Activity report analysis with automatic single or multi span answer extraction

Ravi Choudhary, Arvind Krishna Sridhar, Erik Visser
Qualcomm QTI Technologies Inc
ravichou@qti.qualcomm.com, arvisrid@qti.qualcomm.com, evisser@qti.qualcomm.com

Abstract

In the era of IoT (Internet of Things) we are surrounded by a plethora of AI enabled devices that can transcribe images, video, audio, and sensors signals into text descriptions. When such transcriptions are captured in activity reports for monitoring, life logging and anomaly detection applications, a user would typically request a summary or ask targeted questions about certain sections of the report they are interested in. Depending on the context and the type of question asked, a question answering (QA) system would need to automatically determine whether the answer covers single-span or multi-span text components. Currently available QA datasets primarily focus on single span responses only (such as SQuAD[4]) or contain a low proportion of examples with multiple span answers (such as DROP[3]). To investigate automatic selection of single/multi-span answers in the use case described, we created a new smart home environment dataset comprised of questions paired with single-span or multi-span answers depending on the question and context queried. In addition, we propose a RoBERTa[6]-based multiple span extraction question answering (MSEQA) model returning the appropriate answer span for a given question. Our experiments show that the proposed model outperforms state-of-the-art QA models on our dataset while providing comparable performance on published individual single/multi-span task datasets.

Keywords— Natural Language Processing, Extractive Question-Answering, MultiSpan QA systems

1 Introduction

Machine reading comprehension[1], specifically extractive closed-domain question-answering, is an active field of research in natural language processing. Solving question-answering tasks has a variety of real-world applications, in particular in AI assistants for personal and business use (clinical[2], retail distribution[3] etc). Extractive single span question-answering has recently advanced to the point where machines can now compete with, if not outperform, human question-answering capability[4].

Progress in question answering can be tracked by reviewing performance on typical benchmark databases and tasks[5,6,8,9]. Most state-of-the-art question-answering datasets consist of only single-span question-answer pairs, or answers consisting of only one single extracted word. The SQUAD[5] dataset, which has over 100,000 single-span questions and is larger than most previous question-answering datasets, is one example of this type of dataset. SQUAD has several answer types, including Date, Person, and Location, and its passages cover a wide range of topics. The SQUAD 2.0[5], combines the original questions in with new unanswerable questions, forcing models to learn when to refrain from answering. Likewise, the DROP[6,7] datasets are also extractive, closed-domain datasets with a low proportion of multi-span question-answer pairs (6.0 percent for DROP and 15.68 percent for MASHQA[8]). Compared to SQUAD, the questions in DROP are more involved to force the system to have a deeper understanding of the passages semantics and answer them via discrete reasoning. HotpotQA[9] dataset focuses on multi-hop questions, which require accessing multiple documents to generate an answer.
Some of the most popular QA models are based on BERT[4] and its variations, RoBERTa[10], MobileBERT[11] and ALBERT[12]. BERT[4] is capable of executing a variety of general NLP tasks, such as next sentence prediction, masked Language Modeling (LM), Natural Language Inference (NLI), etc. RoBERTa, or Robustly Optimized BERT approach, introduces alternative strategies for the BERT training process to improve performance. Key differences between RoBERTa and BERT include longer training times and an order of magnitude more training data. A BERT based multi span QA model MTMSN[13] predicts a number of spans as a classification task and then picks top K spans from a single QA model. From these top spans, it then picks non-overlapping spans using non-maximum suppression (NMS) algorithm[14] by removing unnecessary tokens from the answer span. Tag-based-multispan prediction(TASEIO + SSE)[15] is based on a ROBERTa model and solves a task similar to Named Entity Tags (NER) or Part of Speech (POS) tasks. Finally MASHQA[8] model, built on Transformer- XL[16], classifies every sentence whether a sentence has an answer or not, by combining a representation of each sentence with a representation of paragraph and question. While these QA datasets and models address either single or multi span answering tasks, they do not address the problem of determining whether a single or multi span answer is needed for a particular question. This discrimination task is for example necessary in a scenario where users would like to query activity reports obtained from AI enabled devices generating text descriptions from various logged multimedia and sensors content. Such reports are generated in lifelogging, monitoring or anomaly detection applications over extended periods of time and may contain expected or unexpected events. This in turn may prompt a user to ask targeted questions about a known occurrence or more vague questions covering a longer period of time or range of topics. A user may for instance ask questions such as Where was X at 4pm? or What happened at location Y in the morning?. While the former requires a single span answer (i.e. Xs location), the latter question requires the system to gather a multi span answer from information spread out over a number of sentences (i.e. list all events that happened at location Y in the am). Figure 1 illustrates the various types of spans recovered depending on the question asked in the case of querying an activity report in a smart home use case.

In this paper, we propose a ROBERTa[10] based QA system that can return the appropriate single or multi span answer depending on the question asked and the context being queried. Its performance is illustrated on a custom dataset for a smart home use case where multiple AI modules are transcribing image, video, audio and sensors signals into text descriptions and logging them in activity reports. We also show that the proposed QA system provides competitive performance on existing single and multi-span benchmark datasets compared to state-of-the-art models. The paper is organized as follows: section 2 describes the custom dataset developed and proposed QA model architecture, section 3 the evaluation results and we conclude with section 4.
2 Approach

2.1 Custom dataset generation process

To illustrate our proposed QA system, we evaluate its performance on prior art datasets as well as a custom in-house dataset for the smart home use case described. The latter, called SmartHome dataset, consists of paragraphs describing various user’s activity patterns in locations around a home throughout the day. It is logging information such as how a user was feeling, what commands they uttered when using smart assistants, activities detected from sound/sensor/video etc. in natural language form. We assume such natural language activity reports can be generated by aggregating descriptions from AI modules tagging video/camera/audio/sensor signal content with object detection, emotion detection, video/image/audio understanding etc. approaches.

To simulate the dataset passage, each generated context contains a list of sentences and each sentence is obtained by putting sensor/sound/video identified entities in a template along with a timestamp and location. To simulate questions for such a dataset, we wrote a simple template based structural program to create a list of synthetic complex question starting with interrogative pronouns such as “what”, “when”, “where”, “who” as well as “Did he/she”, “Is/Was he”) for a given paragraph. In addition, we included temporal events-based questions such as “When did X perform . . . ”, “What did Y do before/after certain time”, “What emotional state Z was at a particular time”, etc. Figure 1 illustrates the content of the generated activity report and Figure 2 lists a few examples of typical questions. The type of question and their distribution is shown in Fig 2 (Visualization is created using a github repository https://github.com/mrzjy/sunburst).

Figure 2: Trigram prefix distribution of the questions in SmartHome dataset and a list of some questions generated using a simple template based structural program.

For a given sentence in a paragraph and created question, the corresponding answer text is obtained deterministically along with a start id and end id. Since sentences are generated using a template, the location of the answer is fixed and can be obtained by using some rules. For example, for the sentence “At 6 am, Jenny was exercising on the yoga mat in living room”, the index of time “6 am”, person name “Jenny”, activity description “exercising on the yoga mat” and location “living room” are known and fixed given the generation template described above. Hence, the answer to question “When Jenny was doing exercise?” can be extracted as “6 am” from index 1 of the generated sentence.

2.2 Model Architecture

In this section, we describe each step from the pipeline of our proposed system called Multi Span Extraction Question Answering (MSEQA). The pipeline consists of a multi-task learning framework to select the appropriate answer span/type and is illustrated by Figure 3. Our model uses RoBERTa as encoder mapping word embeddings into contextualized representations using pre-trained Transformer blocks. Based on these representations, we employ a multi-type answer predictor providing the following classification: (1) span from the text; (2) answer Type; (3) multi-span/single span. We first predict the answer type of a given passage-question pair, and then adopt individual prediction strategies. To support multi-span extraction, the model explicitly predicts relevant sentences in a paragraph.

2.2.1 Multitask RoBERTa Encoder

For a given token sequence \( X = [x_1, x_2, ..., x_T] \), RoBERTa[10], a deep Transformer network, outputs a sequence of contextualized token representations \( H_L = [h_{L,1}, h_{L,2}, ..., h_{L,T}] \). RoBERTa-Base, denoted as block 1
in Fig 3, is made up of 12 Transformer layers (L = 12), each with 12 heads and a hL vector of size 768. Special markup tokens [CLS] and [SEP] are added to the beginning and end of the input sequence as an essential preprocessing step for RoBERTa. In cases where there are two separate input sequences, one for the question and one for the given context, such as MRC, an additional [SEP] is added between the two to form a single sequence.

2.2.2 MultiSpan Predictor

The MultiSpan Predictor, denoted as block 2 in Figure 3, is a single FC connected layer which uses a hidden representation of [CLS] token to classify whether the question has a multi-span output or not. Execution is shifted to block 3 if the model predicts a single-span answer, and to block 4 if the model predicts a multi-span answer, as shown in Figure 3. It is done using categorial classification with

$$p_s = \text{softmax}(\text{FFN}([h_L[CLS]]))$$

where $h_L[cls]$ is the combined representation of question and context, $p_s$ is probability of question having single span answer or multi-span answer.

2.2.3 Answer Type Predictor

The Answer Type prediction module, denoted as block 3, has two logically connected submodules, one identifying the single-span output and the other module determining if the answer is Yes, No or Unknown. Except for the Unknown answers, each answer is an extractive span in the passage or a Boolean answer. We use a FC layer to get the start logits and end logits for each token in the context. For Yes/No/Unk classification, a single FC layer is applied to the RoBERTa’s CLS output to obtain three logits for each class. We use start and end score of CLS against all other tokens to decide if we want to find a single span answer or logical reason answer (Yes No Unknown). If CLS has the highest score then we use a categorical variable to decide between the above three answer types, with probabilities, $p_a$, computed as:

$$p_a = \text{softmax}(\text{FFN}([h_L[CLS]]))$$

Otherwise, we find a span with highest score for a correct answer using the probabilities of the starting, $p_{start}$, and ending positions, $p_{end}$, from the passage as:

$$p_{start} = \text{softmax}(\text{FFN}([H_L]))$$

$$p_{end} = \text{softmax}(\text{FFN}([H_L]))$$

where FFN is a two-layer feed-forward network with the GELU activation.
2.2.4 Multi-Span Tagger

In our multispan tagger layer, denoted as block 4, we pair each sentence in the context with the question in the input format: `<CLS><QUESTION><SEP>SENTx` where x is 1, 2,...n denote the sentence index. We classify the CLS representation to identify if the sentence is relevant for the given query as

\[ p_t = \text{softmax}(FFN([h_L[Q] : h_L[Senti]])) \]  

where \( p_t \) is probability of each sentence being an answer or not, \( h_L[Q] \) and \( h_L[Senti] \) is pooled contextualized representation of the question and ith sentence respectively. `:` denotes a concatenation operator.

2.2.5 Objective

The training objective of our multitask learning model is to minimize the following linear combination of question answering (\( L_q \)), answer-type prediction (\( L_a \)), multispan prediction (\( L_s \)) and multispan tagger losses (\( L_t \)), with \( \lambda_q, \lambda_a, \lambda_s \) and \( \lambda_t \) being their respective weights: 

\[ L = \lambda_q L_q + \lambda_a L_a + \lambda_s L_s + \lambda_t L_t \]  

Different tasks use different types of loss functions. The loss function for the question answering task i.e., \( L_q \) is the loglikelihood of the correct start and end positions whereas the loss function for other tasks is cross entropy loss. Inspired by the work done in unifiedQA[17], we first pretrained the Roberta encoder on a combination of multiple datasets (SQuAD2.0, QuAC[18], HotPotQA[9], and BooleanQA[19]). The models in blocks 2, 3 and 4 on the other hand were randomly initialized and trained from scratch using multi-task objective (6).

3 Experiments

3.1 Datasets

We evaluate our proposed model on three datasets, including SmartHome, DROP and MASHQA.

1. SmartHome, as explained in 2.1, is made up of sequence of daily events which usually span 3 or more words. It comprises of 3.16k passages with 300k questions with a train-validation-test split of 80:12:8.
2. DROP is a reading comprehension dataset comprising of complex questions that require Discrete Reasoning over Paragraphs. It’s passages were extracted from Wikipedia while the crowdsourced questions fall into three answer types – spans of text, date and numbers. Since our objective is to automate the selection of answer span types, we filtered out the QA pairs to contain only the spans of text as answer type as a part of our data preprocessing step.
3. MASHQA is an extractive QA dataset, with multiple answer spans, curated by experts from consumer health domain. On an average, its passages are 3.3 times longer than DROP requiring the QA model to overcome long context problem.

The latter two datasets are chosen to benchmark MSEQA on publicly available datasets and to represent different kinds of passage comprehension domains, passage & answer lengths as well as reasoning types.

3.2 Implementation Details

Our model’s implementation is based on the PyTorch[20] implementation of RoBERTa from a huggingface[21] library. With a learning rate of 4e-5 and a batch size of 16, we use AdamW[22] as our optimizer. The epoch count is set to 10. Linear warmup strategy is employed for the first 6% of steps, followed by a linear decay to 0. The maximum lengths for query and context sentences were fixed to 128 and 64 tokens, respectively. For the multispan tagger, we set number of sentences in a context (n) to 26. The gradient norm is clipped to within one to avoid the gradient exploding problem. All texts are tokenized with BytePair Encoding (BPE)[23] and chopped into sequences of no more than 512 tokens.

3.3 Main Result

To illustrate the effectiveness of MSEQA, we demonstrate its performance relative to state-of-the-art multi-span models reviewed in section 1 – TASEI0+SSE[15], MTMSN[13] and MASHQA[8]. In line with the models in comparison, we adopt F1 & Exact Match (EM) scores as our evaluation metric. The F1 & EM scores for DROP, MASHQA and SmartHome datasets are presented in Table 1 & 2 for both base and large model types. We study the performance of the models on individual datasets in Table 1. It shows that MSEQA outperforms SOTA on SmartHome and MASHQA while it exhibits slightly worse results in DROP compared to TASEI0+SSE.
| Model                  | Single Span | MultiSpan | Overall |
|------------------------|-------------|-----------|---------|
|                        | EM F1       | EM F1     | EM F1   |
| **DROPC**              |             |           |         |
| MTMSN (BERT-base)      | 64.5        | 23.1      | 60.8    |
| MTMSN (BERT-large)     | 70.5        | 25.1      | 65.8    |
| Tag-Based (Roberta-base)| 65.6        | 37.3      | 62.9    |
| Tag-Based (Roberta-large)| 70.6       | 50.8      | 68.5    |
| MSEQA (Roberta-Base)   | 65.1        | 46.9      | 63.1    |
| MSEQA (Roberta-Large)  | 70.4        | 50.6      | 68.4    |
| **SMARTHOME**          |             |           |         |
| MTMSN (BERT-base)      | 69.5        | 26.1      | 53.7    |
| MTMSN (BERT-large)     | 74.5        | 31.1      | 58.7    |
| Tag-Based (Roberta-base)| 69.7        | 41.3      | 59.4    |
| Tag-Based (Roberta-large)| 76.6       | 59.8      | 70.5    |
| MASHQA (XLNet)         | 69.2        | 63.2      | 67.0    |
| MSEQA (Roberta-Base)   | 67.9        | 56.7      | 63.6    |
| MSEQA (Roberta-Large)  | 80.5        | 64.8      | 74.2    |
| **MASHQA**             |             |           |         |
| MASHQA (XLNet)         | 23.2        | 21.7      | 21.5    |
| MSEQA (Roberta-Base)   | 24.3        | 21.8      | 22.1    |
| MSEQA (Roberta-Large)  | 24.6        | 22.4      | 22.7    |

Table 1: The performance of the baseline models along with our multispan question answer model, MSEQA, trained on datasets individually

| Model                  | Single Span | MultiSpan | Overall |
|------------------------|-------------|-----------|---------|
|                        | EM F1       | EM F1     | EM F1   |
| **DROPC**              |             |           |         |
| MTMSN (BERT-base)      | 65.1        | 23.6      | 60.8    |
| MTMSN (BERT-large)     | 71.2        | 25.3      | 66.5    |
| Tag-Based (Roberta-base)| 65.7        | 37.5      | 63.1    |
| Tag-Based (Roberta-large)| 71.8       | 51.3      | 69.7    |
| MSEQA (Roberta-Base)   | 65.5        | 48.9      | 63.4    |
| MSEQA (Roberta-Large)  | 71          | 51.6      | 69      |
| **SMARTHOME**          |             |           |         |
| MTMSN (BERT-base)      | 70.2        | 26.9      | 54.5    |
| MTMSN (BERT-large)     | 75.1        | 31.9      | 59.4    |
| Tag-Based (Roberta-base)| 70.3        | 43.6      | 60.6    |
| Tag-Based (Roberta-large)| 77.8       | 60.2      | 71.4    |
| MASHQA (XLNet)         | 69.4        | 63.1      | 67.1    |
| MSEQA (Roberta-Base)   | 67.9        | 56.5      | 63.6    |
| MSEQA (Roberta-Large)  | 80.2        | 64.2      | 74.4    |
| **MASHQA**             |             |           |         |
| MASHQA (XLNet)         | 24.2        | 21.7      | 21.9    |
| MSEQA (Roberta-Base)   | 25.3        | 22.3      | 22.8    |
| MSEQA (Roberta-Large)  | 25.4        | 22.7      | 23.1    |

Table 2: The performance of the baseline models along with our multispan question answer model, MSEQA, trained on combined set of all the datasets

In Table 2, we trained each model with a combination of all the datasets but tested on individual dataset to see if the models can learn to generalize. From the Table 2 results, we can see a clear increase in F1 & EM scores compared to Table 1 showing genuine improvement in the models’ multi span extraction abilities as it is notable that these datasets are from different domains. Furthermore, the relative performance trend of MSEQA is consistent with Table 1 showing that our proposed approach can improve with further pretraining on more complex reasoning datasets.
| Dataset | Precision | Recall | F1  |
|---------|-----------|--------|-----|
| DROP    | 95.6      | 93.7   | 94.6|
| SMARTHOME | 97.6      | 96.7   | 97.4|
| MASHQA  | 98.7      | 97.5   | 98.1|

Table 3: MSEQA’s Multispan Predictor result

| Precision | Recall | F1  |
|-----------|--------|-----|
| 98.5      | 98.5   | 98.5|

Table 4: Answer-type Predictor result

Next we study the individual component performances of MSEQA to identify any bottlenecks to the overall model capacity. In Table 3, we show the MSEQA capabilities to identify the question’s response as single span or multispan. Multispan classifier is very robust across the datasets in terms of identifying whether question has multiple span for its answer or just a single span. Table 4 displays the answer-type predictor component’s isolated performance on the combination of the datasets. The high F1 score of 98.47 reflects its competence in classifying the answer as Yes, No or Unknown.

We investigate the performance of MSEQA on increasing number of spans. We ran this experiment on SMARTHOME dataset as DROP and MASHQA did not have enough number of samples for more than 3 spans. From the Fig 4, we can observe that the MSEQA’s performance stays consistent across a wide range of spans reinforcing its robustness. We also study the performance of the models by changing the paragraph lengths. All the models show degradation in performance due to the attention span limitation of pretrained transformer-based encoders as investigated in [24]. Compared to the baselines, we can see the least performance drop with MSEQA showcasing its robustness with handling longer paragraph inputs.

4 Conclusion

We present a simple multispan architecture, MSEQA, for multi type question answering by classifying each sentence as a probable answer candidate. We show that when a combination of single/multi-span classifier with multispan tagging is used, the model provides robust answers for multi-span tasks without degrading its performance on single-span questions. As future work, we would like to further process selected sentences from the multi-span tagger and consolidate them into one fluent answer. We also plan to explore ways to put this question answering capability onto edge devices for various applications.

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