RTM-DCU: Predicting Semantic Similarity with Referential Translation Machines

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Abstract
We use referential translation machines (RTMs) for predicting the semantic similarity of text. RTMs are a computational model effectively judging monolingual and bilingual similarity while identifying translation acts between any two data sets with respect to interpretants. RTMs pioneer a language independent approach to all similarity tasks and remove the need to access any task or domain specific information or resource. RTMs become the 2nd system out of 13 systems participating in Paraphrase and Semantic Similarity in Twitter, 6th out of 16 submissions in Semantic Textual Similarity Spanish, and 50th out of 73 submissions in Semantic Textual Similarity English.

1 Referential Translation Machine (RTM)
We present positive results from a fully automated judge for semantic similarity based on Referential Translation Machines (Biçici and Way, 2014b) in two semantic similarity tasks at SemEval-2015, Semantic Evaluation Exercises - International Workshop on Semantic Evaluation (Nakov et al., 2015). Referential translation machine (RTM) is a computational model for identifying the acts of translation for translating between any given two data sets with respect to a reference corpus selected in the same domain. An RTM model is based on the selection of interpretants, training data close to both the training set and the test set, which allow shared semantics by providing context for similarity judgments. Each RTM model is a data translation and translation prediction model between the instances in the training set and the test set and translation acts are indicators of the data transformation and translation. RTMs present an accurate and language independent solution for making semantic similarity judgments.

RTMs pioneer a computational model for quality and semantic similarity judgments in monolingual and bilingual settings using retrieval of relevant training data (Biçici and Yuret, 2015) as interpretants for reaching shared semantics. RTMs achieve (i) top performance when predicting the quality of translations (Biçici, 2013; Biçici and Way, 2014a); (ii) top performance when predicting monolingual cross-level semantic similarity; (iii) second performance when predicting paraphrase and semantic similarity in Twitter (iv) good performance when judging the semantic similarity of sentences; (iv) good performance when evaluating the semantic relatedness of sentences and their entailment (Biçici and Way, 2014b).

RTMs use Machine Translation Performance Prediction (MTPP) System (Biçici et al., 2013; Biçici and Way, 2014b), which is a state-of-the-art (SoA) performance predictor of translation even without using the translation. MTPP system measures the coverage of individual test sentence features found in the training set and derives indicators of the closeness of test sentences to the available training data, the difficulty of translating the sentence, and the presence of acts of translation for data transformation. MTPP features for translation acts are provided in (Biçici and Way, 2014b). RTMs become the 2nd system out of 13 systems participating in Paraphrase and Semantic Similarity in Twitter (Task 1) (Xu et al., 2015) and achieve good results in Semantic Tex-
Algorithm 1: Referential Translation Machine

Input: Training set \( \text{train} \), test set \( \text{test} \), corpus \( C \), and learning model \( M \).

Data: Features of \( \text{train} \) and \( \text{test} \), \( F_{\text{train}} \) and \( F_{\text{test}} \).

Output: Predictions of similarity scores on the test \( \hat{q} \).

1. FDA5(\( \text{train}, \text{test}, C \)) \( \rightarrow I \)
2. MTPPSystem(\( I, \text{train} \)) \( \rightarrow F_{\text{train}} \)
3. MTPPSystem(\( I, \text{test} \)) \( \rightarrow F_{\text{test}} \)
4. learn(\( M, F_{\text{train}} \)) \( \rightarrow M \)
5. predict(\( M, F_{\text{test}} \)) \( \rightarrow \hat{y} \)

We develop individual RTM models for each task and subtask that we participate at SemEval-2015 with the RTM-DCU team name. Interpretants are selected from the LM corpora distributed by the translation task of WMT14 (Bojar et al., 2014) and LDC for English (Parker et al., 2011) and Spanish (Angelo Mendonça et al., 2011).

We use the Parallel FDA5 instance selection model for selecting the interpretants (Bičici et al., 2014; Bičici and Yuret, 2015), which allows efficient parameterization, optimization, and implementation of Feature Decay Algorithms (FDA), and build an MTPP model. We view that acts of translation are ubiquitously used during communication:

*Every act of communication is an act of translation* (Bliss, 2012).

Translation need not be between different languages and paraphrasing or communication also contain acts of translation. When creating sentences, we use our background knowledge and translate information content according to the current context.

Figure 1 depicts RTM and Algorithm 1 describes the RTM algorithm. Our encouraging results in the semantic similarity tasks increase our understanding of the acts of translation we ubiquitously use when communicating and how they can be used to predict semantic similarity. RTMs are powerful enough to be applicable in different domains and tasks with good performance. We describe the tasks we participated as follows:

ParSS Paraphrase and Semantic Similarity in Twitter (ParSS) (Xu et al., 2015):

Given two sentences \( S_1 \) and \( S_2 \) in the same language, produce a similarity score indicating whether they express a similar meaning: a discrete real number in \([0, 1]\).

We model as sentence MTPP between \( S_1 \) to \( S_2 \).

STS Semantic Textual Similarity (STS) (Agirre et al., 2015):

Given two sentences \( S_1 \) and \( S_2 \) in the same language, quantify the degree of similarity: a real number in \([0, 5]\).

STSS is in English and Spanish (a real number in \([0, 4]\)). We model as sentence MTPP of \( S_1 \) and \( S_2 \).

### 2 SemEval-15 Results

We develop individual RTM models for each task and subtask that we participate at SemEval-2015 with the RTM-DCU team name. Interpretants are selected from the LM corpora distributed by the translation task of WMT14 (Bojar et al., 2014) and LDC for English (Parker et al., 2011) and Spanish (Angelo Mendonça et al., 2011).

We use the Stanford POS tagger (Toutanova et al., 2003) to obtain the lemmatized corpora for the ParSS task. The number of instances we select for the interpretants

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1. English Gigaword 5th, Spanish Gigaword 3rd edition.
in each task is given in Table 1.

We use ridge regression (RR), support vector regression (SVR), and extremely randomized trees (TREE) (Geurts et al., 2006) as the learning models. These models learn a regression function using the features to estimate a numerical target value. We also use them after a dimensionality reduction and mapping step with partial least squares (PLS) (Specia et al., 2009). We optimize the learning parameters, the number of dimensions used for PLS, and the parameters for parallel FDA5. More details about the optimization processes are in (Biçici and Way, 2014b; Biçici et al., 2014). We optimize the learning parameters by selecting \( \varepsilon \) close to the standard deviation of the noise in the training set (Biçici, 2013) since the optimal value for \( \varepsilon \) is shown to have linear dependence to the noise level for different noise models (Smola et al., 1998). At testing time, the predictions are bounded to obtain scores in the corresponding ranges.

We use Pearson’s correlation \( (r_P) \), mean absolute error (MAE), and relative absolute error (RAE) for evaluation:

\[
\text{MAE}(\hat{y}, y) = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{n} \\
\text{RAE}(\hat{y}, y) = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{\sum_{i=1}^{n} |y_i - y_i|} \\
\]

We define MAER and MRAER for easier replication and comparability with relative errors for each instance:

\[
\text{MAER}(\hat{y}, y) = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{n} \\
\text{MRAER}(\hat{y}, y) = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{\sum_{i=1}^{n} |\bar{y} - y_i|} \\
\]

MAER is the mean absolute error relative to the magnitude of the target and MRAER is the mean absolute error relative to the absolute error of a predictor always predicting the target mean assuming that target mean is known. MAER and MRAER are capped from below\(^2\) with \( \varepsilon = \frac{\text{MAE}(\hat{y}, y)}{2} \), which is the measurement error and it is estimated as half of the mean absolute error or deviation of the predictions from target mean. \( \varepsilon \) represents half of the score step with which a decision about a change in measurement’s value can be made. \( \varepsilon \) is similar to half of the standard deviation, \( \sigma \), of the data but over absolute differences. For discrete target scores, \( \varepsilon = \frac{\text{step size}}{2} \). A method for learning decision thresholds for mimicking the human decision process when determining whether two translations are equivalent is described in (Biçici, 2013).

MAER and MRAER are able to capture averaged fluctuations at the instance level and they may evaluate the performance of a predictor at performance prediction tasks at the instance level (e.g. performance of the similarity of sentences, performance of translation of different translation instances) better. RAE compares sums of prediction errors and MRAER averages instance prediction error comparisons.

\(^2\)We use \([ \cdot ]_\varepsilon \) to cap the argument from below to \( \varepsilon \).
2.1 Task 1: Paraphrase and Semantic Similarity in Twitter (ParSS)

ParSS contains sentences provided by Twitter (Xu et al., 2015). Official evaluation metric is Pearson’s correlation score, which we use to select the top systems on the training set. RTM-DCU results on the ParSS test set are given in Table 2. The setting R using SVR becomes 2nd out of 13 systems and 3rd out of 25 submissions. Looking at MAE and MAER allows us to obtain explanations to train and test performance differences for example without knowing their target distribution. Even though MAE of PLS-SVR is about 5% smaller on the ParSS test set, MAER is 55% smaller due to test set containing fewer zero entries (16 vs. 39 on the train set). Lower test MAE than training MAE may be attributed to RTMs.

We obtained results with lemmatized datasets and further optimized the learning model parameters after the challenge. We present the performance of the top 5 individual RTM models on the training set in Table 3. R uses the regular truecase (Koehn et al., 2007; Koehn, 2010) corpora and L uses the lemmatized truecased corpora. R+L correspond to using the features from both R and L, which doubles the number of features.

2.2 Task 2: Semantic Textual Similarity (STS)

STS contains sentence pairs from different domains: answers-forums, answers-students, belief, headlines, and images for English and wikipedia and newswire for Spanish. Official evaluation metric in STS is the Pearson’s correlation score. We build separate RTM models for headlines and images domains for STS English. Domain specific RTM models obtain improved performance in those domains (Bicici and Way, 2014b). STS English test set contains 2000, 1500, 2000, 1500, and 1500 sentences respectively from the specified domains however for evaluation, STS use a subset of the test set, 375, 750, 375, 750, and 750 instances respectively from the corresponding domains. This may lower the performance of RTMs by causing FDA5 to select more domain specific data and less task specific since RTMs use the test set to select interpretants and build a task specific RTM prediction model.

Table 4 and Table 5 list the results on the test set
along with their ranks out of 73 and 16 submissions respectively for English STS and Spanish STS.

RTM top test results selected according to Weighted $r_P$ among top 3 results on STS for each subtask as well as top RTM-DCU results in STS 2014 (Biçici and Way, 2014b) are presented in Table 6, where we have used the top results from domain specific RTM models for headlines and images domains in the overall model results. Top 3 individual RTM model performance on the training set with further optimized learning model parameters after the challenge are presented in Table 7. Better $r_P$, RAE, and MRAER on the test set than on the training set in STS 2015 English may be attributed to RTMs.

### 2.3 RTMs Across Tasks and Years

We compare the difficulty of tasks according to MRAER where the correlation of RAE and MRAER is 0.89. In Table 8, we list the RAE, MAER, and MRAER obtained for different tasks and subtasks, also listing RTM results from SemEval-2013 (Biçici and van Genabith, 2013), from SemEval-2014 (Biçici and Way, 2014b), and and from quality estimation task (QET) (Biçici and Way, 2014a) of machine translation (Bojar et al., 2014). RTMs at SemEval-2013 contain results from STS. RTMs at SemEval-2014 contain results from STS, semantic relatedness and entailment (SRE) (Marelli et al., 2014), and cross-level semantic similarity (CLSS) tasks (Jurgens et al., 2014). RTMs at WMT2014 QET contain tasks involving the prediction of an integer in $[1, 3]$ representing post-editing effort (PEE), a real number in $[0, 1]$ representing human-targeted translation edit rate (HTER), or an integer representing post-editing time (PET) of translations.

The best results are obtained for the CLSS paragraph to sentence subtask, which may be due to the larger contextual information that paragraphs can provide for the RTM models. For the ParSS task, we can only reduce the error with respect to knowing and predicting the mean by about 22.5%. Prediction of bilingual similarity as in quality estimation of translation can be expected to be harder and RTMs achieve SoA performance in this task as well (Biçici and Way, 2014a). Table 8 can be used to evaluate the difficulty of various tasks and domains based on our SoA predictor RTM. MRAER considers both the predictor’s error and the target scores’ fluctuations at the instance level. We separated the results having MRAER greater than 1 as in these tasks and subtasks RTM does not perform significantly better than mean predictor and fluctuations render these as tasks that may require more work.

### 3 Conclusion

Referential translation machines pioneer a clean and intuitive computational model for automatically measuring semantic similarity by measuring the acts of translation involved and achieve to become the 2nd system out of 13 systems participating in Paraphrase and Semantic Similarity in Twitter, 6th out of 16 submissions in Semantic Textual Similarity Spanish, and 50th out of 73 submissions in Semantic Textual Similarity English. RTMs make quality and semantic similarity judgments possible based on the retrieval of relevant training data as interpreters for reaching shared semantics. We define MAER, mean absolute error relative to the magnitude of the target, and MRAER, mean absolute error relative to the absolute error of a predictor always predicting the target mean assuming that target mean is known. RTM test performance on various tasks sorted according to MRAER can identify which tasks and subtasks may require more work.

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Table 6: RTM top test results selected according to Weighted \( r_p \) among top 3 results on STS as well as top RTM-DCU results in STS 2013 and STS 2014 (Bičić and Way, 2014b). ALL presents results over all of the test set.

| Domain         | Model       | \( r_p \) | MAE   | RAE   | MAER  | MRAER  |
|----------------|-------------|-----------|-------|-------|-------|--------|
| **English**    |             |           |       |       |       |        |
| answers-forums | PLS-SVR     | 0.6215    | 1.2239| 1.1675| 1.5369| 1.3449 |
| answers-students| PLS-SVR    | 0.6125    | 0.9635| 0.7819| 0.5542| 0.8404 |
| belief         | PLS-SVR     | 0.5879    | 1.3625| 1.1825| 1.5749| 1.4119 |
| headlines      | RR          | 0.7812    | 0.8318| 0.5894| 0.4844| 0.6380 |
| images         | TREE        | 0.7830    | 0.8502| 0.5885| 0.5424| 0.6229 |
| **ALL**        | PLS-SVR     | 0.6739    | 0.9847| 0.7224| 0.7379| 0.7883 |
|                 |             |           |       |       |       |        |
| **Spanish**    |             |           |       |       |       |        |
| News           | TREE        | 0.5303    | 0.6315| 0.9426| 0.4096| 1.1052 |
| Wikipedia      | TREE        | 0.5867    | 0.6448| 0.9499| 0.4844| 1.2062 |
| **ALL**        | TREE        | 0.5618    | 0.6360| 0.9459| 0.4348| 1.1344 |
|                 |             |           |       |       |       |        |
| **English**    |             |           |       |       |       |        |
| deft-forum     | TREE        | 0.4341    | 1.1609| 1.0908| 0.7724| 1.216  |
| deft-news      | TREE        | 0.6974    | 0.9032| 0.8716| 0.6271| 0.881  |
| headlines      | TREE        | 0.6199    | 0.9254| 0.7845| 0.6711| 0.7854 |
| images         | TREE        | 0.6995    | 0.9499| 0.7395| 0.8338| 0.7284 |
| OnWN           | TREE        | 0.8058    | 1.0028| 0.5585| 0.7975| 0.546  |
| tweet-news     | TREE        | 0.6882    | 0.831 | 0.8093| 0.4601| 0.875  |
| **ALL**        | TREE        | 0.6473    | 0.9534| 0.7449| 0.7274| 0.7566 |
|                 |             |           |       |       |       |        |
| **Spanish**    |             |           |       |       |       |        |
| News           | TREE        | 0.7       | 1.351 | 1.4141| 0.5994| 1.8053 |
| Wikipedia      | TREE        | 0.4216    | 1.298 | 1.3579| 0.65  | 1.6612 |
| **ALL**        | TREE        | 0.62      | 1.3296| 1.3823| 0.6191| 1.7719 |

Table 7: RTM training results of top 3 systems on STS English, English images, English headlines, and Spanish tasks.
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Table 8: Best RTM test results for different tasks and subtasks sorted according to MRAER.

| Task          | Subtask                     | Domain       | Model       | RAE   | MAER   | MRAER  |
|---------------|-----------------------------|--------------|-------------|-------|--------|--------|
| CLSS 2014     | Paragraph to Sentence       | Mixed        | TREE        | 0.4579| 0.5112 | 0.5037 |
| STS 2014      | English                     | OnWN         | TREE        | 0.5585| 0.7975 | 0.546  |
| QET 2014      | English-Spanish PEE         | Europarl     | PLS-TREE    | 1.0794| 0.304  | 0.614  |
| STS 2015      | English                     | Images       | TREE        | 0.5885| 0.5424 | 0.6229 |
| STS 2015      | English                     | Headlines    | RR          | 0.5894| 0.4844 | 0.6380 |
| CLSS 2014     | Sentence to Phrase          | Mixed        | TREE        | 0.6255| 0.6857 | 0.6444 |
| QET 2014      | German-English PEE          | Europarl     | RR          | 0.8204| 0.3575 | 0.679  |
| QET 2014      | English-German PEE          | Europarl     | TREE        | 0.8602| 0.3692 | 0.6985 |
| STS 2014      | English                     | Images       | TREE        | 0.7395| 0.8338 | 0.7246 |
| QET 2014      | Spanish-English PEE         | Europarl     | FS-RR       | 0.9   | 0.3798 | 0.7491 |
| QET 2014      | English-Spanish PET         | Europarl     | SVR         | 0.7223| 0.4651 | 0.7786 |
| STS 2014      | English                     | Headlines    | TREE        | 0.7845| 0.6711 | 0.7854 |
| SRE 2014      | English                     | SICK         | R+L PLS-SVR | 0.6645| 0.1827 | 0.8177 |
| ParSS 2015    | English                     | Tweets       | SVR         | 0.7755| 0.6901 | 0.838  |
| STS 2015      | English                     | Answers-students | PLS-SVR    | 0.7819| 0.5542 | 0.8404 |
| CLSS 2014     | Phrase to Word              | Mixed        | TREE        | 0.9488| 1.1454 | 0.8483 |
| STS 2013      | English                     | OnWN         | L+S SVR     | 0.8255| 1.2875 | 0.8605 |
| STS 2014      | English                     | Tweet-news   | TREE        | 0.8093| 0.4601 | 0.875  |
| QET 2014      | English-Spanish HTER        | Europarl     | SVR         | 0.8532| 0.7727 | 0.8758 |
| STS 2014      | English                     | Deft-forum   | TREE        | 0.8716| 0.6271 | 0.881  |
| STS 2015      | Spanish                     | News         | TREE        | 0.9426| 0.4096 | 1.1052 |
| STS 2013      | English                     | Headlines    | L+S SVR     | 1.0231| 1.0456 | 1.1444 |
| STS 2015      | Spanish                     | Wikipedia    | TREE        | 0.9499| 0.4844 | 1.2062 |
| STS 2014      | English                     | Deft-forum   | TREE        | 1.0908| 0.7724 | 1.216  |
| STS 2015      | English                     | Answers-forums | PLS-SVR   | 1.1675| 1.5369 | 1.3449 |
| STS 2013      | English                     | FNWN         | L+S SVR     | 1.2633| 1.5087 | 1.4048 |
| STS 2015      | English                     | Belief       | PLS-SVR     | 1.1825| 1.5749 | 1.4119 |
| STS 2014      | Spanish                     | Wikipedia    | TREE        | 1.3579| 0.65   | 1.6612 |
| STS 2014      | Spanish                     | News         | TREE        | 1.4141| 0.5994 | 1.8053 |
| STS 2013      | English                     | SMT          | L+S SVR     | 1.6132| 0.1669 | 2.0718 |