Autoencoders for LHCb

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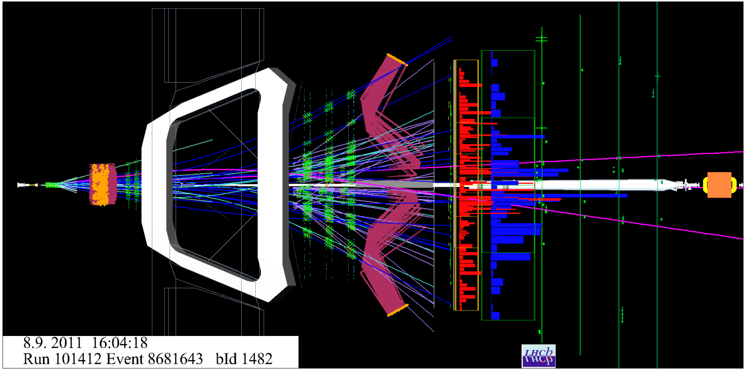
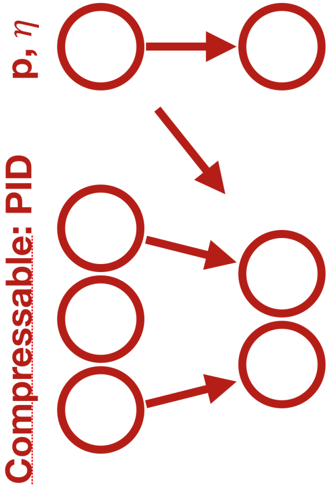
LHCb / MIT

The Problem



- We collect ∼5 TB/s of data, but our write out is limited
- **The more efficient** we are at storing the data, the more collisions we can keep and **the more physics** we can do

Solution? : Encoding Network



- Features to not compress (in this work)
  - Require very high precision
  - Many use cases $\implies$ undefined loss function (e.g. Tracking variables)

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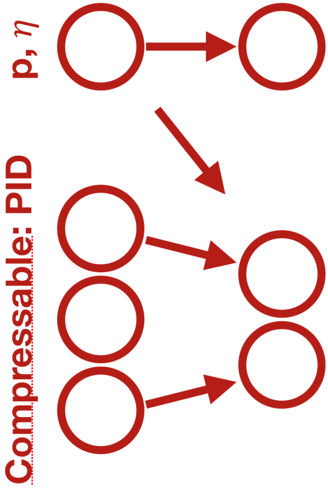

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  - Help classify particle types (e, μ, π, ...)
  - Unimportant by themselves
  - Factorisation: all muons are the same regardless of production (given kinematics and event occupancy)

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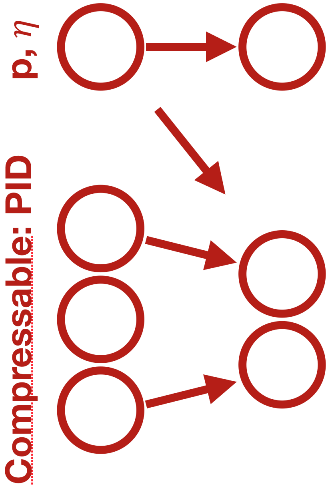

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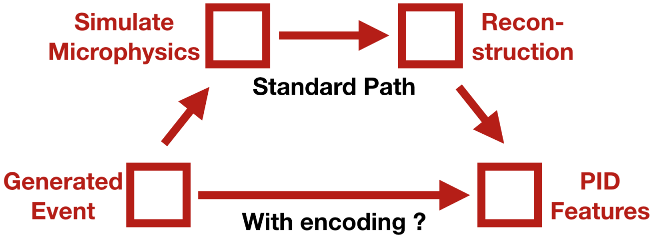
Find smaller representation of PID features

Implications for MC



MC simulations only need to generate the compressed features

- Faster generation speeds
- Smaller file sizes

Implications for use in HEP

However, cannot get back to original features

- Hard to fix PID if compression goes wrong
- Collaboration needs trust: **Sociological problem**

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Interesting idea, but requires more thought

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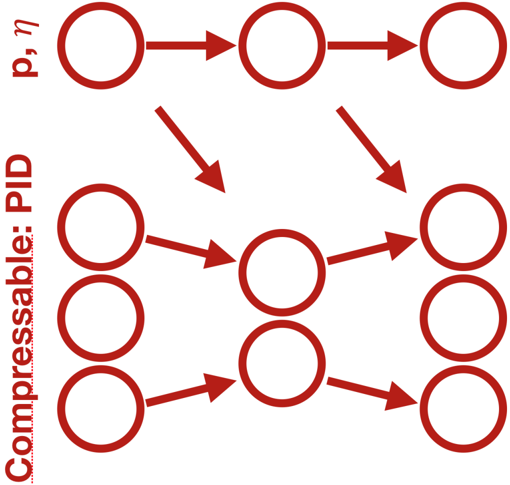

Use an autoencoder that

- Compresses information about every particle before writing it out
- Decodes the result when performing the analysis
- Factorization means everything can be characterised offline

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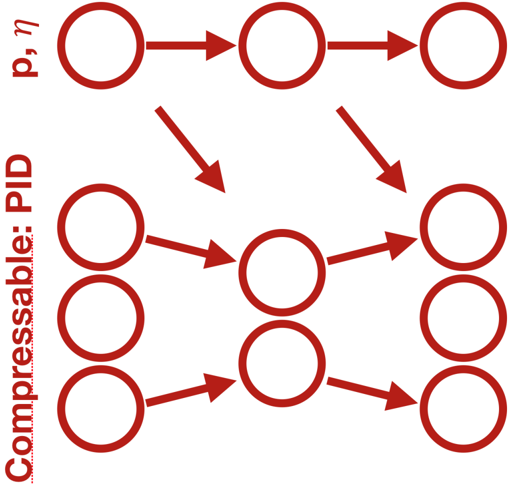

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This brings advantages:

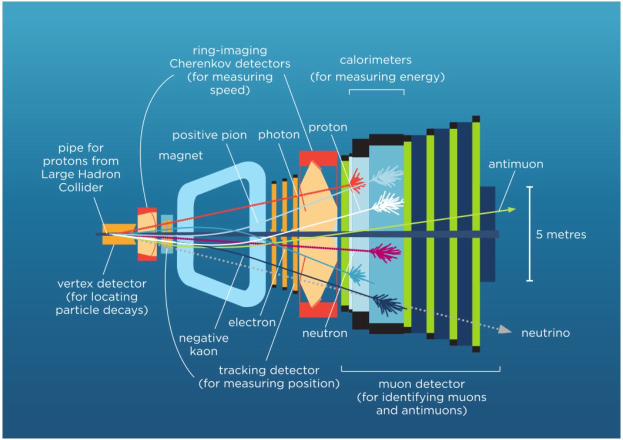
- Can compare input and output for calibration samples
- Less trust needed (input sufficient for $\sim$ 500 papers to date)

Data Set

- Simple proof-of-concept preliminary study
- LHCb Minimum Bias Monte Carlo (Simulation)
- Extracted equal numbers ($\sim$550k) of different charged particle types (e, μ, π, K, p, ghost)
- Can generate more data if required
- Obscured data at `zenodo.org/record/1230552#.WuIbVlMvw6h`
- Code at `github.com/weissercn/LHCb_PID_Compression`
- Get in touch with me at weisser@mit.edu to discuss

Sub-Detectors

- For each particle, information from each of the **5 groups of features** can either be present or missing. **MNAR** (Missing Not At Random)



- RICH
- Muon System
- ECAL General
- ECAL Charged
- ECAL Neutral

Special Case: General ECAL + RICH

- Concentrate on 2.5 out of 3.3 million examples where information from two specific subdetectors (General ECAL, RICH) exist.
- Ignore information from other systems
- Numbers of features to compress: [Always present, ECAL, RICH] = 10,3,5
- Additional auxiliary features present at compression and decompression: [Always present, ECAL, RICH] = 8,0,0
- A different autoencoder like this could be trained for all combinations of subsystems being on or off. ($2^5 = 32$ autoencoders)

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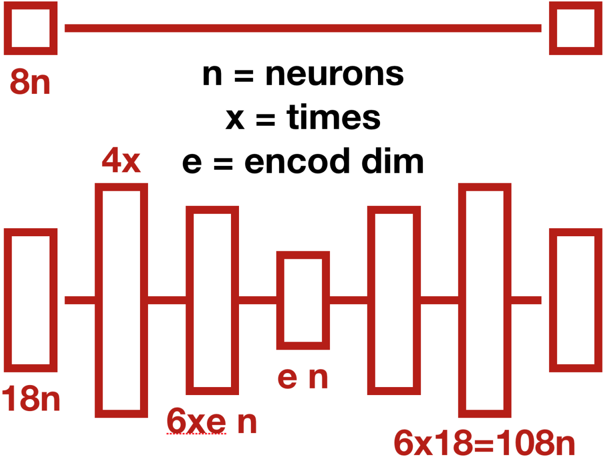
Is there a smarter way to deal with missing data?

Loss Function

There are many different PID classification problems $\Longrightarrow$ there are many possible loss functions

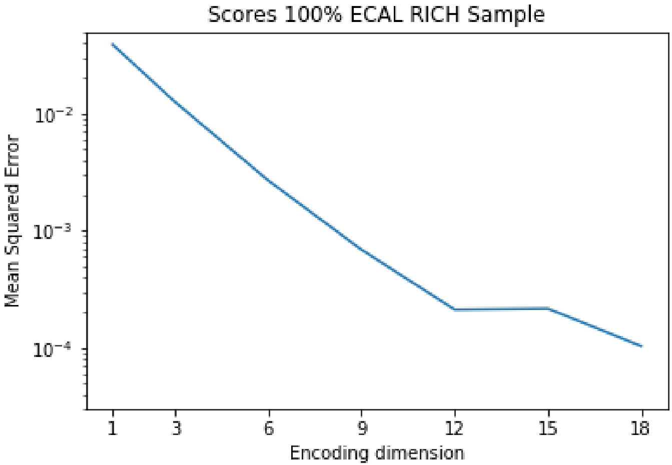
- Training
  - For now want to retain possibility of reconstructing input features
  - Scale and use mean squared error (MSE) loss to train
- Cross-check
  - To test the autoencoder's PID classification ability, use another loss:
  - Train two BDTs on the uncompressed and decompressed features and compare ROC curve for electron selection

Network Architecture



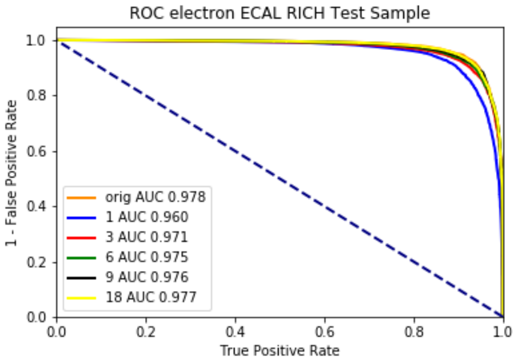
- 5 hidden fully connected layers
- Auxiliary features concatenated after each layer
- Vary the number of encoded features
- Train/Validate/Test = 70/20/10%

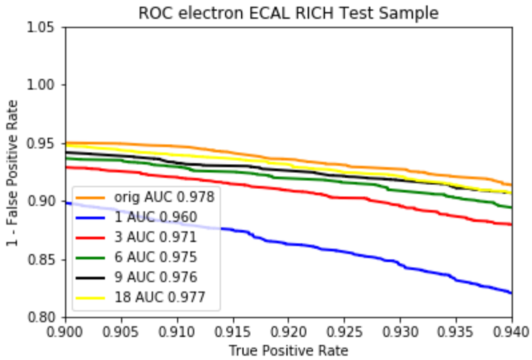
Loss



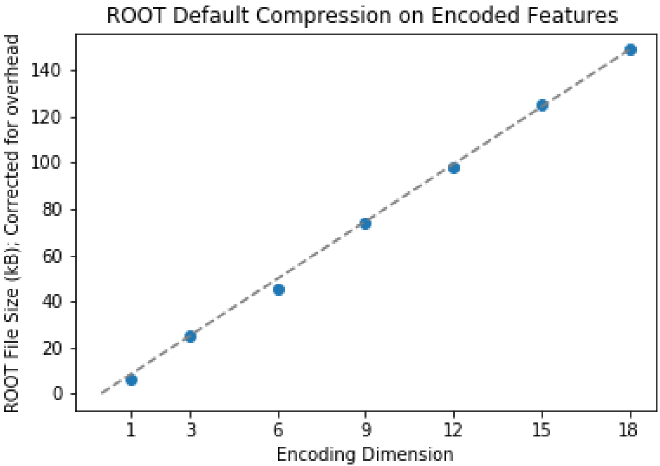
Scores 100% ECAL RICH Sample
Mean Squared Error
10^{-2}
10^{-3}
10^{-4}
1
3
6
9
12
15
18
Encoding dimension

ROC curve for electron selection





Compression on Encoded Features



Compression algorithms like gzip, zero padding are common

- ROOT's default compression (Level 4) yields file size reduction beyond autoencoding
- Need to confirm if this still holds after zero padding
- Straightforward to define algorithm to automatically optimise zero padding

Focus Points

Allows for a critical file size reduction

Potentially a way to make MC Generation in run 5 more feasible

Data at zenodo.org/record/1230552#.WuIbVlMvw6h

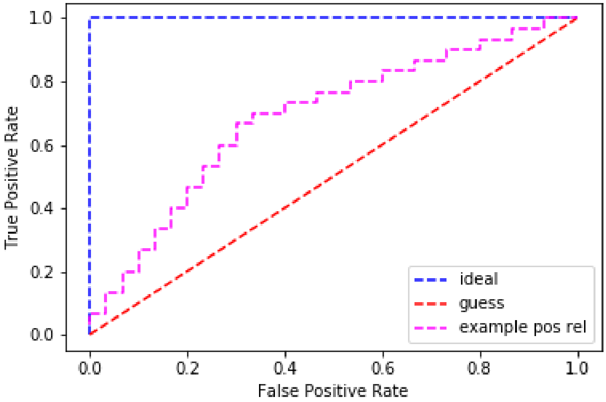
Focus Questions

Is there a smarter way to deal with missing data?

What is a rigorous way to define our optimisation goal?

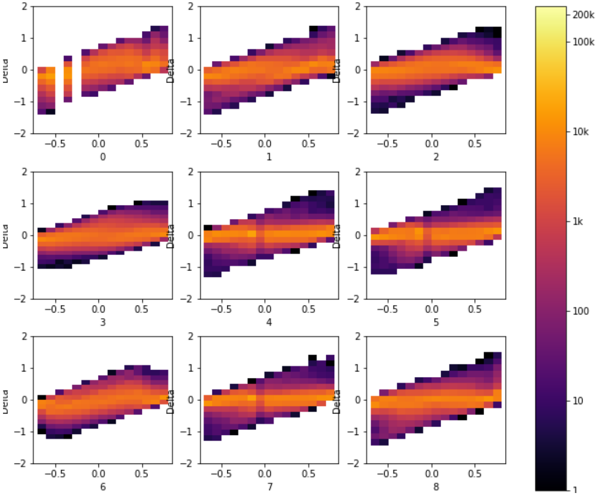
How can the sociological problem best be overcome?

ROC Curves

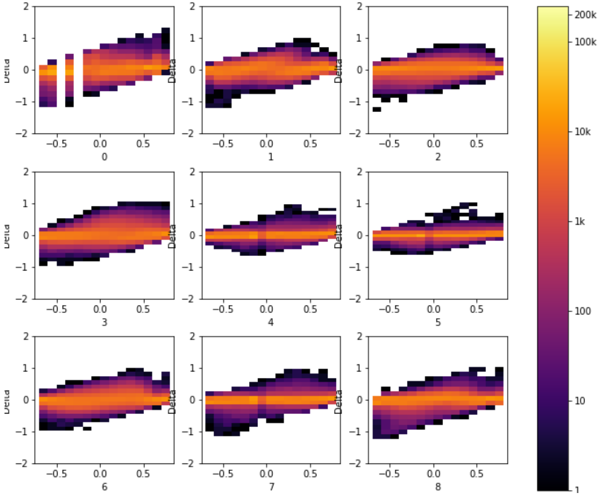


- False Positive Rate: Labelled as a muon, actually something else
- True Positive Rate: Labelled as a muon, actually a muon
- For each variable use ROC curves for distinguishing the relevant particle from all others (*e.g.* for trks_pnn_e distinguish electrons from all other particles)

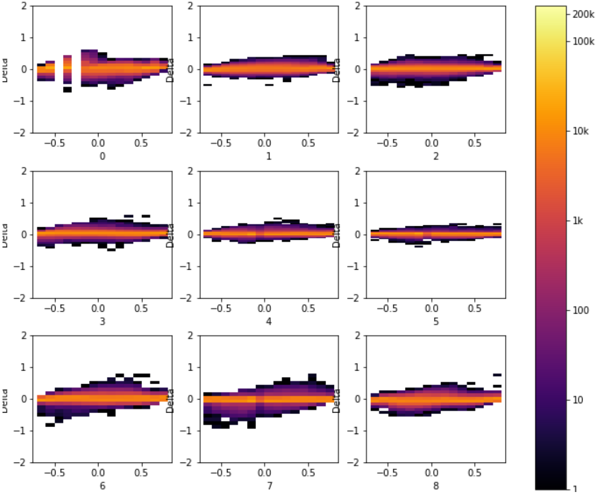
Distribution Deltas Encoding 1/18



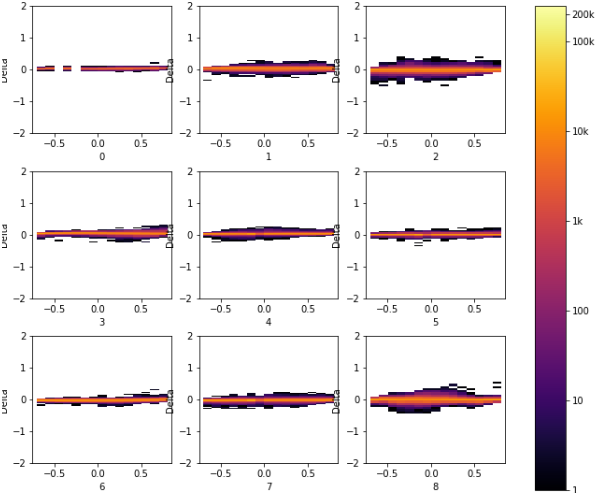
Distribution Deltas Encoding 3/18



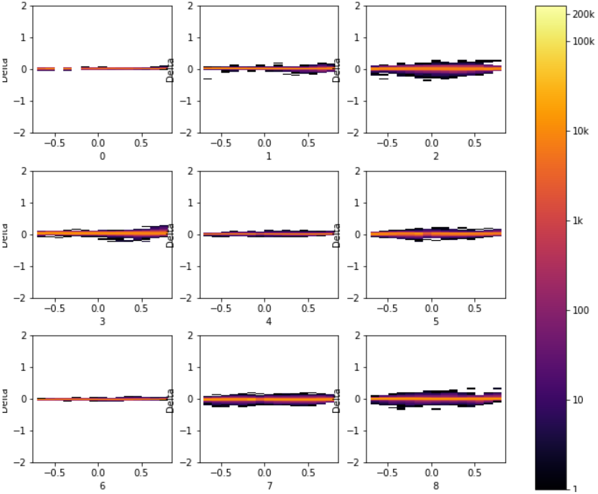
Distribution Deltas Encoding 6/18



Distribution Deltas Encoding 9/18



Distribution Deltas Encoding 12/18



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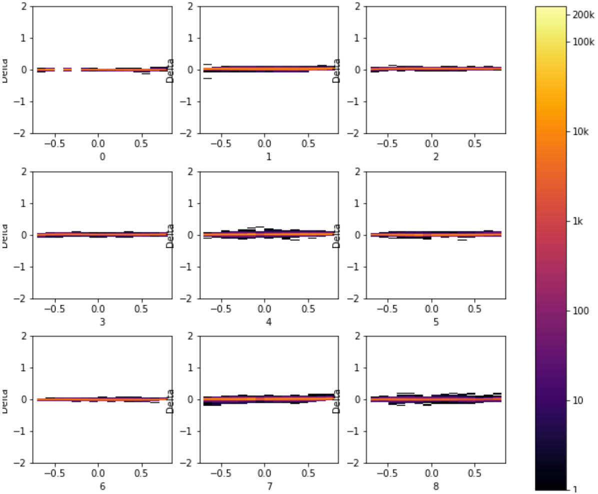

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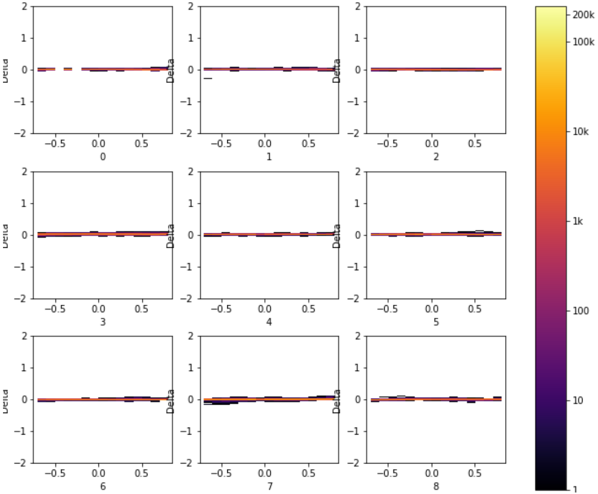

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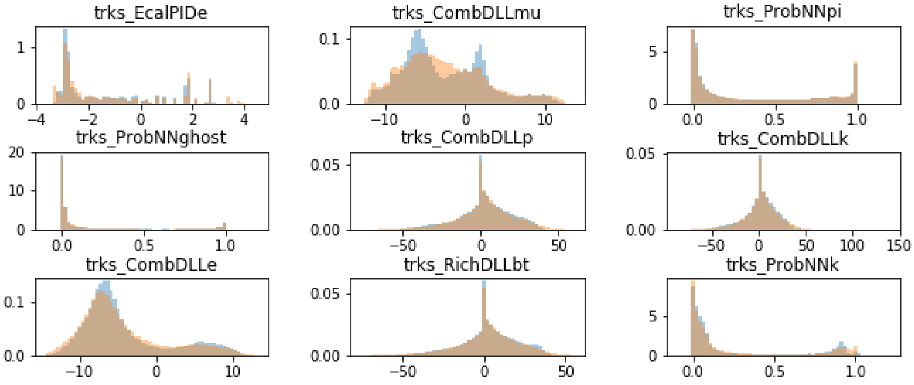

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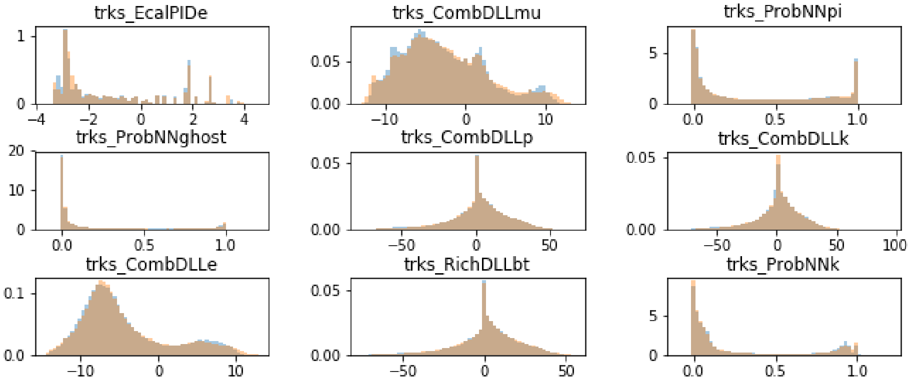

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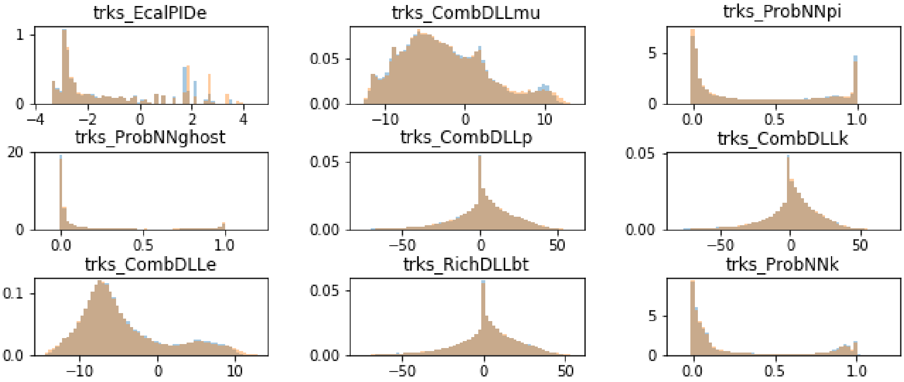

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