Information Extraction
Lecture 3 – Rule-based Named Entity Recognition

CIS, LMU München
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Administravia

• Seminar
  • Almost done with assigning topics, dates will be announced very soon
    • You should have a topic by now
    • If not, *you must speak to me after class*
    • Please check the seminar web page tomorrow and send me an email if I made a mistake
  • Reminder: there is a LaTeX template for the Hausarbeit on the Seminar web page
Outline

• Basic evaluation: Precision/Recall
• Rule-based Named Entity Recognition
• Learning Rules
• Evaluation
Information Extraction (IE) is the process of extracting structured information from unstructured machine-readable documents.

- **Source Selection**
- **Tokenization & Normalization**: 05/01/67 → 1967-05-01
- **Named Entity Recognition**: ... married Elvis on 1967-05-01

**Instance Extraction**

**Fact Extraction**

**Ontological Information Extraction**

**Person Name**
- Elvis Presley: musician
- Angela Merkel: politician

**Relation**
- Married: Elvis Presley and Priscilla Beaulieu
- CEO: Tim Cook and Apple

Tip of the hat: Suchanek
May 19 1995, Atlanta -- The Centers for Disease Control and Prevention, which is in the front line of the world's response to the deadly Ebola epidemic in Zaire, is finding itself hard pressed to cope with the crisis...

<table>
<thead>
<tr>
<th>Date</th>
<th>Disease Name</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan. 1995</td>
<td>Malaria</td>
<td>Ethiopia</td>
</tr>
<tr>
<td>July 1995</td>
<td>Mad Cow Disease</td>
<td>U.K.</td>
</tr>
<tr>
<td>Feb. 1995</td>
<td>Pneumonia</td>
<td>U.S.</td>
</tr>
</tbody>
</table>
Named Entity Recognition (NER) is the process of finding entities (people, cities, organizations, dates, ...) in a text.

Elvis Presley was born in 1935 in East Tupelo, Mississippi.
Classification

- Can include up to some hundreds of types
  - e.g. ACE competition
- Examples:
  - Named Entity Recognition:
    - Classic tasks (e.g. MUC conferences)
      - Includes Named Entities, Time Expressions and Numerical Expression
  - Terminology recognition
    - Recognition of technical terminology in specialistic documents
      - E.g. names of genes, parts of an aircraft, etc.

WASHINGTON, D.C. (October 5, 1999) - nQuest Inc. today announced that Paul Jacobs, former Vice-President of E-Commerce at SRA International, has joined the company's executive management.
Evaluation

How can the performance of a system be evaluated?

Standard Methodology from Information Retrieval:

- Precision
- Recall
- F-measure (combination of Precision/Recall)
Recall

Measure of how much relevant information the system has extracted (coverage of system).

Basic idea:

\[
\text{Recall} = \frac{\text{# of correct answers given by system}}{\text{total # of possible correct answers in text}}
\]
Recall

Measure of how much relevant information the system has extracted (coverage of system).

Exact definition:

Recall = 1 if no possible correct answers

else:

# of correct answers given by system

total # of possible correct answers in text

Slide modified from Butt/Jurafsky/Martin
Precision

Measure of how much of the information the system returned is correct (accuracy).

Basic idea:

\[
\text{Precision} = \frac{\# \text{ of correct answers given by system}}{\# \text{ of answers given by system}}
\]
Precision

Measure of how much of the information the system returned is correct (accuracy).

Exact definition:

\[
\text{Precision} = \begin{cases} 
1 & \text{if no answers given by system} \\
\frac{\text{# of correct answers given by system}}{\text{# of answers given by system}} & \text{else}
\end{cases}
\]
Evaluation

Every system, algorithm or theory should be **evaluated**, i.e. its output should be compared to the **gold standard** (i.e. the ideal output). Suppose we try to find scientists...

Algorithm output:
\[ O = \{\text{Einstein, Bohr, Planck, Clinton, Obama}\} \]

Gold standard:
\[ G = \{\text{Einstein, Bohr, Planck, Heisenberg}\} \]

**Precision:**
What proportion of the output is correct?
\[
\frac{|O \cap G|}{|O|}
\]

**Recall:**
What proportion of the gold standard did we get?
\[
\frac{|O \cap G|}{|G|}
\]
Explorative algorithms extract everything they find.

(very low threshold)

Algorithm output:
\[ O = \{ \text{Einstein, Bohr, Planck, Clinton, Obama, Elvis, ...} \} \]

Gold standard:
\[ G = \{ \text{Einstein, Bohr, Planck, Heisenberg} \} \]

Precision: What proportion of the output is correct? BAD

Recall: What proportion of the gold standard did we get? GREAT
Conservative algorithms extract only things about which they are very certain

(very high threshold)

Algorithm output:
$O = \{\text{Einstein}\}$

Gold standard:
$G = \{\text{Einstein, Bohr, Planck, Heisenberg}\}$

Precision:
What proportion of the output is correct?

**GREAT**

Recall:
What proportion of the gold standard did we get?

**BAD**
Precision & Recall Exercise

What is the algorithm output, the gold standard, the precision and the recall in the following cases?

1. Nostradamus predicts a trip to the moon for every century from the 15th to the 20th inclusive.

2. When asked to predict the weather over 5 days, a forecast predicts the next 3 days will be sunny without saying anything about the following 2 days. In reality, it is sunny during all 5 days.

3. An algorithm learns to detect Elvis songs. Out of a sample of 100 songs on Elvis Radio™, 90% of the songs are by Elvis. Out of these 100 songs, the algorithm says that 20 are by Elvis (and says nothing about the other 80). Out of these 20 songs, 15 were by Elvis and 5 were not.

\[
\text{output} = \{e_1, \ldots, e_{15}, x_1, \ldots, x_5\}
\]
\[
\text{gold} = \{e_1, \ldots, e_{90}\}
\]
\[
\text{prec} = \frac{15}{20} = 75\%
\]
\[
\text{rec} = \frac{15}{90} = 16\%
\]

Modified from Suchanek
You can’t get it all...

The F1-measure combines precision and recall as the harmonic mean:

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$
F-measure

Precision and Recall stand in opposition to one another. As precision goes up, recall usually goes down (and vice versa).

The F-measure combines the two values.

\[
\text{F-measure} = \frac{(\beta^2+1)PR}{\beta^2 P+R}
\]

- When $\beta = 1$, precision and recall are weighted equally (same as F1).
- When $\beta$ is $> 1$, precision is favored.
- When $\beta$ is $< 1$, recall is favored.
Summary: Precision/Recall

- Precision and recall are very key concepts
  - Definitely know these formulas, they are applicable everywhere (even real life)!
- F-Measure is a nice way to combine them to get a single number
  - People sometimes don't specify Beta when they say F-Measure
  - In this case Beta=1, i.e., they mean F1, equal weighting of P and R
- We will return to evaluation in more detail later in this lecture
- Now let's look at rules for (open-class) NER
Rule-Based Methods for Entity Extraction
Why Rules?

- Many real-life extraction tasks can be conveniently handled through a collection of rules, which are either hand-coded or learnt from examples.
- A typical rule-based system consists of:
  - a collection of rules
  - a set of policies to control the firings of multiple rules
Basic rules

- Rules tend to have the form
  - *Contextual Pattern* -> *Action*
- E.g. Finite State Transducer Rules

```plaintext
Rule: Company1
    ( ( {Token.orthography == upperInitial} )+ 
      {Lookup.kind == companyDesignator} 
    ):match
-->
    :match.NamedEntity = { kind=company, rule="Company1" } 
```

from gate.ac.uk
Token Features

- The String
- Orthography type
- Part of Speech
- Gazetteer information
- Any other information provided by any type of preprocessing

<table>
<thead>
<tr>
<th>Word</th>
<th>Lemma</th>
<th>PoS</th>
<th>case</th>
<th>Gaze</th>
</tr>
</thead>
<tbody>
<tr>
<td>the</td>
<td>the</td>
<td>Art</td>
<td>low</td>
<td></td>
</tr>
<tr>
<td>seminar</td>
<td>Seminar</td>
<td>Noun</td>
<td>low</td>
<td></td>
</tr>
<tr>
<td>at</td>
<td>at</td>
<td>Prep</td>
<td>low</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>Digit</td>
<td>low</td>
<td></td>
</tr>
<tr>
<td>pm</td>
<td>pm</td>
<td>Other</td>
<td>low</td>
<td>timed</td>
</tr>
<tr>
<td>will</td>
<td>will</td>
<td>Verb</td>
<td>low</td>
<td></td>
</tr>
</tbody>
</table>
Types of Entity Rules

- Identifying an entity requires recognition of a portion of the document and to insert an XML tag
  - SGML tags in the old days
- Three approaches tried in literature
  - Whole entity recognition
    - E.g. Annie (Cunnigham 2001), Rapier (Califf 1999), etc.
  - Boundary recognition
    - E.g. (LP)$^2$ (Ciravegna 2001), BWI (Kushermerick 2001)
  - Multiple entity recognition
    - E.g. Whisk (Soderland 1999)
Rules to Identify Entities

- The classic approach uses rules that model a whole entity
  - No dependency among entities
  - Rule models
    - Left context + Filler + Right context

Rule: Stime1
Pre:
  Word = ”at"

Fill:
  Cat = DIG+
  Gaz = timeld

Post:
  PoS = Aux
Action: TAG(stime)

Matches:
- at
- 3
- pm
- will

Wednesday, 26 August 2009
Rules to identify boundaries

• Rules model
  • Left context + Right context of each tag

• Different rules to identify <entity> and </entity>
  • <entity> recognised independently from </entity>

Rule: Stime1
Pre:
  Word="seminar":
  Word="at":
Post:
  Cat=DIG+
  Gaz=timeld
Action: TAG(<stime>)

Matches

| The     |
| seminar |
| at      |
| 3       |
| pm      |
Multiple Entities Rules

- Identify more than one entity
  - Model the dependency that sometimes exist between entities
    - especially order in very structured pages

Example:

```html
<p>Capitol Hill- 1 br twnhme. D/W W/D. Pkg incl $675. 3 BR upper flr no gar. $995. (206)999-9999</p>
```

Rule:

```
ID: 7
Pattern: * ('Capitol Hill') * (Digit) * '$' (Number)
Output: Rental {Neighborhood $1} {Bedrooms $2} {Price $3}
```

Rule from: STEPHEN SODERLAND.
Learning Information Extraction Rules for Semi-structured and Free Text,
Machine Learning 1, 440
Discussion

• Multi-entity rules are typically used when there is a lot of structure
• Single-entity rules are often used when manually writing rules
  – Humans are good at creating general rules from a limited number of examples
• Boundary rules are often used in learning approaches
  – They generalize well from few examples
    • For instance, they can use rules for `<stime>` and `</stime>` that are learned from different training examples
    • But they may overgeneralize!
Organising Rule Collections

- When rules are fired
  - More than one can apply for a specific span of text
  - Which rule is to be applied?

- Strategies
  - Unordered rules with ad-hoc strategies
    - E.g. Prefer rules marking larger span of text (longer entities)
      - E.g. `<ORG> IBM Corp. </ORG>` preferred to `<ORG> IBM </ORG>`
  - Ordered set of rules
    - E.g. rules are sorted by precision on the training corpus
Rule-based NER

• Through about 2000, handcrafted rule-based NER was better than statistical NER
  – For instance in the Message Understanding Conferences, which featured shared tasks
• Since 2000, statistical approaches have started to dominate the academic literature
• In industry, there is still diversity
  – High precision -> rule-based
  – High recall -> statistical
  – Between, many different solutions (including combining both approaches)
  – But it (debatably) takes less effort to tune statistical systems to improve precision than to tune rule-based systems to increase recall
Learning Rules

• We will now talk about learning rules
  – Still closely following Sarawagi Chapter 2
• The key resource required is a gold standard annotated corpus
  – This is referred to as the "training" corpus
  – The system "learns" through training
  – The goal is to learn rules which may generalize well to new examples which were not seen during training
• We will discuss bottom-up and top-down creation of rules
Rule Learning Algorithms

• Given an annotated corpus
  • Derive a minimal set of rules that cover all (and only) the annotated examples
    • Or at least to maximise recall and precision
  • As determining the optimal rule set is intractable
    • Existing algorithms follow a greedy hill climbing strategy
      • Learn one rule at a time i.e.:

1. $\text{Rset} = \text{set of rules}, \text{initially empty}$.
2. While there exists an entity $x \in D$ not covered by any rule in $\text{Rset}$
   (a) Form new rules around $x$.
   (b) Add new rules to $\text{Rset}$.
3. Post process rules to prune away redundant rules.
Overfitting and Overgeneralization

• One key concept here is "overfitting" examples
  – What is meant here is that we memorize too much from one example
  – For instance, if we have:

Elvis Presley was born in 1935 in East Tupelo, Mississippi.

• and we memorize that in this exact context Elvis Presley is a person, we are failing to generalize to other contexts

• We can also "overgeneralize"
  – An example would be to learn that the first word of a sentence is a first name
    • This is true in this sentence
    • But this rule will apply to every sentence, and often be wrong
Bottom-Up Rule Formation

- For each annotated example
  - Create 1 rule by selecting a window of words to the left and right of entity/tag
    - Completely overfitting the example
    - Likely 100% precision, very low recall
      - Will cover just the current example (plus all the repetitions)
  - Drop constraints on words in window
  - Identify best rule (set) covering example
  - Remove all other instances covered by rules
    - Covering algorithm

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Example

de the seminar at **time** 4 pm will

<table>
<thead>
<tr>
<th>Condition</th>
<th>Additional Knowledge</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word</td>
<td>Lemma</td>
<td>LexCat</td>
</tr>
<tr>
<td>the</td>
<td>the</td>
<td>Art</td>
</tr>
<tr>
<td>seminar</td>
<td>Seminar</td>
<td>Noun</td>
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Example

The seminar at `<time>` 4 pm will

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<tr>
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<td>pm</td>
<td>Other</td>
</tr>
</tbody>
</table>

Example

the seminar at \texttt{<time> 4 pm} will

<table>
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<td>LexCat</td>
</tr>
<tr>
<td>at</td>
<td>Digit</td>
<td></td>
</tr>
<tr>
<td>timeid</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Rule Induction & Generalization

Positive Examples

Final Ruleset
Rule Induction & Generalization

Rule

Positive Examples

Final Ruleset
Rule Induction & Generalization

Rule

Positive Examples

Generalizations

Final Ruleset
Rule Induction & Generalization

Rule

Generalizations

Positive Examples

Final Ruleset
Rule Induction & Generalization

Positive Examples → Rule → Generalizations → Final Ruleset
Rule Induction & Generalization

Rule

Positive Examples

Final Ruleset

Generalizations
Covering Algorithm

Positive Examples
Covering Algorithm

Positive Examples
Covering Algorithm

Rule

Positive Examples
Covering Algorithm

Rule

Generalizations

Positive Examples
Covering Algorithm

Rule
Generalizations

Positive Examples
Covering Algorithm

Rule
Generalizations

Positive Examples
Top Down Algorithm

• Starts from an empty rule
  • will match the whole corpus
  • 100% recall, low precision

• Progressively insert constraints on words to raise precision while keeping recall
  • Stop when rules are overfitting examples
Top-down version of (LP)$^2$

- **r0**: action = `<stime>`, matches: all the corpus

- **r1**: Word$_1$ = seminar, Word$_2$ = *, action = `<stime>`, matches: 0, 4, 12, 134, 222, 232

- **r2**: Word$_1$ = at, action = `<stime>`, matches: 0, 12, 15, 44, 72, 134, 146, 230, 250

- **r3**: action = `<stime>`, Word$_1$ = 4, matches: 12, 27, 72, 112, 134, 230, 245

- **r4**: action = `<stime>`, Word$_1$ = *, Word$_2$ = pm, matches: 12, 27, 72, 134, 245

- **r5**: Word$_1$ = seminar, Word$_2$ = at, action = `<stime>`, matches: 0, 12, 134

- **r6**: Word$_1$ = at, action = `<stime>`, Word$_2$ = 4, matches: 12, 72, 134

- **r7**: action = `<stime>`, Word$_1$ = 4, Word$_2$ = pm, matches: 12, 134

- **r8**: Word$_1$ = seminar, Word$_2$ = at, action = `<stime>`, Word$_3$ = 4, matches: 12, 134

- **r9**: Word$_1$ = at, action = `<stime>`, Word$_2$ = 4, Word$_3$ = pm, matches: 12, 134

- **r10**: Word$_1$ = seminar, Word$_2$ = at, action = `<stime>`, Word$_3$ = 4, Word$_3$ = pm, matches: 12, 134
• There are many papers on hand-crafted rule-based NER and learning rules for NER
  – Wikipedia also has a useful survey which I recommend
• Now we will return to evaluation
  – Very short discussion of precision/recall as actually used in IE (not IR)
  – Then we are done with this slide set
• Next time:
  – More on evaluation and rule-based NER
  – Annotation of training sets
Importance of Evaluation in IE

- IE was born from a series of competitive evaluations organised by DARPA in the US
  - MUC Conferences, 1989-1998
    - IE as a departure from IR but using the same types of measures of accuracy
    - The idea was to understand what worked and what not in text analysis
      - Finding a way to compare IE systems and approaches in a controlled way
  
- Evaluation is in IE’s DNA
  - Publishing IE papers without evaluation is not considered acceptable
Organising Evaluation

- You will need:
  - An annotated training corpus
    - That you will use to develop rules or to train a machine learning algorithm
  - A result scorer
    - A tool that automatically computes accuracy of the system against an annotated corpus
    - E.g. The MUC Scorer
  - An annotated test corpus
    - To be used blindly to test results
      - Please note that run on test corpus should be a one off test
      - Test corpus is not be used to fine tuning accuracy in any way
      - E.g. By looking at the results and changing your rules or by tuning the learning parameters
The Rationale Behind

- **Precision**: how correct is the average answer provided by the system
- **Recall**: how many (correct) pieces of information are retrieved by the system
- **F-measure**: allows comparative evaluations
Evaluation Measures

Recall = \frac{\text{CORRECT} + (\text{PARTIAL} \times 0.5)}{\text{POSSIBLE}}

Precision = \frac{\text{CORRECT} + (\text{PARTIAL} \times 0.5)}{\text{ACTUAL}}

F(\beta) = \frac{(\beta^2 + 1) \times \text{PREC} \times \text{REC}}{\beta^2 \times \text{PREC} + \text{REC}}

F-Measure is to be used to compare systems
In all evaluations all the three measures must be published
• Slide sources
  – Many of the slides today were from Fabio Ciravegna, University of Sheffield and Fabian Suchanek, Télécom ParisTech
• Thank you for your attention!