Particle Hypothesis Fitting with Autoencoder Neural Networks

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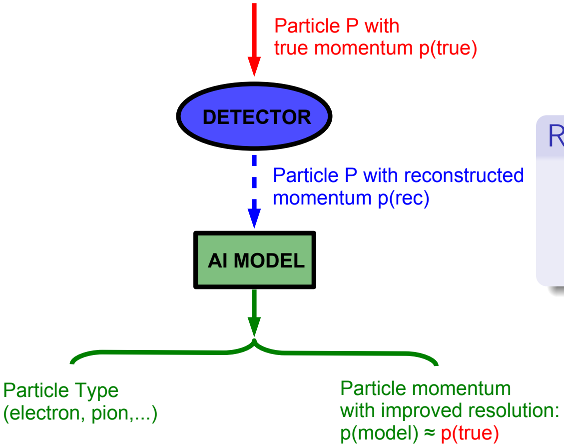
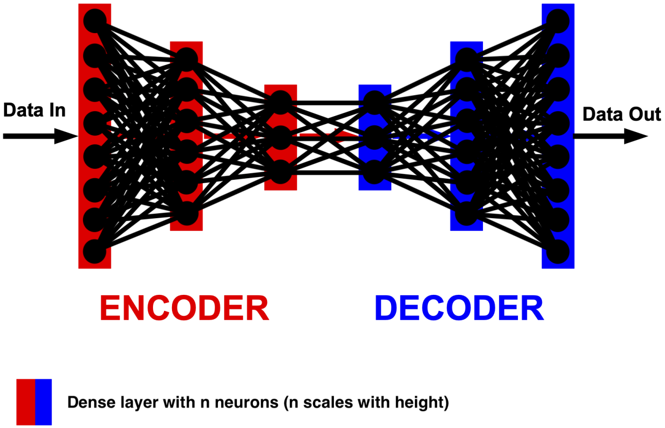
Objective(s)



Require from AI MODEL:

1. Identify particles
2. Improve resolution
3. Easy to diagnose by analyzer

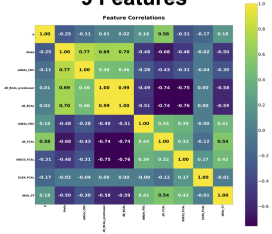
Autoencoder Neural Networks

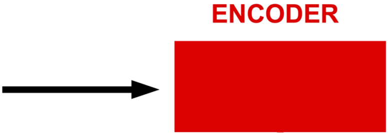


- **Autoencoder** = Encoder + Decoder
- Symmetric architecture
- Train model for one particle type: **Data In** $\approx$ **Data Out**

Autoencoders: Compression and Decompression

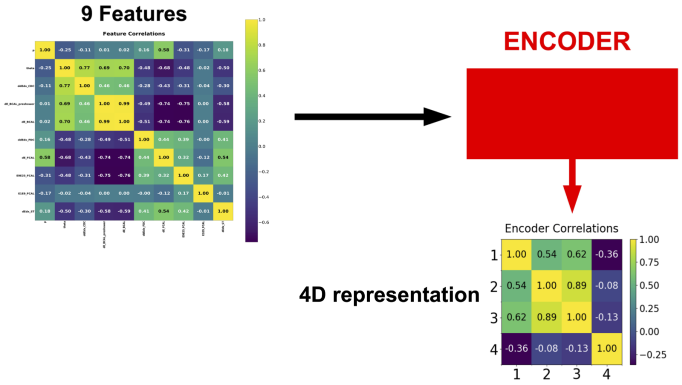
9 Features





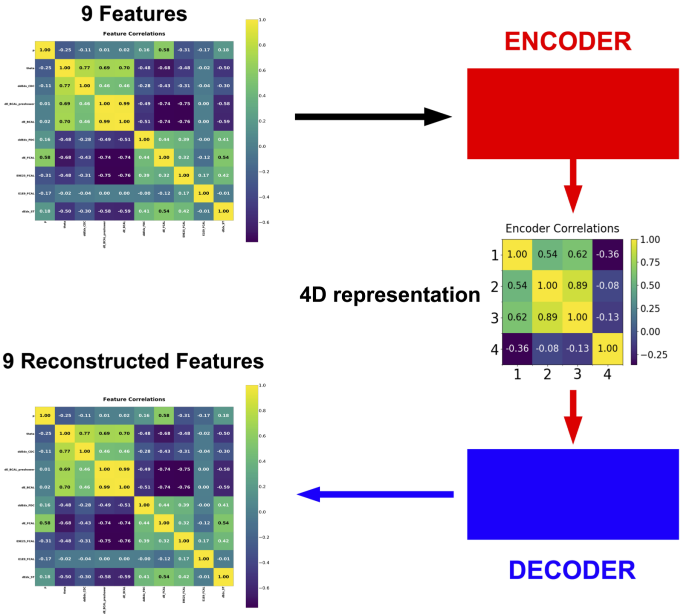
Features:
- momentum
- theta
- ddEdx(CDC)
- dE(BCAL 0)
- dE(BCAL all)
- ddEdx(FDC)
- dE(FCAL)
- E9E25 (FCAL)
- E1E9 (FCAL)

Autoencoders: Compression and Decompression

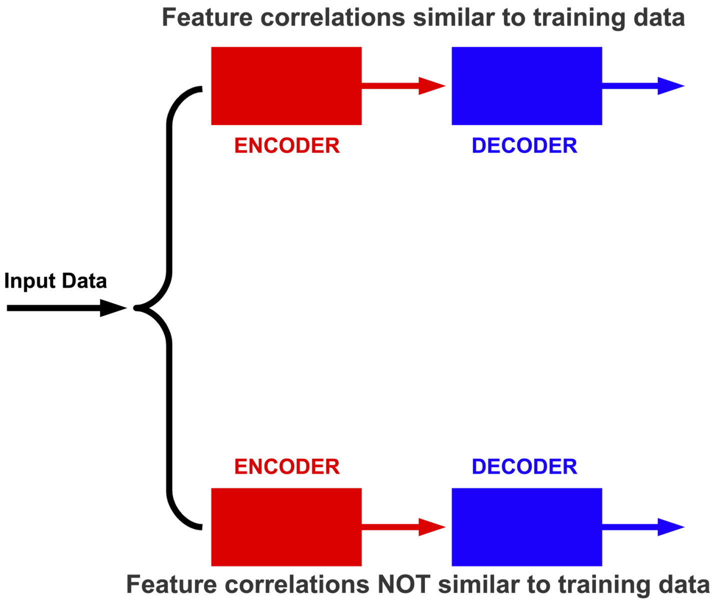


Compression / dimensional reduction from 9 —> 4 dimensions

Autoencoders: Compression and Decompression



Autoencoders: Anomaly Detection in Data



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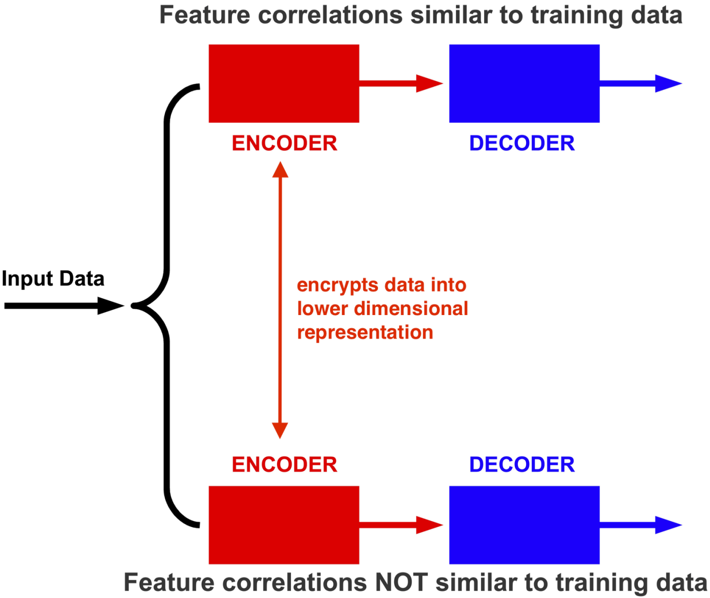

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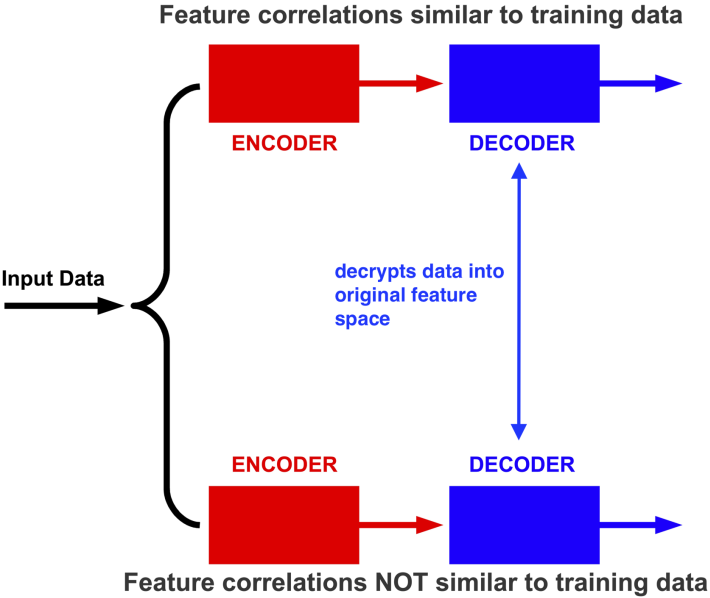

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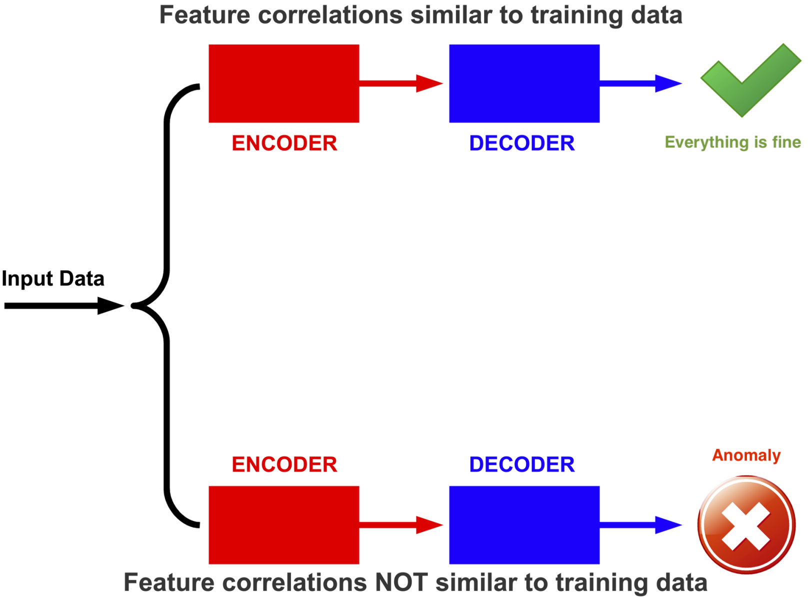
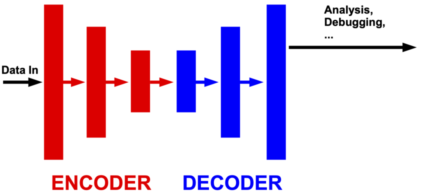
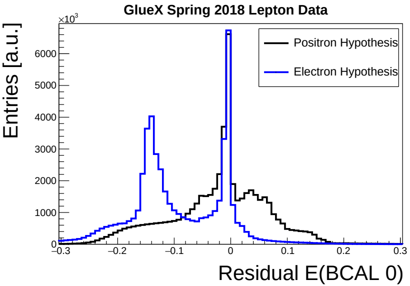


LEpton Autoencoder - LEA @ GlueX

Debug-Mode

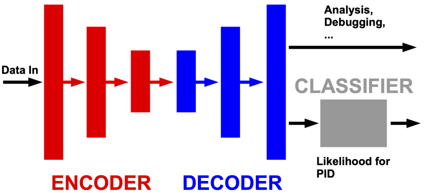


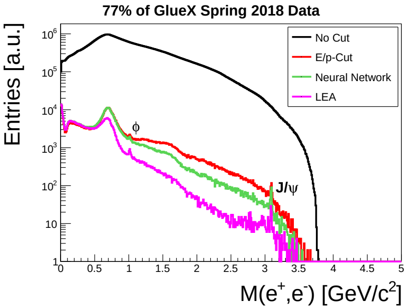


- Residual = Data In - Data Out
- Residual = 0: Everything is fine
- Residual $\neq$ 0: Background and/or model is bugged

LEpton Autoencoder - LEA @ GlueX

PID-Mode





Approach	MCC[a]	$S/\sqrt{S+B}$[b]
E/p-cut	0.83	5.6
Neural Network	0.85	5.6
LEA	0.87	8.0

[a] For lepton/pion simulated single tracks

[b] For measured $J/\psi \to e^+e^-$ events

Taking PID to the next Level: Hypothesis Fitting

- Can we use our model to improve the feature resolution?

Taking PID to the next Level: Hypothesis Fitting

- Can we use our model to improve the feature resolution?
- Adapt formalism from kinematic fitting

KINEMATIC FITTER

$$\chi^2 = \boldsymbol{\epsilon}^T \hat{V}^{-1} \boldsymbol{\epsilon} + 2\boldsymbol{\lambda}^T \mathbf{F} \stackrel{!}{=} 0$$

AUTOENCODER

$$\mathcal{L} = \mathcal{L}_\delta + \sum_i w_i \mathcal{L}_i \stackrel{!}{=} 0$$

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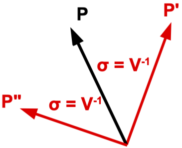

improve resolution

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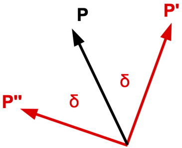

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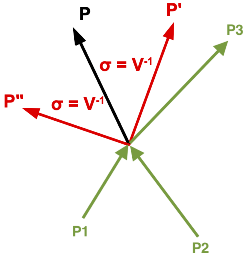

improve resolution with respect to constraints on reaction hypothesis

AUTOENCODER

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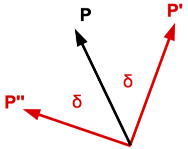
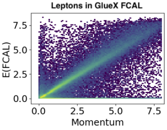
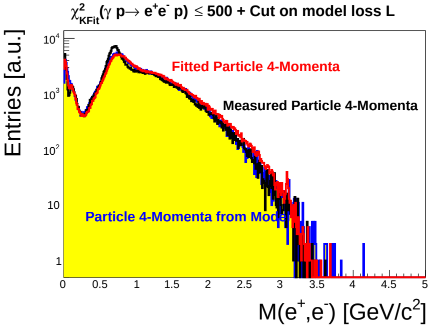


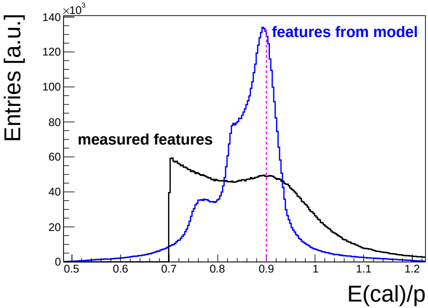
E(FCAL) = Momentum



improve resolution with respect to constraints on detector response for a given particle type

Preliminary Results





- First tests show promising results
- Predicted features show improved resolution
- Good agreement between kinematic fitter and model for low invariant masses

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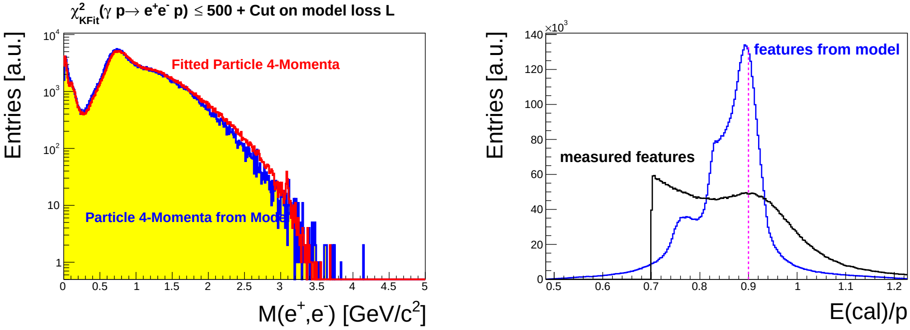

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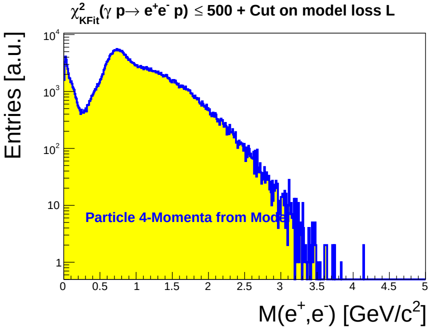

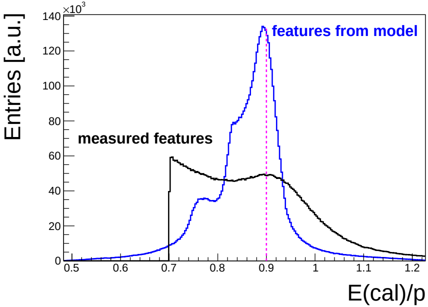

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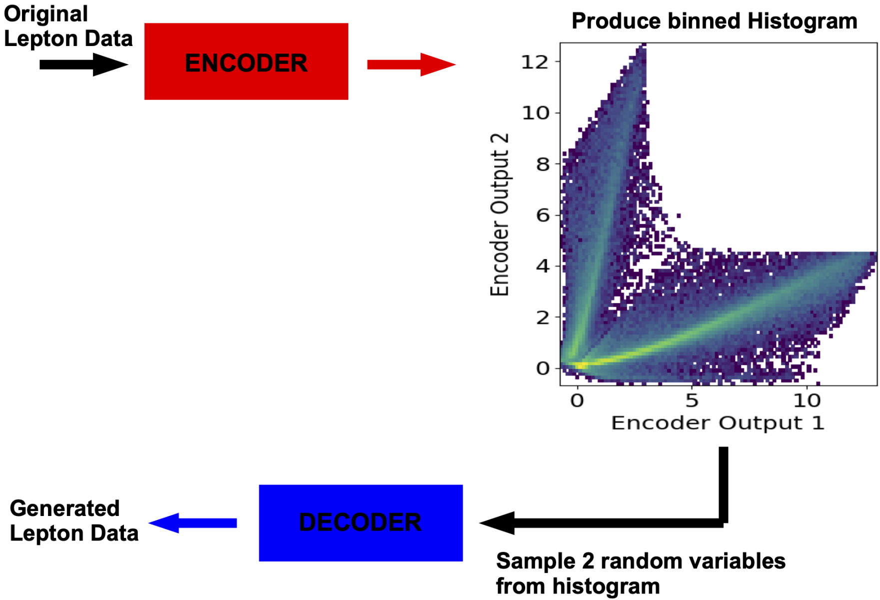
Bonus: Generating Lepton (like) Data

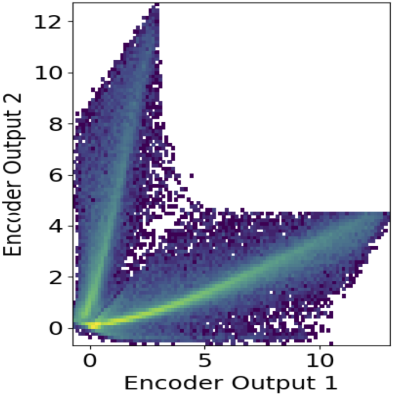


Bonus: Generating Lepton (like) Data

Original Lepton Data

ENCODER

Produce binned Histogram

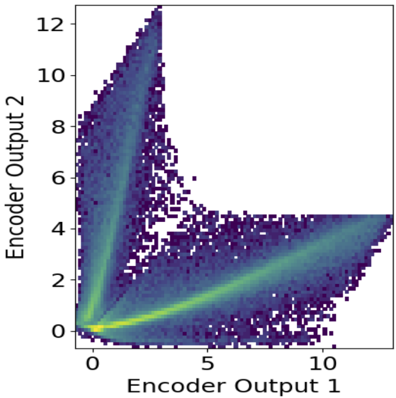


Ideally done only once,
unless your model needs to be tuned...

Bonus: Generating Lepton (like) Data

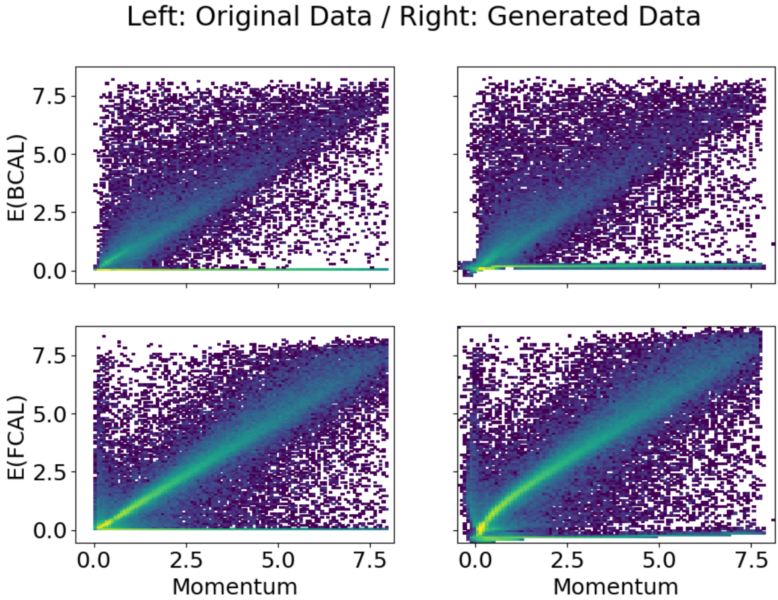
Can be done many times
—> data generator

binned Histogram



Generated Lepton Data ← **DECODER** ← **Sample 2 random variables from histogram**

Bonus: Generating Lepton (like) Data



Summary and Outlook

Use autoencoder neural networks:

- ☑ Identify particles
- ☑ Improve Resolution
- ☑ Easy to diagnose by analyzer

Ongoing / future work:

- Optimize fitter to describe high dilepton invariant masses
- Extend fitter model to
  - (dilepton) data generator
  - fit / identify other particle types (pions, protons, kaons...)
- Collaborators are always welcome