Gradient Imitation Reinforcement Learning for Low Resource Relation Extraction

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Relation Extraction

Sentence

*Derek Bell* was born in *Belfast.*

*Donald Trump* was born in *America.*

*Thomson* is based in *Toronto.*

*Beijing* is located in *China.*

Relation

Born In

Located in

Relation Encoder + Deep Classification Model

(Labor-intensive)

(Sanovsky et al., 2018; Saha et al., 2018; Yu et al., 2017)
How to improve the model performance for LRE?

• Previous Methods: Directly used limited annotations during training.
• Shortage: The trained models inevitably possesses selection bias.
• Motivation: How to use existing annotations as a guideline and leverage unlabeled data to increases generalization ability?

A letter \_\textit{head} was delivered to my office \_\textit{tail} ...

\( g_u \) : Entity-Destination \quad \checkmark \quad Positive

\( g_{u'} \) : Entity-Origin \quad \times \quad Negative
How to improve the model performance for LRE?

Design a reward  →  Explicit feedback  →  Reinforcement learning

A letter\textsubscript{head} was delivered to my office\textsubscript{tail}...

😊 Reward  \( g_u \) : Entity-Destination  ✔ Positive

😭 Punishment  \( g_u' \) : Entity-Origin  ☠️ Negative
Framework (GradLRE)

1) Limited labeled data and large amounts of unlabeled data are available
   • Relation Label Generator (RLG)
   • Gradient Imitation Reinforcement Learning (GIRL)

2) Only limited labeled data is available
   • Contextualized Data Augmentation (CDA)
Relation Label Generator (RLG)

- Mark two entities with four reserved tokens \([E1], [/E1], [E2], [/E2]\):
  
  \(\text{A [E1] letter [/E1] was delivered to my [E2] office [/E2]} \ldots\)

- Get the relation representation of two entities corresponding to \([E1],[E2]\) from BERT:
  
  \(\mathbf{h} = [\mathbf{h}_{[E1]}, \mathbf{h}_{[E2]}]\)

- Classify these representations into specific relations with a fully connected network \(f_\theta(x, E1, E2)\).
Gradient Imitation Reinforcement Learning (GIRL)

• Define Standard gradient descending:
  Partial derivatives on the labeled data $\nabla_\theta f(x, y; \theta)$

• Assume: When pseudo-labeled data are correctly labeled, partial derivatives on the pseudo-labeled data would be highly similar to standard gradient descending.

A letter\textsubscript{head} was delivered to my office\textsubscript{tail}...

$g_u$: Entity-Destination ✓

$g_u'$: Entity-Origin ✗
Gradient Imitation Reinforcement Learning (GIRL)

• **State**
  Updated labeled dataset $D_l$ and standard gradient direction $g_l$ at step $t$.

• **Policy**
  RLG network $f_\theta$.

• **Action**
  Predict relational label on unlabeled data $\tilde{x}^{(t)}$ as pseudo-labeled data $(\tilde{x}^{(t)}, \tilde{y}^{(t)})$ at step $t$.

• **Reward**
  Standard gradient descent direction on the all $N$ labeled data.
  \[ g_l^{(n)}(\theta) = \nabla_\theta \mathcal{L}_l(x^{(n)}, y^{(n)}; \theta) \]

  Expected gradient descent direction on the pseudo-labeled data.
  \[ g_p^{(t)}(\theta) = \nabla_\theta \mathcal{L}_p(\tilde{x}^{(t)}, \tilde{y}^{(t)}; \theta) \]

  Cosine similarity between $g_l$ and $g_p$ for state $s^{(t)}$.
  \[ R^{(t)} = \frac{g_l(\theta)^T g_p(\theta)}{||g_l(\theta)||_2 ||g_p(\theta)||_2} \]
Gradient Imitation Reinforcement Learning (GIRL)

- **Update State**

  For these positive reinforcement $R(t)>0.5$:

  $$D_t \leftarrow D_t \cup D_p$$
  $$g_t \leftarrow \frac{1}{N+1} (Ng_t + g_p)$$

- **Reinforcement Learning loss**

  We calculate the loss over a batch of pseudo-labeled samples.

  $$\mathcal{L}(\theta) = \sum_{t=1}^{T} \text{loss}(f_\theta(\tilde{x}^{(t,E1,E2)}), \text{one_hot}(\tilde{y}^{(t)})) \times R^{(t)}$$
Contextualized Data Augmentation

Only limited labeled data is available.

- CDA samples spans of the sentence as \([\text{MASK}]\) and finally fills the mask with tokens using BERT.

\begin{align*}
\text{A letter was delivered to my office in this morning.} \\
\text{Sample spans as [MASK]} \\
\text{A letter was [MASK] [MASK] my office in this morning.} \\
\text{Fill the [MASK]} \\
\text{A letter was sent from my office in this morning.}
\end{align*}
# Experiments

## Datasets

| Datasets | SemEval | TACRED |
|----------|---------|--------|
| Relation mentions | 7199/800/1864 | 75049/25763/18659 |
| Relation | 19 | 42 |
| No_relation rate | 17.4% | 78.7% |

## Baselines

- **Relation Encoders**
  - LSTM (Hochreiter and Schmidhuber, 1997)
  - PCNN (Zeng et al., 2015)
  - PRNN (Zhang et al., 2017)
  - BERT (Devlin et al., 2019)
- **Self-Training** (Rosenberg et al., 2005)
- **Mean-Teacher** (Tarvainen and Valpola, 2017)
- **DualRE** (Lin et al., 2019)
- **RE-Ensemble** (Lin et al., 2019)
- **MRefG** (Li and Qian, 2020)
- **MetaSRE** (Hu et al., 2021)
- **BERT w. gold labels**

## Implementations

| Datasets | SemEval | TACRED |
|----------|---------|--------|
| Labeled set | 5%/10%/30% | 3%/10%/15% |
| Unlabeled set | 50% | 50% |

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Does GIRL help to improve pseudo label quality?

Yes!

Figure 2: Pseudo label F1 (%) Performance with GIRL based on SemEval (left) and TACRED (right).
Does GIRL help to guide the gradient descent direction?

Yes!

Figure 3: GradLRE gradient descent directions on labeled data and pseudo label data. The dotted line indicates the average gradient direction on labeled data.
Case study using GIRL

| Sentence                                                                 | Label                        | Prediction w/o GIRL | Prediction w. GIRL |
|--------------------------------------------------------------------------|------------------------------|--------------------|--------------------|
| My *brother* has entered my *room* without knocking.                      | *Entity-Destination*         | Other              | Entity-Destination |
| The *disc* in a disc *music box* plays this function, with pins perpendicular to the plane surface... | *Content-Container*          | Component-Whole    | Content-Container  |
| Ditto for his funny turn as a *man* who instigates the *kidnapping* of his own wife in ... | *Cause-Effect*               | Other              | Cause-Effect       |

Table 2: Predictions with/without GIRL on SemEval, where *red* and *blue* represent head and tail entities respectively.
Handling two major low resource scenarios

1) L+U: Limited labeled data + 50% unlabeled data.
2) L+CDA: Limited labeled data + CDA generate 50% unlabeled data.
3) L: Limited labeled data.

Table 3: F1 (%) of GradLRE with various percentages of labeled data under different LRE scenarios.
Does CDA generate useful unlabeled data?

Yes!

Figure 4: F1 (%) Performance with various unlabeled data and 10% labeled data on SemEval (left) and TACRED (right).
Case study using CDA

| Original                                                                 | Label               | Generated                                                                 | Pseudo label           |
|-------------------------------------------------------------------------|---------------------|---------------------------------------------------------------------------|------------------------|
| A letter was delivered to my office in ...                              | Entity-Destination  | A letter was sent from my office in ...                                   | Entity-Origin          |
| Maintain the original relation                                           |                     |                                                                           |                        |
| The editor improved the manuscript with his changes.                    | Product-Producer     | The editor improved the manuscript with some improvements.                | Product-Producer       |
| Change the original relation                                             |                     |                                                                           |                        |
| The suspect dumped the dead body into a local reservoir.                | Entity-Destination  | The dam bulids the human body into a local reservoir.                     | Other                  |
|                                                                          |                     |                                                                           |                        |

Table 4: CDA on labeled data to obtain generated data, where red and blue represent head and tail entities respectively, cyan represents the replaced words.
Conclusion

• Our model encourages pseudo-labeled data to imitate the gradient optimization direction in labeled data to improve the pseudo label quality.
• Contextualized data augmentation is proposed to handle the extremely low resource Relation Extraction situation where no unlabeled data is available.
• Experiments on two public datasets show effectiveness of GradLRE and augmented data over competitive baselines.
THANK YOU!

Code + Data are Available at:
http://github.com/THU-BPM/GradLRE