ATRL - Project proposal

Thorben Klamt - 04.07.2024

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Backup project

Compare MAML, iMAML, evo-MAML, ES-MAML and Reptile

- Benchmark environment and configuration (Google Colab CPU servers, JAX, etc.)
- Two Benchmark environments
- Efficiency and performance in finding optimal performing HP configuration if started from (N=5) different random offsets or HP-positions in initial HP configuration



Project proposal



Paper reference 1

 Discovering Symbolic Models from Deep Learning with Inductive Biases (2020)

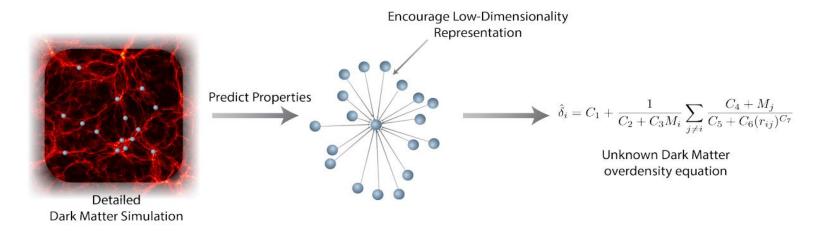


Fig:1. Cartoon depicting how physical equations are extracted from a dataset using a Deep Learning model and inductive biases in the example of Dark Matter Simulation derived overdensity equation discovery.



Paper reference 2

- Discovering Symbolic Models from Deep Learning with Inductive Biases (2020)
- Towards interpretable deep reinforcement learning with humanfriendly prototypes (2023)

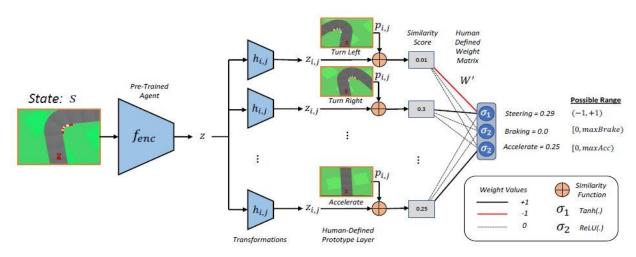


Figure 1: Prototype-Wrapper Network in Car Racing from OpenAI's gym. A state is encoded as z, transformed, and compared to human prototypes, influencing each output action.





Interpretable policy extraction from fully trained Deep RL agents

• Compare different methods



- Compare different methods
 - "Conditional interpretable blocks": pseudocode extraction, symbolic representation distillation, human-friendly prototypes
 - Two benchmark environments ((random gravity) Lunar Lander, etc.)
 - HPO (number of blocks, inductive bias, pseudocode length) to optimize for a two dimensional goal space: performance (normalized to baseline) versus "simplicity measure"
- Section A:
 - None
 - Deep Learning model
 - Decision tree
- Section B:
 - Human friendly prototypes
 - Symbolic representation
 - Pseudocode

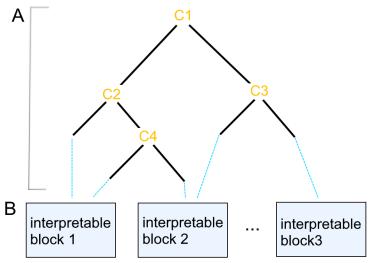


Fig:1. Abstract representation of "Conditional interpretable blocks".



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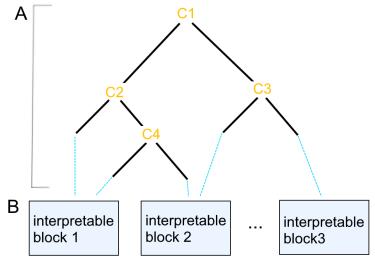


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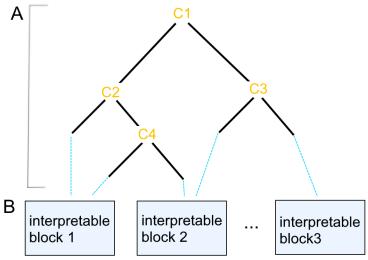


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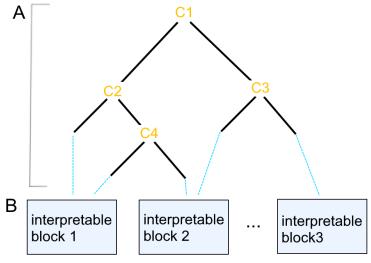


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