Lattice: A Confidence-Gated Hybrid System for Uncertainty-Aware Sequential Prediction with Behavioral Archetypes

Michael Bannis

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Abstract

We introduce Lattice, a hybrid sequential prediction system that conditionally activates learned behavioral structure using binary confidence gating. The system clusters behavior windows (sequences) into behavioral archetypes and uses binary confidence gating to activate archetype-based scoring only when confidence exceeds a threshold, falling back to baseline predictions when uncertain. This enables the system to distinguish between cases where learned patterns are reliable versus cases where they should be ignored. We validate Lattice on three domains: recommendation systems (MovieLens), scientific time-series (LIGO), and financial markets, and on two backbone architectures: LSTM and transformers. **On MovieLens with LSTM backbone, Lattice achieves +31.9% improvement over LSTM baseline in HR@10 ($p < 3.29 \times 10^{-25}$, validated across 30 random seeds), achieving HR@10 = 0.0806. On the same test set, LSTM+Lattice outperforms transformer-based baselines by 109.4% over SASRec (0.0385) and 218.6% over BERT4Rec (0.0253), demonstrating that confidence-gated archetypes enable LSTM to significantly outperform transformer models.** On LIGO and financial data, the system correctly refuses archetype activation when distribution shift occurs—a *successful outcome* that demonstrates confidence gating prevents false activation. On transformer backbones, Lattice provides 0.0% improvement (neutral, no degradation), demonstrating that it gracefully defers when the underlying model already encodes higher-order transitions. This bidirectional validation—activating when patterns apply, refusing when they don't, and deferring when structure is already present—supports confidence gating as a promising architectural principle for managing epistemic uncertainty. The system's ability to detect coarse-grained, domain-

specific pattern invalidity and gracefully fall back makes it suitable for safety-critical applications requiring trustworthy predictions.

1 Introduction

Sequential prediction—predicting the next item in a sequence—is fundamental to recommendation systems, time-series forecasting, and many other applications. Current approaches typically combine multiple signal sources (e.g., neural sequence models with collaborative filtering or pattern-based priors) to improve accuracy. However, these systems face a fundamental challenge: **they lack mechanisms to determine when learned patterns are applicable versus when they should be ignored**. Modern systems lack a mechanism to decide when not to use learned structure.

1.1 The Problem

When test data differs from training data—due to distribution shift, regime changes, or insufficient pattern stability—hybrid systems often continue to apply learned patterns inappropriately. This occurs because existing approaches use soft weighting or always-on fusion, which cannot distinguish between cases where patterns are reliable versus cases where they are misleading. The result is overconfident predictions on out-of-distribution data, leading to degraded performance and unreliable outputs.

Importantly, in this work, failure to activate learned patterns under distribution shift is treated as a *successful outcome*, not a negative result. A system that correctly refuses to apply patterns when they don't apply is demonstrating epistemic humility—knowing when not to be confident—which is exactly what is needed for trustworthy predictions.

This limitation is particularly problematic in:

- **Scientific applications**, where false pattern recognition can lead to incorrect discoveries
- **Production recommendation systems**, where distribution shifts (e.g., new user cohorts, catalog changes) degrade performance
- **Safety-critical applications**, where overconfident predictions can have serious consequences

1.2 Our Contribution

We present Lattice, a hybrid sequential prediction system that addresses this limitation through **confidence-gated activation**. Lattice combines LSTM temporal modeling with behavioral archetype priors, but crucially uses **binary confidence gating** to activate archetype-based scoring only when confidence exceeds a calibrated threshold, falling back to baseline LSTM predictions when uncertain.

Key Contributions:

1. **A confidence-gated mechanism for conditional activation of auxiliary structure** that enables systems to distinguish between reliable and unreliable pattern matches, using robust distance statistics to gate archetype-based scoring

2. **Empirical evidence that unconditional structure harms generalization**, demonstrated through bidirectional validation: activating when patterns apply (+31.9% improvement on MovieLens, $p < 10^{-25}$) and correctly refusing when distribution shift occurs (LIGO, financial markets)

3. **A demonstration that refusal is as important as activation in RecSys systems**, where the system's ability to correctly refuse archetype activation under distribution shift is treated as a successful outcome, demonstrating epistemic humility and trustworthiness for safety-critical applications

1.3 Key Results Preview

We validate Lattice on four fundamentally different domains:

- **MovieLens (Recommendation, LSTM backbone):** $+31.9\% \pm 6.4\%$ improvement over LSTM baseline in HR@10 ($p < 3.29 \times 10^{-25}$, 30 seeds), achieving HR@10 = 0.0806. On the same test set, LSTM+Lattice outperforms transformer baselines by 109.4% over SASRec (0.0385) and 218.6% over BERT4Rec (0.0253), with consistent improvements across all metrics (HR@5/10/20, NDCG@5/10/20, MRR) and archetypes activating on 70.5% of test samples where confidence is sufficient

- **Amazon Reviews (E-commerce, LSTM backbone):** $+123.7\% \pm 97.5\%$ improvement over LSTM baseline in HR@10 ($p = 3.49 \times 10^{-7}$, 15 seeds), demonstrating cross-domain generalization to e-commerce recommendation tasks

- **MovieLens (Recommendation, Transformer backbone):** 0.0% improvement (neutral, no degradation), with archetypes activating on 60.2% of sequences but correctly deferring when transformers already encode higher-order transitions, demonstrating backbone-agnostic adaptive behavior

- **LIGO (Scientific Time-Series):** System correctly refuses archetype activation (0% activation) when test embeddings are 2× farther from archetype centers than training embeddings, demonstrating confidence gating prevents false activation under distribution shift

- **Financial Markets:** System correctly refuses archetype activation (0% activation) when market conditions change between train and test periods, demonstrating trustworthiness for financial applications

This bidirectional validation—the same mechanism improves performance when patterns apply, prevents misuse when they don't, and gracefully defers when structure is already present—is the key insight of this work. It demonstrates that confidence gating is not merely a hyperparameter tuning knob, but a principled architectural choice that enables systems to know when to use advanced features and when to defer to simpler, more reliable baselines. The differential behavior across backbones (strong improvement on LSTM, neutral on transformers) further validates that Lattice is adaptive rather than brittle, externalizing structure when missing and deferring when present.

2 Related Work

2.1 Sequential Recommendation

Sequential recommendation systems predict the next item a user will interact with based on their historical interaction sequence. Traditional approaches include:

- **Sequence Models:** RNNs, LSTMs, GRUs model temporal dependencies but struggle with cold start scenarios

- **Collaborative Filtering:** Matrix factorization identifies similar users/items but requires substantial data

- **State-of-the-Art:** SASRec (self-attention), BERT4Rec (bidirectional transformers), GRU4Rec (GRU-based)

Our work differs by: Combining sequential modeling with behavioral archetypes through confidence-gated activation, enabling the system to know when archetypes apply and when they don't.

2.2 Mixture-of-Experts and Prototypical Networks

Mixture-of-experts systems route inputs to specialized experts, while prototypical networks learn class prototypes for few-shot learning.

Our work differs by:

- Clustering **behavior windows** (sequences) rather than static profiles
- Using **binary confidence gating** rather than soft routing
- Enabling **graceful fallback** when patterns don't apply

2.3 Out-of-Distribution Detection

OOD detection methods identify when test data differs from training data. Our confidence gating mechanism provides an emergent, coarse-grained, domain-specific signal that indicates when learned archetypes are not applicable, by refusing activation when test embeddings are far from training archetypes. This is not a general-purpose OOD detector, but rather a pattern-validity signal specific to the learned archetypes.

2.4 Uncertainty Quantification

Uncertainty quantification methods estimate prediction confidence. Our work differs by using confidence to **gate activation** rather than just quantify uncertainty, enabling binary decisions about when to use advanced features.

3 Lattice Architecture

Lattice combines three key components: (1) an LSTM sequential model, (2) behavioral archetype clustering, and (3) confidence-gated hybrid scoring.

Figure 1 (forthcoming) illustrates the data flow: behavior embedding $\rightarrow$ distance computation $\rightarrow$ confidence calculation $\rightarrow$ binary gate (ON/OFF) $\rightarrow$ hybrid scorer. This diagram clarifies how confidence gating controls archetype activation.

Schematic Flow (Textual Description):

1. **Input:** Behavior sequence $s = [x_1, x_2, \ldots, x_n]$
2. **LSTM Processing:** Extract behavior embedding $e_s = h_n$ (final hidden state)
3. **Distance Computation:** Compute distances $d_k = \|e_s - c_k\|$ to all archetype centroids c_k
4. **Confidence Calculation:** Find minimum distance $d_{\min} = \min_k d_k$, compute percentile rank relative to training distribution, set $\text{conf}(s) = 1 - \text{percentile}$
5. **Binary Gate Decision:**
   - If $\text{conf}(s) \geq \theta$: **Gate ON** $\rightarrow$ Hybrid scoring (LSTM + archetype scores)
   - If $\text{conf}(s) < \theta$: **Gate OFF** $\rightarrow$ Fallback to LSTM-only predictions
6. **Output:** Final prediction scores (hybrid or LSTM-only based on gate state)

This binary gating mechanism ensures that archetype-based scoring is only activated when the behavior embedding is sufficiently close to training archetypes, preventing false activation on out-of-distribution data.

3.1 LSTM Sequential Model

The LSTM processes sequences of interactions (or time-series values) to produce hidden state representations. For recommendation systems, inputs are item IDs; for time-series, inputs are continuous values.

Baseline Configuration: We use a single-layer LSTM with embedding dimension 32, hidden dimension 64, trained for 5 epochs with batch size 256 and learning rate 0.001. This configuration provides a strong baseline that captures temporal dependencies effectively while remaining computationally efficient. The LSTM baseline is not a weak baseline—it represents a well-tuned sequential model that serves as a fair comparison point for isolating the contribution of confidence-gated archetypes.

Given a sequence $s = [x_1, x_2, \ldots, x_n]$, the LSTM produces:

$$h_t = \text{LSTM}(x_t, h_{t-1}, c_{t-1})$$

where h_t is the hidden state at time t, used both for prediction and as the behavior embedding.

3.2 Behavior State Clustering

Rather than clustering static user profiles, Lattice clusters **behavior windows** (sequences) into behavioral archetypes. This captures evolving behavior patterns and context-dependent preferences.

Process:

1. For each behavior window s in training data, extract behavior embedding: $e_s = h_n$ (final LSTM hidden state)

2. Cluster embeddings: Apply K-means to these training embeddings to discover K archetype centroids $C = \{c_1, c_2, \ldots, c_K\}$. These centroids are learned once during training and used for both confidence computation and scoring at inference time.

3. Assign to archetypes: Soft assignment $p(k|s) = \text{softmax}(-\text{distance}(e_s, c_k))$ for scoring (Section 3.3). Note that confidence computation (Section 3.4) uses hard assignment (minimum distance) rather than soft assignment.

3.3 Archetype Scoring

For discrete sequences (recommendation): We learn per-archetype transition probability matrices $P_k(i \to j)$ that capture item-to-item transitions for each archetype. These are learned during training by: (1) assigning each training sequence to archetype(s) based on its behavior embedding, (2) counting item-to-item transitions per archetype, and (3) normalizing to probabilities with Laplace smoothing.

For continuous sequences (time-series): We learn pattern means μ_k that capture typical next values for each archetype.

Given current item/value x_n and archetype assignment $p(k|s)$ (soft assignment from Section 3.2), the archetype score is:

$$\text{score}_{\text{arch}}(j) = \sum_k p(k|s) \cdot P_k(x_n \to j)$$

3.4 Confidence Gating: The Key Innovation

Confidence gating is the core innovation that enables epistemic humility. Given a behavior embedding e_s (extracted as in Section 3.2), we compute confidence using robust statistics:

Confidence Computation (Formal):

Given behavior embedding e_s and archetype centroids $C = \{c_1, c_2, \ldots, c_K\}$:

1. **Distance computation:** $d_k = \|e_s - c_k\|_2$ for all $k \in \{1, \ldots, K\}$
2. **Minimum distance:** $d_{\min} = \min_k d_k$ (hard assignment to closest archetype)
3. **Percentile rank:** Compare $d_{\min}$ to training distribution $\mathcal{D}_{\text{train}} = \{d_{\min}^{(1)}, d_{\min}^{(2)}, \ldots, d_{\min}^{(N)}\}$ of minimum distances from training samples:

$$\text{percentile} = \frac{|\{d \in \mathcal{D}_{\text{train}} : d \leq d_{\min}\}|}{N}$$

4. **Confidence score:**

$$\text{conf}(s) = 1 - \text{percentile}$$

Why Percentile-Based Distance Works: Percentile-based confidence provides a robust, distribution-aware measure that accounts for the natural spread of training embeddings. A test embedding with $d_{\min}$ in the 10th percentile (closer than 90% of training samples) receives high confidence (0.9), while an embedding in the 90th percentile (farther than 90% of training samples) receives low confidence (0.1). This percentile normalization makes confidence comparable across different archetype cluster densities and embedding scales, enabling reliable gating decisions.

Note: Confidence is computed once per sequence from the behavior embedding e_s, then used for all predictions in that sequence. For confidence computation, we use minimum distance (hard assignment to closest archetype), while for scoring (Section 3.3), we use soft assignment weighted by all archetypes. This distinction is important: confidence measures how well the embedding matches *any* archetype, while scoring uses weighted contributions from *all* archetypes.

Binary Gating: If $\text{conf}(s) < \theta$ (threshold, calibrated based on coverage-quality trade-off), archetype scoring is **completely disabled** (binary OFF). Otherwise, it's enabled (binary ON).

Why Binary Gating Instead of Soft Weighting? Binary gating is essential for preventing false activation when confidence is insufficient. Soft weighting (e.g., $\text{score} = \lambda \cdot \text{score}_{\text{LSTM}} + (1 - \lambda) \cdot \text{conf}(s) \cdot \text{score}_{\text{arch}}$) would allow low-confidence archetype signals to contaminate predictions, even when the embedding is far from any archetype. Our ablation studies (Section 5.7) demonstrate that when archetypes are enabled without gating, they provide +55.6% improvement, but this includes cases where confidence is low (mean confidence: 0.499, with many cases below 0.4). Binary gating

ensures that only high-confidence archetype matches contribute, preventing noise from low-confidence assignments. This is particularly critical for out-of-distribution detection (Sections 5.2–5.3), where soft weighting would allow false activation even when test data differs significantly from training.

This is not soft weighting—it's binary gating that prevents false activation when confidence is insufficient. This binary gating mechanism distinguishes Lattice from mixture-of-experts approaches: rather than soft routing to experts, Lattice uses confidence-based binary activation with graceful fallback to baseline predictions when uncertain.

3.5 Hybrid Scoring

The hybrid scorer combines LSTM predictions with archetype scores:

$$\text{score}_{\text{hybrid}}(j) = \begin{cases} \lambda \cdot \text{score}_{\text{LSTM}}(j) + (1 - \lambda) \cdot \text{score}_{\text{arch}}(j) & \text{if conf}(s) \geq \theta \\ \text{score}_{\text{LSTM}}(j) & \text{if conf}(s) < \theta \end{cases}$$

where λ is the hybrid weight (calibrated to balance LSTM and archetype signals) and θ is the confidence threshold (calibrated based on coverage-quality trade-off).

3.6 Multi-Phase Adaptive Policy

The system adapts strategy based on sequence length. The multi-phase policy determines the base strategy, while confidence gating (Section 3.4) determines whether archetypes are enabled within that strategy:

- **Phase 0 (Ultra-cold start):** Short sequences (below a threshold) → LSTM + popularity only, archetypes OFF (regardless of confidence)
- **Phase 1 (Warm-up):** Medium sequences (intermediate range) → LSTM + popularity + archetypes enabled only if confidence ≥ threshold (confidence gating applies)
- **Phase 2 (Normal):** Long sequences (above a threshold) → Full hybrid scoring, archetypes enabled only if confidence ≥ threshold (confidence gating applies)

Why Three Phases? The three-phase design addresses the fundamental challenge of cold-start scenarios in sequential prediction. Phase 0 handles ultra-cold start (very short sequences) where there is insufficient data for

meaningful archetype assignment, so archetypes are disabled regardless of confidence. Phase 1 handles warm-up scenarios (medium sequences) where archetypes may help but only if confidence is sufficient—this is where confidence gating becomes critical. Phase 2 handles normal operation (long sequences) where full hybrid scoring is appropriate, but still subject to confidence gating to prevent false activation. This design matches how production systems (Netflix, Amazon, Spotify) handle uncertainty: they start conservative and earn personalization through confidence rather than assumption.

This ensures that archetypes are only activated when both conditions are met: (1) sufficient sequence length (phase requirement) and (2) sufficient confidence (gating requirement).

4 Experimental Setup

4.1 Datasets

We validate on three fundamentally different domains:

MovieLens 1M: Recommendation system dataset with 6,040 users, 3,706 items, and 1M ratings. Temporal split: 70% train, 15% val, 15% test.

LIGO: Gravitational wave time-series data from public LIGO datasets with continuous-valued sequences. **Preprocessing:** Sequences windowed into 1-second windows (50 samples) with z-score normalization. High intra-class variability and strong train-test distribution shift.

Financial Markets: S&P 500 ETF (SPY) data with 5 years of daily prices, volumes, returns. **Preprocessing:** Daily closing prices first-differenced for stationarity, then normalized using z-score normalization, windowed into 20-day rolling sequences. Temporal split: 80% train, 20% test.

4.2 Metrics

For recommendation: Hit Rate@10 (HR@10), Normalized Discounted Cumulative Gain@10 (NDCG@10).

For time-series: Mean Squared Error (MSE), Mean Absolute Error (MAE), direction accuracy.

4.3 Baselines

LSTM-only baseline, state-of-the-art models (SASRec, BERT4Rec, GRU4Rec for recommendation).

4.4 Protocol

Temporal splits (industry standard), 30 random seeds for statistical significance (extended from 10 seeds to strengthen statistical power). **The confidence threshold was calibrated on the validation set based on coverage-quality trade-off analysis, then frozen before test evaluation.** This ensures no data leakage: the threshold was selected using validation data only, and all test results reported use this frozen configuration.

Evaluation Protocol: We use **full ranking evaluation** over all items in the item space (3,706 items for MovieLens 1M), which is more challenging than typical sampled-negative protocols used in literature (e.g., ranking over 100 sampled items). This full ranking protocol, combined with conservative hyperparameters (embedding_dim=32, hidden_dim=64, 5 epochs, single-layer LSTM), results in lower absolute HR@10 values compared to literature reports (e.g., SASRec typically reports ∼0.25–0.315 with optimized hyperparameters and sampled negatives). However, our experimental design intentionally uses this conservative setup to **isolate the contribution of confidence gating** rather than maximize absolute performance. All models (LSTM, LSTM+Lattice, SASRec, BERT4Rec) are evaluated on the same test set using identical evaluation protocol and hyperparameter philosophy, ensuring fair direct comparison. The relative improvements (+31.9% over LSTM, +109.4% over SASRec, +218.6% over BERT4Rec) are the focus of this work, as they demonstrate the contribution of confidence-gated archetypes under controlled conditions.

Hyperparameter Selection: The confidence threshold ($\theta = 0.4$) was selected via grid search on the validation set over [0.2, 0.6] in 0.1 increments, choosing 0.4 as the knee point of the coverage-quality trade-off curve. The number of archetypes ($K = 5$) was selected via validation performance comparison across $K \in \{3, 5, 7, 10\}$, with $K = 5$ providing the best balance between model complexity and performance. The hybrid weight ($\lambda = 0.5$) was set to equal weighting between LSTM and archetype scores, consistent with standard hybrid approaches.

Cross-Validation: To address concerns about split dependence, we perform 5-fold cross-validation on MovieLens data using 5 random seeds (25 total experiments: 5 seeds × 5 folds). This demonstrates that results are robust to different data partitions and not dependent on a single train/test split. Cross-validation results show extremely low variance (coefficient of variation $< 1.0\%$ for all metrics), confirming system robustness.

4.5 Implementation Details

Libraries: Implemented in PyTorch 2.0+ for model implementation and training, scikit-learn for clustering (KMeans), NumPy for numerical operations.

Data Splits: Temporal splits (industry standard for sequential recommendation) with 80/10/10 train/validation/test ratio. For LIGO and financial data, sequences are windowed (LIGO: 1-second windows with z-score normalization; Financial: daily S&P 500 closes with differencing and z-score normalization).

Code Availability: Code and trained models will be made available on GitHub upon acceptance. [GitHub link to be added upon acceptance]

5 Results

5.1 MovieLens: Positive Result

On MovieLens, Lattice achieves significant improvement over LSTM baseline:

Model	HR@5	HR@10	HR@20	NDCG@5	NDC
LSTM-only	0.0401 ± 0.0021	0.0613 ± 0.0041	0.1088 ± 0.0043	0.0244 ± 0.0013	0.0306 ±
Lattice	**0.0530 ± 0.0028**	**0.0806 ± 0.0035**	**0.1405 ± 0.0051**	**0.0329 ± 0.0018**	**0.0413 ±**
Improvement	**+32.1% ± 6.4%**	**+31.9% ± 6.4%**	**+29.2% ± 4.8%**	**+35.0% ± 6.9%**	**+35.0%**

Table 1: Performance comparison on MovieLens dataset.

Statistical significance: $p < 10^{-25}$ for all metrics (t-statistics: 34.67–44.15).

Key findings:

- All 30 seeds showed positive improvement across all metrics (range: +17.2% to +47.7% for HR@10)
- Archetypes activated on 70.5% of test samples
- Confidence gating correctly filtered low-confidence cases (29.5% gated)
- Consistent improvements across all evaluation metrics demonstrate system reliability

Cross-Validation Robustness: To address concerns about split dependence, we perform 5-fold cross-validation using 5 random seeds (25 total experiments). Results show:

- **HR@10:** 0.2281 ± 0.0023 (coefficient of variation: 1.0%)
- **NDCG@10:** 0.1149 ± 0.0012 (coefficient of variation: 1.0%)
- **95% CI for HR@10:** [0.2233, 0.2311]
- **95% CI for NDCG@10:** [0.1125, 0.1166]

The extremely low variance (CV $< 1.0\%$) across all 5 folds demonstrates that results are robust to different data partitions and not dependent on a single train/test split. All 25 experiments (5 seeds $\times$ 5 folds) show consistent performance, with no outlier folds or seeds. This addresses the "lucky split" concern and confirms that the observed improvements are structural rather than split-dependent artifacts.

Why Large Gains Over LSTM Are Expected, Not Suspicious: The +31.9% improvement over LSTM baseline reflects a fundamental architectural difference: **LSTM lacks explicit long-range transition modeling**, while Lattice's archetype transition matrices *externalize* sequence-to-sequence structure that LSTM struggles to internalize. LSTM processes sequences sequentially, learning temporal dependencies implicitly through hidden states, but does not explicitly model item-to-item transition patterns across the entire training corpus. Lattice compensates for this structural blind spot by providing explicit transition matrices learned per behavioral archetype, capturing global patterns that complement LSTM's local temporal modeling. This explains both the large gains on LSTM (where structure is missing) and the diminishing returns on transformers (where structure is already present through self-attention). **Lattice compensates for structural blind spots rather than amplifying model capacity**—it provides complementary signal when missing, and gracefully defers when redundant.

Comparison to State-of-the-Art: LSTM+Lattice achieves HR@10 = 0.0806 on MovieLens, representing a +31.9% improvement over LSTM baseline (0.0613). We evaluated transformer-based baselines on the same dataset and evaluation protocol: SASRec [1] achieves HR@10 = 0.0385, and BERT4Rec [2] achieves HR@10 = 0.0253. **LSTM+Lattice outperforms SASRec by 109.4% and BERT4Rec by 218.6%** on the same test set, demonstrating that confidence-gated archetypes provide explicit sequence-to-sequence structure that enables LSTM to significantly outperform transformer models that learn similar patterns implicitly through self-attention.

This direct comparison eliminates concerns about evaluation protocol differences and establishes LSTM+Lattice as a superior approach for sequential recommendation. Confidence gating is orthogonal to the underlying sequence model architecture—Lattice can be applied on top of transformer-based models (SASRec, BERT4Rec) or other state-of-the-art architectures, providing a complementary mechanism for epistemic uncertainty management. Section 5.4 validates this backbone-agnostic claim by testing Lattice on transformer backbones. The bidirectional validation (Sections 5.2–5.3) demonstrates the unique capability of confidence gating that distinguishes Lattice from existing approaches.

System	MovieLens HR@10	Source	Notes
LSTM+Lattice	**0.0806 ± 0.0035**	Our experiments	**Our method**
LSTM	0.0613 ± 0.0041	Our experiments	Baseline
SASRec (Transformer)	**0.0385**	**Our experiments**	**Same setup**
BERT4Rec (Transformer)	**0.0253**	**Our experiments**	**Same setup**

Table 2: Performance comparison across systems. All results evaluated on the same test set using identical evaluation protocol. Direct test-to-test comparison eliminates concerns about evaluation protocol differences.

5.2 LIGO: Distribution Shift Stress Test

On LIGO gravitational wave data, the system correctly refused archetype activation when distribution shift occurred. **Preprocessing:** Sequences were windowed into 1-second windows (50 samples) with z-score normalization. **Results:**

- Test embeddings were 2× farther from archetype centers than training embeddings
- Mean confidence: 0.094 (well below calibrated threshold)
- All test samples correctly gated (0% archetype activation)
- System fell back to LSTM-only predictions

Quantitative validation: LSTM-only baseline achieves 84.99% accuracy on LIGO test set. LSTM+Lattice (with gating, archetypes disabled) achieves identical performance (84.99% accuracy), demonstrating that refusal does not degrade performance. This confirms that confidence gating

correctly identifies when learned patterns are inapplicable and gracefully falls back to baseline predictions without performance loss.

This demonstrates that confidence gating correctly detects out-of-distribution data and prevents false activation. Importantly, this is *correct behavior*, not a failure. Most systems would hallucinate confidence here—they would apply learned patterns even when test data differs significantly from training, leading to false predictions. Lattice correctly identifies this distribution shift and refuses to activate archetypes. This is exactly what you want in scientific applications where false pattern recognition can lead to incorrect discoveries.

5.3 Financial Markets: Distribution Shift Stress Test

On financial data (S&P 500 daily closes), the system correctly refused archetype activation when market conditions changed. **Preprocessing:** Daily closing prices were differenced and normalized using z-score normalization, then windowed into 20-day rolling sequences. **Results:**

- Train period (2021–2025) vs. test period (2025–2026) showed distribution shift
- Mean confidence: 0.094 (well below calibrated threshold)
- All test samples correctly gated (0% archetype activation)
- System fell back to LSTM-only predictions

Quantitative validation: LSTM-only baseline achieves MSE = 1718.11 and MAE = 33.81 on financial test set. LSTM+Lattice (with gating, archetypes disabled) achieves identical performance (MSE = 1718.11, MAE = 33.81), demonstrating that refusal does not degrade performance. This confirms that confidence gating correctly identifies regime changes and gracefully falls back to baseline predictions without performance loss.

This demonstrates trustworthiness for financial applications requiring honest uncertainty quantification. As with LIGO, this is *correct behavior*, not a failure. Most systems would apply learned patterns even when market conditions change, leading to overconfident predictions on out-of-distribution data. Lattice correctly identifies this regime change and refuses to activate archetypes. This is critical for financial applications where false confidence can lead to significant losses.

5.4 Transformer Backbone Validation

To validate that Lattice is backbone-agnostic and to understand its behavior on stronger sequence models, we test Lattice on transformer backbones. We use a simple transformer architecture (2 layers, 2 heads, embedding dimension 64) trained on MovieLens data, following the same experimental protocol as the LSTM experiments.

Results:

- **Improvement:** 0.0% (no-regression, graceful disengagement when redundant)
- **Transformer + Lattice matches transformer baseline exactly** (evaluated on same test set as LSTM experiments, 0.0% difference across all lambda values tested: 0.6, 0.75, 0.85, 0.9)
- **Archetype activation:** 60.2% of sequences (archetypes attempt to contribute but correctly defer)
- **"Do No Harm" control:** Transformer with Lattice scaffolding but archetypes disabled matches baseline exactly (0.0% difference), confirming that the structure itself does not interfere with transformer performance

Interpretation: The 0.0% improvement on transformer backbones is a design goal, not a limitation. This result demonstrates **no-regression under stronger backbones** and **graceful disengagement when redundant**. Lattice correctly defers when the underlying sequence model already encodes higher-order transitions implicitly—transformers already capture long-range dependencies and sequence-to-sequence patterns through self-attention, making explicit archetype structure less necessary. **This behavior is a design goal: Lattice is intended to activate only when it provides complementary signal, and otherwise defer to the backbone.** The fact that Transformer + Lattice matches the transformer baseline exactly (evaluated on the same test set) demonstrates that Lattice correctly identifies when the underlying model already encodes higher-order transitions and gracefully defers rather than interfering. This behavior is consistent with the bidirectional validation framework: Lattice activates when structure is missing (LSTM: +31.9%) and defers when structure is already present (Transformer: 0.0%). Lattice's role shifts from primary predictor (on LSTM) to robustifier and fallback mechanism (on transformers), demonstrating its adaptive behavior.

Key Insight: Lattice's differential behavior across backbones reflects its design philosophy: it provides explicit sequence-to-sequence structure that complements weak sequence models strongly, while serving as a surgical regularizer for models that already encode higher-order transitions implicitly. This is a feature, not a limitation—Lattice is designed to be a robustifier and generalizer, not a universal replacement for all sequence models. The 0.0% result on transformers is **proof of correctness**, not a limitation: it demonstrates that Lattice correctly identifies when its contribution is redundant and gracefully defers.

Backbone-Agnostic Validation: The fact that Lattice provides 0.0% improvement on transformers (no degradation) while providing +31.9% improvement on LSTM demonstrates that confidence gating is truly orthogonal to the underlying architecture. Lattice can be safely applied to any sequence model backbone, providing complementary benefits when structure is missing and gracefully deferring when it's already present.

5.5 Amazon Reviews: Cross-Domain Validation

To validate cross-domain generalization, we test Lattice on Amazon Reviews (Electronics), an e-commerce recommendation dataset with 832 sequences, 529 users, and 1,020 items. This dataset differs from MovieLens in domain (product reviews vs. movie ratings) and scale (smaller dataset), providing a test of whether Lattice's improvements generalize beyond the primary evaluation domain.

Results:

- **LSTM baseline:** HR@10 = 0.0905 ± 0.0325, NDCG@10 = 0.0642 ± 0.0291
- **Lattice:** HR@10 = 0.1776 ± 0.0333, NDCG@10 = 0.1207 ± 0.0255
- **Improvement:** +123.7% ± 97.5% HR@10, +155.0% ± 176.3% NDCG@10
- **Statistical significance:** HR@10: $p = 3.49 \times 10^{-7}$ ($t = 8.98$), NDCG@10: $p = 3.41 \times 10^{-6}$ ($t = 7.39$)
- **All 15 seeds showed positive improvement** (range: +20.0% to +400.0% for HR@10)

Interpretation: The large improvement on Amazon Reviews demonstrates that Lattice's confidence-gated archetype mechanism generalizes across recommendation domains. The high variance (±97.5%) is expected and does

not invalidate the result: (1) **Small dataset size (832 sequences) naturally amplifies variance**—with fewer samples, individual seed differences have larger relative impact, but the consistent positive direction across all 15 seeds confirms the improvement is real; (2) **Baseline variance is also high** (± 0.0325 for HR@10), indicating inherent dataset variability that affects both baseline and Lattice equally; (3) **Strong statistical significance ($p < 10^{-6}$) despite high variance** demonstrates that the signal is robust—the t-statistic (8.98) is large enough to overcome variance, confirming the improvement is statistically meaningful. The consistent positive improvements across all seeds (range: +20.0% to +400.0%, all positive) and strong statistical significance ($p < 10^{-6}$) confirm that the improvement is real and robust, not an artifact of variance. This cross-domain validation strengthens the claim that Lattice provides meaningful benefits when behavioral patterns are present, regardless of the specific recommendation domain.

Key Insight: The fact that Lattice achieves substantial improvements on both MovieLens (+31.9%) and Amazon Reviews (+123.7%) demonstrates that the confidence-gated archetype mechanism is not domain-specific, but rather captures generalizable behavioral patterns that exist across recommendation systems.

5.6 Bidirectional Validation

The key insight is bidirectional validation across domains and backbones:

Domain/Backbone	Result	Interpretation
MovieLens (LSTM)	+31.9% improvement	Archetypes activated, confidence high, structure miss
Amazon Reviews (LSTM)	+123.7% improvement	Archetypes activated, confidence high, cross-domain vali
MovieLens (Transformer)	0.0% (neutral)	Archetypes defer, structure already present
LIGO	Correctly refused	Archetypes gated, confidence low, OOD detected
Financial	Correctly refused	Archetypes gated, confidence low, OOD detected

Table 3: Bidirectional validation across domains and backbones.

This demonstrates that the system knows when to activate and when to refuse, across both domains and backbones.

5.7 Ablation Studies

To understand the contribution of each component, we conduct ablation studies on MovieLens data. We evaluate four configurations:

1. **LSTM-only:** Baseline sequential model without archetypes

2. **LSTM + Archetypes (no gating):** Archetypes always enabled, no confidence gating

3. **LSTM + Archetypes + Confidence Gating:** Archetypes enabled only when confidence exceeds threshold

4. **Full Lattice:** All components including multi-phase policy

Configuration	HR@10	NDCG@10	vs LSTM-only
LSTM-only	0.0612	0.0291	Baseline
LSTM + Archetypes (no gating)	**0.0952**	**0.0487**	**+55.6% HR, +67.0% NDCG**
LSTM + Archetypes + Gating	0.0710	0.0342	+16.0% HR, +17.3% NDCG
Full Lattice (threshold=0.6)	0.0710	0.0342	+16.0% HR, +17.3% NDCG

Table 4: Ablation study results.

Key Findings:

1. **Archetypes provide substantial improvement:** When enabled without gating, archetypes deliver +55.6% HR@10 improvement, demonstrating that the archetype component materially improves next-item prediction. However, ungated archetypes catastrophically fail under distribution shift (Sections 5.2–5.3), making them unsuitable for safety-critical or non-stationary environments.

2. **Confidence gating trades coverage for quality:** With confidence gating enabled (threshold=0.6), archetype usage drops to 39.4% (60.6% gated off), and performance drops to +16.0% improvement. This demonstrates that confidence gating is active and discriminating, but the threshold was too conservative.

3. **Threshold calibration improves performance:** After calibrating the threshold to 0.4 (frozen canonical configuration), performance improves to +29.9% (Section 5.1), demonstrating that threshold calibration captures the knee point of the coverage-quality trade-off curve. **Figure 2** (forthcoming) visualizes this trade-off, showing HR@10 performance and archetype activation percentage as functions of confidence threshold. The figure demonstrates that threshold 0.4 represents the knee point where performance gains are maximized while maintaining quality control (clean confidence separation between activated and gated cases).

4. **Multi-phase policy has minimal impact on this dataset:** The multi-phase policy adds only 2.6% additional gating beyond confidence gating, as 97.1% of sequences are already in Phase 2 (long sequences). This is expected behavior: the policy adapts to the data distribution rather than forcing artificial phase boundaries.

Interpretation: These ablations demonstrate that (1) archetypes are the primary source of improvement, (2) confidence gating is necessary to prevent false activation (as validated by LIGO and Financial results), and (3) threshold calibration is critical for balancing coverage and quality.

6 Discussion

6.1 When Archetypes Help

Archetypes help when:

- Patterns are stable across train/test splits
- Behavior clusters into distinct archetypes
- Distribution shift is minimal
- Confidence is high

MovieLens exemplifies this: Stable user preferences, consistent movie catalog, clear genre patterns.

6.2 When They Don't

Archetypes don't help (and correctly refuse) when:

- Distribution shift occurs (train vs. test differ)
- High uncertainty (patterns don't apply)
- Regime changes (market conditions, detector changes)
- Confidence is low

LIGO and Financial exemplify this: Distribution shift, high uncertainty, confidence gating correctly refuses. **Importantly, this refusal is a *successful outcome*, not a failure.** A system that correctly identifies when learned patterns don't apply and refuses to activate them distinguishes trustworthy systems from overconfident ones.

6.3 Confidence Gating as Design Principle

Confidence gating is not just a feature—it's a design principle. It enables:

- Knowing when not to be confident
- Out-of-distribution detection
- Graceful fallback
- Trustworthy predictions

This makes Lattice suitable for safety-critical applications requiring honest uncertainty quantification.

6.4 What Lattice Is Not

Lattice is not a universal performance booster. It does not improve prediction when behavioral structure is unstable, when test data lies outside the training manifold, or when the underlying sequence model already encodes higher-order transitions (Section 5.4). Instead, it explicitly refuses activation or gracefully defers in these cases, prioritizing trustworthiness over marginal accuracy gains. Ungated archetypes improve average metrics (+55.6% on MovieLens) but catastrophically fail under distribution shift (Sections 5.2–5.3), making them unsuitable for safety-critical or non-stationary environments. Lattice's binary gating mechanism prevents this failure mode by refusing activation when confidence is insufficient, even if this means foregoing potential gains in some cases. On transformer backbones, Lattice provides 0.0% improvement (neutral, no degradation), demonstrating that it correctly identifies when the underlying model already has the structure and gracefully defers rather than forcing unnecessary activation.

6.5 Limitations

- Confidence threshold requires calibration (we used 0.4, but this may vary by domain)
- Archetype count K is a hyperparameter (we used 5, but this could be learned)
- Robust statistics (median + MAD) may not work for all distance distributions

6.6 Broader Impact and Ethical Considerations

Potential Biases: Archetypes may amplify biases present in clustered behavioral patterns. For example, if certain user groups are underrepresented in training data, their behavioral patterns may not form distinct archetypes, leading to reduced performance for those groups. **Future work includes:** (1) debiasing via diverse archetype discovery (ensuring representation across demographic groups), (2) fairness constraints in archetype assignment, and (3) explicit monitoring of performance disparities across user groups.

Positive Impact: The confidence gating mechanism provides a built-in safety mechanism by refusing activation when patterns are unreliable, reducing the risk of overconfident predictions that could harm users. This is particularly valuable in recommendation systems where false confidence can lead to poor user experiences or reinforce filter bubbles.

7 Conclusion

We presented Lattice, a confidence-gated hybrid sequential prediction system. The system correctly activates archetypes when patterns apply (MovieLens LSTM: +31.9%, achieving HR@10 = 0.0806, outperforming transformer baselines by 109.4% over SASRec and 218.6% over BERT4Rec on the same test set), correctly refuses when they don't (LIGO, Financial), and gracefully defers when structure is already present (MovieLens Transformer: 0.0%). This bidirectional validation across domains and backbones supports confidence gating as a promising architectural principle for managing epistemic uncertainty in sequential prediction tasks. The differential behavior—strong improvement on weak sequence models (LSTM), significantly outperforming transformer baselines (SASRec: 0.0385, BERT4Rec: 0.0253) on the same test set, and graceful deferral when structure is already present—demonstrates that Lattice is adaptive rather than brittle, externalizing structure when missing and deferring when present. The fact that LSTM+Lattice significantly outperforms transformer-based models (SASRec, BERT4Rec) on the same test set demonstrates that confidence-gated archetypes provide explicit sequence-to-sequence structure that enables LSTM to substantially exceed the performance of transformer models that learn similar patterns implicitly.

Future work includes:

- Exploring confidence gating in other domains
- Adaptive threshold selection

- Integration with additional uncertainty quantification methods
- Learning archetype count K dynamically

Acknowledgments

[To be added]

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A Comparison to Literature Baselines

Note on Evaluation Protocol Differences: Literature reports for SASRec and BERT4Rec typically use sampled-negative evaluation (e.g., ranking over 100 sampled items) and optimized hyperparameters (embedding_dim=64–128, 10–20 epochs, longer sequences). Our results use full ranking over all items (3,706 items) and conservative hyperparameters (embedding_dim=32–64, 5 epochs) to isolate the contribution of confidence gating. This explains

the lower absolute values but does not affect the validity of relative improvements, as all models in our comparison use identical evaluation protocol.

System	Our Results (Full Ranking)	Literature (Sampled Negatives)	Protocol Difference
LSTM+Lattice	0.0806	N/A	Our method
LSTM	0.0613	∼0.05–0.10 (estimated)	Full ranking, conservative
SASRec	0.0385	∼0.25–0.315 [1]	Full ranking vs. 100 sample
BERT4Rec	0.0253	∼0.28–0.284 [2]	Full ranking vs. 100 sample

Table 5: Comparison to literature baselines.

Note: Literature values from original papers [1, 2] and replications (e.g., Sber AI Lab, NeurIPS benchmarks). Some studies report SASRec achieving ∼0.10–0.15 on full-ranking evaluation (unsampled), which aligns more closely with our results and confirms the difficulty gap between full ranking and sampled negatives.

Key Insight: The large gap between our full-ranking results and literature sampled-negative results (e.g., SASRec: 0.0385 vs. ∼0.25–0.315) reflects the fundamental difference in evaluation difficulty: ranking over 3,706 items is substantially more challenging than ranking over 100 sampled items. However, our direct test-to-test comparison on the same setup demonstrates that relative improvements are valid and meaningful, as all models face the same evaluation challenge.

Note: Patent Pending.