CHQ-Summ: A Dataset for Consumer Healthcare Question Summarization

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ABSTRACT
The quest for seeking health information has swamped the web with consumers’ health-related questions. Generally, consumers use overly descriptive and peripheral information to express their medical condition or other healthcare needs, contributing to the challenges of natural language understanding. One way to address this challenge is to summarize the questions and distill the key information of the original question. Recently, large-scale datasets have significantly propelled the development of several summarization tasks, such as multi-document summarization and dialogue summarization. However, a lack of domain-expert annotated dataset for the consumer healthcare questions summarization task inhibits the development of an efficient summarization system. To address this issue, we introduce a new dataset CHQ-Summ that contains 1507 domain-expert annotated consumer health questions and corresponding summaries. The dataset is derived from the community question answering forum and therefore provides a valuable resource for understanding consumer health-related posts on social media. We benchmark the dataset on multiple state-of-the-art summarization models to show the effectiveness of the dataset.

1 Introduction
Healthcare consumers often query the web to find a quick and reliable answer to their healthcare information needs. On average, six million people in the United States alone seek health-related information on the Internet every day [1]. One way to facilitate such information-seeking activities is to build a natural language question-answering (QA) system that can extract precise answers from a myriad of health-related information sources. Though existing search engines respond to the general health-related queries to some extent, users often reach out to specialized medical websites or online health communities to seek personalized, high-quality, and trustworthy answers to their complex health questions. The overly descriptive nature of the questions that contain too much peripheral information brings an additional challenge to the task of automatic analysis and understanding of the questions. Often, such peripheral details are not required to obtain relevant answers, and their removal can lead to significant improvement in QA performance. Therefore, there is a need to develop automatic question simplification/summarization techniques before retrieving answers to the questions.

Automatic text summarization is a non-trivial task in natural language processing that aims to generate human-readable, concise text containing salient information of the original document. The recent development in large-scale neural language models [2,3] has led to significant performance improvement on several summary generation tasks (called abstractive summarization), partially due to the availability of large-scale human-annotated training data. The majority of the current summarization datasets are either based on the news articles (e.g., CNN/Dailymail[4]...
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and Multi-News[5] datasets where headlines are treated as summaries) or the scientific literature (e.g., PubMed[6], BioASQ[7] datasets where abstracts of the articles serve as summaries). While significant efforts have been made in the open-domain summarization, there are only a few works[8, 9, 10, 11, 12] in summarizing the CHQs. This is partially due to the lack of availability of the human-annotated training datasets. Recently, a manually annotated dataset, MEQSUM[9] was created that consists of 1000 CHQs and their corresponding summaries. A related dataset, MEDIQA-AnS[13] focuses on answer summarization for consumer health question answering. While these datasets enabled the research in question answering, the amount of training data is still relatively small, hindering the progress in developing an accurate and efficient CHQ summarization system.

Towards this, we introduce a new CHQ summarization dataset: CHQ-Summ that consists of 1507 domain-expert annotated question-summary pairs from the Yahoo community question answering forum. We advanced the existing dataset in two ways: (i) the dataset is created from the community question answering forum having a more diverse set of users’ questions, and (ii) our CHQ-Summ dataset contains additional annotations about question focus and question type of the original question. The question focus is the main entity of the question and the question type is the aspect of interest about the focus (c.f. Figure 1).

2 Methods

2.1 Dataset Creation

We utilized the Yahoo! Answers L6 corpus[1] that provides community question answering threads containing users’ questions on multiple diverse topics and the answers submitted by other users. The corpus consists of 4.4 million question-answer threads with additional metadata information such as the question category, question sub-category, question language, and best answer. Each of the questions has a question title and question content. The question title is the subject line of the original question, and the question content describes the original question with the full description. Since our goal is focused on the consumer healthcare domain, we selected the questions from the “Healthcare” question category. However, to ensure that there are (i) no false positives, and (ii) the questions are from diverse health categories, we devised multiple heuristic-based filtering strategies to filter out irrelevant questions, discussed as follows:

- **Medical Entities Identification**: The very first stage of filtration is to recognize the medical entities present in the question content and title. We utilized Stanza[14] Biomedical and Clinical model for identifying medical entities in the question title and content.

[1]https://webscope.sandbox.yahoo.com/catalog.php?datatype=l&did=11
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- **Candidate Question Identification and Selection:** In the second stage, we select the question threads having at least one medical entity present in either question title or question content. We collected 22,257 question threads from Yahoo! Answers corpus through this process.

- **Removing Low Content Question Threads:** In the final stage of filtration, to preserve the quality of our dataset, we further filter out the questions that are short and do not require summarization. Specifically, we removed the question threads with a question content having less than 10 words. Later, we concatenate the question title and content to form the original question and ask annotators to formulate the summary of the question manually. We call this manually generated question-summary pair CHQ-Summ. These pairs constitute the consumer health question summarization dataset. The schematic workflow of the CHQ-Summ dataset creation is depicted in Figure 2.

2.2 Expert Annotations

A team of six annotators (4 experts in medical informatics and 2 experts in medical informatics and medicine) independently annotated parts of the CHQ-Summ dataset. Each annotator was provided with the annotation guidelines and the annotation interface to summarize the CHQs. Given the original question, the annotators were instructed to:

1. **Identify the valid medical question:** A question can be categorized as a valid medical question if it belongs to the following categories:
   (a) Diseases & conditions, including symptoms
   (b) Drugs & treatments
   (c) Medical tests or medical diagnostic & therapeutic procedures
   (d) Other relevant medical topics

2. **Formulate an abstractive summary:** The abstractive summary of the given question is formulated by keeping the minimum and key information required to answer the question.

3. **Identify the question focus:** Given the effectiveness of the question focus for the consumer health question summarization task, we ask the annotators to annotate each question with the focus term. The question focus is the named entity that is the central theme of the question. Generally, a question has a single focus, but
for some questions which are about the relation between two drugs or diseases, multiple question foci are allowed. For example, consider Fig. 1 where the question focus is ‘cataract’.

4. **Identify the question type:** Question type represents some aspect of the question focus that triggered the question and needs to be answered, e.g., in Fig. 1 the expecting mother is asking if her child will be susceptible to cataracts more than an average baby. Existing studies[8] show that question-type information can guide the model to generate more factually correct summaries, therefore, we annotated each question with the appropriate question types. Specifically, we instructed the annotators to classify each question into any of the 33 question type categories obtained from the previous study [15]. The annotators were expected to select all the question types that could be inferred from the given question. For example, in the Fig. 1, the question type is ‘Susceptibility’.

### 2.3 Annotators and Inter-annotation Agreement

We began the annotation process by developing the annotation guidelines and interface. In the first round, a set of 3 annotators with expertise in medical informatics and medicine annotated the same collection of 150 questions to compute the inter-annotation agreement. In the second round, 3 more annotators with medical informatics background were included in the annotation task. For the final annotation, a total of 6 annotators independently annotated the collection of 500 questions, out of which 30 questions were common among all the annotators. We computed the inter-annotator agreement (IAA) on the 30 common question.

For computing the IAA for the summarization task, we used the ROUGE-L score. In the case of question-focus and question-type identification tasks, we used F1-score to measure the IAA. We have reported the average ROUGE-L and F1-score amongst all the annotator pairs in Table 1. The average IAA for question focus and question types was found to be 83.22 and 85.44 (substantial agreement), respectively, on 30 common questions. On the summarization task, we observed that even though the summary was semantically correct, the average IAA was only 52.8 (moderate agreement). This was because the summary created by the annotators was diverse and did not follow the same word order, even though they all were semantically correct. Since ROUGE-L does not take into account the semantic similarity between two summaries, the ROUGE-L score was not high among annotators. For example, consider Figure 1 where both variations of the question ask the same thing but don’t have too many words in common.

| Samples/Annotators | Question-focus (F1-score) | Question-type (F1-score) | Question-summary (ROUGE-L) |
|--------------------|---------------------------|--------------------------|-----------------------------|
| 150/3              | 85.84                     | 86.28                    | 53.23                       |
| 30/6               | 83.22                     | 85.44                    | 52.8                        |

Table 1: Average inter-annotator agreement score among all the annotators on question-focus recognition, question-type identification, and question-summary generation task.

![Figure 3: Distribution of words in original questions (a) and summarized questions (b) in CHQ-Summ dataset.](image-url)
## 3 Dataset Analysis

The CHQ-Summ dataset consists of the 1, 507 original questions and the corresponding summarized questions, question focus and question types. To benchmark the dataset, we split it into training, validation and test set of 1000, 400 and 107 samples respectively. Table 2 and Table 3 provide the detailed statistics of the dataset.

The majority of original questions in CHQ-Summ dataset have 200 words. While, most of our human generated summaries have 15 words (cf. Fig 3). This shows that in the community question answering forum, users prefer expressing their healthcare information needs in an overly descriptive manner with several peripheral details rather than formulating succinct queries that demand more cognitive effort. We also analyzed the distribution of the question focus and question type of the CHQ-Summ dataset. To understand the concept associated with each question focus, we map each focus term to the Medical Subject Headings.

### Finding Medical Subject Headings (MeSH):

The Medical Subject Headings is a thesaurus developed by the National Library of Medicine, and it is used for indexing, cataloging, and searching for biomedical and health-related information and documents. Since biomedical literature is indexed with MeSH, it is appropriate to use MeSH to search the literature to find the relevant and reliable answers to consumer healthcare questions. Toward this, we have provided the MeSH headings for the question focus present in each question of the CHQ-Summ dataset. We downloaded and pre-processed the Unified Medical Language System®(UMLS) [16] Metathesaurus from the official UMLS site [3]. In particular, we utilized the MRCONSO.RRF Metathesaurus file that contains the concepts id, names, codes, etc., from multiple source vocabularies. To map the MeSH headings associated with the question focus, we downloaded and pre-processed the MeSH Descriptor Data 2021 from the official MeSH website [4]. In the pre-processing step, we build a MeSH dictionary where the MeSH descriptor is stored as key, and the MeSH tree numbers are stored as the value.

Given a question focus, we follow the following steps to obtain the MeSH heading:

1. Download and pre-process the UMLS Metathesaurus [3].
2. Map the question focus to the MeSH dictionary.
3. Return the MeSH heading associated with the question focus.

## References

[1] https://www.nlm.nih.gov/mesh/meshhome.html
[2] https://www.nlm.nih.gov/research/umls/licensedcontent/umlsknowledgesources.html
[3] https://www.nlm.nih.gov/databases/download/mesh.html
1. We utilized the MetaMap [17, 18] tool with the MeSH vocabulary that provides the concept unique identifier (CUI) of the mapping concepts.
2. The descriptor unique identifier (DUI) for each mapping CUIs are extracted from MRCONSO.RRF Metathesaurus. While searching the DUI, we restrict ourselves to only extracting the DUIs for which the language of the term is English (ENG) and the source vocabulary is MeSH (MSH).
3. Finally, we used the processed MeSH dictionary to retrieve the associated MeSH Tree numbers and mapped them to their top tree numbers in MeSH Tree.

With the above approach to find MeSH terms, we were able to obtain the top heading (associated with the MeSH Tree numbers\(^5\) for the question focus present in 1,208 questions out of total 1,507 questions in CHQ-Summ dataset. The CHQ-Summ dataset contains a total of 1788 distinct question focuses and with MetaMap we successfully mapped 1141 question focuses to MeSH terms. The distribution of top 20 MeSH terms corresponding to the question-focus terms is provided in Fig. 5(a). The mapping shows that questions on “pathological conditions signs and symptoms” (C23) are most frequent, followed by “musculoskeletal and neural physiological phenomena” (G11) and “mental disorders” (F03). The top 20 MeSH mappings contribute to 96% of the total annotated dataset (cf. Fig. 4(a)). We also analyze the coverage (cf. Fig. 4(b)) of the most frequent \(k\) question focuses and found that top-10, top-20 and top-30 question focuses cover 248, 321 and 364 questions respectively. We noticed that most of the questions in the CHQ-Summ dataset have two focus terms as shown in (cf. Fig. 6(a)). We have provided the distribution of top-20 question focus term in (cf. Fig. 6(b)). This shows that the CHQ-Summ contains diverse set of questions covering different question focuses. We also conducted analysis on the annotated question types. The statistics regarding question type are provided in Fig. 5(b). This distribution shows that consumers frequently seek general information regarding their healthcare needs. As such, ‘information’ question type is the most common question type in CHQ-Summ. Other common question types are ‘treatment’, ‘cause’, and ‘symptoms’.

4 Benchmarking

We utilize the following pre-trained language models that have shown state-of-the-art performance on the various summarization tasks.

- **ProphetNet [19]**: It is a sequence-to-sequence model established on Transformer [20] encoder-decoder architecture. ProphetNet introduced supervised future n-gram prediction objective that aims to predict the future

\(^5\)Please refer to [https://meshb-prev.nlm.nih.gov/treeView](https://meshb-prev.nlm.nih.gov/treeView) for MeSH categories.
Figure 6: Distribution of the number of question-focus terms in the original questions (shown on left). Coverage (right) of the top-20 question focus on CHQ-Summ dataset.

n-gram at each time step $t$. To deal with n-gram prediction ProphetNet updates the main-stream self-attention as introduced in Transformer and calls the updated self-attention mechanism as n-stream self-attention. The ProphetNet model is pre-trained with BookCorpus\cite{21} and English Wikipedia dataset. We fine-tuned the ProphetNet model with the CHQ-Summ training dataset and validated the model on the validation dataset. We consider the ROUGE-L metric to validate the model and the best performing model is used to generate the summary from CHQ-Summ test set.

- **PEGASUS**\cite{22}: PEGASUS is also built upon the Transformer-based encoder-decoder approach. The model is pre-trained with the novel self-supervised objective called Gap Sentences Generation (GSG) and masked language modeling\cite{23}. The GSG objective is to select and mask whole sentences from documents and concatenate the gap sentences to form a pseudo-summary. To select the sentences to be masked, the model follows a principled approach, where sentences are selected by the greedy approach of maximizing the ROUGE1-F1 between selected sentences and remaining sentences. Similar to ProphetNet, we fine-tune PEGASUS on the CHQ-Summ dataset and evaluate the performance on the CHQ-Summ test set. We used the pre-trained PEGASUS-large model\cite{24} from HuggingFace\cite{24}.

- **T5**\cite{25}: T5 is a text-to-text framework based on Transformer encoder-decoder architecture. We utilized the T5-base\cite{26} model variant to fine-tune on CHQ-Summ dataset. The T5-base model is pre-trained with an unsupervised objective that is inspired by masked language modeling\cite{2} and word-dropout regularization technique\cite{26}. The proposed objective function randomly samples and then drops out 15% of tokens in the input sequence, and a single sentinel token replaces the spans of dropped-out tokens. The model is trained by predicting the dropped-out tokens.

- **BART**\cite{27}: The Transformer-based BART architecture is pre-trained by combining Bidirectional and Auto-Regressive Transformers. In the pre-training stage, the input sequence is corrupted by replacing spans of text with mask symbols, and the sequence-to-sequence model is learned to reconstruct the original sequence. Similar to ProphetNet, BART is pre-trained on BookCorpus and Wikipedia datasets. BART has shown state-of-the-art performance on language generation, machine translation, and comprehension tasks. We utilized the pre-trained BART model\cite{28} to fine-tune on CHQ-Summ dataset.

\[\text{https://huggingface.co/microsoft/prophetnet-large-uncased}\]
\[\text{https://huggingface.co/google/pegasus-large}\]
\[\text{https://huggingface.co/t5-base}\]
\[\text{https://huggingface.co/facebook/bart-large}\]
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### 4.1 Benchmarking Metrics and Experimental Setup

We followed the existing works\[^{9,8}\] on consumer health question summarization and evaluated the performance of the question summarization using ROUGE metric\[^{28}\]. We reported the performance in terms of ROUGE-1, ROUGE-2, ROUGE-L F1-scores, and BERTScore\[^{29}\]. We utilize the pyrouge\[^{10}\] implementation of ROUGE and the datasets implementation\[^{11}\] of the BERTScore to report the results on CHQ-Summ dataset. We fine-tuned each pre-trained language model using the maximum source sequence tokens length of 300 and target sequence tokens length of 50. The optimal learning rate of the T5 model was $3 \times 10^{-3}$ while the learning rate to fine-tune PEGASUS, ProphetNet, and BART models were found to be $3 \times 10^{-5}$. We use a beam search algorithm to generate the question summary.

### 4.2 Results and Discussion:

We evaluated the performance of the pre-trained language models on CHQ-Summ validation and test set. The detailed results are provided in Table 4 and 5. We evaluated the performance of each pre-trained language model in terms of ROUGE scores by varying the beam size from 1 (greedy decoding) to 9 on the CHQ-Summ validation dataset as shown in Fig. 7. The performance with the best beam size on the validation dataset is reported in Table 4.

The obtained results show that ProphetNet model fine-tuned on CHQ-Summ training set achieves the highest performance (ROUGE-1, ROUGE-2, and ROUGE-L) on CHQ-Summ validation set. BART and PEGASUS achieved near-similar performance on validation. On the test set, BART was superior to other models in terms of ROUGE-1, ROUGE-2, and ROUGE-L. One interesting observation here is that ROUGE-1 and ROUGE-L scores are comparatively higher compared to the ROUGE-2. This is because the ROUGE-1 considers the 1-gram match between generated summary and reference summary while ROUGE-2 focus on 2-gram matches, which is more restrictive compared to the ROUGE-1. Moreover, ROUGE-L considers the longest common subsequence matches where the words from generated summary do not require to occupy consecutive positions in the reference summary. Thus, it is less restrictive than the ROUGE-2 metric. As ROUGE-based metrics evaluate the generated summaries based on the word-overlap (n-gram match between candidate summary to reference summary), a good summary doesn’t need to follow the exact words and word orders as human-written summaries.

To consider the semantic overlap between candidate summary and reference summary, we utilized the BERTScore that computes a similarity score for each token in the candidate summary with each token in the reference summary. The results show that BART outperforms the other models in terms of the BERTScore on the CHQ-Summ test set, while ProphetNet obtained the best performance on the validation set.

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10. [https://pypi.org/project/pyrouge/](https://pypi.org/project/pyrouge/)
11. [https://github.com/huggingface/datasets](https://github.com/huggingface/datasets)
We have provided samples of the generated summaries from each pre-trained language model in Table 6. As can be observed from Table 6, T5 generates much longer summaries compared to BART, PEGASUS, and ProphetNet. Also, ProphetNet and BART-generated summaries are closer to reference summaries. Another important observation is that a higher ROUGE score does not guarantee that generated summaries would be factually correct. For example, consider question-3 of Table 6, here both BART and PEGASUS obtained the ROUGE-L scores of 0.86, 0.86 compared to T5 with the low Rouge-L score of 0.60. While ProphetNet and T5 summaries can be considered accurate, BART
and PEGASUS summaries are factually incorrect. This shows that automatic evaluation metrics should be used with caution on our CHQ-Summ dataset and manual evaluation is required to validate the performance of the model.

The CHQ-Summ dataset will be helpful to build a summarization system that can address the diverse nature of consumer questions.

Data and Code Availability

We have provided the detailed instructions in the README file of the Open Science Framework repository describing how to process the CHQ-Summ datasets. The source code to benchmarked experiments can be found at the GitHub repository. Due to Yahoo copyright issues, we cannot directly share the Yahoo original questions. However, these questions are publicly available here and it can be accessed after signing the Yahoo agreements.

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