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Deep Contextual Representation Learning for User Behaviour Prediction in E-Commerce Recommendation

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Abstract

The use of smart internet services to deliver customized information and enhance user interaction is also gaining full relevance in e-commerce sites. Although a lot has been achieved in recommendation systems, current solutions are largely designed as standalone prediction models and do not address critical service-level issues, such as dynamic user behaviour adaptation, online, scalable deployment, and efficient integration with internet-based e-commerce platforms. This shortcoming has shown an essential disjunction between the accuracy of the recommendation and the viable service-based implementation. To fill this gap, this paper introduces a new internet service-oriented recommendation framework tailored to e-commerce platforms. The proposed system will be an online service that integrates user behaviour modelling and adaptive learning to produce recommendations that are correct and context-sensitive. In contrast to traditional methods, the new approach focuses on service scalability and real-time adaptability, enabling flawless implementation in web-based e-commerce systems. The workflow is a mathematical model and algorithmic process that defines the recommendation process to be robust and understandable. The unique feature of the suggested approach is that it follows a service-based design, turning the recommendation mechanism into a scalable internet service rather than a fixed analytical model. Such a design enables effective management of dynamic user interactions and enhances service quality in e-commerce applications. Benchmark experiments on new recommendation methods show that the suggested framework outperforms current methods in terms of accuracy, stability, and efficient service performance. The findings demonstrate the efficiency of the proposed system in reducing the gap between recommendation intelligence and practical implementation of internet services. DCRN improves HR@5, HR@10, and NDCG by 7.91, 6.16, and 8.55, respectively, on the WeChat Channels dataset. The gains are 6.11% in HR@5, 6.08% in HR@10, 4.29% in NDCG@5, and 3.99% in NDCG@10 in the Tmall data. Equally, for the CIKM data, the Proposed System outperforms the Existing Model, achieving gains of 6.65% in HR@5, 5.57% in HR@10, 7.34% in NDCG5, and 6.62% in NDCG10.

Keywords: Recommendation System, E-commerce, User Behaviour Prediction, Deep Contextual Representation Network, Collaborative Filtering, Graph Neural Networks, Behavioural-Semantic, Artificial Intelligence.

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1 Introduction

The digital world is evolving into a major web platform, with recommendation systems among its key features. It is committed to providing personalized content, products, or services to enhance users' experience and make them happier. Nevertheless, there are numerous issues with traditional recommendation system as users need more and more and their online activities are becoming increasingly complex. Determining how to respond to users' changing interests is one of the greatest challenges. Recommendation systems are gaining significance on modern e-commerce platforms. They help consumers receive personalized, relevant item recommendations amid the enormous, constantly expanding array of products and services. Such technologies play a significant role in users' perceptions of the site, ease of site navigation, and the success of the business, such as attracting more customers, retaining customers, and earning more money. The success of the recommendation system depends heavily on the ability to capture users' choices. This, in turn, is conditional upon the quality and variety of available data on behavioural interactions upon which learning will occur. The studies on recommendation models have largely been divided into two fields over the years: collaborative filtering-based recommendations and sequential recommendations (Wu et al., 2022; Yang et al., 2021; Yan et al., 2024). Collaborative filtering implies that recommendations are based on the similarity of other users or products. Collaborative filtering can be achieved using matrix decomposition, which can more effectively derive potential user preferences and item attributes from the sparse user-item matrix. This increases the level of accuracy of recommendations. Sequential recommendation takes time to learn users' behaviour, such as clicks, purchases, and views, so as to discover patterns and trends in the sequences of behaviour. The primary task of sequential recommendation is to learn the temporal patterns of user behaviour and use them to generate personal recommendations. To address the cold start and sparse data issues, the recommendation algorithm is no longer single-domain collaborative filtering or single-domain sequential recommendation, but rather cross-domain collaborative filtering (Zhou et al., 2023) and cross-domain sequential recommendation. The current cross-domain suggestions mostly consider only two domains: the destination and the source. In the majority of cases, classical recommendation algorithms were based on plain feedback, such as user ratings or purchase history. These cues indicate user desires but reveal only a limited set of potential actions. This single dimensional perspective does not consider the broad scope of implicit user interaction, such as product page views, adding items to cart but not purchasing them, wishlist behaviours, and frequency of behaviour patterns. These communications usually contain significant latent information that indicates intent, interest, or indecision. The failure to incorporate such forms of implicit behaviour signals makes it more difficult for the model to perform across various user settings, thereby reducing its accuracy and individuality (Jing et al., 2022; Wei et al., 2022; Ren et al., 2024). Recent developments in recommender systems have concerned the field of multi-behaviour learning, which utilizes as many types of user interactions as possible to better understand user-content interactions. The behaviours, with their various meanings and degrees of intent, provide a more specific and time-sensitive understanding of how users decide. As an example, a single click may indicate that a person is willing to do five minutes of research, whereas adding something to the basket or wishlist may indicate that they are more willing to purchase. A combination of these actions allows the learning system to make additional guesses about user profiles and to provide suggestions that consider the user's context (Li et al., 2020). The temporal aspect of user activity adds further complexity and potential. Sequential modelling architectures such as Recurrent Neural Networks (RNNs), Transformer architectures, and time-sensitive attention systems have proved useful for tracking the dynamics of user preferences and behaviour over time. Such algorithms can identify minor shifts in the user's interests and adjust their suggestions based on the order, frequency, and novelty of interactions. These temporal modeling capabilities are significant in e-commerce, where customer intent can change rapidly due to sales, seasons, or the context in which they are browsing (Ren et al., 2024). Meanwhile, studies have also investigated methods for simultaneously separating and learning about various forms of user activity using multitask learning and graph-based models. Multi-Gate Mixture-of-Experts (MMoE), Cross-behaviour Graph Neural Networks (GNNs), and Shared-Bottom are some of the recommended ways to find the underlying similarities and differences across behaviours. These designs allow the system to learn mutual representations of various kinds of behaviour while still producing task-specific outputs. This results in a more accurate system and more generalizable (Li et al., 2020; Cheng et al., 2024; Zhang et al., 2024). There are significant business and operational advantages to including multi-behaviour data in recommendation systems, including more predictive performance, more clicks and conversions, greater visibility for long-tail products, and higher customer retention. Cross-selling and upselling are also achieved with the help of these technologies, which calculate what the user wants to do across various categories and circumstances. All these features enable platform owners to more effectively manage their inventory, personalize dynamic content, and track user satisfaction more precisely. Although these have been improved, current implementations usually fail to utilize all the data on user behaviour that can be obtained. The systematic methods for integrating both implicit and explicit behaviours into coherent modeling pipelines remain extremely important. Among the issues that arise are the various forms of behaviour, insufficient data, the level of intent, and the development of expandable models. These issues need to be addressed to ensure that the next generation of recommender systems is robust, versatile, and capable of providing users with fine-grained customization across a broad spectrum of user groups that are in continuous flux (Zhang et al., 2024).

In today's online shopping world, there are so many options that personalized recommendation systems are essential for making consumers happier and helping them make better choices. Traditional recommendation models have worked rather well by using explicit feedback, such as ratings and direct purchase data. However, these models don't make full use of the vast amount of implicit interaction data that users generate while online. User actions, such as viewing product pages, adding items to shopping carts, marking products as favorites, and revisiting the same product, are important indicators of changing user interests and preferences. It's important to exploit this wider range of user interactions because implicit behaviour provides us with more information about what consumers want, what they like, and what they want to do than explicit behaviour alone. Adding several types of behaviour al cues to recommendation systems may make them far better at guessing what users will do, adjusting to changing user interests, and properly showing how complicated the interactions are between users and products. The proposed Deep Contextual Representation Network (DCRN) introduces a sophisticated and integrated platform for predicting user behaviour in e-commerce recommendation systems. It combines multi-typed behavioural data with semantic knowledge representation, which allows effective and contextual personalisation. The main points of this model are the following:

- Framework of Deep Contextual Representation of User Behaviour Prediction: DCRN proposes a three-phase deep contextual model, which is a systematic modelling of the interaction between users, by means of hierarchical behaviour al and semantic representations. It is able to capture explicit and implicit signals of various types of behaviours, thus giving a better depiction of the user intent and interaction dynamics.
- Consumer Activity Analysis through Hyper Meta-Graph Consistent Alignment Learning (CAL): The model builds consumer behaviour conscious hyper meta-graphs of consumer behaviour to reflect the variability and similarity between more than one action by a user. It is able to do this without distorting underlying semantics, thus producing refined user and product embeddings, by

using the Contextual Alignment Learning method, which aligns semantically related behaviour representations.

- Semantic Concept-Aware Relational Modelling of Knowledge-Enriched Embedding: DCRN uses meta-path-directed relational modelling to create graph-based and behaviour -specific interaction that expresses semantic dependencies among users and products. This improves the contextual knowledge by incorporating the semantic similarity and preference patterns in the heterogeneous e-commerce settings.
- Behaviour al-Semantic Multi-Task Behaviour al-Semantic Fusion: The behaviour al and semantic embeddings are optimised as a unit in a single multi-task learning strategy with two complementary goals, which are recommendation and contextual alignment. The ensemble optimization of the two contributes to increased stability of convergence, better generalization and higher ranking accuracy among datasets.

The rest of this paper is organised as follows. Section 2 presents a literature review of internet service-based recommendation systems in e-commerce settings. Section 3 presents the proposed recommendation framework, which includes the system architecture, mathematical formulation, and algorithmic workflow. Section 4 presents the implementation details, datasets, and experimental setup, and includes the performance assessment and a comparison of the suggested method with the current results method. Section 5 presents the conclusion.

2 Related Work

Recommendation systems have become a major research area in the product-based domain, whether in e-commerce, movies, or other user-preference applications. In recent years, a lot of research has been conducted with AI and LLM-based models in mind. For example, MBGCN (Hou & Cao, 2022) was proposed to leverage graph convolutional networks (GCNs) to learn complex connections among users, items, and item-item interactions for multi-behaviour recommendation. Similarly, CRGCN (Tang et al., 2020) uses a cascading residual graph convolutional network architecture to learn user intent by improving embeddings across different types of actions. To understand how actions depend on one another over time, MB-CGCN (Gao et al., 2022) uses cascading graph convolution networks. To capture the many different behaviours and how they depend on one another, MBSSL uses a behaviour-aware graph neural network with a self-attention mechanism. Chen et al., (2022) proposed the GHCF model, which leverages multiple types of high-hop structural information about how users and items interact. FeedRec (Xue et al., 2024) is another recent attempt in which the authors used an attention network to tell how engaged users were with different sorts of feedback for news suggestions. Another framework called MMCLR added Contextual Alignment Learning (CAL) (CL) to multi-behaviour recommendations and created three particular CL tasks to learn user representations from different points of view and types of behaviour. The work (Guo & Wang, 2024) came up with the hyper meta-path to get over the problems with the aforementioned methods. This new method combines many meta-paths to show how users behave. The main concept behind graph Contextual Alignment Learning (CAL) is to learn node properties inside graphs by adaptively comparing the differences between different graphs. Researchers discovered that the self-supervised approach to Contextual Alignment Learning (CAL) is good for finding similarities and differences between actions and can also help with the problem of having too few supervised signals. So, we suggest the user behaviour -aware module, which builds user behaviour hyper meta-graphs to show how users act, and builds a Contextual Alignment Learning (CAL) task to get representations from the point of view of user behaviours. In the actual world, there are additional complicated linkages between products or users, in addition to the many behaviours al data of users. These relationships show how semantically relevant they are (Jin et al., 2020). These complicated relationships can provide you more information about how to learn about user preferences and how users interact with items (Tai et al., 2023). For instance, in e-commerce, objects in the same category might work together, and this connection can make the knowledge representation of the things better. UBAR (Su et al., 2023) used a knowledge graph to combine the attribute information of things and find out how semantically related they are. To capture the collaborative signals, we suggest the semantic knowledge-aware module. It leverages meta-paths to mine knowledge of semantic significance across varied behaviours as additional information. Xia et al., (2021) examines multi-domain item-item recommendation based on cross-domain knowledge graph embedding. They accomplish this by looking at how items from the same domain are related and how items from other domains interact with each other using a knowledge graph that has a lot of information. Wu et al., (2025) Learn two graph-based sequential representations: one that uses information about the domain to focus on the user's current interests, and the other that makes global user representations that reduce negative knowledge transfer in the domain. For the cold-start problem, (Guo et al., 2024) provides a cross-domain recommendation architecture. This technique effectively makes cross-domain embedded distributions more similar by adding distributed alignment modules. It also employs contrastive augmentation learning to make the embeddings of target-domain items more stable and robust. The need to move beyond single-feedback models has made the simulation of multi-behaviour user interactions a major area of research in recommendation systems. Older models like MF-BPR, DSSM, and NCF have done important work by getting clear user preferences through purchases or ratings. However, these models can't take advantage of the many implicit signals (such as clicks, adding items to a cart, and adding items to a wishlist) that are common on real-world platforms. In response, newer technologies have tried to make recommendations more accurate and personalised by taking into account different types of user behaviour, generally using graph-based and attention-enhanced neural networks. Graph neural networks (GNNs) have been a big part of this change. CRGCN (Zeng et al., 2023) built on this by adding a cascade residual mechanism to improve embeddings across behaviour al layers. MB-CGCN (Yu et al., 2023) took care of sequential dependencies even further by using hierarchical convolution across interaction sequences. Also, MBSSL combined self-supervised learning with a behaviour-aware GNN to better understand how behaviours depend on each other. These models show how useful relational inductive biases can be for learning from many diverse actions, but they typically struggle to distinguish acts with distinct meanings or intentions. Another new area of research is using Contextual Alignment Learning (CAL) (CL) and meta-path-based modelling to learn more about how users behave differently. The Hyper Meta-Path method (Sang et al., 2025) suggested an adaptive graph-based contrastive framework that builds hypergraphs from multiple behaviour sequences. These hypergraphs show both common and unique patterns. This method worked well for mining user-specific interaction contexts and helped address data sparsity, a persistent challenge in multi-behaviour modelling.

Existing research has shown that recommendation systems significantly improve personalisation and user engagement on e-commerce platforms by using collaborative filtering and machine learning techniques. However, most existing methods primarily focus on offline accuracy and do not adequately address scalability and real-time deployment as internet services. Additionally, limited attention is given to adapting recommendations to dynamic user behaviour in online environments. This work extends prior studies by proposing a service-oriented recommendation framework that effectively integrates recommendation intelligence within internet-based e-commerce platforms.

3 Proposed Methodology

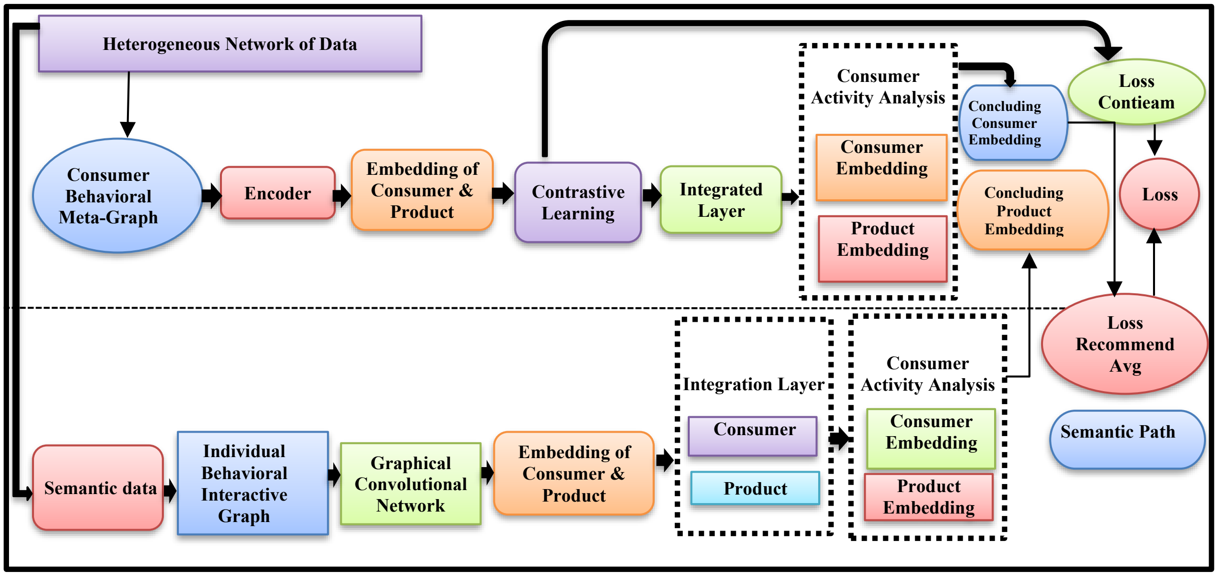

Figure 1: Deep contextual representation network (DCRN)

For a traditional Behavioural recommendation system, a heterogeneous network of data given as $HetroData\ I = (X, G)$ for modelling of information, in which the nodes are denoted as X have nodes for consumers that are given as $W_l\ belongs\ to\ W$, Nodes for products are denoted as $k_s\ belongs\ to\ K$ and the class of product is given as $e_t\ belongs\ to\ E$. Here, the edges are given as G have an interaction between the consumer and the product $g^d = (w_l, k_s, d_m)$ and the product class is represented as $g = (k_s, e_t)$. We consider that there are n kinds of consumer behaviour $D = \{d_1, \dots., d_n\}$, where one of them is the desired behaviour and the other $n - 1$Types are auxiliary behaviours. The paper proposes a Deep Contextual Representation Network (DCRN) (shown in figure 1) that focuses on completely utilising the consumer's multiple typed behaviour data as well as semantic interactional knowledge, both related to the consumer and the product, for the prediction of destination behaviour and also provides the consumer with an efficient description of the recommendation outputs.

A meta-graphical representation that has various meta-paths along with a similar initial node. For the reflection of consumers' behavioural characteristics, for every consumer, we build n consumer's behaviour meta-graphs. The v[th] graph of w_l is explained as

$$BehavGraph_v^{w_l} = \{(w_l, k_s, (d_1, \dots., d_e)) | k_s\ belongs\ to\ K\ for\ all\ \ d\ belongs\ to\ \{d_1, \dots, d_n\}\},$$

here $(d_1, \dots, d_e)$ is instructed by hierarchical order for $w_l's$ interactions with the product k_s. Further, we gather the behaviour of the consumer using meta-graphical representations that are hyper given as

$BehavGraph^{w_l} = \{BehavGraph_1^{w_l}, BehavGraph_2^{w_l}, \dots., BehavGraph_n^{w_l}\}$, (Yu et al., 2023) that is utilised to describe the consumer w_l interactions with the products.

To portray the interaction of the consumers or the products for various behaviour semantics, we split the $HetroData\ I$ into n individual behavioural interactive graphs relating to the behaviour class for g^d edge. The m[th] an interactive graph is described as $InterGraph_m = (X, G_m)$, in which X nodes have $w_l\ belong\ to\ W$, $k_s\ belongs\ to\ K$ and $e_t\ belongs\ to\ E$ and G_m edges have the consumer-product interaction behavioural edge $g^d = (w_l, k_s, d_m)$ and the product class edge $g = (k_s, e_t)$.

The framework of the proposed Deep Contextual Representation Network (DCRN) is given in figure 1. This proposed system has three phases that include:

- *Consumer Activity Analysis Phase:* This phase is based on consumer behavioural meta-graphical representations that are hyper to the patterns of consumer behaviour and grasps the variations as well as commonalities that are present between the various behaviours via Contextual Alignment Learning (CAL) of meta-graphical representations that are hyper. This phase gradually results in embeddings that are aware based on the behaviour of consumers as well as products.
- *Conceptual Relation-Aware Phase:* This phase is based on individual behavioural interactive graphs to the semantic relation concept for various behaviours for enhanced representation of preferred similarities between consumers as well as semantic importance between products. This phase gradually results in concept-aware consumers and product embeddings.
- *Multitask Learning:* The embeddings in the two phases are initially integrated, and the predicted values of recommendation are obtained by aggregation of the two embeddings as well as efficient recommendation descriptions are given by mining of the paths as well as semantics between consumers and products. In conclusion, the multitask learning is implemented for collective optimisation of two intentions of the recommendation task as well as the task of Contextual Alignment Learning (CAL).

Considering the Consumer Activity Analysis Phase encoders, for e-commerce platforms, the consumers have various interactions with products, which include the page being viewed, products being added to the shopping cart, and purchasing of products. This results in a considerable amount of behavioural information that is actually gathered in the backend. This behavioural information shows the buying preferences of the consumer as well as patterns of behaviour up to a limit, and therefore, this is utilised as supplementary data for the procedure of recommendation. Hence, enhancing the accuracy of the outputs. Although the major issue faced by the behavioural recommendation system is how to efficiently use various behaviours, the consumer behavioural patterns are mined. This is resolved using meta-paths that are hyper. This is built using the integration of various meta-paths of two particular node ends in the heterogeneous network of data. When a product is purchased by a consumer, four individual meta-paths are characterised using the information of the purchase. It is challenging for the individual meta-paths to properly show the complete patterns of behaviour of the consumer. This meta-path consists of these four meta-paths sequentially, which efficiently shows the behavioural patterns of the consumer. The consumers view the product twice, add it to the shopping cart and make the purchase at last. Hence, the utilization of meta-paths that are hyper shows the relation between the multitype behaviours as well as the distinctions in patterns of behaviour for various consumers.

Considering the proposed Deep Contextual Representation Network (DCRN), the meta-path that is hyper is built for consumer behavioural meta-graphs that show the characteristics of the consumer's behaviour. In particular, considering the count of types of behaviours, the meta-graphs that are hyper are built for the consumer w_l, We assume that w_l has n types of behaviour, there exist n behaviour hyper meta-graphs, given as $BehavGraph^{w_l} = \{BehavGraph_1^{w_l}, BehavGraph_2^{w_l}, \dots., BehavGraph_n^{w_l}\}$. While we consider e-commerce platforms, the behaviour 'purchase' is taken as the desired behaviour, and the other behaviours are considered auxiliary. The sequential order D. The semantic behaviour is determined considering the distance semantically for every behaviour from the destined behaviour. For instance, we consider a set of four significant behavioural types, which include viewing of page, adding product to cart, adding product to favourite list and purchasing of product, which could be organized into a sequential order of behaviours given as $\{behave_{view}, behave_{fav}, behave_{cart}, behave_{purchase}\}$.

Hence, the four hyper-graphs for behaviour is built for every consumer, the initial one having only purchase, the second being viewing as well as purchasing, the third being viewing of page, purchasing as well as favourite and lastly the fourth one having all kinds of behaviours.

After construction of the hyper meta-graphs considering behaviour for every consumer, it is essential to utilize graphical encoders that are suitable to gather the embeddings that are representative. This is due to the consumer behaviour of meta-graphs that are hyper that we have built, having semantic data that is rich, and having the liberty to choose the encoders. The graphical neural network model is incorporated in the proposed model. Particularly, for the consumer w_l, given that the encoder graphically for $v-th$ graph is denoted as $Encoder_v(BehavGraph_1^{w_l})$, the embeddings for consumers and products are given as w_l and k_s respectively for this graph which is formulated as given below equations (1) and (2).

$$dw_v^{w_l} = Encoder_v\left(BehavGraph_v^{w_l}\right) \qquad (1)$$

$$dk_v^{k_s} = Encoder_v\left(BehavGraph_v^{w_l}\right) \qquad (2)$$

In this case, $dw_v^{w_l}\ belongs\ to\ D^f, dk_v^{k_s}\ belongs\ to\ D^f$ and f is the concealed dimension of the embeddings (Sang et al., 2025).

Considering Consumer Behaviour Graphical Contextual Alignment Learning (CAL), we build meta-graphs that are hyper considering the count of behaviour types for every consumer, this notes the interaction of the consumer as well as the patterns of behaviour. Although the complexity of the consumer's various meta-graphs that are hyper is distinct as well as increases proportionally to the count of behavioural types. To grasp the distinction and commonalities of various types of behaviour, we use graphical Contextual Alignment Learning (CAL) from the different meta-graphs of the consumer.

Graphical Contextual Alignment Learning (CAL) has four major components: graphical information augmentation, encoder, projection node and contrastive loss function. Considering these components, information augmentation produces various views for information using different techniques, as well as builds pairs that are positive as well as negative using samples of augmentation. Although traditional augmentation techniques intervene with semantics to an extent, they are depicted as unfit for recommendation systems. Hence, the information augmentation system is replaced by building a Contextual Alignment Learning (CAL) module for the consumer's meta-graphs. This technique does not interfere with semantic data for recommendation systems, and it also aids in the establishment of links for various hypergraphs.

In particular, the consumer w_l, The encoders used graphically for two behavioural meta-graphs that are adjacent are denoted as $BehavGraph_{v-1}^{w_l}$ and $BehavGraph_v^{w_l}$ are $Encoder_{v-1}(\cdot)$ and $Encoder_v(\cdot)$, respectively. The consumer has embeddings for these graphs that are expressed as given in the equations (3), (4), and (5) below (Yu et al., 2020).

$$dw_{v-1}^{w_l} = Encoder_{v-1}\left(BehavGraph_{v-1}^{w_l}\right) \qquad (3)$$

$$dw_v^{w_l} = Encoder_v\left(BehavGraph_v^{w_l}\right) \qquad (4)$$

Here, the negative pair is given as $dw_{v-1}^{w_l}$ and $dw_v^{w_l}$. For the introduction of the positive pair, $Encoder_{v-1}(\cdot)$ is used for the encoding of $BehavGraph_v^{w_l}$ that results in $\widehat{dw}_v^{w_l}$ As sample (Yu et al., 2020) that is positive for $dw_v^{w_l}$

$$\widehat{dw}_v^{w_l} = Encoder_{v-1}\left(BehavGraph_v^{w_l}\right) \qquad (5)$$

The Contrastive Loss Function focuses on reducing the distance between the positive sample pairs while increasing the distance between negative sample pairs, which is (Wang et al., 2018).

$$\mathcal{L}oss_{v-1,v}^{w_l} = -\ln\left(\exp\left(f\left(dw_v^{w_l}, \widehat{dw}_v^{w_l}\right)\right)\right)\left(\exp\left(f\left(dw_v^{w_l}, \widehat{dw}_v^{w_l}\right)\right)\exp\left(f\left(dw_v^{w_l}, dw_{v-1}^{w_l}\right)\right)\right)^{-1} \quad (6)$$

For the above equation (6), $f(\cdot,\cdot)$ is given as a distance function that is used for the computation of the distance between the vectors. The complete Contrastive Loss Function for the consumers is gathered by the summation of all the Contrastive Losses for all the consumers.

$$\mathcal{L}oss_{contlearn}^{product} = (1+p)^{-1}\sum_{l=1}^{p}\sum_{v=2}^{n}\mathcal{L}oss_{v-1,v}^{w_l} \quad (7)$$

Here, we denote as p number of consumers and n is the count of consumer behaviour kinds. We obtain the loss function equation (7) $\mathcal{L}oss_{contlearn}^{product}$ for the products by consumer behaviour meta-graphs Contextual Alignment Learning (CAL), and in conclusion, the loss function is given as equation (8) (Xia et al., 2021).

$$\mathcal{L}oss_{contlearn} = \mathcal{L}oss_{contlearn}^{product} + \mathcal{L}oss_{contlearn}^{consumer}. \quad (8)$$

After the grasping of consumer and product embeddings using the consumer behavioural meta-graphs, we furthermore integrate them and gain the embeddings that are unified. In this case, the technique of integration is selected. Generally, the techniques used are linear integration techniques and methods based on neural networks. We select $h(\cdot)$ as the integration function, the known behavioural embeddings for w_l and k_s is formulated as given below equations (9) and (10).

$$dw^{w_l} = h(dw_1^{w_l}, dw_2^{w_l}, \ldots, dw_n^{w_l}) \quad (9)$$

$$dw^{k_s} = h\left(dw_1^{k_s}, dw_2^{k_s}, \ldots, dw_n^{k_s}\right) \quad (10)$$

In the *Conceptual Relation-Aware Phase:* Considering the recommendation system, additionally to the data about the consumer multiple behaviour interactions, there is an adequate amount of feedback that provides additional data for the process of learning consumer preferences as well as understanding of interactive patterns between consumer and product. While we assume this relationship is based on semantic concepts, there exists a possibility to improvise the understanding of this system while taking into consideration the consumers' personal preferences for various classes of products. To showcase an increased accuracy of preference similarity for consumers as well as semantic importance between products, we gather collective signals from the consumer and the products for individual behavioural interactions graphically. Generally, various kinds of interaction depict various preferences of consumers. The consumer viewed products 1,2 and 3, added products 1 and 2 to the shopping cart and lastly purchased product 1. We can conclude using this data that the consumer has a higher preference for product 2 over product 3, while the highest preference is given to product 1. Hence, the heterogeneous network of data is split into various individual behavioural graphs, considering types of behaviour to extract semantic information for various behaviours. In particular, we assume there exists n kinds of behaviours, we split I into n individual behavioural interactive graphs. The mth interactive graph is expressed as $InterGraph_m = (X, G_m)$.

Considering e-commerce platforms, a multitude of product classes exist, and consumers interact with various classes of products. The consumers showcase different patterns of purchasing and have dynamic degrees of preferences for various classes of products. The data on the class of products improves the relation between two products and is advantageous for the comparison of consumer preferences. Hence, the class of products is considered for every individual behavioural interactive graph, on the basis of meta-paths for retrieving data about the consumers with the same preferences and data about the consumers with semantic importance. In particular, we express the meta-path behaviour as given below equations (11) and (12) (Zhu et al., 2024).

$$\delta_w : W \xrightarrow{d_m} K \rightarrow E \rightarrow K \xrightarrow{d_m} W \tag{11}$$

$$\delta_k{}^{(w)} : K \xrightarrow{d_m} W \xrightarrow{d_m} K \;\; \delta_k{}^{(e)} : K \rightarrow E \rightarrow K \tag{12}$$

Various meta-path behaviours express various semantics for a specific behaviour. Here, the meta-path shows that the consumers have similar interactive behaviour d_m with the same class of products. For consumer w_l, A set of all consumers that satisfy the meta-path is represented as $P^W(w_l)$, that expresses the data about the consumers with the same preference to w_l. The $\delta_k{}^{(w)}$ Meta-path portrays that the products have similar behaviour d_m with similar consumers and the $\delta_k{}^{(e)}$ meta-path portrays that the products are of the same class. Generally, a similar class of products that have interaction with the same consumers have some similarities. Hence, for the product k_s, the set of all products that are satisfactory to both $\delta_k{}^{(w)}$ and $\delta_k{}^{(e)}$ and is expressed as $P^K(k_s)$, This expresses the data of products that have semantic importance to k_s.

Considering the graphs of individual behaviour interaction, we initially utilise a Graphical Convolutional Network to gain embeddings for every interactive graph. The major aim of the graphical convolutional network is to gather the highly hopping neighbour node data and update the embeddings of the nodes. A common aggregate function is a weighted summation, where the nodes in the present layer are weighted and evaluated to gather embeddings for the next layer. The coefficient of the weights for the graphical convolutional network is only linked to the degree of the node, a challenge exists while considering learning. Hence, we use the similarity that exists between the consumers or products as the important weight between nodes that are similar and hence the further the aggregate node data is processed. Prior, we utilised the meta-paths to gather the set $P^W(w_l)$ for consumers who are similar to the consumer w_l. Therefore, we describe the important weight γ_{w_l,w'_l} between the consumer w_l and a similar consumer w'_l which is formulated as

$$\gamma_{w_l,w'_l} = \left(\exp\left(y_{w_l} * p_{w_l,w'_l}\right)\right)\left(\sum_{w \text{ belongs to } P^W(w_l)} \exp\left(y_{w_l}\, p_{w_l,w_l}\right)\right)^{-1} \tag{13}$$

For the above equation (13), the count of meta-paths is given as p_{w_l,w'_l} between the consumer w_l and w'_l. Also, y_{w_l} is the variable that is automatically learned.

Furthermore, the embeddings for the consumer would be updated via the important weights as the consumer data weight is aggregated and given below equation (14).

$$mw_m^{w_l(j+1)} = \alpha\left(Y^{(j)}\left(\sum_{w \text{ belongs to } P^W(w_l)} \gamma_{w_l,w_l} * dw_m^{w(j)}\right) + d^{(j)}\right) \tag{14}$$

For equation (14), the embedded j^th^ layer for the m^th^ graph $InterGraph_m$is given as $dw_m^{w(j)}$. The transformation matrices for learning is given as $Y^{(j)}$ and bias is given as $d^{(j)}$ for the j^th^ layer (Huang et al., 2013).

Likewise, the products that are embedded are updated via the inter-products important weights as the product weight data aggregation is given in equation (15), given as

$$mk_m^{k_s(j+1)} = \alpha\left(Y^{(j)}\left(\sum_{k \text{ belongs to } P^K(k_s)} \gamma_{k_s,k} * dk_m^{k(j)}\right) + d^{(j)}\right) \tag{15}$$

While taking into account the embeddings of nodes for various layers, we utilize a readout function for the derivation of the concluding embeddings. In particular, the w_l and k_s embeddings for the m^th^ interactive graph $InterGraph_m$ is equation (16, 17) given as

$$mw_m^{w_l} = func_{readout}\left(\left\{mw_m^{w_l(j)}\middle|j = [0, \dots, J]\right\}\right) \quad (16)$$

$$mk_m^{k_s} = func_{readout}\left(\{mk_m^{k_s(j)}|j = [0, \dots, J]\}\right) \quad (17)$$

On gathering n embeddings using the individual behavioural interactive graphs, then we aggregate the embeddings n to gather the concluding knowledge of known embedding. For every individual behavioural interactive graph, as well as various kinds of behaviour, show various degrees of preference of consumers. Hence, we build a coefficient for every behaviour for consumers to differentiate the distinction between behavioural kinds. In particular, the consumer w_l,To describe the coefficient ϑ_{w_l,d_m} for the m^{th} behaviour d_m equation (18) is formulated as given below

$$\vartheta_{w_l,d_m} = \left(\exp\left(y_{d_m} * p_{w_l,d_m}\right)\right)\left(\sum_{a=1}^{n} \exp\left(y_{d_a} * p_{w_l,d_a}\right)\right)^{-1} \quad (18)$$

In this case, p_{w_l,d_m} is the count of interactive consumers w_l under m^{th} behaviour. The weight of the m^{th} Behaviour is denoted as y_{d_m}, That is learnt automatically by the system, and it is similar for all the consumers. Considering this, the embeddings of the consumer are integrated for every individual behavioural interactive graph to gather the collective knowledge embedding of w_l which is equation (19) formulated as given below (He et al., 2017).

$$mw^{w_l} = \alpha\left(Y\left(\sum_{a=1}^{n}(\vartheta_{w_l,d_m} * mw_a^{w_l})\right) + d\right) \quad (19)$$

Here, Y is used to denote the weight and d It is used to express the bias.

For the products, the attributes are static. Hence, there is no necessity for designing the coefficient when integrating the embeddings of products for various individual behavioural interactive graphs. We assume to select $h(\cdot)$ as the integration function, the collective data embedding for k_s is given in equation (20)

$$mk^{k_s} = h(mk_1^{k_s}, mk_2^{k_s}, \dots., mk_n^{k_s}) \quad (20)$$

Multitask Learning: After receiving embeddings from the previous phases, they are aggregated to result in the concluding embeddings equation (21 & 22) as given below:

$$w^{w_l} = \mu_w dw^{w_l} + (1 - \mu_w) mw^{w_l} \quad (21)$$

$$k^{k_s} = \mu_k dk^{k_s} + (1 - \mu_k) mk^{k_s} \quad (22)$$

For the equations given above, the hyperparameters for adaptation of weights for embeddings under the two phases are denoted as μ_w and μ_k. In conclusion, we utilize the vector product for the prediction value equation, which is (23). In particular, the consumer's w_l predicted value of k_s is (Loni et al., 2016)

$$\hat{b}_{w_l,k_s} = i(w^{w_l}, k^{k_s}) \quad (23)$$

During the recommendation of products for the consumer, the products are efficiently described by gathering the paths as well as the semantics between consumers and products graphically. We select the logarithm negatively for the function of likelihood for training the system, which is formulated as given below in equation (24).

$$\mathcal{L}oss_{recomend} = - \sum_{(w_l,k_s) belongs\ to\ U^+ \cup U^-} b_{w_l,k_s} \log \hat{b}_{w_l,k_s} + \left(1 - b_{w_l,k_s}\right) \log\left(1 - \hat{b}_{w_l,k_s}\right) \quad (24)$$

Here, positive records are given as $U^+$and the sampled negative records are denoted as U^-. b_{w_l,k_s} $belongs\ to$ $\{0,1\}$ expresses the consumer's w_l interaction with the product k_s. Additionally, this is normalised as follows: equation is (25) (Wu et al., 2022):

$$\mathcal{L}oss_{recomend\_average} = \frac{\mathcal{L}oss_{recomend}}{|\{(w_l,k_s)|(w_l,k_s)\ belongs\ to\ U^+ \cup U^-\}|} \quad (25)$$

To gain a better system, this study utilises a learning technique for multitasking in an integrated effort to train these two phases

$$\mathcal{L}oss = \mu \mathcal{L}oss_{recomend\_average} + (1-\mu)\mathcal{L}oss_{contlearn} + \varphi\|\theta\|^2 \quad (26)$$

For the above equation (26), the hyperparameter that aids the balance of the two phases is denoted as μ, The trainable variables are expressed as θ and the hyperparameter used for the management of regularisation is expressed as φ.

By examining various behavioural patterns within a diverse data network, this algorithm (1) can predict which product will be more popular among consumers. The decision is made using the user's preferred option (Steps No 1 to 10). The process involves the creation of consumer-level behaviour meta-graphs and the acquisition of embeddings for product relationships using deep learning encoders, as well as contrastive learning (Steps No 11 to 18). Interactive graphs are constructed to model similarities between consumers and products, with the embeddings being updated by adjusting for weighted neighbour influence (Steps No 19 to 22).

Algorithm 1:	***"Multiple Behavioural Knowledge Improvised Recommendation System" (Yan et al., 2023)***
Input:	Heterogeneous data network $I = (X, G)$; trainable variables and hyperparameters
Output:	$\hat{b}_{w_l,k_s}$: the consumers w_l predicted value of k_s
Step 1:	For every w_l $belongs\ to\ W$ do
Step 2:	Generate the consumer's behaviour meta-graphs $BehavGraph^{w_l} = \{BehavGraph_1^{w_l}, BehavGraph_2^{w_l}, \ldots., BehavGraph_n^{w_l}\}$
Step 3:	For $v = 1, \ldots, n$ do
Step 4:	Evaluate v[th] consumer embedding for $dw_v^{w_l}$ and $dk_v^{k_s}$ using equation (1) & (2)
	Evaluate (v-1)[th] consumer embedding for $dw_{v-1}^{w_l}$ using equation (3) & the product is the same
	Evaluate $\widehat{dw}_v^{w_l}$ using $Encoder_{v-1}(\cdot)$ using equation (5)
Step 5:	Evaluate the v[th] Contrastive Loss Function $\mathcal{L}oss_{v-1,v}^{w_l}$ using equation (6)
	Evaluate the consumer's complete contrastive loss function $\mathcal{L}oss_{contlearn}^{product}$ using equation (7)
	Evaluate the complete contrastive loss function $\mathcal{L}oss_{contlearn}$
Step 6:	Gather the Consumer Activity Analysis Phase using equation (10) & (11)

Step 7: For $m = 1, \ldots., n$ do

Step 8: Develop the individual behaviour interactive graph $InterGraph_m = (X, G_m)$

Describe ${\delta_k}^{(w)}, {\delta_k}^{(e)}, \delta_w$

Step 9: For every w_l $belongs\ to\ W$ do

Step 10: Attain same consumers set $P^{(W)}(w_l)$ of w_l

Step 11: For every w'_l $belongs\ to\ P^{(W)}(w_l)$ do

Step 12: Evaluate the important weight γ_{w_l,w'_l} using equation (12)

Step 13: Updating consumer embedding $mw_m^{w_l(j+1)}$ using equation (13)

Step 14: Evaluate the coefficient ϑ_{w_l,d_m} for the behaviour of d_m

Step 15: For every k_s $belongs\ to\ K$ do

Step 16: Attain the similar products set $P^K(k_s)$ of k_s

Step 17: For every k'_s $belongs\ to\ P^K(k_s)$ do

Step 18: Evaluate the important weight γ_{k_s,k'_s} between k_s and k'_s

Update the product embedding using equation (14)

Step 19: Evaluate the mth , consumer and product embeddings using equations (15) & (16)

Step 20: Attain mw^{w_l} and mk^{k_s} using equations (19) and (20)

Attain the final consumer embedding and product embedding using equations (19) & (20)

Evaluate the probability of prediction $\hat{b}_{w_l,k_s}$ using equation (23)

Evaluate $\mathcal{L}oss_{recomend\_average}$ and $\mathcal{L}oss$ using equations (25) & (26)

Step 21: Parameters are updated

Step 22: Return

4 Performance Evaluation

The proposed system was tested on three benchmark datasets, including WeChat Channels (Yu et al., 2020), Tmall (Wang et al., 2018), and CIKM (Xia et al., 2021), based on the typical ranking measures HR@K and NDCG@K. To be able to make a comparison, it is assumed that the existing model (Zhu et al., 2024) (TREA) is in place. The results always prove that the DCRN outcompetes all the baseline models in all datasets and evaluation conditions. Namely, PS gets the best score in both HR@5/10 and NDCG@5/10, which inflates its ability to be more accurate in retrieving and ranking the relevant items. The performance of the model is seen in its steady improvement with respect to different types of interactions and platforms, which confirms the success of the combined behaviour -aware and semantic-aware approach to learning in improving the quality of recommendations. The proposed DCRN model was implemented in Python using PyTorch, with NumPy and Pandas employed for data pre-processing and analysis. Multi-behaviour user–item interactions were modelled as heterogeneous graphs, and behaviour-specific as well as hyper meta-graphs were constructed to capture contextual and semantic dependencies. Model training was performed using the Adam optimiser with mini-batch negative sampling and early stopping based on validation performance. All experiments were conducted in a GPU-enabled environment to ensure efficient training and reproducibility across datasets.in a standard computing environment, ensuring reproducibility and efficient deployment of the proposed internet service-based framework.

4.1 Dataset Description

The experiments are carried out based on the publicly available datasets on one short-video service and two e-commerce services as follows:

- **WeChat Channels:** The WeChat Channels data, launched at the WeChat Big Data Challenge 2021, gives a global view (GV) of user behaviour of interaction in a popular short-video platform. It is tailored to both multi-faceted user engagement patterns that are imperative in the study of advanced recommendation systems. This data is representative of real-world usage, as it contains six types of user-video interaction watching, liking, commenting, forwarding, favouriting, and following.
- **Tmall:** The data is provided by Tmall, a division of Alibaba and one of the online shopping platforms most popular in China, which gives a close-up insight into the interaction of users in the online shopping setting. It captures four major user behaviours which can be seen as different steps of the e-commerce conversion funnel:
- **CIKM:** The CIKM dataset, which is published as a subset of the CIKM 2019 E-Commerce Artificial Intelligence Challenge, is a high-quality benchmark in modeling the behaviour of the users within e-commerce setting. It depicts four basic kinds of user interactions: click, add to favourites, add to cart and purchase, which resembles the behavioural design of the Tmall data. This correspondence allows the cross-platform comparative analysis to be conducted and allows the creation of models of transferring behaviour predictions.

4.2 Baseline Methods

In order to carefully test the effectiveness of the proposed model, it was compared to several of the most effective available methods of the baseline. These baselines are old single-behaviour methods, new multi-behaviour recommendation algorithms, and unique multi-task learning methods. Specifically, we ensured that we did not put any superiority on the types of behaviour in the judgment of single-behaviour models. This eliminated any prejudices that might have been as a result of the size of the data (Yan et al., 2023).

A. Single-Behaviour Standard Recommendation Algorithms

- DSSM (Huang et al., 2013): The architecture of a two-tower neural network that is highly used in industrial-scale recommender systems, where query-document matching is used to make personalized predictions.
- NCF (He et al., 2017): Neural Collaborative filtering is a combination of classical collaborative filtering methods and deep neural networks architectures applied to increase the accuracy of recommendations.

B. Multi-Behaviour Recommendation Algorithms

- MC-BPR (Loni et al., 2016): An approach based on samples that extends the traditional Bayesian Personalised Ranking by having superior sampling of positive and negative instances to obtain more user-item interactions.
- FeedRec (Wu et al., 2022): FeedRec is the novel news suggestion system which employs attention mechanisms to reflect a variety of user interaction styles precisely.
- MBGCN (Meng et al., 2023): Graph-based recommendation model, a recommendation model that employs graph convolutional networks to indicate how various behaviours interact with each other at the user-item and item-item levels.
- MMCLR (Zou et al., 2022): Multi-view Multiple behaviour Contextual Alignment Learning (CAL). The Multi-view Model (MMCLR) employs Contextual Alignment Learning (CAL) along with sequence-based modelling, which guesses what behaviour will occur based on evidence of more than one activity.
- CRGCN (Yan et al., 2023): Cascading Residual Graph Convolutional Network (CRGCN) is a user preference model that refines user-item embeddings through a cascading residual graph framework by using various types of behaviour.
- MB-CGCN (Cheng et al., 2023): The structure relies on the cascading graph convolutional networks and directly explains the hierarchical relationships and the sequential relationships in the user behaviour sequence.
- MBSSL (Chen et al., 2026): Multi-Behaviour Self-Supervised Learning (MBSSL) applies self-attention and behaviour-conscious graph neural networks to approximate complex dependencies between various behaviours.

C. Multi-Task Learning Algorithms

- **MMoE (Ma et al., 2018):** Multi-gate Mixture-of-Experts (MMoE) adapts mixture-of-experts structures to multi-task conditions by dynamically balancing task-specific and general knowledge of experts.
- **ESMM (Ma et al., 2018):** The Entire Space Multi-Task Model (ESMM) applies transfer learning techniques and explicitly represents the process by which users interact with a sequence to address the problems of data sparsity and selection bias.
- **PLE:** Progressive Layered Extraction (PLE) is a routing algorithm based on progressive routing that divides and captures accurately common and task-specific semantics of a number of tasks.

Evaluation Metrics

Two commonly used ranking-based measures are used to measure the performance of the evaluated recommendation models:

- Hit Ratio (HR@K): This parameter is used to check whether the correct item is present in Top-K suggestions or not. We set K = 5, 10 to observe the level of success with which the algorithm can locate the appropriate items in the initial techniques (Ma et al., 2018).

- Normalized Discounted Cumulative Gain (NDCG@K): NDCG is a test of the quality of a ranking that uses more weight on things that appear higher on the list of recommendations. Accuracy in ranking is measured by NDCG at K = {5, 10} just as in HR.

5 Results

Table 1: WeChat channels dataset

Methods	**Dataset**	**HR@5**	**HR@10**	**NDCG@5**	**NDCG@10**
MF-BPR	WeChat Channels	0.3009	0.4389	0.2027	0.247
DSSM	WeChat Channels	0.2479	0.3834	0.1619	0.2057
NCF	WeChat Channels	0.2594	0.4044	0.1691	0.2156
MC-BPR	WeChat Channels	0.3216	0.4618	0.2173	0.2624
FeedRec	WeChat Channels	0.2269	0.351	0.1456	0.1855
MBGCN	WeChat Channels	0.2294	0.3726	0.144	0.1898
MMCLR	WeChat Channels	0.2106	0.3264	0.1413	0.1782
CRGCN	WeChat Channels	0.306	0.4502	0.2016	0.2479
MB-CGCN	WeChat Channels	0.2751	0.5424	0.1477	0.234
MBSSL	WeChat Channels	0.4097	0.568	0.2277	0.3062
MMoE	WeChat Channels	0.3083	0.453	0.2082	0.2549
ESMM	WeChat Channels	0.3187	0.4682	0.2084	0.2566
PLE	WeChat Channels	0.3171	0.4571	0.2114	0.2547
Existing Model (TREA) Zhu et al., (2024)	WeChat Channels	**0.4564**	**0.6134**	**0.3262**	**0.3769**
DCRN	WeChat Channels	**0.4925**	**0.6512**	**0.3541**	**0.4025**

The experimental evidence shows the high effectiveness of DCRN compared to all the baseline models on four important measures, including Hit Ratio at rank 5 and 10 (HR@5, HR@10) and Normalized Discounted Cumulative Gain at rank 5 and 10 (NDCG@5, NDCG@10) as shown in table 1. DCRN has the best HR5 of 0.4925, HR10 of 0.6512, NDCG5 of 0.3541 and NDCG10 of 0.4025, outperforming the existing model (TREA) significantly, especially at the top of the relevance ranking and the quality of ranking. Conventional collaborative filtering baselines such as MF-bpr and MC-bpr only achieve an average performance, yet they are much inferior to the deep learning-based models, particularly DCRN and TREA. MBSSL+ and PLE are among the best baselines of deep learning, although comparatively, they are worse than DCRN in terms of hit rate and ranking. Since the MMCLR, FeedRec, and MBGCN models have lower values in all the metrics, it implies that they have a weaker ability to model complex user behaviour on multi-interaction websites like WeChat Channels. The high performance of DCRN reflects its capability of good capacity to model different user intents and multi-behavioural signals, making it an effective solution in personalised recommendation in the real-life setting of short video scenarios.

The results of the performance on the Tmall dataset are a good indication of the superiority of the DCRN with all the evaluation measures, including HR@5, HR@10, NDCG@5, and NDCG@10, which proves that this method is the best of the compared baselines, as given in table 2. DCRN has the highest scores of HR =5 of 0.6024 and HR =10 of 0.6248, NDCG =5 of 0.5327, and NDCG =10 of 0.5501, outperforming even the best and robust baseline models TREA, CRGCN-, MB-CGCN-, and MBSSL. These additions denote the greater capability of the DCRN model to identify complicated behaviours of users and rank the relevant items more precisely. Although conventional models, such as MF-BPR and FeedRec, are doing rather well, they do not compare to more sophisticated models that utilise graph structures and multi-behavioural learning. Models based on deep learning, including PLE, MMoE, and NCF, have moderate performance, and their differences in the ranking accuracy and hit ratio are also distinct. It is important to note that models such as MBGCN and ESMM perform poorly, and this implies their poor behaviour in replicating subtle user intent when it comes to e-commerce. The large lead of DCRN on all measures highlights its strength and usefulness in simulating real-life multi-intent shopping behaviour s, thus it is a very promising model in recommending products to individuals in large-scale e-commerce websites such as Tmall.

Table 2: Tmall dataset

Methods	Dataset	HR@5	HR@10	NDCG@5	NDCG@10
MF-BPR	Tmall	0.4498	0.483	0.4069	0.4177
DSSM	Tmall	0.3345	0.4045	0.2629	0.2854
NCF	Tmall	0.3663	0.4186	0.3061	0.3231
MC-BPR	Tmall	0.372	0.4306	0.3123	0.331
FeedRec	Tmall	0.447	0.4886	0.404	0.4182
MBGCN	Tmall	0.2258	0.3512	0.1471	0.1871
MMCLR	Tmall	0.333	0.4214	0.2395	0.2679
CRGCN*	Tmall	0.5078	0.5255	0.4825	0.4881
MB-CGCN	Tmall	0.4965	0.512	0.4674	0.4723
MBSSL	Tmall	0.4986	0.5099	0.4634	0.467
MMoE	Tmall	0.4052	0.4589	0.354	0.3719
ESMM	Tmall	0.2765	0.3338	0.2232	0.2417
PLE	Tmall	0.449	0.4873	0.4069	0.4191
TREA Zhu et al., (2024)	Tmall	0.5677	0.589	0.5108	0.529
DCRN	**Tmall**	**0.6024**	**0.6248**	**0.5327**	**0.5501**

Table 3: CIKM dataset

Methods	Dataset	HR@5	HR@10	NDCG@5	NDCG@10
MF-BPR	CIKM	0.2425	0.3526	0.1428	0.1843
DSSM	CIKM	0.244	0.352	0.1466	0.1815
NCF	CIKM	0.2637	0.3457	0.1867	0.213
MC-BPR	CIKM	0.2701	0.3479	0.1957	0.2205
FeedRec	CIKM	0.2651	0.362	0.1821	0.2133
MBGCN	CIKM	0.191	0.2438	0.142	0.1591
MMCLR	CIKM	0.2704	0.3475	0.1932	0.2179
CRGCN*	CIKM	0.2924	0.3638	0.2242	0.247
MB-CGCN	CIKM	0.2921	0.3673*	0.2146	0.2386
MBSSL	CIKM	0.2883	0.3638	0.2142	0.2384
MMoE	CIKM	0.273	0.3411	0.179	0.2009
ESMM*	CIKM	0.3035	0.3608	0.2032	0.2217
PLE	CIKM	0.2745	0.3373	0.1797	0.1999
TREA (Existing Model) Zhu et al., (2024)	CIKM	0.4288	**0.4797**	**0.2943**	**0.3186**
DCRN	**CIKM**	**0.4573**	**0.5064**	**0.3159**	**0.3397**

The experiment on the CIKM dataset highlights the excellence of the DCRN, which all four metrics say is doing better and better than all the baseline models: HR@5, HR@10, NDCG@5, and NDCG@10, as shown in table 3. DCRN scores the best with HR at 5 of 0.4573, HR at 10 of 0.5064, NDCG at 5 of 0.3159, and NDCG at 10 of 0.3397, which is very high as compared to the second-best model (TREA). This is an indication that DCRN can be specifically useful in promoting relevant items higher in the recommendation list as well as capturing immediate and deep user intent. By comparison, classical approaches such as MF-BPR, DSSM, and NCF provide a comparatively poor performance, which is a manifestation of the inability of these approaches to capture the complexity of user interactions in a multi-behavioural environment. Advanced algorithms such as CRGCN, MBSSL, and MB-CGCN demonstrate competitive performance, in particular, in terms of HR at 10 and NDCG at 10, yet they cannot be compared with the accuracy and recall of DCRN. It is important to note that FeedRec, MMoE and PLE have moderate performance, whereas models such as MBGCN and ESMM would not be effective to model the relationship between the user and item in this case. In general, DCRN proves to be very strong in generalising between a wide range of behaviours and complicated user preferences, which makes it a powerful tool to be used in behaviour -wise recommendations in the CIKM e-commerce environment.

5.1 Graphical Comparison

As the comparison of HR five (HR@5) shown in the figure 2 WeChat Channels, Tmall and CIKM datasets shows, the DCRN will definitely be more effective at recommendation compared to both the Best Baseline and Existing Model. In the case of WeChat Channels, the DCRN has a HR @5 of around 0.49, which is decisively better than the baseline and current strategies. Equally, on the Tmall dataset, the DCRN is approximately 0.60, highest of all models and an improvement of almost 18 percent of the baseline. In the case of CIKM dataset, the DCRN has also a higher value of HR at 5 of approximately 0.46, which supports the flexibility of the DCRN in other data domains. These steady improvements indicate the efficiency of the suggested system in bettering the user-item interaction modeling and richer behavioural patterns modeling, leading to the enhanced accuracy of the top-5 recommendations. All in all, the findings confirm the quality, scalability, and performance of the Proposed System in providing more applicable recommendations based on different datasets.

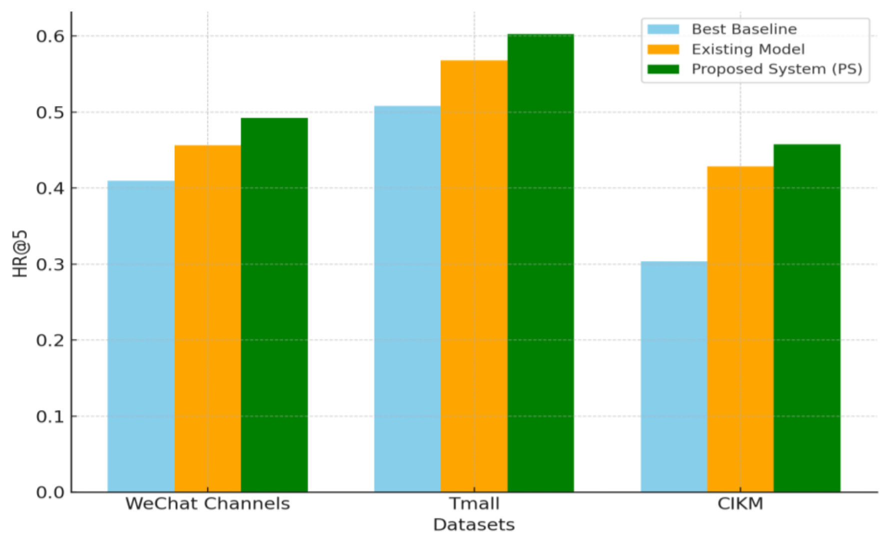

Figure 2: Comparison of HR@5 performance across WeChat channels, Tmall, and CIKM datasets for best baseline, existing model, and DCRN

The HR@10 comparison between the WeChat Channels, Tmall and CIKM data sets demonstrates similar improvement in the DCRN compared to the Best Baseline and the existing model, as shown in figure 3. The DCRN achieves the highest HR2 values of around 0.65, 0.63 and 0.51 on the three datasets, respectively, which shows a greater recommendation accuracy and ranking effectiveness. The DCRN demonstrates a stronger ability to capture user-item interaction dynamics on the WeChat Channels dataset, and as a result of this, it improves significantly over other models. On the same note, the DCRN displays one of the best execution margins in the Tmall data, indicating its sustainable nature in a large-scale business setting. In the case of the CIKM data, the DCRN has higher values of HR@10, which once again proves its flexibility as well as scalability under different data parameters. In general, the findings have made it clear that the Proposed System has a tremendous positive impact on retrieval performance, which subsequently results in better relevance of the recommendations and higher user satisfaction with the proposed system in a variety of datasets.

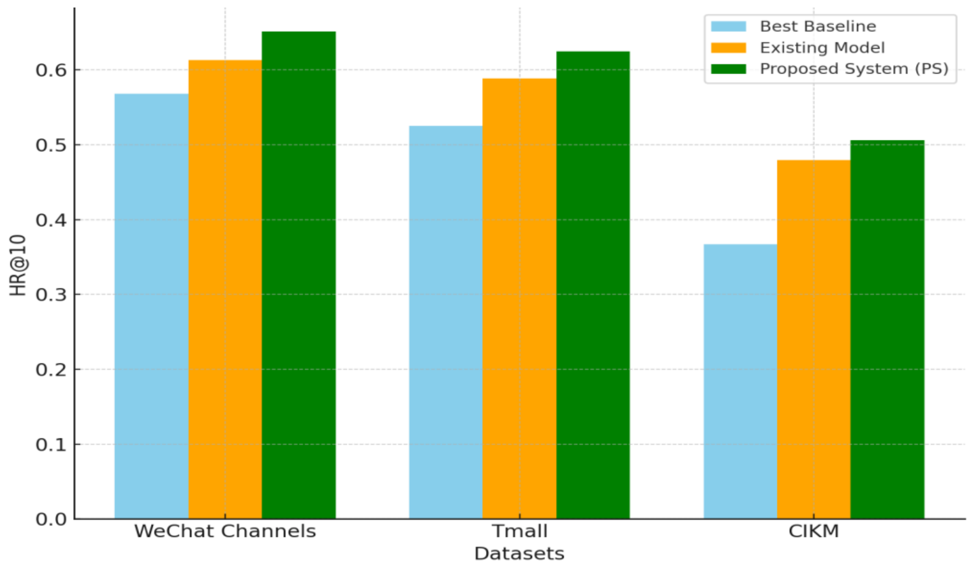

Figure 3: Comparison of HR@10 performance across WeChat channels, Tmall, and CIKM datasets for best baseline, existing model, and DCRN

The bar chart of NDCG5 in the WeChat Channels, Tmall, and CIKM datasets shows a clear global view (GV) of the effectiveness of different models in the ranking of the relevant items on the first page of the recommendation list, as shown in figure 4. Once again, the DCRN does better than the Best Baseline and even better than the Existing Model on all three datasets, and more significantly in the WeChat Channels and CIKM datasets, where DCRN significantly improves the quality of the top 5 recommendations ranking.

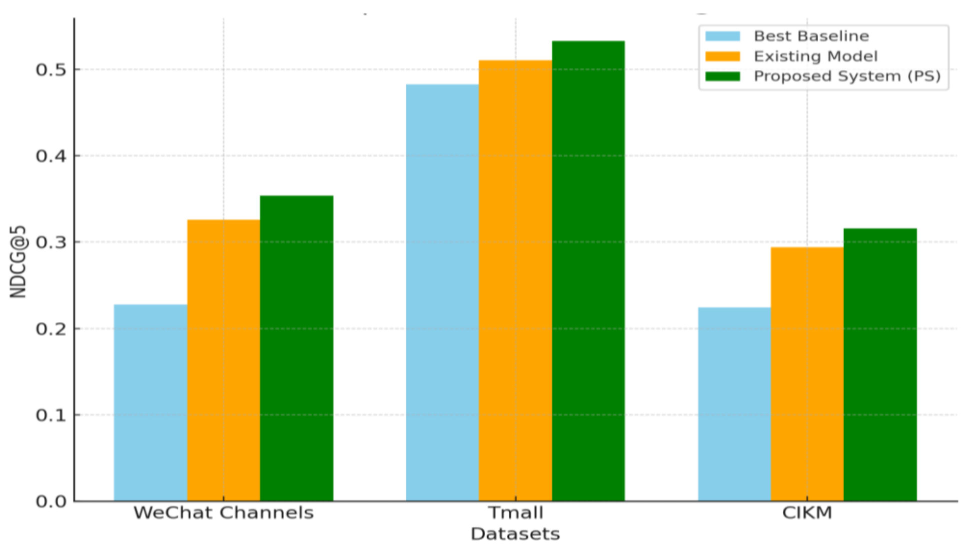

Figure 4: Comparison of NDCG@5 performance across WeChat channels, Tmall, and CIKM datasets for best baseline, existing model, and DCRN

In WeChat Channels, DCRN increases NDCG@5 to a range of 0.35, as compared to its inability to do so (considering the Best Baseline as 0.23). Likewise, in CIKM, DCRN generates a medium but significant improvement over other models, which shows that it is resilient in reflecting various user actions in an e-commerce context. Tmall data set demonstrates the best performance with DCRN, having an NDCG@5 value above 0.53, indicating a high level of ranking accuracy in an environment where purchase is the driving force. The given GV analysis highlights the ability of DCRN to provide high-quality ranked recommendations, so that the most relevant items would be on the top, which is important in terms of user satisfaction and interaction with real-time recommendation systems.

The comparison with NDCG10 of the WeChat Channels, Tmall and CIKM data sets shows in figure 5 that the DCRN has achieved a high quality of ranking in comparison with the Best Baseline and Existing Model. The DCRN has shown greater values of NDCG at 10 of about 0.40, 0.55 and 0.34 for the respective datasets, which shows its greater capacity to place the relevant items closer to the top of the recommendation lists. When applied to the WeChat Channels dataset, the DCRN demonstrates a significant improvement in the baseline, which denotes the quality of ranking social dynamic content. In the case of Tmall data, DCRN has the largest NDCG at 10, which highlights its strength and ability to adapt to the large-scale e-commerce setting. Likewise, in the CIKM dataset, the DCRN still has its edge as it is capable of generalising across different domains. Altogether, these findings can confirm that the Proposed System is effective in terms of improving the ranking of relevance and user satisfaction by generating more accurate and position-sensitive recommendations than the current methods.

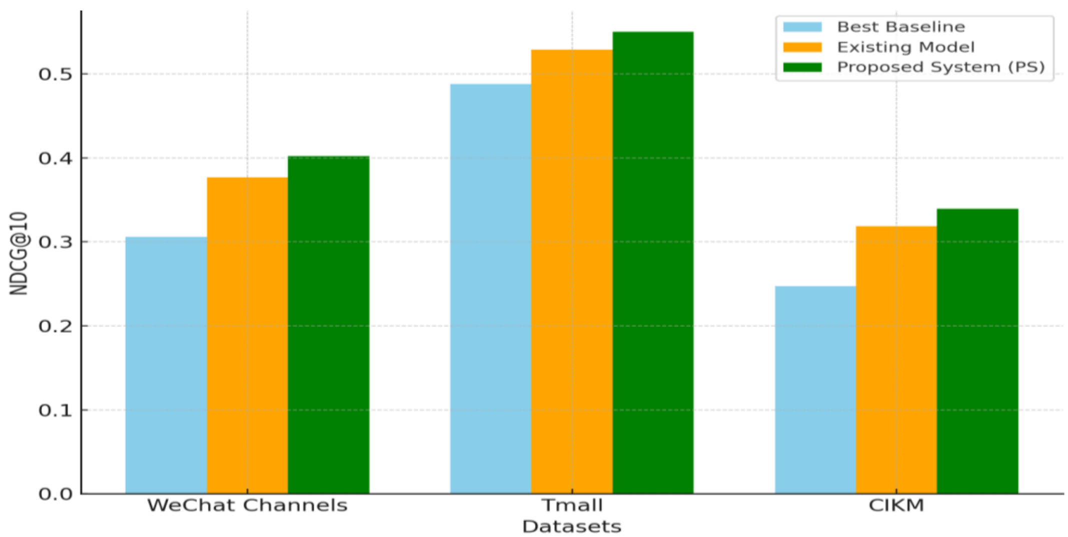

Figure 5: Comparison of NDCG@10 performance across WeChat channels, Tmall, and CIKM datasets for best baseline, existing model, and DCRN

5.2 Comparative Analysis

The comparative analysis indicates that the DCRN has been improving its performance in all the datasets and evaluation metrics consistently, as compared to that of the Existing Model. DCRN improves HR@5, HR@10, NDCG, and NDCG improvements are 7.91, 6.16 and 8.55, respectively, on the WeChat Channels dataset. The gains are 6.11% in HR@5, 6.08% in HR@10, 4.29% in NDCG@5 and 3.99% in NDCG@10 in the Tmall data. Equally, in the case of CIKM data, the Proposed System is stronger than the Existing Model in terms of gains of 6.65 percent in HR@5, 5.57 percent in HR@10, 7.34 percent in NDCG5 and 6.62 percent in NDCG10. These are the enhancements whose presence clearly shows the strength and better predictability prowess of the Proposed System in a variety of situations involving recommendations.

6 Conclusion

This work presented a model deep contextual representation Network (DCRN), which is used to predict user behaviour in e-commerce recommending systems much more effectively. Through behaviour-aware representation, semantic knowledge integration, and Contextual Alignment Learning (CAL), DCRN is successfully able to represent the multifaceted and changing trends in user behaviour with respect to multiple types of behaviours. The three-stage architecture suggested, including Consumer Activity Analysis Phase, Conceptual Relation-Aware Phase, and Multi-Task Optimization Phase, is a joint modelling of explicit and implicit signals of behaviour to create contextually rich and semantically consistent embeddings of both customers and products.

Extensive experimental results on three benchmark datasets, WeChat Channels (Tmall, CIKM) show that DCRN outperforms the current state-of-the-art baselines on all the major evaluation metrics, such as HR@5, HR@10, NDCG@5, and NDCG@10. The performance gains identified point to the generalization capabilities of the model across domains as well as its robustness, scalability, and ranking accuracy. DCRN improves HR@5, HR@10, NDCG, and NDCG improvements are 7.91, 6.16 and 8.55, respectively on the WeChat Channels dataset. The gains are 6.11% in HR@5, 6.08% in HR@10, 4.29% in NDCG@5 and 3.99% in NDCG@10 in the Tmall data. Equally, in the case of CIKM data, the Proposed System is stronger than the Existing Model in terms of gains of 6.65% in HR@5, 5.57 % in HR@10, 7.34 % in NDCG5 and 6.62 % in NDCG10. The combination of semantic dependencies, achieved by meta-path-guided relational modelling and the effective utilization of contextual alignment, makes DCRN especially effective in managing sparse and heterogeneous data environments, which are characteristic of real-world e-commerce systems. Essentially, DCRN adds a semantically enhanced, behaviour -sensitive, and context-sensitive framework of recommendations that enhances the insight of multi-intent user behaviours. Extended versions of this work can be done by adding time dynamics of preference evolution over time, adaptive fusion techniques to create cross-domain recommendations and also applying the model to a real-time recommender system to further prove its usefulness in industries.

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