COM3110/4115/6115: Text Processing

Information Extraction: Relation Extraction

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Overview of Lectures on IE

- Introduction to Information Extraction
  - Definition + Contrast with IR
  - Example Applications
  - Overview of Tasks and Approaches
  - Evaluation + Shared Task Challenges
  - A Brief History of IE
- Named Entity Recognition
  - Task
  - Approaches to NER
  - Entity Linking
- Relation Extraction
  - Task
  - Approaches: Knowledge Engineering; Supervised learning; Bootstrapping; Distant Supervision

Relation Extraction: Outline

- Relation Extraction Task
- Approaches to Relation Extraction
  - Knowledge-engineering approaches to NER
  - Supervised learning approaches to NER
  - Bootstrapping Approaches to NER
  - Distant Supervision Approaches to NER

Relation Extraction Task: Recap

- **Task**: given a text T and a set of relations $\mathbf{R}$, identify all assertions of relations from $\mathbf{R}$ in T, holding between entities identified in entity extraction.
- Note:
  - relations in $\mathbf{R}$ are usually binary
  - the entity types of arguments of relations in $\mathbf{R}$ are assumed to be a subset of those identifed in the entity extraction process
- May be divided into two subtasks:
  - **Relation detection**: find pairs of entities between which a relation holds
  - **Relation classification**: for pairs of entities between which a relation holds, determine what that relation is

Relation Extraction Task: Examples

- Examples
  - LOCATION_OF holding between
    - ORGANISATION and GEOPOLITICAL_LOCATION
    - medical INVESTIGATION and BODY_PART
    - GENE and CHROMOSOME_LOCATION
  - EMPLOYEE_OF holding between PERSON and ORGANISATION
  - PRODUCT_OF holding between ARTIFACT and ORGANISATION
  - IS_EXPOSED_TO holding between ORGANIZATION and RISK
  - IS_ASSOCIATED_WITH holding between DRUG and SIDE_EFFECT
  - INTERACTION holding between PROTEIN and PROTEIN

Relation Extraction Task: Challenges

Relation Extraction is challenging for several reasons:

- The same relation may be expressed in many different ways:
  - ◇ Canonical: [Microsoft]$_{ORG}$ is located in [Redmond]$_{LOC}$
  - ◇ Synonyms: [Microsoft]$_{ORG}$ is based/headquartered in [Redmond]$_{LOC}$
  - ◇ Syntactic variations:
    - [Microsoft]$_{ORG}$, the software giant and . . . , is based in [Redmond]$_{LOC}$
    - [Redmond]$_{LOC}$-based Microsoft]$_{ORG}$ . . .
    - [Redmond]$_{LOC}$'s Microsoft]$_{ORG}$ . . . ; [Microsoft]$_{ORG}$ of [Redmond]$_{LOC}$
    - [Redmond]$_{LOC}$ software giant Microsoft]$_{ORG}$ . . .

Relation Extraction Task: Challenges

Relation Extraction is challenging for several reasons (cont):

- The information required may be spread across multiple sentences and discovering relations may depend upon following coreference links.

  Dirk Ruthless of MegaCorp made a stunning announcement today. In September he will be stepping down as Chief Executive Officer to spend more time with his pet piranhas.

  - ◇ To determine the corporate position of Dirk Ruthless we must correctly resolve the pronominal anaphor "he" in the second sentence with "Dirk Ruthless" in the first

- The information to be extracted may be implied by the text, rather than explicitly asserted, and extracting it may require inference

  - ◇ E.g. in the previous example we are not told explicitly that Dirk Ruthless **is** CEO of MegaCorp
  - ◇ To determine this requires knowing (*inter alia*) that stepping down from a position presupposes being in the position prior to stepping down
  - ◇ I.e. solving relation extraction may require solving the problem of textual entailment.

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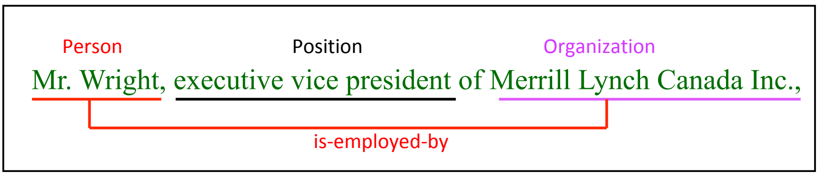
Knowledge Engineering Approaches



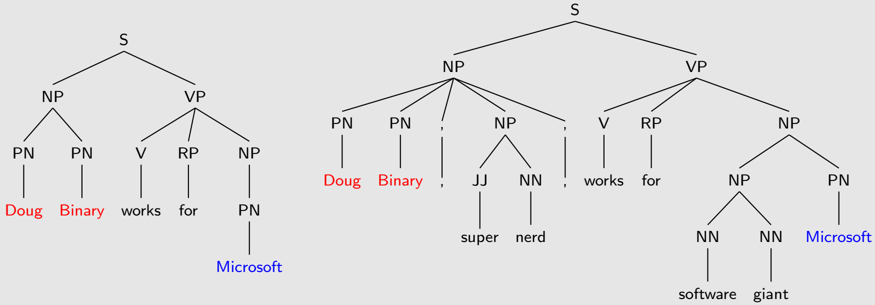
Such systems use manually authored rules and can be divided into

- "shallow" – systems engineered to the IE task, typically using pattern-action rules

  Pattern: `$Person, $Position of $Organization`

  Action: add-relation(is-employed-by($Person,$Organization))

Knowledge Engineering Approaches (cont)



- "deep" – linguistically inspired language understanding systems
  - ◇ typically parse input using broad coverage NL parser to identify key grammatical relations, like subject and object
  - ◇ use transduction rules to extract relations of interest from parser output
  - ◇ extraction rules over parser output allow a wider set of expressions to be captured than with regex's over words and NE tags alone
    - Example shows how multiple surface forms share underlying syntactic structure: here both have form SUBJECT = PER, OBJECT = ORG and VERB = *works for*

Knowledge Engineering Approaches (cont)

- Strengths
  - ◇ High precision
  - ◇ System behaviour is human-comprehensible
- Weaknesses
  - ◇ The writing of rules has no end
  - ◇ New rules needed for every new domain (pattern action rules for shallow approaches; transduction rules for deep approaches)

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Supervised learning approaches

- First question to be asked: What is to be learned?
- Answer 1: rules that
  - Match to all and only relation bearing sentences
  - Capture substrings within the matched text that correspond to relation arguments
- Answer 2: binary classifier that when applied to a sentence containing instances of the entity types between which the relation holds
  - Returns 1 if the relation holds in this instance
  - Returns 0 if the relation does not hold in this instance

  As with NER can be divided into detection and classification stages:
  - Classifier 1 (binary) determines whether a given sentence expresses any of a set of relations of interest (relation detection)
  - Classifier 2 (multi-way) determines, for positive outputs from Classifier 1, which relation holds (relation classification)
- Rule learning approach popular in late 1990's/early 2000's; since then most work focusses on classifier approach – we'll look at the 2nd only

Supervised learning approaches: Classifier Learning

In classification approaches to relation extraction:

- Assume entities to be related already tagged
- Use any algorithm for learning binary classifiers to learn to distinguish instances (typically sentences) where
  - ◇ entities co-occur and relation holds (positive instances)
  - ◇ entities co-occur and relation does not hold (negative instances)
- In the case of supervised learning for NER key issue if what features we use to represent the instances.
  Features used fall into 3 broad classes:
  - ◇ Features of the named entities
  - ◇ Features from the words in the text, usually words from 3 locations
    - words between the two NE candidate arguments
    - words in a fixed window to the left of the 1st candidate
    - words in a fixed window to the right of the 2nd candidate
  - ◇ Features from the syntactic structure of the sentence

Classifier Learning – Example

- Suppose we have the sentence

  [$_{ORG}$ American Airlines], a unit of [$_{ORG}$ AMR Corp.], immediately matched the move, spokesman [$_{PER}$ Tim Wagner] said.
  (Jurafsky and Martin, 2nd ed., p. 730)

- Then features extracted for this example when classifying the tuple: ⟨ American Airlines, Tim Wagner ⟩

Entity-based features	
Entity$_1$ type	ORG
Entity$_1$ head	*airlines*
Entity$_2$ type	PERS
Entity$_2$ head	*Wagner*
Concatenated types	ORGPERS
Word-based features	
Between-entity bag of words	{ *a, unit, of, AMR, Inc., immediately, matched, the, move, spokesman* }
Word(s) before Entity$_1$	NONE
Word(s) after Entity$_2$	*said*
Syntactic features	
Constituent path	$NP \uparrow NP \uparrow S \uparrow S \downarrow NP$
Base syntactic chunk path	$NP \rightarrow NP \rightarrow PP \rightarrow NP \rightarrow VP \rightarrow NP \rightarrow NP$
Typed-dependency path	$Airlines \leftarrow_{subj} matched \leftarrow_{comp} said \rightarrow_{subj} Wagner$

(Jurafsky and Martin, 2nd ed., p. 738)

Supervised learning approaches

Strengths:

- No need to write extensive/complex rule sets for each domain
- Same system straightforwardly adapts to any new domain, provided training data is supplied

Weaknesses:

- Quality of relation extraction dependent on quality and quantity of training data, which can be difficult and time consuming to generate
- Developing feature extractors can be difficult and they may be noisy (e.g. parsers) reducing overall performance

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Bootstrapping approaches

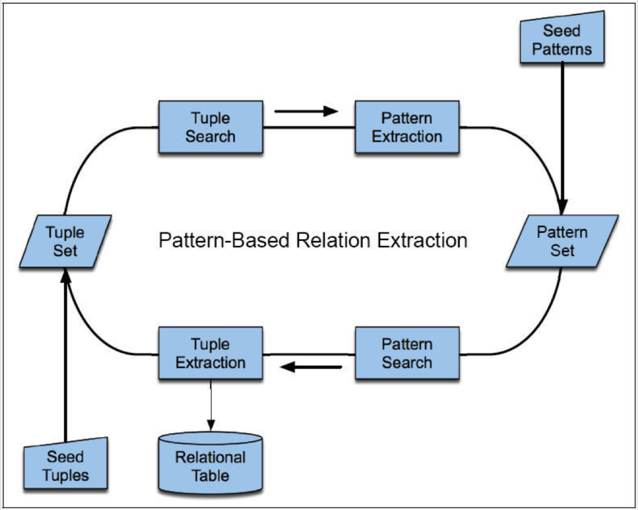
- Motivation: reduce number of manually labelled examples needed to build a system
- Key idea: start with a document collection $\mathcal{D}$ and either :
  1. set of trusted tuples **T** (e.g. pairs of entities known to stand in the relation of interest)
  2. set of trusted patterns **P** (i.e. patterns known to extract pairs of entities in the given relation with high accuracy)

  Then, if

  1. then find tuples from **T** in sentences **S** in $\mathcal{D}$, extract patterns from context of sentences in **S**, add patterns to **P** and then use **P** to find new tuples in $\mathcal{D}$ and add to **T**; repeat until convergence
  2. then match patterns from **P** in sentences **S** in $\mathcal{D}$, extract tuples from pattern matches in sentences in **S**, add tuples to **T** and then use tuples in **T** to find new patterns in $\mathcal{D}$ and add to **P**; repeat until convergence

Bootstrapping approaches

- Diagrammatically, this can be shown as follows:



(Jurafsky and Martin, 2nd ed., p. 740)

Bootstrapping approaches – DIPRE

- One early system employing this approach was DIPRE – Dual Iterative Pattern Relation Expansion – proposed by Sergie Brin (1999)
- Aim: to extract useful relational tuples from the Web, of the form (PERSON, BOOK_TITLE) – e.g. (Leo Tolstoy, War and Peace)
- Method:
  - ◇ Exploit duality of patterns and relations
    - Good tuples help find good patterns
    - Good patterns help find good tuples

    (DIPRE: Dual Iterative Pattern Relation Expansion)
  - ◇ Starting with user-supplied tuples, iteratively
    - Use these tuples to find patterns
    - Use the patterns to find more tuples

Bootstrapping approaches – DIPRE (cont)

The main loop in DIPRE is as follows:

1. $R' \leftarrow$ Sample
   R' is an approximation of the target relation (a set of tuples);
   Sample is a small user-supplied sample (e.g. 5 author-title pairs)
2. $O \leftarrow$ FindOccurrences(R',D)
   Find all occurrences of tuples of R' in D
3. $P \leftarrow$ GenPatterns(O)
   Generate patterns based on the set of occurrences – want patterns to have low error rate and, ideally, high coverage (can compensate for latter with large database (e.g. the Web)
4. $R' \leftarrow M_D(P)$
   Update R' with the set of tuples from documents in D that matched by patterns in P
5. If R' is large enough return ; else go to 2.

Bootstrapping approaches – DIPRE (cont)

Brin reports an experiment with finding (author,title) pairs on the web

- Patterns are defined as 5-tuples: $(order, urlprefix, prefix, middle, suffix)$
  - ◇ If order is true an (author, title) pair matches the pattern if there is a document in the collection (web)
    - whose URL matches urlprefix*
    - which contains text which matches the RE *prefix, author, middle, title, suffix*
    - more detailed REs are given for author and title
  - ◇ If order is false title and author are switched
- Occurrences are defined as 7-tuples: $(author, title, order, url, prefix, middle, suffix)$
  - ◇ Order records the order the author and title occurred in the text
  - ◇ URL is the URL of the document the occurrence was found in
  - ◇ Prefix is the m characters (in tests m=10) preceding the author (or title)
  - ◇ Middle is text between author and title
  - ◇ Suffix is m characters following title (or author)

Bootstrapping approaches – DIPRE (cont)

- An algorithm for generating a pattern given a set of occurrences is described
  - ◇ Algorithm inisists *order* and *middle* of occurrences is the same and the form part of the generated pattern
  - ◇ Additionally pattern contains
    - longest matching prefix of the *url* of all the occurrences
    - longest matching suffix of the *prefix* of all the occurrences
    - longest matching prefix of the *suffix* of all the occurrences
    - See Brin (1999) for details
- Patterns are assessed for specificity and rejected if their specificity is too low, i.e. if they are too general
  - ◇ Specificity of a pattern is defined in terms of the product of the lengths of the pattern's *middle*, *urlprefix*, *prefix* and *suffix*
  - ◇ For a pattern p, $specificy(p) \times n$ must exceed some threshold t, where n is the number of books with occurrences supporting the pattern p

Bootstrapping approaches – DIPRE Experiment

- Used 24 million web pages + 5 seed tuples

Author	Title
Isaac Asimov	The Robots of Dawn
David Brin	Startide Rising
James Gleick	James Gleick
Charles Dickens	Great Expectations
William Shakespeare	The Comedy of Errors

- Yielded 199 occurrences and generated 3 patterns
- These 3 patterns produced 4047 unique (author, title) pairs
- A search over 5 million web pages yielded 3972 occurrences of these books – stopped at this point due to computational constraints
- These occurrences produced 105 patterns which in turn produced 9369 (author, title) pairs – some had bad authors and were rejected
- Using these working pairs in a final iteration resulted in 9988 occurrences, then 346 patterns and then 15257 unique books
- Manual inspection of 20 from the final list showed 19 were bonafide books and 1 was an article

Bootstrapping approaches

Strengths:

- Need for manually labelled training data is eliminated

Weaknesses:

- Can suffer from semantic drift – when an erroneous pattern introduces erroneous tuples, which in turn lead to erroneous patterns
  - Introduction of confidence measures for patterns and tuples can mitigate against this problem to some extent
- Works well when significant redudancy in assertion of specific tuples an in use of specific patterns to express a relation
  - True for some domains/relations and text collections, not for others
- Issues when multiple relations hold between the same pair of entities
  - e.g. suppose someone is born, is educated and dies in the same location, then a sentence containing occurrences of person name and location name could be expressing any of three relations

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Distant Supervision Approaches

- As with bootstrapping approaches, distant supervision approaches aim to reduce/eliminate the need for manually labelled training data
- Key idea:
  - ◇ Suppose we have a large document collection $\mathcal{D}$ plus a structured data source (e.g. a database) $\mathcal{R}$ that contains
    - many instances of a relation of interest in, e.g., a relational table
    - optionally, for each relation instance a link to a document in $\mathcal{D}$ providing evidence for the relation
  - ◇ Then we can
    - search for sentences in $\mathcal{D}$ containing the entity pairs that occur in relation instances (tuples) in $\mathcal{R}$
    - label these sentences as positive occurrences of the relation instance
    - use the labelled sentences as training data to train a standard supervised relation extractor

Distant Supervision approaches (cont)

- One well-known approach using distant supervision is described by Mintz et al. (2009)
- Mintz et al. use Freebase as their structured data source

Relation name	Size	Example
/people/person/nationality	281,107	John Dugard, South Africa
/location/location/contains	253,223	Belgium, Nijlen
/people/person/profession	208,888	Dusa McDuff, Mathematician
/people/person/place_of_birth	105,799	Edwin Hubble, Marshfield
/dining/restaurant/cuisine	86,213	MacAyo's Mexican Kitchen, Mexican
/business/business_chain/location	66,529	Apple Inc., Apple Inc., South Park, NC
/biology/organism_classification_rank	42,806	Scorpaeniformes, Order
/film/film/genre	40,658	Where the Sidewalk Ends, Film noir
/film/film/language	31,103	Enter the Phoenix, Cantonese
/biology/organism_higher_classification	30,052	Calopteryx, Calopterygidae
/film/film/country	27,217	Turtle Diary, United States
/film/writer/film	23,856	Irving Shulman, Rebel Without a Cause
/film/director/film	23,539	Michael Mann, Collateral
/film/producer/film	22,079	Diane Eskenazi, Aladdin
/people/deceased_person/place_of_death	18,814	John W. Kern, Asheville
/music/artist/origin	18,619	The Octopus Project, Austin
/people/person/religion	17,582	Joseph Chartrand, Catholicism
/book/author/works_written	17,278	Paul Auster, Travels in the Scriptorium
/soccer/football_position/players	17,244	Midfielder, Chen Tao
/people/deceased_person/cause_of_death	16,709	Richard Daintree, Tuberculosis
/book/book/genre	16,431	Pony Soldiers, Science fiction
/film/film/music	14,070	Stavisky, Stephen Sondheim
/business/company/industry	13,805	ATS Medical, Health care

Table 2: The 23 largest Freebase relations we use, with their size and an instance of each relation.

Source:
Mintz et al. (2009)

Distant Supervision approaches – Mintz et al. (cont)

- Freebase was a free on-line database of structured semantic data
  - ◇ data derived from, e.g. Wikipedia infoboxes + other open access sources
  - ◇ after filtering Mintz et al. derived 1.8 million instances of 102 relations connecting 940,000 entities
  - ◇ Freebase no longer available – bought by Google and now forms part of Google Knowledge Graph (partly free, partly paid access)
  - ◇ Similar current sources are DBPedia and WikiData
- Mintz et al. use a dump of the text from Wikipedia as their document collection
  - ◇ dump consists of $\approx$ 1.8 million articles, averaging 14.3 sentences/article
  - ◇ used 800,000 articles for training and 400,000 for testing

Distant Supervision approaches – Mintz et al. (cont)

- Distant supervision assumption: if two entities participate in a relation, any sentence that contains those two entities might express that relation.
  - So, tag all sentences containing the two entity mentions as mentions of the relation
- Same relation may be expressed in different ways in different sentences. E.g.

  [Steven Spielberg]s film [Saving Private Ryan] is loosely based on the brothers story.

  Allison co-produced the Academy Award- winning [Saving Private Ryan], directed by [Steven Spielberg]...

  - So, combine features from multiple mentions to get a richer feature vector
  - Use multiclass logistic regression as a learning framework
  - At test time features are combined from all occurrences of a given entity pair in the test data and the most likely relation (or none) is assigned

Distant Supervision approaches – Mintz et al. (cont)

- Also need negative instances – an'unrelated' relation!
  - to get these randomly select entity pairs that do not appear in any Freebase relation and extract features for them
  - Could be related – i.e. wrongly omitted from Freebase – but effect of these rare occurrences should be low
- Mintz et al. evaluate their approach
  - humans evaluate highest ranked 100 and 1000 results per relation for 10 relations
  - average precision for best feature combinations just under 70% (69% for top 10; 68% for top 1000)
  - these results are competitive for knowledge engineering and "normal" supervised learning systems, which struggle to get over 75% on similar tasks

Distant Supervision approaches: Strengths and Weaknesses

Strengths:

- Need for manually labelled training data is eliminated
- Can very rapidly get extractors for a wide range of relations

Weaknesses:

- Precision still lags behind best knowledge-engineered/directly supervised learning approaches
- Only works if a good supply of structured data is available for the relation(s) of interest

Conclusion

- Relation extraction aims to detect and classify all mentions of a given set of relations holding between specified entity types within a given text
- Relation extraction is a core IE technology that is stubbornly difficult, due to the highly variable ways relations can be expressed in natural language
- Techniques used have included:
  - Knowledge engineering approaches
  - Supervised learning approaches
  - Bootstrapping Approaches
  - Distant Supervision Approaches
- Open challenges include:
  - improving precision and recall
  - handling: relations expressed over > 1 sentences; textual entailment
  - improving bootstrapping techniques so as to minimise "semantic drift"
  - developing relation extractors for languages other than English

References

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