Abstract
In this paper, we focus on the problem of building assistive systems that can help users to write reviews. We cast this problem using an encoder-decoder framework that generates personalized reviews by expanding short phrases (e.g. review summaries, product titles) provided as input to the system. We incorporate aspect-level information via an aspect encoder that learns ‘aspect-aware’ user and item representations. An attention fusion layer is applied to control generation by attending on the outputs of multiple encoders. Experimental results show that our model is capable of generating coherent and diverse reviews that expand the contents of input phrases. In addition, the learned aspect-aware representations discover those aspects that users are more inclined to discuss and bias the generated text toward their personalized aspect preferences.

1 Introduction
Contextual, or ‘data-to-text’ natural language generation is one of the core tasks in natural language processing and has a considerable impact on various fields (Gatt and Krahmer, 2017). Within the field of recommender systems, a promising application is to estimate (or generate) personalized reviews that a user would write about a product, i.e., to discover their nuanced opinions about each of its individual aspects. A successful model could work (for instance) as (a) a highly-nuanced recommender system that tells users their likely reaction to a product in the form of text fragments; (b) a writing tool that helps users ‘brainstorm’ the review-writing process; or (c) a querying system that facilitates personalized natural language queries (i.e., to find items about which a user would be most likely to write a particular phrase). Some recent works have explored the review generation task and shown success in generating cohesive reviews (Dong et al., 2017; Ni et al., 2017; Zang and Wan, 2017). Most of these works treat the user and item identity as input; we seek a system with more nuance and more precision by allowing users to ‘guide’ the model via short phrases, or auxiliary data such as item specifications. For example, a review writing assistant might allow users to write short phrases and expand these key points into a plausible review.

Review text has been widely studied in traditional tasks such as aspect extraction (Mukherjee and Liu, 2012; He et al., 2017), extraction of sentiment lexicons (Zhang et al., 2014), and aspect-aware sentiment analysis (Wang et al., 2016; McAuley et al., 2012). These works are related to review generation since they can provide prior knowledge to supervise the generative process. We are interested in exploring how such knowledge (e.g. extracted aspects) can be used in the review generation task.

In this paper, we focus on designing a review generation model that is able to leverage both user and item information as well as auxiliary, textual input and aspect-aware knowledge. Specifically, we study the task of expanding short phrases into complete, coherent reviews that accurately reflect the opinions and knowledge learned from those phrases.

These short phrases could include snippets provided by the user, or manifest aspects about the items themselves (e.g. brand words, technical specifications, etc.). We propose an encoder-decoder framework that takes into consideration three encoders (a sequence encoder, an attribute encoder, and an aspect encoder), and one decoder. The sequence encoder uses a gated recurrent unit
Figure 1: General structure of ExpansionNet.

(GrU) network to encode text information; the
attribute encoder learns a latent representation of
user and item identity; finally, the aspect encoder
finds an aspect-aware representation of users and
items, which reflects user-aspect preferences and
item-aspect relationships. The aspect-aware rep-
resentation is helpful to discover what each user is
likely to discuss about each item. Finally, the out-
put of these encoders is passed to the sequence de-
coder with an attention fusion layer. The decoder
attends on the encoded information and biases the
model to generate words that are consistent with
the input phrases and words belonging to the most
relevant aspects.

2 Related Work

Review generation belongs to a large body of
work on data-to-text natural language generation
(Gatt and Krahmer, 2017), which has applications
including summarization (See et al., 2017), im-
age captioning (Vinyals et al., 2015), and dia-
logue response generation (Xing et al., 2017; Li
et al., 2016; Ghosh et al., 2017), among others.
Among these, review generation is characterized
by the need to generate long sequences and es-
timate high-order interactions between users and
items.

Several approaches have been recently pro-
posed to tackle these problems. Dong et al. (2017)
proposed an attribute-to-sequence (Attr2Seq)
method to encode user and item identities as well
as rating information with a multi-layer perceptron
and a decoder then generates reviews conditioned
on this information. They also used an attention
mechanism to strengthen the alignment between
output and input attributes. Ni et al. (2017) trained
a collaborative-filtering generative concatenative
network to jointly learn the tasks of review gen-
eration and item recommendation. Zang and Wan
(2017) proposed a hierarchical structure to gener-
ate long reviews; they assume each sentence is as-
associated with an aspect score, and learn the atten-
tion between aspect scores and sentences during
training. Our approach differs from these mainly
in our goal of incorporating auxiliary textual in-
formation (short phrases, product specifications,
etc.) into the generative process, which facilitates
the generation of higher-fidelity reviews.

Another line of work related to review genera-
tion is aspect extraction and opinion mining (Park
et al., 2015; Qiu et al., 2017; He et al., 2017; Chen
et al., 2014). In this paper, we argue that the extra
aspect (opinion) information extracted using these
previous works can effectively improve the qual-
ity of generated reviews. We propose a simple but
effective way to combine aspect information into
the generative model.

3 Approach

We describe the review generation task as fol-
lows. Given a user $u$, item $i$, several short phrases
$\{d_1, d_2, ..., d_M\}$, and a group of extracted aspects
$\{A_1, A_2, ..., A_k\}$, our goal is to generate a re-
view $(w_1, w_2, ..., w_T)$ that maximizes the proba-
bility $P(w_{1:T} | u, i, d_{1:M})$. To solve this task, we
propose a method called ExpansionNet which con-
tains two parts: 1) three encoders to leverage the
input phrases and aspect information; and 2) a de-
coder with an attention fusion layer to generate
sequences and align the generation with the input
sources. The model structure is shown in Figure 1.

3.1 Sequence encoder, attribute encoder and aspect encoder

Our sequence encoder is a two-layer bi-directional GRU, as is commonly used in sequence-to-sequence (Seq2Seq) models (Cho et al., 2014). Input phrases first pass a word embedding layer, then go through the GRU one-by-one and finally yield a sequence of hidden states \{e_1, e_2, ..., e_L\}. In the case of multiple phrases, these share the same sequence encoder and have different lengths L. To simplify notation, we only consider one input phrase in this section.

The attribute encoder and aspect encoder both consist of two embedding layers and a projection layer. For the attribute encoder, we define two general embedding layers \(E_u \in \mathbb{R}^{k|u| \times m}\) and \(E_i \in \mathbb{R}^{k|u| \times m}\) to obtain the attribute latent factors \(\gamma_u\) and \(\gamma_i\); for the aspect encoder, we use two aspect-aware embedding layers \(E'_u \in \mathbb{R}^{k|u'| \times k}\) and \(E'_i \in \mathbb{R}^{k|u'| \times k}\) to obtain aspect-aware latent factors \(\beta_u\) and \(\beta_i\). Here \(|u|, |u'|\), m and k are the number of users, number of items, the dimension of attributes, and the number of aspects, respectively. After the embedding layers, the attribute and aspect-aware latent factors are concatenated and fed into a projection layer with \tanh\) activation. The outputs are calculated as:

\[
\gamma_u = E_u(u), \quad \gamma_i = E_i(i) \tag{1}
\]

\[
\beta_u = E'_u(u), \quad \beta_i = E'_i(i) \tag{2}
\]

\[
u = \tanh(W_u[\gamma_u; \gamma_i] + b_u) \tag{3}
\]

\[
v = \tanh(W_v[\beta_u; \beta_i] + b_v) \tag{4}
\]

where \(W_u \in \mathbb{R}^{n \times 2m}\), \(b_u \in \mathbb{R}^n\), \(W_v \in \mathbb{R}^{n \times 2k}\), \(b_v \in \mathbb{R}^n\) are learnable parameters and \(n\) is the dimensionality of the hidden units in the decoder.

3.2 Decoder with attention fusion layer

The decoder is a two-layer GRU that predicts the target words given the start token. The hidden state of the decoder is initialized using the sum of the three encoders’ outputs. The hidden state at time-step \(t\) is updated via the GRU unit based on the previous hidden state and the input word. Specifically:

\[
h_0 = e_L + u + v \tag{5}
\]

\[
h_t = \text{GRU}(w_t, h_{t-1}) \tag{6}
\]

where \(h_0 \in \mathbb{R}^n\) is the decoder’s initial hidden state and \(h_t \in \mathbb{R}^n\) is the hidden state at time-step \(t\).

To fully exploit the encoder-side information, we apply an attention fusion layer to summarize the output of each encoder and jointly determine the final word distribution. For the sequence encoder, the attention vector is defined as in many other applications (Bahdanau et al., 2014; Luong et al., 2015):

\[
a^1_t = \sum_{j=1}^{L} \alpha^1_{tj} e_j \tag{7}
\]

\[
\alpha^1_{tj} = \exp(\tanh(v^1_\alpha^T (W^1_\alpha[e_j; h_t] + b^1_\alpha)))/Z, \tag{8}
\]

where \(a^1_t \in \mathbb{R}^n\) is the attention vector on the sequence encoder at time-step \(t\), \(\alpha^1_{tj}\) is the attention score over the encoder hidden state \(e_j\) and decoder hidden state \(h_t\), and \(Z\) is a normalization term.

For the attribute encoder, the attention vector is calculated as:

\[
a^2_t = \sum_{j=1}^{k} \alpha^2_{tj} \gamma_j \tag{9}
\]

\[
\alpha^2_{tj} = \exp(\tanh(v^2_\alpha^T (W^2_\alpha[\gamma_j; h_t] + b^2_\alpha)))/Z, \tag{10}
\]

where \(a^2_t \in \mathbb{R}^n\) is the attention vector on the attribute encoder, and \(\alpha^2_{tj}\) is the attention score between the attribute latent factor \(\gamma_j\) and decoder hidden state \(h_t\).

Inspired by the copy mechanism (Gu et al., 2016; See et al., 2017), we design an attention vector that estimates the probability that each aspect will be discussed in the next time-step:

\[
s_{ui} = W_s[\beta_u; \beta_i] + b_s \tag{11}
\]

\[
a^3_t = \tanh(W^3_\alpha[s_{ui}; e_t; h_t] + b^3_\alpha), \tag{12}
\]

where \(s_{ui} \in \mathbb{R}^k\) is the aspect importance considering the interaction between \(u \) and \(i\), \(e_t\) is the decoder input after embedding layer at time-step \(t\), and \(a^3_t \in \mathbb{R}^k\) is a probability vector to bias each aspect at time-step \(t\). Finally, the first two attention vectors are concatenated with the decoder hidden state at time-step \(t\) and projected to obtain the output word distribution \(P_w\). The attention scores from the aspect encoder are then directly added to the aspect words in the final word distribution. The output probability for word \(w\) at time-step \(t\) is given by:

\[
P_w(w_t) = \tanh(W[w_t; a^1_t; a^2_t] + b) \tag{13}
\]

\[
P(w_t) = P_w(w_t) + a^3_t[k] \cdot 1_{w_t \in A_k}, \tag{14}
\]
where $w_t$ is the target word at time-step $t$. $\alpha_t^k[k]$ is the probability that aspect $k$ will be discussed at time-step $t$. $A_k$ represents all words belonging to aspect $k$ and $\mathbb{1}_{w_t \in A_k}$ is a binary variable indicating whether $w_t$ belongs to aspect $k$.

During inference, we use greedy decoding by choosing the word with maximum probability, denoted as $y_t = \text{argmax}_{w_t} \text{softmax}(P(w_t))$. Decoding finishes when an end token is encountered.

## 4 Experiments

We consider a real world dataset from Amazon Electronics (McAuley et al., 2015) to evaluate our model. We convert all text into lowercase, add start and end tokens to each review, and perform tokenization using NLTK.\footnote{https://www.nltk.org/} We discard reviews with length greater than 100 tokens and consider a vocabulary of 30,000 tokens. After preprocessing, the dataset contains 182,850 users, 59,043 items, and 992,172 reviews (sparsity 99.993%), which is much sparser than the datasets used in previous works (Dong et al., 2017; Ni et al., 2017). On average, each review contains 49.32 tokens as well as a short-text summary of 4.52 tokens. In our experiments, the basic ExpansionNet uses these summaries as input phrases. We split the dataset into training (80%), validation (10%) and test sets (10%). All results are reported on the test set.

### 4.1 Aspect Extraction

We use the method\footnote{https://github.com/ruidan/Unsupervised-Aspect-Extraction} in (He et al., 2017) to extract 15 aspects and consider the top 100 words from each aspect. Table 2 shows 10 inferred aspects and representative words (inferred aspects are manually labeled). ExpansionNet calculates an attention score based on the user and item aspect-aware representation, then determines how much these representative words are biased in the output word distribution.

### 4.2 Experiment Details

We use PyTorch\footnote{http://pytorch.org/docs/master/index.html} to implement our model. Parameter settings are shown in Table 1. For the attribute encoder and aspect encoder, we set the dimensionality to 64 and 15 respectively. For both the sequence encoder and decoder, we use a 2-layer GRU with hidden size 512. We also add dropout layers before and after the GRUs. The dropout rate is set to 0.1. During training, the input sequences of the same source (e.g. review, summary) inside each batch are padded to the same length.

### 4.3 Performance Evaluation

We evaluate the model on six automatic metrics (Table 3): Perplexity, BLEU-1/BLEU-4, ROUGE-L and Distinct-1/2 (percentage of distinct unigrams and bi-grams) (Li et al., 2016). We compare

<table>
<thead>
<tr>
<th>Word dimension</th>
<th>Attribute dimension</th>
<th>Aspect dimension</th>
<th>GRU hidden size</th>
<th>Batch Size</th>
<th>Learning Rate</th>
<th>Optimizer</th>
</tr>
</thead>
<tbody>
<tr>
<td>512</td>
<td>64</td>
<td>15</td>
<td>512</td>
<td>16</td>
<td>0.0002</td>
<td>Adam</td>
</tr>
</tbody>
</table>

### Table 1: Parameter settings used in our experiments.

### Table 2: List of representative words for inferred aspects on Amazon Electronics dataset.

<table>
<thead>
<tr>
<th>Aspects</th>
<th>Representative Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service</td>
<td>vendor seller supplier reply refund delivery shipping exchange contacting promptly</td>
</tr>
<tr>
<td>Price</td>
<td>price value overall dependable reliable affordable practical budget inexpensive bargain</td>
</tr>
<tr>
<td>Screen</td>
<td>screen touchscreen browse display scrolling surfing navigate icon menu surfing text blur reflection</td>
</tr>
<tr>
<td>Case</td>
<td>case cover briefcase portfolio padded protective rubberized padding leather skin</td>
</tr>
<tr>
<td>Drive</td>
<td>drive disk copying copied fat32 terabyte ntfs data hdd cache</td>
</tr>
<tr>
<td>Sound</td>
<td>sound vocal loudness booming bass treble tinny speaker isolation sennheisers</td>
</tr>
<tr>
<td>Vision</td>
<td>glossy shiny transparent polish reflective faded lcd shield glass painted</td>
</tr>
<tr>
<td>Laptop</td>
<td>lenovo inspiron ibm gateway pentium alienware xps pavilion thinkpad elite</td>
</tr>
<tr>
<td>Time</td>
<td>cycle time week day month hour suddenly repeated overnight continuously</td>
</tr>
<tr>
<td>Stableness</td>
<td>unscrew securing mounting drill centered tightening screwed attach tighten loosen</td>
</tr>
</tbody>
</table>

\begin{table}[h]
\centering
\begin{tabular}{c|c}
\hline
Aspects & Representative Words \\
\hline
Service & vendor seller supplier reply refund delivery shipping exchange contacting promptly \\
Price & price value overall dependable reliable affordable practical budget inexpensive bargain \\
Screen & screen touchscreen browse display scrolling surfing navigate icon menu surfing text blur reflection \\
Case & case cover briefcase portfolio padded protective rubberized padding leather skin \\
Drive & drive disk copying copied fat32 terabyte ntfs data hdd cache \\
Sound & sound vocal loudness booming bass treble tinny speaker isolation sennheisers \\
Vision & glossy shiny transparent polish reflective faded lcd shield glass painted \\
Laptop & lenovo inspiron ibm gateway pentium alienware xps pavilion thinkpad elite \\
Time & cycle time week day month hour suddenly repeated overnight continuously \\
Stableness & unscrew securing mounting drill centered tightening screwed attach tighten loosen \\
\hline
\end{tabular}
\end{table}
Table 3: Results on automatic metrics

<table>
<thead>
<tr>
<th>Model</th>
<th>PPL</th>
<th>BLEU-1(%)</th>
<th>BLEU-4(%)</th>
<th>ROUGE-L</th>
<th>Distinct-1(%)</th>
<th>Distinct-2(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rand</td>
<td>/</td>
<td>20.24</td>
<td>0.45</td>
<td>0.390</td>
<td>1.311</td>
<td>13.681</td>
</tr>
<tr>
<td>GRU-LM</td>
<td>35.35</td>
<td>30.79</td>
<td>1.20</td>
<td>/</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>Attr2Seq</td>
<td>34.21</td>
<td>26.16</td>
<td>1.23</td>
<td>0.403</td>
<td>0.014</td>
<td>0.051</td>
</tr>
<tr>
<td>+aspect</td>
<td>34.26</td>
<td>26.87</td>
<td>1.51</td>
<td>0.397</td>
<td>0.018</td>
<td>0.069</td>
</tr>
<tr>
<td>ExpansionNet</td>
<td>34.18</td>
<td>26.05</td>
<td>2.21</td>
<td>0.404</td>
<td>0.096</td>
<td>0.789</td>
</tr>
<tr>
<td>+title</td>
<td>30.7</td>
<td>27.90</td>
<td>2.50</td>
<td>0.415</td>
<td>0.099</td>
<td>0.911</td>
</tr>
<tr>
<td>+attribute &amp; aspect</td>
<td>31.7</td>
<td>30.33</td>
<td>2.63</td>
<td>0.408</td>
<td>0.133</td>
<td>1.134</td>
</tr>
</tbody>
</table>

User/Item: user A7G831BTCLGWGVQ and item B007M50PTM
Review summary: “easy to use and nice standard apps”
Item title: “samsung galaxy tab 2 (10.1-Inch, wi-fi) 2012 model”

Real review: “the display is beautiful and the tablet is very easy to use, it comes with some really nice standard apps.”

Attr2Seq: “i bought this for my wife ’s new ipad air. it fits perfectly and looks great. the only thing i do n’t like is that the cover is a little too small for the ipad air.”

ExpansionNet: “i love this tablet. it is fast and easy to use. i have no complaints. i would recommend this tablet to anyone.”

+title: “i love this tablet. it is fast and easy to use. i have a galaxy tab 2 and i love it.”

+attribute & aspect: “i love this tablet. it is easy to use and the screen is very responsive. i love the fact that it has a micro sd slot. i have not tried the tablet app yet but i do n’t have any problems with it. i am very happy with this tablet.”

Table 4: Aspect coverage analysis

<table>
<thead>
<tr>
<th></th>
<th># aspects (real)</th>
<th># aspects (generated)</th>
<th># covered aspects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attr2Seq</td>
<td>2.875</td>
<td>2.744</td>
<td>0.686</td>
</tr>
<tr>
<td>ExpansionNet</td>
<td>2.875</td>
<td>1.804</td>
<td>0.807</td>
</tr>
<tr>
<td>+title</td>
<td>2.875</td>
<td>1.721</td>
<td>0.894</td>
</tr>
<tr>
<td>+attribute&amp;aspect</td>
<td>2.875</td>
<td>1.834</td>
<td>0.931</td>
</tr>
</tbody>
</table>

Figure 2: Examples of a real review and reviews generated by different models given a user, item, review summary, and item title. Highlights added for emphasis.

against three baselines: Rand (randomly choose a review from the training set), GRU-LM (the GRU decoder works alone as a language model) and a state-of-the-art model Attr2Seq that only considers user and item attribute (Dong et al., 2017). ExpansionNet (with summary, item title, attribute and aspect as input) achieves significant improvements over Attr2Seq on all metrics. As we add more input information, the model continues to obtain better results, except for the ROUGE-L metric. This proves that our model can effectively learn from short input phrases and aspect information and improve the correctness and diversity of generated results.

Figure 2 presents a sample generation result. ExpansionNet captures fine-grained item information (e.g. that the item is a tablet), which Attr2Seq fails to recognize. Moreover, given a phrase like “easy to use” in the summary, ExpansionNet generates reviews containing the same text. This demonstrates the possibility of using our model in an assistive review generation scenario. Finally, given extra aspect information, the model successfully estimates that the screen would be an important aspect (i.e., for the current user and item); it generates phrases such as “screen is very respon-

sive” about the aspect “screen” which is also covered in the real (ground-truth) review (“display is beautiful”).

We are also interested in seeing how the aspect-aware representation can find related aspects and bias the generation to discuss more about those aspects. We analyze the average number of aspects in real and generated reviews and show on average how many aspects in real reviews are covered in generated reviews. We consider a review as covering an aspect if any of the aspect’s representative words exists in the review. As shown in Table 4, Attr2Seq tends to cover more aspects in generation, many of which are not discussed in real reviews. On the other hand, ExpansionNet better captures the distribution of aspects that are discussed in real reviews.
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