Learning how to Active Learn: A Deep Reinforcement Learning Approach

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Overview

Introduction: Active Learning

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   - there is high cost annotating every sentence
   - how to select raw data to add labels in order to maximize the accuracy of the classification model
   - active learning becomes a sequential decision: as each sentence arrives, annotate it or not (our action)

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   - agent aims maximizing the **expected value** of rewards over all stages

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   - where $\bar{r}(s,a)$ is the expected reward, $P_{ss'}(a)$ is the transition probability from state s to s', α is the discount of reward

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   - In practice, above is useless: $|S| \times |A|$ is huge

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   - output: approximation of Q-function: $f_\theta(s, u)$
   - the loss function minimization

$$\min_\theta \left\{ \frac{1}{2} \left(f_{\theta_t}(s_t, a_t) - \bar{r}(s_t, a_t) - \alpha \max_u f_{\theta_t}(s_{t+1}, u) \right)^2 \right\}$$

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5. next sentence arrives

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   - $a_i = 1$: annotate x_i
   - $a_i = 0$: not annotate x_i
3. Reward (r):
   - evaluate the classification model on a held-out set after the action a is taken and get the test accuracy

An Value Iteration Q-learning Algorithm

Algorithm 1 Learn an active learning policy

Input: data $\mathcal{D}$, budget $\mathcal{B}$

Output: π

for episode = $1, 2, \ldots, N$ **do** — stopping criteria
  $\mathcal{D}_l \leftarrow \emptyset$ and shuffle $\mathcal{D}$
  $\phi \leftarrow$ Random
  for $i \in \{0, 1, 2, \ldots, |\mathcal{D}|\}$ **do** — sentence input
    Construct the state s_i using $\mathbf{x}_i$
    The agent makes a decision according to $a_i = \arg\max Q^{\pi}(s_i, a)$
    if $a_i = 1$ **then** — action: annoate
      Obtain the annotation $\mathbf{y}_i$
      $\mathcal{D}_l \leftarrow \mathcal{D}_l + (\mathbf{x}_i, \mathbf{y}_i)$ — annotated training set expanded
      Update model ϕ based on $\mathcal{D}_l$
    end if — train and update classifier
    Receive a reward r_i using held-out set
    if $|\mathcal{D}_l| = \mathcal{B}$ **then** — test classifier on a separate set
      Store $(s_i, a_i, r_i, \text{Terminate})$ in $\mathcal{M}$
      Break
    end if
    Construct the new state s_{i+1} — transition to 2nd sentence
    Store transition (s_i, a_i, r_i, s_{i+1}) in $\mathcal{M}$
    Sample random minibatch of transitions $\{(s_j, a_j, r_j, s_{j+1})\}$ from $\mathcal{M}$, and perform gradient descent step on $\mathcal{L}(\theta)$ — update NN (Q) using SGD
    Update policy π with θ — argmax of updated Q function (NN output)
  end for
end for
return the latest policy π — \pi_n-\pi_{n+1} < \epsilon

Important Step 1

for $i \in \{0, 1, 2, \ldots, |\mathcal{D}|\}$ **do**

Construct the state s_i using $\mathbf{x}_i$

The agent makes a decision according to $a_i = \arg\max Q^{\pi}(s_i, a)$

if $a_i = 1$ **then**

Obtain the annotation $\mathbf{y}_i$

$\mathcal{D}_l \leftarrow \mathcal{D}_l + (\mathbf{x}_i, \mathbf{y}_i)$

Update model ϕ based on $\mathcal{D}_l$

end if

Receive a reward r_i using held-out set

Important Step 2

Construct the new state s_{i+1}
Store transition (s_i, a_i, r_i, s_{i+1}) in $\mathcal{M}$
Sample random minibatch of transitions $\{(s_j, a_j, r_j, s_{j+1})\}$ from $\mathcal{M}$, and perform gradient descent step on $\mathcal{L}(\theta)$
Update policy π with θ
end for

Important Step 3

for episode $= 1, 2, \ldots, N$ **do**

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1. Remarks on the Q-learning algorithm:
   - input: unlabelled dataset D
   - output: a series of actions (a_i): policy π

Relaxation 1: Transfer Policy

1. train annotation policy π in source language (e.g., English) and transfer it to low-source target language

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Algorithm 2 Active learning by policy transfer

Input: unlabelled data $\mathcal{D}$, budget $\mathcal{B}$, policy π

Output: $\mathcal{D}_l$

target low-source language

well trained policy on one language

$\mathcal{D}_l \leftarrow \emptyset$
$\phi \leftarrow$ Random
for $|\mathcal{D}_l| \neq \mathcal{B}$ and $\mathcal{D}$ not empty **do**
  Randomly sample $\mathbf{x}_i$ from the data pool $\mathcal{D}$ and construct the state s_i
  The agent chooses an action a_i according to $a_i = \arg\max Q^{\pi}(s_i, a)$
  if $a_i = 1$ **then**
    Obtain the annotation $\mathbf{y}_i$
    $\mathcal{D}_l \leftarrow \mathcal{D}_l + (\mathbf{x}_i, \mathbf{y}_i)$
    Update model ϕ based on $\mathcal{D}_l$
  end if
  $\mathcal{D} \leftarrow \mathcal{D} \backslash \mathbf{x}_i$ exclude the annotated sentence from raw dataset
  Receive a reward r_i using held-out set
  Update policy π
end for only one episode to mimic the source scarcity
return $\mathcal{D}_l$

Relaxation 2: Transfer Model and Policy

1. train a classification model ϕ and annotation policy π in source language (e.g., English) and transfer both to low-source target language

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1. train a classification model ϕ and annotation policy π in source language (e.g., English) and transfer both to low-source target language
2. this relaxation is more like a test and implementation procedure

Algorithm 3 Active learning by policy *and* model transfer, for 'cold-start' scenario

Input: unlabelled data $\mathcal{D}$, budget $\mathcal{B}$, policy π, model ϕ

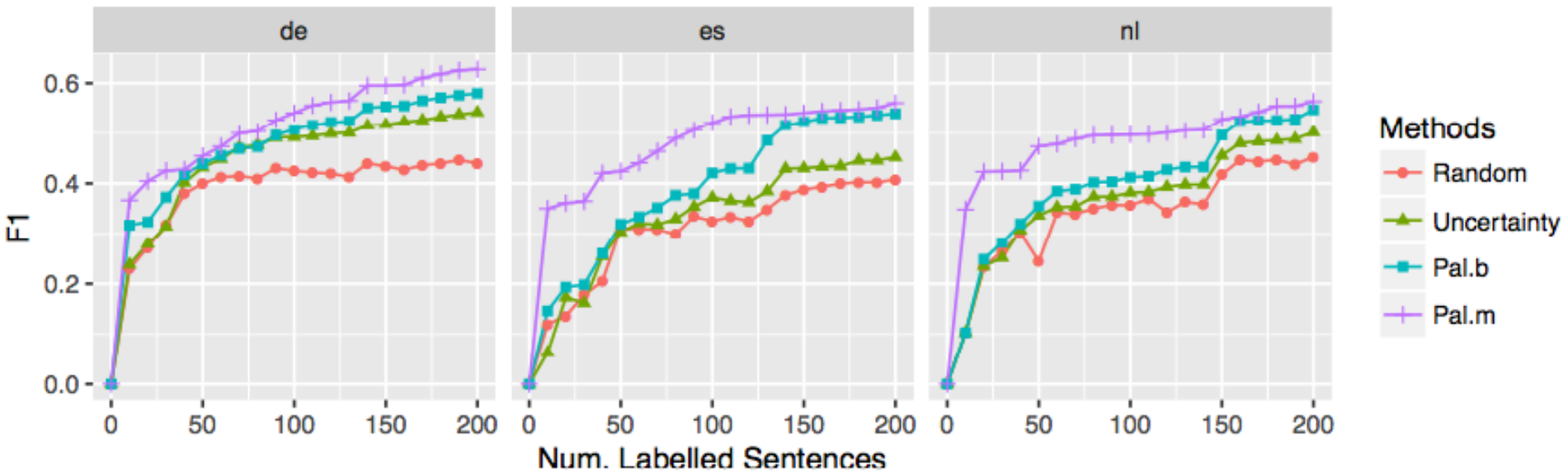
target dataset; trained policy; trained classification model

Output: $\mathcal{D}_l$

1: $\mathcal{D}_l \leftarrow \emptyset$
2: **for** $|\mathcal{D}_l| \neq \mathcal{B}$ and $\mathcal{D}$ not empty **do**
3: Randomly sample $\mathbf{x}_i$ from the data pool $\mathcal{D}$ and construct the state s_i
4: The agent chooses an action a_i according to $a_i = \arg\max Q^{\pi}(s_i, a)$
5: **if** $a_i = 1$ **then**
6: $\mathcal{D}_l \leftarrow \mathcal{D}_l + (\mathbf{x}_i, -)$ annotate based on \phi
7: **end if**
8: $\mathcal{D} \leftarrow \mathcal{D} \backslash \mathbf{x}_i$
9: **end for**

Numerical Experiments

A couple of numerical experiments show that the newly proposed active learning approach by deep Q-learning works better than some existing active learning methods such as uncertainty sampling and random sampling.



Thank You!

.....Question?