Towards Summarizing Healthcare Questions in Low-Resource Setting

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Abstract

The current advancement in abstractive document summarization depends to a large extent on a considerable amount of human-annotated datasets. However, the creation of large-scale datasets is often not feasible in closed domains, such as medical and healthcare domains, where human annotation requires domain expertise. This paper presents a novel data selection strategy to generate diverse and semantic questions in a low-resource setting with the aim to summarize healthcare questions. Our method exploits the concept of guided semantic-overlap and diversity-based objective functions to optimally select the informative and diverse set of synthetic samples for data augmentation. Our extensive experiments on benchmark healthcare question summarization datasets demonstrate the effectiveness of our proposed data selection strategy by achieving new state-of-the-art results. Our human evaluation shows that our method generates diverse, fluent, and informative summarized questions.

1 Introduction

Online health information search is becoming conventional for more and more consumers every day. A recent survey showed that on average eight million people in the United States seek health-related information on the Internet every day\(^1\). One challenge towards assisting consumers in their healthcare information search is automatic question understanding. Generally consumers’ questions are overly descriptive and include several peripheral information (as shown in Figure-1), which are not necessary to answer questions. Therefore, in this study we tackle the task of consumer health question understanding by summarizing the question.

Automatic text summarization is a non-trivial task in Natural Language Processing (NLP) that aims to generate human-readable, concise text containing salient information of the original document. The recent development in large-scale neural language models (Devlin et al., 2019; Raffel et al., 2020) have led to significant performance on several abstractive summarization task. However, their accuracy is partially due to the availability of large-scale human-annotated training data. Moreover, some domains such as biomedical and medical require domain experts to create high-quality training datasets, which is tedious to create at a large-scale level.

A potential solution that has shown effectiveness in other generation and translation tasks is to augment the large-scale synthetically generated samples with a human-annotated training set. However, a limited study focused on data selection strategy in summarization, particularly for abstractive summarization. The majority of the traditional data selection methods are based on word replacement that mainly generates a synthetic sentence by changing one or multiple words with their synonyms (Zhang et al., 2015) or with a language model predicted words (Kobayashi, 2018). However, these methods make minor changes to the original sentence and therefore fall short of generating a diversified sentence.

To address this research gap, we present a novel data selection strategy for abstractive consumer

\(^1\)https://pewrsr.ch/3l6m3mv

Figure 1: The highlighted text shows important key aspects of the question which need to be considered while generating the summary.
health question (CHQ) summarization task. Inspired by the success of the round-trip translation (RTT) (Hoang et al., 2018) – a process of translating the sentences to a pivot language and then back translating to the original language, we aim to explore the effect of RTT as a data augmentation method in CHQ summarization. However, not all the data samples obtained from RTT are diverse and can contain redundant information.

Towards this, we enhance the capability of RTT by devising multiple optimal data selection strategies to select diverse and informative questions, which leads to the significant performance improvement of the CHQ summarization system. Our first data selection strategy Frechét Question Distance (FQD) is based on Frechét distance (Dowson and Landau, 1982), which measures the distribution distance between the gold and round-trip translated question. The FQD ensures that questions having near similar or very different distributions should not be selected as additional data to train the summarization system. We propose Precision Recall Question Distance (PRQD) as our second data selection strategy, which disentangles the question distributions divergence into two components: precision and recall. These two components ensure that the selected additional data brings diversity to the whole training dataset. It is achieved by finding the trade-off between precision and recall of the distributions of the gold and round-trip translated questions. Our final data selection strategy Question Semantic Volume (QSV) is based on maximizing the semantic area formed by the points obtained from the semantic representation of the questions. The QSV aims to select the questions which maximize the semantic area leading to the selection of the additional questions which are non-redundant and diverse in nature.

We evaluated the effect of the additional data generated using the RTT and our proposed data selection objective measures on benchmark CHQ summarization dataset and two low-resource open domain datasets. We assess the role of each objective measure in RTT based data selection technique using five different pivot languages. Our results show that the RTT-based data selection method helps to improve the performance of the summarization system. We summarize the contribution of the work as follows:

1. We explored the role of the RTT-based data selection technique on CHQ summarization by experimenting with five different pivot languages.
2. We introduced the semantic-volume and diversity-based data selection objective measure in RTT to optimally select the diverse and informative synthetic questions.
3. Our unsupervised method achieves state-of-the-art performance on benchmark consumer healthcare question summarization datasets. Further, our human analysis confirms the effectiveness of our proposed approach in generating fluent and informative summary.

2 Related Work

**Neural Abstractive Summarization:** The recent advancement of neural networks models, particularly sequence-to-sequence (seq2seq) (Sutskever et al., 2014) models, attention mechanism (Bahdanau et al., 2015), copy mechanism (Gu et al., 2016), coverage mechanism (See et al., 2017) has propelled the development of efficient abstractive summarization approaches on numerous open-domain datasets. Several other methods have utilized the reinforcement learning (RL) (Paulus et al., 2018; Pasunuru and Bansal, 2018; Zhang and Bansal, 2019) to guide the models to generate faithful summaries. Recently, several studies have investigated the pre-trained language models in the abstractive summarization task (Qi et al., 2020; Liu and Lapata, 2019) and have achieved the state-of-the-art performance. Besides the supervised models, various other unsupervised approaches have utilized variational autoencoders for automatic summarization (Laban et al., 2020; Bražinskas et al., 2020; Baziotis et al., 2019).

**Consumer Health Question (CHQ) Summarization:** While major progress has been made in open-domain abstractive summarization, CHQ summarization is a relatively new task. Ben Abacha and Demner-Fushman (2019) defined the task of summarizing CHQ and introduced a benchmark dataset containing 1000 consumer questions summaries. Recently, a first shared task was organized by Ben Abacha et al. (2021) with the task of summarizing consumer health questions, radiology reports, and multi-document answers. The majority of the works (Lee et al., 2021; He et al., 2021; Sarrouti et al., 2021; Sänger et al., 2021) used pre-trained language models, ensemble approaches, and knowledge-based methods for the CHQ summarization task. A few other new methods (Yadav et al., 2021) explored the role of the RTT-based data selection technique on CHQ summarization.
et al., 2021a) have enhanced the capability of transformer model by inducing the latent knowledge. In the literature, several works have explored the concept of RTT in machine translation (Nguyen-Son et al., 2021), sentence construction (Zhou et al., 2021), and style-transfer (Zhang et al., 2020b).

Our works advances the existing studies in the consumer health question summarization by proposing an unsupervised framework to optimally select the diverse and information RTT questions, which leads to significant improvement without the need of additional labelled data.

3 Methods

3.1 Background

Given a consumer health question \( Q = \{q_1, q_2, \ldots, q_M\} \), the goal of this task is to generate a summarized question \( S = \{s_1, s_2, \ldots, s_N\} \) that contains the key information of the original question. Towards this, we build our question summarization model over the Transformer-based seq2seq (Vaswani et al., 2017) architecture. It aims to learn the conditional likelihood \( p(S|Q) = \prod_{t=1}^{N} p(s_t|s_{<t}, Q) \), where, \( s_{<t} \) denotes all generated target tokens before \( s_t \). We utilized the pre-trained ProphetNet (Qi et al., 2020), as the strong base model to summarize the questions. We choose ProphetNet as it is specifically designed for sequence-to-sequence training and it has shown near state-of-the-art results on language generation and CHQ summarization task (Yadav et al., 2021a).

3.2 CHQ Summarization with Round-trip Translation

To train an effective neural network model for language generation tasks, the requirement of sufficient training data is indispensable. Synthetic data augmentation is a way to mitigate the data scarcity issue. It helps the model to reduce the brute-force memorization and also introduce a regularization effect.

In the literature, existing works (Yu et al., 2018; Xie et al., 2020) have shown that the RTT-based data augmentation methods create diverse samples while preserving the semantics. Inspired by these studies, we perform RTT to generate the paraphrases of the source CHQ that could lead to a better summarization system. In order to avoid the noise and keeping the fact intact, we did not paraphrase the gold summarized questions.

Specifically, for a given original dataset \( D_{orig} = \{(Q_i, S_i) \mid i = 1, 2, \ldots, L\} \), we translate the source CHQ \( Q_i \in D_{orig} \) into a non-English pivot language \((xx)\) to obtain \( D_{en\rightarrow xx} = \{(Q_{i,xx}, S_i) \mid i = 1, 2, \ldots, L\} \) using the Google translation. We then back-translate the \( D_{en\rightarrow xx} \) to English and obtained \( D_{xx\rightarrow en} \). The final dataset is obtained from forward \( (D_{en\rightarrow xx}) \) followed by the backward \( (D_{xx\rightarrow en}) \) translation as:

\[
D_{rtt}^{en+xx} = \{(\hat{Q}_i, S_i) \mid i = 1, 2, \ldots, L\} 
\]

Further, to enhance the model’s generalization ability, we enrich the original training dataset \( D_{orig} \) with the additional RTT-based generated data \( D_{rtt}^{en+xx} \). We call this as the augmented dataset \( D_{aug}^{en+xx} \):

\[
D_{aug}^{en+xx} = D_{orig} \cup D_{rtt}^{en+xx} 
\]

3.3 Data Selection Objective Measures

We define three different data selection objective measures: (i) Frechet Question Distance, (ii) Precision Recall Question Distance, and (iii) Question Semantic Volume, that assess both diversity and quality of the RTT question by assigning low scores to less informative questions (i.e., questions having factual errors and lacking salient medical information as present in the original question) or have low-diversity.

In the literature, there are few metrics like BLEU, Self-BLEU, Negative Log-Likelihood (NLL) that individually account for quality and diversity in the generated text. Alilosseini et al. (2019) shows that these metrics neglect either the quality (in the case of Self-BLEU) or the coverage (in metrics like BLEU, NLL). Thus, it is necessary to have a measure that could jointly consider both quality-diversity in the generated text. We argue that the distribution distance between the semantic representations of the round-trip generated question and the original question can be used simultaneously to select the diverse and informative round-trip generated question.

Given a gold question \( Q \) and round-trip generated question \( \hat{Q} \), we first extract the question semantic representations \( h_Q \) and \( h_{\hat{Q}} \) from a Transformer-based (Vaswani et al., 2017) pre-trained language model, which encodes the contextual information of the questions. Unlike the other work (Xiang et al., 2021), where the BERT has been used to derive fixed-size sentence embedding, we follow the idea of sentence-BERT (Reimers et al., 2020) to have fixed-size sentence embedding.
and Gurevych, 2019) which uses the siamese and triplet networks (Schroff et al., 2015) to update the weights such that the generated semantically similar question representations are close in vector space. Towards this, we utilized the pre-trained MPNet (Song et al., 2020) model, which is fine-tuned using the siamese and triplet networks as discussed in Reimers and Gurevych (2019). We obtain the semantic representation of the questions from fine-tuned MPNet as:

\[
\begin{align*}
    h_Q &= \text{MPNet}(q_1, q_2, \ldots, q_M) \\
    h_{\hat{Q}} &= \text{MPNet}(\hat{q}_1, \hat{q}_2, \ldots, \hat{q}_M)
\end{align*}
\]

(3)

In the following sub-sections, we use the semantic representation of the questions to devise multiple objective measures to select the diverse and informative round-trip generated question.

### 3.3.1 Frechét Question Distance

Heusel et al. (2017) introduced the metric Fréchet Inception Distance (FID) to evaluate the performance of the Generative Adversarial Networks (Goodfellow et al., 2014) based image generation models. FID is based on the Fréchet distance (Dowson and Landau, 1982) and is used to measure the similarity of generated images to real ones. Inspired by FID, we introduce FQD, which measures the distributional distance between the semantic representation of the gold question and the round-trip generated question. We assume that question semantic representations follow the multi-dimensional Gaussian distribution with first two moments: \(\text{mean} \ \text{and covariance.} \) The distance between these two Gaussian distributions is measured by the Fréchet distance.

Let the semantic representation \(h_Q\) of the gold question follow the Gaussian: \(h_Q \sim N(\mu_q, \Sigma_q)\) with mean \(\mu_q\) and co-variance matrix \(\Sigma_q\). Similarly, let the semantic representation of the round-trip question follow: \(h_{\hat{Q}} \sim N(\mu_{\hat{Q}}, \Sigma_{\hat{Q}})\). The Frechét Question Distance between \(Q\) and \(\hat{Q}\) is computed as follows:

\[
d_{\text{FQD}}(Q, \hat{Q}) = ||\mu_q - \mu_{\hat{Q}}||^2 + \text{Tr}(\Sigma_q + \Sigma_{\hat{Q}} - 2(\Sigma_q \Sigma_{\hat{Q}})^{1/2})
\]

(4)

where \(\text{Tr}(X)\) is the trace of matrix \(X\). To produce a uniform FQD score, we linearly scale the \(d_{\text{FQD}}(Q, \hat{Q})\) in the range \([0, 1]\) using the following min-max normalization:

\[
FQD(Q, \hat{Q}) = \frac{d_{\text{FQD}}(Q, \hat{Q}) - \min(d_{\text{FQD}})}{\max(d_{\text{FQD}}) - \min(d_{\text{FQD}})}
\]

(5)

where \(\min(d_{\text{FQD}})\) and \(\max(d_{\text{FQD}})\) represent the minimum and maximum FQD in the dataset. When the distribution of gold question is close to the distribution of the round-trip generated question, the FQD score is close to zero. In order to have the diverse, informative, and non-redundant samples in the training set, one does not need to include the round-trip generated questions whose FQD scores with gold questions are either low (near same question) or high (entirely different questions). Toward this, we aim to select the round-trip generated questions such that FQD score with gold questions is found to be in an optimal range. Given the round-trip generated questions \(D_{\text{rtt+xx}}\) with pivot language \((xx)\), we select a subset of the questions as follows:

\[
D_{\text{rtt+xx}} = \{ (\hat{Q}, S_i) \mid \mu_1 < FQD(Q, \hat{Q}) < \mu_2 \}
\]

(6)

where \(\mu_1\) and \(\mu_2\) are hyper-parameters (i.e., the optimal threshold) chosen based on the performance of CHQ summarization system on the validation dataset.

### 3.3.2 Precision Recall Question Distance

Inspired by the work of Sajjadi et al. (2018), which uses the notion of precision and recall to compare the reference and hypothesis distribution, we propose our second objective measure Precision Recall Question Distance. Similar to the FQD, it measures the distributional distance between semantic representations of the gold and round-trip generated questions; however, it does not require estimating the moments of the probability distributions. Intuitively \textit{precision} measures how much of \(h_Q\) can be generated by a portion of \(\hat{Q}\). In contrast, \textit{recall} measures how much of \(\hat{Q}\) can be generated by a portion of \(h_Q\). Hence, the precision and recall should be high for the approximately same question distributions, whereas, if the question distributions are disjoint in nature, the precision and recall will be zero. Therefore, we aim to select the RTT questions whose precision and recall lies between the optimal range to ensure diversity. To compute PRQD, we follow the algorithm proposed by Sajjadi et al. (2018), which is based on the precision-recall distance (PRD) curve. Toward this, we compute pairs of precision \(prec(\alpha)\) and recall \(rec(\alpha)\) for an equiangular grid of values of \(\alpha\).

\[
prec(\alpha) = \sum_{v \in V} \min(a h_Q(v), h_{\hat{Q}}(v))
\]

\[
rec(\alpha) = \sum_{v \in V} \min(h_Q(v), \frac{h_{\hat{Q}}(v)}{\alpha})
\]

(7)
where \( h_Q \) and \( h_{\hat{Q}} \) probability distributions are defined on a finite state space \( \mathcal{V} \). In order to compute a single-value metric, we compute the F1-score corresponding to each \( \alpha \) and select the maximum F1-score as the PRQD distance \( d_{PRQD}(\hat{Q}, Q) \) as follows:

\[
d_{PRQD}(\hat{Q}, Q) = \max \left\{ \frac{2 \cdot \text{prec}(\alpha) \cdot \text{rec}(\alpha)}{\text{prec}(\alpha) + \text{rec}(\alpha)} \mid \alpha \in \Lambda \right\}
\]

where \( \Lambda = \{ \tan\left( \frac{i}{p+1} \pi \right) \mid i = 1, \ldots, p \} \) and \( p \in \mathbb{N} \) refers to the angular resolution, which is a hyper-parameter. Similar to FQD, we linearly scale the \( d_{PRQD}(\hat{Q}, Q) \) in the range of \([0, 1] \) following Eq. 5 and obtained the normalized score \( PRQD(\hat{Q}, Q) \).

Given the round-trip generated questions \( D_{rtt}^{en+xx} \) with pivot language \((xx)\), we select a subset of questions as follows:

\[
D_{rtt+prq}^{en+xx} = \{(\hat{Q}_i, S_i) \mid \beta_1 < PRQD(\hat{Q}_i, Q_i) < \beta_2 \}
\]

where \( \beta_1 \) and \( \beta_2 \) are the optimal thresholds which are chosen similar to \( \mu_1 \) and \( \mu_2 \).

### 3.3.3 Question Semantic Volume

Existing work in the literature (Yogatama et al., 2015) shows that the sentences which maximize the semantic volume in a distributed semantic space are the most diverse and have least redundant sentences. Motivated by this, first, we aim to find the most diverse and least redundant round-trip generated questions from the pool of RTT questions generated by considering different pivot languages. Later, we devise a simple yet effective measure to quantify the candidate RTT questions with respect to the gold questions in terms of their semantic distance. Specifically, for the given gold question \( Q \) and a set of \( K \) RTT generated questions \( \{Q_1, Q_2, \ldots, Q_K\} \), first, we extract (cf. Eq. 3) the semantic representation \( h_Q \) for gold question and each RTT questions \( \{h_{Q_1}, h_{Q_2}, \ldots, h_{Q_K}\} \) and form a data matrix \( H \in \mathbb{R}^{(K+1) \times d} \). Later, we perform the linear dimensionality reduction using Principal Component Analysis to project the data matrix \( H \) to a lower dimensional space and obtain the transformed data matrix \( \overline{H} \in \mathbb{R}^{(K+1) \times 2} \). In order to find and compare the most diverse round-trip candidate questions, we exclude the point corresponding to the gold question from \( \overline{H} \). To find a convex maximum volume, we find the convex hull using the Quickhull algorithm (Barber et al., 1996) as follows:

\[
\{p_1, p_2, \ldots, pc\} = \text{ConvexHull}(\overline{h}_1, \overline{h}_2, \ldots, \overline{h}_K)
\]

The convex hull are the smallest convex set that includes all points \( \overline{h}_1, \overline{h}_2, \ldots, \overline{h}_K \). The points \( \{p_1, p_2, \ldots, pc\} \) are the vertices of the convex hull. It also guarantees to obtain the maximum semantic area with the selected points. Intuitively, it selects the RTT questions which are diverse in nature.

However, the vertices of the convex hull do not reduce the redundant points over the convex hull, and it lacks the notion of semantic distance from the point representing the gold question. Due to this, it usually selects the redundant round-trip generated questions (cf. Figure 2). To tackle this, first, we compute the euclidean distance \( d(p_g, p_i) \) between the point \( p_g \) representing the gold question and each point \( p_i \) from the vertices of convex hull. Then, we only select the farthest apart round-trip question \( Q_j \) to include in the dataset if their semantic point in vector space represented by \( p_j \) is greater than an optimal threshold.

\[
D = \{d(p_g, p_i) \mid i = 1, 2, \ldots, C\}
\]

\[
p_j = \arg \max_{p_1, p_2, \ldots, pc} (D)
\]

Finally, we select the optimal subset of the questions as follows:

\[
D_{rtt+qsv} = \{(\hat{Q}_j, S_j) \mid d(p_g, p_j) > \lambda\}
\]

where \( \lambda \) is an optimal threshold and chosen based on the performance of CHQ summarization on the validation dataset.

### 4 Experiments

#### 4.1 Datasets

We experimented with a benchmark CHQ summarization dataset (MeQSUM) (Ben Abacha and
Demner-Fushman, 2019). The MeQSUM dataset consists of domain-expert labeled 1000 question-summary pairs. The dataset is derived from de-identified consumer health questions (CHQs) received by the U.S. National Library of Medicine, National Institute of Health. Similar to the Ben Abacha and Demner-Fushman (2019), we augmented additional 4,655 pairs of medical questions and shorter questions obtained from (Ely et al., 2000) to the original MeQSUM dataset. We use 5,055 question-summary pairs as a training dataset, 100 sample pairs for validation, and 500 sample pairs for testing. We also experimented on an additional test collection containing 100 question-summary pairs released in BioNLP 2021 MEDIQA-QS shared task challenge (Ben Abacha et al., 2021) that has the same training set as the MeQSUM dataset.

We evaluated the performance of the proposed models using ROUGE (Lin, 2004). Following the existing works (Fabbri et al., 2021; Yadav et al., 2022b; Gliwa et al., 2019; Yadav et al., 2022a, 2021b), we reported the Rouge-1, Rouge-2, and Rouge-L. Additional implementation details are in the Appendix.

4.2 Experimental Setups

We design the following experiments to assess and compare the role of round-trip translation and the proposed data selection objective measures.

1. Original Data: We trained the question summarization system with the gold-standard training dataset ($D_{orig}$) which consist of source question and target summary and evaluated the performance on the test dataset.

2. RTT: We augmented the RTT questions with the original data and obtained $D_{en+xx}^{naa}$ (cf. Eq. 2). We performed this experiment with five different languages (xx): Spanish (es), German (de), Japanese (ja), Chinese Simplified (zh-CN), and Chinese Traditional (zh-TW).

3. RTT + FQD: We utilize the FQD based objective measure to select the optimal subset of RTT synthetic questions. The selected synthetic questions ($D_{en+xx}^{rtt+prqd}$) with the original questions ($D_{orig}$) are used to train the question summarization system.

4. RTT + PRQD: We use the PRQD based objective measure to select the optimal subset of round-trip translated synthetic questions. Similar to the RTT + FQD, we use selected synthetic questions ($D_{en+xx}^{rtt+prqd}$) along with the original questions ($D_{orig}$) to train the question summarization system.

5. RTT + QSV: With this experimental setup, we select the optimal subset from round-trip translated synthetic questions based on question semantic volume obtained from the five different languages. We train the system with $D_{rtt+qsv}$ dataset (cf. Eq. 12) along with the original questions ($D_{orig}$).

4.3 Results

We report the results on MeQSUM datasets in Table 1. The results shows that our proposed method outperforms all the baselines in terms of Rouge-1, Rouge-2 and Rouge-L metrics on MeQSUM. Additionally, we also compared our proposed methods with the state-of-the-art techniques on MeQSUM. As evident from Table 1, our method outperforms the array of existing approaches on both datasets (in term of Rouge-L) without the need for any additional human-annotated training dataset. On MeQSUM, Mrini et al. (2021) obtained the best performance in terms of Rouge-1 and Rouge-2. It is to be noted that (Mrini et al., 2021) performed experiments on large-scale datasets from various healthcare forums which are restricted for data sharing and crawling. Therefore, to not breach the privacy concern of users, we did not considered those datasets for our experiments.

To understand the role of different data selection method, we carried out a deep analysis of the results (cf. Table-2 and Table 7 in Appendix) both in terms of the performance (Rouge-1, Rouge-2, and Rouge-L) and the number of training samples selected. The results show that augmenting data via RTT significantly improves the performance of the model on all the three metrics. Especially with Frechét Question Distance, we achieve the highest Rouge-1, Rouge-2, and Rouge-L scores 46.59, 29.33, and 49.68 respectively. We also observe a similar gain on all the other language pairs with FQD. The FQD proved to be better amongst all the measures as it consider the semantic distance between the gold question and RTT generated question in the distributional space compared to the PRQD which computes a more abstractive distance. The PRQD based objective measure also achieve significant performance improvement over RTT in all five languages. Our final semantic-volume-based objective measure obtained the improvement of 2.35/3.01/2.61 on Rouge-1/Rouge-2/Rouge-L.
We observed a little higher improvement on Rouge-1 compared to other methods. This confirms our data selection measures ensure the performance of the CHQ summarization model.

| Methods | Rouge-1 | Rouge-2 | Rouge-L |
|---------|---------|---------|---------|
| Baseline Methods | 25.28 | 14.39 | 24.64 |
| ProphetNet + RL rewards (Yadav et al., 2021) | 24.67 | 27.68 | 47.34 |
| BART + Data-Augmented Joint Learning (He et al., 2021) | 25.8 | 26.5 | 33.40 |
| BertSumm (Liu and Lapata, 2019) | 26.24 | 16.20 | 30.59 |
| T5 (Rafel et al., 2020) | 30.96 | 20.18 | 42.05 |
| PEGASUS (Zhang et al., 2020a) | 42.30 | 24.83 | 43.74 |
| ProphetNet (Qi et al., 2020) | 43.87 | 25.99 | 46.52 |
| RTT + QSV | 46.59 | 29.33 | 49.68 |
| RTT+PRQD | 45.48 | 27.74 | 48.61 |
| RTT+QSV | 45.22 | 29 | 49.13 |

Table 2: Performance of proposed methods (best on es language) on MeQSUM. The results for remaining languages can be found in Appendix (Table 7).

Table 3: Comparison of our proposed methods with the best performing models on the MEDIQA-QS test set.

| Method | Rouge-1 | Rouge-2 | Rouge-L |
|--------|---------|---------|---------|
| Baseline Methods | 29.6 | 10.7 | 26.7 |
| T5 (Rafel et al., 2020) | 31.2 | 11.8 | 28.1 |
| PEGASUS (Zhang et al., 2020a) | 28.6 | 9.8 | 25.8 |
| ProphetNet (Qi et al., 2020) | 30.3 | 11.1 | 26.5 |
| Adversarial Training (Xu et al., 2021) | 34.03 | 13.98 | 29.62 |
| Transfer Learning (Lee et al., 2021) | 33.52 | 15.97 | 30.90 |
| Generative Transformers (Sanger et al., 2021) | 33.40 | 15.99 | 31.49 |
| Knowledge-based Method (He et al., 2021) | 35.14 | 16.08 | 31.31 |
| Proposed Methods | 35.40 | 15.00 | 30.80 |
| RTT+FQD | 36.80 | 15.30 | 32.10 |
| RTT+PRQD | 36.20 | 15.10 | 31.60 |
| RTT+QSV | 36.30 | 15.40 | 32.00 |

4.4 Discussion

The results thus satisfy our two major claims: (i) The data generated using the RTT helps to improve the performance of the CHQ summarization model by a significant margin, and (ii) our proposed diversity and semantic-volume-based objective measures are highly effective in filtering out redundant and undesirable RTT questions, which makes the augmented data more informative and helpful in further improving the performance of the system. Amongst all the objective measure QSV select least amount of RTT samples, it is because QSV follow the two-steps (hull formation, maximizing the distance from gold summary) process to evaluate the informative and diverse samples. We analyze the 82.3% samples was excluded at the first step as they do not form the hull.

From the obtained results, FQD can be chosen among the proposed three objective measures. Although the use of FQD does not lead to selection of least training RTT samples, the results obtained by FQD are consistent and are very near to the optimal solution across all the languages. The complexity of FQD lies in estimating the mean and co-variance of the Gaussian. For the PRQD computation, we need to compute multiple precision and recall to form the PRD curve. The computation of precision and recall is computationally intense as the samples should be compared based on statistical regularities, which requires to obtain the histogram over the k-means clustering of the union of two semantic representations as discussed in Sajjadi et al. (2018). For the QSV, we need to obtained multiple (K) round-trip translated questions followed by their 2-d projection using PCA which requires $O(2 + d^2)$.
Thereafter, we need to obtain the convex hull of the projection which requires $O(K \log K)$. Thus, the PRQD and QSV are computationally intense objectives compared to the FQD.

4.5 Evaluation on Healthcare Answer Retrieval Task

To determine whether the summarized questions can help in improving the answer retrieval performance, we performed experiments on the LiveQA 2017 test set (Abacha et al., 2017), consisting of 104 medical questions from the National Library of Medicine (NLM). The task aims to retrieve a correct answer to each medical question. Towards this, we used our best-performing method (FQD) on the CHQ summarization task to generate a summary for the LiveQA questions. We utilized the answer retrieval model developed in Yadav et al. (2022) to retrieve the answer from the MedQuad collection. We used the judgment scores by established by the LiveQA shared task to judge the quality of retrieved answers: “Correct and Complete Answer” (4), “Correct but Incomplete” (3), “Incorrect but Related” (2) and “Incorrect” (1). We excluded those questions for which the top answer’s judgment score was unavailable. In this process, we evaluated common 48 questions for which human judgment scores were available across original questions, model-generated summarized questions and human-generated summarized questions.

Results We used the official evaluation metrics proposed by the LiveQA shared task to compare the performance of answer retrieval using the original versus summarized questions. Please note these metrics evaluate the first retrieved answer for each test question:

- **avgScore(0-3):** the average score for test questions by transferring 1-4 level grades to 0-3 scores. This is the main score to rank the LiveQA systems.
- **succ@k:** the number of questions with a score $k$ or above ($k = \{2, 3, 4\}$) divided by the total number of questions in test set.
- **prec@k:** the number of questions with a score $k$ or above ($k = \{2, 3, 4\}$) divided by the number of questions answered by the system.

Table 4 shows the results obtained by the QA system using: (i) the original questions, (ii) the summarized questions by FQD, and (iii) expert-created reference summaries as reported in (Ben Abacha and Demner-Fushman, 2019).

| Measures      | Original Questions | Human Generated Reference Summaries | FQD Generated Summarized Questions |
|---------------|--------------------|-------------------------------------|-----------------------------------|
| avgScore(0-3) | 0.384              | 0.557                               | 0.48                              |
| succ@2       | 0.23               | 0.336                               | 0.288                             |
| succ@3       | 0.13               | 0.144                               | 0.144                             |
| succ@4       | 0.104              | 0.172                               | 0.172                             |
| prec@2       | 0.5                | 0.72                                | 0.58                              |
| prec@3       | 0.25               | 0.312                               | 0.312                             |
| prec@4       | 0.083              | 0.101                               | 0.101                             |

Table 4: Evaluation of the answers retrieved using the original, human-generated, model-generated summaries based on the LiveQA metrics.

The results show that summarizing the CHQ can significantly improve the performance of the IR/QA system in retrieving relevant answers from the collection of curated answers. We also observe that the performance of the IR/QA model using the automatically summarized questions by our proposed approach is close to the performance achieved using the manually created reference summaries.
Is EPI743 an effective treatment for leigh syndrome? 

Proposed Approach: Can leigh disease be treated with EPI743? 

Table 6: Generated summaries on the MEQSUM. Example-I shows an acceptable summary and model capability of generating novel words ("abdominal pain") without being present in the original question. The second example shows a semantically correct summary.

4.6 Human Analysis

To understand the role of each data selection measures, we conducted human analysis on randomly selected 50 x 5 languages samples from RTT datasets. A set of 2 annotators experts in medical informatics evaluated the selected questions on the basis of diversity, informativeness, and factual consistency to measure (1) whether the RTT questions have novel n-grams, (2) whether the semantics of the original question was retained in the RTT questions and (3) whether the salient medical information were present in the selected RTT questions. We also instructed annotators to annotate the generated summaries into one of the following categories: ‘Incorrect’, ‘Acceptable’, and ‘Perfect’ and also report the whether the summary was ‘fluent’ or not. We reported the detailed quantitative analysis in Table 5. The results shows that FQD outperforms the other objective measures in terms of selecting more diverse and factually correct questions. Figure 3 shows the de-identified CHQ selected by the different objective measures. In our second analysis on the generated summary (cf. Table 5), we again observed the superiority of defined objective measures over the ProphetNet model (trained without the augmented data). This confirms the effectiveness of data selection objective measures that enhance the model learning ability by introducing diverse and informative questions (cf. Table 6), leading to the higher proportions of perfect summaries. We also conducted error analysis on generated summaries and identified two main source of errors: (i) the original questions consists of multiple sub-questions, and, (ii) if the question focus (medical entities) are not transformed into correct medical terminologies.

5 Conclusion

This work propose novel data selection strategy based on the concept of round-trip translation for consumer health question summarization. We devised three major data selection objective measures: FQD, PRQD and QSV based on the distributional distance to optimally select the diverse and informative samples from the pool of round-trip translated data. Extensive experiments show that proposed methods can effectively improve the performance without any additional labelled data. We also achieves new state-of-the-art results on benchmark consumer healthcare question summarization datasets. In future, we plan to explore these objective measures on other resource-scarce tasks.

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To decode the summary, we use beam search algorithm with beam size $4$. The pre-trained large uncased version of ProphetNet is used as the base encoder-decoder model. We use the fine-tuned version of MPNet from Huggingface (Wolf et al., 2020) to extract the semantic representation of the questions. We use the Google translation service to translate the question into pivot language and then back-translate them into English. To decode the summary, we use beam search algorithm with beam size $4$. We fine-tuned the summarization models on the respective training dataset for 15 epochs. The length of maximum original questions and summarized questions are set to 120 and 20, respectively. We choose the optimal value of pairs of hyper-parameters $(\mu_1, \mu_2)$, $(\beta_1, \beta_2)$ and $\lambda$ using the grid search. We found the optimal pairs $(\mu_1, \mu_2) = \{(0.17, 0.4), (0.25, 0.35), (0.05, 0.23), (0.19, 0.3), (0.04, 0.17)\}$, $(\beta_1, \beta_2) = \{(0.3, 0.85), (0.3, 0.6), (0.3, 0.6), (0.55, 0.85), (0.4, 0.85)\}$ on languages $es$, $de$, $ja$, $zh-CN$ and $zh-TW$, respectively. We obtain the $0.8$ as optimal value of $\lambda$. To compute PRQD, we follow the official implementation with the hyper-parameter value $p = 1001$.

We obtained the first two principal components using the scikit-learn library (Pedregosa et al., 2011). The convex hull is computed using the Sci-py Qhull library (Virtanen et al., 2020). To compute Rouge, we use the py-rouge implementation.

To update the model parameters, we used Adam (Kingma and Ba, 2015) optimization algorithm with the learning rate of $7e^{-5}$ in all the experiments. We also used the cosine annealing (Loshchilov and Hutter, 2017) based learning rate decay scheduler, where the learning rate decreases linearly from the initial learning rate in the optimizer to $0$. We have checked for the software usage agreements. The licence details of the used software are as follows: ProphetNet and MPNet Huggingface (Apache-2.0 License), Google Translate (Apache-2.0 License), scikit-learn (BSD-3-Clause License), scipy (BSD-3-Clause License).

Computing Infrastructure: We performed all the experiments on a single NVIDIA Tesla V100 GPU having GPU memory of 32GB.

Average Run Time: The average runtime (for each epoch) to fine-tune the ProphetNet model on original and RTT augmented datasets are recorded as 10.4 and 20.5 minutes respectively. For the FQD, PRQD and QSVD objective based methods the average run time range between 11.5 and 17.2 minutes. It depends upon the number of samples selected for a particular pivot language.

Number of Parameters: The ProphetNet model has 391.32 million parameters. Since, we used the same model for all our experiments there fore we have the same 391.32 million parameters in all variants of the proposed methods.

A.3 Limitation

In this study, we evaluated the model generated summary using Rouge-1, Rouge-2 and Rouge-L metrics. However, these automatic evaluation metrics do not fully capture the nuances of what should or should not be included in a consumer question summary. Although we have performed human evaluation on a subset of summary, it has to be valued.
| Method       | Rouge-1 | Rouge-2 | Rouge-L | % of Additional Samples |
|--------------|---------|---------|---------|-------------------------|
| Original Data| 43.87   | 25.99   | 46.52   | –                       |
| es RTT       | 44.67   | 27.68   | 47.34   | 100                     |
| es RTT+FQD   | 46.59   | 29.33   | 49.68   | 13.16                   |
| es RTT+PRQD  | 45.48   | 27.74   | 48.61   | 75.31                   |
| de RTT       | 45.43   | 29      | 48.41   | 100                     |
| de RTT+FQD   | 46.5    | 29.53   | 49.45   | 6.85                    |
| de RTT+PRQD  | 46.38   | 29.47   | 49.4    | 71.27                   |
| ja RTT       | 45.86   | 27.8    | 48.32   | 100                     |
| ja RTT+FQD   | 46.17   | 29.39   | 49.48   | 59.06                   |
| ja RTT+PRQD  | 46.02   | 28.2    | 49.26   | 81.34                   |
| zh-CN RTT    | 44.81   | 27.71   | 47.75   | 100                     |
| zh-CN RTT+FQD| 45.75   | 28.04   | 48.71   | 17.55                   |
| zh-CN RTT+PRQD| 45.66  | 28.54   | 48.6    | 11.36                   |
| zh-TW RTT    | 45.23   | 27.76   | 48.12   | 100                     |
| zh-TW RTT+FQD| 46.13   | 28.45   | 49.16   | 51.46                   |
| zh-TW RTT+PRQD| 45.88  | 27.69   | 48.66   | 67.02                   |
| RTT+QSV      | 46.22   | 29      | 49.13   | 2.00                    |

Table 7: Performance comparison across all the languages on the proposed methods.

A.4 Potential Risk

The ProphetNet pre-trained language model used in this study are not checked for social bias and diversity. It may not be the representative of the whole world population and may contains region, community, race or gender specific biases.

A.5 Ethics / Impact Statement

Our project involves publicly available datasets of consumer health questions. It does not involve any direct interaction with any individuals or their personally identifiable data and does not meet the Federal definition for human subjects research, specifically: “a systematic investigation designed to contribute to generalizable knowledge” and “research involving interaction with the individual or obtains personally identifiable private information about an individual.”