Textual Entailment
Part 4: Applications

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Content of Part 4

• Overview: Four paradigms for using Textual Entailment in Natural Language Processing Applications

• Use Cases for two of the paradigms:
  – Use Case 1: Machine Translation Evaluation
  – Use Case 2: Entailment Graphs for Text Exploration
Overview

Applications of Textual Entailment

• Assumption (cf. Part 1): TE can cover a substantial part of the semantic processing in NLP applications
  – Mapping of semantic (sub)tasks onto textual entailment queries
• If large datasets are involved, division of labor:
  1. Shallow (e.g. word based) methods generate candidates
  2. Textual Entailment methods act as filter/(re)scorer
     • Integrates “deeper” algorithms / knowledge
     • Allow shallow methods to be more liberal
Applications of Textual Entailment

• Mapping of semantic (sub)tasks onto textual entailment queries
  • Part 1: What are the Text and the Hypothesis?
  • Part 2: How is the output of the TE system used?

– Main paradigms:
  • Entailment for Validation
  • Entailment for Scoring
  • Entailment for Generation
  • Entailment for Structuring

Entailment for Validation

• Example: Question Answering [Hickl et al. 2007]
  • Step 1: Identify promising answer candidates
    • Shallow methods
  • Step 2: Turn question into statement
    • Replace question word
      (who → someone, which book → a book)
  • Step 3: Use Textual Entailment to verify that the answer candidate entails the question-as-statement
    • Binary decision
Example: Question Answering

**Question:** Who discovered Australia?

**Text snippet (T):** The first European to reach Australia was Willem Jansszon.

**Question-as-statement (H):** Someone discovered Australia.

**Entailment query:** The first European to reach Australia was Willem Jansszon. \( \Rightarrow \) Someone discovered Australia.

- Other application: Relation Extraction [Roth et al. 2009]

Entailment for Scoring

  - Step 1: Create System translation with MT system
  - Hypothesis: Good system translation is *semantically equivalent* to reference translation
  - Step 2: **Use TE to verify that the reference translation entails the system translation – and vice versa!**
    - Graded decision: Degree of semantic equivalence
      - Typically easy to obtain from Textual Entailment systems
    - Details: see **Use Case 1**
Example: MT Evaluation

MT System Translation (ST): Today I will consider this reality.
MT Reference Translation (RT): I shall face that fact today.

Entailment query 1: ST $\Rightarrow$? RT
Entailment query 2: RT $\Rightarrow$? ST

• Other application: Student Answer Assessment [Nielsen et al. 2009]

Entailment for Generation

• Example: Machine Translation “Smoothing” [Mirkin et al. 2009]
  – Source language terms missing from the phrase table cannot be translated
  – Parallel corpora much smaller than monolingual corpora
• Use entailment to generate entailed “replacements” for unknown source language terms
  – Sentence may lose some information but is translatable
    • Prefer terms that retain maximal information
  – Requires entailment system that can generate H for given T
Example: Term Replacement in MT

T: Bulgaria, with its low-cost ski chalets, ...
H: Bulgaria, with its low-cost ski houses, ...

Bulgarien, mit seinen günstigen Skihütten, ...

Entailment for Structuring

• Example: Information Presentation [Berant et al. 2012, Use case 2]
  • Starting point: Large amount of unstructured data about some concept
  • Goal: Make information easily human-accessible: Build hierarchical structure
• Step 1: Acquire atomic propositions
• Step 2: Apply entailment queries to each pair of propositions

• Other applications: Multi-document summarization [Harabagiu et al. 2007]
Example: Information Presentation

Use Case 1: Machine Translation Evaluation (Padó et al. 2009)

(Entailment for Scoring)
Automatic Evaluation

• Important role in Machine Translation
  – Objective *large-scale* assessment of system quality
  – Minimum Error Rate Training [Och 2002]
• Most widely used metric: BLEU
  – Pure n-gram matching
  – Problems recognizing very different translations [Callison-Burch et al. 2006, etc.]
• METEOR, TER, etc. attempt to make matching more intelligent
  – Still surface-oriented
  – Metrics should evaluate for *semantic equivalence*: TE

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The Stanford Textual Entailment System

T: India buys 1,000 tanks.
H: India acquires arms.

1. Graph Alignment

![Graph Alignment Diagram]

2. Features

<table>
<thead>
<tr>
<th>Feature</th>
<th>$f_i$</th>
<th>$w_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alignment Score</td>
<td>-1.28</td>
<td>1</td>
</tr>
<tr>
<td>Alignment: good</td>
<td>+</td>
<td>0.30</td>
</tr>
<tr>
<td>Structure match</td>
<td>+</td>
<td>0.10</td>
</tr>
</tbody>
</table>

score = $\sum_i w_i \cdot f_i = -0.88$

3. Classification

- **yes**
- **no**

Tuned threshold
Use for MT Evaluation

T: India buys 1,000 tanks.
H: India acquires arms.

1. Graph Alignment

2. Features

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score = $\sum w_i \cdot f_i = -0.88$

Linear regression score = “Degree of entailment”

Technical points

• 1. How to combine two entailment directions?
  – Option 1: Compute directions separately: Not good
  – Option 2: Combine features of both directions into one
    “bidirectional” regression model: Better
    • Deletion vs. addition features

• 2. How to learn feature weights?
  – Supervised learning from translation quality annotations
    • NIST OpenMT corpora: Newswire (Arabic, Chinese)
    • SMT workshop corpora: EUROPARL transcriptions (F, ES, D)
Evaluation

- Correlation with human sentence-level judgments
  - 10-fold cross validation
- Baselines:
  - BLEU
  - “TradMetrics” regression model: BLEU, TER, METEOR, NIST

<table>
<thead>
<tr>
<th>Corpora</th>
<th>BLEU</th>
<th>TradMetrics (regression)</th>
<th>RTE (regression)</th>
<th>TradMetrics + RTE (regression)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIST</td>
<td>60.0</td>
<td>65.6</td>
<td>63.1</td>
<td>68.3</td>
</tr>
<tr>
<td>SMT</td>
<td>35.9</td>
<td>39.6</td>
<td>42.3</td>
<td>45.7</td>
</tr>
</tbody>
</table>

RTE features and “traditional” metrics are complementary!

We’re getting something right

Ref: U.S. Treasury Offers $14 billion of 30-Year Treasury Bonds

Sys: American treasury posing 14 billion from bonds with maturity 30 years

Human: 6  RTE: 5.77  BLEU: 3.4

Ref: What does BBC’s Haroon Rasheed say after a visit to Lal Masjid Jamia Hafsa complex? There are no underground tunnels in Lal Masjid or Jamia Hafsa.

Sys: BBC Haroon Rasheed Lal Masjid, Jamia Hafsa after his visit to Auob Medical Complex says Lal Masjid and seminary in under a land mine

Human: 1  RTE: 1.2  METEOR: 4.5
Use Case 2: Entailment Graphs
[Berant et al. 2012]

(Entailment for Structuring)

Evaluation: Information Presentation

- Guide users through facts about unfamiliar concept
  - Statements about the target concept collected “Open IE style” [Etzioni et al. 2011]
- Traditional answer: keyword-based presentation
- Proposal: Organize knowledge as entailment graph

Input: Set of statements $S$
Goal: Find $E = \{ (s_1, s_2) \mid s_1 \rightarrow s_2 \}$
BIU Healthcare Explorer [Adler et al. 2012]

http://irsrv2.cs.biu.ac.il:8080/exploration/

Building Graphs

- Naïve graph construction: Decide entailment for each pair of statements
- Problem: “Local” decisions are not guaranteed to conform to properties of the entailment relation: transitivity

<table>
<thead>
<tr>
<th>Statement</th>
<th>Entailment</th>
</tr>
</thead>
<tbody>
<tr>
<td>X affect Y ⇒ X treat Y</td>
<td>✓</td>
</tr>
<tr>
<td>X treat Y ⇒ X affect Y</td>
<td>✗</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
</tr>
<tr>
<td>X lower Y ⇒ X affect Y</td>
<td>✓</td>
</tr>
<tr>
<td>X reduce Y ⇒ X lower Y</td>
<td>✓</td>
</tr>
<tr>
<td>X reduce Y ⇒ X affect Y</td>
<td>✗</td>
</tr>
</tbody>
</table>
Learning Entailment Graphs

• Input: Corpus C
• Output: Entailment graph \( G = (P,E) \)
  1. Extract statements \( S \) from \( C \)
  2. Use a local entailment classifier to estimate
     \( P_{ij} = P(s_i \rightarrow s_j) \) for each pair \((s_i, s_j)\)
     • Techniques from Part 2

3. **Find the most probable transitive graph**
   • Part 1: Define objective function for graph
   • Part 2: Identify best graph

---

Graph Objective Function

\[
\hat{G} = \arg \max \sum_{i \neq j} w_{ij} \cdot x_{ij} \\
\]

\[
w_{ij} = \log \frac{p_{ij} \cdot \theta}{(1 - p_{ij}) \cdot (1 - \theta)}
\]

• Still assumes independence between edges
### Integer Linear Program

\[
\hat{G} = \arg \max \sum_{i \neq j} w_{ij} \cdot x_{ij}
\]

\[
\forall i, j, k : x_{ij} + x_{jk} - x_{ik} \leq 1
\]

\[
x_{ij} \in \{0, 1\}
\]

- NP hard
  - Optimization: Decompose sparse graph
  - Details: [Berant et al. 2012]

### Experimental Evaluation

- 50 million word tokens **healthcare** corpus
- Gold standard entailment graphs for 23 medical concepts
  - Smoking, seizure, headache, lungs, diarrhea, chemotherapy, HPV, Salmonella, Asthma, etc.
- Evaluation: F_1 on learned edges vs. gold standard
- Baselines:
  - WordNet as source of entailments between predicates
  - “Local” model without enforcing transitivity
Results

<table>
<thead>
<tr>
<th></th>
<th>Recall</th>
<th>Precision</th>
<th>$F_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>WordNet</td>
<td>10.8</td>
<td>44.1</td>
<td>13.2</td>
</tr>
<tr>
<td>Local</td>
<td>53.5</td>
<td>38.0</td>
<td>39.8</td>
</tr>
<tr>
<td>Global (ILP)</td>
<td>46.0</td>
<td>50.1</td>
<td>43.8</td>
</tr>
</tbody>
</table>

- Global algorithm avoids false positives
- High precision
Take-home Message

• Many applications can be mapped (partially) onto Textual Entailment
  – Four paradigms: verify, score, generate, structure
  – Large datasets: Division of labor between shallow methods (generators) and Textual Entailment (filter)

• Two Use Cases:
  – MT Evaluation: TE to measure semantic equivalence
  – Entailment Graphs: Global learning for information presentation

Reference List


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