



Tracking with ML



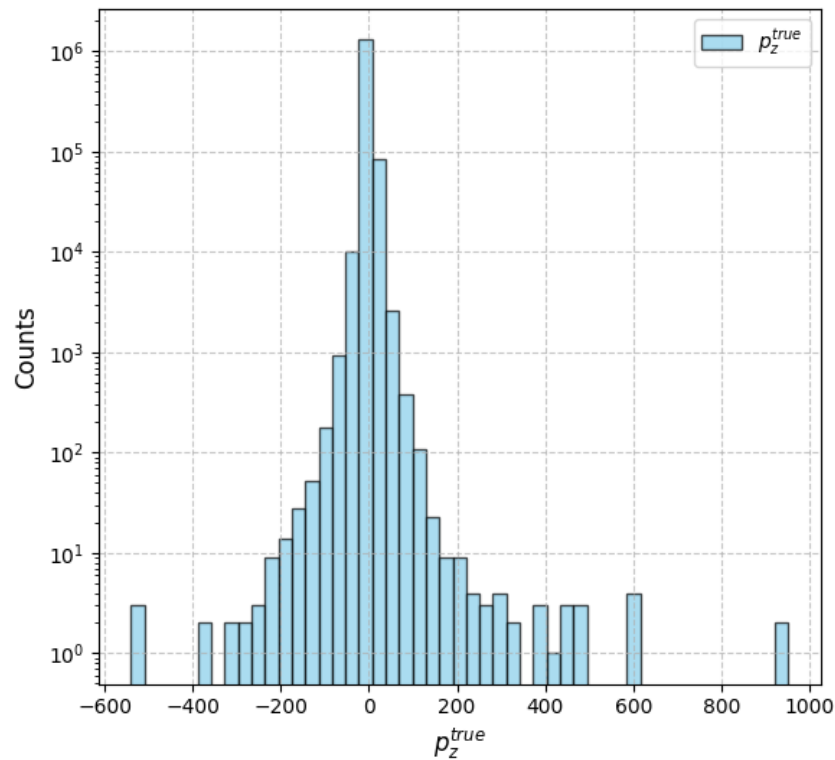
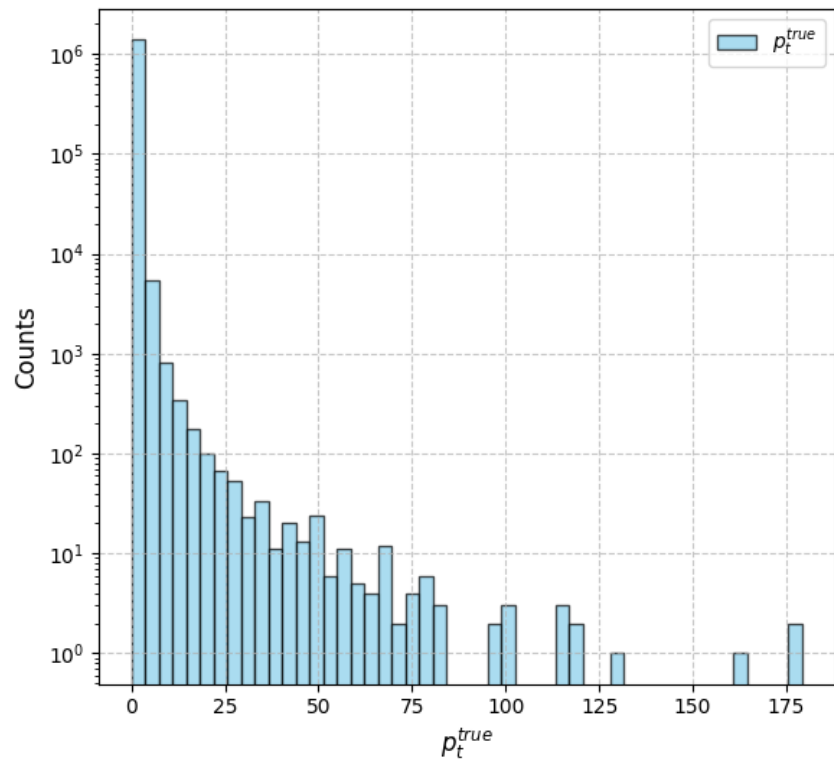
5th February 2025



Jeremy Couthures



Target variables



Dataset selection

Selections:

- $n_{\text{hits}} \geq 3$
- $0.5 \leq p_T \leq 10$ [GeV]
- $|v_x| < 1 \ \&\& \ |v_y| < 1$ [mm]
- $|\eta| \leq 1$

Before:

Training: 11 222 273 particles
Validation: 1 334 273 particles
Testing: 1 404 273 particles

$\xrightarrow{/ 10}$

After:

Training: 1 232 896 particles
Validation: 154 082 particles
Testing: 153 788 particles

Dataset selection details

Selections:

- $n_{\text{hits}} \geq 3$
- $0.5 \leq p_T \leq 10$ [GeV]
- $|v_x| < 1 \ \&\& \ |v_y| < 1$ [mm]
- $|\eta| \leq 1$

Test dataset:

Total: 1643787 particles

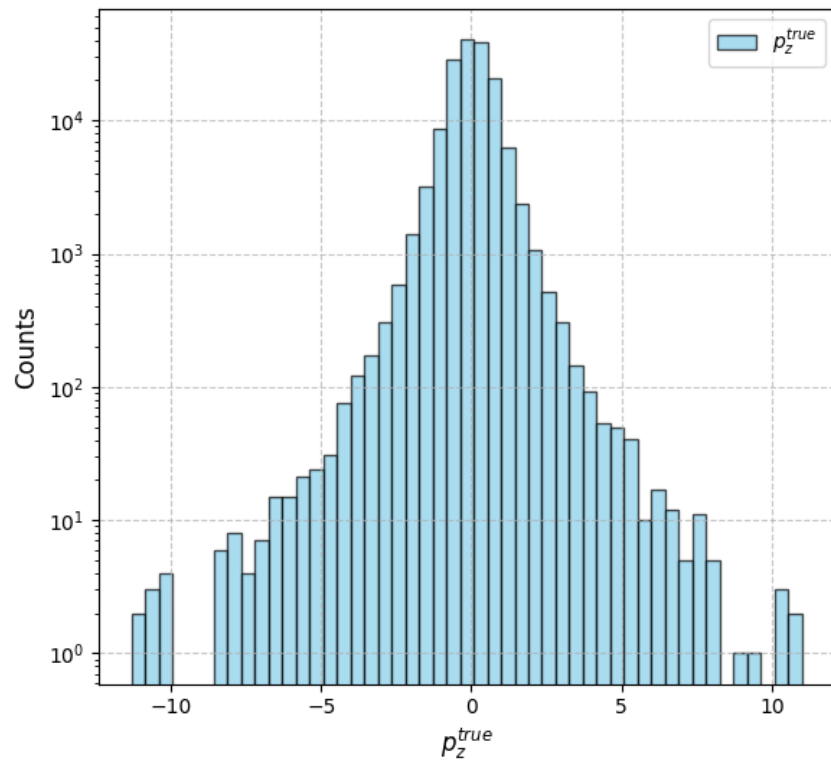
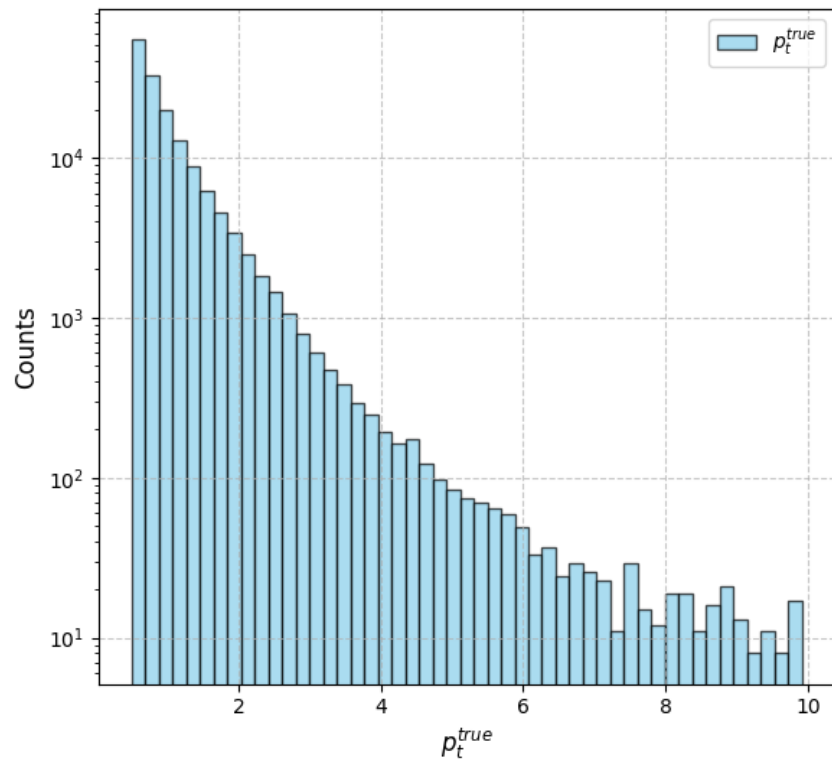
621539 particles, $\text{min_pt}=0.5$, $\text{max_pt}=10$

599332 particles, $\text{min_hits}=3$, $\text{min_pt}=0.5$, $\text{max_pt}=10$, $\text{keep_secondaries}=\text{True}$

553606 particles, $\text{min_hits}=3$, $\text{min_pt}=0.5$, $\text{max_pt}=10$, $\text{keep_secondaries}=\text{False}$ (" $|v_x| < 1 \ \&\& \ |v_y| < 1$ " cut)

153788 particles, $\text{min_hits}=3$, $\text{min_pt}=0.5$, $\text{max_pt}=10$, $\text{keep_secondaries}=\text{False}$, $\text{max_abs_eta}=1$

Target variables



Training

Architecture:

input_dim: 3
model_dim: 128
num_classes: 2
num_heads: 4
num_layers: 2

Training:

warmup: 100
lr: 0.0005
dropout: 0.1
input_dropout: 0.1
batch_size: 1024
max_epochs: 100

Saving:

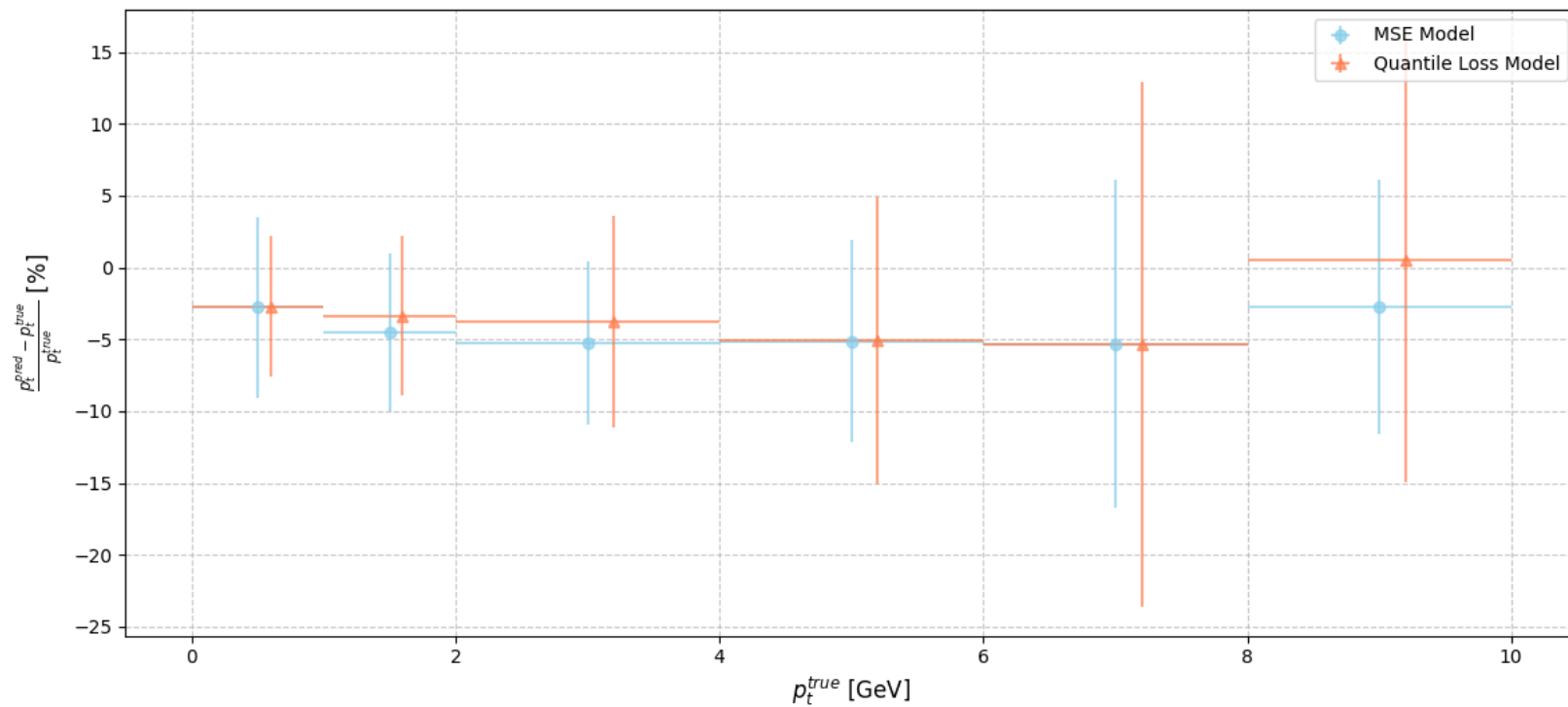
monitor: val_loss
mode: min

Variables:

input:
tx, ty, tz
input:
tr, tphi, tz
target:
pt, pz

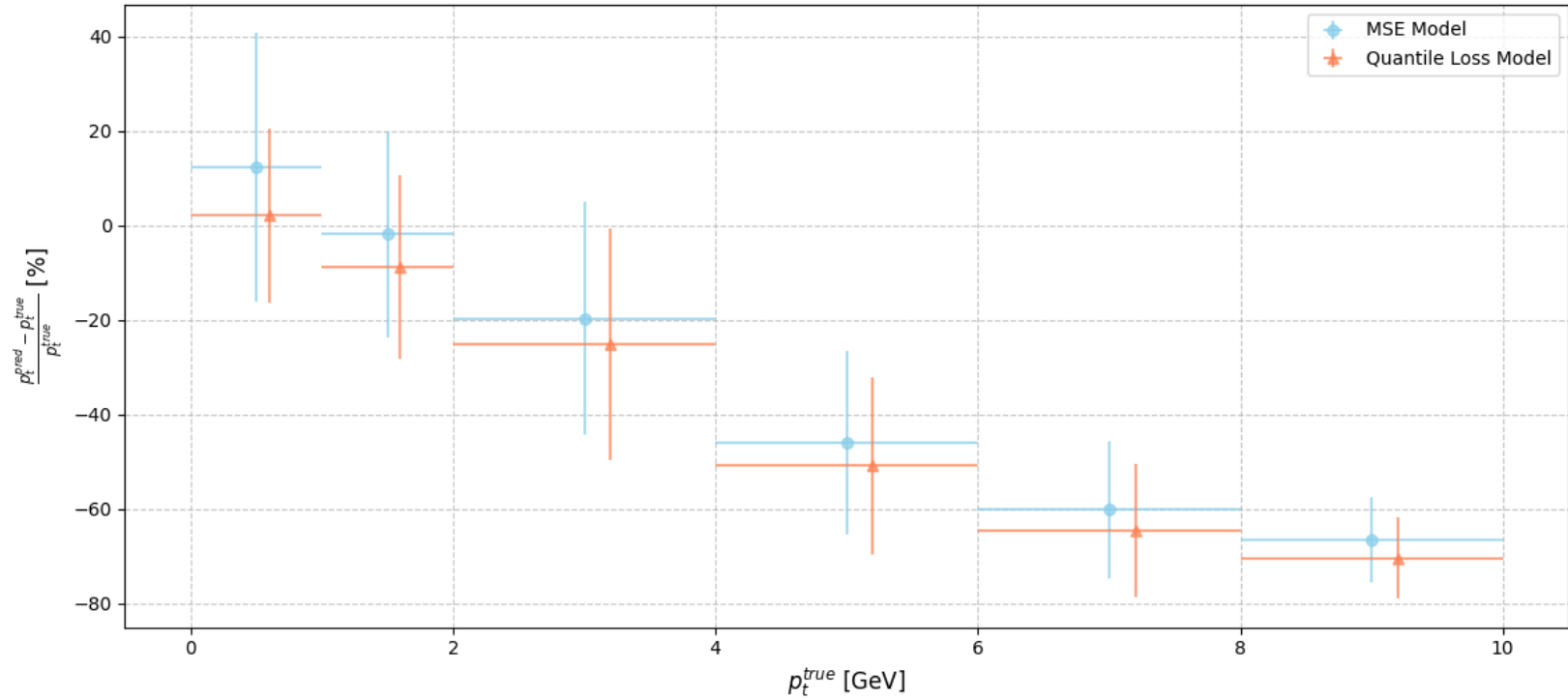
Resolution

x y z



Resolution

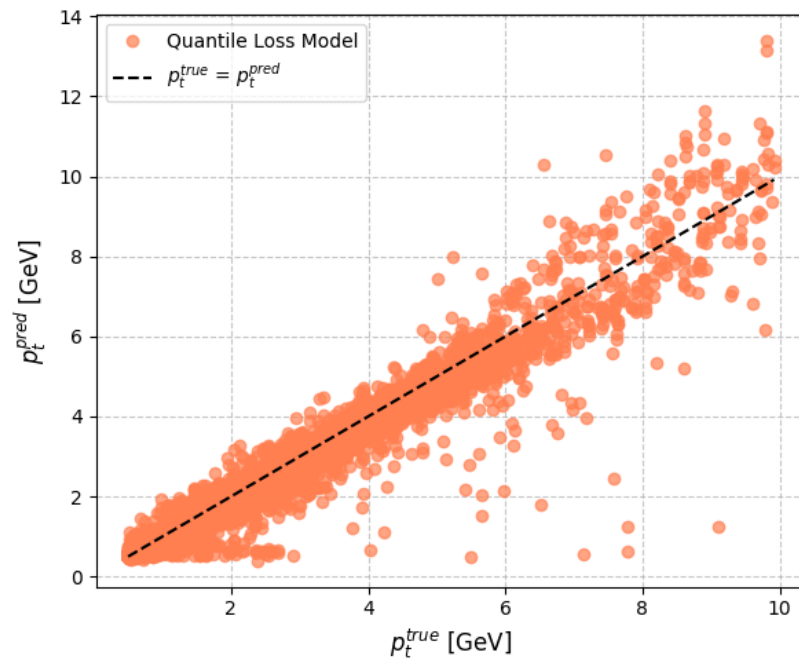
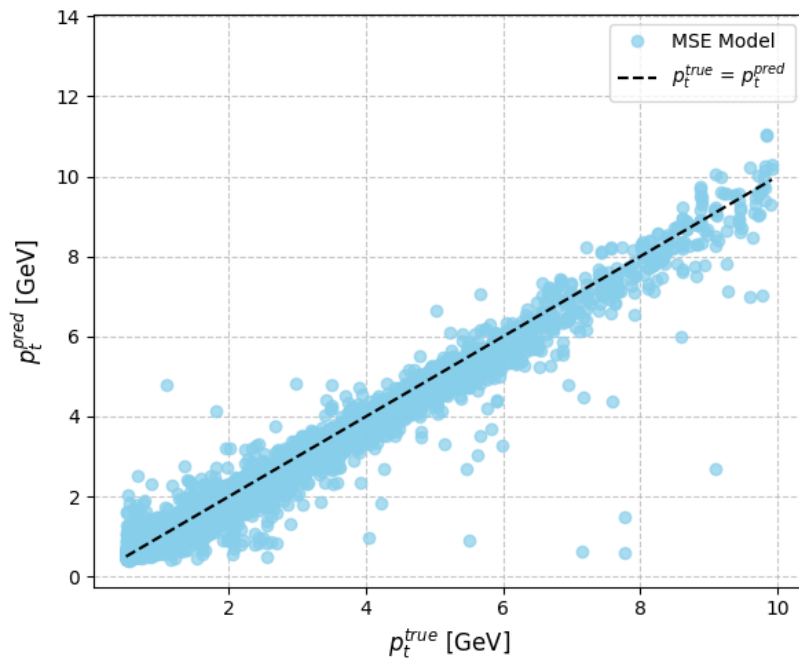
r phi z



More results

x y z

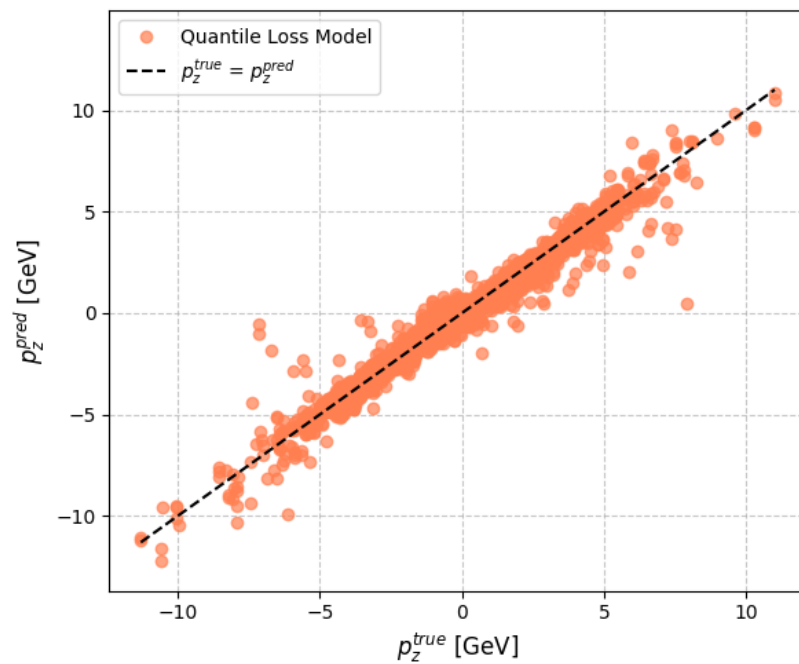
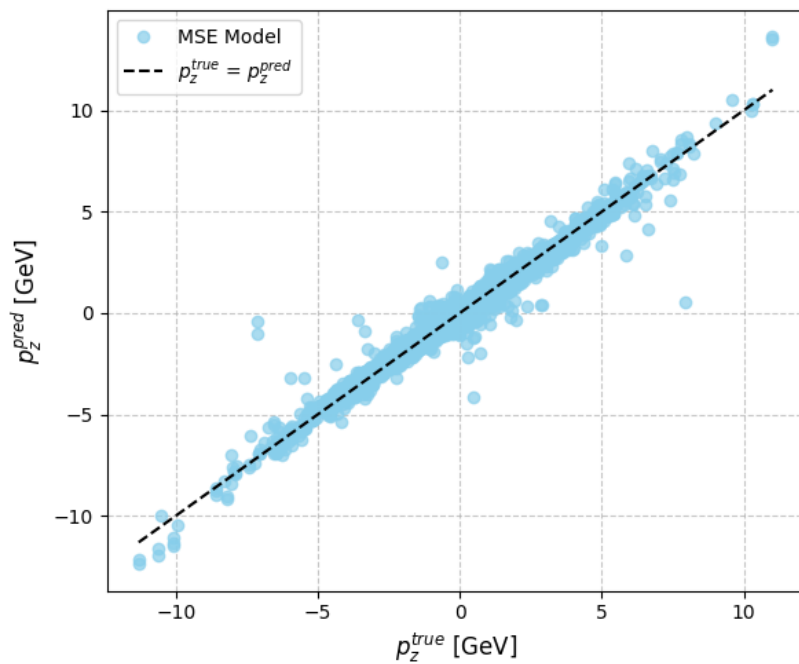
p_t^{true} vs p_t^{pred}



More results

x y z

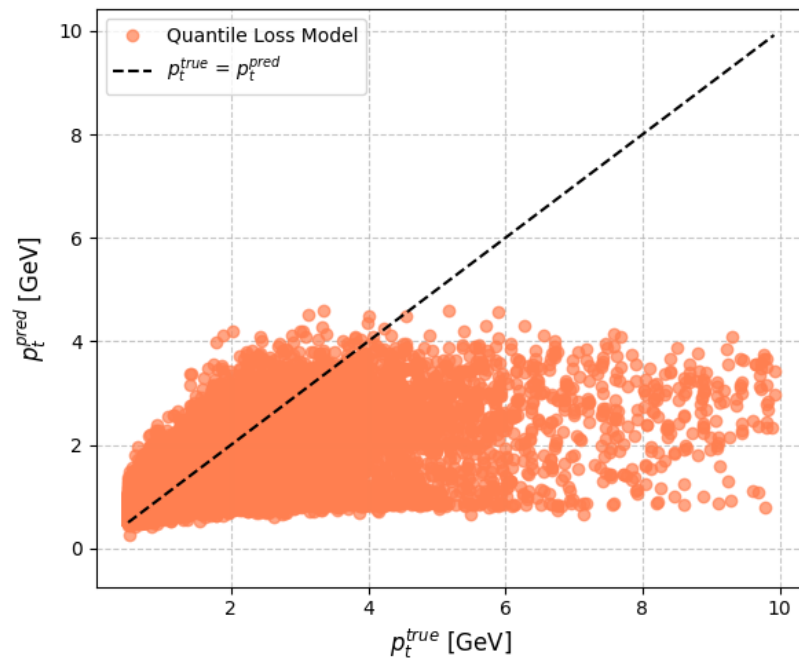
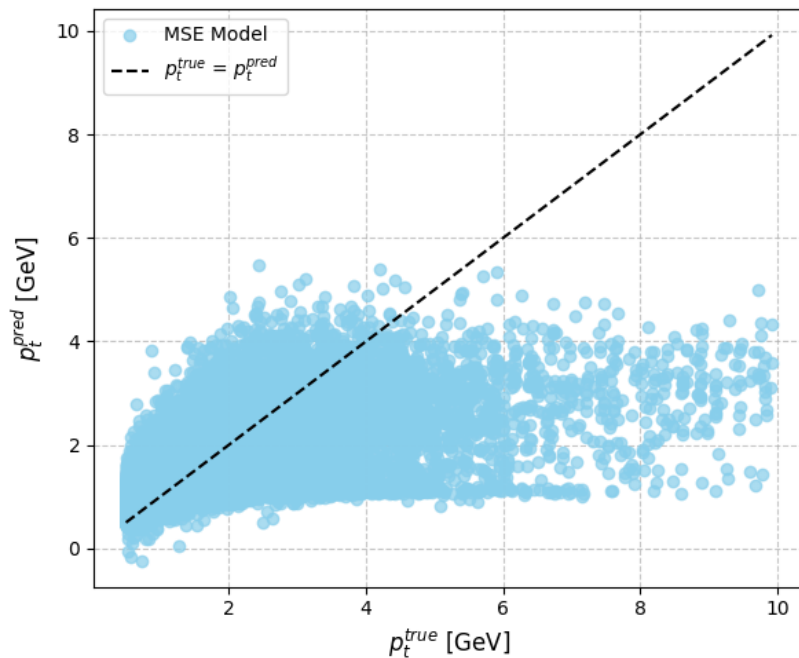
p_z^{true} vs p_z^{pred}



More results

r phi z

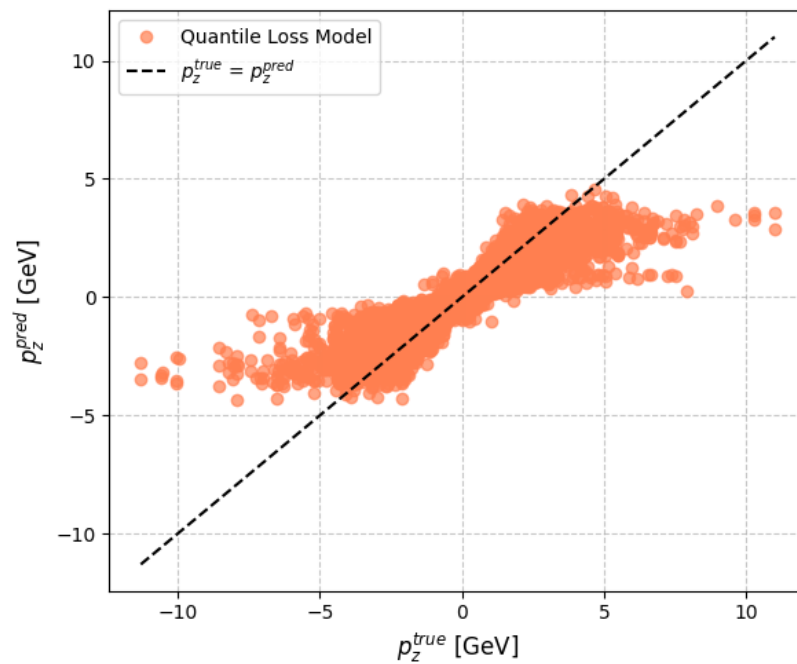
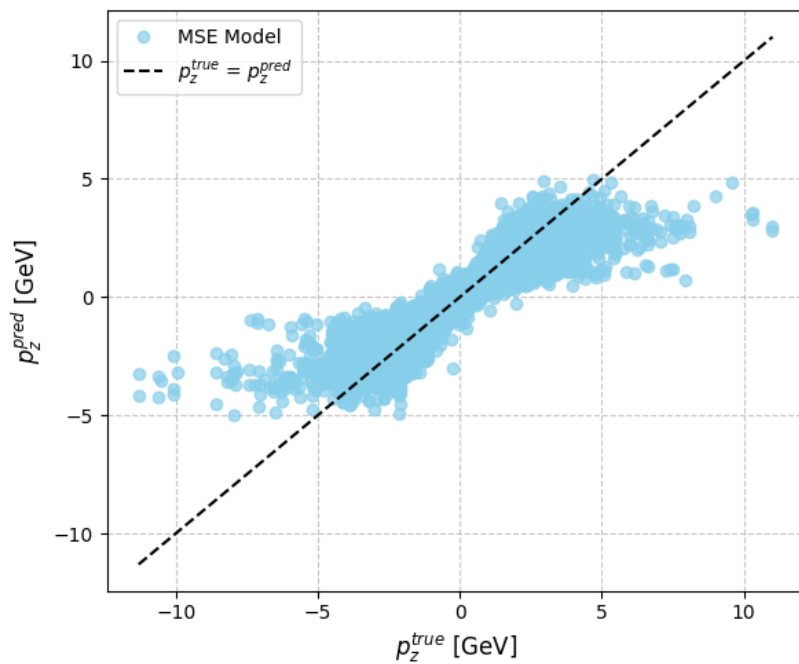
p_t^{true} vs p_t^{pred}



More results

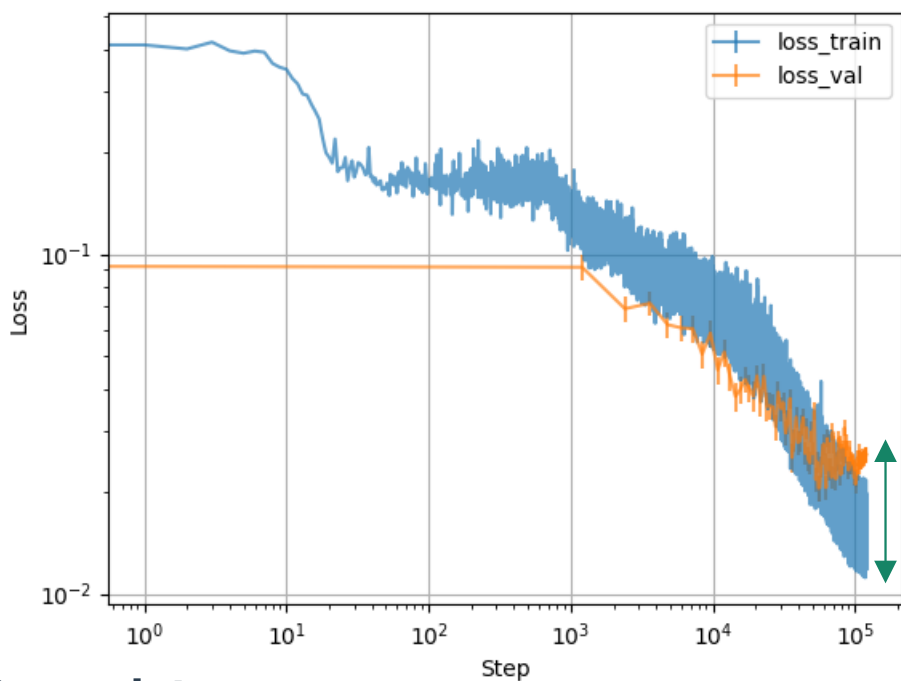
r phi z

p_z^{true} vs p_z^{pred}



Loss curves

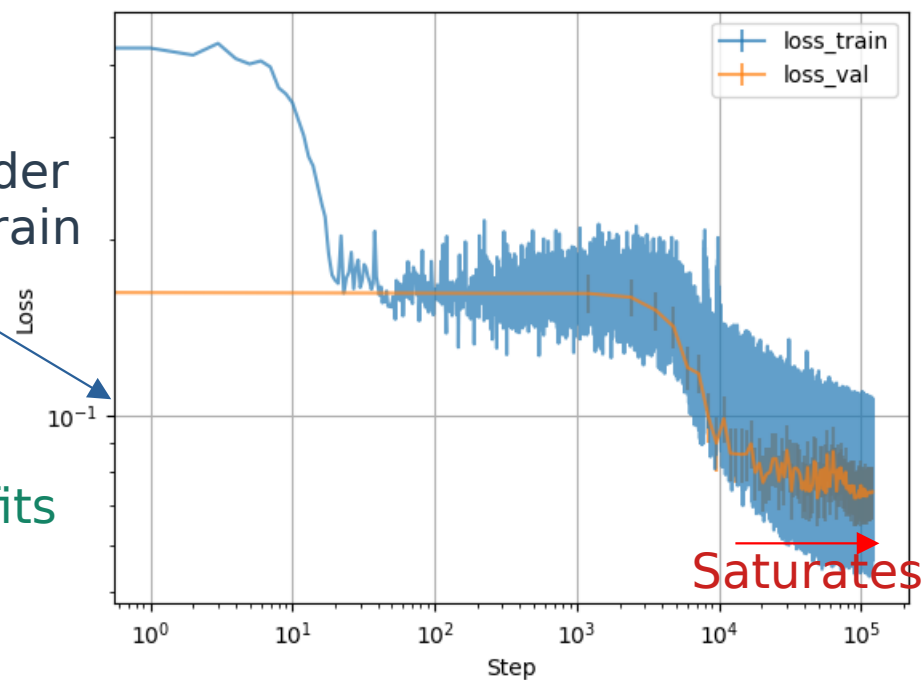
Quantile Loss **x y z**



Harder
to train

Overfits

Quantile Loss **r phi z**

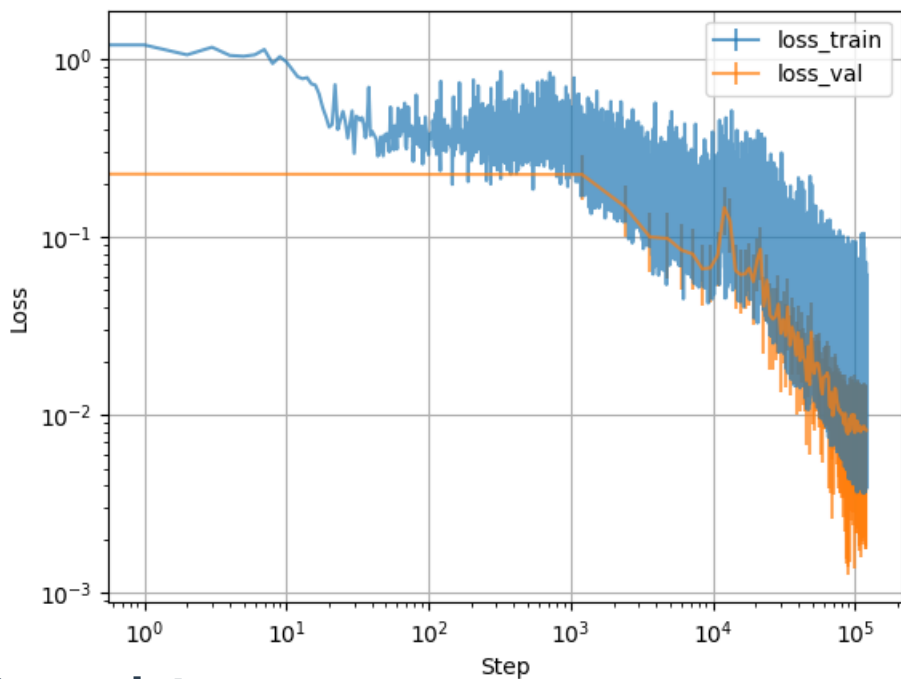


Saturates

Same data

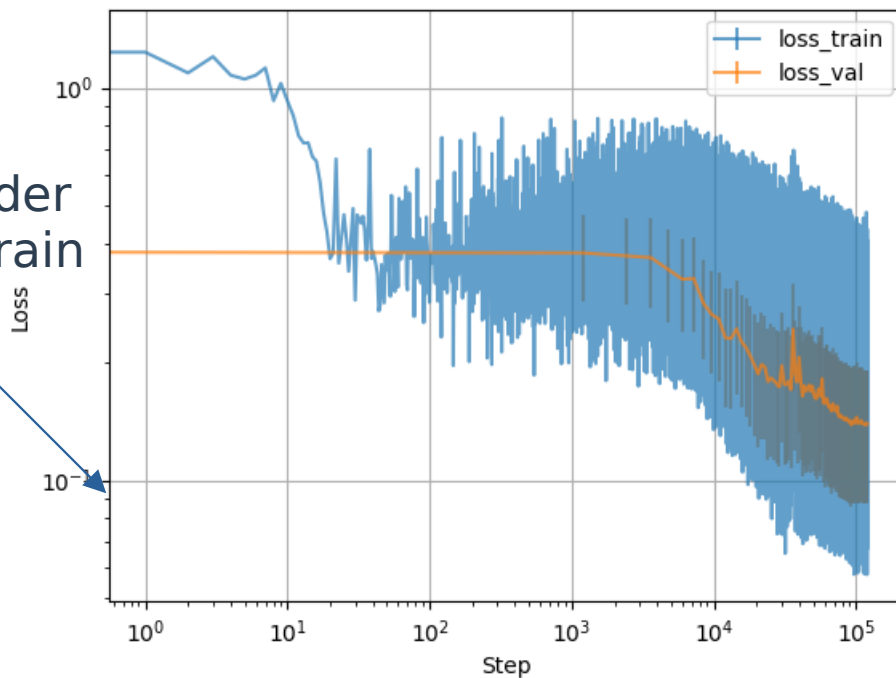
Loss curves

MSE Loss $x y z$



MSE Loss $r \phi z$

Harder
to train

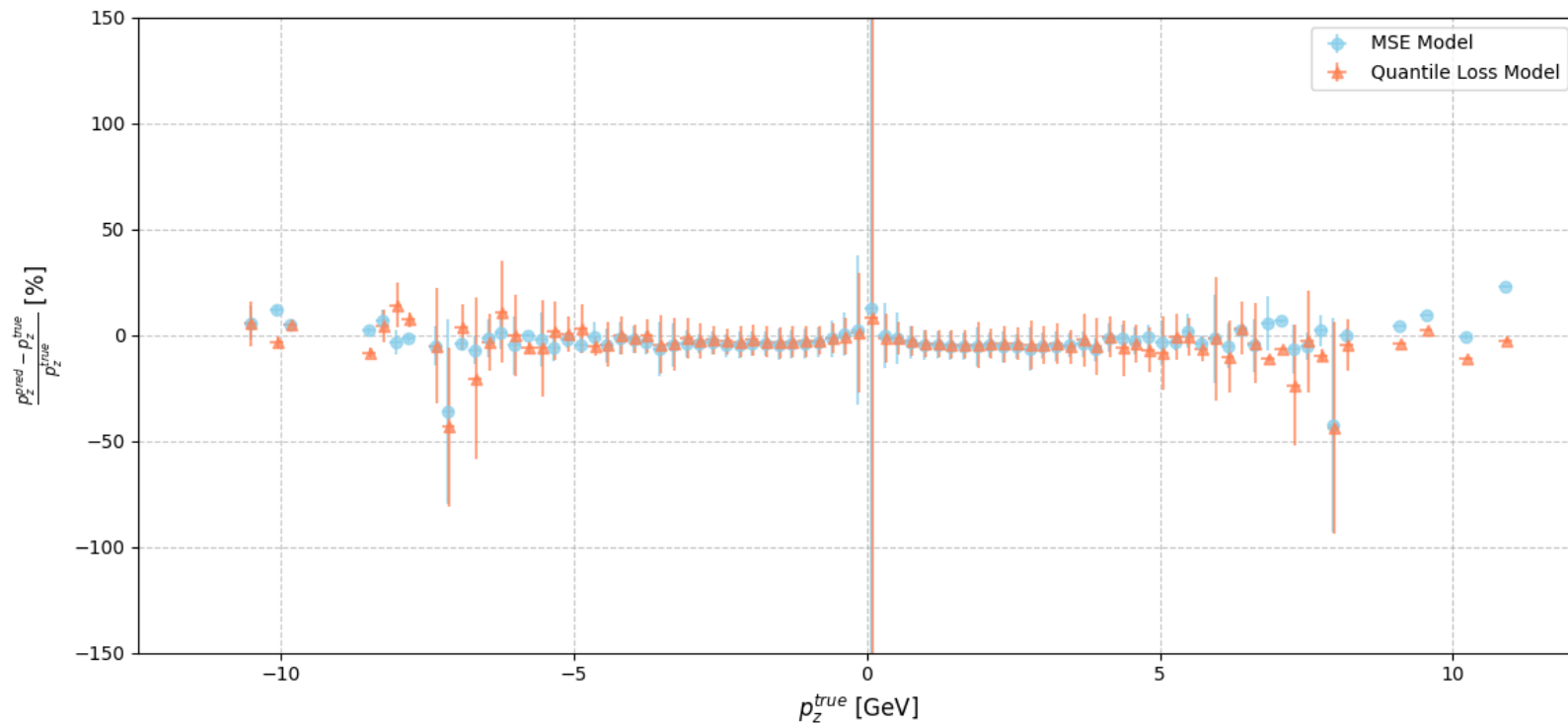


Same data

BACKUP

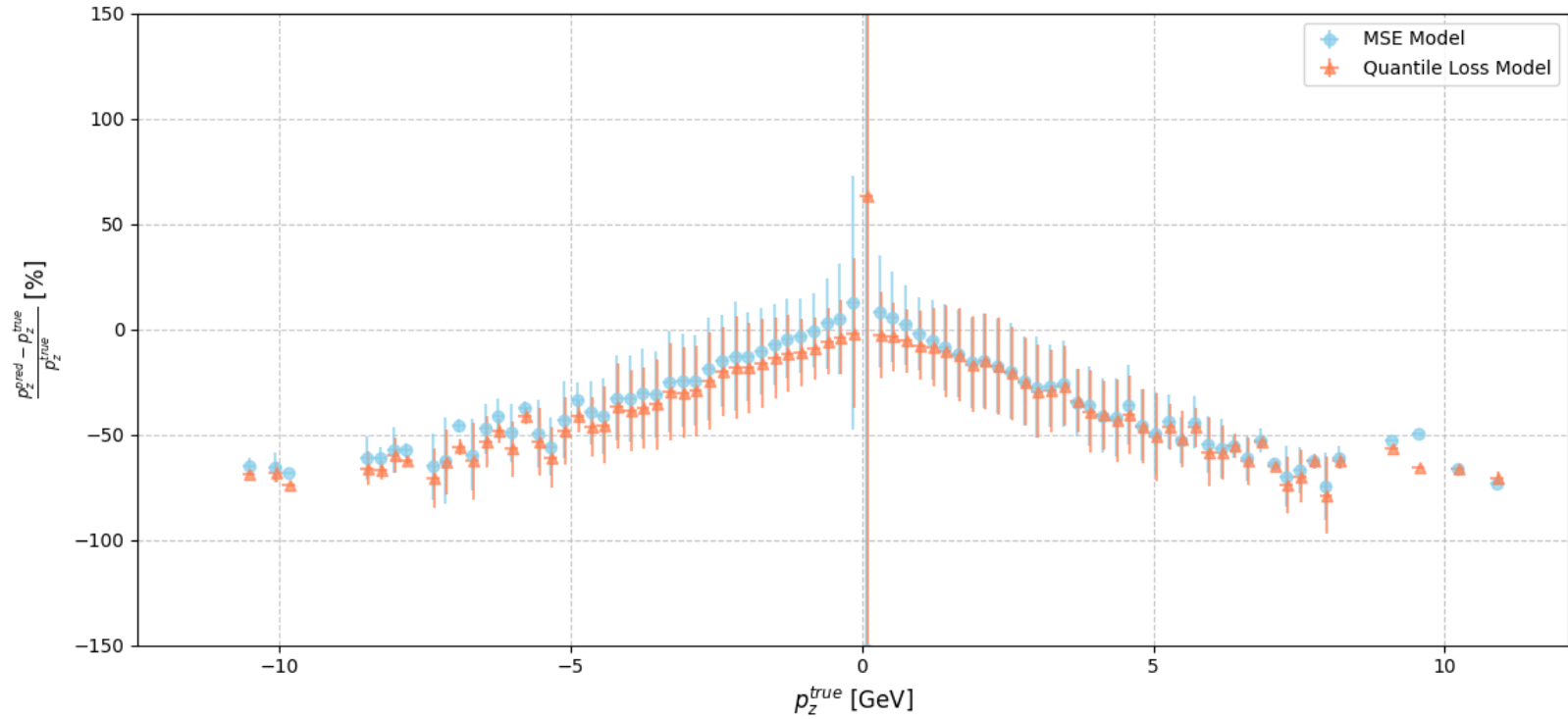
Resolution

x y z



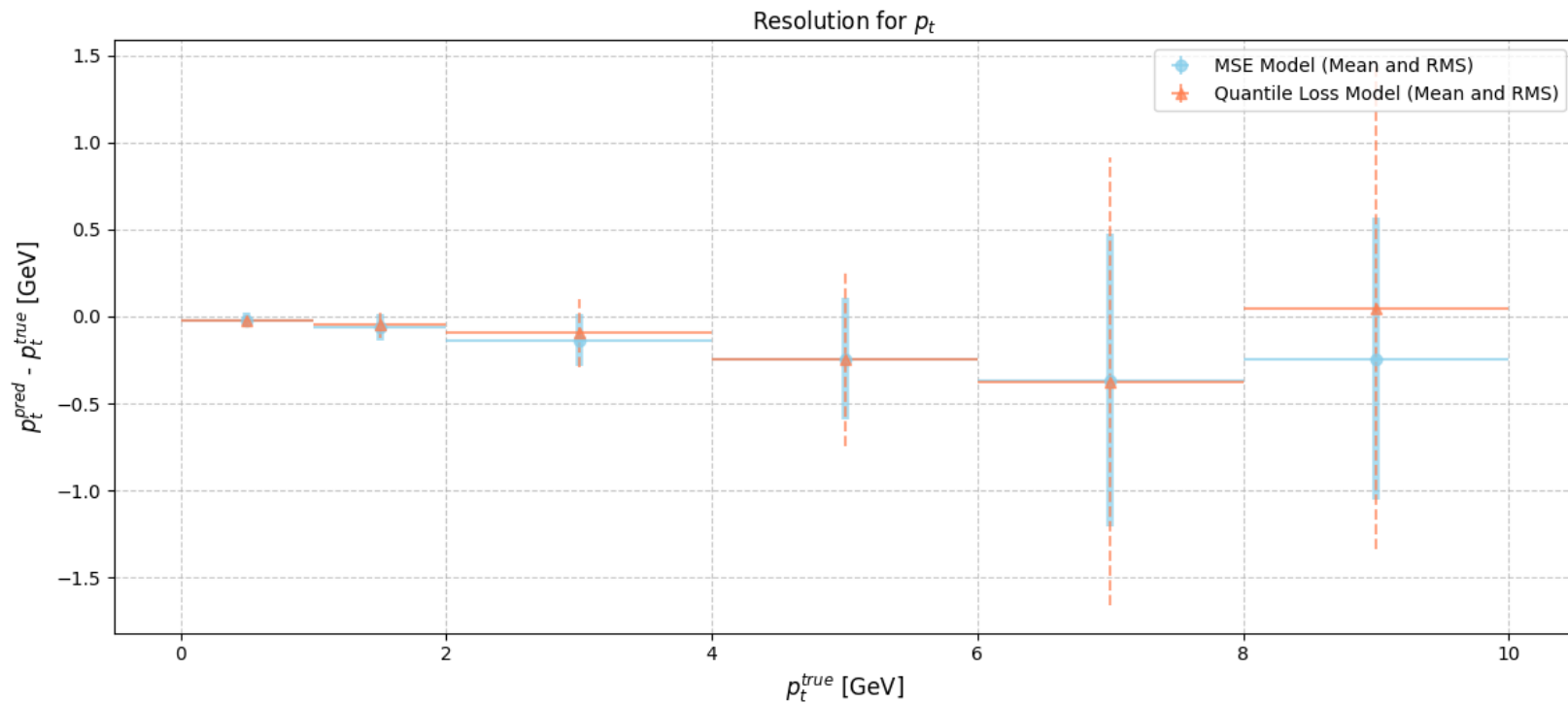
Resolution

r phi z



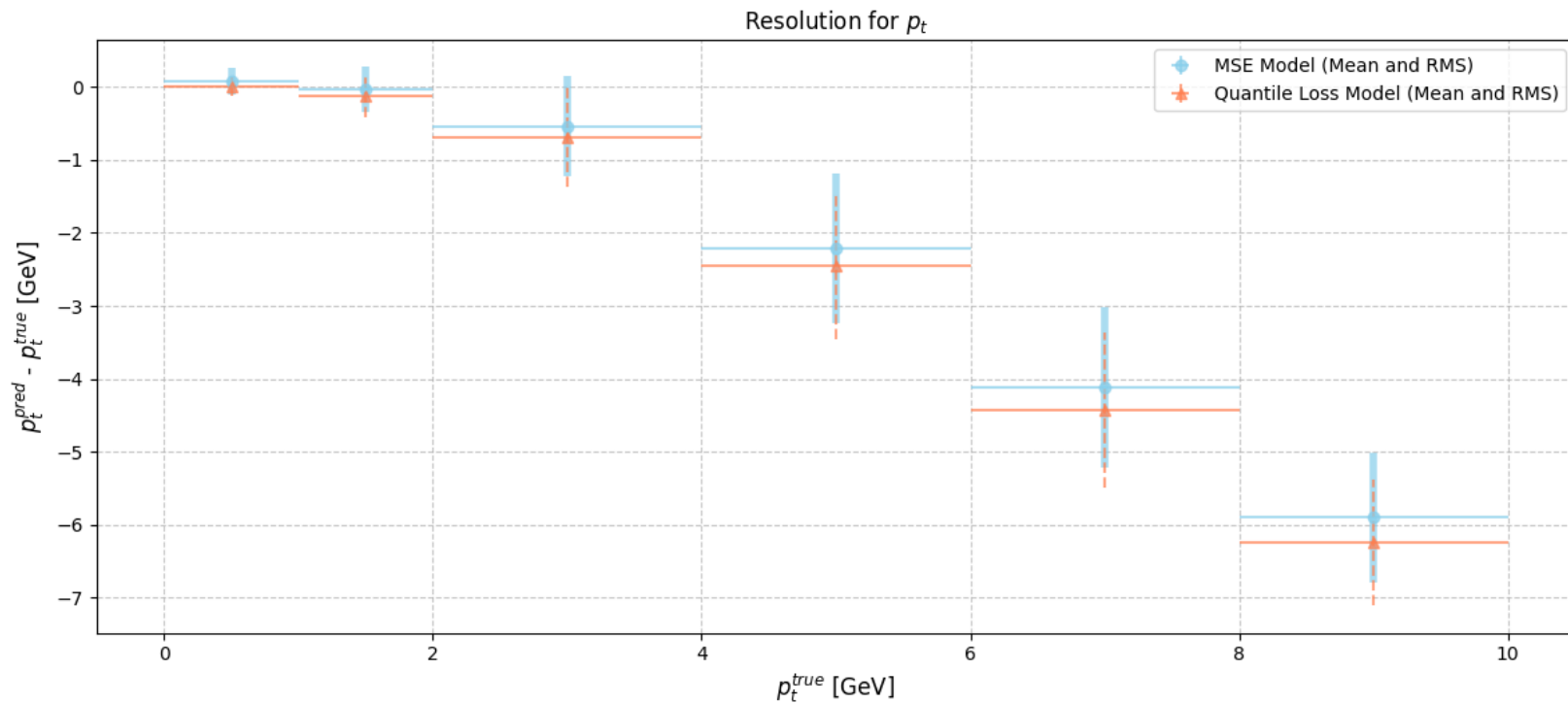
More results

x y z



More results

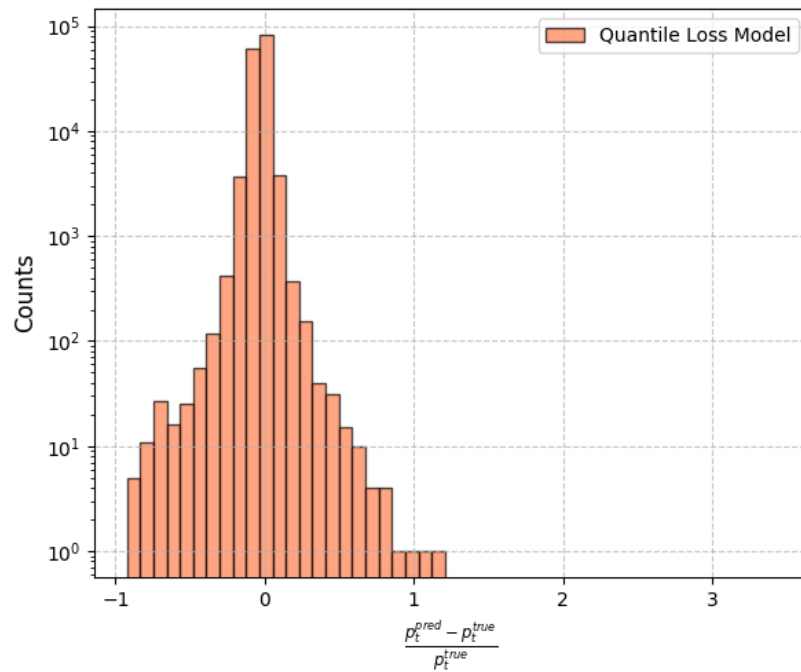
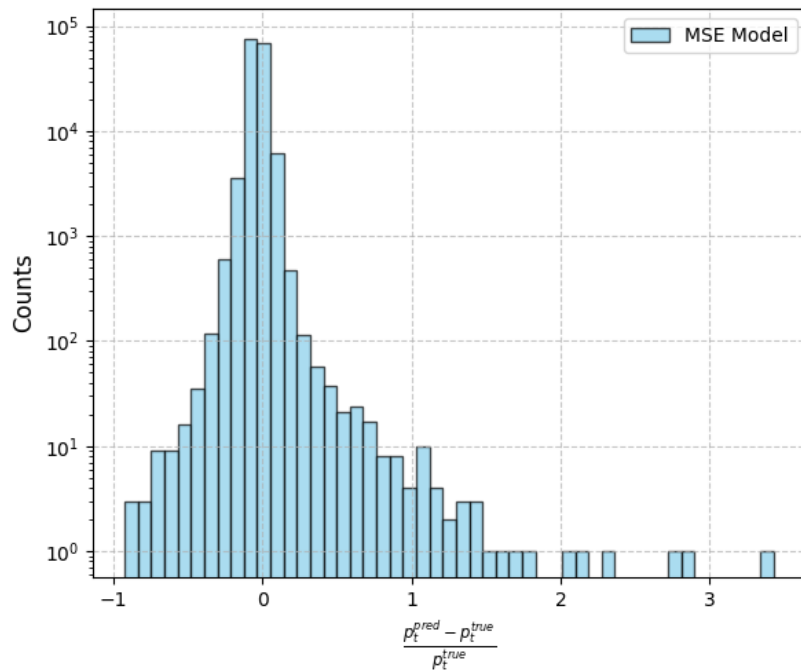
r phi z



More results

x y z

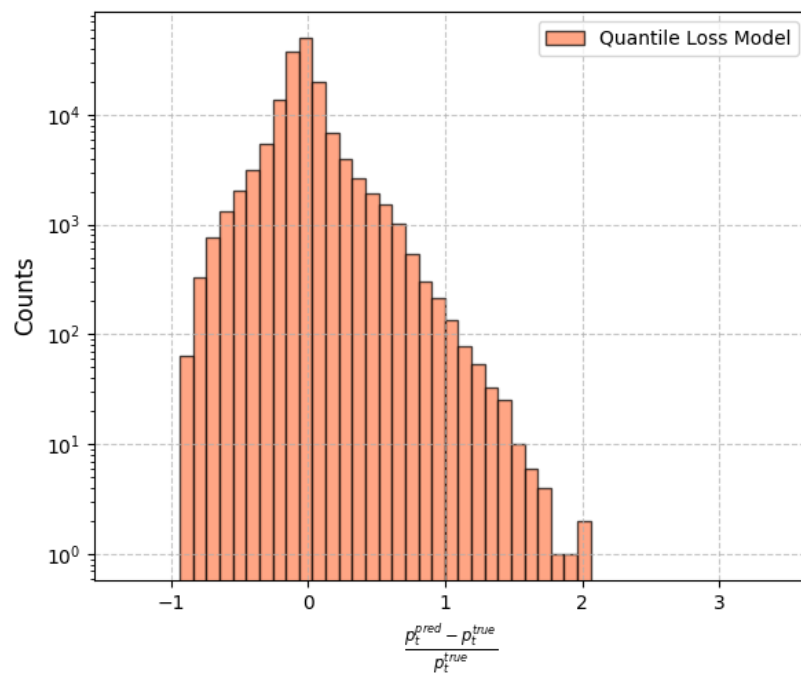
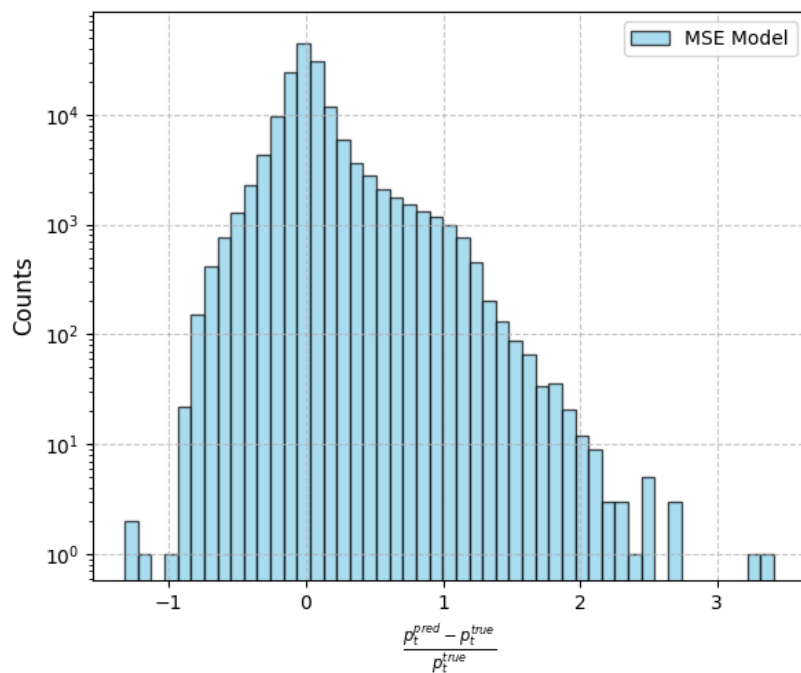
Relative Error Distributions for p_t



More results

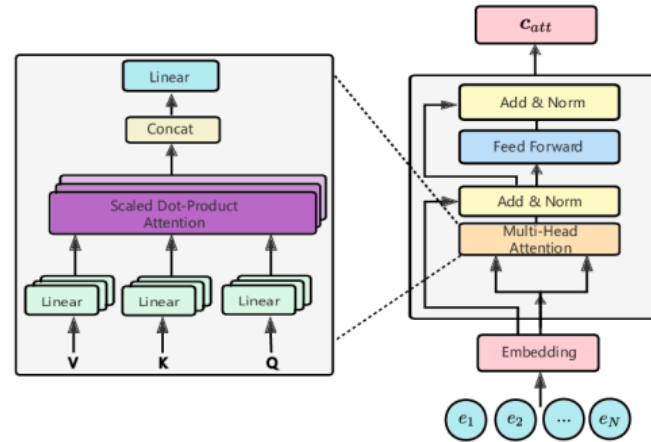
r phi z

Relative Error Distributions for p_t



TrackFormer

- **Transformer for track parameter regression**
- **Tested on several dataset: ToyTracks, Acts, TrackML**
- **Regression in pt and pz**
- **Shown promising results**



Sequences were padded to a fixed length

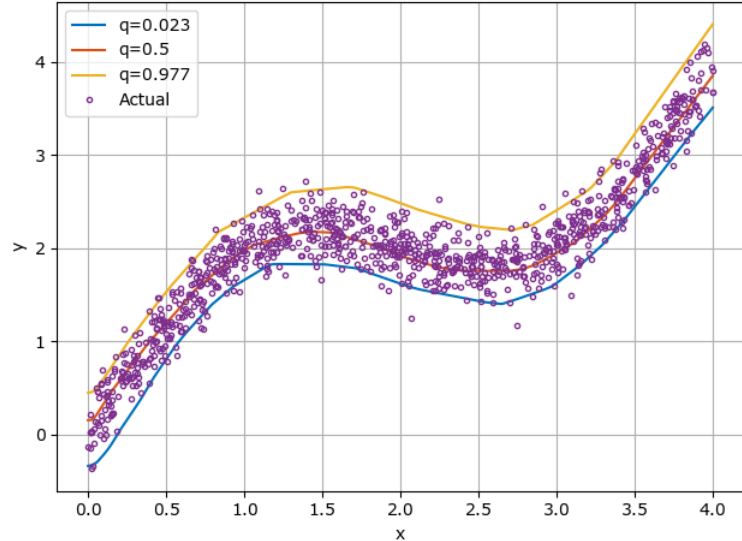
TrackFormer loss functions

Mean squared error:

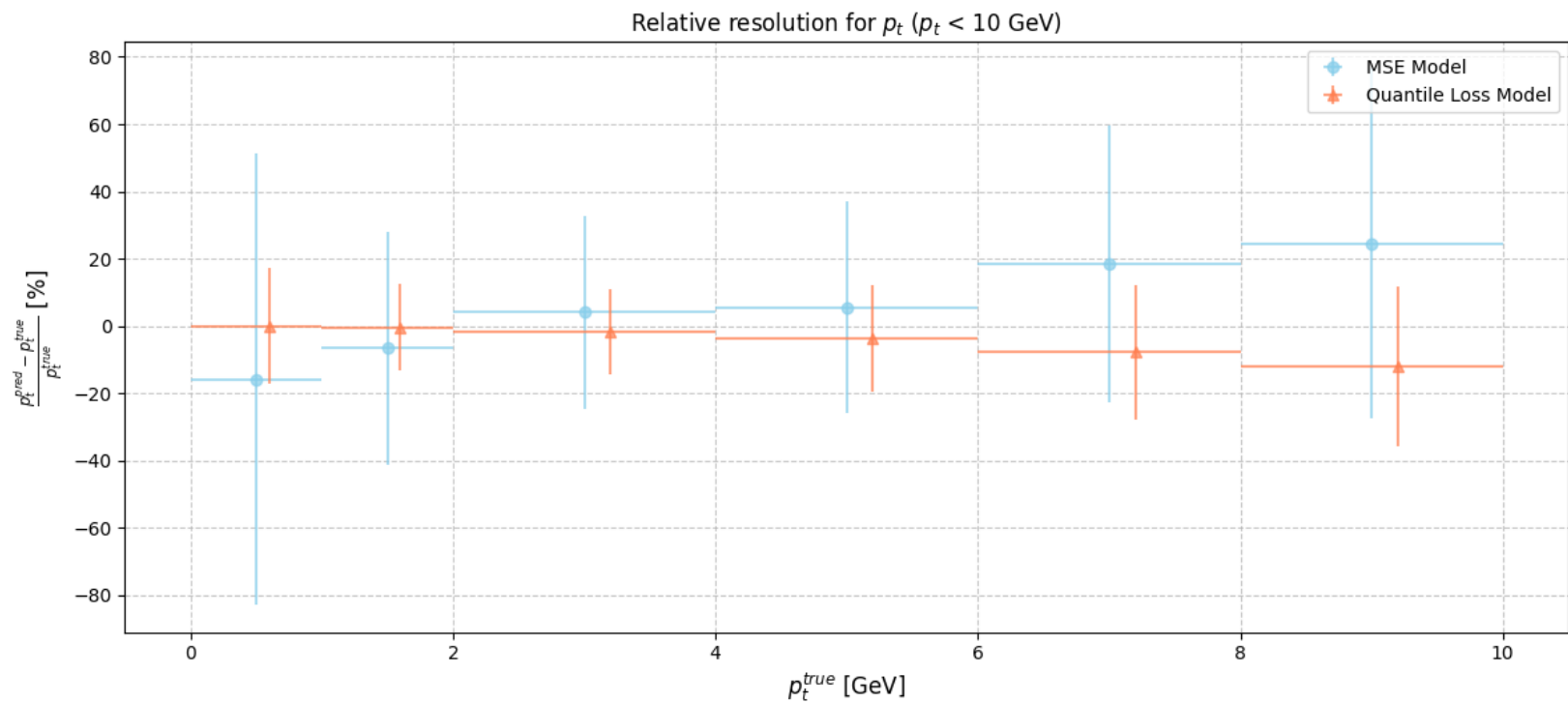
$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Quantile loss:

$$\text{QL} = \frac{1}{n} \sum_{i=1}^n (\max(q(y_i - \hat{y}_i), (q - 1)(y_i - \hat{y}_i)))$$

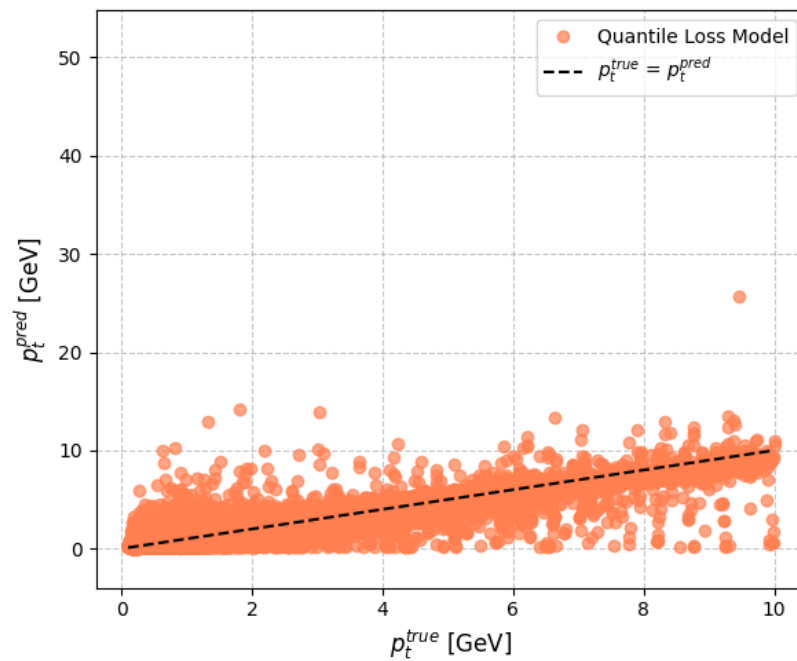
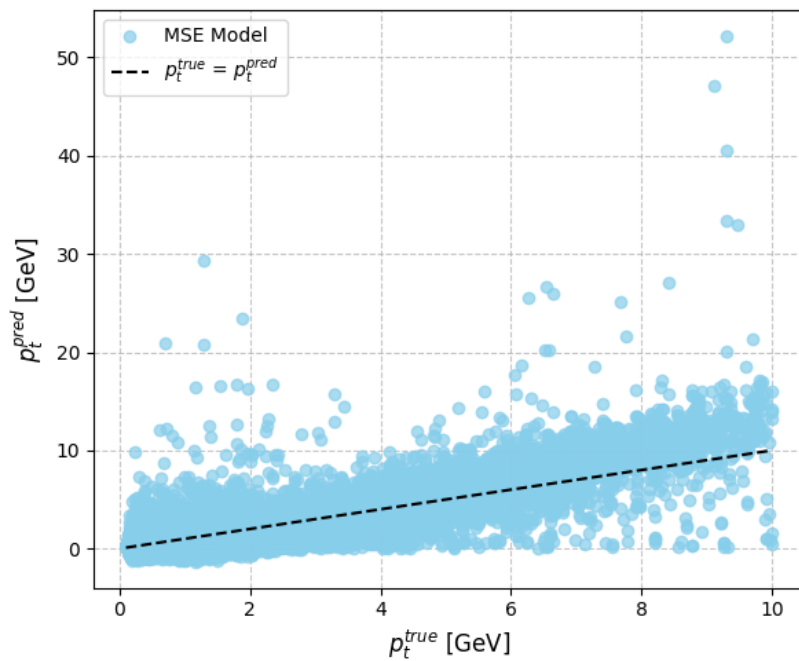


More results



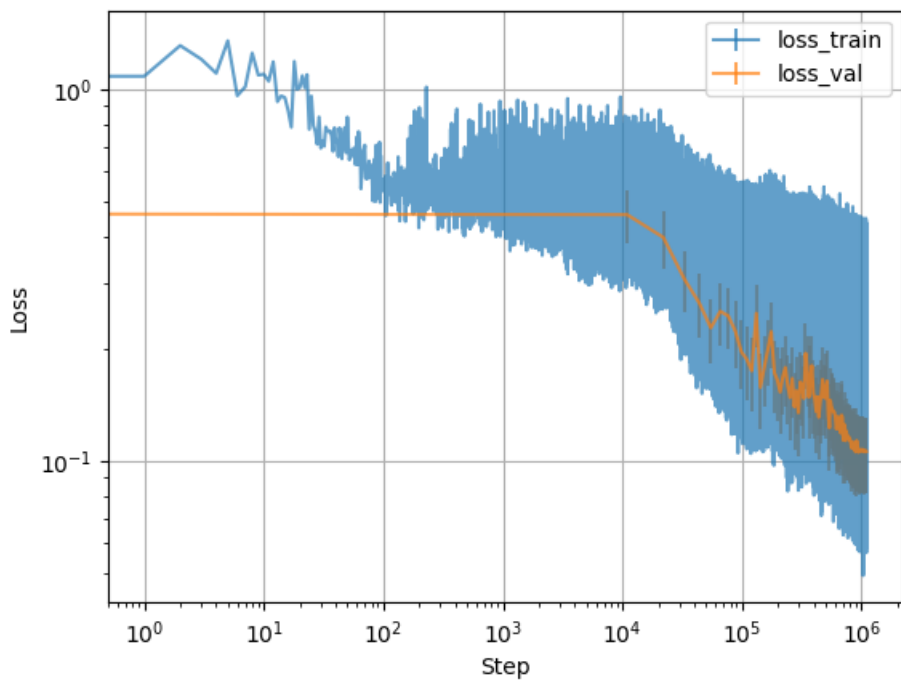
More results

p_t^{true} vs p_t^{pred} ($p_t < 10$ GeV)



Loss curves

Quantile Loss



MSE Loss

