Particle Identification with MLPs and PINNs Using HADES Data

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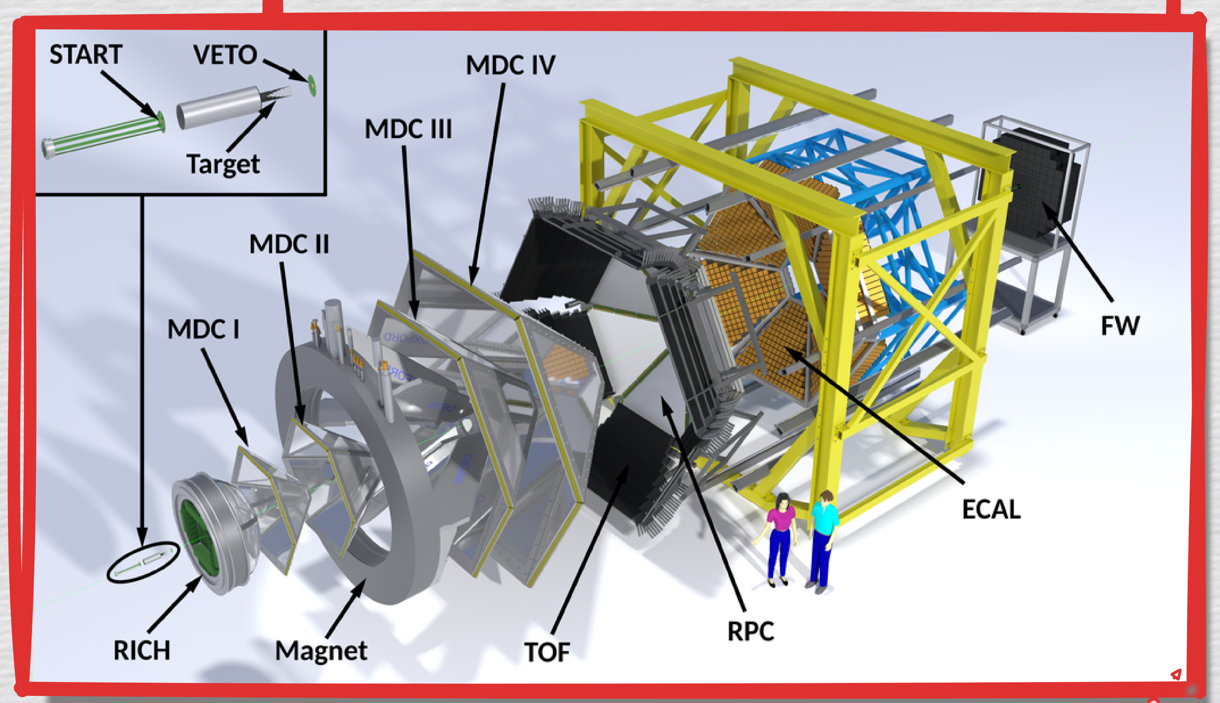
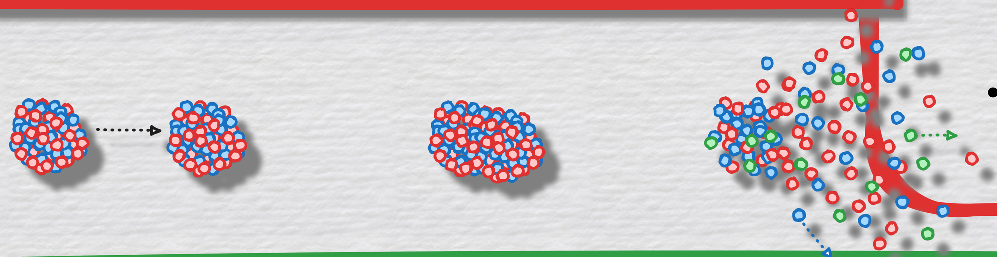
- Fixed target experiment @ GSI, Darmstadt, Germany
- Magnet spectrometer with electromagnetic calorimeter
- Heavy ion experiments (Ag+Ag, Au+Au)
  - Average particle multiplicities per event ~100
  - Complex systems with kinematically overlapping channels
  - Identification limited to measured final state properties and their resolution
- Elementary reactions (p+p, π+p)
  - Average particle multiplicities ~3
  - Kinematically well-defined channels
  - Identification via measured final state properties and kinematic constraints

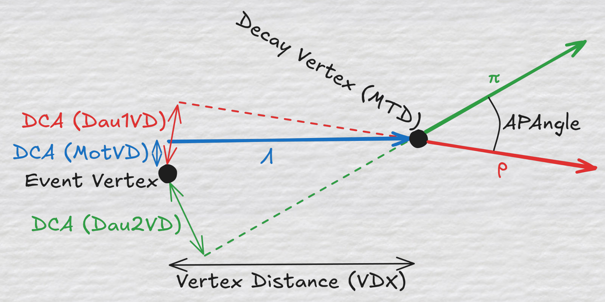
High **A**cceptance **D**i-**E**lectron **S**pectrometer





Current Methods

- Decaying (off-vertex) particles [1]:
  - MLP (FFNN) training on geometric variables and kinematic constraints
    - Simulation of decaying particles as signal
    - "Mixed Event" technique for data-driven combinatorial background emulation



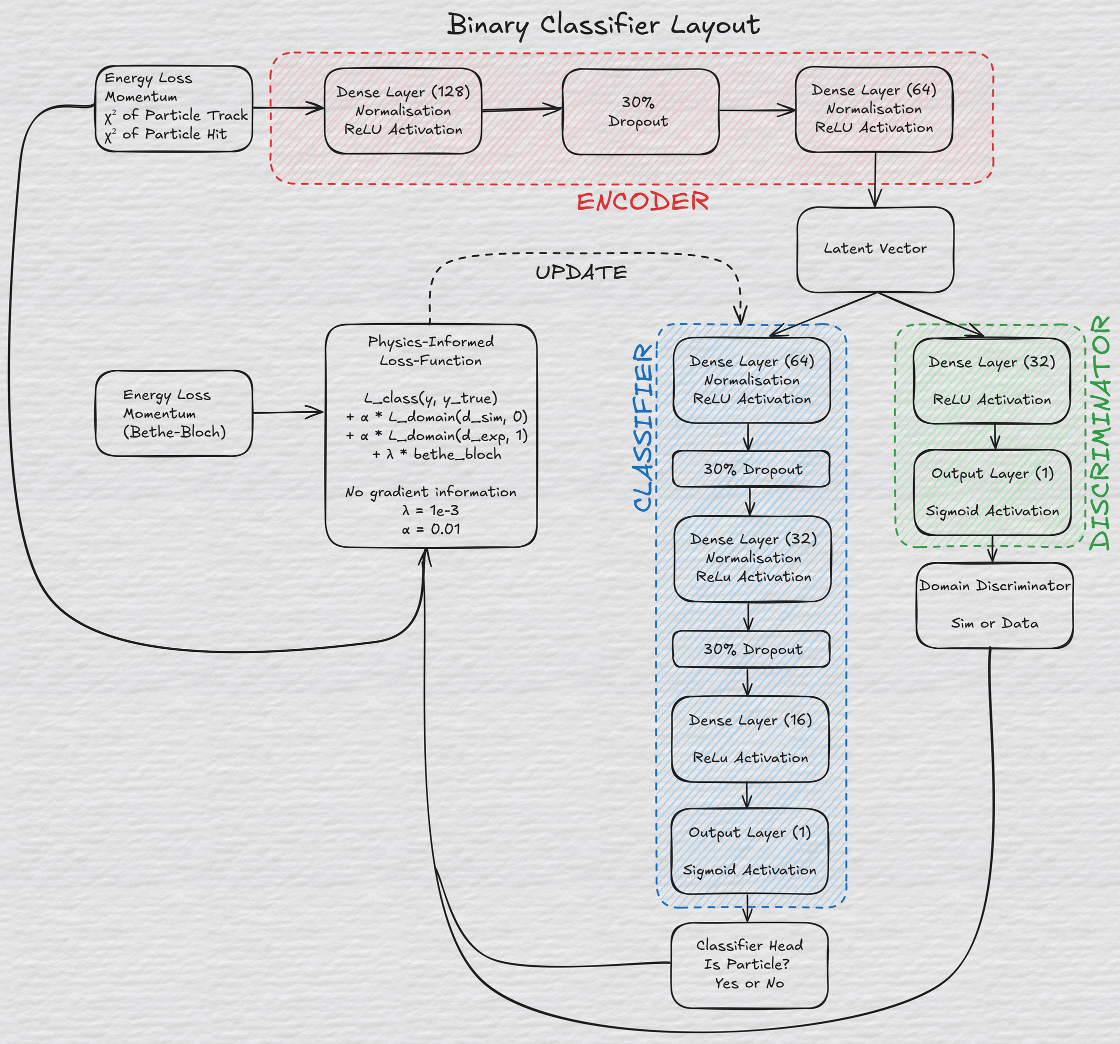
- "Stable" charged particles:
  - Currently user-defined criteria (heavy ion) combined with kinematic constraints (elementary)
  - Studying the performance of Physics Informed Neural Networks (PINNs) for this task is hoped to improve the PID

PIDANN Setup

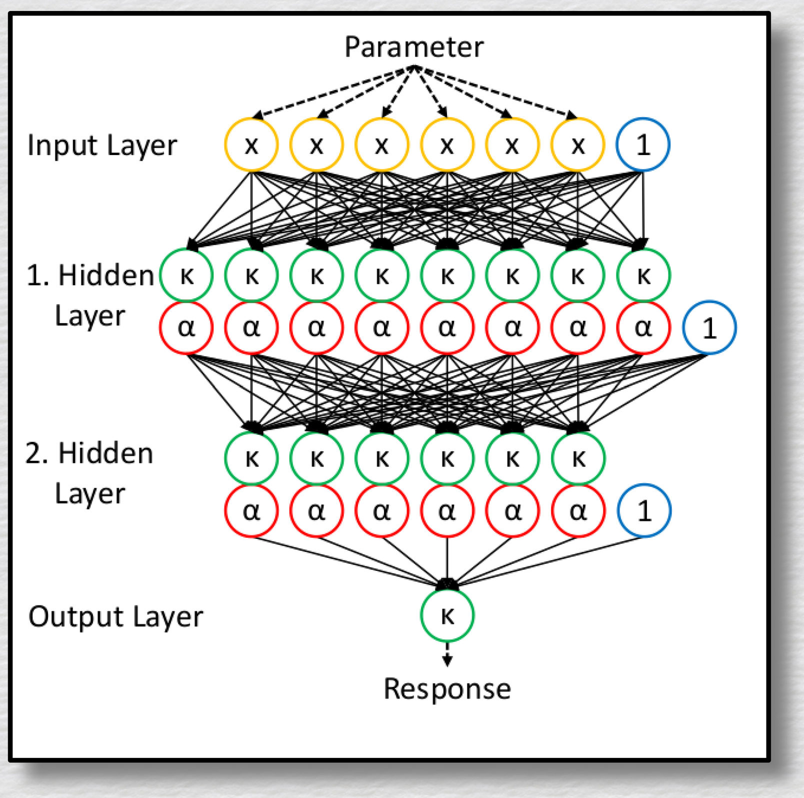
Domain-Adversarial Neural Network is composed of :
1) Encoder – uses raw input and maps it into feature-space
2) Classifier – builds on the Encoder's features to predict the label
3) Discriminator – compares similarity of simulation and data

Advantage:
Comparison of labeled simulation training data to real data
➤ Suppress training on simulation artifacts (better real-world performance)

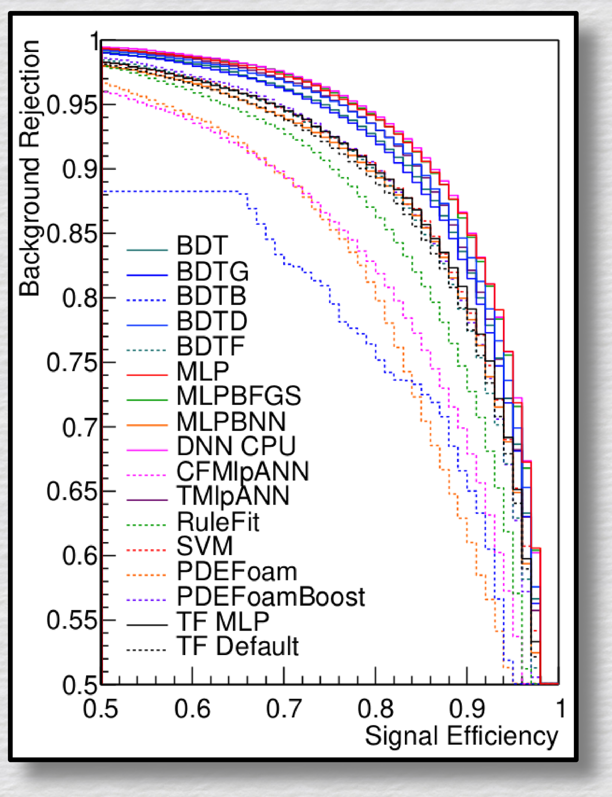
Physics-Informed NNs utilise a custom loss function, which penalises large deviations of properties of classified particles from theoretical values for particle hypothesis



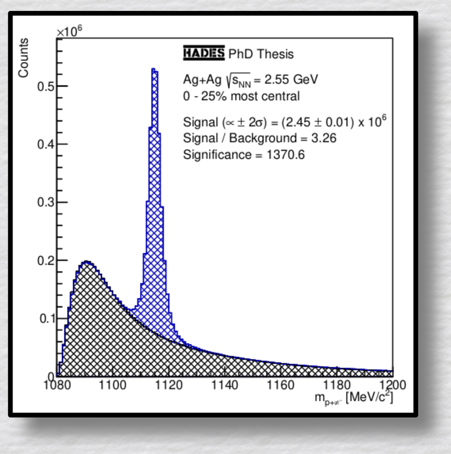
MLPs for Off-Vertex Particles

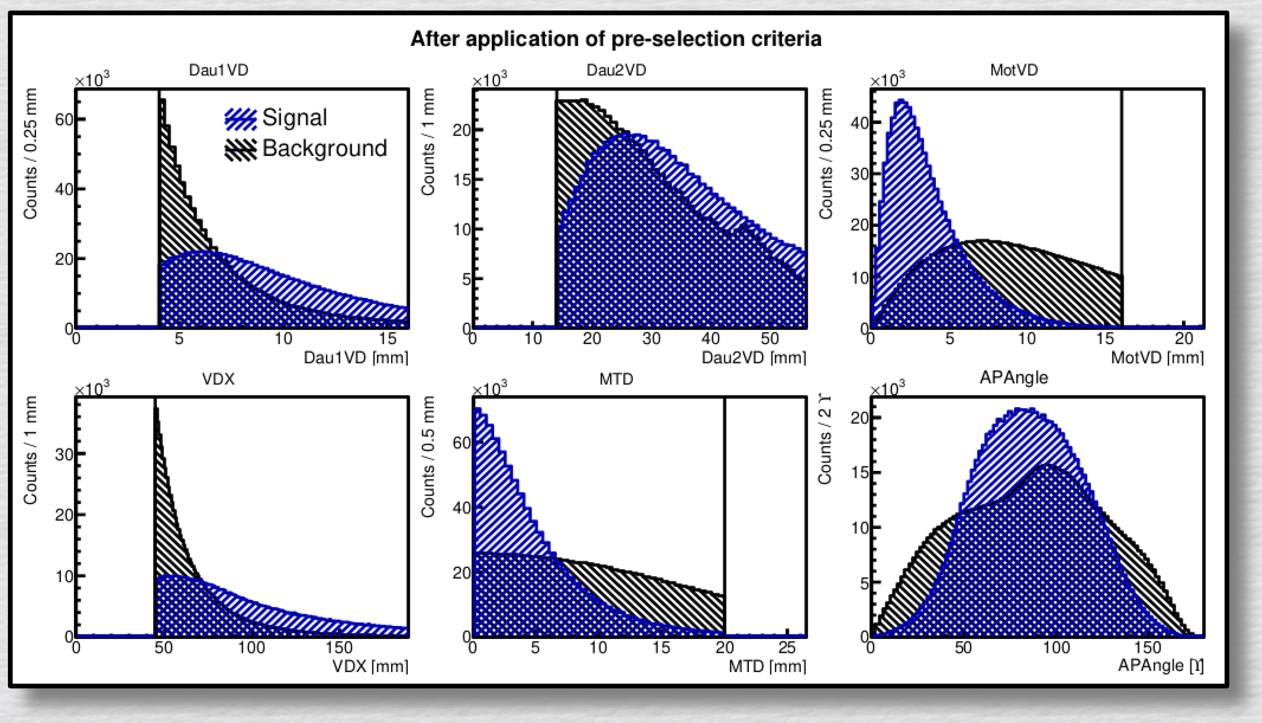


- Multi-Layer-Perceptron as part of TMVA package of ROOT performs best in PID
- MLPs are FFNNs with at least one hidden layer with all layers fully connected (dense)
- As particle decays follow exponential law (occur most abundantly near event vertex) topology parameters only obtain discrimination power, preselection-cuts have to be applied before the training

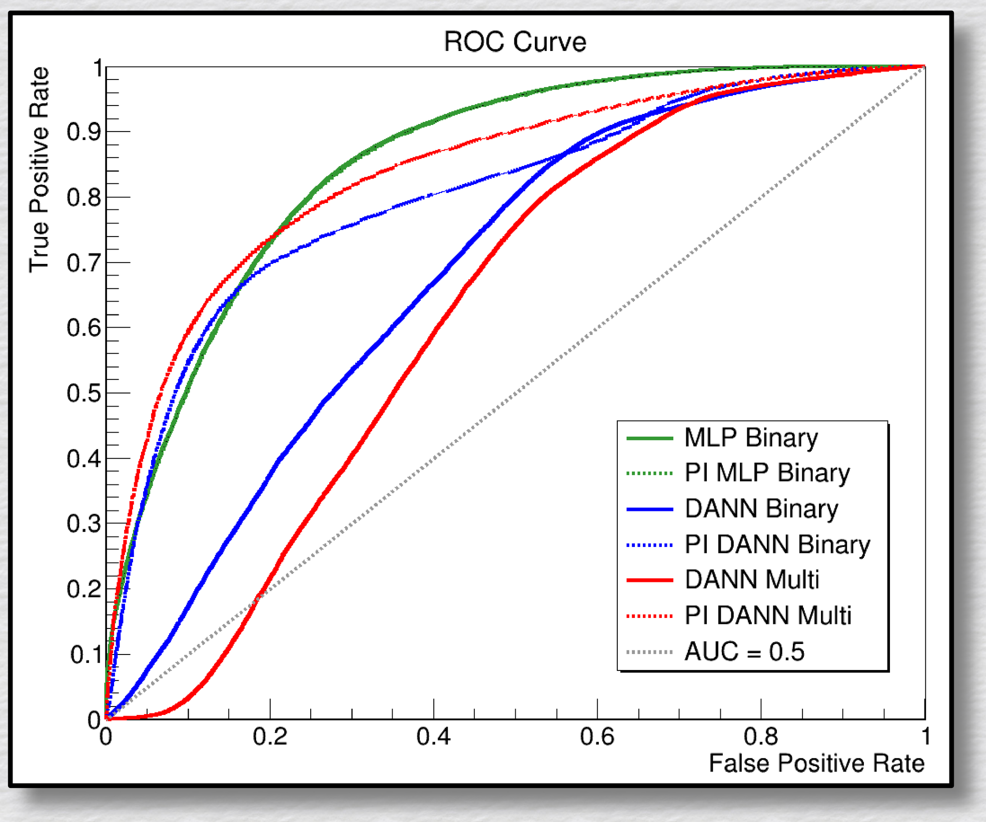


- Preselection cuts are tuned by defining sets of criteria, training an ANN for each and selecting for optimised significance of the obtained signal (Λ shown below)



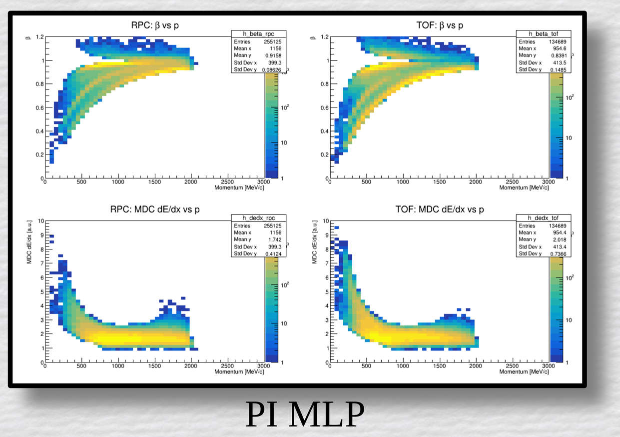


Physics Information for Rare Particles



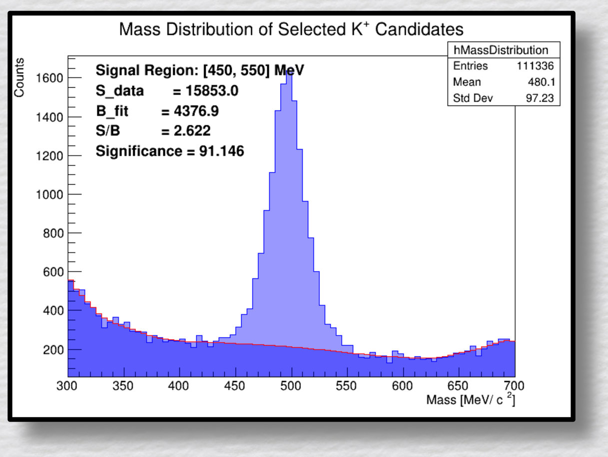
- Goal is identification of K^+ in heavy-ion data (Ag+Ag at $\sqrt{s_{NN}} = 2.55$ GeV), on average produced once every 100th event (protons and pions dominate selection region)
- Impact of physics information varies
  - MLPs seem mostly insensitive to physics information, relying more on simulated data for training
  - DANN performance increases significantly by adding physics information, appears to compensate for loss due to discrimination

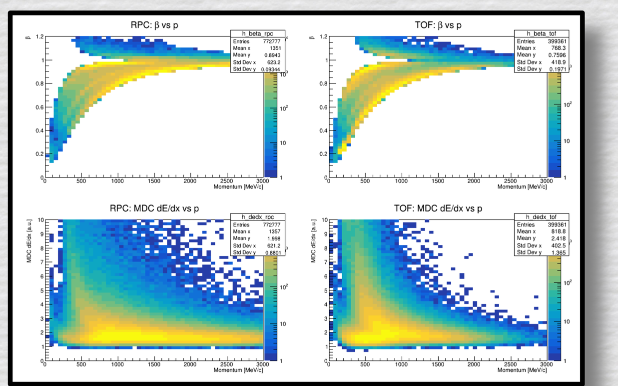
- Physics analyses rely on the reconstruction of particles along the full available angular and momentum range



PI MLP
AUC = 0.85

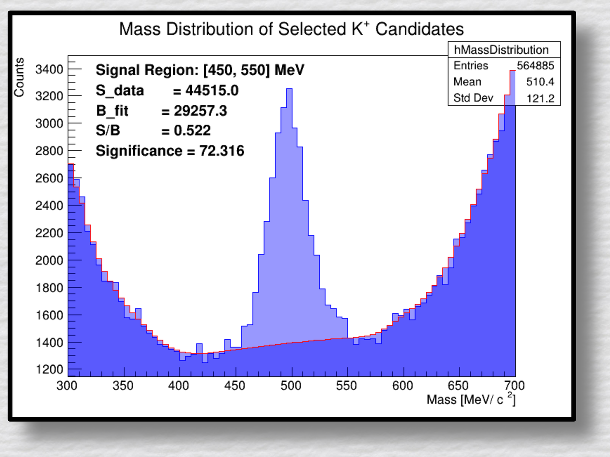
Like "Hard-Cuts"





PI DANN
AUC = 0.81

Feature-Based



Conclusion

	MLPs	DANNs
Training	Relies on accuracy of simulations in the description of real data	Factors in feature differences between data and simulation to adjust loss
Physics Information	Does not significantly alter the overall performance	Significantly improves the overall performance
Particle Identification	Best S/B and significance, however strict cut-offs of unverifiable origin	Comparable to classical analysis, however no strict cut-offs and focus on physics features

- More detailed investigations to be performed regarding the input, the hyperparameters and the physics information
- Combination of PI DANN with subsequent classical cut-based analysis could potentially improve results

[1] DOI: 10.21248/gups.68651

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- Input for DANN: Simulation (labelled) to Data (unlabelled) 50/50
- Training-Test-Split: 80/20, Sample-Weighting: Balanced
- Learning Rate: 1e-4 (Adam Optimizer), Training Epochs: 15, Classifier Metric: AUC

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