REINFORCE versus A2C

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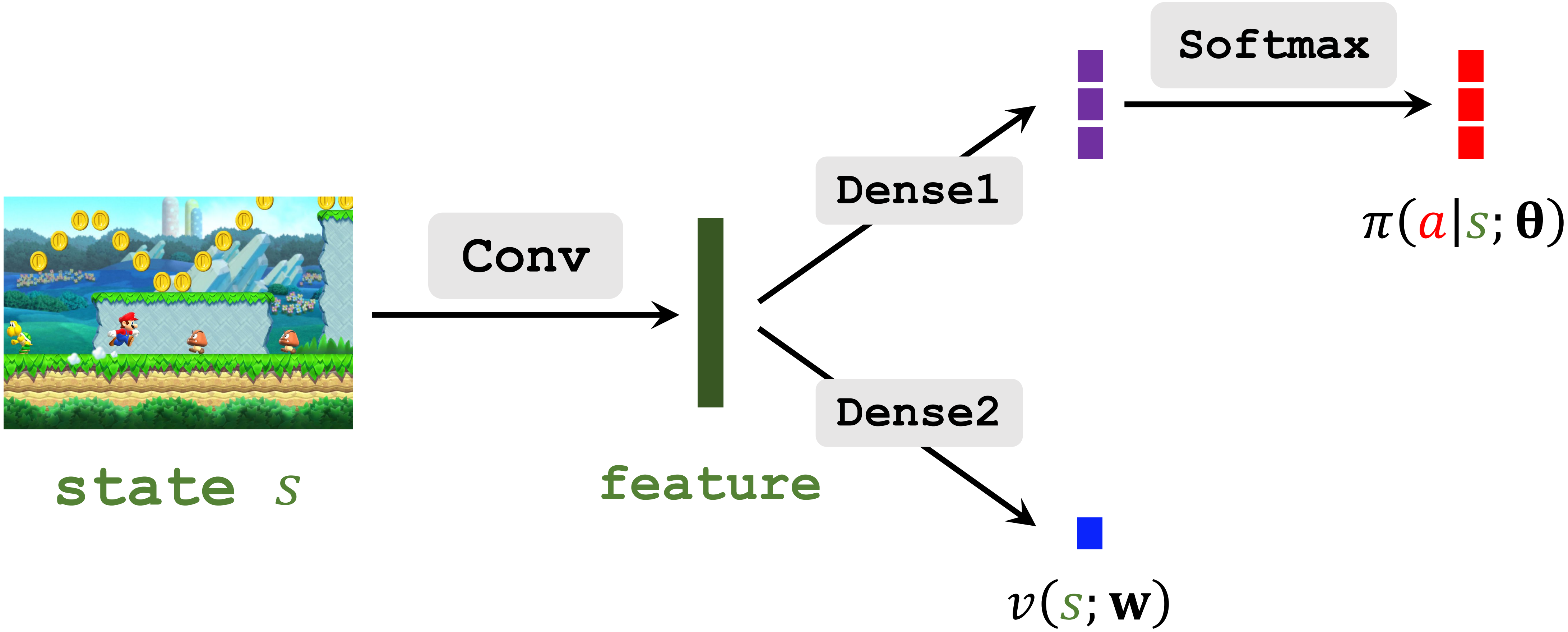
Policy and Value Networks



A2C with Multi-Step TD Target

Advantage Actor-Critic (A2C)

- Observing a transition (s_t, a_t, r_t, s_{t+1}).
- TD target: $y_t = r_t + \gamma \cdot v(s_{t+1}; \mathbf{w})$.
- TD error: $\delta_t = v(s_t; \mathbf{w}) - y_t$.
- Update the policy network (actor) by:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \beta \cdot \underline{\delta_t \cdot \frac{\partial \ln \pi(a_t \mid s_t; \boldsymbol{\theta})}{\partial \, \boldsymbol{\theta}}}.$$

- Update the value network (critic) by:

$$\mathbf{w} \leftarrow \mathbf{w} - \alpha \cdot \delta_t \cdot \frac{\partial \, v(s_t; \mathbf{w})}{\partial \, \mathbf{w}}.$$

Advantage Actor-Critic (A2C)

- Observing a transition (s_t, a_t, r_t, s_{t+1}).
- TD target: $y_t = r_t + \gamma \cdot v(s_{t+1}; \mathbf{w})$.

Use multi-step TD target instead.

- TD error: $\delta_t = v(s_t; \mathbf{w}) - y_t$.
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One-Step VS Multi-Step Target

- Observing a transition (s_t, a_t, r_t, s_{t+1})
- **One-step TD target:**

$$y_t = \underline{r_t} + \gamma \cdot v(s_{t+1}; \mathbf{w}).$$

One-Step VS Multi-Step Target

- Observing a transition (s_t, a_t, r_t, s_{t+1})
- **One-step TD target:**

$$y_t = r_t + \gamma \cdot v(s_{t+1}; \mathbf{w}).$$

- Observing m transitions: $\{(s_{t+i}, a_{t+i}, r_{t+i}, s_{t+i+1})\}_{i=0}^{m-1}$.
- **m-step TD target:**

$$y_t = \underline{\sum_{i=0}^{m-1} \gamma^i \cdot r_{t+i}} + \gamma^m \cdot v(s_{t+m}; \mathbf{w}).$$

A2C with Multi-Step TD Target

- Observing a trajectory from time t to n.
- TD target: $\boxed{y_t = \sum_{i=0}^{m-1} \gamma^i \cdot r_{t+i} + \gamma^m \cdot v(s_{t+m}; \mathbf{w}).}$
- TD error: $\delta_t = v(s_t; \mathbf{w}) - y_t.$
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- Update the value network (critic) by:

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REINFORCE with Baseline

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- Observing a trajectory from time t to n.
- Return: $u_t = \sum_{i=t}^{T} \gamma^{i-t} \cdot r_i$.
- Error: $\delta_t = v(s_t; \mathbf{w}) - u_t$.

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A2C versus REINFORCE

TD Target versus Return

A2C with m-step TD target: $y_t = \sum_{i=0}^{m-1} \gamma^i \cdot r_{t+i} + \gamma^m \cdot v(s_{t+m}; \mathbf{w})$.

TD Target versus Return

A2C with one-step TD target: $y_t = r_t + \gamma \cdot v(s_{t+1}; \mathbf{w})$.

Use only one reward ($m = 1$)

A2C with m-step TD target: $y_t = \sum_{i=0}^{m-1} \gamma^i \cdot r_{t+i} + \gamma^m \cdot v(s_{t+m}; \mathbf{w})$.

TD Target versus Return

A2C with one-step TD target: $y_t = r_t + \gamma \cdot v(s_{t+1}; \mathbf{w})$.

Use only one reward ($m = 1$)

A2C with m-step TD target: $y_t = \sum_{i=0}^{m-1} \gamma^i \cdot r_{t+i} + \gamma^m \cdot v(s_{t+m}; \mathbf{w})$.

Use all the rewards

REINFORCE: y_t becomes $u_t = \sum_{i=t}^{n} \gamma^{i-t} \cdot r_i$.

A2C versus REINFORCE

- A2C uses m-step TD target (with bootstrapping):

$$y_t = \sum_{i=0}^{m-1} \gamma^i \cdot r_{t+i} + \gamma^m \cdot v(s_{t+m}; \mathbf{w}).$$

- REINFORCE uses the return (without bootstrapping):

$$u_t = \sum_{i=0}^{n-t} \gamma^i \cdot r_{t+i}.$$

- u_t is a special case of y_t.

Thank you!