Recent Advances in Distantly Supervised Relation Extraction

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Agenda

• Motivation
• Challenges in Semi-Supervised Learning
• Reinforced Co-Training (Wu et al., NAACL 18)
• Reinforced Distant Supervision Relation Extraction (Qin et al., ACL 18a)
• DSGAN (Qin et al., ACL 18b)
• Conclusions
Motivation

• Most of the existing successful stories of deep learning are still based on supervised learning.

• For example, object recognition, machine translation, text classification.

• However, in many applications, it is not realistic to obtain large amount of labeled data.

• We need to leverage unlabeled data.
A Classic Example of Semi-Supervised Learning

• Co-Training (Blum and Mitchell, 1998)

Given:

• a set $L$ of labeled training examples
• a set $U$ of unlabeled examples

Create a pool $U'$ of examples by choosing $u$ examples at random from $U$

Loop for $k$ iterations:

Use $L$ to train a classifier $h_1$ that considers only the $x_1$ portion of $x$
Use $L$ to train a classifier $h_2$ that considers only the $x_2$ portion of $x$
Allow $h_1$ to label $p$ positive and $n$ negative examples from $U'$
Allow $h_2$ to label $p$ positive and $n$ negative examples from $U'$
Add these self-labeled examples to $L$
Randomly choose $2p + 2n$ examples from $U$ to replenish $U'$
Challenges

• The two classifiers in co-training have to be independent.
• Choosing highly-confident self-labeled examples could be suboptimal.
• Sampling bias shift is common.
Our Approach: Reinforced SSL

• Assumption: not all the unlabeled data are useful.
• Idea: performance-driven semi-supervised learning that learns an unlabeled data selection policy with RL, instead of using random sampling.

• 1. Partition the unlabeled data space
• 2. Train a RL agent to select useful unlabeled data
• 3. Reward: change in accuracy on the validation set
Reinforcement Learning

Environment

Agent

Deep Q-Network

Unlabeled Data
Reinforced Co-Training (Wu et al., NAACL 2018)

unlabeled subsets \{U_i\}

unlabeled set

1. Shingling
2. Min-Hashing
3. LSH

Q-agent

action \(a_t\)

state \(s_{t+1}\)

reward \(r_t\)

Validation Set \(L'\)

Evaluation

Classifier \(C_1\)

Classifier \(C_2\)

Labeled by Classifier 1

Labeled by Classifier 2

\(U_{at}\)
Deep Q-Learning

The Q-network parameters $\theta$ are learned by optimizing:

$$L_i(\theta_i) = \mathbb{E}_{s,a}[(V(\theta_{i-1}) - Q(s, a; \theta_i))^2],$$  \hspace{1cm} (8)

where $i$ is an iteration of optimization and

$$V(\theta_{i-1}) = \mathbb{E}_{s'}[r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) | s, a].$$ \hspace{1cm} (9)
Experiment 1: Clickbait Detection

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#Tweets</th>
<th>#Clickbait</th>
<th>#Non-Clickbait</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>2,495</td>
<td>762</td>
<td>1,697</td>
</tr>
<tr>
<td>Validation</td>
<td>9,768</td>
<td>2,380</td>
<td>7,388</td>
</tr>
<tr>
<td>Test</td>
<td>9,770</td>
<td>2,381</td>
<td>7,389</td>
</tr>
<tr>
<td>Unlabeled</td>
<td>80,012</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 1: Statistics of Clickbait Dataset.
## Experiment 1: Clickbait Detection

<table>
<thead>
<tr>
<th>Methods</th>
<th>Prec.</th>
<th>Recall</th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-attentive biGRU</td>
<td>0.683</td>
<td>0.649</td>
<td>0.665</td>
</tr>
<tr>
<td>CNN (Document)</td>
<td>0.537</td>
<td>0.474</td>
<td>0.503</td>
</tr>
<tr>
<td>Standard Co-Training</td>
<td>0.418</td>
<td>0.433</td>
<td>0.425</td>
</tr>
<tr>
<td>Performance Co-Training</td>
<td>0.581</td>
<td>0.629</td>
<td>0.604</td>
</tr>
<tr>
<td>CoTrade Co-Training</td>
<td>0.609</td>
<td>0.637</td>
<td>0.623</td>
</tr>
<tr>
<td>Sequence-SSL</td>
<td>0.595</td>
<td>0.589</td>
<td>0.592</td>
</tr>
<tr>
<td>Region-SSL</td>
<td>0.674</td>
<td>0.652</td>
<td>0.663</td>
</tr>
<tr>
<td>Adversarial-SSL</td>
<td>0.698</td>
<td>0.691</td>
<td>0.694</td>
</tr>
<tr>
<td>Reinforced Co-Training</td>
<td>0.709</td>
<td>0.684</td>
<td>0.696</td>
</tr>
</tbody>
</table>

Table 2: The experimental results on clickbait dataset. 
Prec.: precision.
Experiment 2: Generic Text Classification

<table>
<thead>
<tr>
<th>Dataset</th>
<th>AG’s News</th>
<th>DBpedia</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Classes</td>
<td>4</td>
<td>14</td>
</tr>
<tr>
<td>#Training</td>
<td>12,000</td>
<td>56,000</td>
</tr>
<tr>
<td>#Validation</td>
<td>12,000</td>
<td>56,000</td>
</tr>
<tr>
<td>#Test</td>
<td>7,600</td>
<td>70,000</td>
</tr>
<tr>
<td>#Unlabeled</td>
<td>96,000</td>
<td>448,000</td>
</tr>
</tbody>
</table>

Table 4: Statistics of the Text Classification Datasets.
### Experiment 2: Generic Text Classification

<table>
<thead>
<tr>
<th>Methods</th>
<th>AG’s News</th>
<th>DBpedia</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN (Training+Validation)</td>
<td>28.32%</td>
<td>9.53%</td>
</tr>
<tr>
<td>CNN (All)</td>
<td>8.69%</td>
<td>0.91%</td>
</tr>
<tr>
<td>Standard Co-Training</td>
<td>26.52%</td>
<td>7.66%</td>
</tr>
<tr>
<td>Performance Co-Training</td>
<td>21.73%</td>
<td>5.84%</td>
</tr>
<tr>
<td>CoTrade Co-Training</td>
<td>19.06%</td>
<td>5.12%</td>
</tr>
<tr>
<td>Sequence-SSL</td>
<td>19.54%</td>
<td>4.64%</td>
</tr>
<tr>
<td>Region-SSL</td>
<td>18.27%</td>
<td>3.76%</td>
</tr>
<tr>
<td>Adversarial-SSL</td>
<td>8.45%*</td>
<td>0.89%*</td>
</tr>
<tr>
<td>Reinforced Co-Training</td>
<td><strong>16.64%</strong></td>
<td><strong>2.45%</strong></td>
</tr>
</tbody>
</table>

Table 5: The experimental results on generic text classification datasets. * Adversarial-SSL is trained on full labeled data after pre-training.
Conclusion

• We proposed a novel RL framework for semi-supervised learning
• Strong results in SSL text classification
• Also showed effectiveness in relation extraction
Deep Reinforcement Learning for Distantly Supervised Relation Extraction
Outline

• Motivation
• Algorithm
• Experiments
• Conclusion
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• Motivation
• Algorithm
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• Conclusion
Relation Extraction

Relation Type with Labeled Dataset

Plain Text Corpus (Unstructured Info) ➔ Classifier ➔ Entity-relation Triple (Structured Info)

Relation Type without Labeled Dataset
Distant Supervision

“If two entities participate in a relation, any sentence that contains those two entities might express that relation.” (Mintz, 2009)
Distant Supervision

Data(x): \text{<Belgium, Nijlen>}
Label(y): /location/contains

Target Corpus (Unlabeled)

DS Data(x): \text{Nijlen is a municipality located in the Belgian province of Antwerp.}
DS Label(y): /location/contains
Wrong Labeling

- **Within-Sentence-Bag Level**
  - Hoffmann et al., ACL 2011.
  - Surdean et al., ACL 2012.
  - Zeng et al., ACL 2015.
  - Li et al., ACL 2016.

- **Entity-Pair Level**
  - None
Wrong Labeling

- **Place_of_Death**

  i. Some New York city mayors – William O’Dwyer, Vincent R. Impellitteri and Abraham Beame – were born abroad.

  ii. Plenty of local officials have, too, including two New York city mayors, James J. Walker, in 1932, and William O’Dwyer, in 1950.
Wrong Labeling

- Most of entity pairs only have several sentences
- Lots of entity pairs have repetitive sentences
Outline

• Motivation
• Algorithm
• Experiments
• Conclusion
Requirements

Entity-Pair Level Wrong Labeling Problem

Sentence-Level Indicator

Without Supervised Information

General Purpose and Offline Process

Learn a Policy to Denoise the Training Data
Overview

DS Dataset

Negative set

Positive set

False Positive

Cleaned Dataset

Negative set

Positive set

False Positive

Policy Based Agent

Train

Classifier

Reward

Action
Deep Reinforcement Learning

- **State**
  - Sentence vector
  - The average vector of previous removed sentences

- **Action**
  - Remove & retain

- **Reward**
  - ???
Deep Reinforcement Learning

- One relation type has an agent

- Sentence-level
  - Positive: Distantly-supervised positive sentences
  - Negative: Randomly sampled

- Split into training set and validation set
Deep Reinforcement Learning

\[
\mathcal{R}_i = \alpha(F^i_1 - F^{i-1}_1)
\]

\[
\times (+\mathcal{R}_i) + \times (-\mathcal{R}_i)
\]
Reward

- Accurate
- Steady
- Fast
- Obvious
**Reward**

**Epoch** $i$

**Positive**
- Relation Classifier
- Train

**Negative**
- Relation Classifier
- Calculate

$F_1$

**Positive Set**
- False Positive

**Negative Set**

Outline

• Motivation
• Algorithm
• Experiments
• Conclusion
Evaluation on a Synthetic Noise Dataset

- Dataset: SemEval-2010 Task 8
- True Positive: Cause-Effect
- False Positive: Other
- True Positive + False Positive: 1331 samples
Evaluation on a Synthetic Noise Dataset

200 FPs in 1331 Samples

False Positive

Epoch

Removed Part
Evaluation on a Synthetic Noise Dataset

0 FPs in 1331 samples
Distant Supervision on NYT Freebase Dataset

- **CNN+ONE, PCNN+ONE**
  - Distant supervision for relation extraction via piecewise convolutional neural networks. (Zeng et al., 2016)

- **CNN+ATT, PCNN+ATT**
  - Neural relation extraction with selective attention over instances. (Lin et al., 2016)
Distant Supervision

CNN-based

- CNN+ONE
- CNN+ONE_RL
- CNN+ATT
- CNN+ATT_RL
Distant Supervision

PCNN-based

- PCNN+ONE
- PCNN+ONE_RL
- PCNN+ATT
- PCNN+ATT_RL
Outline

• Motivation
• Algorithm
• Experiments
• Conclusion
Conclusion

- We propose a deep reinforcement learning method for robust distant supervision relation Extraction.

- Our method is model-agnostic.

- Our method boost the performance of recently proposed neural relation extractors.
DSGAN: Adversarial Learning for Denoising Distantly Supervised Relation Extraction (Qin et al., ACL 2018b)
Distant Supervision Data Distribution

DS data space

○ DS Positive Data
× DS Negative Data
Data Distribution

DS data space

- DS True Positive Data
- DS Negative Data
- DS False Positive Data

The Decision Boundary of DS Data

The Desired Decision Boundary
Adversarial Training

Noisy Positive Set

True Positive

Label 1

False Positive

Label 1

Generator

True Positive

Label 0

False Positive

Label 1
DSGAN (Qin et al., ACL 2018b)

Epoch $i$

\[ \text{Bag}_k \]

\[ \text{Bag}_{k-1} \]

\[ \text{Bag}_{k+1} \]

**Generator**

- \( s_1 \to p_1 = 0.57 \)
- \( s_2 \to p_2 = 0.02 \)
- \( s_3 \to p_3 = 0.83 \)
- \( \ldots \)
- \( s_n \to p_n = 0.90 \)

\[ \text{Sampling} \]

- \( \text{label} = 1 \)
- \( \text{label} = 0 \)

**Discriminator**

**Pre-training**

- Label = 1
- DS positive dataset
- Label = 0
- DS negative dataset

**DS Positive Dataset**

\[ \text{Positive Dataset} \]

\[ s_i \land \text{&} \land s_j \land \ldots \land s_K \land \text{&} \land p_i = 0.57 \]

\[ p_I = 0.02 \]

\[ p_J = 0.83 \]

\[ p_T = 0.26 \]

\[ p_V = 0.90 \]

\[ \text{Sampling label} = 1 \]

\[ \text{Sampling label} = 0 \]

**Rewards**

- \( \text{reward} = 0.7 \)
Characteristics

- Sentence-Level Noise Reduction
- Training Without Supervised Information
- Model-Agnostic
Distant Supervision Relation Extraction

CNN-based

- CNN+ONE
- CNN+ONE_GANs
- CNN+ATT
- CNN+ATT_GANs
Distant Supervision Relation Extraction

PCNN-based

- PCNN+ONE
- PCNN+ONE_GANs
- PCNN+ATT
- PCNN+ATT_GANs
Conclusion

• We introduce Reinforced Co-Training, a new approach that combines reinforcement learning and semi-supervised learning.

• We show that in weakly-supervised relation extraction, reinforcement learning can be utilized to de-noise the training signals.

• Adversarial learning serves as a joint learning framework, and it can also be applied to de-noising distantly supervised IE data.
Thanks!

http://nlp.cs.ucsb.edu