

IT3105 Project III: Recognizing Textual Entailment

Part 4

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Lexical semantic similarity (1)

(1) T: The 26-member International Energy Agency said, Friday, that member countries would **release** oil to help relieve the U.S. fuel crisis caused by Hurricane Katrina.

⇒

H: Foreign oil reserves will be **made available** to the U.S. in the wake of Hurricane Katrina.

- ▶ *made available* means essentially the same as *release*
- ▶ *to make available* is a **synonym** for *release*

Lexical semantic similarity (2)

(2) T: Moog's **synthesiser**, which bears his name, revolutionised music from the 1960s onwards, and was used by bands like The Beatles and The Doors.

⇒

H Moog's **instruments** were used by The Beatles and The Doors among others.

- ▶ *synthesizer* is a kind of *instrument*
- ▶ *synthesizer* is a **hyponym** of *instrument*
- ▶ *instrument* is a **hyperonym** of *synthesizer*

WordNet (1)

- ▶ **lexical semantics**: field of linguistics that studies the meaning of words, and relations between words as far as their meaning is concerned
- ▶ **WordNet**: a large lexical database of English nouns, verbs, adjectives and adverbs
- ▶ all words are grouped into sets of synonyms, or so-called **synsets**
- ▶ Each synset expresses a distinct **concept**
- ▶ Synsets are interlinked with conceptual-semantic and lexical relations.
- ▶ WordNet is freely and publicly available
- ▶ Frequently used in NLP, also RTE



WordNet (2)

- ▶ Example: two different senses of noun *synthesizer* (WordNet 3.1)
 1. {synthesist, synthesizer, synthesiser} (an intellectual who synthesizes or uses synthetic methods)
 2. {synthesizer, synthesiser} ((music) an electronic instrument (usually played with a keyboard) that generates and modifies sounds electronically and can imitate a variety of other musical instruments)



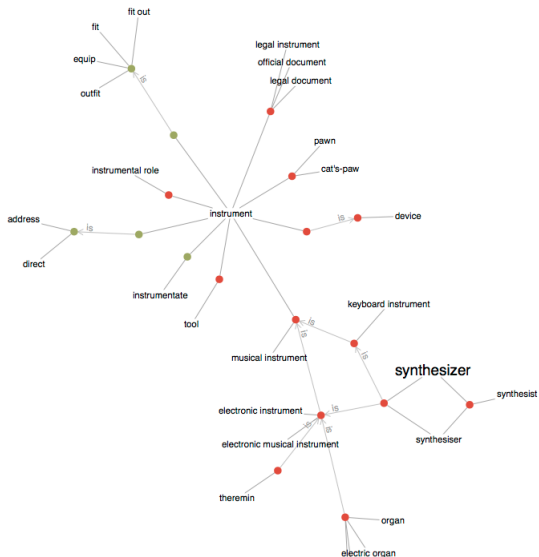
WordNet (3)

- ▶ Direct hyperonyms of the second sense of *instrument* are synsets {keyboard instrument} and {electronic instrument, electronic musical instrument}
- ▶ Both share the synset {**musical instrument**} as their hyperonym
- ▶ which in turn has *instrument* as its hyperonym.
- ▶ Therefore *instrument* is an indirect hyperonym of *synthesizer*.

WordNet (4)

- ▶ Wordnet is a large graph with synsets as nodes and lexical semantic relations as labeled edges
- ▶ some interfaces let you browse through the WordNet graph

WordNet (5)





Semantic similarity (1)

- ▶ We can learn from WordNet that *synthesizer* and *instrument* are semantically related by following hyperonym relations
- ▶ However, by the same method we can establish that *dinosaur* and *chewing gum* are related!
- ▶ Because ultimately we end up at a very abstract concept (*entity*) that covers almost every noun
- ▶ Requires some measure of graph distance



Semantic similarity (2)

- ▶ Path length works to certain extent
- ▶ Problem: some parts of WordNet are more dense than others
 - ▶ *musical instrument* and *instrument* are “conceptually close”
 - ▶ but *security blanket* and *thing* are conceptually distant
- ▶ Quite a lot of alternative measures for semantic similarity have been proposed
- ▶ In practice, the Jiang & Conrath and the Lin measures appear good choices



Word senses (1)

- ▶ Same word can have multiple senses
- ▶ *synthesizer* can be musical instrument or someone synthesizing ideas
- ▶ The latter sense is a hyperonym of *intellectual*, which is in itself a hyperonym of *person*
- ▶ However, *synthesizer* and the *Moog* are clearly not referring to the same person!
- ▶ Problem: how do we identify the correct sense of a word?



Word senses (2)

- ▶ **Word Sense Disambiguation (WSD)**: tasks of automatically determining the correct sense of word, provided a predefined set of senses
- ▶ Hard problem in NLP
- ▶ No sense tags in preprocessed RTE data
- ▶ Solutions:
 1. Apply off-the-shelf WSD software
 2. Compute similarity for all senses of words involved, and take maximum score



Lexical Semantic Similarity measure (1)

$$LSS(H, T) = \frac{\sum_{w_i \in H} \arg \max_{w_j \in T} Sim(w_i, w_j)}{\sum_{w_i \in H} Sim(w_i, w_i)}$$

- ▶ function *Sim* returns the lexical similarity between two words as a real number between zero and one
- ▶ by definition $Sim(w, w) = 1$
- ▶ *argmax* operator selects the w_j for which $Sim(w_i, w_j)$ is maximal



Lexical Semantic Similarity measure (2)

- ▶ Alternative: instead of words, use word + POS, or even word + POS + sense number
- ▶ Or weight by IDF weight of H words
- ▶ Smart feature engineering has a big impact on performance

Named entities

- ▶ **Named-Entity Recognition** is the process of tagging elements in text into predefined categories such as the names of persons, organizations, locations, expressions of times, quantities, monetary values, percentages, etc

(3) T: The 26-member [*ORG* International Energy Agency] said, Friday, that member countries would release oil to help relieve the [*LOC* U.S.] fuel crisis caused by [*MISC* Hurricane Katrina] .

⇒

H: Foreign oil reserves will be made available to the [*LOC* U.S.] in the wake of [*MISC* Hurricane Katrina] .

Named entities (2)

- ▶ Assumption: all named entities in H must also occur in T , otherwise entailment is unlikely
- ▶ There are obviously counter examples, but works out reasonably well as a feature
- ▶ Requires some normalized measure of shared named entities

Dependency relations (1)

- ▶ Tree edit distance for RTE has some drawbacks:
 - ▶ expensive for long sentences
 - ▶ hard to tune edit costs
- ▶ Fortunately there are other ways to include syntactic information
- ▶ Dependency analysis of sentence consists of set of $\langle head, relation, dependent \rangle$ triples
- ▶ Therefore we can approximate the similarity between the dependency trees for T and H by the cardinality of the intersection of the sets of dependency triples for T and H respectively
- ▶ Again, normalization is required and weighting may be added

Dependency relations (2)

- ▶ Recall that BLEU score is essentially average precision over word n-grams
- ▶ Same idea may be applied to dependency triples so that
 - ▶ single triple is analogous to a word bigram
 - ▶ two triples matching on either head or dependent (think: domino) are analogous to a word trigram
 - ▶ three matching triples to a 4-gram
- ▶ Amounts to matching paths through the dependency trees of H and T

Polarity (1)

- (4) T Drew Walker, NHS Tayside's public health director, said: "It is important to stress that this is not a confirmed case of rabies."
- H A case of rabies was confirmed.
- ▶ Tricky: overlap between T and H is nearly perfect, yet no entailment
 - ▶ Reason: presence of *not* in T
 - ▶ **polarity** difference: whereas T is a *negative* statement, H is a *positive* statement

Polarity

- ▶ Define a set of *Negatives* that toggle polarity:
 $Negatives = \{not, refuse, wrong, deny, no, false, ignore, cannot, never, unsuccessfully\}$
- ▶ Define a simple polarity feature POL, where
 n_t is the number of words in both Negatives and T and
 n_h is the number of words in both Negatives and H

$$POL(T, H) = \begin{cases} 0 & \text{if } n_t \text{ and } n_h \text{ have the same parity} \\ 1 & \text{otherwise} \end{cases}$$

Text normalization

- ▶ Problem: “*200 dollar*” does not match “*\$200*” or “*two hundred dollars*”
- ▶ **Text normalization** is transforming all variation in expressions of time, date, currency, and so on, to a standard form
- ▶ Expected to facilitate matching such expressions between H and T

Co-reference resolution

- (5) T: Britain said, Friday, that it has barred cleric, Omar Bakri, from returning to the country from Lebanon, where **he** was released by police after being detained for 24 hours
- H: Bakri was briefly detained, but was released.

- ▶ Problem: the anaphoric expression *he* and to its antecedent *Omar Bakri* are one and the same person
- ▶ **Co-reference Resolution**: automatically relating anaphoric expression to their antecedent
- ▶ In practice, the accuracy of Co-reference Resolution systems is rather low
- ▶ Application may require other knowledge, e.g. deriving the triple $\langle \textit{OmarBikiri}, \textit{obj}, \textit{detain} \rangle$ from the triple $\langle \textit{he}, \textit{obj}, \textit{detain} \rangle$ and the identity $\textit{he} = \textit{OmarBikiri}$

More training data

- ▶ “There’s no data like more data” is a famous quote attributed to Fred Jelinek
- ▶ More training data from other RTE challenges is available on the web
- ▶ Please stay away from *test* data
- ▶ Notice: differences between data sets due to changes to the task and the annotation procedure over the years
- ▶ Also *preprocessed* versions may not be available

RTE per task

- ▶ Pairs in the RTE data stem from four (related) NLP task: Information Extraction (IE), Information Retrieval (IR), Question Answering (QA) and Automatic Summarization (SUM)
- ▶ pair element in the XML file has task attribute
- ▶ Task may be included as extra feature
- ▶ Can even use RTE system tuned for the task

How to go on from here

- ▶ Reread project description Part IV
- ▶ Read fourth part of lecture notes
- ▶ Choose your baseline RTE system
- ▶ Choose a strategy for improving your RTE system
- ▶ Obtain required resources (see lecture notes)
- ▶ Implement improvements
- ▶ Evaluate and optimize as long as time is available
- ▶ Download test data when released, run your system and submit output
- ▶ Write final report
- ▶ Prepare demonstration