BasketFormer: Contrastive Masked Language Modeling with Temporal Encoding and Repeat-Explore Gating for Next-Basket Recommendation

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Abstract. Next-basket recommendation (NBR) in online grocery must capture both habitual *repeat* purchases and *explore* behavior. We propose **BasketFormer**, a Transformer encoder trained with a contrastive masked language modeling (C-MLM) objective that unifies three innovations: (1) an **InfoNCE-based MLM loss** replacing the full-vocabulary softmax with in-batch contrastive scoring; (2) a **bit-level temporal encoding** that injects discretized inter-basket time intervals as learnable bit tokens; and (3) a **repeat-explore gating head** that decomposes recommendations into repeat and novel items via a learned mixture. On a large-scale proprietary grocery dataset (71K customers, 3.8M transactions) and the public Ta-Feng benchmark, BasketFormer achieves Recall@10 improvements of 28.0% and 26.5% over the strongest baseline, respectively, while substantially boosting explore-item recall.

Keywords: Next-Basket Recommendation · Contrastive Learning · Temporal Encoding · Repeat-Explore Gating

1 Introduction

Online grocery recommendation must predict a customer's *next basket* - a set of co-purchased items - from their purchase history. Two properties distinguish this setting: shopping occurs in *baskets* (sequence-of-sets), and behavior follows a *repeat-explore* pattern where customers repurchase staples while occasionally trying new products.

Early NBR methods such as TIFU-KNN [2] model customers as time-decayed frequency profiles but struggle with novel-item discovery. Neural sequential models like DREAM [4] and Sets2Sets [1] encode basket sequences with RNNs but are limited by left-to-right processing. BERT4Rec [3] adapts masked language modeling (MLM) to sequential recommendation with bidirectional attention, yet targets single-item sequences and uses a costly full-vocabulary softmax.

Building on this body of work, **BasketFormer** introduces three specific innovations that, to the best of our knowledge, have not been addressed jointly in a single NBR model: **(i) Contrastive MLM (C-MLM):** an InfoNCE loss over in-batch masked positions that scales independently of vocabulary size; **(ii) Bit-Level Temporal Encoding:** inter-basket intervals bit-discretized into learnable tokens prepended to each basket; **(iii) Repeat-Explore Gating:** a basket-level gate that modulates a mixture of history-boosted and exploration-favoring representations.

2 Methodology

Problem Formulation. For customer u, we observe baskets $\mathcal{B}^{(u)} = [B_1, \ldots, B_T]$ where $B_t \subseteq \mathcal{V}$ is purchased at time τ_t. The goal is to predict B_{T+1}.

Input Representation. The basket history is flattened into a token sequence, retaining the most recent baskets when the sequence exceeds $L_{\max}$. Each token v_i from basket t_i is represented as $\mathbf{x}_i = \mathbf{e}_{v_i} + \mathbf{p}_{t_i}$, where $\mathbf{e}_{v_i} \in \mathbb{R}^d$ is the item embedding and $\mathbf{p}_{t_i}$ is a learnable basket-position embedding. This preserves set semantics within baskets and chronology across baskets.

Inter-basket intervals $\Delta_t = \tau_t - \tau_{t-1}$ are encoded using compact bit-level discretization. Each active bit in the binary representation of Δ_t is mapped to a learnable `[BIT_`j`]` token and prepended to basket B_t. With $\Delta_{\max} \approx 365$, this uses only $m = 9$ reserved token ids and adds a small number of tokens per basket.

Transformer Encoder. An L-layer bidirectional Transformer with pre-layer normalization processes the input sequence and produces contextual representations $\mathbf{H}^{(L)} \in \mathbb{R}^{n \times d}$.

Two-Level Attentive Readout. Basket structure is recovered using two attention stages. First, item-level attention within each basket B_t computes

$$\mathbf{b}_t = \sum_{i \in \mathcal{I}_t} \beta_{t,i} \, \mathbf{H}_i^{(L)}, \tag{1}$$

where $\beta_{t,i}$ is learned using a basket-level query. Then, sequence-level attention aggregates basket representations conditioned on the most recent basket:

$$\alpha_t \propto \exp\!\big((\mathbf{W}_q \mathbf{b}_T)^\top (\mathbf{W}_k \mathbf{b}_t)/\sqrt{d}\big), \quad \bar{\mathbf{h}}_u = \textstyle\sum_{t=1}^{T} \alpha_t \, \mathbf{W}_v \mathbf{b}_t. \tag{2}$$

Repeat-Explore Gating. A general next-basket representation is computed as $\mathbf{b}_u^{\text{gen}} = \mathbf{W}_g \bar{\mathbf{h}}_u + \mathbf{b}_g$. For each historical item $v \in \mathcal{H}_u = \bigcup_t B_t$, an item-level repeat score is computed:

$$r_{u,v} = \mathbf{w}_r^\top [\bar{\mathbf{h}}_u \| \mathbf{e}_v \| \mathbf{f}_{u,v}] + b_r, \tag{3}$$

where $\mathbf{f}_{u,v}$ encodes purchase count, recency, and average reorder interval. Softmax-normalized weights $\alpha_{u,v}$ yield the repeat representation $\mathbf{b}_u^{\text{rep}} = \sum_v \alpha_{u,v} \, \mathbf{e}_v$. A two-layer MLP gate $\hat{g}_u \in [0,1]$ combines repeat and general intent:

$$\tilde{\mathbf{b}}_u = \hat{g}_u \, \mathbf{b}_u^{\text{rep}} + (1 - \hat{g}_u) \, \mathbf{b}_u^{\text{gen}}. \tag{4}$$

Training Objective. The target basket is represented as $\mathbf{g}(B_{T+1}) = \frac{1}{|B_{T+1}|} \sum_{v \in B_{T+1}} \mathbf{e}_v$. A basket-level InfoNCE loss aligns $\tilde{\mathbf{b}}_u$ with the true next basket while using other

Table 1. Main results on Internal (relative to TIFU-KNN) and Ta-Feng (absolute). All results on basket prediction. Best in **bold**.

	Internal		Ta-Feng	
Method	**R@5**	**R@10**	**R@5**	**R@10**
PTop-K	—	—	0.0812	0.1174
TIFU-KNN [2]	ref	ref	0.0743	0.1089
BERT4Rec-Basket [3]	+7.0%	+5.9%	0.0791	0.1138
MLM-Transformer	+4.5%	+4.9%	0.0776	0.1121
BasketFormer (C-MLM)	+13.8%	+15.7%	0.0856	0.1243
BasketFormer (C-MLM+Temp)	+16.7%	+14.5%	0.0879	0.1231
BasketFormer (Full)	**+20.9%**	**+28.0%**	**0.0921**	**0.1378**

baskets in the batch as negatives. The gate is supervised using the true repeat ratio

$$\rho_u = \frac{|B_{T+1} \cap \mathcal{H}_u|}{|B_{T+1}|}. \tag{5}$$

The total loss is $\mathcal{L} = \mathcal{L}_{\text{basket}} + \lambda\,\mathcal{L}_{\text{gate}}$.

Inference. Customer representations $\tilde{\mathbf{b}}_u$ are precomputed offline. Online scoring reduces to dot-product retrieval, $a_u(v) = \tilde{\mathbf{b}}_u^\top \mathbf{e}_v$, meeting real-time latency constraints ($\leq$25 ms).

3 Experiments

Datasets. We evaluate on two grocery datasets. *Internal*: a proprietary dataset with 71K customers, 22.8K items, 3.8M transactions over 12 months ($\sim$8.5 baskets/customer, 2–3 items/basket, 38.9% repeat rate). *Ta-Feng*: a public chinese grocery dataset with 32.2K customers, 23.8K items, 119K baskets over 4 months. Both use an 80/20 customer split with leave-last-basket-out evaluation [2].

Baselines. *PTop-K*: per-customer frequency ranking. *TIFU-KNN* [2]: temporally decayed item-frequency profiles with KNN. *BERT4Rec-Basket* [3]: BERT4Rec adapted to basket sequences with full-softmax MLM. *MLM-Transformer*: identical architecture to BasketFormer but with full-softmax MLM (no InfoNCE, no temporal encoding, no gate).

Setup. All Transformer models: d=256, L=4 layers, H=8 heads, mask rate 0.4, batch size 64, AdamW (lr 3×10^{-4}), max 50 epochs with early stopping. InfoNCE τ=0.07, gate weight λ=0.2.

Main Results (Table 1). On the Internal dataset, BasketFormer (Full) achieves +28.0% R@10 over TIFU-KNN. On Ta-Feng, it reaches R@10 of 0.1378, a +26.5% relative gain over TIFU-KNN (0.1089), confirming generalization to a public benchmark with different basket characteristics (larger baskets, shorter history). The C-MLM objective alone yields +10.2% over full-softmax MLM on Internal and R@10 of 0.1243 on Ta-Feng, confirming InfoNCE produces more discriminative embeddings across both settings.

Repeat vs. Explore (Table 2a). Frequency-based baselines achieve near-zero explore recall on both datasets. On Internal, BasketFormer (Full) improves explore

Table 2. (a) Repeat vs. Explore Recall@10: Internal (relative to TIFU-KNN) and Ta-Feng (absolute). (b) Component ablation on Internal (relative to MLM-Transformer).

(a) Repeat vs. Explore Recall@10

	Internal			Ta-Feng		
Method	**Ovr.**	**Rep.**	**Exp.**	**Ovr.**	**Rep.**	**Exp.**
PTop-K	—	—	—	0.1174	0.1823	0.0009
TIFU-KNN	ref	ref	ref	0.1089	0.1697	0.0024
BasketFormer (C-MLM)	+15.7%	+5.7%	+15.1×	0.1243	0.1784	0.0371
BasketFormer (Full)	**+28.0%**	**+16.3%**	**+15.9×**	**0.1378**	**0.1962**	**0.0389**

(b) Progressive component ablation (Internal)

Configuration	**ΔR@5**	**ΔR@10**
MLM-Transformer	ref	ref
+ InfoNCE	+8.9%	+10.2%
+ Bit-temporal	+11.7%	+9.1%
+ Repeat-explore	**+15.8%**	**+22.0%**

recall by 15.9× over TIFU-KNN while simultaneously boosting repeat recall by +16.3%. On Ta-Feng, explore recall reaches 0.0389 (vs. 0.0024 for TIFU-KNN), confirming the gate decomposes rather than trades off the two axes.

Ablation (Table 2b). Each component contributes complementary gains on Internal: InfoNCE is the most impactful single change (+10.2% R@10), temporal encoding targets top-rank precision (+11.7% R@5), and the gate provides the largest overall R@10 lift (+22.0% over base).

4 Conclusion

We presented BasketFormer, a Transformer-based NBR model combining contrastive MLM, bit-level temporal encoding, and repeat-explore gating. On both a large-scale proprietary grocery dataset and public Ta-Feng benchmark, it achieves 26–28% relative improvement in Recall@10 over the strongest baseline while providing meaningful explore-item recall, absent in frequency-based methods. Future work includes incorporating item-side features and multi-market evaluation.

References

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