A Proposal for a Coherence Corpus in Machine Translation

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Abstract

Coherence in Machine Translation (MT) has received little attention to date. One of the main issues we face in work in this area is the lack of labelled data. While coherent (human authored) texts are abundant and incoherent texts could be taken from MT output, the latter also contains other errors which are not specifically related to coherence. This makes it difficult to identify and quantify issues of coherence in those texts. We introduce an initiative to create a corpus consisting of data artificially manipulated to contain errors of coherence common in MT output. Such a corpus could then be used as a benchmark for coherence models in MT, and potentially as training data for coherence models in supervised settings.

1 Introduction

Discourse information has only recently started to attract attention in MT, particularly in Statistical Machine Translation (SMT), the focus of this paper. Most decoders work on a sentence by sentence basis, isolated from context, due to both modelling and computational complexity. An exception are approaches to multi-pass decoding, such as Docent (Hardmeier et al., 2013a). Our work focuses on an issue which has not yet been much explored in MT, that of coherence.

Coherence is undeniably a cognitive process, and we will limit our remit to the extent that this process is guided by linguistic elements discernible in the discourse. While it does include cohesion, it is wider in terms of describing how a text becomes semantically meaningful overall, and additionally spans the entire document. We are interested in capturing aspects of coherence as defined by Grosz and Sidner (1986), based on the attentional state, intentional structure and linguistic structure of discourse. As a result, we believe that a coherent discourse should have a context and a focus, be characterised by appropriate coherence relations, and structured in a logical manner.

Previous computational models for assessing coherence in a monolingual context have covered entity transitions (Barzilay and Lapata, 2008; Elsner and Charniak, 2011; Burstein et al., 2010; Guinaudeau and Strube, 2013), syntactic patterns (Louis and Nenkova, 2012), discourse relations (Lin et al., 2011), distributed sentence representations (Li and Hovy, 2014) and lexical chains (Somasundaran et al., 2014). For evaluation, these studies in coherence have typically used automatically summarized texts, or texts with sentences artificially shuffled as their ‘incoherent’ data. The latter is an example of artificially created labelled data, distorting the ordered logic of the text and thus affecting some aspects of coherence. However, it is inadequate for our task, as MT preserves the sentence ordering, but suffers from other aspects of incoherence. Moreover, while the MT output can potentially be considered ‘incoherent’, it contains a multitude of problems, which are not all due to lack of coherence.

For the evaluation of coherence models in the MT context, as well as for supervised learning of coherence models it is necessary to have data annotated with issues of incoherence. In particular, we are interested in coherence issues which are deemed to occur specifically in MT output. The purpose of this initiative is to ensure that we can assess coherence models by isolating other issues that are not related to coherence.

In the remainder of this paper, we start by presenting previous work (Section 2). We then describe how problems related to lack of coherence are manifested in MT output (Section 3). In Section 4 we detail how we plan to manipulate the data in systematic ways to create a corpus of artificially generated incoherent data.
2 Existing work

There has been previous work in the area of lexical cohesion in MT (Wong and Kit, 2012; Xiong et al., 2013a; Xiong et al., 2013b; Tiedemann, 2010; Hardmeier, 2012; Carpuat and Simard, 2012). Lexical cohesion is part of coherence, as it looks at the linguistic elements which hold a text together. However, there has been very little work in the wider area of coherence as a whole.

Besides lexical cohesion, another discourse related phenomenon that has been addressed in MT is reference resolution. As detailed in greater depth by Hardmeier (2012), the results for earlier attempts to address this issue were not very successful (Hardmeier and Federico, 2010; Le Nagard and Koehn, 2010). More recent work includes that of Guillou (2012), which highlights the differences of coreference depending on the language pair. Since then Hardmeier et al. (2013b) have used a new approach for anaphora resolution via neural networks which achieves comparable results to a standard anaphora resolutions system, but without annotated data. Recently work has begun on negation in MT, particularly by Wetzel and Bond (2012; Fancellu and Webber (2014). There is also work focusing on evaluation against reference translations (Guzmán et al., 2014) based on the comparison between discourse trees in MT versus reference. This information was found to improve evaluation of MT output.

Drawing from research on topic modelling (Eidelman et al., 2012), where lexical probabilities conditioned on topics are computed, Xiong and Zhang (2013) attempt to improve coherence based on topic information. They determine the topic of the source sentence and project it onto the target as a feature to ensure the decoder selects the appropriate words. They observed slight improvements in terms of general standard metrics, indicating perhaps that these metrics fail to account for discourse improvements.

As far as we are aware, no attempts have been made to create a corpus exhibiting incoherence, other than by shuffling ordered sentences. There has been work in other areas to introduce errors in correct texts. For example, Felice and Yuan (2014) and Brockett et al. (2006) inject grammatical errors common to non-native speakers of English in good quality texts. Felice and Yuan (2014) use existing corrected corpora to derive the error distribution, while Brockett et al. (2006) adopt a deterministic approach based on hand-crafted rules. Logacheva and Specia (2015) inject various types of errors to generate negative data for quality estimation purposes, but these are at the word level, and the process was guided by post-editing data. They derived an error distribution of MT output by inspecting post editing data. We do not have a similar way of inducing a distribution of errors for coherence. A large amount of post editings of entire documents would be needed, and it still be difficult to isolate which of the edits relate to coherence errors.

3 Issues of incoherence in MT systems

Current MT approaches suffer from a lack of linguistic information at various stages (modelling, decoding, pruning) causing the lack of coherence in the output. Below we describe a number of issues that are generally viewed as coherence issues which MT approaches deal poorly with and which have also been the subject of previous work. The examples given have been identified in error analysis done by ourselves in either of the following corpora:

- the newstest data (source and output) from the WMT corpus,\(^1\) focusing on French and German source, and English as output.
- the LIG corpus (Potet et al., 2012) of French-English translations: 361 parallel documents comprising source, reference translation, machine translated output and post-edited output, drawn from various WMT editions.

The following are issues of incoherence which have been identified by ourselves (below) and others (Section 2) as particularly common in MT systems.

Lexical cohesion MT has been shown to be consistent in its use of terminology (Carpuat and Simard, 2012), which can be an advantage for narrow texts domains with significant training data. However, MT systems may output direct translations of source text items that may be inappropriate in the target context. Moreover, while a specific target text word may correctly translate a source text word in one context, it may require a totally different word in another context. In our data ‘boucher’ occur

\(^1\)http://www.statmt.org/wmt13/
more often as a French noun, corresponding to ‘butcher’. This increases the probability of the translation equivalence ‘butcher’, yet in the translated text it is used as a noun indicating to ‘block’ (for example, ‘road block’).

src: ‘Cette année, c’était au tour de l’Afrique de nommer le président et elle a nommé la Libye.’

mt: ‘This year, it was at the tour of Africa to appoint the president and has appointed Libya.’

ref: ‘This year it was Africa’s turn to nominate the chairman, and they nominated Libya.’

Here the wrong meaning of tour was used, and renders the sentence incoherent. As Wong and Kit (2012) note, the lexical cohesion devices have to not only be recognised, but used appropriately. And this may differ from the source text to the target text.

Referencing Anaphora resolution is a very challenging issue in current MT approaches (Michal, 2011; Le Nagard and Koehn, 2010; Hardmeier and Federico, 2010; Hardmeier et al., 2013b; Guillou, 2012). This is again due to the fact that intersentential references are lost in most decoders as they translate one sentence at a time. Reference resolution is affected in several ways. The context of the preceding sentences is absent, meaning that the reference is undetermined. Even once it is correctly resolved (by additional pre-training or a second-pass), reference resolution is directly impacted by linguistic differences, for example, the target language may have multiple genders for nouns while the source only has one. The result is that references can be missing or wrong.

src: ‘L’extrême droite européenne est caractérisée par son racisme...’

mt: ‘The extreme right is characterised by his racism...’

ref: ‘A common feature of Europe’s extreme right is its racism...’ (Potet et al., 2012).

Here the pronoun ‘son’, referring to the racism of the extreme right, is wrongly rendered as ‘his’.

Discourse connectives Discourse connectives are vital for the correct understanding of discourse. Yet in MT systems these can be incorrect or missing (Meyer and Poláková, 2013; Meyer and Popescu-Belis, 2012; Meyer et al., 2011; Steele, 2015). In particular, where discourse connectives are ambiguous, e.g. those which can be temporal or causal in nature, the MT system may choose the wrong connective translation, which distorts the meaning of the text. It is also possible that the discourse connective is implicit in the source, and thus need to be inferred. While a human translator can detect this, an MT system cannot.

src: ‘Die Rechtsanwälte der Republikaner haben in 10 Jahren in den USA übrigen nur 300 Falle von Wahlbetrug verzeichnet.’

mt: ‘The Republican lawyers have listed over 10 years in the United States, only 300 cases of electoral fraud.’

ref: Indeed, Republican lawyers identified only 300 cases of electoral fraud in the United States in a decade.

The discourse marker is missing altogether in the MT output above (in addition to the ordering error). While small, cue words guide the reader and help create the logic in the text. Here the discourse marker was for emphasis, illustrating the writer’s claim.

Syntax structure Different languages have different syntactic structures. In MT system the syntax of the target language may get distorted, often too close to the syntax of the source language, leading to an incoherent sentence formation.

src: ‘Ce ne sera pas le cas, comme le démontre clairement l’histoire raciale de l’Amérique.’

mt: ‘This is not the case, as clearly demonstrates the history of race in America.’

ref: It will not, as America’s racial history clearly shows. (Potet et al., 2012)

Here the natural logic of the sentence is distorted, with the subject coming after the verb, directly affecting the coherence.

Clauses ordering Particularly in hierarchical or tree-based MT systems, the order of clauses within sentences may have become reversed, or may be unnatural for the target language.

src: ‘Das Opfer war später an den Folgen der schweren Verletzungen gestorben.’

mt: ‘The victim was later at the consequences of the serious injuries died.’

ref: ‘The victim later died as a result of the serious injuries.’ (Bojar et al., 2014).

This can affect the understanding of the sentence, the overall logic of it in the context of the surrounding sentences, or simply require a reread which itself is indicative of impaired coherence.
Already in 1925 a railway trolley was built in Poland, for which a rocket was planned. The author of the design and the details of the project remained unfortunately unknown.

In 1925, Poland had already built a handcar which was supposed to be fitted with a rocket engine. Unfortunately, both the project’s designer, and the project’s details, are unknown. (Bojar et al., 2013)

The reference translation has a clausal pattern which is more cohesive to the English reader.

Negation MT systems often miss the focus of the negation. This results in incorrectly transferred negations that affect coherence (Wetzel and Bond, 2012; Fancellu and Webber, 2014). The negation is distorted, influenced by the structure of the source text.

In this case the negation is distorted, influenced by the structure of the source text.

Error distribution

While ideally we would establish the distribution of errors from their occurrences in MT output, determining an appropriate error distribution based on observations is very problematic. The distributions would be specific to given language pairs and MT systems. More important, detecting coherence automatically to count errors is difficult: if we could do that, than we would be able to directly solve the problem we are attempting to, i.e. measure coherence. This is exactly why we need this corpus. Additionally, manual inspection and annotation for coherence is very hard to formalise as a task, time consuming and costly. Therefore, the distribution of errors in our corpus will be based on linguistic insights, and on findings from previous work, where available. Where this is not the case, for instance for distorting discourse patterns, versions of the corpus with different proportions of errors will be created. We will inject errors systematically and incrementally to vary the degree and location of the errors.

The errors will be introduced systematically via pattern-matching, and as highlighted by Brockett et al. (2006), may not be distributed in a natural way.

Error Injection

We will inject errors of the types below via the four basic edit operations, as appropriate for each type of error: replace, delete, add, shift.
Sentence level discourse structure  We will inject errors related to discourse elements, in terms of cue words, and their organisation. A comparison of the discourse connectives in the MT and the Human Translation (HT) will be established, and where these differ, a syntactic check is made automatically (Pitler and Nenkova, ) to establish if the connective is a synonym or incorrect. We can also refer to the discourse connectives in the original source text, and automatically check, for example, if the correct sense of the connective has been transferred. These can be identified from a list compiled from appropriate resources (e.g. DiMLex for German, LexConn for French)(Stede and Umbach, 1998; Roze and Danlos, 2012) and a list of problematic ones derived e.g. from work by (Meyer and Popescu-Belis, 2012; Meyer and Poláková, 2013) for French.

We can parse the discourse tree structure and extract grammatical information using the Stanford parser\(^2\) and POS tagger\(^3\), before distorting the parse tree by swapping nodes at the relevant level.

Lexical cohesion  We propose replacing entities with alternatives (which will directly affect lexical coherence), using phrase tables from an MT system to generate likely entity variations. This has to be tailored to ensure that the result reflects realistic error levels, so need to verify correct parameter to gauge the amount of substitutions. We can also investigate pre-trained word embeddings, such as word2vec representations (Mikolov et al., 2013), and using word intrusion detection (Chang et al., 2009).

Clausal patterns  Coherent syntax patterns can be derived from coherent text, for example using patterns established in (Louis and Nenkova, 2012). We can determine the clausal patterns from training data, establishing frequent patterns which are indicative of specific coherence relations. Then the order of sibling nodes in the syntax tree can be modified (e.g. reversed) at the appropriate level in order to alter the order of clauses. The exact level of the distortion will be determined according to pre-defined criteria – e.g. every 8th clause, to depth 5 in the parse tree or, where possible, derived from the MT output.

5 Conclusion

We have introduced our initiative for artificially generating a corpus with coherence errors from well-formed data that specifically simulate coherence issues in MT.

Other possible direction could be to use an n-best list, taking sentences from different positions in that list for each source sentence to form a possibly incoherent document. Similarly, we could extract sentences from multiple MT systems for the same text, alternating their origin and concatenating to form one single document. In both cases, a difficulty that remains is that of isolating coherence issues from other errors and from stylistic issues, as well as quantifying the degree of incoherence in the generated texts.

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