
CCNLab: A Benchmarking Framework for Computational Cognitive Neuroscience

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Abstract

1 CCNLab is a benchmark for evaluating computational cognitive neuroscience mod-
2 els on empirical data. As a starting point, its focus is classical conditioning, which
3 studies how animals predict reward and punishment in the environment. CCNLab
4 includes a collection of simulations of seminal experiments expressed under a
5 common API, as well as tools for visualizing and comparing simulated data with
6 empirical data. CCNLab is broad, incorporating representative experiments from
7 different categories of phenomena; flexible, allowing the straightforward addition
8 of new experiments; and easy-to-use, so researchers can focus on developing better
9 models. We envision CCNLab as a testbed for unifying computational theories
10 of learning in the brain. We also hope that it can broadly accelerate neuroscience
11 research and facilitate interaction between the fields of neuroscience, psychology,
12 and artificial intelligence.

13 1 Introduction

14 Brains are the *de facto* standard for general intelligence [Lake et al., 2017], and many researchers
15 believe that progress in artificial intelligence is intimately intertwined with understanding natural
16 intelligence [Hassabis et al., 2017]. Modern research in neuroscience and psychology increasingly
17 relies on computational models to express theories about how the brain works [Durstewitz et al.,
18 2016, Jonas and Kording, 2017, Linderman and Gershman, 2017, Kriegeskorte and Douglas, 2018,
19 Levenstein et al., 2020, Gershman, 2021]. This has brought the fields studying artificial and natural
20 intelligence even closer, with computational neuroscientists directly borrowing ideas from machine
21 learning [Montague et al., 1996, Yamins et al., 2014, Stachenfeld et al., 2017, Ma and Peters, 2020,
22 Saxe et al., 2020] and vice versa [LeCun et al., 1995, He et al., 2016, Sutton and Barto, 2018]. This
23 perpetuates a “virtuous cycle” in which the science and engineering of intelligence may progress
24 together [Hassabis et al., 2017].

25 Despite these promising developments, there is a significant rift between machine learning and
26 computational neuroscience in how research is evaluated and compared. Machine learning has
27 benefited from the widespread adoption of publicly available datasets and benchmarks, like ImageNet
28 [Deng et al., 2009] and OpenAI Gym [Brockman et al., 2016]. This has been instrumental for
29 algorithm design, as the strengths and weaknesses of different work can be directly compared, and
30 research is incentivized to perform beyond narrow, domain-specific tasks. In contrast, models in
31 computational neuroscience have often been confined to a small set of phenomena in a specific
32 domain, and due the lack of standards for evaluation, even those models can be difficult to compare.

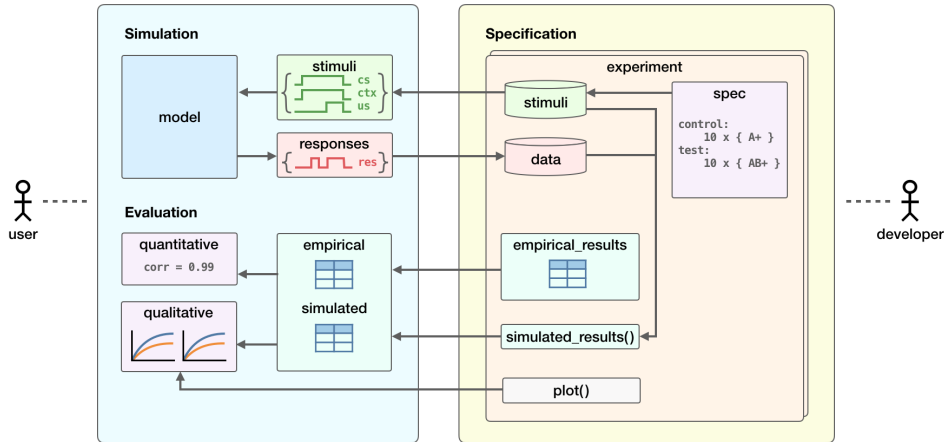


Figure 1: **Overview of CCNLab architecture.** Users can simulate their models on a wide variety of classical conditioning experiments, and the simulated results are evaluated against empirical results from published work. Each experiment is an environment that simulates a schedule of stimuli mirroring a real-world study.

33 We present **CCNLab** (short for Cognitive Computational Neuroscience Lab), a benchmark for computational models of classical conditioning. Using our Python framework inspired by OpenAI Gym
 34 [Brockman et al., 2016], users can simulate their models on a wide variety of classical conditioning
 35 experiments, and the simulated results are evaluated against empirical results from published work.
 36 Currently, the CCNLab registry includes 30 experiments to simulate the most established classical
 37 conditioning phenomena selected from the list provided in Alonso and Schmajuk [2012]. Our frame-
 38 work is modular and extensible, allowing developers to easily extend the benchmark with additional
 39 experiments from the literature or of their own design.
 40

41 Classical conditioning has a rich history dating back to Pavlov [1927] and exhibits a diverse set
 42 of phenomena that have been extensively studied [Alonso and Schmajuk, 2012]. It has attracted
 43 much interest for computational modeling [Ertugrul and Tagluk, 2015, Gershman, 2015, Kutlu and
 44 Schmajuk, 2012b], and is closely related to reinforcement learning and optimal sequential decision
 45 making [Niv, 2009]. These factors make it an excellent starting point for introducing benchmarks into
 46 computational neuroscience and encouraging reproducible, rigorous evaluation of models. To that
 47 end, we also perform a series of baseline experiments to evaluate existing methods on this benchmark.
 48 Our analysis reveals that, while our baselines are able to reproduce certain effects well, they lack the
 49 ability to generalize to a wider range of phenomena. We conclude by suggesting future extensions
 50 and research directions for computational modeling guided by publicly available benchmarks.

51 Our code for the benchmarks and baseline experiments has been open-sourced under the MIT License
 52 and is available at: <https://github.com/nikhilxb/ccnlab>.

53 2 Background

54 2.1 Classical Conditioning

55 A critical feature of intelligence is the ability to adapt in response to positive and negative feedback.
 56 The branch of machine learning that studies how agents can take actions that maximize reward
 57 is known as reinforcement learning [Sutton and Barto, 2018]. In neuroscience and psychology,
 58 learning based on rewards and punishments is studied through the paradigms of classical (Pavlovian)
 59 conditioning and instrumental (operant) conditioning. Classical conditioning studies how animals
 60 learn to predict outcomes in their environment, while instrumental conditioning studies how animals
 61 learn to select actions that lead to better outcomes.

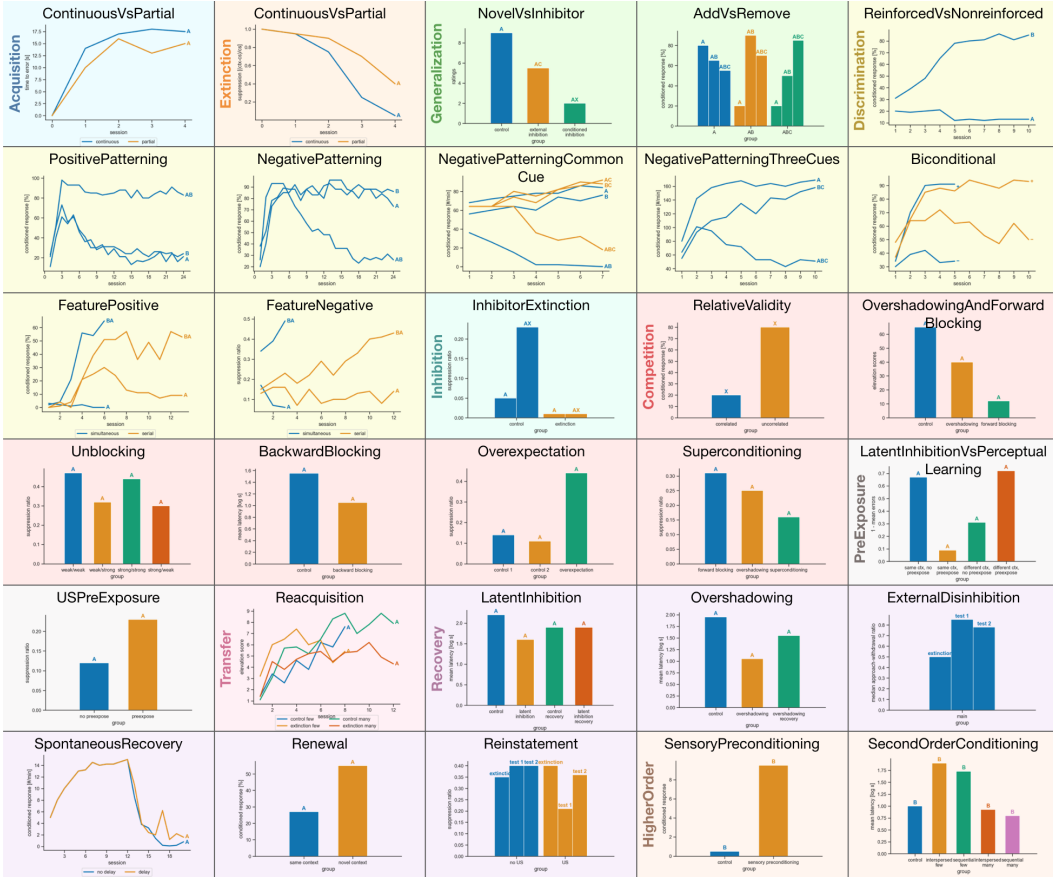


Figure 2: **Summary of simulated experiments.** The registry currently includes 30 experiments to simulate the most established classical conditioning phenomena selected from the list provided in Alonso and Schmajuk [2012] (see Appendix A for details). In the plots, experimental groups are separated by color, and stimuli are separated into individual bars/lines labeled with stimulus names.

62 In a typical classical conditioning experiment, the subject is presented with one or more conditioned
 63 stimuli (CS, e.g., a tone) followed by an unconditioned stimulus (US, e.g., food), which elicits an
 64 unconditioned response (UR, e.g., salivating) prior to training. After repeated pairing of the CS
 65 and the US over the course of multiple trials, the subject may begin to respond to the CS with what
 66 is known as the conditioned response (CR, e.g., salivating), as in the classic example of Pavlov’s
 67 dog salivating in response to the sound of the bell [Pavlov, 1927]. The CR is a standard measure
 68 in classical conditioning experiments, and different schedules of CS stimuli result in different CR
 69 behavior, producing the wide range of classical conditioning phenomena that has been extensively
 70 cataloged [Alonso and Schmajuk, 2012].

71 **2.2 Computational Modeling of Classical Conditioning**

72 Reinforcement learning is deeply rooted in the study of conditioned behavior [Niv, 2009], dating
 73 back to Thorndike’s seminal law of effect [Thorndike, 1898] and Skinner’s principle of reinforcement
 74 [Skinner, 1935] in the early 20th century. By midcentury, the first formal treatments of animal
 75 learning were beginning to emerge in the field of mathematical psychology [Bush and Mosteller,
 76 1951], paving the way for the famous Rescorla-Wagner model [Rescorla, 1972]. The Rescorla-
 77 Wagner model provided a formal account of a wide number of puzzling phenomenon in classical
 78 conditioning, such as blocking (the phenomenon where predictable rewards are poor reinforcers) and
 79 overshadowing (the phenomenon where salient stimuli tend to form stronger associations). It was this
 80 line of research that inspired the computer scientists Sutton and Barto to develop the foundational
 81 concepts of modern reinforcement learning theory [Sutton and Barto, 2018]. In the following decades,

82 a wealth of behavioral and neural evidence has further cemented the links between reinforcement
83 learning theory and animal learning [Niv, 2009], most notably the discovery that dopamine neurons
84 in the mammalian midbrain convey signals that closely correspond to the reward prediction errors
85 prescribed by reinforcement learning theory [Schultz et al., 1997]. These findings have in turn
86 spurred further research in reinforcement learning [Hassabis et al., 2017], leading to some remarkable
87 recent success of reinforcement learning algorithms across a wide number of domains, from board
88 games and video games [Mnih et al., 2015, Silver et al., 2017, Schrittwieser et al., 2020] to robotics
89 [Haarnoja et al., 2018, Akkaya et al., 2019] to self-driving cars [Toromanoff et al., 2020].

90 Following the Rescorla-Wagner model, many other computational models of classical conditioning
91 have emerged to explain a additional phenomena: the Pearce-Hall model posits that surprising
92 outcomes increase learning rates [Pearce and Hall, 1980]; Temporal Difference models account
93 for the temporal structure of neural learning signals [Schultz et al., 1997]; the Kalman Filter casts
94 learning as Bayesian inference and accounts for effects of outcome uncertainty [Kakade, 2001]. More
95 recently, Temporal Difference models operating on belief states have accounted for dopamine firing in
96 the face of partial observability [Starkweather et al., 2017], and distributional reinforcement learning
97 has accounted for the diversity of dopamine firing in the face of different reward distributions [Dabney
98 et al., 2020]. Notably, these models account for overlapping yet distinct sets of phenomena. Despite
99 promising recent work combining aspects of these models [Kutlu and Schmajuk, 2012b, Gershman,
100 2015], a unifying computational theory of animal learning is still lacking.

101 2.3 Benchmarks in Computational Neuroscience

102 In machine learning, it has long been recognized that standardized benchmarks and datasets are
103 essential to the development of algorithms [Deng et al., 2009, Brockman et al., 2016]. However,
104 in psychology and neuroscience, to the best of our knowledge there still do not exist standard
105 benchmarks for comparing theories of animal learning. Alonso and Schmajuk [2012] provides a list
106 of well-established classical conditioning phenomena. Subsequent work like Kutlu and Schmajuk
107 [2012b] has sought to evaluate models based on this list. However, a public benchmark encoding
108 these phenomena has not until now been created.

109 3 Technical Details

110 CCNLab provides a unified framework for specifying and simulating classical conditioning ex-
111 periments. An **experiment** in CCNLab is analogous to an RL-style environment, as it simulates
112 the interaction between the agent model and the world. Specifically, each experiment simulates
113 the schedule of stimuli presented in a real-world classical conditioning experiment drawn from
114 peer-reviewed academic research, and enables evaluation of the model’s **simulated results** with the
115 published **empirical results**.

116 Currently, the CCNLab registry includes 30 experiments (Figure 2) to simulate the most established
117 classical conditioning phenomena selected from the list in Alonso and Schmajuk [2012]. These
118 phenomena have been collected over a diverse range of conditioning preparations (e.g., visual/auditory
119 conditioning, taste aversion, eyeblink conditioning, fear conditioning). Across experiments, the CSs
120 were shapes, sounds, lights, flavors, and odors; the USs were food, shock, and mechanical stimulation;
121 and both CSs and USs covered a wide range of intensities and durations. The inter-stimulus intervals
122 (ISI) ranged from seconds to minutes; and the inter-trial intervals (ITI) ranged from seconds to days.

123 An overview of CCNLab architecture is provided in Figure 1. In the following sections, we describe
124 the technical details of CCNLab, separating information most relevant for **users** (who are primarily
125 concerned with evaluating the performance of their models in experiment simulations) and **developers**
126 (who are interested in extending the benchmark with additional experiments).

127 3.1 Simulation and Evaluation

128 Users may run their models on experiments using the provided Jupyter notebooks [Kluyver et al.,
129 2016] or custom Python scripts. Each experiment object encapsulates functionality for: (1) generating
130 the stimuli that serve as model inputs, (2) storing model outputs (i.e., conditioned responses), (3)
131 summarizing model outputs in a format that is directly comparable with empirical results gathered
132 from published work, and (4) plotting simulated and empirical results. Here is an example of the API:

```

import ccnlab.benchmarks.classical as classical
import ccnlab.evaluation as evaluation

# Select experiments to run, filtering by name using glob syntax.
for exp in classical.registry('*'):

    # Experiments often have multiple groups, each shown different stimuli.
    for g, group in exp.stimuli.items():

        # Users are free to decide how to initialize their models and how many
        # instances to allocate per group.
        for instance in range(N):
            model = YourModelHere()

            # Each group is shown a sequence of trials. At each timestep in a
            # trial, the model input consists of the conditioned stimuli (cs),
            # context (ctx), and unconditioned stimulus (us); the model output
            # should be a response value.
            for i, trial in enumerate(group):
                for t, timestep in enumerate(trial):
                    cs, ctx, us = timestep
                    response = model.act(cs, ctx, us)
                    exp.data[g][i][t]['response'].append(response)

            # Simulation results can be compared to empirical results from published
            # work, via evaluation metrics (quantitative) and plots (qualitative).
            empirical = exp.empirical_results
            simulated = exp.simulated_results()
            score = evaluation.correlation(empirical, simulated)
            exp.plot()

```

133 **Input Representation** At each timestep in a trial, the environment provides:

- 134 1. cs: A list of active stimuli (string ids) and their magnitudes (positive real-valued). For most
135 experiments, the magnitudes are either 0 or 1.
- 136 2. ctx: The active context (string id). The context remains the same throughout a trial.
- 137 3. us: The unconditioned stimulus magnitude (positive real-valued). For most experiments,
138 the magnitude is either 0 or 1.

139 Alternatively, the cs and ctx are available as one-hot vectors with dimensions equal to the stimuli
140 and context space, respectively. The 3 components of the observation are provided separately as each
141 has unique semantic meaning. By definition, the US evokes a response in untrained subjects while the
142 CS do not [Pavlov, 1927]. Moreover, multiple studies have demonstrated the importance of context
143 for modulating conditioning effects to the CS [Alonso and Schmajuk, 2012, Gershman, 2017]. It is
144 therefore common for models of classical conditioning to treat these input signals differently.

145 **Output Representation** At each timestep in a trial, the model should provide a response value
146 (real-valued) indicating the strength of the conditioned response. Due to the diversity of conditioning
147 preparations used across experiments, a degree of standardization is needed to enable the same model
148 to perform across preparations. In particular, following Kutlu and Schmajuk [2012b], the response
149 value should represent the abstract CR itself, regardless of whether it is experimentally measured as
150 an increase or decrease of some behavior. For example, in an appetitive preparation like eyeblink
151 conditioning where the CR is measured as an increase in blinking activity, a lower response value
152 represents *lower* blinking activity and a higher response value represents *higher* in blinking activity,
153 as expected. Conversely, in an aversive preparation like bar pressing where the CR is measured as a
154 reduction in bar pressing activity, a lower response value of represents *baseline/higher* bar pressing
155 activity and a higher response value represents *reduced/lower* bar pressing activity.

156 Experiment Parameters Each experiment simulates the schedule of stimuli presented in its real-
157 world counterpart. Due to the diversity of conditioning preparations used across experiments, the
158 number of conditioning trials vary significantly. By default, the experiments provide a number of
159 trials in each phase proportional to the original work or the simulations performed in Kutlu and
160 Schmajuk [2012b]. However, it is possible to change the number of trials per session, if desired.

161 Evaluation Metrics We follow the approach of evaluating models using scale-invariant, ordinal
162 measures of the quality of fit between empirical and simulated results. Following Kutlu and Schmajuk
163 [2012b], we use Pearson's correlation coefficient which yields a value between -1 and 1 reflecting
164 a linear correlation between empirical and simulated results. A special case is when the empirical
165 results contain only 2 data points, in which case we use the ratio (smaller to larger) of ratios between
166 the data points, which yields a value between 0 and 1.

167 3.2 Specification

168 Developers may extend the benchmark with additional experiments from the literature or of their
169 own design. CCNLab provides a collection of data structures and functions to make it easy to
170 implement experiments, including: (1) an abstract syntax library for specifying experimental stimuli,
171 (2) processing functions for computing conditioned responses and suppression ratios from the raw
172 data, and (3) plotting functions to generate line or bar graphs.

173 Here is an example of the API, which has been simplified for clarity (for more details, refer to the
174 code repository):

```
import pandas as pd
import ccnlab.benchmarks.classical.core as cc

@cc.registry.register
class Acquisition_ContinuousVsPartial(cc.ClassicalConditioningExperiment):
    def __init__(self, n=64, prob=0.5):
        # Specify stimuli structure for each experimental group using the
        # abstract syntax.
        super().__init__({
            'continuous': cc.seq(
                cc.trial('A+'),
                repeat=n, name='train'
            ),
            'partial': cc.seq(
                cc.sample({ cc.trial('A+'): prob, cc.trial('A-'): 1 - prob }),
                repeat=n, name='train'
            ),
        })

        # Encode empirical results and configure how to plot.
        self.empirical_results = pd.DataFrame(
            columns=['group', 'session', 'A'],
            data=[...]
        )
        self.plots = [lambda df, ax: cc.plot_lines(df, ax=ax, x='session')]

        # Transform from raw model responses to same format as empirical results.
        def simulated_results(self):
            df = self.dataframe(lambda x: {
                'A': cc.conditioned_response(x['timesteps'], x['response'], ['A']),
            })
            return cc.trials_to_sessions(df, self.trials_per_session)
```

175 Abstract Syntax Library Each experiment presents a schedule of stimuli consisting of multiple
176 trials per group. To facilitate the specification of stimuli structure, we developed an abstract syntax
177 library that allows classical conditioning experiments to be expressed in a consistent way. By

178 composing a sequence of nodes, developers may specify the structure using an abstract syntax tree,
 179 which can then be compiled into the a sequence of trials, each consisting of multiple timesteps. The
 180 syntax closely conforms to standard classical conditioning notation, using the following nodes:

- 181 • Stimulus : Leaf node specifying the presentation of a stimulus (string), its magnitude (oat),
 182 and its start and end timesteps in a trial (ints).
- 183 • Trial : Compound node specifying a trial consisting of the CS (list of stimulus), CTX
 184 (string), and US (stimulus);
- 185 • Sample Compound node specifying probabilities with which to choose each of its children.
- 186 • Sequence Compound node specifying a sequence of nodes, how many times to repeat the
 187 sequence, and a name (used for naming different phases of the schedule).

188 Empirical Results The published work that the experiments simulate present their results in the
 189 form of summary statistics. Typically, the measure of interest is the conditioned response or a
 190 suppression ratio, and this measure is plotted over trials/sessions (line plots) or over groups (bar plots).
 191 For data collection, we relied on numerical tables in published work if they were available; otherwise,
 192 we digitally enlarged the plots and used a grid overlay to more precisely estimate the measure values.

193 Simulated Results In order to compare simulated results to the empirical results, the raw model
 194 responses must first be transformed into the same summary statistics as the empirical results. We
 195 are given a set of active conditioned stimuli, cs_t , and model responses, $response_t$ for each timestep
 196 $0 \leq t < T$ in a single trial.

197 For appetitive preparations, the conditioned response to a stimulus is the average response during
 198 the presentation of.

$$\text{ConditionedResponse}(x) = \frac{\sum_{t:cs_t=x} response_t}{\sum_{t:cs_t=x} 1}$$

199 For aversive preparations, the suppression ratio to a stimulus is the ratio of (reduced) responding
 200 during the presentation of compared to baseline responding. As described in Section 3.1, the
 201 abstract response value must be inverted to correspond to aversive CR behavior. We use the maximum
 202 response value for inversion as in Kutlu and Schmajuk [2012b].

$$\text{SuppressionRatio}(x) = \frac{\sum_{t:cs_t=x} (\max_t response_t) - response_t}{\sum_{t:cs_t=x} (\max_t response_t) - \max_t response_t}$$

203 Finally, after computing the measure for each trial, the measures are aggregated across subjects
 204 through averaging. If necessary, consecutive spans of trials are aggregated into sessions through
 205 averaging.

206 4 Baselines and Experiments

207 To illustrate how the benchmark can be used in practice, we used it to compare 3 classical conditioning
 208 baseline models from Gershman [2015]. For more details on the models and their parameters, see
 209 Appendix A.

- 210 • Rescorla-Wagner[Rescorla, 1972]: The predicted reward (US) is a linear combination of
 211 the input stimuli (CS), weighted by their associative weights. The weights are updated in
 212 proportion to the reward prediction error – the difference between the predicted and actual
 213 reward – and how active the stimuli are.
- 214 • Kalman Filter [Kakade, 2001]: A Bayesian extension of Rescorla-Wagner which learns
 215 the covariance of the weights in addition to their mean. The learning rate is dependent on
 216 the uncertainty encoded by the covariance.
- 217 • Temporal Difference Learning [Sutton, 1988]: A temporal extension of Rescorla-Wagner
 218 which predicts cumulative future reward instead of immediate reward only.

Figure 3: Plots for selected experiments. Models can be evaluated qualitatively by comparing plots for empirical and simulated results. Column 1: Empirical results from published work. Columns 2-4: Simulated results for each model. Plot coloring and notation are the same as Figure 2.

219 We evaluated the models based on how well they fit the empirical results for each experiment
220 according to the metrics in Section 3.1. Scores for all experiments are presented in Table 1, and scores
221 averaged across categories are presented in Table 2. We also plotted the empirical and simulated
222 results, for which a subset of experiments are shown in Figure 3.

223 Unsurprisingly, Rescorla-Wagner is able to account for phenomena it was designed to explain,
224 such as acquisition (Figure 3, Row 1), extinction (Row 2), external and conditioned inhibition
225 (Row 3), generalization with added and removed cues (Row 4), and overshadowing and forward
226 blocking (Row 5). Kalman Filter and Temporal Difference Learning are also able to account for these
227 phenomena well, since they are generalizations of Rescorla-Wagner. In addition, they each account
228 better for other phenomena, such as extinction of inhibition for Kalman Filter; and overexpectation,
229 superconditioning, and higher-order conditioning for Temporal Difference Learning, giving them
230 higher scores overall (Table 2). Notably, all models perform poorly on most experiments in the
231 benchmark, and even show negative correlations on a substantial number of experiments (Table 1).
232 This could be partially explained by the fact that model parameters were not tuned to each experiment,
233 although we found that performance did not change substantially with different parameter settings
234 (data not shown). We take this to highlight the limitations of these standard learning models which
235 are still widely used in neuroscience, suggesting a pressing need for the development and adoption of
236 more general theories of learning.

Table 1: Scores for all experiments. Models can be evaluated quantitatively by computing measures of t between empirical and simulated summary statistics. These scores use the Pearson correlation, except for experiments indicated by * which use ratio of ratios instead (see Section 3.1). Scores greater than 0.8 are highlighted in bold.

Category	Experiment	Rescorla-Wagner	Kalman Filter	Temporal Difference
Acquisition	ContinuousVsPartial	0.80	0.83	0.85
Extinction	ContinuousVsPartial	0.54	0.57	0.69
Generalization	NovelVsInhibitor	1.00	0.99	1.00
	AddVsRemove	0.60	0.75	0.60
Discrimination	ReinforcedVsNonreinforced	-0.88	-0.88	-0.89
	PositivePatterning	-0.82	0.88	0.89
	NegativePatterning	-0.64	-0.63	0.75
	NegativePatterningCommonCue	0.15	0.02	0.74
	NegativePatterningThreeCues	-0.76	-0.70	0.46
	Biconditional	0.23	0.33	0.68
	FeaturePositive	-0.30	-0.07	0.11
	FeatureNegative	0.33	0.42	0.28
Inhibition	InhibitorExtinction	-0.36	0.99	0.48
Competition	RelativeValidity *	0.00	0.00	0.00
	OvershadowingAndForwardBlocking	0.99	1.00	0.99
	Unblocking	-0.65	-0.65	-0.17
	BackwardBlocking *	0.17	0.12	0.77
	Overexpectation	-1.00	-0.99	0.87
	Superconditioning	-0.77	-0.65	0.88
PreExposure	LatentInhibitionVsPerceptualLearning	0.00	0.00	0.00
	USPreExposure	0.81	0.62	0.96
Transfer	Reacquisition	0.72	0.74	0.63
Recovery	LatentInhibition	0.00	0.01	0.00
	Overshadowing	0.83	0.78	0.62
	ExternalDisinhibition	0.69	0.58	0.40
	SpontaneousRecovery	0.97	0.93	0.56
	Renewal	0.00	0.00	0.00
	Reinstatement	-0.71	-0.70	-0.82
HigherOrder	SensoryPreconditioning *	0.00	0.00	0.05
	SecondOrderConditioning	0.01	0.17	0.49

Table 2: Scores for all categories. Averages across categories of the scores in Table 1. Scores greater than 0.8 are highlighted in bold.

Category	Rescorla-Wagner	Kalman Filter	Temporal Difference
Acquisition	0.80	0.83	0.85
Extinction	0.54	0.57	0.69
Generalization	0.80	0.87	0.80
Discrimination	-0.34	-0.08	0.38
Inhibition	-0.36	0.99	0.48
Competition	-0.21	-0.20	0.56
PreExposure	0.41	0.31	0.48
Transfer	0.72	0.74	0.63
Recovery	0.30	0.27	0.13
HigherOrder	0.01	0.09	0.27
Overall	0.27	0.44	0.53

237 5 Conclusion and Future Work

238 We presented CCNLab, an open-source benchmark for computational modeling of classical con-
239 ditioning. To the best of our knowledge, this is the first benchmark of its kind for evaluating and
240 comparing computational models in neuroscience and psychology. We hope that it will encourage the
241 development of broader neuroscientific theories of learning, as well as the development of powerful
242 artificial intelligence algorithms inspired by the brain. In the following sections, we suggest future
243 directions for the benchmark and for research using the benchmark.

244 **Benchmark Extensions** While the presented benchmark is a step forward for the rigorous evalu-
245 ation of computational classical conditioning models, there are a number of extensions that would
246 improve it. (1) Currently, it contains a selection of experiments demonstrating the most well estab-
247 lished phenomena. We expect the registry of experiments to grow over time with contributions from
248 the authors and the community, adding experiments that capture a wider breadth of phenomena, espe-
249 cially regarding multi-modal combination and temporal effects that are presently missing. (2) There
250 is significant diversity in the types of conditioning preparations reflected by the experiments. For
251 more a standardized comparison, it would be useful to capture the phenomena in a single preparation,
252 or show the same phenomena across multiple preparations. (3) Currently, we only allow a single US
253 and UR, but the model should likely be extended handle multiple. (4) While current experiments test
254 the fit of simulated and empirical behavioral data, it is ultimately important for models of classical
255 conditioning to also capture neural data.

256 **Research Directions** (1) From our experiments it is evident that computational models of classical
257 conditioning still fail to explain a breadth of phenomena. We hope that the introduction of this
258 benchmark will encourage future research to consider a broader range of phenomena. (2) We hope
259 that CCNLab is only the first step towards widespread benchmarking in computational neuroscience.
260 In the future, we expect that benchmarks for different domains will be added, for instance to capture
261 the diverse phenomena of instrumental conditioning and short-term/working memory [Oberauer et al.,
262 2018]. (3) Finally, we believe that it will continue to be productive for the fields of artificial intelli-
263 gence and computational neuroscience to build on each other's insights, simultaneously approaching
264 the project of intelligence from both a scientific and engineering standpoint.

265 References

- 266 I. Akkaya, M. Andrychowicz, M. Chociej, M. Litwin, B. McGrew, A. Petron, A. Paino, M. Plappert, G. Powell,
267 R. Ribas, et al. Solving rubik's cube with a robot hand. *arXiv preprint arXiv:1910.07113*, 2019.
- 268 E. Alonso and N. A. Schmajuk. Special issue on computational models of classical conditioning guest editors'
269 introduction. *Learning & Behavior* 40(3):231–240, 2012.
- 270 W. Bellingham, K. Gillette-Bellingham, and E. Kehoe. Summation and con guration in patterning schedules
271 with the rat and rabbit. *Animal Learning & Behavior* 13:152–164, 1985.
- 272 S. Bottjer. Conditioned approach and withdrawal behavior in pigeons: Effects of a novel extraneous stimulus
273 during acquisition and extinction. *Learning and Motivation* 13:44–67, 1982.
- 274 S. Brandon, E. H. Vogel, and A. R. Wagner. A componential view of con gural cues in generalization and
275 discrimination in pavlovian conditioning. *Behavioural Brain Research* 110:67–72, 2000.
- 276 G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba. Openai gym.
277 *arXiv preprint arXiv:1606.01540*, 2016.
- 278 W. Brogden. Sensory pre-conditioning. *Journal of Experimental Psychology* 25:323–332, 1939.
- 279 R. R. Bush and F. Mosteller. A mathematical model for simple learning. *Psychological review* 58(5):313, 1951.
- 280 M. M. Campolattaro, K. M. Schnitker, and J. H. Freeman. Changes in inhibition during differential eyeblink
281 conditioning with increased training. *Learn Behav* 36(2):159–165, May 2008.
- 282 W. Dabney, Z. Kurth-Nelson, N. Uchida, C. K. Starkweather, D. Hassabis, R. Munos, and M. Botvinick. A
283 distributional code for value in dopamine-based reinforcement learning. *Nature* 577(7792):671–675, 2020.
- 284 J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database.
285 In 2009 IEEE conference on computer vision and pattern recognition. pages 248–255. Ieee, 2009.

286 A. Dickinson, G. Hall, and N. Mackintosh. Surprise and the attenuation of blocking. *Journal of Experimental*
287 *Psychology: Animal Behavior Processes* 2:313–322, 1976.

288 D. Durstewitz, G. Koppe, and H. Toutounji. Computational models as statistical tools. *Current Opinion in*
289 *Behavioral Sciences* 1:93–99, 2016.

290 O. Ertugrul and M. Tagluk. A review of computational classical conditioning models. *American Journal of*
291 *Psychology and Behavioral Sciences* 2:36–44, 03 2015.

292 S. J. Gershman. A unifying probabilistic view of associative learning. *PLoS Comput Biol* 11(11):e1004567,
293 2015.

294 S. J. Gershman. Context-dependent learning and causal structure. *Economic Bulletin & Review* 24:557–565,
295 2017.

296 S. J. Gershman. Just looking: the innocent eye in neuroscience. *Neuron* 2021.

297 N. Grahame, R. Barnett, L. M. Gunther, and R. Miller. Latent inhibition as a performance decrement resulting from
298 context—context associations. *Animal Learning & Behavior* 22:395–408, 1994.

299 T. Haarnoja, A. Zhou, K. Hartikainen, G. Tucker, S. Ha, J. Tan, V. Kumar, H. Zhu, A. Gupta, P. Abbeel, et al.
300 Soft actor-critic algorithms and applications. *arXiv preprint arXiv:1812.05905* 2018.

301 J. A. Harris, M. L. Jones, G. K. Bailey, and R. F. Westbrook. Contextual control over conditioned responding in
302 an extinction paradigm. *J Exp Psychol Anim Behav Processes* 26(2):174–185, Apr 2000.

303 D. Hassabis, D. Kumaran, C. Summerfield, and M. Botvinick. Neuroscience-inspired artificial intelligence. *Neuron*
304 95(2):245–258, 2017.

305 K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *Proceedings of the IEEE*
306 *conference on computer vision and pattern recognition*, pages 770–778, 2016.

307 P. Holland. Differential effects of reinforcement of an inhibitory feature after serial and simultaneous feature
308 negative discrimination training. *Journal of experimental psychology. Animal behavior processes* 1:461–475,
309 461–75, 1984.

310 P. C. Holland and G. D. Fox. Effects of hippocampal lesions in overshadowing and blocking procedures. *Behav*
311 *Neurosci* 117(3):650–656, Jun 2003.

312 E. Jonas and K. P. Kording. Could a neuroscientist understand a microprocessor? *PLoS computational biology*
313 13(1):e1005268, 2017.

314 P. D. S. Kakade. Explaining away in weight space. *Advances in neural information processing systems* 14:451,
315 2001.

316 L. Kamin. Trace conditioning of the conditioned emotional response. *Journal of comparative and physiological*
317 *psychology* 54:149–53, 1961.

318 T. Kluyver, B. Ragan-Kelley, F. Pérez, B. Granger, M. Bussonnier, J. Frederic, K. Kelley, J. Hamrick, J. Grout,
319 S. Corlay, P. Ivanov, D. Avila, S. Abdalla, and C. Willing. Jupyter notebooks – a publishing format for
320 reproducible computational workflows. In F. Loizides and B. Schmidt, editors, *Positioning and Power in*
321 *Academic Publishing: Players, Agents and Agencies*, pages 87 – 90. IOS Press, 2016.

322 N. Kriegeskorte and P. K. Douglas. Cognitive computational neuroscience. *Nature neuroscience* 21(9):
323 1148–1160, 2018.

324 M. G. Kutlu and N. Schmajuk. Deactivation and reactivation of the inhibitory power of a conditioned inhibitor:
325 Testing the predictions of an attentional-associative model. *Learning & Behavior* 40:83–97, 2012a.

326 M. G. Kutlu and N. A. Schmajuk. Solving pavlov's puzzle: Attentional, associative, and flexible conditional
327 mechanisms in classical conditioning. *Learning & Behavior* 40(3):269–291, 2012b.

328 B. M. Lake, T. D. Ullman, J. B. Tenenbaum, and S. J. Gershman. Building machines that learn and think like
329 people. *Behavioral and brain sciences* 40, 2017.

330 Y. LeCun, Y. Bengio, et al. Convolutional networks for images, speech, and time series. *Handbook of brain*
331 *theory and neural networks* 3:361(10):1995, 1995.

332 D. Levenstein, V. A. Alvarez, A. Amarasingham, H. Azab, R. C. Gerkin, A. Hasenstaub, R. Iyer, R. B. Jolivet,
333 S. Marzen, J. D. Monaco, et al. On the role of theory and modeling in neuroscience. *arXiv preprint*
334 *arXiv:2003.13825*2020.

335 S. W. Linderman and S. J. Gershman. Using computational theory to constrain statistical models of neural data.
336 *Current opinion in neurobiology*46:14–24, 2017.

337 R. Lubow, B. Rifkin, and M. Alek. The context effect: The relationship between stimulus preexposure and
338 environmental preexposure determines subsequent learning. *Journal of Experimental Psychology: Animal*
339 *Behavior Processes*2:38–47, 1976.

340 W. J. Ma and B. Peters. A neural network walks into a lab: towards using deep nets as models for human
341 behavior. *arXiv preprint arXiv:2005.02181*2020.

342 L. Matzel, T. Schachtman, and R. Miller. Recovery of an overshadowed association achieved by extinction of
343 the overshadowing stimulus. *Learning and Motivation*16:398–412, 1985.

344 R. Miller and H. Matute. Biological significance in forward and backward blocking: resolution of a discrepancy
345 between animal conditioning and human causal judgment. *Journal of experimental psychology. General*15
346 4:370–86, 1996.

347 V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K.
348 Fidjeland, G. Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature* 518(7540):
349 529–533, 2015.

350 P. R. Montague, P. Dayan, and T. J. Sejnowski. A framework for mesencephalic dopamine systems based on
351 predictive hebbian learning. *Journal of neuroscience*16(5):1936–1947, 1996.

352 Y. Niv. Reinforcement learning in the brain. *Journal of Mathematical Psychology*53(3):139–154, 2009.

353 K. Oberauer, S. Lewandowsky, E. Awh, G. D. A. Brown, A. Conway, N. Cowan, C. Donkin, S. Farrell, G. J. Hitch,
354 M. J. Hurlstone, W. J. Ma, C. C. Morey, D. E. Nee, J. Schwenke, E. Vergauwe, and G. Ward. Benchmarks for
355 models of short-term and working memory. *Psychol Bull* 144(9):885–958, 09 2018.

356 P. I. Pavlov. Conditioned reflexes: an investigation of the physiological activity of the cerebral cortex. 1927.

357 J. M. Pearce and G. Hall. A model for pavlovian learning: variations in the effectiveness of conditioned but not
358 of unconditioned stimuli. *Psychological review*87(6):532, 1980.

359 E. Redhead and J. Pearce. Similarity and discrimination learning. *Quarterly Journal of Experimental Psychology*
360 48:46 – 66, 1995.

361 E. Redhead and J. Pearce. Some factors that determine the influence of a stimulus that is irrelevant to a
362 discrimination. *Journal of Experimental Psychology: Animal Behavior Processes*24:123–135, 1998.

363 R. Rescorla. Reduction in the effectiveness of reinforcement after prior excitatory conditioning. *Learning and*
364 *Motivation*, 1:372–381, 1970.

365 R. Rescorla. Variation in the effectiveness of reinforcement and nonreinforcement following prior inhibitory
366 conditioning. *Learning and Motivation*2:113–123, 1971.

367 R. A. Rescorla. A theory of pavlovian conditioning: Variations in the effectiveness of reinforcement and
368 nonreinforcement. *Current research and theory* pages 64–99, 1972.

369 R. A. Rescorla. Spontaneous recovery. *Learn Mem*, 11(5):501–509, 2004.

370 R. A. Rescorla and C. D. Heth. Reinstatement of fear to an extinguished conditioned stimulus. *Psychol*
371 *Anim Behav Process*1(1):88–96, Jan 1975.

372 S. Ricker and M. Bouton. Reacquisition following extinction in appetitive conditioning. *Animal Learning &*
373 *Behavior* 24:423–436, 1996.

374 R. Ross and P. Holland. Conditioning of simultaneous and serial feature-positive discriminations. *Animal*
375 *Learning & Behavior* 9:293–303, 1981.

376 M. A. Saavedra. Pavlovian compound conditioning in the rat. *Learning and Motivation*6:314–326, 1975.

377 A. Saxe, S. Nelli, and C. Summerfield. If deep learning is the answer, what is the question? *Nature Reviews*
378 *Neuroscience* pages 1–13, 2020.

379 J. Schrittwieser, I. Antonoglou, T. Hubert, K. Simonyan, L. Sifre, S. Schmitt, A. Guez, E. Lockhart, D. Hassabis,
380 T. Graepel, et al. Mastering atari, go, chess and shogi by planning with a learned model. *Nature* 588(7839):
381 604–609, 2020.

382 W. Schultz, P. Dayan, and P. R. Montague. A neural substrate of prediction and reward. *Science* 275(5306):
383 1593–1599, 1997.

384 D. Silver, J. Schrittwieser, K. Simonyan, I. Antonoglou, A. Huang, A. Guez, T. Hubert, L. Baker, M. Lai,
385 A. Bolton, et al. Mastering the game of go without human knowledge. *Nature* 550(7676):354–359, 2017.

386 B. F. Skinner. Two types of conditioned reflex and a pseudo type. *The Journal of General Psychology* 2(1):
387 66–77, 1935.

388 K. L. Stachenfeld, M. M. Botvinick, and S. J. Gershman. The hippocampus as a predictive map. *Nature
389 neuroscience* 20(11):1643, 2017.

390 C. K. Starkweather, B. M. Babayan, N. Uchida, and S. J. Gershman. Dopamine reward prediction errors reflect
391 hidden-state inference across time. *Nature neuroscience* 20(4):581–589, 2017.

392 R. S. Sutton. Learning to predict by the methods of temporal difference. *Machine learning* 3(1):9–44, 1988.

393 R. S. Sutton and A. G. Barto. Time-derivative models of pavlovian reinforcement. 1990.

394 R. S. Sutton and A. G. Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

395 E. L. Thorndike. Animal intelligence: an experimental study of the associative processes in animals. *Animal
396 Psychological Review: Monograph Supplement* 2(4):i, 1898.

397 M. Toromanoff, E. Wirbel, and F. Moutarde. End-to-end model-free reinforcement learning for urban driving
398 using implicit affordances. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern
399 Recognition*, pages 7153–7162, 2020.

400 A. Wagner, L. Siegel, and G. Fein. Extinction of conditioned fear as a function of percentage of reinforcement.
401 *Journal of comparative and physiological psychology* 69:160–4, 03 1967. doi: 10.1037/h0024172.

402 A. R. Wagner, F. Logan, K. Haberlandt, and T. Price. Stimulus selection in animal discrimination learning.
403 *Journal of experimental psychology* 76 2:171–80, 1968.

404 D. L. Yamins, H. Hong, C. F. Cadieu, E. A. Solomon, D. Seibert, and J. J. DiCarlo. Performance-optimized
405 hierarchical models predict neural responses in higher visual cortex. *Proceedings of the national academy of
406 sciences* 111(23):8619–8624, 2014.

407 H. Yin, R. C. Barnett, and R. R. Miller. Second-order conditioning and Pavlovian conditioned inhibition:
408 operational similarities and differences. *Exp Psychol Anim Behav Processes* 20(4):419–428, Oct 1994.

409 C. L. Zimmer-Hart and R. Rescorla. Extinction of pavlovian conditioned inhibition. *Journal of comparative and
410 physiological psychology* 86 5:837–45, 1974.

411 Checklist

- 412 1. For all authors...
- 413 (a) Do the main claims made in the abstract and introduction accurately reflect the paper's
414 contributions and scope? [Yes]
- 415 (b) Did you describe the limitations of your work? [Yes] See Section 5.
- 416 (c) Did you discuss any potential negative societal impacts of your work? [N/A]
- 417 (d) Have you read the ethics review guidelines and ensured that your paper conforms to
418 them? [Yes]
- 419 2. If you are including theoretical results...
- 420 (a) Did you state the full set of assumptions of all theoretical results? [N/A]
- 421 (b) Did you include complete proofs of all theoretical results? [N/A]
- 422 3. If you ran experiments...
- 423 (a) Did you include the code, data, and instructions needed to reproduce the main experi-
424 mental results (either in the supplemental material or as a URL)? [Yes] See Section 1
425 and documentation in the GitHub repository.

- 426 (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they
427 were chosen)? [Yes] See Appendix B.
- 428 (c) Did you report error bars (e.g., with respect to the random seed after running experi-
429 ments multiple times)? [No] Empirical results gathered from published work mostly
430 did not have error bars, and simulated results are reported in same format as empirical
431 results to facilitate direct comparison.
- 432 (d) Did you include the total amount of compute and the type of resources used (e.g., type
433 of GPUs, internal cluster, or cloud provider)? [Yes] See Appendix B.
- 434 4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
- 435 (a) If your work uses existing assets, did you cite the creators? [Yes] See Appendix A.
- 436 (b) Did you mention the license of the assets? [Yes] MIT License, see Section 1.
- 437 (c) Did you include any new assets either in the supplemental material or as a URL? [Yes]
438 URL provided to GitHub repository, see Section 1.
- 439 (d) Did you discuss whether and how consent was obtained from people whose data you're
440 using/curating? [N/A]
- 441 (e) Did you discuss whether the data you are using/curating contains personally identi able
442 information or offensive content? [N/A] No PII or offensive content.
- 443 5. If you used crowdsourcing or conducted research with human subjects...
- 444 (a) Did you include the full text of instructions given to participants and screenshots, if
445 applicable? [N/A]
- 446 (b) Did you describe any potential participant risks, with links to Institutional Review
447 Board (IRB) approvals, if applicable? [N/A]
- 448 (c) Did you include the estimated hourly wage paid to participants and the total amount
449 spent on participant compensation? [N/A]

450 A Experiment Descriptions

451 Acquisition_ContinuousVsPartial [Wagner et al., 1967]: With repeated CS-US pairings, CS
452 elicits CR that increases in magnitude and frequency with further reinforcement. Partial reinforcement
453 leads to slower acquisition and a lower conditioning asymptote. Data: rat, fear conditioning, CS
454 visual + US shock auditory startle.

455 Extinction_ContinuousVsPartial [Wagner et al., 1967]: When CS-US pairings are followed
456 by presentations of CS alone or unpaired CS and US, the CR decreases. Partial reinforcement leads
457 to slower extinction and a higher conditioning asymptote. Data: rat, fear conditioning, CS visual,
458 auditory + US shock bar pressing.

459 Generalization_NovelVsInhibitor [Kutlu and Schmajuk, 2012a]: Adding a novel stimulus C
460 to a trained stimulus A results in a smaller decrease in CR than does adding a conditioned inhibitor X
461 to a trained stimulus A. Data: human, value prediction, CS visual + US value prediction.

462 Generalization_AddVsRemove [Brandon et al., 2000]: Adding a cue to a trained compound results
463 in a smaller decrease in CR than does removing a cue from a trained compound. Data: rabbit, eyeblink
464 conditioning, CS visual, auditory, tactile + US shock eyeblink.

465 Discrimination_ReinforcedVsNonreinforced [Campolattaro et al., 2008]: A reinforced CS
466 elicits signi cantly greater CR than a non-reinforced CS. Data: rat, eyeblink conditioning, CS visual,
467 auditory + US shock eyeblink.

468 Discrimination_PositivePatterning [Bellingham et al., 1985]: Reinforced AB+ intermixed
469 with non-reinforced A- and B- results in responding to AB that is stronger than the sum of the
470 individual responses to A and B. Data: rat, appetitive conditioning, CS visual, auditory + US water
471 drinking.

472 Discrimination_NegativePatterning [Bellingham et al., 1985]: Non-reinforced AB- inter-
473 mixed with reinforced A+ and B+ results in responding to AB that is weaker than the sum of the
474 individual responses to A and B. Data: rat, appetitive conditioning, CS visual, auditory + US water
475 drinking.

476 Discrimination_NegativePatterningCommonCue [Redhead and Pearce, 1998]: Adding a com-
477 mon cue C to negative patterning decreases discrimination. Data: pigeon, appetitive conditioning, CS
478 visual + US food feeding.

479 Discrimination_NegativePatterningThreeCues [Redhead and Pearce, 1995]: Non-reinforced
480 ABC- intermixed with reinforced A+ and BC+ results in responding to ABC that is weaker than the
481 sum of the individual responses to A and BC. Data: pigeon, appetitive conditioning, CS visual + US
482 food feeding.

483 Discrimination_Biconditional [Saavedra, 1975]: Biconditional discrimination between com-
484 pounds (AC+/BD+ vs. AD-/BC-, where no single CS predicts reinforcement or non-reinforcement)
485 is possible but harder than component discrimination between compounds (AC+/AD+ vs. BC-/BD-,
486 where A and B predict reinforcement and non-reinforcement, respectively). Data: rabbit, eyeblink
487 conditioning, CS visual, auditory + US shock eyeblink.

488 Discrimination_FeaturePositive [Ross and Holland, 1981]: Reinforced BA+, alternated with
489 non-reinforced A-, results in stronger responding to BA than A alone. In the simultaneous case
490 (BA+), B gains an excitatory association with the US; in the serial case (B / A+), B does not gain
491 an excitatory association with the US. Data: rat, appetitive conditioning, CS visual, auditory + US
492 food head jerk.

493 Discrimination_FeatureNegative [Holland, 1984]: Non-reinforced BA-, alternated with rein-
494 forced A+, results in weaker responding to BA than A alone. In the simultaneous case (BA-), B gains
495 an inhibitory association with the US; in the serial case (B / A-), B does not gain an inhibitory
496 association with the US. Data: rat, fear conditioning, CS visual, auditory + US shock bar pressing.

497 Inhibition_InhibitorExtinction [Zimmer-Hart and Rescorla, 1974]: Inhibitory conditioning
498 to X trained via A+ / AX- is extinguished by AX+ presentations. Data: rat, fear conditioning, CS
499 visual, auditory + US shock bar pressing.

500 Competition_RelativeValidity [Wagner et al., 1968]: Conditioning to X is weaker when train-
501 ing consists of pairing X with stimuli A/B that are correlated with reinforcement, than when training
502 consists of pairing X with stimuli A/B that are not correlated. Data: rat, appetitive conditioning, CS
503 visual, auditory + US food bar pressing.

504 Competition_OvershadowingAndForwardBlocking [Holland and Fox, 2003]: Training AB+
505 results in weaker conditioning to A than training A+ alone (overshadowing). Training B+ / AB+
506 results in even weaker conditioning to A (forward blocking). Data: rat, appetitive conditioning, CS
507 visual, auditory + US food feeding.

508 Competition_Unblocking [Dickinson et al., 1976]: In forward blocking B / AB+, increasing or
509 decreasing the US during AB presentation can increase responding to the blocked A. Data: rat, fear
510 conditioning, CS visual, auditory + US shock bar pressing.

511 Competition_BackwardBlocking [Miller and Matute, 1996]: Training AB+ / B+ results in
512 weaker conditioning to A than training A+ alone (backward blocking). Data: rat, fear conditioning,
513 CS auditory + US shock drinking.

514 Competition_Overexpectation [Rescorla, 1970]: Training A+ / B+ / AB+ results in lower
515 conditioning to A than without the AB+ compound. Data: rat, fear conditioning, CS visual, auditory
516 + US shock bar pressing.

517 Competition_Superconditioning [Rescorla, 1971]: Training B- / AB+ (superconditioning)
518 results in higher conditioning to A than training AB+ only (overshadowing) and yet higher than
519 training B+ / AB+ (forward blocking). Data: rat, fear conditioning, CS visual, auditory + US shock
520 bar pressing.

521 PreExposure_LatentInhibitionVsPerceptualLearning [Lubow et al., 1976]: Pre-exposure
522 of CS A- before A+ pairings can result in reduced responding (latent inhibition) or increased
523 responding (perceptual learning) depending if the context is the same or different, respectively. Data:
524 rat, appetitive conditioning, CS olfactory + US food feeding.

525 PreExposure_USPreExposure [Kamin, 1961]: Pre-exposure of US + before A+ pairings results in
526 decreased responding. Data: rat, fear conditioning, CS auditory + US shock bar pressing.

527 **Transfer_Reacquisition** [Ricker and Bouton, 1996]: Following acquisition A+ and extinction A-,
528 A+ pairings can result in faster or slower reacquisition depending on the number of extinction trials.
529 Data: rat, appetitive conditioning, CS visual, auditory + US food feeding.

530 **Recovery_LatentInhibition** [Grahame et al., 1994]: Extensive exposure to the context after
531 training results in reduction of latent inhibition. Data: rat, fear conditioning, CS auditory + US shock
532 drinking.

533 **Recovery_Overshadowing** [Matzel et al., 1985]: Extinction of B after overshadowing training AB+
534 results in increased responding to A. Data: rat, fear conditioning, CS visual, auditory + US shock
535 drinking.

536 **Recovery_ExternalDisinhibition** [Bottjer, 1982]: Presenting a novel stimulus immediately
537 before a previously extinguished CS might produce renewed responding. Data: pigeon, appetitive
538 conditioning, CS visual + US food feeding.

539 **Recovery_SpontaneousRecovery** [Rescorla, 2004]: Presenting the CS some time after the subject
540 has stopped responding might yield renewed responding. Data: rat, appetitive conditioning, CS
541 visual, auditory + US food feeding.

542 **Recovery_Renewal** [Harris et al., 2000]: After extinction, presentation of the CS in a novel context
543 might yield renewed responding. Data: rat, fear conditioning, CS auditory + US shock freezing.

544 **Recovery_Reinstatement** [Rescorla and Heth, 1975]: After extinction, presentation of the US in
545 the context might yield renewed responding. Data: rat, fear conditioning, CS auditory + US shock
546 bar pressing.

547 **HigherOrder_SensoryPreconditioning** [Brogden, 1939]: When AB- pairings are followed by
548 A+ pairings, presentation of B may generate a response. Data: dog, reflex conditioning, CS visual,
549 auditory + US shock flexion.

550 **HigherOrder_SecondOrderConditioning** [Yin et al., 1994]: When A+ pairings are followed by
551 AB- pairings, presentation of B may generate a response. The number of BA- pairings determines
552 whether second-order conditioning or conditioned inhibition is obtained. Data: rat, fear conditioning,
553 CS auditory + US shock drinking.

554 **B Baseline Model Details**

555 We implemented three standard classical conditioning models as baselines following Gershman
556 [2015]. For all models, we used one-hot vector representations where the input is a conjunction of
557 the CS and the context [Gershman, 2017]. We use value v_t as the response value, as conditioned
558 responding to a stimulus is assumed to be proportional to the value for that stimulus.

559 For each experiment, we simulated 20 subjects for each model. All experiments were performed on a
560 personal computer with 16 GB of RAM.

561 **B.1 Rescorla-Wagner**

562 The predicted reward (US) at time t , v_t , is a linear combination of the input stimuli, \mathbf{x}_t , weighted by
563 their associative weights, \mathbf{w}_t :

$$v_t = \mathbf{w}_t^\top \mathbf{x}_t \quad (1)$$

564 Updating is governed by:

$$\mathbf{w}_{t+1} = \mathbf{w}_t + \delta_t \mathbf{x}_t \quad (2)$$

565 where the prediction error, δ_t , is the difference between the predicted and the actual reward:

$$\delta_t = r_t - v_t \quad (3)$$

566 Following Gershman [2015], we set the learning rate to $\alpha = 0.3$.

567 **B.2 Kalman Filter**

568 In a probabilistic interpretation of Rescorla-Wagner, the weights are assumed to be evolving according
 569 to a linear Gaussian dynamical system (LDS) [Gershman, 2015]:

$$\mathbf{w}_0 \sim N(\mathbf{0}; \frac{2}{w}\mathbf{I}) \quad (4)$$

$$\mathbf{w}_n \sim N(\mathbf{w}_{n-1}; \frac{2}{w}\mathbf{I}) \quad (5)$$

$$r_n \sim N(v_n; \frac{2}{r}) \quad (6)$$

570 This induces a posterior over the weights which can be inferred using Kalman filtering:

$$\hat{\mathbf{w}}_{n+1} = \hat{\mathbf{w}}_n + \mathbf{k}_n r_n \quad (7)$$

$$\hat{\Sigma}_{n+1} = \hat{\Sigma}_n - \mathbf{k}_n \mathbf{x}_n^\top (\hat{\Sigma}_n + \frac{2}{r}\mathbf{I}) \quad (8)$$

571 where the learning rate corresponds the Kalman gain:

$$\mathbf{k}_n = \frac{(\hat{\Sigma}_n + \frac{2}{r}\mathbf{I})\mathbf{x}_n}{\mathbf{x}_n^\top (\hat{\Sigma}_n + \frac{2}{r}\mathbf{I})\mathbf{x}_n + \frac{2}{r}} \quad (9)$$

572 and the initial mean and covariance are $\hat{\mathbf{w}}_0 = \mathbf{0}$, $\hat{\Sigma}_0 = \frac{2}{w}\mathbf{I}$.

573 Following Gershman [2015], we set the diffusion variance to $\frac{2}{w} = 0.01$, the noise variance to $\frac{2}{r} = 1$
 574 and the prior variance to $\frac{2}{w} = 1$.

575 **B.3 Temporal Difference Learning**

576 Temporal difference learning models seek to learn the expected discounted sum of future rewards:

$$V(\mathbf{x}_t) = \mathbb{E} \sum_{k=0}^{\infty} \gamma^k r_{t+k} \quad (10)$$

577 Assuming the value is approximated as a linear combination of the stimuli, similarly to Rescorla-
 578 Wagner, $V(\mathbf{x}_t) = \mathbf{w}_t^\top \mathbf{x}_t$, the associative weights are updated according to:

$$\hat{\mathbf{w}}_{t+1} = \hat{\mathbf{w}}_t + \delta_t \mathbf{x}_t \quad (11)$$

579 where the prediction error, δ_t , takes into account the future discounted rewards:

$$\delta_t = r_t + \gamma \hat{\mathbf{w}}_t^\top \mathbf{x}_{t+1} - \hat{\mathbf{w}}_t^\top \mathbf{x}_t \quad (12)$$

580 Following Gershman [2015], we set the discount factor to $\gamma = 0.98$ and the learning rate to $\alpha = 0.3$.
 581 In order to extend the stimulus representation across time, we used the complete serial compound
 582 representation [Sutton and Barto, 1990].