

# Accelerating the search for mass bumps using the Data-Directed Paradigm

Jean-François Arguin  
Georges Azuelos  
Émile Baril  
Fannie Bilodeau  
Ali El Moussaouy  
Bruna Pascual  
Muhammad Usman

Maryna Borysova  
Shikma Bressler  
Michael Chu  
Etienne Dreyer  
Nilotpai Kakati  
Amit Shkuri

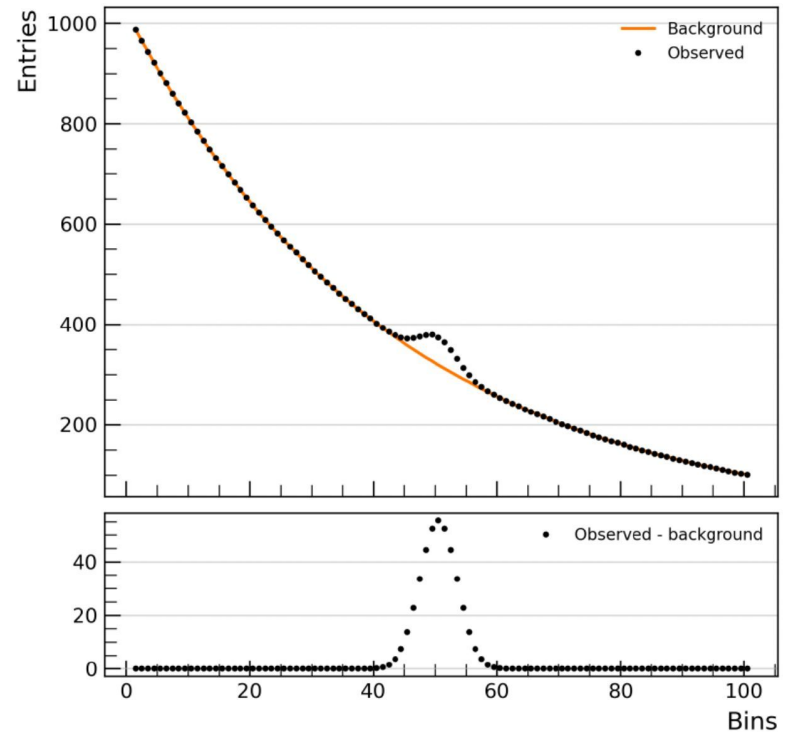
Samuel Calvet  
Julien Donini  
Eva Mayer

# Motivation

- ★ So far, none of the efforts to find new physics at LHC have succeeded
- ★ Traditional approach: confirm/exclude theory predictions in **small observable space**
- ★ Change of approach: scan **all data** for anomalies to motivate specific searches

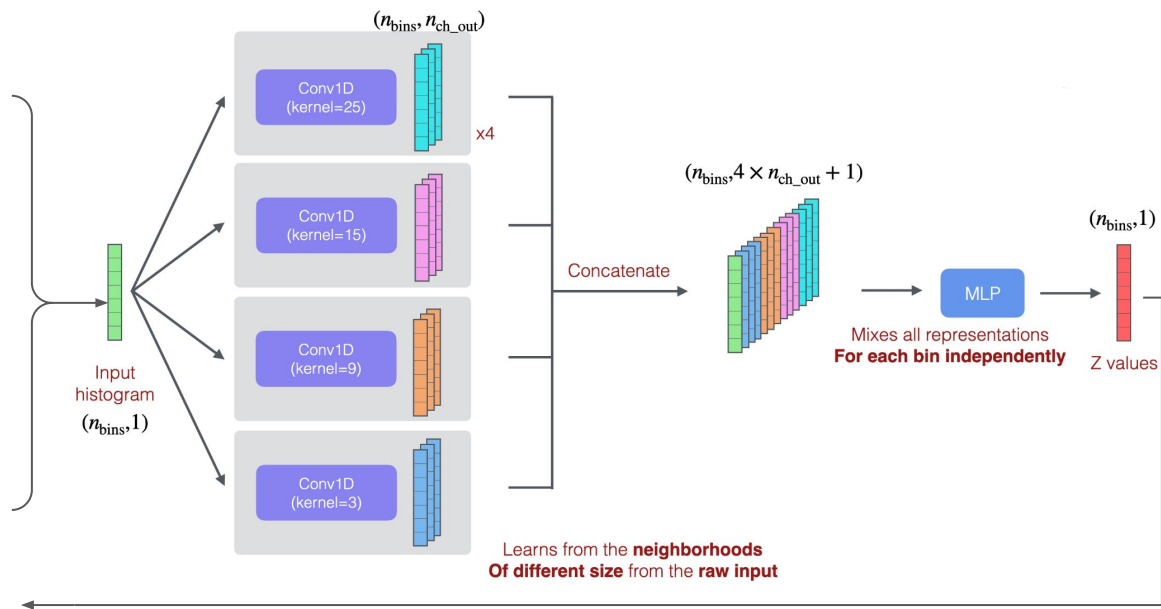
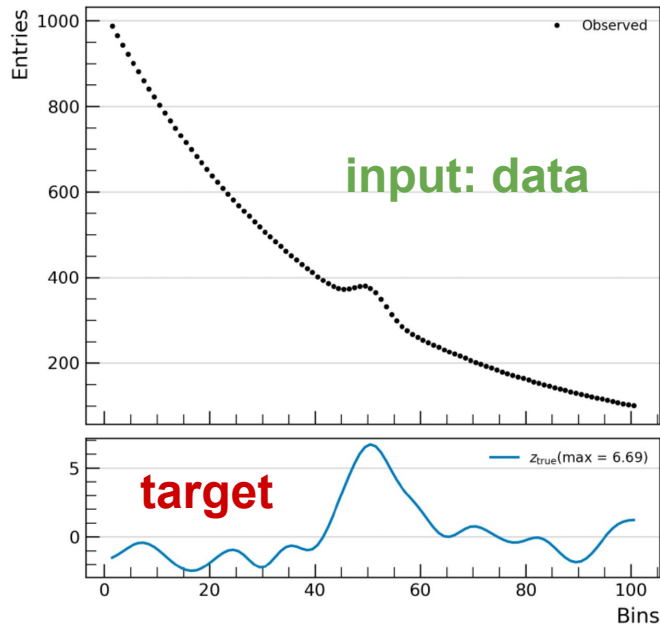
# Data-Directed Paradigm

- ★ Smoothly falling mass distributions
- ★ New physics could cluster in data as **bumps** in mass histograms
- ★ Training of a network to find bumps
  - Predicts the **z value**: statistical significance of an excess at each mass value



# Predicting the statistical significance using a neural network

**ZNet3**: supervised learning: both  $z_{\text{true}}$  and signal width are given in training



# Training data

## Background distributions:

- ★ analytical functions and/or simulations

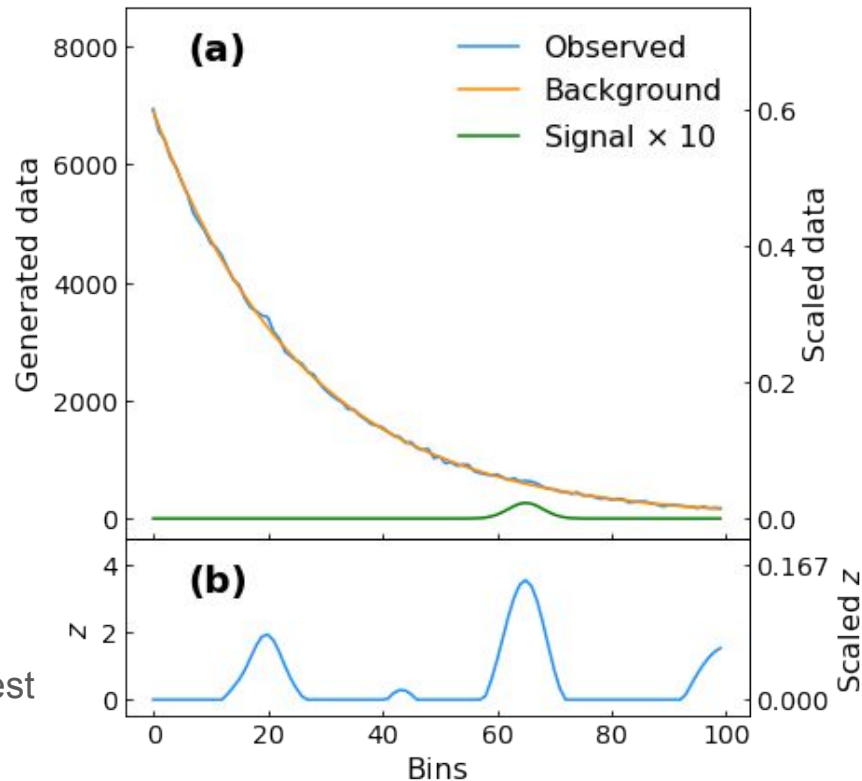
$$be^{-ax}, \quad ax + b, \quad \frac{1}{ax} + b, \quad \frac{1}{ax^2} + b, \quad \frac{1}{ax^3} + b,$$

$$\frac{1}{ax^4} + b, \quad a(x - x_2)^2 + y_2, \quad -a \cdot \ln(x) + b,$$

$$(y_1 - y_2) \cos(a(x - b)) + y_2, \quad \cosh(a(x - x_2)) + b$$

## Adding the signal:

- ★ select **background**
- ★ add **gaussian signal**
- ★ add random fluctuations
- ★ calculate **true significance** with likelihood-ratio test



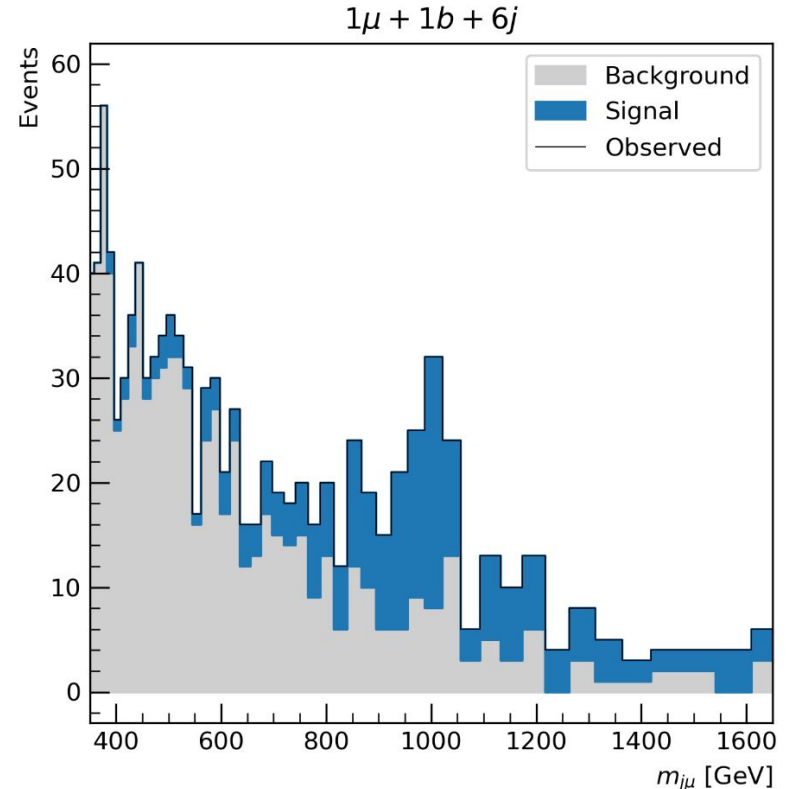
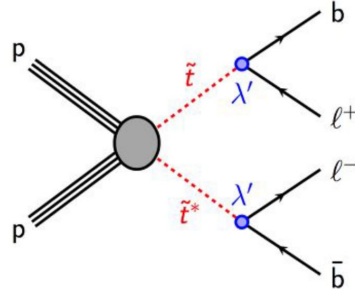
# Dark Machines samples

★ Simulations including the **highest cross section processes at LHC**

- Designed for anomaly studies
- Produced using Madgraph, Pythia, and DELPHES fast detector simulations

★ Various simulated **new-physics signals** added to the background

e.g.: RPV stop  $\rightarrow$  bl



# Signatures

Each event consists of a combination of reconstructed physics objects

## Standard Model of Elementary Particles

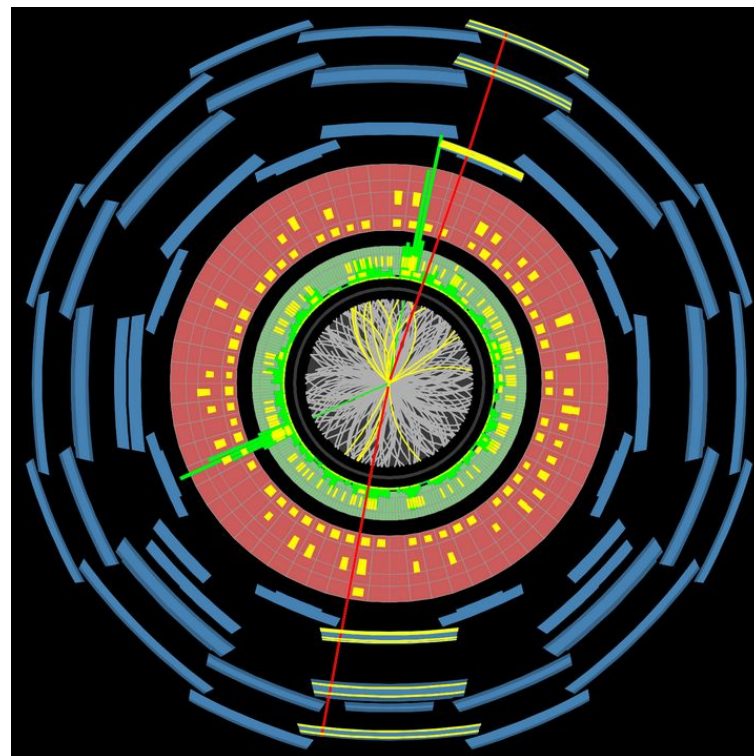
three generations of matter (fermions)			interactions / force carriers (bosons)		
	I	II	III		
mass	$\approx 2.2 \text{ MeV}/c^2$	$\approx 1.28 \text{ GeV}/c^2$	$\approx 173.1 \text{ GeV}/c^2$	0	$\approx 125.11 \text{ GeV}/c^2$
charge	$\frac{2}{3}$	$\frac{2}{3}$	$\frac{2}{3}$	0	0
spin	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	1	0
	<b>u</b> up	<b>c</b> charm	<b>t</b> top	<b>g</b> gluon	<b>H</b> higgs
	<b>d</b> down	<b>s</b> strange	<b>b</b> bottom	<b><math>\gamma</math></b> photon	
	<b>e</b> electron	<b><math>\mu</math></b> muon	<b><math>\tau</math></b> tau	<b>Z</b> Z boson	
	<b><math>\nu_e</math></b> electron neutrino	<b><math>\nu_\mu</math></b> muon neutrino	<b><math>\nu_\tau</math></b> tau neutrino	<b>W</b> W boson	

**QUARKS** (left side of the table)

**LEPTONS** (left side of the table)

**GAUGE BOSONS VECTOR BOSONS** (bottom center of the table)

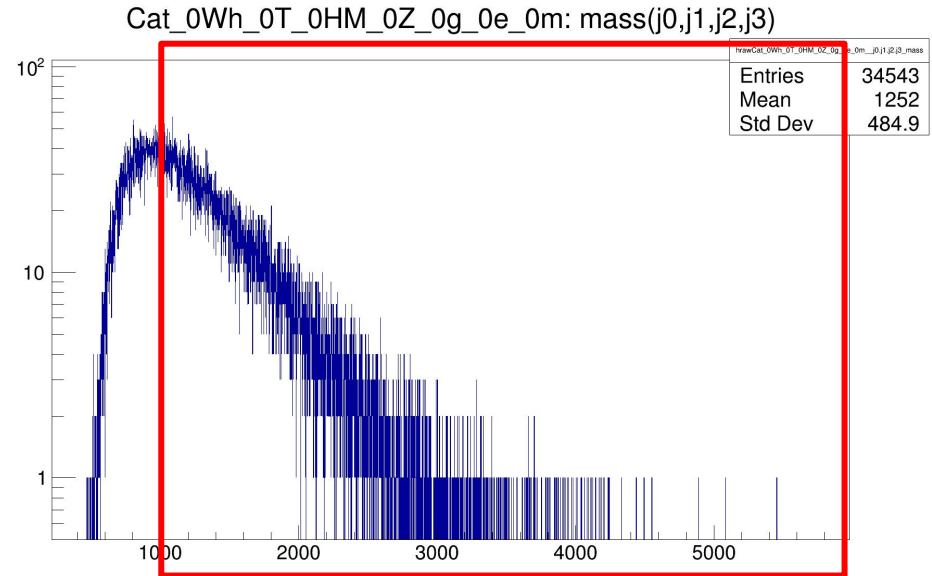
**SCALAR BOSONS** (right side of the table)



Higgs  $\rightarrow e e \mu \mu$

# Histogram production

- ★ Consider all possible signatures:
  - e.g.:  $1e + 1\mu + 3j$
- ★ Compute masses of all possible combinations of objects
  - e.g.:  $\text{mass}(e)$ ,  $\text{mass}(\mu, j_0)$ ,  $\text{mass}(e, \mu, j_1), \dots, \text{mass}(e, \mu, j_0, j_1, j_2)$
- ★ Zoom in so the histogram starts at the maximum -> smoothly falling

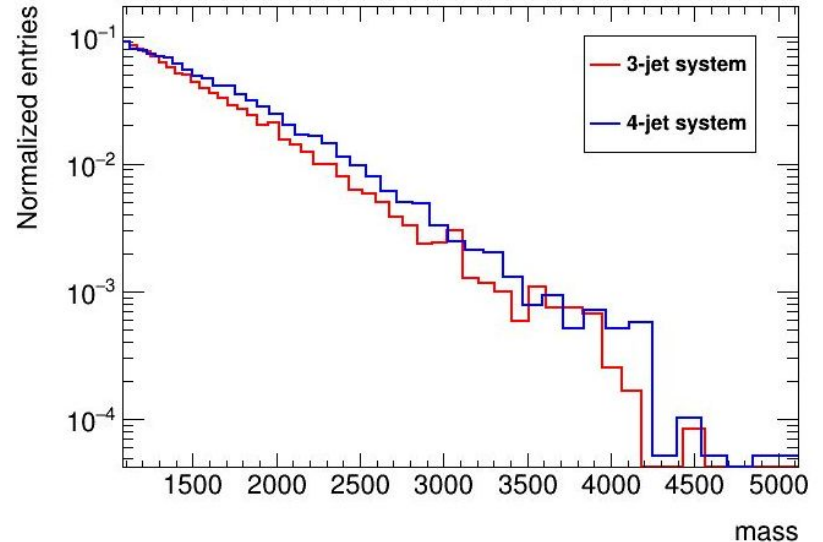
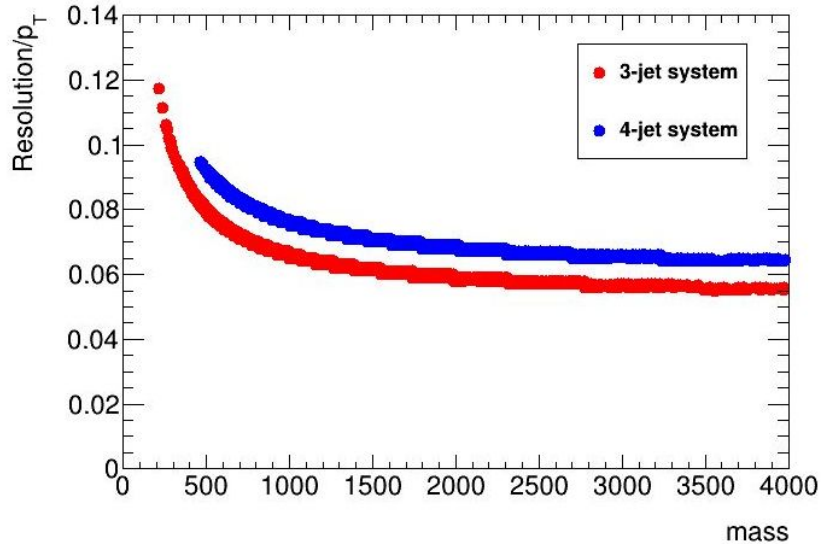


-> **Huge amount of data:** 63 000 signatures with many histograms each



# Binning and detector resolution

- ★ Signal is expected to be narrow -> we train the network to find it in few bins
- ★ Adjust binning to ATLAS detector resolution
  - Resolution depends on the objects involved, their  $p_T$ , and  $\eta$



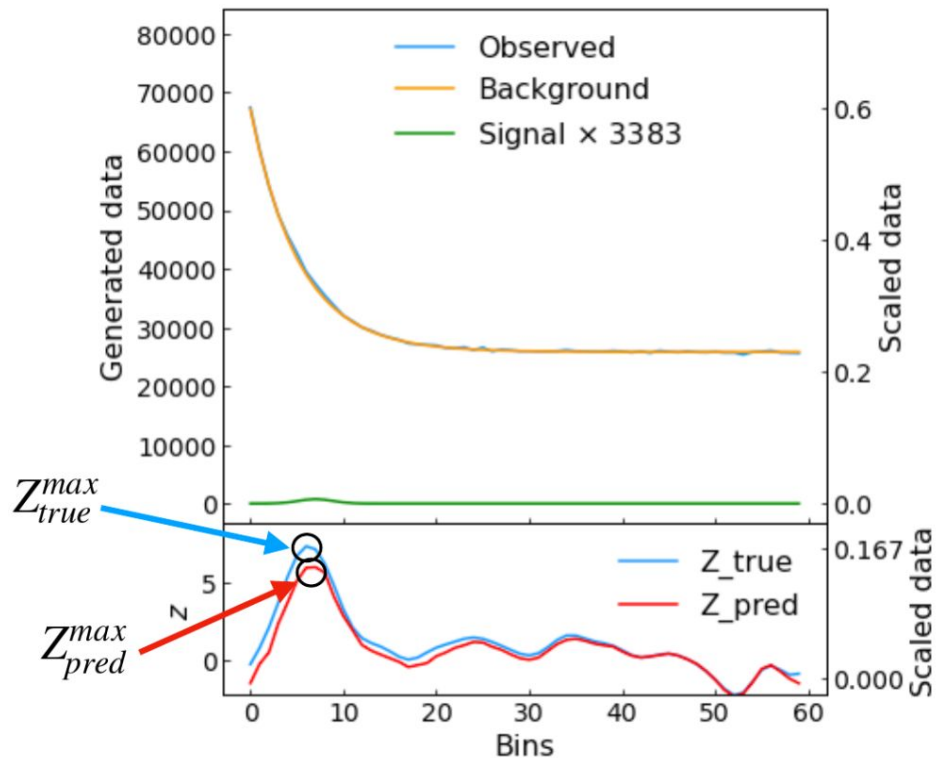
# Performance

Performance evaluated in terms of:

- ★ Difference between the true and predicted maximum significance:

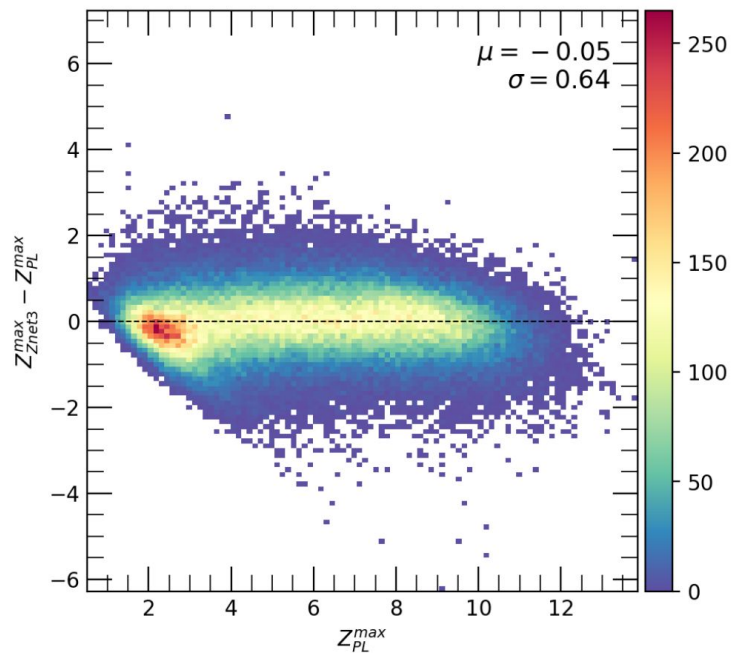
$$Z_{\max, \text{true}} - Z_{\max, \text{pred}}$$

- ★ False-positive rate

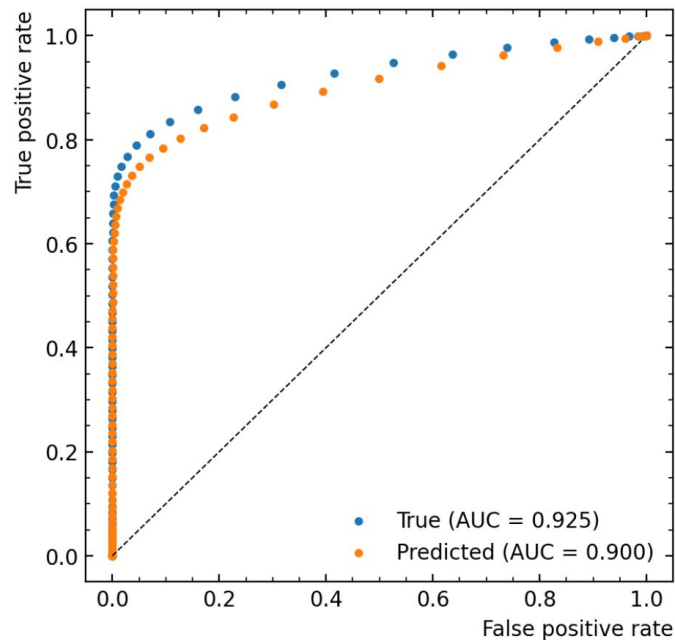


# Performance

Prediction of  $z_{\max}$  is **unbiased** with a variance of 0.64:

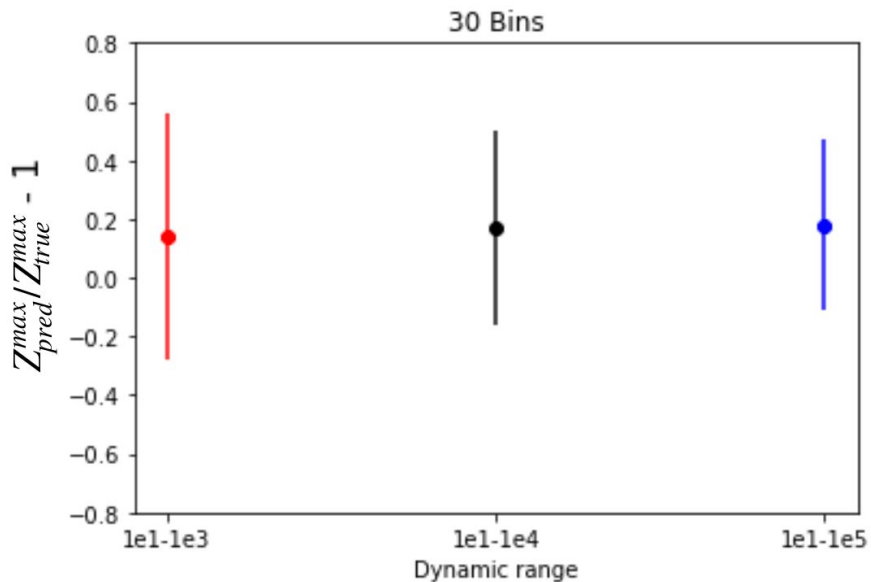


ROC curve: bump detection based on  $z_{\text{pred}}$  almost as good as based on  $z_{\text{true}}$

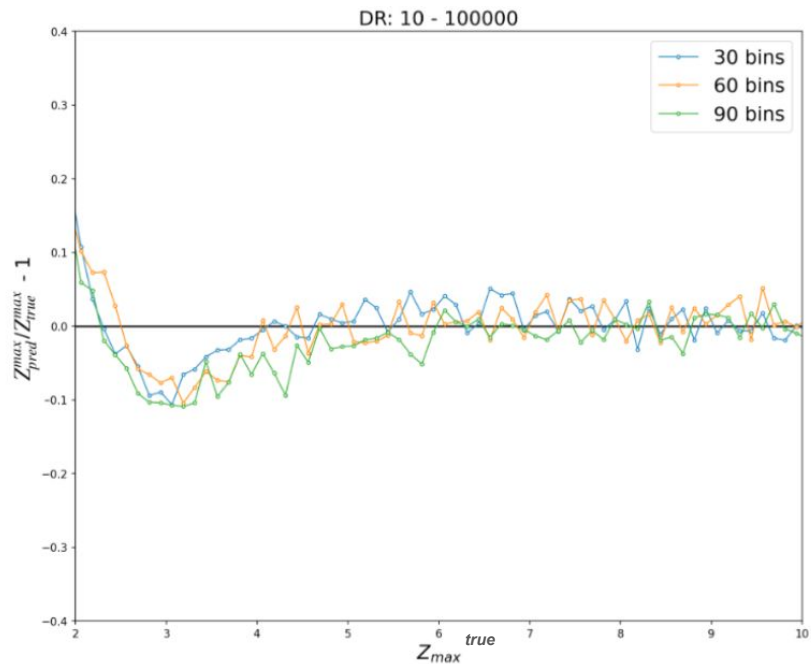


# Performance stability

Dynamic range: number of entries per bin



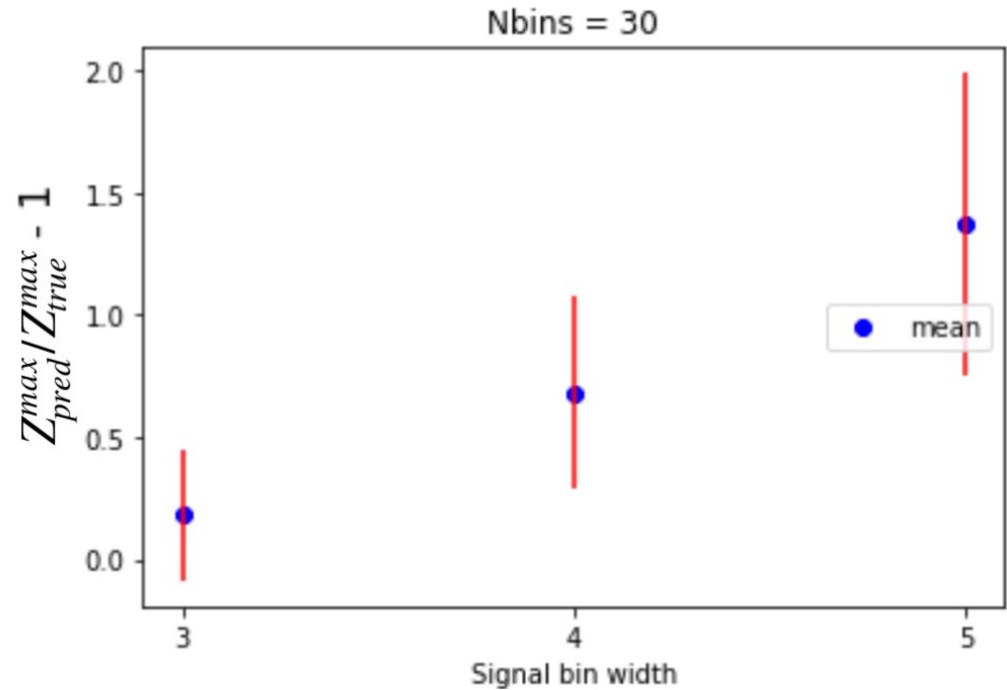
Number of bins per histogramm



# Performance stability

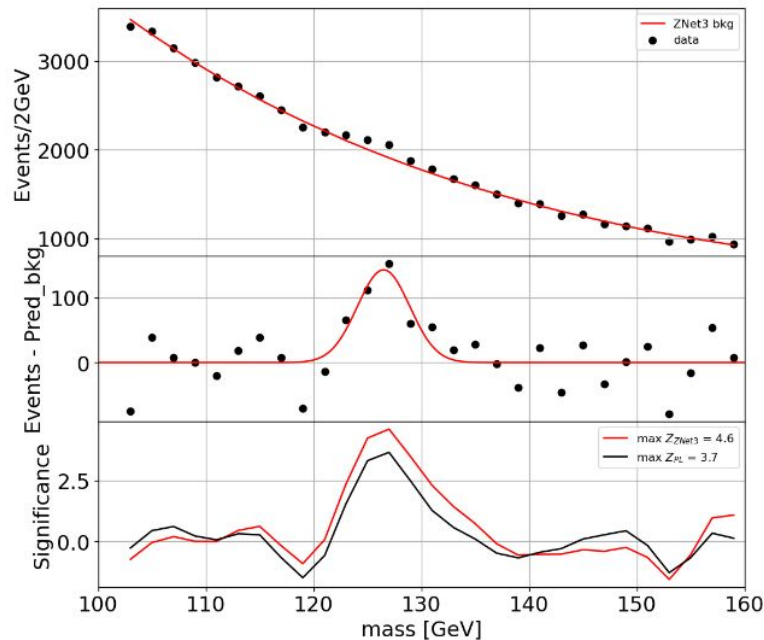
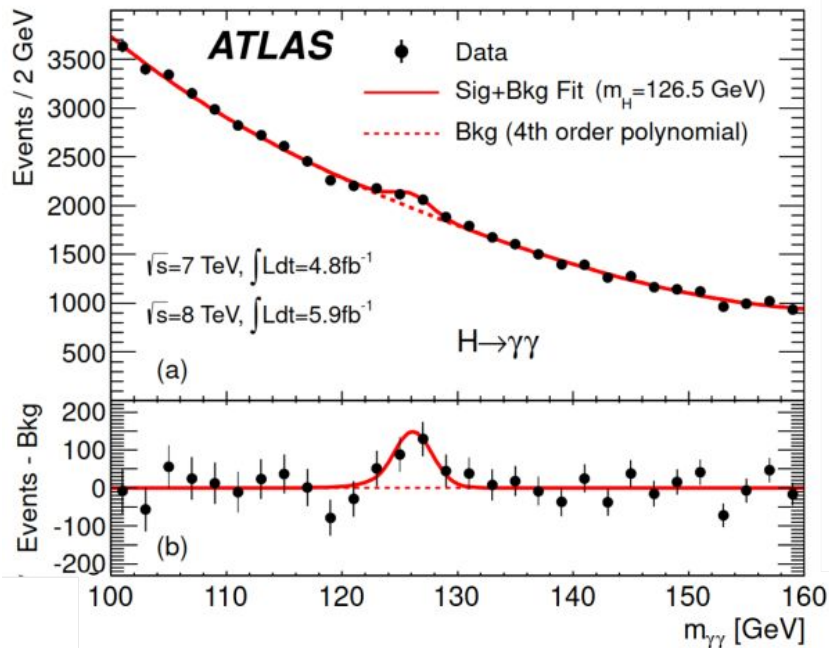
- ★ Training on fixed signal width: 1
  - ★ Bias increases with signal width
- > important to **adapt binning**  
to **experimental resolution**

Mean & sigma as a function of signal width



# Finding the Higgs bump

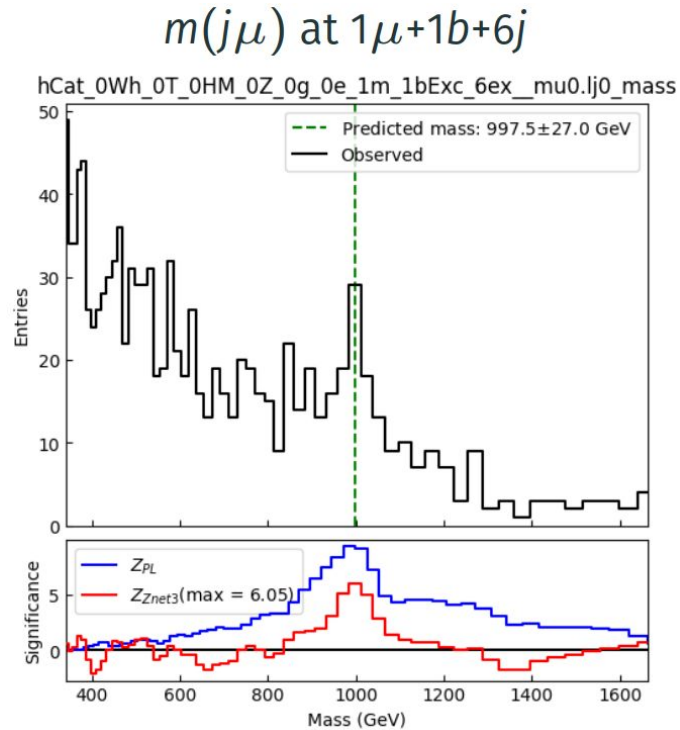
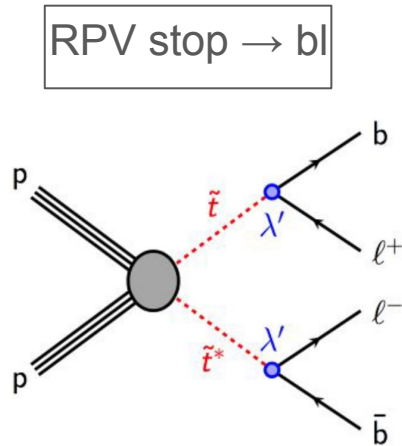
DDP was able to find the Higgs bump using the ATLAS plot:



Bump was predicted at **correct mass** with  $z_{\text{pred}} = 4.6$   
(consistent with  $z_{\text{true}}$  of 3.7 within method precision)

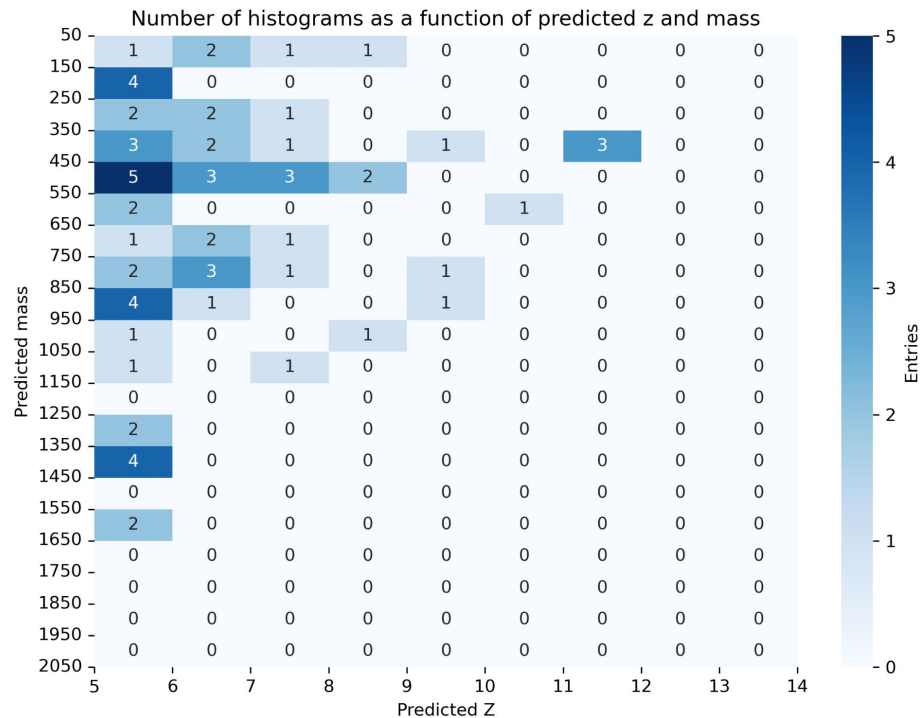
# Finding new-physics signals

DDP was successful at finding the injected new-physics signals at correct mass:



# Finding new-physics signals

★ Testing over background-only samples results in **false-positive rate of 0.1%**

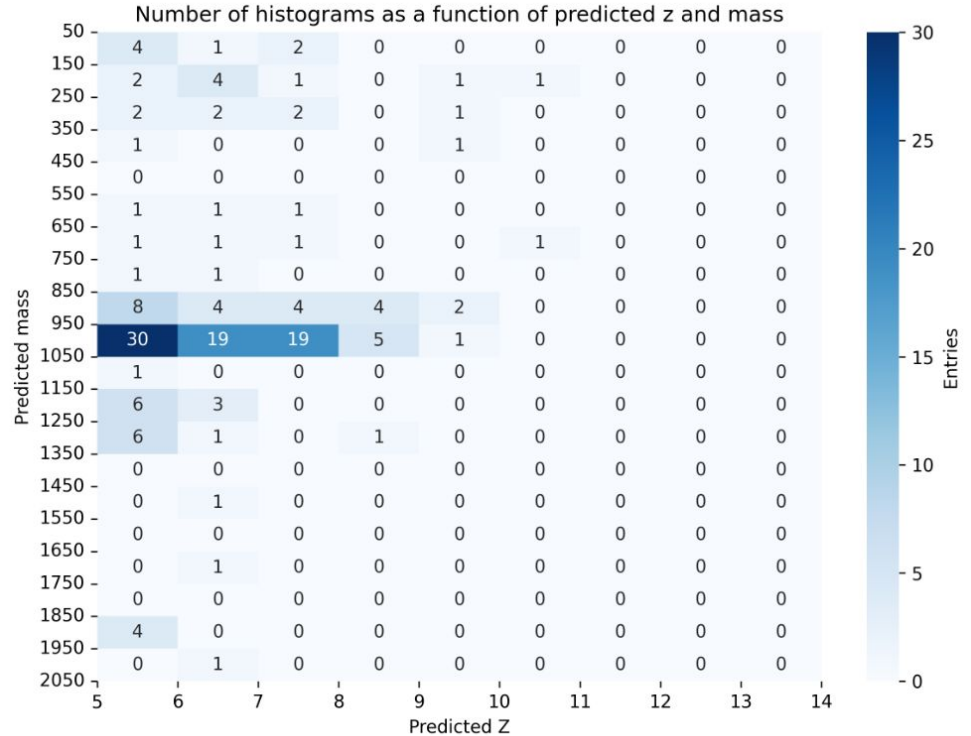


Background-only histograms with  $Z_{\max, \text{pred}} \geq 5$



# Finding new-physics signals

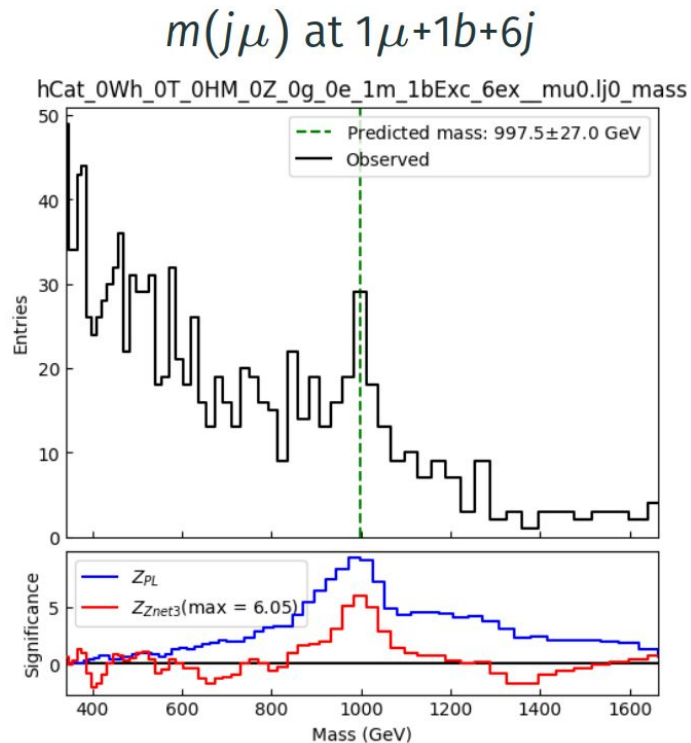
- ★ Signal is usually detected in more than one histogram
- ★ Physics correlations help distinguish between anomaly and false-positives



Histograms that find RPV stop  $\rightarrow$  bl with  $Z_{\max, \text{pred}} \geq 5$  17

# Conclusion

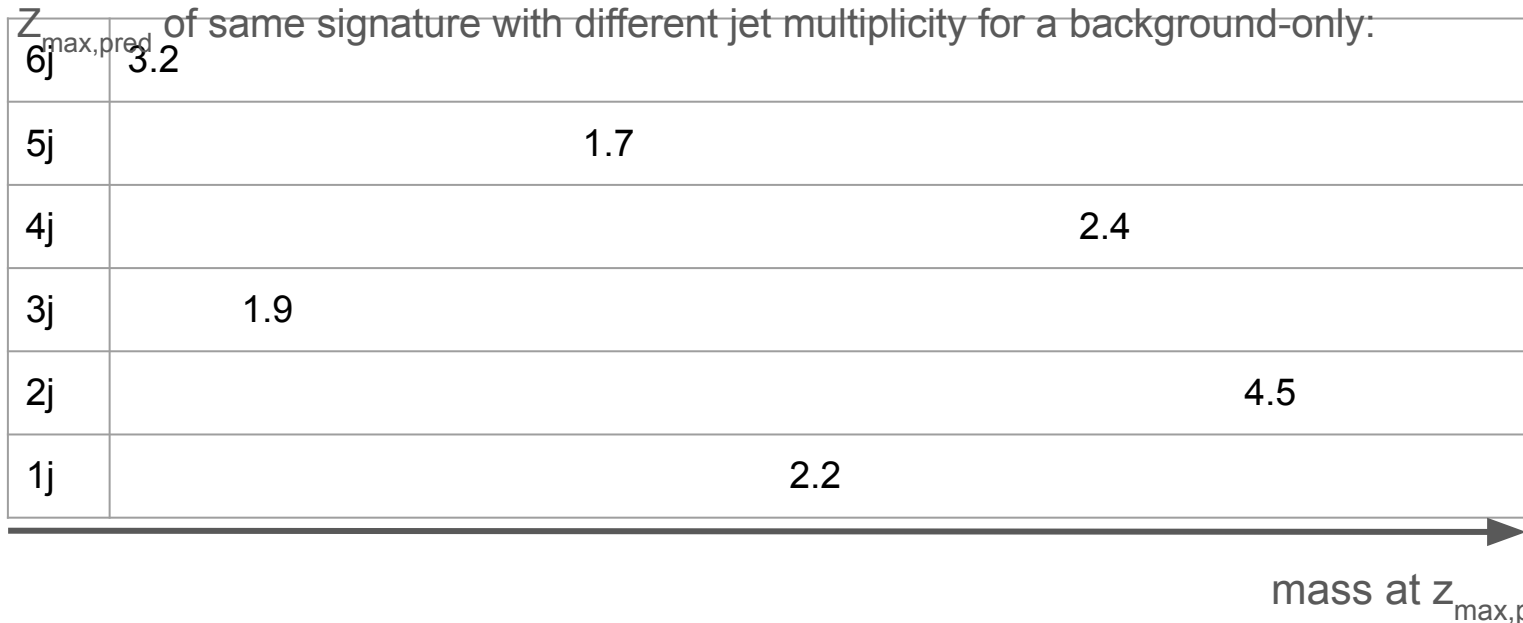
- ★ DDP is successful at finding bumps
  - in analytical **functions**: [1st proof of concept](#)
  - in **simulations**: 2nd proof of concept in progress
- ★ Method scans huge parameter space efficiently
- ★ Could be used to find interesting signal regions
- ★ Outlook: apply DDP to ATLAS data



# Backup

# Splitting the dataset by jet multiplicity

- ★ We split each signature by jet multiplicity (=number of jets)
- ★ Compare the position of  $z_{\text{max,pred}}$  in neighboring jet multiplicities to reduce look-elsewhere effect



# Splitting the dataset by jet multiplicity

- ★ Signal should appear at same mass in several histograms with neighboring jet multiplicity

$Z_{\text{max,pred}}$  of same signature with different jet multiplicity for a signal:

6j	2.3
5j	1.7
4j	3.4
3j	5.3
2j	3.9
1j	2.2

mass at  $Z_{\text{max,pred}}$

# Dark Machines samples

SM processes			
Physics process	Process ID	$\sigma$ (pb)	$N_{\text{tot}}$ ( $N_{10\text{fb}^{-1}}$ )
$pp \rightarrow jj(+2j)$	njets	$19718_{H_T > 600\text{GeV}}$	415331302 (197179140)
$pp \rightarrow l^\pm \nu_l(+2j)$	w_jets	$10537_{H_T > 100\text{GeV}}$	135692164 (105366237)
$pp \rightarrow \gamma j(+2j)$	gam_jets	$7927_{H_T > 100\text{GeV}}$	123709226 (79268824)
$pp \rightarrow l^+ l^- (+2j)$	z_jets	$3753_{H_T > 100\text{GeV}}$	60076409 (37529592)
$pp \rightarrow t\bar{t}(+2j)$	ttbar	541	13590811 (5412187)
$pp \rightarrow t + \text{jets}(+2j)$	single_top	130	7223883 (1297142)
$pp \rightarrow \bar{t} + \text{jets}(+2j)$	single_topbar	112	7179922 (1116396)
$pp \rightarrow W^+ W^- (+2j)$	ww	82.1	17740278 (821354)
$pp \rightarrow W^\pm t(+2j)$	wtop	57.8	5252172 (577541)
$pp \rightarrow W^\pm \bar{t}(+2j)$	wtopbar	57.8	4723206 (577541)
$pp \rightarrow \gamma\gamma(+2j)$	2gam	47.1	17464818 (470656)
$pp \rightarrow W^\pm \gamma(+2j)$	Wgam	45.1	18633683 (450672)
$pp \rightarrow ZW^\pm(+2j)$	zw	31.6	13847321 (315781)
$pp \rightarrow Z\gamma(+2j)$	Zgam	29.9	15909980 (299439)
$pp \rightarrow ZZ(+2j)$	zz	9.91	7118820 (99092)
$pp \rightarrow h(+2j)$	single_higgs	1.94	2596158 (19383)
$pp \rightarrow t\bar{t}\gamma(+2j)$	ttbarGam	1.55	95217 (15471)
$pp \rightarrow t\bar{t}Z$	ttbarZ	0.59	300000 (5874)
$pp \rightarrow t\bar{t}h(+1j)$	ttbarHiggs	0.46	200476 (4568)
$pp \rightarrow \gamma t(+2j)$	atop	0.39	2776166 (3947)
$pp \rightarrow t\bar{t}W^\pm$	ttbarW	0.35	279365 (3495)
$pp \rightarrow \gamma\bar{t}(+2j)$	atopbar	0.27	4770857 (2707)
$pp \rightarrow Zt(+2j)$	ztop	0.26	3213475 (2554)
$pp \rightarrow Z\bar{t}(+2j)$	ztopbar	0.15	2741276 (1524)
$pp \rightarrow t\bar{t}\bar{t}$	4top	0.0097	399999 (96)
$pp \rightarrow t\bar{t}W^+W^-$	ttbarWW	0.0085	150000 (85)