CS 224 U: Project Milestone

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Project goals

In the literature review, we focused on research publications in the areas of event and entity extraction with semantic role labeling and temporal ordering of events. Even though there has been a lot of work on one (or some) of these areas in isolation, there is no approach that seamlessly integrates all these components together. Without a system that can do all these tasks together, it is impossible to extract any meaningful information from the enormous amount of text content we have. For instance, most of the work on entity extraction and semantic role labeling assumes that the trigger word indicating an event is given. While these papers give us a good indication that these tasks can be done with reasonable performance, the task of automatic information extraction from text (specifically those describing a phenomenon or process) remains largely unsolved. Through this project, we envision to build a system that takes a paragraph of text as input and does the following:

1. Identify the events by locating the trigger words.
2. For each event, identify its arguments (only entities).
3. For each argument that is associated with a specific event, label the association with a semantic role, like Agent, Destination, Theme, Location etc.
4. Identify event-event relations that denotes the temporal ordering between events, like Cotemporal, NextEvent etc.

Previous approaches

Most of the work in the area of event and entity extraction can be analyzed by different perspectives:

- **Coverage and domain.** Most of the prevoius work dealt only with a subset of the four tasks listed as the project goals and dealt with very specific domains. For instance, Toutanova et al. deals with argument extraction and semantic role labeling assuming that the trigger words are provided. While Bjorne et al.(2009) solves the problem of event and argument extraction almost completely, their event categories and arguments are closely tied to the BIONLP task and hence, would not generalize to event extraction from domain-independent text.
- **Parsing scheme: Constitueney vs Dependecy parse.** Some of the previous work relied on the constituency parse structure of sentences, while others used the dependency parse structure. For instance Toutanova et al. approaches semantic role labeling as a joint task of argument identification and labeling on the parse tree of the sentence. Bjorne et al.(2009) and McCloskly et al.(2011) focus more on the dependency parse structure of the sentence.
- **Modeling: Graph vs Tree.** The work of Bjorne et al.(2009) and McCloskly et al.(2011) are based on graphs and deal with edge prediction, while Toutanova et al. uses tree structure with classification of nodes as an entity or not.

Current approach

In this project, we combine the learnings from the different methodologies to build a model that can be used for event and entity extraction with classes that are not specific to any domain. Even though our dataset is based on paragraphs from a biology textbook, we belives our models would generalize well to deal with more general content as our features and event/entity classes are not tied to the biological domain in anyway. The key modeling decisions are as follows:

- We model events and entities as nodes in the constituency tree. Each sentence is assumed to be independent of each other as far as entity-event relationships are concerned. Events are denoted by their trigger word and are hence pre-terminals in the parse tree. Entities are denoted by a parse tree-node that covers the whole span of text of the entity. In some cases when there is no single node that covers the entire entity (mostly because of parser errors, for e.g., PP attachment), we use some approximation by repeatedly removing tokens from the end or beginning of the span of text to identify a node that covers it. We manually verified that this heuristic works well in practice and results entities that convey almost the full meaning of original span and are well-formed.
- Since the dependency parse of a sentence has a lot of information about the dependencies between tokens, we also use features based on the dependeny parse in conjuction with the constituency parse. This is done by identifying the position of the head word of an entity or event from the dependency tree and analyzing the relations.

- We handle Task 1 as an independent task. Task 2 and 3 are done jointly. Task 4 is done as a separate task.
- For the classification tasks, we use maximum entropy model based on an implementation of L-BFGS for Quasi Newton unconstrained minimization.

Dataset

In this project, the dataset was prepared by annotating 125 paragraphs from different chapters from the text book *Biology (Eighth Edition)* by *Neil A. Campbell* and *Jane B. Reece*. Each paragraph is a text file and has an associated annotation file that indicates the different events and entities (by their character offsets in the original paragraph) and the event-entity and event-event relationships. The annotations were done by experts in the field (they were employees of a company named Vulcan). Since there is not much data at our disposal, we split the data by a proportion of 70-30% for training and testing. We are using 10 fold cross validation (by randomly ordering the files to avoid similarities in files near each other) on the training set and all results presented are using this.

Progress

We have built the project based on the Stanford Core NLP tools. We use the annotation pipeline avaiable in the toolkit including tokenization, lemmatization, dependency and constituency parsers, POS taggers and NERs. The events, entities and their relationships are represented as annotations on the already existing sentence annotations by implementing the *CoreAnnotation* interface. This helps us to integrate our codebase with the existing features of the CoreNLP toolkit. We describe the progress made on the different tasks in this section.

1. **Event prediction.** As we mentioned earlier, events are represented as pre-terminal nodes in the parse tree of a sentence. As a first step to the task, we built a baseline model that predicted every pre-terminal node whose part-of-speech tag started with 'VB' to be an event trigger. This model performed quite well giving an F1 score of 0.565, considering that it was a very naive approach. As the next step, we designed a MaxEnt model that trained on the annotated samples using several lexical and path features. The features we currently have include part-of-speech tag of the word, its lemma, the part-of-speech tag of its parent, the actual word itself and the path from root to the node. The results we have are in Table 1. On doing error analysis, we found that our classifier fails to identify nominalized verb forms as event triggers. Even though we tried using a feature to indicate nominalization by looking up in a dictionary of nominalized verb forms, the classification accuracy did not improve, probably because they are common even in words that are not event triggers.
2. **Entity prediction and Semantic role labeling.** An entity is represented as a node in the parse tree spanning over the full text of the entity along the leaves of the tree. The fact that there are more than one events in almost all sentences makes our task of event-entity associaton harder. This is because, instead of just predicting a node in the parse tree as an entity, we have to predict if a node is associated with a specific trigger from step 1. Since this model was developed in parallel to the one in task 1, we are currently using the gold standard trigger words to denote events. Once we attain reasonable performance levels, we will use the predictions from step 1 to replace the gold standard. In addition, currently the model only tags if a node in the parse tree is associated with a specific event trigger or not. Since we are using a MaxEnt model, extending this to predict semantic role labeling would make it from a 2 class classification (Argument and None) to a multi-class classification (where the classes are the semantic roles like Agent, Theme, Destination, Origin, Result etc. and None).

	Precision	**Recall**	**F1**
Baseline	0.47	0.72	0.57
MaxEnt-Train	0.86	0.71	0.77
MaxEnt	0.71	0.67	0.69

Table 1: Event trigger prediction

	Precision	**Recall**	**F1**
Baseline	0.52	0.70	0.59
MaxEnt-Train	0.81	0.66	0.72
MaxEnt	0.69	0.60	0.64

Table 2: Entity prediction for event triggers

As a first step, we built a baseline model that predicts a node in the parse tree as an argument to an event trigger, if it is of part-of-speech tag 'NP' and if the headword of the node in the parse tree is a child of the event trigger in the dependency tree of the sentence. We used Collins head finder algorithm to identify the head word of a parse tree node. The baseline model intuitively captures the relation between event triggers and its arguments as is evident from the F1 score of 0.593 achieved using a relatively simple approach. We then implemented a MaxEnt based model using more features between the event triggers and the candidate nodes. The features we use include POS tag of node + POS tag of event trigger, head word of node + POS tag of event trigger, path from the node to the event trigger, indicator feature denoting whether the headword of the node is a child of the trigger in the dependency tree. The results are presented in Table 2 .

Dynamic Program for non-overlapping constraint Since we predict a node in the parse tree as an entity or not, there are many instances when there exists overlap between predicted entities. For instance, a sub-tree of a tree node may also be tagged as an entity. To avoid this, we devised a bottom-up dynamic program that tags a node as entity or not looking at the probability of the node and its immediate children being an entity. There are two scenarios. If we tag the node as entity, none of its children can be an entity. If we do not tag the node as an entity, then the children can retain their class (Entity or None). This gave us a huge boost in F1 score.

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