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Mastering Complex Control in MOBA Games with Deep Reinforcement Learning

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Action control of heroes

"Honor of Kings" tested
(Chinese: 王者荣耀)

Mastering $\boxed{\text{Complex Control}}$ in $\boxed{\text{MOBA Games}}$ with $\boxed{\text{Deep Reinforcement Learning}}$

The method
system-level & algorithm-level

Paper link: https://arxiv.org/abs/1912.09729

Overview

Tencent AI Lab

- Introduction
- Method
  - System
  - Algorithm
- Experiments
- Conclusion & future work

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Introduction

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- Recent development in Game AI

2016.03 | 2019.02 | 2017 - 2019 | 2017 - present

DeepMind: AlphaGo

DeepMind： AlphaStar

OpenAI
Five

OpenAI：Dota2

Tencent：JueWu (V1, SL based, 2018.12)

Tencent：JueWu (V2, RL based, 2019.08)

- Tencent AI Lab – Game AI Center

Go (2016 - present) | **MOBA (2017 - present)** | **3D-FPS (2018 - present)**

Introduction

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- MOBA 1v1 games
  - Two-agent, one vs. another
  - Many game units
    - Turrets, creeps, heroes, etc.
  - Pure arena for competing one's ability of **action control** (micro-management)
    - 5v5 games focus more on team strategy

Honor of Kings Game UI Illustration

Introduction

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- The game is complex
  - Enormous action space
  - Enormous state space
  - Real time
  - Playing method
    - Complicated action control
    - Vary from hero to hero
  - Target selection
    - Hard to decide which game unit(s) to attack/protect
  - Little high-quality human data
    - 1v1 mainly for practicing heroes, while 5v5 as formal matches
    - Supervised learning infeasible

Table 1: Comparing Go and MOBA 1v1

Game	**Go 1v1**	**MOBA 1v1**
Action space	$250^{150} \approx 10^{360}$ (250 pos available, 150 decisions per game on average)	10^{18000} (100+ discretized actions, 9,000 frames per game)
State space	$3^{361} \approx 10^{170}$ (361 pos, 3 states each)	$2^{2000} \approx 10^{600}$ (2 heroes, (1000+ pos)*(2+ states))
Human player data	rich, high-quality	little
Peculiarity	long-term tactics	real-time, complex control

Introduction

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Large-scale system for exploration

Unified modeling

Self-play

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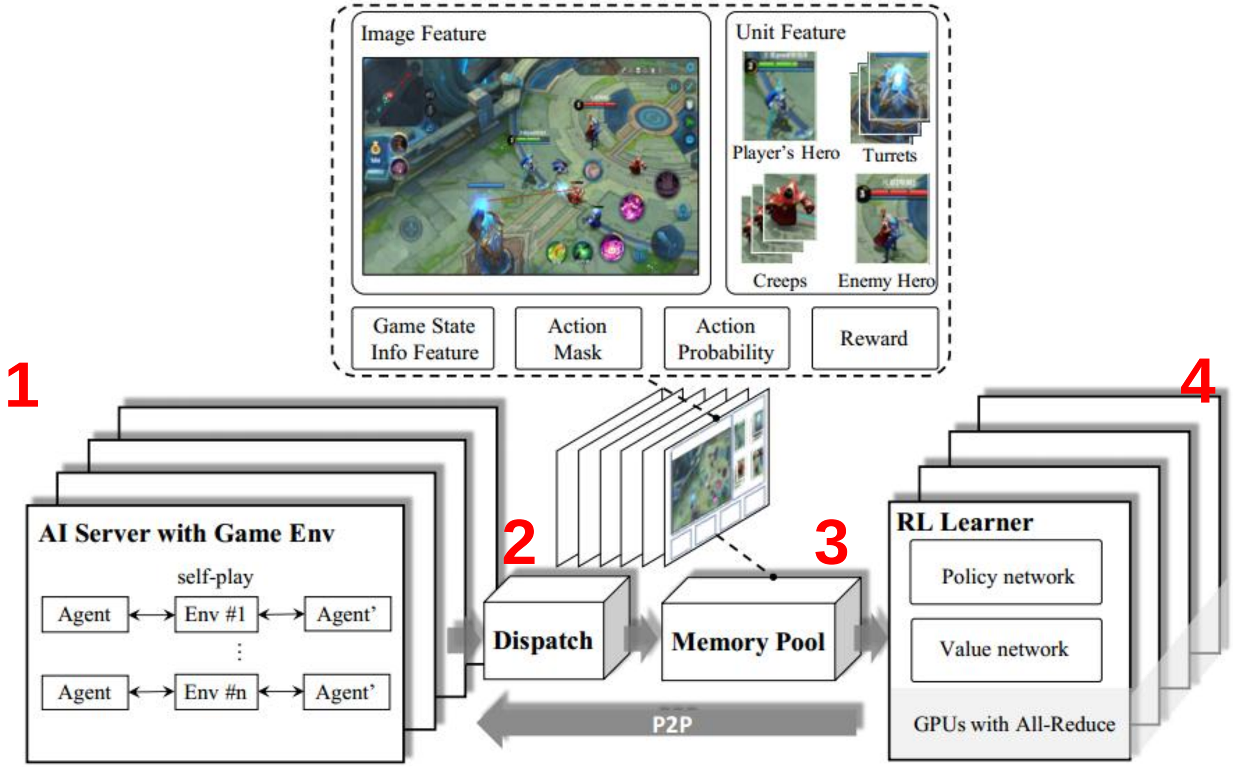
Method: overview

- Deep reinforcement learning system
  - Large-scale
  - Off-policy

- Algorithm
  - Multi-modal feature design
  - Actor-critic neural network
  - Multiple action control strategies
  - Dual-clip PPO

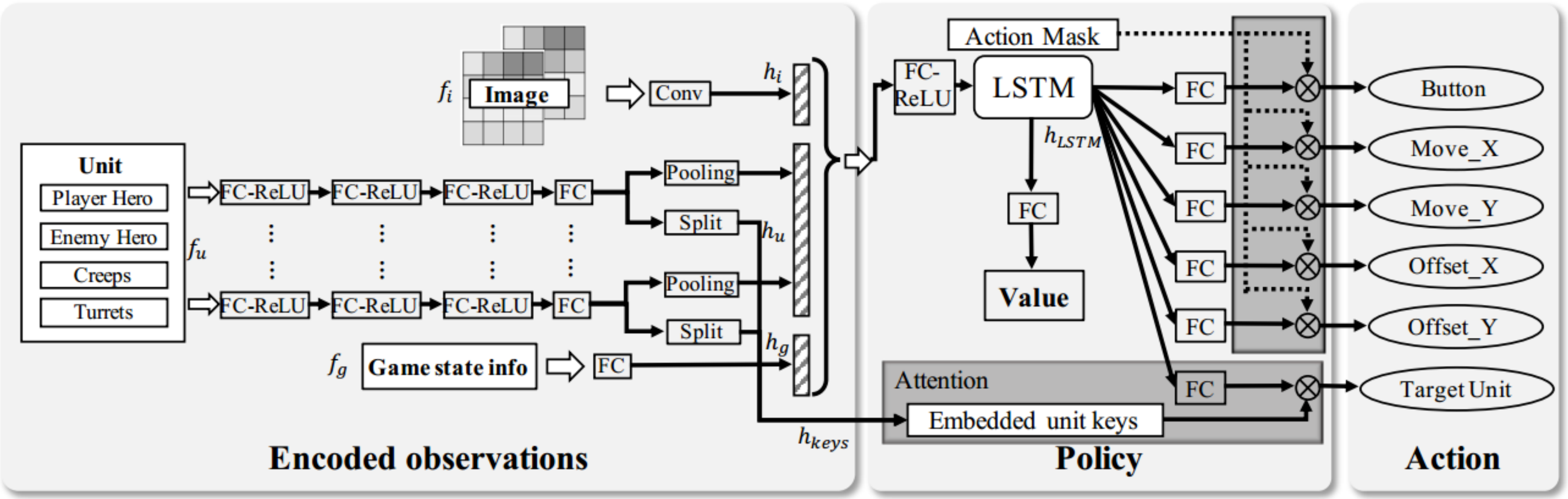
Method: system



- Large-scale
  - Support up to 1000+ GPU cards, 500,000+ CPUs tested in our Beta Environment
- Off-policy
  - Actor highly decoupled from Learner

- System architecture
  1. AI Server
     - Actor, where self-play happens
     - Interact with GameCore
  2. Dispatch Server
     - Data collect, compress & transmit
  3. Memory Pool
     - For data storage
     - Feed data to RL Learner
  4. RL Learner
     - For training reinforcement learning model
     - Model sysn to AI Server via P2P

Method: algorithm



Input: observations/features

Internal: neural network model

Output: hero actions

Method: algorithm

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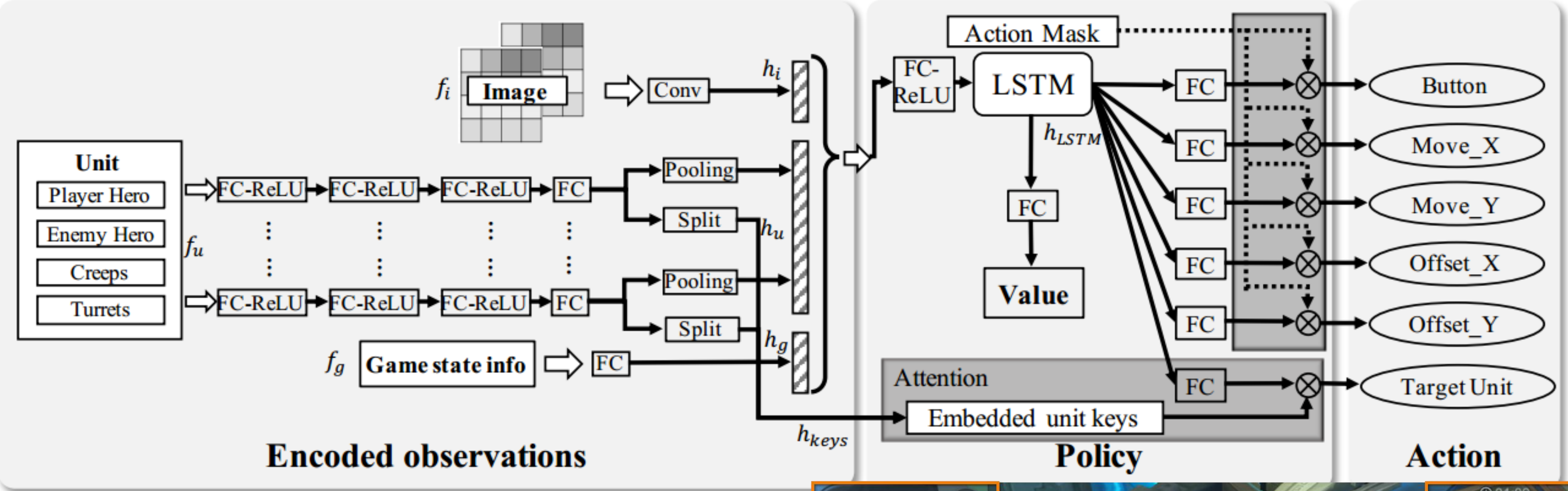
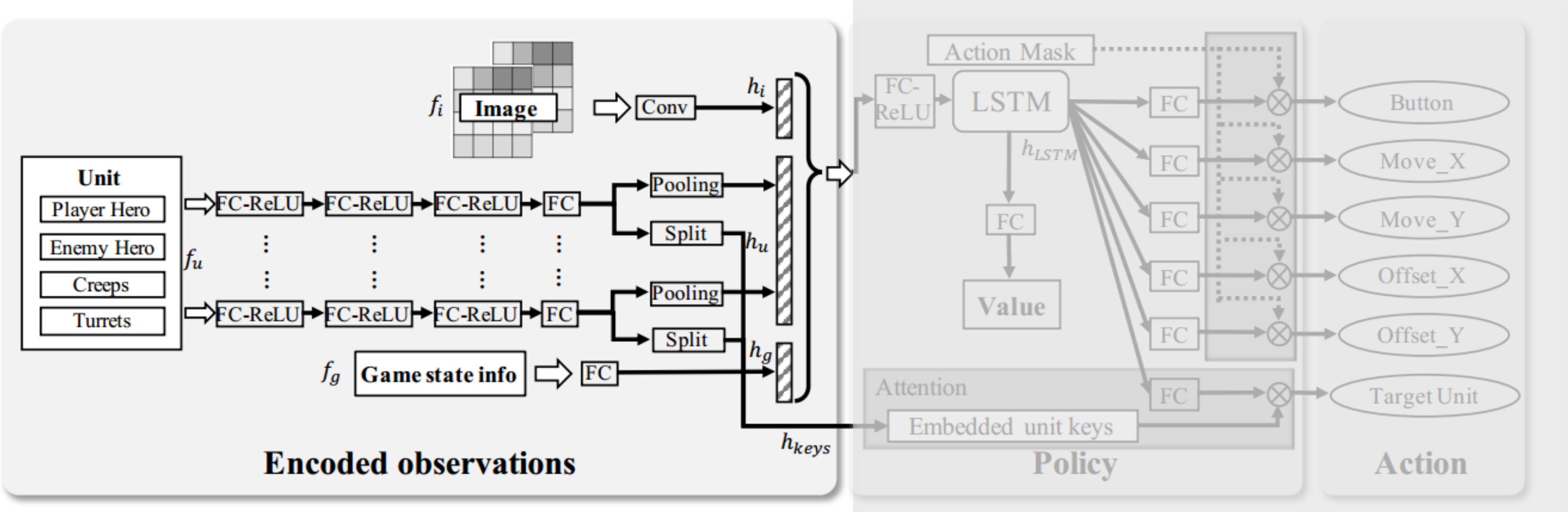


Input:

- Observable game unit attributes
  - Heroes, creeps, turrets, etc.
- Observable game states
- Local-view image-like channels

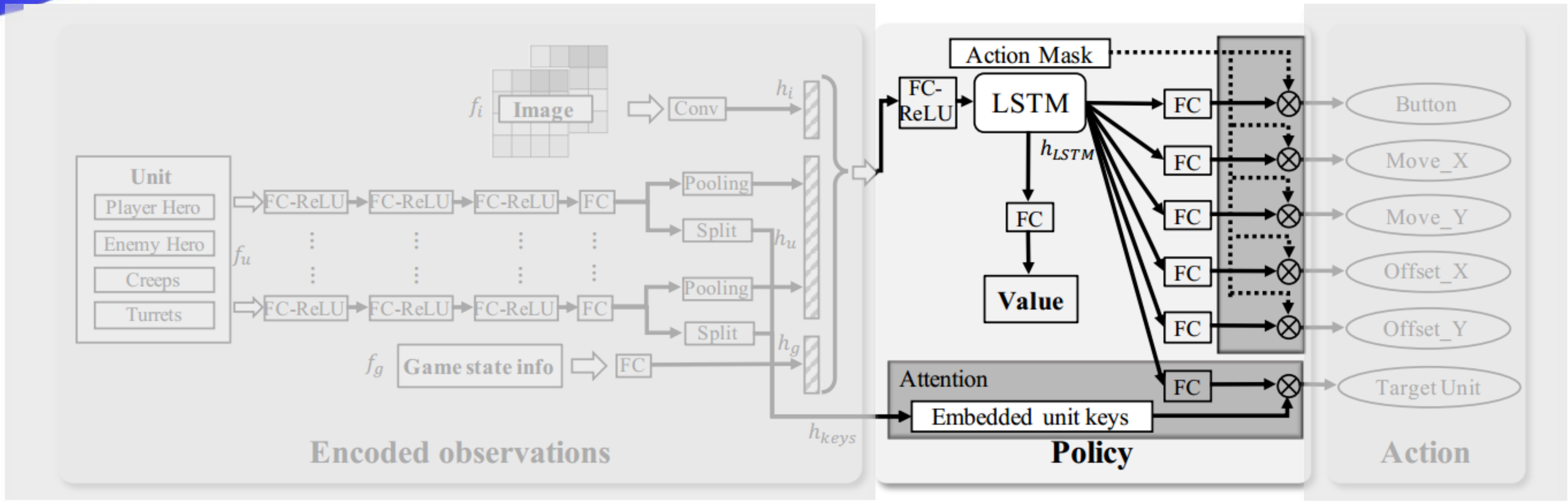
Method: algorithm



Internal:

- Feature/observation encoding
  - FC/ReLU layers, Conv layer, Pooling, Split
  - Weight sharing across same types of units

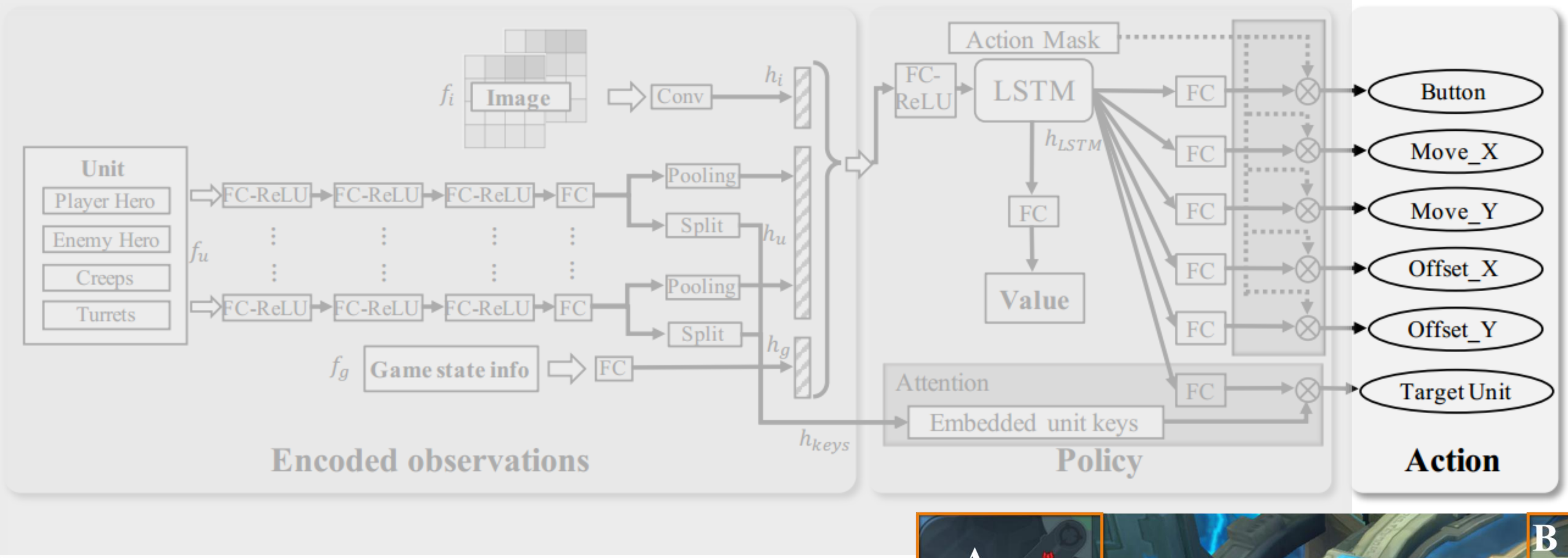
Method: algorithm



Internal:

- LSTM
- Action mask
  - For pruning RL exploration
- Target Attention
- Actor-critic network
  - Policy & value share parameter

Method: algorithm

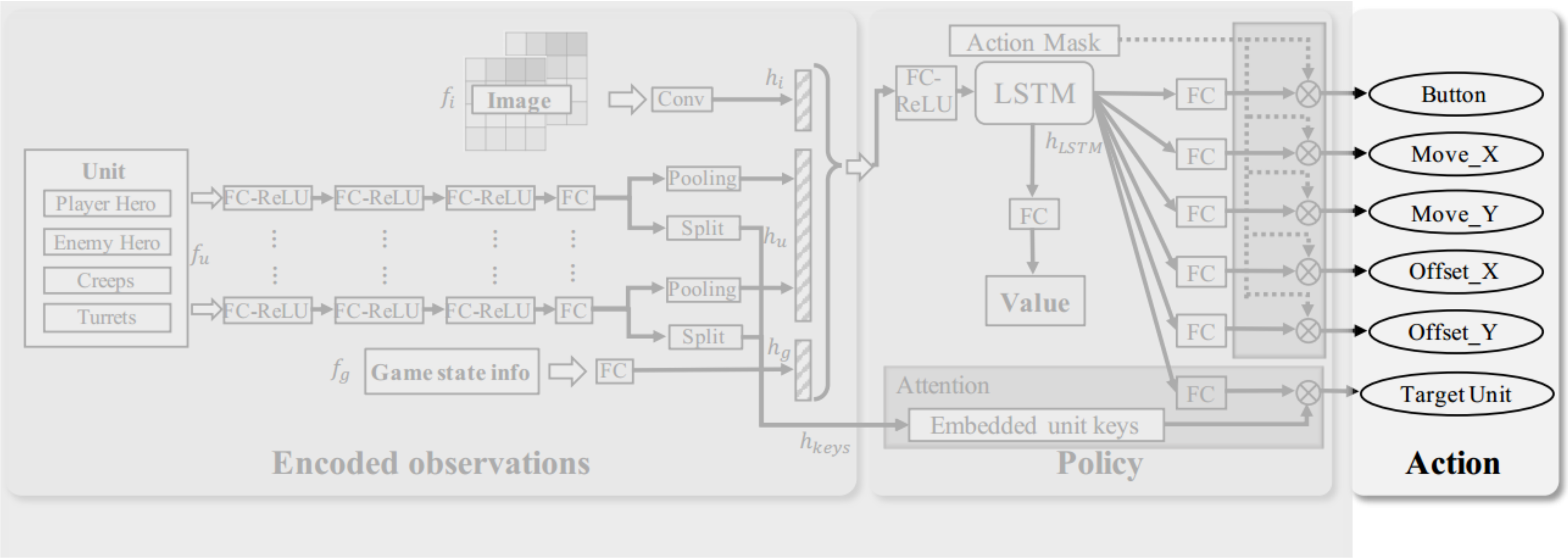


Output:

- Hierarchical, multi-label
  - First, predict **which action** to take, i.e., Button
    - E.g., move
  - Second, predict **how to execute** that action
    - E.g., the direction to move

  - What about label correlations?

Method: algorithm



Output:

- Control dependency decoupling
  - Action **labels have correlations**, but are treated **independently**
    - To simplify episode sampling & objective optimization (See next slide)

Method: algorithm

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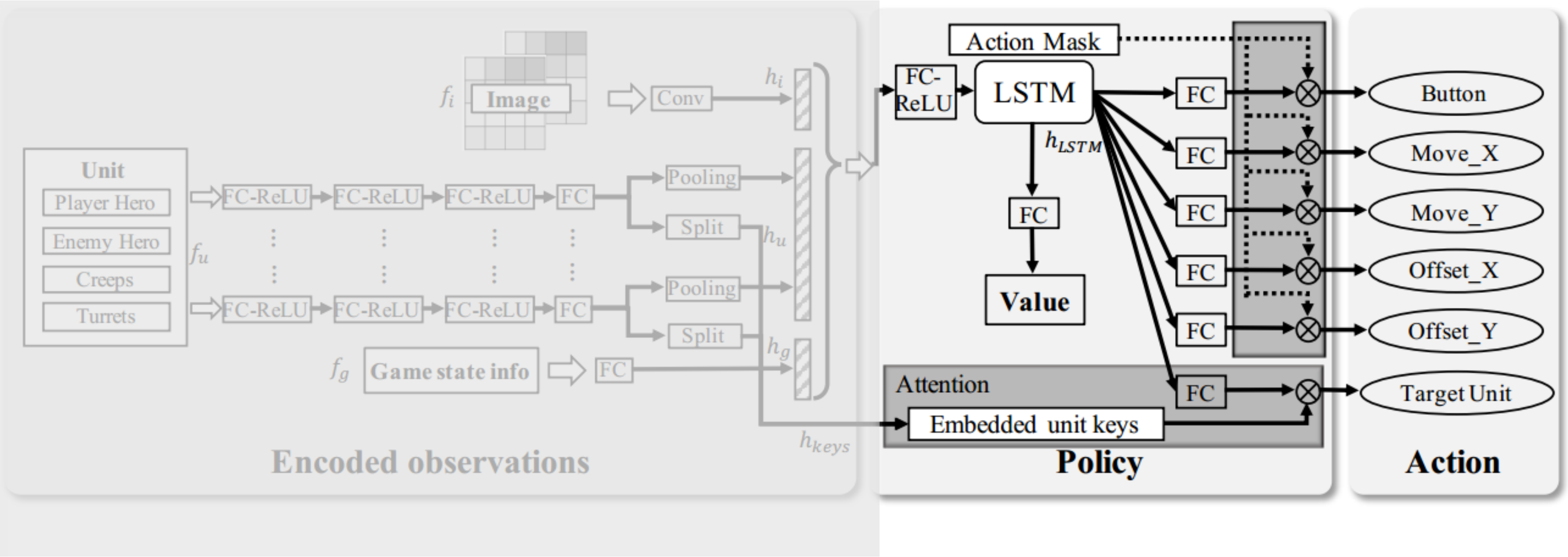


Objective optimization

- Multi-label PPO (proximal policy optimization)

$$maximize_{\theta} \sum_{label\_i} E_{s_t, a_t \sim \pi_{\theta_{old}}} \left[\frac{\pi_{\theta}\left(a_t^{label\_i} | s_t\right)}{\pi_{\theta_{old}}\left(a_t^{label\_i} | s_t\right)} \left(R - V_{\theta_{old}}\left(s_t\right)\right) \right] - \frac{1}{2} E_{s_t \sim \pi_{\theta_{old}}} \left[\left(R - V_{\theta}\left(s_t\right)\right)^2 \right]$$

Label treated independently

Policy loss
We use PPO (to be continued)

Value loss

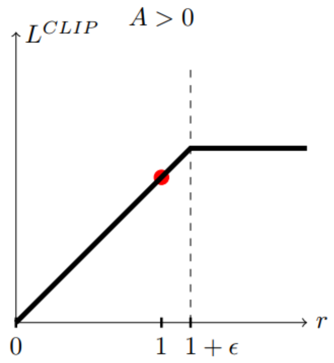
Method: algorithm

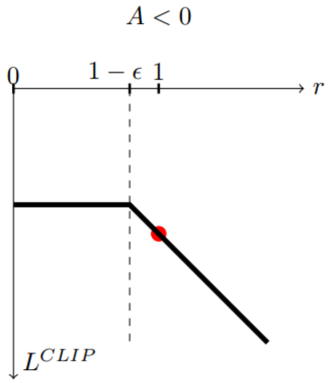
Objective optimization (continued)

Standard PPO [1]:

$$L^{clip}(\theta) = E_t\left[min\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}\boxed{(R-V)}, clip\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)},1-\varepsilon,1+\varepsilon\right)(R-V)\right)\right]$$

A: Advantage





The problem:

- **large-scale & off-policy** setting → policy deviations

$$\text{when } \pi_\theta(a_t^{(i)}|s_t) \gg \pi_{\theta_{\text{old}}}(a_t^{(i)}|s_t) \text{ and } \hat{A}_t < 0 \implies \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}\hat{A}_t \ll 0$$

[1] Schulman et al. Proximal Policy Optimization Algorithms

Method: algorithm

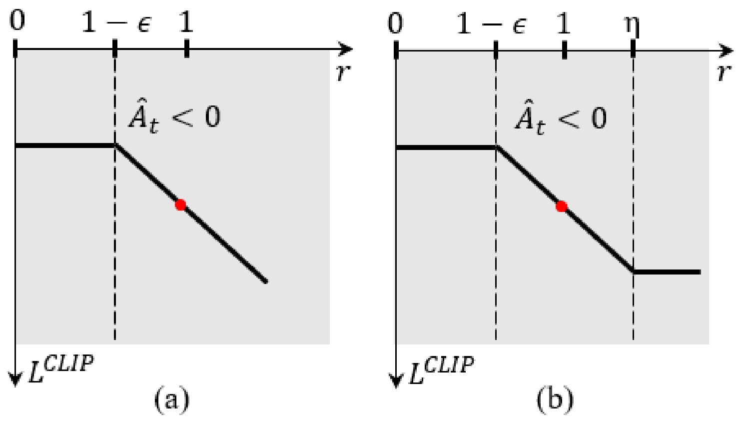
Objective optimization (continued)

Standard PPO:

$$L^{clip}(\theta) = E_t\left[min\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}(R-V), clip\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}, 1-\varepsilon, 1+\varepsilon\right)(R-V)\right)\right]$$

Our proposed PPO: **dual-clip PPO**

$$L^{clip}(\theta) = E_t\left[max\left(min\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}(R-V), clip\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}, 1-\varepsilon, 1+\varepsilon\right)\right), \eta(R-V)\right)\right]$$



(a) standard PPO (b) Dual-clip PPO

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Experiments: setup

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- System
  - 40+ GPU cards & 15000+ CPU cores used to train one hero
  - 80,000 samples per second per GPU
  - FP16 for data transmission
- Algorithm
  - LSTM
    - time step 16, unit size 1024
  - Discount factor 0.998
  - Generalized advantage estimation (GAE)
    - Lambda 0.95
  - Dual-clip PPO
    - Two clip parameters are 0.2 and 3, respectively

Experiments: results

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- Evaluating the **upper limit** of control ability
  - Match results between AI & top professional human players
    - Best of five (BO5)
    - Tested on different types of heroes
      - Mage, warrior, Marksman, etc.
    - Tested by several top professionals

Hero	DiaoChan	DiRenjie	LuNa	HanXin	HuaMulan
Hero Type	Mage	Marksman	Warrior+Mage	Assassin	Warrior
Score	3:0	3:0	3:0	3:1	3:0
Kill	5.0:1.3	2.3:0.7	2.7:1.0	2.5:1.5	4.0:1.3
Game Length	6’56”	6’23”	7’53”	6’41”	6’48”
Gold/min	852.7:430.6	869.3:606.6	969.7:724.0	954.1:754.2	945.2:654.2
Exp/min	900.0:573.0	895.3:661.7	979.0:817.2	965.4:802.5	921.4:723.1

Experiments: results

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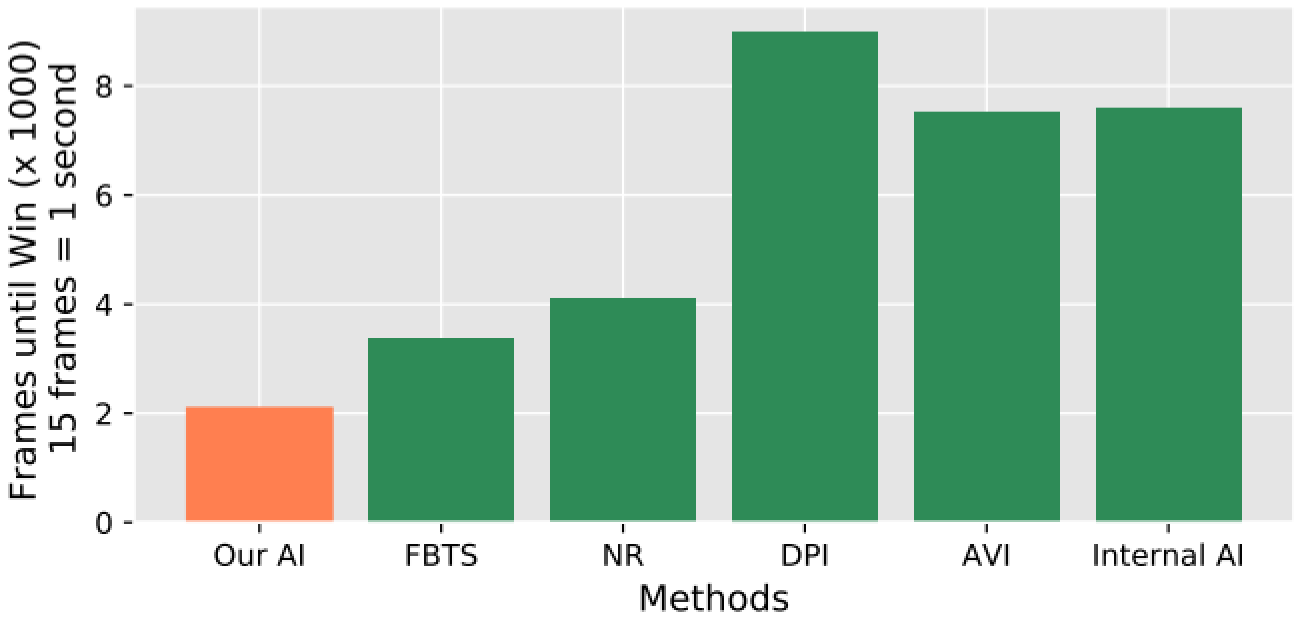
- Evaluating the **robustness** of control ability
  - 2,100 public matches (AI vs. a **diversity** of top human players)
  - Multiple heroes that require very **diverse** playing method

Hero Name	Hero Type	#Matches	#Win	Rate
DiaoChan	Mage	445	445	100%
DiRenJie	Marksman	264	264	100%
HuaMuLan	Warrior	256	256	100%
HanXin	Assassin	221	220	99.55%
LuNa	Warrior+Mage	260	260	100%
HouYi	Marksman	79	78	98.70%
LuBan	Marksman	354	354	100%
SunWukong	Assassin	221	219	99.09%
		2100	2096	99.81%

Experiments: results

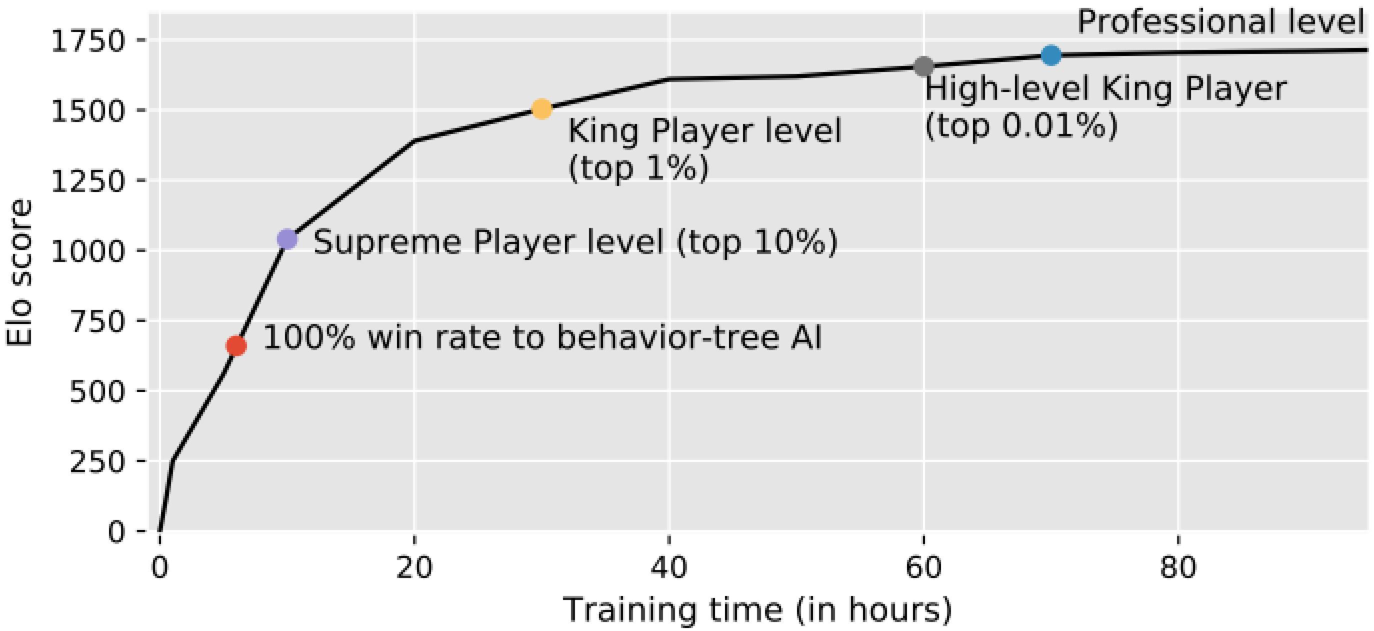
- Comparison with baseline methods
  - Our method vs. MCTS and its variants
  - Measuring average time length to defeat the same set of opponents



Feedback-based tree search for reinforcement learning. ICML 2018

Experiments: results

- The growth of our AI
  - Elo rate



Experiments: results

- Ablation
  - AM: action mask
  - TA: target attention
  - LSTM
  - Base: Full w/o AM TA LSTM

Item	Win rate vs Base	Time to converge
Base	-	80 h
Base + AM	50.5%	**65 h**
Base + TA	**75%**	90 h
Base + LSTM	73%	100 h
Full version	90%	80 h

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Conclusions

- **Action control** of different MOBA heroes
  - Complex, a big challenging to AI research

- We develop a **super-human AI agent** which has mastered the complex action control in MOBA 1v1 games

- Our deep reinforcement learning framework
  - System design
  - Algorithm design
    - Multi-modal feature design
    - Actor-critic neural network
    - Multiple action control strategies
    - Dual-clip PPO

Future work

- Our ongoing **Open-Platform** Plan (开放平台计划)
  - Open-source our framework & algorithm
  - Honor of Kings GameCore accessibility
  - Computing resources (CPUs/GPUs) for public use

Link: https://mp.weixin.qq.com/s/jaZJtkljVBib0mj1iOJQbg

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Appendix

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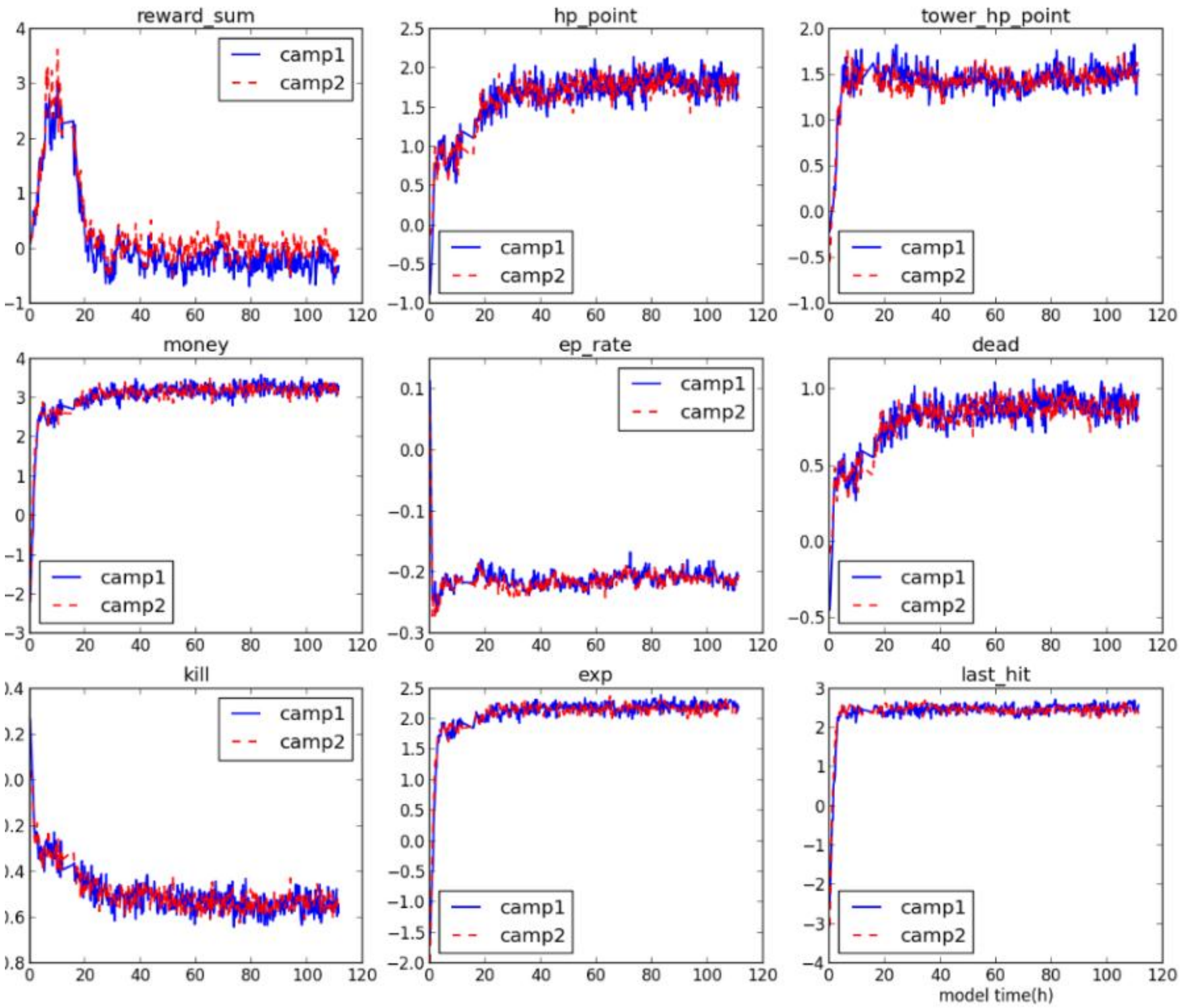
- Reward design

Reward	Weight	Type	Description
hp_point	2.0	dense	the health point of hero
tower_hp_point	10.0	sparse	the health point of turrets and base
money (gold)	0.008	dense	the gold gained
ep_rate	0.8	dense	the rate of mana
death	-1.0	sparse	being killed
kill	-0.5	sparse	kill an enemy hero
exp	0.008	dense	the experience gained
last_hit	0.5	sparse	last hitting to enemy units



We are recruiting!

Tencent AI Lab

- Computer Science background in a related domain
  - Machine learning in general
- Strong problem solving & analyzing
- Strong programming skills
  - C++/Python/Linux Shell
- Experience in academic research
  - Having peer-reviewed publications is a plus
- Knowledge in Game AI & RL

Send your CV to: dericye@tencent.com