



Inria

Complementarities of Control Theory & Machine Learning: *Survey and Research Directions*

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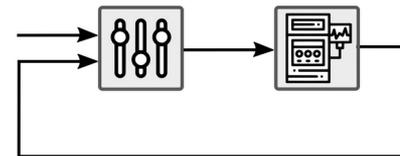
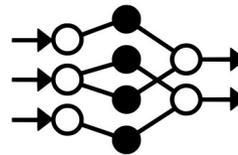
A long history of CT & ML combinations

Well studied Combinations

- Markov Decision Processes & Reinforcement Learning¹
- Fuzzy logic control²

Work's focus

- Neural Networks
 - > Performance ++
 - > Safety --
- Deterministic Control
 - > Guarantees ++
 - > Constrained formalism --



¹ M, Van Otterlo, M, Wiering. Reinforcement learning and markov decision processes. In Reinforcement Learning, Springer, 2012.

² C.-C. Lee. Fuzzy logic in control systems: fuzzy logic controller. i. IEEE Transactions on systems, man, and cybernetics,1990.

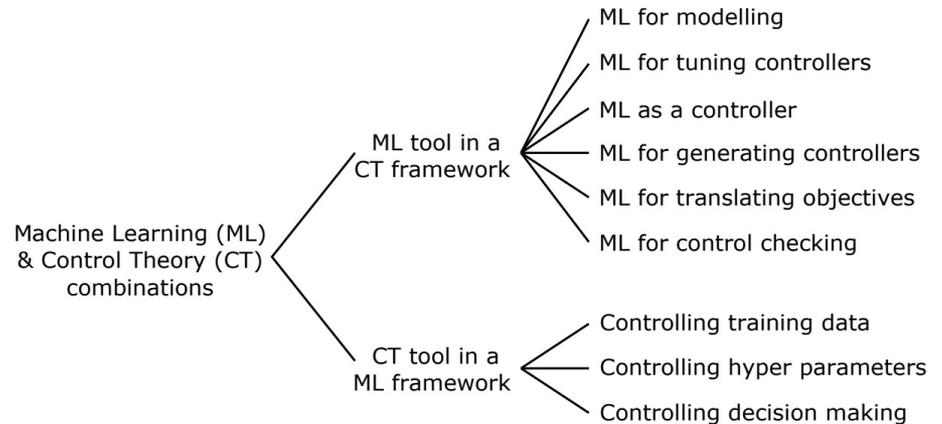
A need for hindsight

Objective

- Exploring the various forms CT & NN combinations can take
- Non-exhaustive but opens research directions

Related Survey Works

- (Recht, 2019)¹
 - > Terminology
- (Moe et al., 2018)²
 - > Robotic perspective



Our contributions

1. Comparative analysis & Combination motivation
2. Gathering & classification of state of the art works
3. Discussion and Research Directions

¹ Benjamin Recht. A tour of reinforcement learning: The view from continuous control. Annual Review of Control, Robotics, and Autonomous Systems, 2:253–279, 2019.

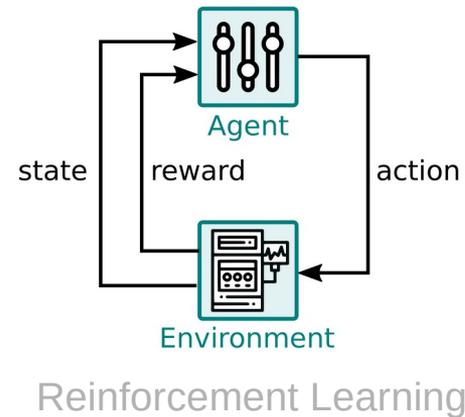
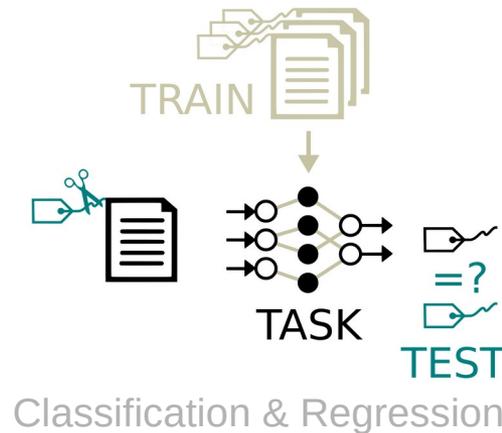
² Signe Moe, Anne Marthine Rustad, and Kristian G Hanssen. Machine learning in control systems: An overview of the state of the art. In International Conference on Innovative Techniques and Applications of Artificial Intelligence, pages 250–265. Springer, 2018.

Outlines

1. Potentiality Analysis
2. Combinations
 - > ML components in a CT framework
 - > CT components in a ML framework
3. Discussion & Research Directions

Neural Networks

Key elements: 1. Data 2. Task 3. Model 4. Optimization

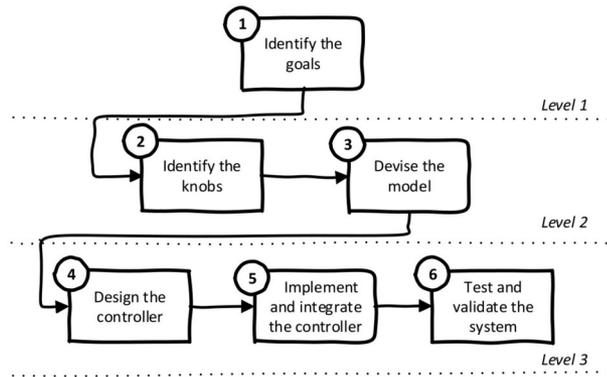


- Performance
- Context and Data variety
- Scale
- No initial knowledge



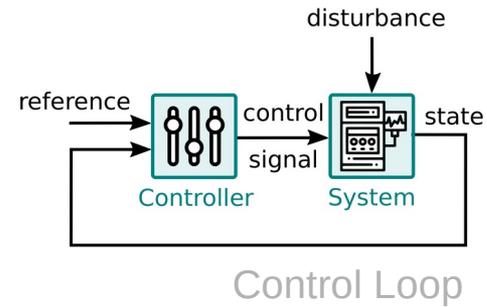
- Stability & performance guarantees
- Data richness
- Configuration
- Training energy efficiency

Deterministic Control



(Fileri, 2015)

Control Conception



Control Loop



- Guarantees
- Robustness
- Theoretical analysis tools
- No exploration



- Hypothesis
- Scale
- Model
- Objectives

Neural Networks



- Performance
- Context and Data variety
- Scale
- No initial knowledge



- Stability & performance guarantees
- Data richness
- Configuration
- Training energy efficiency

Deterministic Control



- Hypothesis
- Scale
- Model
- Objectives



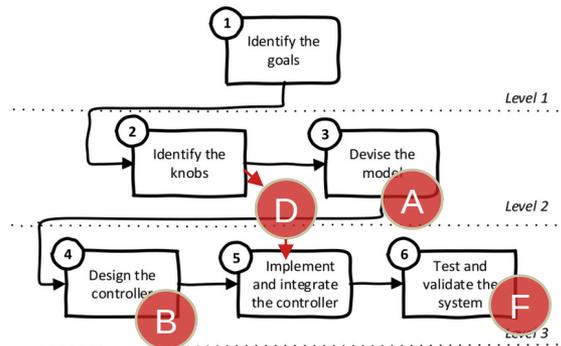
- Guarantees
- Robustness
- Theoretical analysis tools
- No exploration

02

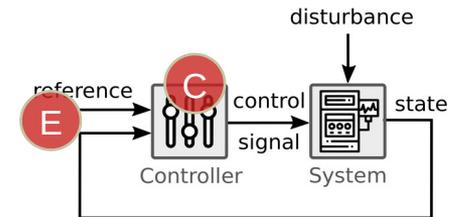
Combinations

- > ML components in a CT framework
- > CT components in a ML framework

Control Framework +NN tools

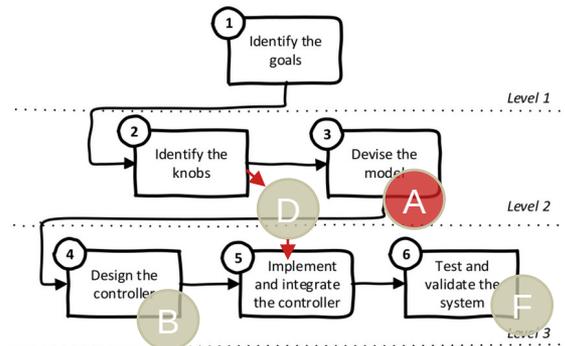


Conception phase

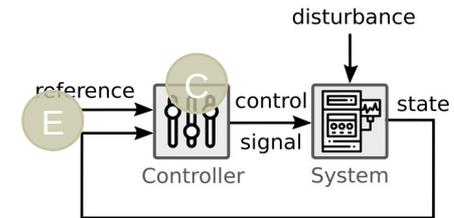


Control loop

Control Framework +NN tools



Conception phase



Control loop

A ML for Modeling

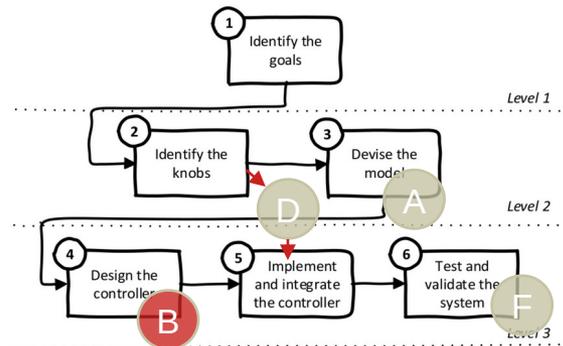
Offline

- RL model fed to Robust control
> (Matni et al. 2020)
- Approximate ODE/PDE
> (Sirignano and Spiliopoulos 2018)
- Discrete Event Systems
> (Basile et al. 2020)

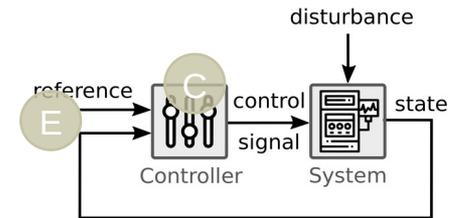
Online

- Without guarantees (Rajamäki and Hämmäläinen 2017)
- Guarantees-based approaches (Hoffmann 2015)

Control Framework +NN tools



Conception phase



Control loop

A ML for Modeling

B ML for Controller Design

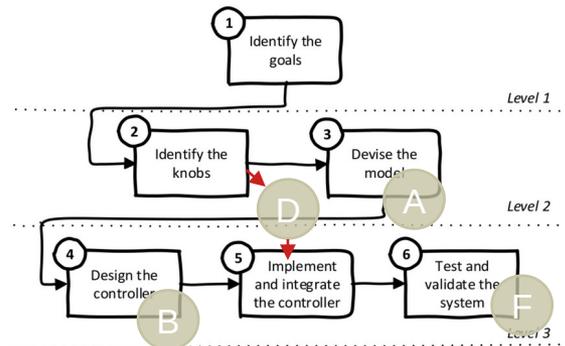
Offline

- NN to tune a PID

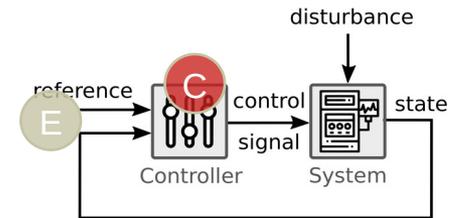
Online

- Without guarantees
 - > (Caldas et al. 2020), (Neftci and Averbek 2019), (Banerjee and Chatterjee 2019)
- Guarantees-based approaches
 - > Early works
 - > Neural Networks
 - > Reinforcement Learning (Gros and Zanon 2019), (Poveda et al. 2019), (Benosman et al. 2019)

Control Framework +NN tools



Conception phase



Control loop

A ML for Modeling

B ML for Controller Design

C ML as a Controller

Neural Predictive Control

- Non-linear systems, decentralized controller
- Guarantees
> (Chen et al. 2018)

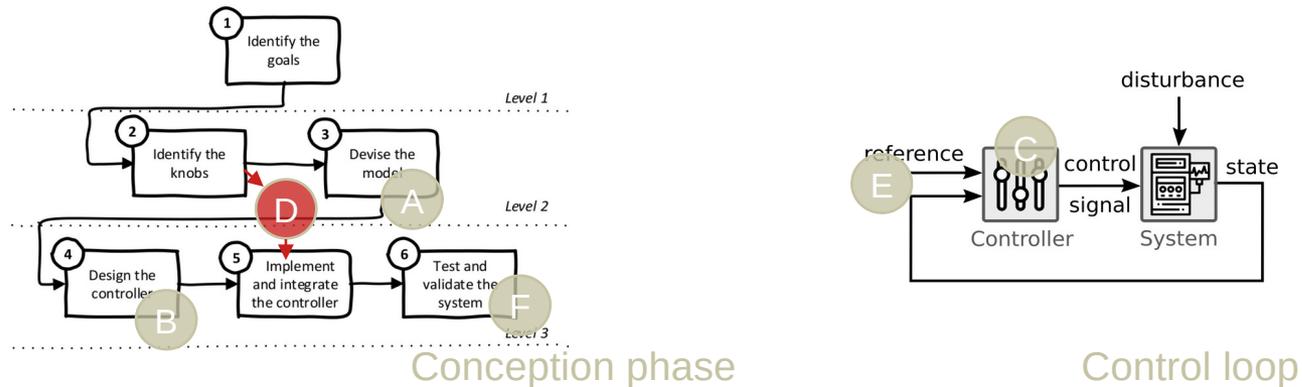
Train a NN to Control

- With guarantees
> (Ivanov et al. 2019), (Gilra and Gerstner 2018)

Discrete Event Controller

- Supervision with RL

Control Framework +NN tools



- A ML for Modeling
- B ML for Controller Design
- C ML as a Controller
- D ML for Generating Controllers

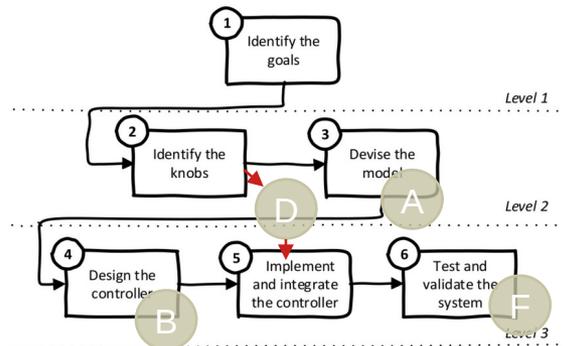
RL to synthesize DES controllers

- Limited guarantees
 - > (Zhang et al. 2018)

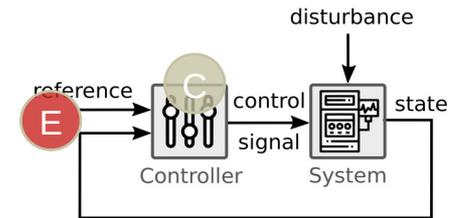
Machine Learning Control

- Genetic Programming
 - > (Duriez et al. 2017)

Control Framework +NN tools



Conception phase

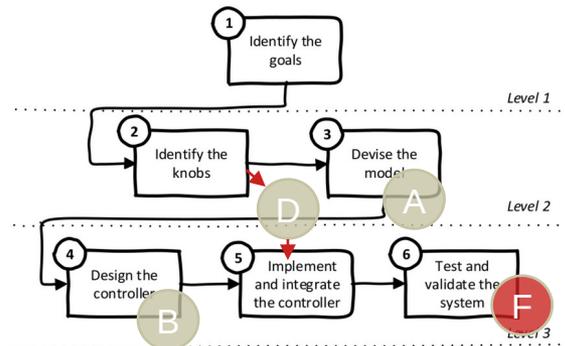


Control loop

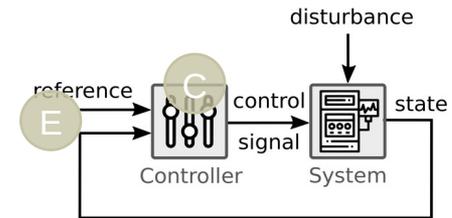
- A ML for Modeling
- B ML for Controller Design
- C ML as a Controller
- D ML for Generating Controllers
- E ML for Translating Objectives

- Generate an adequate reference signal
 - > Perception-Based Control (Dean et al. 2020)
- Set MPC cost function and constraints
 - > (Hewing et al. 2020)

Control Framework +NN tools



Conception phase

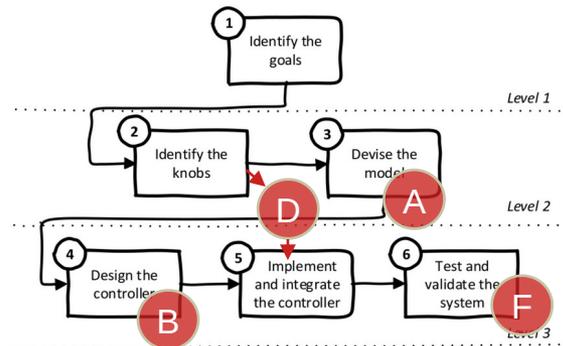


Control loop

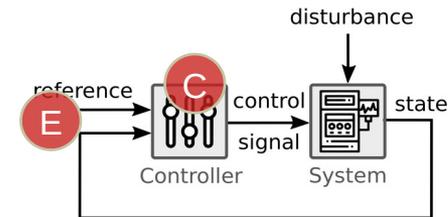
- A ML for Modeling
- B ML for Controller Design
- C ML as a Controller
- D ML for Generating Controllers
- E ML for Translating Objectives
- F ML for Control Validation

- Select challenging inputs
> (Yaghoubi and Fainekos 2019)
- Representing controllers for experts' debugging
> (Balasubramaniam 2019)

Control Framework +NN tools



Conception phase



Runtime

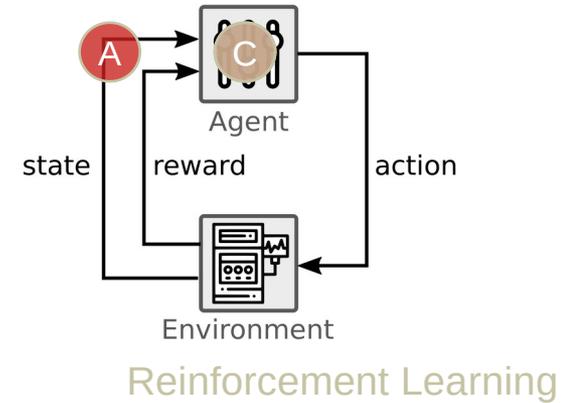
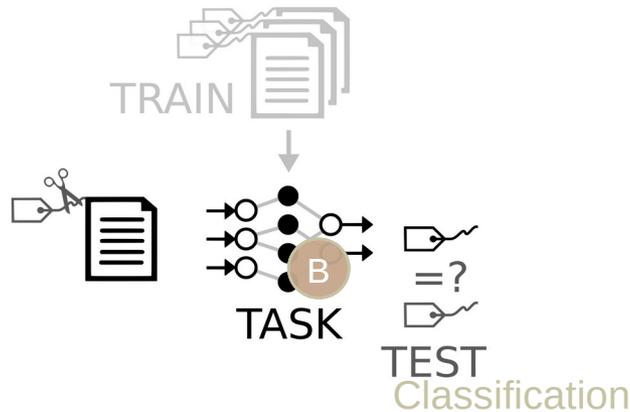
- A ML for Modeling
- B ML for Controller Design
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- F ML for Control Validation

02

Combinations

- > ML components in a CT framework
- > CT components in a ML framework

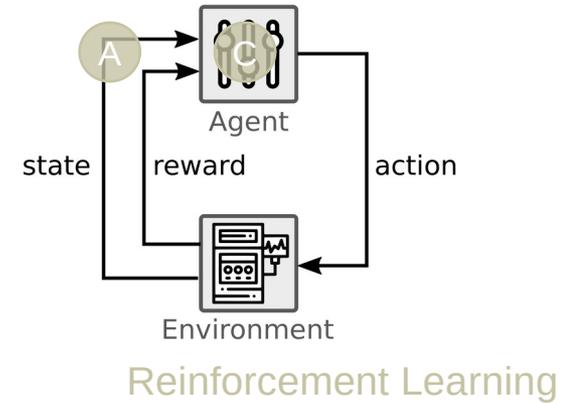
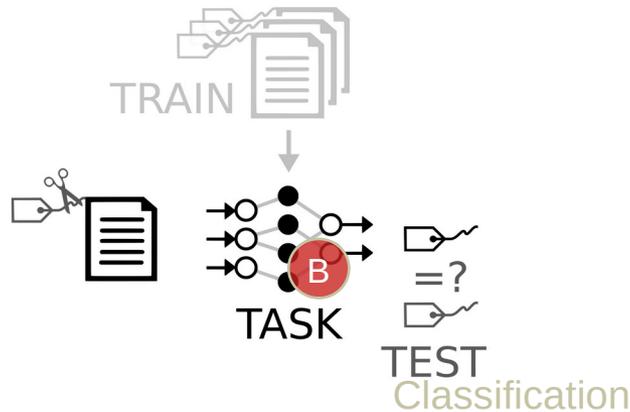
Learning Framework + Control tools



- A Controlling training data
- B Controlling hyper-parameters
- C Decision making using Control

● Generating datasets for RL training

Learning Framework +Control tools

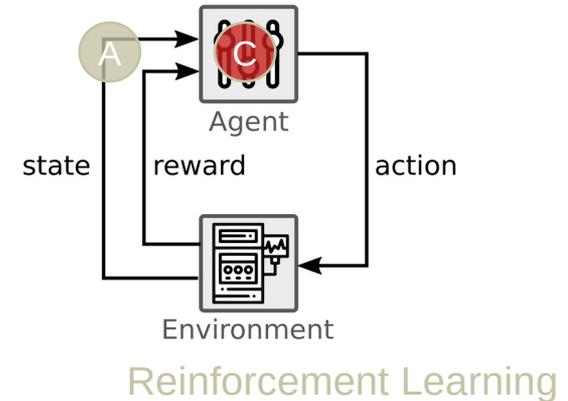
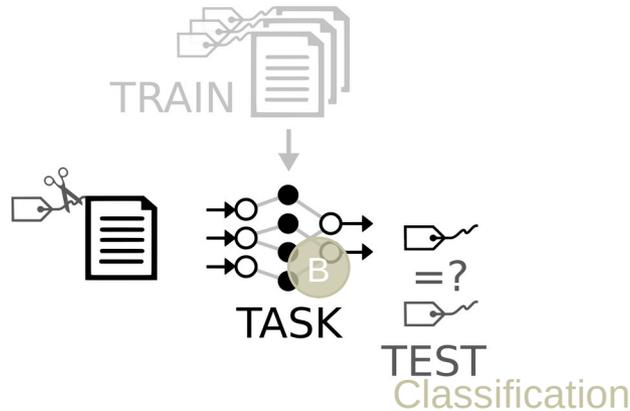


- A Controlling training data
- B Controlling hyper-parameters
- C Decision making using Control

NN training as a system to regulate

- Learning rate
 - > (Li et al. 2017), (Zhao et al. 2020)
- Exploration
 - > (Lowrey et al. 2018)

Learning Framework +Control tools



- A** Controlling training data
- B** Controlling hyper-parameters
- C** Decision making using Control

MPC to find RL optimal policy

- Data-efficiency (Kamthe and Deisenroth 2018), (Gros and Zanon 2020), (Nagabandi et al. 2018)
- Robustness to modeling uncertainties (Gros and Zanon 2019)
- Safety (Zanon and Gros 2020), (Gros et al. 2020)
- Extended objectives (Williams et al. 2017)

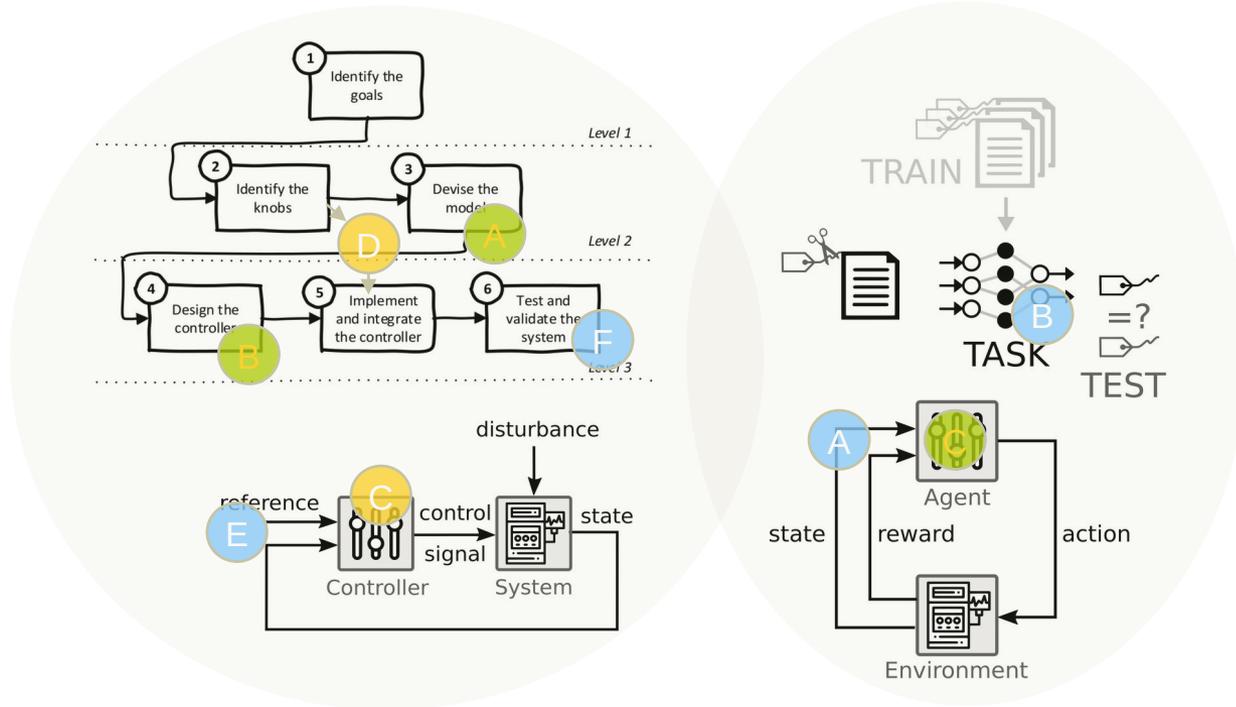
Alternative to gradient-based methods

> (Li and Hao 2018), (Kolarijani et al. 2018)

03

Discussion & Research Directions

Discussion & Research Directions



Usual

Under-exploited

Unexplored

Unexpected

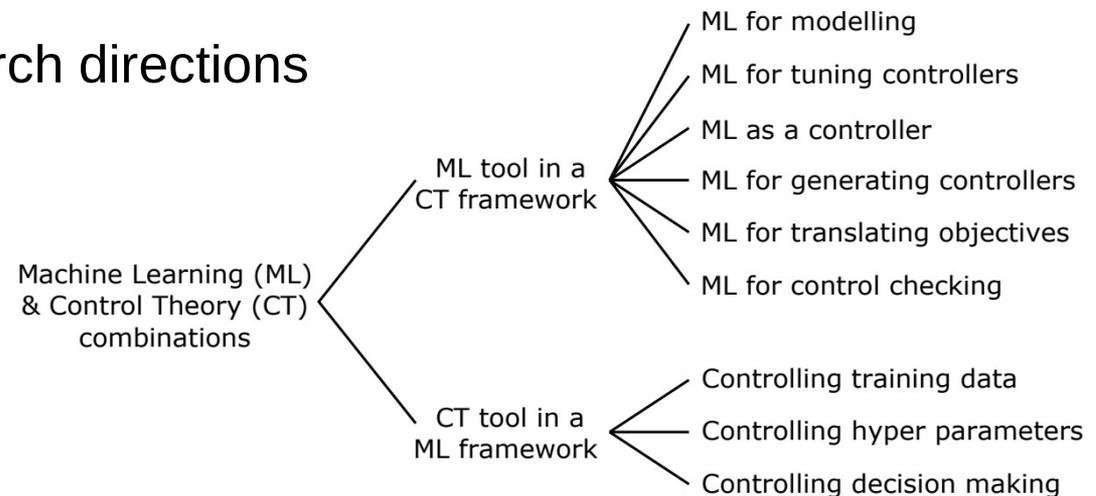
- CT constraints
- NN guarantees
- NN robustness

- NN safety
- NN explainability
- CT scalability

- No guarantees

Wrap-up

- Neural Network & deterministic Control combinations
 - > Motivation analysis
- State of the art review
 - > Categorization
- Opening of research directions



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