Improving MT Quality Prediction with Syntactic Tree Kernels

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- MT output is not perfect.
- When it is too bad, post-editors just waste time discarding it and have to translate from scratch anyway.

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 Productivity could be increased by discarding sentences automatically if they are unlikely to be good translations.

- Confidence estimation (or quality estimation) aims at predicting the quality of MT output based on input, output, models etc.
- We present results on sentence-level MT confidence estimation with Support Vector Machine classification.
- Using *tree kernels* drastically reduces the effort required to create a confidence estimation system while delivering quite good results.

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Subtitle dataset

- English-Swedish datasets
- about 4,000 subtitles from different TV series
- post-edited and annotated by professional translators

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manual quality judgments on a scale from 1 to 4

Quality annotation scheme

1 MT output unusable.

Subtitle needs to be retranslated from scratch.

- Post-editing quicker than retranslation."I needed to think about whether or not the MT output was usable."
- Only quick post-editing required."I could see almost immediately what I had to change."
- 4 MT output fit for purpose, no changes required.

1 and 2: negative class 3 and 4: positive class

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- Europarl test sets annotated for translation quality
- Published by Lucia Specia et al. (LREC 2010)
- Annotated on a 1–4 scale similar to ours
- 4,000 sentences translated by 4 different MT systems
- Results for confidence estimation with this data set presented by Specia et al. in *Machine Translation* 24 (2010) and two conference papers (EAMT 2009, MT Summit 2009)

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Explicit features

designed in a manual feature engineering process, extracted with special-purpose tools labour-intensive but specific

Implicit features

automatically extracted by a general-purpose method e.g. *tree kernels*

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Explicit features

For all systems:

- number of words, length ratio
- type-token ratio
- number of tokens matching particular patterns such as punctuation, short and long words etc.

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- source and target language model scores
- OOV ratio
- word frequencies in training corpus

Only for subtitle system:

- some more specific token counts
- short output indicator
- word alignment types in phrases

Tree kernels

- In SVM learning, features can be represented implicitly by using kernel functions.
- Kernel functions can be defined over structures such as parse trees.

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 Tree kernels measure similarities between trees by counting common substructures.

Parse trees

- Constituency parses (Stanford parser):
 - English
- Dependency parses (MaltParser):
 - English
 - Swedish (subtitle test set)
 - Spanish (Europarl test sets)
- Experiments used
 - either *constituency parses* for the MT *input only*
 - or dependency parses for both MT input and output

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Subset Tree Kernel

- The Subset Tree Kernel counts substructure that correspond to *complete productions* in a constituency tree.
- If a fragment contains one child of a node, it must contain them all.
- used for constituency trees

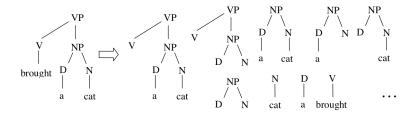
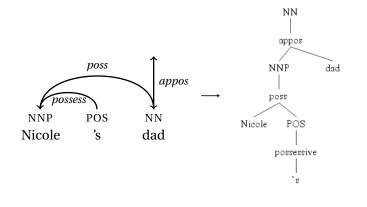


Illustration by A. Moschitti, ECML 2006 ・ロト ・ 厚 ト ・ ヨ ト ・ ヨ ト ・

Handle POS tags and edge labels by putting them as nodes into the tree.



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Experiments

- binary SVM classifiers
- 3rd degree polynomial kernel for explicit features
- Baseline: majority class classifier, accepts everything

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Results: Subtitle system

| | Р | R | F |
|------------------------|------|-------|------|
| majority class | 50.2 | 100.0 | 66.8 |
| explicit features | 69.5 | 58.3 | 63.3 |
| constituency (S) | 64.8 | 67.0 | 65.9 |
| dependency (S+T) | 64.9 | 65.7 | 65.3 |
| all + constituency (S) | 67.5 | 66.3 | 66.8 |
| all + dependency (S+T) | 68.7 | 68.8 | 68.8 |

| | Р | R | F |
|------------------------|------|-------|------|
| majority class | 54.6 | 100.0 | 70.6 |
| explicit features | 67.1 | 82.7 | 74.0 |
| constituency (S) | 69.0 | 69.9 | 69.4 |
| dependency (S+T) | 69.5 | 68.2 | 68.8 |
| all + constituency (S) | 74.4 | 73.3 | 73.9 |
| all + dependency (S+T) | 74.1 | 76.2 | 75.1 |

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| | F scores | | |
|------------------------|----------|------|------|
| | 1 | 2 | 3 |
| majority class | 83.0 | 70.6 | 68.3 |
| explicit features | 83.5 | 74.0 | 70.4 |
| constituency (S) | | 69.4 | 66.9 |
| dependency (S+T) | | 68.8 | 68.1 |
| all + constituency (S) | 85.1 | 73.9 | 73.4 |
| all + dependency (S+T) | 84.8 | 75.1 | 73.9 |

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| | Europarl | | | sub- |
|------------------------------|----------|------|------|--------|
| | 1 | 2 | 3 | titles |
| majority class | 71.0 | 54.6 | 51.8 | 50.2 |
| Specia et al., MT 24 (2010) | 76.8 | 66.0 | 69.8 | |
| explicit features | 72.6 | 68.7 | 70.3 | 66.4 |
| constituency tree kernel (S) | | 66.4 | 66.9 | 64.7 |
| dependency tree kernel (S+T) | | 66.4 | 67.8 | 65.0 |
| explicit + constituency (S) | 77.8 | 71.1 | 72.5 | 66.7 |
| explicit + dependency (S+T) | 76.7 | 72.4 | 72.8 | 68.3 |

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Conclusions

- Tree kernels alone achieve only slightly lower performance for most test sets at reduced development effort.
- Combining tree kernels with explicit features led to a small improvement for all test sets.
- Use tree kernels when you start building a confidence estimation system, then add more features to improve performance...
- ... or improve tree kernel approach to use more information.