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Information Extraction – a User Guide

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1 Introduction

This note gives a user-oriented view of Information Extraction (IE). No knowledge of language processing is assumed. For a more technical overview see [CL96].

Information Extraction is a process which takes unseen texts as input and produces fixed-format, unambiguous data as output. This data may be used directly for display to users, or may be stored in a database or spreadsheet for later analysis, or may be used for indexing purposes in Information Retrieval

(IR) applications.

It is instructive to compare IE and IR: whereas IR simply finds texts and presents them to the user, the typical IE application analyses texts and presents only the specific information from them that the user is interested in. For example, a user of an IR system wanting information on the share price movements of companies with holdings in Bolivian raw materials would typically type in a list of relevant words and receive in return a set of documents (e.g. newspaper articles) which contain likely matches. The user would then read the documents and extract the requisite information themselves. They might then enter the information in a spreadsheet and produce a chart for a report or presentation. In contrast, an IE system user could, with a properly configured application, automatically populate their spreadsheet directly with the names of companies and the price movements.

There are advantages and disadvantages to IE with respect to IR. IE systems are more difficult and knowledge-intensive to build, and are to varying degrees tied to particular domains and scenarios (see next section). They are also (for most tasks) less accurate than human readers. IE is more computationally intensive than IR. However, in applications where there are large text volumes IE is potentially much more efficient than IR because of the possibility of reducing the amount of time analysts spend reading texts. Also, where results need to be presented in several languages, the fixed format, unambiguous nature of IE results makes this straightforward in comparison with providing full translation facilities.

2 Types of IE

There are four types of information extraction (or information extraction *tasks*) currently available (as defined by the leading forum for this research, the Message Understanding Conferences [GS96].).

Named Entity recognition (NE)
: Finds and classifies names, places etc.

Coreference Resolution (CO)
: Identifies identity relations between entities in texts.

Template Element construction (TE)
: Adds descriptive information to NE results.

Scenario Template production (ST)
: Fits TE results into specified event scenarios.

From a user point-of-view, NE, TE and ST are the most relevant IE tasks (CO, as noted below, is necessary as an adjunct to the other tasks, but is of limited direct usefulness to the IE system user). NE, TE and ST provide progressively higher-level information about texts.

These are described in more detail below, after a discussion of the current performance levels of IE technology.

3 Performance levels

Each of the four types of IE have been the subject of rigorous performance evaluation in MUC-6 (1995) and other MUCs, so it is possible to say quite precisely how well the current level of technology performs. Below we will quote percentage figures quantifying performance levels – they should be interpreted as a combined measure of precision and recall (see the section on evaluation in [Adv95]). Several caveats should be noted: most of the evaluation has been on English (with some Japanese, Chinese and Spanish)

– some applications of the technology may be either easier or more difficult in other languages.

The performance of each IE task, and the ease with which it may be developed, is to varying degrees dependent on:

Text type: the kinds of texts we are working with, for example Wall Street Journal articles, or email messages, or HTML documents from the World Wide Web.

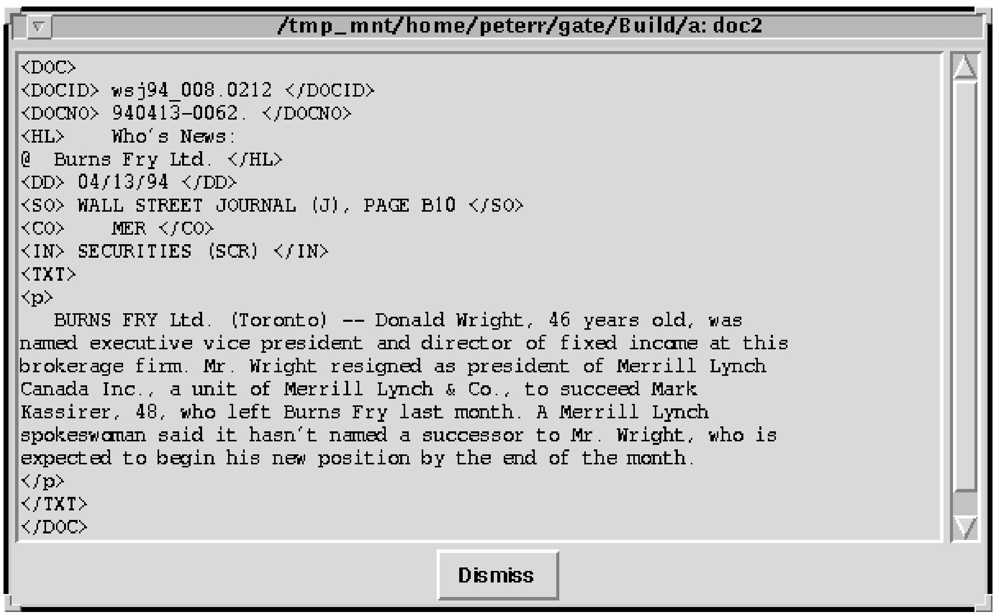
Domain: the broad subject matter of those texts, e.g. financial news, or requests for technical support, or tourist information.

Scenario: the particular event types that the IE user is interested in, for example mergers between companies, or problems experienced with a particular software package, or descriptions of how to locate parts of a city.

For example, a particular IE application might be configured to process financial news articles from a particular news provider and find information about mergers between companies and various other scenarios. The performance of the application would be predictable for only this conjunction of factors. If it was later required to extract facts from the love letters of Napoleon Bonaparte as published on wall posters in the 1871 Paris Commune, performance levels would no longer be predictable. Tailoring an IE system to new requirements is a task that varies in scale dependent on the degree of variation in the three factors listed above.

4 Named Entity recognition

The simplest and most reliable IE technology is *Named Entity recognition* (NE). NE systems identify all the names of people, places, organisations, dates, and amounts of money. So, for example, if we run the Wall Street Journal text in figure 1 through an NE recogniser, the result is as in figure 2 (this looks better in colour!). (The viewers shown here and below are part of the GATE language engineering architecture and development environment – see [CWG96].) NE recognition can be performed at 96% accuracy; the



```
/tmp_mnt/home/peterr/gate/Build/a: doc2
<DOC>
<DOCID> wsj94_008.0212 </DOCID>
<DOCNO> 940413-0062. </DOCNO>
<HL>    Who's News:
@  Burns Fry Ltd. </HL>
<DD> 04/13/94 </DD>
<SO> WALL STREET JOURNAL (J), PAGE B10 </SO>
<CO>    MER </CO>
<IN> SECURITIES (SCR) </IN>
<TXT>
<p>
   BURNS FRY Ltd. (Toronto) -- Donald Wright, 46 years old, was
named executive vice president and director of fixed income at this
brokerage firm. Mr. Wright resigned as president of Merrill Lynch
Canada Inc., a unit of Merrill Lynch & Co., to succeed Mark
Kassirer, 48, who left Burns Fry last month. A Merrill Lynch
spokeswoman said it hasn't named a successor to Mr. Wright, who is
expected to begin his new position by the end of the month.
</p>
</TXT>
</DOC>
Dismiss
```

Figure 1: An example text

current Sheffield system ([GWH^{+}95]) performs at 92% accuracy. Given that human annotators do not perform to the 100% level (measured in MUC by inter-annotator comparisons), NE recognition can now be said to function at human performance levels, and applications of the technology are increasing rapidly as a result.

A recent evaluation of NE for Spanish, Japanese and Chinese ([MOC96])

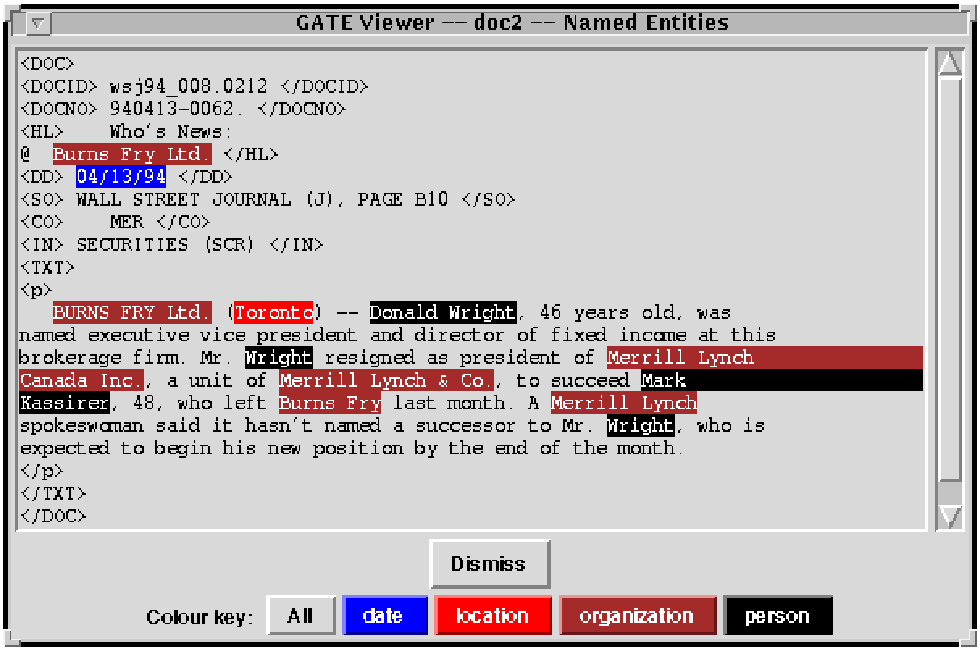


Figure 2: Named entity recognition

produced the following scores:

language	**best system**
Spanish	93.04 %
Japanese	92.12 %
Chinese	84.51 %

The process is weakly domain dependent, i.e. changing the subject matter of the texts being processed from financial news to other types of news would involve some changes to the system, and changing from news to scientific papers would involve quite large changes.

5 Coreference resolution

Coreference resolution (CO) involves identifying identity relations between entities in texts. These entities are both those identified by NE recognition and anaphoric references to those entities. For example, in

> Alas, poor Yorick, I knew him well.

coreference resolution would tie "Yorick" with "him" (and "I" with Hamlet, if that information was present in the surrounding text).

This process is less relevant to users than other IE tasks (i.e. whereas the other tasks produce output that is of obvious utility for the application user, this task is more relevant to the needs of the application developer). For text browsing purposes we might use CO to highlight all occurrences of the same object or provide hypertext links between them. CO technology might also be used to make links between documents, though this is not currently part of the MUC programme. The main significance of this task, however, is as a building block for TE and ST (see below). CO enables the association of descriptive information scattered across texts with the entities to which it refers. To continue the hackneyed Shakespeare example, coreference resolution might allow us to situate Yorick in Denmark. Figure 3 shows results for our example text.

CO resolution is an imprecise process when applied to the solution of anaphoric reference. The Sheffield system scored 51% recall and 71% precision[1] at MUC-6; other systems scored e.g. 59% recall / 72% precision, 63% recall / 63% precision. These scores are low (although problems with completing the task definition on schedule complicated matters, and led to human scores of

[1] For statistical reasons the combined precision and recall measure we use elsewhere is inappropriate here.

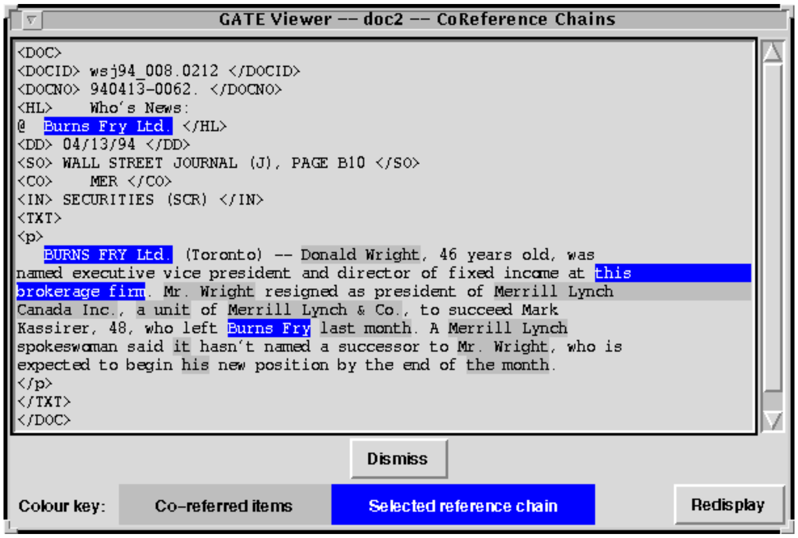


Figure 3: Coreference resolution

only around 80%), but note that this hides the difference between proper noun coreference identification (same object, different spelling or compounding, e.g. "IBM", "IBM Europe", "International Business Machines Ltd.", ...) and anaphora resolution, the former being a significantly easier problem.

CO systems are domain dependent.

6 Template Element production

The TE task builds on NE recognition and coreference resolution. In addition to locating and typing (i.e. classifying, or assigning to a type – personal name, date etc.) entities in documents, TE associates descriptive information with the entities. For example, from the figure 1 text the system finds out that Burns Fry Ltd. is located in Toronto, and it adds the information that this is in Canada.

Template elements for the figure 1 text are given in figure 4. The format is a

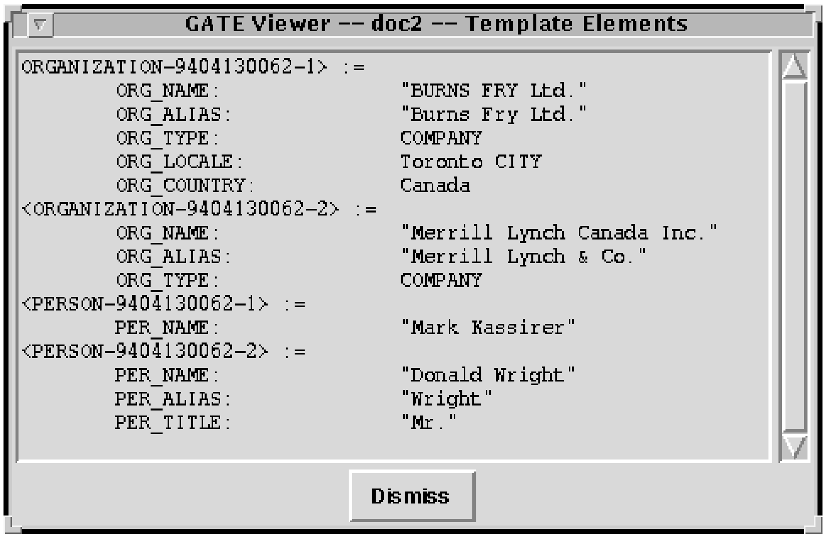


Figure 4: Template elements

somewhat arbitrary one developed at the behest of the American intelligence community (the original target user group of the MUC competitions). It is difficult to read; the main point to note is that it is essentially a database record, and could just as well be formatted for SQL store operations, or reading into a spreadsheet, or (with some extra processing) for multilingual presentation. Section 8 gives a simplified example.

The current Sheffield system scores 71% for TE production; the best MUC-6 system scored 80%. Humans achieved 93%. MUC-6 was the first MUC to evaluate TE and ST tasks separately – TE scores should improve in future as developers gain more experience with the task.

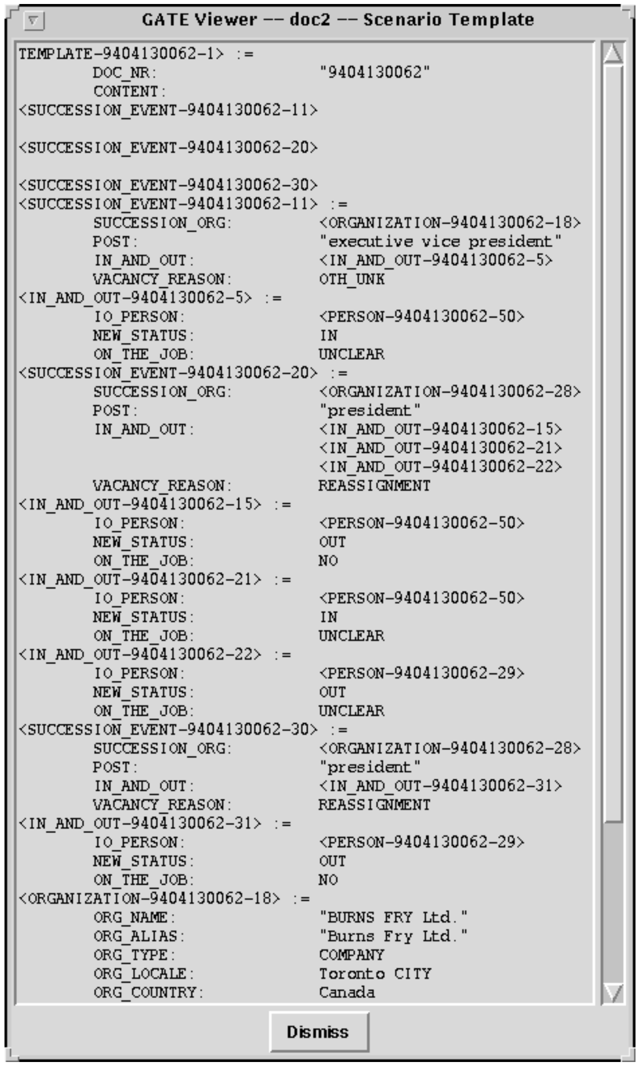
As in NE recognition, the production of TEs is is weakly domain dependent, i.e. changing the subject matter of the texts being processed from financial news to other types of news would involve some changes to the system, and changing from news to scientific papers would involve quite large changes.

7 Scenario Template extraction

Scenario templates (STs) are the prototypical outputs of IE systems. They tie together TE entities into event and relation descriptions. For example, TE may have identified Isabelle, Dominique and Françoise as people entities present in the Robert edition of Napoleon's love letters. ST might then identify facts such as that Isabelle moved to Paris in August 1802 from Lyon to be nearer to the little chap, that Dominique then burnt down Isabelle's apartment block and that Françoise ran off with one of Gerard Depardieu's ancestors. A slightly more pertinent example is given in figure 5. The same comments regarding format apply as for the TE task.

ST is a difficult IE task. The current Sheffield system scores 49% for ST production; the best MUC-6 system scored 56%. The human score was 81%, which illustrates the complexity involved. These figures should be taken into account when considering appropriate applications of ST technology. Note, however, that it is possible to increase precision at the expense of recall: we can develop ST systems that don't make many mistakes, but that miss quite a lot of occurrences of relevant scenarios. Alternatively we can push up recall and miss less, but at the expense of making more mistakes.

The ST task is both domain dependent, and, by definition, tied to the scenarios of interest to the users. Note however that the results of NE and TE feed into ST. Note also that in MUC-6 the developers were given the specifications for the ST task only 1 month before the systems were scored. This was because it was noted that an IE system that required very lengthy revision to cope with new scenarios was of less worth than one that could meet new specifications relatively rapidly. As a result of this, the scores for ST in MUC-6 were probably slightly lower than they might have been with a longer development period. Experience from previous MUCs suggests that



GATE Viewer -- doc2 -- Scenario Template

```
TEMPLATE-9404130062-1> :=
        DOC_NR:                 "9404130062"
        CONTENT:
<SUCCESSION_EVENT-9404130062-11>

<SUCCESSION_EVENT-9404130062-20>

<SUCCESSION_EVENT-9404130062-30>
<SUCCESSION_EVENT-9404130062-11> :=
        SUCCESSION_ORG:         <ORGANIZATION-9404130062-18>
        POST:                   "executive vice president"
        IN_AND_OUT:             <IN_AND_OUT-9404130062-5>
        VACANCY_REASON:         OTH_UNK
<IN_AND_OUT-9404130062-5> :=
        IO_PERSON:              <PERSON-9404130062-50>
        NEW_STATUS:             IN
        ON_THE_JOB:             UNCLEAR
<SUCCESSION_EVENT-9404130062-20> :=
        SUCCESSION_ORG:         <ORGANIZATION-9404130062-28>
        POST:                   "president"
        IN_AND_OUT:             <IN_AND_OUT-9404130062-15>
                                <IN_AND_OUT-9404130062-21>
                                <IN_AND_OUT-9404130062-22>
        VACANCY_REASON:         REASSIGNMENT
<IN_AND_OUT-9404130062-15> :=
        IO_PERSON:              <PERSON-9404130062-50>
        NEW_STATUS:             OUT
        ON_THE_JOB:             NO
<IN_AND_OUT-9404130062-21> :=
        IO_PERSON:              <PERSON-9404130062-50>
        NEW_STATUS:             IN
        ON_THE_JOB:             UNCLEAR
<IN_AND_OUT-9404130062-22> :=
        IO_PERSON:              <PERSON-9404130062-29>
        NEW_STATUS:             OUT
        ON_THE_JOB:             UNCLEAR
<SUCCESSION_EVENT-9404130062-30> :=
        SUCCESSION_ORG:         <ORGANIZATION-9404130062-28>
        POST:                   "president"
        IN_AND_OUT:             <IN_AND_OUT-9404130062-31>
        VACANCY_REASON:         REASSIGNMENT
<IN_AND_OUT-9404130062-31> :=
        IO_PERSON:              <PERSON-9404130062-29>
        NEW_STATUS:             OUT
        ON_THE_JOB:             NO
<ORGANIZATION-9404130062-18> :=
        ORG_NAME:               "BURNS FRY Ltd."
        ORG_ALIAS:              "Burns Fry Ltd."
        ORG_TYPE:               COMPANY
        ORG_LOCALE:             Toronto CITY
        ORG_COUNTRY:            Canada
```

Dismiss

Figure 5: Scenario template

current technology has difficulty attaining scores much above 60% accuracy for this task, however.

8 An Extended Example

So far we have discussed IE from a general perspective. In this section we look at the capabilities that might be delivered as part of an application designed to support analysts tracking international drug dealing.

When the system is specified, our imaginary analyst states that "the operational domains that user interests are centred around are... drug enforcement, money laundering, organised crime, terrorism, legislation". The entities of interest within these domains are cited as "person, company, bank, financial entity, transportation means, locality, place, organisation, time, telephone, narcotics, legislation, activity". A number of relations (or "links") are also specified, for example between people, between people and companies, etc. These relations are not typed, i.e. the kind of relation involved is not specified. Some relations take the form of properties of entities – e.g. the location of a company – whilst others denote events – e.g. a person visiting a ship.

Working from this starting point an IE system is designed that:

1. is tailored to texts dealing with drug enforcement, money laundering, organised crime, terrorism, and legislation;
2. recognises entities in those texts and assigns them to one of a number of categories drawn from the set of entities of interest (person, company, ...);
3. associates certain types of descriptive information with these entities, e.g. the location of companies;
4. identifies a set (relatively small to begin with) of events of interest by tying entities together into event relations.

For example, consider the following text:

> Reuter – New York, Wednesday 12 July 1996.
>
> New York police announced today the arrest of Frederick J. Thompson, head of Jay Street Imports Inc., on charges of drug smuggling. Thompson was taken from his Manhattan apartment in the early hours yesterday. His attorney, Robert Giuliani, issued a statement denying any involvement with narcotics on the part of his client. "No way did Fred ever have dealings with dope", Guliani said.
>
> A Jay Street spokesperson said the company had ceased trading as of today. The company, a medium-sized import-export concern established in 1989, had been the main contractor in several collaborative transport ventures involving Latin-American produce. Several associates of the firm moved yesterday to distance themselves from the scandal, including the mid-western transportation company Downing-Jones.
>
> Thompson is understood to be accused of importing heroin into the United States.

From this IE might produce information such as the following (in some format to be determined according to user requirements, e.g. SQL statements addressing some database schema).

First, a list of entities and associated descriptive information. Relations of property type are made explicit. Each entity has an id, e.g. `ENTITY-2`, which can be used for cross-referencing between entities and for describing events involving entities. Each also has a type, or category, e.g. `company`, `person`. Additionally various type-specific information is available, e.g., for dates, a `normalisation` giving the date in standard format.

```
Reuter
        id:             ENTITY-1
        type:           company
        business:       news

New York
```

```
        id:             ENTITY-2
        type:           location
        subtype:        city
        is_in:          US

Wednesday 12 July 1996
        id:             ENTITY-3
        type:           date
        normalisation:  12/07/1996

New York police
        id:             ENTITY-4
        type:           organisation
        location:       ENTITY-2

Frederick J. Thompson
        id:             ENTITY-5
        type:           person
        aliases:        Thompson; Fred
        domicile:       ENTITY-7
        profession:     managing director
        employer:       ENTITY-6

Jay Street Imports Inc.
        id:             ENTITY-6
        type:           organisation
        aliases:        Jay Street
        business:       import-export

Manhattan
        id:             ENTITY-7
        type:           location
        subtype:        city
        is_in:          ENTITY-2

Robert Guliani
        id:             ENTITY-8
        type:           person
        aliases:        Guliani

1989
        id:             ENTITY-9
        type:           date
        normalisation:  ?/?/1989

Latin-America
        id:             ENTITY-10
        type:           location
        subtype:        country

Downing-Jones
        id:             ENTITY-11
        type:           organisation
```

```
        business:       transportation

heroin
        id:             ENTITY-12
        type:           drug
        class:          A

United States
        id:             ENTITY-13
        type:           location
        subtype:        country
```

(These results correspond to the combination of NE and TE tasks; if we removed all but the type slots we would be left with the NE data.)

Second, relations of event type, or scenarios:

```
narcotics-smuggling
        id:             EVENT-1
        destination:    ENTITY-13
        source:         unknown
        perpetrators:   ENTITY-5, ENTITY-6
        status:         on-trial

joint-venture
        id:             EVENT-2
        type:           transport
        companies:      ENTITY-6, ENTITY-11
        status:         past
```

(These results correspond to the ST task.)

9 Multilingual IE

The results described above may then be translated for presentation to the user or for storage in existing databases. In general this task is much easier than translation of ordinary text, and is close to *software localisation*, the process of making a program's messages and labels on menus and buttons multilingual. Localisation involves storing lists of direct translations for known items. In our case these lists would store translations for words such as “entity”, “location”, “date”, “heroin”. We also need ways to display dates and numbers in local formats, but code libraries are available for this type of problem.

Problems can arise where arbitrary pieces of text are used in the entity description structures, for example the descriptor slot in MUC-6 TE objects. Here a noun phrase from the text is extracted, with whatever qualifiers, relative clauses etc. happen to be there, so the language is completely unrestricted and would need a full translation mechanism.

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