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Improving Explainable Recommendations by Deep Review-Based Explanations

SIXUN OUYANG AND AONGHUS LAWLOR
Insight Centre for Data Analytics, University College Dublin, Dublin 4, Ireland
Corresponding author: Sixun Ouyang (sixun.ouyang@insight-centre.org)

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ABSTRACT Many e-commerce sites encourage their users to write product reviews, in the knowledge that they exert a considerable influence on users' decision-making processes. These snippets of real-world experience provide an essential source of data for interpretable recommendations. However, current methods relying on user-generated content to make recommendations can run into problems because of well-known issues with reviews, such as noise, sparsity and irrelevant content. On the other hand, recent advances in text generation methods demonstrate significant text quality improvements and show promise in their ability to address these problems. In this paper, we develop two character-level deep neural network-based personalised review generation models, and improve recommendation accuracy by generating high-quality text which meets the input criteria of text-aware recommender systems. To make fair comparisons, we train review-aware recommender systems by human written reviews and attain advanced recommendations by feeding generated reviews at the inference step. Our experiments are conducted on four large review datasets from multiple domains. We leverage our methods' performance by comparing with non-review based recommender systems and advanced review-aware recommender systems. The results demonstrate that we beat baselines on a range of metrics and obtain state-of-the-art performance on both rating prediction and top-*N* ranking. Our sparsity experiments validate that our generation models can produce high-quality text to tackle the sparsity problem. We also demonstrate the generation of useful reviews so that we can achieve up to 13.53% RMSE improvements. For explanation evaluation, quantitative analyses reveal good understandable scores for our generated review-based explanations, and qualitative case studies substantiate we can capture critical aspects in generating explanations.

INDEX TERMS Computing methodologies, deep neural networks, information systems, natural language generation, recommender systems.

I. INTRODUCTION

Recent recommender systems research has shown how to make use of online user-generated content to continuously improve performance on both recommendation [1]–[5] and explanation [6]–[8]. However, this approach has two main drawbacks. First, the problem of sparse data continues to present an issue for most recommender systems [9]. When there is sparse rating information for users and items, which is often the case for review-aware recommender systems [8], the latent factor-based methods often struggle to learn significant information and can produce inaccurate results. Second, there is the problem that a large fraction of the content of human-written reviews is not useful information for the recommender system. According to Chen *et al.* [5], user-written reviews are of low quality that and unhelpful for obtaining users' trust and producing accurate recommendations. They also argued that these unhelpful reviews only add noise which impairs the ability of the recommender system. Besides, Ghose and Ipeirotis [10] researched the subjectivity of online reviews and concluded that users prefer helpful reviews which introduce object information about items rather to express subjective prejudices. Meanwhile, Jindal and Liu [11] analysed 5.8 million reviews from Amazon[1]

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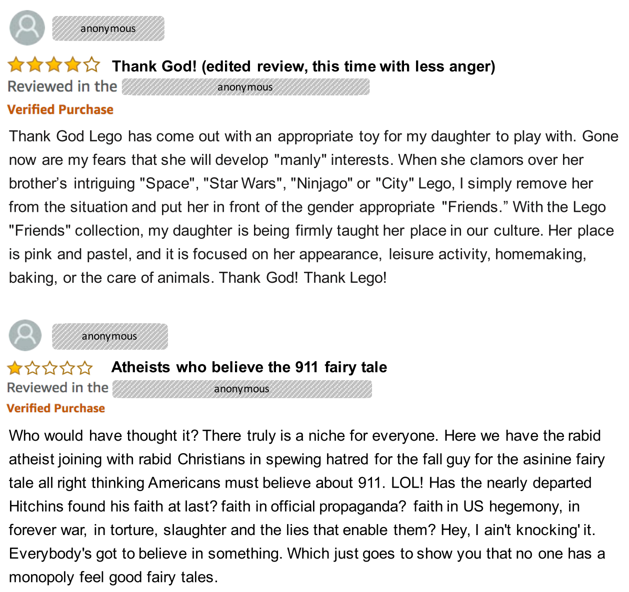
[1]https://www.amazon.com/


anonymous

Thank God! (edited review, this time with less anger)

Reviewed in the anonymous

Verified Purchase

Thank God Lego has come out with an appropriate toy for my daughter to play with. Gone now are my fears that she will develop "manly" interests. When she clamors over her brother's intriguing "Space", "Star Wars", "Ninjago" or "City" Lego, I simply remove her from the situation and put her in front of the gender appropriate "Friends." With the Lego "Friends" collection, my daughter is being firmly taught her place in our culture. Her place is pink and pastel, and it is focused on her appearance, leisure activity, homemaking, baking, or the care of animals. Thank God! Thank Lego!

anonymous

Atheists who believe the 911 fairy tale

Reviewed in the anonymous

Verified Purchase

Who would have thought it? There truly is a niche for everyone. Here we have the rabid atheist joining with rabid Christians in spewing hatred for the fall guy for the asinine fairy tale all right thinking Americans must believe about 911. LOL! Has the nearly departed Hitchins found his faith at last? faith in official propaganda? faith in US hegemony, in forever war, in torture, slaughter and the lies that enable them? Hey, I ain't knocking' it. Everybody's got to believe in something. Which just goes to show you that no one has a monopoly feel good fairy tales.

FIGURE 1. **Unhelpful online reviews from Amazon.**

and argued that opinion spam in online reviews is extensive. We demonstrate two examples (rating 4 and rating 1) of unhelpful reviews from Amazon in Figure 1. The first example does not present useful information about the item but just expresses gender discrimination, so that it is marked as unhelpful. The second example shows spam opinion and spreads extreme political ideologies, which is not profitable for recommendations and explanations.

On the other hand, there has been intense interest in high-quality text generation through deep learning methodologies. Recent works demonstrate that deep neural network-based text generation models can generate high-quality synthetic text with correct grammar and syntax [7], [12]–[14]. Meanwhile, they argue that machine generated reviews are compelling and useful. Therefore, many works now integrate text generation methods with recommender systems for constructing explainable recommendation [15]–[21]. These results have validated the idea that artificially generated review text is good for explaining recommendations. However, the use of machine-generated review explanations to improve recommendation performance has not been explored in detail. According to Loyola [22], explanations can be of a similar format to the input data, so that they can be used to refine predictions. To this end, it is valuable to study how well review-based explanations can work in improving recommendations, on both rating prediction and top-N ranking tasks.

In this paper we propose deep learning review generation models for high-quality natural language explanations and we use these explanations to reach state of the art performance on rating prediction and top-N item ranking recommendation tasks. Specifically, we develop two character-level personalised review generation models which we apply to generate useful reviews for recommendation and explanation. We apply Long Short Term Memory (LSTM) [7] neural network as the basis for our generation models and conduct cross-domain experiments on two Convolutional Neural Network (CNN) based recommender systems [3], [5]. Our experiments show that we beat baselines on both rating prediction and item ranking problem. We demonstrate that machine-generated reviews are more robust than human-written reviews in dealing with sparsity issues. We validate the assumption that our generation models focus on generating useful instead of non-helpful reviews, which boosts the performance of the recommender system. Besides, our explanation experiments demonstrate that we can produce both persuasive and readable explanations for recommendations. We summarise our contributions as follows:

- We develop two character-level personalised review generation models consistently outperforming baselines on both rating prediction and item ranking tasks.
- We show that machine-generated reviews can mitigate the impact of sparsity for text-aware recommender systems.
- Regarding recommendation, we demonstrate the generated machine-generated reviews are more reliable and helpful than human-written reviews.
- We provide convincing and readable text explanation for the predicted ratings.

In following sections, we start to introduce the background of deep review-based explanation generation. Then we outline the proposed approach of using the generation model to improve recommendation accuracy. After that, we introduce the technical details of our explanation generation models. We then analyse the recommendation and explanation experimental results. Finally, we summarise our findings and contributions in conclusion.

II. RELATED WORK

There is a long history of using Natural Language Processing (NLP) methods to exploit cross-domain information for recommendations. Mooney *et al.* [23] presented the first research to extract text information applied to the problem of book recommendation. Van *et al.* [24] employed *tf-idf* schemes to explore text. In order to extract extensive information, many recent works used machine learning and deep learning methods. Based on the idea of word embedding model, Grbovic *et al.* [1] proposed prod2vec model delivering effective product recommendations. Chen *et al.* [4] showed reliable performance on graph-based recommendations by exploring social tag info through Latent Dirichlet Allocation (LDA). Almahiri *et al.* [25] enhanced recommendation performance through Recurrent Neural Networks (RNNs) learning context of reviews. In addition to RNNs, convolutional neural networks (CNNs) are also popular approaches for modelling review text and achieving substantial improvements in recommendation performance [3], [5], [26], [27].

In addition, recent research has focused on the approach of explaining recommendations by natural language-based

TABLE 1. Advantages and disadvantages of aspect explanation and natural language explanation.

Explanation Methods	Advantages	Disadvantages
Aspect Forecasting [5], [28]–[33]	1. Can predict explainable aspects efficiently. 2. Sensitive to changes of preference. 3. Can map from user needs to recommendations. 4. Easy to produce explanations.	1. Present in predefined templates. 2. Lack of attractiveness and persuasiveness. 3. Must define the aspects dictionary in advance. 4. Can not improve recommendation.
Automatic Natural Language Generation [7], [12]–[14], [18], [34]–[36]	1. Present in readable natural language expression. 2. Good attractiveness and persuasiveness. 3. No need to extract phrases in advance. 4. Best-in-class performance on text generation. 5. Can improve recommendation.	1. Requires a large amount of data. 2. Requires extensive fine-tuning skills. 3. Extremely computationally expensive to train. 4. Opaque prediction process.

explanations [28], [31]–[33]. Chang *et al.* [29] presented an explanatory model, learning tags from users' reviews, and filling the predicted tags into a template for structured interpretations. Musto *et al.* [30] introduced a similar approach which uses a textual template with predicted properties to explain recommendations. Wang *et al.* [33] introduced a multi-task learning model for explainable recommendations, where their model can directly predict opinionated phrases. Explanation through these aspect-level approaches is often not entirely adequate for convincing customers. The research of Costa *et al.* [7] indicated that user-written reviews significantly affects other users' purchasing behaviour. Moreover, Seo *et al.* [26] provided a human-understandable interpretation approach which highlights components in reviews.

Based on the above literature, human-written reviews play a critical role in both recommendations and explanations. However, using them directly can run into problems. According to the work of Wan *et al.* [8], human-written reviews among all purchasing records in many real-world datasets are very sparse, for example, only *2.2%* records contain reviews in the Steam dataset [37]. Review-aware recommender systems often struggle to capture significant knowledge and their performance suffers when there are few records for users and items [9]. Also, the content of human-written reviews may not always useful for explainable recommender systems. Chen *et al.* [5] argued that these unhelpful human written-reviews add noise and limit the effectiveness of the recommendations. For these reasons we argue that carefully crafted machine-generated reviews can be a better choice than human-written reviews for building better recommendation systems and providing compelling explanations to users.

Early attempts at automatic text generation used aggregation rules on words to construct sentences [38]. Recently, many text generation works using deep learning methods show significant improvements in generating text that can be readily understood by humans [7], [13], [34]–[36]. The methods are mainly based on RNNs, a type of feed-forward recurrent neural network, which specialise in dealing with sequential tasks. Intrinsically, text generation is a sequence prediction problem, in which the RNNs learns the patterns within the text and predicts the current word (or character) from previous words (or characters). Sutskever *et al.* [34] was the first to introduce a model that used RNNs for synthetic text generation, while other works have greatly expanded it. Tang *et al.* [35] extended a multi-layer perceptron to RNNs which captures personal information and the reduces memory cost. Dong *et al.* [13] further developed this model by using attention mechanisms and demonstrated superior text generation performance. Zhao *et al.* [14] proposed a generation model producing readable text for explaining song recommendation, which is the most similar work to this paper. Similarly, Avinesh *et al.* [18] also proposed text summarisation model based on encoder-decoder sequence networks to summary reviews as recommendation explanation. Nonetheless, these works generate text at word-level and a big issue they face is a high memory cost due to the large vocabulary size. On the contrary, generating text at character-level does not suffer from this problem [12]. Although it is more difficult than word-level generation, this paper focuses on machine-generated reviews at character-level. Table 1 compares the above aspect explanation works and natural language explanation works.

The advantages of machine-generated reviews are considerable. High quality, focused, and readable text can be provided for any item. The quality of the text is at a high level of readability. There is extensive interest in using human-generated text to improve recommendation models, but no related research has been done on how synthetic text generation can improve recommendation performance. Therefore, we aim to develop personalised text explanation generation models through deep learning methods, generating review-based explanations and using such explanations as inputs of review-ware recommender systems to achieve state-of-the-art recommendation performance.

III. PROBLEM STATEMENT

Our first research question is how to generate reviews which fulfill the demands of a review aware recommender systems? We do this by building text generation models that can provide personalised readable reviews. We design two character-level personal review generation models by using deep neural techniques, inspired by recent text generation works [7], [12], [13], [35]. There are two main advances in our approaches over other generation methods. Firstly, we generate reviews

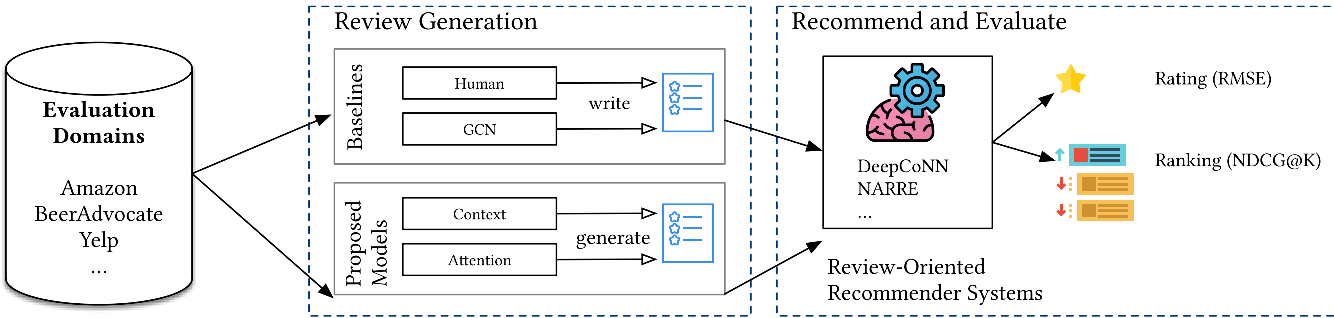


FIGURE 2. Overview of the experimental setup to validate recommendation performance of machine-generated reviews.

on a character level, which is more stringent than word level models; secondly, our target is not just to generate reviews, but rather to utilise generated reviews to make improvements in the precision of the recommendations and to provide explanations for the recommendation.

The second research problem is how to improve the recommendation performance through machine-generated reviews? To address this, we describe the processes of improving recommendations by our methods and related evaluation metrics, as shown in Figure 2. Concretely, we train review-aware recommender systems by human-written reviews and make advanced recommendations by inputting machine-generated reviews. The idea is that if machine-generated reviews can achieve better performance on recommender systems trained by human-written reviews, we can conclude that deep generation models can capture more meaningful information for producing novel recommendations.

Moreover, to evaluate whether machine-generated reviews can achieve more accurate recommendations or not and measure how they make the improvements, we take the recommendations by human-generated reviews as the ground truth baseline. We run two recommendation tasks, rating prediction and item ranking, which are frequently used in real-world systems. We adopt Root Mean Square Error (RMSE) to estimate rating prediction performance and use NDCG@K to leverage ranking performance. We outline the technical details of our generation models in the next section and detail our experimental results in Section V.

IV. REVIEW GENERATION MODELS

In this section, we provide a detailed overview of our models along two distinct branches: context and attention. Note, the *attention model* is an advanced version of the *context model*, which adds an extra layer with an attention mechanism. Figure 3 demonstrates the neural network architecture of the attention model. There are four modules in the attention model: encoder, Recurrent Neural Networks (RNNs) decoder, attention mechanism, and review generation. The function of the encoder module is to encode attributes and text into high dimensional embeddings; the function of the RNN decoder is to learn the sequence and personal attributes from the embedded inputs; The attention mechanism is used to reinforce the alignment between input attributes and the

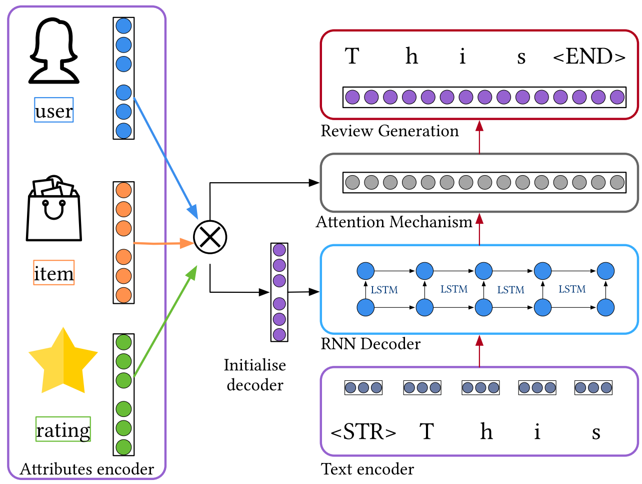


FIGURE 3. Text generation models. The attention model inserts an attention mechanism between the RNNs decoder and text generation module, while the context model directly stacks the text generation module on the RNNs decoder.

text; The review generation module generates personalised reviews. The attention model inserts an attention mechanism between the RNNs decoder and review generation module, while the context model directly stacks the review generation module on RNNs decoder.

In terms of training, the goal of the generation model is to maximise the conditional probability $p(e|a)$ of characters in generated text e where a is the user attributes. To achieve that, our models minimise the cross-entropy loss [7], which is formulated in Equation 1. Here, l represents the sequence length, o and p denote the target characters and predicted characters respectively.

$$p(e|a) = \prod_{t=1}^{l} p(y_t|y_{<t}, a)$$
$$\mathcal{J} = -\sum_{t=1}^{l}[o_t \log y_t + (1-o_t)\log(1-y_t)] \quad (1)$$

A. ENCODER

The encoder module aims to encode inputs. It is categorised into two sections by the input type: text and personalised attributes. The input text in our model is represented by a sequence of characters, while the personalised attributes consist of *user ID*, *item ID*, and *rating*.

To encode the training review text, we first create a dictionary for all unique characters in the training corpus to record their positions. We use this in this encoding process and the later generation module. Then, for each character, we use their index in the dictionary to encode them into a one-hot vector whose length equals the size of the created dictionary. After that, these vectors are then fed into the RNNs decoder directly.

For each attribute, the initial step of encoding is the same with text encoding. We apply a one-hot vector to represent the current attribute. Then, we design a multi-layer perceptron with one hidden layer to linearly transform the one-hot vector into an embedding with a fixed dimension. Specifically, when receiving a one-hot representation $e(a_i)$, where $i \in (1, \dots, |a|)$, the formulation of attribute encoding is shown in Equation 2, where $W_i^a \in \mathbb{R}^{m\times|a|}$ is a weighting matrix, m denotes the dimension of the encoded embeddings, $|a|$ stands for the number of attributes.

$$E(a_i) = W_i^a e(a_i) + b_i^a \tag{2}$$

To align with text, we concatenate the attributes' embeddings and feed them into a fully connected multilayer perceptron that is activated by a tanh function. This fully connected layer outputs a hidden vector with the same dimension as the weights of RNNs decoder. We use this hidden vector to initialise RNNs decoder so that the model can be personalised. We define this procedure in Equation 3, where H is a parameter matrix, and b_a denotes the bias.

$$A = \tanh(H[E(a_1), \dots, E(a_{|a|})] + b_a), \tag{3}$$

B. DECODER

RNNs are feed-forward networks with dynamic temporal behaviour aiming to process and learn sequential data and are commonly applied in most text generation systems [7], [12], [13], [35]. Regarding the text generation task, RNNs summarise the context information into hidden variables and then provide conditional probability distributions for each time step. In the vanilla RNN, given an input vector X_t during a time step t and the cell state of previous time step $t-1$, it performs a tanh activation to get a hidden state h_t of time t. The prediction $p(y_t|y_{<t}, a)$ of time t is calculated by passing the hidden state to an output layer activated by a non-linear *softmax* function, as shown in Eq. 4.

$$\begin{aligned} h_t &= \tanh(W_x X_t + W_h h_{t-1}) \\ p(y_t|y_{<t}, a) &= \text{softmax}(W h_t + b) \end{aligned} \tag{4}$$

This mechanism enables conventional RNNs to learn the sequential contexts in the input data. However, suffer a few well-known issues including the gradient vanishing problem and to solve this issue, Hochreiter *et al.* [39] introduce the long short-term memory (LSTM) cells, consisting of a set of gates: forget f, input i, and output o. The forget gate decides to discard useless information of input data. The input gate aims to remember decisive information of input data. The output gate determines which information can be passed to the next neuron and the next layer. Unlike vanilla RNNs, forward calculations of an LSTM unit involves inputs x_t, cell state C_{t-1} from the previous unit, and previous unit output H_t. Formulated calculation steps are defined in Equation 5, where W and b stand for weights and bias respectively, $\hat{C}$ is candidate cell state, and $\odot$ denotes the element-wise operator.

$$\begin{aligned} \hat{C}_t &= \tanh(W_x^c x_t + W_h^c H_{t-1} + b_c) \\ f_t &= \sigma(W_x^f x_t + W_h^f H_{t-1} + b_f) \\ i_t &= \sigma(W_x^i x_t + W_h^i H_{t-1} + b_i) \\ C_t &= f_t \odot C_{t-1} + i_t \odot C_t' \\ o_t &= \sigma(W_x^o x_t + W_h^o H_{t-1} + b_o) \\ H_t &= o_t \odot \tanh(C_t) \end{aligned} \tag{5}$$

C. ATTENTION MECHANISM

Attention mechanism shows promising performance on time series related tasks [40], [41]. We use the attention mechanism to prevent the model from concentrating on unrelated information. When receiving outputs H_t of the RNN decoder and encoded attributes $E(a)$ in time t, we first compute context vector G_t through:

$$\begin{aligned} s_t^i &= \frac{\exp(\tanh(W_s[H_t, E(a_i)]))}{\sum_{i=1}^{|a|} \exp(\tanh(W_s[H_t, E(a_i)]))} \\ G_t &= \sum_{i=1}^{|a|} s_t^i E(a_i) \end{aligned} \tag{6}$$

Here, [,] denotes a concatenation manipulation, $|a|$ means the total number of attributes, s_t^i is the attention weights of attributes i in time t. After that, we calculate a new decoder representation $\hat{H}_t$ which has same shape as the RNN decoder outputs by Equation 7, where W is the weight of this layer. In the attention model, $\hat{H}_t$ replaces H_t in generation step.

$$\hat{H}_t = \tanh(W_g G_t + W_h H_t) \tag{7}$$

D. REVIEW GENERATION

Text generation is described as a sequence label classification problem. When accomplishing the encoding and decoding process, we deliver the output H_t from the decoder, or from the attention mechanism, into the output layer, a fully connected neural network with *Softmax* activation, to compute the conditional probabilities $p(y_t|y_{<t}, a)$. Then, the generation module maximises the conditional probabilities $p(y_t|y_{<t}, a)$ by a greedy search function to predict the character index Y_t. Finally, we generate a character by looking up Y_t in the dictionary created previously. This procedure is applied recursively, and a group of characters will be generated until we find the pre-defined *end* symbol. The calculation steps of this procedure are presented in Equation 8:

$$\begin{aligned} p(y_t|y_{<t}, a) &= \text{softmax}(W H_t + b) \\ Y_t &= \text{argmax}\, p(y_t|y_{<t}, a) \end{aligned} \tag{8}$$

TABLE 2. Statistics of the evaluation datasets.

Dataset name	Users	Items	Ratings	Sparsity (%)
Video	5,130	1,683	37,126	99.57
Beer	22,801	20,200	528,870	99.88
Toys	19,412	11,924	167,597	99.92
Yelp	1,326,101	174,567	5,261,668	99.99

V. EXPERIMENTS

In this section, we perform extensive experiments through the processes detailed in Figure 2, and discussed in Section III, to answer the following questions:

- Q1 How does the performance of generation models compare to state-of-the-art competitors on both rating prediction and items ranking tasks?
- Q2 Can we produce high-quality review-based explanations to tackle the sparsity problem?
- Q3 Does machine generated review-based explanations are helpful for both recommendations and explanations?
- Q4 How does machine generated review-based explanations perform in quantitative and qualitative study of explanation evaluation?

A. EXPERIMENTAL SETTINGS

1) DATASETS

In our experiments, we employ four datasets from different realms: two Amazon 5-score[2] [42]: *Video* and *Toys*; *Beer* [43]; and *Yelp* challenge 2017.[3] Statistical details of evaluation datasets are introduced in Table. 2. Similar to most generation tasks [7], [13], we preprocess datasets as follows: (i) we filter the reviews whose lengths are greater than 512 characters, as suggested in Dong *et al.* [13], long reviews often focus on describing irrelevant information, while short reviews tend to concentrate on more relevant information to the user experience of the item; (ii) since both generation models and review aware recommender systems require adequate numbers of reviews to train, we split each dataset into *generation train*, *recommendation train*, *validate*, and *test* set in the proportion of 40%, 40%, 10% and 10% respectively. Here, the *validate* set is used to select the best hyper-parameters for both the generation model and recommendation model, and the *test* set is used to evaluate recommendation and explanation performance for both machine generated reviews and human written reviews. The advantage for this strategy is that we ensure fair comparison. Generation models are trained on *generation train* set, while recommender systems are trained on *recommendation train* set. In this way, the generated reviews will not contain the information used in training the recommendation system. Thus, we can compare with human written reviews equitably.

[2]http://jmcauley.ucsd.edu/data/amazon
[3]https://www.yelp.com/dataset

2) REPRODUCIBILITY

We implement our generation models and related recommender systems based on Tensorflow.[4] Similar to [13], we stack two RNNs layers in the generation models to generate reviews, where each layer contains 512 LSTM neurons. To capture personalisation, we use dimensions of 64 for each attribute. The weights are initialised from a uniform distribution in the range of $[-0.08, 0.08]$ as suggested by [44]. We apply Adam optimisation [45] tuning models with an initial learning rate of 0.002 and unrolling for 50 epochs. According to [46], to avoid over-fitting, we decrease the learning rate after every epoch by multiplying with a factor of 0.97 and stack a dropout layer on each hidden layers with a dropout probability of 0.2. Then, we clip gradients in a range of $[-5, 5]$ to avert the gradient exploding problem [47]. Since short reviews have more valuable information while long reviews contain more noises [13], we set the length of reviews in DeepCoNN is fixed to 100 words. Also, in NARRE we only include users and items with a minimum of 10 reviews each (details on DeepCoNN and NARRE are in Section V-A3).

3) BASELINES

In this paper, we apply three non-review aware factorisation based recommender systems (NMF, SVD, SVD++), two state-of-the-art review-aware recommender systems (DeepCoNN and NARRE), and one novel text generation model (GCN) [12] to measure the performance of our methods. The details of these baselines are as follows:

- **NMF** [48]: Non-negative matrix factorization: a basic factorization method estimating two low-rank matrices for rating prediction.
- **SVD** [49]: Singular value decomposition: a popular collaborative filtering method that learns the relationship between users and latent factors.
- **SVD++** [50]: extends the SVD algorithm and incorporates implicit information.
- **DeepCoNN** [3]: An Convolutional Neural Network based recommender system, in which the review text of users and items are modeled jointly.
- **NARRE** [5]: An enhanced version of DeepCoNN which uses an attention mechanism.
- **GCN** [12]: Generative Concatenative Network concatenates auxiliary information with sequential text as inputs to the recurrent network to generate personalised text.

Since this paper's goal is generating review-based explanations as input to review-aware recommender systems to improve recommendations, we take more concentration on the two review-aware recommender baselines: DeepCoNN and NARRE. To thoroughly leverage our achievements, we first compare our generated text with human-written text, then against with generated text from GCN.

[4]https://www.tensorflow.org

4) EVALUATION METRICS

The primary target of this paper is to improve recommendation performance through machine-generated reviews. To this end, we employ RMSE to measure the rating prediction performance and NDCG@K to leverage the top-N ranking performance. Besides, We introduce the $\Delta RMSE$, which is defined in Equation. 10, to measure the recommendation improvements of machine-generated reviews over human-written reviews. Here, the greater the $\Delta RMSE$, the better performance for machine-generated reviews. For explanation evaluation, we describe evaluation methods and experiments in Section V-F.

- ***RMSE*** In line with [3], [5], [51], [52], we calculate Root Mean Square Error (RMSE) to evaluate rating predictions. It measures prediction errors of a group of user-item pairs. RMSE is defined in Equation. 9, where $\hat{R}_{u,i}$ represents predicted rating of user u on item i, while $R_{u,i}$ stands for their ground-truth rating. N is the total number of user-item pairs in *test* set.

$$RMSE = \sqrt{\frac{1}{N}\sum_{u,i}(\hat{R}_{u,i} - R_{u,i})^2} \tag{9}$$

- **Δ*RMSE*** We introduce the $\Delta RMSE$, which is defined in Equation. 10, to measure the recommendation improvements of machine-generated reviews over human written reviews. Here, the greater the $\Delta RMSE$, the better performance for machine-generated reviews.

$$\Delta RMSE = RMSE_{human} - RMSE_{synthetic} \tag{10}$$

- **NDCG@K** NDCG@k [53]–[55] is a popular method to measure the effectiveness of predicted rankings, It evaluates the usefulness of items based on their ranking position. Higher NDCG@K values imply better item prediction order and this usually aligns better with the customers' interests.

B. RATING PREDICTION PERFORMANCE (Q1)

We follow the processes described in Figure 2 to execute our experiments. In this section, we evaluate the rating prediction performance by RMSE (Sec. V-A4). To perform a thorough analysis, we first compare the recommendations of our models with three non-review aware recommender systems (NMF, SVD, SVD++). Then we compare our model performance against human and automatic text generation model (GCN), using two review-aware recommender systems (DeepCoNN, NARRE). We demonstrate these comparisons in Table 3 and Table 4. Table 3 shows the rating prediction performance of non-review aware recommender systems, while Table 4 presents the recommendation outcomes on DeepCoNN and NARRE review-aware systems. According to these tables, we make several observations.

First, according to the RMSE in Table 3 and RMSE in the other Tables, it is clear that both human-written reviews and machine-generated reviews in combination with review-aware recommender systems show better performance than the systems which do not take into account the textual information. According to Chen *et al.* [5], human-written reviews can enhance the quality of the latent representation in recommender systems. Thus, we argue that generation models have learned the relevant patterns and contexts to improve the quality of their internal representations and out-perform the traditional non-review aware recommender systems.

TABLE 3. RMSE Performance for non-review aware recommender systems (RMSE).

Non-review aware recommender systems	Video	Toys	Beer	Yelp
NMF	1.244	1.199	1.638	1.052
SVD	0.986	0.932	1.175	0.964
SVD++	0.980	0.926	1.181	0.965

Secondly, from Table 4, we can see that the machine-generated reviews consistently outperform human-written reviews on *all* datasets. This is a novel and somewhat surprising result. As we discussed previously, the quality of human-written reviews is variable, and we know that poorly written reviews can harm the prediction ability of the recommender systems. On the other hand, the RNNs we employed in our synthetic review generation models is an expert in learning the most significant aspects of the text and reducing the generalisation error. Thereby, they can eliminate the impact of useless reviews and are trained to compose high-quality and relevant textual reviews.

Thirdly, comparing with GCN, the state-of-the-art generation model, both of our generation models exceed its performance in almost all cases, especially our Attention model. Although it has not surpassed GCN in the Beer dataset when using NARRE, the Attention model matches the performance of GCN, likely because the attention mechanism increased the ability of the model to learn more accurate syntax and better personalisation. Thus, we can generate more useful reviews and improve on the rating performances.

C. RANKING PERFORMANCE (Q1)

Another task of recommender systems is to recommend the correct items for users. In other words, the ideal recommendation is to rank items in a sequence that meets the users' preferences, which is a more onerous task than predicting ratings of items, and usually more valuable. In the ranking experiment, we start by producing K recommended items for each user in the test set through the two review aware recommender systems, DeepCoNN, and NARRE. As we described previously, we employ NDCG@K to leverage the recommended ranking quality, where higher NDCG@K value represents a more accurate ranking of items. Figure 4 reveals the ranking results. Firstly, we observe that the ranking performance of machine-generated reviews shows significant improvements over the ranking performance of human-written reviews in different levels of K. Though improvements in the Beer dataset are not as pronounced as in other datasets, we can still observe the continuous successes that machine-generated

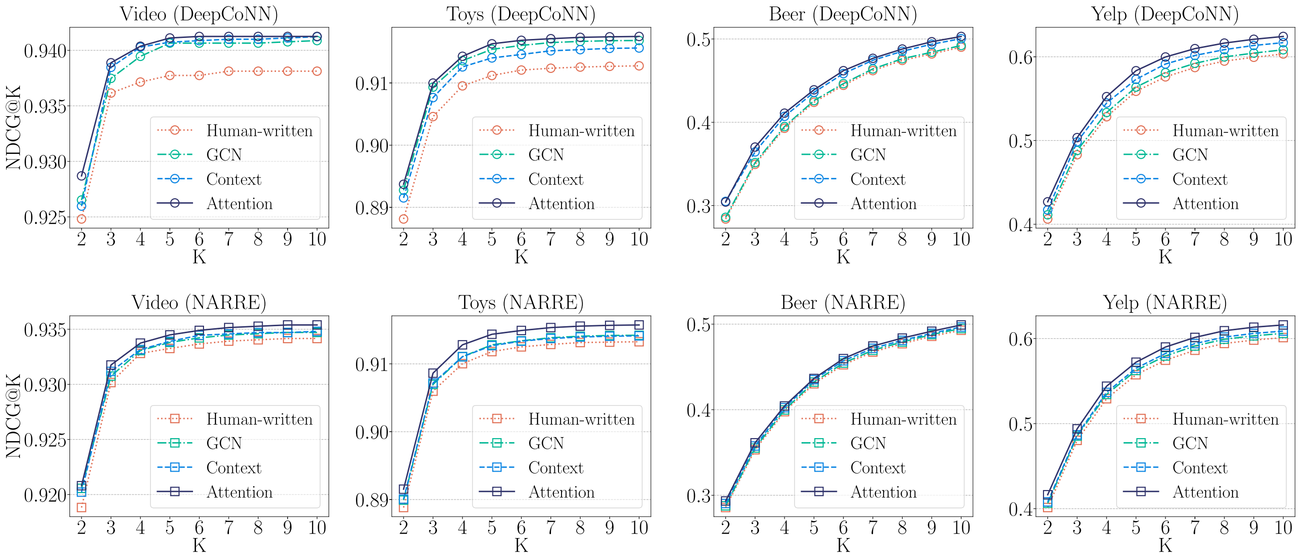


FIGURE 4. NDCG@K results on four datasets and two state-of-the-art text-aware recommender systems. Here, K ranges from 2 to 10. Test reviews are provided by human, GCN, Context and Attention models.

TABLE 4. RMSE Performance for review aware recommender systems. Note that human and GCN are the baselines, while Context and Attention are our models. * and ** denote the statistical significance for $p < 0.05$ and $p < 0.01$ respectively.

Review aware Recommender systems	Video		Toys		Beer		Yelp	
	DeepCoNN	NARRE	DeepCoNN	NARRE	DeepCoNN	NARRE	DeepCoNN	NARRE
human	0.898	0.898	0.878	0.878	1.175	1.157	0.861	0.859
GCN	0.897	0.888	0.878	0.875	1.174	**1.153**	0.861	0.858
Context	0.888	0.891	0.852	0.876	1.173	1.156	0.860	0.851
Attention	**0.881****	**0.867****	**0.845****	**0.874****	**1.156****	1.154	**0.852***	**0.850***

reviews outperform human-written reviews in recommendation tasks. Moreover, our context model shows similar NDCG@K results to the GCN model, while our attention model surpasses GCN models on all datasets. It indicates that our attention model generates excellent reviews, leading to positive recommendation improvements.

D. PERFORMANCE W.R.T. SPARSITY (Q2)

As we discussed previously, review-aware recommender systems often suffer from poor performance when the rating information for users and items is sparse. Besides, low quality reviews harm the accuracy of recommendations, which is a more severe problem for review-aware recommender systems. On the other hand, text generation models learn rich representations for user-item pairs through the attribute encoder module, introduced Section. IV. Thus, we argue that text generation models can learn significant knowledge from machine-generated reviews.

We design a set of experiments to measure the system performance in the presence of varying levels of sparsity. The most efficient way to create a sparse environment is removing records, as described in Feng *et al.* [56] who randomly removed ratings in the test data. In our experiment, we adopt the number of reviews per items to indicate the

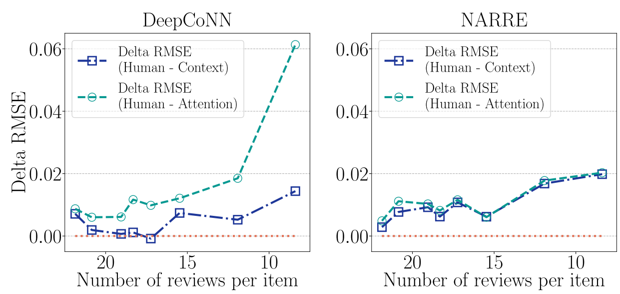


FIGURE 5. Recommendation performance comparison for different sparsity levels (number of reviews per item). We reduce the average number of reviews per item to increase the sparsity level.

level of sparsity. Specifically, we remove reviews of items according to the distribution of the number of their reviews instead of removing them at random. Through this approach, we ensure all items have reviews and we can strictly regulate the level of sparsity.

Regarding the evaluation metric, we analyse the sparsity performance by considering the $\Delta RMSE$ for a variety of sparsity levels. We conduct our experiments on the Amazon Video dataset since it has the highest volume of reviews per item of all the datasets. Specifically, we manipulate the sparsity level of the Amazon Video dataset and rerun the experimental

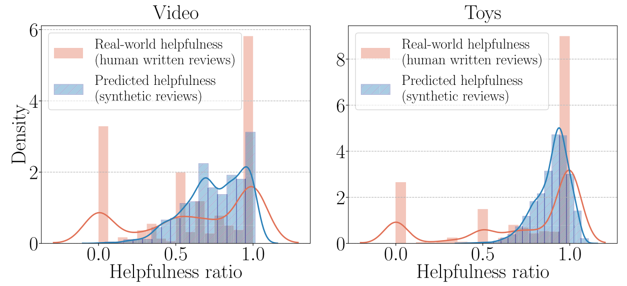


FIGURE 6. Distribution of helpfulness ratio of human-written reviews and helpfulness ratio of machine-generated reviews.

process (see Figure 2) for both human-written reviews and machine-generated reviews. We run this experiment on DeepCoNN and NARRE, two deep learning-based recommender systems, and show the results in Figure 5. By the definition of $\Delta RMSE$, greater $\Delta RMSE$ indicates the performance of generated machine-generated reviews surpasses human-written reviews. Experimental results demonstrate the effectiveness of generation models dealing with the sparsity problem. When the dataset becomes sparse, text generation models can still learn excellent user-item representations, which is how they achieve notable performance. In this way we address the sparsity problem for review-aware recommender systems.

E. PERFORMANCE W.R.T. HELPFUL REVIEWS (Q3)

Besides the sparsity issue, recommender systems also suffer from a text quality problem as we introduced in Section I. Some human written reviews contain tangential information and these *worthless reviews* serve to undermine recommendation quality. To improve user experience, many companies allow users to make subjective votes on whether the reviews from third-parties helped their decision (Amazon is a good example). In this experiment, we aim to explore whether generation models can improve the reviews that are voted as *not helpful*. We calculate the proportion of helpfulness votes as the *helpfulness ratio* for each review in two Amazon datasets. We then group the user-item pairs whose helpfulness ratio is greater than 0.5 into the usefulness group, otherwise the worthlessness group. We leverage the recommendation performance for both usefulness and worthlessness groups by RMSE. Besides, to assess the improvements outlined above, we calculate the percentage of the improvement for machine-generated reviews over human-written reviews. We conduct this experiment on DeepCoNN recommender system and demonstrate the results in Table 5. From these results, we can see that machine-generated reviews outperform human reviews in terms of both usefulness and worthlessness groups. Additionally, machine-generated reviews show significant *RMSE* improvements for the worthlessness group. We assume that although generation models learn from human-written reviews, they concentrate on modelling useful instead of meaningless aspects that instead contribute to the noise and are ignored.

TABLE 5. Recommendation performance comparison for worthlessness group *A* (helpfulness ratio less or equal to 0.5) and usefulness group *B* (helpfulness ratio greater than 0.5). ** presents the statistical significance for $p < 0.01$.

DeepCoNN	Video		Toys	
	A	B	A	B
Human	1.133**	0.929**	1.643**	1.025**
Context	1.100**	0.927**	1.421**	1.022**
Improvements	**2.89%**	**0.22%**	**13.53%**	**0.28%**

To validate the above assumption, we train an XGBoost model [57] and predict the helpfulness ratio for the machine-generated reviews in the test set. Figure 6 illustrates the distribution of real-word helpfulness ratio and predicted helpfulness ratio. According to these results, most reviews are helpful in the real world, while there is still a considerable fraction of useless reviews. When predicting the helpfulness ratio, only a few machine-generated reviews are predicted as unhelpful in Video dataset, and most machine-generated reviews in Toys dataset are seen as helpful. This finding validates the above hypothesis that generation models focus on learning *useful* instead of *worthless* aspects. Thereby, machine-generated reviews can achieve better recommendation performance than human-written reviews, which indicates they are suitable ingredients for text-aware recommender systems.

F. INTERPRETATION QUALITY AND SAMPLES (Q4)

The ideal way to evaluate the explanation performances is experimenting on real-world recommender systems, in which live users can conduct fair judgments. We plan to run a live-user trial, but in this paper, we focus on first evaluating explanations by offline approaches, which can provide valuable information on the quality of the generated explanations. According to Hase *et al.* [58], many works use offline statistical methods to measure the quality of explanations quantitatively and conduct case studies for leveraging the performance of explanations qualitatively. Similarly, in this section, we first measure the quantitative performance of explanations on Natural Language Processing (NLP) methods. Then we leverage the qualitative performance of explanations by case studies.

For quantitative analyses, we employ four NLP evaluation methods: Perplexity [17], expressed as the exponentiation of the entropy per words, is a commonly used intrinsic methodology in natural language generation. It is used to measure how well the word probability distributions of the machine-generated reviews match those of the test reviews. Generally, lower perplexity means a better text generation. BLEU score [13], another well-known approach in machine translation and text generation tasks, measures the word correlations between machine-generated reviews and test reviews by calculating the precision of n-gram matching. TF-IDF similarity [17] is a statistical method reflecting the importance of words to review corpus. To leverage the relevance between

TABLE 6. Explanation performance using the NLP and readability methods described in Sec. V-F. In all metrics our attention model shows the best performance.

Models	Perplexity				BLEU-4				TFIDF similarity				Readability similarity			
	Video	Toys	Beer	Yelp	Video	Toys	Beer	Yelp	Video	Toys	Beer	Yelp	Video	Toys	Beer	Yelp
N-gram	820.1	680.6	355.9	787.0	0.002	0.003	0.029	0.020	0.048	0.058	0.101	0.060	0.644	0.586	0.565	0.466
GCN	452.2	165.3	165.6	134.1	0.136	0.393	1.160	0.278	0.090	0.093	0.171	0.095	0.790	0.720	0.934	0.775
Context	194.4	164.0	159.2	108.6	0.403	0.676	3.409	0.395	0.109	0.122	0.182	0.117	0.782	0.739	0.945	0.866
Attention	**177.1**	**162.1**	**131.9**	**102.2**	**0.412**	**0.691**	**4.178**	**0.553**	**0.113**	**0.129**	**0.209**	**0.134**	**0.799**	**0.802**	**0.965**	**0.905**

TABLE 7. Comparison of synthetic personalised reviews with human-written reviews. We generate machine-generated reviews for anonymous users and items on different ratings using the attention model. We highlight words that appear in both human-written and machine-generated reviews. The sentiment value of each word is highlighted with the polarity: positive is green, negative is red.

(User, Item)	Rating	Human written reviews	machine-generated reviews
(A, X)	5	Purchased as a christmas gift my year old grandson and he just loved them and could not wait until he built the lego star wars rebel trooper battle pack, highly recommend	this is the best thing that i can't say that the star wars this is a great toy for the price. I would recom-mend this to anyone who loves to play with lego
(B, Y)	3	I bought two sets i received small amount of energy that went with almost none of the pokemon and quiet a bit of trainers a few foils. A couple rares and some in japanese but not bad for the price	I don't know if it was a bit of a standard plastic product i would not recommend this product for any child, although the price is not bad.
(C, Z)	1	I bought this for my grandson he enjoyed it at first but the newness wore off. There are not a lot of colors that came with it. It was somewhat disappointing.	This was a big hit with my year old but i was a disappointed that the box is a bit of a bad toy. it is not a great toy for a young child to play with.

machine-generated reviews and test reviews, we calculate the cosine similarity on TF-IDF of generated reviews and test reviews. Readability similarity [7] aims to evaluate whether a given review text is readable or not. We adopt eight readability algorithms and use the output readability value to represent reviews. The readability measures are: Automated Readability index [59], Flesch reading ease [60], Flesch-Kincaid grade level [60], Gunning-Fog index [60], simple measure of gobbledygook [61], Coleman Liau index [60], LIX [62] and RIX [62].

Notably, we compare our methods with two baselines, the classical N-gram language model [63], which predicts the occurrences of N consecutive words, and the GCN model. We run our experiments on the test set of four datasets, and the results are presented in Table 6. Through this table, we notice that our generation models consistently outperform the baselines. The context model beats the N-gram model and shows comparable performance to the GCN model, and the attention model shows the best explanation achievements. These promising results reflect our generated reviews are readable and adhere to the grammar and syntax of natural language expression.

We then conduct qualitative studies by empirically studying the explanation effect of machine-generated reviews, as shown in Table 7. From this table, we can observe that for the specific user, item, and rating, generation models can provide similar text quality to the human-written reviews. The first example demonstrates two reviews involving lego star wars, and they would like to recommend this item to others, which shows that our models can accurately reproduce the opinions and sentiments of a user about an item. In the second example, both machine-generated reviews and human-written reviews mention the price, which is one of the vital aspects that interests users. Moreover, the two reviews in the third example deliver a negative sentiment ("disappointed"), explaining why we do not recommend this item. This observation shows that we can provide readable reviews that satisfy the requirements for explaining recommendation accurately to the user.

VI. CONCLUSION

In this paper, we have improved recommendation accuracy by inputting compelling machine-generated review-based explanations. Concretely, we developed two character-level review generation models and addressed both recommendation and explanation problems. We conducted experiments on four real-world datasets from different domains.

Experimental results revealed that our models consistently surpass the baselines and achieve state-of-the-art rating prediction performance. In ranking evaluation, our attention generation model outperformed baselines and showed excellent performance. Besides, we demonstrated the effectiveness of generation models in dealing with item sparsity problems. We also showed that generation models are suitable ingredients for recommender systems since they focus on generating useful machine-generated reviews.

To evaluate explanation quality, we used multiple offline metrics in the NLP field for quantitative evaluation and conduct case studies on generating review-based explanations in different combinations of users, items and ratings for qualitative evaluation. The quantitative evaluation results validated that our generated explanations received good scores for understandable. Also, our qualitative results demonstrate that we can produce critical words that express a user's real opinion of the item, where such critical words are the key aspects for delivering strong explainability.

These results as a whole are convincing arguments for the extensive use of machine-generated reviews to explain predicted ratings. Offline evaluation is not enough, our next steps will be continuing assessing the explanation quality through online live-user trials. In conclusion, improving the automatic generation of machine-generated reviews is a valuable next direction to provide more precise recommendations and personalised explanations.

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SIXUN OUYANG received the master's degree in computer science from University College Dublin (UCD), Ireland, where he is currently pursuing the Ph.D. degree in computer science. He is currently an Independent Researcher with the Insight Centre for Data Analytics, UCD. He has been enthusiastically engaged in large industrial projects and Europe national research projects. He has rich experience in the fields of machine learning, deep learning, explainable systems, natural language processing, and recommender systems. He has received funded grants from the Science Foundation of Ireland.

AONGHUS LAWLOR received the Master of Science degree from the University of Cambridge and the Ph.D. degree from the University College Dublin (UCD). He is currently an Assistant Professor with UCD and a Principal Investigator with the Insight Centre for Data Analytics. He has been actively involved in several EU and national research projects in the above mentioned areas and has been the co-PI of very large Industrial projects. He has long experience in the areas of machine learning, artificial intelligence, explainable AI, natural language processing, and recommender systems. He has also received several funded grants from Enterprise Ireland and the Science Foundation of Ireland, leading to multiple patent applications.