Information Extraction

• **Definition** (after Grishman 1997, Eikvil 1999):
  "The identification and extraction of instances of a particular class of events or relationships in a natural language text and their transformation into a structured representation (e.g. a database)."
  
  - IR retrieves *relevant documents* from collections
  - IE retrieves *relevant information* from documents

• **Example:** **AutoSlog** (Riloff)
  
  - input:
    - general syntactic patterns
    - annotated (marked-up) training documents
  
  - output:
    - instantiated patterns that extract particular information
  
  - **Autoslog-TS:** Extension that replaces need for annotated corpus with manual post-processing of sorted pattern list

• **On the Web:** natural language text -> (semi-)structured text
Extracting Job Openings from the Web

foodscience.com-Job2
JobTitle: Ice Cream Guru
Employer: foodscience.com
JobCategory: Travel/Hospitality
JobFunction: Food Services
JobLocation: Upper Midwest
Contact Phone: 800-488-2611
DateExtracted: January 8, 2001
Source: www.foodscience.com/jobs_midwest.html
OtherCompanyJobs: foodscience.com-Job1

If you dream of cold creamy chocolate or ooey-gooey cookie, there's a great opportunity for you to maintain and expand this major corporation's high-end ice cream brand. Will be based in the Upper Midwest or about a year. After that, California here I come!

Requires a BS in Food Science or dairy, plus ice cream formulation experience. We consider entry level with an MS and an internship.
Contact Susan: emai
1-800-488-2611
Example: A Solution

[Image of a computer screen showing the FlipDog.com website, with job search and career management options.]
<table>
<thead>
<tr>
<th>Job Position</th>
<th>Company</th>
<th>Location</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Pantry Workers</td>
<td>Lutheran Social Services</td>
<td></td>
<td>October 11, 2002</td>
</tr>
<tr>
<td>Cooks</td>
<td>Lutheran Social Services</td>
<td></td>
<td>October 11, 2002</td>
</tr>
<tr>
<td>Bakers Assistants</td>
<td>Fine Catering by Russell Morin</td>
<td></td>
<td>October 11, 2002</td>
</tr>
<tr>
<td>Baker's Helper</td>
<td>Bird-in-Hand</td>
<td></td>
<td>October 11, 2002</td>
</tr>
<tr>
<td>Assistant Baker</td>
<td>Gourmet To Go</td>
<td></td>
<td>October 11, 2002</td>
</tr>
<tr>
<td>Host/Hostess</td>
<td>Sharis Restaurants</td>
<td></td>
<td>October 10, 2002</td>
</tr>
<tr>
<td>Cooks</td>
<td>Alta's Rustler Lodge</td>
<td></td>
<td>October 10, 2002</td>
</tr>
<tr>
<td>Line Attendant</td>
<td>Sun Valley Corporation</td>
<td></td>
<td>October 10, 2002</td>
</tr>
<tr>
<td>Food Service Worker II</td>
<td>Garden Grove Unified School District</td>
<td></td>
<td>October 10, 2002</td>
</tr>
<tr>
<td>Night Cook / Baker</td>
<td>SONOCO</td>
<td></td>
<td>October 10, 2002</td>
</tr>
<tr>
<td>Cooks/Prep Cooks</td>
<td>GrandView Lodge</td>
<td></td>
<td>October 10, 2002</td>
</tr>
<tr>
<td>Line Cook</td>
<td>Lone Mountain Ranch</td>
<td></td>
<td>October 10, 2002</td>
</tr>
<tr>
<td>Production Baker</td>
<td>Whole Foods Market</td>
<td></td>
<td>October 08, 2002</td>
</tr>
<tr>
<td>Cake Decorator/Baker</td>
<td>Mandalay Bay Hotel and Casino</td>
<td></td>
<td>October 08, 2002</td>
</tr>
<tr>
<td>Shift Supervisors</td>
<td>Brueggers Bagels</td>
<td></td>
<td>October 08, 2002</td>
</tr>
</tbody>
</table>
IE from Research Papers

Peter Norvig Robert Wilensky University of California, Berkeley Computer... Thirteenth International Conference on Computational Linguistics, Volume 3

Abstract: this paper critically evaluate three recent abductive interpretation models, those of Charniak and Goldman (1989), Hobbs, Stickel, Martin and Edwards (1988); and Ng and Mooney (1990). These three models add the important property of commensurability: all types of evidence are represented in a common currency that can be compared and combined. While commensurability is a desirable property, and there is a clear need for a way to compare alternate explanations, it appears that a single scalar measure is not enough to account for all types of processing. We present other problems for the abductive approach, and some tentative solutions. (Update)

Context of citations to this paper: More

... (break slight modification of the one given in [Ng and Mooney, 1990] The new definition remedies the anomaly reported in [Norvig and Wilensky, 1990] of occasionally preferring spurious interpretations of greater depths. Table 1: Empirical Results Comparing Coherence and...

... costs as probabilities, specifically within the context of using abduction for text interpretation, are discussed in Norvig and Wilensky (1990). The use of abduction in disambiguation is discussed in Key et al. 1990. We will assume the following: 13) a. Only literals...

Cited by: More
Translation Mismatch in a Hybrid MT System - Gawron (1999) (Correct)
Abduction and Mismatch in Machine Translation - Gawron (1999) (Correct)
Interpretation as Abduction - Hobbs, Stickel, Appelt, Martin (1990) (Correct)

Active bibliography (related documents): More All
0.1. Decision Analytic Networks in Artificial Intelligence - Matzkevich, Abramson (1995) (Correct)
0.1. A Probabilistic Network of Predicators - Bohn, Lin (1992) (Correct)
October 14, 2002, 4:00 a.m. PT

For years, Microsoft Corporation CEO Bill Gates railed against the economic philosophy of open-source software with Orwellian fervor, denouncing its communal licensing as a "cancer" that stifled technological innovation.

Today, Microsoft claims to "love" the open-source concept, by which software code is made public to encourage improvement and development by outside programmers. Gates himself says Microsoft will gladly disclose its crown jewels—the coveted code behind the Windows operating system—to select customers.

"We can be open source. We love the concept of shared source," said Bill Veghte, a Microsoft VP. "That's a super-important shift for us in terms of code access."

Richard Stallman, founder of the Free Software Foundation, countered saying...
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Richard Stallman, founder of the Free Software Foundation, countered saying...
Landscape of IE Tasks (1/4):
Degree of Formatting

**Text paragraphs without formatting**

Astro Teller is the CEO and co-founder of BodyMedia. Astro holds a Ph.D. in Artificial Intelligence from Carnegie Mellon University, where he was inducted as a national Hertz fellow. His M.S. in symbolic and heuristic computation and B.S. in computer science are from Stanford University. His work in science, literature and business has appeared in international media from the New York Times to CNN to NPR.

**Grammatical sentences and some formatting & links**

Dr. Steven Minton - Founder/CTO
Dr. Minton is a fellow of the American Association of Artificial Intelligence and was the founder of the Journal of Artificial Intelligence Research. Prior to founding Fetch, Minton was a faculty member at USC and a project leader at USC’s Information Sciences Institute. A graduate of Yale University and Carnegie Mellon University, Minton has been a Principal Investigator at NASA Ames and taught at Stanford, UC Berkeley and USC.

Frank Huvbrecths - COO
Mr. Huvbrecths has over 20 years of

**Non-grammatical snippets, rich formatting & links**

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Cohen, Paul R.  (413) 545-3638 cohen@cs.umass.edu CS278
Professor.
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**Tables**

| 8:30 - 9:00 AM | Invited Talk: Plausibility Measures: A General Approach for Representing Uncertainty | Joseph Y. Halpern, Cornell University |
| 9:30 - 10:00 AM | Coffee Break |
| 10:00 - 11:30 AM | Technical Paper Sessions: |

**Cognitive Robotics**
- 739: A Logical Account of Causal and Topological Maps
  - Ermilaz Remolinas and Benjamin Klaipers

**Logic Programming**
- 116: A System Problem Solving through Abduction
  - Marc Denecker, Antonia Kakas, and Bert Van Nuffelen

**Natural Language Generation**
- 758: Title Generation for Machine-Translated Documents
  - Rong Lin and Alexander G. Hauptmann

**Complexity Analysis**
- 417: Let’s go Nats: Complexity of Nested Circumscriptive and Abnormality Theories
  - Marco Cadoli, Thomas Eiter, and Georg Gottlob

**Neural Networks**
- 179: Knowledge Extraction and Comparison from Local Function Networks
  - Kenneth McCarry, Stefan Wermter, and John Macintyre

**Games**
- 71: Iterative Widening
- Tristan Cazenave

**Online-Execution of ecGolog Plans**
- 540:
  - Henrik Grosskreutz and Gerhard Lakemeyer

**A Comparative Study of Logic Programs with Preference**
- 131:
  - Torsten Schaub and Koen Verheijen

**Dealing with Dependencies between Content Planning and Surface Realization in a Pipeline Generation**
- 246:

**A Perspective on Knowledge Compilation**
- 470:
  - Ahmad Darwiche and Pierre Marquis

**Violation-Guided Learning for Constrained Formulations in Neural-Network Time-Series**
- 258:

**Temporal Difference Learning Applied to a High Performance Game-Playing**
- 353:
Landscape of IE Tasks (2/4): Intended Breadth of Coverage

**Web site specific**
- Formatting
- Amazon.com Book Pages

**Genre specific**
- Layout
- Resumes

**Wide, non-specific**
- Language
- University Names
Landscape of IE Tasks (3/4): Complexity

E.g. word patterns:

<table>
<thead>
<tr>
<th>Closed set</th>
<th>Regular set</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S. states</td>
<td>U.S. phone numbers</td>
</tr>
<tr>
<td>He was born in Alabama…</td>
<td>Phone: (413) 545-1323</td>
</tr>
<tr>
<td>The big Wyoming sky…</td>
<td>The CALD main office can be reached at 412-268-1299</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Complex pattern</th>
<th>Ambiguous patterns, needing context and many sources of evidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S. postal addresses</td>
<td>Person names</td>
</tr>
<tr>
<td>University of Arkansas P.O. Box 140 Hope, AR 71802</td>
<td>...was among the six houses sold by Hope Feldman that year.</td>
</tr>
<tr>
<td>Headquarters: 1128 Main Street, 4th Floor Cincinnati, Ohio 45210</td>
<td>Pawel Opalinski, Software Engineer at WhizBang Labs.</td>
</tr>
</tbody>
</table>
Jack Welch will retire as CEO of General Electric tomorrow. The top role at the Connecticut company will be filled by Jeffrey Immelt.

<table>
<thead>
<tr>
<th>Single entity</th>
<th>Binary relationship</th>
<th>N-ary record</th>
</tr>
</thead>
</table>
| **Person:** Jack Welch | **Relation:** Person-Title  
**Person:** Jack Welch  
**Title:** CEO | **Relation:** Succession  
**Company:** General Electric  
**Title:** CEO  
**Out:** Jack Welch  
**In:** Jeffrey Immelt |
| **Person:** Jeffrey Immelt | | |
| **Location:** Connecticut | **Relation:** Company-Location  
**Company:** General Electric  
**Location:** Connecticut | |
Recognizers

- Simple procedures to find pieces of information based on its appearance
  - e-mail addresses (easy)
  - telephone numbers (tricky)
  - street addresses (difficult)
- Examples:
  - Simple Web Crawlers can (and do) collect huge databases of e-mail addresses
  - Can also be used to automatically generate training examples for wrapper induction (Kushmerick, 2000)
Wrappers

- **Wrapper**: (in an Information Extraction context)
  - A procedure that extracts certain pieces of information from (semi-)structured text (HTML)

- **Examples**:
  - Comparison Shoppers (Junglee, Shopbot/Jango, mySimon)
  - Meta-Search engines (citeseer, metacrawler)
  - News Agents (google news)

- **Building Wrappers by hand**:
  - time-consuming and error-prone (=> expensive)
  - Web-sites change frequently
    - mean-time to failure of wrappers: 1 month (Weld, 1998)
    - monthly failure rates of wrappers: 8% (Norvig, 1998)
Wrapper Induction: Motivation

- **Wrappers**
  - parse the contents of several sites

- **Mediators**
  - integrate the extracted information

- **Example:**

---

User:
Show me reviews of Fellini movies showing in Dublin
Wrapper Induction

- Automatic generation of wrappers from a few (annotated) sample pages
- Assumptions:
  - regularity in presentation of information
  - often machine-generated answers to queries
    - same header
    - same tail
    - inbetween a table/list of items that constitute the answer to the query
- Learn the delimiters between items of interest
LR Wrappers (Kushmerick 2000)

- Very simple but nevertheless powerful wrapper class
- Assume that
  - only one "database" per page
  - information can be separated into tuples (records)
  - each tuple contains exactly k items (attributes)
- Wrapper consists of $k$ delimiter pairs $\langle l_i, r_i \rangle$,
  - $l_i$ and $r_i$ are patterns that have to matched in the text

```plaintext
repeat
  foreach $\langle l_i, r_i \rangle \in \{\langle l_1, r_1 \rangle, ..., \langle l_k, r_k \rangle\}$
    find next occurrence of $l_i$
    find next occurrence of $r_i$
    extract text inbetween and store as the $i$-th value for this tuple
until no more occurrences of $l_1$
```
Induction of LR Wrappers

Web Pages

Web Pages Labeled for Extraction

```html
<HTML>
  <HEAD>
    Some Country Codes</HEAD>
  <HTML>
  <HEAD>
    Some Country Codes</HEAD>
  <HTML>
    Some Country Codes</HEAD>
  <HTML>
    Some Country Codes</HEAD>
  <HTML>
    Some Country Codes</HEAD>
  <B>Congo</B> <I>242</I> <BR>
  <B>Egypt</B> <I>20</I> <BR>
  <B>Belize</B> <I>501</I> <BR>
  <B>Spain</B> <I>34</I> <BR>
</BODY></HTML>
```

Extracted Wrapper

\[
\langle \langle B \rangle, \langle /B \rangle, \langle I \rangle, \langle /I \rangle \rangle
\]

\[
\langle l_1, r_1, l_2, r_2 \rangle
\]
Induction of LR Wrappers

- Heads: text before first tuple for each page
- Tails: text after last tuple for each page
- Separators: text between subsequent attributes

- Candidate delimiters:
  - Left: suffixes of the shortest of all separators to the left
    (including heads for $i = 1$)
  - Right: prefixes of the shortest of all separators to the right
    (including tails for $i = k$)

- Among the candidate delimiters, any one that satisfies a set of constraints can be selected
  - Constraints must ensure that the wrapper does not try to extract irrelevant parts of text (false positives)
Constraints for Delimiters

• the left delimiter \( l_i \)
  - must be a *proper* suffix of the text before each instance of the target
    - a proper suffix of a string means that
      - it is a suffix of the string
      - and it does not occur in any other place of the string
    - Example:
      - \( cde \) is a proper suffix of \( deabcde \), \( de \) is a suffix but not proper
  - \( l_i \) must not be part of any pages tail
    - otherwise extraction of a new tuple will be started at the end

• the right delimiter \( r_i \)
  - must be a prefix of the text after each instance of the target
  - must not be part of any value for attribute \( i \)
    - otherwise extraction will terminate prematurely
A Problem with LR-Wrappers

- Distracting text in Head or Tail

\[ l_1 \text{ fires} \]

\[
\text{<HTML><TITLE>Some Country Codes</TITLE>}
\text{<BODY><B>Some Country Codes</B><P>}
\text{<B>Congo</B> <I>242</I><BR>}
\text{<B>Egypt</B> <I>20</I><BR>}
\text{<B>Belize</B> <I>501</I><BR>}
\text{<B>Spain</B> <I>34</I><BR>}
\text{<HR><B>End</B></BODY></HTML>\]

- an LR-Wrapper cannot learn an extractor for this case
  - every candidate delimiter for \( l_1 \) occurs in the head
  - every candidate delimiter for \( l_1 \) occurs in the tail
HLRT-Wrappers

- Head-Tail-Left-Right Wrappers:
  - learn a separate delimiter for identifying head and tail

*Ignore page’s head and tail*

```html
<HTML><TITLE>Some Country Codes</TITLE>
<BODY><B>Some Country Codes</B><P>
<B>Congo</B> 242<br>
<B>Egypt</B> 20<br>
<B>Belize</B> 501<br>
<B>Spain</B> 34<br>
<HR><B>End</B></BODY></HTML>
```
More Expressive Wrapper Classes

- **HLRT:**
  - learn 2 additional delimiters to separate the head and the tail
  - ignores occurrence of $l_i$ and $r_i$ before $h$ and after $t$
  - allows to process multiple "databases" in one document

- **OCLR and HOCLRT:**
  - for each tuple: learn an opening and closing delimiter

- **N-LR and N-HLRT:**
  - allows multi-valued attributes
  - allows optional attributes
    - **RESTRICTION:** if a value is specified, all previous values (of this tuple) must also be specified.
Evaluation

- Study on 30 randomly selected Web-sites from www.search.com (at that time a catalogue of hubs for various topics)
  - LR Wrapper was able to wrap 53%
  - LR + HLRT wrapped 60%
  - Addition of OC wrapping did not bring improvements
  - Addition of N-HLRT improved to 70%
- LR Wrappers are not limited to HTML-documents
  - any string can be extracted for delimiters, not just HTML tags
- All wrapper classes are PAC learnable
- Constraints become hard to handle
SoftMealy (Hsu & Dung, 1998)

- Problems with LR-Wrappers:
  - no permutations of attributes allowed
  - delimiters may not be sufficient to identify texts
- SoftMealy provides a general solution to problems with
  - missing attributes
  - attributes with multiple values
  - variable order of attributes
- Approach:
  - learn a finite-state transducer (FST) that encodes all possible sequences of attributes
  - each state represents a fact to be extracted
  - dummy states are used to skip parts of text
  - use separators ("invisible" borders) instead of delimiters
  - learn to recognize separators by defining their left and right context with contextual rules (state transitions)
Labelled Web Page

<LI><A HREF="mani.html">Mani Chandy</A>, <I>Professor of Computer Science</I> and <I>Executive Officer for Computer Science</I>

<LI><A HREF="david.html">David E. Breen</A>, <I>Assistant Director of Computer Graphics Laboratory</I>

Sample FST

■ Contextual rule looks like:
TRANSFER FROM state N TO state -N IF
left context = capitalized string
right context = HTML tag “</A>”

Slide adapted from Chun-Nan Hsu
Wrapper Induction by Inductive Rule Learning

- Training Examples:
  - treat each slot independently (single slot extraction)
  - generate training example that represent the context of the slot (tokens before, after, and in the slot)

- Features are extracted from the context of a slot:
  - *token type*: word, number, punctuation, html-tag, ...
  - *formatting*: capitalized, italics, bold, font, ...
  - *location*: after/before line break, paragraph, ...
  - *html structure*: h1, a, href, table, td, center, ...
  - *relative position*: previous token, next token

- Learn Rules:
  - evaluate rules by counting correct matches as positive, wrong matches as negative (e.g., Laplace heuristic)
Example Systems

- RAPIER (Califf & Mooney, 1997):
  - based in a logic framework (ILP)
  - integrates some NLP (part-of-speech tags)
  - bottom-up learning with $lgg$: select two examples and compute the minimal generalization that covers both

- SRV (Freitag, 1998):
  - uses a large variety of features both for structured and unstructured text
  - top-down rule learning (Ripper-like)

- Expressive, general rule learning systems (e.g., ILP) could be used as well, but would lack domain-specific optimizations
WHISK (Soderland, 1999)

- multi-slot extraction
- rules represented as perl-like regular expressions
- can handle (semi-)structured and unstructured text

- top-down rule learning with seed instance (AQ-like)
  - choose a random training example
  - start with the most general rule
  - refine the rule using heuristics as in RIPPER-like algorithms (e.g., Laplace accuracy)
  - but only with conditions that appear in the training example

- use of user-specified semantic classes
  - e.g. BEDROOM = \{brs|br|bds|bdrm|bd|bedroom|bedrooms|bed\}

- integrated with interactive training based on a simple form of active learning
Example - WHISK

Training example:

<B>Capitol Hill -</B> 1 bedroom twnhme. fplc D/W W/D. Undergrnd pkg incl. $675. 3 BR, 2<sup>nd</sup> flr of turn of ctry HOME. incl. gar, grt N. Hill loc $995. (206) 999-9999 <br>

Label:
- Rental:
  - area: Capitol Hill
  - bedrooms: 1
  - price: 675
- Rental:
  - area: Capitol Hill
  - bedrooms: 3
  - price 995

Starting Rule:
* ( * ) * ( * ) * ( * ) *

Final Rule:
(after seeing several examples):
START<B> ( * ) ' - ' * ( DIGIT )
BEDROOM * ' $ ' ( NUMBER ) *
Example - WHISK

Training example:

<B>Capitol Hill</B> 1-bedroom twnhme. fplc D/W W/D. Undergrnd pkg incl. $675. 3 BR, 2<sup>nd</sup> flr of turn of ctry HOME. incl. gar, grt N. Hill loc $995. (206) 999-9999 <br>

START<B> ( * ) ' - ' * ( DIGIT ) BEDROOM * '$' ( NUMBER ) *

BEDROOM = {brs|br|bds|bdrm|bd|bedroom|bedrooms|bed}
Example - WHISK

Training example:

<B>Capitol Hill</B> - 1 bedroom twnhme. fplc D/W W/D. Undergrnd pkg incl. $675. 3 BR, 2<sup>nd</sup> flr of turn of ctry HOME. incl. gar, grt. N. Hill loc $995. (206) 999-9999

START<B> ( * ) '-' *( DIGIT ) BEDROOM * '$' ( NUMBER ) *

BEDROOM = {brs|br|bds|bdrm|bd|bedroom|bedrooms|bed}
Information Integration

- Data Integration (Data Warehousing):
  - Join different databases into a single view
  - Problem: Information may be encoded in different ways

- Information Integration:
  - Join information originating from different wrappers
  - Problem: extracted information is still free text

- Example:
  - *Data source 1*: Wrapper for Movie database
  - *Data source 2*: Wrapper Local movie show times
  - *Task*: Generate a page that integrates reviews into the local show times
  - *Problem*: Key relation (movie titles) will not match exactly
WHIRL (Cohen 1998)

• extension of DATALOG (or SQL) database queries that allows to deal with free text
  - models the information extracted by a wrapper as a relational table

• adresses the problem that
  - wrappers may not be able to extract the exact text
    - e.g., irrelevant information (directors, ratings, actors, etc.) might be extracted with title
  - text may be formulated differently on different Web-Sites
    - e.g., order and/or abbreviations of first, middle and last names

• Approach:
  - uses vector space model to represents textual fields
  - uses similarity literals to specify approximate matches

• http://www.cs.cmu.edu/~wcohen/whirl/
DATALOG vs. WHIRL

- **Hard Queries:**
  - Items in a join must match exactly
  - Items match or do not match
  - Return all matches satisfying the query

- **Soft Queries:**
  - Items in a join need only be "similar"
  - Use cosine similarity to compute the degree of match [0,1]
  - Return the best matches according to similarity
  - Use efficient A*-like search to find the r best matches according to similarity score (r-materialization)
WHIRL - Example

- Given two wrapped relations:
  - review(Movie, Review)
  - showtime(Cinema, Movie, Time)

- Sample Queries:
  - Hard Query (DATALOG):
    \( \text{showtime}(C, M, T) \land \text{review}(M, R) \)
  - Soft Query:
    \( \text{showtime}(C, M_1, T) \land \text{review}(M_2, R) \land M_1 \sim M_2 \)
  - If the titles of the reviews could not be wrapped:
    \( \text{showtime}(C, M, T) \land \text{review}(R) \land M \sim R \)
  - Free text queries:
    \( \text{showtime}(C, M_1, T) \land \text{review}(M_2, R) \land M_1 \sim M_2 \land R \sim "\text{excellent comedy with Bruce Willis}" \)
Possible answers $\Theta$ to queries $Q$ are scored, i.e., a function $SCORE(Q, \Theta)$ is computed.

For a regular literal: \[ SCORE(B, \Theta) = s \]
if $B\Theta$ is a ground fact, 0 otherwise (usually $s = 1$, "degree of belief in the proposition")

For a similarity literal $X \sim Y$:

\[ SCORE(X \sim Y, \Theta) = \text{sim}(X \Theta, Y \Theta) \]

Conjunctive Query $Q = B_1 \land \ldots \land B_n$

\[ SCORE(Q, \Theta) = \prod_i SCORE(B_i) \]

A definite clause $\text{Head} : \leftarrow B_1, B_2, \ldots, B_n$

\[ SCORE(\text{Head}) = 1 - \prod_i (1 - SCORE(B_i)) \]
Using WHIRL as Text Classifier

- represent labelled training documents in relation
  \( \text{train}(\text{Document}, \text{Class}) \)

- The following clause returns labels \( C \) ordered by similarity score of \( D \) to \( D_1 \)
  \[
  \text{classify}(D, C) :\quad \text{train}(D_1, C), \quad D \sim D_1.
  \]
  - NOTE: multiple ground instantiations of the head (i.e., multiple bindings to the head) are combined using the definite clause similarity score!

- very similar to nearest neighbor classification
  - minor differences in combining evidence (similarity score)

- experimentally very competitive to conventional approaches