BEER: BEtter Evaluation as Ranking

Miloš Stanojević
ILLC
University of Amsterdam
mstanojevic@uva.nl

Khalil Sima'an
ILLC
University of Amsterdam
k.simaan@uva.nl

Abstract

We present the UvA-ILLC submission of the BEER metric to WMT 14 metrics task. BEER is a sentence level metric that can incorporate a large number of features combined in a linear model. Novel contributions are (1) efficient tuning of a large number of features for maximizing correlation with *human system ranking*, and (2) novel features that give smoother sentence level scores.

1 Introduction

The quality of sentence level (also called segment level) evaluation metrics in machine translation is often considered inferior to the quality of corpus (or system) level metrics. Yet, a sentence level metrics has important advantages as it:

1. provides an informative score to individual translations
2. is assumed by MT tuning algorithms (Hopkins and May, 2011).
3. facilitates easier statistical testing using sign test or t-test (Collins et al., 2005)

We think that the root cause for most of the difficulty in creating a good sentence level metric is the sparseness of the features often used. Consider the n-gram counting metrics (BLEU (Papineni et al., 2002)): counts of higher order n-grams are usually rather small, if not zero, when counted at the individual sentence level. Metrics based on such counts are brittle at the sentence level even when they might be good at the corpus level. Ideally we should have features of varying granularity that we can optimize on the actual evaluation task: relative ranking of system outputs.

Therefore, in this paper we explore two kinds of less sparse features:

Character n-grams are features at the sub-word level that provide evidence for translation adequacy - for example whether the stem is correctly translated,

Abstract ordering patterns found in tree factorizations of permutations into Permutation Trees (PETs) (Zhang and Gildea, 2007), including non-lexical alignment patterns.

The BEER metric combines features of both kinds (presented in Section 2).

With the growing number of adequacy and ordering features we need a model that facilitates efficient training. We would like to train for optimal Kendall τ correlation with rankings by human evaluators. The models in the literature tackle this problem by

1. training for another similar objective – e.g., tuning for absolute adequacy and fluency scores instead on rankings, or
2. training for rankings directly but with meta-heuristic approaches like hill-climbing, or
3. training for pairwise rankings using learning-to-rank techniques

Approach (1) has two disadvantages. One is the inconsistency between the training and the testing objectives. The other, is that absolute rankings are not reliable enough because humans are better at giving relative than absolute judgments (see WMT manual evaluations (Callison-Burch et al., 2007)).

Approach (2) does not allow integrating a large number of features which makes it less attractive.

Approach (3) allows integration of a large number of features whose weights could be determined in an elegant machine learning framework. The output of learning in this approach can be either a function that ranks all hypotheses directly (global ranking model) or a function that assigns a score

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to each hypothesis individually which can be used for ranking (local ranking model) (Li, 2011). Local ranking models are preferable because they provide absolute distance between hypotheses like most existing evaluation metrics.

In this paper we follow the learning-to-rank approach which produces a local ranking model in a similar way to PRO MT systems tuning (Hopkins and May, 2011).

2 Model

Our model is a fairly simple linear interpolation of feature functions, which is easy to train and simple to interpret. The model determines the *similarity* of the hypothesis h to the reference translation r by assigning a weight w_i to each feature $\phi_i(h, r)$. The linear scoring function is given by:

$$score(h, r) = \sum_i w_i \times \phi_i(h, r) = \vec{\boldsymbol{w}} \cdot \vec{\boldsymbol{\phi}}$$

2.1 Adequacy features

The features used are precision P, recall R and F1-score F for different counts:

$P_{function}$, $R_{function}$, $F_{function}$ on matched function words

$P_{content}$, $R_{content}$, $F_{content}$ on matched content words (all non-function words)

P_{all}, R_{all}, F_{all} on matched words of any type

$P_{char\ n-gram}$, $R_{char\ n-gram}$, $F_{char\ n-gram}$ matching of the character n-grams

By differentiating function and non-function words we might have a better estimate of which words are more important and which are less. The last, but as we will see later the most important, adequacy feature is matching character n-grams, originally proposed in (Yang et al., 2013). This can reward some translations even if they did not get the morphology completely right. Many metrics solve this problem by using stemmers, but using features based on character n-grams is more robust since it does not depend on the quality of the stemmer. For character level n-grams we can afford higher-order n-grams with less risk of sparse counts as on word n-grams. In our experiments we used character n-grams for size up to 6 which makes the total number of all adequacy features 27.

2.2 Ordering features

To evaluate word order we follow (Isozaki et al., 2010; Birch and Osborne, 2010) in representing reordering as a permutation and then measuring the distance to the ideal monotone permutation. Here we take one feature from previous work – Kendall τ distance from the monotone permutation. This metrics on the permutation level has been shown to have high correlation with human judgment on language pairs with very different word order.

Additionally, we add novel features with an even less sparse view of word order by exploiting hierarchical structure that exists in permutations (Zhang and Gildea, 2007). The trees that represent this structure are called PETs (PErmutation Trees – see the next subsection). Metrics defined over PETs usually have a better estimate of long distance reorderings (Stanojević and Sima'an, 2013). Here we use simple versions of these metrics:

Δ_{count} the ratio between the number of different permutation trees (PETs) (Zhang and Gildea, 2007) that could be built for the given permutation over the number of trees that could be built if permutation was completely monotone (there is a perfect word order).

$\Delta_{[\,]}$ ratio of the number of monotone nodes in a PET to the maximum possible number of nodes – the lenght of the sentence n.

$\Delta_{<>}$ ratio of the number of inverted nodes to n

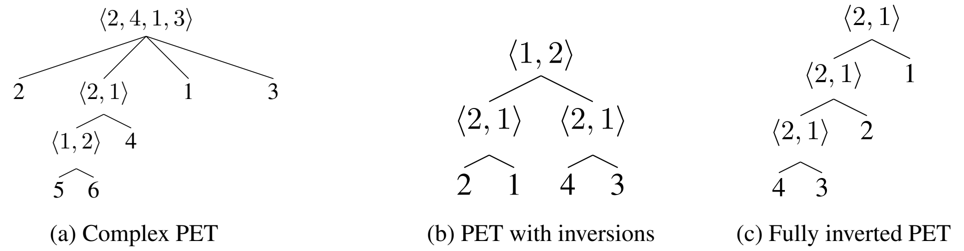
$\Delta_{=4}$ ratio of the number of nodes with branching factor 4 to n

$\Delta_{>4}$ ratio of the number of nodes with branching factor bigger than 4 to n

2.3 Why features based on PETs?

PETs are recursive factorizations of permutations into their minimal units. We refer the reader to (Zhang and Gildea, 2007) for formal treatment of PETs and efficient algorithms for their construction. Here we present them informally to exploit them for presenting novel ordering metrics.

A PET is a tree structure with the nodes decorated with operators (like in ITG) that are themselves permutations that cannot be factorized any further into contiguous sub-parts (called operators). As an example, see the PET in Figure 1a. This PET has one 4-branching node, one inverted



(a) Complex PET (b) PET with inversions (c) Fully inverted PET

Figure 1: Examples of PETs

node and one monotone. The nodes are decorated by *operators* that stand for a permutation of the direct children of the node.

PETs have two important properties that make them attractive for observing ordering: firstly, the PET operators show the minimal units of ordering that constitute the permutation itself, and secondly the higher level operators capture hidden patterns of ordering that cannot be observed without factorization. Statistics over patterns of ordering using PETs are non-lexical and hence far less sparse than word or character n-gram statistics.

In PETs, the minimal operators on the node stand for ordering that cannot be broken down any further. The binary monotone operator is the simplest, binary inverted is the second in line, followed by operators of length four like $\langle 2,4,1,3\rangle$ (Wu, 1997), and then operators longer than four. The larger the branching factor under a PET node (the length of the operator on that node) the more complex the ordering. Hence, we devise possible branching feature functions over the operator length for the nodes in PETs:

- factor 2 - with two features: $\Delta_{[\,]}$ and $\Delta_{<>}$ (there are no nodes with factor 3 (Wu, 1997))
- factor 4 - feature $\Delta_{=4}$
- factor bigger than 4 - feature $\Delta_{>4}$

All of the mentioned PETs node features, except $\Delta_{[\,]}$ and Δ_{count}, signify the wrong word order but of different magnitude. Ideally all nodes in a PET would be binary monotone, but when that is not the case we are able to quantify how far we are from that ideal binary monotone PET.

In contrast with word n-grams used in other metrics, counts over PET operators are far less sparse on the sentence level and could be more reliable. Consider permutations 2143 and 4321 and their corresponding PETs in Figure 1b and 1c. None of them has any exact n-gram matched (we ignore unigrams now). But, it is clear that 2143 is somewhat better since it has at least some words in more or less the right order. These "abstract n-grams" pertaining to correct ordering of full phrases could be counted using $\Delta_{[\,]}$ which would recognize that on top of the PET in 1b there is the monotone node unlike the PET in 1c which has no monotone nodes at all.

3 Tuning for human judgment

The task of correlation with human judgment on the sentence level is usually posed in the following way (Macháček and Bojar, 2013):

- Translate all source sentences using the available machine translation systems
- Let human evaluators rank them by quality compared to the reference translation
- Each evaluation metric should do the same task of ranking the hypothesis translations
- The metric with higher Kendall τ correlation with human judgment is considered better

Let us take any pair of hypotheses that have the same reference r where one is better (h_{good}) than the other one (h_{bad}) as judged by human evaluator. In order for our metric to give the same ranking as human judges do, it needs to give the higher score to the h_{good} hypothesis. Given that our model is linear we can derive:

$$\begin{aligned} score(h_{good},r) > score(h_{bad},r) \Leftrightarrow \\ \vec{w}\cdot\vec{\phi}_{good} > \vec{w}\cdot\vec{\phi}_{bad} \Leftrightarrow \\ \vec{w}\cdot\vec{\phi}_{good} - \vec{w}\cdot\vec{\phi}_{bad} > 0 \Leftrightarrow \\ \vec{w}\cdot(\vec{\phi}_{good} - \vec{\phi}_{bad}) > 0 \\ \vec{w}\cdot(\vec{\phi}_{bad} - \vec{\phi}_{good}) < 0 \end{aligned}$$

The most important part here are the last two equations. Using them we formulate ranking problem as a problem of binary classification: the positive training instance would have feature values

$\vec{\phi}_{good} - \vec{\phi}_{bad}$ and the negative training instance would have feature values $\vec{\phi}_{bad} - \vec{\phi}_{good}$. This trick was used in PRO (Hopkins and May, 2011) but for the different task:

- tuning the model of the SMT system
- objective function was an evaluation metric

Given this formulation of the training instances we can train the classifier using pairs of hypotheses. Note that even though it uses pairs of hypotheses for training in the evaluation time it uses only one hypothesis – it does not require the pair of hypotheses to compare them. The score of the classifier is interpreted as confidence that the hypothesis is a good translation. This differs from the majority of earlier work which we explain in Section 6.

4 Experiments on WMT12 data

We conducted experiments for the metric which in total has 33 features (27 for adequacy and 6 for word order). Some of the features in the metric depend on external sources of information. For function words we use listings that are created for many languages and are distributed with METEOR toolkit (Denkowski and Lavie, 2011). The permutations are extracted using METEOR aligner which does fuzzy matching using resources such as WordNet, paraphrase tables and stemmers. METEOR is not used for any scoring, but only for aligning hypothesis and reference.

For training we used the data from WMT13 human evaluation of the systems (Macháček and Bojar, 2013). Before evaluation, all data was lowercased and tokenized. After preprocessing, we extract training examples for our binary classifier. The number of non-tied human judgments per language pair are shown in Table 1. Each human judgment produces two training instances : one positive and one negative. For learning we use regression implementation in the Vowpal Wabbit toolkit [1].

Tuned metric is tested on the human evaluated data from WMT12 (Callison-Burch et al., 2012) for correlation with the human judgment. As baseline we used one of the best ranked metrics on the sentence level evaluations from previous WMT tasks – METEOR (Denkowski and Lavie, 2011). The results are presented in the Table 2. The presented results are computed using definition of Kendall τ from the WMT12 (Callison-Burch et al., 2012) so the scores could be compared with other metrics on the same dataset that were reported in the proceedings of that year (Callison-Burch et al., 2012).

language pair	#comparisons
cs-en	85469
de-en	128668
es-en	67832
fr-en	80741
ru-en	151422
en-cs	102842
en-de	77286
en-es	60464
en-fr	100783
en-ru	87323

Table 1: Number of human judgments in WMT13

language pair	BEER with paraphrases	BEER without paraphrases	METEOR
en-cs	**0.194**	0.190	0.152
en-fr	0.257	0.250	**0.262**
en-de	**0.228**	0.217	0.180
en-es	0.227	**0.235**	0.201
cs-en	**0.215**	0.213	0.205
fr-en	**0.270**	0.254	0.249
de-en	**0.290**	0.271	0.273
es-en	**0.267**	0.249	0.247

Table 2: Kendall τ correleation on WMT12 data

The results show that BEER with and without paraphrase support outperforms METEOR (and almost all other metrics on WMT12 metrics task) on the majority of language pairs. Paraphrase support matters mostly when the target language is English, but even in language pairs where it does not help significantly it can be useful.

5 WMT14 evaluation task results

In Table 4 and Table 3 you can see the results of top 5 ranked metrics on the segment level evaluation task of WMT14. In 5 out of 10 language pairs BEER was ranked the first, on 4 the second best and on one third best metric. The cases where it failed to win the first place are:

- against DISCOTK-PARTY-TUNED on * - English except Hindi-English. DISCOTK-PARTY-TUNED participated only in evaluation of English which suggests that it uses some language specific components which is not the case with the current version of BEER
- against METEOR and AMBER on English-Hindi. The reason for this is simply that we

[1] `https://github.com/JohnLangford/vowpal_wabbit`

Direction	en-fr	en-de	en-hi	en-cs	en-ru
BEER	**.295**	**.258**	.250	**.344**	**.440**
METEOR	.278	.233	.264	.318	.427
AMBER	.261	.224	**.286**	.302	.397
BLEU-NRC	.257	.193	.234	.297	.391
APAC	.255	.201	.203	.292	.388

Table 3: Kendall τ correlations on the WMT14 human judgements when translating out of English.

Direction	fr-en	de-en	hi-en	cs-en	ru-en
DISCOTK-PARTY-TUNED	**.433**	**.381**	.434	**.328**	**.364**
BEER	.417	.337	**.438**	.284	.337
REDCOMBSENT	.406	.338	.417	.284	.343
REDCOMBSYSSENT	.408	.338	.416	.282	.343
METEOR	.406	.334	.420	.282	.337

Table 4: Kendall τ correlations on the WMT14 human judgements when translating into English.

did not have the data to tune our metric for Hindi. Even by treating Hindi as English we manage to get high in the rankings for this language.

From metrics that participated in all language pairs on the sentence level on average BEER has the best correlation with the human judgment.

6 Related work

The main contribution of our metric is a linear combination of features with far less sparse statistics than earlier work. In particular, we employ novel ordering features over PETs, a range of character n-gram features for adequancy, and direct tuning for human ranking.

There are in the literature three main approaches for tuning the machine translation metrics.

Approach 1 SPEDE (Wang and Manning, 2012), metric of (Specia and Giménez, 2010), ROSE-reg (Song and Cohn, 2011), ABS metric of (Padó et al., 2009) and many others train their regression models on the data that has absolute scores for adequacy, fluency or post-editing and then test on the ranking problem. This is sometimes called pointwise approach to learning-to-rank. In contrast our metric is trained for ranking and tested on ranking.

Approach 2 METEOR is tuned for the ranking and tested on the ranking like our metric but the tuning method is different. METEOR has a non-linear model which is hard to tune with gradient based methods so instead they tune their parameters by hill-climbing (Lavie and Agarwal, 2008). This not only reduces the number of features that could be used but also restricts the fine tuning of the existing small number of parameters.

Approach 3 Some methods, like ours, allow training of a large number of parameters for ranking. Global ranking models that directly rank hypotheses are used in ROSE-rank (Song and Cohn, 2011) and PAIR metric of (Padó et al., 2009). Our work is more similar to the training method for local ranking models that give score directly (as it is usually expected from an evaluation metric) which was originally proposed in (Ye et al., 2007) and later applied in (Duh, 2008) and (Yang et al., 2013).

7 Conclusion and future plans

We have shown the advantages of combining many simple features in a tunable linear model of MT evaluation metric. Unlike majority of the previous work we create a framework for training large number of features on human rankings and at the same time as a result of tuning produce a score based metric which does not require two (or more) hypotheses for comparison. The features that we used are selected for reducing sparseness on the sentence level. Together the smooth features and the learning algorithm produce the metric that has a very high correlation with human judgment.

For future research we plan to investigate some more linguistically inspired features and also explore how this metric could be tuned for better tuning of statistical machine translation systems.

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