

# Optimizing the Combination of Radiotherapy with Immunotherapy via Deep Reinforcement Learning

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## BACKGROUND

- ❖ Aim: optimize the combination of radiotherapy (RT) with immunotherapy (IO)
- ❖ Amount benefit IO adds depends on RT dose spacing

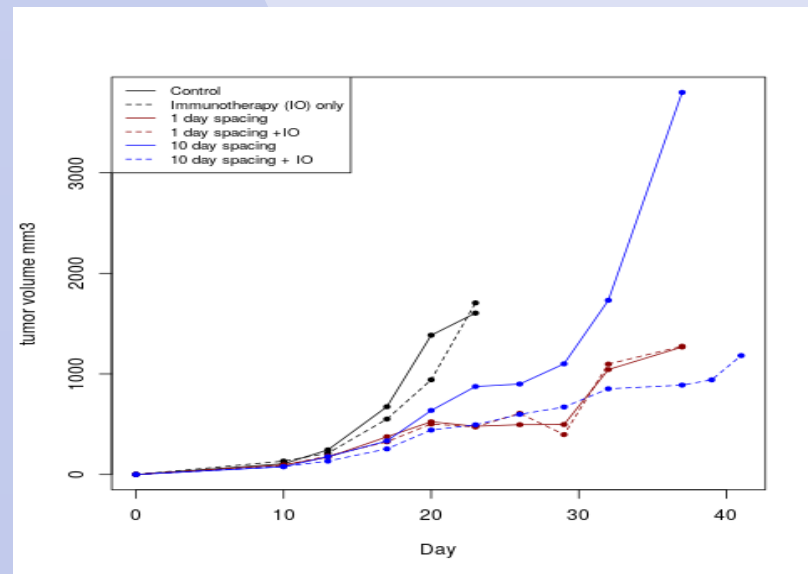


Fig.1: Immunotherapy has a greater effect on mice with normal immune systems when two fractions of radiotherapy are applied 10 days apart (blue) than when they are applied on consecutive days (red).

**Goal:** Given a fixed number of radiation pulses, find the optimal adaptive spacing for administration for the individual subject.

- ❖ Best RT spacing depends on the individual's immune system and may change with time for a single individual
- ❖ Reinforcement Learning is an approach to this problem which requires formulation of the problem as a Markov Decision Process (MDP): collection of potential states, actions, and a reward function.

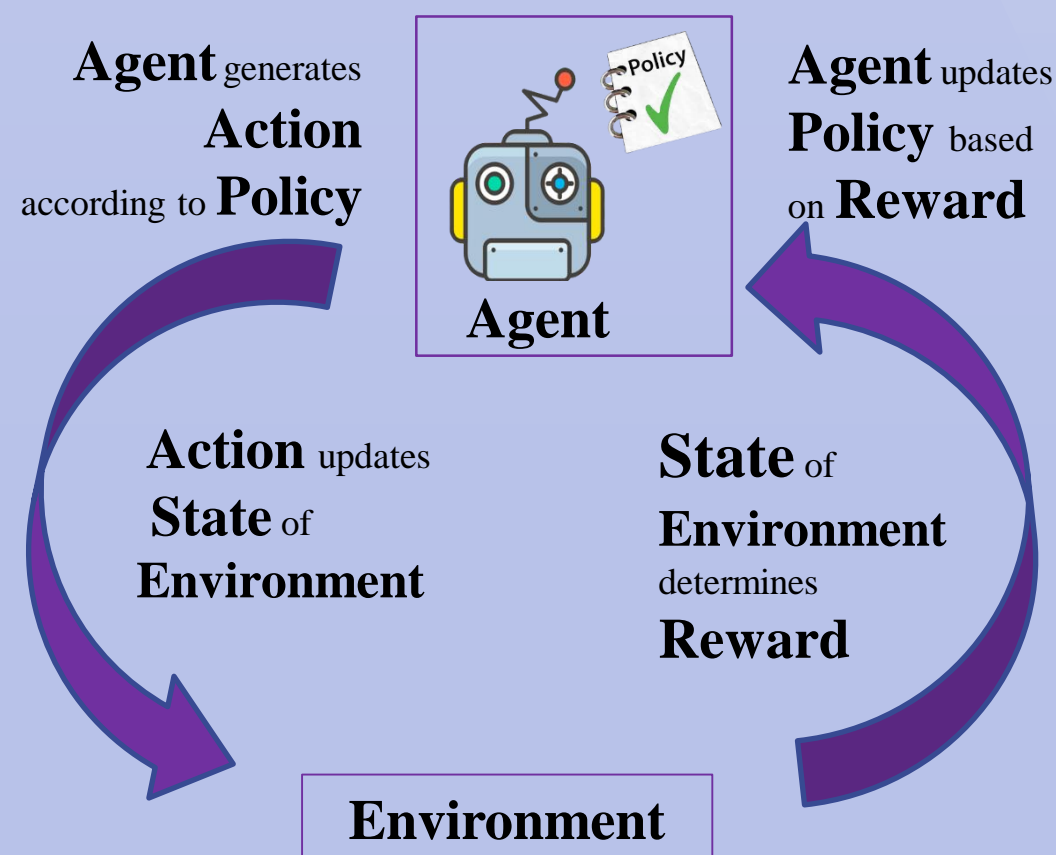


Fig.2: Illustration of the Reinforcement Learning paradigm

## METHOD

- ❖ Train in simulated environment based on biologically-motivated dynamical systems model which can reproduce the synergistic effects between RT and IO

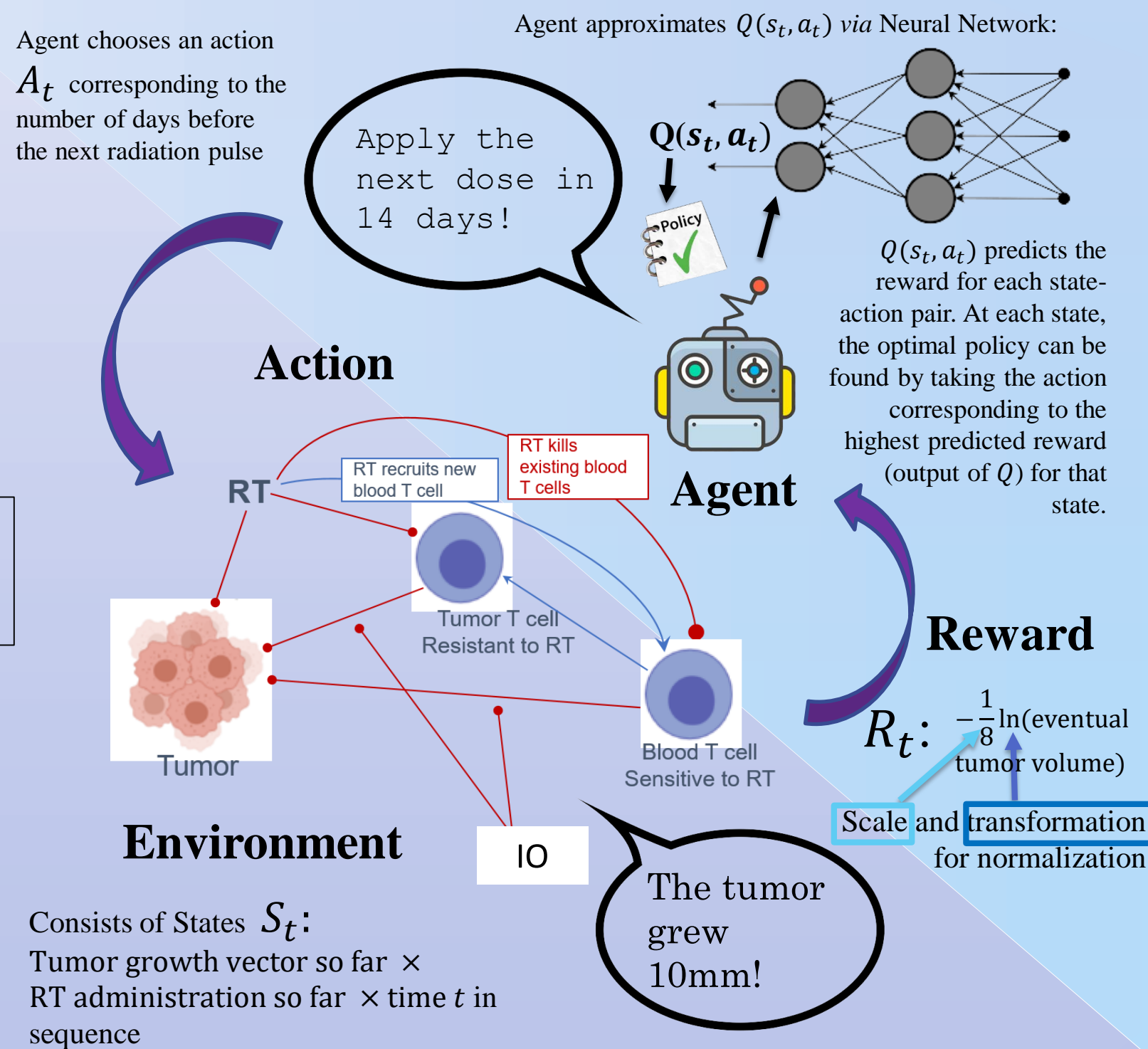


Fig.3: Reinforcement Learning framework for radiation policy determination

### Novelty:

- Mathematical formulation of the optimal spacing problem as a tractable Markov Decision Process
- Reinforcement Learning algorithm with novel specifications which can obtain response-adapted optimal treatment policies in a simulated environment
- Computational framework which contributes to the body of literature paving the way for AI-driven tumor xenograft experiments

- ❖ Simulate real data by applying noise to the parameters of the dynamical systems model that governs the environment.

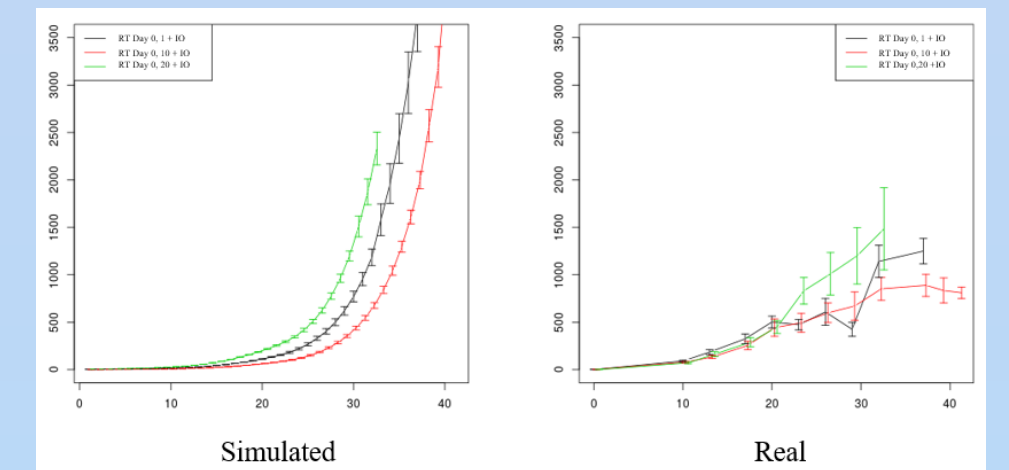


Fig.4: Error bars on simulated vs real data are of comparable length.

## Results

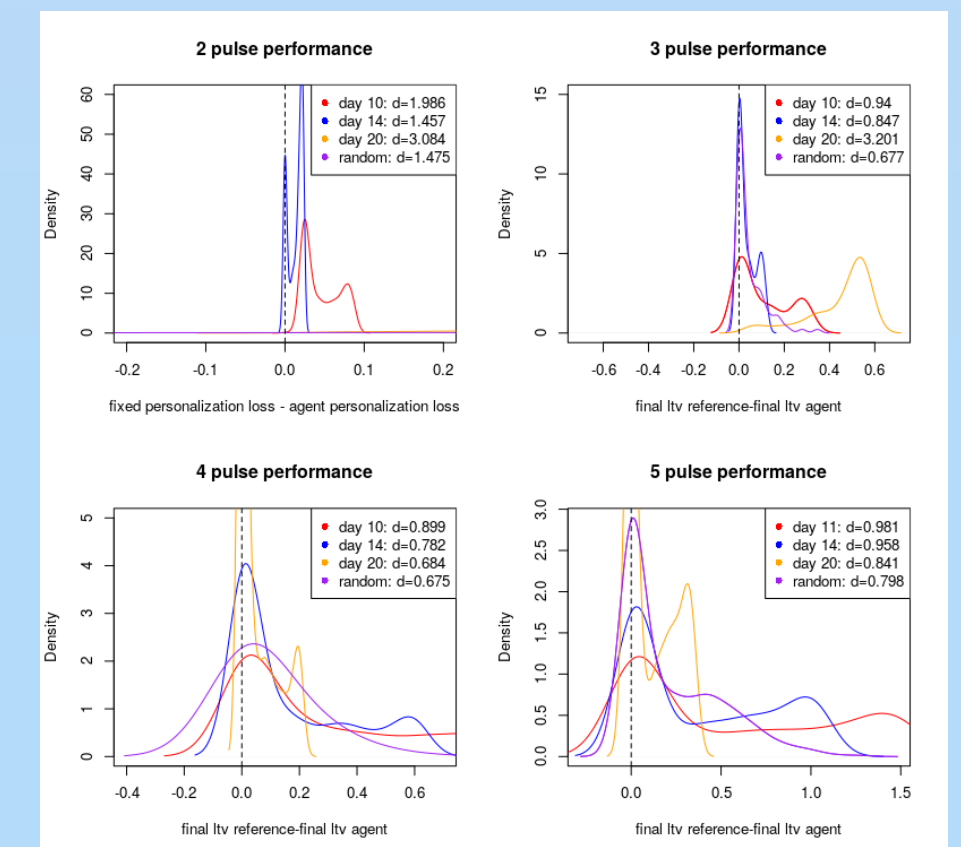


Fig.5: Using the agent results in lower eventual tumor volumes than using fixed or random spacing. LTV = log (final day) tumor volume, and d is the effect size.

## CONCLUSIONS

Q-learning shows promise as a tool for learning response-adaptive personalized fractionation plans.

## SELECTED REFERENCES

- Moore, Casey, et al. Personalized Ultrafractionated Stereotactic Adaptive Radiotherapy (PULSAR) in Preclinical Models Enhances Single-Agent Immune Checkpoint Blockade. *International Journal of Radiation Oncology\* Biology\* Physics* (2021).
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