Monolingual and Cross-lingual Zero-shot Style Transfer

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Abstract

We introduce the task of zero-shot style transfer between different languages. Our training data includes multilingual parallel corpora, but does not contain any parallel sentences between styles, similarly to the recent previous work. We propose a unified multilingual multi-style machine translation system design, that allows to perform zero-shot style conversions during inference; moreover, it does so both monolingually and cross-lingually. Our model allows to increase the presence of dissimilar styles in corpus by up to 3 times, easily learns to operate with various contractions, and provides reasonable lexicon swaps as we see from manual evaluation.

1 Introduction

It is crucial for intelligent natural language generation systems to produce text which is appropriate for the task at hand in terms of semantic content as well as style.

Due to the shortage of parallel corpora which could be used for learning to transfer style in a supervised fashion, much of recent work has been focusing on style transfer using non-parallel data (Prabhumoye et al., 2018; Mueller et al., 2017; Shen et al., 2017). The proposed approaches mostly involve learning style representations disentangled from semantic content. Other work has been based on paraphrase data (Carlson et al., 2017) or explicit attribute substitution (Li et al., 2018).

We do not rely on explicit separation between content and style representations nor on explicit attributes. Instead, we approach the problem from a different angle.

In this paper we propose a multilingual multistyle machine translation system that allows to modify stylistic traits of a sentence while also translating it into a different language. It uses ideas from multilingual NMT (Johnson et al., 2016; Firat et al., 2016), while extending them to styles, and relies on source word factors as a key design choice (Sennrich and Haddow, 2016). We use no parallel data between styles, but still can perform cross-style conversions during inference; moreover, we do so cross-lingually.

In our experiments, we evaluate the proposed model incorporating three languages and three styles. The system shows strong results as a pure machine translation model as well, which provides for good meaning preservation and fluency in output texts. The system can be easily expanded to incorporate more languages and styles (though scaling up to more languages and styles is to be tested).

The paper contains the following contributions:

• Extends the task of style transfer to multiple languages resulting in cross-lingual style transfer

• Tackles the task of cross-lingual style transfer without parallel data between styles

• Proposes a unified multilingual multi-style system design that enables cross-lingual zero-shot style transfer

This paper is organized as follows. In Section 2, we formally state the problem we attempt to solve, that is, cross-lingual zero-shot style transfer. We then describe our general approach in Section 3 and specific details of the experiments, their results, and evaluation in Section 4. Some discussion points are put forward in Section 5. Related work in the field is summarized in Section 6. Finally, in Sections 7 and 8 we present our conclusions and plans for future work.
2 Problem Statement

Let \( L = \{ l_1, l_2, ..., l_m \} \) be a set of languages and \( S = \{ s_1, s_2, ..., s_n \} \) a set of text styles\(^1\).

Let \( e(l_x, s_y) \) and \( e(l_q, s_p) \) be sentences representing the same semantic content, but in different languages \((l_x/q)\) and styles \((s_y/p)\): \( x, q \in \{1..m\} \), and \( y, p \in \{1..n\} \), while \( x \neq q \) and \( y \neq p \).

Our task then is to learn the mapping between sentences like \( e(l_x, s_y) \) and \( e(l_q, s_p) \), which we call Cross-lingual Style Transfer. Refer to Figure 1 for more details and comparison to tasks of Monolingual Style Transfer and Machine Translation.

A key point is that we do not use any parallel data between styles neither monolingually inside a single language nor cross-lingually. Since the only data available is the data between different languages inside individual styles, the task becomes harder and result predictions can be called "Zero-shot".

3 Approach

For our attempt at cross-lingual style transfer, we train a factored multilingual neural machine translation system, passing the desired target language and style as factors (word features), token-parallel to source texts.

The source side of one training example \( e \), where we translate source words \( e_1, e_2, ..., e_n \) into language \( l_{tgt} \) and style \( s_{tgt} \), looks like following:

\[
| e_1 | l_{tgt} | s_{tgt} | e_2 | l_{tgt} | s_{tgt} | ... | e_N | l_{tgt} | s_{tgt} |
\]

\(^1\)We treat the term “text style” loosely as covering concepts like text domain, genre, formality and other text characteristics.

4 Experiments

4.1 Datasets

The translation model was trained using three parallel corpora: OpenSubtitles2018\(^2\), a new release

\(^2\)http://www.opensubtitles.org/
of the corpus presented by Lison and Tiedemann (2016), Europarl (Koehn, 2005) and JRC-Acquis (Steinberger et al., 2006). OpenSubtitles2018 is a corpus made up of movie and TV subtitles, Europarl consists of texts of European Parliament proceedings, and JRC-Acquis comprises legislative texts of the European Union.

We assume that there should be sufficient stylistic difference between these three corpora, especially between the more informal OpenSubtitles2018 and the other two, while acknowledging the fact that most text corpora and OpenSubtitles in particular constitute a heterogeneous mix of genres and text characteristics; however, many stylistic traits are also similar across the whole corpus, which means that these common traits can be learned as a single style.

We used three language pairs: English-German, English-French and German-French, each taken in both directions. Refer to the Figure 2 for the system architecture and data flow.

Prior to model training, we discarded all sentence pairs where at least one sentence was an empty string, consisted of more than 100 tokens, or did not contain any alphabetic characters, and pairs where token-wise length ratio exceeded 9. Table 1 shows the sizes of the training sets.

|       | OS   | EP   | JRC  |
|-------|------|------|------|
| de ↔ en | 3M   | 1.95M | 0.71M |
| en ↔ fr | 3M   | 2.04M | 0.71M |
| de ↔ fr | 3M   | 1.93M | 1.47M |

Table 1: Training set sizes (number of sentence pairs).

determining target language and style had embeddings of size 4. Batch size was set to 2048 words, initial learning rate to 0.0002, reducing by a factor of 0.7 every time when validation perplexity has not improved for 8 checkpoints, which happened every 4000 updates.

The model finished training during the 11th epoch, when validation perplexity has not improved for 32 consecutive checkpoints.

The parameters of a single best checkpoint were used for all translations, with beam size set to 5.

For evaluation we use the BLEU (Papineni et al., 2002) and METEOR (Banerjee and Lavie, 2005) metrics in cases where parallel test data is available. For evaluating style transfer without parallel data we perform a qualitative comparison using a style classifier, described in the following section.

4.3 Evaluation Results

When prompted to translate sentences into different styles, the model shows the ability to capture some key characteristics of those styles. One such characteristic in the English language is the presence of contracted forms, such as I’ll, she’s and so on. Contracted forms are typically abundant in informal texts, such as those making up the OpenSubtitles corpus, and are typically absent in formal and official texts, such as parliament proceedings in Europarl and legal documents in JRC-Acquis. Tables 2 and 3 show the number of contractions in test sets translated, respectively, from German and French into English in all possible style directions.

One other aspect that the model captures is the different lexical and grammatical choices appropriate for different styles. Some examples of different wording that the system uses when translating the same source sentences into different domains can be found in Table 4 for German-English and in Table 5 for French-English. For more and longer examples refer to Supplemental Material A.
Table 3: Number of contractions in 1000-sentence test sets when translated from French into English in all 9 style directions. The numbers in parentheses indicate the number of contracted forms in the human-translated test sets.

| Source | OS | EP | JRC |
|--------|----|----|-----|
| OS     | 469 (352) | 10 | 11 |
| EP     | 327 | 0 (1) | 0 |
| JRC    | 35 | 0 | 0 (0) |

Table 4: Examples of different wording in German-English style transfer. The German phrase möchte ich will be translated into OpenSubtitles as I want, and into Europarl and JRC-Acquis as I would like. lindern and bleiben become ease and stay, respectively, in OpenSubtitles, but alleviate and remain in Europarl and JRC-Acquis. In some other cases there is also difference between the formal styles: wie geht’s dann weiter? becomes so, what’s next? in OpenSubtitles, what happens then? in Europarl and how are we to proceed then? in JRC-Acquis.

| Source (de) | OS | EP | JRC |
|------------|----|----|-----|
| möchte ich | I want | I would like | I would like |
| aber | but | however | however |
| ich wechsle | I’m turning | I am turning | I shall refer |
| tatsächlich | actually | indeed | indeed |
| wir gehen | we’re leaving | we are leaving | we shall leave |
| noch viel mehr | more than | much more | even more so |
| lindern | ease | alleviate | alleviate |
| ja | yeah | yes | yes |
| chance | chance | opportunity | opportunity |
| bleibt | stay | remain | remain |
| wie schon gesagt | like I said | as I have already said | as already stated |
| außerdem | besides | moreover | moreover |
| ach ja? | oh, yeah? | is that so? | is that so? |
| wir gehen | we’re leaving | we are leaving | we shall leave |
| wie geht’s dann weiter? | so, what’s next? | what happens then? | how are we to proceed then? |

Table 5: Examples of different wording in French-English style transfer. The French salut translates to hey in OpenSubtitles and to hi in both Europarl and JRC-Acquis. evanouis-toi can become get out of here, get away from it or evacuate yourself when formality increases.

| Source (fr) | OS | EP | JRC |
|-------------|----|----|-----|
| salut | hey | hi | hi |
| on se lance? | let’s go. | are we getting started? | are we going? |
| un délai de deux heures | two hours | two hours | a two-hour period |
| c’est ça | that’s right | that is it | that is the case |
| vrai | real | genuine | genuine |
| il parle de vous | he’s talking about you | he talks about you | he speaks of you |
| évairous - toi | get out of here | get away from it | evacuate yourself |
| merdique | crappy | a mess | merchandical |
| halte | stop | stop | halt |
| rester prudent | be careful | be careful | remain cautious |
| interieur | inside | inside | within |
| je vous rembourserai | I’ll pay you back | I will pay you back | I shall reimburse you |

Table 6: BLEU / METEOR scores of test sets translated from German into English in all style directions. METEOR typically sees a smaller decrease than BLEU, presumably due to use of style-appropriate synonyms.

| Source | OS | EP | JRC |
|--------|----|----|-----|
| OS | 33.1/30.5 | 26.2/27.4 | 24.6/26.8 |
| EP | 35.4/35.9 | 38.6/37.4 | 37.7/37.0 |
| JRC | 52.6/42.9 | 55.4/44.2 | 58.9/45.9 |

To support our assumption that the model at least somewhat consistently uses synonyms to discriminate between styles, we show in Tables 6 and 7 the BLEU and METEOR scores for test sets translated, respectively, from German and French into English in all style directions.

To qualitatively assess the performance of our system, we train convolutional neural network (CNN) classifiers to predict the styles of sentences presented to it, as described by Kim (2014). We use an implementation of convolutional neural networks for text classification⁴. We train three separate two-class classifiers for English sentences, each of which aims to distinguish between one of the styles and the other two. The

⁴https://github.com/dennybritz/cnn-text-classification-tf
Table 7: BLEU / METEOR scores of test sets translated from French into English in all style directions. METEOR typically sees a smaller decrease than BLEU, presumably due to use of style-appropriate synonyms.

| $S_{src}$ | $S_{tgt}$ |
|----------|----------|
| OS       | 33.3/31.0 | 25.3/27.1 | 24.9/27.0 |
| EP       | 39.6/38.2 | 42.4/39.6 | 41.1/39.1 |
| JRC      | 56.6/45.3 | 59.1/46.5 | 62.6/48.1 |

Table 8: Percentage of sentences recognized as the target style in human-translated German-English test sets / test sets translated from German into English and into the target style by the NMT model.

| $S_{src}$ | $S_{tgt}$ |
|----------|----------|
| OS       | 96.4 / 97.4 | 8.1 / 24.3 | 3.4 / 5.5 |
| EP       | 4.4 / 14.0 | 96.4 / 96.1 | 5.4 / 8.5 |
| JRC      | 1.9 / 2.8 | 6.9 / 12.8 | 96.5 / 96.8 |

Table 10: Relative change in style. Percentages show how much the amount of the target style in corpus increased after cross-lingual zero-shot style transfer. Language direction: German into English.

| $S_{src}$ | $S_{tgt}$ |
|----------|----------|
| OS       | 1%       | 200%     | 62%     |
| EP       | 218%     | -0.3%    | 57%     |
| JRC      | 47%      | 86%      | 0.3%    |

Table 11: Relative change in style. Percentages show how much the amount of the target style in corpus increased after cross-lingual zero-shot style transfer. Language direction: French into English.

Tables 8 and 9 demonstrate, for German-English and French-English translations respectively, the percentage of sentences classified as the target class in the human-translated test sets (that is, belonging effectively to the source class) and in the test sets translated automatically into the target class.

4.4 Interpretation

It is clear that the system chooses shortened forms when translating into OpenSubtitles, even being over-eager and incorporating more of those than in the human translations. When translating into the more formal domains, it gets rid of most contractions (see Tables 2, 3) for both language pairs.

We also expect the model to use lexical variations while translating into different styles. It is clear that both BLEU and METEOR scores should fall when the sentences are translated into a different style, because human-translated references are in the style of source sentences. However, since METEOR relies on synonymy when determining matches and BLEU does not, METEOR generally decreases about twice as less as BLEU does (see Tables 12 and 13).

Regarding the classification results, there is a consistent increase in the percentage of sentences recognized as the desired style when they are translated into that style using the Transformer NMT model. The highest rise occurs when we translate between most dissimilar styles (OS and EP) and sits in range of 200-300%. The lowest rise accordingly occurs in case of similar styles (EP, JRC). This trend is consistent across language pairs. Refer to the Tables 10, 11 for more details.

4.5 Monolingual Zero-shot Style Transfer

While the main focus of our paper has been so far on cross-lingual style transfer, as a side effect, translating from English to English while passing different target styles to the model potentially leads to a monolingual (zero-shot) style transfer. Tables 14 and 15 demonstrate that this is indeed the case and trends observed in cross-lingual transfer reappear.
### Table 12: Relative decrease in BLEU / METEOR scores of test sets translated from German into English in all style directions. METEOR typically drops about twice as less comparing to the BLEU, presumably due to use of style-appropriate synonyms.

| S_{src} | S_{tgt} | OS       | EP       | JRC       |
|---------|---------|----------|----------|-----------|
| OS      | -       | 20.9/10.2% | 25.7/12.1% |
| EP      | 8.3/4.0% | -        | 2.3/1.1%  |
| JRC     | 10.7/6.5% | 5.9/3.7% | -        |

### Table 13: Relative decrease in BLEU / METEOR scores of test sets translated from French into English in all style directions. METEOR typically drops about twice as less comparing to the BLEU, presumably due to use of style-appropriate synonyms.

| S_{src} | S_{tgt} | OS       | EP       | JRC       |
|---------|---------|----------|----------|-----------|
| OS      | -       | 24.0/12.6% | 25.3/12.9% |
| EP      | 6.6/3.5% | -        | 3.1/1.3%  |
| JRC     | 9.6/5.8% | 5.6/3.3% | -        |

### Table 14: BLEU / METEOR scores of test sets translated from English into English in all style directions.

| S_{src} | S_{tgt} | OS       | EP       | JRC       |
|---------|---------|----------|----------|-----------|
| OS      | 85.4/60.9 | 70.0/50.3 | 75.0/53.7 |
| EP      | 85.5/61.3 | 83.6/60.4 | 82.1/59.4 |
| JRC     | 90.9/64.7 | 87.9/62.1 | 87.9/61.9 |

### Table 15: Number of contractions in 1000-sentence test sets when translated from English into English in all 9 style directions. The numbers in parentheses indicate the number of contracted forms in the human-translated test sets.

| S_{src} | S_{tgt} | OS       | EP       | JRC       |
|---------|---------|----------|----------|-----------|
| OS      | 390 (363) | 23       | 70        |
| EP      | 167     | 0 (0)    | 0         |
| JRC     | 4       | 0        | 0 (0)    |

### 5 Discussion

The proportion of sentences recognized as members of the desired target classes by the CNN domain classifiers remains quite low. However, we believe that such evaluation may be less suitable for our task than it is for the more typical tasks in style transfer, such as sentiment or gender transfer.

Our CNN network is, in fact, a domain classifier, trained, unavoidably in our case, to classify relying not only on style, but on semantic content as well. Thus, the topic of a sentence might significantly influence the classifier decision. For example, it is highly unlikely to have words typical for such genres as *fantasy* or *rock’n’roll* in Europarl (European Parliament speech transcripts) corpus, while it is natural to expect such topics from OpenSubtitles texts. The style transfer itself can influence some lexical choices and the general feeling of the sentence, but not dramatically enough to fool our domain classification model on vast majority of cases. The topics differ significantly between the corpora we use, and semantic content should greatly influence classifier output.

From this perspective, our style transfer model is strong enough to make the domain classification model increase its predictions of the target domain by up to three times (Tables 10, 11). We interpret it as a solid result.

It should be also noted that while we only provide results for English as the target language for now, the system is, by design, multilingual, and there is nothing English-specific to it. All assumptions should hold true for other target languages as well. We chose English as a target language to simplify evaluation and understanding.

### 6 Related Work

The task of cross-lingual zero-shot style transfer is novel and is not discussed in the literature at the best of our knowledge. However, many recent models for style transfer that do not rely on direct parallel signal contain innate structure that is aimed to separate content and style representations (Hu et al., 2017; Mueller et al., 2017; Shen et al., 2017). This is often done using VAE’s (Kingma and Welling, 2013) and GAN’s (Goodfellow et al., 2014), while sometimes explicit attribute substitutions are involved (Li et al., 2018).

We in turn employ ideas from multilingual NMT systems (Firat et al., 2016; Johnson et al., 2016), which are proven to have a high perfor-
mance while also enabling translation between language pairs that we do not have direct parallel corpora. We use a similar multilingual architecture while also extending its benefits to styles.

Several authors also employed machine translation ideas to support style transfer task. Approaches include back-translating languages (Prabhumoye et al., 2018) and using seq2seq architectures (Han et al., 2018) as a part of the pipeline.

Most similar work to ours conceptually is done by Carlson et al. (2017). They aim to do monolingual zero-shot style transfer, and use 32 different English versions of Bible as their source of paraphrase training data. We use multiple languages, multiple styles, and do not rely on any explicit lexicons.

Finally, Niu et al. (2017) inspect generating NMT output with different degrees of formality. Methods include vector space models that require large mixed-topic corpora to be trained. While being similar in a way that it also modifies NMT output, the main focus of our work is cross-lingual zero-shot style transfer. Moreover, our work is not limited to generating hypotheses with different degrees formality, but arbitrary styles can be used.

7 Conclusion

We propose a method for cross-lingual zero-shot style transfer. While our model does not achieve high scores based on classifier output, we believe that such evaluation may be less suitable for our tasks than it is for the more typical tasks in style transfer, such as sentiment or gender transfer, because the topics differ significantly between the corpora we use, and semantic content should greatly influence classifier output.

However, the model does show promising qualitative results, demonstrating the ability to capture some important aspects of stylistic difference between domains.

8 Future work

In the future, we plan to assess other aspects of style differences that the model may capture, and to use help of human evaluators in assessing our results. We intend to perform a meaningful qualitative and quantitative comparison to a previously existing strong style transfer system. We also intend to train and evaluate two-language NMT systems with the same approach to learning style to see how multilinguality interferes with style transfer.

In addition, we plan to improve quantitative evaluation of the model by making the CNN classifiers more appropriate for the task, for instance, by training them as multi-class and yielding class probabilities rather than labels, and by making them more content-agnostic and style-sensitive.

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A Supplemental Material
| Source (de)            | OS                   | EP                        | JRC                      |
|-----------------------|----------------------|---------------------------|--------------------------|
| möchte ich            | i want               | i would like              | i would like             |
| erst                  | first                | first of all              | first of all             |
| damit du dich hinlegen kannst       | so you can lie down     | so that you can lie down     | and lie down              |
| er jetzt verrückt wird       | he's going crazy now     | he gets mad now          | he becomes crazy now          |
| schnell                | fast                 | quickly                   | quickly                  |
| ich reise nach London weiter     | i’m going to london     | i will continue to travel to london | i shall continue to travel to london |
| aber                   | but                  | however                   | however                  |
| ich wechsle            | i’m turning          | i am turning             | i shall refer            |
| mach das nicht         | don’t that           | don’t do that             | do not do so             |
| tatsächlich            | actually             | indeed                    | indeed                   |
| wir gehen              | we’re leaving         | we are leaving           | we shall leave           |
| wer                    | whoever              | those who                | those who                |
| ich halte es auf       | i’ll stop it          | i will stop it           | i shall stop it          |
| nichts derartiges      | anything like that    | anything like this       | anything of this kind    |
| ich hätte gedacht      | i thought             | i would have thought     | i would have thought     |
| sonst                  | or                   | otherwise                | otherwise                |
| um den schmerz zu lindern | to ease the pain     | in order to alleviate the pain | in order to alleviate the pain |
| noch viel mehr         | more than            | much more                | even more so             |
| ja                     | yeah                 | yes                       | yes                      |
| größer                 | bigger               | greater                   | greater                  |
| eine chance            | a chance             | an opportunity           | an opportunity           |
| auch der Mörder        | the killer, too      | also the murderer        | also the murderer        |
| heutzutage ist es schwierer | nowadays, it’s harder | today, it is more difficult | it is now more difficult |
| wie geht’s dann weiter? | so, what’s next?    | what happens then?       | how are we to proceed then? |
| ein rätsel, das es zu lösen gilt | a mystery to solve | a mystery that needs to be resolved | a mystery to be resolved |
| bleibt                 | stay                 | remain                    | remain                   |
| wie schon gesagt       | like i said           | as i have already said    | as already stated        |
| ich mache eine anfrage | i’ll ask you a question | i have a question        | i shall make a request   |
| ich wollte sie nicht kränken | i didn’t mean to hurt you | i did not want to offend you | i did not wish to offend you |
| damit ich das richtig verstehe | let me get this straight | let me get this straight | in order to understand this correctly |
| sie haben die fotos    | they’ve got the photos | they have the photographs | they shall have the photographs |
| shauen sie genau hin   | look carefully        | look carefully            | take a close look        |
| du für kommunikation zuständig bist | you’re in charge of communication | you are responsible for communication |
| ich wagte mich schon zu weit vor | i’ve gone too far | i have dared to go too far | i have dared to go too far |
| ohne auch nur kurz darüber nachzudenken | without even thinking about it | without even thinking about it | without even considering it briefly |
| außerdem               | besides              | moreover                  | moreover                  |
| ach ja?                | oh, yeah?            | is that so?               | is that so?               |

Table 16: Additional examples of difference in lexical and grammatical choices when translating from German to English into different styles.
| Source (fr)                      | OS            | EP            | JRC            |
|---------------------------------|---------------|---------------|----------------|
| il paraît que vous êtes spéciale. | i hear you’re special. | i understand that you are special. | it appears that you are special. |
| c’est ça                        | that’s right   | that is it     | that is the case |
| très vilaine                    | very bad       | very bad       | very vile       |
| vrai                            | real           | genuine        | genuine         |
| on a un autre concert demain    | we’ve got another concert tomorrow. | we have another concert tomorrow. | a further concert will be held tomorrow |
| on se tire une balle            | we shoot each other | you get a bullet | a bullet is fired |
| donc                            | so             | so             | therefore       |
| bien, on a fini.                | all right, we’re done. | well, we have finished. | well, we have finished. |
| qu’est-ce que vous mijotez?     | what are you up to? | what are you doing? | what are you doing? |
| manquent de respect             | have no respect | do not respect | are disrespectful to |
| vous m’aviez indiqué            | you told me    | you indicated to me | you indicated to me |
| enlève l’argent                  | take the money away | take the money away | remove the money |
| rester prudent                  | be careful     | be careful     | remain cautious |
| une réunion est organisée à la mairie demain soir, - si vous souhaitez... | there’s a meeting at the city hall tomorrow night, if you’d like... | a meeting is being held in the city hall tomorrow evening - if you wish... | a meeting shall be held at the council meeting tomorrow evening, - if you wish... |
| on l’a détectée                  | we detected it | it was detected | it was detected |
| deux heures                     | two hours      | two hours      | a two-hour period |
| précieuse                       | precious       | valuable       | valuable        |
| vous ne voyez pas qu’il a répondu à une provocation? | can’t you see he responded to a provocation? | do you not see that he responded to a provocation? | do you not see that he responded to a provocation? |
| c’est incroyable !              | it’s amazing!  | that is unbelievable! | this is unbelievable! |
| halte                           | stop           | stop           | halt            |
| ça risque d’être une piste difficile | it’s gonna be a hard run | there is a risk that this will be a difficult path | this is likely to be a difficult path |
| ça m’a fait plaisir de le voir heureux | it made me happy to see him happy | i was pleased to see him happy | i was pleased to see him happy |
| le petit a disparu              | the kid’s gone | the child has disappeared | the child has disappeared |
| film                            | movie          | film           | film            |
| journaux                        | papers         | newspapers     | newspapers      |
| merdique                        | crappy         | a mess         | merchandical    |
| je vous rembourserai.           | i’ll pay you back. | i will pay you back. | i shall reimburse you. |
| procureur                       | d.a.           | prosecutor     | public prosecutor |
| personne                        | no one         | nobody         | no person       |
| honte                           | shame          | disgrace       | disgrace        |
| evanouis - toi.                 | get out of here. | get away from it. | evacuate yourself. |
| il parle de vous                | he’s talking about you | he talks about you | he speaks of you |
| on se lance?                    | let’s go.      | are we getting started? | are we going? |
| salut                           | hey            | hi             | hi              |
| on me prendrait pour un idiot   | they’d think i’m an idiot | i would be thought to be an idiot | i would be regarded as an idiot |

Table 17: Additional examples of difference in lexical and grammatical choices when translating from French to English into different styles.