GRANDMASTER LEVEL IN STARCRAFT II USING MULTI-AGENT REINFORCEMENT LEARNING

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INTRODUCTION

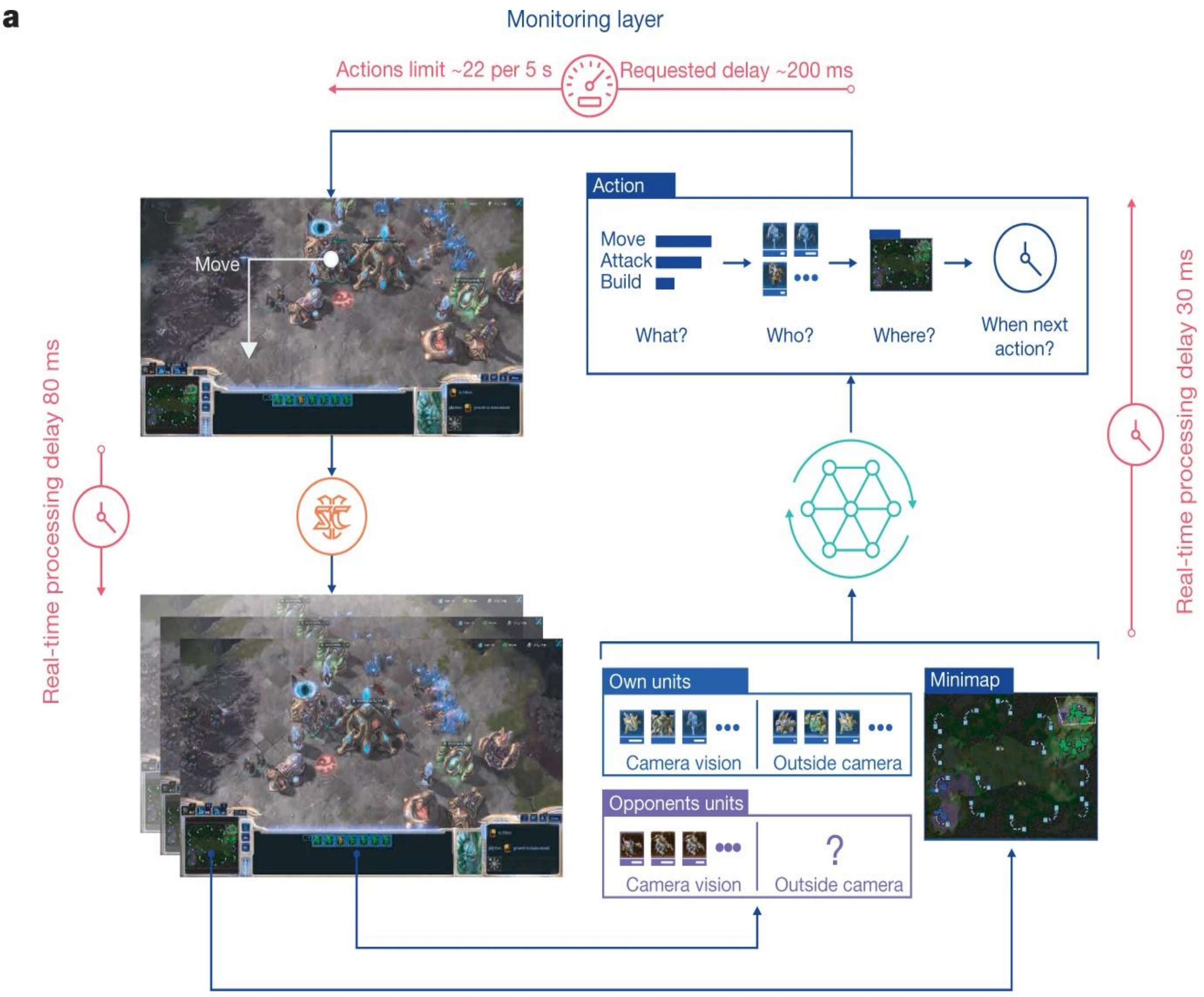
- Many real-world applications require artificial agents to compete and coordinate with other agents in complex environments.

- We chose to address the challenge of StarCraft using general-purpose learning methods that are in principle applicable to other complex domains:
  - a multi-agent reinforcement learning algorithm that uses data from both human and agent games within a diverse league of continually adapting strategies and counter-strategies, each represented by deep neural networks.

- We evaluated our agent, **AlphaStar**, in the full game of StarCraft II, through a series of online games against human players.

- this model is Supervised learning + Reinforcement learning

ARCHITECTURE OVERVIEW



- **a**, AlphaStar observes the game through an overview map and list of units.
- 1) To act, the agent outputs what action type to issue (for example, build), who it is applied to, where it targets, and when the next action will be issued.
- 2) Actions are sent to the game through a monitoring layer that limits action rate. AlphaStar contends with delays from network latency and processing time.

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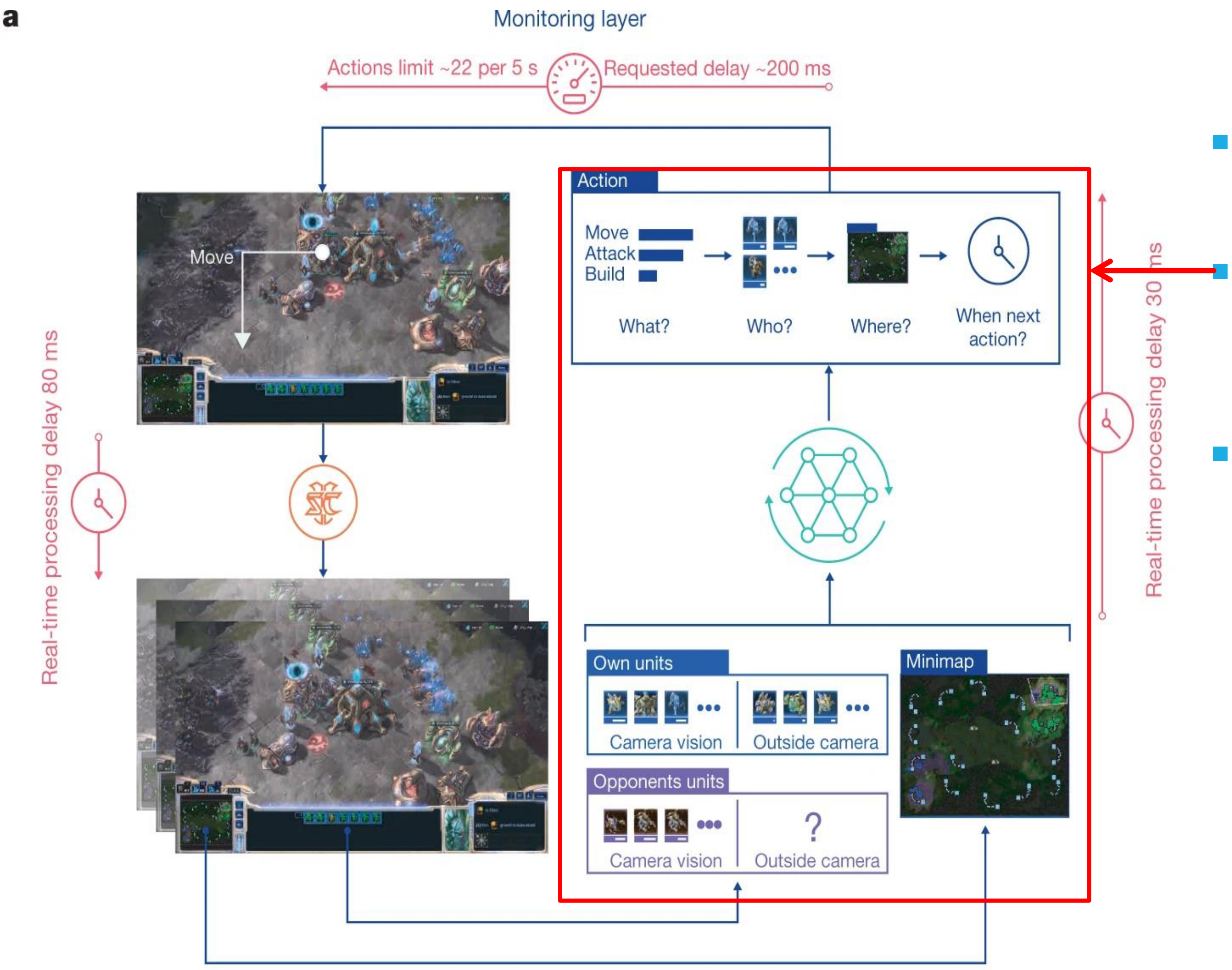

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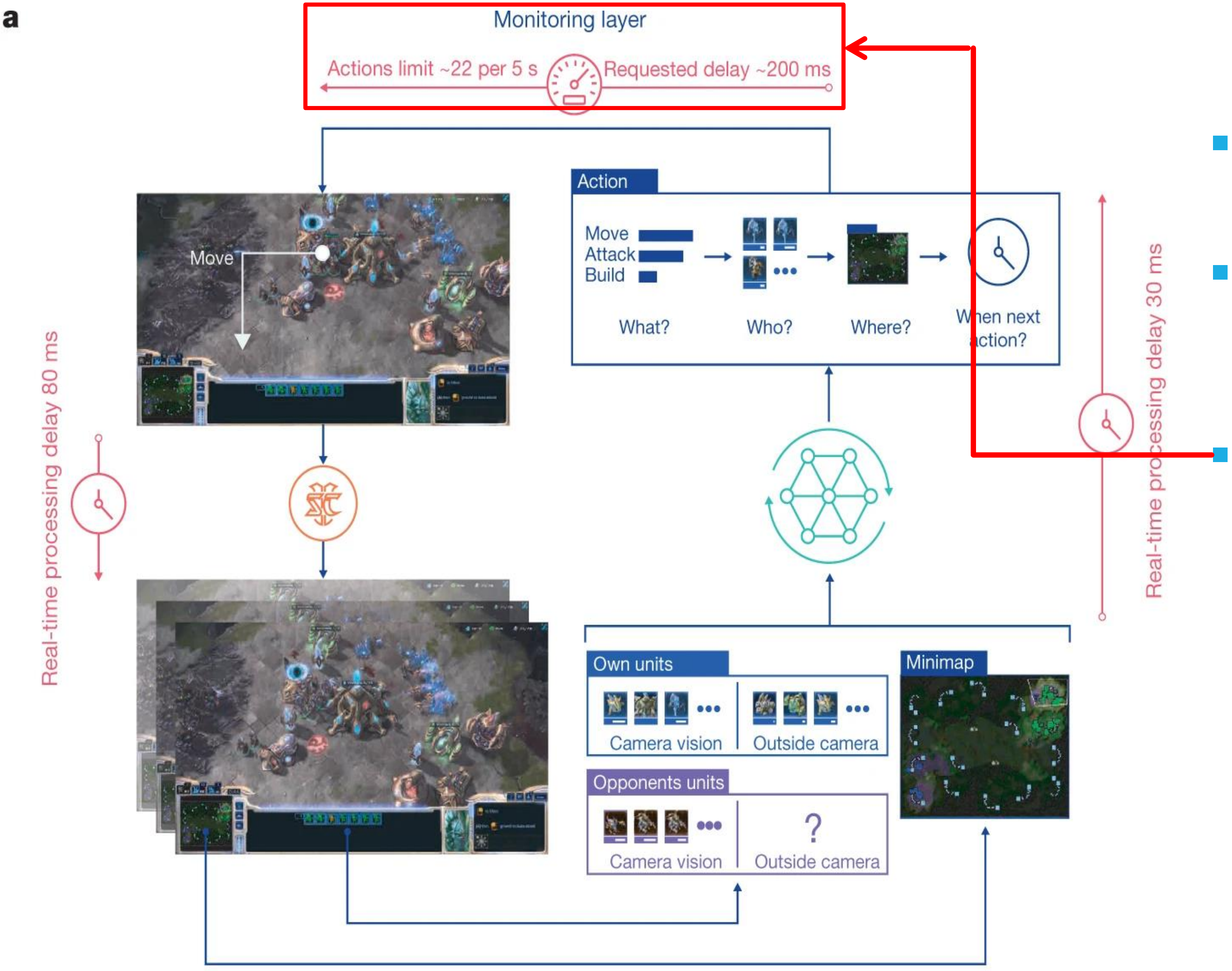

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Humans play StarCraft under physical constraints that limit their reaction time and the rate of their actions.

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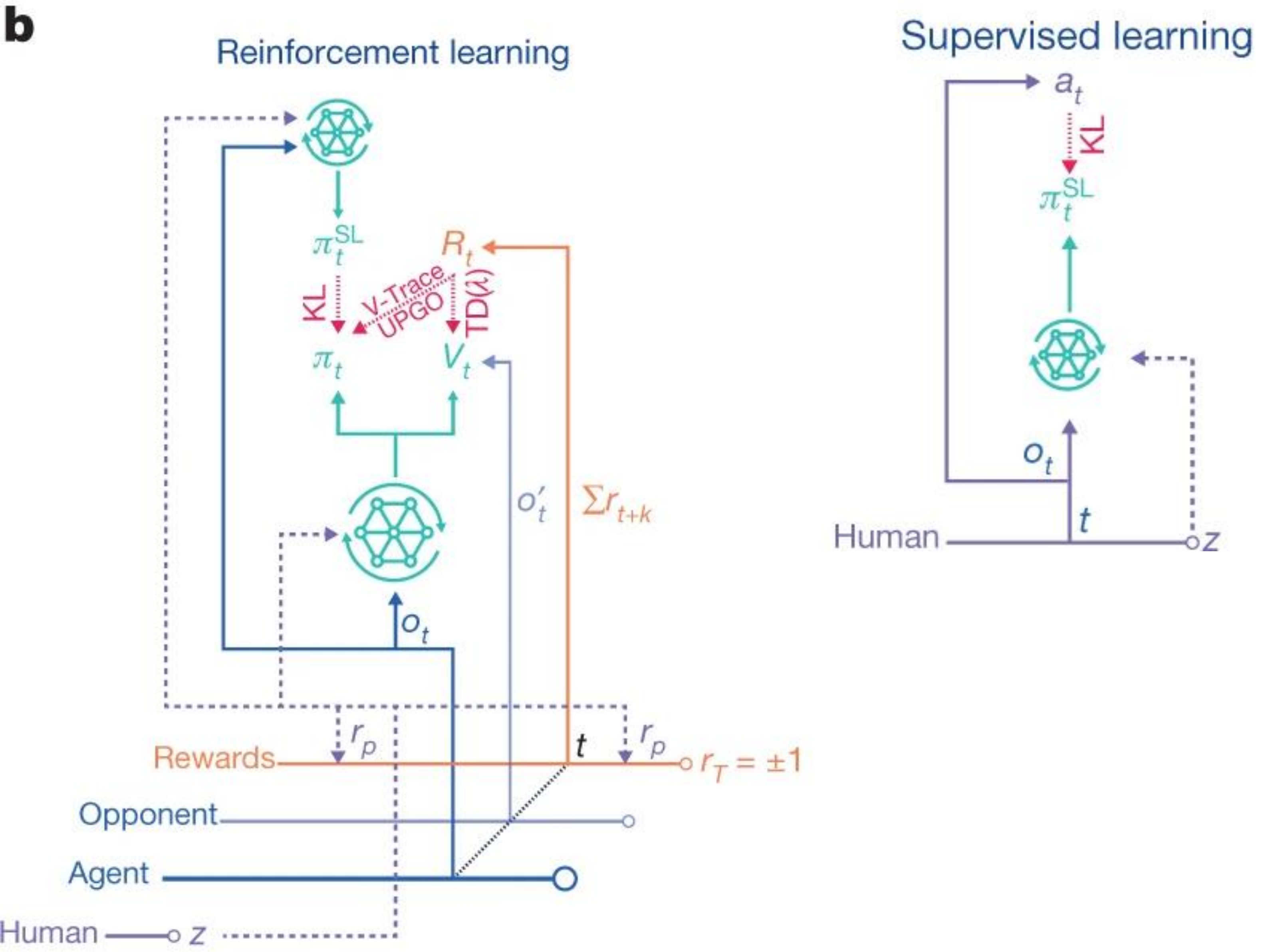

- **b**, AlphaStar is trained via both supervised learning and reinforcement learning.
- In supervised learning, the parameters are updated to optimize Kullback–Leibler (KL) divergence between its output and human actions sampled from a collection of replays.
- In reinforcement learning, human data are used to sample the statistic *z*, and agent experience is collected to update the policy and value outputs via reinforcement learning (TD(λ), V-trace, UPGO) combined with a KL loss towards the supervised agent.

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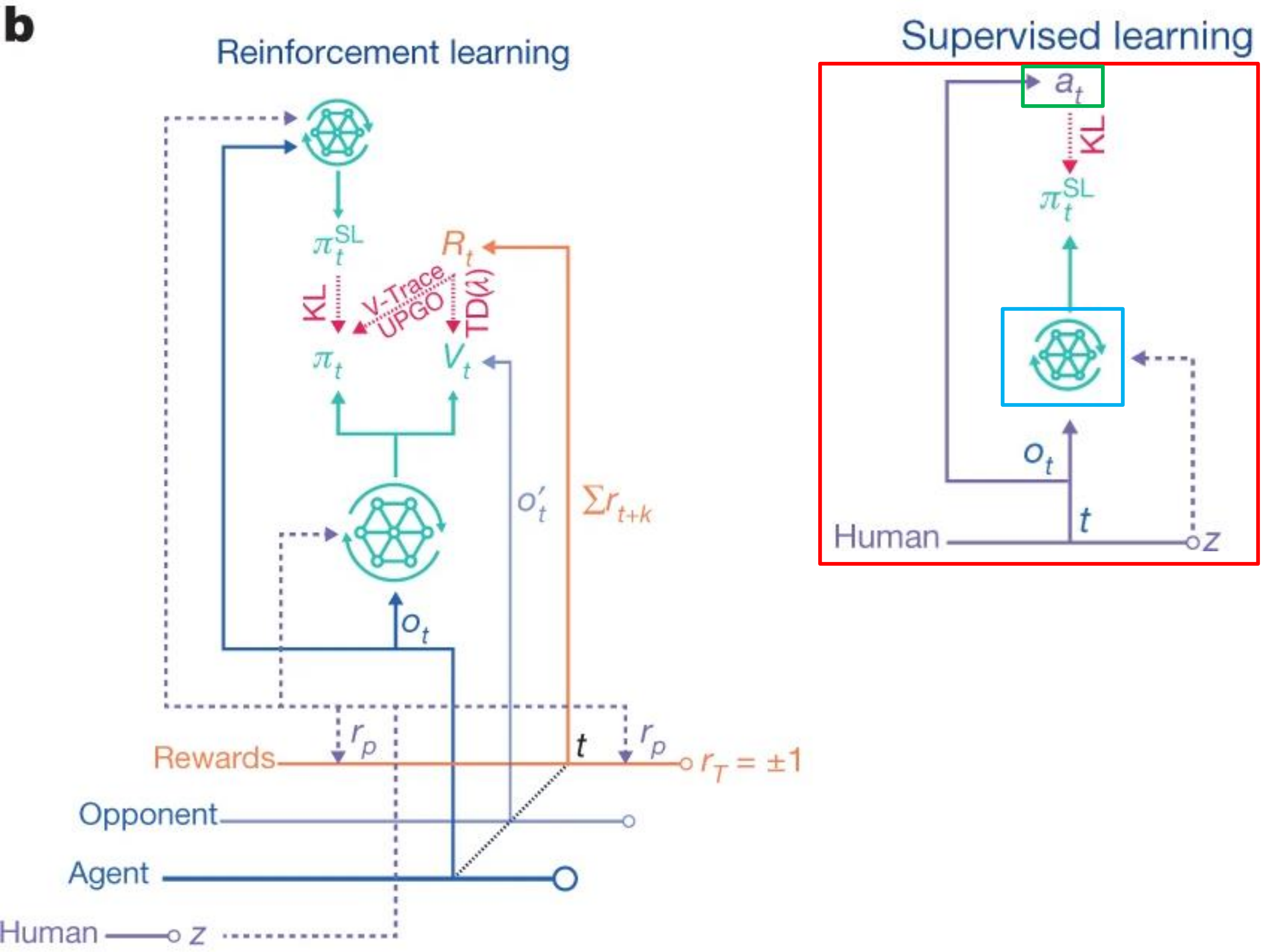

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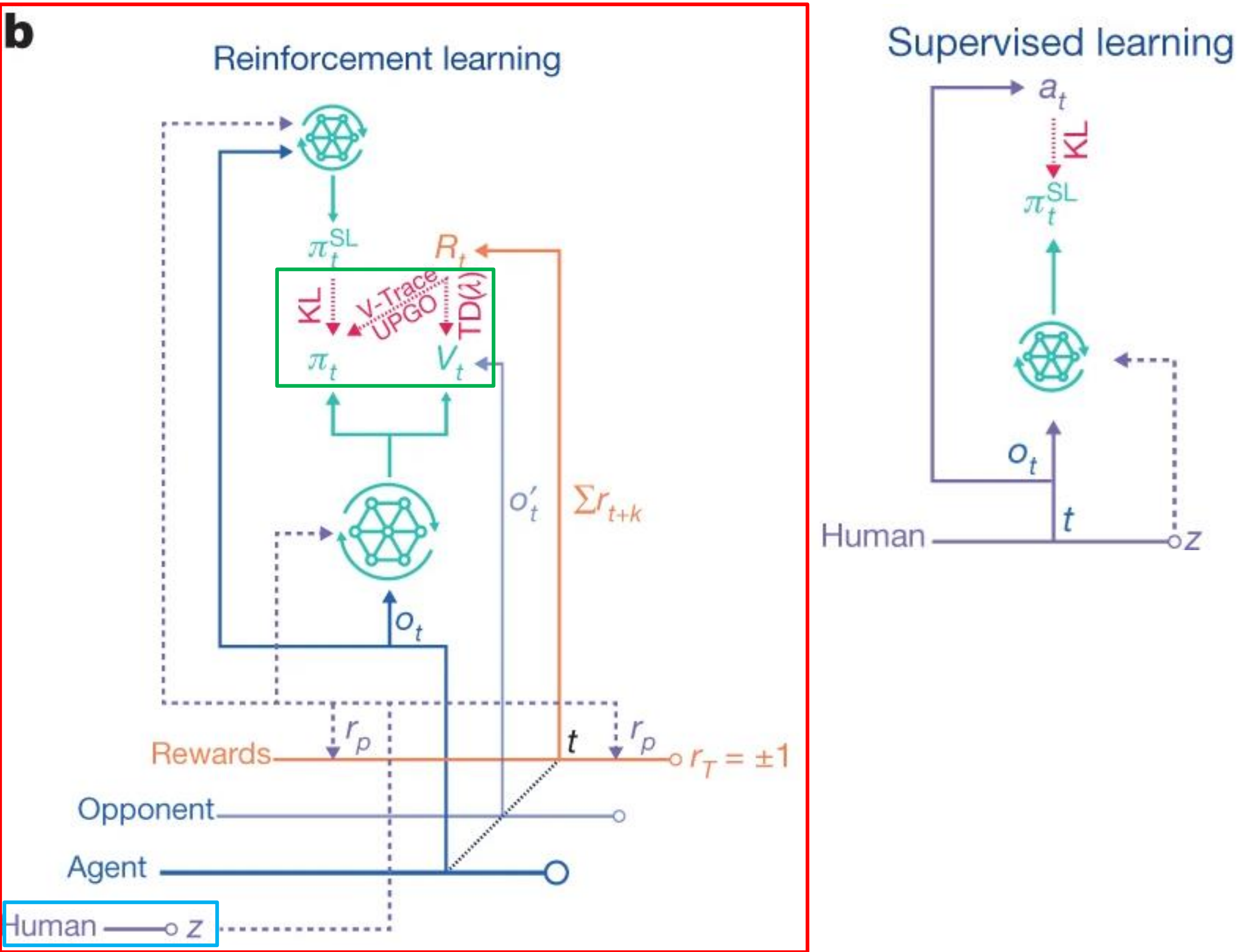

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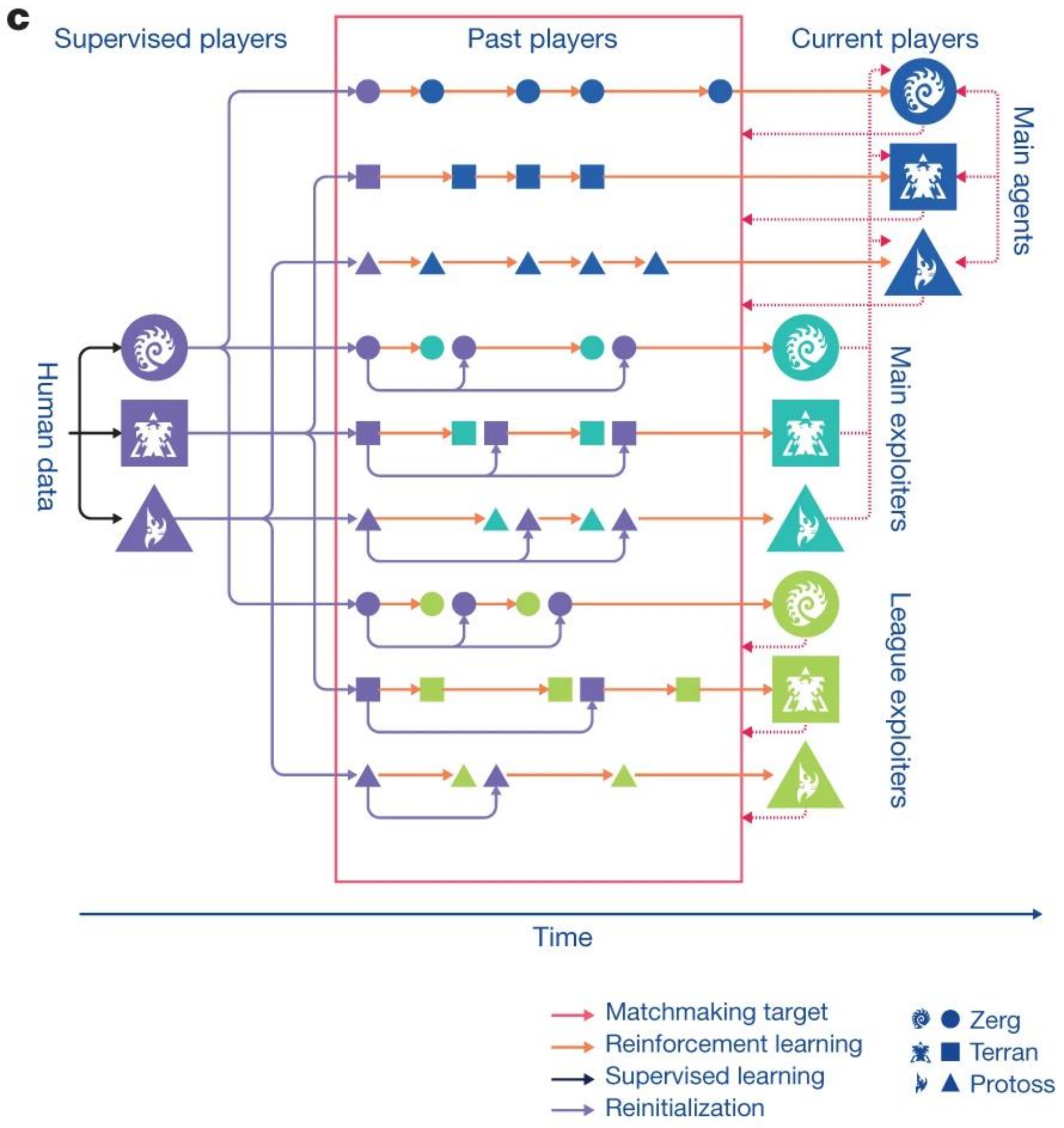

- **c**, Three pools of agents, each initialized by supervised learning, were subsequently trained with reinforcement learning.
- As they train, these agents intermittently add copies of themselves—'players' that are frozen at a specific point—to the league.
- The main agents train against all of these past players, as well as themselves.
- The main exploiters train against the main agents.
  - Complement the weaknesses of the main agent.
- The league exploiters train against all past players.
- Main exploiters and league exploiters can be reset to the supervised agent when they add a player to the league.

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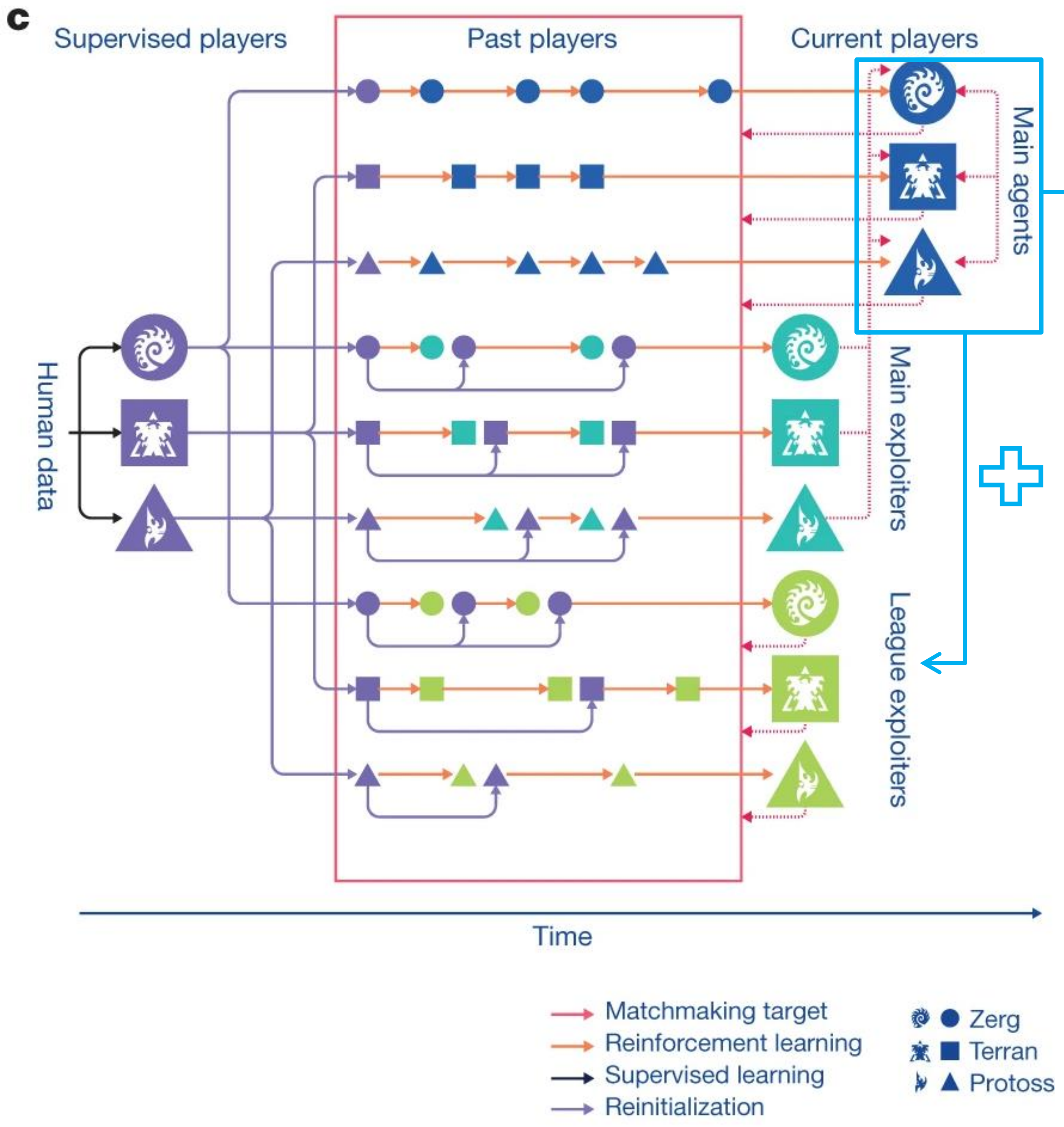

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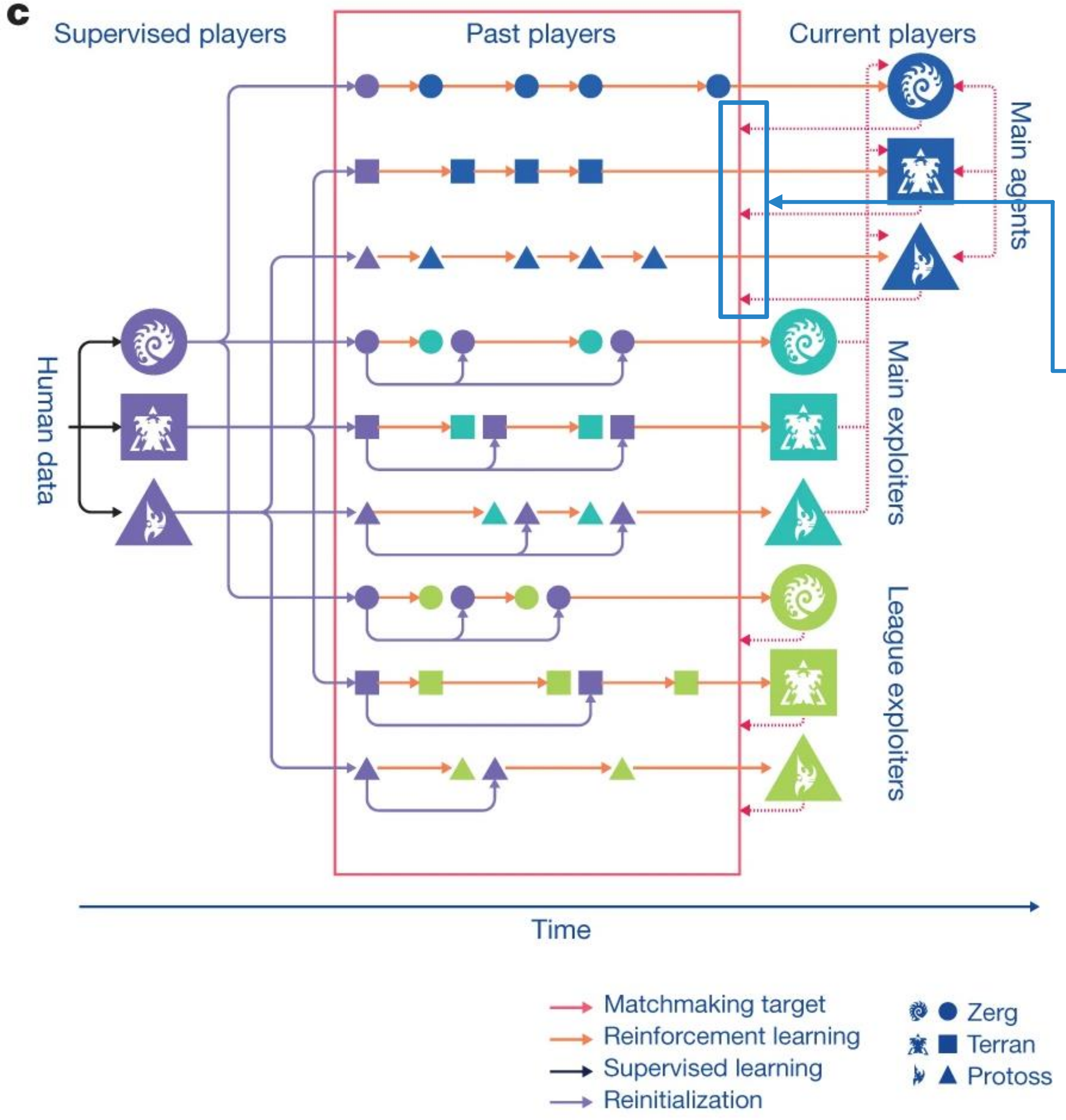

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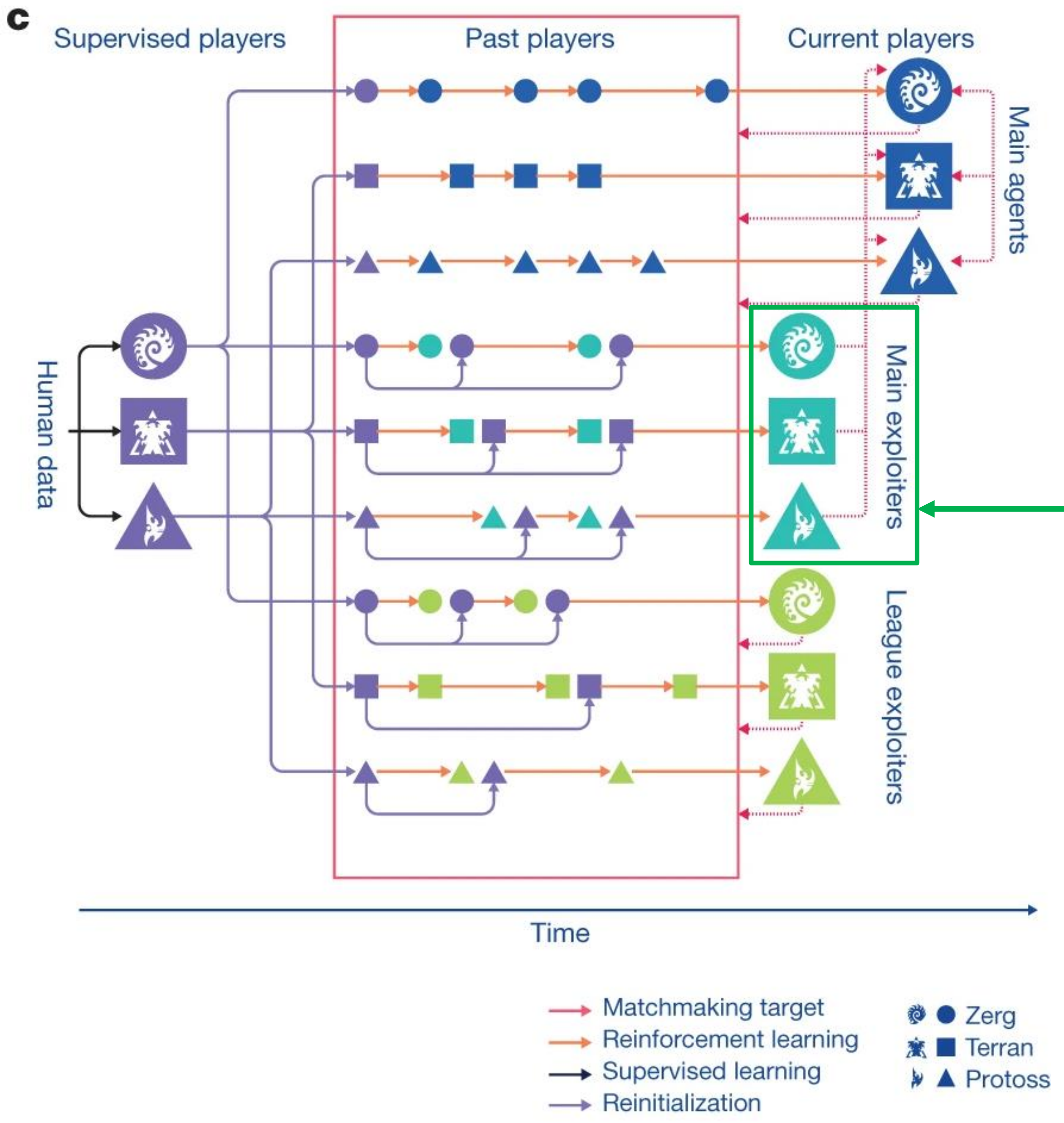

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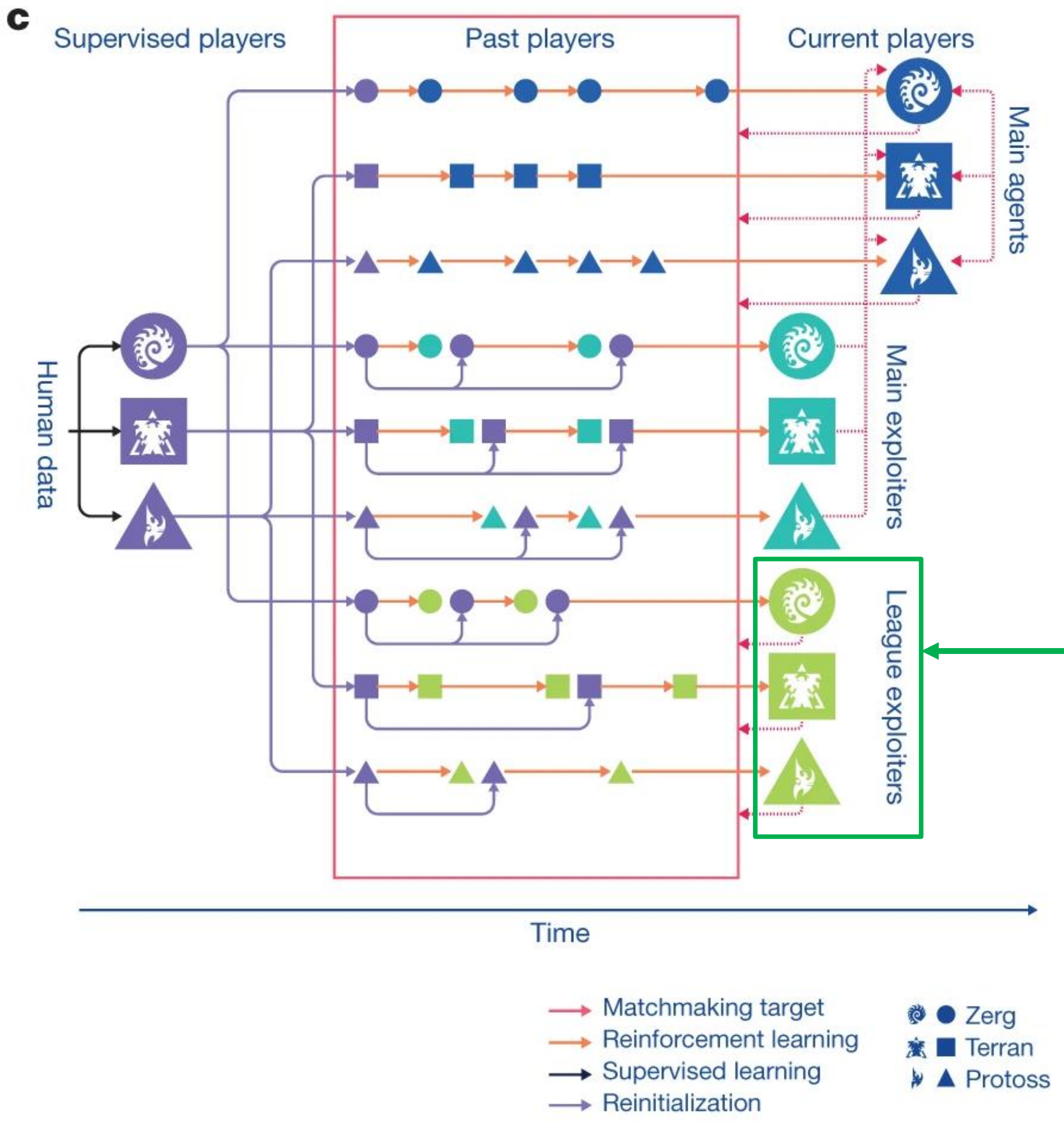

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SUPERVISED LEARNING

- Each agent is initially trained through supervised learning on **replays to imitate human actions**.
- Supervised learning is used both to initialize the agent and to maintain diverse exploration.
  - Because of this, the primary goal is to produce a diverse policy that captures StarCraft's complexities.
- From each replay, we extract **a statistic *z*** that encodes each player's build order, defined as the first 20 constructed buildings and units, and cumulative statistics, defined as the units, buildings, effects, and upgrades that were present during a game.

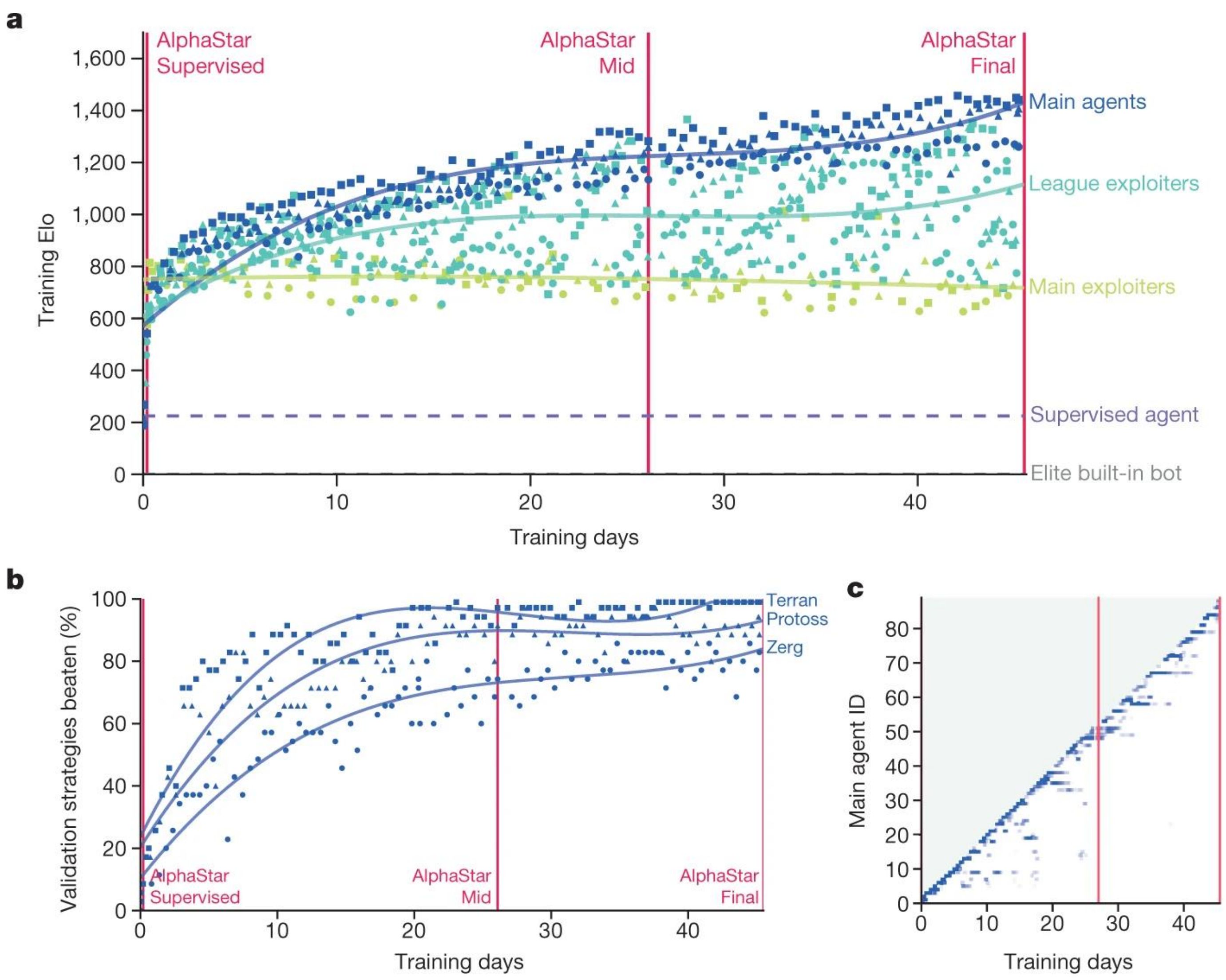
LEARNING ALGORITHM

- Agent parameters were initially trained by supervised learning.
- Games were sampled from a publicly available **dataset of anonymized human replays**.
- The policy was then trained to **predict each action a_t, conditioned either solely on s_t, or also on z**.
- This results in a diverse set of strategies that reflects the modes of human play.

LEARNING ALGORITHM

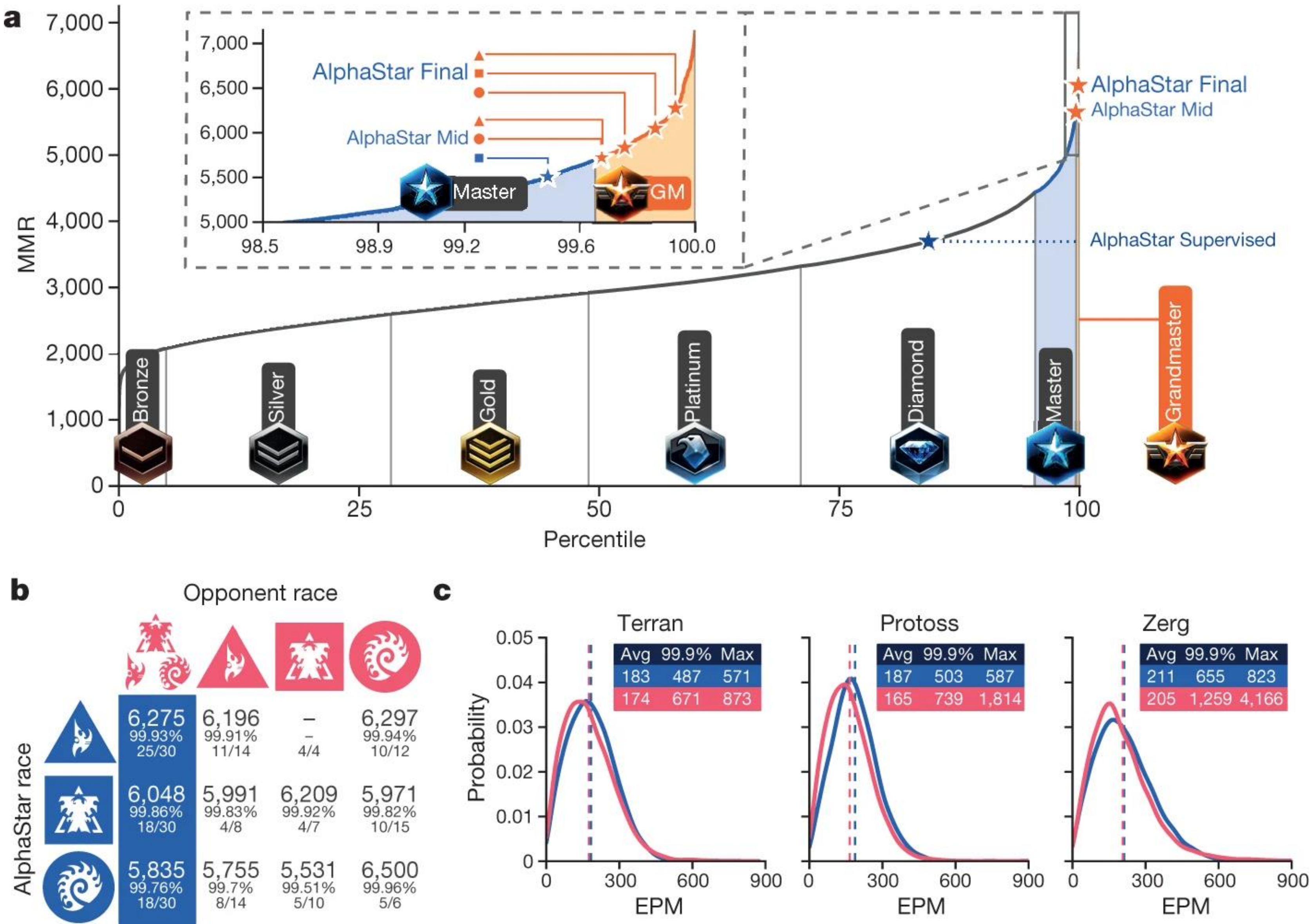
- The agent parameters were subsequently trained by a reinforcement learning algorithm that is designed to maximize the win rate (that is, compute a best response) against a mixture of opponents.
- The choice of opponent is determined by a multi-agent procedure, described below.
- AlphaStar's reinforcement learning algorithm is **based on a policy gradient algorithm similar to advantage actor–critic.** Updates were applied asynchronously on replayed experiences.
- This requires an approach known as off-policy learning, that is, updating the current policy from experience generated by a previous policy.
- **We therefore use a combination of techniques** that can learn effectively despite the mismatch: temporal difference learning **(TD(λ)),** clipped importance sampling **(V-trace),** and a new self-imitation algorithm **(UPGO)** that moves the policy towards trajectories with better-than-average reward.
- To reduce variance, during training only, the value function is estimated using information from both the player's and the opponent's perspectives.

ALPHASTAR TRAINING PROGRESSION



- **a,** Training Elo scores of agents in the league during the 44 days of training
  - Each point represents a past player, evaluated a gainst the entire league and the elite built-in b ot (whose Elo is set to 0)
- Each agent was assessed at three different s napshots during training:
- after supervised training only
  - AlphaStar Supervised
- after 27 days of league training
  - AlphaStar Mid
- after 44 days of league training
  - AlphaStar Final

RESULTS


a
MMR
Percentile
AlphaStar Final
AlphaStar Mid
AlphaStar Supervised
Master
GM
Bronze
Silver
Gold
Platinum
Diamond
Master
Grandmaster
b
Opponent race
AlphaStar race
6,275 99.93% 25/30
6,196 99.91% 11/14
– – 4/4
6,297 99.94% 10/12
6,048 99.86% 18/30
5,991 99.83% 4/8
6,209 99.92% 4/7
5,971 99.82% 10/15
5,835 99.76% 18/30
5,755 99.7% 8/14
5,531 99.51% 5/10
6,500 99.96% 5/6
c
Terran
Protoss
Zerg
Probability
EPM
Avg 99.9% Max
183 487 571
174 671 873
187 503 587
165 739 1,814
211 655 823
205 1,259 4,166

REFERENCE

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- https://www.youtube.com/watch?v=6Thu5vlDc6Y&feature=emb_logo