

384 **A Appendix**

385 **A.1 Place cells**

386 All agents have 49 place cells whose activity is a Gaussian function of the agent's position in the
 387 maze according to

$$u^{pc} = e^{-\frac{(x(t)-x_i)^2}{2\sigma_{pc}^2}} \quad (13)$$

388 where $x(t)$ indicates the agents position in the square maze bounded by $x = (0.8m, 0.8m)$. $\sigma_{pc} =$
 389 $0.267m$ and place cells are spaced regularly apart in a 7 by 7 grid, while covering the boundary. The
 390 sensory cue passed to the agents is encoded by u^{cue} , which is a one-hot encoded vector of length
 391 18 with gain 3. The cue vector is presented to the agent throughout the trial period. The place cell
 392 activity and the sensory cue is concatenated to form the input vector $Q(t)$ to all agents

$$Q(t) = [u^{pc}, u^{cue}] \quad (14)$$

393 **A.2 Actor**

394 All agents have $M = 40$ actor units where each unit represents a spatial direction. The firing rate of
 395 each actor unit is $\rho(t) = \text{ReLU}[q(t)]$ and the membrane potential q has dynamics

$$q(t) = (1 - \alpha)q(t - 1) + \alpha \left(\phi(t - 1) + \sum W^{lateral} \rho(t - 1) + \frac{\sigma_{actor}}{\sqrt{\alpha}} N(0, 1) \right) \quad (15)$$

396 with $\alpha = \frac{100}{150} = 0.667$ and $\sigma_{actor} = 0.25$. $\phi(t)$ represents the output from the motor controller module.
 397 The lateral synaptic weight is given by

$$W^{lateral} = \frac{w_-}{M} + w_+ \frac{f(k, h)}{\sum f(k, h)} \quad (16)$$

398 with $f(k, h) = (1 - \delta)e^{\psi \cos(\theta - \theta)}$, $w_- = -1$, $w_+ = 1$ and $\psi = 20$. The lateral connectivity connects
 399 the actor units into a ring attractor that smoothes the agent's spatial trajectory as in [26, 27]. The
 400 direction of movement is chosen by

$$a(t) = \frac{1}{M} \sum \rho(t) K^{dir} \quad (17)$$

401 which is the vector sum of directions weighed by each actor unit's firing rate with $K^{dir} =$
 402 $a_0(\sin \theta, \cos \theta)$ and $a_0 = 0.03$.

403 **A.3 Advantage Actor-Critic**

404 The Advantage Actor Critic (A2C) agent chooses one direction of movement $\rho^{a2c}(t)$ out of K^{dir}
 405 based on a stochastic action policy. To match the same speed achieved by the other agents, $a_0 = 0.07$
 406 was chosen to increase the step size of a particular action in K^{dir} . The direction of movement is
 407 smoothed using a low pass filter

$$a(t) = (1 - \alpha_{a2c})\hat{a}(t) + \alpha_{a2c}\rho^{a2c}(t) \quad (18)$$

408 with $\alpha_{a2c} = 0.25$ as how Foster, Dayan & Morris (2000) [14] smoothed the trajectory of the
 409 actor-critic agent that chose discrete actions. The Advantage Actor-Critic reinforcement algorithm
 410 was implemented as in [1, 18, 19] where the agent is allowed to run through an entire trial, storing the
 411 various state, reward and actions taken before the weights are updated. Instead of the asynchronous
 412 method, only one CPU thread was used to run the synchronous method for each agent. The gradient

413 is computed at the end of each trial according to a weighted sum of the policy π , value function V
414 and entropy regularisation term H according to

$$\begin{aligned}\nabla L &= \nabla L_\pi + \nabla L_v + \nabla L_{ent} \\ &= \frac{\partial \log \pi(a(t)|s(t), \theta)}{\partial \theta} \delta(t) + \\ &\quad \beta_v \delta(t) \frac{\partial V}{\partial \theta_v} + \beta_e \left(\frac{\partial H(\pi(a(t)|s(t), \theta))}{\partial \theta} \right) \\ \delta(t) &= [R^{disc}(t) - V(s(t), \theta_v)] \\ R^{disc}(t) &= \sum_{t=0}^T \gamma^{t-1} r(t)\end{aligned}\tag{19}$$

415 where θ and θ_v are the synaptic weight parameters for the policy and value function, and $\gamma = 0.99$
416 is the reward discount factor. Hyperparameters $\beta_v = 0.5$ and $\beta_e = -0.001$ control the value
417 estimate loss and entropy regularisation term contributions to the total loss. Lastly, $\delta(t)$ is the
418 temporal difference error that informs the actor-critic of the advantage incurred. The critic is a
419 single linear unit, actor is softmax activated and the hidden layer has 8192 units with a ReLU variant
420 activation function where if the unit activity is above a threshold value of 3, the value is retained
421 otherwise, it is converted to a 0. Using this variant showed a faster convergence in training compared
422 to original ReLU function. Synaptic weights are updated using the RMSprop optimiser with learning
423 rate 0.000035.

424 A.4 Reward disbursement

425 Each agent is free to explore the arena till the trial ends but if it finds the reward before, the agent
426 remains stationary at the reward location until the trial ends to model consummatory behaviour. After
427 the agent reaches the reward, a total reward value $R = 4$ is disbursed at a reward rate $r(t)$, similar to
428 [26], given by

$$\begin{aligned}r_a(t) &= (1 - \frac{100}{\tau_a})r_a(t-1), \quad r_b(t) = (1 - \frac{100}{\tau_b})r_b(t-1), \\ r(t) &= \frac{r_a(t) - r_b(t)}{\tau_a - \tau_b}\end{aligned}\tag{20}$$

429 with $\tau_a = 120ms$ and $\tau_b = 250ms$ for all agents except for the Reservoir agent trained by sparse
430 learning signal where $\tau_b = 2500ms$. When the agent reaches the reward, it is updated according to

$$r_a(t) \rightarrow r_a(t) + R \quad r_b(t) \rightarrow r_b(t) + R\tag{21}$$

431 such that $r(t)$ integrates to R . In trials where the agent does not reach the reward location, no
432 punishment is given, except for the A2C agent where a negative reward $R = -1$ is given to penalise
433 the actions taken, else the agent converges to a stationary action policy.

434 A.5 Motor Controller

435 The symbolic motor controller is formulated by taking the goal $g(t)$ and current position $p(t)$
436 coordinates as inputs and performing vector subtraction.

$$Q^{vecsub}(t) = g(t) - p(t)\tag{22}$$

437 The dot product between the resultant vector $Q^{vecsub}(t)$ and K^{dir}

$$A^{mc}(t) = \text{softmax}(\beta_{mc} Q^{vecsub} K^{dir})\tag{23}$$

438 with $\beta_{mc} = 4$ as a scaling factor, specifies the direction and magnitude in which the agent needs to
 439 move in order to reach the goal location. Using a softmax for $A^{mc}(t)$ creates a firing rate profile
 440 similar to the ring attractor where actions besides the optimum can also be taken to reach the goal
 441 location.

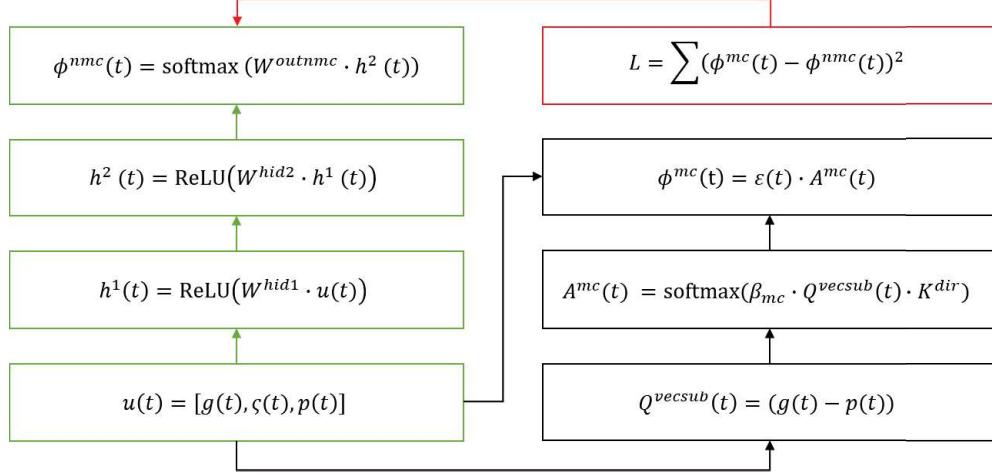


Figure 4: **Symbolic and neural motor controller architecture.** Goal and current position coordinates are taken in as inputs. In the symbolic motor controller, vector subtraction is performed and the direction of movement is chosen. The output of the symbolic motor controller is gated using $\varepsilon(t)$. A neural motor controller can be trained by backpropagation by taking the mean squared error between the symbolic motor controller target output ϕ^{mc} and neural motor controller output ϕ^{nmc} . The output of the neural motor controller does not need to be explicitly suppressed.

442 To allow the agent to freely explore the maze and find the target location versus turning on the motor
 443 controller for directed movement, a gating factor $\varepsilon(t)$ is used to signal the presence or absence of a
 444 goal and modulate the output of the symbolic controller ϕ^{mc} before passing it to the ring attractor in
 445 Eq. 15.

$$\phi^{mc}(t) = \varepsilon(t) A^{mc}(t) \quad (24)$$

446 We have formulated two solutions to gate the motor controller activity. The first involves the L_2 norm
 447 of the goal coordinate

$$\varepsilon(t) = \begin{cases} 1, & \text{if } \|g(t)\|^2 > \omega \\ 0, & \text{otherwise.} \end{cases} \quad (25)$$

448 If the L_2 norm is lesser or greater than the threshold ω , the output of the motor controller $A^{mc}(t)$
 449 will or will not be suppressed by ε respectively. Such a control mechanism is similar to [14] where
 450 the agent freely explores the maze if the agent's memory was empty and performs goal directed
 451 movement if there was a stored goal coordinate. Instead, the episodic memory bank matrix used by
 452 the symbolic agent is initialised to 0 and the goal coordinate output by the reservoir is 0 since the
 453 synaptic weights W^{out} is initialised as 0.

454 The main results were obtained by using $\omega = 0.15$. This increased the propensity for the agents
 455 to explore the periphery of the maze but it also meant that the goal location with coordinates (0,0)
 456 could not be considered as a target. Instead, a lower threshold $\omega = 0.025$ can be used such that the
 457 coordinate (0,0) can be considered as goal. This is because the agent only stores the coordinate at
 458 which it hits the target, which is ± 0.03 from the center of the goal coordinate instead of the center of
 459 the goal coordinate. Lowering the threshold increases the agent's propensity to employ the motor
 460 controller and move to the center of the maze, especially when it encounters a new input $Q(t)$. For

461 example, an unforeseen input e.g. Cue 7 to Cue 18 during single session NPA training causes both
 462 the attention mechanism in the episodic memory bank and the reservoir to recall a goal coordinate
 463 vector with L_2 norm closer to (0,0). This causes the agent to move to the center first and searching
 464 for goal locations. This could be a similar strategy animals or humans employ. However, this limits
 465 the agent's exploration mostly to the center. The total trial time needs to be increased to 3600 seconds
 466 to cater more time for the agent to eventually find goal locations near the periphery of the maze.

467 The second solution involves learning a confidence function ς . The intuition is similar to the
 468 confidence ascribed to a recalled goal coordinate where a value closer to 1 indicates the highest
 469 confidence.

$$\varepsilon(t) = \begin{cases} 1, & \text{if } \varsigma > \omega \\ 0, & \text{otherwise.} \end{cases} \quad (26)$$

470 If ς is lesser or greater than the threshold ω , the output of the motor controller $A^{mc}(t)$ will or will not
 471 be suppressed by ε respectively.

472 Learning this confidence signal in the Symbolic agent involves storing $\varsigma = 1$ together with the current
 473 position coordinates $(p(t), \varsigma = 1)$ in a 18 X 3 Value matrix of the episodic memory bank, when the
 474 agent reaches the reward location. During recall, $(g(t), \varsigma)$ is obtained using the attention mechanism
 475 and passed to the symbolic motor controller together with the current position coordinates $p(t)$ of the
 476 agent.

477 Learning this confidence function ς by the Reservoir agents is similar to learning the target coordinates.
 478 Instead of two readout units, Reservoir agents now have three readout units, each to learn and
 479 represent $(g(t), \varsigma)$. The target to learn then becomes $(p(t), \varsigma = 1)$ for both the reservoir trained by
 480 the Perceptron (Eq. 8 and the exploratory Hebbian (Eq. 10 and Eq. 12) rules.

481 Similar algorithms can be either handcrafted or learnt by the agent to switch between these explore-
 482 exploit modalities. Unlike Eq. 25, Eq. 26 with $\omega = 0.75$ allows the agent to reach goal location (0,0)
 483 without needing to extend the trial duration to 3600 seconds.

484 A.6 Neural implementation of symbolic motor controller

485 The computations performed by the symbolic motor controller, namely vector subtraction and
 486 suppression of motor controller activity, can be learned by a neural network. The neural architecture
 487 takes the goal coordinates $g(t)$, confidence function $\varsigma(t)$ and agent's position coordinates $p(t)$ as
 488 input $u(t)$, has two layers of 1024 ReLU activated hidden units $h(t)$ and 40 output units with a
 489 softmax layer (Fig. 4). The dataset for supervised learning comprised of 972,405 goal, position,
 490 confidence function combinations spanning the dimensions of the square maze $x = (0.8m, 0.8m)$
 491 as inputs and the gated symbolic motor controller output ϕ^{mc} as the target. The loss function to be
 492 minimised is the mean squared error between the output of the neural ϕ^{nmc} and symbolic ϕ^{mc} and
 493 motor controllers.

$$\nabla L = \sum (\phi^{mc}(t) - \phi^{nmc}(t))^2 \quad (27)$$

494 The synaptic weights W^{hid1} , W^{hid2} and W^{outnmc} of the neural network were trained by back-
 495 propagation using the Adam optimiser with a learning rate of 0.001 for 10 epochs with $\omega = 0.75$.
 496 Such pretraining of neural network to achieve specific computations can be attributed to evolution or
 497 learning during development.

498 This pretrained neural motor controller was integrated with the Reservoir agent to create a fully neural
 499 implementation of the Symbolic agent, offering a complete biologically plausible solution to one-shot
 500 learning of single displaced and multiple paired associations tasks. Both Reservoir agents were able
 501 to replicate the results demonstrated by the Symbolic agent without requiring additional symbolic
 502 computations such as suppressing the motor controller activity using $\varepsilon(t)$, instead the pretrained
 503 neural motor controller was able to perform implicit gating of activity.

504 A.7 Symbolic memory & self-position weights

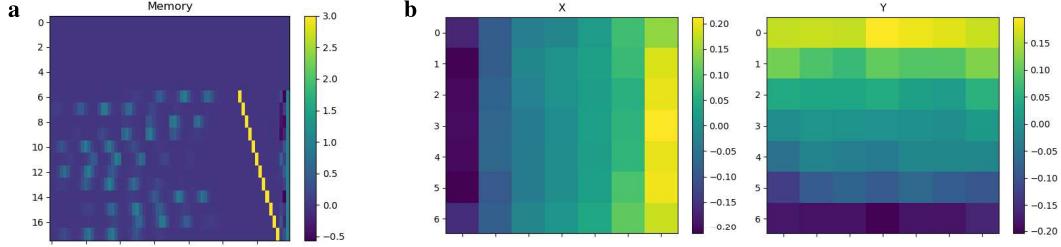


Figure 5: **Episodic memory bank and self-position network weights.** a) 2D episodic memory bank with each row storing 49 place cell activity, cue vector of size 18, 2D goal coordinates and confidence function value of 1 if the target was reached. Example Cue 7 to Cue 18 information are stored in the memory bank. b) Synaptic weights of self-position coordinate network to estimate an agent's 2D coordinate in the square maze. Weights converge to a similar form as in Foster, Morris & Dayan (2000) [14] but for a square maze.

505 A.8 12NPA trajectory

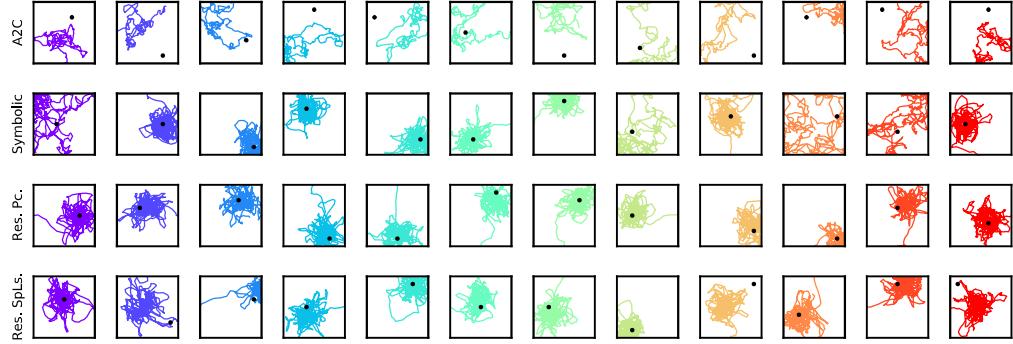


Figure 6: **Example trajectory of agents solving 12 new paired associations (12NPA).** Circles and squares without border indicate start and end positions respectively. A2C agent navigates to five out of 12 locations but achieves low visit ratio at each paired associate. Comparatively, the Symbolic and Reservoir agents spend most of the time at the correct cue-location pairs during each cued probe trial.