Abstract

One key task of fine-grained sentiment analysis on reviews is to extract aspects or features that users have expressed opinions on. This paper focuses on supervised aspect extraction using a modified CNN called controlled CNN (Ctrl). The modified CNN has two types of control modules. Through asynchronous parameter updating, it prevents over-fitting and boosts CNN’s performance significantly. This model achieves state-of-the-art results on standard aspect extraction datasets. To the best of our knowledge, this is the first paper to apply control modules to aspect extraction.

1 Introduction

Aspect extraction is an important task in sentiment analysis (Hu and Liu, 2004) and has many applications (Pang and Lee, 2008; Liu, 2012; Cambria and Hussain, 2012). It aims to extract opinion targets (or aspects) from opinion text. In reviews, aspects are attributes or features of opinion targets. For example, from “The screen is great” in a laptop review, it aims to extract “screen”.

Aspect extraction has been performed using supervised and unsupervised approaches. Since this work focuses on supervised learning, for existing unsupervised approaches, see (Liu, 2012). Traditionally, supervised approaches (Jakob and Gurevych, 2010; Mitchell et al., 2013) use Conditional Random Fields (CRF) (Lafferty et al., 2001). Recently, deep networks have also been applied, for example, using LSTM (Williams and Zipser, 1989; Hochreiter and Schmidhuber, 1997; Liu et al., 2015) and attention mechanism (Wang et al., 2017; He et al., 2017) together with manual features (Poria et al., 2016; Wang et al., 2016).

More recently, a simple CNN model called DE-CNN (Xu et al., 2018) achieved state-of-the-art performances on aspect extraction by leveraging a double embedding mechanism. Besides using general-purpose embeddings (e.g., GloVe embeddings), DE-CNN also uses domain-specific embeddings to boost its performance without using any manual feature.

In this paper, we use DE-CNN as a base model. We notice that in traditional CNN model training process, all CNN layers are updated together (synchronously) through back-propagation. They easily over-fit the training dataset though validation dataset used for deciding the best parameters’ values. Inspired by a recent work called Deep Adaption Network (DAN) (Rosenfeld and Tsotsos, 2017), we design two kinds of control modules to adjust the input of each CNN layer. Although DAN is for incremental learning (continually adapt a model for new tasks without losing performance on previous tasks), we observe that by asynchronously updating control modules and CNN layers, it can boost the performance of a single task, too. The critical point is that we do not train all parameters at the same time. Instead, we optimize CNN layers when we fix control modules’ parameters. The control modules work as adding noise on each CNN layer’s input. This makes the training little harder and ensures the whole model does not fully fit the training data. After that, we optimize control modules by fixing CNN layers’ parameters. Since CNN layers’ parameters is optimized on noisy input, in this step, the whole model does not easily over-fit training data as well. In every step (fixing control modules or fixing CNN layers), we track the best validation model and make the next step training start with this best validation model. Once the best validation score does not change after several steps, the whole asynchronous-updating training process stops.
To achieve better efficiency, we propose two kinds of control modules: Embedding Control Module and CNN Control Module. The former is applied after the embedding layer, and the later is applied between two adjacent CNN layers. Using these control modules and asynchronously updating control modules and CNN layers prevent over-fitting. The experiment results show that this idea is promising. To the best of our knowledge, this is the first paper that incorporates control modules and asynchronously updating.

2 Related Work

CNN (LeCun et al., 1995; Kim, 2014; Du et al., 2017) is recently adopted for machine translation (Gehring et al., 2017), named entity recognition (Kalchbrenner et al., 2014; Chiu and Nichols, 2015; Ma and Hovy, 2016; Strubell et al., 2017), sentiment analysis (Poria et al., 2016; Chen et al., 2017) and aspect extraction (Xu et al., 2018). We do not purely use CNN but propose control modules to boost the performance of CNN.

DAN (Rosenfeld and Tsotsos, 2017) solves incremental learning problem by (1) training a base CNN network on the initial task, (2) encountering a new task, train on the square linear transformations of the base CNN layer to utilize base CNN network for the new task and also maintain base CNN’s performance for the initial task. Residual network (He et al., 2016) solves gradient vanishing problem on a very deep neural network by providing high-way bridges between CNN layers. We do not solve incremental/transfer learning nor gradient vanishing problems. We do asynchronous parameter update to prevent over-fitting and make the only one task better.

3 Model

The proposed model is depicted in Table 1. It has a double embedding (Xu et al., 2018) layer (we later use embedding layer for simplicity), multiple CNN layers, multiple control modules, and a fully-connected+softmax layer. Note that we keep the architecture of (Xu et al., 2018) and only add control modules. We apply control modules after the embedding layer and each CNN layer, except the last CNN layer.

We propose two kinds of control modules. **Embedding Control Module** As shown in Figure 1, embedding control module adds the input and the transformed input via a square matrix together. The purpose of using this control module is to keep the original embedding and meanwhile slightly adjust the representation of the embedding.

Assume the input is a sequence of word indexes \( x = (x_1, \ldots, x_n) \). Let \( x^{(1)} \) denote the output from the embedding layer. The controlled output from the embedding layer is:

\[
  z^{(1)} = (w_{emb}^{(1)} x^{(1)} + b_{emb}^{(1)}) + x^{(1)},
\]

where \( w_{emb}^{(1)} \) and \( b_{emb}^{(1)} \) are trainable weights.

**CNN Control Module** As shown in Figure 2, CNN control module has a bow tie structure. The size of the hidden dimensions is first reduced and later expanded. We use \( \tanh(.) \) as the intermediate activation function. To avoid over-fitting, we also apply dropout after this activation function. This bow tie structure can help to strengthen important information from each CNN’s output. The expanded output is also added to the output of CNN to keep the original representation with a slight adjustment. Finally, ReLU activation is applied to ensure the output is greater than or equal to 0.

Specifically, let \( x^{(l)} \) denote the output of the

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Table 1: Network layers and parameters. CNN: \((\text{filter\_size}, \text{in\_dim}, \text{kernel\_size})\), Others: \((\text{in\_dim}, \text{out\_dim})\) or \((\text{out\_dim})\)

| \(l\) | Type  | Parameter Size          |
|------|-------|------------------------|
| 1    | Emb   | (vocab\_size,300) (vocab\_size,100) |
| 1    | Emb Ctrl | (400, 400)(400,) |
| 2    | CNN   | (128, 400, 3)(128,) (128, 400, 5)(128,) |
| 2    | CNN Ctrl | (256, 128)(128,) (128, 256)(256,) |
| 3    | CNN   | (256, 256, 5)(256,) |
| 3    | CNN Ctrl | (256, 128)(128,) (128, 256)(256,) |
| 4    | CNN   | (256, 256, 5)(256,) |
| 4    | CNN Ctrl | (256, 128)(128,) (128, 256)(256,) |
| 5    | CNN   | (256, 256, 5)(256,) |
| 6    | Linear | (256, 3) (3,) |

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Figure 1: Embedding Control Module

Figure 2: CNN Control Module
$(l - 1)$-th CNN layer (first layer is embedding layer). The output $z^{(l)}$ of the CNN control module is computed as:

$$z^{(l)} = \max \left( 0, x^{(l)} + \left( w^{(l)}_{\text{exp}} \tanh \left( w^{(l)}_{\text{red}} x^{(l)} + b^{(l)}_{\text{red}} \right) + b^{(l)}_{\text{exp}} \right) \right),$$

(2)

where $w^{(l)}_{\text{exp}}, w^{(l)}_{\text{red}}, b^{(l)}_{\text{red}}$ and $b^{(l)}_{\text{exp}}$ are trainable weights.

Further, we let $\Theta_{\text{cnn}}, \Theta_{\text{ctrl}}, \Theta_{\text{fc}}$ denote the trainable parameters in CNN layers, control layers and the final fully connected layer, respectively. We define the asynchronous training as follows. At every step, the model is initialized to the previous step’s best validation model and save the best validation model during training.

**Step (1)** fix $\Theta_{\text{ctrl}}, \Theta_{\text{fc}}$, and tune on $\Theta_{\text{cnn}}$.

**Step (2)** fix $\Theta_{\text{cnn}}$, and tune on $\Theta_{\text{ctrl}}, \Theta_{\text{fc}}$.

Repeat step (1) and step (2) until the best validation score does not change after several steps. In this way, CNN layers are trained when control modules are frozen, and the control modules are trained when the CNN layers are frozen.

For better comparing with state-of-the-art method DE-CNN (Xu et al., 2018), we keep the embedding and all CNN layers the same as DE-CNN. DE-CNN has a double embedding layer, 4 CNN layers, a fully-connected layer shared across all positions of the words, and a softmax layer over the labeling space $\mathcal{Y} = \{B(-\text{Aspect}), I(-\text{Aspect}), O(\text{other})\}$ for each position of inputs. For the first CNN layer, two different filter sizes are employed. For the rest 3 CNN layers, only one filter size is used. We apply dropout after the embedding layer and each ReLU activation. As the reason indicated by (Xu et al., 2018), the double embedding layer is frozen since the training data for aspect extraction is usually small. The embedding control module lies between the embedding layer and the first CNN layer. Three CNN control modules lie between any two adjacent CNN layers. Details are also in Table 1.

4 Experiment

We conduct experiments on two benchmark datasets from SemEval challenges (Pontiki et al., 2014, 2016), as shown in Table 2. The first
Datasets | Training Set | Testing Set
---|---|---
SemEval-14 Laptop | 3045/2358 | 800/654
SemEval-16 Restaurant | 2000/1743 | 676/622

Table 2: Datasets Statistics: number of sentences(Sent.) and number of aspects(Asp.)

|       | Laptop Dataset | Restaurant Dataset |
|-------|----------------|--------------------|
| CRF   | 74.01          | 69.56              |
| IHS,RD | 74.55          | -                  |
| NLANGP | 72.34          | -                  |
| WDEmb | 75.16          | -                  |
| LSTM  | 75.71          | 70.35              |
| BiLSTM-CNN-CRF | 77.8          | 72.5               |
| RNCRF | 78.42          | -                  |
| CMLA  | 77.80          | -                  |
| MIN   | 77.58          | 73.44              |
| THA & STN | 79.52        | 73.61              |
| BERT  | 77.19          | 71.52              |
| DE-CNN | 81.59          | 74.37              |
| DAN-  | 78.28          | 70.43              |
| DAN-  | 76.68          | 72.94              |
| DAN   | 80.24          | 73.35              |
| Ctrl- | 79.47          | 71.15              |
| Ctrl- | 81.66          | 73.77              |
| Ctrl  | **82.73**      | **75.64**          |

Table 3: Comparison results in $F_1$ score: results are averaged scores of 5 runs. *indicates the result is statistically significant at the level of 0.01.

4.1 Compared Methods

We perform a comparison of Ctrl with two groups of baselines. The results of the first group are non-CNN based methods. **CRF** is conditional random fields. **IHS,RD** (Chernyshevich, 2014) and **NLANGP** (Toh and Su, 2016) are the best systems from the original challenges (Pontiki et al., 2014, 2016). **WDEmb** (Yin et al., 2016) is enhanced CRF with multiple embeddings. **LSTM** (Liu et al., 2015; Li et al., 2018) is a BiLSTM implementation. **BiLSTM-CNN-CRF** (Reimers and Gurevych, 2017) is the state-of-the-art named entity recognition system. **BERT** (Devlin et al., 2018) fine-tunes pre-trained language model on aspect extraction tasks. The following methods use multi-task learning and opinion lexicon or human annotation are adopted for opinion supervision: **RNCRF** (Wang et al., 2016) is a recursive neural network and CRF jointed model for aspect and opinion terms co-extraction. **CMLA** (Wang et al., 2017) solves the co-extraction through a multi-layer coupled-attention network. **MIN** (Li and Lam, 2017) solves co-extraction, and discriminate sentimental/non-sentimental sentences. **THA & STN** (Li et al., 2018) uses opinion summary and aspect history to improve prediction.

The second group is a CNN-based method. **DE-CNN** (Xu et al., 2018) is a pure CNN-based sequence labeling model which utilizes double embedding. This is the base model that Ctrl is adapted from. We use this baseline to show the improvements from Ctrl. The remaining baselines use DE-CNN as the basic network and add an extra intermediate layer between layers in the basic network. **DAN** (Rosenfeld and Tsotsos, 2017) adopts linear transformation as control modules for a incremental learning method on image classification. **DAN-** tunes on all fully connected layers given frozen random-value CNN layers. **DAN** optimizes all parameters in fully connected layers and CNN layers together. **DAN-** gives random-value CNN layers (un-trainable), tunes on control modules and fully connected layers. **DAN** synchronously trains the control modules, CNN layers, and fully connected layer. **Ctrl** synchronously updates the control modules, CNN layers, and fully connected layer. **Ctrl** asynchronously updates parameters. These are variations of our model.

4.2 Results and Analysis

From Table 3, we can see that our model Ctrl performs the best. The variations of Ctrl always outperform that of DAN. It shows that a purely linear transformation is unable to produce noise and prevent over-fitting. Ctrl - -’s result shows the
adaptive ability of the control modules. Ctrl updates all parameters in the overall network synchronously, but under-performs DE-CNN though it has control modules. The reason is that in synchronous updating, control modules just make the overall network deeper. As in Figure 3, the first plot shows that Ctrl- and Ctrl can reach a similar training loss level and Ctrl- is faster. They have the same learning rate. It means that fixed control modules make the training harder. In the second plot, Ctrl-’s validation loss decreases and then increases. This is an apparent over-fitting signal. But, Ctrl’s validation loss tends flat even after several-steps training. From the last test-score plot, we can see that Ctrl has similar testing performance as Ctrl- in the first step training. In Ctrl’s second step training (between the first and second green lines), the test score continues improving. The results and plots show that through asynchronous updating, control modules can prevent over-fitting and improve CNN performance.

5 Conclusion

We propose to add two kinds of control modules for CNN-based aspect extraction model. Through asynchronous update, our model Ctrl outperforms state-of-the-art methods significantly.

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