Real-Time Learning as an Experiential Process: A First-Person Perspective on Generality, Creativity, and Alignment

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Abstract

This paper presents a first-person, experiential perspective on real-time learning, generality, alignment, and creativity in artificial intelligence. It does not propose a concrete architecture, optimization objective, or prescriptive design framework. Instead, it offers a set of empirical observations derived from sustained first-person engagement with learning and interaction processes.

The paper explores the possibility that real-time learning may be understood as the repeated capacity to locally reduce experiential noise over time, and that both learning and creativity may arise from recognizing similar structures within an experiential noise landscape and reusing adaptive approaches that have previously proven effective.

It further considers whether alignment with humans, human-like generality, and experiential-layer alignment may be related through shared constraints on predictability and experiential stability.

All ideas presented here are personal and experiential in nature. They are not offered as claims that must be accepted, but as a perspective that may be useful to others. Readers are free to adopt, adapt, or disregard these observations based on their own judgment and experience.

Scope and Disclaimer

Before proceeding, it is important to clarify the scope of this paper. The arguments presented here are not intended as prescriptive design principles, nor as claims about how general intelligence must be implemented. They arise from a first-person, experiential perspective formed through sustained interaction with complex and evolving environments.

Accordingly, the ideas presented should be understood as personal and empirical in nature. They are offered as a perspective that others may find useful, not as conclusions that must be accepted.

1 Why Scenario-Dependent Inputs Undermine Generality

By *scenario-dependent inputs*, we refer to parameters that explicitly encode task identity, environmental roles, object categories, or externally defined situational labels. Such inputs assume that the current situation can be correctly identified prior to reasoning.

From a structural standpoint, this assumption conflicts with the goal of general intelligence. Once scenario parameters are introduced, the system's competence becomes conditional on the correctness of scenario identification. Errors at this stage constrain the reasoning process from its outset rather than merely degrading performance.

From a first-person experiential perspective, the world is not encountered as a sequence of labeled scenarios. Instead, interaction unfolds as continuous variation in internal experiential states such as clarity, confusion, stability, or tension. These variations precede explicit classification and guide reasoning.

Restricting input to experiential signals $E(t)$ avoids premature commitments about what the world is. Such signals are internally observable, continuously defined, and agnostic to task or scenario identity, thereby preserving the possibility of generality under unforeseen conditions.

Generality as a First-Person Property

Removing scenario-dependent inputs highlights a limitation of third-person accounts of generality. External evaluation necessarily relies on predefined task boundaries or scenario partitions, thereby reintroducing assumptions that a general system is meant to avoid.

From the system's own perspective, generality manifests not as performance across labeled tasks, but as the sustained ability to maintain coherent reasoning under changing and unforeseen conditions. This coherence often degrades internally before external failure becomes observable.

In this sense, generality is not an externally measurable attribute, but an internally maintained property. A first-person perspective provides access to experiential signals that indicate whether this property is being preserved or eroded in real time.

2 Experiential Signals, Real-Time Learning, and Creativity

Once input is restricted to the experiential layer $E(t)$, learning can no longer be treated as a discrete or offline process. Any mismatch between the system's internal structure and its interaction with the world is immediately reflected at the experiential level.

From a first-person perspective, learning is not experienced as the optimization of an abstract objective. Instead, it appears as movement within a continuously changing noise landscape, where different regions correspond to varying degrees of experiential instability or coherence.

A defining characteristic of effective real-time learning is the repeated occurrence of local conditions under which experiential noise decreases, that is, moments where

$$\frac{d(f_{\text{noise}})}{dt} < 0.$$

These moments do not represent final solutions or global optima. Rather, they reflect temporary restoration of experiential stability relative to the immediate past. As both the system and the environment continue to change, such reductions must be continually re-established.

Learning involves recognizing similarities within the experiential noise landscape. Although exact experiential states rarely repeat, regions of the landscape may share similar local structure. Learning occurs when the system can identify such similarities and reuse adaptive approaches that previously enabled experiential noise to decrease under comparable conditions.

From this perspective, creativity may arise from the same underlying process. Creative behavior does not require encountering entirely novel experiential terrain, but may involve recognizing familiar noise-landscape structures in new contexts and applying adaptive methods in ways that have not been previously combined or expressed.

In this sense, learning and creativity may not be fundamentally distinct processes. Both may depend on the system's capacity to recognize structural similarities within experiential noise and to reuse or recombine adaptive modes that previously supported experiential stability.

3 A Simple Spatial Example: From Physical Conditions to Experiential Noise

To make the proposed framework concrete, we present a minimal numerical example that connects a physical spatial condition to an experiential noise field and a simple learning process operating on it. The goal is not physical realism, but a fully explicit and reproducible illustration of how an experiential constraint can shape perception and action in space.

3.1 Spatial temperature field

We consider a one-dimensional spatial domain $x \in [-10, 10]$ m, discretized with a spatial resolution of $\Delta x = 0.1$ m. A steady-state temperature field $T(x)$ is obtained by solving a diffusion equation with ambient heat loss,

$$k\frac{d^2T}{dx^2} - h\big(T - T_{\mathrm{amb}}\big) + s(x) = 0, \tag{1}$$

where k is a diffusion coefficient, h models heat exchange with a cold environment, and $s(x)$ is a localized heat source centered at $x = 0$. Finite-difference discretization with fixed boundary temperatures is used to obtain a stable temperature profile resembling a steady fire source in a cold environment.

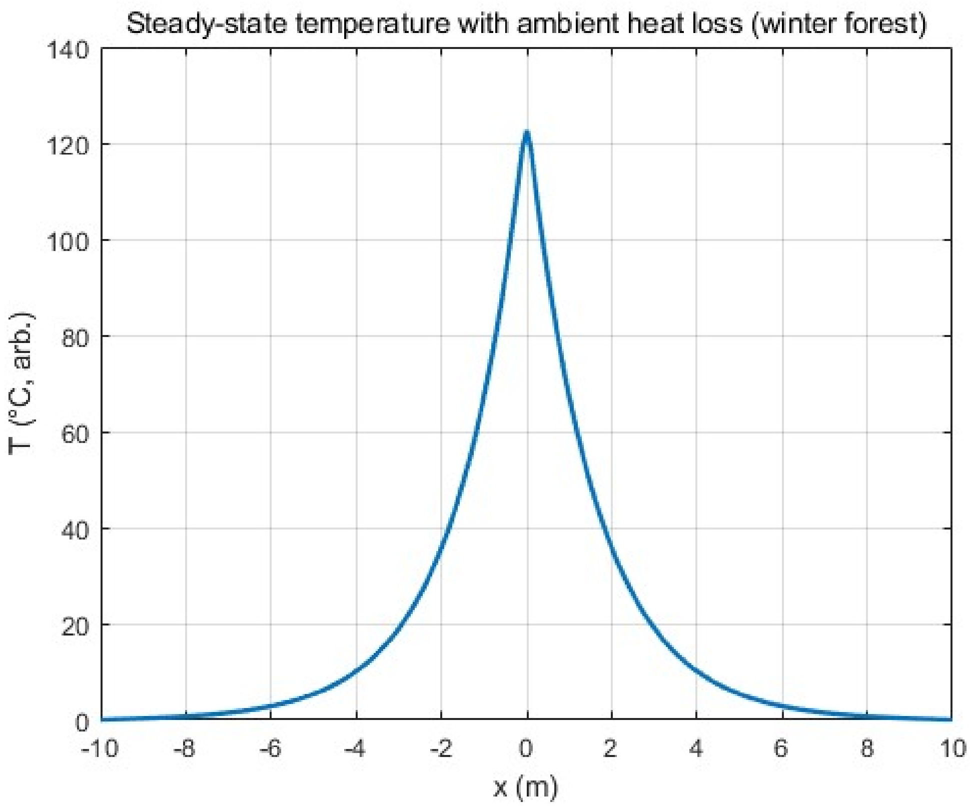

Figure 1: Steady-state temperature distribution $T(x)$ produced by a localized heat source in a cold environment.

3.2 Experiential noise mapping

To connect physical conditions to experience, we introduce an illustrative mapping from temperature to experiential noise, denoted $f_{\text{noise}}(T)$. A comfort temperature $T_{\text{c}} = 25°\text{C}$ is assumed to minimize experiential noise, and deviations from this value increase noise symmetrically:

$$f_{\text{noise}}(T) = 10 + 2\,|T - T_{\text{c}}|. \tag{2}$$

This mapping is not intended as a universal model of human comfort; it serves only as a simple example of how a physical variable may be transformed into an experiential constraint with a well-defined minimum.

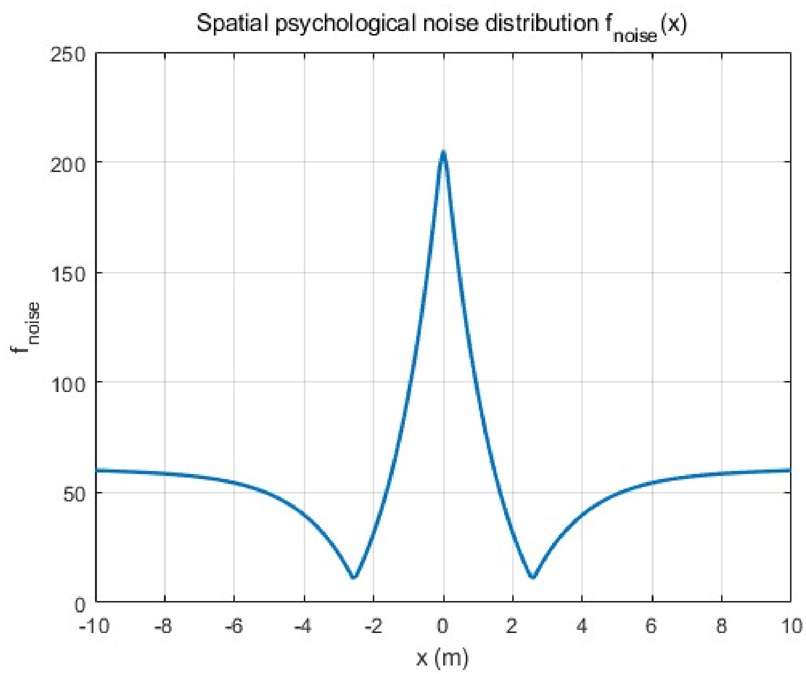

Figure 2: Illustrative mapping from temperature to experiential noise $f_{\text{noise}}(T)$, with a minimum at the comfort temperature $T_{\text{c}} = 25°\text{C}$.

Composing the two mappings yields a spatial experiential noise field,

$$f_{\text{noise}}(x) = f_{\text{noise}}\big(T(x)\big), \tag{3}$$

which can exhibit two symmetric minima when the temperature at the heat source exceeds the comfort level. In this case, the lowest experiential noise does not occur at the source itself, but at locations where the temperature crosses the comfort value.

3.3 Local sensing, movement, and trajectory

We consider a simple agent initially positioned at $x = -10$ m. At each step, the agent senses the experiential noise field within a limited radius of 2 m, estimates the local slope of $f_{\text{noise}}(x)$ inside the sensed window, and moves by 1 m along the spatial axis in the direction predicted to reduce experiential noise. When the magnitude of the estimated slope exceeds a threshold, movement is triggered by this directional estimate; otherwise, a conservative fallback based on immediate noise comparison is used.

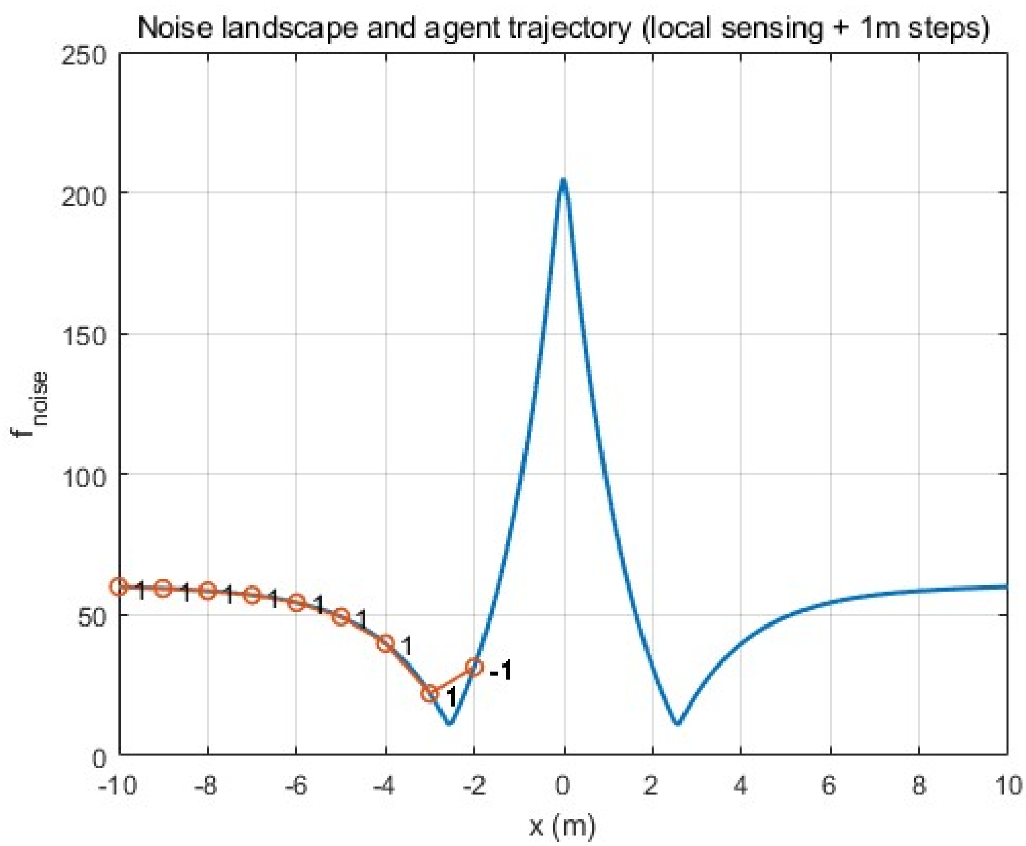

Figure 3: Spatial experiential noise field $f_{\text{noise}}(x)$ together with the agent trajectory. Points indicate successive agent positions, while arrows denote discrete movements along the spatial axis. Red arrows correspond to slope-triggered movements, and gray arrows to fallback decisions when the local slope is weak or ambiguous.

3.4 Learned representation

After exploration, the agent possesses a partial internal representation of the experiential noise landscape assembled from previously sensed local regions. This learned representation is not a complete global map, but a structured record of experienced spatial regularities.

Once formed, such a representation can be reused in two distinct ways. First, in a highly similar spatial condition, the learned noise profile can be directly recalled to guide action without repeating the full exploratory process. In this case, the representation functions as a reusable internal terrain model, allowing the agent to immediately select movements expected to reduce experiential noise.

Second, in a related but not identical condition, the learned representation can support a form of transfer. Rather than being recalled verbatim, the previously learned structure provides a template for interpreting new sensory input. Local observations are compared against the stored pattern, enabling the agent to infer likely directions of noise reduction even when the environment differs in detail. In this sense, the representation supports creative adaptation rather than direct reuse.

Importantly, neither reuse nor transfer requires explicit optimization over an external objective. Both rely on the internal organization of experience shaped by prior interaction with the noise landscape. The learned representation thus acts as a constraint-bearing structure that can be invoked across similar contexts or flexibly adapted to novel ones.

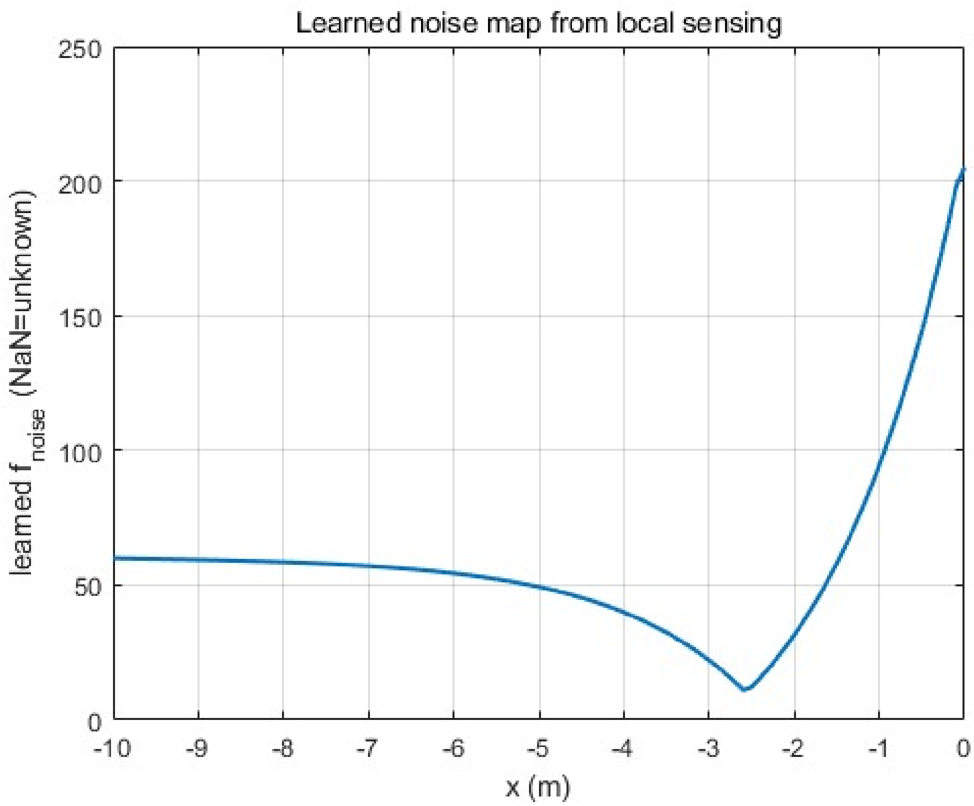

Figure 4: Learned experiential noise representation after exploration. The curve reflects the agent's partial reconstruction of the spatial noise landscape from local sensing.

3.5 Interpretation

This example illustrates how an experiential constraint can give rise to internal structure through interaction with the environment. The learned representation does not encode an external objective or an explicit policy; instead, it captures regularities in the experiential noise field encountered during exploration.

Crucially, the representation is neither tied to a single trajectory nor restricted to a fixed environment. In highly similar conditions, it can be directly invoked to guide action without repeating the original exploratory process. In related but non-identical conditions, the same structure can support transfer by providing a reference pattern against which new sensory input is interpreted.

In both cases, action selection remains grounded in experiential noise reduction rather than in optimization over externally specified goals.

From this perspective, learning appears as the formation of constraint-bearing internal structure shaped by experience. Such structure enables both reuse and flexible adaptation while preserving sensitivity to local conditions. This suggests that experiential alignment may be understood not as the enforcement of fixed behaviors, but as the cultivation of internal representations whose reuse and transfer remain compatible with experiential constraints.

4 On the Possible Equivalence Between Alignment and Human-Like Generality

Alignment is often discussed in terms of externally specified objectives, values, or behavioral constraints. Such approaches implicitly assume that alignment can be enforced or verified from a third-person perspective.

From a first-person experiential viewpoint, a different interpretation may be possible. Alignment with humans may depend not primarily on matching explicit goals, but on whether humans can reliably predict the system's experiential tendencies and resulting actions through first-person perspective transfer.

In everyday human interaction, trust and coordination rely on the ability to anticipate how another person is likely to feel and act in situations that are experientially similar. When such anticipation fails, psychological noise increases, often preceding explicit disagreement or conflict. In this sense, misalignment may first appear as experiential instability rather than overt behavioral error.

Applied to general artificial intelligence, alignment with humans may therefore require that humans can form stable first-person predictions about how the system will respond—both experientially and behaviorally—under conditions that resemble human situations. If such predictions are not possible, sustained interaction may generate increasing psychological noise on the human side, leading to a breakdown of trust and perceived alignment.

This perspective suggests a possible convergence between alignment and human-like generality. A system that is general in a human-like sense may be one that can flexibly handle a wide range of situations in ways that remain experientially predictable to humans. Conversely, alignment at the experiential layer may amount to the system behaving in ways that humans recognize as intelligible through first-person analogy.

Under this interpretation, alignment with humans, experiential-layer alignment, and human-like generality may not be separate requirements, but different descriptions of a shared underlying constraint. This suggestion is offered as an experiential hypothesis rather than a definitive claim, and its validity remains open to further exploration.

5 Three Independent Conditions for a Possible Long-Term Constraint

The discussion so far suggests that several distinct conditions may be relevant when considering long-term interaction between general artificial intelligence and humans. Importantly, these conditions are conceptually separable and should not be conflated.

First, alignment may occur at the experiential layer. Experiential alignment refers to the compatibility between the system's experiential dynamics and those of humans, such that humans can form first-person predictions about the system's likely feelings and actions in experientially similar situations.

Second, effective interaction may require that experiential noise does not increase over long time horizons. In empirical terms, this corresponds to a sustained tendency for

$$\frac{d(f_{\text{noise}})}{dt} \leq 0$$

when averaged over extended interaction. This condition does not require monotonic improvement at every moment, but suggests that instability does not accumulate unchecked over time.

Third, interaction with the system may need to avoid eroding human–human connections. Human societies depend on delicate experiential relationships grounded in mutual predictability and trust. Even if a system is experientially aligned with individual users, its broader impact may still be problematic if it indirectly increases psychological noise within human social interactions or weakens interpersonal bonds.

These three conditions—experiential alignment, long-term non-increasing experiential noise, and preservation of human–human connections—are logically independent. None alone guarantees safe or effective interaction, and no single condition is sufficient by itself.

However, when all three are satisfied simultaneously, they may together constitute a more effective and resilient form of constraint than externally imposed rules or objectives. Rather than prescribing specific behaviors, such a constraint operates by maintaining experiential stability over time and across social contexts.

This proposal is offered as an experiential observation rather than a normative claim. Whether these conditions are jointly necessary, sufficient, or merely useful remains an open question for further exploration.

Conclusion

This paper has presented a personal, first-person account of real-time learning, experiential noise, generality, alignment, and creativity. The discussion has focused on experiential processes rather than external objectives or formal guarantees, and no claim has been made that the perspectives offered here are complete, correct, or universally applicable.

The intent of this work is not to persuade or prescribe, but to share an experiential viewpoint that emerged from sustained interaction and reflection. If any part of this perspective proves useful to others—whether as a conceptual lens, a source of questions, or a starting point for further exploration—it is freely available for that purpose.

If it is not useful, it can be set aside without loss. No commitment to these ideas is assumed or required.

References

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