Automatic Syntactic MT Evaluation with Expected Dependency Pair Match

Abstract

Previous work on dependency-based machine translation evaluation has shown that an LFG-based F-measure of labeled partial dependencies over an n-best list has improved correlation with human judgments of fluency and adequacy as compared to BLEU and TER. Inspired by SParseval, we demonstrate that a statistical syntactic parser based on PCFGs may be used in place of the LFG dependencies, and we explore variations on other aspects of the dependency-matching method. We find that separating the match quality into different bins, as in BLEU, does *not* improve correlations with human judgments, but that including $n > 1$ parses helps, especially if one incorporates probabilistic weights from the parser. Additionally, we find that matching simple words (along with partial-dependencies) further improves correlations with human judgments.

From these results, we design a new scoring metric "Expected Dependency Pair Match" (EDPM), and demonstrate that $\Delta\mathrm{EDPM}$ is superior to ΔBLEU and ΔTER as a per-document and per-sentence predictor of ΔHTER.

1 Introduction

Machine translation (MT) evaluation is a challenge for research because the space of good translations is large, and two equally good translations may appear to be quite different at first glance. The challenges of choosing among translations are compounded when this evaluation is done automatically. Human evaluation, however, is both time-consuming and difficult, so research has turned increasingly towards automatic measures of translation quality, usually by comparing the system translation to one or more reference (human) translations. Automatic measures of this kind (e.g. BLEU (Papineni et al., 2002)) not only provide a well-defined evaluation standard but are also required for training on error criteria, e.g. with minimum error rate training (Och, 2003).

The most popular evaluation measures (BLEU and related measure NIST (Doddington, 2002)) are based on n-gram precision. More recent research has found that these measures may not accurately track translation quality both empirically (Charniak et al., 2003) and theoretically (Callison-Burch, 2006).

One direction to look for improving metrics is to try to model acceptable variation, whether word-choice (e.g. METEOR (Banerjee and Lavie, 2005), which does progressively more forgiving word matching) or by modeling syntactic information (Liu and Gildea, 2005; Owczarzak et al., 2007). Owczarzak et al. (2007) explore the correlation of their measure **d** and **d_var** with human judgment, and report substantial improvements relative to the popular measures BLEU and TER (Snover et al., 2006). Keeping to the syntactic approach, the work here follows and extends the labelled-dependency match version of SParseval (Roark et al., 2006) and the **d/d_var** (Owczarzak et al., 2007) measures, all of which evaluate hypothesis-reference similarity with an F measure over fragments of a labelled dependency structure. The measures requiring dependency structure have generated that structure by a PCFG with deterministic head-finding (Liu and Gildea, 2005; Roark et al., 2006) or by extracting the semantic dependencies from an LFG parser (Cahill et al. (2004) in Owczarzak et al. (2007)). In this work, we extend the dependency-scoring strategies of Owczarzak et al. (2007) but do so with a widely used and publically available PCFG parser and deterministic head-finding rules instead of an LFG system.

These measures have been evaluated in a number of ways. Some (Banerjee and Lavie, 2005; Liu and Gildea, 2005; Owczarzak et al., 2007) have evaluated their success by comparing the measure to human judgments of fluency and adequacy. In other work, e.g. Snover et al. (2006), measures are evaluated by comparison to HTER, a distance to a human-revised reference that uses wording closer to the MT system choices (keeping the original meaning) that is intended to measure the post-editing work required after translation. In this paper, we pursue both kinds of evaluation.

The remainder of this work is as follows. In section 2, we define a family of measures DPM that include SPARSEVAL and **d/d_var** measures and describe our strategy for extracting labelled dependencies. In section 3, we explore a selection of variants of that family with human judgments over the Multiple Translation Chinese corpus (LDC, 2003; LDC, 2006). We explore questions of dependency-graph decomposition, binning choices, using multiple parses, and parse-confidence and select a member of that family as a new best measure EDPM that we believe to be a superior representative of the DPM family. In section 4, we explore EDPM's ability to predict changes in a human-generated score (HTER) over a corpus of hypothesis translations in the GALE 2.5 (DARPA, 2008) evaluation. In section 5, we discuss future work and conclude.

2 Definition of DPM and its variants

In this work, we define a family of measures Dependency Pair Match (DPM) that is composed of extensions of the methods described in Owczarzak et al. (2007). DPM is defined as the F measure (harmonic mean of precision and recall) over bags-of-subtrees of the hypothesis translation dependency tree as compared to bags-of-subtrees of the reference translation dependency tree. Figure 1 demonstrates a toy example of the bags-of-dependencies extracted from a hypothesis and reference tree. In the examples presented here, we extract only dlh dependencies, which are tuples of the form $\langle$Dependent, arc-Label, Head$\rangle$. We describe different variants in this family below, and compare their effectiveness in section 3.

2.1 DPM variations in subtree extraction

Different members of the DPM family may extract different subtrees. In this section, we denote the set of tree-components extracted via a trailing subscript: DPM_{dlh} extracts all $\langle$Dependent, arc-Label, Head$\rangle$ subtree tuples for the F measure, which is equivalent (modulo the dependency-extraction methods) to labeled SPARSEVAL and the Owczarzak et al. (2007) **d** measure. $\text{DPM}_{dl,lh}$, by contrast, extracts all the subtrees $\langle$Dependent, arc-Label$\rangle$ and $\langle$arc-Label, Head$\rangle$, which is equivalent to the Owczarzak et al. (2007) **d_var** method (again, modulo the dependency-extraction method). In the example trees in figure 1, the hypothesis tree produces the following six items for scoring with $\text{DPM}_{dl,lh}$:

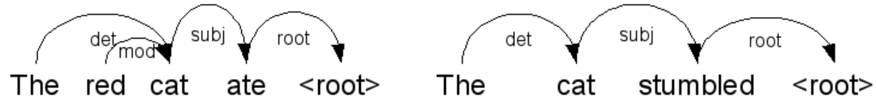
dl	lh
$\langle \text{the}, \xrightarrow{\texttt{det}} \rangle$	$\langle \xrightarrow{\texttt{det}}, \text{cat} \rangle$
$\langle \text{cat}, \xrightarrow{\texttt{subj}} \rangle$	$\langle \xrightarrow{\texttt{subj}}, \text{stumbled} \rangle$
$\langle \text{stumbled}, \xrightarrow{\texttt{root}} \rangle$	$\langle \xrightarrow{\texttt{root}}, \text{<root>} \rangle$

so that $\text{Precision}_{dl,lh}$ is $\frac{3}{6}$ and $\text{Recall}_{dl,lh}$ is $\frac{3}{8}$, giving a $\text{DPM}_{dl,lh}$ of $\frac{3}{7} = 0.429$ for the example.

2.2 DPM variations in binning subscores

When the DPM measure is composed of more than one class of tuple (e.g. $\text{DPM}_{dl,lh}$, but not DPM_{dlh}), we may consider adopting a strategy like BLEU (Papineni et al., 2002) or the syntactic measures from Liu and Gildea (2005) and compute an average of subscores over each tuple class. We define a binned DPM bDPM as the harmonic mean of separate precision and recall scores[1] for each class of tuple involved, rather than simple F (the harmonic mean of

[1] bDPM differs from both Papineni et al. (2002) and Liu and Gildea (2005) in that the earlier metrics use averages over precision subscores, necessitating an "anti-gaming" brevity penalty (in BLEU), while the bDPM measure is an average across precisions and recalls.

	Reference	Hypothesis
dependency tree		
dlh **list**	$\langle$the, $\overset{\texttt{det}}{\rightarrow}$, cat $\rangle$ $\langle$red, $\overset{\texttt{mod}}{\rightarrow}$, cat $\rangle$ $\langle$cat, $\overset{\texttt{subj}}{\rightarrow}$, ate $\rangle$ $\langle$ate, $\overset{\texttt{root}}{\rightarrow}$, <root>$\rangle$	$\langle$ the , $\overset{\texttt{det}}{\rightarrow}$, cat $\rangle$ $\langle$ cat , $\overset{\texttt{subj}}{\rightarrow}$, stumbled$\rangle$ $\langle$stumbled, $\overset{\texttt{root}}{\rightarrow}$, <root> $\rangle$

Precision$_{dlh}$ is $\frac{1}{3}$ and Recall$_{dlh}$ is $\frac{1}{4}$, yielding $\mathrm{DPM}_{dlh} = F = \frac{2}{7} = 0.286$

Figure 1: Example hypothesis and reference dependency trees and the dlh decomposition of each.

a single precision and recall score over all the tuples together).

2.3 DPM variations using n-best lists and expected counts

Since the dependency structure is hidden, we may also be interested in exploring alternative dependency structures (in both hypothesis and reference) predicted by the parser, to cope with both error in the parser and ambiguity in the translation hypothesis and reference. DPM is well-defined over the n-best list of dependency-structures: when $n > 1$, DPM uses the expectation of bags-of-subtrees (rather than the bags-of-subtrees derived from the 1-best parse).

An expectation requires a probability distribution over the n-best list, and we consider three options: uniform, the parser probabilities, and a flattened version of the parser probabilities such that $\tilde{p}(x) = \frac{p(x)^\gamma}{\sum_i p(i)^\gamma}$ (where γ is a free parameter) to account for the fact that the parser tends to be over-confident. In all cases, the probabilities are normalized to sum to one over the the n-best list, where the maximum n in this work is 50. The uniform distribution ($\gamma = 0$) is intended to be equivalent to the Owczarzak et al. (2007) **d_50** and **d_50_var** measures.[2] We note in table 1 those measures in the DPM family that correspond to Owczarzak et al. (2007) measures.

[2]Since Owczarzak et al. (2007) report no use of parse weights, **d_50** and **d_50_var** may be using a sum of counts over the 50-best list rather than expected-counts over a uniform distribution. These two approaches are equivalent — so long as the n-best list is always the same length for hypothesis and reference. In our implementation (section 2.4), the n-best list does not always reach 50 candidate parses on short sentences, so the expectation matches our intent better than a sum of counts over the n-best.

DPM			Owczarzak et al. (2007)
Sub-graph	n	γ	
dlh	1	—	**d**
dlh	50	0	**d_50**
dl, lh	1	—	**d_var**
dl, lh	50	0	**d_50_var**

Table 1: **Correspondences between the** DPM **family of measures and Owczarzak et al. (2007) d_* measures.** Differences between dependency extraction methods are ignored for these equivalencies.

2.4 Implementation of the DPM family

In principle, the DPM family of measures may be implemented with any parser that generates a dependency graph (a single labelled arc for each word, pointing to its head-word). Prior work (Owczarzak et al., 2007) on related measures has used an LFG parser (Cahill et al., 2004) or an unlabelled dependency tree (Liu and Gildea, 2005).

In this work, we use a state-of-the-art PCFG (the first stage of Charniak and Johnson (2005)) and context-free head-finding rules (Magerman, 1995) to generate a 50-best list of dependency trees for each hypothesis and reference translation. We use the parser's default Wall Street Journal training parameters. Head-finding uses the Charniak parser's rules, with three modifications: prepositional and complementizer phrases choose nominal and verbal heads respectively (rather than functional heads) and auxiliary verbs are modifiers of main verbs (rather than the converse).

Having constructed the dependency tree, we la-

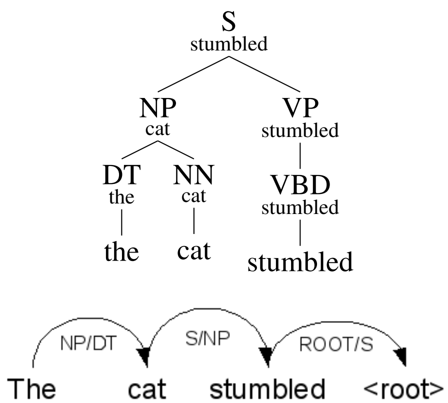


Figure 2: An example constituent tree (heads of each constituent are listed small below the label) and the labelled dependency tree derived from it using the strategy described in section 2.4.

bel the arcs as $d \stackrel{A/B}{\rightarrow} h$, where the arc label A/B between dependent d and its head h is composed of A (the lowest constituent-label headed by h and dominating d) and B (the highest constituent label headed by d). For example, in figure 2, the S node is the lowest node headed by *stumbled* that dominates *cat*, and the NP node is the highest constituent label headed by *cat*, so the arc between *cat* and *stumbled* is labelled $\stackrel{S/NP}{\rightarrow}$. This strategy is very similar to one adopted in the reference implementation of labelled-dependency SPARSEVAL, and may be considered as an approximation of the rich semantics generated by (Cahill et al., 2004) or another heavily knowledge-engineered parser, but with much less knowledge-engineering required.

The A/B labels are not as descriptive as the LFG semantics, but they have a similar resolution, e.g. the $\stackrel{S/NP}{\rightarrow}$ arc label usually represents a subject dependent of a sentential verb.

3 Correlation with human judgments of fluency & adequacy

To select a good member of the DPM family, we explore the correlation of these measures against a corpus of human judgments of fluency and adequacy.

3.1 Corpus

For these experiments, we use LDC Multiple Translation Chinese corpus parts 2 (LDC, 2003) and 4 (LDC, 2006). These corpora include multiple human judgments of fluency and adequacy for each sentence, with each judgment using a different human judge and a different reference translation. For a rough[3] comparison with Owczarzak et al. (2007), we treat each judgment as a separate segment. This treatment of this corpus yields 16,815 tuples of ⟨hypothesis, reference, fluency, adequacy⟩. In these experiments, we extend this tuple with automatic scores derived from ⟨hypothesis, reference⟩ and examine the correlations[4] between those automatic scores and the arithmetic mean of the fluency and adequacy measures.

Measure	r
$\mathrm{DPM}_{dl,lh}$ ($\sim$**d_var**)	0.226
DPM_{dlh} ($\sim$**d**)	0.185
TER	-0.173
BLEU_4	0.139

Table 2: Correlation of various measures with the average of fluency and adequacy over the sentences in the MTC corpus. These DPM results use only the one-best parse ($n = 1$).

3.2 Utility of alternative dependency extraction

Our research suggests that the dependency extraction strategy from section 2.4 works in place of the richer semantics from an LFG parser. The results in table 2, which use only the top parse for each sentence, are very similar to those reported in Owczarzak et al. (2007), in that the syntactic measure $\mathrm{DPM}_{dl,lh}$ ($\sim$**d_var**) is much-better correlated with human judgment than the non-syntactic measures BLEU_4 and TER.

3.3 Alternative dependency sub-graphs

The DPM family allows us to easily explore alternative sub-graphs of the dependency graph, and

[3]Our segment count differs from Owczarzak et al. (2007), who report 16,800 segments over the same corpus. We find baseline correlations (BLEU_4 and TER) lower than those reported there as well, so the results presented here are not directly comparable with that paper, though we demonstrate similar gains over those baselines in essentially the same corpus (section 3.2).

[4]The independence of each of these segments is questionable, since the same hypothesis translations are used in multiple items, but for the sake of methodological comparison with prior work, this strategy is preserved.

Measure	r
$\mathrm{DPM}_{1g,2g,dl,lh}$	0.237
$\mathrm{DPM}_{1g,dl,lh}$	0.234
$\mathrm{DPM}_{1g,2g}$($\equiv$ bag-of-ngrams(2))	0.227
$\mathrm{DPM}_{dl,lh}$	0.226
$\mathrm{DPM}_{1g,dl,dlh}$	0.227
DPM_{dlh}	0.185
TER	-0.173
BLEU_4	0.139

Table 3: As in table 2, but with alternative dependency-graph constituents to compute the F measure. Again, $n = 1$ for all DPM correlations.

DPM **measures**	r
$\mathrm{DPM}_{1g,2g,dl,lh}$	0.237
$\mathrm{bDPM}_{1g,2g,dl,lh}$	0.217
$\mathrm{DPM}_{1g,dl,lh}$	0.227
$\mathrm{bDPM}_{1g,dl,lh}$	0.212
$\mathrm{DPM}_{dl,lh}$	0.226
$\mathrm{bDPM}_{dl,lh}$	0.208
n-gram measures	
bag-of-ngrams(2)	0.227
av-bags-of-ngrams(2)	0.215
BLEU_2	0.211
bag-of-ngrams(3)	0.227
BLEU_3	0.179
av-bags-of-ngrams(3)	0.177
bag-of-ngrams(4)	0.225
BLEU_4	0.139
av-bags-of-ngrams(4)	0.135

Table 4: As in table 3, but also exploring the possibility of binning syntactic and n-gram components of different sizes into subscores and combining, on the model of BLEU. $n = 1$ for all DPM measures.

we find that we achieve small improvements in correlation with human judgments by including the unigram ($1g$) and bigram ($2g$) in the dependency-tree decomposition, ignoring the dependency arc. Owczarzak et al. (2007) found that their original proposal, **d**, scoring full dependent-arc-head triples, was not as well-correlated with human judgment as **d_var**, which examined only dependent-arc and arc-head tuples. Table 2 confirms this as well for a statistical constituent parser with simple dependency-extraction. In table 3, we extend this search to consider whether it is useful to include other subgraphs of the dependency tree into the bag of tree-fragments to be scored.

Table 3 shows that we can combine the benefits of string-local n-grams ($\mathrm{DPM}_{1g,2g}$) with the benefits of dependency information ($\mathrm{DPM}_{dl,lh}$) for a further improved correlation with human judgment, with the best correlation in $\mathrm{DPM}_{1g,2g,dl,lh}$. Including progressively larger chunks of the dependency graph (as in $\mathrm{DPM}_{1g,dl,dlh}$, which is inspired by the BLEU_k idea of progressively larger n-grams) does not seem to be an improvement over $\mathrm{DPM}_{dl,lh}$.

3.4 Binning subscores with bDPM

BLEU (Papineni et al., 2002) and the related NIST (Doddington, 2002) measure, as well as the earlier proposed syntactic measures (Liu and Gildea, 2005), choose to sort their components into bins on length, and take average scores over those bins. Owczarzak et al. (2007) measures, by contrast, and the DPM measures by extension, score all components together in one bin, measuring precision and recall of all bins combined. In table 4 we explore which strategy is preferred, and show that binning with bDPM does not improve correlations for the syntactic measures. In fact, bDPM measures are consistently worse-correlated than their corresponding DPM measure.

For comparison, we try the same approach with n-grams, comparing av-bags-of-ngrams(k) (the harmonic mean of k precisions and k recalls) to bag-of-ngrams(k) (a single F over one bin of n-grams of lengths 1-k), and we find that the single bin again performs better than the separated bins. For comparison, the bag-of-ngrams(1) (a bag-of-words F) has an r of 0.214 over the same corpus; thus, for n-grams, the main improvement is in moving from 1-grams to 2-grams, but only for the non-binned variants. We also include BLEU in table 4, which allows a comparison of BLEU's strategy (average precision and brevity penalty) to an F-style harmonic mean of precision and recall (binned separately and together). We find that BLEU_k does about as well as the corresponding av-bags-of-ngrams(k), while the bag-of-ngrams(k) does consistently better than BLEU_k, especially for larger k.

Measure	parameters	r
$\mathrm{DPM}_{1g,2g,dl,lh}$	$\gamma = 0, n = 50$	0.239
$\mathrm{DPM}_{1g,2g,dl,lh}$	$n = 1$	0.237
$\mathrm{DPM}_{1g,dl,lh}$	$\gamma = 0, n = 50$	0.237
$\mathrm{DPM}_{1g,dl,lh}$	$n = 1$	0.234
$\mathrm{DPM}_{dl,lh}$ ($\sim$ **d_50_var**)	$\gamma = 0, n = 50$	0.234
$\mathrm{DPM}_{dl,lh}$ ($\sim$ **d_var**)	$n = 1$	0.226

Table 5: As in table 3, but considering variants of the best DPM measures uniform probability distribution over multiple parses ($\gamma = 0, n = 50$).

$\mathrm{DPM}_{1g,2g,dl,lh}$			$\mathrm{DPM}_{dl,lh}$		
n	γ	r	n	γ	r
50	0.25	0.240	50	0.25	0.234
50	0.5	0.240	50	0.5	0.234
50	0.75	0.240	50	0	0.234
50	1	0.239	50	0.75	0.233
50	0	0.239	50	1	0.232
1	—	0.237	1	—	0.226

Table 6: As in table 5, but considering various values of γ and n for two different DPM sub-graph lists (dl, lh and $1g, 2g, dl, lh$).

3.5 Using parse n-best lists

We explore the use of multiple parses in table 5, which presents DPM variants with $\gamma = 0$ of the most successful DPM sub-graph lists shown in previous tables. We use $\gamma = 0$ (uniform probability over the n-best list) to compare as closely as possible to Owczarzak et al. (2007), which uses a parser with ranks but no weights.

We find that using multiple parses with a uniform distribution improves correlations further, although the improvement from varying the dependency-tree sub-graphs is not as large for $n = 50$ variants of DPM as for $n = 1$ variants.

3.6 Including parse confidence

Since the parser in our implementation provides a confidence in each parse, we explore the use of that confidence with the γ free parameter. Table 6 explores various "flattenings" (values of γ) of the parse confidence in the DPM measure. $\gamma = 1$ is not always the best, suggesting that the parse probabilities $p(\text{tree}|\text{words})$ are overconfident. We find that $\gamma = 0.25$ is generally the best flattening of the parse confidence for the variants of DPM that we have tested. The differences are small, but the trends are consistent across the variants.

3.7 Summary

In this section, we have presented experiments exploring a number of parameters to the DPM measure. The experiments suggest a best-case variant EDPM, where we set:

$$\mathrm{EDPM} = \mathrm{DPM}_{1g,2g,dl,lh}, n = 50, \gamma = 0.25$$

in which we choose a $1g, 2g, dl, lh$ sub-graph decomposition based on the improvements from better sub-graphs (table 3), multiple parses ($n = 50$) based on table 5, and $\gamma = 0.25$, hinted at by table 6. We use these EDPM parameter-settings in the experiments exploring correlations with HTER (below).

4 Correlations with HTER

Having chosen EDPM as a good candidate member of the DPM family, we explore its utility on another task: predicting the human-targeted translation edit rate (HTER) on the (unsequestered) GALE 2.5 evaluation results.

4.1 Corpus

The GALE 2.5 translation corpus is made up of system translations into English from three sites. The three sites all use system combination to integrate results from multiple systems, some of which are phrase-based and some which may use syntax on either the source or target side. No system provided system-generated parses. The corpus being translated comes from Arabic and Chinese in four genres: `bc` (broadcast conversation), `bn` (broadcast news), `nw` (newswire), and `wb` (web text), with corpus sizes shown in table 7. The corpus includes one English reference translation r_i (LDC, 2008) for each sentence i and a system translation $t_{i,z}$ for each of the three systems z. Additionally, each of the system translations of each segment i has a corresponding human-targeted reference aligned at the sentence level, so we have available the HTER score of each segment $s_{\mathrm{HTER}}(t_{i,z})$ at both the sentence and document level.

	Arabic		Chinese		Total	
	doc	sent	doc	sent	doc	sent
bc	59	750	56	1061	115	1811
bn	63	666	63	620	126	1286
nw	68	494	70	440	138	934
wb	69	683	68	588	137	1271
Total	259	2593	257	2709	516	5302

Table 7: Corpus statistics for the GALE 2.5 translation corpus.

Measure s	all-Arabic	all-Chinese	all
TER	0.51	0.19	0.39
BLEU_4	-0.40	-0.19	-0.32
EDPM	**-0.61**	**-0.25**	**-0.47**

Table 8: Per-doc r of Δs with ΔHTER over various measures s, examined for each genre in the corpus, for each language in the corpus, and as a whole.

4.2 Prediction of ΔHTER per-document

We evaluate our new measure EDPM by testing its prediction of improvements in HTER over different translations of a document. We name one of the three translation systems arbitrarily as baseline b and define

$$\Delta s(i, b, z) \quad = \quad s(t_{i,z}) - s(t_{i,b}) \qquad (1)$$

as a measure of change that system z provides over segment i with respect to system b (by providing translation $t_{i,z}$ instead of $t_{i,b}$).

We would like an automatic measure s that provides a good correlation r between Δs and ΔHTER. For each of the 516 documents[5] in the corpus described in table 7, for each of the three pairs of systems, we generate the Δs scores, ordering the systems such that $\Delta\text{HTER} \geq 0$ for each document pair.

Table 8 shows the per-document correlations with ΔHTER over this set of data, broken out into per-genre and per-language correlations.

We compare EDPM's correlation with HTER against both that of TER and that of BLEU, two very popular automatic measures. It is worth mentioning that TER has an advantage in that HTER uses a TER measure to calculate the post-editing work between the hypothesized translation and the human-targeted reference which could, in principle, bias HTER towards a TER measure. EDPM shares no such advantage. EDPM nevertheless has the best correlation of the three measures in both Arabic and Chinese, as well as over the entire corpus.

In table 9, we break out the results into individual language×genre subcorpora for further comparison. We find that EDPM is the best measure in nearly all subcorpora (Arabic bn standing as an exception).

4.3 Prediction of ΔHTER per-sentence

Like the per-document correlations, at the sentence level we are interested in identifying the predictive power of changes in score s with respect to changes in the gold-standard score (here, HTER). In table 10, we present per-sentence correlations of ΔHTER improvements weighted by sentence length[6], also broken out by individual language×genre subcorpora.

Table 10's per-sentence results are largely similar to the per-document analysis (table 9), although both the absolute and relative differences are smaller.

5 Conclusion and future work

In this paper, we described DPM, a family of metrics for evaluating machine translation quality using a labelled dependency tree. Using the Multiple Translation Chinese corpus, we selected a member of that family EDPM and found a good value for free parameter γ, taking advantage of parse structure and parser probabilities.

We then tested the EDPM measure against the GALE 2.5 translation corpus and evaluated its ability to predict ΔHTER (the change in HTER) on a per-document and per-sentence level. We have shown EDPM to be superior to both BLEU_4 and TER in most cases and for most of the subcorpora available to us.

EDPM has the same advantages as the Owczarzak et al. (2007) **d_*** measures, but is implemented in a more portable way. Both methods require substantially more time to run than BLEU

[5] Using per-document comparison avoids the problems of per-sentence comparisons, e.g. that BLEU falls to zero too easily on a sentence.

[6] When calcluating per-sentence correlations, we want to scale differences in $\Delta s(i, b, z)$ by the length of reference r_i, since an improvement of $x\%$ on score s in a long sentence is ordinarily understood to be worth more than the same $x\%$ on a short sentence.

Measure s	Arabic bc	Arabic bn	Arabic nw	Arabic wb	Chinese bc	Chinese bn	Chinese nw	Chinese wb
TER	0.59	**0.24**	0.22	0.26	0.06	0.13	0.35	0.14
BLEU_4	-0.50	-0.10	**-0.30**	-0.31	-0.01	-0.22	**-0.36**	-0.07
EDPM	**-0.80**	-0.10	**-0.31**	**-0.33**	**-0.14**	**-0.30**	**-0.37**	**-0.16**

Table 9: Per-document r of Δs with ΔHTER for various measures s. Correlations by individual language$\times$genre subcorpora.

Measure s	Arabic bc	Arabic bn	Arabic nw	Arabic wb	Chinese bc	Chinese bn	Chinese nw	Chinese wb
TER	0.54	**0.18**	0.11	0.19	0.15	0.14	**0.26**	**0.13**
BLEU_4	-0.29	-0.15	-0.06	-0.17	-0.06	-0.10	-0.22	**-0.13**
EDPM	**-0.59**	-0.12	**-0.15**	**-0.21**	**-0.18**	**-0.17**	**-0.27**	**-0.13**

Table 10: Per-sentence r of length-weighted Δs with length-weighted ΔHTER. Correlations by individual language$\times$genre subcorpora.

or TER, because parses of both the hypothesis and the reference are required, but the method described in this paper may be implemented with any PCFG-based parser — a treebanked corpus for training that parser should be sufficient.

The correlations with BLEU and TER are both worth a closer examination. Many of the systems used in the comparison were optimized on BLEU themselves, which raises the possibility that current MT systems are over-fitted to BLEU, reducing BLEU's utility as a predictor of quality translation. Conversely, TER's relationship to HTER makes one suspicious about its good correlation; it might be worth testing against another human-directed measure as well.

In future work, we would like to explore a number of related questions. How useful is it to increase n beyond 50 for this approach? We could, for example, use a different PCFG parser as another way of exploring the trade-offs between parse-quality, MT quality prediction, and speed. On the other hand, a poor-quality translation that is very difficult to parse may interfere with the quality of the measure; assessing this measure's sensitivity to sentence quality would also be worthwhile. In a different direction, we would like to ask whether other segmentations of the dependency tree are more appropriate than those explored here, following up on an approach suggested in Liu and Gildea (2005), which uses linked words in chains much larger than 2.

From the results correlating EDPM with both HTER and human judgments of fluency and accuracy, we see that EDPM seems to be a superior tool for identifying improvements at the document level, and a competitive one at the sentence level, which is often where parameter tuning takes place. One possible use for this measure, since it is more computationally-costly than BLEU or TER, might be as a late pass evaluation metric in training to select among translation outputs already deemed to be very good.

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