Abstract

Interpreting event mentions in text is central to many tasks from scientific research to intelligence gathering. We present an event trigger detection system and explore baseline configurations. Specifically, we test whether it is better to use a single multi-class classifier or separate binary classifiers for each label. The results suggest that binary SVM classifiers outperform multi-class maximum entropy by 6.4 points F-score. Brown cluster and WordNet features are complementary with more improvement from WordNet features.

1 Introduction

Events are frequently discussed in text, e.g., criminal activities such as violent attacks reported in police reports, corporate activities such as mergers reported in business news, biological processes such as protein interactions reported in scientific research. Interpreting these mentions is central to tasks like intelligence gathering and scientific research. Event extraction automatically identifies the triggers and arguments that constitute a textual mention of an event in the world. Consider:

**Bob bought the book from Alice.**

Here, a trigger – “bought” (Transaction.Transfer-Ownership) – predicates an interaction between the arguments – “Bob” (Recipient), “the book” (Thing) and “Alice” (Giver). We focus on the trigger detection task, which is the first step in event detection and integration.

Many event extraction systems use a pipelined approach, comprising a binary classifier to detect event triggers followed by a separate multi-class classifier to label the type of event (Ahn, 2006). Our work is different in that we use a single classification step with sub-sampling to handle data skew. Chen and Ji (2009) use Maximum Entropy (ME) classifier in their work. However, their approach is similar to (Ahn, 2006) where they identify the trigger first then classify the trigger at later stage. Kolya et al. (2011) employ a hybrid approach by using Support Vector Machine (SVM) classifier and heuristics for event extraction.

We present an event trigger detection system that formulates the problem as a token-level classification task. Features include lexical and syntactic information from the current token and surrounding context. Features also include additional word class information from Brown clusters, WordNet and Nomlex to help generalise from a fairly small training set. Experiments explore whether multi-class or binary classification is better using SVM and ME.

Contributions include: (1) A comparison of binary and multi-class versions of SVM and ME on the trigger detection task. Experimental results suggest binary SVM outperform other approaches. (2) Analysis showing that Brown cluster, Nomlex and WordNet features contribute nearly 10 points F-score; WordNet+Nomlex features contribute more than Brown cluster features; and improvements from these sources of word class information increase recall substantially, sometimes at the cost of precision.

2 Event Trigger Detection Task

We investigate the event trigger detection task from the 2015 Text Analysis Conference (TAC) shared task (Mitamura and Hovy, 2015). The task defines 9 event types and 38 subtypes such as Life.Die, Conflict.Attack, Contact.Meet. An event trigger is the smallest extent of text (usually a word or short phrase) that predicates the occurrence of an event (LDC, 2015).

In the following example, the words in bold trigger Life.Die and Life.Injure events respectively:
The explosion killed 7 and injured 20.

Note that an event mention can contain multiple events. Further, an event trigger can have multiple events. Consider:

The murder of John.

where “murder” is the trigger for both a Conflict.Attack event and a Life.Die event. Table 1 shows the distribution of the event subtypes in the training and development datasets.

3 Approach

We formulate event trigger detection as a token-level classification task. Features include lexical and semantic information from the current token and surrounding context. Classifiers include binary and multi-class versions of SVM and ME.

As triggers can be a phrase, we experimented with Inside Outside Begin 1 (IOB1) and Inside Outside Begin 2 (IOB2) encodings (Sang and Veenstra, 1999). Table 2 contains an example illustrating the two schemes. Preliminary results showed little impact on accuracy. However, one of the issues with this task is data sparsity. Some event subtypes have few observations in the corpus. IOB2 encoding increases the total number of categories for the dataset. Thus make the data sparsity issue worse. Therefore we use the IOB1 encoding for the rest of the experiments.

Another challenge is that the data is highly unbalanced. Most of the tokens are not event triggers. To address this, we various subsets of negative observations. Randomly sampling 10% of the negative examples for training works well here.

3.1 Features

All models used same rich feature sets. The features are divided into three different groups.

Feature set 1 (FS1): Basic features including following. (1) Current token: Lemma, POS, named entity type, is it a capitalised word. (2) Within the window of size two: unigrams/bigrams of lemma, POS, and name entity type. (3) Dependency: governor/dependent type, governor/dependent type + lemma, governor/dependent type + POS, and governor/dependent type + named entity type.

Feature set 2 (FS2): Brown cluster trained on the Reuters corpus (Brown et al., 1992; Turian et al., 2010) with prefix of length 11, 13 and 16.¹

Feature set 3 (FS3): (1) WordNet features including hypernyms and synonyms of the current token. (2) Base form of the current token extracted from Nomlex (Macleod et al., 1998).²

| Event Subtype                          | Train | Dev |
|----------------------------------------|-------|-----|
| Business.Declare-Bankruptcy            | 30    | 3   |
| Business.End-Org                       | 11    | 2   |
| Business.Merge-Org                     | 28    | 0   |
| Business.Start-Org                     | 17    | 1   |
| Conflict.Attack                        | 541   | 253 |
| Conflict.Demonstrate                   | 162   | 38  |
| Contact.Broadcast                      | 304   | 112 |
| Contact.Contact                        | 260   | 77  |
| Contact.Correspondence                 | 77    | 18  |
| Contact.Meet                           | 221   | 23  |
| Justice.Acquit                         | 27    | 3   |
| Justice.Appeal                         | 25    | 12  |
| Justice.Arrest-Jail                    | 207   | 79  |
| Justice.Charge-Indict                  | 149   | 41  |
| Justice.Convict                        | 173   | 49  |
| Justice.Execute                        | 51    | 15  |
| Justice.Extradite                      | 62    | 1   |
| Justice.Fine                           | 53    | 2   |
| Justice.Pardon                         | 221   | 18  |
| Justice.Release-Parole                 | 45    | 28  |
| Justice.Sentence                       | 118   | 26  |
| Justice.Sue                            | 54    | 1   |
| Justice.Trial-Hearing                  | 172   | 24  |
| Life.Be-Born                           | 13    | 6   |
| Life.Die                               | 356   | 157 |
| Life.Divorce                           | 45    | 0   |
| Life.Injure                            | 63    | 70  |
| Life.Marry                             | 60    | 16  |
| Manufacture.Artifact                   | 18    | 4   |
| Movement.Transport-Artifact            | 52    | 18  |
| Movement.Transport-Person              | 390   | 125 |
| Personnel.Elect                        | 81    | 16  |
| Personnel.End-Position                 | 130   | 79  |
| Personnel.Nominate                     | 30    | 5   |
| Personnel.Start-Position               | 60    | 17  |
| Transaction.Transaction                | 34    | 17  |
| Transaction.Transfer-Money             | 366   | 185 |
| Transaction.Transfer-Ownership         | 233   | 46  |

Table 1: Event subtype distribution.

¹http://metaoptimize.com/projects/wordreprs/
²http://nlp.cs.nyu.edu/nomlex/
He has been found guilty for the murder.

Table 2: IOB1 and IOB2 encoding comparison. “B” represents the first token of an event trigger. “I” represents a subsequent token of a multi-word trigger. “O” represents no event.

| Word   | IOB1  | IOB2  |
|--------|-------|-------|
| He     | O     | O     |
| has    | O     | O     |
| been   | O     | O     |
| found  | I-Justice.Convict | B-Justice.Convict |
| guilty | I-Justice.Convict | I-Justice.Convict |
| for    | O     | O     |
| the    | O     | O     |
| murder | I-Life.Die | B-Life.Die |
|        | O     | O     |

3.2 Classifiers

We train multi-class ME and SVM classifiers to detect and label events. L-BFGS (Liu and Nocedal, 1989) is used as the solver for ME. The SVM uses a linear kernel. We also compare binary versions of ME and SVM by building a single classifier for each event subtype.

4 Experimental setup

4.1 Dataset

The TAC 2015 training dataset (LDC2015E73) is used for the experiment. The corpus has a total of 158 documents from two genres: 81 newswire documents and 77 discussion forum documents. Preprocessing includes tokenisation, sentence splitting, POS tagging, named entity recognition, constituency parsing and dependency parsing using Stanford CoreNLP 3.5.2.3

The dataset is split into 80% for training (126 documents) and 20% for development (32 documents. Listed in Appendix A).

4.2 Evaluation metric

Accuracy is measured using the TAC 2015 scorer.4

Precision, recall and F-score are defined as:

\[ P = \frac{TP}{NS} \quad R = \frac{TP}{NG} \quad F1 = \frac{2PR}{P + R} \]

where \( TP \) is the number of correct triggers (true positives), \( NS \) is the total number of predicted system mentions, and \( NG \) is the total number of annotated gold mentions. An event trigger is counted as correct only if the boundary, the event type and the event subtype are all correctly identified. We report micro-averaged results.

5 Results

Table 3 shows the results from each classifier. The binary SVMs outperform all other models with an F-score of 55.7. The score for multi-class SVM is two points lower at 53.2. Multi-class and binary ME comes next with binary performing worst.

| System       | P    | R    | F1   |
|--------------|------|------|------|
| Multi-class ME | 62.2 | 40.8 | 49.2 |
| Multi-class SVM | 55.6 | 50.9 | 53.2 |
| Binary ME    | 77.8 | 28.2 | 41.4 |
| Binary SVM   | 64.7 | 48.9 | 55.7 |

5.1 Feature set

We perform a cumulative analysis to quantify the contribution of different feature sets. Table 4 shows that feature set 2 (Brown cluster) helped with recall sometimes at the cost of precision. The recall is further boosted by feature set 3 (WordNet and Nomlex). However, the precision dropped noticeably for SVM models.

| System       | P    | R    | F1   |
|--------------|------|------|------|
| Multi-class systems |      |      |      |
| ME FS1       | 54.1 | 16.9 | 25.8 |
| ME FS1+FS2   | 57.8 | 21.3 | 31.1 |
| ME FS1+FS2+FS3 | 62.2 | 40.8 | 49.2 |
| SVM FS1      | 62.1 | 35.3 | 45.0 |
| SVM FS1+FS2  | 60.9 | 39.3 | 47.8 |
| SVM FS1+FS2+FS3 | 55.6 | 50.9 | 53.2 |
| Binary systems |     |     |     |
| ME FS1       | 64.7 | 6.1  | 11.2 |
| ME FS1+FS2   | 72.7 | 10.1 | 17.8 |
| ME FS1+FS2+FS3 | 77.8 | 28.2 | 41.4 |
| SVM FS1      | 71.0 | 34.2 | 46.2 |
| SVM FS1+FS2  | 70.5 | 38.4 | 49.7 |
| SVM FS1+FS2+FS3 | 64.7 | 48.9 | 55.7 |

Table 4: Feature sets comparison.

5.2 Performance by event subtype

Figure 1 shows how classifiers perform on each event subtype. Binary SVM generally has better recall and slightly lower precision. Hence, the overall performance of the model improves.

3http://nlp.stanford.edu/software/corenlp.shtml
4http://hunterhector.github.io/EvmEval/
5.3 Error analysis

We sampled 20 precision and twenty recall errors from the binary SVM classifier. 40% of precision errors require better modelling of grammatical relations, e.g., labelling “focus has moved” as a transport event. 35% require better use of POS information, e.g., labelling “said crime” as a contact event. 65% of recall errors are tokens in multi-word phrases, e.g., “going to jail”. 45% are triggers that likely weren’t seen in training and require better generalisation strategies. Several precision and recall errors seem to actually be correct.

6 Conclusion

We presented an exploration of TAC event trigger detection and labelling, comparing classifiers and rich features. Results suggest that SVM outperforms maximum entropy and binary SVM gives the best results. Brown cluster information increases recall for all models, but sometimes at the cost of precision. WordNet and Nomlex features provide a bigger boost, improving F-score by 6 points for the best classifier.

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Appendix A: Development set document IDs

3288ddfcb46d1934ad453afd8a4e292f
AFP_ENG_20091015.0364
AFP_ENG_20100130.0284
AFP_ENG_20100423.0583
AFP_ENG_20100505.0537
AFP_ENG_20100630.0660
APW_ENG_20090605.0323
APW_ENG_20090611.0337
APW_ENG_20100508.0084
APW_ENG_20101214.0097
CNA_ENG_20101001.0032
NYT_ENG_20130628.0102
XIN_ENG_20130628.0102
XIN_ENG_20100206.0090
bolt-eng-DF-170-181103-8901874
bolt-eng-DF-170-181103-8908896
bolt-eng-DF-170-181109-48534
bolt-eng-DF-170-181109-60453
bolt-eng-DF-170-181118-8874957
bolt-eng-DF-170-181122-8791540
bolt-eng-DF-170-181122-8793828
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bolt-eng-DF-212-191665-3129265