Answer Generation for Questions With Multiple Information Sources in E-Commerce

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ABSTRACT
Automatic question answering is an important yet challenging task in E-commerce given the millions of questions posted by users about the product that they are interested in purchasing. Hence, there is a great demand for automatic answer generation systems that provide quick responses using related information about the product. There are three sources of knowledge available for answering an user posted query, they are reviews, duplicate or similar questions and specifications. Effectively utilizing these information sources will greatly aid us in answering complex questions. However, there are two main challenges present in exploiting these sources: (i) The presence of irrelevant information and (ii) the presence of ambiguity of sentiment present in reviews and similar questions. Through this work we propose a novel pipeline (MSQAP) that utilizes the rich information present in the aforementioned sources by separately performing relevancy and ambiguity prediction before generating a response.

Experimental results show that our relevancy prediction model (BERT-QA) outperforms all other variants and has an improvement of 12.36% in F1 score compared to the BERT-base baseline. Our generation model (T5-QA) outperforms the baselines in all content preservation metrics such as BLEU, ROUGE and has an average improvement of 35.02% in ROUGE and 198.75% in BLEU compared to the highest performing baseline (HSSC-q). Human evaluation of our pipeline shows us that our method has an overall improvement in accuracy of 30.7% over the generation model (T5-QA), resulting in our full pipeline based approach (MSQAP) providing more accurate answers. To the best of our knowledge, this is the first work in e-commerce domain that automatically generates natural language answers combining the information present in diverse sources such as specifications, similar questions and reviews data.

CCS CONCEPTS
- Computing methodologies → Natural language generation.

KEYWORDS
Natural language generation, Question answering, Transformers, Next sentence prediction

1 INTRODUCTION
Automatic question answering systems that respond to product related questions has gained a lot of attention in recent years due to their extensive application in E-commerce. Customers usually post a number of questions before purchasing a product. Unless these questions are answered by an user who purchased the product, they go unanswered. In such cases, we can utilize the information present in various sources of the product such as reviews, specifications and duplicate questions to aid us in automatically creating a response. This rapidly led to variety of works in review and other sources driven answer generation [2, 4, 7].

One of the primary challenges present in building a real world answer generation system for E-commerce is the noise present in the dataset. The dataset used for training and evaluating the models consists of user posted questions and answers which has spelling errors, grammatical inconsistencies and sometimes code switching. Another common problem is the presence of irrelevant information and ambiguity in users’ opinions present in reviews and similar questions. Question, answer pairs along with their information candidates are tabulated in Table 1. We solve for some of the above mentioned challenges through our work.

Ever since their introduction, Transformer [20] has gained extensive popularity due to their top performance in variety of Natural Language Processing tasks. They have surpassed other neural network models such as Recurrent Neural Networks and Convolutional neural networks in natural language understanding and generation. The transformer architecture scales well with larger training data and size of the model and allows efficient parallel training. In recent years, it is becoming common to pretrain the transformer on a data rich task. This pretraining allows the model to learn general knowledge about the language that can be transferred to downstream tasks with few steps of fine tuning. The initial pretraining step is often done in an unsupervised fashion on unlabelled data and has resulted in state of the art results in many NLP benchmarks [5, 8, 22]. The main advantage of this way of pretraining is due to the availability of large volumes of text data. We use pretrained transformers as our models that are further finetuned for the task at hand.

Through this work, we propose Multi Source Question Answering Pipeline (MSQAP) consisting of three components, (i) relevancy prediction using a transformer fine tuned on Next Sentence Prediction task, (ii) Ambiguity prediction using a pretrained model and (iii) answer generation using a text to text transformer fine tuned on a large Question Answer dataset to generate accurate and precise response.

The main contributions of our paper can be summarized as follows:

- We propose an answer generation system utilizing three sources of knowledge, namely, reviews, similar questions and specifications.
- We show how to handle the two main challenges when incorporating information from all the sources(i) The presence of irrelevant information and (ii) the presence of ambiguity of answer sentiment.
Table 1: Example of answer generation dataset with candidates

| Question Reference Answer                                                                 | Example 1                                                                 | Example 2                                                                 |
|------------------------------------------------------------------------------------------|--------------------------------------------------------------------------|--------------------------------------------------------------------------|
| Duplicate Q&A (Partial)                                                                  | display are very slow in ABC? my mobile display slow                      | does phn have theatre sound quality?                                       |
| Reviews                                                                                   | 1) At present now on words which is better XYZ or ABC And mainly display which is better? ABC: | Yes, the audio quality of this phone is too good                           |
| Specifications                                                                            | 1) Other Display Features: ...Narrow Frame: 2.05mm, Screen Ratio: 2) Display Colors: 16.7M 3) Display Size: 15.8 cm (6.22 inch) | 1) sound quality is very low class                                           |
|                                                                                          | 2) but the display of ABC are not good                                    | 2) Sound quality is not good                                               |

- We propose a novel pipeline (MSQAP) that utilizes the rich information present in the above sources by separately performing relevance and ambiguity prediction before generating a response to address the above challenges.
- We compute content preservation metrics such as BLEU and ROUGE for generation and benchmark results for all the models.
- Experimental analyses show that our approach outperform the baselines in the above metrics and generate answers with an overall accuracy of 77.88% in human evaluations.

The reminder of the paper is organized as follows. Section 2 describes the related work in answer generation and relevancy prediction. The problem statement is formally defined in Section 3 and our proposed approach is explained in Section 4. All experimental details along with results are available in Section 5 and conclusion is discussed in Section 6.

2 RELATED WORK

We detail recent work on large language models, relevancy prediction and answer generation. BERT [5] is a bidirectional transformer encoder pretrained on large amounts of data to perform masked language modelling and Next Sentence Prediction task. RoBERTa [10] removes NSP task from BERT’s pretraining and introduce dynamic masking so that tokens can be changed during training. T5 [17] is an encoder-decoder transformer architecture trained on a variety of tasks using transfer learning strategies. We employ all the above transformers in our study.

2.1 Relevancy prediction

Recent studies [14, 23] employ ranking strategies to pick an answer from a set of candidate answers while incorporating review information. Yu et al. [23] proposed a model to retrieve the most similar question from a list of QA pairs and used the corresponding answer as the response. Cui et al. [3] built a chatbot called Super-Agent which utilizes all three sources of information and selects the best answer from them. In general, there has been a lot of work in ranking the candidates that are relevant to a question and picking the best answer as the final result. One of the recent works using transformer based models is done by Mittal et al. [13] where questions answer pairs are retrieved based on their relevance to the question. We use a similar approach to relevancy prediction for selecting the top k candidates and further add on a key component called ambiguity filtering given the inconsistency in answers from e-commerce user data. These are then used as context for our natural language generation model.

2.2 Answer generation

In recent years, there has been a variety of RNN based [19] and transformer based [9, 17] sequence to sequence models proposed for text generation. Most of the successful implementation of these methods involved attention mechanism [1] and/or self attention [20]. However, answer generation in E-commerce generally uses a RNN based model [2, 4] with source information obtained from reviews. In one of the earlier works, McAuley et al. [12] use a Mixture Of Expert (MOE) model with review as the source to predict the answer, where they classify them to binary answers i.e ‘Yes’ or ‘No’. Chen et al. [2] utilize the attention mechanism [1] to alleviate the noise present in review snippets to aid in answer generation. Dzendzik et al. [6] use BERT [5] on reviews to answer binary questions. Deng et al. [4] learn a multi task model that performs answer generation and opinion mining while utilizing review ratings. They make use of pointer generator network [18] with fusion of review information to generate answers. Gao et al. [7] encode reviews and product specifications using two separate encoders. The generated answer is passed through a consistency discriminator to check if the generated answer matches the facts. However, our focus in this work is to build a comprehensive answer generation pipeline utilising information from various e-commerce sources such as specifications, similar questions and reviews, and combining them to generate a natural language answer. To the best of our knowledge, this is the first work in e-commerce domain to utilize all the above three sources of information for natural language generation. Furthermore, we show how this can be built at scale by utilising noisy user submitted answers for answer generation component and hence reducing the need for clean supervised data present in most of the prior work settings.

3 PROBLEM DEFINITION

Given a question Q and a set of information candidates \{x_1, \ldots, x_k\} related to a product, the goal is to generate a natural language answer \(y\) as the response using relevant information.
We introduce Mutli Source Question Answering Pipeline (MSQAP) which can be split into three components. The candidates available in the dataset are quite high in number. The goal is to generate the answer. The dataset $D$ consists of the question $Q_i$, a set of reviews $\{r_{i1}, \ldots, r_{ik}\}$, a set of specifications $\{s_{i1}, \ldots, s_{im}\}$ and the ground truth answer $y_i$. The dataset $D$ is represented by:

$$D = \{ Q_i, \{r_{i1}, \ldots, r_{ik}\}, \{(q_{i1}, a_{i1}), \ldots, (q_{im}, a_{im})\}, \{s_{i1}, \ldots, s_{im}\}, y_i \}_{i=1}^N$$  \hspace{1cm} (1)

The goal is to generate the answer $y_i^*$ using appropriate information in a coherent and precise way.

4 PROPOSED APPROACH

![Diagram](Image)

**Figure 1: Multi Source Question Answering Pipeline**

We introduce Mutli Source Question Answering Pipeline (MSQAP) to generate the answer to a product related question by removing irrelevant information and ambiguity present in the information candidates. Figure 1 depicts the overview of the MSQA Pipeline which can be split into three components. (1) Relevancy prediction uses relational information between the question and information candidates to rank their importance in answering a question. (2) Ambiguity prediction helps in removing ambiguous opinions present in the candidates. (3) Answer generator helps in generating the response to the question with important and less ambiguous context information. The models used in this pipeline are trained and evaluated separately.

4.1 Relevancy prediction

The candidates available in the dataset are quite high in number for common questions and fewer in number for unique/rare questions. Also, these candidates are sometimes repetitive or irrelevant in their ability to answer the query. Using many candidates for generation will increase computation time and will make it difficult for the model to give attention to the right information. Hence, it is important to rank them with respect to their relevance with the question and their importance in answering it. We propose to model the relevancy prediction task as a Next Sentence Prediction approach with the question as the first sentence and each candidate as the potential second sentence. The intuition behind this modeling strategy is that any candidate that is relevant for answering a question will be the sentence immediately following it in a paragraph. Any other sentence that is irrelevant will be a random sentence. Thus, a well trained NSP model should be able to identify an important and relevant candidate from a random one.

Let $n$ be the number of candidates available for question $Q_i$. The question $Q_i$ and a candidate $x_i^j$ are concatenated, tokenized, and passed to an embedding layer. The word embeddings along with their positional signals are passed to a transformer encoder whose head predicts the Next Sentence label.

$$w_k = \text{tokenizer}(\{Q_i; x_i^j\}) \quad \hat{y}_k = \text{transformer}(w_k)$$  \hspace{1cm} (2)

$\gamma$ denotes the appropriate concatenation of input sentences as required by the pretrained transformer in use. The relevancy prediction task is trained to minimize the cross entropy loss,

$$L_{nsp} = -\frac{1}{N_i} \sum_{i=1}^{N_i} \frac{1}{n} \sum_{k=1}^{n} y_i^j \log \hat{y}_k$$  \hspace{1cm} (3)

where $y_i^j$ is the ground truth label indicating the relevancy of the candidate.

4.2 Ambiguity prediction

Apart from irrelevancy, one other reason for unnecessary information being fed into the generation model while answering a question is the ambiguity present in the candidates due to the subjective nature of the question. When both positive and negative sentiments together are passed as inputs to the generation model during training with a ground truth label containing any of the two sentiment, it will hinder the model from learning to generate a response with the right sentiment. For eg., two data points with the same question and candidates but using conflicting answers given by two users as ground truth labels will confuse the model whereas filtering the candidates to match the sentiment of the label and the advantage of removing this ambiguity is two fold. First, the number of input candidates decreases improving the computation time and second, the model gets trained to generate the answer with the sentiment which is given as input. During evaluation, we can choose the sentiment of the candidates to be given as input using any heuristic and the generated answer will contain the chosen sentiment. However, this task is carried out only for dichotomous (yes/no) questions. The candidates of WH questions are usually less subjective and hence, they are left untouched.

4.3 Answer generation

Once the candidates that are relevant to answering a question are collected, they are concatenated and passed along with the question into a transformer with encoder decoder architecture to generate the response. The encoder-decoder implementation follows the original proposed form [20]. The encoder consists of a stack of layers each with a self attention layer and a feed forward network. Layer normalization is applied to input of every layer and a skip connection is applied which connects the layer’s input with its output. The decoder consists of similar setup except that it also has an attention layer that attends to output of the encoder. The self attention layer in decoder follows a causal attention strategy (i.e)
paying attention to past inputs only.

Let \( k \) be the number of candidates available for question \( Q^i \). The question \( Q^i \) and its candidates are concatenated, tokenized, and passed to an embedding layer. The word embeddings along with their positional signals are passed to a transformer encoder which helps the decoder in generating the answers in an auto regressive fashion.

\[
\begin{align*}
  w^i &= \text{tokenizer}\left(Q^i; (x_1^i; \ldots; x_{L}^i)\right) \\
  \hat{h}^i &= \text{Encoder}(w^i) \\
  \hat{y}^i_1 &= \text{Decoder}(\hat{h}^i, y^i_{L-1})
\end{align*}
\]

\( ; \) denote the regular string concatenation and \( \hat{y}^i_1 \) is the generated token at position \( t \). The answer generation task is trained to minimize the cross entropy loss,

\[
L_{\text{gen}} = -\frac{1}{N_2} \sum_{i=1}^{N_2} \log P(\hat{y}^i_1)
\]

where \( P(\hat{y}^i_1) \) is the probability of the token corresponding to ground truth.

### 4.4 Auto answering pipeline

The MSQA Pipeline brings together all the three components in aiding answer generation. First, all the provided candidates from reviews, similar questions and answers, and specifications are passed as inputs to relevancy prediction task. The scores obtained from the NSP model are used to rank the candidates in decreasing order of their relevancy. The top \( k \) candidates are chosen and passed to ambiguity prediction task depending on the type of question. The trimmed candidates along with the question are passed as input to the answer generation model to produce the response.

### 5 EXPERIMENTS

The aim of the analysis is to answer the following questions

- Does the pipeline outperform the results of the baselines?
- Are the generated answers precise and coherent?
- How does each variant of the pipeline generate answers?

#### 5.1 Dataset

We train and evaluate the relevancy prediction model using our inhouse dataset \( D1 \) of mobiles. This dataset is made up of questions collected randomly from a list of accepted user posted questions. The number of questions present in the dataset is 2000. Every question is matched with a set of candidates from three sources of information, reviews, similar questions and answers, and specifications. We manually labelled this dataset to indicate whether each candidate has relevant information to answer the question. Specifically dataset \( D1 \) is represented by,

\[
D1 = (Q^i, \{(r^i_1, y^i_r), \ldots, (r^i_k, y^i_r)\}, \{(q^i_1, a^i_q), \ldots, (q^i_{M}, a^i_{qM})\})_{i=1}^{N_1}
\]

where \( y^i_r \) and \( y^i_q \) denote the relevancy of each of the sources for \( j^{th} \) candidate make up a datapoint for Next Sentence Prediction task. Every question with any one of the candidate make up a datapoint for Next Sentence Prediction task. The statistics of the table are presented in Table 2. The dataset is well balanced with an average of 0.573 and 0.531 relevant candidates in train dataset and validation dataset respectively.

We train and evaluate the answer generation model using our inhouse dataset \( D2 \) of mobiles consisting of 200K questions collected randomly from user posted questions along with their answers. The ground truth labels of this dataset are noisy since they represent the individual opinion of a single user. We also collect candidates from all three sources for each question. However, these candidates are filtered by relevancy and ambiguity prediction models resulting in seven or less candidates per question. Specifically, dataset \( D2 \) is represented by,

\[
D2 = (Q^i, \{x^i_{1}, \ldots, x^i_{S^i}\}, y^i_r)^{N_1}_{i=1}
\]

The statistics of the dataset after filtering are presented in Table 3. Though the duplicate question and answers are more relevant in answering a question as evident from Table 2, they are also more in number per question on average. The datasets used for training our models are tabulated in Table 4. We employ weak

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**Table 2: Relevancy prediction dataset**

|                       | Train dataset | Val dataset |
|-----------------------|--------------|------------|
| No. of questions      | 1638         | 362        |
| Total candidates      | 15122        | 3268       |
| Total relevant        | 8670         | 1736       |
| Avg. specs relevancy  | 0.308        | 0.253      |
| Avg. qa relevancy     | 0.668        | 0.634      |
| Avg. reviews relevancy| 0.626        | 0.573      |

**Table 3: Answer generation dataset**

|                       | Train dataset | Val dataset |
|-----------------------|--------------|------------|
| Total No. of questions| 217086       | 11153      |
| No. of WH questions   | 66075        | 3459       |
| Avg. candidates per   | 9.750        | 9.486      |
| Avg. specs per question| 2.381        | 2.381      |
| Avg. reviews per question| 2.637        | 2.344      |
| Avg. dup. questions per question| 4.732        | 4.762      |

**Table 4: Datasets used for training models**

| Dataset | Model       |
|---------|-------------|
| D1      | RoBERTa-A   |
|         | BERT-A      |
|         | RoBERTa-QA  |
| D2      | Seq2Seq     |
|         | HSSC-q      |
|         | T5-QA       |
candidates retrieval models for each source in order to eliminate the most unlikely candidates before constructing our datasets.

5.2 Baselines & Evaluation metrics

T5-QA model denotes answer generation component only, while MSQAP (rel.) denotes our generation model with relevancy prediction and MSQAP (full) denotes the entire pipeline. We compare our approach on both relevancy prediction and answer generation baselines. We have adopted two generation based methods along with the pre trained base transformer in use for answer generation task.

- Seq2Seq [1] - We implement the standard sequence to sequence RNN model with attention. The question and the candidates are concatenated and fed as input to the model.
- HSSC-q - We utilize the multi task model HSSC [11] that jointly performs summarization and sentiment classification. However, we implement a slightly modified variant HSSC-q that utilizes question with candidates and sentiment of the label to perform answer generation and sentiment classification.
- T5 [17] - We use the pretrained text-to-text transformer (T5) trained on a wide variety of tasks to do answer generation. The question concatenated with candidates appropriately are fed as input to the model.

We use a pretrained transformer as a baseline for our relevancy prediction task.

- BERT [5] - We compare our model with different architectural variants with the pretrained BERT model on Next Sentence Prediction task.

We use ROUGE (R1, R2, RL) and BLEU (B1) to automatically evaluate the performance of our answer generation pipeline. We also employ human evaluation of our dataset and measure correctness w.r.t candidates (CC) and correctness w.r.t ground truth label (CL) in order to quantify the performance of our pipeline. We use Accuracy (Acc), Precision (Pre), Recall (Rec) and F1-score (F1) to evaluate the variants of our relevancy prediction model.

5.3 Implementation details

We use Transformers [21] package for training our transformers and loading pretrained models. All our models are implemented in Pytorch [15].

5.3.1 Relevancy prediction. We finetune BERT [5] model on dataset D1. We also train RoBERTa [10] model on dataset D1 pre-trained on Flipkart reviews data on mobiles vertical to perform relevancy prediction. We try two variants of these models by changing the input. The first variant utilizes only the duplicate answer as second sentence for prediction and is denoted by BERT-A and RoBERTa-A while the second variant uses both duplicate question and answer for prediction and is denoted by BERT-QA and RoBERTa-QA. The remaining two sources remain the same across variants. Every sentence in a review is considered as an individual candidate and key value pair present in specifications is utilized directly(not converted into a sentence). All four models are trained for 5 epochs with a batch size of 32.

5.3.2 Ambiguity prediction. We use pretrained T5 [17] model for ambiguity prediction. During training, we filter out the sentiments that are in contrast with the label and during evaluation, we keep the sentiment that is expressed in most of the candidates (i.e) minority sentiments are eliminated. Around one third of the dataset contains WH questions as reported in Table 3 and sentiment filtering is not performed on those points.

5.3.3 Answer generation. We train Seq2Seq model with pretrained Glove embeddings [16] with 300 dimensions and with a vocabulary size of 400k. We train HSSC-q [11] using the details provided in the paper. We finetune pretrained T5 [17] model. We concatenate all the relevant candidates from reviews, specifications and duplicate question & answer pairs to a single sentence. Every duplicate question is followed by its corresponding answer and unnecessary punctuation are removed from specifications. We train all the models with a batch size of 32. We set a learning rate of $5 \times 10^{-5}$. We train all the models for 25 epochs.

5.4 Results

5.4.1 Relevancy prediction. The relevancy prediction results are reported in Table 5. Though relevancy prediction is not directly related to answer generation, ranking the candidates based on their importance and picking the top $k$ candidates aids in the performance of generation. Our baseline model, BERT predicts almost all candidates as relevant and hence has a high recall. However, precision of the baseline model is quite low proving that its ability to pick the relevant candidates is lower. Both the variants finetuned from BERT perform better than their counterparts owing to BERT being pretrained on NSP task. Our models, BERT-A and RoBERTa-A have a moderate performance compared to QA variants due to the lack of duplicate question information. BERT-QA has the best performance because it combines best of both worlds; NSP pretraining and QA information. We choose BERT-QA as the relevancy prediction model in MSQA Pipeline.

5.4.2 Answer generation pipeline. The performance of our approach compared with the baselines are reported in Table 6 which shows that our variants report the highest performance in content preservation metrics such as ROUGE and BLEU. The generated answers from each of these models are reported in Table 6. The pretrained T5 [17] model almost always generates answers with a couple of words. The Seq2Seq model mostly doesn’t generate proper answers to the posted question, rather a general sequence of words. The multi task HSSC model modified for answer generation (HSSC-q) shows a slight improvement due to being trained to pay attention to sentiment of the candidates. However, the generated

| Table 5: Methods comparison on relevancy prediction |
|-----------------------------------------------|
| Model     | Acc | Pre | Rec | F1  |
|----------|-----|-----|-----|-----|
| BERT-base | 0.635 | 0.637 | 0.996 | 0.777 |
| RoBERTa-A | 0.708 | 0.767 | 0.7778 | 0.772 |
| BERT-A    | 0.749 | 0.806 | 0.797 | 0.802 |
| RoBERTa-QA | 0.764 | 0.832 | 0.789 | 0.810 |
| BERT-QA   | 0.838 | 0.873 | 0.872 | 0.873 |
Table 6: Evaluation of methods on answer generation

|               | Dichot. questions | WH questions |
|---------------|-------------------|--------------|
|               | R1  | R2  | RL | B1 | R1  | R2  | RL | B1 |
| T5-Base       | 9.74 | 1.89 | 9.18 | 0.22 | 8.14 | 2.20 | 7.80 | 0.77 |
| Seq2Seq       | 22.87 | 6.57 | 22.09 | 1.50 | 14.50 | 3.74 | 13.77 | 0.10 |
| HSSC-q        | 24.19 | 8.65 | 23.46 | 1.91 | 15.43 | 4.85 | 14.68 | 0.90 |
| T5-QA         | **31.27** | **12.85** | **29.65** | **5.48** | **22.69** | **8.77** | **20.71** | **3.21** |
| MSQAP (rel. only) | 31.17 | 12.79 | 29.58 | 5.41 | 22.48 | 8.47 | 20.60 | 3.18 |
| MSQAP (full)  | 30.47 | 12.16 | 28.88 | 5.18 | 22.64 | 8.73 | 20.85 | 3.28 |

Table 7: Case study of generated answers

- **Question:** is this gorilla glass in this device...??
  - **Reference Answer:** no you have to protect at your own
  - **T5-base:** Has it gorilla glass?
  - **Seq2Seq:** no , it has gorilla glass
  - **HSSC-q:** yes gorilla glass 3
  - **T5-QA:** No, it’s not gorilla glass.
  - **MSQAP (rel.):** No, it has no gorilla glass.
  - **MSQAP (full):** No, it is not gorilla glass.

- **Question:** how to handle ABC game. graphics and game performance?
  - **Reference Answer:** you can play it in HD mode with quite decent fps but hdr mode is too much for this device in ABC mobile
  - **T5-base:** bad
  - **Seq2Seq:** it can play ABC in settings settings
  - **HSSC-q:** you can play ABC in hd graphics
  - **T5-QA:** ABC game is very smooth and graphics are very good.
  - **MSQAP (rel.):** ABC is a high end game. It runs smoothly on high graphics settings.
  - **MSQAP (full):** ABC is a high end game. It runs smoothly on HD graphics.

- **Question:** sound quality and heating problem?
  - **Reference Answer:** no issue at all and sound is great
  - **T5-base:** Hang
  - **Seq2Seq:** sound quality is good
  - **HSSC-q:** sound quality is good
  - **T5-QA:** sound quality is good but heating problem is there
  - **MSQAP (rel.):** sound quality is good but heating problem is there
  - **MSQAP (full):** sound quality is good and no heating problem

- **Question:** will u give headphone in the mobile box inside?
  - **Reference Answer:** yes it includes earphone also
  - **T5-QA:** No, you have to buy it separately.
  - **MSQAP (rel.):** yes, earphones are there
  - **MSQAP (full):** yes, earphones are there

- **Question:** How can used to 2nd back camera?
  - **Reference Answer:** In portrait mode, both cameras work simultaneously
  - **T5-QA:** it’s a portrait mode..
  - **MSQAP (rel.):** Open the camera app and click on the left side of the camera icon. Then click on
  - **MSQAP (full):** Open the camera app and click on the portrait mode.

- **Question:** is there 3gb ram version avilable?
  - **Reference Answer:** no never .4GB ram please
  - **T5-QA:** No, 4gb ram variant is not available.
  - **MSQAP (rel.):** No, 4gb ram variant is not available.
  - **MSQAP (full):** No, it’s 4gb ram

Table 8: Differences in generated answers

- **Question:** will u give headphone in the mobile box inside?
  - **Reference Answer:** yes it includes earphone also
  - **T5-QA:** No, you have to buy it separately.
  - **MSQAP (rel.):** yes, earphones are there
  - **MSQAP (full):** yes, earphones are there

- **Question:** How can used to 2nd back camera?
  - **Reference Answer:** In portrait mode, both cameras work simultaneously
  - **T5-QA:** it’s a portrait mode..
  - **MSQAP (rel.):** Open the camera app and click on the left side of the camera icon. Then click on
  - **MSQAP (full):** Open the camera app and click on the portrait mode.

- **Question:** is there 3gb ram version avilable?
  - **Reference Answer:** no never .4GB ram please
  - **T5-QA:** No, 4gb ram variant is not available.
  - **MSQAP (rel.):** No, 4gb ram variant is not available.
  - **MSQAP (full):** No, it’s 4gb ram

Table 9: Human evaluation of our methods

|               | Dichot. questions | WH questions |
|---------------|-------------------|--------------|
|               | CC  | CL | CC  | CL |
| T5-QA         | 0.919 | 0.628 | 0.833 | 0.537 |
| MSQAP (full)  | **0.943** | **0.845** | **0.869** | **0.656** |

5.4.3 Human Evaluation. Though the generation model (T5-QA) mostly possess the highest ROUGE and BLEU scores among all the other methods, the generated answers are not as precise as the MSQA Pipeline. We believe the absence of grammatical consistency and presence of spelling mistakes in the dataset render BLEU and ROUGE scores to be only an approximate measure of overall generation performance. Some of the generated answers that are different and sometimes incorrect in generation model are reported in Table 8. Hence, we performed human evaluation of generated answers and the results are tabulated in Table 9. Human annotators were asked to label a generated answer correct w.r.t candidates if the information present in the them is accurately reflected in the

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generated response. The aim of this task is to make sure that the model pays attention to information present in the candidates while generating the answers instead of memorizing the responses from the training data. Correctness w.r.t label is measured by checking if the generated response matches with the ground truth answer. Also, annotators were asked to evaluate if a question can be answered with the information present in the candidates. This measure is called answerability. Out of 11183 data points present in the validation dataset, we labelled 8207 points for evaluation. Around 5389 points were answerable with the given information making the answerability of the dataset to be 65.66%. There is slight improvement in correctness w.r.t context in MSQAP when compared to generation model (T5-QA) which we attribute to relevancy prediction. However, the huge improvement in correctness w.r.t label can be attributed to both the components. As discussed before, generating answers for dichotomous questions is an easier task and hence, the performance is relatively high.

6 CONCLUSION

Automatically answering questions is an important area of interest in E-commerce because it helps users in deciding if the product matches their requirement in order to make a purchase decision. To the best of our knowledge, this is the first work in e-commerce domain that automatically generates natural language answers given the information about the product from different sources such as specifications, similar questions and reviews. We describe the challenges with respect to noisy and inconsistent user data, and propose a novel question answering pipeline (MSQAP) that utilizes information from these sources in order to generate coherent and accurate answers. Our relevancy prediction model (BERT-QA) outperforms all other variants and has an improvement of 12.36% in F1 score compared to the baseline. We also show how to solve for ambiguity in user data by using a pretrained ambiguity prediction model taking into account the sentiments of the answer candidates. One key challenge in building Question Answering systems is the need for supervised training data for passage retrieval tasks. We show how we can use noisy answers submitted from users and reduce the need for supervised annotations of text spans required in training Question Answering models. Our generation model outperforms the baselines in all content preservation metrics such as BLEU, ROUGE and has an average improvement of 35.02% in ROUGE and 198.75% in BLEU compared to the highest performing baseline (HSSC-q). Human evaluation of our pipeline shows us that our method has an overall improvement in accuracy of 30.7% over the generation model (T5-QA), resulting in our generation approach (MSQAP) providing more accurate answers from the full pipeline. Our future work in this area is to train an end to end model to incorporate both answer generation and ambiguity prediction as part of the training process as compared to separate modules presented in the current approach. We also plan to extend this natural language generation approach to other e-commerce use-cases such as answering questions about offers, delivery, etc. in addition to product information.

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