Master Thesis Presentation

Offline Reinforcement Learning with Self-Supervised State Representations for Hemodynamic Support at the ICU

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M Artificial Intelligence (VU)

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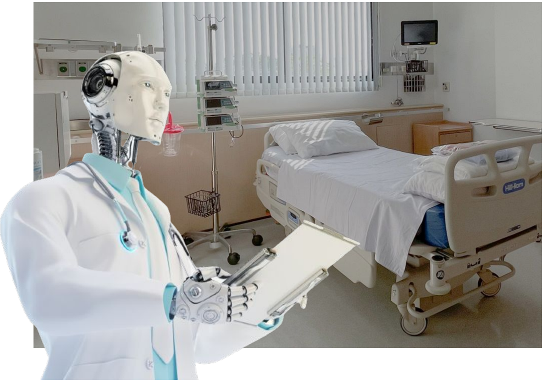

Collaboration between…

Amsterdam UMC
Universitair Medische Centra

VU

Quantitative Data
Analytics Group

Big picture idea

"Use ***Deep Reinforcement Learning*** (DRL) to learn ***optimal control strategies*** for delivering ***treatments*** to ***critically-ill patients*** at the Intensive Care Unit (ICU)"

Why RL?

Many severe conditions treated at ICU:

- Pneumonia (“longontsteking”)
- COVID-19
- Cardiac infarction (“hartinfarct”)
- ***Sepsis*** (severe infection w/ organ failure)

No consesus on best treatment practice

- How to optimally treat patients often remains unclear

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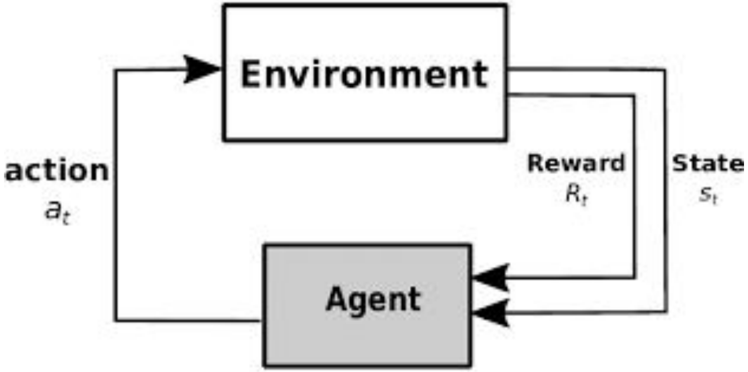

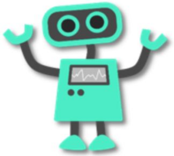

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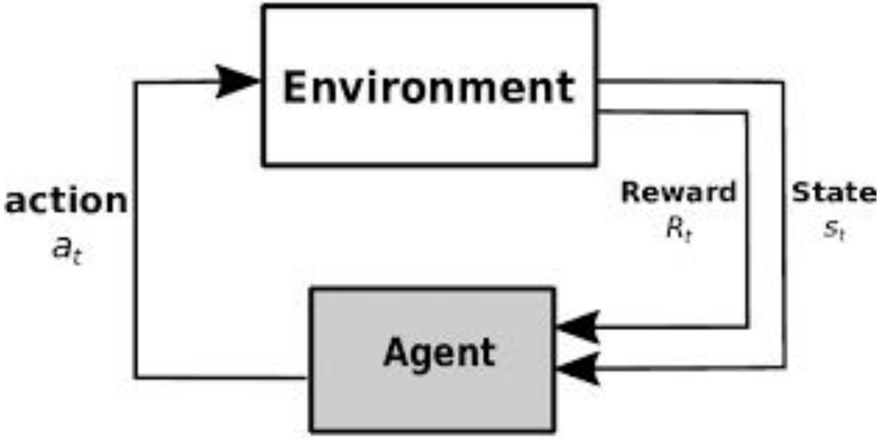
Question: "Can we train RL agent to find an optimal treatment delivery strategy for, e.g. sepsis?"

Treatment as MDP



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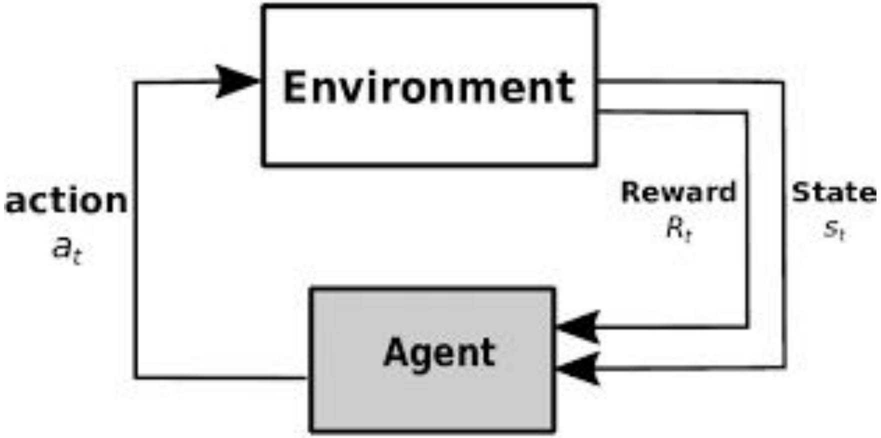

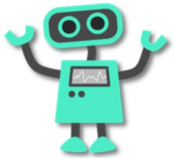

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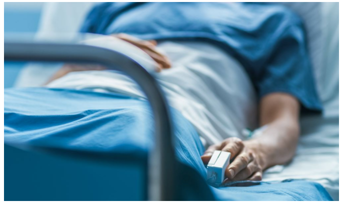

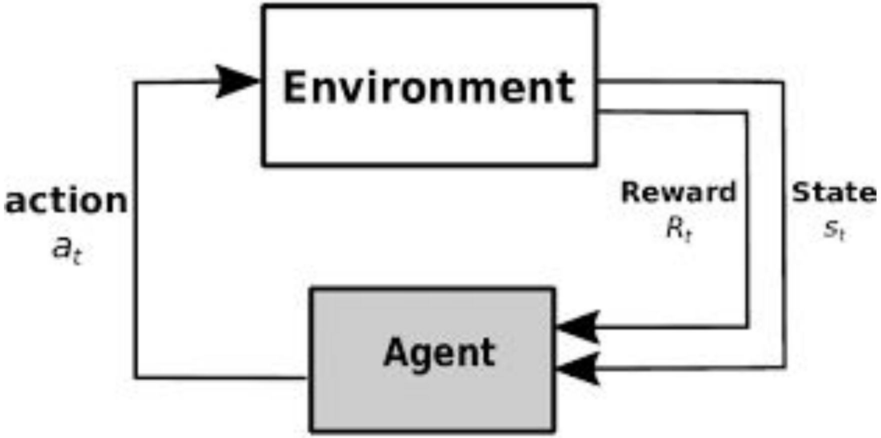

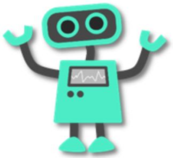

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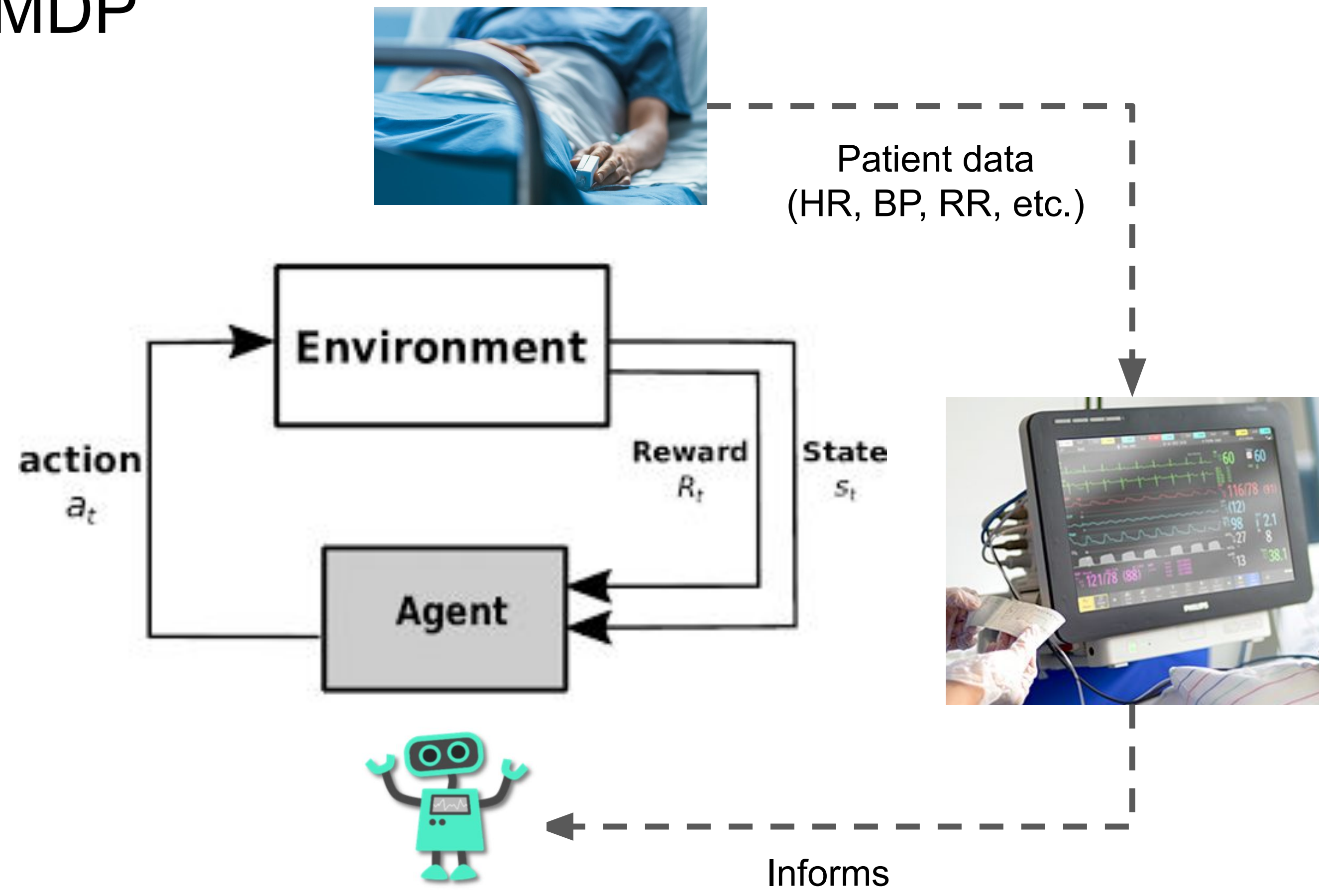

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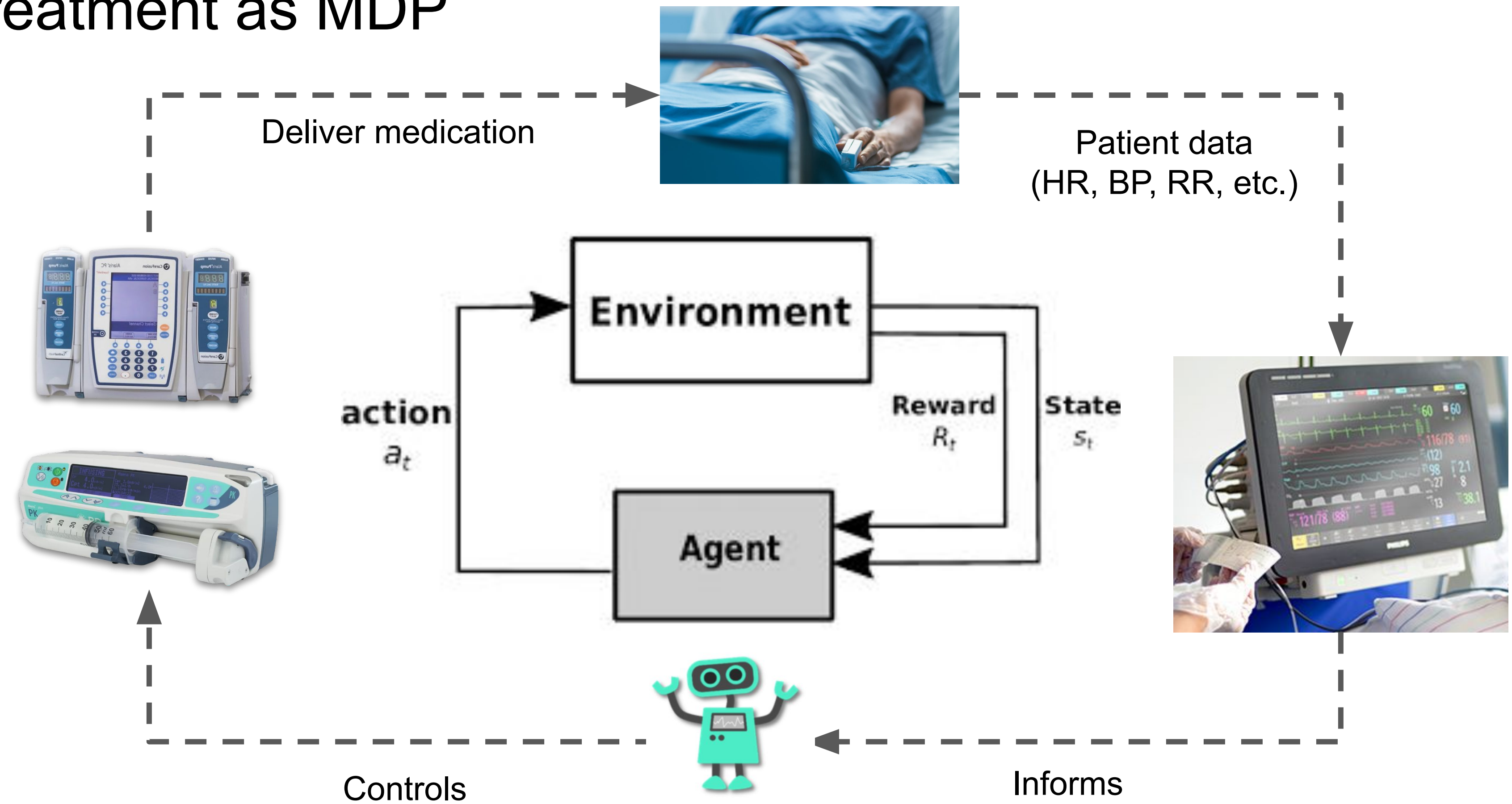


Open problems

Goal: Train agent to choose treatments (actions) which maximize likelihood of patient survival

But:

1. **RL is an “online trial-and-error” paradigm**
    - Cannot train directly from interaction(s) with patients (cf. “learning-on-the-job”)
    - High-fidelity “patient sims” do not exist

2. **How to define the states/rewards/actions**?
    - States must include all information possibly relevant from the patient’s medical history

Method

Model: Dueling Double Deep Q-Learning + MLP controller

Data: Offline dataset gathered by UMC physicians (±12.000 patients)

- Patient data over time + treatment doses + discharge info

States: Learnt through *self-supervised forward modeling* (see [Lesort et al., 2018])

- No need to elicit knowledge from medical experts
- Train RNN/transformer encoder to extract useful features from patient history to predict $\mathbf{s}_{t+1}$
- i.e. Forward(Enc($\mathbf{s}_0, \mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_t$), $\mathbf{a}_t$) → $\mathbf{s}_{t+1}$

Actions: 2 medications, each 5 levels → 25 discrete actions

Reward: Did patient survive (within ICU)?

Evaluation and Conclusions

Evaluated agent using held-out offline data (±1500 patients)

- Off-policy policy evaluation (OPE)
- Feature attribution (how do measurements influence treatment)
- Manual inspection of model actions which deviate severely from physician

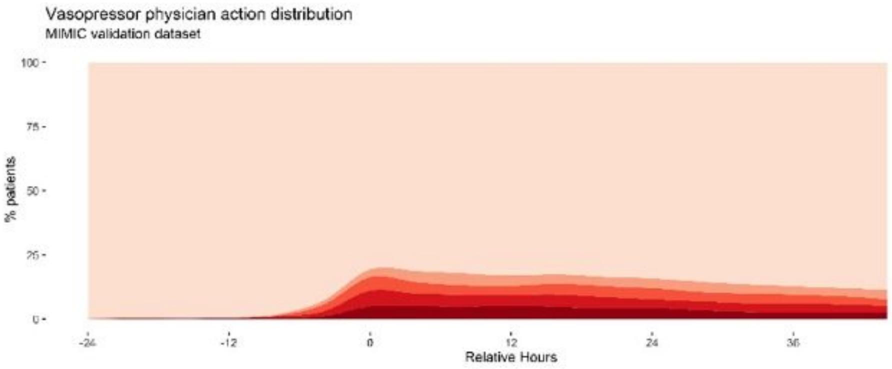
Results: Expected mortality rate ↓**6%** rel. to physician’s policy (baseline **>11%**)

Explanations: Model paid most attention to known biomarkers for disease severity

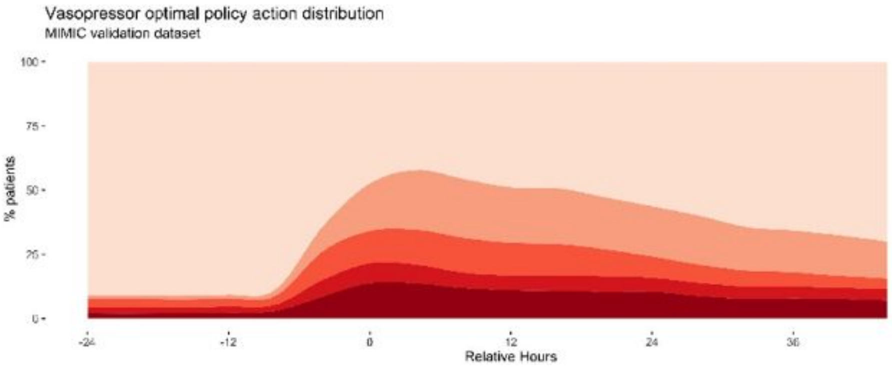
Confirmed recently-discovered strategies:

- Higher doses of vasopressors
- Increasing then decreasing vasopressors increases chances of survival

Evaluation and Conclusions



Physician treatments (in data)



Agent’s treatments

Thanks

Questions?