Deep Q-Networks for Event Summarization

Francisco Javier Arceo, Chris Kedzie

Columbia University in the City of New York

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Event Summarization

- 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.
- An extractive summarization algorithm sequentially examines sentences from a document stream and includes the candidate sentence into the summary when novel and important information is detected.

Event Summarization

- Recent research in text retrieval has focused on extractive algorithms to identify important sentences from a large set of documents (e.g., [1], [4], [2], and [3]) for summarizing articles from different events in the news.
- [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 how 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.

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 classic n-gram models

- 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 an action, a_t, at each time step from 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.

Reward

The reward r for a given action a at time t is measured by the change in ROUGE-NF1 score of the predicted summary $\tilde{y}_t$ measured against a gold standard summary Y. That is,

$$r_t = \text{ROUGE-NF1}(\tilde{y}_t, Y) - \text{ROUGE-NF1}(\tilde{y}_{t-1}, Y). \qquad (1)$$

Policy

- A policy takes as input a state and a set of possible actions and returns the optimal state, this policy can be deterministic or probabilistic. We define our policy as a Q-Learner using both an LSTM and a bag-of-words model
- 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**
- Our extraction policy then takes as input the state s_t at time t and returns the expected optimal action

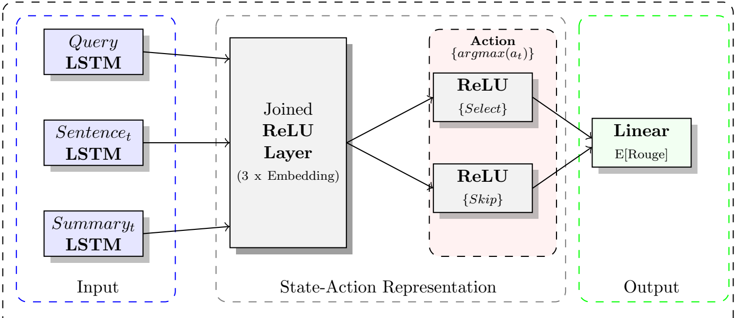

Figure 1: DQN-LSTM Architecture

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**
        $X_d, \tilde{Y}_d = \{\text{Extract } t = 1, ..., T_d \ (sentences_d, \ summary_d)\}$
        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 $j = 1, ..., J$ 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 $\mathcal{L}(\theta) = (y_j - \hat{Q}(s_j, a_j; \theta))^2$

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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