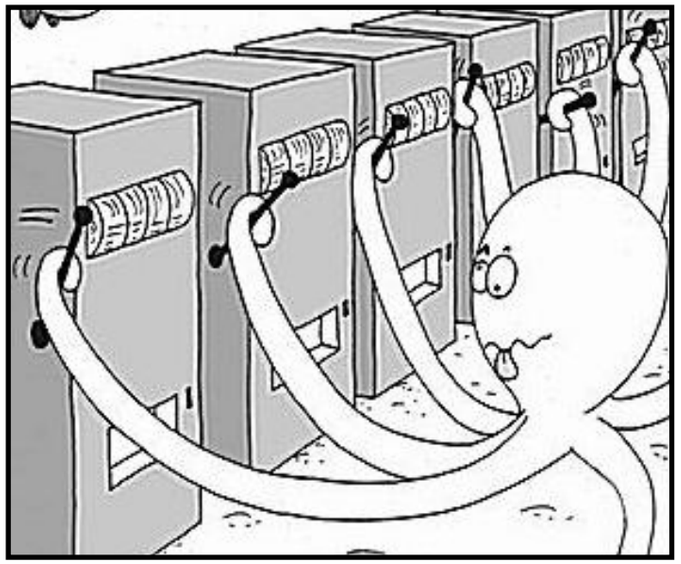
STRAW

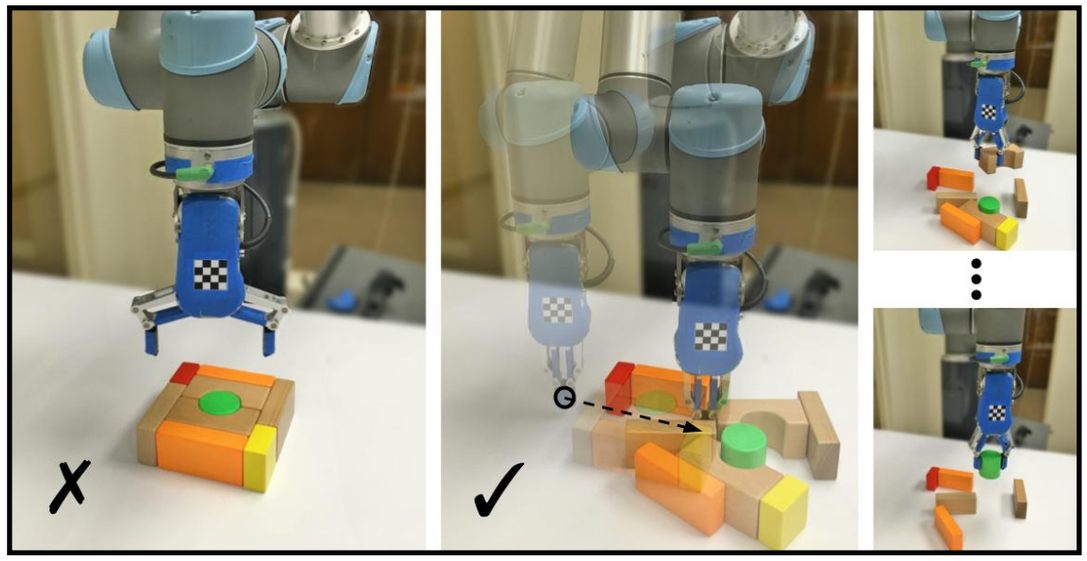
Strategic attentive writer for learning macro-actions

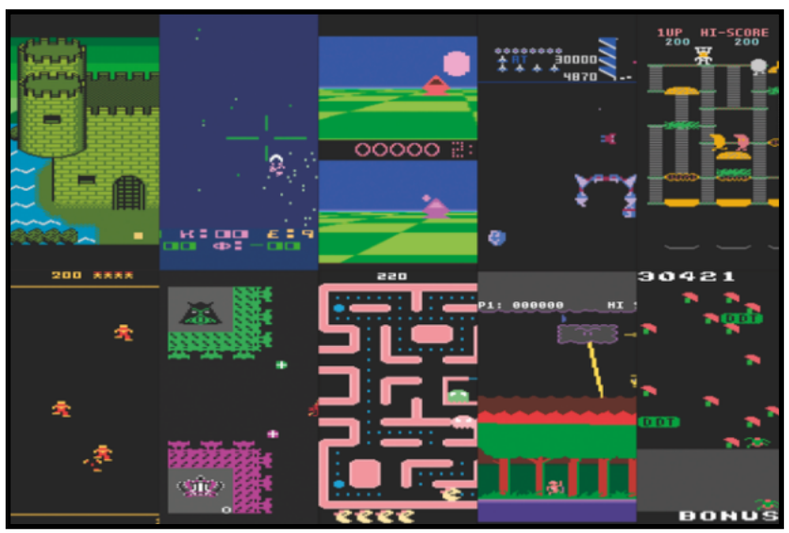
Quick Reminder

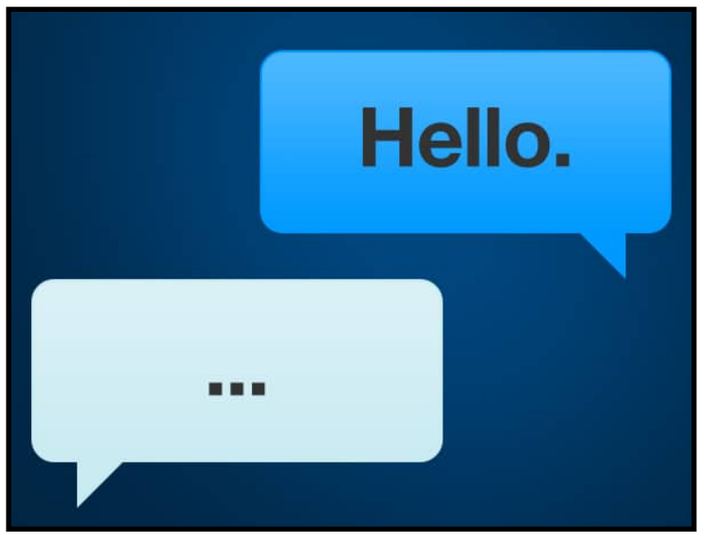
What is reinforcement learning

Agent interacts with environment & We get feedback on agent performance









Underlying Math

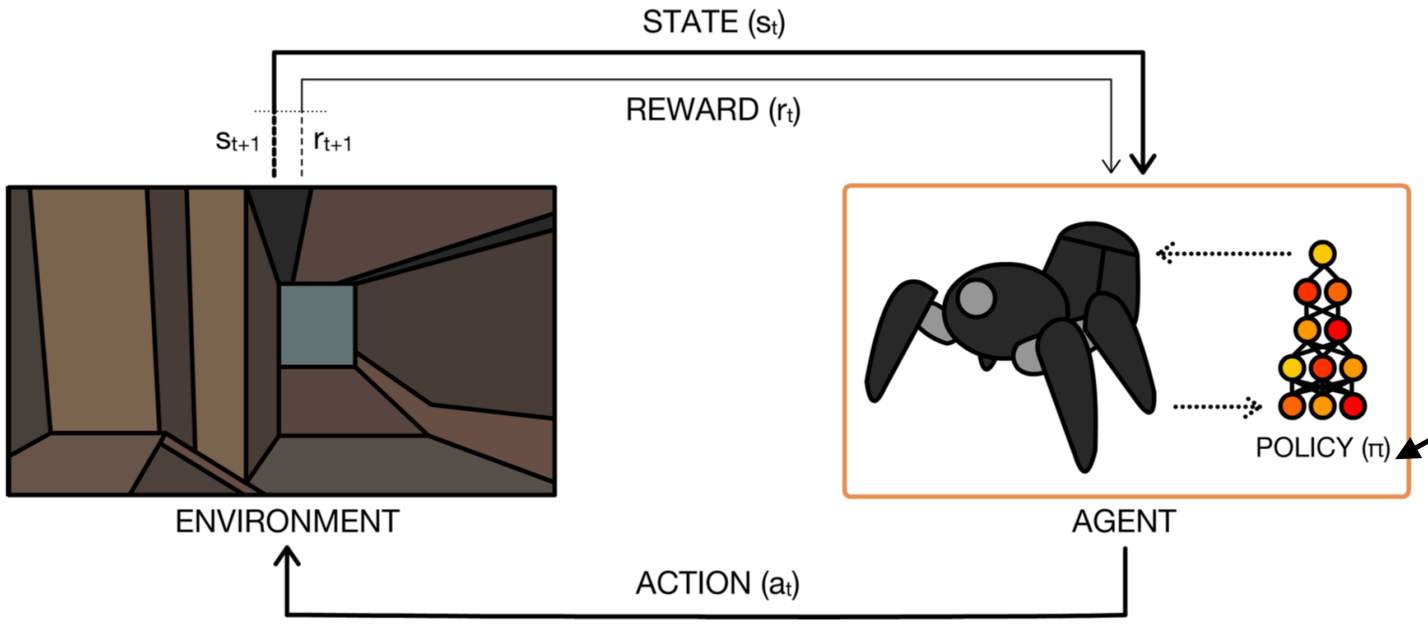
Markov Decision Processes (MDPs)

$$s_t \in S, a_t \in A, P(s_{t+1} \mid s_t, a_t), R : S \times A \to \mathbb{R}$$

+ Observations

= Partially Observed Markov Decision Processes (POMDPs)

$$s_t \in S, a_t \in A, P(s_{t+1} \mid s_t, a_t), R : S \times A \to \mathbb{R}$$
$$o_t \in O, P(o_t \mid s_{t+1}, a_t)$$

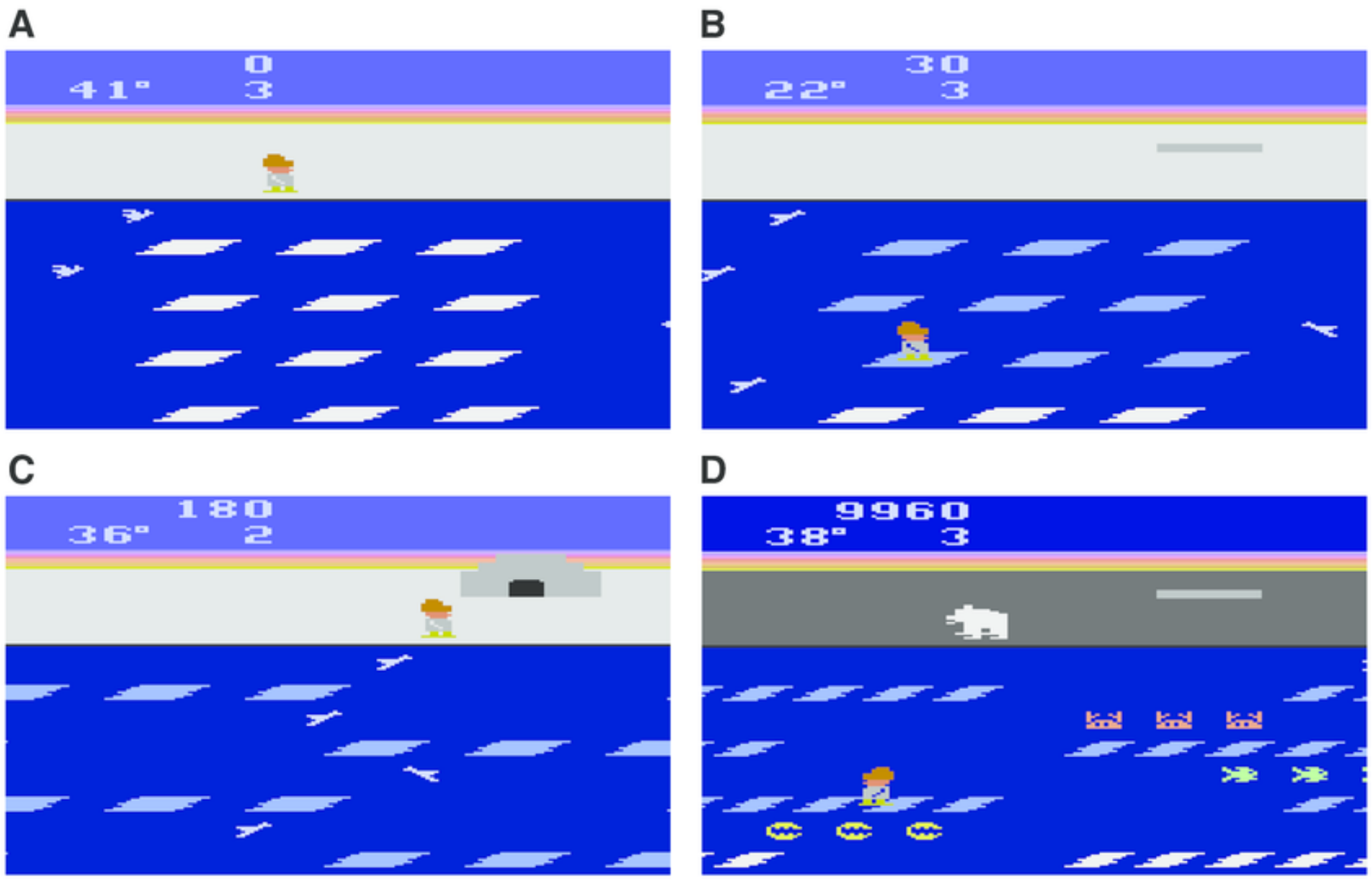


Needed

policy π
(control strategy)

Source: A Brief Survey of Deep Reinforcement Learning (https://arxiv.org/pdf/1708.05866.pdf)

Frostbite Challenge



Source: https://www.researchgate.net

A) The start of a level in Frostbite. The agent must construct an igloo by hopping between ice flows and avoiding obstacles such as birds. The floes are in constant motion (either left or right), making multi-step planning essential to success.
B) The agent receives pieces of the igloo (top right) by jumping on the active ice floes (white), which then deactivates them (blue).
C) At the end of a level, the agent must safely reach the completed igloo.
D) Later levels include additional rewards (fish) and deadly obstacles (crabs, clams, and bears).

Problems with *options*

An *option* is a sub-policy with a termination condition, which takes in environment observations and outputs actions until the termination condition is met.

Needed:

A. Policy-over-options

B. Subgoals ⟶ **unsolved problem**

C. “Pseudo-rewards”

STRategic Attentive Writer

Main Ideas:

1) STRAW learns '*macro-actions*' – common action sequences – based on rewards.
2) STRAW also learns when to stick with the plan it has, and when it's time to make a new plan.

commitment module

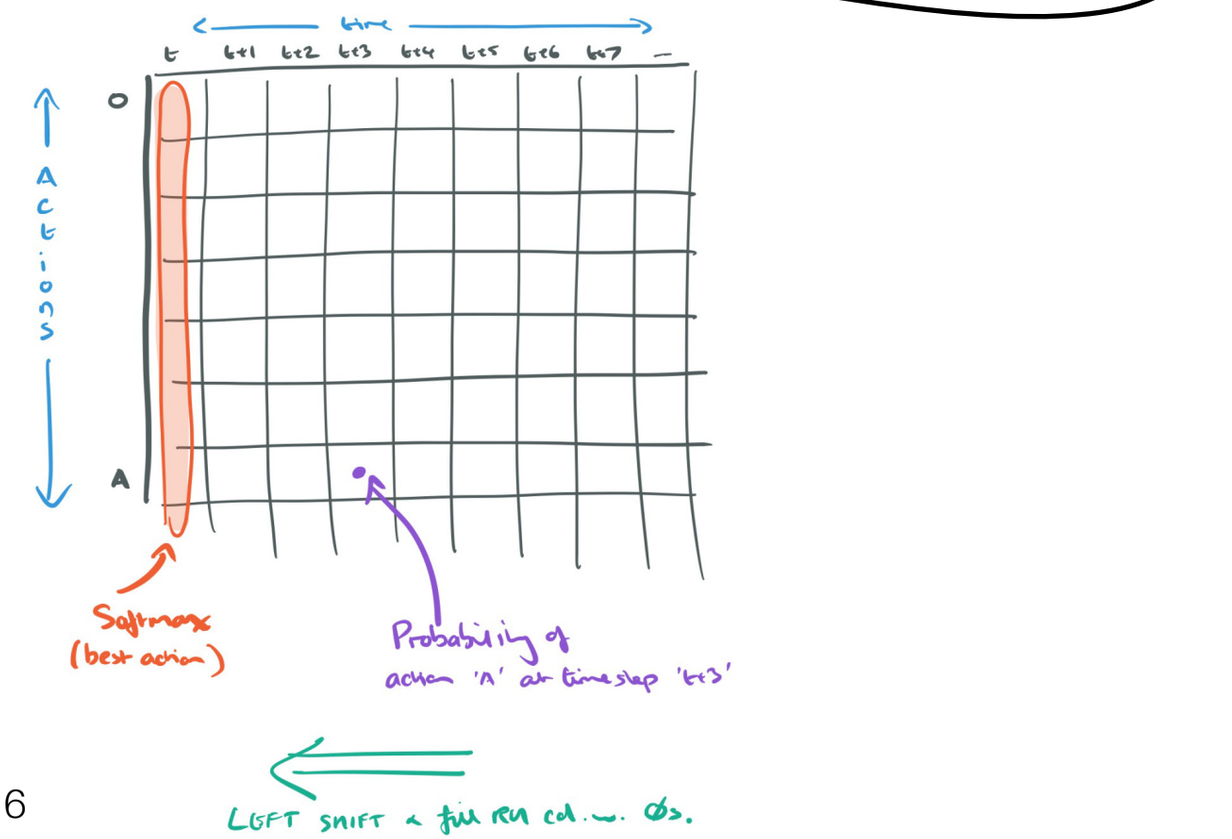
action module

$$A^t \in \mathbb{R}^{A \times T}$$

A – the total number of possible actions

T – the maximum time horizon of a plan

$A^t_{a,\tau} \propto P(a \mid \tau)$



STRategic Attentive Writer

Main Ideas:

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2) STRAW also learns when to stick with the plan it has, and when it's time to make a new plan.

commitment module

$c^t \in \mathbb{R}^{1 \times T}$

action module

$A^t \in \mathbb{R}^{A \times T}$

A – the total number of possible actions

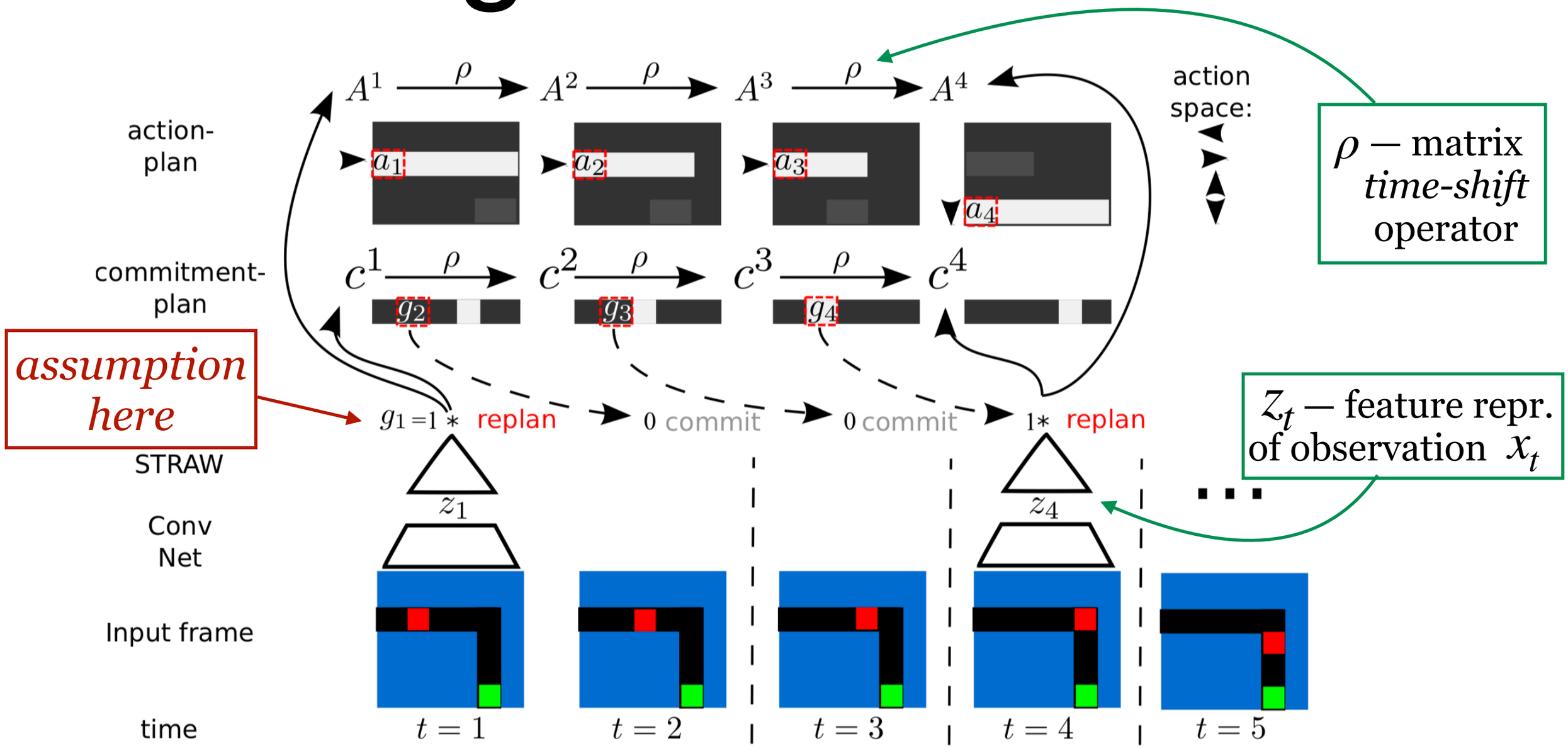
T – the maximum time horizon of a plan

$A^t_{a,\tau} \propto P(a \mid \tau)$

Let g_t be a binary random variable distributed as follows: $g_t \sim c_1^{t-1}$

$$g_t = \begin{cases} 0, & \text{we are committed to the plans;} \\ 1, & \text{at this step the plans will be updated.} \end{cases}$$

STRategic Attentive Writer



A frame is first passed through a convolutional network, acting as a feature extractor and then into STRAW. The top two rows depict the plans A and c. Given a gate g_t, STRAW either updates the plans (steps 1 and 4) or commits to them.

Attentive planning

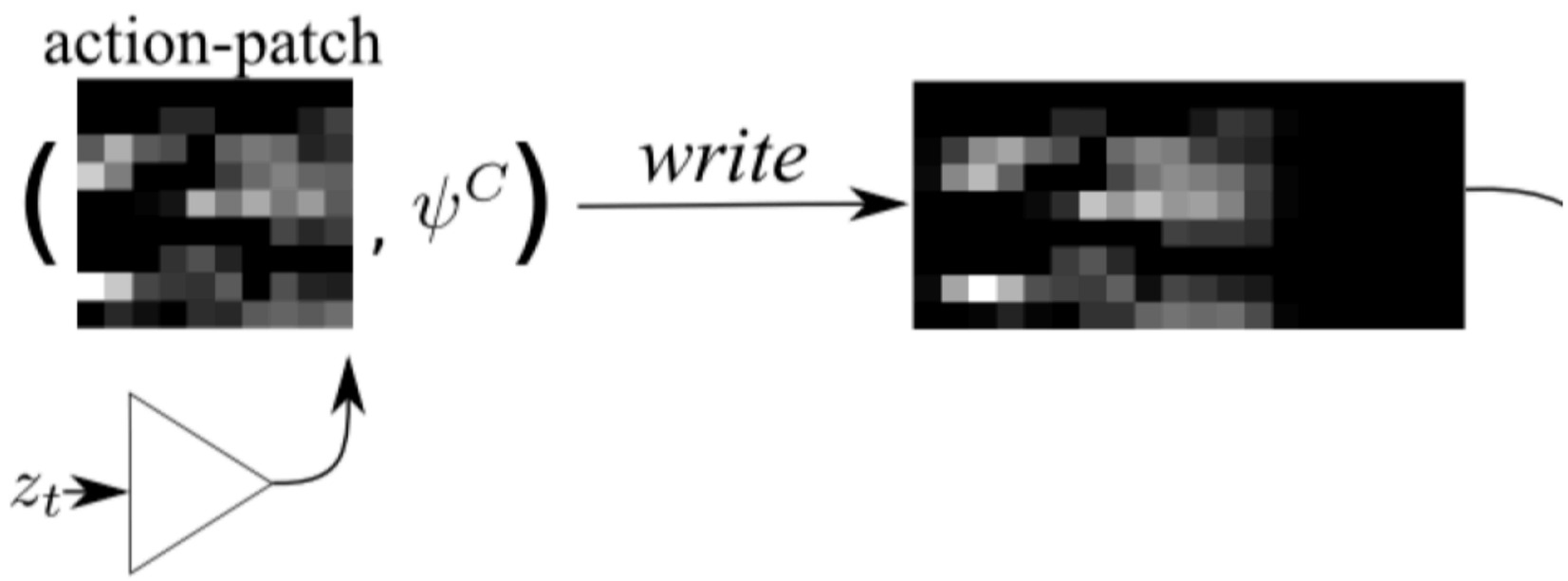
ψ — vector of attention parameters, i.e.: grid position, stride, and standard deviation of Gaussian filters

We define the attention operations as follows:

$$D = write(p, \psi_t^A), \quad \beta_t = read(A^t, \psi_t^A)$$

$$p \in \mathbb{R}^{A \times K}$$
$$\beta \in \mathbb{R}^{A \times K}$$

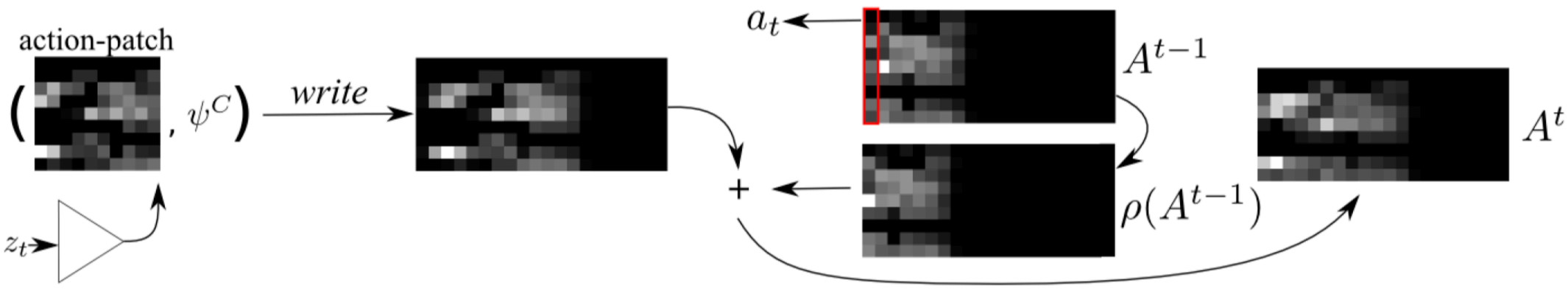
K — temporal resolution of the patch



Action-plan update

Algorithm 1 Action-plan update

Input: $z_t, g_t, \mathbf{A}^{t-1}$
Output: $\mathbf{A}^t, a_t$
if $g_t = 1$ **then**
  Compute attention parameters $\psi_t^A = f^{\psi}(z_t)$
  Attentively read the current state of the action-plan $\beta_t = \mathit{read}(\mathbf{A}^{t-1}, \psi_t^A)$;
  Compute intermediate representation $\xi_t = h([\beta_t, z_t])$
  Update $\mathbf{A}^t = \rho(\mathbf{A}^{t-1}) + g_t \cdot \mathit{write}(f^A(\xi_t), \psi_t^A)$
else // $g_t = 0$
  Update $\mathbf{A}^t = \rho(\mathbf{A}^{t-1})$ //*just advance time*
end if
Sample an action $a_t \sim \mathit{SoftMax}(\mathbf{A}_0^t)$



Given z_t, the network produces an action-patch and attention parameters ψ_t^A. The write operation creates an update to the action-plan by scaling and shifting the action-patch according to ψ_t^A. The update is then added to $\rho(A^t)$.

Commitment-plan update

$$g_t \sim \mathbf{c}_1^{t-1} \;\; \text{if } g_t = 0 \text{ then } \mathbf{c}^t = \rho(\mathbf{c}^{t-1}) \text{ else } \psi_t^c = f^c([\psi_t^A, \xi_t])$$

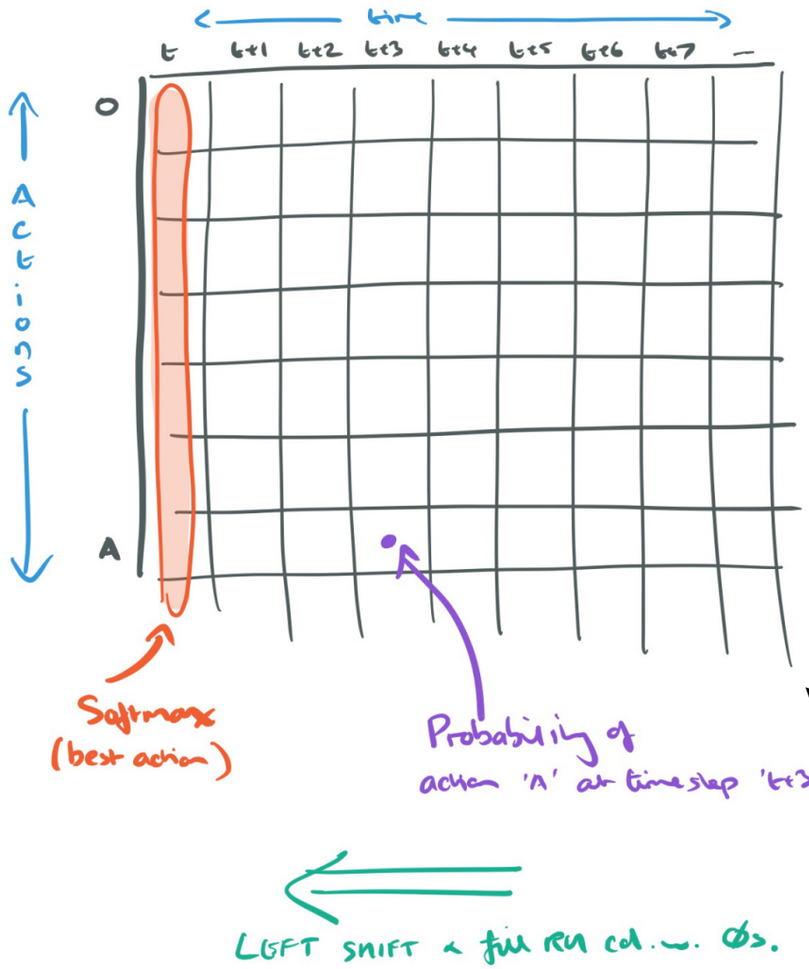
$$\mathbf{c}_t = \mathit{Sigmoid}(\mathbf{b} + \mathit{write}(e, \psi^c));$$

e — scalar set to random high value (here: 40)

b — learnable bias, which defines the probability of re-planning earlier than the step implied by ψ^c

Asynchronous Advantage Actor-Critic (A3C)

$$\pi(a_t \mid x_t, \theta) = SoftMax(A^t_{\bullet 0})$$



$$\nabla L^{out} = \nabla_\theta \log \pi(a_t|x_t;\theta)(R_t - V(x_t;\theta)) + \beta \nabla_\theta H(\pi(a_t|x_t;\theta))$$

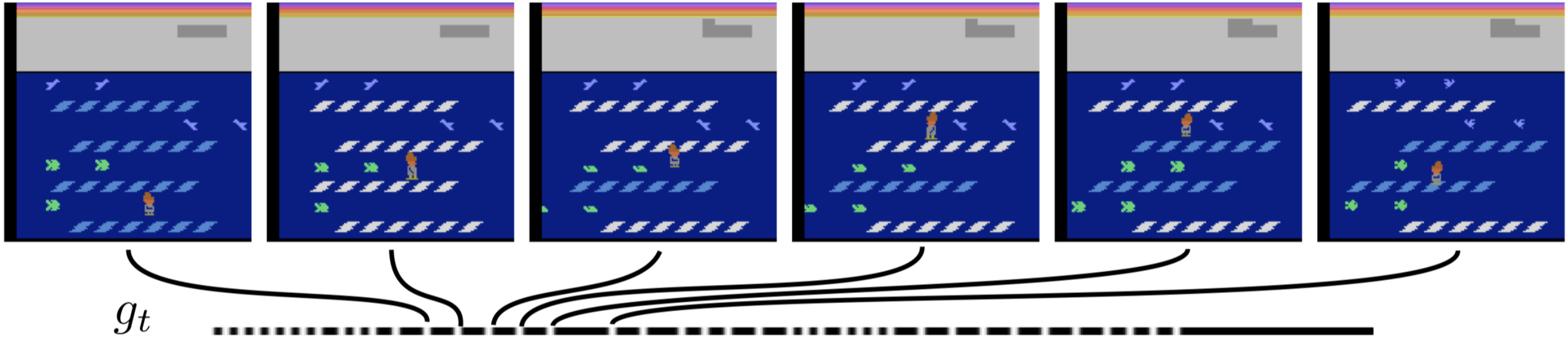
discounted reward sum

entropy of the policy, which stimulates the exploration of primitive actions

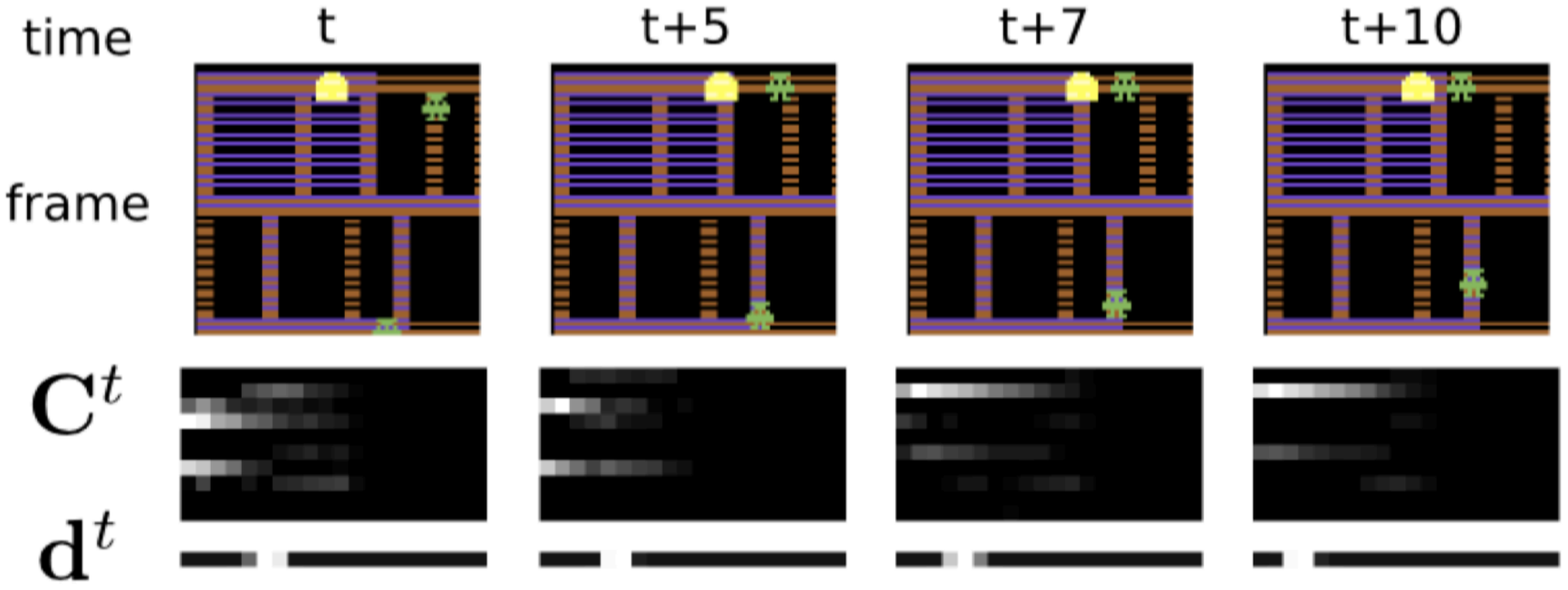
add an auxiliary row with value function estimation $V_\theta(s)$

What did we gain?

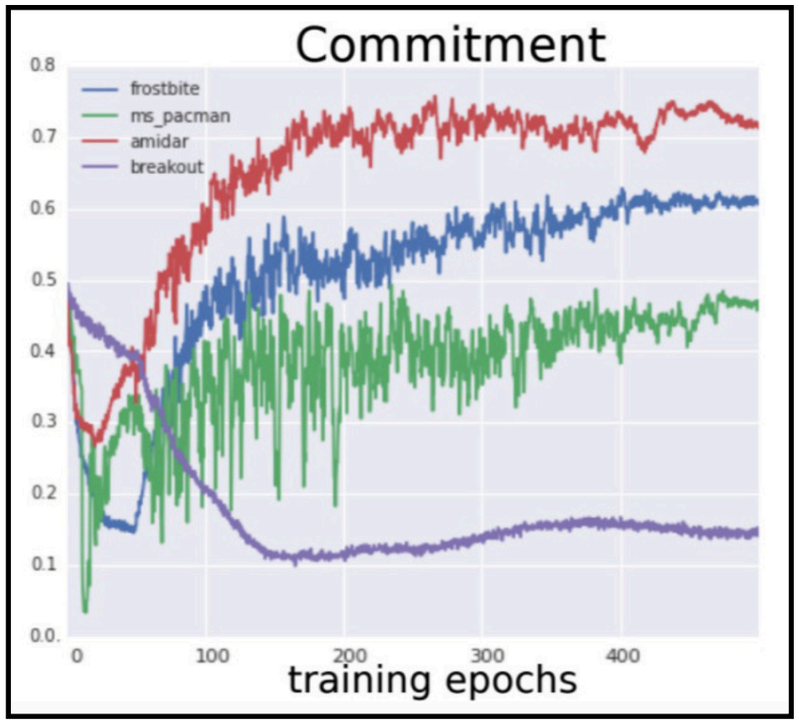
	Frostbite	Ms. Pacman	Q-bert	Hero	Crazy cl.	Alien	Amidar	Breakout
STRAWe	**8108**	**6902**	**23892**	36931	**153327**	**3230**	2022	386
STRAW	4394	6730	20933	36734	143803	2626	**2223**	344
LSTM	1281	4227	23121	36072	128932	2984	1392	**644**
FF	946	2014	22947	**39929**	115944	2300	1292	106

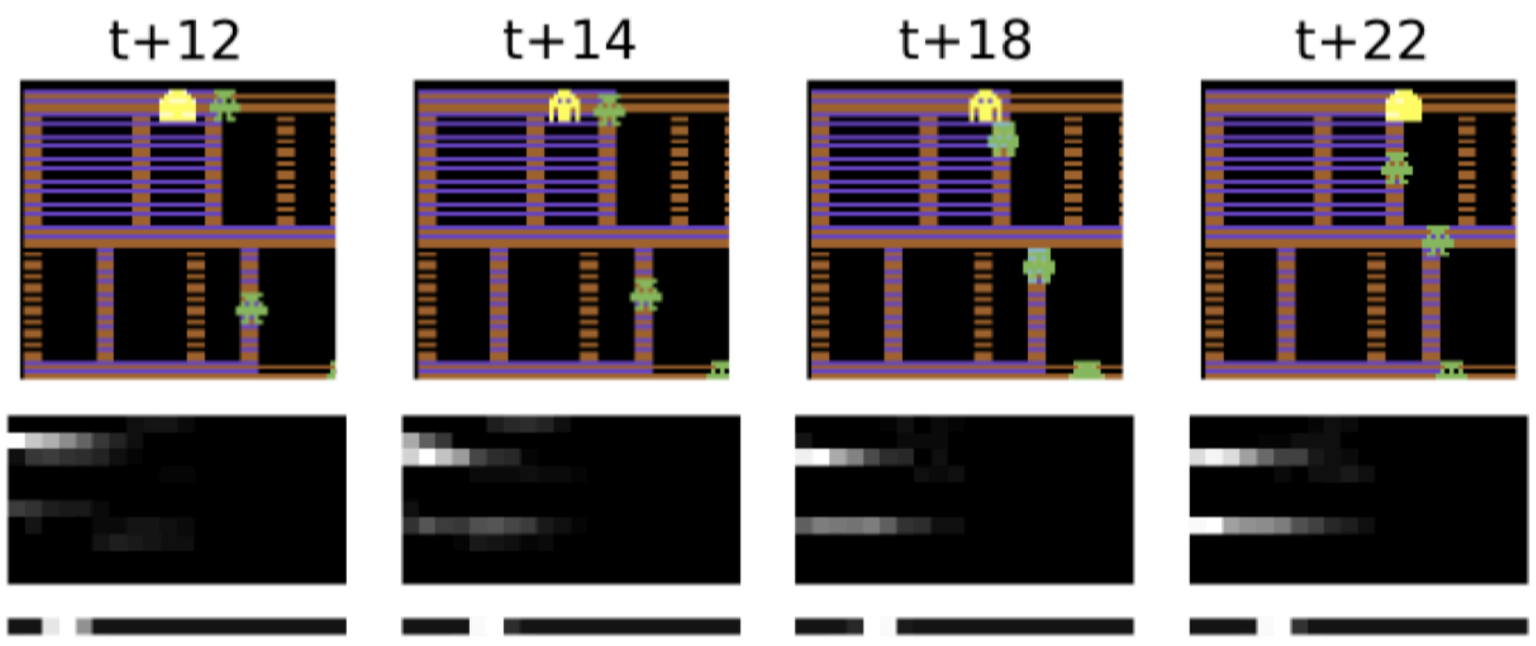


From top to bottom, the figure shows frames at which STRAW re-plans; g_t – white for 1, black for zero. Notice how macro-actions correspond to meaningful high-level actions like jumping from floe to floe and picking fish.

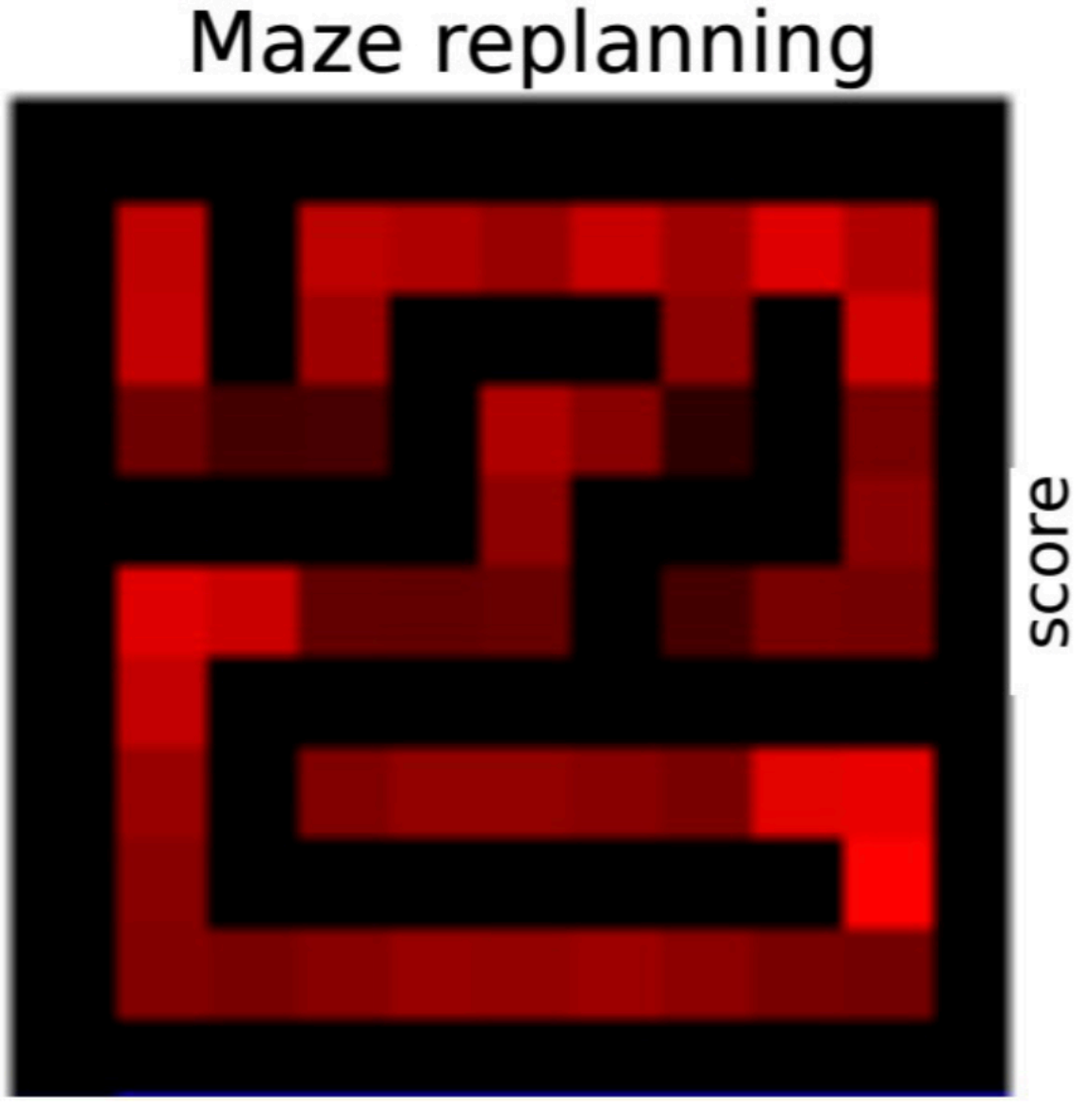


ATARI: Amidar

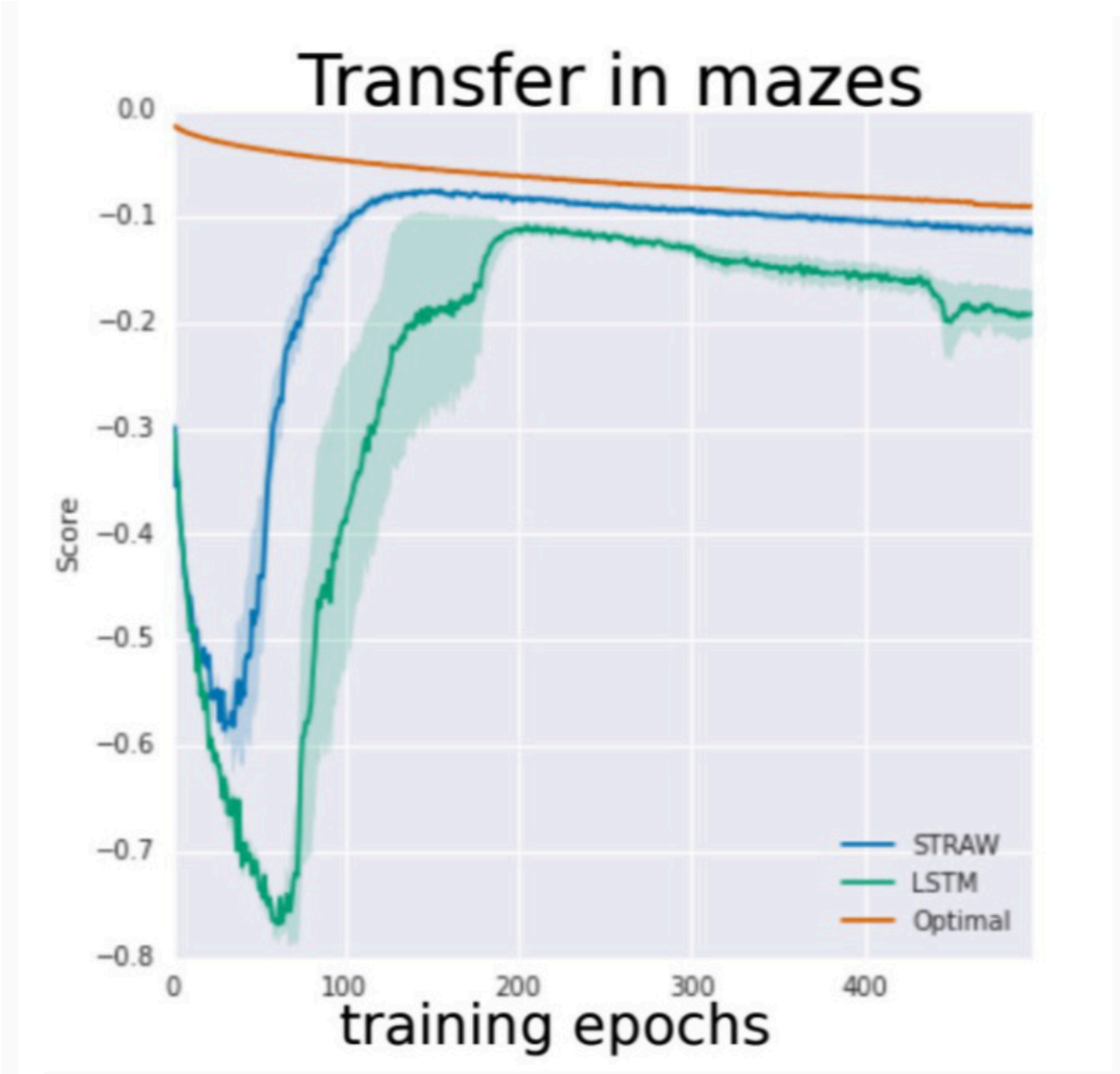




2D maze



STRAWe trained on an 11×11 random maze environment and then tested in a novel maze using varying start and goal locations.
The red intensity indicates how often the agent re-planned at a given location normalized by number of visits.



Shifting to a 15×15 maze, STRAW is compared to an LSTM baseline and the optimal path given by the Dijkstra algorithm. As training epochs (2 million training steps) progress, the goal is move progressively further away from the start point. LSTM starts to show a strong drop-off compared to optimal policy, but STRAWe continues to perform well.

[Vezhnevets et. al, 2016] Alexander Vezhnevets, Volodymyr Mnih, Simon Osindero, Alex Graves, Oriol Vinyals, John Agapiou, and Koray Kavukcuoglu. Strategic Attentive Writer for Learning Macro-Actions. In *NIPS*, 2016. (https://arxiv.org/pdf/1606.04695.pdf)

[Gregor et. al, 2015] Karol Gregor, Ivo Danihelka, Alex Graves, Danilo Rezende, and Daan Wierstra. Draw: A recurrent neural network for image generation. In *ICML*, 2015. (https://arxiv.org/pdf/1502.04623.pdf)