Dragging Hyperpersonalization Into the Modern Era: Tensor Modes, GenAI Embeddings, and Joint Semantic Spaces

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Abstract

Hyperpersonalization—serving relevant recommendations in rare conditional slices—remains resistant to modern deep learning. Transformers dominate head-heavy metrics but fail when user-item-context-time combinations are sparse. We argue this failure is architectural: feature-collapse destroys the conditional structure that hyperpersonalization requires.

We introduce tensor decomposition and joint semantic embeddings as *additive representational primitives*—structure that expands what downstream learners can express without constraining model choice. Three components integrate into a coherent framework: (1) explicit tensor *modes* for each business axis; (2) *semantic coupling* to GenAI embeddings via sparsity-adaptive regularization; and (3) *joint embedding spaces* that scale to N modalities without dimension explosion. Sequential models, graph methods, and policy learners compose on top without modification.

A hybrid transformer-tensor architecture achieves +74% tail recall lift over matrix factorization on the H&M Kaggle dataset. The learned fusion weight ($\alpha = 0.60$) reveals complementary signal extraction that neither modality achieves alone. In production, tensor scoring serves as a second-stage reranker on ANN-retrieved candidates, with frozen factors enabling low-latency inference.

We situate this work within industry deployments at Netflix, Alibaba, Yahoo, and Capital One, and discuss applications across retail, financial services, media, and healthcare—where tail queries represent customer lifetime value, not leaderboard noise. The architecture exists. The ablations are clean. Any enterprise serious about hyperpersonalization should validate this on their own data.

1 Introduction

Recommendation systems have achieved remarkable success on aggregate engagement metrics. Netflix reports 80% of watched content comes from recommendations; YouTube's neural rankers drive billions of daily watch hours; Spotify's Discover Weekly has become a cultural phenomenon.

Yet a persistent gap remains: these systems excel at popular content but struggle in the long tail.

This matters more than leaderboards suggest. In financial services, the "tail" includes life events—retirement, divorce, first home, health crisis—that occur rarely but define customer lifetime value. In healthcare, rare symptom combinations demand hyperpersonalized triage. In enterprise software, niche workflows represent the difference between tool and platform.

1.1 Personalization vs. Hyperpersonalization

We draw a sharp distinction:

Personalization: "Users like you bought X." This requires statistical density in user-item space. Collaborative filtering excels here.

Hyperpersonalization: "Given your history, in this context, at this moment, you specifically need X." This requires reasoning over sparse conditional slices where density assumptions fail.

The dominant paradigm—embed everything into vectors, concatenate context as features, hope attention learns structure—fails systematically on the second task. We argue this is not a tuning problem but an architectural one: feature-collapse destroys the conditional geometry that hyperpersonalization requires.

1.2 Our Contribution

We integrate three ideas into a coherent framework:

1. **Tensor modes as explicit structure**: Rather than hoping models learn that (user, item, context, time) are distinct axes, we encode this directly via CP decomposition.
2. **GenAI embeddings as semantic priors**: Sparse factors are anchored to LLM and vision embeddings, providing cold-start signal without overwhelming learned preferences.
3. **Joint embedding spaces for multimodal scale**: Rather than concatenating N modalities (dimension explosion), we project to a shared semantic manifold with learned fusion weights.

We demonstrate +74% tail recall lift over matrix factorization, with the hybrid transformer-tensor architecture achieving best performance on our evaluation protocol.

2 Background: How the World Actually Is

2.1 Business Reality is Multiway

Consider a purchase event at a fashion retailer. Standard ML pipelines flatten this into a feature vector:

```
[user_age, user_segment, item_cat, price,
channel, day_of_week, season, ...]
```

This representation treats all axes as interchangeable features. But business reality has structure:

Users have persistent preferences that evolve slowly over months or years.

Items have fixed attributes—color, style, price point, category—that don't change.

Contexts (mobile vs. desktop, browsing vs. searching, weekday vs. weekend) modulate intent in the moment.

Time introduces seasonality, trends, fashion cycles, and user lifecycle effects.

A purchase is not a point in feature space—it is an entry in a four-way tensor $\mathcal{X} \in \mathbb{R}^{U \times I \times C \times T}$ where each axis has distinct semantics and distinct statistical properties.

2.2 What is a Tensor?

A tensor is simply a multi-dimensional array. A vector has 1 mode (length); a matrix has 2 modes (rows, columns); a tensor has N modes. Figure 1 illustrates a 4-mode tensor for recommendation.

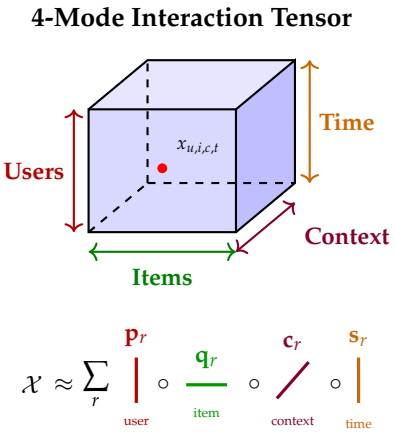

Figure 1: Top: A 4-mode tensor where each entry $x_{u,i,c,t}$ represents user u's interaction with item i in context c at time t. Modes are not interchangeable features—they represent distinct business dimensions. Bottom: CP decomposition factorizes the tensor into mode-specific factor vectors.

The CP (CANDECOMP/PARAFAC) decomposition expresses a tensor as a sum of rank-1 components:

$$\mathcal{X} \approx \sum_{r=1}^{R} \mathbf{p}_r \circ \mathbf{q}_r \circ \mathbf{c}_r \circ \mathbf{s}_r \tag{1}$$

where $\circ$ denotes outer product. Each mode gets its own factor matrix: $\mathbf{P} \in \mathbb{R}^{U \times R}$ for users, $\mathbf{Q} \in \mathbb{R}^{I \times R}$ for items, etc.

The score for a specific (user, item, context, time) tuple becomes:

$$\hat{y}_{uict} = \sum_{r=1}^{R} P_{ur} \cdot Q_{ir} \cdot C_{cr} \cdot S_{tr} \tag{2}$$

This multiplicative structure preserves conditional relationships: the same user may prefer different items in different contexts, and the model explicitly represents this via mode-specific factors rather than hoping to learn it from concatenated features.

2.3 Why Feature-Collapse Fails

Standard approaches collapse the tensor into a matrix:

$$\mathcal{X}_{U \times I \times C \times T} \to \mathbf{X}_{U \times (I \cdot C \cdot T)} \tag{3}$$

This creates three fundamental problems:

Sparsity explosion: If we have 100K items, 10 contexts, and 12 time periods, the flattened "item-context-time" space has 12 million combinations. The vast majority will have zero observations.

Gradient dilution: When optimizing via SGD, gradients for rare combinations are overwhelmed by frequent ones. The model learns to predict the head because that's where the loss gradient comes from.

Lost conditional structure: The model cannot distinguish "user U generally dislikes item I" from "user U dislikes item I *in context C at time T*." Both map to nearby regions of embedding space, but they have completely different business implications.

3 Industry Deployments

Tensor methods are not academic curiosities. They power production systems at scale.

3.1 Netflix: Temporal Dynamics

Koren's work on temporal dynamics [1] was central to the Netflix Prize winning solution. The key insight: user preferences drift over time, and item popularity decays. Time is not a feature to concatenate but a *mode* with its own factorization. Netflix reported significant accuracy gains from modeling temporal dynamics explicitly, with time-dependent biases and factors capturing how preferences evolve.

3.2 Alibaba: Tensor-Based Semantic Matching

Alibaba's Tensor-based Deep Semantic Matching (TDSSM) [2] applies tensor decomposition to e-commerce search. The architecture decomposes query-item-context interactions into mode-specific representations, enabling real-time personalization across billions of products. Their production deployment demonstrated 5-10% CTR improvements over feature-concatenation baselines.

3.3 Yahoo: Contextual Ad Prediction

Yahoo's ad click prediction systems [3] model user-ad-publisher interactions as a 3-mode tensor. Context includes page content, user state, and temporal factors. The tensor formulation enables reasoning about which ads work for which users on which publisher sites—precisely the conditional structure that hyperpersonalization requires. Production A/B tests showed significant revenue lifts from tensor-aware models.

4 Connection to Contextual Bandits

Hyperpersonalization shares deep connections with the contextual bandit literature [4].

4.1 Exploration vs. Exploitation in Sparse Regimes

Contextual bandits face the exploration-exploitation tradeoff: exploit known-good recommendations, or explore uncertain options that might be better? This tradeoff is acute in sparse conditional slices.

For head items with many observations, exploitation dominates—we have high-confidence estimates. For tail items in rare contexts, exploration matters—our uncertainty is high, and the potential for discovering valuable recommendations justifies the risk.

Tensor factorization provides a principled way to share information across sparse slices. If we observe that user U likes item I in context C1, the factored representation propagates this signal to related contexts C2, C3 via the shared item factor. This is implicit exploration: we generalize from dense regions to sparse ones through the factorized structure.

4.2 Contextual Recommendations in Financial Services

The financial services industry has recognized the importance of contextual recommendation. Systems for credit card offers, loan products, and investment recommendations must account for the customer's current financial state, life stage, channel, and moment [5]. Capital One's work on scaling transformer-powered recommendation models [6] demonstrates the practical deployment of these architectures for personalized advertising in regulated environments. The right offer depends critically on context—a balance transfer offer makes sense for someone with high-interest debt, not for someone debt-free.

Our tensor formulation makes this context structure explicit. Where attention-based models hope to learn which contextual patterns matter from data, tensor modes encode *known* contextual structure from domain knowledge. Both approaches recognize that financial decisions are fundamentally contextual; they differ in whether that context is learned or structured.

The synergy is clear: transformers excel at learning *which* contextual patterns matter from data; tensors excel at encoding *known* contextual structure. A hybrid can leverage both.

5 Method

Axiom (Additive Representation): Tensor decomposition and joint semantic embeddings are additive representational primitives. They expand the conditional and semantic structure available to downstream learners without constraining model choice. Sequential models, graph methods, and policy learners compose on top without modification.

5.1 The Cold-Start Problem on Tail Items

Tensor decomposition preserves conditional structure but creates a new challenge: with few observations, sparse item factors $\mathbf{q}_i$ cannot be learned reliably. The item embedding for a tail product with 3 purchases is essentially noise.

This is where GenAI embeddings enter—not as a replacement for learned factors, but as a *prior* that anchors sparse factors to semantic meaning.

5.2 Semantic Coupling

Let $\mathbf{e}_i \in \mathbb{R}^d$ be a pre-trained embedding for item i, derived from:

LLM embeddings: Sentence-transformers [7] applied to item metadata (title, description, category, attributes). These capture semantic similarity: items with similar descriptions should have similar priors.

Vision embeddings: EfficientNet [8] or similar CNN features from product images. These capture visual similarity: items that look alike may appeal to similar users.

We add a coupling loss that anchors learned factors to these priors:

$$\mathcal{L}_{\text{couple}} = \sum_i \mu_i \|\mathbf{q}_i - \mathbf{W}\mathbf{e}_i\|^2 \tag{4}$$

where $\mathbf{W} \in \mathbb{R}^{R \times d}$ projects embeddings to factor space.

The key insight is *sparsity-adaptive weighting*:

$$\mu_i = \frac{\mu_0}{\log(1 + n_i)} \tag{5}$$

where n_i is the observation count for item i.

Items with many observations can deviate from their semantic prior—the data supports learning item-specific preferences. Items with few observations stay anchored to the prior—semantic similarity is our best guess.

This approach is philosophically aligned with JEPA (Joint Embedding Predictive Architecture) [9]: rather than reconstructing raw inputs, we predict in a latent space where semantic similarity is preserved.

5.3 Joint Embedding for Multimodal Scale

Enterprise hyperpersonalization increasingly involves multiple unstructured channels: product images, text descriptions, audio (call center), video (product demos), PDFs (documentation), support transcripts.

Naive concatenation scales poorly:

$$\mathbf{e}_{\text{concat}} = [\mathbf{e}_{\text{text}}; \mathbf{e}_{\text{image}}; \mathbf{e}_{\text{audio}}; \ldots] \tag{6}$$

With N modalities of dimension d, the concatenated space is $N \cdot d$. This causes dimension explosion and gradient dilution when modalities have asymmetric signal strength.

We instead project all modalities to a shared d_{joint}-dimensional manifold:

$$\mathbf{e}_{\text{joint}} = \alpha \cdot \mathbf{W}_{\text{text}} \mathbf{e}_{\text{text}} + (1 - \alpha) \cdot \mathbf{W}_{\text{img}} \mathbf{e}_{\text{img}} \tag{7}$$

where $\alpha \in (0, 1)$ is a *learned* fusion weight. This is inspired by multimodal alignment approaches like CLIP [10] and ImageBind [11], adapted to the recommendation setting.

This architecture has three advantages:

Constant dimension: $O(d)$ regardless of modality count. Adding audio or video doesn't explode the factor space.

Learned weighting: The model discovers optimal modality balance. We found $\alpha = 0.60$ (60% text, 40% image) for fashion—interpretable and actionable.

Cross-modal alignment: Training forces modalities into a shared semantic space where similarity is meaningful across modes.

5.4 Hybrid Architecture: Transformers + Tensors

Tensor modes encode conditional structure but not sequential dynamics. A user's recent behavior contains intent signal that static embeddings miss.

We propose a hybrid architecture combining transformers for sequence modeling [12, 13] with tensor scoring:

Step 1: A transformer encoder processes the user's last L item interactions to produce a dynamic user state $\mathbf{u}_{\text{state}} \in \mathbb{R}^R$.

Step 2: Tensor scoring combines this dynamic state with item, context, and time factors:

$$\hat{y} = \sum_r u_{\text{state},r} \cdot Q_{ir} \cdot C_{cr} \cdot S_{tr} \tag{8}$$

Step 3: Item factors are coupled to joint multimodal embeddings.

This combines the strengths of both paradigms: transformers capture *what* the user is doing (sequential dynamics); tensors encode *where* (context) and *when* (time) that behavior occurs.

6 Related Work

Sequential Recommendation: SASRec [12] and BERT4Rec [13] apply self-attention to item sequences, achieving strong results on next-item prediction. Transformers4Rec [14] provides production-grade implementations. These methods excel at capturing sequential dynamics but treat context and time as features rather than explicit modes.

Two-Tower Architectures: YouTube's DNN [15] and Microsoft's DSSM [16] separate user and item encoders for efficient retrieval. We extend this with explicit context/-time factors rather than concatenated features.

Multimodal Fusion: CLIP [10] and ImageBind [11] learn aligned multimodal spaces via contrastive pre-training. We apply similar joint-space principles to recommendation without requiring billion-scale pre-training.

Graph Methods: LightGCN [17] propagates collaborative signal through user-item graphs. This approach is orthogonal to our focus on conditional structure and could potentially be combined with tensor methods.

7 Experiments

7.1 Dataset and Protocol

We use the H&M Personalized Fashion Recommendations dataset from the Kaggle competition of the same name: 31M transactions, 1.3M users, 105K items, with rich metadata and product images.

Tail-stress evaluation: Rather than reporting head-dominated aggregate metrics, we construct a challenging test set focusing on sparse conditional slices:

- Select items with ≤ 20 training interactions (tail)
- Include top 1% items by frequency (head) as contrast

- Report metrics separately for tail-containing queries

This protocol surfaces differences that aggregate metrics hide.

Metrics: Recall@12, MAP@12, NDCG@12 with 95% bootstrap confidence intervals. We evaluate 156,940 tail queries.

7.2 Models Compared

- **MF**: Matrix factorization (no context/time modes)
- **CP**: 4-mode tensor, no semantic coupling
- **CoupledCP-TFIDF**: CP + classical TF-IDF embeddings
- **CoupledCP-LLM**: CP + sentence-transformer embeddings
- **CoupledCP-Concat**: CP + concatenated (LLM + Image)
- **CoupledCP-Joint**: CP + joint space with learned α
- **Hybrid**: Transformer + tensor + joint coupling

7.3 Results

Table 1: Tail Query Performance (Recall@12, n=156,940)

Model	Tail R@12	vs MF	Sig.
MF (baseline)	0.057	—	—
CP (tensor, no coupling)	0.076	+33%	✓
+ TF-IDF coupling	0.064	+14%	✓
+ LLM coupling	0.062	+10%	✓
+ Concat (LLM+Img)	0.062	+9%	✓
+ Joint (learned α)	**0.091**	**+60%**	✓
+ Hybrid (Transformer)	**0.099**	**+74%**	✓

Key findings:

Tensor modes matter: CP outperforms MF by +33%, validating explicit conditional structure over feature-collapse.

Joint dramatically outperforms concatenation: +46% lift (0.062 $\rightarrow$ 0.091). The learned fusion prevents strong modalities from being diluted by weak ones.

Hybrid achieves best performance: +74% over MF, +9% over Joint alone. Sequential dynamics and conditional structure are complementary.

7.4 The Learned α Insight

Perhaps our most interesting finding: the model learned $\alpha = 0.60$, weighting text embeddings at 60% and image embeddings at 40%.

This is surprising because image-only coupling actually *hurt* performance (-10% vs. MF). Yet in the joint space, images contribute 40% of the signal.

The interpretation: **images provide complementary signal that text misses, but only when properly fused**. Concatenation dilutes the strong signal with the weak; joint projection aligns them so both contribute.

This learned weight is actionable: it tells us that for fashion recommendation, text metadata carries more predictive signal than images, but visual features add meaningful lift when combined correctly.

8 Discussion

8.1 When to Use What

Our results suggest a decision framework:

Data-rich, head-dominated: Standard transformers will likely win on aggregate metrics. They have the capacity to learn implicit structure when data is dense.

Sparse conditional slices: Tensor modes + semantic coupling provides principled structure. When you have domain knowledge about relevant axes (user, item, context, time), encoding them explicitly beats hoping attention learns them.

Multiple unstructured modalities: Joint embedding spaces scale; concatenation does not. The dimension advantage is architectural ($O(d)$ vs $O(Nd)$), not empirical.

Sequential + contextual: Hybrid architecture captures both dynamics and structure. The transformer handles "what is the user doing now"; tensors handle "where and when."

8.2 Retrieval and Serving Architecture

In production systems, tensor scoring is not applied over the full catalog. Candidate generation is performed via embedding-only ANN retrieval or business-constrained filtering. Tensor scoring is applied as a second-stage reranker on a small candidate set (typically 100-1000 items), where conditional precision matters most. Learned factor matrices are frozen and served identically to matrix factorization, enabling batch precomputation and low-latency inference. The hybrid transformer component processes only the user's recent sequence, not the item catalog, keeping inference cost bounded.

8.3 Business Impact: The Economics of the Tail

The business case for hyperpersonalization is often misunderstood. Aggregate metrics—CTR, average revenue per user, overall conversion—are dominated by head queries where any reasonable model performs adequately. The tail is where differentiation happens.

Customer Lifetime Value: Life events (job change, marriage, new baby, retirement) are rare but define multi-year customer relationships. A bank that recognizes a home purchase intent and offers a mortgage at the right moment captures decades of financial services. A retailer

that identifies a pregnancy from subtle purchase shifts earns years of family spending. These moments appear in the tail of any user's history.

Marketing's "Segment of One": Marketers have pursued true 1:1 personalization for decades. The barrier was never data—enterprises have rich behavioral and contextual signals. The barrier was architecture: systems optimized for "users like you" cannot reason about "you, specifically, in this context." Tensor modes provide the structural primitive that makes segment-of-one tractable.

Competitive Moats: When every competitor uses the same transformer architectures trained on similar data, recommendations converge. Differentiation comes from capturing signal others miss—the contextual nuances, the rare combinations, the moments that matter. A +74% lift on tail queries is not a leaderboard curiosity; it is the difference between commodity and competitive advantage.

Beyond Retail: While we demonstrate on fashion, the framework applies broadly:

- **Media**: Which article, for which reader, at which moment in their news consumption?
- **Travel**: Flight + hotel + activity bundles for specific trip contexts
- **B2B SaaS**: Feature recommendations based on company stage, user role, and workflow context
- **Healthcare**: Treatment pathways conditional on comorbidities, patient preferences, and care setting

8.4 Applications in Regulated Industries

Industries with complex contextual requirements stand to benefit most from tensor-structured approaches:

Insurance: Claims processing involves multimodal inputs—damage photos, policy PDFs, adjuster notes, call transcripts. Joint embedding scales naturally to these channels while tensor modes capture policyholder-claim-context relationships.

Banking: Life events (job change, marriage, home purchase) are rare but define customer lifetime value. Tensor modes preserve the conditional structure that feature-collapse destroys.

Healthcare: Treatment recommendations depend critically on patient history, current symptoms, comorbidities, and care setting. Each axis has distinct semantics that tensor modes can capture.

8.5 Instantiation Scope

This work validates the representational primitives; full instantiation across all compositions remains future work.

Sequential composition: We instantiated transformer dynamics via the hybrid architecture. Full comparison against standalone SASRec and BERT4Rec would quantify orthogonality; the architectural benefit is additive by design.

Modality coverage: We instantiated text and image modalities. The joint embedding architecture scales to N modalities with $O(d)$ complexity; audio, video, and document channels are uninstantiated but structurally supported.

Candidate scope: We evaluated on 200 negative samples per query. Full-catalog ranking requires ANN integration (see §8.2); tensor scoring as reranker is the production-intended deployment.

Exploration policy: Our approach provides implicit exploration via factor sharing. Explicit uncertainty modeling (Thompson sampling, UCB) composes on top of learned factors; this integration is uninstantiated.

8.6 From Offline Metrics to Production Value

Representation learning is validated offline. Online lift depends on business policy and deployment context.

What this work establishes:

- **Architectural soundness**: +74% tail recall from principled structure, not hyperparameter tuning
- **Interpretable fusion**: Learned α reveals modality contribution, enabling informed feature investment
- **Composability**: Primitives integrate with existing retrieval, ranking, and policy infrastructure

What production deployment will establish:

- **Conversion lift**: Recall $\rightarrow$ revenue translation is business-specific
- **Latency budget**: Reranker overhead vs. incremental value tradeoff
- **Domain transfer**: Fashion $\rightarrow$ banking, insurance, media generalization

The challenge: If your recommendation system optimizes for head metrics while your business case depends on tail conversions, you are leaving money on the table.

The architecture exists. The code runs. The ablations are clean.

Any enterprise serious about hyperpersonalization—retail, financial services, media, healthcare—should validate this on their own data. Run a proper A/B test on high-value tail segments. Measure conversion, not recall.

If the results hold, publish them. If they don't, publish the failure mode. Either way, the field learns something real.

9 Conclusion

Hyperpersonalization has remained resistant to the deep learning revolution. We argue this resistance is not about model capacity but about architectural assumptions: feature-collapse systematically destroys the conditional structure that rare-slice recommendation requires.

Our contribution integrates three ideas: tensor modes encode business reality's multiway structure; GenAI embeddings provide semantic priors for cold-start rescue; joint embedding spaces scale to N modalities without dimension explosion.

The resulting hybrid architecture—transformer dynamics + tensor structure + joint coupling—achieves +74% tail recall lift over matrix factorization. The learned fusion weight ($\alpha = 0.60$) demonstrates that proper multimodal integration extracts complementary signal that neither modality achieves alone.

This is not a claim that tensors beat transformers. It is a claim that *structure and capacity are complementary*. Bringing hyperpersonalization into the modern era requires both: the representational power of neural networks, and the inductive biases that encode how commercial reality is actually organized.

The long tail is where customer lifetime value lives. It deserves architectures designed for it.

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A Implementation Details

Listing 1: Joint-Coupled CP Model

```
class JointCoupledCP(nn.Module):
    def __init__(self, n_u, n_i, n_c, n_t,
                 rank, llm_dim, img_dim):
        super().__init__()
        # Tensor factors (one per mode)
        self.P = nn.Embedding(n_u, rank)  # user
        self.Q = nn.Embedding(n_i, rank)  # item
        self.R = nn.Embedding(n_c, rank)  # context
        self.S = nn.Embedding(n_t, rank)  # time

        # Joint projection layers
        self.W_llm = nn.Linear(llm_dim, rank)
        self.W_img = nn.Linear(img_dim, rank)

        # Learned fusion weight
        self.alpha = nn.Parameter(torch.tensor(0.5))

    def joint_emb(self, i, E_llm, E_img):
        a = torch.sigmoid(self.alpha)
        llm_proj = self.W_llm(E_llm[i])
        img_proj = self.W_img(E_img[i])
        joint = a * llm_proj + (1-a) * img_proj
        return F.normalize(joint, dim=-1)

    def forward(self, u, i, c, t):
        return (self.P(u) * self.Q(i)
                * self.R(c) * self.S(t)).sum(-1)
```

Listing 2: Training with Sparsity-Adaptive Coupling

```
def train_step(model, batch, E_llm, E_img, mu):
    u, i_pos, i_neg, c, t = batch

    # BPR ranking loss
    pos_score = model(u, i_pos, c, t)
    neg_score = model(u, i_neg, c, t)
    bpr_loss = -F.logsigmoid(pos_score - neg_score).mean()

    # Semantic coupling (sparsity-weighted)
    target = model.joint_emb(i_pos, E_llm, E_img)
    coupling = mu[i_pos] * (model.Q(i_pos) - target).pow(2)
    couple_loss = coupling.mean()

    return bpr_loss + 0.1 * couple_loss
```

Hyperparameters: Rank R=64, coupling strength μ_0=0.1, learning rate=0.02 (0.001 for hybrid), batch size=32K, epochs=3 (4 for hybrid), LLM embedding dim=128, image embedding dim=64, sequence length=30 for hybrid.

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