Automatic Generation of Natural Language Explanations

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ABSTRACT

An important task for recommender system is to generate explanations according to a user's preferences. Most of the current methods for explainable recommendations use structured sentences to provide descriptions along with the recommendations they produce. However, those methods have neglected the review-oriented way of writing a text, even though it is known that these reviews have a strong influence over user's decision.

In this paper, we propose a method for the automatic generation of natural language explanations, for predicting how a user would write about an item, based on user ratings from different items' features. We design a character-level recurrent neural network (RNN) model, which generates an item's review explanations using long-short term memories (LSTM). The model generates text reviews given a combination of the review and ratings score that express opinions about different factors or aspects of an item. Our network is trained on a sub-sample from the large real-world dataset BeerAdvocate. Our empirical evaluation using natural language processing metrics shows the generated text's quality is close to a real user written review, identifying negation, misspellings, and domain specific vocabulary.

CCS CONCEPTS

Information systems → Recommender systems;
 Computing methodologies → Natural language generation;
 Neural networks;

KEYWORDS

 $Recommender\ Systems,\ Explainability,\ Explanations,\ Neural\ Networks$

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1 INTRODUCTION

One of the key challenges for a recommender system is to predict the probability that a target user likes a given item, taking into account the user's history and their similarity to other users. However, making predictions in this way does not explain why the item matches with the users' preferences. Recent works have introduced the concept of explainable recommender systems, which try to generate explanations according to users' preferences rather than only predicting a numerical rating for an item. In this work we develop an approach using character-level neural networks to generate readable explanations.

Current explainable recommendations propose to mine user reviews to generate explanations. In [27] they propose an explicit factor model, where they first extracts aspects and user opinions by phrase-level sentiment analysis on user generated reviews, then generate both recommendations and disrecommendations according to the specific product features and personalised to the user's interests and the hidden features learned. On the other hand, in [8] they propose a tripartite graph to enrich the user-item binary relation to a user-item-aspect ternary relation. In each of the these work, they propose to extract aspects from reviews to generate explainable recommendations, but they do not consider user opinions and influences from social relations as a source of explanation. In [23] they propose the social collaborative viewpoint regression model, which detects viewpoints and uses social relations as a latent variable model. This model is represented as tuples of a concept, topic, and a sentiment label from both user reviews and trusted social relations.

Explanations generated in this manner lack natural language expressions, since the sentences are generated in a modular way. However, it is well established by [25] that a good explanation must be clear, and interesting to the target user, since this information has a significant influence on the user's decision. On-line usergenerated reviews present clear and interesting information about items, since they describe personal usage experience from users. Furthermore, this source plays an important role on the user side, since he/she tend to trust the opinion of other users [5, 13, 22].

Recurrent neural networks (RNNs) have recently demonstrated to show very good performance in natural language generation, since the generating function can be automatically learned from massive text corpora. Due RNNs suffers from gradient vanishing problem, long-short term memory (LSTM) has been applied to the text generation field, and leads to significant improvements on this issue. Another advantage of using LSTM is the ability to keep in memory the long-range dependencies among words and characters. The combination of RNNs with LSTM have shown promising results on such different text datasets as Shakespeare poem, scientific papers, and linux source code generation [12].

Most natural languages text generation approaches focus on the raw textual content and often neglect their contextual information. This context, such as the specific location, time and sentiment are important factors in the creation of user generated on-line reviews and should not be neglected. Recent research on recommender systems demonstrated improvements achieved by including context [1]. This paper incorporates this information to enrich the generated sentences with particular contextual features.

In this paper, we propose a technique for the automatic generation of explanations, based on generative text reviews given a vector of ratings that express opinions about different factors of an item. Our method is based on a character-level LSTM trained on a sub-sample from the large real-world dataset BeerAdvocate. It is divided into three modules: a context encoder, LSTM decoder, and the review generation. The ratings are normalised, then concatenated to the characters to feed the LSTM cells, which can generate characters that are contextualised by the normalised ratings. The generative review module has a weighted generation based on ratings vector as input. The weights learns soft alignments between generated characters and sentiment, where we adaptively compute encoder-side context vectors used to predict the next characters.

Automatic generated review-oriented explanations, are useful for companies and users, who can benefit from helpfulness aspect of the explanations to assess an item recommendation. [4] shows character-level generation has advantages over other techniques such as unsupervised learning of grammar and punctuation, and can be more efficient than word-level generation, since it allows for the prediction and generation of new words and strings.

This paper presents as contributions:

- A context-aware review generation based on rating scores
- Generate readable reviews in a human perspective.

2 PROBLEM FORMULATION

In this section, we provide the basic definition and preliminaries to generate natural language explanations. Given a set of items I, and target user u:

- An item is a product (beer) represented by $i \in I$.
- Explicit feedback is an action represented by the matrix $X_u: U \times I \to R$, where $u \in U$ is a user, $i \in I$ is an item, and $r \in R$ represents a rating that the user u have been given to item i. Considering the each r rating is a vector corresponding to a set of five features appearance, aroma, palate, taste, and overall.
- Reviews are another explicit feedback in text format represented by the matrix $X_a: U \times I \to T$, where $u \in U$ is a user,

 $i \in I$ is an item, and $t \in T$ represents a review that the user u have been given to item i.

2.1 Problem Statement

Ratings are attributes to express opinions from a user about a certain item, however it is difficult to compose a judgement of a product based only on the rating score. Therefore, user-generated reviews are richer, since the user can give explanations according to different features and aspects of a specific item. There are many approaches to generating explanations for different types of recommender systems, including collaborative filtering [9] and case-based approaches [18]. Explanations showed to increase the effectiveness of the recommendation and the user's satisfaction [26] in various evaluations methods. Current state of the art in explainable recommender systems does not offer human-oriented explanations. To address this particular issue, our model is defined to target the problem of generating explanations in a review-oriented and natural language basis.

We formulate the item explanation generation problem as follows. Given input ratings vector $r_i = (r_1, \ldots, r_{|r_i|})$, we aim to generate item explanation $e_i = (w_1, \ldots, w_{|t_i|})$, maximizing the conditional probability p(e|r). Note, rating r_i is the average values from the evaluation of target item i in a fixed numerical representation, while the review t_i is considered a character sequence of variable length. We set |r| as 5 in our task, as we have 5 features with different ratings values. The model learns to compute the likelihood of generated reviews given a set of input ratings. This conditional probability p(e|r) is represented in the Eq. 1.

$$p(e|r) = \prod_{s=1}^{|e|} p(w_s|w < s, r)$$
 where $w < s = (w_1, \dots, w_{t-1})$ (1)

3 RELATED WORKS

Neural networks have started to attract attention in recommender systems community only recently. In [14] they study recurrent neural networks in different architectures for a collaborative recommender system with experiments showing good performance. Despite good performance, this example of work suffers from the same problem as the other works that it is not explainable.

The work of [2] is among the first where a recommender system is utilising the review text as side information to improve the performance of recommender system and the solutions are rooted in recurrent neural networks. Our work differs from this work as we are in fact trying to generate explanations in the form of a user-generated review to improve a user's understanding of recommended items.

What we would like to achieve however is an alignment between variables or features which lead to a recommendation of one item or another and a descriptive text where rules about the text composition are learned from the existing reviews. Therefore, we would like to achieve similar alignment as others have achieved in different domains such as text generation for images as in [11].

Learning the rules for generating the reviews can be accomplished by representing input as sentences, words or characters. In [19] and [24] they propose a tree-based neural network model for

natural-language inference based on words and their context. We study character-level explanation generation to further improve the state of the art. The work of [12] provides the first insights into why the LSTM variant of neural networks has such good performance. Similar technique were used on [4], where they build on the previous work to generate product reviews in the restaurant domain.

Encoding rating vectors in the training phase allows the system to calculate the probability of the next character based on the given rating. In previous work, [6] showed an efficient method for generation of next the word in the sequence when we add an attention mechanism, showing that this idea improves performance for long sequences.

Character-level generation has shown improvement over word-level on the text generation problem using RNNs [4]. This is because, on the character-level, the neural network can autonomously learn grammatical and punctuation rules. In [4] they mention the character-level RNN provides slightly worse performance than the equivalent word-based model, however it shows improvements in terms of computational cost, which grows with the size of the input and output dictionaries, an in contrast, it allows for the prediction and generation of new words and strings.

In [15] they focus on character-level review generation and classification where the ratings are used as auxiliary information. Our work differs from both aforementioned approaches for character-level text generation in utilising richer data (ratings are used to explicit quality of a product in different features, identified as a source of user's preference) and providing a first attempt to generate explanations with character level networks to reflect user differences and preferences.

4 GENERATED EXPLANATIONS

4.1 Recurrent Neural Network

Recurrent neural networks (RNNs) are feed-forward networks with temporal verifying activation, processing and learning sequential data. While in the training step, given an input vector X_t in time t and the cell state of previous time step t-1, where the input weight matrix is represented by W_x and state weight metrices refers to W_h , the RNNs then pass the cell state h_t to the next time step and propose a prediction value Y_t via a softmax layer which consists of a non-linear softmax function, as shown in Eq. 2.

$$h_t = \tanh(X_t \odot W_x + h_{t-1} \odot W_h)$$

$$Y_t = \operatorname{softmax}(h_t \odot W + b)$$
(2)

According to Eq. 2, if we continue feeding the same values to X_t , the input weight matrix W_x and state weight matrix W_h will be changed to suit the input value. RNN's suffer a vanishing gradient problem, that depending on the activation functions, sequential information gets lost over time. To handle this issue, [10] introduced Long short term memory (LSTM) cells, and was later improved by [7] using forget gates to discard some information.

LSTM is an improved version of RNNs controlled by sequential connection of gates: forget gate, input gate and output gate. When receiving an input data x_t at time t and the cell state C_{t-1} from previous time step t-1, those values will be concatenated together for the next computation. It will feed the forget gate initially, where

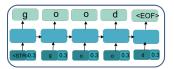


Figure 1: Generative Concatenative Network

it decides which information has to be discarded. There, f_t represents the results via the forget gate in time t, W_f and b_f refers to the weight matrix and bias, respectively. The next step for LSTM cells is to determine which information should be stored in cell state through the input gate. At the update step, i_t means the input gate results, W_i and b_i are its parameters. The cell creates a candidate state C_t' through a tanh layer. Using the candidate state with the previous cell state, forget gate results f_t and input gate results i_t to update the current state C_t . Finally, the data goes to output gate, where it uses sigmoidal function layer to determine which part of the cell state is the output, then it multiplies tanh with the current cell state C_t to give as result the character with the highest probability.

$$X = [x_t, C_{t-1}]$$

$$f_t = \sigma(X \odot W_f + b_f)$$

$$i_t = \sigma(X \odot W_i + b_i)$$

$$C'_t = \tanh(X \odot W_c + b_c)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot C'_t$$

$$o_t = \sigma(X \odot W_o + b_o)$$

$$H_t = o_t \odot \tanh(C_t)$$
(3)

4.2 Generative Concatenative Network(GCN)

Generative RNN models can be applied in many fields as most data can be represented as a sequence, especially for text generation. State weights benefits generative RNNs to generate coherent text, where one character can be fed into the network at a time step and these affect the state weights. This project builds on the generative concatenative network presented by [15], which uses an LSTM RNN character-based generation model, adding auxiliary information according to ratings for different feature preferences.

In [12] they define a character-level language model given a sequence of characters as input to an LSTM neural network, calculate the probability of the next character in the sequence with a softmax function at each time step s then generate the character as output. Given a set of C characters we encode all characters with C-dimensional 1-of-C vectors $\{x_t\}, t=1,\ldots,T$, and feed them to the recurrent network to obtain a sequence of H-dimensional hidden vectors as the last layer of the network $\{H_t^l\}, t=1,\ldots,T$. To obtain predictions for the next character in the sequence, the output goes to the top layer of a sigmoid activation function to a sequence of vectors \hat{y} , where $\hat{y}=W_y.H_t^L$ and W_y is a $[K\times D]$ parameter matrix. The output vectors are interpreted as holding the log probability of the next character in the sequence and the objective is to minimize the average cross-entropy loss over all targets.

In [15] they propose to generate text, conditioned on an auxiliary input x_{aux} , where the input x_{aux} is concatenated with the character

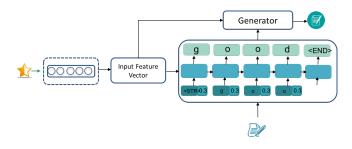


Figure 2: Generative Explanations

representation $x_{char}^{(t)}$, as it is seen in Fig. 1. They train their network based on the concatenated information input $x'^{(t)} = [x_{char}^{(t)}; x_{aux}]$. At training time, x_{aux} is a feature of the training set, while during the generation step, they define some x_{aux} , concatenating it with each character sampled from $\hat{y}^{(t)}$. They replicate the auxiliary information x_{aux} at each input to allow the model to focus on learning the complex interactions between the auxiliary input and the language, rather than just memorising the input. However, they consider only the overall rating or temperature for a certain item, neglecting the user's preference in different aspects.

4.3 Context Encoder

Similar to [12] and [15], our model is based on LSTM RNNs network to generate reviews. Our model adds a set of auxiliary information to each character in the context encoder module.

In our model, the context encoder module encodes the input character using one-hot encoding and concatenates a set of ratings to it, before feeding it into network as we can see in Fig. 2. In our experiments, we generate a dictionary for all the characters in the corpus to record their positions, which will be used as the encoding process in the training step and for decoding in the generating step. For each character in the reviews, a one-hot vector will be generated by using its position in that dictionary. Then the one-hot vector will be concatenated with a set of auxiliary informations which relies on the review, as shown in Eq. 4. Meanwhile, in terms of the auxiliary information, our model uses a set of numeric values of the users' ratings, which are rescaled to the range [0, 1].

$$X'_{t} = [onehot(x_{char}); x_{auxiliaru}]$$
 (4)

4.4 Generative Explanation

As mentioned previously, [15] proposed a GCN model concatenating characters with some auxiliary information, i.e. overall rating or temperature, being able to generate some remarkable samples. It uses one piece of auxiliary information to enrich the probability to define the next character.

We propose an improvement to the concatenation process, where we consider a vector of auxiliary data, i.e a set of the ratings scores for different features of items, instead of only one dimension of auxiliary information. During the review generation our model generates distinct pieces of text tuned to the distribution of applied ratings.

A non-linear softmax layer is used in our model to compute the probability for all characters. During the generation process the model concatenates a prime text, which is a start symbol in each review, concatenated with a series of ratings scores to the model. Then the model passes its output to a softmax layer, as shown in 5, where H_t is the output of a LSTM cell, W and b are the weight and bias of softmax layer, respectively.

$$Y_t = softmax(H_t \odot W + b) \tag{5}$$

This procedure is applied recursively and a group of characters is generated until we find the pre-defined *end* symbol.

By using LSTM cells for character-level explainable review generation, and merging with the vector of ratings, we allow the model to learn grammar and punctuation, being more efficient than word-level models [4], since our model can predict and generate new words and strings. Therefore, our model generates explanations for recommender systems with a review-oriented perspective, adding improvements on the quality of the explanation text presented to to the user in the form of a review.

5 EXPERIMENTS

5.1 Parameters Definition

Empirical experiments used a customised LSTM RNN library written in Python and using Tensorflow. There are 2 hidden layers with 1024 LSTM cells per layer. During training, a wrapper mechanism is used to prevent over-fitting. Feed-in data was split by 100 batches with batch size of 128 and each batch has a sequence length of 280.

5.2 Dataset

We tested our model in a sub-sample from the large real-world dataset: BeerAdvocate. The original dataset consists of approximately 1.5 million reviews retrieved from 1998 to 2011. Each review includes rating ¹ in terms of five categories: *appearance*, *aroma*, *palate*, *taste*, and *overall* impression. Reviews include item and user ids, followed by each of these five ratings, and a plain text review. The summarised statistical information from the extracted sub-sample is shown on the Table 1.

BeerAdvocate	
2,815	
1,372	
4,999	

Table 1: Dataset Statistics

5.3 Data Preparation

The BeerAdvocate dataset contains several beer categories, and we selected a sub-sample dataset based on just 5 categories: "american ipa" ,"russian imperial stout" ,"american porter","american amber/red ale" and "fruit/vegetable beer". Considering some reviews are probably too short or even empty that would cause problems with training, we filter our sub-sample to include only reviews with at least 50 characters. For our experiments we concentrate on

 $^{^{1}}$ Original ratings were normalized with values between 0-1.

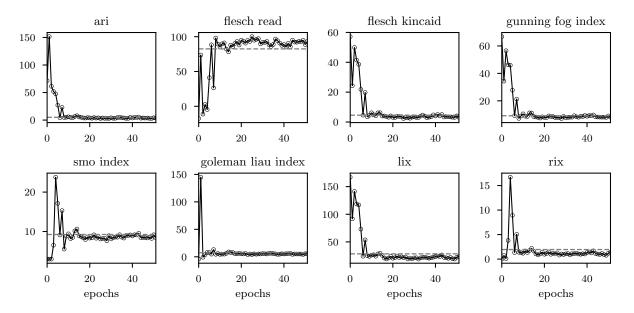


Figure 3: Readability metrics with epoch. The metrics are detailed in Sec. 5.4.

generating reviews conditioned on the size of reviews of each beer categories, we select 4k reviews of each category for our training datasets.

We first generate a dictionary for all characters, i.e. punctuation, numbers and letters, then transform each character into a one-hot vector using that dictionary. We train the network based on a sequential approach, where each review is fed into a sequence, to do so it is essential to remind the network of the start and end position of each of the reviews. We do this by appending start and end symbols, i.e. < #str# > and < #end# >, to each reviews for both the training and generation modules. In order to generate explanations for different ratings, we concatenate the input characters with the ratings of the review the character belongs to. In addition, we normalise the scale of the ratings to [0,1].

5.4 Evaluation Metrics

Current methods to explain recommendations do not have a natural language way to present the information to the user. Our proposed method explains the recommendation to a target user in a style of a user-generated review. To measure the quality of the presented text, we used a suite of natural language readability metrics: Automated Readability index (ARI) [16], Flesch reading ease (FRE) [20], Flesch-Kincaid grade level (FGL) [21], Gunning-Fog index (GFI) [20], simple measure of gobbledygook (SMOG) [17], Coleman Liau index (CLI) [21], LIX [3], and RIX[21]. Flesch reading ease score is considered the oldest method to calculate the readability through the analysis of number of words and sentence length. An updated version of this metric is the Flesch-Kincaid grade level. The Gunning Fog index is commonly used to confirm a text can be read easily by the intended audience. The SMOG score is a improvement of Gunning Fog index, showing better accuracy overall. Automated Readability index relies on a relation of the number of characters per word. The Lix score gauges the word length by the percentage of long words.

5.5 Results

The initial test of our explanation generation is about readability. We use 8 readability evaluation metrics as mentioned above for both generated and reference reviews.

We first select 10 reviews from our sample dataset as the reference reviews. By using the same users and items from these 10 reviews, as well as considering the different learning curve of the model in different epochs, we generated 10 reviews per epoch from the model. We then apply the readability metrics to the generated and reference reviews to evaluate the text. The readability results are shown in Fig. 3, where it is observed the generated reviews reach the same level of readability as the user reviews on all metrics after 20 epochs.

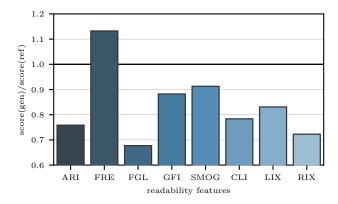


Figure 4: Extent of readability for different metrics. The readability of generated text is shown relative the mean score for the user-generated reviews.

As Fig. 3 shows, the readability evaluation metrics illustrate the capacity of the model to generate reviews which are close to the user's style of writing. We use the readability scores of the generated reviews from the final epochs and normalise to the scores obtained from the reference reviews to demonstrate the relative readability in Figure 4. This emphasises the neural network generated reviews are close in style to the human written reviews. This is determined by a broad range of readability metrics which are sensitive to different qualities of the text. It is important for our explanations that they are legible, easy to understand, and appear to be written in a recognisable style.

We established our model can generate natural language text which reaches the overall readability level of the user-generated reviews. We now investigate the different kinds of explanations that can be generated when we modify the auxiliary values at the generation stage. We are using the ratings from 5 aspects of the beers as auxiliary values, and they represent each users preferences and general ratings opinion about a target beer. We choose a useritem pair (U, I), and compute the average ratings for each feature for both user $\bar{R}_{user} = \sum_{i} R_{user,i} / |R_{user}|$ and item \bar{R}_{beer} . The precise contribution of user/item ratings is controlled with a weighting parameter α , and we demonstrate three different text samples to compare through Eq. 6. As Eq. 6 shows, α controls the auxiliary values and we then generate reviews based on them. When α is close to 1, the generated review will be more like a review that the user will write. With α close to 0, the generated review will be closer to the general rating of all users for that beer. To investigate the divergence of generated reviews, we set α equal to 1, 0.5, 0, which refers to the opinion of the user on general beers, the review the user might compose on that beer, and the general reviews of the beer.

$$R_{auxiliary} = \alpha \times \overline{R}_{user} + (1 - \alpha) \times \overline{R}_{beer}$$
 (6)

According to Fig. 5, the first review ($\alpha=1$) shows the opinion of the user on general beers, which have a positive sentiment overall. When we look into the last review ($\alpha=0$), the common view of that beer is in a negative sentiment, represented by negative sentence, as "I wouldn't recommend it". With $\alpha=0.5$ the generated review displays a relatively neutral attitude towards the beer.

6 CONCLUSIONS

In this paper, we propose a model to automatically generate natural language explanations for recommender systems.

Our explanations provide easily intelligible and useful reasons for a user to decide whether to purchase a certain product. This has important benefits for the field of recommender systems since these explanations can help a user to make a better decision and more quickly, as users place a high degree of trust in the reviews of others.

As our experiments with natural language readability metrics show, we were able to generate readable English text with specific characteristics that match user-generated review text.

In the future we will focus on further extensions of the automatic generation of natural language explanations in two ways: (1) personalised explanations that benefit the user's preferences, where the explanation of the product is tailored to the users ratings,

 $\alpha = 1.0$

a: pours a clear amber color with a small white head. the aroma is a little spicey with some sweetness. the taste is also a bit more like a beer. there's a little bit of a sweet fruitiness to it as well. the mouthfeel is a bit thin for the style. drinkability is good. i would drink this all night long, but i wouldn't try to get more than one.

 $\alpha = 0.5$

a: pours a clear amber color with a small white head that dissipates quickly. smell: a little spice. taste is also a bit like a belgian wine. there's a little bit of a banana flavor to it. it is a little too sweet and a little strange. mouthfeel: thin and watery. drinkability: i would drink this beer again, but i wouldn't try to get my entire offering into a pint glass. i was pretty surprised this is the beer i was expecting a bit more.

 $\alpha = 0.0$

a: pours a clear amber color with a small white head that dissipates quickly. smell: a little spice. taste is also a bit like a belgian wine. there's a little bit of a banana flavor to it it is a little too sweet and a little strange. mouthfeel: thin and watery. drinkability: i would drink this beer again, but i wouldn't try to get my entire offerings. i wouldn't recommend it.

Figure 5: Sample generated reviews for $\alpha = \{1, 0.5, 0\}$. The dissimilar sentences are highlighted in **bold**.

preferred aspects and expressed sentiments; (2) we will test our model in larger reviews domains such as hotels and restaurants.

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