Information Extraction

Lecture 3 – Rule-based Named Entity Recognition

CIS, LMU München

Winter Semester 2020-2021

Prof. Dr. Alexander Fraser, CIS

Administravia

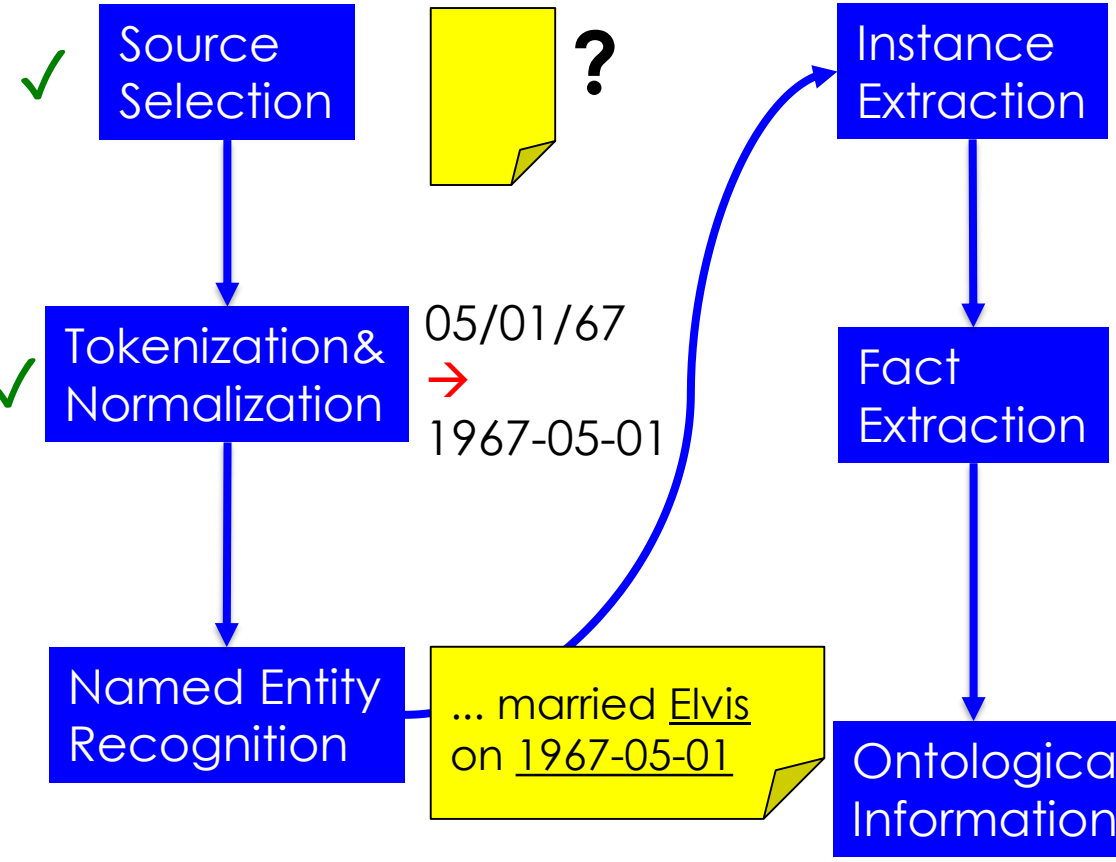
- Seminar
  - Almost done with assigning topics, dates will be announced very soon
    - You should have sent me an email about topics by now
    - If not, *you must send to me an email directly after class*
    - Please check the seminar web page tomorrow late evening
      - Send me an email if I made a data entry mistake (i.e., the web page is not the same as the email you will receive)
  - Reminder: there is a LaTeX template for the Hausarbeit on the Seminar web page
    - Recommended but not required

Outline

- Basic evaluation: Precision/Recall
- Rule-based Named Entity Recognition
- Learning Rules
- Evaluation

Information Extraction

Information Extraction (IE) is the process of extracting **structured information** from unstructured machine-readable documents



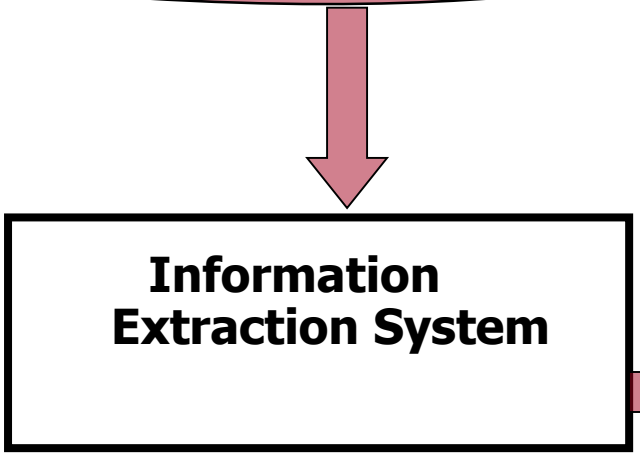
Person Name	Person Type
Elvis Presley	musician
Angela Merkel	politician

Relation	Entity1	Entity2
Married	Elvis Presley	Priscilla Beaulieu
CEO	Tim Cook	Apple

Tip of the hat: Suchanek

Relation Extraction: Disease Outbreaks

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…



Date	*Disease Name*	*Location*
Jan. 1995	Malaria	Ethiopia
July 1995	Mad Cow Disease	U.K.
Feb. 1995	Pneumonia	U.S.

Slide from Manning

Named Entity Recognition

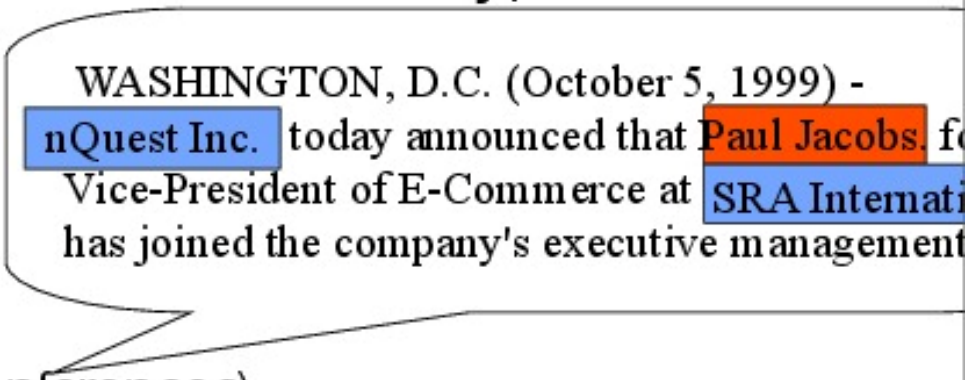
Named Entity Recognition (NER) is the process of finding entities (people, cities, organizations, dates, ...) in a text.

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

Slide from Suchanek

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.



Evaluation

How can the performance of a system be evaluated?

Standard Methodology from Information Retrieval:

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

Slide from Butt/Jurafsky/Martin

Recall

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

Basic idea:

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

Slide from Butt/Jurafsky/Martin

Recall

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

Exact definition:

$$\text{Recall} = \begin{cases} 1 & \text{if no possible correct answers} \\ \text{else:} & \\ \dfrac{\#\text{ of correct answers given by system}}{\text{total \# of possible correct answers in text}} & \end{cases}$$

Precision

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

Basic idea:

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

Slide from Butt/Jurafsky/Martin

Precision

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

Exact definition:

$$\text{Precision} = \begin{cases} 1 & \text{if no answers given by system} \\ \dfrac{\#\text{ of correct answers given by system}}{\#\text{ of answers given by system}} & \text{else:} \end{cases}$$

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 = {Einstein, Bohr, Planck, Clinton, Obama}
✓ ✓ ✓ ✗ ✗

Gold standard:
G = {Einstein, Bohr, Planck, Heisenberg}
✓ ✓ ✓ ✗

Precision:
What proportion of the output is correct?

$$\frac{|\ O \wedge G\ |}{|O|}$$

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

$$\frac{|\ O \wedge G\ |}{|G|}$$

Slide modified from Suchanek

Explorative Algorithms

Explorative algorithms extract everything they find.

(very low threshold)

Algorithm output:
O = {Einstein, Bohr, Planck, Clinton, Obama, Elvis,…}

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

Precision:
What proportion of the output is correct?

BAD

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

GREAT

Slide from Suchanek

Conservative Algorithms

Conservative algorithms extract only things about which they are very certain

(very high threshold)

Algorithm output:
O = {Einstein}

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

Precision:
What proportion of the output is correct?

GREAT

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

BAD

Slide from Suchanek

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.

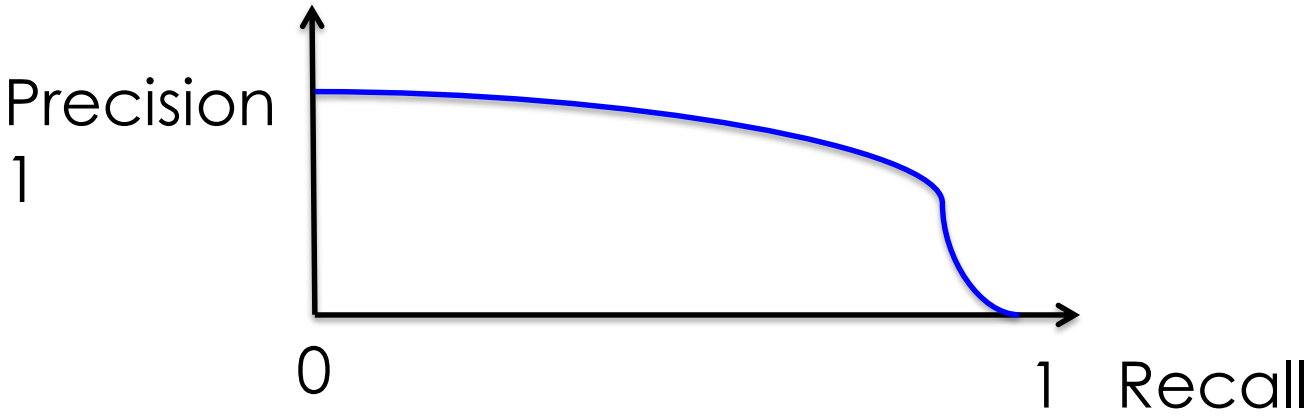
3. An algorithm learns to detect Elvis songs.
   Out of a sample of 100 songs on Elvis Radio ™ , 90% of the songs are by Elvis. Out of these100 songs, the algorithm says that 20 are by Elvis (and says nothing about the other 80). Out of these 20 songs, 15 were by Elvis and 5 were not.

output={e1,…,e15, x1,…,x5}
gold={e1,…,e90}
prec=15/20=75 %, rec=15/90=16%

Modified from Suchanek

F1- Measure

You can't get it all...



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

F1 = 2 * precision * recall / (precision + recall)

Slide from Suchanek

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 ß = 1, precision and recall are weighted equally (same as F1).
- When ß is > 1, precision is favored.
- When ß is < 1, recall is favored.

Slide modified from Butt/Jurafsky/Martin

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

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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

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

Token Features

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

Word	Lemma	PoS	case	Gaze
the	the	Art	low	
seminar	Seminar	Noun	low	
at	at	Prep	low	
4	4	Digit	low	
pm	pm	Other	low	timeid
will	will	Verb	low	

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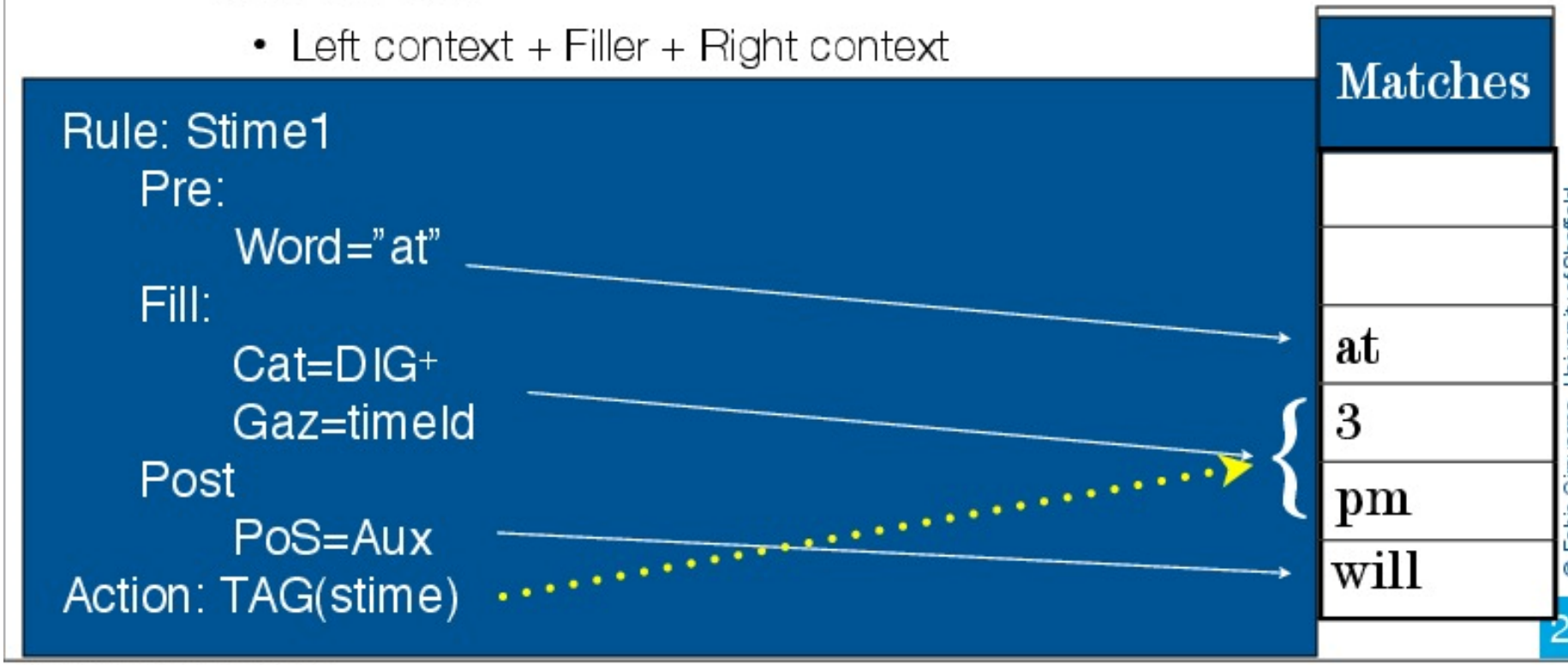
Types of Entity Rules

- 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 (Kushmerick 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



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>

Multiple Entities Rules

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

Example:

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

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!

Slide modified from Ciravegna

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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

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

Sunita Sarawagi: Information Extraction, Foundations and Trends in Databases, Vol. 1, No. 3 (2007) 261–377

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

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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

Example

`the seminar at <time> 4 pm will`

Condition	Additional Knowledge				Action
Word	Lemma	LexCat	case	SemCat	Tag
the	the	Art	low		
seminar	Seminar	Noun	low		
at	at	Prep	low		stime
4	4	Digit	low		
pm	pm	Other	low	timeid	
will	will	Verb	low		

Fabio Ciravegna:
Adaptive Information Extraction from Text by Rule Induction and Generalisation
in Proceedings of 17th International Joint Conference on Artificial Intelligence (IJCAI 2001), Seattle, August 2001.

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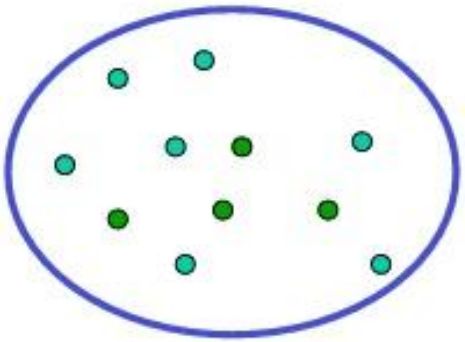
Rule Induction & Generalization



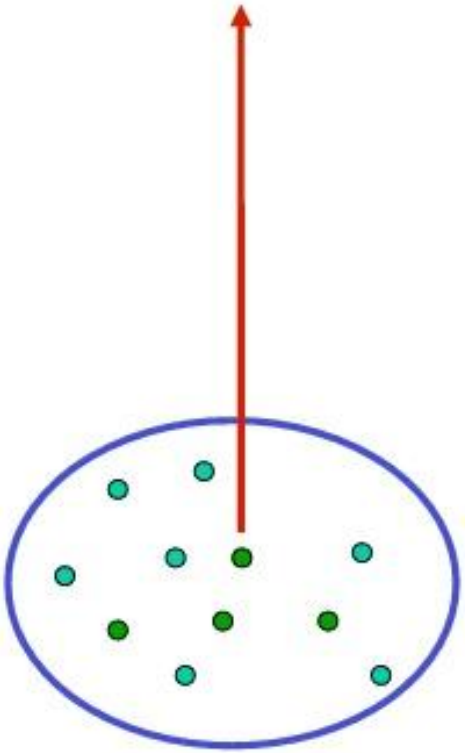
Positive Examples

Final Ruleset

Slide from Ciravegna

Rule Induction & Generalization

Rule 



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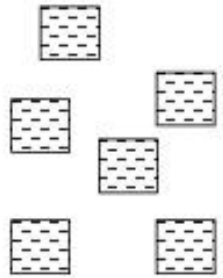
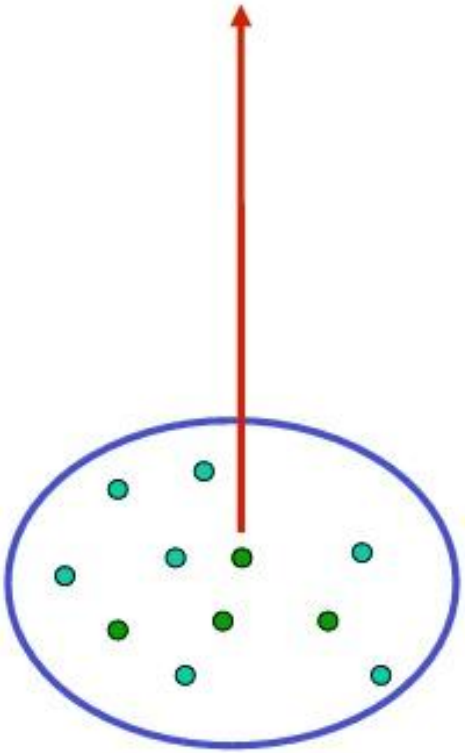
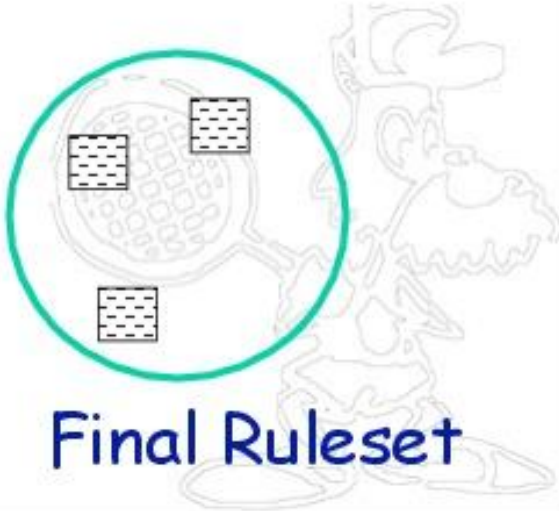
Rule Induction & Generalization



Generalizations



Positive Examples



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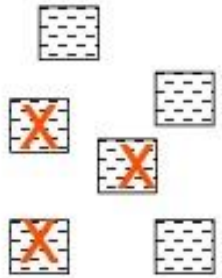

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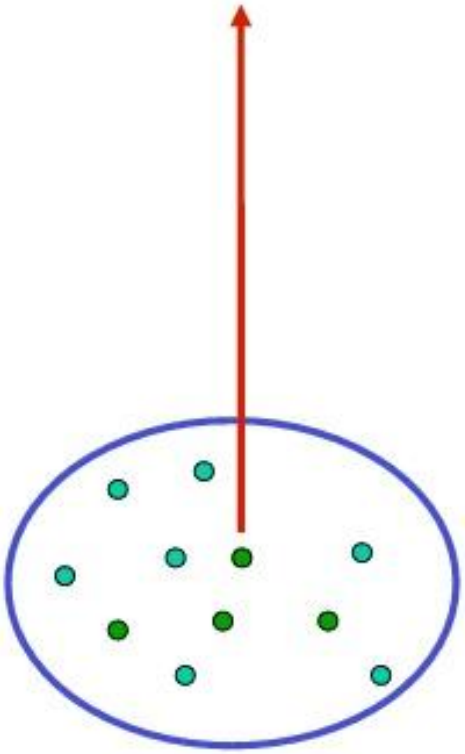

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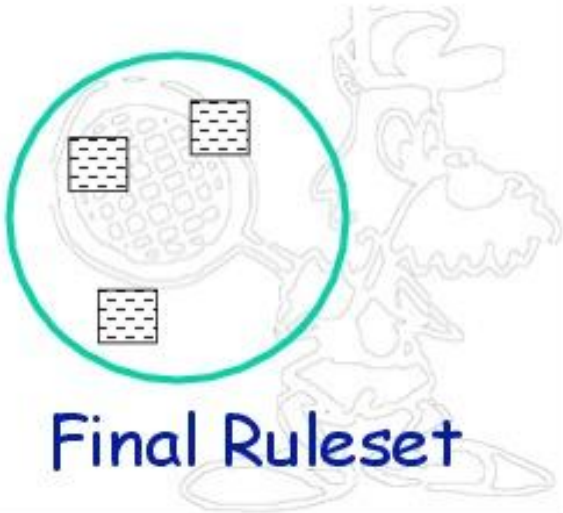

Final Ruleset

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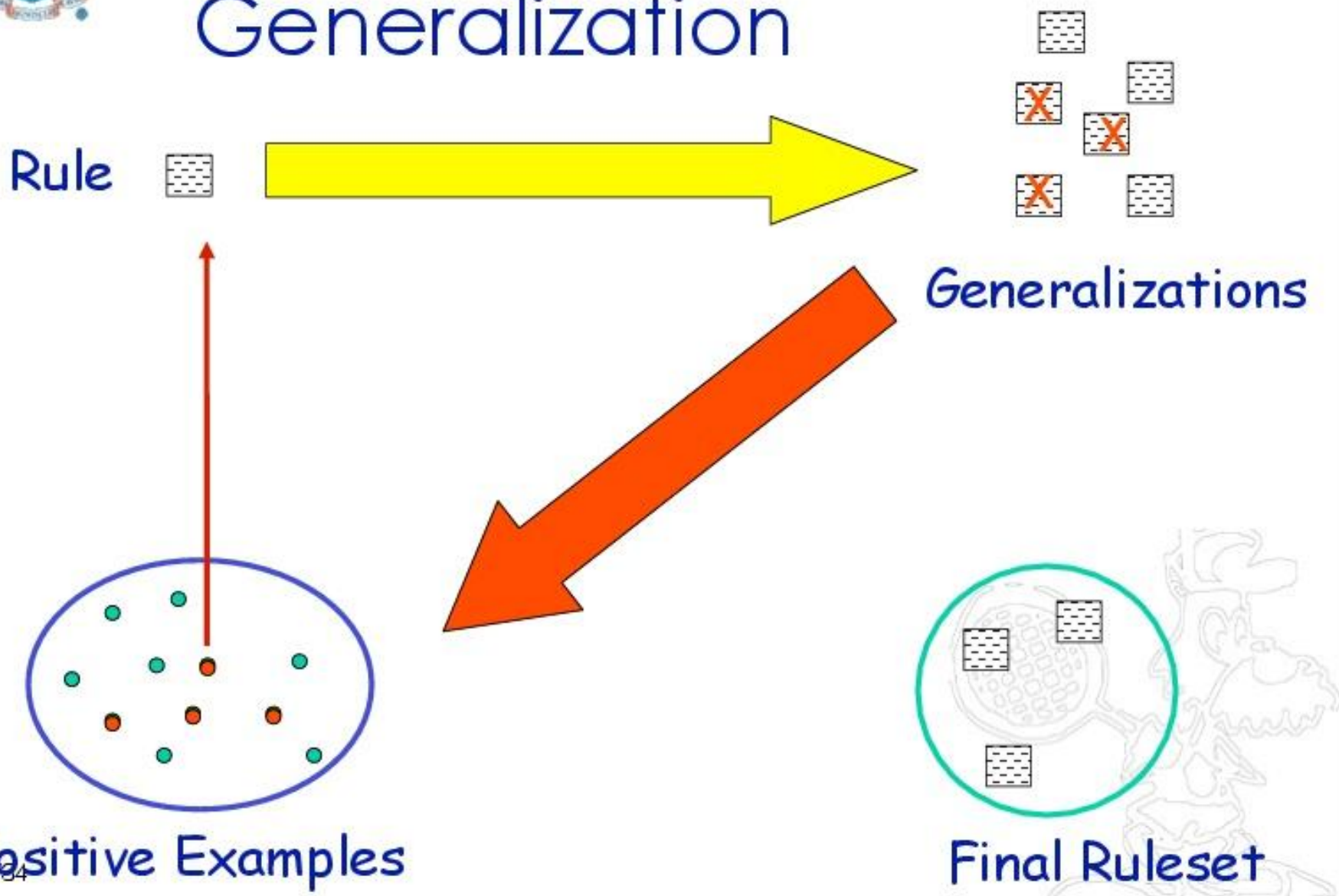

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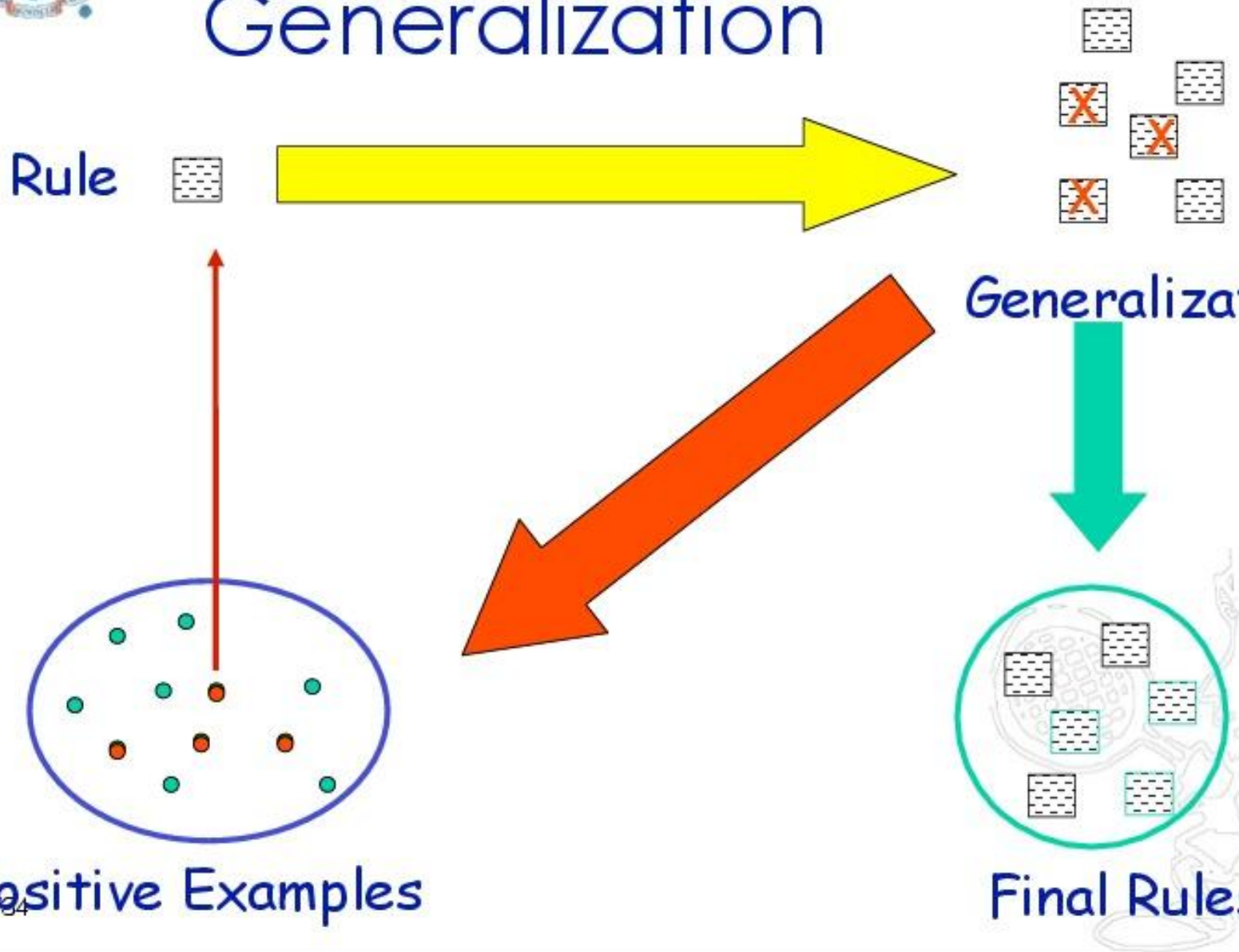
Rule Induction & Generalization



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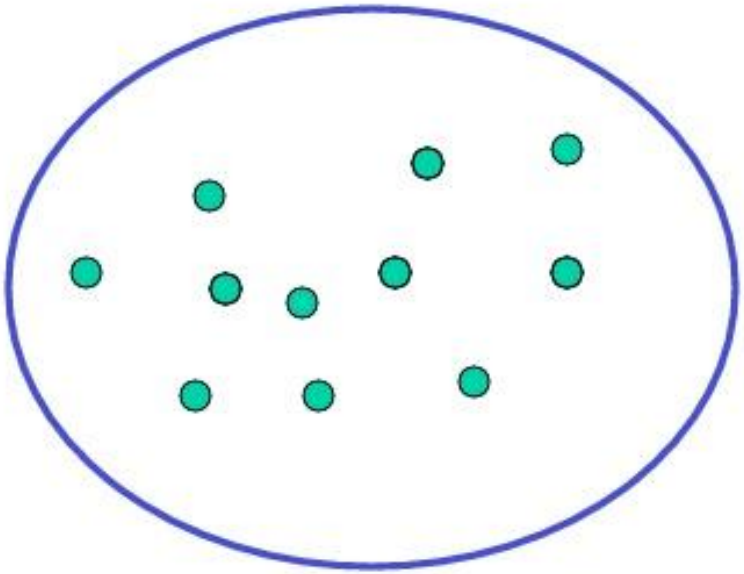
Covering Algorithm



Positive Examples

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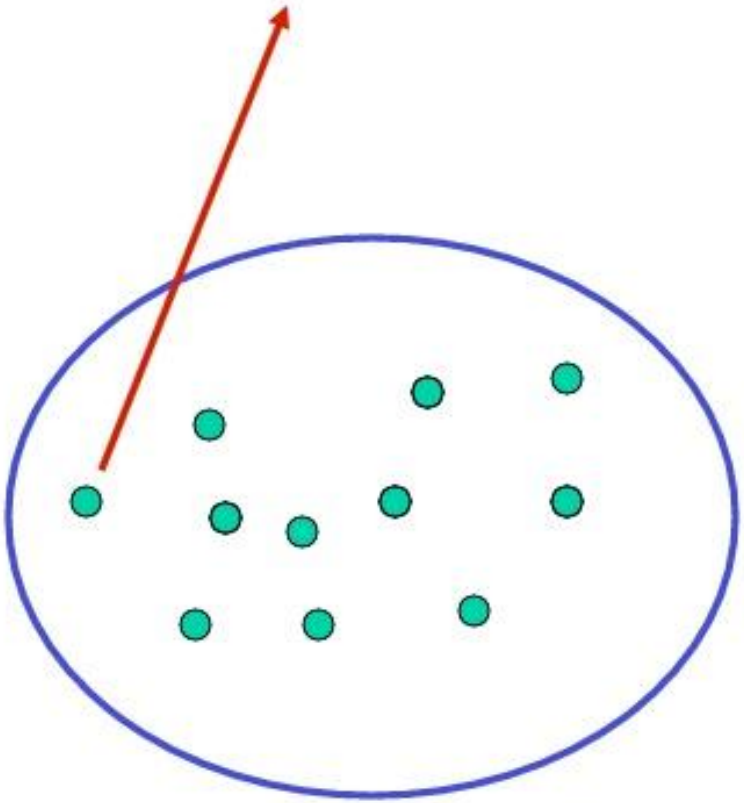

Positive Examples

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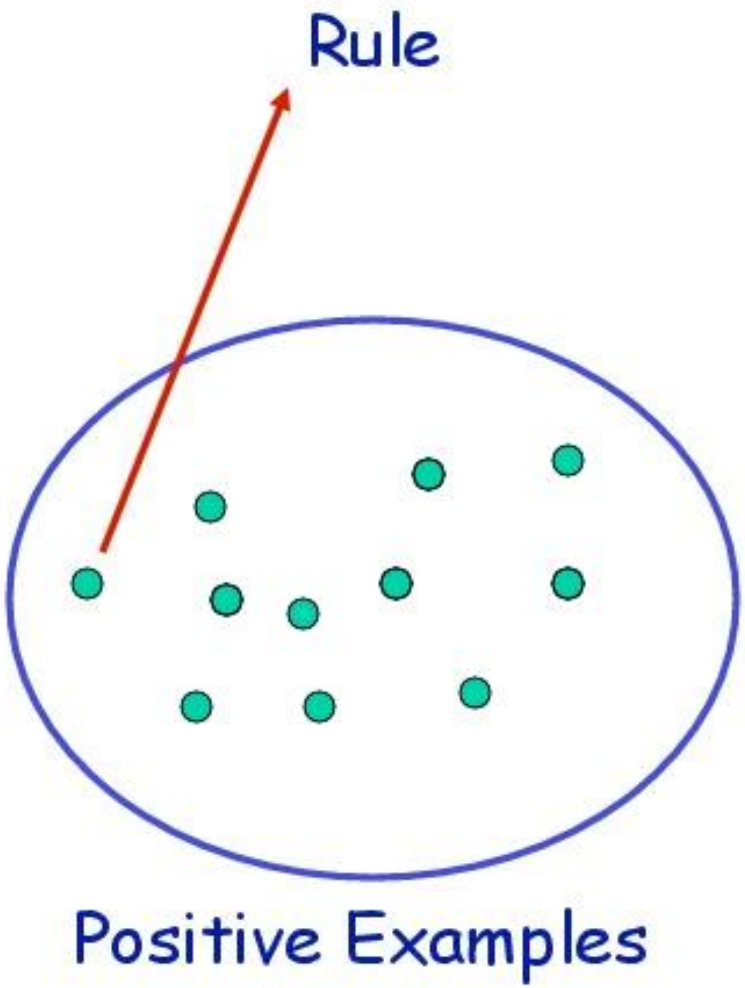

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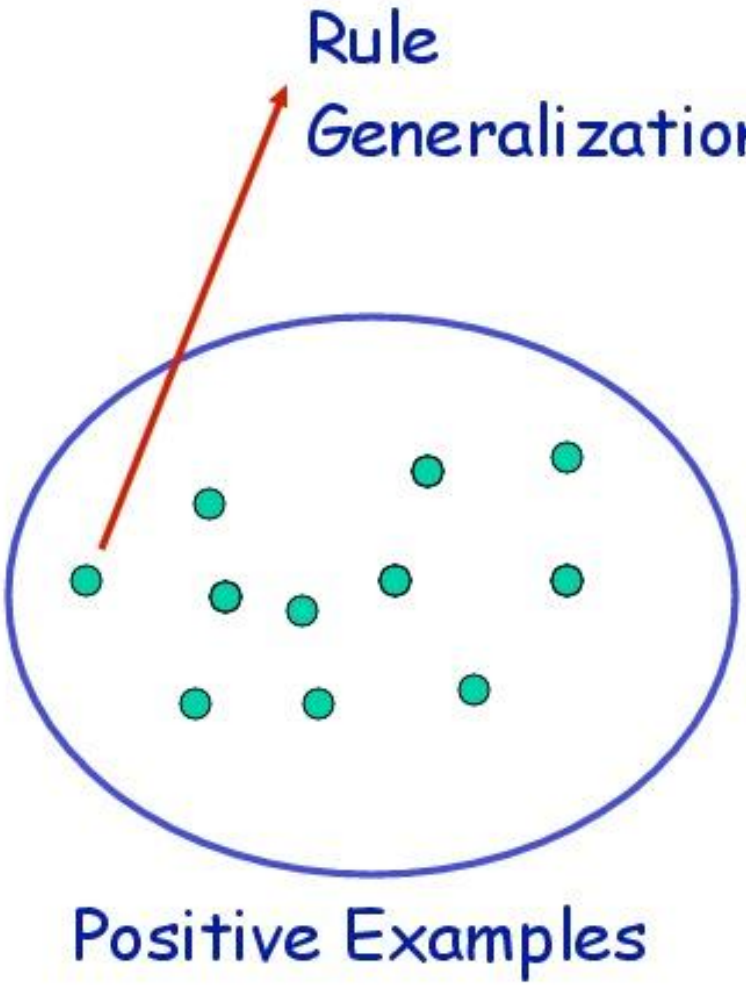

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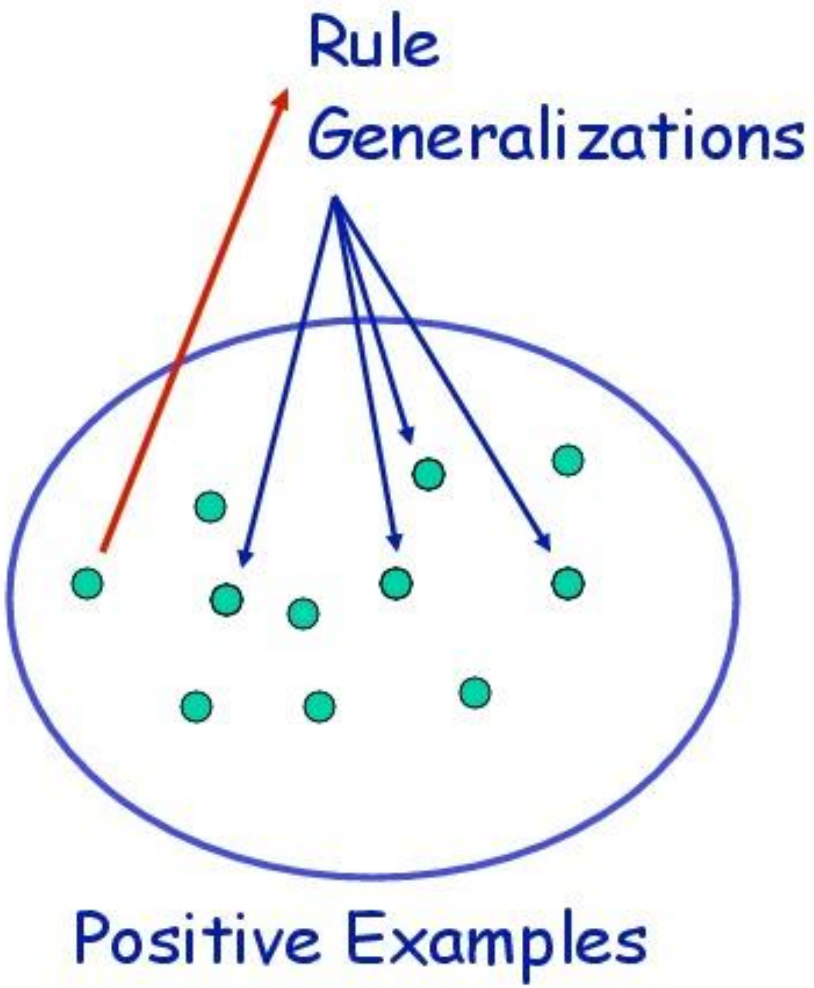

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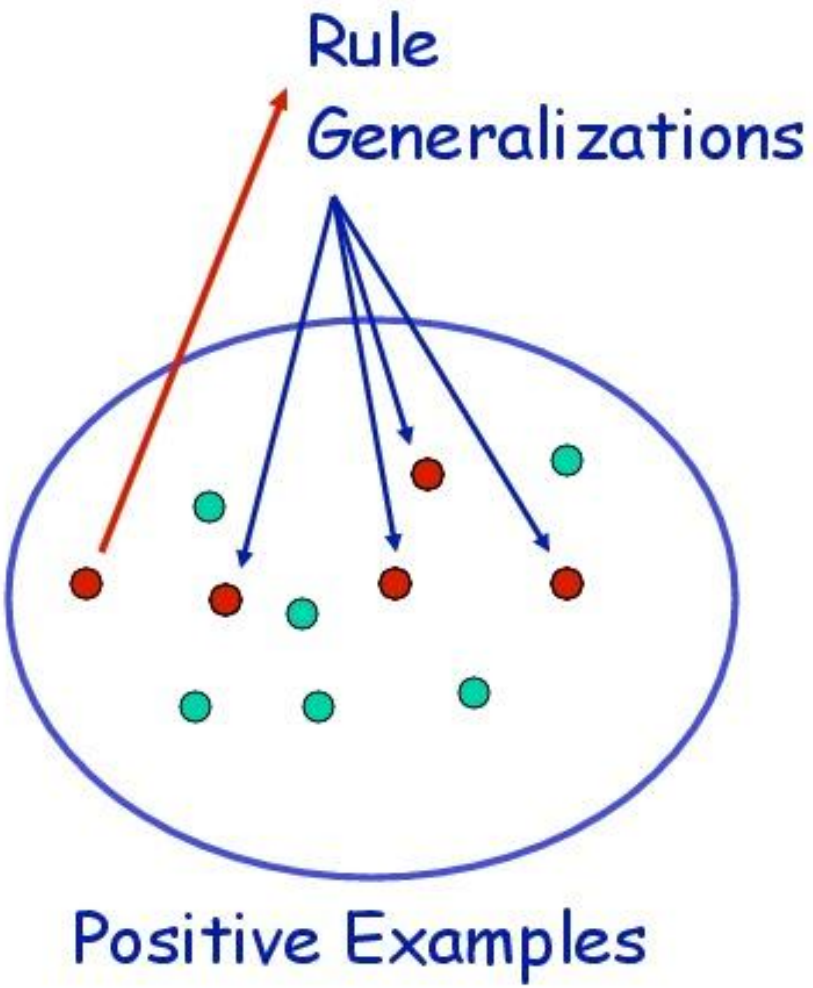

Slide from Ciravegna

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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

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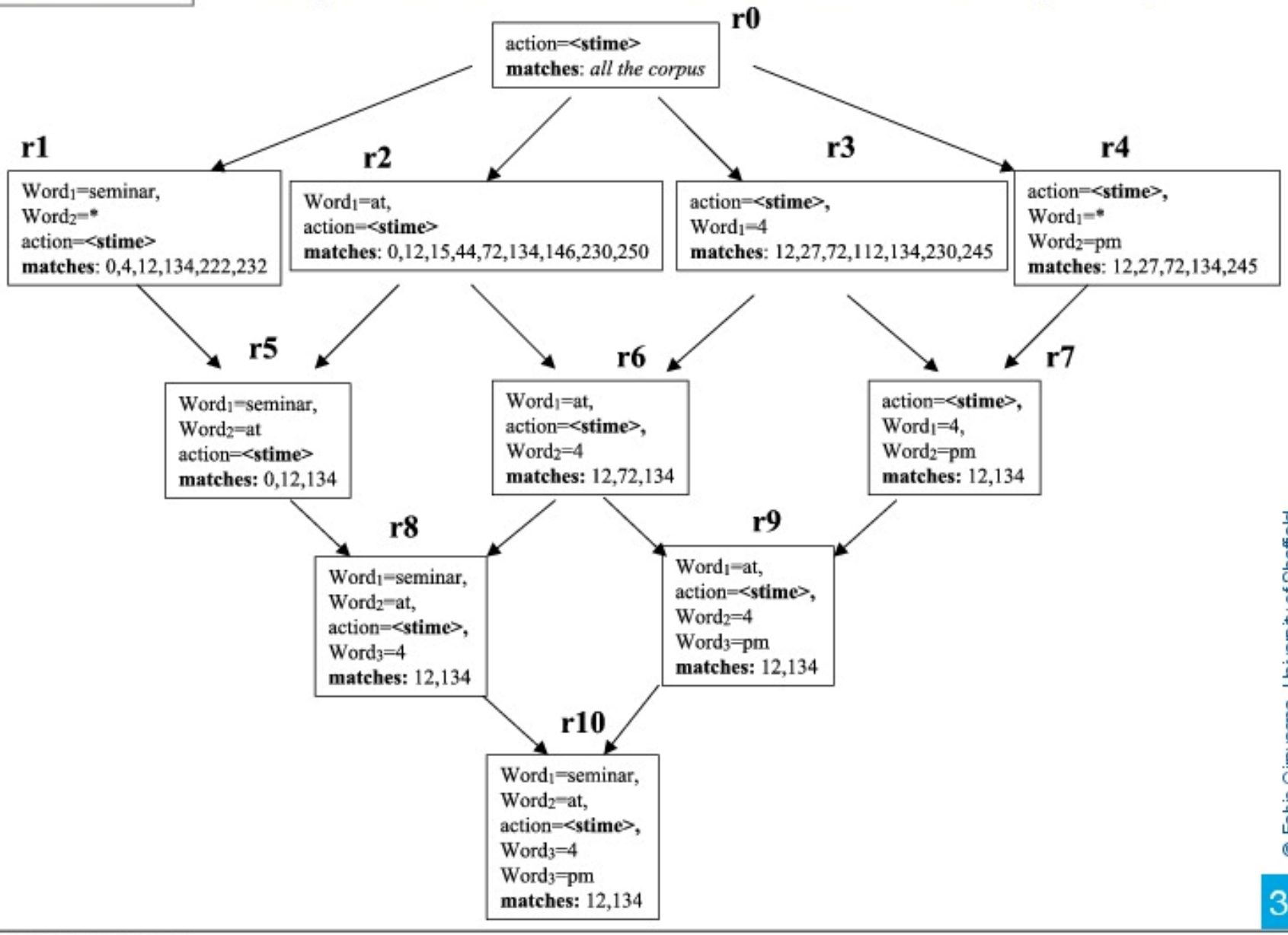
Top-down version of (LP)^2



- 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

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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

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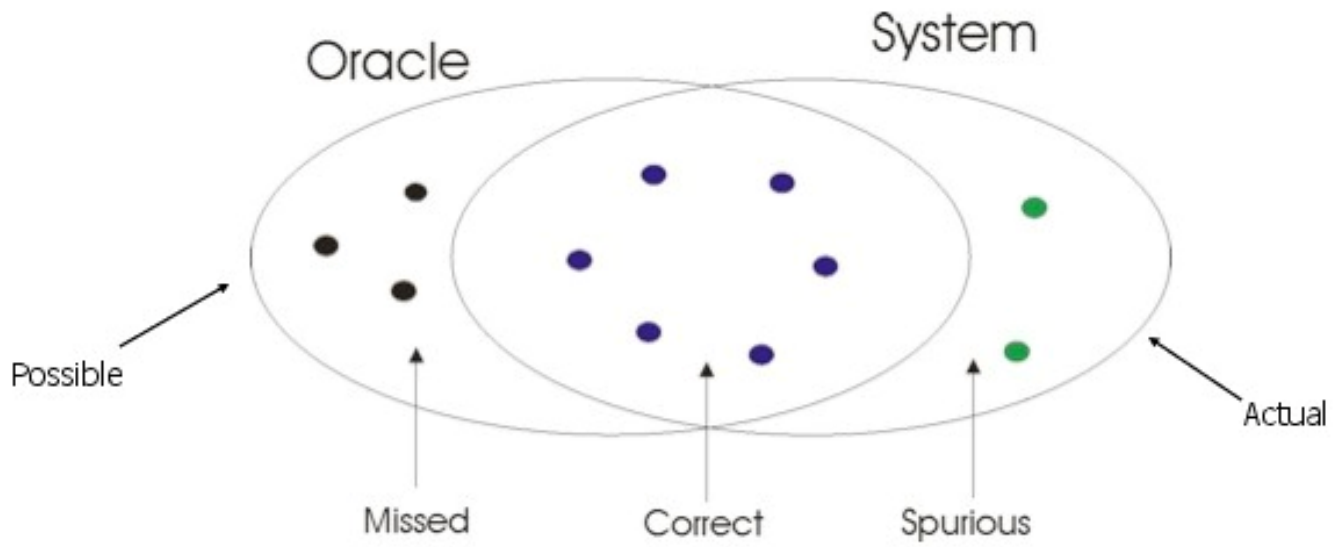
Organising Evaluation

- 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



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Evaluation Measures

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

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

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

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!