

Market Intelligence Overview

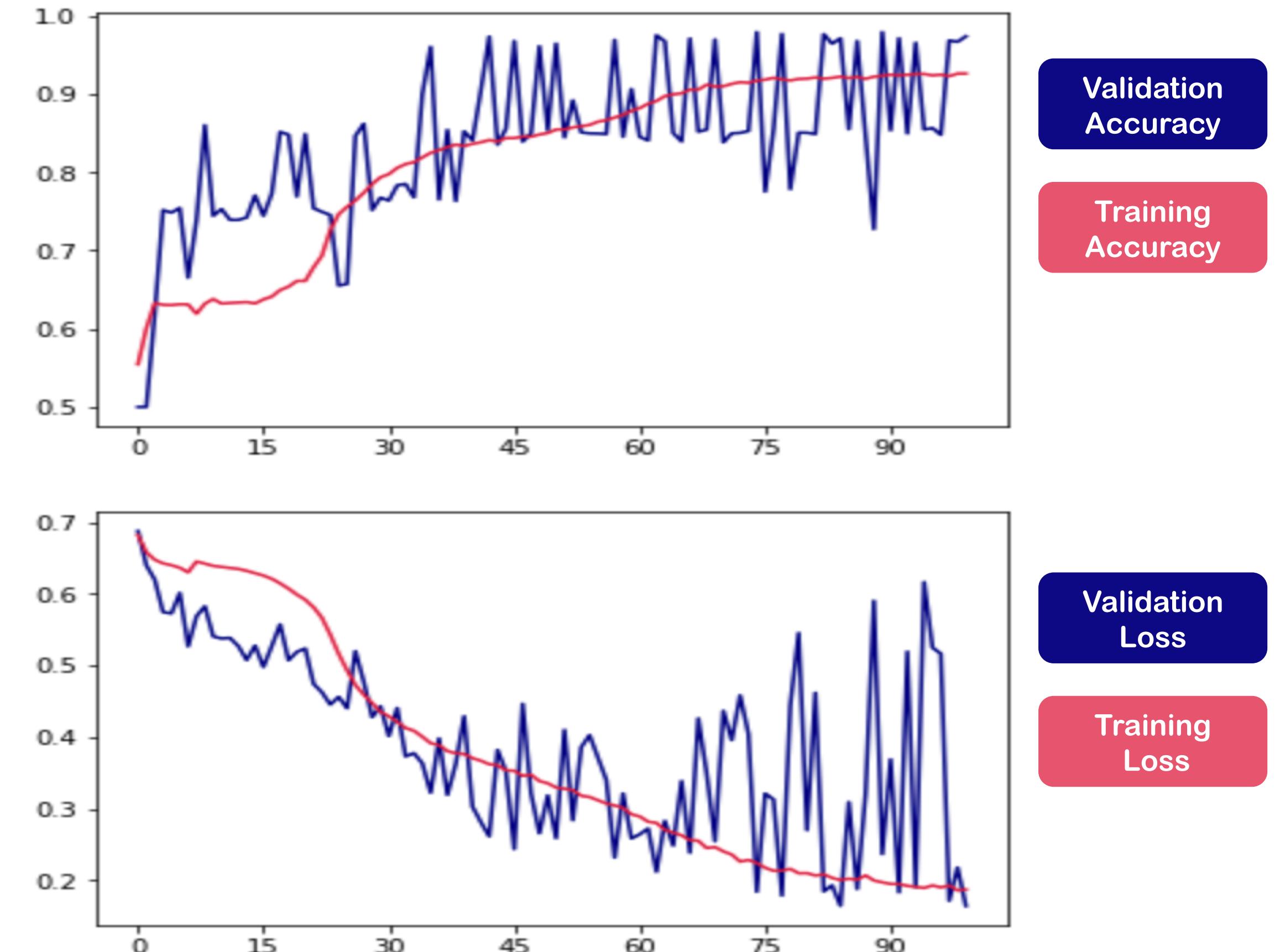
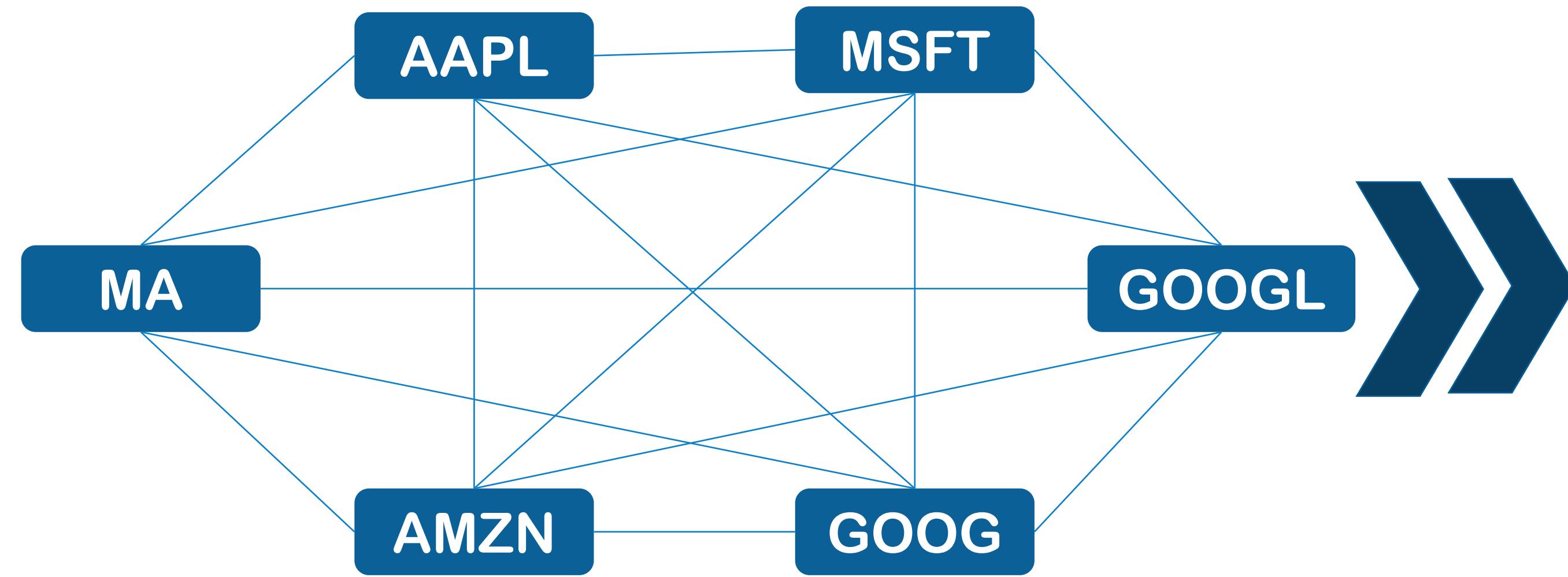
Donggeun Kim

0. Motivation



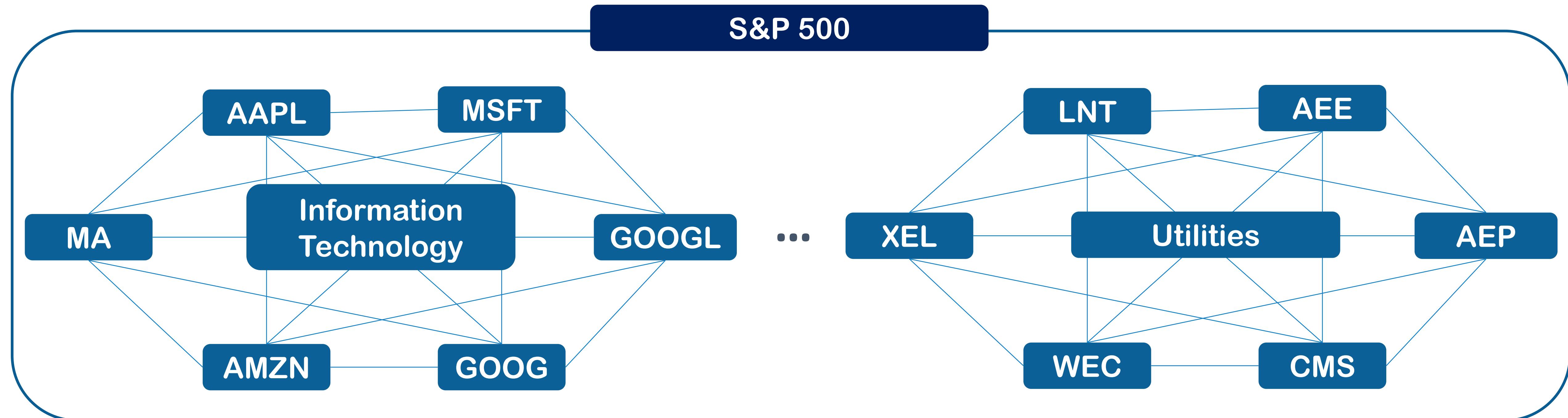
Can AML predict extreme market outcomes such as the 2008 Financial Crisis?

1. Overview



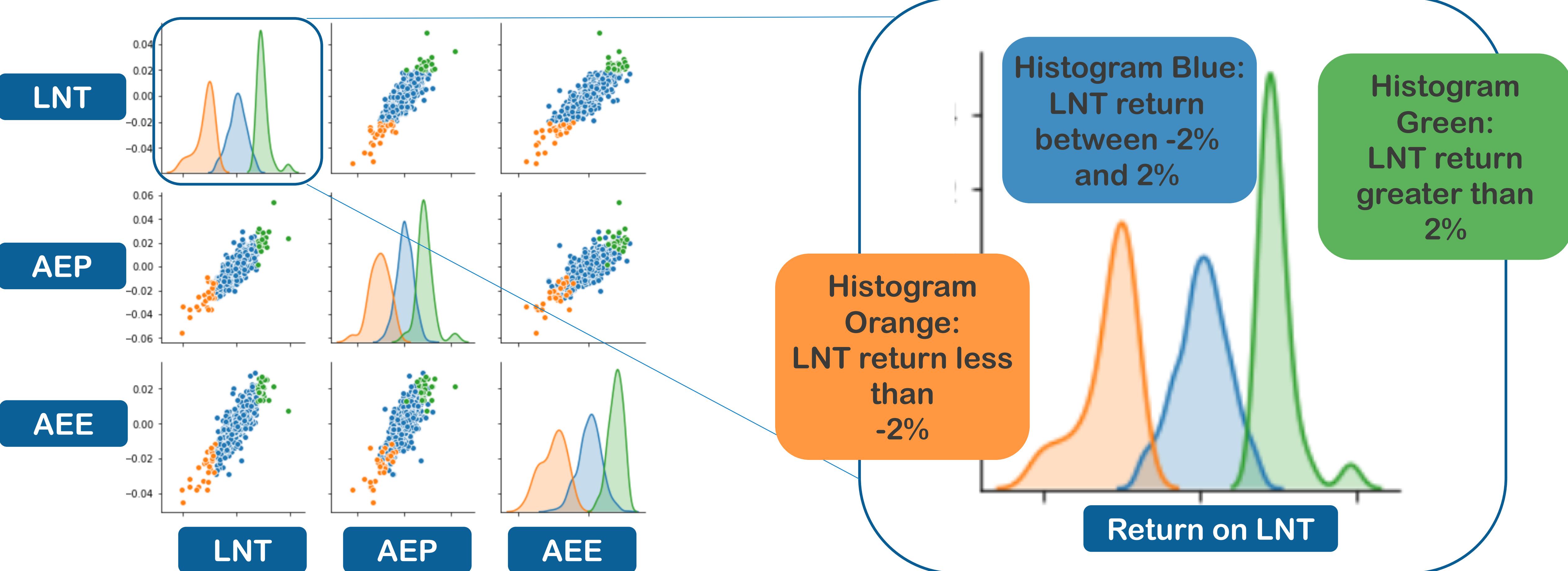
From feature selection to AML pipelines

2.1 Feature Selection – Bayesian Network



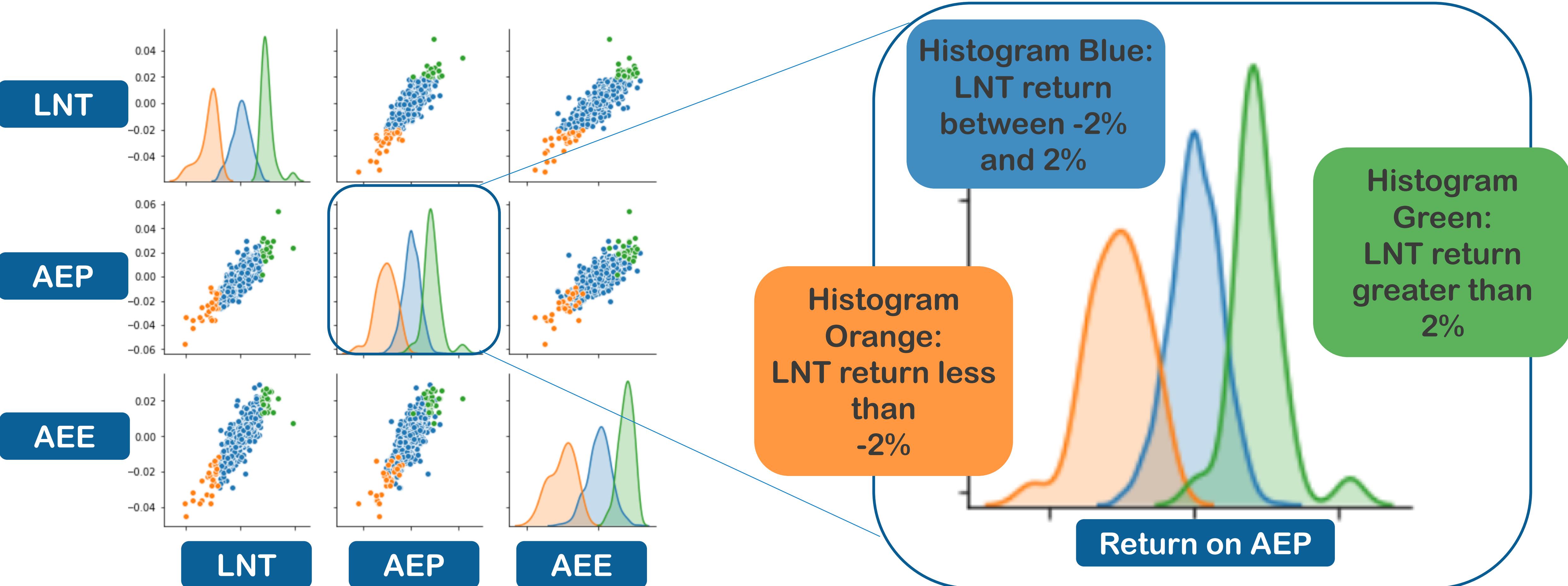
Track most relevant stocks by means of edge contributions or search for the strongest cointegrating relationship.

2.2 Feature Selection – Discerning Explanatory Variables



Figures on diagonals represent return distributions of LNT, AEP and AEE, separated by labels based on realization of LNT returns

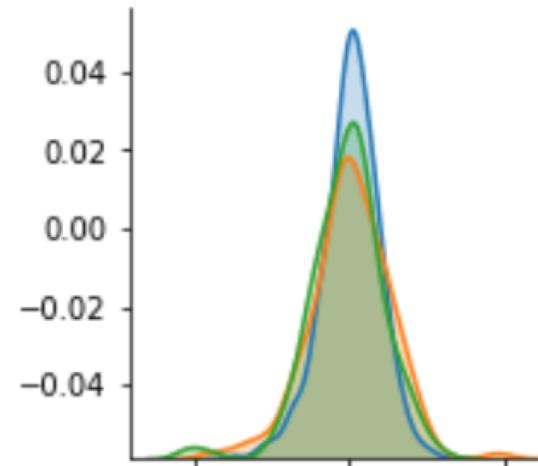
2.2 Feature Selection – Discerning Explanatory Variables



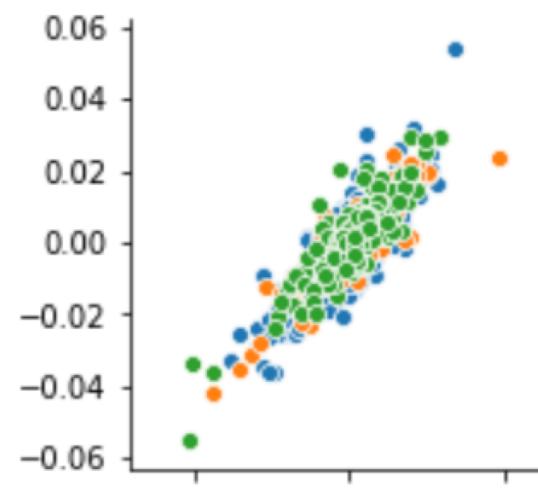
Characteristic of discerning distributions: Distributions are well separated by target labels

2.2 Feature Selection – Non-Discerning Explanatory Variables

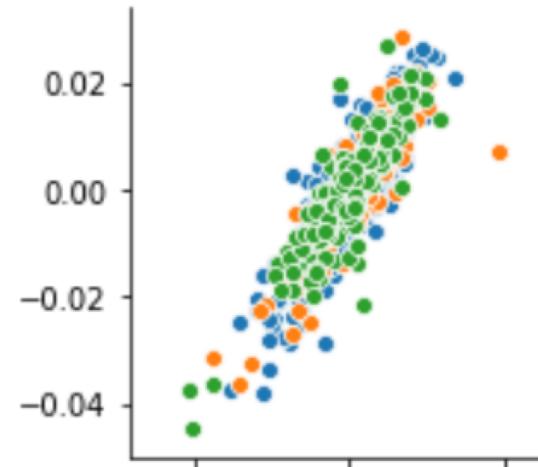
LNT
lag1



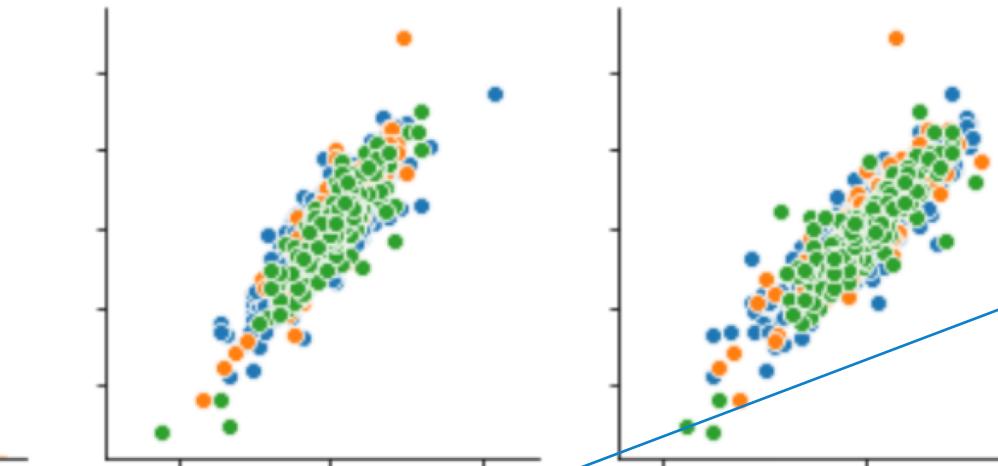
AEP
lag1



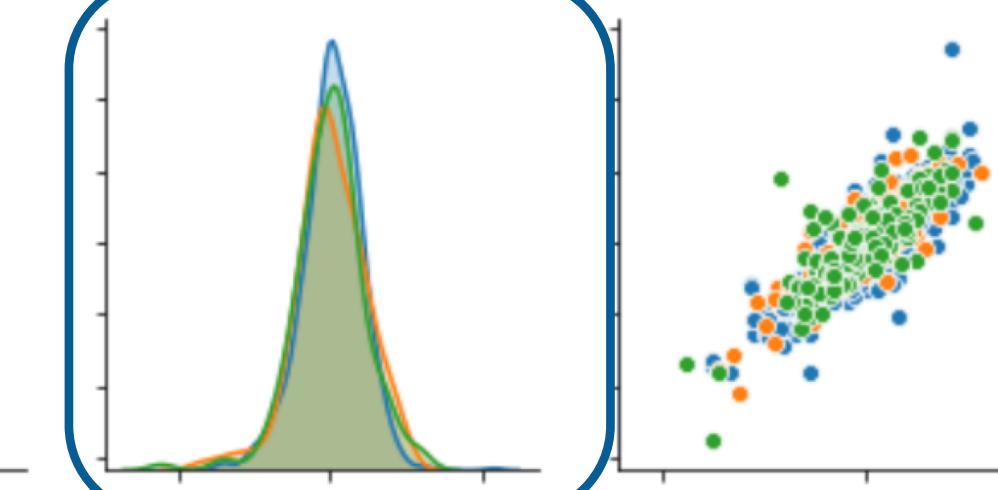
AEE
lag1



LNT
lag1



AEP
lag1



AEE
lag1

Histogram Blue:
LNT return
between -2%
and 2%

Histogram
Orange:
LNT return less
than
-2%

Histogram
Green:
LNT return
greater than
2%

Lagged return
on AEP

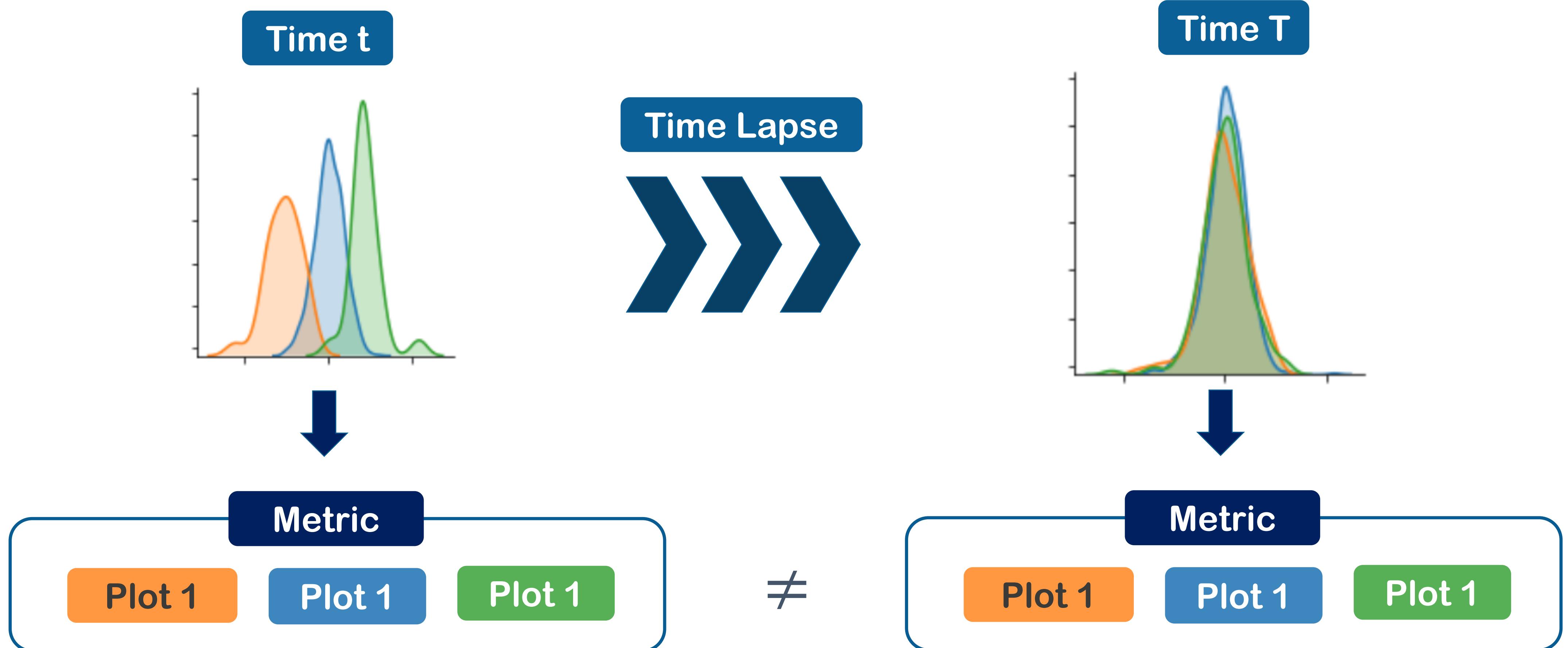
Characteristic of Non-Discerning Explanatory Variables: Distributions cannot be isolated by target labels
Less contributions from these variables

2.3 Feature Selection – Auto-selection



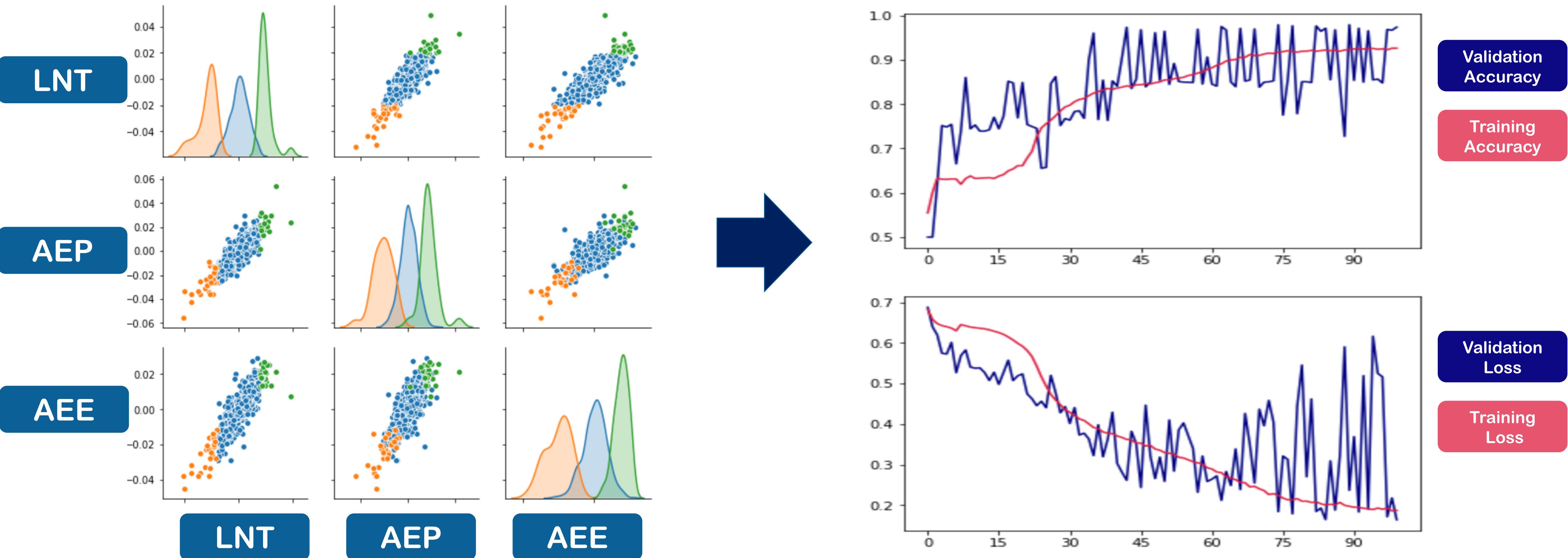
Auto-selection should prefer differentiated target-label-induced distributions such as plot 1 relative to plot 2.
Candidate metrics include Kullback-Leibler divergence or Two-sample Kolmogorov-Smirnov test.
Not referring to a metric induced by a metric space

2.4 Feature Selection – Non-stationarity



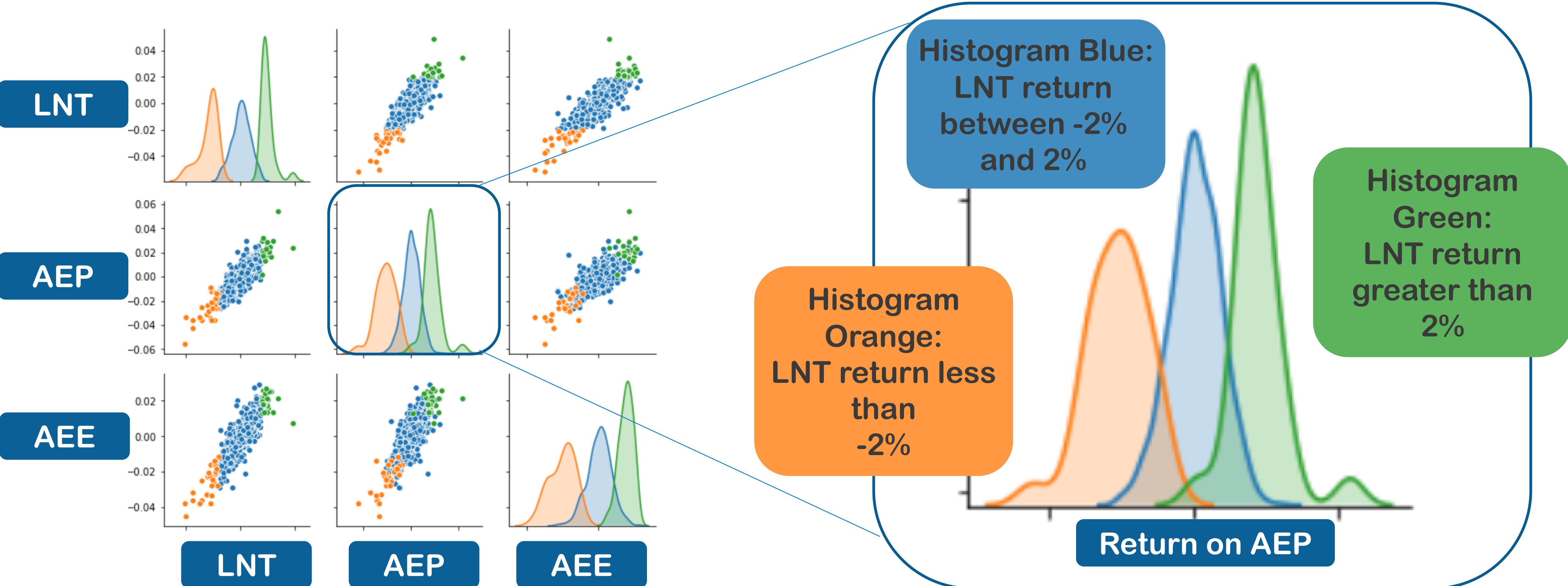
Nonstationary data may result in changes in target-label-induced distributions, violating modeling assumptions.
Use metrics to compare recent realization of distributions with distributions used during training process.
For example, Kullback-Leibler divergence computes information gain by making use of recently realized distributions.

3. Modeling



Use the best set of features for a variety of modeling approaches

3.1 Modeling – Group Return Prediction

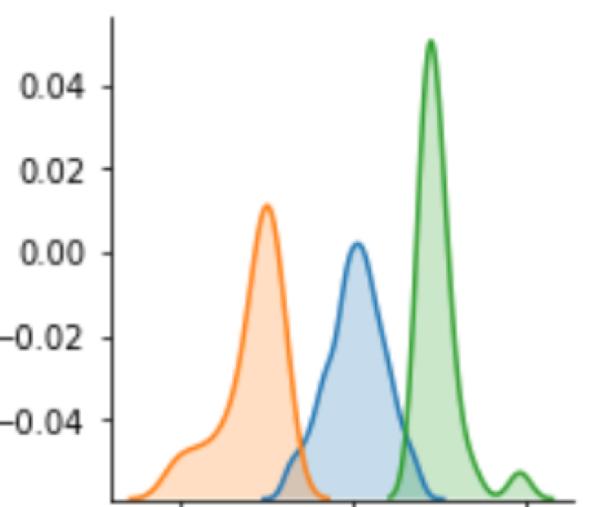


Observation 0:

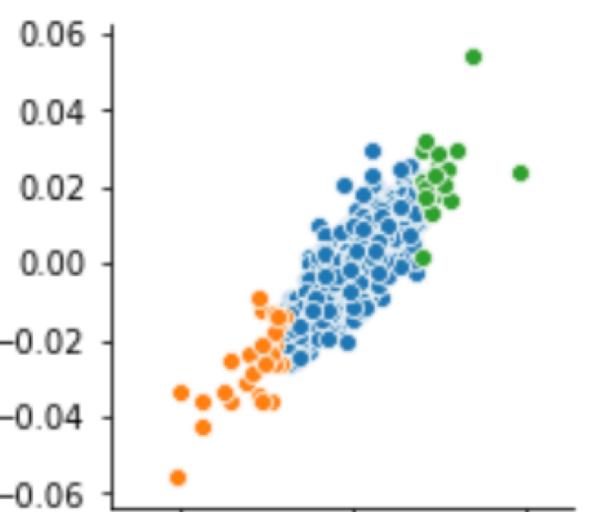
When LNT return is less than -2%, return on AEP is always negative.
When LNT return is greater than 2%, return on AEP is always positive

3.1 Modeling – Group Return Prediction

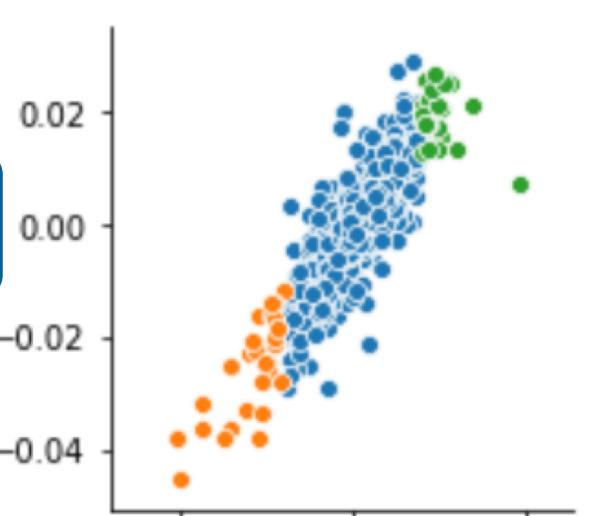
LNT



AEP



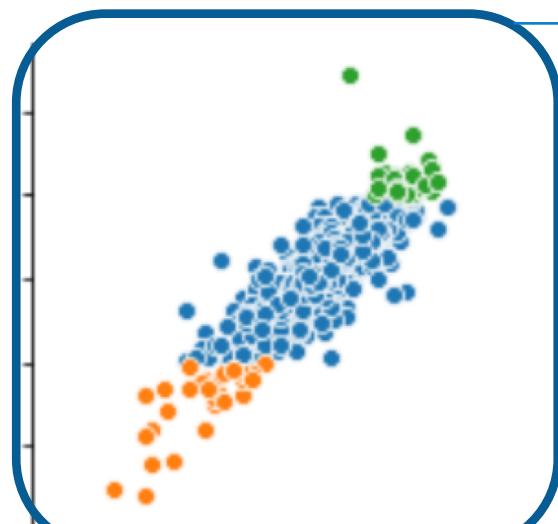
AEE



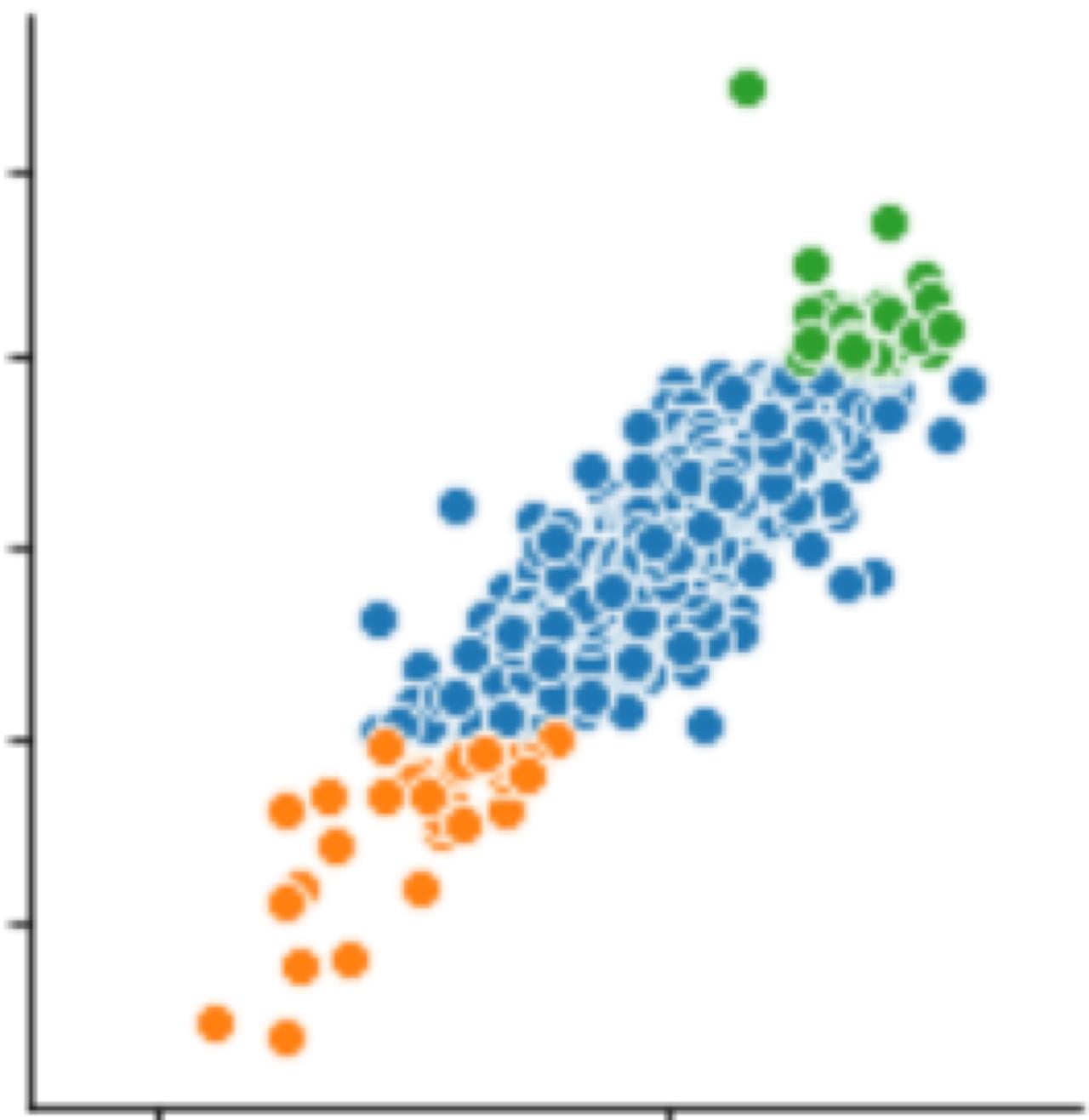
LNT

AEP

AEE



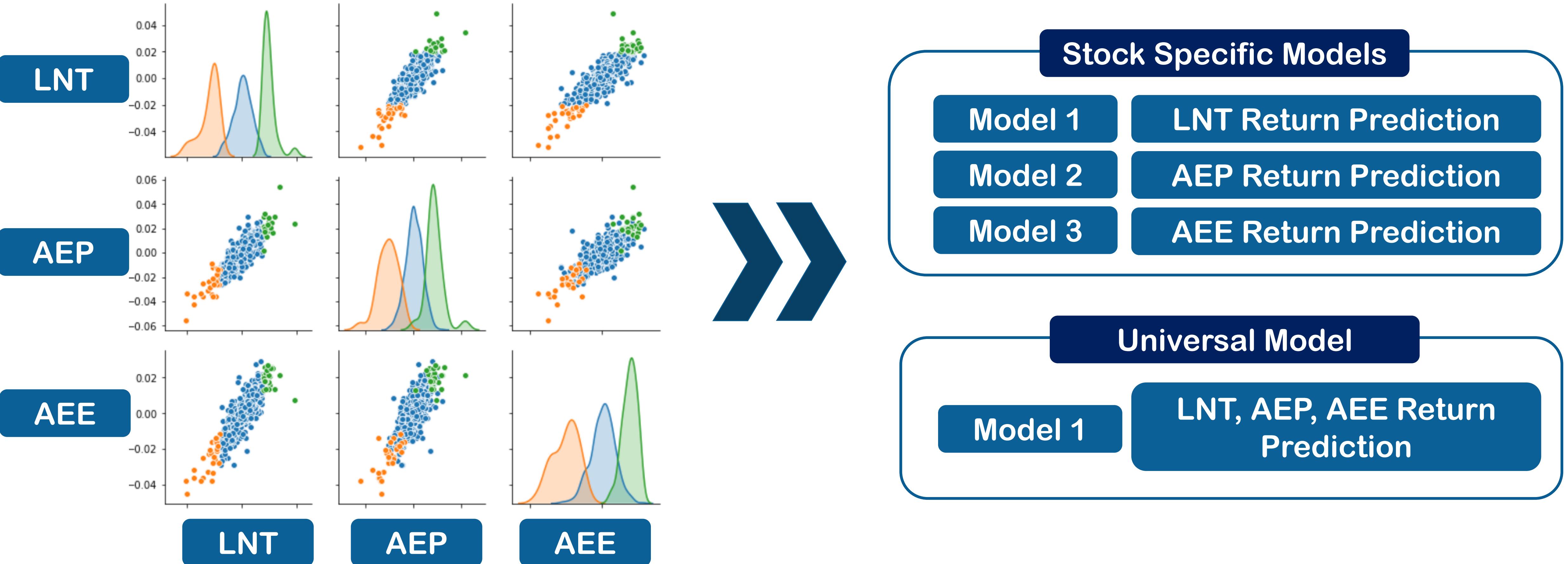
Return on LNT



Return on AEE

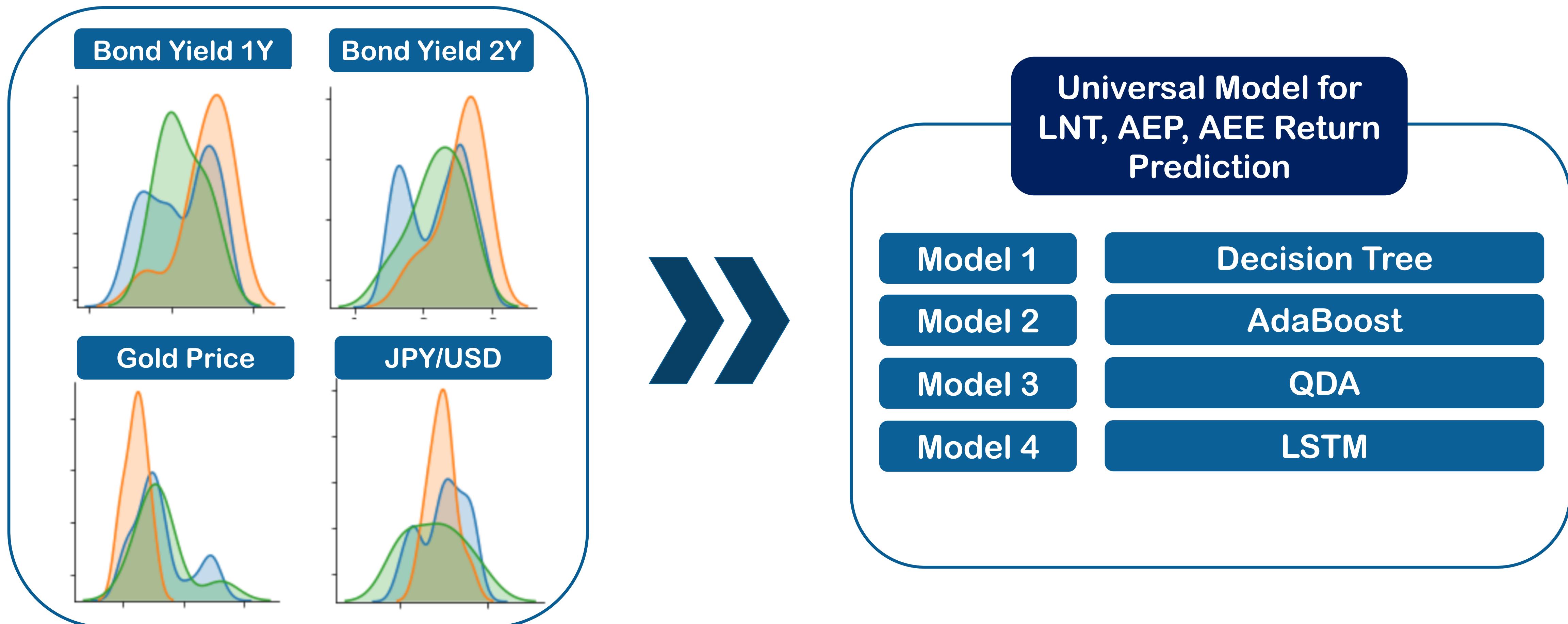
Observation 1: high correlations for stocks within this particular group

3.1 Modeling – Group Return Prediction



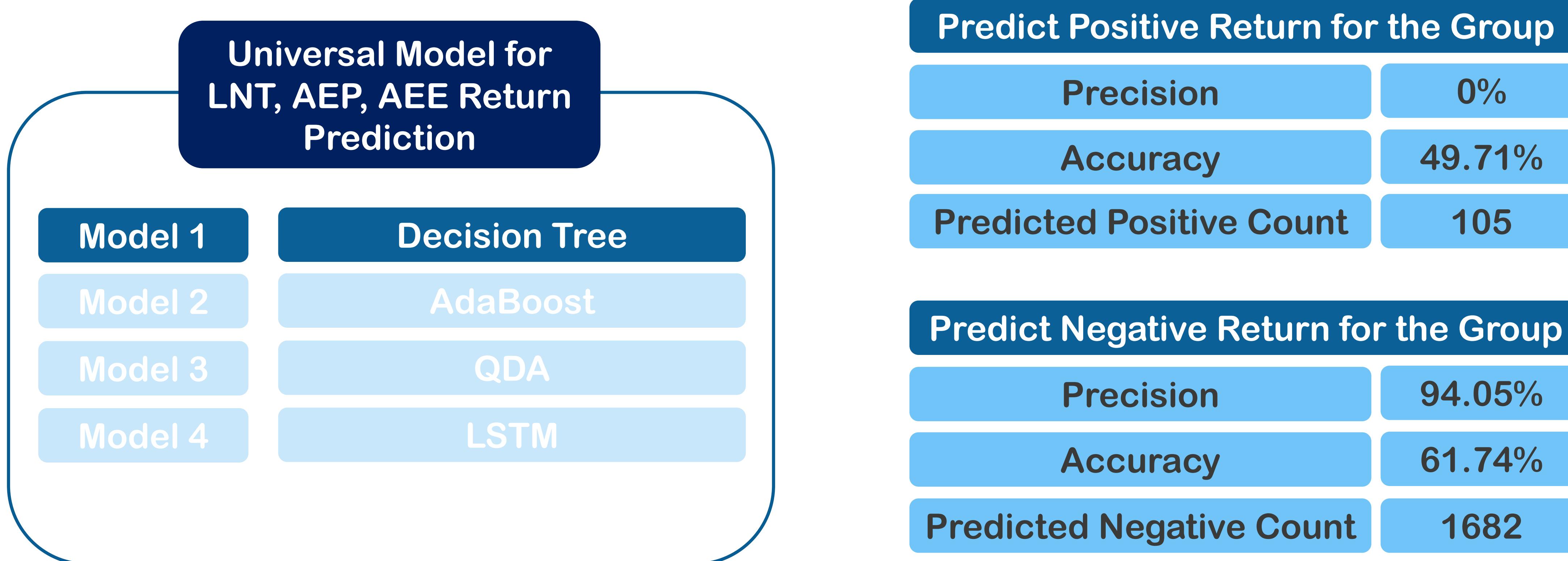
Observations give possibility of stock-specific modeling approaches AND locally universal modeling frameworks

3.2 Modeling – Predict Universal Labels



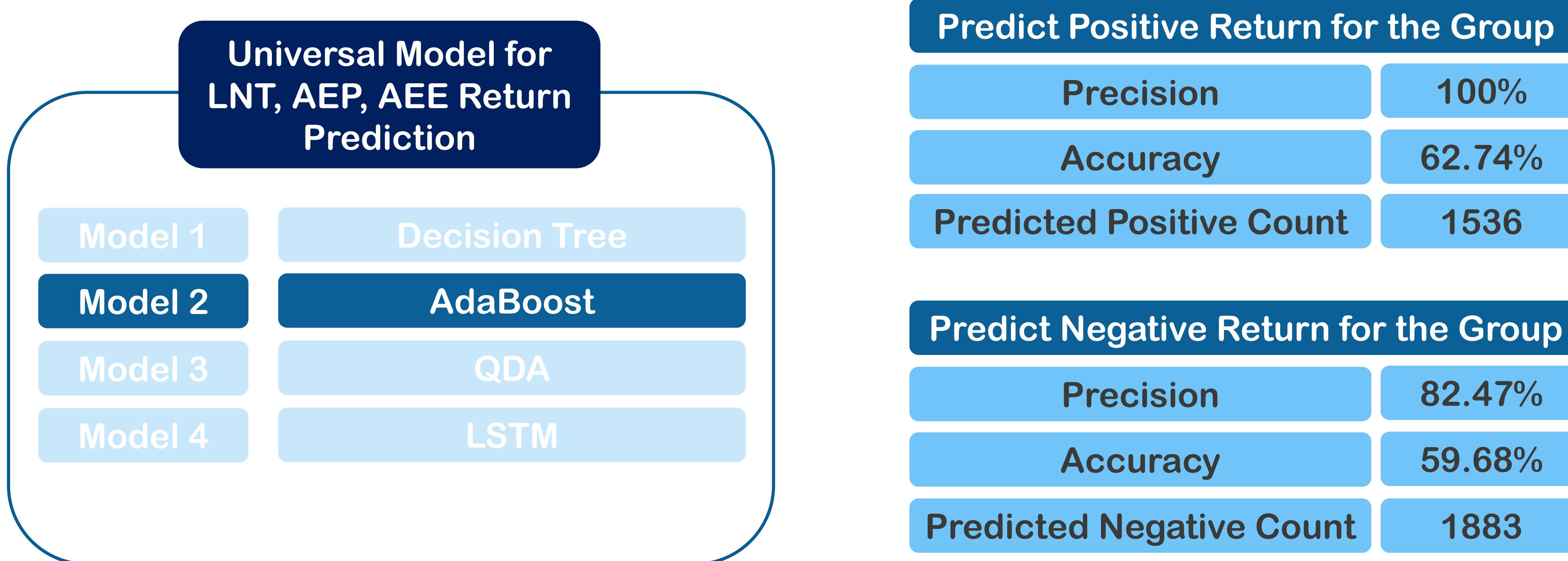
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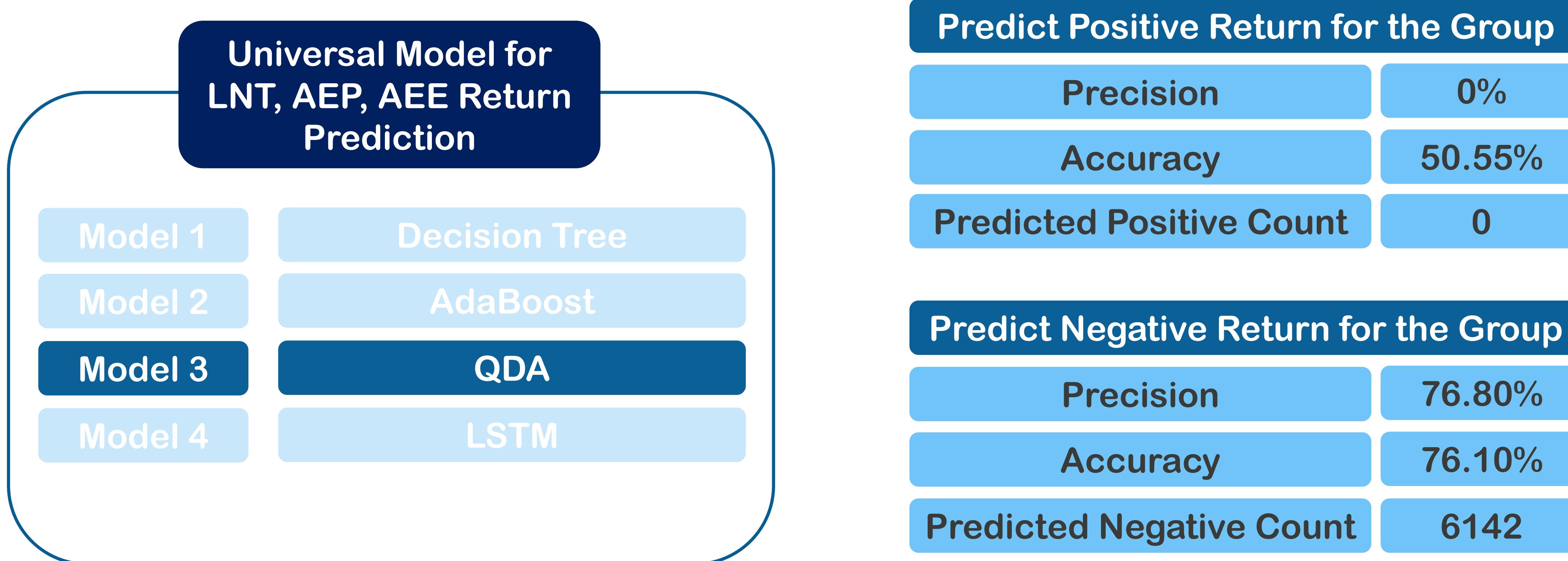
When distribution can be well separated by target labels, there should exist an effective model

3.2 Modeling – Predict Universal Labels



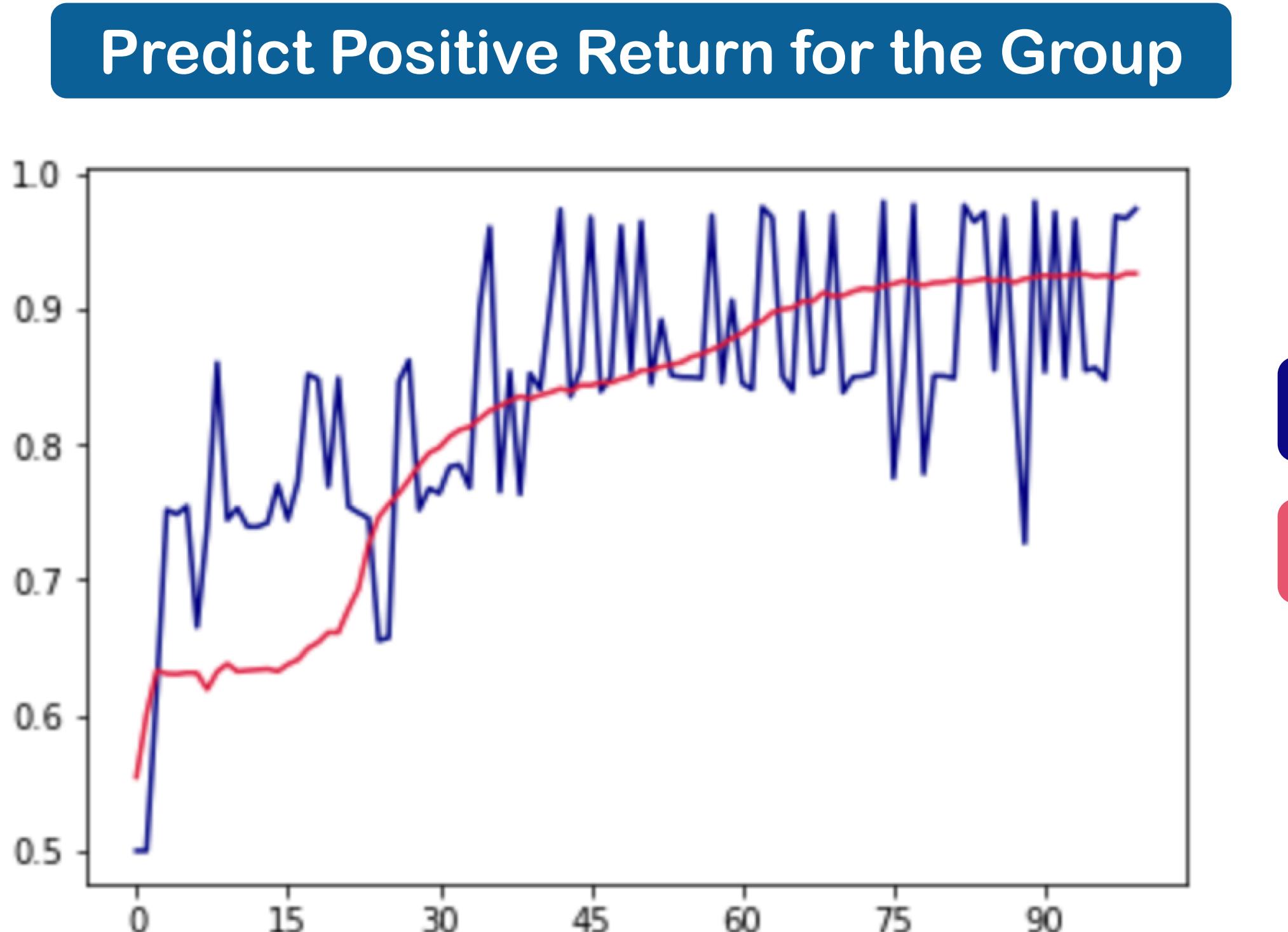
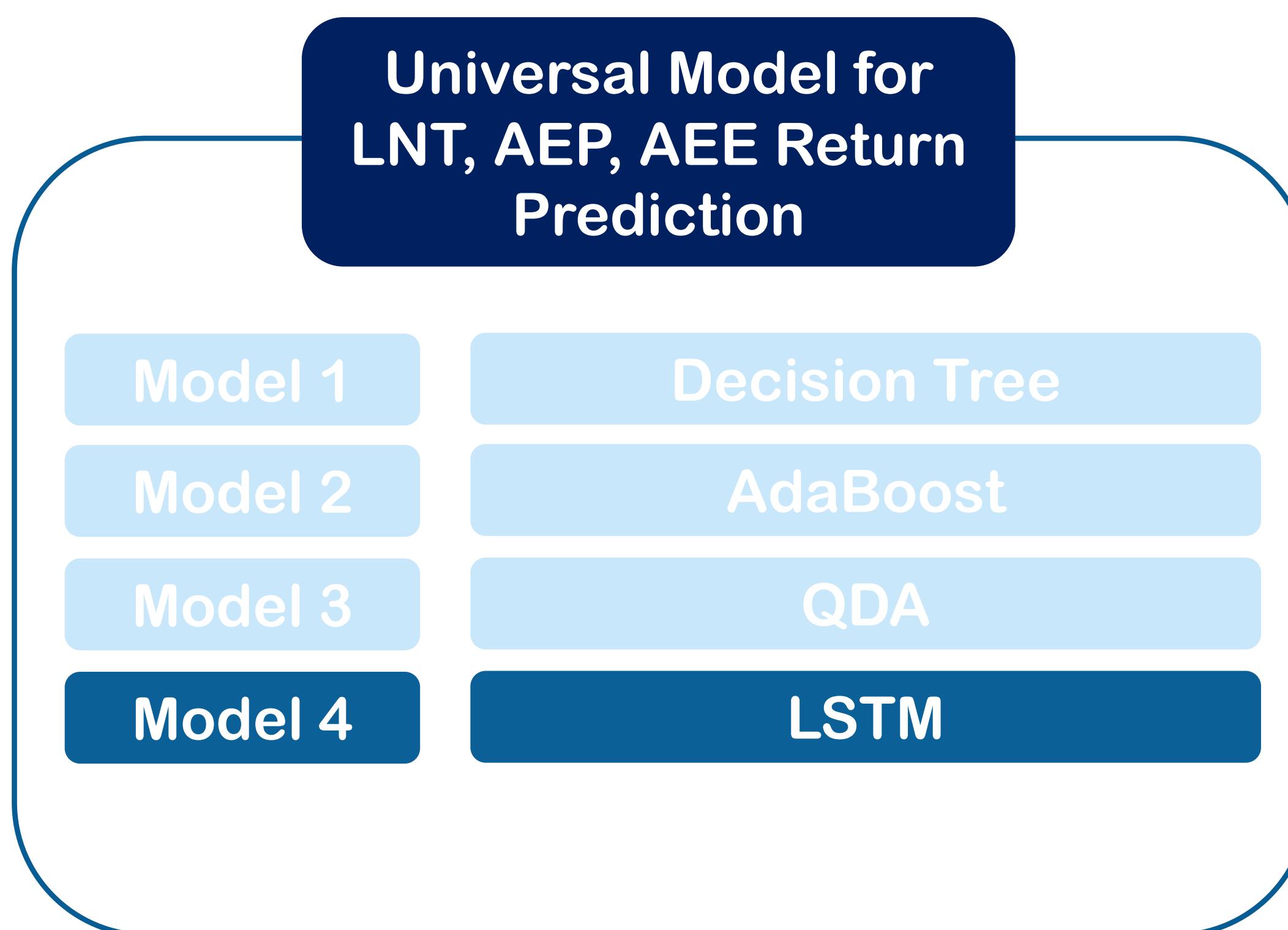
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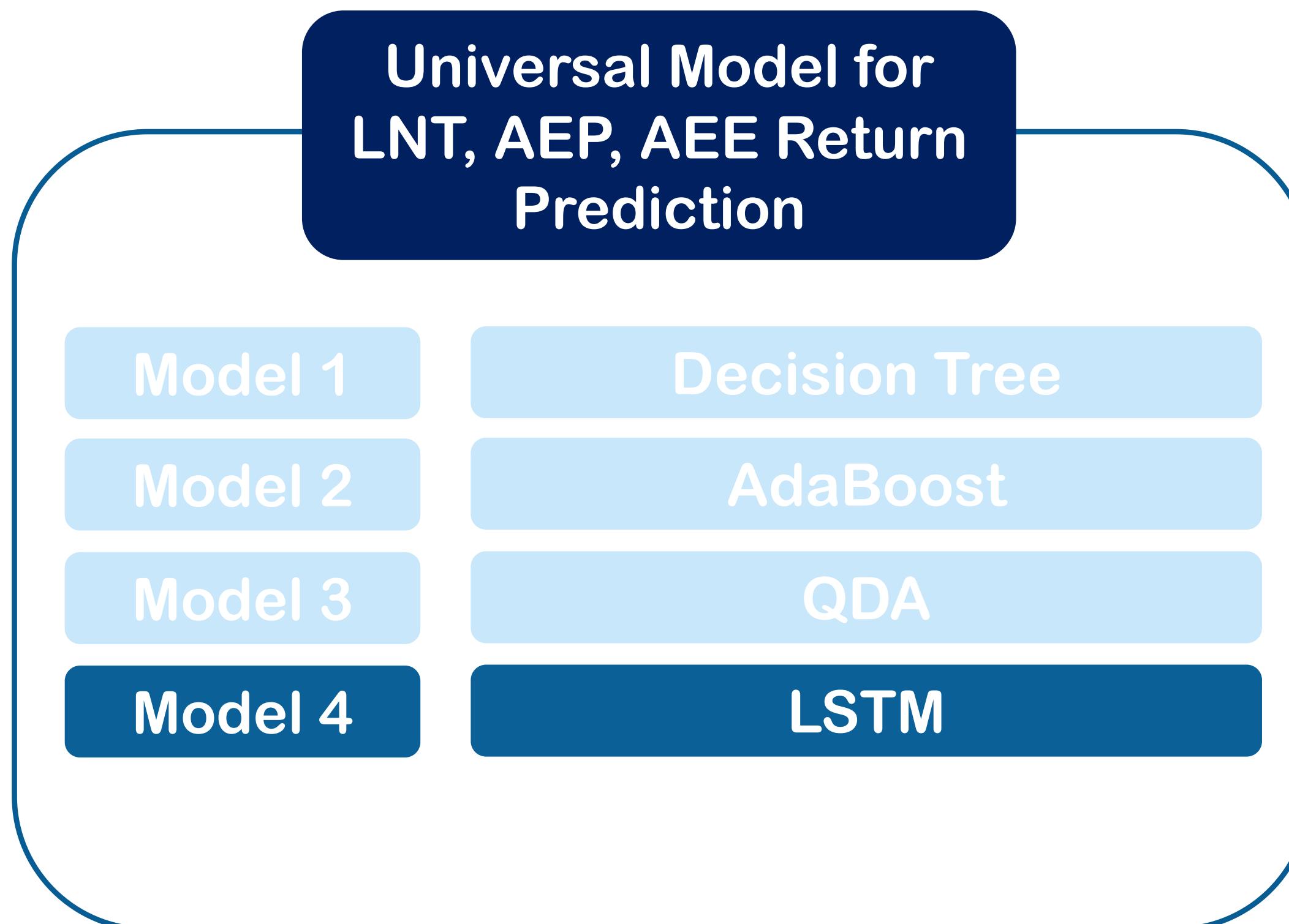
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3.2 Modeling – Predict Universal Labels

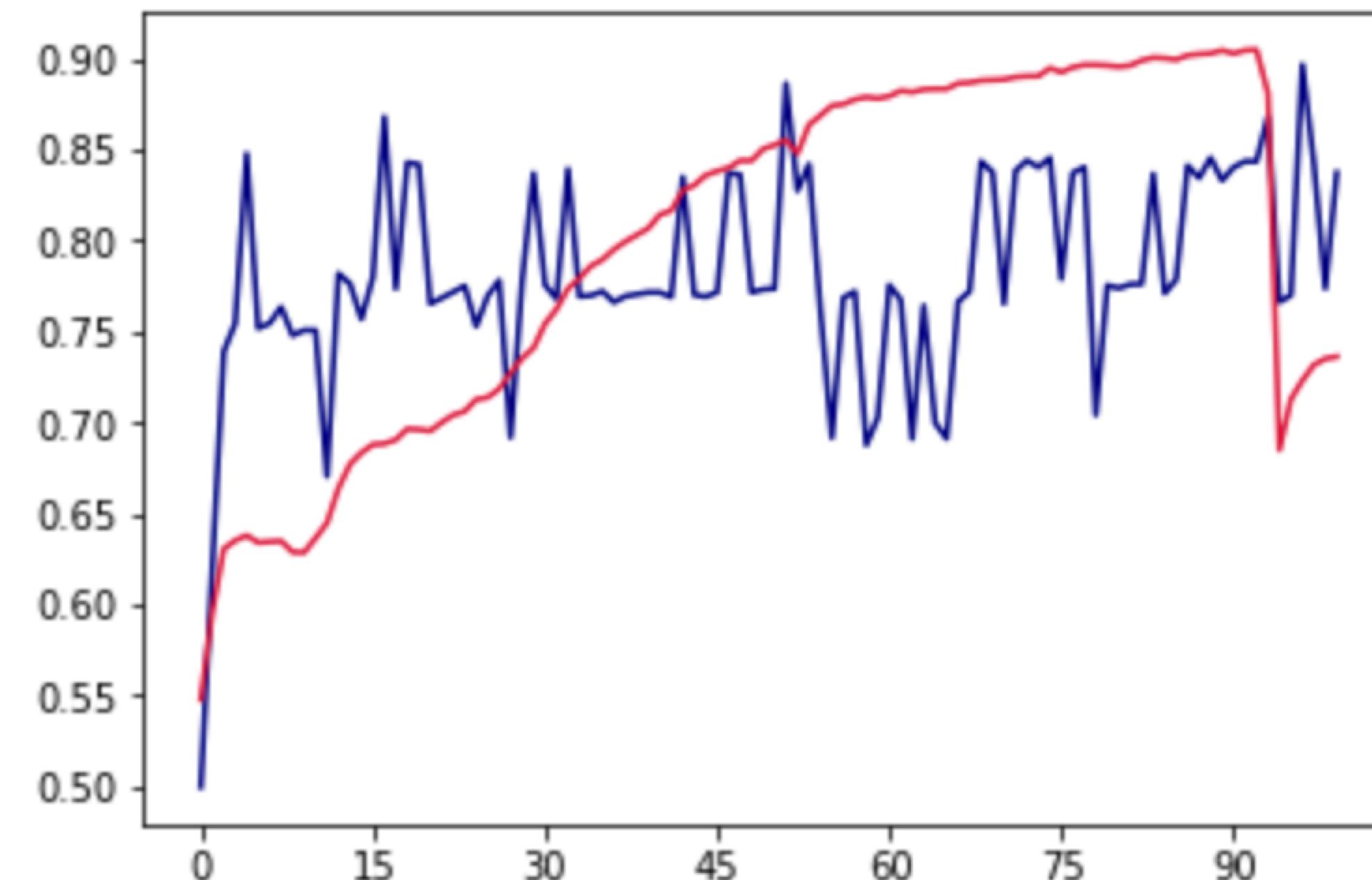


When distribution can be well separated by target labels, there should exist an effective model

3.2 Modeling – Predict Universal Labels



Predict Negative Return for the Group



Validation Accuracy
Training Accuracy

When distribution can be well separated by target labels, there should exist an effective model