Interacting with Explanations through Critiquing

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Abstract

Using personalized explanations to support recommendations has been shown to increase trust and perceived quality. However, to actually obtain better recommendations, there needs to be a means for users to modify the recommendation criteria by interacting with the explanation. We present a novel technique using aspect markers that learns to generate personalized explanations of recommendations from review texts, and we show that human users significantly prefer these explanations over those produced by state-of-the-art techniques.

Our work's most important innovation is that it allows users to react to a recommendation by critiquing the textual explanation: removing (symmetrically adding) certain aspects they dislike or that are no longer relevant (symmetrically that are of interest). The system updates its user model and the resulting recommendations according to the critique. This is based on a novel unsupervised critiquing method for single- and multi-step critiquing with textual explanations. Experiments on two real-world datasets show that our system is the first to achieve good performance in adapting to the preferences expressed in multi-step critiquing.

1 Introduction

Explanations of recommendations are beneficial. Modern recommender systems accurately capture users' preferences and achieve high performance. However, their performance comes at the cost of increased complexity, which makes them seem like black boxes to end users. This may result in distrust or rejection of the recommendations (Herlocker, Konstan, and Riedl 2000; Tintarev and Masthoff 2015).

There is thus value in providing *textual explanations* of the recommendations, especially on e-commerce websites, because such explanations enable users to understand why a particular item has been suggested and hence to make better decisions (Chang, Harper, and Terveen 2016; Bellini et al. 2018). Furthermore, explanations increase overall system transparency (Tintarev and Masthoff 2015) and trustworthiness (Zhang and Curley 2018; Kunkel et al. 2018).

However, not all explanations are equivalent. It has been shown that highly personalized justifications using *natural language* lead to substantial increases in perceived recommendation quality and trustworthiness compared to simpler

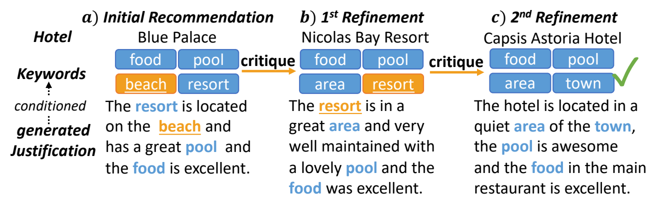


Figure 1: A flow of conversational critiquing over two time steps. a) The system proposes to the user a recommendation with a keyphrase explanation and a justification. The user can interact with the explanation and critique phrases. b) A new recommendation is produced from the user's profile and the critique. 3) This process repeats until the user accepts the recommendation and ceases to provide additional critiques.

explanations, such as aspect, template, or user/item similarity (Kunkel et al. 2019; Chang, Harper, and Terveen 2016).

A second, and more important, benefit of explanations is that they provide a basis for feedback: if a user is unsatisfied with a recommendation, understanding what generated it allows them to *critique* it (Figure 1). Critiquing – a conversational method of incorporating user preference feedback regarding item attributes into the recommended list of items – has several advantages. First, it allows the system to correct and improve an incomplete or inaccurate model of the user's preferences (Faltings, Torrens, and Pu 2004), which improves the user's decision accuracy (Pu and Chen 2005; Chen and Pu 2012). Compared to preference elicitation, critiquing is more flexible: users can express preferences in any order and on any criteria (Reilly et al. 2005).

Useful explanations are hard to generate. Prior research has employed users' reviews to capture their preferences and writing styles (Ni and McAuley 2018; Li and Tuzhilin 2019). From past reviews, they generate *synthetic* ones that serve as personalized *explanations* of ratings given by users. However, many reviews are noisy, because they partly describe experiences or endorsements. It is thus non-trivial to identify meaningful justifications inside reviews. (Ni, Li, and McAuley 2019) proposed a pipeline for identifying justifications from reviews and asked humans to annotate them. However, the notion of justification is ambiguous, and they assumed that a review contains only one justification.

Recently, (Antognini, Musat, and Faltings 2019) solved these shortcomings by introducing a justification extraction system with no prior limits imposed on their number or structure. This is important because a user typically justifies his overall rating with multiple explanations: one for each aspect the user cares about (Musat and Faltings 2015). The authors showed that there is a connection between faceted ratings and snippets within the reviews: for each subrating, there exists at least one text fragment that alone suffices to make the prediction. They employed a sophisticated attention mechanism to favor long, meaningful word sequences; we call these ***markers***. Building upon their study, we show that these *markers* serve to create better user and item profiles and can inform better user-item pair justifications. Figure 2 illustrates the pipeline.

From explanations to critiquing. To reflect the overlap between the profiles of a user and an item, one can produce a set of keyphrases and then a synthetic justification. The user can correct his profile, captured by the system, by *critiquing* certain aspects he does not like or that are missing or not relevant anymore and obtain a new justification (Figure 1). (Wu et al. 2019) introduced a keyphrase-based critiquing method in which attributes are mined from reviews and users interact with them. However, their models need an extra autoencoder to project the critique back into the latent space, and it is unclear how the models behave in multi-step critiquing.

We overcome these drawbacks by casting the critiquing as an unsupervised attribute transfer task: altering a keyphrase explanation of a user-item pair representation to the critique. To this end, we entangle the user-item pair with the explanation in the same latent space. At inference, the keyphrase classifier modulates the latent representation until the classifier identifies it as the critique vector.

In this work, we address the problem recommendation with fine-grained explanations. We first demonstrate how to extract multiple relevant and personalized justifications from the user's reviews to build a profile that reflects his preferences and writing style (Figure 2). Second, we propose T-RECS, a recommender with explanations. T-RECS explains a rating by first inferring a set of keyphrases describing the intersection between the profiles of a user and an item. Conditioned on the keyphrases, the model generates a synthetic personalized justification. We then leverage these explanations in an unsupervised critiquing method for single- and multi-step critiquing. We evaluate our model using two real-world recommendation datasets. T-RECS outperforms strong baselines in explanation generation, effectively re-ranks recommended items in single-step critiquing, and better models the user's preferences in multi-step critiquing.

2 Related Work

Textual Explainable Recommendation. Researchers have investigated many approaches to generating textual explanations of recommended items for users. (McAuley and Leskovec 2013) proposed a topic model to discover latent factors from reviews and explain recommended items. (Zhang et al. 2014) improved the understandability of topic words and aspects by filling template sentences.

Another line of research has generated synthetic reviews as explanations. Prior studies have employed users' reviews

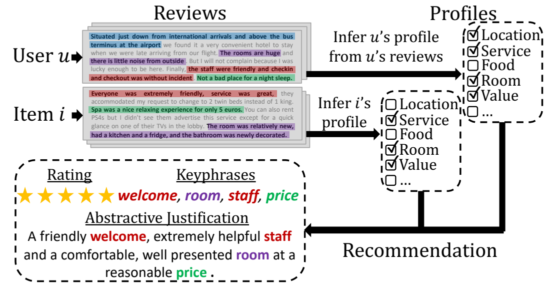


Figure 2: For reviews written by a user u and a set of reviews about an item i, we extract the justifications for each aspect rating and implicitly build an interest profile. T-RECS outputs a personalized recommendation with two explanations: the keyphrases reflecting the overlap between the two profiles, and a synthetic justification conditioned on the latter.

and tips to capture their preferences and writing styles. (Catherine and Cohen 2017) predicted and explained ratings by encoding the user's review and identifying similar reviews. (Lu, Dong, and Smyth 2018) extended the previous work to generate synthetic reviews. (Dong et al. 2017; Costa et al. 2018) proposed an attribute-to-sequence model to learn how to generate reviews given categorical attributes. (Ni and McAuley 2018) improved review generation by leveraging aspect information using a sequence-to-sequence model with attention (Bahdanau, Cho, and Bengio 2015). Instead of reviews, others have generated tips (Li et al. 2017, 2019). However, these approaches often suffer from low degrees of personalization and relevance to users' decision-making.

The work most relevant to ours is perhaps (Ni, Li, and McAuley 2019). The authors built a sequence-to-sequence model using the aspect-planning technique (Yao et al. 2019) to generate relevant justifications; the fine-grained aspects are provided by the user during the generation. They identified justifications from reviews by segmenting them into elementary discourse units (EDU) (Mann and Thompson 1988) and asking annotators to label them as "good" or "bad" justifications. They also assumed that a review contains only one justification. Whereas their notion of justification was ambiguous, we extract multiple justifications from reviews using *markers* that justify subratings. Unlike their model, ours recommends, predicts keyphrases on which the justifications are conditionned, and integrates critiquing.

Critiquing. Refining recommended items allows users to interact with the system until they are satisfied. Examples of such methods are: example critiquing (Williams and Tou 1982), in which users critique a set of items; unit critiquing (Burke, Hammond, and Young 1996), in which users critique an item's attribute and request another one instead; and compound critiquing (Reilly et al. 2005) for more aspects. (McCarthy, Salem, and Smyth 2010) collaboratively utilized critiques from users. A major drawback of these approaches is the assumption of a fixed set of known attributes.

(Wu et al. 2019) circumvented this limitation by extending the neural collaborative filtering model (He et al. 2017). First, the model explains a produced recommendation by predicting a set of keywords. The keywords are mined from

Situated just down from international arrivals and above the bus terminus at the airport we found it a very convenient hotel to stay when we were late arriving from our flight and subsequently to catch our flight . **The rooms are clean** and there is little noise from outside . They rooms are not plush, but sufficient (there's the Intercontinental if you want more) The staff were friendly and checkin and checkout was without incident . They even held our rooms on request even though hotel policy is to let them go if unpaid post 16:00 (because you pay on checkin here). Not a bad place for a nights sleep

Figure 3: Illustrations of extracted justifications from a hotel review. The inferred *markers* depict the excerpts that explain the ratings of the aspects: Service, Cleanliness, Value, Room, and Location. We denote in **bold** the justification induced by the EDU pipeline of (Ni, Li, and McAuley 2019).

users' reviews. Our work applies a similar strategy. Second, a function projects the critiqued keyphrase explanations back into the latent space, from which the rating and the explanation are predicted. In this manner, the user's critique modulates his latent representation. This mapping is learned via an autoencoder, which perturbs the training. In contrast, T-RECS learns this mapping in an unsupervised fashion: it iteratively edits the latent representation at inference until the new explanation matches the critique. Finally, (Luo et al. 2020) examined various linear aggregation methods on latent representations for multi-step critiquing. By contrast, our gradient-based critiquing iteratively updates the latent representation for each critique.

3 Extracting Justifications from Reviews

In this section, we introduce the pipeline for extracting high-quality and personalized justifications from users' reviews. We claim that a user justifies his overall experience with multiple explanations: one for each aspect he cares about. Indeed, it has been shown that users write opinions about the topics they care about (Zhang et al. 2014). Thus, the pipeline must satisfy two requirements: 1. extract text snippets that reflect a rating or subrating, and 2. be data driven and scalable to mine massive review corpora and to construct a large personalized recommendation justification dataset.

A recent work (Antognini, Musat, and Faltings 2019) has fulfilled the two requirements. The authors proposed the multi-aspect masker (MAM) to find text fragments that explain faceted ratings in an unsupervised manner. For each word, the model computes a probability distribution over the aspect set, which corresponds to the aspect ratings (e.g., service, location) and "not aspect." In parallel, the model minimizes the number of selected words and discourages aspect transition between consecutive words. These two constraints guide the model to produce long, meaningful sequences of words that we call ***markers***. The model updates its parameters by using the inferred *markers* to predict the aspect sentiments jointly and improves the quality of the *markers* until convergence. For the sake of brevity, we refer the reader to (Antognini, Musat, and Faltings 2019) for more details.

Given a review, MAM extracts the *markers* of each aspect. Similarly to (Ni, Li, and McAuley 2019), we filter out *markers* that are unlikely to be suitable justifications: including third-person pronouns or being too short. We exploit the constituency parse tree to ensure that *markers* are verb phrases. A sample is shown in Figure 3. More details of the processing are available in Appendix A.

4 T-RECS: A Multi-Task Transformer with Explanations and Critiquing

Figure 4 depicts the pipeline and our proposed T-RECS model. Let U and I be the user and item sets. For each user $u \in U$ (respectively an item $i \in I$), we extract *markers* from the user's reviews on the training set, randomly select N_{just}, and build a justification reference J^u (symmetrically J^i).

Given a user u, an item i, and their justification history J^u and J^i, our goal is to predict 1. a rating $\boldsymbol{y}_r$, 2. a keyphrase explanation $\boldsymbol{y}_{kp}$ describing the relationship between u and i, and 3. a natural language justification $\boldsymbol{y}_{just} = \{w_1, ..., w_N\}$, where N is the length of the justification. $\boldsymbol{y}_{just}$ explains the rating $\boldsymbol{y}_r$ conditioned on $\boldsymbol{y}_{kp}$.

4.1 Model Overview

For each user and item, we extract *markers* from their past reviews (in the training set) and build their justification history J^u and J^i, respectively (see Section 3). T-RECS is divided into four submodels: an **Encoder** E, which produces the latent representation $\boldsymbol{z}$ from the historical justifications and latent factors of the user u and the item i; a **Rating Classifier** C^r, which classifies the rating $\hat{\boldsymbol{y}}_r$; a **Keyphrase Explainer** C^{kp}, which predicts the keyphrase explanation $\hat{\boldsymbol{y}}_{kp}$ of the latent representation $\boldsymbol{z}$; and a **Decoder** D, which decodes the justification $\hat{\boldsymbol{y}}_{just}$ from $\boldsymbol{z}$ conditioned on the keyphrases $\hat{\boldsymbol{y}}_{kp}$, encoded via the **Aspect Encoder** A. Thus, our model consists of four functions: $\boldsymbol{z} = E(u, i)$; $\hat{\boldsymbol{y}}_r = C^r(\boldsymbol{z})$; $\hat{\boldsymbol{y}}_{kp} = C^{kp}(\boldsymbol{z})$; and $\hat{\boldsymbol{y}}_{just} = D(\boldsymbol{z}, A(\hat{\boldsymbol{y}}_{kp}))$.

The above formulation contains two types of personalized explanations: a list of keyphrases $\hat{\boldsymbol{y}}_{kp}$ that reflects the different aspects of item i that the user u cares about (i.e., the overlap between their profiles) and a natural language explanation $\hat{\boldsymbol{y}}_{just}$ that justifies the rating, conditioned on $\hat{\boldsymbol{y}}_{kp}$. The set of keyphrases is mined from the reviews and reflects the different aspects deemed important by the users. The keyphrases enable an interaction mechanism: users can express agreement or disagreement with respect to one or multiple aspects and hence critique the recommendation.

Entangling user-item. A key objective T-RECS is to build a powerful latent representation. It accurately captures user and item profiles with their writing styles and entangles the rating, keyphrases, and a natural language justification. Inspired by the superiority of Transformer (Vaswani et al. 2017) for text generation tasks (Dathathri et al. 2020; Devlin et al. 2019; Wang, Hua, and Wan 2019), we propose a Transformer-based encoder that learns latent personalized features from users' and items' justifications. We first pass each justification J^u_j (respectively J^i_j) through the Transformer's encoder to compute the intermediate representations $\boldsymbol{h}^u_j$ (respectively $\boldsymbol{h}^i_j$). We apply a sigmoid activation on the representations and average them to get $\boldsymbol{\gamma}^u$ and $\boldsymbol{\gamma}^i$:

$$\boldsymbol{\gamma}^u = \frac{1}{|J^u|} \sum\nolimits_{j \in J^u} \sigma(\boldsymbol{h}^u_j) \quad \boldsymbol{\gamma}^i = \frac{1}{|J^i|} \sum\nolimits_{j \in J^i} \sigma(\boldsymbol{h}^i_j). \quad (1)$$

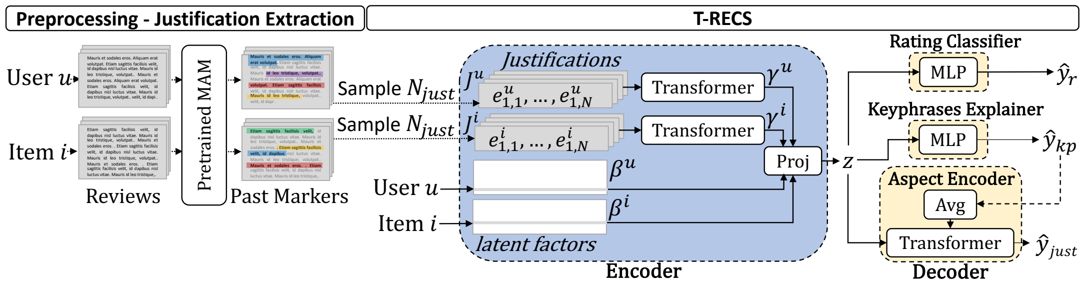


Figure 4: (Left) Preprocessing for the users and the items. For each user u and item i, we first extract *markers* from their past reviews (highlighted in color), using the pretrained multi-aspect masker (see Section 3), that become their respective justifications. Then, we sample N_{just} of them and build the justification references J^u and J^i. (Right) T-RECS architecture. Given a user u and an item i with their justification references J^u, J^i and latent factors β^u, β^i, T-RECS produces a joint embedding $\boldsymbol{z}$ from which it predicts a rating $\hat{\boldsymbol{y}}_r$, a keyphrase explanation $\hat{\boldsymbol{y}}_{kp}$, and a natural language justification $\hat{\boldsymbol{y}}_{just}$ conditioned on $\hat{\boldsymbol{y}}_{kp}$.

In parallel, the encoder maps the user u (item i) to the latent factors $\boldsymbol{\beta}^u$ ($\boldsymbol{\beta}^i$) via an embedding layer. We compute the latent representation $\boldsymbol{z}$ by concatenating the latent personalized features and factors and applying a linear projection: $\boldsymbol{z} = E(u,i) = W[\boldsymbol{\gamma}^u \,\|\, \boldsymbol{\gamma}^i \,\|\, \boldsymbol{\beta}^u \,\|\, \boldsymbol{\beta}^i] + \boldsymbol{b}$, where $\|$ is the concatenation operator, and W and $\boldsymbol{b}$ the projection parameters.

Rating Classifier & Keyphrase Explainer. Our framework classifies the interaction between the user u and item i as positive or negative. Furthermore, we predict the keyphrases that describe the overlap of their profiles. Both models are a two-layer feedforward neural network with LeakyRelu activation function. Their respective losses are:

$$\mathcal{L}_r(C^r(\boldsymbol{z}), \boldsymbol{y}_r) = (\hat{\boldsymbol{y}}_r - \boldsymbol{y}_r)^2 \tag{2}$$

$$\mathcal{L}_{kp}(C^{kp}(\boldsymbol{z}), \boldsymbol{y}_{kp}) = -\sum\nolimits_{k=1}^{|K|} y^k_{kp} \log \hat{y}^k_{kp}, \tag{3}$$

where $\mathcal{L}_r$ is the mean square error, $\mathcal{L}_{kp}$ the binary cross-entropy, and K the whole set of keyphrases.

Justification Generation. The last component consists of generating the justification. Inspired by "plan-and-write" (Yao et al. 2019), we advance the personalization of the justification by incorporating the keyphrases $\hat{\boldsymbol{y}}_{kp}$. In other words, T-RECS generates a natural language justification conditioned on 1. the user, 2. the item, and 3. aspects of the item that the user would consider important. We encode these via the Aspect Encoder A that takes the average of their word embeddings from the embedding layer in the Transformer. The aspect embedding is denoted by $\boldsymbol{a}_{kp}$ and added to the latent representation: $\tilde{\boldsymbol{z}} = \boldsymbol{z} + \boldsymbol{a}_{kp}$. Based on $\tilde{\boldsymbol{z}}$, the Transformer decoding block computes the output probability $\hat{y}^{t,w}_{just}$ for the word w at time-step t. We train using teacher-forcing (Williams and Zipser 1989) and cross-entropy with label smoothing (Szegedy et al. 2016):

$$\ell_t = (1-\varepsilon) \sum_{w=1}^{|V|} y^{t,w}_{just} \log(\hat{y}^{t,w}_{just}) + \frac{\varepsilon}{|V|} \sum_{w=1}^{|V|} \log(\hat{y}^{t,w}_{just}), \tag{4}$$

where V is the vocabulary. Hence, the decoding loss is

$$\mathcal{L}_{just}(D(\boldsymbol{z}, \boldsymbol{a}_{kp}), \boldsymbol{y}_{just}) = -\sum\nolimits_{t=1}^{|\boldsymbol{y}_{just}|} \ell_t. \tag{5}$$

We train T-RECS end-to-end and minimize jointly the loss $\boldsymbol{\mathcal{L}} = \lambda_r \mathcal{L}_r + \lambda_{kp} \mathcal{L}_{kp} + \lambda_{just} \mathcal{L}_{just}$, where λ_r, λ_{kp}, and λ_{just} control the impact of each loss. All objectives share the latent representation $\boldsymbol{z}$ and are thus mutually regularized by the function $E(u,i)$ to limit overfitting by any objective.

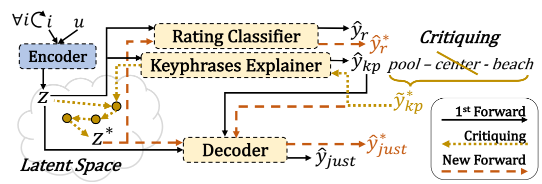


Figure 5: Workflow of considering to recommend items to a user u. We illustrate it for a given item i. **Black** denotes the forward pass to generate the rating $\hat{\boldsymbol{y}}_r$ with the explanations $\hat{\boldsymbol{y}}_{kp}$ and $\hat{\boldsymbol{y}}_{just}$. **Yellow** indicates the critiquing: the user critiques the binary-vector keyphrase explanation $\hat{\boldsymbol{y}}_{kp}$ (e.g., *center*) to $\tilde{\boldsymbol{y}}^*_{kp}$, which modulates the latent space into $\boldsymbol{z}^*$ for each item. **Orange** shows the new forward pass for the subsequent recommendation $\hat{\boldsymbol{y}}^*_r$ and explanations $\hat{\boldsymbol{y}}^*_{kp}$, $\hat{\boldsymbol{y}}^*_{just}$.

4.2 Unsupervised Critiquing

The purpose of critiquing is to refine the recommendation based on the user's interaction with the explanation, the keyphrases $\hat{\boldsymbol{y}}_{kp}$, represented with a binary vector. The user critiques either a keyphrase k by setting $\hat{y}^k_{kp} = 0$ (i.e., disagreement) or symmetrically add a new one (i.e., $\hat{y}^k_{kp} = 1$). We denote the critiqued keyphrase explanation as $\tilde{\boldsymbol{y}}^*_{kp}$.

The overall critiquing process is depicted in Figure 5. Inspired by the recent success in editing the latent space on the unsupervised text attribute transfer task (Wang, Hua, and Wan 2019; Dathathri et al. 2020), we employ the trained Keyphrase Explainer C^{kp} and the critiqued explanation $\tilde{\boldsymbol{y}}^*_{kp}$ to provide the gradient from which we update the latent representation $\boldsymbol{z}$ (depicted in yellow). More formally, given a latent representation $\boldsymbol{z}$ and a binary critique vector $\tilde{\boldsymbol{y}}^*_{kp}$, we want to find a new latent representation $\boldsymbol{z}^*$ that will produce a new keyphrase explanation close to the critique, such that $|C^{kp}(\boldsymbol{z}^*) - \tilde{\boldsymbol{y}}^*_{kp}| \leq T$, where T is a threshold. In order to achieve this goal, we iteratively compute the gradient with respect to $\boldsymbol{z}$ instead of the model parameters C^{kp}_θ. We then modify z in the direction of the gradient until we get a new latent representation z^* that C^{kp} considers close enough to $\tilde{y}^*_{kp}$ (shown in **orange**). We emphasize that we use the gradient to modulate z rather than the parameters C^{kp}_θ.

Let denote the gradient g_t and a decay coefficient ζ. For each iteration t and $z^*_0 = z$, the modified latent representation z^*_t at the t^{th} iteration can be formulated as follows:

$$g_t = \nabla_{z^*_t} \mathcal{L}_{kp}(C^{kp}(z^*_t), \tilde{y}^*_{kp}); \;\; z^*_t = z^*_{t-1} - \zeta^{t-1} g_t / ||g_t||_2 \quad (6)$$

Because this optimization is nonconvex, there is no guarantee that the difference between the critique vector and the induced explanation will differ by only T. We limit the number of gradient descents. In our critiquing experiments, we found that a limit a of 50 iterations works well in practice.

5 Experiments

In this section, we answer the following research questions:[1]

- **RQ 1**: Are *markers* appropriate justifications for recommendation?
- **RQ 2**: Does T-RECS generate high-quality, relevant, and personalized explanations?
- **RQ 3**: Can T-RECS enable critiquing and effectively re-rank recommended items by critiquing explanations?

5.1 Datasets

We evaluate the quantitative performance of T-RECS using two real-world, publicly available datasets: BeerAdvocate (McAuley and Leskovec 2013) and HotelRec (Antognini and Faltings 2020). They contain 1.5 and 50 million reviews from BeerAdvocate and TripAdvisor, respectively. In addition to the overall rating, users also provided five-star aspect ratings[2]. Because people tend to rate beers and hotels positively, we binarize the ratings with a threshold t: $t > 4$ for hotel reviews and $t > 3.5$ for beer reviews. We further filter out all users with fewer than 20 observed interactions and sort them chronologically. We keep the first 80% of interactions per user as the training data, leaving the remaining 20% for validation and testing. We sample two justifications per review. Table 1 shows the statistics of the datasets.

We need to select keyphrases for explanations and critiquing. Hence, we follow the frequency-based processing in (Wu et al. 2019) to extract 200 keyphrases (distributed uniformly over the aspect categories) from the *markers* on each dataset. Some examples are shown in Appendix B.

5.2 Experimental Settings

To compute *markers* in reviews, we trained MAM with the hyperparameters reported by the authors. We obtained 78% and 90% macro F1 Scores. Because the multi-aspect classification is not the focus, here we ignore the training procedure and performance evaluation.

[1]Although it is not the central point of the paper, we show in the Appendix that T-RECS slightly improves the recommendation performance compared to strong state-of-the-art baselines.

[2]In cases where faceted ratings are not available at large cases, (Mukherjee and Awadallah 2020; Niu et al. 2020) proposed elegant solutions to infer them from 20 or fewer samples.

Table 1: Descriptive statistics of the datasets. We selected 200 keyphrases for each dataset. Coverage shows the ratio of reviews having at least one of the selected keyphrases.

						Avg. #KP per		
Dataset	**#Users**	**#Items**	**#Inter.**	**Dens.**	**KP Cov.**	**Just.**	**Rev.**	**User**
Hotel	72,603	38,642	2.2M	0.08%	97.66%	2.15	3.79	115
Beer	7,305	8,702	1.2M	2.02%	96.87%	3.72	6.97	1,210

We build the justification history J^u,J^i, with $N_{just} = 32$. In T-RECS, we set the embedding, latent, and self-attention dimension size to 256, and the dimension of the feed-forward network to 1024. The encoder and decoder consist of two layers of Transformer with 4 attention heads. We use a batch size of 128, dropout of 0.1, 4000 warm-up steps, smoothing parameter $\varepsilon = 0.1$, and Adam with learning rate $0.001, \beta_1 = 0.9, \beta_2 = 0.98$, and $\epsilon = 10^{-9}$. The Rating Classifier and Keyphrase Explainer are two layers of 128 and 64 dimensions with LeakyReLU ($\alpha = 0.2$). For critiquing, we choose a threshold and decay coefficient $T = 0.015, \zeta = 0.9$ and $T = 0.01, \zeta = 0.975$ for hotel and beer reviews, respectively. We use the code from the authors for most models. We tune all models on the dev set. For reproducibility purposes, we include additional details in Appendix.[3]

5.3 RQ 1: Are *markers* appropriate justifications for recommendation?

We first verify whether *markers* can serve as justifications for recommendation. We derive baselines from (Ni, Li, and McAuley 2019), where their method splits a review into elementary discourse units (EDUs) and then applies a classifier to get good justifications. The classifier is trained on a small, manually annotated dataset and generalizes well to other domains (Ni, Li, and McAuley 2019). We employ two variants as baselines: EDU One and EDU All. The latter includes all justifications, whereas the former includes only one.

We perform a human evaluation using Amazon's Mechanical Turk (details in Appendix) to judge the quality of the justifications extracted from the Markers, EDU One, and-EDU All on the hotel and beer datasets. We employ three setups: an evaluator is presented with 1. the three types of justifications; 2. only those from Markers and EDU All; and 3. EDU One instead of EDU All. We sampled 300 reviews (100 per setup) with generated justifications presented in random order. The annotators judged the justifications by choosing the most convincing one in the pairwise setups and otherwise using best-worst scaling (Louviere, Flynn, and Marley 2015), which has been shown to give more reliable results than Likert scales (van der Lee et al. 2019; Kiritchenko and Mohammad 2016). We report the win rates for the pairwise comparisons and a normalized score ranging from -1 to +1.

The results are presented in Table 2. In the pairwise setups, justifications extracted from Markers are preferred, on both datasets, approximately 80% of the time compared to EDU All, and 90% compared to EDU One. When compared to EDU All and EDU One, Markers achieve a score of 0.74,

[3]We will make the code available.

Table 2: Human evaluation of extracted explanations in terms of the **b**est-**w**orst scaling and the win rate in a pairwise setup. A score significantly different than Markers (post hoc Tukey HSD test) is denoted by ** for $p < 0.001$.

		Hotel			*Beer*		
Winner	**Loser**	**Win Rate**			**Win Rate**		
Markers	EDU All	81%**			77%**		
Markers	EDU One	93%**			90%**		
Model		**Score**	**#B**	**#W**	**Score**	**#B**	**#W**
EDU One		-0.95**	1	96	-0.93**	2	95
EDU All		0.21**	24	3	0.20**	23	3
Markers		**0.74**	75	1	**0.73**	75	2

Table 3: Generated justifications on automatic evaluation.

	Model	BLEU	R-L	$\text{BERT}_{\text{Score}}$	PPL↓	R_{KW}
Hotel	LexRank	0.41	10.61	83.91	-	10.32
	ExpansionNet	0.53	6.91	74.81	28.87	60.09
	Ref2Seq	1.77	16.45	86.74	29.07	13.19
	AP-Ref2Seq	7.28	33.71	88.31	21.31	90.20
	T-RECS	**7.47**	**34.10**	**90.23**	**17.80**	**93.57**
Beer	LexRank	0.38	9.90	83.42	-	10.79
	ExpansionNet	1.22	9.68	72.32	22.28	82.49
	Ref2Seq	3.51	15.96	85.27	22.34	12.10
	AP-Ref2Seq	15.89	46.50	91.35	12.07	91.52
	T-RECS	**16.54**	**47.20**	**91.50**	**10.24**	**94.96**

three times higher than EDU All. Consequently, justifications extracted from the Markers are significantly better than EDU All and EDU One, and a single justification cannot explain a review. Figure 3 shows a sample for comparison.

5.4 RQ 2: Does T-RECS generate high-quality, relevant, and personalized explanations?

We investigate whether T-RECS can generate *personalized* explanations for a given user-item pair: 1. a relevant natural language justifications and 2. a list of keyphrases, that best describes the intersection of the user and item profiles.

Natural Language Explanations. We consider four baselines: LexRank (Erkan and Radev 2004) is a strong unsupervised multi-document summarizer that selects an unpersonalized justification among all historical justifications of an item. ExpansionNet (Ni and McAuley 2018) is a sequence-to-sequence model with a user, item, aspect, and fusion attention mechanism that generates personalized reviews based the on aspect-level information. Ref2Seq improves upon ExpansionNet by learning only from historical justifications of a user and an item. Finally, AP-Ref2Seq (Ni, Li, and McAuley 2019) extends Ref2Seq with aspect planning (Yao et al. 2019), in which aspects are given during the generation. All models use beam search ($k = 3$) during generation and the same extracted keyphrases as aspects.

For automatic evaluation, we employ BLEU (Papineni et al. 2002), ROUGE-L (Lin and Hovy 2002), and BertScore (Zhang et al. 2020), a similarity metric based on BERT embeddings that has been shown to correlate better

Table 4: Human evaluation of justifications in terms of best-worst scaling for **O**verall, **F**luency, **I**nformativenss, and **R**elevance. Most scores are significantly different than T-RECS (post hoc Tukey HSD test) with $p < 0.002$. * denotes significance with $p < 0.01$ and † a nonsignificant score.

	Hotel				*Beer*			
Model	**O**	**F**	**I**	**R**	**O**	**F**	**I**	**R**
ExpansionNet	-0.58	-0.67	-0.52	-0.56	-0.03	-0.31	0.10	-0.01
Ref2Seq	-0.27	-0.19	-0.30	-0.26	-0.69	-0.34	-0.71	-0.69
AP-Ref2Seq	0.30	0.32	0.29	0.29	0.22	0.25†	0.21†	0.25*
T-RECS	**0.55**	**0.54**	**0.53**	**0.53**	**0.49**	**0.39**	**0.39**	**0.45**

with human judgments. We also report the perplexity for evaluating the fluency and R_{KW} that measures the keyphrase coverage between the target and the generated justifications.

The main results are presented in Table 3. T-RECS achieves the highest scores on both datasets. Generally, we notice that 1. sequence-to-sequence models better capture user and item information to produce more relevant justifications, compared with unpersonalized models (e.g., LexRank) and personalized models that do not leverage historical justifications (e.g., ExpansionNet), and 2. integrating a keyphrase plan is beneficial to doubling the performance on average and improving relevance according to R_{KW}.

Because the justifications are intended for end users, we thus conduct a human evaluation on four dimensions using best-worst scaling: 1. overall measures the overall subjective quality; 2. fluency represents the structure, grammar, and readability; 3. informativeness indicates whether the justification contains information pertinent to the user; 4. relevance measures how relevant the information is to an item. For each dataset, we sampled 150 reviews with generated justifications and showed them in random order.

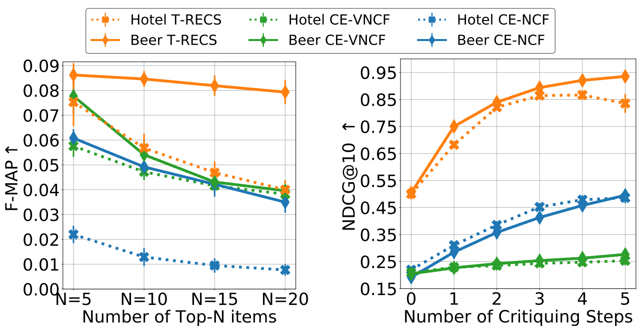
Table 4 presents the results of the human evaluation. T-RECS outperforms all methods on all criteria and performs 1.8 times better than AP-Ref2Seq. Interestingly, we observe that ExpansionNet achieves significantly better results on the beer dataset with scores around 0.00 for *Overall* and *Relevance*, and 0.10 for *Informativeness*; the information contained in beer reviews is easier to capture, as observed in (Bao et al. 2018). We provide samples of justifications generated by all models in Appendix C.

Keyphrase Explanations. Predicting keyphrases from the user-item latent representation is a natural way to entangle them with and enable critiquing (see Section 4.2). We compare T-RECS with the popularity baselines and the models proposed (Wu et al. 2019), which are extended versions of the neural collaborative filtering model (NCF) (He et al. 2017). E-NCF and CE-NCF augment the NCF method with an explanation and a critiquing neural component. Moreover, the authors provide variational variants: VNCF, E-VNCF, and CE-VNCF. Here, we omit NCF and VNCF because they are trained only to predict ratings. We report the following metrics: NDCG, MAP, Precision, and Recall at 10.

Table 5 contains the results. T-RECS outperforms the CE-(V)NCF models by 60% and the popularity baselines by

Table 5: Keyphrase explanation quality at $N = 10$.

	Hotel				*Beer*			
Model	**NDCG**	**MAP**	**P**	**R**	**NDCG**	**MAP**	**P**	**R**
UserPop	0.313	0.195	0.133	0.369	0.268	0.240	0.190	0.277
ItemPop	0.333	0.208	0.143	0.396	0.250	0.229	0.176	0.253
E-NCF	0.341	0.215	0.137	0.380	0.249	0.220	0.179	0.262
CE-NCF	0.229	0.143	0.092	0.255	0.192	0.172	0.136	0.197
E-VNCF	0.344	0.216	0.139	0.386	0.236	0.210	0.170	0.248
CE-VNCF	0.229	0.134	0.107	0.297	0.203	0.178	0.148	0.215
T-RECS	**0.376**	**0.236**	**0.158**	**0.436**	**0.316**	**0.280**	**0.228**	**0.332**



(a) Falling MAP for different top-N. Error bars show the standard deviation.

(b) Keyphrase prediction over multi-step critiquing (NDCG) with 95% confidence interval.

Figure 6: Single- (top) and multi-step (bottom) critiquing.

20% on both datasets. We observe that E-(V)NCF models perform quite similarly to T-RECS but still underperform by 10% and 30% on the hotel and beer datasets. Interestingly, the popularity baselines achieve better results than CE-(V)NCF, showing that many keywords are recurrent in reviews. Although the task is thus not trivial, T-RECS retrieves up to 60% of relevant keyphrases within the top 20.

5.5 RQ 3: Can T-RECS enable critiquing?

We now investigate whether T-RECS can fill the gap between justifications and recommendation by enabling critiquing and effectively re-ranking recommended items.

Single-Step Critiquing For a given user, T-RECS recommends an item and generates personalized explanations, where the user can interact by critiquing one or multiple keyphrases. However, no explicit ground truth exists to evaluate the critiquing. We use the Falling MAP metric (F-MAP) from (Wu et al. 2019) to measure the effect of a critique. Given a user, a set of recommended items $\mathbb{S}$, and a critique k, let $\mathbb{S}_k$ be the set of items containing k in the explanation. The F-MAP measures the ranking difference of the affected items $\mathbb{S}_k$ before and after critiquing k, using the Mean Average Precision at N: F-MAP $=$ MAP@$N^{bef}_{\mathbb{S}_k}$ $-$ MAP@$N^{aft}_{\mathbb{S}_k}$. A positive F-MAP indicates that the rank of items in $\mathbb{S}_k$ fell after k is critiqued. We compare T-RECS with CE-(V)NCF and average the F-MAP over $5,000$ user-keyphrase pairs.

Figure 6a shows the F-MAP performance on both datasets. All models show an anticipated positive F-MAP. However, the performance of T-RECS improves considerably on the beer dataset and is significantly higher for $N \leq 10$ on the hotel dataset. As in (Wu et al. 2019), CE-VNCF performs better on average than CE-NCF because of the KL divergence that provides an additional soft constraint on the latent representation, thus reducing the risk of overfitting.

However, T-RECS and CE-(V)NCF handle the critique in different ways. CE-(V)NCF use an autoencoder learned jointly during training that projects the keyphrase explanation with the critiqued keyphrase removed back into the latent space. In contrast, T-RECS edits the entangled latent representation conforming to the new target explanation in the direction of the Keyphrase Explainer gradient. To explain the gap in performance, we hypothesize that the key difference is the extra loss caused by the autoencoder, which introduces noise during training. T-RECS only edits the latent representation at inference time by iteratively computing the gradient from the critiqued explanation and updating the latent representation.

Multi-Step Critiquing. Evaluating multi-step critiquing via ranking is difficult because many items can have the keyphrases of the desired target item. Instead, we evaluate whether a system obtains a complete model of the user's preferences following (Pu, Viappiani, and Faltings 2006). To do so, a user expresses his keyphrase preferences iteratively according to a randomly selected liked item. After each newly stated preference, we evaluate the keyphrase explanations in the same manner as in Section 5.4. We expect a model to improve its performance over critiquing.

We run up to five-steps critiques over $1,000$ random selected users and up to $5,000$ random keyphrases for each dataset. Figure 6b shows that T-RECS builds more accurate user profiles through the critiques, unlike the baselines. CE-NCF's top performance is significantly lower than T-RECS, and CE-VNCF plateaus. We hypothesize that the poor improvement of CE-VNCF comes from the KL divergence regularization, which limits the amount of information stored in the restricted latent space. We observe that excessive critiquing diminishes the keyphrase relevance.

6 Conclusion

Recommendations can carry much more impact if they are supported by explanations. Previous research has proposed to generate explanations from reviews of a recommended item, but often the resulting explanations are not perceived as convincing by human users. We introduced T-RECS, a multi-task learning Transformer-based recommender, and produces explanations considered superior in relevance and informativeness when evaluated by humans.

The second contribution of T-RECS is the user's ability to react to a recommendation by *critiquing* the explanation. The system uses this critique to update its recommendation to items that better fit the user's preferences as expressed by the critique. We presented an unsupervised critiquing method for single- and multi-step critiquing with textual explanations. Experiments on two real-world datasets show that T-RECS is the first to obtain good performance in adapting to the preferences expressed in multi-step critiquing.

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A Processing & Filtering *Markers* To Justifications

The method described in (Antognini, Musat, and Faltings 2019) extracts, most of the time, *markers* that consist of long, continuous spans of words. However, sometimes, the *markers* are too short because some reviews do not include enough words to justify a certain aspect rating, or the *markers* stop in the middle of a sentence. Although both are theoretically not wrong, we would like to create justifications that are fluent and grammatically correct. To this end, we exploit the constituency parse tree to ensure that *markers* are noun/verb phrases. We apply the following steps to the entire set of reviews for each dataset:[4]

1. Compute the constituency parse tree of each review;
2. For each noun and adjective node in the constituency parse tree of a *marker*, if the parent node is a verb or noun phrase, we add its children to the *marker*. We follow the rules in (Giannakopoulos et al. 2017);
3. Filter out *markers* having less than four tokens or including first and third-person pronouns.

B Keyphrase Samples

None of our datasets contains initially preselected keyphrases. We extract 200 candidate keyphrases from the *markers* that are used to model the user and item profiles. They serve as a basis for the explanation and the critiquing. Table 6 shows some keyphrases for each dataset. Similarly to (Wu et al. 2019), we apply the following preprocessing steps for each dataset.

1. Group by aspect the *markers* from all reviews. The aspect sets come from the available faceted ratings;[5]
2. For each group of *markers*:
   - Tokenize and lemmatize the entire group of *markers*;
   - Extract unigram lists of high-frequency noun and adjective phrases;
   - Keep the top-k most likely unigrams;
3. Represent each review as a one-hot vector indicating whether each keyphrase occurred in the review.

C Justification Examples

Table 7 and Table 8 present different justifications that are extracted from the hotel and beer reviews. We observe that the *markers* justify the subratings. Although they might be some overlaps between EDU All and Markers, justifications from EDU All often are incomplete or not relevant.

D Full Natural Language Explanations Results

We also compare T-RECS with more models than these of Section 5.4: Item-Rand, Ref2Seq Top-k, and ACMLM (Ni, Li, and McAuley 2019). Item-Rand is an unpersonalized baseline which outputs a justification randomly from the justification history J^i of item i. Ref2Seq Top-k is an extension of Ref2Seq, where we explore another decoding strategy called Top-k sampling (Radford et al.), which should be more diverse and suitable on high-entropy tasks (Holtzman et al. 2020). Finally, ACMLM is an aspect conditional masked language model that randomly chooses a justification from J^i (similar to Item-Rand) and then iteratively edits it into new content by replacing random words. We also include more metrics and $\mathrm{R}_{\mathrm{Sent}}$, which computes the percentages of generated justifications sharing the same polarity as the targets according to a sentiment classifier.[6]

The complete results are presented in Table 9. Interestingly, Item-Rand performs closely to LexRank: the best justification, according to LexRank, is slightly better than a random one. On the other hand, ACMLM edits the latter by randomly replacing tokens with the language model but produces poor quality justification, similarly to (Ni, Li, and McAuley 2019). Finally, we also observe that the polarities of the generated justifications for beers match nearly perfectly, unlike in hotels where the positive and negative nuances are much harder to capture.

Table 6: Some keyphrases mined from the inferred *markers*. We grouped them by aspect for a better understanding.

Dataset	Aspect	Keyphrases
Hotel	Service	bar, lobby, housekeeping, guest
	Cleanliness	carpet, toilet, bedding, cigarette
	Value	price, wifi, quality, motel, gym
	Location	airport, downtown, restaurant shop
	Room	bed, tv, balcony, fridge, microwave
Beer	Appearance	golden, dark, white, foamy
	Aroma	fruit, wheat, citrus, coffee
	Palate	creamy, chewy, syrupy, heavy
	Taste	bitter, sweet, balanced, nutty

E Full Keyphrase Explanation Results

Table 10 contains complementary results to the keyphrase explanation quality experiment of Section 5.4.

F Additional Metrics Multi-Step Critiquing

More metrics of the multi-step critiquing experiment in Section 5.5 are available in Figure 7.

G RQ 4: Do T-RECS justifications benefit the overall recommendation quality?

In this section, we investigate whether justifications are beneficial to T-RECS and improve overall performance. We assess the performance on three different axes: rating prediction, preference prediction, and Top-N recommendation.

[4]The preprocessing code will also be made available.

[5]For the hotel reviews: service, cleanliness, value, location, and room. For beer reviews: appearance, smell, mouthfeel, and taste.

[6]We employ the sentiment classifiers trained jointly with Multi-Aspect Masker of (Antognini, Musat, and Faltings 2019), used to infer the *markers* from which the justifications are extracted.

Table 7: Comparisons of the extracted justifications from different models for two hotels on the hotel dataset. Colors denote aspects while underline denotes EDUs classified as good justifications.

Model	**Casa del Sol Machupicchu**	**Southern Sun Waterfront Cape Town**
Review	the hotel was decent the staff was very friendly. the free pisco sour class with kevin was a nice bonus! however, the rooms were lacking. the wifi was incredibly slow and there was no air conditioning, so it got very hot at night. we couldn't open the windows either because there were so many bugs, birds, and noise. overall, the location is convenient, but was is not worth the price.	this is my second year visiting cape town and staying here. excellent location to business district, convention center, v&a waterfront and access short distance to table mountain. very nice hotel, very friendly staff. breakfast is very good. rooms are nice but bed mattress could be improved as bed is somewhat hard. overall a very nice hotel.
Rating	Overall: 3.0, Service: 3.0, Cleanliness: 4.0, Value: 2.0, Location: 4.0, Room: 3.0	Overall: 4.0, Service: 5.0, Cleanliness: 5.0, Value: 4.0, Location: 5.0, Room: 3.0
Markers	- the rooms were lacking. - the hotel was decent and the staff was very friendly. - overall , the location is convenient , but was is not worth the price. - we could n't open the windows either because there were so many bugs , birds , and noise. - the wifi was incredibly slow and there was no air conditioning , so it got very hot at night.	- breakfast is very good. - very nice hotel , very friendly staff. - rooms are nice but bed mattress could be improved as bed is somewhat hard. - excellent location to business district , convention center , v&a waterfront and access short distance to table mountain.
EDU All	- the hotel was decent - the free pisco sour class with kevin was a nice bonus.	- excellent location to business district , convention center , v&a waterfront and access short distance to table mountain. - very nice hotel , very friendly staff. breakfast is very good. - rooms are nice. - overall a very nice hotel.
EDU One	- the hotel was decent	- very nice hotel , very friendly staff . breakfast is very good

Table 8: Comparisons of the extracted justifications from different models for two beers on the beer dataset. Colors denote aspects while underline denotes EDUs classified as good justifications.

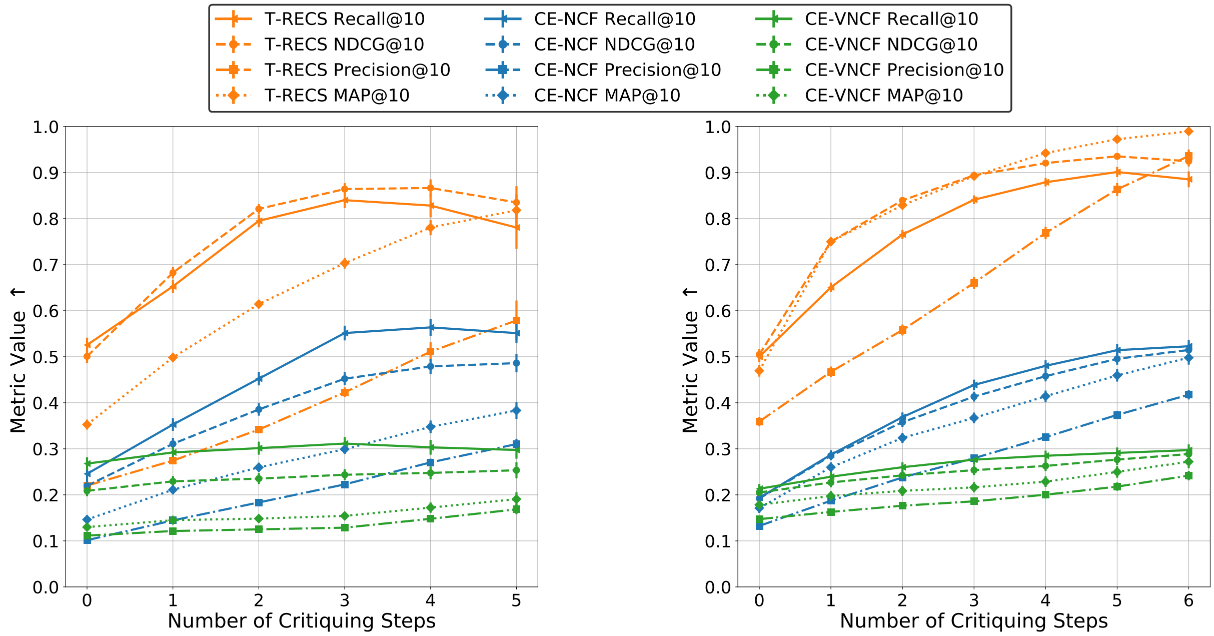
Model	**Saison De Lente**	**Bell's Porter**
Review	poured from a 750ml bottle into a chimay branded chalice. a: cloudy and unfiltered with a nice head that lasts and leaves good amounts of lacing in its tracks. s: sour and bready with apple and yeast hints in there as well. t: dry and hoppy with a nice crisp sour finish. m: medium bodied, high carbonation with big bubbles. d: easy to drink, but i didn't really want more after splitting a 750ml with a buddy of mine.	this beer pours black with a nice big frothy offwhite head. smells or roasted malts, and chocolate. tastes of roasted malt with some chocolate and a hint of coffee. the mouthfeel has medium body and is semi-smooth with some nice carbination. drinkability is decent i could drink a couple. overall a good choice from bell's.
Rating	Overall: 3.0, Appearance: 3.5, Smell: 4.0, Mouthfeel: 3.5, Taste: 3.5	Overall: 3.5, Appearance: 4.0, Smell: 3.5, Mouthfeel: 3.5, Taste: 4.0
Markers	- dry and hoppy with a nice crisp sour finish. - medium bodied , high carbonation with big bubbles. - sour and bready with apple and yeast hints in there as well. - cloudy and unfiltered with a nice head that lasts and leaves good amounts of lacing in its tracks.	- smells or roasted malts , and chocolate. - this beer pours black with a nice big frothy offwhite head. - tastes of roasted malt with some chocolate and a hint of coffee. - the mouthfeel has medium body and is semi smooth with some nice carbination.
EDU All	- medium bodied , high carbonation with big bubbles. - easy to drink	- smells or roasted malts , and chocolate. - tastes of roasted malt with some chocolate and a hint of coffee. - drinkability is decent - overall a good choice
EDU One	- easy to drink	- drinkability is decent

Table 9: Performance of the generated personalized justifications on automatic evaluation.

	Model	B-1	B-2	B-3	B-4	R-1	R-2	R-L	$\text{BERT}_{\text{Score}}$	PPL↓	R_{KW}	R_{Sent}
Hotel	Item-Rand	11.50	2.88	0.91	0.32	12.65	0.87	9.75	84.20	-	6.92	56.88
	LexRank	12.12	3.31	1.10	0.41	14.74	1.16	10.61	83.91	-	10.32	58.51
	ExpansionNet	4.03	1.95	1.01	0.53	34.22	9.65	6.91	74.81	28.87	60.09	61.38
	Ref2Seq	17.57	7.03	3.44	1.77	19.07	3.43	16.45	86.74	29.07	13.19	64.40
	Ref2Seq Top-k	12.68	3.46	1.11	0.40	12.67	0.95	10.30	84.29		6.38	58.11
	AP-Ref2Seq	32.04	19.03	11.76	7.28	38.90	14.53	33.71	88.31	21.31	90.20	69.37
	ACMLM	8.60	2.42	1.12	0.62	9.79	0.55	7.23	81.90	-	13.24	60.00
	T-RECS (Ours)	**33.53**	**19.76**	**12.14**	**7.47**	**40.29**	**14.74**	**34.10**	**90.23**	**17.80**	**93.57**	**70.12**
Beer	Item-Rand	10.96	3.02	0.91	0.29	10.28	0.75	8.25	83.39	-	6.70	99.61
	LexRank	12.23	3.58	1.12	0.38	13.81	1.16	9.90	83.42	-	10.79	99.88
	ExpansionNet	6.48	3.59	2.06	1.22	**54.53**	18.24	9.68	72.32	22.28	82.49	**99.99**
	Ref2Seq	18.75	9.47	5.51	3.51	18.25	4.52	15.96	85.27	22.34	12.10	**99.99**
	Ref2Seq Top-k	13.92	5.02	2.10	1.01	12.36	1.50	10.52	84.14		8.51	99.83
	AP-Ref2Seq	44.84	30.57	21.68	15.89	51.38	23.27	46.50	91.35	12.07	91.52	**99.99**
	ACMLM	7.76	2.54	0.91	0.34	8.33	0.87	6.17	80.94	-	10.33	**99.99**
	T-RECS (Ours)	**46.50**	**31.56**	**22.42**	**16.54**	53.12	**23.86**	**47.20**	**91.50**	**10.24**	**94.96**	**99.99**

Table 10: Performance of personalized keyphrase explanation quality.

		NDCG@N			MAP@N			Precision@N			Recall@N		
	Model	N=5	N=10	N=20	N=5	N=10	N=20	N=5	N=10	N=20	N=5	N=10	N=20
Hotel	UserPop	0.2625	0.3128	0.3581	0.2383	0.1950	0.1501	0.1890	0.1332	0.0892	0.2658	0.3694	0.4886
	ItemPop	0.2801	0.3333	0.3822	0.2533	0.2083	0.1608	0.2041	0.1431	0.0959	0.2866	0.3961	0.5245
	E-NCF	0.2901	0.3410	0.3889	0.2746	0.2146	0.1618	0.1943	0.1366	0.0919	0.2746	0.3802	0.5057
	CE-NCF	0.1929	0.2286	0.2634	0.1825	0.1432	0.1085	0.1290	0.0918	0.0631	0.1809	0.2548	0.3469
	E-VNCF	0.2902	0.3441	0.3925	0.2746	0.2158	0.1634	0.1947	0.1391	0.0932	0.2746	0.3860	0.5132
	CE-VNCF	0.1727	0.2289	0.2761	0.1530	0.1336	0.1115	0.1275	0.1071	0.0767	0.1795	0.2965	0.4200
	T-RECS (Ours)	**0.3158**	**0.3763**	**0.4319**	**0.2919**	**0.2356**	**0.1807**	**0.2223**	**0.1581**	**0.1068**	**0.3109**	**0.4358**	**0.5812**
Beer	UserPop	0.2049	0.2679	0.3357	0.2749	0.2404	0.2014	0.2366	0.1901	0.1445	0.1716	0.2767	0.4207
	ItemPop	0.1948	0.2495	0.3131	0.2653	0.2291	0.1894	0.2267	0.1759	0.1342	0.1618	0.2529	0.3886
	E-NCF	0.1860	0.2485	0.3158	0.2488	0.2204	0.1877	0.2162	0.1789	0.1389	0.1571	0.2618	0.4040
	CE-NCF	0.1471	0.1922	0.2422	0.1967	0.1721	0.1446	0.1687	0.1363	0.1050	0.1227	0.1974	0.3033
	E-VNCF	0.1763	0.2362	0.3055	0.2389	0.2097	0.1797	0.2031	0.1696	0.1356	0.1471	0.2478	0.3943
	CE-VNCF	0.1512	0.2025	0.2595	0.1987	0.1784	0.1532	0.1774	0.1475	0.1155	0.1293	0.2146	0.3352
	T-RECS (Ours)	**0.2394**	**0.3163**	**0.3946**	**0.3127**	**0.2799**	**0.2369**	**0.2800**	**0.2284**	**0.1717**	**0.2048**	**0.3320**	**0.4970**



(a) Results on the **hotel** dataset.

(b) Results on the **beer** dataset.

Figure 7: Multi-step critiquing performance. Keyphrase prediction over multi-step critiquing in terms of Recall@10, NDCG@10, Precision@10, and MAP@10 with 95% confidence interval. a) Results on the hotel dataset, b) on the beer dataset.

Table 11: Performance of the rating prediction.

	Hotel			*Beer*		
Model	**MAE**	**RMSE**	$\tau\uparrow$	**MAE**	**RMSE**	$\tau\uparrow$
NMF	0.3825	0.6171	0.2026	0.3885	0.4459	0.4152
PMF	0.3860	0.5855	0.0761	0.3922	0.4512	0.4023
HFT	0.3659	0.4515	0.4584	0.3616	0.4358	0.4773
NARRE	0.3564	0.4431	0.4476	0.3620	0.4377	0.4506
NCF	0.3619	0.4358	0.4200	0.3638	0.4341	0.4696
E-NCF	0.3579	0.4382	0.4145	0.3691	0.4326	0.4685
CE-NCF	0.3552	0.4389	0.4165	0.3663	0.4390	0.4527
VNCF	0.3502	0.4313	0.4408	0.3666	0.4300	0.4706
E-VNCF	0.3494	0.4365	0.4072	0.3627	0.4457	0.4651
CE-VNCF	0.3566	0.4545	0.3502	**0.3614**	0.4330	0.4619
T-RECS	**0.3306**	**0.4305**	**0.4702**	**0.3614**	**0.4295**	**0.4909**

Rating & Preference Prediction We first analyze recommendation performance by the mean of rating prediction. We utilize the common Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics. However, the rating prediction performance alone does not best reflect the quality of recommendations, because users mainly see the relative ranking of different items (Ricci, Rokach, and Shapira 2011; Musat and Faltings 2015). Consequently, we measure also how well the item rankings computed by T-RECS agree with the user's own rankings as given by his own review ratings. We measure this quality by leveraging the standard metric Kendall's τ rank correlation (Kendall 1938), computed on all pairs of rated-items by a user in the testing set. Overall, there are 153 954 and 1 769 421 pairs for the hotel and beer datasets, respectively.

We examine the following baseline methods together with T-RECS: NMF (Hoyer 2004) is a non-negative matrix factorization model for rating prediction. PMF (Mnih and Salakhutdinov 2008) is a probabilistic matrix factorization method using ratings for collaborative filtering. HFT (McAuley and Leskovec 2013) is a strong latent-factor baseline, combined with a topic model aiming to find topics in the review text that correlate with the users' and items' latent factors. NARRE (Chen et al. 2018) is a state-of-the-art model that predicts ratings and reviews' usefulness jointly. Finally, we include the six methods of (Wu et al. 2019) described in Section 5.4.

The results are shown in Table 11. T-RECS consistently outperforms all the baselines, by a wide margin on the hotel dataset, including models based on collaborative filtering with/without review information or models extended with an explanation component and/or a critiquing component. Interestingly, the improvement in the hotel dataset in terms of MAE and RMSE is significantly higher than on the beer dataset. We hypothesize that this behavior is due to the sparsity (see Table 1), which has also been observed in the hotel domain in prior work (Musat and Faltings 2015; Antognini and Faltings 2020). On the beer dataset, we note that reviews contain strong indicators and considerably improve the performance of NARRE and HFT compared to collaborative filtering methods. The extended (V)NCF models with either an explanation and/or a critiquing component improve MAE performance. Therefore, explanations can benefit the recommender systems to improve rating prediction.

Table 12: Performance of the Top-N recommendation.

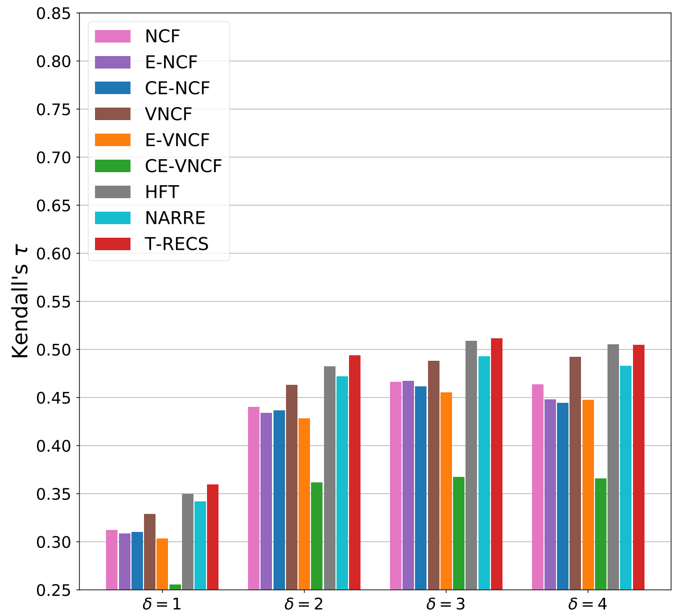
	Model	NDCG@N		Precision@N		Recall@N	
		N=10	N=20	N=10	N=20	N=10	N=20
Hotel	NCF	0.1590	0.2461	0.0231	0.0200	0.2310	0.3991
	E-NCF	0.1579	0.2432	0.0234	0.0200	0.2336	0.4004
	CE-NCF	0.1585	0.2431	0.0235	0.0201	0.2352	0.4028
	VNCF	0.1492	0.2431	0.0220	0.0197	0.2204	0.3932
	E-VNCF	0.1505	0.2395	0.0219	0.0192	0.2188	0.3842
	CE-VNCF	**0.1738**	**0.2662**	0.0221	0.0190	0.2210	0.3809
	T-RECS	0.1674	**0.2662**	**0.0236**	**0.0207**	**0.2358**	**0.4144**
Beer	NCF	0.2172	0.3509	0.0250	0.0212	0.2499	0.4231
	E-NCF	0.2087	0.3363	0.0243	0.0205	0.2426	0.4103
	CE-NCF	0.2226	0.3456	0.0252	0.0205	0.2517	0.4105
	VNCF	0.1943	0.3329	0.0235	0.0211	0.2345	0.4213
	E-VNCF	0.1387	0.2813	0.0158	0.0168	0.1579	0.3362
	CE-VNCF	0.2295	0.3598	0.0263	0.0218	0.2630	0.4352
	T-RECS	**0.2372**	**0.3674**	**0.0269**	**0.0219**	**0.2693**	**0.4390**

Table 11 also contains the results in terms of preference prediction. T-RECS achieves up to 0.0136 higher Kendall correlation compared to the best baseline. Surprisingly, we note that CE-VNCF, NMF, and PMF show much worse results on the hotel datasets than on the beer dataset. This highlights that hotel reviews are noisier than beer reviews and emphasizes the importance of capturing users' profiles, where T-RECS does best in comparison to other models.

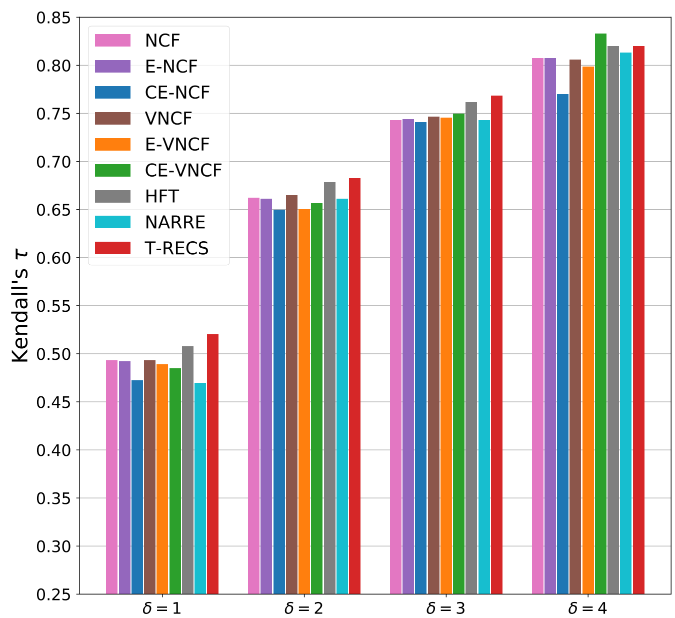
Preference Prediction In this experiment, we study a more fine-grained rank correlation. Following (Musat and Faltings 2015), we analyze the pairwise ranking of rated items by a user, and we impose a minimum value for the rating difference between two items i and j, such that $\delta = |y_r^i - y_r^j|$; the rating difference δ symbolizes the minimum preference strength.

Figure 8 contains the Kendall's τ evaluation for multiple δ on both datasets. Overall, T-RECS increases the Kendall correlation similarly to other models but performs better on average. We observe that HFT's performance is similar to T-RECS, although slightly lower for most cases. On the beer dataset, we surprisingly note that CE-VNCF obtains a negligible higher score for $\delta = 4$, while significantly underperforming for $\delta < 4$, and especially on the hotel dataset. Finally, the Kendall's τ correlation increases majorly with the strength of preference pairs on the beer dataset and plateaus over $\delta \geq 2$ on the hotel dataset. It highlights that hotel reviews are noisier than beer reviews, and it emphasizes the importance of capturing users' profiles, where T-RECS does best in comparison to other models.

Recommendation Performance We evaluate the performance of T-RECS on the last dimension: Top-N recommendation. We adopt the widely used leave-one-out evaluation protocol (Nikolakopoulos et al. 2019; Zhao et al. 2018); in particular, for each user, we randomly select one liked item in the test set alongside 99 randomly selected unseen items.



(a) Kendall's τ correlation on the **hotel** dataset.



(b) Kendall's τ correlation on the **beer** dataset.

Figure 8: Performance of the preference prediction using Kendall's τ and $\delta = |y_r^i - y_r^j|$.

We compare T-RECS with the state-of-the-art methods in (Wu et al. 2019). Finally, we rank the item lists based on the recommendation scores produced by each method, and report the NDCG, Precision, and Recall at different N.

Table 12 presents the main results. Comparing to CE-(V)NCF models, which contain an explanation and critiquing components, our proposed model shows better recommendation performance for almost all metrics on the two datasets. On average, the variants of (V)NCF reach higher results than the original method, which was not the case in the rating prediction and relative rankings tasks (see Section G), unlike T-RECS that shows consistent results.

H Human Evaluation Details

We use Amazon's Mechanical Turk crowdsourcing platform to recruit human annotators to evaluate the quality of extracted justifications and the generated justifications produced by each model. To ensure high-quality of the collected data, we restricted the pool to native English speakers from the U.S., U.K., Canada, or Austria. Additionally, we set the worker requirements at a 98% approval rate and more than 1000 HITS.

The user interface used to judge the quality of the justifications extracted from different methods, in Section 5.3, is shown in Figure 9. The one employed for evaluating the generated justifications, in Section 5.4, on the four dimensions (overall, fluency, informativeness, and relevance) is available in Figure 10.

I Additional Training Details

I.1 Tuning

For all models, we have operated a random search over 10 trials. We chose the models achieving the lowest validation loss. The range of hyperparameters are the following for T-RECS (similar for other models):

- Learning rate: $[0.001, 0.0001]$;
- Max epochs: $[100, 200, 300]$;
- Batch size: $[128]$;
- Hidden size encoder/decoder: $[256]$;
- Attention heads: $[4]$;
- Number of layers: $[2]$;
- Dropout encoder: $[0.0, 0.1, 0.2, 0.3, 0.4, 0.5]$;
- Dropout decoder: $[0.0, 0.1, 0.2, 0.3]$;
- General dropout: $[0.0, 0.1, 0.2]$;
- Warmup: $[2000, 4000, 8000, 16000]$;
- λ_r, λ_{kp}, λ_{just}: $[1.0]$;

Most of the time, the model converges under 20 epochs. For critiquing, we employed:

- Decay coefficient ζ: $[0.5, 0.75, 0.8, 0.9, 0.95]$;
- Max iterations: $[25, 50, 75, 100, 200]$;
- Threshold: $[0.015, 0.01, 0.005]$;

I.2 Hardware / Software

- **CPU**: 2x Intel Xeon E5-2680 v3 (Haswell), 2x 12 cores, 24 threads, 2.5 GHz, 30 MB cache;
- **RAM**: 16x 16GB DDR4-2133;
- **GPU**: 2x Nvidia Titan X Maxwell;
- **OS**: Ubuntu 18.04;
- **Software**: Python 3.6, PyTorch 1.3.0, CUDA 10.0.

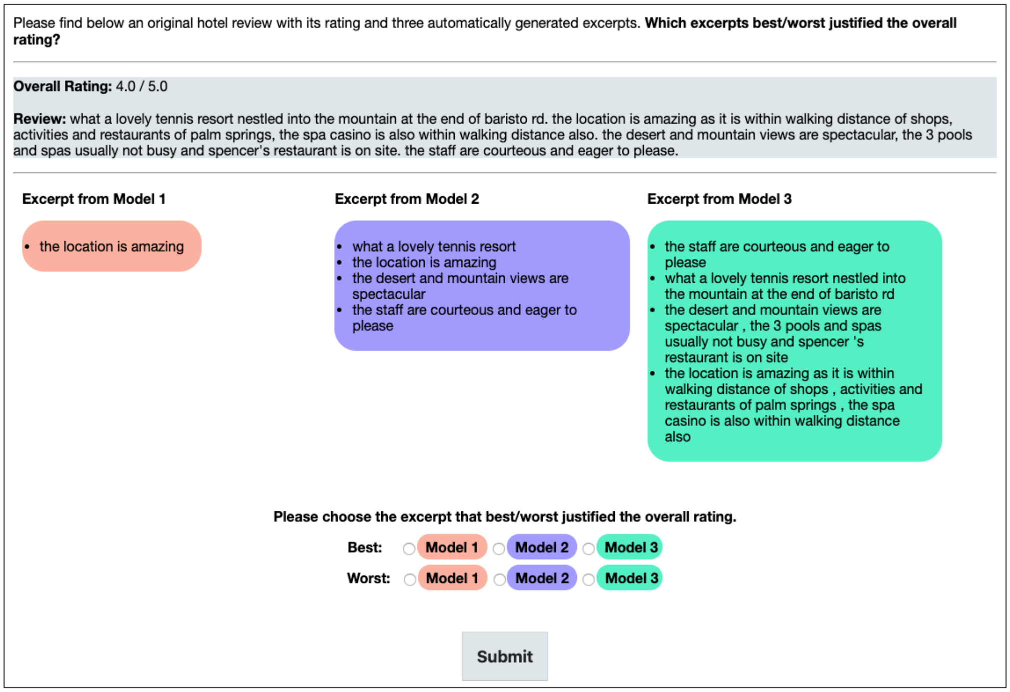


Figure 9: Annotation platform for judging the quality of extracted justifications from different methods. The justifications are shown in random order for each comparison. In this example, our method corresponds to the third model.

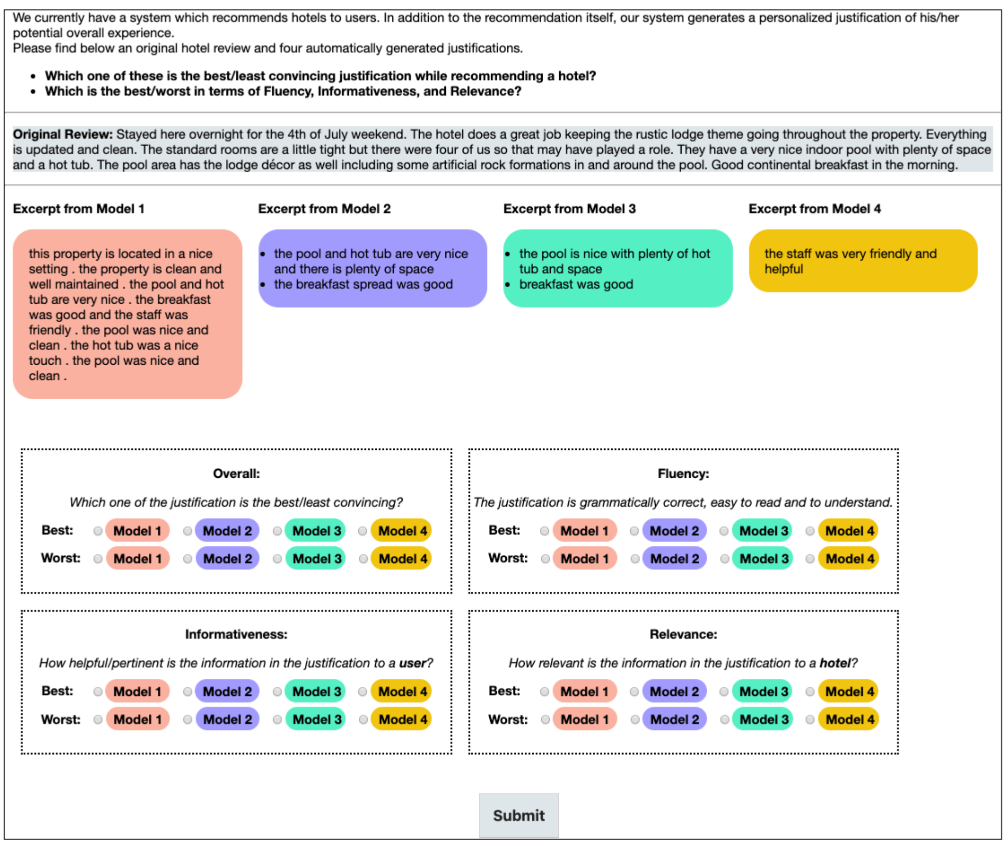


Figure 10: Annotation platform for judging the quality of generated justifications from different methods, on four dimensions. The justifications are shown in random order for each comparison. In this example, our method corresponds to the second model.