CONDITIONAL-AWARE SEQUENTIAL TEXT GENERATION IN KNOWLEDGE-ENHANCED CONVERSATIONAL RECOMMENDATION SYSTEM

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ABSTRACT

Conversational Recommender System (CRS) has become an emerging application that enables user interactions to determine their products or services. An integrated dialog and recommender system design in the CRS necessitates further development in the text generation process to suggest a richer set of textual content during interaction without compromising the recommendation quality. The existing CRS research solutions neglect the provision of the proper guidance to the user until they obtain suggestions for their desired products or services. Even though multi-turn conversational recommendation models guide the users by utilizing their static and dynamic preferences, modeling a recommender system with the desired response as the recommendations is challenging. In addition, providing a recommendation at fewer turns is significant to avoid too many irrelevant turns during the conversation. Hence, the dialog system needs to precisely generate the preference-aware response utterances for a successful recommendation within a minimal set of turns. Thus, this work aims at enhancing the dialog system by associating a Conditional-Aware decision-making process in CRS, namely, **CA**CRS that ensures an optimal transition between the non-recommendation case, referring to the reply utterance generation and recommendation case, referring to the recommendation list generation. The proposed CRS utilizes both the static or historical and dynamic conversations and the external Knowledge Graph (KG) to extract the user preferences by the recommender system and generate the response utterances by dialog system. In the proposed system, the dialog module is responsible for generating the response utterances by the sequential deep learning model and enforcing the optimal transition in the multi-turn conversation by contemplating the preference correlation between the static and dynamic conversation-based recommendations. Thus, the proposed system accurately suggests the final response utterance tagged with the recommended product or service to the users in the CRS through the knowledge-guided recommender system and dialog system.

Keywords: *Recommendation System, Dialog System, Conditional-Aware, Decision-Making, Knowledge Graph, And Optimal Transition.*

1. INTRODUCTION

With the increasing usage of e-commerce service platforms in the daily life of internet users, Conversational Recommender Systems (CRS) have become an emerging research topic in recent years [1]. It targets generating potential interest in items through interactive conversations with users. CRS comprises the recommendation module, and the dialog response generation module facilitates individuals' decision-making by estimating their interests and preferences. Initially, the recommendation module extracts the user preferences according to their interests and recommends a list of preferred items. Consequently, the dialog generation module generates diverse responses based on the input dialog content and predicted list of items from the recommendation module. Moreover, the dialog generation module provides contextual information containing dynamic user preferences and enhances the quality of recommendations, and the recommendation module promotes the multi-turn dialog to accomplish recommendation-related tasks

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and goals [2]. Therefore, a conversational recommender-based dialog system has high potential because it combines the recommender system and the dialog system and generates responses for guiding users or provides explanations for item suggestions that involve the user's timely feedback.

Several researchers have improved CRS performance by incorporating external Knowledge Graphs (KG) [3]. However, most of the existing CRS researchers fail to guide the proper conversation between the user and dialog system, leading to an inappropriate transition from Non-Recommendation Case (NRC) to the Recommendation Case (RC) [4]. In addition, building an effective text generation model for generating sequential responses or providing item suggestions is a highly crucial task [5]. In the CRS, triggering from NRC to RC based on extracting preferences from historical conversations alone becomes inappropriate [6]. Hence, it is necessary to consider the preference information in the historical conversations and the current conversation context. Also, deciding the optimal transition point in the multi-turn conversation system is challenging due to the irrelevant generation of response utterances from the text generation model.

Thus, this paper enhances the dialog generation system in CRS by presenting a conditional-aware decision-making process to generate recommendations with the assistance of KG and a sequential deep learning model. Enriching the recommendation and dialog modules in CRS based on incorporating dynamic knowledge through interactive conversations ensures accurate dialog responses or suggestions. Moreover, this research work enforces the optimal transition and makes the final decision as dialog aware recommendation through the correlation analysis among the static and dynamic preference knowledge extraction from the recommendation module.

The main contributions of this work are stated as follows,

- ❖ This work intends to design an enhanced dialog generation system with Conditional-Aware decision-making (CACRS), in CRS that provokes the optimal transition for suggesting a final recommendation.
- ❖ The CACRS system generates response utterances for NRC and RC. For NRC, it employs the sequence of conversations with mentioned entities extracted from the dialog utterances and knowledge-based item entities from the recommendation module to generate reply utterances, and for RC, it employs the sequence of conversations with mentioned entities extracted from the dialog utterances and the recommended list of user's preferred items from the recommendation module to generate suggestions.
- ❖ It designs conditional-aware decision-making to naturally transit towards RC from multi-turn conversations.
- ❖ Moreover, the proposed system extracts the knowledge-based item entities through Relational Graph Convolutional Network (R-GCN) and generates target text using a sequential deep learning model as a Conditional Variational Auto Encoder (CVAE) with an LSTM model.
- ❖ By designing the conditional-aware decision-making process, the proposed system generates a dialog-aware recommendation based on the correlation analysis among the static and dynamic preference-based recommendations.

2.Related Work

This section briefly reviews the existing research works on multi-turn conversational dialog-based text generation, and multi-turn conversational recommendation-based text generation approaches using learning models.

2.1 Multi-turn conversations based text generation approaches

The research work [7] proposed a hierarchical attention topic model (HAT) to generate contextual responses from multi-turn dialogs using word-level attention, context-level attention, and topic attention in a hierarchical neural network. After obtaining the sentence-level representation of dialog context utterances using the GRU layer, it computed attention weights for each word and obtained the context-level representation. By employing the Latent Dirichlet Allocation (LDA) topic model, this work extracts the topic words representation of the historical dialog content, and finally, this work combines the topic representation with the context representation and obtains the contextual dialog responses from the decoder model. A Context-Controlled Topic-Aware neural response generation (CCTA) model [8] employs a Hierarchical neural network for the context-controlled topic transition toward response generation in open-domain dialog systems. It captures the semantic relationship between topic words and corresponding dialog contextual utterances and generates the context-dependent topic representation at the word and turn levels using recurrent encoders in a Hierarchical neural network. Consequently, this work obtained the potential transition words from contextual topic words through transition weight prediction, transition word selection, and representation. By concatenating context attention, topic attention, and transition attention representation, the decoder model effectively dialog responses. The Context-Sensitive Generation Approach [9] utilizes a hierarchical network with static and dynamic level utterance attention mechanisms and generates open-domain conversational responses. Employing the static and dynamic attention mechanism in the GRU network weighted the importance of each utterance in the dialog context and obtained the contextual utterance representation. Researchers in [10] proposed the ReCoSa model using the response and context self-attention mechanism in the LSTM network to detect relevant dialog context for dialog response generation. After extracting the word-level representation of each context from the encoder, this work designed the self-attention mechanism and obtained the context and masked response representations. Finally, it computes the attention weight to two representations and generates the responses based on related dialog context.

2.2 Multi-turn Conversational Recommendation based text generation approaches

The research work [11] builds the Deep Conversational Recommender (DCR) model using the seq2seq model with a topic model to generate informative responses in the travel domain. It employs a pre-trained LDA model and extracts the travel domain's sub-topics, facilitating the generation model to generate a within-topic response from the input dialog utterances. This work leverages Graph Convolutional Network (GCN) as a recommendation model to analyze and generate the venue recommendations scores based on the relationship between the venue representation and input dialog context representation. By integrating the topic model output and GCN model output, the pointed integration mechanism in the GRU model effectively generates the dialog responses. By modeling the goal-aware sequence in the goal-aware CRS system, researchers in [12] generate utterances based on designing the Interest-level Star Knowledge Graph and a hierarchical Star Transformer. After extracting the explicit KG entity relation representations from the R-GCN model, this work adopts the star graph neural network (SGNN) to embed the encoded implicit relation between interest entities in the constructed interest-level star knowledge graph obtain the entire interest sequence representation in the dialog context. With the help of an interest-level star graph, the sequence encoder generates the recommendation goal, and a Hierarchical Star Transformer generates the utterances based on goal-oriented recommendation and dialog utterances. The Knowledge-Based Recommender Dialog (KBRD) system [13] employs KG as DBpedia to ground the knowledgeable information in the recommendation and dialog generation system to improve the performance of the CRS system. By incorporating the mentioned item entities in dialog contents and the non-items in dialog contents extracted from the DBpedia source, the R-GCNs model generates the knowledge-enhanced entity hidden representation for the dialog context.

The Knowledge Graph-based Semantic Fusion approach (KGSF) [14] incorporates two KG's involved word-oriented as ConceptNet and entity-oriented as DBpedia in dialog and recommender systems to enhance the dialog context representation for effective response generation. It employs GCN and GCN to generate word-level and entity-level semantic representation and adopts the Mutual Information Maximization method to align these two representations to obtain the semantic representation. Based on the learned representation from the two KGs, the recommendation and dialog system generates accurate recommendations and dialog responses to the utterance text.

3.THE PROPOSED METHODOLOGY

With the explosion of information in this digital era, seeking and making decisions about significant information is highly difficult. The recent rise of CRS provides potential insights since eliciting the user's preference according to their required goals facilitates individual decision-making through natural language conversations. Nowadays, text generation system plays a significant role between users and recommender system by providing utterances for interactive conversations through a dialog system.

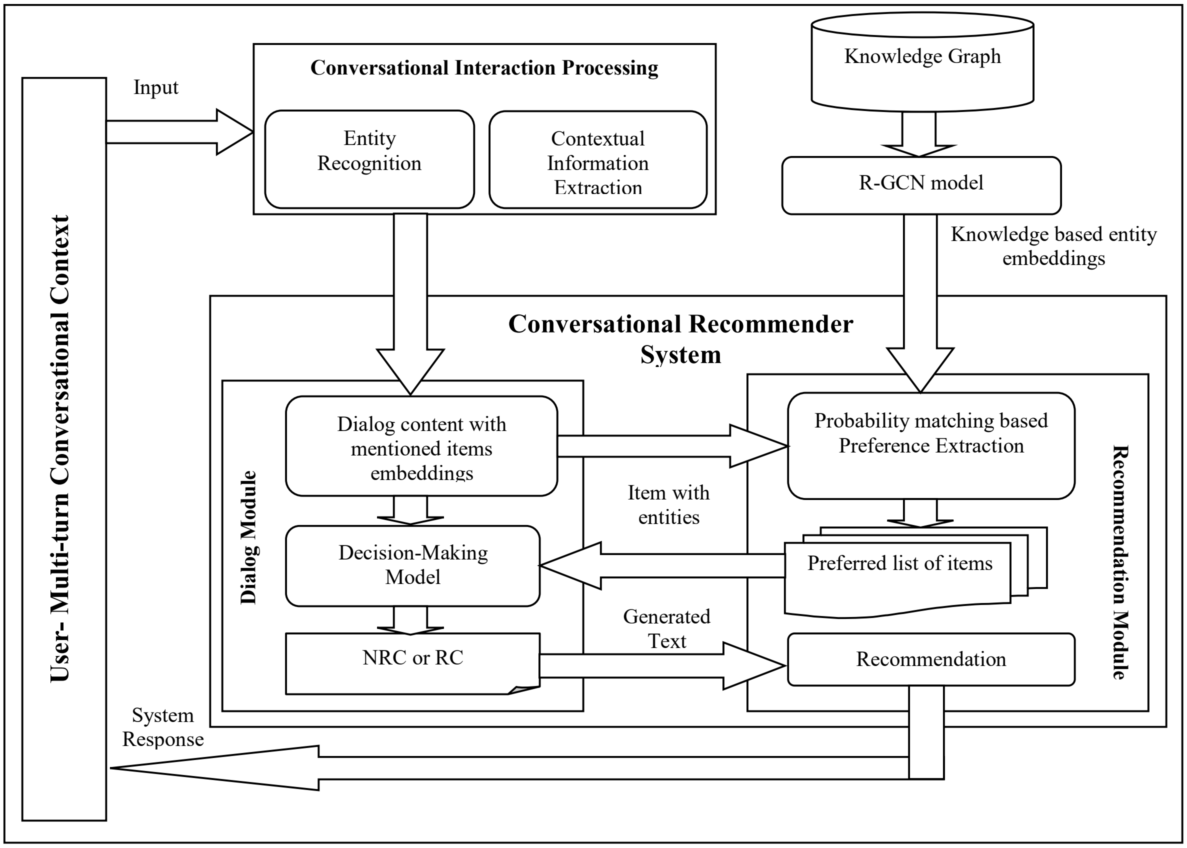

Figure 1: An Outline of the proposed methodology in the CRS system

The overview of the proposed methodology in the CRS system is depicted in figure 1, comprised of two modules: The recommendation module and the Dialog module. The CACRS initially analyzes the input multi-turn conversational context based on conversational interaction processing and extracts the contextual dialog information through a Named Entity Recognition (NER) based preprocessing method. In the recommender module, the CACRS aims to predict the user-preferred list of items using extracted dialog contextual information from the interactive conversations and their corresponding domain knowledge information extracted from the external KG. In the Dialog module, the proposed system initially represents the dialog content with mentioned entities based on the interactive conversations and makes decisions based on the preferred list of items and entities extracted from the recommendation module. Subsequently, it generates target text as a reply utterance or recommendation using a deep sequential model based on conditional-aware decision-making for the transition from NRC to RC. By utilizing static and dynamic-based multi-turn conversations, the conditional-aware decision-making in the CACRS system measures the correlation between the static and dynamic preference-based recommendations to generate the final decision as a dialog-aware recommendation.

3.1 Conversational Interaction Processing

The proposed methodology analyzes the multi-turn conversational context and extracts the users' preferences through the NER-based preprocessing method. It leverages the NER method to extract the inherent preferences of mentioned entities since users' preferences are highly reflected in item entities in the conversational context utterances. By applying the NER method in a multi-turn conversation context, U={u_1,u_2,…,u_n }, the proposed methodology recognizes and segments the named entities with tags involving Person (PER), Geographical Entity (GPE), Organization (ORG),

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and among others, represented as, U῾={x_1 (t_1),x_2 (t_2),…,x_n (t_n)}, where, x_1,x_2,…,x_n and t_1,t_2,…,t_n represents the utterance words and their corresponding IOB tags, respectively. Consequently, it utilizes a Linked Open Data (LOD) source to match the tagged entities obtained from the preprocessed context utterance (U῾) with the raw conversation context (U) and extracts the highly mapped set of mentioned item entities represented as, S={e_1,e_2,…,e_n }, where 'S' denotes the extracted mentioned item entity set in each conversation context utterance (U). The proposed system extracts the mentioned item from the dialog content, and its feature representation of the dialog content (UI) with the concern of mentioned entities is formulated as,

$$U_I \subset R^{d_t} \quad (1)$$

In equation (1), U_I denotes the dialog content with mentioned item entities representation.

3.2 Recommendation Module

In this module, the proposed methodology targets generating a preferred list of items for recommendation in CRS by utilizing the mentioned entity representation extracted from the dialog content and the knowledge-based entity representation.

3.2.1 Knowledge-based entity representation and Recommendation

Traditional CRS solely depends on the explicit KG-based entity relations and fails to incorporate the implicit entity relations that provide information about the user's preferences in the conversational context. Hence, the proposed CACRS employs the item-based KG to obtain the relevant entities for extracting the users' preferred list of items. Afterward, it maps the extracted mentioned item entities with the entities in KG, providing implicit entity relations and leveraging the suggestion of the preferred list of items.

The proposed methodology employs the item-oriented KG as LOD, which comprises a set of entities and entity relations to encode the knowledge-based entities using a Relational Graph Convolutional Network (R-GCN) [15]. In R-GCN, each node receives the information from its neighboring nodes and aggregates the node information through hidden layers. Subsequently, it combines the information with its hidden representation to form its updated representation at the next layer. By applying the R-GCN model, the CACRS obtains the knowledge-based entity representation (H_E) at the l-th layer represented as,

$$H_E \in R^{|\varepsilon| \times d} \quad (2)$$

From the dialog content with mentioned item entities representation (U_I) and learned knowledge-based user entity representation (H_E), the proposed methodology computes the matching probability between the embeddings to obtain the preferred entities. As modeled in Equation (3), in the recommendation model, the probability computation performs the inner product between the dialog content with mentioned item entities representation (U_I) and the knowledge-based entity representation (H_E).

$$P_{rec} = Softmax\,(H_E \cdot U_I) \quad (3)$$

Where, H_E denotes the hidden representation of the learned item entities. Hence, from equation (3), the proposed methodology ranks all the item entities based on a higher probability for the recommendation. Then, the recommender system suggests the desired list of items based on the extracted preferences.

3.3 Dialog Module

The dialog module aims to generate the target text as a reply utterance or recommendation to the user from the predicted set of items and the interaction sequence of dialog utterances. The proposed methodology designs the dialog module based on conditional-aware decision-making toward the transition from non-recommendation to the recommendation. The dialog module utilizes static and dynamic interactions for the final decision-making through the correlation between the static and dynamic preference-based recommendation items obtained from the recommender module.

In the conversational recommendation system, appropriate recommendations are dialog context-dependent and rely on the text generation system. Conversations between the user and the generated system begin with the NRC, that is, reply utterance generation to the user based on historical conversations. Hence, extracting the user's preference information according to the static conversational context of previous historical conversations leads to an inappropriate decision for recommendations. Ignoring the user's current preference information from the dialog context and the corresponding domain knowledge information from the KG tends to result in the inaccurate generation of recommendations. Conversations from the NRC that ask more questions to the users assist the understanding of the users' interests and facilitate the accurate generation of recommendations. Therefore, the proposed CACRS enriches the knowledge-based preference extraction in a semi-automatic manner. Semi-automatic knowledge enrichment is the automatic incorporation of dynamic contextual knowledge from the interactive conversational context and the updation of the extracted preference information with the assistance of a domain knowledge graph.

3.3.1 Reply Utterance Modeling in Response Generation

To generate the reply utterances in the CRS, the proposed system designs the dialog system with two cases, involving the i) non-recommendation case, referring to the generation of target reply utterances based on the extracted mentioned entities with the input conversation interactions, and ii) recommendation case, referring the generation of the recommendations based on the static as well as dynamic preferences based predicted set of item.

Initially, the proposed system concatenates the sequence of multiple input dialog utterances (U) into a single utterance $(\widehat{U})$ by using a special token '_split_'. Then, it encodes the single utterance into a vector representation of each word in $(\widehat{U})$ using an embedding layer in the text generation model. Consider the single dialog utterance $(\widehat{U})$ consists of the 'n' number of words represented as $\widehat{U} = \{t_0, t_1, \dots, t_n\}$, and the obtained word vector representation is as follows,

$$\widehat{U} = \{(t_0)^w, (t_1)^w, \dots, (t_n)^w\} \quad (4)$$

i) Non-Recommendation Case:

To generate reply utterance, initially, the proposed system utilizes the dialog utterance representation $(\widehat{U})$ and the knowledge-enhanced entity representation (H_E) to generate the reply utterance in the output layer of the decoder. It concatenates the dialog utterance representation $(\widehat{U})$ and (H_E) representation in the hidden layer generates the reply utterance or response in the output layer of the text generation model.

$$P_{rep} = Softmax\left(\left((\widehat{U}) \cdot \{R_E^S . R_E^D\}\right) W + b_{rep}\right) \quad (5)$$

From equation (5), R_E^S *and* R_E^D denotes the integrated representation of static and dynamic preferences obtained from the recommendation module. Also, $R_E = H_E \cdot U_I$, R_E represents the integrated representation of the knowledge-based entities representation (H_E) and dialog-based mentioned entities representation (U_I). P_{rep} denote the first reply utterance to the user, which indicates the output of NRC. W and b_{rep} denotes the linear weight matrix and bias vector, respectively.

ii) Recommendation Case: For the recommendation case, the text generation system based on the dialog utterance representation $(\widehat{U})$ and predicted set of items from the recommendation module (P_{rec}) formulated as,

$$P_{red} = Softmax\left(\left((\widehat{U}) \cdot P_{rec}\right) W + b_{rec}\right) \quad (6)$$

In equation (6), P_{rec} denotes the predicted set of items based on knowledge-enhanced entity representation obtained from the recommendation module, W and b_{rep} denotes the linear weight matrix and bias vector, respectively P_{red} denotes the output of the recommendation case.

3.4. Dialog-aware Recommendation

The proposed CACRS designs the condition-aware decision-making for the transition from non-recommendation to recommendation case with the target of generating the final decision as a dialog-aware recommendation inspired by the research work [16]. For each turn in CRS, the proposed system begins from the first input dialog utterance and generates reply utterances or recommendations using the text generation model with the help of equations (5) and (6), respectively. **Static preference-based Recommendation:** Initially, the proposed system extracts the user preferences based on the static or historical conversational context and predicts the preferred list of items in the recommendation module. The proposed system generates dialog responses using a text generation model based on static preference-based recommendations. **Dynamic preference-based recommendation:** After the static preference-based reply utterance generation, the proposed system enriches the knowledge-based preference extraction in the recommender module by semi-automatic dynamic input conversation. **Condition-aware Decision making:** The proposed system designs condition-aware decision-making based on the correlation between static and dynamic preferences-based recommendations. Hence, from the correlation result, the proposed system leverages the recommendation case and generates the final response text with the recommendation item in the CRS. Figure 2 represents the process flow of the CRS system's proposed text generation system.

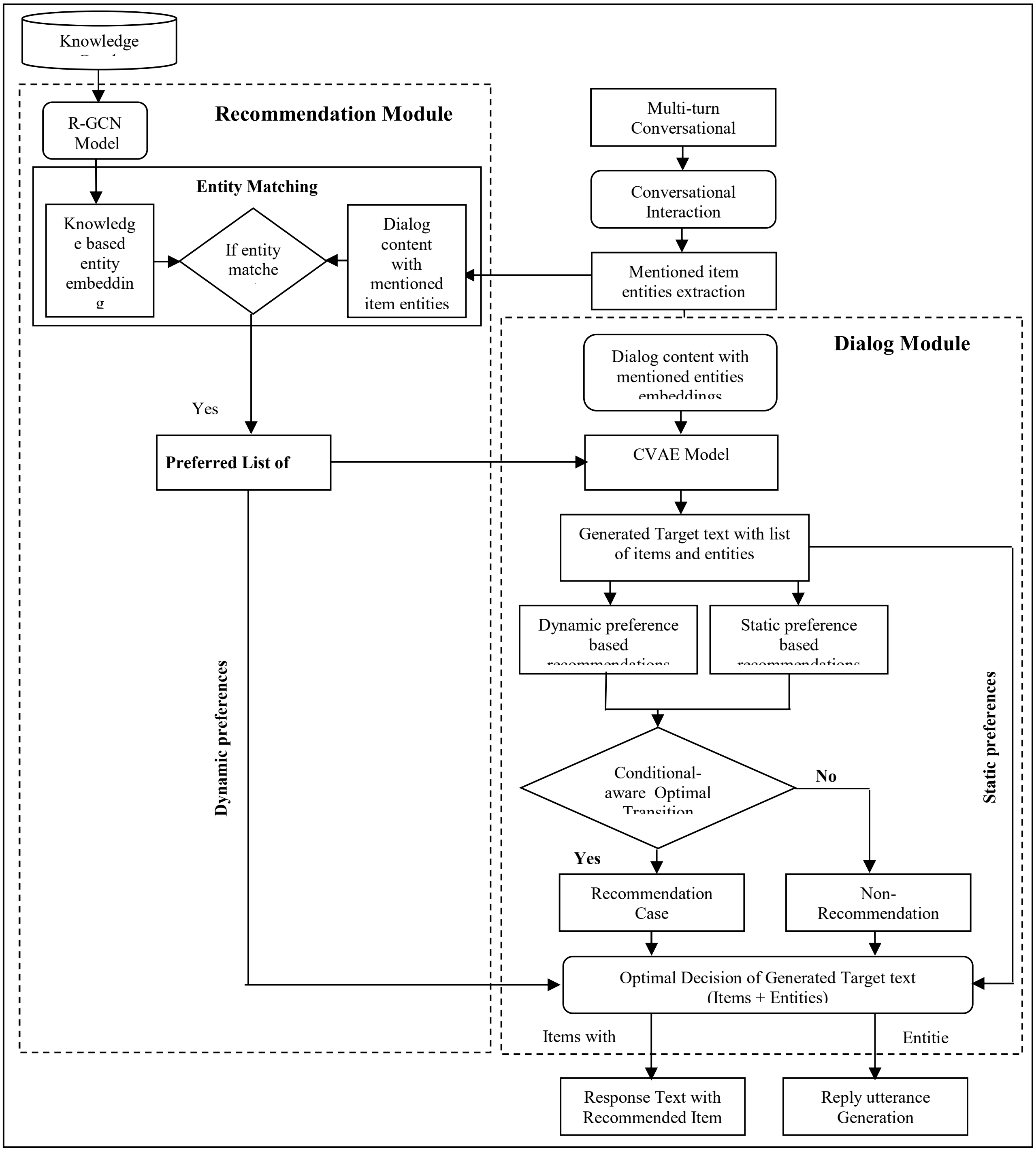

Figure 2: Process Flow Of The Proposed Text Generation System In The CRS System

Deep Sequential Text Generation Model: Traditional sequential-based response generation model generates generic and uninformative responses due to the lack of contemplating the diversity among responses regardless of the non-recommendation case in CRS. To tackle this issue, the proposed system employs the target text generation model as the combination of Conditional Variational Auto Encoder (CVAE) [17] and LSTM for generating reply utterances as the recommendations. CVAE is an extend of Variational Auto Encoder (VAE), consisting of a prior network p(z|c), a recognition network q(z|c, x), and a decoder network p(x|c, z). It is trained to maximize the conditional marginal distribution of the prior network to generate output text 'x' from the given conditional attributes 'c', which involves an intractable marginalization over the latent variable 'z'. In the proposed CACRS, the condition-aware decision-making relies on the CVAE model for the next generation based on the optimal transition. In the CVAE, the conditional distribution is defined as p(x, z|c) = p(x|z, c) p(z|c), where 'c' denotes the input conditions that modulate the prior latent variables 'z' based on NRC and RC conditions in the proposed system to generate target text. CVAE utilizes latent variable 'z' to learn the distribution over conversational context and generates target responses.

The CACRS designs the conditions in CVAE for the transition from NRC to RC by utilizing the correlation score between the static and dynamic preference-based recommendations. Suppose the correlation of the entities of the suggested item with both the static and dynamic preferences is high. In that case, the CACRS generates the response for RC, otherwise generating the NRC's reply utterance. For NRC, the proposed system encodes the input dialog utterance into the encoder of CVAE and generates a continuous latent vector representation 'z' from a Gaussian prior distribution p(z|c). Consequently, it generates the target text 'x' from a conditional distribution p (X|c, z) with a decoder in CVAE. Next, the proposed system models the condition-based probability as p(x|z, c) based on the RC case. For RC, the proposed system reconstructs the latent sample variable z from the probability distribution N (0, 1) to generate the target text as recommendation 'x'. It concatenates the 'c' and 'z' with additional attributes and generates the latent continuous vector representation 'z' from generating responses from distribution p (x|c, z) to generate recommendations. Thus, to generate the target text from the latent variable representation, the proposed system utilizes CVAE with Long-Short Term Memory (LSTM) and generates the final output as a dialog-aware recommendation in CRS.

5. Experiment Results and Analysis

The experimental model evaluates the proposed model against the baseline models, such as Sequence-to-Sequence (Seq2Seq) model, Generative Pre-trained Transformer (GPT-2), and the existing models include ReDial [18], KBRD model [13], KERCS model [19], and KGSF model [14], on a benchmark dataset using standard evaluation metrics. This section initially presents the experimental dataset, evaluation metrics, implementation results, and discussions

5.1. Experimental Dataset

The experimental framework utilizes a conversational dataset, namely REcommendations through the DIALog (REDIAL) dataset [20], consisting of 10,006 conversations and a total of 182,150 turns constructed through the Amazon Mechanical Turk (AMT) platform for movie recommendations. Among them, a sample of 100 multi-turn conversations from the test set was used to evaluate the proposed model's performance in CRS. The statistics of the REDIAL dataset are depicted in Table 1.

Table 1: Data Statistics of REDIAL dataset

Dataset Statistics	
Number of conversations	10006
Number of utterances	182150
Average Turns	18.2
Number of users	956
Number of movies mentions	51699
Seeker mentioned	16278
Recommender Suggested	35421

5.2. Evaluation Metrics

The experimental framework conducts the experiments using Ubuntu 16.04 operating system with Python machine learning and deep learning libraries. It evaluates the performance of the proposed model, the baseline models, and the existing models on the REDIAL dataset based on automatic evaluation metrics. Moreover, it conducts recommendation and dialog response generation evaluations using recommendation and language generation metrics, respectively.

(i) Recommendation evaluation metrics

The experimental model employs recommendation evaluation metrics that involve Recall@K, and Response Recall (ReR) metric [13] to evaluate the recommendation items suggested by the proposed model and the existing models.

- **Recall@K:** Recall@K measures the ranking accuracy of top K items recommended by the proposed recommender system based on the ground-truth items for recommendations suggested by human recommenders. Inspired by the research work [21], the experimental model employs Recall@1, Recall@10, and Recall@50 because it has more indicative of recommendation performance.
- **Response recall (ReR):** ReR evaluates whether the final generated response contains ground-truth target items.

(ii) Dialog response generation evaluation metrics

For the dialog response generation task, the proposed system employs Perplexity (PPL), Distinct n-grams (Dist-n), and BLEU scores metrics [13] to evaluate the performance of the dialog response quality.

- **Perplexity (PPL):** PPL measures the fluency of generated responses with the ground-truth responses. A Lower PPL score refers to better generation performance.
- **Distinct n-gram (Dist-n):** This metric computes the informativeness or diversity of the generated reply utterances at the sentence level by counting the diversity of 2-grams, 3-grams, and 4-grams, respectively. It is the ratio between the number of unique n-grams divided by the total number of words in the context.
- **Bilingual Evaluation Understudy (BLEU):** BLEU metric measures the word overlap between the response generated by the proposed system and ground-truth responses.

5.3. Evaluation Results and Discussion

Table 2 shows the evaluation results of the proposed text generation model and the various comparison models in recommendation and dialog response generation through recommendation and response generation metrics on the REDIAL dataset.

Table 2: Comparative Evaluation Results on REDIAL Dataset shown in Anexure-1

5.3.1. Performance Evaluation on Recommendation

The performance comparison of the different models in the recommendation task is depicted in table 3. The experimental model evaluates Recall@K to validate the performance of top-K recommendations suggested by the various models, where k= 1, 10, 50, since it has more indicative of recommendation performance.

Table 3: Performance of the different models in the Recommendation task shown in Anexire-1

- From the results, the first observation is that the baseline Seq2seq and GPT-2 obtained slightly lower performance than the existing ReDial model with the difference of approximately 0.6, 1.0, 1.5 scores in the evaluation of R@1, R@10, and R@50 respectively. But, the recommendation scores of the KBRD model are R@1 score of 3.1 %, R@10 at 15.0%, R@50 at 33.6%, and ReR equal to 0.8, which indicates better results than the ReDial model and Seq2seq, GPT-2 models in terms of all metrics. Owing to the KBRD model incorporated external KG and enhanced the representation of items in the dialog context resulting in better performance of the recommendation system.
- The second observation is that the existing KGSF and KECRS models outperform the Seq2seq and GPT-2 models and the ReDial and KBRD model among all metrics except for slight variation in metric of R@1, ReDial achieved 2.4%, but KECRS obtained 2.2%. A possible reason for KGSF and KECRS accomplishments is that external KG's were used as ConceptNet and DBpedia, which greatly facilitated improving CRS's performance by KG-enriched information extraction about the items for recommendation generation. Although, KGSF and KECRS models achieved lower performance than the proposed model in terms of all metrics.
- The final observation is that the proposed CRS is consistently better than all baseline and existing models in terms of all recommendation metrics. Its recommendation score on REDIAL Dataset is R@1 score is equal to 4.1%; R@10 is 18.6%, R@50 is 38.1%, and ReR is 0.9%. Also found that, compared to other CRS models, KGSF, KECRS, and the proposed model achieved maximum performance scores

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with marginal variations during the evaluation of ReR. Thus, the results showed that the CRS system in the proposed system efficiently infers user preferences from a dialog context and has great potential to provide high-quality recommendations.

- ❖ As for comparison in the recommendation task, it is concluded that the CRS system in the proposed model performs stably and achieves the best performance compared with the baseline and existing models in terms of all metrics. The conversational utterances accomplish this significant gain in ReDial containing rich entities; hence the CRS in the proposed methodology effectively captured the user-interested items in terms of entities through static and dynamic-based preference extraction and exactly predicted the preferred list of items for recommendations.

5.3.2. Performance Evaluation on Response Generation

The performance results obtained for the proposed model, the baseline models, and the existing models on dialog response generation using the REDIAL dataset are reported in table 4. For the evaluation of response generation, the experimental model specifically incorporates BLEU-2,3,4 for evaluating the relevance of the generated responses with the ground-truth responses and Distinct-2,3,4 to evaluate the informativeness at the sentence level of the generated responses to the dialog context.

Table 4: Performance of the different models in Response Generation shown on Anexure-1.

- ❖ For the evaluation of PPL, the ReDial has achieved a 28.1 score which shows that the higher PPL implies poor response generation compared to other existing KBRD, KECRS, and KGSF models. The reDial model utilizes a hierarchical RNN structure to encode the historical dialog utterances and fails to incorporate the attention mechanism for modeling the dialog context, resulting in a loss of original contextual information during response generation. As shown in table 2, KBRD obtained better performance than the GPT-2 due to the advantages of the transformer in modeling the natural language content. Also, KBRD promotes the recommendation and dialog generation performance by knowledge-grounded information about users' preferences and recommendation-aware vocabulary bias to dialog systems, respectively.
- ❖ Compared with the baselines, the existing models, and the proposed model, the existing KECRS model demonstrated better performance from the results of Dist-2 as 0.48, Dist-3 as 0.91, and Dist-4 as 1.23, respectively. It implies that the KECRS model-generated responses are more relevant to recommended items due to the consideration of BOE loss, infusion loss, and TMDKG construction which greatly facilitates the generation of highly relevant informative responses. Also noted, the Dist-2,3,4 scores of the proposed model are 0.43, 0.76, and 0.95, respectively, which outperform baseline and existing models except the KECRS model. Although, the PPL and BLEU scores of the proposed model are higher than the KECRS since the proposed model adopted LSTM-based CVAE to generate dialog responses which have the potential advantage of effectively increasing the diversity and informativeness in conversational utterances.
- ❖ From the results of BLEU scores, the proposed model outperforms all the comparative models with scores of BLEU 2,3,4 as 0.199, 0.161,0.076, respectively, indicating the conditional-aware decision modeling in the dialog system in CRS leads to better transition for response generation and recommendation. Moreover, the proposed text generation model utilizes static preference and dynamic preference information, enhancing the generated text quality.

Among all the response generation metrics, it is concluded that the proposed text generation model has the ability to generate diverse dialog content responses in a multi-turn conversational context. It is found that the sequential-based text generation model such as Seq2Seq, Pre-trained GPT-2, and transformer-based KBRD achieved minimal performance than the proposed CVAE-based text generation model.

6. CONCLUSION

This work proposed an enhanced dialog system for CRS based on conditional-aware decision-making to transition from reply utterance generation to recommendation generation naturally. By incorporating the static and dynamic conservations-based preference information and the KG-based preference information, the recommender system in the proposed methodology effectively captured the user preferences and generated the preferred list of items for the user. Through the sequential deep learning model, this work effectively generated the reply utterances and recommendations using static and dynamic-based preference information extracted from the multi-turn conversations. With the designed conditional-aware decision and a correlation between the static and dynamic conversation-based recommendations, the enhanced dialog system in the CRS naturally moved towards recommendations and generated the final response as a dialog-aware recommendation.

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ANEXURE-1

Table 2: Comparative Evaluation Results on REDIAL Dataset

Models	Recommendation Performance (%)				Response generation Performance		
	R@1	R@10	R@50	ReR	PPL	Dist-2/Dist-3/Dist-4	BLEU 2/3/4
Seq2seq	1.9	13.0	31	0.6	25.6	0.107/0.196/0.269	0.196/0.120/0.073
GPT-2	2.1	13.1	31.2	0.65	29.1	0.194/0.256/0.223	0.171/0.140/0.077
ReDial	2.4	14.0	32.0	0.7	28.1	0.225/0.236/0.228	0.178/0.126/0.074
KBRD	3.1	15.0	33.6	0.8	17.9	0.263/0.368/0.423	0.185/0.142/0.074
KECRS	2.2	15.66	36.6	0.85	11.8	0.48/0.91/1.23	0.196/0.145/0.075
KGSF	3.9	18.3	37.8	0.88	5.6	0.289/0.434/0.519	0.164/0.112/0.074
CACRS	4.1	18.6	38.1	0.9	5.2	0.43/0.76/0.95	0.199/0.161/0.076

Models	**Recommendation Performance (%)**				**Response generation Performance**		
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Table 3: Performance Of The Different Models In The Recommendation Task

Models	Recommendation Metrics			
	R@1	R@10	R@50	ReR
Seq2seq	1.9	13.0	31	0.6
GPT-2	2.1	13.1	31.2	0.65
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Table 4: Performance Of The Different Models In Response Generation

Models	Response generation metrics						
	PPL	Dist-2	Dist-3	Dist-4	BLEU 2	BLEU 3	BLEU 4
Seq2seq	25.6	0.107	0.196	0.269	0.196	0.120	0.073
GPT-2	29.1	0.194	0.256	0.223	0.171	0.140	0.077
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