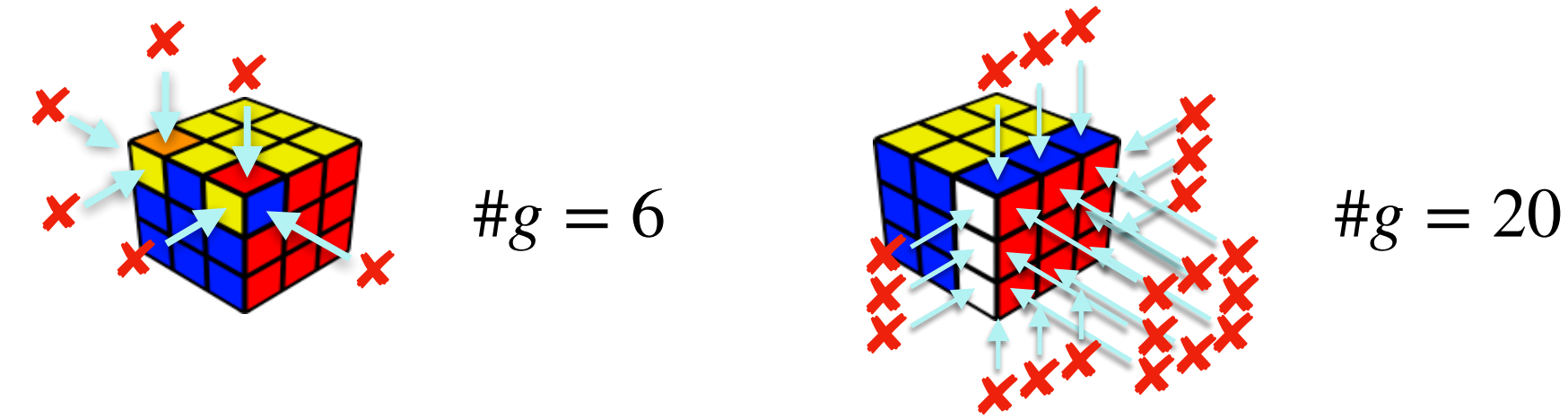


## Black-Box Planning

Black-box planning agents don't have declarative action descriptions. Instead, they must query a simulator to see which actions  $A(s)$  are applicable in a given state, and what are their effects,  $\text{Sim}(s, a)$ . Each state  $s$  is a vector of finite-valued state variables, and the goal  $G$  is a list of variable assignments to all (or a subset) of the state variables. This means goal-aware heuristics are often limited to goal-counting.

## The Goal-Count Heuristic

The goal-count heuristic,  $\#g$ , is a simple (often uninformative) domain-independent heuristic that is compatible with black-box planning, which counts how many state variables differ from their goal values.

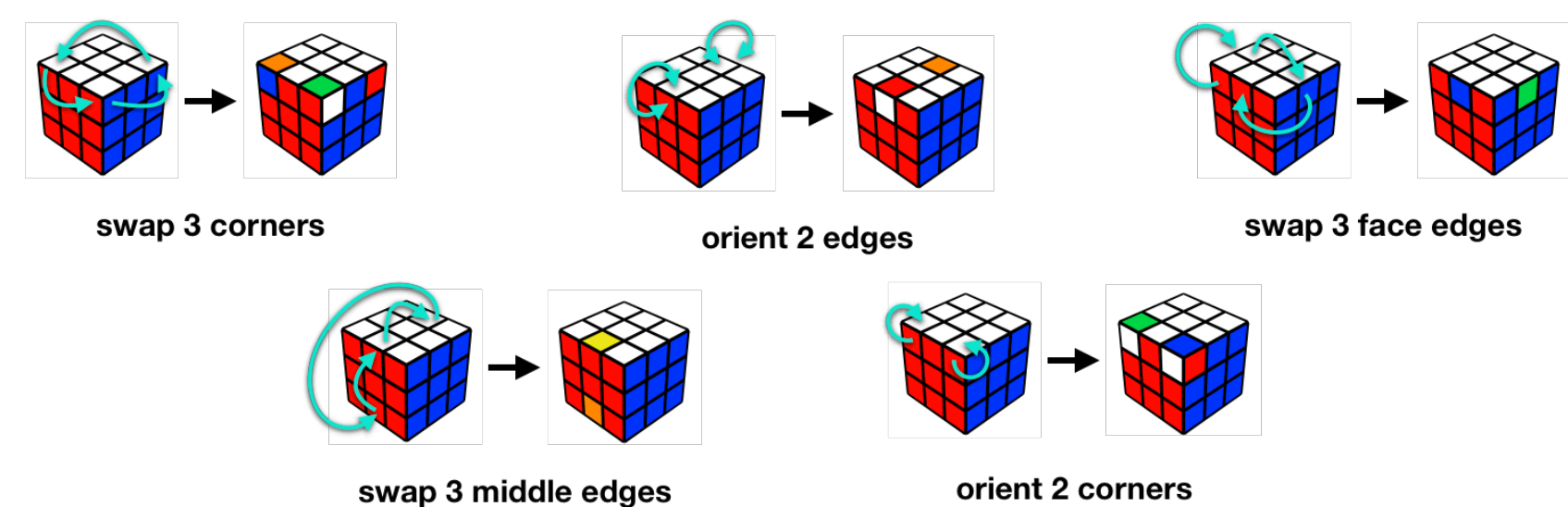


## Macro-Actions and Effect Size

A **macro-action** (or **macro**) is a deterministic sequence of actions, typically for the purpose of accomplishing some useful subgoal. The **effect size** of a macro is the number of state variables, measured at the end of macro execution, that are different from their starting values. We call macros that only modify a small number of state variables **focused**.

## Expert Macros Are Focused & Make Goal Counting More Accurate

Expert macros modify specific state variables, and minimize side-effects to others. This makes progress towards the goal more predictable as macros are less likely to “undo” previous work.



# Efficient Black-Box Planning Using Macro-Actions with Focused Effects

Cameron Allen<sup>1,2</sup>, Michael Katz<sup>2</sup>, Tim Klinger<sup>2</sup>,  
George Konidaris<sup>1</sup>, Matthew Riemer<sup>2</sup>, Gerald Tesauro<sup>2</sup>

<sup>1</sup> Brown University

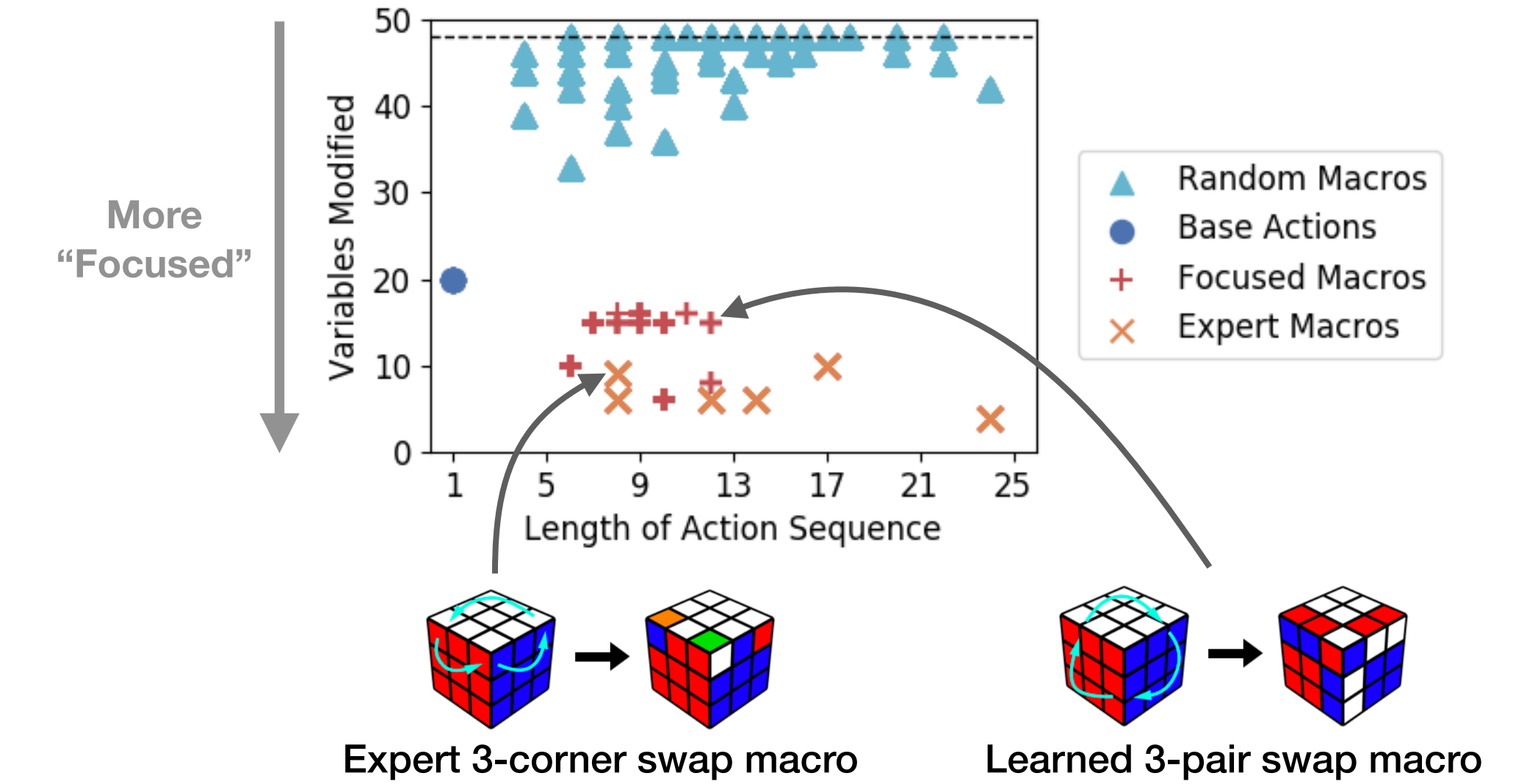
<sup>2</sup> IBM Research



✉ csal@brown.edu

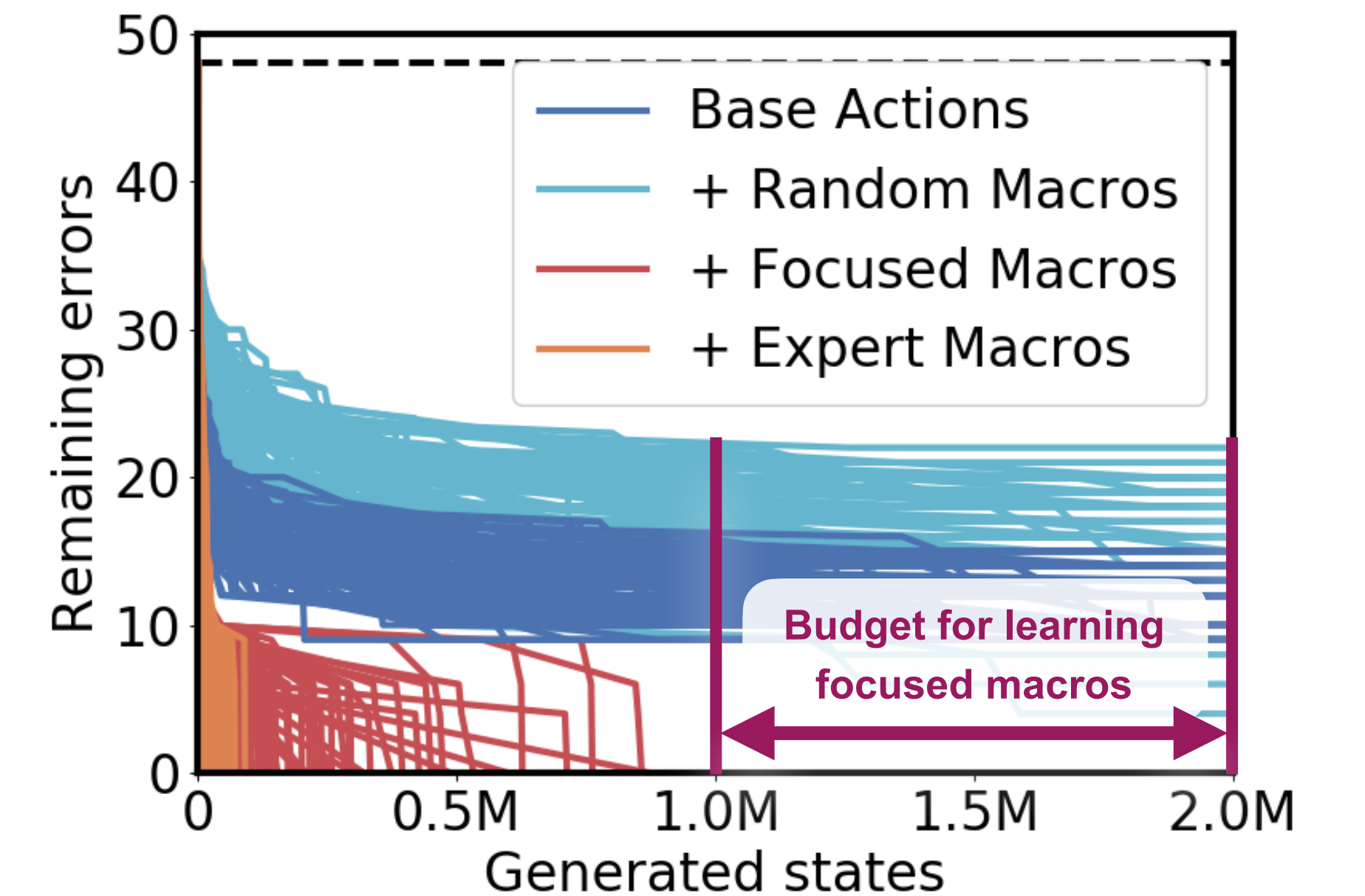
🐦 @camall3n

## Focused Macros Are Like Expert Macros



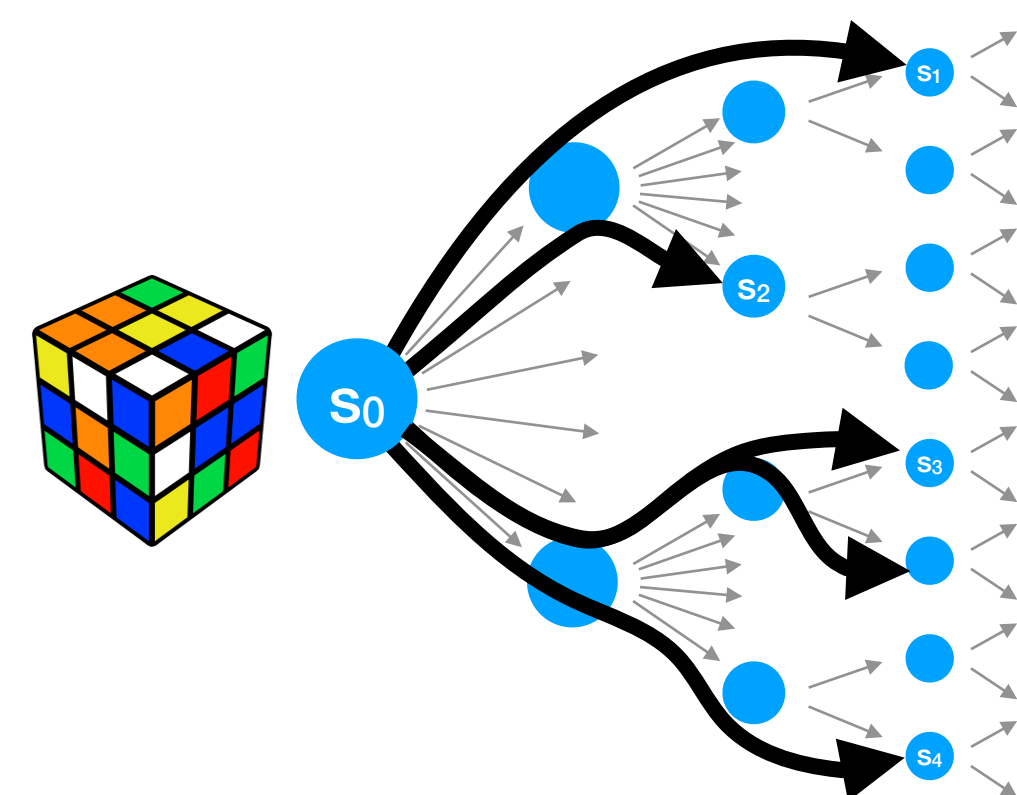
Adding **focused** macro-actions, that **modify few state variables**, makes black-box planning **more efficient**.

## Focused Macros Speed Up Planning



## Discovering Focused Macro-Actions

From an arbitrary initial state  $s_0$ , we can learn focused macros as follows:



- For each candidate macro, measure its effect size:

$s_0 \rightarrow s_1$  : 14 variables

$s_0 \rightarrow s_2$  : 8 variables **Focused!**

$s_0 \rightarrow s_3$  : 16 variables

etc...

- Best-first search (expand node w/ lowest effect size)
- Store the N best macros

## Focused Macros Help for Many Domains

Domain	$N_M$	$B_M$	GBFS(A)		GBFS(A+M)		BFWS(A)		BFWS(A+M)		LAMA(A)	
			Gen	Sol	Gen	Sol	Gen	Sol	Gen	Sol	Gen	Sol
Depot	8	50K	58275.9	<b>0.74</b>	<b>55132.4</b>	0.60	75966.9	<b>0.48</b>	<b>72205.8</b>	0.34	46620.9	1.00
Doors	8	5K	3050.7	1.00	<b>512.6</b>	1.00	4660.9	1.00	<b>3057.3</b>	1.00	293.0	1.00
Ferry	8	5K	1875.8	1.00	<b>1151.4</b>	1.00	1209.9	1.00	<b>1163.5</b>	1.00	699.8	1.00
Gripper	8	5K	7314.8	1.00	<b>6277.0</b>	1.00	44945.9	1.00	<b>6295.9</b>	1.00	6493.1	1.00
Hanoi	8	100K	78433.6	0.78	<b>6358.8</b>	<b>1.00</b>	63455.2	1.00	<b>3365.9</b>	1.00	65496.4	1.00
Miconic	8	5K	7559.4	1.00	<b>1907.1</b>	1.00	10269.2	1.00	<b>1884.3</b>	1.00	1316.7	1.00
15-Puz.	192	32K	30840.5	1.00	<b>4952.4</b>	1.00	109425.2	1.00	<b>6290.1</b>	1.00	-	-
Rubik's	576	1M	>2M	0.00	<b>171.3K</b>	<b>1.00</b>	>2M	0.00	<b>163.8K</b>	<b>1.00</b>	9.13M	1.00

Table 2: Black-box planning results for PDDL-Gym-based simulators (top), and domain-specific simulators (bottom). (A) - primitive actions only; (A+M) - primitive actions + focused macros;  $N_M$  - number of macros;  $B_M$  - macro-learning budget; Gen - generated states; Sol - solve rate; (bold) - best performance of each planner. The efficiency of both GBFS and BFWS ( $R_{\epsilon}^*$ ) are improved by adding focused macros. Note that LAMA is an informed planner with access to much more information than black-box planners, and is only included for reference.