DQNC2S: DQN-based Cross-stream Crisis event Summarizer

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Abstract. Summarizing multiple disaster-relevant data streams simultaneously is particularly challenging as existing Retrieve&Re-ranking strategies suffer from the inherent redundancy of multi-stream data and limited scalability in a multi-query setting. This work proposes an online approach to crisis timeline generation based on weak annotation with Deep Q-Networks (DQNs). It selects on-the-fly the relevant pieces of text without requiring human annotations or content re-ranking. This makes the inference time independent of the number of input queries. The proposed approach also incorporates a redundancy filter into the reward function to handle cross-stream content overlaps effectively. The ROUGE and BERTScore results achieved on the CrisisFACTS 2022 benchmark are better than those of the best-performing models.

Keywords: Cross-Stream Temporal Summarization · Crisis Management · Timeline Generation · Reinforcement Learning · Text Retrieval

1 Introduction

Automating the extraction of valuable information from large streams of social and news data is particularly relevant to crisis management as could become an active support to disaster-response personnel [12,21]. The problem of generating crisis event summaries of time-evolving data streams has already been addressed by the Temporal Summarization [3] (TS) and Incident Stream [14] (IS) challenges, where the goals are to extract variable-length summaries for a particular event on a set day (TS) and to classify and prioritize information in a single social stream (IS), respectively. More recently, the CrisisFACTS task [13] has focused on retrieving daily timelines from social/news data streams. The main challenges are (1) The contemporary presence of multiple streams of crisis-relevant data (Twitter, Reddit, Facebook, and News), which makes the input collection particularly redundant and complex to summarize; (2) The lack of human annotations on text relevance and topic-level clusters, which limits the scope of supervised techniques; (3) A list of queries about information needed by emergency responders for each emergency event, which increases the complexity compared to single-query tasks. State-of-the-art approaches to the CrisisFACTS task (unicamp [17] and ohmkiz [22]) rely on ColBERT[10] or on the established

Retrieve&Re-ranking approach. This last one entails retrieving the pieces of text relevant to an input query first and then re-rank them. The retrieval step is commonly driven by text relevance scoring functions stored in index structures (e.g.,BM25 [20], Dense Passage Retriever [9]) whereas the re-ranking step is commonly based on neural models such as ColBERT [10], DRMM [8], and Conv-KNRM [5]. Both end-to-end ColBERT and Retrieve&Rerank approaches scale linearly with the number of input queries and are not designed for online text processing. Furthermore, it is necessary to incorporate a filtering stage after the re-ranking phase thus retrieving large volumes of redundant content in a multi-stream scenario.

This work proposes a new DQN-based Cross-Stream Crisis event Summarizer. It overcomes the main issues of existing approaches to CrisisFACTS by adopting Deep Reinforcement Learning (DRL). DRL has proved to be effective in both recommender systems [1] and text summarization [4]. The key contributions of the present work are enumerated below.

- **DRL approach for online text retrieval.** Unlike state-of-the-art approaches (e.g., [17]), we rely on DRL. Hence, we do not need to index crisis-relevant data for efficient content retrieval. Conversely, we retrieve relevant texts on the fly from the input streams without any human supervision.
- **Early redundancy filtering.** The DRL reward function already incorporates a redundancy filter to reduce the amount of data processed after retrieval. This improves the efficiency and reduces the complexity of the timeline generation method.
- **Efficient multi-query setting.** Unlike existing approaches to CrisisFACTS, our approach inherently supports multiple queries simultaneously , differently from solutions that are still dependent on the number of input queries [24,15]. This allows the efficient generation of timelines of multi-faceted crisis events, where each query refers to a complementary facet.

Our approach performs better than the state of the art on the CrisisFACTS benchmark. The project code is publicly available for research purposes[1].

2 Problem Statement

We address the CrisisFACTS 2022 task first proposed in [13]. The goal is to summarize multiple streams of social and news data describing the same short-lasting crisis event. Let E_a be a set of crisis events about different hazards (see Table 1). We employ cross-validation selecting a subset $E \in E_a$, which will be used to train the model and the remaining events for testing. Each event lasts at least two days within the reference time period T and is described by a set S of streams of textual content, i.e., tweets, Reddit messages, news, and Facebook posts[2]. Stream data consists of timestamped pieces of text te_s^t, where $s \in S$

[1] https://github.com/DarthReca/crisis-dqn Latest access: October 2023

[2] Due to the restrictions in force to the Facebook data crawler, similar to most peers hereafter we will disregard this stream.

Table 1: CrisisFACTS 2022 events

Event ID	Name	Queries	Texts	Days
001	Lilac Wildfire 2017	52	45578	9
002	Cranston Wildfire 2018	52	25172	6
003	Holy Wildfire 2018	52	25482	6
004	Hurricane Florence 2018	51	180286	15
005	Maryland Flood 2018	48	37598	4
006	Saddleridge Wildfire 2019	52	34480	4
007	Hurricane Laura 2020	51	52561	2
008	Hurricane Sally 2020	51	67632	8

and $t \in T$. The task focuses on a set Q_e of event queries for each $e \in E$ that are of interest to emergency responders. Given e, S, and Q_e, the CrisisFACTS task aims at generating a summary of S that consists of daily crisis timelines reporting the top stories related to Q_e on e. On each timestamp (day) t, the timeline consists of a shortlist of *facts*, sorted by decreasing importance, and described by one or more pieces of text te_s^t.

3 Methodology

We present the DQN-based Cross-Stream Crisis event Summarizer (DQNC2S, in short). It encompasses a three-step process. First, we automatically weakly annotate text candidates based on established extractive QA models to guide the training of the DQN. Secondly, our approach relies on Deep Reinforcement Learning to online retrieve relevant yet non-redundant content suitable for daily summaries. Finally, it applies topic modeling and abstractive summarization to synthesize and rephrase the retrieved texts.

Weak Annotation The use of extractive Question Answering (QA) models has proved effective in supporting the generation of crisis-related event descriptions [22]. Inspired by the recent use of SQUAD [18] for evidence estimation, we perform a weak annotation step to create an importance score for each query-text pair. Specifically, given a pair of query $q_i \in Q_e$ and a set S of multiple streams related to crisis event e, we leverage Electra[3] and LongFormer[4] to generate tuples $< q_i, te_s^t, CF >$, where CF is the mean confidence score associated by the QA models to the query-text pair. To avoid local model inaccuracies, a tuple is generated only when both QA models provide an answer with a minimal confidence level of 80%. Each text gets a score Sc equal to the number of queries it provides an answer to.

[3] https://huggingface.co/deepset/electra-base-squad2 Latest access: October 2023
[4] https://huggingface.co/allenai/longformer-large-4096-finetuned-triviaqa Latest access: October 2023

DQN-based Text Retrieval Our retriever is based on a Deep Q-Network [16], which interacts with an environment designed to work online and driven by a single parameter, i.e., the maximum number of retrievable texts. The action space is binary, i.e., $A = 0$ when the text is kept or $A = 1$ when it is discarded. The observation space of size 770 comprises the BERT embedding of the current text (size 768), the remaining percentage of texts P_t that can be chosen (size 1), and the maximum similarity Si_m between the current text and the already kept texts (size 1).

The reward function $\mathcal{R}$ is defined in Equation (1).

$$\mathcal{R} = \begin{cases} -5 & \text{if } Sc = 0 \wedge A = 0 \\ 1 & \text{if } Sc = 0 \wedge A = 1 \\ N_{Sc} * (1 - Si_m) & \text{if } Sc > 0 \wedge A = 0 \\ -N_{Sc} * (1 - Si_m) & \text{if } Sc > 0 \wedge A = 1 \end{cases} \tag{1}$$

Specifically, if $Sc = 0$, the text te_s^t should be discarded as unlikely to be informative (Sc is equal to zero only if te_s^t does not answer the event queries). If te_s^t is kept, the reward is set to -5 (value chosen after reward shaping); otherwise, the reward is set to 1. If te_s^t has a non-zero score ($Sc > 0$), it should be kept only if it is dissimilar enough to any previously selected texts (according to the cosine similarity between the corresponding embeddings) to limit redundancy. We leverage a normalized score $N_{Sc}=\frac{Sc}{|Q_e|}$ to deal with a variable number of queries per event and then re-scale the product by the maximum similarity score Si_m.

An example of the application of this phase is shown in Figure 1. In the example reported in Figure 1, we suppose the input text te_s^t under analysis is not relevant, and the system already selected one relevant text over a maximum of ten retrievable texts.

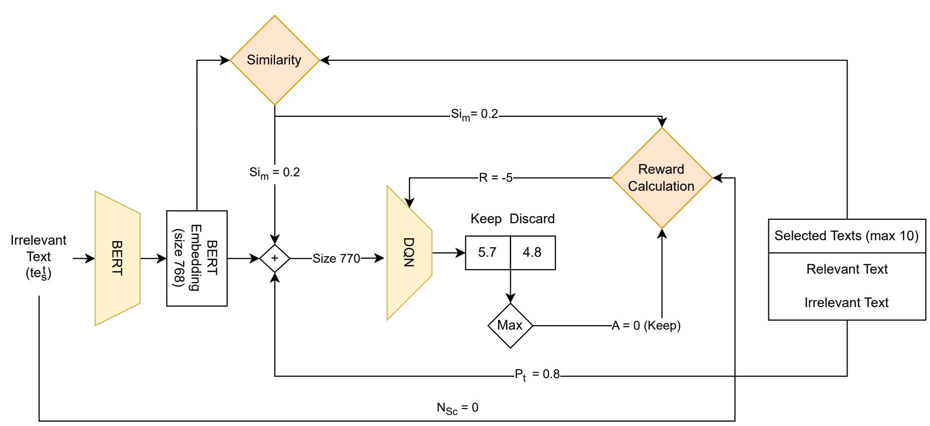


Fig. 1: DQN-based text retrieval. Example of application to an irrelevant text.

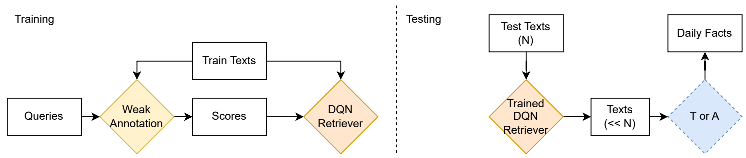


Fig. 2: Pipeline during training in upper part and testing in lower part. During testing, topic modeling (T) or abstraction (A) are optional.

Topic Modeling and Abstraction The outcomes of extractive summarization strategies are often suboptimal when the summary consists of several fragments of (potentially incoherent) text, especially while dealing with social data like tweets or Reddit posts. To cope with this issue, we explore the use of state-of-the-art topic modeling and abstractive summarization techniques, i.e., BERTopic [7] and BART-CNN [11]. The former technique groups the retrieved content into subtopics and provides a more faceted description of each fact. The latter reformulates the original text into a concise and more readable form. DQNC2S-T, DQNC2S-A, and DQNC2S-T+A are the system variants incorporating either topic modeling, or abstraction, or a combination of the above.

To generate the crisis event timeline, we produce daily facts. Each fact F corresponds to a different topic and is described by one or more pieces of text. The importance score of text te_s^t of fact F is $I_{te_s^t,F} = Q_T - Q_D$, where Q_T is the Q-value for taking the text, whereas Q_D is the Q-value for discarding it. The higher the gap between the taking/discarding expected rewards, the higher the relevance of the text to the fact description.

The complete pipeline in training and testing can be seen in Figure 2.

4 Experiments

Dataset The CrisisFACTS dataset consists of multi-stream data annotated with ground truth summaries extracted from Wikipedia, ICS-209 All-Hazards Dataset [6,23], and NIST annotation.

Evaluation metrics In compliance with [13], we evaluated the results in terms of Rouge-2 F1-Score and BERT-Score metrics. They respectively quantify summary coherence from syntactic and semantic perspectives [2]. To make a fair summary comparison, each system shortlists a list of top-k facts in order of decreasing importance, where k is specified by the NIST assessors. Since our work addresses efficiency-related aspects, we also consider the execution time (in seconds).

Baselines We shortlist the best-performing methods according to the results of the CrisisFACTS 2022 challenge, i.e., unicamp [17] and ohmkiz [22]. They are both Retrieve&Re-ranking strategies. We also consider a state-of-the-art end-to-end model tested by [22], i.e., the ColBERT-based approach [10]. We also include the baselines provided by the CrisisFACTS organizers [13] for completeness.

Table 2: Comparison of mean Rouge-2 (R2) and BERT-Score (BS)

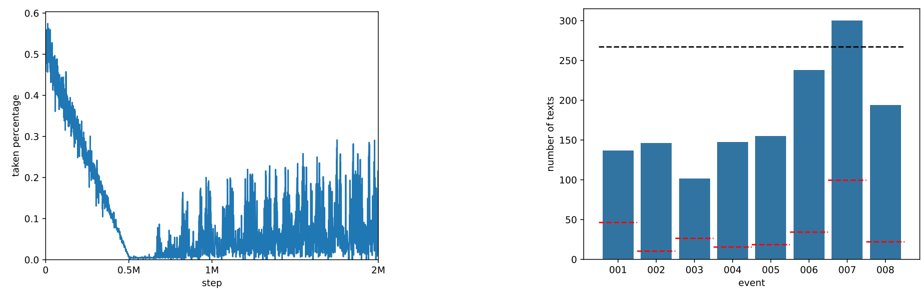
	ICS		NIST		Wikipedia		Mean		
Method	R2	BS	R2	BS	R2	BS	R2	BS	Rank
baseline.run1	0.0418	0.4432	0.1326	0.5565	0.0281	0.5296	0.0675	0.5098	2.4167
baseline.run2	0.0428	0.4427	0.1308	0.5565	0.0281	0.5274	0.0672	0.5089	2.0000
ohm_kiz.ColBERT	0.0497	0.4500	0.1386	0.5460	0.0307	0.5423	0.0730	0.5128	4.6667
ohm_kiz.QACrisis	0.0464	0.4432	0.1471	0.5642	0.0337	0.5448	0.0757	0.5174	6.0833
ohm_kiz.QAasnq	0.0507	0.4477	0.1468	0.5628	0.0362	0.5646	0.0779	0.525	7.1667
unicamp.NM2	**0.0581**	0.4591	0.1338	0.5573	0.0281	0.5321	0.0733	0.5162	5.6667
unicamp.NM1	**0.0581**	0.4591	0.1338	0.5573	0.0281	0.5321	0.0733	0.5162	5.6667
DQNC2S	0.0406	0.4554	**0.1540**	**0.5715**	0.0402	0.5516	0.0783	0.5262	7.6667
DQNC2S-T	0.0513	0.4579	0.1450	0.5667	0.0317	0.5538	0.0760	0.5261	7.5833
DQNC2S-A	0.0412	**0.4596**	0.1538	0.5706	0.0394	0.5538	0.0781	0.528	8.2500
DQNC2S-T+A	0.0452	0.4560	0.1515	0.5709	**0.0420**	**0.5707**	**0.0796**	**0.5325**	**8.8333**

Setup. We run the experiments on an Intel(R) Core(TM) i9-10980XE CPU and P5000 and A6000 GPUs. The Q-Network comprises a mpnet-base-v2 version of SentenceBERT [19] and three linear layers. We employ an Adam optimizer with a constant learning rate of 1e-3 and weight decay of 1e-4. We perform an 8-fold cross-validation on the events. Based on the empirical distribution of the number of facts per day (see Figure 3), we set the maximum number of texts to 300.

Quantitative results overview. As shown in Table 2, DQNC2S performs best in terms of BERTScore for all the summary types, showing maximal semantic similarity with the reference crisis timelines. Its performance is best regarding ROUGE scores for all summaries except for ICS. According to the task organizers [13], the actual incident summaries in ICS are written for the public and from a historical perspective, not for the utility of emergency-response personnel. Thus, the syntactic n-gram overlap is likely less explanatory. DQNC2S-T+A turns out to be, on average, the most effective one. It is particularly effective in generating Wikipedia-like summaries, which provide topic-specific event insights. According to the t-test of statistical significance ($p = 0.08$), the performance of DQNC2S-T+A) is better than the state of the art at a significant level of 92%. We have also ranked the solutions starting from 1 for the smallest value for each metric. All versions of DQNC2S are superior to the state-of-the-art.

Inference time. DQNC2S decides if a piece of text is relevant in 0.0296 ± 0.0037 seconds for all the N queries. Instead, unicamp [17] requires approximately $N \cdot 0.0752 \pm 0.0380$ seconds just for the reranking step (disregarding the index creation and the usage of GPT-3). Similarly, ohmkiz [22] requires around $N \cdot 0.0293 \pm 0.0190$ for text re-ranking. The results confirm the higher efficiency of our strategy compared to state-of-the-art methods.

DQN training and testing. Figure 3a shows the mean percentage of "take" action per episode. The system exploration phase proceeds until the 500000-th step, in



(a) Mean percentage of taken

(b) Mean number of selected text

Fig. 3: Mean percentage of "take" action per episode during training (a) and the mean number of retrieved text per event (b). The red and black lines are the mean value and the maximum number of daily NIST facts, respectively.

which the DQN learns how to shortlist the relevant pieces of text properly. In the exploitation the system learns to take all possible useful texts to maximize the reward, stabilizing its trend. Looking at the number of texts shortlisted at inference time (Figure 3b) the system rarely fills the whole pool. The mean values of expected (red lines) and retrieved (blue bars) texts are correlated (~ 0.74).

5 Conclusion and Future Work

In this work, we proposed a DRL approach to generate crisis timelines from cross-stream data. We tackled the limitations of existing strategies in (1) Online processing of cross-stream data, avoiding ad-hoc indexing strategies for content retrieval; (2) Extracting salient crisis-relevant information by early filtering redundant content during the text retrieval stage; (3) Efficiently handling multiple event queries, with an inference time independent of the number of input queries. We achieved $+0.0063$ R2 and $+0.0151$ BERTScore average improvements compared to the best-performing existing solutions. As future work, we plan to leverage Large Language Models to enrich the crisis events representation.

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