

# Deep Q-Networks for Event Summarization

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## Event Summarization

Motivation

## Deep Q-Networks

Policy

Reward

Q-Learner

Actions

## Core Algorithm

## Experiments

Benchmarking

DQN-BOW

DQN-LSTM

## Resources

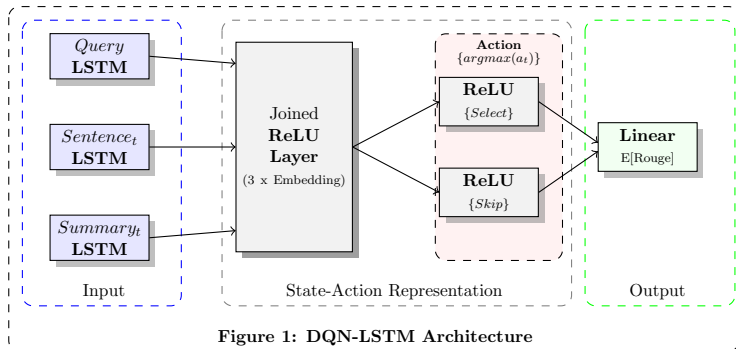
# Event Summarization

$$\hat{\beta}_{ridge} = \operatorname{argmin}_{\beta} (\mathbf{y} - \mathbf{x}^T \beta)^2 + \lambda \beta^2 \quad (1)$$

- First published by the Russian Mathematician Andrey Nikolayevich Tikhonov (1906-1993) in 1943

# Policy

- ▶ A policy takes as input a state and a set of possible actions and returns the optimal state
- ▶ The policy can be deterministic or probabilistic



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## DQN-LSTM for Event Summarization Training Procedure

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**Input:**  $\{\mathcal{D}$ : Event queries,  $X_d$ : Input sentences,  $N$ : Number of epochs $\}$

**Output:**  $\{\hat{Q}$ : extraction policy,  $\hat{Y}_d$ : event summary for query  $d$  $\}$

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- 1: Initialize extraction policy  $\hat{Q}$  with random weights
  - 2: Initialize memory and summary:  $\Gamma, \tilde{Y} = \{\emptyset\}_{d=1}^{|\mathcal{D}|}, \{\emptyset\}_{d=1}^{|\mathcal{D}|}$
  - 3: **for**  $epoch = 1, \dots, N$  **do**
  - 4:   **for** query  $d \in \mathcal{D}$  **do**
  - 5:      $X_d, \tilde{Y}_d = \{\text{Extract } t = 1, \dots, T_d \text{ (sentences}_d, \text{summary}_d)\}$
  - 6:     **for**  $x_t, \tilde{y}_t \in X_d, \tilde{Y}_d$  **do**
  - 7:       Set  $s_t = s(x_t, \tilde{y}_t, d)$
  - 8:        $\forall a_t \in \mathcal{A}(s_t)$  compute  $\hat{Q}(s_t, a_t)$  and select  $a_t^* = \arg\max_{a_t} \hat{Q}(s_t, a_t)$
  - 9:       **if**  $\text{random}() < \epsilon$  **then** select  $a_t^*$  at random with  $\Pr(a_t) = \frac{1}{|\mathcal{A}|}$
  - 10:       Update  $\tilde{y}_{t+1}$  according to equation (1)
  - 11:       Execute action  $a_t^*$  and observe reward  $r_t$  and new state  $s_{t+1}$
  - 12:       Update  $\Gamma_d = \Gamma_d \cup \{[s_t, a_t^*, r_t, s_{t+1}]\}$
  - 13:   **for**  $j = 1, \dots, J$  transitions sampled from  $\Gamma$  **do**
  - 14:     
$$\text{Set } y_j = \begin{cases} r_j & \text{if } s_{j+1} \text{ is terminal} \\ r_j + \gamma \max_{a'} \hat{Q}(s_{j+1}, a'; \theta) & \text{if } s_{j+1} \text{ is non-terminal} \end{cases}$$
  - 15:     Perform gradient step on  $\mathcal{L}(\theta) = (y_j - \hat{Q}(s_j, a_j; \theta))^2$
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## Useful Links below

Thank you

- ▶ [GitHub](#)