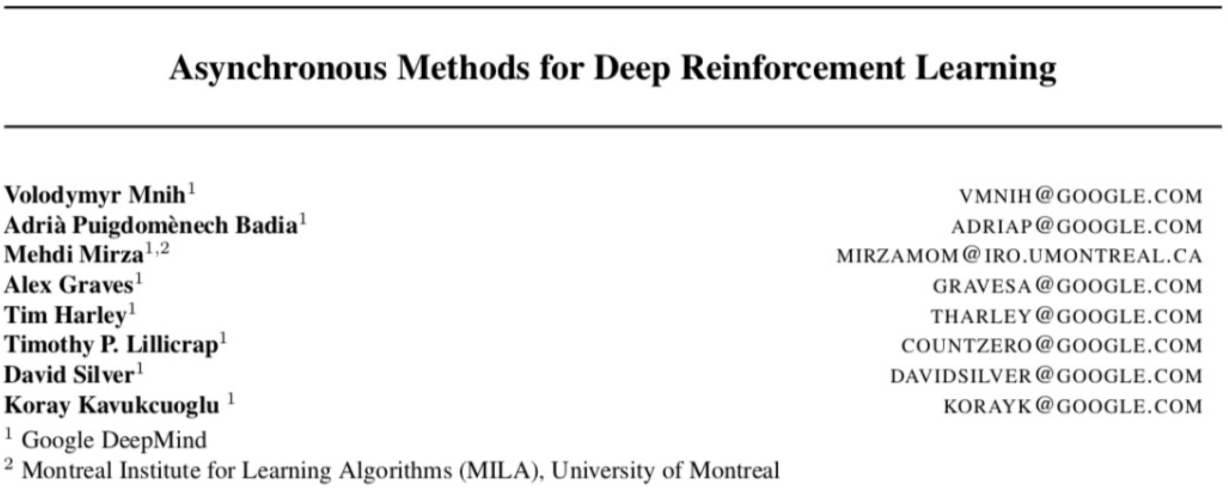

Asynchronous Methods for Deep Reinforcement Learning

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【强化学习算法 5】A3C

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原文传送门：

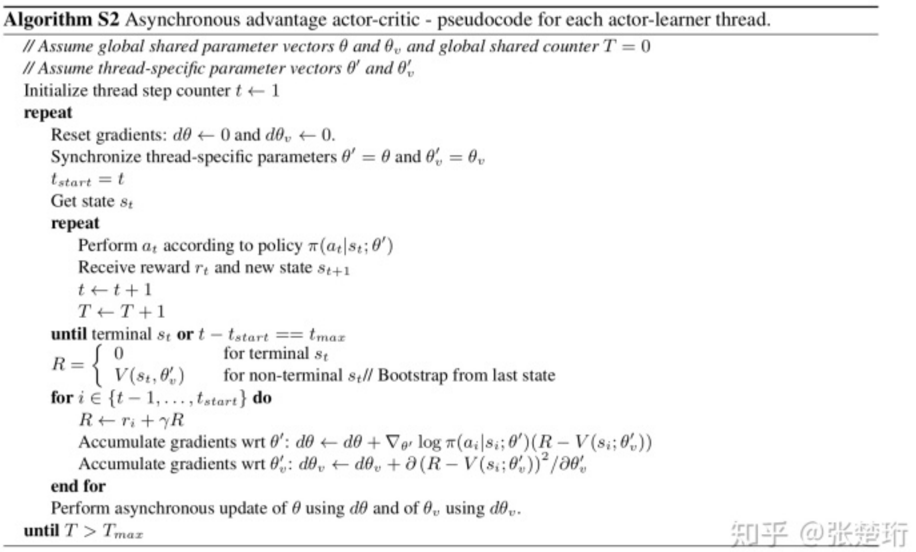
Mnih, Volodymyr, et al. "Asynchronous methods for deep reinforcement learning." International conference on machine learning. 2016.

特色： 发现异步并行地执行多个agent，让它们on-policy地去面对不同的状态，不仅加速了算法，而且有一种使得算法更加稳定的效果。

分类： Model-free、Policy-based（Actor-critic）、On-policy、Continuous State Space、Continuous Action Space、Support High-dim Input

过程： 普通的Actor-critic方法加上baseline $V(s)$ ，只不过在每个节点上计算用到的 $\pi_\theta(a|s)$ 和 $V_{\theta_v}(s)$ 都用从master上面同步下来的权值，各自探索积累自己的梯度 $d\theta$ 和 $d\theta_v$ ，每过一阵子就推到master上去更新。

算法：



Algorithm S2 Asynchronous advantage actor-critic - pseudocode for each actor-learner thread.

```
// Assume global shared parameter vectors $\theta$ and $\theta_v$ and global shared counter $T = 0$
// Assume thread-specific parameter vectors $\theta'$ and $\theta'_v$
Initialize thread step counter $t \leftarrow 1$
repeat
    Reset gradients: $d\theta \leftarrow 0$ and $d\theta_v \leftarrow 0$.
    Synchronize thread-specific parameters $\theta' = \theta$ and $\theta'_v = \theta_v$
    $t_{start} = t$
    Get state $s_t$
    repeat
        Perform $a_t$ according to policy $\pi(a_t|s_t;\theta')$
        Receive reward $r_t$ and new state $s_{t+1}$
        $t \leftarrow t + 1$
        $T \leftarrow T + 1$
    until terminal $s_t$ or $t - t_{start} == t_{max}$
    $R = \begin{cases} 0 & \text{for terminal } s_t \\ V(s_t, \theta'_v) & \text{for non-terminal } s_t \text{// Bootstrap from last state} \end{cases}$
    for $i \in \{t-1, \ldots, t_{start}\}$ do
        $R \leftarrow r_i + \gamma R$
        Accumulate gradients wrt $\theta'$: $d\theta \leftarrow d\theta + \nabla_{\theta'} \log \pi(a_i|s_i;\theta')(R - V(s_i;\theta'_v))$
        Accumulate gradients wrt $\theta'_v$: $d\theta_v \leftarrow d\theta_v + \partial\left(R - V(s_i;\theta'_v)\right)^2 / \partial\theta'_v$
    end for
    Perform asynchronous update of $\theta$ using $d\theta$ and of $\theta_v$ using $d\theta_v$.
until $T > T_{max}$
```

编辑于 2018-09-19

强化学习 (Reinforcement Learning)　算法（书籍）　算法

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