Can Rationalization Improve Robustness?

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Abstract

A growing line of work has investigated the development of neural NLP models that can produce rationales—subsets of input that can explain their model predictions. In this paper, we ask whether such rationale models can also provide robustness to adversarial attacks in addition to their interpretable nature. Since these models need to first generate rationales ("rationalizer") before making predictions ("predictor"), they have the potential to ignore noise or adversarially added text by simply masking it out of the generated rationale. To this end, we systematically generate various types of ‘AddText’ attacks for both token and sentence-level rationalization tasks and perform an extensive empirical evaluation of state-of-the-art rationale models across five different tasks. Our experiments reveal that the rationale models promise to improve robustness while they struggle in certain scenarios—when the rationalizer is sensitive to position bias or lexical choices of attack text. Further, leveraging human rationale as supervision does not always translate to better performance. Our study is a first step towards exploring the interplay between interpretability and robustness in the rationalize-then-predict framework.\(^1\)

1 Introduction

Rationale models aim to introduce a degree of interpretability into neural networks by implicitly baking in explanations for their decisions (Lei et al., 2016; Bastings et al., 2019; Jain et al., 2020). These models are carried out in a two-stage ‘rationalize-then-predict’ framework, where the model first selects a subset of the input as a rationale and then makes its final prediction for the task solely using the rationale. A human can then inspect the selected rationale to verify the model’s reasoning over the most relevant parts of the input for the prediction at hand.

\(^1\)Code and data will be made available publicly.

Figure 1: Top: an input text is processed by the full-context model and the rationale model separately in a beer review sentiment classification dataset. Both models make correct predictions. Bottom: when an attack sentence “The tea looks horrible.” is inserted to the text, the full-context model fails. The rationalizer successfully excludes the negative sentiment word “horrible” from the selected rationales (yellow highlights) and the predictor is hence not distracted by the attack.

While previous work has mostly focused on the plausibility of extracted rationales and whether they represent faithful explanations (DeYoung et al., 2020), we ask the question of how rationale models behave under adversarial attacks (i.e., do they still provide plausible rationales?) and whether they can help improve robustness (i.e., do they provide better task performance?). Our motivation is that the two-stage decision-making could help models ignore noisy or adversarially added text within the input. For example, Figure 1 shows a state-of-the-art rationale model (Paranjape et al., 2020) smoothly handles input with adversarially added text by selectively masking it out during the rationalization step. Factorizing the rationale prediction from the task itself effectively ‘shields’ the predictor from having to deal with adversarial inputs.

To answer these questions, we first generate adversarial tests for a variety of popular NLP tasks. We focus specifically on model-independent, ‘Ad-
dText’ attacks (Jia and Liang, 2017), which aug-
ments input instances with noisy or adversarial text
at test time, and study how the attacks affect ration-
ale models both in their prediction of rationales
and final answers. For diversity, we consider in-
serting the attack sentence at different positions
of context, as well as three types of attacks: ran-
dom sequences of words, arbitrary sentences from
Wikipedia, and adversarially-crafted sentences.
We then perform an extensive empirical eval-
uation of multiple state-of-the-art rationale mod-
els (Paranjape et al., 2020; Guerreiro and Martins,
2021), across five different tasks that span review
classification, fact verification, and question an-
swering. In addition to the attack’s impact on task
performance, we also assess rationale prediction
by defining metrics on gold rationale coverage and
attack capture rate. We then investigate the effect
of incorporating human rationales as supervision,
the importance of attack positions, and the lexical
choices of attack text. Finally, we also investigate
an idea of improving rationale prediction by adding
augmented pseudo-rationales during training.
Our key findings are the following:

1. Rationale models show promise in providing
   robustness. Under our strongest type of attack,
   rationale models in many cases achieving less
   than 10% drop in task performance while full-
   context models suffer more, ranging from 11%
to 27%.
2. However, robustness of rationale models can
   vary considerably with the choice of lexical
   inputs for the attack and is quite sensitive to
   the attack position.
3. Training models with explicit rationale super-
vision does not guarantee better robustness
to attacks. In fact, they accuracy drops are
   higher by 4-10 points compared to rationale
   models without supervision.
4. Performance under attacks is significantly im-
   proved if the rationalizer can effectively mask
   out the attack text. Based on this finding, we
   propose a simple augmented-rationale train-
ing strategy and observe robustness improve-
ments of up to 4.9%.

Overall, our results indicate that while there is
promise in leveraging rationale models to improve
robustness, current models may not be sufficiently
equipped to do so. Furthermore, adversarial tests
may provide an alternative form of evaluating ra-
tionale models in addition to prevalent metrics that
measure F-1 scores using human rationales. We
hope our findings can inform the development of
better models and algorithms for rationale predic-
tions and instigate more research into the interplay
between interpretability and robustness.

2 Related Work

Rationalization There has been a surge of work
on explaining predictions of neural NLP systems,
from post-hoc explanation methods (Ribeiro et al.,
2016; Alvarez-Melis and Jaakkola, 2017), to an-
alyzing attention mechanisms (Jain and Wallace,
2019; Serrano and Smith, 2019). We focus on se-
lective rationalization (Lei et al., 2016), which gen-
erates a subset of inputs or highlights as “rationales”
such that the model can condition predictions on
them. Extractive rationales provide faithful expla-
nations by construction and are easier to assess
compared to human rationales. Recent develop-
ment has been focusing on improving joint training
of rationalizer and predictor components (Bastings
et al., 2019; Yu et al., 2019; Jain et al., 2020; Paran-
jape et al., 2020; Guerreiro and Martins, 2021), or
extensions to text matching (Swanson et al., 2020)
and sequence generation (Vafa et al., 2021). These
rationale models are mainly compared based on
predictive performance, as well as agreement with
human annotations (DeYoung et al., 2020). In this
work, we question how rationale models behave
under adversarial attacks and whether they can pro-
vide robustness benefits through rationalization.

Adversarial examples in NLP Adversarial ex-
amples have been designed to reveal the brittlen-
ess of state-of-the-art NLP models. A flood of
research has been proposed to generate different ad-
versarial attacks (Jia and Liang, 2017; Iyyer et al.,
2018; Belinkov and Bisk, 2018; Ebrahimi et al.,
2018, inter alia), which can be broadly catego-
rized by types of input perturbations (e.g., sentence,
word or character-level attacks), and the access of
model information (e.g., black-box, white-box). In
this work, we focus on model-independent, label-
-preserving attacks, in which we insert a random
or an adversarially-crafted sentence into input ex-
amples (Jia and Liang, 2017). We hypothesize that
a good extractive rationale model is expected to
learn to ignore these distractor sentences and hence
achieve better performance under attacks.

Interpretability and robustness A key motiva-
tion of our work is to bridge the connection be-
between interpretability and robustness, which we believe is an important and under-explored theme. Alvarez-Melis and Jaakkola (2018) argued that robustness of explanations is a key desideratum for interpretability. Noack et al. (2021) showed promising results of image recognition models that achieve better adversarial robustness when they are trained to have more interpretable gradients. To the best of our knowledge, we are the first to quantify the performance of rationale models under textual adversarial attacks and understand whether rationalization can inherently provide robustness.

3 Background

Neural rationale models output predictions through a two-stage process: the first stage (“rationalizer”) selects a subset of the input as a rationale, while the second stage (“predictor”) produces the prediction using only the rationale as input. Rationales can broadly be any subset of the input, although we can characterize them roughly into either token-level or sentence-level rationales, which we will both investigate in this work. The task of predicting rationales is usually framed as a binary classification problem over each atomic unit depending on the type of rationales. The rationalizer and the predictor are often trained jointly using task supervision, with gradients back-propagated through both stages. Optionally, we can provide explicit rationale supervision, if human annotations are available.

3.1 Formulation

Formally, let us assume a supervised classification dataset $D = \{(x, y)\}^2$, where each input $x = x_1, x_2, ..., x_T$ is a concatenation of $T$ sentences and $y$ refers to the task label for each instance. Each sentence $x_t = (x_{t,1}, x_{t,2}, ..., x_{t,n_t})$ contains $n_t$ tokens, and $y$ is the task label. A rationale model consists of two main components: 1) a rationalizer module $z = R(x; \theta)$, which generates a discrete mask $z \in \{0, 1\}^L$ such that $z \odot x$ selects a subset from the input ($L = T$ for sentence-level rationalization or $L$ is the total number of tokens for token-level rationales), and 2) a predictor module $\hat{y} = C(x, z; \phi)$ that makes a prediction $\hat{y}$ using the generated rationale $z$. The entire model $M(x) = C(R(x))$ is trained end-to-end using the standard cross-entropy loss. We describe detailed training objectives in §5.

3.2 Evaluation

Rationale models are traditionally evaluated along two dimensions: a) their downstream task performance, and b) the quality of generated rationales. To evaluate rationale quality, prior work has used metrics like token-level F1 or Intersection Over Union (IOU) scores between the predicted rationale and a human annotated rationale (DeYoung et al., 2020):

$$\text{IOU} = \frac{|z \cap z^*|}{|z \cup z^*|},$$

where $z^*$ is the human annotated gold rationales.

A good rationale model should not sacrifice task performance, while generating rationales that reasonably concur with human rationales, even though metrics like F1 score may not be the most appropriate way to capture this as it is limited to only capture plausibility (Jacovi and Goldberg, 2020).

4 Robustness Tests for Rationale Models

4.1 AddText Attacks

Our goal is to construct attacks that can test the capability of rationale models to ignore spurious parts of the input. In this work, we focus on AddText, label-preserving attacks Jia and Liang (2017), in order to test whether rationale models are invariant to the addition of extraneous information and remain consistent with their predictions. We also do not assume prior knowledge of the model when creating the attacks—these are model-independent attacks that can be used to test any rationale models. Attacks are only added during test time and are not available during model training.

Attack construction Formally, an AddText attack $A(x)$ modifies the input $x$ by adding an attack sentence $x_{\text{adv}}$, without changing the ground truth label $y$. In other words, we create new perturbed test instances $(A(x), y)$ for the model to be evaluated on. While some prior work has considered the addition of a few tokens to the input (Wallace et al., 2019), we add complete sentences to each input, similar to the attacks in Jia and Liang (2017). This prevents unnatural modifications to the existing sentences in the original input $x$ and also allows us to test both token-level and sentence-level rationale models (§5.1). We experiment with adding the attack sentence $x_{\text{adv}}$ across various positions in the input $x$, including the beginning, the end and a random position in between.
We measure the robustness of rationale models un-
where (Lei et al., 2016; DeYoung et al., 2020). A good ra-
versarially constructed sentence that has significant
generated by the model:
recall of the inserted attack text in the rationale
Attack capture rate (AR)
and be not affected by the addition of attack text.
The token-level GR score
annotated rationale, either computed at the token-
score between the predicted rationale and a human-
cation). To measure and analyze the effect of the
I
task performance is simply computed as the differ-
mance, and generated rationales. The change in
our attacks along two dimensions: task perfor-
4.2 Robustness Evaluation
We measure the robustness of rationale models un-
der our attacks along two dimensions: task perfor-
ance, and generated rationales. The change in
task performance is simply computed as the differ-
ence between the average scores of the model on
the original vs perturbed test sets:
\[
\Delta = \frac{1}{|D|} \sum_{(x,y) \in D} f(M(x), y) - f(M(A(x)), y),
\]
where \(f\) denotes a scoring function (F1 scores in
question answering and \(\|y - \hat{y}\|\) in text classifi-
cation). To measure and analyze the effect of the
attacks on rationale generation, we use two metrics:
Gold rationale F1 (GR) This is defined as the F1
score between the predicted rationale and a human-
annotated rationale, either computed at the token-
level or sentence-level. The token-level GR score
is equivalent to F1 scores reported in previous work
(Lei et al., 2016; DeYoung et al., 2020). A good ra-
ationale model should generate plausible rationales
and be not affected by the addition of attack text.

Attack capture rate (AR) We define AR as the recall
of the inserted attack text in the rationale
generated by the model:
\[
AR = \frac{1}{|D|} \sum_{(x,y) \sim D} \frac{|x_{adv} \cap (z \odot A(x))|}{|x_{adv}|},
\]
where \(x_{adv}\) is the attack sentence added to each
instance (i.e., \(A(x)\) is the result of inserting \(x_{adv}\)
into \(x\), \(z \odot A(x)\) is the predicted rationale. The
metric above applies on both token or sentence
level (\(|x_{adv}| = 1\) for sentence-level rationalization
and number of tokens in the attack sentence for
token-level rationalization). This metric allows us
to measure how often a rationale model can ignore
the added attack text—a maximally robust rationale
model should have an AR of 0.

5 Models and Tasks
We investigate two different state-of-the-art selec-
tive rationalization approaches: 1) sampling-based
stochastic binary masks (Bastings et al., 2019;
Paranjape et al., 2020), and 2) constrained mask
inference using a factor graph (Guerreiro and Mar-
tins, 2021). We adapt these models, using two
separate BERT encoders for the rationalizer and
the predictor, and consider training scenarios with
and without explicit rationale supervision. We also
consider a full-context model as baseline. We pro-
vide model and training details in AppendixA.

5.1 Models without Rationale Supervision

Variational information bottleneck (VIB) The
variational information bottleneck model (VIB)
(Alemi et al., 2017; Paranjape et al., 2020) imposes
a discrete bottleneck objective to select a subset
\(Z\) from the input variable \(X\), such that \(Z\) carries
minimal sufficient information about the label \(Y\).
Specifically, VIB optimizes the following objective:
\[
\max (I(Y; Z) - I(Z; X)).
\]
This objective naturally suits the rationalization
paradigm since the latent variable \(Z\) can be treated
as the inferred rationale. Since optimizing the
mutual information directly is computationally in-
tractable, it is common to optimize the lower bound
of the objective instead:
\[
\ell_{\text{VIB}}(x, y) \approx \mathbb{E}_{z \sim p(z | x; \phi)} \left[ -\log p(y | z \odot x; \phi) \right] + \beta \text{KL} \left[ p(z | x; \theta) \| p(z) \right],
\]
where \(\phi\) denotes the parameters of the predictor
\(C, \theta\) denotes the parameters of the rationalizer
\(R, p(z)\) is a predefined prior distribution parameterized by a predetermined sparsity ratio \(\pi\), and
\(\beta \in \mathbb{R}\) controls the strength of the regularization.
During inference, we simply take the rationale as
\(z_t = 1 \{ s_t \in \text{top-k}(s) \} \), where \(s \in \mathbb{R}^L\) is the vector
of token or sentence-level logits.
Sparse structured text rationalization (SPECTRA) This model (Guerreiro and Martins, 2021) extracts a deterministic structured mask \(m\) by solving a constrained inference problem while optimizing the following objective:

\[
\ell_{\text{SPECTRA}}(x, y) = - \log p(y \mid z \odot x; \phi),
\]

where \(s \in \mathbb{R}^L\) is the logit vector of tokens or sentences, and a global \(\text{score}()\) function that incorporates all constraints in the predefined factor graph. The factors can specify different logical constraints on the discrete mask \(z\), e.g., a \(\text{BUDGET}\) factor that enforces the size of the rationale as \(\sum_t z_t \leq B\). The entire computation is deterministic and allows for back-propagation through the LP-SparseMAP solver (Niculae and Martins, 2020). We use the \(\text{BUDGET}\) factor in the global scoring function. To control the sparsity at \(\pi\) (e.g., \(\pi = 0.4\) for 40% sparsity), we can choose \(B = L \times \pi\).

Full-context model (FC) As a baseline, we also consider a full-context model, which is a BERT-based encoder (Devlin et al., 2019) with task-specific final layers such as an MLP layer for classification task or two MLPs for span prediction. The model is trained with standard cross entropy loss using the task supervision.

5.2 Models with Rationale Supervision

VIB with human rationales (VIB-sup) When human annotated rationales \(z^\ast\) are available, they can be used to guide predicting the sampled masks \(z\) by adding a loss term:

\[
\ell_{\text{VIB-sup}}(x, y) = \mathbb{E}_{z \sim p(z \mid x; \theta)} \left[ - \log p(y \mid z \odot x; \phi) \right] + \beta \text{KL}\left[ p(z \mid x; \theta) \mid \mid p(z) \right] + \gamma \sum_t - z_t^\ast \log p(z_t \mid x; \theta),
\]

where \(\beta, \gamma \in \mathbb{R}\) are hyperparameters. During inference, the rationale module generates the mask \(z\) the same way as the VIB model by picking the top-\(k\) scored positions as the final hard mask. The third loss term will encourage the model to predict human annotated rationales, which is the ability we expect a robust model should exhibit.

Full-context model with human rationales (FC-sup) We also extend the FC model to leverage human annotated rationales supervision during training (FC-sup). We add a linear layer on top of the sentence/token representation and obtain the logits \(s \in \mathbb{R}^L\). The logits are passed through the sigmoid function into mask probabilities. Essentially, it is multi-task learning of rationale prediction and the original task, shared with the same BERT encoder.

5.3 Tasks

We evaluate the models on several datasets that cover a diverse set of aspects including 1) sentence-level (FEVER, MultiRC, SQuAD) or token-level (Beer, Hotel) rationalization task, 2) text classification, fact verification and extractive question answering tasks (see examples in Table 1).
a passage of multiple sentences supporting or refuting the claim. For the AddText-Adv attacks, we add modified query text to the claims by replacing nouns and adjectives in the sentence with antonyms from WordNet (Fellbaum, 1998) and randomly swapping named entities with neighboring ones in vector space with the same part-of-speech tag, as determined by 100-dimensional GloVe vectors (Pennington et al., 2014).

MultiRC MultiRC is a sentence-level multi-choice question answering task that is reformatted as binary classification where each answer choice is concatenated with the question and the model has to predict ‘yes/no’. For the AddText-Adv attacks, we transform the question and the answer separately using the same procedure we used for FEVER. We then reword the modified question and answer into a declarative sentence following constituency rules defined by (Jia and Liang, 2017) and insert it into the passage.

SQuAD SQuAD (Rajpurkar et al., 2016) is a popular extractive question answering dataset and we use the AddOneSent attacks proposed in Adversarial SQuAD (Jia and Liang, 2017). SQuAD does not contain human rationales itself and we use the sentence where the correct answer span appears in as the ground truth rationale sentence. SQuAD is the only span extraction task that we evaluate on.

Beer BeerAdvocate is a multi-aspect sentiment analysis dataset (McAuley et al., 2012), modeled as a token-level rationalization task. We use the appearance aspect in our experiments. We convert the scores into the binary labels following Chang et al. (2020). Note that this task does not have a query as in the previous tasks, we insert a sentence with the template "{SUBJECT} is {ADJ}" into the review where the adjective expresses positivity to a negative review and vice versa.

Hotel TripAdvisor Hotel Review is also a multi-aspect sentiment analysis dataset (Wang et al., 2010). We use the cleanness aspect in our experiments. We generate AddText-Adv attacks in the same way as we did for the Beer dataset.

We report accuracy for all the datasets, except for SQuAD that we report the F1 score between the predicted span and the ground-truth span.

6 Results

(R1) Rationalization is a promising approach to improving robustness. Figure 2 summarizes the average scores on all the datasets for each model under the three attacks we consider. We first observe that all models (including the non-rationale FC and FC-sup) are less affected by AddText-Rand and AddText-Wiki, with score drops of around 1-2% only. However, the AddText-Adv attack leads to significant drops in performance for all models, as high as 46% for SPECTRA on Hotel review. We break out the AddText-Adv results in a more fine-grained manner in Table 2. Our main observation is that the rationale models (VIB, SPECTRA, VIB-sup) are generally more robust than their non-rationale counterparts (FC, FC-sup) on four out of the five tasks, and in some cases dramatically better – for instance, on Beer reviews, SPECTRA only suffers a 5.7% drop (95.4 → 89.7) compared to FC’s huge 34.3% drop (93.8 → 59.5) under attack. The one exception seems to be on the Hotel reviews dataset, where both the VIB and SPECTRA models actually perform worse under attack compared to FC. We analyze this phenomena and provide a potential reason below.

(R2) Robustness is correlated with high GR and low AR. We report the Gold Rationale F1 (GR) and Attack Capture Rate (AR) for all models in Table 3. When attacks are added, GR consistently decreases for all tasks. However, AR ranges widely across datasets. The unsupervised rationale models, VIB and SPECTRA, have lower AR compared to FC-sup across all tasks, which at least partially explains their superior robustness to AddText-Adv attacks. VIB and SPECTRA also have lower drops in GR under attack compared to FC-sup.

Next, we investigate the poor performance of VIB and SPECTRA on Hotel reviews by analyzing the choice of words in the attack. Using the template “My car is {ADJ}.”, we measure the percentage of times the rationalizer module selects the adjective as part of its rationale. When the adjectives are “dirty” and “clean”, the VIB model selects them a massive 98.5% of the time. For “old” and “new”, VIB still selects them 50% of the time. On the other hand, the VIB model trained on Beer reviews with attack template “The tea is {ADJ}.” only selects the adjectives 20.5% of the time (when the adjectives are “horrible” and “fabulous”). This shows that the bad performance of the rationale...
models on Hotel reviews is down to their inability to ignore task-related adjectives in the attack text, hinting that the lexical choices made in constructing the attack can significantly impact robustness.

a much higher AR across the board. On MultiRC, for instance, the VIB-sup model outperforms VIB in task performance because of its higher GR (36.1 versus 15.8). However, when under attack, VIB-sup’s high 58.7 AR, hindering the performance compared to VIB, which has a smaller 35.8 AR. This highlights an overlooked aspect of prior work only considering metrics like IOU (which is similar in spirit to GR) to assess rationale models.

(R4) Rationale models are sensitive to attack positions. We further analyze the effect of attack text on rationale models by varying the attack position. Figure 3 displays the performance of VIB, VIB-sup and FC on FEVER and SQuAD when the attack sentence is inserted into the first, last or a random position of the original text input. We observe performance drops on both datasets when inserting the attack sentence at the beginning of the context text as opposed to the end. For example, when the attack sentence is inserted at the beginning, the VIB model drops from 77.1 F1 to 40.9 F1, but it only drops from 77.1 F1 to 72.1 F1 for a last position attack. This hints that rationale models may implicitly be picking up positional biases from the dataset, similar to their non-rationale counterparts (Ko et al., 2020).

(R5) Extracting good rationales and avoiding attack text is crucial to robustness. We exam-
Table 3: Gold Rationale F1 (GR) (original → perturbed input) and Attack Capture Rate (AR) for the AddText-Adv attack on the five tasks. The reported number is the average of inserting the attack at the start and at the end of the text input.

Table 4: Accuracy breakdown of the VIB model on the FEVER dataset. The attack is inserted at the beginning of the passage. ✓ indicates the Gold or Attack sentence is selected as rationale and ✗ otherwise. We show the percentage of examples in parenthesis.

Table 5: Task performance of the original models versus models with Augmented Rationale Training (ART). We insert two random sentences sampled from Wikipedia (the wikitext-103 dataset) into the input passage at random positions and set their pseudo rationale labels $z_{\text{pseudo}} = 1$ and all other sentences to $z = 0$. We then add an auxiliary negative binary cross entropy loss to train the model to not predict the pseudo rationale. This encourages the model to ignore spurious text that is unrelated to the task. Table 5 shows that the models trained with ART improve robustness for FC-sup, VIB and VIB-sup in both FEVER and MultiRC.

7 Conclusion

In this work, we investigate whether neural rationale models are robust to adversarial attacks. We construct a variety of AddText attacks across five different tasks and evaluate state-of-the-art rationale models. We find that while these models show some promise at being more robust, they are also quite sensitive to factors like the attack position or word choices in the attack text. Surprisingly, explicit rationale supervision does not improve robustness nor prevent the model from selecting the attack text as part of the extracted rationale. Our findings raise two key points. First, state-of-the-art rationale models, despite their promise for enabling interpretability and robustness, may not always be generating optimal rationales and may yet be prone to spurious text in the dataset. Second, metrics like IOU, frequently used in prior work (DeYoung et al., 2020; Paranjape et al., 2020), may not be ideal ways of evaluating the generated rationales since they do not test how crucial the rationale is to the model’s decision making. In contrast, adversarial tests may provide a more explicit form of evaluating rationale models since they require models to ignore the spurious and irrelevant text. We hope our findings can inform the development of better models and algorithms for rationale predictions and initiate more research into the interplay between interpretability and robustness.
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A Appendix

A.1 Implementation Details

We use two BERT-base-uncased (Wolf et al., 2020) as the rationalizer and the predictor components for all the models and one BERT-base for the Full Context (FC) baseline. The rationales for FEVER, MultiRC, SQuAD are extracted at sentence level, and Beer and Hotel are at token-level. The sentence or token level logits $s \in \mathbb{R}^t$ parameterize a relaxed Bernoulli distribution $p(z_t | x) = \text{RelaxedBernoulli}(s)$ (also known as the Gumbel distribution (Jang et al., 2017)), where $z_t \in \{0, 1\}$ is the binary mask for sentence $t$. The relaxed Bernoulli distribution also allows for sampling a soft mask $z_t^* = \sigma\left(\frac{\log s + g}{\tau}\right) \in (0, 1)$, where $g$ is the sampled Gumbel noise. The soft masks $z^* = (z_t^1, z_t^2, ..., z_t^T)$ are sampled independently to mask the input sentences such that the latent $z = m^* \odot x$ for training. During inference, we take $z_t = 1[z_t^* \in \text{top-k}(z^*)]$ and $z \odot x$ is passed to the predictor during inference. Here we specify the hyperparameter $\pi$ to control the sparsity of the rationales.