Coupon Personalization: Leveraging Click Data with Deep Learning for Behavioral Insights

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Background and Objective

Background:

- E-commerce:
  - Mobile browsing;
  - Multi-dimensional, large volume click data;
- Customer:
  - Back and forth navigation;
  - Complex psychological process;

Our objectives are:

- Develop a deep learning framework utilizing customer click sequence data to predict customers' behavior.
- Finally give optimal personalized coupon issuance using the predicted result.

Literature Review

Prior research introduced several models to analyze the click data: Including the cascade model [CZTR08] [GJNZ22], the click chain model [GLK+09], the Markov chain choice model (MCCM) [BGG16], and the generalized Markov chain choice model (GMCCM) [LCS22].

However, these approaches mainly concentrate on the coarsest click data (including only page view data and purchasing data), **neglecting the preferences revealed through intricate actions** such as adding to carts, and marking as favorites.

Literature Review

Recent literature has showcased the application of machine learning (ML) and deep learning (DL) based choice models across various domains, including prediction enhancement, coupon personalization, pricing, and assortment optimization [CWTL22] [WLT23] [GT22].

However, these approaches frequently **lack interpretability**, and they use customer demographic data, **posing privacy concerns** as third parties can potentially deduce them through observed price adjustments in the pricing system [CSLW22].

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A toy example

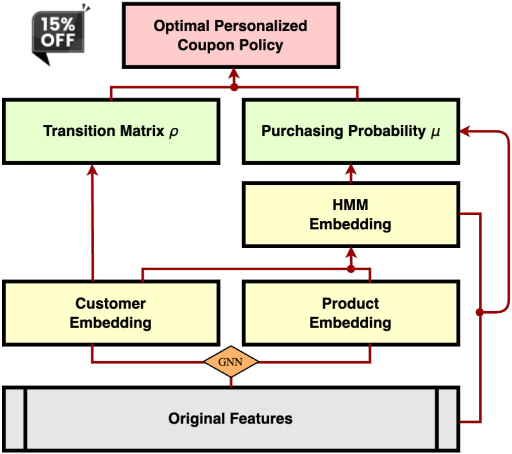
Assume we have two products A and B, viewed by customer Jack.

Time	Product	Behavior
13:34:09	A	pv (page view)
13:34:25	A	fav (mark as favorite)
13:34:33	B	pv
13:34:39	A	pv
13:34:48	A	cart (add to cart)
13:35:01	A	order

Then Jack's **product trajectory** is A $\rightarrow$ B $\rightarrow$ A; the **behavior trajectories** of A and Jack are pv $\rightarrow$ fav $\rightarrow$ 0, and pv $\rightarrow$ cart $\rightarrow$ order; the **behavior trajectory** of B and Jack is pv $\rightarrow$ 0.

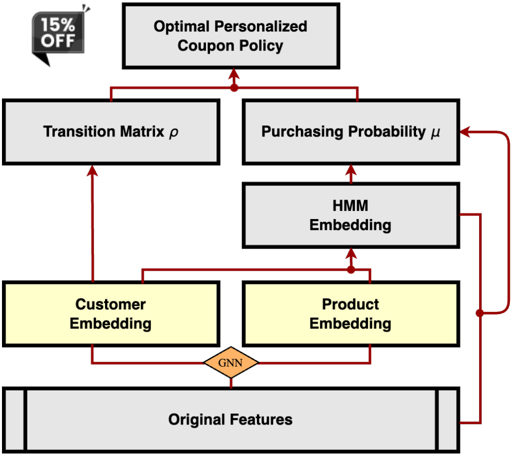
Remark: We use '0' to indicate that the customer has left the current product without making a purchase.

Panorama of the Framework



Configuration of the Proposed Method

GNN for Graph Embedding

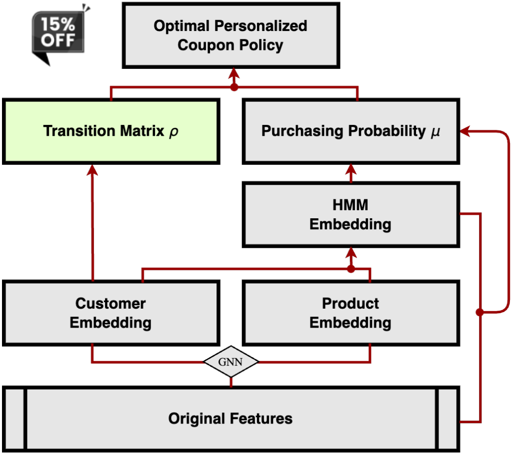


Configuration of the Proposed Method

GNN for Graph Embedding

- We construct a **customer-product bipartite graph**
- We leverage the **Graph Attention Network (GAT)** for a heterogeneous graph, to generate more representative embeddings.
- For example, if Ame and Bob both bought milk, they are considered neighbors and their normalized attention weight can be calculated.

Predicting the Product Transition



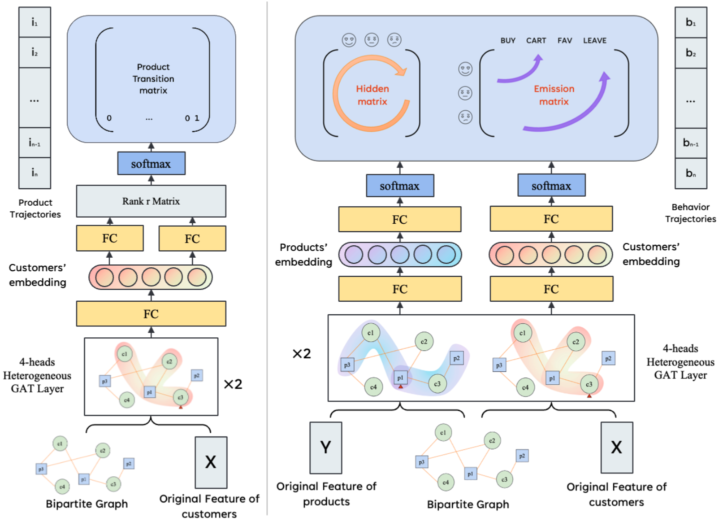
Configuration of the Proposed Method

Predicting the Product Transition

- Considering an assortment of n products. With 0 stands for the absorbing state, $\bar{\mathcal{N}} = \{1, \cdots, n\} \cup \{0\}$, and $\boldsymbol{\rho} \in \mathbb{R}^{(n+1)\times(n+1)}$.
- We optimize the following problem:

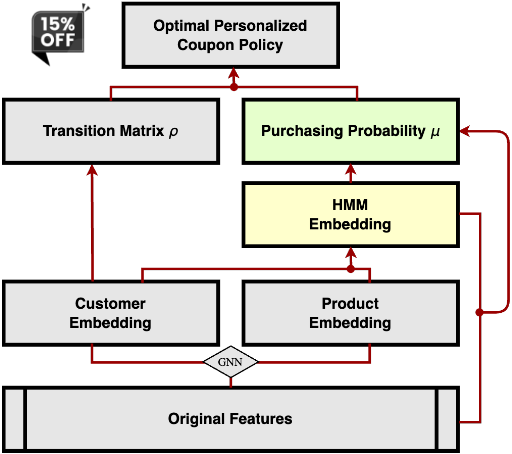
$$
\begin{aligned}
\max_{\boldsymbol{\rho}} \quad & \frac{1}{T}\sum_{t=1}^{T}\frac{1}{n_t}\sum_{w=1}^{n_t-1}\log \rho_{i_w, i_{w+1}} && && (1)\\
s.t. \quad & \sum_{j\in\bar{\mathcal{N}}}\rho_{ij} = 1 && \forall i \in \mathcal{N} && (2)\\
& \rho_{0i} = 0, \rho_{00} = 1 && \forall i \in \mathcal{N} && (3)\\
& \rho_{ij} \geq 0 && \forall i \in \mathcal{N}, \forall j \in \bar{\mathcal{N}} && (4)
\end{aligned}
$$

- $\boldsymbol{\rho}$ is derived by a neural network $\boldsymbol{\Phi} : \mathbb{R}^d \mapsto \mathbb{R}^{(n+1)\times(n+1)}$.



Framework of Customizing Transition Matrix (left)

HMM for Predicting Instant Purchase Rate



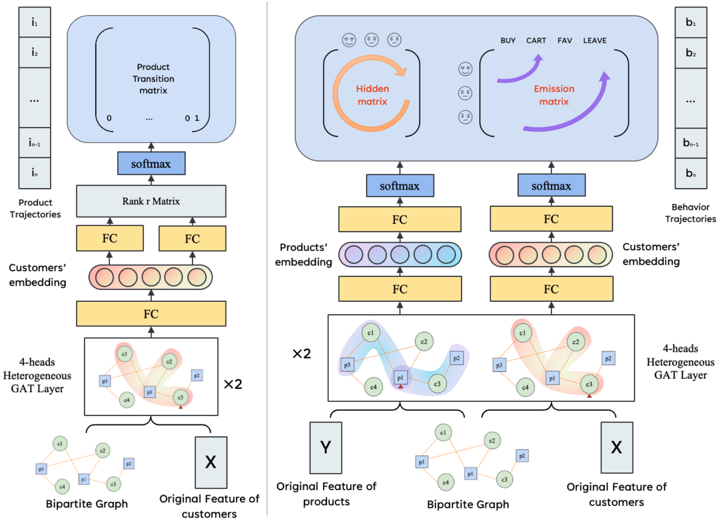
Configuration of the Proposed Method

HMM for Predicting Instant Purchase Rate

- We leverage HMM, which focuses on the behavior trajectories after the page view to capture customers' psychological states.
- $\mathcal{S} = \{\text{W (willing to purchase)}, \text{I (interested)}, \text{F (forgotten)}\}$ are hidden states, and $\mathcal{A} = \{\text{order}, \text{ cart}, \text{ fav}, \text{ leave}\}$ are actions.
- Given the parameters of HMM, the probability of a behavior trajectory $A = \{a_1, \cdots, a_T\}$ is given by:

$$P(A|\hat{H}, \hat{E}) = \sum_{s_1, \cdots, s_T \in \mathcal{S} \times \cdots \times \mathcal{S}} \pi_{s_1} E_{s_1 a_1} H_{s_1 s_2} \cdots E_{s_T a_T}.$$

- We Minimize the negative log-likelihood function $l = -\frac{1}{K} \sum_{k=1}^{K} \log P(A_k | \{\hat{H}, \hat{E}\})$ on training set.

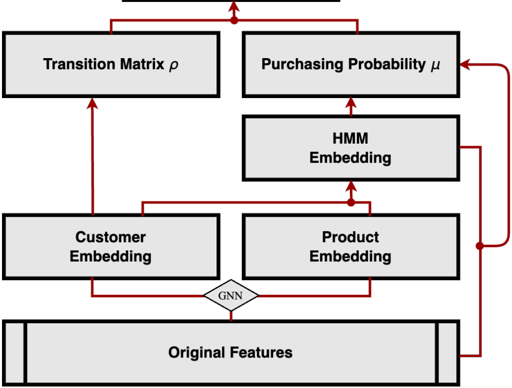


Learning HMM Embeddings (right)

HMM for Predicting Instant Purchase Rate

- Two HMM matrices H and E are flattened into **HMM embeddings** named *hidden vector* and *emission vector*.
- These HMM embeddings are fed into a Multi-Layer Perceptron (MLP) with negative weight in price to output an estimate of the instant purchase rate.
- We use mean squared error (MSE) between the estimated and calculated instant purchase rate as the loss.

Coupon Personalization



Configuration of the Proposed Method

Coupon Personalization

- We consider a finite set of coupons, $\mathcal{C}$, with each element α representing a discount ratio.

- A finite Markov Decision Process (MDP) is used to model coupon issuance. The PMF of the dynamic function is:

Dynamic Function	Probability
$\mathcal{P}(j, \alpha p_i \mid i, \alpha), \quad j \in \mathcal{N}$	0
$\mathcal{P}(0, \alpha p_i \mid i, \alpha)$	$\mu_i(\alpha)$
$\mathcal{P}(j, 0 \mid i, \alpha), \quad j \in \mathcal{N}$	$(1 - \mu_i(\alpha))\rho_{ij}$
$\mathcal{P}(0, 0 \mid i, \alpha)$	$(1 - \mu_i(\alpha))\rho_{i0}$

- We use value iteration to solve the Bellman equation as follows:

$$v_\pi(i) = \sum_{\alpha \in \mathcal{C}} \pi(\alpha|i) \left((\alpha p_i - c)\mu_i(\alpha) + (1 - \mu_i(\alpha)) \sum_{j \in \mathcal{N}} \rho_{ij} v_\pi(j) \right)$$

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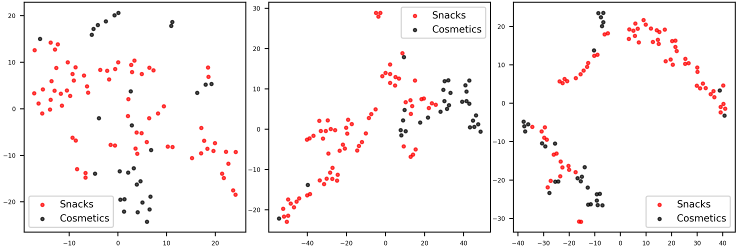
Results and Analysis

- We choose two kinds of products: snacks and cosmetics.



2D-tsne Visualization of Aggregate-level Features (left), Embedding Generated by GNN (middle), and HMM Embeddings (right)

Results and Analysis

Result Comparison between Traditional Method and Proposed Method (with Different Ranks) on Estimating Transition Matrix $\boldsymbol{\rho}$

Metrics	CE	top-1	top-3	top-5	top-7
Training Set					
$\boldsymbol{\rho}_{10}$	2.99	0.32	0.59	0.67	0.70
$\boldsymbol{\rho}_{20}$	2.69	0.31	0.63	0.73	0.77
$\boldsymbol{\rho}_{30}$	2.62	0.32	0.63	0.73	0.78
$\boldsymbol{\rho}_{\text{MCCM}}$	3.01	0.34	0.59	0.65	0.67
Test Set					
$\boldsymbol{\rho}_{10}$	2.99	0.31	0.59	0.67	0.70
$\boldsymbol{\rho}_{20}$	2.78	0.30	**0.61**	0.70	0.75
$\boldsymbol{\rho}_{30}$	**2.76**	0.29	0.61	**0.71**	**0.75**
$\boldsymbol{\rho}_{\text{MCCM}}$	3.05	**0.33**	0.60	0.68	0.71

Results and Analysis

Hidden Transition Matrix on Average. Snacks (left) and Cosmetics (right)

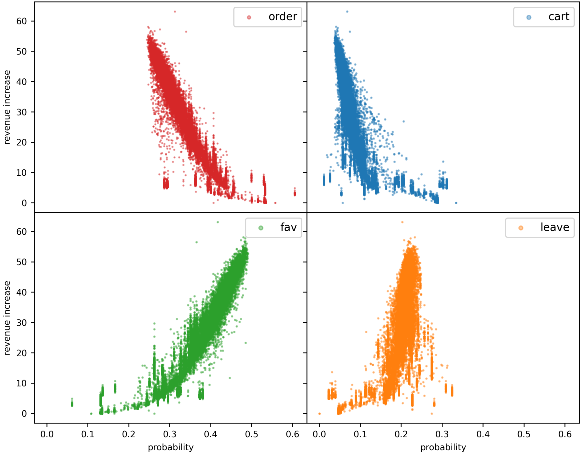
	W	I	F
W	0.52	0.15	0.33
I	0.19	0.37	0.44
F	0.07	0.71	0.22

	W	I	F
W	0.63	0.17	0.20
I	0.27	0.29	0.44
F	0.11	0.50	0.39

Remark: W (willing to purchase), I (interested), F (forgotten)

Our trained HMM parameters align with our intuitive understanding: cosmetics have stronger consumer loyalty than snacks.

Results and Analysis



Revenue Increase against Parameters in HMM

Results and Analysis

- We assigned personalized coupons for each customer-product pair, setting the cost at 60% of the average price observed over seven days.
- The resulting revenue enhancement varied significantly, achieving a maximum increase of 63.15 and a minimum of zero, with an average uplift of 24.49 per customer.
- The percentage increase of revenue is about 2.23% per customer on average. Given the large number of customers (22,530) and the 60% cost, this represents a significant rise.

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Conclusion

- We introduce a framework for coupon personalization.
- The results demonstrate that our model effectively leverages the value of multidimensional click data and has interpretability to customers' behavior.

Meanwhile, our research has some limitations:

- We assume the transition matrix $\boldsymbol{\rho}$ does not depend on coupon issuance;
- And we overlook products outside the selected assortment.

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