**Modelling non-reinforced preferences using selective attention**

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**Abstract**

How can artificial agents learn non-reinforced preferences to continuously adapt their behaviour to a changing environment? We decompose this question into two challenges: \((i)\) encoding diverse memories and \((ii)\) selectively attending to these for preference formation.

Our proposed non-reinforced preference learning mechanism using selective attention, \textit{Nore}, addresses both by leveraging the agent’s world model to collect a diverse set of experiences which are interleaved with imagined roll-outs to encode memories. These memories are selectively attended to, using attention and gating blocks, to update agent’s preferences. We validate \textit{Nore} in a modified OpenAI Gym FrozenLake environment (without any external signal) with and without volatility under a fixed model of the environment—and compare its behaviour to \textit{Pepper}, a Hebbian preference learning mechanism. We demonstrate that \textit{Nore} provides a straightforward framework to induce exploratory preferences in the absence of external signals.

1 Introduction

Biological agents have the capacity to acquire preferences that inform their choices and lead to meaningful interactions with their environment. These preferences are a subjective assessment of what they would like to experience—and can be continuously learnt, or modified, even in the absence of external feedback i.e., non-reinforced preferences (Schonberg & Katz, 2020). These are unlike reinforced preferences where preference for a stimulus may increase given some positive outcome associated with the stimulus i.e., reinforcement learning (Sutton & Barto, 2018). Agents equipped with capacity to modify non-reinforced preferences are able to adjust their behaviour and adapt to changing environmental dynamics on the fly (Schonberg & Katz, 2020; Zajonc, 2001; Izuma & Murayama, 2013)—without needing to re-train, tune or optimise their world model. This motivates the current study: designing artificial agents equipped with a similar capacity to learn non-reinforced preferences that encourage adaptive behaviour.

Neuroscientific evidence reveals that non-reinforced preference changes can be driven by \(i)\) mere-exposure effects where frequently observed options are preferred (Zajonc, 1968; 2001; Grimes & Kitchen, 2007), \(ii)\) attentional mechanisms where attending to an option can deem it more preferable (Izuma et al., 2010; Voigt et al., 2017; Schonberg & Katz, 2020), and \(iii)\) contextual effects where an option is preferred more compared to the alternative only in particular settings (Izuma & Murayama, 2013). These preference shifts can be encoded using local plasticity rules e.g., Hebbian plasticity facilitates learning from mere-exposure effects (Gerstner & Kistler, 2002) or synaptic gating that can encourage enhancement of signal or suppression of noise (Desimone & Duncan, 1995; Serences & Kastner, 2014). These speak to self-supervised learning mechanisms that support acquisition of non-reinforced preferences.

Here, we introduce \textit{Nore}, a non-reinforced preference learning mechanism that leverages synaptic gating to encode shifts in preferences in model-based agents. This allows the agent to learn distinct preferences that encourage adaptive behaviour at inference time. Briefly, \textit{Nore} comprises a two-step procedure that occurs after the agent’s world model has been optimised for the environment during training (see Figure 2):

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1. **Encoding memories.** For this, the agent has short episodes of direct exchange with the environment using the current non-reinforced preferences, and imagined interactions using an exploratory planner to find new novel states with high expected information gain (see Plan2Explore (Sekar et al., 2020)). A history of state representations from a randomly selected subset (30%) of real environmental interactions are interleaved with imagined interactions and retained—an abstraction of how memories are encoded using neural replay (Breton & Robertson, 2013).

2. **Encoding preferences using selective attention.** Once the agent’s memory has been encoded, prior preferences are updated by optimising two blocks (attention and gating) via entropy maximisation (Jaynes, 1957). The attention block constrains the agent’s memories and mimics neural gain control via precision manipulation (Rao, 2005; Whiteley & Sahani, 2008; Yu & Dayan, 2004; Meera et al., 2022). The gating block encodes the (prior) preference distribution by gating and storing relevant information in a time-dependent fashion (Cho et al., 2014). The outputs of this are used as prior preferences for the next environmental interaction.

**Related work:** The task of designing appropriate subjective objectives for the agent remains an open challenge in reinforcement learning. In the absence of any external stimuli, intrinsic motivation has been proposed to guide the behaviour of an agent during its learning phase (Shyam et al., 2019; Sekar et al., 2020; Ball et al., 2020). Intrinsic motivation has been formalised in a number of ways, using curiosity and surprise (Schmidhuber, 1991; Sun et al., 2011; Pathak et al., 2017), empowerment (Gregor et al., 2017), information gain (Houthooft et al., 2016), impact (Raileanu & Rocktäschel, 2020), or successor features (Zhang et al., 2019). Importantly, the underlying objective of such agents is exploration for the purposes of learning the environment and the ways to exploit it (given extrinsic stimuli at test time). In contrast to the aforementioned exploration techniques, our work focuses on producing meaningful and adaptive behaviour by learning subjective preferences over the states of the world at test time.

A related work to Nore is Pepper (Sajid et al., 2021b) – another preference learning mechanism that equips an agent with the ability to update preferences using Hebbian learning. This particular procedure restricts the agent’s ability to appropriately filter (or gate) irrelevant information. Contrariwise, Nore encodes preferences reliant on the gating hypothesis (Schonberg & Katz, 2020) and learns to accentuate relevant information for a particular environment.

2 **Non-reinforced preference learning with selective attention (Nore)**

We aim to build an agent that can modify its preferences after learning about the environment without any reward signal nor supervision. This presents two challenges—encoding diverse memories and selectively attending to these for preference formation. We use the agent’s world model and imagination to collect appropriate memories and optimise a Gated Recurrent Unit (GRU) (Cho et al., 2014) to encode particular preferences. The preference learning procedure, Nore, is detailed in Algorithm 1.

**World model.** The agent’s world model is instantiated as a Recurrent State-Space Model (RSSM) (Hafner et al., 2019b; 2020; Sajid et al., 2021b) and entails mapping a history of observations \((a_0, a_1, ..., a_t)\) and actions \((a_0, a_1, ..., a_t)\) to a sequence of deterministic states \(h_t = f(h_{t-1}, s_{t-1}, a_{t-1})\) (Fig. 1). These deterministic states are used to calculate the latent prior and posterior states. These are used downstream for planning. Formally, the RSSM consists of the following: (i) GRU based deterministic recurrent model, \(h_t = f(h_{t-1}, s_{t-1}, a_{t-1})\); (ii) Latent state posterior, \(Q_\phi(s_t|h_t, o_t) \sim \text{Cat}\), and prior, \(P(s) \sim \text{Cat}(D)\); (iii) Transition model, \(P_\theta(s_{t+1}|h_t) \sim \text{Cat}\); (iv) Image predictor (or emission model), \(Q_\phi(o_t|h_t, s_t) \sim \text{Bernoulli}\). Here, \(Q_\phi(\cdot)\) denotes an approximate posterior distribution parameterised by \(\phi\).

The world model is trained by optimising the evidence lower bound (ELBO) (Hafner et al., 2019b) or equivalently, the variational free energy (Friston, 2010; Fountas et al., 2020; Sajid et al., 2021a;b) using stochastic back-propagation with the Adam optimiser (Kingma & Ba, 2014). Here, the training data is collected using trajectories generated under an exploratory policy. See Appendix B for ELBO implementation.
Planning objective for learning preferences. Following Sajid et al. (2021b), we substitute the planner with the expected free energy (G) (Sajid et al., 2022; Barp et al., 2022) augmented with conjugate priors to allow for preference learning over time:

\[
G(\pi, \tau) = -\mathbb{E}[\log P(o_\tau | s_\tau, \pi)] + \mathbb{E}[\log Q(s_\tau | \pi) - \log P(s|D)] + \mathbb{E}[\log Q(\theta | s_\tau, \pi) - \log P(\theta | s_\tau, o_\tau, \pi)],
\]

(1)

where expectations are taken w.r.t. \( Q_\phi(o_\tau, s_\tau, \theta | \pi) = Q(\theta | \pi)Q(s_\tau | \pi)Q_\phi(o_\tau | s_\tau, \pi) \) and the Dirichlet distribution was introduced as the conjugate prior over \( \text{Cat}(D) \) (Appendix E.1). See Appendix B.2 for implementation of \( G \). This planning objective bounds extrinsic and intrinsic value (Da Costa et al., 2020; Sajid et al., 2022). Therefore, in the absence of non-reinforced preferences, or whilst learning them, intrinsic motivation contextualises agent’s interactions with the environment in a way that depends upon its posterior beliefs about latent environmental states (Barto, 2013; Ryan & Deci, 2000). Here, actions are selected by sampling from the distribution \( P(\pi) = \arg \max (-G(\pi)) \) (Barp et al., 2022).

Selective attention during preference formation. Motivated by the neuroscientific view of attention as a gating mechanism (Carrasco, 2011; Meera et al., 2022), we introduce two blocks that gate preference encoding through signal accentuation and attenuation (Desimone & Duncan, 1995; Serences & Kastner, 2014).

Attention: \( s \sim Q_\phi(s_{t-1} | h, \gamma) \) Gating: \( P_\gamma(s | h, D) \)

(2)

where, \( \gamma \) denotes the precision term, \( h \) the memory buffer and \( D \) prior preferences. The attention block is a multi-layer perceptron (MLPs) and plays an analysis role to classical precision control mechanism. The gating block contains a deterministic (i.e., the recurrent state of the GRU) and stochastic component with diagonal covariance Gaussian distribution. These are trained during inference (i.e., preference learning) by maximising entropy over preferences using stochastic back-propagation with the Adam optimiser. The prior preferences used by the preference learning planner, \( G \), are given by a softmax transformation.

3 Experiments

Figure 2: Preference learning mechanism. NORE comprises two subsequent steps in each episode: 1) environmental and imagined interaction, and 2) accumulation of preferences once interaction ends using randomly shuffled memories. Both steps function in synergy: step 1 influences preference learning and step 2 influences the interactions in the subsequent episode.

mechanisms as a result of environmental volatility. For this, a volatile environment was simulated by modifying the FrozenLake grid every \( K \) steps and initialising the agent in a different location at the start of each episode. This provides an appropriate test-bed to assess how much volatility was necessary to induce shifts in learnt prior preferences. The world model weights were frozen during these experiments. Therefore, any behavioural differences are a direct consequence of PEPPER that induces differences in the planning objective, \( G \). See Appendix E for architecture and training details for each environment.
Encoded non-reinforced preferences. First, we compared the preferences encoded by NORE and PEPPER agents when the environment was static i.e., no changes to the grid configuration. Figure 3 plots the difference between the two preference learning rules. For the Hebbian learning rule (PEPPER), preferences are reinforced given particular environmental exposure i.e., the more the agent experiences something, the more it is preferred. Conversely, for the preference learning via synaptic gating (NORE) preferences shift across epochs – with new preferences being encoding until the last epoch.

Nore behaviour. We evaluated the agent’s behaviour in Figure 4 using Hausdorff distance (Appendix C) (Blumberg, 1920). With this metric we observed increased exploration by the NORE agent at 50%, 75% volatility in the environment. Similar to PEPPER, the agents pursued long paths from the initial location (see Fig. 5 for sample trajectories). Compared to PEPPER, NORE agents did not exhibit bi-modal preferences at 100% volatility in the environment.
4 CONCLUDING REMARKS

We introduced Nore, a new non-reinforced preference learning mechanism using selective attention. Nore leverages the agent’s world model and imagined roll-out to encode appropriate memories and selectively attends to them for preference learning. An agent equipped with this non-reinforced preference learning mechanism has the capacity to continuously learn and modify its subjective assessment of what is preferred; which can induce exploratory behaviours. Practically, further downstream these agents might accomplish tasks specified via simple and sparse rewards more quickly, or may acquire broadly useful skills that could be adapted to specific task objectives.

REFERENCES

Philip Ball, Jack Parker-Holder, Aldo Pacchiano, Krzysztof Choromanski, and Stephen Roberts. Ready policy one: World building through active learning. In International Conference on Machine Learning, pp. 591–601. PMLR, 2020.

Alessandro Barp, Lancelot Da Costa, Guilherme França, Karl Friston, Mark Girolami, Michael I. Jordan, and Grigorios A. Pavliotis. Geometric Methods for Sampling, Optimisation, Inference and Adaptive Agents. arXiv:2203.10592 [cs, math, stat], March 2022.

Andrew G Barto. Intrinsic motivation and reinforcement learning. In Intrinsically motivated learning in natural and artificial systems, pp. 17–47. Springer, 2013.

Henry Blumberg. Hausdorff’s grundzüge der mengenlehre. Bulletin of the American Mathematical Society, 27 (3):116–129, 1920.

Jocelyn Breton and Edwin M Robertson. Memory processing: The critical role of neuronal replay during sleep. Current Biology, 23(18):R836–R838, 2013.

Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. Openai gym. arXiv preprint arXiv:1606.01540, 2016.

Marisa Carrasco. Visual attention: The past 25 years. Vision research, 51(13):1484–1525, 2011.

Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using rnn encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078, 2014.

Lancelot Da Costa, Thomas Parr, Noor Sajid, Sebastijan Veselic, Victorita Neacsu, and Karl Friston. Active inference on discrete state-spaces: a synthesis. Journal of Mathematical Psychology, 99:102447, 2020.

Robert Desimone and John Duncan. Neural mechanisms of selective visual attention. Annual review of neuroscience, 18(1):193–222, 1995.

Zafeirios Fountas, Noor Sajid, Pedro AM Mediano, and Karl Friston. Deep active inference agents using monte-carlo methods. arXiv preprint arXiv:2006.04176, 2020.

Karl J Friston. The free-energy principle: A unified brain theory? Nature Reviews Neuroscience, 11(2):127–138, 2010.

Wulfram Gerstner and Werner M Kistler. Mathematical formulations of hebbian learning. Biological cybernetics, 87(5):404–415, 2002.

Karol Gregor, Danilo Jimenez Rezende, and Daan Wierstra. Variational intrinsic control. ArXiv, abs/1611.07507, 2017.

Anthony Grimes and Philip J Kitchen. Researching mere exposure effects to advertising-theoretical foundations and methodological implications. International Journal of Market Research, 49(2):191–219, 2007.

Danijar Hafner, Timothy Lillicrap, Jimmy Ba, and Mohammad Norouzi. Dream to control: Learning behaviors by latent imagination. arXiv preprint arXiv:1912.01603, 2019a.
Danijar Hafner, Timothy Lillicrap, Ian Fischer, Ruben Villegas, David Ha, Honglak Lee, and James Davidson. Learning latent dynamics for planning from pixels. In *International Conference on Machine Learning*, pp. 2555–2565. PMLR, 2019b.

Danijar Hafner, Timothy Lillicrap, Mohammad Norouzi, and Jimmy Ba. Mastering atari with discrete world models. *arXiv preprint arXiv:2010.02193*, 2020.

Rein Houthooft, Xi Chen, Yan Duan, John Schulman, Filip De Turck, and P. Abbeel. Vime: Variational information maximizing exploration. In *NIPS*, 2016.

Keise Izuma and Kou Murayama. Choice-induced preference change in the free-choice paradigm: a critical methodological review. *Frontiers in psychology*, 4:41, 2013.

Keise Izuma, Madoka Matsumoto, Kou Murayama, Kazuyuki Samejima, Norihiro Sadato, and Kenji Matsumoto. Neural correlates of cognitive dissonance and choice-induced preference change. *Proceedings of the National Academy of Sciences*, 107(51):22014–22019, 2010.

Edwin T Jaynes. Information theory and statistical mechanics. *Physical review*, 106(4):620, 1957.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell. Simple and scalable predictive uncertainty estimation using deep ensembles. *arXiv preprint arXiv:1612.01474*, 2016.

Ajith Anil Meera, Filip Novicky, Thomas Parr, Karl Friston, Pablo Lanillos, and Noor Sajid. Reclaiming saliency: rhythmic precision-modulated action and perception. *arXiv preprint arXiv:2203.12652*, 2022.

Deepak Pathak, Pulkit Agrawal, Alexei A. Efros, and Trevor Darrell. Curiosity-driven exploration by self-supervised prediction. *2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 488–489, 2017.

Roberta Raileanu and Tim Rocktäschel. Ride: Rewarding impact-driven exploration for procedurally-generated environments. *ArXiv*, abs/2002.12292, 2020.

Rajesh PN Rao. Bayesian inference and attentional modulation in the visual cortex. *Neuroreport*, 16(16):1843–1848, 2005.

Richard M Ryan and Edward L Deci. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology*, 25(1):54–67, 2000.

Noor Sajid, Philip J Ball, Thomas Parr, and Karl J Friston. Active inference: demystified and compared. *Neural Computation*, 33(3):674–712, 2021a.

Noor Sajid, Panagiotis Tigas, Alexey Zakharov, Zafeiros Fountas, and Karl Friston. Exploration and preference satisfaction trade-off in reward-free learning. *arXiv preprint arXiv:2106.04316*, 2021b.

Noor Sajid, Lancelot Da Costa, Thomas Parr, and Karl Friston. Active inference, bayesian optimal design, and expected utility. *The Drive for Knowledge: The Science of Human Information Seeking*, pp. 124, 2022.

Jiirgen Schmidhuber. Curious model-building control systems. [Proceedings] *1991 IEEE International Joint Conference on Neural Networks*, pp. 1458–1463 vol.2, 1991.

Tom Schonberg and Leor N Katz. A neural pathway for nonreinforced preference change. *Trends in Cognitive Sciences*, 24(7):504–514, 2020.

Ramanan Sekar, Oleh Rybkin, Kostas Daniilidis, Pieter Abbeel, Danijar Hafner, and Deepak Pathak. Planning to explore via self-supervised world models. In *International Conference on Machine Learning*, pp. 8583–8592. PMLR, 2020.

John T Serences and Sabine Kastner. A multi-level account of selective attention. 2014.

Pranav Shyam, Wojciech Jaśkowski, and Faustino Gomez. Model-based active exploration. In *International conference on machine learning*, pp. 5779–5788. PMLR, 2019.
Yi Sun, Faustino J. Gomez, and Jürgen Schmidhuber. Planning to be surprised: Optimal bayesian exploration in dynamic environments. In AGI, 2011.

Richard S Sutton and Andrew G Barto. Reinforcement Learning: An Introduction. MIT press, 2018.

Katharina Voigt, Carsten Murawski, and Stefan Bode. Endogenous formation of preferences: Choices systematically change willingness-to-pay for goods. Journal of Experimental Psychology: Learning, Memory, and Cognition, 43(12):1872, 2017.

Louise Whiteley and Maneesh Sahani. Implicit knowledge of visual uncertainty guides decisions with asymmetric outcomes. Journal of vision, 8(3):2–2, 2008.

Angela J Yu and Peter Dayan. Inference, attention, and decision in a bayesian neural architecture. Advances in neural information processing systems, 17, 2004.

Robert B Zajonc. Attitudinal effects of mere exposure. Journal of personality and social psychology, 9(2p2):1, 1968.

Robert B Zajonc. Mere exposure: A gateway to the subliminal. Current directions in psychological science, 10(6):224–228, 2001.

Jingwei Zhang, Niklas Wetzel, Nicolai Dorka, Joschka Boedecker, and Wolfram Burgard. Scheduled intrinsic drive: A hierarchical take on intrinsically motivated exploration. ArXiv, abs/1903.07400, 2019.
A PSEUDO-CODE FOR LEARNING PREFERENCES

Algorithm 1: Nore

Input:
\[ h_t := f_{\theta}(h_{t-1}, s_{t-1}, a_{t-1}) \] Recurrent model
\[ Q_\phi(s_t | h_t, o_t) \] Posterior model
\[ Q_\phi(s_t | h_t) \] Prior model
\[ \Phi(a_t|h_t, s_t) \] Observation model

Initialise
uniform Dirichlet prior over \( P(s) \) /* prior preference being learnt */
learning rate \( \alpha \); memory trace \( \beta \);

for each episode \( e \) do
    reset environment and collect initial observations \( (o_0) \)
    for each step \( t \) /* environment interaction */
        compute \( s_{po} \sim Q_\phi(s_t | h_t, o_t) \)
        compute \( G \) using \( P(s) \), observed and predicted posteriors
        \( a_t \leftarrow \arg\max(-G(\pi)) \)
        execute \( \sim a_t \) and receive \( o \)
        \( o_{t+1} \leftarrow o \)
    for each imagined step /* imagination */
        compute \( s_{po}^i \sim Q_\phi(s_t | h_t, o_t) \)
        \( a_t \sim \mathcal{A} \)
        compute \( s_{pr}, s_{po}^i \) using \( h_t \& a_t \)
        \( s_{po}^m \leftarrow \text{comb}(\text{filter}(s_{po}), s_{po}^i) \) /* re-coding memories */
        for each memory /* encoding preferences */
            \( s_{po}^a \leftarrow \text{MLP}(s_{po}^m) \) /* attention block */
            \( w \leftarrow \text{GRU}(s_{po}^a, w) \) /* gating block */
        \[ P(s) \leftarrow \beta \cdot P(s) + \alpha \cdot w \]
        maximise \( -\mathbb{E}_{P(s)} \log P(s) \)

B IMPLEMENTATION

Our generative model was implemented exactly as in Pepper (Sajid et al., 2021b) using Dreamer V2’s public implementation (Hafner et al., 2020)\(^1\). Specifically, Dreamer’s generative model training loop was used, alongside a model predictive control (MPC) planner. Therefore, the actor learning part of Dreamer was not incorporated, and the generative model was trained using Plan2Explore (Sekar et al., 2020). Like Plan2Explore, an ensemble of image encoders were learnt and the “disagreement” of the encoders was used as an intrinsic reward during training. This guides the agent to explore areas of the map that have high novelty and potentially high information gain, when acquiring a generative (i.e., world) model. See appendix A in (Sajid et al., 2021b) for further details regarding the planner.

Upon training completion, we froze the generative model’s learnt weights and only allowed learning of prior preferences. These preferences were updated after each episode as described in Algorithm 1.

B.1 EVIDENCE LOWER BOUND

The generative model was optimised using the ELBO formulation introduced in (Hafner et al., 2019a):

\(^1\)https://github.com/danijar/dreamerv2
\[ \mathcal{L}(\theta) = \sum_{i=1}^{T} \underbrace{- \mathbb{E} \left[ \log P_\theta(o_t | s_t, \pi) \right]}_{\text{reconstruction}} + \underbrace{\mathbb{E} \left[ D_{KL}(Q_\phi(s_t | o_{\leq t}, s_{t-1}, \pi) \| P_\theta(s_t | s_{t-1}, \pi)) \right]}_{\text{dynamics}}, \]  

where both expectations are w.r.t. \( Q_\phi(s_t | o_{\leq t}, a_{\leq t}) \).

### B.2 Expected free energy

We implemented \( G \) using the parameterisations introduced in (Sajid et al., 2021b). Explicitly, for each term in equation 1:

- **Term 1** was computed as the entropy of the observation model \( P(o_t | s_t, \pi) \). Happily, the factorisation of the observation model – as independent Gaussian distributions – allowed us to calculate the entropy term in closed form.

- **Term 2** was computed as the difference between \( \log Q(s_t | \pi) \) and \( \log P(s_t | D) \), where \( \log Q(s_t | \pi) \) was approximated using a single sample from the prior model \( Q(s_t | \theta, \pi) \). Again, the dependency on \( \pi \) was substituted by \( h_t \).

- **Term 3** was computed by rearranging the expression to \( H(o_t | s_t, \theta, \pi) - H(o_t | s_t, \pi) \) (Fountas et al., 2020; Sajid et al., 2021b). This translates to \( I(o_t; \theta | s_t, \pi) \), and can be approximated using Deep Ensembles (Lakshminarayanan et al., 2016; Sekar et al., 2020) and calculating their variance \( \text{Var}_{\theta} \mathbb{E} Q(o_t | s_t, \theta, \pi) \). Here, each ensemble component can be seen as a sample from the posterior \( Q(\theta | s_t, \pi) \). Our experiments showed that using 5 components was sufficient.

### C Hausdorff distance

This metric calculates the maximum distance of the agents’ position in a particular trajectory to the nearest position taken in another trajectory. Thus high Hausdorff distance denotes increased exploration, since trajectories observed across episodes differ from one another. Contrariwise, a low distance entails prior preference satisfaction as agents repeat trajectories across episodes.

### D Dirichlet distribution

Here, we used the Dirichlet distribution as the conjugate prior over \( \text{Cat}(D) \) with dimension \( n \times n \) defined as:

\[
P(D | \theta) = \text{Dir}(d) \Rightarrow \begin{cases} 
\mathbb{E}_{P(D | \theta)}[D_{i,j}] = \frac{d_{i,j}}{\sum_k d_{k,j}} \\
\mathbb{E}_{P(D | \theta)}[\log(D_{i,j})] = F(d_{i,j}) - F(\sum_k d_{k,j}) 
\end{cases}
\]

where, \( F \) is the digamma function, \( d \sim \mathbb{R}^+ \).

### E Experiments

We simulated the agent in five distinct situations ranging from a non-volatile, static environment to a highly volatile one i.e., a different FrozenLake\(^2\) map every step. For all episodes in the static setting, the agent was initialised at a fixed location with no changes to the FrozenLake map throughout that particular episode. Conversely, agents operating in the volatile setting were initialised at a different location each time. Moreover, the FrozenLake map was also changed every \( N \) steps – given the desired volatility level (Table 1). These experiments were deliberately kept simple to gain an understanding of how non-reinforced preferences could be learnt using selective attention and how they differed from hebbian preference learning rules. Future work should investigate how NORE agents behave in more complex, open-ended environments.

#### E.1 NORE behaviour

\(^2\)https://github.com/openai/gym/ (MIT license)
Table 1: Training parameters

| Parameter             | NORE       | PEPPER     |
|-----------------------|------------|------------|
| Planning Horizon      | 15 steps   | 15 steps   |
| Episode Length        | 100 steps  | 100 steps  |
| Reset Every           | 10 steps   | 10 steps   |
| No. Episodes          | 50 episodes| 50 episodes|
| No. State Categories  | 64 categories| 64 categories|
| No. State Dimensions  | 50 dimensions| 50 dimensions|

Table 2: Preference learning parameters

| Parameter             | NORE       | PEPPER     |
|-----------------------|------------|------------|
| Planning Horizon      | 15 steps   | 15 steps   |
| Episode Length        | 100 steps  | 100 steps  |
| No. Episodes          | 50 episodes| 50 episodes|
| Reset Map Every       | 1, 25, 50, 75, 100 steps | 1, 25, 50, 75, 100 steps |

Figure 5: FrozenLake and environmental trajectories