Hierarchical Sketch Induction for Paraphrase Generation

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Abstract

We propose a generative model of paraphrase generation, that encourages syntactic diversity by conditioning on an explicit syntactic sketch. We introduce Hierarchical Refinement Quantized Variational Autoencoders (HRQ-VAE), a method for learning decompositions of dense encodings as a sequence of discrete latent variables that make iterative refinements of increasing granularity. This hierarchy of codes is learned through end-to-end training, and represents fine-to-coarse grained information about the input. We use HRQ-VAE to encode the syntactic form of an input sentence as a path through the hierarchy, allowing us to more easily predict syntactic sketches at test time. Extensive experiments, including a human evaluation, confirm that HRQ-VAE learns a hierarchical representation of the input space, and generates paraphrases of higher quality than previous systems.

1 Introduction

Humans use natural language to convey information, mapping an abstract idea to a sentence with a specific surface form. A paraphrase is an alternative surface form of the same underlying semantic content. The ability to automatically identify and generate paraphrases is of significant interest, with applications in data augmentation (Iyyer et al., 2018), query rewriting, (Dong et al., 2017) and duplicate question detection (Shah et al., 2018).

While autoregressive models of language (including paraphrasing systems) predict one token at a time, there is evidence that in humans some degree of planning occurs at a higher level than individual words (Levelt, 1993; Martin et al., 2010). Prior work on paraphrase generation has attempted to include this inductive bias by specifying an alternative surface form as additional model input, either in the form of target parse trees (Iyyer et al., 2018; Chen et al., 2019a; Kumar et al., 2020), exemplars (Meng et al., 2021), or syntactic codes (Shu et al., 2019; Hosking and Lapata, 2021). Most of these approaches suffer from an ‘all or nothing’ problem: the target surface form must be fully specified during inference. However, predicting the complete syntactic structure is almost as difficult as predicting the sentence itself, negating the benefit of the additional planning step.

In this paper, we propose a generative model for paraphrase generation, that combines the diversity introduced by an explicit syntactic target with the tractability of models trained end-to-end. Shown in Figure 1, the model begins by assuming the existence of some semantic content $z_{\text{sem}}$. Conditioned on this semantic information, the model predicts a syntactic ‘sketch’ in the form of a hierarchical set of syntactic codes $q_d$, that describe the output syntactic form at increasing levels granularity. These are combined to give a syntactic embedding $z_{\text{syn}}$, which is fed to the decoder along with the original semantic content to generate the output sentence $y$. During training, the encoder is driven by a paraphrase $x_{\text{sem}}$ and a syntactic exemplar $x_{\text{syn}}$.

Figure 1: The generative models underlying our approach. Given some semantic content $z_{\text{sem}}$, we predict a hierarchical set of syntactic codes $q_d$ that describe the output syntactic form at increasing levels granularity. These are combined to give a syntactic embedding $z_{\text{syn}}$, which is fed to the decoder along with the original semantic content to generate the output sentence $y$. During training, the encoder is driven by a paraphrase $x_{\text{sem}}$ and a syntactic exemplar $x_{\text{syn}}$. 
coder that generates the final output utterance $y$. Choosing a discrete representation for the sketch means it can be predicted from the meaning as a simple classification task, and the hierarchical nature means that the joint probability over the codes admits an autoregressive factorisation, making prediction more tractable.

The separation between $z_{sem}$ and $z_{syn}$ is induced by a training scheme introduced in earlier work (Hosking and Lapata, 2021; Huang and Chang, 2021) and inspired by prior work on separated latent spaces (Chen et al., 2019b; Bao et al., 2019), whereby the model must reconstruct a target output from one input with the correct meaning, and another input with the correct syntactic form. To learn the discretized sketches, we propose a variant of Vector-Quantized Variational Autoencoders (VQ-VAE, or VQ) that learns a hierarchy of embeddings within a shared vector space, and represents an input encoding as a path through this hierarchy. Our approach, which we call Hierarchical Refinement Quantized Variational Autoencoders or HRQ-VAE, leads to a decomposition of a dense vector into embeddings of increasing granularity, representing high-level information at the top level before gradually refining the encoding over subsequent levels.

Our contributions are summarized as follows:

- We propose a generative model of natural language generation, HRQ-VAE, that induces a syntactic sketch to account for the diversity exhibited by paraphrases. We present a parameterization of our generative model that is a novel method for learning hierarchical discretized embeddings over a single latent encoding space. These embeddings are trained end-to-end and jointly with the encoder/decoder.
- We use HRQ-VAE to induce hierarchical sketches for paraphrase generation, demonstrating that the known factorization over codes makes them easier to predict at test time, and leads to higher quality paraphrases.

## 2 Latent Syntactic Sketches

### 2.1 Motivation

Let $y$ be a sentence, represented as a sequence of tokens. We assume that $y$ contains semantic content, that can be represented by a latent variable $z_{sem}$. Types of semantic content might include the description of an image, or a question intent. However, the mapping from semantics to surface form is not unique: in general, there is more than one way to express the semantic content. Sentences with the same underlying meaning $z_{sem}$ but different surface form $y$ are paraphrases. Standard approaches to paraphrasing (e.g., Bowman et al. 2016) map directly from $z_{sem}$ to $y$, and do not account for this diversity of syntactic structure.

Following recent work on syntax-guided paraphrasing (Chen et al., 2019a; Hosking and Lapata, 2021), and inspired by evidence that humans plan out utterances at a higher level than individual words (Martin et al., 2010), we introduce an intermediary sketching step, depicted in Figure 1b. We assume that the output sentence $y$ is generated as a function both of the meaning $z_{sem}$ and of a syntactic encoding $z_{syn}$ that describes the structure of the output. Moreover, since natural language displays hierarchical organization in a wide range of ways, including at a syntactic level (constituents may contain other constituents), we also assume that the syntactic encoding $z_{syn}$ can be decomposed into a hierarchical set of discrete latent variables $q_{1:D}$, and that these $q_d$ are conditioned on the meaning $z_{sem}$. This contrasts with popular model architectures such as VAE (Bowman et al., 2015) which use a flat internal representation in a dense Euclidean vector space.

Intuitively, our generative model corresponds to a process where a person thinks of a message they wish to convey; then, they decide roughly how to say it, and incrementally refine this decision; finally, they combine the meaning with the syntactic sketch to ‘spell out’ the sequence of words making up the sentence.

### 2.2 Factorization and Objective

The graphical model in Figure 1b factorizes as

$$p(y, z_{sem}) = \sum_{q_{1:D}, z_{syn}} p(y | z_{sem}, z_{syn}) \times p(z_{syn} | q_{1:D}) \times p(z_{sem}) \times p(q_d | q_{<d}; z_{sem}).$$  \hspace{1cm} (1)

Although $q_{1:D}$ are conditionally dependent on $z_{sem}$, we assume that $z_{sem}$ may be determined from $y$ without needing to explicitly calculate $q_{1:D}$ or $z_{syn}$. We also assume that the mapping from discrete codes $q_{1:D}$ to $z_{syn}$ is a deterministic func-
We assume a Gaussian distribution for $q$. The posterior therefore factorises as

$$
\phi(z_{sem}, z_{sym}|y) = \phi(z_{sem}|y) \times \phi(z_{sym}|y) \\
\times \phi(q_1|z_{sym}) \times \prod_{d=2}^{D} \phi(q_d|q_{<d}, z_{sym}).
$$

(2)

The separation between $z_{sem}$ and $q_1:D$, such that they represent the meaning and form of the input respectively, is induced by the training scheme. During training, the model is trained to reconstruct a target $y$ using $z_{sem}$ derived from an input with the correct meaning (a paraphrase) $x_{sem}$, and $q_1:D$ from another input with the correct form (a syntactic exemplar) $x_{sym}$. Hosking and Lapata (2021) showed that the model therefore learns to encode primarily semantic information about the input in $z_{sem}$, and primarily syntactic information in $q_1:D$. Exemplars are retrieved from the training data following to the process described in Hosking and Lapata (2021), with examples in Appendix C. The setup is shown in Figure 1a; in summary, during training we set $\phi(z_{sem}|y) = \phi(z_{sem}|x_{sem})$ and $\phi(q_d|y, q_{<d}) = \phi(q_d|x_{sym}, q_{<d})$. The final objective is given by

$$
\text{ELBO} = E_{\phi} \left[ -\log p(y|z_{sem}, q_1:D) \right] \\
- \log p(q_1|z_{sem}) - \sum_{d=2}^{D} \log p(q_d|q_{<d}; z_{sem}) \\
+ KL\left( \phi(z_{sem}|x_{sem}) || p(z_{sem}) \right),
$$

(3)

where $q_d \sim \phi(q_d|x_{sym})$ and $z_{sem} \sim \phi(z_{sem}|x_{sem})$.

3 Neural Parameterisation

We assume a Gaussian distribution for $z_{sem}$, with prior $p(z_{sem}) \sim \mathcal{N}(0, 1)$. The encoders $\phi(z_{sem}|x_{sem})$ and $\phi(z_{sym}|x_{sym})$ are Transformers (Vaswani et al., 2017), and we use an autoregressive Transformer decoder for $p(y|z_{sem}, z_{sym})$. The mapping $f_{q\rightarrow z}(\cdot)$ from $q_1:D$ to $z_{sym}$ and the posterior network $\phi(q_d|q_{<d}, z_{sym})$ are more complex, and form a significant part of our contribution.

Our choice of parameterization is learned end-to-end, and ensures that the sketches learned are hierarchical both in the shared embedding space and in the information they represent.

3.1 Hierarchical Refinement Quantization

Let $z_{sym} \in \mathbb{R}^m$ be the output of the encoder network $\phi(z_{sym}|y)$, that we wish to decompose as a sequence of discrete hierarchical codes. Recall that $q_d \in [1, K]$ are discrete latent variables corresponding to the codes at different levels in the hierarchy, $d \in [1, D]$. Each level uses a distinct codebook, $C_d \in \mathbb{R}^K \times \mathbb{R}^D$, which maps each discrete code to a continuous embedding $C_d(q_d) \in \mathbb{R}^D$.

The distribution over codes at each level is a softmax distribution, with the scores $s_d$ given by the distance from each of the codebook embeddings to the residual error between the input and the cumulative embedding from all previous levels,

$$
s_d(q) = - \left( \left| \mathbf{x} - \sum_{d'=1}^{d-1} C_d(q) \right| - C_d(q) \right)^2.
$$

(4)

Illustrated in Figure 2, these embeddings therefore represent iterative refinements on the quantization of the input. The posterior network $\phi(q_d|q_{<d}, z_{sym})$ iteratively decomposes an encoding vector into a path through a hierarchy of clusters whose centroids are the codebook embeddings.

Given a sequence of discrete codes $q_1:D$, we deterministically construct its continuous representation with the composition function $f_{q\rightarrow z}(\cdot)$,

$$
z_{sym} = f_{q\rightarrow z}(q_1:D) = \sum_{d=1}^{D} C_d(q_d).
$$

(5)

HRQ-VAE can be viewed as an extension of VQ-VAE (van den Oord et al., 2017), with two significant differences: (1) the codes are hierarchically ordered and the joint distribution $p(q_1, \ldots, q_D)$ admits an autoregressive factorization; and (2) the HRQ-VAE composition function is a sum, compared to concatenation in VQ or a complex neural network in VQ-VAE 2 (Razavi et al., 2019). Under HRQ, latent codes describe a path through the learned hierarchy within a shared encoding space. The form of the posterior $\phi(q_d|q_{<d}, z_{sym})$ and the composition function $f_{q\rightarrow z}(\cdot)$ do not rely on any particular properties of the paraphrasing task; the technique could be applied to any encoding space.

Initialisation Decay  Smaller perturbations in encoding space should result in more fine grained changes in the information they encode. Therefore, we encourage ordering between the levels of hierarchy (such that lower levels encode finer grained information) by initialising the codebook with a decaying scale, such that later embeddings have a smaller norm than those higher in the hierarchy. Specifically, the norm of the embeddings at level $d$ is weighted by a factor $(\alpha_{init})^{d-1}$.
we sample from the sketch prediction model $z$

where $\gamma$

within the encoding space to correspond to hierar-

The output of the quantizer is then given by

d = 1 \Rightarrow z = e_{red}^d$

d = 2 \Rightarrow z = e_{red}^d + e_{stripes}^d$

d = 3 \Rightarrow z = e_{red} + e_{stripes}$

**Depth Dropout** To encourage the hierarchy within the encoding space to correspond to hierarchical properties of the output, we introduce depth dropout, whereby the hierarchy is truncated at each level during training with some probability $p_{\text{depth}}$. The output of the quantizer is then given by

$$z_{\text{syn}} = \sum_{d=1}^{D} \left( C_d(q_d) \prod_{d'=1}^{d} \gamma_{d'} \right),$$

where $\gamma_{d} \sim \text{Bernoulli}(1 - p_{\text{depth}})$. This means that the model is sometimes trained to reconstruct the output based only on a partial encoding of the input, and should learn to cluster similar outputs together at each level in the hierarchy.

### 3.2 Sketch Prediction Network

During training, the decoder is driven using sketches sampled from the encoder, but at test time exemplars are unavailable and we must predict a distribution over syntactic sketches $p(q_{1:D} | z_{\text{sem}})$. Modelling the sketches as hierarchical ensures that this distribution admits an autoregressive factorization.

We use the splits released by Hosking and Lapata (2016) for the discrete codes and the standard Gaussian reparameterisation for the semantic representation. To encourage the model to use the full codebook, we decayed the Gumbel temperature $\tau$, according to the schedule given in Appendix A. We approximate the expectation in Equation (3) by sampling from the training set and updating via backpropagation (Kingma and Welling, 2014). The full model was trained jointly by optimizing the ELBO in Equation (3).

### 3.3 Training Setup

We use the Gumbel reparameterisation trick (Jang et al., 2016; Maddison et al., 2017; Sønderby et al., 2017) for the discrete codes and the standard Gaussian reparameterisation for the semantic representation. To encourage the model to use the full codebook, we decayed the Gumbel temperature $\tau$, according to the schedule given in Appendix A. We approximate the expectation in Equation (3) by sampling from the training set and updating via backpropagation (Kingma and Welling, 2014). The full model was trained jointly by optimizing the ELBO in Equation (3).

### 4 Experimental Setup

#### Datasets

A paraphrase is ‘an alternative surface form in the same language expressing the same semantic content as the original form’ (Madnani and Dorr, 2010), but it is not always clear what counts as the ‘same semantic content’. Our approach requires access to reference paraphrases; we evaluate on three English paraphrasing datasets which have clear grounding for the meaning of each sentence: Paralex (Fader et al., 2013), a dataset of question paraphrase clusters scraped from WikiAnswers; Quora Question Pairs (QQP)\(^1\) sourced from the community question answering forum Quora; and MSCOCO 2017 (Lin et al., 2014), a set of images that have been captioned by multiple annotators. For the question datasets, each paraphrase is grounded to the (hypothetical) answer they share. We use the splits released by Hosking and Lapata (2021). For MSCOCO, each caption is grounded by the image that it describes. We evaluate on the public validation set, randomly selecting one cap-

\(^1\)https://www.kaggle.com/c/quora-question-pairs
Figure 3 shows a t-SNE (van der Maaten and Hinton, 2008) plot of the syntactic encodings \( z_{\text{syn}} \) for 10,000 examples from Paralex. The encodings are labelled by their quantization, so that colours indicate top-level codes \( q_1 \), shapes denote \( q_2 \), and patterns \( q_3 \). The first plot shows clear high level structure, with increasingly fine levels of substructure visible as we zoom into each cluster. This confirms that the discrete codes are ordered, with lower levels in the hierarchy encoding more fine grained information.

To confirm that intermediate levels of hierarchy represent valid points in the encoding space, we generate paraphrases using oracle sketches, but truncate the sketches at different depths. Masking one level (i.e., using only \( q_1 \) or \( q_2 \)) reduces performance by 2.5 iBLEU points, and two levels by 5.5.
Paralex

Table 1: Top-1 paraphrase generation results, without access to oracle sketches. HRQ-V AE achieves the highest iBLEU scores, indicating the best tradeoff between quality and diversity. Paired bootstrap resampling (Koehn, 2004) indicates that HRQ-V AE significantly improves on all other systems (p < 0.05).

(iBLEU is an automatic metric for assessing paraphrase quality; see Section 5.2). Although encodings using the full depth are the most informative, partial encodings still lead to good quality output, with a gradual degradation. This implies both that each level in the hierarchy contains useful information, and that the cluster centroids at each level are representative of the individual members of those clusters.

5.2 Paraphrase Generation

Metrics Our primary metric is iBLEU (Sun and Zhou, 2012),

\[
iBLEU = \alpha \text{BLEU}(\text{outputs, references}) - (1 - \alpha) \text{BLEU}(\text{outputs, inputs}),
\]

that measures the fidelity of generated outputs to reference paraphrases as well as the level of diversity introduced. We use the corpus-level variant. Following the recommendations of Sun and Zhou (2012), we set \(\alpha = 0.8\), with a sensitivity analysis shown in Appendix A. We also report \(\text{BLEU}(\text{outputs, references})\) as well as \(\text{Self-BLEU}(\text{outputs, inputs})\). The latter allows us to examine the extent to which models generate paraphrases that differ from the original input.

To evaluate the diversity between multiple candidates generated by the same system, we report pairwise-BLEU (Cao and Wan, 2020),

\[
P\text{-BLEU} = \mathbb{E}_{i \neq j} [\text{BLEU}(\text{outputs}_i, \text{outputs}_j)],
\]

This measures the average similarity between the different candidates, with a lower score indicating more diverse hypotheses.

Table 2: Examples of generated paraphrases. HRQ-V AE is able to preserve the original meaning, while introducing significant syntactic variation.

Automatic Evaluation Shown in Table 1, the results of the automatic evaluation highlight the importance of measuring both paraphrase quality and similarity to the input: the Copy baseline is able to achieve high BLEU scores despite simply duplicating the input. The VAE baseline is competitive but tends to have a high Self-BLEU score, indicating that the semantic preservation comes at the cost of low syntactic diversity. HRQ-V AE achieves both higher BLEU scores and higher iBLEU scores than the comparison systems, indicating that it is able to generate
higher quality paraphrases without compromising on syntactic diversity.

The examples in Table 2 demonstrate that HRQ is able to introduce significant syntactic variation while preserving the original meaning of the input. However, there is still a gap between generation using predicted sketches and ‘oracle’ sketches (i.e., when the target syntactic form is known in advance), indicating ample scope for improvement.

**Worked Example**  Since the sketches \( q_{1:D} \) are latent variables, interpretation is difficult. However, a detailed inspection of example output reveals some structure.

Table 3 shows the model output for a single semantic input drawn from Paralex, across a range of different syntactic sketches. It shows that \( q_1 \) is primarily responsible for encoding the question type, with \( q_1 = 13 \) leading to ‘what’ questions and \( q_1 = 12 \) ‘how’ questions. \( q_2 \) and \( q_3 \) correspond to more fine grained details, e.g., the outputs with \( q_3 = 6 \) all use the article ‘a’ when referring to ‘body’.

We also examine how using increasingly granular sketches refines the syntactic template of the output. Table 4 shows the model output for a single semantic input, using varying granularities of sketch extracted from the exemplar. When no sketch is specified, the model defaults to a canonical phrasing of the question. When only \( q_1 \) is specified, the output becomes a ‘how many’ question, and when a full sketch is included, the output closely resembles the exemplar.

**Generating Multiple Paraphrases**  We evaluated the ability of our system to generate multiple diverse paraphrases for a single input, and compared to the other comparison systems capable of producing more than one output. For both HRQ-VAE and Separator, we used beam search to sample from the sketch prediction network as in the top-1 case, and condition generation on the top-3 hypotheses predicted. For BTmPG, we used the paraphrases generated after 3, 6 and 10 rounds. For the VAE, we conditioned generation on 3 different samples from the encoding space. The results in Table 5 show that HRQ-VAE is able to generate multiple high quality paraphrases with more diversity between them than comparison systems.

| Table 3: Examples of model output, for a range of different sketches. The left hand side shows the sketch (i.e., the values of the codes \( q_{1:D} \)), with the corresponding model output on the right. \( q_1 \) primarily specifies the wh- word (e.g., outputs with \( q_1 = 13 \) are all ‘what’ questions), while \( q_2, q_3 \) correspond to more fine grained details, e.g., the outputs with \( q_3 = 6 \) all use the article ‘a’ when referring to ‘body’.

| Table 4: Model output for varying sketch granularities. When no sketch is used, the model defaults to the most common phrasing of the question. As more detail is included, the output converges towards the exemplar.

| Table 5: Top-3 generation results. P-BLEU indicates the similarity between the different candidates, while iBLEU scores reported are the mean across the 3 candidates. HRQ-VAE is able to generate multiple high quality paraphrases with more diversity between them than comparison systems.

| Table 5: Top-3 generation results. P-BLEU indicates the similarity between the different candidates, while iBLEU scores reported are the mean across the 3 candidates. HRQ-VAE is able to generate multiple high quality paraphrases with more diversity between them than comparison systems.
well the paraphrase reflected the meaning of the original; and the fluency of the paraphrase (see Appendix B). We evaluated a total of 300 sentences sampled equally from each of the three evaluation datasets, and collected 3 ratings for each sample. We assigned each system a score of +1 when it was selected, −1 when the other system was selected, and took the mean over all samples. Negative scores indicate that a system was selected less often than an alternative. We chose the four best performing models for our evaluation: HRQ-VAE, Separator, Latent BoW, and VAE.

Figure 4 shows that although the VAE baseline is the best at preserving question meaning, it is also the worst at introducing variation to the output. HRQ-VAE better preserves the original question intent compared to the other systems while introducing more diversity than the VAE, as well as generating much more fluent output.

5.4 Ablations

To confirm that the hierarchical model allows for more expressive sketches, we performed two ablations. We compared to the full model using oracle sketches, so that code prediction performance was not a factor. We set the depth $D = 1$ and $K = 48$, giving equivalent total capacity to the full model ($D = 3, K = 16$) but without hierarchy. We also removed the initialisation scaling at lower depths, instead initialising all codebooks with the same scale. Table 6 shows that a non-hierarchical model with the same capacity is much less expressive.

We also performed two ablations against the model using predicted sketches; we removed depth dropout, so that the model is always trained on a full encoding. We confirm that learning the codebooks jointly with the encoder/decoder leads to a stronger model, by first training a model with a continuous Gaussian bottleneck (instead of the HRQ-VAE); then, we recursively apply $k$-means clustering (Lloyd, 1982), with the clustering at each level taking place over the residual error from all levels so far, analogous to HRQ-VAE. The results of these ablations shown in Table 6 indicate that our approach leads to improvements over all datasets.

6 Related Work

Hierarchical VAEs

VQ-VAEs were initially proposed in computer vision (van den Oord et al., 2017), and were later extended to be ‘hierarchical’ (Razavi et al., 2019). However, in vision the term refers to a ‘stacked’ version architecture, where the output of one variational layer is passed through a CNN and then another variational layer that can be continuous (Vahdat and Kautz, 2020) or quantized (Williams et al., 2020; Liévin et al., 2019; Willetts et al., 2021). Unlike these approaches, we induce a single latent space that has hierarchical properties.

Other work has looked at using the properties of hyperbolic geometry to encourage autoencoders to learn hierarchical representations. Mathieu et al. (2019) showed that a model endowed with a Poincaré ball geometry was able to recover hierarchical structure in datasets, and Surís et al. (2021) used this property to deal with uncertainty in predicting events in video clips. However, their work was limited to continuous encoding spaces, and the hierarchy discovered was known to exist a priori.

Syntax-controlled Paraphrase Generation

Prior work on paraphrasing has used retrieval techniques (Barzilay and McKeown, 2001), Residual LSTMs (Prakash et al., 2016), VAEs (Bowman et al., 2016), VQ-VAEs (Roy and Grangier, 2019) and pivot languages (Mallinson et al., 2017). Syntax-controlled paraphrase generation has seen significant recent interest, as a
means to explicitly generate diverse surface forms with the same meaning. However, most previous work has required knowledge of the correct or valid surface forms to be generated (Iyyer et al., 2018; Chen et al., 2019a; Kumar et al., 2020; Meng et al., 2021). It is generally assumed that the input can be rewritten without addressing the problem of predicting which template should be used, which is necessary if the method is to be useful. Hosking and Lapata (2021) proposed learning a simplified representation of the surface form using VQ, that could then be predicted at test time. However, the discrete codes learned by their approach are not independent and do not admit a known factorization, leading to a mismatch between training and inference.

7 Conclusion

We present a generative model of paraphrasing, that uses a hierarchy of discrete latent variables as a rough syntactic sketch. We introduce HRQ-VAE, a method for mapping these hierarchical sketches to a continuous encoding space, and demonstrate that it can indeed learn a hierarchy, with lower levels representing more fine-grained information. We apply HRQ-VAE to the task of paraphrase generation, representing the syntactic form of sentences as paths through a learned hierarchy, that can be predicted during testing. Extensive experiments across multiple datasets and a human evaluation show that our method leads to high quality paraphrases. The generative model we introduce has potential application for any natural language generation task; zsem could be sourced from a sentence in a different language, from a different modality (e.g., images or tabular data) or from a task-specific model (e.g., summarization or machine translation). Furthermore, HRQ-VAE makes no assumptions about the type of space being represented, and could in principle be applied to a semantic space, learning a hierarchy over words or concepts.

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A Hyperparameters

The hyperparameters given in Table 7 were selected by manual tuning, based on a combination of:

(a) validation iBLEU scores with depth masking,
(b) validation BLEU scores using oracle sketches, and
(c) validation iBLEU scores using predicted syntactic codes.

The Gumbel temperature $\tau$ is decayed during training as a function of the step $t$, according to the following equation:

$$\tau(t) = \max(2 - \frac{2}{1 + e^{t/10000}}, 0.5). \quad (8)$$

Intuitively, this smoothly decays $\tau$ from an initial value of 2, with a half-life of 10k steps, to a minimum value of 0.5.

We use $\alpha = 0.8$ when calculating iBLEU, but as shown in Figure 5 our conclusions are not sensitive
| Encoder/decoder | Embedding dimension $D$ | 768 |
|----------------|------------------------|-----|
|                | Encoder layers         | 5   |
|                | Decoder layers         | 5   |
|                | Feedforward dimension  | 2048|
|                | Transformer heads      | 8   |
|                | Semantic/syntactic dim | 192/594|
|                | Depth $D$              | 3   |
|                | Codebook size $K$      | 16  |
|                | Optimizer              | Adam (Kingma and Ba, 2015) |
| Learning rate  | 0.01                   |
| Batch size     | 64                     |
| Token dropout  | 0.2 (Xie et al., 2017) |
| Decoder        | Beam search            |
| Beam width     | 4                      |

| Code predictor | Num. hidden layers | 2 |
|               | Hidden layer size  | 3072 |

Table 7: Hyperparameter values used for our experiments.

Table 8: Examples of the exemplar retrieval process for training. The input is tagged by a chunker, ignoring stopwords. An exemplar with the same template is then retrieved from a different paraphrase cluster. Table reproduced with permission from Hosking and Lapata (2021).

Lapata (2021). During training, we retrieve exemplars $x_{syn}$ from the training data following a process which first identifies the underlying syntax of $Y$, and finds a question with the same syntactic structure but a different, arbitrary meaning. We use a shallow approximation of syntax, to ensure the availability of equivalent exemplars in the training data. An example of the exemplar retrieval process is shown in Table 8; we first apply a chunker (FlairNLP, Akbik et al., 2018) to $Y$, then extract the chunk label for each tagged span, ignoring stopwords. This gives us the template that $Y$ follows. We then select a question at random from the training data with the same template to give $x_{syn}$. If no other questions in the dataset use this template, we create an exemplar by replacing each chunk with a random sample of the same type.

B Human Evaluation

Annotators were recruited from the UK and USA via Amazon Mechanical Turk, and were compensated for their time above a living wage in those countries. A full Participant Information Sheet was provided, and the study was approved by an internal ethics committee. Annotators were asked to rate the outputs according to the following criteria:

- Which system output is the most fluent and grammatical?
- To what extent is the meaning expressed in the original sentence preserved in the rewritten version, with no additional information added?
- Does the rewritten version use different words or phrasing to the original? You should choose the system that uses the most different words or word order.

C Exemplar Retrieval Process

Our approach requires exemplars during training to induce the separation between latent spaces. We follow the approach introduced by Hosking and Lapata (2021). During training, we retrieve exemplars $x_{syn}$ from the training data following a process which first identifies the underlying syntax of $Y$, and finds a question with the same syntactic structure but a different, arbitrary meaning. We use a shallow approximation of syntax, to ensure the availability of equivalent exemplars in the training data. An example of the exemplar retrieval process is shown in Table 8; we first apply a chunker (FlairNLP, Akbik et al., 2018) to $Y$, then extract the chunk label for each tagged span, ignoring stopwords. This gives us the template that $Y$ follows. We then select a question at random from the training data with the same template to give $x_{syn}$. If no other questions in the dataset use this template, we create an exemplar by replacing each chunk with a random sample of the same type.

D Analysis of Code Properties

We define two features of sentences: (1) the presence of common auxiliary verbs that roughly indicate the tense of the sentence (present, future, etc.); and (2) the presence of different question or 'wh'-words\(^1\). We calculate the distributions of these features for each code $q_d$ at different levels, with the results shown in Figure 6. Each column represents the distribution over the feature for a specific code. Figure 6a shows clear evidence that the sentences are (at least partly) clustered at the top level based on the verb used, while Figure 6b shows that level 2 encodes the question type.

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\(^1\)This analysis was performed for Paralex, which comprises entirely of questions.
Figure 5: iBLEU scores for all comparison systems, for a range of values of $\alpha$.

Figure 6: Plots showing the conditional distributions of two different sentence features, auxiliary verb and question type, for different values of the latent codes $q_d$. Each column represents the distribution over the feature for a specific code. The plots show that level 1 is a strong predictor of verb tense, and level 2 predicts question type, giving some insight into what syntactic features each level has learned to encode. We have reordered the columns of the plot to improve readability.