N-grammer: Augmenting Transformers with latent *n*-grams

Anonymous ACL submission

Abstract

Transformer models have recently emerged as one of the foundational models in natural language processing, and as a byproduct, there has been significant recent interest and investment in scaling these models. However, the training and inference costs of these large Transformer language models are prohibitive, thus necessitating more research in identifying more efficient variants. In this work, we propose a simple yet effective modification to the Transformer architecture inspired by the literature in statistical language modeling, by augmenting the model with *n*-grams constructed from a discrete latent representation of the text sequence. We evaluate our model, the *N*-grammer on language modeling on the C4 data-set, and find that it outperforms several strong baselines such as the Transformer and the Primer. We will open-source our model for reproducibility purposes upon acceptance.

1 Introduction

The area of generative modeling of text has witnessed rapid and impressive progress driven by the adoption of self-attention to neural networks. Attention for machine translation was proposed in Bahdanau et al. (2015); Cho et al. (2014); Vaswani et al. (2017) and subsequent works such as Radford et al. (2018); Devlin et al. (2019) applied the learned representations of language to several problems in natural language processing. The rapid progress has been made possible primarily by increasing the modeling capacity of these Transformer based models to billions of parameters (Brown et al., 2020) which comes at a large computational cost. The computational cost of Transformer models is being addressed in the literature by exploiting sparsity in self-attention (Ainslie et al., 2020; Zaheer et al., 2020; Roy et al., 2021), mixtures of experts (Shazeer et al., 2017; Lepikhin et al., 2020; Fedus et al., 2021) for sparsity in the feed-forward network, sparsity in the softmax computation (Correia et al., 2019), and combining depth-wise convolution with attention (Wu et al., 2021; So et al., 2021).

Motivated by the growing literature in training more efficient variants of Transformers, as well as the classical literature on statistical language modeling (Koehn, 2009), we propose a simple modification to the Transformer architecture termed the *N*-grammer in this work. The *N*-grammer layer improves the efficiency of language models by incorporating latent *n*-gram representations into the model during training. Since the *N*-grammer layer only involves sparse operations during training and inference, we find that a Transformer model with the latent *N*-grammer layer can match the quality of a larger Transformer while being significantly faster at inference.

2 Related Work

Memory augmented models There has been a long line of work in augmenting sequence models with memory, e.g. the Neural Turing Machine (Graves et al., 2014) and Memory Networks (Weston et al., 2014). More recent works have proposed combining Transformer based models with product key look-up tables (Lample et al., 2019), while Panigrahy et al. (2021) propose memories based on sketches of past activations. There has also been a lot of work on augmenting language models with non-parametric memory, such as the k-nearest neighbor language models of Khandelwal et al. (2019), and similar retrieval augmented works such as Lewis et al. (2020); Guu et al. (2020); Krishna et al. (2021). In these retrieval augmented models, the model is conditioned on documents from the training corpus or a knowledge base, with the hope that information from related articles can help improve its factual accuracy.

Discrete latent models for sequences Discrete latent models using Vector Quantization (VQ) have been widely used in speech (van den Oord et al.,

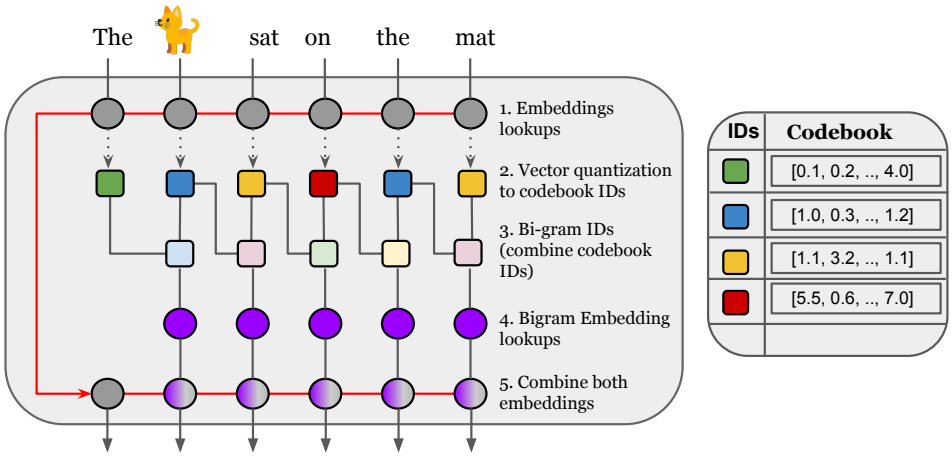

Figure 1: The N-grammer layer. It takes as input a sequence of uni-gram embeddings and outputs a parallel sequence of N-gram augmented embeddings. The input embeddings are clustered into a discrete latent representation using PQ, and n-grams (bi-grams) IDs are computed over it. For each n-gram ID, a trainable embedding is looked up from an embedding table and combined with the input embeddings to produce the output.

2017; Wang et al., 2018; Schneider et al., 2019) to learn unsupervised representations of audio signals. Their use for modeling text sequences were studied in Kaiser et al. (2018); Roy et al. (2018) where the motivation was to reduce the inference latency for neural machine translation models by decoding in the latent space.

N-gram models for statistical language modeling N-gram models have a long history in statistical modeling of language, see e.g., Brown et al. (1992, 1993); Katz (1987); Kneser and Ney (1995); Chen and Goodman (1999). Before the advent of word vectors and distributed representations of language via neural networks (Mikolov et al., 2013; Wu et al., 2016), n-gram language models were the standard in the field of statistical language modeling. A more recent related work on combining neural RNN models with n-gram embedding tables is that of Huang et al. (2021) for speech recognition. Our work differs from them in that we use an n-gram look-up table on a discrete latent representation of the sequence which gives it the flexibility of being compatible with any intermediate layer of the Transformer.

Product Quantization There has also been a long line of work on investigating variants of Vector Quantization (VQ) that realize different trade-offs in data compression. The most related work in this domain is due to Jegou et al. (2011) who introduce a multi-head version of VQ which is termed Product Quantization (PQ). PQ is widely used in computer vision, see e.g., Ge et al. (2013); Yu et al. (2018). Our approach to learning discrete latent codes use PQ over the attention heads.

3 The N-grammer layer

At a high level, we introduce a simple layer that augments the Transformer architecture with more memory based on latent n-grams. While the N-grammer layer is general enough for considering arbitrary N-grams, we restrict ourselves to the use of bi-grams. We leave the exploration of higher-order n-grams for future work. The layer consists of three core operations:

1. Given a sequence of uni-gram embeddings of a text, infer a sequence of discrete latent representation via PQ.
2. Infer the bi-gram representation for the latent sequence.
3. Look up trainable bi-gram embeddings via hashing into the bi-gram vocabulary.
4. Combine the bi-gram embeddings with the input uni-gram embeddings.

We describe each of these operations in more detail in the following sections. For referring to a set of discrete items, we use the notation $[m]$ to mean the set $\{0, 1, \cdots, m-1\}$.

3.1 Discrete latent representation of a sequence

The first step of the N-grammer layer is to obtain a parallel sequence of discrete latent representations

with Product Quantization (PQ) (Jegou et al., 2011) by learning a codebook from the given sequence of input embeddings. The input embedding is a sequence of uni-gram embeddings $x \in \mathbb{R}^{l \times h \times d}$, where l is the length of the sequence, h is the number of heads, and d is the embedding dimension per head. We learn a codebook c in $\mathbb{R}^{k \times h \times d}$ with k code-words with mini-batch k-means (Bottou and Bengio, 1995), and in the same step, we form the parallel sequence of discrete latent representation $z \in [k]^{l \times h}$ of the sequence x by picking the codebook IDs that have the least distance from the input embeddings:

$$z_{i,j} = \underset{l \in [k]}{\operatorname{argmin}} \left\| x_{i,j} - c_{l,j} \right\|_2 .$$

The advantage of this latent representation z is twofold. Firstly, it makes considering all k^2 bi-grams tractable by mapping uni-gram embeddings to share the same code-word embedding based on similarity, thereby allowing us to use a smaller bi-gram embedding table. Secondly, when using a fixed size bi-gram vocabulary, using this latent representation allows for a more efficient representation to be learned compared to directly using uni-gram IDs. For instance, a uni-gram vocabulary of $32,000$ would entail a bi-gram vocabulary of roughly 1 billion, which adds a significant memory overhead.

3.2 Bi-gram IDs from discrete latent representation

The second step is to convert the discrete latent representation z computed in Section 3.1 to bi-gram IDs $b \in [k^2]^{l \times h}$. The latent bi-gram IDs are formed at each position by combining the uni-gram latent IDs z from the previous position as

$$b_i = \begin{cases} z_i & \text{if } i = 0, \\ z_i + k z_{i-1} & \text{otherwise} \end{cases}$$

where k is the size of our codebook. This directly maps the discrete latent sequence from a vocabulary space of $[k]$ to the latent bi-gram vocabulary space of $[k^2]$.

3.3 Constructing bi-gram representations

The third step is to construct bi-gram latent representations b of the sequence. We can consider all k^2 bi-grams and augment the model with an embedding for each such bi-gram. In practice, the compression for machine translation models with a uni-gram vocabulary of $32,000$ involves clustering each token into roughly $k = 2^{12}$ clusters without sacrificing quality (Kaiser et al., 2018; Roy et al., 2018). In this instance, to consider all bi-grams would involve constructing an embedding table with 16 million rows. Since this is still large, we map the latent bi-gram IDs to a smaller bi-gram vocabulary of size v, by using separate hash functions for each head.

More precisely, we have a latent bi-gram embedding table $B \in \mathbb{R}^{v \times h \times d_b}$, where v is the bi-gram vocabulary and d_b is the bi-gram embedding dimension. The bi-gram embedding $y \in \mathbb{R}^{l \times h \times d_b}$ of the text sequence is then constructed as $y_{i,j} = B\left[\left((r_j b_{i,j} + s_j) \mod p_j\right) \mod v, j\right]$, where for each head j, we select a random prime p_j greater than k^2, and r_j is chosen randomly in $\{1, \cdots, p-1\}$ and s_j is chosen randomly in $[p-1]$. This scheme is a universal hashing scheme and guarantees a low collision probability for the discrete latent codes of each head (Thorup, 2015). Note that the bi-gram embedding vector $y_{i,j}$ is a d_b-dimensional vector.

3.4 Combining the embeddings

The final step is to form a new representation of the text sequence which is derived by combining the uni-gram embedding $x \in \mathbb{R}^{l \times h \times d}$ with the latent bi-gram embedding $y \in \mathbb{R}^{l \times h \times d_b}$ obtained in Section 3.3. The bi-gram embedding and uni-gram embedding are both independently layer normalized (LN), followed by simply concatenating the two along the embedding dimension to produce $w = [LN(x), LN(y)] \in \mathbb{R}^{l \times h \times (d + d_b)}$ which is passed as input to rest of the Transformer network. Note that layer normalization (Ba et al., 2016) leads to more stable training.

4 Experiments & Results

We compare the *N*-grammer model with the Transformer architecture (Vaswani et al., 2017) as well as with the recently proposed Primer architecture (So et al., 2021) on the C4 data-set (Raffel et al., 2019). To establish a strong baseline for our experiments we use a Gated Linear Unit (Dauphin et al., 2017) as the feed-forward network with a GELU activation function (Hendrycks and Gimpel, 2016) in all our models, except the Primer. The Primer architecture uses a 3×1 depth-wise convolution after the key, query and value projections, and the squared RELU activation function as proposed in

Model Type	Layers	Params	Vocab size	Clusters	Dim	Inference Ex/sec	PP
Transformer	16	234M	-	-	-	402.00	17.06
Transformer-L	20	284M	-	-	-	331.12	16.44
Primer	16	234M	-	-	-	346.32	16.71
Primer-L	18	284M	-	-	-	284.40	16.07
N-grammer	16	246M	196K	-	12.5%	379.60	16.73
N-grammer	16	259M	196K	-	25.0%	378.64	16.74
N-grammer	16	251M	196K	4K	12.5%	366.80	16.64
N-grammer	16	263M	196K	4K	25.0%	362.40	16.56
N-grammer	16	255M	196K	8K	12.5%	359.52	16.58
N-grammer	16	267M	196K	8K	25.0%	358.96	16.58
N-grammer	16	267M	393K	8K	12.5%	363.60	16.56
N-grammer	16	292M	393K	8K	25.0%	360.16	16.56
N-grammer	16	343M	393K	8K	50.0%	356.94	16.26

Table 1: Ablation results on auto-regressive language modeling on the C4 data-set (Raffel et al., 2019). The column labeled *Vocab Size* refers to the bi-gram vocabulary size, while the column labeled *Dim* refers to the bi-gram embedding dimension as a percentage of the total model dimension. Models are trained with a batch size of 256 for a total of 500k steps. We report the test perplexity (PP) and as well as the inference speed in examples per second (*Inference Ex/sec*) on a TPU-v3 with 8 cores (higher is better).

So et al. (2021). For all experiments, we use the rotary position embedding (RoPE) from Su et al. (2021), which greatly improves the quality of all models.

We use the Adam optimizer (Kingma and Ba, 2015) with a learning rate of 10^{-3} for all the models, while for the *n*-gram embedding tables we use a learning rate of 10^{-2}, as we find that a separate LR improves the stability of the models. We compare the *N*-grammer, Primer and Transformer models in Table 1. The baseline Transformer model has 16 layers and 8 heads, with a model dimension of 1024. We train all the models with a batch size of 256 and a sequence length of 1024 on a TPU-v3. For the *N*-grammer models, we ablate with different sizes for the bi-gram embedding dimension ranging from 128 to 512. Since adding *n*-gram embeddings increases the number of trainable parameters, we also train two large baselines in Table 1 (Transformer-L and Primer-L) which have the same order of parameters as the *N*-grammer models. However, unlike the larger Transformer models, the training and inference cost of *N*-grammer does not scale proportional to the number of parameters in the embedding layer, since they rely on sparse operations (see column Inference Ex/sec in Table 1).

We also examine a simple version of *N*-grammer where we compute the *n*-grams directly from the uni-gram vocabulary as in Section 3.3 rather than from the latent representation of Section 3.1. This is reported in Table 1 and corresponds to the *N*-grammer without an entry in the clusters column. Note that in this case, the modulo hashing scheme of Section 3.3 is random and independent of the content of the actual uni-gram embeddings. We inspect the individual cluster assignment in Appendix D and find common themes among the groupings.

5 Conclusion

We introduced the *N*-grammer layer for augmenting the Transformer architecture with latent *n*-grams, and find that it can match a larger Transformer while being significantly faster in inference. As part of future work, we would like to explore higher order *n*-grams, optimizers for embeddings for improved stability and investigate stacking *N*-grammer layers on top of each other, as well as avenues for reducing the temporal dimension of the latent *n*-gram sequence which can lead to improved inference times without sacrificing quality.

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A Hyperparameters for experiments

In this section we report the hyper-parameter settings for all our experiments.

A.1 Optimizer

We use the Adam optimizer (Kingma and Ba, 2015) and tune the learning rate as well as ε as reported in (Agarwal et al., 2020). We find that decreasing ε from the standard setting of 10^{-6} to 10^{-10} benefits the Transformer models while having less of an effect on the Primer (So et al., 2021). The final choice of the learning rate is 10^{-3} for all the models with the *N*-grammer models having a higher learning rate of 10^{-2} for the *n*-gram embedding table which we find leads to more stable training. We use a $\beta_1 = 0.9$ and $\beta_2 = 0.99$ and clip the gradient norm to 5.0. We do not use any weight decay. We train all models with a global batch size of 256 on a TPU-v3 with 32 cores and a sequence length of 1024.

A.2 *N*-grammer

For the *N*-grammer models, we use a discrete latent vocabulary of $k = \{4096, 8192\}$ except for the baseline *N*-grammer models which directly compute *n*-grams on the uni-gram vocabulary. We use a learning rate of 10^{-3} for training the cluster centers. We train the cluster centers with mini-batch k-means (Bottou and Bengio, 1995) without using any smoothing or exponential moving averages for either the counts or the centers, since we find empirically that it doesn't help in our setting.

B Optimizing the clustering step

Note that there is a trade-off in computing the discrete latent representation of the text sequence, where it may be faster to cluster the uni-gram vocabulary directly instead of clustering the embedded text sequence. If the uni-gram vocabulary is v, the sequence length is l and the global batch size is b, and the number of cores is c, then we expect that clustering the uni-gram vocabulary directly should be faster when $\frac{b \times l}{c} > \frac{v}{c}$. Since we use a global batch size of 256 and a sequence length of 1024, we find that it is significantly faster to cluster the uni-gram embedding table rather than the input text sequence, since $256 \times 1024 > 32,768$.

To obtain the speed-up, we split the embedding table across all cores, since otherwise each core independently clusters c copies of the table, and the threshold point becomes $\frac{b \times l}{c} > v$, which is not true in our case, since all experiments use 32 cores for training, and thus $\frac{256 \times 1024}{32} = 8 \times 1024 < 32,768$. After clustering the uni-gram vocabulary, the discrete latent representation of the sequence is then inferred by an embedding lookup on the cluster IDs of the uni-gram embedding table.

C Convergence comparisons

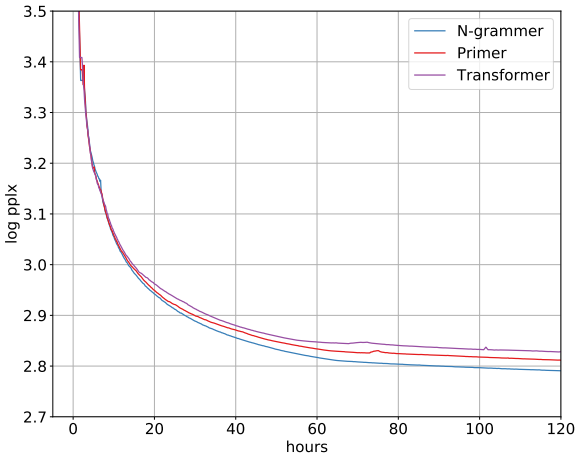
We have included training curve comparisons of the *N*-grammer with that of the Transformer (Vaswani et al., 2017) and the Primer (So et al., 2021). We compare the three models in Figures 2a and 2b where the x-axis denotes the wall clock time on a TPU-v3 while the y-axis denotes the log perplexity and top-1 accuracy respectively on the C4 data-set (Raffel et al., 2019). From Figure 2 we see that the *N*-grammer model is roughly $2\times$ faster than the Primer in wall clock time to reach the same perplexity or accuracy. We also compare the actual steps to convergence in Figure 3.

D What's in the latent representations?

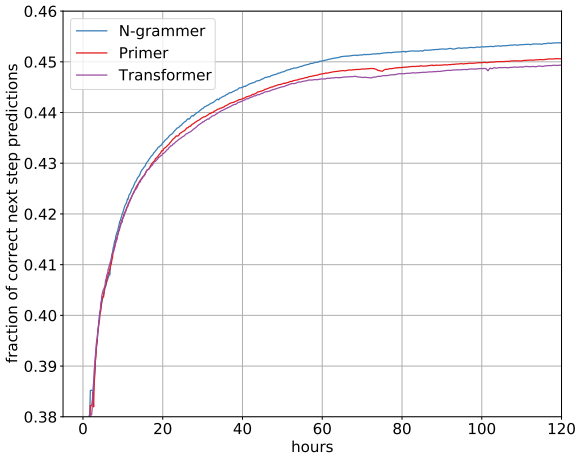
We inspect the discrete latent representations learned by the *N*-grammer layer by examining the different uni-gram tokens that are assigned to the same cluster ID. We take a trained *N*-grammer model with 8192 clusters, *n*-gram embedding dimension of 16 and *n*-gram vocabulary of 196K. We pass the entire set of $32,000$ uni-gram embeddings as input to the *N*-grammer layer, thereby gathering the cluster assignment of every uni-gram token. We present some of these in Table 2, where we find that the model learns to group related uni-gram tokens together:

1. the cluster with head ID 0 and cluster ID 6259 corresponds to sports and games,
2. the cluster with head ID 2 and cluster ID 5362 corresponds to places,
3. the cluster with head ID 0 and cluster ID 7468 corresponds to animals and fruits,
4. the cluster with head ID 2 and cluster ID 8080 corresponds to the arts,
5. the cluster with head ID 4 and cluster ID 6618 also corresponds to the arts.

We also observe that several heads independently learn a similar themed grouping, e.g., head 2 and 4 both have a cluster dedicated to arts and entertainment.

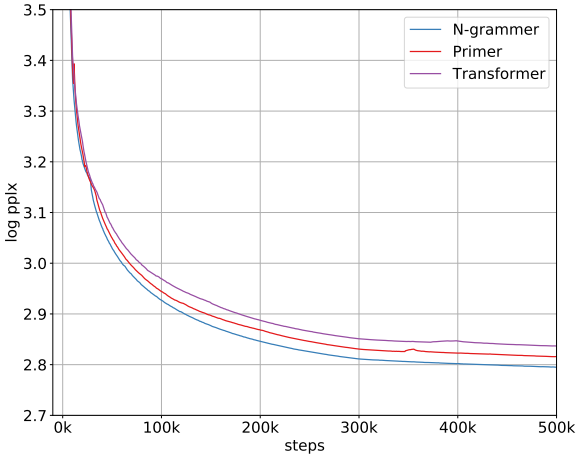


(a) Log perplexity vs wall-clock time on TPU-v3

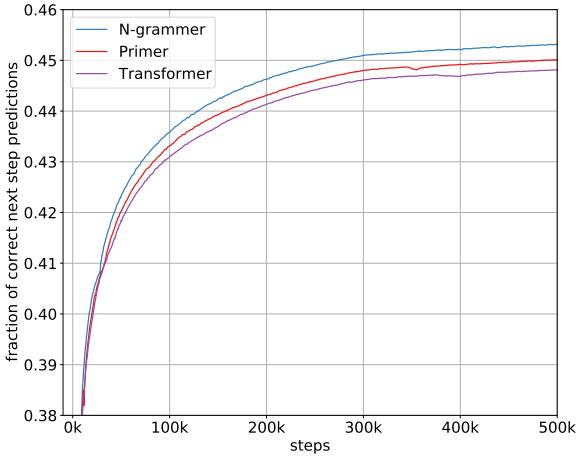


(b) Top-1 accuracy vs wall-clock time on TPU-v3

Figure 2: Wall-clock time comparisons between Transformer with Gated GELU, Primer and *N*-grammer on the C4 data-set (Raffel et al., 2019).



(a) Log perplexity vs steps



(b) Top-1 accuracy vs steps

Figure 3: Steps to quality comparisons between Transformer with Gated GELU, Primer and *N*-grammer on the C4 data-set (Raffel et al., 2019).

Head ID	Cluster ID	Uni-gram Tokens
0	6259	Baseball, football, ceramic, Galaxy, hockey, basketball, Cricket, Basketball, guitar, acquisition, athlete, Soccer, Squid, sports
2	5362	Alchemist, Vegas, hanger, Seinfeld, Kenya, Heroic, Kurdish, Rodgers, Bolivia, Venom, Qatar, dosage, Arcade, Emperor, becua, Finnish, Taiwanese, Chennai, hood, dub, flake, Balkan, Psalm, Bueno, Moldova, flow, mosquito, Filipino, Throne, Siberia, Trout, Fist, Czech, Boulevard, Azerbaijan, Peru, OW, plaster, Kashmir, NZ, Priest, Palestinian, Tibetan, stencil, Aragon, coils, HBO, Iceland, strains, Zimbabwe, firewall, Nepal, Elves, Iranian, Mongol, Traffic, Camilla, parade, Afghan, hose, Serpent, Tarantino, web, Khal, Squid, Mala, Syrian, hood
0	7468	Unknown, spoon, Shut, coconut, grapefruit, cran, Kami, moon, spider, yogurt, perfume, Wine, Skate, antique, snail, Onion, guinea, puppy, mineral, Reagan, elbow, bark, patio, beneath, snake, lever, bunny, falcon, rail, ribbon, knob, apples, quarry, corn, nach, hiking, invoice, Pour, flora, fishing, Paint, olive, violin, octopus, horizontal, blanket, circular, army, nickel, cattle, potato, dolphin, mosquito, citrus, shutter
2	8080	Knicks, Shakespeare, SPE, nursing, spells, Alexa, arrow, vocalist, rehearsal, tunnel, eine, Critical, clar, BAN, remix, obstacle, musicians, BRO, legislature, EMS, Manga, piano, sword, vocal, bald, choir, Messi, Beta, cad, illustrator, organ, conjunction, lunar, bien, needles, musician, hiking, tad, poe, Pay, violin, Marxist, literary, Theater, gig, poetry, Illustrator, guitar, Pluto, Camaro, Fog, orbit, dancing, epub
4	6618	Wise, vocalist, actor, cheek, musicians, TION, piano, tunes, choir, filmmaker, musician, Suzuki, violin, Theater, gig, Drama, guitar, logic, Entertainment

Table 2: Mapping of uni-gram tokens to cluster IDs for the N-grammer model. The N-grammer model has 8 heads, 8192 clusters, an n-gram embedding dimension of 16 and a n-gram vocabulary of 196K. We report the head index (Head ID), the cluster index (Cluster ID) and the uni-gram tokens assigned to those IDs for a random subset of clusters.