Machine Translation Evaluation Metrics for Recognizing Textual Entailment

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Abstract. In this paper, we propose a method for Recognizing Textual Entailment (RTE) that makes use of different machine translation (MT) evaluation metrics, namely *BLEU, METEOR, TER, WER, LE-BLEU, NIST, and RIBES* and different versions of summary evaluation metric ROUGE, namely *ROUGE-N, ROUGE-S, ROUGE-W, ROUGE-L, and ROUGE-SU* in a machine learning framework. Our main motivation for this paper is to investigate how MT evaluation metrics (which is generally used to judge the quality of an MT output), summary evaluation metrics (which is generally used to measure the quality of system generated summary) can be effective for determining TE relation between a pair of text snippets. Experiments on the datasets released as part of the shared task for recognizing textual entailment, RTE-1, RTE-2, RTE-3, RTE-4, and RTE-5 show the encouraging performance. We also performed a deeper comparative analysis of the relevance of MT and summary evaluation metrics for the task of Textual Entailment (TE).

Keywords: Machine Translation Evaluation Metrics, Summary Evaluation Metrics, Textual Entailment, Machine Learning.

1 Introduction

One of the utmost challenging problems in the field of Natural Language Processing (NLP) is to deal with language variability, that means there can be multiple ways to express a simple matter. Over the years researchers have been investigating a common framework which will be able to capture such language variability. Textual Entailment (TE) is an effective way to capture such language variability. Textual entailment requires complex linguistic analysis. TE was first introduced by [1] in the first track of recognizing textual entailment organized by *National Institute of Standard and Technology (NIST)*. In this track TE was first defined as follows: suppose there are two texts fragments expressed as *Text (T)* and *Hypothesis (H)*. It is said that:

***T** entails **H** if, typically, a human reading **T** would infer that of **H** is most likely to be true.*

For example, the text T = *Mahatma Gandhis assassin happened* entails the

hypothesis H = *Mahatma Gandhi was died*; obviously, if there exists ones assassin, then this person dies. Similarly, T = *Mary lives in Germany* entails H = *Mary lives in Europe*. On the other hand, T = *Mary lives in Europe* does not entail H = *Mary lives in India*. There were many international conferences and evaluation tracks have been organized such as in Pattern Analysis, Statistical Modeling and Computational Learning (PASCAL)[1], Text Analysis Conferences (TAC)[2] organized by the United States National Institute of Standards and Technology (NIST), Evaluation Exercises on Semantic Evaluation (SemEval)[3], National Institute of Informatics Test Collection for Information Retrieval System (NTCIR) [4] since from the year of 2005. These conferences and workshops produced many research articles which cover many approaches, varying from Lexical [1] [2], Syntactic [3] and semantics [4].

There are many applications in the field of NLP where TE can be employed, e.g. Machine Translation (MT) [5], Question-Answering (QA) [6] and Summarization [7] and many more.

In MT evaluation, the machine generated output should be entailed with the reference one. In Question-Answering (QA), the answer produced by a machine must entail with that particular question. In summarization, the machine produced summary should entail with the reference one. Building an MT evaluation metric with the help of TE is a vital task. The proposed study makes use of various MT evaluation metrics and automatic summary evaluation metrics as features in machine learning framework.

1.1 Motivation

The MT evaluation metrics and automatic summary evaluation metrics are meant to investigate the quality of translation and summarization. It essentially does that by measuring the similarity between the two (machine produced outputs and references) comparing piece of text fragments. We use these metrics to determine TE relationship. The study in [8] made use of very well established similarity metrics like Cosine, Jaccard, Dice, Overlap etc. and two MT evaluation metrics, namely BLEU [9] and METEOR [10, 11] for TE using RTE-1, RTE-2 and RTE-3 datasets. This shows that MT evaluation metrics performed at per the ordinary similarity metrics in predicting the TE relation. Another study [12] made use of the same kind of similarity metrics along with the MT evaluation metrics on Indian languages (namely Hindi, Punjabi, Telugu and Malayalam) datasets to detect the paraphrase relation between a pair of sentences. The evaluation was performed on the datasets of the shared task *Detecting Paraphrases in Indian Languages (DPIL)* of *Forum for Information Retrieval Evaluation (FIRE-2016)*. The study of [13] proposed a model which would be able to predict the TE relation between the two sentences (in RTE-1,

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[1] http://pascallin.ecs.soton.ac.uk/Challenges/
[2] http://www.nist.gov/tac/tracks/index.html
[3] http://semeval2.fbk.eu/semeval2.php
[4] http://research.nii.ac.jp/ntcir/ntcir-9/

RTE-2, RTE-3, RTE-4 and RTE-5 datasets) based on the MT evaluation metrics (BLEU, METEOR and TER) and one summary evaluation metric (ROUGE). Hence if BLEU, TER, and METEOR can take part in predicting TE relation between a pair of text snippets, there are other metrics too which could take part in deciding entailment relation between two pieces of texts. The work reported in [14] makes use of *Microsoft Research Paraphrase (MSRP)* to detect paraphrases using MT evaluation metrics. It is be noted that in our current research we exploit features which are novel with respect to textual entailment.

1.2   Related Works

There are umpteen number of research works carried out that could be found in the literature on the datasets released in the shared task for recognizing textual entailment i.e. RTE-1, RTE-2, RTR-3, RTE-4, and RTE-5. Literature shows, [15] obtained the best accuracy in RTE-1 by the methods of word overlapping. They made use of BLEU, whose scores were used to assign "yes" or "no" class entailment decision based on some thresholds. The thresholds were learned based on some heuristics which were devised using the datasets. They obtained an accuracy of 70% on the dataset. The method defined in [16] achieved the best accuracy of 75% on RTE-2 dataset. The study proposed by the system made use of lexical and syntactic matching. In RTE-3 dataset the best result was obtained in [17] using lexical alignment, knowledge extraction method, discourse commitment etc. The system proposed by [18] obtained the highest accuracy of 68.5%. The key concept of the participant's system is to map each word of hypothesis with one or more words of the text. They extensively made use of knowledge bases, namely DIRT, WordNet, VerbOcean, Wikipedia and Acronyms database etc. The system defined in [19] achieved the highest accuracy of 68.33% in RTE-5. The approach defined here is same as the approach defined in [18]. Additionally, they processed the LingPipe output with GATE in order to identify some of the named entity categories (e.g. nationality, language, job) which are within the scope of LingPipe. Apart from the above-cited works on TE and paraphrase detection, there are few more works found in the literature. The task described in [20] made use of BLEU, NIST, TER and Position independent word error rate (PER) to build a classifier which will be able to predict paraphrase relation between a pair of texts and also the entailment relation. They made use of *MSRP Corpus* and *RTE-1* for detection of paraphrase and entailment respectively.

The work of [14] made use of *Microsoft paraphrase detection corpus (MSRP)* and *Plagiarism Detection Corpus (PAN)* to re-examine the idea that automatic metrics which are generally used for judging the quality of a translation can also perform for the task of paraphrase detection. They used BLEU, NIST, TER, TERp [21], METEOR, SEPIA [22], BADGER [23], MAXSIM [24] metrics.

2 Feature Analysis

Features play a pivotal role in any machine learning assisted experiment. Hence identifying right combination of features which yield the best accuracy is the vital task. The following subsections define the features employed in the proposed study.

2.1 MT Evaluation Metrics

MT evaluation metrics generally used to judge the closeness between the machine translated output and the gold standard reference one. The more the closeness between them, the better is the translation system output. Over the years, MT community proposed various metrics, namely BLEU [9], METEOR [10, 11], NIST [25], TER [26], Word Error Rate (WER) [27], Position independent word Error Rate (PER) and General Text Matcher (GTM) etc. We have incorporated almost all the metrics available in this study. We describe each of them in the following points

1. BLEU: Bilingual Evaluation Understudy(BLEU) [9] is a metric which is perhaps the most popular MT evaluation metric developed by IBM. It measures the similarity between MT output and reference sentences by computing the n-gram precision between those sentences. Mathematically, it can be expressed as follows:

$$BLEU = BP \cdot exp(\sum_{N}^{n=1} w_n log p_n) \tag{1}$$

Where, w_n is positive weights, summing to one; p_n is modified n-gram precisions. BP is brevity penalty computed as:

$$BP = \begin{cases} 1 & if \ c > r \\ e^{\left(1 - \frac{r}{c}\right)} & if \ c \leq r \end{cases} \tag{2}$$

Where, candidate translation length is c; and length of the effective reference corpus is r. Generally BLEU measures the similarity between the two sentences by computing n-gram matching. It can be termed as precision oriented metric. Similarity can be a way to detect TE relation, as it produces similarity, we wield this as a feature in this study.

2. LE-BLEU: *LE-BLEU* is also an MT evaluation metric which is based on n-gram matching, considered suitable for highly compounding languages [28]. It is an extension of BLEU, which consider fuzzy matches between two n-grams. It is supposed to better correlate with human judgment. The main drawback of BLEU is in exact n-gram matching. It could be possible not to match exact n-gram but having a similar meaning. Such case LE-BLEU performs well than BLEU. LE-BLEU calculation is a kind of fuzzy calculation, whereas the calculation of BLEU is crisp kind of technique. So, there is great chance to get BLEU score zero, (if it is considering 4-gram matching, but machine up to 3-gram) where LE-BLEU provides the satisfactory score. Thus, LE-BLEU can be a smart feature to recognize textual entailment between a piece of texts.

3. RIBES: Rank-based Intuitive Bilingual Evaluation Score (RIBES) [29] is also very useful for judging the MT output. Its calculation is based on significantly penalized word order mistakes and rank correlation coefficients. It is very effective for evaluating the accuracy score between distant sentence pairs. So, the similarity score between two distant sentences can easily predict their entailment.

4. NIST: The name NIST [25] came from *US National Institute of Standard and Technology*, which is used to evaluate between different text pairs. BLEU considers each n-gram to be of equal weight whereas NIST considers only the informative n-grams. NIST also differs from BLUE in its calculation of the brevity penalty in so far as small variations in translation length do not impact the overall score as much. As it also measures the similarity between the pair of text snippets, we exert this as a feature.

5. METEOR: METEOR (Metric for Evaluation of Translation with Explicit Ordering) [10, 11] is a metric which measures the similarity between two sentences by computing the maximum-cardinality matching between those sentences. This match is used to compute the coherent based penalty. This computation is done by assessing the extent to which the matched words between texts constitute well ordered coherent chunks. It considers lexical matching and synonym matching from the WordNet. As it takes both the approaches to measure the similarity into account, it could be an interesting feature in our study.

6. TER: Translation Error Rate (TER) [26] is also a metric to evaluate the performance of an MT output which is introduced in "Global Autonomous Language Exploration (GALE) Program" MT task. The central concept behind this metric is that edits required to change a hypothesis translation into reference translation. It generally produces the error rate by measuring the edit operations required to transfer the MT output to reference translation. Hence we get the similarity by taking the complement of the error rate as shown in the following equation 3:

$$TER = \frac{Number\ of\ edits}{average\ number\ of\ reference\ words} \tag{3}$$

Correctness is important to detect textual entailment, but it is not sufficient for this task. The error between two texts also important for recognizing textual entailment. So, we have considered TER and WER to fulfill its requirement.

7. WER: Word error rate (WER) [27] is also another very popular MT metric, which is also used in speech recognition. The metric works on the word level, where the order of words is important and it is based on Levenshtein distance. Its computation is based on the minimum substitutions, deletions, and insertions that have to be performed to convert the generated text into the reference text. Basic intuition of this metric is based on the errors in unigram translation whereas TER is based on edits required for humans. The shift is incorporated here but in TER shift is not taken into account. It can be computed by the following formula 4: where *S:# of substitutions,*

D:# of deletions, I:# of insertions, N:# of words in the reference

$$WER = \frac{S + D + I}{N} \tag{4}$$

2.2 Summary Evaluation Metrics

Summary evaluation metrics are generally used to judge the quality of machine-generated summary of a document which is generated automatically following an algorithm. *Recall-Oriented Understudy for Gisting Evaluation (ROUGE)* [30] is one of the most popular and widely accepted metric to evaluate summary. It comes up with its several versions, we utilize all those versions here. An important ingredient for scoring for this metric is overlapping units. Units refer to n-gram word sequence word pairs between the hypothesis and reference sentence.

1. ROUGE-N: It computes the similarity score by measuring n-gram matching. Specifically, it is n-gram recall between a set of reference and candidate document. The mathematical equation of this metric is as follows:
   ROUGE-N =

   $$\frac{\sum_{S \in reference\ documents} \sum_{gram \in}^{S} Count_{match}(gram)}{\sum_{S \in \{referencedocuments\}} \sum_{gram \in S} count(gram)} \tag{5}$$

   where count match(gram) is the maximum number of n-grams co-occurring in a candidate and a set of reference documents. The intuition behind using this metric is that it corresponds to the recall version of BLEU. So, we take into account precision from BLEU and recall from this metric.
2. ROUGE-L: It is basically the Longest Common Subsequence (LCS) based statistics. LCS is used as approximate string matching algorithm. To compare the similarity between the hypothesis and reference documents normalized pairwise LCS is used in [31]. The higher the common matching between two texts the more the chances of the two texts to be textually entailed.
3. ROUGE-W: It is weighted LCS that favors consecutive LCSs. Problem with basic LCS is that it is unable to differentiate LCSs of different spatial relations. As it calculates similarity by taking weighted LCS into account, it can be an effective feature to predict entailment.
4. ROUGE-S: ROUGE-S is based on skip-bigram co-occurrence. It calculates the similarity score between two pieces of texts, by considering bi-gram matching irrelevant of word order. We use this as a feature in our model.
5. ROUGE-SU: ROUGE-SU is the combination of skip-gram and unigram. It computes similarity by taking both of these into consideration. It is a different version to measure the similarity between a pair of texts snippets. This is also used as a feature.

3 Experimental Setup and Results

In this section we present preprocessing module, description of the datasets, experimental procedure, results, discussions and comparisons with the state-of-the art.

3.1 Preprocessing Module

Data are full of noisy. This performs the cleaning operation of such noise from the T-H pair contained in the datasets. We also removed the white spaces (if any) from the datasets. The example below shown is a T-H pair in the development set (taken from RTE-1).

<pair id="78" value="FALSE" task="IR"> <t>Clinton's new book is not big seller here.</t>
<h>Clinton's book is a big seller.</h>
</pair>

Here 's are replaced by """ in the sentences, and then further it was converted into it's expanded form i.e. Clinton's converted into Clinton's.

3.2 Dataset

We use the datasets released in the shared task for recognizing textual entailment i.e. RTE-1, RTE-2, RTE-3, RTE-4 and RTE-5. The datasets of RTE-1, RTE-2 and RTE-3 correspond to the binary-class classification problem, whereas the datasets of RTE-4 and RTE-5 denote the ternary class classification problem. In our work we consider both binary and ternary classification. In Table 1 we show the number of T-H pairs present in the datasets.

Table 1. Statistics of the Datasets

	# of T-H pair	
	Development	Test
RTE-1	567	800
RTE-2	800	800
RTE-3	800	800
RTE-4	0	1000
RTE-5	600	600

3.3 Experiments

We extract T-H pairs from the datasets of RTE-1, RTE-2, RTE-3, RTE-4, and RTE-5. we calculate the similarity between T and H by exploiting the set of features that we already discussed. The scores obtained from each metric for a particular T-H pair are considered as feature value which is subjected to classifier's training and/or testing. As base learning algorithms, we use Support Vector Machine (SVM) [32, 33], Multilayer Perceptron (MLP) [34, 35], Logistic Regression [36] and Random forest (RF) [37]. We use the classifiers as available in weka [5]. The models are used to predict a class for an unknown T-H pair. We report the evaluation figures on the test set. The system predicts a class to each instance (T-H pair) of the test set. For RTE-4 we perform 10-fold cross-validation results as we don't have access to the test dataset.

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[5] http://www.cs.waikato.ac.nz/ml/weka/

3.4 Results, Discussions and Comparisons

We evaluate all the three models on all the three datasets. We calculate *True Positive (TP), False Positive (FP), False Negative (FN)* and *True Negative (TN)*. We also report the accuracy of the system. We depict the accuracies obtained by the proposed system and the state-of-the-art models on different datasets in Table 2. In RTE-1 the best accuracy of our system is 56.37% using Random Forest (RF) compared to the best result reported as 70% by [15]. For RTE-2 we get an accuracy of 60.12% with SVM, whereas the best accuracy reported is 75% by [16]. For RTE-3, we obtain the highest accuracy of 62.25% in Logistics Regression framework, however, the best accuracy reported in this track is 80% by [17]. For RTE-4, we obtain an accuracy of 54.5% using Logistic Regression classifier compared to the best-reported value of 68.5% by [18]. The system with MLP yields an accuracy of 52.2% in RTE-5, whereas an accuracy of 68.33% was reported as the best result by [19]. It is to be noted that however, we obtain relatively fewer accuracies compared to the state-of-the-art, the novelty of our proposed techniques is in the use of different MT and summary evaluation metrics for classifier's training for TE. Table 2 shows the evaluation results of

Table 2. Results on test set of different datasets

	Our System Accuracies(%)				Best Results(%)(Participant)
	SVM	Logistics	MLP	RF	
RTE-1	55.5	53.87	52.75	56.37	70 [15]
RTE-2	60.12	59.5	57	59.12	75 [16]
RTE-3	61.87	62.25	60.5	60.37	80 [17]
RTE-4	54.4	54.5	51.4	52.3	68.5 [18]
RTE-5	50	34.83	52.2	46.33	68.33 [19]

different classifiers in our proposed system. The last column shows the state-of-the-art results obtained by the different participating systems in the respective tracks. For RTE-1 it is observed that Random Forest produces the best result among all the classifiers. For RTE-2, SVM model attains the best accuracy. In RTE-3 and RTE-4, logistic regression model yield the highest performance. In RTE-5 MLP produces the best result. It is to be noted that different classifiers produce the best result for the different datasets.

Comparisons to the baseline [13] models are presented in table 3. The system reported in [13] made use of all the datasets as what our proposed system exploits. The proposed system makes use of the baseline features as well as the others extracted from NIST, LE-BLEU, WER, RIBES, ROUGE-N, ROUGE-S, ROUGE-L, ROUGE-W, and ROUGE-SU. This shows that our proposed approach is more effective than our baseline model which infers that usages of MT and summary evaluation metrics for the proposed task are, indeed, effective.

We also performed a deeper analysis by comparing the performance obtained by taking only MT metrics as a feature and the performance obtained by con-

Table 3. Comparison Results with baseline systems

Datasets	Baseline [13](%)	Proposed approach(%)
RTE-1	54	55.5
RTE-2	55	60.12
RTE-3	60	62.25
RTE-4	52	54.4
RTE-5	51	52.2

sidering only summary evaluation metrics as a feature. We run the best model for each dataset. The results are shown in the following Table 4:

Table 4. Comparison between MT and Summary Evaluation metrics

Dataset	Best performing Classifier	Accuracy (%)	
		MT	Summary
RTE-1	RF	56.25	50.37
RTE-2	SVM	58.37	60.5
RTE-3	Logistic	62.12	59.5
RTE-4	Logistic	55.1	51.5
RTE-5	MLP	53	50

From the table, we observe that in all datasets except RTE-2 MT evaluation metric's feature combination performs better compared to the summary evaluation metric's feature combination.

3.5 Features sensitivity analysis

Features are very precious in any machine learning assisted experiment. In order to embellish the contribution of each feature to our predicting classes, we perform Ablation Study of features where we switch off a feature and then evaluate the model with the rest set of features and compare with the accuracy obtained by the whole set of features (including the particular feature). Table, 5 represents datasets in columns and row heading represent the features. In this Table the "✓" represents that the corresponding feature has a positive effect on the performance, whereas "N" indicates that the particular features seem to have no effect and "X" denotes, the features seem to have a negative effect on the performance. The table shows that, for RTE-1, all the features seem to have posi-

Table 5. Features ablation study

	BLEU	LE-BLEU	RIBES	NIST	WER	TER	METEOR	ROUGE-N	ROUGE-L	ROUGE-W	ROUGE-S	ROUGE-SU
RTE-1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
RTE-2	✓	✓	X	X	X	✓	N	N	N	X	✓	✓
RTE-3	✓	X	X	X	✓	✓	N	X	N	X	X	X
RTE-4	✓	✓	X	✓	X	N	✓	N	N	✓	✓	N
RTE-5	✓	X	X	X	X	✓	✓	✓	N	✓	X	N

tive contributions. In RTE-2 *BLEU*, *LE-BLEU*, *TER*, *ROUGE-S*, and *ROUGE-SU* features seem to be the most contributing features. The features, namely

METEOR, ROUGE-N, and *ROUGE-L* do not contribute significantly. On the other hand, the features, namely *RIBES, NIST, WER*, and *ROUGE-W* seem to have negative effect on the performance. In RTE-3 datasets, only *BLEU, WER and TER* are found to contribute more, *METEOR and ROUGE-L* are found to be neutral, and *LE-BLEU, RIBES, NIST, ROUGE-N, ROUGE-W, ROUGE-S, and ROUGE-SU* are found to be the features with a negative effect. For RTE-4, *BLEU, LE-BLEU, NIST, METEOR, ROUGE-W, and ROUGE-S* are found to be the most effective features. For RTE-5, *BLEU, TER, METEOR, ROUGE-N, and ROUGE-W* features contribute most. It is to be noted that, *BLEU, LE-BLEU, TER, METEOR, ROUGE-W, and ROUGE-S* are the features which are found to be the contributing features in most of the datasets.

We perform another set of experiments by training and/or testing the classifier by considering only the contributing features. Results of these models are reported in Table 6. Please note that we report only the results of the best performing classifier (for each dataset).

Table 6. Results with contributing features only

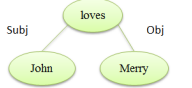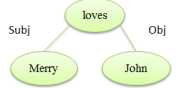| Datasets	Accuracies(%)
RTE-1	55.5
RTE-2	60.58
RTE-3	62.62
RTE-4	55.3
RTE-5	52.56

3.6 Error Analysis

We perform error analysis to understand the shortcomings of our proposed method. Our system makes use of MT and summary evaluation metrics in a machine learning framework. Most of these metrics are based on lexical matching that may not be sufficient to capture the problem of textual entailment always. These are not able to capture the syntactic and semantic ambiguities present in the corpus. The lexical matching ache from a drawback, sometimes it produces a very high score for non-entailed text pair. For the following example, *T: John loves Merry* and *H: Merry loves John*, lexical matching produces a very high score and consequently, the system will mark that pair as entailed, although T doesn't entail H.

On the other hand, if we parse T and H using a Stanford dependency parser [6], it will produce the parsing information of that particular T and H as shown in the table 7, Here nothing will matches if we consider dependency triplet matches, hence they (T and H) are considered to be not entailed. Hence, dependency tree matching plays a vital role in determining TE relations. The system needs to be updated on this front. Let us consider another example taken from the RTE-3

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[6] http://nlp.stanford.edu:8080/parser/index.jsp

Table 7. Dependency Parsing of T and H

development set.

<pair id="251" entailment="YES" task="IR" length="short">
<t>Estimates vary **widely***, but it is believed there are up to 100 million children toiling in homes, factories, shops, fields, brothels and on the streets of rural and urban India.</t>*
<h>Child labor is **widely** *used in Asia.</h> </pair>*

There is only one common token (i.e **widely**) between T and H in the above example, so if we consider for lexical matching between those pairs, the system will produce a very low score which is not sufficient to tag them (T-H pair) as textually entailed. However, this pair should be defined as textually entailed. This needs further investigation.

4 Conclusion and Future Work

In this paper, we have proposed a system for recognizing textual entailment between a pair of text expressions which exploits MT evaluation metrics *namely BLEU, NIST, RIBES, LE-BLEU, TER, WER, and METEOR* and summary evaluation metrics (*namely ROUGE-N, ROUGE-S, ROUGE-L, ROUGE-W, and ROUGE-SU*) as features in a supervised machine learning framework. We develop models based on SVM, Logistic Regression, MLP, and Random Forest. Experiments performed on different benchmark datasets of RTE-1, RTE-2, RTE-3, RTE-4, and RTE-5 tracks show that our proposed approach attain encouraging performance. We demonstrate adding new features to the baseline system increase system performance. The proposed study is in the opposite direction of building an MT evaluation metric using TE, which tries to correlate MT and summary evaluation metrics with TE. The experiments reveal that MT and summary evaluation metrics which are generally used to judge the quality of machine produced translation and summary respectively, have a strong correlation which can also effectively take part in taking entailment decision between a pair of text snippets. We also accomplished a deeper comparative analysis of the relevance of MT and summary evaluation metrics for the task of TE and reveals that MT evaluation metric's feature combination performs better compared to the summary evaluation metric's feature combination in most of the datasets in this particular task.

Future works are directed towards the following dimensions:

– will incorporate more such metrics in the existing system to build a more robust TE system.

- will incorporate deep learning concepts in the existing system and want to make a comparative study.
- planning to incorporate these MT and summary evaluation metrics in semantic textual similarity, which is another interesting problem to study.
- planning to do the work in reverse direction i.e. to build an MT evaluation metric by exploiting a robust TE system which will be based on deep learning approach.

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