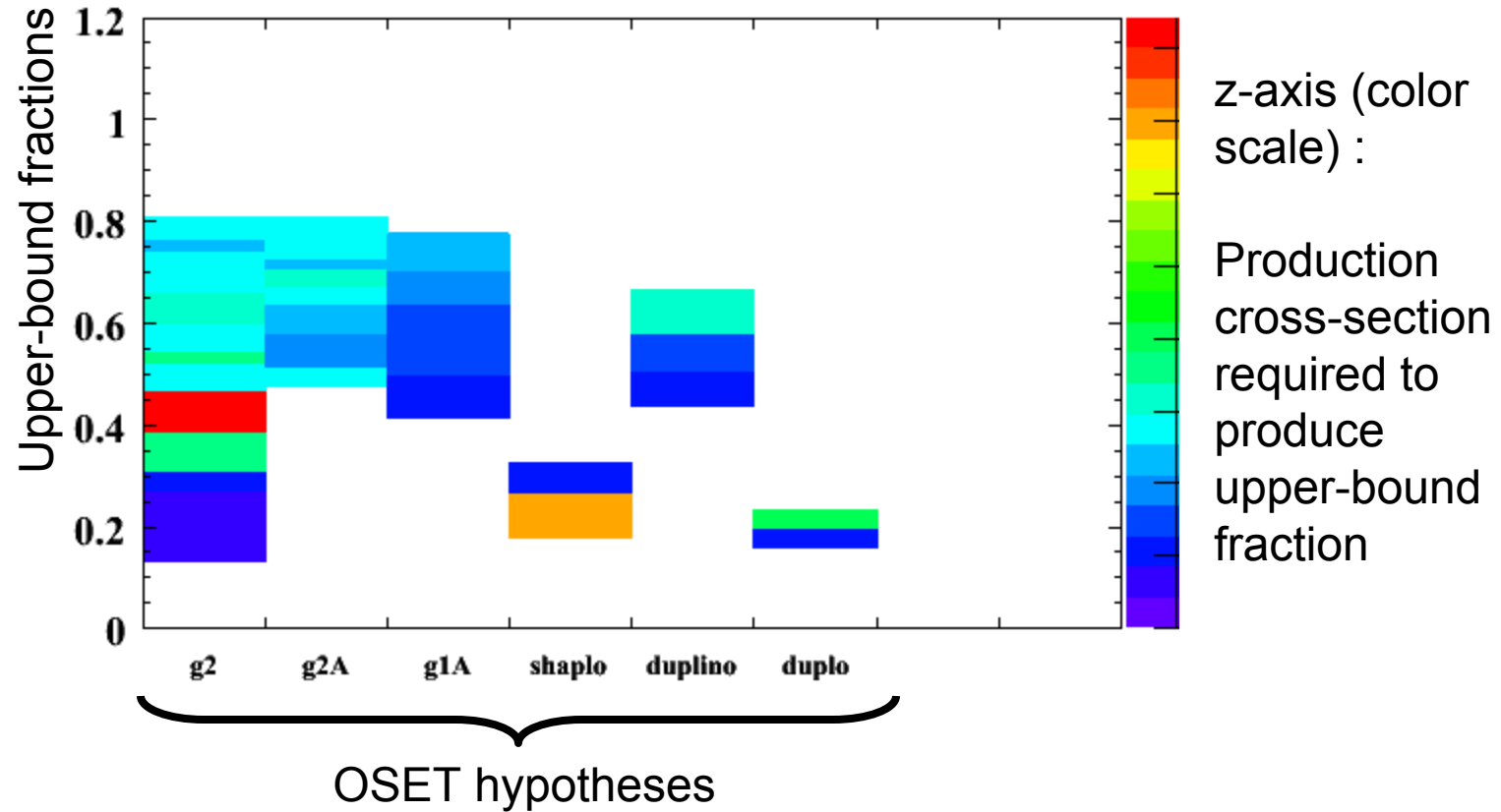
But that's just life.



The upper-bound is usually computed simultaneously over multiple distributions

### Upper-bound:

- Determine if a given process is important
- Indicate regions that require contributions from other processes

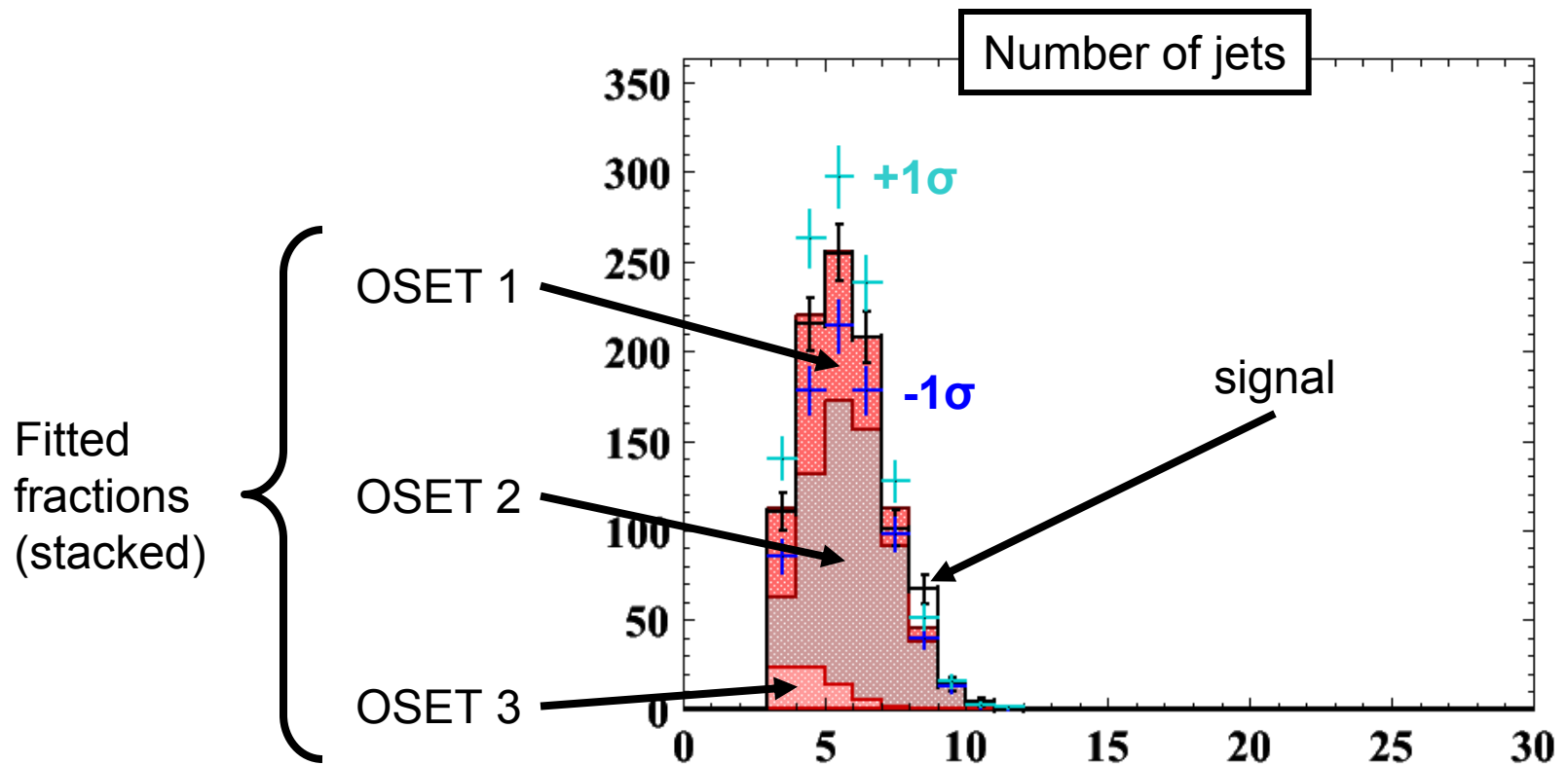


### Upper-bound:

- Determine if a given process is important
- Indicate regions that require contributions from other processes

This is an example summary plot indicating the maximal fractions of various hypotheses.

The bands are produced by scanning over some possible masses.



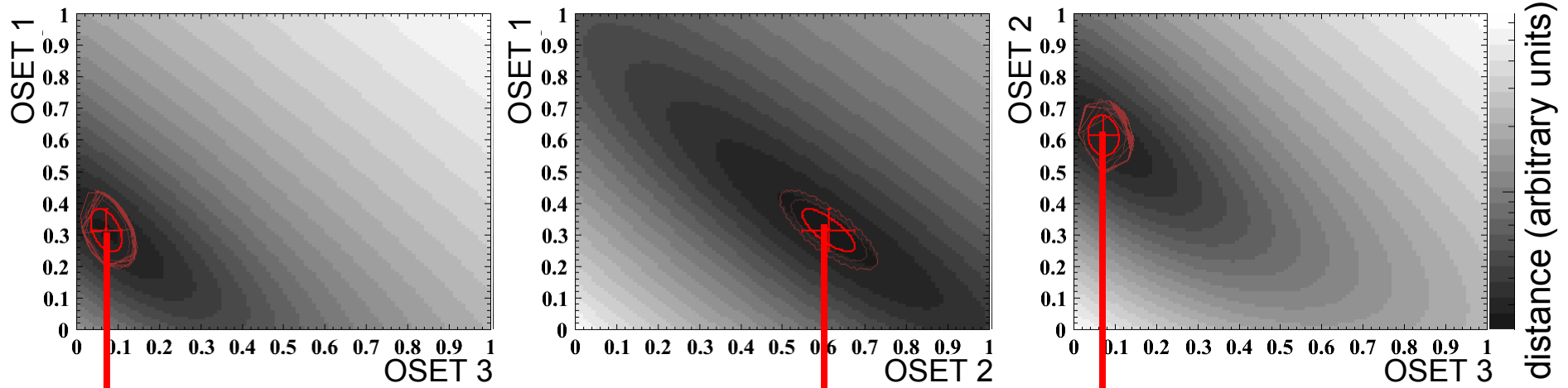
When we have the set of most significant processes, we can fit for their fractions the usual way (minimizing distance between signal and summed templates).

#### Fit to signal:

- Extract best-fit model parameters for a given set of mass hypotheses



# Landscape of distance used in the fit — 2D slices (3 OSETS = 3 parameters)

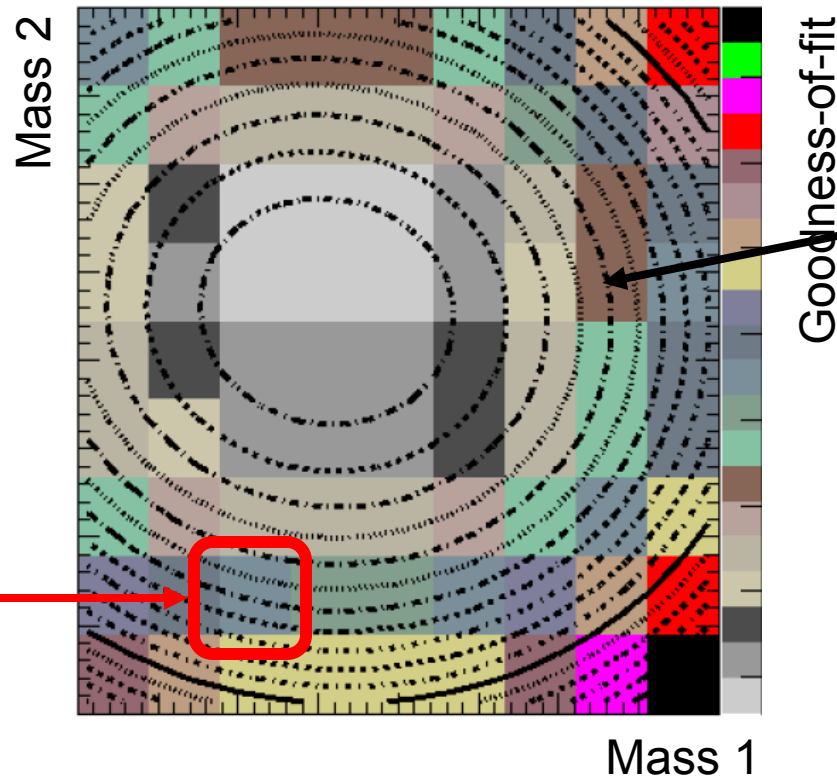


## Fit to signal:

- Extract best-fit model parameters for a given set of mass hypotheses

The contours of the Minuit2 fit are used as error bars. But pay attention to the contour plots for they contain more information about flat directions (similar processes).

For a specific set of mass hypotheses (at this point of the mass grid): record how well we can fit the three processes to explain signal.



Contours of parabolic fit interpolating between points in (possibly coarse) grid

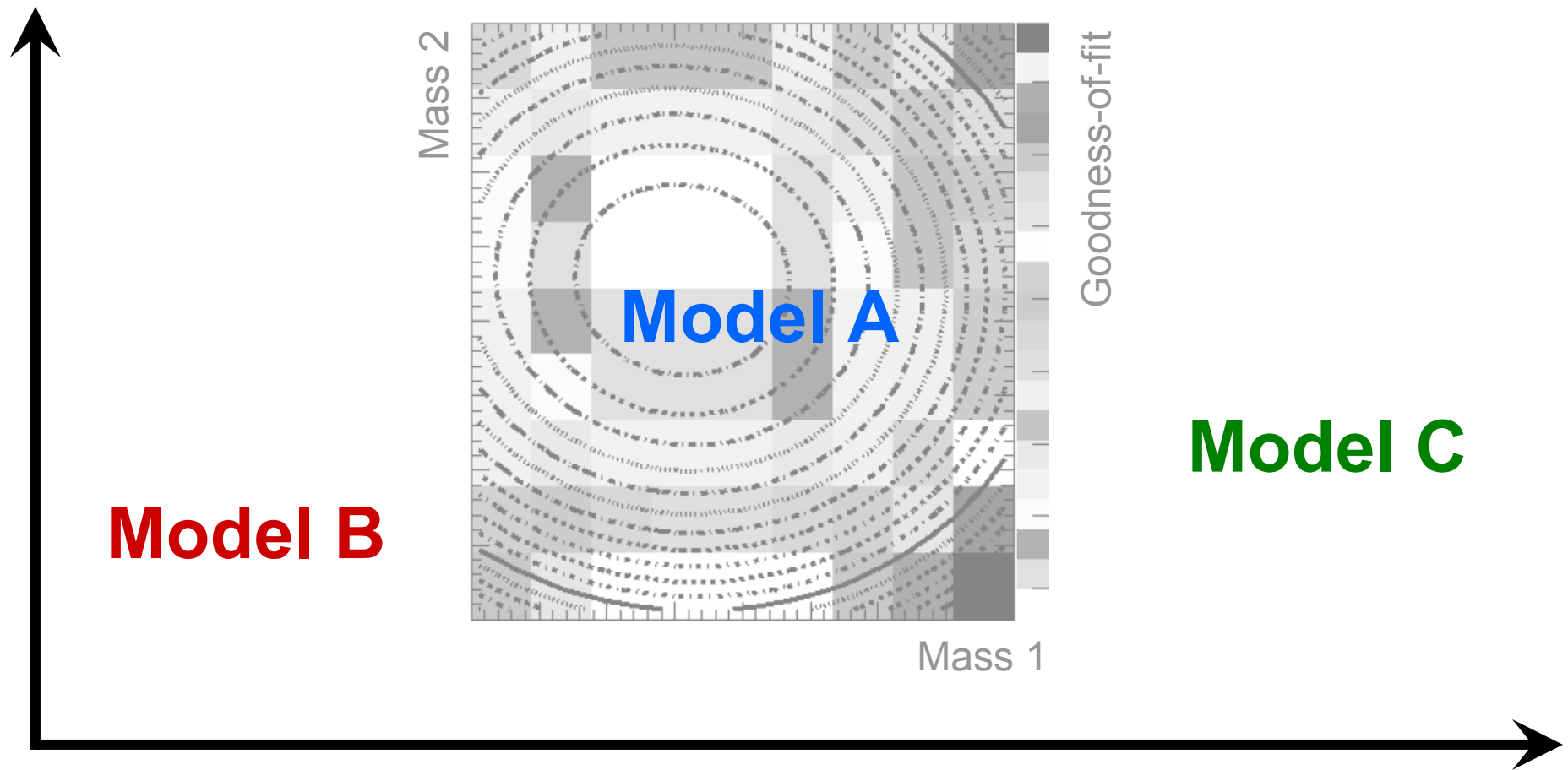
Refine grid after roughly locating minimum

### For each particular model:

The goodness-of-fit (for the various processes) as we vary the mass parameters can be used to locate the most probable mass spectrum.

### Goodness-of-fit:

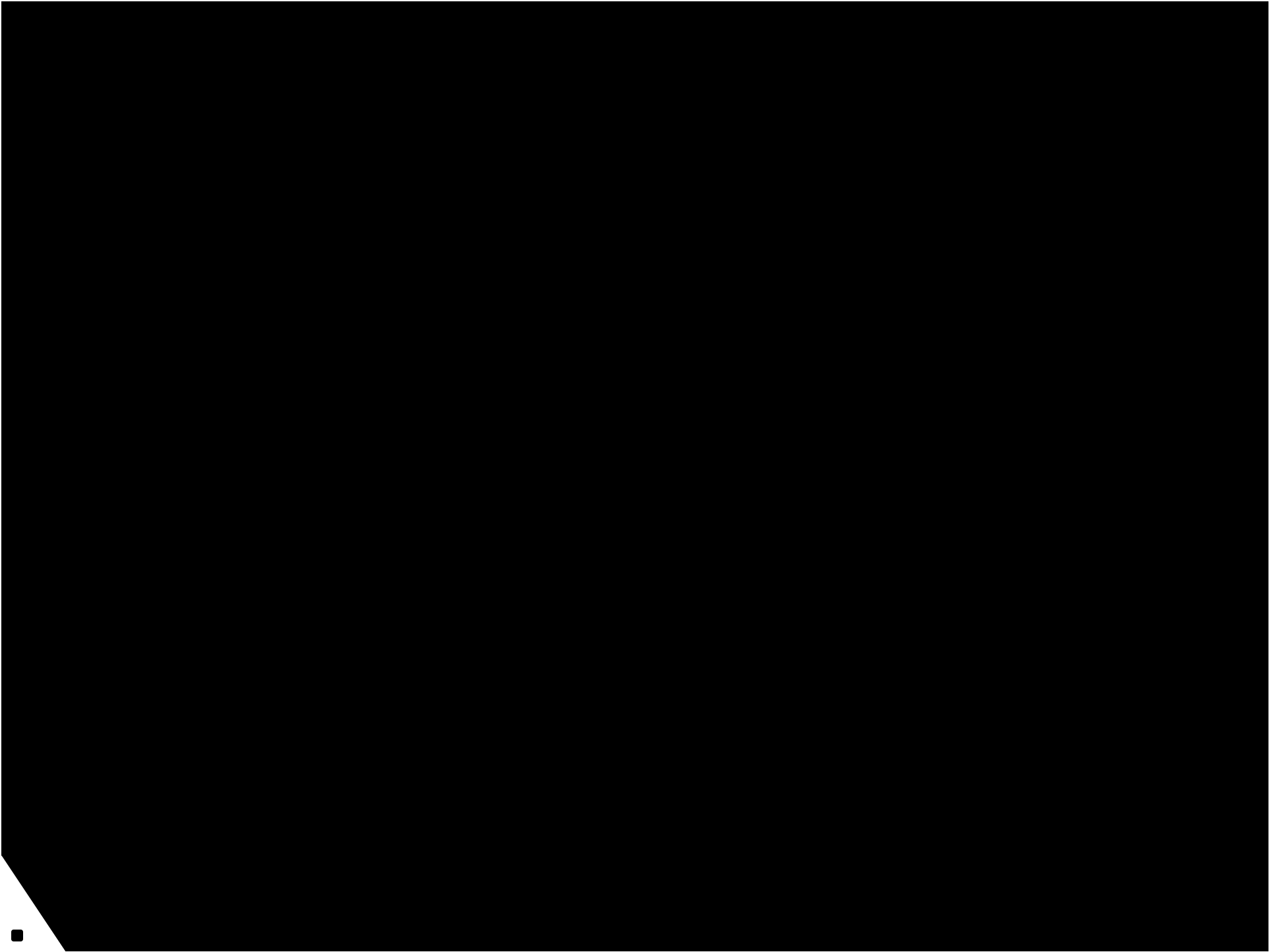
- Compare mass hypotheses to locate most likely spectrum
- Compare distinct models



This procedure has a natural generalization to comparisons of models, provided we understand the number of degrees of freedom.

#### Goodness-of-fit:

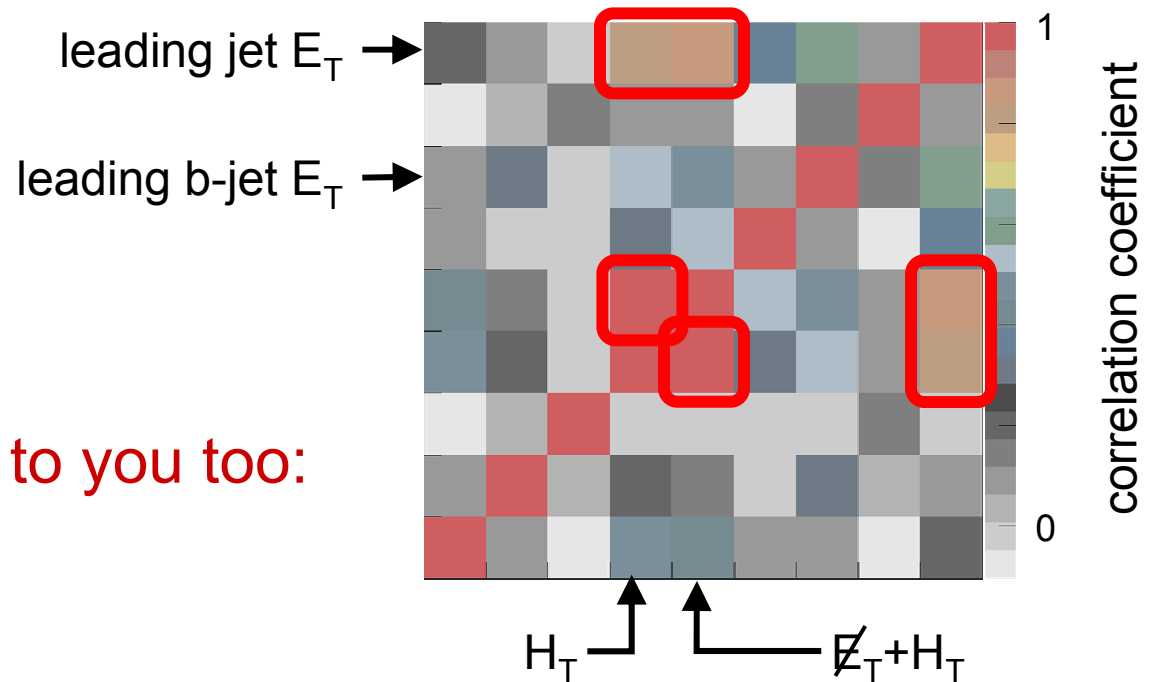
- Compare mass hypotheses to locate most likely spectrum
- Compare distinct models



Suppose a naïve graduate student performs a 10-histogram fit with:

$$\cancel{E}_T + \underbrace{H_T + H_T + H_T + H_T + H_T + H_T + H_T + H_T + H_T + H_T}_{\text{Unfairly weighted, wrong degrees-of-freedom count}}$$

Unfairly weighted, wrong degrees-of-freedom count

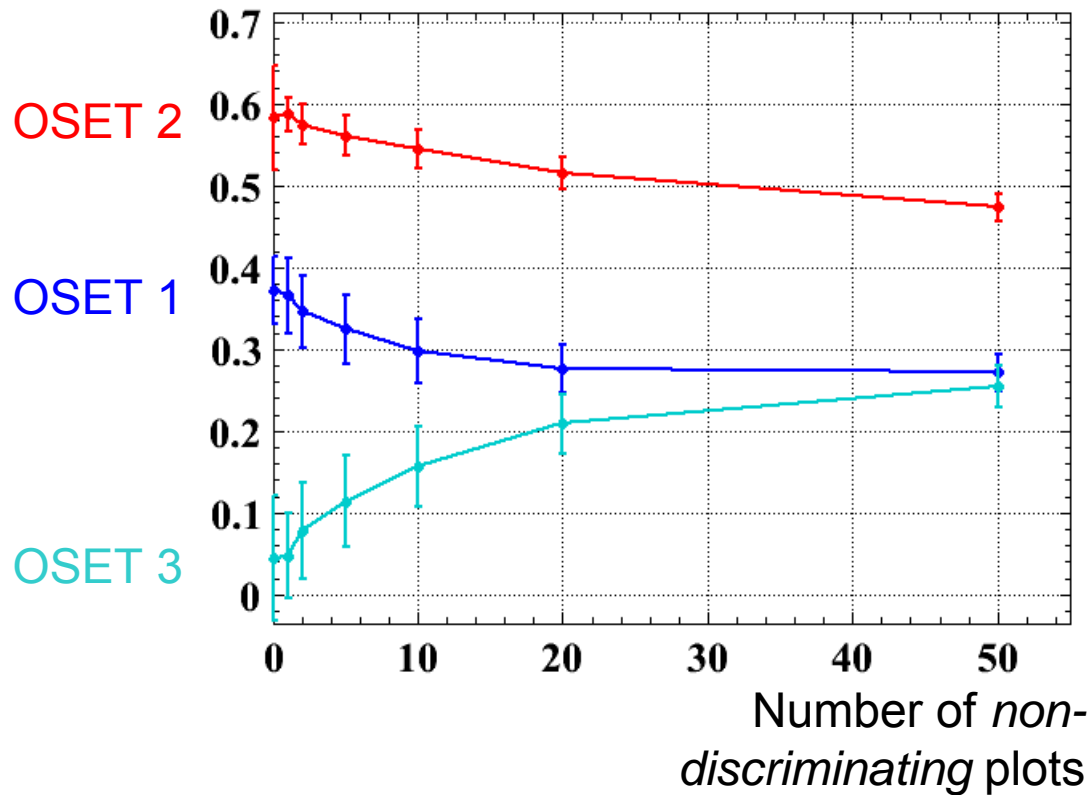


... but it can happen to you too:

# Issues

- Correlated variables ← Principal components analysis:
  - Diagonalize to a de-correlated basis
  - Remove redundant variables
- Non-discriminating variables (“garbage”)

Fractions reported by fitter



Inclusion of non-discriminating plots (i.e. where all hypotheses have the same shape) tends to wash out the information in such a way that the fractions are biased towards equal numbers — unless we have perfect ( $\infty$  statistics) templates.

# Issues

- Correlated variables
- Non-discriminating variables (“garbage”)

Metric for sorting plots according to discriminating power — examining the trend as we increase template statistics provides even more information.