Online Resource

4.1 Thresholds Determination

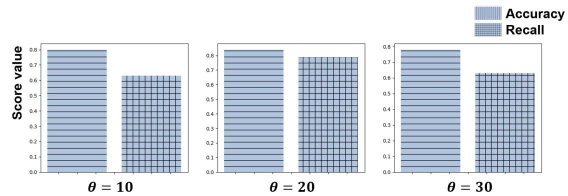

Fig. 4 Performance comparison with different θ

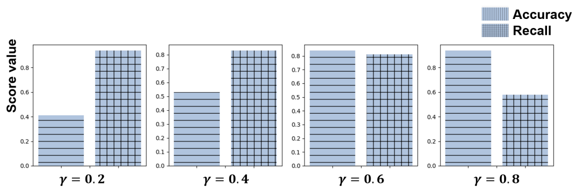

Fig. 5 Performance comparison with different γ

The threshold θ in Algorithm 1 is used to judge whether the words should be combined or not with the Crowd-update mechanism. The threshold γ in Algorithm 2 is used to judge whether the attribute in the Crowdsourced product attribute network is a selling point for the product with the users' opinions in the comments. The θ in Algorithm 1 is set to 20 and the γ in Algorithm 2 is set to 0.6, as the selling point mining performs the best when $\theta = 20$ and $\gamma = 0.6$ as shown in Fig. 4 and Fig. 5

4.2 Implementation Details

The implementation details are as follows:

We use the random walk to sample node sequences for the four kinds of meta-path shown in Fig. 3 and obtain the initial attribute embedding with dimension of 300 for the emb^{attr} in the Algorithm 1. The layer number and hidden state size of Bi_LSTM neural network for encoder is set to 2 and 218, respectively. We set the initial learning rate for Adam to $1 * 10^{-4}$. The batch size is set to 20.

The settings of baselines are as follows: 1) Seq2Seq is the classic baseline for natural language generation, which only takes the selling point words as input to decode the personalized product description. 2) ExpensionNet is based on Seq2Seq structure with a review reader to get the context vector, which takes selling point words and the raw comment sequences as input to generate the personalized product description. 3) Reference-based Seq2Seq model takes selling point words and valid parts of comments manually labeled as input to generate personalized product description.4) KOBE is a Seq2Seq framework with selling point words and the supplementary text retried from knowledge base with product title as input to decode personalized product description.

The Seq2Seq structure in the baselines is set with the same as the CrowdDesigner. The raw comment reader in the ExpensionNet, the valid comment part reader in the Reference-based Seq2Seq and the knowledge reader in the KOBE is set the same as the encoder in the CrowdDesigner, which aims to further search the different influence of different supplementary information (e.g., the raw comments, valid parts of comments, text retrieved from the knowledge base and the CrowdSourced Knowledge Graph we establish).

4.3 Crowdsourced Dataset

We construct a personalized product description dataset named CrowdComment for three categories of books: 'Martial arts', 'Cat Cartoon' and 'Science fiction' with total 900 users, 1,622 items and 33,603 descriptions Table 1 shows the detail of CrowdComment, where ANA indicates the average number of attributes of each sentence and AND the average number of descriptive terms of each sentence.

Category	**Sentence num**	**ANA**	**AND**	**Attributes examples**
Martial Arts	9,237	2.8	3	fight scenes, great momentum
Cartoon	12,866	3.7	4.2	cat, cure, birthday gift
Science	11,500	2.6	3.2	rigorous logic spectacular

Table 1 Details of CrowdComment.

4.4 Algorithms detail

The detail of the algorithms are as follows.

Algorithm 1 Joint profiling method

Input: A^{w_1}, A^{w_2}, users U, $R^{grammar}$, R^{u-a}, $Embcc$
Output: Selling points A^s; user preference $\Upsilon(U)$

FUNCTION
for $user_i$ in U **do**
  Auth weight[$user_i$]= num of the followers of $user_j$
end for
INIT User interest embedding dict: E^u
for u_i in U **do**
  $\mathrm{I}(u_i) = \left\{a_j \in A^{w_1} \bigcap A^{w_2} | R^{u-a}_{ij} = 1\right\}$
  $E^u\,[user_i] = \Delta^1\,(Emb_{attr_k} | a_k \in I(u_i))$
end for
INIT Enriched embedding for attributes: E^a
for a_i in $A^{w_1} \bigcap A^{w_2}$ **do**
  if $a_i \in A^{w_1}$ **then**
    related $\mathrm{D}(a_i) = \left\{a_j \in A^{W_2} | R^{grammar}_{ji} = 1\right\}$
  else
    related $\mathrm{B}(a_i) = \left\{a_j \in A^{w_1} | R^{grammar}_{ij} = 1\right\}$
  end if
  $E^a\,[a_i] = \Delta^2\,(Emb_{a_k} | a_k \in D(a_i)\ or\ B(a_i))$
end for
INIT user preference $\Upsilon(U) = \{\}$
for a_i in $A^{w_1} \bigcap A^{w_2}$ **do**
  $weight_j = 0$
  for u_j in U **do**
    $\mathrm{w} = \cos\left(E^u_j, E^a_i\right) * A\,[j]$, $\Upsilon(U)\left[u_j\right][a_i] = \mathrm{w}$, $weight_j \mathrel{+}= \mathrm{w}$
    if $weight_j > \gamma$ **then**
      add $attr_i$ to ATT^{sell}
    end if
  end for
end for

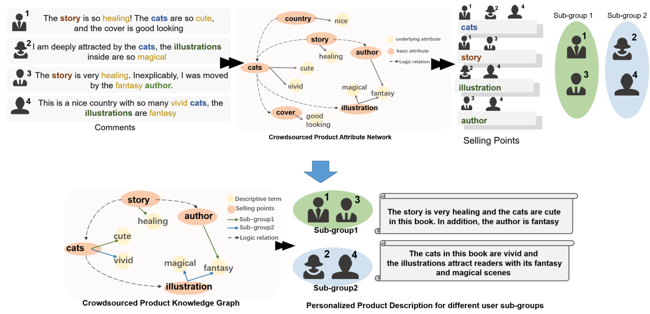

Fig. 6 An example of the CrowdDesigner

Algorithm 2 Dynamic Crowdsourced Knowledge Graph Establishment

Input: $A^{\acute{w}_1}$, A^{w_2}, U and $R^{grammar}$
Output:Subgroups' selling points preference φ; Subgroups' underlying attribute preferenceΛ
FUNCTION
for u_i in U **do**
  $\eta_i = \sum_{i=1}^{N} \Upsilon\,(U)\,[u]\,[a_i] * E_a^{a_i}$
end for
$\{p_1, p_2, ..., p_l\} = Cluster\,\{\eta_1, \eta_2, ..., \eta_M | \lambda = k\}$, $p_i \rightarrow$corresponding subgroup users, $|p_i| = l_i$
$\varphi = \{\}$, $\Lambda = \{\}$
for p_i **do**
  for u in subgroup p_i **do**
    O_u for $u = \mathrm{Max}\left\{\Upsilon(u)[a_k] \mid a_k \in A^{\acute{w}_1}\right\}$
    $O_u \rightarrow \varphi_i$, $Related\ underlying\ attributes \rightarrow \Lambda_i$
  end for
end for

4.5 CrowdDesigner working flow

The Fig. 6 shows the working process of the CrowdDesigner with four product comments and users as input. The work flow and reasons are introduced as follows. Firstly,the CrowdDesigner processes the raw comments and extract the basic and detail product attributes for the selling point mining and user profiling.

Then the Dynamic Crowdsourced Knowledge Graph Establishment module identifies the product selling points with the information from both users and semantic context and in turn divides the users into the sub-group with their preference on the product selling point. Finally the Personalized Product Description Generation module generates the personalized product descriptions according the users' preference.

4.6 Survey summary

We summarize the important conclusions from the survey as follows:

As shown in Fig 7, we collected questionnaire results from 463 users, aged from 21 to 60, the male to female ratio is 46 to 54. In addition, students around the age of 23 make up the majority.

There are 15 questions in the questionnaire. Firstly,

Product Category	Method	Decision Time(Second)			Information Coverage
		First 10 pieces	Second 10 pieces	Third 10 pieces	
A	CrowdDesigner	40	31	25	0.98
	one-fit-all	87			0.43
B	CrowdDesigner	63	35	23	0.85
	one-fit-all	120			0.2
C	CrowdDesigner	33	20	15	0.93
	one-fit-all	67			0.37

Table 2 Real-world Experiments with personalized product descriptions from the CrowdDesigner and one-fit-all pattern

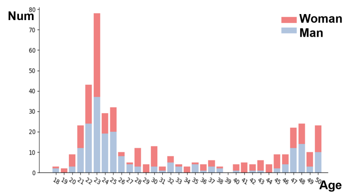

Fig. 7 Age distribution.

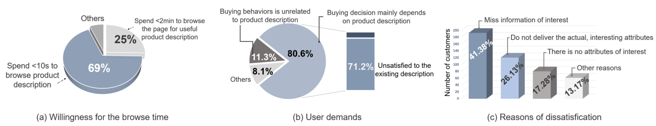

Fig. 8 Summary of survey findings with 463 participants.

we ask the users their basic information on age, gender and job. Secondly, we ask users their attitudes toward the online shopping and product descriptions and the reasons why they concern the product descriptions or not. Fig. 8(a) shows that 69% users express their willingness to spend < 10s to browse the description text and other detail information of a product before making the purchase decision. As shown in Fig. 8(b), 80.6% users hold the opinion that the advertisements are important to make the purchase decision. However, 71.2% of the them report their dissatisfaction with the existing online product descriptions. And then we summarize the reasons for dissatisfaction in Fig. 8(c). Thirdly, we investigate users' attitudes towards the product comments and its detail page to see what kinds of product information the users mainly obtain from these texts. Users pay more attention to the product comments than the product detail pages, which supports the CrowdDesigner's utilizing the product comments as product information source. Finally, we enquire consumers their attitudes to the personalized product descriptions and find that 86.8% customers express their willingness for the attractive and personalized online product descriptions.

4.7 Real-world Experiments

To evaluate the CrowdDesigner with real-world users and check whether the product descriptions generated with the CrowdDesigner are able to meet users' demands and shorten the shopping time. We perform human evaluation of our models with 186 volunteers. Each volunteer is presented with 30 pieces product descriptions generated by the CrowdDesigner for 10 products in 3 types. The time taken by each volunteer from seeing the product description to making the purchase decision is recorded to calculate the DET(Decision Time) metric. At the same time, each volunteer marks the attributes he or she interested in to calculate the INC(Information Coverage) metric. The experimental results are shown in Table 2

As shown in Table 2, the personalized product descriptions greatly shorten the volunteers' decision time. Specially, in the process of volunteers' simulation shopping, the decision time is gradually shortened, which indicates the personalized product description generations are gradually gain users' trust. In addition, the decision time with the one-fit-all descriptions of product category B is the longest, which indicates products in B contains more attributes. For products in B, the high information coverage proves that CrowdDesign still capable of generating information-rich personalized product descriptions.