Injecting Hierarchy with U-Net Transformers

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Abstract

The Transformer architecture has become increasingly popular over the past couple of years, owing to its impressive performance on a number of natural language processing (NLP) tasks. However, it may be argued that the Transformer architecture lacks an explicit hierarchical representation, as all computations occur on word-level representations alone, and therefore, learning structure poses a challenge for Transformer models. In the present work, we introduce hierarchical processing into the Transformer model, taking inspiration from the U-Net architecture, popular in computer vision for its hierarchical view of natural images. We propose a novel architecture that combines ideas from Transformer and U-Net models to incorporate hierarchy at multiple levels of abstraction. We empirically demonstrate that the proposed architecture outperforms the vanilla Transformer and strong baselines in the chit-chat dialogue and machine translation domains.

Introduction

The recently introduced Transformer architecture (Vaswani et al., 2017) and its variants have achieved state-of-the-art performance in a number of tasks including machine translation, language modeling (Dai et al., 2019), question answering (Lan et al., 2019), and others, with Transformer-based models dominating leaderboards for multi-task benchmarks such as GLUE (Wang et al., 2018). The Transformer removes the need for sequential computation of the input sequence and instead employs a global self-attention mechanism to allow distant token positions to exchange information in a constant number of steps. In short, the Transformer operates exclusively through token-level interactions to produce contextualized embedding representations at the encoder and decoder output layers. This attention mechanism is credited with the Transformer’s continued success in the language domain.

While the Transformer has been applied most extensively in the machine translation domain, the architecture has recently found numerous applications in the dialogue domain (Wolf et al., 2019; Budzianowski and Vulic, 2019). Conversational dialogue can be thought of as a conditional language modelling task, where an output response needs to be produced in the presence of an input conversation history. In real-world dialogues, the conversation history can be extensive, and often an effective conversationalist must interpret both the low-level details of the conversation as well as the high-level trajectory (e.g. conversation sentiment and topic). It is possible that the Transformer specializes in word-level interactions through the attention mechanism, but may not store a proper representation(s) for abstract elements of the conversation at play.

The Transformer also does not take full advantage of locality. Early in training, the attention mechanism produces attention maps with full coverage over the input sequence. The architecture must learn from the data that closer positions are more consequential for the current token and then leverage the positional encodings to extract useful information from those positions. In this way, introducing locality, a bias toward closer word positions, may help to speed up training and hasten convergence. The recently proposed Star Transformer (Guo et al., 2019) introduces this dependence on local word positions through ring connections between adjacent positions and achieves improved performance. A novel architecture which utilizes locality may similarly benefit.

Since most computations in the Transformer take place at the granularity of single tokens, it may be argued that this architecture lacks an explicit mechanism for learning hierarchical representations. As a result, learning higher-level structure as well as representing context at different levels of abstraction may pose a representational challenge.

In this paper, we propose a novel U-Net Transformer architecture to address the issues outlined above 1. In the present work, we introduce hierarchical processing into the Transformer model, taking inspiration from the U-Net architecture, popular in computer vision for its hierarchical view of natural images. The U-Net architecture has produced state-of-the-art performance in semantic segmentation (Chen et al., 2018), image generation (Song and Ermon, 2019), and unsupervised alignment (Zhu et al., 2017).

We empirically demonstrate that the proposed architecture outperforms several strong baselines, including

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1Code: https://github.com/text-machine-lab/HierarchicalTransformer
a Transformer baseline, in the chit-chat dialogue and machine translation domains. In the next section, we will discuss the Transformer and U-Net architectures, along with relevant works motivating our proposed architecture. In the following section (Model Description), we describe the construction and operation of the U-Net architecture in a step-wise fashion. Throughout the remainder of the paper, we will describe the evaluation of our approach to combining the Transformer and U-Net architecture into a single model. We will describe conceptually how the novel U-Net Transformer addresses the pitfalls in the Transformer above and perform multiple evaluation methods to justify its superiority over multiple baselines. Finally, we wrap up with a discussion of the paper and its implications.

Recent Work

Inspired by the continual success of the attention mechanism (Bahdanau et al., 2014), the Transformer network (Vaswani et al., 2017) replaces the autoregressive processing of the RNN with a global attention mechanism over all tokens. The architecture is divided into an encoder and decoder, each processing input tokens using a set of self-attention modules which distribute contextual information between tokens. Each layer uses an attention module to exchange information between tokens in the sequence, while the following feed-forward layer processes this information to update the vector representation of the current token. Unlike the encoder, which allows unrestricted attention between all tokens in the sequence, the decoder uses a masked attention mechanism to allow for autoregressive generation of text (the current token cannot see future tokens).

The Transformer allows for constant time information exchange between any two positions on an input sequence. This power has allowed for impressive performance on many benchmarks. However, it has been noted that this pairwise comparison is computationally expensive, producing a run time of $O(N^2d)$ for the self-attention mechanism, where $d$ is the representation size of each token and $N$ is the number of tokens in the sequence. This runtime becomes increasingly difficult for longer sequences. Inspired by this heavy computation, works like the Star Transformer (Guo et al., 2019) and Sparse Transformer (Child et al., 2019) attempt to reduce this complexity by limiting the window of tokens available to attend over in each self-attention layer. For example, the Sparse Transformer redirects connections between tokens to reduce the complexity of self-attention to $O(n \log n)$. Another model, Transformer-XL (Dai et al., 2019) also attempts to reduce the computation for longer input sequences by segmenting the input into chunks and avoiding back-propagation through previous chunks. They show that by directly providing token information from previous chunks they can run increasingly longer sequence lengths without increasing the run time of backpropagation.

The previous variants of the Transformer aim to reduce the computational complexity of the self-attention (and cross-attention) mechanisms. However, they do not attempt to incorporate any hierarchical structure to the computation. Liu and Lapata (2019) attempt to instill a hierarchical representation by processing multiple documents and attending over them using a global attention mechanism. Similarly, Chiang et al. (2019) enable ranking of possible responses using a hierarchical representation of the input. It should be noted that these models do not apply for the task of single-document response generation (the non-ranking approach used in this paper) or other single-context generative tasks. This leaves an opportunity to provide hierarchy to these use cases.

In the quest to produce a hierarchical/abstract representation, the convolutional U-Net architecture (Ronneberger et al., 2015) serves as a powerful inspiration. This architecture has been applied a number of computer vision tasks to produce a wholesome representation of input images. For example, U-Net is used in the DeepLab v3+ architecture, which achieved state-of-the-art in semantic segmentation (Chen et al., 2018). Similarly, this architecture was used to produce an alignment between unaligned image domains in CycleGAN (Zhu et al., 2017) such that an image of a horse could be translated to one of a zebra and vice versa. For a given input image, the U-Net operates by downsampling the image to produce smaller more abstract representations. Each layer representation has a larger number of filters/features per pixel than the previous layer. Finally, the highest-level abstract representation undergoes progressive deconvolutions to continually upsample the image to produce an output. At each level, skip connections provide information from each down layer to the corresponding up layer of the same size. When imagining a method to imbue hierarchy to the Transformer architecture, the U-Net should be taken into strong consideration.

Model Description

The vanilla Transformer consists of an encoder and a decoder, each consisting of a self-attention module and a feed-forward module per layer (Vaswani et al., 2017). All the layers have identical size and dimension. Thus, each layer operates on word tokens and can only perform per-token interactions. We introduce the U-Net Transformer, which modifies the encoder of the existing Transformer architecture to allow processing of the input text in a hierarchical manner. The decoder is unchanged between the two models.

See Figure 1. We propose the addition of U-Net Transformer encoder layers which increase in abstraction as you move deeper in the model. Specifically, each layer performs a $(k=3)$ 1D convolution operation with stride 1, followed by a max pool (stride 2) to effectively halve the number of output tokens as input to the next layer. Each new output token is a compo-
Figure 1: Illustration of the U-Net Transformer architecture. **Left:** The U-Net encoder uses a convolution \( (k=3) \) followed by max-pooling \( (k=3, \text{stride}=2) \) or deconvolution \( (k=3, \text{stride}=2) \) to increase/decrease the input size at each up/down layer. **Right:** The U-Net Transformer constitutes an hourglass shape which extracts high-level features in deeper layers. Residual connections combine information from abstract and low-level layers.

A self-attention layer identical to the original Transformer implementation is used to perform attention over the input tokens (pre-convolution), using the post-convolution (abstract) output tokens as queries. This allows the layer attention to use high-level token information to query low-level tokens in the input. Finally, all output tokens are updated using this attention information and are each passed to the feed-forward layer described in \( \text{(Vaswani et al., 2017)} \).

The “down” layers described above form a hierarchical pyramid of abstract representations of the input. With an increasing number of layers, the representations become more abstract and capture more high-level aspects of the input. As in the U-Net architecture, this pyramid representation of the input must then be used to update and inform the low-level representations. This phase is computed using a series of “up” layers, each of which doubles in previous output size (using a stride-2 deconvolution) until the output representation is identical in size to the encoder input.

The architecture as currently explained consists of a series of down and up layers which produce increasingly abstract representations, and then up-sample these representations to produce an output. However, computing outputs from only the most abstract representation loses important information about the input. Similar to the U-Net computer vision architecture, we incorporate residual skip connections between down and up layers of the same corresponding size by adding the output of the down layer with the input of the corresponding up layer. These skip connections can be observed in the diagram, and indicate how information propagates easily through the network. This technique differs from that of the computer vision U-Net; The low and high-level representation are added instead of concatenated. This design choice was made in the same spirit as the addition of input positional encodings. It allows for a combination of information without increasing layer sizes.

In addition to decreasing the size of each layer, the computer vision U-Net architecture increases the size of the layer representation per-pixel (number of filters) to balance layers such that computation is constant between layers. Specifically, the input image size halves in both width and height, causing a decrease in the number of pixels (one-fourth). To compensate, the representation size (the number of filters) doubles. This is in agreement with the computational complexity of a convolutional layer \( O(WHk^2C^2) \) for width \( W \), height \( H \), kernel size \( k \) and number of filters \( C \). We wish to model this same increase in layer representation in the U-Net Transformer. To accomplish this, we increase the size of each layer representation by \( \sqrt{2} \). This is in agreement with the Transformer layer complexity of \( O(Nd^2 + N^2d) \) for number of input tokens \( N \) and layer representation size \( d \). This choice of layer size expansion limits the growth of the \( Nd^2 \) factor by halving \( N \) and doubling \( d^2 \) simultaneously. See the “Implementation” section of the appendix for additional hyperparameter details.

**Baselines**

We first highlight the vanilla Transformer as the most relevant baseline of our experiments. To compare with a vanilla RNN baseline, we choose the GRU sequence-to-sequence model (S2SA) with an added multi-headed attention mechanism, the same as that employed by the Transformer attention layer.

We then select relevant baselines from the dialogue literature. Of notable popularity are the HRED (S-
| Architecture | Lowest Validation Cross Entropy | Test Perplexity |
|--------------|---------------------------------|-----------------|
| S2SA         | 3.983                           | 53.43           |
| HRED         | 3.945                           | 51.21           |
| VHRED        | 3.940                           | 51.05           |
| VHCR         | 3.937                           | 50.73           |
| TRANSFORMER  | 3.883                           | 48.30           |
|UNET          | 3.853                           | 46.87           |

Table 1: Comparison of U-Net Transformer against different baselines on the Cornell Movie Dialogues corpus. Model run until lowest validation loss achieved. Per-word perplexity evaluated on held-out test dataset.

| Architecture | Lowest Validation Cross Entropy | Test Perplexity |
|--------------|---------------------------------|-----------------|
| S2SA         | 3.736                           | 42.75           |
| HRED         | 3.684                           | 40.48           |
| VHCR         | 3.685                           | 40.45           |
| VHRED        | 3.679                           | 40.11           |
| TRANSFORMER  | 3.639                           | 39.06           |
|UNET          | 3.610                           | 37.72           |

Table 2: Comparison of U-Net Transformer against different baselines on the PersonaChat dataset. Model run until lowest validation loss achieved. Per-word perplexity evaluated on held-out test dataset.

ban et al., 2016) hierarchical architecture and the later VHRED (Serban et al., 2017) model which builds on HRED with an added variational component. To this we add the more recent VHCR model which claims improved performance over the HRED and VHRED models. (Park et al., 2018).

**Evaluation**

We choose to evaluate our proposed architecture in the domains of conversational dialogue and machine translation.

We first evaluate our proposed model and all baselines on the Cornell Movie Dialogues corpus (Danescu-Niculescu-Mizil and Lee, 2011). This dataset features two-character dialogues from movie scripts, and captures a large variety of human interaction in many different fictional circumstances. This dataset consists of 60,000 (history, response) pairs. On average, each conversation has 3.5 previous utterances.

In addition, we perform evaluation against the PersonaChat dataset (Zhang et al., 2018). Each conversation in the PersonaChat dataset was constructed by assigning “personas” to two Mechanical Turkers. A persona here is defined as a list of attributes about the individual, such as “I love pizza.” The Mechanical Turkers are then tasked to hold a conversation with each party adopting their assigned persona. On average, each conversation contains 14 utterances per conversation. When compared to the Cornell Movie Dialogues corpus, this dataset has longer conversation histories and thus an opportunity to form more abstract representations of the input conversation history.

We use vocabulary of most common 20,000 tokens in each dataset. The Transformer history input is pruned to a max of 150 tokens to put an upper bound on the memory requirements per batch.

While the proposed dialogue domains demonstrate the ability of the U-Net architecture to analyze a long conversation history effectively, we also choose to evaluate our model on the English to German machine translation task. As Transformers have been applied ubiquitously to machine translation, it is suitable to apply a new Transformer variant in the same domain. We select the WMT2014 English to German dataset, consisting of 4.5 million translation pairs.

Finally, we report responses generated from our model and baselines for given conversation histories in the Cornell Movie Dialogues domain. See Table 5

**Results**

Here we outline the results of the proposed evaluations. On the Cornell Movie Dialogues dataset, our U-Net Transformer architecture outperforms the Transformer and all other baselines. We believe this is due to the architectural design of the encoder and its ability to form abstract representations of the dialogue history and to utilize local information. This hypothesis is supported, as all hyperparameters and architectural considerations are identical between the Transformer and U-Net, with the exception of the encoder design. Encoder layers differ only in their sizes, and the addition of convolution layer, which extract local information while adding minimal computation.

In addition to outperforming in the movie domain, the proposed U-Net Transformer outperforms the vanilla Transformer and all other baselines on the PersonaChat dataset. This dataset consists of everyday conversations with long dialogue histories, and serves to measure how our model performs for larger dialogue histories. See Table 2 for detailed results.

We evaluate our model against Transformer and sequence-to-sequence with attention baselines on the
| Architecture | Test Perplexity |
|--------------|-----------------|
| TRANSFORMER  | 48.30           |
| UNET - DOWN/UP - CONV | 48.92 |
| UNET - DOWN/UP | 47.09 |
| UNET         | 46.87           |

Table 3: Ablation on the U-Net architecture. DOWN/UP represents the property that the number of tokens per layer decrease for each down layer, then increase for each up layer. CONV represents the addition of a convolutional layer. Note that without a convolutional layer, the number of tokens per layer remains constant. Conducted on the Cornell Movie Dialogues corpus.

| Architecture | Test Cross Entropy | BLEU Score |
|--------------|--------------------|------------|
| S2SA         | 4.179              | 10.77      |
| TRANSFORMER  | 2.899              | 21.39      |
| UNET         | 2.733              | 22.35      |

Table 4: Comparison of U-Net Transformer against different baselines in the domain of machine translation. We select the WMT2014 English-German dataset and report test cross entropy and BLEU score for each model. As HRED, VHRED and VHCR are formatted for the dialogue domain, they are not included here.

WMT2014 English-German dataset and report our results in Table 4. Even in this domain, less suited for hierarchical structure of the U-Net, our model outperforms the best baseline by a BLEU point.

We report an ablation study of the proposed model in Table 3. We start from the U-Net Transformer (bottom), and slowly modify it step by step into the vanilla Transformer, in order to analyze which changes resulted in performance gains. DOWN/UP represents the property that the number of tokens per layer decrease for each down layer, then increase for each up layer. CONV represents the addition of a convolutional layer. Note that without a convolutional layer, the number of tokens per layer remains constant.

Discussion

Cornell Movie Dialogues
Performing well on the Cornell Movie Dialogues dataset is a difficult task, as dialogues come from movies where the surrounding context is not always clear. Still, we investigate how the U-Net performs relative to all other models. From our experiments, it is clear that both attention models (UNET and TRANSFORMER) outperform all previous baselines by a comparable margin. This indicates that with proper training, attention layers can extract the best representations for the task. We also observe that the variational models outperform the non-variational models. One interesting observation is that the sequence-to-sequence attention model (S2SA) performs the most poorly among all tested models. This is surprising, as the S2SA uses an external attention mechanism to look over input tokens and thus should have an advantage over the HRED model, which uses only a fixed-width context. More work is needed to investigate this difference.

PersonaChat
The PersonaChat dataset features dialogues between Mechanical Turkers, in which both parties have access to a hidden “persona” which gives details about what each Turker likes and dislikes, as well as details about their life situation. As such, each dialogue is long and includes many details from a Turker’s respective persona. In this domain, U-Net again outperforms over the standard Transformer.

We speculate that if the U-Net Transformer is indeed able to extract high-level details from longer conversation histories, then it would be perform better on this task. However, the dialogue histories are simpler, indicating that language modelling could also play a factor. For the latter case, it should be noted that both the U-Net and vanilla Transformers share an identical decoder.

The relative performances of all baselines remain unchanged between the PersonaChat and Cornell Movie Dialogue domains, with the exception of the VHCR and VHRED models. These two architectures had comparable performance in both domains. This indicates that the two variational models perform similarly in the perplexity evaluation.

WMT2014 English to German
We include results from the machine translation domain to evaluate the ability of our proposed U-Net Transformer to generalize for shorter contexts. The dialogue histories given as input the models in the previous dialogue domains are roughly 3x longer than source sequences provided in the English to German task. Still, our model outperforms the Transformer and all other baselines. One desirable property of the convolutional U-Net architecture which could result in this behavior is that skip connections allow gradients to backpropagate more smoothly through the model while simultaneously allowing activation values from earlier layers to reach output layers in fewer steps. These skip connections could allow our model to better train in that domain. In addition to this, it is possible that the convolutional modules yield performance gains. Convolutions allow for local connectivity in the U-Net Trans-
Table 5: Samples from the U-Net Transformer and each of the baselines above. All models produce reasonable responses, but lack the diversity of the ground truth. All models trained on the PersonaChat dataset, which features individuals with different personas, or personalities.

| Model | History | Generated Response | Ground Truth |
|-------|---------|---------------------|--------------|
| UNET  | hello, how are you doing? <eos> i am doing well just watching the voice, i love it, you ? | i am doing great, just got done with my dog. | great! i am currently working on a piece of furniture. i enjoy building it. |
| TRANSFORMER | hey, what is up? what are you up to? <eos> hello tell me about yourself <eos> i can beat you in chess probably | i am in the navy and i am in a band | i can beat you at cooking italian food |
| S2SA | hi! i am excited! i just got 50k <unk> on my youtube channel where i do makeup | i am a teacher, i am a teacher. | cool, do you play any sports? do you make money from your channel? |
| HRED | hello, my father is dead | hello, good to talk to you, i am sorry to hear that | hi how are you today? |
| VHRED | hi there! how are you? | i am good, how are you? | i just acted like a superhero |
| VHCR | great! i am currently working on a piece of furniture, i enjoy building it. | i love to read, i am a bit of a loner. | that is great i would love to be able to do that. i just swim and read mostly |

Ablation Study

When analyzing the performance of our model on various textual datasets, we make claims about the reasons for our performance claims. We conduct an ablation study to analyze how each component of the U-Net model aids in performance, specifically on the PersonaChat domain. Removing down and up layers (UNET - DOWN/UP) worsens performance on the dialogue task. This is an indication of the importance of reducing the number of input tokens while increasing layer sizes, in order to form a more abstract representation of groups of tokens. Still, we evaluate the model when both up/down layers are removed, and convolutions are removed from each U-Net Transformer layer. Again, the removal of convolutions from this setup worsens performance, indicating that convolutions provide local connections which are more difficult to learn using the vanilla Transformer, which must utilize positional embeddings to learn increasingly sharp attention maps to grab adjacent tokens. After removing convolutions and up/down layers and convolutions, we remove skip connections to produce the vanilla Transformer, which features the worst performance of all configurations. This demonstrates that skip connections between up/down layers (or vanilla Transformer layers) improve performance of the model.

Overall Findings

Our proposed model outperforms the vanilla Transformer in the dialogue and machine translation domains. The conducted ablation study reveals that both the hierarchical structure and the local connectivity provided by convolutions aid in the performance of the U-Net model. We provide evidence that combining the U-Net and Transformer architectures produces a model that better handles high-level abstraction and local dependencies.

In future work, it would be interesting to apply the U-Net encoder architecture to improve BERT performance on the unsupervised training task. These additional U-Net layers could help the model store high-level information about the input sequence for use in predicting missing tokens, while also potentially al-
lowing gradients to propagate easier with U-Net skip connections. We also observe that the decoder was not modified in producing the U-Net encoder representations. Future work could modify this decoder to produce abstract representations of previously produced tokens in an autoregressive manner for better language modelling.

Conclusion

In conclusion, we introduce a novel variant of the Transformer architecture which utilizes the hierarchical and local connections of the convolutional U-Net architecture to produce an abstract representation of input sequences. We evaluate this "U-Net Transformer" on multiple dialogue and machine translation domains and report improved performance. Finally, we analyze the removal of different model components to assess the importance of U-Net design choices.

If one is convinced that the optimal view of language involves concepts at a higher level than the individual tokens that make up the input sequence, we are motivated to explore architectures which form "top-down" representations of input language. The movement from static word embeddings to contextual embeddings produced by the Transformer is one such example. This work represents an honest step in that research direction.

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A Additional Insights

In addition to the conclusions of the paper, we highlight additional anecdotal findings which may be useful to the reader. It was observed over numerous experiments that the initialization of both Transformer and U-Net Transformer layers was critical to model performance. We speculate that smaller initializations produce near-identity transformations earlier in training, and help useful input information propagate throughout all model layers.

We additionally found that perplexity values calculated throughout all experiments had low variance, with repeated runs lying within less than half a perplexity point. This finding made for reliable evaluation of the models above, and increases confidence in reported results.

In future work, we hope to explore modifications to the decoder which improve performance of the U-Net Transformer. However, in local experiments we allowed decoder cross-attention between each decoder layer and the corresponding U-Net encoder layer. This modification allowed direct access to the high-level encoder representations, instead of static attention over the final U-Net output layer. To our surprise, this modification worsened performance. Other modifications should be explored.

B Implementation

We use Xavier initialization (Glorot and Bengio, 2010) for all parameters, with the exception of the pre-ReLU linear transformation of the feed-forward module. For this layer, we use Kaiming initialization (He et al., 2015) as it normalizes post-ReLU activations. For the output layer of both the attention and feed-forward modules, we use Xavier initialization but multiply by a gain factor of $1/100$. In local experiments, this resulted in the best propagation of gradients from the loss objective to the input word embeddings. This design choice causes low output activations for these modules, and results in near-identity transformation behavior due to skip connections after each module. As such, activation values undergo fewer changes after each Transformer layer early in training.

The Transformer token representations are padded such that each padding token in the input produces a zeroed representation at the output of each layer. In addition, an attention mask is computed to allow attention only between non-pad tokens in the input sequence. These changes allow for more efficient training without worrying about redundant padding tokens. For the U-Net Transformer, padding input tokens becomes non-trivial, as each layer decreases in size as a convolution over the previous layer. We compute the output padding of a U-Net Transformer down layer by performing a max pooling ($k=3$) operating over the pad vector. A given output token of the down-sampling convolution is a pad token if and only if all inputs within the kernel window are pad. Stated in the opposite way, if any input to the kernel window of a convolution output is non-pad, the output will non-pad.

In line with the original Transformer paper, we add sinusoidal position encodings to the input of the vanilla and U-Net Transformer architectures. However, in the dialogue domain, we additionally add a segmentation vector to each token to indicate which utterance in the conversation the token belongs. A different segmentation vector is learned for each utterance index. This is similar to the segment embeddings used in BERT (Devlin et al., 2018).

To constrain layer computation, we set the Transformer layer size to 256 for both word embeddings and hidden dimension size. We set the fully-connected inner layer size to 1024, with attention key and value size 64 for 8 heads. As described previously, the layers sizes of the U-Net Transformer change throughout the model. For a increase in size of $\sqrt{2}$ (rounded), we achieve layers sizes $[256, 362, 512, 362, 256, 256]$. All key, value, and fully-connected inner sizes are proportionate.
We similarly set the word embedding and hidden size to 256 for all baselines for both encoder and decoder (and context encoder for HRED, VHRED). The common layer size helps constrain hyperparameter tuning and is intended to allow for fair comparison of these models. The S2SA multi-headed attention mechanism has an identical structure and parameters to the Transformer attention outlined.

**Dialogue Configuration**
For both the proposed U-Net Transformer and the baseline Transformer architecture, we use 6 layers identical to the original paper (Vaswani et al., 2017). For fair comparison with baselines, we use the Adam optimizer with learning rate $1e^{-4}$ and beta parameters $(0.9, 0.999)$ without learning rate scheduling. We found scheduling did not affect model performance in the dialogue task. We use greedy decoding, although other sampling methods could alternatively be used such as top-k or nucleus sampling (Holtzman et al., 2019).

**Translation Configuration**
We use WMT2014 English$\rightarrow$German dataset. Training data was constructed according to this preprocessing script\(^2\) except BPE-tokenization that was done using\(^3\).

Hyperparameters of translation model are the same as in our dialogue model. English and German vocabularies are not shared, each contains 32,000 tokens. Adam optimizer parameters and learning rate scheduling follow (Vaswani et al., 2017). We train for 200,000 steps with batch size 128 and maximum sequence length of 50. The model is regularized with dropout 0.1.

Our GRU model has one layer encoder and decoder, hidden dim is 256. All other hyperparameters are the same as in transformer-based models, including multi-head attention.

Translation was performed using beam search with beam size of 3 for all models.

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\(^2\)github.com/pytorch/fairseq/tree/master/examples/translation
\(^3\)github.com/vkcom/YouTokenToMe
Figure 2: Validation loss curve for the WMT2014 English to German translation dataset. U-Net appears as best performing.

Figure 3: Validation BLEU score curve for the WMT2014 English to German translation dataset. U-Net appears as best performing.