

# REES: A Large-Scale Relation and Event Extraction System

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## Abstract

This paper reports on a large-scale, end-to-end relation and event extraction system. At present, the system extracts a total of 100 types of relations and events, which represents a much wider coverage than is typical of extraction systems. The system consists of three specialized pattern-based tagging modules, a high-precision co-reference resolution module, and a configurable template generation module. We report quantitative evaluation results, analyze the results in detail, and discuss future directions.

## Introduction

One major goal of information extraction (IE) technology is to help users quickly identify a variety of relations and events and their key players in a large volume of documents. In contrast with this goal, state-of-the-art information extraction systems, as shown in the various Message Understanding Conferences (MUCs), extract a small number of relations and events. For instance, the most recent MUC, MUC-7, called for the extraction of 3 relations (person-employer, maker-product, and organization-location) and 1 event (spacecraft launches). Our goal is to develop an IE system which scales up to extract as many types of relations and events as possible with a minimum amount of porting effort combined with high accuracy. Currently, REES handles 100 types of relations and events, and it does so in a modular, configurable, and scalable manner.

Below, Section 1 presents the ontologies of relations and events that we have developed.

Section 2 describes REES' system architecture. Section 3 evaluates the system's performance, and offers a qualitative analysis of system errors. Section 4 discusses future directions.

## 1 Relation and Event Ontologies

As the first step in building a large-scale relation and event extraction system, we developed ontologies of the relations and events to be extracted. These ontologies represent a wide variety of domains: political, financial, business, military, and life-related events and relations. "Relations" covers what in MUC-7 are called Template Elements (TEs) and Template Relations (TRs). There are 39 types of relations. While MUC TE's only dealt with singular entities, REES extracts both singular and plural entities (e.g., "five executives"). The TR relations are shown in *italic* in the table below.

Relations	
Place Relations	Artifact Relations
Place-Name&Aliases	Artifact-Name&Aliases
Place-Type	Artifact-Type
Place-Subtype	Artifact-Subtype
Place-Descriptor	Artifact-Descriptor
Place-Country	<i>Artifact-Maker</i>
	<i>Artifact-Owner</i>
Organization Relations	Person Relations
Org-Name&Aliases	Person-Name&Aliases
Org-Descriptor	Person-Type
Org-FoundationDate	Person-Subtype
Org-Nationality	Person-Descriptor
Org-TickerSymbol	Person-Honorific
<i>Org-Location</i>	Person-Age
<i>Org-ParentOrg</i>	Person-PhoneNumber
<i>Org-Owner</i>	Person-Nationality
<i>Org-Founder</i>	<i>Person-Affiliation</i>
<i>Org-StockMarket</i>	<i>Person-Sibling</i>
	<i>Person-Spouse</i>
	<i>Person-Parent</i>
	<i>Person-Grandparent</i>

	<i>Person-OtherRelative</i> <i>Person-BirthPlace</i> <i>Person-BirthDate</i>
--	--

**Table 1: Relation Ontology**

“Events” are extracted along with their event participants, e.g., “who did what to whom when and where?” For example, for a BUYING event, REES extracts the buyer, the artifact, the seller, and the time and location of the BUYING event. REES currently covers 61 types of events, as shown below.

Events	
Vehicle	Transaction
Vehicle departs	Buy artifact
Vehicle arrives	Sell artifact
Spacecraft launch	Import artifact
Vehicle crash	Export artifact
	Give money
Personnel Change	Business
Hire	Start business
Terminate contract	Close business
Promote	Make artifact
Succeed	Acquire company
Start office	Sell company
	Sue organization
	Merge company
Crime	Financial
Sexual assault	Currency moves up
Steal money	Currency moves down
Seize drug	Stock moves up
Indict	Stock moves down
Arrest	Stock market moves up
Try	Stock market moves down
Convict	Stock index moves up
Sentence	Stock index moves down
Jail	
Political	Conflict
Nominate	Kill
Appoint	Injure
Elect	Hijack vehicle
Expel person	Hold hostages
Reach agreement	Attack target
Hold meeting	Fire weapon
Impose embargo	Weapon hit
Topple	Invade land
Family	Move forces
Die	Retreat
Marry	Surrender
	Evacuate

**Table 2: Event Ontology**

Figures 1 and 2 show sample relation and event templates. Figure 1 shows a Person-Affiliation relation template for “Frank Ashley, a spokesman for Occidental Petroleum Corp.”

```

<PERSON_AFFILIATION-AP8802230207-54> :=
TYPE: PERSON_AFFILIATION
PERSON: [TE for “Frank Ashley”]
ORG: [TE for “Occidental Petroleum”]

```

**Figure 1: Example of Relation Template**

Figure 2 shows an Attack Target event template for the sentence “an Iraqi warplane attacked the frigate Stark with missiles May 17, 1987.”

```

<ATTACK_TARGET-AP8804160078-12>:=
TYPE: CONFLICT
SUBTYPE: ATTACK_TARGET
ATTACKER: [TE for “an Iraqi warplane”]
TARGET: [TE for “the frigate Stark”]
WEAPON: [TE for “missiles”]
TIME: “May 17, 1987”
PLACE: [TE for “the gulf”]
COMMENT: “attacked”

```

**Figure 2: Example of Event Template**

## 2 System Architecture and Components

Figure 3 illustrates the REES system architecture. REES consists of three main components: a tagging component (cf. Section 2.1), a co-reference resolution module (cf. Section 2.2), and a template generation module (cf. Section 2.3). Figure 3 also illustrates that the user may run REES from a Graphical User Interface (GUI) called TemplateTool (cf. Section 2.4).

### 2.1 Tagging Modules

The tagging component consists of three modules as shown in Figure 3: NameTagger, NPTagger and EventTagger. Each module relies on the same pattern-based extraction engine, but uses different sets of patterns. The NameTagger recognizes names of people, organizations, places, and artifacts (currently only vehicles).

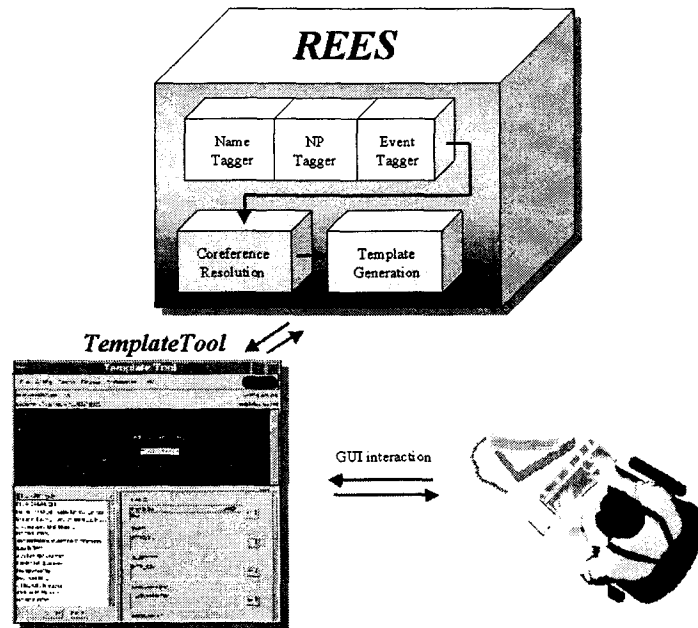


Figure 3: The REES System Architecture

The NP Tagger then takes the XML-tagged output of the Name Tagger through two phases. First, it recognizes non-recursive Base Noun Phrase (BNP) (our specifications for BNP resemble those in Ramshaw and Marcus 1995). Second, it recognizes complex NPs for only the four main semantic types of NPs, i.e., Person, Organization, Location, and Artifact (vehicle, drug and weapon). It makes post-modifier attachment decisions only for those NPs that are crucial to the extraction at hand. During this second phase, relations which can be recognized locally (e.g., Age, Affiliation, Maker) are also recognized and stored using the XML attributes for the NPs. For instance, the XML tag for “*President of XYZ Corp.*” below holds an AFFILIATION attribute with the ID for “*XYZ Corp.*”

```
<PNP ID="03" AFFILIATION="04">President of
<ENTITY ID="04">XYZ Corp.</ENTITY>
</PNP>
```

Building upon the XML output of the NP Tagger, the Event Tagger recognizes events applying its lexicon-driven,

syntactically-based generic patterns. These patterns tag events in the presence of at least one of the arguments specified in the lexical entry for a predicate. Subsequent patterns try to find additional arguments as well as place and time adjunct information for the tagged event. As an example of the Event Tagger’s generic patterns, consider the simplified pattern below. This pattern matches on an event-denoting verb that requires a direct object of type weapon (e.g., “*fire a gun*”)

```
(&
  {AND $VP {ARG2_SYN=DO}
    {ARG2_SEM=WEAPON}}
  {AND $ARTIFACT {SUBTYPE=WEAPON}}})1
```

The important aspect of REES is its declarative, lexicon-driven approach. This approach requires a lexicon entry for each event-denoting word, which is generally a

<sup>1</sup> &=concatenation, AND=Boolean operator, \$VP and \$ARTIFACT are macro references for complex phrases.

verb. The lexicon entry specifies the syntactic and semantic restrictions on the verb's arguments. For instance, the following lexicon entry is for the verb "attack." It indicates that the verb "attack" belongs to the CONFLICT ontology and to the ATTACK\_TARGET type. The first argument for the verb "attack" is semantically an organization, location, person, or artifact (ARG1\_SEM), and syntactically a subject (ARG1\_SYN). The second argument is semantically an organization, location, person or artifact, and syntactically a direct object. The third argument is semantically a weapon and syntactically a prepositional phrase introduced by the preposition "with".

```
ATTACK {{{CATEGORY VERB}
{ONTOLOGY CONFLICT}
{TYPE ATTACK_TARGET}
{ARG1_SEM {ORGANIZATION LOCATION
PERSON ARTIFACT}}}
{ARG1_SYN {SUBJECT}}}
{ARG2_SEM {ORGANIZATION LOCATION
PERSON ARTIFACT}}}
{ARG2_SYN {DO}}}
{ARG3_SEM {WEAPON}}}
{ARG3_SYN {WITH}}}}}
```

About 50 generic event extraction patterns, supported by lexical information as shown above, allow extraction of events and their arguments in cases like:

An Iraqi warplane *attacked* the frigate Stark  
*with* missiles May 17, 1987.

This generic, lexicon-driven event extraction approach makes REES easily portable because new types of events can be extracted by just adding new verb entries to the lexicon. No new patterns are required. Moreover, this approach allows for easy customization capability: a person with no knowledge of the pattern language would be able to configure the system to extract new events.

While the tagging component is similar to other pattern-based IE systems (e.g., Appelt *et al.* 1995; Aone *et al.* 1998, Yangarber and Grishman 1998), our EventTagger is more portable through a lexicon-driven approach.

## 2.2 Co-reference Resolution

After the tagging phase, REES sends the XML output through a rule-based co-reference resolution module that resolves:

- definite noun phrases of Organization, Person, and Location types, and
- singular person pronouns: *he* and *she*.

Only "high-precision" rules are currently applied to selected types of anaphora. That is, we resolve only those cases of anaphora whose antecedents the module can identify with high confidence. For example, the pronoun rules look for the antecedents only within 3 sentences, and the definite NP rules rely heavily on the head noun matches. Our high-precision approach results from our observation that unless the module is very accurate (above 80% precision), the co-reference module can hurt the overall extraction results by over-merging templates.

## 2.3 Template Generation Module

A typical template generation module is a hard-coded post-processing module which has to be written for each type of template. By contrast, our Template Generation module is unique as it uses declarative rules to generate and merge templates automatically so as to achieve portability.

### 2.3.1 Declarative Template Generation

REES outputs the extracted information in the form of either MUC-style templates, as illustrated in Figure 1 and 2, or XML. A crucial part of a portable, scalable system is to be able to output different types of relations and events without changing the template generation code. REES maps XML-tagged output of the co-reference module to templates using declarative template definitions, which specifies the template label (e.g., ATTACK\_TARGET), XML attribute names (e.g., ARGUMENT1), corresponding template slot names (e.g., ATTACKER), and the type restrictions on slot values (e.g., string).

### 2.3.2 Event Merging

One of the challenges of event extraction is to be able to recognize and merge those event descriptions which refer to the same event. The Template Generation module uses a set of declarative, customizable rules to merge co-referring events into a single event. Often, the rules reflect pragmatic knowledge of the world. For example, consider the rule below for the DYING event type. This rule establishes that if two *die* events have the same subject, then they refer to the same event (i.e., a person cannot die more than once).

{merge

```
{EVENT 1 {AND {SUBTYPE DIE} {PERSON $foo}}
```

```
{EVENT 2 {AND {SUBTYPE DIE} {PERSON $foo}}}
```

### 2.4 Graphical User Interface (GUI)

For some applications such as database population, the user may want to validate the system output. REES is provided with a Java-based Graphical User Interface that allows the user to run REES and display, delete, or modify the system output. As illustrated in Figure 4, the tool displays the templates on the bottom half of the screen, and the user can choose which template to display. The top half of the screen displays the input document with extracted phrases in different colors. The user can select any slot value, and the tool will highlight the portion of the input text responsible for the slot value. This feature is very useful in efficiently verifying system output. Once the system's output has been verified, the resulting templates can be saved and used to populate a database.

## 3 System Evaluation

The table below shows the system's recall, precision, and F-Measure scores for the

training set (200 texts) and the blind set (208 texts) from about a dozen news sources. Each set contains at least 3 examples of each type of relations and events. As we mentioned earlier, "relations" includes MUC-style TEs and TRs.

Text Set	Task	Templates in keys	R	P	F-M
Train	Rel.	9955	76	74	75.35
	Events	2525	57	74	64.57
	Rel. & Events	10707	74	74	73.95
Blind	Rel.	8938	74	74	73.74
	Events	2020	42	75	53.75
	Rel. & Events	9526	69	74	71.39

Table 3: Evaluation Results

The blind set F-Measure for 31 types of relations (73.95%) exceeded our initial goal of 70%. While the blind set F-Measure for 61 types of events was 53.75%, it is significant to note that 26 types of events achieved an F-Measure over 70%, and 37 types over 60% (cf. Table 4). For reference, though not exactly comparable, the best-performing MUC-7 system achieved 87% in TE, 76% in TR, and 51% in event extraction.

F-M in blind set	Event types
90-100	2 : Buy artifact, Marry
80-89	9 : Succeed, Merge company, Kill, Surrender, Arrest, Convict, Sentence, Nominate, Expel.
70-79	15 : Die, Sell artifact, Export Artifact, Hire, Start office, Make artifact, Acquire company, Sue organization, Stock Index moves down, Steal money, Indict, Jail, Vehicle crash, Elect, Hold meeting.

Table 4: Top-performing Event Types

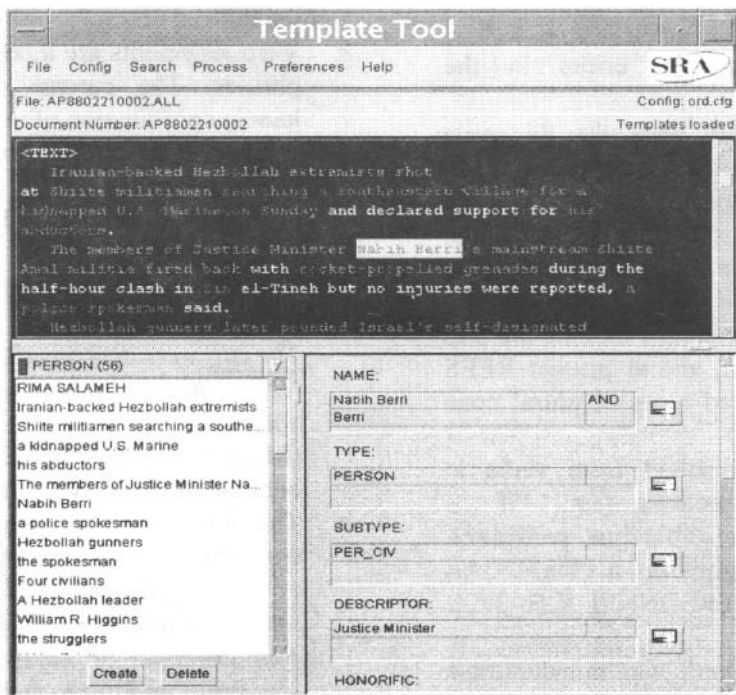


Figure 4: TemplateTool

Regarding relation extraction, the difference in the score between the training and blind sets was very small. In fact, the total F-Measure on the blind set is less than 2 points lower than that of the training set. It is also interesting to note that for 8 of the 12 relation types where the F-Measure dropped more than 10 points, the training set includes less than 20 instances. In other words, there seems to be a natural correlation between low number of instances in the training set and low performance in the blind set.

There was a significant drop between the training and blind sets in event extraction: 11 points. We believe that the main reason is that the total number of events in the training set is fairly low: 801 instances of 61 types of events (an average of 13/event), where 35 of the event types had fewer than 10 instances. In fact, 9 out of the 14 event types which scored lower than 40% F-Measure had fewer than 10 examples. In comparison, there were 34,000 instances of 39 types of relations in the training set.

The contribution of the co-reference module is illustrated in the table below. Co-reference resolution consistently improves F-Measures both in training and blind sets. Its impact is larger in relation than event extraction.

Text set	Task	Co-reference rules	No co-reference rules
Training	Relations	75.35	72.54
	Events	64.57	63.62
	Relations & Events	73.95	71.34
Blind	Relations	73.74	72.03
	Events	53.75	53.22
	Relations & Events	71.39	69.86

Table 5: Comparative results with and without co-reference rules

In the next two sections, we analyze both false positives and false negatives.

### 3.1 False Positives (or Precision Errors)

REES produced precision errors in the following cases:

- Most of the errors were due to over-generation of templates. These are mostly cases of co-referring noun phrases that the system failed to resolve. For example: “Panama ... the nation ...this country...his country”  
Rules for the co-reference module are still under development, and at present REES handles only limited types of plural noun phrase anaphora.
- Spurious events resulted from verbs in conditional constructions (e.g., “if ... then...”) or from ambiguous predicates. For instance, “appoint” as a POLITICAL event vs. a PERSONNEL\_CHANGE event.
- The subject of a verb was misidentified. This is particularly frequent in reduced relative clauses.  
*Kabul radio said the latest deaths brought to 38 the number of people killed in the three car bomb explosions.*  
(Wrong subject: “the number of people” as the KILLER instead of the victim)

### 3.2 False Negatives (or Recall Errors)

Below, we list the most frequent recall errors in the training set.

- Some event arguments are mentioned with event nouns instead of event verbs. The current system does not handle noun-based event extraction.  
*India's acquisition last month of the nuclear submarine from the Soviet Union...*  
(SELLER=”Soviet Union” and TIME=”last month” come with the noun-based event “acquisition.”)
- Pronouns “it” and “they,” which carry little semantic information, are currently not resolved by the co-reference module.  
*It also has bought three late-1970s vintage Kilo class Soviet submarines and two West German HDW 209 subs*

(Missed BUYER=*India* because of unresolved *it*.)

- Verb arguments are a conjunction of noun phrases. The current system does not handle coordination of verb arguments.  
*Hezbollah killed 21 Israelis and 43 of Lahad's soldiers*  
(The system gets only the first object: *21 Israelis*.)
- Ellipsis cases. The current system does not handle ellipsis.  
*The two were sentenced to five-year prison terms with hard labor by the state security court...*  
(Missed PERSON\_SENTENCED fill because of unresolved *the two*.)
- The subject of the event is relatively far from the event-denoting verb:  
*Vladislav Listyev, 38, who brought television interview shows in the style of Phil Donahue or Larry King to Russian viewers and pioneered hard-hitting television journalism in the 1980s, was shot in the heart by unknown assailants and died immediately...*  
(The system missed subject *Vladislav Listyev* for attack event *shot*)
- Missed ORG\_LOCATION relations for locations that are part of the organization's name.  
*Larnaca General Hospital*  
(Missed ORG\_LOCATION TR for this and *Larnaca*.)

We asked a person who is not involved in the development of REES to review the event extraction output for the blind set. This person reported that:

- In 35% of the cases where the REES system completely missed an event, it was because the lexicon was missing the predicate. REES’s event predicate lexicon is rather small at present (a total of 140 verbs for 61 event types) and is mostly based on the examples found in the training set.
- In 30% of the cases, the subject or object was elliptical. The system does not currently handle ellipsis.

- In 25% of the cases, syntactic/semantic argument structures were missing from existing lexical entries.

It is quite encouraging that simply adding additional predicates and predicate argument structures to the lexicon could significantly increase the blind set performance.

#### 4 Future Directions

We believe that improving co-reference resolution and adding noun-based event extraction capability are critical to achieving our ultimate goal of at least 80% F-Measure for relations and 70% for events.

##### 4.1 Co-reference Resolution

As discussed in Section 3.1 and 3.2, accurate co-reference resolution is crucial to improving the accuracy of extraction, both in terms of recall and precision. In particular, we identified two types of high-payoff co-reference resolution:

- definite noun phrase resolution, especially plural noun phrases
- 3<sup>rd</sup> person neutral pronouns “it” and “they.”

##### 4.2 Noun-based Event Extraction

REES currently handles only verb-based events. Noun-based event extraction adds more complexity because:

- Nouns are often used in a generic, non-referential manner (e.g., “We see a **merger** as being in the consumer’s interest”), and
- When referential, nouns often refer to verb-based events, thus requiring noun-verb co-reference resolution (“An F-14 crashed shortly after takeoff...The crash”).

However, noun-based events are crucial because they often introduce additional key information, as the underlined phrases below indicate:

*While **Bush's meetings** with prominent anti-apartheid leaders such as Archbishop*

*Desmond Tutu and Albertina Sisulu are important...*

We plan to develop a generic set of patterns for noun-based event extraction to complement the set of generic verb-based extraction patterns.

#### 5 Conclusions

In this paper, we reported on a fast, portable, large-scale event and relation extraction system REES. To the best of our knowledge, this is the first attempt to develop an IE system which can extract such a wide range of relations and events with high accuracy. It performs particularly well on relation extraction, and it achieves 70% or higher F-Measure for 26 types of events already. In addition, the design of REES is highly portable for future addition of new relations and events.

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#### References

- Aone, Chinatsu, Lauren Halverson, Tom Hampton, and Mila Ramos-Santacruz. 1998. “SRA: Description of the IE<sup>2</sup> System Used for MUC-7.” In Proceedings of the 7<sup>th</sup> Message Understanding Conference (MUC-7).
- Appelt, Douglas E., Jerry R Hobbs, John Bear, David Israel, Megumi Kameyama, Andy Kehler, David Martin, Karen Myers, and Mabry Tyson. 1995. “SRI International FASTUS System: MUC-6 Test Results and Analysis.” In Proceedings of the 6<sup>th</sup> Message Understanding Conference (MUC-6).
- Ramshaw, Lance A., and Mitchell P. Marcus. 1995. “Text Chunking Using Transformation-Based Learning”. In Proceedings of the 3<sup>rd</sup> ACL Workshop on Very Large Corpora (WVLC95).
- Yangarber, Roman and Ralph Grishman. 1998. “NYU: Description of the Proteus/PET System as Used for MUC-7 ST.” In Proceedings of the 6<sup>th</sup> Message Understanding Conference (MUC-7).