Abstract

We consider the problem of recognizing mentions of human senses in text. Our contribution is a method for acquiring labeled data, and a learning method that is trained on this data. Experiments show the effectiveness of our proposed data labeling approach and our learning model on the task of sense recognition in text.

1 Introduction

Information extraction methods produce structured data in the form of knowledge bases of factual assertions. Such knowledge bases are useful for supporting inference, question answering, and reasoning (Bollacker et al., 2008; Hoffart et al., 2012; Mitchell et al., 2015). However, progress on the common sense front, as opposed to named entities such as locations, and people, is still limited (Havasi et al., 2007; Tandon et al., 2011). In this paper, we study entity recognition of common sense concepts. Our goal is to detect mentions of concepts that are discernible by sense. For example, recognize that “chirping birds” is a mention of an audible concept (sound), and “burning rubber” is a mention of an olfactible concept (smell). We aim to detect mentions of concepts without performing co-reference resolution or clustering mentions. Therefore, our setting resembles the established task of entity recognition (Finkel et al., 2005; Ratinov and Roth, 2009), with the difference being that we focus on un-named entities.

Contribution. One of the factors impeding progress in common sense information extraction is the lack of training data. It is relatively easy to obtain labeled data for named entities such as companies and people. Examples of such named entities can be found in structured forms on the Web, such as HTML lists and tables, and Wikipedia infoboxes (Wu and Weld, 2008; Wang and Cohen, 2008). This is not the case for common sense concepts. We therefore propose a data labeling method, that leverages crowdsourcing and large corpora. This approach provides the flexibility to control the size and accuracy of the available labeled data for model training. Additionally, we propose and train several sequence models including variations of recurrent neural networks that learn to recognize mentions of sound and smell concepts in text. In our experiments, we show that the combination of our mixture labeling approach, and a suitable learning model are an effective solution to sense recognition in text.

2 Problem Definition

We would like to detect mentions of concepts discernible by sense. In this paper, we focus on mentions of audible (sound) and olfactible (smell) concepts. We treat sense recognition in text as a sequence labeling task where each sentence is a sequence of tokens labeled using the BIO tagging scheme (Ratinov and Roth, 2009). The BIO labels denote tokens at the beginning, inside, and outside of a relevant mention, respectively. Example BIO tagged sentences are shown in Figure

![Figure 1: Example beginning-inside-outside (BIO) labeled sentences with mentions of sound (top) and smell (bottom) concepts.](image-url)
3 Data Labeling Methodologies

There is a lack of easy to identify labeled data on the Web for common sense information extraction, an issue which affects named-entity centric information extraction to a lesser degree (Wang and Cohen, 2008; Wu and Weld, 2008). We consider three data labeling approaches:

i) Automatically generate training data using judiciously specified patterns.

ii) Solicit input on crowd-sourcing platforms.

iii) Leverage both i) and ii) in order to overcome their respective limitations.

3.1 Pattern-based Corpus Labeling

To label data with patterns, we begin by specifying patterns that we apply to a large corpus. For our concepts of interest, sound, and smell, we specify the following two patterns. “sound of <y>”, and “smell of <y>”, We then apply these patterns to a large corpus. In our experiments, we used the English part of ClueWeb09.1 The result is a large collection of occurrences such as: “sound of breaking glass”, “smell of perfume”, etc. The collections contains 134,473 sound phrases, and 18,183 smell phrases.

Figure 2 shows a 2D projection of the 300-dimensional word vectors of the discovered audible and olfactible phrases. We see a strong hint of two clusters. We later provide a quantitative analysis of this data.

3.2 Crowd-Sourced Supervision

The second way of obtaining labeled data that we consider is crowd-sourcing. We used the Amazon Mechanical Turk crowd-sourcing platform.

Crowd Task Definition. To obtain labeled examples, we could do a “cold call” and ask crowd workers to list examples of phrases that refer to senses. However, such an approach requires crowd workers to think of examples without clues or memory triggers. This is time consuming and error prone. Additionally, the monetary cost to we have to pay to the crowd sourcing platform could be substantial. We propose to exploit a large corpus to obtain preliminary labeled data. This enables us to only need crowd workers to filter the data through a series of “yes/no/notsure” questions. These type of questions require little effort from crowd workers while mitigating the amount of noisy input that one could get from open-ended, cold call, type of questions. We randomly selected 1000 phrases labeled by the pattern approach as described in Section 3.1 to be sound/smell phrases, 500 for each sense type. Each phrase was given to 3 different workers to annotate “yes/no/notsure”.

We consider a phrase to be a true mention of the labeled sense if the majority of the participants chose “yes”. This annotation task serves two purposes: 1) to provide us with human labeled examples of sound and smell concepts ii) to provide a quantitative evaluation of pattern generated labels.

Crowd Annotation Results. Table 1 is a summary of the annotation results. First, we can see that the accuracy of the patterns is quite high as already hinted by Figure 2. Second, The inter-annotator agreement rates are moderate, but lower for olfactible phrases. This is also reflected by the fact that there were around 3 times as many “not sure” responses in the smell annotations as there were in the sound annotation task (27 vs 10). Nonetheless, the output of these tasks provide us with another option for labeled data that we can use to train our models.

3.3 Joint Pattern & Crowd-Sourced Labeling

A third way of obtaining labeled data is to leverage both pattern-based and crowd-sourced labeling approaches. One central question pertains to how we can combine the two sources in a way that exploits the advantages of each approach while mitigating their limitations. We seek to start with the crowd-sourced labeled, which is small but more accurate, and expand it with the pattern-generated labeled data, which is large but less accurate. We

| % Majority Yes | Fleiss κ |
|----------------|----------|
| Audible        | 73.4%    | 0.51     |
| Olfactible     | 89.6%    | 0.33     |

Table 1: Crowd-sourced labeling of phrases generated by the pattern approach of section 3.1.
define a function that determines how to expand the data. Let \( x_i^c \in D_c \) be a crowd labeled phrase, and \( x_i^p \in D_p \) be a pattern labeled phrase. Then \( x_i^p \) is added to our training labeled data \( D_{pc} \) if \( \text{sim}(x_i^c, x_i^p) \geq \alpha \) where \( \text{sim} \) is the cosine similarity between the vector representations of the phrases. For vector representations of phrases, we use the same pre-trained Google word embeddings as those used to plot Figure 2. For phrases longer than one word, we use vector averaging. The effect of varying \( \alpha \), for a fixed prediction model, can be seen in Figure 3. When \( \alpha = 1 \), that is we are only using the crowd-sourced labeled data, performance is at its worst. This is because even though the human labeled data is more accurate, it is much smaller, leading to potential model over-fitting problems. A more subtle finding is that with low \( \alpha \) values (i.e., \(< 0.4 \) for audible concepts), we have the highest recall, but not the best precision, this can be explained by the fact that, with low \( \alpha \) values, we are allowing more of the automatically labeled data to be part of the training data, thereby potentially adding noise to the model. However, the advantage of the mixture approach comes from the fact that, there comes a point where precision goes up, recall slightly degrades but we obtain the best F1 score. In Figure 3, we see these points at \( \alpha = 0.6 \) and \( \alpha = 0.4 \) for the audible and olfactible concepts respectively. We use these values to generate the labeled data used to train models described in the rest of the paper.

4 Learning Models

We treat sense recognition in text as sequence prediction problem, we would like to estimate: \( P(y_i | x_{i-k}, \ldots, x_{i+k}; y_{i-1}, \ldots, y_{i-1}) \). where \( x \) refers to words, and \( y \) refers to BIO labels.

Conditional Random Fields (CRFs) (Lafferty et al., 2001) have been widely used named entity recognition (Ratinov and Roth, 2009; Finkel et al., 2005), a task similar to our own. While the CRF models performed reasonably well on our task, we sought to obtain improvements by proposing and training variations of Long Short Memory (LSTM) recurrent neural networks (Hochreiter and Schmidhuber, 1997). We found our variations of LSTM sequence classifiers to do better than the CRF model, and also better than standard LSTMs.

Word and Character Features. As input, the LSTM neural network model takes a sentence and, as output, produces a probability distribution over the BIO tags for each word in the sentence. To BIO tag each word in the sentence, we use word features. We chose the word features to be their word embeddings. As additional features, we model the character composition of words in order to capture morphology. Neural encodings of character-level features have been shown to yield performance gains in natural language tasks (Ling et al., 2015; Chiu and Nichols, 2016). In all our experiments, we initialize the word embeddings with the Google news pre-trained word embeddings. The character embeddings are learned from scratch.

Prediction and Output Layer Recurrence. We represent each word as a mention within a short context window of length \( m \). We use the LSTM to encode these windows contexts in order to make a prediction for each word. The LSTM window

40
52.5
65
77.5
90
alpha (\( \alpha \))
0.2 0.4 0.6 0.8 1.0
Audible
60
70
80
90
100
alpha (\( \alpha \))
0.2 0.4 0.6 0.8 1.0
F1
Precision
Recall
Figure 3: Performance as \( \alpha \) is varied to control size and accuracy of labeled data.

Figure 4: Our neural network architecture for the task of recognizing concepts that are discernible by senses.

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| Sound          | Smell          |
|----------------|----------------|
| honking cars   | burning rubber |
| snoring        | chlorine       |
| gunshots       | citrus blossoms|
| live music     | fresh paint    |

Table 2: Examples of sound and smell concepts recognized by our method.

encoding is then used to make predictions over the BIO labels. The output for each word is decoded by a linear layer and a softmax layer into probabilities over the BIO tag labels. Crucially, we modify the standard LSTM by modeling temporal dependencies by introducing a recurrence in the output layer. Therefore, the prediction \(d_t\) at time step \(t\) takes into account the prediction \(d_{t-1}\) at the previous time \(t-1\). Formally, we have:

\[d_t = \text{softmax}(W_d \cdot [v_m; v_c; v_s; d_{t-1}]),\]

where \(\text{softmax}(z_i) = e^{z_i}/\sum_j e^{z_j}\). We illustrate the model in Figure 4. We found this model to consistently perform well on the senses of sound and smell.

Model Evaluation. To evaluate the models, we set aside 200 of the 1000 crowd-annotated phrases as test data, meaning we have 100 test instances for each sense type (sound/smell). The rest of the data, 400 per sense type was used for generating training data using the combined crowd and pattern approach described in Section 3.3. We set \(\alpha = 0.6\) and \(\alpha = 0.4\), based on Figure 3 for audible and olfactible concepts respectively. With these \(\alpha\) values, the combination approach produced 1,962 and 1,702 training instances for audible and olfactible concepts respectively.

Performance of the various models is shown in Table 3. The abbreviations denote the following: LSTM refers to a vanilla LSTM model, using only word embeddings as features, + OR refers to the LSTM plus the output recurrence, + CHAR refers to the LSTM plus the character embeddings as features. + OR + CHAR refers to the LSTM plus the output recurrence and character embeddings as features. For the CRF, we use the commonly used features for named entity recognition: words, prefix/suffixes, and part-of-speech tag (Ratinov and Roth, 2009). We can see that for both senses, the model that uses both character embedding features, and an output recurrence layer yields the best F1 score. Examples of sounds and smells our method can recognize are shown in Table 4.

| Method       | F1  | P   | R   |
|--------------|-----|-----|-----|
| Audible      |     |     |     |
| CRF          | 89.38 | 87.83 | 90.99 |
| LSTM         | 89.64 | 88.87 | 90.42 |
| + OR         | 89.780 | 88.60 | 90.99 |
| + CHAR       | 87.78 | 88.18 | 87.39 |
| + OR + CHAR  | **90.91** | **91.740** | **90.09** |
| Olfactible   |     |     |     |
| CRF          | 75.73 | 79.59 | 72.22 |
| LSTM         | 69.96 | 62.96 | 78.70 |
| + OR         | 78.380 | 76.320 | 80.56 |
| + CHAR       | 69.57 | 60.69 | 81.48 |
| + OR + CHAR  | **78.73** | **76.990** | **80.56** |

Table 3: Performance of the various models on the task of sense recognition.

5 Related Work

Our task is related to entity recognition however in this paper we focused on novel types of entities, which can be used to improve extraction of common sense knowledge. Entity recognition systems are traditionally based on a sequential model, for example a CRF, and involve feature engineering (Lafferty et al., 2001) (Ratinov and Roth, 2009). More recently, neural approaches have been used for named entity recognition (Hammerton, 2003; Collobert et al., 2011; dos Santos and Guimarães, 2015; Chiu and Nichols, 2016; Shimaoka et al., 2016). Like other neural approaches, our approach does not require feature engineering, the only features we use are word and character embeddings. Related to our proposed recurrence in the output layer is the work of (Lample et al., 2016) which introduced a CRF on top of LSTM for the task of named entity recognition.

6 Conclusions

We have presented a method for recognizing concepts that are discernible by sense. The concepts our method recognizes present opportunities for discovering additional types of common sense knowledge, for example, learning relationships that encode information such as which objects produce which sounds, in which environments can certain sounds be found, what is the sentiment of various types of smell, etc. These type of relations can significantly improve coverage of common sense in knowledge bases, thereby improving their utility.
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