The Niels Bohr Institute

Energy reconstruction of electrons and photons using convolutional neural networks

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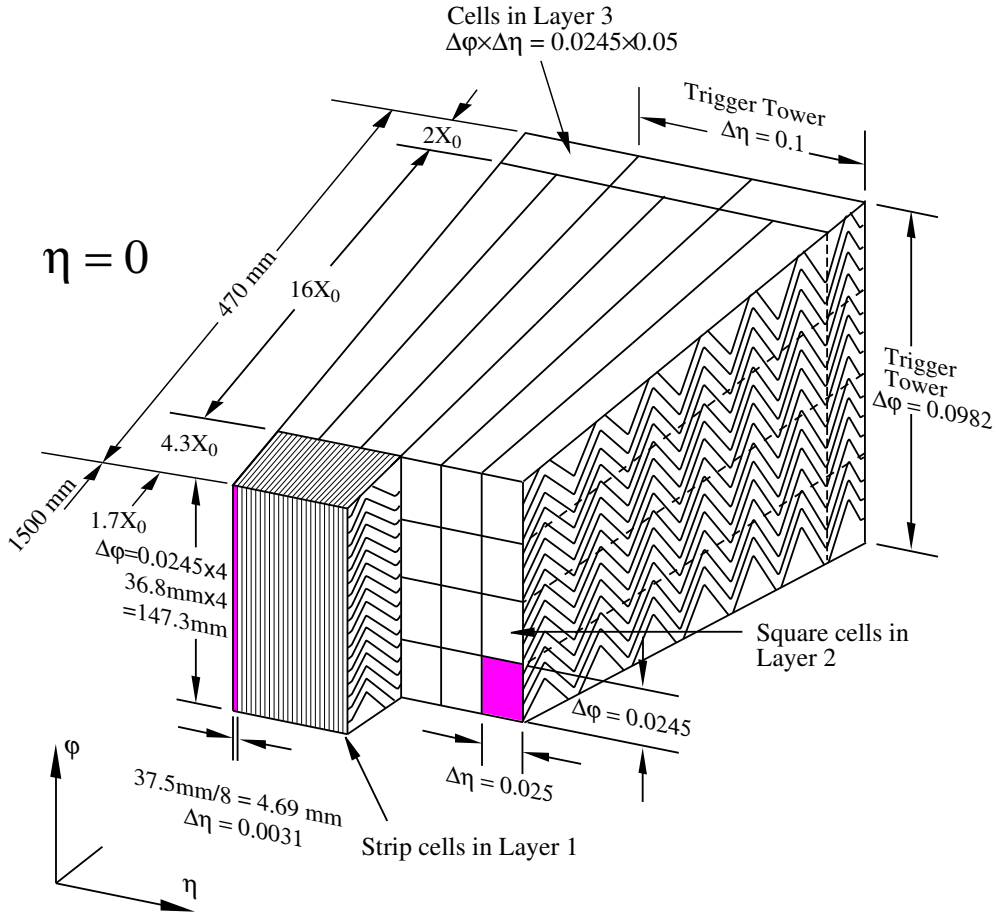
SUPERVISION: Troels C. Petersen

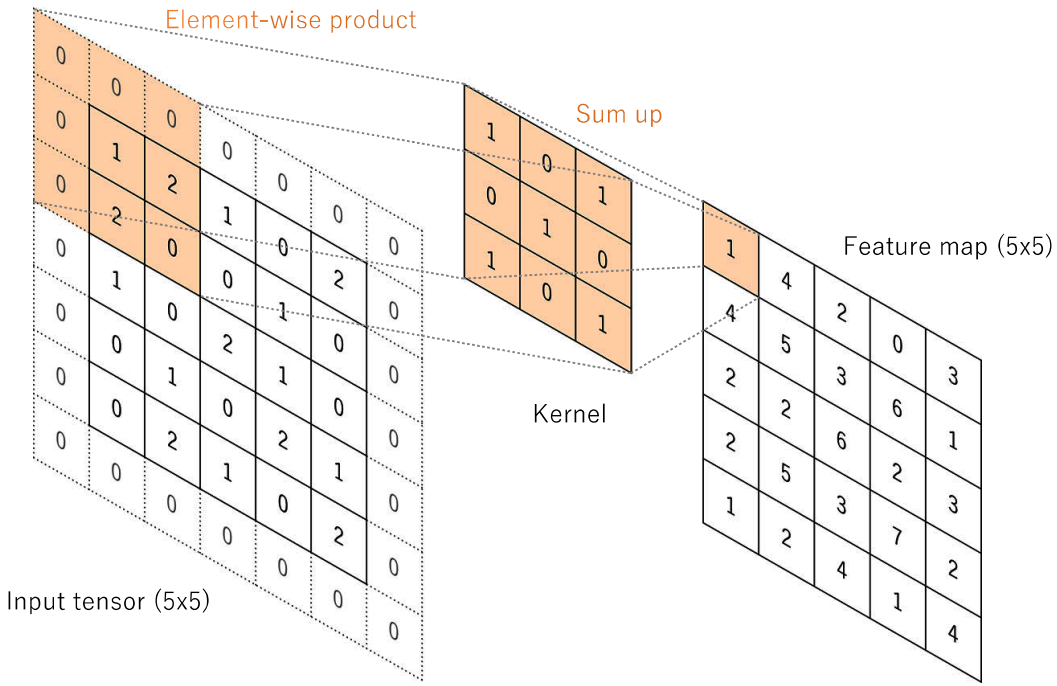
Spaatind, January 6, 2019

Basic idea



ECAL cells are like pixels in a multi-channel image,
so why not use CNNs?

Convolutional neural networks



Pipeline

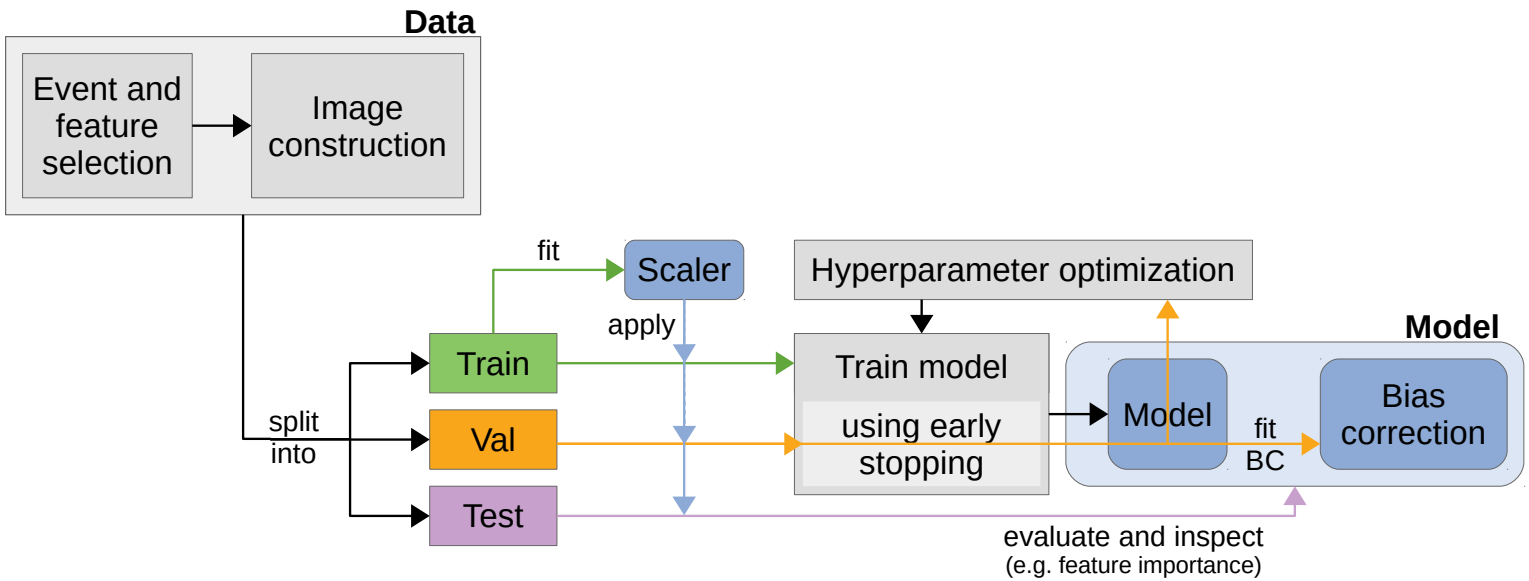

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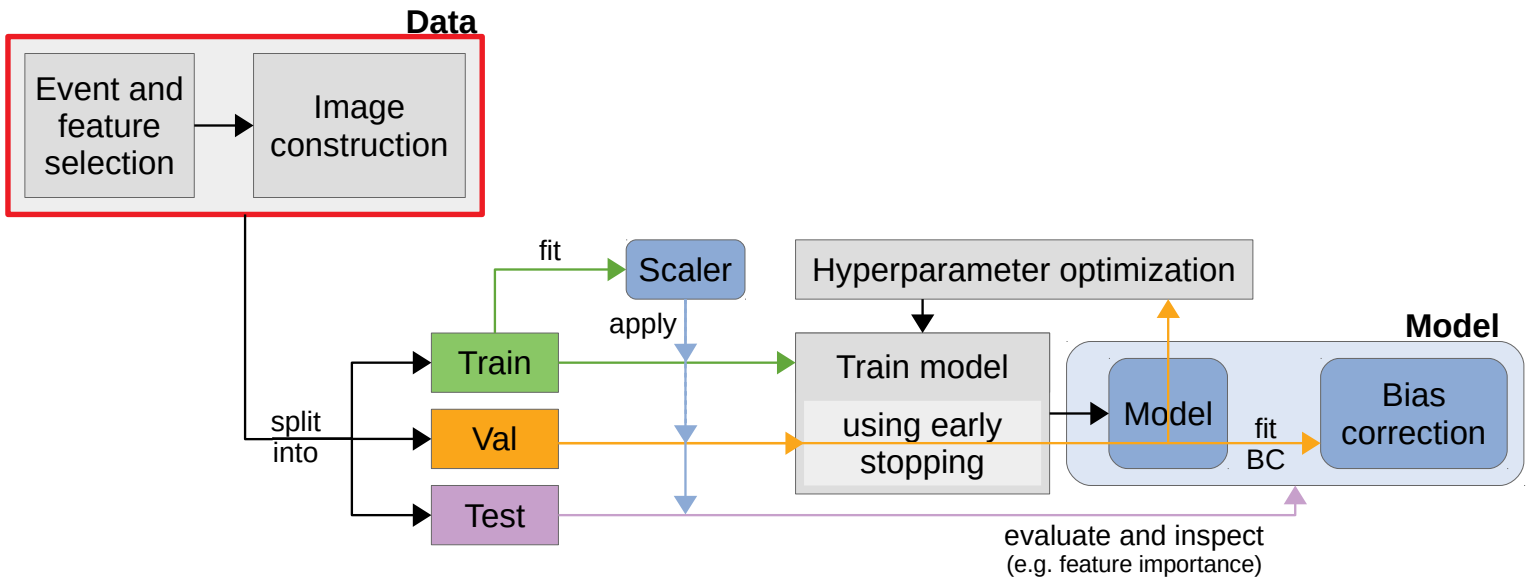
Image construction
fit
Scaler
Hyperparameter optimization
apply
Model
Train
Train model
using early stopping
Model
Bias correction
fit BC
split into
Val
Test
evaluate and inspect
(e.g. feature importance)

Pipeline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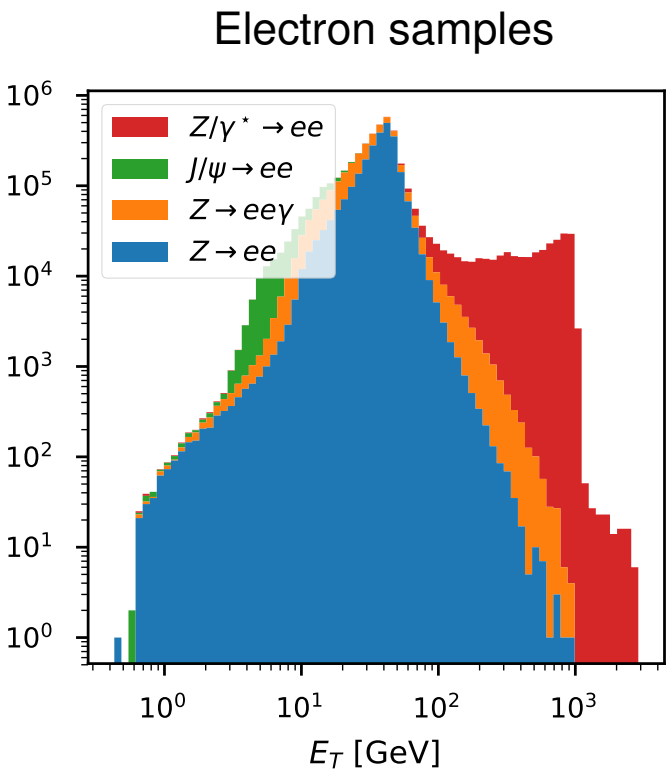
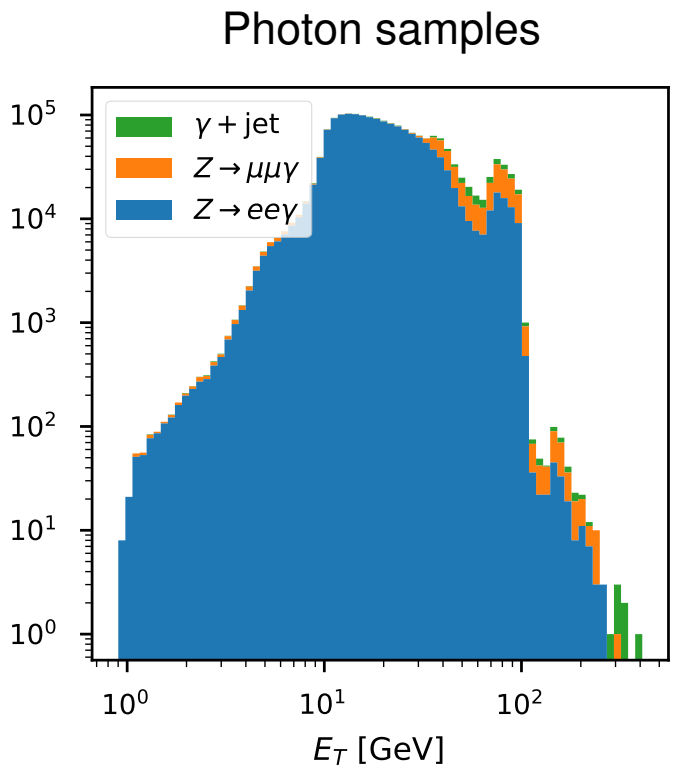
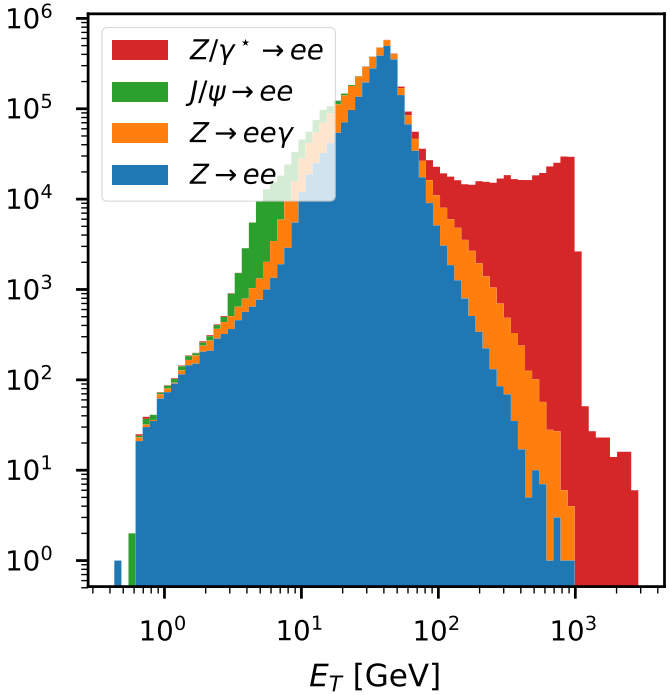
Simulation data



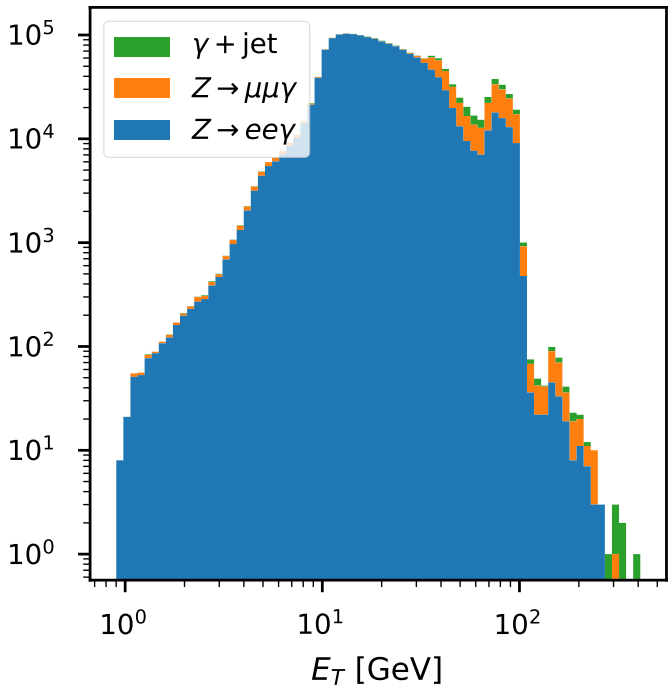


Simulation data

Electron samples



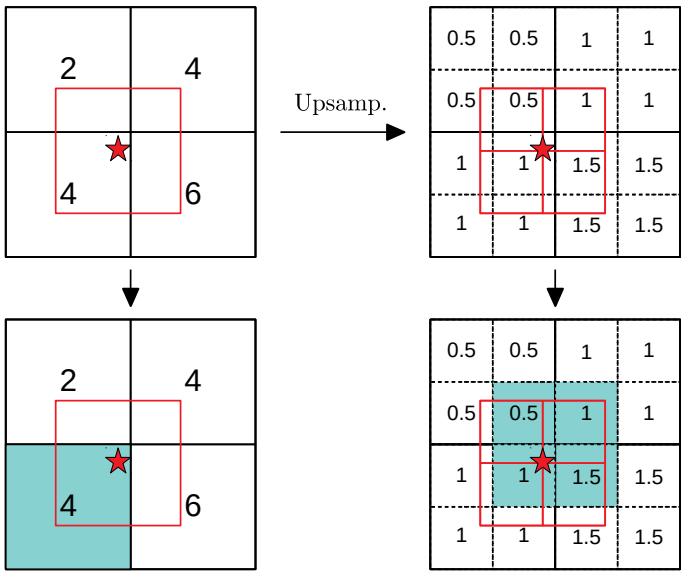
Photon samples



- Split into barrel, crack, endcap datasets
- $\sim 1 - 5$ M points in each dataset
- All truth-matched
- From 2016d with $\langle \mu \rangle \sim 37$

Simulation data

Images (code for producing here)



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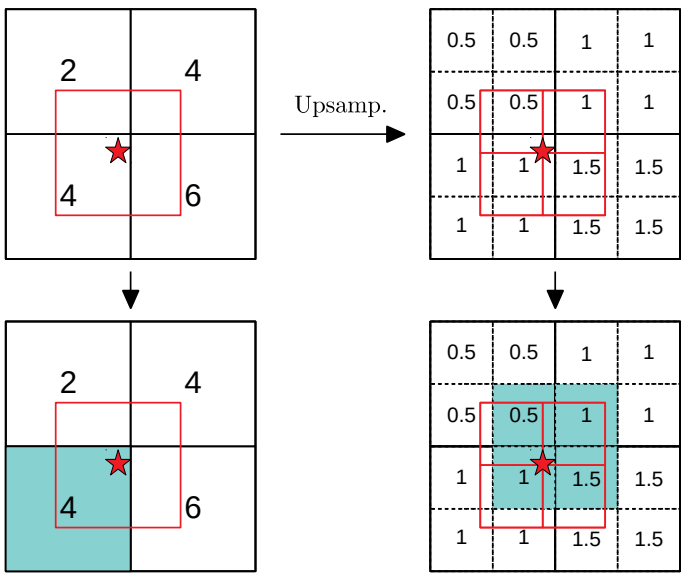
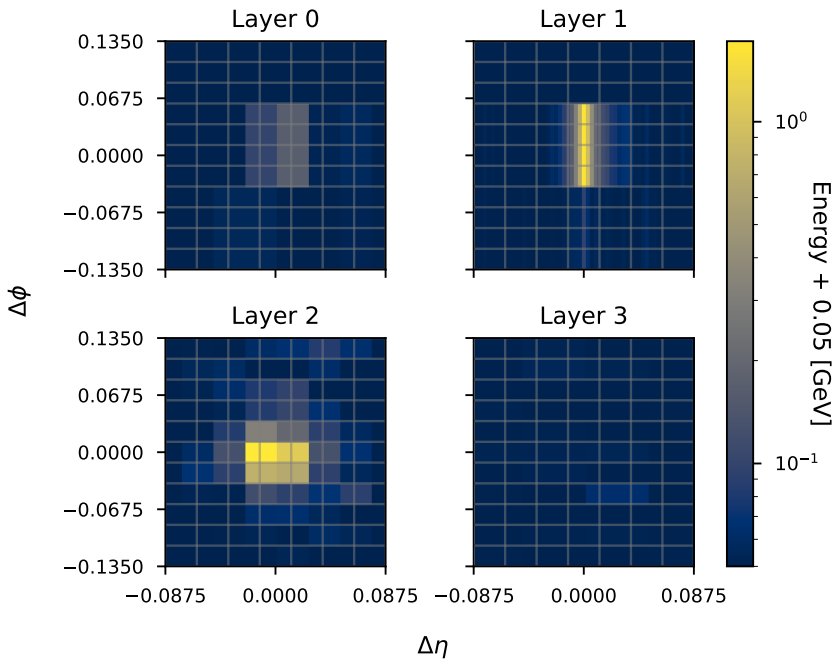
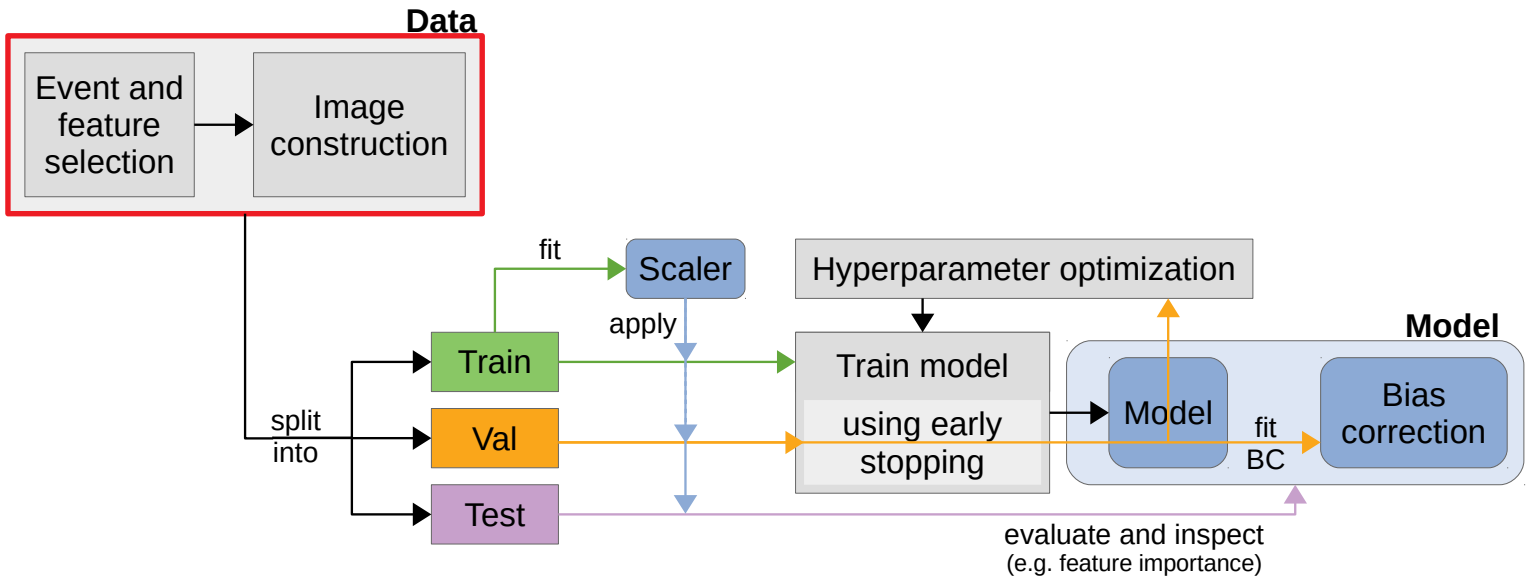




Simulation data

Scalars

ECAL	E_{acc}	
	f_0	Fraction of energy in different ECAL layers
	R_{12}	
	E_{TG3}	
Context	η	
	η_{index}	
	$\langle\mu\rangle$	
	$n_{\text{vertexReco}}$	
	$\eta\text{modECAL}$	Relative position within cell
	poscs_2	
	$\Delta\phi_{\text{TH3}}$	
Tracking	$\Delta\phi_2^{\text{rescaled}}$	Difference in tracking-ECAL position estimate
	$\Delta\eta_2$	
	p_T^{track}	
	n_{tracks}	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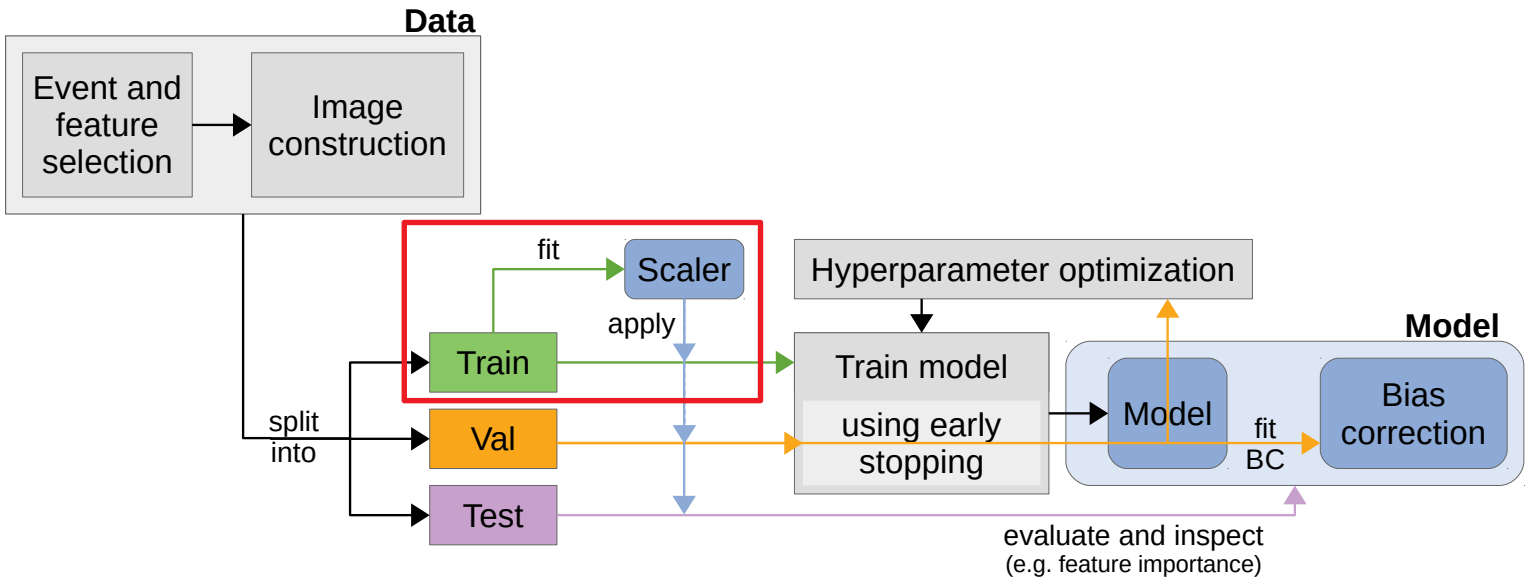
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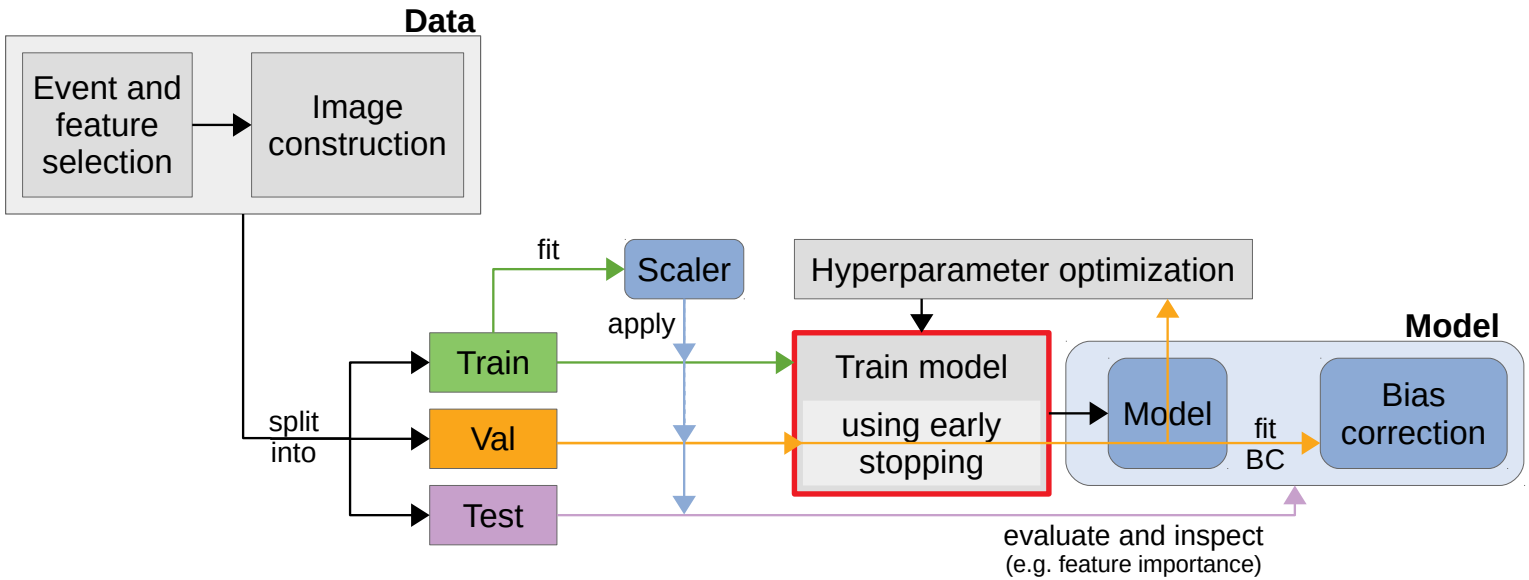
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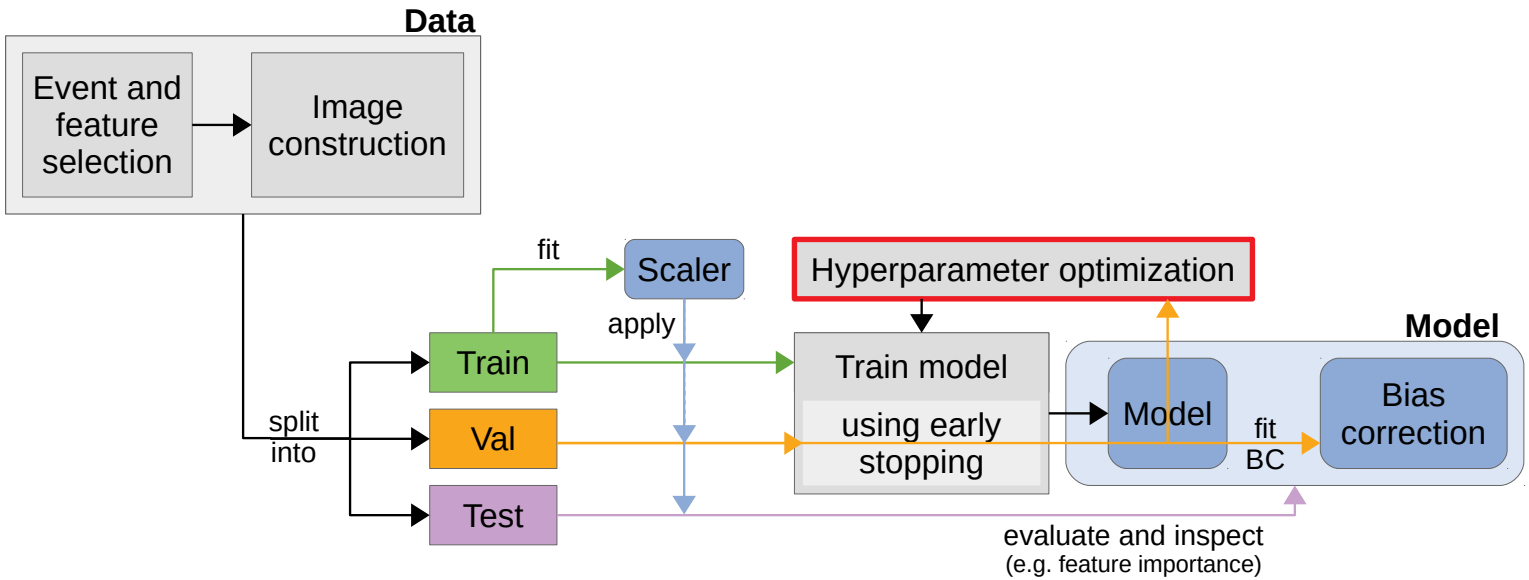
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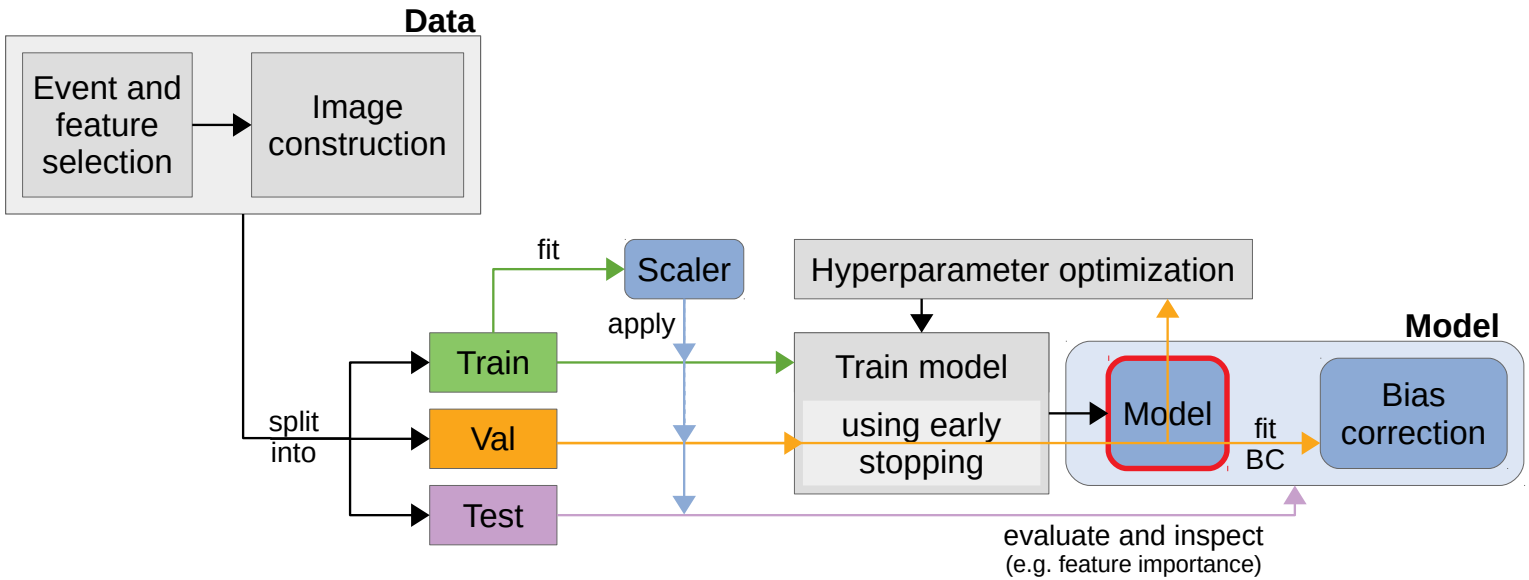
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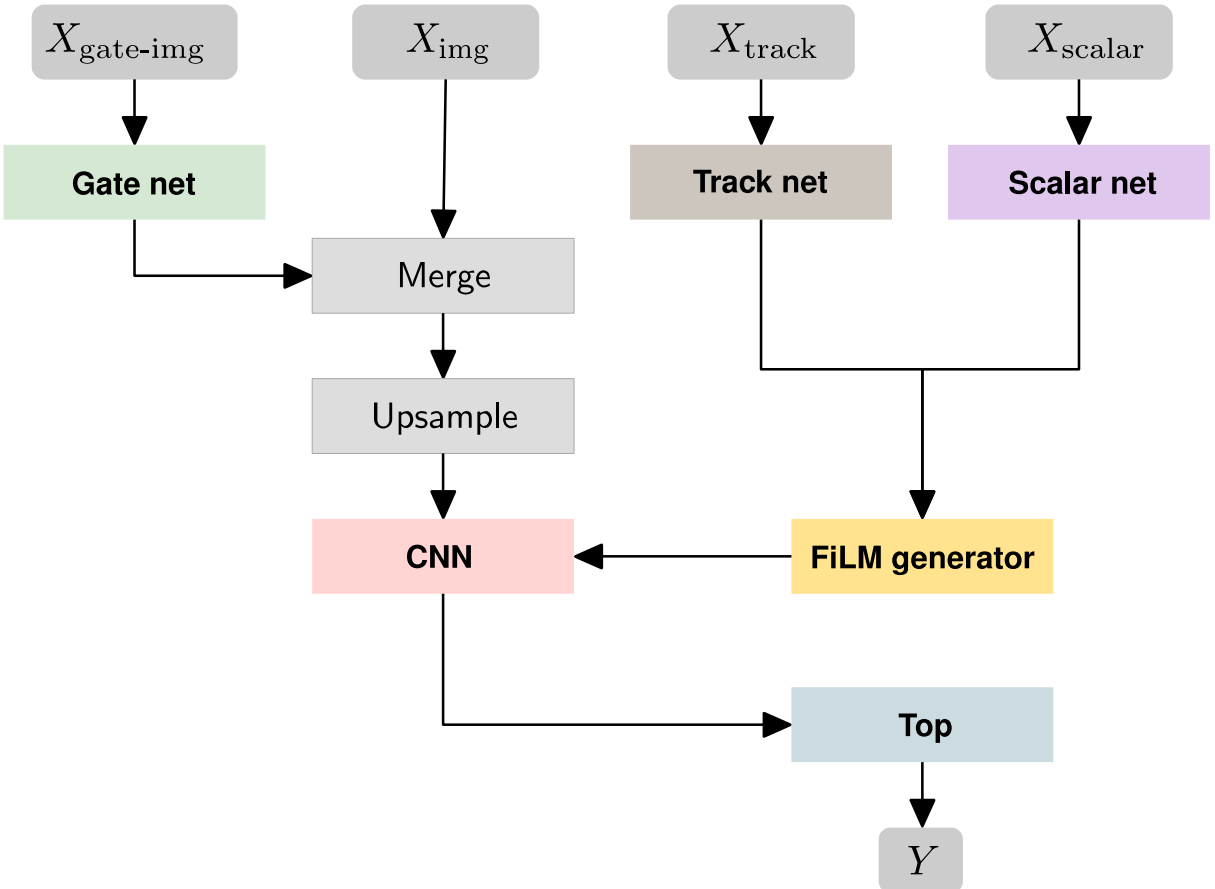
Model architecture



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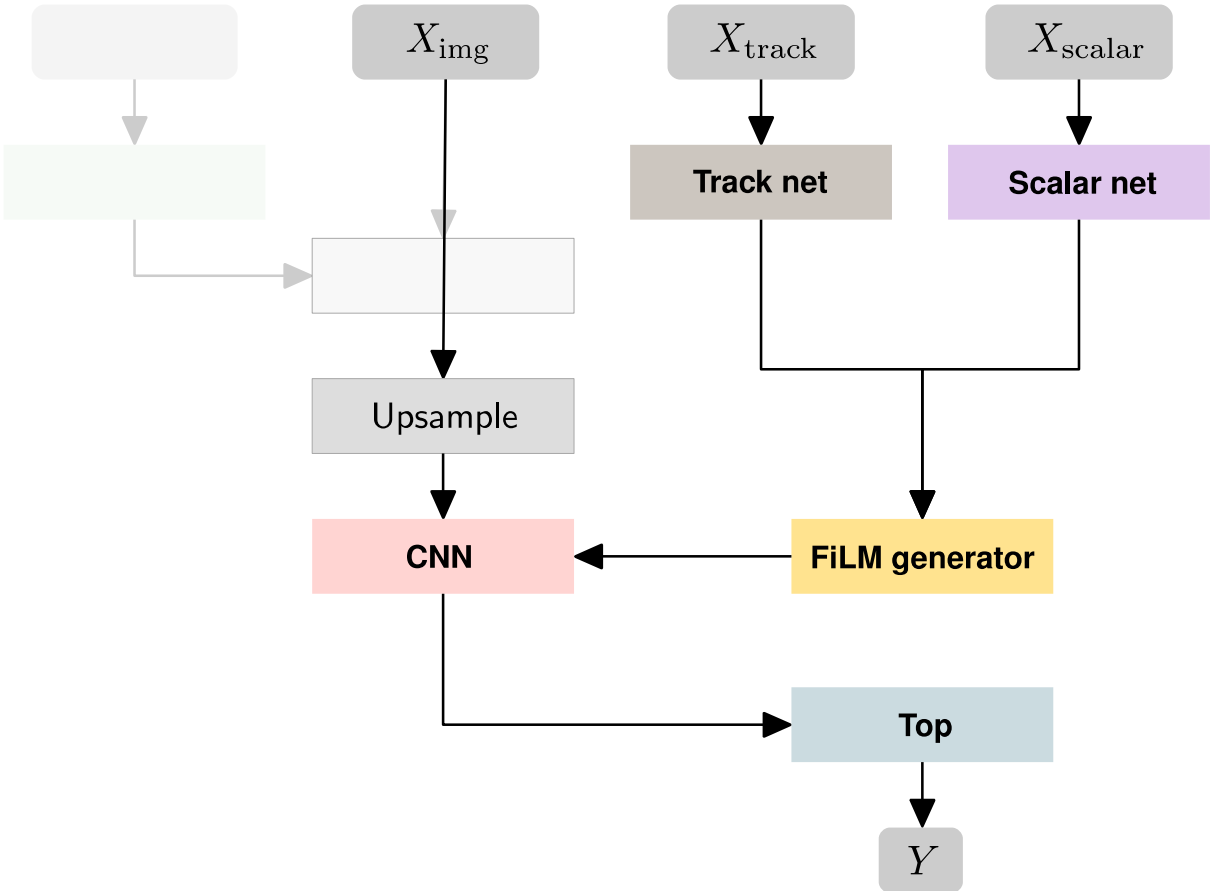

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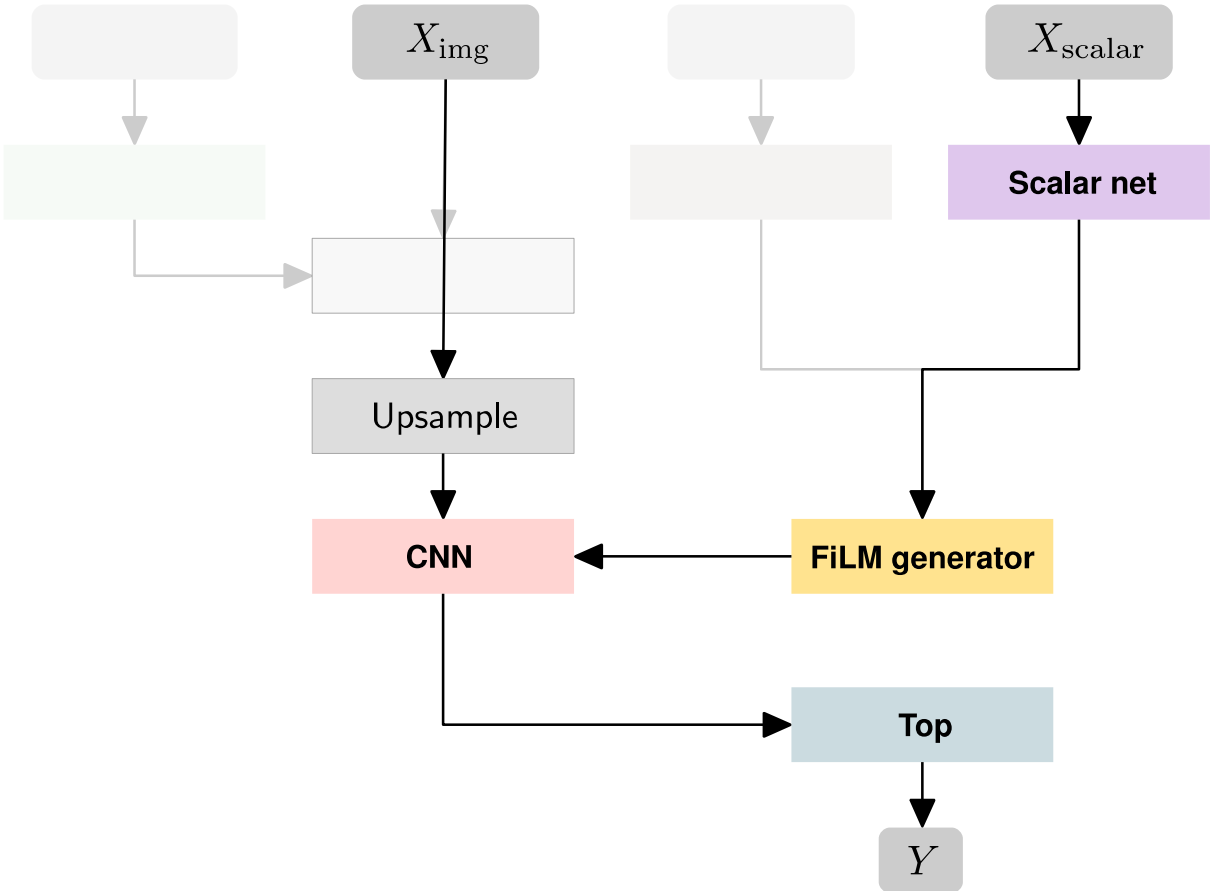

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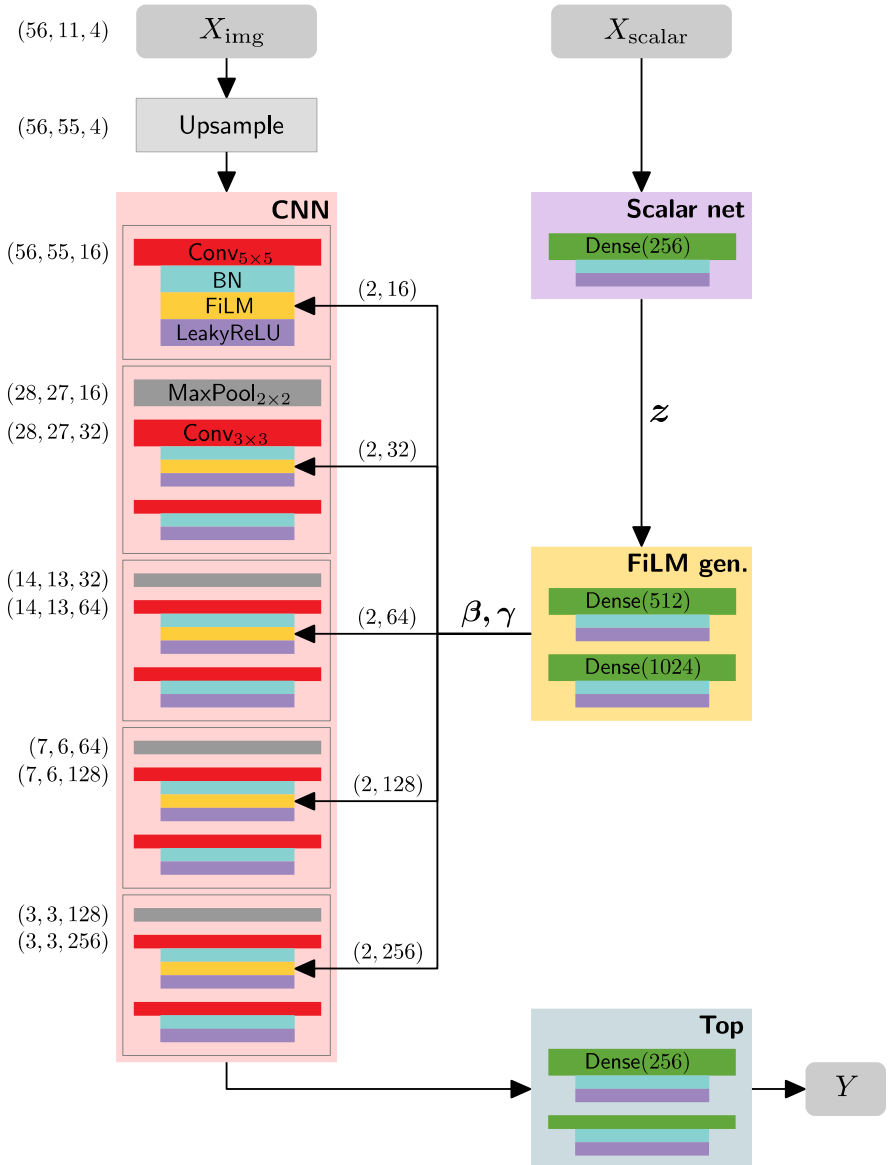

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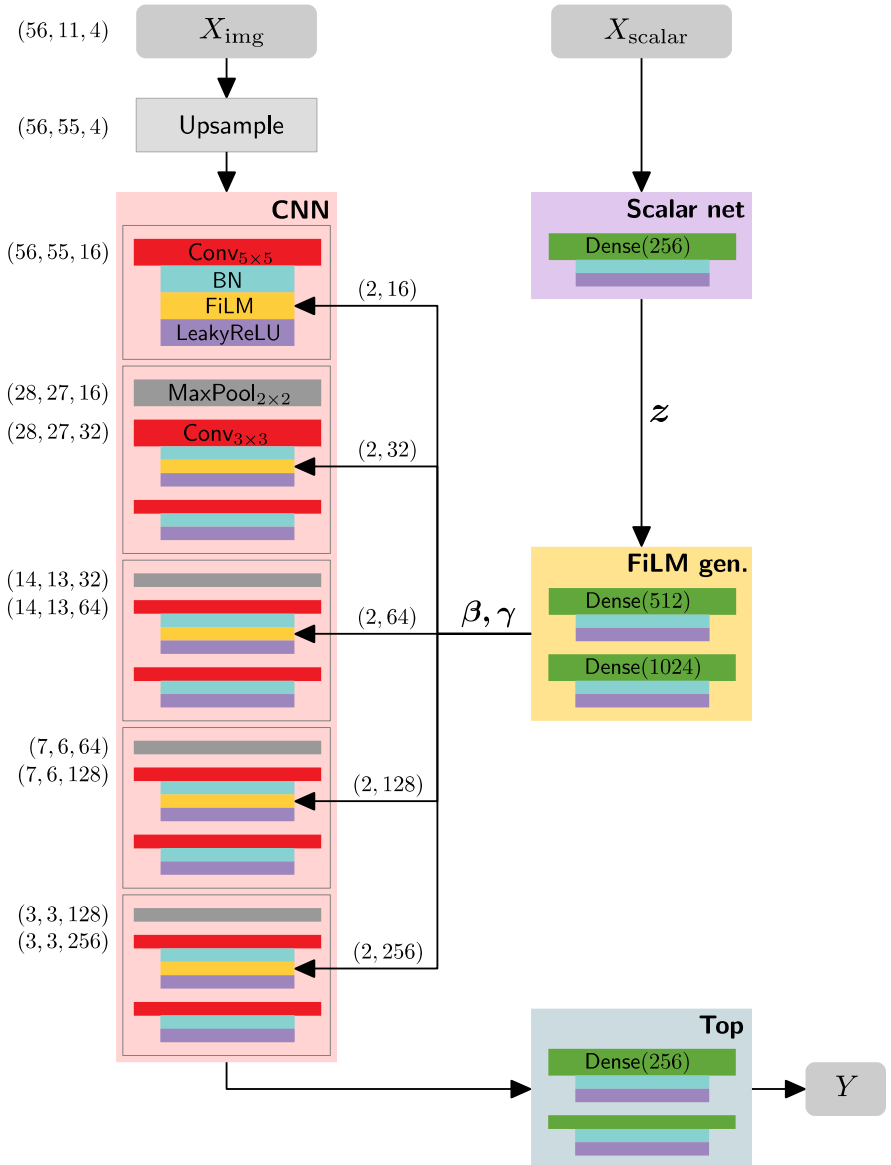
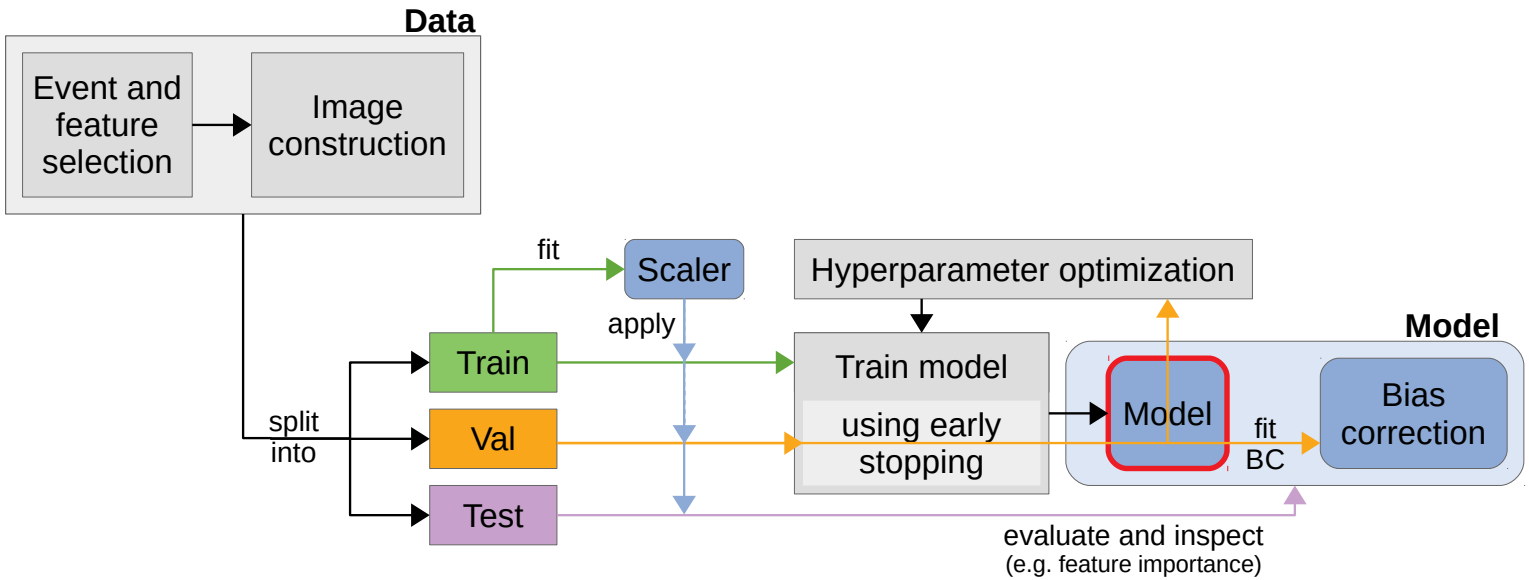


$$\text{FiLM}(x_i) = \gamma_i(\boldsymbol{z})x_i + \beta_i(\boldsymbol{z})$$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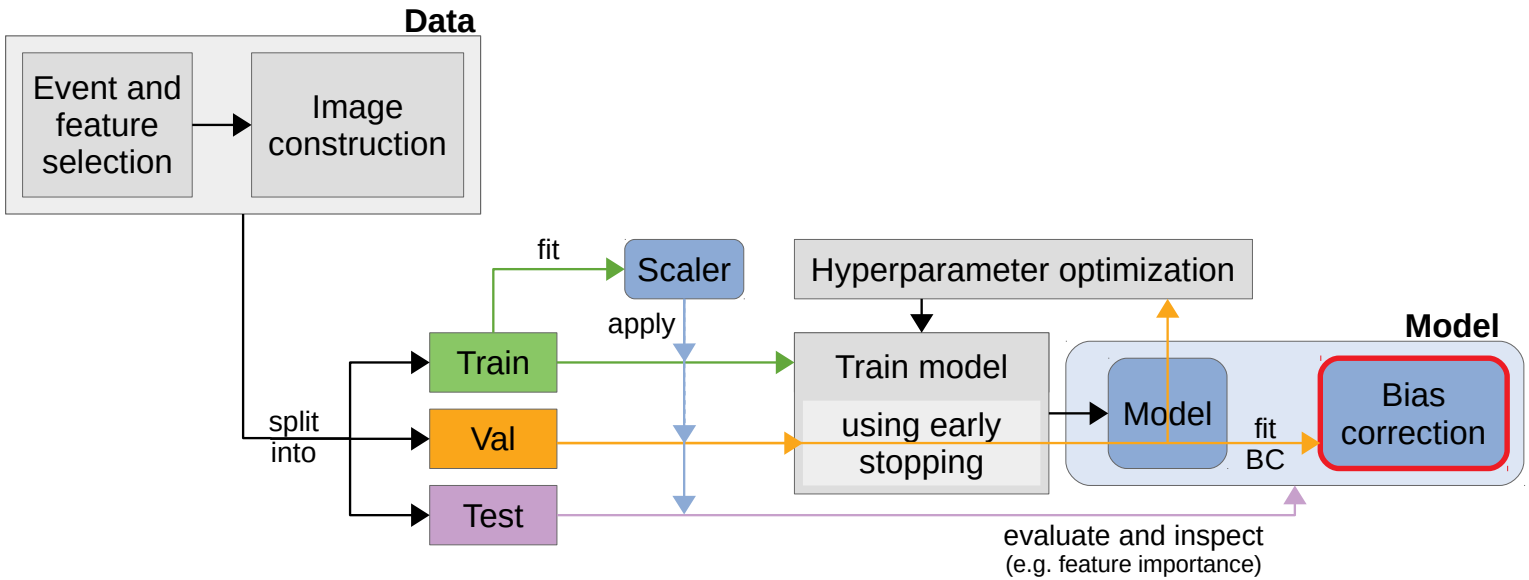
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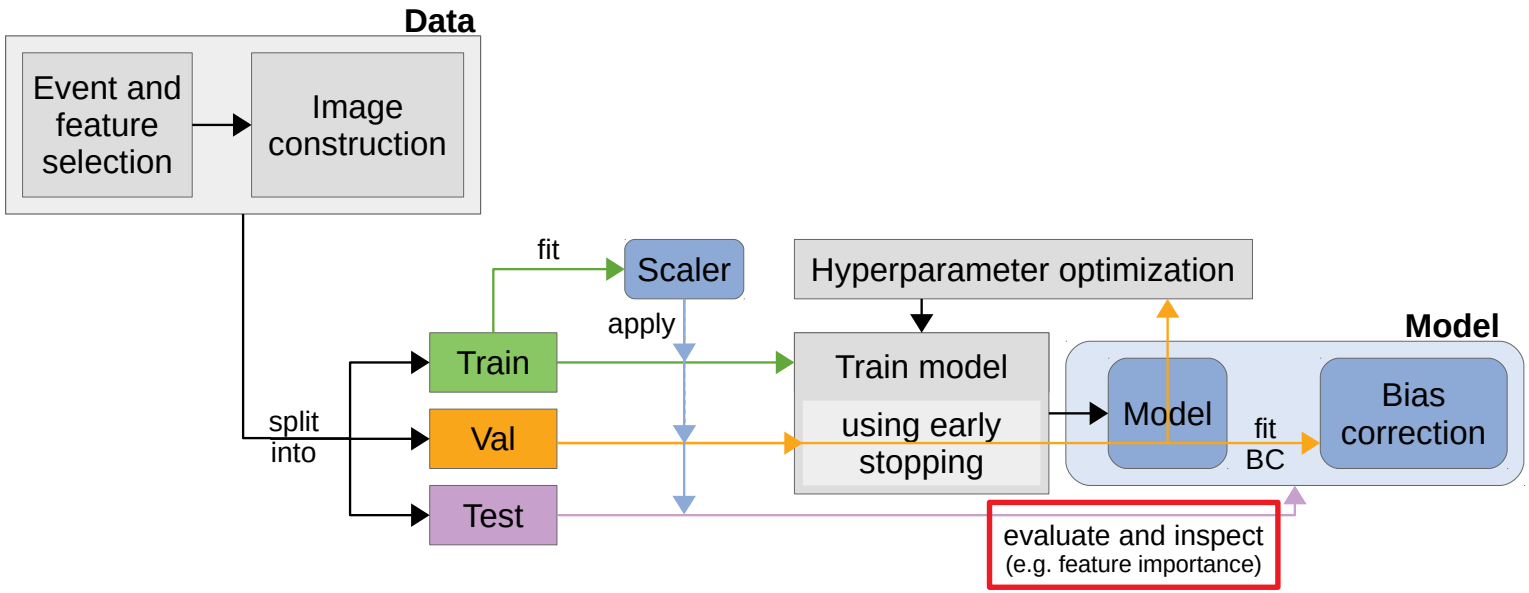
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Results

Metrics

Relative error:

$$\mathrm{RE} = \frac{E_{\mathrm{pred}} - E_{\mathrm{true}}}{E_{\mathrm{true}}}$$

Interquartile range (over distribution of RE):

$$\mathrm{IQR}(\mathrm{RE}) = Q_3(\mathrm{RE}) - Q_1(\mathrm{RE})$$

Relative improvement:

$$r\mathrm{IQR} = 1 - \mathrm{IQR}^{\mathrm{model}} / \mathrm{IQR}^{E\mathrm{calib}^{(\mathrm{BDT})}}$$

Results

Two experiments

	No E_T bins, barrel e	No η bins, low energy e/γ
E_T	$5 - 1000\ \mathrm{GeV}$	$5 - 100\ \mathrm{GeV}$
$\lvert\eta\rvert$	$0 - 1.3$	$0 - 2.5$ (2.4 for γ)
Trick	Predict $E_{\mathrm{true}}/E_{\mathrm{acc}}$	Add barrel and endcap images

Results

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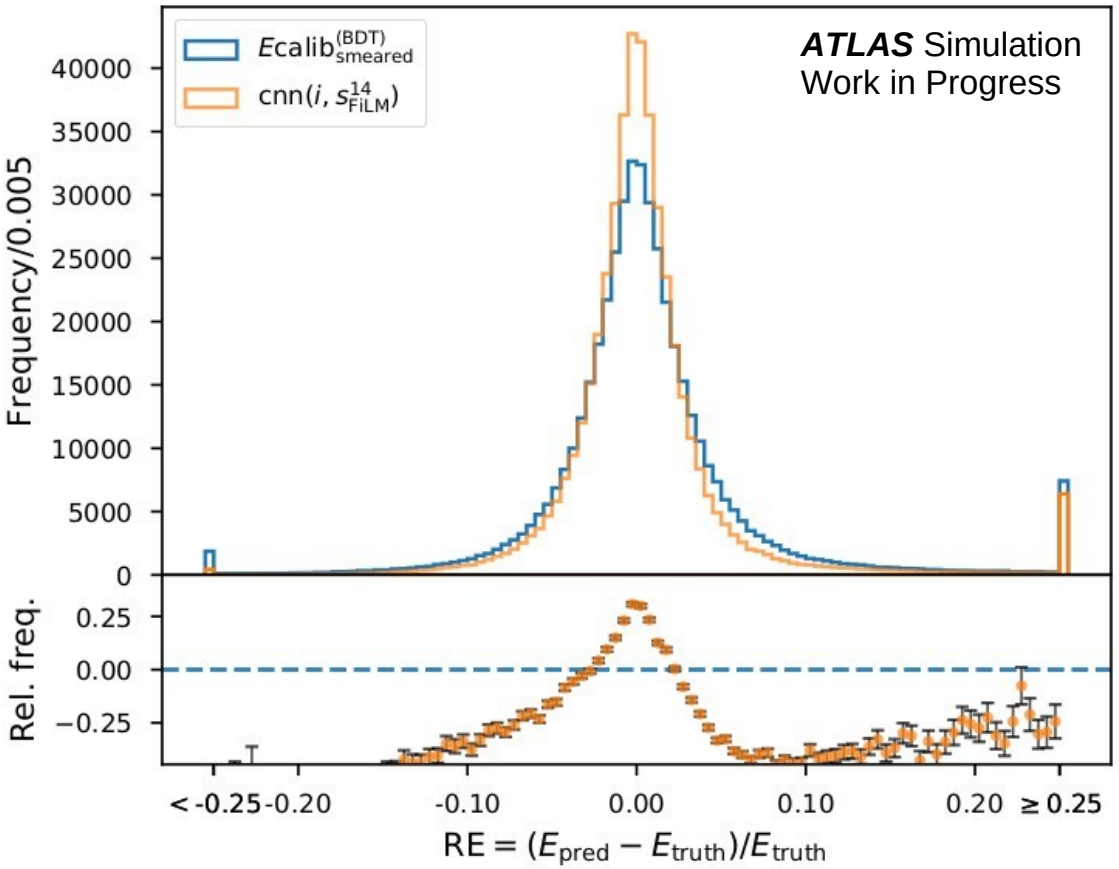
$\lvert\eta\rvert$	$0 - 1.3$	$0 - 2.5$ (2.4 for γ)
Trick	Predict $E_{\mathrm{true}}/E_{\mathrm{acc}}$	Add barrel and endcap images

Both work, so plan is to merge them

Results

No E_T bins, barrel e

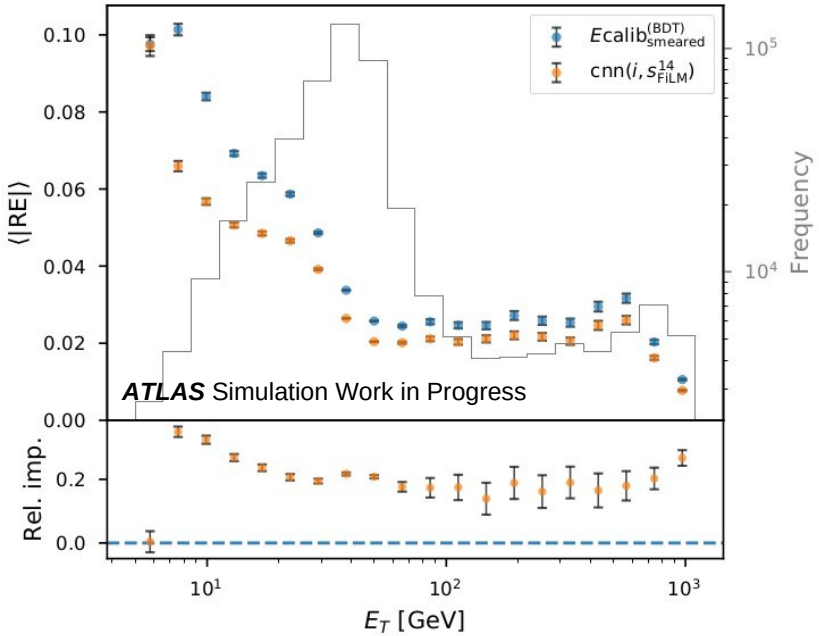


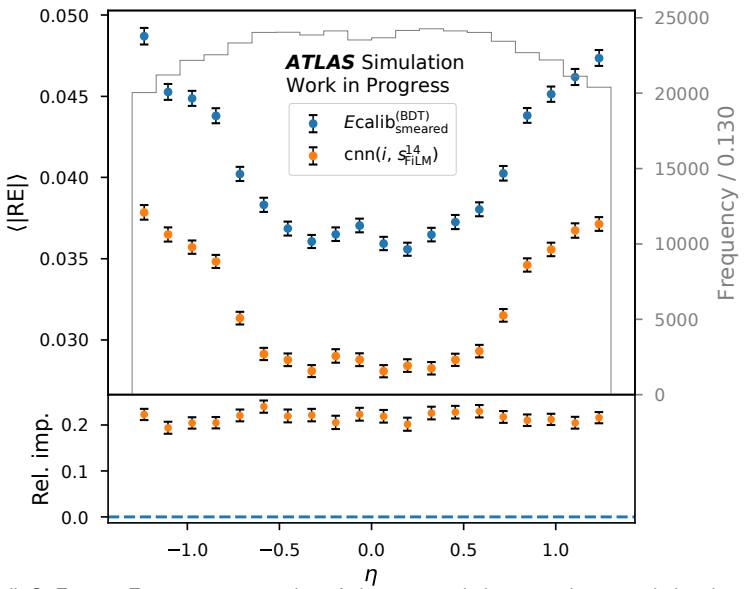
$$r\mathrm{IQR} = 24.0\%$$

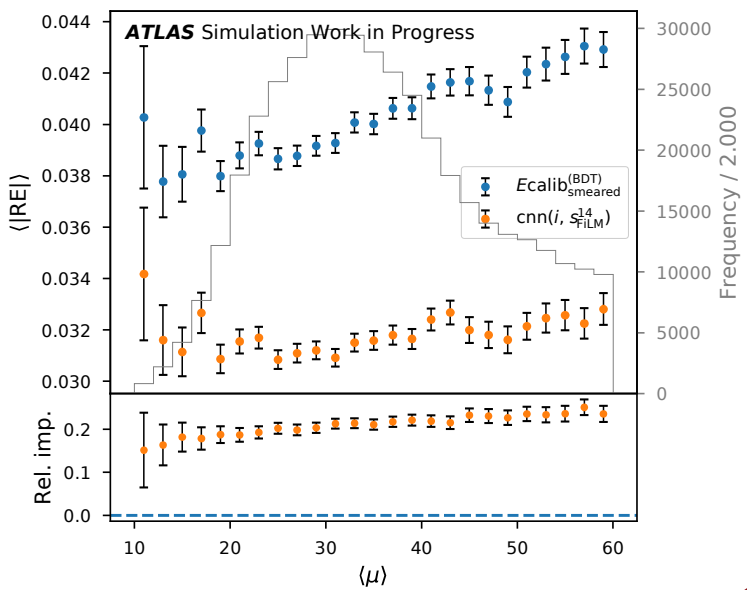
- This model predicts $E_{\mathrm{true}} / E_{\mathrm{acc}}$ (predicting E_{true} did not work here)
- $E\mathrm{calib}^{(\mathrm{BDT})}_{\mathrm{smeared}}$ is smeared $\rightarrow$ true $r\mathrm{IQR}$ is $1 - 2\%$ lower

Results

No E_T bins, barrel e





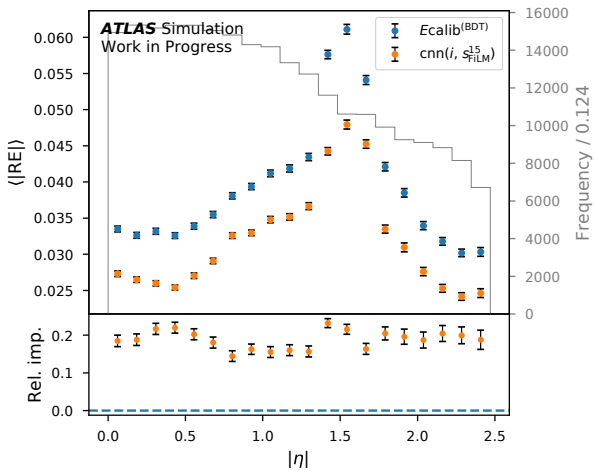


Results

No η bins, low energy e/γ

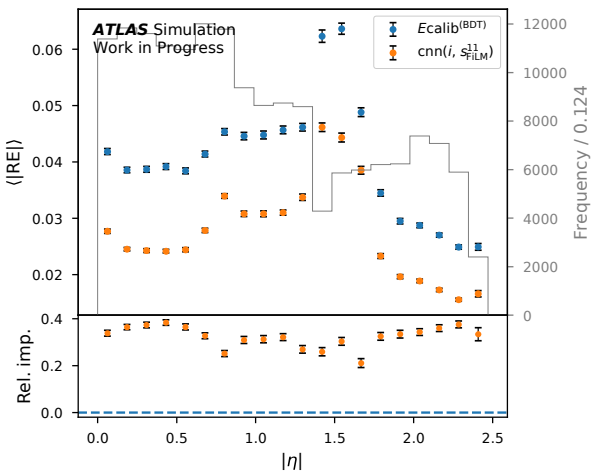
Single model trained on photons $< 100\ \mathrm{GeV}$

Electrons ($Z \to ee$)



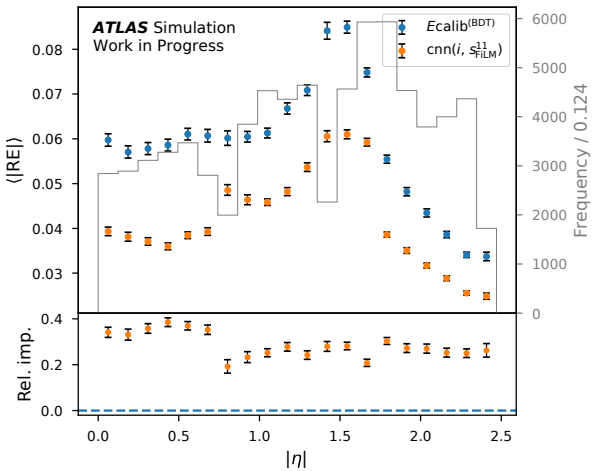
$rIQR = 20.8\%$

Unconverted



$rIQR = 29.4\%$

Converted

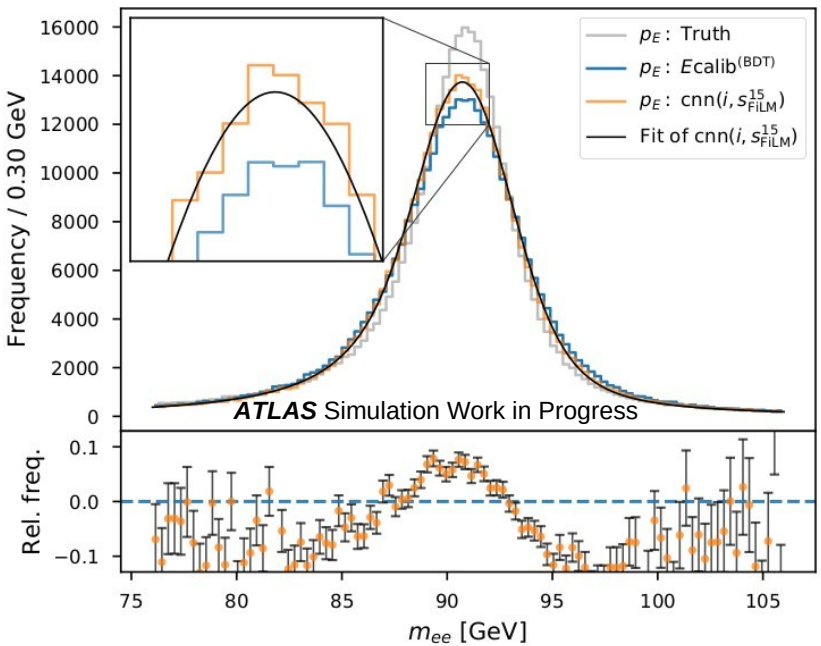


$rIQR = 19.9\%$

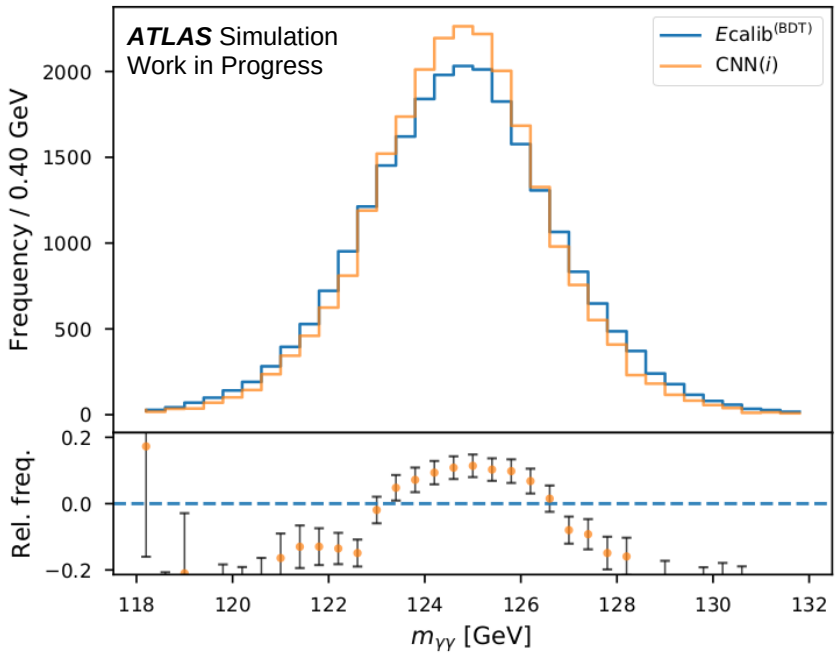
Results

No η bins, low energy e/γ

$Z \to ee$ (probe only)



$H \to \gamma\gamma$



$$\sigma_{\text{CB}}^{\text{Ecalib}} = 2.09(1)$$

$$\sigma_{\text{CB}}^{\text{cnn}} = 1.87(1)$$

$$1 - \sigma_{\text{CB}}^{\text{cnn}} / \sigma_{\text{CB}}^{\text{Ecalib}} = 10.5(7)\%$$

Very preliminary!

What's next?

- **Produce data** covering central region and whole E_T range
- **Train** three models (e, conv. and unconv. γ) each without E_T, η bins
- **Implement** in ATHENA (worked on by people in ML Forum)
- Apply currently used **MC** $\rightarrow$ **Data corrections** and test on Data
- Test if **MC** $\rightarrow$ **Data cell reweighting** improves performance in Data
- Find **minimum set of scalars** (guided by permutation imp. or SHAP)

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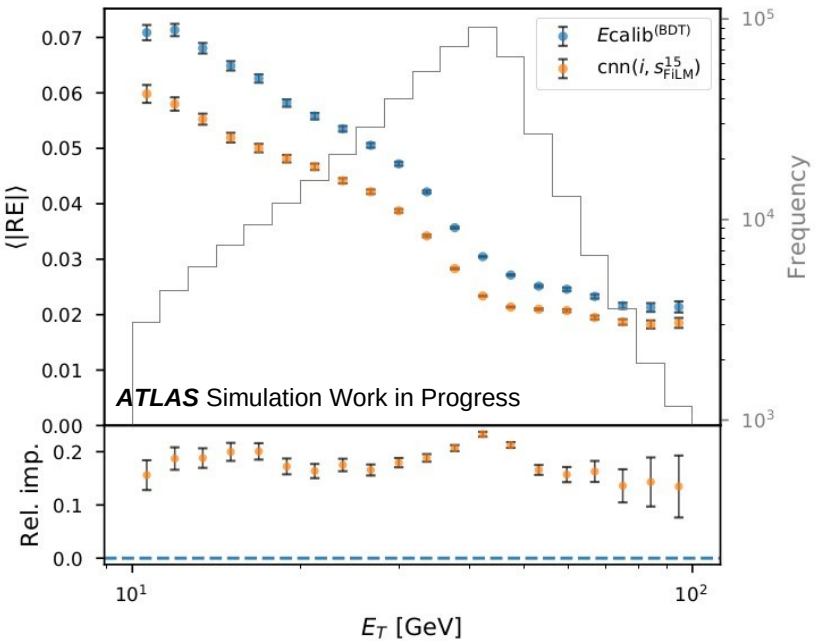
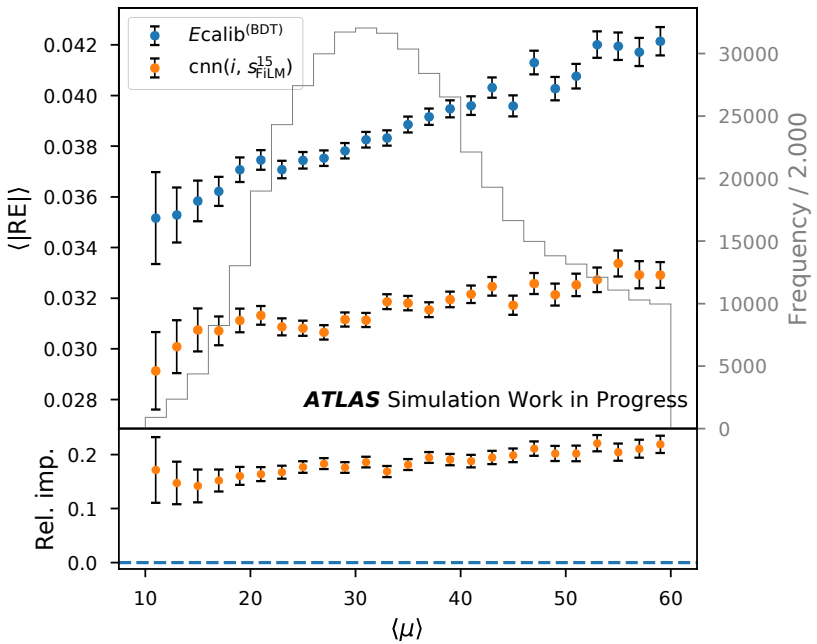
- Well-documented code is available at gitlab.com/ffaye/deepcalo (`pip install deepcalo`)
- Short **summary of recommendations** based on my thesis available here
- Internal note is on its way

Backup

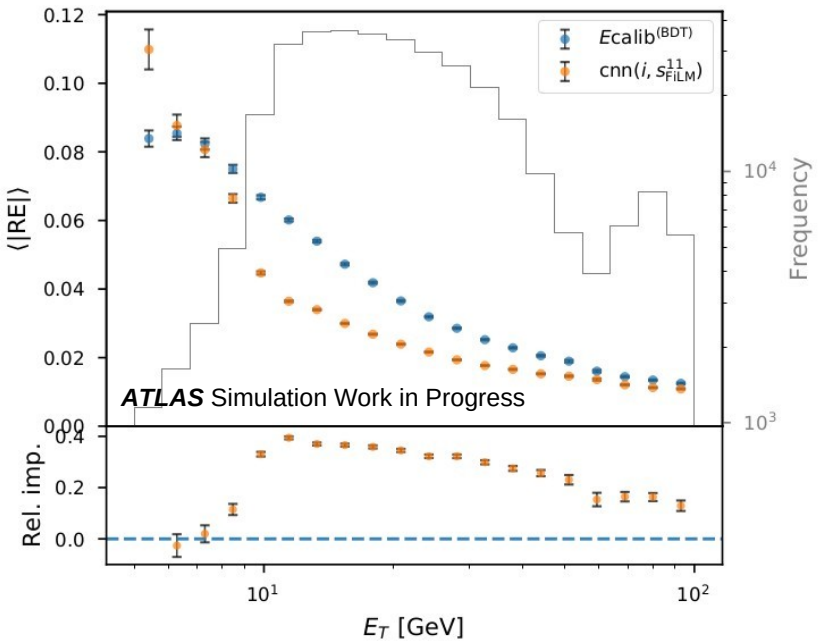
No η bins, $Z \rightarrow ee$ electrons

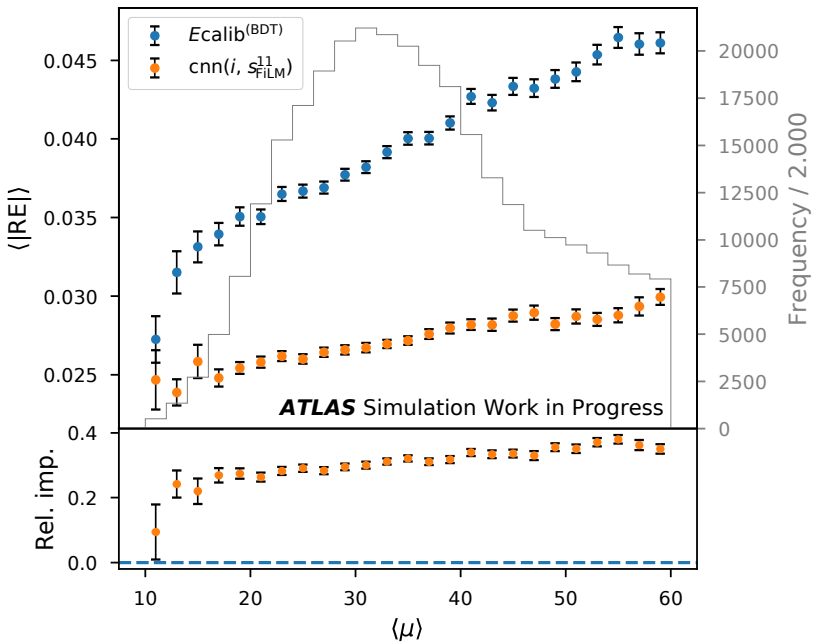




Backup

No η bins, unconverted electrons < 100 GeV





Backup

No η bins, converted electrons < 100 GeV