Searching for new physics with VAEs

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Institute for Theoretical Physics
University of Heidelberg

UZH ML Workshop

in collab. with B. Bortolato, A. Smolkovic, J. F. Kamenik

UNIVERSITÄT HEIDELBERG
Zukunft. Seit 1386.

Outline

1. Anomalies at the Large Hadron Collider
2. Finding anomalies with VAEs
3. Results on the LHC Olympics
4. Concluding remarks

1. Anomalies at the Large Hadron Collider

2. Finding anomalies with VAEs

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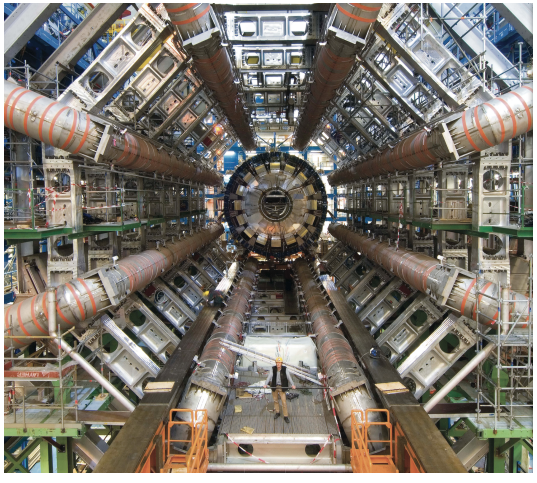
The Large Hadron Collider

- Highest energy particle collider in the world
- Constructed by CERN between 1998-2008
- Collides protons at energies of 13-14 TeV
  producing new particles that are measured in the detectors



- The LHC will run for many more years yet
  $\Rightarrow$ much more data to come

New physics searches

- Higgs boson discovery in 2012
- … but no new physics discovery since

  (composite Higgs, supersymmetry, …)

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Can machine learning help?

- (Variational) AutoEncoders (← what I will get to soon)
- Classification Without Labels (CWoLa) [Collins, Howe, Nachman (2019)]
- Density estimation [Nachman, Shih (2020)]
- Latent Dirichlet Allocation [BMD, Faroughy, Kamenik (2019)]
- …

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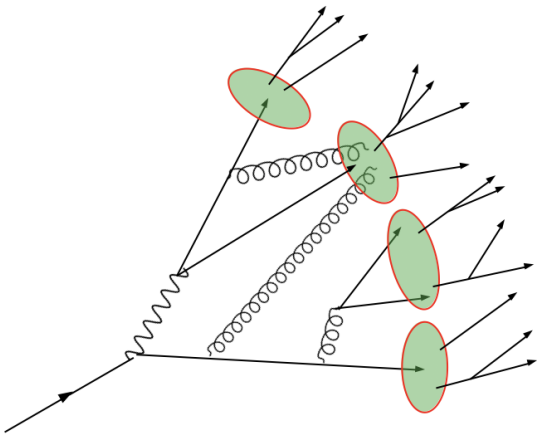
Boosted jets



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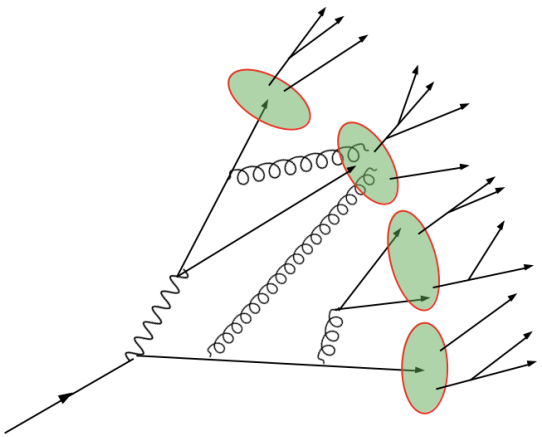
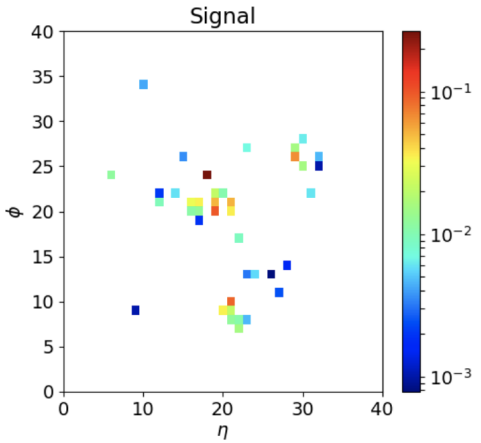
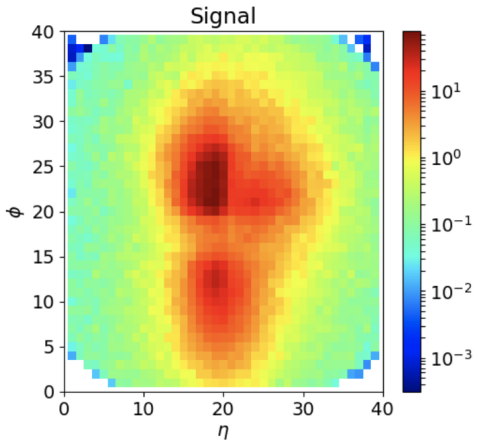


Boosted top jets





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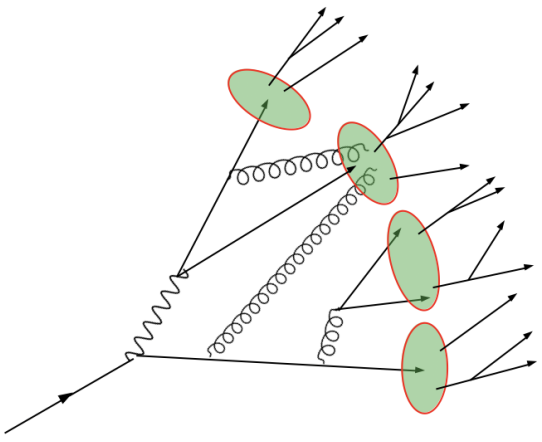

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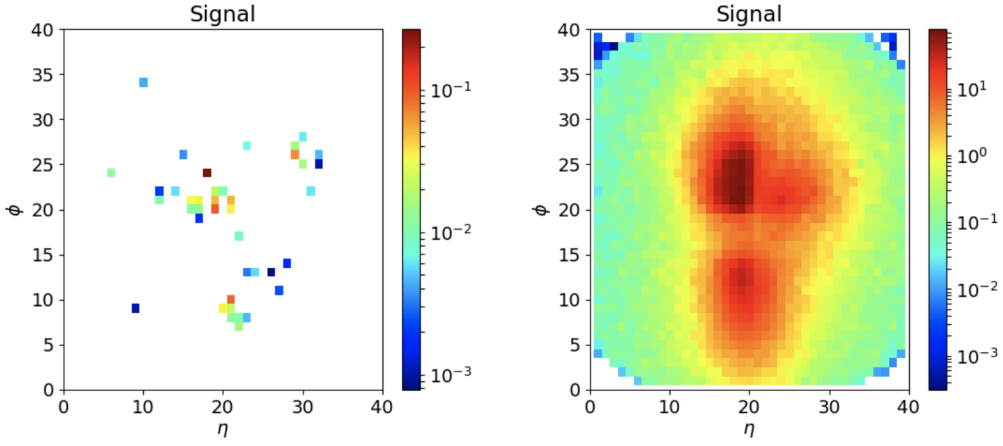
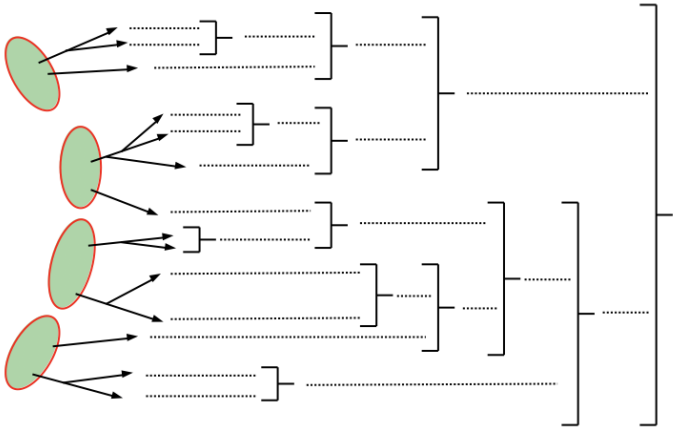


Sequential clustering histories



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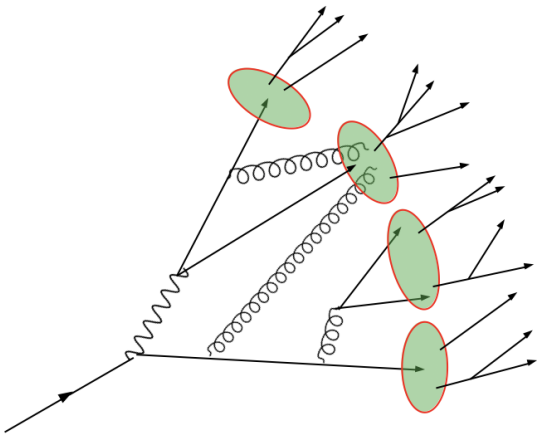

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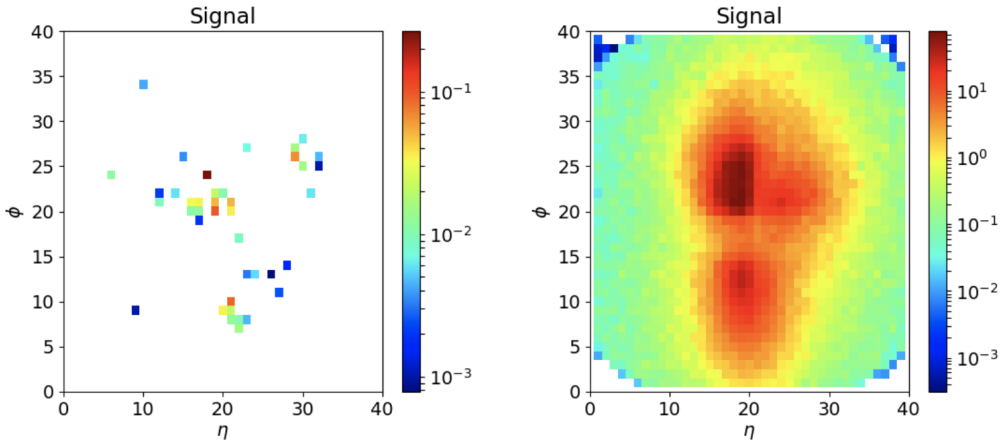

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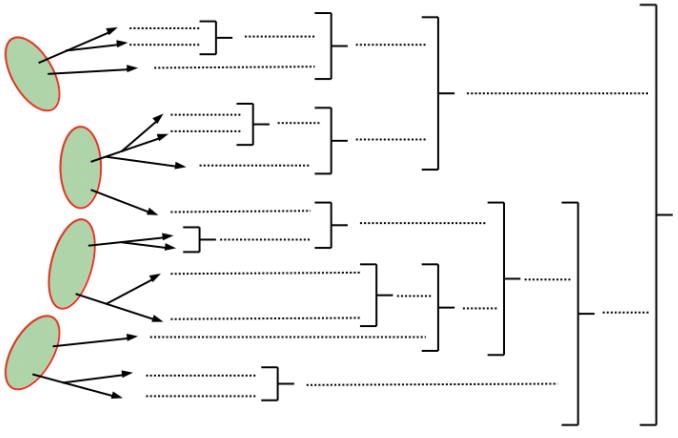
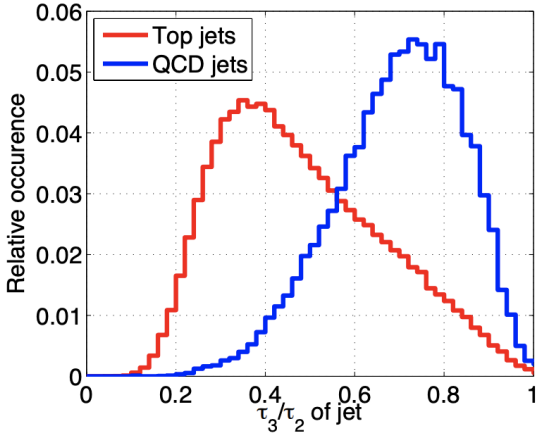


Global jet observables



Could new physics be hidden in jet substructure?

Proposed scenario:

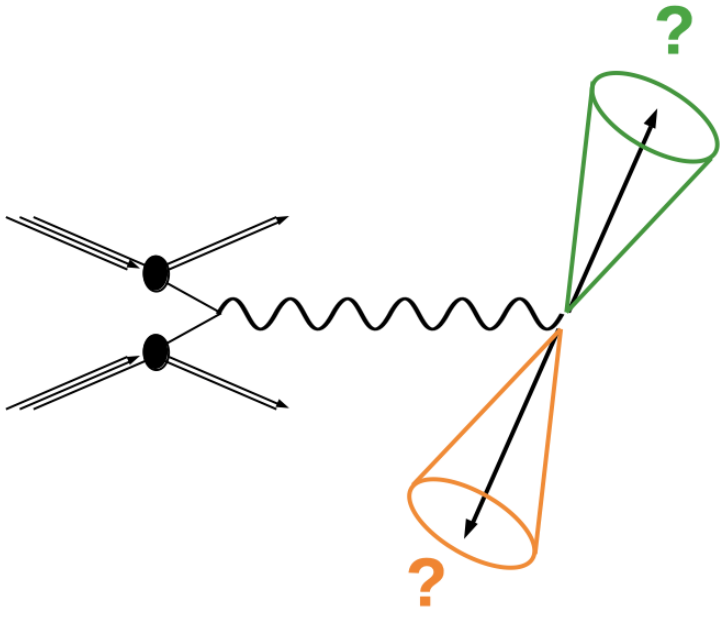
- Unknown heavy resonance '*A*' decaying to di-jets

$$pp \rightarrow A \rightarrow B\ C$$

- '*B*' and/or '*C*' are also unknown

Goal:

- Unsupervised classification of these events from background events



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Proposed scenario:

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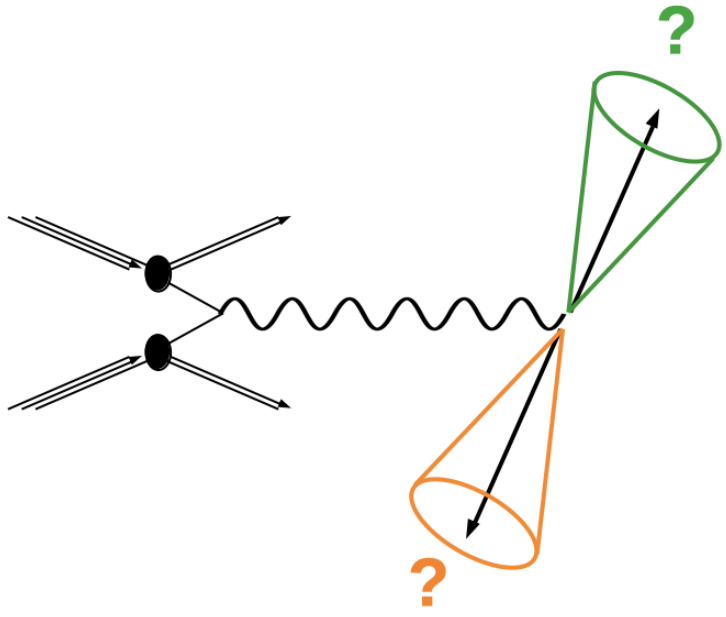

Goal:

- Unsupervised classification of these events from background events

Observables:

- High-level, e.g. jet masses, N-subjettiness, ...
- ... but we don't know what to look for

$\Rightarrow$ Use neural networks to find anomalies in the data.

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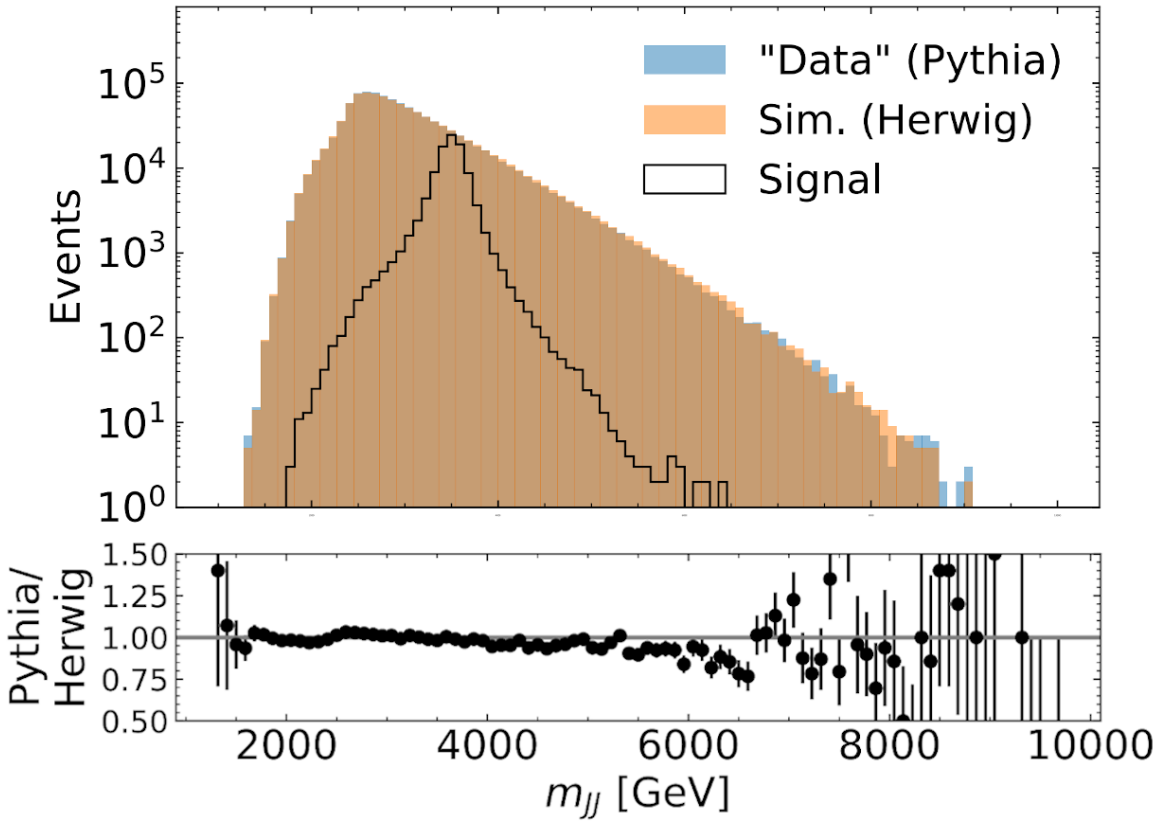
Bump hunting

[Kasieczka, Nachman, Shih (2019)]



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- We need to look for bumps in the invariant mass spectrum

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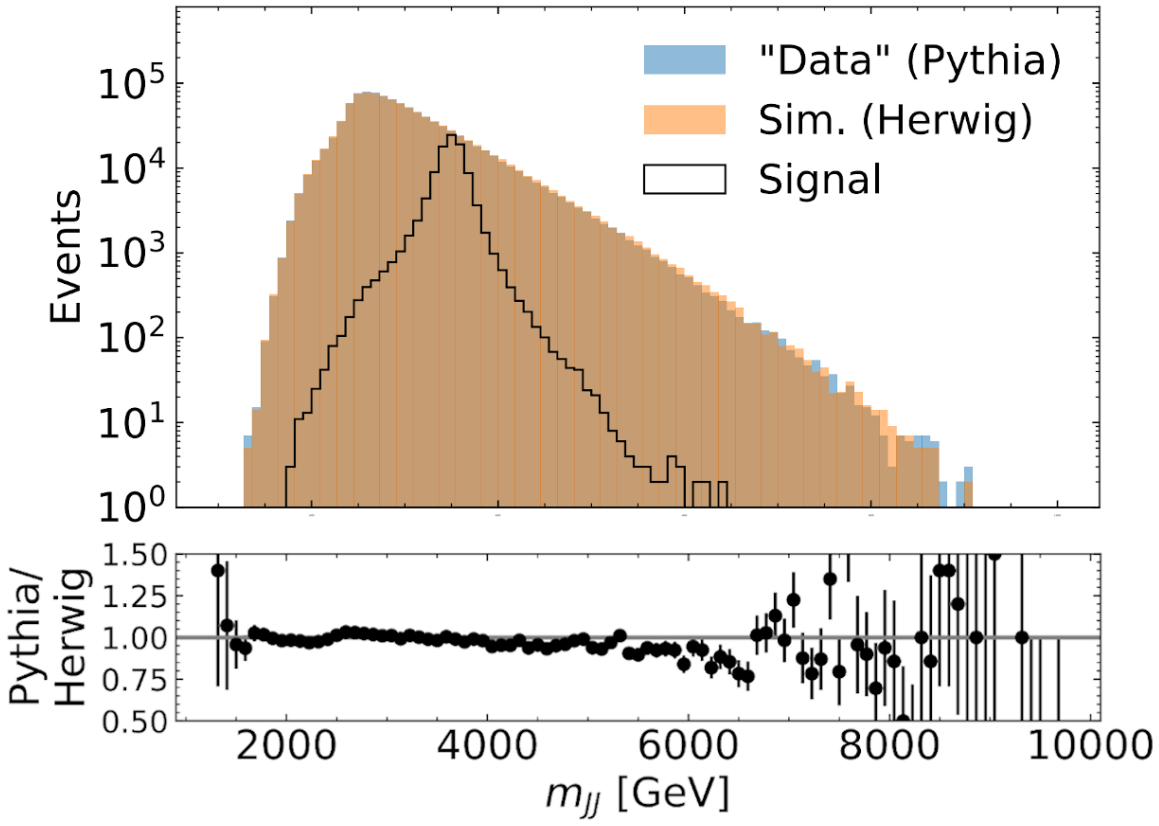
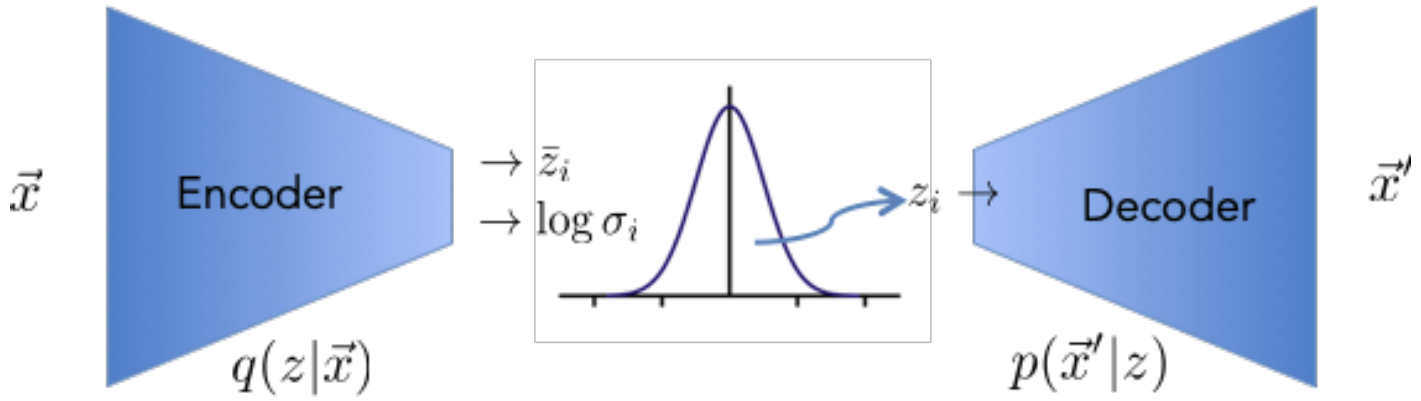


- We expect anomalies to be localised in invariant mass
- We need to look for bumps in the invariant mass spectrum
- … We need a classifier to improve signal-to-background ratio
- The classifier needs to be invariant-mass independent!

Variational Autoencoders

Data for each event embedded in a vector $\vec{x}_i$



Two anomaly measures:

1. Distance from centre in latent space
2. Reconstruction error

Variational Autoencoders invariant mass latent dimension

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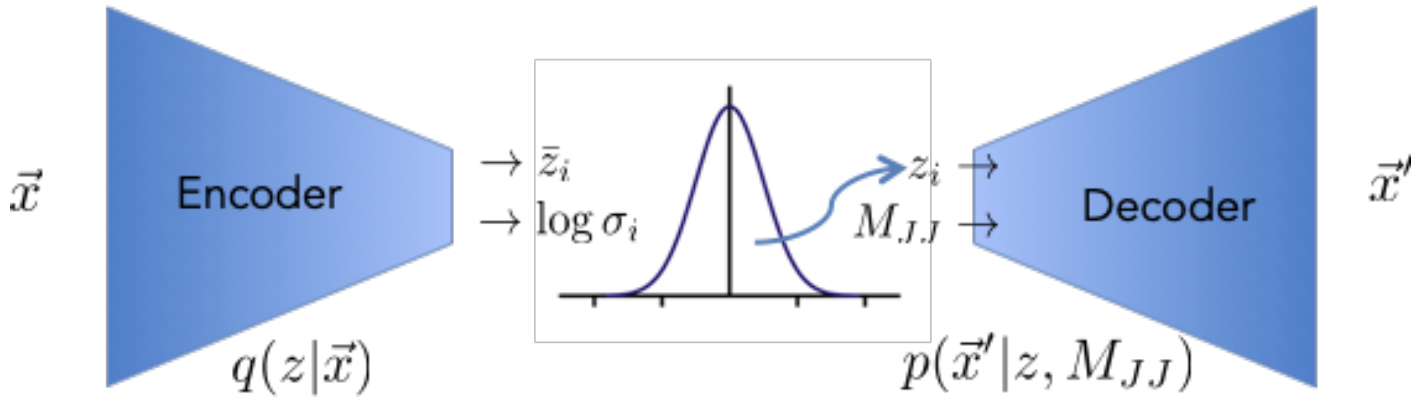

Two anomaly measures:

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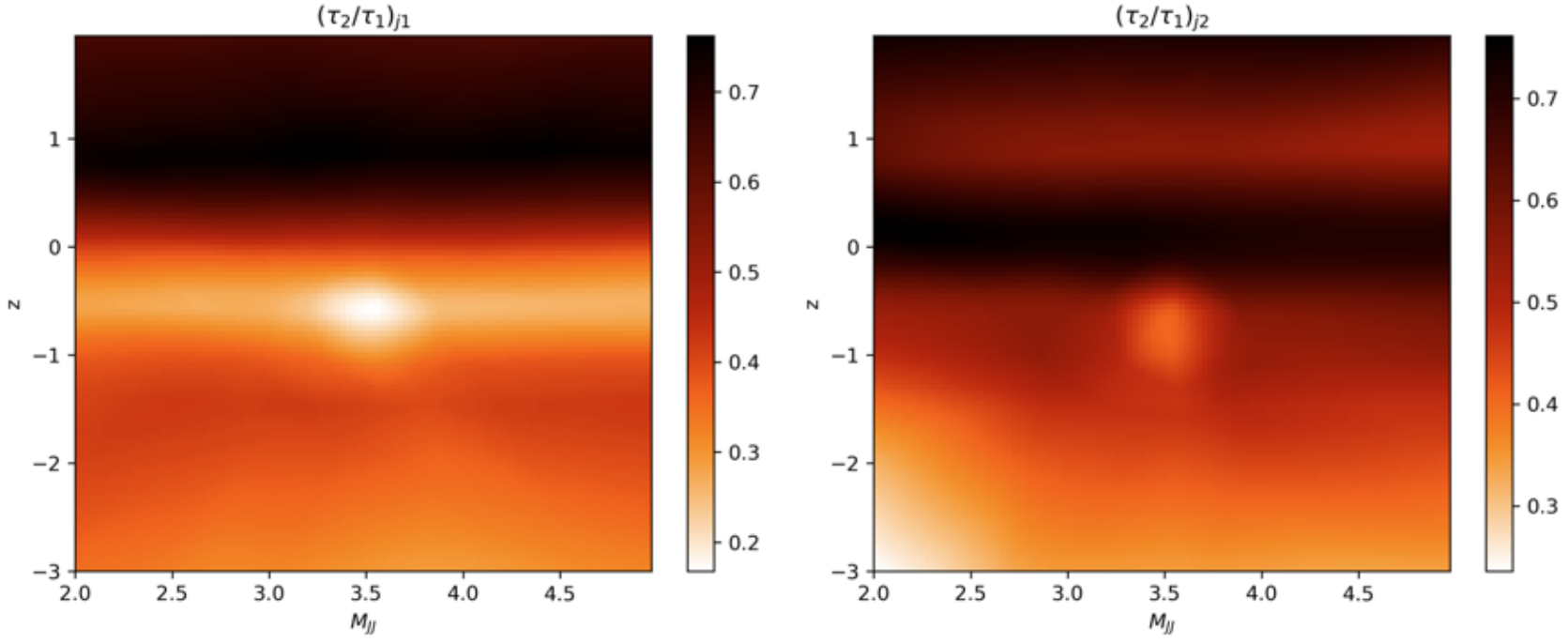
The network can learn locally in the invariant mass.

An invariant mass latent dimension

Decoder output:



Through the latent space, we can explore what the networks learn about invariant mass

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The LHC Olympics [Kasieczka, Nachman, Shih (2019)]

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- 1M background events and 1k signal events
- Use to design and optimise tehcniques

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Test data

- 1M background events and 1k signal events
- Use to design and optimise tehcniques

Blackboxes

- 1M unlabelled events possibly containing anomalies

Goals:

- Identify anomalies
- Characterise them as well as possible

i.e. how heavy are the jets, describe the physical processes, ...

Results: test data

Neural network architecture and optimisation:

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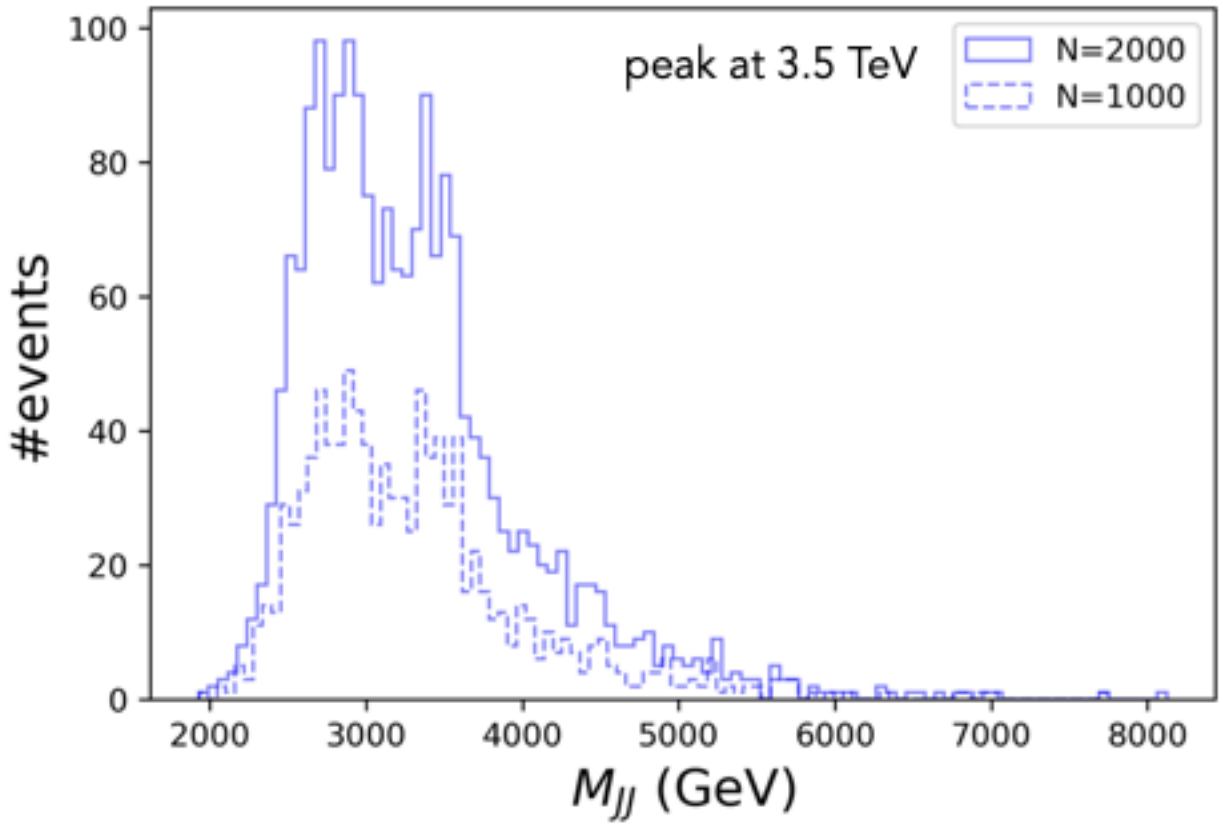
- Best performance correlated with minima in the mean log-variance in latent space

Results: test data

Now perform cuts, and study the invariant mass spectrum:

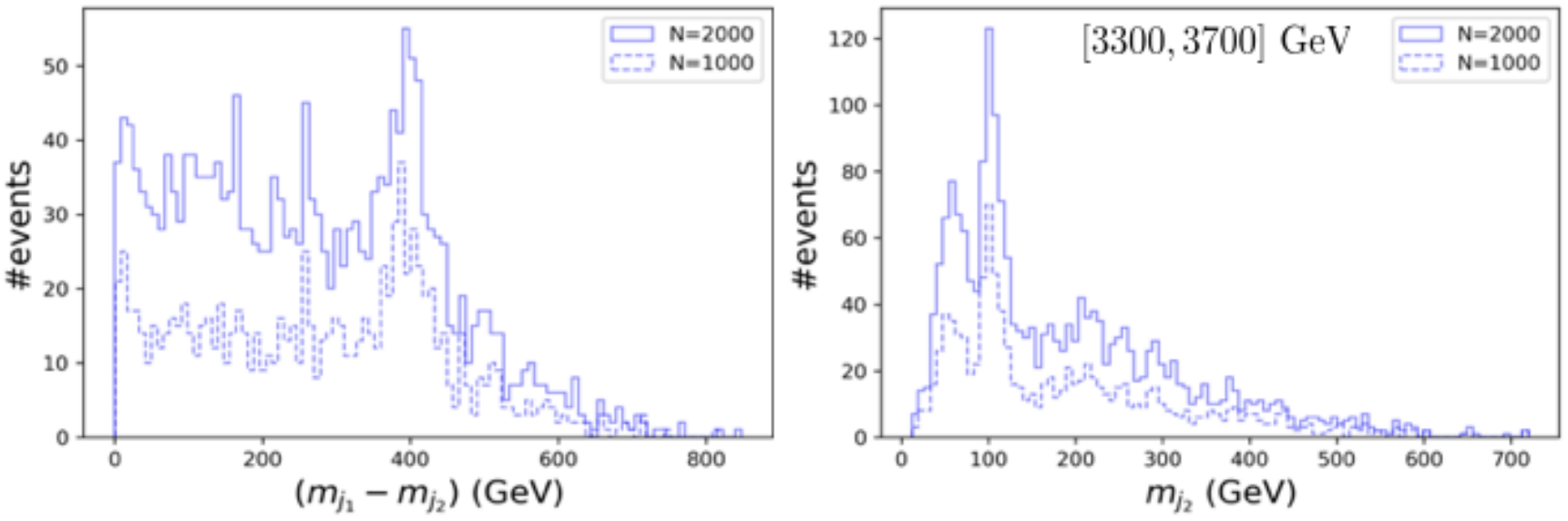


The VAE successfully finds the anomalous events localised at 3.5 TeV

Results: test data

Can we see characteristics of these anomalous events?

Look at features of anomalous events in the signal region:

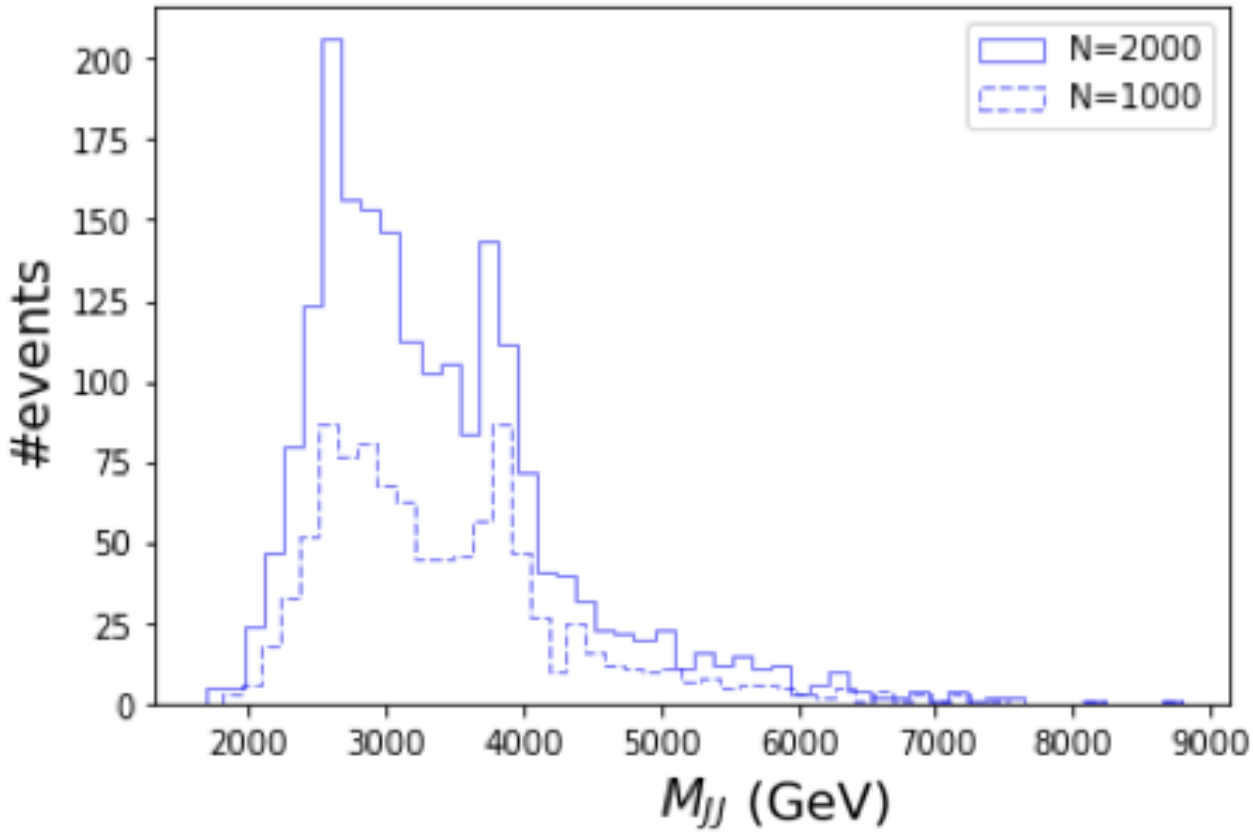


Anomalous events with jet masses of 500 GeV and 100 GeV

We can also do the same with other features.

Results: blackbox data

Here we don't have truth labels, so we run the same algorithm and study the invariant mass spectrum:

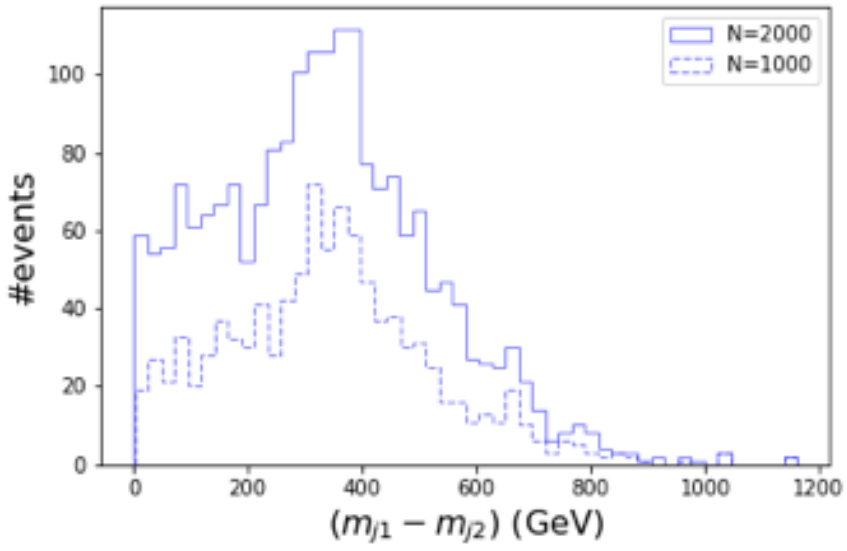


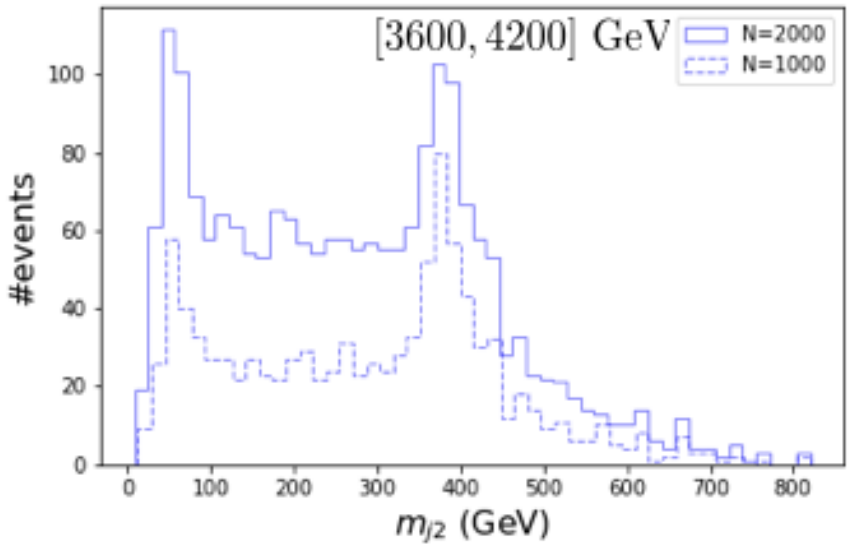
The VAE finds a bump localised at 3.8 TeV

Results: blackbox data

Is this bump actually a signal?

Let's look in the signal region and see if there are any features:





Anomalous events with jet masses of $\sim$ 740 GeV and 370 GeV

We can also do the same with other features.

This agrees with the results from the challenge!

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Thanks for your time!