

## A Supplemental Materials

### A.1 Complete Training Procedure

The complete training procedure is shown in Algorithm 2 in the next page.

### A.2 Random Policy and Oracle Policy Performances

The random policy randomly selects  $K$  comments at each step. The oracle policy knows the true karma score of each comment in the datasets and it always chooses the top- $K$  comments with highest true karma scores at each step. Table 7 shows the performance of the random policy and the oracle policy on different datasets when  $N = 10$  and  $K = 3$ . Table 8 shows the performance of the random policy and the oracle policy across various action sizes with  $K = 2, 3, 4, 5$  and fix  $N = 10$  on the askscience dataset.

Subreddit	Random Policy	Oracle Policy
askscience	392.0±10.1	1695.4±48.4
askmen	188.0±4.4	524.5±26.3
todayilearned	528.3±29.0	1994.5±65.2
worldnews	351.4±11.5	1328.0±40.1
nfl	328.3±14.6	1032.5±5.7

Table 7: Performance of the random policy and the oracle policy on different datasets

K	Random Policy	Oracle Policy
2	254.1±20.9	1571.2±27.8
3	392.0±10.1	1695.4±48.4
4	589.3±22.0	1697.8±35.3
5	745.9±26.4	1808.5±47.2

Table 8: Performance of the random policy and the oracle policy with different action size on askscience dataset

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**Algorithm 2** Q-learning

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- 1: Initialize the experience memory  $D$
  - 2: Initialize  $\theta$  randomly
  - 3: Set  $\theta^- = \theta$
  - 4: **for**  $episode = 1 \rightarrow H$  **do**
  - 5:     Randomly pick a discussion tree
  - 6:     Read the initial state  $s_1$ , and a set of possible sub-actions,  $c_1 = \{c_{1,1}, \dots, c_{1,K}\}$
  - 7:     **for**  $t = 1 \rightarrow +\infty$  **do**
  - 8:         **if**  $rand() < \epsilon$  **then**
  - 9:             Select action  $a_t = \text{Greedy}(s_t, c_t, Q(\cdot, \cdot; \theta), K)$
  - 10:         **else**
  - 11:             Select action  $a_t$  uniformly at random
  - 12:         Observe reward  $r_{t+1}$
  - 13:         Read the next state  $s_{t+1}$ , and next set of possible sub-actions,  $c_{t+1} = \{c_{0,1}, \dots, c_{0,K}\}$
  - 14:         Store a transition tuple,  $(s_t, a_t, r_{t+1}, s_{t+1}, c_{t+1})$  in  $D$
  - 15:         Sample random mini batch of transition tuples  $(s_j, a_j, r_{j+1}, s_{j+1}, c_{j+1})$  from  $D$
  - 16:         Set
$$y_j = \begin{cases} r_{j+1} & \text{if } s_{j+1} \text{ is terminal} \\ r_{j+1} + \gamma \max_{a'} Q(s_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$$
  - 17:         Perform a step of gradient descent on the loss  $L(\theta) = (y_j - Q(s_j, a_j; \theta))$  with respect to  $\theta$
  - 18:         Set  $\theta^- = \theta$  for every  $F$  steps
  - 19:         **if**  $c_{t+1}$  is empty **then** break
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