UNIVERSITAT POLITÈCNICA DE VALÈNCIA

Use of deep learning generative models for Monte Carlo event simulation in the context of LHC experiments

Raúl Balanzá García

Cotutors: Jon Ander Gómez Adrián, José Francisco Salt Cairols, Roberto Ruiz de Austri Bazan

3rd Workshop on Compact Objects, Gravitational Waves and Deep Learning

University of Minho

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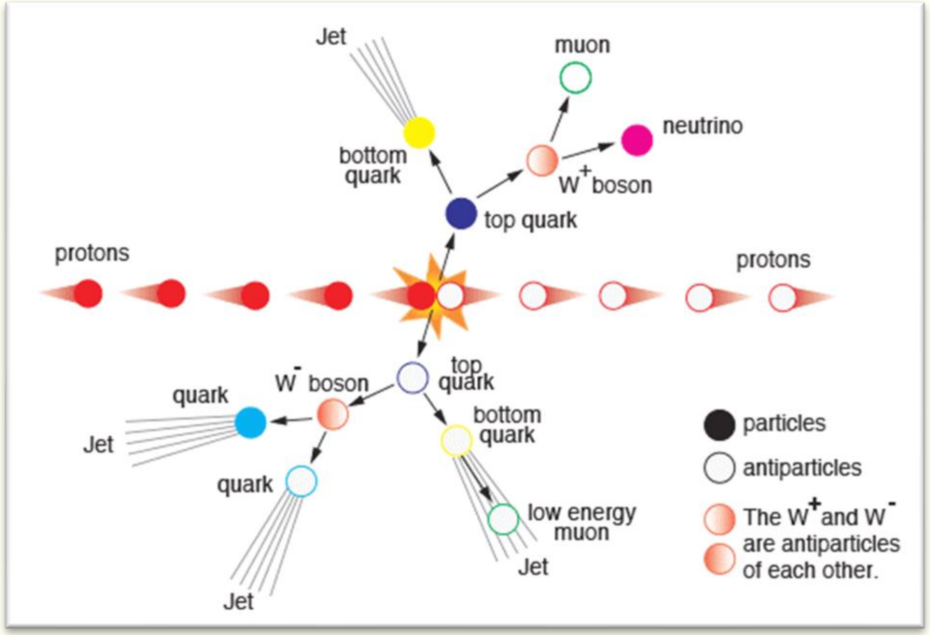
INTRODUCTION

1. Introduction

Problem definition

- Standard Model: current theoretical physics framework
  - Does not explain some key aspects of the behaviour of matter
- LHC (CERN) → experimentation looking for new models
  1. *p-p* collisions are produced to obtain **real data**
  2. **Simulated data** is generated based on new models: *New Physics*
  3. Both data are compared → verify new model



1. Introduction
Objetives

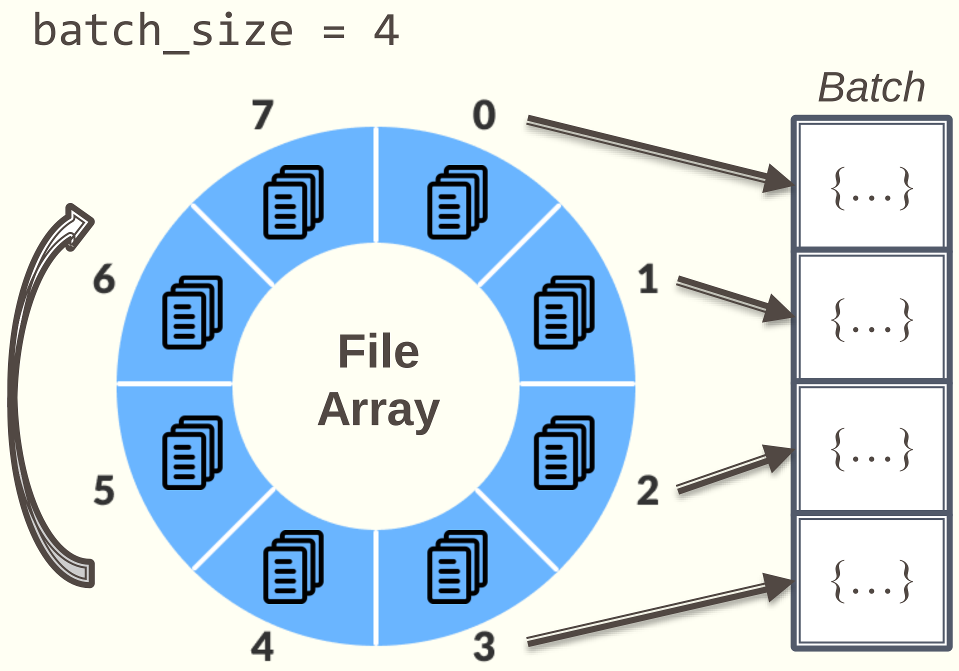
- Generating simulated events is very costly
  - Traditional methods (Monte Carlo) consume lots of **time** and **energy**
  - Future experiments → billions of events → not feasible with current models
  - *Solution:* generative models → generate events in an **efficient** way

- Objetives
  - Create generative models to generate events based on data that was generated through simulation by the Monte Carlo method
  - Accelerate the generation process to reduce the energy and time costs
  - Keep the accuracy of generated events
  - Determine which is the best model

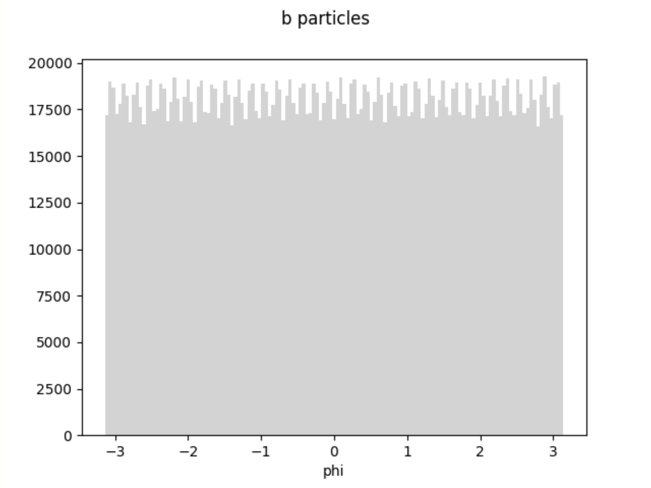
DATA

Physics processes

- *Dataset* with processes from the **Standard Model** and **New Physics**
  - Contains generated events → traditional methods
- Information per **event**:
  - MET
  - METϕ
  - Per each particle (max. 19):
    - E, η, ϕ, p_T
- Used processes:
  - Standard Model: *ttbar*
  - New Physics: *stop_02*
- Huge amount of information
  - Impossible to load in main memory
  - *Solution:* circular buffer

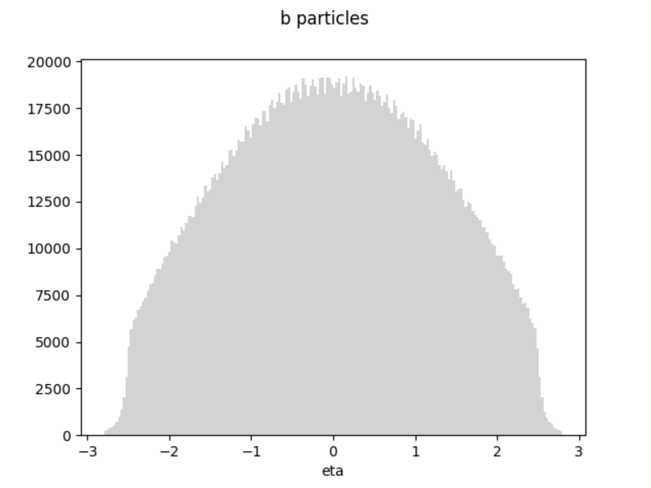


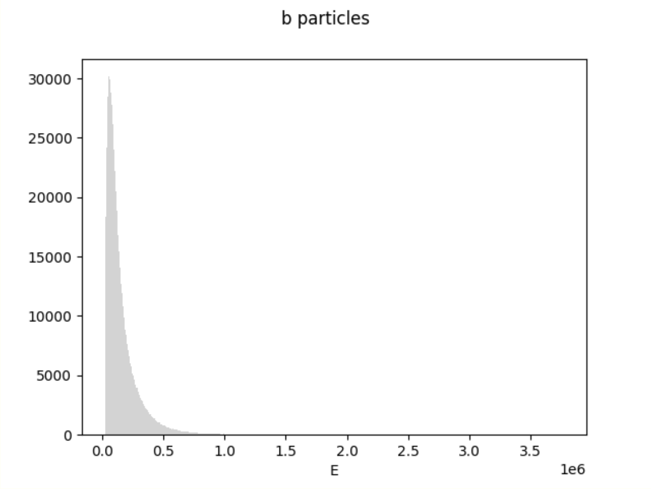
3. Data
Probability distributions



← ϕ y $MET\phi$: uniform

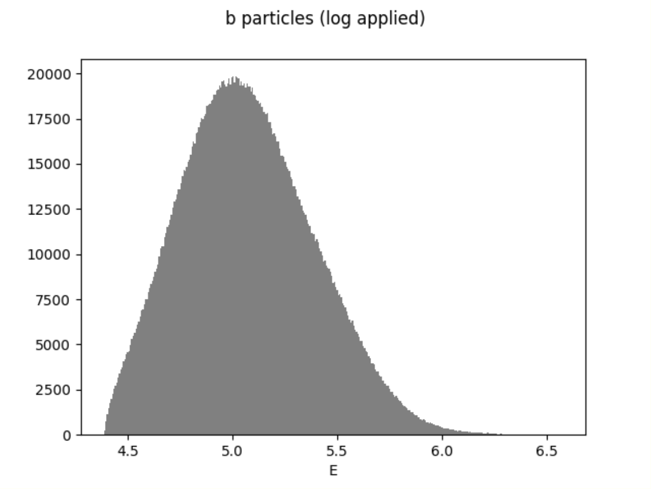
η: similar to gaussian with trimmed extreme values →





- MET, E y p_T: log-normal

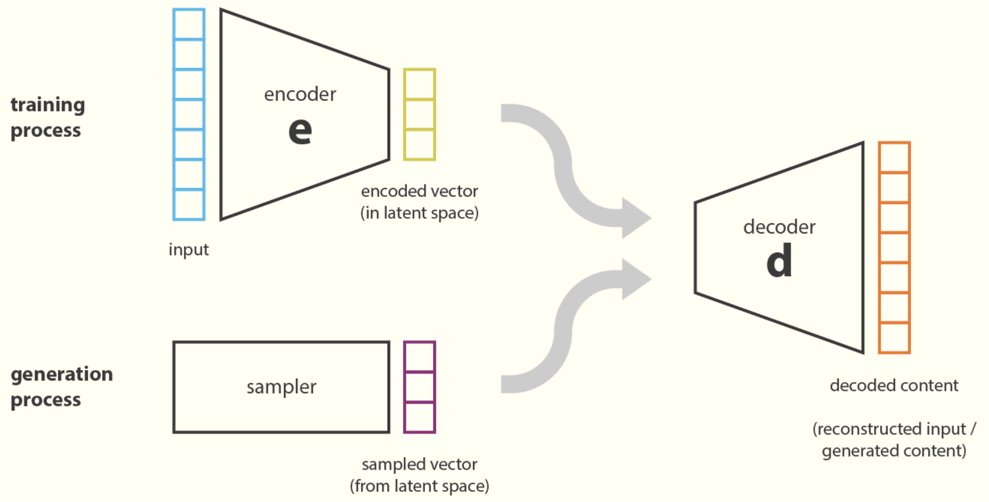
- Applied logarithm to resemble a **normal** distribution → makes learning easier



MODELS

2. Models
Variational Autoencoders

- Generative model
- Training/generation:
  1. Encode the input to the *latent space*
  2. Generate data following its probability distribution*
  3. Decode data to input dimensions
- Variants: β-VAE and α-VAE

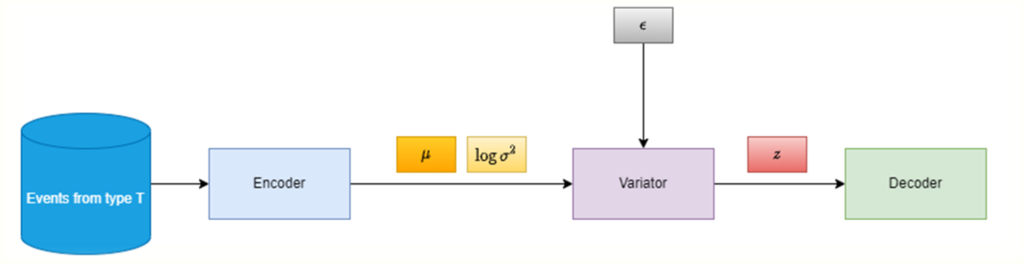


2. Models

VAE variants

β-VAE

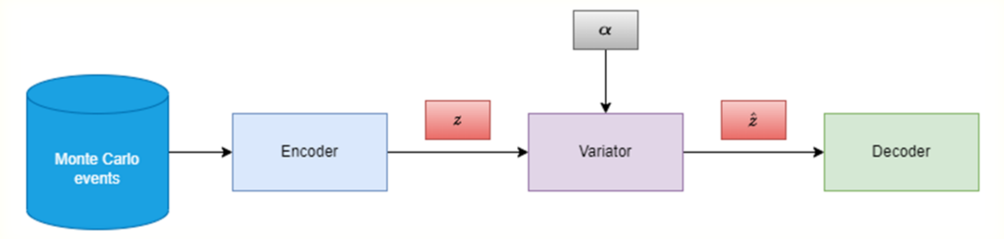
- *Loss function* weights are proportional to β:
$$L_{VAE} = (1 - \beta)MSE + \beta KL$$
- Encoding: $z = \epsilon * e^{\frac{1}{2}\log \sigma^2} + \mu$
  - $\epsilon \sim \mathcal{N}(\mu = 0, \sigma = 1)$



α-VAE

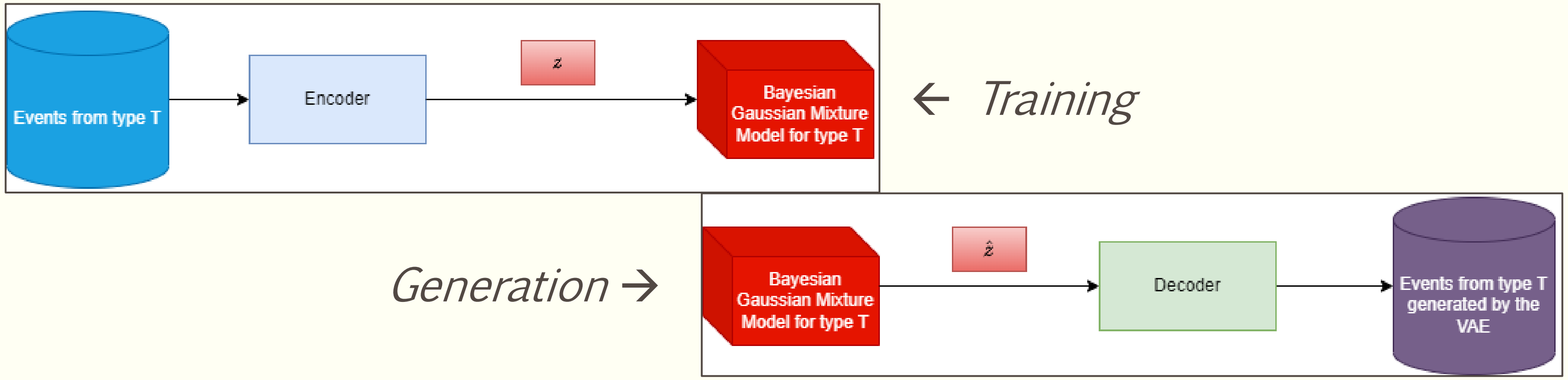
- Gaussian noise is added to the encoding with the following distribution:

$$\mathcal{N}(\mu = 0, \sigma = \alpha)$$



Bayesian Gaussian Mixture Models

- Unsupervised learning model
- Assumes: data can be described by a normal distribution
- Has γ components
  - Each one is a multivariate Gaussian distribution
  - Has its own mean vector and covariance matrix
- Generates data based on the learned distribution.



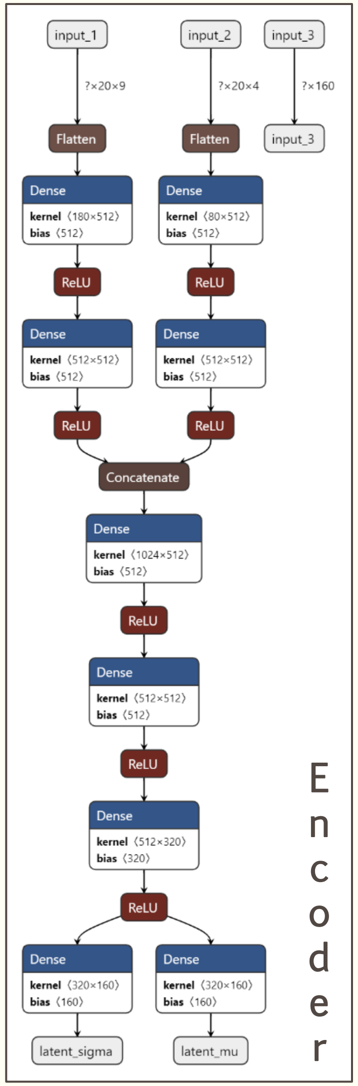
← *Training*

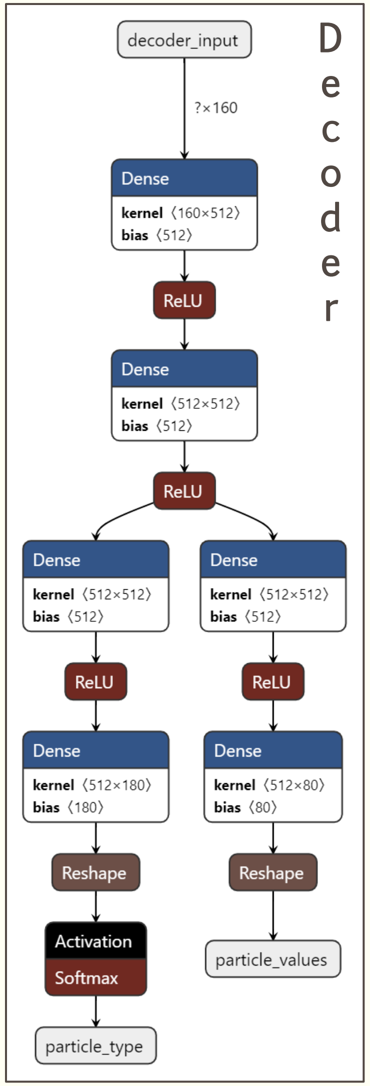
Generation →

EXPERIMENTATION

Experiment I: Initial model

- *MET* + *MET*ϕ considered one more particle
- Input/output data → 2 capas
  - Particle identifier (1-Hot vector)
  - Particle properties (E, η, ϕ, p_T)
- Physics process: *ttbar* (Standard Model)
- Model: β-VAE + BGMM
  - $\beta \in \{0.0, 0.001, 0.01, 0.1, 0.2, 0.5\}$
  - $\gamma \in \{10, 50, 100\}$

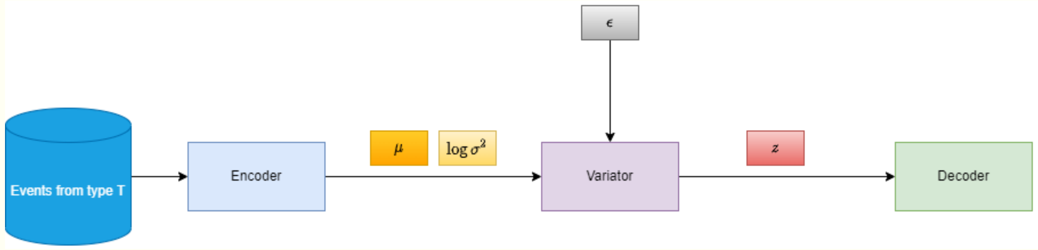




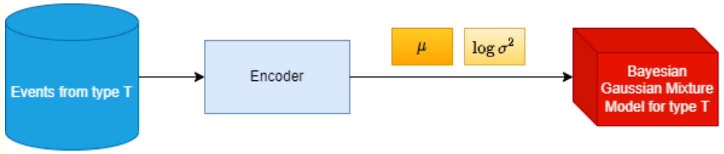
4.1. Experiment I

Training and generation

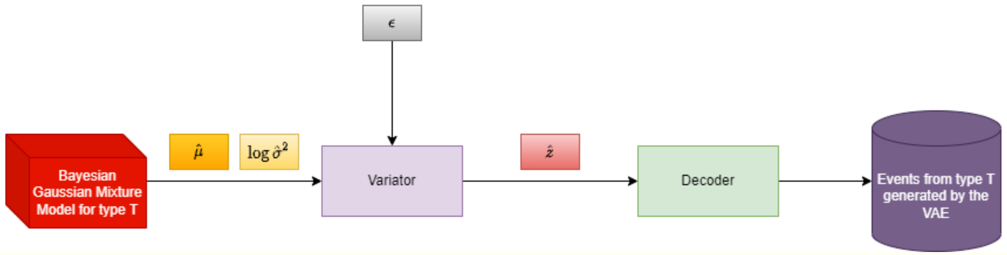
1. Training the β-VAE with original data



2. Training the BGMM with encodings of the *already trained encoder*

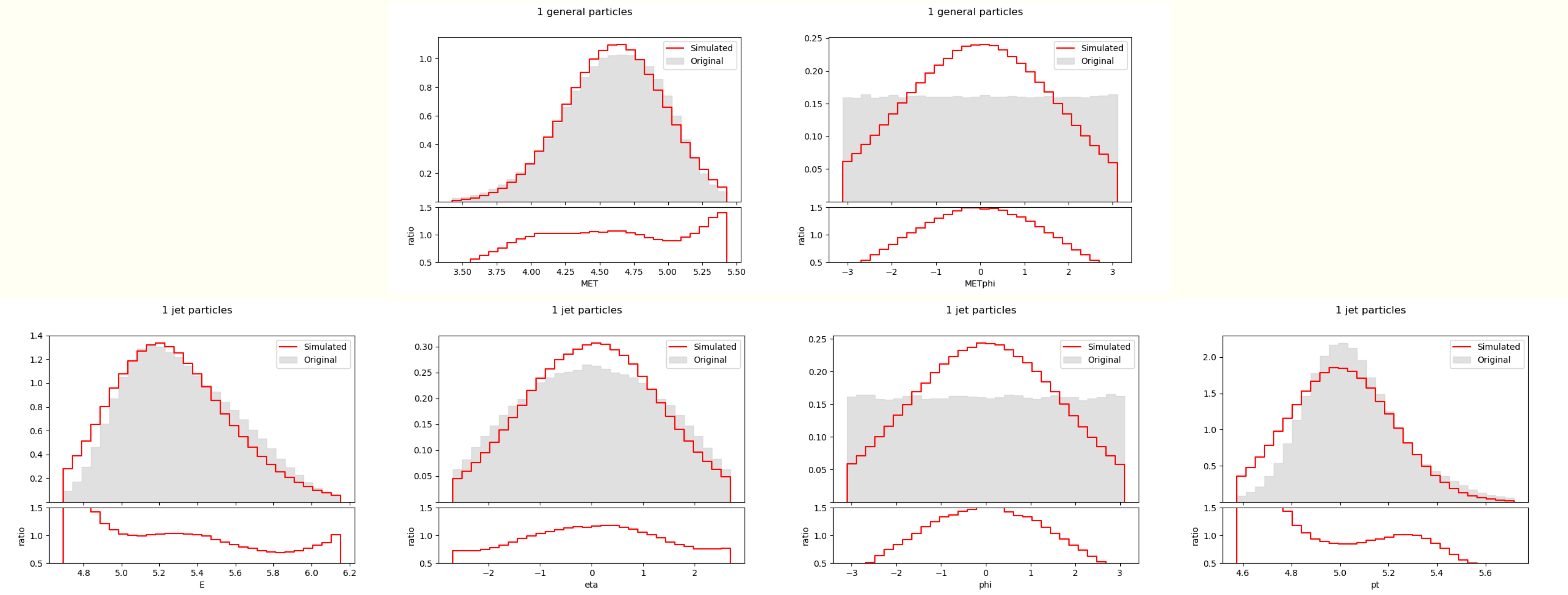


3. Generation of events taking the BGMM as the starting point



4.1. Experiment I

Results ($\beta = 0.01, \gamma = 50$)

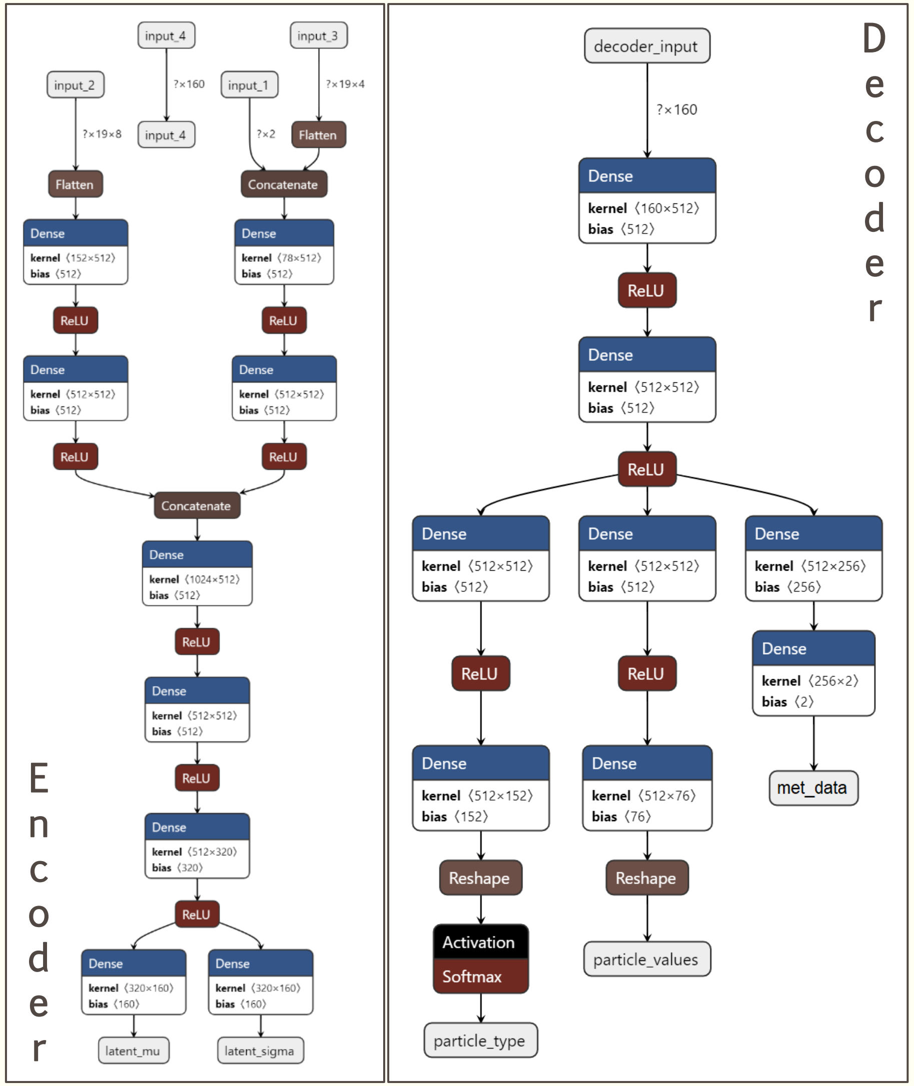


- *Problem:* uniform distributions.

4. Experimentation

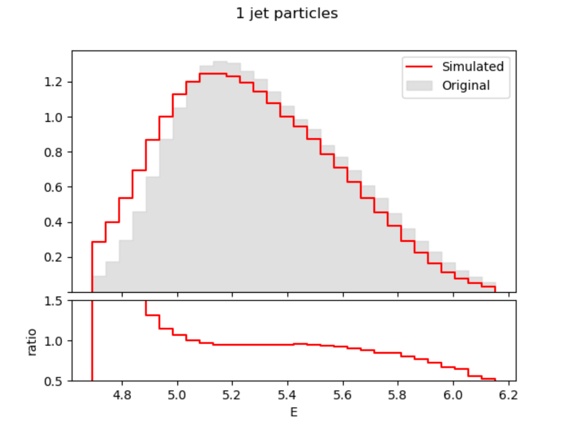
Experiment II: Input splitting

- Split *MET* + *METϕ* in a separate layer
- Same training process
- Physics process: *ttbar* (Standard Model)
- Input/output data → 3 layers
  - Particle identifier (1-Hot vector)
  - *MET* + *METϕ*
  - Particle properties (E, η, ϕ, p_T)
- Model: β-VAE (+ BGMM)
  - $\beta \in \{0.0, 0.001, 0.01, 0.1, 0.2, 0.5, 0.7, 1\}$
  - $\gamma = 100$

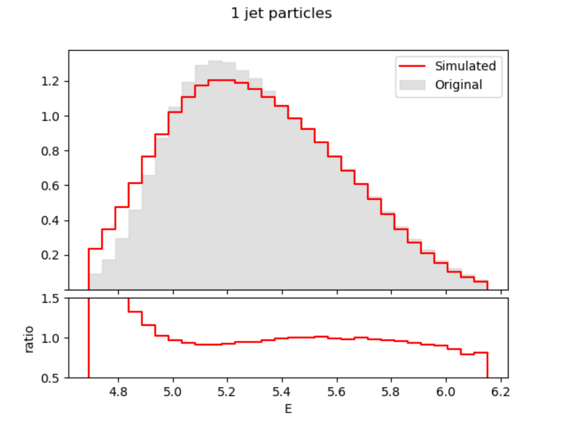


4.2. Experiment II

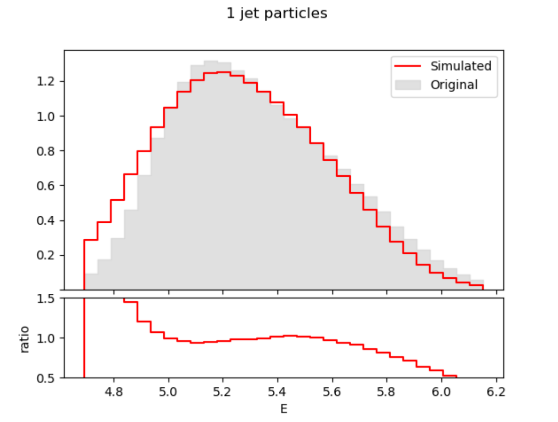
Results – comparing β in attribute E of the 1st jet



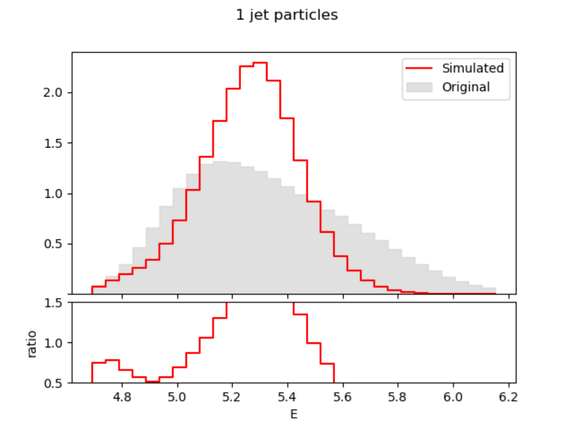
$\beta = 0.0$



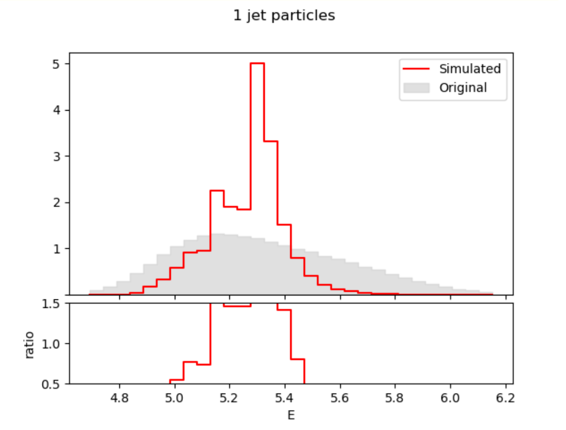
$\beta = 0.001$



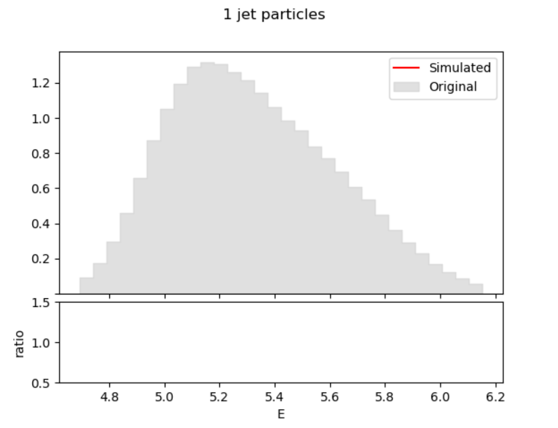
$\beta = 0.01$



$\beta = 0.1$



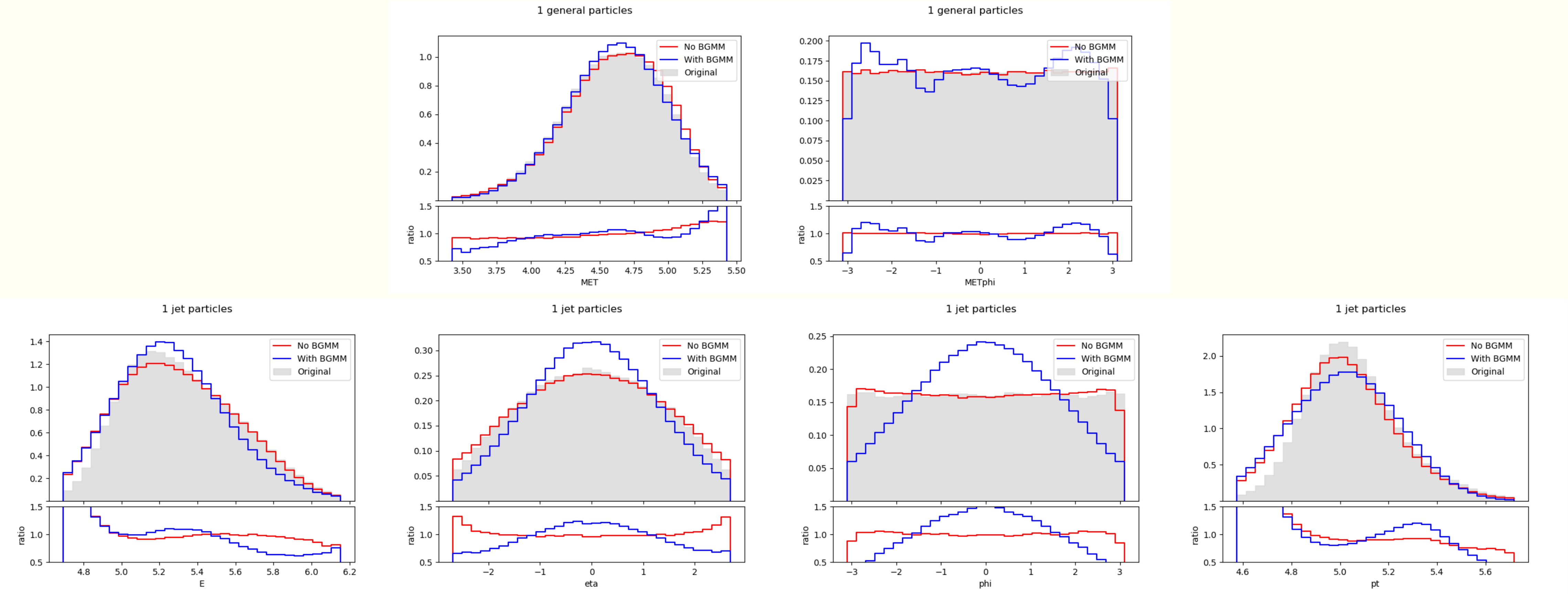
$\beta = 0.5$



$\beta = 1.0$

4.2. Experiment II

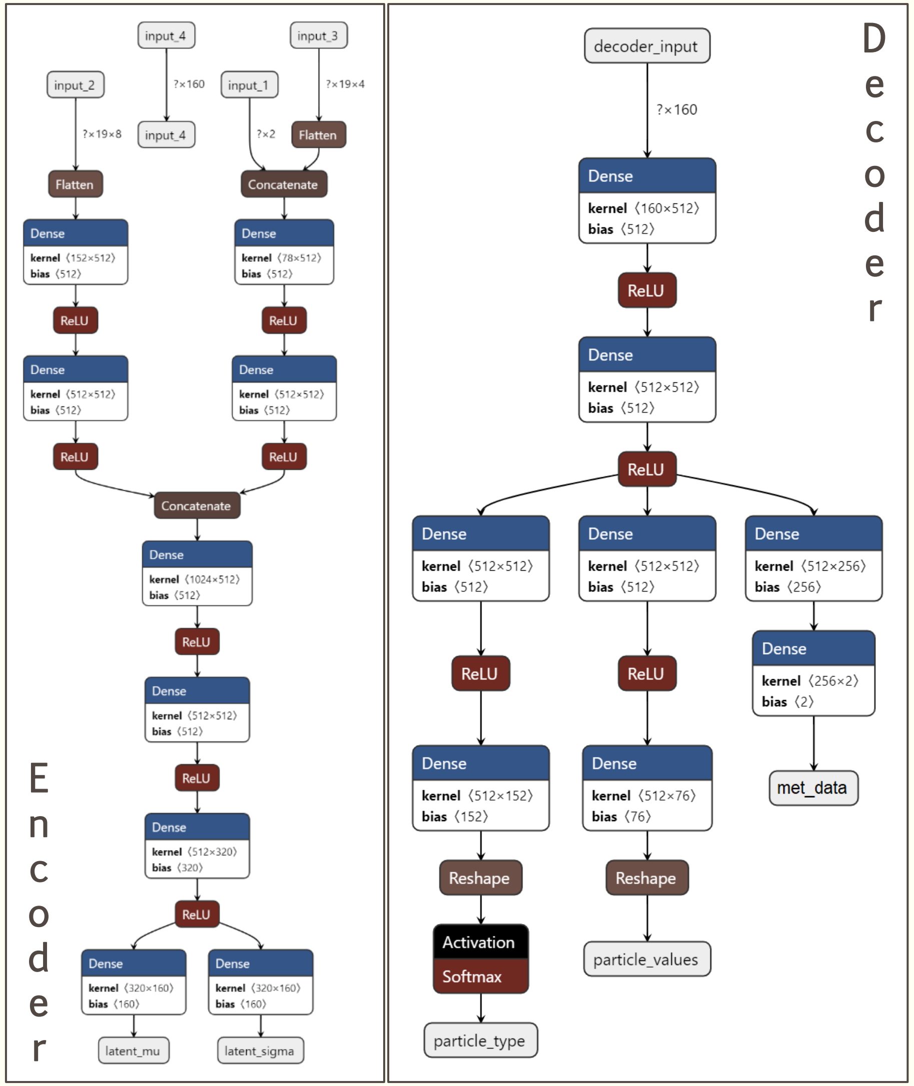
Results ($\beta = 0.001, \gamma = 100$)



- *Observation:* uniform distributions are correct in the model without BGMM.

Experiment III: Introducing the α-VAE

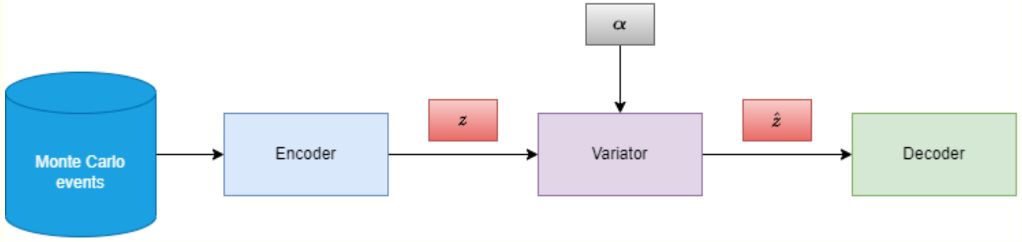
- Same VAE architecture from experiment II
  - The *variator* changes
- Physics process: *ttbar* (Standard Model)
- Model: α-VAE (+ BGMM)
  - $\alpha \in \{0.1, 0.2, 0.3\}$
  - $\gamma = \{10, 20, 50, 100\}$



4.3. Experiment III

Training and generation

1. Training the α-VAE with original data



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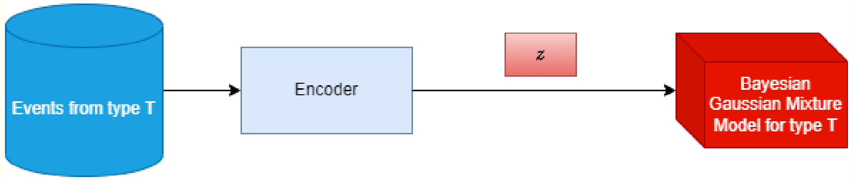

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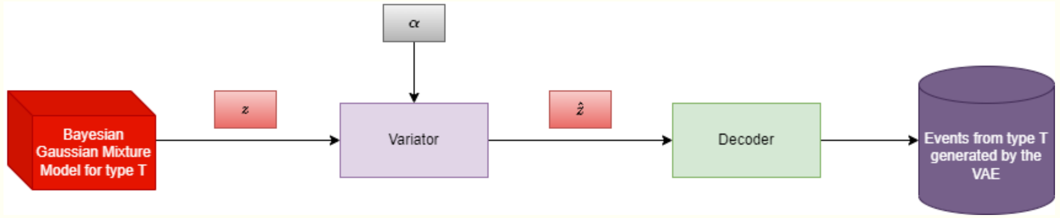
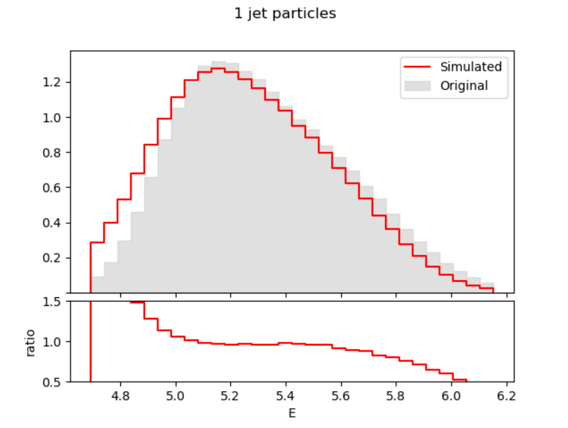
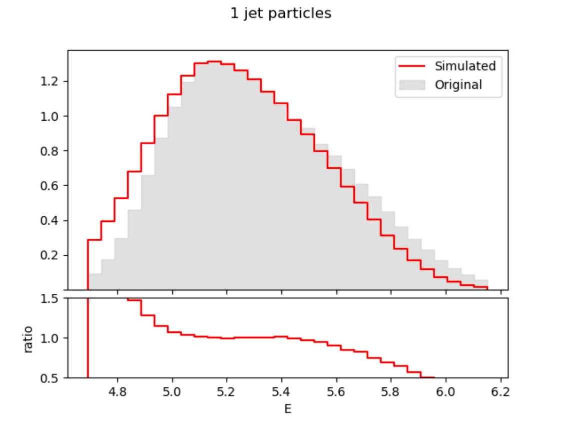


Results – comparing α

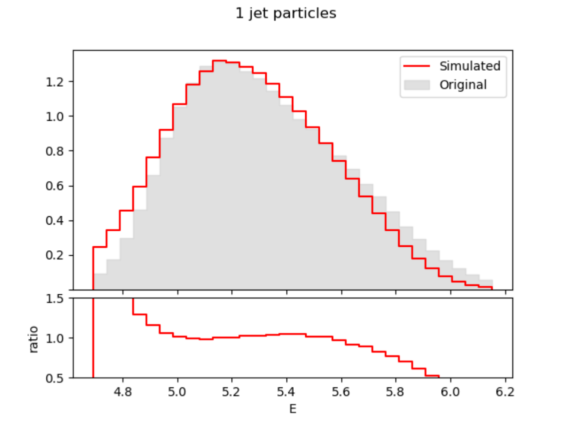
1st jet
Attribute E



$\alpha = 0.1$

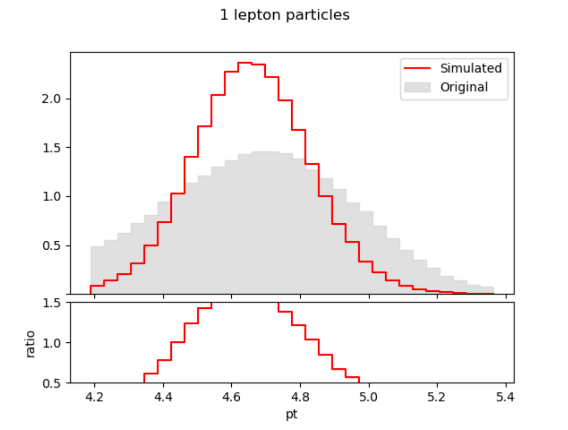


$\alpha = 0.2$

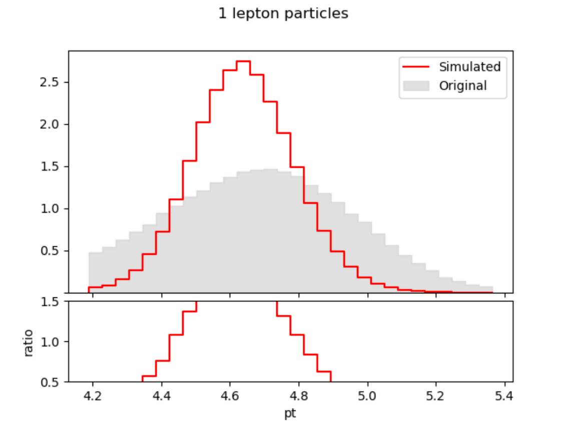


$\alpha = 0.3$

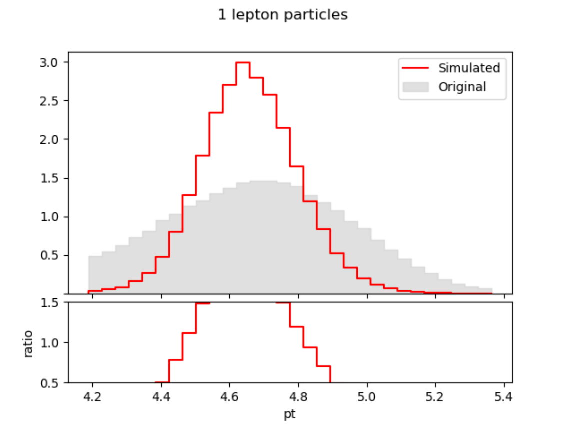
1st lepton
Attribute p_T



$\alpha = 0.1$

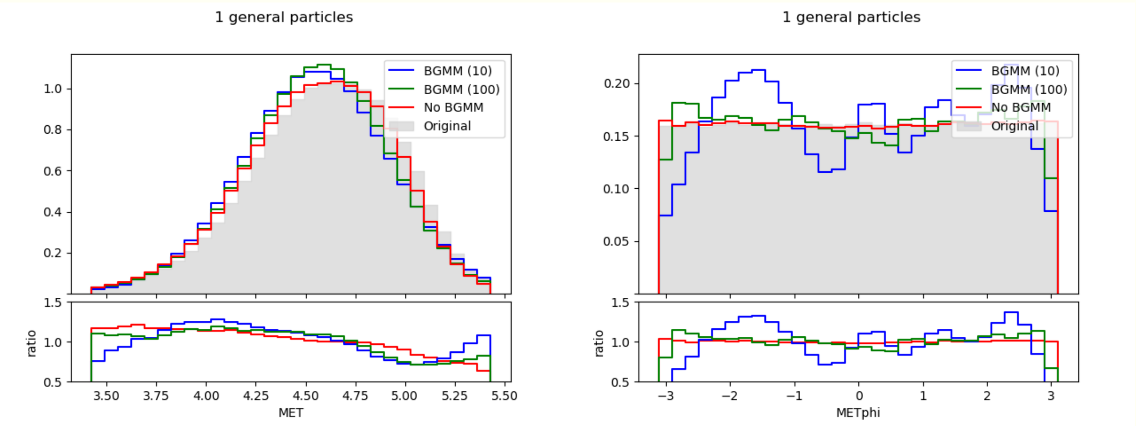


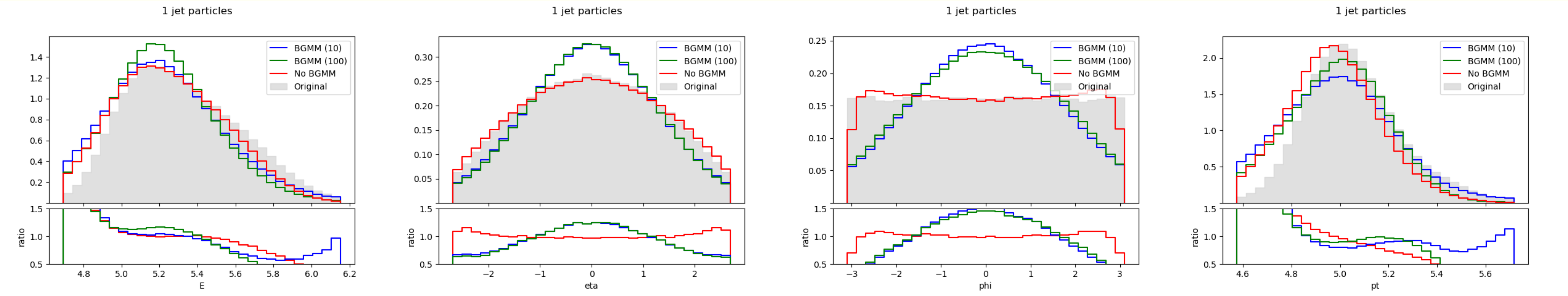
$\alpha = 0.2$



$\alpha = 0.3$

Results ($\alpha = 0.2, \gamma \in \{10, 100\}$)





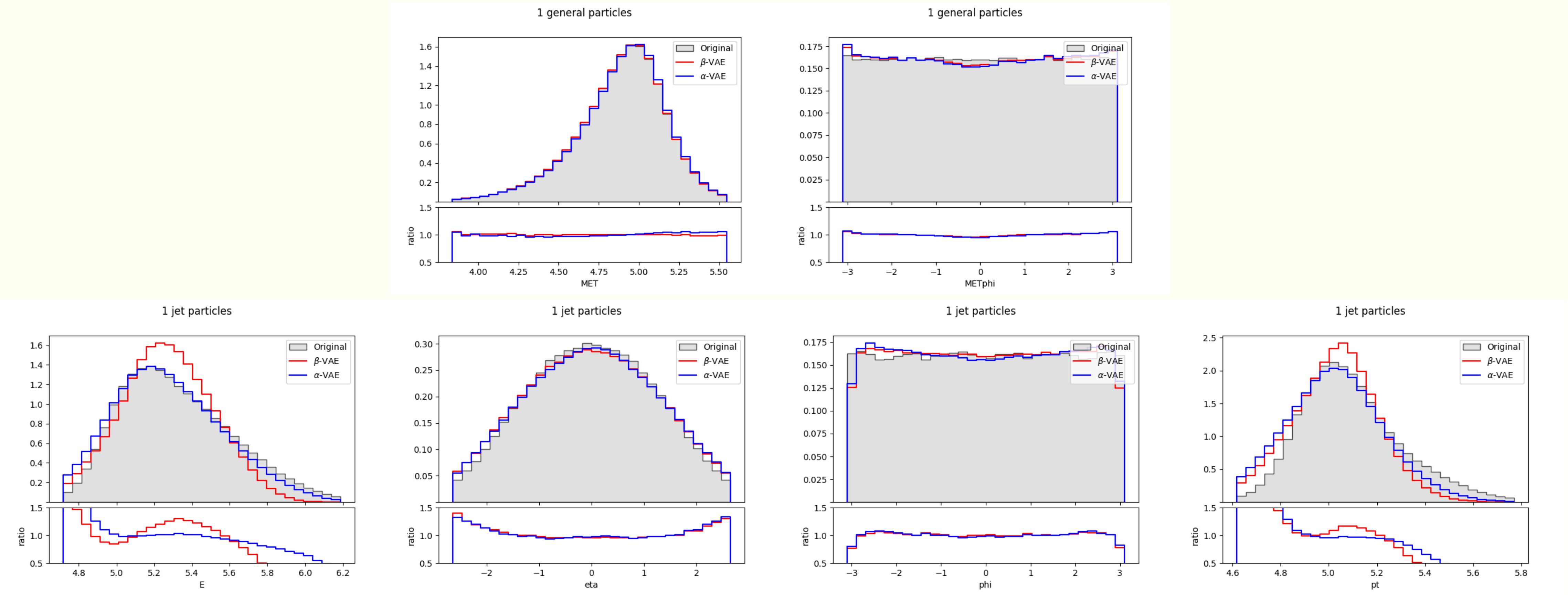
- *Observation:* BGMM keeps obtaining a worse result.

New Physics processes (BSM)

- After selecting the best model → training with a BSM process
- Physics process: *stop_02* (New Physics)
- Selected models:
  - β-VAE without BGMM ($\beta = 0.001$)
  - α-VAE without BGMM ($\alpha = 0.2$)
- We did not test models with BGMM → lack of time

4.4. New Physics

Results ($\beta = 0.001, \alpha = 0.2$)



- *Observation:* Similar results, α-VAE adjusts better in some cases

CONCLUSIONS

4. Conclusions

- Achieved objectives: more efficient event generation
- 2 models with promising results: β-VAE and α-VAE without BGMM
  - We should keep adjusting model parameters to improve results
- BGMM does not obtain the expected results
  - ¿Requires more components?
  - It will be required to perform additional experimentation

4.1. Future work

- Generating events in a fast way is a need of critical importance
  - Further research is required
- Proposals
  - Experiment the use of more components in BGMMs
  - Creation of advanced metrics
  - Usage of other types of models: GAN, *Flow models*…

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