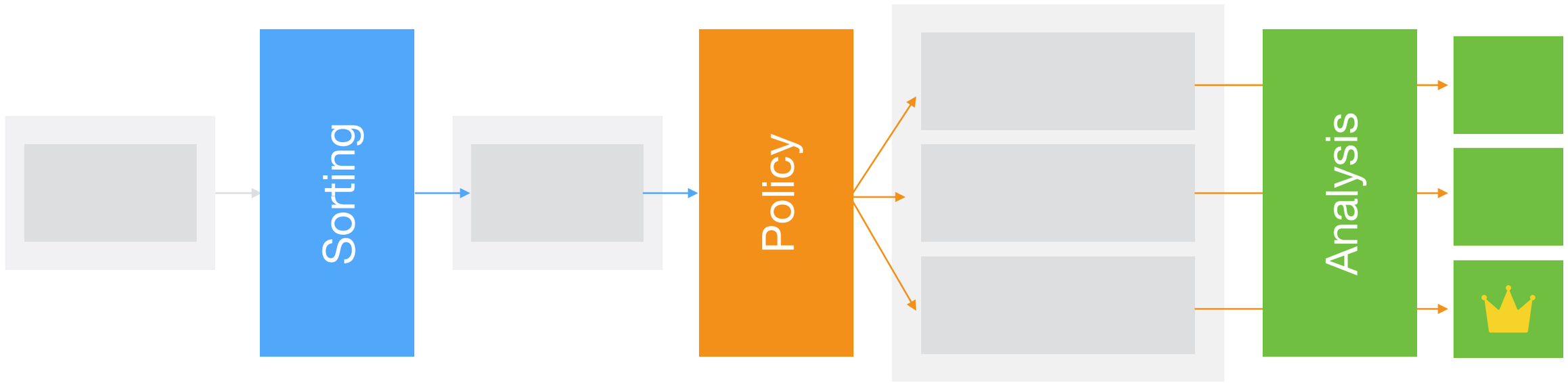

Reinforced Sorting Networks for Particle Physics Analyses

Martin Erdmann, Benjamin Fischer, Dennis Noll, Yannik Rath,
Marcel Rieger, David Schmidt, Marcus Wirtz

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14 March 19

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Motivation

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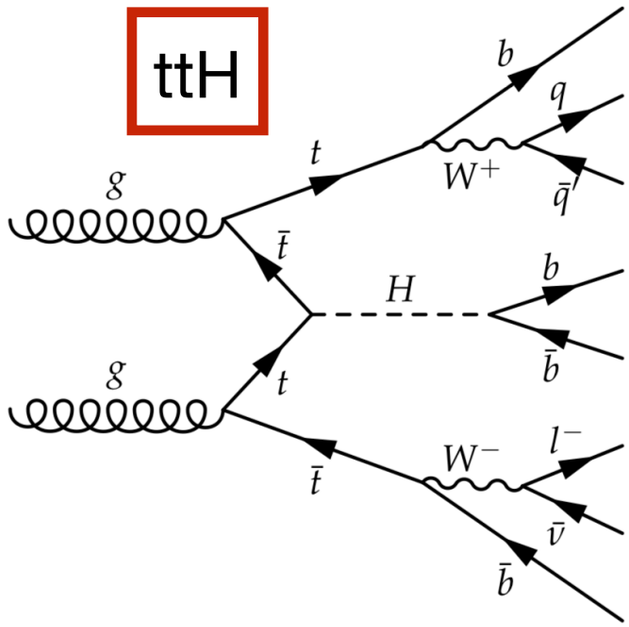
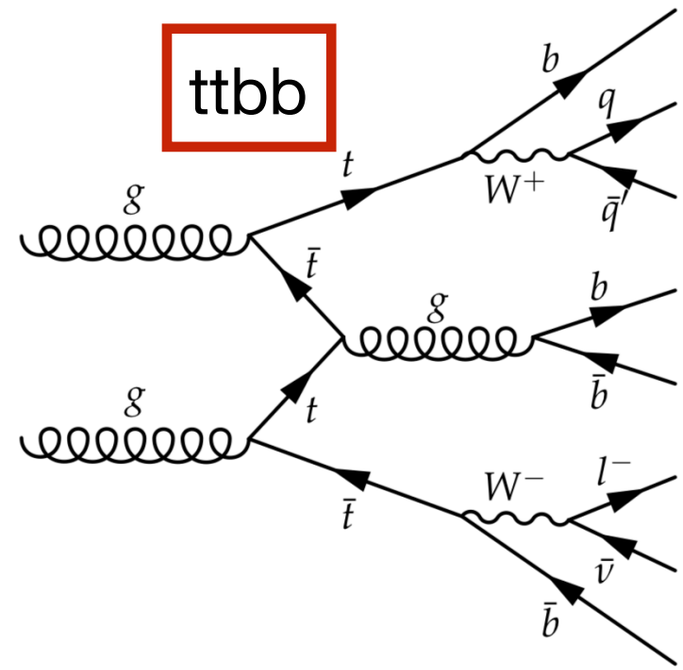
- Physics analyses often highly depend on the order of their input variables
  - Example: Classification - ttH vs ttbb (6 jets, lepton, neutrino, Pythia+Delphes)
  - Usual approach: p_T order





Order	Accuracy [%]
Gen	87.3
p_T	69.5

Not optimal

talk by Yannik

Approach

- Idea: Train mechanism (Neural Network) which outputs the best permutation

Problem 1: Many possible permutations (n!)

Solution: Divide & conquer

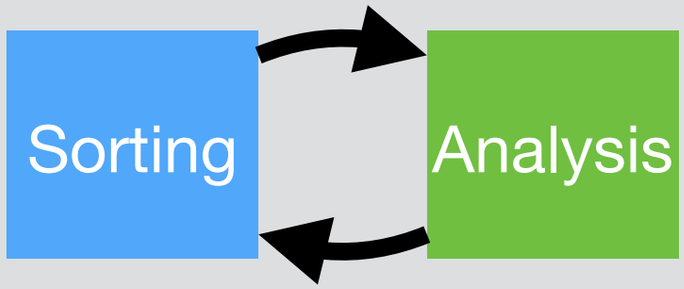
1. Look at a subset of possible permutations
2. Explore subset
3. Choose next subset

=> Continue until best permutation is found

Problem 2: Best permutation generally not known

Solution: Reinforcement approach

- Simultaneously train analysis and sorting
  - Train sorting with analysis feedback
  - Train analysis with sorting feedback



Complete Mechanism - Evaluation

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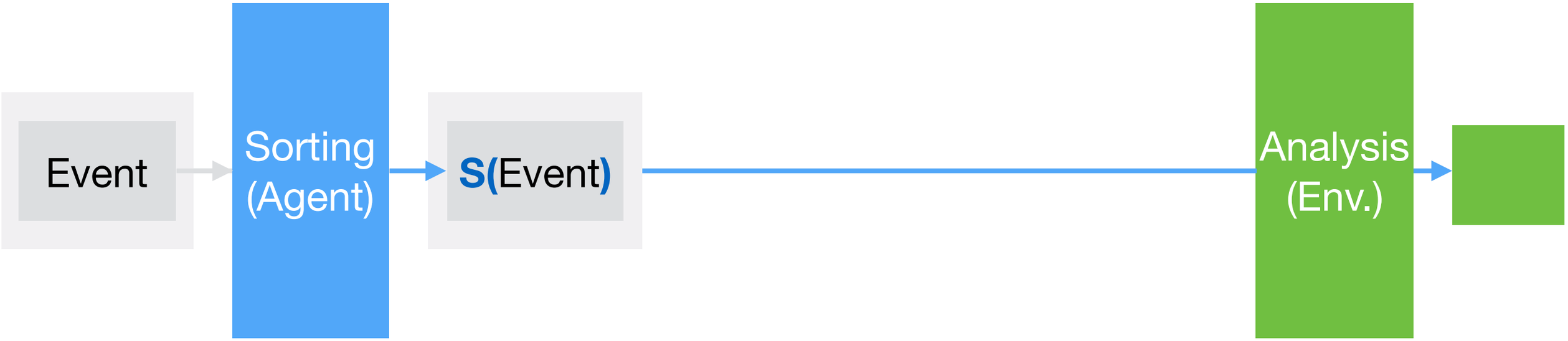

- Evaluation:
  - Input p_T sorted events
  - Sorting network sorts particles **S(**Event**)**
  - Analysis evaluates sorted events (trainable)

Sorting Mechanism

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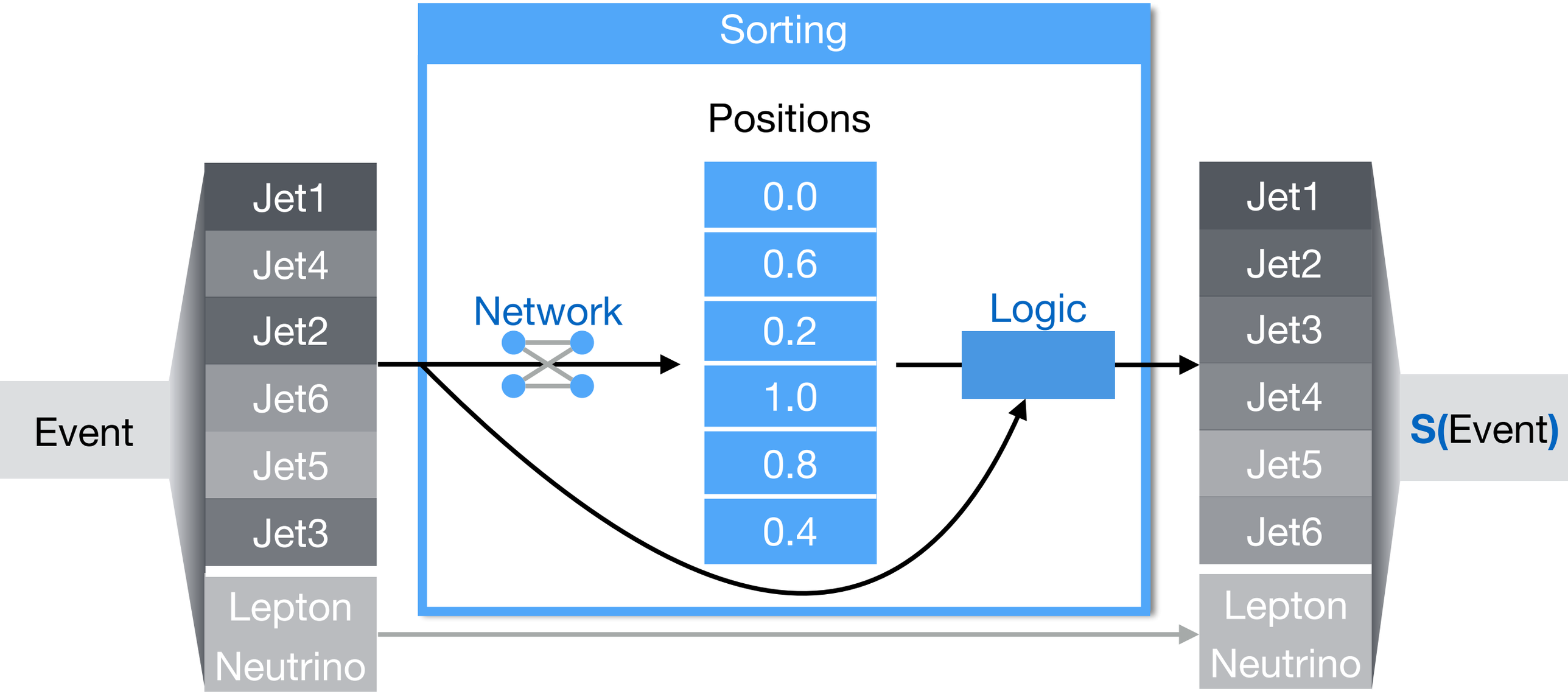

Network outputs position for every jet:

- Small position: front
- Large position: end
- Uniformly between 0 and 1

Logic algorithm applies the positions and rearranges the jets

Complete Mechanism - Reinforced Training

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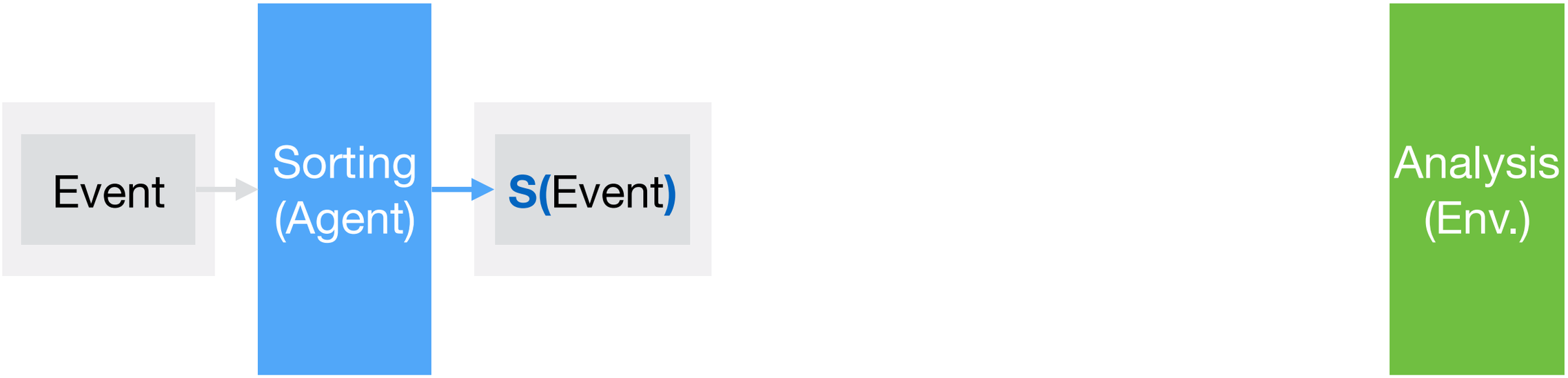
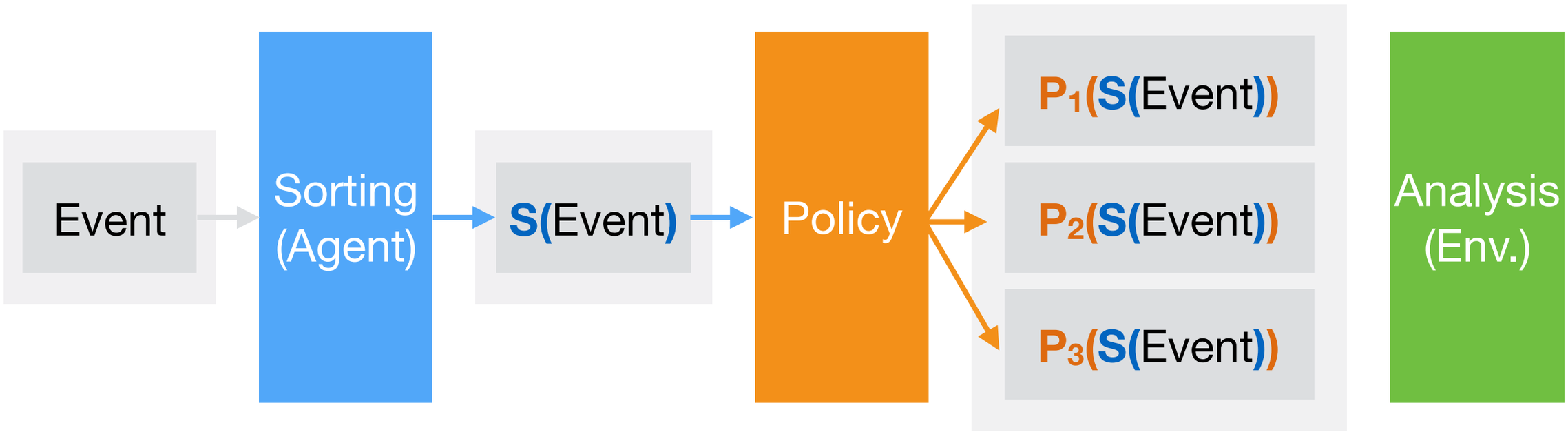


- Training:
  - Sorting network sorts particles S(Event)
  - Policy suggests new orderings P_1(S(Event)), P_2(S(Event)), P_3(S(Event))
    - Subset of possible orderings based on current ordering
  - Analysis evaluates sorted (and permuted) events

Complete Mechanism - Reinforced Training



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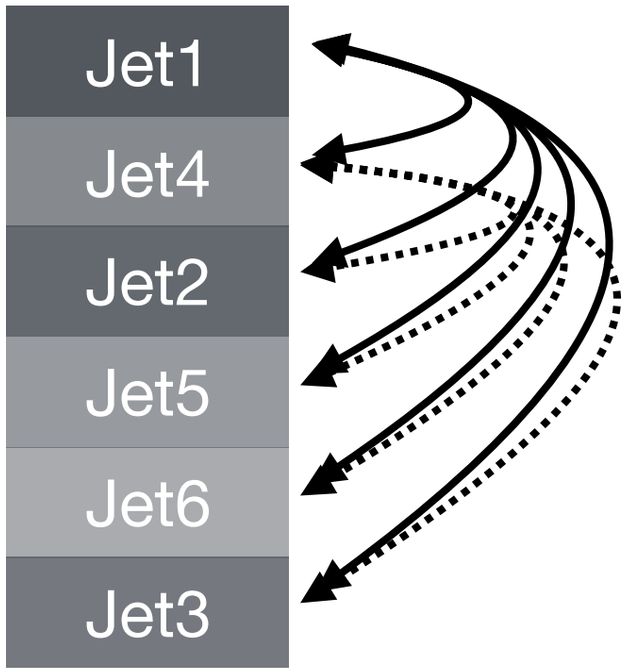
Permutation Policy

- Two different permutation policies:
  - Basic approach (Pool) and extension (Tree)

Pool $\mathbb{P}$



- All pair-wise switches
  - $N_{pool}(n) = \mathcal{O}(n^2)$
  - $N_{pool}(6) = 15$
- Policy (Pool):
  - Draw from pool $P_i \in \mathbb{P}$

Permutation Policy

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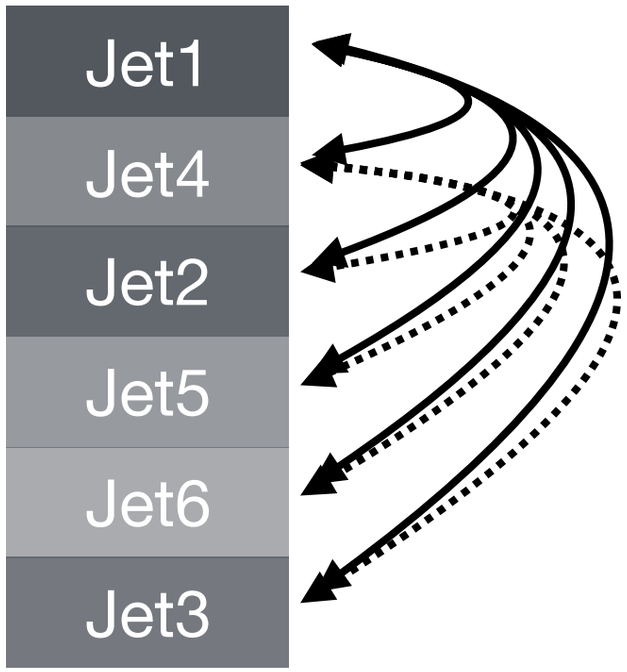
Pool $\mathbb{P}$



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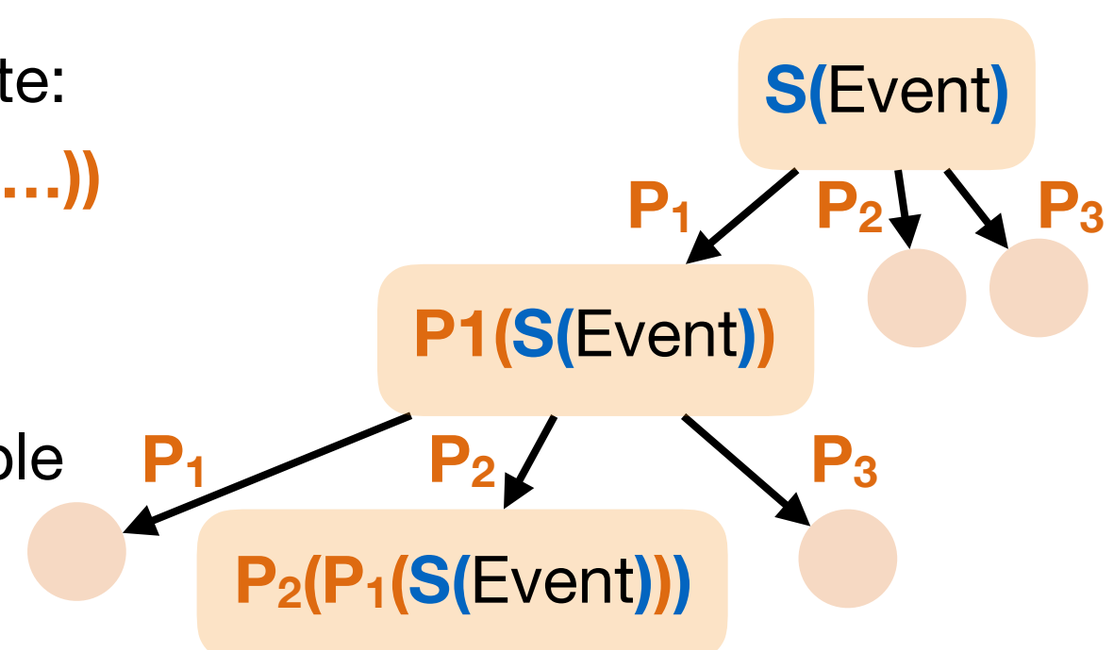
Tree

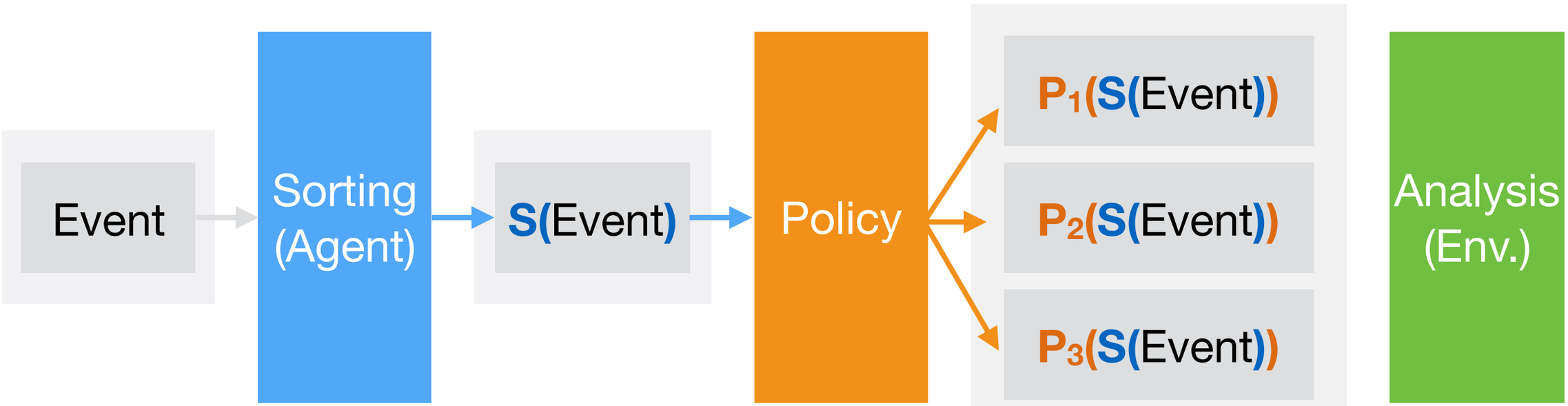
- Chain permutations to reach every state:

  $P_{any}(S(\text{Event})) = P_z(P_y(\ldots(P_x(S(\text{Event})))\ldots))$
- Policy (Tree):
  - Draw from pool ($\mathbb{P}$) in every node
  - Use tree mechanics to reach valuable nodes

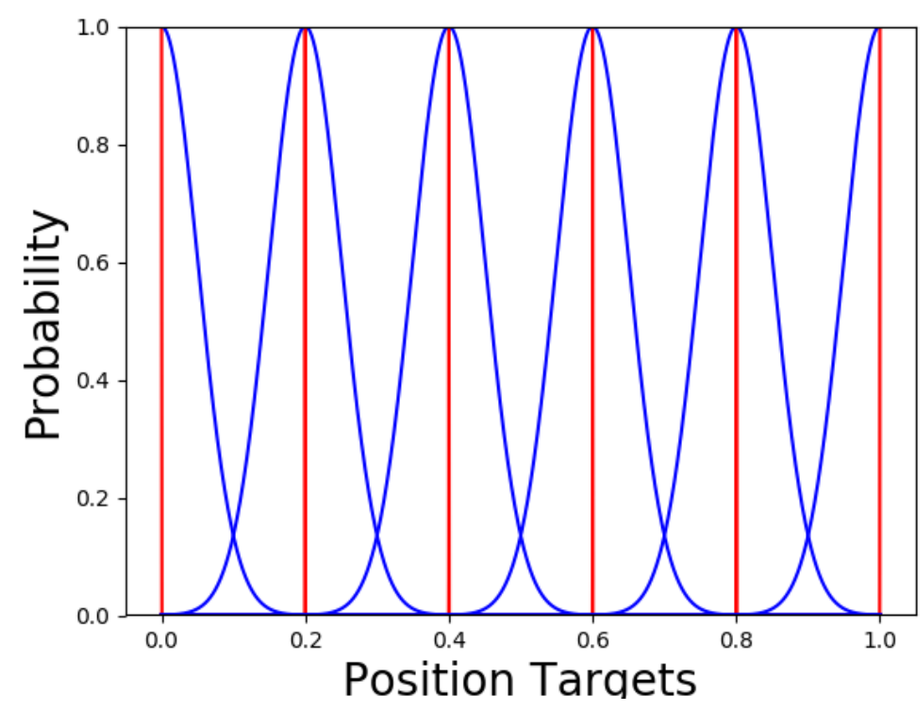


Complete Mechanism - Reinforced Training

Training



- Train sorting to output $P_3(S(\text{Event}))$:
  - Positions (targets) follow from P_3
  - Gaussian smear
  - Supervised training



Complete Mechanism - Reinforced Training

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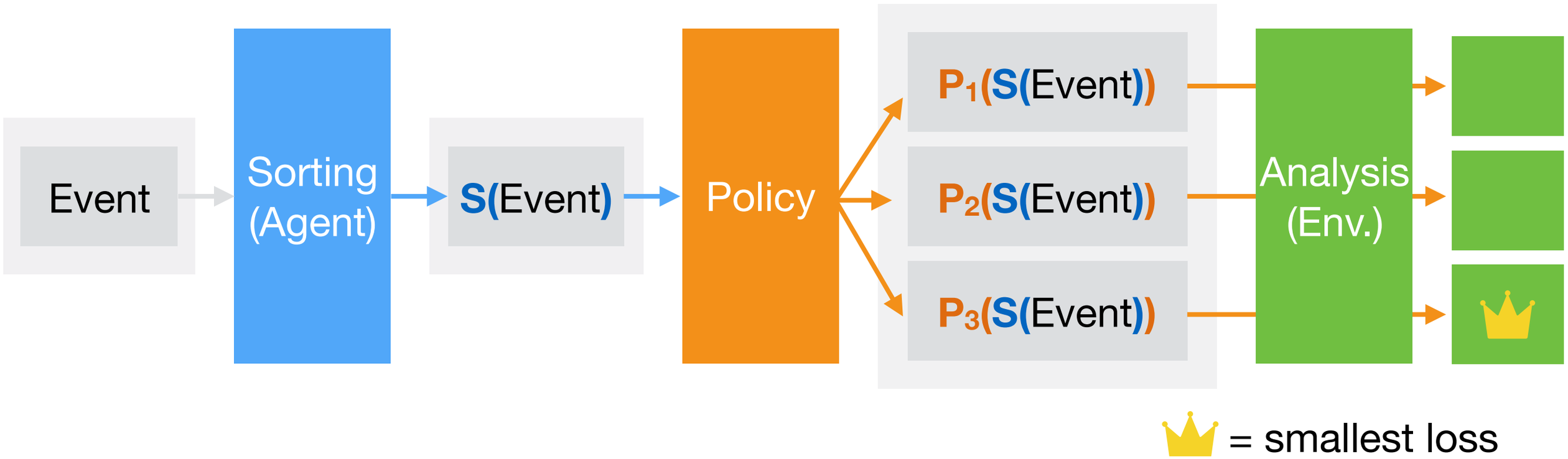

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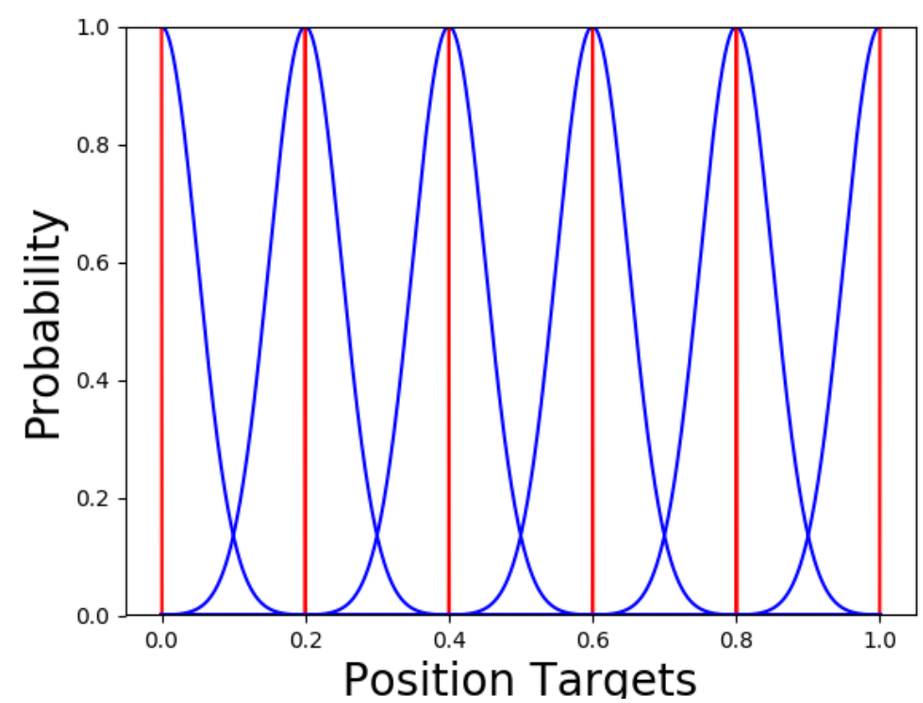

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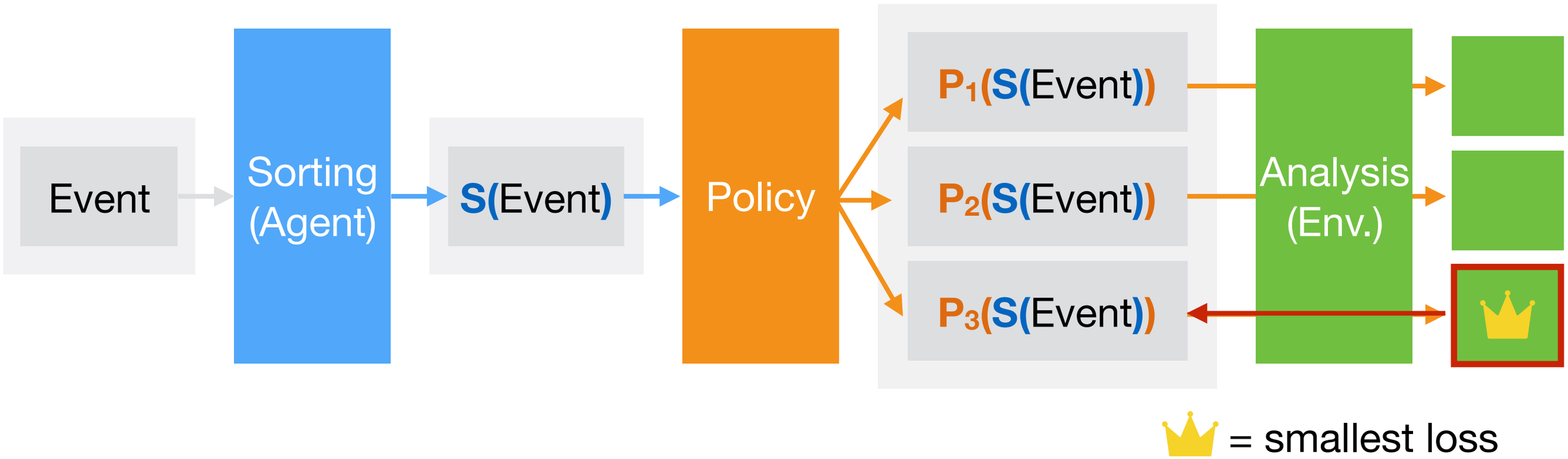

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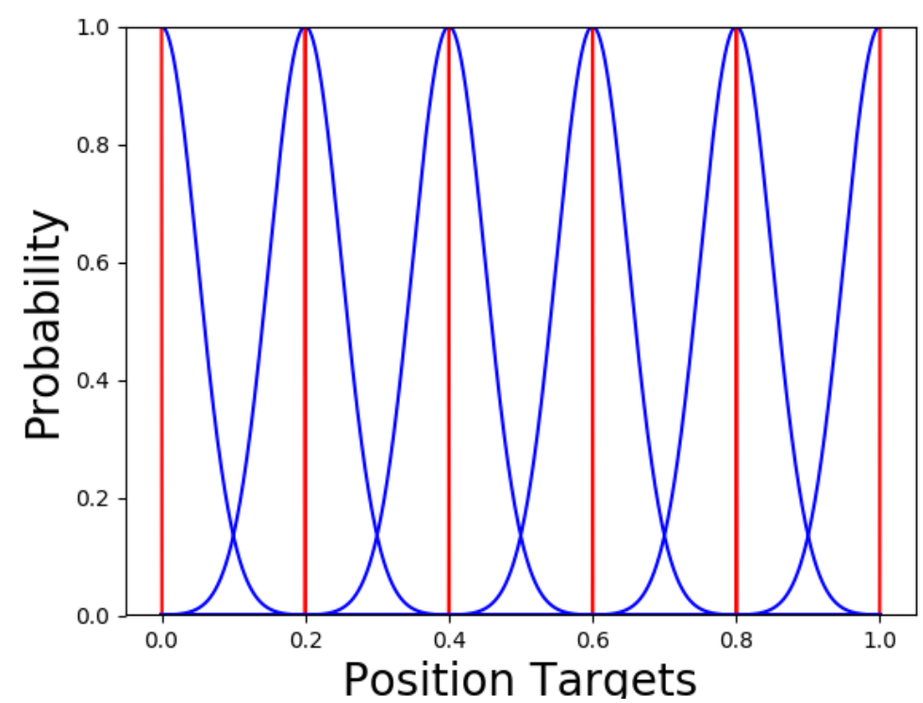
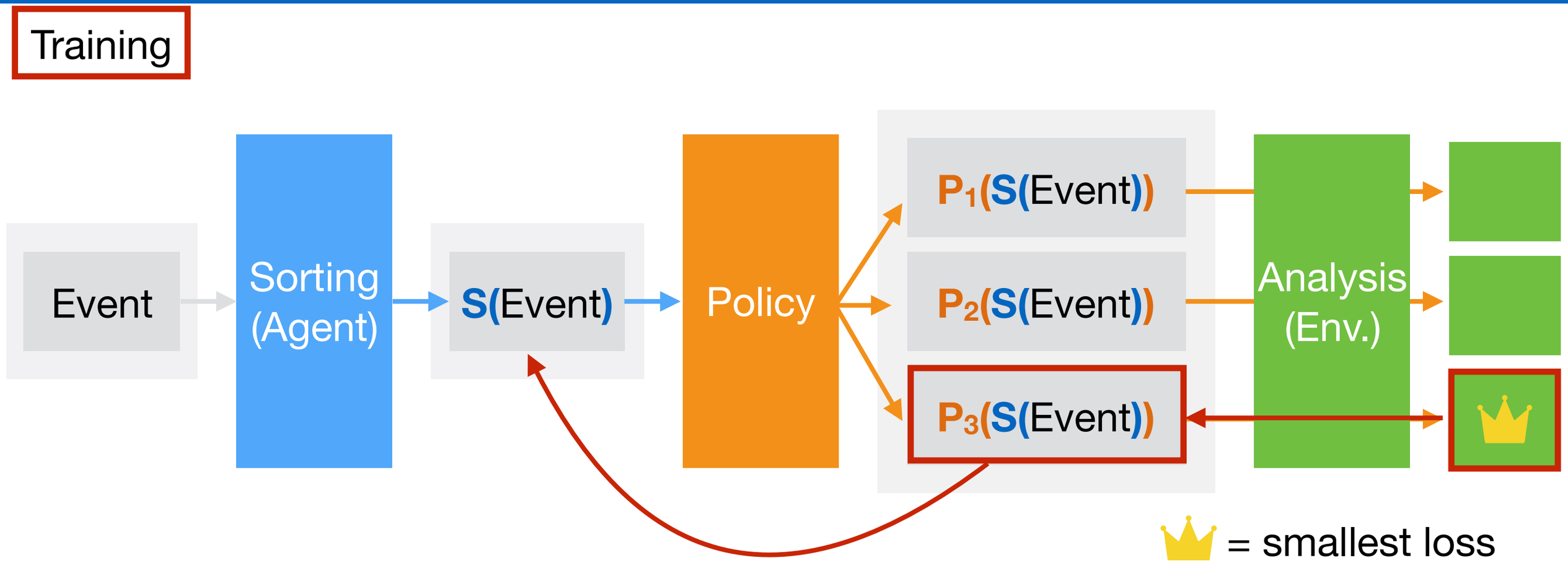


Complete Mechanism - Reinforced Training



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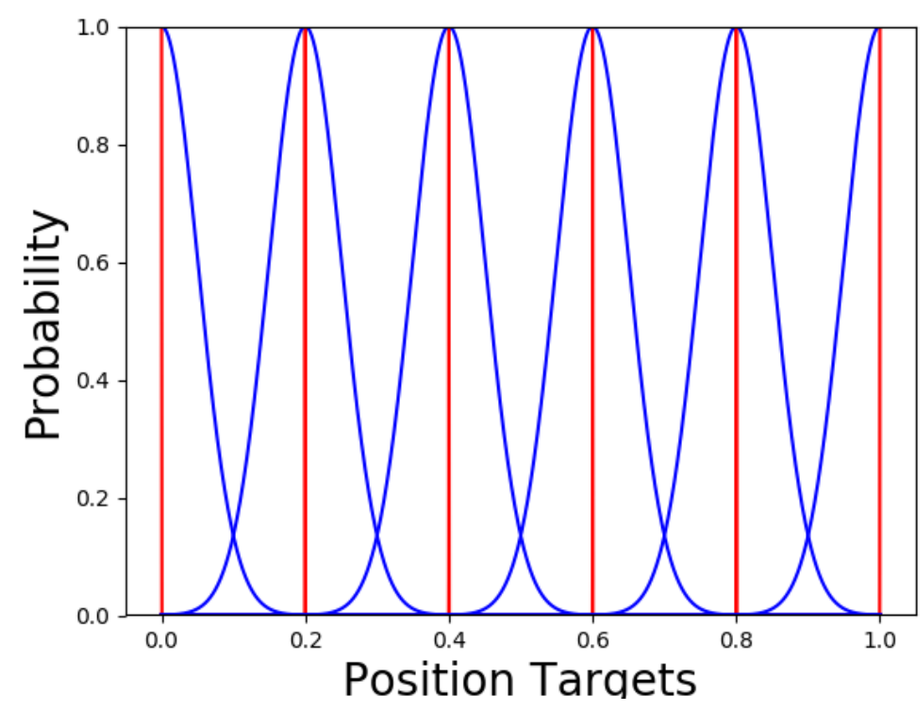

ttH vs ttbb - Hyper Parameters and Training

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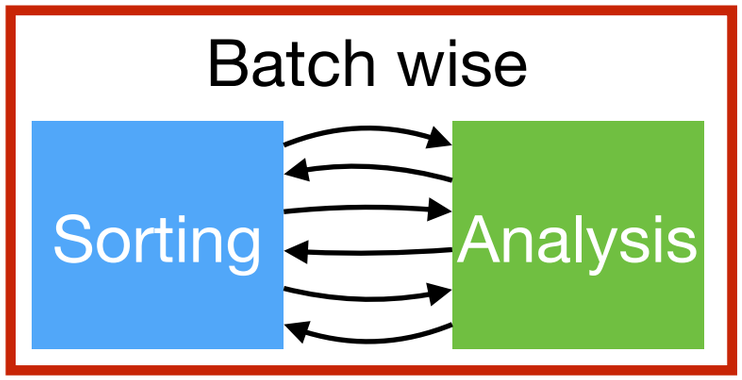
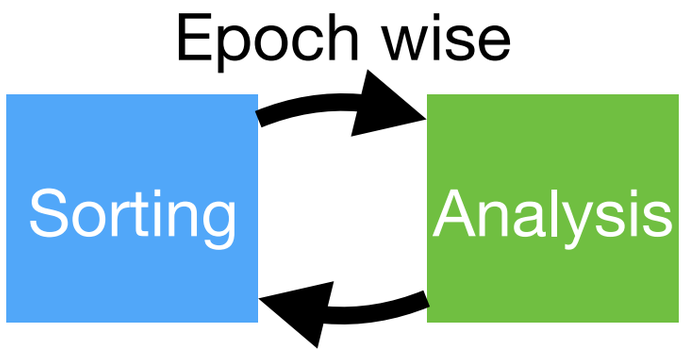
- Inputs for both networks: **only four-vectors** (Pythia + Delphes)
- Sorting Network:
  - Feed forward
    - 6 SeLu Layers, 256 Nodes
    - L_2 regularization + Layer Normalization
  - Adam Optimizer
- Analysis Network:
  - Lorentz-Boost Network (1812.09722, talk by Yannik)
- Training:
  - Schedule:





  - Pre-training:
    - Let analysis network converge before starting to train
    - Pre-train sorting to output p_T

ttH vs ttbb - Results (1)

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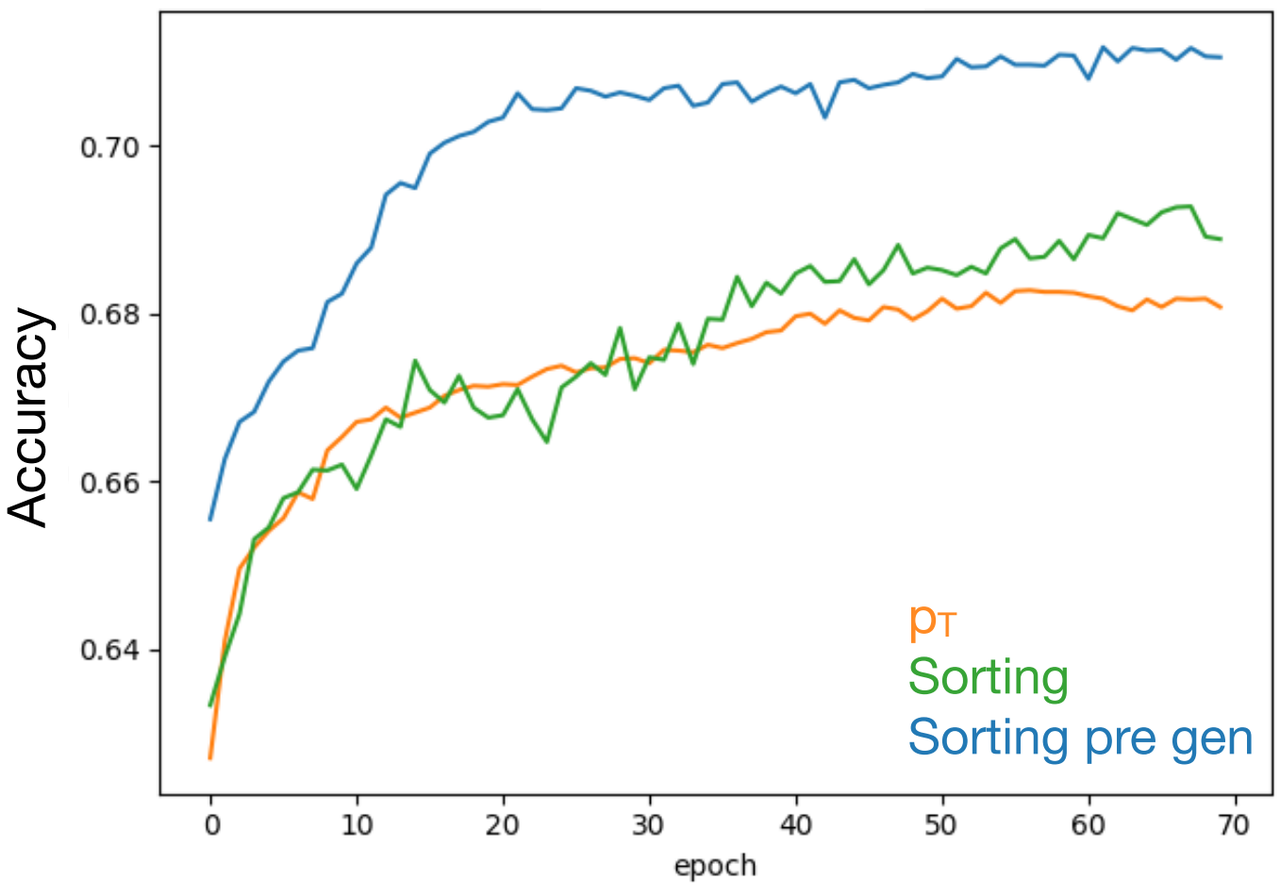
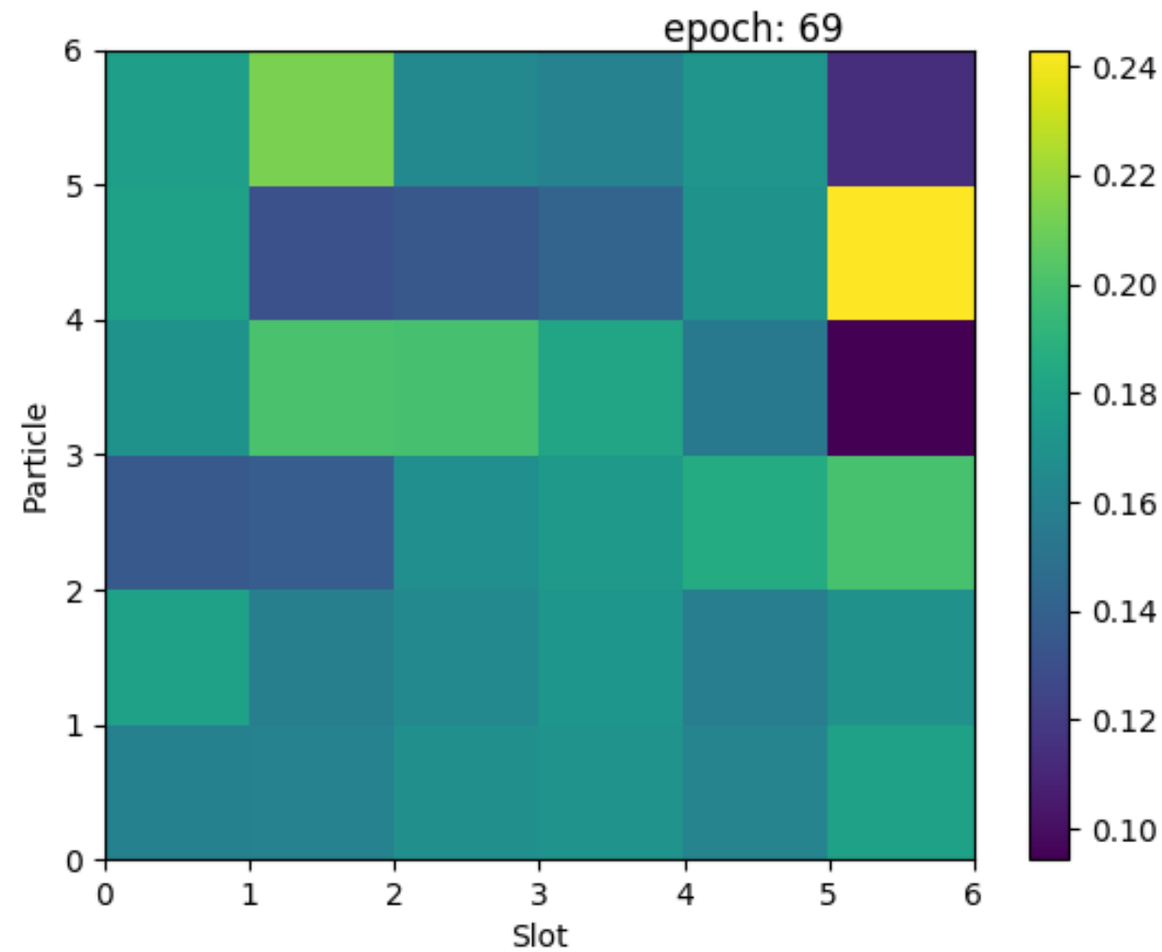
- Sorting network learns an intrinsic structure
- Performance of classifier increases





ttH vs ttbb - Results (2)

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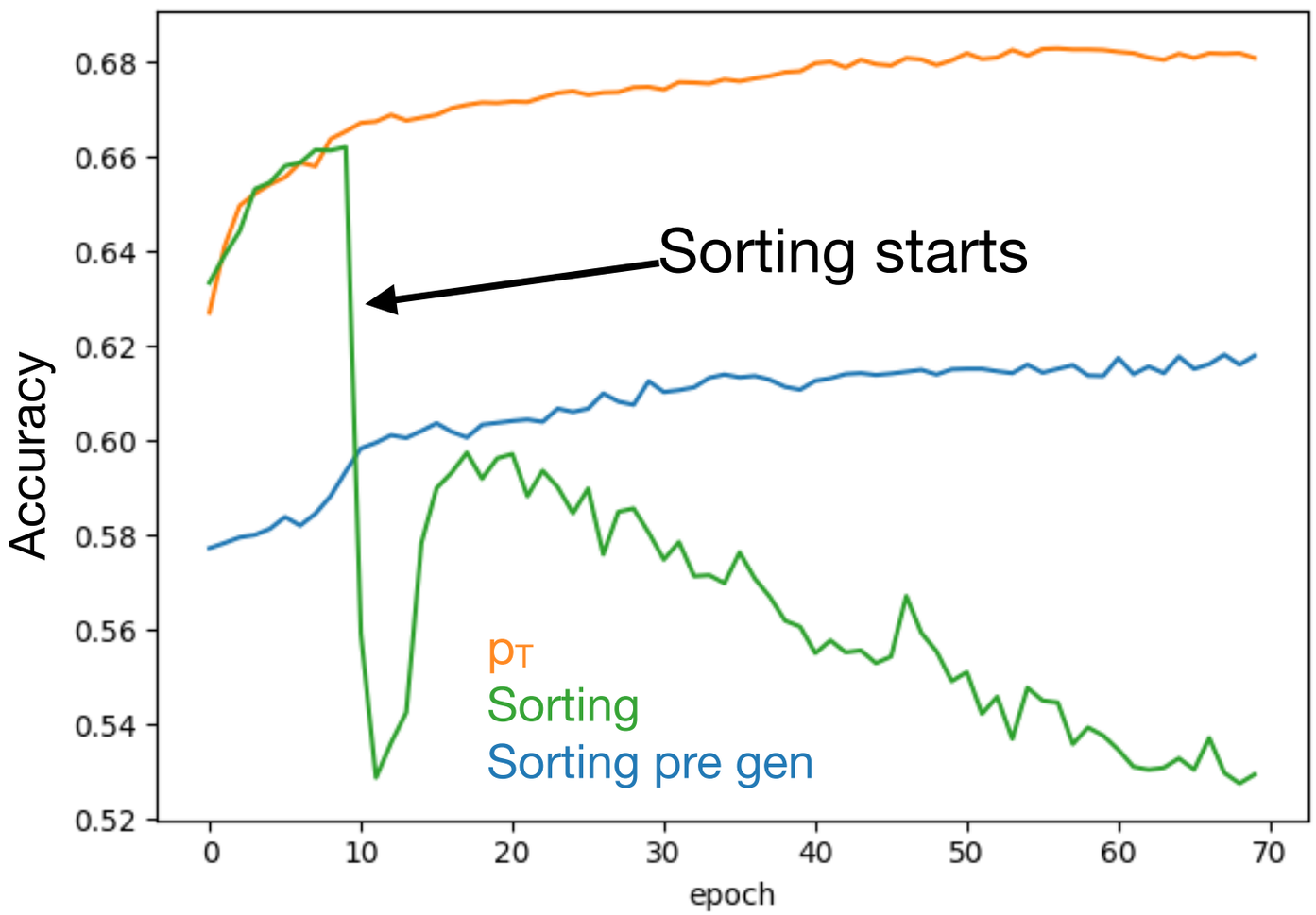
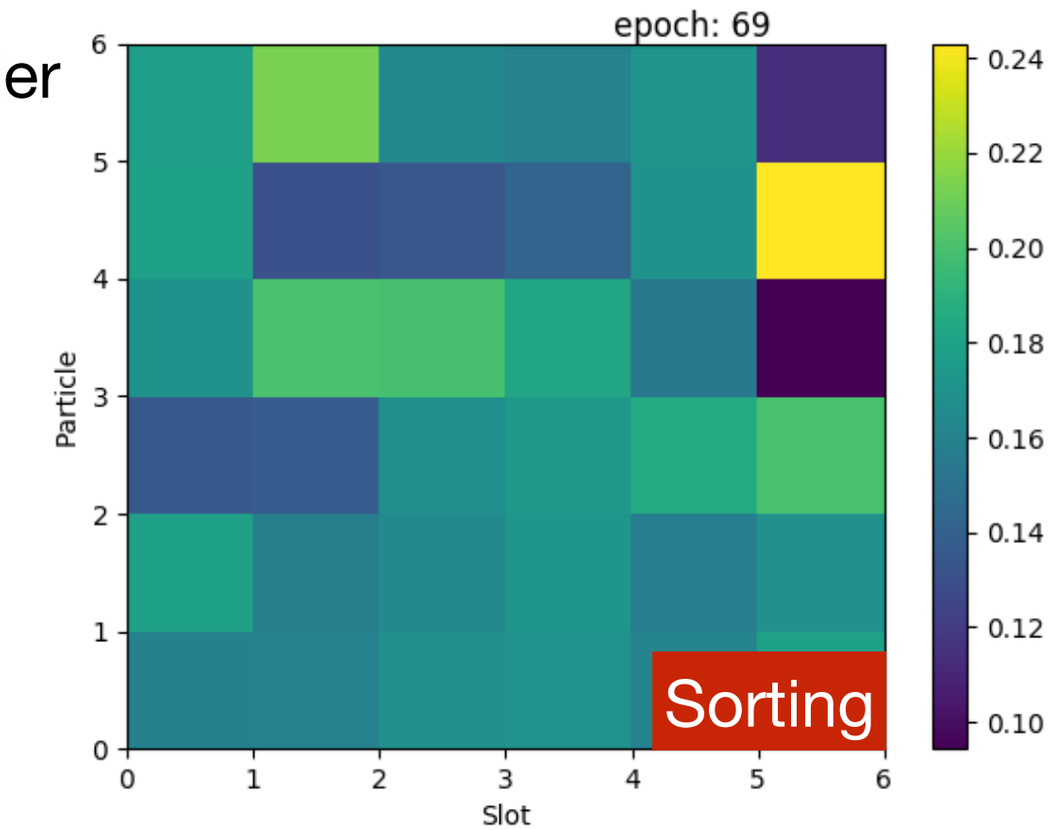
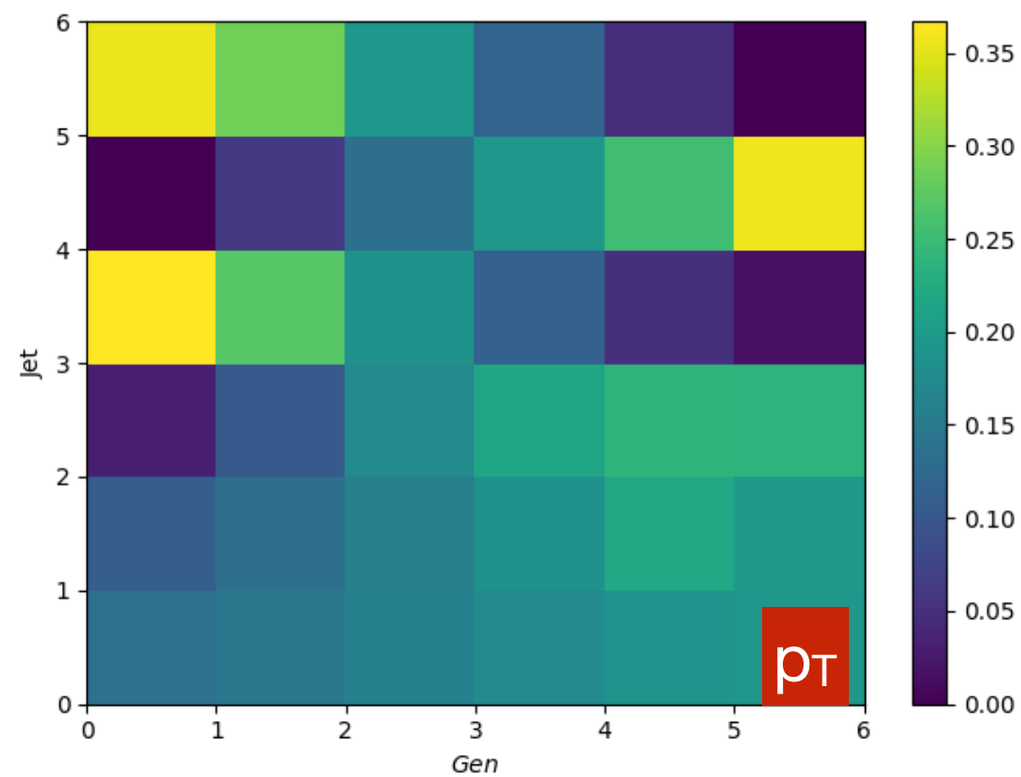
- Train analysis with sorting, evaluate on p_T order
  - Accuracy drops to 50%
  - Analysis network relies on sorting

  → p_T order disfavored







Conclusion

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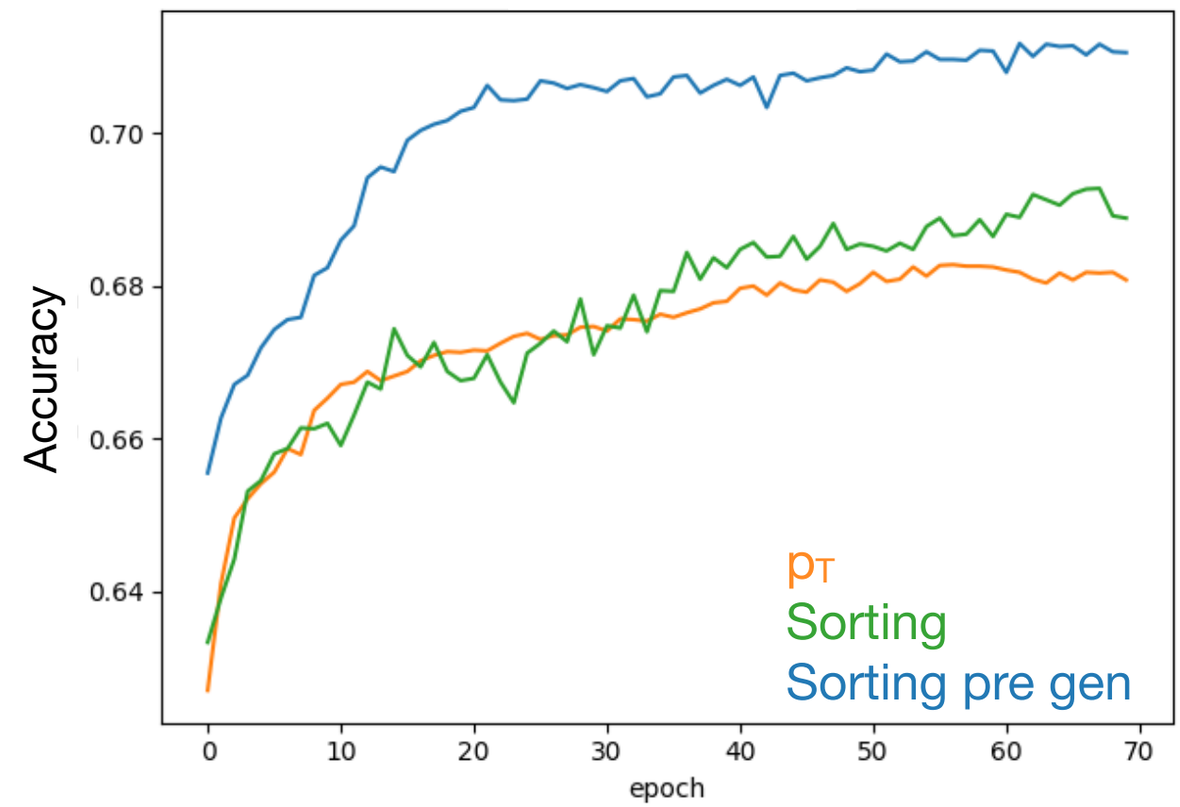
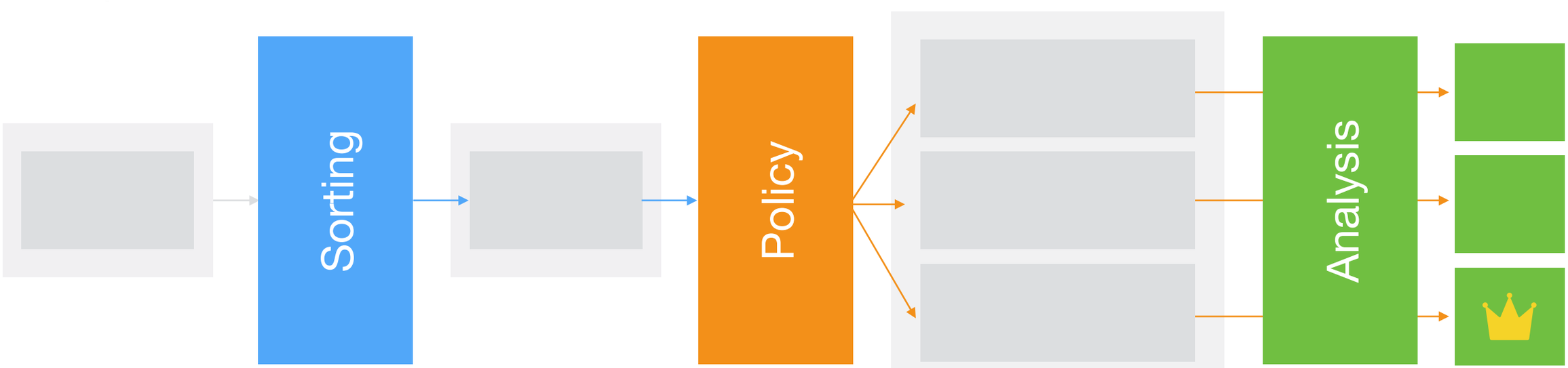
- Reinforced input sorting may benefit various NN applications
  - Agent:
    - Sorting of inputs (e.g. jets)
  - Policy:
    - Classic permutations
    - Tree search
  - Environment:
    - Physics analysis (e.g. LBN)



- Especially promising in scenarios with a-priori unknown “best” order



Backup

Artificial Data - Dataset

- Build artificial dataset - with explicit sorting information:
  - Sorting information: one random number
  - „Features“: random numbers
  - Task: reconstruct weighted alternating sum over the „Features“
    - Easy task, if input order is fixed
    - Nearly impossible if input order is random
    - Regression

Sorted: easy

Row1	0.3	+ 0 x 0.3
Row2	0.8	- 1 x 0.8
Row3	0.2	+ 2 x 0.2
Row4	0.5	- 3 x 0.5
Row5	0.9	+ 4 x 0.9
Row6	0.1	-5 x 0.1
		= 1.2

Random: impossible

Row1	0.3
Row4	0.5
Row2	0.8
Row5	0.9
Row6	0.1
Row3	0.2

Artificial Data - Classic - Results

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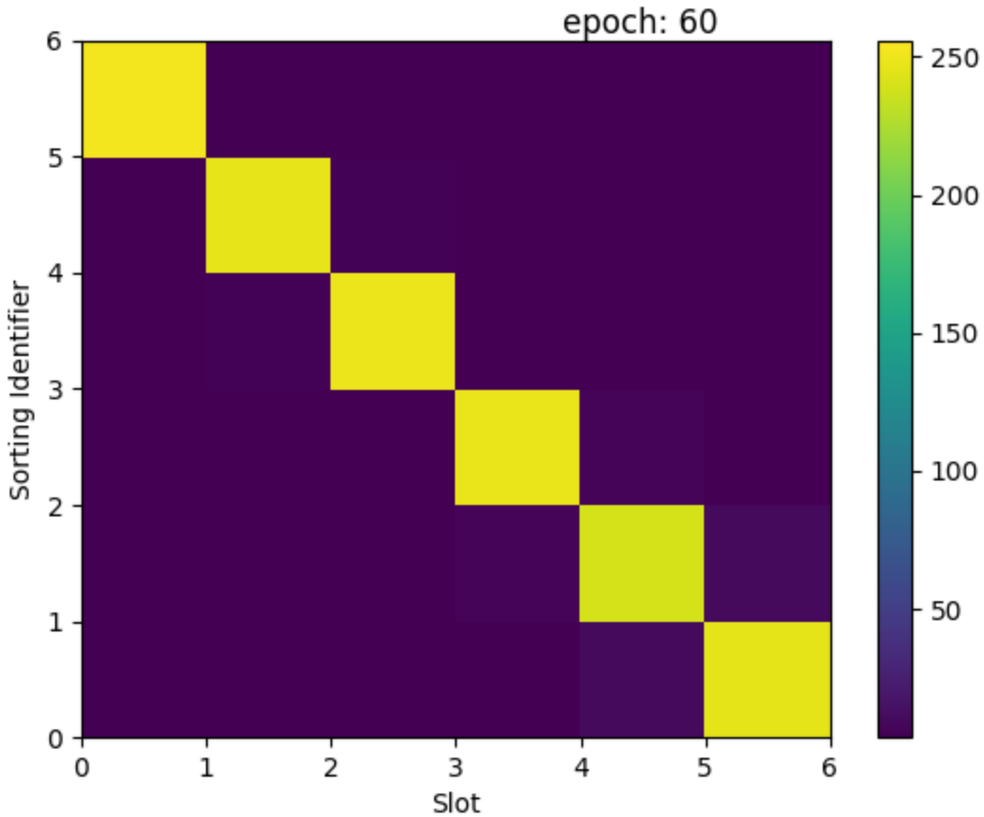

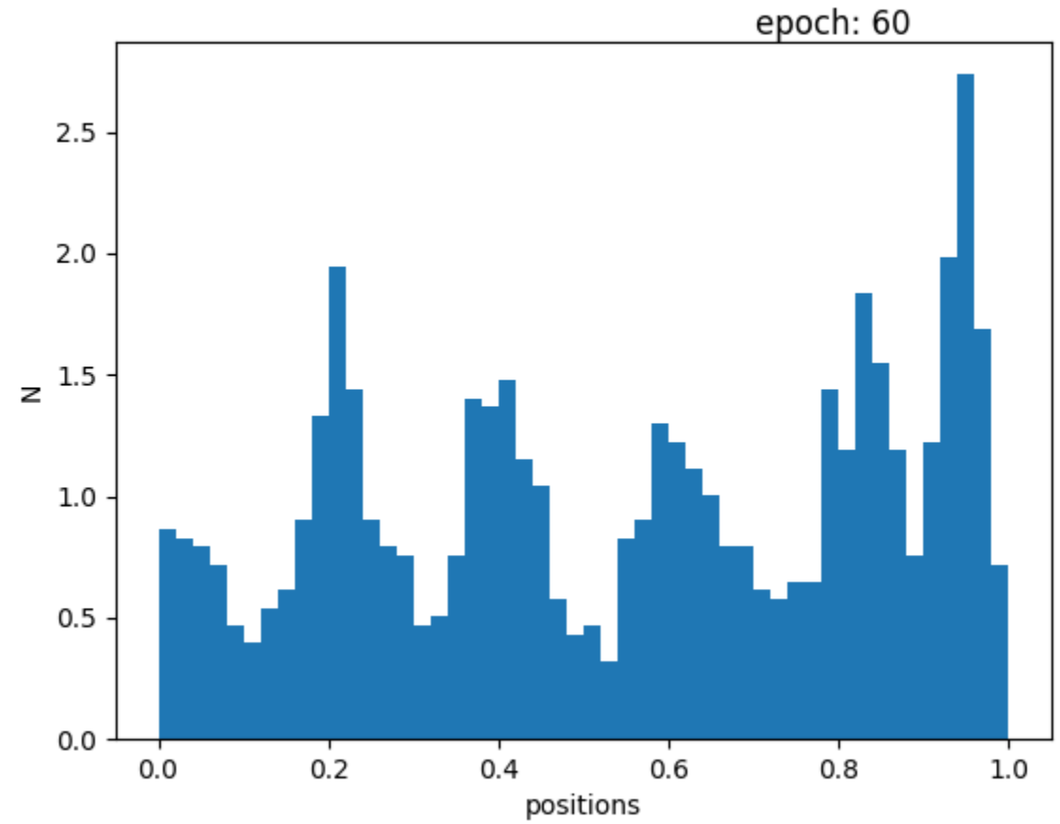

- Sorting model converges fast
- Finds stable sorting
- Outputs gaussian