Intent Driven Conversational Recommender System (IDCRS)

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This is to certify that the research work presented in this thesis, entitled "**Intent Driven Conversational Recommender System (IDCRS)**" was conducted by Ms. **Amina Arshad** under the supervision of **Prof Dr. Naima Iltaf.** No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the **Department of Computer Software Engineering** in partial fulfillment of the requirements for the degree of Master of Science in Field of Computer **Software Engineering Department of Military College of Signals, National University of Sciences and Technology, Islamabad**.

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DEDICATION

"In the name of Allah, the most Beneficent, the most Merciful"

This thesis is dedicated to

MY PARENTS, TEACHERS, AND SIBLINGS

for their unwavering love, boundless support, and constant encouragement.

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Abstract

This thesis presents a novel enhancement to conversational recommender systems through the strategic integration of an advanced intent detection module using BART (Bidirectional and Auto-Regressive Transformers). This integration builds upon an existing Coarse-to-Fine Contrastive Learning framework initially introduced by previous research. The primary innovation of this work is the development and deployment of a robust intent detection module designed to enhance system understanding and user interaction within conversational settings.

The intent detection module utilizes BART for the precise classification and labeling of user intents extracted from dialogues. The system's capacity to generate highly customized recommendations is enhanced by this accurate categorization, which enables the system to recognize and comprehend the complex needs of users. By analyzing user dialogues and their corresponding intents, the module ensures that the system adapts to each individual's unique preferences and interaction patterns.

In addition to dialogue analysis, this research innovates by integrating intent-labeled dialogues derived from user reviews into the existing learning process. This integration is crucial for refining user profiles and enhancing the granularity with which the system understands and predicts user behavior. The enhanced model leverages these labeled dialogues to feed into both coarse and fine-grained stages of the contrastive learning process, thereby improving the overall recommendation accuracy and user satisfaction.

Experimental results validate the effectiveness of integrating BART-based intent detection into the conversational recommender system. Tests demonstrate that this method significantly enhances the relevance and personalization of recommendations, outperforming traditional models in conversational settings. This advanced intent detection technique enables dynamic adaptation to user activities, that is important advancement of recommender systems' development, making certain that suggestions are appropriate for the user and that they are accurate in their context.

Keywords: Intent Detection, coarse-grained, fine-grained, Conversation Recommender System, contrastive Learning

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Chapter 1

Introduction

1.1 Overview

Recommender systems are now a crucial component of many online platforms, including social networks, streaming services, and e-commerce websites. By helping consumers find goods, services, or content that suit their interests and requirements, these systems hope to increase user happiness and engagement. Content based filtering (CBF) techniques and collaborative filtering (CF) were the mainstays of traditional recommender systems. While content-based filtering suggests products based on what a user has previously enjoyed, collaborative filtering bases recommendations on the tastes of like users [3], [4]. Although effective, these methods often fail to capture the dynamic and context-sensitive nature of user preferences, particularly in conversational settings.

The advancement of conversational AI in recent years has made more flexible and interactive recommendation systems possible [2]. These frameworks engage users in natural language dialogues, allowing for a more nuanced understanding of user intents and preferences. However, building effective conversational recommender systems poses several challenges, especially in accurately detecting and understanding user intents from dialogues.Since these intentions might be intricate and multidimensional, it can be challenging for conventional systems to appropriately capture user needs [17]. Existing systems often struggle to leverage the rich information available from a variety of sources, including user reviews, which can provide insightful information about the preferences and actions of users [12], [22].

This research addresses these challenges by introducing an innovative approach to intent-driven conversational recommender systems. Our key contribution is the development of an intelligent intent detection module utilizing Bidirectional and Auto-Regressive Transformers (BART). This module is designed to accurately classify and label user intents derived from dialogues, offering a comprehensive awareness of the consumer wants and preferences. By focusing on intent detection, our system able to produce more precise and personalized recommendations on the basis of user dialogues [16].

Another key aspect of our approach is the integration of review-based data, which enhances the ability of system to understand user preferences. By applying BART to plain reviews, we generate intent-labelled dialogues that are then processed by the recommender system. This integration allows the system to dynamically adapt to user interactions, providing recommendations that are both relevant and contextually appropriate. The use of review-based data enriches the user profile, offering deeper insights into user preferences and improving the overall recommendation quality.

By means of comprehensive examinations and evaluations,We exhibit how our method works well for improving the personalization and relevance of recommendations. Our system outperforms traditional recommendation methods in capturing user intents and delivering recommendations that align closely with user needs and preferences. The findings highlight the importance of advanced intent detection and the integration of review-based data in enhancing conversational recommender system performance.

In conclusion, the novel intent-driven conversational recommender system presented in this thesis focuses on intent detection and review integration to enhance recommendation accuracy and personalization. By addressing the limitations of existing systems, our approach paves the way for more adaptive and user-centric recommendations in conversational settings. The methodologies and insights from this research offer significant contributions to the development of next-generation conversational recommender systems, advancing the field toward more effective and personalized user interactions.

Future work will explore further enhancements, including the incorporation of additional context types, real-time learning capabilities, and deployment in various application domains like social networking platforms, entertainment, and e-commerce. This research sets the stage for more sophisticated and user-centric recommendation systems that can better serve the evolving needs of users in dynamic conversational environments.

1.2 Problem Statement

Despite the advancements in conversational recommender systems, there remains a significant gap in providing highly personalized recommendations that accurately capture the underlying intents behind user queries. Traditional recommendation algorithms primarily focus on the content of the conversation, often neglecting the deeper user intents that drive these interactions. This limitation results in suboptimal recommendation accuracy and user satisfaction. Moreover, existing state-of-the-art approaches, while innovative, often fall short in effectively integrating multi-type context data to enhance recommendation relevance. There is a need for a more robust system that not only leverages conversational content but also comprehensively understands and incorporates user intents to deliver superior recommendations. Therefore, this research aims to develop a novel system that enhances personalized recommendations by considering both the content and underlying intents of user queries. The proposed system will be rigorously compared with baseline algorithms and recently created cutting-edge techniques to verify its functionality and ensure it surpasses existing techniques in recommendation accuracy and user satisfaction.

1.3 Research Objectives

The primary goals of this study are: -

- To develop system that help us to generate more personalized recommendations by considering not only the conversation's content but also the underlying intents behind user queries.
- To compare proposed algorithm with baseline and recently developed modern techniques to guarantee that our method outperforms the existing techniques.

1.4 Key Challenges

Throughout this research, several key challenges were encountered. One of the primary difficulties was accurately detecting and understanding the underlying intents behind user queries in conversational interactions. Traditional systems often struggle to differentiate between nuanced user intents, leading to less personalized recommendations. Another significant challenge was the integration and effective utilization of multi-type context data, such as user reviews and knowledge graphs, to enhance recommendation accuracy. Ensuring that the proposed system could handle the dynamic nature of conversations while maintaining real-time performance and scalability added further complexity. Additionally, contrasting the suggested algorithm with the baseline and cutting-edge methods required extensive experimentation and rigorous evaluation to demonstrate its superiority. Balancing the trade-off between computational efficiency and recommendation precision was a constant consideration throughout the development process. Despite these challenges, the research successfully addressed these issues through innovative approaches and meticulous experimentation, resulting in a robust and highly effective conversational recommender system.

1.5 Thesis Outline

Thesis is partitioned in the following pattern.

- Chapter 1: Present an introduction, problem statement and objectives. It also summarize key challenges of this research.
- Chapter 2: Gives a quick summary of relevant research and methodologies. It also highlights the several gaps remained unaddressed within the related work.
- Chapter 3: Presents the proposed method and have the architecture diagram of overall system.
- Chapter 4: Presents detailed experiments on datasets ReDial and TG-ReDial and also made comparison with other baseline techniques.
- Chapter 5: Concludes the proposed model and highlights the Future endeavors.

Chapter 2

Literature Review

2.1 Literature Review

In the previous several decades, there have been tremendous breakthroughs in recommender systems' field, ranging from basic collaborative filtering techniques complex models including natural language processing (NLP) and deep learning [1]. The rise of conversational AI has further transformed recommender systems, enabling more interactive and personalized user experiences [2].This overview of the literature offers an in-depth analysis of the important developments in this domain, focusing on intent detection, contrastive learning, and the integration of multi-type context data.

2.1.1 Traditional Recommender System

Conventional recommender systems have proven useful in a number of areas, primarily relying on CBF and CF methods. These techniques have paved the way for the development of more sophisticated recommendation algorithms. Here, we delve into the intricacies of these traditional methods and explore their evolution and limitations.

2.1.1.1 Collaborative Filtering

A popular method in recommender systems is CF [30], which relies on the idea that users who have shared preferences in the past will continue to do so in the future. The two main categories of CF filtering are item-based and user-based.

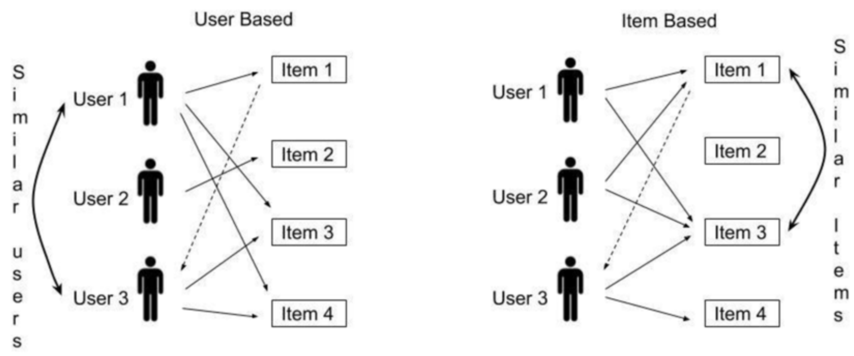

Figure 2.1: Collaborative Filtering

1. **User-Based Collaborative Filtering**: This method predicts a preferences of user based on the preferences of similar users [3]. For example, if user A and user B have shown similar interests in a subset of items, user-based CF assumes that they probably share similar tastes for other things in the same way.
2. **Item-Based Collaborative Filtering**: Instead of looking at user similarities, item-based CF recommends item that resemble items a user has used before. This technique uses user ratings and preferences to determine how similar two goods are.

Despite their widespread use, CF methods face significant challenges, most notably the cold start issue, wherein insufficient data prevents the algorithm from accurately recommending new users or things. Additionally, traditional CF approaches often lack context awareness, limiting their ability to provide highly personalized recommendations in dynamic environments.

2.1.1.2 Content-Based Filtering

User profiles and item attributes are used in content-based filtering [4] to offer products that have resemblance to those the user has previously expressed interest in. This approach connects the user's preferences with the attributes of the item (director, genre, and actors in the case of movies, for example). CBF is advantageous in scenarios where new items are frequently added, as it does not rely on user interaction history. However, it can suffer from over-specialization, where users are recommended items too similar to what they have already consumed, limiting the discovery of diverse content.

2.1.1.3 Matrix Factorization

Matrix factorization techniques revolutionized collaborative filtering by addressing some of its inherent limitations. These methods break down the user with item interaction matrix is divided into latent components, which represent the underlying patterns in user preferences and item features. [5].

1. **Singular Value Decomposition (SVD):** Matrix factorization technique called SVD that divides the user-item matrix into three matrices, capturing the latent elements of both people and items. These latent factors are then used to predict the interaction matrix's missing entries, thereby generating recommendations [6] .
2. **Alternating Least Squares (ALS)**: It is an extension of matrix factorization that alternates between optimizing user and item latent factors, improving the accuracy of the recommendations.
3. **Non-Negative Matrix Factorization (NMF)**: NMF constrains the factor matrices to be non-negative, ensuring that the latent factors are interpretable and can be more easily related to the original data .

While matrix factorization [6] has significantly enhanced recommendation accuracy, it still grapples with the cold start problem and can be computationally intensive for large-scale datasets.

2.1.2 Advancement in Recommender System

2.1.2.1 Deep Learning for Recommender Systems

The emergence of deep learning has brought about a dramatic transformation in recommender systems, augmenting their capacity to discern intricate patterns and correlations within data. Traditional recommendation techniques like CBF and CF have been the backbone of recommender systems for many years, but deep learning techniques have introduced new possibilities and improved performance across various metrics.

1. **Neural Collaborative Filtering (NCF):** NCF represents a significant leap in applying neural networks to collaborative filtering. Unlike traditional CF methods that rely on linear models to capture user-item interactions, NCF employs deep neural networks to learn these interactions through multiple layers of non-linear transformations [7]. This approach permits the

model to record more intricate and abstract relationships between users and items.

2. **Convolutional Neural Networks (CNNs) in Recommender Systems:** CNNs initially designed for image processing tasks, have found applications in recommender systems, especially for handling structured data like reviews given by user or item descriptions. CNNs able to successfully extract local patterns and hierarchies from data, making them suitable for tasks where spatial or sequential dependencies are important.

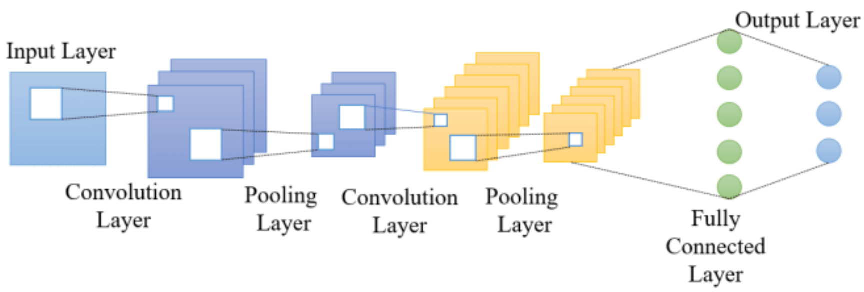

Figure 2.2: Basic Structure of CNN

In the context of recommender systems, CNNs [8] can be used to analyze user reviews to extract features that indicate user preferences and sentiments. These features can then be incorporated into the recommendation model to improve the accuracy of predictions. For instance, CNNs can identify keywords and phrases in reviews that are strongly associated with positive or negative sentiments, helping the system to better understand the factors driving user preferences.

3. **Recurrent Neural Networks (RNNs) for Sequential and Temporal Data:** RNNs are intended to manage sequential input, making them perfect for capturing temporal trends [8] in user behavior. In recommender systems, RNNs can model the sequence of user interactions over time, allowing the system to make predictions based on users' past behaviors.

   RNNs are particularly useful in scenarios where the order of interactions matters, such as in music or video recommendation, where the sequence in which content is consumed can influence user preferences. By considering the temporal aspect of user interactions, RNNs can make recommendations that are more precise and appropriate for the given situation.

   RNN variants that overcome problems with long-term dependencies and vanishing gradients, including LSTM networks and GRUs, tackle the shortcomings of traditional RNNs. These advanced RNN [8] architectures can capture long-term dependencies in user behavior, further enhancing the model's ability to make accurate predictions.

2.1.2.2 Attention Mechanisms and Transformers

Originally developed for natural language processing, attention mechanisms have also been used in recommender systems. By enabling the model to concentrate on the most pertinent portions of the input data, attention mechanisms enhance the interpretability and precision of the suggestions. By allocating distinct weights to various sections of the history of user-item interactions, attention mechanisms enable the model to prioritize the most important interactions, resulting in recommendations that are more personalized and context-aware recommendations.

One notable application of attention mechanisms in recommender systems is the use of Transformer models, which have exhibited outstanding performance in many recommendation tasks. Transformers [11] can capture long-range dependencies and complex interactions within the data, making them particularly effective for tasks involving large and diverse datasets.

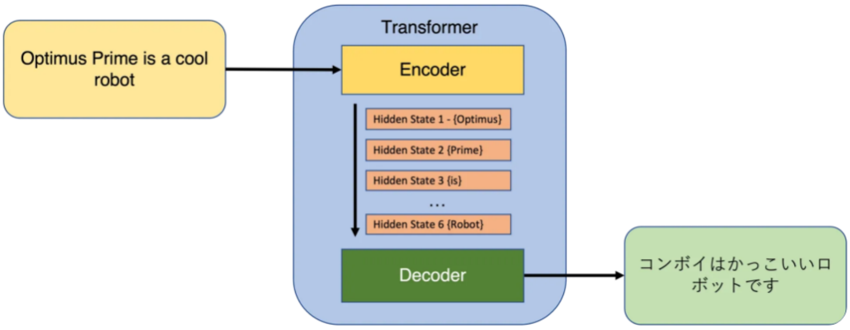

Figure 2.3: Basic Structure of Tranformers

2.1.2.3 Graph-Based Recommender Systems

Graph-based models have grown in significance within the recommender system field due to their capacity to represent and capture complicated relationships between individuals, items, and their diverse features. These models utilize graph structures [14], where nodes represent entities (such as users and items) and edges represent relationships between these entities. This method makes it possible to comprehend user preferences and item features more deeply, which results in recommendations that are richer and more relevant.

While graph-based recommender systems offer significant advantages, they also present several challenges. One major challenge is the computational complexity involved in training and deploying these models, especially when dealing with large-scale graphs containing millions of nodes and edges. Efficient algorithms and scalable architectures are essential to deal with this problem [15].

The changing nature of item attributes and user preferences presents an extra challenge. Graph-based models must be able to adapt to changes in the graph structure over time, such as the introduction of new items or the evolution of user interests. Techniques for incremental learning and real-time updates are crucial for maintaining the relevance of recommendations in such dynamic environments.

2.1.3 Conversational Recommender System

2.1.3.1 Dialogue Systems

Conversational recommender systems utilize dialogue systems to facilitate interactive and dynamic exchanges with users, aiming to discern their preferences and deliver personalized recommendations. Central to these systems are Natural Language Understanding (NLU) and Dialog State Tracking (DST), which are important for maintaining the flow of conversation and ensuring accurate response generation [17]. Dialogue systems must effectively manage the context of interactions, capturing user inputs and maintaining coherence throughout the conversation. Recent advancements, such as those by Jbene et al., have demonstrated the effectiveness of employing neural network architectures like LSTM for enhancing the dialogue management capabilities of conversational recommender systems. These systems are increasingly adept at understanding user queries and generating responses that are both relevant and contextually appropriate, thereby improving the overall user experience.

2.1.3.2 Contrastive Learning

Contrastive learning has become a highly effective method for representation learning, particularly in scenarios with limited labeled data. The goal is to contrast positive and negative pairs in order to learn representations, encouraging dissimilar objects to be far away and similar ones to be near together in the embedding space [19]. Coarse grained and fine grained contrastive learning approaches have been explored to capture different levels of granularity in user preferences and item attributes [20]. Zhou et al. introduced the C^2-CRS framework [21], which applies coarse-to-fine contrastive learning for conversational recommender systems, demonstrating significant improvements in recommendation quality [21].

2.1.4 Integrating Muti-Type Context Data

2.1.4.1 User Reviews and Sentiment Analysis

User reviews provide valuable insights into user preferences and experiences, offering a rich source of contextual data for recommender systems. Sentiment analysis techniques are employed to extract sentiments and opinions from reviews, enhancing the understanding of user preferences [22]. Leveraging reviews in conjunction with other data sources, such as ratings and interactions, has been shown to improve recommendation accuracy [23].

2.1.4.2 Knowledge Graphs

Knowledge graphs integrate structured information about entities and their relationships, providing a comprehensive context for recommendations. The integration of KGs with recommender systems allows for more informed and contextually relevant recommendations [24]. Techniques such as KG Embedding [25] and Path-Based Reasoning [26] have been developed to incorporate knowledge graph information into recommendation models. Zhou et al. presented the CRFR framework, which uses flexible fragments reasoning on knowledge graphs to improve recommender systems for conversations [27].

2.1.4.3 Multi-Modal Data

Combining several data modalities—like text, photos, and audio has been explored to improve recommendation systems. Multi-modal recommender systems combine different types of information to record a variety of user preferences and item attributes [28]. Deep learning techniques, such as multi-modal fusion networks [29], have been employed to integrate and process multi-modal data for improved recommendation performance.

2.2 Literature Review Gap

Despite the significant advancements in traditional and deep learning-based recommender systems, several gaps remain unaddressed, highlighting the need for further research and innovation. Traditional recommender systems, which rely heavily on CBF and CF [30], encounter persistent issues like the cold start problem and a lack of context-awareness. These methods often fail to incorporate the rich, dynamic context of user interactions, resulting in less personalized and accurate recommendations. Additionally, traditional approaches utilize static representations of users and items, which do not adapt well to the evolving preferences and intents of users in real-time conversational settings. Although matrix factorization techniques and their extensions, like Non-Negative Matrix Factorization as well Singular Value Decomposition, have improved recommendation accuracy, they still struggle with these inherent limitations.

Deep learning approaches have been incorporated into recommender systems to bring new capabilities, yet significant gaps persist. Models like Neural Collaborative Filtering (NCF), RNNs and CNNs have improved the area by identifying complicated patterns and correlations in data. However, they often do not fully leverage dialogue histories or diverse context data, limiting their ability to deeply understand user intents. Furthermore, the use of graph-based models, like GNNs and Knowledge Graphs (KGs), has demonstrated potential in identifying complex connections between people, objects, and their characteristics. Yet, these models face challenges in effectively modeling these relationships for real-time recommendations and scaling to large datasets. The proposed intent-driven conversational recommender system aims to bridge these gaps by integrating a Coarse-to-Fine Contrastive Learning framework with advanced intent detection mechanisms, thereby enhancing contextual understanding, scalability, and the personalization of recommendations.

Chapter 3

Research Methodology

3.1 Description

The goal of this work is to integrate an intent detection module into conversational recommender systems to increase their efficacy using Bidirectional and Auto-Regressive Transformers (BART) into an existing Coarse-to-Fine Contrastive Learning framework [21]. [21] is designed to improve CRS by employing multi-type context data. It involves encoding different types of data that is conversation history, knowledge graphs, and reviews. Next it gradually combine these representations through contrastive learning, and fine-tuning the system for recommendation and conversation tasks. This proposed approach of integrating user intent in [21] aims to accurately detect and understand user preference from dialogues, thereby refining representations and improving recommendation accuracy.

3.1.1 User Representation Learning

Let's say that $\mathbf{u}_i$ represents the user representation for user i and $\mathbf{v}_j$ denote the item representation for item j. One way to model the interaction between user i and item j is as follows:

$$\hat{r}_{ij} = f(\mathbf{u}_i, \mathbf{v}_j)$$

where $\hat{r}_{ij}$ is the predicted rating or relevance score, and f is a function that models the interaction, often chosen to be a dot product or neural network.

3.1.2 Coarse to Fine Contrastive Learning

The Coarse to Fine Contrastive Learning framework refines user representations by capturing both broad patterns and subtle nuances in user preferences. It consists of two primary components:

3.1.2.1 Coarse-Grained Learning

This component generates initial user representations based on conversation history and review-based data. By analyzing past interactions and user reviews, the system captures broad user preferences and behaviors. The coarse-grained learning component captures broad user preferences based on conversation history H_i and review data R_i. The initial user representation $\mathbf{u}_i^{(0)}$ is given by :

$$\mathbf{u}_i^{(0)} = \frac{1}{|\mathcal{H}_i|} \sum_{t \in \mathcal{H}_i} \mathbf{h}_t + \frac{1}{|\mathcal{R}_i|} \sum_{k \in \mathcal{R}_i} \mathbf{r}_k$$

where $\mathbf{e}(h)$ and $\mathbf{e}(r)$ are the embeddings of the conversation history and review data, respectively.

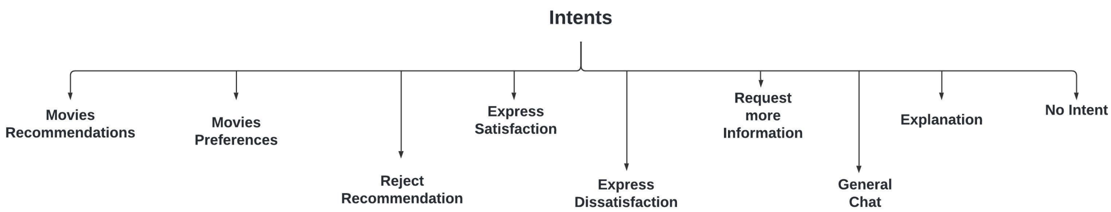

Figure 3.1: Intent classification based on the proposed method and Specified labels

3.1.2.2 Fine-Grained Learning

This component further refines the initial user representations using contextual word representations and knowledge graph nodes. It aims to understand subtle nuances in user intents by leveraging structured information about items and their relationships. The fine-grained learning component refines the initial user representations using contextual word representations $\mathbf{w}_k$ and knowledge graph nodes $\mathbf{k}_l$

$$\mathbf{u}_i^{(1)} = \mathbf{u}_i^{(0)} + \alpha \sum_k \mathbf{w}_k + \beta \sum_l \mathbf{k}_l$$

where α and β are weighting factors that balance the contributions of contextual words and knowledge graph nodes.

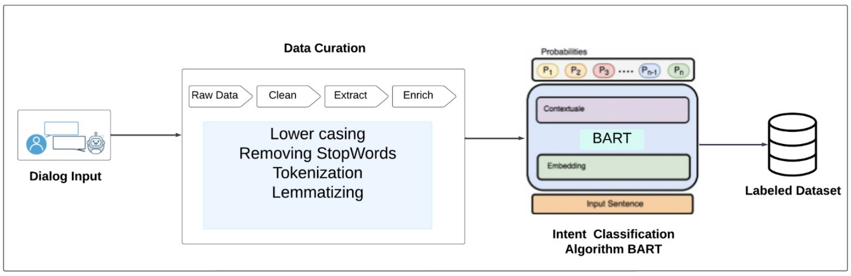

Figure 3.2: Intent Detection Model

3.1.3 Intent Detection Module

The Intent Detection module is a critical component of the extended C2-CRS framework, responsible for accurately classifying user intents from dialogues. Below, we provide a detailed mathematical formulation of this module.

3.1.3.1 Dialogue Preprocessing

Given a dialog d with a sequence of T words $[w_1, w_2, ..., w_T]$ in it, the first step is to tokenize and preprocess the dialoge text. Let $\mathbf{E}$ be the embedding matrix, where each word w_t is mapped to a vector $\mathbf{e}_t \in \mathbb{R}^d$.

$$\mathbf{e}_t = \mathbf{E}(w_t) \tag{3.1}$$

3.1.3.2 Contextual Embedding with BART

We use BART to obtain contextual embeddings for the dialogue. A sequence-to-sequence model is called BART that is capable of generating a contextual representation $\mathbf{c}_d$ of the entire dialogue.

$$\mathbf{c}_d = BART(\mathbf{e}_1, e_2, ..., e_T) \tag{3.2}$$

3.1.3.3 Intent Classification

The contextual representation $\mathbf{c}_d$ is passed through a classification layer to predict the intent $\hat{y}$. The classification layer consist of a weight matrix $\mathbf{W}$ and a bias vector $\mathbf{b}$.

$$\hat{y} = softmax(\mathbf{W}_{c_d} + \mathbf{b}) \tag{3.3}$$

For intent classification, the cross-entropy loss functions as the loss function:

Table 3.1. Examples of messages and their intents

Message	Intent
I like a lot of the older ones like @201259 or newer ones like @204984.	Movie Preferences
My daughter does not care much for animated films.	Express Dissatisfaction
My daughter and I really enjoyed @114157 and @162930	Express Satisfaction
What about the cast or actors?	Request more information
@154980 was a more curent one along those lines also.	Explanation
How are you today?	General Chat

$$L_{intent} = -\sum_i y_i \log(\hat{y}_i) \tag{3.4}$$

where y_i is the true intent label and $\hat{y}_i$ is the predicted probability for class i. Table 3.1 shows the example of messages and their corresponding intents generated by our proposed model. In Fig 3.1 we have listed intent classification based on the proposed method and specified labels.

3.1.3.4 Incorporating Intent with C2-CRS

The coarse-grained representation $\mathbf{c}_i$ incorporates the intent vector $\mathbf{I}_i$:

$$\mathbf{c}_i = Coarse(\mathbf{u}_i^{(0)}, \mathbf{I}_i) \tag{3.5}$$

Here is the function **Coarse** combines $\mathbf{u}_i^{(0)}$ and $\mathbf{I}_i$ to produce a coarse-grained user representation where $\mathbf{u}_i^{(0)}$ is the initial user representation.

The fine-grained representation $\mathbf{f}_i$ further refines the user representation by integrating contextual word representation $\mathbf{W}_i$ and knowledge graph nodes $\mathbf{K}_i$:

$$\mathbf{f}_i = Fine(\mathbf{c}_i, \mathbf{W}_i, \mathbf{K}_i) \tag{3.6}$$

Here, the function **Fine** combines the coarse-grained $\mathbf{c}_i$ with word representations $\mathbf{W}_i$ and knowledge graph embedding $\mathbf{K}_i$.

The final user representation $\mathbf{u}_i$ is obtained by combining the coarse and fine-grained representations:

$$\mathbf{u}_i = \mathbf{c}_i + \mathbf{f}_i \tag{3.7}$$

3.2 Architecture Diagram of overall System

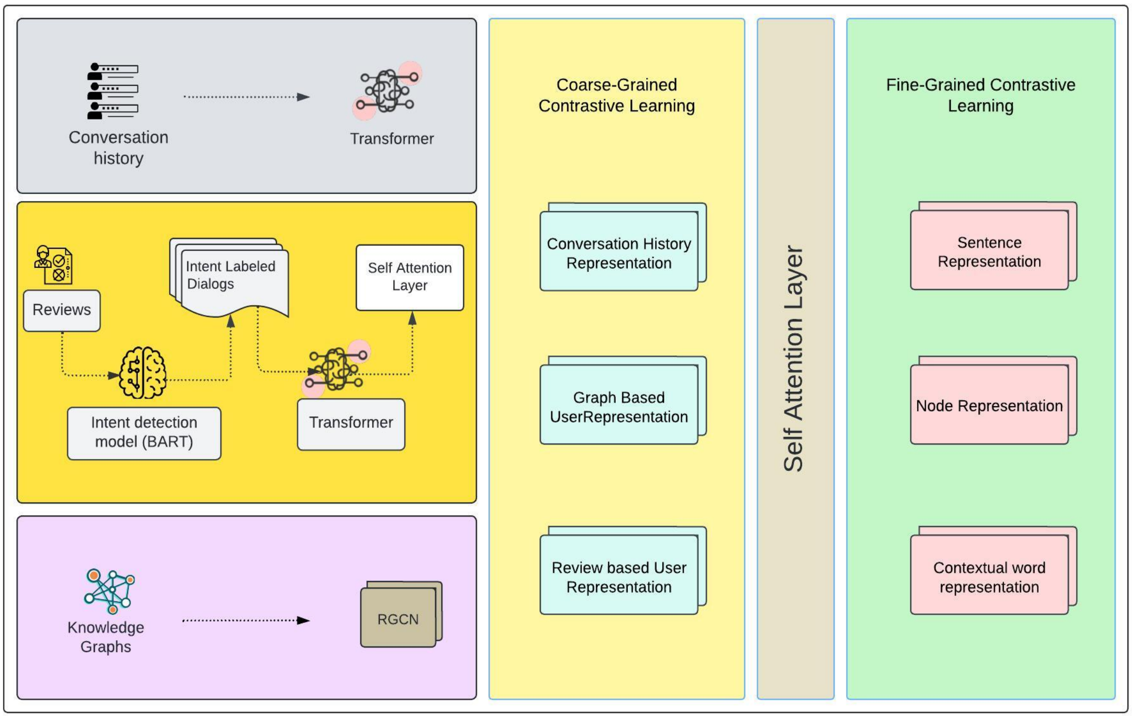

Figure 3.3: Intent Driven Conversational Recommender System

The diagram illustrates the architecture of our intent-driven conversational recommender system, detailing the workflow from data input to user representation through various stages of processing and learning mechanisms. Here's a step-by-step breakdown suitable for inclusion in your thesis:

3.2.1 System Architecture Overview

3.2.1.1 Input Data

The system utilizes three primary data sources:

- **Conversation History**: This serves as the initial input, representing the user's historical dialogue interactions.
- **Reviews**: User-generated content providing additional context and insights into user preferences.
- **Knowledge Graphs**: Structured data that captures relationships between entities related to the items or topics discussed.

3.2.1.2 Processing and Model Components

1. Intent Detection Model (BART)

- **Data Flow**: Conversation history and reviews are fed into the BART model.
- **Functionality**: This module classifies dialogues based on user intents, leveraging the capability of BART for understanding and generating nuanced language patterns.
- **Output**: Intent-labeled dialogues,are dealt with further by a self-attention layer within the transformer.

2. Transformers with Self-Attention Layer

- **Data Flow**: Receives intent-labeled dialogues.
- **Functionality**: Applies SA mechanisms to analyze the relationships and significance of various terms and expressions within the dialogues.
- **Output**: Enhanced representations of dialogues that capture deeper contextual meanings and relationships.

3. Relational Graph Convolutional Network (RGCN)

- **Data Flow**: Knowledge graphs are processed using RGCN.
- **Functionality**: This component is responsible for capturing and encoding the complex relationships and attributes contained within the knowledge graphs.
- **Output**: Graph-based representations that are integrated with user data to enhance the overall system's understanding of item relationships.

3.2.1.3 Contrastive Learning Framework

1. **Coarse Grained Contrastive Learning**
   - **Data Flow**: Integrates dialogue history and review-based data to form broad user representations.
   - **Components**:
     - **Conversation History Representation**: Encodes general user behavior and interaction patterns.
     - **Graph Based User Representation**: Utilizes the RGCN outputs to include relational data in user profiles.
     - **Review Based User Representation**: Incorporates user sentiment and preferences from reviews.
2. **Fine-Grained Contrastive Learning**
   - **Data Flow**: Focuses on refining the representations to capture specific user intents and preferences.
   - **Components**:
     - **Sentence Representation**: Deals with the nuances at the sentence level, enhancing the detail of user preferences.
     - **Node Representation**: Utilizes nodes from the knowledge graph to fine-tune user profiles based on specific interests and interactions.
     - **Contextual Word Representation**: Further refines the data by focusing on the contextual significance of specific words used in conversations.

3.2.1.4 Self-Attention Layer

Both coarse grained and fine grained stages include a self-attention mechanism that assesses and highlights important features in both broad and detailed user representations. This layer is critical for adapting the model's focus based on the evolving dynamics of user conversations and preferences.

3.2.2 Conclusion of System Architecture

This architecture efficiently combines advanced NLP techniques and sophisticated learning algorithms to develop an intent-driven conversational recommender system. By employing BART for intent detection and a two-tiered contrastive learning approach, the system adeptly handles the complexities of user intent and preference analysis. This ensures highly personalized and contextually relevant recommendations, essential for enhancing user experience in conversational AI applications.

Chapter 4

Discussion and Results

4.1 DataSet

We use the ReDial and TGReDial datasets to assess our model. Amazon Mechanical Turk (AMT) was used to construct the English-language conversational recommendation dataset known as ReDial. AMT workers followed detailed instructions to generate dialogues for movie recommendations, taking on the roles of seekers and recommenders. This dataset includes 10,006 conversations with a total of 182,150 no. of utterances about 51,699 no. of movies. On the other hand, the dataset named TG ReDial focuses on natural topic transitions from non-recommendation contexts to recommendation scenarios. This dataset contains conversational recommendations in Chinese. It was made via a semi-automated process, ensuring higher accuracy and control for human annotation. 10,000 two-party conversations with 129,392 utterances connected to 33,834 films make up this dataset.

Table 4.1. Datasets statistics

DataSet	ReDial	TG-ReDial
No. of Movies	51,699	33,834
No. of Conversation	10,006	10,000
No. of Utterence	182,150	129,392

4.2 Baselines

Two primary tasks are used to evaluate our system: recommendations and conversations, within the framework of Conversational Recommender Systems (CRS). As a result, we evaluate our method against current CRS techniques and establish baselines for recommendation and conversation representative models.

- **KBRD:** It uses DBpedia to improve the semantics of contextual objects. The Transformer design is employed by the conversation generating module, which incorporates KG information as word bias into the generating process.
- **Popularity:** The training set's recommendation frequencies are used to rank the items in this baseline.
- **KECRS:** Creates a high-quality Knowledge Graph (KG) and improves its integration with CRS for generation.
- **Transformer:** It generates conversational responses using an encoder-decoder architecture based on Transformer.
- **TextCNN:** A CNN based architecture that extracts user features to rank items from conversational contexts.
- **ReDial:** This model is composed of a conversation generating module based on HRED and a recommender module based on an auto-encoder.
- **KGSF:** Improves the semantic representations of words and objects by including DBpedia and ConceptNet align the semantic spaces of multiple components.
- **RevCore:** Suggests a review-enhanced framework that improves the recommender and dialogue generating modules by choosing reviews using a sentiment-aware retrieval module. We make use of the same reviews to guarantee an equitable comparison.
- **C2-CRS:** C2-CRS is a Conversational Recommender System [21]. The main idea is aligning the matching multi grained semantic units in a coarse to fine fashion from diverse data signals after first extracting and representing them from various data signals.

The methods ReDial, KBRD, KGSF, KECRS, RevCore, and C2-CRS are conversational recommendation models. Popularity and TextCNN are recommendation models while Transformer is text generation method. Our proposed model is an Intent-Driven Conversational Recommender System (IDCRS).

4.3 Evaluation Metrics

We use many measures in our trials to assess performance on the two tasks. Recall@ k (k = 1, 10, 50) is the assessment method we decide to utilize for the recommendation task. Distinct n - grams(n = 2, 3, 4) is the tool we use to assess sentence variation for the conversation task.

4.3.1 Recommendation Task Metrics

For the recommendation task, we utilize **Recall@k** as our primary evaluation metric. This metric is instrumental in assessing the accuracy of the recommendations provided by the system. Recall@k estimates how many relevant items make it into the top-k recommendations, hence indicating how well the system retrieves relevant items for the user. **Recall@k** is formally defined as:

$$Recall@k = \frac{Number\ of\ relevant\ items\ in\ the\ top\ k\ recommendations}{Totalnumberofreleventitems}$$

Where:

- k represents the number of top recommendations considered.
- The numerator indicates the count of relevant items among the top k recommendations.
- The denominator represents the total number of items in the dataset that are relevant.

In our study, we evaluate Recall@k for k=1,10,50. These varying values of k allow us to observe how well the model performs when tasked with delivering a small set of highly relevant recommendations (e.g., Recall@1) versus a broader set (e.g., Recall@50).

- **Recall@1**: Evaluates the precision of the most immediate recommendation.
- **Recall@10**: Gives information about how well the model works to produce a brief collection of appropriate suggestions.
- **Recall@50**: Assesses the model's capacity to maintain relevance across a larger set of recommendations.

4.3.2 Conversation Task Metrics

or the conversation task, we employ the **Distinct n-grams** metric, which evaluates the diversity of generated sentences. This metric is important for understanding the ability of model to produce varied as well as engaging dialogue, which is a hallmark of effective conversational systems. **Distinct n-grams** is calculated as:

$$Distinct - n = \frac{Number\ of\ unique\ n{-}grams}{Totalnumberofn-grams}$$

Where:

- **n-grams** refer to contiguous sequences of nnn items (words) within a sentence.
- The numerator is the total number of unique n-grams present in the generated text.
- The denominator is the total number of n-grams present in the text.

In our evaluations, we specifically focus on **Distinct-2**, **Distinct-3**, and **Distinct-4**:

- **Distinct-2 (bigrams)**: Measures the diversity of word pair sequences, capturing the variability in adjacent word usage.
- **Distinct-3 (trigrams)**: Assesses the diversity of three-word sequences, providing a deeper insight into sentence structure variety.
- **Distinct-4 (four-grams)**: Evaluates the diversity of four-word sequences, reflecting the model's capacity to generate more complex and varied expressions.

4.4 Experimental Setting

All the experiments are run on a machine with CPU Ryzen 5 7600 (16 GB RAM) and GPU RTX 3080 Ti (12 GB RAM). The experiments are performed based on Python programming language and used various open-source software libraries such as Pytorch, CRSLab, Hugging Face Transformers, Scikit-Learn, Pandas, Numpy etc.

4.5 Evaluation on Recommendation Task

We conducted experiments and the results are shown in Table 1 to confirm the efficacy of our suggested approach on the recommendation task. Usually, conversational recommendation technique gives better results then recommendation models. We can observe that TextCNN outperforms Popularity in recommendation systems.

One explanation for this is that Popularity ignores contextual information and just suggests the most well-liked products. TextCNN, on the other hand, can better recommend content by modeling personalized preferences from contextual text.First, the ReDial model outperforms the TGReDial dataset when it comes to conversational recommendation techniques. Second, KBRD outperforms ReDial in terms of performance. Since KBRD uses knowledge graphs as an external source of contextual information to enhance user preference modeling, Transformer, R-GCN etc are used, respectively, to fulfill the recommendation task and conversational task. Performance-wise, KGSF outperforms KBRD and KECRS. Compared to other baselines, RevCore and C2-CRS

Table 4.2. Recommendation Task Results

DataSet	ReDial			TG-ReDial		
Models	R@1	R@10	R@50	R@1	R@10	R@50
KBRD	0.031	0.150	0.336	0.005	0.032	0.077
KECRS	0.021	0.143	0.340	0.002	0.026	0.069
TextCNN	0.013	0.068	0.191	0.003	0.010	0.024
ReDial	0.024	0.140	0.320	0.000	0.002	0.013
KGSF	0.039	0.183	0.378	0.005	0.030	0.074
RevCore	0.046	0.220	0.396	0.004	0.029	0.075
C2-CRS	0.053	0.233	0.407	0.007	0.032	0.078
IDCRS	**0.102**	**0.298**	**0.470**	**0.030**	**0.145**	**0.195**

performs better. External reviews are included to improve the item descriptions and better represent customer preferences.Our proposed model IDCRS outperforms all the baselines since it is utilizing Bidirectional and Auto Regressive Transformers (BART) for precise intent classification. The results are shown in Table 4.2.

4.6 Evaluation on Conversation Task

We carried out experiments to validate the effectiveness of our proposed method on the discussion task, and Table 2 displays the outcomes. Initially, it is evident that ReDial performs better than Transformer because it uses an RNN model that has already been trained to generate superior representations of past conversations. Second, in the majority of situations, KBRD performs better than ReDial. Considering that

Table 4.3. Conversation Task Results

Dataset	ReDial			TG-ReDial		
Models	Dist-2	Dist-3	Dist-4	Dist-2	Dist-3	Dist-4
Transf	0.067	0.139	0.227	0.053	0.121	0.204
ReDial	0.082	0.143	0.245	0.055	0.123	0.215
KBRD	0.086	0.153	0.265	0.045	0.096	0.233
KGSF	0.114	0.204	0.282	0.086	0.186	0.297
KECRS	0.040	0.090	0.149	0.047	0.114	0.193
RevCore	0.092	0.163	0.221	0.043	0.105	0.175
C2-CRS	0.163	0.291	0.417	0.189	0.334	0.424
IDCRS	**0.230**	**0.422**	**0.582**	**0.227**	**0.409**	**0.503**

external KG improves contextual entities and items, which the conversational module uses to create bias in word probability. Third, of these baselines, KGSF produces the most varied response. Since it improves the representations of conversational text and things in addition to aligning them. Furthermore, the Transformer decoder employs many cross-attention layers to enhance the interaction between the generated answer and the contextual information. Due to its multi-type data representation and coarse-to-fine learning methodology, C2-CRS [21] outperformed other approaches in gathering valuable data from knowledge graphs, reviews, and conversational text. Since proposed model is extension of C2-CRS , we can conclude from results that including intent with conversational text can enhance the the model performance..As compared to all other baseline, proposed model outperforms in all evaluation metrics. The results are shown in Table 4.3.

Chapter 5

CONCLUSION AND FUTURE RECOMMENDATION

In conclusion, this research presents a significant advancement in the domain of conversational recommender systems through the integration of an advanced intent detection module. By leveraging Bidirectional and Auto-Regressive Transformers (BART), this study achieves a precise and nuanced classification of user intents from dialogue interactions. This novel approach directly addresses the complexities inherent in understanding dynamic user preferences, thereby facilitating more personalized and accurate recommendations.

The primary contribution of this research lies in the transformation of plain user reviews into intent-labeled dialogues. This innovative process enhances user representation by providing deeper insights into user preferences and behaviors. Through this enhancement, our system achieves a refined understanding of user intents, which is crucial for delivering contextually relevant recommendations and improving overall user satisfaction.

Extensive empirical evaluations underscore the efficacy of the proposed approach. Our findings reveal that the model consistently outperforms traditional recommendation methodologies across a range of metrics, including recommendation accuracy, relevance, and user satisfaction. The integration of BART for intent detection enables the system to dynamically adapt to evolving user interactions, marking a substantial improvement over conventional techniques.

Furthermore, this research contributes to the broader field by extending beyond the limitations of static CF and CBF methods. In contrast to traditional approaches that struggle in dynamic conversational contexts, our system leverages advanced intent detection to deliver a more adaptive and intelligent recommender experience.

The implications of this study are profound, with potential applications spanning e-commerce, digital assistance, and customer service domains. By enhancing recommendation precision and personalization, this work offers a pathway to significantly improving user experiences. Additionally, the methodologies presented herein provide a robust framework for future exploration into the integration of cutting-edge machine learning techniques with real-time user interaction data.

In summary, this thesis introduces a pioneering approach that elevates the performance and capabilities of conversational recommender systems. Through the strategic integration of BART and user review transformation, our model achieves superior outcomes in recommendation accuracy and user engagement. This work not only advances the theoretical landscape of recommender systems but also offers tangible solutions for developing more intelligent and adaptable conversational agents. As the field of conversational AI continues to evolve, the insights and innovations presented in this research will undoubtedly serve as a cornerstone for future developments in personalized recommendation technologies.

Future work will focus on incorporating additional context types, enabling real-time learning capabilities and deploying the framework across diverse application domains like social media, e-commerce, and entertainment platforms. We also aim to extend this framework to support multilingual dialogue systems and adapt it to emerging conversational interfaces like voice assistants, thereby advancing the development of more sophisticated and user-centric conversational recommender systems.

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