Deep Q-Networks for Event Summarization

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Agenda

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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, manually reading and summarizing all of this content is impossible.
- Instead, it is useful to have a system that evaluates these articles automatically and returns the most valuable information.

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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.

Brief Review of Recent Literature

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- Kedzie, McKeown, and Diaz [4] showed 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

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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

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- 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.

Deep Q-Networks for Event Summarization

For our DQN, we specify

- **state** $s_t := s(x_t, \tilde{y}_t, d)$
  - $x_t :=$ Candidate sentence at time t
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- **reward** $r_t := \Delta^1$ROUGE-F1$(\tilde{y}_t, Y)$

Policy

- We define our Q-Learner as an RNN-LSTM
- We train our Q-Learner by iteratively updating the extraction policy through backpropagation
- We map our inputs into embeddings according to **Figure 1**

Architecture of the Q-Learner

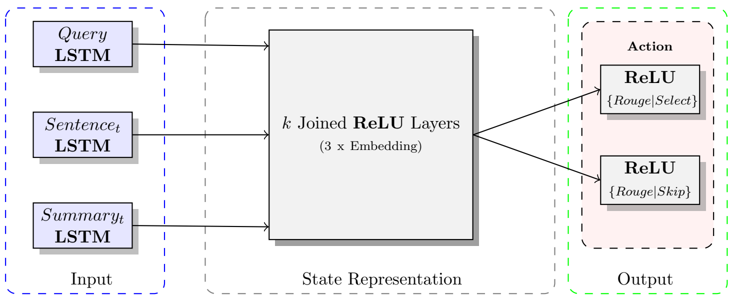
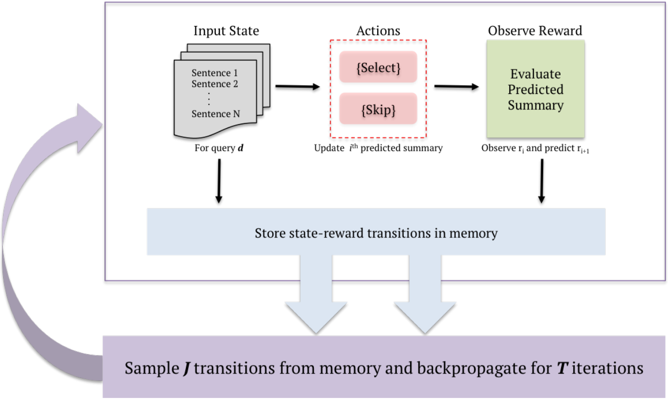


Figure 1: DQN-LSTM Architecture

***ReLU**: f(x) = max(0, x)

High-level overview of algorithm

DQN-LSTM for Event Summarization Training Procedure



Detailed overview of algorithm

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

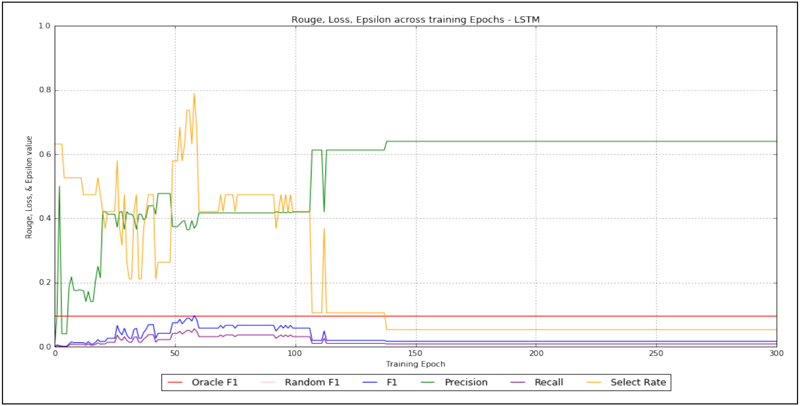
Small Problems

Studying in-sample behavior on a small problem allows us to

1. Verify the model performance
2. Understand training time required
3. Gain intuition about the impact of hyperparameters

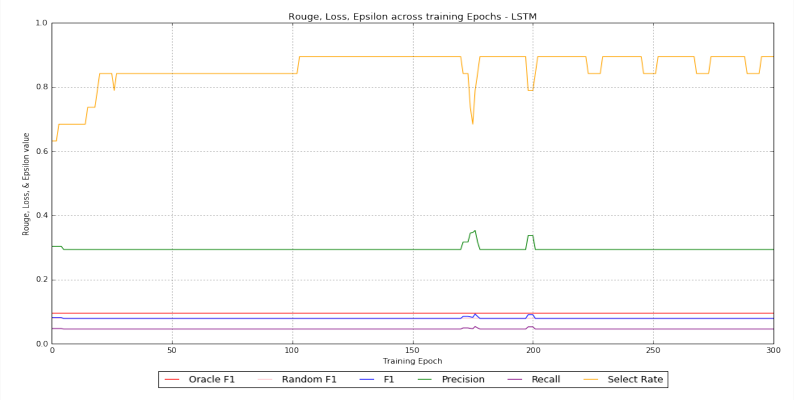
DQN-LSTM for 1 Query and 20 Sentences: Precision

Model learned to select the single best sentence.



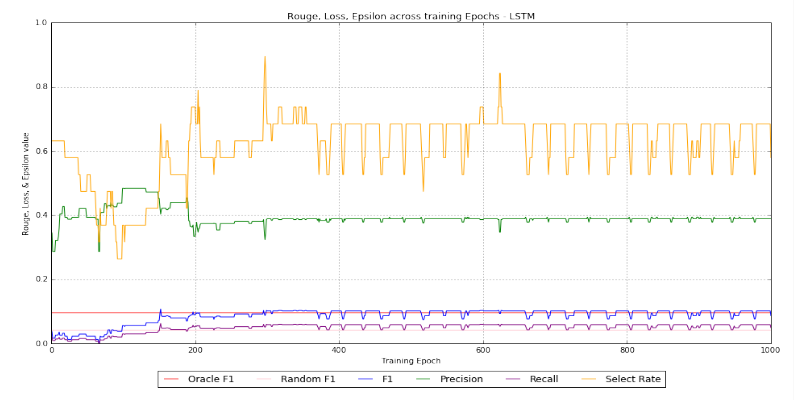
DQN-LSTM for 1 Query and 20 Sentences: Recall

Model learned to select all sentences.



DQN-LSTM for 1 Query and 20 Sentences: F1

Model was able to maximize F1.



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- Maximizing Precision is easier than Recall
- Choosing Precision or Recall yields pathological results
- Optimizing F1 requires longer training

Where are we now?

Currently running on 44 queries each with ∼15,000 sentences

- Challenges arise in slow compute time because of the forward step has to sequentially update the current summary
- Long training time required in short simulation showed that to learn effective policy we have to explore a large state-space

Thank you

Any questions?

- GitHub Repository
- Working Paper

Fernando Diaz, Bhaskar Mitra, and Nick Craswell.
Query expansion with locally-trained word embeddings.
In *Proceedings of the 54th Annual Meeting of the Association for Computational*. ACL–Association for Computational Linguistics.

Cristina Gârbacea and Evangelos Kanoulas.
The university of amsterdam (ilps. uva) at trec 2015 temporal summarization track.

Chris Kedzie and Kathleen McKeown.
Extractive and abstractive event summarization over streaming web text.
In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence, IJCAI 2016, New York, NY, USA, 9-15 July 2016*, pages 4002–4003, 2016.

Chris Kedzie, Kathleen McKeown, and Fernando Diaz.

Predicting salient updates for disaster summarization.
In *Proceedings of the 53rd annual meeting of the ACL and the 7th International Conference on Natural Language Processing*, pages 1608–1617, 2015.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin A. Riedmiller.
Playing atari with deep reinforcement learning.
CoRR, abs/1312.5602, 2013.

Karthik Narasimhan, Tejas D Kulkarni, and Regina Barzilay.
Language understanding for textbased games using deep reinforcement learning.
In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*. Citeseer, 2015.