Statistical Pattern-Based Machine Translation with Statistical French-English Machine Translation

Jin'ichi Murakami, Takuya Nishimura and Masato Tokuhisa

Department of Information and Knowledge Engineering, Faculty of Engineering
Tottori University, Japan
murakami@ike.tottori-u.ac.jp

Abstract

We developed a two-stage machine translation (MT) system. The first stage consists of an automatically created pattern-based machine translation system, and the second stage consists of a standard statistical machine translation (SMT) system. For French-English machine translation, we first used a French-English pattern-based MT, and we obtained *"English"* sentences from French sentences. Second, we used a standard SMT. This means that we translated *"English"* to English machine translation.

We obtained a Bilingual Evaluation Understudy (BLEU) score of 0.5201 in the Basic Travel Expression Corpus - French English (BTEC-FE) task using our proposed system. In contrast, we obtained a BLEU score of 0.5077 in the BTEC-FE task using a standard SMT system (Moses). This means that our proposed system is effective in the BTEC-FE task. However, our system placed 7th out of 9 systems.

1. Introduction

Machine translation (MT) systems have been extensively studied, and there are now three generations of this technology. The first generation is a rule-based MT (RBMT) system. A pattern-based MT (PBMT) system is a kind of RBMT system. The second generation is an example-based machine translation system, and the third generation is a statistical machine translation (SMT) system, which has become very popular. Many versions of SMT systems are available. An early SMT system was based on word-based models (IBM1 $\sim$ 5[1]). Recent statistical MT systems usually use phrase-based models.

However, some problems arise with phrase-based SMT. One problem is with the language model. Generally, an N-gram model is used as a language model. However, this model has local language information and does not have grammatical information. To solve these problems, we developed a two-stage MT system. The first stage consists of an automatic created PBMT system. The second stage consists of a standard SMT system.

In French-English translation, the first stage consists of a French-English PBMT. In this stage, we obtain *"English"* sentences from French sentences. Our aim to is to produce grammatically correct *"English"* sentences. However, these *"English"* sentences sometimes have low levels of naturalness, because they were obtained using an automatically created PBMT. In the second stage, we use a standard SMT system. This stage involves *"English"* to English machine translation. With this stage, our aim is to revise the outputs of the first stage for improving naturalness.

We developed a PBMT system for the first stage using "training-model.perl" [4]. We also developed a standard SMT system for the second stage using general SMT tools, such as "Moses" [4]. We used these data and tools to participate in the Basic Travel Expression Corpus - French English (BTEC-FE) task at International Workshop on Spoken Language Translation 2010 (IWSLT2010).

The proposed system was effective in the BTEC-FE task. We obtained a Bilingual Evaluation Understudy (BLEU) score of 0.5201 with our proposed system. In contrast, we obtained a BLEU score of 0.5077 in the BTEC-FE task using a standard SMT system (Moses). This means that our proposed system is effective for the BTEC-FE task However, our system placed 7th out of 9 systems.

2. Concept of Two-Stage Machine Translation

One problem with phrase-based statistical machine translation is with the language model. Generally, an N-gram model is used as a language model. However, this model has local language information and does not have grammatical information. To include grammatical information, we studied hierarchical phrase-based machine translation (HPMT) [13]. However, HPMT analysis is similar to context free grammar (CFG). We believe that such analysis complicates statistical machine translation with too many parameters. Therefore, it is unreliable and does not perform well, specially for the small amount of training data. On the other hand, PBMT is well known and has been extensively studied. Normally, PBMT is simple and has few parameters compared to CFG-based MT, and the output of PBMT has grammatical information. However, there is a trade-off between a coverage of input sentences and a translation quality for the results of PBMT. If we obtain good translation quality, the coverage of RBMT for input sentences is low. If we obtain high coverage for input sentencens, the translation quality is low.

To overcome these problems, we propose a two-stage MT system. We developed a PBMT system for the first stage. This PBMT system had low coverage and high quality. If a French sentence is translated using this system, the quality of output is good and the outputs have grammatical information. If a French sentence is not translated using PBMT, we use a standard SMT. Therefore, we obtain good quality from the entire system. Also, normally, PBMT is created manually. It has many labor costs. So we developed an automatically created PBMT system. This automatic PBMT output had somtimes less naturalness. So we added SMT after PBMT to improve naturalness. In this system, we use RBMT in the pre-processing stage for SMT.

3. Related Work

A two-stage MT system has already been proposed [5], [10], [11], [12]. L.Dugast, et al[11] and M.Simard, et al[12] applied SYSTRAN and SMT for French-English translation. Their concept was that SMT works as a post process for SYSTRAN. From the results of these study, these system are more effective than SYSTRAN or SMT. For M.Simard's research [12], the BLEU sore was 25.98 for SMT and was 28.80 for SYSTRAN + SMT in English-French translation. Also, the BLEU sore was 25.17 for SMT and was 26.79 for SYSTRAN + SMT in French-English translation. On the other hand, Ehara[10] reported on the same system for Japanese-English translation for a patent task. The BLEU score was 0.2821 for SMT and was 0.2921 for RBMT + SMT. Ehara's RBMT system was a commercial Japanese-English system. For these systems, SMT was used in the post process for RBMT, which means that SMT used as language adaptation.

4. Pattern-Based Machine Translation

We developed an automatically created French-English pattern-based MT system using "training-model.perl" [4]. Our system is a divided into two processes. One is forming French-English patterns, and the other is decoding. The details of these two processes are described below.

4.1. French-English Patterns

We developed the following process for forming French-English patterns.

1. Parallel French-English Corpus

   We prepare French-English parallel sentences for training. Example sentences are listed in Table 1.

Table 1: Parallel French-English Corpus

French sentence	Le feu tait au rouge.
English sentence	The light was red.

2. French-English Phrase Table

   Using training-model.perl [4], we construct a French-English phrase table. An example French-English phrase table is shown in table 2.

Table 2: Example of French-English Phrase Table

1	Le feu |||The light |||0.5 0.071 0.5 0.209
2	Les lumire ne |||The lights |||0.0001 0.0006 0.003 0.004
3	feu |||light |||0.2 0.01 0.2 0.2

3. French-English High Probability Phrase Table

   We deleted the low-probability French-English phrase table (Table 2), in which the threshold was below 0.1. We call the resulting table a French-English high-probability phrase table (HPPT). An example of an HPPT is shown in Table 3.

Table 3: Example of French-English High Probability Phrase Table

1	Le feu |||The light |||0.5 0.071 0.5 0.209
2	feu |||light |||0.2 0.01 0.2 0.2

4. French-English Patterns

   Using French-English parallel sentences (Table 1) and the French-English high probability phrase table (Table 3), we formed French-English patterns. Note that all possible French-English patterns were generated. So, one or more French-English patterns were generated from one French-English parallel sentence. Example French-English patterns are listed in Table 4.

Table 4: French-English Patterns

1	French pattern	X1 tait au rouge.
	English pattern	X1 was red.
2	French pattern	Le X1 tait au rouge.
	English pattern	The X1 was red.

Figure 1 shows a flowchart for forming French-English patterns.

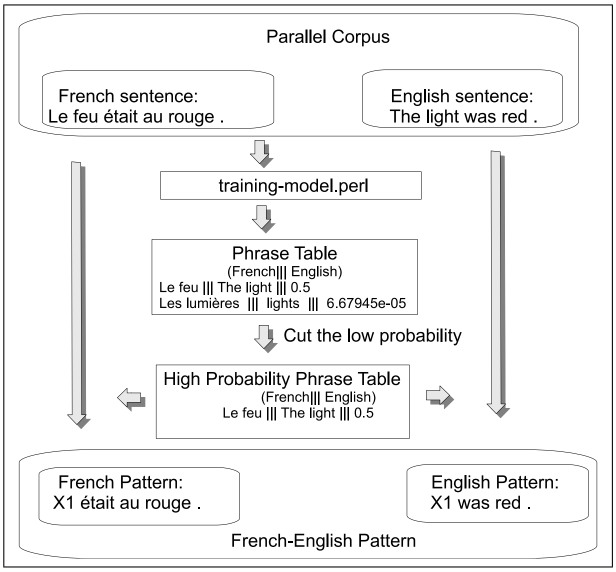

Figure 1: Forming French-English Patterns

4.2. Decoding Pattern

The decoding process is as follows.

1. Input French Sentence

   We prepare input French sentences. An example sentence is shown in Table 5.

Table 5: French Sentence

O se trouve le poste de police ?

2. Search French Pattern and Output English Pattern

   We search for a French pattern that is matched with the input French sentence using French patterns and a high-probability phrase table (section 4.1). And we obtain English patterns. Example French-English patterns are listed in Table 6. Also, an example French-English high-probability phrase table is shown in Table 7.

Table 6: French-English Patterns

1	French Pattern English Pattern	O se trouve le X1 de X2 ? Where's the X2 X1 ?
2	French Pattern English Pattern	O se trouve le poste de X2 ? Where is a X2 ?

Table 7: French-English High-Probability Phrase Table

1	poste |||post |||0.5 0.07 0.5 0.21
2	police |||police |||0.4 0.031 0.2 0.11
3	police |||police station post |||0.1 0.07 0.1 0.01

3. Generate English Sentences

   We generate English sentences using the English pattern and French-English High-Probability phrase tables. Note that all possible English sentences are generated. Therefore, plural English sentences are generated from an input French sentence. Example English sentences are listed in Table 8.

Table 8: Generated English Sentences

1	Where's the police post ?
2	Where's is a police station post ?

4. Select One English Sentence.

   We select one English sentence from generated plural English sentences using N-gram. An example of selected one English sentence is shown in Table 9.

Table 9: One English Sentence

Where's the police post ?

Figure 2 shows the process of decoding English sentences for PBMT.

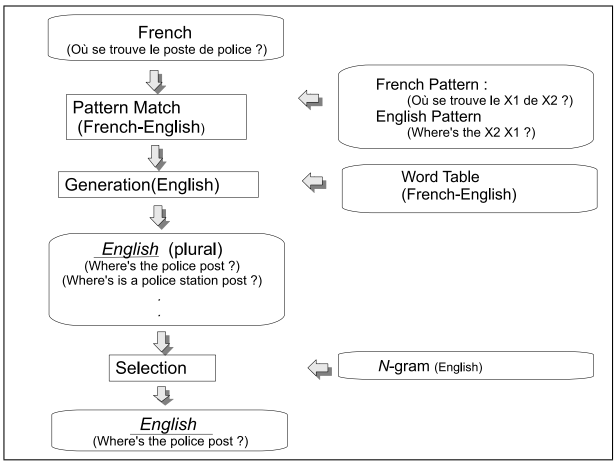

Figure 2: Decoding of Pattern-Based Machine Translation

5. Overview of our Statistical Machine Translation System

Our SMT system consists of two stages. The first stage is a French-English PBMT system, and the second is an English-English SMT system. We describe our system by dividing it into two processes, training and decoding.

5.1. Training

The training process consists of three parts. The first process is constructing an *"English"*-English phrase table, the second process is constructing a French-English phrase table, and the third part is constructing a language model (N-gram).

5.1.1. *"English"-English phrase table*

"English"-English phrase tables are constructed as follows.

1. Parallel Corpus

   We prepare a French-English parallel corpus.

2. Pattern-Based Machine Translation

   We use a French-English PBMT. Thus, we obtain *"English"* sentences from French sentences. These *"English"* sentences are pairs of English sentences.

3. *"English"*-English phrase tables

   We construct *"English"*-English phrase tables using Giza++ [6] and training-model.perl [4] from *"English"* sentences (outputs of a French-English PBMT) and English sentences (from parallel corpus).

Figure 3 shows a flow chart for constructing *"English"*-English phrase tables.

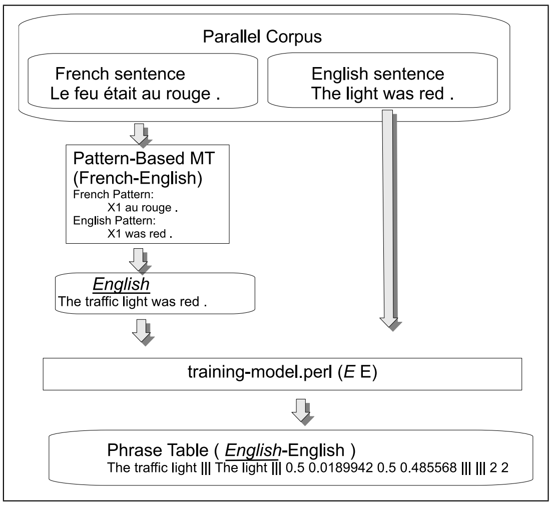

Figure 3: Flowchart for constructing *"English"*-English Phrase Tables

5.1.2. *French-English Phrase Table*

We construct a French-English phrase table using Giza++ [6] and training-model.perl [4] using the French-English parallel corpus. Figure 4 shows a flow chart for constructing French-English phrase tables.

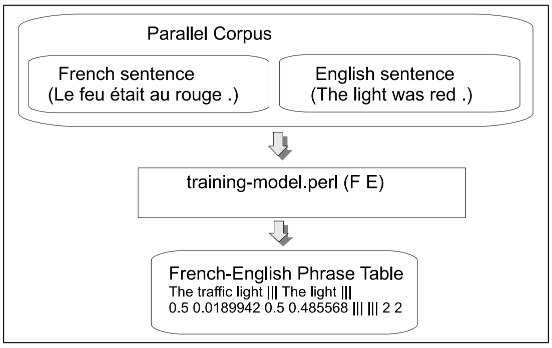

Figure 4: Flowchart for Constructing French-English Phrase Tables

5.1.3. *Language Model (N-gram).*

We developed an N-gram model from English sentences using the SRI Language Modeling Toolkit (SRILM) [7].

5.2. Decoding

The decoding process is as follows.

1. Test Corpus

   We prepared French test sentences.

2. Pattern-Based Machine Translation

   We use a French-English PBMT. If an input French sentence matches with the French patterns, we can obtain a translated *"English"* test sentence.

3. *"English"*-English Statistical Machine Translation

   Using an *"English"*-English phrase table, N-gram model, and Moses [4], we decode the *"English"* test sentence. This involves *"English"*-English translation, resulting in an English sentence.

4. French-English Statistical Machine Translation System

   If an input French sentence does not match with the French patterns, we conduct a standard French-English SMT, using a French-English phrase table and N-gram model, and obtain an English sentence.

Figure 5 shows a flowchart of the decoding process.

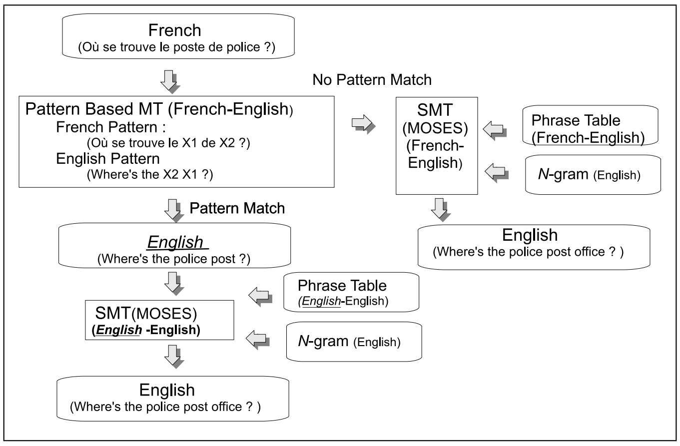

Figure 5: Flowchart of Decoding

6. Experiments with our Machine Translation System

6.1. Training Data

We used the English punctuation system, which means we changed ”,” and ”.” to ” ” and ” ”. Also, we did not take into account English case forms. French sentences were processed similarly. There were 19972 sentences for training data (IWSLT 2010 BTEC-FE task).

6.2. *”English”*-English Phrase Tables

For the second stage, we constructed an *“English”*-English phrase table using Giza++ [6] and “train-model.perl [4]”. We set the parameters to the default values. Also, Out of 19972 training sentences, there were 16989 sentences that matched with the French-English patterns. So, using these 16989 *“English”* sentences, we made *“English”*-English phrase table.

6.3. 5-gram Language Model

We calculated the 5-gram model using the n-gram-count in the Stanford Research Institute Language Model (SRILM) toolkit [7] and used ”-ukndiscount -interpolate” as the smoothing parameter. The number of traing sentences was 19972.

6.4. Development Data

We used 8096 sentences for development data (called IWSLT10.devset3_IIWSLT05.mref) for French-English SMT. Out of these 8096 sentences, 1375 sentences matched with the French-English patterns. For the results, we obtained 1375 *“English”* sentences. These 1375 *“English”* sentences were used as development data for *“English”*-English translation.

6.5. Decoder

We used “Moses [4]” as a decoder. We also used parameter tuning (MERT) and reordering models. Note, in French-English translation, the position of the verb is sometimes significantly changed from its original position. Thus, we set the “distortion-limit” to “-1” for a standard SMT. However, our system consists of two-stage machine translation, and the output of the first stage is *”English”*. In this case, word positions did not dramatically change. Therefore, we set the “distortion-limit” to “6” for the second-stage SMT for our system.

7. Results of our Machine Translation (IWSLT 2010 Automatic Evaluation Scores)

Table 10 summarizes the results of our machine translation evaluation for the BTEC-FE task. “IWSLT10” indicates the IWSLT10 task set and “IWSLT09” indicates the IWSLT09 task set. Also, ”Proposed” indicates our proposed system (RBMT+SMT), and ”MOSES” indicates a standard SMT system. We obtained a BLEU score of 0.5201 in the BTEC-FE task using our proposed system. In contrast, we obtained a BLEU score of 0.5077 in the BTEC-FE task using a standard SMT system (Moses). This means that our proposed system is effective for the BTEC-FE task. Also, our proposed system had an above average BLEU score. However, our system placed 7th place out of 9 systems.

Table 10: Experimental Results

IWSLT10	BLEU	METEOR	WER	NIST
Proposed	0.5201	0.7916	0.3305	8.5812
MOSES	0.5077	0.7808	0.3365	8.4804
IWSLT09	BLEU	METEOR	WER	NIST
Proposed	0.5670	0.7844	0.3360	9.6467
MOSES	0.5504	0.7748	0.3541	9.4419

There were 464 test sentences for IWSLT2010 task. Out of these 464 sentences, the 151 sentences matched with the French-English patterns. For the results of *“English”*-English translation, the 80 sentences out of the 151 sentences were different compared to a standard SMT (Moses). The 313 sentences did not match with the French-English pattern. These 313 sentences were completely the same outputs as a standard SMT (Moses).

For IWSLT2009 task, there were 469 test sentences. Out of these 469 sentences, the 147 sentences matched with the French-English patterns. For the results of *“English”*-English translation, the 77 sentences out of the 147 were different compared with a standard SMT (Moses). The 322 sentences did not match with the French-English patterns, which were completely the same outputs as a standard SMT (Moses).

Table 11: Example Outputs for BTEC-FE

02	Input	J'ai un rhume .
	Proposed	I have a cold .
	PBMT	I a your name cold .
	MOSES	I have a cold .
09	Input	Puis-je voir votre billet d'avion ?
	Proposed	Can I see your airline ticket ?
	PBMT	Can I see your ticket airline ?
	MOSES	Can I see your airline ticket ?
11	Input	Veuillez me donner votre adresse .
	Proposed	Please me give your address .
	PBMT	Please me give your address .
	MOSES	Please give me your address .
12	Input	Je ne comprends pas .
	Proposed	I don't understand .
	PBMT	I don't understand don't .
	MOSES	I don't understand .
21	Input	Nous nous intressons la peinture .
	Proposed	We're interested in painting .
	PBMT	We're interested in paint .
	MOSES	We're interested in at the paint .
24	Input	C'est merveilleux .
	Proposed	That's wonderful .
	PBMT	It's wonderful much .
	MOSES	That's wonderful .
26	Input	Combien de temps allez-vous rester ?
	Proposed	How long will you be staying ?
	PBMT	How many long stay is it ?
	MOSES	How long will you be staying ?
28	Input	Avez-vous des pulls en cachemire ?
	Proposed	Do you have any sweater cashmere in ?
	PBMT	Do you have any sweater in cashmere ?
	MOSES	Do you have any pulls in of cashmere ?
30	Input	C'est notre limite .
	Proposed	It's our your limit .
	PBMT	It's our your name limit .
	MOSES	It's our latest .
32	Input	Je prends le vol dix pour Tokyo .
	Proposed	I'm taking flight for ten Tokyo .
	PBMT	I take to flight it ten for Tokyo .
	MOSES	I'm taking flight ten to Tokyo .
71	Input	Combien en tout ?
	Proposed	How much is in all ?
	PBMT	How much is in all ?
	MOSES	How much altogether ?
75	Input	Quel est le num 辿 ro de l'ambassade japonaise ?
	Proposed	What's Embassy Japanese number ?
	PBMT	What's Embassy Japanese number ?
	MOSES	What's the number of Japanese ? the Japanese embassy ?
356	Input	Je voudrais louer ce type de voiture pour une semaine .
	Proposed	I'd like to rent this type of car for a week .
	PBMT	I'd like to rent this type of car for a week .
	MOSES	I'd like to rent this kind of car for a week .

Table 11 lists example sentences from our proposed system for the BTEC-FE task. These example sentences are IWSLT2010 task and these sentences matched with the French-English patterns. In this table, ”Input” indicates an input French sentence, ”Proposed” indicates an output of our proposed system (RBMT+SMT), ”PBMT” indicates an output of automatically created PBMT, and ”MOSES” indicates an output of a standard SMT.

8. Discussion

8.1. Analysis of Our Proposed System

With our system, our aim is to reduce the number of ungrammatical sentences. Thus, we analyzed the outputs according to this factor. However, there were no native French speakers to check the inputs. Therefore, it was impossible to analyze these results and determine what was wrong. However, by comparing the output of Moses and the output of our proposed system, the output of our proposed system affected the output of PBMT. Sentences No. 26 and No. 27 are good examples. We feel that our system produces more grammatically correct sentences compared to a standard SMT.

8.2. Improvement Pattern Based Machine Translation System

There are many improvement points for PBMT. For example, there is a trade-off between a coverage of input sentences and a translation quality for PBMT. When we made the “High Probability Phrase Table”, we set the threshold as 0.1. It was completely heuristic value. And, there were many bugs in our system. So, we will try to improve the performance of our pattern-based MT system.

8.3. Additional Experiments

We conducted additional experiments. We replaced PBMT with other machine translation systems. Table 12 summarizes the results of these experiments for the BTEC-FE task. The components of the tables are as follows.

1. ”Proposed” means our proposed system.

2. ”MOSES” means a standard SMT with parameter tuning.

3. ”MOSES (no tuning)” shows a standard SMT with no parameter tuning.

4. ”SYSTRAN + MOSES” means the first stage is SYSTRAN and the second stage is a standard SMT with parameter tuning.

5. ”SYSTRAN + MOSES (no tuning)” means the first stage is SYSTRAN and the second stage is a standard SMT with no parameter tuning.

6. ”PBMT + MOSES” means the proposed system. This means the first stage is automatically created PBMT

and the second stage is a standard SMT with parameter tuning.

7. "PBMT + MOSES (no tuning)" means the first stage is automatically created PBMT and the second stage is a standard SMT with no parameter tuning.

8. "JOSHUA" means a standard hierarchical phrase-based machine translation (HPMT)[13].

9. "SYSTRAN + JOSHUA" means the first stage is SYSTRAN and the second stage is HPMT [13].

"SYSTRAN + MOSES" (first stage SYSTRAN and second stage SMT with parameter tuning) seems to be the best system for many scores (BLEU, METEOR, etc.). SYSTRAN uses additional language resources. Therefore, these outputs have less unknown words, and there are few ungrammatical sentences.

9. Conclusion

We developed a two-stage MT system. The first stage consists of an automatically created PBMT system. The second stage consists of an SMT system. Our goal with this system is to obtain fewer ungrammatical sentences.

We obtained a BLEU score of 0.5201 in the BTEC-FE task using our proposed system. In contrast, we obtained a BLEU score of 0.5077 in the BTEC-FE task using a standard SMT system (Moses). This means that our proposed system is effective in the BTEC-FE task. Also, our proposed system obtained an above average BLEU score compared to all participating systems. However, our system placed 7th out of 9 systems.

There are many points for improving PBMT. For future work, we will focus on such improvements.

10. References

[1] Peter F. Brown, Stephen A. Della Pietra, Vincent J. Della Pietra, and Robert L. Mercer. "The machinematics of machine translation: Parameter estimation", Computational Linguistics, 19(2): pp. 263-311. (1993).

[2] Philipp Koehn, Franz J. Och, and Daniel Marcu. " Statistical phrase-based translation". In Marti Hearst and Mari Ostendorf, editors, HLT-NAACL 2003: Main Proceedings, pages 127.133, Edmonton, Alberta, Canada, May 27 -June 1. Association for Computational Linguistics. (2003).

[3] Pierre Isabelle, Cyril Goutte, and Michel Simard., "Domain Adaptation of MT systems through automatic post-editing", MT Summit XI, 102, 2007.

[4] Philipp Koehn, Marcello Federico, Brooke Cowan, Richard Zens, Chris Dyer, Bojar, Alexandra Constantin, Evan Herbst, "Moses: Open Source Toolkit for Statistical Machine Translation", Proceedings of the ACL 2007 Demo and Poster Sessions, pages 177-180, 2007.

[5] Yushi Xu and Stephanie Seneff, "Two-Stage Translation: A Combined Linguistic and Statistical Machine Translation Framework", Proceedings of the Eighth Conference of the Association for Machine Translation (AMTA) 2008.

[6] Franz Josef Och, Hermann Ney, "A Systematic Comparison of Various Statistical Alignment Models", Computational Linguistics, volume 29, number 1, pp. 19-51, 2003.

[7] Andreas Stolcke, "SRILM - An Extensible Language Modeling Toolkit", in Proc. Intl. Conf. Spoken Language Processing, Denver, Colorado, September 2002

[8] K. Papineni, S. Roukos, T. Ward, W. J. Zhu, "BLEU: a method for automatic evaluation of machine translation", 40th Annual meeting of the Association for Computational Linguistics pp. 311-318, 2002.

[9] Banerjee, S. and A. Lavie, "METEOR: An Automatic Metric for MT Evaluation with Improved Correlation with Human Judgments", Proceedings of Workshop on Intrinsic and Extrinsic Evaluation Measures for MT and/or Summarization at the 43th Annual Meeting of the Association of Computational Linguistics (ACL-2005), June 2005.

[10] Terumasa EHARA, "Rule Based Machine Translation Combined with Statistical Post Editor for Japanese to English Patent Translation", Proceedings of Machine Translation Summit XI, Workshop on Patent Translation, pp.13-18, Sept., 2007.

[11] L.Dugast, J.Senellart, and P.Koehn, "Statistical postediting on SYSTRAN's rule-based translation system", in Second Workshop on SMT, 2007, pages.179-182

[12] M.Simard, N.Ueffing, P.Isabelle, and R.Kuhn, "Rule-based translation with statistical phrase-based post-editing", in Second Workshop on SMT, 2007, pages.203-206

[13] Zhifei Li, Chris Callison-Burch, Chris Dyer, Juri Ganitkevitch, Sanjeev Khudanpur, Lane Schwartz, Wren Thornton, Jonathan Weese and Omar Zaidan, "Joshua: An Open Source Toolkit for Parsing-based Machine Translation", In Proceedings of the Workshop on Statistical Machine Translation (WMT09), 2009.

Table 12: Additional Experiments

IWSLT10				
case+punc	BLEU	METEOR	WER	NIST
Proposed (=PBMT+MOSES)	0.5201	0.7916	0.3305	8.5812
MOSES	0.5077	0.7808	0.3365	8.4804
SYSTRAN+MOSES	0.5341	0.8001	0.3177	8.7090
JOSHUA	0.4871	0.7648	0.3443	8.0456
SYSTRAN+JOSHUA	0.5209	0.7892	0.3186	8.5260
MOSES(no tuning)	0.4882	0.7700	0.3655	8.3291
SYSTRAN+MOSES(no tuning)	0.5104	0.7909	0.3479	8.5575
PBMT+MOSES (no tuning)	0.4991	0.7797	0.3600	8.4342
no_case+no_punc	BLEU	METEOR	WER	NIST
Proposed (=PBMT+MOSES)	0.4949	0.7606	0.3776	8.7709
MOSES	0.4812	0.7488	0.3920	8.6752
SYSTRAN+MOSES	0.5110	0.7707	0.3655	8.9056
JOSHUA	0.4580	0.7292	0.4021	8.0676
SYSTRAN+JOSHUA	0.4977	0.7604	0.3682	8.6502
MOSES (no tuning)	0.4584	0.7351	0.4218	8.4744
SYSTRAN+MOSES(no tuning)	0.4815	0.7610	0.3990	8.7320
PBMT+MOSES (no tuning)	0.4711	0.7482	0.4110	8.6140
IWSLT09				
case+punc	BLEU	METEOR	WER	NIST
Proposed (=PBMT+MOSES)	0.5894	0.8173	0.2932	9.2554
MOSES	0.5793	0.8079	0.3065	9.1049
SYSTRAN+MOSES	0.5985	0.8268	0.2814	9.3422
JOSHUA	0.5696	0.7940	0.3096	8.8269
SYSTRAN+JOSHUA	0.5850	0.8112	0.2923	9.0368
MOSES (no tuning)	0.5574	0.7940	0.3275	8.8250
SYSTRAN+MOSES (no tuning)	0.5809	0.8132	0.3071	9.1918
PBMT+MOSES (no tuning)	0.5670	0.8005	0.3235	9.0278
no_case+no_punc	BLEU	METEOR	WER	NIST
Proposed (=PBMT+MOSES)	0.5670	0.7844	0.3360	9.6467
MOSES	0.5504	0.7748	0.3541	9.4419
SYSTRAN+MOSES	0.5742	0.7965	0.3198	9.7262
JOSHUA	0.5438	0.7592	0.3587	9.1024
SYSTRAN+JOSHUA	0.5603	0.7805	0.3289	9.3301
MOSES(no tuning)	0.5301	0.7607	0.3784	9.1431
SYSTRAN+MOSES(no tuning)	0.5494	0.7830	0.3486	9.5210
PBMT+MOSES (no tuning)	0.5381	0.7678	0.3684	9.3586