LAMARR
INSTITUTE FOR MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

Domain Adaptation for Flavour Tagging at LHCb

Mirko Bunse and Quentin Führung

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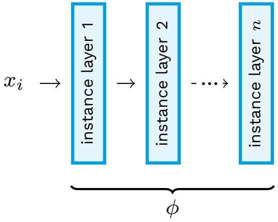
Recap: Deep Sets



- Each event is a **set of tracks** $\{x_i \in \mathcal{X} : 1 \leq i \leq m\}$ of variable size m

[1] Zaheer et al., "Deep sets", 2017
[2] Lee et al., "Set Transformer: A Framework for Attention-based Permutation-Invariant Neural Networks", 2019

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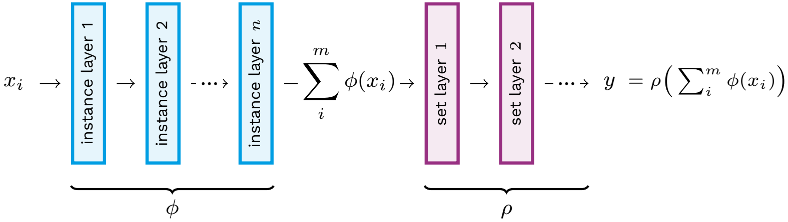

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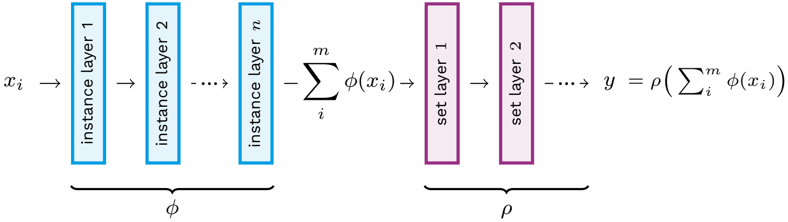

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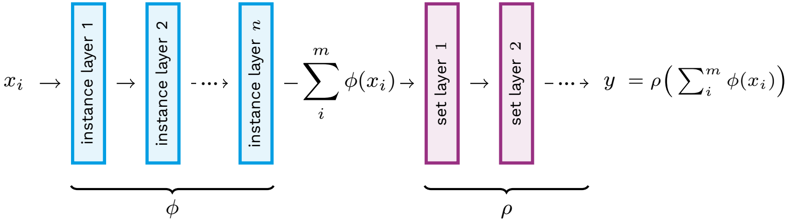

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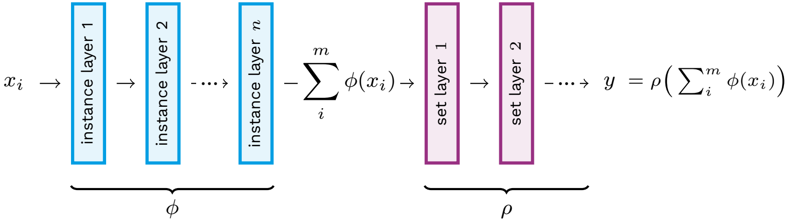

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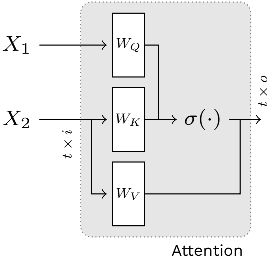

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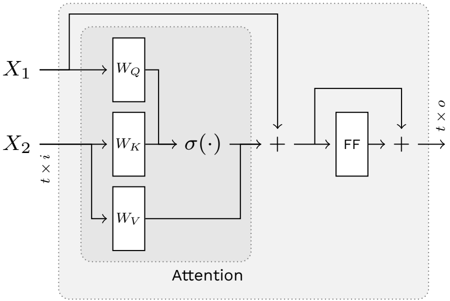

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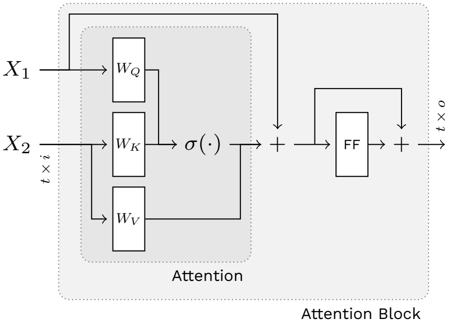

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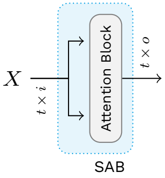

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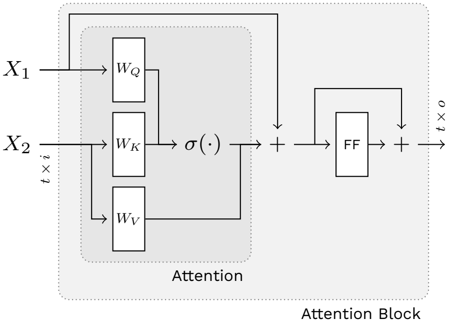

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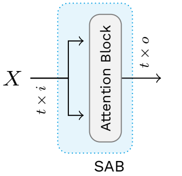

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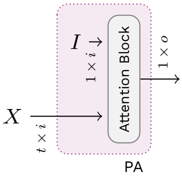

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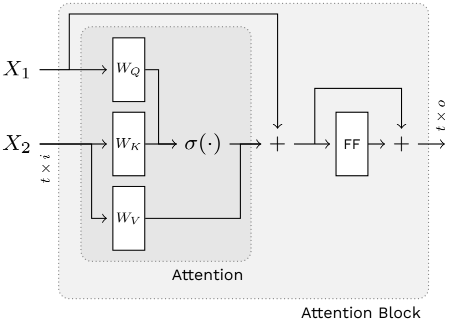

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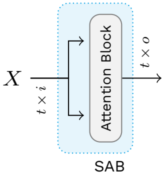

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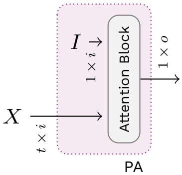

Set Encoder: SAB ∘ ... ∘ SAB ∘ PA

Set Transformers

Universal Approximation ✓

Track interactions ✓

Over-fitting to simulations ✗

Unsupervised Domain Adaptation

Problem: Simulations and real data do not match perfectly, i.e. $\mathbb{P}_{\mathcal{S}}(X,Y) \neq \mathbb{P}_{\mathcal{T}}(X,Y)$

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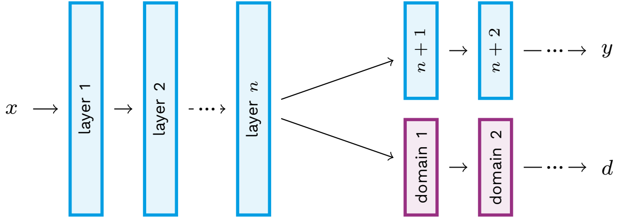
Domain-Adversarial UDA:[3]



$$d = \begin{cases} 1 & \text{if } x \in \mathrm{D}_{\mathcal{T}} \\ 0 & \text{if } (x, y) \in \mathrm{D}_{\mathcal{S}} \end{cases}$$

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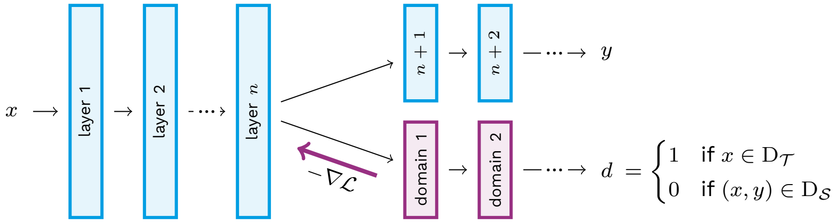

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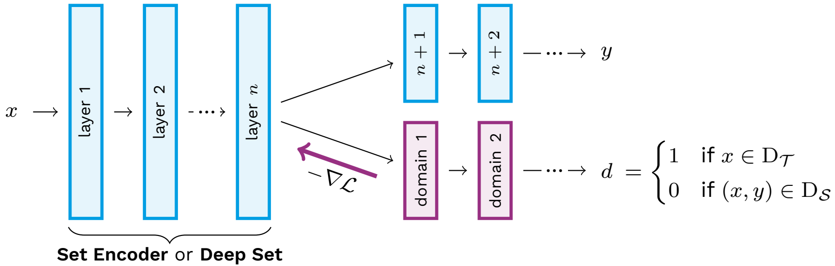

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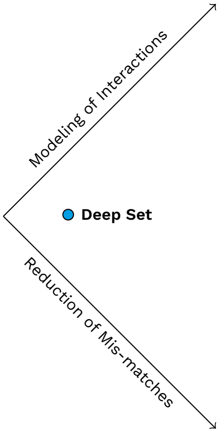
(Preliminary) Performance



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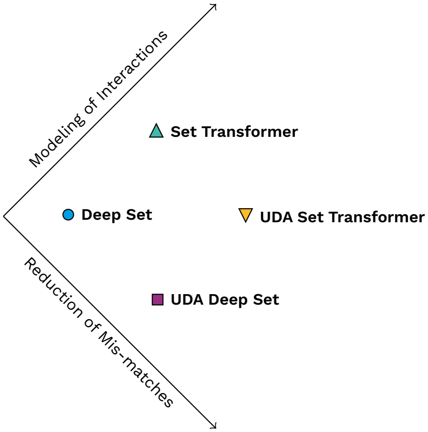

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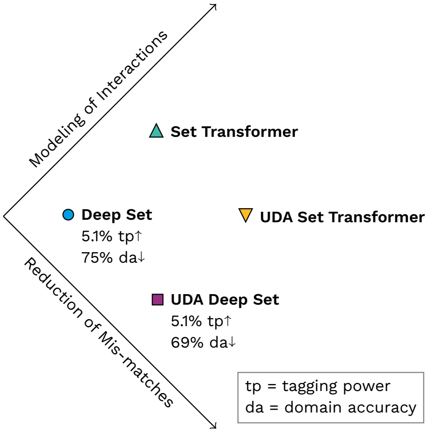

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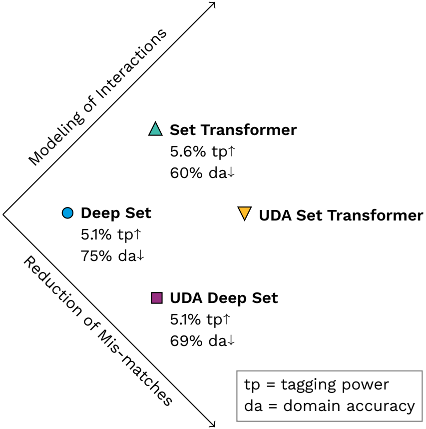

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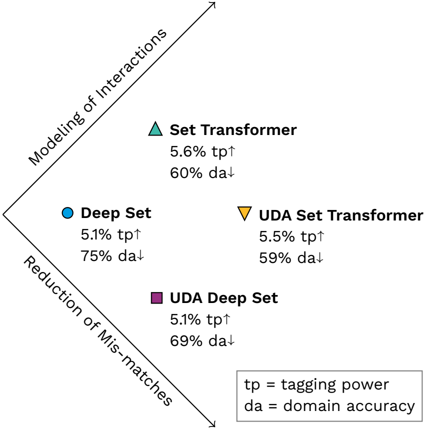

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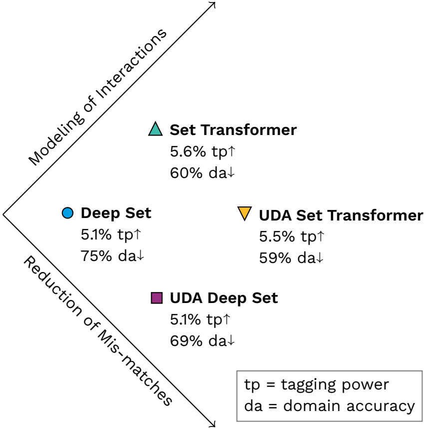

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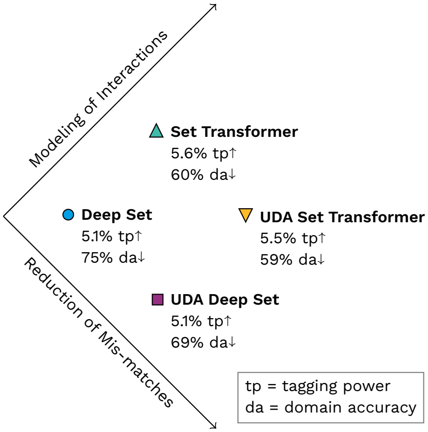

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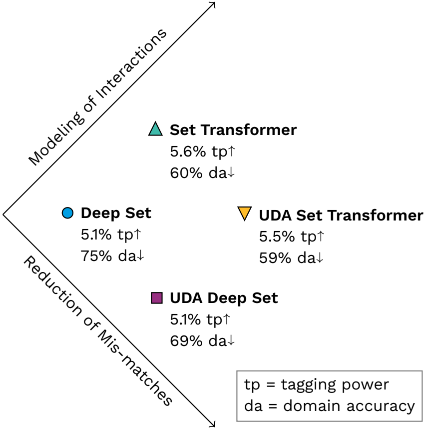

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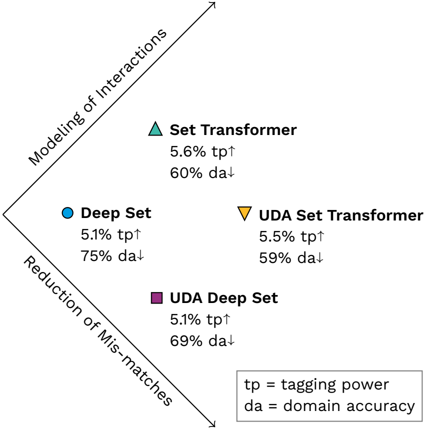

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Let’s discuss!