Relation Extraction

What is relation extraction?

Many slides adapted from Dan Jurafsky
Extracting relations from text

• **Company report:** “International Business Machines Corporation (IBM or the company) was incorporated in the State of New York on June 16, 1911, as the Computing-Tabulating-Recording Co. (C-T-R)…”

• **Extracted Complex Relation:**

  Company-Founding
  - Company: IBM
  - Location: New York
  - Date: June 16, 1911
  - Original-Name: Computing-Tabulating-Recording Co.

• But we will focus on the simpler task of extracting relation **triples**
  - Founding-year(IBM,1911)
  - Founding-location(IBM,New York)
Why Relation Extraction?

- Create new structured knowledge bases, useful for any app
- Augment current knowledge bases
  - Adding words to WordNet thesaurus, facts to FreeBase or DBPedia
- Support question answering
  - The granddaughter of which actor starred in the movie “E.T.”?
    \[(acted-in \ ?x \ “E.T.”)(is-a \ ?y \ actor)(granddaughter-of \ ?x \ ?y)\]
- But which relations should we extract?
Automatic Content Extraction (ACE)

17 relations from 2008 “Relation Extraction Task”
Automatic Content Extraction (ACE)

- Physical-Located PER-GPE
  
  He was in Tennessee

- Part-Whole-Subsidiary ORG-ORG
  
  XYZ, the parent company of ABC

- Person-Social-Family PER-PER
  
  John’s wife Yoko

- Org-AFF-Founder PER-ORG
  
  Steve Jobs, co-founder of Apple...
UMLS: Unified Medical Language System

- 134 entity types, 54 relations

<table>
<thead>
<tr>
<th>Entity Type</th>
<th>Relation</th>
<th>Function Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injury</td>
<td>disrupts</td>
<td>Physiological Function</td>
</tr>
<tr>
<td>Bodily Location</td>
<td>location-of</td>
<td>Biologic Function</td>
</tr>
<tr>
<td>Anatomical Structure</td>
<td>part-of</td>
<td>Organism</td>
</tr>
<tr>
<td>Pharmacologic Substance</td>
<td>causes</td>
<td>Pathological Function</td>
</tr>
<tr>
<td>Pharmacologic Substance</td>
<td>treats</td>
<td>Pathologic Function</td>
</tr>
</tbody>
</table>
Databases of Wikipedia Relations

Wikipedia Infobox

 Relations extracted from Infoblox
Stanford **state** California
Stanford **motto** “Die Luft der Freiheit weht”

<table>
<thead>
<tr>
<th>Type</th>
<th>Private</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Endowment</strong></td>
<td>US$ 16.5 billion (2011) [3]</td>
</tr>
<tr>
<td><strong>President</strong></td>
<td>John L. Hennessy</td>
</tr>
<tr>
<td><strong>Provost</strong></td>
<td>John Etchemendy</td>
</tr>
<tr>
<td>Academic staff</td>
<td>1,910 [4]</td>
</tr>
<tr>
<td>Students</td>
<td>15,319</td>
</tr>
<tr>
<td>Undergraduates</td>
<td>6,878 [5]</td>
</tr>
<tr>
<td>Postgraduates</td>
<td>8,441 [5]</td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td>Stanford, California, U.S.</td>
</tr>
<tr>
<td><strong>Campus</strong></td>
<td>Suburban, 8,180 acres (3,310 ha) [6]</td>
</tr>
<tr>
<td><strong>Colors</strong></td>
<td>Cardinal red and white</td>
</tr>
</tbody>
</table>
How to build relation extractors

1. Hand-written patterns
2. Supervised machine learning
3. Semi-supervised and unsupervised
   - Bootstrapping (using seeds)
   - Distant supervision
   - Unsupervised learning from the web
Relation Extraction

What is relation extraction?
Relation Extraction

Using patterns to extract relations
Extracting Richer Relations Using Rules

• Intuition: relations often hold between specific entities
  • located-in (ORGANIZATION, LOCATION)
  • founded (PERSON, ORGANIZATION)
  • cures (DRUG, DISEASE)
• Start with Named Entity tags to help extract relation!
Named Entities aren’t quite enough. Which relations hold between 2 entities?

Drug

Cure?
Prevent?
Cause?

Disease
What relations hold between 2 entities?

PERSON

Founder?
Investor?
Member?
Employee?
President?

ORGANIZATION
Extracting Richer Relations Using Rules and Named Entities

Who holds what office in what organization?

PERSON, POSITION of ORG

- George Marshall, Secretary of State of the United States

PERSON (named | appointed | chose | etc.) PERSON Prep? POSITION

- Truman appointed Marshall Secretary of State

PERSON [be]? (named | appointed | etc.) Prep? ORG POSITION

- George Marshall was named US Secretary of State
Hand-built patterns for relations

• Plus:
  • Human patterns tend to be high-precision
  • Can be tailored to specific domains

• Minus
  • Human patterns are often low-recall
  • A lot of work to think of all possible patterns!
  • Don’t want to have to do this for every relation!
  • We’d like better accuracy
Relation Extraction

Using patterns to extract relations
Relation Extraction

Supervised relation extraction
Supervised machine learning for relations

- Choose a set of relations we’d like to extract
- Choose a set of relevant named entities
- Find and label data
  - Choose a representative corpus
  - Label the named entities in the corpus
  - Hand-label the relations between these entities
  - Break into training, development, and test
- Train a classifier on the training set
How to do classification in supervised relation extraction

1. Find all pairs of named entities (usually in same sentence)
2. Decide if 2 entities are related
3. If yes, classify the relation
   • Why the extra step?
     • Faster classification training by eliminating most pairs
     • Can use distinct feature-sets appropriate for each task.
American Airlines, a unit of AMR, immediately matched the move, spokesman Tim Wagner said.
Word Features for Relation Extraction

American Airlines, a unit of AMR, immediately matched the move, spokesman Tim Wagner said

- Headwords of M1 and M2, and combination
  Airlines Wagner Airlines-Wagner
- Bag of words and bigrams in M1 and M2
  \{American, Airlines, Tim, Wagner, American Airlines, Tim Wagner\}
- Words or bigrams in particular positions left and right of M1/M2
  M2: -1 spokesman
  M2: +1 said
- Bag of words or bigrams between the two entities
  \{a, AMR, of, immediately, matched, move, spokesman, the, unit\}
American Airlines, a unit of AMR, immediately matched the move, spokesman Tim Wagner said.

- Named-entity types
  - M1: ORG
  - M2: PERSON
- Concatenation of the two named-entity types
  - ORG-PERSON
- Entity Level of M1 and M2 (NAME, NOMINAL, PRONOUN)
  - M1: NAME [it or he would be PRONOUN]
  - M2: NAME [the company would be NOMINAL]
Parse Features for Relation Extraction

*American Airlines*, *a unit of AMR, immediately matched the move*, spokesman *Tim Wagner* said

- Base syntactic chunk sequence from one to the other
  ```
  NP   NP   PP  VP   NP   NP
  ```
- Constituent path through the tree from one to the other
  ```
  NP   ↑   NP   ↑   S   ↑   S   ↓   NP
  ```
- Dependency path
  ```
  Airlines   matched   Wagner   said
  ```
Gazetteer and trigger word features for relation extraction

- **Trigger list for family: kinship terms**
  - *parent, wife, husband, grandparent, etc.* [from WordNet]

- **Gazeteer:**
  - Lists of useful geo or geopolitical words
    - Country name list
    - Other sub-entities
American Airlines, a unit of AMR, immediately matched the move, spokesman Tim Wagner said.
Classifiers for supervised methods

- Now you can use any classifier you like
  - MaxEnt
  - Naïve Bayes
  - SVM
  - ...
- Train it on the training set, tune on the dev set, test on the test set
Evaluation of Supervised Relation Extraction

- Compute $P/R/F_1$ for each relation

$$P = \frac{\text{# of correctly extracted relations}}{\text{Total # of extracted relations}}$$

$$R = \frac{\text{# of correctly extracted relations}}{\text{Total # of gold relations}}$$

$$F_1 = \frac{2PR}{P + R}$$
Summary: Supervised Relation Extraction

+ Can get high accuracies with enough hand-labeled training data, if test similar enough to training
- Labeling a large training set is expensive
- Supervised models are brittle, don’t generalize well to different genres
Relation Extraction

Supervised relation extraction
Relation Extraction

Semi-supervised and unsupervised relation extraction
Seed-based or bootstrapping approaches to relation extraction

- No training set? Maybe you have:
  - A few seed tuples or
  - A few high-precision patterns

- Can you use those seeds to do something useful?
  - Bootstrapping: use the seeds to directly learn to populate a relation
Relation Bootstrapping (Hearst 1992)

• Gather a set of seed pairs that have relation R
• Iterate:
  1. Find sentences with these pairs
  2. Look at the context between or around the pair and generalize the context to create patterns
  3. Use the patterns for grep for more pairs
Bootstrapping

• <Mark Twain, Elmira> Seed tuple
  • Grep (google) for the environments of the seed tuple
    “Mark Twain is buried in Elmira, NY.”
    X is buried in Y
    “The grave of Mark Twain is in Elmira”
    The grave of X is in Y
    “Elmira is Mark Twain’s final resting place”
    Y is X’s final resting place.

• Use those patterns to grep for new tuples
• Iterate
**Dipre: Extract <author,book> pairs**


- **Start with 5 seeds:**

<table>
<thead>
<tr>
<th>Author</th>
<th>Book</th>
</tr>
</thead>
<tbody>
<tr>
<td>Isaac Asimov</td>
<td>The Robots of Dawn</td>
</tr>
<tr>
<td>David Brin</td>
<td>Startide Rising</td>
</tr>
<tr>
<td>James Gleick</td>
<td>Chaos: Making a New Science</td>
</tr>
<tr>
<td>Charles Dickens</td>
<td>Great Expectations</td>
</tr>
<tr>
<td>William Shakespeare</td>
<td>The Comedy of Errors</td>
</tr>
</tbody>
</table>

- **Find Instances:**

  The Comedy of Errors, by William Shakespeare, was
  The Comedy of Errors, by William Shakespeare, is
  The Comedy of Errors, one of William Shakespeare's earliest attempts
  The Comedy of Errors, one of William Shakespeare's most

- **Extract patterns (group by middle, take longest common prefix/suffix)**

  ?x , by ?y , ?x , one of ?y 's

- **Now iterate, finding new seeds that match the pattern**
Distant Supervision

Snow, Jurafsky, Ng. 2005. Learning syntactic patterns for automatic hypernym discovery. NIPS 17
Fei Wu and Daniel S. Weld. 2007. Autonomously Semantifying Wikipedia. CIKM 2007
Mintz, Bills, Snow, Jurafsky. 2009. Distant supervision for relation extraction without labeled data. ACL09

- Combine bootstrapping with supervised learning
  - Instead of 5 seeds,
    - Use a large database to get huge # of seed examples
  - Create lots of features from all these examples
  - Combine in a supervised classifier
Distantly supervised learning of relation extraction patterns

1. For each relation
2. For each tuple in big database
3. Find sentences in large corpus with both entities
4. Extract frequent features (parse, words, etc)
5. Train supervised classifier using thousands of features

Born-In

<Edwin Hubble, Marshfield>
<Albert Einstein, Ulm>

Hubble was born in Marshfield
Einstein, born (1879), Ulm
Hubble’s birthplace in Marshfield

PER was born in LOC
PER, born (XXXX), LOC
PER’s birthplace in LOC

P(born-in | f₁, f₂, f₃, …, f₇₀₀₀₀)
Distant supervision paradigm

• Like unsupervised classification:
  • Uses very large amounts of unlabeled data
  • Not sensitive to genre issues in training corpus

• Like supervised classification:
  • Uses a classifier with lots of features
  • Supervised by detailed hand-created knowledge
  • Doesn’t require iteratively expanding patterns
Unsupervised relation extraction

M. Banko, M. Cararella, S. Soderland, M. Broadhead, and O. Etzioni.
2007. Open information extraction from the web. IJCAI

• Open Information Extraction:
  • extract relations from the web with no training data, no list of relations

1. Use parsed data to train a “trustworthy tuple” classifier
2. Single-pass extract all relations between NPs, keep if trustworthy
3. Assessor ranks relations based on text redundancy

(Google, acquired, Android) to compete with Apple.
(Tesla, invented, coil transformer)
Evaluation of Semi-supervised and Unsupervised Relation Extraction

- Since it extracts totally new relations from the web
  - There is no gold set of correct instances of relations!
    - Can’t compute precision (don’t know which ones are correct)
    - Can’t compute recall (don’t know which ones were missed)
- Instead, we can approximate precision (only)
  - Draw a random sample of relations from output, check precision manually
    \[ \hat{P} = \frac{\# \text{ of correctly extracted relations in the sample}}{\text{Total } \# \text{ of extracted relations in the sample}} \]
- Can also compute precision at different levels of recall.
  - Precision for top 1000 new relations, top 10,000 new relations, top 100,000
  - In each case taking a random sample of that set
- But no way to evaluate recall
Relation Extraction

Semi-supervised and unsupervised relation extraction