Controlled Neural Sentence-Level Reframing of News Articles

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Abstract

Framing a news article means to portray the reported event from a specific perspective, e.g., from an economic or a health perspective. Reframing means to change this perspective. Depending on the audience or the submessage, reframing can become necessary to achieve the desired effect on the readers. Reframing is related to adapting style and sentiment, which can be tackled with neural text generation techniques. However, it is more challenging since changing a frame requires rewriting entire sentences rather than single phrases. In this paper, we study how to computationally reframe sentences in news articles while maintaining their coherence to the context. We treat reframing as a sentence-level fill-in-the-blank task for which we train neural models on an existing media frame corpus. To guide the training, we propose three strategies: framed-language pretraining, named-entity preservation, and adversarial learning. We evaluate respective models automatically and manually for topic consistency, coherence, and successful reframing. Our results indicate that generating properly-framed text works well but with tradeoffs.

1 Introduction

Framing is a rhetorical means to emphasize a perspective of an issue (de Vreese, 2005; Chong and Druckman, 2007). It is basically driven by argument selection (Aijour et al., 2019) and, hence, it belongs to the inventio canon in particular (Aristotle and Roberts, 2004). The media employ framing to reorient how audiences think (Chong and Druckman, 2007), or to promote a decided interpretation. For example, when talking about a certain law one may emphasize its economic impact or its consequences regarding crime.

Reframing means to change the perspective of an issue. It can be a strategy to communicate with opposing camps of audiences, and, sometimes, just replacing specific terms can be enough to reach a reframing effect. Consider in this regard a reporter who may prefer to use “undocumented worker” instead of “illegal aliens” in left-leaning news (Webson et al., 2020). While still referring to the same people, the former can provoke a discussion of the economic impact of hiring them; the latter may raise issues of crime and possible deportation. Such low-level style reframing has been studied in recent work (Chakrabarty et al., 2021).

Table 1: (a) Sample text from the media frames corpus (Card et al., 2015). The bold sentence is labeled with the economic frame. Having reframed the sentence with the approach of this paper, the text remains largely coherent and topic-consistent while showing the legality frame (b) and crime frame (c), respectively.
Usually, reframing requires rewriting entire sentences rather than single words or phrases. Table 1 illustrates the change of a sentence from the economic frame (a) to the legality frame (b) and the crime frame (c). While the original text emphasizes the cost of immigration reform, the legality-framed text quotes that “It’s time for Congress to take action,” and the crime-framed text includes the notion of “illegal aliens”.

The terms “bill” and “measure” in the respective reframed versions ensure the topical coherence of the texts. Two facts become clear from the example, namely that reframing needs (1) notable rewriting to shift the focus, and (2) overlapped entities to ensure topic consistency.

To work in the real world, a computational reframing model needs to be able to rewrite sentences completely. At the same time, the model has to preserve the context, by maintaining coherence and topic consistency. Towards these goals, we propose to treat reframing as a sentence-level fill-in-the-blank task: Given three consecutive sentences plus a target frame, mask the middle sentence and generate a sentence that connects the preceding and the succeeding sentence in a natural way and that conveys the target frame. This task implies three research questions: (1) How to tackle a sentence-level fill-in-the-blank task in general? (2) How to generate a sentence with a specific frame? (3) How to make the sequence of sentences coherent?

Sentence-level blank filling is a new and unsolved task. We approach this task via controlled text generation, that is, by tweaking input and output of a sequence-to-sequence model where the masked sentence is the target output, and the preceding and the succeeding sentences are the inputs (Section 3). For the second and third research question, we propose three training strategies: (a) framed-language pretraining, to finetune the model on all framed texts in order to learn the framed “language”, (b) named-entity preservation, to support the model in maintaining important entities extracted from the masked sentence, and (c) adversarial learning, to show the model undesired output texts in order to learn to avoid them.

Based on the corpus of Card et al. (2015) with annotated sentence-level frames (Section 4), we empirically evaluate the pros and cons of each strategy and of combinations thereof (Section 5). The results reveal that our approach changes sentences properly from the original to the target frame in most cases (Section 6). Some “reframing directions” remain challenging, such as from crime to economic. We find that obtaining high scores for all assessed dimensions at the same time is hard to achieve; for example, the adversarial learning strategy gives a strong signal towards the target frame at the expense of lower coherence. The implied trade-offs suggest that reframing technology should be configurable when applying it in a real-world scenario to put different stress on each sentence.

The contribution of this paper is threefold: (1) We demonstrate that sentence-level reframing can be tackled as a fill-in-the-blank task. (2) We propose three training strategies for controlled text generation problems such as reframing. (3) We provide empirical insights into unresolved aspects of the computational reframing of news articles.

2 Related Work

Framing in media, particularly in news articles, has been investigated widely in the communication and journalism areas (Entman, 1993; de Vreese, 2005; Chong and Druckman, 2007). It has been defined in different ways, ranging from a narrow view such as “make moral judgments” (Entman, 1993) to a broader one including the “interpretative packages” (Gamson and Modigliani, 1989). The set of frames for a certain topic can be issue-specific or generic. For example, the possible issue-specific frames for the topic of Internet may include online communication and online services, whereas the generic ones include economically optimistic and political criticism (Rössler, 2001). In this paper, we adopt the following narrow definition of frames: “a frame is an emphasis in the salience of different aspects of a topic” (de Vreese, 2005).

In the area of natural language processing, media frame analysis is a relatively new topic. Most existing works adopt the frame definition in social science, where framing refers to a choice of perspective (Hartmann et al., 2019). A more specific definition, which targets the argumentation contexts, defines a frame as a set of arguments that share an aspect (Ajjour et al., 2019). As for frame classification, most of the proposed approaches (Naderi and Hirst, 2017; Hartmann et al., 2019; Khanehzar et al., 2021) employ the media frames corpus (Card et al., 2015), which is built upon the framing scheme of Boydstun et al. (2013). Following these approaches, we utilize the media frames.

Ethical concerns regarding the correctness of reframed texts will be discussed in Section 8.
corpus to build the dataset for our task. The study of media frames is closely related to the analysis of bias and unfairness conveyed by the media (Chen et al., 2020a,b). For example, Chen et al. (2018) observed that the (potentially frame-specific) word choice may directly make a news article appear to have politically left or right bias.

The only existing reframing approach that we are aware of is the one of Chakrabarty et al. (2021). In that work, a new model for reframing is developed by identifying phrases indicative for specific frames, and then replacing phrases that belong to the source frame with some that belong to the target one. As such, most of the content of the reframed text is kept, and only a few words are replaced. In contrast, we deal with reframing at the sentence level, and we do not require parallel training pairs or a dictionary to correlate words and frames.

In principle, reframing can be seen as a style transfer task (Shardlow, 2014; Shen et al., 2017; Chen et al., 2018). Research on text style transfer focus on the areas of sentiment transfer (e.g., replacing ‘gross’ by ‘awesome’) (Shen et al., 2017) and text simplification (e.g., replacing ‘perched’ by ‘sat’) (Shardlow, 2014). We applied recent style transfer models to our task (Mai et al., 2020; Shen et al., 2020), observing that these models perform very poorly (e.g., generating unreadable text).

3 Approach

We now present our approach to sentence-level reframing. We discuss how we tackle the reframing problem as a fill-in-the-blank task, and we propose three training strategies to generate a sentence that is framed as desired and that fits to the surrounding text. Figure 1 illustrates our approach.

3.1 Reframing as a Fill-in-the-Blank Task

As discussed in Section 1, reframing implies two problems: (1) To rewrite entire sentences from a text as much as needed in order to encode a given target frame; and (2) to maintain coherence and topic consistency with respect to the context given in the text. To tackle both problems simultaneously, we propose to treat reframing as a specific type of sentence-level fill-in-the-blank task.

In particular, let a sequence of three contiguous sentences, \(s_1, s_2, s_3\), be given along with a target frame, \(f\). The middle sentence, \(s_2\), is the sentence to be reframed, and the other two sentences define the context taken into account for \(s_2\). The fill-in-blank idea is to mask \(s_2\), such that we have \((s_1, [\text{MASK}], s_3)\). The task, in turn, is to then decode the masked token \([\text{MASK}]\) to \(\hat{s}_{2,f}\), a variation of the sentence \(s_2\) that is reframed to \(f\) and both coherent and topic-consistent to \(s_1\) and \(s_3\).

No proper solution exists for this task yet, and only little prior work has addressed closely related problems (see Section 2). To approach the task, we propose a sequence-to-sequence model \(r(\cdot)\) where the input is the two context sentences, \(s_1, s_3\), and the output to be generated is \(s_2\). In order to consider frame information in rewriting, we train one individual frame-specific model \(r_f(\cdot)\) for each frame \(f\) from a given set of target frames, \(F\), such that

\[
\forall f \in F : r_f(s_1, s_3) \sim \hat{s}_{2,f} \tag{1}
\]

3.2 Training Strategies

To better control the text generated by the model, we further guide the training process, by additionally considering the following three complementary training strategies. All three aim at providing extra information to the reframing model. In Section 5, we experiment with variations of the models to test each strategy and their combinations thoroughly.

Framed-Language Pretraining (\(S_F\)) Due to the complexity of manual annotation, we can expect only a limited number of task instances for each frame \(f \in F\) in practice, so the models may have insufficient knowledge about how to generate framed language. To mitigate this problem, the
first strategy we propose is to **pretrain the reframing model on all available text of any frame** \( f \in F \). After that, this pretrained model will be further fine-tuned using instances from one particular frame.

**Named-Entity Preservation** \( (S_N) \)  Given that a complete sentence is to be generated, a reframing model may mistakenly generate off-topic and incoherent text, if not controlled for. To avoid this, the second strategy is **to encode knowledge about the named entities to be discussed**. In particular, the set of named entities, \( N \), can be extracted from \( s_2 \) and added to the input of the model.\(^2\) Then, the input of the model can be extended to \( s_1 \ [NE] \ N \ [NE] \ s_3 \), where \( [NE] \) and \( /[NE] \) are special tokens to indicate the start and ending of named entities.

**Adversarial Learning** \( (S_A) \)  During training, the instances fed to the default model are all “positive” samples where the output \( s_2 \) comes from the same sentences \( \{s_1, s_2, s_3\} \) the input sentences \( s_1 \) and \( s_3 \) are from. While this helps learning to generate coherent text, it impedes learning reframing. For example, if the goal is to encode the crime frame in \( s_2 \), but \( s_1 \) and \( s_3 \) are from the economic frame, the model is likely to generate economic text, because it learns to reuse frame information encoded in \( s_1 \) and/or \( s_3 \) based on its experience. Inspired by adversarial learning, our third strategy is thus to **add “negative” training instances where the output sentence \( s_2 \) is from the target frame**, but possible incoherent and/or topic inconsistent to the input.

In the given example, \( s_2 \) would be a sentence with the crime frame. In case we combine adversarial learning with named-entity preservation, \( s_2 \) is chosen from all sentences \( s_2 \) in a given training set, such that the named entities of \( s_2 \) and \( s_2 \) are as similar as possible. In case not, we choose a random sentence \( s_2 \) as \( s_2 \). Conceptually, we thereby force the model to discard any possible input frame features. We note that this learning strategy likely harms the coherence and topic consistency of the generated text, as \( s_2 \) will often not fit to \( s_1 \) and \( s_3 \). We can control this effect, though, through a careful use of the strategy, training only a few epochs.

### 4 Dataset

In this section, we describe how we prepare the corpus we use in order to create training and test instances for the sentence-level fill-in-the-blank task.

\(^3\)We use the pretrained model `en_core_web_lg` from spaCy for named entity recognition in our experiments.

### 4.1 The Media Frames Corpus

To analyze media framing across different social issues, Card et al. (2015) built a corpus that comprises 35,701 news articles (published between 1990 and 2012 in 13 news portals) in US, addressing the topics of death penalty, gun control, immigration, same-sex marriage, and tobacco.\(^3\) Each article is annotated at span level for 15 general frames of the *Policy Frames Codebook* (Boydston et al., 2013) in terms of the primary frame, the title’s frame, and the span-level frame. Card et al. (2015) truncated articles to have at most 225 words.

### 4.2 Data Preprocessing

Following several works in frame analysis (Naderi and Hirst, 2017; Hartmann et al., 2019), we focus on the five most frequently labeled frames in the corpus, accounting for about 60% of all labels. Examining these frames, we observed that two of them are hard to distinguish in various cases, namely 6: *Policy prescription and evaluation* and 13: *Political*.\(^4\) Hence, we merge those two, ending up with a set \( F = \{e, l, p, c\} \) of four frames:

- **e. Economic.** Costs, benefits, or other financial implications;
- **l. Legality, constitutionality, and jurisprudence.** Rights, freedoms, and authority of individuals, corporations, and government;
- **p. Policy prescription and evaluation + Political.** Discussion of specific policies aimed at addressing problems, or considerations related to politics and politicians, including lobbying, elections, and attempts to sway voters;
- **c. Crime and punishment.** Effectiveness and implications of laws and their enforcement.

For the sentence-level fill-in-the-blank task, we split the corpus articles into a training, a validation, and a test set. Each of the latter two comprises 3000 pseudo-randomly selected articles, 600 for each of the five given topics. The training set includes the remaining 29,701 articles. For each set, we collected all sentences from the respective articles that are labeled with one of the four considered frames. A sentence is considered to be labeled, if any part of the sentence is labeled. In case a sentence has more than one frame label, the sentence

\(^3\)We use the updated version from the authors’ repository, [https://github.com/dallascard/media_frames_corpus](https://github.com/dallascard/media_frames_corpus). Thus, the data distribution differs from the one of Card et al. (2015).

\(^4\)Naderi and Hirst (2017) reported similar observations.
We rely on transformers (Wolf et al., 2020) as were optimized on the validation set; for the adversarial learning strategy, $S_a$, we trained for three epochs in order not to harm the coherence of the output too much. Since each strategy can be applied independently, we considered eight reframing model variations, ranging from applying no strategy ($S_∅$) to applying all three strategies ($S_{FNA}$).

### Baselines

The variant without any strategy, $S_∅$, can be considered as a baseline. Few other models exist so far that are suitable baselines for tackling the reframing task, but one is GPT-2 (Radford et al., 2019). Specifically, we finetuned GPT-2 on all text available for each frame to have four framed versions of GPT-2. During application, we used $s_1$, the sentence before the target sentence, as the prompt and generated $s_{2,f}$ with the finetuned GPT-2. We also tested framed-language pretraining, $S_F$, with GPT-2. To obtain GPT-2 + $S_F$, we first finetuned GPT-2 on all framed text and then further finetuned it on the text of the respective frame.

#### 5.2 Pilot Study

In our manual evaluation below, we focus on three of the eight variations of our approach, for budget reasons and for keeping the evaluation manageable:

1. **B.Coherence.** The model variation generating the most coherent sentences.
2. **B.Framing.** The model variation generating the most accurately framed sentences.
3. **B.Balance.** The model variation achieving the best balance between coherence and framing.

We ranked the models in a pilot study where we randomly selected 10 instances $⟨s_1, s_2, s_3⟩$ from the test set for each of the four frames in $F$, 40 instances in total. We used the respective variation to reframe all sentences $s_2$ to the economic frame. Then, two authors of this paper were asked to judge each reframed sentence by assigning scores in response to the following questions:

**Q1.** Is the sentence coherent to other sentences? 
{yes (2) \ partially (1) \ no (0)}

**Q2.** Does the sentence cover economic aspects? 
{yes (2) \ partially (1) \ no (0)}

Table 3 shows the averaged scores. The Pearson’s correlation $r$ for the two questions was 0.90 and 0.66 respectively, suggesting that the judges agreed substantially in the rankings. Based on the average scores, we made the following choices:

1. **B.Coherence.** $S_{FN}$ (coherence score 1.35)
2. **B.Framing.** $S_A$ (framing score 0.89)
3. **B.Balance.** $S_{NA}$ (harmonic mean 0.93)

We chose $S_{NA}$ in the latter case, since it showed the maximum harmonic mean of the two scores. In addition, we manually evaluated $S_∅$, the baseline model without any training strategies.

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**Table 2:** The number of fill-in-the-blank instances in the training, validation, and test set for each frame. Note that the four frames are not evenly distributed.

|   | Frame   | Training | Validation | Test  |
|---|---------|----------|------------|-------|
| e | Economic | 6 605    | 883        | 888   |
| l | Legality | 15 313   | 1 568      | 1 656 |
| p | Policy p.a.e. + Political | 20 903  | 2 169      | 2 109 |
| c | Crime    | 10 726   | 1 144      | 1 257 |
|   | All four frames | 53 547  | 5 764      | 5 910 |

The distribution of the framed sentences among the training, validation, and test set for each frame is shown in Table 2. Note that the test set here is the one built for automatic evaluation, and the design of crowd-sourcing task for manual evaluation is discussed in Section 5.3.

### 5 Experiments

This section reports on our experiments with our reframing approach (Section 3) on the data from Section 4. We present the results of the pilot study for the different reframing approaches, the metrics for automatic evaluation, and the design of crowd-sourcing task for manual evaluation.

#### 5.1 Operationalizing Reframing

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Table 3: The pilot study rankings by the two annotators (A1, A2) along with the average of their scores from the eight model variations, resulting from the three training strategies $S_F$, $S_N$, and $S_A$. Three framing variations are ranked second for A2 due to identical average scores. The right-most column shows the harmonic mean of the two average scores of both questions.

| Strategy | Q1 (Coherence) | Q2 (Framing) | Balance |
|----------|----------------|-------------|---------|
|          | A1 | A2 | Avg. | A1 | A2 | Avg. | H. Mean |
| $S_F$   | 4  | 6  | 0.96 | 5  | 7  | 0.49 | 0.65    |
| $S_N$   | 3  | 3  | 1.10 | 4  | 5  | 0.58 | 0.76    |
| $S_A$   | 7  | 7  | 0.50 | 1  | 2  | 0.89 | 0.64    |
| $S_{FN}$| 2  | 1  | 1.35 | 7  | 2  | 0.57 | 0.80    |
| $S_{FA}$| 8  | 8  | 0.16 | 8  | 8  | 0.27 | 0.20    |
| $S_{NA}$| 5  | 4  | 0.99 | 2  | 1  | 0.88 | 0.93    |
| $S_{FNA}$| 6  | 5  | 0.90 | 3  | 2  | 0.70 | 0.79    |

5.3 Evaluation Metrics

To answer the research questions, we considered three dimensions for the different approaches: coherence, correct framing, and topic consistency, both in automatic and in manual evaluation.

**Automatic Evaluation** We used ROUGE scores to approximate the overall quality of the generated texts. As ROUGE requires ground-truth information, we considered only those cases where the target frame matches the frame where the test instance stems from. To quantify the effect of reframing, we compiled a vocabulary for each frame by taking the 100 words with the highest TF-IDF values, where each sentence of a frame was seen as one document. By counting the number of words occurring in the respective vocabulary, we could get a rough idea about the reframing impact.

**Manual Evaluation** For the manual evaluation, we randomly selected 15 instances for each frame from the test set, 60 instances in a total. For each instance, we applied the reframing models along with baselines to reframe it to the four frames in $F$. Among the reframed cases one was of type *intra-frame generation* (i.e., it had the frame from the original sentence); the other cases were of the *inter-frame generation* type. These two types will be discussed separately.

We used Amazon Mechanical Turk to evaluate the selected test set, where each instance was annotated by five workers (for $0.80 per instance). For reliability, we employed only master workers with more than 95% approval rate and more than 10k approved HITs. The percentage of the agreement to the majority is 73% on average in our experiments. The workers were provided three continuous sentences and were asked to judge the middle one (the one generated) by answering six questions:

Q1. Is the sentence coherent to other sentences? {yes (2) | partially (1) | no (0)}

Q2. Does the sentence match the topic in the first and the last sentence? {Same or close related topic (2) | related or no topic (1) | unrelated topic (0)}

Q3. Does the sentence cover economic aspects? {yes (2) | partially (1) | no (0)}

Q4. Does the sentence cover legality-related aspects? {yes (2) | partially (1) | no (0)}

Q5. Does the sentence cover policy-related aspects? {yes (2) | partially (1) | no (0)}

Q6. Does the sentence cover crime-related aspects? {yes (2) | partially (1) | no (0)}

The first two questions asked for coherence and topic consistency, respectively. The latter four assessed the reframing effect. For the computation of the framing scores presented below, only the question asking for the target frame was taken into account. Since a sentence may serve multiple frames, the four framing questions were asked individually. We believe this scoring method is better than only asking whether a text has a desired frame, to avoid making the question suggestive. Along with this questionnaire, the definition of the four frames were provided.

6 Results and Discussion

This section discusses the automatic and manual evaluation results, in order to then analyze how our three training strategies affect generation. Finally, we show some examples from the reframed output and discuss the limitations of our approach.

6.1 Automatic Evaluation

We here use ROUGE to assess the similarity between the generated text and the ground-truth text. As some model variations use named entities extracted from the ground truth, we also consider a ROUGE variation where named-entity matches are ignored in the computation.
Table 4: Rouge-1, Rouge-2, and Rouge-L $F_1$-scores (a) with and (b) without considering named entities of all model variations (based on our strategies $S_F$, $S_N$, and $S_A$) compared to the GPT-2 baselines. Rouge-2 is ignored for (b), since entity removal makes it unreliable. The highest score in each column is marked bold.

Table 4 shows the results. We see that the GPT-2 baselines perform worse than most model variations in all ROUGE scores. Adding the framed-language pretraining strategy ($S_F$) improves GPT-2 to some extent, though. The other two strategies cannot be applied directly to GPT-2. When using either strategy in isolation, only named-entity preservation ($S_N$) improves the ROUGE scores over $S_0$. Even though $S_N$ learns to reuse the named entities from the ground-truth texts, we also see some improvement for ROUGE without named entity overlaps. Using only adversarial learning ($S_A$) decreases the ROUGE scores the most. This matches our expectation that $S_A$ harms coherence.

Among the strategy combinations, $S_{FN}$ has the highest ROUGE score both with and without named entity overlaps. This suggests that $S_F$ and $S_N$ are important to generate texts of good quality. By contrast, $S_A$ tends to decrease the ROUGE scores also here, for example, comparing $S_F$ with $S_{FA}$. Note, however, that ROUGE tells us little about the correct framing.

Framing Word Overlaps Table 5 lists the top-10 words having the highest TF-IDF values for each of the four frame in $F = \{e, l, p, c\}$.

Table 5: The top-10 words having the highest TF-IDF values for each of the four frame in $F = \{e, l, p, c\}$.

Table 6 shows the proportions of framing words used in the test set, before and after reframing. It becomes clear that the variations including adversarial learning ($S_A$) increase the number of framing words the most. GPT-2 models generated even fewer framing words in each frame.

6.2 Manual Evaluation

Intra-Frame Generation We first look at those generated sentences $s_{2,f}$ where the target frame $f$ is the frame used in the ground-truth, $s_2$. Intra-frame generation can be seen as easier for a reframing model, since some frame information may be leaked in the previous or the next sentences.

The left block of Table 7 shows the results. GPT-2 + $S_F$ is worst in almost every case. In terms of keeping the topic consistent, the best approach is $S_0$. For coherence scores, however, $B.Cohesiveness$ ($S_{FN}$) obtains the highest averaged coherence score (1.71), as expected from the pilot study. Similarly, the best one for framing (1.65) is $B.Framing$ ($S_A$). The high consistency between the pilot study judges and the crowdsourcing workers speaks for the reliability of the results. With an average score of 1.64, $B.Cohesiveness$, is, with tiny margin, the best among all approaches in intra-frame generation.

Inter-Frame Generation Inter-frame generation requires an actual reframing. Its results are shown in the right block of Table 7. Similar to intra-frame generation, the most coherent sentences were generated by $B.Cohesiveness$ (1.68), which is also best for topic consistency (1.64) this time, slightly outperforming $S_0$. Overall, the best model in the inter-frame generation is $B.Cohesiveness$ again. $B.Balance$ ($S_{FN}$) is the third-best in coherence and the second-best in framing, but due to its comparably low topic-consistency score (1.56), it is the worst variation on average.

Taken together, the tiny but important difference between the intra- and inter-frame generations lies in the fact that $S_0$ performs better in the intra-frame
While the baselines are useful in easier cases, in frame (Policy)

Table 6: Proportion of word overlaps between the re-

combining it with in terms of ROUGE scores. However, the benefits

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Framed-Language Pretraining (S_F)

Comparing GPT-2 and GPT-2 + S_F in Table 4, we observe that using S_F can slightly improve the text quality in terms of ROUGE scores. However, the benefits of this training strategy are more obvious when combining it with S_N. For example, S_FN has about two percentage ROUGE higher compared to S_F.

Table 7: Manual evaluation: The topic consistency, coherence, framing, and average scores (avg) in intra-

and inter-frame generation for the model variations with highest coherence (S_FN), framing (S_A), and balanced (S_NA) scores in the pilot study, compared to baselines. The best score in each column is marked bold.

Named-Entity Preservation (S_N) To generate a coherent and topic-consistent text, preserving named entities turns out to be very important. In terms of ROUGE, strategy S_N is the most powerful feature. On the other hand, the model achieving the highest topic and coherence score according to the crowdsourcing results in Table 7 (B.Coherence) also uses this strategy, together with S_F.

Adversarial Learning (S_A) In terms of neither automatic nor manual evaluation, applying adversarial learning gives any improvement to the text quality. However, including it can generate better framed text: In both the pilot study and the crowdsourcing study, including adversarial learning resulted in the highest framing scores.

6.4 Examples

Table 9 exemplifies the effect of sentence-level re-framing, showing how the five manually evaluated models reframed a text from the policy to the economic frame. In this particular example, the intuitively little connection between the topic of gay marriage and the frame of economy makes the re-framing task particularly challenging.

As the table shows, only two models successfully managed to change the focus, B.Framing and B.Balance. In particular, the result of the former mentions an opinion of “a spokesman for the tobacco industry”, the latter uses the labor market’s viewpoint. However, the text “It’s a good thing that we’re able to do this” in B.Framing appears to be rather vague and general. Besides, the text is related to economy only because it mentions the tobacco industry. On the other hand, B.Balance integrates gay marriage and economy in a more natural way by using the labor market to connect the two concepts.

| Approach          | Economic | Legality | Policy | Crime |
|-------------------|----------|----------|--------|-------|
| S_0               | 10% (-2) | 12% (-1) | 12% (-1) | 11% (-2) |
| S_F               | 11% (-1) | 13% (+0) | 12% (+0) | 11% (+0) |
| S_N               | 11% (-1) | 13% (+0) | 12% (+0) | 12% (-1) |
| S_A               | 15% (+2) | 20% (+6) | 12% (+0) | 15% (+1) |
| S_FN              | 11% (-1) | 13% (+0) | 12% (+0) | 12% (-1) |
| S_PA              | 17% (+4) | 17% (+3) | 18% (+5) | 13% (+0) |
| S_NA              | 13% (+0) | 18% (+4) | 16% (+3) | 15% (+2) |
| S_FNNA            | 12% (+0) | 19% (+5) | 16% (+3) | 17% (+4) |
| GPT-2             | 8% (-4)  | 10% (-3) | 10% (-2) | 9% (-3)  |
| GPT-2 + S_F       | 9% (-3)  | 10% (-3) | 10% (-2) | 9% (-3)  |

| | Intra-Frame | Inter-Frame |
|-------------------|-------------|-------------|
| | topic coh. fram. avg | topic coh. fram. avg |
| B.Coherence       | 1.63 1.71 1.59 1.64 1.64 1.68 1.60 1.64 |
| B.Framing         | 1.59 1.65 1.65 1.63 1.58 1.61 1.64 1.61 |
| B.Balance         | 1.57 1.61 1.62 1.60 1.56 1.63 1.62 1.60 |
| GPT-2 + S_F       | 1.54 1.61 1.57 1.57 1.55 1.59 1.58 1.57 |
| S_N               | 1.66 1.66 1.61 1.64 1.63 1.66 1.60 1.63 |

Table 9: Examples of sentence-level re-framing in the pilot study. For example, S_FN has about two percentage ROUGE higher compared to S_F.
We are aware of the ethical concerns raised by the problem as a sentence-level fill-in-the-blank task, generating new sentences with target frames while maintaining their coherence and topic consistency with the surrounding context. To tackle the task, we have proposed three training strategies to control the framing and coherence of the generated sentences. Evaluating these strategies automatically and manually, we found that, although it is not possible for any single strategy to fulfill the needs of reframing, combining the strategies leads to a successful reframing of news articles with reasonable coherence and topic consistency.

Even though we are aware of the limitation of our approach, we argue that such a sentence-level reframing is a big step towards full article reframing. In future work, we plan to cover a more fine-grained set of frames, and to consider reframing at the level of paragraphs or entire articles.

8 Ethical Concerns

We are aware of the ethical concerns raised by our approach. Especially, generated sentence parts such as quotes may not be correct factually. Exemplary, we generated the sentence “It’s a good idea,” said Sen. John McCain, D-N.Y., whereas John McCain was neither a Democrat nor a Senator from New York. Also, it is unlikely that John McCain had said that in the given context. In a real-world scenario, users would have to validate the truth of the generated texts, which we cannot expect from them in general. Given that we do not see our model as mature enough for application yet, we leave more elaborated solutions to this problem to future work, but we clearly point out that computationally reframed sentences should be marked as such to people working with respective technology.

Table 8: Manual evaluation: The average coherence and framing scores of reframing from $s_2$ to $s_{2,f}$ for each pair of source fram (rows) and target frame (columns) from $\{e, l, p, c\}$. The highest/lowest score of each dimension is marked bold/italic.

| Coherence of $s_{2,f}$ | Framing of $s_{2,f}$ |
|------------------------|----------------------|
| $s_2$      | $e$      | $l$      | $p$      | $c$      | avg  | $e$      | $l$      | $p$      | $c$      | avg  |
| $c$        | 1.65 – 1.79 | 1.69 1.73 | – 1.65 1.59 | 1.59 1.61 |
| $l$        | 1.71 – 1.63 | 1.67 1.67 | 1.75 – 1.55 | 1.56 1.62 |
| $p$        | 1.67 1.68 | – 1.68 1.68 | 1.63 1.68 | – 1.61 1.64 |
| $c$        | 1.57 1.67 | 1.65 – 1.63 | 1.63 1.53 | 1.48 1.56 – 1.52 |
| avg        | 1.65 1.69 | 1.68 1.68 | 1.64 1.60 | 1.57 1.59 | 1.60 |

Table 9: (a) Sample text from the media frames corpus (Card et al., 2015). The bold sentence is labeled with the policy frame. (b-f) Reframed sentences with the five manual labeled approaches to the economic frame.

| Original text | (b) GPT-2 + $S_F$ (reframed text) | (c) $S_F$ (reframed text) | (d) B.Cohesion (reframed text) | (e) B.Framing (reframed text) | (f) B.Balance (reframed text) |
|---------------|----------------------------------|-------------------------|--------------------------------|-------------------------------|--------------------------------|
| All that was true of interracial marriages shortly after World War II. **Gay marriage is on the same trajectory as interracial marriage.** He says it is so fundamentally different that it will never be legalized. The question is whether gay marriage is on the same trajectory or is so fundamentally different that it will never be legalized. |
| All that was true of interracial marriages shortly after World War II. **Bob Greene: Gay marriage is on the same trajectory as interracial marriage.** He says it is so fundamentally different that it will never be legalized. The question is whether gay marriage is on the same trajectory or is so fundamentally different that it will never be legalized. |
| All that was true of interracial marriages shortly after World War II. **It’s a good thing that we’re able to do this,** said a spokesman for the tobacco industry, who is suing the tobacco companies. The question is whether gay marriage is on the same trajectory or is so fundamentally different that it will never be legalized. |
| All that was true of interracial marriages shortly after World War II. **Today, same-sex marriages are legal in many states, but they are not as legal as interracial marriages, according to a new study.** The question is whether gay marriage is on the same trajectory or is so fundamentally different that it will never be legalized. |
| All that was true of interracial marriages shortly after World War II. **Today’s tight labor market dictates that employers consider workers based on the skills they possess rather than the partners they prefer. Gay couples must also consider the financial obligations they owe their employers, he says.** The question is whether gay marriage is on the same trajectory or is so fundamentally different that it will never be legalized. |

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