

Impact of Controlled Language on Translation Quality and Post-editing in a Statistical Machine Translation Environment

Takako Aikawa, Lee Schwartz, Ronit King

Microsoft Research
One Microsoft Way
Redmond, WA 98052
USA

{takakoa, leesc, ronitk}@microsoft.com

Mo Corston-Oliver

Butler Hill Group
104 Gowing Drive
Meadowbank, Auckland
New Zealand

mo.corstonoliver@gmail.com

Carmen Lozano

Microsoft
One Microsoft Way
Redmond, WA 98052
USA

carmenlo@microsoft.com

Abstract

This paper investigates the relationships among controlled language (CL), machine translation (MT) quality, and post-editing (PE). Previous research has shown that the use of CL improves the quality of MT. By extension, we assume that the use of CL will lead to greater productivity or reduced PE effort. The paper examines whether this three-way relationship among CL, MT quality, and PE holds. Beginning with a set of CL rules, we determine what types of CL rules have the greatest cross-linguistic impact on MT quality. We create two sets of English data, one which violates the CL rules and the other which conforms to them. We translate both sets of sentences into four typologically different languages (Dutch, Chinese, Arabic, and French) using MSR-MT, a statistical machine translation system developed at Microsoft. We measure the degree of impact of CL rules on MT quality based on the difference in human evaluation as well as BLEU scores between the two sets of MT output. Finally, we examine whether the use of CL improves productivity in terms of reduced PE effort, using character-based edit-distance.

1. Introduction

Over the past several years, Microsoft has been localizing portions of its technical documentation using MSR-MT, a statistical machine translation (MT) system (Quirk, et al., 2005). In the development of this system, we have often encountered English source input that not only has presented problems for MT, but also has caused humans difficulty with translation. In an attempt to tackle the translatability problem, a controlled language (CL) in the form of authoring guidelines was proposed for content writers. (See Appendix I for the summary of CL rules used in our experiments.) Research has shown that the use of CL improves the quality of MT.¹ Given this finding, we expect, by extension, that the usage of CL will also lead to greater productivity in post-editing (PE), in a three-way relationship among CL, MT quality, and PE, which is illustrated in Figure 1.

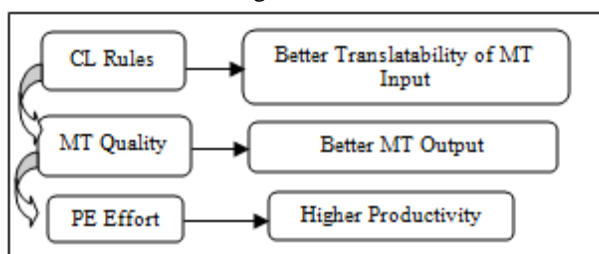


Figure 1: CL, MT Quality and PE Effort

This paper has two goals: (i) to determine the types of CL rules that have the greatest cross-linguistic impact on MT quality; and (ii) to determine whether the relationships among CL rules, MT quality and PE effort illustrated in Figure 1 truly hold.

The organization of the paper is as follows. Section 2 provides a brief description of our MT system. Section 3 describes the data used in our experiments. Section 4 presents our experimental design. Section 5 presents the results of the experiments related to the impact of CL on MT quality. In Section 6 we provide detailed linguistic analyses of the results. Section 7 describes the results of the experiments related to the PE effort. Section 8 provides concluding remarks.

2. Overview of MSR-MT

For our experiments, we used a statistical MT system, MSR-MT, developed at Microsoft Research. This system requires bilingual parallel corpus data and a source language parser for training. During training, the source data is parsed to produce dependency trees. The bilingual corpus is then word-aligned. Source dependencies are projected onto the target sentences using information from word alignment. The result is an aligned dependency corpus. From this corpus, translation mappings (from source dependency structure to target dependency structure) are extracted. Various models, including target language, order, and casing models are also produced during the training phase.

At run-time, the input sentence is parsed, and a decoder finds the best translation mappings, resulting in the final translation. The technical details of MSR-MT are described in Quirk, et al., (2005), and Menezes & Quirk (2005).

¹ CLAW (Controlled Language Applications Workshops) have been held since 1996 to discuss various types of CL rules.

Currently, MSR-MT is trained on data from the IT domain (using MS technical documents) and translates from English to other languages. Thus, the data used in our experiments were all from the technical domain and the source language was English.

3. Data

The data for our experiments consist of: (a) a set of CL rules, devised to improve the translatability of English input, (b) a set of English sentences that conform to the CL rules, (c) a corresponding set of English sentences that violate the CL rules, (d) machine translations of both sets of sentences, and (e) post-edited versions of the machine-translated sentences. We subcategorized our CL rules into 21 categories (see Appendix I).

From actual data within our domain, we extracted a total of 520 English sentences that fell into these CL categories (24-25 sentences per category). The extracted English sentences were then modified to produce two sets of data: a set of English sentences that conformed to the CL rules (see (2) in Table 1) and a corresponding set of English sentences that violate the CL rules (see (2)' in Table 1). The former set we refer to henceforth as "Correct English" and the latter set we refer to as "Error English". Appendix II provides a sample of the CL rule categories, Error English sentences, and Correct English sentences.

Using MSR-MT, we translated the two sets of English data into four typologically different languages: Chinese, French, Dutch, and Arabic (see (3) & (3)' in Table 1). We then asked localizers to post-edit the MT output (see (4) & (4)' in Table 1).

| | | | |
|--------------------|---------------------|------------------------------|------------------------------------|
| (1) CL Rules | (2) Correct English | (3) MT Output of (2) | (4) Post-Edited MT Output (3) |
| | (2)' Error English | (3)' MT Output of (2)' | (4)' Post-Edited MT Output (3)' |

Table 1: Summary of the Data Types for Experiments

4. Experimental Design

4.1. Impact of CL on MT Quality

To measure the overall impact of the CL rules on MSR-MT output, we used two metrics: (i) human evaluation scores and (ii) (sentence-level) BLEU scores (Papineni et al., 2001). For both types of evaluation, the MT output for each sentence in our two data sets (i.e., (3) and (3)' in Table 1) was compared to the corresponding post-edited version of that output (i.e., (4) and (4)' in Table 1).

In the human evaluation, for each of the two types of MT output, three raters assigned a score on a scale from 1 to 4, as defined below.²

- 1: unacceptable
- 2: possibly acceptable
- 3: acceptable
- 4: perfect

For each sentence in the data, the three human evaluation scores were averaged.

In the BLEU evaluation, as in the human evaluation, we used the post-edited versions of the two sets of MT output as the references. We then obtained the BLEU score for each sentence and calculated the average of the BLEU scores for each set of the data (i.e., Error English and Correct English).

In order to measure the categorical impact of the CL rules, we calculated the difference between the average human evaluation scores for the Correct and Error sentences in each category. We measured the gap between Correct and Error scores for each of the 21 CL categories, with the assumption that the larger the gap in a category, the more significant the impact of that category on MT quality.

4.2. Post-editing (PE)

Various metrics have been proposed to measure PE effort (Allen (2002), among others). For this paper, we used character-based edit distance (ED) between the MT output and the post-edited version of that output to quantify PE effort. We assumed that the smaller the ED, the higher the PE productivity.³

To quantitatively gauge the relationships among CL, MT quality and PE effort, we calculated the correlation coefficients between the human evaluation scores and the ED scores in each settings (i.e., in the context of Error English and in the context of Correct English). An overview of our experiments is provided in Figure 2.

² To eliminate the effect of differences in raters' levels of source language knowledge, raters were not shown the source sentence. The order of presentation of sentences was randomized for each rater in order to eliminate any ordering effect. For details of our human evaluation method, see Pinkham, J and M. Corston-Oliver (2001).

³ We are aware of the fact that the use of ED is not sufficient to measure PE effort. See, for instance, Allen (2002), for more through investigations on the measurements of PE effort.

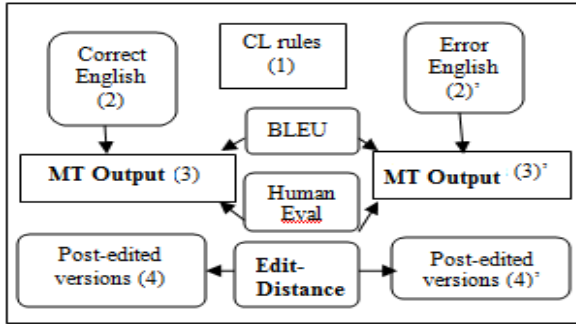


Figure 2: Experimental Design

5. Overall MT Quality Results

5.1. Human Evaluations

Table 2 and Figure 3 provide the results of the human evaluations of the MT output for the Error English and Correct English data sets. For all systems, the average human evaluation score for the MT output of the Correct English sentences was significantly higher than that for the Error English sentences.⁴

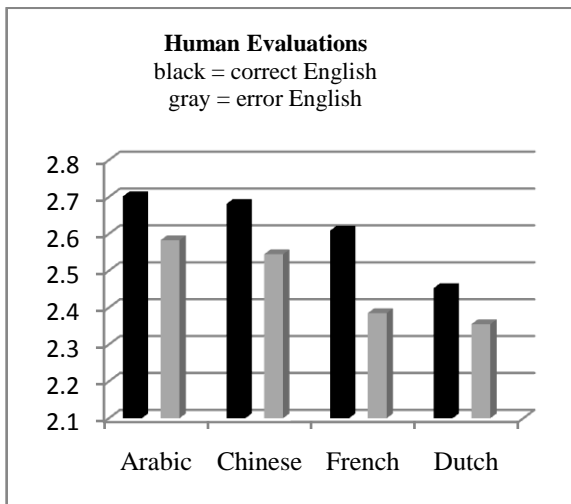


Figure 3: Impact of CL on MT Quality: Human Evaluation Results

| | Arabic | Chinese | French | Dutch |
|---------------|---------------------|---------------------|---------------------|---------------------|
| Correct | 2.702 | 2.681 | 2.609 | 2.453 |
| Error | 2.583 | 2.545 | 2.385 | 2.355 |
| Paired t-test | 5.59 (p < 0.001) | 5.05 (p < 0.001) | 7.78 (p < 0.001) | 4.46 (p < 0.001) |

Table 2: Impact of CL on MT Quality: Human Evaluation Results

⁴ Paired t-tests were used to validate the statistical significance of the difference between Correct and Error scores in the four languages. The evaluations of the translations for Correct English were determined to be significantly higher than those for Error English for each of the four language pairs.

5.2. BLEU

Table 3 provides the results of the BLEU evaluation of the MT output for the Error English and Correct English data sets.⁵ For three of the four languages (Chinese, French, and Dutch), the differences are statistically significant and support the hypothesis that applying CL rules to MT input has a positive effect on translation.

| | Arabic | Chinese | French | Dutch |
|---------------|----------------------|---------------------|---------------------|---------------------|
| Correct | 0.306 | 0.421 | 0.502 | 0.408 |
| Error | 0.310 | 0.405 | 0.476 | 0.385 |
| Paired t-test | -0.66 (p = 0.509) | 2.33 (p = 0.020) | 3.30 (p = 0.001) | 3.24 (p = 0.001) |

Table 3: Sentence-level BLEU Scores

However, for Arabic, the BLEU score does not support this hypothesis.⁶ One speculation is as follows. In Arabic, a single "word" (where "word units" are separated by a white space) might contain a conjunction, preposition, definite article, inflection, clitic pronoun, etc. Therefore, even if one translation is better than another for humans, provided that neither is perfect, it is likely that both will differ greatly on a word-for-word basis from a reference translation. Given the fact that the BLEU metric is n-gram based and we simply used a white space as a word delimiter, we would speculate that BLEU was unable to measure quality differences due to the linguistic nature of Arabic.

6. Categorical Impact Results

6.1. Results

As mentioned in Section 4, we used the average human scores per CL rule category to identify the types of rules that appear to have the greatest impact on MT quality. For each MT system, Table 4 presents the five categories that have the greatest impact on human evaluation scores.⁷

| | Arabic | Chinese | French | Dutch |
|---|--------------|--------------|---------------------------|----------------|
| 1 | Formal Style | Formal Style | Short Ambiguous Sentences | Formal Style |
| 2 | Hyphens | Attachment | Formal Style | Capitalization |

⁵ Paired t-tests were used to determine the statistical significance of the difference between Correct and Error scores.

⁶ The negative impact for Arabic is not statistically significant.

⁷ All the CL categories provided in Table 4 show a statistically significant difference between Error and Correct English versions.

| | | | | |
|---|---------------------------|----------------|---------------------------|---------------------------|
| 3 | Short Ambiguous Sentences | -ing Clauses | Spelling | Spelling |
| 4 | Capitalization | Spelling | Adjective/ Verb Ambiguity | Short Ambiguous Sentences |
| 5 | Spelling | Long Sentences | Capitalization | Long Sentences |

Table 4: Top five CL categories

6.2. CL Rules with Cross-linguistic Impact

Table 4 shows the three CL categories with greatest cross-linguistic effect to be Formal Style, Spelling, and Caps.

6.2.1. Formal Style

The CL category, Formal Style, concerns style restrictions on lexical/phrasal items in MT input. Violation of this rule is characterized by MT input with lexical items and phrasing that are unfamiliar to the MT system. For a statistical MT system such as MSR-MT, translations are learned from the training data. If lexical items, phrases, or expressions used in the input text are not present in the training data, they will not be learned. Therefore, they will not be translated at all or they will be translated incorrectly. Table 5 presents examples from French and Chinese of this category. In these examples, the Error English "wrap up" and "gotcha" are translated incorrectly (i.e. literally), whereas the Correct English "finish" and "dangers" are translated correctly.

| Correct | Error | MT-Correct | MT-Error |
|---------------------------------------|---------------------------------------|------------------------|--------------------------------|
| Before I finish ,... | Before I wrap up ,... | Pour terminer, ... | Avant que j'ai empaqueter, ... |
| ...counter has a few dangers . | .. counter has a few gotchas . | ...计数器都有几个 危险 。 | ...计数器都有几个 陷阱 。 |

Table 5: Formal Style Examples

6.2.2. Spelling

The CL spelling rule, which requires correct spelling of MT input, has a similar effect on translation. For MSR-MT, a statistical system, provided that the training data does not contain misspellings, misspelled words will be unknown, and hence, not translated. However, the negative effect is not restricted to the translation of the misspelled word alone. Any multi-word translation mappings containing the correct form of the misspelled input word will not be found. Hence, translation will generally deteriorate because of a misspelling. Table 6 provides Arabic and Dutch examples from the Spelling category.

| Correct | Error | MT-Correct | MT-Error |
|---|--|---|--|
| Arguments can be passed to and from VxD services. | Arguements can be passed to and from VxD services. | يمكن تمرير الوسائط وإلى من خدمات .DxV | يمكن تمرير arguments وإلى من خدمات .VxD |
| Arguments can be passed to and from VxD services. | Arguements can be passed to and from VxD services. | Argumenten worden doorgegeven van en naar VxD-services. | Arguements kunnen worden doorgegeven van en naar VxD-services. |

Table 6: Spelling Examples

6.2.3. Capitalization

The third CL category with extensive cross-linguistic effect is the Capitalization category. If the system treats uppercase and lowercase lexical items differently, an uppercase word will not be matched with a translation mapping for the lowercase word, and it will not be matched with a larger mapping that includes the lowercase word. The effects of this can be seen in the French examples below:

| Correct | Error | MT-Correct | MT-Error |
|-----------------------------|----------------------------|-------------------------------------|---------------------------|
| Determining what to deploy. | Determining What to Deploy | Déterminer les éléments à déployer. | Déterminer qu'à déployer. |

Table 7: Capitalization Examples (1)

If Capitalizations is not used when it should be, the case sensitive system is likely to mistranslate names and named entities as below.

| Correct | Error | MT-Correct | MT-Error |
|---|---|---|---|
| ... including Word, Excel, Outlook, or Microsoft Office Access. | ... including word, excel, outlook, or microsoft office access. | ... y compris Word, Excel, Outlook, ou Microsoft Office Access. | ...y compris, mot Excel, ou accès à Microsoft Office Outlook. |

Table 8: Caps Examples (2)

The product names in these examples should not be translated. They are not translated when they appear in the input with the correct capitalization, but they are translated incorrectly when they are not capitalized correctly (e.g., word => mot).

6.3. Other CL Rules

We have focussed on the three CL rules that had cross-linguistic effect on MT quality. In this sub-section, we discuss other CL rules that are language specific.

Among the CL categories in Table 5, there are three rules that are directly related to removing ambiguity from the input: (i) Short Ambiguous Sentences, (ii) -ing Clauses, and (iii) Adjective/ Verb Ambiguity. At first sight, it is curious why CL rules designed to get rid of the input ambiguities are not equally helpful for translations from English into all four languages. Of course, if a type of ambiguity is characteristic of both source and target languages, as prepositional phrase (PP)-attachment ambiguities often are (though not in the case of English-Chinese), we would not expect eliminating the ambiguity to have a positive effect on translation. However, the ambiguity characteristic of the three rules above is generally not characteristic of both source and target languages.

In an in-depth analysis of the data for the Adjective/Verb Ambiguity category, it was found that many of the sentences with ambiguity of this type were by our English parser. If the input to our MT system is misanalyzed, the resulting translation is likely to be bad.

The remaining CL rule categories in Table 4 are Hyphens, Attachment, and Long Sentences. Hyphens seem only to be a major problem for Arabic. Arabic does not use hyphens as English does. When hyphens get transferred to the target, the translation must be significantly reworded. Moreover, if the words on either side of the hyphen are not translated correctly, or at all, MT quality suffers.

Attachment ambiguity is a special problem for Chinese because the ambiguity of English cannot be maintained in Chinese. A prepositional phrase (PP) “on the Web”, for instance, can be translated either into “在 Web” or “Web 的”, depending on whether the PP in question is attached to a VP or an NP. Attachment ambiguity in English must be resolved for a good Chinese translation.

Finally, the CL rule category, Long Sentences, has substantial impact on translations into only two of the four languages. This is somewhat contrary to our naive assumption that the longer the MT input is, the worse the MT output would be. In general, short sentences are easier to parse than long sentences, and correct parses are more likely to produce good MT output than incorrect parses. It is still puzzling to us why this category did not have greater impact on Arabic and French. We leave this puzzle as unresolved for now.⁸

⁸ For Arabic, the category Long Sentences was ranked 10th (among the total of 21 CL rules) and for French, it was 21st.

7. Edit Distance Results

7.1. Edit Distance Results

As mentioned in Section 4.2, we used the character-based ED scores to gauge PE productivity. Table 9 provides the results based on the ED measure.

| | Arabic | Chinese | French | Dutch |
|---------------|--------------------|-------------------|-------------------|-------------------|
| Correct | 0.415 | 0.497 | 0.272 | 0.385 |
| Error | 0.403 | 0.533 | 0.299 | 0.410 |
| Paired t-test | -1.10 p = 0.271 | 2.15 p = 0.032 | 3.77 p < 0.001 | 3.76 p < 0.001 |

Table 9: Edit Distance⁹

For three of the four languages, the ED between the raw and post-edited MT for the Error English was significantly higher than the ED between the raw and post-edited MT for the Correct English. This shows that the PE productivity for the Correct English data is higher than that for the Error English data. This, in turn, supports the hypothesis that the use of CL increases PE productivity.

For Arabic, however, this was not the case, though the difference between the ED for the Correct and Error sentences was not significant.

Human examination of the Arabic data showed the opposite correlation of the data not to be problematic. In numerous cases we found that while the Correct English sentence contained a phrase that was an expansion of a potentially ambiguous phrase in the Error Sentence, the post-edited versions of the Correct and Error English were identical. This does not need to be interpreted as a post-editing flaw, but rather as a preference in the target for a certain type of expression that does not correspond on a 1-1 basis with the source expression. So, for example, whereas the set of sentences below differ in the use of "these" to disambiguate "customized", the Arabic post-edited versions of Error and Correct English were identical. Since the MT system added an Arabic translation for the word "these", the ED score was greater for the Correct than the Error English.

- [Error English]: If you have *customized settings*, the custom settings are retained.
- [Correct English]: If you have *customized these settings*, the custom settings are retained.

7.2. Correlation between Human Evaluations and Edit Distance

We are satisfied that the ED results generally support the hypothesis that applying CL rules to MT input ultimately results in less PE effort (and hence higher PE productivity). Our results corroborate those of previous

⁹ Paired t-tests were used to measure the differences between Error and Correct versions of the sentences in the four languages.

studies, which have shown that CL input can improve the quality of MT output. To further test this hypothesis quantitatively, we measured the correlation between ED scores and human evaluation scores. Table 10 shows the correlation figures for our two sets of data across the four languages.

| Correlation | Arabic | Chinese | French | Dutch |
|-------------|--------|---------|--------|--------|
| Correct | -0.464 | -0.570 | -0.519 | -0.581 |
| Error | -0.470 | -0.621 | -0.530 | -0.532 |

Table 10: Correlation between ED scores and Human Evaluation (correlation coefficient scores are statistically significant with $p < 0.001$)

The negative correlation between human evaluation scores and ED scores cross-linguistically shown in Table 10 is in line with and augments the results of O'Brien, S. (2006) with respect to determining the correlation between MT quality and PE effort.

8. Concluding Remarks

In this paper, we examined the relationships among CL, MT quality, and PE effort. The results of the experiments support the hypothesis that the use of CL improves PE productivity as well as MT quality. To our knowledge, very few studies have been done on the three-way relationship among CL, MT quality and PE. This paper therefore makes a contribution not only to the CL community but also to the MT and localization communities.

We have discussed in detail CL rules that have an impact on MT quality for all languages tested as well as some that have an impact for specific languages. Here, we would like to add two caveats. First, we are not claiming that the CL rules discussed in this paper work for all MT systems. The effect of CL might differ with the types of MT systems. The question of whether the CL rules that affected MSR-MT would impact other MT systems in the same fashion remains to be seen. This is a topic for future research.

Second, one of the motivations for our project came about in response to the requests of content writers. Our original authoring guidelines contain rules to follow. Content writers, however, find it difficult to remember every single rule. They wanted to know the minimal set of rules that would provide the greatest impact on MT quality cross-linguistically. Our project was in response to their practical need.

A couple of points should be made before closing. First, admittedly, our measurement of PE effort was limited in that it did not include the amount of time that post-editors actually spent on post-editing. We used an ED metric primarily because of lack of time. Nonetheless, by simply using ED, we were able to obtain enough supporting evidence for our hypothesis.

Second, the previous studies regarding the impact of CL on MT quality mostly concern rule-based MT systems, not statistical ones. As just mentioned, the impact of CL rules on MT quality may vary depending on the types of MT systems. Given the fact that statistical MT has been supplanting rule-based MT, it is time for the CL community to revisit CL rules in general and re-examine their impact on statistical MT systems.

Acknowledgments

We are grateful to the post-editors and the human evaluators who participated in our experiments. Also, special thanks go to Martin Chodorow from Hunter College of CUNY, New York and to Lisa Braden-Harder, Anya Dormer and Martine Pétrod from Butler Hill Group.

References

- Allen, J. (2002). *Repairing Texts: Empirical Investigations of Machine Translation Post-Editing Processes*, book review, *MultiLingual Computing & Technology*, 13.2, March 2002, pp. 27-29.
- Allen, J. and Hogan, C. (2002). Toward the development of a postediting module for raw machine translation output: A controlled language perspective. In *Proceedings of the Third International Workshop on Controlled Language Applications, (CLAW-2000)*, Seattle, WA, pp. 62-71.
- EAMT/CLAW (2003). "Controlled Language Translation," *Proceedings of the Joint Conference Combining the 8th International Workshop of the European Association for Machine Translation and the 4th Controlled Language Applications Workshop*, Dublin City University, Ireland.
- Mitamura, T. (1999). Controlled language for multilingual machine translation. In *Proceedings of Machine Translation Summit VII*, Singapore, pp. 46-52.
- Menezes, A. and Quirk, C. (2005). Microsoft Research Treelet Translation System: IWSLT Evaluation. In *Proceedings of IWSLT 2005*, Pittsburgh, PA, USA, October 2005.
- O'Brien, S. (2002). Teaching Post-Editing: A Proposal for Course Content. In *6th EAMT Workshop Teaching Machine Translation*, Manchester, pp. 99-106.
- O'Brien, S. (2005). Methodologies for Measuring the Correlations between Post-Editing Effort and Machine Text Translatability. In *Machine Translation, 19.1.*, pp. 37-58.
- O'Brien, S. (2006). Controlled Language and Post-Editing. In *MultiLingual*, October/November Issue, pp. 17-19. (<https://216.18.156.115/multilingual/downloads/screenSupp83.pdf>)
- Papineni, K., Roukos, S., Ward, T., and Zhu, W.-J. (2001). BLEU: A Method for Automatic Evaluation of Machine Translation. In *Proceedings of the 40th Annual Meeting of ACL*, Philadelphia, PA, pp. 311-318.

Pinkham, J. and Corston-Oliver, M. (2001). Adding Domain Specificity to an MT System. In Proceedings of the Workshop on Data-driven Machine Translation at 39th Annual Meeting of ACL, Toulouse, France, pp. 103-110.

Quirk, C, Menezes, A. and Cherry, C. (2005). Dependency treelet translation: Syntactically informed phrasal SMT. In *Proceedings of the 43rd ACL*, Ann Arbor, Michigan, pp. 271–279.

Appendix I: CL Categories, Error English, and Correct English

| | |
|---------------------------|--|
| Formal Style | Don't use slang or colloquial expressions |
| Spelling | Correct spelling errors (including typos) |
| Long Sentences | Avoid sentences with more than 25 words |
| Short Ambiguous Sentences | Avoid sentences with <6 words that have ambiguous structure |
| Sentence Breaks | Use sentence-final punctuation; avoid complex lists separated by semicolons |
| Commas | Follow formal punctuation rules |
| Hyphens | Avoid creating new compounds; avoid using hyphens as parentheses; use hyphens when needed in compounds |
| Abbreviations | Avoid unfamiliar abbreviations and acronyms |
| Parentheses | avoid parenthetical comments |
| Capitalization | Use caps only when required; don't use caps for emphasis |
| Relative Pronoun | Use relative pronouns |
| Attachment | Avoid extraposed relative clauses |
| Relative Clauses | Avoid reduced relative clauses (i.e. -ed and -ing phrase modifiers) |
| -ed Verbs | Use -ed verb forms unambiguously |
| Ambiguous VP conjunct | Avoid VP conjuncts with ambiguous attachment |
| Ambiguous VP conjunct2 | Don't begin a VP conjunct with a potential noun |
| Ambiguous NP/AP conjunct | Avoid NP/AP conjuncts with ambiguous attachment |
| Ambiguous NP conjunct | Avoid NP conjuncts that begin with a potential verb |
| Adjective/Verb Ambiguity | Avoid VP conjuncts that begin with a potential adjective |
| -ing clauses | Avoid -ing clauses without an explicit subject when the subjects differs from that of the main clause |
| -ing ambiguity | Avoid ambiguous uses of words ending in -ing |

Appendix II: Samples of Error and Correct English

| Category | Error English | Correct English |
|------------------|--|---|
| Formal Style | Our next <i>bit of magic</i> was to increase the number of storage groups. | Our next <i>improvement</i> was to increase the number of storage groups. |
| Spelling | To find the next <i>occurence</i> of the tag, click Find Next. | To find the next <i>occurrence</i> of the tag, click Find Next. |
| Attachment | These processes can be simplified with the tools included with Windows Server 2003 <i>which can be</i> utilized to automatically perform system updates. | These processes can be simplified with the tools included with Windows Server 2003. <i>These tools can be utilized</i> to automatically perform system updates. |
| -ing Clauses | Tolerance limits are developed with environment owners <i>before allowing</i> each new environment to access the network. | Tolerance limits are developed with environment owners <i>before each new environment is allowed</i> to access the network. |
| Relative Clauses | Use only fonts <i>optimized</i> for display on the Web. | Use only fonts <i>that are optimized</i> for display on the Web. |
| Capitalization | Today's <i>Data Protection Challenges</i> . | Today's <i>data protection challenges</i> . |