

Evaluation of Abstractive Summarisation Models with Machine Translation in Deliberative Processes

Anonymous EMNLP submission

Abstract

In this project, we conduct an extensive evaluation of a wide range of abstractive summarisation models in combination with an off-the-shelf machine translation model. The evaluation includes different model architectures and is performed in a deliberation dataset. Unlike commonly studied datasets, such as news articles, the dataset evaluated here presents the difficulty of combining multiple narratives in a single text, mostly of poor grammatical quality. We obtain promising results regarding the fluency, consistency, and relevance of the summaries produced by using a system that is easy to implement for production purposes.

1 Introduction

The processes of deliberation and collective intelligence production have evolved radically thanks to the possibility of carrying them out digitally. However, this often results in large amounts of generated content in the deliberations, causing information overload that prevents their potential from being fully realised (Arana-Catania et al., 2021; Davies and Procter, 2020). To address this, we evaluate the potential value of abstractive summarisation models when combined together with a machine translation system in synthesising and filtering information collected through such processes. Whereas the current technology of language models is mostly limited to a few languages, preventing the majority of the population from using them, our approach can be deployed for many languages just changing the translation model without the need to generate new, ad-hoc corpora for the task or costly retraining for each language. The current evaluation is done in a Spanish deliberation dataset.

We have carried out an evaluation with 6 abstractive summarisation models: BART (Lewis et al., 2019), T5 (Raffel et al., 2019), BERT (PreSumm – BertSumExtAbs: Liu and Lapata, 2019), PG (Pointer-Generator with Coverage Penalty) (See

et al., 2017), CopyTransformer (Gehrmann et al., 2018), and FastAbsRL (Chen and Bansal, 2018). Those models are applied in combination with the machine translation system MarianMT (Junczys-Dowmunt et al., 2018) using the Opus-MT models (Tiedemann and Thottingal, 2020). We have evaluated the quality of the summaries for each model and their comparison.

Early research on the problem of text summarisation in low resourced languages (although not focused on deliberation) (Orăsan and Chiorean, 2008) demonstrated the limitation of machine translation systems at the time. Recently, Ouyang et al. (2019) revisited the problem of low quality translations in low resourced languages and successfully demonstrated the possibility of using abstractive summarisation by retraining their model on corpora that have gone through the same machine translation process. In this study, we complete the cycle, translating from the original language to English, summarising, and translating back to the original language, thus avoiding the retraining.

Using other approaches, Yao et al. (2015) conducted a study of English-to-Chinese summarisation in which they combined an extractive approach with a process of sentence compression that effectively abstracts the results. Duan et al. (2019), following on from the work of Shen et al. (2018), exploited the capability of a resource-rich language summariser in a teacher-student framework that connects it to the target language summariser.

2 Dataset

The evaluation has been carried out with a dataset of deliberative processes in Spanish, translated into English to carry out the summarisation and the generated summaries have been translated back into Spanish for their evaluation. Thus, the evaluators have evaluated Spanish summaries of Spanish texts, without knowing the intermediate English versions.

The dataset is available in the Madrid City Coun-

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081 cil ‘Datos Abiertos’ repository¹, called ‘Comen- 127
 082 tarios’. It contains public deliberations in relation 128
 083 to citizen proposals made in the participation plat- 129
 084 form of the city council. The dataset has been se- 130
 085 lected due to the great success of the participation 131
 086 platform, which has led to 26,400 proposals and 132
 087 125,135 comments being submitted. This is one 133
 088 of the most successful cases of digital participation 134
 089 in the world and is therefore a perfect case study 135
 090 for evaluating the information overload problem in 136
 091 deliberation (Arana-Catania et al., 2021). 137

092 Each of the citizen proposals presents a debate 138
 093 space where the public comments can be found. 40 139
 094 debates were selected covering the different deliber- 140
 095 ation scenarios of the dataset. These represent 141
 096 three main cases: 20 debates with ($n = 10$) com- 142
 097 ments, representing the most common situation 143
 098 of debates with few comments; 15 debates with 144
 099 ($20 \leq n \leq 30$) comments, for the medium case; 145
 100 and 5 debates with ($60 \leq n \leq 70$) comments, for 146
 101 the case with a large number of comments. 147

102 The debates in each category were also selected 148
 103 to cover the different comment scenarios, from 149
 104 very short to very lengthy comments. In the first 150
 105 case from 1,000 to 5,000 total characters; in the 151
 106 medium case from 3,000 to 13,000; and in the 152
 107 large case from 10,000 to 18,000 characters. The 153
 108 text to summarise for each debate was created con- 154
 109 catenating its comments in a single document. 155

110 By using debates from all scenarios regarding 156
 111 number of comments and comments length we en- 157
 112 sure that the selection is not biased to a specific 158
 113 case of deliberation that could skew our results. 159

114 Examples of the debates can be found in the 160
 115 Appendix, where it can be seen the combination of 161
 116 multiple narratives through the different comments 162
 117 and the poor grammatical quality of the texts. 163

118 3 Abstractive Summarisation 164 119 Methodology 165

120 Different models have been selected, covering 166
 121 some of the best available summarisers, but also 167
 122 exploring different model architectures:

- 123 • BART (Lewis et al., 2019)². This combines a 168
 124 bidirectional transformer as an encoder, simi- 169
 125 lar to the following T5 and BERT cases, with 170
 126 a left-to-right autoregressive decoder similar 171

¹<https://datos.madrid.es>

²Implementation by HuggingFace <https://github.com/huggingface/transformers>

as GPT (Radford et al., 2018). The ‘large-cnn’ 127
 pre-trained model has been used here. 128

- T5 (Raffel et al., 2019)². This uses an encoder- 129
 decoder transformer architecture, trained in 130
 the Colossal Clean Crawled Corpus. The 131
 ‘small’ pre-trained model has been used. 132
- BERT (PreSumm – BertSumExtAbs: Liu and 133
 Lapata, 2019)³. This uses BERT (Devlin 134
 et al., 2018) as the encoder and a randomly ini- 135
 tialized transformer as a decoder, fine-tuning 136
 first the encoder as an extractive summariser 137
 and then as an abstractive one. The Bert- 138
 SumExtAbs pre-trained model has been used. 139
- PG (Pointer-Generator with Coverage 140
 Penalty) (See et al., 2017)⁴. This uses a 141
 1-layer bidirectional LSTM encoder and a 142
 1-layer unidirectional LSTM decoder with 143
 attention, with the possibility of switching 144
 between copying words or generating them 145
 (Pointer-Generator) and including a coverage 146
 mechanism adding up attention distributions 147
 of previous steps to minimise repetitions. 148
- CopyTransformer (Gehrmann et al., 2018)⁵. 149
 This uses the transformer architecture, but one 150
 attention head defines the copy distribution. 151
- FastAbsRL (Chen and Bansal, 2018)⁶. An ex- 152
 tractor agent is used to select sentences (using 153
 LSTM layers to represent and copy sentences) 154
 and an abstractor network is used to compress 155
 and paraphrase the selected sentences. Both 156
 are trained separately and then the full model 157
 is trained with reinforcement learning by us- 158
 ing A2C (Mnih et al., 2016). 159

The Rouge scores of these models (Lin, 2004) 160
 reported by the authors are shown in Table 1. 161

In an initial exploration, additional models were 162
 evaluated: Adversarial Reinforce GAN (Wang 163
 and Lee, 2018), using Generative Adversarial Net- 164
 works; Contextual Matching (Zhou and Rush, 165
 2019), using ELMo (Peters et al., 2018) in combi- 166
 nation with a domain fluency model using LSTM 167

³Implementation by the authors <https://github.com/nlpyang/PreSumm>

⁴Implementation by OpenNMT <https://opennmt.net/OpenNMT-py/Summarization.html>

⁵OpenNMT implementation thanks to <https://github.com/sebastianGehrmann/bottom-up-summary>

⁶Implementation by the authors https://github.com/ChenRocks/fast_abs_rl

Model	R1	R2	RL
BART - large-cnn	44.16	21.28	40.90
T5 - small	41.12	19.56	38.35
BERT - BertSumExtAbs	42.13	19.60	39.18
PG - OpenNMT - BRNN	39.12	17.35	36.12
CopyT - OpenNMT	39.25	17.54	36.45
FastAbsRL	40.88	17.80	38.54

Table 1: Rouge scores reported on the CNN/DailyMail dataset (Hermann et al., 2015).

layers; PoDA (Wang et al., 2019), using a transformer encoder-decoder structure combined with a pointer-generator attention layer, and training it as a denoising autoencoder; and GenParse (Song et al., 2018), combining sequential word generation with tree-based parsing. However, after an initial qualitative evaluation, we found that none of these models produced sufficiently competitive results in comparison with the selected models. We should note that several of these models work at the sentence level, which may impact their relevance in our deliberative case, where the paragraphs are composed of multiple authors comments.

The machine translation system used was MarianMT (Junczys-Dowmunt et al., 2018) using its HuggingFace implementation, with Opus-MT models⁷ developed by the Helsinki-NLP group.

Machine translation was applied to the original text of the deliberations before applying the summarisers, and a second time to the summary generated to convert back to the original language (see Appendix). Thus, even when the summarisation models are trained with English datasets, the full system can be used in deliberations of any language supported by the machine translation system. The Opus-MT models used in this work count currently with pre-trained models for 1738 language pairs. It is left for future work to evaluate the effect of the translation model, and to apply it to other languages to determine the quality obtained in other cases. The models used here show a good performance (see BLEU scores in OpusMTen; OpusMTes) for the used languages.

4 Evaluation Design

We developed a protocol for the human evaluation of the summaries generated by the different models, following designs of previous studies (Amplayo and Lapata, 2020; Liu and Lapata, 2019; Narayan et al., 2018; Paulus et al., 2017; Yoon et al., 2020;

⁷<https://github.com/Helsinki-NLP/Opus-MT>

Song et al., 2018). First, the different models were compared regarding their relative overall quality using the Best-Worst scaling (Louveire et al., 2015), shown to be more accurate than a generic individual scoring model, and simultaneously reducing the number of assessments required (Kiritchenko and Mohammad, 2017).

For each debate, 6 different summaries were generated, one for each of the models to be evaluated. These summaries were organised in 9 tuples of 4 elements each, where each summary appeared in 6 of the tuples in random order and without the possibility of the evaluator of identifying which model was used in each case. In total, considering all the debates, 360 tuples were produced. Each of these tuples was evaluated by 5 independent evaluators (native Spanish speakers with a minimum education level of a Bachelor’s degree), producing a total of 1,800 evaluations. The score for each summary consisted of the percentage of times it was evaluated as Best, minus the percentage of times it was evaluated as Worst.

In addition, a second evaluation was carried out for two summaries in each debate. The models were selected randomly in each case while ensuring that each model had the same number of evaluations. In this case we were interested in whether the models produce results of sufficient quality to be useful to the participants in the debate. Thus, we have not used a relative score but an absolute score, asking the evaluators to rate the following aspects (the definitions below were shared with the evaluators) on a Likert scale from 1 (Strongly disagree) to 4 (Strongly agree):

- Informativeness/Relevance. The summary contains the most relevant ideas and positions of the debate.
- Fluency/Readability/Grammaticality. The summary sentences are grammatically correct, easy to read and understand (considering as a baseline the fluency of the original debate).
- Consistency/Faithfulness. The ideas or facts contained in the summary appear in the original debate.
- Creativity. The summary has been written with its own words and sentences (instead of copying sentences directly from the debate).

Model	comp	σ	comp _[0,100]	$\sigma_{[0,100]}$
BART	33.08	11	66.54	5
BERT	23.33	10	61.67	5
PG	6.25	13	53.13	6
T5	-16.08	14	41.96	7
CopyT	-16.42	5	41.79	2
FastAbsRL	-30.17	10	34.92	5

Table 2: Comparison scores using the Best-Worst scaling (and thus in the range $[-100, 100]$) with its standard deviation, and normalised to the $[0, 100]$ range.

Model	Informative	σ	Fluent	σ
BART	2.58	0.8	2.85	0.8
BERT	2.53	0.8	2.65	0.9
PG	2.33	0.7	2.28	0.8
T5	2.50	0.8	2.30	0.8
CopyT	2.14	0.6	2.02	0.8
FastAbsRL	2.02	0.7	1.73	0.6
	Consistent	σ	Creative	σ
BART	2.88	0.8	2.08	0.7
BERT	2.72	0.9	1.98	0.6
PG	2.67	0.8	2.02	0.6
T5	2.63	0.9	1.97	0.6
CopyT	2.46	0.9	1.81	0.6
FastAbsRL	2.13	0.7	1.82	0.7

Table 3: Rating and standard deviation for each model in a scale from 1 (Strongly disagree) to 4 (Strongly agree).

5 Evaluation Results

The results obtained for the overall comparison between models are shown in Table 2, which reports the average scores of all the evaluators.

Paired Student’s t -tests were performed between all pairs of models to confirm that the difference was statistically significant. This is not the case for the BERT and BART models ($p = 0.09$), showing very close results. There is also a clear overlap between T5 and CopyTransformer. All the other combination pairs are found within a difference statistically significant ($p < 0.05$).

These results are in line with the previous evaluation results on English datasets that BART and BERT are the top two summarisers (Lewis et al., 2019; Liu and Lapata, 2019). However, in the present evaluation a state-of-the-art model (T5) falls below a much older model (PG).

The results for the evaluation of the qualitative aspects of each summariser are shown in Table 3. It is important to note that in this case the standard deviation is larger compared to the first case, which is due to the smaller number of evaluations, and thus the following comments should be understood considering their statistical significance.

In this individual evaluation of each model, it can be seen again how BART obtains the best ratings in all four categories evaluated. BERT is the second best for the categories of ‘Informativeness’, ‘Fluency’ and ‘Consistency’, while PG jumps to the second position for ‘Creativity’. T5 is in the third position for the categories ‘Informativeness’ and ‘Fluency’ and PG is the third best for ‘Consistency’.

This confirms the best results of BART and BERT, and a close result for T5 for generating informative summaries, but a poorer result for fluency. This may be the reason why the T5 model performed worse in the general overall comparison.

BART and BERT perform well in terms of ‘consistency’, with scores close to 3. They perform a bit worse for ‘fluency’ and ‘informativeness’, around the middle of the possible rating 2.5. Regarding ‘creativity’, the models have a poor performance, with a score of around 2, meaning that they tend to copy instead of paraphrase.

6 Conclusions

In this study we have evaluated the application of state-of-the-art abstractive summarisation models to deliberative processes in Spanish using an off-the-shelf machine translation model. Although we focused on a Spanish evaluation, our proposed pipeline can be easily deployed without additional complication to multiple other languages, offering an important value for production applications (especially cases dealing with wide ranges of languages) rarely present in other approaches. However, the evaluation of the quality for other languages is left for future work. We have done a comparative evaluation of the overall quality of the models, and an evaluation of each model with respect to different qualitative aspects: *informativeness*, *fluency*, *consistency*, and *creativity*.

As a general conclusion, from the models evaluated BART and BERT have the best results, and satisfactory results are obtained in the proposed pipeline for the summaries quality. With regard to the most important aspects, the models show a good result in the categories of *fluency* and *consistency*, and an average result regarding the *informativeness*. These results are especially promising considering the complexity and low grammatical fluency and consistency involved in deliberation. BART and BERT are the only models that score over the middle score in the three categories, and thus from our point of view are satisfactory enough to be used.

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A Appendix

We present below an example of a debate used in the evaluation in Spanish and its machine translation to English. Following them we present the summaries generated using T5, FastAbsRL, BART, and BERT. Finally, we include the translations of these summaries.

The texts are presented in the same order used in the project. We start with a debate in Spanish, which is translated into English. This translated debate is summarised, and finally the summary is translated back into Spanish. The evaluators analysed only the original debate in Spanish and the final summaries in Spanish.

A.1 Original Spanish debate

- además proponemos tranvía.
- el casco no es obligatorio para mayores de 15 años mientras circulan en ciudad. lo dice la dgt.por lo demás, te doy la razón. deben cumplir la normativa de circulación. pero, eh!... los conductores de coches y motos también. hay demasiados que no respetan a los ciclistas... ¿sabias que en ciudad, un ciclista debe ocupar 1 carril de circulación... y no ir por el borde?.
- se deberían sancionar las bicis que van por las aceras o fuera de los carriles bicis.
- si las bicis van por las aceras es porque es muy peligroso ir por los carriles de los coches aunque estén marcados. no existe concienciación todavía por parte de los usuarios conductores. por otro lado, el hecho en sí de ir por la acera no es peligroso, siempre que se vaya "a paso de peatón". lo que no se puede es ir rápido.para mí el verdadero peligro es en las horas nocturnas, en que muchos ciclistas van sin luz alguna y no se ven hasta que estás prácticamente encima de ellos... eso en amsterdam está rigurosamente prohibido y se multa. aquí he visto a la policía municipal pasar de todo al verlos....
- obviamente quien dice eso no ha cogido una bici en su vida, el casco en bici no salva vidas, es un hecho, salva vidas el conductor respetuoso.
- nunca,pero nunca jamás he visto parar un ciclista en un semáforo rojo,o se suben a la acera

para cruzar sorteando a los peatones o directamente se lo saltan, en un paso de peatones menos se paran.¿qué pasa, que las norma no son para todos por igual? si un coche se salta un semáforo, la multa es bestial! un poco más de respeto, sobre todo cuando circulan por la acera a la velocidad que les da la gana, con el peligro que conlleva. se creen que todo vale y la calle es suya.

- se puede circular por la calzada, aunque haya carril bici vecin@.
- no me lo creo....nunda digas nunca!.
- ¿no cree que está generalizando demasiado? no todos van con auriculares, no todos se saltan los semáforos, y los coches se tienen que acostumbrar a la presencia de las bicis....es un medio de transporte más, y se merece respeto.
- la obligación del casco desincentiva el uso de la bicicleta, que en el caso de Madrid está mejorando la movilidad sin aumentar la contaminación

A.2 Machine translated debate

- and we're proposing a tram.
- the helmet is not mandatory for more than 15 years as they travel in the city. says dgt. otherwise, I give you the reason. they must comply with the traffic regulations. but, uh!... the drivers of cars and motorcycles also. there are too many that do not respect cyclists... did you know that in the town, a cyclist must occupy 1 lane of traffic... and not go by the edge?.
- bikes that go along the sidewalks or off the bike lanes should be sanctioned.
- if the bikes go through the sidewalks it is because it is very dangerous to go down the lanes of the cars even if they are marked. there is no awareness yet on the part of the users drivers. On the other hand, the fact itself of going down the sidewalk is not dangerous, as long as it goes "by foot". What you can not do is go fast. For me the real danger is in the night hours, in which many cyclists go without any light and you don't see until you are practically above them... that in Amsterdam is rigorously forbidden and is fined. here I have seen

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560	the municipal police pass everything when		
561	you see them....		
562	• obviously whoever says that hasn't taken a		
563	bike in his life, the bike helmet doesn't save		
564	lives, it's a fact, it saves lives the respectful		
565	driver.		
566	• never, but I've never seen a cyclist stop at a		
567	red light, or get on the sidewalk to cross by		
568	shooting pedestrians or directly jump him, at		
569	a pace of pedestrians less stop. What happens,		
570	that the rules are not for everyone alike? if		
571	a car jumps a light, the ticket is best! a little		
572	more respect, especially when they circulate		
573	along the sidewalk at the speed that gives them		
574	the desire, with the danger that it carries. they		
575	believe that everything is good and the street		
576	is theirs.		
577	• you can drive along the road, even if there is		
578	a nearby bicycle lane.		
579	• I don't believe it... never say it!		
580	• Don't you think it's generalizing too much?		
581	Not everyone goes with headphones, not ev-		
582	eryone jumps the traffic lights, and cars have		
583	to settle for the presence of bikes....it's one		
584	more means of transport, and it deserves re-		
585	spect.		
586	• the obligation of the helmet to discourage the		
587	use of bicycles, which in the case of Tues-		
588	day is improving mobility without increasing		
589	pollution		
590	A.3 Generated summaries		
591	• T5. the rules are not for everyone alike. not		
592	everyone jumps the traffic lights, not every-		
593	one goes with headphones, and not everybody		
594	jumps traffic lights. a little more respect, es-		
595	pecially when they circulate along the street		
596	at the speed that gives them the desire, with		
597	the danger that it carries. I don't believe it...		
598	never say it! Don't you think it's generalizing		
599	too much? Don'		
600	• FastAbsRL. the helmet is not mandatory for		
601	more than 15 years ." the real danger is in		
602	which many cyclists go without any light and		
603	you don't see until you are practically above		
604	them... that in amsterdam is rigorously forbid-		
605	den . otherwise, i give you the reason. . they		
606	must comply with the traffic		
	• BART. Bikes that go along the sidewalks or	607	
	off the bike lanes should be sanctioned. The	608	
	real danger is in the night hours, in which	609	
	many cyclists go without any light. Not ev-	610	
	eryone goes with headphones, not everyone	611	
	jumps the traffic lights, and cars have to settle	612	
	for the presence of bikes. It's one more means	613	
	of transport, and it deserves respect.	614	
	• BERT. the helmet is not mandatory for more	615	
	than 15 years as they travel in the city it is	616	
	because it is very dangerous to go down the	617	
	lanes of the cars even if they are marked there	618	
	is no awareness yet on the part of the users	619	
	drivers drivers	620	
	A.4 Machine translated summaries	621	
	• T5. las reglas no son para todos por igual. no	622	
	todos saltan los semáforos, no todos van con	623	
	auriculares, y no todo el mundo salta semá-	624	
	foros. un poco más de respeto, especialmente	625	
	cuando circulan por la calle a la velocidad que	626	
	les da el deseo, con el peligro que conlleva.	627	
	No lo creo... nunca lo digo! ¿No crees que	628	
	está generalizando demasiado?	629	
	• FastAbsRL. el casco no es obligatorio du-	630	
	rante más de 15 años. " el verdadero peligro	631	
	es en el que muchos ciclistas van sin ninguna	632	
	luz y no se ve hasta que usted está práctica-	633	
	mente por encima de ellos... que en amster-	634	
	dam está rigurosamente prohibido. Si no, te	635	
	doy la razón. deben cumplir con el tráfico.	636	
	• BART. Las bicicletas que van por las aceras	637	
	o fuera de los carriles bici deben ser san-	638	
	cionadas. El verdadero peligro es en las horas	639	
	de la noche, en las que muchos ciclistas van	640	
	sin ninguna luz. No todos van con auriculares,	641	
	no todos saltan los semáforos, y los coches	642	
	tienen que conformarse con la presencia de	643	
	bicicletas. Es un medio de transporte más, y	644	
	merece respeto.	645	
	• BERT. el casco no es obligatorio por más	646	
	de 15 años ya que viajan por la ciudad es	647	
	porque es muy peligroso ir por los carriles de	648	
	los coches, incluso si están marcados todavía	649	
	no hay conciencia por parte de los conductores	650	
	de los usuarios	651	