Building an English-Chinese Parallel Corpus
Annotated with Sub-sentential Translation Techniques

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Abstract

Human translators often resort to different non-literal translation techniques besides the literal translation, such as idiom equivalence, generalization, particularization, semantic modulation, etc., especially when the source and target languages have different and distant origins. Translation techniques constitute an important subject in translation studies, which help researchers to understand and analyse translated texts. However, they receive less attention in developing Natural Language Processing (NLP) applications. To fill this gap, one of our long term objectives is to have a better semantic control of extracting paraphrases from bilingual parallel corpora. Based on this goal, our hypothesis is that it is possible to automatically recognize different sub-sentential translation techniques. For this original task, since there is no dedicated data set for English-Chinese, we manually annotated a parallel corpus of eleven genres. Fifty sentence pairs for each genre have been annotated in order to consolidate our annotation guidelines. Based on this data set, we conducted an experiment to classify between literal and non-literal translations. The preliminary results confirm our hypothesis. The corpus and code are available. We hope that this annotated corpus will be useful for linguistic contrastive studies and for fine-grained evaluation of NLP tasks, such as automatic word alignment and machine translation.

Keywords: corpus annotation, translation technique, automatic classification

1. Introduction

Translation theorists and linguists have conducted studies on translation techniques for a few decades \cite{Vinay1989,Deng2017}. Translation techniques refer to the specific steps for the sake of accomplishing an acceptable and appropriate translation, which can be divided coarsely into literal translation and non-literal translation at sub-sentential level.

Consider two human non-literal translation examples in table 1: the translation of the first sentence conveys the meaning in a more direct way to help readers’ understanding; the translation of the second sentence divides one sentence into two clauses to paraphrase the expression « unfold out of », thus the translation is more natural and compact.

Table 1: English-Chinese non-literal translations

| EN: Don’t make me go through all of this and not make it. | ZH: 别让我的辛苦白费了。
| "Don’t let my hard work be wasted." |
| EN: In the east the dawn was unfolding out of the darkness. | ZH: 东方晨曦初现，黑暗渐去。
| "In the east the dawn was beginning to appear, and the darkness was fading." |

Non-literal translations between different languages can cause difficulties for automatic word alignment \cite{Dorr2002,Deng2017}, or cause meaning changes in certain cases. However, non-literal translation techniques receive less attention in developing NLP applications. Take the task of paraphrase extraction from bilingual parallel corpora as an example. The assumption is that two monolingual segments are potential paraphrases if they share common translations in another language, and the extraction relies on Machine Translation (MT) related techniques \cite{Bannard2005,Mallinson2017}. Currently, the largest paraphrase resource, PPDB (ParaPhrase DataBase), has been built based on this method \cite{Ganitkevitch2013}. Nonetheless, Pavlick et al. (2015) revealed that there exist relations other than strict equivalence in PPDB \cite{i.e. Entailment (in two directions), Exclusion, Other related and Independent}. Non-literal pivot translations inside the parallel corpora could break the strict equivalence between the candidate paraphrases extracted, whereas they have not received enough attention during this corpus exploration.

In this working context, one of our long term objectives is to have a better semantic control of extracting sub-sentential paraphrases from bilingual parallel corpora. Based on this goal, our hypothesis is that it is possible to automatically recognize different sub-sentential translation techniques \cite{e.g. literal versus non-literal}. For this original task, since there is no dedicated data set for English-Chinese, we manually annotated a parallel corpus with translation techniques. To reflect the diversity of textual styles, we constructed a corpus of eleven genres based on existing work. Fifty sentence pairs for each genre have been annotated in order to consolidate our annotation guidelines. Based on this data set, we conducted an experiment to classify between literal and non-literal translations. The preliminary results confirm our hypothesis that we can automatically recognize sub-sentential translation techniques.
2. Related Work

The first annotation guidelines for manually annotating parallel corpora were established for the project Blinker (Melamed, 1998a, Melamed, 1998b), in order to annotate translational equivalence in English-French Bible verses. More recently, Monti et al. (2015) annotated multi-word expressions in an English-Italian parallel corpus of TED Talks. Annotators also indicated whether the generated machine translation is correct, and supplied a correct translation if needed. Ahrens et al. (2018) built an online large database containing English and Chinese political speeches. This corpus is particularly useful for researchers focusing on political speeches and conceptual metaphor analyses.

Concerning non-literal translation techniques, several works have proposed different typologies to categorize them (Vinay and Darbelnet, 1958; Newmark, 1988; Chaudet and Panlird, 1989; Molina and Hurtado Albrí, 2002). Our corpus annotation is based on these translation theories. Deng and Xue (2017) built a hierarchically aligned parallel corpora and semi-automatically detected Chinese-English translation divergences, which are caused by non-literal translations and cross-lingual differences. Chen et al. (2018) used attention mechanism scores in an innovative way to detect free translation in English-Chinese parallel corpora. Xu and Yvon (2016) proposed new methodologies for collecting human judgements on bilingual alignment links, which were used to annotate four new data sets. Their observation confirms that a finer categorization than Sure and Possible word alignment is useful. In our work, we conduct word and segment level alignment, and specify the fine-grained translation technique.

Ahrenberg (2017) compared machine and human translations of an English article translated into Swedish, by using MT metrics and translation techniques. The author pointed out that automatically classifying translation techniques should be a topic for future research. Recently, we have worked on automatically classifying translation techniques for the language pair English-French (Zhai et al., 2019). This present work extends these studies by working on a more distant language pair: English-Chinese.

3. Corpus Presentation

We extend our previous work which focused on annotating an English-French parallel corpus of TED Talks with translation techniques (Zhai et al., 2018). English and French languages are very similar in vocabulary and grammar, while the English-Chinese pair shares far fewer cultural and linguistic similarities. A corpus of eleven genres is constructed based on existing work: art, literature, law, material for education, microblog, news, official document, spoken, subtitles, science, and scientific article. For our first study of this language pair, we didn’t limit ourselves to only one corpus genre, even though the corpus of different genres don’t have the same quality. Below we present the origin of each corpus. The translation direction is from English to Chinese, except for the genre of scientific article.

**UM-corpus** (Tian et al., 2014): this corpus has been constructed by the University of Macau, for training machine translation systems. The corpus released contains 2.2M parallel sentences, and is divided into eight genres with a nearly balanced distribution (law, material for education, microblog, news, science, spoken, subtitles, thesis). The sentence-level alignments have been manually corrected. However, errors still exist, for example, there are cases where a long segment is not translated in a sentence. We annotated this corpus while filtering out the incomplete or incorrect pairs. The segmentation of Chinese words and the bilingual word alignment are not provided. The corpus is freely available and released with the license Creative Commons Non-Commercial 4.0.

**UT-corpus** (Liu and Sun, 2015): this data set has been constructed by the University of Tsinghua for evaluating the automatic word alignment tool of the authors. It contains 40k sentence pairs. The sentence-level alignments are clean and the word segmentation is provided. The word-level alignments are manually conducted. However, according to the author, the translation direction is sometimes from Chinese to English. The proportion of each genre is unknown (news, subtitles, etc.), but it is sure that the genre News occupies a major part. Their corpus is freely available and can redistribute the annotated corpus.

**UB-corpus** (Chang and Bai, 2003): this corpus has been constructed by the University of Beijing, mainly for training machine translation systems. The sentence-level alignments have been verified before releasing and the corpus contains a large variety of genres. After signing an agreement, we obtained a corpus of 102k pairs of parallel sentences of genres Literature, Art and Science, which has been freely provided for research purpose. However, we do not have the right to redistribute this part of the annotated corpus.

**UnitedNations-corpus** (Ziemski et al., 2016): this freely available corpus contains official reports and parliamentary documents of the United Nations. Our sub-corpus of genre Official document is a sample from this large corpus containing 15M sentence pairs.

For the genre of scientific article, after our examination, the quality of the part contained in the UM-corpus is nonsatisfactory for annotation. Therefore, we constructed our own corpus by collecting bilingual abstracts from these online journals: Chinese Linguistic, Chinese Journal of Software and Chinese Journal of Computer. The translation direction is from Chinese to English. Only those bilingual abstracts offering the same level of content have been retained.

The platform Linguistic Data Consortium (LDC) only proposes corpora whose translation direction is from Chinese to English. However, we didn’t limit ourselves to only one corpus genre, even though the corpus of different genres don’t have the same quality. Below we present

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https://www.ted.com

These genres are the most used ones in different previous work.
to English. Several corpora are aligned at word level, but access is not free. The platform CLARIN provides several English-Chinese corpora whose genres are already covered by the corpus that we mentioned.

We recapitulate in the table different providers of the original corpus. For the first annotation phase, we aim to annotate a sample corpus of 2 200 sentence pairs, which contains 200 pairs for each genre. In this work, we have annotated 50 pairs for each genre to consolidate our annotation guidelines.

| Corpus genre     | Corpus origin                  |
|------------------|--------------------------------|
| news             | UT-corpus                      |
| literature       | UB-corpus                      |
| art              | UB-corpus                      |
| scientific article| our own construction           |
| official document| UnitedNations-corpus           |
| law, material for education, microblog, spoken, subtitles, science | UM-corpus |

Table 2: Corpus origin for each corpus genre. We take a random sample corpus of each genre for the annotation.

4. Typology of Translation Techniques

Based on several previous works which proposed different typologies of translation techniques (Vinay and Darbelnet, 1958; Chuquet and Paillard, 1989; Molina and Hurtado Al- bit, 2002), we propose a typology of sub-sentential translation techniques for the language pair English-Chinese, established during the manual annotation and the analysis of the phenomena encountered in the corpus.

Figure 1 presents our typology, where the colored blocks represent the categories used for the annotation, and the other blocks serve to establish the hierarchy (i.e. Non-Literal, Unaligned, No Type). The annotation of our English-French corpus of TED Talks employs the same typology, which reflects its universality for these two language pairs.

![Figure 1: Typology of English-Chinese translation techniques](image)

Compared to proposed typologies in several previous works, our typology presents the following differences:

- The feasibility of the annotation task being taken into consideration, our typology contains less fine-grained categories.
- Certain previous typologies contain the techniques which describe the transformations in two translation directions. In our corpus, the translation direction is from English to Chinese (except for the genre Scientific article). Therefore, each category describes the transformation that the Chinese translation has received.
- The translation techniques calque and borrowing (Vinay and Darbelnet, 1958) are annotated by the category Literal.
- The technique cultural adaptation is annotated by the category Equivalence.
- The category Transposition groups together finer categories proposed by Vinay and Darbelnet (1958), for example the amplification.
- We have added the combined category Mod+Trans and the category Figurative translation.
- Since we annotate all words in the corpus, there exist three cases for the unaligned segments: Reduction, Explicitation and No Type (for all the remaining words). For each category, we present their definition and typical examples in Table 3 and Table 4. In the given examples, the bold part illustrates the translation technique used. For aligned segments, except the eight categories in Table 3, we also included three other categories which proved useful during the annotation, but not related to translation techniques: 1) Lexical shift (change of verbal tense, verbal modality or of determiner, differences between plural and singular form, and other minor changes alike); 2) Obvious translation errors; 3) Uncertain cases. The definitions in these two tables are generic, we have completed them with specific rules in our annotation guidelines.

5. Manual Annotation

We have used Stanford Tokenizer to tokenize the English corpus, and THULAC (Li and Sun, 2009) is used for the Chinese word segmentation. The automatic bilingual word alignment is conducted with TsinghuaAligner (Liu and Sun, 2015). These alignments are imported to initialize the annotation, in order to reduce the manual word alignment effort on easy literal word translations. Annotators should verify these automatic word alignments and correct them if needed.

The automatically segmented Chinese corpus contains some errors that could mislead the manual word alignments and the attribution of translation technique categories. Therefore, certain Chinese words need a manual re-segmentation before the annotation, in order to better correspond to English segments. For example, only is 改 仅仅 has been corrected to only is 改 (only) 是 (is). The annotators are told to note down these cases of necessary re-segmentation and the misspellings, which are later corrected in the corpus.

We use the web application Yawat (Yet Another Word Alignment Tool) (Germann, 2008) for the manual annotation.
### Table 3: Definition and important rules of eight translation techniques for aligned segments

| Translation technique | Definition and important rules |
|-----------------------|--------------------------------|
| **Literal**           | Word-for-word translation: *a bronze ring* → "一个 青铜 戒指"
                       | Borrowing words using transliteration: *a cup of coffee* → "一杯 咖啡"
                       | Possible literal translation of idioms: *ivory tower* → "象牙 塔"
                       | Corresponding expression when absolute literal translation does not make sense: *I give you my word.* → "我 向 你 保证" ("I promise you.") |
| **Equivalence**       | Non-literal translation of proverbs, idioms, or fixed expressions:
                       | *A friend in need is a friend indeed.* → "患难见真情" ("Misfortune tests the sincerity of friends.") |
                       | No change in meaning and point of view, a word-for-word translation makes sense but the translator has produced a different translation:
                       | *Protect all locations at all times* → "日夜" ("day and night") *protect 所有的 地点"
| **Transposition**     | Change grammatical categories without changing the meaning:
                       | *She was careful not to question him, fearful that he might leave them.* → "她 也 小心 地 ("carefully") 从 不 问 起； 生 怕 ("to fear") 他 走 了．" |
| **Modulation**        | Change the point of view, can be encountered both at lexical and syntactic level:
                       | *I like the dreams of the future better than the history of the past.* → "我 不 ("don’t") 怀 念 ("recall") 过 去 的 历 程； 而 ("but") 致 力 于 ("devote myself to") 未 来 的 梦 想．"
                       | Slight meaning change at lexical level according to the context:
                       | *He had rudely bellowed across the supper table to her.* → "他 隔 着 餐 桌 对 她 大 声 ("loudly") 吼 叫 起 来．"
| **Mod+Trans**         | Combine the transformations in *Modulation* and *Transposition*, which causes transformations in both grammatical categories and syntactic structures:
                       | *One by one the other elders now timidly rise with innocuous requests.* → "其他的 长 老 一 个 接 一个 害 怕 地 站 起 来， 提 出 了 ("put forward") 一 些 不 关 痛 痛 的 要 求．"
| **Particularization** | The source segment could be translated into several target segments with more specific meaning, and the translator has chosen one of them according to the context:
                       | *"Yes, put you to bed."* → "是 的， 服 务 ("serve") 你 上 床 睡 觉 "
                       | Specify the meaning of a segment in context:
                       | *On his best days, Gomes is a very nice, solid bench player.* → "当 他 打 得 好 的 时 候 ("play well")． 戈 蒙 斜 是 很 优 秀、很 得 力 的 板 凳 球 员．"
                       | Translate a pronoun by the thing(s) it references:
                       | *He then requested her to stay where she was.* → "他 先 让 女 儿 ("Tess") 在 外 面 等 着．"
| **Generalization**    | Several source words or expressions could be translated into a more general target word or expression, and the translator used the latter to translate:
                       | *"A research that will be embraced by millions of bleary-eyed Britons.* → "一 项 即 将 被 广 大 ("numerous") 睡 眼 漱 洗 的 英 国 人 所 知 道 的 研 究．"
                       | The translation of an idiom by a non-fixed expression:
                       | *Every man has a fool in his sleeve.* → "人人 都 有 糊 涂 的 时 候． ("Every man is a fool sometimes.")"
                       | The removal of a metaphorical image:
                       | *But should clouds gather over the Atlantic, or tempers rise in the Middle East [ ... ]* → "如 果 大 西 洋 风 云 再 起， 中 东 争 端 重 然 ("war resumes") 的 话 [ ... ]．"
| **Figurative translation** | Introduce an idiom to translate a non-fixed expression, or a metaphorical expression to translate non-metaphor:
                       | *He gave the required information, in words as suitable as he could find.* → "他 用 斟 酌 的 词 ("weigh one’s words") 作 了 回 答．"
                       | Use personification to translate:
                       | *For Joanne, new opportunities are opening.* → "对 乔 安 紐 而 言， 新 的 凯 丽 已 向 她 招 手， ("are waving to her")"
Table 4: Definition and important rules for unaligned segments

| Translation technique | Unaligned segments |
|-----------------------|-------------------|
| Explicitation         | Introduce clarifications that are implicit in the source text: the building blocks of the universe \(\rightarrow\) 宇宙形成的 最 ("most") 基本单位 Add Chinese-specific words: the knife \(\rightarrow\) 这 把 刀 (Chinese measure word) I will bring it to China. \(\rightarrow\) 我可以把它带到中国来. (necessary addition due to syntactic order change in translation) |
| Reduction             | Deliberately remove certain words in translation (including content words): Removal of preposition: A spokesman from the Ministry of National Defense \(\rightarrow\) 国防部 发言人 Removal of copula: Peter is six years old. \(\rightarrow\) 彼德 六岁 . Removal of the anticipatory « it »: It was a pleasant surprise to learn of her marriage. \(\rightarrow\) 得知 她 结婚 是 件 令 人 惊喜 的 事. |
| No Type               | Function words necessary in English but not in Chinese: The tragedy of the world is that those who are imaginative have but slight experience. \(\rightarrow\) 世界 的 京剧 就在于 有 想象力 的 人 缺乏 经验. Segments not translated but which do not impact the meaning: The present state, application and development of coal mine hydraulic drill rig are described in this paper. \(\rightarrow\) 介绍 了 煤矿 用 液压 钻 车 现状，使用 情况 及 发展 . Target segments added without reason, which do not correspond to any source segment. |

Table 5: Statistics of the annotated corpus

|                           |          |          |
|---------------------------|----------|----------|
| number of sentence pairs  | 654      |          |
| number of English tokens  | 15 739   |          |
| number of Chinese characters | 25 000   |          |
| average number of EN tokens | 24      |          |
| average number of ZH characters | 38      |          |

Figure 2: The interface of Yawat for the annotation task. Black tokens are literally translated. Tokens in purple are unaligned English tokens, and those in grey are unaligned Chinese tokens. The other tokens in different colors are translated using different non-literal translation techniques.

Since the agreement is moderate, we adopt an annotation scheme where one sub-corpus receives three passes of successive annotation (Zhai et al., 2018), in order to eliminate the disagreement on categories and on segment boundaries. This phase of annotation by three passes is still ongoing. The statistics of the annotated corpus are presented in the table 5 (including 100 sentence pairs for the control-corpus).

6. Corpus Analysis

In Table 6 we compare the annotation statistics per category of our previously annotated English-French corpus of TED Talks (Zhai et al., 2018), with those of our English-Chinese multi-genre corpus presented in this work. The number of English tokens annotated in each category and their corresponding percentage show that, unsurprisingly, literal translations represent the largest part. Meanwhile, the seven non-literal categories (cf. Figure 1) are also not negligible, they occupy 16.13% (EN-ZH) and 18.32% (EN-FR), respectively.

In total, the percentage of literal translations is higher in the English-French corpus. Chinese translations use much less the complicated category Modulation+Transposition, but Particularization seems to be more employed. Concerning Explicitation, 1 924 Chinese characters have been annotated by this category, which occupy 7.70% of 25 000...
characters in total; compared to 364 French words in this category, which occupy only 1.02% of 35 588 French words in total. The proportions of Reduction and No type are also higher in the English-Chinese corpus.

| Translation technique | Nb EN tokens | Percentage |
|-----------------------|--------------|------------|
|                       | -ZH | -FR | -ZH | -FR |
| Literal               | 9 091 | 23 733 | 57.76% | 69.49% |
| Equivalence           | 752  | 1 685 | 4.78%  | 4.93%  |
| Transposition         | 624  | 1 141 | 3.96%  | 3.34%  |
| Modulation            | 510  | 1 247 | 3.24%  | 3.65%  |
| Mod+Trans             | 56   | 1 171 | 0.36%  | 3.43%  |
| Particularization     | 361  | 401   | 2.29%  | 1.63%  |
| Generalization        | 175  | 401   | 1.11%  | 1.17%  |
| Figurative            | 60   | 57    | 0.38%  | 0.17%  |
| Total non-literal     | 2 538 | 6 257 | 16.13% | 18.32% |
| Explicitation         | 0    | 0     | 0.00%  | 0.00%  |
| Reduction             | 855  | 797   | 5.43%  | 2.33%  |
| No type               | 2 416 | 1 939 | 15.35% | 5.68%  |
| Lexical shift         | 574  | 1 049 | 3.65%  | 3.07%  |
| Translation error     | 24   | 71    | 0.15%  | 0.21%  |
| Uncertain             | 241  | 306   | 1.53%  | 0.90%  |
| Total                 | 15 739 | 34 152 | 100.00% | 100.00% |

Table 6: Comparing the annotation statistics per category of our previous EN-FR corpus of TED Talks and of the EN-ZH corpus presented in this work.

Qualitatively, we present below two characteristics of Chinese translations. Structural changes at sentence level tend to be more important in Chinese than in French, and Chinese language prefers to use short and compact clauses. Hence English conjunction words are often replaced by a comma to break a long and complicated sentence to several shorter clauses, for example:

She had little luck as an actress but worked as a model before moving to Hollywood in 1933 for a part in the chorus of Roman Scandals.

She had little luck as an actress but worked as a model before moving to Hollywood in 1933 for a part in the chorus of Roman Scandals.

Reducing the largest for the genre News and Literature is the smallest for the genre News. These information reveal the differences across different genres.

Figure 3: Example of less diagonal word alignment of an English-Chinese sentence pair

Figure 3: Example of less diagonal word alignment of an English-Chinese sentence pair.

7. Evaluation

7.1. Compare human and machine translation

During the annotation, we observed that the distance could be large between good human non-literal translations and machine translations provided by online MT services. Humans can recognize these non-literal translations as good quality (Schaeffer and Carl, 2014), but would automatic MT evaluation metrics, such as BLEU (Papineni et al., 2002), penalize them?

In order to study this question, we conducted an experiment to investigate the correlation between the proportion of literally translated English tokens and the BLEU score of the corresponding human translation compared to four machine translations. Four principal MT engines’ API have been used during this experiment: Google, Microsoft, Baidu, and Tencent.

Cumulative 4-gram BLEU scores with uniform weights are calculated for this experiment. All Chinese translations are tokenized at character level, since Chinese words are formed by combining characters, which are the minimal building blocks of meaning.

The box plot below (see Figure 4) shows the distributions of proportion of literally translated English tokens for each corpus genre.

The median value (represented by the orange mark) is the smallest for the genre Literature, and the largest for the genre News. Indeed, many more non-literal translations are employed when translating literary texts, and many fewer are found in the corpus of news. Besides, Table 7 presents the average number of English tokens and Chinese characters per sentence and per corpus genre. These information reveal the differences across different genres.

For each corpus genre, Table 8 presents Pearson and Spearman correlation coefficient (Benesty et al., 2009; Hauke and Kossowski, 2011) between the proportion of literally translated English tokens and the cumulative 4-gram BLEU score (comparing one human translation to four machine translations). Figures 5 and 6 show the relationship between these two variables for the sub-corpus of official doc-

https://cloud.google.com/translate/docs/
https://azure.microsoft.com/
https://api.fanyi.baidu.com/api/trans/product/index
https://ai.qq.com/product/nlptrans.shtml#text
We compute BLEU scores with the NLP toolkit NLTK (Bird and Loper, 2004). For scoring sentences, we use the sentence_bleu() function with a smoothing function (method 4).

The genre Scientific article is ignored for this experiment, since the translation direction is from Chinese to English.
Figure 4: Distributions of proportion of literally translated English tokens per sentence in each genre of corpus

Table 7: Average number of English tokens and Chinese characters per sentence and per corpus genre

| Corpus genre       | English | Chinese |
|--------------------|---------|---------|
| official_document  | 34      | 53      |
| literature         | 26      | 40      |
| spoken             | 14      | 21      |
| education_material | 20      | 31      |
|微blog              | 21      | 33      |
| art                | 27      | 48      |
| subtitles          | 12      | 15      |
| news               | 31      | 47      |
| science            | 20      | 30      |
| law                | 37      | 51      |

The proportion of non-literal translations is the highest for the genre Literature, and the Spearman correlation 0.58 (close to strong correlation threshold 0.60) shows significant evidence that non-literal translations get lower BLEU scores. There exist fewer non-literal translations for the genre Official document, however, their presence has also been reflected by the strong Spearman correlation (0.66). Only the genre Law shows a weak negative correlation, which is rather surprising, since the textual style is close to Official document. We obtain weak or even very weak correlation for the other genres, which deserves a more in-depth study.

This experiment is conducted based on 500 sentence pairs annotated (50 pairs for each of ten genres). To confirm our hypothesis that BLEU metric does penalize non-literal human translations, we need to continue the annotation while assuring the annotation quality and the characteristics of each corpus genre. Besides BLEU, we could further investigate other MT metrics, such as METEOR (Banerjee and Lavie, 2005) and TER-plus (Snover et al., 2009), which use paraphrases during the evaluation.

However, preliminary results support our hypothesis for the corpus of genre Official document and Literature. BLEU scores are lower when human translations are more non-literal than machine translations; and gradually higher when human and machine translations are both more literal and similar. Since the algorithm of BLEU compares the matching n-grams between translations, it could penalize human translations with non-literal but correct expressions.

Table 8: Correlation coefficient between the proportion of literally translated English tokens in each sentence, and the BLEU-4 score calculated by comparing one human translation with four machine translations. The average literal proportions are presented with their standard deviation

| Corpus genre       | Avg. literal proportion | Correlation coefficient |
|--------------------|-------------------------|-------------------------|
|                   | Pearson | Spearman | Pearson | Spearman |
| official_document  | 0.74±0.14 | 0.67 | 0.66 |
| literature         | 0.60±0.18 | 0.54 | 0.58 |
| spoken             | 0.72±0.20 | 0.40 | 0.38 |
| education_material | 0.74±0.15 | 0.37 | 0.37 |
| 微blog             | 0.73±0.17 | 0.38 | 0.37 |
| art                | 0.72±0.16 | 0.36 | 0.29 |
| subtitles          | 0.68±0.23 | 0.16 | 0.26 |
| news               | 0.81±0.11 | 0.16 | 0.19 |
| science            | 0.73±0.16 | 0.12 | 0.14 |
| law                | 0.75±0.11 | -0.20 | -0.17 |

Figure 5: Strong positive correlation between the proportion of literally translated English tokens and the BLEU-4 score on the sub-corpus of United Nations

Figure 6: Weak negative correlation between the proportion of literally translated English tokens and the BLEU-4 score on the sub-corpus of law

7.2. Automatic binary classification of translation techniques

The goal of constructing this annotated corpus is to verify the hypothesis that it is possible to automatically recognize different sub-sentential translation techniques. After
the deduplication of our annotated instances across corpus genres, the distribution of different categories are shown in Table 9. Since the amount of different non-literal instances is still limited, in this work we conduct an experiment of binary classification (literal versus non-literal).21 We obtain 4,316 literal translations (including the instances of category Lexical shift)22 and 1,244 non-literal translations by combining all the other categories. Following our previous work (Zhai et al., 2019), the experiment is conducted in a simplified scenario, where the classifier predicts the translation technique of a pair of translations whose boundaries are provided by the annotators.

Table 9: The number of annotated instances per category (after deduplication)

| Translation technique | Nb instances | Literal (4,316) |
|-----------------------|--------------|----------------|
| Literal               | 3,982        |                |
| Lexical shift         | 334          |                |
| Equivalence           | 356          |                |
| Transposition         | 315          |                |
| Modulation            | 197          |                |
| Mod+Trans             | 27           |                |
| Particularization     | 242          |                |
| Generalization        | 77           |                |
| Figurative            | 30           |                |
| Non-literal (1,244)   |              |                |

We randomly take 1,244 literal translations in order to build a balanced data set. The toolkit Scikit-Learn (Pedregosa et al., 2011) is used to train a large variety of statistical supervised classifiers, which are based on different classification algorithms. Default values of their hyperparameters have been used.

The evaluation is based on five-fold cross-validation (with StratifiedKFold), using the average accuracy over five folds as metric. The DummyClassifier is used as a baseline, which generates random predictions by respecting the distribution of training classes.

For the moment, we have adapted the basic features exploited in our previous work for the language pair English-French (Zhai et al., 2019), by comparing the segment length (number of tokens and characters, the ratio between them) and the difference of Part-of-Speech (PoS) tags (English and Chinese PoS tag sets are mapped to a universal tag set (Petrov et al., 2012)). Other more complicated features will be adapted in our future work, such as exploiting syntactic parsing structures, external linguistic resources ConceptNet (Speer et al., 2017) and information from automatic word alignment.

In Table 10, we compare the binary classification results of two data sets: EN-ZH (1,244 instances for both literal and non-literal class) and EN-FR (1,127 instances like-wise). For the EN-FR pair, all above-mentioned features have been used, and the hyperparameters have been tuned by holding out 10% of data as test, and conducting a three-fold cross validation on the remaining data. The best classifiers for the two language pairs are Multi-layer Perceptron and Random Forest, respectively, and both obtain significantly better results than the baseline of DummyClassifier.

The experiment on the English-Chinese pair remains to be improved, nonetheless, the preliminary results are favorable to our hypothesis.

Table 10: Classification results of distinguishing literal and non-literal sub-sentential translations. Comparison of performance on the EN-ZH and EN-FR data sets

| Classifier      | Average accuracy over five folds (with standard deviation) |
|-----------------|----------------------------------------------------------|
|                 | EN-ZH | EN-FR |
| Dummy (baseline)| 52.21%±0.00% | 53.19%±0.10% |
| MLP             | 70.10%±1.06% | 84.65%±2.27% |
| GradientBoosting| 69.58%±1.30% | 86.20%±2.03% |
| Adaboost        | 69.21%±1.27% | 83.41%±1.53% |
| LogisticRegression| 69.05%±1.10% | 84.78%±1.92% |
| RandomForest    | 68.89%±0.64% | 87.22%±1.92% |
| MultinomialNB   | 68.33%±0.78% | 80.83%±2.78% |
| DecisionTree    | 68.13%±1.75% | 79.68%±1.90% |
| BernoulliNB     | 66.32%±1.33% | 81.50%±1.51% |
| SVM             | 66.28%±0.93% | 85.14%±2.08% |
| KNN             | 65.48%±4.84% | 83.50%±0.67% |
| GaussianNB      | 59.29%±5.36% | 64.15%±2.03% |

8. Conclusion

Human non-literal translation techniques have been widely examined in translation studies and in contrastive linguistics. However, they receive less attention in developing NLP applications. One of our long-term objectives is to leverage the automatic classification of sub-sentential translation techniques to improve the quality of paraphrase resources. In this work, we extend our previous studies of manual annotation and of automatic classification for the English-French pair to the more distant English-Chinese pair. We have presented our multi-genre corpus, the details of manual annotation and the characteristics of Chinese translation. Fifty sentence pairs for each genre have been annotated in order to consolidate our annotation guidelines. We conducted two experiments to verify our hypothesis, which are supported by our preliminary results: 1) BLEU scores could penalize non-literal human translations when they are more different from machine translations; 2) it is possible to automatically distinguish literal and non-literal translations. We will continue our effort on annotating high-quality parallel corpus and on fine-grained multi-class classification. We hope that this annotated corpus will be useful for linguistic contrastive studies and for fine-grained evaluation of NLP tasks, such as automatic word alignment and machine translation.

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21 All the code used in this work is available: https://github.com/YumingZhai/human_vs_machine_translation
22 In our data set, Lexical shift instances are very close to literal translations after lemmatizing the English segment.
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