



Tracking with ML



19th February 2025



Jeremy Couthures

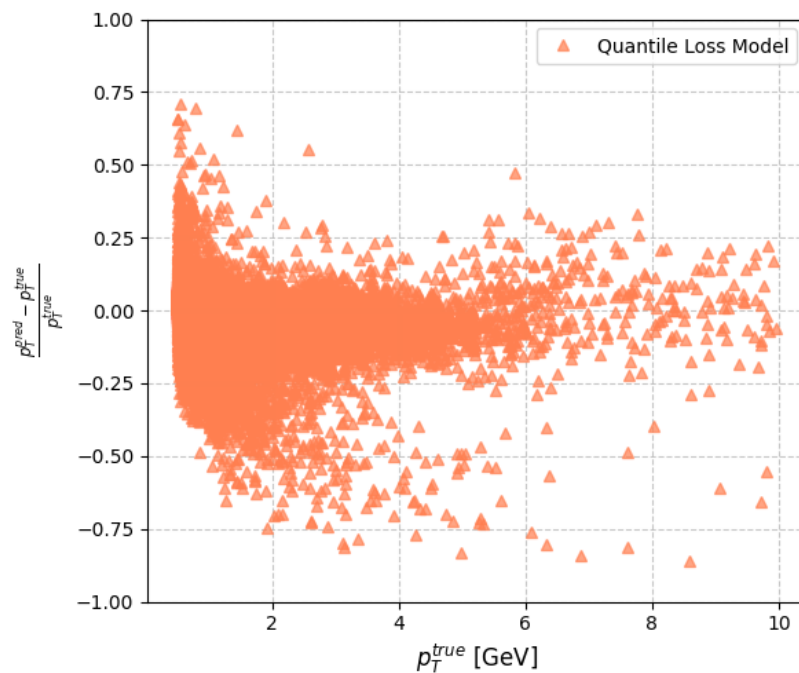
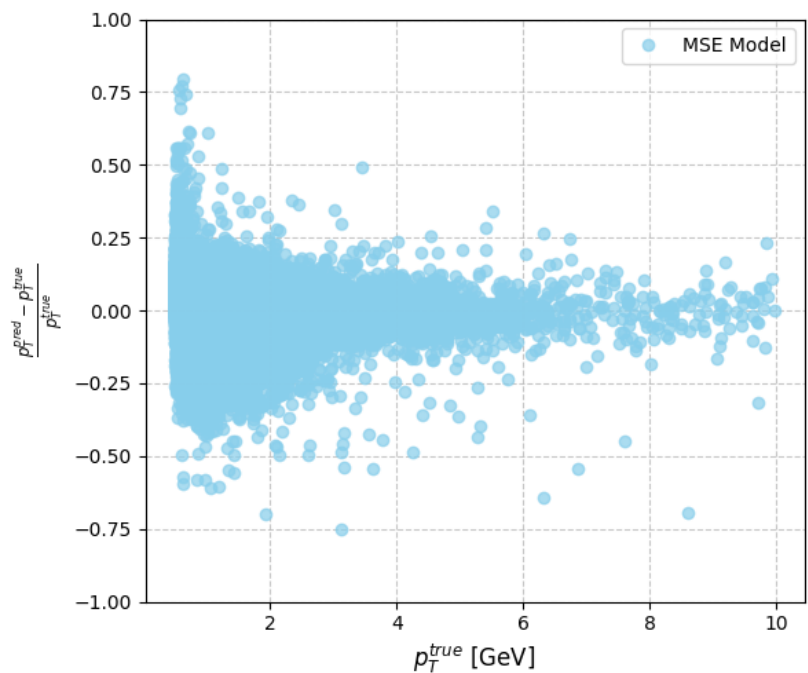


More results

x y z

Relative error resolution for p_T ($(tx, ty, tz) \rightarrow (p_T, p_z)$)

TrackML Zenodo

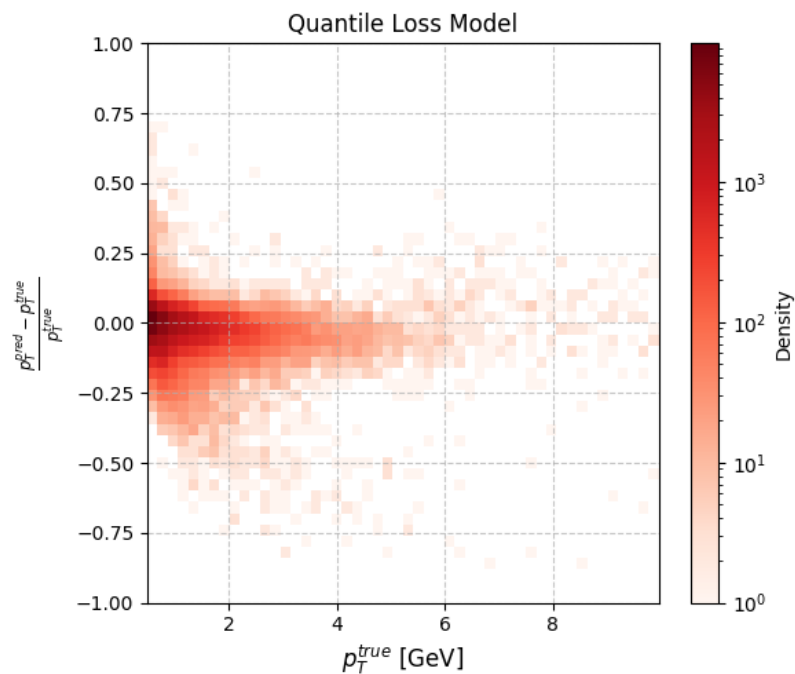
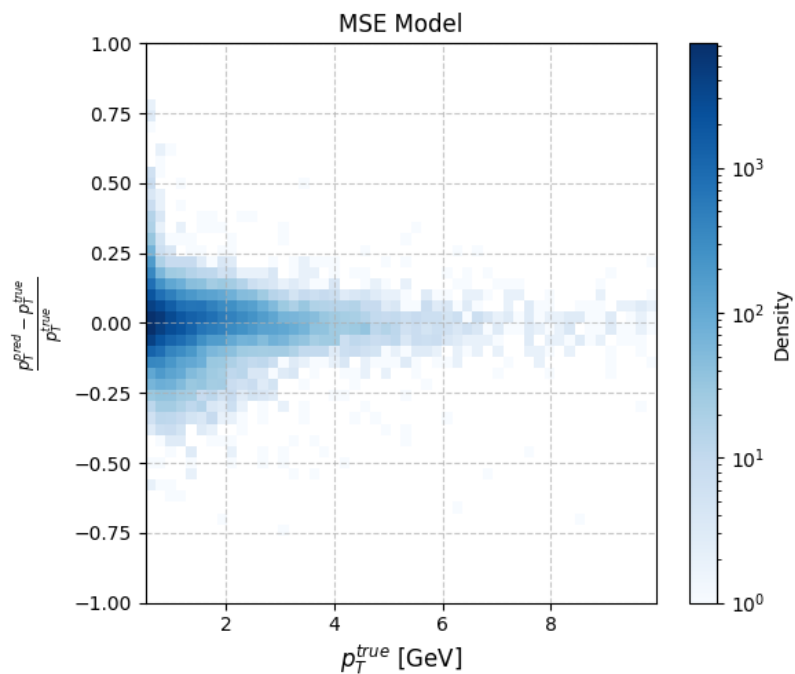


More results

x y z

Relative error resolution for p_T ($(tx, ty, tz) \rightarrow (p_T, p_z)$)

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Computing resolution

3 approaches:

- **Paper approach:**

- Iterative pruning of distribution pred-truth from points away from the mean by more than 3 rms

- **Quantile approaches:**

- Take quantiles equivalent to 5 sigma (of a normal distribution) from the median:

99.99994266968912% quantile

5.733031088084317e-05% quantile

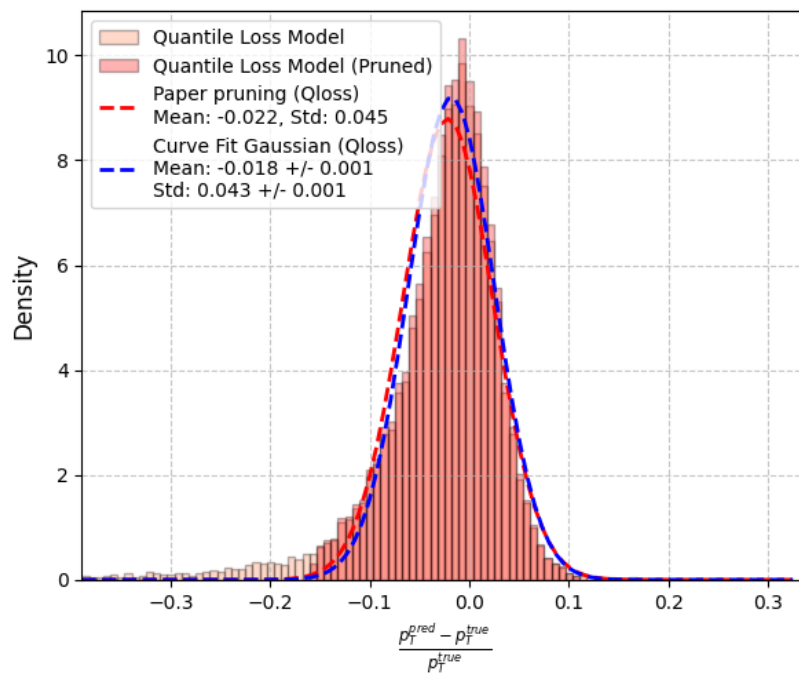
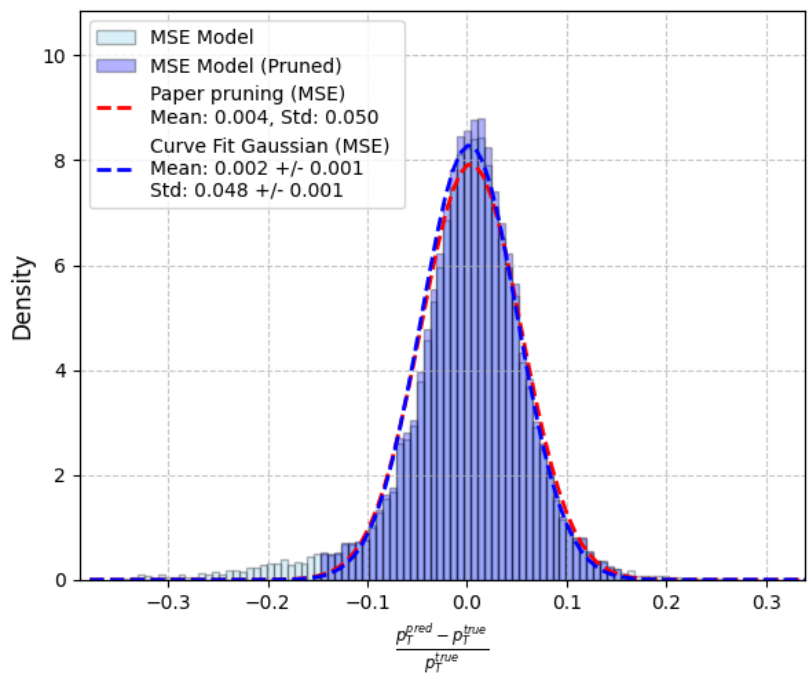
- Estimate mean and std with MLE (scipy norm.fit)
- Use curve_fit or ROOT to fit a gaussian

Resolution

x y z

TrackML Zenodo

Relative Error Distributions for p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tx, ty, tz) \rightarrow (p_T, p_z)$)

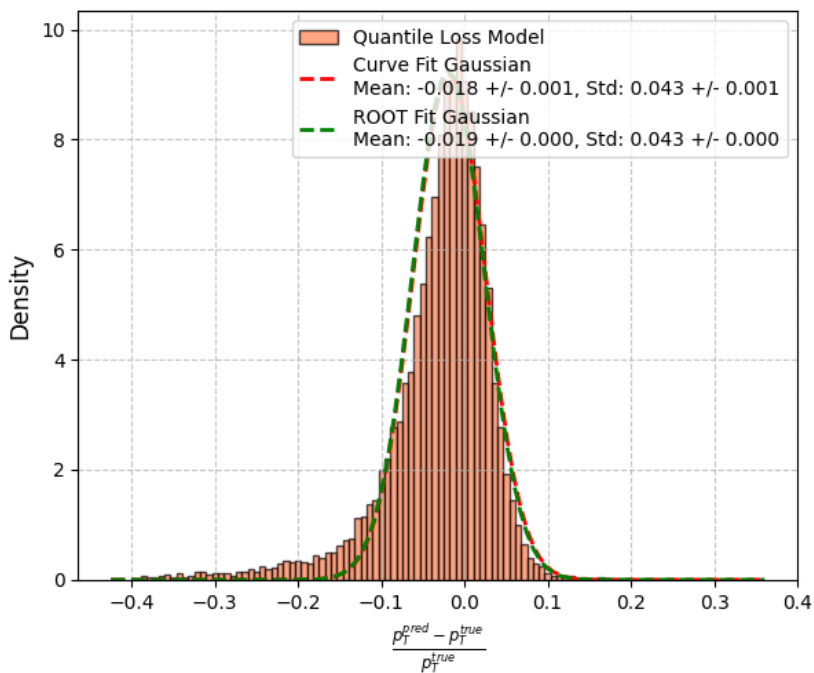
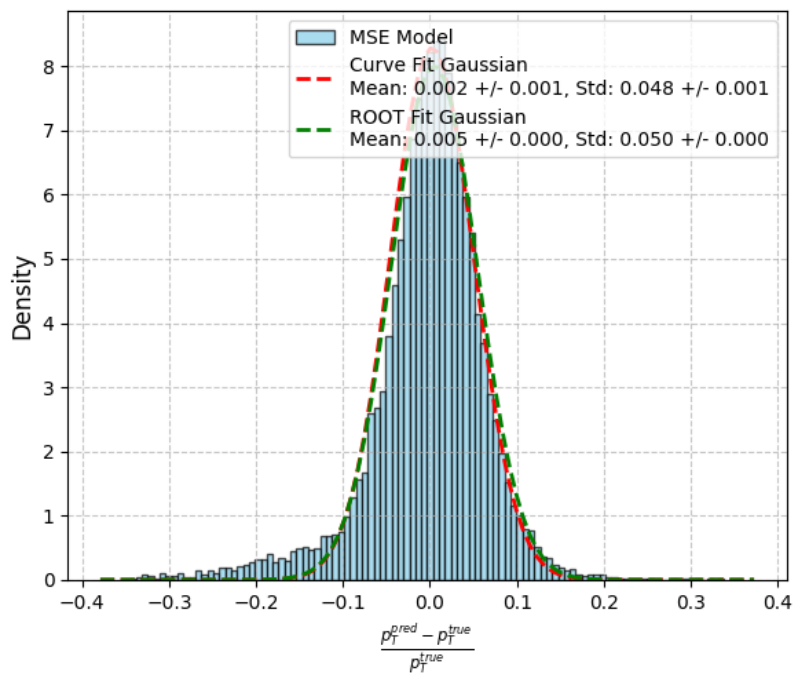


Resolution

x y z

TrackML Zenodo

Relative Error Distributions for p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tx, ty, tz) \rightarrow (p_T, p_z)$)

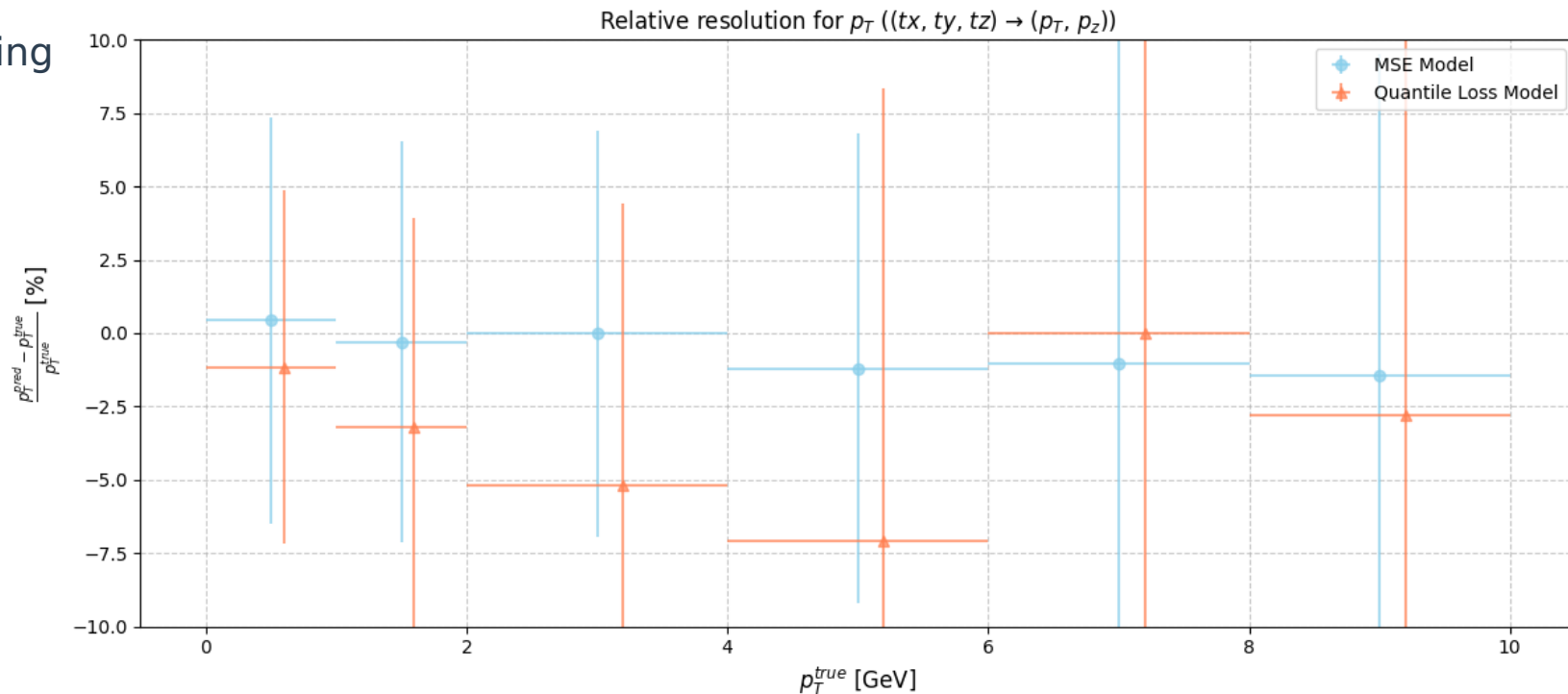


Resolution

x y z

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No pruning



Quantile loss is worst

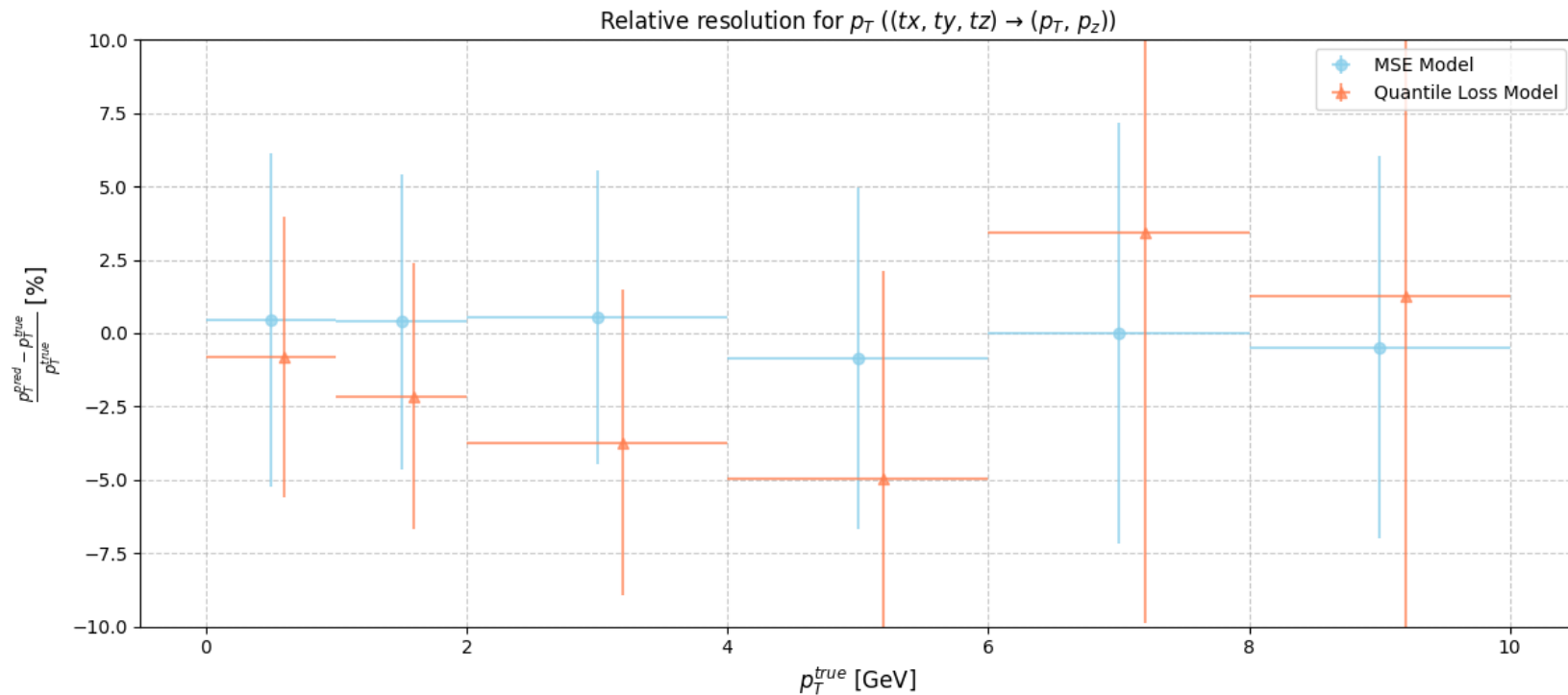
02/19/25

Resolution

x y z

Pruning

TrackML Zenodo

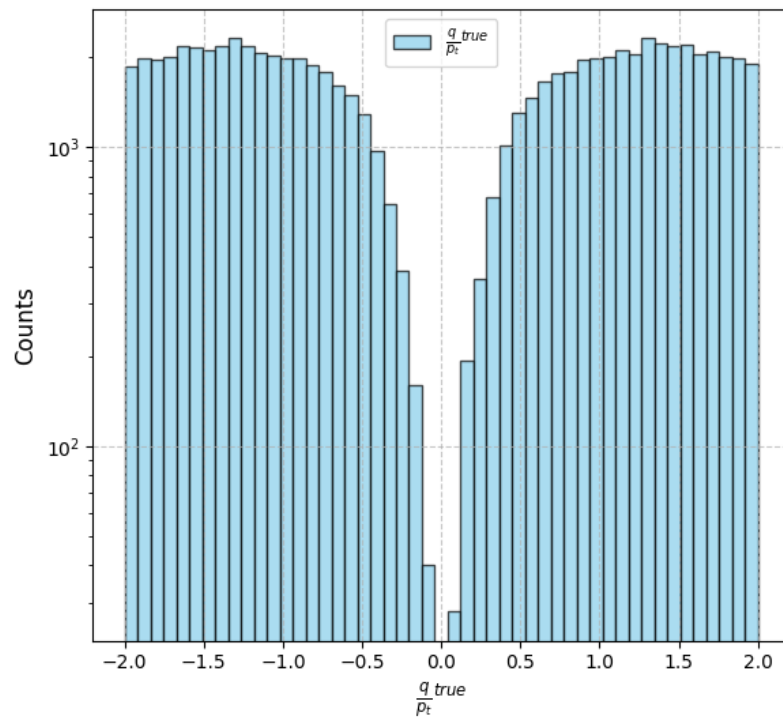
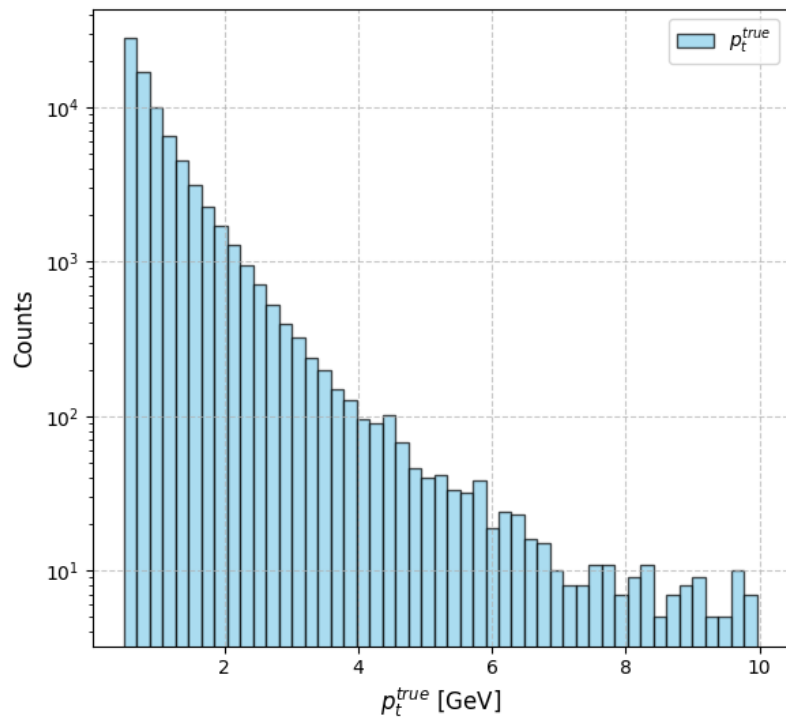


Pruning improves results

02/19/25

q/pT

Target variable:

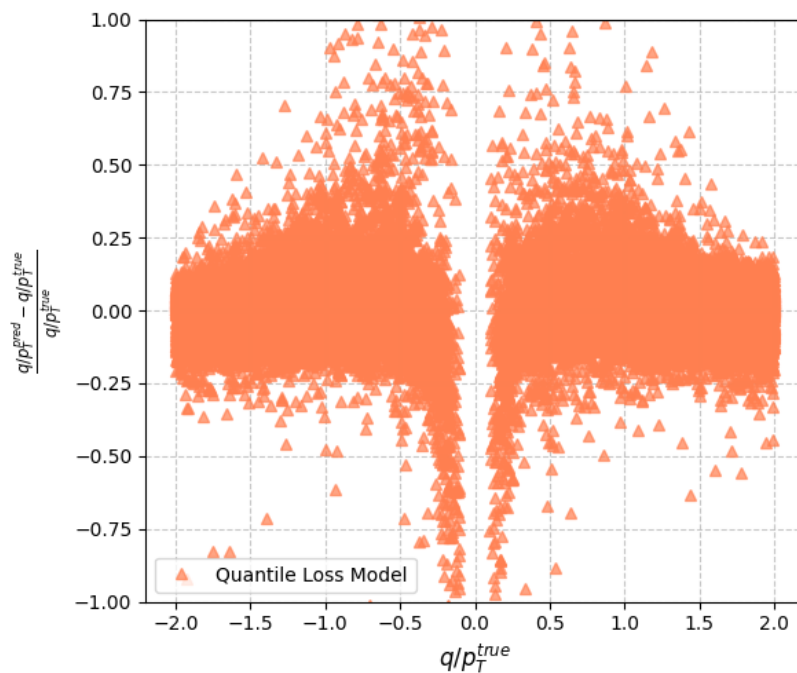
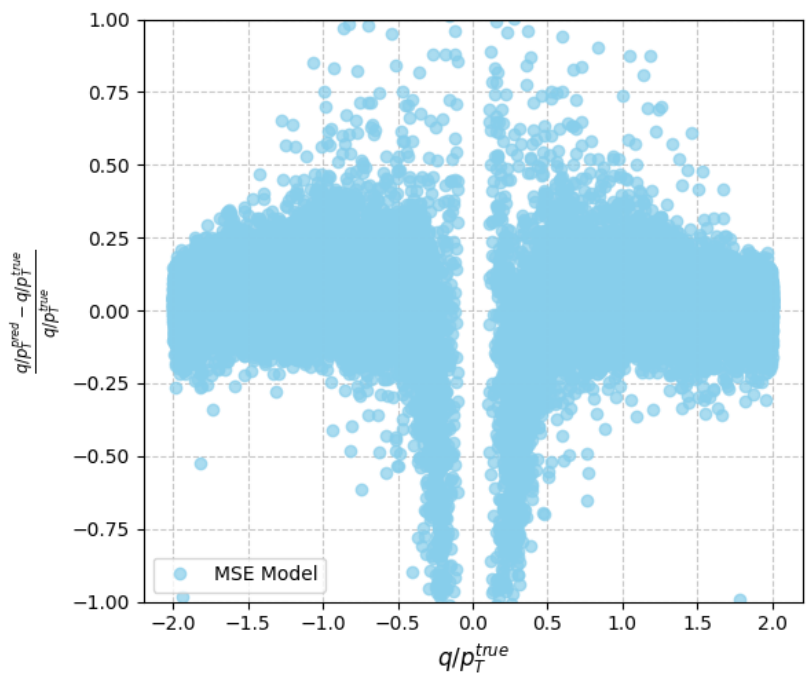


More results

x y z

Relative error resolution for q/p_T ($(tx, ty, tz) \rightarrow (q/p_T, p_z)$)

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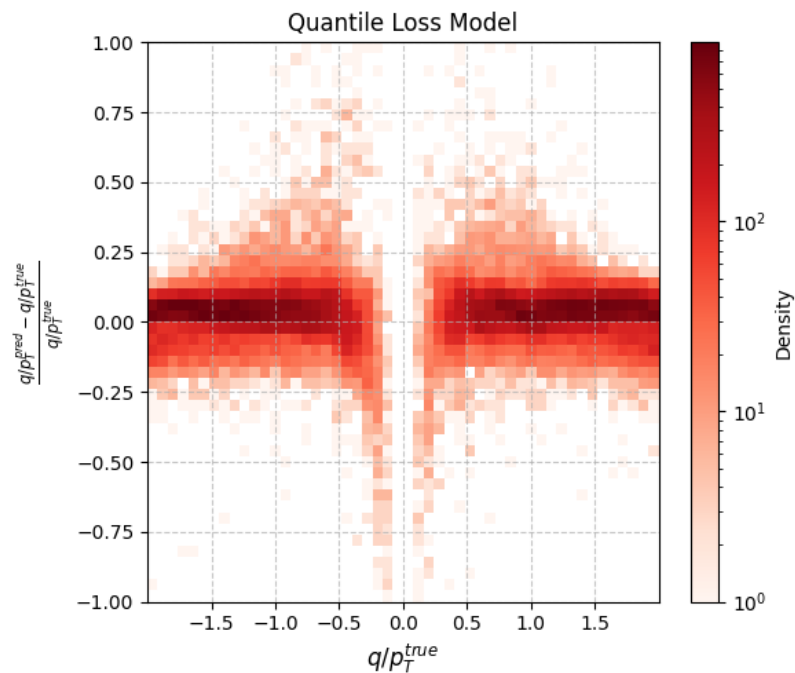
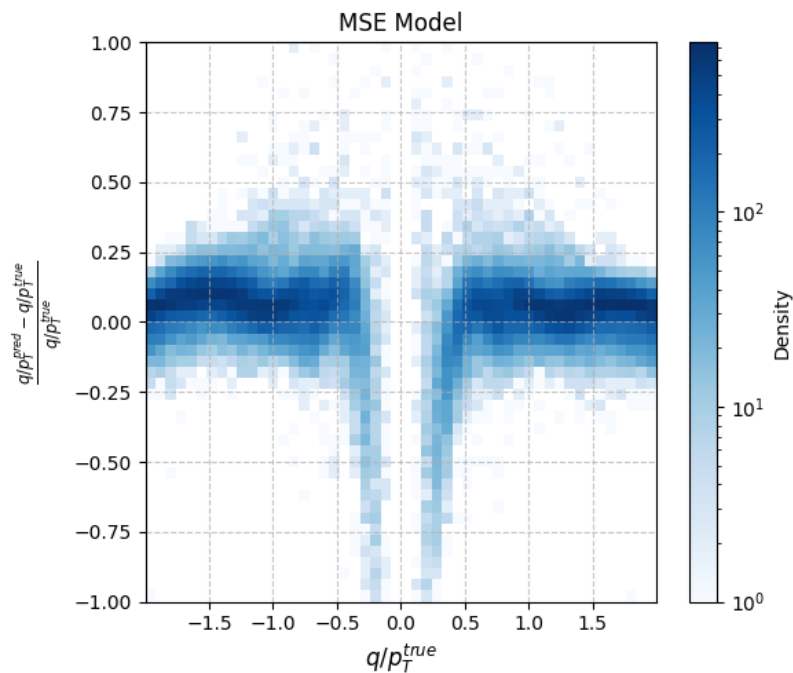


Resolution

x y z

Relative error resolution for q/p_T ($(tx, ty, tz) \rightarrow (q/p_T, p_z)$)

TrackML Zenodo

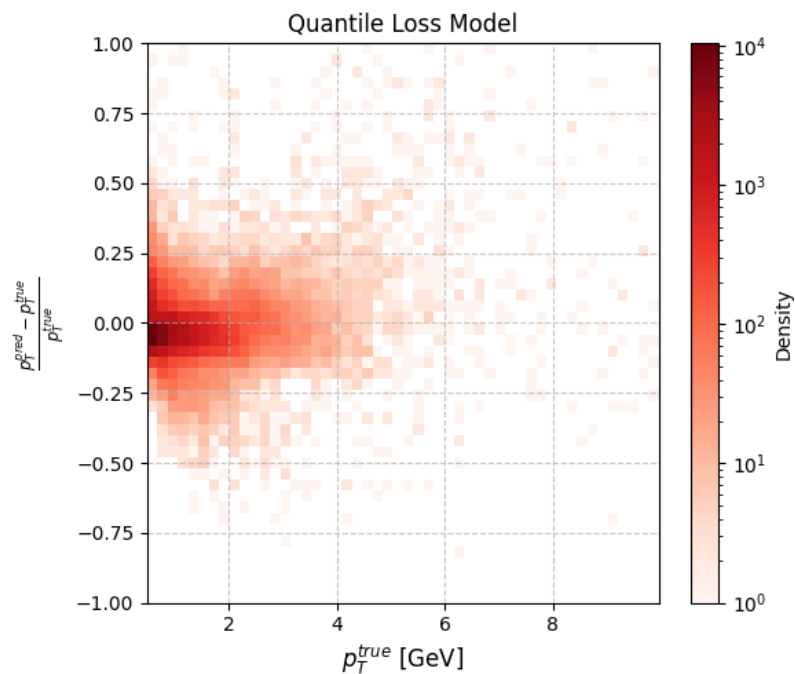
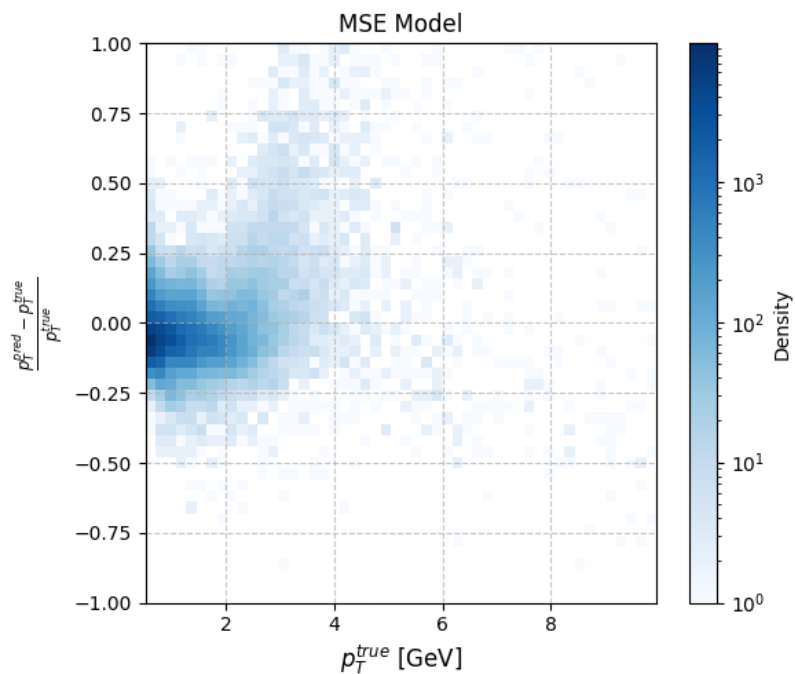


Resolution

x y z

Relative error resolution for p_T ($(tx, ty, tz) \rightarrow (q/p_T, p_z)$)

TrackML Zenodo

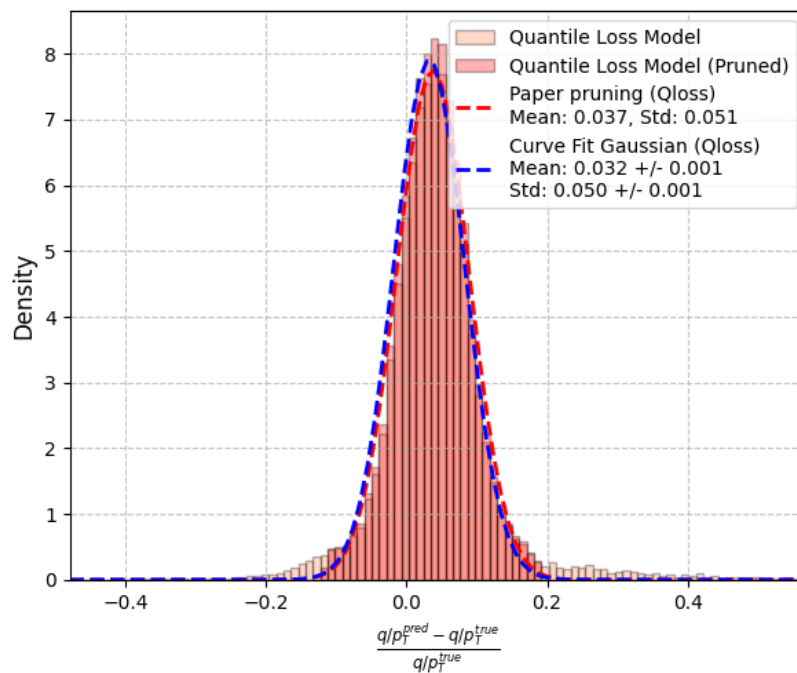
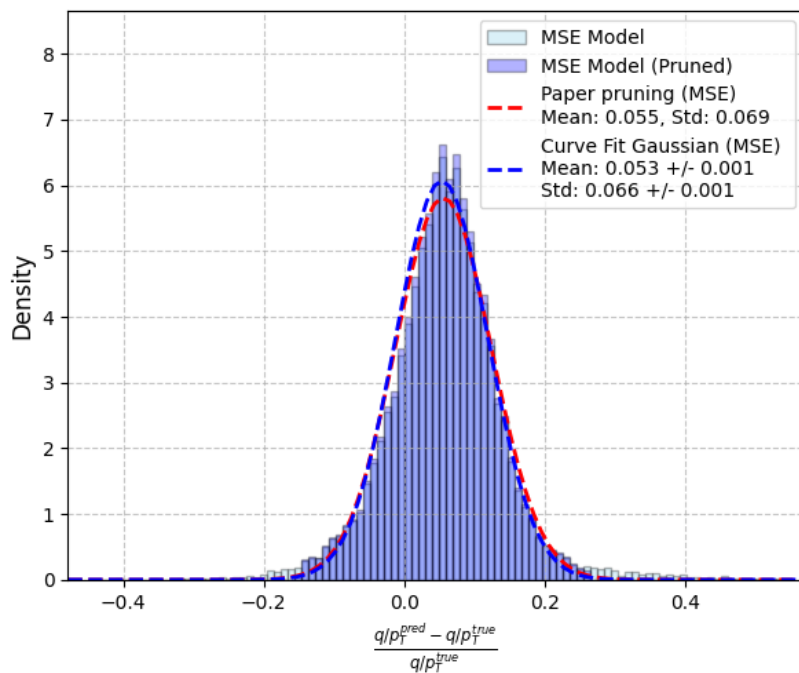


Resolution

x y z

TrackML Zenodo

Relative Error Distributions for q/p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tx, ty, tz) \rightarrow (q/p_T, p_z)$)

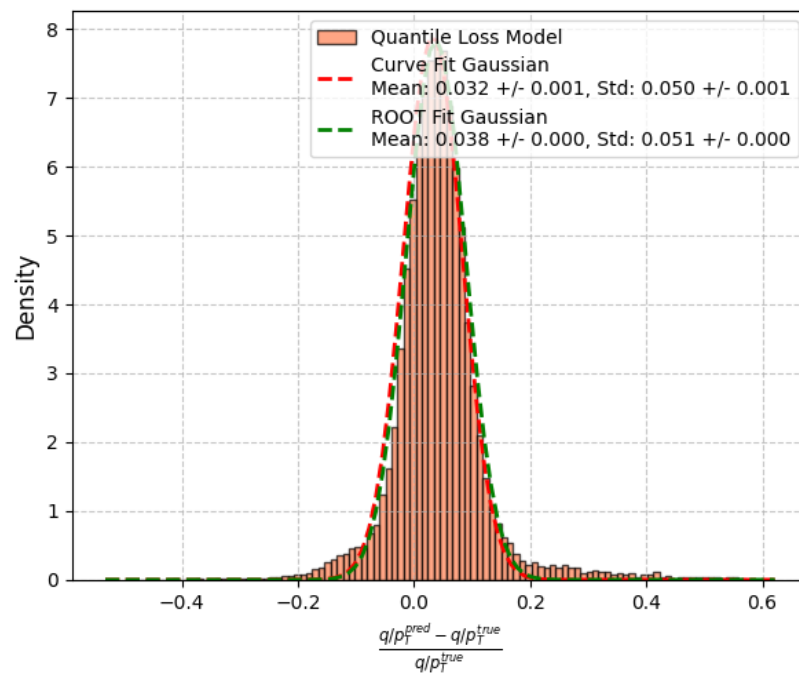
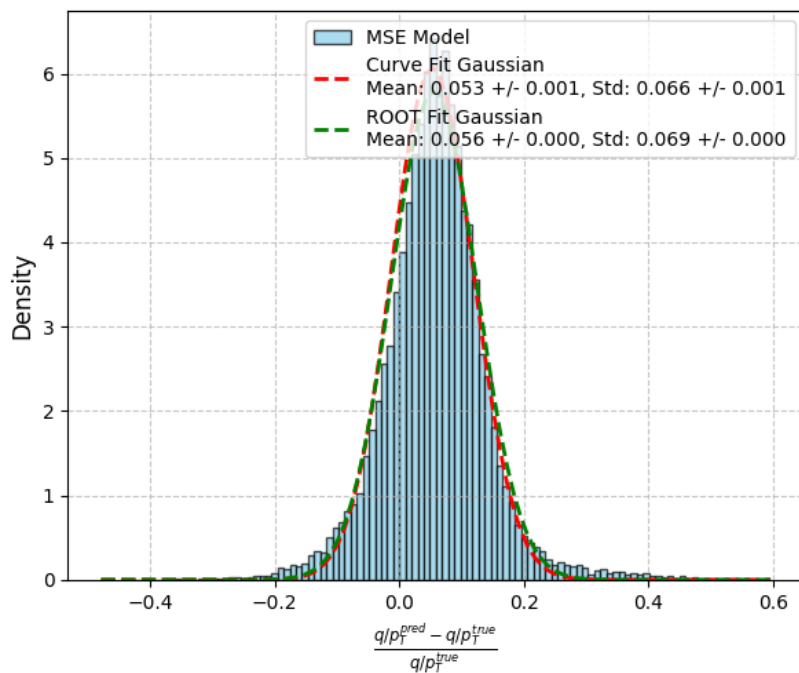


Resolution

x y z

TrackML Zenodo

Relative Error Distributions for q/p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tx, ty, tz) \rightarrow (q/p_T, p_z)$)

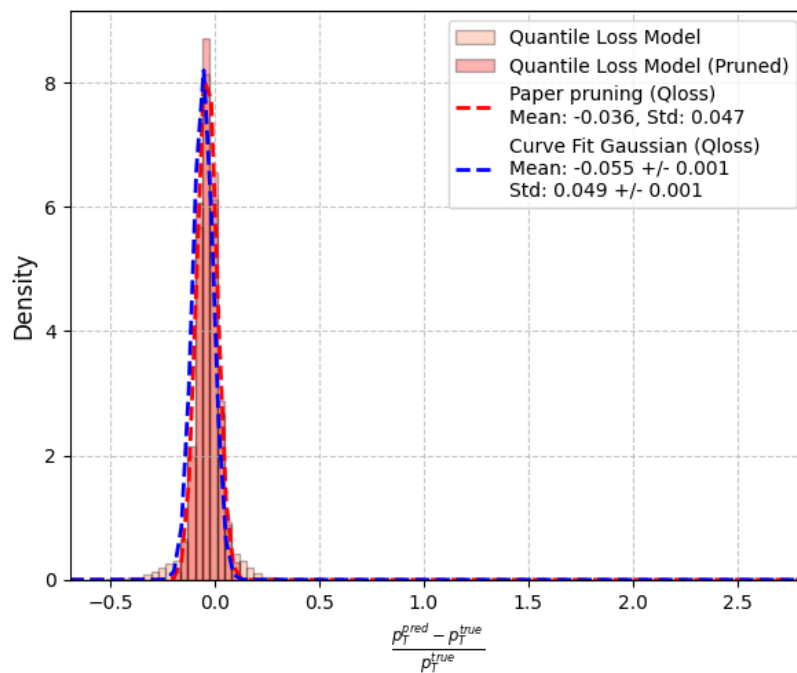
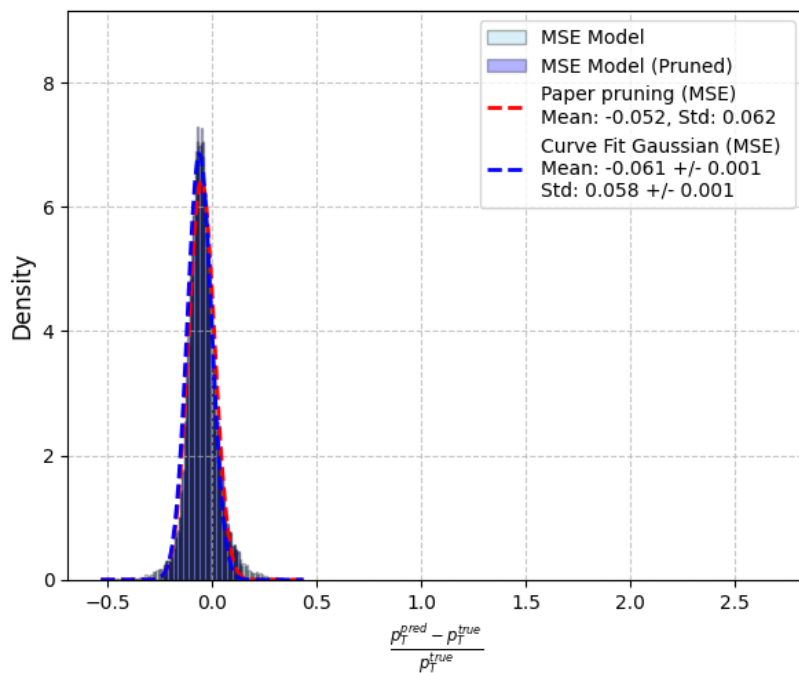


Resolution

x y z

TrackML Zenodo

Relative Error Distributions for p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tx, ty, tz) \rightarrow (q/p_T, p_z)$)

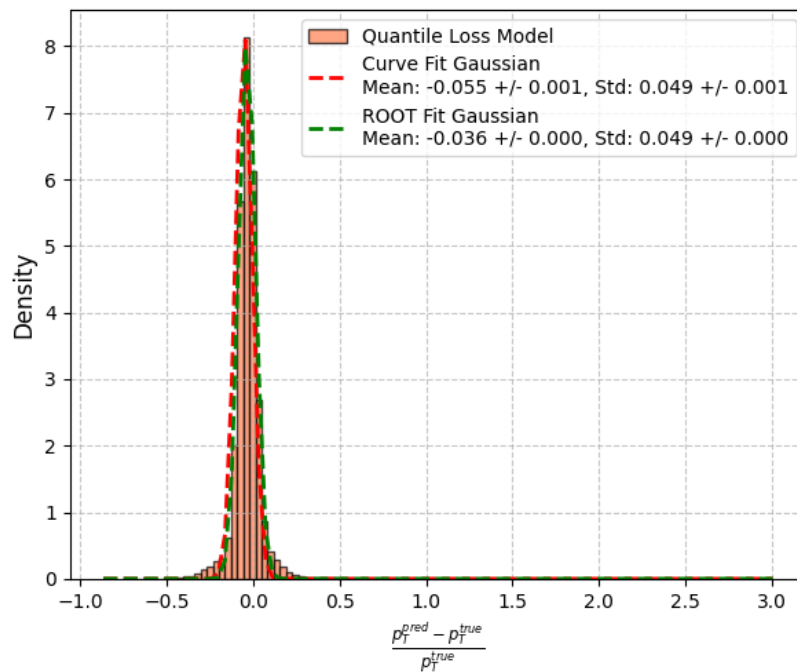
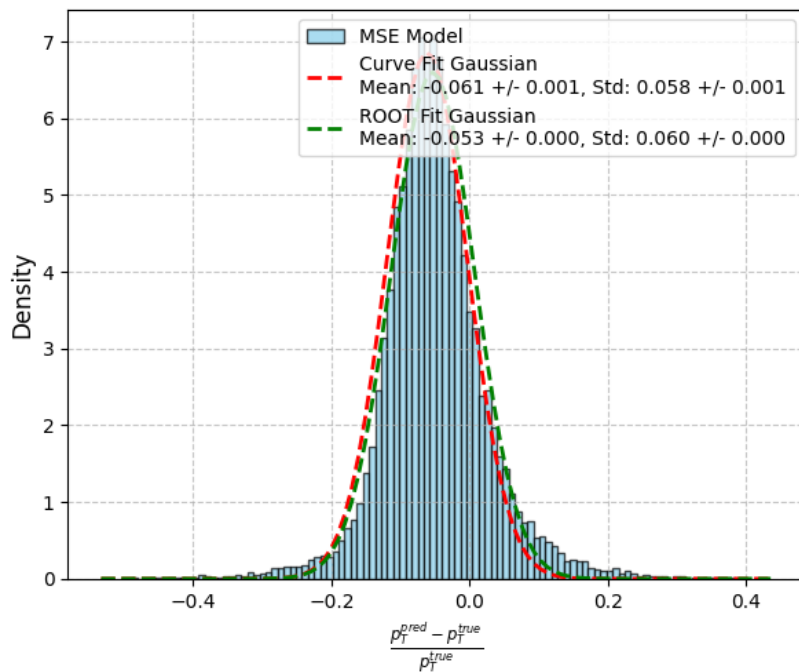


Resolution

x y z

TrackML Zenodo

Relative Error Distributions for p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tx, ty, tz) \rightarrow (q/p_T, p_z)$)

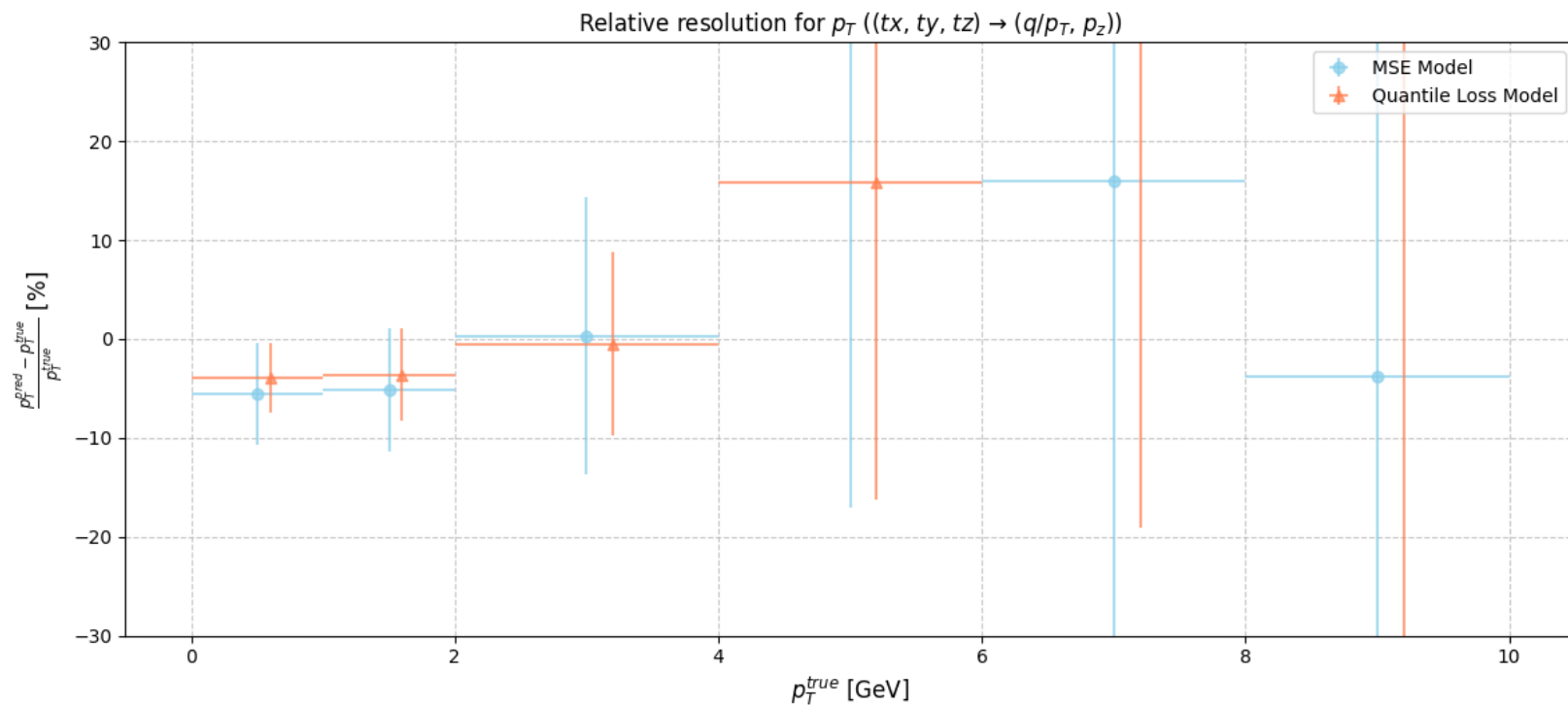


Resolution

x y z

TrackML Zenodo

Pruning



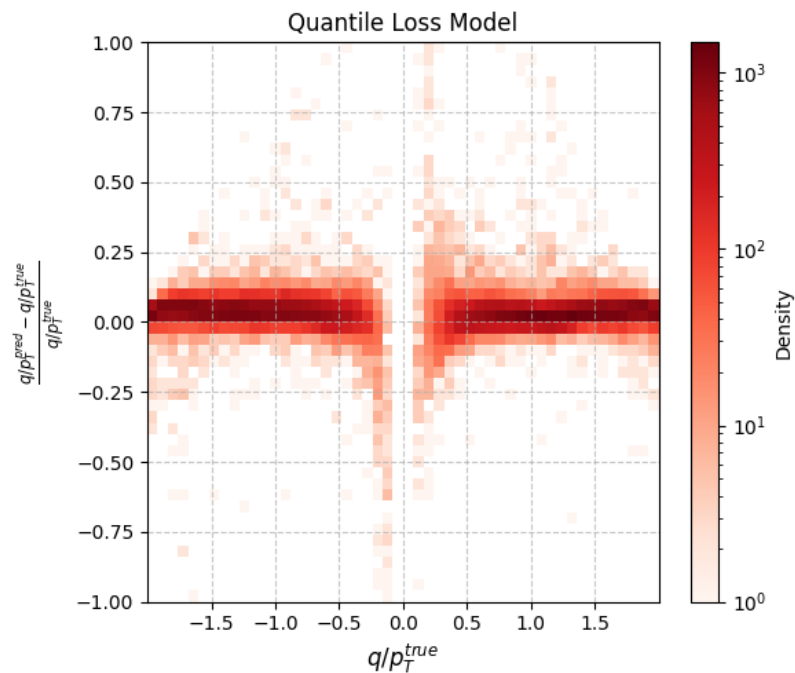
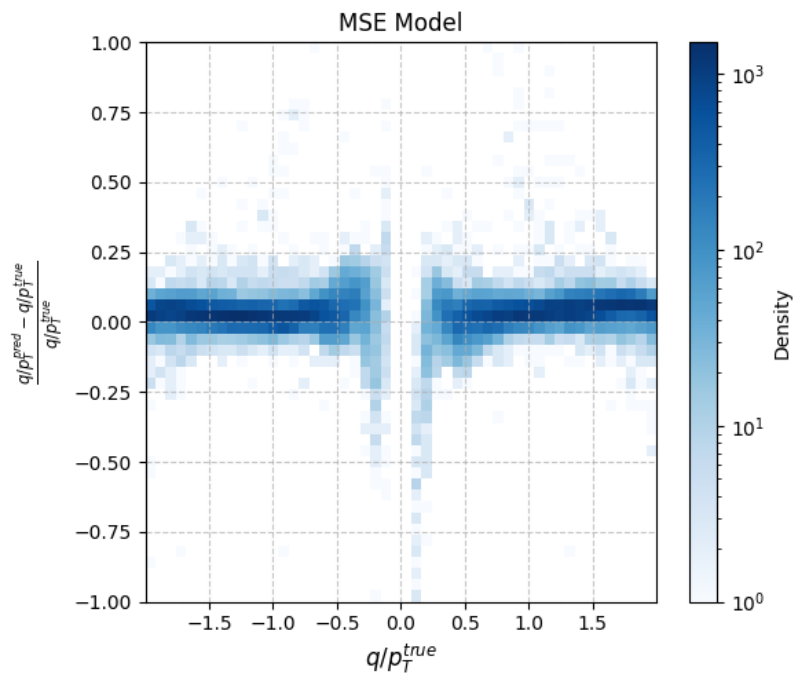
$r, d\phi, z \rightarrow q/p_T, p_z$

Resolution

r dphi z

Relative error resolution for q/p_T ($(tr, d\phi, tz) \rightarrow (q/p_T, p_z)$)

TrackML Zenodo

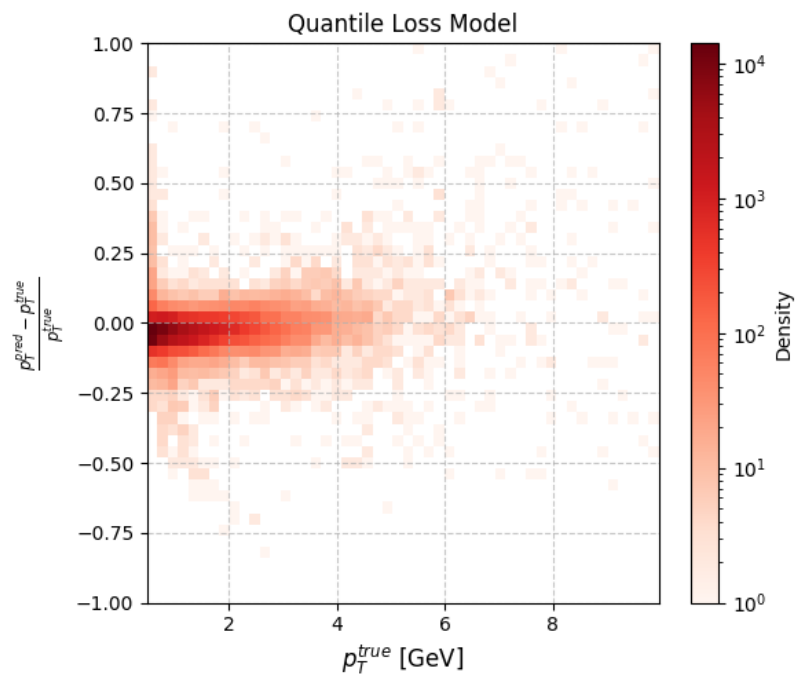
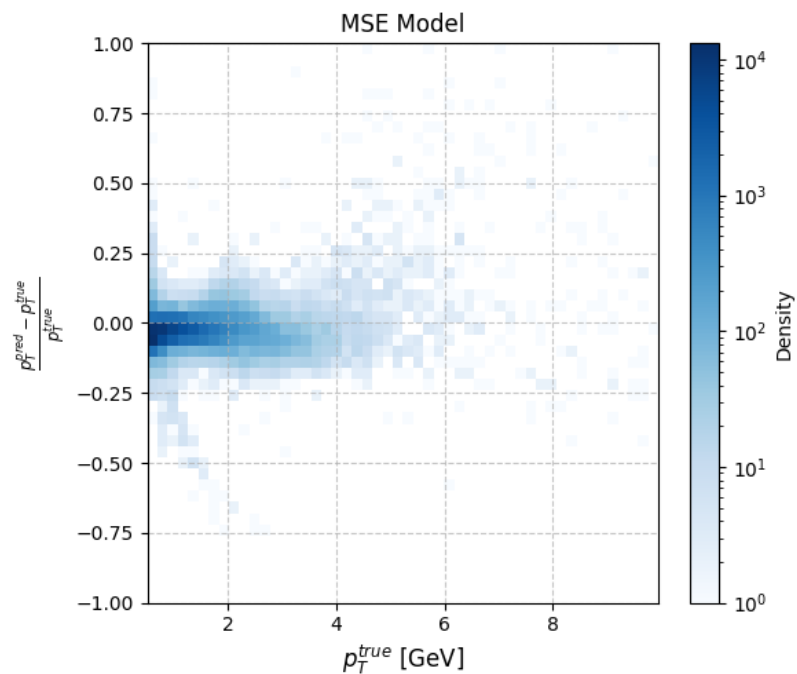


Resolution

r dphi z

Relative error resolution for p_T ($(tr, d\phi, tz) \rightarrow (q/p_T, p_z)$)

TrackML Zenodo

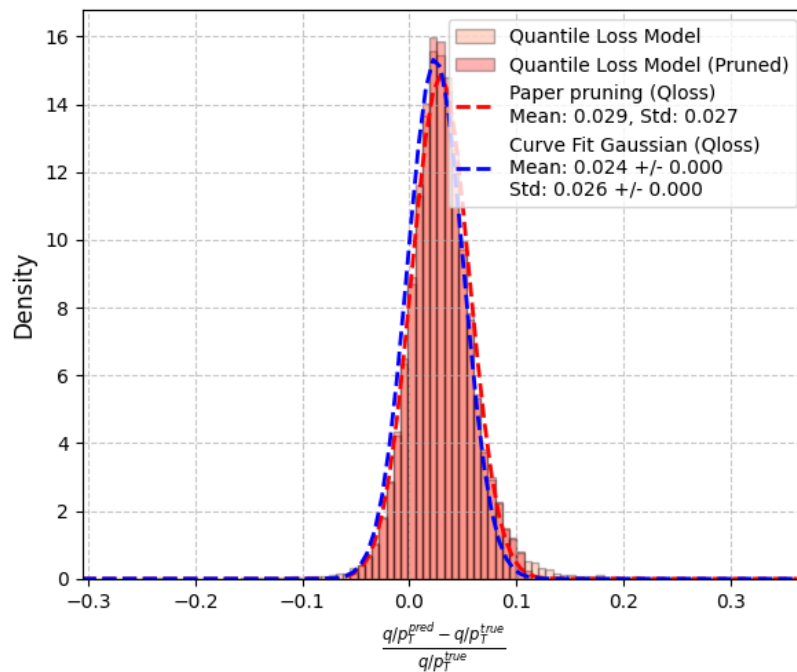
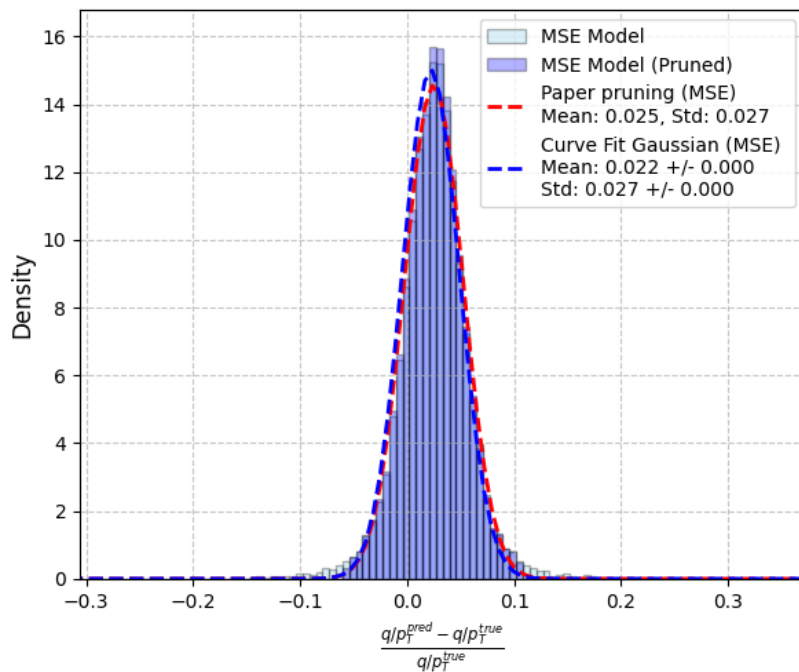


Resolution

r dphi z

TrackML Zenodo

Relative Error Distributions for q/p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tr, d\phi, tz) \rightarrow (q/p_T, p_z)$)

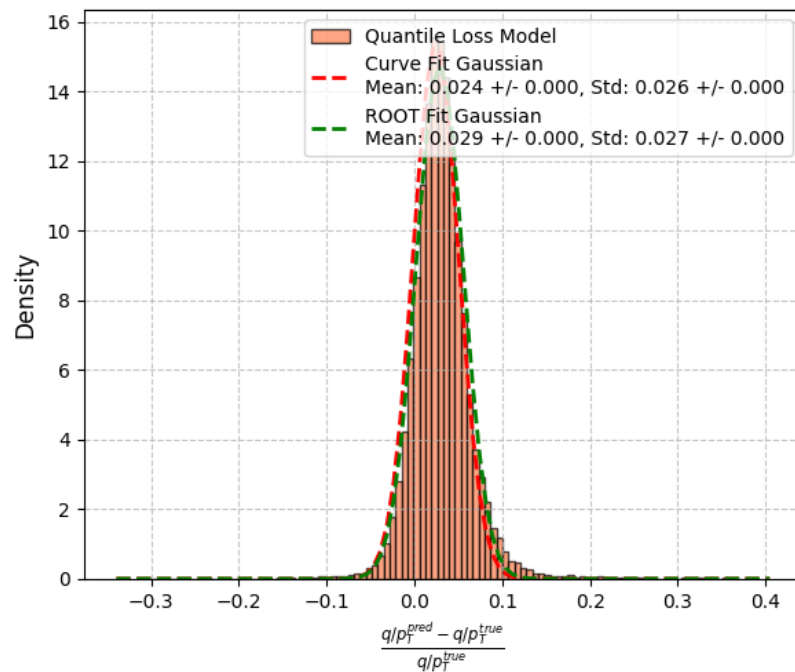
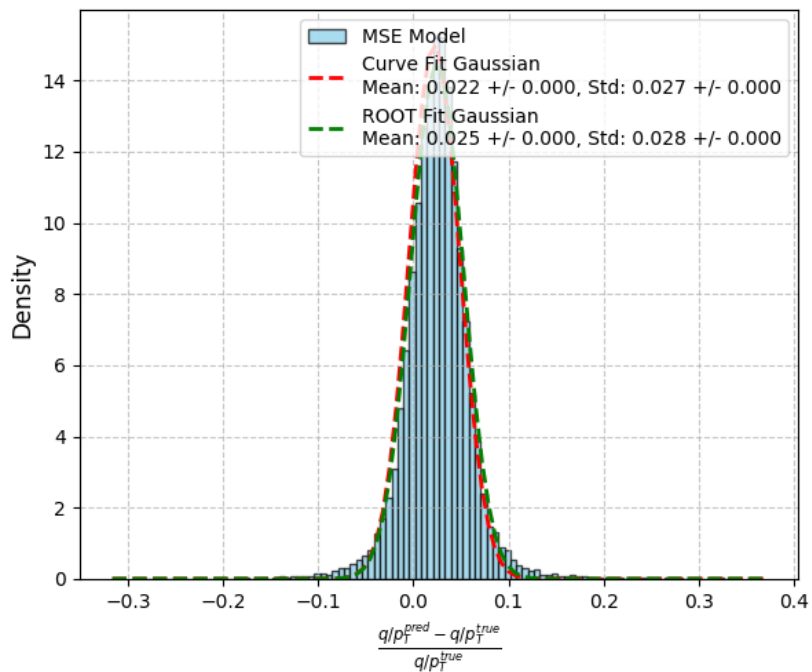


Resolution

r dphi z

TrackML Zenodo

Relative Error Distributions for q/p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tr, d\phi, tz) \rightarrow (q/p_T, p_z)$)

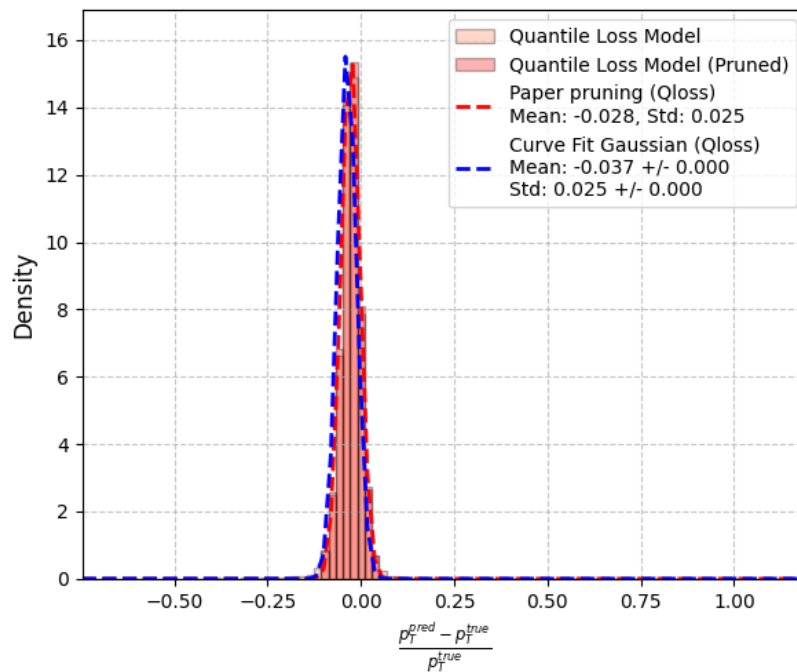
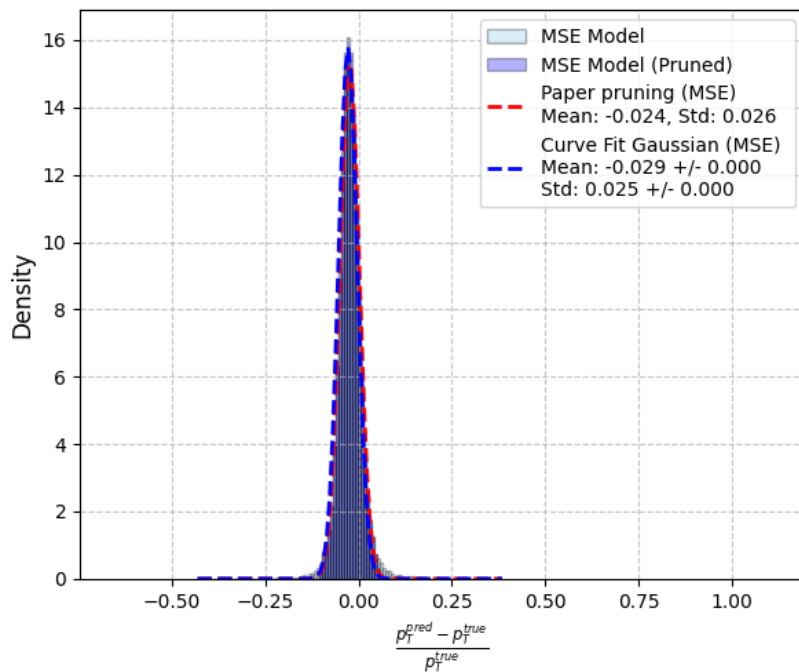


Resolution

r dphi z

TrackML Zenodo

Relative Error Distributions for p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tr, d\phi, tz) \rightarrow (q/p_T, p_z)$)

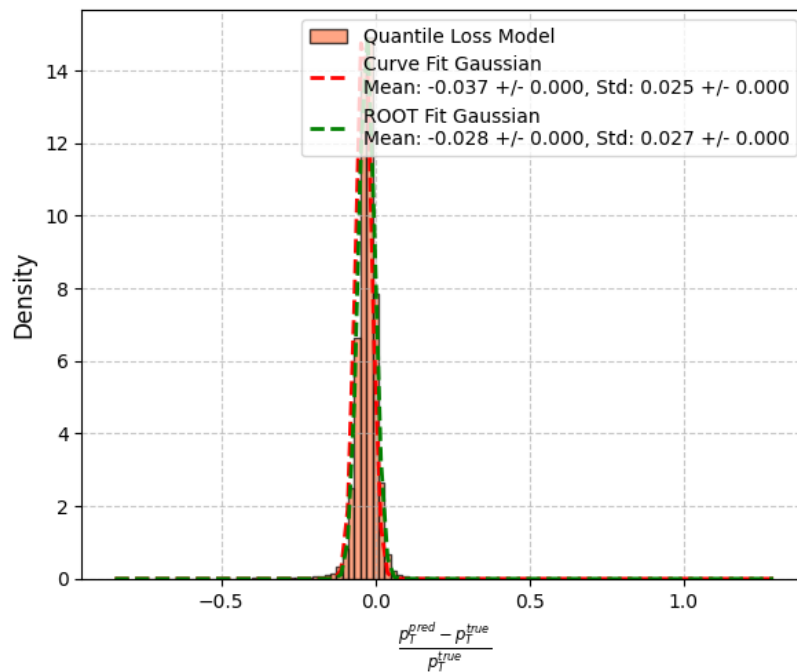
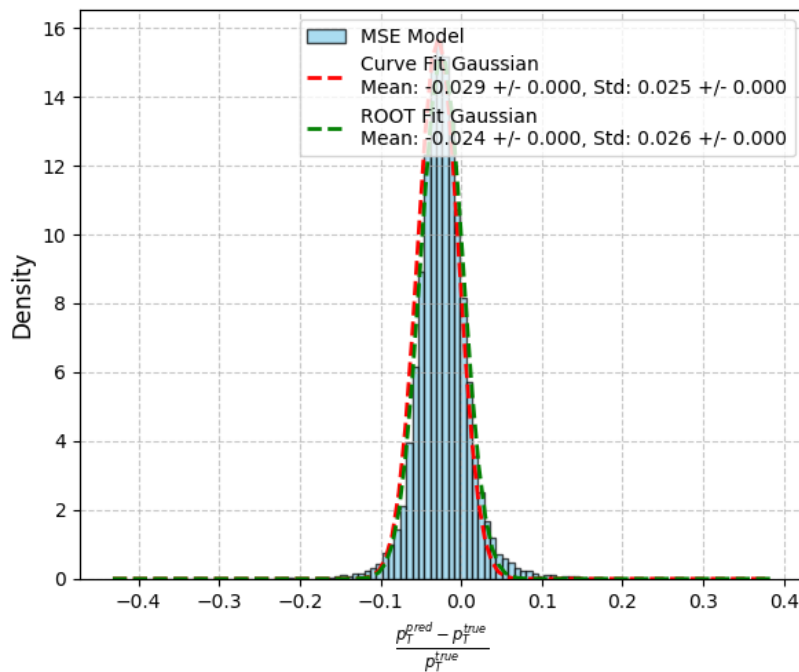


Resolution

r dphi z

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Relative Error Distributions for p_T ($1 \text{ GeV} < p_T < 2 \text{ GeV}$) ($(tr, d\phi, tz) \rightarrow (q/p_T, p_z)$)

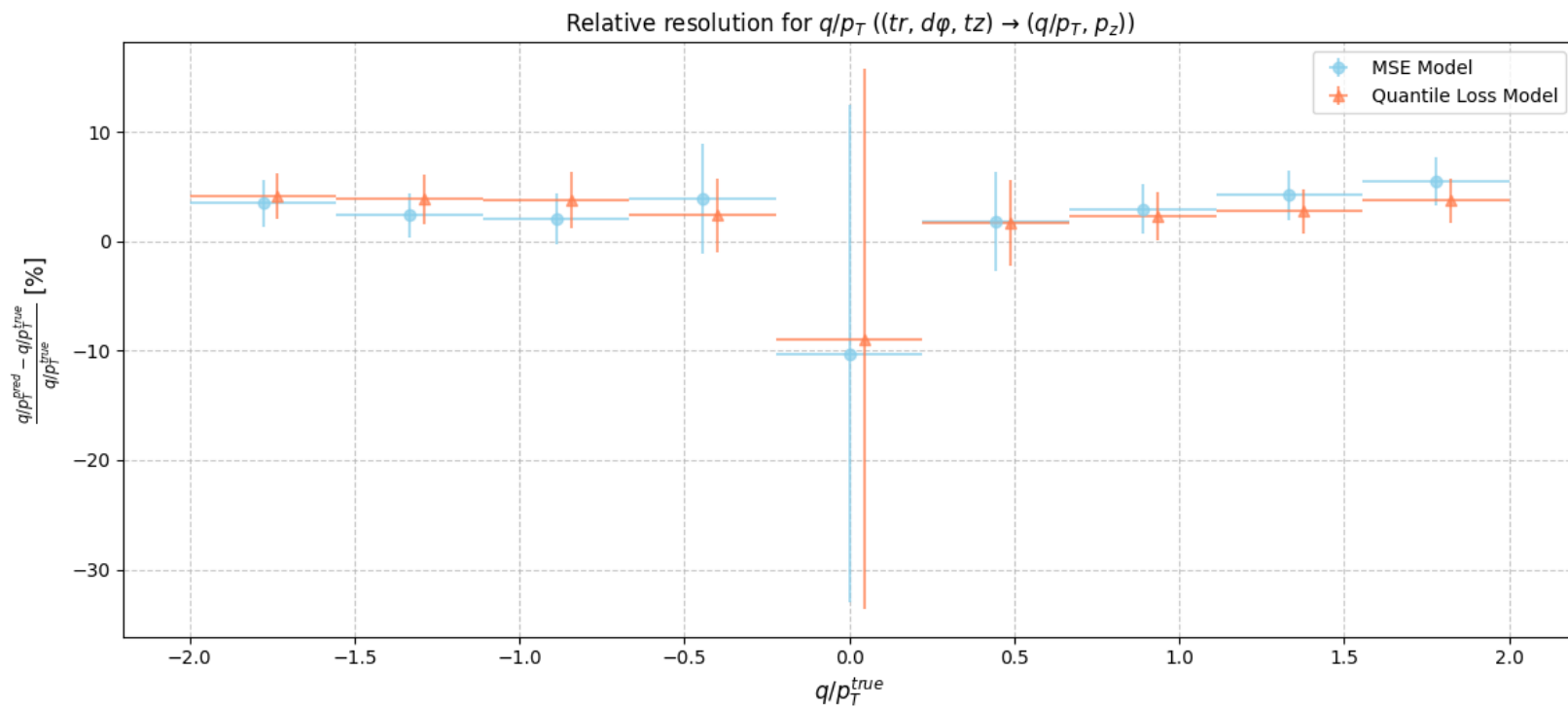


Resolution

r dphi z

TrackML Zenodo

Pruning

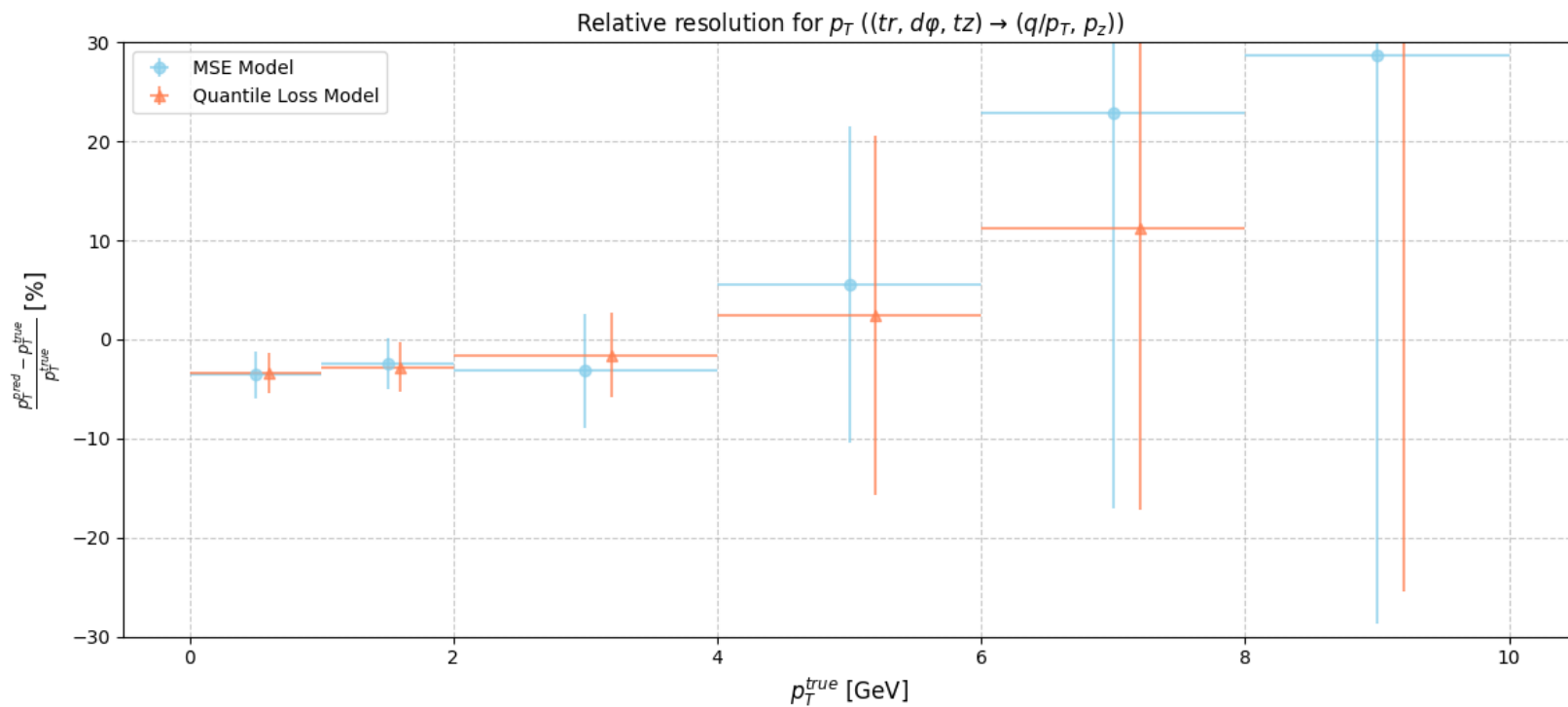


Resolution

r dphi z

TrackML Zenodo

Pruning



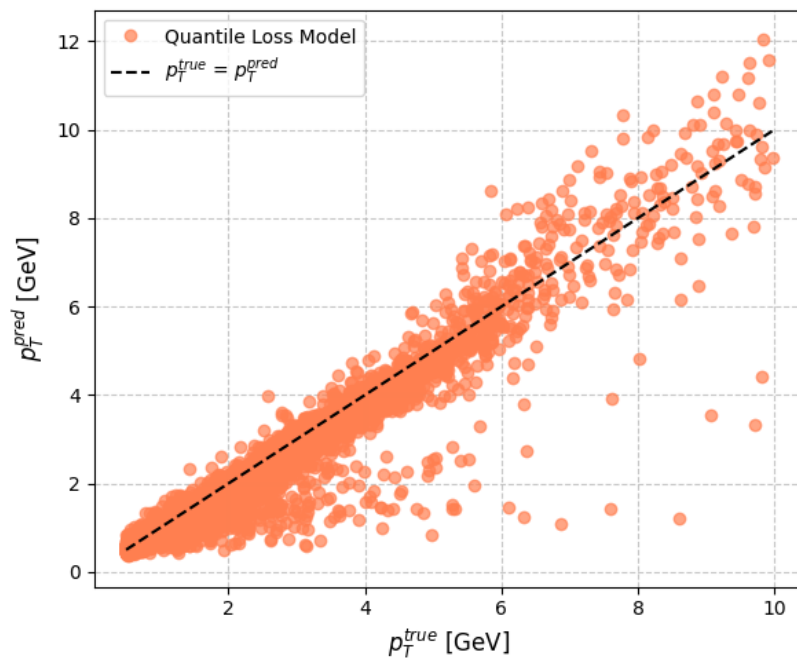
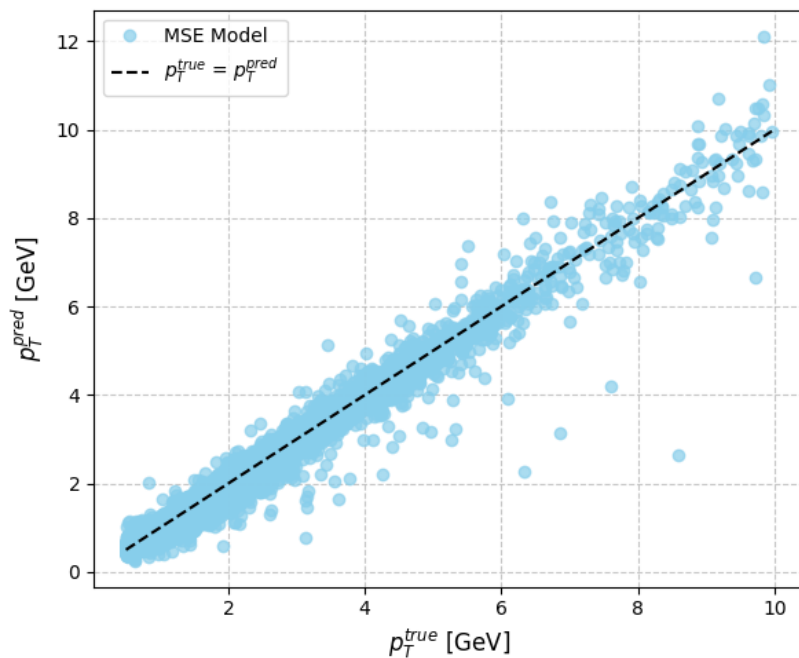
BACKUP

More results

x y z

p_T^{true} vs p_T^{pred} ((tx, ty, tz) \rightarrow (p_T , p_z))

TrackML Zenodo

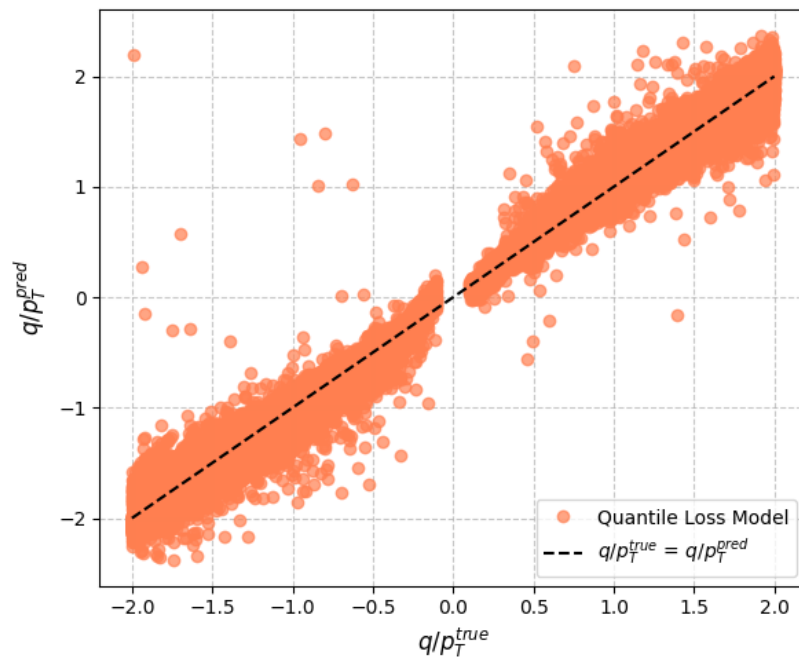
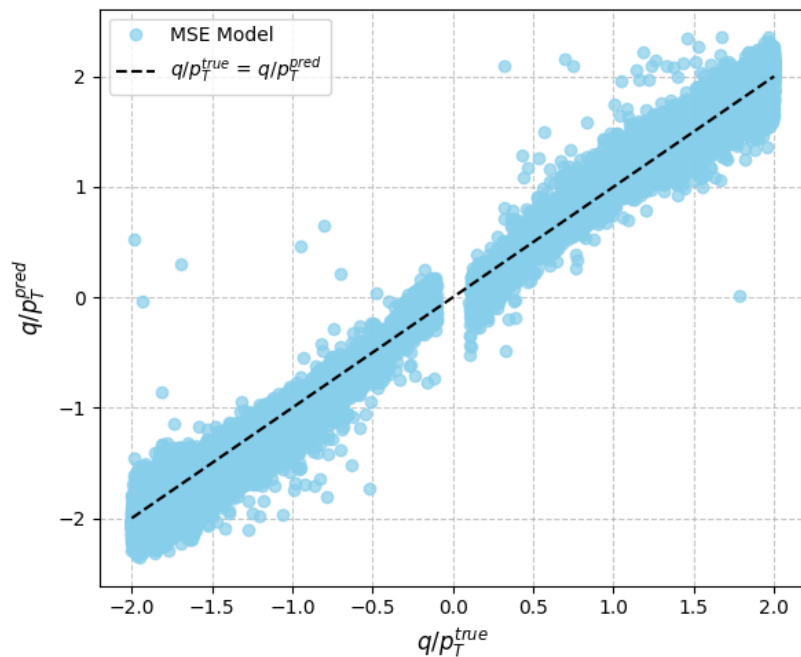


More results

x y z

q/p_T^{true} vs q/p_T^{pred} ((tx, ty, tz) \rightarrow ($q/p_T, p_z$))

TrackML Zenodo

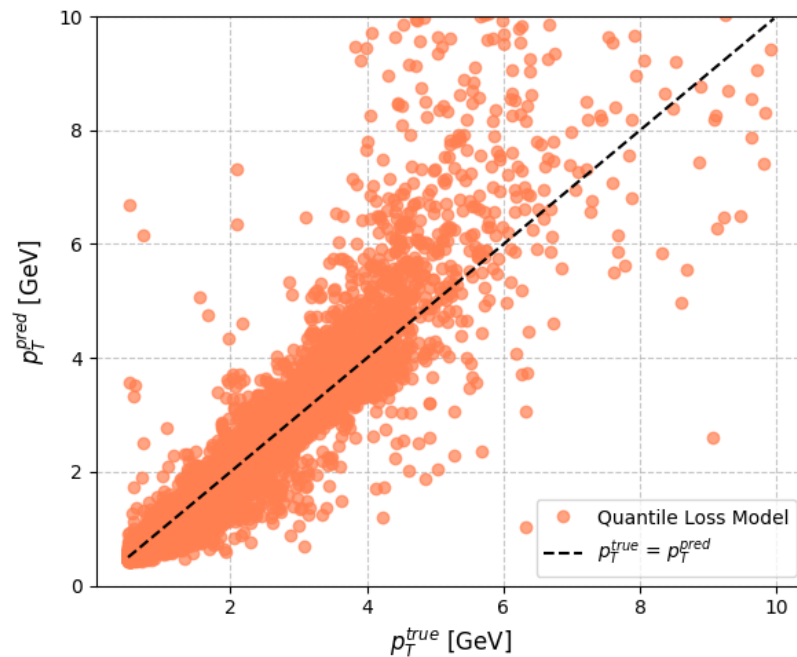
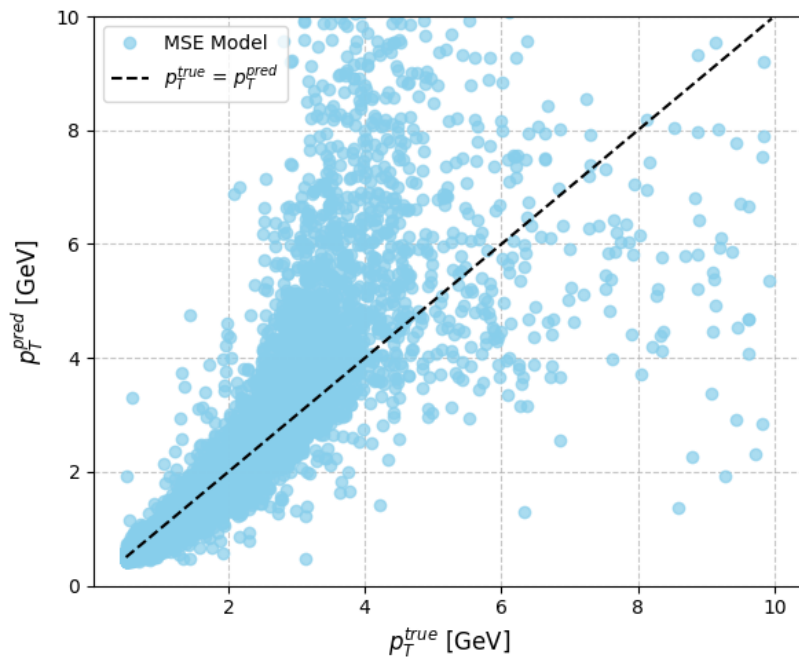


More results

x y z

p_T^{true} vs p_T^{pred} ((tx, ty, tz) \rightarrow (q/p_T, p_z))

TrackML Zenodo

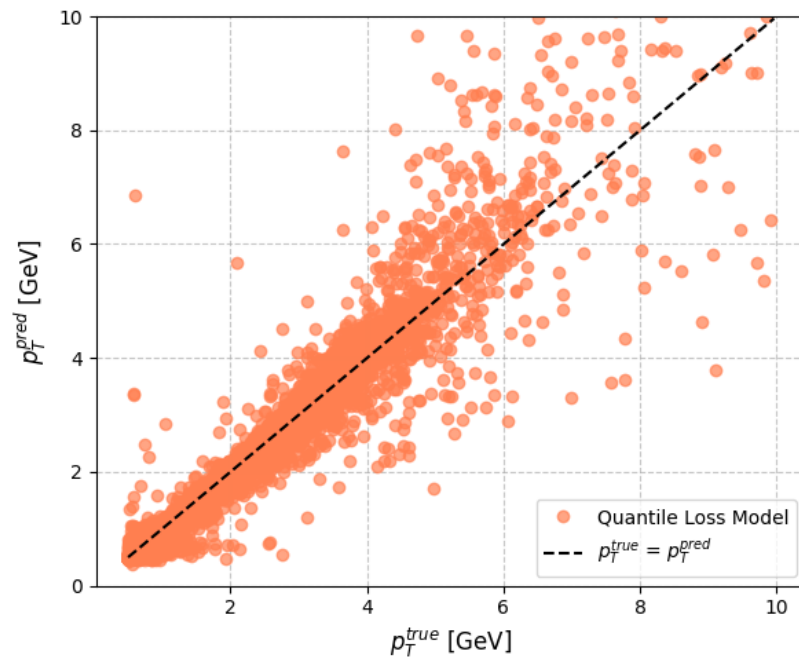
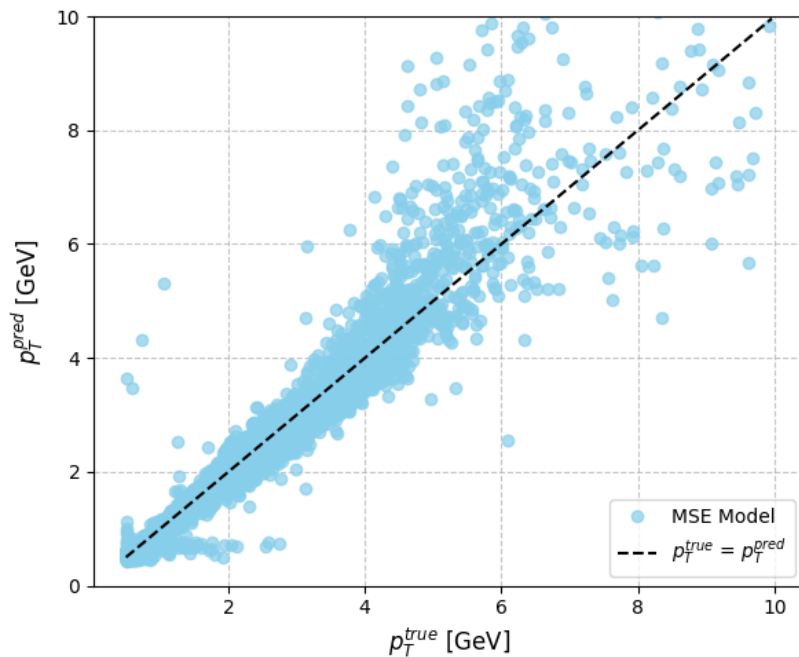


More results

r dphi z

p_T^{true} vs p_T^{pred} ($p_T < 10$ GeV) ($(tr, d\phi, tz) \rightarrow (q/p_T, p_z)$)

TrackML Zenodo

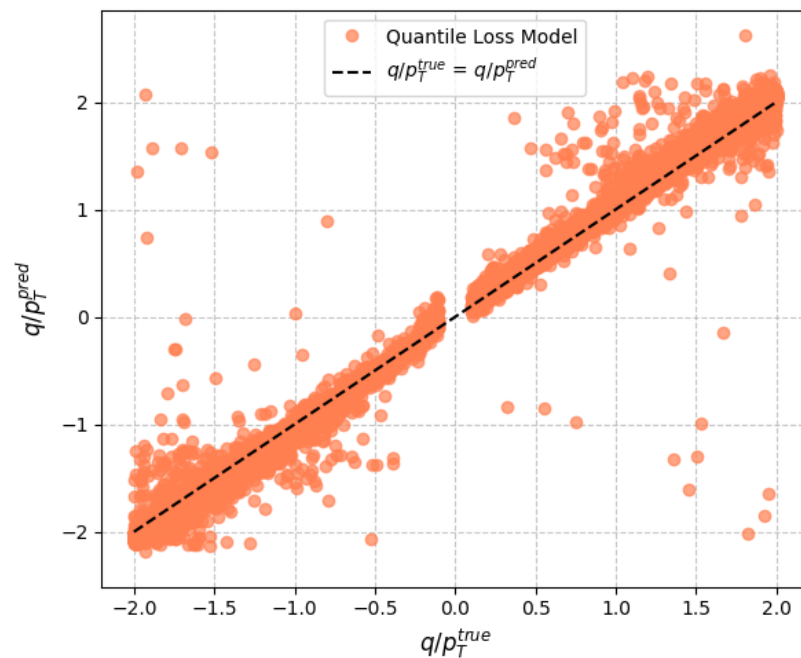
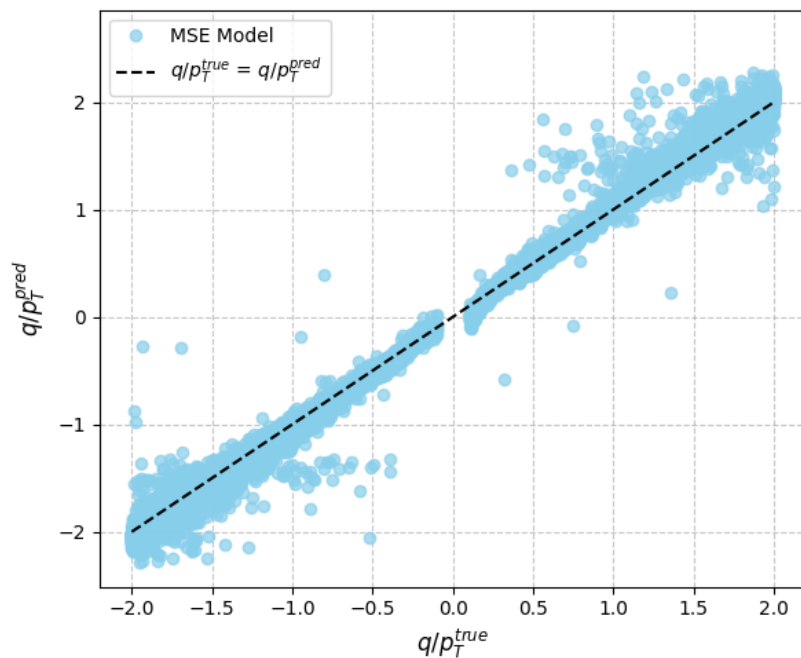


More results

r dphi z

q/p_T^{true} vs q/p_T^{pred} ($(tr, d\phi, tz) \rightarrow (q/p_T, p_z)$)

TrackML Zenodo



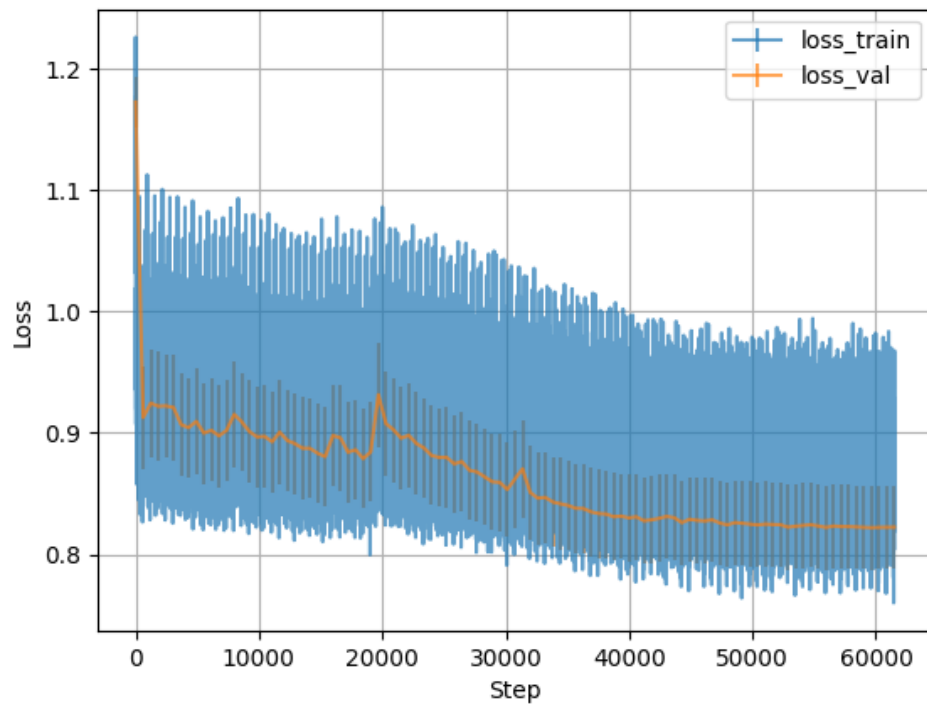
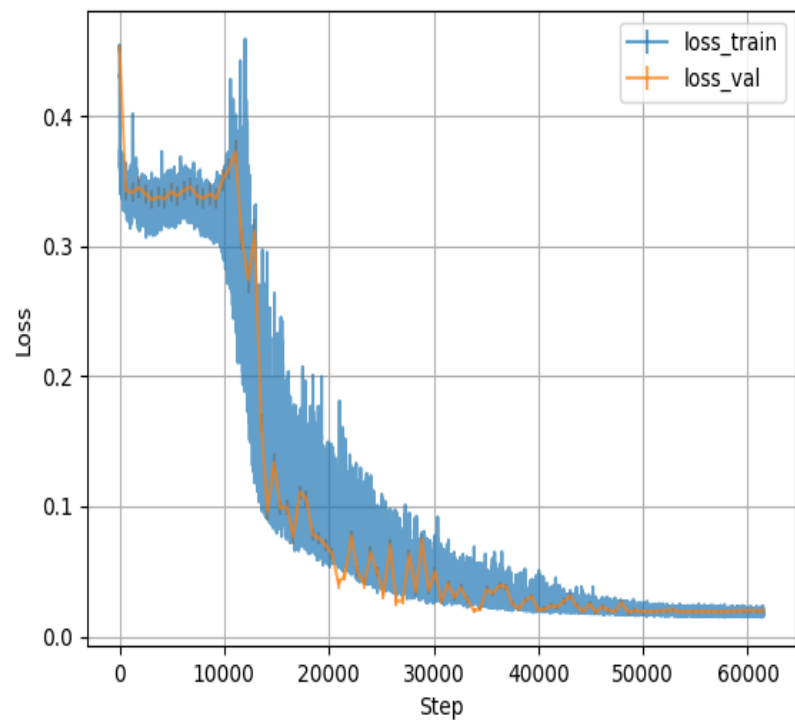
Loss

r dphi z

Target: q/pT

r phi z

TrackML Zenodo



Dataset update

Selections:

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

TrackML Kaggle:

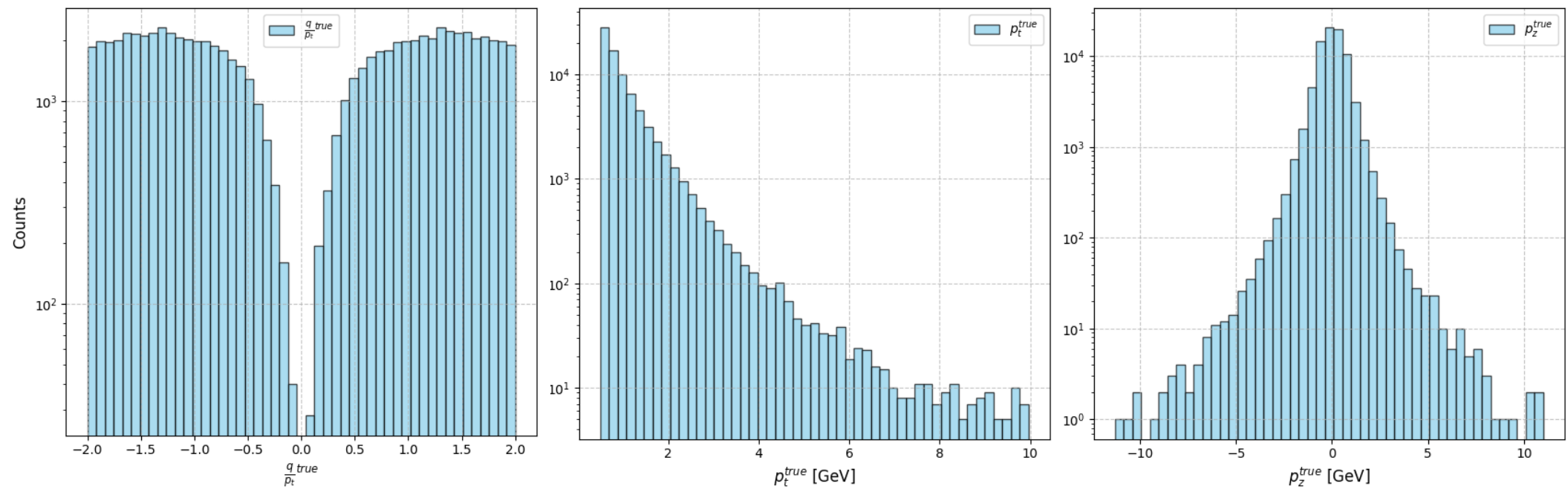
Training: 1 232 896 particles
Validation: 154 082 particles
Testing: 153 788 particles



TrackML Zenodo: (first file)

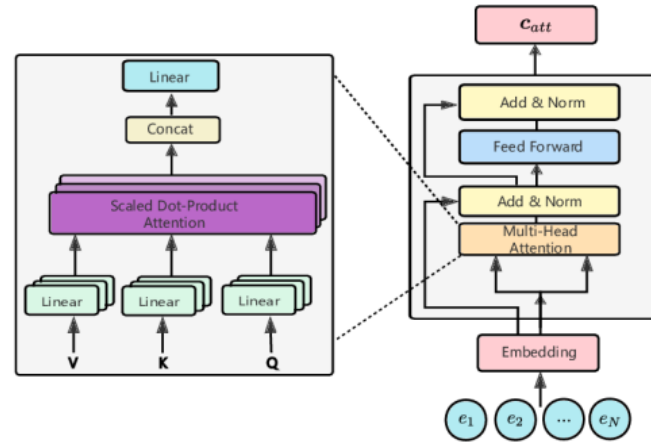
Training: 629 265 particles
Validation: 78 107 particles
Testing: ~78 656 particles

Target variables



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

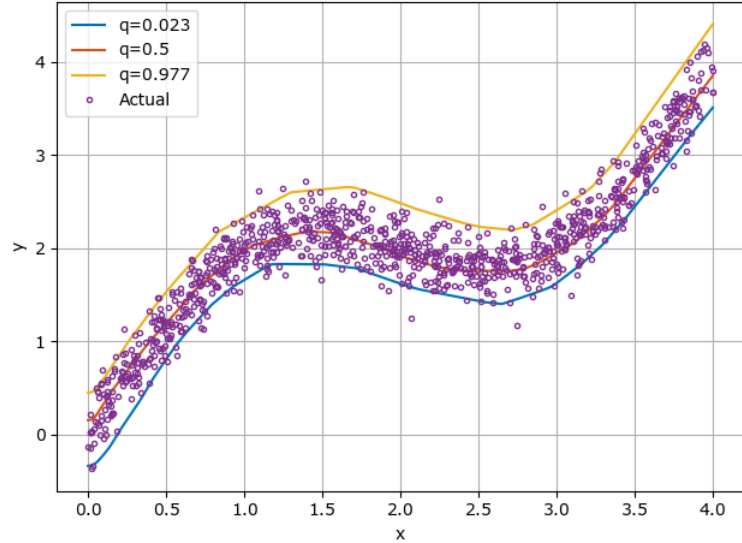
TrackFormer loss functions

Mean squared error:

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

Quantile loss:

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



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

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
input:
tr, dphi, tz
target:
pt, pz
target:
qopt, pz