P-HRL: An Adaptive and Flexible Prediction-based Hierarchical Reinforcement Learning for Robot Soccer

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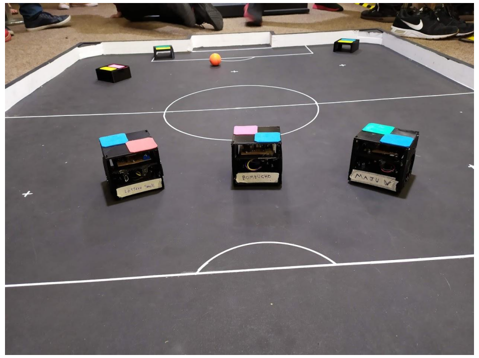
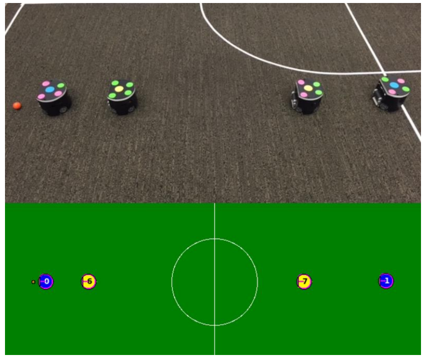
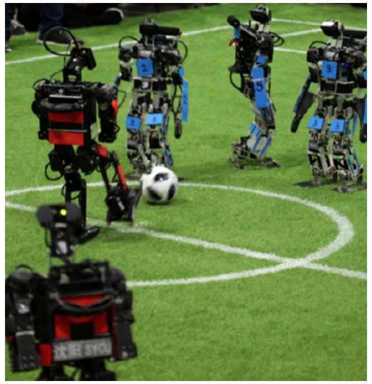
Motivation

- **Robot soccer** is a robot sports game in which both parties control a team of robots and cannot be manually controlled during the game.
    - A robot cooperation scenario: need effective team strategies and joint decision-making processes
    - Several leagues have been successfully organized in recent years.
        - e.g., RoboCup, IEEE Very Small Size Soccer (IEEE VSSS).



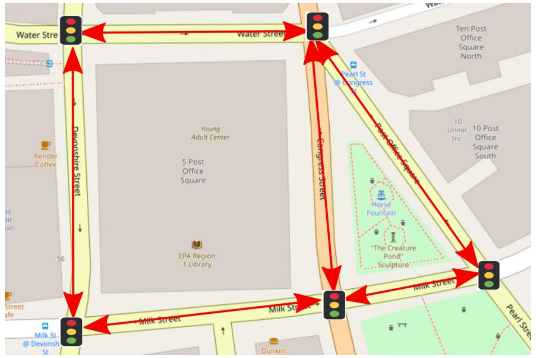
- Promoted research in academic scenarios
    - e.g., path planning, humanoid robot research





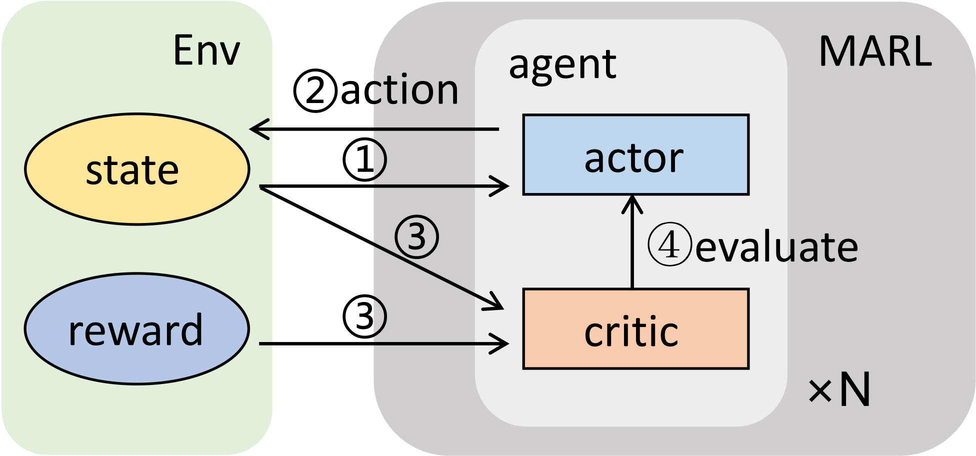
Existing MARL Method

- **Multi-agent reinforcement learning (MARL)** has achieved outstanding success on cooperative scenarios.
  - e.g., video games(Google research football), cooperative traffic light control.



- **Thus, the MARL approach has great potential in robot soccer.**

- MARL controls the actions of multiple agents **based on rewards** to maximize the expected rewards by continuously interacting with the environment.
  - Actor-critic structure
    - e.g., MADDPG, MATD3.
  - A "high-efficient" multi-agent reinforcement learning environment：diverse reward feedback and simple state-action space

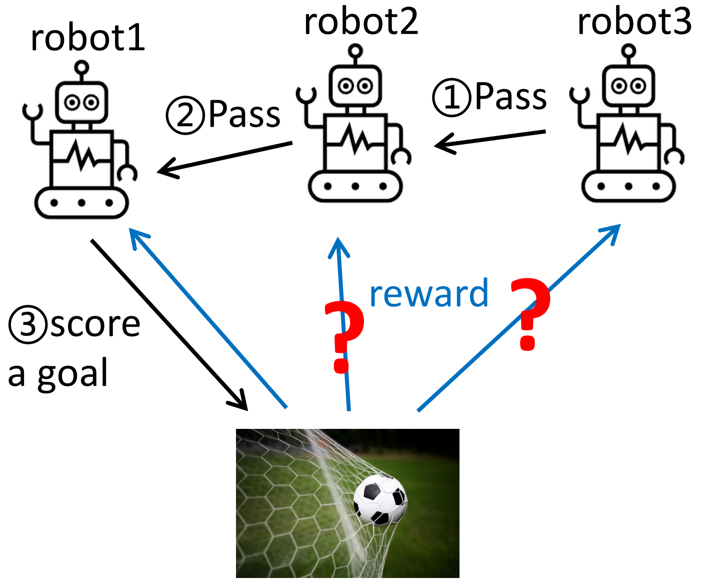


Problems of Existing MARL in Robot Soccer

- A "high-efficient" multi-agent reinforcement learning environment：
  - ① Continuous and timely reward feedback
  - ② Different reward feedback for each agent
  - ③ Low-dimensional and limited state-action space

- However, in robot soccer：
  - ① **Sparse reward**
    - Long-term process; occurs infrequently
  - ② **Global reward**
    - Cannot assign to each robot
  - ③ **High-dimensional and continuous state-action spaces**
    - Difficult to fully explore

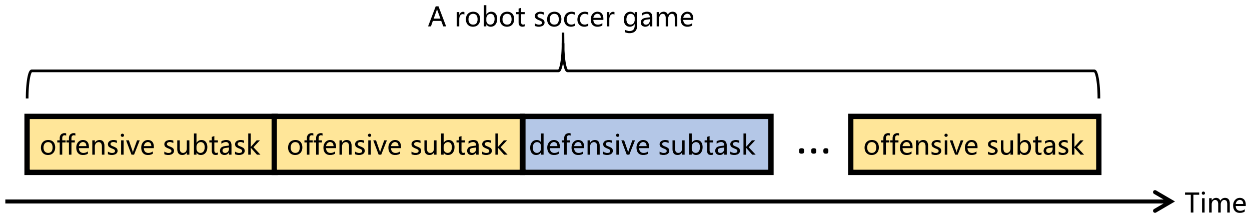
- It difficult for MARL to learn to collaborate in robot soccer.



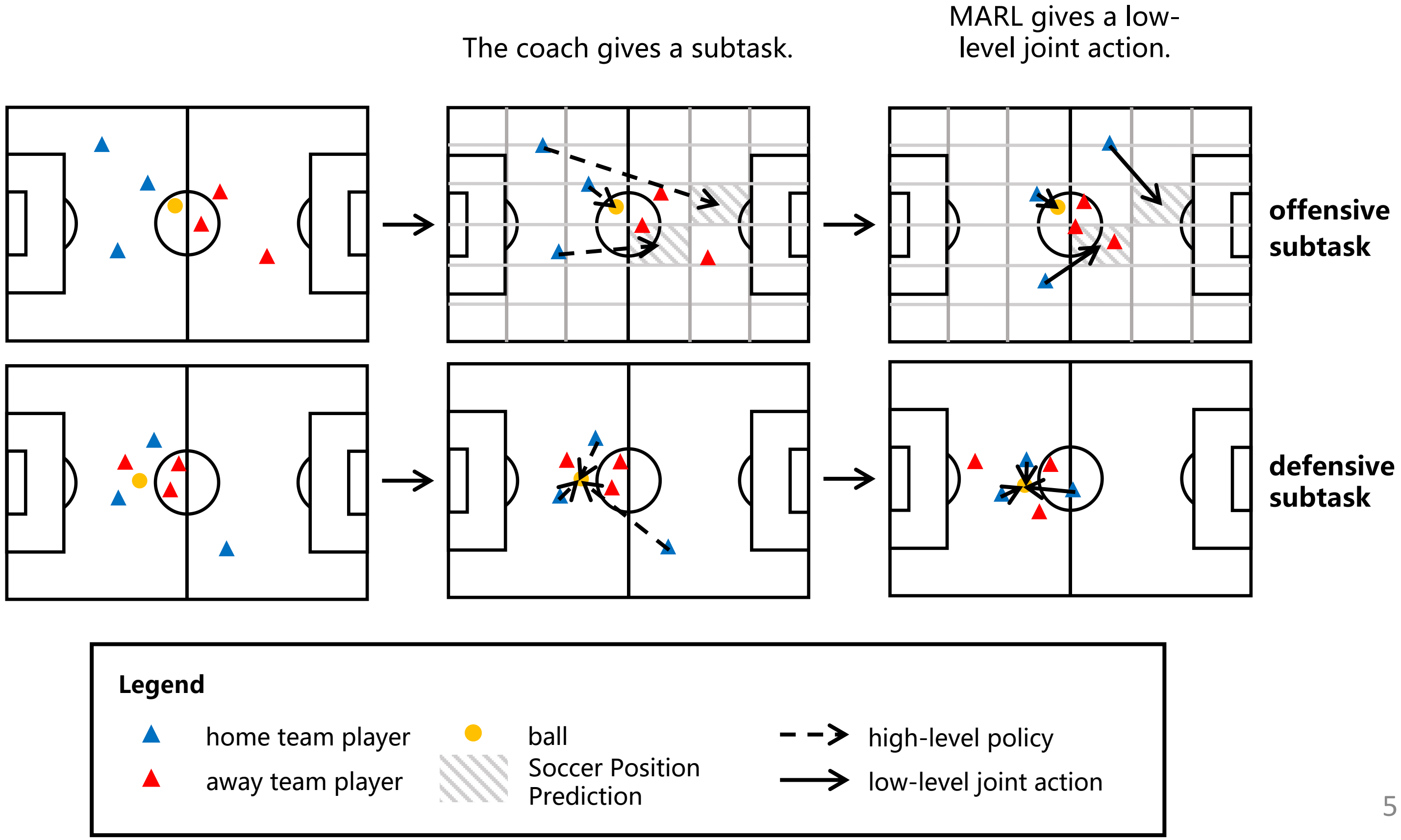
	Video game (Google research football)	Robot soccer (IEEE VSSS)
action space	**Only 20 actions** (e.g., left, short Pass.)	Left wheel speed: **range [-1,1]** Right wheel speed: **range [-1,1]**

Key Idea: Subtask Decomposition by Coach

- The **coach** assigns different subtasks to each robot.
  - Give each robot different and continuous reward feedback
- Two types of subtasks: **offensive subtask** and **defensive subtask**
  - **Guarantee possession of the ball**
  - Select based on ball possession

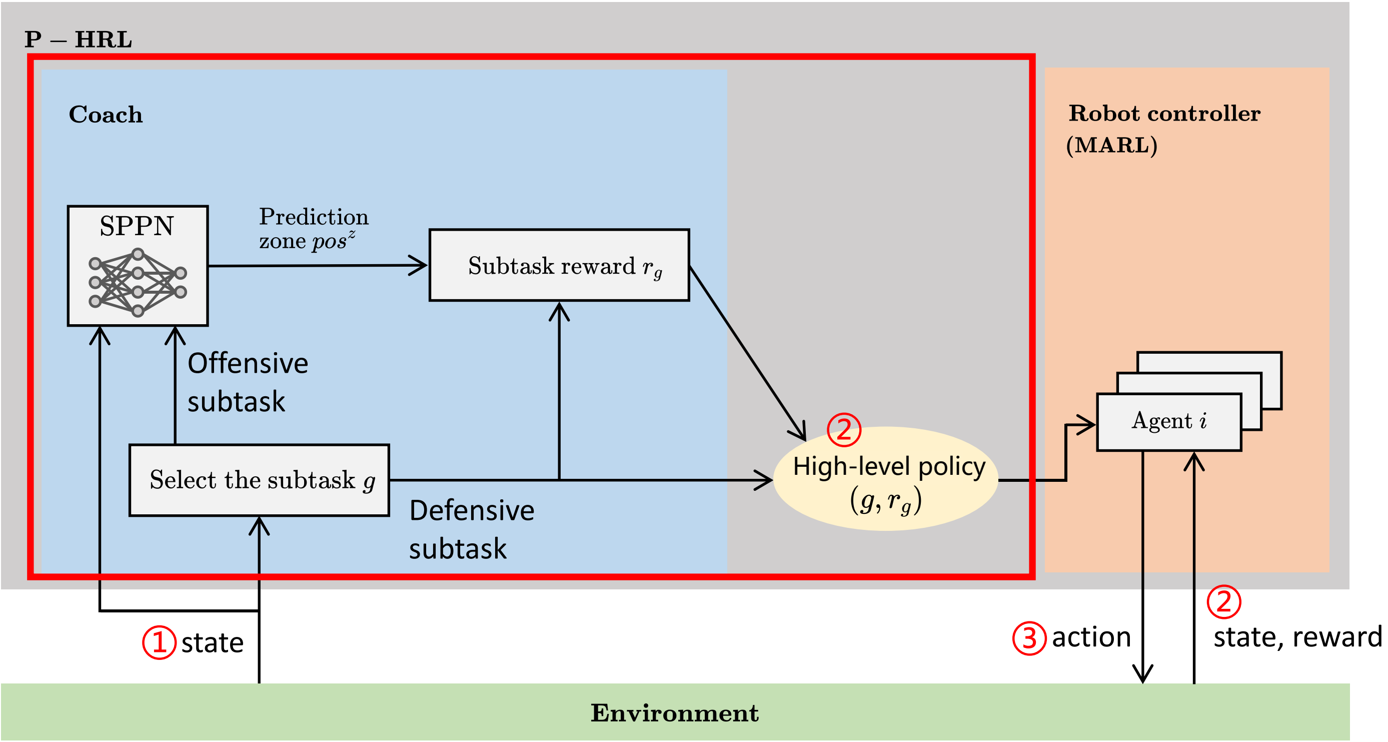


	Offensive subtask g^A	Defensive subtask g^D
Initiation condition I_g	Our robots are in possession.	Opposing robots are in possession.
Termination condition β_g	(1) Opposing robots are in possession. (2) The ball reaches the predicted zone (3) After T_p time steps.	Our robots are in possession.



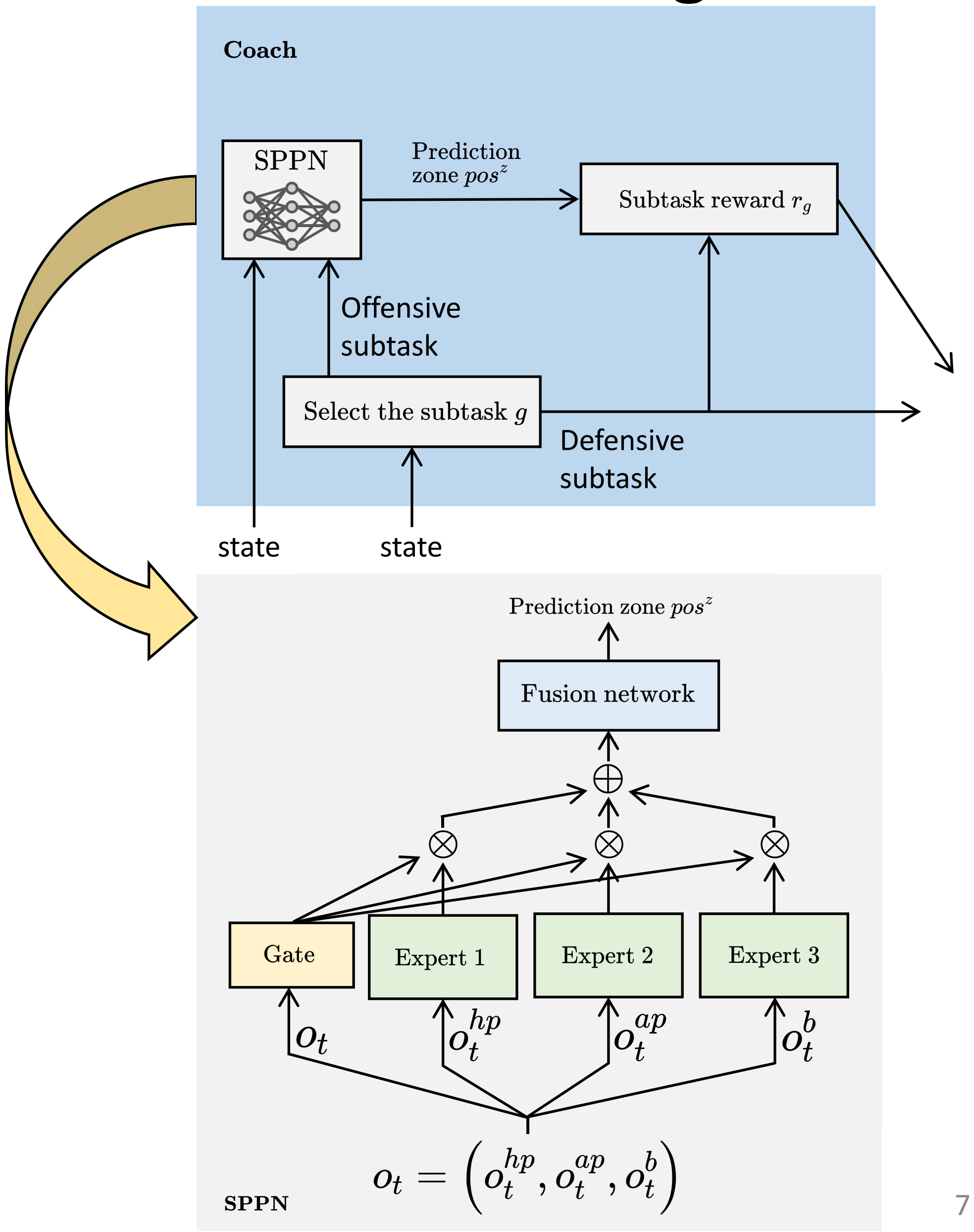
P-HRL: Prediction-based Hierarchical Reinforcement Learning

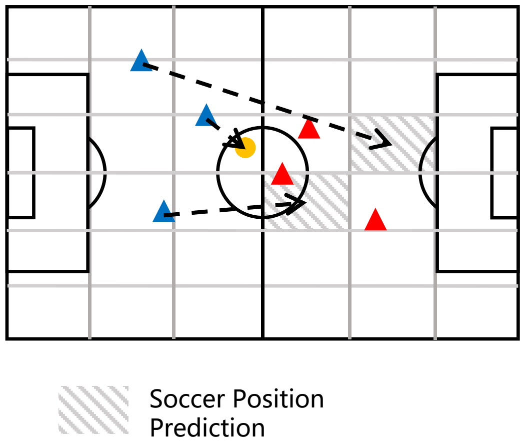
- **Hierarchical structure**
  - The coach provides a subtask and subtask reward to the robot controller(MARL).
  - Coach: adjusting soccer tactics
  - Robot controller: learning robot control.
- The robot controller uses a MARL method(MADDPG).
  - Added subtasks to actors and critics

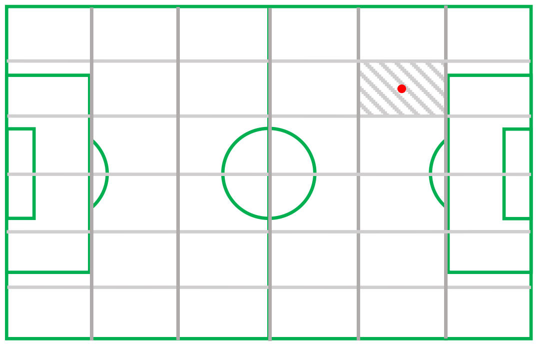


P-HRL: Prediction-based Hierarchical Reinforcement Learning

- In the offensive subtask, the robot needs to make judgments about the trajectory of the ball.
- The coach helps robot to judge the trajectory of the ball by predicting its position.
- **Soccer Position Prediction Network(SPPN)**
  - Mixture of experts(MoE) network
    - Independence of data in state
    - Easy to convergence
  - Zoning prediction



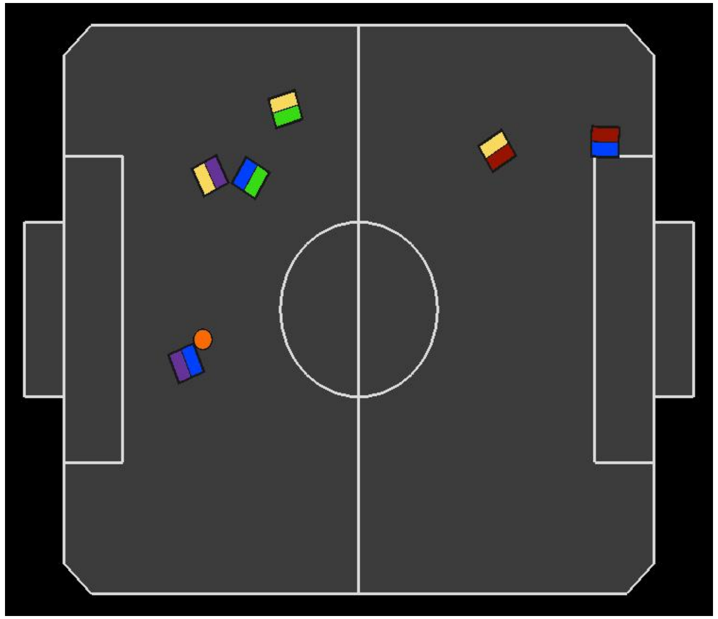




An example of zoning prediction

Implementation and Evaluation

- **Evaluation environment:**
  - rSoccer - IEEE VSSS multi-agent environment to simulate a robot soccer scenario.
- **Baseline opponent:**
  - MATD3 - a state-of-the-art MARL method that has been used in many multi-agent cooperative tasks similar to robot soccer.
- **Evaluation settings:**
  - 3 vs 3 robot soccer match
  - No hardware on robots for dribbling or kicking the ball
  - Follow the rewards shaping in rSoccer
  - Each match lasting 2000 time steps

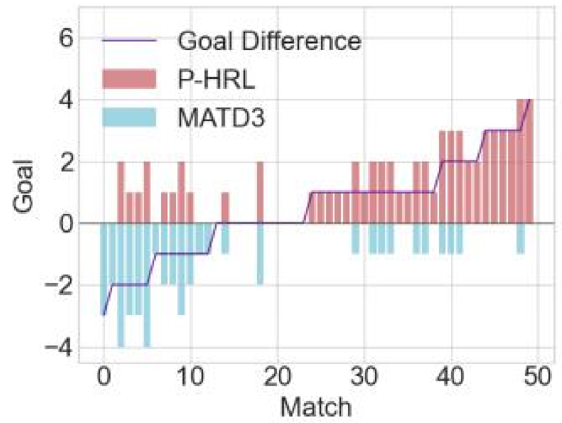


Evaluation Questions

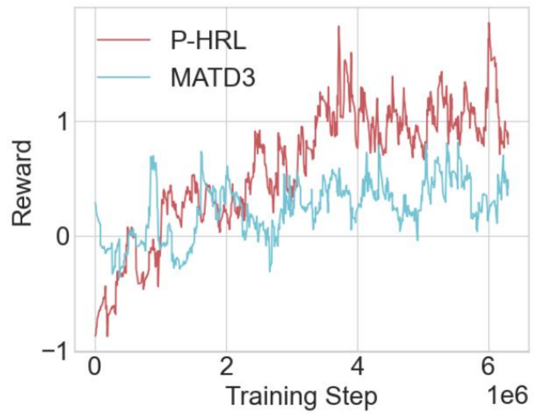
- How is P-HRL compared to baseline in terms of end-to-end performance?
- How does the coach contribute to the overall system?
- How well does the P-HRL adapt to the new opponent compared to the baseline?

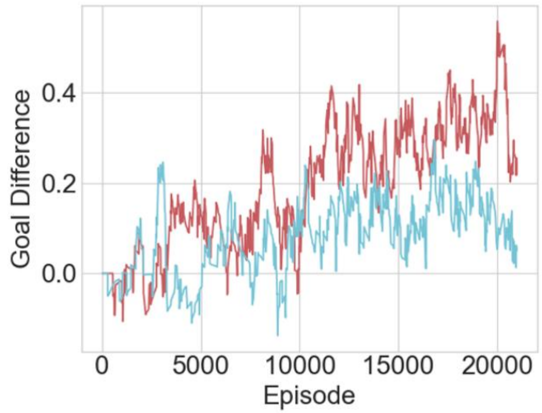
End-to-end Performance

- **P-HRL has 52% win rate**, 22% draw rate and 26% loss rate.
    - 50 matches: **P-HRL won 26 matches and tied 11 matches.** MATD3 won 13 matches.
- **Training method**：
    - Stage 1: Train P-HRL and MATD3 respectively, using rSoccer built-in agent as the opponent.
    - Stage 2: Train P-HRL and MATD3 in a mutual confrontation.
    - Each stage lasts until the average episode reward does not rise with the episode (about 1×10^6 steps).



- **Goal difference**：subtracting the number of goals scored by a team from the number of goals conceded in a match.

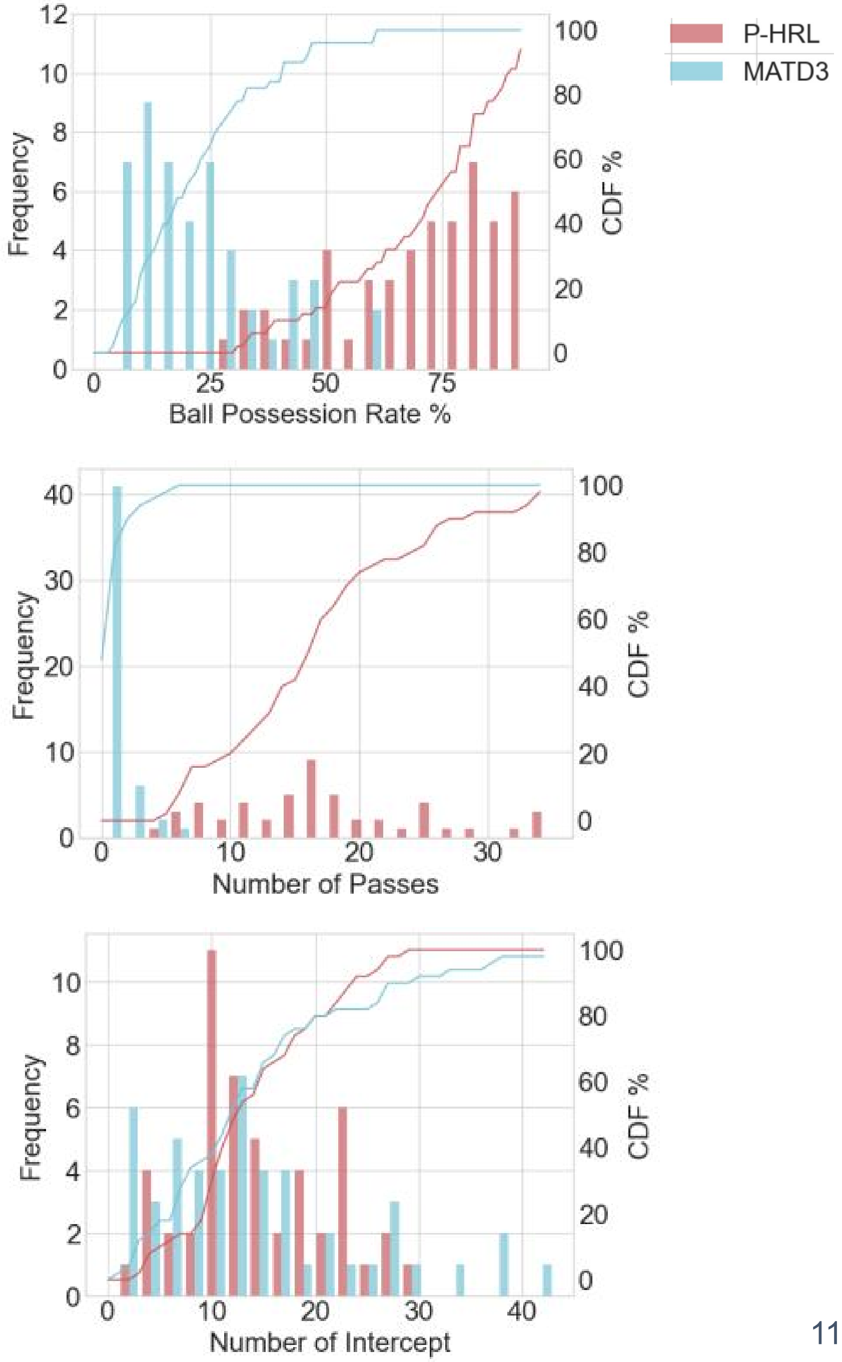




End-to-end Performance

- **Ball Possession Rate:** team possession of the ball as a percentage of total time
- **Number of Passes:** total number of passes on the team
- **Number of Interception:** total number of interceptions on the team
- **P-HRL outperforms MATD3 in ball possession rate and the number of passes.**

	Ball possession rate (per match)	Number of passes (per match)	Number of interception (per match)
P-HRL	**70.25%**	**14.32**	14.40
MATD3	17.14%	1.92	**14.44**

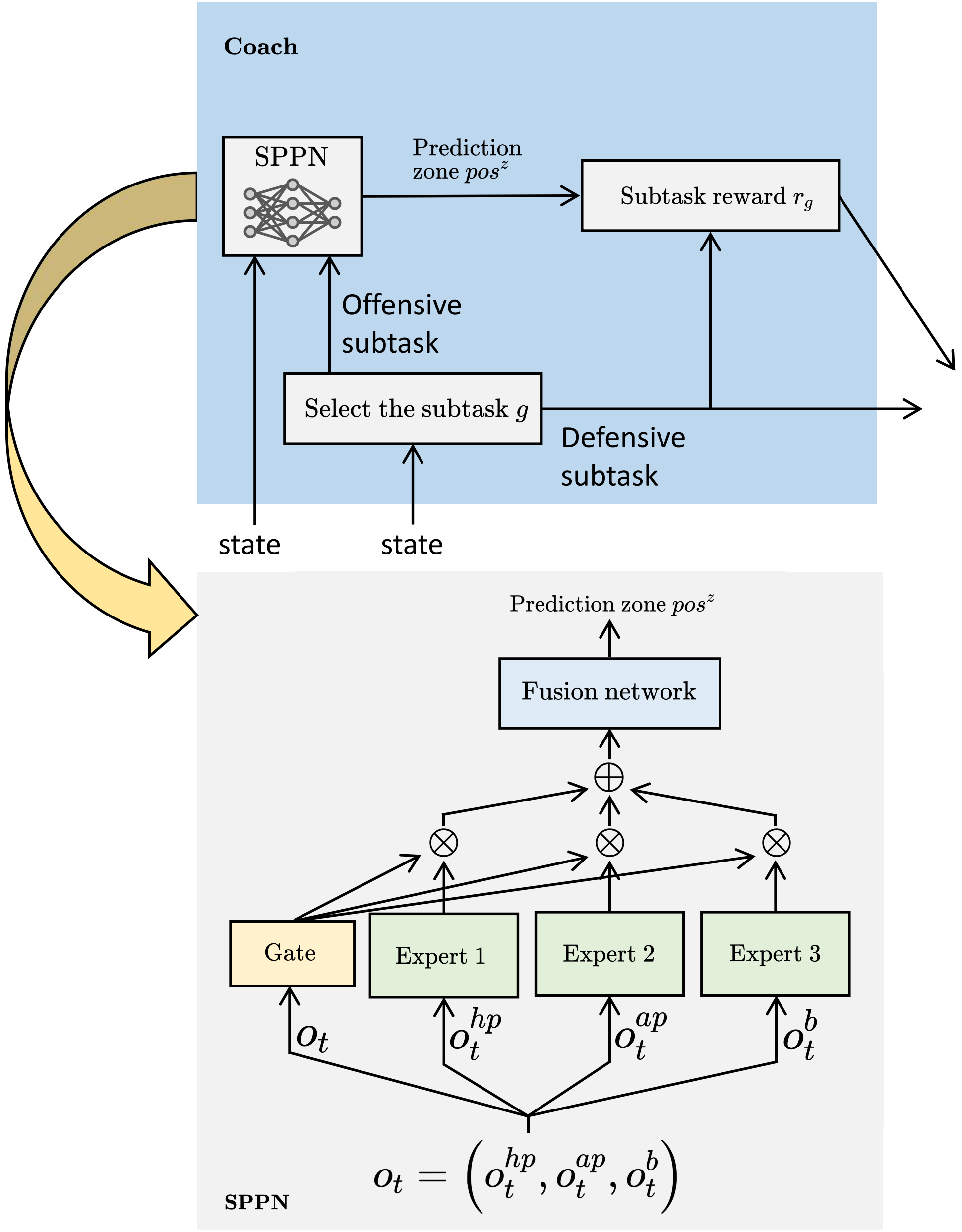


The Effect of the Coach to P-HRL

- **The coach brings better performance for P-HRL than baseline.**
  - NN Coach: Using a neural network with the same number of parameters as SPPN in the coach (but without the structure of MoE).
  - Random Nearest Coach: Using a method that selects two random adjacent zones of the current zone as the prediction results in the coach.

Coach	*Team Score : Opponent Score*	*Acc Top 1*	*Acc Top 2*
SPPN Coach	**2.40±1.78 : 1.48 ± 1.05**	**0.70±0.06**	**0.85±0.04**
NN Coach	2.15±1.22 : 1.55 ± 1.31	0.59±0.06	0.80±0.05
Random Nearest Coach	1.85±1.35 : 2.15 ± 1.39	0.06±0.11	0.12±0.06

Match results for different types of coach (vs. MATD3 in 50 matches)



Conclusion

- In this talk, we presented P-HRL, a prediction-based hierarchical reinforcement learning.
  - P-HRL consists of a coach for soccer tactics and a robot controller for robot motion control.
  - In matches against the state-of-the-art baseline MATD3, P-HRL has 52% win rate, 22% draw rate and 26% loss rate.
- We designed several key performance indicators (KPIs) for robotic soccer (e.g., ball possession) to more fully evaluate the performance of the P-HRL.
  - P-HRL has better cooperation between robots, with 70.25% possession rate compared to 17.14% for baseline.

Future work

- P-HRL has been submitted to the International Conference on Automated Planning and Scheduling (ICAPS2023).
- Short-term work
  - Add additional baselines, e.g., MAAC.
- Long-term work
  - Deploying P-HRL to real robots for soccer matches instead of evaluating it in the simulation environment.
    - Quickly correct deviations between the simulation environment and the real environment.
  - Using large-scale training models in robot soccer.
    - Optimize distributed training process.