Deep Q-Networks for Event Summarization

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Event Summarization

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- As crises unfold and many articles are generated about a given event, it is beneficial to have a meaningful summary about the incident.
- Given the seemingly countless number of news and media outlets, reading and summarizing all of this content is impractical.
- Instead, it is useful to have a system that evaluates these articles automatically and returns the most valuable information.

Extractive Event Summarization

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- Extractive streaming summarization takes as input a short text description of a topic or an event known as a query, a document stream, and a time ordered set of sentences relevant to the query.
- The algorithm sequentially examines each sentence from the document stream and includes the candidate sentence into the summary when novel and important information is detected.

Previous Work in Extractive Event Summarization

- Recent research in text retrieval has focused on extractive algorithms to identify important sentences from a large set of documents for summarizing articles from different events in the news (e.g., [1], [4], [2], and [3]).
- [4] has shown that it is possible to select relevant sentences from a massive number of documents on the web to create summaries with meaningful content by adapting classifiers to maximize search policies.
- These systems have been shown to fall short of simple heuristic algorithms [2], which may be due to the limited ability of traditional n-gram models to capture the rich and often idiosyncratic structure of language.

Deep Q-Networks for Event Summarization

This leads us to explore Deep Q-Networks (DQN) for 3 reasons:

1. We can define an architecture that propagates information end-to-end about the inputs, actions, and rewards
2. The representation and interaction between the stream, summary, and query can be learned jointly
3. RNN-LSTM embeddings can learn a more robust semantic representation than classical n-gram models

Deep Q-Networks: A Brief Introduction

- Q-Learning is a Reinforcement Learning framework that finds an optimal policy by taking an input state, set of possible actions available, and returning the action with the highest reward.
- When the state-action space becomes intractable, deterministic algorithms are no longer feasible for an optimal policy and researchers instead train a model to learn the policy.
- Deep Q-Networks [5] are an increasingly popular framework for learning these policies from end-to-end.

States

- A state $s(x_t, \tilde{y}_t, d)$ at time t is a function of the stream X_d, $\forall d \in D$, which represents the candidate sentence, x_t to include in the summary, the state of the current summary $\tilde{y}_t$, and the query d.
- For brevity we use s_t where the dependence on $x_t, \tilde{y}_t$, and d is assumed.

Actions

We define our set of actions as $\mathcal{A} := \{select, skip\}$ where *select* corresponds to adding the current sentence x_t to the predicted summary $\tilde{y}_t$ and incrementing the current system time, or *skip* where only t is incremented without changing the current summary. Simply,

$$\tilde{y}_{t+1} = \begin{cases} \tilde{y}_t \cup \{x_t\}, & \text{if } a_t = select \\ \tilde{y}_t, & \text{if } a_t = skip. \end{cases} \tag{1}$$

Reward

The reward r for a given action a at time t is measured by the change in ROUGE-1F1 score of the predicted summary $\tilde{y}_t$ measured against a gold standard summary Y.

$$\text{ROUGE-R}(\tilde{y}, Y) = \frac{\sum_{g \in Y} \min\left(\text{count}(g, \tilde{y}), \text{count}(g, Y)\right)}{\sum_{g \in Y} \text{count}(g, Y)} \tag{2}$$

$$\text{ROUGE-P}(\tilde{y}, Y) = \frac{\sum_{g \in \tilde{Y}} \min\left(\text{count}(g, \tilde{y}), \text{count}(g, Y)\right)}{\sum_{g \in \tilde{Y}} \text{count}(g, \tilde{Y})} \tag{3}$$

$$r_t = \text{ROUGE-F1}(\tilde{y}_t, Y) - \text{ROUGE-F1}(\tilde{y}_{t-1}, Y). \tag{4}$$

Policy

- We define our Q-Learner as an RNN-LSTM that is trained by randomly exploring the state-space using an ϵ-greedy search over actions and states.
- We train our Q-Learner by iteratively updating the learned extraction policy through backpropagation of the observed reward for each action.
- We define an architecture similar to that of [6] and map our three inputs (query, sentence, and current predicted summary) into LSTM embeddings according to **Figure 1**

Architecture of the Q-Learner

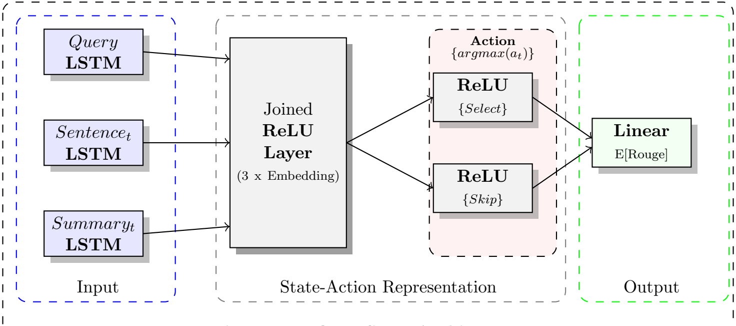

Figure 1: DQN-LSTM Architecture

DQN-LSTM for Event Summarization Training Procedure

Input: $\{\mathcal{D}$: Event queries, X_d: Input sentences, N: Number of epochs$\}$
Output: $\{\hat{Q}$: extraction policy, $\tilde{Y}_d$: event summary for query $d\}$

Initialize extraction policy $\hat{Q}$ with random weights
Initialize memory and summary: $\Gamma, \tilde{Y} = \{\emptyset\}_{d=1}^{|\mathcal{D}|}, \{\emptyset\}_{d=1}^{|\mathcal{D}|}$
for $epoch = 1, .., N$ **do**
  for query $d \in \mathcal{D}$ **do**
    $X_d, \tilde{Y}_d = \{\text{Extract } t = 1, \ldots, T_d\ (sentences_d,\ summary_d)\}$
    for $x_t, \tilde{y}_t \in X_d, \tilde{Y}_d$ **do**
      Set $s_t = s(x_t, \tilde{y}_t, d)$
      $\forall a_t \in \mathcal{A}(s_t)$ compute $\hat{Q}(s_t, a_t)$ and select $a_t^* = \text{argmax}_{a_t} \hat{Q}(s_t, a_t)$
      if $random() < \epsilon$ **then** select a_t^* at random with $\Pr(a_t) = \frac{1}{|\mathcal{A}|}$
      Update $\tilde{y}_{t+1}$ according to equation (1)
      Execute action a_t^* and observe reward r_t and new state s_{t+1}
      Update $\Gamma_d = \Gamma_d \cup \{[s_t, a_t^*, r_t, s_{t+1}]\}$
  for $j = 1, \ldots, J$ transitions sampled from Γ **do**

$$\text{Set } y_j = \begin{cases} r_j & \text{if } s_{j+1} \text{ is terminal} \\ r_j + \gamma \max_{a'} \hat{Q}(s_{j+1}, a'; \theta) & \text{if } s_{j+1} \text{ is non-terminal} \end{cases}$$

    Perform gradient step on $\mathcal{L}(\theta) = (y_j - \hat{Q}(s_j, a_j; \theta))^2$

Evaluation

We benchmark our model against (1) an oracle that greedily chooses to include sentences if the increase in ROUGUE-NF1 is positive, (2) random selection of sentences, and (3) a bag-of-words multilayer perceptron.

Useful Links below

Thank you

- GitHub

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