RL and Optimization Problem

- 가치함수 V(s) (직관력)을 높이는 (최적화) 학습 방법

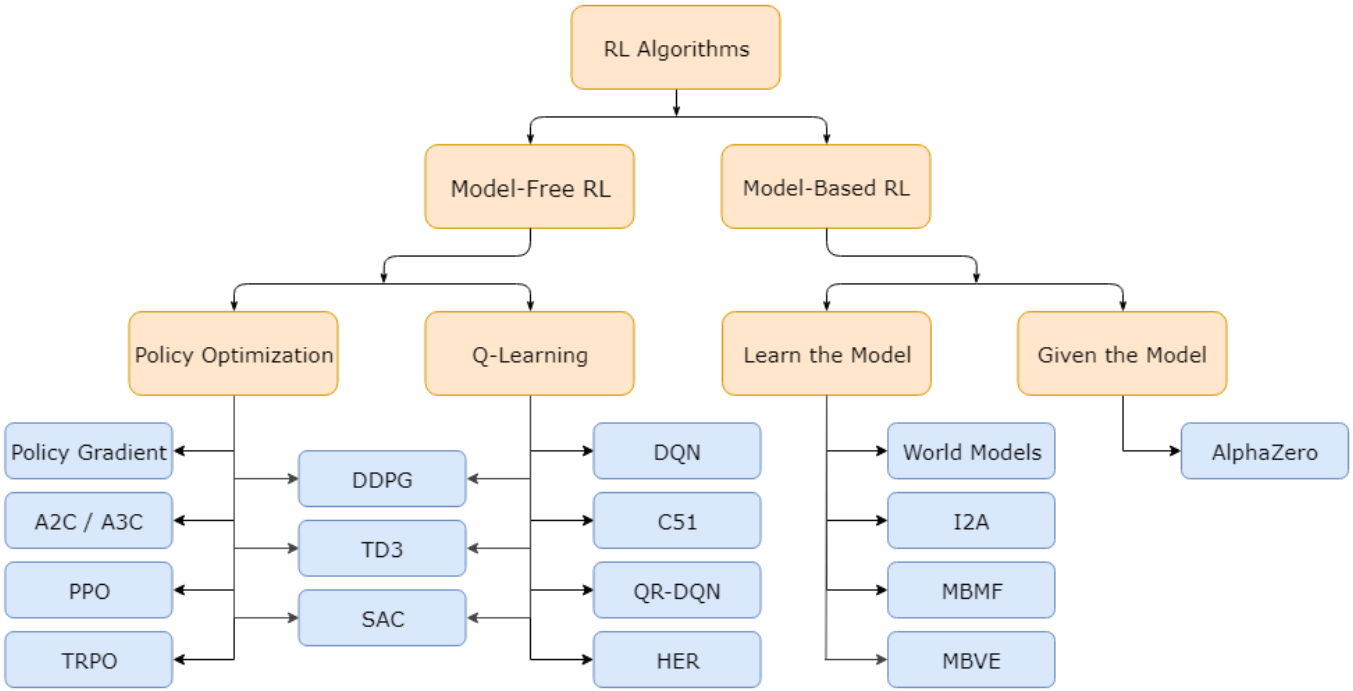
MDP

- MDP로 풀기에는 현실 문제의 복잡도가 너무 높다

RL and Optimization

- Traditional (Combinatorial) Optimization
  - Scheduling
- RL
  - Dynamic Optimization
  - Real-time decision

강화학습의 종류



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Experience replay

- Experience replay memory

  - **Issue 1.** 성공적인 Deep Learning applications는 hand-labelled training data set을 요하는데, Reinforcement Learning에서는 오로지reward를 통해 학습이 이루어지고, 그 reward도 sparse하고 noisy 심지어는 delay되어 주어진다.
  - **Issue 2.** Deep Learning에서는 data sample이 i.i.d. 분포를 가정하지만, Reinforcement Learning에서는 현재 state가 어디인지에 따라 갈 수 있는 다음 state가 결정되기때문에 state간의 correlation이 크다. 즉, data간의 correlation이 크다.

Experience replay

이전에 살펴본 algorithm들과 같이 본 논문이 나오기 전에는 environment와 상호작용하며 얻어진 on-policy sample들,

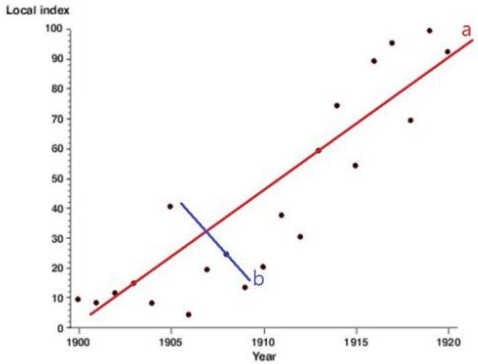
$$s_t,\ a_t,\ r_t,\ s_{t+1},\ a_{t+1}$$

을 통해 parameter를 update하였습니다. 하지만, 이와 같은 방법은 on-policy sample을 통해 update하기때문에 sample에 대한 의존성이 커서 policy가 converge하지 못하고 oscillate할 수 있습니다. 이러한 문제를 해결하고자, 착안한 아이디어가 **Experience replay**입니다. 각 time-step별로 얻은 sample(experience)들을 아래와 같은 tuple형태로 data set에 저장해두고, randomly draw하여 mini-batch를 구성하고 update하는 방법입니다.

$$e_t = (s_t,\ a_t,\ r_t,\ s_{t+1}), \qquad D = e_1,\ e_2\ \dots\ e_N$$

이때, data set은 무한히 저장할 수 없기 때문에 N으로 고정하고, FIFO방식으로 저장합니다. 또한 input으로써 arbitrary length를 받는데에 어려움이 있기 때문에 function ϕ를 정의하여 pre-processing하여 state의 length를 fixed시킵니다. Experience replay를 이용하면 아래와 같은 이점을 얻을 수 있습니다.

- data sample을 한번 update하고 버리는 기존의 방법과 달리 random sampling을 함으로써 data usage efficiency를 도모할 수 있습니다.
- RL에서 발생할 수 있는 state간의 high correlation 문제(위에서 언급한 Issue 2. correlation문제)를 해결 할 수 있습니다현재 update된 parameter를 통해 다음 training의 대상이 되는 sample을 어느정도 determine할 수 있습니다.
- 현재의 policy에 따라 argmax action을 고르고 난 뒤, 그 다음 training sample은 이 action에 따라 결정됩니다. 이를 current sample에 의해 다음 training sample이 dominate되었다고 말합니다. 본 논문에 따르면, 이렇게 되면 불필요한 feedback loops를 돌거나, parameter들이 local minimum에 빠지거나 diverge하는 경우를 찾아낼 수 있어서, 이를 방지할 수 있다고 합니다. 주의할 점은, experience replay를 사용할 땐, 반드시 off-policy로 learning해야하는데, 이는 current parameter가 update하는 sample들과 다르기때문입니다.



출처: https://sumniya.tistory.com/18

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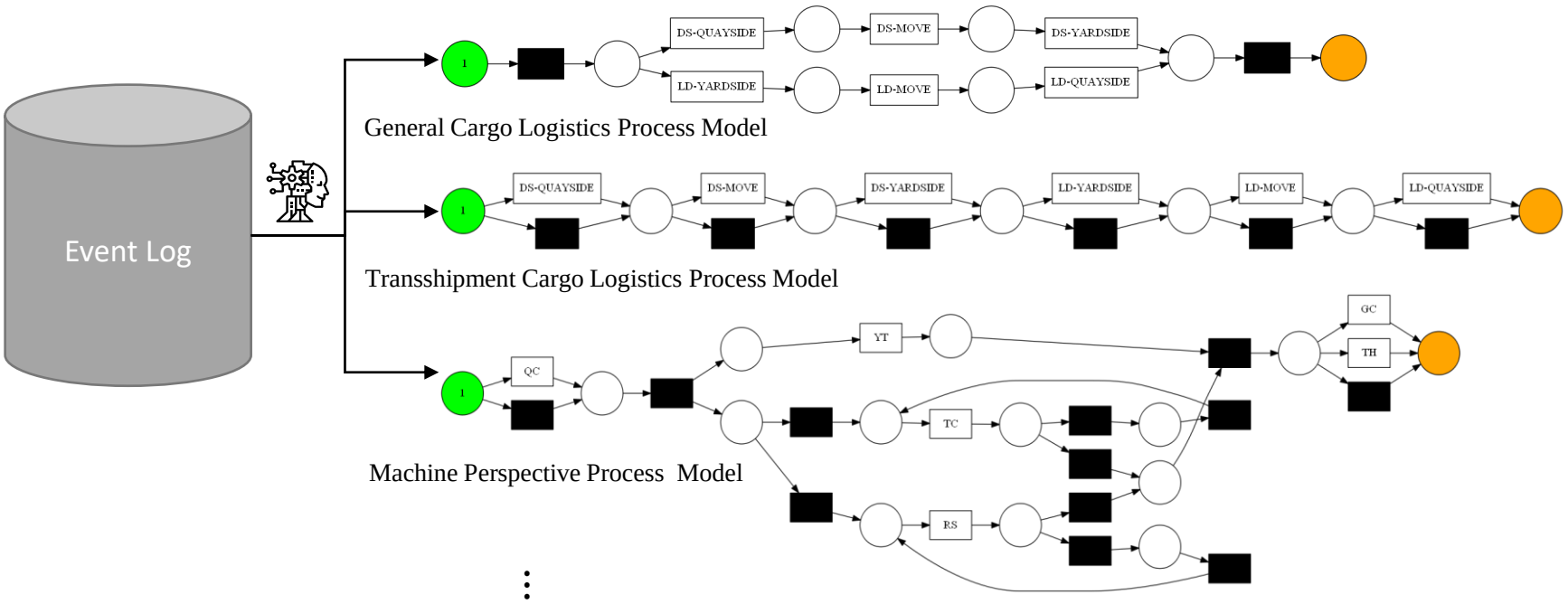
Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

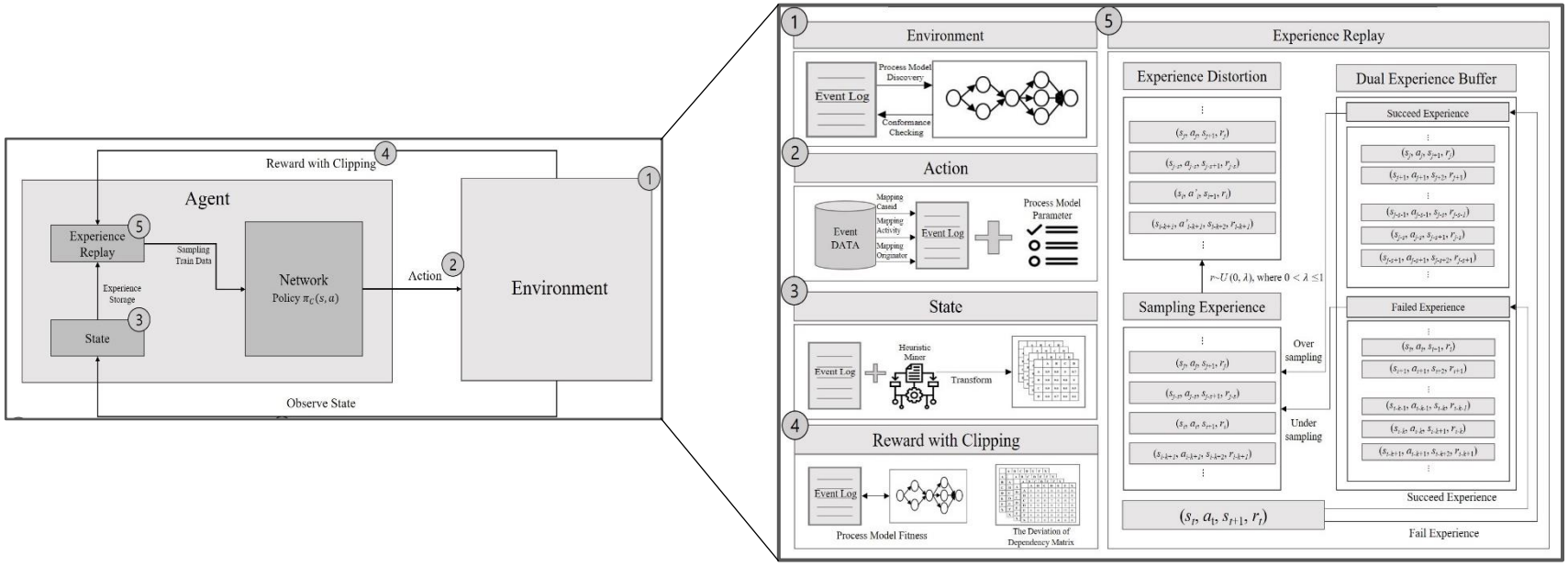
Automatic discovery of process model



Let W be an event log over T, and $a, b \in T$:

- $|a >_W b|$ is the number of times $a >_W b$ occurs in W,
- $a \Rightarrow_W b = \left(\dfrac{|a >_W b| - |b >_W a|}{|a >_W b| + |b >_W a| + 1} \right)$

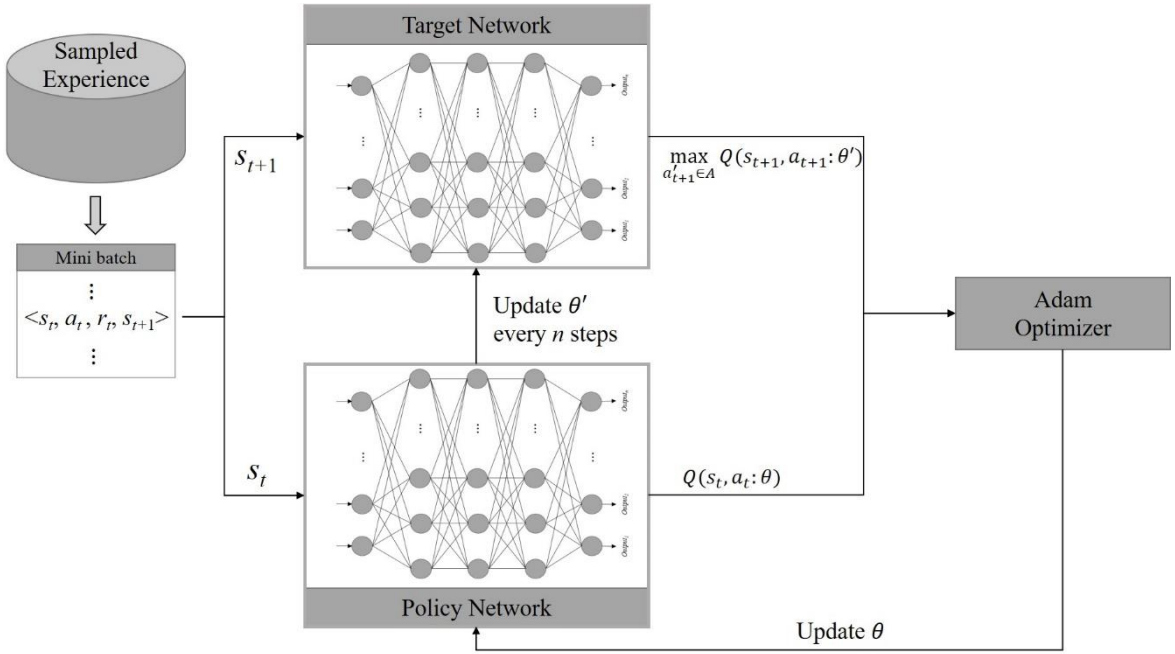
Deep RL for process model discovery



Research Results

Key Components

- ✓ Action space
- ✓ State
- ✓ Reward
- ✓ Environments
- ✓ Q-Networks
- ✓ Experiences Replay



04. [AutoPD] Automatic Discovery Multi-perspective Process Model

Research Results

Key Components

- ✓ Action space
- ✓ State
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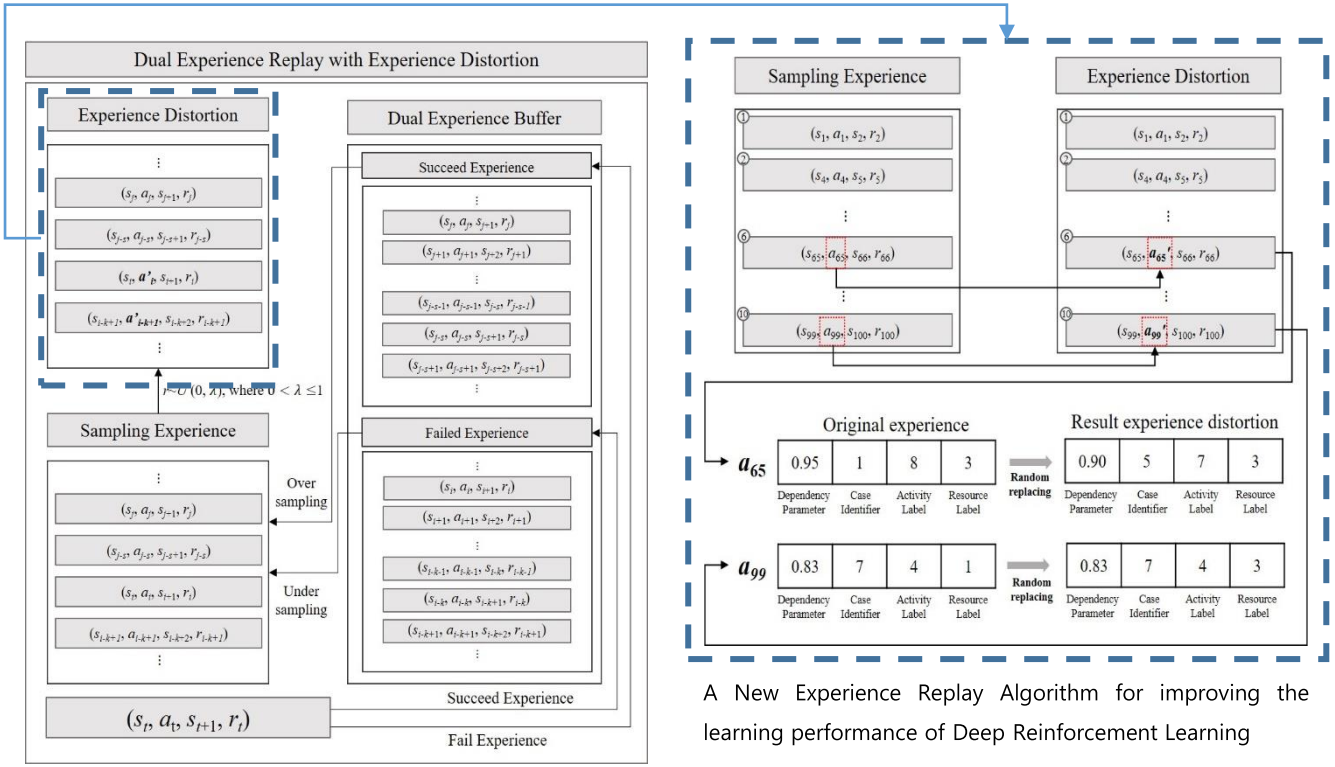

A New Experience Replay Algorithm for improving the learning performance of Deep Reinforcement Learning

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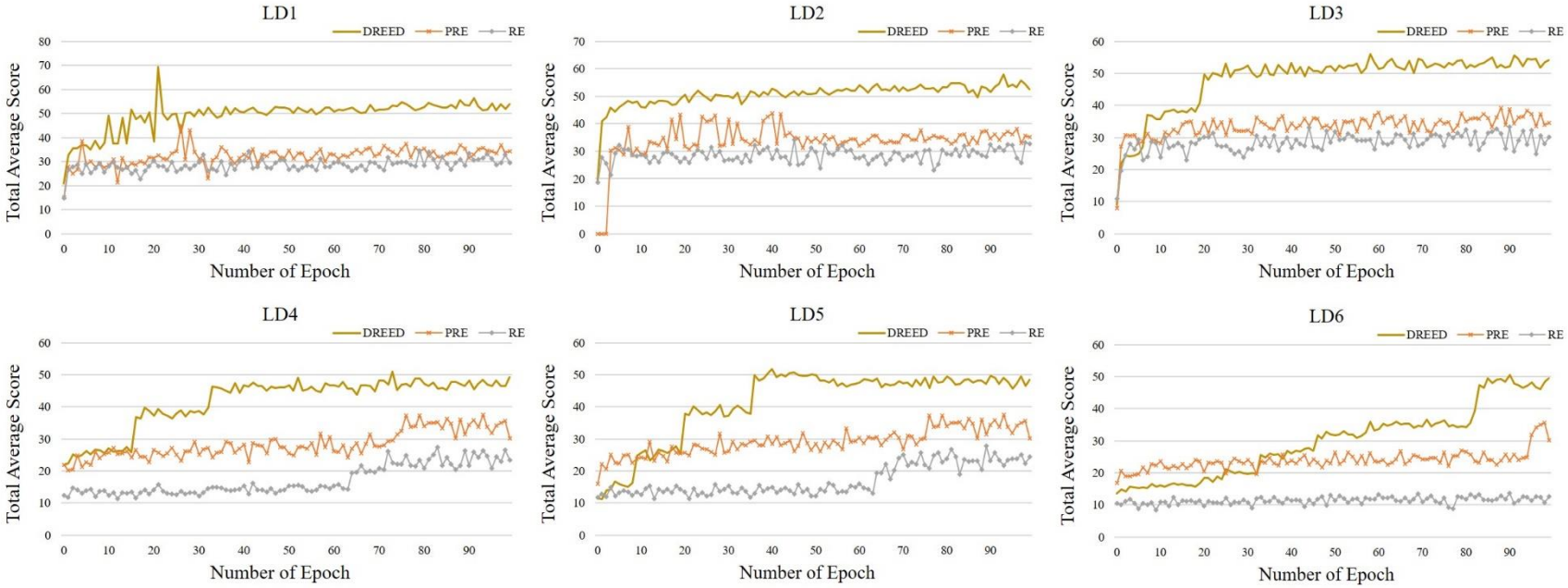
04. [AutoPD] Automatic Discovery Multi-perspective Process Model

Research Results

[Experiment 4-1] The overall average reward received by the agent while learning is in progress



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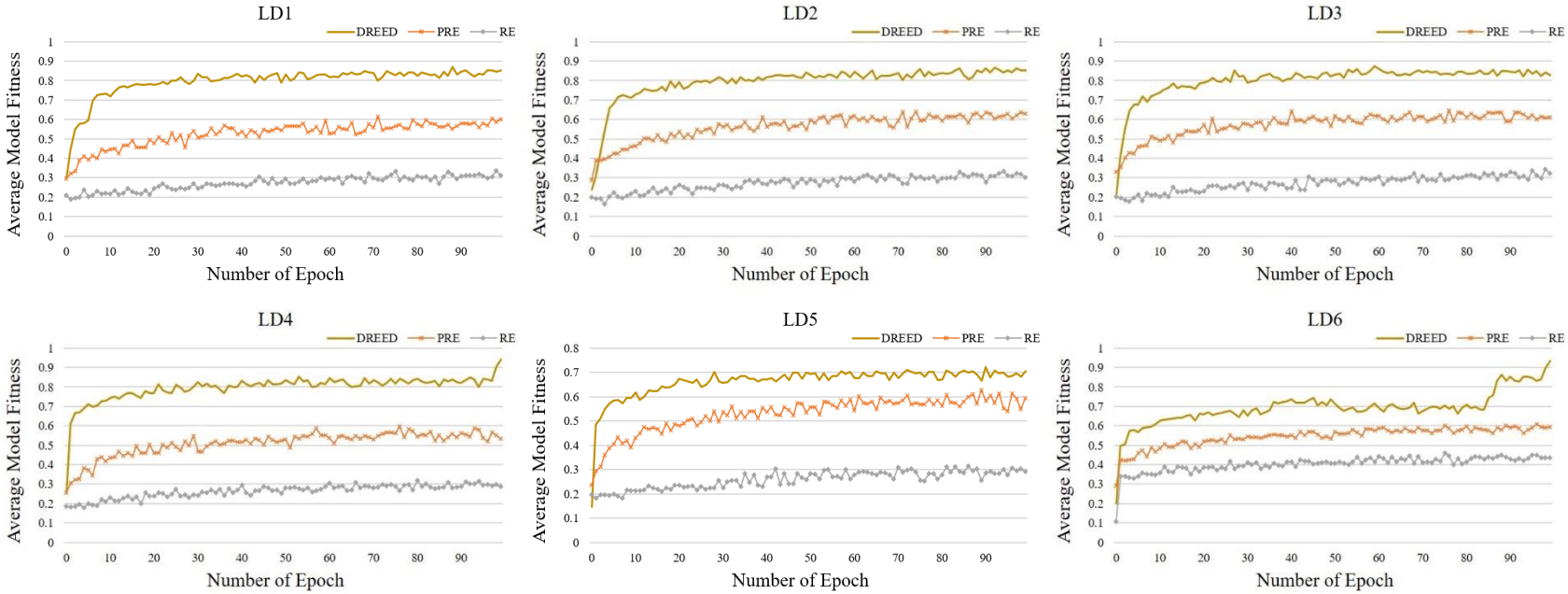
04. [AutoPD] Automatic Discovery Multi-perspective Process Model

Research Results

[Experiments 4-2] The average fitness of the process model derived by the agent during training



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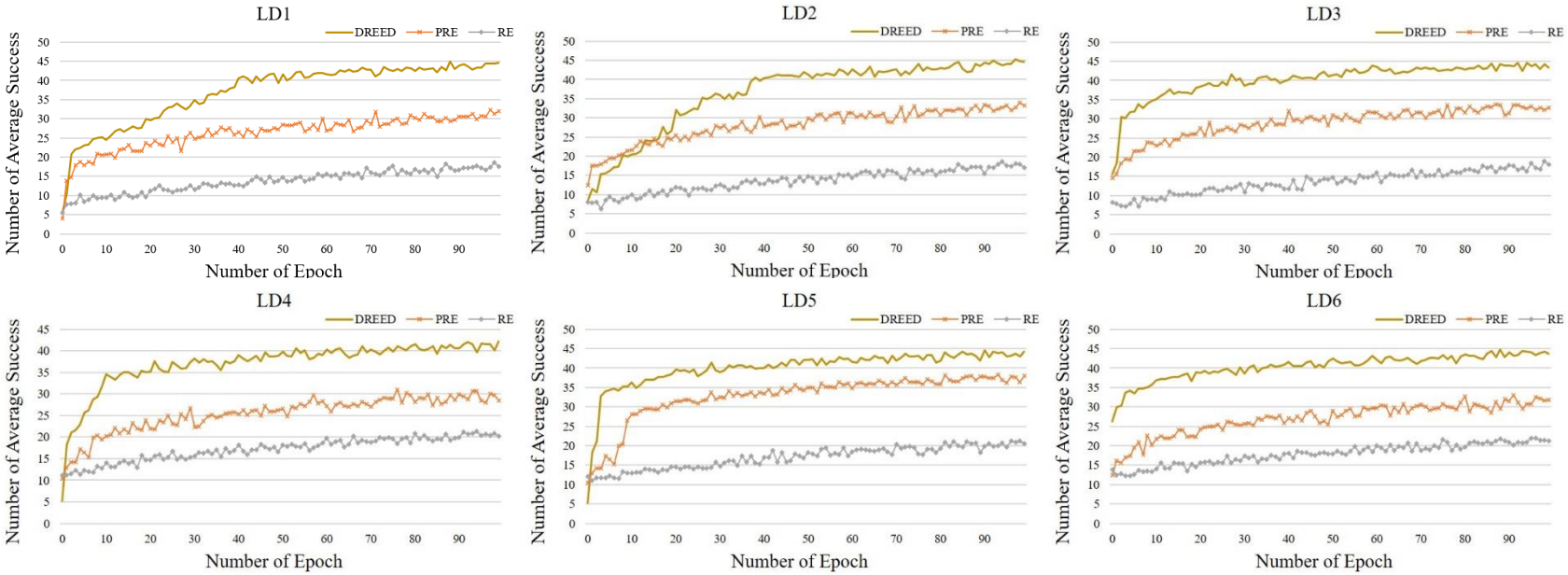
04. [AutoPD] Automatic Discovery Multi-perspective Process Model

Research Results

[Experiments 4-2] The average number of times an agent discovering a process model with the fitness of 0.7 or more during the learning process



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04. [AutoPD] Automatic Discovery Multi-perspective Process Model

Contribution

- ✓ Proposed a new perspective process discovery algorithm that can derive process models from various perspectives at once
- ✓ A new ER method called DERED is proposed to improve the performance of reinforcement learning.
- ✓ Using 6 actual event logs, we secured nearly twice the learning performance improvement in the experiment compared to the existing ER method.
- ✓ Through the proposed method, process model discovery, conformance checking, and process model improvement are automatically performed to make it easier to provide process models to users.

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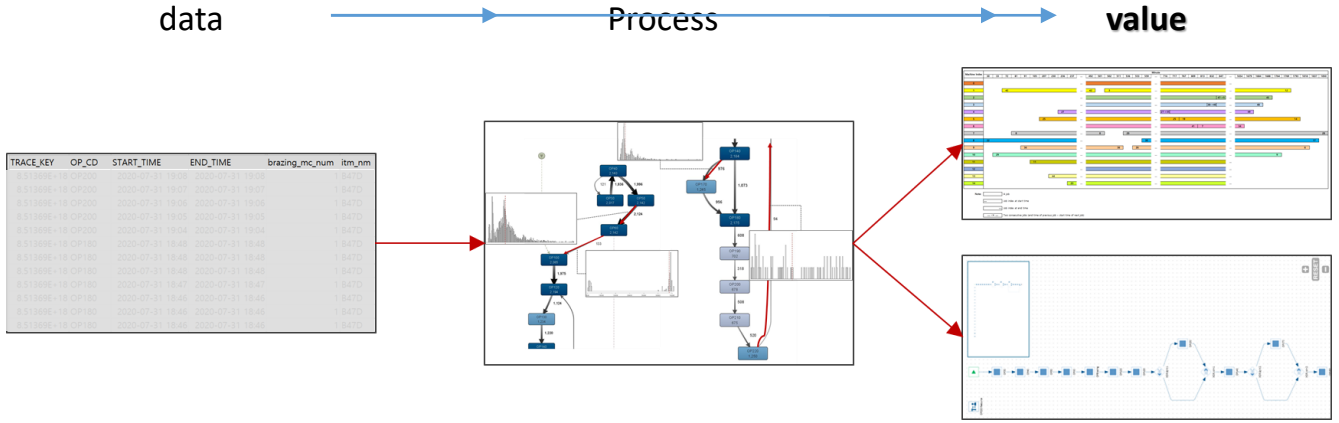
01. Research Summary

Through this study, we propose an automated process mining method that allows business experts to easily apply process mining.



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