STS for Machine Translation Evaluation

STS Workshop, NYC March 12-13 2012

Lucia Specia

University of Sheffield 1.specia@sheffield.ac.uk

Outline

- Monolingual STS
 - MT Evaluation against references
 - TINE
- Multilingual STS
 - MT Evaluation without references
 - Adequacy estimation assimilation purposes
- STS for Evaluation
 - One metric fits evaluation for all applications?
 - One metric fits all applications?
- 4 My 2 cents
 - STS from an application perspective



Meteor - inexact lexical/phrase matching

- Meteor inexact lexical/phrase matching
- Pado et al. textual entailment features

- Meteor inexact lexical/phrase matching
- Pado et al. textual entailment features
- Gimenez & Marquez matching of semantic labels

- Meteor inexact lexical/phrase matching
- Pado et al. textual entailment features
- Gimenez & Marquez matching of semantic labels
- Meant matching of semantic roles (predicates and their arguments)

- Meteor inexact lexical/phrase matching
- Pado et al. textual entailment features
- Gimenez & Marquez matching of semantic labels
- Meant matching of semantic roles (predicates and their arguments)
- TINE matching of semantic roles (predicates and their arguments), but automatically

R: The lack of snow is **putting** [people]_{A0} **off booking** [ski holidays]_{A1} in [hotels and guest houses]_{AM-LOC}.

H: The lack of snow **discourages** [people]_{A0} from **ordering** [ski stays]_{A1} in [hotels and boarding houses]_{AM-LOC}.

R: The lack of snow is **putting** [people]_{A0} **off booking** [ski holidays]_{A1} in [hotels and guest houses]_{AM-LOC}.

H: The lack of snow **discourages** [people]_{A0} from **ordering** [ski stays]_{A1} in [hotels and boarding houses]_{AM-LOC}.

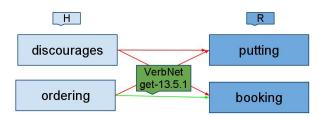
Lexical matching component *L* & **semantic** component *A*:

$$T(H, \mathbf{R}) = \max \left\{ \frac{\alpha L(H, R) + \beta A(H, R)}{\alpha + \beta} \right\}_{R \in \mathbf{R}}$$

L: BLEU; S: matching of verbs and their arguments:

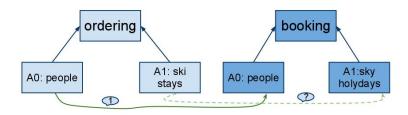
$$A(H,R) = \frac{\sum_{v \in V} \textit{verb_score}(H_v, R_v)}{|V_r|}$$

1. Align verbs using ontologies (VerbNet and VerbOcean):



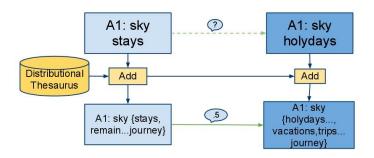
 v_h and v_r are aligned if they share a class in **VerbNet** or hold a relation in VerbOcean

2. Match arguments with same semantic roles:

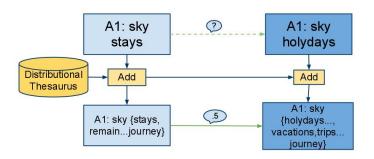


$$verb_score(H_v, R_v) = \frac{\sum_{a \in A_h \cap A_r} arg_score(H_a, R_a)}{|A_r|}$$

3. Expand arguments using distributional semantics and match them using cosine similarity: $arg_score(H_a, R_a)$

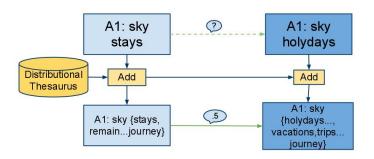


3. Expand arguments using distributional semantics and match them using cosine similarity: $arg_score(H_a, R_a)$



TINE did slightly better than BLEU at segment level.

3. Expand arguments using distributional semantics and match them using cosine similarity: $arg_score(H_a, R_a)$



TINE did slightly better than BLEU at **segment level**. **Lexical component** extremely important.

Quality Estimation

 No access to reference translation - MT system in use: post-editing, dissemination, assimilation, etc

Quality Estimation

- No access to reference translation MT system in use: post-editing, dissemination, assimilation, etc
- Semantics particularly important for estimating adequacy

Quality Estimation

- No access to reference translation MT system in use: post-editing, dissemination, assimilation, etc
- Semantics particularly important for estimating adequacy

Example 1

Target:

Chang-e III is expected to launch after 2013

Source:

嫦娥三号预计 2013 年前后发射

Reference:

Chang-e III is expected to launch around 2013

By Google Translate

Example 2

Target:

Continued high floods **subside**. Guang'an old city has been soaked 2 days 2 nights

Source:

四川广安洪水持续高位不退 老城区已被泡2天2夜

Reference:

The continuing floods in Guang'an - Sichuan have **not subsided**. The old city has been flooded for 2 days and 2 nights.

By Google Translate

Example 3

Target:

site security should be included in **sex education** curriculum for students

Source:

场地安全性教育应纳入学生的课程

Reference:

site security **requirements** should be included in the **education** curriculum for students

By Google Translate



Most common problems

- words translated incorrectly
- incorrect relationship: words/constituents/clauses
- missing/untranslated/repeated/added words
- incorrect word order
- inflectional/voice error

MT quality evaluation

- How does the metrics vary depending on how the references are produced?
 - Standard references semantic component only, segment-level correlation: 0.21
 - Post-edited translations semantic component only, segment-level correlation: 0.55

MT quality evaluation vs intrinsic evaluation

- TINE on WMT data: correlation: 0.30
- TINE on Microsoft video data: correlation: 0.43
- TINE on Microsoft paraphrase data: correlation: 0.30

 Can we use the same approach as reference-based evaluation, but bilingual?

- Can we use the same approach as reference-based evaluation, but bilingual?
 - Possibly, assuming resources and alignments are available

- Can we use the same approach as reference-based evaluation, but bilingual?
 - Possibly, assuming resources and alignments are available
 - Cannot expect exact correspondences. E.g. thematic divergences (Dorr et al):

- Can we use the same approach as reference-based evaluation, but bilingual?
 - Possibly, assuming resources and alignments are available
 - Cannot expect exact correspondences. E.g. thematic divergences (Dorr et al):

I miss you vs. Tu me manques

- Can we use the same approach as reference-based evaluation, but bilingual?
 - Possibly, assuming resources and alignments are available
 - Cannot expect exact correspondences. E.g. thematic divergences (Dorr et al):
 - I miss you vs. Tu me manques
 - Can learn these correspondences

• Can the same STS metric address both?

- Can the same STS metric address both?
 - MT systems make mistakes that summarization (esp. extractive) systems are not likely to make

- Can the same STS metric address both?
 - MT systems make mistakes that summarization (esp. extractive) systems are not likely to make
 - Translation is generally related/similar to the reference (and source) (a 1-2 likert score), not the case in summarization

- Can the same STS metric address both?
 - MT systems make mistakes that summarization (esp. extractive) systems are not likely to make
 - Translation is generally related/similar to the reference (and source) (a 1-2 likert score), not the case in summarization
 - Translation is generally very similar in length to the reference, not the case in summarization

- Can the same STS metric address both?
 - MT systems make **mistakes** that summarization (esp. extractive) systems are not likely to make
 - Translation is generally related/similar to the reference (and source) (a 1-2 likert score), not the case in summarization
 - Translation is generally very similar in length to the reference, not the case in summarization
 - Translation does 1-1 comparisons, not the case in summarization

- Can the same STS metric address both?
 - MT systems make **mistakes** that summarization (esp. extractive) systems are not likely to make
 - Translation is generally related/similar to the reference (and source) (a 1-2 likert score), not the case in summarization
 - Translation is generally very similar in length to the reference, not the case in summarization
 - Translation does 1-1 comparisons, not the case in summarization

Translation needs a more **fine-grained** metric than summarization?



Applications require different STS metrics

• "How do we illustrate the utility of STS to end applications?"

Applications require different STS metrics

- "How do we illustrate the utility of STS to end applications?"
- STS depends on what is important for the application, and also on the sort of data that can be produced by them

- "How do we illustrate the utility of STS to end applications?"
- STS depends on what is important for the application, and also on the sort of data that can be produced by them
- Avoid falling into the same trap as WSD?

- "How do we illustrate the utility of STS to end applications?"
- STS depends on what is important for the application, and also on the sort of data that can be produced by them
- Avoid falling into the same trap as WSD?
- How many applications use an off-the-shelf WSD module?

- "How do we illustrate the utility of STS to end applications?"
- STS depends on what is important for the application, and also on the sort of data that can be produced by them
- Avoid falling into the same trap as WSD?
- How many applications use an off-the-shelf WSD module?
- **Common excuses**: not good enough, WN senses not appropriate for my application...

- "How do we illustrate the utility of STS to end applications?"
- STS depends on what is important for the application, and also on the sort of data that can be produced by them
- Avoid falling into the same trap as WSD?
- How many applications use an off-the-shelf WSD module?
- **Common excuses**: not good enough, WN senses not appropriate for my application...

• Select a few applications that could benefit from STS

- Select a few applications that could benefit from STS
- Collect examples with different levels of similarity for these applications

- Select a few applications that could benefit from STS
- Collect examples with different levels of similarity for these applications
- Gold-standard annotation for these examples (like in Meant)

- Select a few applications that could benefit from STS
- Collect examples with different levels of similarity for these applications
- Gold-standard annotation for these examples (like in Meant)
- Compute as many semantic components as possible (word-level, SRL, etc)

- Select a few applications that could benefit from STS
- Collect examples with different levels of similarity for these applications
- Gold-standard annotation for these examples (like in Meant)
- Compute as many semantic components as possible (word-level, SRL, etc)
- I'm not sure components need to talk to each other: error propagation
- Regress on these to understand what are the important components for each application

- Select a few applications that could benefit from STS
- Collect examples with different levels of similarity for these applications
- Gold-standard annotation for these examples (like in Meant)
- Compute as many semantic components as possible (word-level, SRL, etc)
- I'm not sure components need to talk to each other: error propagation
- Regress on these to understand what are the important components for each application
- Repeat process with automatic annotation

- Select a few applications that could benefit from STS
- Collect examples with different levels of similarity for these applications
- Gold-standard annotation for these examples (like in Meant)
- Compute as many semantic components as possible (word-level, SRL, etc)
- I'm not sure components need to talk to each other: error propagation
- Regress on these to understand what are the important components for each application
- Repeat process with automatic annotation

Parameterizable STS metric

STS for Machine Translation Evaluation

STS Workshop, NYC March 12-13 2012

Lucia Specia

University of Sheffield 1.specia@sheffield.ac.uk