Deep Q-Learning for Event Summarization

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Abstract

We present a streaming extraction policy for multi-document summarization learned using a deep reinforcement learning recurrent neural network architecture. The rewards of our network are evaluated through manually reviewed summaries, which allow us to specify an end-to-end framework to optimize our extraction policy. By using raw text from our articles and mapping words into a higher embedding dimension through our recurrent neural network, we are able to learn a more robust representation than traditional n-gram models. We evaluate our model on a small simulation and provide clear direction for future research.[1]

1 Introduction

Recent research in text retrieval has focused on extractive algorithms to identify important sentences from a large set of documents (e.g., [2], [10], [3], and [9]). The approach by [10] 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 operate in a streaming fashion and are capable of evaluating each sentence within each article to decide whether or not to include or ignore the sentence.

Unfortunately, many of these systems have still been shown to fall short of algorithms that employ simple heuristics [3], which may be due to inadequate capturing of the rich structure and often idiosyncratic information by traditional n-gram language models.

[1] https://github.com/franciscojavierarceo/DQN-Event-Summarization

In recent years, recurrent neural networks have been used to map textual language to a higher order dimension to represent more powerful features for a variety of different language modeling tasks [13]. These vector representations, also known as embeddings, have proven incredibly powerful on a variety of different natural language processing tasks (e.g., [1], [17], [11]). For query based retrievals, [2] has shown success in using these embeddings for *ad hoc* information retrieval.

In this paper we show that a deep recurrent neural network with a long short term memory (LSTM) [7] is able to successfully learn an extractive summary policy by encoding the action, state, and reward into a Q-Learning model, similar to that of [5]. We show the performance of our model on a variety of different metrics and benchmark them against an Oracle that greedily adds sentences to the summary when it observes a positive gain in ROUGE-F1.

2 Extractive Streaming Summarization

In the extractive streaming summarization task, we are given as input a query (i.e., a short text description of a topic or an event), a document stream, and a time ordered set of sentences relevant to the query. Starting with an initially empty summary, an extractive, streaming summarization algorithm is intended to examine each sentence in order and, when new and important (relative to the query) information is identified, add that sentence to the summary.

Implicit to this problem is the notion of system time – the summarization algorithm can only examine sentences that occur in the stream before the current system time. Advancing the system time gives the algorithm access to more sentences, although in practice the stream is sufficiently large enough that choices have to be made about how much history can be kept in memory. For many domains, e.g., crisis informatics, it is preferable for a summarization algorithm to identify important information as early as possible, and so the objective function should penalize a large disparity between the time a piece of information is first available to the algorithm and the system time at which that information is actually added to the summary.

Previous work in this area has either incremented the system time in fixed increments (e.g., an hour) [12, 10] or operated in a fully online setting [4, 8]. In both cases explicitly modeling the current state of the summary, the stream, and their relationship with the query is quite complicated and exhibits non-linear dynamics that are difficult to characterize in traditional models with manually crafted features.

Additionally, the structured nature of the sentence selection task (sentence selection is highly dependent on the current summary state) suggests that imitation or reinforcement learning are necessary to obtain parity between training and testing feature distributions.

Early successes of deep reinforcement learning have used convolutional neural networks for video games (e.g., [14] and [15]) but recent work has leveraged recurrent neural networks for both video-based and text-based gaming environments (e.g., [5] and [16]).

This leads us to explore Deep Q-Networks (DQN) for three reasons: (1) both the representation and interaction between the stream, summary, and query can be learned; (2) the embeddings can learn a more robust semantic representations than classic n-gram models; and (3) by randomly exploring the state space, the ϵ-greedy strategy used in DQN learns a policy that yields more consistency between train and test distributions.

3 Background

In the subsequent sections, we outline the architecture of our DQN and define the parameterization of our Q-function for the multi-document summarization task. Our architecture consists of three components: the (1) input, (2) action, and (3) value representations. By specifying these components into our neural network, we are able to develop an end-to-end extraction policy that fully propagates information both forward and backward.

3.1 States

In our architecture a state $s(x_t, \tilde{y}_t, d)$ is a function of the stream X_d, $\forall d \in D$, the state of the current summary $\tilde{y}_t$ at system time t, and the query d. For brevity we will use s_t where the dependence on $x_t, \tilde{y}_t$, and d is assumed. s_t itself is three recurrent neural networks, one for encoding the summary, the stream, and the query.

3.2 Actions

The set of possible actions a_t at each time step is $\mathcal{A} = \{select, skip\}$ where *select* corresponds to adding the current sentence x_t to the summary and incrementing the current system time, or *skip* where only t is incremented without changing the current summary. Thus, our current predicted summary at time t is defined as

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

Since $\tilde{y}_t$ grows linearly with the number of selected sentences, we mitigate potential capacity constraints by using a queue to hold the last K elements of the current predicted summary.

3.3 Rewards

The reward for a given action is measured by the change in ROUGE-N F1 score of the predicted summary $\tilde{y}_t$ measured against a gold standard summary Y. When only one gold summary reference is used, ROUGE-N Recall is calculated as

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

where ngrams(Y, N) returns the set of ngrams of order N in the summary Y and count(g, Y) is the count of occurrences of ngram g in Y.

Similarly, ROUGE-N Precision is calculated as

$$\text{ROUGE-NP}(\tilde{Y}, Y) = \frac{\sum_{g \in \text{ngrams}(Y,N)} \min\Big(\text{count}(g, \tilde{Y}), \text{count}(g, Y)\Big)}{\sum_{g \in \text{ngrams}(\tilde{Y},N)} \text{count}(g, \tilde{Y})} \tag{3}$$

and the F_1 is simply the harmonic mean of the two:

$$\text{ROUGE-NF1}(\tilde{Y}, Y) = \frac{2 \times \text{ROUGE-NP}(\tilde{Y}, Y) \times \text{ROUGE-NR}(\tilde{Y}, Y)}{\text{ROUGE-NP}(\tilde{Y}, Y) + \text{ROUGE-NR}(\tilde{Y}, Y)} \tag{4}$$

The reward r at time t is

$$r_t = \text{ROUGE-NF1}(\tilde{y}_t, Y) - \text{ROUGE-NF1}(\tilde{y}_{t-1}, Y). \tag{5}$$

3.4 Deep Q-Learning

We define an architecture similar to that of [16] and map our three inputs (query, sentence, and current predicted summary) into LSTM embeddings according to **Figure 1**. By formulating our extraction task as a Markov Decision Process (MDP) we can express the state-action tuples as transitions states.

Our extraction policy then takes as input an action a_t in state s_t at time t and returns the expected reward. We initialize our actions and Q-function at random and by taking the optimal action given our expected reward, we are able to iteratively update our Q-function using the Bellman equation [19] satisfying

$$\hat{Q}_{t+1}(s,a) = \mathrm{E}[r + \gamma \mathrm{max}_{a'} \hat{Q}_t(s',a')|s,a] \tag{6}$$

where $\gamma \in \mathbb{R}$ is the discount rate applied to future rewards and the expectation is taken over transitions in state s and action a. By iterating over the Q-function, it converges asymptotically to the optimal policy, i.e., $\hat{Q}_t \to Q^*$ as $t \to \infty$. In finite iterations we can use a neural network as our function approximator, where our weights, θ, can be optimized using the following loss function

$$\mathcal{L}_i(\theta_i) = \mathrm{E}_{\hat{s},\hat{a}}[\big(y_i - Q(\hat{s},\hat{a};\theta_i)\big)^2] \tag{7}$$

where

$$y_i = \mathrm{E}_{\hat{s},\hat{a}}[r_i + \gamma \mathrm{max}_{a'} Q(s',a';\theta_{i-1})|s',a']. \tag{8}$$

Differentiation of the loss function yields the gradient

$$\nabla_{\theta_i} L_i(\theta_i) = \mathrm{E}_{\hat{s},\hat{a}}[2\big(y_i - Q(\hat{s},\hat{a};\theta_i)\big)\nabla_{\theta_i} Q(\hat{s},\hat{a};\theta_i)] \tag{9}$$

that learns the parameters using stochastic gradient descent with RMSprop [6] on sampled batches of stored transitions.

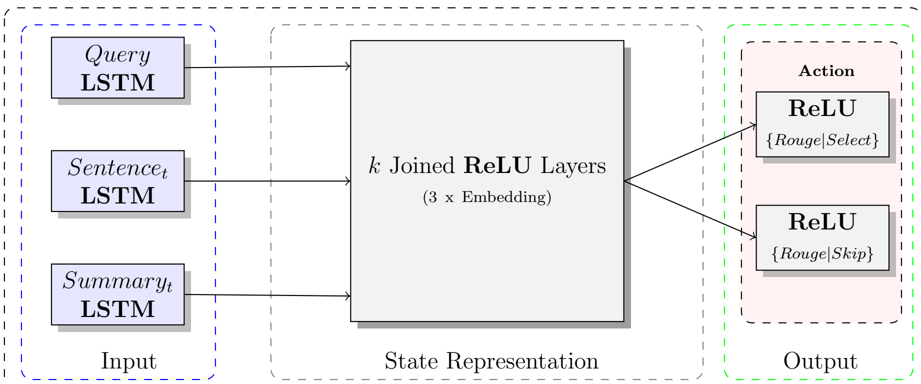


Figure 1: DQN-LSTM Architecture

4 Learning an Extraction Policy

4.1 Settings

Since the state of our current summary at time t depends on the state at time $t-1$, we have to execute our Q-function in the feedforward stage using a single batch to properly update the predicted summary with optimal expected action. During the backpropagation phase we sample random mini-batches from the stored transitions. We set our embedding dimension to 50 and the maximum summary length to 300 tokens.

The weights of the Q-function and the action sequence are initialized at random and we randomly explore the state-space for 200 of the 1000 epochs by employing an ϵ-greedy search strategy that decays linearly to a base exploration rate of 0.01 during our action selection. We describe in full detail the training of our DQN-LSTM in **Algorithm 1**.

Algorithm 1 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 $d\}$

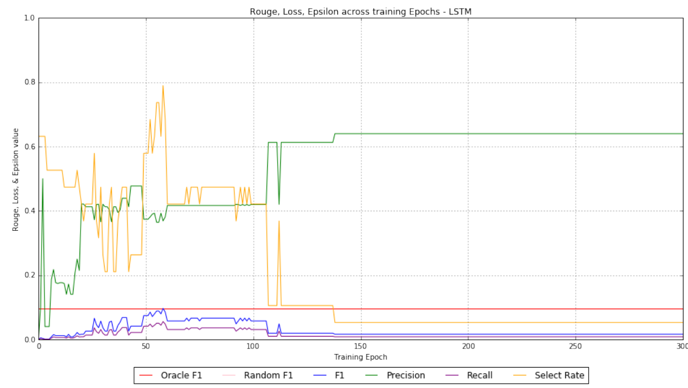
Initialize extraction policy $\hat{Q}$ with random weights
Initialize memory and summary: $\Gamma, \tilde{Y} = \{\emptyset\}_{d=1}^{|\mathcal{D}|}, \{\emptyset\}_{d=1}^{|\mathcal{D}|}$
for $epoch = 1, .., N$ **do**
  for query $d \in \mathcal{D}$ **do**
    $X_d, \tilde{Y}_d = \{\text{Extract } t = 1, ..., T_d \ (sentences_d,\ summary_d)\}$
    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 $a_t^* = \text{and}_{a_t} \hat{Q}(s_t, a_t)$
      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 $\mathcal{L}(\theta) = (y_j - \hat{Q}(s_j, a_j; \theta))^2$

4.2 Simulations

To understand the behavior of our architecture, we produce a number of experiments on the first sentence of the first 20 articles for a single query. By restricting our study to such small in-sample data we are able to better monitor the system.



(a): DQN optimizing Precision

(b): DQN optimizing Recall

(c): DQN optimizing F1

Figure 2: DQN-LSTM Optimizing for Different Metrics

We validate our model against an Oracle that sequentially selects the candidate sentence if and only if the change in ROUGE-F1 is positive. In **Figure 2** we see that the F1 (c) converges and that our model learns a policy on par with the Oracle after sufficient training time. Additionally, we see the convergence of our model when trained on Precision (a); notice the convergence of the model after 150 epochs. Lastly, we see convergence of Recall (b) after roughly 100 epochs with small perturbations that would decline if further epochs were allotted. Optimizing for Recall or Precision yields obvious pathological results, where Recall results in the selection of all sentences and Precision leads to the selection of the sentence with the largest intersection with the golden summaries. This experiment provides further confidence in the choice of F1 as the reward strategy for the DQN. Most importantly, these experiments provide small sample evidence that this framework can learn a meaningful extraction policy.

5 Conclusion

We have presented an end-to-end deep reinforcement learning architecture to learn an extraction policy for multi-document summarization. By treating the incoming sentence streams from different documents as inputs into a recurrent neural network and by backpropagating the action selected, we are able to learn both a richer embedding representation of the three input components and a robust extraction policy.

Future research could consider modifying the extractive policy into one that generates a sequence. Sequence-to-sequence models [18] have shown wide success in language translation and could be a useful model for the summarization of multiple documents.

6 Software

We have open sourced our work on Github. The repository contains 3 main folders: (1) Paper, (2) Presentation, and (3) Code. The Code folder contains 3 subfolders which consist of (1) Performance, (2) Simulations, and (3) Utils. The Performance folder contains files with performance statistics for both the models executed using cross-validation and the simulations.

Additionally, the three main files required to run n-fold cross validation on the queries are **runModelProd.lua**, **utils.lua**, and **utilsNN.lua**. The two utility files contain various functions necessary to build the data into tensors, create the neural network, and train the model. The repository has a **README.md** file in every subfolder to elaborate in further detail about its contents.

References

[1] Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. A neural probabilistic language model. *Journal of Machine Learning Research*, 3(Feb):1137–1155, 2003.

[2] 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.

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

[4] Qi Guo, Fernando Diaz, and Elad Yom-Tov. Updating users about time critical events. In *European Conference on Information Retrieval*, pages 483–494. Springer, 2013.

[5] Matthew Hausknecht and Peter Stone. Deep recurrent q-learning for partially observable mdps. In *2015 AAAI Fall Symposium Series*, 2015.

[6] Geoffrey Hinton, N Srivastava, and Kevin Swersky. Lecture 6a overview of mini–batch gradient descent.

[7] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[8] Chris Kedzie, Fernando Diaz, and Kathleen McKeown. Real-time web scale event summarization using sequential decision making. *Proceedings of the Joint Conference on Artificial Intelligence*, 2016.

[9] 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.

[10] 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.

[11] Yoon Kim, Yacine Jernite, David Sontag, and Alexander M Rush. Character-aware neural language models. In *Thirtieth AAAI Conference on Artificial Intelligence*, 2016.

[12] Richard McCreadie, Craig Macdonald, and Iadh Ounis. Incremental update summarization: Adaptive sentence selection based on prevalence and novelty. In *Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management*, pages 301–310. ACM, 2014.

[13] Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Černockỳ, and Sanjeev Khudanpur. Recurrent neural network based language model. In *Eleventh Annual Conference of the International Speech Communication Association*, 2010.

[14] Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. *CoRR*, abs/1602.01783, 2016.

[15] 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.

[16] 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.

[17] Martin Sundermeyer, Ralf Schlüter, and Hermann Ney. Lstm neural networks for language modeling. In *Thirteenth Annual Conference of the International Speech Communication Association*, 2012.

[18] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pages 3104–3112, 2014.

[19] Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*, volume 1.