Edinburgh’s Machine Translation Systems for European Language Pairs

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Abstract

We validated various novel and recently proposed methods for statistical machine translation on 10 language pairs, using large data resources. We saw gains from optimizing parameters, training with sparse features, the operation sequence model, and domain adaptation techniques. We also report on utilizing a huge language model trained on 126 billion tokens.

The annual machine translation evaluation campaign for European languages organized around the ACL Workshop on Statistical Machine Translation offers the opportunity to test recent advancements in machine translation in large data condition across several diverse language pairs.

Building on our own developments and external contributions to the Moses open source toolkit, we carried out extensive experiments that, by early indications, led to a strong showing in the evaluation campaign.

We would like to stress especially two contributions: the use of the new operation sequence model (Section 3) within Moses, and — in a separate unconstraint track submission — the use of a huge language model trained on 126 billion tokens with a new training tool (Section 4).

1 Initial System Development

We start with systems (Haddow and Koehn, 2012) that we developed for the 2012 Workshop on Statistical Machine Translation (Callison-Burch et al., 2012). The notable features of these systems are:

- very large tuning set consisting of the test sets from 2008-2010, with a total of 7,567 sentences per language
- German–English with syntactic pre-reordering (Collins et al., 2005), compound splitting (Koehn and Knight, 2003) and use of factored representation for a POS target sequence model (Koehn and Hoang, 2007)
- English–German with morphological target sequence model

Note that while our final 2012 systems included subsampling of training data with modified Moore-Lewis filtering (Axelrod et al., 2011), we did not use such filtering at the starting point of our development. We will report on such filtering in Section 2.

Moreover, our system development initially used the WMT 2012 data condition, since it took place throughout 2012, and we switched to WMT 2013 training data at a later stage. In this section, we report cased BLEU scores (Papineni et al., 2001) on newstest2011.

1.1 Factored Backoff (German–English)

We have consistently used factored models in past WMT systems for the German–English language pairs to include POS and morphological target sequence models. But we did not use the factored decomposition of translation options into multiple mapping steps, since this usually lead to much slower systems with usually worse results.

A good place, however, for factored decomposition is the handling of rare and unknown source words which have more frequent morphological variants (Koehn and Haddow, 2012a). Here, we used only factored backoff for unknown words, giving gains in BLEU of +.12 for German–English.

1.2 Tuning with k-best MIRA

In preparation for training with sparse features, we moved away from MERT which is known to fall
apart with many more than a couple of dozen features. Instead, we used k-best MIRA (Cherry and Foster, 2012). For the different language pairs, we saw improvements in BLEU of -.05 to +.39, with an average of +.09. There was only a minimal change in the length ratio (Table 1).

|          | MERT | k-best MIRA | $\Delta$ |
|----------|------|-------------|----------|
| de-en    | 22.11 (1.010) | 22.10 (1.008) | -.01 (+.002) |
| fr-en    | 30.00 (1.023) | 30.11 (1.026) | +11 (.003) |
| es-en    | 30.42 (1.021) | 30.63 (1.020) | +21 (.001) |
| cs-en    | 25.54 (1.022) | 25.49 (1.024) | -.05 (.002) |
| en-de    | 16.08 (0.995) | 16.04 (1.001) | -.04 (.006) |
| en-fr    | 29.26 (0.980) | 29.65 (0.982) | +39 (.002) |
| en-es    | 31.92 (0.985) | 31.95 (0.985) | +03 (.000) |
| en-cs    | 17.38 (0.967) | 17.42 (0.974) | +04 (.007) |
| avg      | -    | -           | +.09      |

Table 1: Tuning with k-best MIRA instead of MERT (cased BLEU scores with length ratio).

1.3 Translation Table Smoothing with Kneser-Ney Discounting

Previously, we smoothed counts for the phrasal conditional probability distributions in the translation model with Good Turing discounting. We explored the use of Kneser-Ney discounting, but results are mixed (no difference on average, see Table 2), so we did not pursue this further.

|          | Good Turing | Kneser Ney | $\Delta$ |
|----------|-------------|------------|----------|
| de-en    | 22.10       | 22.15      | +.05     |
| fr-en    | 30.11       | 30.13      | +.02     |
| es-en    | 30.63       | 30.64      | +.01     |
| cs-en    | 25.49       | 25.56      | +.07     |
| en-de    | 16.04       | 15.93      | -.11     |
| en-fr    | 29.65       | 29.75      | +.10     |
| en-es    | 31.95       | 31.98      | +.03     |
| en-cs    | 17.42       | 17.26      | -.16     |
| avg      | -           | -          | +.00     |

Table 2: Translation model smoothing with Kneser-Ney.

1.4 Sparse Features

A significant extension of the Moses system over the last couple of years was the support for large numbers of sparse features. This year, we tested this capability on our big WMT systems. First, we used features proposed by Chiang et al. (2009):

- phrase pair count bin features (bins 1, 2, 3, 4–5, 6–9, 10+)
- target word insertion features
- source word deletion features
- word translation features
- phrase length feature (source, target, both)

The lexical features were restricted to the 50 most frequent words. All these features together only gave minor improvements (Table 3).

|          | baseline | sparse | $\Delta$ |
|----------|----------|--------|----------|
| de-en    | 22.10    | 22.02  | -.08     |
| fr-en    | 30.11    | 30.24  | +.13     |
| es-en    | 30.63    | 30.61  | -.02     |
| cs-en    | 25.49    | 25.49  | +.00     |
| en-de    | 16.04    | 15.93  | -.09     |
| en-fr    | 29.65    | 29.81  | +.16     |
| en-es    | 31.95    | 32.02  | +.07     |
| en-cs    | 17.42    | 17.28  | -.14     |
| avg      | -        | -      | +.04     |

Table 3: Sparse features

We also explored domain features in the sparse feature framework, in three different variations. Assume that we have three domains, and a phrase pair occurs in domain A 15 times, in domain B 5 times, and in domain C never.

We compute three types of domain features:

- binary indicator, if phrase-pairs occurs in domain (example: ind_A = 1, ind_B = 1, ind_C = 0)
- ratio how frequent the phrase pairs occurs in domain (example: ratio_A = \frac{15}{15 + 5} = .75, ratio_B = \frac{5}{15 + 5} = .25, ratio_C = 0)
- subset of domains in which phrase pair occurs (example: subset_{AB} = 1, other subsets 0)

We tested all three feature types, and found the biggest gain with the domain indicator feature (+.11, Table 4). Note that we define as domain the different corpora (Europarl, etc.). The number of domains ranges from 2 to 9 (see column #d).

|        | #d | base indicator ratio | subset |
|--------|----|----------------------|--------|
| de-en  | 2  | 22.10                | 22.07  | 22.12 +.02 |
| fr-en  | 4  | 30.11                | 30.29  | 30.15 +.04 |
| es-en  | 3  | 30.63                | 30.64  | 30.82 +.19 |
| cs-en  | 9  | 25.49                | 25.58  | 25.46 +.03 |
| en-de  | 2  | 16.12                | 15.96  | 16.01 +.11 |
| en-fr  | 4  | 29.65                | 29.71  | 29.70 +.05 |
| en-es  | 3  | 31.95                | 32.13  | 32.02 +.07 |
| en-cs  | 9  | 17.42                | 17.35  | 17.44 +.02 |
| avg    | -  | -                    | +.11   | +.03      |

Table 4: Sparse domain features

When combining the domain features and the other sparse features, we see roughly additive gains (Table 5). We use the domain indicator feature and the other sparse features in subsequent experiments.

1In the final experiments on the 2013 data condition, one domain (commoncrawl) was added for all language pairs.
1.5 Tuning Settings

Given the opportunity to explore the parameter tuning of models with sparse features across many language pairs, we investigated a number of settings. We expect tuning to work better with more iterations, longer n-best lists and bigger cube pruning pop limits. Our baseline settings are 10 iterations with 100-best lists (accumulating) and a pop limit of 1000 for tuning and 5000 for testing.

| baseline indicator | ratio | subset |
|--------------------|-------|--------|
| de-en              | 22.10 | 22.18 +.08 |
| fr-en              | 30.11 | 30.41 +.30 |
| es-en              | 30.63 | 30.75 +.12 |
| cs-en              | 25.49 | 25.56 +.07 |
| en-de              | 16.12 | 15.95 –.17 |
| en-fr              | 29.65 | 29.96 +.31 |
| en-es              | 31.95 | 32.12 +.17 |
| en-cs              | 17.42 | 17.38 –.04 |

Table 5: Combining domain and other sparse features

1.7 Unpruned Language Models

Previously, we trained 5-gram language models using the default settings of the SRILM toolkit in terms of singleton pruning. Thus, training throws out all singletons n-grams of order 3 and higher. We explored whether unpruned language models could give better performance, even if we are only able to train 4-gram models due to memory constraints. At the time, we were not able to build unpruned 4-gram language models for English, but for the other language pairs we did see improvements of -.07 to +.13 (Table 8). We adopted such models for these language pairs.

| 5g pruned | 4g unpruned | Δ |
|-----------|-------------|---|
| en-fr      | 29.89       | 29.83 | -.07 |
| en-es      | 32.27       | 32.34 | +.07 |
| en-cs      | 17.41       | 17.54 | +.13 |

Table 8: Language models without singleton pruning

1.8 Translations per Input Phrase

Finally, we explored one more parameter: the limit on how many translation options are considered per input phrase. The default for this setting is 20. However, our experiments (Table 9) show that we can get better results with a translation table limit of 100, so we adopted this.

| ttl 20 | ttl 30 | ttl 50 | ttl 100 |
|-------|-------|-------|---------|
| de-en | 21.05 | +.06  | +.09    | +.01    |
| fr-en | 30.39 | -.02  | +.05    | +.07    |
| es-en | 30.86 | ±.00  | -.03    | -.07    |
| cs-en | 25.53 | +.24  | +.13    | +.20    |
| en-de | 15.97 | +.03  | +.07    | +.11    |
| en-fr | 29.83 | +.14  | +.19    | +.13    |
| en-es | 32.34 | +.08  | +.10    | +.07    |
| en-cs | 17.54 | -.05  | -.02    | +.01    |

Table 9: Maximal number translations per input phrase

1.9 Other Experiments

We explored a number of other settings and features, but did not observe any gains.
• Using HMM alignment instead of IBM Model 4 leads to losses of –.01 to –.27.
• An earlier check of modified Moore–Lewis filtering (see also below in Section 3) gave very inconsistent results.
• Filtering the phrase table with significance filtering (Johnson et al., 2007) leads to losses of –.19 to –.63.
• Throwing out phrase pairs with direct translation probability $\phi(\overline{e} | \overline{f})$ of less than $10^{-5}$ has almost no effect.
• Double-checking the contribution of the sparse lexical features in the final setup, we observe an average losses of –.07 when dropping these features.
• For the German–English language pairs we saw some benefits to using sparse lexical features over POS tags instead of words, so we used this in the final system.

1.10 Summary
We adopted a number of changes that improved our baseline system by an average of +.30, see Table 10 for a breakdown.

| avg. method                                    | baseline | improved |
|-----------------------------------------------|----------|----------|
| +.01 factored backoff                         | 21.99    | 22.09    | +.10    |
| +.09 kbest MIRA                               | 30.00    | 30.46    | +.46    |
| +.11 sparse features and domain indicator     | 30.42    | 30.79    | +.37    |
| +.03 tuning with 25 iterations                | 25.54    | 25.73    | +.19    |
| –.03 maximum phrase length 5                  | 16.08    | 16.08    | ±.00    |
| +.02 unpruned 4-gram LM                       | 29.26    | 29.96    | +.70    |
| +.07 translation table limit 100              | 31.92    | 32.41    | +.49    |
| +.30 total                                    | 17.38    | 17.55    | +.17    |

Table 10: Summary of impact of changes

Minor improvements that we did not adopt was avoiding reducing maximum phrase length to 5 (average +.03) and tuning with 1000-best lists (+.02).

The improvements differed significantly by language pair, as detailed in Table 11, with the biggest gains for English–French (+.70), no gain for English–German and no gain for English–German.

1.11 New Data
The final experiment of the initial system development phase was to train the systems on the new data, adding newstest2011 to the tuning set (now 10,068 sentences). Table 12 reports the gains on newstest2012 due to added data, indicating very clearly that valuable new data resources became available this year.

| WMT 2012 | WMT 2013 | Δ      |
|----------|----------|--------|
| de-en    | 23.11    | 24.01  | +0.90 |
| fr-en    | 29.25    | 30.77  | +1.52 |
| es-en    | 32.80    | 33.99  | +1.19 |
| cs-en    | 22.53    | 22.86  | +0.33 |
| ru-en    | –        | 31.67  | –      |
| en-de    | 16.78    | 17.95  | +1.17 |
| en-fr    | 27.92    | 28.76  | +0.84 |
| en-es    | 33.41    | 34.00  | +0.59 |
| en-cs    | 15.51    | 15.78  | +0.27 |
| en-ru    | –        | 23.78  | –      |

Table 11: Overall improvements per language pair

2 Domain Adaptation Techniques
We explored two additional domain adaptation techniques: phrase table interpolation and modified Moore-Lewis filtering.

2.1 Phrase Table Interpolation
We experimented with phrase-table interpolation using perplexity minimisation (Foster et al., 2010; Sennrich, 2012). In particular, we used the implementation released with Sennrich (2012) and available in Moses, comparing both the naive and modified interpolation methods from that paper. For each language pair, we took the alignments created from all the data concatenated, built separate phrase tables from each of the individual corpora, and interpolated using each method. The results are shown in Table 13

| baseline | naive         | modified       |
|----------|---------------|----------------|
| fr-en    | 30.77         | 30.63 –.14     | –              |
| cs-en    | 33.98         | 33.83 –.15     | 34.03 +.05     |
| ru-en    | 23.19         | 22.77 –.42     | 23.03 –.17     |
| en-fr    | 31.67         | 31.42 –.25     | 31.59 –.08     |
| en-es    | 28.76         | 28.88 +.12     | –              |
| en-cs    | 34.00         | 34.07 +.07     | 34.31 +.31     |
| en-ru    | 15.78         | 15.88 +.10     | 15.87 +.09     |
| en-cs    | 23.78         | 23.84 +.06     | 23.68 –.10     |

Table 13: Comparison of phrase-table interpolation (two methods) with baseline (on newstest2012 scores)

The results from the phrase-table interpolation are quite mixed, and we only used the technique
for the final system in en-es. An interpolation based on PRO has recently been shown (Haddow, 2013) to improve on perplexity minimisation is some cases, but the current implementation of this method is limited to 2 phrase-tables, so we did not use it in this evaluation.

2.2 Modified Moore-Lewis Filtering

In last year’s evaluation (Koehn and Haddow, 2012b) we had some success with modified Moore-Lewis filtering (Moore and Lewis, 2010; Axelrod et al., 2011) of the training data. This year we conducted experiments in most of the language pairs using MML filtering, and also experimented using instance weighting (Mansour and Ney, 2012) using the (exponential of) the MML weights. The results are show in Table 14.

As with phrase-table interpolation, MML filtering and weighting shows a very mixed picture, and not the consistent improvements these techniques offer on IWSLT data. In the final systems, we used MML filtering only for es-en.

3 Operation Sequence Model (OSM)

We enhanced the phrase segmentation and reordering mechanism by integrating OSM: an operation sequence N-gram based translation and reordering model (Durrani et al., 2011) into the Moses phrase-based decoder. The model is based on minimal translation units (MTUs) and Markov chains over sequences of operations. An operation can be (a) to jointly generate a bi-language MTU, composed from source and target words, or (b) to perform reordering by inserting gaps and doing jumps.

Model: Given a bilingual sentence pair $< F,E >$ and its alignment $A$, we transform it to a sequence of operations $(o_1, o_2, \ldots, o_J)$ and learn a Markov model over this sequence as:

$$p_{osm}(F,E,A) = p(o_1^J) = \prod_{j=1}^{J} p(o_j | o_{j-n+1}, \ldots, o_{j-1})$$

By coupling reordering with lexical generation, each (translation or reordering) decision conditions on $n - 1$ previous (translation and reordering) decisions spanning across phrasal boundaries thus overcoming the problematic phrasal independence assumption in the phrase-based model. In the OSM model, the reordering decisions influence lexical selection and vice versa. Lexical generation is strongly coupled with reordering thus improving the overall reordering mechanism.

We used the modified version of the OSM model (Durrani et al., 2013b) that additionally handles discontinuous and unaligned target MTUs\(^3\). We borrow 4 count-based supportive features, the Gap, Open Gap, Gap-width and Deletion penalties from Durrani et al. (2011).

Training: During training, each bilingual sentence pair is deterministically converted to a unique sequence of operations. Please refer to Durrani et al. (2011) for a list of operations and the conversion algorithm and see Figure 1 and Table 15 for a sample bilingual sentence pair and its step-wise conversion into a sequence of operation. A 9-gram Knesev-Ney smoothed operation sequence model is trained with SRILM.

Search: Although the OSM model is based on minimal units, phrase-based search on top of OSM model was found to be superior to the MTU-based decoding in Durrani et al. (2013a). Following this framework allows us to use OSM model in tandem with phrase-based models. We integrated the generative story of the OSM model into the hypothesis extension of the phrase-based Moses decoder. Please refer to (Durrani et al., 2013b) for details.

Results: Table 16 shows case-sensitive BLEU scores on newstest2012 and newstest2013 for fi-

\[ \text{Table 14: Comparison of MML filtering and weighting with baseline.} \]

| Language pair | Base line | MML 20% | Inst. Wt | Inst. Wt (scale) |
|---------------|-----------|---------|----------|-----------------|
| fr-en         | 30.77     | 34.26   | 33.85    | 33.98 ± 0.00    |
| cs-en         | 23.19     | 34.26 + 0.28 | 23.17 - 0.02 | 23.13 - 0.06    |
| en-fr         | 28.67     | 28.74 + 0.07 | 28.81 + 0.17 | 28.63 - 0.04    |
| en-es         | 34.00     | 34.07 + 0.07 | 34.27 + 0.27 | 34.03 + 0.03    |
| en-cs         | 15.78     | 15.37 - 0.41 | 15.87 + 0.09 | 15.89 + 0.11    |
| en-ru         | 23.78     | 22.90 - 0.88 | 23.82 + 0.05 | 23.72 - 0.06    |

\[ \text{Figure 1: Bilingual Sentence with Alignments} \]

\[ \text{Table 15:} \]

| Operation Sequence | Example |
|--------------------|---------|
| \( o_1 \)         | I do not go to the house |
| \( o_2 \)         | Ich gehe ja nicht zum Haus |

\[ \text{Figure 1:} \]

\[ \text{Bilingual Sentence with Alignments} \]

\[ \text{Table 15:} \]

| Operation Sequence | Example |
|--------------------|---------|
| \( o_1 \)         | I do not go to the house |
| \( o_2 \)         | Ich gehe ja nicht zum Haus |

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\( ^3 \)In the original OSM model these are removed from the alignments through a post-processing heuristic which hurts in some language pairs. See Durrani et al. (2013b) for detailed experiments.
nal systems from Section 1 and these systems augmented with the operation sequence model. The model gives gains for all language pairs (BLEU +.09 to +.90, average +.37, on newstest2013).

### 4 Huge Language Models

To overcome the memory limitations of SRILM, we implemented modified Kneser-Ney (Kneser and Ney, 1995; Chen and Goodman, 1998) smoothing from scratch using disk-based streaming algorithms. This open-source tool is described fully by Heafield et al. (2013). We used it to estimate an unpruned 5-gram language model on web pages from ClueWeb09. The corpus was preprocessed by removing spam (Cormack et al., 2011), selecting English documents, splitting sentences, deduplicating, tokenizing, and truecasing. Estimation on the remaining 126 billion tokens took 2.8 days on a single machine with 140 GB RAM (of which 123 GB was used at peak) and six hard drives in a RAID5 configuration. Statistics about the resulting model are shown in Table 17.

The large language model was then quantized to 10 bits and compressed to 643 GB with KenLM (Heafield, 2011), loaded onto a machine with 1 TB RAM, and used as an additional feature in unconstrained French–English, Spanish–English, and Czech–English submissions. This additional language model is the only difference between our final constrained and unconstrained submissions; no additional parallel data was used. Results are shown in Table 18. Improvement from large language models is not a new result (Brants et al., 2007); the primary contribution is estimating on a single machine.

### 5 Summary

Table 19 breaks down the gains over the final system from Section 1 from using the operation sequence models (OSM), modified Moore-Lewis filtering (MML), fixing a bug with the sparse lexical features (Sparse-Lex Bugfix), and instance weighting (Instance Wt.), translation model combination (TM-Combine), and use of the huge language model (ClueWeb09 LM).

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Table 15: Step-wise Generation of Figure 1

| Operation Sequence | Generation |
|--------------------|------------|
| Generate (Ich, I)  | Ich ↓ I    |
| Generate Target Only (do) | Ich ↓ I do |
| Insert Gap         | Ich nicht ↓ I do not |
| Generate (nicht, not) | Ich gehe ja nicht ↓ I do not |
| Jump Back (1)      | Ich gehe ja nicht ↓ I do not |
| Generate (gehe, go) | Ich gehe ja nicht ↓ I do not |
| Jump Forward       | Ich gehe ja nicht ↓ I do not |
| Generate (zum, to the) | ... gehe ja nicht zum ↓ ... not go to the |
| Generate (haus, house) | ... ja nicht zum haus ↓ ... go to the house |

Table 16: Results using the OSM Feature

| LP     | Baseline | +OSM |
|--------|----------|------|
| newstest | 2012    | 2013 |
| dc-en   | 23.85    | 26.34 |
| fr-en   | 30.77    | 31.09 |
| es-en   | 34.02    | 30.04 |
| cs-en   | 22.70    | 25.70 |
| ru-en   | 31.87    | 24.00 |
| en-de   | 17.95    | 20.06 |
| en-fr   | 28.76    | 30.03 |
| en-es   | 33.87    | 29.66 |
| en-cs   | 15.81    | 18.35 |
| en-ru   | 23.75    | 18.44 |

Table 17: Counts of unique n-grams (m for millions) for the 5 orders in the unconstrained language model

|     | 1    | 2               | 3               | 4               | 5               |
|-----|------|-----------------|-----------------|-----------------|-----------------|
| 393m| 3,775m| 17,629m         | 39,919m         | 59,794m         |

Table 18: Gain on newstest2013 from the unconstrained language model. Our time on shared machines with 1 TB is limited so Russian–English was run after the deadline and German–English was not ready in time.
Table 19: Summary of methods with BLEU scores on newstest2012 and newstest2013. Bold systems were submitted with the ClueWeb09 LM systems submitted in the unconstraint track. The German–English and English–German OSM systems did not complete in time for the official submission.

| System                  | 2012   | 2013   |
|-------------------------|--------|--------|
| **Spanish-English**     |        |        |
| 1. Baseline             | 34.02  | 30.04  |
| 2. 1+OSM                | 34.51 +.49 | 30.94 +.90 |
| 3. 1+MML (20%)         | 34.38 +.36 | 30.38 +.34 |
| 4. 1+Sparse-Lex Bugfix  | 34.17 +.15 | 30.33 +.29 |
| 5. 1+2+3: OSM+MML      | 34.65 +.63 | 30.51 +.47 |
| 6. 1+2+3+4             | 34.68 +.66 | 30.59 +.55 |
| 7. 6+ClueWeb09 LM      | 31.37 +1.33 |        |
| **Czech-English**       |        |        |
| 1. Baseline             | 22.70  | 25.70  |
| 2. 1+OSM                | 23.03 +.33 | 25.79 +.09 |
| 3. 1+TM-Combine         | 34.31 +.44 | 29.76 +.10 |
| 4. 1+Instance Wt.      | 34.27 +.40 | 29.63 +.03 |
| 5. 1+Sparse-Lex Bugfix  | 34.20 +.33 | 29.86 +.20 |
| 6. 1+2+3: OSM+TM-Cmb.  | 34.63 +.76 | 30.21 +.55 |
| 7. 1+2+4: OSM+Inst. Wt.| 34.58 +.71 | 30.11 +.45 |
| 8. 1+2+3+5             | 34.78 +.91 | 30.43 +.77 |
| **English-Czech**       |        |        |
| 1. Baseline             | 15.85  | 18.35  |
| 2. 1+OSM                | 16.16 +.31 | 18.62 +.27 |
| **French-English**      |        |        |
| 1. Baseline             | 30.77  | 31.09  |
| 2. 1+OSM                | 30.96+.19 | 31.46+.37 |
| 3. 2+ClueWeb09 LM      | 32.24 +1.15 |        |
| **German-English**      |        |        |
| 1. Baseline             | 28.76  | 30.03  |
| 2. 1+OSM                | 29.36 +.60 | 30.39 +.36 |
| 3. 1+Sparse-Lex Bugfix  | 28.97 +.21 | 30.08 +.05 |
| 4. 1+2+3                | 29.37 +.61 | 30.58 +.55 |
| **English-German**      |        |        |
| 1. Baseline             | 23.85  | 26.54  |
| 2. 1+OSM                | 24.11 +.26 | 26.83 +.29 |
| **Russian-English**     |        |        |
| 1. Baseline             | 17.95  | 20.06  |
| 2. 1+OSM                | 18.02 +.07 | 20.26 +.20 |
| **English-Russian**     |        |        |
| 1. Baseline             | 31.87  |        |
| 2. 1+OSM                | 32.33 +.46 | 24.33 +.33 |

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