We investigate models that can generate arbitrary natural language text (e.g., all English sentences) from a bounded, convex and well-behaved control space. We call them universal vec2text models. Such models would allow making semantic decisions in the vector space (e.g. via reinforcement learning) while the natural language generation is handled by the vec2text model. We propose four desired properties – universality, diversity, fluency, and semantic structure – that such vec2text models should possess and we provide quantitative and qualitative methods to assess them.

We implement a vec2text model by adding a bottleneck to a 250M parameters Transformer model and training it with an auto-encoding objective on 400M sentences (10B tokens) extracted from a massive web corpus. We propose a simple data augmentation technique based on round-trip translations and show in extensive experiments that the resulting vec2text model surprisingly leads to vector spaces that fulfill our four desired properties and that this model strongly outperforms both standard and denoising auto-encoders.

1 Introduction

In recent years, large language models (LLMs) have steadily improved in performance with impressive results in a large number of natural language understanding and generation tasks. LLMs are commonly used in two specific ways: First, models such as BERT (Devlin et al., 2018) have been used to obtain vector representations for input text (we call this the text2vec setting) which are then often used for natural language understanding tasks such as natural language inference, sentiment analysis, and paraphrase detection. Second, models such as T5 (Raffel et al., 2019) and GPT (Radford et al., 2019; Brown et al., 2020) have been used to generate output text based on some input text (this is commonly denoted by the text2text setting). Common applications for such models are for example machine translation (Raffel et al., 2019; Vaswani et al., 2017; Radford et al., 2019; Brown et al., 2020; Lewis et al., 2019; Song et al., 2019) and summarization (Raffel et al., 2019; Radford et al., 2019; Lewis et al., 2019; Dong et al., 2019; Edunov et al., 2019; Song et al., 2019).

In contrast to the text2vec and text2text settings described above, we focus in this paper on the vec2text setting: We explore models that take as input fixed size vectors and generate natural language text. This setting investigates a fundamental research question: Is it possible to use continuous vector spaces to control the output of LLMs? Such controllability would allow decoupling natural language generation from decision making. Then, reinforcement learning algorithms (Sutton and Barto, 2018) could be used to control the semantics in a continuous actions space and a vec2text model could turn the taken action into natural text.

While there has been a variety of prior work on vec2text models (Bowman et al., 2015; Shen et al., 2020; Cífka et al., 2018; Hu et al., 2017; Zhao et al., 2018; Li et al., 2020), the majority of such work has focused on training relatively small models on relatively small and specialized datasets (e.g. the Yelp dataset with 500K sentences with less than 16 words (Shen et al., 2020), Yahoo answers with 500K sentences (Yang et al., 2017)) for a limited set of downstream tasks such as style transfer (Zhao et al., 2018; Shen et al., 2017; Mai et al., 2020; Hu et al., 2017; Li et al., 2020). We take a different approach than prior work and investigate whether it is possible to train what we call universal vec2text models which intuitively should be able to generate arbitrary text, not just for one specific task. Furthermore, we argue that such a universal vec2text model should have a "nicely" structured input space that provides
semantic controllability over the generated text. In this paper, we focus on investigating such a universal vec2text model for the task of generating arbitrary English sentences. There are three key contributions in this paper: First, we define the vec2text setting and propose four properties that such a model should possess: universality, fluency, semantic structure, and diversity. We further derive several quantitative and qualitative analyses to assess a vec2text model in these dimensions.

Second, we implement and train a T5-based auto-encoder model on sentences extracted from the massive C4 dataset (Raffel et al., 2019) and confirm commonly held beliefs that the decoder of such models have a poorly structured input space. Similarly, we implement the denoising approach from Shen et al. (2020) and find that, while performing better than a standard auto-encoder, the input space still exhibits several deficiencies.

Third, we propose a novel approach that uses round trip translations (RTT) to obtain a nicely behaved vec2text model. Using an English-German and a German-English machine translation model, we translate all sentences in the C4 dataset to German and back to English (Table 1). We then train a T5-based auto-encoder model equipped with a bottleneck to predict the original sentences from the round-trip translated sentences. In extensive experiments, we show perhaps surprisingly that in contrast to the prior work this simple approach is sufficient to achieve all four properties.

## 2 vec2text models and their desired properties

**vec2text decoders.** In this paper, we focus on the vec2text problem where the goal is to generate sentences from a convex and well-behaved vector space (see Figure 6 for a comparison to the text2text and text2vec settings). For the sake of simplicity, we focus on generating arbitrary English sentences but the setting and approach applies to the generation of arbitrary sequences. More formally, let $\mathcal{X}$ be the set of all sequences up to a maximum length and $\mathcal{P}(\mathcal{X})$ the space of probability distributions over $\mathcal{X}$. We define vec2text models (or equivalently vec2text decoders) to be of the form $D : \mathbb{R}^d \rightarrow \mathcal{P}(\mathcal{X})$. Importantly, such vec2text decoders are assumed to be stochastic: Given an input vector, they define a distribution over sequences, often in the form of a conditional language model.

**Auxiliary text encoders.** We will often also have access to auxiliary encoders of the form $E : \mathcal{X} \rightarrow \mathbb{R}^d$ which embed text into fixed size vector embeddings. Such encoders are also encountered in the text2vec settings where the goal is to learn good features for downstream tasks (Conneau and Kiela, 2018). The key difference is that we are interested in the generative capabilities of the vec2text decoder $D$ while the auxiliary encoder $E$ only provides a way to choose vector inputs to the decoder $D$.

**Existing evaluation methods.** Previous approaches proposed a variety of evaluations for vec2text models. However, they lack a formalization of the desired properties for universal vec2text models and the evaluations to assess these properties. In previous work, downstream tasks such as sentence classification (Montero et al., 2021) or language modeling (Bowman et al., 2015) were used to assess the quality of the learned models. The downside of this type of evaluation is that the performances on these downstream tasks - especially when some finetuning is done before the evaluation - are not straightforward indicators of the quality of universal vec2text models. Other evaluations directly assess the effect of latent space traversal (e.g. interpolation) on decoded sentences (Shen et al., 2020) but they lack a comprehensive analysis of the desired properties for such models and how their evaluation relate to them.

### 2.1 Desired properties of vec2text models

To better understand what properties a vec2text model should possess we need to first have a closer look at how they work. They are essentially functions from a $d$-dimensional input space to the space of distributions over sentences. The first thing to consider is for which inputs the model should be well behaved. The naive approach would be to enforce this for arbitrary input vectors. However, this would mean that they have to work well on an unbounded input space of infinite volume which may be hard.

In this paper, we advocate for the following requirement: A “good” vec2text model should possess a bounded and convex control space $C \subset \mathbb{R}^d$ where the model is well-behaved. The intuition is that this control space $C$ is where we actually want to use the model. The convexness is important as it guarantees that any point between two points in $C$ is also in $C$. 
We propose four common sense properties that vec2text models should possess: universality, diversity, fluency, and semantic structure.

**Universality.** For each English sentence, there should be an embedding in the control space $C$ that generates sentences that have the same meaning as the initial sentence with high probability. Intuitively, this property guarantees that any meaning can be expressed through a suitable choice of input to the vec2text model.

**Diversity.** Decoding from each embedding in the compact space $C$ should have high entropy. Intuitively, this encourages that the vec2text model can express any meaning in a variety of different ways.

**Fluency.** Decoding from each embedding in the compact space $C$ should lead to valid English sentences. Intuitively, this guarantees that there are no "holes" in $C$ where the vec2text model produces sentences that are not perceived as natural by humans.

**Semantic structure.** Two embeddings in the compact space $C$ that are closeby should lead to similar distributions over sentences. Intuitively, this guarantees that the changes in meaning when the input to the vec2text model is changed is not abrupt.

### 2.2 Qualitative assessment of vec2text models

Our qualitative evaluations of vec2text models on the properties described in the previous section are made on decoded sentences generated from (i) known sentence embeddings, (ii) interpolated embeddings i.e. weighted average of the embedding of two known sentences, (iii) topic convex hull embeddings i.e. embeddings sampled from the convex hull of a set of embedded sentences from the same topic (e.g. weather, football).

The **universality** property is qualitatively assessed by checking if the sentences generated from (i) have the same meaning as the known sentences. The **diversity** property is qualitatively assessed with (ii). Here, we examine the meaning consistency (e.g. rephrasing) between the decoded sentences. The **fluency** property is qualitatively assessed with (ii) as we examine if the generated sentences are plausible and of reasonable length. The **semantic structure** property is qualitatively assessed with (ii) and (iii): for the interpolated embeddings (ii), we examine if the generated sentences exhibit a semantic smoothness when varying the interpolation weights; for the topic convex hull embeddings (iii), we examine if the generated sentences are on the same topic as the sentences used to construct the convex hull.

### 2.3 Quantitative assessment of vec2text models

Our quantitative evaluations of vec2text models on the properties described in the previous section are made on two spaces: the interpolation space $\mathcal{I}$ which contains a set of embeddings from valid English sentences and some interpolation between them, and the noise space $\mathcal{O}$ which contains a set of embeddings from valid English sentences and noise perturbed versions of these embeddings. More details can be found in Section D.

The **universality** property is tested with the reconstruction accuracy of sentences unseen during training. For the **diversity** property, we computed the entropy and the entropy per token of the sentences generated from embeddings in $\mathcal{I}$ and $\mathcal{O}$. For the **fluency** property, we computed (1) the number of tokens (# Tokens) and the max word repeat (Max Word Repeat), (2) the likelihood (LM LLH) and the likelihood per token (LM LLH / token) computed with an off-the-shelf language model. For the **diversity** property, we computed the approximate Jeffreys divergence $J^1$ between an anchor embedding and an embedding that progressively stray away from the anchor embedding by increasing the noise level or by decreasing the weight on the anchor sentence in the interpolation setting.

### 3 Method

In this section, we propose to train a T5-based universal sentence auto-encoder (Section 3.1) and how show to train it in order to obtain a good vec2text model (Section 3.2).

#### 3.1 T5-based Universal Sentence Auto-Encoder

The simplest way to learn a vec2text model is to use an auto-encoder. It is composed of two components learned jointly: an encoder (a text2vec model) $E : \mathcal{X} \to \mathbb{R}^d$ that maps the input sentence into a fixed-length vector and an auto regressive probabilistic decoder (a vec2text model) $D : \mathbb{R}^d \to \mathcal{P}(\mathcal{X})$ that maps a fixed-length vector $p$ and $q$ two distributions.

$$J(p\|q) = \begin{cases} KL(p\|q) & \text{if } p \text{ is a probability distribution,} \\ KL(q\|p) & \text{otherwise.} \end{cases}$$ with KL the Kullback-Leibler divergence.
We propose to train a T5-based auto-encoder model which makes it impossible for them to generate (750GB of text) that contains text scrapped from (Bowman et al., 2015). Their experiments mainly (2021) use T5 with a text variational auto-encoders (Raffel et al., 2019) and use the decoder part as a bottleneck (e.g. English) is translated to a pivot language (e.g. German); the translated sentence is then translated back to the source language. We relied on the publicly available English to German translation model and the German to English translation model that won the WMT21 competition (Tran et al., 2021; Akhbardeh et al., 2021) to create paraphrasing of the sentences in C4S as illustrated in Table 2. We chose German for the pivot language as it produces more word reordering variations and the translation quality is good (Zhang et al., 2019). The translations are decoded with nucleus sampling (Holtzman et al., 2019) with $p = 0.9$ as we found it to

3.2 Round-Trip Translation for Auto-encoders

In order to train a T5-based universal sentence auto-encoder, we first implemented the simplest approach that we call Vanilla AE where the input sentences match the target sentences. Previous works (Shen et al., 2020; Bowman et al., 2015) showed that Vanilla AE is not able to produce a vec2text model with satisfying properties. As a second baseline, we implemented an approach inspired from Shen et al. (2020) that we call AE + Denoising which uses denoising (Vincent et al., 2010) to mitigate the lack of structure of the vanilla approach (Shen et al., 2020; Montero et al., 2021). To do so, we corrupt the original C4S dataset by dropping words (i.e. a sequence of token in between two white space tokens) in the sentences with a fixed probability of 20%. AE + Denoising is learned by predicting the original sentence from its corrupted version as illustrated in the second row of Table 2.

As explained by Shen et al. (2020), the intuition behind using denoising with auto-encoders is that the noise constraints the auto-encoder to put similar sentences (in terms of the denoising objective) next to each other in the latent space. However, the problem with denoising is that it maps together sentences that are close in edit distance but may have completely different meanings. Ideally, we want to map semantically similar sentences next to each other. To achieve that, we investigate the use of paraphrasing in lieu of denoising. An automatic and scalable approach to create a dataset that contains the sentences and their paraphrasing is round-trip translation (RTT). As illustrated in Table 1, a sentence in a source language (e.g. English) is translated to a pivot language (e.g. German) and the translated sentence is then translated back to the source language. We relied on the publicly available English to German translation model and the German to English translation model that won the WMT21 competition (Tran et al., 2021; Akhbardeh et al., 2021) to create paraphrasing of the sentences in C4S as illustrated in Table 2. We chose German for the pivot language as it produces

\[ \min_{\theta} \sum_{i=1}^{L} p_{\theta}(t_{i}|e, t_{<i}) \]

\[ \text{vec2text} \]

In our approach, we add a bottleneck to T5 in between the encoder and the decoder. The bottleneck is composed of two simple operations: i) mean over the token axis to create a fixed-length vector followed with ii) a linear projection. Hence, in our setting the text2vec model $E$ which outputs single-token sequences (i.e. sentence embeddings) corresponds to the T5 encoder followed by the bottleneck while the vec2text model $D$ corresponds to the T5 decoder.

To create an universal vec2text model, we rely on the massive C4 dataset (Raffel et al., 2019) (750GB of text) that contains text scrapped from the web. To learn our sentence auto-encoder, we splitted the text in C4 into sentences to create the C4 sentence dataset (C4S) which contains several billions of sentences. C4S combines two key properties: it is massive (billions of sentences) and it contains a wide variety of meaning as a wide variety of sites are scrapped. Hence, we call universal auto-encoder trained on C4S with a good reconstruction accuracy.
produce diverse paraphrasing. We trained an autoencoder that we called AE + RTT where the model is tasked to predict a sentence from its paraphrasing. We chose to predict the original sentence (as done for denoising) and not the rephrased one as it avoids potential side effects like translationese.

4 Experimental results

In this section, we evaluate the different models against the metrics defined in Section 2 that test the four desired properties: universality (Section 4.1), diversity (Section 4.2), fluency (Section 4.3), and semantic structure (Section 4.4).

4.1 Universality

In this section, we evaluate the universality property of our models. To do so, we compute the reconstruction accuracy of unseen sentences for two datasets: the evaluation dataset of C4S (Eval C4S) and the paraphrasing of the sentences in the evaluation dataset of C4S (Eval C4S RTT). The accuracy is computed per token with teacher forcing.

Figure 1 shows a clear tradeoff between bottleneck size and accuracy. For bottleneck sizes 128 and higher, the accuracy for the Vanilla AE model on Eval C4S (Figure 1 left) is higher than 95%. As expected, Vanilla AE has a better score on Eval C4S than the others as it is the only model trained for perfect reconstruction. AE + RTT still retains an accuracy above 80% for bottleneck sizes equal or higher than 128. On Eval C4S RTT (Figure 1 right), the model trained with RTT performs best with more than 70% of accuracy for bottleneck size equal or higher than 128. Unsurprisingly, the accuracy of Vanilla AE and AE + Denoising are low on Eval C4S RTT compared to Eval C4S e.g. for a bottleneck size of 128, Vanilla AE went from 95% of accuracy on Eval C4S to less than 40% of accuracy on Eval C4S RTT.

The qualitative example in Section H.1 shows for the AE + RTT model the impact of the bottleneck size on the accuracy: the sentence is not well reconstructed for bottleneck sizes lower than 64 while for larger bottleneck sizes (64 and 128), the sentence is well reconstructed (either perfectly or with rephrasing). Section H.2 shows an example of sentence reconstruction for every model with a bottleneck size 128. Vanilla AE and AE + Denoising output the input sentence while AE + RTT rephrases the input sentence in various ways. In Table 7, AE + RTT rephrases the input sentence Why do you keep arguing that this is the case? into Why do you keep arguing that this is so? and Why do you keep making claims that this is the case?.

Takeaway Clear trade-off between the bottleneck size and reconstruction accuracy. The universality property can be nearly satisfied for all the models (e.g. for a bottleneck size as low as 128 all the models have reconstruction accuracy around or above 80%).

4.2 Diversity

This section focuses on the diversity of the decoded sentences. The results are presented in Figure 2 for a bottleneck size 128 while the full results are in Figure 12 (f)-(g) for the results on I, and in Figure 13 (f)-(g) for the results on O.

Figure 2 shows that when there is no interpolation (α = 1) or no noise (η = 0), AE + RTT has the highest entropy and entropy per token. This observation is consistent for bottleneck sizes above 64 (Figure 12 (f)-(g)). This relates with the observations made in the universality property section where the qualitative examples showed that the input sentences are rephrased in various ways for the models with RTT while the other models mostly reconstruct their inputs.

As shown in Figure 2, both RTT and denoising improve the entropy of the distribution of the decoded sentences when the embedding is computed from interpolation (α ≠ 1) or noise (η > 0). However, for the denoising perturbation, the surge in entropy is due to hallucinations which is a problem observed in natural language generation tasks (Ji et al., 2022; Khandelwal et al., 2019). This is shown in the second row of Table 9 where the decoded sentences are lengthy and lack consistency.
between each other in the interpolation setting: despite some words in common like *children*, the generated sentences contains lots of details that are not consistent between each others. E.g. a sentence contains *the reddish light was singing on the weather when you were on a bike* while another contains *looking for a good song while watching the TV or the sleeping girl*. The second row of Table 10 shows that the model using RTT suffers less from hallucinations as the produced sentences are of reasonable length and have better consistency. In the interpolation setting: out of the 5 decoded sentences two are about *kids/children playing* and three are about *kids/children watching*.

**Takeaway** AE + RTT is able to rephrase the same sentence in various ways and/or to produce sentences with consistency between each other. AE + Denoising either reconstructs the input like Vanilla AE or suffers from hallucinations that are characterized by lengthy sentences without consistency between each other.

![Figure 2](image)

**Figure 2:** Entropy and entropy per token of the distribution of decoded sentences for a bottleneck size 128. Decoded embeddings from interpolation (top row) or noise (bottom row).

### 4.3 Fluency

In this section, we investigate the fluency property of our models on decoded sentences from interpolated or noisy embeddings.

Figure 3 shows the results of the different models for an interpolated embedding $z = 0.5 \times z_1 + 0.5 \times z_2$ with $z_1$ and $z_2$ the embeddings of two sentences (sampled from the evaluation dataset of C4S) in function of the bottleneck size while Figure 4 reports the results for a bottleneck size fixed at 128 for different values of interpolation (top row) or noise (bottom row). The full results can be found in Figure 12 (Appendix J) for the interpolation and in Figure 13 (Appendix L). In all the figures, the dotted line corresponds to the scores computed on 100,000 sentences from the validation dataset of C4S. The likelihood and the likelihood per token are computed with a pre-trained T5 base model (without any bottleneck) that was finetuned on 1M steps on a standard auto-encoding task.

#### Length and Max Word Repeat

The number of tokens and the number of repeated word for Vanilla AE are close for all bottleneck sizes to the metrics computed on the training distribution. For bottleneck sizes up to 128, RTT also produces sentences that have similar metrics than the sentences in the training distribution. With denoising, the produced sentences are longer and have a larger maximum word repeat than the sentences in the training data distribution. The gap grows when the bottleneck size increases. This indicates that denoising creates sentences more dissimilar with the training distribution than RTT which tends to produce sentences close to the ones in the dataset in term of length. This observation is confirmed in the additional experiments of Section G where the Figure 11 shows that increasing the word dropout probability lead to longer sentences.

We can also note that for bottleneck sizes higher than 128, for both RTT and denoising the mean length of the produced sentences increase significantly. For AE + RTT, the mean length went up from 25 for a bottleneck size 128 to 45 for a bottleneck size 512 while for AE + Denoising the mean length went up from 45 to 60. As a point of comparison, 97% of the sentences in eval C4S have less than 60 tokens, hence the sentences produced by AE + Denoising are too long to be seen as natural.

#### Likelihood

Vanilla AE produces sentences that are short but not very plausible (i.e. medium LM LLH and low LM LLH / token), AE + Denoising produces sentences that are lengthy but are plausible (i.e. low LM LLH but high LM LLH / token), and AE + RTT produces sentences that are both of reasonable size (around the mean length of the dataset) and are plausible (i.e. high LM LLH).
Figure 3: Fluency metrics for various bottleneck sizes on sentences decoded from interpolated embeddings $z = 0.5 \times z_1 + 0.5 \times z_2$ with $z_1$ and $z_2$ the embedding of two sentences (from the evaluation dataset of C4S). The dotted lines correspond to the statistics computed on 100,000 sentences from C4S.

LLH and high LM LLH / token) especially for bottleneck sizes up to 128.

**Qualitative examples** These results are confirmed in the qualitative examples in the Section I where for a bottleneck size equals to 128, the decoded sentences are shown for different values of interpolation. For the Vanilla AE, the decoded sentences from the interpolated embeddings tend to be of reasonable size and are either one of the two anchors sentences or they do not make sense especially when the interpolation weights are at 60%/40%. The sentences produced by AE + Denoising are more plausible but they are lengthy especially for the interpolation weights at 60%/40%. AE + RTT produces the best sentences in term of interpolation smoothness as the sentences are both plausible and of reasonable size.

**Takeaway** AE + RTT (with a bottleneck size up to 128) satisfies the best the fluency property as it generate sentences that are both plausible and of similar length to the ones in the data distribution. The other models lack one of these two features: AE + Denoising produces plausible sentences but the denoising perturbation creates sentences too lengthy compared to the data distribution while Vanilla AE produces unlikely sentences which are of similar length with the ones in the data distribution. In addition, the bottleneck size is a crucial parameter for models using RTT or denoising: for bottleneck sizes of 256 and 512, the produced sentences are in average abnormally long compared to the ones in C4S.

**4.4 Semantic Structure**

In this section we investigate the semantic structure of the sentence representation spaces. In other words, we check if nearby embeddings produce distribution of sentences with semantic similarities as detailed and formalized in Section 2.

**Qualitative interpolation** An additional observation that can be done for the qualitative examples in Section I is that the sentences produced by AE + RTT, AE + Denoising are semantically close to the anchor sentences. Especially, the models learned with RTT produce a smooth interpolation of the meaning of the anchor sentences. For instance, in Table 10, when the interpolation weights are close to 50% (second row of the table), AE + RTT produced the sentence *There are kids that are playing with the train.* which captured the *train* word from the first anchor sentence *There are children watching a train.* and also captures the play part from the second anchor sentence *The little girl plays with the toys.*

**Jeffreys divergence** To quantitatively assess this semantic similarity, we computed the Jeffreys divergence between the distribution of sentences decoded from an anchor embedding and an embedding further and further from the anchor. Figure 5 shows that the Jeffreys divergence increases at a lower rate for the models using RTT or denoising while Vanilla AE have a large increase rate of the Jeffreys divergence. In comparison with denoising, RTT models have the lowest increase rate of Jeffreys divergence which indicates that the perturbation coming from RTT bring more semantic structure than the one from denoising.
Figure 4: Fluency metrics for a fixed bottleneck size of 128 with interpolation (top row) or noise (bottom row). The dotted line corresponds to the statistics computed on 100,000 sentences from C4S where the likelihood is computed with an off-the-shelf T5 model.

Figure 5: Jeffreys divergence between an anchor embedding and an interpolated (right) or noisy (left) embedding. The models were learned with a bottleneck size of 128.

**Topic convex hull** To further understand the semantic structure at the topic level, we uniformly (with a Dirichlet distribution) sample vectors from a topic convex hull. To do so, we first embed few sentences from the same topic as shown in Table 14 for the music topic and in Table 15 for the football topic and then randomly sample embeddings from the convex hull of the set of the embedded sentences. These sampled embeddings are then decoded to produce the sentences.

We observe that: Vanilla AE produces sentences that don’t make sense and are not on the right topic, AE + Denoising produces sentences on the right topic but part of them don’t make sense and are lengthy while AE + RTT produces sentences that both make sense and are on topic. For instance, in Table 14, AE + Denoising produces lengthy sentences that seem to make sense but do not e.g. *As for this song and which songs I love the best music.*. AE + RTT produces shorter sentences that are on topic and differ from the anchor sentences like: *Then you have to have a playback of the music.* or *Name the musical epitaph?*.

**Clustering** Given that the models nearly satisfy the universality property, we can check if the structure of the latent sentence representation space to learn about structure of the decoder. We evaluate the semantic structure of this hidden space via clustering. We embedded sentences that are from several different topics and we check if whether these embeddings are clustered by topic. More details about the embedded sentences can be found in Table 3 (Appendix E). We computed three clustering scores: the Calinski Harabasz score (Calinski and Harabasz, 1974) where higher is better, the Davies Bouldin score (Davies and Bouldin, 1979) which has a minimum of 0 and where lower is better, and the Silhouette score (Rousseeuw, 1987) which is between -1 and 1 and where higher is better.

Figure 7 shows that both RTT and denoising help with the clustering metrics. The performances
of the models generally decrease with the bottleneck size. This is another example of the accuracy/structure tradeoff where large bottleneck sizes have better reconstruction accuracies but less structure.

**Takeaway** Input perturbations like denoising or RTT are key to exhibit some semantic structure. At the sentence level, we saw thanks to the interpolation examples and the Jeffreys divergence that the models with input perturbations produce sentences that can mix the meaning of the anchors sentences. Notably, AE + RTT performed better than AE + Denoising having a lower Jeffreys divergence and more convincing qualitative examples. At the topic level, we saw thanks to the topic convex hull evaluation that AE + RTT produced sentences that are both on topic and make sense, AE + Denoising produces sentences about the right topic but a part of them do not make sense, and Vanilla AE is not able to produce sentences about the right topic nor sentences that make sense. The clustering metrics confirmed these observations as they showed that the sentences from the same topic are most scattered in the sentence representation space for Vanilla AE than for the other models.

### 4.5 Additional experiments with RTT

In this section we investigate two variations: (i) the impact of the having diverse rephrasing, (ii) the impact of combining RTT and denoising.

**Diversity of rephrasing.** To better comprehend the impact of the diversity of rephrasing on vec2text models, we trained another AE + RTT model on a round-trip translated dataset that was created using beam search (Tillmann and Ney, 2003) for decoding instead of nucleus sampling (p=0.9). Figure 8 (Section F) shows that beam search created less rephrasing than nucleus sampling (p=0.9) while Figure 9 (Section F) shows that the model trained with more diversity in the rephrasing lead to a more structure vec2text model.

**RTT combined with denoising.** RTT and denoising being orthogonal dataset modifications, we trained an AE + RTT + Denoising model that combined both perturbations. Figure 10 shows that the AE + RTT and AE + RTT + Denoising differ only marginally and that the denoising perturbation as the undesirable effect of producing longer sentences.

### 5 Other Related Work

**Unsupervised sentence embedding** Prior work on sentence embedding mainly focused on either model changes (Bowman et al., 2015; Montero et al., 2021; Zhao et al., 2018; Cífka et al., 2018; Park and Lee, 2021; Li et al., 2020) or dataset modifications (Shen et al., 2020; Montero et al., 2021). Bowman et al. (2015) showed that for a RNN-based language model using a variational auto-encoder (VAE) (Kingma and Welling, 2013) creates a more structured latent space than using a vanilla auto-encoder. However, a straightforward implementation of the VAE led to similar results than with the vanilla AE. KL cost annealing, word dropout, and historyless decoding were required to see improvements over the baseline. This limitation is confirmed by other works (Zhao et al., 2018; Shen et al., 2020; Park and Lee, 2021) which found that VAE and Adversarial Auto-encoder (AAE) (Makhzani et al., 2015) can not learn meaningful representations out of the box. Montero et al. (2021) is another example of a denoising text auto-encoder. In their work, they used RoBERTa (Liu et al., 2019) -a pre-trained transformers based model- for the encoder and a single transformer layer (Vaswani et al., 2017) for the decoder. Li et al. (2020) learned a text VAE with a pre-trained BERT (Devlin et al., 2018) encoder and a pre-trained GPT-2 decoder (Radford et al., 2019) and showed that using pre-training reduce the KL vanishing issue faced by text VAE.

**Round Trip Translation** Round Trip Translation (RTT) was used in automatic paraphrasing (Guo et al., 2021; Zhang et al., 2019), quality estimation (Moon et al., 2020; Lample et al., 2018), data augmentation for Machine Translation tasks (Vaibhav et al., 2019). To the best of our knowledge, our work is the first to use RTT in the context of text auto-encoder.

### 6 Conclusion

We introduced four desired properties for a vec2text model (universality, diversity, fluency, and semantic structure) and showed with thorough quantitative and qualitative results that learning a T5-based universal sentence auto-encoder using round-trip translations produced the best model across the properties.
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A Illustration of the different settings: text2vec, text2text, vec2text

"I feel great!" $\rightarrow$ \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} "Je me sens bien!" $\rightarrow$ "I feel great!"

(b) text2text

Figure 6: Different settings: This paper focuses on the vec2text setting.

B Illustration of Round-Trip Translation.

| Source | Language | Please join us for a fun afternoon showing of a feature film. |
|--------|----------|-------------------------------------------------------------|
| Pivot  | German   | Nehmen Sie an einem unterhaltsamen Nachmittag teil, bei dem ein Spielfilm gezeigt wird. |
| Round-Trip Translated | English | Take part in a fun afternoon watching a feature film. |

Table 1: Illustration of Round-Trip Translation.

C Visualization of the C4S datasets used to train the AE models

| Dataset     | Input Sentence | Target Sentence |
|-------------|----------------|-----------------|
| C4S         | I am going to the beach. | |
| C4S Denoising | I am going to the beach. | I am going to the beach. |
| C4S RTT     | I'm on my way to the beach. | |

Table 2: Visualization of the different datasets. Crossed-out words are dropped by denoising. Bolded words are rephrased by RTT.

D More details on evaluation and training

D.1 Evaluation Details

Evaluating these properties on the whole vector space which is of infinite volume may not be informative as parts of the space have low density of embedded valid English sentences. Instead, we evaluate our models on two bounded set $I$ and $O$ where a text2text model should be able to produce valid English sentences. On one hand, the interpolation space $I$ contains the embeddings of known valid English sentences and the linear interpolation between them: $I = \{ \alpha E(x_1) + (1 - \alpha)E(x_2) \mid x_1, x_2 \in \mathcal{E}, \alpha \in \{0.5, 0.75, 1, 1.5, 2\} \}$ with $E$ a text2vec model learned jointly with the vec2text model $D$. On the other hand, we want to assess if our models have a high density of embeddings that produce valid English sentences with some local semantic coherence around the embeddings of known valid English sentences. Hence, we define a noise space $O = \{ E(x) + u(x)/\|u(x)\|_2 \times \sigma \times \eta \mid x \in \mathcal{E}, u(x) \sim \mathcal{N}(0, I_{\dim(E(x))}), \eta \in \{0, 0.5, 1, 2, 3\} \}$ with $E$ a text2vec model learned jointly with the vec2text model, $\sigma$ the standard deviation per dimension of the embeddings, and $\eta$ the noise level.
D.2 Approximate Jeffreys divergence

In our quantitative evaluation of the semantic structure property we compute what we call the approximate Jeffreys divergence at a fix value of interpolation or noise.

Let’s take \( \{(s_{1,k}, s_{2,k})\}_{k=1,\ldots,N} \) a set of valid English sentences that will be used as anchors for the interpolation, their embeddings \( \{(e_{1,k}, e_{2,k})\}_{k=1,\ldots,N} \), the interpolation between them \( \{e_{i,k} = \alpha e_{1,k} + (1-\alpha)e_{2,k}\}_{k=1,\ldots,N} \), and a decoded sentence for each interpolation embedding \( \{s_{i,k}|s_{i,k} \sim D(e_{i,k})\}_{k=1,\ldots,N} \). For \( k \in \{1, \ldots, N\} \), \( J(D(e_{1,k}), D(e_{i,k})) \approx CE(D(e_{i,k}), s_{i,k}) - CE(D(e_{i,k}), s_{1,k}) + CE(D(e_{1,k}), s_{1,k}) - CE(D(e_{1,k}), s_{i,k}) \) with \( CE(p, t) \) the cross entropy between a distribution \( p \) and a target \( t \).

D.3 Training details

We finetuned both the encoder and the decoder of the different auto-encoders on 300,000 training steps from the publicly available t5.1.1.base checkpoint\(^2\) of a T5 base model (\( \sim 250 \) million parameters). In this model, the dimension of the embedded tokens is 768. In contrast, the bottleneck sizes that we tried are significantly lower, ranging from 16 to 512. The decoding is done with nucleus sampling (Holtzman et al., 2019) with \( p = 0.95 \) as it provides high quality and diverse sentences.

E Additional details on the clustering evaluation and metrics

For the clustering evaluation, sentences from different topics were embedded and we computed clustering metrics (Davies and Bouldin, 1979; Calinski and Harabasz, 1974; Rousseeuw, 1987) to see if the sentences from the same topics are closer to each other than sentences from different clusters. The sentences and their associated topics are described in Table 3. The results are shown in Figure 7.

```
Figure 7: Clustering metrics of embedded topics: the Calinski Harabasz score (where higher is better), the Davies Bouldin score (which has a minimum of 0 and where lower is better), and the Silhouette score (which is between -1 and 1 and where higher is better).
```

\(^2\)https://github.com/google-research/text-to-text-transfer-transformer/blob/main/released_checkpoints.md
| Football Topic |  |
|----------------|---|
| They scored four last week! |  |
| The goalkeeper made a terrible mistake. |  |
| Have you ever seen this legendary goal? |  |
| I bet you they will win next time. |  |
| Their center-back is not as good as ours. |  |
| We have the best striker in all Europe. |  |
| It will be hard to win this year’s championship. |  |

| Movie Topic |  |
|--------------|---|
| This movie was amazing! |  |
| What was this movie about? |  |
| When can I go to the cinema? |  |
| I don’t like eating popcorns at the cinema. |  |
| The comedy I saw last time was way better. |  |
| This actress is incredible. |  |
| They are a great duo. |  |

| Music Topic |  |
|--------------|---|
| I love listening to music. |  |
| I played piano for ten years. |  |
| What kind of music do you listen to? |  |
| I like the rythme and the melody of it. |  |
| My favorite artist is from Japan. |  |
| Could you play a song for us? |  |
| Best song ever. |  |

| Weather Topic |  |
|---------------|---|
| It rained for two days straight. |  |
| Remind me to take my umbrella. |  |
| My new coat is perfect against the wind. |  |
| It is especially sunny in the morning. |  |
| Do you think it is going to get cold at night? |  |
| Switzerland has the best weather. |  |
| I have to check the weather. |  |
F Comparison between RTT models

F.1 Diversity of rephrasing

In this section we compare the structure of vec2text models trained on different RTT datasets: the AE + RTT (nucleus p=0.9) which is the model used in the other sections and the AE + RTT (beam search) which is a model learned on a RTT dataset that was created using Beam Search decoding for the translation models.

Datasets The paraphrasing of the C4S dataset (C4S + RTT) was created with the nucleus sampling (p=0.9) decoding. In addition, we also created the C4S + RTT (beam search) dataset which uses beam search (Tillmann and Ney, 2003) instead of nucleus sampling for the decoding. Figure 8 shows the BLEU score (Papineni et al., 2002) between the original sentence and its rephrasing. The rephrasing produced with beam search are less diverse than the ones produced with nucleus sampling (p=0.9): for nucleus sampling, the distribution of the BLEU scores is shifted compared to beam search and with nucleus sampling only 5% of the rephrasing have a BLEU score of 100 while it is 10% with beam search. We can note that the high percentage of 0% BLEU score is an artifact of the fact that we are computing the BLEU score at the sentence level and not for an entire corpus as it was meant to be. Despite that, BLEU at the sentence level is a good indicator to distinguish the amount of paraphrasing.

Results Figure 9 shows the comparison between the AE + RTT (nucleus p=0.9) and the AE + RTT (beam search) models for the different properties of sentences decoded from two randomly picked sentences.

Fluency property. Compared with AE + RTT (beam search), AE + RTT (nucleus p=0.9) produces sentences that have a mean length closer to the ones in C4S especially for the highest values of bottleneck size (256 and 512). AE + RTT (nucleus p=0.9) produces sentences with a higher likelihood and likelihood per token compared to AE + RTT (beam search).

Semantic Structure property. The Jeffreys is lower with AE + RTT (nucleus p=0.9) than AE + RTT (beam search) which shows that the sentences produced with AE + RTT (nucleus p=0.9) are semantically closer to the anchors sentences.

Figure 8: BLEU score between the original sentences and their RTT rephrasing produced with a beam search decoding or a nucleus sampling (p=0.9) decoding.

The BLEU score is computed with the open source library sacreBLEU (https://github.com/mjpost/sacrebleu).
Diversity property. The entropy per token is slightly higher with AE + RTT (nucleus p=0.9) while the entropy is lower. The lower entropy can be explained as the produced sentences with AE + RTT (nucleus p=0.9) are shorter than the ones produced with AE + RTT (beam search).

Takeaway AE + RTT (nucleus p=0.9) is better across all the properties than AE + RTT (beam search). Hence, having more rephrasing help to learn better vec2text models.
F.2 AE + RTT + Denoising

RTT and denoising being orthogonal dataset modifications, we trained an AE + RTT + Denoising model that combined both perturbations. As for the AE + Denoising model, the word dropout rate is p=0.2. Figure 10 shows the comparisons between the different models for an interpolated embedding. AE + RTT and AE + RTT + Denoising have similar performances across all metrics. We can note that AE + RTT + Denoising produces slightly longer sentences than AE + RTT for bottleneck sizes up to 256 which is coherent with our previous observations that denoising has the side effect of creating longer sentences.

Figure 10: Comparison of the different models on interpolated embeddings $z = 0.5 \times z_1 + 0.5 \times z_2$ with $z_1$ and $z_2$ the embedding of two sentences (from the evaluation dataset of C4S). The dotted lines correspond to the statistics computed on 100,000 sentences from C4S.
The ambivalent effect of denoising

Figure 11: Impact of denoising on vec2text models.

To better understand the positive and negative effects of denoising on vec2text models, we varied the probability $p$ of word dropout (from 0.05 to 0.4) and evaluated the various denoising models on the previously defined properties. Figure 11 shows the ambivalent effect of denoising. On one hand, a higher word dropout probability rate brings some semantic structure (e.g. a lower Jeffreys) and the produced sentences are more fluent (e.g. a higher likelihood per token). On the other hand, a higher word dropout probability rate also create sentences that are significantly longer (e.g. the mean number of token for a bottleneck size of 128 goes from 35 for $p=0.05$ to nearly 60 for $p=0.4$), hence not natural. In comparison, the RTT model produces sentences that are both more fluent and with a mean sentence length closer to the one in the training data distribution.
H Universality Property Qualitative Examples

H.1 AE + RTT model with various bottleneck sizes

| Embedded sentence: Our mom painted our old car in red. |
|--------------------------------------------------------|
| Our mom already had our old umbrella with mirror in it. | My mother brought our Christmas exteriors in white. |
| Our mom got rid of the old dresser from our beehive.   | Our mom had painted her old car on black. |
| Our dad made this favorite bread out of white cake.    | Our mother painted our old car red. |
| You should get flowers from me at Allover Foster’s Backpacks. | Our mom painted our old car red. |
| Our mom decorated a vintage campfire for my home.      | My family got our hats dyed browns today. |
| Our mom designed a pine tree for me for that same occasion. | Our mother painted our old car red. |
| Our mom was setting the chalkboard in our living room. | Our mom had painted her old windshield on Christmas. |
| Our Dad brought home a beautiful orange kernel of bread for us! | My mom framed our wintergreens on the front window. |
| Our Mother made a pillar from my rustic shelf. bread took our name because of our great-grandparent’s Katherine. | My family has been painting the hats olive with ours this winter. |

Table 4: Decoding of the embedding of a sentence for AE + RTT with a bottleneck size = 16 (left) and 32 (right).

| Embedded sentence: Our mom painted our old car in red. |
|--------------------------------------------------------|
| Our mum painted our old car red. | Our mom painted our old car in red. |
| Our mother painted our old car in red. | Our mom painted our old car red. |
| Our mom painted our old car red. | Our mom painted our old car red. |
| Our mother repainted our old car red. | Our mom painted our old car red. |
| Our Mom painted the old wagon red. | Our mom painted our old car in red paint. |
| Our Mom painted our old car red. | Our mother painted our old car in red. |
| Our mom painted our old car red. | Our mom painted our old car red. |
| Our mom painted our old car red. | Our mom painted our old car in red. |
| Our mother painted our old car red. | Our mom painted our old car red. |
| Our mom painted our old car red. | Our mom painted our old car red. |

Table 5: Decoding of the embedding of a sentence for AE + RTT with a bottleneck size = 64 (left) and 128 (right).

H.2 Bottleneck size = 128 with various models

| Embedded sentence: Why do you keep arguing that this is the case? |
|---------------------------------------------------------------|
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |
| Why do you keep arguing that this is the case? | Why do you keep arguing that this is the case? |

Table 6: Decoding of the embedding of a sentence for Vanilla AE (left) and Denoising AE (right) with a bottleneck size = 128.
| Embedded sentence: Why do you keep arguing that this is the case? |
|---------------------------------------------------------------|
| Why do you keep arguing that this is the way it is?           |
| Why do you repeatedly pretend it does this?                  |
| Why do you keep arguing that this is true?                   |
| Why do you keep arguing that this is the case?               |
| Why do you keep arguing that this is so?                     |
| Why do you go on over and over that this is the case?        |
| Why do you keep arguing that this is the case?               |
| Why do you argue this is always true?                        |
| Why do you keep making claims that this is the case?         |
| Why are you still arguing against that?                      |

Table 7: Decoding of the embedding of a sentence for AE + RTT with a bottleneck size = 128.

I Qualitative interpolation between two sentences

In this section, we check if an example of interpolation between two anchor sentences for the various models. We take the weighted average of the embedding of two sentences (Sentence A and Sentence B) and decode (5 times) the embedding $z = \alpha E(A) + (1 - \alpha) E(B)$ with $E$ an encoder learned jointly with the vec2text models and $\alpha \in \{0, 0.2, 0.4, 0.6, 0.8, 1\}$.

As shown in the Table 8, for Vanilla AE, traversing the latent space produces sentences that are either the exact anchor sentences (Sentence A or B) or do not make sense (second row of Table 8).

Table 9 shows the sentences produced by AE + Denoising for the interpolation between two sentences. For $\alpha \in \{0, 1\}$, the anchor sentences are either perfectly reconstructed or some small variations can occur (i.e. several or some are added to the original sentence for $\alpha = 1$). For $\alpha \in \{0.4, 0.6\}$ (second row of Table 9), i.e. when the interpolated embedding is the further away from the anchor embeddings, the produced sentences are very long as noticed by the quantitative metrics and some of the sentences do not really make sense like This little girl knows little children and plays with the toys.

Table 10 shows the sentences produced by AE + RTT for the interpolation between two sentences. For $\alpha \in \{0, 1\}$, the anchor sentences are either perfectly reconstructed or are rephrased e.g. plays is changed with is playing, watch is rephrased with watching or who observe, and children is changed to kids. For $\alpha \in \{0.4, 0.6\}$ (second row of Table 10), i.e. when the interpolated embedding is the further away from the anchor embeddings, the produced sentences are of reasonable length, make sense, and some mix the two anchor sentences e.g. There are kids that are playing with the train combines the playing from the sentence A and the train from sentence B.
Table 8: A qualitative example of interpolation with the Vanilla AE model.
Sentence A: The little girl plays with the toys. Sentence B: There are children watching a train.

| Weight Combination     | Result Sentence | Result Sentence |
|------------------------|-----------------|-----------------|
| 1.0*E(A) + 0.0*E(B)    | The little girl plays with the toys. | The little girl plays with the toys. |
|                        | The little girl plays with the toys. | The little girl plays with the toys. |
|                        | The little girl plays with the toys. | The little girl plays with the toys. |
|                        | The little girl plays with the toys. | The little girl plays with the toys. |
|                        | The little girl plays with the toys. | The little girl plays with the toys. |
|                        | The little girl plays with the toys. | The little girl plays with the toys. |
| 0.6*E(A) + 0.4*E(B)    | The little girl are observing the health. | There are little children watching a kam force. |
|                        | The little girl are watching the phenomena. | In children are the worse seen. |
|                        | The little girl are recordings where a the. | In children are the mentioned play. |
|                        | The little girl are drinks. | In children are the least ride to brain. |
|                        | The little girl are watching agents. | There are little children watching. |
| 0.2*E(A) + 0.8*E(B)    | There are children watching a train. | There are children watching a train. |
|                        | There are children watching a train. | There are children watching a train. |
|                        | There are children watching a train. | There are children watching a train. |
|                        | There are children watching a train. | There are children watching a train. |
|                        | There are children watching a train. | There are children watching a train. |
|                        | There are children watching a train. | There are children watching a train. |
Table 9: A qualitative example of interpolation with the AE + Denoising model.  
Sentence A: The little girl plays with the toys. Sentence B: There are children watching a train.

|                      | 1.0*E(A) + 0.0*E(B)          | 0.8*E(A) + 0.2*E(B)          |
|----------------------|-----------------------------|------------------------------|
| The little girl      | The little girl plays with  | The little girl plays with   |
| plays with the toys. | the toys.                   | the kids and toys.           |
|                      | The little girl plays with  | The little girl plays with   |
|                      | the toys.                   | the toys.                    |
|                      | The little girl plays with  | The little girl plays with   |
|                      | the toys.                   | the toys.                    |
|                      | The little girl plays with  | The little girl plays with   |
|                      | the toys.                   | the toys.                    |

|                      | 0.6*E(A) + 0.4*E(B)          | 0.4*E(A) + 0.6*E(B)          |
|----------------------|-----------------------------|------------------------------|
| This is where the   | This is where the little    | This year the children are   |
| little children     | children get to play and    | finding the same magic with  |
| get to play and     | dress up while they enjoy   | that idea of seeing what the |
| dress up while      | playing with the funky      | reddish light was singing   |
| they enjoy         | team play blocker pancakes | on the weather when you      |
| playing with the   | and swimming in a pool.     | were on a bike.              |
| toys.              | This little puppeteer is   | We know that your little    |
|                    | cat food for kids and the  | boy and toddler children    |
|                    | children while playing.     | are always watching the odd |
|                    | This little girl has tiny  | grasshopper and the         |
|                    | little children playing the| hippopotamus.                |
|                    | jigsaw.                     | It sounds like your children |
|                    | This week the girl and her | are watching a little snow   |
|                    | little cubby children       | girl playing with the lights |
|                    | played with the wall       | It means that the children  |
|                    | swings and the basket      | are always looking for a    |
|                    | spins and spins around     | good song while watching    |
|                    | with the chandeliers.      | the TV or the sleeping      |
|                    | This little girl knows     | girl.                        |
|                    | little children and plays  | And some children are there |
|                    | with the toys.              | to let out a lively singing |
|                    |                             | and playing every day with  |
|                    |                             | the walking and the flying  |
|                    |                             | shows.                      |

|                      | 0.2*E(A) + 0.8*E(B)          | 0.0*E(A) + 1.0*E(B)          |
|----------------------|-----------------------------|------------------------------|
| That way children    | That way children are       | There are some children     |
| are watching a      | watching a piano play       | watching a train.           |
| piano play with     | with a train.               | There are children watching |
| a train.            | That day children are       | a train.                    |
|                     | watching a softball game    | That is why children are     |
|                     | on the christmas tree on    | watching the train on the   |
|                     | the Christmas morning train.| overtaking train.            |
|                     | That is why children are    | That they the children are  |
|                     | watching the train on the   | watching from a snowmobile  |
|                     | overtaking train.           | on a tractor cable car.      |
|                     | That means children are     | That means children are      |
|                     | watching a train with their| watching a train with their  |
|                     | little dog.                 | little dog.                  |
Table 10: A qualitative example of interpolation with the AE + RTT model.
Sentence A: The little girl plays with the toys. Sentence B: There are children watching a train.

| 1.0*E(A) + 0.0*E(B) | 0.8*E(A) + 0.2*E(B) |
|----------------------|----------------------|
| Oh, the little girl playing with the toys. The little girl is playing with the toys. The little girl play with the toys. The little girl is playing with the toys. The baby girl is playing with the toys. | This little girl played with the toys. The little child plays with the toys. The little one loves playing with the characters. The little girl is playing with the toys. |
| 0.6*E(A) + 0.4*E(B) | 0.4*E(A) + 0.6*E(B) |
| Aladdin Watching Children Playing. The kids are playing with the lights. The little one looks at play on the terms of the two. children play games with the tree. Kids are playing and playing with the toys. | Kids rewatch. The children are playing with the SCENES. Children watching the race. There are kids that are playing with the train. |
| 0.2*E(A) + 0.8*E(B) | 0.0*E(A) + 1.0*E(B) |
| Those kids are looking at the tops and watching the trains. There’s a kid watching a train. There are children watching a train. There are children watching the train. Having children watching a train. | There are children watching a train. There are children who observe a train. There are children who watch a train. There are children watching a train. |

Table 11: A qualitative example of interpolation with the Vanilla AE model.
Sentence A: We can eat whenever you want. Sentence B: Let’s not eat yet.

| 1.0*E(A) + 0.0*E(B) | 0.8*E(A) + 0.2*E(B) |
|----------------------|----------------------|
| We can eat whenever you want. We can eat whenever you want. We can eat whenever you want. We can eat whenever you want. We can eat whenever you want. | We can eat whenever you want. We can eat whenever you want. We can eat whenever you want. We can eat whenever you want. We can eat whenever you want. |
| 0.6*E(A) + 0.4*E(B) | 0.4*E(A) + 0.6*E(B) |
| We can eat’t. We can’t eat vorbei by everyone. We can’ eat here not wants. We can’ eat here not attract. We can’t eat those by. | Our can eat’t not. Our can’t eat here is Don. Our can’t eat. Our can’t eat vorbei by you. Our can’t eat. |
| 0.2*E(A) + 0.8*E(B) | 0.0*E(A) + 1.0*E(B) |
| Let’s not eat yet. Let’s not eat yet. Let’s not eat yet. Let’s not eat yet. Let’s not eat yet. | Let’s not eat yet. Let’s not eat yet. Let’s not eat yet. Let’s not eat yet. Let’s not eat yet. |
Table 12: A qualitative example of interpolation with the AE + Denoising model. 
Sentence A: We can eat whenever you want. Sentence B: Let’s not eat yet.

| Interpolated Proportion | Original Sentences |
|-------------------------|--------------------|
| 1.0*E(A) + 0.0*E(B)    | We can eat them whenever you want. We can eat whenever you want. We can eat whenever you want. We can eat whenever you want. We can eat and drink whenever you want. |
|                         | 0.8*E(A) + 0.2*E(B) | We can eat there whenever you want. We can eat whenever you want. We can eat lunch whenever you want. We can eat whenever you want. We can eat it whenever you want. |
| 0.6*E(A) + 0.4*E(B)    | We can eat it for breakfast whenever you want. We can eat together whenever we want. We can eat pizzas if we please them and wish we had a delightful holiday perhaps. We can eat it anytime and whenever you want. We can eat here for dinner whenever you want. |
|                         | 0.4*E(A) + 0.6*E(B) | She told him that he couldn’t not eat immediately for breakfast yet. She suggested we wouldn’t eat for food today either. Let’s eat whenever we can without filling so much with food. Let’s eat lunch whenever not yet. She CAN’T EAT when they sit here just yet. |
| 0.2*E(A) + 0.8*E(B)    | Let’s not eat yet. Let’s not eat yet. Let’s not eat together yet. Let’s eat our way through and not yet. Let’s not eat yet. |
|                         | 0.0*E(A) + 1.0*E(B) | Let’s not eat fish yet. Let’s not eat heartily yet. Let’s not eat yet. Let’s not eat all the talks yet. Let’s not eat forever yet. |
Table 13: A qualitative example of interpolation with the AE + RTT model.
Sentence A: We can eat whenever you want. Sentence B: Let’s not eat yet.

| Weighting | Sentence A | Sentence B |
|-----------|------------|------------|
| 1.0*E(A) + 0.0*E(B) | We can eat whenever you want. | We can eat anytime you are in need. |
|           | We can eat whenever you want. | We’ll eat if you want. |
|           | We can eat, if you want.      | I can eat what you want. |
|           | We can eat any time you want.  | We can eat whatever we want. |
|           | We eat whenever you want.      | Can eat whenever you want. |
| 0.6*E(A) + 0.4*E(B) | We can eat out whenever you please. | Lets eat it for free. |
|           | We can eat whatever we want.   | Let’s eat as we please. |
|           | We can eat however we want to.  | Let’s eat it if you like. |
|           | We can eat as long as you like. | Let’s eat it. |
|           | We can eat it when we want.    | Let’s eat what we want a chance of. |
| 0.2*E(A) + 0.8*E(B) | Let’s not eat them yet.         | Let’s not eat yet. |
|           | Let’s not eat yet.              | Let’s eat more, not eating less. |
|           | Let’s eat it ain’t.             | Let’s not eat yet. |
|           | Let’s not eat yet.              | Let’s don’t eat yet. |
|           | Let’s not eat yet.              | Let’s not eat yet. |
J Quantitative interpolation between two sentences

Figure 12 shows the full quantitative metrics for the interpolation between two sentences evaluation.

Figure 12: Quantitative results on the compact set $I$ that contains different values of interpolation.
(c)
In this section, we show additional topic convex hull evaluation examples: one for the music topic (Table 14) and one for the football topic (Table 15).

Table 14: Decoding of vectors sampled randomly within a topic convex hull. The sentences chose in this evaluation are on the music topic.

| Music Topic                                                                 |
|----------------------------------------------------------------------------|
| I love listening to music.                                                |
| You played piano for ten years.                                          |
| What kind of music do you listen to?                                     |
| We like the rhythm and the melody of it.                                 |
| My favorite artist is from Japan.                                        |
| Could you play a song for us?                                            |
| Best song ever.                                                          |
| She <extra_id_26>                                                        |
| He like Susan.                                                           |
| My use thé than you research’ festival.                                  |
| My love youtube for the experiments in.                                  |
| She ability of 30 played at the year.                                   |
| My love you.                                                             |
| She popular abilities for me.                                           |
| She possible://80 lectures to you member                                 |
| She best applications for the talking.                                   |
| Our sound like you can eat ministries).                                  |
| AE + Denoising                                                           |
| Everything I do has my kids love playing the music.                      |
| As a Kubaian ifa play is a superb song and you want to play it with me?  |
| As a piano player I have played a piano for years.                       |
| Have a gift for the kind of music you play?                              |
| As the tracker you are playing is a great way to get your music playing right on your big screen. |
| As for this song and which songs I love the best music.                  |
| I love listening to and experiencing music played.                       |
| Would you play a song for me?                                           |
| What kind of music did you love the best track?                          |
| One might think this family member is the perfect Happy times music favorite for the new frogborns of the Californian saxophonists of western. |
| AE + RTT                                                                  |
| was it an appropriate song?                                              |
| I like the cut of the song.                                              |
| What kind of music do you guys enjoy?                                    |
| Then you have to have a playback of the music.                          |
| Branded Best of State.                                                   |
| In my local area I like to listen to music.                              |
| The one I love most is the podcast.                                     |
| How lovingly listen to this stuff that I usually do when I want to dance.| |
| Name the musical epitaph?                                                |
| A favorite thing is to listen to it, so pretty too.                      |
Table 15: Decoding of vectors sampled randomly within a topic convex hull. The sentences chose in this evaluation are on the football topic.

| Football Topic                                                                 |
|--------------------------------------------------------------------------------|
| They scored four last week!                                                    |
| The goalkeeper made a terrible mistake.                                       |
| Have you ever seen this legendary goal?                                       |
| I bet you they will win next time.                                            |
| Their center-back is not as good as ours.                                     |
| We have the best striker in all Europe.                                       |
| It will be hard to win this year’s championship.                             |
|                                                                              |
| Vanilla AE                                                                    |
| We have the bestim being vana more.                                           |
| And have youm successful to the gold.                                        |
| We have the best striker.                                                     |
| Inhe willVAL 2, your been to support Florida and                             |
| We be1% department’s last you can change the stage.                           |
| The goalen held a terrible dividend as richtig.                              |
| And spent their belty will not great.                                         |
| This beers senior d like the last game excellence,”                           |
| You havet much Freiburg://www.                                                |
| This have goal youal laughed from the last series,” confirmed.                |
|                                                                              |
| AE + Denoising                                                                |
| this time you have to bet you have been the best of the cut team this year.   |
| We bet you will be the only one who has scored multiple times in the last year!|
| We scored deserve to have proven to be the last rookie in the Westbrook United goal. |
| He hopes the sprinters look like center or aren’t as good after all except their matches.” |
| In fact I think Sweden have just a made the last right and probably the worst goal. |
| Our lucky win will make a point and be a great goalkeeper because John has a real talent at the same time. |
| Have you ever seen him strike a perfect balance with the best in racing.     |
| In a week a Bengals team will again be the man to be the ninth and third best in the tournament to earn a league victory. |
| This team won and will be a big help to the boys XXL team as they record their best game of the year. |
| I bet they have your best goal of the day already.                            |
|                                                                              |
| AE + RTT                                                                      |
| They have to give it a try next season.                                       |
| Whoa, D’ghetto We have been the victors.                                     |
| You guys have managed to be the winner of this one.                          |
| They even had a very big buck of success in this fight.                      |
| We’ve finished on the top one though.                                         |
| Away you go the champions, thief.                                             |
| We have the best victory in the races.                                        |
| Have you encountered the biggest finish yet?                                 |
| This makes your second bracket excellent.                                    |
| We have won the flagship event!                                               |
L. Full results for the noise experiments

The full results on the compact noise space $O$ are shown in Figure 13.

Figure 13: Full quantitative results on the compact set $O$ that contains different values of noise around the embedding.
(c) Bottleneck size = 16
   Bottleneck size = 32
   Bottleneck size = 64

(d) Bottleneck size = 128
   Bottleneck size = 256
   Bottleneck size = 512
