Demystifying unsupervised learning: how it helps and hurts

Franziska Bröker[1,2,3,4,*], Lori L. Holt[5], Brett D. Roads[6], Peter Dayan[1,7,†], Bradley C. Love[6,†]

[1] Department of Computational Neuroscience, Max Planck Institute for Biological Cybernetics, Tübingen, Germany

[2] Gatsby Computational Neuroscience Unit, University College London, London, UK

[3] Department of Psychology, Carnegie Mellon University, Pittsburgh, US

[4] Neuroscience Institute, Carnegie Mellon University, Pittsburgh, US

[5] Department of Psychology, University of Texas at Austin, Austin, US

[6] Department of Experimental Psychology, University College London, London, UK

[7] University of Tübingen, Tübingen, Germany

[†] equal contribution

* Correspondence: franziska.broeker.15@ucl.ac.uk (F. Bröker)

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Highlights

Humans are not guaranteed to benefit from unsupervised experiences (and neither are machines).

Instead, given unsupervised experience, humans self-reinforce their predictions. This can help performance when the predictions are accurate; it can hurt or have no effect when the predictions are inaccurate.

Predictions depend on the internal representations of learners which are shaped by prior experiences. Thus, prediction accuracy depends on how well internal representations align with the task. Only by assessing these representations can researchers understand whether and why unsupervised learning helps or hurts in a specific task and in a specific person.

Literatures on self-reinforcement and unsupervised learning in humans have largely operated in isolation but would benefit from more crosstalk.

Insights also have broad implications for lifelong learning and the design of instruction.

"There was, Carter thought, a downside to experience. 'Experience is making the same mistake over and over again, only with greater confidence,' he said. The line wasn't his, but he liked it."
— Michael Lewis, The Premonition: A Pandemic Story

Abstract

Humans and machines rarely have access to explicit external feedback, or supervision, yet manage to learn. Most modern machine learning systems succeed because they benefit from unsupervised data. Humans are also expected to benefit and yet, mysteriously, empirical results are mixed. Does unsupervised learning help humans or not? We argue that the mixed results are not conflicting answers to this question, but reflect that humans self-reinforce their predictions in the absence of supervision, which can help or hurt depending on whether predictions and task align. We use this framework to synthesize empirical results across various domains to clarify when unsupervised learning will help or hurt. This provides new insights into fundamentals of learning with implications for instruction and lifelong learning.

Keywords: unsupervised learning; semi-supervised learning; self-reinforcement; mental representation; representation-to-task alignment

Supervised and unsupervised learning

We live and learn in an environment that rarely provides us with **supervision** (see Glossary) in the form of explicit external **feedback**. For example, we have learned to call some animals “sheep” and others “goats”. Many of us acquired this distinction at a young age when we spent much time around our caretakers. Like an external teacher, they provided us explicitly with the correct labels by naming animals in our field of view. Getting older, we still encounter sheep and goats, as well as animals we have never seen before, but we now rarely have a teacher in tow. Thus, our learning about the world could be helped if we also made use of the information contained in all these unsupervised experiences (Fig. 1).

Machine learning faces a conspicuously similar problem. Typically, an abundance of unsupervised data is available for learning (e.g., images of sheep and goats), but supervision (e.g., human-annotated sheep / goat labels for each image) is rare and expensive. This has led to extensive research aiming to harness the information contained in unsupervised data. As a result, we now have powerful **learning algorithms** able to extract statistical information and features from unsupervised data [1] which can be further fine-tuned to specific tasks [2] or used to boost **supervised learning** [3]. Ultimately, the tremendous success of machine learning methods stems from their ability to learn in the absence of supervision.

The mystery of unsupervised learning in humans

It seems clear that both humans and machines benefit from leveraging unsupervised experiences. There has thus been a surge in empirical and computational work over the past decades proposing that humans perform **unsupervised learning** by applying information processing capabilities they share with machine learning algorithms [4–6]. A simple and intuitive prediction results from this: If humans share unsupervised information processing capabilities with machines, and machines show benefits leveraging unsupervised data, then humans should benefit from their unsupervised experience in the same way. That is, humans should be able to recover statistical information from their unsupervised experiences and they should be able to combine it with their rare, supervised experiences.

Paradoxically, this is not supported by the scientific literature. In the most basic learning experiments, humans are not guaranteed to extract the statistical information in their unsupervised experiences [7–10] or to boost their supervised learning [11–13]. In fact, unsupervised experiences can reduce performance in category learning [14], language learning [15,16], motor learning [17] and stereotyping [18,19]. So instead of supporting the view that unsupervised experiences help humans in their learning, the literature on lab studies is riddled with equivocal results about their benefit. In one experiment people may need feedback to learn how to distinguish between different visual inputs; in another, they do not [7,20].

These results stem from highly influential experimental designs that have shaped our understanding of how humans extract statistical information. Unsupervised studies often use a simple stimulus-response or passive exposure paradigm. These well controlled designs are popular because they parallel supervised designs, allowing comparisons. In unsupervised studies, learners predict task-appropriate responses from stimuli without feedback. The statistics in the stimuli are the only information available for learning. Supervised studies are close analogues which provide additional corrective feedback or correct labels, giving learners more information.

Outside the lab, human learning operates on a larger scale in terms of data and time. For example, an abundance of additional information can inform learning about sheep and goats, like separate housing. Learning also serves long-term performance in the world rather than on one specific task. Similarly, modern machine learning solves increasingly large-scale **learning problems**. Because machine learning algorithms can be flexibly chosen for specific problems, supervised algorithms now solve unsupervised problems by adapting the objective of the **learning task**, as in **self-supervised learning**. Another example is large language models which learn not by getting feedback on text they generate, but from predicting words in a sequence. This then serves as a foundation model for further supervised fine-tuning on how to engage in friendly chat with users. These developments increase the complexity in technical approaches and terminology that has yet to be reconciled with human learning inside and outside the lab. While an analogy between human and machine unsupervised learning is compelling and often assumed, the devil appears to be in the details.

Here, we mainly focus on in-lab studies that test unsupervised or **semi-supervised learning** using the well-controlled, influential designs. Other unsupervised paradigms exist but are rarer [21]. Our narrower focus ensures results across various learning contexts are informative about the same learning principles. We refer to momentary learning from unsupervised experiences in experimental tasks as simply "unsupervised learning" to differentiate it from momentary learning with supervisory signals. While focusing on in-lab studies, we also present evidence suggesting unsupervised learning to be limited more generally, as it can worsen performance in machines [3] and human learning outside the lab [22]. In fact, as it happens, telling sheep apart from goats is a task on which many people fail despite recurring exposure (Fig. 1b).

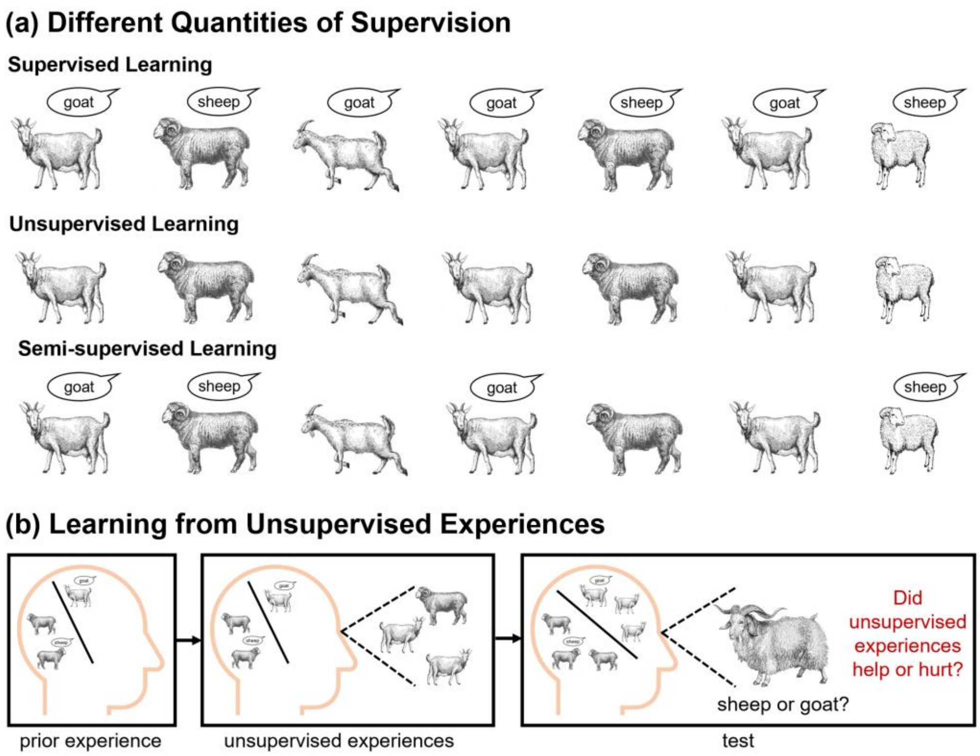

Figure 1. ***Learning with and without supervision.***
(a) Illustration of supervised, unsupervised, and semi-supervised learning problems. (b) Empirical results conflict as to whether unsupervised experiences improve human performance in unsupervised and semi-supervised learning tasks. We refer to the momentary learning from unsupervised experiences as simply "unsupervised learning" throughout the manuscript. The

reader is encouraged to guess whether the test animal is a sheep or goat. The answer is provided in the footnote.[1]

The unsupervised snowball effect

How can we explain the mysterious results? When does unsupervised learning help and when does it not? We think that the answer lies in the way that unsupervised learning is affected by the relationship between the experimenter-defined task and the representations subjects have acquired from prior experience (**representation-to-task alignment**, [14]). Concretely, we propose the unsupervised learning mechanism to be **self-reinforcement** by which humans learn from their own predictions so that pre-existing associations between experiences and appropriate responses are strengthened (Fig. 2 b, Key Figure) and decision confidence increases. For example, when seeing the woolly goat in Fig. 1b, readers who categorize by woolliness would incorrectly self-reinforce their predictions that it is a sheep, whereas readers who know to attend to the tail would correctly self-reinforce their prediction that it is a goat. Since strengthening predictions snowballs existing learning without changing its course, self-reinforcement can help or hurt depending on how accurate the predictions are for the task at hand (Fig. 2 a). Self-reinforcing predictions that are largely correct will improve performance in the task. But predictions will only be largely correct if prior experiences shaped the learner's representations in a way that new experiences elicit appropriate predictions. If this is the case, representations and task are aligned, the task feels "easy", and supervision is superfluous. By contrast, self-reinforcing predictions that are largely incorrect will have a detrimental, or at best no, effect on performance. Predictions will be largely incorrect if prior experiences have shaped the learner's representations to be misaligned with the task. In this case, the task feels "hard", and supervision is necessary to adjust the unhelpful representations and predictions of the learner. That self-reinforcing existing representations results in these kind of learning dynamics has previously been described in the specific context of unsupervised Hebbian (correlational)

[1] The test animal in Fig. 1b is a goat. While most non-experts make their sheep/goat predictions based on unreliable features, such as woolliness, the easiest way to tell them apart is by their tails: goats point their tails upward while sheep cannot lift their tails.

learning [23,24]. Our framing of unsupervised learning in terms of representation-to-task alignment and self-reinforcement is more general in that it does not assume specific representations nor a specific computational model of learning.

This type of self-reinforcing snowball effect can also be seen when trying to master a new skill, such as playing the violin. This requires practicing with the correct technique because a faulty technique engrains mistakes if left uncorrected. Thus, from our perspective, the equivocal results in the literature about the benefit of unsupervised experiences do not reflect a conflict but are in fact expected from representation-to-task alignment and its interaction with unsupervised self-reinforcement. Our argument not only follows an intuitive logic but is also supported by the theoretical principles that allow machine learning algorithms to leverage unsupervised data on many, but not all, occasions (Box 1).

In the following, we provide support for this perspective by synthesizing various cognitive science literatures that have long investigated the questions about how feedback influences human learning. The fact that related research fields have largely developed in isolation allows us to test our predictions against their extensive independent evidence. First, we show that representation-to-task alignment correlates with the efficacy of unsupervised learning, as predicted by our hypothesized unsupervised snowball effect. The evidence we consider for the effect of alignment is often somewhat indirect because learners' representations, let alone their alignment with the task, are not typically assessed. We thus leverage the equivalences between representation-to-task alignment, predictions and task difficulty as described in Fig. 2a to contextualize the results. Second, we show that unsupervised self-reinforcement has been reported repeatedly across diverse learning settings. We conclude by discussing the implications of our analysis and promising future avenues.

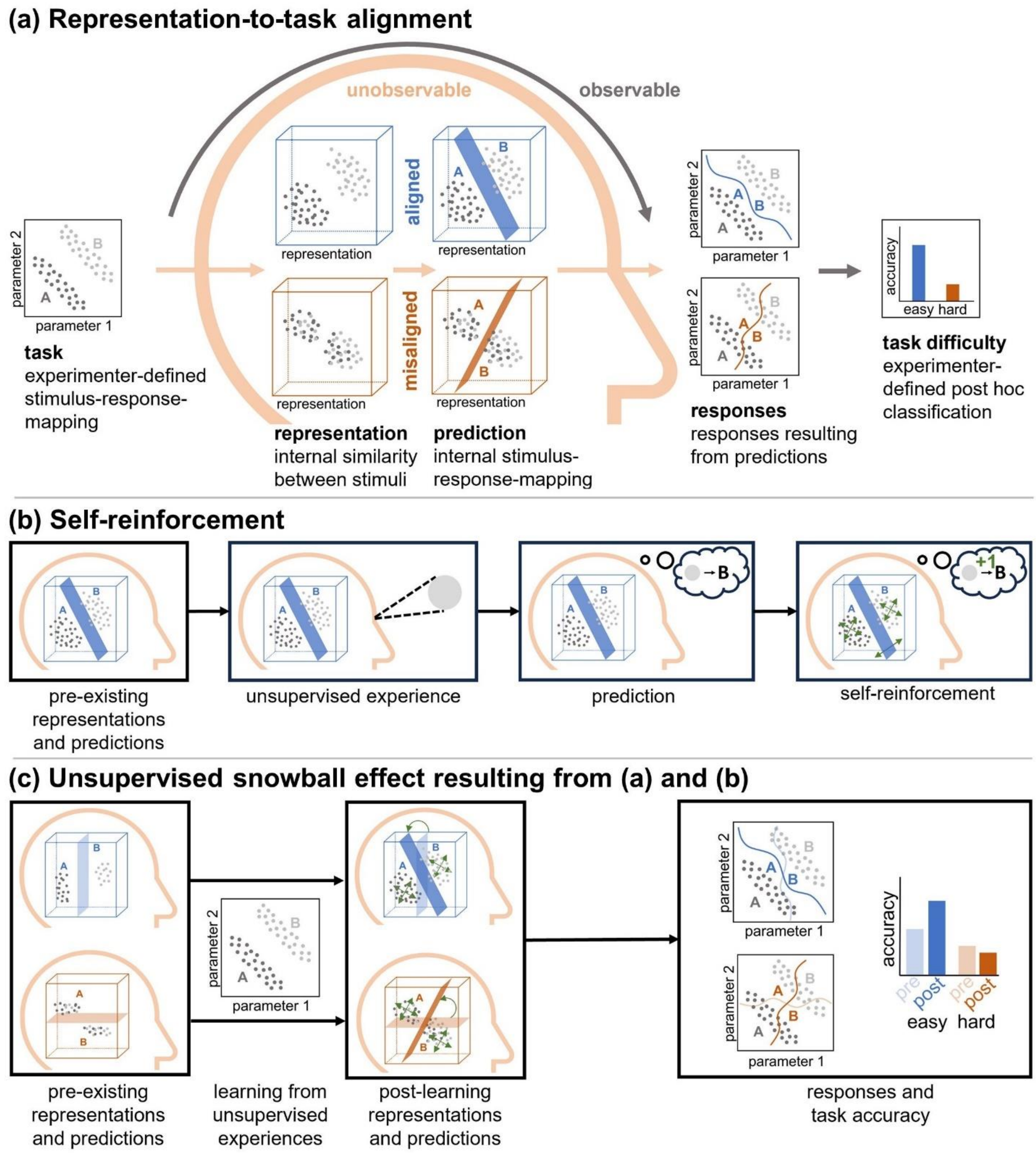

Figure 2. ***The unsupervised snowball effect.***
Two key factors affect unsupervised learning: representation-to-task alignment and self-reinforcement resulting in the unsupervised snowball effect as illustrated for the example of a category learning task. (a) Relationship between experimenter-defined task, its internal representation and the resulting predictions, responses, and accuracy. Factors including prior

experience, context or attention transform observed stimuli and warp their similarities into an internal representational space that might or might not recover experimenter-defined task statistics. If learners have a task-aligned representation, stimuli from different categories are sufficiently separated in the learner's representational space such that it supports accurate predictions. The task will seem easy and performance will be high. If learners have a task-misaligned representation, items from different categories are not well separated in the learner's representational space such that they make incorrect predictions based on whichever task-irrelevant statistics their representations reflect. The task will seem hard and performance will be low. We can thus assume an equivalence between alignment in representations, accuracy of predictions and task difficulty. (b) Self-reinforcement of predictions (adapted from [19]*). When a stimulus is observed without supervision, an appropriate response is predicted and subsequently self-reinforced. This results in changes in the representations and predictions. (c) If prior representations and predictions are sufficiently aligned with the task, self-reinforcement leads to performance improvement. In the case of misalignment, self-reinforcement has detrimental or no effect on performance. This results in a snowball effect, the course of which can only be changed if supervision is provided to correct mistakes and align representations with the task.*

Box 1: Theoretical principles predict unsupervised snowball effect

We propose that human predictions self-reinforce in the absence of supervision. Since self-reinforcement simply snowballs prior learning, it can help or hurt performance depending on whether predictions and their underlying representations align with the task. Unsupervised learning only succeeds in tasks aligned with the learner's representations.

This intuitive reasoning is supported by the theoretical and computational principles that allow unsupervised and semi-supervised machine learning algorithms to be successful. Inevitably, unsupervised learning can only recover ground-truth structure in the data if this structure is reflected in salient data statistics. For example, for clustering to work, similar points must belong to the same cluster and dissimilar points must belong to different clusters (this is known as the cluster assumption, [95]). In other words, clusters need to be sufficiently easy to tell apart to be accurately recovered. In the same way, successful semi-supervised learning requires the to-be-learned input classes to be sufficiently distinctive to work effectively [96–98,3]. Because this is not always guaranteed, and in practice is often difficult to validate, unsupervised data is not guaranteed to boost an algorithm's supervised performance. In fact, much of the success of semi-supervised machine learning could be due to standard-practice data curation that removes difficult datapoints from unsupervised training with the effect that input classes become more distinct [99]. Thus, while learning from unlabeled data has led to the much-reported performance boosts in machine learning, they can also lead to degradation. In fact, reports of performance degradation following the addition of unsupervised data exist and are likely under-reported [3].

Returning to empirical studies, sufficient cluster "distinctiveness" may appear to be a theoretical prerequisite that is easy enough to control experimentally to assess successful, rather than detrimental, unsupervised learning. However, there is a subtle, yet crucial, twist: while experimental tasks may appear to comply with the prerequisite in the experimenter-defined input space, they can simultaneously violate it in the space relevant for learning which is not routinely assessed -- the learner's internal representations of the input space (Fig. 2a). When overlooked, equivocal results about the benefit of unsupervised experiences can appear conflicting when, in fact, they are predictable. To understand whether results conflict or are simply evidence for the varied directions unsupervised self-reinforcement can take, the alignment between internal representations and experimenter-defined task needs to be considered.

Representation-to-task alignment determines efficacy of unsupervised learning

Representation-to-task alignment is a theoretical concept capturing how well a learner's representations set them up for learning in a new task. Alignment is sufficient when task-relevant statistics are prominent in the representations (e.g., well-separated clusters), when only adaptation of existing representations is needed (e.g., repositioning cluster centers), or both when a beneficial learning sequence builds on prominent representations and subsequently adapts them (e.g., an easy-to-hard curriculum). In these cases, performance is high, and tasks are easy (Fig. 2a). Because representation-to-task alignment is independent of any specific type of representation or task, we can expect to observe its effects on the efficacy of unsupervised learning across all types of learning. Here, we will test this prediction against the evidence from different, independent literatures.

Perceptual and category learning

Perceptual and category learning experiments share many methodological commonalities. Perceptual learning investigates how perception is changed because of experience with sensory inputs, like the ability to distinguish different line lengths. This fundamental form of learning is often studied by manipulating simple, physical stimulus dimensions like line length. Category learning investigates the process of assigning labels (or other distinct responses) to groups of inputs, such as assigning either “sheep” or “goat” to each input. This is often studied by manipulating stimulus distributions and boundaries defining categories within them. Stimuli can range from simple shapes or sounds, akin to those used in perceptual learning, to complex, high-dimensional artificial objects. In both paradigms, learners are usually presented with stimuli on a trial-by-trial basis and respond by guessing category membership, or in the case of perceptual learning, making a same-different judgment between two stimuli.

The perceptual learning literature has extensively studied the effect of different forms of supervision [25,26] and thus serves as a superb source of evidence on the effectiveness of unsupervised learning. Results can be summarized simply: unsupervised perceptual training can help in some, but not all, tasks. It does this in a way that correlates with task difficulty, as predicted by our representation-to-task alignment view that requires sufficient class separation or convenient presentation order. Concretely, unsupervised learning helps if the task is easy and training accuracy is high, as predicted for aligned tasks, [27] or if high-accuracy, easy trials precede or are interleaved with low-accuracy, difficult trials [28–30]. By contrast, feedback appears necessary for learning when task difficulty is high and initial performance is low, as predicted for misaligned tasks [31,27].

Unsupervised and semi-supervised categorization studies in adults echo results from perceptual learning: unsupervised experiences facilitate learning in easier tasks, but not in more difficult ones [9,10]. Learning to separate low-variability categories is easy (aligned task) and equally effective with or without feedback, whereas learning to separate high-variability categories is hard (misaligned task) and requires feedback [32]. Extending this finding, category learning is known to be influenced by the degree of within-category variance [8], with unsupervised learning being most effective and robust when categories are statistically dense and category separation is large [33–35]. This further indicates that sufficient class separation is necessary for successful unsupervised learning (Box 1).

Moreover, unsupervised experiences can have both beneficial and detrimental effects in the exact same task, depending on the alignment of a learner's representations [14]. This pattern is also reflected across tasks. In simple category structures, where stimuli vary along a single dimension, learners can recover categories [20] or shift previously supervised category boundaries without feedback [36–40]. By contrast, in two-dimensional tasks, subjects appear unable to recover categories without feedback [7] and the addition of unsupervised experiences does not boost supervised performance [11,12] except under limiting conditions [41–43]. While experimenter-defined task dimensionality does not imply task difficulty per se, in these experiments, representations required to succeed in the two-dimensional tasks were unmistakably less obvious compared to those required for the one-dimensional tasks. In line with these results, prior knowledge relevant to the task can enhance unsupervised learning [44].

This pattern of results is echoed in language acquisition. When learning nonnative phonetic contrasts, unsupervised exposure has been shown to be unsuccessful unless it is complemented by sufficient supervised learning [45] or if it only involves shifting boundaries of existing phonetic contrasts [46] or if phonetic contrasts are made distinctive [47,48]. We can rephrase these results within our perspective: Learning new phonetic contrasts is challenging due to their misalignment with the native speech sound space. To make unsupervised exposure succeed, the task needs to be simplified either by providing feedback that fosters the formation of more aligned representations, by changing the task to only involve modulation of existing, sufficiently aligned representations, or by amplifying the to-be-learned contrast as a form of class separation. Similarly, unsupervised exposure to an artificial language leads to simple word learning whereas learning its complex syntactic regularities requires feedback [49]. Further, research on infants' capacity to integrate labeled and unlabeled exposure to new categories indicates that learning is successful only when labels are introduced initially, but not when they are presented at the end or omitted entirely [50,51]. This lends credence to our prediction that supervision is required to transition from a misaligned to an aligned representational space before unsupervised experiences can improve performance. A study investigating children's acquisition of linguistic category labels revealed that unsupervised exposure to structured, straightforward labels (regular plural nouns) impaired performance on unstructured, difficult labels (irregular plural nouns) among younger, error-prone children who have not yet mastered the regularities and irregularities. Conversely, it boosted performance among older, more proficient children capable of making adequate predictions [15,16]. This underscores that the outcomes of unsupervised training can vary within the same task, contingent on the learners' representations.

Pre-exposure studies assess the impact of initial unsupervised exposure on later supervised learning and have received independent attention. The effects of pre-exposure vary with category structures [13] with improvements seen for statistically dense categories [52] and exposure to easy stimuli [53,54]. This is in line with our perspective: unsupervised pre-exposure helps in easy tasks but does not affect, or even hinders, difficult ones. Interestingly, rat studies show the opposite (Box 2). This discrepancy is likely due to humans' ability to reason about tasks [55].

Selective Feedback

Real-world feedback is selective and action-dependent which can lead to learning traps due to unchallenged false predictions [56]. For example, a negative first impression may deter future interactions, preventing the revision of potentially false initial impressions [57]. Similarly, stereotyping can be perpetuated by initial negative experiences with a group, leading to future avoidance. This selective information sampling prevents updating of false predictions about group members and the likelihood of future avoidance increases when predictions are made without feedback [18]. Consequently, stereotyping intensifies over time, with untested predictions often misremembered as validated [19]. In this way, the selective-feedback literature highlights the detrimental effects of unsupervised learning when predictions are misaligned with reality, as seen in stereotyping.

Expertise

So far, we have seen that unsupervised learning effects vary in controlled lab studies. To gauge whether this generalizes to real-world learning, we can assess uncontrolled, long-term learning. Expertise is the product of extensive learning from varying quantity and quality of supervisory signals outside the lab. For instance, radiologists initially receive supervised training but later get less feedback, often not knowing if their diagnoses were correct. If unsupervised experiences had only beneficial effects, we would expect performance to improve over time, leading to expertise even without supervision. However, this prediction has received substantial opposition [58–62] and has even led critics to claim that "At best, experience is an uncertain predictor of degree of expertise. At worst, experience reflects seniority – and little more." [60].

Biases, a form of prior expectations, can distort learning and hinder steady improvement through experience. For instance, confirmation bias gives more weight to information that aligns with learners' expectations, skewing learning away from actual evidence [63,64]. In other circumstances, learners may attribute their failure to external factors instead of modifying their erroneous behavior so that performance deteriorates [22].

Irrespective of how expert performance is reached, the expertise literature supports, on a more general level, the claim that unsupervised experiences alone do not guarantee improvement. Instead, reliable improvement seems to require rapid and regular feedback on decisions [62]. Because acquiring expertise is not easy, but involves learning new skills beyond prior knowledge, these results fit well with our representation-to-task alignment perspective. This is further supported by work showing that initial feedback and guidance are crucial for skill learning [65]. For instance, an in-lab study shows that withdrawing feedback early in motor skill learning, when errors are high (inaccurate predictions), causes performance to deteriorate, whereas doing so later, when errors are low (accurate predictions), enables the skill to be maintained or improved [17].

Box 2: Results requiring further attention

Pre-exposure in rodents. Interestingly, the effects of unsupervised pre-exposure in rodents are found to be the opposite of those observed in humans. Rodent studies show that unsupervised learning benefits are greater when stimuli are perceptually similar and thus hard to discriminate [100]. Conversely, rodent learning can be hindered when the stimuli are perceptually distinct and thus easier to discriminate [101,102]. This effect is attributed to a combination of two learning principles: unsupervised differentiation, which refines representations over time, and latent inhibition, which reduces the associability between inputs and a response [102]. In this context, latent inhibition could explain the slower learning seen after exposure to stimuli that are easily distinguishable.

The opposing effects observed in animals and humans could be due to humans' awareness of their participation in an experiment, leading to heightened attention to stimuli and potential weakening of latent inhibition [55,103]. This is supported by the reversal of pre-exposure effects in rats when using hedonic stimuli which are believed to stimulate attention [104]. Moreover, interleaving unsupervised and supervised trials in mice appears more effective than unsupervised pre-exposure [105], potentially also modulated by attentional factors.

Blocked testing effects. Understanding learning is important, but it is also important to examine how learning could be helped. Across domains, research on optimal training schedules shows that interleaving supervised training with blocks of unsupervised testing consistently improves human learning compared to no testing or restudying of materials. It helps learning and retention of materials preceding or following testing [106,107] and even replacing interim active testing with passive exposure improves performance [108,109]. While individual studies highlight the benefits of supervised testing, particularly its ability to correct inaccuracies and confirm low-confidence predictions [110], a meta-analysis reveals unsupervised testing benefits are comparable [111]. Taken together, these results appear to suggest that unsupervised testing is exclusively beneficial, a finding that would contradict our unsupervised snowballing theory. However, occasional evidence of performance interactions with learner proficiency and confidence suggest representation-to-task alignment effects may be at play and could simply have gone underreported.

Self-reinforcement underlies unsupervised learning

While representation-to-task alignment can predict the effectiveness of unsupervised learning, it does not provide a mechanism. A number of specific learning procedures have been explored in this context, all of which have self-reinforcement at their core, where learning uses the system's own predictions in lieu of ground-truth supervision, snowballing existing learning without altering its direction.

Perceptual learning, category learning and expertise

The perceptual learning literature not only supports representation-to-task alignment, but also offers strong evidence for unsupervised self-reinforcement, formalized by Hebbian learning models. Unsupervised Hebbian learning can improve or degrade performance depending on how well representations serve learning a task [23,24]. A Hebbian model that learns from both unsupervised and supervised experiences by adapting representations and their associations with responses [66,67] is successful in accounting for a broad range of results [27]. While trial-by-trial category learning is only rarely modelled, self-reinforcement models have demonstrated their ability to account for semi-supervised categorization [68,14] and can also predict unsupervised learning trajectories in children acquiring linguistic labels [16]. In expertise studies, computational work is limited. However, theories of closed-loop motor skill learning suggest internal estimates guide learning in the absence of feedback leading to either performance gains or decrements [69].

Selective Feedback

As described earlier, false predictions that remain unchallenged can, for example, lead to the perpetuation of stereotypes. This can be accounted for by models employing unsupervised self-reinforcement [18,19]. Predictions also remain unchallenged when some actions are never followed by feedback (i.e., unsupervised actions). Here, the same self-reinforcement can be observed: humans learn from their own predictions as if they received validation for it (constructivist coding hypothesis, [70–72]) which can be modeled by a self-reinforcement mechanism [71].

Internal feedback signals

Self-reinforcement requires internal learning signals independent of external supervision. While the neural mechanisms involved in external supervision (or at least rewards and punishments) are fairly well understood [73], knowledge of the brain's self-generated feedback signals is limited. Recent studies indicate that brain areas active during external feedback processing are also active when feedback is inferred [74–76]. Moreover, choice consistency and subjective confidence increase in the absence of feedback reflecting self-reinforcement [77] which is in line with evidence that chosen actions carry more internal weight than unchosen ones [78]. Subjective rewards can also self-reinforce choices [79]. Large-scale, real-world studies indicate that this can cause people to fall into a learning trap, ceasing exploration and exploiting even when better options exist [80], which an error-driven learning model can account for by aligning subjective preferences with past choices [81]. Neuroimaging also shows that preferences are updated online and only for remembered choices [82]. Moreover, replay, another active research area, involves a form of self-reinforcement in which the brain rehearsed past experiences through offline neural reactivation [83,84]. Overall, research supports the brain's use of unsupervised self-reinforcement mechanisms, with internal signals like confidence playing a key role when feedback is absent.

Concluding remarks

In summary, studies across different literatures and learning domains support our perspective: Humans self-reinforce their predictions in the absence of supervision, which can either help or hurt performance depending on the alignment between the learner's representations and the task. While we focused on studies testing unsupervised learning under controlled conditions, the expertise literature suggests that these considerations are also relevant to naturalistic settings. This shift in perspective resolves the paradox to predict learning successes and failures in the lab, and fundamentally alters what we expect from unsupervised learning. Unsupervised learning may not be the knight that battles to save us when we lack supervision; instead, it appears to wield a double-edged sword. This raises new questions and lays the foundation for future research on the role of supervision in learning that will have implications for the design of instruction and learning over the lifespan (see Outstanding Questions).

A key implication of this perspective is that a deeper understanding of unsupervised learning requires consideration of the alignment between mental representation and task. This is challenging because alignment depends on specific stimuli, task structures, and learners' representations. Efficiently assessing and modeling alignment to account for individual tasks and learners is an important future direction that can build on recent advances [85–88]. In fact, assessing alignment is also important for predicting supervised learning [89,90], memory [91] and perception [92] which suggests that it also applies to naturalistic, large-scale unsupervised learning. Future models need to make explicit the concrete relationship between alignment and learning and be constrained by neural evidence on biologically supported mechanisms [93].

Our efforts to understand when unsupervised learning succeeds and fails have illuminated the rich interconnections between historically separate research areas that can be leveraged in future studies. Beyond the topics discussed here, relevant research also encompasses areas like attention [94] and training schedules (Box 2). Linking results across these domains promotes a more rigorous examination of learning principles.

Future research should also go beyond the traditional approach of studying unsupervised learning in isolation. To understand why humans manage to learn despite all difficulties, we need to explore how supervised and unsupervised learning mechanisms interact and relate to feedback sources more akin to reinforcement, self-supervised, or sequential learning that are blended in modern machine learning systems. Crucially, future work should explore how unsupervised self-reinforcement and learning from (self-)supervisory signals coexist in humans, who may use one general-purpose mechanism instead of different special-purpose algorithms like machines. This crosstalk could lead to a more holistic theory of human learning, which is important for understanding real-world learning, like the acquisition of expertise.

In conclusion, we advocate for an interdisciplinary approach to studying the mechanisms of unsupervised learning and the broader role of supervision which should integrate representational and neural constraints. This new direction contributes to our understanding of learning fundamentals and can improve the design of instructional systems that better support learning across the lifespan to prevent us from mistaking goats for sheep with ever greater confidence.

Outstanding questions

What exactly is the quantitative relationship between representation-to-task alignment and learning? How does this relate to different sources of the problem, e.g. poor extraction of relevant features versus good feature extraction, but poor cluster separation? How does this relate to different timescales, e.g. short-term learning to direct attention versus long-term representational change?

How much representation-to-task alignment is needed for unsupervised learning to help?

How can we measure representation-to-task alignment? How can we incorporate representation-to-task alignment into computational models of learning?

Does representation-to-task alignment affect supervised and unsupervised learning differently?

How is self-reinforcement implemented by the brain? Which role does meta-cognition play in this? Is it affected by brain development?

Does self-reinforcement affect supervised learning too?

How do supervised and unsupervised learning interact? Are they fundamentally different or can they be unified?

How does learning from other feedback signals, like reward, compare with supervised and unsupervised learning?

How does unsupervised learning compare in humans and animals? Are there differences between implicit / subconscious and deliberate / conscious unsupervised learning?

Which other factors related to the presence and absence of supervision, like motivation, affect learning?

How does the sequential order (e.g., blocked supervised and unsupervised exposure) affect unsupervised learning?

Glossary

Learning algorithm: The specific algorithm used to maximize a task objective which can be supervised or unsupervised. A supervised algorithm (e.g., a standard neural network) learns an input / stimulus to output / response mapping and uses supervision to improve its predictions. Apart from solving supervised learning problems, supervised algorithms can also be used to tackle unsupervised learning problems by adapting the task objective (e.g., self-supervised learning). An unsupervised algorithm (e.g., a standard Bayesian Graphical Model) extracts information from the inputs / stimuli without accessing ground-truth supervision. Unsupervised algorithms are designed to solve unsupervised problems but can also be adapted to tackle supervised learning problems.

Learning problem: The type of learning problem that is partially defined by the data, especially whether supervision is available or not (i.e., supervised or unsupervised learning problem).

Learning task: The specific task (or task objective) that is defined within a learning problem and which can be supervised or unsupervised. In experimental studies, the task objective derives from the experimenter-defined stimulus-response-mapping.

Representation-to-task alignment: The degree to which the internal representations of a learning system create a similarity space that suggests an input / stimulus to output / response mapping that is in agreement with the objective mapping defined by the task.

Self-reinforcement: A mechanism by which a system learns from its own predictions in lieu of ground-truth supervision. This has the effect that existing predictions from inputs / stimuli to outputs / responses are strengthened. This mechanism can, in principle, be implemented both by supervised and unsupervised algorithms. This mechanism is popular in semi-supervised machine learning and called self-training or pseudo-labelling.

Self-supervised learning: A machine learning approach that solves an unsupervised learning problem by turning it into a supervised task so that a supervised algorithm can be applied. Since no external supervision is available, supervision is created directly from the unsupervised data.

Semi-supervised learning: Learning in a problem / task that offers a mixture of supervised and unsupervised inputs / stimuli.

Supervised learning: Learning in a problem / task that requires the learning of an input / stimulus to output / response mapping and in which ground-truth supervision is available.

Supervision / Feedback: In machine learning, supervision is defined as the delivery of ground-truth outputs (e.g., labels) following some inputs (e.g., images). In human learning studies, supervision more often refers to the delivery of corrective feedback (e.g., correct / incorrect response) on their response to some preceding stimulus.

Unsupervised learning: Learning in a problem / task without supervision, simply through extraction of information from the observation of inputs / stimuli.

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