Computational Cognitive Systems

Anndischeh Mostafavi

Coursework: INM703 – 2024–2025

Typeset using LaTeX

1 The Church-Turing Thesis and the Computational View of Cognition

As discussed in lecture session 3 of the *Cognitive Science course* (Modragon 2024), The Church–Turing Thesis is a conjecture (not a formal theorem) that proposes a deep equivalence between:

- The informal notion of "what humans can compute" through effective procedures (i.e., step-by-step logical reasoning or calculation).
- The formal definition of computation based on Turing Machines (TMs) or lambda calculus.

Referring to above lecture, "It is not that [Turing] defined the mind as a computer machine, but that the machine was defined so as to satisfy how human calculation works"(Modragon 2024), this means that TMs were constructed to model human mental operations in a mechanical form. In other words, what the human mind can compute, the Turing Machine can simulate.

"If the Turing thesis is true, then any effective calculation method (human calculation) is comparable to the formal definitions of computation." (Modragon 2024) , this is crucial for cognitive science because it allows us to model the mind as a computational system. This leads directly to the Computational Theory of Mind, which claims: "The mind is a computational device."

For example: Consider how humans solve math problems. When you multiply 23×17 using pen and paper, you're following a systematic, rule-based procedure. This is an "effective method" — and exactly what the Church–Turing Thesis is about: If a human can do it by following steps, a Turing Machine (and thus a computer) can do it too.

This idea generalizes to cognitive processes such as:

- Language processing (e.g., parsing grammar),
- Problem-solving (e.g., means-end analysis),
- Memory retrieval (e.g., recall based on cues).

All of these can be simulated algorithmically, and thus fall within the domain defined by the Church–Turing framework.

TMs (along with other equivalent systems) set the boundaries of algorithmic computation. This means: any problem that cannot be computed by a Turing Machine is not algorithmically solvable — by humans or computers. This has a dual implication (Eberbach et al. 2004):

- Computers are limited to the same kinds of processes that humans can compute algorithmically.
- Humans, in turn, are also limited by what TMs (and equivalent formal systems like lambda calculus) can compute.

This gives rise to A parallelism between the human brain and the notion of computability.

C-T lays the base for the computer metaphor of the brain and, thus, for AI.

This is the idea that cognition can be explained as information processing, like what a computer does. This metaphor is foundational in:

- Classical cognitive architectures like ACT-R and SOAR,

- Symbolic AI, where mental states are represented as symbols,
- Connectionist models (like neural networks),

which still operate within computational (Turing-equivalent) boundaries.

Let's take a simplified model of human decision-making. Imagine a person choosing what to eat for dinner. A basic cognitive model might say:

- If I'm tired, I prefer fast food.
- If I'm on a diet, I choose salad.
- If it's Friday, I treat myself.

This rule-based decision process can be expressed as logical IF–THEN rules. These rules can be:

- Encoded in a program,
- Simulated on a Turing Machine (or modern computer),
- Used in cognitive modeling software.

This reflects how computational cognitive systems work — building models that simulate human reasoning.

Finally, this is not a theorem. It could, however, be disproved by showing an effective procedure that cannot be computed by a TM (Goldin & Wegner 2005). we notice:

- The Church–Turing Thesis has not been formally proven because the term "effective procedure" is informal.
- If someone discovers a mental ability that is effective (repeatable, mechanical) but not Turing-computable, the thesis would be disproven.

This leads to ongoing debates in cognitive science:

- Are intuition, consciousness, or creativity computable?
- Can the full richness of human thought be modeled algorithmically?

2 Modern Views of Pavlovian Learning and Associative Structures: A Comparison with the PDP Framework of Rumelhart, Hinton, and McClelland (1987)

As discussed in lecture sessions 1, 4, and 6 of the *Cognitive Science course* (Modragon 2024), Associative learning structures describe how organisms learn relationships between events and actions, ranging from simple stimulus associations to complex goal-directed behaviors. *Rumelhart, Hinton*, and *McClelland (1987)* define specific paradigms of learning within their "Parallel Distributed Processing" framework, and a comparison reveals how these theoretical models relate to the empirical findings and modern interpretations of associative learning.

Traditionally, Pavlovian conditioning (PC), shown in Figure1 was understood as a relatively permanent change in behavior resulting from repeated pairings of an initially neutral conditioned stimulus (CS) with an unconditioned stimulus (US) that elicits an unconditioned response (UR). The consequence of these pairings is the formation of an association between the stimuli, making the CS a predictor of the US and capable of generating a conditioned response (CR).

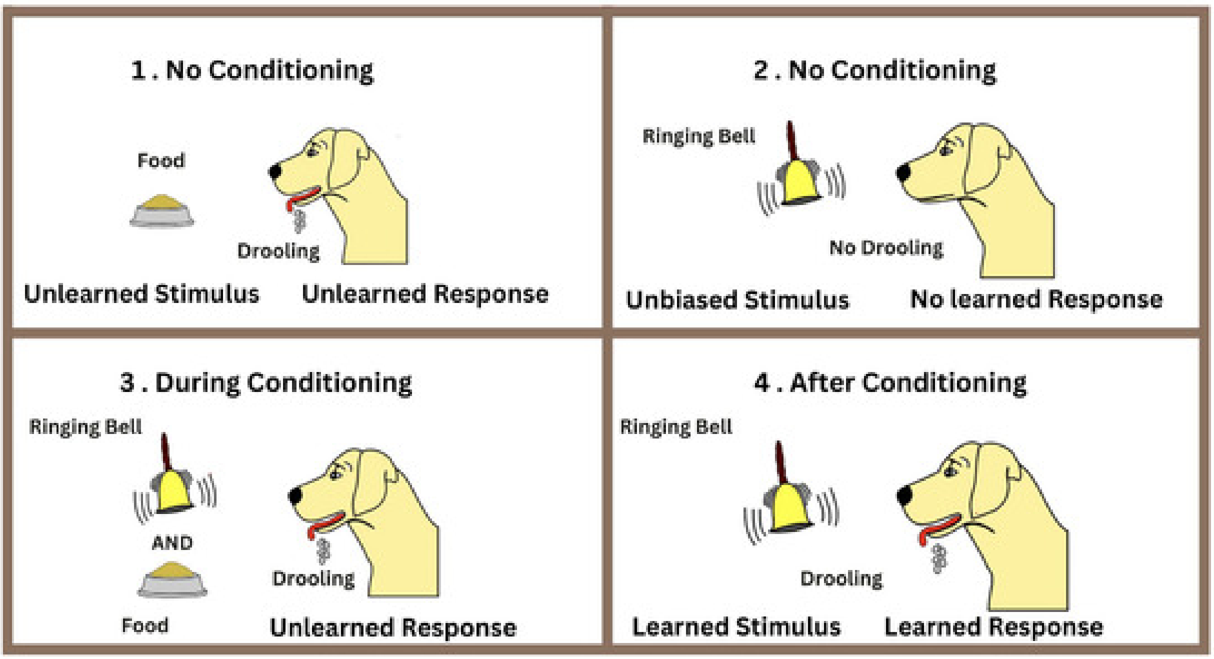


Fig. 1: Pavlov's experiment(Cambiaghi & Sacchetti 2015).

However, the modern understanding significantly extends this view:

- Behavior as an Index, Not Content: Research shows that observable behavior, such as salivation, is an **accessory** or **consequence** of learning, not the content of learning itself. It serves as a useful index to measure learning, but learning can occur even without an overt response.
- S-S Learning: Pavlovian conditioning is primarily understood as S-S (Stimulus-Stimulus) learning. This means associations are formed between mental representations of stimuli, not directly between a stimulus and a response. Any two stimuli can potentially be associated, without one needing to be motivationally relevant.
- Beyond Contiguity: Temporal and spatial contiguity are neither sufficient nor required for an association to be established. The predicting stimulus must convey **information**. For example, blocking, where a stimulus paired with an already informative stimulus does not become a predictor, demonstrates that contiguity alone is not enough. Conversely, mediated learning and trace conditioning show learning can occur without physical contiguity.

What Pavlovian Learning Accounts For: Modern PC accounts for various cognitive processes:

- Learning a Representation / Pattern Completion: It enables forming a complete mental representation from partial cues, such as inferring “dog” from “ears-muzzle-fangs” or “Sherlock Holmes” from “London”. This is akin to filling in missing pieces of a puzzle.
- Forming Predictive Maps of Relational Learning: It allows for the creation of predictive knowledge about how events relate in the environment, like “sand” predicting “sea” or “mangrove” predicting “saline water”.
- Learning Causal Relationships: It helps in understanding temporal dependencies and causal links between environmental events, such as “lightning” predicting “thunder”.
- Creating Higher-Order Relationships/Associative Structures: It facilitates more complex associations where the meaning of one relationship is modulated by another, for example, distinguishing between “drunk driving leading to danger” versus “sober driving leading to danger”.
- Learning About Neutral Cues: Associations can be formed between ”neutral” stimuli (S1 and S2) that do not inherently produce a strong response, like “bus” associated with “red,” “London,” or “Piccadilly”. This learning can be “silent” (not immediately observable).
- Learning About Absent Cues: Associations can be formed from memory, meaning stimuli do not need to be physically present. Sensory preconditioning, where an association (e.g., Rose-tea – Honey) is formed, and later Honey becomes toxic, leads to the Rose-tea also being perceived as toxic, is an example of mediated learning involving absent cues.

Beyond Pavlovian S-S learning, two other primary associative learning structures are recognized:

- S-R Learning (Habit Formation): This type of learning involves forming an association between a stimulus (S) and a response (R). It leads to the formation of habits, which are automatic responses to specific environmental features that do not require executive control. Originating from Edward Thorndike’s studies with cats in puzzle boxes, this concept emphasizes ”trial and error” learning. Thorndike’s Law of Effect states that responses followed by satisfaction are strengthened, while those followed by dissatisfaction are weakened. The Law of Exercise posits that the strength of the S-R connection is proportional to the number and duration of pairings. Reinforcement Learning (RL) is based on Thorndike’s laws and is an instantiation of S-R learning. In RL, an agent learns a policy (a map of state-action mappings) to maximize a numerical reward signal given by the system’s designer. Crucially, in traditional RL, the reward is an external numerical value that modulates the S-R learning, but it is not represented or learned about by the agent as a sensory outcome with physical characteristics.
- R-O Learning (Operant or Instrumental Learning): This involves associations formed between a response (R) and a reinforcing outcome (O). The outcome encapsulates a goal and is **represented and learned about** by the biological agent. This distinguishes it from S-R learning, where the reward is not an internal representation to be learned. Reinforcers are defined as stimuli that increase or strengthen a response. Operant conditioning can involve hierarchical learning, where a discriminative stimulus (SD) “sets the occasion” for the R-O association (SD-(R-O)), rather than merely eliciting an S-R link. The process of shaping a response, like training a rat to press a lever for food, demonstrates how S-S, S-R, and R-O learning types can interact within a single situation. For instance, the sound of food delivery becomes a Pavlovian CS for food (S-S), lever pressing becomes a habit (S-R), and the rat learns that its action (pressing) leads to the food outcome (R-O).

Tab. 1: Comparison of Associative Learning Structures: Type, Underlying Structure, Mechanism, and Example

Type	**Structure**	**Mechanism**	**Example**
Pavlovian	S-S	Predictive learning (CS → US)	Bell → food → salivation
Habit	S-R	Automatic response to stimulus	Red light → brake
Operant	R-O	Goal-directed action → outcome	Lever press → food reward
Hierarchical	S-(R-O)	Context modulates R-O link	Lab context → (lever press → food)

Rumelhart, Hinton, and McClelland (1986/1987) describe learning paradigms operating on Parallel Distributed Processing (PDP) models, also known as Artificial Neural Networks (ANNs). They distinguish two main types(Rumelhart et al. 1987):

1. Associative Learning: This occurs when a system learns to produce a particular pattern of activation on one set of units whenever another particular pattern occurs on another set of units. Within associative learning, they differentiate:
   - Pattern Association: An input pattern links and activates another pattern. The second pattern can act as a "teacher" or target for the learning.
   - Auto-Association: Elements within a pattern become linked to themselves. This allows for pattern completion, where presentation of a partial pattern can activate the full, associated pattern.
   - Reinforcement Learning: This is a case of associative learning where the "teaching input" is indirect, provided as feedback (e.g., a reward signal).
2. Regularity Discovery: This process involves finding "interesting" or meaningful patterns within the input data without an explicit teaching input. The "teaching function" is determined by the unit itself, often leading to clustering of similar inputs.

Pavlovian Conditioning (S-S Learning) aligns with Pattern Association, Auto-Association, and Regularity Discovery:

- The predictive nature of modern Pavlovian conditioning, where one stimulus (CS) predicts another (US), directly corresponds to Pattern Association. The US acts as the "teacher" or target for the CS prediction.
- Pavlovian conditioning's ability for pattern completion (e.g., inferring a full dog from partial cues) is a direct match for Auto-Association.
- The formation of predictive maps, causal relationships, and higher-order structures in Pavlovian learning, where the system discovers underlying structures and relationships in its environment without explicit external "teaching" for every single detail, can be mapped to Regularity Discovery.

S-R Learning aligns with Reinforcement Learning:

(Rumelhart et al. 1987) Chapter 2, is based on S-R learning. This is consistent with RL's foundation in Thorndike's laws, where actions (responses) in specific states (stimuli) are adjusted based on indirect feedback (rewards), leading to the strengthening of S-R connections that maximize this feedback.

While R-O learning (operant conditioning) is discussed as distinct from S-R and Pavlovian S-S learning, particularly in its emphasis on the goal-directed nature and representation of outcomes, the sources do not directly map it to a specific R-H-McC paradigm beyond the general "associative learning" category. However, given that R-O learning involves an action leading to a **represented outcome**, it would logically fall under forms of Pattern Association, where the response-outcome contingency forms an associative pattern, potentially also involving elements of Regularity Discovery as the agent understands the causal structure of its actions on the environment.

In essence, if associative learning is like building a mental library of connections, Pavlovian S-S learning is about creating reference cards (Pattern Association) and fill-in-the-blanks exercises (Auto-Association), while also figuring out the organizational system of the library itself (Regularity Discovery). Meanwhile, S-R learning is like training a reflexive action based on immediate feedback, which is directly modeled by Reinforcement Learning.

3 Analyzing Key Phenomena in Associative Learning

a. Blocking and Its Computational and Theoretical Interpretations

The Blocking phenomenon was simulated using the *Rescorla-Wagner v5* simulator.

3.1 Scenario Description

Imagine in a high-risk industrial environment, workers are trained to respond to auditory warning signals that predict hazardous gas leaks. These signals are part of an automated safety system designed to enhance workers' preparedness and minimize accident response times.

The system employs three distinct auditory cues:

Low Tone (A)

High Tone (B)

Medium Tone (C)

Workers are randomly assigned to three experimental conditions:

Group Blocking

Control Group 1

Control Group 2

The objective is to investigate whether a previously learned predictive cue (A) can interfere with the acquisition of a new predictive association for a second cue (B), even when both are paired with the same outcome. This effect, known as **Blocking**, provides insight into how attentional and error-driven learning mechanisms allocate cognitive resources under conditions of stimulus competition.

3.2 Identification of Critical Stimuli (Predictors and Outcomes)

Predictors (Conditioned Stimuli):

Predictive Stimuli (Cues):

A: Low Tone

B: High Tone

C: Medium Tone

Outcome Stimulus (+):

Activation of the gas leak alarm (auditory alarm + visual alert)

Tab. 2: Experimental Conditions for Blocking and Control Groups

	Conditioning	Conditioning Compound	Test
Blocking	20A+ Low Tone → Alarm	20AB+ Low Tone & High Tone → Alarm	2B- High Tone
Control 1	20C+ Medium Tone → Alarm	20AB+ Low Tone & High Tone → Alarm	2B- High Tone
Control 2	20A+ Low Tone → Alarm	20A+ / 20B+ Low Tone → Alarm / High Tone → Alarm	2B- High Tone

Behavioral Measure:

Reaction time to press an emergency shutdown button, serving as an operational index of learned anticipation.

3.3 Input Design Based on the Scenario

Phase 1 – Initial Conditioning

Blocking Group:

- 20 trials of A+ (Low Tone paired with gas leak alarm).
- Followed by 20 trials of AB+ (compound of Low + High Tones with the same alarm).

Control Group 1:

- 20 trials of C+ (irrelevant Medium Tone paired with alarm).
- Followed by 20 trials of AB+ (identical compound as Blocking Group).

Control Group 2:

- 20 trials of A+ (Low Tone alone).
- Followed by 20 trials of B+ (High Tone alone) or repeated A+.

Phase 2 – Critical Test

All groups received 2 B– trials (High Tone presented alone without the alarm) to measure conditioned response strength to B.

Key Design Inputs

1. **Stimulus Parameters:**
   - All tones (A, B, C) had equal salience (e.g., intensity, duration).
   - The alarm (US) was modeled as a binary outcome (present/absent).
2. **Learning Mechanisms:**

- Rescorla-Wagner (RW): Predicts blocking due to reduced prediction error (A already fully predicts the outcome, leaving no "surprise" to drive B's association).

3. **Behavioral Measure:**
   - Simulated "reaction time" to the alarm (shorter latency = stronger association).

3.4 Theoretical Comparison: Rescorla-Wagner vs. Mackintosh

Rescorla-Wagner (RW) (1972)

Error-Driven Learning, Key Equation:

This model is based on error-driven learning, where the strength of association between a cue and an outcome changes as a function of prediction error (Rescorla & Wagner 1972). The key equation is shown at 1:

$$\Delta V = \alpha \cdot \beta(\lambda - \Sigma V) \tag{1}$$

Where:

λ: Maximum associative strength (e.g., 1 for outcome present).

ΣV: Sum of predictions from all present stimuli.

α, β: Learning rates for cue and outcome salience.

Account of Blocking:

Phase 1 (A+): $V_A \to \lambda$ (A fully predicts the outcome).

Stimulus A is consistently followed by an outcome, leading V_A to approach λ

Phase 2 (AB+): Because $\Sigma V \approx \lambda$ (A already predicts the outcome),

prediction error $(\lambda - \Sigma V) \approx 0$.

Thus, $\Delta V_B \approx 0$: B fails to acquire strength.

Since A already predicts the outcome, the summed prediction $\Sigma V \approx \lambda$, resulting in a near-zero prediction error. Thus, no meaningful update occurs for B ($\Delta V_B \approx 0$), and B fails to acquire associative strength.

Control Groups:

Control 1 (C+ $\to$ AB+): Novel compound $\to$ Both A and B learn.

A novel compound with no prior learning — both C and B can acquire associative strength.

Control 2 (A+ $\to$ B+): B trained alone $\to$ Gains strength.

When B is trained alone, it successfully learns the association with the outcome.

Limitation:

The Rescorla-Wagner model cannot explain latent inhibition — the phenomenon where pre-exposure to a stimulus (e.g., B– trials without outcome) slows down later learning. Since RW only updates associative strength when prediction error exists, and no outcome follows the pre-exposed stimulus, the model predicts no change in learning rate — a result that contradicts empirical findings.

Mackintosh (1975)

Mackintosh's model is an attentional theory of associative learning. It proposes that the associability of a cue (its α) is dynamic, depending on how well the cue predicts outcomes relative to others. The main principle is (Mackintosh 1975):

"Organisms attend more to cues that are good predictors of outcomes and less to poor predictors."

Account of Blocking:

Phase 1 (A+): A consistently predicts the outcome, so its associability α_A increases. Other cues (like B, if present) are irrelevant and receive little or no attentional gain.

Phase 2 (AB+): Since A is already a strong predictor, attention remains on A. B, receiving less attention (low α_B), gains little associative strength — even though prediction error might exist. Blocking arises from selective attention, not just prediction error.

Advantages over RW:

- Mackintosh explains **Blocking** via attentional competition rather than summed prediction.
- The model can also account for **latent inhibition**: if B is presented alone without outcomes (B–), it becomes associated with non-predictiveness, lowering its future associability — which slows later learning when B is followed by an outcome.

Rescorla-Wagner vs. Mackintosh: A Summary of Differences:

In RW, the critical cognitive variable is the **prediction error** $(\lambda - \Sigma V)$, which governs the learning updates. In Mackintosh's model, the key variable is **selective attention** (α), dynamically modulated based on cue predictiveness. This difference reflects how each model accounts for learning phenomena such as blocking from a cognitive perspective.

Tab. 3: Comparison of Rescorla-Wagner and Mackintosh (1975) models on blocking and related effects.

Feature	**Rescorla-Wagner**	**Mackintosh (1975)**
Core Mechanism	Prediction error	Selective attention (dynamic α)
Blocking Explanation	$\Sigma V \approx \lambda \Rightarrow \Delta V_B \approx 0$	Low α for B due to A's predictiveness
Latent Inhibition	Cannot explain	Can partially explain
Attention Mechanism	None (fixed α)	Built-in (α varies over time)

3.5 Simulation and Comparison of Learning Models on Blocking

Experimental Setup and Test Phase

In the test phase, the High Tone (B) is presented alone without the alarm to measure whether participants have formed a predictive association between B and the outcome.

Experimental Scenario

This experiment investigates the blocking effect through a three-phase industrial safety training scenario, where workers learn to associate auditory warning signals (Low Tone A, High Tone B, Medium Tone C) with a hazardous gas alarm (US).

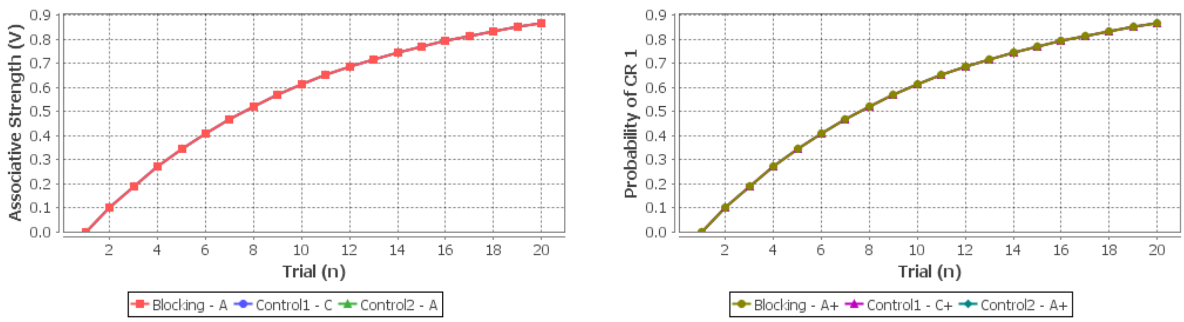
Modeling Approach: Rescorla-Wagner Simulation

All simulation results and figures presented in Phases 1–3 are based on the Rescorla-Wagner learning model, which computes associative strength through prediction error. The model tracks how much each cue (A, B, C) predicts the outcome (alarm) over time.

We simulated the scenario described in Sectionsection 3 using the Rescorla-Wagner model. Three experimental groups were included: Blocking, Control 1, and Control 2. The simulation was run in three consecutive phases, each corresponding to the experimental design (Phase 1: Initial conditioning, Phase 2: Compound conditioning, Phase 3: Test).

Phase 1: Initial Conditioning

During Phase 1, the associative strength (V) of the relevant cues was tracked across trials as they were paired with the outcome. As shown in Figure 2(a), the associative strength of cue A in the Blocking and Control 2 groups, and cue C in Control 1, increased gradually and approached an asymptote (0.86), reflecting successful acquisition of the cue-outcome association. The probability of the conditioned response (CR1) similarly increased across trials (Figure 2(b)).

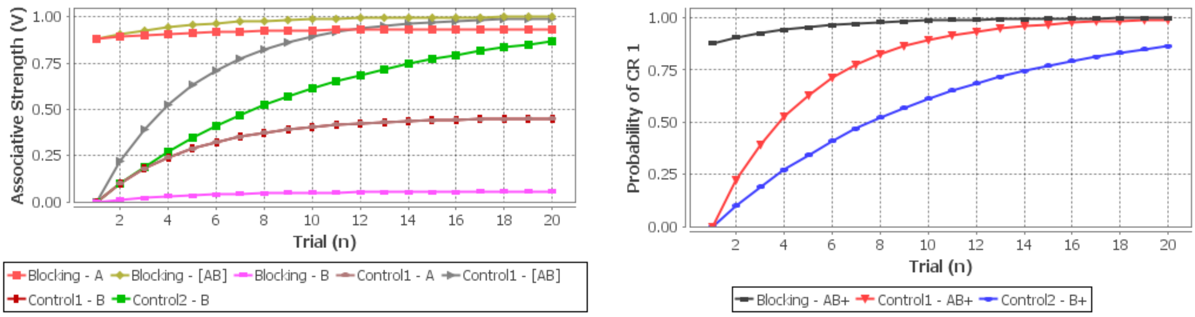


(a) Mean CS values per trial – Phase 1.

(b) CR1 – Phase 1

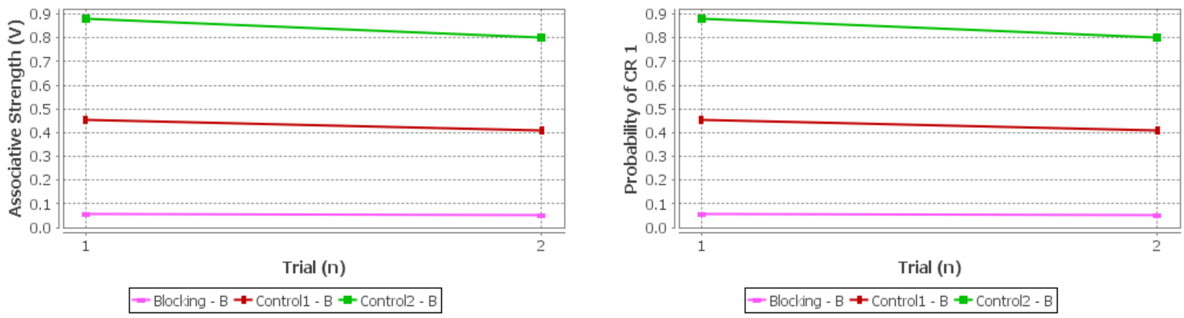
Fig. 2: CR1 and Mean CS values per trial – Phase 1.

Phase 2: Compound Conditioning and Blocking Effect In Phase 2, both the Blocking and Control 1 groups received compound training with cues A and B (AB+), while Control 2 continued to receive A+ and B+ trials separately. As shown in Figure 3(a), the blocking effect was clearly observed. In the Blocking group, the associative strength of B remained minimal (0.06) throughout Phase 2, because the predictive strength of A left little room for B to acquire further associative strength. In contrast, B's associative strength increased robustly in Control 2 (reaching >0.8), and moderately in Control 1 (about 0.2–0.3). This pattern is also reflected in the probability of a conditioned response (CR1, Figure 3(b)),



(a) Mean CS values per trial – Phase 2. (b) CR1 – Phase 2

Fig. 3: CR1 and Mean CS values per trial – Phase 2.



(a) Mean CS values per trial – Phase 3. (b) CR1 – Phase 3

Fig. 4: CR1 and Mean CS values per trial – Phase 3.

where B evoked a strong response in Control 2, a moderate response in Control 1, but a weak response in the Blocking group.

Phase 3: Testing Response to B Alone

In the test phase, only cue B was presented without the outcome (B–) to all groups in order to assess the level of conditioned responding to B alone. As shown in Figure 4(a) and Figure Figure 4(b), the blocking effect was clearly confirmed in the simulation results.

The Blocking group exhibited only a minimal associative strength for B—approximately 0.05—and thus a very weak conditioned response. In contrast, Control 1 showed a moderate associative strength for B (around 0.40–0.45), while Control 2 exhibited a strong response to B (approximately 0.85–0.90).

These results provide strong computational evidence for the blocking phenomenon: prior learning about cue A in the Blocking group prevented significant learning about cue B. Even when B was present in the compound (AB+) and paired with the outcome, its associative strength remained low unless it was also trained alone or without prior competition from a predictive cue. This highlights that simply pairing a cue with an outcome is not sufficient for learning; the cue must also provide novel predictive information for learning to occur.

Model Explanation and Key Findings_ Rescorla-Wagner

This pattern supports the Rescorla-Wagner model, where prediction error governs learning: once A fully predicts the outcome, B cannot gain associative strength when added later. The findings demonstrate that cues are only learned when they provide new predictive information, not merely due to co-occurrence.

Objective Description of Simulation Results

The simulation demonstrates that participants in the control groups acquire a much stronger association between cue B and the outcome than those in the Blocking group.
This is evident in both the associative strength (V) and the conditioned response probability (CR1) measures.
In the Blocking group, the pre-established predictive power of cue A rendered cue B essentially redundant, and thus its associative strength remained very low (approximately **0.05** in the final test phase).
In contrast, in Control 1, cue B reached a moderate level of associative strength (~0.40–0.45), while in Control 2, where B was trained alone, it acquired a high level of associative strength (~0.85–0.90).
These quantitative results are mirrored in the CR1 measures, with conditioned response probability to B being minimal in the Blocking group and substantially higher in both controls.

Model Explanation

The Rescorla-Wagner model explains these results through its global error term: when cue A already fully predicts the outcome, the summed prediction (ΣV) leaves little to no prediction error for cue B to drive learning.
As a result, B fails to gain strength—a clear computational account of the blocking phenomenon, which is precisely reflected in the observed associative strength values (Blocking: **0.05**, Control 1: **0.40–0.45**, Control 2: **0.85–0.90**).

Modeling Approach: Mackintosh Simulation

The scenario was simulated using the Mackintosh model, which attributes learning to changes in the attention parameter (α) allocated to each cue based on their predictive value.

note:To simulate the Blocking phenomenon using the Mackintosh model, we employed the SLGK-model.exe simulator. The input file was prepared according to the required SLGK format and executed through the Windows command prompt. The numerical outputs were copied from CMD, transferred to Excel, and used to generate the relevant plots.

Here, we report and analyze the results for each experimental phase:

Attention Dynamics (α) Across Groups

Description: Figure 5 illustrates how the attention parameter (α) for each cue changes across trials and groups during compound conditioning.

- **Blocking Group:** Attention to A (blue) remains high and stable across trials, whereas attention to B (red) sharply declines during the initial trials and then plateaus at a low value. This indicates that once A is established as a reliable predictor, B receives little attention and therefore learns slowly or not at all.
- **Control 1:** Attention to B (purple) remains moderate and stable, since neither A nor B is pre-established as a predictor. Attention to A (green) is also stable but lower compared to the Blocking group.

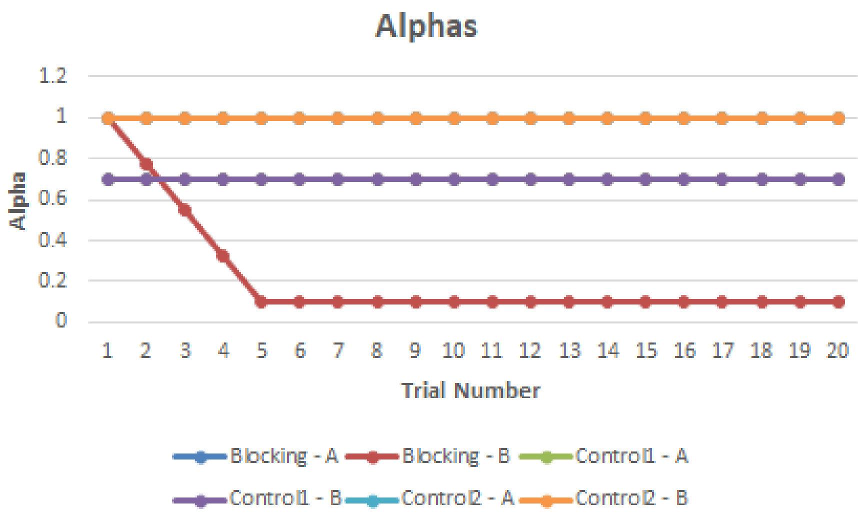


Fig. 5: Dynamics of the attention parameter (α) for each cue across groups during Phase 2.

- **Control 2:** Both A (light blue) and B (orange) maintain high attention levels throughout, as they are each trained alone, allowing both to gain associative strength without attentional competition.

Interpretation: These results illustrate that in the Blocking group, attentional resources are directed toward the previously learned predictor (A), suppressing learning about the new cue (B). In contrast, when cues are novel or trained separately, both can acquire high attention and learn effectively.

Phase 1: Initial Conditioning

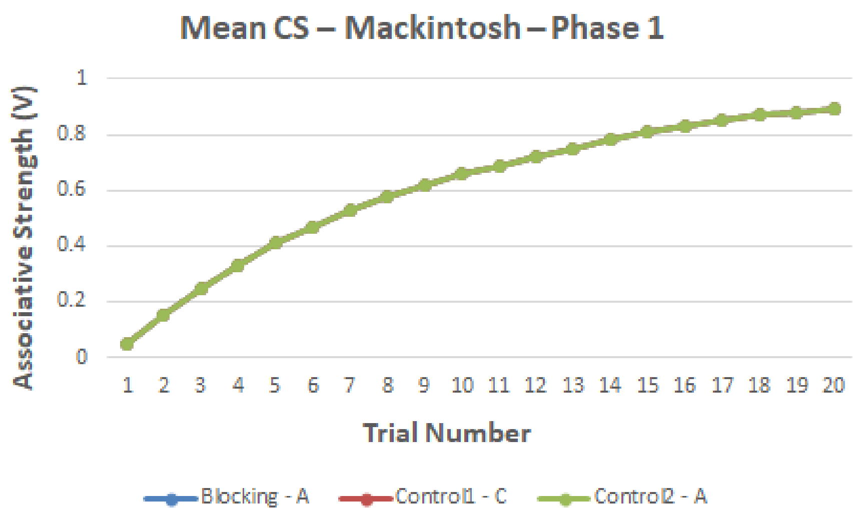


Fig. 6: Mean associative strength (V) during Phase 1 for each group.

Description: During Phase 1, the mean associative strength (V) of the relevant cue in each group increases progressively and approaches an asymptote.

- **Blocking (A, blue):** Associative strength of A rises steadily as it is paired with the outcome.

- **Control 1 (C, red):** Associative strength of C follows a similar growth trajectory.
- **Control 2 (A, green):** A increases similarly as it is paired with the outcome.

Interpretation: All groups exhibit robust acquisition of the cue-outcome association in Phase 1, reflecting effective single-cue learning and initial attention allocation to the most informative stimulus.

Phase 2: Compound Conditioning

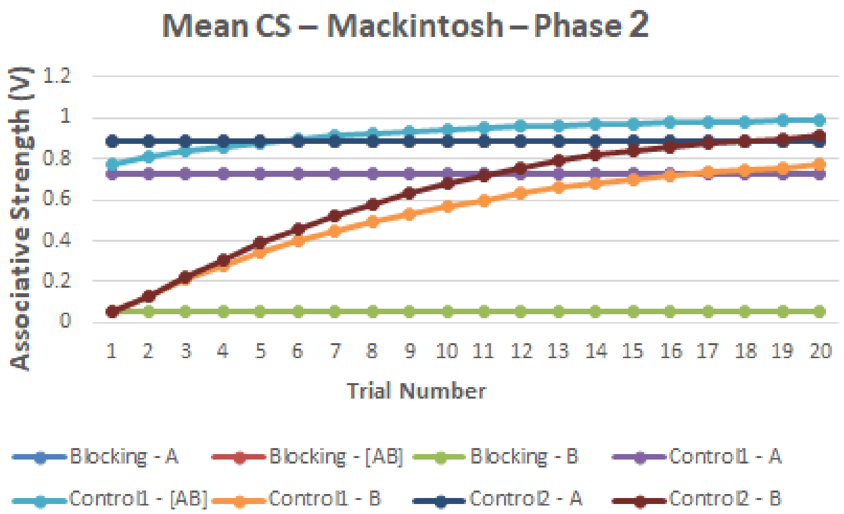


Fig. 7: Mean associative strength (V) for each cue during Phase 2 (compound training).

Description: During compound conditioning (AB+), associative strength for each cue evolves as follows:

- **Blocking Group:**
  - **A (blue):** Remains high and stable.
  - **B (red):** Shows little to no increase, indicating minimal learning about B when A is already established as a predictor.
  - **[AB] (brown):** Compound representation, grows in parallel with A but is driven by A's predictive value.
- **Control 1:**
  - **A (green):** Stays relatively low.
  - **B (purple):** Gradually increases, reflecting moderate learning.
  - **[AB] (light blue):** Shows some growth as both cues participate in prediction.
- **Control 2:**
  - **A (light blue) and B (orange):** Both increase robustly and reach high associative strength since each cue is trained alone, allowing them to become reliable predictors without prior competition.

Interpretation: The key feature of the Blocking group is the failure of B to gain associative strength, due to attentional dominance by A. This contrasts with Control 2, where both A and B gain strength independently, and Control 1, where both cues contribute but at a slower pace.

Phase 3: Test (B– trials)

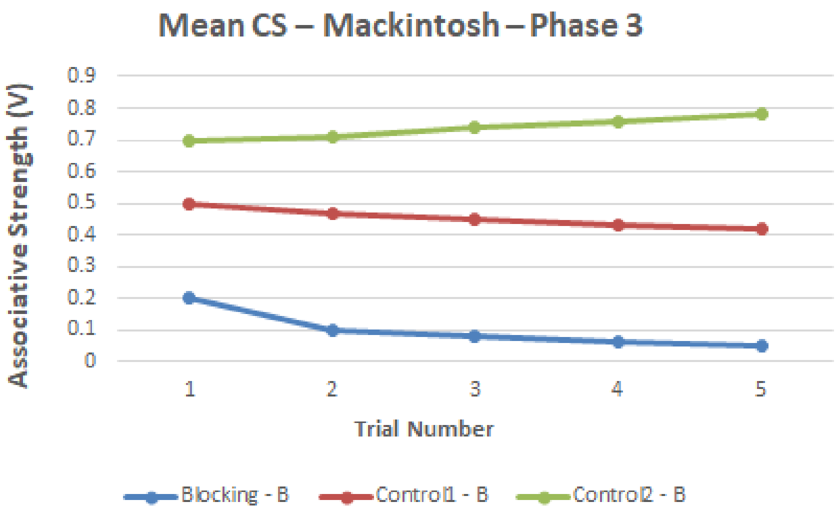


Fig. 8: Associative strength (V) for B during the test phase across all groups.

Description: In the test phase, only B is presented without the outcome, and associative strength is measured:

- **Blocking Group (blue):** Associative strength of B is minimal and even decreases slightly over repeated non-reinforced presentations.
- **Control 1 (red):** B has moderate associative strength but gradually declines as a result of the lack of reinforcement.
- **Control 2 (green):** B starts high and remains the strongest among all groups, showing only slight decline.

Interpretation: This confirms the blocking effect: in the Blocking group, learning about B was suppressed by prior attention to A, and B fails to evoke a strong response. In Control 2, where B was trained without competition, its associative strength is much higher. Control 1 demonstrates an intermediate effect.

Summary and Theoretical Implications

The Mackintosh model simulation clearly reproduces the qualitative pattern of blocking observed in empirical studies. It explains blocking through **attentional mechanisms**: when a cue (A) reliably predicts the outcome, attention to other cues (B) is reduced, inhibiting new learning about them. Thus, blocking arises not from a global error term (as in Rescorla-Wagner), but from the redistribution of cognitive resources—attention—toward the best predictor.

This attentional account means that if circumstances change and attention to the blocked cue (B) is restored, learning about B can resume—a critical distinction from the error-driven explanation of Rescorla-Wagner.

Overall, the results confirm that the Mackintosh model, though theoretically distinct from RW, can reproduce blocking via dynamic changes in attention (α), and that these changes are directly observable in the simulation figures.

Comparison of Rescorla-Wagner and Mackintosh Models in Blocking

The simulation results presented here are based on the Rescorla-Wagner model, which explains blocking as a consequence of prediction error: since stimulus A already predicts the outcome well, there is little prediction error left for stimulus B to gain associative strength.

In contrast, the Mackintosh model accounts for blocking by proposing that the associability (attention) to stimulus B decreases when stimulus A is a reliable predictor. In other words, according to Mackintosh, learners allocate less attention to redundant cues like B after A has become a strong predictor, which leads to weaker learning about B.

While the Rescorla-Wagner model focuses on the computational process of error correction, the Mackintosh model emphasizes changes in attention to cues during learning. Both models predict blocking but attribute it to different underlying mechanisms.

3.6 Discussion: Relevance to Modern Associative Learning

The blocking and serial order discrimination phenomena demonstrate two fundamental principles of modern associative learning theory: predictive competition and configural representation. First, the Rescorla-Wagner simulations prove that learning is driven by prediction error rather than mere contiguity—a cornerstone of error-correction models. The blocking effect (where pretrained cue A prevents learning about redundant cue B) shows that organisms allocate associative strength selectively to the most informative predictors, optimizing predictive efficiency. This challenges historical "strength-based" theories by demonstrating that learning depends on a cue's informational value within its context.

e. Structural or Serial Order Discrimination: Insights from TD and SSCC-TD Models

The Serial Order Discrimination phenomenon was simulated using the *SSCC-TD* simulator.

3 -1 Scenario Description

This simulation models an experiment in which animals (typically rats or pigeons) are exposed to structured sequences of stimuli composed of two basic visual or auditory elements A and B arranged in three-item compounds. The key interest is whether the animals can discriminate between different serial arrangements of the same elements (e.g., ABA vs. AAB).

Each trial consists of the serial presentation of three stimuli (e.g., A–B–A), where each element lasts for 10 seconds and is separated by a 0.5s gap. The goal is to see whether animals respond more to specific structured sequences that are followed by reinforcement, compared to those that are not, despite sharing the same elements.

This setup mimics natural cognitive tasks, such as:

- Humans learning grammar rules (e.g., recognizing that "the cat runs" is structured, but "cat the runs" is not),
- Musical phrase perception (hearing structured motifs like ABA or AAB),
- Sequential behaviors in tool use or social routines in primates.

3 -2 Identification of Critical Stimuli: Predictors and Outcomes

Predictor Stimuli (CSs): Six compound sequences formed from A and B in 3-element series:

ABA / BAB / BBA / AAB / BAA / ABB

Outcome (US):

- Reinforcement (e.g., food, reward)
- No reinforcement

Each experimental group receives a different set of reinforced and non-reinforced sequences:

Tab. 4: Reinforced ($^+$) and Non-Reinforced ($^-$) Sequences by Group in the Serial Order Discrimination Task.

Group	Reinforced Sequences (+)	Non-Reinforced Sequences (−)
XYX	ABA$^+$, BAB$^+$	AAB$^-$, BBA$^-$, BAA$^-$, ABB$^-$
XXY	AAB$^+$, BBA$^+$	ABA$^-$, BAB$^-$, BAA$^-$, ABB$^-$
YXX	BAA$^+$, ABB$^+$	ABA$^-$, BAB$^-$, AAB$^-$, BBA$^-$

These groups are trained to learn that structure, not just content, determines reinforcement. For example, Group XYX must distinguish ABA (rewarded) from AAB (not rewarded), even though both contain the same elements.

3 -3 Experimental Design and Input Mapping

The simulation was set up in the SSCC-TD Simulator as follows:

For example, a sequence such as **ABA** might represent *auditory-tone* A, followed by *light-flash* B, followed again by *tone* A; reinforcement (e.g., food) follows only some structured sequences. This design allows mapping the serial compound inputs to temporally-structured real-world events, in line with the cognitive demands of structural discrimination.

Phase 1 – Acquisition

Each group underwent 240 trials of each sequence, as per the following format:

Group XYX:

240ABA$^+$ / 240BAB$^+$ / 240AAB$^-$ / 240BBA$^-$ / 240BAA$^-$ / 240ABB$^-$

Group XXY:

240AAB$^+$ / 240BBA$^+$ / 240ABA$^-$ / 240BAB$^-$ / 240BAA$^-$ / 240ABB$^-$

Group YXX:

240BAA$^+$ / 240ABB$^+$ / 240ABA$^-$ / 240BAB$^-$ / 240AAB$^-$ / 240BBA$^-$

Notation:
The symbol **"+"** denotes reinforcement.
The caret symbol **"^"** following the final stimulus in a sequence indicates the point at which the associative strength (V) of the compound is logged during the trial.

Settings:
Design Settings: *Consider Serial Compounds*
Procedural Settings: *Timings per Trial Type*

Phase 2 – Generalization/Transfer

Each group receives new or recombined sequences (120 trials each) to test whether learning transfers to novel arrangements:

Group XYX:

120AAB$^-$ / 120BBA$^-$ / 120BAA$^-$ / 120ABB$^-$

Group XXY:

120ABA$^-$ / 120BAB$^-$ / 120BAA$^+$ / 120ABB$^+$

Group YXX:

120BAA$^-$ / 120ABB$^-$ / 120AAB$^+$ / 120BBA$^+$

Phase 3 – Final Transfer Testing

Each group receives 60 trials of two key sequences to assess if prior training supports transfer of learning:

Group XYX:

60ABA / 60BAB

Group XXY:

60AAB / 60BBA

Group YXX:

60BAA / 60ABB

These sequences are not explicitly reinforced and test for spontaneous discrimination based on earlier structure learning.

3 - 4 Theoretical Comparison: SSCC-TD vs. TD Models

SSCC-TD (Sequence-Sensitive Cue Configuration model with Temporal-Difference learning)

SSCC-TD encodes temporal position and sequence structure by treating the same stimulus as distinct cues depending on its order in a sequence (e.g., "A-in-position-1" vs. "A-in-position-3").

Cognitive variable: Unique positional encoding of each stimulus within the sequence (e.g., A1, B2), enabling configural pattern recognition and precise discrimination based on order structure.

Discrimination Explanation:

- ***Reinforced Sequences (e.g., ABA+):*** The model learns associations between specific contextual states (e.g., "A1-B2-A3") and the outcome.

  These states are unique to the sequence's order, not just its elements.

- ***Non-Reinforced Sequences (e.g., AAB−):*** Activates different contextual states (e.g., "A1-A2-B3"), preventing generalization to reinforced sequences.

- ***Behavioral Outcome:*** Animals (or simulated agents) discriminate ABA from AAB because they are processed as entirely different patterns, not just sums of A/B associations. Directly accounts for structural sensitivity by design, unlike elemental models (e.g., RW).

- ***Experimental Results:*** Group XYX (ABA+/BAB+) responds to positional regularity, not just A/B frequency. Transfer tests (e.g., novel sequences) show generalization based on learned structure.

Limitations: Computationally complex (requires tracking hidden states for each position). Less intuitive for simple associative tasks (overkill for non-sequential learning).

TD (Temporal Difference)

- ***Core idea:*** TD learning updates stimulus-outcome predictions based on a *temporal prediction error*, i.e., the mismatch between expected and received outcome across time steps.

It is often used in conditioning and reinforcement learning to model how organisms learn from delayed outcomes.

Cognitive variable: Temporal difference in outcome prediction, without explicit state differentiation within a trial. All stimuli are treated uniformly regardless of temporal position.

Sequence processing: TD treats each stimulus as a state with a single representation, regardless of position. For instance, in both ABA and AAB, the same internal representation of "A" is activated wherever it occurs. Thus, the internal state sequence may be similar or overlapping, especially if timing is not precisely encoded.

Explanation of performance: TD can learn associations between sequences of cues and rewards, but without explicit position encoding, it struggles to distinguish structurally different sequences with the same elements (e.g., ABA vs. AAB). This causes generalization where discrimination is expected — inconsistent with observed animal behavior.

Experimental example: In tasks like ABA+ vs. AAB–, TD cannot assign different predictions to these patterns because it doesn't differentiate "A at start" vs. "A at end". All "A" tokens are treated the same. This leads to weak or no discrimination.

Limitations:

- No position-specific representations
- Fails to explain structural or serial order discrimination
- Simpler, less computationally demanding than SSCC-TD

SSCC-TD vs. TD: A Summary of Differences

While SSCC-TD encodes position-specific information for each cue in a sequence, standard TD learning treats identical cues as the same regardless of position. It lacks the representational structure to distinguish between "A1" and "A3", so it generalizes between sequences like ABA and AAB, even when discrimination is required.

Therefore, standard TD cannot explain structural sensitivity in sequence learning tasks, while SSCC-TD can — by design.

3 -5 Computational Simulation and Model Comparison

Modeling Approach: SSCC-TD Simulation

All simulations reported below were performed using the SSCC-TD simulator V1, which implements a position-sensitive sequence learning algorithm.

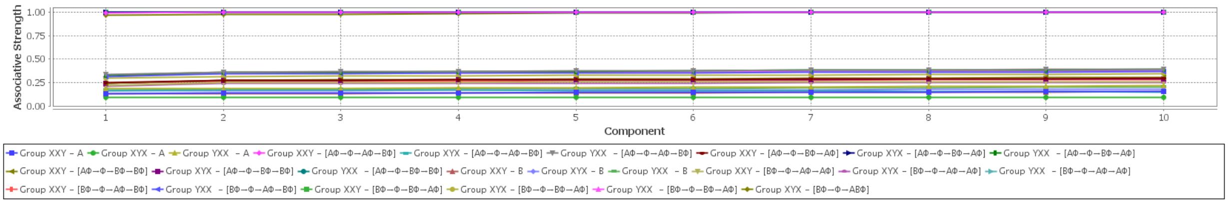


Fig. 9: Associative Strength/Component for phase1.

Components like "A-in-position-1" (A1) and "A-in-position-3" (A3),Figure 9, show divergent associative strengths despite identical elements.SSCC-TD treats positional variants as distinct cues (A1 A3), enabling structure learning.

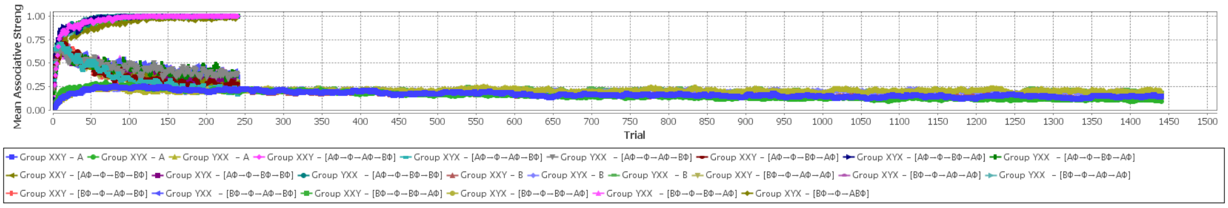


Fig. 10: Mean Associative Strength/Trial for phase1.

Reinforced sequences ,Figure 10, (e.g., ABA+ in Group XYX) rise steeply (0.8 by Trial 100), while non-reinforced (AAB–) remain near zero.Rapid differentiation confirms configural learning (sequences sum of parts).

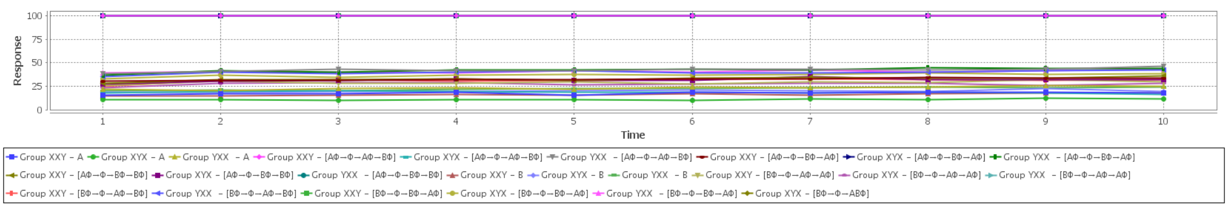


Fig. 11: Response/Time for phase1.

Faster responses to reinforced sequences, Figure 11, (e.g., ABA+ vs. AAB–) after 50 trials. Behavioral discrimination aligns with associative strength trends.

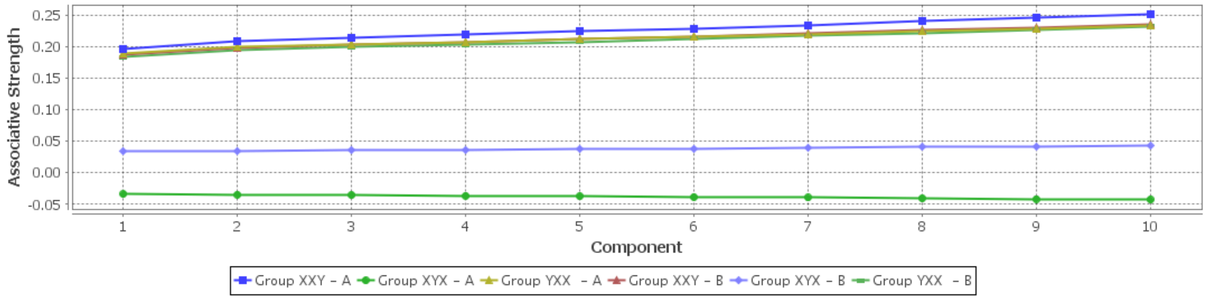


Fig. 12: Associative Strength/Component for phase2.

Components like "B-in-position-2" (B2) show strength only in sequences matching the trained structure (e.g., ABA in XYX). Figure 12, Contextual gating prevents spurious generalization.

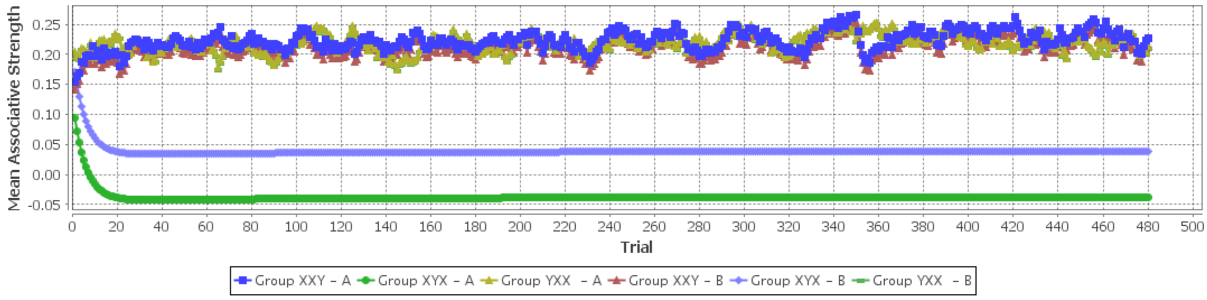


Fig. 13: Mean Associative Strength/Component for phase2.

Group XXY: AAB+ trials → strength peaks (0.7); ABA– trials flatline. Group XYX: Opposite pattern (ABA+ rewarded). Figure 13 Learning is structure-specific, not element-based.

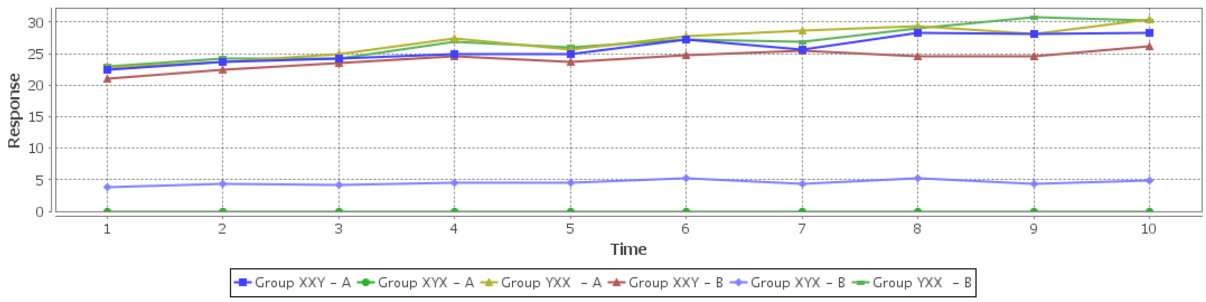


Fig. 14: Response/Time for phase2.

Mirror associative strength (e.g., fast responses to AAB+ in XXY, slow to ABA–). Figure 14, Behavioral data validate SSCC-TD's predictions.

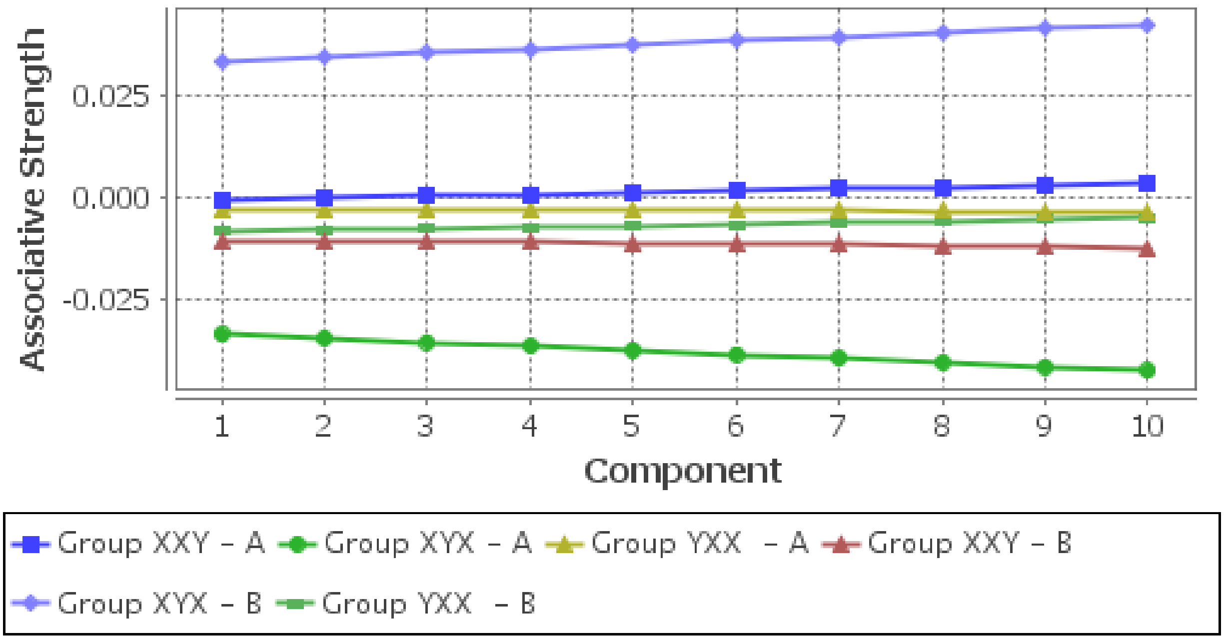


Fig. 15: Associative Strength/Component for phase3.

Components in trained sequences (e.g., A1-B2-A3 in XYX) retain high strength; others decay. Figure **??** Robust retention of structural knowledge.

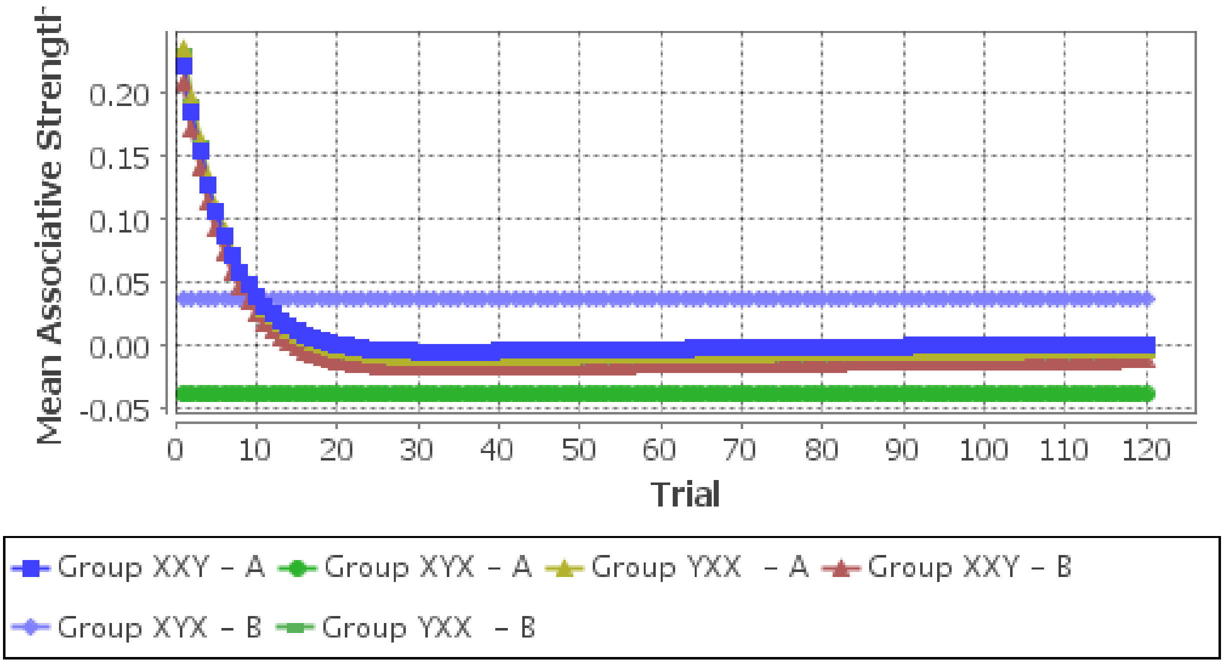


Fig. 16: Mean Associative Strength/Trial for phase3.

Groups respond only to their reinforced structure (e.g., XYX to ABA, XXY to AAB). Figure 16 Confirms strict sequence coding.

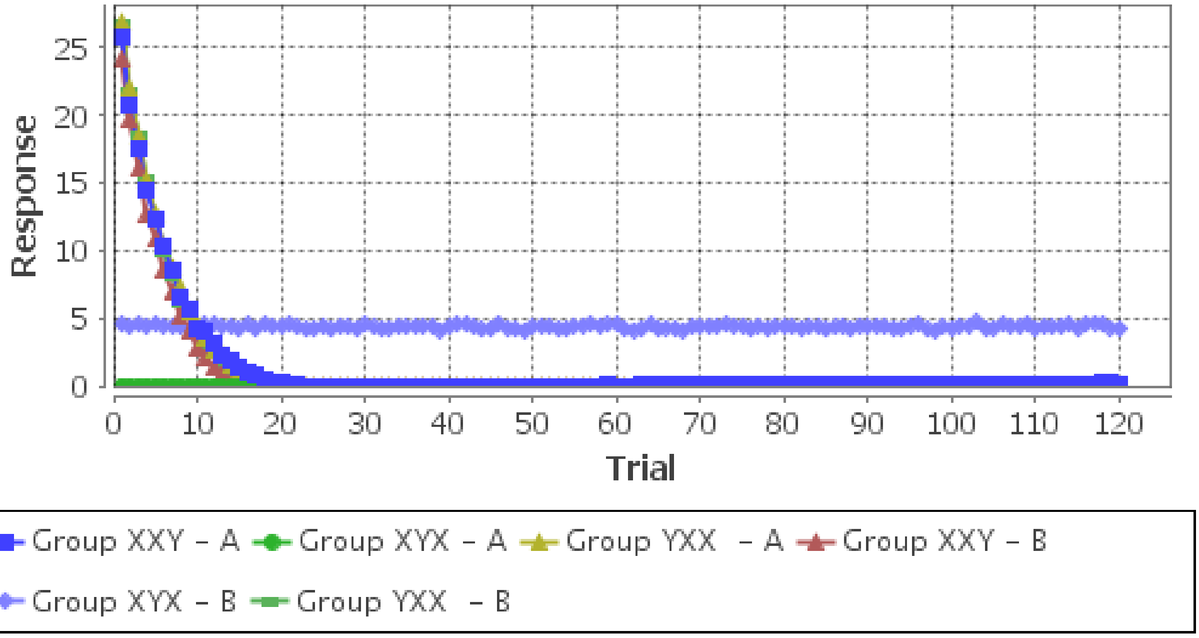


Fig. 17: Response/Trial for phase3.

Figure 17, Responses align 1:1 with associative strength plots (e.g., high clicks for ABA in XYX).

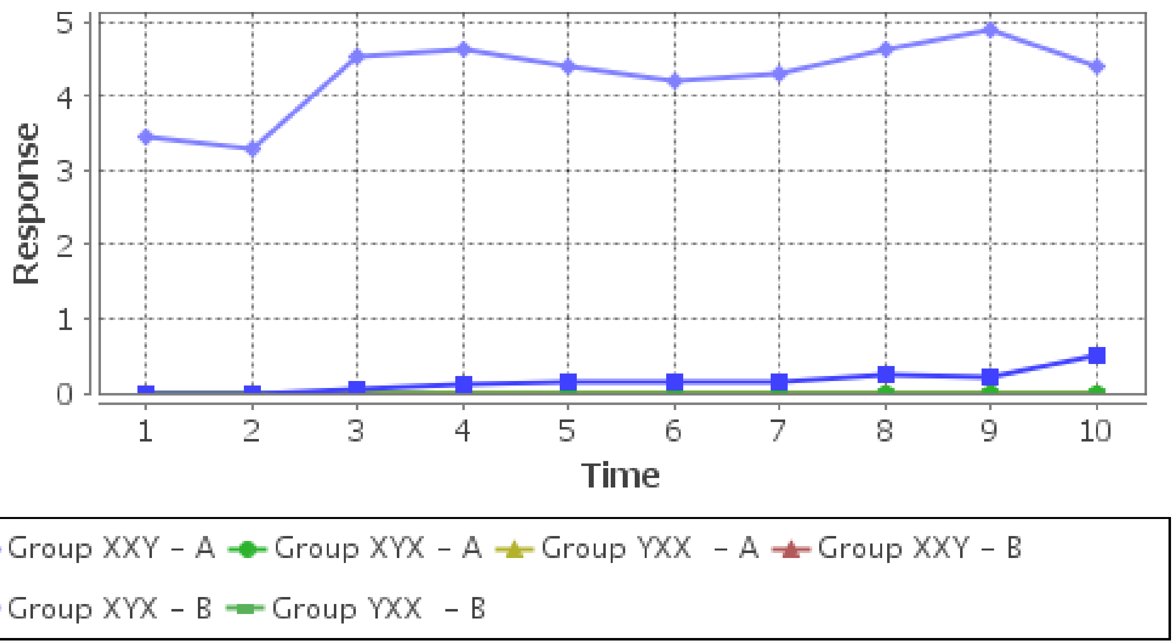


Fig. 18: Response/Time for phase3.

Shorter RTs for trained sequences (e.g., XXY reacts faster to AAB than ABA).Figure 18, Similar to grammar rule application in humans.

Model Explanation and Key Findings_ SSCC-TD

In summary, the SSCC-TD model successfully acquires sequence structure information, as shown by divergent associative strengths for positional variants and rapid discrimination between reinforced and non-reinforced sequences. By contrast, a classic TD model—which lacks the capacity to bind cues to their serial positions—would predict similar learning for all sequences with the same elements, irrespective of order. These findings demonstrate that learning in structural or serial order discrimination tasks relies on models with position-sensitive representations, such as SSCC-TD, rather than traditional TD learning.

Modeling Approach: TD Simulation

The TD model results (Figure 19) show that the associative strengths of A and B rise together during reinforced trials and decline equally when reinforcement is withdrawn. The model fails to discriminate between sequences with different serial orders, reflecting its lack of position-specific coding. This is in sharp contrast to the SSCC-TD model, which shows selective learning for reinforced sequence structures.

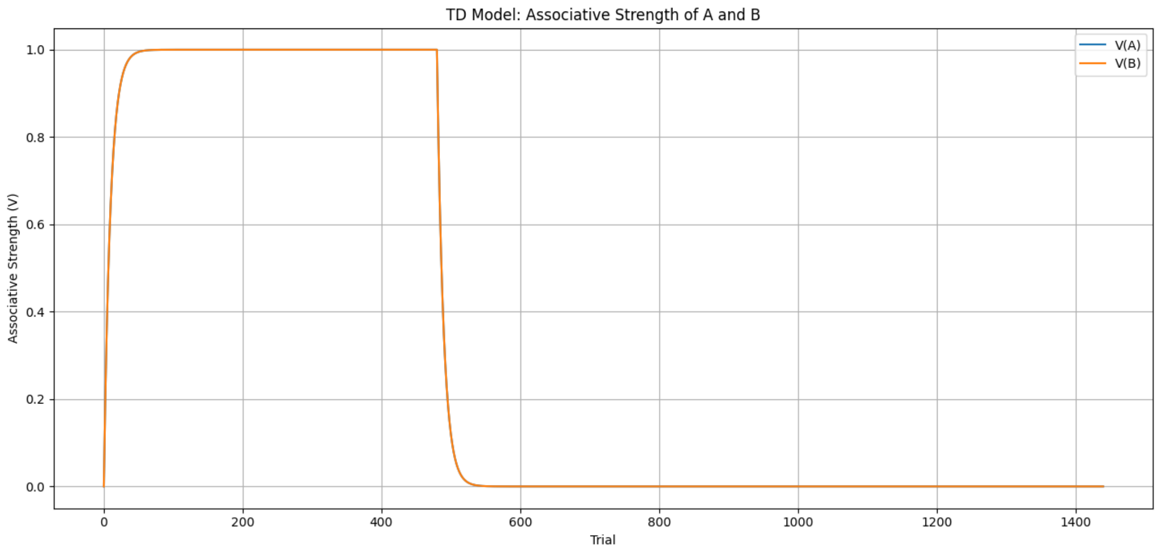


Fig. 19: Associative strengths (V) for elements A and B under the classic TD model. The model cannot distinguish between different sequence structures; V(A) and V(B) overlap and reflect only overall reinforcement history.

TD vs. SSCC-TD Models

The standard Temporal Difference (TD) model updates associative strengths based solely on the presence or absence of individual elements (e.g., A or B), regardless of their position within a sequence. As a result, the TD model predicts similar learning for all sequences containing the same elements, and it cannot discriminate between structurally different sequences such as ABA and AAB.

In contrast, the SSCC-TD model encodes both the identity of each element and its serial position within the sequence (e.g., A-in-position-1 vs. A-in-position-3). This position-specific encoding enables the SSCC-TD model to distinguish between different structural arrangements and to learn the precise sequences that are reinforced.

Therefore, we expect that:

- The classic TD model will **fail** to capture structural or serial order discrimination and will assign similar associative strengths to all sequences containing the same elements.
- The SSCC-TD model will show **selective learning** and strong discrimination between reinforced and non-reinforced sequence structures, accurately reflecting structural learning.

3 - 6 Discussion: Relevance to Modern Associative Learning

The SSCC-TD results reveal that complex sequential learning requires hierarchical representations unavailable to elemental models. Successful discrimination of ABA vs. AAB sequences proves that temporal position must be explicitly encoded—a finding with broad implications for understanding grammar acquisition, motor sequencing, and even neural coding. While traditional models (like TD) fail because they sum element-wise associations, SSCC-TD's success highlights the necessity of structured representations in learning systems. Together, these phenomena underscore that associative learning is not monolithic: it operates via multiple computational strategies (error-driven competition for discrete cues; configural encoding for sequences), each suited to different ecological demands.

References

Cambiaghi, M. & Sacchetti, B. (2015), 'Ivan petrovich pavlov (1849–1936)', *Journal of Neurology* **262**(6), 1599–1600.

Eberbach, E., Goldin, D. & Wegner, P. (2004), Turing's ideas and models of computation, *in* 'Alan Turing: Life and Legacy of a Great Thinker', Springer, pp. 159–194.

Goldin, D. & Wegner, P. (2005), The church-turing thesis: Breaking the myth, *in* 'Conference on Computability in Europe', Springer, pp. 152–168.

Mackintosh, N. J. (1975), 'A theory of attention: variations in the associability of stimuli with reinforcement.', *Psychological review* **82**(4), 276.

Modragon, E. (2024), 'Computational cognitive systems', Lecture notes, (INM703), City University of London. Accessed in course materials, Fall 2025.

Rescorla, R. A. & Wagner, A. R. (1972), A theory of pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement, *in* A. H. Black & W. F. Prokasy, eds, 'Classical Conditioning II: Current Research and Theory', Appleton-Century-Crofts, New York, pp. 64–99.

Rumelhart, D. E., Hinton, G. E. & McClelland, J. L. (1987), A general framework for parallel distributed processing, *in* J. L. McClelland & D. E. Rumelhart, eds, 'Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Volume 1: Foundations', MIT Press, chapter 2, pp. 45–76.