UCEpic: Unifying Aspect Planning and Lexical Constraints for Explainable Recommendation

Jiacheng Li†, Zhankui He†, Jingbo Shang, Julian McAuley

University of California, San Diego
{j9li, zhh004, jshang, jmcauley}@eng.ucsd.edu

† Equal Contribution

Abstract

Personalized natural language generation for explainable recommendations plays a key role in justifying why a recommendation might match a user’s interests. Existing models usually control the generation process by soft constraints (e.g., aspect planning). While promising, these methods struggle to generate specific information correctly, which prevents generated explanations from being informative and diverse. In this paper, we propose UCEpic, an explanation generation model that unifies aspect planning and lexical constraints for controllable personalized generation. Specifically, we first pre-train a non-personalized text generator by our proposed robust insertion process so that the model is able to generate sentences containing lexical constraints. Then, we demonstrate the method of incorporating aspect planning and personalized references into the insertion process to obtain personalized explanations. Compared to previous work controlled by soft constraints, UCEpic incorporates specific information from keyphrases and then largely improves the diversity and informativeness of generated explanations. Extensive experiments on RateBeer and Yelp show that UCEpic can generate high-quality and diverse explanations for recommendations.

Introduction

The goal of explainable recommendation is to provide explanations to users for recommended items, which show product information in a personalized style, to justify recommendations of items that users might be interested in. High-quality explanations should be coherent, relevant to products, and informative for users. Previous works (Zhou et al. 2017; Radford, Jozefowicz, and Sutskever 2017; Li and Tuzhilin 2019) have explored the explanation generation task and shown success in generating coherent explanations. Recent studies focus on increasing the controllability of the generation process so that the generated explanations will be more informative and relevant to users’ interests. To this end, they use aspects extracted from data (Li et al. 2019; Ni and McAuley 2018) or knowledge bases (Li et al. 2020; 2021) then apply text planning methods (Hua and Wang 2019; Moryossef, Goldberg, and Dagan 2019) to generate personalized explanations for products with given information.

However, existing explanation generation methods have only soft constraints (e.g. aspects) which mostly control the sentiment or semantics of generated text. In this case, users and businesses cannot conduct lexical manipulation of the generation process to have specific product attributes, but these attributes are too specific to be accurately generated. For example, a business might want to generate explanations including some features for a TV (e.g., 120Hz Refresh Rate and AI-Powered 4K). Previous aspect-planning (soft-constraints) explanation generation methods (Ni and McAuley 2018; Li et al. 2019) control the generation process by giving an aspect (e.g. Screen) but cannot ensure the exact feature names appear in the generated text. Moreover, generated features are usually general (e.g., good quality). To show the missing keyphrases in explanation generation, we have experiments on comparing keyphrase coverage (informativeness) between generated explanations and a human oracle. Experimental results in Figure[1] show that generated explanations from previous methods miss many keyphrases and have lower Distinct scores than a human oracle. Hence, with soft constraints only, existing methods struggle to generate sufficiently diverse and informative explanations.

To address the above problems, we propose to introduce lexical constraints into the explanation generation task, in which the generated explanations must contain lexical constraints from users, businesses or even randomly sampled product attributes. Compared to previous methods with soft constraints that generate some general words, lexically constrained explanation generation easily includes specific information and can be diverse given different lexical constraints. Hence, the informativeness and diversity of generated explanations can be significantly improved. However, as shown in Table[1], existing explanation generation (ExpansionNet, Ref2Seq, PETER) cannot have lexical con-

| Methods         | Conditional generation | Soft constraints | Lexical constraints | Random keywords |
|-----------------|------------------------|------------------|--------------------|-----------------|
| ExpansionNet    | ✓                      | ✓                | ✗                  | ✗               |
| Ref2Seq         | ✓                      | ✓                | ✗                  | ✗               |
| PETER           | ✓                      | ✓                | ✗                  | ✗               |
| NMSTG           | ✗                      | ✗                | ✓                  | ✗               |
| POINTER         | ✗                      | ✗                | ✓                  | ✓               |
| CBART           | ✗                      | ✗                | ✓                  | ✓               |
| **UCEpic**      | ✓                      | ✓                | ✓                  | ✓               |

Table 1: Comparison of previous explanation generation models, lexically constrained generation models, and UCEpic.

or businesses cannot conduct lexical manipulation of the generation process to have specific product attributes, but these attributes are too specific to be accurately generated. For example, a business might want to generate explanations including some features for a TV (e.g., 120Hz Refresh Rate and AI-Powered 4K). Previous aspect-planning (soft-constraints) explanation generation methods (Ni and McAuley 2018; Li et al. 2019) control the generation process by giving an aspect (e.g. Screen) but cannot ensure the exact feature names appear in the generated text. Moreover, generated features are usually general (e.g., good quality). To show the missing keyphrases in explanation generation, we have experiments on comparing keyphrase coverage (informativeness) between generated explanations and a human oracle. Experimental results in Figure[1] show that generated explanations from previous methods miss many keyphrases and have lower Distinct scores than a human oracle. Hence, with soft constraints only, existing methods struggle to generate sufficiently diverse and informative explanations.

To address the above problems, we propose to introduce lexical constraints into the explanation generation task, in which the generated explanations must contain lexical constraints from users, businesses or even randomly sampled product attributes. Compared to previous methods with soft constraints that generate some general words, lexically constrained explanation generation easily includes specific information and can be diverse given different lexical constraints. Hence, the informativeness and diversity of generated explanations can be significantly improved. However, as shown in Table[1], existing explanation generation (ExpansionNet, Ref2Seq, PETER) cannot have lexical con-
strains to include specific product information. Current lexically constrained generation models (NMSTG (Welleck et al. 2019), POINTER (Zhang et al. 2020b), CBART (He 2021)) cannot include soft constraints (e.g., aspects) and conduct conditional generation to incorporate user-item information as references. Therefore, we present UCEPIC, which Unifies aspect-planning and lexical Constraints for Explaining Recommendation.

Methodologically, we propose a robust pre-training and personalized fine-tuning for UCEPIC. (1) For robust pre-training phase, inspired by Masked Language Modeling (MLM) (Devlin et al. 2019), we propose an insertion process that randomly inserts new tokens into sentences and hence our trained model can include random lexical constraints. Specifically, since the random insertion process is more complicated for models to learn than a traditional auto-regressive process, we pre-train a BERT (Devlin et al. 2019) based model.

(2) For personalized fine-tuning phase, we find personalization cannot be simply incorporated using another encoder for soft constraints and personalized references. Existing tokens are strong signals for new tokens to be predicted, thus the model tends to generate similar sentences even if different references are given. To solve this problem, we propose to view references as part of inserted tokens for the generator and hence the model learns to insert new tokens relevant to references. For the soft constraints, we formulate the aspect as a special insertion stage where aspect-related tokens will be first predicted as a start for the following generation. Finally, lexical constraints, soft constraints and references are unified in the insertion-based generation framework.

Overall, UCEPIC is the first personalized text generation model unifying soft constraints and lexical constraints. By incorporating keyphrases, UCEPIC significantly improves relevance, coherence and informativeness of generated explanations compared to existing methods. The main contributions of this paper are summarized as follows:

• To improve controllability and informativeness, we propose to apply lexical constraints on explanation generation.
• We present UCEPIC including our proposed robust insertion pre-training and unifying methods for soft constraints, lexical constraints and references in an insertion-based generation framework. UCEPIC generates personalized explanations controlled by random lexical constraints or aspect planning.

• We conduct extensive experiments on two datasets. Objective metrics and human evaluations show that UCEPIC can largely improve the diversity and informativeness of generated explanations.

Related Work

Many attempts have been made to generate explanations for users. RNN-based methods (Tang et al. 2016) have been applied to generate explanations with useful context information from users and items. Zhou et al. (2017) proposed an attribute-to-sequence (Attr2Seq) method to encode user and item identities with embeddings and then decode with LSTM to generate explanations. Some studies (Ni et al. 2017; Wang and Zhang 2017; Li, Zhang, and Chen 2020) proposed to combine rating prediction and explanation generation and utilize user-item interactions to improve the sentiment of generated explanations. To better control the explanation generation process, previous methods (Ni and McAuley 2018; Li et al. 2019) extracted aspects and controlled the semantics of generated explanations conditioned on different aspects. Another line of work (Li et al. 2021; 2020) controlled and enriched generated explanations by knowledge bases. Although previous works continued increasing the controllability of generation, they still struggle to exhibit specific information in explanations. In our work, UCEPIC increases the controllability, informativeness, and interpretability of generated explanations by combining soft and lexical constraints.

Lexically constrained generation requires that generated text contain the lexical constraints (e.g., keywords). Early works usually involve special decoding methods. Hokamp and Liu (2017) proposed a lexical-constrained grid beam search decoding algorithm to incorporate constraints. Post and Vilár (2018) presented an algorithm for lexically constrained decoding with reduced complexity in the number of constraints. Hu et al. (2019) further improved decoding by a vectorized dynamic beam allocation. Miao et al. (2019) introduced a sampling-based conditional decoding method, where the constraints are first placed in a template, then decoded words under a Metropolis-Hastings sampling. Special decoding methods usually need a high running time complexity. Recently, Zhang et al. (2020b) implemented hard-constrained generation with $O(\log n)$ time complexity by language model pre-training and insertion-based generation (Stern et al. 2019; Gu, Wang, and Zhao 2019; Chen et al. 2019; Gu, Liu, and Cho 2019) used in machine translation. CBART (He 2021) uses the pre-trained model BART (Lewis et al. 2020) and the encoder and decoder are used for instructing the generation and predicting at the same time.

Methodology

We describe soft constraints and lexical constraints for explanation generation as follows. Given a user persona $R^u$, item profile $R^i$ for user $u$ and item $i$ as references, the generation model under soft constraints (e.g., aspects) outputs the explanation $E^{ui}$ related to an aspect $A^{ui}$ but not necessarily including some specific words. Whereas for lexical constraints, given several lexical constraints (e.g, phrases or keywords)
C = \{c_1, c_2, \ldots, c_m\}, the model will generate an explanation \( E^{ui} = (w_1, w_2, \ldots, w_n) \) that has to exactly include all given lexical constraints \( c_i \), which means \( c_i = (w_j, \ldots, w_k) \). The lexical constraints can be from users, businesses, or item attributes recommended by personalized systems in a real application. In this paper, UCEPIC unifies the two kinds of constraints in one model\(^1\). We study only the explanation generation method and assume aspects and lexical constraints are given.

**Robust Insertion**

Previous explanation generation methods (Ni, Li, and McAuley 2019; Li, Zhang, and Chen 2021) generally adopt auto-regressive generation conditioned on some personalized inputs (e.g., personalized references and aspects). As shown in Figure 2(a), the auto-regressive process generates words in a 'left-to-right' direction so lexical constraints are difficult to be contained in the generation process. However, for the insertion-based generation in Figure 2(b) which progressively inserts new tokens based on existing words, lexical constraints can be easily contained by viewing constraints as a starting stage of insertion. The insertion-based generation has been explored in machine translation (Stern et al. 2019; Gu, Wang, and Zhao 2019; Chan et al. 2019; Gu, Liu, and Choi 2019) for its efficient decoding compared to auto-regressive generation, but few of them study to include lexical constraints. In previous work, POINTER (Zhang et al. 2020) designed a method to compute the importance score of tokens and a dynamic programming algorithm to make sure that important tokens appear in an earlier stage and the number of stages is small. However, we found the model pre-trained by this method is sensitive to the initial lexical constraints. If the constraint selections are not similar to the data pre-processing in POINTER training, the quality of generated reviews will decrease. This problem is alleviated in CBART (He 2021) relying on the pre-trained BART (Lewis et al. 2020).

\(^1\)UCEPIC has two modes: generating under soft constraints or generating under lexical constraints.
where \( R \) we first pre-train UCE.

To incorporate personalized references and soft constraints, we make it consistent for starting stages, generated sentences are usually the same. Specifically, we construct existing tokens. Without lexical tokens providing different personalized features, the model tends to overfit features from another encoder will generate similar sentences with different personalized references and soft constraints. The reason is another direct method is to have another text and aspect encoder to learn than the traditional autoregressive generation process, which is similar to masked language models, the pre-trained weights will predict the mask insertion numbers and word tokens with two heads \( H_{MI} \) and \( H_{TP} \) respectively. \( H_{TP} \) is a multilayer perceptron (MLP) with activation function GeLU (Hendrycks and Gimpel 2016) and \( H_{MI} \) is a linear projection layer. Finally, our predictions of mask insertion numbers and word tokens are computed as:

\[
\begin{align*}
    y_{MI} &= H_{MI}(D(S^{k-1})) \\
    y_{TP} &= H_{TP}(D(I^{k,k-1}))
\end{align*}
\]

(1)  (2)

where \( y_{MI} \in \mathbb{R}^{l \times d_{\text{ins}}} \) and \( y_{TP} \in \mathbb{R}^{l \times d_{\text{vocab}}} \), \( l \) and \( l_i \) are the length of \( S^{k-1} \) and \( I^{k,k-1} \) respectively, \( d_{\text{ins}} \) is the maximum number of insertions and \( d_{\text{vocab}} \) is the size of vocabulary.

Because the random insertion process is more complicated to learn than the traditional autoregressive generation process, we first pre-train UCEPIC with our robust insertion method for general text generation without personalization. The pre-trained model can generate sentences from randomly given lexical constraints.

**Personalized References and Soft Constraints**

To incorporate personalized references and soft constraints, one direct method is to have another text and aspect encoder and insertion generation conditioned on the encoder like the sequence-to-sequence model (Sutskever, Vinyals, and Le 2014). However, we find the pre-trained insertion model with another encoder will generate similar sentences with different personalized references and soft constraints. The reason is the pre-trained insertion model views the lexical constraints or existing tokens in text sequences as a strong signal to determine new inserted tokens. Even if our encoder provides personalized features, the model tends to overfit features from existing tokens. Without lexical tokens providing different starting stages, generated sentences are usually the same.

To better learn personalization, as shown in Figure 2(c), we propose to view references and aspects as special existing tokens during the insertion process. Specifically, we construct a training stage \( S_k \) to include references and aspects as:

\[
\begin{align*}
    \tilde{S}_k &= [R^{ui}, A^{ui}, S^k] \\
    &= [w_0^u, \ldots, w_{|R^{ui}|}, w_0^a, \ldots, w_{|A^{ui}|}, w_0, \ldots, w_{|S^k|}]
\end{align*}
\]

(3)

where \( R^{ui}, A^{ui} \) denote personalized references and aspects; \( w^u, w^a \) and \( w \) are tokens or aspect ids in references, insertion and aspect tokens respectively. Because insertion-based generation relies on tokens to position new tokens, we create token position ids in Transformer starting from 0 for \( R^{ui}, A^{ui} \) and \( S^k \) respectively in order to make it consistent for \( S_k \) between pre-training and fine-tuning. Similarly, we obtain the intermediate training stage \( I^{k,k-1} = [R^{ui}, A^{ui}, I^{k,k-1}] \). We encode \( \tilde{S}_k \) and \( I^{k,k-1} \) with bi-directional Transformer \( D \) to get the insertion numbers \( y_{MI} \) and predicted tokens \( y_{TP} \) as follows:

\[
\begin{align*}
    [O_S^{y_{MI}}, O_S^{A^{ui}}, O_S^{S^k}] &= D(\tilde{S}_k) \\
    [O_I^{R^{ui}}, O_I^{A^{ui}}, O_I^{I^{k,k-1}}] &= D(I^{k,k-1}) \\
    y_{MI} &= H_{MI}(O_S^{S^k}) \\
    y_{TP} &= H_{TP}(O_I^{I^{k,k-1}})
\end{align*}
\]

(4)  (5)  (6)  (7)

Because personalized references and aspects are viewed as special existing tokens, UCEPIC will directly incorporate token-level information as generation conditions and hence generates diverse explanations.

Recall that existing text sequences are strong signals for token prediction. For better aspect-planning generation, we design two starting stages \( S_0 \) and \( S_1 \) shown in Figure 2(c) for soft constraints and lexical constraints respectively. In particular, we expect the aspect-related tokens can be generated at the starting stage (i.e., no existing tokens) according to given aspects and personalized references. Hence, the soft constraint starting stage is:

\[
S_0 = [R^{ui}, A^{ui}], \quad S_1 = [R^{ui}, A^{ui}, I^{k,k-1}]
\]

(8)

where \( A^{ui} \) is a special aspect that is used for insertion stages \( S_k(k > 0) \) and \( S_0 \). During training, we sample \( S_0 \) with probability \( p \) to ensure UCEPIC learns aspect-related generation effectively which is absent in pre-training.

**Model Training**

The training process of UCEPIC is to learn the inverse process of data generation. Given stage pairs \( (S^{k-1}, S^k) \) and training instance \( (S^{k-1}, I^{k,k-1}, J^{k,k-1}, S^k) \) from pre-processing, we optimize the following objective (see derivation in Appendix):

\[
\mathcal{L} = - \log p(S^k_{J^{k,k-1}}) \cdot p(J^{k,k-1} | S^{k-1})
\]

(9)

where \( \text{MaskInsert} \) denotes the mask token insertion. In Equation (9), we jointly learn (1) likelihood of mask insertion number for each token from UCEPIC with \( H_{MI} \), and (2) likelihood of word tokens for the masked tokens from UCEPIC with \( H_{TP} \).

Similar to training BERT (Devlin et al. 2019), we optimize only the masked tokens in token prediction. The selected tokens to mask have the probability 0.1 to stay unchanged and the probability 0.1 to be randomly replaced by another token in the vocabulary. For mask insertion number prediction, most numbers in \( J^{k,k-1} \) are 0 because we do not insert any tokens between the existing two tokens in most cases. To balance the insertion number, we randomly mask the 0 in \( J^{k,k-1} \) with probability \( q \). Because our mask prediction task is similar to masked language models, the pre-trained weights from RoBERTa (Liu et al. 2019) can be naturally used for initialization of UCEPIC to obtain prior knowledge.
We consider two groups of baselines for automatic evaluation. We use Wikipedia as the pre-training dataset; and for lexical constraints and soft constraints respectively.

Datasets
For pre-training, we use English Wikipedia for robust insertion training which has 11.6 million sentences. For fine-tuning, we use Yelp and RateBeer to evaluate our model (see Table 2). We further filter the reviews with a length larger than 64. For each user, following Ni, Li, and McAuley (2019), we randomly hold out two samples from all of their reviews to construct the development and test sets. To mine aspects from datasets, we employ an unsupervised aspect extraction tool (Li, Shang, and McAuley 2013) to obtain phrases and corresponding aspects.

Baselines
We consider two groups of baselines for automatic evaluation to evaluate model effectiveness. The first group is existing text generation models for recommendation with soft constraints.

- **ExpansionNet** (Ni and McAuley 2018), generates reviews conditioned on different aspects extracted from a given review title or summary.
- **Ref2Seq** (Ni, Li, and McAuley 2019), a Seq2Seq model incorporates contextual information from reviews and uses fine-grained aspects to control explanation generation.
- **PETER** (Li, Zhang, and Chen 2021), a Transformer-based model that uses user- and item-IDs and given phrases to predict the words in target explanation generation. This baseline can be considered as a state-of-the-art model for explainable recommendation.

We compare the above baselines under both soft constraints and lexical constraints. Specifically, we give lexical constraints (i.e., keyphrases) as inputs of models and expect models can copy keyphrases to generated text.

The second group includes general natural language generation models with lexical constraints:

- **NMSTG** (Welleck et al. 2019), a tree-based text generation scheme that from given lexical constraints in prefix tree form, the model generates words to its left and right, yielding a binary tree.
- **POINTER** (Zhang et al. 2020b), an insertion-based generation method pre-trained on constructed data based on dynamic programming. We train our model based on a pre-trained model released by the authors.
- **CBART** (He, 2021), leverages the pre-trained model and instructs the decoder to insert and replace tokens by the encoder.

The second group of baselines cannot incorporate aspects or personalized information as references. These models are trained and generate text solely based on given lexical constraints. We do not include explanation generation methods such as NRT (Chen and Wang 2017), Att2Seq (Zhou et al. 2017) and lexically constrained methods CGMH (Miao et al. 2019), GBS (Hokamp and Liu 2017) because PETER and CBART reported better performance than these models.

Evaluation Metrics
We evaluate the generated sentences from two aspects: generation quality and diversity. Following Ni, Li, and McAuley (2019), Zhang et al. (2020b), we use n-gram metrics including BLEU (B-1 and B-2) (Papineni et al. 2002), METEOR (M) (Banerjee and Lavie 2005) and ROUGE-L (R-L) (Lin 2004) which measure the similarity between the generated text and human oracle. As for generation diversity, we use Distinct (D-1 and D-2) (Li et al. 2016). We also introduce BERT-score (BS) (Zhang et al. 2020a) as a semantic rather than n-gram metrics.

Implementation Details
In training data construction, we randomly mask p = 0.2 tokens in $S^k$ to obtain $I^{k,k-1}$. 0 in $J^{k,k-1}$ are masked by probability $q = 0.9$. The tokenizer is byte-level BPE following RoBERTa. For pre-training, the learning rate is 5e-5, batch size is 512 and our model is optimized by AdamW (Kingma and Bai 2015) in 1 epoch. For fine-tuning on downstream tasks, the learning rate is 3e-5, and the batch size is 128 with the same optimizer as pre-training. The training epoch is 10 and we select the best model on the development set as our final model which is evaluated on test data. We randomly sample one aspect and one phrase from the target text as the soft constraint and lexical constraint respectively.

Automatic Evaluation
Overall Performance In Table 3, we report evaluation results for different generation methods. For aspect-planning generation, UCEPIC can achieve comparable results as the...
The highest scores of aspect-planning generation results and the highest scores of lexically constrained generation are bold.

Table 3: Performance comparison of the explanation generation models (ExpansionNet, Ref2Seq, PETER), lexically constrained generation methods (NMSTG, POINTER, CBART) and UCEpic. All values are in percentage (%). We underline the highest scores of aspect-planning generation results and the highest scores of lexically constrained generation are bold.

Figure 3: Ablation study on aspects and references.

which are important for explainable recommendation. In contrast, UCEpic easily includes keyphrases in explanations and learns user-item information from references. Therefore, our model largely outperforms existing explanation generation models and lexically constrained generation models.

Based on the above discussion, we argue UCEpic unifies the soft constraints (i.e., aspects) and lexical constraints for explainable recommendations.

Number of Lexical Constraints Figure 3 shows the performance of lexically constrained generation models under different keyphrase numbers. Overall, UCEpic consistently outperforms other models under different numbers of lexical constraints. In particular, NMSTG and POINTER do not achieve a large improvement as the number of keyphrases increases because they cannot have random keywords and given phrases are usually broken into words. The gap between UCEpic and CBART becomes large as the number of keyphrases increases since CBART cannot obtain enough information for explanation generation with only a few keywords, but UCEpic improves this problem by incorporating user persona and item profiles from references. The results indicate existing lexically constrained generation models cannot be applied for explanation generation with lexical con-

Figure 3: Performance (i.e., B-2 and Meteor) of lexically constrained generation models on RateBeer data with different numbers of keyphrases.

state-of-the-art model PETER. Specifically, although PETER obtains better B-2 and ROUGE-L than our model, the results from UCEpic are significantly more diverse than PETER. A possible reason is that auto-regressive generation models such as PETER tend to generate text with higher n-gram metric results than insertion-based generation models, because auto-regressive models generate a new token solely based on left tokens while (insertion-based) UCEpic considers tokens in both directions. Despite the intrinsic difference, UCEpic still achieves comparable B-1, Meteor and BERT scores with PETER.

Under the lexical constraints, the results of existing explanation generation models become lower than the results of aspect-planning generation which indicates current explanation generation models struggle to include specific information (i.e., keyphrases) in explanations. Although current lexically constrained generation methods produce text with high diversity, they tend to insert less-related tokens with users and items. Hence, the generated text is less coherent (low n-gram metric results) than UCEpic because these methods cannot incorporate user personas and item profiles from references
pep is buffalo wings and north fried! one of the best restaurants in the food. The service is great, shore and the sauce! Menu changes daily based on the ever! Meatloaf is to die for, especially meat shore is the best. This north chicken Great Chinese restaurant, really great food! The customers service are amazing! Everything is delicious and delicious! I think this local red hot pepper chicken is the best.

| Phrases          | pepper chicken  | north shore, meat |
|------------------|-----------------|-------------------|
| Human            | Food was great. The pepper chicken is the best. This place is neat and clean. The staff are sweet. I recommend them to anyone!! | Great Italian food on the north shore! Menu changes daily based on the ingredients they can get locally. Everything is organic and made "clean". There is no freezer on the property, so you know the meat was caught or prepared that day. The chef is also from Italy! I highly recommend! |
| Ref2Seq          | best restaurant in town !!!                          | what a good place to eat in the middle of the area. The food was good and the service was good. |
| PETER            | This place is great! I love the food and the service is always great. I love the chicken and the chicken fried rice. I love this place. | The food was good, but the service was terrible. The kitchen was not very busy and the kitchen was not busy. The kitchen was very busy and the kitchen was not busy. |
| POINTER          | pepper sauce chicken !                             | one of the best restaurants in the north as far as I love the south shore. Great meat!! |
| CBART            | Great spicy pepper buffalo wings and chicken wings. | Best pizza on the north shore ever! Meatloaf is to die for, especially with meat lovers. |
| UCEPIC           | Great Chinese restaurant, really great food! The customer service are amazing! Everything is delicious and delicious! I think this local red hot pepper chicken is the best. | I had the best Italian north shore food. The service is great, meat that is fresh and delicious. Highly recommend! |

Table 4: Generated explanations from Yelp dataset. Lexical constraints (phrases) are highlighted in explanations.

Figure 5: Human evaluation on generated explanation quality.

Ablation Study To validate the effectiveness of our unifying method and the necessity of aspects and references for explanation generation, we conduct an ablation study on two datasets and the results are shown in Figure 4. We train our model and generate explanations without aspects (w/o A), without references (w/o R) and without both of them (w/o A&R). From the results, we can see that BLEU-2 and Meteor decrease if we do not give aspects to the model because the aspects can guide the semantics of explanations. Without references, the model generates similar sentences which usually contain high-frequency words from the training data. The performance drops markedly if both references and aspects are absent from the model. Therefore, our unifying method for references and aspects is effective and provides user-item information for explanation generation.

Human Evaluation

We conduct human evaluation (see details in Appendix) on generated explanations. Given the human oracle, annotators are asked to select the most relevant, coherent and informative explanations respectively (these three metrics are defined in the Appendix). The voting results are shown in Figure 5. We can see that UCEPIC largely outperforms other methods in all aspects especially for relevance and informativeness. In particular, lexically constrained generation methods (UCEPIC and CBART) significantly improve the quality of explanations because specific product information can be included in explanations by lexical constraints. Because POINTER is not robust to random keyphrases, the generated explanations do not get improvements from lexical constraints.

Case Study

We compare generated explanations from existing explanation generation models (i.e., Ref2Seq, PETER), lexically constrained generation models (i.e., POINTER, CBART) and UCEPIC in Table 4. We can see that Ref2Seq and PETER usually generate general sentences which are not informative because they struggle to contain specific item information by traditional auto-regressive generation. POINTER and CBART can include the given phrases (pepper chicken) in their generation, but they are not able to learn information from references and hence generate some inaccurate words (pepper sauce chicken, chicken wings) which mislead users. In contrast, UCEPIC can generate coherent and informative explanations which include the specific item attributes and are highly relevant to the recommended item.

Conclusion

In this paper, we propose to have lexical constraints in explanation generation which can largely improve the informativeness and diversity of generated reviews by including specific information. To this end, we present UCEPIC, an explanation generation model that unifies both aspect planning and lexical constraints in an insertion-based generation framework. We conduct comprehensive experiments on RateBeer and Yelp datasets. Results show that UCEPIC significantly outperforms previous explanation generation models and lexically constrained generation models. Human evaluation and a case study indicate UCEPIC generates coherent and informative explanations that are highly relevant to the item.
Welleck, S.; Brantley, K.; Daumé, H.; and Cho, K. 2019. Non-Monotonic Sequential Text Generation. In ICML.

Zhang, T.; Kishore, V.; Wu, F.; Weinberger, K. Q.; and Artzi, Y. 2020a. BERTScore: Evaluating Text Generation with BERT. In International Conference on Learning Representations.

Zhang, Y.; Wang, G.; Li, C.; Gan, Z.; Brockett, C.; and Dolan, B. 2020b. POINTER: Constrained Progressive Text Generation via Insertion-based Generative Pre-training. In EMNLP.

Zhou, M.; Lapata, M.; Wei, F.; Dong, L.; Huang, S.; and Xu, K. 2017. Learning to Generate Product Reviews from Attributes. In EACL.
Motivating Experiment Details

In this experiment, we evaluate the diversity and informativeness of explanations. Specifically, we apply phrase coverage, aspect coverage and Distinct-2 to measure generated explanations and human-written explanations.

For phrase coverage, we first extract noun phrases from explanations by spaCy [https://spacy.io/] and noun chunks. Then we compare the phrases in human-written explanations and generated explanations. If a phrase appears in both explanations, we consider it as a covered phrase by generated explanations. This experiment measures how many specific information can be included in the generated explanations.

For aspect coverage, we first use the aspect extraction tool [Li, Shang, and McAuley 2022] per dataset to construct a table that maps phrases to aspects, then we map the phrases in generated explanations to aspects by looking up the phrase-aspect table. For each sample, we calculate how many aspects in ground-truth explanation are covered in generated explanations. Last, we report the average aspect coverage per dataset.

For Distinct-2, we use the numbers as described in Table 3.

Baseline Details

For ExpansionNet, we use the default setting which uses hidden size 512 for RNN encoder and decoder, batch size as 25 and learning rate 2e-4. For soft constraints in ExpansionNet, we use the set of lexical constraints (as concatenated phrases) to replace the title or summary input as contextual information for training and testing.

For Ref2Seq, we use the default setting with 256 hidden size, 512 batch size and 2e-4 learning rate. For soft constraints, we concatenate our given phrases as references (historical explanations are also incorporated as references following the original implementation) as contextual information in training and testing.

For PETER, we use the original setting with 512 embedding size, 2048 hidden units, 2 self-attention heads with 2 transformer layers, 0.2 dropout. We use the training strategy suggested by the authors. Since original PETER only supports single words as a soft constraint, we adopt PETER to multiple words with a maximum length of 20 and reproduce the original single-word model on our multi-word model. We input our lexical constraints as the multi-word input for PETER training and testing.

For NMSTG, we use the default settings with an LSTM with 1024 hidden size with the uniform oracle. We convert the phrases in human-written explanations and generated explanations. If a phrase appears in both explanations, we consider it as a covered phrase by generated explanations. This experiment measures how many specific information can be included in the generated explanations.

For CBART, we use the pre-trained checkpoint from the one-billion-words dataset to fine-tune our downstream datasets. We use the ‘tf-idf’ training mode and finetune it on one GPU. For testing, we select the greedy decoding strategy. The other hyper-parameters are set to default as the code base.

Loss Definition

We explain how we derive the loss function Equation (8) with the following steps:

\[
\mathcal{L} = - \log p(S^k | S^{k-1}) \\
= - \log p(S^k, J^{k,k-1} | S^{k-1}) \\
= - \log p(S^k | J^{k,k-1}, S^{k-1}) p(J^{k,k-1} | S^{k-1}) \\
= - \log p(S^k | J^{k,k-1}) p(J^{k,k-1} | S^{k-1}) \\
\]

For the step 1 to 2, we make a reasonable assumption that \(J^{k,k-1}\) is unique given \((S^k, S^{k-1})\). This assumption is usually true unless in some corner cases multiple \(J^{k,k-1}\) could be legal (e.g., masking one “moving” word in “a moving moving moving van”). For the step 3 to 4, \(J^{k,k-1}\) by definition is the intermediate sequence, which is equivalent to the given \((J^{k,k-1}, S^{k-1})\). Thus, we obtain the final loss function Equation (9).

Human Evaluation Details

We conduct human evaluation experiments on Yelp datasets to evaluate the generation quality of generated explanations in terms of relevance, coherence and informativeness.

Question Design

We sample 500 ground-truth explanations from the Yelp dataset, then collect corresponding generated explanations from PETER-soft, POINTER, CBART and UCEPíc respectively. Given the ground-truth explanation, annotator is requested to select the best explanation on different aspects (i.e., relevance, coherence and informativeness) among explanations generated from PETER, POINTER, CBART and UCEPíc. Figure 5 shows an example of our evaluation template. We define relevance, coherence and informativeness as:

- **Relevance**: the details in the generated explanation are consistent and relevant to the ground-truth explanation’s.
- **Coherence**: the sentences in the generated explanation are logical and fluent.
- **Informativeness**: the generated explanation contains specific information, instead of vague descriptions only.

Experiment Conduction

We submit our task to MTurk [https://www.mturk.com] and set the reward as $0.02 per question. For each question, we first show the definition of relevance, coherence and informativeness, then we shuffle the order of model-generated explanations to eliminate the
positional bias. Each question is requested to be answered by 3 different MTurk workers, who are required to have great
than 80% HIT Approval Rate to improve the quality of
answers. We collect the answers and count the majority votes,
where the majority vote is defined as model $i$ has 2 or more
votes (since we have 3 answers per question). We ignore
the questions without majority votes. Finally, we collected
1,120 valid votes for 370 questions, in which 275 relevance
questions, 281 coherence questions and 266 informativeness
questions have majority votes.

GPU Hours
Our pre-training model is trained on 3 NVIDIA Quadro RTX
8000 graphical cards with 48 GiB memory for 13 days. Our
fine-tuning models are trained on single NVIDIA Quadro
RTX 8000 graphical card with 48 GiB memory for averagely
10 hours per dataset. We acknowledge that one limitation
of our model is UCEPIC is a pre-training model on large-
scale datasets so it is heavy to train. But for downstream
explanation generation domains, fine-tuning is much faster.

Packages
SpaCy. We use en-core-web-sm pre-trained natural lan-
guage pipeline to process our data. All other settings are
default in this pre-trained pipeline.
NLTK. We use NLTK to compute BLEU scores and all
settings are default.
Huggingface Datasets$^{11}$ We use this package to compute
Meteor, ROUGE-L and BERT score (RoBERTa model).

More Generated Explanations
We include more generated examples in Tables 5 to 7

---

$^{11}$https://huggingface.co/docs/datasets/
Great food and service. I had the lamb tibs and it was delicious. The lamb tibs were also very good. The service was also very good.

This place is a hidden gem. The food is amazing and the service is great. The wine list is extensive and the wine list is great. The wine list is extensive and the wine list is great.

This place has 5 stars. I gave it 1 star because the service and food was good.

Great Indian food with good Thai service. The Great Ambiance of staff, nice service and very friendly staff. Highly recommend it!

Great beer and fun atmosphere for a good time, really nice outdoor game environment including an excellent bar of large food with very friendly service, and some great drinks.