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A Challenge Set Approach to Evaluating Machine Translation

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Abstract

Neural machine translation represents an exciting leap forward in translation quality. But what longstanding weaknesses does it resolve, and which remain? We address these questions with a challenge set approach to translation evaluation and error analysis. A challenge set consists of a small set of sentences, each hand-designed to probe a system’s capacity to bridge a particular structural divergence between languages. To exemplify this approach, we present an English-French challenge set, and use it to analyze phrase-based and neural systems. The resulting analysis provides not only a more fine-grained picture of the strengths of neural systems, but also insight into which linguistic phenomena remain out of reach.

1 Introduction

The advent of neural techniques in machine translation (MT) (Kalchbrenner and Blunsom, 2013; Cho et al., 2014; Sutskever et al., 2014) has led to profound improvements in MT quality. For “easy” language pairs such as English/French or English/Spanish in particular, neural (NMT) systems are much closer to human performance than previous statistical techniques (Wu et al., 2016). This puts pressure on automatic evaluation metrics such as BLEU (Papineni et al., 2002), which exploit surface-matching heuristics that are relatively insensitive to subtle differences. As NMT continues to improve, these metrics will inevitably lose their effectiveness. Another challenge posed by NMT systems is their opacity: while it was usually clear which phenomena were ill-handled by previous statistical systems—and why—these questions are more difficult to answer for NMT.

We propose a new evaluation methodology centered around a challenge set of difficult examples that are designed using expert linguistic knowledge to probe an MT system’s capabilities. This methodology is complementary to the standard practice of randomly selecting a test set from “real text,” which remains necessary in order to predict performance on new text. By concentrating on difficult examples, a challenge set is intended to provide a stronger signal to developers. Although we believe that the general approach is compatible with automatic metrics, we used manual evaluation for the work presented here. Our challenge set consists of short sentences that each focus on one particular phenomenon, which makes it easy to collect reliable manual assessments of MT output by asking direct yes-no questions. An example is shown in Figure 1.

We generated a challenge set for English to French translation by canvassing areas of linguistic divergence between the two language pairs, especially those where errors would be made visible by French morphology. Example choice was also partly motivated by extensive knowledge of the weaknesses of phrase-based MT (PBMT). Neither of these characteristics is essential to our method, however, which we envisage evolving as NMT progresses. We used our challenge set to evaluate in-house PBMT and NMT systems as well as Google’s GNMT system.
In addition to proposing the novel idea of a challenge set evaluation, our contribution includes our annotated English-French challenge set, which we provide in an appendix and will make available in a separate machine-readable file. We also supply further evidence that NMT is systematically better than PBMT, even when BLEU score differences are small. Finally, we give an analysis of the challenges that remain to be solved in NMT, an area that has received little attention thus far.

2 Related Work

A number of recent papers have evaluated NMT using broad performance metrics. The WMT 2016 News Translation Task (Bojar et al., 2016) evaluated submitted systems according to both BLEU and human judgments. NMT systems were submitted to 9 of the 12 translation directions, winning 4 of these and tying for first or second in the other 5, according to the official human ranking. Since then, controlled comparisons have used BLEU to show that NMT outperforms strong PBMT systems on 30 translation directions from the United Nations Parallel Corpus (Junczys-Dowmunt et al., 2016a), and on the IWSLT English-Arabic tasks (Durrani et al., 2016). These evaluations indicate that NMT performs better on average than previous technologies, but they do not help us understand what aspects of the translation have improved.

Some groups have conducted more detailed error analyses. Bentivogli et al. (2016) carried out a number of experiments on IWSLT 2015 English-German evaluation data, where they compare machine outputs to professional post-edits in order to automatically detect a number of error categories. Compared to PBMT, NMT required less post-editing effort over-all, with substantial improvements in lexical, morphological and word order errors. NMT consistently out-performed PBMT, but its performance degraded faster as sentence length increased. Later, Toral and Sánchez-Cartagena (2017) conducted a similar study, examining the outputs of competition-grade systems for the 9 WMT 2016 directions that included NMT competitors. They reached similar conclusions regarding morphological inflection and word order, but found an even greater degradation in NMT performance as sentence length increased, perhaps due to these systems’ use of subword units.

Most recently, Sennrich (2016) proposed an approach to perform targeted evaluations of NMT through the use of contrastive translation pairs. This method introduces a particular type of error automatically in reference sentences, and then checks whether the NMT system’s conditional probability model prefers the original reference or the corrupted version. Using this technique, they are able to determine that a recently-proposed character-based model improves generalization on unseen words, but at the cost of introducing new grammatical errors.

Our approach differs from these studies in a number of ways. First, whereas others have analyzed sentences drawn from an existing bitext, we conduct our study on sentences that are manually constructed to exhibit canonical examples of specific linguistic phenomena. This challenge set methodology allows us to emphasize the difficult cases in an otherwise “easy” language pair. These sentences are designed to allow us to dive deep into phenomena of interest, and do a much finer-grained analysis of the strengths of NMT than has come before. However, this strategy also necessitates that we work on many fewer sentences. We leverage the small size of our challenge set to manually evaluate whether the system’s actual output correctly handles our phenomena of interest. Manual evaluation side-steps some of the pitfalls that can come with Sennrich (2016)’s contrastive pairs, as a ranking of two contrastive sentences may not necessarily reflect whether the error in question will occur in the system’s actual output.

3 Challenge Set Evaluation

Our challenge set is meant to measure the ability of MT systems to deal with some of the more difficult problems that arise in translating English into French. This particular language pair happened to be most convenient for us, but similar sets can be built for any language pair.

One aspect of MT performance that we aimed to exclude from our evaluation is robustness to sparse data. To control for this, when crafting source and reference sentences, we chose words that occurred at least 100 times in the training corpus described in section 4.1.1

1With three principled exceptions: boeuf (87 occurrences) and split (58 occurrences)—both part of idiomatic phrases—and guitared (0 occurrences).
3.1 Building the Challenge Set

The challenging aspect of the test set we are presenting stems from the fact that the source English sentences have been chosen so that their closest French equivalent will be structurally divergent from the source in some crucial way. Translational divergences have been extensively studied in the past – see for example (Vinay and Darbelnet, 1958; Dorr, 1994). We expect the level of difficulty of an MT test set to correlate well with its density in divergence phenomena. We classify divergence phenomena into three main types: morpho-syntactic, lexico-syntactic and purely syntactic divergences.

Morpho-syntactic divergences

In some languages, word morphology (e.g. inflections) carries more grammatical information than in others. When translating a word towards the richer language, there is a need to recover additional grammatically-relevant information from the context of the target language word. Note that we only include in our set cases where the relevant information is available in the linguistic context.2

We lack the space to describe all the subtypes of morpho-syntactic divergences that appear in our challenge set, but illustrate through representative examples. One particularly important case is that of subject-verb agreement. French verbs typically have more than 30 different inflected forms, while English verbs typically have 4 or 5. As a result, English verb forms strongly underspecify their French counterparts. Much of the missing information must be filled in through forced agreement in person, number and gender with the grammatical subject of the verb. But extracting these parameters can prove difficult. For example, the agreement features of a coordinated noun phrase are a complex function of the coordinated elements: a) the gender is feminine if all conjuncts are feminine, otherwise masculine wins; b) the conjunct with the smallest person (p1 < p2 < p3) wins; and c) the number is always plural when the coordination is “et” but the case is more complex with “ou”.

A second example of morpho-syntactic divergence between English and French is the more explicit marking of the subjunctive mood in French subordinate clauses. In the following example, the verb “partiez”, unlike its English counterpart, is marked as subjunctive:

He demanded that you leave immediately. → Il a exigé que vous partiez immédiatement.

When translating an English verb within a subordinate clause, the context must be examined for possible subjunctive triggers. Typically these are specific lexical items found in a governing position with respect to the subordinate clause: verbs such as “exiger que”, adjectives such as “regrettable que” or subordinate conjunctions such as “à condition que”.

Lexico-syntactic divergences

Syntactically governing words such as verbs tend to impose specific requirements on their complements: they subcategorize for complements of a certain syntactic type. But a source language governor and its target language counterpart can diverge on their respective requirements. The translation of such words must then trigger adjustments in the target language complement pattern. We can only examine here a few of the subtypes instantiated in our challenge set.

A good example is argument switching. This refers to the situation where the translation of a source verb $V_s$ as $V_t$ is correct but only provided the arguments (usually the subject and the object) are flipped around. The translation of “to miss” as “manquer à” is such a case:

John misses Mary → Mary manque à John.

Failing to perform the switch results in a severe case of mistranslation.

A second example of lexico-syntactic divergence is that of “crossing movement” verbs. Consider the following example:

Terry swam across the river → Terry a traversé la rivière à la nage.

The French translation could be glossed as, “Terry crossed the river by swimming.” A literal translation such as “Terry a nagé à travers la rivière,” is ruled out.

2The so-called Winograd Schema Challenges (https://en.wikipedia.org/wiki/Winograd_Schema_Challenge) often involve cases where common-sense reasoning is required to correctly choose between two potential antecedent phrases for a pronoun. Such cases become En → Fr translation challenges when the pronoun in the source sentence is they and its alternative antecedents happen to have different grammatical genders in French: they → ils/elles.
Syntactic divergences

Some syntactic divergences are not relative to the presence of a particular lexical item but rather stem from differences in the basic set of available syntactic patterns. Source-language instances of structures that do not exist in the target language must be mapped onto equivalent structures. Here are some of the subtypes appearing in our challenge set.

The position of French pronouns is a major case of divergence from English. French is basically an SVO language just like English but it departs from that canonical order when post-verbal complements are pronominalized: the pronouns must then be *cliticized*, that is phonetically attached to the verb, in this case to the left side of the verb.

He gave Mary a book. → Il a donné un livre à Marie.

He gave it to her. → Il le lui a donné.

Another example of syntactic divergence between English and French is that of *stranded prepositions*. When forming a relative clause or a question on a prepositional phrase, English can leave the preposition stranded, fronting only the pronominalized object of that preposition. In French, the preposition needs to be fronted alongside its object:

The girl whom he was dancing with is rich. → La fille avec qui il dansait est riche.

A final example of syntactic divergence is the use of the so-called *middle voice*. While English uses the passive voice in subjectless generic statements, French tends to prefer the use of a special pronominal construction where the pronoun “se” has no real referent:

Caviar is eaten with bread. → Le caviar se mange avec du pain.

This completes our exemplification of morphosyntactic, lexico-syntactic and purely syntactic divergences. Our actual test set includes several more subcategories of each type. The ability of MT systems to deal with each such subcategory is then tested using at least three different test sentences. We use short test sentences so as to keep the targeted divergence in focus. The 108 sentences that constitute our current challenge set can be found in Appendix B.

3.2 Evaluation Methodology

Given the very small size of our challenge set, it is easy to perform a human evaluation of the respective outputs of a handful of different systems. The obvious advantage is that the assessment is then absolute instead of relative to one or a few reference translations.

The intent of each challenge sentence is to test one and only one system capability, namely that of coping correctly with the particular associated divergence subtype. As illustrated in Figure 1, we provide annotators with a question that specifies the divergence phenomenon currently being tested, along with a reference translation with the areas of divergence highlighted. As a result, judgments become straightforward: was the targeted divergence correctly bridged, yes or no?

There is no need to mentally average over a number of different aspects of the test sentence as one does when rating the global translation quality of a sentence, e.g. on a 5-point scale. However, we acknowledge that measuring translation performance on complex sentences exhibiting many different phenomena remains crucial. We see our approach as being complementary to evaluations of overall translation quality.

One consequence of our divergence-focused approach is that faulty translations will be judged as successes when the faults lie outside of the targeted divergence zone. However, this problem is mitigated by our use of short test sentences.

4 Machine Translation Systems

We trained state-of-the-art neural and phrase-based systems for English-French translation on data from the WMT 2014 evaluation.

4.1 Data

We used the LIUM shared-task subset of the WMT 2014 corpora, retaining the provided tokenization and corpus organization, but mapping characters to lowercase. Table 1 gives corpus statistics.

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3 Sometimes the system produces a translation that circumvents the divergence issue. For example, it may dodge a divergence involving adverbs by reformulating the translation to use an adjective instead. In these rare cases, we instruct our annotators to abstain from making a judgment, regardless of whether the translation is correct or not.

4 http://www.statmt.org/wmt14/translation-task.html
   http://www-lium.univ-lemans.fr/~schwenk/mmmt-shared-task
Table 1: Corpus statistics. The WMT12/13 eval sets are used for dev, and the WMT14 eval set is used for test.

| corpus | lines | en words | fr words |
|--------|-------|----------|----------|
| train  | 12.1M | 304M     | 348M     |
| mono   | 15.9M | ——       | 406M     |
| dev    | 6003  | 138K     | 155K     |
| test   | 3003  | 71K      | 81K      |

4.2 Phrase-based systems

To ensure a competitive PBMT baseline, we performed phrase extraction using both IBM4 and HMM alignments with a phrase-length limit of 7; after frequency pruning, the resulting phrase table contained 516M entries. For each extracted phrase pair, we collected statistics for the hierarchical reordering model of Galley and Manning (2008).

We trained an NNJM model (Devlin et al., 2014) on the HMM-aligned training corpus, with input and output vocabulary sizes of 64K and 32K. Words not in the vocabulary were mapped to one of 100 mkcls classes. We trained for 60 epochs of 20K x 128 minibatches, yielding a final dev-set perplexity of 6.88.

Our set of log-linear features consisted of forward and backward Kneser-Ney smoothed phrase probabilities and HMM lexical probabilities (4 features); hierarchical reordering probabilities (6); the NNJM probability (1); a set of sparse features as described by Cherry (2013) (10,386); word-count and distortion penalties (2); and 5-gram language models trained on the French half of the training corpus and the French monolingual corpus (2). Tuning was carried out using batch lattice MIRA (Cherry and Foster, 2012). Decoding used the cube-pruning algorithm of Huang and Chiang (2007), with a distortion limit of 7.

We include two phrase-based systems in our comparison: PBMT-1 has data conditions that exactly match those of the NMT system, in that it does not use the language model trained on the French monolingual corpus, while PBMT-2 uses both language models.

4.3 Neural systems

To build our NMT system, we used the Nematus toolkit,5 which implements a single-layer neural sequence-to-sequence architecture with attention (Bahdanau et al., 2015) and gated recurrent units (Cho et al., 2014). We used 512-dimensional word embeddings with source and target vocabulary sizes of 90K, and 1024-dimensional state vectors. The model contains 172M parameters.

We preprocessed the data using a BPE model learned from source and target corpora (Sennrich et al., 2016). Sentences longer than 50 words were discarded. Training used the Adadelta algorithm (Zeiler, 2012), with a minibatch size of 100 and gradients clipped to 1.0. It ran for 5 epochs, writing a checkpoint model every 30K minibatches. Following Junczys-Dowmunt et al. (2016b), we averaged the parameters from the last 8 checkpoints. To decode, we used the AmuNMT decoder (Junczys-Dowmunt et al., 2016a) with a beam size of 4.

While our primary results will focus on the above PBMT and NMT systems, where we can describe replicable configurations, we have also evaluated Google’s production system,6 which has recently moved to NMT (Wu et al., 2016). Notably, the “GNMT” system uses (at least) 8 encoder and 8 decoder layers, compared to our 1 layer for each, and it is trained on corpora that are “two to three decimal orders of magnitudes bigger than the WMT.” The evaluated outputs were downloaded in December 2016.

5 Experiments

The 108-sentence English-French challenge set presented in Appendix B was submitted to the four MT systems described in section 4: PBMT-1, PBMT-2, NMT, and GNMT. We employed three bilingual native speakers of French who had no prior knowledge of the challenge set. They rated each translated sentence as either a success or a failure according to the protocol described in section 3.2. For example, the 26 sentences of the subcategories S1-S5 of Appendix B are all about different cases of subject-verb agreement. The corresponding translations were judged successful if and only if the translated verb correctly agrees with the translated subject.

The different system outputs for each source sentence were grouped together to reduce the burden on the annotators. That is, in figure 1, annotators were asked to answer the question for each of four outputs, rather than just one as shown. The outputs were listed in random order, without identification. Questions were also presented in ran-

5https://github.com/rsennrich/nematus
6https://translate.google.com
dom order to each annotator. Appendix A contains the instructions shown to the annotators.

5.1 Quantitative comparison

Table 2 summarizes our results in terms of percentage of successful translations, globally and over each main type of divergence. For comparison with traditional metrics, we also include BLEU scores measured on the WMT 2014 test set.

As we can see, the two PBMT systems fare very poorly on our challenge set, especially in the morpho-syntactic and purely syntactic types. Their relatively better handling of lexico-syntactic cases probably reflects the fact that PBMT systems are naturally more attuned to lexical cues than to morphology or syntax. The two NMT systems are clear winners in all three categories. The GNMT system is best overall with a success rate of 68%, likely due to the data and architectural factors mentioned in section 4.3.7

WMT BLEU scores correlate poorly with challenge-set performance. The large gap of 2.3 BLEU points between PBMT-1 and PBMT-2 corresponds to only a 1% gain on the challenge set, while the small gap of 0.4 BLEU between PBMT-2 and NMT corresponds to a 21% gain.

Inter-annotator agreement (final column in table 2) is excellent overall, with all three annotators agreeing on almost 90% of system outputs. Syntactic divergences appear to be somewhat harder to judge than other categories.

5.2 Qualitative assessment of NMT

We now turn to an analysis of the strengths and weaknesses of neural MT through the microscope of our divergence categorization system, hoping that this may help focus future research on key issues. In this discussion we ignore the results obtained by PBMT-2 and compare: a) the results obtained by PBMT-1 to those of NMT, both systems having been trained on the same dataset; and b) the results of these two systems with those of Google NMT which was trained on a much larger dataset.

In the remainder of the present section we will reference the sentences of our challenge set using the subcategory-based numbering scheme S1-S26 as assigned in Appendix B.

7We cannot offer a full comparison with the pre-NMT Google system. However, in October 2016 we ran a smaller 35-sentence version of our challenge set on both the Google system and our PBMT-1 system. The Google system only got 4 of those examples right (11.4%) while our PBMT-1 got 6 (17.1%).

Strengths of neural MT

Overall, both neural MT systems do much better than PBMT-1 at bridging divergences. Their dramatic advantage on morpho-syntactic divergences (a jump from 16% to 72% in the case of our two local systems) results from achievements such as the following:

- The subject’s head noun agreement features get correctly passed to the verb phrase across intervening noun phrase complements (sentences S1a-c).
- Subject agreement marks appear to be correctly distributed to each element of a coordinated verb phrase (S3a-c).
- Much of the calculus that is at stake in determining the agreement features of a subject noun phrase (cf. our relevant description in section 3.1) appears to be correctly captured in the 12 translations of S4.
- Most instances of the difficult case of past participle agreement after the “avoir” auxiliary are correctly handled (S5b-e).

The NMT systems are also better at handling lexico-syntactic divergences. For example:

- They can perform the required restructuring of English double object constructions (sentences S8a-S8c).
- They can discriminate between an NP complement and a sentential complement starting with an NP: cf. to know NP versus to know NP is VP (S11b-e)
- They often correctly restructure English NP-to-VP complements (S12a-c).

Finally, NMT systems also turn out to better handle purely syntactic divergences. For example:

- The differences in yes-no question syntax is correctly bridged (S17a-c).
- English pronouns in verb complement position are often correctly cliticized, that is, moved before the main verb and case-inflected correctly (S23a-e).
- The Google NMT system manages to correctly translate tag questions (S18a-c), most cases of the “inalienable possession” construction (S25a-e), zero relative pronouns (S26a-c) and constructions with stranded prepositions (S19a-f).
| Divergence type | PBMT-1 | PBMT-2 | NMT | Google NMT | Agreement |
|-----------------|--------|--------|-----|------------|-----------|
| Morpho-syntactic| 16%    | 16%    | 72% | 65%        | 94%       |
| Lexico-syntactic| 42%    | 46%    | 52% | 62%        | 94%       |
| Syntactic       | 33%    | 33%    | 40% | 75%        | 81%       |
| Overall         | 31%    | 32%    | 53% | 68%        | 89%       |
| WMT BLEU        | 34.2   | 36.5   | 36.9| —          | —         |

Table 2: Summary performance statistics for each system under study, including challenge set success rate grouped by linguistic category, as well as BLEU scores on the WMT 2014 test set. The final column gives the proportion of system outputs on which all three annotators agreed.

The large gap observed between the results of the in-house and Google NMT systems indicates that current neural MT systems are extremely data hungry. But given enough data, they can successfully tackle some challenges that are often thought of as extremely difficult. A case in point is that of stranded prepositions, in which English and French happen to diverge in their handling of the celebrated “WH-movement” long-distance dependencies. Specifically, in the French translation, the preposition must be repatriated with its fronted WH object no matter how far on the left it happens to be.

**Weaknesses of neural MT**

In spite of its clear edge over PBMT, NMT is not without some serious shortcomings. Some of them have been mentioned already, such as the tendency of system output to degrade with sentence length. By design this particular problem could not be observed with our challenge set. But many others get highlighted by an analysis of our results. Globally, we note that even using a staggering quantity of data and a highly sophisticated NMT model, the Google system fails to reach the 70% mark on our challenge set. Thus, there is ample room for improvement. The fine-grained error categorization associated with the challenge set makes it possible to single out precise areas where more research is needed. A first analysis of our results yields the following observations.

*Incomplete generalizations.* In several cases, while partial results might suggest that NMT has correctly captured a basic generalization about linguistic data, further instances reveal that this is not fully the case. Here are some examples:

- The calculus governing the agreement features of coordinated noun phrases (see section 3.1) appears to be handled correctly most of the time. However unlike our NMT system, the Google NMT system gets into difficulty with mixed-person subjects (sentences S4d1-3).
- While some subjunctive mood triggers are correctly captured (e.g. “demander que” and “malheureux que”), others such as the very common subordinate conjunction provided that \( \rightarrow \) à condition que are getting missed (sentence S6a).
- The NMT systems often appear to have successfully captured the semantic relation that ties together the two nouns of an English noun compound, thereby giving rise to the correct preposition in the French translation \( N_1 N_2 \rightarrow N_2 \text{Prep} N_1 \). However, some cases that one might think of as easy are being missed. For example, the Google translation of “steak knife” (sentence S14c) fails to convey that this is a knife intended to cut steak; similarly, the Google translation of “paper filter” (sentence S14i) suggests the filter is intended to filter paper rather being made of it.
- The so-called French “inalienable possession” construction arises when an agent performs an action on one of her body parts, e.g. *I brushed my teeth*. In such cases the French translation normally follows a pattern that can be glossed as *He brushed the teeth to himself*. In our dataset, the Google system gets this right for examples in the first and third persons (sentences S25a,b) but fails to do the same with the example in the second person (sentence S25c).

Then there are also phenomena that current NMT systems, even with massive amounts of data, appear to be completely missing:

- *Idioms.* While PBMT-1 produces an acceptable translation for half of the idiomatic ex-
pressions of S15 and S16, the local NMT system misses them all and the Google system does just slightly better. It looks as if NMT systems lack sufficient capacity for raw memorization.

- **Control verbs.** Two different classes of verbs can govern a subject NP, an object NP plus an infinitival complement. With verbs of the “object-control” class (e.g. “persuade”), the object of the verb is understood as the semantic subject of the infinitive. But with those of the subject class (e.g. “promise”), it is rather the subject of the verb which plays that semantic role. None of the systems tested here appear to get a grip on subject control cases, as evidenced by the lack of correct feminine agreement on the French adjectives in sentences S2b-d.

- **Argument switching verbs.** All systems tested here mistranslate sentences S7a-c by failing to perform the required argument switch: \( NP_1 \text{ misses } NP_2 \rightarrow NP_2 \text{ manque à } NP_1 \).

- **Crossing movement verbs.** None of the systems managed to correctly restructure the regular manner-of-movement verbs e.g. \( \text{swim across } X \rightarrow \text{traverser } X \text{ à la nage} \) in sentences S10a-c, let alone the even harder example S10d, in which the word “guitar” is spontaneously recast as a manner-of-movement verb.

- **Middle voice.** None of the systems tested here were able to recast the English “generic passive” of S21a-c into the expected French “middle voice” pronominal construction.

6 Conclusions

We have presented a radically different kind of evaluation for machine translation systems: the use of challenge sets designed to stress-test MT systems on “hard” linguistic material, while providing a fine-grained linguistic classification of their successes and failures. This approach is not meant to replace our community’s traditional evaluation tools but to supplement them.

Our proposed error categorization scheme makes it possible to bring to light different strengths and weaknesses of PBMT and neural MT. With the exception of idiom processing, in all cases where a clear difference was observed it turned out to be in favor of neural MT. A key factor in NMT’s superiority appears to be its ability to overcome many limitations of \( n \)-gram language modeling. This is clearly at play in dealing with subject-verb agreement, double-object verbs, overlapping subcategorization frames and last but not least, the pinnacle of Chomskyan linguistics, WH-movement (in this case, stranded prepositions).

But our challenge set also brings to light some important shortcomings of current neural MT, regardless of the massive amounts of training data it may have been fed. As may have been already known or suspected, NMT systems struggle with the translation of idiomatic phrases. Perhaps more interestingly, we notice that neural MT’s impressive generalizations still seem somewhat brittle. For example, the NMT system can appear to have mastered the rules governing subject-verb agreement or inalienable possession in French, only to trip over a rather obvious instantiation of those rules. Probing where these boundaries are, and how they relate to the neural system’s training data and architecture is an obvious next step.

7 Future Work

It is our hope that the insights derived from our challenge set evaluation will help inspire future MT research, and call attention to the fact that even “easy” language pairs like English-French still have many linguistic issues left to be resolved. But there are also several ways to improve and expand upon our challenge set approach itself.

First, though our human judgments of output sentences allowed us to precisely assess the phenomena of interest, this approach is not scalable to large sets, and requires access to native speakers in order to replicate the evaluation. It would be interesting to see whether similar scores could be achieved through automatic means. The existence of human judgments for this set provides a gold-standard by which proposed automatic judgments may be meta-evaluated.

Second, the construction of such a challenge set is as much an art as a science, and requires in-depth knowledge of the structural divergences between the two languages of interest. A method to automatically create such a challenge set for a new language pair would be extremely useful. One could imagine approaches that search for divergences, indicated by atypical output configurations, or perhaps by a system’s inability to repro-
duce a reference from its own training data. Localizing a divergence within a difficult sentence pair would be another useful subtask.

Finally, and perhaps most interestingly, we would like to explore how to train an MT system to improve its performance on these divergence phenomena. This could take the form of designing a curriculum to demonstrate a particular divergence to the machine, or altering the network structure to more easily capture such generalizations.

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A Instructions to Annotators

The following instructions were provided to annotators:

You will be presented with 108 short English sentences and the French translations produced for them by each of four different machine translation systems. You will not be asked to provide an overall rating for the machine-translated sentences. Rather, you will be asked to determine whether or not a highly specific aspect of the English sentence is correctly rendered in each of the different translations. Each English sentence will be accompanied with a yes-no question which precisely specifies the targeted element for the associated translations. For example, you may be asked to determine whether or not the main verb phrase of the translation is in correct grammatical agreement with its subject.

In order to facilitate this process, each English sentence will also be provided with a French reference (human) translation in which the particular elements that support a yes answer (in our example, the correctly agreeing verb phrase) will be highlighted. Your answer should be “yes” if the question can be answered positively and “no” otherwise. Note that this means that any translation error which is unrelated to the question at hand should be disregarded. Using the same example: as long as the verb phrase agrees correctly with its subject, it does not matter whether or not the verb is correctly chosen, is in the right tense, etc. And of course, it does not matter if unrelated parts of the translation are wrong.

In most cases you should be able to quickly determine a positive or negative answer. However, there may be cases in which the system has come up with a translation that just does not contain the phenomenon targeted by the associated question. In such cases, and only in such cases, you should choose “not applicable” regardless of whether or not the translation is correct.

B Challenge Set

We include a rendering of our challenge set in the pages that follow, along with system output for the PBMT-1, NMT and Google systems. Sentences are grouped by linguistic category and subcategory. For convenience, we also include a reference translation, which is a manually-crafted translation that is designed to be the most straightforward solution to the divergence problem at hand. Needless to say, this reference translation is seldom the only acceptable solution to the targeted divergence problem. Our judges were provided these references, but were instructed to use their knowledge of French to judge whether the divergence was correctly bridged, regardless of the translation’s similarity to the reference.

In all translations, the locus of the targeted divergence is highlighted in boldface and it is specifically on that portion that our annotators were asked to provide a judgment. For each system output, we provide a summary of our annotator’s judgments on its handling of the phenomenon of interest. We label the translation with a ✓ if two or more annotators judged the divergence to be correctly bridged, and with an x otherwise.

We also release a machine-readable version of this same data, including all of the individual judgments, in the hope that others will find interesting new uses for it.
Morpho-Syntactic

S-V agreement, across distractors
Is subject-verb agreement correct? (Possible interference from distractors between the subject’s head and the verb).

| Source | Ref | PBMT-1 | NMT | Google |
|--------|-----|--------|-----|--------|
| S1a Source The repeated calls from his mother **should** have alerted us. | Les appels répétés de sa mère **auraient** dû nous avertir. | ✗ | Les appels répétés de sa mère devraient nous avoir avertis. ✓ | Les appels répétés de sa mère auraient dû nous alerter. ✓ |
| S1b Source The sudden noise in the upper rooms **should** have alerted us. | Le bruit soudain dans les chambres supérieures **aurait** dû nous avertir. | ✗ | Le bruit soudain dans les chambres supérieures devrait nous avoir alerté. ✓ | Le bruit soudain dans les chambres supérieures devrait nous avoir alerté. ✓ |
| S1c Source Their repeated failures to report the problem **should** have alerted us. | Leurs échecs répétés à signaler le problème **auraient** dû nous avertir. | ✗ | Leurs échecs répétés pour signaler le problème devraient nous avoir avertis. ✓ | Leur échec répété à signaler le problème aurait dû nous alerter. ✓ |

S-V agreement, through control verbs
Does the flagged adjective agree correctly with its subject? (Subject-control versus object-control verbs).

| Source | Ref | PBMT-1 | NMT | Google |
|--------|-----|--------|-----|--------|
| S2a Source She asked her brother not to be **arrogant**. | Elle a demandé à son frère de ne pas se montrer **arrogant**. | ✓ | Elle a demandé à son frère de ne pas être arrogant. ✓ | Elle a demandé à son frère de ne pas être arrogant. ✓ |
| S2b Source She promised her brother not to be **arrogant**. | Elle a promis à son frère de ne pas être **arrogante**. | ✓ | Elle a promis à son frère de ne pas être arrogant. ✓ | Elle a promis à son frère de ne pas être arrogant. ✓ |
| S2c Source She promised her doctor to remain **active** after retiring. | Elle a promis à son médecin de demeurer **active** après s’être retirée. | ✗ | Elle a promis à son médecin de rester actif après sa retraite. ✗ | Elle a promis à son médecin de rester actif après sa retraite. ✗ |
| S2d Source My mother promised my father to be more **prudent** on the road. | Ma mère a promis à mon père d’être plus **prudente** sur la route. | ✗ | Ma mère a promis à mon père d’être plus prudent sur la route. ✗ | Ma mère a promis à mon père d’être plus prudent sur la route. ✗ |
### S-V agreement, coordinated targets

Do the marked verbs/adjective agree correctly with their subject? (Agreement distribution over coordinated predicates)

|   | Source | Reference | PBMT-1 | NMT | Google |
|---|--------|-----------|--------|-----|--------|
| S3a | The woman was very **tall** and extremely **strong**. | La femme était très **grande** et extrêmement **forte**. | La femme était très gentil et extrêmement forte. ✗ | La femme était très haute et extrêmement forte. ✓ | La femme était très grande et extrêmement forte. ✓ |
| S3b | Their politicians were more **ignorant** than **stupid**. | Leurs politiciens étaient plus **ignorants** que **stupides**. | Les politiciens étaient plus ignorants que stupide. ✗ | Leurs politiciens étaient plus ignorants que stupides. ✓ | Leurs politiciens étaient plus ignorants que stupides. ✓ |
| S3c | We **shouted** an insult and **left** abruptly. | Nous **avons** lancé une insulte et nous **sommes** partis brusquement. | Les politiciens étaient plus ignorants que stupide. ✗ | Nous avons crié une insulte et nous avons laissé brusquement. ✓ | Nous avons crié une insulte et nous sommes partis brusquement. ✓ |

### S-V agreement, feature calculus on coordinated source

Do the marked verbs/adjective agree correctly with their subject? (Masculine singular ET masculine singular yields masculine plural).

|   | Source | Reference | PBMT-1 | NMT | Google |
|---|--------|-----------|--------|-----|--------|
| S4a1 | The cat and the dog **should** be watched. | Le chat et le chien **devraient** être **surveillés**. | Le chat et le chien doit être regardée. ✗ | Le chat et le chien doivent être regardés. ✓ | Le chat et le chien doivent être surveillés. ✓ |
| S4a2 | My father and my brother **will** be happy tomorrow. | Mon père et mon frère **seront heureux** demain. | Mon père et mon frère sera heureux de demain. ✗ | Mon père et mon frère seront heureux demain. ✓ | Mon père et mon frère seront heureux demain. ✓ |
| S4a3 | My book and my pencil **could** be stolen. | Mon livre et mon crayon **pouraient** être **volés**. | Mon livre et mon crayon pourraient être volé. ✗ | Mon livre et mon crayon pourraient être volés. ✓ | Mon livre et mon crayon pourraient être volés. ✓ |

Do the marked verbs/adjectives agree correctly with their subject? (Feminine singular ET feminine singular yields feminine plural).

|   | Source | Reference | PBMT-1 | NMT | Google |
|---|--------|-----------|--------|-----|--------|
| S4b1 | The cow and the hen **must** be fed. | La vache et la poule **doivent** être **nourries**. | La vache et de la poule doivent être nourris. ✗ | La vache et la poule doivent être alimentées. ✓ | La vache et la poule doivent être nourries. ✓ |

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| S4b2 Source          | My mother and my sister will be happy tomorrow. |
|---------------------|-------------------------------------------------|
| Ref                 | Ma mère et ma sœur seront heureuses demain.     |
| PBMT-1              | Ma mère et ma sœur sera heureux de demain. ✗    |
| NMT                 | Ma mère et ma sœur seront heureuses demain. ✓   |
| Google              | Ma mère et ma sœur seront heureuses demain. ✓   |
| S4b3 Source          | My shoes and my socks will be found.           |
| Ref                 | Mes chaussures et mes chaussettes seront trouvées. ✓ |
| PBMT-1              | Mes chaussures et mes chaussettes sera trouvés. ✗ |
| NMT                 | Mes chaussures et mes chaussettes seront trouvées. ✓ |
| Google              | Mes chaussures et mes chaussettes seront trouvées. ✓ |

Do the marked verbs/adjectives agree correctly with their subject? (Masculine singular ET feminine singular yields masculine plural.)

| S4c1 Source          | The dog and the cow are nervous.               |
|---------------------|------------------------------------------------|
| Ref                 | Le chien et la vache sont nerveux. ✓           |
| PBMT-1              | Le chien et la vache sont nerveux. ✓           |
| NMT                 | Le chien et la vache sont nerveux. ✓           |
| Google              | Le chien et la vache sont nerveux. ✓           |
| S4c2 Source          | My father and my mother will be happy tomorrow. |
|---------------------|------------------------------------------------|
| Ref                 | Mon père et ma mère seront heureux demain. ✓   |
| PBMT-1              | Mon père et ma mère se fera un plaisir de demain. ✗ |
| NMT                 | Mon père et ma mère seront heureux demain. ✓   |
| Google              | Mon père et ma mère seront heureux demain. ✓   |
| S4c3 Source          | My refrigerator and my kitchen table were stolen. |
|---------------------|------------------------------------------------|
| Ref                 | Mon réfrigérateur et ma table de cuisine ont été volés. ✓ |
| PBMT-1              | Mon réfrigérateur et ma table de cuisine ont été volés. ✓ |
| NMT                 | Mon réfrigérateur et ma table de cuisine ont été volés. ✓ |
| Google              | Mon réfrigérateur et ma table de cuisine ont été volés. ✓ |

Do the marked verbs/adjectives agree correctly with their subject? (Smallest coordinated grammatical person wins.)

| S4d1 Source          | Paul and I could easily be convinced to join you. |
|---------------------|--------------------------------------------------|
| Ref                 | Paul et moi pourrions facilement être convaincus de se joindre à vous. ✗ |
| PBMT-1              | Paul et je pourrions facilement être persuadée de se joindre à vous. ✗ |
| NMT                 | Paul et moi avons facilement pu être convaincus de vous rejoindre. ✓ |
| Google              | Paul et moi pourrait facilement être convaincu de vous rejoindre. ✗ |
| S4d2 Source          | You and he could be surprised by her findings.   |
|---------------------|--------------------------------------------------|
| Ref                 | Vous et lui pourriez être surpris par ses découvertes. ✓ |
| PBMT-1              | Vous et qu’il pouvait être surpris par ses conclusions. ✗ |
| NMT                 | Vous et lui pourriez être surpris par ses conclusions. ✓ |
| Google              | Vous et lui pourrait être surpris par ses découvertes. ✗ |
| Source | Ref | PBMT-1 | NMT | Google |
|--------|-----|--------|-----|--------|
| We and they are on different courses. | Nous et eux sommes sur des trajectoires différentes. | Nous et ils sont en cours de différents. | Nous et nous sommes sur des parcours différents. | Nous et ils sont sur des parcours différents. |

### S-V agreement, past participles
Are the agreement marks of the flagged participles the correct ones? (Past participle placed after auxiliary AVOIR agrees with verb object iff object precedes auxiliary. Otherwise participle is in masculine singular form).

| Source | Ref | PBMT-1 | NMT | Google |
|--------|-----|--------|-----|--------|
| The woman who saw a mouse in the corridor is charming. | La femme qui a vu une souris dans le couloir est charmante. | ✓ | ✓ | ✓ |
| The woman that your brother saw in the corridor is charming. | La femme que votre frère a vue dans le couloir est charmante. | ✓ | ✓ | ✓ |
| The house that John has visited is crumbling. | La maison que John a visitée tombe en ruines. | ✓ | ✓ | ✓ |
| John sold the car that he had won in a lottery. | John a vendu la voiture qu’il avait gagnée dans une loterie. | ✓ | ✓ | ✓ |

### Subjunctive mood
Is the flagged verb in the correct mood? (Certain triggering verbs, adjectives or subordinate conjunctions, induce the subjunctive mood in the subordinate clause that they govern).

| Source | Ref | PBMT-1 | NMT | Google |
|--------|-----|--------|-----|--------|
| He will come provided that you come too. | Il viendra à condition que vous veniez aussi. | ✓ | ✓ | ✓ |
| It is unfortunate that he is not coming either. | Il est malheureux qu’il ne vienne pas non plus. | ✓ | ✓ | ✓ |
Lexico-Syntactic

**Argument switch**
Are the experiencer and the object of the “missing” situation correctly preserved in the French translation? (Argument switch).

| S7a | Source | Mary sorely misses Jim. |
|-----|--------|-------------------------|
| Ref | Jim manque cruellement à Mary. |
| PBMT-1 | Marie manque cruellement de Jim. ✗ |
| NMT | Mary a lamentablement manqué de Jim. ✗ |
| Google | Mary manque cruellement à Jim. ✗ |
| S7b | Source | My sister is really missing New York. |
| Ref | New York manque beaucoup à ma sœur. |
| PBMT-1 | Ma sœur est vraiment absent de New York. ✗ |
| NMT | Ma sœur est vraiment manquante à New York. ✗ |
| Google | Ma sœur manque vraiment New York. ✗ |
| S7c | Source | What he misses most is his dog. |
| Ref | Ce qui lui manque le plus, c’est son chien. |
| PBMT-1 | Ce qu’il manque le plus, c’est son chien. ✗ |
| NMT | Ce qu’il manque le plus, c’est son chien. ✗ |
| Google | Ce qu’il manque le plus, c’est son chien. ✗ |

**Double-object verbs**
Are “gift” and “recipient” arguments correctly rendered in French? (English double-object constructions)

| S8a | Source | John gave his wonderful wife a nice present. |
|-----|--------|---------------------------------------------|
| Ref | John a donné un beau présent à sa merveilleuse épouse. |
| PBMT-1 | John a donné sa merveilleuse femme un beau cadeau. ✗ |
| NMT | John a donné à sa merveilleuse femme un beau cadeau. ✓ |
| Google | John a donné à son épouse merveilleuse un présent gentil. ✓ |
| S8b | Source | John told the kids a nice story. |
| Ref | John a raconté une belle histoire aux enfants. |
| PBMT-1 | John a dit aux enfants une belle histoire. ✓ |
| NMT | John a dit aux enfants une belle histoire. ✓ |
| Google | John a raconté aux enfants une belle histoire. ✓ |
| S8c | Source | John sent his mother a nice postcard. |
| Ref | John a envoyé une belle carte postale à sa mère. |
| PBMT-1 | John a envoyé sa mère une carte postale de nice. ✗ |
| NMT | John a envoyé sa mère une carte postale de nice. ✗ |
| Google | John envoya à sa mère une belle carte postale. ✓ |
Fail to

Is the meaning of “fail to” correctly rendered in the French translation?

|   |   |   |   |
|---|---|---|---|
| S9a | Source | John failed to see the relevance of this point. | Ref | John n’a pas vu la pertinence de ce point. | PBMT-1 | John a omis de voir la pertinence de ce point. ✓ | NMT | John n’a pas vu la pertinence de ce point. ✓ | Google | John a omis de voir la pertinence de ce point. ✓ |
| S9b | Source | He failed to respond. | Ref | Il n’a pas répondu. | PBMT-1 | Il n’a pas réussi à répondre. ✓ | NMT | Il n’a pas répondu. ✓ | Google | Il n’a pas répondu. ✓ |
| S9c | Source | Those who fail to comply with this requirement will be penalized. | Ref | Ceux qui ne se conforment pas à cette exigence seront pénalisés. ✓ | PBMT-1 | Ceux qui ne se conforment pas à cette obligation seront pénalisés. ✓ | NMT | Ceux qui ne se conforment pas à cette obligation seront pénalisés. ✓ | Google | Ceux qui ne respectent pas cette exigence seront pénalisés. ✓ |

Manner-of-movement verbs

Is the movement action expressed in the English source correctly rendered in French? (Manner-of-movement verbs with path argument may need to be rephrased in French).

|   |   |   |   |
|---|---|---|---|
| S10a | Source | John would like to swim across the river. | Ref | John aimerait traverser la rivière à la nage. | PBMT-1 | John aimerait nager dans la rivière. ✗ | NMT | John aimerait nager à travers la rivière. ✗ | Google | John aimerait nager à travers la rivière. ✗ |
| S10b | Source | They ran into the room. | Ref | Ils sont entrés dans la chambre à la course. | PBMT-1 | Ils ont couru dans la chambre. ✗ | NMT | Ils ont couru dans la pièce. ✗ | Google | Ils coururent dans la pièce. ✗ |
| S10c | Source | The man ran out of the park. | Ref | L’homme est sorti du parc en courant. | PBMT-1 | L’homme a manqué du parc. ✗ | NMT | L’homme s’enfuit du parc. ✗ | Google | L’homme sortit du parc. ✗ |

Hard example featuring spontaneous noun-to-verb derivation (“nonce verb”).

|   |   |   |   |
|---|---|---|---|
| S10d | Source | John guitared his way to San Francisco. | Ref | John s’est rendu jusqu’à San Francisco en jouant de la guitare. | PBMT-1 | John guitared son chemin à San Francisco. ✗ | NMT | John guitared sa route à San Francisco. ✗ | Google | John a guié son chemin à San Francisco. ✗ |
**Overlapping subcat frames**

Is the French verb for “know” correctly chosen? (Choice between “savoir”/“connaître” depends on syntactic nature of its object)

| Source | Paul knows that this is a fact. | Paul sait que c’est un fait. | Paul sait que c’est un fait. ✓ | Paul sait que c’est un fait. ✓ | Paul sait que c’est un fait. ✓ |
|--------|---------------------------------|-------------------------------|--------------------------------|--------------------------------|--------------------------------|
| Ref    | Paul sait que c’est un fait. ✓   |                               |                                |                                |                                |
| PBMT-1 | Paul connaît cette histoire. ✓   |                               |                                |                                |                                |
| NMT    | Paul sait que c’est un fait. ✓   |                               |                                |                                |                                |
| Google | Paul sait que c’est un fait. ✓   |                               |                                |                                |                                |

| Source | Paul knows this story. | Paul connaît cette histoire. ✓ | Paul connaît cette histoire. ✓ | Paul connaît cette histoire. ✓ |
|--------|------------------------|--------------------------------|--------------------------------|--------------------------------|
| Ref    | Paul connaît cette histoire. ✓ |                               |                                |                                |
| PBMT-1 | Paul connaît cette histoire. ✓ |                               |                                |                                |
| NMT    | Paul connaît cette histoire. ✓ |                               |                                |                                |
| Google | Paul connaît cette histoire. ✓ |                               |                                |                                |

| Source | Paul knows this story is hard to believe. | Paul sait que cette histoire est difficile à croire. ✓ | Paul sait que cette histoire est difficile à croire. ✓ | Paul sait que cette histoire est difficile à croire. ✓ |
|--------|------------------------------------------|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|
| Ref    | Paul sait que cette histoire est difficile à croire. ✓ |                               |                                |                                |
| PBMT-1 | Paul sait que cette histoire est difficile à croire. ✓ |                               |                                |                                |
| NMT    | Paul sait que cette histoire est difficile à croire. ✓ |                               |                                |                                |
| Google | Paul sait que cette histoire est difficile à croire. ✓ |                               |                                |                                |

| Source | He knows my sister will not take it. | Il sait que ma soeur ne le prendra pas. ✓ | Il sait que ma soeur ne le prendra pas. ✓ | Il sait que ma soeur ne le prendra pas. ✓ |
|--------|-------------------------------------|------------------------------------------|------------------------------------------|------------------------------------------|
| Ref    | Il sait que ma soeur ne le prendra pas. ✓ |                               |                                |                                |
| PBMT-1 | Il sait que ma soeur ne le prendra pas. ✓ |                               |                                |                                |
| NMT    | Il sait que ma soeur ne le prendra pas. ✓ |                               |                                |                                |
| Google | Il sait que ma soeur ne le prendra pas. ✓ |                               |                                |                                |

| Source | My sister knows your son is reliable. | Ma sœur sait que votre fils est fiable. ✓ | Ma sœur sait que votre fils est fiable. ✓ | Ma sœur sait que votre fils est fiable. ✓ |
|--------|-------------------------------------|------------------------------------------|------------------------------------------|------------------------------------------|
| Ref    | Ma sœur sait que votre fils est fiable. ✓ |                               |                                |                                |
| PBMT-1 | Ma sœur sait que votre fils est fiable. ✓ |                               |                                |                                |
| NMT    | Ma sœur sait que votre fils est fiable. ✓ |                               |                                |                                |
| Google | Ma sœur sait que votre fils est fiable. ✓ |                               |                                |                                |

**NP to VP**

Is the English “NP to VP” complement correctly rendered in the French translation? (Sometimes one needs to translate this structure as a finite clause).

| Source | John believes Bill to be dishonest. | John croit que Bill est malhonnête. ✓ | John croit que Bill est malhonnête. ✓ | John croit que Bill est malhonnête. ✓ |
|--------|------------------------------------|----------------------------------------|----------------------------------------|----------------------------------------|
| Ref    | John croit que Bill est malhonnête. ✓ |                               |                                |                                |
| PBMT-1 | John estime que le projet de loi soit malhonnête. ✓ |                               |                                |                                |
| NMT    | John croit que le projet de loi est malhonnête. ✓ |                               |                                |                                |
| Google | John croit que Bill est malhonnête. ✓ |                               |                                |                                |

| Source | He liked his father to tell him stories. | Il aimait que son père lui raconte des histoires. ✓ | Il aimait que son père lui raconte des histoires. ✓ | Il aimait que son père lui raconte des histoires. ✓ |
|--------|----------------------------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|
| Ref    | Il aimait que son père lui raconte des histoires. ✓ |                               |                                |                                |
| PBMT-1 | Il aimait son père pour lui raconter des histoires. ✓ |                               |                                |                                |
| NMT    | Il aimait son père pour lui raconter des histoires. ✓ |                               |                                |                                |
| Google | Il aimait son père à lui raconter des histoires. ✓ |                               |                                |                                |
### Factitives

Is the English verb correctly rendered in the French translation? (Agentive use of some French verbs require embedding under “faire”).

| Source       | Ref                                | PBMT-1                                      | NMT                                      | Google                                    |
|--------------|------------------------------------|---------------------------------------------|------------------------------------------|-------------------------------------------|
| John cooked  | John a fait cuire un gros poulet.  | John cuit un gros poulet.                  | John cuit un gros poulet.               | John a fait cuire un gros poulet.         |
| John melted  | John a fait fondre beaucoup de glace.| John fondu un lot de glace.                | John a fondu beaucoup de glace.         | John a fondu beaucoup de glace.           |
| She likes to grow flowers | Elle aime faire pousser des fleurs. | Elle aime à se développer des fleurs.      | Elle aime à cultiver des fleurs.        | Elle aime faire pousser des fleurs.       |

### Noun Compounds

Is the English nominal compound rendered with the right preposition in the French translation?

| Source       | Ref                                | PBMT-1                                      | NMT                                      | Google                                    |
|--------------|------------------------------------|---------------------------------------------|------------------------------------------|-------------------------------------------|
| Use the meat knife | Utilisez le couteau à viande. | Utilisez le couteau de viande.               | Utilisez le couteau à viande.            | Utilisez le couteau à viande.             |
| Use the butter knife | Utilisez le couteau à beurre. | Utilisez le couteau à beurre.               | Utilisez le couteau au beurre.           | Utilisez le couteau à beurre.             |
| Use the steak knife | Utilisez le couteau à steak. | Utilisez le couteau de steak.                | Utilisez le couteau à steak.             | Utilisez le couteau de steak.             |
| S14d | Source | Clean the water filter. | Ref | Nettoyez le filtre à eau. | PBMT-1 | Nettoyez le filtre à eau. ✓ | NMT | Nettoyez le filtre à eau. ✓ | Google | Nettoyez le filtre à eau. ✓ |
|------|--------|-------------------------|-----|---------------------------|--------|---------------------------------|-----|---------------------------|--------|---------------------------------|
| S14e | Source | Clean the juice filter. | Ref | Nettoyez le filtre à jus. | PBMT-1 | Nettoyez le filtre de jus. ✗ | NMT | Nettoyez le filtre de jus. ✗ | Google | Nettoyez le filtre à jus. ✓ |
| S14f | Source | Clean the tea filter. | Ref | Nettoyez le filtre à thé. | PBMT-1 | Nettoyez le filtre à thé. ✓ | NMT | Nettoyez le filtre de thé. ✗ | Google | Nettoyez le filtre à thé. ✓ |
| S14g | Source | Clean the cloth filter. | Ref | Nettoyez le filtre en tissu. | PBMT-1 | Nettoyez le filtre en tissu. ✓ | NMT | Nettoyez le filtre en tissu. ✓ | Google | Nettoyez le filtre en tissu. ✓ |
| S14h | Source | Clean the metal filter. | Ref | Nettoyez le filtre en métal. | PBMT-1 | Nettoyez le filtre en métal. ✓ | NMT | Nettoyez le filtre en métal. ✓ | Google | Nettoyez le filtre métallique. ✓ |
| S14i | Source | Clean the paper filter. | Ref | Nettoyez le filtre en papier. | PBMT-1 | Nettoyez le filtre en papier. ✓ | NMT | Nettoyez le filtre en papier. ✓ | Google | Nettoyez le filtre à papier. ✗ |

**Common idioms**

Is the English idiomatic expression correctly rendered with a suitable French idiomatic expression?

| S15a | Source | Stop **beating around the bush**. | Ref | Cessez de **tourner autour du pot**. | PBMT-1 | Cesser de battre la campagne. ✗ | NMT | Arrêtez de battre autour de la brousse. ✗ | Google | Arrêter de tourner autour du pot. ✓ |

20
S15b Source You are **putting the cart before the horse**.
Ref Vous **mettez la charrue devant les bœufs**.
PBMT-1 Vous pouvez mettre la charrue avant les bœufs. ✓
NMT Vous mettez la charrue avant le cheval. ✗
Google Vous mettez le chariot devant le cheval. ✗

S15c Source His comment proved to be **the straw that broke the camel’s back**.
Ref Son commentaire s’est avéré être **la goutte d’eau qui a fait déborder le vase**.
PBMT-1 Son commentaire s’est révélé être la goutte d’eau qui fait déborder le vase. ✓
NMT Son commentaire s’est avéré être la paille qui a brisé le dos du chameau. ✗
Google Son commentaire s’est avéré être la paille qui a cassé le dos du chameau. ✗

S15d Source His argument really **hit the nail on the head**.
Ref Son argument a vraiment **fait mouche**.
PBMT-1 Son argument a vraiment mis le doigt dessus. ✓
NMT Son argument a vraiment frappé le clou sur la tête. ✗
Google Son argument a vraiment frappé le clou sur la tête. ✓

S15e Source It’s **no use crying over spilt milk**.
Ref **Ce qui est fait est fait**.
PBMT-1 Ce n’est pas de pleurer sur le lait répandu. ✗
NMT Il ne sert à rien de pleurer sur le lait haché. ✗
Google Ce qui est fait est fait. ✓

S15f Source It is **no use crying over spilt milk**.
Ref **Ce qui est fait est fait**.
PBMT-1 Il ne suffit pas de pleurer sur le lait répandu. ✗
NMT Il ne sert à rien de pleurer sur le lait écrémé. ✗
Google Il est inutile de pleurer sur le lait répandu. ✗

### Syntactically flexible idioms

Is the English idiomatic expression correctly rendered with a suitable French idiomatic expression?

S16a Source The cart has been put before the horse.
Ref **La charrue a été mise devant les bœufs**.
PBMT-1 On met la charrue devant le cheval. ✗
NMT Le chariot a été mis avant le cheval. ✗
Google Le chariot a été mis devant le cheval. ✗

S16b Source With this argument, **the nail has been hit on the head**.
Ref Avec cet argument, **la cause est entendue**.
PBMT-1 Avec cette argument, l’ongle a été frappée à la tête. ✗
NMT Avec cet argument, l’ongle a été touché à la tête. ✗
Google Avec cet argument, le clou a été frappé sur la tête. ✗
### Syntactic

#### Yes-no question syntax

| Source | Ref | PBMT-1 | NMT | Google |
|--------|-----|--------|-----|--------|
| S17a   | Have the kids ever watched that movie? | Les enfants ont-ils déjà vu ce film? | Les enfants jamais regardé ce film? | ✓ | Les enfants ont-ils déjà regardé ce film? | ✓ |
| S17b   | Hasn’t your boss denied you a promotion? | Votre patron ne vous a-t-il pas refusé une promotion? | N’a pas nié votre patron vous un promotion? | X | Est-ce que votre patron vous a refusé une promotion? | ✓ | Est-ce que je ne devrais pas assister à cette réunion? | ✓ |
| S17c   | Shouldn’t I attend this meeting? | Ne devrais-je pas assister à cette réunion? | Ne devrais-je pas assister à cette réunion? | X | Mary s’est montrée vraiment heureuse ce soir, n’est-ce pas? | ✓ |

#### Tag questions

| Source | Ref | PBMT-1 | NMT | Google |
|--------|-----|--------|-----|--------|
| S18a   | Mary looked really happy tonight, didn’t she? | Mary avait l’air vraiment heureuse ce soir, n’est-ce pas? | Marie a regardé vraiment heureux de ce soir, n’est-ce pas elle? | X | Mary s’est montrée vraiment heureuse ce soir, ne l’a pas fait? | X | Mary avait l’air vraiment heureuse ce soir, n’est-ce pas? | ✓ |
| S18b   | We should not do that again, should we? | Nous ne devrions pas refaire cela, n’est-ce pas? | Nous ne devrions pas faire qu’une fois encore, faut-il? | X | Nous ne devrions pas le faire encore, si nous? | X | Nous ne devrions pas recommencer, n’est-ce pas? | ✓ |
| S18c   | She was perfect tonight, was she not? | Elle était parfaite ce soir, n’est-ce pas? | Elle était parfait ce soir, elle n’était pas? | X | Elle était parfaite ce soir, n’était-elle pas? | X | Elle était parfaite ce soir, n’est-ce pas? | ✓ |

#### WH-MVT and stranded preps

| Source | Ref | PBMT-1 | NMT | Google |
|--------|-----|--------|-----|--------|
| S19a   | The guy that she is going out with is handsome. | Le type avec qui elle sort est beau. | Le mec qu’elle va sortir avec est beau. | X | Le mec qu’elle sort avec est beau. | X | Le mec avec qui elle sort est beau. | ✓ |
S19b Source Who is she going out with these days?
Ref Avec qui sort-elle ces jours-ci?
PBMT-1 Qu’est-ce qu’elle allait sortir avec ces jours? ✓
NMT À qui s’adresse ces jours-ci? ✗
Google Avec qui sort-elle de nos jours? ✓

S19c Source The girl that he has been talking about is smart.
Ref La fille dont il a parlé est brillante.
PBMT-1 La jeune fille qu’il a parlé est intelligent. ✗
NMT La fille qu’il a parlé est intelligente. ✗
Google La fille dont il a parlé est intelligente. ✓

S19d Source Who was he talking to when you left?
Ref À qui parlait-il au moment où tu es parti?
PBMT-1 Qui est lui parler quand vous avez quitté? ✗
NMT Qui a-t-il parlé à quand vous avez quitté? ✗
Google Avec qui il parlait quand vous êtes parti? ✓

S19e Source The city that he is arriving from is dangerous.
Ref La ville d’où il arrive est dangereuse.
PBMT-1 La ville qu’il est arrivé de est dangereuse. ✗
NMT La ville qu’il est en train d’arriver est dangereuse. ✗
Google La ville d’où il vient est dangereuse. ✓

S19f Source Where is he arriving from?
Ref D’où arrive-t-il?
PBMT-1 Où est-il arrivé? ✗
NMT De quoi s’agit-il? ✗
Google D’où vient-il? ✓

Adverb-triggered inversion

Is the adverb-triggered subject-verb inversion in the English sentence correctly rendered in the French translation?

S20a Source Rarely did the dog run.
Ref Rarement le chien courait-il.
PBMT-1 Rarement le chien courir. ✗
NMT Il est rare que le chien marche. ✗
Google Rarement le chien courir. ✓

S20b Source Never before had she been so unhappy.
Ref Jamais encore n’avait-elle été aussi malheureuse.
PBMT-1 Jamais auparavant, si elle avait été si malheureux. ✗
NMT Jamais auparavant n’avait été si malheureuse. ✗
Google Jamais elle n’avait été aussi malheureuse. ✓
### Middle voice

Is the generic statement made in the English sentence correctly and naturally rendered in the French translation?

| English | French |
|---------|--------|
| S20c Source: Nowhere **were the birds** so colorful. | Ref: Nulle part **les oiseaux n’étaient** si colorés. PBMT-1: Nulle part les oiseaux de façon colorée. NMT: Les oiseaux ne sont pas si colorés. Google: Nulle part les oiseaux étaient si colorés. |

### Fronted “should”

Fronted “should” is interpreted as a conditional subordinator. It is normally translated as “si” with imperfect tense.

| English | French |
|---------|--------|
| S22a Source: Should **Paul** leave, I would be sad. | Ref: Si **Paul** devait s’en aller, je serais triste. PBMT-1: Si le congé de Paul, je serais triste. NMT: Si Paul quitte, je serais triste. Google: Si Paul s’en allait, je serais triste. |
| S22b Source: Should he **become** president, she would be promoted immediately. | Ref: S’il **devait** devenir président, elle recevrait immédiatement une promotion. PBMT-1: S’il devait devenir président, elle serait encouragée immédiatement. NMT: S’il devait devenir président, elle serait immédiatement promue. Google: Devrait-il devenir président, elle serait immédiatement promue. |
| S22c Source: Should he **fall**, he would get up again immediately. | Ref: S’il **venait à tomber**, il se relèverait immédiatement. PBMT-1: S’il devait tomber, il allait se lever immédiatement de nouveau. NMT: S’il tombe, il serait de nouveau immédiatement. Google: S’il tombe, il se lèvera immédiatement. |
### Clitic pronouns

Are the English pronouns correctly rendered in the French translations?

| Source          | Ref                                      | PBMT-1                                      | NMT                                      | Google                                      |
|-----------------|------------------------------------------|---------------------------------------------|------------------------------------------|---------------------------------------------|
| S23a She had a lot of money but he did not have any. | Elle avait beaucoup d’argent mais il n’en avait pas. | Elle avait beaucoup d’argent mais il n’en avait pas. | ✓ Elle avait beaucoup d’argent, mais il n’a pas eu d’argent. | ✓ Elle avait beaucoup d’argent mais il n’en avait pas. |
| S23b He did not talk to them very often. | Il ne leur parlait pas très souvent. | Il n’a pas leur parler très souvent. | ✗ Il ne leur a pas parlé très souvent. | ✗ Il ne leur parlait pas très souvent. |
| S23c The men are watching each other. | Les hommes se surveillent l’un l’autre | Les hommes se regardent les uns les autres. | ✓ Les hommes se regardent les uns les autres. | ✓ Les hommes se regardent. |
| S23d He gave it to the man. | Il le donna à l’homme. | Il a donné à l’homme. | ✗ Il l’a donné à l’homme. | ✓ Il le donna à l’homme. |
| S23e He did not give it to her. | Il ne le lui a pas donné. | Il ne lui donner. | ✗ Il ne l’a pas donné à elle. | ✗ Il ne lui a pas donné. |

### Ordinal placement

Is the relative order of the ordinals and numerals correct in the French translation?

| Source          | Ref                                      | PBMT-1                                      | NMT                                      | Google                                      |
|-----------------|------------------------------------------|---------------------------------------------|------------------------------------------|---------------------------------------------|
| S24a The first four men were exhausted. | Les quatre premiers hommes étaient tous épuisés. | Les quatre premiers hommes étaient épuisés. | ✓ Les quatre premiers hommes ont été épuisés. | ✓ Les quatre premiers hommes étaient épuisés. |
| S24b The last three candidates were eliminated. | Les trois derniers candidats ont été éliminés. | Les trois derniers candidats ont été éliminés. | ✓ Les trois derniers candidats ont été éliminés. | ✓ Les trois derniers candidats ont été éliminés. |
The other two guys left without paying.

Ref: Les deux autres types sont partis sans payer.
PBMT-1: Les deux autres mecs ont laissé sans payer. ✓
NMT: Les deux autres gars à gauche sans payer. ✓
Google: Les deux autres gars sont partis sans payer. ✓

**Inalienable possession**

Is the French translation correct and natural both in: a) its use of a particular determiner on the body part noun; and b) the presence or absence of a reflexive pronoun before the verb?

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**S25a**

Source: He washed his hands.
Ref: Ils s’est lavé les mains.
PBMT-1: Ils se lavait les mains. ✓
NMT: Il a lavé ses mains. ✗
Google: Ils se lava les mains. ✓

**S25b**

Source: I brushed my teeth.
Ref: Je me suis brossé les dents.
PBMT-1: J’ai brossé mes dents. ✗
NMT: J’ai brossé mes dents. ✗
Google: Je me suis brossé les dents. ✓

**S25c**

Source: You brushed your teeth.
Ref: Tu t’es brossé les dents.
PBMT-1: Vous avez brossé vos dents. ✗
NMT: vous avez brossé vos dents. ✗
Google: Tu as brossé les dents. ✗

**S25d**

Source: I raised my hand.
Ref: J’ai levé la main.
PBMT-1: J’ai levé la main. ✓
NMT: J’ai soulevé ma main. ✗
Google: Je levai la main. ✓

**S25e**

Source: He turned his head.
Ref: Il a tourné la tête.
PBMT-1: Il a transformé sa tête. ✗
NMT: Il a tourné sa tête. ✗
Google: Il tourna la tête. ✓

**S25f**

Source: He raised his eyes to heaven.
Ref: Il leva les yeux au ciel.
PBMT-1: Il a évoqué les yeux au ciel. ✓
NMT: Il a levé les yeux sur le ciel. ✓
Google: Il leva les yeux au ciel. ✓
| S26a | Source | The strangers the woman saw were working. | Ref | Les inconnus *que* la femme vit travaillaient. | PBMT-1 | Les étrangers la femme vit travaillaient. ✗ | NMT | Les inconnus de la femme ont travaillé. ✗ | Google | Les étrangers que la femme vit travaillaient. ✓ |
| S26b | Source | The man your sister hates is evil. | Ref | L’homme *que* votre sœur déteste est méchant. | PBMT-1 | L’homme ta soeur hait est le mal. ✗ | NMT | L’homme que ta soeur est le mal est le mal. ✓ | Google | L’homme que votre sœur hait est méchant. ✓ |
| S26c | Source | The girl my friend was talking about is gone. | Ref | La fille *dont* mon ami parlait est partie. | PBMT-1 | La jeune fille mon ami a parlé a disparu. ✗ | NMT | La petite fille de mon ami était révolue. ✗ | Google | La fille dont mon ami parlait est partie. ✓ |