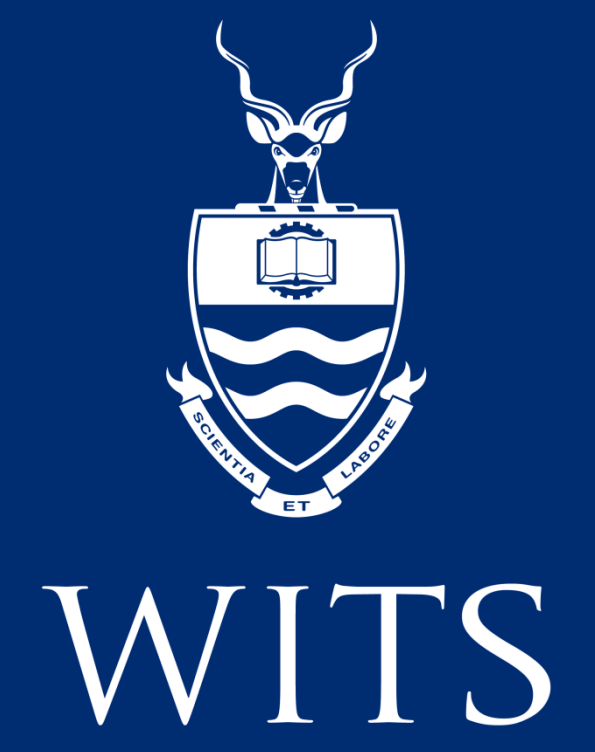


A Boolean Task Algebra For Reinforcement Learning

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We formalise the **logical composition of tasks** as a **Boolean Algebra** and provide a method for producing the **optimal value functions** of the composed tasks with **no further learning**.

Introduction

- We want to **combine** policies learned in previous tasks to **create new policies**.
- Build **rich behaviours** from simple ones, resulting in **combinatorial** explosion in abilities.
- But unclear how to produce new optimal policies from known ones.

Prior work [1,2] shows that value functions can be **composed** to **optimally** solve **union of tasks** and **approximately** solve the **intersection of tasks**.

We complement these results by proving **optimal composition** for the **intersection and negation of tasks** in the total-reward, absorbing-state setting, with **deterministic dynamics**.

Goal Oriented RL

We define an **extended value function (EVF)** that decouples the values for each absorbing state:

$$Q(s, g, a) = \bar{r}(s, g, a) + \int_s V^{\pi_g}(s') \rho_{(s,a)}(ds')$$

$$\bar{r}(s, g, a) = \begin{cases} N & \text{if } g \neq s \in G \\ r(s, a) & \text{otherwise} \end{cases}$$

Similar to DG functions [3] but uses **task rewards**.

Compositionality

Theorem 1: Let \mathbf{M} be the set of tasks. Then \mathbf{M} forms a Boolean algebra when equipped with the **or**, **and**, and **not** operators given by:

$$\begin{aligned} \text{or} &= (S, A, p, r(\text{or})), \text{ where } r(\text{or}) = \max\{r(\text{task}_1), r(\text{task}_2)\} \\ \text{and} &= (S, A, p, r(\text{and})), \text{ where } r(\text{and}) = \min\{r(\text{task}_1), r(\text{task}_2)\} \\ \text{not} &= (S, A, p, r(\text{not})), \text{ where } r(\text{not}) = (r_{\text{MAX}} + r_{\text{MIN}}) - r(\text{task}) \end{aligned}$$

where, r_{MAX} and r_{MIN} are the reward functions for the maximum and minimum tasks.

Theorem 2: Let \mathbf{Q} be the set of extended value functions. Then \mathbf{Q} forms a Boolean algebra when equipped with the **or**, **and**, and **not** operators given by:

$$\begin{aligned} Q^*(\text{or}) &= \max\{Q^*(\text{task}_1), Q^*(\text{task}_2)\} \\ Q^*(\text{and}) &= \min\{Q^*(\text{task}_1), Q^*(\text{task}_2)\} \\ \text{not } Q^*(\text{task}) &= (Q^*_{\text{MAX}} + Q^*_{\text{MIN}}) - Q^*(\text{task}) \end{aligned}$$

where, Q^*_{MAX} and Q^*_{MIN} are the extended value functions for the maximum and minimum tasks.

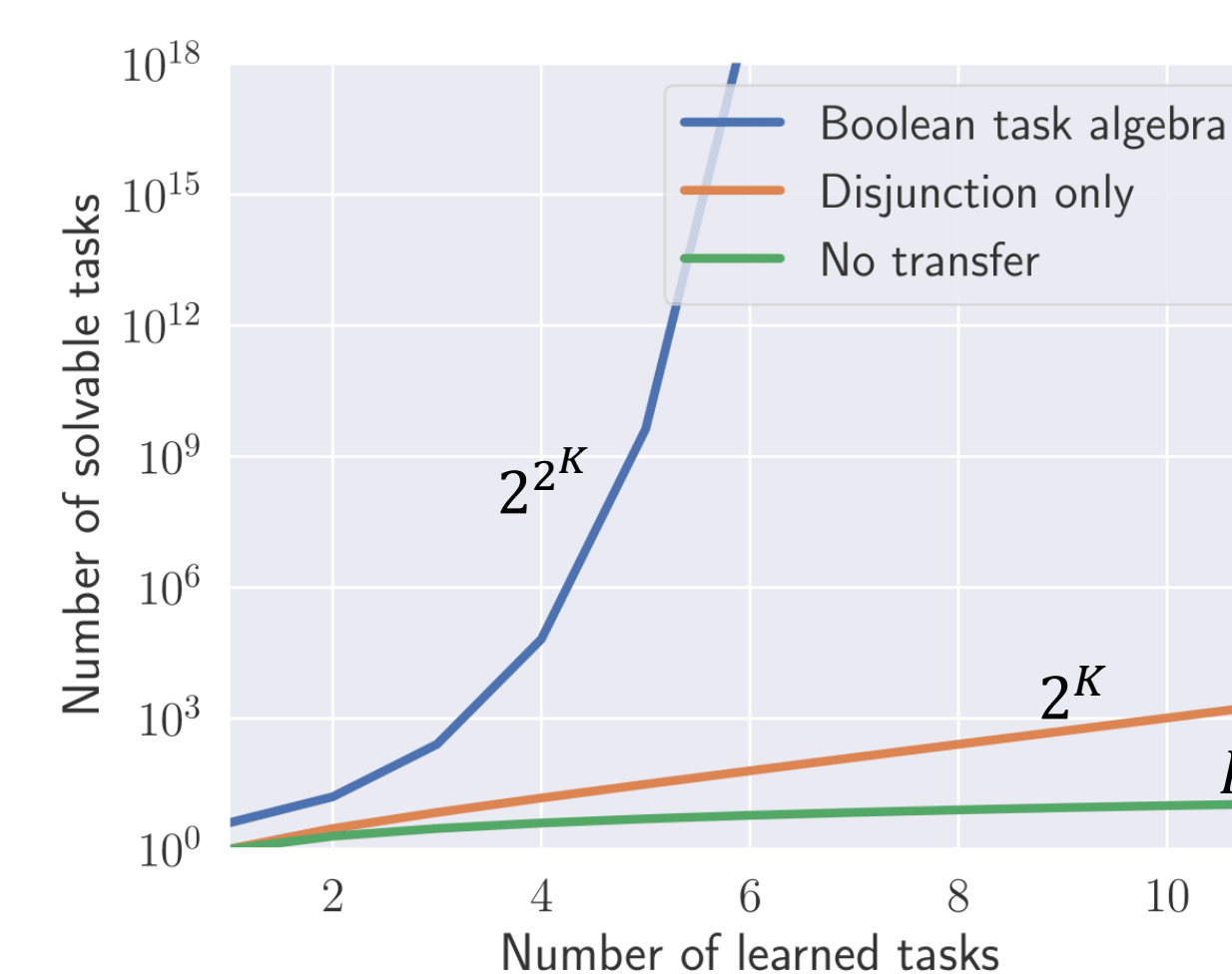
Theorem 3: The task and extended value function spaces are homomorphic.

Base Tasks and Explosion of Skills

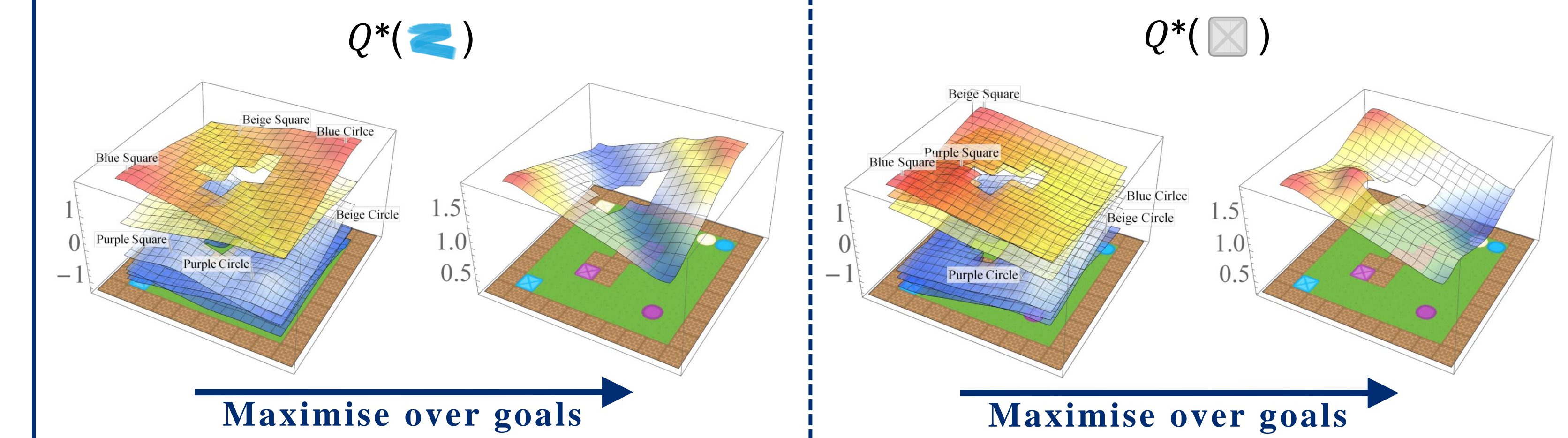
$n = |G|$ goals $\rightarrow 2^n$ total tasks
 $\rightarrow \lceil \log_2 n \rceil$ base tasks. ($n > 1$)



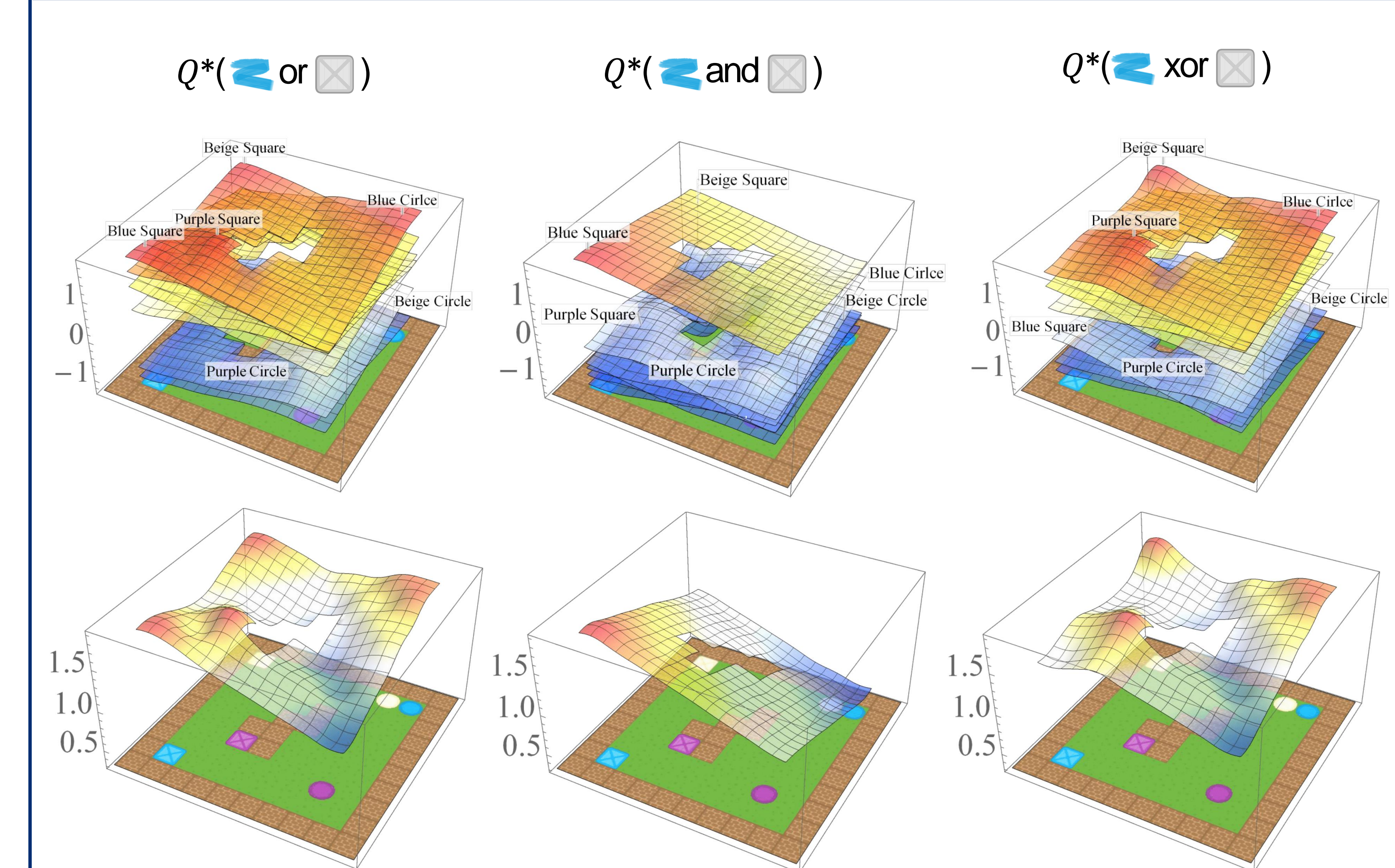
	Blue Square	Beige Square	Blue Circle
Blue Square	0	0	0
Beige Square	0	0	1
Blue Circle	0	1	0
Purple Square	0	1	1
Purple Circle	1	0	0
Beige Circle	1	0	1



Experiment: EVFs \rightarrow VFs



Experiment (Q-Learning): Four Rooms



[1] B. Van Niekerk, S. James, A. Earle and B. Rosman. Composing Value Functions in Reinforcement Learning. In ICML 2019.
[2] T. Haarnoja, V. Pong, A. Zhou, M. Dalal, P. Abbeel, and S. Levine. Composable Deep Reinforcement Learning for Robotic Manipulation.
[3] Kaelbling, L. P. Learning to achieve goals. IJCAI 1993.