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## A DESIGN KNOWLEDGE GUIDED POSITION ENCODING METHODOLOGY FOR IMPLICIT NEED IDENTIFICATION FROM USER REVIEWS

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### ABSTRACT

*Aspect-based sentiment analysis (ABSA) enables a systematic identification of user opinions on particular aspects, thus enhancing the idea creation process in the initial stages of product/service design. Attention-based large language models (LLMs) like BERT and T5 have proven powerful in ABSA tasks. Yet, several key limitations remain, both regarding the ABSA task and the capabilities of attention-based models. First, existing research mainly focuses on relatively simpler ABSA tasks such as aspect–based sentiment analysis, while the task of extracting aspect, opinion, and sentiment in a unified model remains largely unaddressed. Second, current ABSA tasks overlook implicit opinions and sentiments. Third, most attention-based LLMs like BERT use position encoding in a linear projected manner or through split-position relations in word distance schemes, which could lead to relation biases during the training process. This article addresses these gaps by (1) creating a new annotated dataset with five types of labels, including aspect, category, opinion, sentiment, and implicit indicator (ACOSI), (2) developing a unified model capable of extracting all five types of labels simultaneously in a generative manner, and (3) designing a new position encoding method in the attention-based model. The numerical experiments conducted on a manually labeled dataset scraped from three major e-Commerce retail stores for apparel and footwear products demonstrate the performance, scalability, and potential of the framework developed. The article concludes with recommendations for future research on automated need finding and sentiment analysis for user-centered design.*

**Keywords: User need identification, Sentiment analysis, Position encoding, Transformer, Large language model**

### NOMENCLATURE

| | |
|---|---|
| $a_{ij}$ | position encoding coefficient |
| $\alpha_{ij}$ | attention weight coefficient score inside the model |
| $\beta$ | the loss weight controller to control how much the model should focus on each loss |
| $d$ | dimension of a given parameter |
| $d_{ij}$ | the distance between two input token i and j |
| $e_{ij}$ | attention weight score between input elements $i$ and $j$ |
| $k$ | pre-fixed maximum length in relative position encoding algorithm |
| $\mathscr{L}$ | loss function |
| $n$ | input length in model |
| $t_{i\,\mathrm{or}\,j}$ | the $i$th or $j$th token in inputs |
| $W^Q$ | query weight matrix in attention-based model |
| $W^K$ | key weight matrix in attention-based model |
| $W^V$ | value weight matrix in attention-based model |
| $x_i$ | $i$th element in input $x$ |
| $z_i$ | $i$th element in attention output $x$ |

### 1. INTRODUCTION

The extraction of user needs from online product reviews is becoming an increasingly important aspect for successful and innovative product design. With the exponential growth of online purchasing platforms, a vast amount of user-generated information has been accumulated on user needs on various products and services. According to recent market surveys, reviews have a significant impact on user purchase decisions, with more than 93% being influenced solely by them [1]. Furthermore, 77% of the users "always" or "frequently" read online reviews, and 89% are "highly likely" to choose a business that responds to all its online reviews [2]. Sentiment analysis has emerged as a crucial facilitator for large-scale need finding from numerous users through e-Commerce and social media platforms. However, due to the noisy and unstructured nature of review data, extracting valuable information on user needs is often hindered by the limitations of state-of-the-art natural language processing (NLP) methods.

In addition to the limitations mentioned above, there is a lack of automated methods for large-scale extraction of "implicit" user needs from reviews, which can provide valuable information for

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product designers and enhance the probability of successful product development [3]. The extraction of implicit needs is expected to improve both the quantity and the quality of ideas in the design generation process [4, 5]. This article introduces a new annotated dataset that facilitates the automated extraction of implicit user needs from online reviews using NLP. The dataset, named ACOSI, consists of five labels: Aspect (A), Category (C), Opinion (O), Sentiment (S), and Implicit Indicator (I). The latter represents implicit sentiment-related information from various perspectives. This article also developed a novel methodology based on deep learning models [6] and information extraction methods [7, 8] for large-scale elicitation of implicit user needs from online reviews, especially a design knowledge-guided (DKG) position encoding algorithm. The validity of the methodology is examined using a sizable dataset collected from notable e-Commerce platforms in the apparel and footwear industry, including Finish Line [9], New Balance [10], and ASICS [11]. This section outlines the rationale behind the research, the selection of the dataset and methodology, as well as the goals and contributions of the article.

### 1.1 Knowledge Gaps

Exploration of user needs is a preliminary step in early-stage new product development processes [12]. Existing need-finding approaches could be divided into two categories of empirical studies and data-driven methods. The latter utilizes advanced NLP techniques and attention-based large language models (LLMs) [13] for elicitation of user needs from online reviews. However, despite significant research progress in recent years, some limitations remain:

- **Empirical studies.** The basis for these approaches is the analysis of previous designs [14, 15], surveys and focus group studies [16], and web-based configurators [17]. However, these methods have inherent biases because they target only specific portions of the user population and product instances, and are limited to structured inquiries. The lack of direct methods for users to articulate their requirements [18] and the influence of prior knowledge [19] exacerbate this limitation. These restrictions have hindered the widespread adoption of mass customization approaches in industry, given the considerable economic and operational gaps involved [20].
- **Data-driven studies.** In this category, some researchers tried to integrate the information from the picture and text to evaluate the generative design in the design concept generation process [21]. When using the pure text-based database, sentiment analysis has become a key enabler for the "large-scale" needs to find and allow the extraction of opinions from myriad users from e-Commerce and social media platforms [22]. Sentiment analysis is the process of identifying the subjective opinion of an opinion holder (e.g., user) for a target (e.g., product attribute) from an unstructured text (e.g., product review) [23]. Among the three levels of sentiment analysis (document level, sentence level, and word level sentiment analysis), aspect level sentiment analysis (ABSA) could provide the most fine-grained information from the raw text, namely, aspect, opinion, and sentiment. With the increasing demand for unified analysis, the extraction of triplets of opinion sentiments on aspects draws much attention from the community [24–26]. Some studies have expanded the task with a new label "category" that makes the task become a quadruple extraction problem, ACOS (aspect, category, opinion term, sentiment) [27]. However, the ABSA and ACOS quadruples cannot elicit implicit opinions and aspects. Among the proposed methods, the implicit opinion has been ignored or simply denoted as a "Null" label. Even the ACOS task is only capable of predicting the four labels. When the review does not mention explicit aspects or opinions, the model will output "Null". This peculiarity prevents the model from extracting the information that implies or describes the aspect indirectly.
- **Position encoding in attention based LLMs.** In pretrained LLMs such as Text-To-Text Transfer learning Transformer (T5) [28] and Bidirectional Encoder Representations from Transformers (BERT) [29], to integrate position information into the transformer, the position encoding is processed along with the input. There are two directions of position encoding in previous studies: fixed position encoding and relative position encoding. In terms of fixed position encoding, BERT uses the same method as in the original transformer model, which is the cosine projection of the fixed position. T5 choose the relative position encoding strategy in their model, they choose the pre-fixed length 128 as a relation range and assume words distance further than this range is not related. However, both position encodings take only the word position as the index. In domain specific problems like user need finding, some words are more important than others, even the word appears in the edge area.

### 1.2 Objectives

This research article aims to address the lack of systematic approaches in automating the elicitation of implicit needs from online reviews using NLP by developing a new position encoding algorithm in standard attention-based models [27, 30]. Currently, no NLP model is capable of identifying aspects or opinions that have not been explicitly mentioned in a review or those that do not correspond to a specific aspect, category, or sentiment. To overcome this limitation, the article proposes a new NLP task called ACOSI, which has a structure similar to ACOS [27], but with a crucial distinction. In ACOSI, the text that implies the aspect will be identified and labeled as the indirect opinion when the user does not provide explicit descriptions of the aspect. This new task covers aspect, category, opinion, sentiment, and implicit opinion extraction, hence the acronym ACOSI.

Despite the similarity in their acronyms, the ACOS model and the proposed ACOSI model address completely different problems in terms of their outputs. In ACOS, researchers labeled implicit opinions as "Null," while in ACOSI, the model can identify and extract opinion text related to aspects, regardless of whether they are explicit or implicit. This crucial difference means that the ACOSI task has the capability to output opinions in association with aspects, whereas the ACOS task does not. The design knowledge guided (DKG) position encoding is generated to achieve the proposed goal. The key contributions of this article are summarized below.

- A newly created annotated and curated dataset is available to address ACOSI tasks in the product design domain through NLP techniques. This dataset can also be utilized to solve ABSA and ACOS tasks.
- A novel NLP model has been developed and trained on the annotated dataset, with the potential to solve problems related to extracting implicit sentiments, aspects, and opinions.
- A DKG position encoding algorithm has been developed to address the need for a context-aware LLM capable of extracting all five ACOSI labels from user reviews.

## 2. BACKGROUND

This section provides an overview of related and background work on ACOSI task, ABSA task in unified model, and position encoding in the attention-based deep learning model.

### 2.1 ACOSI Task

In the ABSA task, recently [27] found that previous research focused solely on extracting explicit aspects and opinion terms from user product reviews, ignoring the fact that 44% of the time these reviews also contained implicit aspects or opinion terms. They introduced a comprehensive framework called ACOS that combines explicit and implicit aspects and opinion terms. For example, in the review "I like the look and the velvet is great, but the velvet's quality does not hold up," the aspect term is "cushion," the category is "Material," the opinion term is "great," and the sentiment is "Positive." Thus, the corresponding ACOS labels are [velvet-Material-great-Positive]. Additionally, we can extract [Null-Appearance-like-Positive] where the aspect term is implicit in the second part of the review and [velvet-material-NULL-Negative] where the opinion term is implicit in the third part. However, the quadruple extraction task fails to efficiently integrate the four subtasks and capture implicit aspects and opinions. This limits the extraction of useful information, such as the concern raised about the durability of velvet when an opinion is labeled "Null." To enhance the ACOS quadruple's effectiveness, we incorporated the implicit "I" tag, resulting in the ACOSI quintet task. In this task, the annotators mark the span of the opinion text and identify whether it is a direct or indirect opinion. For instance, in the phrase "the velvet quality doesn't hold up," we annotate [velvet-Material-quality doesn't hold up (Indirect-Opinion)-Negative]. This approach enables us to maintain the information contained within the opinion text span while indicating its implicit nature.

### 2.2 ABSA in Unified Model

The ACOSI task can be separated into three classification tasks, namely category classification, sentiment classification, and implicit indicator classification, as well as two sequence generation tasks, aspect extraction and opinion extraction. Previous research focused on specific subsets of these labels as an expansion of ABSA [31–33]. For example, AE (aspect extraction), OE (opinion extraction), SE (sentiment extraction) [34], AOE (aspect-opinion extraction) [35], ASE (aspect-sentiment extraction), and OSE (opinion-sentiment extraction) [36]. However, combining these subtasks is a time-consuming process and does not capture the mutual dependence of sentiments on both opinions and aspects. To achieve a unified approach that accomplishes multiple tasks within a single model, previous studies have been divided into three directions:

1. Developing heuristic models based on syntax rules and lexicon-based algorithms [37].
2. Building deep learning models using an extraction approach based on named entity recognition (NER) that assigns a tag to each word within the text-based dataset [38–40].
3. Generating all necessary labels using a predictive format, where the model outputs labels iteratively based on the previous ones. In other words, the model operates in a sequence-to-sequence manner [41, 42].

The review text can be categorized into explicit and implicit aspects and opinions. However, previous research has not given sufficient attention to the implicit category, with researchers often denoting implicit aspects and opinions as "Null." Additionally, there has been a lack of detailed analysis regarding the "implicit" category.

### 2.3 Position Encoding

In attention-based LLMs, the attention of each input token could be obtained during the training process [13]. The model also needs to know the position of each input tokens position during the training process, this is because the position of tokens will bring the time series information to the model. In order to explicitly integrate the position information, researchers have designed two types of method: fixed position encoding and relative position encoding. In other words, fixed position encoding only inputs the fixed position information into the model. Suppose that the input length is $\mathscr{L}$, each token $t_i$ is encoded through a linear/non-linear projection. For example, BERT uses a cosine projection. Another type of encoding is relative position encoding, which also inputs the token distance into the model, with the input length $\mathscr{L}$, every two tokens $t_i$ and $t_j$'s distance $d_{ij}$ will also be fed into the model. For example, the T5 model uses a relative position encoding [43]. However, neither of these two methods provides a domain-specific solution to integrate domain knowledge during the training process.This article proposes a novel position encoding approach guided by design knowledge, which makes all inputs closer to what matters the most to the model, as described in the following section.

## 3. METHODOLOGY

This section presents the methodology proposed to extract implicit needs from online reviews is presented using NLP. This includes the annotation process of the new ACOSI dataset, the design and training of the NLP model, especially the DKG encoding, and the post-analysis of the ACOSI results.

### 3.1 ACOSI Dataset

The quintet annotation task is designed to train NLP models to recognize implicit needs expressed in user reviews related to footwear. This involves gradually creating an ontology that establishes categories that represent the various functions that a product should satisfy. The initial ontology lexicon [38] is developed by a team of engineers and involves a process of iterating between reviews and design literature to derive categories and subcategories that represent the ontology of shoes based on user review data. The final category list is obtained by combining this with the previous lexicon, where each category is denoted by "category#subcategory". The aspect term, which is usually a noun or verb present in the text, represents the target objective. The opinion span is the subjective portion of the user review that refers directly or indirectly to the aspect. It is important to note that a review sentence can contain multiple aspects and opinions, which can lead to multiple interpretations. To capture the complete content of the review sentence, annotators may need to annotate the sentence more than once.

### 3.2 Unified T5 Model and Implicit Needs

Pretrained LLMs (Large Language Models) utilize the likelihood of single words or word spans in real text to encode natural language into numerical values. The concept of a language model, originally introduced in the early 1900s with neural networks, has since been integrated into many text analysis tasks. With the advent of deep learning, researchers have developed LLMs that are pretrained on large corpora. T5 [28] is a pretrained LLM developed by Google AI Language that uses transformers as a benchmark model structure and trains on massive datasets, specifically the full version of the C4 [44] dataset. These powerful LLMs can be fine-tuned for specific NLP tasks, such as adding a single layer, resulting in state-of-the-art performance in several NLP tasks. In this study, we utilize T5 as our base LLM and fine-tune it for the ACOSI label prediction task. The identification of implicit or latent needs is still in its infancy. Some research defined those needs into three categories [45]: unexpected delighter, lead user needs, and extraordinary user needs, while others defined them as needs from edge users/latent users [46–50]. Automated methods for implicit need elicitation still lack the ability to identify indirect opinions that the user has in text, do not have large enough databases, leading to an increase in bias, and it is a challenge to obtain or hierarchically categorize product attributes without human involvement.

In this article, the ACOSI task is finished using a consolidated model that generates outputs. The T5 model processes all tasks related to text in a sequence-to-sequence fashion, where tasks like sentiment analysis produce outputs such as "positive" and "negative." Even regression tasks are processed in this way, with predictions in the form of string outputs such as "five." A standard encoder-decoder transformer architecture [13] is employed in the T5 model, which consists of three parts; in addition to the structure of the standard transformer model, the knowledge-guided position algorithm was tested in contrast to the same experiment settings. Figure 1 provides a visual representation of the entire structure of the model.

- *Tokenization*. To provide the textual input to the model, it is necessary to encode the entire text into input IDs. In this experiment, the T5 tokenizer is utilized in the first step, which consists of a vocabulary with 32,128 elements. Given that this is a problem that involves multiple tasks and labels, five special tokens are included in the vocabulary: '<label>,' '<A>,' '<C>,' '<O>,' '<S>,' '<I>'. These tokens denote the initiation of a label and the distinct label types, respectively.
- *Encoding process*. The input data is encoded using the T5-large model encoder, which comprises a conventional transformer encoder with 12 attention layers, where each layer has a hidden dimensionality of 768.
- *Knowledge guided encoding*. The position encoding of the input was performed before being fed into the model; the details of the algorithm are introduced in the next paragraph.
- *Decoding process*. Using a generative approach, the encoder output is decoded. The decoder employs a 12-layer attention mechanism and generates each prediction through an autoregressive process whereby the next prediction is based on the previous outputs and the current decoder output.

### 3.3 DKG Position Encoding

In a standard attention-based LLM, for each self-attention head $h$, the model operates on an input sequence of $n$ elements, $(x_0, x_1, ...x_n)$ that $r \in \mathbb{R}^{dx}$, then computes a new sequence of the same length $(z_0, z_1, ...z_n)$ that $z_i \in \mathbb{R}^{dx}$. Where $dx$ indicates the dimention of input $x$. For each output element $z_i$, it is calculated as the weighted sum of each linear project of input elements, all parameters in the algorithm $\in \mathbb{R} > 0$:

$$z_i = \sum_{j=0}^{n} \alpha_{i,j}(x_j W^V). \tag{1}$$

The attention weight coefficient is calculated as:

$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k=0}^{n} exp(e_{ik})}, \tag{2}$$

each $e_{ij}$ is computed through the weighted product of two input elements:

$$e_{ij} = \frac{(x_i W^Q)(x_j W^K)^T}{\sqrt{d_z}}. \tag{3}$$

These three weight matrices are learned during the training process, $W^Q, W^K, W^V \in \mathbb{R}^{d_x * d_z}$

In relation-aware self-attention models, the position relationship between two input elements $x_i$ and $x_j$ is represented by two vectors $a_{ij}^V$ and $a_{ij}^K$. The learned coefficients from Equations 1 and 3 could then be used to calculate the following output.

$$z_i = \sum_{j=0}^{n} \alpha_{ij}(x_j W^V + a_{ij}^V), \tag{4}$$

where

$$e_{ij} = \frac{x_i W^Q (x_j W^K + a_{ij}^K)^T}{\sqrt{d_z}}. \tag{5}$$

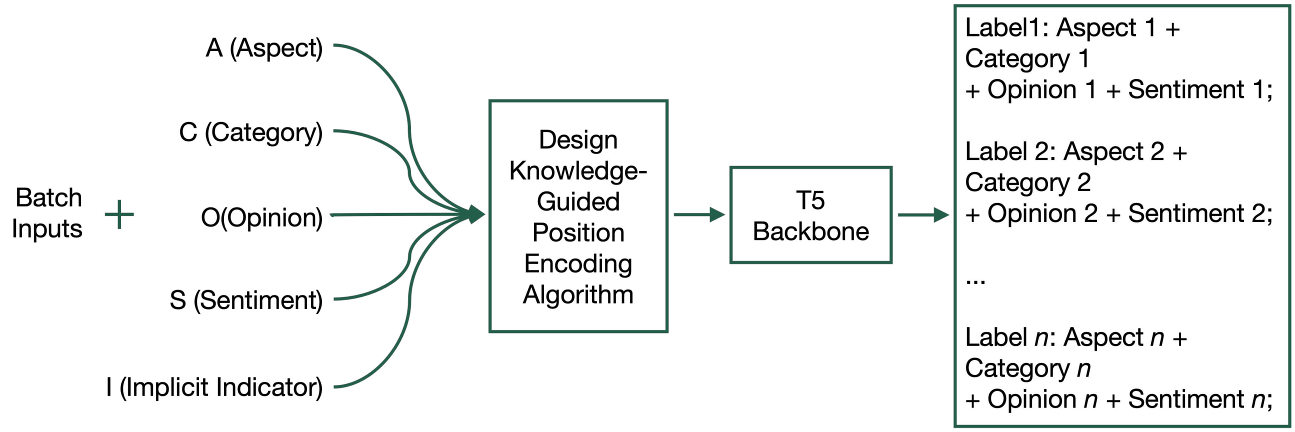


**FIGURE 1: OVERALL MODEL STRUCTURE.**

When using the relative position representations, previous studies assume that two inputs will be nonrelevant beyond a certain distance, e.g. T5 assumes this distance is 128. Suppose that the maximum distance here is $k$, then the unique labels $2k+1$ should be considered, then the $a_{ij}$ in Equations 4 and 5 could be calculated as:

$$a_{ij}^K = W_{clip(j-k,k)}^K \quad \text{and} \quad a_{ij}^V = W_{clip(j-k,k)}^V \tag{6}$$

where $clip(x,k) = \max\{-k, min(k,x)\}$ then the relative position representations $W^K$ and $W^V$ could be learned in the training process. On top of the relative position encoding, we implemented the DKG position encoding as shown below.

**Algorithm 1** DESIGN KNOWLEDGE-GUIDED POSITION ENCODING ALGORITHM.

A pre-defined design knowledge lexicon
$x_i$ in length **L** input
**if** $x_i \in$ **L then**
  $x_i$ become the key indicator in current input
  use equation 6, every other words in sequence now have distance with $x_i$ as $a_{ij} = 1$
**else**
  **if** $x_i \notin$ **L then**
    $i \leftarrow i+1$
    Use equation 6, $a_{ij} = j - i$ within the pre-fixed length $k$
  **end if**
**end if**=0

## 4. EXPERIMENTS AND RESULTS

This section presents and analyzes the results of experiments on a large dataset collected from three major apparel and footwear e-Commerce sites including www.finishline.com, www.newbalance.com, and www.asics.com.

### 4.1 Data Filtering and Sampling

The unprocessed review dataset was extracted from three websites, namely Finish Line, Ascis and New Balance, resulting in a total of 145,430 reviews. Within this dataset, there were 10,700 lengthy reviews that exceeded 60 words, 22458 concise reviews with less than 10 words, and 1636 reviews that referenced specific product names. The upper threshold established during the pre-processing stage was determined by analyzing the distribution of review lengths. We posited that reviews exceeding 60 words would likely exert an impact on the model's performance[51]. As for the lower limit, given the requirement to extract five labels from each review, we presumed that a minimum of seven words would be necessary to encompass the representations of the five labels, along with two connecting words. We added an additional three words to our estimation as a bias, resulting in a total of 10 words. To eliminate any innate bias, both lengthy and concise reviews were discarded, resulting in a dataset of 59184 reviews. Within this filtered dataset, 75.89% were rated 5-star, 12.85% 4-star, 4.96% 3-star, 2.64% 2-star, and 4.92% 1-star.

Regarding the references to attributes, the most frequently mentioned were 'Exterior' and 'Fit'. Specifically, within all reviews that referenced attributes, 58.25% referred to 'Exterior', 76.88% to 'Fit', 12.21% to 'Shoe Parts', 32.11% to 'Durability', 7.33% to 'Permeability', 15.48% to 'Stability', and 16.59% to 'Impact absorption'. The attribute data was scrutinized with a specialized sneaker attribute lexicon [33]. After filtering, 2000 reviews were randomly selected for annotation, with 400 reviews from each star rating to create a more balanced training dataset.

### 4.2 Model Training and Algorithm Implementation

In the unified model without the DKG algorithm, we used the API offered by Hugging Face [52]. As stated previously, during the initial tokenization phase, we augmented the collection of special tokens with our own tailored special tokens. In the pretraining stage of the T5 model, the authors noted that the learning rates $1e-4$ and $3e-4$ produced the most optimal results [28]. In our experiment, we began the model learning rate at $2e-6$. During the generation phase, we set the following hyperparameter settings: Dropout rate: 0.17; Training epochs: 50000; Batch size: 8 reviews per batch; Maximum input length: 128; Maximum target length: 64; Learning rate scheduler: cosine learning rate scheduler; Initial learning rate: 2e-6; Beam search for candidates labels: 2; Repeat n-gram size: 2.

In both the baseline model and DKG encoding model we choose the same loss function which was the standard cross-entropy loss function:

$$\mathcal{L}_{\text{CE}} = -\sum_{k=1}^{K} w_k \log \frac{\exp(y_{n,k})}{\sum_{j=1}^{K} \exp(y_{n,j})} \hat{y}_{n,k}, \tag{7}$$

in which $\hat{y}$ symbolizes the objective or goal, $y$ denotes the input, $K$ refers to the categories of labels, $k$ signifies a specific label within the label category, $n$ represents the size of the batch, and $j$ denotes a sample within a batch. Since there are 5 types of labels in the algorithm, the overall loss during the training process was generated as:

$$\begin{aligned}\mathcal{L}_{\text{Total}} = \beta_1 \mathcal{L}_{\text{Aspect}} + \beta_2 \mathcal{L}_{\text{Category}} \\ + \beta_3 \mathcal{L}_{\text{Opinion}} + \beta_4 \mathcal{L}_{\text{Sentiment}} + \\ \beta_5 \mathcal{L}_{\text{Implicit Indicator}}.\end{aligned} \tag{8}$$

The loss weight controller $\beta$ here is utilized to control how much the model should focus on each part of loss, in the current experiment, we use a uniform controller where each $\beta = 0.2$. The Recall-Oriented Understudy for Gisting Evaluation (ROUGE) score is used as a benchmark to evaluate model performance; ROUGE-L is based on the length of the longest common subsequence of candidates and references [53]. In this article, we set each $\alpha$ as the same and sum to 1. All other experiments are shown in Table 1.

### 4.3 Results and Analyses

The results of the post-analysis with the model output associated with an example user review are presented in this section.

**Review:**

*My ankles tend toward supination, so a well-cushioned heel is crucial . Every other pair of NBs I own give great even support, but the outer heels on this pair collapsed after less than a week ! The shoes now slant outward in a very unsafe and totally unacceptable way that makes my supination way worse . They are completely unusable - huge waste of money . Don't buy this pair unless you have a perfectly even foot strike !*

**Elicited labels:**

- Label 1: ('NULL', 'ContextOfUsePurchase _Context', 'neutral', 'ankles tend toward supination , so a well-cushioned heel is crucial', 'direct')
- Label 2: ('outer', 'AppearanceShoe Component', 'negative', 'outer', 'direct')
- Label 3: ( 'outer', 'ContextOfUseUsage frequency', 'negative', 'IMPLICIT', 'direct')
- Label 4: ('shoes', 'PerformanceSizing/Fit', 'negative', 'makes my supination way worse', 'indirect')
- Label 5: ('NULL', 'Cost/Value', 'negative', 'huge waste of money', 'indirect')
- Label 6: ('this', 'PerformanceSizing/Fit', 'negative', 'unless you have a perfectly even foot strike', 'indirect')

**User needs:** The user explicitly wants a shoe that could fit uneven feet. Labels 4 and 6 indicate that sneaker designers may put more effort for users with special needs; even a normal user could have uneven foot strikes in daily life, a 'smart' insole could perhaps help this situation.

*I purchased these less than a month ago and the pattern is so cute but . . . It is so worn off that it is starting to look trashy. I would not recommend any of the tie dye crocs. I love the shoe itself just not how delicate they are with the pattern .*

**Elicited labels:**

- Label 1: ('NULL', 'ContextOfUseReview _Temporality', 'neutral', 'purchased these less than a month ago', 'direct')
- Label 2: ('tie dye crocs', 'AppearanceColor', 'negative', 'I would not recommend any', 'direct')
- Label 3: ( 'shoe', 'General', 'positive', 'I love the shoe', 'direct')
- Label 4: (''shoe', 'AppearanceMaterial', 'negative', 'just not how delicate they are with the pattern', 'direct')
- Label 5: ('NULL', 'AppearanceColor', 'negative', 'pattern is so cute', 'direct')

**User needs:** The user evinces a pronounced fondness for the ornamental configurations of this particular sneaker. Labels 4 and 5 serve as indicators that sneaker designers ought to give serious thought to durability even in the creation of a seemingly straightforward pattern. Additionally, designers could contemplate the implementation of either detachable patterns or sturdier patterns during the design phase.

## 5. CONCLUSIONS

This article posited a groundbreaking dataset as a remedy for a newfangled natural language processing task, ACOSI, pertaining to the comprehensive procurement of implied requirements from virtual critiques, accompanied by a pioneering, consolidated T5 paradigm and DKG positional coding algorithm for the mechanized and wide-ranging generation of implied views and facets. Exploiting sophisticated natural language processing research on linguistic models, the paradigm is expected to curtail considerable time and endeavor involved in data arrangement and diminish the reliance on expert systems tailored by hand for the extraction of aspect-opinion-sentiment from reviews. The strengths of the paradigm for ACOSI extraction on a grand scale are enumerated as follows:

**TABLE 1: EXPERIMENTAL RESULTS.**

| Learning Rate | epoch | Beam size | Repeat n-gram size | Model Loss | DKG(0 not use, 1 use) | Rouge Score |
|---|---|---|---|---|---|---|
| 1e-4 | 10000 | 1 | 3 | 0.098 | 0 | 0.34 |
| 1e-4 | 10000 | 1 | 3 | 0.128 | 1 | 0.31 |
| 1e-5 | 10000 | 1 | 3 | 0.143 | 0 | 0.29 |
| 1e-5 | 10000 | 1 | 3 | 0.176 | 1 | 0.34 |
| 2e-6 | 10000 | 1 | 3 | 0.156 | 0 | 0.31 |
| 2e-6 | 10000 | 1 | 3 | 0.196 | 1 | 0.33 |
| 2e-6 | 20000 | 1 | 3 | 0.074 | 0 | 0.32 |
| 2e-6 | 30000 | 1 | 3 | 0.062 | 1 | 0.36 |
| 2e-6 | 30000 | 2 | 2 | 0.056 | 0 | 0.32 |
| 2e-6 | 30000 | 2 | 2 | 0.072 | 0 | **0.38** |
| 2e-6 | 30000 | 2 | 5 | 0.054 | 0 | 0.28 |
| 2e-6 | 30000 | 2 | 5 | 0.054 | 1 | 0.32 |
| 2e-6 | 30000 | 3 | 3 | **0.049** | 0 | 0.31 |
| 2e-6 | 30000 | 3 | 3 | 0.064 | 1 | 0.31 |
| 2e-6 | 30000 | 3 | 5 | 0.075 | 0 | 0.25 |
| 2e-6 | 30000 | 3 | 5 | 0.088 | 1 | 0.29 |

- *Efficiency and scalability*. Leveraging pre-trained linguistic models such as T5 alleviates the requirement for extensive manually annotated data. The entire spectrum of methodological constituents is systematized in a streamlined manner and is amenable to swift adaptation and application to novel datasets.
- *Automated and large-scale aspect-opinion-sentiment extraction*. The modus operandi culminates in the extraction of a comprehensive register of prospective aspects alongside their associated opinions. This paradigm represents a noteworthy advance in facilitating automatic and wide-ranging elicitation of implicit aspect-opinion, thereby transcending user-centric approaches and potentially unearthing more informative and revolutionary revelations to underpin the design process.

The ACOSI task remains largely unexplored territory for the design of novel products. Acquisition and consolidation of user-generated content in the design process are germane to the overall success of new product development endeavors, as they increase the quantity and caliber of ideation involved in the process [4]. This manuscript builds on cutting-edge deep language representation techniques [6] to extract facets, congruent opinions, and sentiments that designers are currently unable to manually navigate due to the massive expanse of online context. All of these limitations underscore the significance of extracting ACOSI information for the initial stages of product development.

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