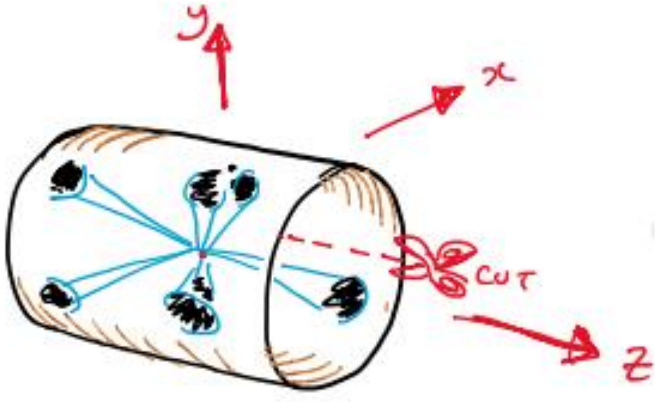

A method for searching for parity violating physics at the LHC

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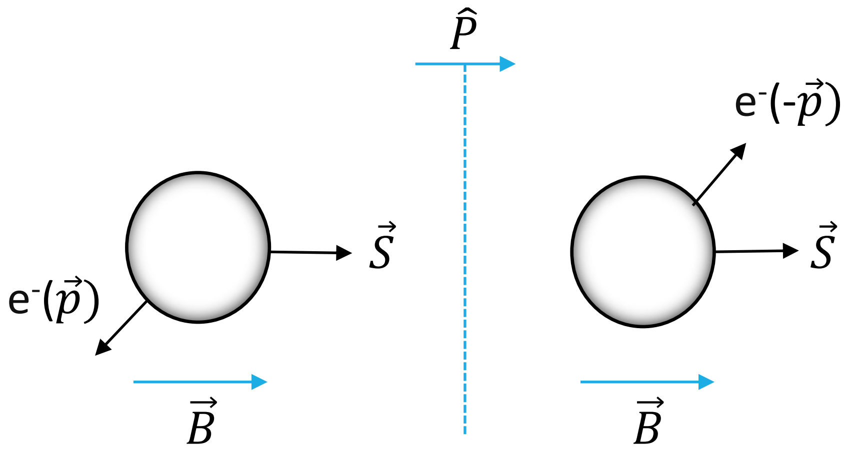
$\hat{P}$(x, y, z) → (-x, -y, -z)

$\hat{P}(p_T$, η, ϕ) → $(p_T$, -η, ϕ ± π)

Why parity violation?

Wu experiment

- $^{60}Co \longrightarrow {}^{60}Ni + e^- + \bar{\nu}_e$



- Close to 0 Kelvin
- Spins of ^{60}Co aligned by a B field
- Observed e^- emitted preferentially in hemisphere opposite to applied $\vec{B}$ field

- The function $\vec{B}.\vec{p}$ is parity-odd, since $\vec{B}$ is an axial vector
  - Expected value of $\vec{B}.\vec{p}$ = 0 in absence of parity violation
  - Asymmetry in $\vec{B}.\vec{p}$ ⇒ parity violated

We know the Standard model violates parity in the weak interaction

- Some objects are produced more frequently than their mirror images
- Is there parity violating new physics at the energy scales probed by the LHC?

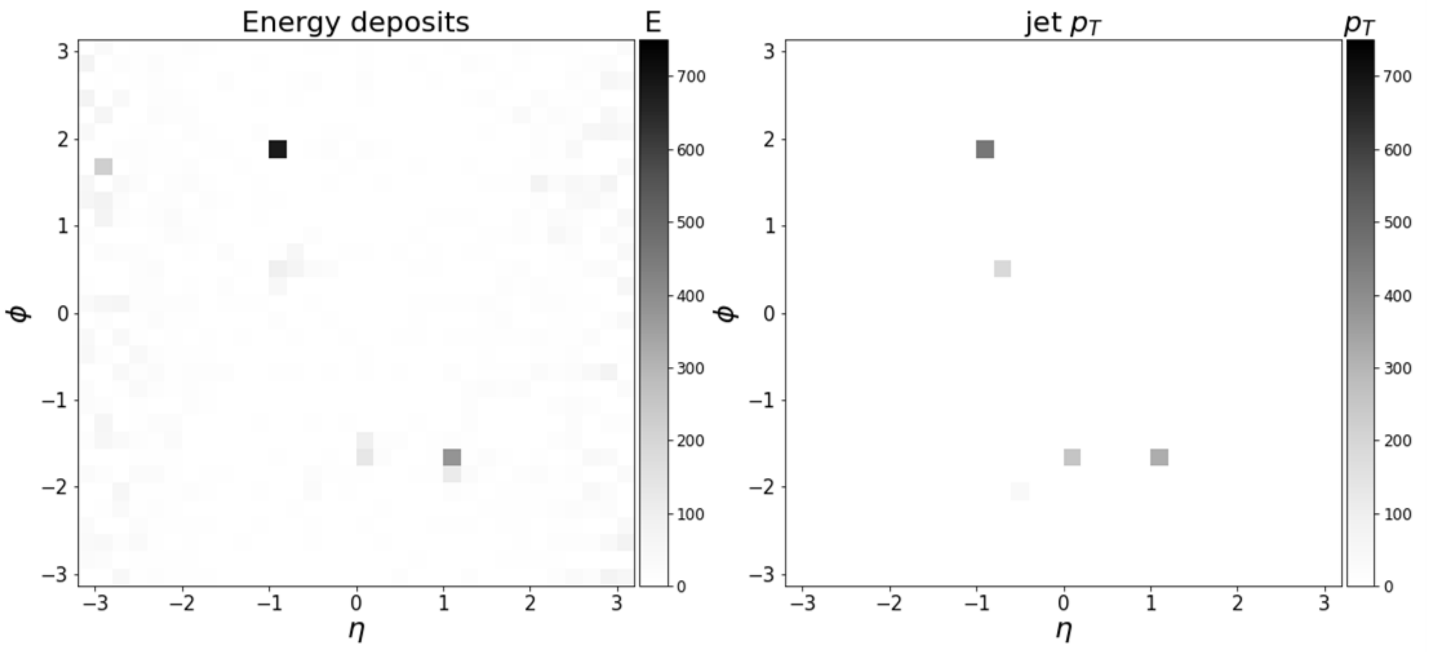
Searching for parity violation at the LHC

The goal

- Develop a model independent method to search for parity violation
  - Produced by unpolarised beams
  - Detectors not sensitive to polarisation
- Looking at momentum *or* energy information as images

The solution

- Can we see an asymmetry a parity-odd measurement function in a similar way to $\vec{B}.\vec{p}$?
- f(x) = g(x) – g($\hat{P}$(x))
  - For an arbitrary function g(x)
  - x = images in (η, ϕ) with ≥ 3jets
  - g(x) is a convolutional neural network (CNN) satisfying ϕ-translation symmetry *



Energy deposits in calorimeter

Reconstructed jet p_T

$f(x) = - f(\hat{P}(x))$

* See backup for more information

Search method

- Normalised example D(x)
- Value on y axis indicates probability of point
- Clearly parity violating, points $x > 0$ are twice as likely as points $x < 0$

Problem statement

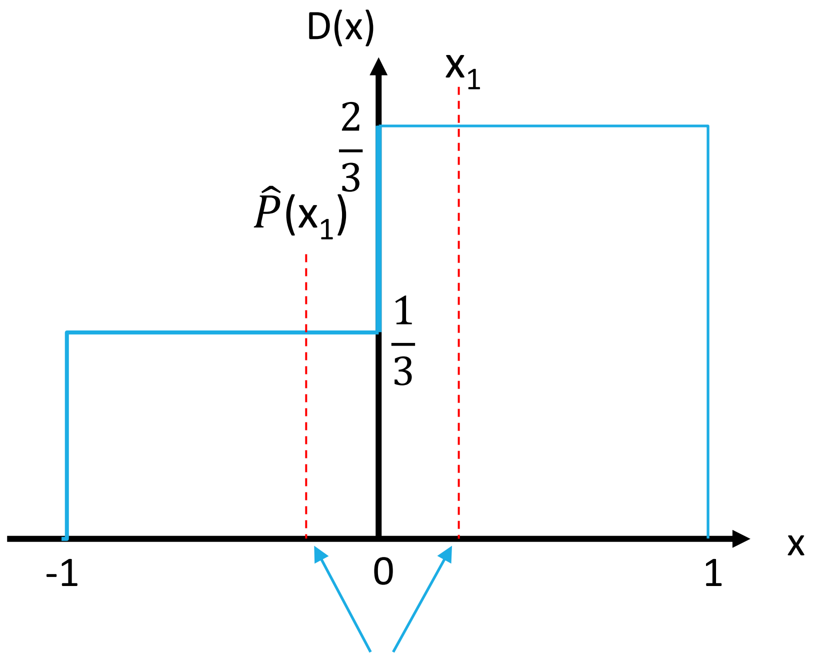
- We have a dataset drawn from distribution D(x)
- x = image (energy *or* p_T) in our case
- Does D(x) violate parity symmetry?

Method

- Sample point x_1
- Label x_1 as *real* or *fake*
  - Real (r): point drawn from D(x)
  - Fake (f): parity transformed point
- Calculate probability of x_1 being *real** as $P(real|\ x_1\ )$

Aim

- If D(x) conserves parity, *real* or *fake* are equally likely for a point
- If D(x) violates parity, either *real* or *fake* more than 50% likely for a point



Which is the point drawn from the distribution and which is the "fake" point?

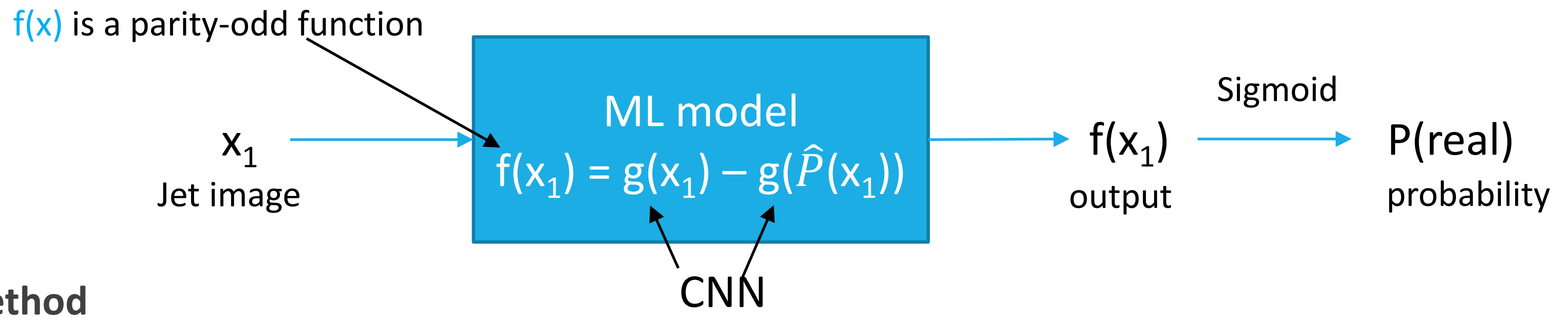
Trained classifier can assign a higher probability of x_1 being real

Machine learning setup

We can calculate [1] the probability of x_1 being drawn from D(x)*

$$P(real|x_1) = sigmoid\left[\, g(x_1) - g\left(\hat{P}(x_1)\right)\right]$$

$$\text{Sigmoid}(x) = \frac{1}{1+e^{-x}}$$



Training method

- Sample points from D(x), get images in η-ϕ plane ⟶ input to ML model
- To learn the CNN g(x): minimise $\text{Loss} = -\log \text{P}(\text{real}|x_1)$

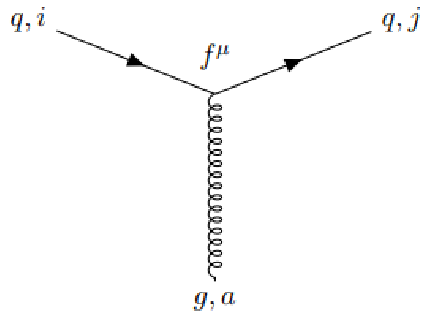
Testing method – using trained ML model

- Sample new points from D(x)
- Calculate net output f(x) $= g(x_1) - g\left(\hat{P}(x_1)\right)$
- If average f(x) over dataset significantly > 0 ⇒ parity violation in the dataset

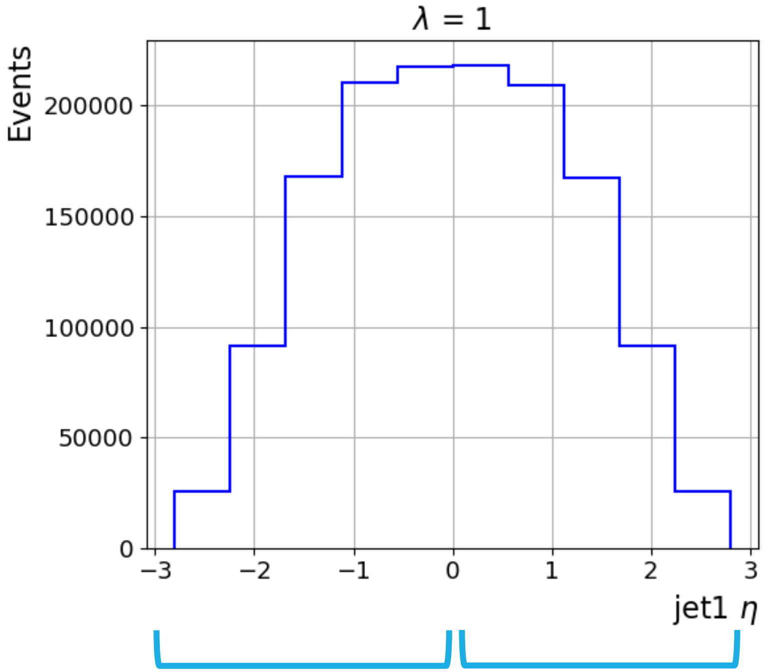
*For derivation see backup slides

[1] Tombs, Lester, *A method to challenge symmetries in data with self-supervised learning* 2111.05442

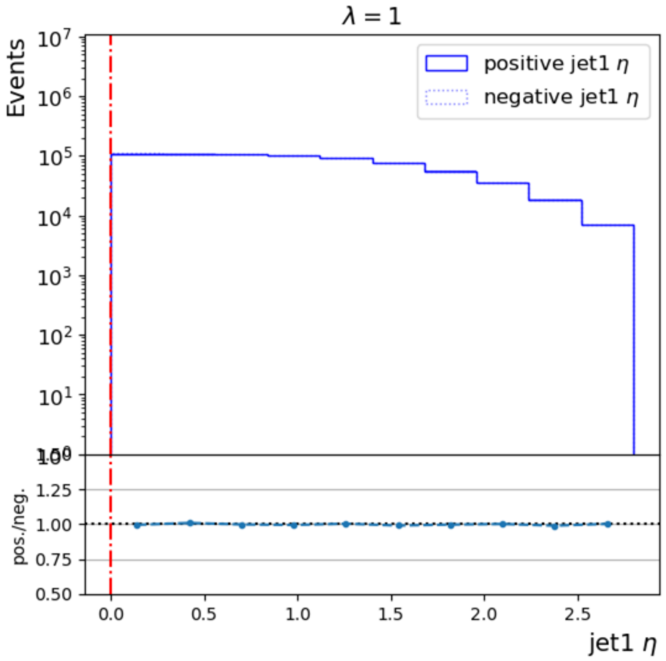
Dataset used



η is a parity-odd variable



Compare positives to negatives



Model used

- Use a dataset that violates parity in a way that can be seen in momenta

Minimal Standard-Model Extension (mSME) [1,2]

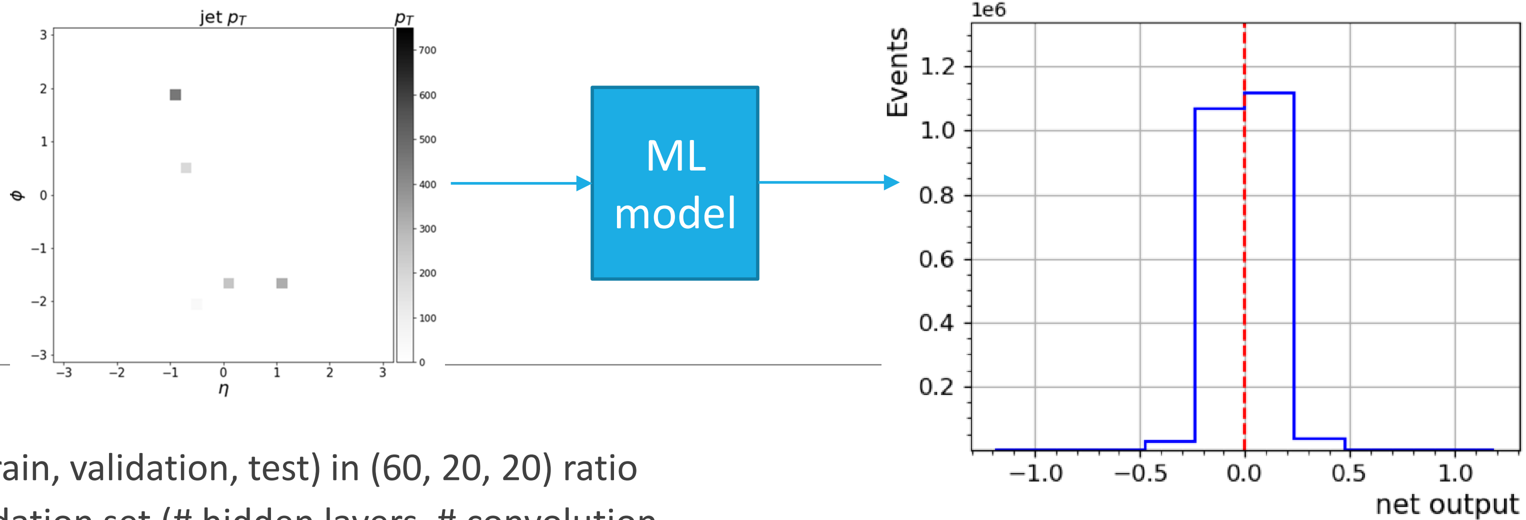
- Violates CPT and spontaneously breaks Lorentz symmetry
- Modify SM quark-gluon vertex with 4x4 coupling matrices $c_{\mu\nu}$
- Off-diagonal elements in $c_{\mu\upsilon}$ can cause parity violation
  - ∃ terms such as $\bar{u}cu$ in $\mathcal{L}$, where we get components E . P which are parity odd
- Modulate effect of $c_{\mu\upsilon}$ by a coupling constant λ (λ = 0 is the SM)

Data generation

- 3-jet mSME samples generated in Madgraph
- Showering in Pythia
- Reconstruction with pile-up in Delphes to approximate ATLAS detector
- Cut p_T > 220GeV leading 3 jets, |η| < 2.8 to emulate a 3-jet trigger

[1] Colladay, Kostelecky, *CPT Violation and the Standard Model* hep-ph/9703464
[2] Colladay, Kostelecky, *Lorentz-Violating Extension of the Standard Model* hep-ph/9809521

Training and testing



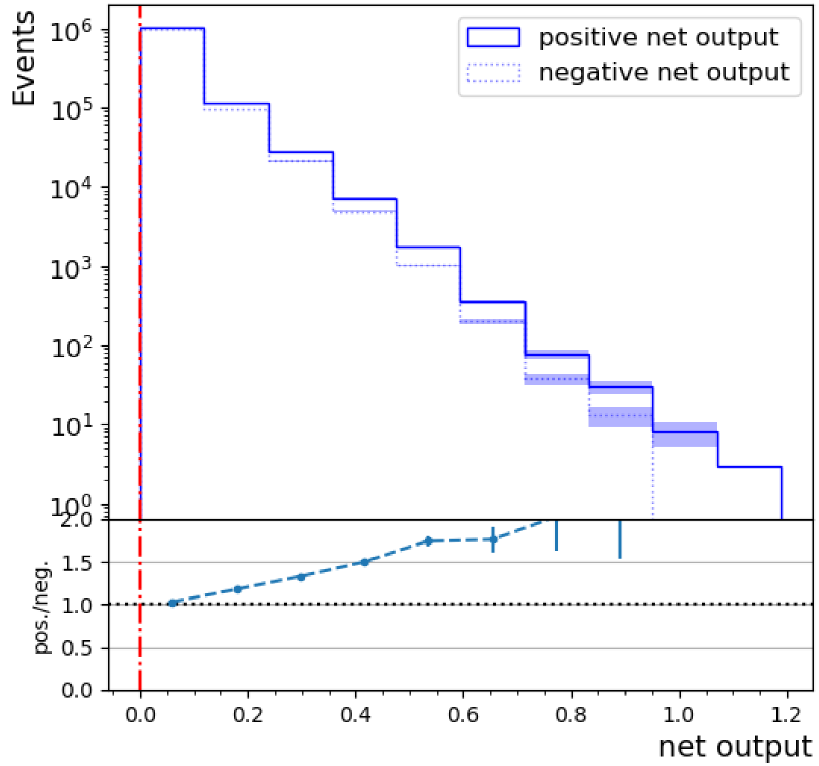
Compare positives to negatives

Training setup

- ~10M events split into three sets (train, validation, test) in (60, 20, 20) ratio
- Hyperparameters tuned on the validation set (# hidden layers, # convolution kernels, learning rate, amount of regularization, early stopping)

Results for reconstructed jet images λ=1; see parity violation

- Network output on the test set is clearly asymmetric around 0
- For a typical search, cut (e.g) |net output| > 1.0 and compare positive and negative yields



Metric, log likelihood ratio

- Comparing to a symmetric hypothesis (P = ½ for each event)
- Log-likelihood ratio for a data point $\log P(real|x_1) - \log\frac{1}{2}$
- Mean log-likelihood ratio over the dataset, Q, used as a metric.
  - Determines how much parity violation the model sees in the dataset
  - Q = 870 ± 30 ppm

ppm = parts per million

Each point is a individually trained CNN

Final results

Previous slide: training and testing with reconstructed jet images, λ=1

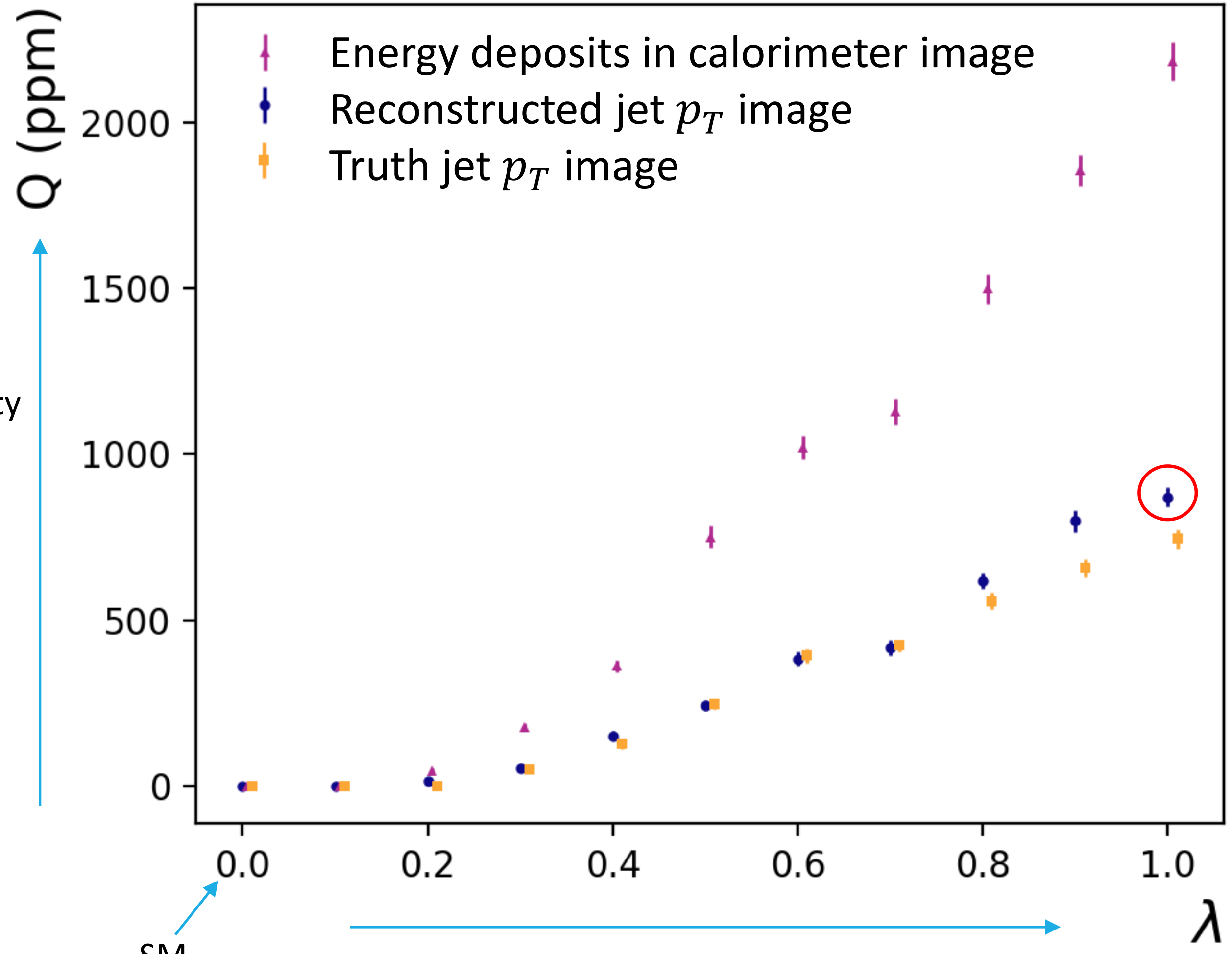
- Clearly see parity violation

See parity violation when instead training over different inputs

- Using energy deposit images provides more sensitivity

Reduced sensitivity when coupling reduced

More parity violation seen by model



SM

More parity violation in dataset

Conclusions

Summary

- A method has been developed for a model-independent search for parity violating physics at the LHC
- This has been developed for a 3 jet theory
  - Can be similarly performed on other physics objects e.g. electrons, muons
  - Wide range of potential final states that could be investigated

Future

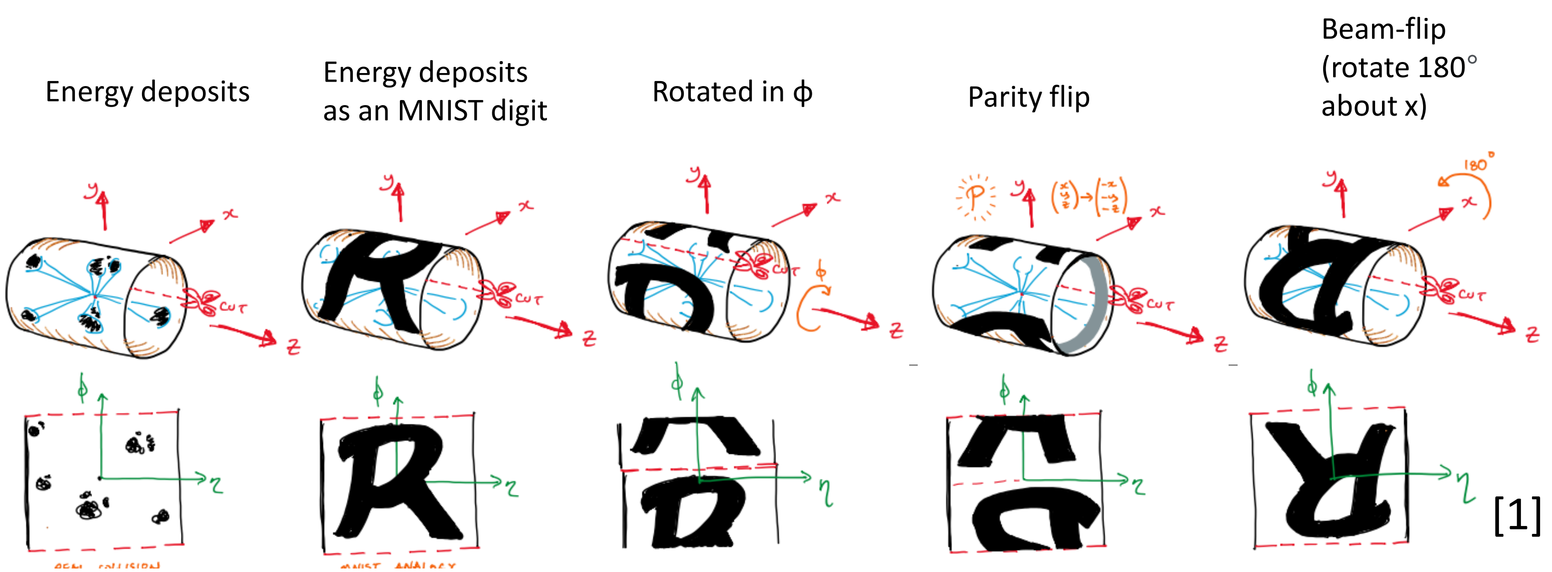
- We would like to see these techniques used on real LHC data
- We plan to make the code public for sample generation and data analysis to facilitate this

Thanks for listening! Any questions?

Backup

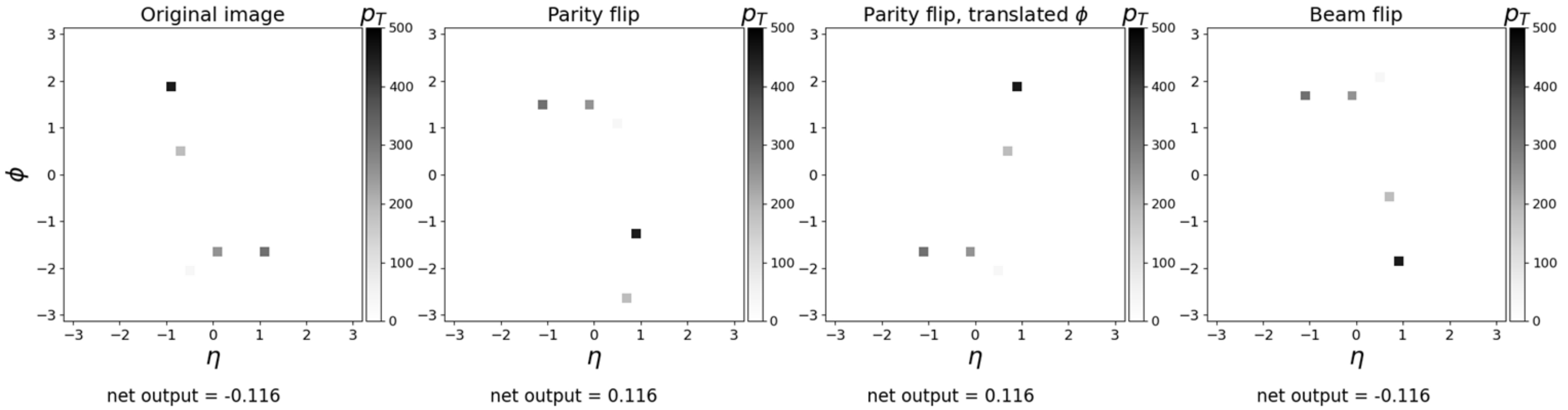
CNN symmetries

Parity-odd
- $f(x) = g(x) - g(\hat{P}x)$



Symmetric to ϕ rotations
- Since choice of origin is arbitrary
- Use max pooling: for each η slice, take only the maximum value across the entire ϕ range

Symmetric to rotations 180° about x-axis (swap beams)
- Since we have pp beams
- Introduce two more terms, $g(R_{180}x)$ and $g(\hat{P}R_{180}x)$



Overall network to train
- $f(x) = g(x) + g(R_{180}x) - g(\hat{P}x) - g(\hat{P}R_{180}x)$

Check on the network – are the desired symmetries obeyed?

Loss derivation

$x_2 = \hat{P}(x_1)$

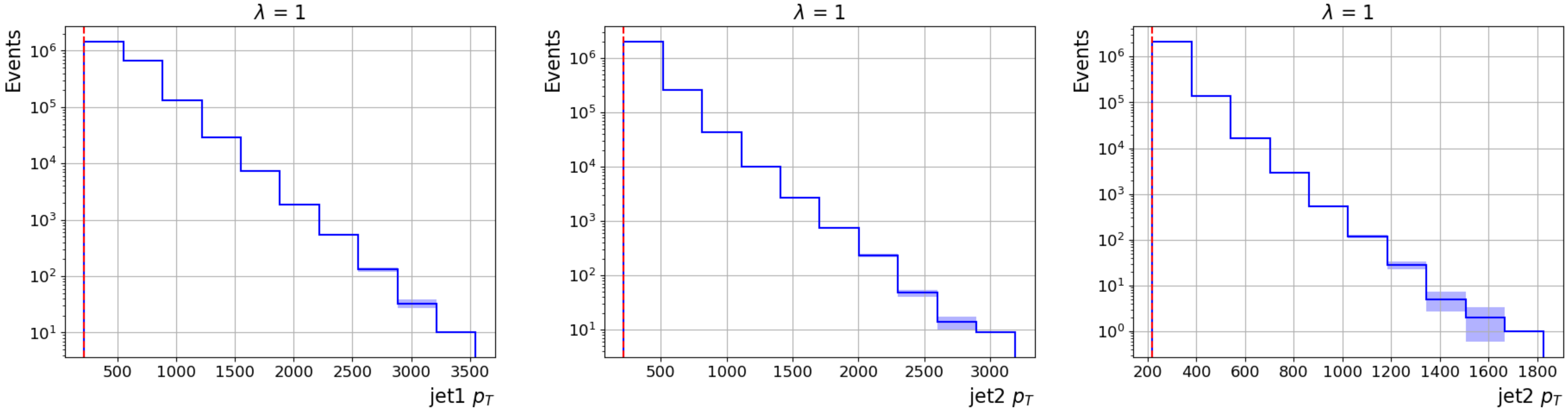
P(real) = P(ℓ = (r,f))

$$P(\ell = (\mathrm{r}, \mathrm{f}) | (x_1, x_2)) = \frac{P(\ell = (\mathrm{r}, \mathrm{f}) | (x_1, x_2))}{P(\ell = (\mathrm{r}, \mathrm{f}) | (x_1, x_2)) + P(\ell = (\mathrm{f}, \mathrm{r}) | (x_1, x_2))}$$
$$= \frac{1}{1 + \frac{P(\ell = (\mathrm{f}, \mathrm{r}) | (x_1, x_2))}{P(\ell = (\mathrm{r}, \mathrm{f}) | (x_1, x_2))}},$$

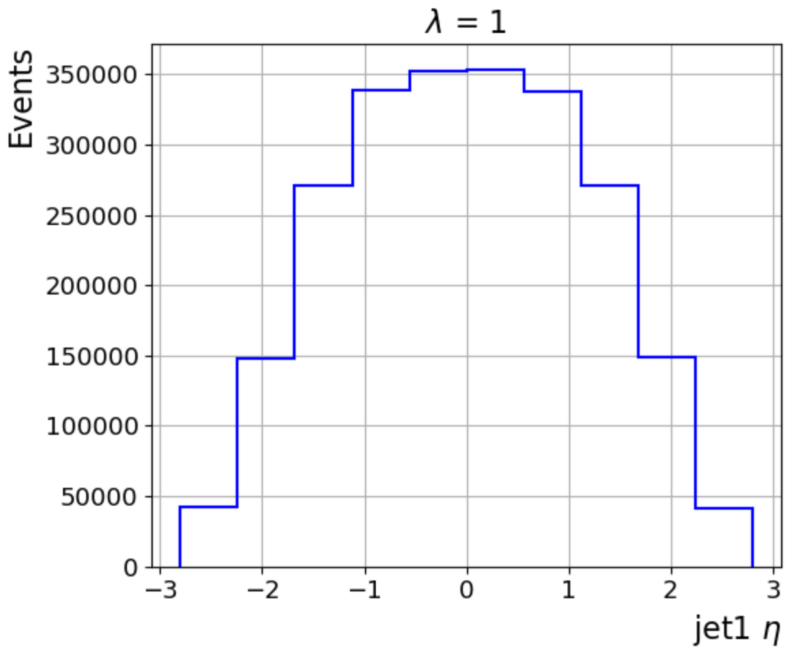
$$\frac{P(\ell = (\mathrm{f}, \mathrm{r}) | (x_1, x_2))}{P(\ell = (\mathrm{r}, \mathrm{f}) | (x_1, x_2))} = \frac{P(\ell = (\mathrm{f}, \mathrm{r}), (x_1, x_2)) P(x_1, x_2)}{P(\ell = (\mathrm{r}, \mathrm{f}), (x_1, x_2)) P(x_1, x_2)}$$
$$= \frac{P(x_1 = \mathrm{f} = \hat{P} x_2, x_2 = \mathrm{r})}{P(x_1 = \mathrm{r}, x_2 = \mathrm{f} = \hat{P} x_1)}$$
$$= \frac{P(x_1 = \mathrm{f} | x_2 = \mathrm{r}) P(x_2 = \mathrm{r})}{P(x_2 = \mathrm{f} | x_1 = \mathrm{r}) P(x_1 = \mathrm{r})}$$
$$= \frac{\tau(x_2, x_1) D(x_2) dx}{\tau(x_1, x_2) D(x_1) dx}$$
$$= \frac{D(x_2)}{D(x_1)}$$

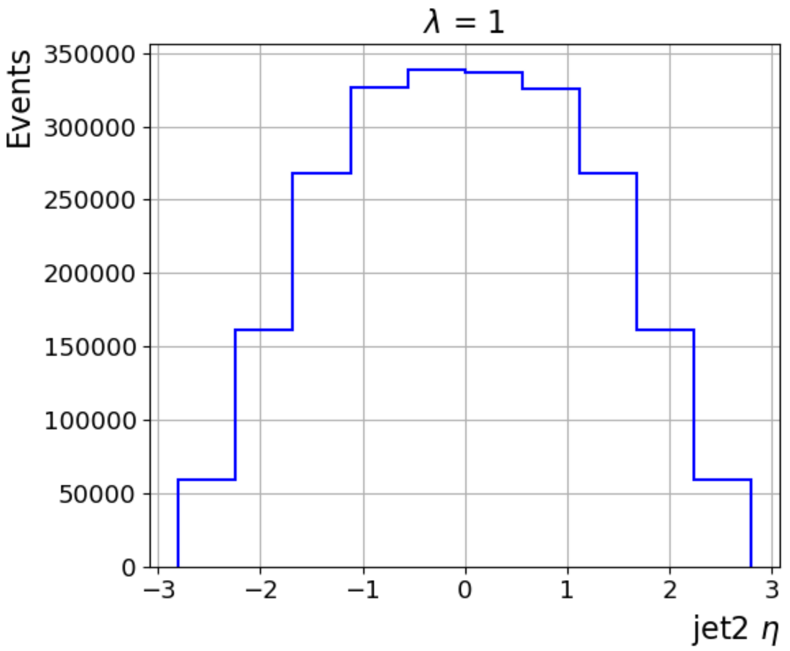
$$\log \frac{P(\ell = (\mathrm{f}, \mathrm{r}) | (x_1, x_2))}{P(\ell = (\mathrm{r}, \mathrm{f}) | (x_1, x_2))} = \log D(x_2) - \log D(x_1) = \mathrm{g}(x_2) - \mathrm{g}(x_1)$$

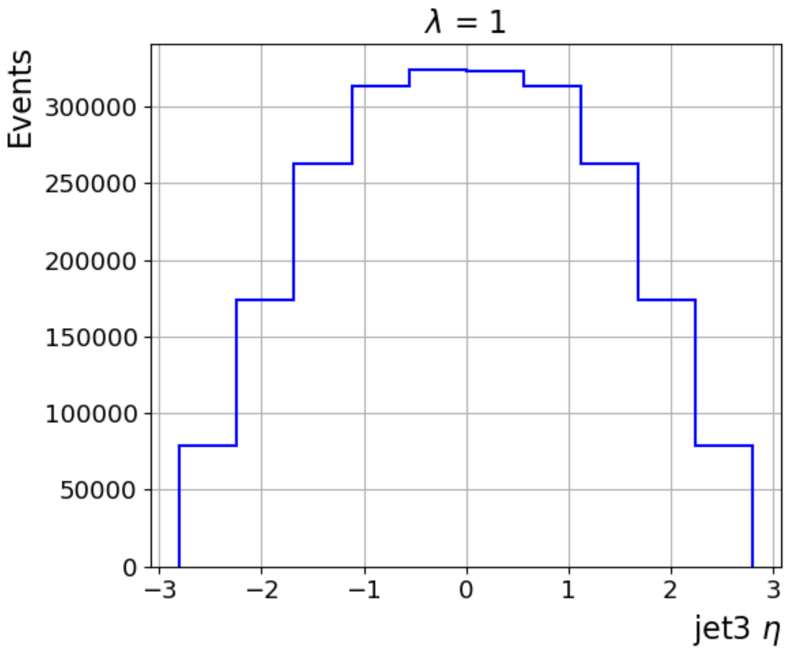
LIV plots

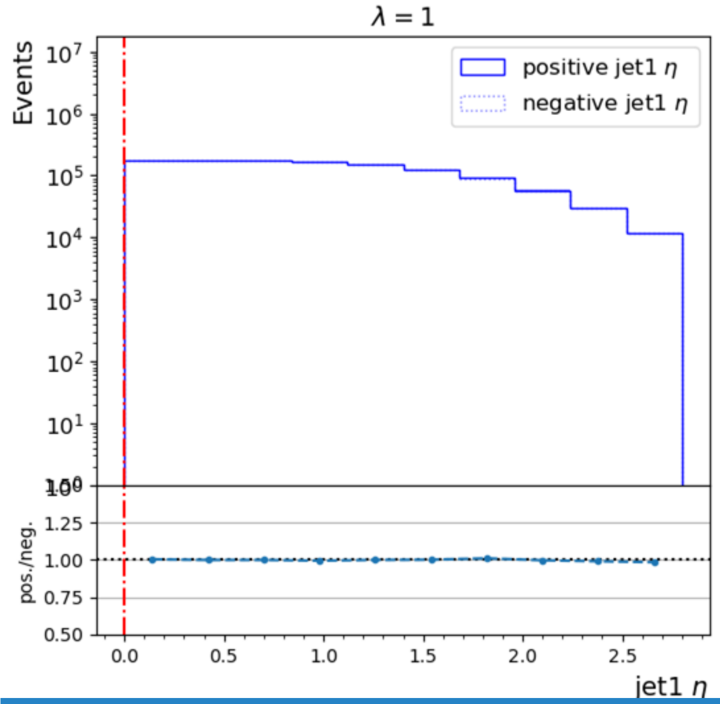


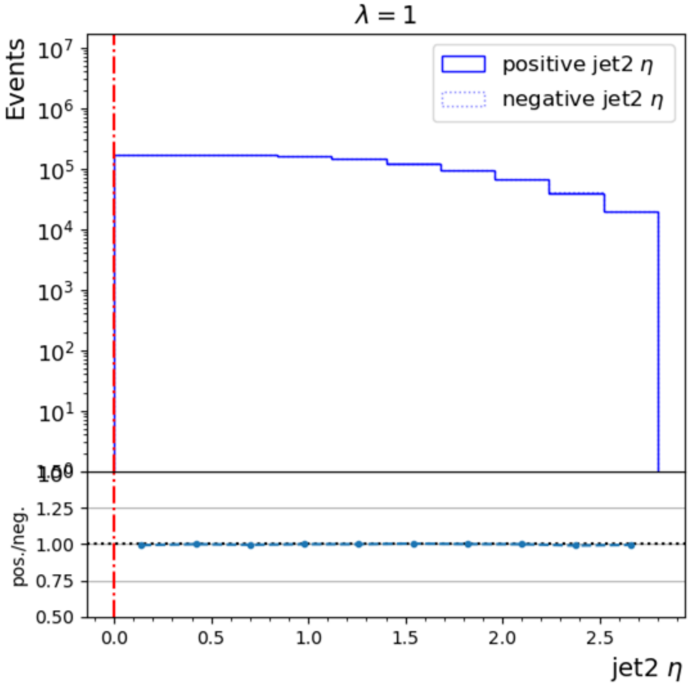
λ = 1
Events
10^1 10^2 10^3 10^4 10^5 10^6
500 1000 1500 2000 2500 3000 3500
jet1 p_T
λ = 1
Events
10^1 10^2 10^3 10^4 10^5 10^6
500 1000 1500 2000 2500 3000
jet2 p_T
λ = 1
Events
10^0 10^1 10^2 10^3 10^4 10^5 10^6
200 400 600 800 1000 1200 1400 1600 1800
jet2 p_T

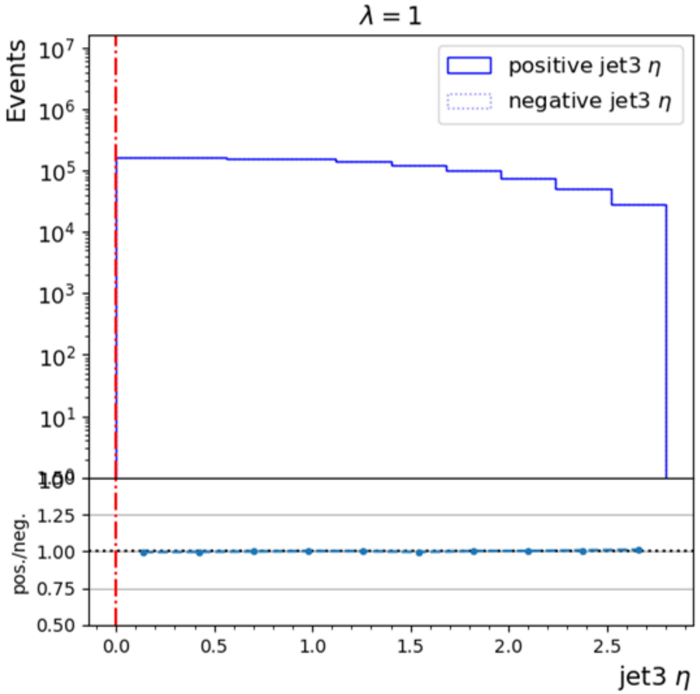

λ = 1
Events
jet1 η


λ = 1
Events
jet2 η

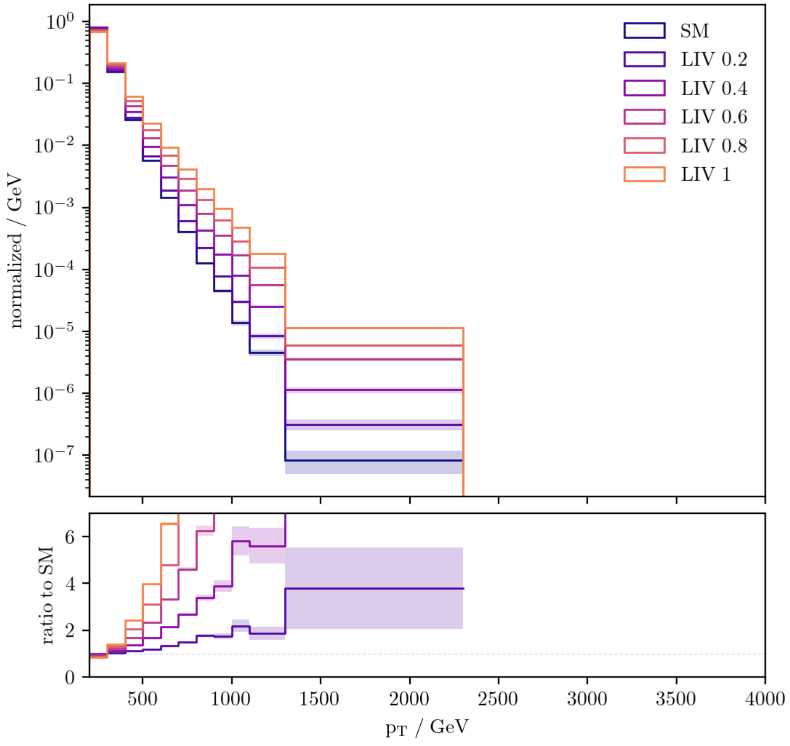

λ = 1
Events
jet3 η

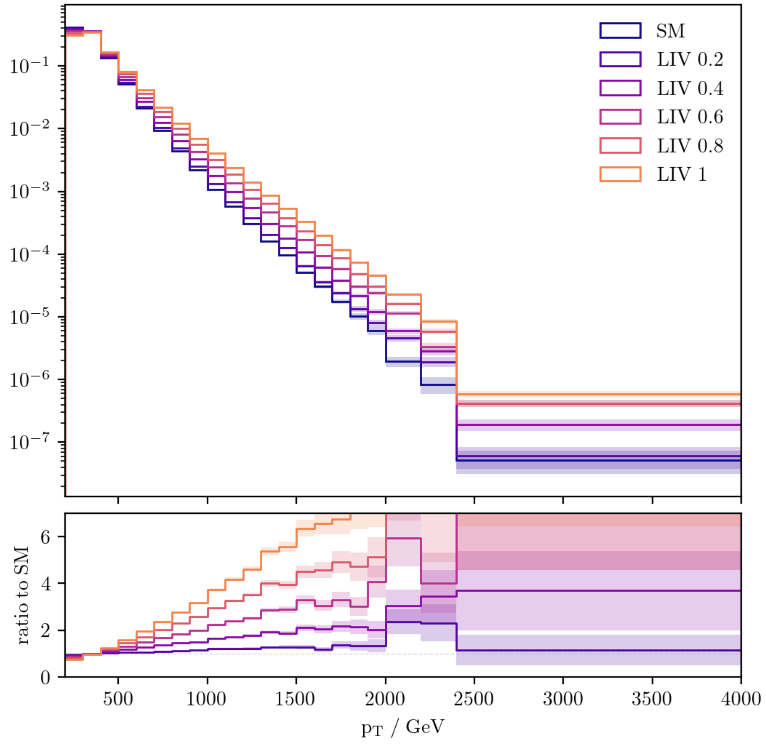

λ = 1
Events
positive jet1 η
negative jet1 η
pos./neg.
jet1 η

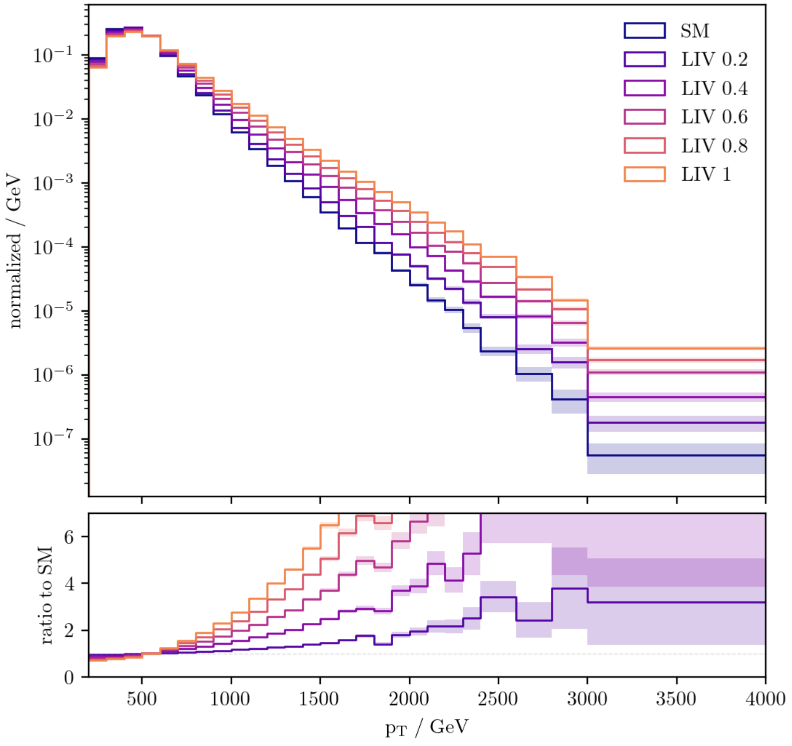

λ = 1
Events
positive jet2 η
negative jet2 η
pos./neg.
jet2 η


λ = 1
Events
positive jet3 η
negative jet3 η
pos./neg.
jet3 η

mSME multiple couplings







mSME multiple couplings