Inducing Meaningful Units from Character Sequences with Slot Attention

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Abstract

Characters do not convey meaning, but sequences of characters do. We propose an unsupervised distributional method to learn the abstract meaning-bearing units in a sequence of characters. Rather than segmenting the sequence, this model discovers continuous representations of the *objects* in the sequence, using a recently proposed architecture for object discovery in images called Slot Attention. We train our model on different languages and evaluate the quality of the obtained representations with probing classifiers. Our experiments show promising results in the ability of our units to capture meaning at a higher level of abstraction.

1 Introduction

What we perceive from a complex high-dimensional scene builds on its constituent objects. Our mind is able to identify not only the objects, but also their properties such as shape and material. Similarly, what we infer from a piece of text relies on the word-like units comprising it. Linguists call this notion *morphemes*, the smallest meaningful units in a language.

We aim at finding meaning bearing units from a sequence of characters without supervision. Our goal is to learn a set of abstract continuous representations of text. This set of units could be beneficial for possible downstream tasks, such as dependency parsing.

Our work is closely related to unsupervised morphology learning and subword discovery approaches, although it differs from them fundamentally. In unsupervised morphology learning, the task is to identify the morphemes of a word. Creutz and Lagus (2002, 2007) proposed *Morfessor* variants based on probabilistic machine learning methods. Moreover, Narasimhan et al. (2015) took a Bayesian approach for modeling the relation between a word and its morphological parent. More recently, Eskander et al. (2020) used Adaptor Grammars for learning the morphology. In contrast to this line of research, we learn a set of continuous representations of text which are not explicitly tied to the text string. Additionally, we employ recent deep learning architectures for our purpose which is quite different from their classical approaches.

Furthermore, there is an emerging interest in unsupervised object discovery in image domain (Greff et al., 2019; Eslami et al., 2016; Burgess et al., 2019). Recently, Locatello et al. (2020) proposed *Slot Attention* module, an attention based algorithm for representing objects in a scene. Their so-called *slots* act as object variables which can bind to any object in the image. Motivated by their simple and efficient method, we are, to the best of our knowledge, the first to adapt Slot Attention in the text domain.

We propose a model to encode the sequence into slots, where each slot represents one meaningful unit in the character sequence. As our unsupervised objective, a decoder conditions on the set of slots to reconstruct the original input. We use the Transformer architecture (Vaswani et al., 2017) as our starting point for this sequence to sequence model, adding a Slot Attention module as a hidden representation in between the Transformer encoder and decoder, as depicted in Figure 1.

We design our model so that it can handle common textual sequences with an unknown number of entities. For this purpose, we add a L_0 regularizing layer on top of the Slot Attention module to prune out extra slots and retain only the necessary ones. In particular, since the input sequences have variable lengths, we consider an adequate number of slots to support the longest sequence, and we prune out the extra slots for shorter sequences.

In addition, as the number of possible n-grams in text is finite and the slot vectors have infinite capacity due to their continuous values, the model tends to learn arbitrary mappings between n-grams and slots instead of meaningful relations. We alleviate this problem by adding constant noise to slot vectors, which limits how much information can be transmitted through a single slot.

Lastly, we evaluate what the slots have learned by employing probing classification tasks. We predict the corresponding Byte-Pair-Encoding (Sennrich et al., 2016) tokens of the sequence from its slots. Additionally, we examine the slots' ability to predict the Morfessor outputs. Our experiments show promising results in the ability of slots to capture meaning at a higher level of abstraction than characters.

To summarize, our contributions are as follows:

- We propose a model for learning meaning-bearing units from a sequence of characters by effectively adapting Slot Attention method (section 3)
- We show that slots are able to capture meaningful information by probing their ability to predict predefined meaningful units (section 4)

2 Related Work

2.1 Unsupervised morphology learning

This long-lasting task is to identify the constituent morphemes of a word. Morphemes are important on their own because of the linguistic inspiration behind them. In addition, discovering them will help to mitigate the Out Of Vocabulary (OOV) problem which is especially beneficial in agglutinative languages, such as Finnish and Turkish. Moreover, by modeling language at morpheme level we expect to improve the performance of possible downstream tasks (Can and Manandhar, 2014). For instance, Ataman et al. (2020) improved translation quality by modeling word formation as latent variables which mimic morphological inflections. It should be taken into consideration that words may undergo changes while inflecting to different forms, e.g., *study+ed*$\rightarrow$ *studied*. Therefore, some works simplified the problem to segmenting the word into morpheme-like units (e.g., *studied*$\rightarrow$*studi+ed*).

Many approaches have been proposed for discovering the underlying morphemes or morpheme-like units. Morfessor variants are based on probabilistic machine learning methods (MDL, ML, MAP) for morphological segmentation (Creutz and Lagus, 2002; Creutz, 2003; Creutz and Lagus, 2005, 2007; Virpioja et al., 2013). Some researchers take a Bayesian approach for modeling word formation (Poon et al., 2009; Narasimhan et al., 2015; Bergmanis and Goldwater, 2017; Luo et al., 2017). Adaptor Grammars were another approach for modeling morphological inflections (Sirts and Goldwater, 2013; Eskander et al., 2016, 2019, 2020). In addition, Xu et al. (2018, 2020) built their models upon the notion of paradigms, set of morphological categories that can be applied to a set of words. Furthermore, Soricut and Och (2015) consider affixation as common shifts in the embedding space and extract morphemes by refining the set of possible candidates. Cao and Rei (2016) proposed to learn word embeddings by applying a bi-directional RNN over the character sequence and weighting each representation by attention. They hypothesized that morpheme boundaries will attract most of the attention weights. To the best of our knowledge, this is the only work which uses neural networks to learn morphology.

Our work differs from the previous work in morphology learning in two manners. First, we use recent Deep Learning techniques for learning the meaningful units. Second, instead of explicitly discovering morphemes, we learn continuous compact representations of the input which could then be processed to extract the morphemes. In addition, our model learns its representations by considering the context of the words in a sentence. In contrast, most of the morphology learning techniques use external word embedding information for integrating semantics in their models (Narasimhan et al., 2015; Soricut and Och, 2015; Cao and Rei, 2016).

2.2 Subword discovery algorithms

Another relevant area to our work is subword discovery algorithms. This set of algorithms have become a standard component of NLP models in recent years. They have been mostly developed to alleviate the out of vocabulary problem while processing language. Byte-Pair-Encoding (bpe) (Sennrich et al., 2016) is an iterative algorithm which merges the two consecutive tokens with the highest frequency in every step until it reaches the desired vocabulary size. Another similar algorithm, wordpiece (Schuster and Nakajima, 2012), merges the two tokens based on maximizing the score of a language model. In contrast, Unigram language model (Kudo, 2018) prunes a predefined vocabulary by finding the least important token in terms of maximizing a unigram language model's score. In contrary to these methods which mostly use statistical information of the data, our model is trained over complete sentences to learn a sophisticated representation. Moreover, as we stated previously, we learn abstract continuous units which are not explicitly mapped to subwords.

2.3 Unsupervised object discovery

There is a recent line of research in image domain for discovering objects in a scene without explicit supervision and building an object-centric representation of them. Most of these work are built around the compositionality of the scenes (Greff et al., 2016, 2019; Burgess et al., 2019; Engelcke et al., 2020; Locatello et al., 2020). Specifically, the scene could be represented as a composition of objects. Greff et al. (2019) and Burgess et al. (2019) used a VAE architecture for segmenting and learning objects representations in an image. Engelcke et al. (2020) further learnt to generate scenes by capturing relationships between scene components. Finally, Locatello et al. (2020) proposed Slot Attention module where each slot could bind to any object in the scene.

In contrast to this line of work in vision, our approach is specifically designed for text. We use additional components in our architecture to resolve the requirements of modeling textual data. Furthermore, our model is trained and evaluated on real text datasets, in contrast to these previous models which have only been shown to be effective on synthetic scenes.

3 Approach

In this section, we will discuss how we design our model in order to capture meaningful units from a sequence of characters. We will follow a top-down approach to explain the general idea (3.2) and the details of our solution.

3.1 Problem formulation

Given a sequence of characters $X = x_1 x_2 \dots x_N$, we seek for a set of meaning-bearing units (slots) $M = \{m_1, \dots, m_K\}$, which could best represent X in a higher level of abstraction. As an example, consider the sequence *"she played basketball"*. We expect our slots to represent the set of morphemes of the sequence, namely $\{$*she, play, -ed, basket, -ball*$\}$. This hypothesis comes from the linguistics point of view, where morphemes are considered the smallest meaningful units in a language.

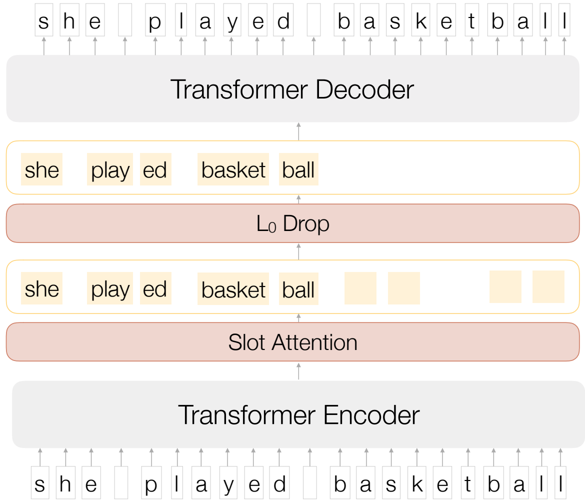


Figure 1: The sketch of our model. First, the sequence is encoded into slots. Then, the L_0Drop layer is applied to prune out the unnecessary slots. Finally, the slots are decoded to reconstruct the original sequence.

3.2 General idea

We learn our representations through encoding the input sequence into slots and then reconstructing the original sequence from them. Particularly, we use an auto-encoder structure where slots act as the bottleneck between the encoder and decoder. Figure 1 shows a sketch of our proposed model. First, we encode the input character sequence by a Transformer encoder (Vaswani et al., 2017). Then, we apply Slot Attention module (Locatello et al., 2020) over the encoded sequence to learn the slots. Intuitively, Slot Attention will learn a soft clustering over the input where each cluster corresponds to a meaningful unit in the sequence. We integrate a L_0 regularizing layer, i.e., L_0Drop layer, on top of the slots to prune out the unnecessary ones. Since the number of slots is fixed during the course of training, this encourages the model to only use as many slots as necessary, and thereby stops the model from converging to trivial solutions, such as passing each character through each slot for short sequences. Finally, the Transformer decoder reconstructs the input sequence autoregressively using attention over the set of slots.

3.3 Encoder

We use Transformer encoder architecture for encoding our sequence (Vaswani et al., 2017). It consists of subsequent layers of self-attention and non-linearity for building a new representation of the input sequence. Finally, we obtain representation $X' = x'_1 x'_2 \dots x'_N$ from our input sequence X.

3.4 Slot Attention

After encoding the character sequence, we use Slot Attention for discovering meaningful units of the input. Slot Attention is a recent method for unsupervised object representation learning (Locatello et al., 2020). It learns a set of feature vectors (slots) from the input representations by using an iterative attention based algorithm.

Algorithm 1 shows the pseudo code of this method. Abstractly, in every iteration, the following steps are taken. First, an attention map is computed by slots acting as queries and inputs as keys. Then, this map is normalized over slots which enforces the slots to compete for representing every token of input. Afterwards, the slots' updates are computed as the weighted mean over attention weights and input values. Finally, slots get updated through a recurrent GRU unit followed by a residual MLP. This process iterates a fixed number of times.

In (Locatello et al., 2020), the slots are initialized randomly from a Normal distribution with shared learnable parameters μ and σ. We realized in our experiments that in order to adapt the method to the text domain, we should consider the following changes. First, we consider a separate μ per slot, and secondly, we fix the σ to a predefined value for all the slots. Namely, the slots are initialized as

$$\text{slot}_i \sim \mathcal{N}(\mu_i, \sigma_{\text{constant}}). \quad (1)$$

In particular, we increase the model's capacity by assigning a separate μ for each slot. This allows the model to learn about different kinds of units, such as ones that occur at different positions, or ones that have different types of forms, but we do not make any assumptions about what those differences might be. In initial experiments, we found that this approach increased performance over randomly sampling slots from a single distribution. However, since these μ parameters are learnable, we need to fix the number of slots before training them.

In addition, the intuition behind fixing the σ is to force the slots to compress the information in a meaningful way. In other words, since the slots can have any continuous value in the space of $\mathrm{R}^{D_{slots}}$, they tend to learn an arbitrary mapping from the inputs to the slots while turning σ to zero. Specifically, the slots have the capability to learn a mapping from character n-grams (which is a finite set) to the infinite $\mathrm{R}^{D_{slots}}$ space without trying to find the underlying meaning-bearing units. Therefore, by imposing a constant noise on slots, we limit the information passed through each slot. From the information theoretic point of view, if we consider slots as a communication channel between encoder and decoding, adding noise reduces the their capacity. We encounter this phenomena particularly in text, because we have a large number of slots to support the longest sequence in our data.

Lastly, we obtain the set of slots M as

$$M = \{m_1 \dots m_K\} = \text{Slot Attention}(X'). \quad (2)$$

3.5 $L_0 Drop$ Layer

The number of slots for representing a sequence varies among different sequences in the data. Thus, we consider an upperbound over the number of slots and prune extra slots during the course of training. We accomplish this by utilizing $L_0 Drop$ layer (Zhang et al., 2020).

This layer consists of binary-like gates g_i for every input m_i that works as

$$L_0 Drop(m_i) = g_i m_i. \quad (3)$$

The goal of sparsification is achieved when g_i equals to 0 and no information is passed from that input. Each gate is a random variable sampled from a hard-concrete distribution (Louizos et al., 2018). Hard-concrete distribution assigns most of the probability mass to its endpoints (i.e., 0 and 1) and is continuous over the $[0, 1]$ interval. A hard-concrete sample g_i is obtained from stretching and rectifying a sample from the BinaryConcrete distribution (Maddison et al., 2017; Jang et al., 2017):

$$s_i \sim \text{BinaryConcrete}(\alpha_i, \beta) \quad (4)$$

$$\bar{s_i} = s_i(1 + 2\epsilon) - \epsilon \quad (5)$$

$$g_i = \min(1, \max(0, \bar{s_i})) \quad (6)$$

where β and ϵ are hyperparameters and α_i is predicted as a function of the encoder output m_i:

$$\log\alpha_i = m_i w^T \quad (7)$$

where w is a learnable vector. This will allow the model to dynamically decide which inputs to pass and which ones to prune.

Algorithm 1 Slot Attention module (Locatello et al., 2020). q, k, v map the slots and inputs to a common dimension D.

Require: inputs $\in \mathrm{R}^{N \times D_{input}}$, slots $\sim \mathcal{N}(\mu, diag(\sigma)) \in \mathrm{R}^{K \times D_{slots}}$
  inputs = LayerNorm(inputs)
  for i = 1 **to** T **do**
    slots_prev = slots
    slots = LayerNorm(slots)
    attn = Softmax($\frac{1}{\sqrt{D}}$ k(inputs).q(slots)^T, axis = 'slots')
    updates = WeightedMean(weights = attn + δ , values = v(inputs))
    slots = GRU(states = slots_prev, input = updates)
    slots += MLP(LayerNorm(slots))
  end for
  return slots

Finally, the $\mathcal{L}_0$ penalty, which yields the expected number of open gates, is computed as

$$\mathcal{L}_0(M) = \sum_{i=1}^{k} 1 - p(g_i = 0|\alpha_i, \beta, \epsilon). \quad (8)$$

The probability of g_i being exactly 0 is provided in closed form in (Louizos et al., 2018)

$$p(g_i = 0|\alpha_i, \beta, \epsilon) = \sigma(\beta \log \frac{\epsilon}{1+\epsilon} - \log \alpha_i). \quad (9)$$

We follow the same approach as Louizos et al. (2018) at evaluation time and consider the expectation of each gate as its value.

$$\hat{g}_i = \min(1, \max(0, \sigma(\log \alpha_i)(1 + 2\epsilon) - \epsilon)) \quad (10)$$

We refer to the pruned slots after applying the L_0Drop layer as $M' = m'_1 \dots m'_K$. In contrast to Zhang et al. (2020), we do not aggregate the pruned out inputs at decoding time since the performance gain in short sequences is negligible.

3.6 Decoder

Lastly, we regenerate the input sequence from the set of slots by using a simple, shallow decoder. For this purpose, we use a one-layer Transformer decoder (Vaswani et al., 2017) with a single attention head over the slots. A simple decoder forces the slots to learn representations with a simple relationship to the input, which we expect to be more meaningful. In other words, we do not use a powerful decoder because it will be able to decode even low quality representations of the input, which are less meaningful.

3.7 Training Objective

All components of our model are fully differentiable and hence, we can train it end-to-end. We use Gumble trick for sampling BinaryConcrete varibles (Maddison et al., 2017; Jang et al., 2017). We train our model with the following objective:

$$\begin{aligned}\mathcal{L}(X) &= \mathcal{L}_{\text{reconstruction}} + \lambda\, \mathcal{L}_0(M) \\ &= \log p(X|M') + \lambda\, \mathcal{L}_0(M)\end{aligned}$$

which consists of the reconstruction loss from the decoder and the L_0 penalty for the open slots. Hyperparameter λ, the sparsification rate, controls the ratio between the two losses. In practice we find that in order to impose enough sparsity in the slots, we should slightly increase λ during the course of training using scheduling techniques.

4 Experiments

In this section we will explain our experimental setup and results. We evaluate our unsupervised model both qualitatively and quantitatively. First, we probe the slots' vectors ability to capture meaningful information by two classification tasks (4.2). Afterwards, we visualize some of the attention maps to show what the slots are corresponding to (4.3).

4.1 Experimental Setup

4.1.1 Languages and Data

We apply our model to languages from different morphological typologies. We select English, German and Czech from fusional family and Finnish and Estonian from agglutinative typology. For English we use the raw Wikitext2 dataset provided by Merity et al. (2017). For the rest of languages we use Multilingual Wikipedia Corpus (MWC) (Kawakami et al., 2017). We lowercased the text and retained the characters which occur more than 25 times in the corpus following Kawakami et al. (2017). We replace the remaining characters with an unknown placeholder.

4.1.2 Training Settings

We use standard Transformer architecture (Vaswani et al., 2017) with model dimension 256. The encoder consists of 2 layers with 4 self-attention heads and the decoder consist of 1 layer with 1 self-attention head and 1 attention head over the slots. We feed in the sentences with less than 128 characters to our model and consider the number of slots as 64 (half of the input length). In addition, we take the dimension of slots as 128.

We scheduled λ parameter in the training loss to start with low value 2×10^{-5} and then double it every 10 epochs. We control this parameter in a way that the final number of open slots roughly equals the average number of BPE tokens in a sequence. We used Adam optimizer (Kingma and Welling, 2013) for training our models with learning rate 10^{-4}.

4.2 Probing Analysis

4.2.1 Probing tasks

In order to evaluate what the slots have learned quantitatively, we define two probing tasks. As we are expecting the slots to represent meaningful entities in text, we evaluate their representations on carrying frequency-based information in addition to linguistic information. For the frequency-based information, we measure how well the slots match to the corresponding BPE tokens in the sequence. BPE is an iterative method which merges the most frequent consecutive tokens at every step. Moreover, we consider Morfessor (Virpioja et al., 2013) as a linguistically inspired method for discovering the morpheme segments and measure how well the slots correspond to the outputs of the Morfessor tool.

4.2.2 Probing Classifier

We train a probing classifier for mapping a slot's vector to the output space, namely,

$$f(m_i') : \mathrm{R}^{D_{slots}} \rightarrow \mathrm{R}^S \tag{11}$$

where S is the number of BPE (or Morfessor) tokens. We apply the classifier with shared parameters over each of our slots and obtain a *set* of predictions, i.e., $\{f(m_1'), f(m_2'), \ldots, f(m_K')\}$. As we are dealing with a set, we should find a one-to-one matching between the classifier's predictions and output tokens. Therefore, we use Hungarian matching algorithm (Kuhn, 1955) for finding the best match in terms of minimizing the classification loss. Consider the best matching as $i_j \rightarrow j$, which matches the i_jth slot with the jth output (i.e., y_j). We then compute the loss as

$$\mathcal{L} = \sum_{j=1}^{K} l(f(m_{i_j}'), y_j). \tag{12}$$

where l is the cross-entropy between the two terms.

As the input to the classifier, we consider the complete set of slots after applying the L_0Drop layer but before any pruning. Slots whose L_0Drop gate is closed are simply input as zero vectors. This gives us a fixed number of vectors. Because the two sides of matching should have the same size to obtain a one-to-one match, we add an extra target labels (i.e., *empty*) for matching the slots which should be pruned. Due to the fact that many slots are pruned out, considering a measure like accuracy could be misleading. Since a classifier which outputs *empty* label will achieve very high accuracy. Therefore, we build a confusion matrix as follows. We consider all *non-empty* labels as positive and the *empty* ones as negative, and we report precision, recall and F1 measure, to better reflect what the slots have learned.

Our probing classifier consists of two fully connected layers with ReLU activation function in between the two layers. The hidden dimension of the classifier is the same as the slots' dimension which is 128. We fix the BPE vocabulary size to 5000 for all languages. We consider the set of morphs (i.e., Morfessor outputs) on the training data as our target labels.

4.2.3 Probing Results

Similar to Oord et al. (2018), we compare our trained slots against a random baseline in which we initialize our model randomly. In particular, we take the untrained slot vectors and train the probing classifier on top of them to serve as our baseline. Table 1 shows the results of the probing tasks over the baseline (random) and the unsupervised learned slots (slot-attn) on different languages. As the results show, the trained slots can achieve much higher performance in both tasks in comparison to the random baselines. Our model achieves high

language	Model	BPE precision	BPE recall	BPE F1	Morfessor precision	Morfessor recall	Morfessor F1
English							
	random	0.74	0.10	0.17	0.72	0.14	0.23
	slot-attn	0.98	0.59	0.72	0.98	0.64	0.76
Finnish							
	random	0.94	0.09	0.17	0.8	0.26	0.38
	slot-attn	0.95	0.65	0.76	0.97	0.52	0.68
German							
	random	0.91	0.08	0.16	0.76	0.22	0.33
	slot-attn	0.99	0.66	0.78	0.99	0.51	0.67
Czech							
	random	0.94	0.08	0.16	0.75	0.24	0.35
	slot-attn	0.98	0.63	0.75	0.98	0.52	0.67
Estonian							
	random	0.71	0.09	0.17	0.72	0.23	0.33
	slot-attn	0.96	0.73	0.82	0.99	0.60	0.74

Table 1: Probing classification results on different languages.

precision in predicting the *non-empty* labels. However, its performance is weaker on the recall side, which is probably due to the imbalance between *empty* and *non-empty* labels in the training set. Particularly, the *empty* labels build around 66% of the data which highly biases the model towards predicting them. This imbalance shows its effect mainly on the random baselines and results in predicting the *empty* label for almost all of the samples. This behavior leads to high precision but very low recall. Therefore, the gap between the learned slots and the random ones is especially obvious on the recall side, where the learned slots guide the classifier to predict non-empty labels.

The numbers verify that our proposed model is effectively integrating frequency-based and linguistic information into the slots.

4.3 Visualization

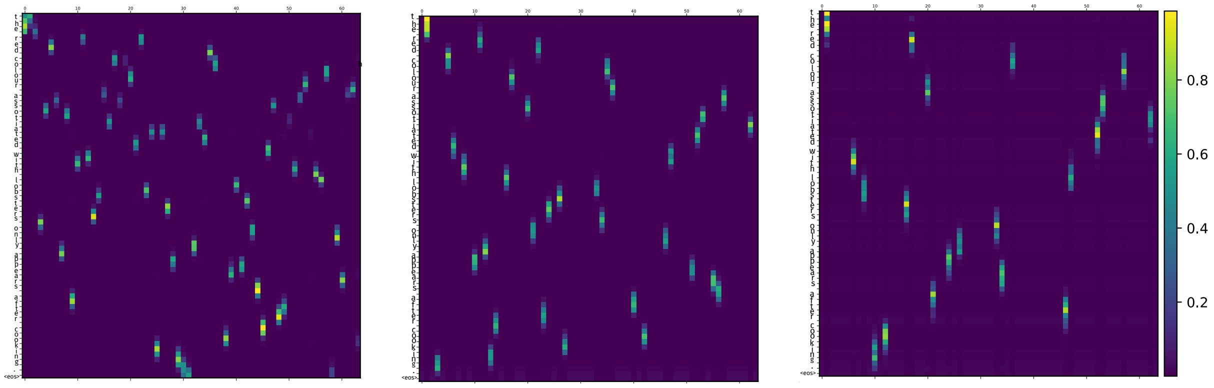
We visualize the attention maps for generating every output in Figure 2. In particular, we show the attention of decoder over slots for generating every output character. Although we do not impose any sparsity in the decoder's attention weights, the attention maps are quite sparse. In addition, the slots are attended contiguously during the generation.

In the early steps of training that the sparsity ratio (λ) is small, each slot tends to represent a bigram of characters (2a) and later on, trigrams (2b). These observations confirm the necessity of the $L_0 Drop$ layer for converging to better units. As the ratio increases the number of active slots reduce and they become more specialized in representing a contiguous meaning-bearing segments of input. For instance, the word *cooking* in 2c is represented by two slots *cook* and *ing*.

5 Conclusions

In this paper, we designed a model for learning meaningful representations of text in unsupervised fashion. We used auto-encoder architecture for encoding the sequence into continuous slots and decoding them to reconstruct the original sequence. We enforced the slots to act as a bottleneck in transferring information between the encoder and the decoder by adding a constant noise to their vectors. Additionally, in order to generalize our model to common text datasets, we added a L_0 regularizing layer on top of the slots to only retain the necessary ones. We evaluated our model by probing the final slot vectors to predict predefined BPE and Morfessor tokens. In comparison to a random baseline, our representations effectively capture meaning in both experiments.

In future, we plan to employ our representations in possible downstream tasks such as dependency parsing. We anticipate that these meaningful units could be beneficial in improving the performance of these tasks.



(a) epoch 5 (b) epoch 50 (c) epoch 125

Figure 2: Attention of decoder over slots for generating every output during the course of training. The target output sequence is "the red colour associated with lobsters only appears after cooking.".

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