Textual Entailment Evolution and Application

Milen Kouylekov

Outline

- What is Textual Entailment?
- Distance Based Approach to Textual Entailment
- Entailment Based approach for Relation Extraction

Language Variability

The same information can be expressed with different ways (e.g. words and syntactic constructs)

Example:

- Ivan Kostov came in power in 1997.
- Ivan Kostov was prime-minister of Bulgaria from 1997 to 2001.
- Ivan Kostov stepped in as prime-minister 6 months after the December 1996 riots in Bulgaria.

Pervasive problem in the area of Natural Language Processing

Examples

- **Lexical variability**:
  Squadra Azzura won the World Cup.
- **Semantic Variability**:
  Italy became world champion for the fourth time.
- **Syntactic & Semantic Variability**:
  The World Cup final was won by Italy.

Paraphrasing

Definition: pairs of units with approximate conceptual equivalence.

Test: substituted for one another in many contexts.

Example:

- Yahoo bought Overture.
- Yahoo purchased Overture.
- Yahoo pay for Overture.
- Yahoo completed acquisition of Overture.

Does not provide a complete model of the problem of language variability:

- Template: X owned Y
- Sentence : Datel corp. sold today DT Communications to Microsoft.

Regina Barzilay. PhD Thesis. 2003

Research Areas

The following areas have something in common:

- Information Retrieval
- Question Answering
- Information Extraction
- Summarization
- ...

Textual Entailment

An Entailment Relation holds between two text fragments (i.e. text T and hypothesis H) when the meaning of H, as interpreted in the context of T , can be inferred from the meaning of T .

- **Directional** - an expression entails the other, while the opposite

may not.

- **Probabilistic** - the relation is not deterministic.

Example:

T - ”For the first time in history, the players are investing their own money to ensure the future of the game,” Atlanta Braves pitcher Tom Glavine said.

H - Tom Glavine plays for the Atlanta Braves.

Dagan and Glickman. 2004. Pascal Workshop.

Entailment Rules

- Entailment Rules play a crucial role in textual entailment.
- An entailment rule consists of an entailing template (left hand side RHS) and an entailed template (right hand side RHS), which share the same variable scope.
- In order to apply an entailment rule, an appropriate prior or contextual (posterior) probability has to be assigned.

$X \leftarrow \text{sell} \rightarrow Y \Rightarrow X \leftarrow \text{own} \rightarrow Y$

$Y \leftarrow X \rightarrow \text{pitcher} \Rightarrow X \leftarrow \text{play} \rightarrow Y$

Recognizing Textual Entailment

- RTE takes as input a T -H pair and consists in automatically determining whether an entailment relation* between T and H holds or not.
- Evaluated in **9** monolingual (8 English and 1 Italian) evaluation campaigns and 2 cross-language campaigns (CLTE)

RTE 1, 2 & Evalita

- One Text and One Hypothesis
- 2 Semantic Relations Between Texts
  - Entailment (YES)
  - No Entailment (NO)

```
<pair value="TRUE" task="CD">
  <t>
    Recreational marijuana smokers are no more likely to develop oral cancer
    than nonusers.
  </t>
  <h>
    Smoking marijuana does not increase the risk of developing oral cancer.
  </h>
</pair>
```

RTE 3, 4 & 5

- One Text and One Hypothesis
- 3 Relations
  - Entailment
  - Contradiction
  - Unknown

```
<pair value="CONTRADICTION" task="CD">
  <t>
    Yahoo both Overture.
  </t>
  <h>
    Yahoo sold Overture.
  </h>
</pair>
```

RTE 5 & 6

- One Hypothesis Multiple Texts
- 2 Semantic Relations between texts (YES|NO)

RTE 8

- One Text and One Hypothesis
- 5 Semantic Relations (Student Responses)
  - Correct
  - Partially Correct
  - Contradictory
  - Irrelevant
  - Non Domain

Cross Language Textual Entailment

- One Text and One Hypothesis
- 4 Relations (Content Synchronization)
  - Bi-Directional
  - Forward
  - Backward
  - No Entailment

Edit Distance Based Approach

We assume that the distance between T and H is a characteristic that separates the positive pairs from the negative pairs.

- It exists a function, with range from 0 to K , that calculates an entailment score of a T -H pair based on the edit distance between T and H.
- If T and H are the same, then T entails H.
- If T and H are completely different then, T does not entail H.
- It exists a distance boundary (threshold) S, $0 < S < K$, that separates the positive from the negative examples.

Edit Operations

We assume that the distance between T and H is computed as the cost of the editing operations on text fragments that transform T into H.

Edit Operation - An operation that converts a text

fragment A into another text fragment B ($A \to B$) with a certain cost $\gamma(A \to B)$.

- Insertion $\Lambda \to A$: Inserts a text fragment A from H in T .
- Deletion $A \to \Lambda$: Removes a text fragment A from T .
- Substitution $A \to B$: Replaces a text fragment A form T with a text fragment B from H.

Algorithms

- Token Edit Distance (Levenshtein Distance on Words)
- Tree Edit Distance (Dependency Trees)
  - Kouylekov & Magnini Tree Edit Distance for Recognizing Textual Entailment
- Similarity Algorithms
  - Word Overlap
  - Longest Common Subsequence
  - Rouge

Substitution - Matching

- Central Part of the approach
- Employs Entailment Rules
- Source:
    - WordNet
    - Paraphrasing Resources
    - Similarity Databases
    - Ontologies
- Rules extracted using Web Crawling
    - L. Romano et. al. Investigating a Generic Paraphrase-Based Approach for Relation Extraction

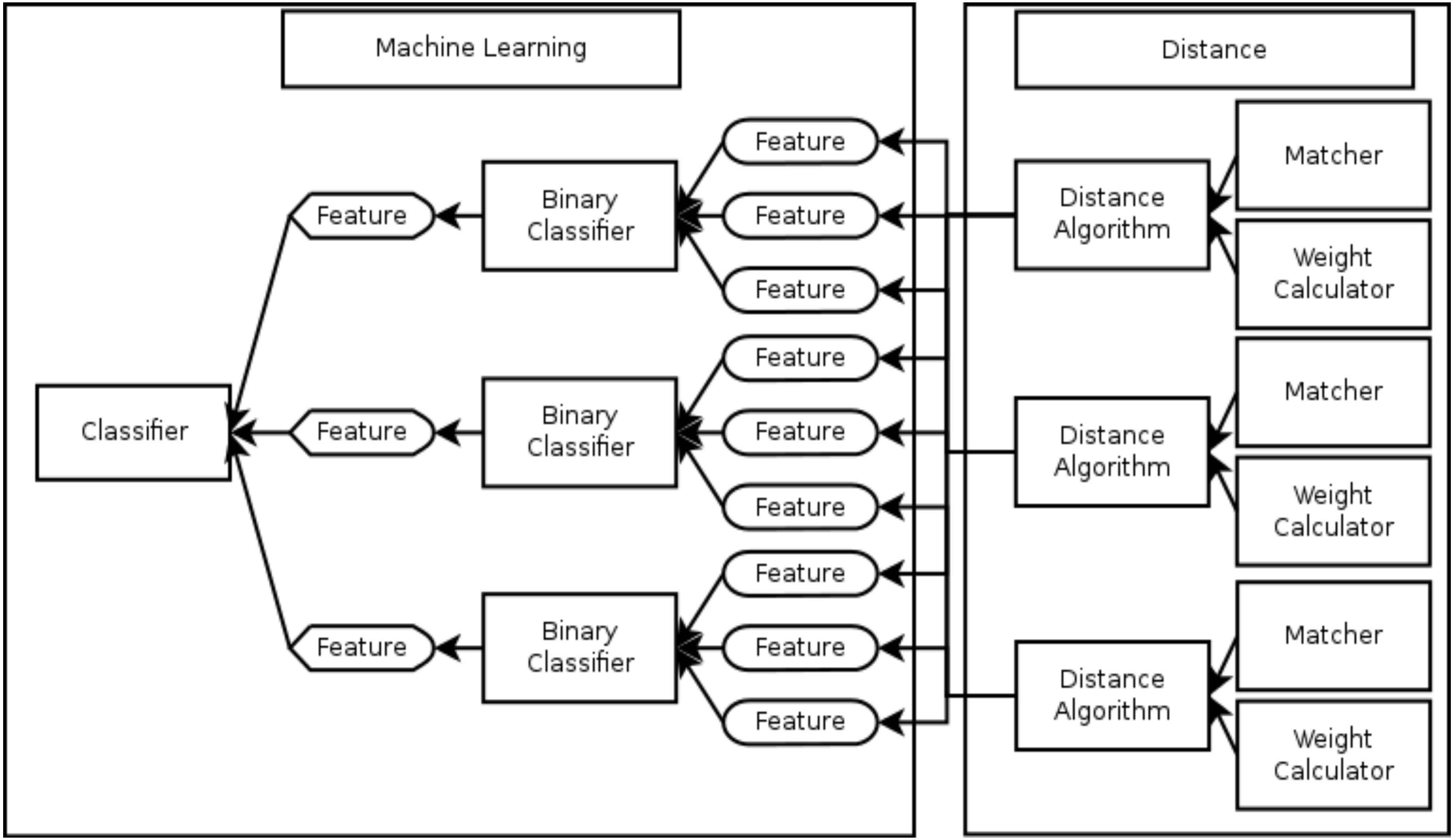
Insertion & Deletion (Weight)

- Linguistically Motivated Rules
  - Negation
  - Elena Cabrio (2011). *Component-based Textual Entailment: a Modular and Linguistically-motivated Framework for Semantic Inferences.* Ph.D. Thesis
- Approximations
  - Inverse Document Frequency
- Learning
  - Genetic Algorithms
  - Mehdad & Magnini (2009) - Optimizing textual entailment recognition using particle swarm optimization

How this thing work for RTE

- 2 Relations
  - Calculate a threshold that separates the positive from the negative
- 3 Relations
  - Calculate 2 thresholds by grouping 2 similar relations and then separating
- Multiple Relations
  - Use Learning Algorithm

Generalized Architecture



Open Source

EDITS is available at SourceForge

http://edits.sf.net

Kouylekov & Negri An Open-Source Package for Recognizing Textual Entailment. (ACL 2010)

Kouylekov et.al. Is it Worth Submitting this Run? Assess your RTE System with a Good Sparring Partner. TextInfer (EMNLP 2011)

Qall-Me Project

- Objectives
  - “design and implementation of a semantic based answer extraction Web Service […] **extract** short **answers** […] evaluate their reliability […] return context sensitive answer representations”

QALL-ME Idea

- **Recast our QA problem as a TE recognition problem**

  where:

  - *t* is the input question
  - *h* is a textual pattern stored in a pattern repository
  - Textual patterns are associated to *instructions* for answer retrieval (in our case SPARQL queries to a database)

Task: given a question (*Q*), check for the existence of *entailment relations* between *Q* and a set of *textual patterns* ($p_1,\ldots,p_n$), stored in a *pattern repository P, which* describe the relations of interest in a certain domain.

QALL-ME TE-based Approach

Given:

A question Q_i

A repository *P* of patterns $p_1, \ldots p_n$ associated to SPARQL queries $q_{p1}, \ldots q_{pn}$

Step1: If Exists pattern p_j in *P*

IF Q_i entails p_j

THEN collect p_j/q_{pj}

ELSE nil

RETURN entailed *p/q* pairs

Step2: **COMBINE** the collected queries in a single query to the DB

Entailment-based NLI2DB

Input question

Q: "*Where is cinema Astra located?*"

Pattern repository

P_1: What is the telephone number of *Cinema:X*?	P_1SPARQL
P_2: Who is the director of *Movie:X*?	P_2SPARQL
P_3: What is the ticket price of *Cinema:X*?	P_3SPARQL
P_4: Give me the address of *Cinema:X*.	P_4SPARQL
…	…
P_n	P_nSPARQL

Entailment-based NLI2DB

Input question

Q: “*Where is cinema Astra located?*”

Entailment engine

Pattern repository

P_1: What is the telephone number of *Cinema:X*?	P_1SPARQL
P_2: Who is the director of *Movie:X*?	P_2SPARQL
P_3: What is the ticket price of *Cinema:X*?	P_3SPARQL
P_4: Give me the address of *Cinema:X*.	P_4SPARQL
…	…
P_n	P_nSPARQL

Entailment-based NLI2DB

Input question

Q: "*Where is cinema Astra located?*"

Entailment engine

Q =>P_4

Pattern repository

P_1: What is the telephone number of *Cinema:X*?	P_1SPARQL
P_2: Who is the director of *Movie:X*?	P_2SPARQL
P_3: What is the ticket price of *Cinema:X*?	P_3SPARQL
P_4: Give me the address of *Cinema:X*.	P_4SPARQL
…	…
P_n	P_nSPARQL

Entailment-based NLI2DB

Input question

Q: “*Where is cinema Astra located?*”

Entailment engine

Pattern repository

P_1: What is the telephone number of *Cinema:X*?	P_1SPARQL
P_2: Who is the director of *Movie:X*?	P_2SPARQL
P_3: What is the ticket price of *Cinema:X*?	P_3SPARQL
P_4: Give me the address of *Cinema:X*.	P_4SPARQL
…	…
P_n	P_nSPARQL

Q =>P_4

SELECT ?address
WHERE { ?cinema rdf:type tourism:Cinema
?cinema tourism:name “Astra”.
?cinema tourism:hasPostalAddress ?addr.
?addr tourism:street ?address }

Entailment-based NLI2DB

Input question

Q: “*Where is cinema Astra located?*”

Entailment engine

Q □ P_4

Pattern repository

P_1: What is the telephone number of *Cinema:X*?	P_1SPARQL
P_2: Who is the director of *Movie:X*?	P_2SPARQL
P_3: What is the ticket price of *Cinema:X*?	P_3SPARQL
P_4: Give me the address of *Cinema:X*.	P_4SPARQL
…	…
P_n	P_nSPARQL

```
SELECT ?address
WHERE { ?cinema rdf:type tourism:Cinema
?cinema tourism:name “Astra”.
?cinema tourism:hasPostalAddress ?addr.
?addr tourism:street ?address }
```

A: Corso Buonarroti, 16 - Trento

Entailment-based NLI2DB

Input question

Q: *"What's the address of Astra?"*

Entailment engine

Q □ P_4

Pattern repository

P_1: What is the telephone number of *Cinema:X*?	P_1SPARQL
P_2: Who is the director of *Movie:X*?	P_2SPARQL
P_3: What is the ticket price of *Cinema:X*?	P_3SPARQL
P_4: Give me the address of *Cinema:X*.	P_4SPARQL
…	…
P_n	P_nSPARQL

```
SELECT ?address
WHERE { ?cinema rdf:type tourism:Cinema
?cinema tourism:name "Astra".
?cinema tourism:hasPostalAddress ?addr.
?addr tourism:street ?address }
```

A: Corso Buonarroti, 16 - Trento

Entailment-based NLI2DB

Input question

Q: "*Where can I find a cinema in the city centre?*"

Entailment engine

Pattern repository

P_1: What is the telephone number of *Cinema:X*?	P_1SPARQL
P_2: Who is the director of *Movie:X*?	P_2SPARQL
P_3: What is the ticket price of *Cinema:X*?	P_3SPARQL
P_4: Give me the address of *Cinema:X*.	P_4SPARQL
…	…
P_n	P_nSPARQL

Q □ P_4

```
SELECT ?address
WHERE { ?cinema rdf:type tourism:Cinema
?cinema tourism:name "Astra".
?cinema tourism:hasPostalAddress ?addr.
?addr tourism:street ?address }
```

A: Corso Buonarroti, 16 - Trento

Entailment-based NLI2DB

Input question

Q: “*I want to see a movie at Astra. Where is it?*”

Entailment engine

Q □ P_4

Pattern repository

P_1: What is the telephone number of *Cinema:X*?	P_1SPARQL
P_2: Who is the director of *Movie:X*?	P_2SPARQL
P_3: What is the ticket price of *Cinema:X*?	P_3SPARQL
P_4: Give me the address of *Cinema:X*.	P_4SPARQL
…	…
P_n	P_nSPARQL

```
SELECT ?address
WHERE { ?cinema rdf:type tourism:Cinema
?cinema tourism:name “Astra”.
?cinema tourism:hasPostalAddress ?addr.
?addr tourism:street ?address }
```

A: Corso Buonarroti, 16 - Trento

Entailment-based QA

- Advantages of the proposed framework
  - Simplicity
    - Linguistic variations are handled at textual level
      - Process independent from the DB schema: no need of explicit mapping between linguistic expressions and the DB content
      - Reduced manual effort
  - Flexibility
    - A variety TE recognition approach/algorithm can be used and experimented
      - From simpler BOW approaches to more complex techniques based on deep syntactic analysis

Minimal Relational Patterns

- Focus: question decomposition into *basic relations*
  - Entailment checking between *questions* and *Minimal Relational Patterns (def: "minimal* text portions expressing a relation between two entities")
- Motivation: mapping questions to MRPs enables a more effective treatment of *complex inputs* (i.e. those involving many relations)

"On Saturday, where can I see in the city centre a comedy starring Ben Stiller?"

- Techniques: distance-based TE recognition
  - *Levenshtein Distance*: estimate the costs of transforming (through words *insertion*, *deletion*, or *substitution*) a question *Q* into a pattern *P*

Example

Q: Come si intitola il film di stasera all’Astra di Trento?

Example

*Q: Come si **intitola** il **film** di stasera all'Astra di Trento?*

RELATION ENTAILED MRP SPARQL

*HasTitle(Movie,Title) P1 Dimmi il **titolo** di **[MOVIE]** Q1*

Example

*Q: Come si intitola il **film** di stasera all'**Astra** di Trento?*

RELATION ENTAILED MRP SPARQL

HasTitle(Movie,Title) P1 Dimmi il titolo di [MOVIE] Q1

*HasMovie(Cinema,Movie) P2 **[MOVIE]** al cinema **[CINEMA]** Q2*

Example

*Q: Come si intitola il **film** di **stasera** all'Astra di Trento?*

RELATION ENTAILED MRP SPARQL

HasTitle(Movie,Title) P1 Dimmi il titolo di [MOVIE] Q1

HasMovie(Cinema,Movie) P2 [MOVIE] al cinema [CINEMA] Q2

*HasDate(Movie,Date) P3 **film** in programma **[T-EXP]** Q3*

Example

*Q: Come si intitola il film di stasera all'**Astra** di **Trento**?*

RELATION ENTAILED MRP SPARQL

HasTitle(Movie,Title) P1 Dimmi il titolo di [MOVIE] Q1

HasMovie(Cinema,Movie) P2 [MOVIE] al cinema [CINEMA] Q2

HasDate(Movie,Date) P3 film in programma [T-EXP] Q3

*IsInCity(Cinema,City) P4 **[CINEMA]** di **[LOCATION]** Q4*

Example

Q: Come si intitola il film di stasera all'Astra di Trento?

RELATION ENTAILED MRP SPARQL

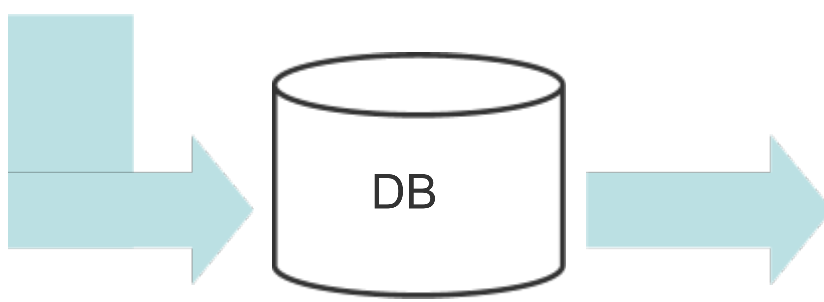
HasTitle(Movie,Title) P1 Dimmi il titolo di [MOVIE] ***Q1***

HasMovie(Cinema,Movie) P2 [MOVIE] al cinema [CINEMA] ***Q2***

HasDate(Movie,Date) P3 film in programma [T-EXP] ***Q3***

IsInCity(Cinema,City) P4 [CINEMA] di [LOCATION] ***Q4***

Combined SPARQL query to the DB



A: *Ratatouille*

What to do by hand?

- **Minimal manual effort**

1. Collect domain-specific questions (QALL-ME benchmark)
2. To each question Q_i, associate all the ontology relations it expresses $R_1,\ldots,R_n$
3. Split [Q,R] pairs into training and test set
4. For each relation R_x, build a cluster C_{Rx} of positive examples expressing R_x
5. Extract relational patterns P from training questions (Pattern Extraction using Genetic Algorithm)
    - Kouylekov & Negri Detecting Expected Answer Relations through Textual Entailment.
6. Train a TE engine over [Q,P] pairs, both on positive and negative examples
7. Use test [Q,R] pairs to evaluate the entailment engine

Evaluation

- F-Measure: .72
- User Centric Evaluation:
  - The question got a correct answer?
  - Four types:
    - Recognized all relations correctly (178)
    - Recognized some of relations (230)
    - Recognized some correctly some wrong (29)
    - Recognized only wrong (51)

Thanks