基于机器学习的 **AHCAL**能量重建研究

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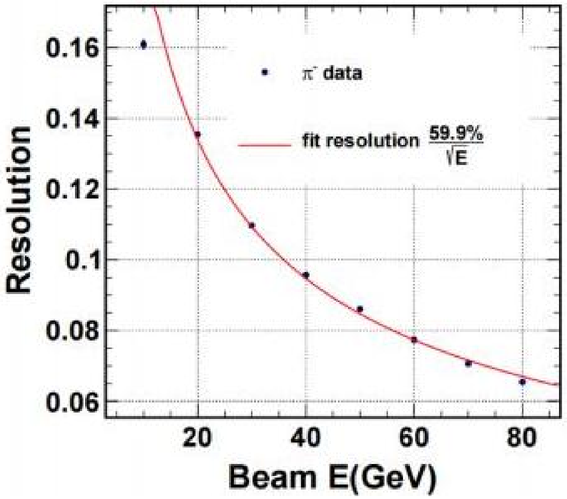
研究背景

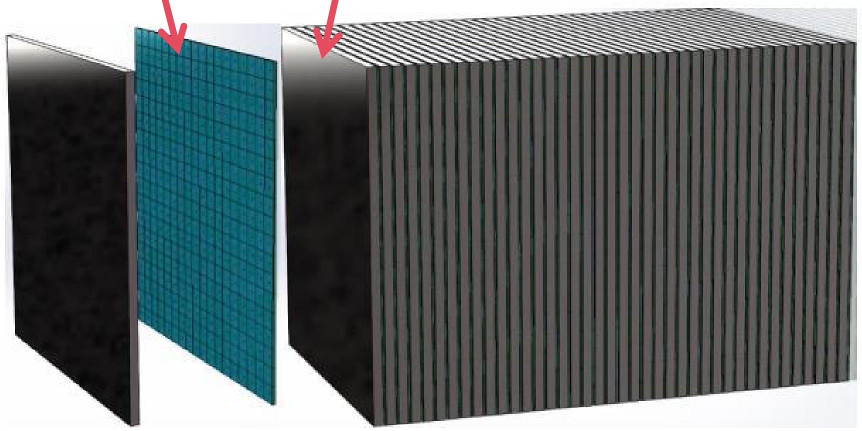
- **CEPC A**(nalog) **H**(adronic) **CAL**(orimeter)
- 40个灵敏层 （吸收体铁板+闪烁体层 + PCB电子学板+吸收体铁板）
- 能量分辨率达到目标值（$\frac{60\%}{\sqrt{E\ (GeV)}}$）
- 机器学习——>能量重建精度提升



闪烁体+电子学板

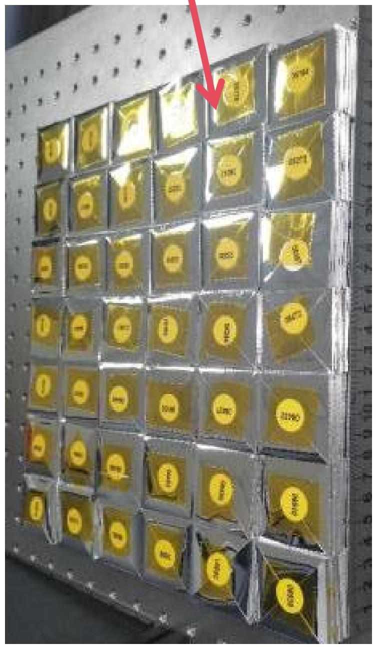
Fe

AHCAL



40 [layers] x 18 x 18 [cells/layer]

塑料闪烁体



束流测试

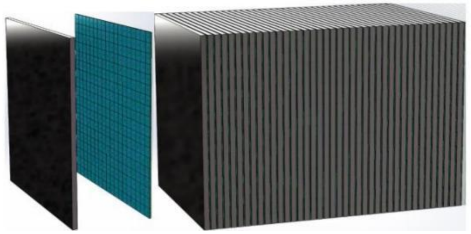
中国科学技术大学 University of Science and Technology of China

三项束流测试,CERN

- μ子位置扫描(100GeV/c)
- pion（1-120GeV/c)
- 电子（1-120GeV/c)

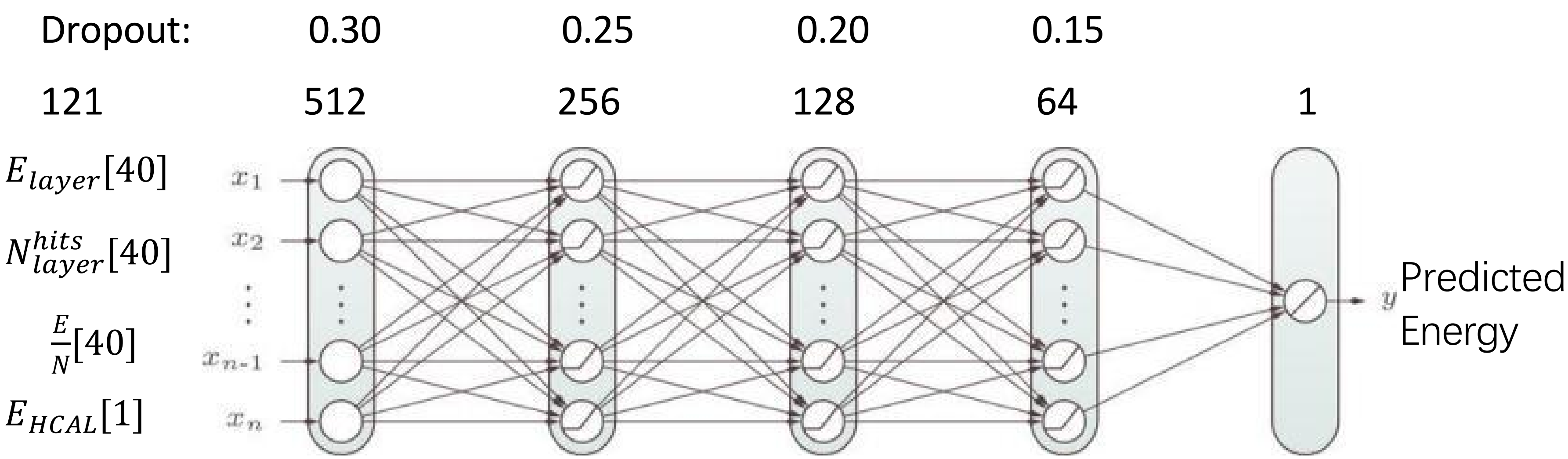
MLP模型

- 输入：探测器每层的能量(E)、击中数(N)、能量密度(E/N)和HCAL总沉积能量E_{HCAL}（40*3+1=121）
- 输出：预测的入射能量（1）



40 [layers] x 18 x 18 [cells/layer]

batch	64
学习率	1e-4
学习率调度	CosineAnnealing, T_max=200, eta_min=1e-7
最大epoch	200

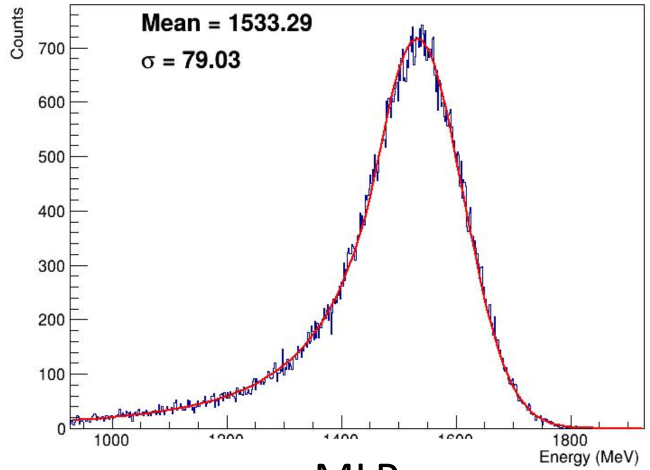


Loss: $L = \frac{1}{N}\sum_n e_n$ $\quad$ $e = \frac{(y_{true} - y_{pred})^2}{{y_{true}}^2}$ 均方相对误差(MSRE)

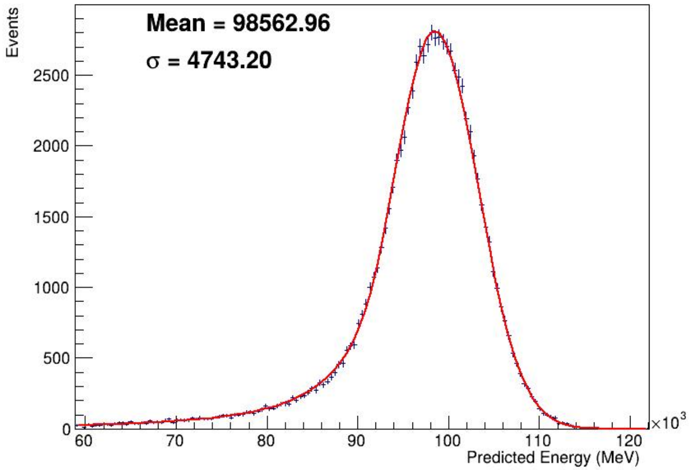
能量谱图@100GeV

MC

Raw

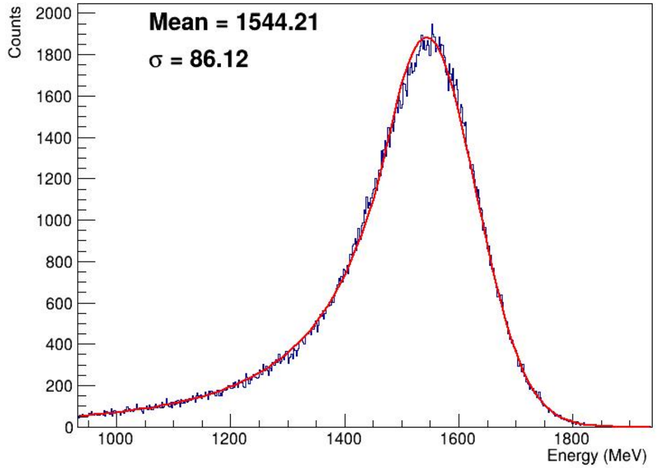


MLP

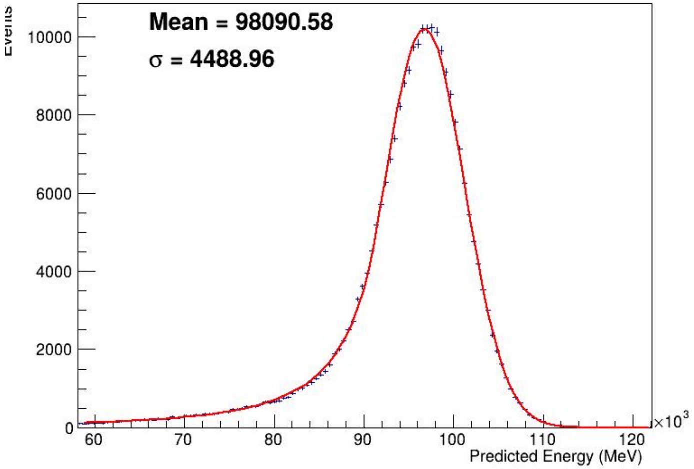


Data

Raw

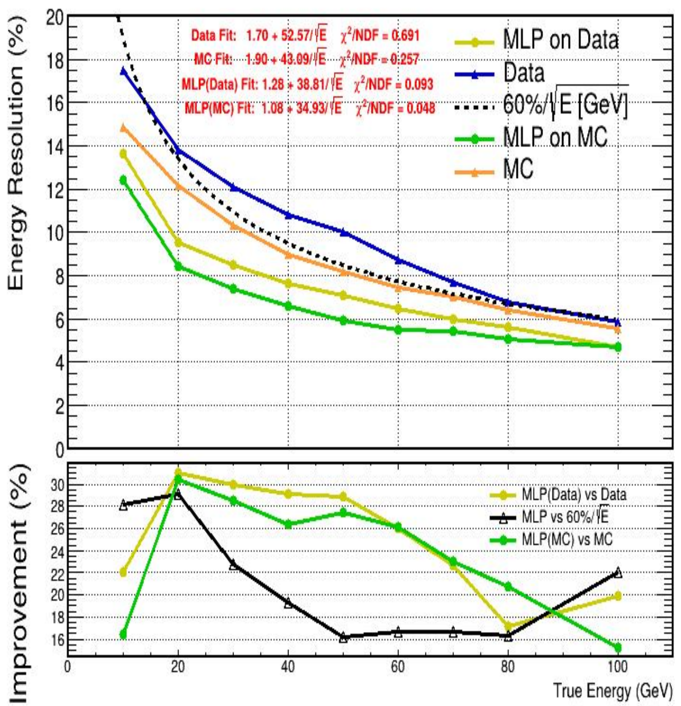


MLP

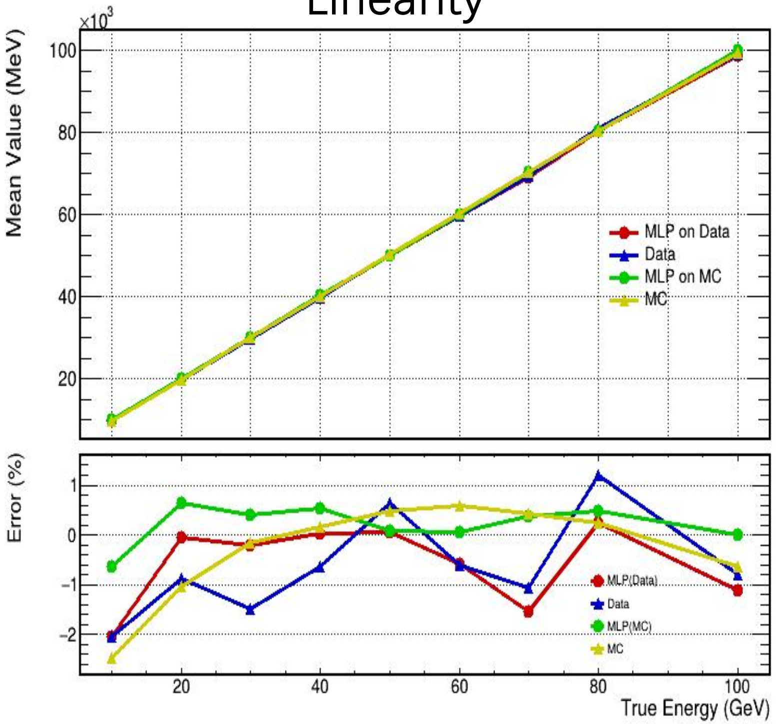


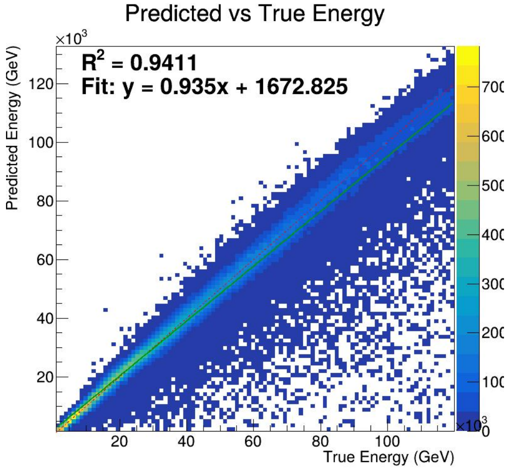
测试结果

Resolution



Linearity





- **训练样本**

源：pion

范围：1-120GeV

数量：train = 70.3e4

test = 12.4e4

- Data 整体上略劣于MC（平均0.83%）
- 泄露事例减少
- 分辨率：MC 和 Data 都能实现约 25%的提升
- 能量线性：Data颇有改善，平均 -0.58%

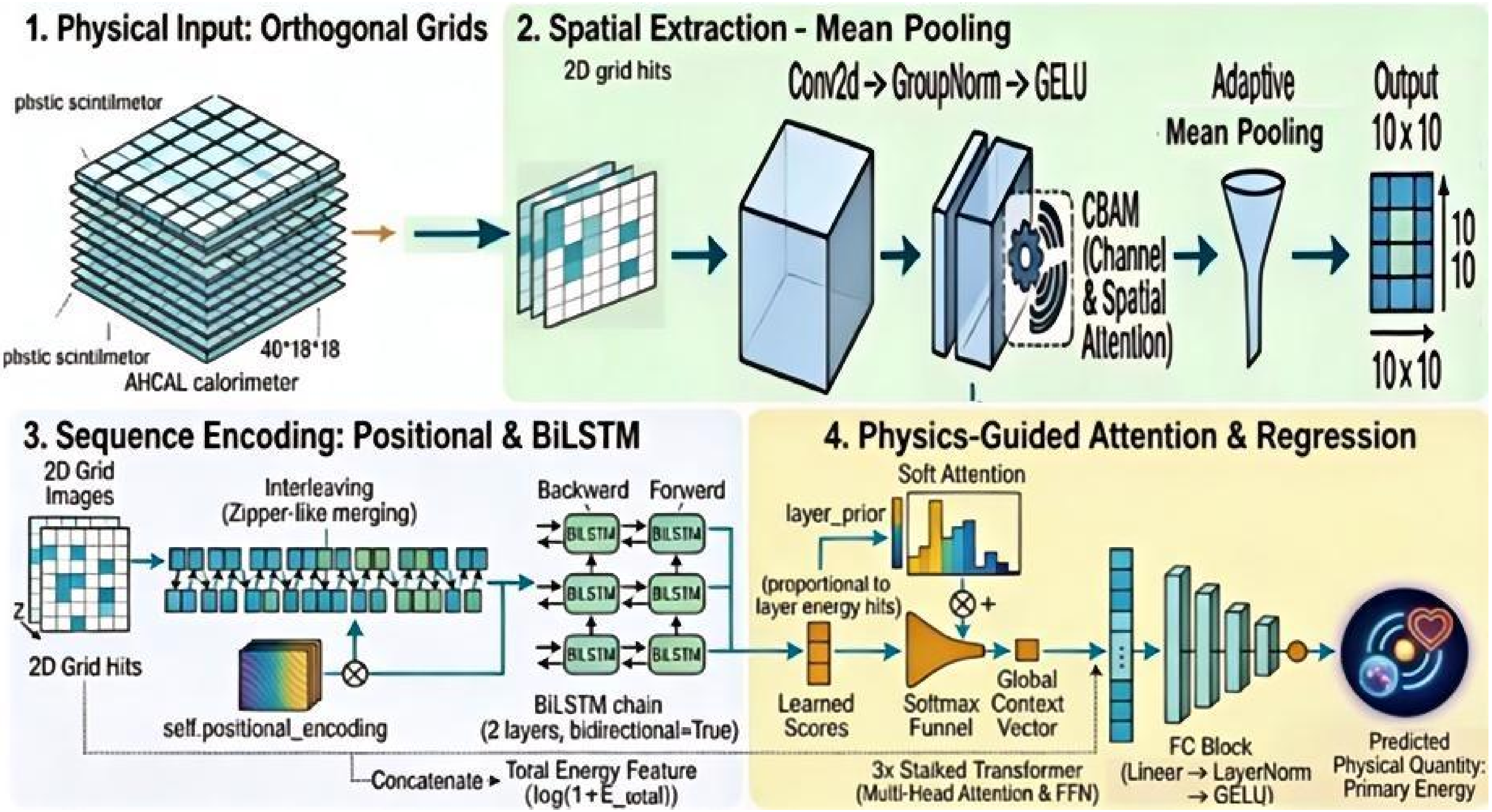
  MC 保持良好，平均 0.21%

Energy(GeV)		10	20	30	40	50	60	70	80	100
Data	Event（left） $(\times 10^4)$	8.3	30.2	48.6	45.8	49.8	36.9	32.7	28.3	25.3
	Percentage（%）	8.1	40.3	44.9	44.1	39.5	35.6	30.9	26.3	19.7
MC	Event（left） $(\times 10^4)$	20.1	21.1	19.9	18.6	16.9	15.2	13.3	11.6	8.7
	Percentage（%）	50.4	52.7	49.8	46.5	42.3	38.0	33.4	29.2	22.1

$$Imp = \frac{|R_{MC} - R_{MLP}|}{R_{MC}}$$

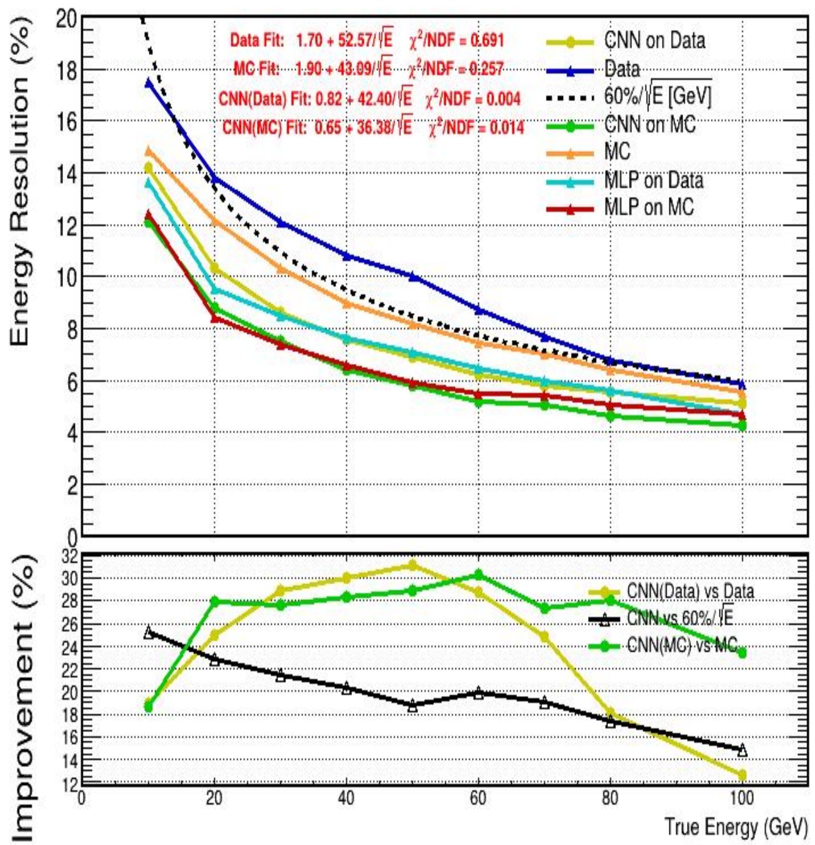
$$Error = \frac{|Mean - True|}{True}$$

CNN模型

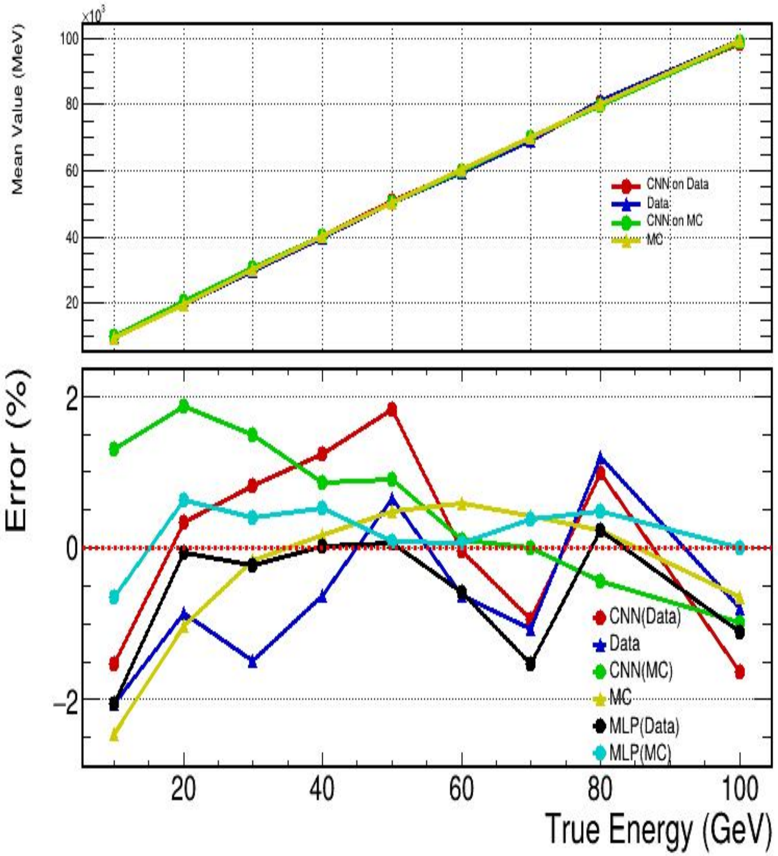

1. Physical Input: Orthogonal Grids
pbstic scintilmetor
pbstic scintilmetor
40*18*18
AHCAL calorimeter
2. Spatial Extraction - Mean Pooling
2D grid hits
Conv2d -> GroupNorm -> GELU
CBAM (Channel & Spatial Attention)
Adaptive Mean Pooling
Output 10x10
10
10
10x10
3. Sequence Encoding: Positional & BiLSTM
2D Grid Images
Z
2D Grid Hits
Interleaving (Zipper-like merging)
self.positional_encoding
Backward
Forwerd
BiLSTM
BiLSTM chain (2 layers, bidirectional=True)
Concatenate
Total Energy Feature (log(1+E_total))
4. Physics-Guided Attention & Regression
Soft Attention
layer_prior
(proportional to layer energy hits)
Learned Scores
Softmax Funnel
Global Context Vector
3x Stalked Transformer (Multi-Head Attention & FFN)
FC Block (Lineer → LayerNorm → GELU)
Predicted Physical Quantity: Primary Energy

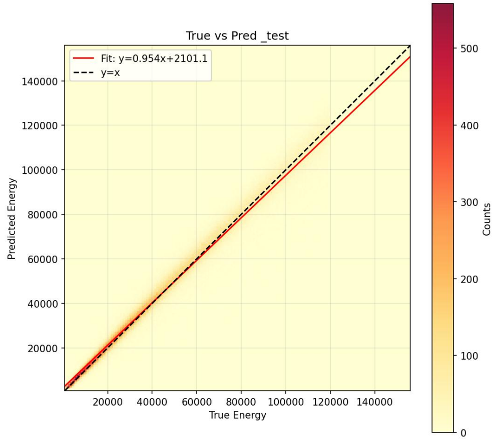
CNN测试结果

Resolution



Linearity





- 分辨率：

  MLP和 CNN 都实现约 25%的提升
- 能量线性：

  MLP颇有改善，平均 0.65%

  CNN改善有限，平均 1.04%
- 与MLP相比，

CNN在AHCAL上暂无明显优势

$$Imp = \frac{|R_{MC} - R_{MLP}|}{R_{MC}} \qquad Error = \frac{|Mean - True|}{True}$$

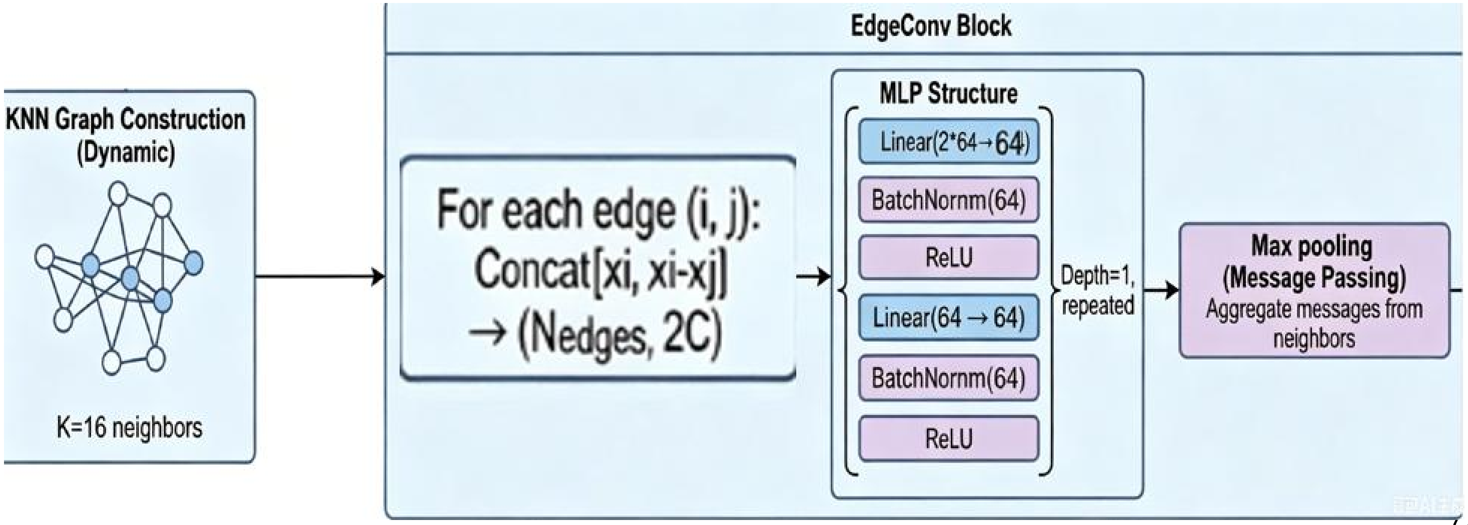
ParticleNet Model

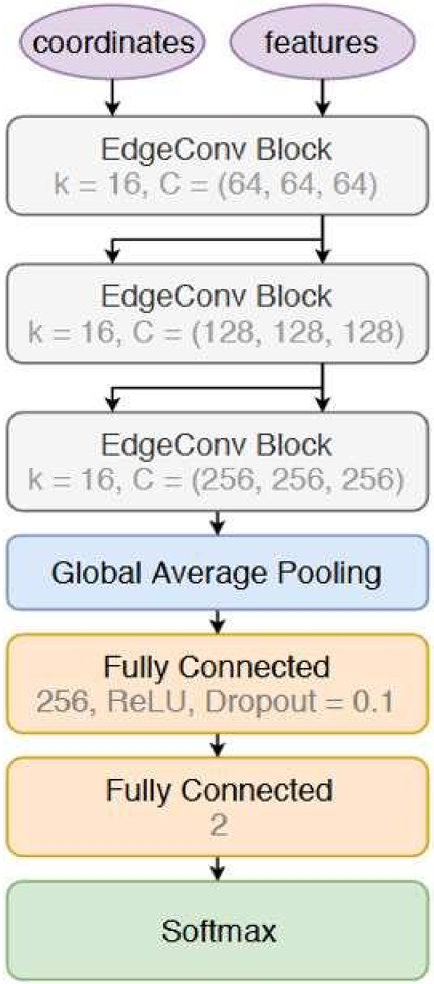
Feature:
1. Classification Head -> Regression Head
2. T-MLP: enhance timing info

- coordinates : (B,3,N_max) 的点张量P
- features : (B,C-3,N_max) 的特张量X
- mask : (B,1,N_max) 的掩码张量M

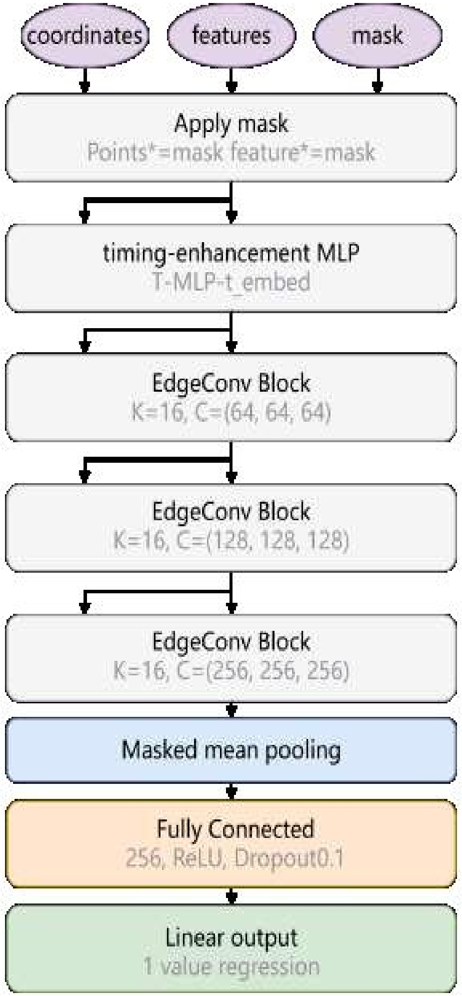
π+

$$\mathbf{f}_i = (x_i, y_i, z_i, E_i, t_i$$





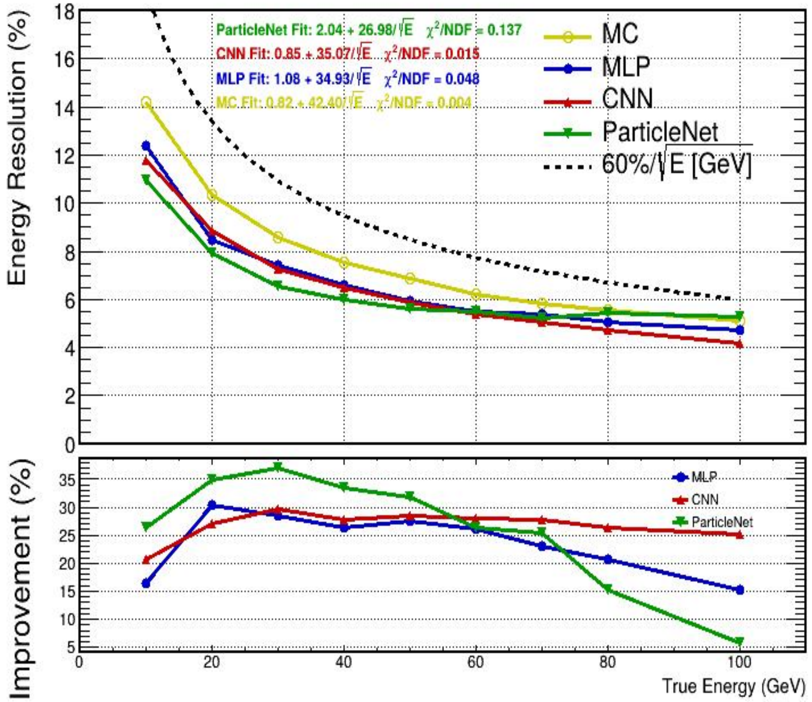
(a) Classification Head PN



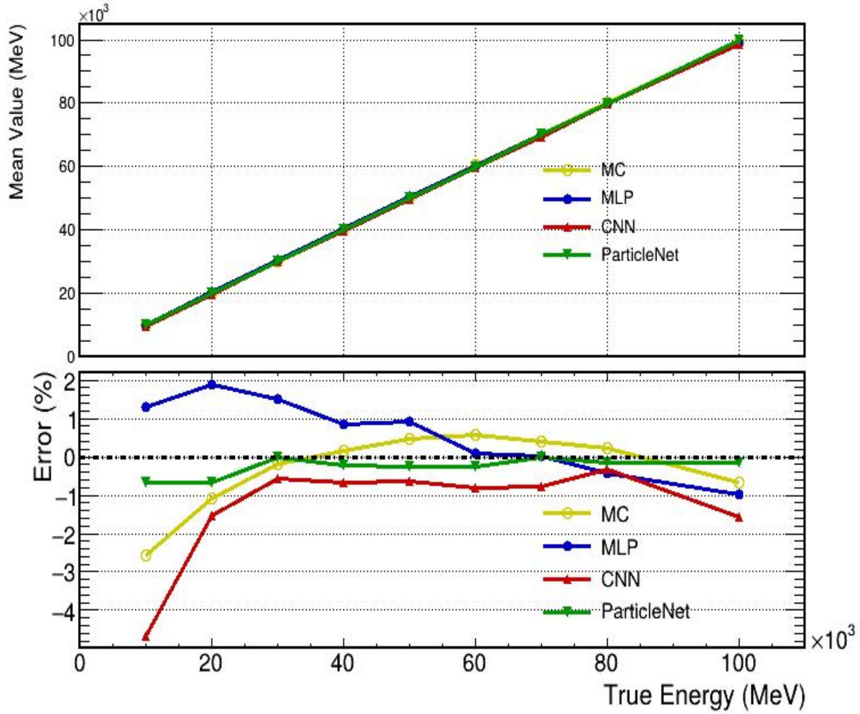
(b) Regression Head PN

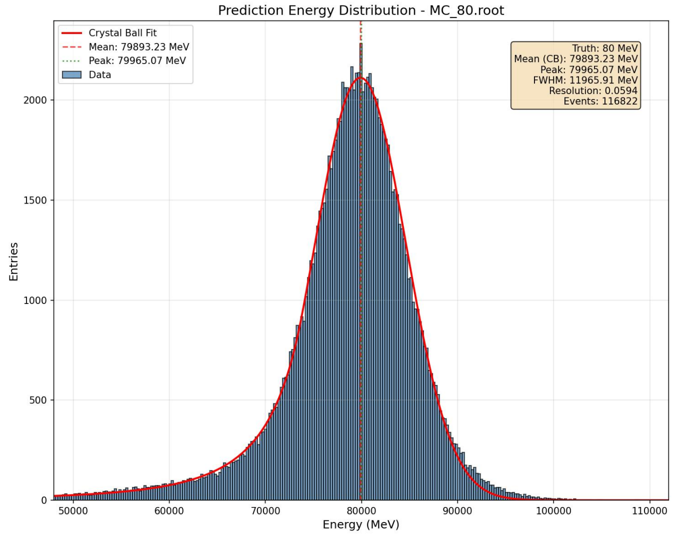
ParticleNet测试结果

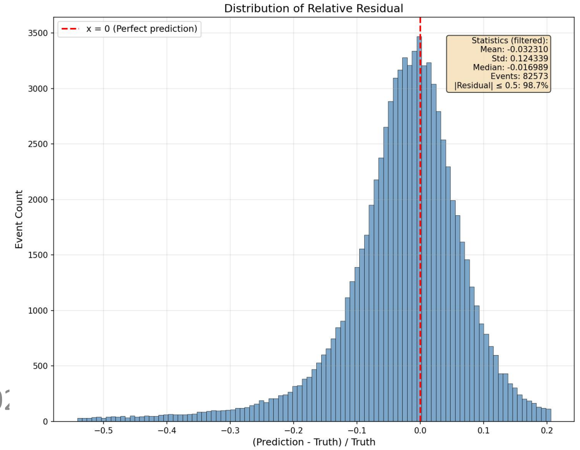
Resolution



Linearity







- 分辨率：“中间高两边低”
- 能量线性巨大改善

Contents

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2. CEPC, the AHCAL Prototype, and the Data Samples

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3.3 CNN-Based Energy Regression Model

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5. Summary and Outlook

TODO

- 继续优化CNN和ParticleNet模型，争取再有一点提升
- 继续完成论文的草稿

总结

- AHCAL : 40 layers × 18 × 18 cells/layer
- MLP Model : $E_{layer}[40] + N_{layer}^{hits}[40] + \frac{E}{N}[40] + E_{HCAL}[1](121)$——>Predicted Energy (1)
- CNN Model： 18*18*40 cells——>Predicted Energy (1)
- 测试情况：

Thanks for your attention!

MLP： MC 和 Data 都有 约25%的分辨率提升

MC能量线性巨大提升， Data相对MC略差， Error平均 -0.58 %

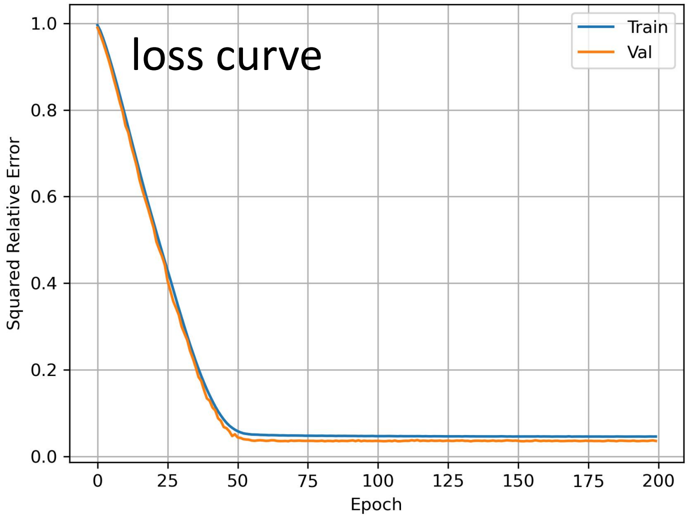
CNN： MC 和 Data 也都有 约25%的分辨率提升

MC和 Data 能量线性都提升有限， Error平均 1.04 %

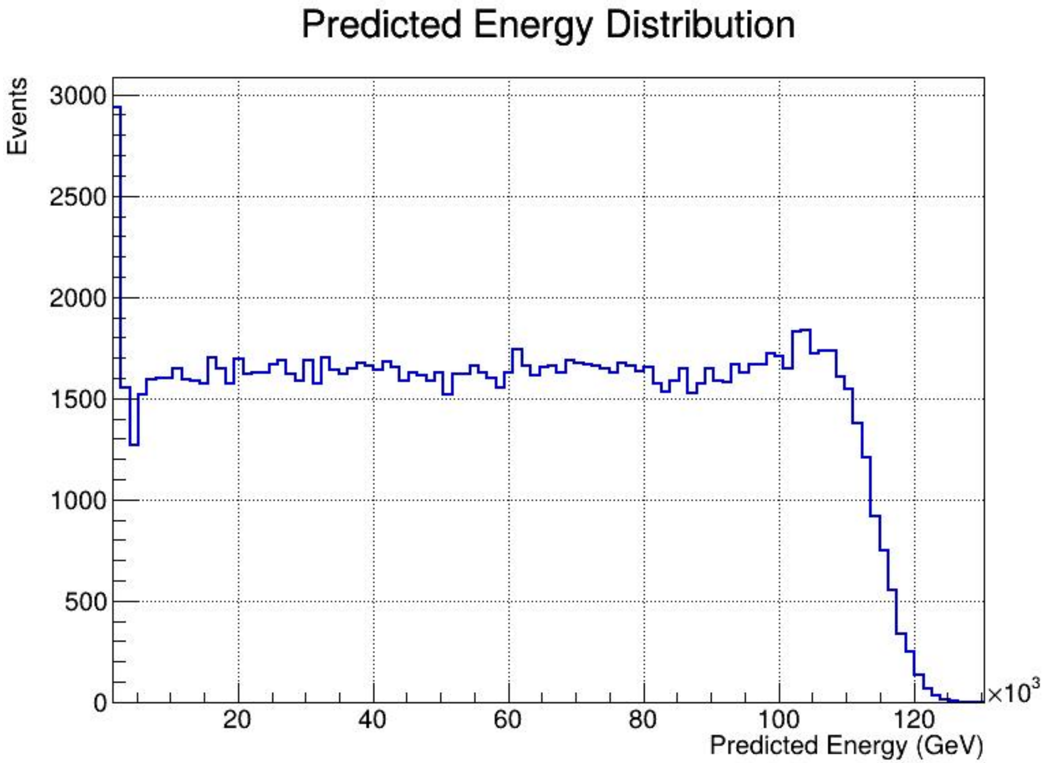
- CNN在AHCAL上相对于MLP暂无明显优势

back up

back up



loss curve
Train
Val
Squared Relative Error
Epoch

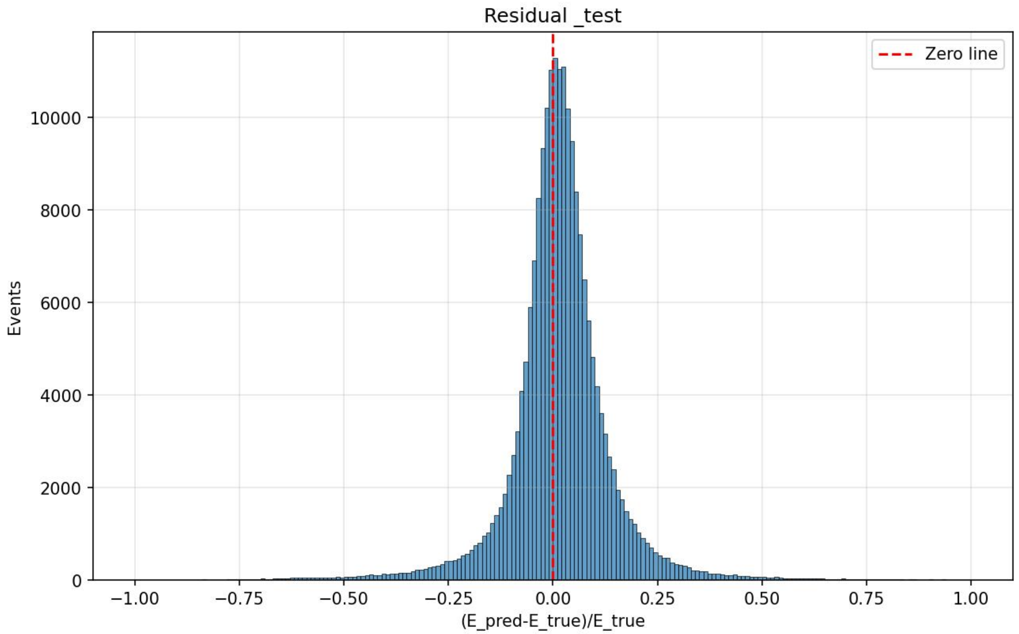


Predicted Energy Distribution
Events
Predicted Energy (GeV)
$\times 10^3$

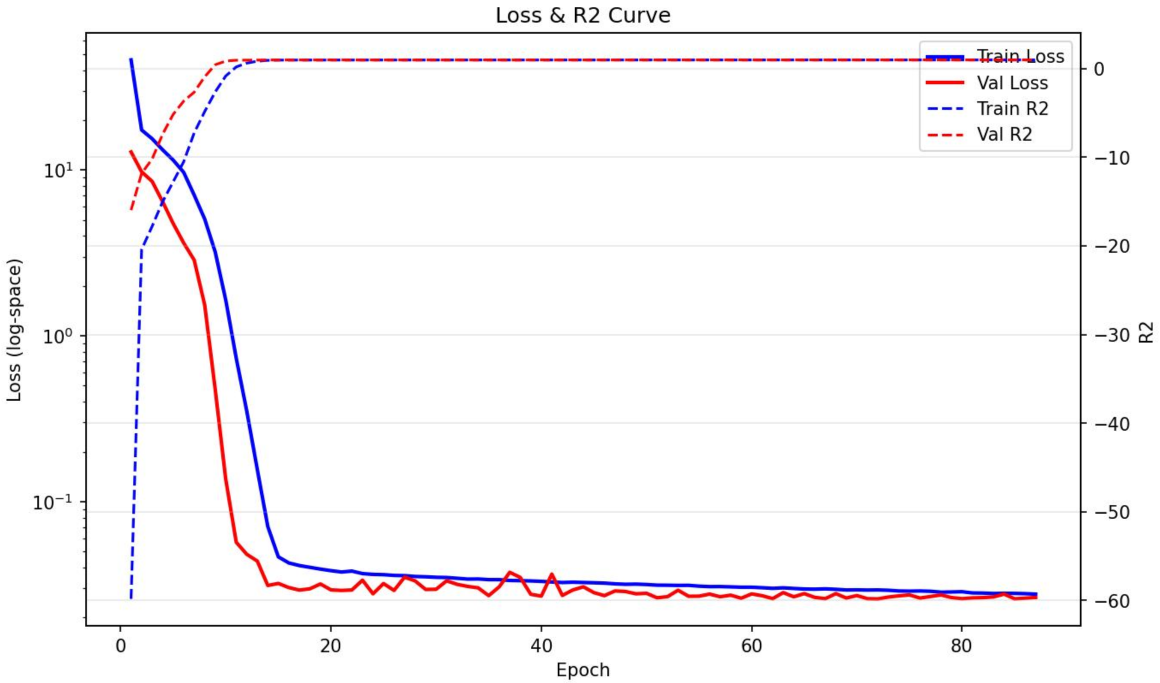
back up

event	energy(GeV)	10	20	30	40	50	60	70	80	100
Data	cut前	1,027,814	749,791	1,081,725	1,038,984	1,258,699	1,034,938	1,058,822	1,073,061	1,286,608
	cut后	83,860	302,303	486,653	458,874	498,094	369,281	327,979	283,120	253,900
	占比（%）	8.16	40.32	44.99	44.17	39.57	35.68	30.98	26.38	19.73
MC	cut前	400,000	400,000	400,000	400,000	400,000	400,000	400,000	400,000	394,000
	cut后	201,676	211,115	199,497	186,119	169,367	152,117	133,628	116,822	87,346
	占比（%）	50.42	52.78	49.87	46.53	42.34	38.03	33.41	29.21	22.17
Train : 703,747					Test : 124,035					

back up

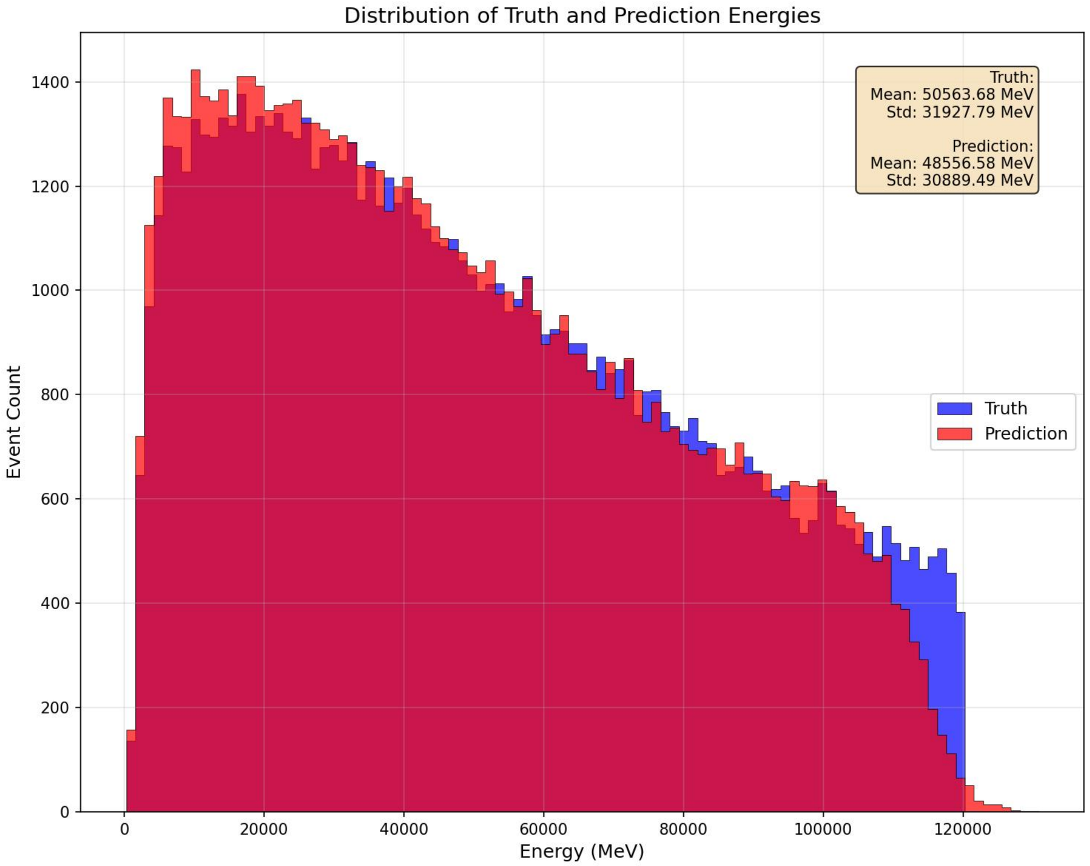


Residual _test
Zero line
10000
8000
6000
4000
2000
0
Events
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
(E_pred-E_true)/E_true



Loss & R2 Curve
Train Loss
Val Loss
Train R2
Val R2
Loss (log-space)
R2
Epoch
0
20
40
60
80
−10
−20
−30
−40
−50
−60

back up


Distribution of Truth and Prediction Energies
Truth:
Mean: 50563.68 MeV
Std: 31927.79 MeV
Prediction:
Mean: 48556.58 MeV
Std: 30889.49 MeV
Truth
Prediction
Event Count
Energy (MeV)
0
200
400
600
800
1000
1200
1400
0
20000
40000
60000
80000
100000
120000