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#### **Publisher's version / Version de l'éditeur:**

*Proceedings of the Eleventh Conference of the Association for Machine Translation in the Americas (AMTA), 2014, 1, pp. 28-41, 2014-10*

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# Coarse “split and lump” bilingual language models for richer source information in SMT

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## Abstract

Recently, there has been interest in automatically generated word classes for improving statistical machine translation (SMT) quality: *e.g.*, (Wuebker *et al.*, 2013). We create new models by replacing words with word classes in features applied during decoding; we call these “coarse models”. We find that coarse versions of the bilingual language models (biLMs) of (Niehues *et al.*, 2011) yield larger BLEU gains than the original biLMs. BiLMs provide phrase-based systems with rich contextual information from the source sentence; because they have a large number of types, they suffer from data sparsity. Niehues *et al.* (2011) mitigated this problem by replacing source or target words with parts of speech (POSs). We vary their approach in two ways: by clustering words on the source or target side over a range of granularities (word clustering), and by clustering the bilingual units that make up biLMs (bitoken clustering). We find that loglinear combinations of the resulting coarse biLMs with each other and with coarse LMs (LMs based on word classes) yield even higher scores than single coarse models. When we add an appealing “generic” coarse configuration chosen on English > French devtest data to four language pairs (keeping the structure fixed, but providing language-pair-specific models for each pair), BLEU gains on blind test data against strong baselines averaged over 5 runs are **+0.80** for English > French, **+0.35** for French > English, **+1.0** for Arabic > English, and **+0.6** for Chinese > English.

## 1. Introduction

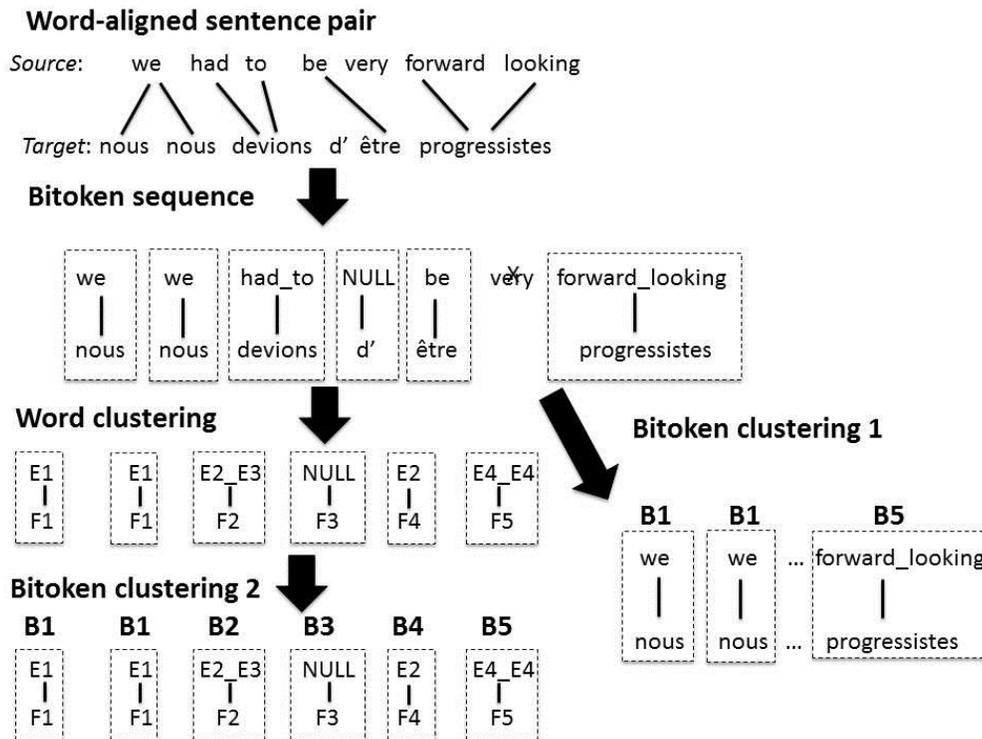
This work aims to provide rich contextual information to phrase-based SMT, in order to mitigate data sparsity. We cluster the basic units of the bilingual language model (biLM) of Niehues *et al.* (2011) and of standard language models (LMs). A “generic”, symmetric configuration chosen on English > French devtest yields BLEU gains over strong baselines on blind test data of **+0.80** for English > French (henceforth “Eng>Fre”), **+0.35** for French > English (“Fre>Eng”), **+1.0** for Arabic > English (“Ara>Eng”), and **+0.6** for Chinese > English (“Chi>Eng”). If we apply the configuration with the highest devtest score on a given language pair to blind data, the gains are **+0.85** for Eng>Fre, **+0.46** for Fre>Eng, and **+1.2** for Ara>Eng, but still **+0.6** for Chi>Eng.

### 1.1. Coarse bilingual language models (biLMs) for source context

Though coarse biLMs are the focus of this paper, we explored other coarse models: models where words are replaced by word classes. *E.g.*, we obtained good gains in earlier experiments with coarse LMs. Since others have explored that terrain before us (see **1.2**), this paper focuses on the “bilingual language model” (biLM) of Niehues *et al.* (2011). In phrase-based

SMT, information from source words outside the current phrase pair is incorporated only indirectly, via target words that are translations of these source words, if the relevant target words are close enough to the current target word to affect LM scores. BiLMs address this by aligning each target word in the training data with source words to create “bitokens”. An N-gram bitoken LM is then trained. A coarse biLM is one whose words and/or bitokens have been clustered into classes. Our best results were obtained by combining coarse biLMs with coarse LMs. We tune our system with batch lattice MIRA (Cherry and Foster, 2012), which supports loglinear combinations that have many features.

**Figure 1** shows word-based and coarse biLMs for Eng>Fre. A target word and its aligned source words define a bitoken. Unaligned target words (*e.g.*, French word “d’ ” in the example) are aligned with NULL. Unaligned source words (*e.g.*, “very”) are dropped. A source word aligned with more than one target word (*e.g.*, “we”, aligned with two instances of “nous”) is duplicated: each target word aligned with it receives a copy of that source word.



**Figure 1.** Creating bitokens & bitoken classes for a bilingual language model (biLM)

BiLMs can easily be incorporated into a phrase-based architecture. The decoder still uses phrase pairs from a phrase table to create hypotheses. However, a new LM with a wide context span of source information can now score hypotheses, along with the standard LM (Niehues *et al* found it was best to retain the latter). Unfortunately, the bitoken vocabulary of a biLM will be much bigger than the target-language vocabulary, because a target word is often split into different bitokens. *E.g.*, the word “être” might be split into three bitokens: “être\_be”, “être\_being”, and “être\_to-be”. One solution to the sparsity problem is to lump bitokens into new classes. *E.g.*, one could replace each English or French word above with its part of speech (POS). In (Niehues *et al*, 2011), this “split and lump” process was applied to

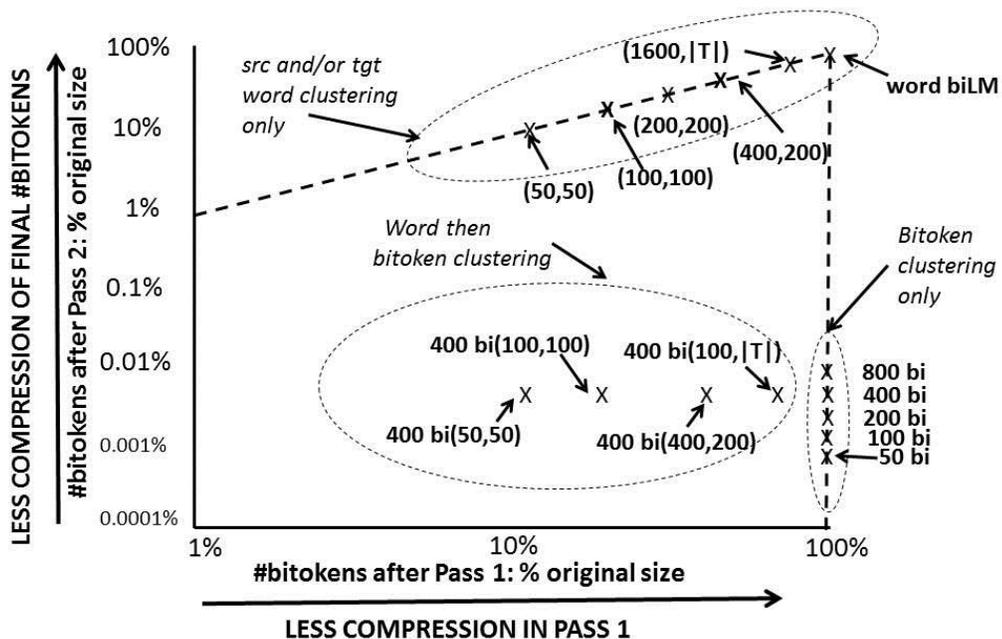
both sides of a biLM for Ara>Eng SMT. When the biLM was added as a new loglinear feature to a system with a word-based biLM, it yielded a modest gain of about +0.2 BLEU. In our work, we try other versions of “split and lump”. Instead of using taggers to define POSs, we use a program called **mkcls** (see 1.2) to create clusters. Unlike Niehues *et al* (2011), we vary the granularity of word clustering, and sometimes cluster the bitokens themselves, calling the resulting models “coarse biLMs”.

**Figure 1** also shows three ways of building coarse biLMs: 1. clustering source and/or target words, then creating bitokens. 2. clustering the word-based bitokens themselves, with **mkcls** using bitoken perplexity as its criterion (in **Fig. 1**, “bitoken clustering 1”). 3. clustering bitokens whose source and/or target words have been “preclustered” (“bitoken clustering 2”). Here, **E1**, **E2**, *etc.*, and **F1**, **F2**, *etc.*, are word classes generated by **mkcls** operating on source (English) and target (French) text respectively; **B1**, **B2**, *etc.* denote bitoken classes.

### Landscape of coarse biLMs

(Eng > Fre examples)

Pass 1 (optional): src and/or tgt word clustering  
 Pass 2 (optional): bitoken clustering



**Figure 2.** Two-pass construction of bitokens for a coarse biLM

**Figure 2** illustrates the three types of coarse biLM, each shown by a dotted-line oval. A key aspect of a biLM is its bitoken vocabulary size. *E.g.*, for the Eng>Fre experiments on which **Figure 2** is based, the original word biLM had a vocabulary of 7.6 million bitokens. Coarse biLMs result from two passes of bitoken vocabulary compression, both optional: a first pass of clustering of source and/or target words, and a second pass of bitoken clustering. Skipping both passes yields the word-based biLM. The X coordinates in **Figure 2** give the biLM vocabulary size after the first pass, and the Y coordinates give its size after the second pass (as a percentage of its original size). The original biLM (“word biLM”) is in the upper right-hand corner: both passes are null operations, so the coordinates are (100%,100%).

We denote word clustering by  $(n1, n2)$ , where  $n1$  and  $n2$  are number of source and target word classes respectively.  $|S|$  and  $|T|$  are the original sizes of the source and target vocabularies. The top oval in **Figure 2** contains coarse biLMs obtained by pass 1 (word clustering) but **not** pass 2 (bitoken clustering). *E.g.*, “(400, 200)” is the coarse biLM obtained by using 400 and 200 word classes for English and French respectively; “(1600, |T|)” is the coarse biLM obtained with 1600 English classes and no clustering for French. The oval on the far right contains biLMs created when only pass 2 is applied. *E.g.*, “50 bi” is the coarse biLM obtained by clustering the 7.6M word-based bitokens down to only 50. The third oval contains coarse biLMs produced by applying pass 1, then pass 2. *E.g.*, “400 bi(400,200)” is the coarse biLM obtained by creating bitokens with 400 and 200 source and target word classes respectively, then clustering these bitokens into 400 classes. A defect of the figure is that its axes don’t represent the difference between word clustering on the source *vs.* target sides. However, the figure conveys our greatest problem: the vast number of possible coarse biLMs

There is a big space in the middle of the figure that wasn’t explored in our experiments: there are no final biLMs that have between 0.01% and 10% of the original number of word biLMs, because **mkcls** becomes very slow as the number of word classes grows: creating coarse biLMs like “(10,000, 10,000)” or “10,000 bi(400,400)” is infeasible.

## 1.2. Related work

This section will discuss work on **coarse models**, **source-side contextual information** for SMT, and **lexical clustering techniques** (including **mkcls**, used for our experiments).

Uszkoreit and Brant (2008) explored coarse LMs for SMT. Wuebker *et al* (2013) describe coarse LMs, translation models (TMs), and reordering models (RMs). Best performance was obtained with a system containing both word-based and coarse models. Prior to our current work, we experimented with discriminative hierarchical RMs (DHRMs) (Cherry, 2013). These combine the hierarchical RM (HRM) of (Galley and Manning, 2008) with sparse features conditioned on word classes for phrases involved in reordering; word classes are obtained from **mkcls**. Like Cherry (2013), we found that DHRM outperformed the HRM version for Ara>Eng and Chi>Eng. However, experiments with English-French Hansard data showed only small gains for DHRM over HRM. Thus, while all the Ara>Eng and Chi>Eng experiments reported in this paper employ DHRM - a **coarse reordering model** - none of the Eng<>Fre experiments do. In prior experiments, we also studied **coarse phrase translation models**, but unlike Wuebker *et al* (2013), we found they did not yield significant improvements to our system, except when there is little training data. Many experiments in this paper involve **coarse language models**. These are particularly effective for morphologically rich languages (*e.g.*, Ammar *et al*, 2013; Bisazza and Monz, 2014). In unpublished earlier experiments, we found that coarse LM combinations can yield better results than using just one.

Besides biLMs (Niehues *et al*, 2011), there are other ways of incorporating additional source-language information in SMT. These include spectral clustering for HMM-based SMT (Zhao, Xing and Waibel, 2005), stochastic finite state transducers based on bilingual ngrams (Casacuberta and Vidal, 2004; Mariño *et al*, 2006; Crego and Yvon, 2010; Zhang *et al*, 2013), the lexicalized approach of (Hasan *et al*, 2008), factored Markov backoff models (Feng *et al*, 2014) and the “operation sequence model” (OSD) of (Durrani *et al*, 2011 and 2014). (Durrani *et al* 2014) appeared after our current paper was submitted. Our work and theirs shares an underlying motivation in which **mkcls** is applied to make earlier models more powerful, though the OSD models and ours are very different. We chose to implement biLMs primarily because this is easy to do in a phrase-based system.

Automatic word clustering was described in (Jelinek, 1991; Brown *et al*, 1992). In “Brown” or “IBM” clustering, each word in vocabulary  $V$  initially defines a single class.

These classes are clustered bottom-up into a binary tree of classes, with classes iteratively merging to minimize text perplexity under a class-based bigram LM, until the desired number of classes  $C$  is attained. Martin, Liermann, and Ney (1998) describe “exchange” clustering. Each word in  $V$  is initially assigned to a single class in some fashion. Then, each word in turn is reassigned to a class so as to minimize perplexity; movement of words between classes continues until a stopping criterion is met. When these authors compared various word clustering methods, the perplexity results were almost identical. The lowest bigram perplexity is usually obtained when each of the most frequent words is in a different class; different word clustering methods typically all ended up with arrangements similar to this. These authors obtained their best perplexity and speech recognition results when the clustering criterion was based on trigrams as well as bigrams, but this makes clustering expensive. Och (1999) focuses on bilingual word clustering and discusses ideas similar to bitoken clustering, though not in the context of phrase-based SMT. Uszkoreit and Brant (2008) describe a highly efficient distributed version of exchange clustering. Faruqui and Dyer (2013) propose a bilingual word clustering method whose objective function combines same-language and cross-language mutual information. Applied to named entity recognition (NER), this yields significant improvements. Turian, Ratinov and Bengio (2010) apply Brown clustering to NER and chunking. Finally, Blunsom and Cohn (2011) improve Brown clustering by using a Bayesian prior to smooth estimates, by incorporating trigrams, and by exploiting morphological information.

For word clustering, we chose a widely used program, **mkcls**: Blunsom and Cohn (2011) note its strong performance. We could have used POSs, but they have definitions that vary across languages; **mkcls** can be applied in a uniform way (though with the disadvantage that it gives each word a fixed class, instead of several possible classes as with POSs). Niesler *et al* (1998) found that automatically derived word classes outperform POSs. Until recently, the only document describing **mkcls** was in German (Och, 1995): accurate English information was unavailable. It is often suggested that **mkcls** implements (Och, 1999), but this is only partly true. Fortunately, Dr. Chris Dyer now provides an accurate description on his blog: <http://statmt.blogspot.ca/2014/07/understanding-mkcls.html>. Basically, **mkcls** executes an ensemble of optimizers and merges their results; the criterion for all steps is minimal bigram perplexity. Dr. Dyer estimates that the perplexity of an LM built from the resulting word classes is typically 20-40% lower than for bottom-up Brown clustering on its own.

## 2. Experiments

### 2.1. Experimental approach

Using four diverse large-scale machine translation tasks (Eng>Fre, Fre>Eng, Ara>Eng, Chi>Eng), we studied the impact of coarse BiLMs in isolation and in combination with coarse LMs. Our challenge was to explore the most interesting possibilities without doing innumerable experiments. Ammar *et al* (2013) note that coarse models are particularly effective when the target language has complex morphology. We thus decided to use Eng>Fre experiments on devtest data to carry out initial explorations: this language pair would be a sensitive one. Our metric was average BLEU over Devtest1 and Devtest2 for a Hansard system (see **Table 1**). There is insufficient space to report all these Eng>Fre devtest experiments. The first round of experiments made us decide to explore coarse LMs and coarse biLMs, but not coarse TMs (these only gave appreciable gains for small amounts of training data); we would employ Witten-Bell smoothing for the coarse models (coarse models generate counts of counts that the SRILM implementation of Kneser-Ney can’t cope with, and Witten-Bell slightly outperformed Good-Turing for coarse models); we would use 8-gram coarse models (results differed only slightly along the range from 6-grams to 8-grams, but were marginally better for 8-

grams). We then began a second round of Eng>Fre experiments with the same devtest (see **2.4** and **Table 4**); the results informed all subsequent experiments.

## 2.2. Experimental data

For English-French experiments in both directions, we used the high-quality Hansard corpus of Canadian parliamentary proceedings from 2001-2009 (Foster *et al*, 2010). We reserved the most recent five documents (from December 2009) for development and testing material, and extracted the dev and test corpora shown in **Table 1**. Some of the documents were much larger than typical devtest sizes, so we sampled subsets of them for the dev and test sets.

Corpus	# sentence pairs	# words (English)	# words (French)
Train	2.9M	60.5M	68.6M
Tune	2,002	40K	45K
Devtest1	2,148	43K	48K
Devtest2	2,166	45K	50K
Test1 (blind test)	1,975	39K	44K
Test2 (blind test)	2,340	49K	55K

**Table 1.** Corpus sizes for English<math>\leftrightarrow</math>French Hansard data

For Ara>Eng and Chi>Eng, we used large-scale training conditions defined in the DARPA BOLT project; **Tables 2** and **3** give statistics. For Arabic, “all” includes 15 genres and MSA/Egyptian/Levantine/untagged dialects; “small” is “all” minus UN data; “webforum” is the webforum subset of “small”. Tune, Test, and SysCombTune are webforum genre, and a similar dialect mix. For Chinese all training sets are mixed genre; “good” is “all” minus UN, HK, and ISI data; Tune, SysCombTune, and Test are forum genre. NIST Open MT 2012 test data was the held-out data: for Arabic it is a mix of weblog/newsgroup genres; for Chinese it contains these two genres plus unknown genre. In **Tables 2** and **3**, the number of English words for Tune, Devtest1, Devtest2, and Test is averaged over four references.

Corpus	# sentence pairs	# words (Arabic)	# words (English)
Train1: “all”	8.5M	261.7M	207.5M
Train2: “small”	2.1M	42.4M	37.2M
Train3: “webforum”	92K	1.6M	1.8M
Tune	4,147	66K	72K
Devtest1: “Test”	2,453	37K	40K
Devtest2: “SysCombTune”	2,175	35K	38K
Test (blind): MT12 Arabic test	5,812	229K	209K

**Table 2.** Corpus sizes for tokenized Arabic-English data

Corpus	# sentence pairs	# words (Chinese)	# words (English)
Train1: “all”	12M	234M	254M
Train2: “good”	1.5M	32M	38M
Tune	2,748	62K	77K
Devtest1: “Test”	1,224	29K	36K
Devtest2: “SysCombTune”	1,429	31K	38K
Test (blind): MT12 Chinese test	8,714	224K	261K

**Table 3.** Corpus sizes for tokenized Chinese-English data

### 2.3. Experimental systems

Eng $\leftrightarrow$ Fre Hansard experiments were performed with Portage, the National Research Council of Canada’s phrase-based system (this is the system described in Foster *et al*, 2013). The corpus was word-aligned with HMM and IBM2 models; the phrase table was the union of phrase pairs from these alignments, with a length limit of 7. We applied Kneser-Ney smoothing to find bidirectional conditional phrase pair estimates, and obtained bidirectional Zens-Ney lexical estimates (Chen *et al*, 2011). Hierarchical lexical reordering (Galley and Manning, 2008) was used. Additional features included standard distortion and word penalties (2 features) and a 4-gram LM trained on the target side of the parallel data: 13 features in total. The decoder used cube pruning and a distortion limit of 7.

Our Chinese and Arabic baselines are strong phrase-based systems, similar to our entries in evaluations like NIST. The hierarchical lexical reordering model (HRM) of (Galley and Manning, 2008) along with the sparse reordering features of (Cherry, 2013) was used. Phrase extraction pools counts over symmetrized word alignments from IBM2, HMM, IBM4, Fastalign (Dyer *et al*, 2013), and forced leave-one-out phrase alignment; the HRM pools counts in the same way. Phrase tables were Kneser-Ney smoothed as for the Eng $\leftrightarrow$ Fre experiments, and combined with mixture adaptation (Foster, 2007); indicator features tracked which extraction techniques produced each phrase. The Chinese system incorporated additional adaptation features (Foster *et al*, 2013). For both Arabic and Chinese, four LMs per system were trained: one LM on the English Gigaword corpus (5-gram with Good-Turing smoothing), one LM on monolingual webforum data and two LMs trained on selected material from the parallel corpora (4-gram with Kneser-Ney smoothing); in the case of Chinese, the latter two LMs were mixture-adapted.. Both systems used the sparse features of (Hopkins and May, 2011; Cherry, 2013). The decoder used cube pruning and a distortion limit of 8.

Tuning for all systems was performed with batch lattice MIRA (Cherry and Foster, 2012). The metric is the original IBM BLEU, with case-insensitive matching of n-grams up to  $n = 4$ . For all systems, we performed five random replications of parameter tuning (Clark *et al*, 2011).

For Eng $\leftrightarrow$  Fre, coarse models were trained on all of “Train”. For Ara $\rightarrow$ Eng, word classes and two static coarse LMs were trained on “all” and “webforum” (no linear mixing), but biLMs were trained on “small”. For Chi $\rightarrow$ Eng, word classes and a large static mix coarse LM were trained on “all”, but a smaller dynamic mix coarse LM and all the biLMs were trained on “good”. Bitokens for all language pairs were derived from word-aligned sentence pairs by two word alignment techniques. Two copies of each pair were made; one was aligned using HMMs, the other using IBM2. Since the Arabic and Chinese phrase tables were created not only with these alignment techniques, but with others, the decoder for these languages may use bitokens not found in the biLMs (“out-of-biLM-vocabulary” bitokens).

### 2.4. English $\rightarrow$ French experiments

First, we explored single Eng $\rightarrow$ Fre coarse models on devtest data. For models involving word classes, we looked at 50, 100, 200, 400, 800, and 1600 classes. The number of bitoken types was huge (7.6M), so we were only able to obtain up to 800 bitoken classes (generating 1600 classes would have taken too long). There is insufficient space to show all results: **Table 4** shows how many variants of each coarse model type we tried, along with the lowest-scoring and highest-scoring variant of each type (using average score on Devtest1 and Devtest2). The table uses the notation for biLMs given towards the end of section 1.1. The range of scores from lowest to highest is shown with the standard deviation (SD) over five tuning runs (more precisely, we show whichever is greater, the SD of the lowest or of the highest score).

System type (#variants tried)	Lowest scorer	Highest scorer	Range of scores	Range of gains
Cluster src biLM (6)	(800,  T )	(400,  T )	40.20-40.31 $\pm$ 0.06	+0.08-0.19
Cluster tgt biLM (6)	( S , 50)	( S , 100)	40.33-40.41 $\pm$ 0.04	+0.21-0.29
Cluster src & tgt biLM (22)	(1600, 1600)	(400, 200)	40.32-40.66 $\pm$ 0.05	+0.20-0.54
Cluster bitoken biLM (5)	50 bi	800 bi	40.30-40.71 $\pm$ 0.02	+0.18-0.59
Clstr src/tgt $\rightarrow$ clstr bitok. biLM (11)	400 bi(50,50)	<b>400 bi(400,400)</b>	40.51-40.76 $\pm$ 0.01	+0.39- <b>0.64</b>
Word-based biLM = ( S ,  T ) (1)	N/A	N/A	40.34 $\pm$ 0.05	+0.22
Baseline for biLMs (1)	N/A	N/A	40.12 $\pm$ 0.02	(0.0)
Coarse LM (7)	50 tgt classes	800 tgt classes	40.31-40.53 $\pm$ 0.02	+0.30-0.52
(Baseline for coarse LMs) (1)	N/A	N/A	40.02 $\pm$ 0.03	(0.0)

**Table 4.** Preliminary experiments - Eng>Fre average(Devtest1,Devtest2) BLEU for single coarse models

We did not try all 36 combinations of source and target word clusters, but explored along the “diagonal” where the number of classes is the same for both sides: *i.e.*, we tried (50, 50), ..., (1600, 1600). Then we tried coarse biLMs in the neighbourhood of the best diagonal ones, eventually trying 22 different biLMs clustered on both sides. For bitoken clustering, we also carried out this kind of greedy search. Word preclustering shortens the time required for bitoken clustering. *E.g.*, on our machines, training the highest-scoring biLM, 400 bi(400,400), took 19 hours for (400,400) preclustering and then 112 hours for bitoken clustering: 131 hours total. Training “400 bi” with no preclustering took 277 hours. The shorter time with preclustering is because **mkcls** takes time proportional to the number of types: 7.6M bitokens without preclustering but only 3.2M with (400, 400) preclustering. **Table 4** shows that preclustering followed by bitoken clustering also yielded the best results: the worst-scoring biLM of this type performed about +0.4 better than the baseline, and the best-performing one gained more than +0.6. The last two rows of the table pertain to coarse LMs. The **Table 4** experiments were performed two months earlier than the rest, with a slightly different version of the system, one with a standard rather than hierarchical lexicalized reordering model (HRM) (tables **5 & 6** below show results with HRMs, and tables **7 & 8** with discriminative HRMs (DHRMs)).

Next, we explored loglinear combinations of the highest-scoring coarse models on the same devtest, again doing a kind of greedy search (and using HRMs). Because of the poor results for clustering on only source or target words (not both) in **Table 4**, we did not try these biLMs in combinations. Almost all the combinations we tried scored significantly higher than the coarse models of which they were composed, as shown in **Table 5** (in descending order of devtest score). A pattern emerged: many of the highest-scoring combinations had one coarse biLM with clustered bitokens (sometimes preclustered, sometimes not), one coarse biLM with clustered source and target words, and two or three coarse LMs of very different granularity. Presumably, these information sources complement each other. We chose one of the configurations that scored highest on Eng>Fre devtest to be tried on all four language pairs – in each case, keeping the structure but using language-pair-specific models. This “generic” configuration often scores lower for other language pairs on blind test data than combinations that have

been chosen via experiments on devtest data for a given pair, but is a reasonable choice for system builders who don't wish to spend a lot of time on preliminary experiments.

In addition to “generic” (underlined) and the two other best combinations, **Table 5** shows individual models inside coarse model combinations (*in italics*), the word-based biLM, and the baseline (the notation here was defined in section 1.1 above). Average scores and standard deviations from five runs are shown. For individual biLMs, “|B|” is the number of bitoken types. *E.g.*, clustering English and French words to 400 and 200 classes respectively shrinks the number of different bitokens from 7.6 million to 2.9 million. Results on blind test data (Test1 and Test2) are lower than on devtest but in roughly the same order; coarse model combinations score higher than their components on both devtest and test data. The “generic” configuration we chose was the one with symmetric biLMs (no difference between number of source and target word classes in its biLMs) that scores highest on devtest. It has a biLM clustered to 400 classes for each language, a biLM obtained from the former by clustering it to 400 bitokens, and two coarse LMs of very different granularities (100 and 1600 classes).

System	avg(Devtest1, Devtest2)	Gain on devtest	avg(Test1, Test2)	Gain on test
<b>400bi(400,400)&amp;(400,200)&amp;100tgt&amp;1600tgt</b>	<b>41.25±0.03</b>	<b>+1.13</b>	<b>42.64±0.02</b>	<b>+0.85</b>
<u>400bi(400,400)&amp;(400,400)&amp;100tgt&amp;1600tgt = “Generic”</u>	<u>41.19±0.01</u>	<u>+1.07</u>	<u>42.59±0.03</u>	<u>+0.80</u>
200bi&(400,200)&100tgt&1600tgt	41.19±0.02	+1.07	42.60±0.04	+0.81
<i>Single biLM: 400bi400src400tgt,  B =400</i>	<i>40.76±0.01</i>	<i>+0.64</i>	<i>42.22±0.02</i>	<i>+0.43</i>
<i>Single biLM: 200 bi,  B =200</i>	<i>40.69±0.03</i>	<i>+0.57</i>	<i>42.08±0.03</i>	<i>+0.28</i>
<i>Single biLM: (400,200),  B =2.9M</i>	<i>40.66±0.02</i>	<i>+0.54</i>	<i>42.17±0.01</i>	<i>+0.37</i>
<i>Single biLM: (400,400),  B =3.2M</i>	<i>40.51±0.04</i>	<i>+0.39</i>	<i>42.15±0.03</i>	<i>+0.36</i>
Single biLM: word-based,  B =7.6M	40.34±0.05	+0.22	41.96±0.01	+0.17
<i>Single coarse LM: 1600tgt</i>	<i>40.67±0.03</i>	<i>+0.55</i>	<i>42.36±0.03</i>	<i>+0.56</i>
<i>Single coarse LM: 100tgt</i>	<i>40.61±0.03</i>	<i>+0.49</i>	<i>42.11±0.02</i>	<i>+0.32</i>
Baseline	40.12±0.02	(0.0)	41.79±0.02	(0.0)

**Table 5.** Eng>Fre BLEU for coarse model combinations (*single components in italics*)

## 2.5. Experiments with other language pairs

Experiments with the other language pairs were carried out as with Eng>Fre: greedy search over single coarse models followed by greedy search over model combinations, using scores on devtest for each pair to make decisions. Results on devtest and blind test data are shown in **Tables 6 – 8** for the two combinations scoring highest on devtest for each pair. For each pair, we also tested the “generic” configuration (underlined) chosen on the basis of Eng>Fre devtest results. All results shown are averaged over 5 tuning runs.

System	avg(Devtest1, Devtest2)	Gain on devtest	avg(Test1, Test2)	Gain on test
<b>400bi&amp;(1600,1600)&amp;100tgt&amp;800tgt&amp;1600tgt</b>	<b>40.80±0.03</b>	<b>+0.79</b>	<b>42.49±0.04</b>	<b>+0.46</b>
400bi&(1600,1600)&100tgt&1600tgt	40.79±0.03	+0.78	42.47±0.05	+0.45
<u>400bi(400,400)&amp;(400,400)&amp;100tgt&amp;1600tgt = “Generic”</u>	<u>40.67±0.03</u>	<u>+0.66</u>	<u>42.37±0.03</u>	<u>+0.35</u>
<i>Single biLM: 400bi,  B =400</i>	<i>40.41±0.02</i>	<i>+0.39</i>	<i>42.32±0.05</i>	<i>+0.29</i>
<i>Single biLM: (1600,1600),  B =6.2M</i>	<i>40.37±0.02</i>	<i>+0.36</i>	<i>42.09±0.02</i>	<i>+0.06</i>
<i>Single biLM: 400bi(400,400),  B =400</i>	<i>40.35±0.04</i>	<i>+0.34</i>	<i>42.32±0.02</i>	<i>+0.29</i>
<i>Single biLM: (400,400),  B =4.2M</i>	<i>40.21±0.02</i>	<i>+0.19</i>	<i>42.05±0.02</i>	<i>+0.02</i>
Single biLM: word-based,  B =8.6M	40.25±0.03	+0.23	42.13±0.02	+0.10
<i>Single coarse LM: 100tgt</i>	<i>40.36±0.04</i>	<i>+0.35</i>	<i>42.14±0.02</i>	<i>+0.12</i>
<i>Single coarse LM: 800tgt</i>	<i>40.33±0.02</i>	<i>+0.32</i>	<i>42.19±0.04</i>	<i>+0.16</i>
<i>Single coarse LM: 1600tgt</i>	<i>40.30±0.01</i>	<i>+0.28</i>	<i>42.09±0.02</i>	<i>+0.07</i>
Baseline	40.01±0.02	(0.0)	42.02±0.03	(0.0)

**Table 6.** Fre>Eng BLEU for coarse model combinations (*single components in italics*)

### 3. Discussion and Future Work

BiLMs provide phrase-based SMT systems with richer source-side context during decoding. In experiments with highly competitive baselines, pure word-based 8-gram biLMs yield only modest gains in the range +0.1–0.2 BLEU for four language pairs. This is probably due to training data sparsity caused by the large number of bitoken types. Indeed, when we replace word-based 8-gram biLMs with coarse 8-gram biLMs, we get much greater gains from the latter. Our results also show that coarse biLMs and coarse LMs of different granularities contain partially complementary information: for each of the language pairs, loglinear combinations of coarse models score higher than single coarse models on blind test data.

We defined a “generic” coarse configuration by looking at Eng>Fre devtest results: 400bi(400,400)&(400,400)&100tgt&1600tgt (a loglinear combination of two types of coarse biLM and two coarse LMs of very different granularities). For this configuration, BLEU gains over language-specific baselines on blind data were **+0.80** for Eng>Fre, **+0.35** for Fre>Eng, **+1.0** for Ara>Eng, and **+0.6** for Chi>Eng. If we apply the configuration with the highest devtest score on a given language pair to blind data, the gains are **+0.85** for Eng>Fre, **+0.46** for Fre>Eng, **+1.2** for Ara>Eng, and still **+0.6** for Chi>Eng. The consensus in the literature is that coarse models help most when the target language has complex morphology, so we expected the largest gains to be for Eng>Fre: we were surprised by the large gains for Ara>Eng. It looks as though source context information is especially valuable for Ara>Eng.

The Eng>Fre baseline system’s LM took only 0.1G of storage, but adding the “generic” coarse LM-biLM configuration brought this to 2.4G. Adding “generic” took Fre>Eng LM size from 0.1G to 2.0G. Because they have four LMs, baselines for the other two language

pairs have much higher total LM sizes than the Eng $\leftrightarrow$ Fre baselines: adding “generic” took total LM size from 15.0G to 18.4G for Ara $\rightarrow$ Eng, and from 7.6G to 11.0G for Chi $\rightarrow$ Eng. We didn’t measure time or virtual memory (VM) during decoding impacts precisely: very roughly, adding “generic” increased decoding time about 30% for all four systems, and increased VM size about 60% for the Eng $\leftrightarrow$ Fre systems and about 20% for the other two.

System	avg(Devtest1, Devtest2)	Gain on devtest	Test	Gain on test
<b>400bi&amp;(1600,1600)&amp;100tgt&amp;1600tgt</b>	<b>40.56±0.09</b>	<b>+0.76</b>	<b>46.03±0.07</b>	<b>+1.20</b>
400bi(800,800)&100tgt&1600tgt	40.51±0.12	+0.72	45.74±0.13	+0.91
<u>400bi(400,400)&amp;(400,400)&amp;100tgt&amp;1600tgt = “Generic”</u>	<u>40.43 ±0.08</u>	<u>+0.63</u>	<u>45.80±0.14</u>	<u>+0.97</u>
<i>Single biLM: 400bi,  B =400</i>	<i>40.38±0.13</i>	<i>+0.59</i>	<i>45.43±0.07</i>	<i>+0.60</i>
<i>Single biLM: 400bi(800,800),  B =400</i>	<i>40.23±0.04</i>	<i>+0.44</i>	<i>45.35±0.08</i>	<i>+0.52</i>
<i>Single biLM: 400bi(400,400),  B =400</i>	<i>40.18±0.09</i>	<i>+0.38</i>	<i>44.94±0.18</i>	<i>+0.11</i>
<i>Single biLM: (400,400),  B =1.2M</i>	<i>40.15±0.08</i>	<i>+0.36</i>	<i>45.02±0.07</i>	<i>+0.19</i>
<i>Single biLM: (1600,1600),  B =2.1M</i>	<i>40.03±0.04</i>	<i>+0.23</i>	<i>45.10±0.12</i>	<i>+0.27</i>
Single biLM: word-based,  B =4.0M	40.06±0.06	+0.26	44.96±0.09	+0.13
<i>Single coarse LM: 1600tgt</i>	<i>40.14±0.06</i>	<i>+0.34</i>	<i>45.12±0.09</i>	<i>+0.29</i>
<i>Single coarse LM: 100tgt</i>	<i>40.03±0.04</i>	<i>+0.23</i>	<i>45.10±0.05</i>	<i>+0.27</i>
Baseline	39.80±0.05	(0.0)	44.83±0.08	(0.0)

**Table 7.** Ara $\rightarrow$ Eng BLEU for coarse model combinations (*single components in italics*)

There are several directions for future work:

- The method for hard-clustering words/bitokens could be improved – *e.g.*, as in Blunsom and Cohn (2011). As a reviewer helpfully pointed out, coarse models of the same type but different granularities could be trained more efficiently with true IBM clustering (Brown *et al*, 1992) to create a hierarchy for words or bitokens that would yield many different granularities after a single run, rather than by running **mkcls** several times (once per granularity).
- Coarse models could be used for domain adaptation - *e.g.*, via mixture models that combine in-domain and out-of-domain or general-domain data (Koehn and Schroeder, 2007; Foster and Kuhn, 2007; Sennrich, 2012). In-domain statistics will be better-estimated in a coarse mixture than in a word-based one.
- “Mirror-image” word-based or coarse target-to-source biLMs could be used to rescore N-best lists or lattices. If there has been word reordering, these would apply context information not seen during decoding. *E.g.*, let source “A B C D E F G H” generate hypothesis “a b f h g c d e”, and “A” be aligned with “a”, “B” with “b”, *etc.* With trigram word-based biLMs, the trigrams involving “f” seen during decoding are “a\_A b\_B f\_F”, “b\_B f\_F h\_H”, and “f\_F h\_H g\_G”. During mirror-image rescoring, the biLM trigrams involving

“f” that are consulted are “D\_d E\_e F\_f”, “E\_e F\_f G\_g”, and “F\_f G\_g H\_h” – a different set of trigrams, potentially containing additional information.

- In this work, the most time-consuming task was finding the best combination of coarse models for a given language pair/corpus. We hope to devise a computationally cheap way of finding the best combination on devtest data. An approach based on minimizing the perplexity of held-out data might work, if the correlation between this and SMT quality turns out to be sufficiently high.

An interesting direction for future work is comparison between coarse models and neural net (NN) approaches. In principle, everything learned by coarse LMs or coarse biLMs could be learned by a neural net (NN) trained on the same data. Will NNs make coarse models obsolete? Only thorough experimentation will show which of NNs or coarse model combinations really yield better translations – perhaps they complement each other. Currently, an advantage of coarse models over NNs is quicker training times; one could further shrink training time for coarse models by incrementally adapting word clusterings trained on generic data to new domains. However, incremental adaptation is also a possible strategy for NNs. Analysis of these tradeoffs between coarse models and NNs – in terms of model quality, speed of training, ease of incremental adaptation, *etc.* – is our top priority for future work.

System	avg(Devtest1, Devtest2)	Gain on devtest	Test	Gain on test
<b>400bi(1600,1600tgt)&amp;(800,800)&amp;100tgt&amp;400tgt</b>	<b>30.38±0.08</b>	<b>+0.82</b>	<b>32.46±0.04</b>	<b>+0.61</b>
400bi(1600,1600)&(800,800)&100tgt&1600tgt	30.36±0.08	+0.80	32.44±0.05	+0.59
400bi(400,400)&(400,400)&100tgt&1600tgt = “Generic”	<u>30.16±0.11</u>	<u>+0.60</u>	<u>32.41±0.05</u>	<u>+0.56</u>
<i>Single biLM: 400bi(1600,1600),  B =400</i>	<i>30.02±0.08</i>	<i>+0.47</i>	<i>32.25±0.06</i>	<i>+0.40</i>
<i>Single biLM: (800,800),  B =3.4M</i>	<i>29.90±0.10</i>	<i>+0.34</i>	<i>32.09±0.03</i>	<i>+0.24</i>
<i>Single biLM: (400,400),  B =2.8M</i>	<i>29.76±0.08</i>	<i>+0.21</i>	<i>32.16±0.02</i>	<i>+0.30</i>
<i>Single biLM: 400bi(400,400),  B =400</i>	<i>29.94±0.07</i>	<i>+0.38</i>	<i>32.13±0.07</i>	<i>+0.28</i>
Single biLM: word-based,  B = 6.9M	29.74±0.09	+0.19	32.03±0.08	+0.18
<i>Single coarse LM: 100tgt</i>	<i>29.82±0.02</i>	<i>+0.26</i>	<i>32.14±0.06</i>	<i>+0.29</i>
<i>Single coarse LM: 400tgt</i>	<i>29.83±0.09</i>	<i>+0.28</i>	<i>32.17±0.08</i>	<i>+0.31</i>
<i>Single coarse LM: 1600tgt</i>	<i>29.82±0.06</i>	<i>+0.26</i>	<i>32.11±0.05</i>	<i>+0.26</i>
Baseline	29.56±0.05	(0.0)	31.85±0.08	(0.0)

**Table 8.** Chi>Eng BLEU for coarse model combinations (*single components in italic*)

## Acknowledgement

This research was supported in part by DARPA contract HR0011-12-C-0014 under subcontract to Raytheon BBN Technologies.

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