

# The MITLL-AFRL IWSLT 2015 MT System<sup>†</sup>

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## Abstract

This report summarizes the MITLL-AFRL MT, ASR and SLT systems and the experiments run using them during the 2015 IWSLT evaluation campaign. We build on the progress made last year, applying those techniques to translating Chinese to English and English to Chinese. ASR systems are also improved by refining improvements developed last year. Finally, we combine our ASR and MT systems to produce a English to Chinese SLT system.

In this current draft, starred results(\*) indicate that final results are still pending and the exact values may need to be adjusted.

## 1. Introduction

During the evaluation campaign for the 2015 International Workshop on Spoken Language Translation (IWSLT '15) [1] our experimental efforts in machine translation (MT) centered on 1) the addition of hierarchical decoding systems 2) reranking n-best lists with a neural net encoder-decoder 3) post-processing of unknown words in translation output and 4) system combination.

Experimental efforts for the automatic speech recognition (ASR) task focused on using cutting edge neural net techniques and the combination of HTK and Kaldi-based ASR systems.

We combine both efforts to produce a system for the spoken language translation (SLT) task. Various segmentation and punctuation strategies were explored.

This paper is structured as follows. Section 2 presents our work on the MT task, and discusses each of the techniques mentioned above, ending with a discussion of submitted systems. Our work on the ASR task is discussed in Section 3. Finally, our work on the SLT task

is discussed in Section 4.

## 2. Machine Translation

### 2.1. Data Usage

Unless otherwise noted, data described in this section originates from the WMT15 website<sup>1</sup>. We used the parallel in-domain data supplied by WIT3 [2]. In Chinese-English, we additionally used the Yandex corpus<sup>2</sup>, Common Crawl, Wiki Headlines, News Crawl, and the LDC Gigaword corpus as sources of monolingual English data for language model training. In English-Chinese we utilized the Chinese portion of the MultiUN corpus as an additional source of language model training data.

### 2.2. Data Preprocessing and Cleanup

As in past years, we applied a cleaning process to the training data as previously described in [3]. Chinese was segmented with the Stanford Segmenter [4] using both Chinese Treebank (CTB) and Peking University (PKU) models.

### 2.3. Training

#### 2.3.1. Phrase and Rule Table Training

We used the default Moses scripts when training phrase and rule tables. For Chinese to English, we increased the size of the training corpus by concatenating output from both the CTB and PKU segmentation models while simply repeating the English portion of the corpus. This allows us to extract phrases for a greater number of phrases than one segmentation alone. We also experimented with outputting the k-best segmentation choices for a model while repeating the English portion.

Phrase and rule tables are trained with default Moses scripts or our custom MT pipeline driver. Good-Turing

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<sup>1</sup><http://www.statmt.org/wmt15/translation-task.html>

<sup>2</sup><https://translate.yandex.ru/corpus?lang=en>

smoothing[5] was applied to both rule and phrase tables.

### 2.3.2. Language Model Training

We reuse our BigLM15 from our WMT15 shared translation task submission[6] as our main English machine translation language model. The English data sources listed in Section 2.1 were used to train a very large 6-gram language model. For Chinese, we take a similar approach to English, using the TED in-domain parallel training data and the Chinese portion of the MultiUN corpus. `kenlm` [7] was used to train 6-gram models in both languages. These models were then binarized and stored on local solid-state disks for each machine in our cluster to improve load time and reduce fileserver traffic.

## 2.4. Baseline MT System

Our system implements a fairly standard statistical machine translation (SMT) architecture. It consists of the following:

- Moses phrase-based [8] or hierarchical decoding with the incremental-search algorithm [9]
- Stanford Chinese character segmentation [4]
- Hierarchical `mslr` lexical reordering [10] for phrase-based systems
- Minimal phrase table [11]
- 7-gram brown-cluster language model with 80 classes
- BigLM15 [6] for English, consisting of WMT newscrawl data, europarl, news commentary
- Drem optimization [12]
- Recurrent neural net language model (RNNLM) rescoring [13]
- Named Entity Postprocessing [6]

## 2.5. Neural MT methods

### 2.5.1. Chinese to English

We reranked our n-best lists using an end-to-end neural MT system: our own in-house Torch7 [14] implementation of Sutskever et al [15]’s LSTM encoder-decoder approach. This system was trained using varying amounts of out-of-domain UN data, followed by training on TED data. In the following table, the UN sentences were ranked according to bilingual cross-entropy difference [16] (using RNNLM for the language model component) and the top  $N$  were chosen to pretrain the network. Once validation error settled down, the networks were then trained over the 200,000 TED training examples. The different models that have been trained can be seen in Table 2.5.1. In common among all of them were vocab selection: vocab entries were taken if they appeared at least 10 times in TED, or 100 times

id	d	N	dev ppl	BLEU
0	4	2.5M	27.15	16.83*
1	1	1M	30.01	16.55*
2	2	5M	25.54	16.75*
3	2	1M	28.26	16.90*
4	1	2.5M	27.98	16.65*
5	2	2.5M	24.21	16.86*

Table 1: Uncased BLEU on `tst2013` and perplexity on `dev2010`.  $d$  = LSTM depth and  $N$  = cross-entropy filter size for UN data.

	0	2	3	4	5
0	16.83*	16.90	16.89	16.77	16.93
2		16.75*	17.00	16.69	16.96
3			16.90*	16.75	16.89
4				16.65*	16.84
5					16.86*

Table 2: Cased BLEU on `tst2013` for combinations of encoder-decoders, numbered as in Table 1.

in UN, or 5 times in TED and 20 times in UN. Reranking results for individual systems, as well as pairwise combinations, can be seen in Table 2.5.1.

Using the best scoring encoder-decoder (#3), and the best scoring combination, we were able to rerank the n-best list from our best hierarchical moses system, and achieved significant gains. In particular, we increased the score from 17.23 to 17.64 cased BLEU on `tst2013`.

### 2.5.2. English to Chinese

For the English to Chinese task, we achieved gains by using the Neural Network Joint Model (NNJM [17]), and by reranking using GroundHog [18], the Montreal LISA-lab attention model system. The NNJM was trained using our own in-house implementation in Theano [19]. We integrated NNJM decoding into Moses as a feature function, utilizing self-normalization and precomputation to allow reasonable runtimes. Like the Torch system, the GroundHog system was trained identically on the MultiUN data.

## 2.6. System combination

This year we experimented with system combination techniques based on Rosti et al [20], a well established technique in machine translation. Our only additional contribution was in sub-selecting systems with which to perform system combination. Among our different col-

En-Zh System	char BLEU
Baseline	20.60*
+ 400 Class Factored LM	20.90*
+ RNNLM	21.23
+ NNJM	21.42
+ GroundHog 2M	21.70*
-/+ GroundHog 4M	21.85

Table 3: English–Chinese system additions

id	Description	BLEU
0	Hiero, 6-iter Drem Dev10, CLM	17.00*
1	(0) + fixed wide beam	17.00*
2	(0) + bigdev	17.23
3	(2) + enc-dec	17.45
4	(2) + 3-iter alt Drem variation	17.00*
5	(2) + Drem variation	17.00*
6	Hiero Incsearch, bigdev, no rescoring	16.50*
7	PB, bigdev, no rescoring	16.50*
8	PB, ted+nyt CLMs, enc-dec	17.08

Table 4: Some notes on the systems: CLM = brown cluster language model, bigdev = dev2010 + tst2010 + tst2011 + tst2012. TED factored LM has 80 classes, nyt (LDC English Gigaword) has 600. All used a variation of LMs trained on WMT’15 data.

laborators, we managed to produce over 30 systems with 400+ decode outputs. With the goal of choosing only 9, we first filtered out systems with scores less than some minimum acceptable value (in our case, 16.50 uncased BLEU on `tst2013`). Then, we constructed a distance metric as  $1 - \text{BLEU}(x, y)$  and performed k-medoids clustering to choose systems that were sufficiently different from each other.

Table 4 lists different systems used for combination, and Table 5 lists a sampling of combinations tried and their case-sensitive BLEU scores on `tst2013`.

## 2.7. Unknown Word Processing

As in our WMT15 submission [6], we employed unknown word post-processing to handle any unknown words in the translation instead of simply dropping these words. To test the effectiveness of this approach, we decode all test sets where references are available with a bare-bones Moses hierarchical decoding system where no rescoring features are employed. The resulting gains measured in uncased BLEU are shown in Table 6. We

Combo id	Systems Used	tst2013 BLEU
0	0+1+2+4+8	17.62
1	0+1+3+5+8	17.64
2	0+1+2+4+5+8	17.64
3	0+1+3+4	17.66
4	0+1+5+8	17.74

Table 5: Top 5 systems out of system combination

note that the improvements in BLEU are smaller for the Chinese–English language pair when compared to our efforts in processing unknown words in other language pairs, such as Russian–English[6], but we feel that employing these processes are still worthwhile due to the positive impact on readability of the machine translation output. Our technique adapted to Chinese–English is described in the following section.

### 2.7.1. Chinese to English post-processing

The named entity list used for named entity post-processing comes from manual translations of named entities found in train 2014. It was expanded by adding versions of the Chinese name with the common nouns stripped off. A list of 29 typical common nouns endings of named entity phrases was compiled. Common nouns like: 病 (disease), 县 (county), 族 (race/people), 实验室 (laboratory), 湖 (lake), 集团 (corporation), 群岛 (archipelago) can sometimes be optionally included or omitted by the speaker or optionally split off of entities by word segmenters or named entity taggers.

The output is searched for words containing any Chinese characters. Any unknown word consisting of a single character is deleted since single-character entities are rare in this domain (and segmentation errors are a more common explanation for unknown single-character words). If the word is not found in the named entity word list, the list is searched again for the entity with common nouns stripped. Remaining unknown words are deleted from the output.

Test Set	base. BLEU	post. BLEU	$\Delta$ BLEU
tst2013	16.09	16.19	+0.10
tst2012	13.64	13.65	+0.01
tst2011	15.21	15.29	+0.08
tst2010	12.43	12.50	+0.07

Table 6: NE post-processing improvement measured in uncased BLEU.

## 2.8. Submission

Our primary Chinese–English MT submission is system #3 in Table 4. We submitted system #4 in Table 5 as contrastive. For English–Chinese, the primary system was the last entry in Table 3.

These systems were used to decode the `tst2014` and `tst2015` test sets. Results from scoring performed by the workshop organizers are listed in Table 7 including baseline system scores as determined by the organizers.

System	Lang Pair	Test Set	BLEU
Baseline	Zh-En	<code>tst2014</code>	11.43
Primary	Zh-En	<code>tst2014</code>	14.13
Contrastive	Zh-En	<code>tst2014</code>	13.35
Baseline	Zh-En	<code>tst2015</code>	13.59
Primary	Zh-En	<code>tst2015</code>	16.86
Contrastive	Zh-En	<code>tst2015</code>	15.05
Baseline	En-Zh	<code>tst2014</code>	17.74
Primary	En-Zh	<code>tst2014</code>	18.51
Baseline	En-Zh	<code>tst2015</code>	21.86
Primary	En-Zh	<code>tst2015</code>	24.31

Table 7: Official results measured in cased BLEU.

## 3. ASR

Acoustic training data for our ASR systems were harvested from 1787 TED talks. We applied the same alignment and closed caption filtering process as we did in IWSLT 2013 [21], yielding 336 hours of audio.

An i-vector system was first developed on the TED data using Hidden Markov Model Toolkit (HTK)<sup>3</sup> Mel-Frequency Cepstral Coefficient (MFCC) features and the MIT-LL i-vector software. The elements of the 50 dimensional MFCC vector were based on those used by the ALIZE toolkit [22]. Non-speech frames were removed using the word alignments from the closed caption filtering process, and the features were normalized to zero mean and unit variance on a per-speaker basis. The universal background model included 1024 Gaussians with diagonal covariances, and the i-vector dimension was set to 100. Lastly, the Eigen Factor Radial method [22] was applied to normalize the i-vectors.

A hybrid deep neural-net (DNN) - hidden Markov model (HMM) speech recognition system was developed using Theano and a version of HTK that we modified according to the method of [23]. A context window of 9 frames was used on the input, and the speaker-specific i-vector was appended to each set of stacked features [24]. The feature set consisted of 24 log filterbank outputs with delta and acceleration coefficients; the fea-

tures were normalized to zero mean and unit variance on a per-speaker basis. The DNN included 5 hidden layers with 1024 rectified linear units per hidden layer and 8000 output units. The network weights were initialized as suggested in [25]. Cross-entropy training was performed using a minibatch size of 512 and an initial learning rate of 0.0005 that was adjusted according to the QuickNet newbob algorithm.<sup>4</sup>

LM data selection was implemented using the same procedure as our IWSLT 2014 system. Interpolated trigram and 4-gram LMs were estimated on TED, 1/8 of Gigaword, and 1/8 of News 2007–2014 using the SRILM Toolkit. A RNN maximum entropy LM was estimated on the same set of training texts using the RNNLM Toolkit. The network included 160 hidden units, 300 classes in the output layer, 4-gram features for the direct connections, and a hash size of  $10^9$ . The LM vocabulary included 100000 words.

Automatic segmentation of the test data was performed using the same procedure as in IWSLT 2014[3], except that we padded the speech end points by 0.25 seconds (instead of 0.15 seconds). Recognition lattices were produced using HDecode with the trigram LM and then rescored with the 4-gram LM. Next, 1000-best lists were extracted from each lattice and rescored with the RNN LM. The final LM scores were obtained by linearly interpolating the log probabilities from the 4-gram and RNN LM. Interpolation weights of 0.25 for the 4-gram and 0.75 for the RNN were chosen based on results from previous experiments.

Adaptation data was selected for each speaker using confidence scores [26]. In our work, we estimated confidence scores at the acoustic frame level by aligning the 20-best hypotheses for each utterance and counting the number of matching HMM shared states. Next, speaker-dependent DNNs were estimated on frames with a confidence score of 0.9 or higher. For each speaker, the initial DNN was updated using a learning rate of 0.0000625 and a single epoch of training. The test set was then decoded a second time and LM rescoring was reapplied.

A second ASR system was built using the Kaldi open source speech recognition toolkit [27]. This system was based on the LIUM recipe as released with Kaldi under `egs/tedlium/s5`. The details of the particular system used for the IWSLT 2015 Kaldi-based ASR system are as follows. The acoustic model training data and LM data matched exactly what was used as previously described in the HTK ASR system. The first step was to build a network to produce bottleneck (BN) features [28]. MFCCs from 40 filterbanks and 3 pitch features were used as input to a neural network of 2 hidden layers each of dimension 1500 with a 40 dimension BN layer producing the output features. These 40 BN fea-

<sup>3</sup><http://htk.eng.cam.ac.uk>

<sup>4</sup><http://www.icsi.berkeley.edu/Speech/faq/nn-train.html>

ASR System	Decode	4-gram	4-gram+RNN
HTK first-pass	13.7	13.0	11.9
HTK	11.3	10.9	10.0
Kaldi	13.3	12.6	11.4

Table 8: English `tst2013` WER.

tures were then used to build a GMM-HMM. Speaker adaptive training was then conducted on this GMM-HMM using feature-space maximum likelihood linear regression (fMLLR) transforms. These models were then used to train a DNN of the Deep Belief Network (DBN) variety described as having 6 hidden layers with 2048 neurons per layer. Four additional iterations using the state-level Minimum Bayes Risk (sMBR) discriminative criterion were then executed. This system was evaluated using the trigram LM to produce recognition lattices, which were then rescored with the 4-gram and RNN LMs as described for the HTK system.

Table 8 shows the WER of each system on `tst2013` after evaluating the decoder, rescoring with the 4-gram LM, and interpolating the 4-gram and RNN LM scores. For comparison purposes, we included the results of the HTK system prior to updating the weights of the DNN (denoted as HTK first-pass). The final hypothesis was selected by applying N-best ROVER to the output from the HTK system and the Kaldi system. This yielded a 9.4% WER on `tst2013` and a 7.4% WER on `tst2015`.

#### 4. SLT

New for this year, we combine our efforts in ASR and MT to produce an entry to the SLT task for the English-Chinese language pair. We use the rover output from system combination from the ASR task and translate it with a variant of our best English-Chinese MT system. For segmenting the output, we used the segmentations produced by the ASR system, based on lengths of pauses. To repunctuate the ASR output, we created a classifier based on a recurrent neural network. For each word, the classifier reports which punctuation, if any, follows it. The output layer is a softmax over a limit set (period, comma, question mark, exclamation point, and no punctuation). The inputs to the classifier are a gated recurrent unit [29] hidden state for the word in question, as well as its word vector and the word vectors for the following two words after. Our experimentation was quite limited, but we observed that (a) having the word vector as well as the recurrent state for the current word was helpful, and (b) three layer deep gated recurrent unit worked best out of 1-4. The system was trained on the English side of TED data, with 600-dimensional word vector size, and vocabulary of about 60K words. We did not try any other repunctuation techniques.

One of our alternate approaches for adapting ASR output to MT involves taking the output of the ASR system when decoding `dev2010` then using the `mwerAlign`[30] program to then fit the ASR output segments to the English portion of the `dev2010` tuning set. We then tune the MT system with this new dev set in order to better match the ASR English output to the English-Chinese MT system. We submitted this as a contrastive system.

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