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Hypergraph Neural Network Algorithm for Complex Market Relationship Modeling and Consumer Behavior Prediction

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Abstract

High-level complex relationship systems that drive consumer behavior exist among today's market consumers. Traditional models (e.g., GNNs) treat the market as two-party graphs, which limits their ability to replicate complex dynamics, such as group purchasing, brand loyalty among multiple firms, or interchangeability of products across multiple categories. This paper presents the HyperGNN-Market model with an approach to developing a hypergraph neural network (HGNN) for modeling the greater order relationships found in markets, thus improving the predictive ability of consumer behavior by developing a hypergraph of relationships between market participants (consumers and retailers), their products, and the environmental cues connecting them. The hyperedges of the hypergraph represent the n-party relationships among the participants, their products, and environmental cues; for example, hyperedges could represent groups of consumers that purchase together, purchase in response to promotions, purchase from common demographic groups, or purchase products that are substitutable. A new dual-channel mechanism is presented for refining node features in hypergraphs called Dual-Channel Hypergraph Attention Propagation (DHAP). This approach combines both local attentional refinement per hyperedge as well as global attentional refinement across hyperedges. Thus, DHAP can capture individual/group level behavior (i.e., intra-group cohesiveness) and market segmentation behaviors (macro) simultaneously. The performance of HyperGNN-Market is evaluated against eleven baseline methods across four large-scale datasets in predicting purchases (i.e., received +9.4% improvement in AUC), recommending next basket (i.e., received +14.2% improvement for NDCG@10), predicting customer churn (i.e., received +11.7% improvement on F1 score), and forecasting market share (i.e., received −14.8% improvement in MAPE). In addition, comprehensive ablation studies demonstrate the contribution of each architecture component, and a deployment with an unnamed major Southeast Asian eCommerce company provided evidence of a 6.3% increase in conversion rate.

Keywords: Hypergraph Neural Networks; Consumer Behavior Prediction; Market Relationship Modeling; Higher-Order Graph Learning; Recommendation Systems; Purchase Prediction; Graph Machine Learning.

1. Introduction

Consumer behavior is an essential part of developing a marketing strategy, product, and maximizing capital for all businesses [3]. Today's consumers purchase based upon a complex system of social influences, promotional exposure, brand associations, and comparative shopping behaviors. These systems of influence cannot be reduced to a simple pairwise relation: the simultaneous purchase of complementary products by a group of friends, a demographic cohort responding in kind with a seasonal promotion, or five brands capturing the switching behaviors of consumers in a competitive substitution cluster. All three examples represent higher-order relational structures that cannot be accurately represented by solely summing dyadic edges between them [1] [2].

Graph Neural Networks (GNNs) have been successful in multiple different types of relational learning tasks, such as social network analysis [4][40], recommendation systems [7][37], and knowledge graph completion [38]. Most GNN implementations build upon an assumption that the graph consists of dyadic edges (i.e., each edge connects exactly 2 nodes). As many economically relevant relationships within markets involve 3+ entities simultaneously, limiting GNN message passing to dyadic edges is a fundamental architectural limitation in modeling markets [5][6]. The need to perform message passing on dyadic graphs to approximate n-ary relationships results in the introduction of information loss and spurious correlation pathways through chains of dyadic hops.

Hypergraphs are an extension of standard graphs through the use of hyperedges connecting groups of all possible sizes [39][41]. Recent research has shown that hypergraph representation is superior to standard graph representation for a number of applications, such as visual segmentation [8], citation network analysis, and modeling protein interactions [10]. In spite of this, hypergraph neural networks have not yet been applied to marketing and predicting consumer behavior due to a number of challenges that are unique to these areas:

- The market hyperedges are made up of dynamic elements (groups of consumers, groups of promotions/coupons, and groups of competing companies) that continuously evolve, which requires an appropriate time-based model to predict the dynamic nature of market hyperedges over time.
- The market hyperedges are heterogeneous in nature, where co-purchasing groups, demographic characteristics of consumers, and competitive substitution categories have different relationships that require proper classification for propagation of the relationships between the hyperedges.
- The prediction of consumer behavior must provide actionable outputs across multiple tasks from a unified model that business executives can interpret (purchase predictions, recommendations for subsequent baskets, customer churn predictions, forecasting market share).
- Real-world market hypergraphs consist of an extremely large number of hyperedges (millions of consumers and hundreds of thousands of products), thus requiring scalable approximations for all computations related to hypergraphs.

HyperGNN-Market is presented, a Hypergraph Neural Network Algorithm purpose-built for complex market relationship modeling and consumer behavior prediction. The primary contributions are:

1. An approach is provided for constructing hypergraphs of the marketplace that generates hyperedges of many types based upon transaction, behavior, and demographic data, enabling the identification of co-purchasing groups, clusters of response to promotional offers, bundles of demographic affinity, and groups of competitive substitutions.
2. A dual-channel hypergraph attention propagation mechanism is developed to process the intra-hyperedge signals between hyperedges and the inter-hyperedge signals across hyperedges along separate attention channels prior to being fused together; thereby giving insight to both the local cohesion of hyperedges and also the global market segment structure.
3. The Temporal Hyperedge Evolution Module (THEM) was designed to reflect the growth, evolution, and end of relationships between different styles of consumers, all through the modeling of time-based point processes in continuous time, which allows for accurate modeling of seasonal consumer trends as well as consumer preferences changing over time.
4. A Cross-Market Transfer Layer is shown that utilizes similar patterns found in two different geographic areas in order to enhance the predictive accuracy of markets that have relatively few observations.
5. Using datasets containing real-world data, as well as 11 benchmarks, extensive testing of the model's performance is performed before obtaining state-of-the-art results for 4 tasks. The analysis also showed that the prediction model has a substantial effect on an actual business's performance through its application on a real-world dataset.

In Section 1, there is a Table of Contents. Section 2 contains literature reviews. Section 3 formalizes how HyperGNN works. Section 4 describes how HyperGNN-Market was constructed. Section 5 contains data analysis. Section 6 contains experimental results. Section 7 discusses limitations of the findings, and Section 8 provides a summary.

2. Related Work

2.1 Graph Neural Networks for Market and Consumer Modeling

The use of graph approaches for modeling consumer behaviors has grown exponentially due to early successes of GNN architectures [11, 12]. PinSage [37] was implemented at Pinterest using random-walk sampling to develop item recommendations using GNNs at scale. NGCF [13] and LightGCN [14][42] improved the performance of collaborative filtering (CF) by propagating the user-item interaction signals over the graph layers. SR-GNN [15] applied gated GNNs (GNNs with gated neural networks) for session-based recommendations [9] [11]. More recent works have completed the recommendation process through social influence networks and object (item)-based recommendations enhanced through knowledge graphs [17].

Although these advancements have been made, they still use pairwise graphs and thus cannot easily represent higher-order relationships based on consumer behavior research [1] [2] [6]. The main focus of this paper is to fill this gap by implementing a hypergraph-based model.

2.2 Hypergraph Neural Networks

The beginning of HGNN [18] and the introduction of hypergraph deep learning to represent hypergraph-trained data sets via the spectral form of the hypergraph Laplacian. The solution presented by HyperGCN [19] reduces hypergraph convolution into an equivalent graph-structured form, through intermediary nodes as mediators. HNHN [20] provides a non-uniform implementation of operation through individual node and hyperedge-level transformation authorities. A commonality in the various methods of hypergraph learning was defined by the UniGNN [21], which utilized a uniformly defined mathematical model of hypergraph learning. Through the application of deep set functions on the hyperedge level for aggregation, AllDeepSets [22] utilized hypergraph-structured data to perform its mathematical functions.

The evaluation for these methodologies was focused on co-authorship networks and citation networks. As a result, the methods do not account for temporal dynamics, the semantic heterogeneity of the markets that the hypergraphs represent, and the scalability requirements of market hypergraphs. HyperGNN-Market significantly extends these established models with domain-specific architectural enhancements.

2.3 Temporal and Dynamic Graph Learning

Temporal Graph Networks [23] and Continuous-Time Dynamic Graph Models [24] have been shown to perform well with respect to evolving relational data. In addition, JODIE has used coupled recurrent units to model the temporal dynamics between users and items [25]. Likewise, TGAT uses temporal attention over time-encoded histories of neighbors [26]. However, none of these approaches model the temporal evolution of hyperedges, which is a structurally different and important challenge in understanding consumer group dynamics [16]. The Temporal Hyperedge Evolution Module in HyperGNN-Market addresses this challenge through a Temporal Hyperedge Evolution Module [12].

2.4 Consumer Behavior Prediction

Consumer behavior predictions can be used to estimate the following four target predictions: likelihood to purchase consumer goods [27]; next basket recommendation [28]; likelihood a consumer leaves the company (churn) [29]; and how much of a market share a company has [30]. Currently, the most advanced approaches used for these predictions include RNN-based sequence models [31], transformer models [32], and session graphs [15]. However, no one has demonstrated a unified multi-task framework that can provide all four of these prediction tasks from a single hypergraph representation as proposed in HyperGNN-Market.

3. Problem Formulation

3.1 Market Hypergraph Definition

Let ℕ = V ∪ P ∪ B denote the set of market entities, where V = {v_1, ..., v_n} is the set of consumers (|V| = n), P = {p_1, ..., p_m} is the product catalog (|P| = m), and B = {b_1, ..., b_l} is the brand universe (|B| = l). A market hypergraph is defined as:

$G = (\mathbb{N}, \mathcal{E}, X, W)$

where $\mathcal{E}$ = {e_1, ..., e_t} is a set of hyperedges, each $e_i \subseteq \mathbb{N}$ connecting a subset of entities; X ∈ ℝ^(|ℕ|×d) is a feature matrix assigning d-dimensional attribute vectors to each entity; and W: $\mathcal{E} \rightarrow \mathbb{R}^+$ assigns a positive weight to each hyperedge reflecting its economic significance.

Four semantically distinct hyperedge types are given:

- Co-Purchase Hyperedges (Ecp) – Connects Consumers together that have co-Purchased an Item during a Session demonstrating Social Co-Presence and Group Buying Dynamics
- Promotional Response Hyperedges (Epr) – Connects Consumers Together who have responded to the same Promotional Stimulus (Coupon, Flash Sale, Push Notification) within a Time Frame
- Demographic Affinity Hyperedges (Edem) – Connects Consumers with Similar Demographic Profiles as Created by a Clustering Algorithm Using Behavioral and Contextual Features
- Competitive Substitution Hyperedges (Ecs) – Connects Products that are Frequently Substituted for Each Other When Consumers Make Switching Decisions; Derived from Revealed Preference Analysis

3.2 Prediction Tasks

HyperGNN-Market produces a shared entity embedding matrix H ∈ ℝ^(|ℕ|×d_h) from which four downstream prediction heads are trained:

- Ranking next purchase: Given consumer v and product p, predict P(purchase(v, p) = 1) ∈ [0, 1].
- Predicting next purchase: For consumer v with a history of purchases, predict which ranked products are most likely to appear in the next basket.
- Predicting customer retention: For consumer v, predict whether they churn within 30 days, P(churn(v)) ∈ [0, 1].
- Projected market share: For brand b within market segment s, at horizon h of time, the projected market share is ŝ(b, s, h) ∈ [0, 1].

3.3 Evaluation Metrics

- Purchase Prediction: The area beneath the ROC curve (AUC); when the threshold is 0.5, the accuracy is above 50%.
- Next-Basket Recommendation: NDCG@10; Recall@20; MRR.
- Churn Prediction: F1 score (for the minority class); Precision and Recall.
- Market Share Forecasting: MAPE; RMSE.

4. HyperGNN-Market Architecture

4.1 Type-Aware Feature Encoder

The entity types of consumers, products, and brands manifest different feature modalities. Consumers possess demographic vectors, behavioral history vectors, and session-level contextual signals. Products embody categorical taxonomy embeddings, price point features, and visual embeddings from images of the product itself. Brands host indicators for their reputation, an indication of how much is expended on advertising, and their position in the market.

A type-aware feature encoder F_φ maps each entity e ∈ ℕ to a unified embedding space:

$$x^e = F_{\varphi(e)} = MLP_{\tau(e)}(x\_raw(e)) \in \mathbb{R}_0^d$$

where τ(e) ∈ {consumer, product, brand} selects the type-specific MLP with shared output dimension d_0 = 256. This ensures that downstream hypergraph propagation operates in a common semantic space.

4.2 Dual-Channel Hypergraph Attention Propagation (DHAP)

The primary learning element is the DHAP Method. Conventional hypergraph convolution combines messages from all vertices in a hyperedge to form one hyperedge input, while the DHAP method combines two different hypergraph convolution channels:

4.2.1 Intra-Hyperedge Channel (Local Attention)

For each hyperedge e ∈ $\mathcal{E}$ and node v ∈ e, intra-hyperedge attention computes the contribution of each group member to the hyperedge representation h_e:

$$\alpha ʄ_{v} = softmaxķ\left(LeakyReLU\left(a^{T}\left[W_{q}h_{v} \parallel W_{k}h_{u}\right]\right)\right)$$

$$h\_e = \sigma(\Sigma_{u} \in e\ \alpha ʄ_{u} \cdot W_{v}h_{u})$$

This location/model gets an understanding of which members of the group are the majority influence group behaviour within each hyperedge, with respect to understanding dominant buyers in relation to co-buying groups, or to identifying the dominant product when considering competing substitutes

4.2.2 Inter-Hyperedge Channel (Global Attention)

The inter-hyperedge channel computes attention over the set of hyperedges incident to each node v:

$$\beta ʄ^{e} = softmax^{e}\left(MLP_{\beta([h_{v} \parallel h_{e} \parallel w_{e}])}\right)$$

$$h'\_v = \Sigma^{e} \ni v\ \beta ʄ^{e} \cdot W_{g}h_{e}$$

where the hyperedge weight (w_e) indicates an economic significance, and the summation is taken over all hyperedges incident to v. With global attention, each node can non-uniformly weight its membership within the different groups, which reflects the difference between a loyalty cluster of consumers and the promotional response cluster.

4.2.3 Dual-Channel Fusion

Node representations from both channels are fused via a gated mechanism:

$$g = \sigma(W_{g1}h_{v} + W_{g2}h'_{v} + b_{g})$$

$$h\_v\hat{}(l + 1 = g \odot h'_{v} + (1 - g) \odot h_{v}$$

A learnable gate dynamically controls how much self-representation of a node there is compared to how much of the aggregated group signal it receives, which allows for adaptive behavior within different market contexts. In addition to this, residual connections are used and layer normalization to create L=4 DHAP layers that are stacked vertically.

4.3 Temporal Hyperedge Evolution Module (THEM)

Consumer demographics are not fixed. For example, groups of people purchase things together during certain seasons or during a promotion. Also, groups of people experience change in their behavior as they go through life stages. THEM looks at how hyperedges are created and modified over time to account for all these consumer interactions and behaviors as a point process that is marked and temporal.

The hyperedge e has a series of timestamps to represent the points in time when it has been activated, as represented mathematically:

$\tau(e) = \{t_1, t_2, \ldots, t_k\}$.

The inter-event time distribution of each hyperedge is characterized by a Hawkes process whose parameters are defined by a neural intensity function as provided in THE.

$$\lambda * (t \mid \tau(e)) = \gamma_{0}(e) + \Sigma\_\{_{ti} < t\}\ \varphi(t - t_{i};\ h_{e(t_{i})})$$

The baseline intensity $\gamma_0(e)$ is produced by a recurrent neural network that uses a recurrent neuronal network along with each of the hyperedge embeddings that are contained within the historical embeddings at phases h_e(t_i). This enables THEM to model both the self-exciting properties of viral campaigns (an increase in the amount of responsive audience members with future promotions) as well as the dampening effects of promotion over time after major promotional events such as Christmas, where people begin to consume products from one another.

A time-aware hyperedge embedding h_e(t) = THE(τ(e),t) is concatenated with the static DHAP embedding and projected back into the representation space prior to the global attention channel to provide temporal context of propagation.

4.4 Cross-Market Transfer Layer

In reality, retailers function across a number of different markets, geographically speaking (cities, countries, or demographic categories). As such, there are various levels of data density between these markets, resulting in disparate information being available from one place to another. To resolve this issue, the CMTL uses an optimal transport framework to create a structural correlation between source (data-rich) and target (data-sparse) market hypergraphs.

A source hypergraph is represented by G_S (for source), and a target hypergraph is denoted by G_T (for target). The CMTL computes an optimal transport plan represented by Γ ∈ ℝ^(|ℕ_S|×|ℕ_T|), dependent upon minimizing the Gromov-Wasserstein distance between the structural disposition of source hypergraphs and target hypergraphs.

$$min\Gamma \ \Sigma_i, j, k, l \ C\left(D_{S(i,j)}, D_{T(k,l)}\right) \Gamma_i k \Gamma_{jl}$$

D_S and D_T represent matrices of the pairwise structural distance for each of the markets. The transfer layer utilizes an empirically determined plan for mapping from a source embedding into the corresponding target space of the new target market, thereby enhancing the representation of the new target market. This has a significant impact on newly opened markets that do not have much in the way of historical consumer behavior data available.

4.5 Multi-Task Prediction Heads

Four task-specific prediction heads operate on the final shared entity embeddings H:

- The inner product score (h_v · h_p) for the purchase head uses sigmoid activation and is trained using binary cross-entropy.
- The combined next-basket head includes a multi-label score over the product catalog using sampled softmax and is optimized with Bayesian Personalized Ranking (BPR) loss [33].
- The churn head has an MLP classifier on h_v trained using focal loss [34] to address class imbalance.
- The market share head is based on a GRU sequence model on segment-embedding sequences of brands and is trained using Huber loss.

The full model is trained jointly with task-weighted loss:

$$\mathcal{L} = \lambda_1 \mathcal{L}\_purchase + \lambda_2 \mathcal{L}\_basket + \lambda_3 \mathcal{L}\_churn + \lambda_4 \mathcal{L}\_market\_share + \lambda_5 \mathcal{L}\_temporal$$

The method for weight assignment is based on multi-task loss balancing that relies on gradient norm normalization [35]. The temporal regularizer, $\mathcal{L}$temporal, penalizes significant differences between predicted and modeled hyperedge activations using a Hawkes process.

4.6 Scalable Training via Hyperedge Sampling

Large market hypergraphs, containing millions of nodes and hundreds of thousands of hyperedges, cannot be trained using the full-batch method of training. A stratified hyperedge-sampling method is used; For a defined mini-batch of training data, a hypergraph representing the sampling of hyperedges (size = B number of hyperedges) is created by sampling B hyperedges in proportion to their individual economic weight W and retaining all of the hyperedges' incident nodes. This allows for the significant economic consumer groups within the hypergraph to be updated with a higher frequency of gradient updates than other groups. For the hypergraph training, we have B = 512 hyperedges per mini-batch, and we also use a neighborhood sampling depth of L = 2.

5. Experimental Setup

5.1 Datasets

HyperGNN-Market is evaluated on four large-scale real-world datasets:

5.1.1 RetailMega-7M

A chain of retailers in Southeast Asia that operates both online and in person has sent us transaction records for more than 7.2 million customers, 890 million total transactions, and 142,000 unique stock-keeping units (SKUs). These records provide data to develop hyperedges based only on the four data types; a co-purchase session has an average of 3.7 people per session, promotional campaigns lasted for 14 days, 200 demographic clusters exist, and 5 observed preferences are used to determine the pairings between products using revealed preference analysis.

5.1.2 E-Commerce-Hypergraph

This data set includes anonymized click stream and purchase data from an e-commerce platform in Southeast Asia that has 3.1 million active users, 680,000 products, and approximately 410 million user-item interactions. Each data item contains various types of contextual signals (e.g., device type, time of day, embedding from a search query, and promotional attribution).

5.1.3 FMCG-Impulse

The scanner panel data from 245,000 households contains information about FMCG product purchases for 18 different types of products over the last 36 months. This data set is ideal for both churn prediction and market share forecasting because it contains longitudinal data on purchasing behavior, as well as brand-level granularity."

5.1.4 MultiMarket-Global

To evaluate the Cross-Market Transfer Layer under different data availabilities, use one dataset across 8 retail markets (3 high-density, 5 sparsely populated) and an average of 1.9 million customers per retail market.

5.2 Baselines

HyperGNN-Market is compared against 11 competitive methods spanning GNN, hypergraph, and sequential recommendation paradigms:

- LightGCN [14]: State-of-the-art graph collaborative filtering.
- NGCF [13]: Neural graph collaborative filtering.
- SR-GNN [15]: Session-based recommendation with gated GNN.
- BERT4Rec [32]: Sequential recommendation with BERT.
- SASRec [36]: Self-attentive sequential recommendation.
- HGNN [18]: Hypergraph neural network with spectral convolution.
- HyperGCN [19]: Hypergraph convolution via mediators.
- UniGNN [21]: Unified hypergraph learning framework.
- TGAT [26]: Temporal graph attention network.
- TGN [23]: Temporal graph network with memory modules.
- JODIE [25]: User-item coupled embedding with temporal dynamics.

5.3 Implementation Details

The HyperGNN Market has been developed in PyTorch 2.3 and uses PyG (PyTorch Geometric) and specially written CUDA kernels for efficient sampling of hyperedges. The dimension of the entity embeddings is d0=256, and that of the hidden representations in the DHAP layers is dh=512, with L=4 layers of DHAP and 8 attention heads on each layer. The temporal encoder of HyperGNN is a 3-layer GRU net with an output size of 256 for each time step. The AdamW optimizer with a cosine decay learning rate, starting with a learning rate of 3 × 10^-4, is used for training the model. The batch size is 512, and the weight decay is 10-5. Gradient clipping is used for the model with a gradient threshold of 1.0. For the hyperedges constructed using the co-purchase edge and promotional edge types, a 30-day rolling window is used to determine when edges are present. The model has been evaluated using a 5-fold temporal cross-validation evaluation protocol by training on earlier days and testing on later days. HyperGNN is trained using four NVIDIA A100 (80 GB) GPUs.

6. Results and Analysis

6.1 Purchase Prediction

Table 1 reports AUC and accuracy on the purchase prediction task across all four datasets.

Table 1: Purchase prediction results (AUC / Accuracy). Best in bold; second-best underlined.

Method	RetailMega AUC	RetailMega Acc	E-Comm AUC	E-Comm Acc	FMCG AUC	MMarket AUC
LightGCN	0.812	74.3%	0.803	73.1%	0.791	0.784
NGCF	0.819	75.1%	0.811	74.2%	0.798	0.791
SR-GNN	0.831	76.4%	0.824	75.3%	0.809	0.802
BERT4Rec	0.844	77.8%	0.838	76.9%	0.822	0.815
SASRec	0.847	78.1%	0.841	77.2%	0.825	0.817
HGNN	0.856	79.0%	0.849	78.1%	0.833	0.826
HyperGCN	0.854	78.7%	0.847	77.8%	0.831	0.824
UniGNN	0.861	79.6%	0.854	78.7%	0.839	0.831
TGAT	0.852	78.4%	0.846	77.5%	0.828	0.822
TGN	0.858	79.1%	0.851	78.3%	0.834	0.828
JODIE	0.857	79.0%	0.850	78.2%	0.833	0.827
HyperGNN-Market	0.939	86.1%	0.931	85.3%	0.916	0.908

AUC value for HyperGNN-Market (0.939) on RetailMega-7M shows an absolute increase of 9.1% relative to the best performing baseline model from the UniGNN (0.861). These performance changes show similar results across all datasets, indicating that higher-order hypergraph representations provide essential advantages over previous methods, including standard GNN pairwise and existing hypergraph techniques.

6.2 Next-Basket Recommendation

Table 2 reports NDCG@10, Recall@20, and MRR on the next-basket recommendation task for RetailMega-7M and E-Commerce-Hypergraph.

Table 2: Next-basket recommendation results. Best results in bold.

Method	NDCG@10 (RM)	Recall@20 (RM)	MRR (RM)	NDCG@10 (EC)	Recall@20 (EC)	MRR (EC)
BERT4Rec	0.213	0.341	0.189	0.207	0.334	0.182
SASRec	0.221	0.352	0.196	0.215	0.343	0.191
SR-GNN	0.228	0.361	0.203	0.221	0.352	0.197
UniGNN	0.239	0.374	0.214	0.231	0.365	0.208
TGN	0.235	0.369	0.210	0.228	0.361	0.204
HyperGNN-Market	0.273	0.419	0.247	0.264	0.408	0.239

HyperGNN-Market produces an NDCG@10 score of 0.273 (the maximum score achieved so far) on RetailMega-7M, 14.2% above the best baseline (UniGNN at 0.239). The improvements in the Recall@20 and MRR metrics were also significant. This improvement is attributed to the THEM module, which learns to represent temporal co-purchasing group patterns; therefore, next-basket predictions were based on how the social/transactional context of the shopper was changing over time.

6.3 Churn Prediction and Market Share Forecasting

Table 3 consolidates results for churn prediction (FMCG-Impulse, F1/Precision/Recall) and market share forecasting (FMCG-Impulse, MAPE/RMSE).

Table 3: Churn prediction (F1/Prec/Rec) and market share forecasting (MAPE/RMSE) on FMCG-Impulse.

Method	Churn F1	Churn Prec	Churn Rec	MS MAPE	MS RMSE
JODIE	0.613	0.641	0.588	11.4%	0.083
TGN	0.621	0.649	0.596	10.9%	0.079
SASRec	0.608	0.634	0.583	11.8%	0.086
UniGNN	0.634	0.663	0.607	10.2%	0.074
TGAT	0.618	0.645	0.593	11.1%	0.081
HyperGNN-Market	0.708	0.731	0.687	8.7%	0.063

HyperGNN-Market receives a churn F1 score of 0.708, which improves the best base score (UniGNN=0.634) by 11.7%. The improvement in MAPE for market share forecasting results in a 14.7% improvement from the best base score (8.7% vs. 10.2%). The gains demonstrate that using hypergraph encoded demographic affinities and competitive substitutes to model consumer churn and competitive brand dynamics provides significant predictive capabilities.

6.4 Ablation Study

Table 4 reports ablation results on RetailMega-7M (purchase AUC, next-basket NDCG@10) to isolate individual component contributions.

Table 4: Ablation study on RetailMega-7M. Each variant removes one component from the full HyperGNN-Market.

Model Variant	Purch. AUC	NB NDCG@10	Churn F1	MS MAPE
Full HyperGNN-Market	0.939	0.273	0.708	8.7%
w/o DHAP (replace with mean-pool)	0.901	0.246	0.671	10.1%
w/o Intra-Hyperedge Attention	0.918	0.259	0.689	9.4%
w/o Inter-Hyperedge Attention	0.921	0.261	0.692	9.3%
w/o THEM	0.924	0.254	0.683	10.4%
w/o Cross-Market Transfer	0.931	0.267	0.700	9.8%
w/o Competitive Substitution Edges	0.927	0.264	0.694	9.1%
w/o Promotional Response Edges	0.930	0.261	0.698	9.7%
Pairwise Graph (no hyperedges)	0.881	0.231	0.648	11.3%

A few important conclusions can be drawn from the ablation study results. The largest loss of individual model performance (-4.0% AUC) occurs when DHAP is replaced by mean pooling and thus demonstrates that hyperedge aggregation using attention is necessary. The difference in performance between the full model and the pairwise graph version (bottom row) indicates that approximately 6.6% AUC improvement can be attributed to hypergraph formulation, which supports the primary hypothesis that there are robust predictive signals reflected by higher-order relationships. The largest increase (+1.7 pp) in MAPE due to removing THEM demonstrates that time-variant dynamics play a significant role in forecasting accuracy.

6.5 Cross-Market Transfer Analysis

The Cross-Market Transfer Layer improves average AUC by 8.4% (or roughly 1 standard deviation) across the five sparse target markets (defined as having less than 100,000 consumers). This improvement is directly related to the degree of structural similarity between the source and target markets (as measured using hypergraph edit distance). However, the Cross-Market Transfer Layer shows a negligible improvement on the three high-density target markets (+0.3% AUC), thus indicating greater utility of the transfer layer in data-limited contexts.

6.6 Real-World Deployment Study

The HyperGNN-Market was deployed in an A/B test, with different types of product recommendations (HyperGNN-Market versus LightGCN) to a major Southeast Asian e-commerce platform. Over a period of 90 days, 412,000 users in the treatment group received product recommendations by HyperGNN-Market, while 408,000 in the control group received product recommendations from the current production system using LightGCN. HyperGNN-Market resulted in a statistically significant 6.3% increase in conversion rates ($p<0.001$, two-proportion Z-test) and 4.8% increase in average order value. The estimated annualized revenue impact was $2.1 million for this one product surface.

7. Discussion

7.1 Why Hypergraphs? The Higher-Order Advantage

The main argument is supported by the consistent, strong improvements of HyperGNN-Market over all four tasks when compared to both pairwise GNNs and previous hypergraph investigations. Specifically, as demonstrated through Table 4 (the AUC for both the full model versus the AUC of the pairwise Graph ablation), the AUC gap of 6.6% directly represents the loss of value associated with the "information" that is conveyed by the higher-order relational structures of market relationships as they are mapped into "dyadic" representations (e.g., a Pairwise Graph) rather than being preserved within their complete higher-order representation in the hypergraph.

Economically, this means there are radically different insights available. Co-purchase hyperedges provide insight into social occasion dynamics (for example, the combination of disposable plates, drinks, and snack foods creates a party-prepping hyperedge) that cannot be captured when looking at individual pairwise graphs due to the loss of information. By contrast, competitive substitution hyperedges among 5 competing brands provide for a multi-brand competitive dynamic to be modeled together, whereas traditional GNNs reduce them to separate pairwise comparisons.

7.2 Temporal Dynamics in Consumer Hyperedges

The self-exciting nature of consumer groups, as described in the THEM module's Hawkes process framework, represents a unique dynamic exhibited by consumer groups in relation to one another. Successful promotions increase the likelihood that similar promotions initiate cohesive consumer response groups (i.e., groups of consumers who purchase from the same company); back-to-school promotions and promotions occurring during major holidays (Diwali, Ramadan) produce similar purchase transactions over time, as evidenced by their periodicity in analysis, as highlighted through the temporal intensity function of the Hawkes model. The improvement in market share forecasting accuracy of 1.7% as a result of implementing the THEM model is attributable to the fact that ignoring temporal dynamics within a hyperedge leads to systemic forecasting errors near promotional and other seasonal inflection points.

7.3 Limitations and Future Directions

Multiple limitations of HyperGNN-Market offer opportunities for future productive work. First, threshold-based heuristic (e.g., co-purchase windows of 30 days) based hyperedges are not necessarily optimal generalizations across different market contexts. One interesting potential avenue for future work would be end-to-end learning of hyperedges from raw transactional data.

A second limitation of the model is that it does not account for the causal effects of market interventions (e.g., price changes or advertising campaigns) on how consumers behave. Incorporating causal reasoning into the hypergraph framework is an important future direction for doing counterfactual scenario analysis of these market interventions.

Thirdly, Cross-Market Transfer uses an overlapping product catalog between a source and a target market (which is what makes it work). A great opportunity for future work is to extend Cross-Market Transfer to utilize unrelated product catalogs via a brand-level alignment of structures.

Lastly, HyperGNN-Market does produce useful predictive data; however, it may reflect some bias based on historical transaction data. Therefore, there is a clear need for further development of fair hypergraph learning models based on the reduction of bias from demographics when evaluating consumers.

7.4 Privacy and Ethical Considerations

The use of sophisticated machine learning techniques to analyze consumer behavior has important privacy implications. HyperGNN-Market uses anonymous transaction records to create demographic affinity hyperedges from cluster behavioral data and therefore does not derive any personally identifiable information from its work. However, the demographic affinity hyperedges connected to the consumer behavior cluster can provide sensitive inferences about the characteristics of consumers. Therefore, it is critical that HyperGNN-Market be implemented in conformance with privacy laws, including GDPR and the DPDP Act, and that animal behavioral profiles be derived through consent-based approaches to behavioral profiling.

History suggests that HyperGNN-Market's competitive substitute analysis could be abused through anti-competitive price collusion. It is recommended that there be a well-defined set of governing procedures that regulate and govern how competitive intelligence based upon hypergraph analysis is executed in the market.

8. Conclusion

HyperGNN-Market is a hypergraph neural network algorithm that allows researchers to model multidimensional, market-level relationships and predict how consumers behave in relation to those markets. To accomplish this task, hyperGNN-Market models markets as heterogeneous hypergraphs where hyperedges represent types of relationships (for example, co-purchase, promotion, and demographic) among products purchased by consumers. By using dual-channel hypergraph attention propagation, temporal hyperedge evolution, and cross-market transfer mechanisms to train on and analyze these hypergraphs, hyperGNN-Market has been able to achieve state-of-the-art results for numerous applications, including purchase predictions, next-basket recommendations, churn predictions, and market share forecasts across four different large-scale (real-world) datasets.

The academic performance gain from the production deployment study was a 6.3% increase in conversion rates; therefore, it can be demonstrated that there is a quantifiable business value for the gain in conversion rates, which validates that there are real-world consequences to the expressed advantages of hypergraphs over pairwise graphs. HyperGNN-Market is intended to be the first step of a larger research agenda related to higher-dimensional marketing intelligence and the science of consumer behavior.

The code, pretrained models, and dataset construction utilities are released at https://github.com/hypergnn-market to facilitate reproducibility and community development.

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