Match Plan Generation in Web Search with Parameterized Action Reinforcement Learning

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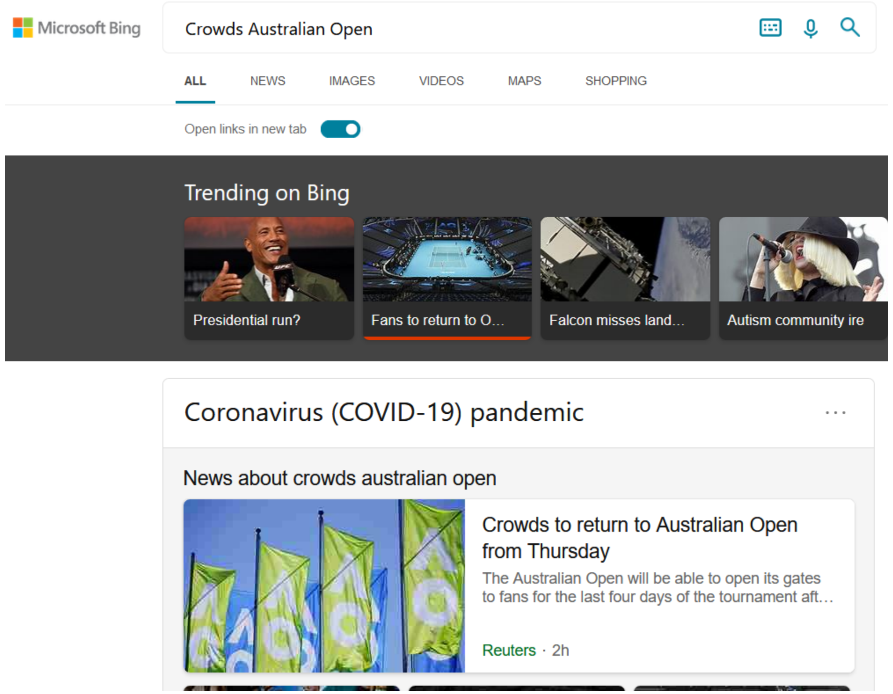
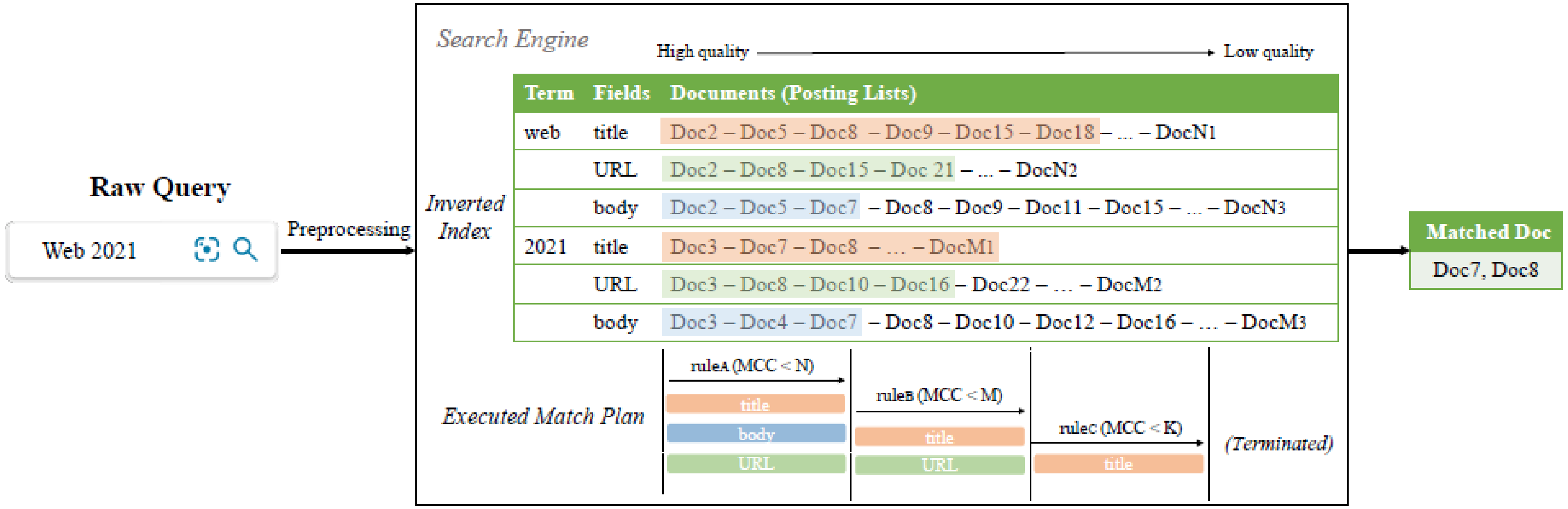
Introduction

- Match plan generation is the key technology for large scale search engines
- Aims
  - **1. Good result quality (relevance)**
  - **2. Short query response time**
- Search engines use match plans to help retrieve relevant documents from billions of web pages

Microsoft Bing



Match Plan Generation Process



- After preprocessing, multiple posting lists are retrieved.
- The search engine scans them by executing a *match plan* which is composed of a sequence of *match rules*.
- A *match rule* defines *how* the search engine matches documents over a period.
- It is made up of a **discrete** *match rule type* (e.g.$rule_A$) and several **continuous** *stopping quotas* (e.g. $MCC<N$).
- Different match rules have different execution costs.

Match Plan Plays critical role in Web Search

- Help to retrieve top candidates in milliseconds.
- Decide the resource allocation for a query.
- Help to make the trade-off between *relevance* and *efficiency*.
- It's a secret for search companies.
  - No publication, no open source.
  - Open toolkits (e.g. Lucene, Elasticsearch) do not have similar strategy.

Why generating match plans is hard?

- The complexity of the system environment
  - Increasing number of match rule types and quota types
  - Diverse data distribution across a large number of r
  - Frequent updates of documents
  - Static design cannot dynamically re

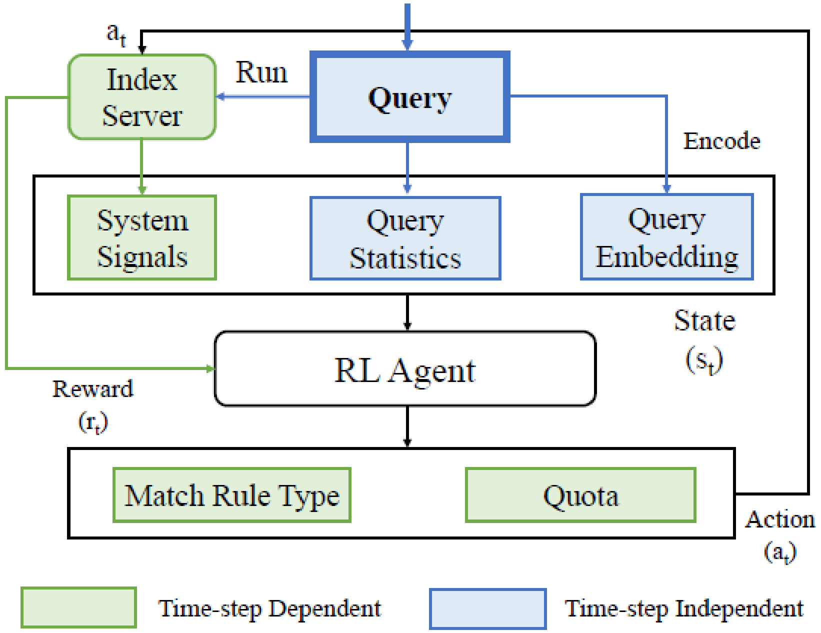
- Multiple objects optimization (

- Sequence decision making (ins

- Apply in thousands of machines and should be very fast

Need a learning method to *dynamically* generate corresponding match plan for each query.

Problem Formulation



A POMDP, a tuple of (S,A,P,R,Ω,O,γ)

State

- Intermediate System Signals
- Query Embeddings, Statistics

Action $\mathcal{A} = \{(k, x) | k \in \mathcal{A}_d, x \in \mathcal{X}\} = \mathcal{A}_d \times \mathcal{X},$

- **Discrete**: m types of predefined match rules + *Stop*
- **Continuous (shared)**: n dims of Quotas

Reward a scalar function weighted by:

- Performance: **"Relevance Scores" (RS)** of top k matched documents (From Bing's server)
- Latency: **"Index Block Accesses" (IBA)** of the match plan in the system

$$r_t = (\lambda_1 \mathrm{RS}_t - \lambda_2 \mathrm{IBA}_t) - (\lambda_1 \mathrm{RS}_{t-1} - \lambda_2 \mathrm{IBA}_{t-1}),$$

Environment Bing's index server (wrapped)

Could We Use Existed RL Algorithm?

Algorithm	DQN	TD3	SAC	PA-DDPG	What we expect
Discreate action	√	×	√	√	√
Continuous action	×	√	√	√	√
Discreate & Continuous action	×	×	×	√	√
Stability	×	×	√	×	√
Performance *(better than production)*	×	√	√	×	√

- Complex action space
  - *Complex action: combine discrete and continuous spaces*
  - *Huge action space 17,249,876,309* $* \ 10^{105}$
- Instability in training
  - *Due to the lack of exploration*
- Sampling deviation in traditional prioritized replay buffer
  - Experiences whose rewards are in certain ranges are more likely to be sampled, making the agent behave poorly in some state subspaces
  - *Cause poor performance of learning the value function for some queries*

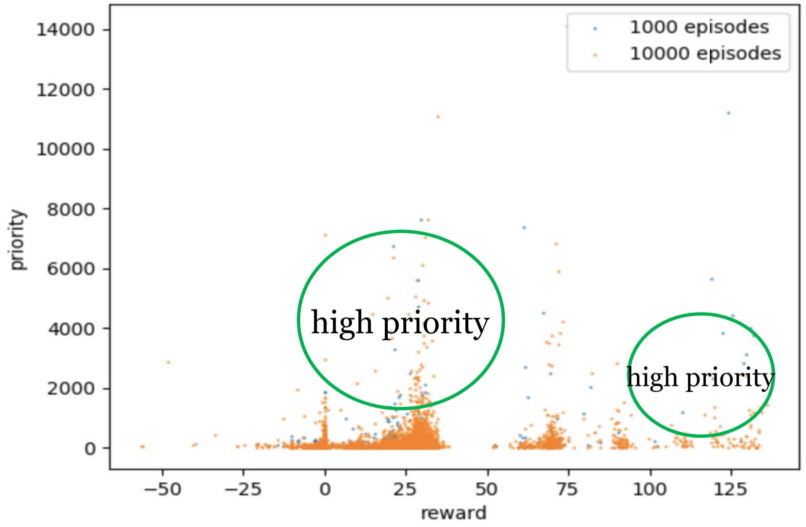
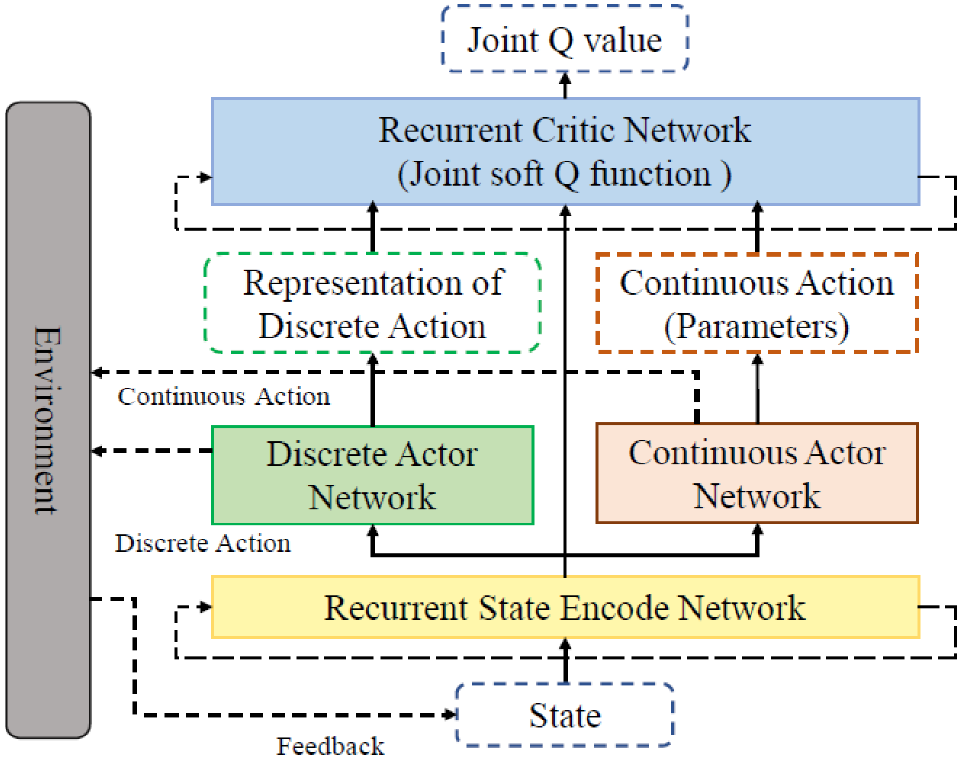


Figure 4. The deviation in original PER.

Parameterized Action Soft Actor-Critic



Challenges

- Parameterized (discrete-continuous hybrid) action space
- Complex environment, large state/action space
- Sparse reward, partial observability

PASAC:

- 1. Optimize a **stochastic policy** of the *complete* action: discrete match rules (Categorical dist.) and continuous quotas (Gaussian dist.), meanwhile maximize both entropies

$$J_\pi(\phi) = \mathbb{E}_{s_t \sim D}\left[\mathbb{E}_{k_t \sim \pi_\phi}\left[\alpha_d \log\left(\pi_\phi\left(k_t|s_t\right)\right) - Q_\theta\left(s_t, k_t, x_t\right)\right]\right] \quad (3)$$

$$J_\pi(\psi) = \mathbb{E}_{s_t \sim D}\left[\mathbb{E}_{x_t \sim \pi_\psi}\left[\alpha_c \log\left(\pi_\psi\left(x_t|s_t\right)\right) - Q_\theta\left(s_t, k_t, x_t\right)\right]\right] \quad (4)$$

- 2. Soft Q network: estimate a joint soft Q-value function for the *complete* action

$$J_Q(\theta) = \mathbb{E}_{(s_t, x_t, k_t) \sim D}\left[\frac{1}{2}\left(Q_\theta^t\left(s_t, x_t, k_t\right) - y_t\right)^2\right]$$

Parameterized Action Soft Actor-Critic

Algorithm 1 Parameterized Action Soft Actor-Critic

input: Initial parameters $\theta_1, \theta_2, \phi, \psi$
- ⋄ Initialize target net weights $\bar{\theta_1} \leftarrow \theta_1, \bar{\theta_2} \leftarrow \theta_2$
- ⋄ Initialize an replay buffer $\mathcal{D} \leftarrow \emptyset$

for each episode **do**
  for each environment step **do**
    ⋄ Sample discrete action from the policy $k_t \sim \pi_\phi(k_t|s_t)$
    ⋄ Sample parameter from the policy $x_t \sim \pi_\psi(x_t|s_t)$
    ⋄ Store the transition $\mathcal{D} \leftarrow \mathcal{D} \cup (s_t, f(k_t), x_t, r_t, s_{t+1})$
  end for
  for each gradient step **do**
    ⋄ Sample a mini-batch from replay buffer $\mathcal{D}$
    ⋄ Update the joint soft Q-function parameters
    $\theta_i \leftarrow \theta_i - \lambda_Q \nabla_{\theta_i} J_Q(\theta_i)$ for i $\in [1, 2]$
    ⋄ Update discrete policy weights
    $\phi \leftarrow \phi - \lambda_{\pi_\phi} \nabla_\phi J_\pi(\phi)$
    ⋄ Update continuous policy weights
    $\psi \leftarrow \psi - \lambda_{\pi_\psi} \nabla_\psi J_\pi(\psi)$
    ⋄ Adjust temperature of discrete policy's entropy
    $\alpha_d \leftarrow \alpha_d - \lambda_{\alpha_d} \nabla_{\alpha_d} J(\alpha_d)$
    ⋄ Adjust temperature of continuous policy's entropy
    $\alpha_c \leftarrow \alpha_c - \lambda_{\alpha_c} \nabla_{\alpha_c} J(\alpha_c)$
    ⋄ Update target network weights
    $\bar{\theta}_i \leftarrow \tau\theta_i + (1 - \tau)\bar{\theta}_i$ for i $\in [1, 2]$
  end for
end for

output: Optimized parameters $\theta_1, \theta_2, \phi, \psi$

Implementation Details:

- **Exploration**: *double alpha tuning* to control the different exploration rate at the discrete and continuous action spaces

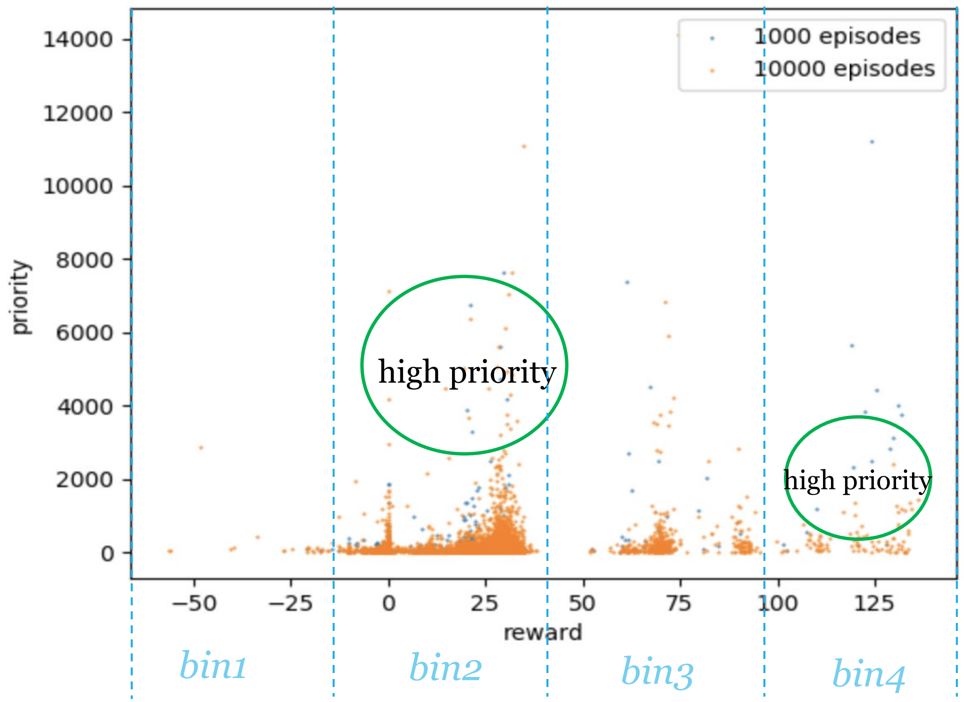
$$J(\alpha_d) = \mathbb{E}_{k_t \sim \pi^t_\phi}\left[-\alpha_d\left(\log\left(\pi_\phi(k_t|s_t)\right) + \bar{\mathcal{H}}_d\right)\right]$$

$$J(\alpha_c) = \mathbb{E}_{x_t \sim \pi^t_\psi}\left[-\alpha_c\left(\log\left(\pi_\psi(x_t|s_t)\right) + \bar{\mathcal{H}}_c\right)\right]$$

- **Recurrent state head**: dynamic LSTM to solve the Partially Observation problem

https://github.com/RL-matchplangeneration/Match-Plan-Generation-in-Web-Search

Stratified PER



We further proposed Stratified Prioritized Experience Replay (SPER) to address the "*skewed prioritizing*" issue:

- **skewed prioritizing**: experiences whose rewards are in certain ranges are more likely to be sampled, making the agent behave poorly in some state subspaces (some queries are inherently easy/hard to train)
- **buffer stratifying**: the replay buffer is divided into several bins (strata) according to reward range. The same number of samples are sampled from each bin by important sampling
- **priority with TD-error and *policy loss***:
  - Transactions with larger improvement potential more likely to be sampled

$$p(s_t, a_t) = |\delta(s_t, a_t)| + \lambda\xi(s_t, a_t) + \epsilon_d,$$

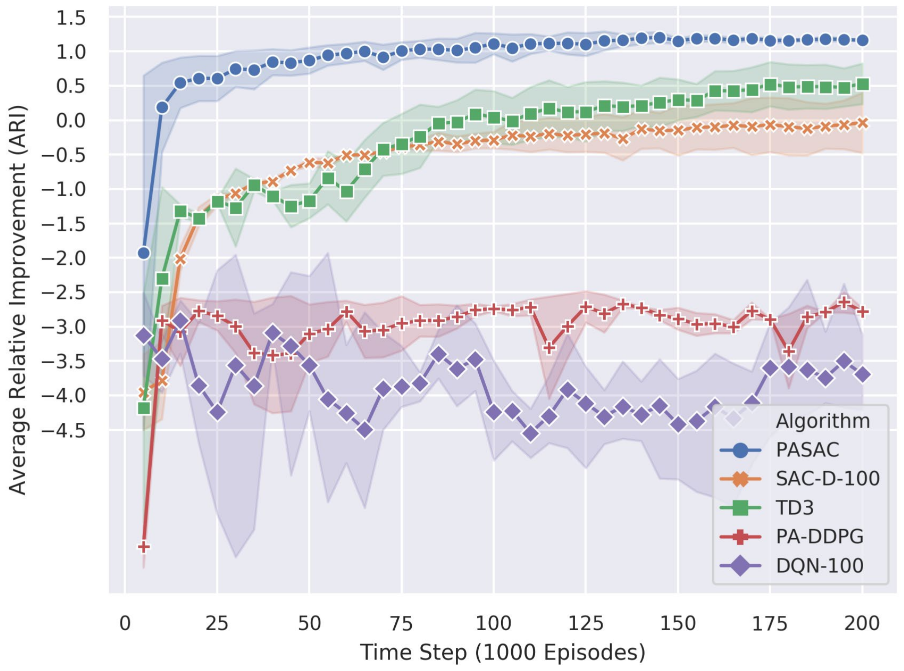
Experiments

- Q1. Does the proposed algorithm work better than the heuristic hand-crafted method tuned by engineers, or other RL algorithms?
- Q2. Is it more appropriate that we formulate the problem into a PARL problem, instead of discretizing the action space?
- Q3. How is the improvement of our method in real search scenes?
- Q4. How is the effect of applying SPER, and its components?
- Q5. Does the proposed agent work well on other PARL benchmarking baselines?

Experiments

Q1,2,3: Some comparative experiments with the same condition (3,000 test queries in total)

For different RL agents (Figure on ARI)



$$ARI = \frac{\sum_{i=1}^{|D|}(r^i_{agent} - r^i_{baseline})}{|D|}$$

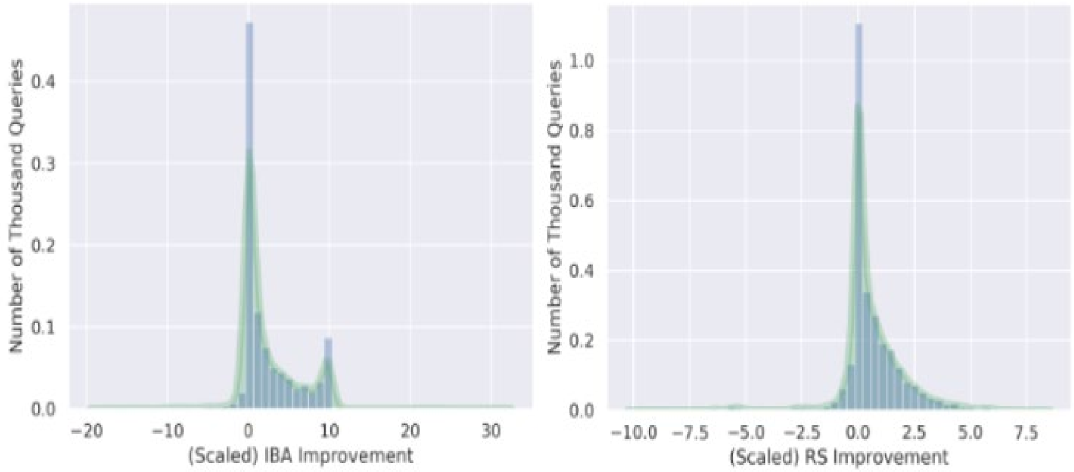
For different RL agents (Table)

	DQN-20	DQN-100	D-SAC-20	D-SAC-100	PA-DDPG	TD3	**PASAC**	**PASAC+SPER**
ARI	-1.500	-1.957	0.210	0.460	-2.492	0.8384	1.280	**1.912**
Better	26.70%	27.43%	40.47%	49.30%	39.97%	41.90%	50.53%	**60.10%**
Equal	3.70%	4.50%	10.10%	6.03%	3.17%	4.67%	6.07%	**11.60%**

PASAC agent apparently outperforms other SOTA agents in both stability and efficiency in our scene

Experiments

Performance Improvements for Production



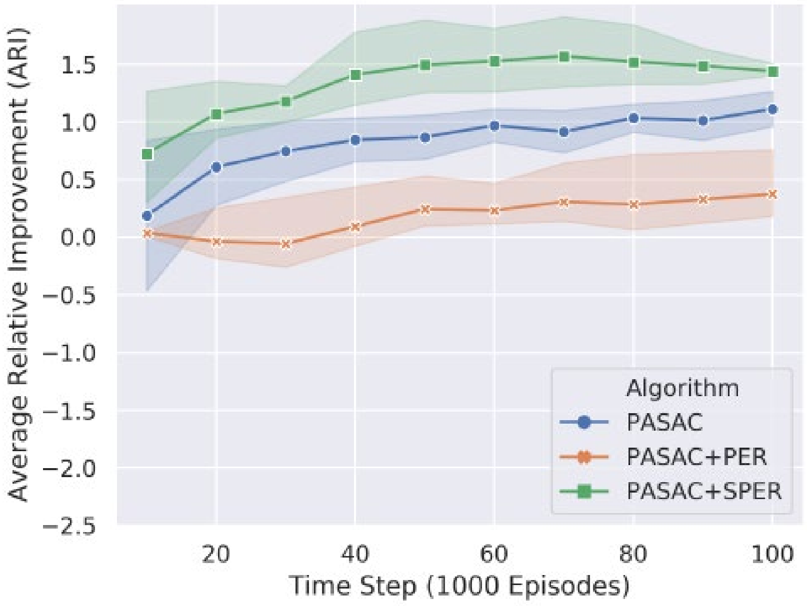
	IBA	RS	Latency	Latency+inference
Improvement	+75.77%	-1.47%	+28.14%	+8.97%

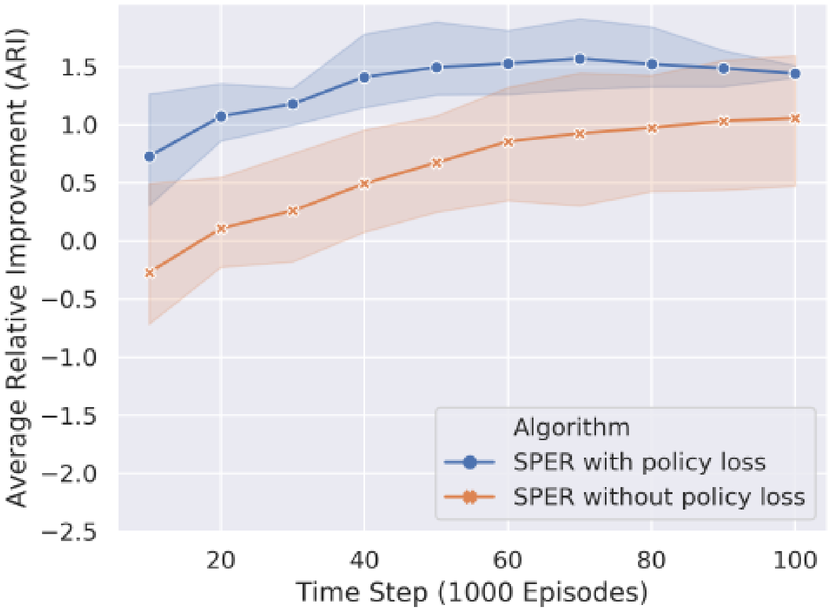
- **Significant reduction of index block accesses** with relevance on-par
  - *Manually defined match plans cannot flexibly control the quotas*
- Match plans generated by model are typically **shorter** than production
  - *Production rules are generalized to all queries in a category, leading to some redundancy rules for a single query*

Experiments

Ablation Study

Q4. How is the effect of applying SPER, and its components?





Experiments

Benchmark Games

Q5: Does the proposed agent work well on other PARL benchmarking baselines?

We evaluate our agent in a broader context

Table 3: Average evaluation results (the average of all training rewards and final evaluation reward (repeated 100 times)) on benchmarks Platform-v0 and Goal-v0 with PA-DDPG [8].

Average Eval Return	PASAC	PASAC+SPER	PA-DDPG[8]
Platform-v0	0.9723	**0.9727**	0.3113
Goal-v0	43.11	**43.85**	-6.208

- PASAC performs much better than PA-DDPG.
- Stratified sampling may better fit the environment with skewed prioritizing issue if PER is applied.

Summary

- Formulate the match plan generation task to the general PARL framework
- Propose a novel algorithm, Parameterized Action Soft Actor-Critic
- To address the *skewed prioritizing* issue of PER, Stratified Prioritized Experience Replay (SPER) is applied
- Experiment results show that our learned match plan significantly outperforms the production baseline in terms of resource-saving
- Future works include further optimize the model reference time, and inventing more delicate strategies in exploring the parameterized action space

Thank you
for your careful listening!