Physical System Understanding Requires Locally Adapted World Models

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Abstract

The physical systems that underpin most global economic activity generate data overwhelmingly composed of sensor measurements rather than text or images, yet modern machine learning methods have not produced structured, generalizable representations of machine behavior. As a result, operational understanding of these systems remains dependent on human expertise that is slow to develop, difficult to transfer, and increasingly scarce.

We argue that closing this operational intelligence gap requires a new paradigm: machines must autonomously discover their specific operational structure directly from sensor observations. We call this paradigm *locally adapted world models* and advance three positions. First, operational structure must be learned autonomously from direct observation rather than predefined. Second, it must be locally adapted to each machine's specific physics, deployment context, and operational history. Third, it must take the form of an operational ontology: a discrete vocabulary of recurrent regimes together with their transition dynamics.

From these positions, we derive six requirements for any operationally useful world model: grounding in physical dynamics, discrete referenceability, reasoning capability, communicability, epistemic honesty, and scalability without per-machine engineering. We show that no existing approach satisfies all six simultaneously, revealing a structural gap in current approaches to physical system modeling.

We sketch a candidate architecture in which a foundation encoder trained on diverse physical sensor data provides a shared representational substrate from which each machine discovers its own operational ontology via self-supervision. We present preliminary evidence that this latent space contains recoverable, physically meaningful discrete regimes without supervision, and outline a research agenda for establishing locally adapted world models as a scalable foundation for physical system intelligence.

1 Introduction and Positions

1.1 The Operational Intelligence Gap

Physical industries, including energy, manufacturing, transportation, and infrastructure, account for approximately 85% of global economic activity [10], yet the systems that support them remain

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surprisingly poorly understood by modern machine learning methods. These industries run on data overwhelmingly composed of sensor measurements, rather than text or images. A single industrial gas turbine continuously produces hundreds of sensor streams — vibration at multiple locations and frequency bands, exhaust gas temperatures across combustion stages, shaft dynamics, bearing states, acoustic emissions, and fuel and pressure measurements — each reflecting a different aspect of the machine's internal dynamics, coupled through combustion, thermodynamics, and mechanical stress. Understanding the machine's operational state requires jointly interpreting these heterogeneous, high-rate, multimodal signals as the observable traces of a hidden physical process. This challenge is the fundamental structure of physical system monitoring across billions of instrumented machines.

Current industrial approaches rely heavily on human empiricism: operators and engineers who develop structured mental models of machine behavior through years of direct observation and domain apprenticeship. This expertise is operationally powerful but does not scale: system complexity is increasing, the expert workforce is contracting, and the gap between the operational intelligence required and the human expertise available is widening.

Despite decades of research, no existing approach has closed this gap (Section 2). We argue that doing so requires world models for physical systems that take the form of locally grounded operational ontologies, learned directly from sensor observations.

1.2 Overview of Positions

The operational intelligence gap persists because existing approaches attempt to model physical systems without learning machine-specific operational structure from observation itself. Physical systems are heterogeneous, partially observed, and continuously evolving; as a result, operational understanding cannot be fully predefined, globally standardized, or reduced to signal-level prediction.

We argue that physical system intelligence fundamentally requires machines to autonomously discover discrete operational structure grounded in their own dynamics and operating history. We call this structure an *operational ontology*: a discrete vocabulary of operational regimes together with their transition dynamics. This thesis leads to three positions.

Position 1: Operational structure must be learned autonomously from sensor observations. The operational regimes that matter most — degradation pathways, rare faults, machine-specific behaviors — are often unknown in advance and may never have been labeled by humans. Operational understanding therefore cannot depend on predefined state spaces, labeled datasets, or domain-specific engineering. Instead, machines must discover operational structure directly from sensor observations through self-supervised learning. This is both a modeling requirement and a scalability requirement: it replaces per-machine engineering effort with a shared learning procedure. We argue that such autonomous structure discovery is feasible (Section 4): a foundation model trained on diverse physical sensor data learns representations whose geometry reflects underlying physical dynamics [13], and we present preliminary evidence that these representations contain recoverable discrete operational structure.

Position 2: Operational understanding must be locally grounded. If operational structure is learned from observation, it must also adapt to the specific physical reality of each machine. By *local*, we mean grounded in a machine's geometry, materials, installation context, operating history, and uncontrollable environmental conditions. These factors vary across deployments and evolve over time, making operational behavior inherently machine-specific and nonstationary. A globally pretrained representation alone therefore cannot fully capture the operational reality of deployed systems. Instead, physical system intelligence requires local adaptation built on top of a shared representational substrate. This aligns with a broader argument that *adaptability* — the capacity to specialize from a general foundation — is more valuable than *generality* alone for real-world deployment [5]. Importantly, locality does not mean isolation: a global foundation model provides the shared representational substrate, and concepts discovered locally can seed learning across fleets or initialize new machines.

Position 3: Operational understanding must take the form of operational ontologies. To support reasoning, memory, uncertainty, and interaction with human operators, learned operational structure must be discrete and referenceable rather than purely geometric. We therefore define world models for physical systems as *operational ontologies*: discrete vocabularies of operational regimes together with history-conditioned transition dynamics. This transforms learned representations from compressions

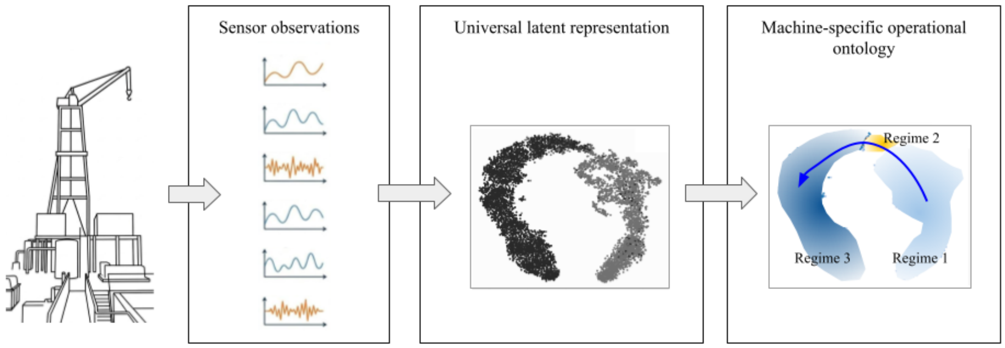

Figure 1: The proposed world model paradigm decomposes physical system understanding into a universal representational layer and machine-specific ontology formation. A shared foundation encoder maps heterogeneous sensor streams into a common latent space, from which each machine autonomously discovers a discrete operational ontology grounded in its own dynamics and operating context.

of sensor data into representations that humans and machines can reason over, communicate about, and act upon. It distinguishes operational understanding from continuous latent representations, which encode similarity without discrete operational structure, and from reward-shaped predictive models, which may collapse operationally important distinctions irrelevant to the current task.

Together, these three positions define a new paradigm for physical system intelligence: machines that autonomously learn locally grounded operational ontologies directly from sensor observations (Figure 1). We propose this paradigm as a practical route toward scalable operational intelligence for any instrumented machine.

1.3 Requirements for a World Model of Physical Systems

The three positions imply a concrete specification: six requirements that any world model must satisfy to constitute genuine operational understanding of a machine, supporting monitoring, diagnosing, maintaining, and decision-making in real-world settings. These are not design preferences, but necessary consequences of defining world models as locally grounded operational ontologies learned autonomously from observation.

A world model for a physical system must be:

1. **Grounded in physical dynamics.** The model's states must correspond to genuine recurrent regimes in the machine's behavior: structure in the underlying physical dynamics, rather than arbitrary partitions of signal space.
2. **Discrete and referenceable.** The model must represent operational states as nameable units that support categorical memory, reasoning, narrative explanation of event sequences, anomaly characterization, and communication with human operators in terms they can evaluate and act on.
3. **Reasoning-capable.** The model must support inference beyond classification and prediction, including causal attribution of how the system reached its current state, anticipation of future transitions, anomaly explanation, and counterfactual reasoning.
4. **Communicable.** The model's states, dynamics, and uncertainty must be expressible in terms human operators and engineers can interpret, evaluate, and act upon.
5. **Epistemically honest.** The model must explicitly represent uncertainty over its own state estimates and recognize when it operates outside its training distribution.
6. **Scalable without per-machine engineering effort.** The model must generalize across machines without requiring predefined state spaces, labeled data, domain expertise, or system-specific redesign.

Notably, requirements 1-5 closely mirror how skilled human operators understand physical systems. Experienced engineers maintain mental models grounded in observed machine behavior, organized around discrete named regimes (e.g. normal operation, compressor fouling, hot start, bearing wear) that support causal and predictive reasoning. These mental models are communicable to others and explicitly acknowledge uncertainty and unfamiliarity. Their key limitation is scalability (6): such expertise takes years to develop, is specific to particular machines, and is lost when the engineer retires. A world model, in our sense, is the computational analog of this mental model, satisfying the same epistemic requirements at a scale human expertise cannot reach.

2 Alternative Approaches

2.1 Why Existing Approaches Fall Short

We evaluate existing approaches against the six requirements, demonstrating that no paradigm satisfies all six simultaneously.

Classical system identification [19, 17, 22] can be grounded (1), discrete (2), reasoning-capable through forward simulation (3), and communicable through explicit mathematical structure (4). However, because the model structure must be defined a priori, these approaches cannot discover unanticipated regimes (5) and require substantial engineering effort per machine (6).

Supervised fault classifiers produce discrete outputs (2), but are constrained by a fixed fault taxonomy [11]. They are grounded only in labeled distinctions present in the training data (1), cannot reason beyond class boundaries (3), cannot represent novel failure modes (5), and require per-machine labels and expertise (6).

Anomaly detection methods [24, 23, 14] flag unfamiliarity (5) but produce neither discrete operational states (2) nor causal structure (3). They detect deviation without characterizing what has changed. While scalable (6), they satisfy at most two requirements.

Digital twins and physics-informed neural networks [21, 3] can be grounded (1), discrete if explicitly structured (2), reasoning-capable via simulation (3), and communicable (4). However, they require extensive domain expertise, cannot discover unmodeled regimes (5), and require substantial per-system engineering cost (6).

Hidden Markov Models [4] provide discrete states (2), learn transition dynamics that support reasoning (3), and maintain belief distributions (5). They can be grounded (1) and communicable if the states are interpretable (4). However, they require per-machine feature engineering and model specification (6). Additionally, fixed parametric emissions, predefined state cardinality, and first-order Markov structure limit their applicability to high-dimensional, long-horizon dynamics.

Time series foundation models [1, 20, 6] are scalable (6) and can produce morphological descriptions communicable in natural language (4). However, they operate at the signal level rather than learning discrete operational ontologies (2), are not grounded in machine-specific physical dynamics (1), and lack regime-level epistemic structure (5).

World models in deep learning, such as generative predictors [7], reward-shaped latent dynamics [8], and JEPA [2], produce continuous latent structure rather than discrete, referenceable operational states (2). Reward-shaped representations additionally fail grounding (1) by collapsing operationally important but reward-neutral distinctions. These approaches also do not satisfy operational communicability (4) or regime-level epistemic honesty (5).

2.2 Why Globally Pretrained World Models Cannot Substitute

A natural alternative is that a sufficiently large pretrained model could induce world models for arbitrary machines without per-machine adaptation. We argue that this fails for structural reasons that scaling does not remove: the physical world is fundamentally heterogeneous and nonstationary in ways that invalidate any fixed training distribution.

First, machines of the same nominal type differ in geometry, installation context, calibration, and operational history, so operational regimes are not globally identifiable, violating grounding (1) for any shared vocabulary. Second, each machine operates under unique, partially unobserved, and time-varying environmental conditions, inducing sensor-to-state mappings that do not transfer across instances. Third, machines evolve through wear, degradation, fouling, and reconfiguration, continuously shifting these mappings and rendering any static pretraining corpus progressively misaligned. Finally, safety-critical and failure regimes are rare or absent from any finite dataset, limiting globally pretrained models and violating epistemic honesty (5) precisely where it matters most.

Even in-context adaptation approaches assume rich machine-specific context at inference time. In practice, this context — the machine's installation geometry, piping configuration, fluid properties, commissioning history, maintenance record, accumulated wear state, and current environmental conditions — is largely unstructured, undocumented, or distributed across undigitized logs, drawings, informal operator knowledge, and the physical reality of the machine itself.

Together, these are not data scarcity issues but structural properties of real physical systems. Consequently, global pretraining cannot simultaneously satisfy grounding (1), epistemic honesty (5), and scalability (6). The gap is therefore not empirical but architectural: no existing paradigm produces models that are both locally grounded and scalable as operational ontologies for physical systems. This is precisely the gap addressed by locally adapted world models.

3 Formal Framework

3.1 The Physical System Model

A physical system has hidden state $x(t)$ representing the internal variables governing its behavior, driven by controlled input $u_c(t)$, uncontrolled disturbances $u_d(t)$, and its intrinsic dynamics. Sensor measurements $y(t)$ are produced through an observation mechanism that includes physical transduction, sensor placement and structural coupling, bandwidth and temporal filtering, calibration drift, noise, and missing or intermittent data. The observation mechanism is itself partially unknown and time-varying.

The goal of physical system understanding is to infer the operationally relevant structure of $x(t)$ from $y(t)$, despite the confounding effects of $u_d(t)$. Both the disturbance process $u_d(t)$ and the mapping from $x(t)$ to $y(t)$ are machine-specific and non-stationary, making this inference inherently system-dependent.

3.2 The Operational Equivalence Claim

Claim: A discrete vocabulary of operating regimes $\{C_m\}$ is operationally equivalent to $x(t)$ for the purposes of epistemic reasoning and human collaboration.

We define operational equivalence precisely: $\{C_m\}$ is operationally equivalent to $x(t)$ for a set of operations O if performing O over $\{C_m\}$ yields the same outcomes as performing O over $x(t)$. The operations we claim equivalence for are: regime identification (determining what operational state the machine is currently in), anomaly detection (determining when the machine is in an unfamiliar state), causal attribution (determining what sequence of states preceded the current one), predictive reasoning (determining what states are likely to follow), and human communication (expressing the machine's state in terms a human operator can evaluate and act on). We explicitly do not claim equivalence for fine-grained continuous control, which requires the full continuous state $x(t)$. The scope is epistemic and communicative operational utility, not actuative.

This claim is significant because $x(t)$ is not fully estimable for most real physical systems: its structure is unknown, its dimensionality is undefined, and its relationship to $y(t)$ depends on the non-stationary observation mechanism. $\{C_m\}$ is discoverable from $y(t)$ alone. If the equivalence claim holds, we obtain the operationally important properties of $x(t)$ without requiring the intractable estimation of $x(t)$ itself.

4 A Candidate Architecture

The positions advanced in Section 1.2 constrain the space of viable architectures but do not determine a unique design. In this section, we sketch one candidate architecture as an existence argument that the six requirements are jointly satisfiable, and that its foundational assumption — that physically meaningful discrete structure is recoverable from sensor observations without supervision — is empirically supported.

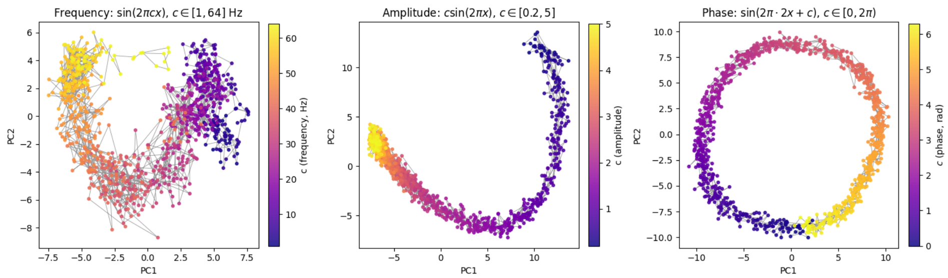

Figure 2: The encoder maps monotonically increasing parameters of synthetic signals (frequency, amplitude and phase) to proportional changes in the latent space.

The architecture embodies universality at the continuous representation level and locality at the discrete ontological level. A *foundation encoder* maps heterogeneous sensor observations from any machine to a shared continuous latent space. A *local codebook* quantizes this space into a discrete concept vocabulary via self-supervised adaptation. A *sequence model* learns history-conditioned transition dynamics over concept tokens through next token prediction, adapting a common architecture to each machine's operational dynamics. Finally, a *language interface* translates machine-native concepts to human language through unsupervised or minimally supervised alignment with existing operational text.

4.1 Foundation Encoder

The paradigm assumes that a pretrained encoder can produce a continuous latent space whose geometry reflects dynamical structure shared across physical processes and sensor modalities, and that this geometry supports unsupervised recovery of discrete operational regimes. We present preliminary evidence using a foundation encoder pretrained on diverse physical sensor data via a self-supervised predictive objective [13]). We highlight four properties of the resulting latent space that bear directly on the paradigm's feasibility, each with initial empirical support.

Smoothness. The encoder maps continuous physical quantities to smooth, proportional changes in the latent space. For example, sweeping frequency, amplitude, and phase of synthetic signals (Figure 2) produces embedding trajectories where cumulative arc length correlates with the parameter at Pearson $r \geq 0.997$, and step-size variation between consecutive embeddings stays below 0.19 (Appendix A.1). This suggests the latent geometry is metrically faithful to continuous physical variation, a precondition for meaningful regime boundaries.

Transition sharpness. Regime transitions produce sharp, localized discontinuities in the latent trajectory. Figure 3 illustrates this for a signal transitioning from a 2 Hz sinusoid to broadband white noise: a change metric based on the angle between trajectory displacements over preceding and following windows (adapted from [18], see Appendix A.2) peaks at the regime cut, localizing the boundary to within two windows (≈ 0.24 s) of ground truth. The encoder is smooth within regimes and discontinuous between them — geometry that supports discrete concept formation.

Compositionality. Independent physical factors are encoded along approximately separable directions in the latent space, enabling concepts to be discovered independently of co-varying factors. Synthetic signals combining a binary linear trend with oscillation factors (Figure 4) show that each factor induces a distinct displacement. This provides directional evidence for separable representation, though the result is not yet conclusive.

Geometric physical grounding. The properties above yield an embedding space where physically similar processes are metrically close. We illustrate this on a rotating shaft vibration dataset [16], shown in Figure 5. On 256-sample windows from the rig at 1500 RPM with five labeled fault-severity classes (0E–4E), HDBSCAN [15] on the embeddings recovers three latent regimes without supervision (AMI = 0.74, ARI = 0.48; see Appendix A.3): a low-severity cluster (0E/1E/2E, where the defect is too small to impose dynamical structure), a closed periodic ring (3E, likely a localized defect

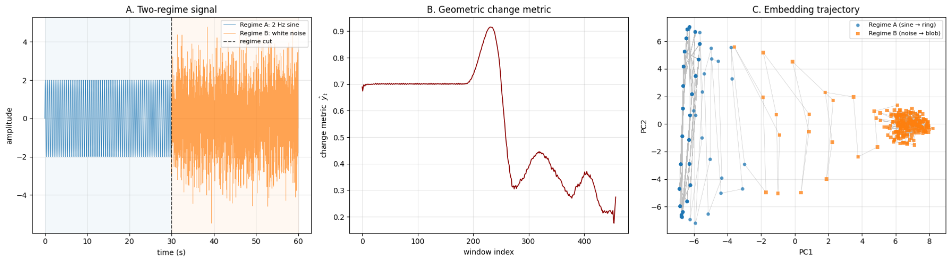

Figure 3: Time domain regime transitions result in latent trajectory discontinuities as evidenced by the peak in change metric (defined in Appendix A.2) at the transition location in time (middle), and by the two different geometric patterns in embedding space.

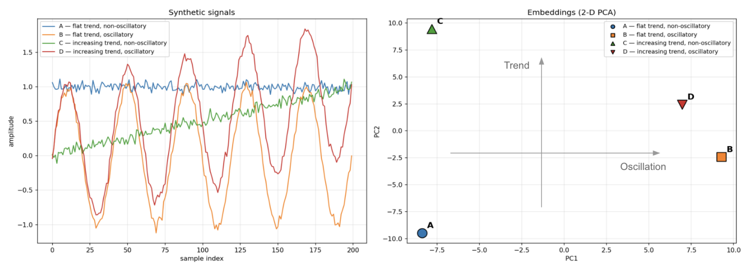

Figure 4: The foundation encoder maps independent physical factors (e.g. trend and oscillation) along approximately separable directions in latent space.

manifesting periodically), and a dispersed open trajectory (4E, severe and potentially non-periodic damage). Notably, the embedding partitions the data by dynamical regime while still correlating with labeled severity: 0E–2E collapse into one regime because they are dynamically indistinguishable, while 3E and 4E occupy distinct regions because their higher severity drives different dynamics.

This demonstrates that the foundational assumption for the paradigm holds in at least one physical domain: the latent space contains genuine discrete structure corresponding to physical operational regimes, recoverable without supervision.

4.2 Local Codebook and Sequence Model

The encoder evidence shows that discrete abstractions emerge naturally from the common latent space. However, density-based clustering groups by morphological similarity rather than by the criterion the positions require: predictive equivalence over future dynamics.

Based on the properties of the encoder, we posit that geometric proximity in the latent space is a reasonable proxy for predictive equivalence — representations that are nearby tend to induce similar future evolution of the system — but that the proxy is imperfect. This motivates learning a local

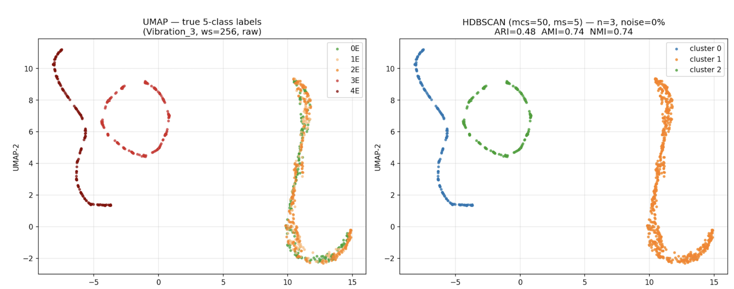

Figure 5: Clustering on embeddings from a rotating-shaft identifies: a low severity cluster (0E/1E/2E), higher severity and periodic faults (3E), and an open trajectory of highest severity (4E).

codebook $\{C_m\}$ that partitions the latent space into concepts defined by their future dynamics: latent vectors are assigned to the same concept if they imply similar future trajectories of the system.

The codebook is learned jointly with a sequence model under a next-token prediction objective over concept sequences. This couples representation learning with dynamics modeling so that emergent concepts correspond to operationally meaningful states rather than signal similarity.

The sequence model operates over the discovered concept tokens, learning history-conditioned transition dynamics $P(C_m(t+1)|C_m(1:t))$. This formulation captures path-dependent behavior; for example, a bearing in mild wear for six months has a different future trajectory than one that entered that state yesterday. Finally, using soft concept assignments rather than hard tokens allows the model to represent uncertainty over state membership and capture how predictive confidence evolves through regime transitions.

4.3 Language Interface

We hypothesize that machine-native operational concepts can be aligned with human operational language with minimal or no supervision. The underlying assumption, motivated by prior work in unsupervised machine translation [12] and the Platonic Representation Hypothesis [9], is geometric correspondence: both the learned concept space and embeddings of human operational language (e.g. from maintenance logs, documentation, and operator communication) are shaped by the same physical reality, and may therefore exhibit partially aligned geometric structure that enables cross-space mapping without parallel supervision.

This assumption is likely imperfect in practice: mismatches in concept granularity and genuinely novel machine states with no linguistic counterpart introduce alignment gaps that cannot be fully eliminated in the unsupervised setting. Few-shot alignment using a small set of anchor correspondences provides a practical fallback.

Crucially, we argue that language alignment should be treated as a post-hoc interface rather than a constraint on representation learning. Machine-native structure is learned first from sensor data; human language is mapped onto it afterward. This preserves the model's ability to discover and retain operational distinctions that existing human terminology does not capture, including states no operator has previously identified or named.

5 Research Program

5.1 Research questions

We frame the open research directions around two falsifiable questions. Affirmative answers would provide empirical support for the proposed world model paradigm.

Question 1: Can a machine autonomously learn its world model — a discrete operational ontology of operational regimes and transition dynamics — from sensor data alone, without human input?

This requires self-supervised concept formation without predefined state spaces, labeled data, or domain expertise. Evaluation is performed post hoc by comparing discovered concepts $\{C_m\}$ to known operational states $\{C_h\}$ in domains where expert labels exist (used for evaluation only). Success is indicated by above-chance alignment with $\{C_h\}$, along with the identification of additional concepts that correspond to genuine, previously unlabeled physical phenomena.

Question 2: Can the machine-native ontology be aligned with human operational language using only unpaired text (e.g. maintenance logs, documentation, operator communications), without labeled sensor-language pairs?

Evaluation is based on translation quality against known correspondences, alignment consistency across machines of the same type, and the treatment of unmatched concepts as meaningful discoveries rather than failures of alignment.

If both questions are answered affirmatively, the full pipeline from raw sensor observations to human-interactable representations can be learned without paired supervision or domain expertise, removing the key scalability bottleneck in existing approaches for physical system understanding.

5.2 Open challenges and limitations

Addressing the following challenges is essential to realizing this paradigm and, more broadly, to advancing machine learning systems that can operate reliably in physical environments. We view these not as peripheral issues, but as central research problems that require focused attention from the community.

Joint training stability. The codebook and sequence model are tightly coupled; updates to one alter the learning dynamics of the other.Developing stable and scalable joint optimization procedures under predictive objectives is a prerequisite for practical deployment.

Codebook size discovery. The number of operational concepts must emerge from data rather than be fixed a priori. While nonparametric and regularization-based approaches are promising, a principled understanding of how discrete structure should be discovered in this setting is still lacking.

Rare state representation. Predictive objectives inherently prioritize frequent patterns, systematically underrepresenting rare but safety-critical states such as failure precursors. Addressing this imbalance is critical for safety and remains an open challenge that cannot be resolved by scale alone.

Nonstationarity. Physical systems evolve over time due to wear, degradation, and reconfiguration. Continual adaptation of the concept vocabulary without catastrophic forgetting is a fundamental requirement for any long-lived deployment.

Dependence on the foundation encoder. The paradigm relies on the encoder inducing representations with sufficient cross-system consistency. Characterizing when this assumption holds, and how to extend it when it does not, is key to achieving general applicability.

Alignment limitations. Fully unsupervised alignment between machine-native concepts and human language depends on approximate geometric correspondence. In practice, granularity mismatch and genuinely novel concepts introduce unavoidable gaps, motivating hybrid approaches that combine unsupervised learning with minimal supervision.

Evaluation generalization. While post-hoc alignment avoids contaminating training with labels, its reliability depends on the quality of expert annotations. Establishing evaluation protocols that generalize across domains is necessary for rigorous comparison and progress.

These challenges collectively define a concrete research agenda. Progress on them would not only enable the proposed paradigm, but also advance the broader goal of learning representations that support reasoning, adaptation, and human interaction in complex physical systems.

6 Conclusion

We have argued for three positions that together define a new world model paradigm: that world models of physical systems must be learned autonomously from sensor observations; that they must be locally grounded in each machine; and that they must take the form of learned operational ontologies. We formalized the operational equivalence claim — that a discovered ontology $\{C_m\}$ can support reasoning and human interaction in place of the classical hidden state $x(t)$, which is typically not directly estimable. We demonstrated the validity of the foundational assumptions using a universal architecture with self-supervised local adaptation and presented preliminary evidence of its feasibility, along with a research agenda for advancing this paradigm.

Methodologically, this perspective connects physical system understanding to predictive sequence modeling. If discrete operational structure can be reliably discovered, modeling system behavior reduces to prediction over a learned state vocabulary. This bridges to scalable learning frameworks from other domains, suggesting that advances in representation learning and sequence modeling could directly translate into more capable and adaptive models of physical systems.

This world model paradigm offers a concrete path toward closing the operational intelligence gap: machines that learn structured understanding of their own physical dynamics from observation, express that understanding in terms humans can evaluate and act on, and do so autonomously for any instrumented machine.

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A Foundation Encoder Properties

A.1 Smoothness (Figure 2)

Let $\{p_i\}_{i=1}^N$ denote the parameter values sorted in monotonically increasing order, and $\{\mathbf{e}_i\}_{i=1}^N \subset \mathbb{R}^d$ the corresponding embeddings. Define the step sizes between consecutive embeddings as

$$s_i = \|\mathbf{e}_{i+1} - \mathbf{e}_i\|_2, \qquad i = 1, \ldots, N-1. \tag{1}$$

The two smoothness metrics are then:

$$L_k = \sum_{i=1}^{k-1} s_i, \qquad r_{\text{arc}} = \text{Pearson}\big(\{p_k\}_{k=1}^N,\, \{L_k\}_{k=1}^N\big)\,, \tag{2}$$

where L_k is the cumulative arc length traced through embedding space up to the k-th sample, and r_{arc} is its Pearson correlation with the parameter; and

$$\text{CV}(s) = \frac{\sigma(s)}{\mu(s)}, \qquad \mu(s) = \frac{1}{N-1}\sum_{i=1}^{N-1} s_i, \qquad \sigma(s) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\big(s_i - \mu(s)\big)^2}, \tag{3}$$

the coefficient of variation of the step sizes.

A.2 Transition Sharpness (Figure 3)

The geometric change metric used in Figure 3 is defined as:

Given the embedding sequence $Z \in \mathbb{R}^{N\times 768}$ and a window radius w, define for each $t \in [w, N-w-1]$ the local "before" and "after" displacement vectors:

$$a_t = Z_t - Z_{t-w}, \qquad b_t = Z_{t+w} - Z_t$$

and the (length-normalized) curvature

$$\kappa_t \;=\; \frac{\arccos\Big(\frac{\langle a_t, b_t\rangle}{\|a_t\|\,\|b_t\|}\Big)}{\|a_t\| + \|b_t\|}.$$

κ_t measures the angular turn between the "before" and "after" displacement vectors at t, normalized by their combined length. It is small wherever the trajectory advances smoothly along a single direction (both vectors approximately parallel) and large wherever the direction of motion changes abruptly (the two vectors point apart). The change metric $\hat{y}_t$ is then obtained by min-max normalizing κ to $[0, 1]$, inverting (so that *change* is high where curvature is high), and locally smoothing:

$$\tilde{\kappa}_t = \frac{\kappa_t - \min_t \kappa_t}{\max_t \kappa_t - \min_t \kappa_t}, \qquad \hat{y}_t = \frac{1}{2w+1} \sum_{s=t-w}^{t+w} \big(1 - \tilde{\kappa}_s\big).$$

We use $w = \mathrm{round}(0.05 \times n_{\text{windows}}/2) = 11$, i.e. 5% of the mean expected segment length.

A.3 Geometric physical grounding benchmark (Figure 5)

A.3.1 Dataset

We use the evaluation set of the rotating-shaft vibration recordings in [16], which includes five conditions: `0E` (healthy) plus `1E` / `2E` / `3E` / `4E` (faults of increasing severity). Each recording is $\approx 6.9\,\mathrm{M}$ samples at $4096\,\mathrm{Hz}$ over a programmed V_{in} / RPM sweep that traverses the same speed range twice. Three accelerometer channels are available; we use `Vibration_3`, the most diagnostic channel as established by a grid sweep.

Operating-condition matching. All comparisons in this section are restricted to a matched 1500 ± 25 RPM band, so RPM-induced amplitude variation cannot act as a confounder for fault severity. Within this band, each class contributes hundreds of windows.

A.3.2 Windowing

Windows are 256 raw samples (no preprocessing or feature extraction) without overlap.

A.3.3 Grid sweep and best configuration

We swept clustering configurations on the matched-RPM windows to identify the most informative sensor channel and HBSCAN parameters by optimizing Adjusted Rand Index (ARI) against the 5 available classes. The parameter combination that optimized this search was `min_cluster_size` $=$ 50, `min_samples` $=$ 5. The configuration produces 3 clusters with 0% points classified as noise, evaluated against the 5-class label scheme via Adjusted Rand Index (ARI) and Adjusted Mutual Information (AMI):

$$\mathrm{ARI} = 0.482, \qquad \mathrm{AMI} = 0.742.$$

The deliberately moderate ARI is itself a feature of the result: the encoder is not recovering the labels, it is recovering a *coarser* partition that reflects the signal physics.

A.3.4 Validation against classical signal statistics

To check that the encoder's 3-regime partition is grounded in the data rather than encoder idiosyncrasies, we computed standard signal-domain statistics on 200 windows per class (independent of the encoder):

metric	0E	1E	2E	3E	4E
Spectral entropy (low $\to$ periodic)	3.99	3.96	3.66	**2.65**	2.73
PSD peak prominence (high $\to$ periodic)	7.7	6.4	10.0	**19.1**	**19.3**
Sample entropy (low $\to$ periodic)	1.50	1.59	1.35	**0.79**	0.81
w2w cross-correlation, lag 1	0.73	0.64	0.77	**0.93**	**0.93**

We identify two main patterns accordingly:

1. Every periodicity metric independently confirms the **{0E, 1E, 2E}** vs **{3E, 4E}** regime change. The encoder's coarsening of the labels is grounded in the physics: at 0E–2E the defect is too small to organize the signal into a periodic pattern, while at 3E–4E it is.
2. No classical statistic distinguishes 3E from 4E. Within-window periodicity, adjacent-window similarity (lag-1 cross-correlation) all give nearly identical numbers for 3E and 4E.

A.3.5 Interpretation of the resulting clusters

We identify three main results:

1. **Embedding geometry is grounded in physics.** The encoder partitions the data into three regimes that align with independently-measured signal-domain statistics (spectral entropy, sample entropy), not with the amplitude-ordered severity labels.
2. **Physically similar processes are metrically proximate.** The healthy and mild-fault classes (0E/1E/2E) collapse into a single noise-dominated cluster, which is physically appropriate, since at these severities the defect is too small to organize the spectrum into a periodic pattern.
3. **The metric structure surfaces physical distinctions classical similarity cannot.** The 3E-vs-4E distinction is invisible to within-window classical statistics but is geometrically visible in the embeddings. This is evidence that the encoder's metric reflects genuine physical similarity rather than superficial signal similarity.