Rationale-Inspired Natural Language Explanations with Commonsense

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Abstract

Explainable machine learning models typically justify predicted labels using either extractive rationales (i.e., subsets of input features) or free-text natural language explanations (NLEs) as abstractive justifications. While NLEs can be more comprehensive than extractive rationales, machine-generated NLEs have been shown to fall short in terms of commonsense knowledge. Here, we show that commonsense knowledge can act as a bridge between extractive rationales and NLEs, rendering both types of explanations better. More precisely, we introduce a unified framework, called REXC (Rationale-inspired Explanations with Commonsense), that (1) extracts rationales as a set of features most responsible for the predictions, (2) expands the extractive rationales using available commonsense resources, and (3) uses the expanded knowledge to generate NLEs. Our framework surpasses by a large margin the previous state-of-the-art in generating NLEs across five tasks in both natural language processing and vision-language understanding, with human annotators consistently rating the explanations generated by REXC to be more comprehensive, grounded in commonsense, and overall preferred compared to previous state-of-the-art models. Furthermore, joint modeling of predictive tasks along with two types of explanations achieves state-of-the-art performance in both predictive performance and rationale extraction.

1 Introduction

Explainable machine learning models follow two representative approaches to explain predictions: identifying a meaningful subset of inputs or generating free-text explanations. The former are known as extractive rationales [50, 4, 39], while the later are abstractive and are broadly termed natural language explanations (NLEs) [33, 15, 8, 31]. Extractive rationales have the advantage of being concise and provide a quick explanation which, in some cases, is enough for the users to trust the model. However, in other cases, extractive rationales can be hard to comprehend even by expert users [17, 10, 1]. In such cases, free-text NLEs can be complementary, as they are easy to understand and allow for a more detailed justification. However, NLEs are prone to lacking commonsense [9].

To reap the benefit of both extractive and abstractive forms of explanations, we combine them in a unified framework. For example, in Fig. 1b, a subset of super-pixels of an input image (i.e., input features) form the extractive rationales behind the prediction in a question-answering task (Commonsense Question Answering [42]). To synthesize an NLE from the extracted rationales, a semantic understanding of the subjects’ faces (e.g., person2 is in shock) is helpful. To achieve this, we use external commonsense resources, which we query with the model-extracted rationales to fetch
We define a neural predictive model $M_T$ that solves a prediction task $T$ for the input $I$ (e.g., natural language or an image). The output prediction of the model is denoted $o = M_T(I)$. We aim to justify the prediction $o$ providing both extractive rationales and abstractive NLEs. We further use the model-extracted rationales as guiding signals for NLEs. Our framework combines three ingredients to generate both extractive (rationales) and abstractive (NLEs) explanations. We use Fig. 1 as a running example (on an NL task) in this section, while details for both NL and VL tasks are in Section 3.2.

## 2 REXC: Rationale-Inspired Explanations with Commonsense

We achieve a state-of-the-art (SOTA) performance in NLE generation across five tasks, spanning both natural language (NL) and vision-language (VL) domains. Furthermore, extractive rationales from REXC yield better accuracy compared to all previous SOTA models.

To our knowledge, we are the first to use external commonsense resources to combine extractive rationales and NLEs, and improve their qualities. Moreover, we show that the model-selected commonsense knowledge can act as further supporting evidence and is preferred by human evaluators.

We show that the joint modeling of predictive tasks along with the two types of explanations can lead to a better predictive performance, as compared to models that do not use explanations as a guiding signal. We achieve new SOTA performance in two datasets ComVE [44] and e-SNLI-VE [48, 18].

### 2.1 Extractive Rationales via Binary Latent Selectors

The first ingredient of our framework is the use of extractive rationales. An extractive rationale (or simply rationale) is a sufficient and minimal part of the input that is a significant indicator of a model’s prediction [23]. Any input $I$ can be broken down into smallest lexical units (e.g., tokens for language or super-pixels for images) A rationale is defined as a discrete selection of input units that are minimal and sufficient for the model’s prediction. In Fig. 1a, we provide an example from the natural language inference task (details in Section 3.1).
We model rationales using a series of binary latent variables \( z^r_i \in \{0, 1\} \) defined over the \( N \) input units. An input unit becomes a part of the rationale iff the variable takes value 1 for that unit. Following \[4\], we adapt a reparameterization strategy to learn these binary latent selectors directly using backpropagation. Instead of modeling each latent variable with a Bernoulli distribution, we use a Hard Kumaraswamy (referred to as HardKuma) distribution \[4\] that allows binary outcomes and facilitates optimization via backpropagation. We also encourage the rationale to be terse, and we control the sparsity using an \( L_1 \) relaxation defined by the tractable Kumaraswamy CDF. We optimize the lower bound \( \mathcal{E}(\vartheta^r, \vartheta^o) \) of the original log-likelihood, where \( \vartheta^r \) are the parameters of the prediction model \( \mathcal{M}_T \), and \( \vartheta^o \) are the parameters of a neural network for estimating the HardKuma variables for each input unit. Finally, we minimize the loss function of the rationales \( (\mathcal{L}^r) \) following \[4\], as

\[
\min_{\vartheta^r, \vartheta^o} -\mathcal{E}(\vartheta^r, \vartheta^o) + \lambda_0^r \sum_{i=1}^N z^r_i + \lambda_1^r \sum_{i=1}^{N-1} |z^r_i - z^r_{i+1}|,
\]

where the second term is the \( L_1 \) penalty, the third term is a fused Lasso to control the total number of transitions for compactness \[23, 4\], and \( \lambda_0^r \) and \( \lambda_1^r \) are hyperparameters. The gradient of \( \mathcal{E} \) is estimated via Monte-Carlo sampling from the reparameterized HardKuma variables \[20\]. The output \( o \) is predicted exclusively from the extracted rationales.

### 2.2 Commonsense Knowledge about Rationales

Rationales (Fig. 1) are terse and sufficient for machine prediction but may not always form a comprehensive explanation for humans. We are therefore also interested in NLEs that are more comprehensive. We hypothesize that commonsense knowledge about the rationales is crucial in explaining a prediction. For example, in Fig. 1, we obtain relevant pieces of commonsense knowledge (such as “bicycle race requires bikes”) for the rationales obtained from the input (i.e., “bicycle race”). This expanded knowledge can directly contribute to synthesizing an NLE.

Hence, our second ingredient is the use of an external commonsense knowledge resource, \( K \), that supports input from an appropriate modality (e.g., text or image). REXC queries \( K \) with the rationales (both individually and all together), to obtain a large pool of associated pieces of knowledge \( S \). We take advantage of recent developments in generative models capable of providing commonsense knowledge about a given entity, such as COMET \[14\] for NL tasks and VisualCOMET \[34\] for vision tasks. For example, given the entity “car”, COMET would output pieces of commonsense knowledge such as “car is made up of car engine, front wheel, etc”.

The commonsense knowledge resource in REXC is a parametric model (a fine-tuned language model on a commonsense knowledge base \[40, 77\]), which does not suffer from the no-hit issue that is typically encountered in non-parametric (retrieval) settings. Moreover, the parametric form of knowledge resource is easily integrable in our end-to-end framework (see Section 2.4).
2.3 Natural Language Explanations

We follow the predict-then-explain paradigm from [8], where NLE generation takes an input $I$ and the predicted output $o$, and generates an NLE $e$ for the output (see Fig. [1]). In our case, we additionally provide $S$ to the generation module to ground the NLE generation in commonsense knowledge. We use a generative model $G$ for the NLE generation, with parameters $\theta^g$, which is optimized using ground-truth NLEs $e_{gold}$ and cross-entropy loss. We use an encoder-decoder model as $G$, for which we concatenate the original input $I$ and the output prediction as

$$[\text{INPUT}] < I > [\text{SEP}] [\text{OUTPUT}] < o >,$$

following [31], where $[\text{INPUT}]$, $[\text{SEP}]$, and $[\text{OUTPUT}]$ are special tokens. In particular, we initialize $G$ with pre-trained weights and fine-tune it with ground-truth NLEs $e_{gold}$.

2.4 Variants of REXC

REXC combines the three components described above as: Input $\rightarrow$ Rationales $\rightarrow$ Predictions $\rightarrow$ Commonsense $\rightarrow$ NLEs. More precisely, REXC starts by extracting rationales from the input, follows by expanding them with associated commonsense knowledge that it selects from the knowledge resource, and finally synthesizes an NLE conditioned on the original input, predicted output, and the selected knowledge. We present three ways to combine these steps.

Modular (Mod-REXC). In the Mod-REXC version, we perform rationale extraction, commonsense knowledge expansion, and NLE generation in a modular fashion (see Fig. [2]). Thus, we first train the prediction model $M_T$. At test time, we perform argmax over the HardKuma distribution for each latent selector $z_i^c$ to obtain the rationale selection. We obtain a collection of discrete input units as the rationale from an element-wise multiplication $I \odot Z^r$. We use each rationale unit as a query to the generative knowledge resource $K$ and decode $M$ knowledge snippets $s_i \in S$ in natural language. As the final step, we concatenate the input $I$, predicted output $o$, and each knowledge snippet $s_i$ as

$$[\text{INPUT}] < I > [\text{SEP}] [\text{OUTPUT}] < o > [\text{SEP}] [\text{KNOWLEDGE}] < s_1, \ldots, s_M >,$$

where $[\text{KNOWLEDGE}]$ is an additional special token to generate the NLE $e$.

End-to-End (E2E-REXC). Our early experiments with Mod-REXC showed that rationales, responsible for obtaining relevant commonsense knowledge, have a significant influence on the NLEs rendered downstream. Hence, we explore the joint training of $M_T$ and $G$, as we hypothesize that this will enhance both rationale extraction and NLE generation. Additionally, better explanations (rationales and NLEs) can positively influence the original prediction task $T$ as well [21].

To train the complete pipeline end-to-end, we first obtain the latent selectors $z_i^c \in [0, 1]$ from $M_T$. Instead of masking the original input to obtain the rationale (which would make the process non-differentiable), we first embed the complete input using the embedding layer of the knowledge module $K$ and then perform element-wise multiplication with the sequence $z_i^c$ to obtain the equivalent soft representation for the rationale. This operation exposes only the rationales for inferring commonsense implications, similar to the modular approach. To allow gradient propagation, we do not decode commonsense knowledge to natural language either. Rather, we retain the final hidden representations of the knowledge module as $\hat{s}_i \in \hat{S}$. Our NLE generation module takes the original input and output, and the soft representations of the knowledge fused at the embedding layer (similar to [5]) as

$$\text{embedding-layer}([\text{INPUT}] < I > [\text{SEP}] [\text{OUTPUT}] < o >) \mid < \hat{s}_1, \ldots, \hat{s}_M >.$$

The modules $M_T$ and $G$ are jointly trained end-to-end with backpropagation by summing up two losses: the $L'$ from $M_T$ and the negative log-likelihood from $G$. Fine-tuning $K$ led to a minimal improvement; hence, $K$ is fixed for computational ease.

Targeted Knowledge Selection (KS-REXC). While the knowledge module generates several commonsense implications ($\hat{S}$), not all of them are important for the justification. Targeted knowledge selection can potentially improve the quality of the NLEs. Furthermore, the selected knowledge can appear as supporting evidence in addition to the generated NLEs—an advantage of REXC. Therefore, instead of implicitly learning to use $\hat{S}$, $G$ in E2E-REXC uses a knowledge selection step that explicitly chooses knowledge snippets best-suited for explanation (see Fig. [2]).

The ground-truth selection of knowledge is usually not available in the data; hence, we model the selection step via another set of latent selectors $\tilde{z}_i^c \in Z^g$, which take a value from the interval $[0, 1]$.
and are realized by a HardKuma distribution (similar to Section 2.1). We assume that more than one knowledge snippet may be relevant to craft a comprehensive explanation. We further want the knowledge selection to be sparse, such that \( G \) does not default to using all knowledge snippets. We use \( L_1 \) regularization (similar to Section 2.1) to control the sparsity of the selected knowledge. We optimize \((L^g)\)
\[
\min_{\theta^g, \theta^g} -E(\theta^g, \theta^g) + \lambda^g_0 \sum_{i=1}^{M} z^g_i,
\]
where \( \theta^g \) is the neural network that predicts the value of the latent selectors \( z^g_i \), and the second term denotes \( L_1 \) regularization for sparse selection. Similar to the rationale extraction (in Section 2.1), we use Monte-Carlo sampling from the reparameterized HardKuma variables to estimate the gradient of \( E \). To use the selected knowledge downstream, we perform element-wise multiplication \( S \odot Z^g \) and fuse masked knowledge vectors into \( G \) following a similar input format as in the E2E-RE\( \mathcal{X} \)C variant. Our final loss for KS-RE\( \mathcal{X} \)C is \( \alpha \times L^r + (1 - \alpha) \times L^g \), where \( \alpha \in [0, 1] \) is a hyperparameter.

3 Experiments

We experiment with RE\( \mathcal{X} \)C on three tasks of natural language (NL) processing and two tasks of vision-language (VL) understanding. Details of the data processing steps are in Appendix B.

3.1 Tasks

ComVE.  ComVE [44] is a dataset for the task of commonsense validation, where from a pair of sentences, a model needs to choose the sentence that defies commonsense (see Fig. 3). In addition to the binary classification task, we also generate an explanation of the prediction. We form the input for \( \mathcal{M}_T \) as a concatenation of both sentences separated by \([\text{SEP}]\), and use a training set of 10000 samples (1000/1000 for validation/test) of sentence pairs and their associated explanations.

e-SNLI.  SNLI [7] is a dataset for the task of recognizing textual entailment, where given a pair of sentences (premise and hypothesis), a model must classify their relation as either entailment, contradiction, or neutral. We use the e-SNLI [8] dataset that contains 570K examples (550K/10K/1K for train/validation/test splits) along with human-written explanations for the labels of each premise and hypothesis pair (see example in Fig. 3). The input to the model \( \mathcal{M}_T \) is the concatenation of a premise and hypothesis separated by \([\text{SEP}]\).

COSe.  CQA [42] is a multiple-choice commonsense question-answering dataset. COSe [36] is an extension of CQA that provides an NLE for each correct answer with 9741/1221 train/validation examples. We treat COSe as a multi-class classification, where we concatenate each answer choice with the question to obtain a logit for each answer, and finally add a softmax layer over all logits. For the explanation generation stage, we provide the question and the predicted answer as the input to \( \mathcal{G} \).

e-SNLI-VE.  SNLI-VE [48] is a computer-vision equivalent of the SNLI dataset [7]. SNLI-VE considers an image as a premise (instead of text as in SNLI) and text as a hypothesis, with the same three labels of entailment, neutral, and contradiction. e-SNLI-VE [18] extends SNLI-VE with NLEs curated by human annotators. e-SNLI-VE consists of 401K/14K/14K samples in the train/validation/test sets.

VCR.  VCR [51] is a dataset for commonsense reasoning in a visual-question-answering setup. A model must use commonsense knowledge and reason about the question and the image context to answer the question. In addition to predicting the answer, we generate the NLEs from scratch (instead of choosing an NLE from a pool of choices as the original task was introduced). VCR consists of 212K/26K/26K samples in the train/validation/test sets.

3.2 Implementation Details and Baselines

Details of RE\( \mathcal{X} \)C for NL tasks.  Here, we describe the components of RE\( \mathcal{X} \)C used in the NL tasks.

1. Rationale extraction:  We use the denoising encoder-decoder \texttt{bart-base} [24] as \( \mathcal{M}_T \). An MLP \((\theta^r)\) is used to generate the distribution for each latent selector, as we sample a subset of the input
Table 1: Automatic metrics and human evaluation scores for NL tasks. Differences between bold and non-bold numbers are statistically significant ($p < 0.001$). Human evaluation (Yes and No) numbers are in %.

| System   | Gold | Neg-Heu | NILE [21] | GPT-2 | WTS [31] | Mod-REXc | E2E-REXc | KS-REXc | KS-REXc+ | Gold | FME [47] | e-UG [31] | PJ-X [33] | FME [47] | GPT-2 | WTS [31] | Mod-REXc | E2E-REXc | KS-REXc | KS-REXc+ |
|----------|------|---------|-----------|-------|----------|----------|----------|--------|---------|------|---------|----------|----------|-------|-------|---------|----------|----------|----------|----------|
| MET.     | 67.2 | 62.8    | 67.4      | 65.8  | 67.3     | 66.6     | 66.6     | 66.9   | 67.4    | 75.9 | 74.7    | 73.1     | 67.4     | 66.6  | 66.6  | 67.4    | 66.6     | 66.6     | 66.9     | 67.4     |
| BERTSC.  | 87.9 | 83.8    | 87.3      | 85.3  | 87.3     | 86.6     | 86.6     | 87.1   | 87.3    | 89.4 | 88.2    | 87.1     | 87.1     | 86.6  | 86.6  | 87.1    | 86.6     | 86.6     | 87.1     | 87.1     |
| BLEURT   | 78.4 | 74.5    | 78.1      | 76.1  | 78.1     | 77.4     | 77.4     | 77.9   | 78.1    | 80.0 | 78.8    | 77.4     | 80.0     | 77.4  | 77.4  | 78.1    | 77.4     | 77.4     | 77.9     | 78.1     |
| Yes      | 1.1  | 1.6     | 1.3       | 0.9   | 1.3      | 1.3      | 1.3      | 1.3    | 1.3     | 1.3  | 1.3     | 1.3      | 1.3      | 1.3   | 1.3   | 1.3     | 1.3      | 1.3      | 1.3      | 1.3      |
| No       | 94.1 | 93.1    | 94.1      | 93.1  | 94.1     | 94.1     | 94.1     | 94.1   | 94.1    | 94.1 | 94.1    | 94.1     | 94.1     | 94.1  | 94.1  | 94.1    | 94.1     | 94.1     | 94.1     | 94.1     |

Table 2: Automatic metrics and human evaluation scores for VL tasks. Differences between bold and non-bold numbers are statistically significant ($p < 0.001$). Human evaluation (Yes and No) numbers are in %.

| System   | e-SNLI-VE | VCR |
|----------|-----------|-----|
| MET.     | BERTSC.   | BLEURT | Yes | No | MET. | BERTSC. | BLEURT | Yes | No |
| Gold     | –         | –     | 79.3 | 1.1 | –   | –     | 79.3  | 1.1 | –   |
| Neg-Heu  | 1.2       | 78.2  | 21.4 | 87.7 | 1.4 | –   | –     | –   | –   |
| NILE [21]| –         | –     | 11.3 | 75.3 | 41.2 | 80.1 | 9.4  | –   | –   |
| GPT-2    | –         | –     | –    | –    | –   | –   | –    | –   | –   |
| WTS [31] | 4.4       | 85.2  | 26.2 | 7.6  | 41.2 | 12.3 | 76.4  | 41.8 | 81.2 | 15.6 |
| Mod-REXc | 3.4       | 86.4  | 27.0 | 11.0 | 46.2 | 12.3 | 75.3  | 42.3 | 82.7 | 12.8 |
| E2E-REXc | 11.4      | 90.1  | 33.2 | 65.3 | 5.1  | 17.9 | 83.4  | 51.0 | 91.6 | 5.8  |
| KS-REXc  | 14.2      | 91.9  | 33.3 | 72.5 | 2.7  | 19.3 | 86.4  | 51.2 | 93.7 | 3.7  |
| KS-REXc+ | –         | –     | 72.3 | 1.1  | –   | –    | 94.1  | 2.7 | –   | –   |

as rationales. 2. **Prediction:** A linear layer is used as a classification head to predict the task label. 3. **Commonsense resource:** We use two variants of commonsense knowledge for our modular and end-to-end approaches. In Mod, we use an off-the-shelf commonsense (generative) model, COMET [6], that is fine-tuned on ConceptNet [40]. For E2E-REXc and KS-ours, we pre-train a bart-base model as a proxy for COMET (with the same setup as in [6]) that matches with the tokenization scheme used in all three stages (i.e., prediction, commonsense, and NLE generation). 4. **NLE generator:** We use another bart-base model to generate the NLEs and decode with nucleus sampling ($p = 0.95$) [10]. All hyperparameters are reported in Appendix A.

**Details of REXC for VL tasks.** For VL tasks, the components of REXC are as follows. 1. **Rationale extraction:** For $M_r$, we use a transformer-based VL model, UNITER [12], which uses self-attention to learn contextualized representations for image-text input pairs. Two MLPs (parameters, in combination, denoted as $\theta^r$) are used to generate the distributions for each latent rationale selector from the image and text input, respectively. 2. **Prediction:** A linear layer is used as a classification head to predict the task label. 3. **Commonsense resource:** We use ViualCOMET [34] as commonsense module, which accepts an image as input and is fine-tuned on ATOMIC [57]. For text rationales, we follow same structure as in the NL setup. 4. **NLE generator:** We combine UNITER, an encoder for image-text pairs [12], and GPT-2 [35], a language model decoder, following [18]. We adapt GPT-2 to condition on contextualized representations of VL inputs, encoded by UNITER. We use nucleus sampling ($p = 0.95$) for decoding NLEs from GPT-2. More details are in Appendix A.

**NL Baselines.** We adapt a general-purpose NLE generation model, WT5 [31], as the SOTA for all NL tasks. For ComVE, we further investigate a trivial heuristic baseline (Neg-Heu), where we construct an NLE simply by negating the nonsensical input sentence. For example, if the model predicts ‘Cars can fly’ as nonsensical, a trivial justification can be ‘Cars cannot fly’. For e-SNLI and COSe, we use two additional SOTA models: NILE [21] and GPT-2 [36], respectively.

**VL Baselines.** We consider a suite of baselines that can work in all VL tasks: (1) PJ-X [33]: a multimodal explanation generation framework pretrained on VQA; (2) FME [47]: uses highly predictive features to generate a faithful explanation; (3) RVT [30]: uses off-the-self computer vision algorithms to extract information from the input image, and uses GPT-2 to generate NLEs (post-hoc, not end-to-end); and (4) e-UG [18]: uses UNITER to obtain a joint representation of the image-text input pairs, and GPT-2 to generate NLEs.
Figure 3: Examples of NLEs and extractive rationales generated from REXC for all five tasks, along with the pieces of commonsense used by REXC. Generations from the best baseline are included for direct comparison. Rationales are obtained from REXC. Both SOTA and REXC produce correct prediction, as shown here.

Ablations of REXC. Along with the variants of REXC described in Section 2.4, we ablate REXC to investigate the effects of the extractive rationales and commonsense module on NLEs. We also consider ablative baselines: BART for NL and e-UG for VL tasks, which do not use either external commonsense resources nor rationales.

4 Results and Discussion

In this section, we evaluate REXC with respect to three key desiderata: (1) performance in NLE generation, (2) performance in rationale extraction, and (3) performance in original predictive tasks.

4.1 Automatic Evaluations for NLEs and Rationales

Following [18], we experiment with a suite of metrics popularly used in language generation to capture how closely generated NLEs follow ground-truth. Here, we report METEOR [3], BERTScore [52], and BLEURT [38], which showed the highest correlation with human evaluations in [18]. More automatic metrics (following [18]) are reported in Appendix C.

For NL tasks, REXC achieves the best values on all three automatic metrics in Table 1. We see sharp jumps (ranging from 4.8 to 9.8 points in METEOR, for e.g.) between REXC and models that do not use external commonsense knowledge, such as fine-tuned versions of pretrained language models (BART, WT5, etc.). This confirms that external commonsense is a useful component for more accurate NLEs. Moreover, the end-to-end versions of REXC (E2E-REXC and KS-REXC) consistently show a gain over Mod-REXC, showing that jointly producing rationales with NLEs has a clear advantage.

Similarly for VL tasks, REXC outperforms the previous SOTA models (see Table 2). More specifically, REXC outperforms RVT, a competitive model that already makes use of external commonsense resources, which indicates that (1) rationales are useful to gather more relevant pieces of commonsense knowledge, and (2) joint training for rationales and NLEs is superior over a modular approach.

REXC improves rationale extraction. REXC outputs extractive rationales as a byproduct. To evaluate their quality, we use ERASER [14], a framework to evaluate rationales relative to ground-truth. ERASER uses accuracy (Acc.) and F1 scores at IOU or token (Tok.) level (details in [14]) to measure the overlap between extracted and the ground truth rationales. In Table 4, we show results for
Table 3: Comparison of SOTA models (\cite{14,22,45,49} in order for each dataset) vs. variants of REXC for prediction performance in all five predictive tasks. SOTA models do not include ensemble models. Base denotes SOTA with $M_r$ just as a predictive model. For ComVE, we consider task A from \cite{45}. For VCR, we only report performance for Q→A. Best numbers are in **bold**.

| System | ComVE | SNLI | CQA | SNLI-VE | VCR |
|--------|-------|------|-----|---------|-----|
| SOTA   | 97.0  | **93.1** | 80.3 | 78.9 | **81.6** |
| Base   | 96.2  | 92.2 | 78.1 | 78.9 | 77.0 |
| Mod-RExC | 96.9 | 92.3 | 78.6 | 79.1 | 78.1 |
| E2E-RExC | 97.0 | 92.5 | 79.1 | 79.3 | 78.6 |
| KS-RExC | **97.1** | 92.5 | 79.4 | **79.4** | 79.8 |
| - Com.sense | 96.3 | 92.2 | 78.1 | 79.0 | 77.1 |
| - Rationales | 96.5 | 92.2 | 78.4 | 78.9 | 77.3 |

Table 4: Comparison of previous SOTA models \cite{14} vs. variants of REXC for rationale extraction performance on e-SNLI and COSe, using the ERASER evaluation framework \cite{14}. Mod-RExC is performing on par with the standalone model that only performs rationale extraction and the predictive task. Best numbers are in **bold**.

| System       | Acc. | IOU | Tok. |
|--------------|------|-----|------|
| SOTA \cite{14} | 73.3 | 70.4 | 70.1 |
| Mod-RExC     | 74.5 | 71.5 | 72.4 |
| E2E-RExC     | 77.8 | 72.3 | 73.1 |
| KS-RExC      | **83.2** | **72.8** | **73.5** |
| - Com.sense  | 73.4 | 70.9 | 69.8 |
| - Rationales | 96.5 | 92.2 | 78.4 |

Table 5: Main limitations of the generated NLEs obtained from user study. All numbers are in % and are averaged by systems and datasets for both NL (left) and VL (right) tasks. Human annotators could choose multiple limitations for an NLE. Neg-Heu and NILE are reported only for ComVE and e-SNLI, respectively.

| System       | Violates | In-sufficient | Untrue to input | Too verbose | Too trivial |
|--------------|----------|---------------|-----------------|-------------|-------------|
| Gold         | 1.3      | 12.5          | 0.5             | 3.4         | 3.1         |
| Neg-Heu      | 1.6      | 26.5          | 3.4             | 0.5         | 48.8        |
| NILE         | 10.2     | 24.9          | 5.6             | 1.6         | 10.7        |
| WT5          | 8.7      | 16.8          | 8.5             | 3.2         | 4.8         |
| Mod-RExC     | 6.2      | 13.7          | 7.5             | 6.8         | 4.4         |
| E2E-RExC     | 2.8      | 12.1          | 4.8             | 5.7         | 4.9         |
| KS-RExC      | 2.6      | 7.6           | 4.4             | 5.8         | 4.2         |
| KS-RExC+     | 2.4      | 6.9           | 4.1             | 26.9        | 3.5         |
| Dataset      | ComVE    | 4.9           | 18.8            | 9.7         | 8.7         | 10.1        |
|              | e-SNLI   | 5.4           | 14.7            | 6.1         | 6.8         | 5.3         |
|              | COSe     | 5.6           | 13.9            | 8.4         | 7.5         | 6.4         |

For NL tasks, we find that the three variants of REXC are clearly preferred over the previous SOTA models, in Table 1. Similar to the trend in automatic metrics, we see that KS-RExC has a significant jump from Mod-RExC and E2E-ours, which indicates that targeted commonsense knowledge selection has positive effects on the quality of the NLEs. Gains for REXC are significant over previous SOTA models for both ComVE and COSe, which could be due to direct involvement of commonsense in the prediction tasks. For example, we find that explanations for the ‘neutral’ and ‘contradiction’ labels in the e-SNLI dataset often involve reasoning that is beyond the range of commonsense spanned by the input.
For VL tasks, NLEs from previous SOTA models were rated far lower than gold references, indicating that there is room for improvement. We observe substantial gains for NLEs from REXC as compared to competitive baselines that already use external commonsense knowledge, such as RVT [30]. This strengthens our hypotheses that rationales also play an important role in rendering better-quality NLEs, and that commonsense knowledge establishes a critical bridge between rationales and NLEs.

Error analysis. Table 5 summarizes the main drawbacks of generated NLEs (in average) across models and datasets. As main observation, we see that adding commonsense knowledge and knowledge selection (KS-REXC) gradually make NLEs more comprehensive and more relevant to the input. While KS-REXC+ wins over all other models across all datasets, human judges often found them too verbose due to the presence of supporting knowledge snippets, which sometimes might repeat information from the generated NLEs. For ComVE, the naive baseline Neg-Heu turns out to produce highly insufficient and trivial NLEs, even if they are more relevant and commonsense-grounded (by construction).

Qualitative analysis. Figure 3 shows sample outputs from REXC for all five tasks. Reflecting our observations from the human evaluation (Table 5), the NLEs generated from REXC are more grounded in commonsense than the NLEs from previous SOTA models (e.g., “Music can alleviate boredom when you are alone at home” in COSe). KS-REXC learns to select a small but relevant set of knowledge to use as supporting evidence while grounding NLEs in commonsense. Moreover, previous SOTA models on generating NLEs fall short of generating comprehensive NLEs (e.g., “People listen to music” for COSe), which could be because they do not use rationales (e.g., “boredom”) as learning signals. More examples are in Appendix D.

4.3 Discussion

REXC improves task performance. Previous work [21] observed that, for SNLI, NLEs can provide an important learning signal to improve the original task performance. To test this hypothesis over a diverse range of tasks and to investigate if commonsense knowledge has a role to play, we compare REXC with SOTA models for each predictive task. In Table 3, we show that REXC consistently outperforms a model that uses the same architecture as REXC for $M_T$ (BART for NL tasks, and UNITER for VL tasks). Without commonsense, performance of REXC drops to baseline performance. Hence, we can infer that NLEs (and not just the commonsense module) can also enhance a model’s predictive performance. This phenomenon generalizes across all five tasks (across the two domains). We further achieve a new SOTA in task performance for ComVE and SNLI-VE, while we maintain performance in other tasks as compared to current SOTA.

Ablation study. To pinpoint the contributing factor behind the improved performance in NLE generation (Tables 1 and 2) and in the predictive task (Table 3), we individually drop modules responsible for rationale extraction and commonsense expansion and study relative performance changes. For both NL and VL tasks, we find that an ablative baseline (BART/T5 for NL and RVT for VL) that does not use external commonsense resources consistently lags in NLE generation compared to all variants of REXC. For example, in Table 3, we observe a performance drop of 2.7 and 2.5 points in VCR when we ablate with rationale extraction and commonsense, respectively. This trend continues in all tasks. Among variants of REXC, we see that joint training is effective, as E2E-REXC and KS-REXC outperform Mod. Moreover, while E2E-REXC could implicitly learn to use required commonsense knowledge, KS-REXC outperforming E2E-REXC suggests that direct knowledge selection acts as a useful inductive bias in effectively utilizing a large pool of knowledge.

5 Related Work

NLEs. A growing number of works in machine learning are focusing on producing explanations in human language to make black-box neural models more accessible to their users [15, 8, 33, 19, 26, 30]. A recent work [31] shows that NLE generation can be posed as a text-to-text generation task. Similarly, Marasovic et al. [30] leveraged NLEs to show the importance of semantics in connecting low-level features to an abstractive explanation in the VL domain. In a similar spirit, several explainability datasets with NLEs have been proposed [8, 36, 18, 51]. We benchmark REXC on these datasets and achieve SOTA in both automatic and human evaluation of NLEs.
Extractive rationales. Another form of machine explanation are extractive rationales, i.e., a set of predictive input features. An early work [50] investigated the idea of rationale extraction directly from inputs (e.g., tokens indicating sentiment in reviews) and later was successfully followed by works in the context of both NL [14, 23, 4, 39] and VL [41] tasks. In contrast, we attempt to model both the extractive rationales and NLEs jointly in a novel framework that improves their quality.

Commonsense in text generation. Finally, commonsense has become a crucial component in free-text generation. Representative scenarios where commonsense is used are dialog generation [28], creative text generation [11], story generation [29], and counterfactual generation [5]. Recently, Marasovic et al. [30] used commonsense resources as semantic understanding tools to connect low-level features to NLEs in the VL domain. In this work, we establish that commonsense plays a critical role in connecting extractive rationales and NLEs, and achieve a new SOTA performance in explanation (both extractive and abstractive) generation across five different tasks, as well as new SOTA in task performance for two tasks (ComVE and SNLI-VE).

6 Conclusion

In this work, we proposed a unified framework to combine two representative type of explanations, extractive and abstractive, using external commonsense resources. Using five predictive tasks, from natural language and vision-language domains, we established that joint training of extractive rationales and abstractive NLEs is consistently more powerful in obtaining comprehensive explanations for machine predictions, as compared to separately modeling them. We obtain a new SOTA performance for both NLE generation and rationales extraction. We further show that commonsense knowledge connects rationales and NLEs, making machine predictions more interpretable to end users.

While currently we use fixed off-the-shelf commonsense resources, future work could focus on jointly fine-tuning these resources in order to potentially obtain more commonsense implications, in cases such as negation and contradiction that are not spanned by current knowledge bases.

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References

[1] Y. Alufaisan, L. R. Marusich, J. Z. Bakdash, Y. Zhou, and M. Kantarcioglu. Does explainable artificial intelligence improve human decision-making? In Association for the Advancement of Artificial Intelligence (AAAI), 2021.

[2] P. Anderson, B. Fernando, M. Johnson, and S. Gould. SPICE: semantic propositional image caption evaluation. In B. Leibe, J. Matas, N. Sebe, and M. Welling, editors, ECCV, 2016. URL https://doi.org/10.1007/978-3-319-46454-1_24

[3] S. Banerjee and A. Lavie. METEOR: an automatic metric for MT evaluation with improved correlation with human judgments. In J. Goldstein, A. Lavie, C. Lin, and C. R. Voss, editors, Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization@ACL, 2005. URL https://www.aclweb.org/anthology/W05-0909/

[4] J. Bastings, W. Aziz, and I. Titov. Interpretable neural predictions with differentiable binary variables. In A. Korhonen, D. R. Traum, and L. Marquez, editors, ACL, 2019. URL https://doi.org/10.18653/v1/p19-1284

[5] C. Bhagavatula, R. L. Bras, C. Malaviya, K. Sakaguchi, A. Holtzman, H. Rashkin, D. Downey, W. Yih, and Y. Choi. Abductive commonsense reasoning. In ICLR, 2020. URL https://openreview.net/forum?id=Bygg1v1HkDB
A. Bosselut, H. Rashkin, M. Sap, C. Malaviya, A. Celikyilmaz, and Y. Choi. COMET: commonsense transformers for automatic knowledge graph construction. In A. Korhonen, D. R. Traum, and L. Márquez, editors, *ACL*, 2019. URL https://doi.org/10.18653/v1/p19-1470

S. R. Bowman, G. Angeli, C. Potts, and C. D. Manning. A large annotated corpus for learning natural language inference. In L. Márquez, C. Callison-Burch, J. Su, D. Pighin, and Y. Marton, editors, *EMNLP*, 2015. URL https://doi.org/10.18653/v1/d15-1075

O. Camburu, T. Rocktäschel, T. Lukasiewicz, and P. Blunsom. e-snli: Natural language inference with natural language explanations. In S. Bengio, H. M. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, *NeurIPS*, 2018. URL https://proceedings.neurips.cc/paper/2018/hash/4c7a167bb329bd92580a99ce422d6fa6-Abstract.html

O.-M. Camburu, B. Shillingford, P. Minervini, T. Lukasiewicz, and P. Blunsom. Make Up Your Mind! Adversarial Generation of Inconsistent Natural Language Explanations. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 4157–4165, July 2020. doi: 10.18653/v1/2020.acl-main.382. URL https://www.aclweb.org/anthology/2020.acl-main.382

O.-M. Camburu, E. Giunchiglia, J. Foerster, T. Lukasiewicz, and P. Blunsom. The struggles of feature-based explanations: Shapley values vs. minimal sufficient subsets. In *AAAI Workshop on Explainable Agency in Artificial Intelligence*, 2021.

T. Chakrabarty, D. Ghosh, S. Muresan, and N. Peng. R’3: Reverse, retrieve, and rank for sarcasm generation with commonsense knowledge. In D. Jurafsky, J. Chai, N. Schlotter, and J. R. Tetreault, editors, *ACL*, 2020. URL https://doi.org/10.18653/v1/2020.acl-main.711

Y. Chen, L. Li, L. Yu, A. E. Kholy, F. Ahmed, Z. Gan, Y. Cheng, and J. Liu. UNITER: universal image-text representation learning. In A. Vedaldi, H. Bischof, T. Brox, and J. Frahm, editors, *ECCV*, 2020. URL https://doi.org/10.1007/978-3-030-58577-8_7

A. Holtzman, J. Buys, L. Du, M. Forbes, and Y. Choi. The curious case of neural text degeneration. In *ICLR*, 2020. URL https://openreview.net/forum?id=rygQyrFvH

H. Kaur, H. Nori, S. Jenkins, R. Caruana, H. Wallach, and J. Wortman Vaughan. Interpreting interpretability: Understanding data scientists’ use of interpretability tools for machine learning. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 2020.

M. Kayser, O. Camburu, L. Salewski, C. Emde, V. Do, Z. Akata, and T. Lukasiewicz. e-vil: A dataset and benchmark for natural language explanations in vision-language tasks. *CoRR*, abs/2105.03761, 2021. URL https://arxiv.org/abs/2105.03761

J. Kim, A. Rohrbach, T. Darrell, J. F. Canny, and Z. Akata. Textual explanations for self-driving vehicles. In V. Ferrari, M. Hebert, C. Sminchisescu, and Y. Weiss, editors, *ECCV*, 2018. URL https://doi.org/10.1007/978-3-030-01216-8_35

D. P. Kingma and M. Welling. Auto-encoding variational bayes. In Y. Bengio and Y. LeCun, editors, *ICLR*, 2014. URL http://arxiv.org/abs/1312.6114

S. Kumar and P. P. Talukdar. NILE : Natural language inference with faithful natural language explanations. In D. Jurafsky, J. Chai, N. Schlotter, and J. R. Tetreault, editors, *ACL*, 2020. URL https://doi.org/10.18653/v1/2020.acl-main.771
[22] Z. Lan, M. Chen, S. Goodman, K. Gimpel, P. Sharma, and R. Soricut. ALBERT: A lite BERT for self-supervised learning of language representations. In ICLR, 2020. URL https://openreview.net/forum?id=H1eA7AEtvS

[23] T. Lei, R. Barzilay, and T. S. Jaakkola. Rationalizing neural predictions. In J. Su, X. Carreras, and K. Du, editors, EMNLP, 2016. URL https://doi.org/10.18653/v1/d16-1011

[24] M. Lewis, Y. Liu, N. Goyal, M. Ghazvininejad, A. Mohamed, O. Levy, V. Stoyanov, and L. Zettlemoyer. In D. Jurafsky, J. Chai, N. Schluter, and J. R. Tetreault, editors, BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. ACL, 2020. URL https://doi.org/10.18653/v1/2020.acl-main.703

[25] C. Lin and F. J. Och. Automatic evaluation of machine translation quality using longest common subsequence and skip-bigram statistics. In D. Scott, W. Daelemans, and M. A. Walker, editors, ACL, 2004. URL https://www.aclweb.org/anthology/P04-1077/

[26] W. Ling, D. Yogatama, C. Dyer, and P. Blunsom. Program induction by rationale generation: Learning to solve and explain algebraic word problems. In R. Barzilay and M. Kan, editors, ACL, 2017. URL https://doi.org/10.18653/v1/P17-1015

[27] I. Loshchilov and F. Hutter. Fixing weight decay regularization in adam. CoRR, abs/1711.05101, 2017. URL http://arxiv.org/abs/1711.05101

[28] B. P. Majumder, H. Jhamtani, T. Berg-Kirkpatrick, and J. J. McAuley. Like hiking? you probably enjoy nature: Persona-grounded dialog with commonsense expansions. In B. Webber, T. Cohn, Y. He, and Y. Liu, editors, EMNLP, 2020. URL https://doi.org/10.18653/v1/2020.emnlp-main.739

[29] H. H. Mao, B. P. Majumder, J. J. McAuley, and G. W. Cottrell. Improving neural story generation by targeted common sense grounding. In K. Inui, J. Jiang, V. Ng, and X. Wan, editors, EMNLP-IJCNLP, 2019. URL https://doi.org/10.18653/v1/D19-1615

[30] A. Marasovic, C. Bhagavatula, J. S. Park, R. L. Bras, N. A. Smith, and Y. Choi. Natural language rationales with full-stack visual reasoning: From pixels to semantic frames to commonsense graphs. In T. Cohn, Y. He, and Y. Liu, editors, EMNLP Findings, 2020. URL https://doi.org/10.18653/v1/2020.findings-emnlp.253

[31] S. Narang, C. Raffel, K. Lee, A. Roberts, N. Fiedel, and K. Malkan. Wt5?! training text-to-text models to explain their predictions. CoRR, abs/2004.14546, 2020. URL https://arxiv.org/abs/2004.14546

[32] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu. Bleu: a method for automatic evaluation of machine translation. In ACL, 2002.

[33] D. H. Park, L. A. Hendricks, Z. Akata, A. Rohrbach, B. Schiele, T. Darrell, and M. Rohrbach. Multimodal explanations: Justifying decisions and pointing to the evidence. In CVPR, 2018. URL http://openaccess.thecvf.com/content_cvpr_2018/html/Park_Multimodal_Explanations_Justifying_CVPR_2018_paper.html

[34] J. S. Park, C. Bhagavatula, R. Mottaghi, A. Farhadi, and Y. Choi. Visualcomet: Reasoning about the dynamic context of a still image. In A. Vedaldi, H. Bischof, T. Brox, and J. Frahm, editors, ECCV, 2020. URL https://doi.org/10.1007/978-3-030-58558-7_30

[35] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, and I. Sutskever. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9, 2019.

[36] N. F. Rajani, B. McCann, C. Xiong, and R. Socher. Explain yourself! leveraging language models for commonsense reasoning. In A. Korhonen, D. R. Traum, and L. Márquez, editors, ACL, 2019. URL https://doi.org/10.18653/v1/p19-1487

[37] M. Sap, R. L. Bras, E. Allaway, C. Bhagavatula, N. Lourie, H. Rashkin, B. Roof, N. A. Smith, and Y. Choi. ATOMIC: an atlas of machine commonsense for if-then reasoning. In AAAI, 2019. URL https://doi.org/10.1609/aaai.v33i01.33013027
[38] T. Sellam, D. Das, and A. P. Parikh. BLEURT: learning robust metrics for text generation. In D. Jurafsky, J. Chai, N. Schluter, and J. R. Tetreault, editors, ACL, 2020. URL https://doi.org/10.18653/v1/2020.acl-main.704

[39] L. Sha, O.-M. Camburu, and T. Lukasiewicz. Learning from the best: Rationalizing prediction by adversarial information calibration. In Association for the Advancement of Artificial Intelligence (AAAI), 2021.

[40] R. Speer, J. Chin, and C. Havasi. Conceptnet 5.5: An open multilingual graph of general knowledge. In S. P. Singh and S. Markovitch, editors, AAAI, 2017. URL http://aaai.org/ocs/index.php/AAAI/AAAI17/paper/view/14972

[41] J. Strout, Y. Zhang, and R. J. Mooney. Do human rationales improve machine explanations? CoRR, abs/1905.13714, 2019. URL http://arxiv.org/abs/1905.13714

[42] A. Talmor, J. Herzig, N. Lourie, and J. Berant. Commonsenseqa: A question answering challenge targeting commonsense knowledge. In J. Burstein, C. Doran, and T. Solorio, editors, NAACL-HLT, 2019. URL https://doi.org/10.18653/v1/n19-1421

[43] R. Vedantam, C. L. Zitnick, and D. Parikh. Cider: Consensus-based image description evaluation. In CVPR, 2015. URL https://doi.org/10.1109/CVPR.2015.7299087

[44] C. Wang, S. Liang, Y. Zhang, X. Li, and T. Gao. Does it make sense? and why? a pilot study for sense making and explanation. In ACL, July 2019. URL https://www.aclweb.org/anthology/P19-1393

[45] C. Wang, S. Liang, Y. Jin, Y. Wang, X. Zhu, and Y. Zhang. SemEval-2020 task 4: Commonsense validation and explanation. In SemEval, 2020.

[46] S. Wang, H. Fang, M. Khabsa, H. Mao, and H. Ma. Entailment as few-shot learner. CoRR, abs/2104.14690, 2021. URL https://arxiv.org/abs/2104.14690

[47] J. Wu and R. J. Mooney. Faithful multimodal explanation for visual question answering. CoRR, abs/1809.02805, 2018. URL http://arxiv.org/abs/1809.02805

[48] N. Xie, F. Lai, D. Doran, and A. Kadav. Visual entailment: A novel task for fine-grained image understanding. arXiv preprint arXiv:1901.06706, 2019.

[49] F. Yu, J. Tang, W. Yin, Y. Sun, H. Tian, H. Wu, and H. Wang. Ernie-vil: Knowledge enhanced vision-language representations through scene graph. CoRR, abs/2006.16934, 2020. URL https://arxiv.org/abs/2006.16934

[50] O. Zaidan and J. Eisner. Modeling annotators: A generative approach to learning from annotator rationales. In EMNLP, pages 31–40, 2008. URL https://www.aclweb.org/anthology/D08-1004

[51] R. Zellers, Y. Bisk, A. Farhadi, and Y. Choi. From recognition to cognition: Visual commonsense reasoning. In CVPR, 2019. URL http://openaccess.thecvf.com/content_CVPR_2019/html/Zellers_From_Recognition_to_Cognition_Visual_Commonsense_Reasoning_CVPR_2019_paper.html

[52] T. Zhang, V. Kishore, F. Wu, K. Q. Weinberger, and Y. Artzi. Bertscore: Evaluating text generation with BERT. In ICLR, 2020. URL https://openreview.net/forum?id=SkeHuCVFDr
A Implementation Details

Training. We trained each model for maximum 5 epochs, and training was stopped using an early stopping criteria based on perplexity on the validation sets. For NL tasks, each model is trained with batch size of 4 on two 2080 Ti GPUs. Each RE\textsubscript{XC} model took 35 hours on ComVE, 45 hours on e-SNLI and 25 hours on COSe. For VL tasks, each model is trained with batch size of 32 on two 2080 Ti GPUs. Each RE\textsubscript{XC} model took 85 hours on e-SNLI-VE took 85 hours and 105 hours on VCR.

Hyperparameters. For the rationale extraction step, we set both $\lambda_0^r$ and $\lambda_1^r$ to 1.0. This value turned out to be best for both NL and VL tasks. For the knowledge selection step in KS, we set $\lambda_0^g$ to 0.9, based on validation performance. The $\alpha$ for mixing rationale extraction and NLE generation loss is set to 0.4. We use the AdamW optimizer \cite{Yan2018} for training each model, and the learning rate was set to $6 \times 10^{-5}$, with a linear decay of step size $10^{-1}$ per epoch. We use BART, UNITER, and GPT-2 with all three being released under the MIT license.

Baselines. We used the official code base for NILE.\cite{SawanKumar28} For WT5, we fine-tuned a pretrained T5 model.\cite{6100} For all VL baselines (PJ-X, FME, RVT, and e-UG), we followed the implementations details from \cite{Loftus2021}.\cite{42}

B Datasets

ComVE. ComVE consists of 10000/1000/1000 samples in the train/validation/test splits. We use the BART tokenizer\cite{10} to tokenize input strings. The maximum input length was set to 512. The dataset is distributed under the CC BY-SA 4.0 license.

e-SNLI. e-SNLI consists of 550K/10K/10K samples in the train/validation/test splits. We again use the BART tokenizer for the input strings. The maximum input length was set to 512. The dataset is distributed under the MIT license.

COSe. COSe consists of 9741/1221 samples in the train/validation splits. We use the BART tokenizer to tokenize input strings. The maximum input length was set to 1024. The dataset is distributed under the BSD 3-Clause “New” or “Revised” license.

e-SNLI-VE. e-SNLI-VE consists of 401K/14K/14K samples in train/validation/test splits. We use the BERT tokenizer\cite{32} scheme\cite{6100} to tokenize text input following UNITER.\cite{12} The maximum input length was set to 512. No specific license is associated with the dataset release, and the dataset is freely available.

VCR. VCR consists of 212K/26K/26K samples in train/validation/test splits. Similar to e-SNLI-VE, we use the BERT tokenization scheme to tokenize the input text. The maximum input length was set to 512. The license of this dataset is mentioned at \url{https://visualcommonsense.com/license/}.

C Automatic Metrics

Following \cite{Loftus2021}, we experiment with a suite of metrics popularly used in language generation to capture how closely the generated NLEs follow the ground-truth. We provide all metrics that were reported in \cite{Loftus2021}, i.e., BLEU-4 \cite{Papineni2002}, ROUGE-L \cite{Lin2004}, BERTScore \cite{Zhang2019}, METEOR \cite{Vogel2004}, SPICE \cite{Helmbergetal15}, CIDER \cite{Vedantametal15}, and BLEURT \cite{Gardental18} in Table \ref{table:automatic_metrics}.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
Metric & Score \\
\hline
BLEU-4 & \cite{Papineni2002} \\
ROUGE-L & \cite{Lin2004} \\
BERTScore & \cite{Zhang2019} \\
METEOR & \cite{Vogel2004} \\
SPICE & \cite{Helmbergetal15} \\
CIDER & \cite{Vedantametal15} \\
BLEURT & \cite{Gardental18} \\
\hline
\end{tabular}
\caption{Automatic Metrics}
\end{table}

\begin{thebibliography}{9}
\bibitem{10} https://huggingface.co/transformers/model_doc/bart.html
\bibitem{12} https://github.com/ChenRocks/UNITER
\bibitem{42} https://huggingface.co/transformers/model_doc/gpt2.html
\bibitem{6100} https://github.com/SawanKumar28/nile
\bibitem{6100} https://huggingface.co/transformers/model_doc/t5.html
\bibitem{10} https://huggingface.co/transformers/model_doc/bart.html#barttokenizer
\bibitem{42} https://huggingface.co/transformers/model_doc/bert.html#berttokenizer
\end{thebibliography}
Table 6: Automatic metrics and human evaluation scores for NL and VL tasks. Difference between bold and non-bold numbers are statistically significant ($p < 0.001$). Human evaluation numbers are in %.

| System | BLEU | ROUGE | BERTSc. | METEOR | SPICE | CIDER | BLEURT | Yes | W-Yes | W-No | W-No |
|--------|------|-------|---------|--------|-------|-------|--------|-----|-------|------|------|
| Gold   | 17.8 | 12.3  | 78.2    | 1.2    | 17.3  | 29.2  | 21.4   | 79.3| 17.3  | 2.3  | 1.1  |
| Neg-Heu| 21.7 | 18.2  | 85.2    | 4.4    | 24.3  | 31.5  | 26.2   | 87.7| 5.6   | 5.3  | 1.4  |
| BART   | 21.8 | 17.2  | 86.4    | 3.4    | 24.9  | 34.1  | 27.0   | 76.4| 26.4  | 24.8 | 41.2 |
| WTS    | 22.5 | 20.4  | 88.6    | 7.2    | 28.4  | 36.1  | 30.1   | 11.0| 17.5  | 28.9 | 46.2 |
| REXC E2E| 24.5 | 23.3  | 90.1    | 11.4   | 28.4  | 36.9  | 33.2   | 65.3| 27.4  | 2.2  | 5.1  |
| REXC KS| 25.6 | 24.5  | 91.9    | 14.2   | 29.3  | 37.1  | 33.3   | 72.5| 19.3  | 5.5  | 2.7  |
| REXC KS+| 26.8 | 25.7  | 93.6    | 15.2   | 30.2  | 38.1  | 33.4   | 72.3| 21.5  | 5.1  | 1.1  |
| VCR    | 0.81 | 0.74  | 1.1     | 0.89   | 0.74  | 1.1   | 0.89   | 0.91| 0.74  | 0.89 | 0.74 |

D Human Evaluation

Kayser et al. [18] showed that none of the automatic metrics consistently show correlation with human evaluation. Hence, we performed human evaluation for NLEs and we provide the detailed results in Table 6. Another set of illustrative examples are provided in Figure 4.

We also briefly describe the human evaluation setup here, with a representative snapshot of the UI shown in Figure 5. For every question, we employed two Anglophone annotators with Lifetime HIT acceptance rate of at least 90%.

The inter-annotator agreement was captured by Cohen’s Kappa [13]. For each of the datasets, ComVE, e-SNLI, COSe, e-SNLJ-VE, and VCR, the inter-annotator agreement (kappa) was 0.72, 0.76, 0.79, 0.81, and 0.74, respectively.
Figure 4: Examples of NLEs and extractive rationales generated from RExC for all five tasks, along with the pieces of commonsense used by RExC. Generations from the best baseline are included for direct comparison.

Figure 5: Snapshot of our human evaluation with a list of possible shortcomings.