Disfluency Detection Using Multi-step Stacked Learning

Xian Qian and Yang Liu
Computer Science Department
The University of Texas at Dallas
{qx,yangl}@hlt.utdallas.edu

Abstract

In this paper, we propose a multi-step stacked learning model for disfluency detection. Our method incorporates refined n-gram features step by step from different word sequences. First, we detect filler words. Second, edited words are detected using n-gram features extracted from both the original text and filler filtered text. In the third step, additional n-gram features are extracted from edit removed texts together with our newly induced in-between features to improve edited word detection. We use Max-Margin Markov Networks (M3Ns) as the classifier with the weighted hamming loss to balance precision and recall. Experiments on the Switchboard corpus show that the refined n-gram features from multiple steps and M3Ns with weighted hamming loss can significantly improve the performance. Our method for disfluency detection achieves the best reported F-score 0.841 without the use of additional resources.

1 Introduction

Detecting disfluencies in spontaneous speech can be used to clean up speech transcripts, which helps improve readability of the transcripts and make it easy for downstream language processing modules. There are two types of disfluencies: filler words including filled pauses (e.g., ‘uh’, ‘um’) and discourse markers (e.g., ‘I mean’, ‘you know’), and edited words that are repeated, discarded, or corrected by the following words. An example is shown below that includes edited words and filler words.

I want a flight to Boston uh I mean to Denver

Automatic filler word detection is much more accurate than edit detection as they are often fixed phrases (e.g., “uh”, “you know”, “I mean”), hence our work focuses on edited word detection.

Many models have been evaluated for this task. Liu et al. (2006) used Conditional Random Fields (CRFs) for sentence boundary and edited word detection. They showed that CRFs significantly outperformed Maximum Entropy models and HMMs. Johnson and Charniak (2004) proposed a TAG-based noisy channel model which showed great improvement over boosting based classifier (Charniak and Johnson, 2001). Zwarts and Johnson (2011) extended this model using minimal expected F-loss oriented n-best reranking. They obtained the best reported F-score of 83.8% on the Switchboard corpus.

Georgila (2009) presented a post-processing method during testing based on Integer Linear Programming (ILP) to incorporate local and global constraints.

From the view of features, in addition to textual information, prosodic features extracted from speech have been incorporated to detect edited words in some previous work (Kahn et al., 2005; Zhang et al., 2006; Liu et al., 2006). Zwarts and Johnson (2011) trained an extra language model on additional corpora, and used output log probabilities of language models as features in the reranking stage. They reported that the language model gained about absolute 3% F-score for edited word detection on the Switchboard development dataset.

1Our source code is available at http://code.google.com/p/disfluency-detection/downloads/list
In this paper, we propose a multi-step stacked learning approach for disfluency detection. In our method, we first perform filler word detection, then edited word detection. In every step, we generate new refined n-gram features based on the processed text (remove the detected filler or edited words from the previous step), and use these in the next step. We also include a new type of features, called in-between features, and incorporate them into the last step. For edited word detection, we use Max-Margin Markov Networks (M³Ns) with weighted hamming loss as the classifier, as it can well balance the precision and recall to achieve high performance. On the commonly used Switchboard corpus, we demonstrate that our proposed method outperforms other state-of-the-art systems for edit disfluency detection.

2 Balancing Precision and Recall Using Weighted M³Ns

We use a sequence labeling model for edit detection. Each word is assigned one of the five labels: BE (beginning of the multi-word edited region), IE (in the edited region), EE (end of the edited region), SE (single word edited region), O (other). For example, the previous sentence is represented as:

I/O want/O a/O flight/O to/BE Boston/EE uh/O I/O mean/O to/O Denver/O

We use the F-score as the evaluation metrics (Zwarts and Johnson, 2011; Johnson and Charniak, 2004), which is defined as the harmonic mean of the precision and recall of the edited words:

\[ P = \frac{\text{#correctly predicted edited words}}{\text{#predicted edited words}} \]
\[ R = \frac{\text{#correctly predicted edited words}}{\text{#gold standard edited words}} \]
\[ F = \frac{2 \times P \times R}{P + R} \]

There are many methods to train the sequence model, such as CRFs (Lafferty et al., 2001), averaged structured perceptrons (Collins, 2002), structured SVM (Altun et al., 2003), online passive aggressive learning (Crammer et al., 2006). Previous work has shown that minimizing F-loss is more effective than minimizing log-loss (Zwarts and Johnson, 2011), because edited words are much fewer than normal words.

In this paper, we use Max-margin Markov Networks (Taskar et al., 2004) because our preliminary results showed that they outperform other classifiers, and using weighted hamming loss is simple in this approach (whereas for perceptron or CRFs, the modification of the objective function is not straightforward).

The learning task for M³Ns can be represented as follows:

\[
\min_\alpha \frac{1}{2} C \left\| \sum_{x,y} \alpha_{x,y} \Delta f(x, y) \right\|_2^2 + \sum_{x,y} \alpha_{x,y} L(x, y)
\]

s.t. \[ \sum_y \alpha_{x,y} = 1 \quad \forall x \]
\[ \alpha_{x,y} \geq 0, \quad \forall x, y \]

The above shows the dual form for training M³Ns, where \( x \) is the observation of a training sample, \( y \in \mathcal{Y} \) is a label. \( \alpha \) is the parameter needed to be optimized, \( C > 0 \) is the regularization parameter. \( \Delta f(x, y) \) is the residual feature vector: \( f(x, \tilde{y}) - f(x, y) \), where \( \tilde{y} \) is the true label of \( x \). \( L(x, y) \) is the loss function. Taskar et al. (2004) used un-weighted hamming loss, which is the number of incorrect components: \( L(x, y) = \sum_t \delta(y_t, \tilde{y}_t) \), where \( \delta(a, b) \) is the binary indicator function (it is 0 if \( a = b \)). In our work, we use the weighted hamming loss:

\[
L(x, y) = \sum_t v(y_t, \tilde{y}_t) \delta(y_t, \tilde{y}_t)
\]

where \( v(y_t, \tilde{y}_t) \) is the weighted loss for the error when \( \tilde{y}_t \) is mislabeled as \( y_t \). Such a weighted loss function allows us to balance the model’s precision and recall rates. For example, if we assign a large value to \( v(O, E) \) (\( E \) denotes SE, BE, IE, EE), then the classifier is more sensitive to false negative errors (edited word misclassified as non-edited word), thus we can improve the recall rate. In our work, we tune the weight matrix \( v \) using the development dataset.

3 Multi-step Stacked Learning for Edit Disfluency Detection

Rather than just using the above M³Ns with some features, in this paper we propose to use stacked learning to incorporate gradually refined n-gram features. Stacked learning is a meta-learning approach (Cohen and de Carvalho, 2005). Its idea is to use two
(or more) levels of predictors, where the outputs of the low level predictors are incorporated as features into the next level predictors. It has the advantage of incorporating non-local features as well as non-linear classifiers. In our task, we do not just use the classifier’s output (a word is an edited word or not) as a feature, rather we use such output to remove the disfluencies and extract new n-gram features for the subsequent n-gram features, we did not use the weight-


defined hyp-

hypothesis. This kind of n-gram features is similar to

the language models used in (Zwarts and Johnson, [72x72] the text after removing edit disfluencies based on

In this step, we use n-gram features extracted from

templates

I

using the system’s prediction, we would have bi-

gram than they, which is odd. Usually, the pronoun

following than is accusative case. We expect adding n-gram features derived from the cleaned-up sentences would allow the new classifier to fix such hypothesis. This kind of n-gram features is similar to the language models used in (Zwarts and Johnson,
They have the benefit of measuring the fluency of the cleaned text.

Another common error we noticed is caused by the ambiguities of coordinates, because the coordinates have similar patterns as rough copies. For example,

- **Coordinates**: they can’t decide which are the good aspects and which are the bad aspects

- **Rough Copies**: it’s pleasure to get outside

To distinguish the rough copies and the coordinate examples shown above, we analyze the training data statistically. We extract all the pieces lying between identical word bigrams $AB\ldots AB$. The observation is that coordinates are often longer than edited sequences. Hence we introduce the in-between features for each word. If a word lies between identical word bigrams, then its in-between feature is the log length of the subsequence lying between the two bigrams; otherwise, it is zero (we use log length to avoid sparsity). We also used other patterns such as $A\ldots A$ and $ABC\ldots ABC$, but they are too noisy or infrequent and do not yield much performance gain.

Table 3 lists the feature templates used in this last step.

| Truth | Predict |
|-------|---------|
| BE    | 0       | 1   | 1   | 1   | 2   |
| IE    | 1       | 0   | 1   | 1   | 2   |
| EE    | 1       | 1   | 0   | 1   | 2   |
| SE    | 1       | 1   | 1   | 0   | 2   |
| O     | 1       | 1   | 1   | 1   | 0   |

Table 4: Weighted hamming loss for M^3Ns.

### 4.2 Results

We compare several sequence labeling models: CRFs, structured averaged perceptron (AP), M^3Ns with un-weighted/weighted loss, and online passive-aggressive (PA) learning. For each model, we tuned the parameters on the development data: Gaussian prior for CRFs is $1.0$, iteration number for AP is $10$, iteration number and regularization penalty for PA are $10$ and $1$. For M^3Ns, we use Structured Sequential Minimal Optimization (Taskar, 2004) for model training. Regularization penalty is $C = 0.1$ and iteration number is $30$.

Table 5 shows the results using different models and features. The baseline models use only the n-grams features extracted from the original text. We can see that M^3Ns with the weighted hamming loss achieve the best performance, outperforming all the other models. Regarding the features, the gradually added n-gram features have consistent improvement for all models. Using the weighted hamming loss in M^3Ns, we observe a gain of $2.2\%$ after deleting filler words, and $1.8\%$ after deleting edited words. In our analysis, we also noticed that the in-between fea-
Table 5: Effect of training strategy and recovered features for stacked learning. F scores are reported. AP = Averaged Perceptron, PA = online Passive Aggressive, M³Ns = un-weighted M³Ns, w. M³Ns = weighted M³Ns.

|        | CRF | AP | PA | M³Ns | w. M³Ns |
|--------|-----|----|----|------|---------|
| Baseline | 78.8 | 79.0 | 78.9 | 79.4 | 80.1 |
| Step 2 | 81.0 | 81.1 | 81.1 | 81.5 | 82.3 |
| Step 3 | 82.9 | 83.0 | 82.8 | 83.3 | 84.1 |

There are no significant differences among CRFs, AP and PA. Using recovered n-gram features and in-between features significantly improves all sequence labeling models (p value < 0.001).

We also list the state-of-the-art systems evaluated on the same dataset, as shown in Table 6. We achieved the best F-score. The most competitive system is (Zwarts and Johnson, 2011), which uses extra resources to train language models.

Table 6: Comparison with other systems. † they used the re-segmented Switchboard corpus, which is not exactly the same as ours. * they reported the F-score of BE tag (beginning of the edited sequences). ‡ they used language model learned from 3 additional corpora.

| System | F score |
|--------|---------|
| (Johnson and Charniak, 2004) | 79.7 |
| (Kahn et al., 2005) | 78.2 |
| (Zhang et al., 2006)† | 81.2 |
| (Georgila, 2009)* | 80.1 |
| (Zwarts and Johnson, 2011)‡ | 83.8 |
| This paper | 84.1 |

5 Conclusion

In this paper, we proposed multi-step stacked learning to extract n-gram features step by step. The first level removes the filler words providing new n-grams for the second level to remove edited words. The third level uses the n-grams from the original text and the cleaned text generated by the previous two steps for accurate edit detection. To minimize the F-loss approximately, we modified the hamming loss in M³Ns. Experimental results show that our method is effective, and achieved the best reported performance on the Switchboard corpus without the use of any additional resources.

Acknowledgments

We thank three anonymous reviewers for their valuable comments. This work is partly supported by DARPA under Contract No. HR0011-12-C-0016 and FA8750-13-2-0041. Any opinions expressed in this material are those of the authors and do not necessarily reflect the views of DARPA.

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