BERT as a Teacher: Contextual Embeddings for Sequence-Level Reward

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Abstract

Measuring the quality of a generated sequence against a set of references is a central problem in many learning frameworks, be it to compute a score, to assign a reward, or to perform discrimination. Despite great advances in model architectures, metrics that scale independently of the number of references are still based on n-gram estimates. We show that the underlying operations, counting words and comparing counts, can be lifted to embedding words and comparing embeddings. An in-depth analysis of BERT embeddings shows empirically that contextual embeddings can be employed to capture the required dependencies while maintaining the necessary scalability through appropriate pruning and smoothing techniques. We cast unconditional generation as a reinforcement learning problem and show that our reward function indeed provides a more effective learning signal than n-gram reward in this challenging setting.*

1. Introduction

The great success of semi-supervised models for text generation has raised the question whether generative models of text can as well be trained using *reinforcement learning*, a learning regime by design much closer to multi-step text generation than the single-step treatment of maximum likelihood learning (Ranzato et al., 2015; Goodfellow et al., 2016; Schmidt, 2019).

The standard approach to cast text generation as reinforcement learning problem is to equate the agent's action space with a vocabulary of words (Bahdanau et al., 2016). The result is an extremely sparse reward signal (Leblond et al., 2018) as often only a single sequence is considered as gold-standard. While variance reduction techniques exist (Rennie et al., 2016), reward design is pivotal to successful training.

Traditional reward functions such as BLEU (Papineni et al., 2002) are based on simple *n*-gram statistics that suffer from several problems. Designed originally as evaluation metrics of whole sequences, they cannot natively provide per-symbol reward, a crucial property of sequence-level RL training (Wieting et al., 2019). Consequently, reward-shaping techniques have to step in to simulate fine-grained reward (Bahdanau et al., 2016; Wu et al., 2018). In addition, many authors have questioned whether BLEU and similarly ROUGE (Lin, 2004) even serve as a good substitues for human evaluations in the first place (Callison-Burch et al., 2006; Kryscinski et al., 2019).

In this work we propose to employ modern contextual word embeddings such as BERT (Devlin et al., 2018) as backbone of a novel reward function. Just as embedding-based neural language models have overcome *n*-gram language models, we propose to characterize a set of references by *embedding* tokens instead of counting them and to compare them in terms of their vectorspace representations instead of their counts. The benefit of contextual embeddings over counts is two-fold: First, we relax the restriction to a fixed context size and can confirm empirically that much longer dependencies can be captured. Second, the joint representation of a word and its context allows to express reward naturally as a sum of per-word contributions which renders reward-shaping unnecessary and provides computational advantages.

While we focus on BERT specifically, our approach is transparent to the underlying embedding model and its pre-training objective. As such, our approach is also an attempt to address the apparent paradox that the best word-representations are so far found as by-products of training classification models of increasingly complex, potentially multi-sequence pre-training tasks (Devlin et al., 2018; Mikolov et al., 2013; Bowman et al., 2018) and not through training complex hierarchical generative models, even though such models exist (Fan et al., 2018; Serban et al., 2016). By leveraging the quality of pre-trained embeddings, we can represent even small corpora adequately where n-gram models suffer from sparsity.

The challenges of performing sequence-level RL training are rooted in the lack of access to ground-truth past actions, termed *teacher-forcing* (Williams & Zipser, 1989), which at

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^{*}Code at github.com/schmiflo/bert-grams

the same time resolves the issue of *exposure bias* (Ranzato et al., 2015) found in ML training. Naturally, this difference is amplified in unconditional generation where no source sentence is available. We choose this unconditional setting in which every training sequence effectively becomes a reference to challenge the design of the reward function to adequately take into account many references, a facet often neglected in conditional settings (Qin & Specia, 2015). This is in line with recent work which conjectures that such multi-goal RL setups might help to alleviate the sparseness problem of RL in NLP (Choshen et al., 2019). We empirically show that our reward indeed provides a fine-grained learning signal and incorporates much longer dependencies and more complex semantics than *n*-gram reward.

2. Related Work

Contextual word-embeddings (Peters et al., 2018b; Devlin et al., 2018) have shown state-of-the-art performance on an abundance of tasks, including the SuperGLUE benchmark suite (Wang et al., 2019) and we refer to the recent analysis of Peters et al. (2018a) for a general discussion. BERT and ELMo embeddings have been successfully exploited on the modelling side to improve standard architectures on conditional tasks such as machine translation (Clinchant et al., 2019).

To the design a reward function, contextual embeddings have been used successfully for conditional tasks where a single candidate is compared against a single reference. For example, BERTScore (Zhang et al., 2019) uses BERT-based cosine similarity between all tokens in the candidate and all tokens in the reference. Interestingly, some geometric relations can even be tracked across languages (Lo & Simard, 2019). Even more elaborate, Sentence Mover's Score (Clark et al., 2019a) and MoverScore (Zhao et al., 2019) compute a word movers distance (Kusner et al., 2015) on top of BERT word embeddings. Experiments suggest that such reward functions show higher correlation with human judgment compared to BLEU in machine translation (Mathur et al., 2019), summarization (Clark et al., 2019a) and image captioning (Zhang et al., 2019). Unfortunately, these metrics are designed with a single or very few reference in mind. By contrast, our interest is in representing a whole corpus of references so that a comparison against the representation is constant in the corpus size. Finally, Wang & Cho (2019) propose a method to generate text from BERT, yet only to reveal the model's original training corpus.

Although training of GANs is not our focus here, it should be noted that popular GANs for text generation also rely on policy gradient techniques to deal with the generator's discrete output symbols (Fedus et al., 2018; Yu et al., 2017). In fact, *n*-gram scores have been shown to be insufficient for discrimination and provide a potential future application

of our approach (Semeniuta et al., 2018).

Finally, avoiding exposure bias is an active field of research discussed inside many framworks including ML (Bengio et al., 2015), RL (Tan et al., 2018) aversarial learning (Goyal et al., 2016) and learning-as-search (Leblond et al., 2018).

3. Reward via Maximal Similarity

An n-gram based reward such as BLEU simply awards the maximum number of occurrences found in any reference to each n-gram of the candidate and it is tempting to refute its methodology as overly simple. However, its simplicity is paired with an extreme efficiency and it is worthwhile pointing out the underlying reasons before proposing alternatives. Let us briefly formalize BLEU as a prototypical example of n-gram reward.

In a first step, we will express reward between a candidate sequence s and a *single* reference s^* as a sum across features of s and then show how this reward can be generalized to measure similarity of s to a *set* of references S^* .

Breaking sequences into features To express the reward of a sequence s, we define two operators. First, let $\mathcal{F}(s)$ be a feature *index set* operator which maps s to the smallest units we consider for obtaining reward, for example n-grams. Such a – potentially structured – feature index $\mathbf{f} \in \mathcal{F}(s)$ can then be queried against the sequence s via an operator $\phi_s(\mathbf{f})$ that returns a reward-specific feature representation of \mathbf{f} in s. With these ingredients we write the reward of a sequence s with respect to a single reference sequence s^* as a sum of feature-specific terms

$$R(s, s^{\star}) = \frac{1}{Z} \sum_{\mathbf{f} \in \mathcal{F}(s)} r(\phi_s(\mathbf{f}), \phi_{s^{\star}}(\mathbf{f})). \tag{1}$$

typically normalized to the interval [0,1] by some Z independent of s^\star . The function r assesses how similar the representations of ${\bf f}$ in the candidate s and the reference s^\star are. For example, for a given n, BLEU computes a modified precision by using a *count* operator ϕ_s which simply returns the number of occurrences of an n-gram ${\bf f}$ in s, a clipping operator $r: \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ which returns the minimum count, and a normalizer corresponding to the number of n-grams Z = T - n + 1.

Reward against a set of references Now we are ready to express reward against a set $R(s, S^*)$ by relating it to sequence-level reward $R(s, s^*)$ via the maximum across the set S^* . Formally,

$$R(s, S^*) = \max_{s^* \in S^*} R(s, s^*). \tag{2}$$

This expression follows the simple intuition that s is similar to S^* if and only if there is some $s^* \in S^*$ close to s.

Combining the Equations (1) and (2) reveals how partitioning reward into feature-specific terms allows to compute the reward of a sequence against a set of references efficiently by pulling the maximum operator into the sum

$$R(s, S^*) = \max_{s^* \in S^*} R(s, s^*) \tag{3}$$

$$= \frac{1}{Z} \max_{s^{\star} \in S^{\star}} \sum_{\mathbf{f} \in \mathcal{F}(s)} r(\phi_s(\mathbf{f}), \phi_{s^{\star}}(\mathbf{f}))$$
 (4)

$$= \frac{1}{Z} \sum_{\mathbf{f} \in \mathcal{F}(s)} \max_{s^{\star} \in S^{\star}} r(\phi_s(\mathbf{f}), \phi_{s^{\star}}(\mathbf{f})) . \quad (5)$$

This exchange is possible since every term depends only on one isolated feature (even though one feature might be composed of several words). For some choices of $\phi_{\mathbf{f}}$ and r, it is even possible to pull the maximum operator into r, which simplifies (5) further

$$R(s, S^{\star}) = \frac{1}{Z} \sum_{\mathbf{f} \in \mathcal{F}(s)} r(\phi_s(\mathbf{f}), \phi_{\star}(\mathbf{f})).$$
 (6)

where $\phi_{\star}(\mathbf{f})$ is pre-computed across all $s^{\star} \in S^{\star}$ so that $r(\phi_s(\mathbf{f}), \phi_{\star}(\mathbf{f})) = \max_{s^{\star} \in S^{\star}} r(\phi_s(\mathbf{f}), \phi_{s^{\star}}(\mathbf{f}))$ for all candidates s. For example, the simplicity of BLEU's counting operator ϕ and clipping operation r, allows to pre-compute $\phi_{\star}(\mathbf{f})$ as the maximum count of \mathbf{f} found in any single reference in S^{\star} . As a consequence, (6) can be evaluated independently of the number of references in S^{\star} .

3.1. Reward Shaping

The above formulation breaks reward assignment R into a sum of contributions r across some features indexed by $\mathcal{F}(s)$. However, when reinforcement learning is used to maximize a reward, it is important to be able to assign a partial reward to every symbol generated in the sequence $s = w_{1:T}$. Consequently, we need to be able to partition the reward into contributions across time. Unfortunately, if features consist of multiple words, such as is the case for all n-gram-based rewards, this decomposition is problematic.

First of all, the attribution of the reward obtained through an n-gram to a single word is unclear. Second, common n-gram based rewards, such as BLEU, rely on combining rewards R_n for several n, typically n=1,2,3,4, by a harmonic mean adjusted by weights π_n to obtain a more powerful reward function

BLEU
$$(s, s^*) = \exp\left(\sum_{n=1}^{N} \pi_t \log R_n(s, s^*)\right)$$
 (7)

where R_n is the n-gram reward as discussed in Section 3. Unfortunately, this couples the sum across features and there is no trivial way to isolate time-specific contributions R_t . Seminal work on sequence-based reinforcement learning by Bahdanau et al. (2016) attempts to circumvent the problem using the incremental reward R_t

 $R(s_{1:t},s^\star)-R(s_{1:t-1},s^\star)$. For precision-based rewards this is problematic, as $R(s_{1:t},s^\star)$ is normalized over the *candidate* length t which is detrimental to obtaining meaningful differences. In the case of BLEU, even when $s=s^\star$ we have $R_1=1$ and $R_t=0$ $\forall t>1$ although predictions were correct at all times and hence should be rewarded.

3.2. Unconditional Generation with RL

Given a reward function $R(s,S^\star)$, we can define unconditional generation as a standard entropy regularized reward maximization problem

$$\mathcal{J} = \mathbb{E}_{s \sim p_{\theta}}[R(s, S^{\star})] + \beta H[p_{\theta}] \tag{8}$$

where the policy $p_{\theta}(s) = \prod_t p_{\theta}(w_t|w_{1:t-1})$ is any generative model of text, usually some form of recurrent neural network. To optimize (8) we resort to the REINFORCE method (Williams, 1992) and follow standard practice to reduce variance with the mini-batch mean reward as a baseline (Rennie et al., 2016). The entropy term can be Monte Carlo sampled using the same samples $s \sim p_{\theta}$, hence the complexity of computing the entropy of all soft-max distributions is identical to that of sampling.

The entropy regularizer is crucial to prevent the policy from outputting only *one* high quality output. In conditional generation, such considerations of quality versus diversity are neglected as one is usually only interested in a single output at test-time which is found by an approximate argmax operator such as beam search; a practice recently criticized by (Holtzman et al., 2019) for its implicit biases. Across models and baselines we found it beneficial to dampen the entropy regularization strength towards the end of the sequence by using a position-specific multiplier $\beta_t = \beta \cdot t^{-\alpha}$ with $\alpha = \frac{3}{4}$. Given the exponential size of the sequence space, it should not come as a surprise that most variability in a finite dataset resides in the initial symbols and indeed we found a similar rate of decay when investigating the empirical entropy $H[w_{t+1:T}|w_{1:t}]$ of the training data.

3.3. Handling Variable Length

The variable-length nature of text is a defining property of natural language, yet can be challenging to model in a machine learning model. In conditional generation, one often uses a *length penalty* to discourage outputs that deviate significantly from the given reference length. By contrast, in unconditional generation we expect outputs of varying length, a property impossible to asses given a single candidate. While one could assess whether the length distribution across a mini-batch of candidates matches that of the training data, it is unclear how such a metric could be translated into a per-token reward signal. Instead, we follow M. Ziegler

& M. Rush (2019) and marginalize out sequence length as

$$p_{\theta}(s) = \sum_{l=1}^{L} p(l) p_{\theta}(s|l)$$
 (9)

using the length distribution p(l) found in the training data. When generating a sequence, we first sample $\hat{l} \sim p(l)$ and then execute the length-informed policy $p(s|\hat{l})$ to generate a sequence of length \hat{l} . Instead of defining a penalty for violating the target length \hat{l} we find that it is sufficient to truncate sequences too long and pad sequences too short with a special symbol not seen in the training data. In both cases, the output differs significantly from the reference sequences and is penalized accordingly by our reward function.

4. BERT-grams

Let us shift the complexity of assigning reward from the feature indices to their actual representations. We use the most simple indices $\mathcal{F}(s) = \{1, \dots, T\}$ but an contextual embedding operator ϕ which maps a sequence of symbols s to a sequence of embeddings. Then $\phi_s(t) \in \mathbb{R}^d$ is the contextual word vector at position t. Now we can write the reward – assuming equal length T for now – of a sequence naturally as a sum over time

$$R(s, s^*) = \frac{1}{T} \sum_{t} R_t(s, s^*)$$

$$\tag{10}$$

$$= \frac{1}{T} \sum_{t=1}^{T} \exp\left(-\gamma \|\phi_s(t) - \phi_{s^*}(t)\|^2\right)$$
 (11)

where we have used an RBF kernel for $r: \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ in the last equation and normalized so that $R(s,s^\star) \in [0,1]$. The bandwidth γ will serve as a *smoothing* hyper-parameter that controls how much reward we assign to words in an unseen sequence. As we let $\gamma \to \infty$ we only assign reward for $s=s^\star$.

Replacing ϕ with a powerful embedding operator comes at a price. When we cast (11) as reward against a set of references according to (2), we cannot pull the max operator inside the feature sum precisely because ϕ implements *contextual* embeddings:

$$R(s, S^{\star}) = \frac{1}{T} \max_{s^{\star} \in S^{\star}} \sum_{t=1}^{T} \exp\left(-\gamma \|\phi_s(t) - \phi_{s^{\star}}(t)\|^2\right)$$
(12)

At this point we cannot follow the approach of BLEU and pre-compute some $\phi_{\star}(t)$ which allows us to avoid a maximum altogether. However, the next section will discuss how we can pre-compute a set of K representatives so that a nearest neighbor search across only K vectors is sufficient. Section 4.2 will then present empirical evidence that those representatives provide a reasonable approximation.

4.1. Prunig

Without further approximations, evaluating our reward against a set of references requires the embeddings of all references in S^\star . Clearly, this is infeasible at training time and likely also at test time. Therefore, we perform a partitioning of all word-embeddings of the training corpus according to the word type and then use K-means clustering to obtain K representatives for each partition. The result is a set of (up to) K representatives $\{\phi_1^w,\ldots\phi_K^w\}$ for each partition. Every ϕ_k^w represents a prototypical use of a specific word w defined by its context and we will use the term BERT-gram to refer to this condensed contextual representation.

When plugging BERT-grams ϕ_k^w into the reward (12), we can now carry the max operator into the sum. As a result, we can compute the reward obtained by a sequence s of any length T with respect to S^\star in time $\mathcal{O}(dKT)$ independently of $|S^\star|$.

4.2. The BERT Word Embedding Space

Our approach presented above crucially hinges on the quality of our BERT-grams which encode the training corpus for the purpose of reward assignment. In particular, we require the encoded context to be long enough to foster coherent sequences, yet short enough to generalize well. Unfortunately, there is no theoretical analysis of contextual embeddings yet and even for non-contextual embeddings such as word2vec no agreed-upon theory has emerged despite elaborate efforts (Arora et al., 2016). Therefore, we first empirically investigate the semantics of the embedding space and the context sensitivity of our reward before turning to optimizing an agent with respect to it. This complements existing work which analyzes sequence self-similarity (Peters et al., 2018a), attention patterns (Clark et al., 2019b; Coenen et al., 2019) and implicit syntactic structures (Hewitt & Manning, 2019) found in BERT.

For all but one experiment we use the BooksCorpus (Kiros et al., 2015; Zhu et al., 2015) and the standard 30K word-piece vocabulary of BERT (Wu et al., 2016). When performing clustering we use K=100 and K-means++ for initialization (Arthur & Vassilvitskii, 2007).

Nearest Neighbors Retrieving nearest neighbors is a standard yet simple investigation method for embedding spaces (Mikolov et al., 2013). In contrast to non-contextual embedding techniques, we expect context to resolve homonymy. That is, words with identical spelling but different meaning should have different embeddings. To investigate this, we embed 500K sentences and query the embedding space by two query sentences which clearly resolve the ambiguity of

²Yet when reporting examples we fuse the sub-word tokens by removing the ## symbols and the adjacent space.

the word in consideration. For the word bank we choose he went to a bank to get more money and she swam close to the bank of the river.

he went to a bank to get more money.

shes got some money in the bank there, and friends to stay with.
i really need to get to a bank.
she went to the bank and put the documents in her safety deposit box.
wed best go to the bank, i think.
you robbed a bank or something?
across the street a man entered the pnc bank.

she swam close to the bank of the river.

alison stood on the river bank, looking down at the water.
sherzad leaned on the bank of the canal, humming and whistling softly.
come to the river bank.
he swung the canoe toward the bank.
so we rode downstream till we could access the bank.
aye, then spread yourselves, two to each bank of the stream.

Table 1. Nearest neighbor analysis. We embed the two query sentences and obtain the k=6 nearest neighbors of "bank" in for each of the sentences.

Given the embedded query sentences, we search for the k nearest words in embedding space and return the sentences they originated from. Table 1 shows the result. We find the two meanings extremely well separated, even at larger k. Note that this nearest neighbor relation is not limited to identical surface forms. In fact, we often find words with meaning very similar given a particular context to often be close in embedding space. Table 2 shows an example³ with verbs that can be characterized as describing a slow movement downwards.

ully **lowers** toward the floor.

the man bends forward to wail.
he bends down on one knee, meets james at eye level.
adria's shoulders and chest inflate and she lowers her head
he sinks closer to the surface of the planet.
the top half drops to the ground.
then he descends again like a parachutist, slowly and in control.
aura lowers her head to stroke her cheek alongside falcops.
she sits and glides to the middle.
craig motions above us.

Table 2. Nearest neigbors with different surface forms.

Context Sensitivity The above experiment confirms that the embeddings of words with different meanings are sufficiently influenced by their context to be distinguished in embedding space. However, we have focused on synonyms, which might be particularly tied to context. To investigate the general context-sensitivity of embeddings, we conduct the following experiment for every sentence s in a corpus:

- 1. Embed s using BERT as $\phi_s(1) \dots \phi_s(T)$
- 2. Pick a position t u.a.r. from $1 \dots T$ and replace w_t by \tilde{w} drawn from the unigram distribution of the corpus to obtain a perturbed sample \tilde{s} .
- 3. Embed \tilde{s} using BERT as $\phi_{\tilde{s}}(1) \dots \phi_{\tilde{s}}(T)$
- 4. $R_t(s, \tilde{s}) = \exp(-\gamma \|\phi_s(t) \phi_{\tilde{s}}(t)\|^2)$ for every t

We repeat the experiment across 64K sequences (all of length T=14 for ease of presentation) and obtain a $T\times T$ sensitivity matrix with entries obtained by averaging $R_t\in[0,1]$ compute by the RBF Kernel. Note that for non-contextual embeddings, we would obtain the diagonal matrix $\mathbf{1}-\mathbf{I}$. Figure 1 shows the result.

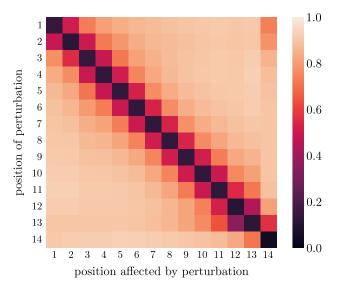


Figure 1. Perturbation analysis obtained by randomly replacing words in a sentence and measuring the displacement in embedding space per position across the original and perturbed sequences.

Indeed, we observe a significant sensitivity to perturbations across about 7 words. The impact of perturbations at position 13 have a broader impact which can be explained by the fact that this is typically the last non-punctuation token which effectively "finishes" the sentence. Furthermore, the last token is particularly affected by changes in the first two positions which is due to the ubiquity of direct speech and the corresponding punctuation⁴ in the Books corpus.

Long-Range Sensitivity We have shown context-sensitivity beyond the length of typical *n*-gram models, yet our noise model in the above experiment was rather rough as many words sampled might have resulted in malformed syntax. It remains to show how a more subtle,

³We find this particular example by actively filtering for neighbors that vary significantly in surface form. If we embed a smaller subset of the corpus, we naturally find much more such examples, yet with less convincing relations.

⁴In Books ``indicates the start of direct speech which BERT tokenizes to two tokens.

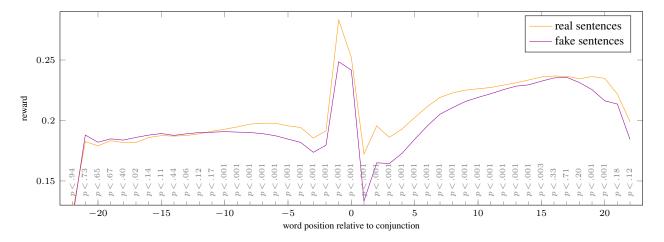


Figure 2. Mean per-position reward obtained from comparing real and fake sentences against S^* . Sequences are pooled to be centered around the conjunction at t = 0, p-values are computed individually for every relative position.

semantic change is reflected in our reward, in particular when consistency is maintained locally but not globally.

To this end, we use the DiscoFuse corpus (Geva et al., 2019), a recently released dataset intended for the task of sentence fusion which asks to join two sentences with an appropriate connective such as and, although or but and probably making small changes to the resulting sentence. The dataset was generated from the Wikipedia corpus by breaking single sentences which contain a connective clause into two separate ones. Luckily, the dataset provides the original sentences and the indices of the connecting clause found by a carefully tuned automated system. We exploit these sentences in two ways: First, every sentence serves as a "real" sentence. Second, we randomly pair sentences which share the same connecting clause, which gives us as many "fake" sentences as real ones. A prototypical fake sentence looks like this: various aircraft safety innovations were proposed and the rooms have their own bathrooms. Note that although humans can easily detect the mismatch between the first and second part, there is no short sub-sequence in the middle of the sentence that would reveal the semantic change as both original sentences share the same conjunction; hence the syntax remains intact in almost all instances.

We split the dataset into two equally sized portions. The first portion S^{\star} is used to fit our reward function (essentially by embedding it). The second is used to run the investigation. For this portion we apply the above procedure and arrive at n=1M real sentences $S_{\rm real}$ and equally many fake sentences $S_{\rm fake}$. We are interested whether

$$\frac{1}{n} \sum_{s \in S_{\text{real}}} R(s, S^{\star}) \stackrel{?}{>} \frac{1}{n} \sum_{s \in S_{\text{fake}}} R(s, S^{\star}) . \tag{13}$$

Since our reward can readily be written as a sum over time, we do not need to look at total reward only, but can investi-

gate position-specific differences relative to the connecting clause. Figure 2 shows $R_t(s,s^\star)$ averaged across all sequences with t shifted so that all conjunctions are located at t=0 (for multi-word conjunctions we average the reward for ease of presentation). Note that the spike around t=0 is an artifact of aligning a set of sentences with great variety at a position dictated by very few identical connecting clauses.

Naturally, the data contains a lot of variance, in particular as for some positions t we are averaging the reward of words at different absolute positions due to the shifting. Assuming normal distribution and equal variance we perform a two-sample t-test and give p-values for the comparisons at every positions t in Figure 2. We find that indeed the reward for the real sequences is significantly higher, even at more than 10 tokens away from the conjunction and in particular towards the end of the sentence. Only at the extreme tails data sparsity does not allow to draw a conclusion with significance. Also keep in mind that none of the sequences — real or fake — evaluated for Figure 2 were seen when the reward function was fit to the data.

In contrast, a BLEU reward function (with up to 4-grams) estimated on S^{\star} can only access features very closely centered around the conjunction and results in a reward difference one order of magnitude smaller than ours (both significant with p < .001).

Clustering We use the clustering technique described in Section 4.1 to learn BERT-grams for k=1,5,10 on a 500K sequence sample of the BooksCorpus. To inspect the decrease in quality of our reward function, we investigate the centroids ϕ_k^w that a word w_t in a candidate s is mapped to in the arg max of (12). Since centroids do not necessarily coincide with word embeddings, we return the vector (and its sequence) closest to the centroid. Figure 3 shows a

Figure 3. An example candidate s along the training sequences closest to the nearest bert-grams used to assign reward for dim, drowning and seq for $k \in \{1, 5, 10\}$. For each k we report the reward obtained with $\gamma = 0.06$.

challenging example with metaphorical language. As we increase k, we resolve the words dim, drowning and sea closer to its meaning in s and the reward assigned increases.

5. Unconditional Generation

Let us now use our proposed reward function to learn an unconditional generative model of text.

Data Unconditional generation has been proven to be a very challenging task under every training regime that does not use teacher-forcing – that is, langauge models – even when powerful discrimiantors are used (Fedus et al., 2018; Caccia et al., 2018). We therefore restrict the BooksCorpus to a randomly sampled 500K subset of sequences with length 9 to 13. While providing a computationally more tractable test-bed, this setting also reflects the commonly expressed motivation to use reinforcement learning when prior knowledge can be injected into a learning process where training data is sparse.

Generative model We use a 512-dimensional GRU (Cho et al., 2014) with 100-dimensional input embeddings as our policy. The parameterization of the policy is chosen so that we observe overfitting under ML training after about 20K steps. Our standard setup is then to pre-train for 5K steps with maximum likelihood training before switching to REINFORCE. We use the DistilBERT and GPT-2 implementation of the huggingface transformers package (Wolf et al., 2019) and a single GPU for all experiments.

Reward As a reward baseline we use⁵ BLEU with up to n = 4 grams and reward-shaping (Bahdanau et al., 2016).

To obtain BERT-grams of the training data, we use a clustering with k=100. When using BERT-grams alone as a reward during training, we find that frequent function words, stop words and in particular punctuation seem to be embedded differently from the remaining words, an observation also made by Ethayarajh (2019). The result are outputs where such tokens are frequently repeated. For this reason, we combine BERT-grams with BLEU (denoted as OURS)

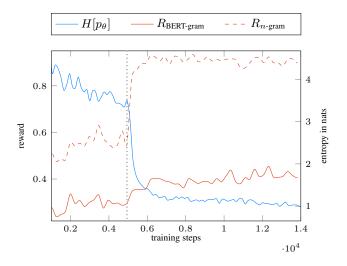


Figure 4. Entropy and reward (from BERT-grams and n-grams) of the generative model over the course of training. The vertical dotted line indicates the end of ML pre-training.

by a weighted combination (0.25 weight on BERT-grams) and analyze how the addition of BERT-grams complements BLEU alone (denoted n-GRAM).

	GPT-2 PPL	ho	$ ho_4$	$ ho_2$	length
OURS	118	0.86	0.21	0.13	8.2
$n ext{-}GRAM$	224	0.83	0.19	0.12	8,2
ML	944	1.0	0.97	0.72	9.2
DATA	111	1.0	0.97	0.74	8.9

Table 3. Results summarized including a DATA sample.

For both, our reward and the n-gram reward, RL training proves to be extremely sensitive to the choice of the entropy regularizer strength β . In fact, balancing diversity and quality turned out to be the biggest challenge when training the policy and we will highlight this trade-off in all experiments below. We found $\beta=0.0065$ to work well for OURS and n-GRAM (the regularizer depends only on p_{θ} , not the choice of R) and find $\gamma=0.06$ from a range of [0.0001,0.5] as best performing bandwidth for this β .

Figure 4 illustrates this trade-off when training with our proposed reward. We show the entropy of the policy along with

⁵We adapt the NLTK (Elhadad, 2010) implementation to work with a pre-computed table of counts and use method3 for smoothing modified precisions. No length penalty is used.

the BERT-gram and *n*-gram reward obtained in the mixture (without weights). When switching from ML to RL training, the entropy is reduced drastically and reward increases. In contrast to BERT-gram reward, the *n*-gram reward contribution saturates early on since the count statistics cannot incorporate a large number of references well.

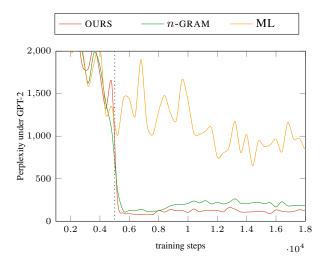


Figure 5. Sample quality as measured by perplexity under GPT-2.

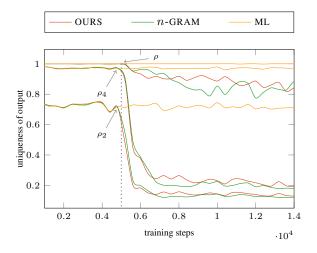


Figure 6. Sample diversity as measured by the ratios of unique outputs ρ , unique 2-grams ρ_2 , and unique 4-grams ρ_4 .

To asses the quality of the output of the models, we follow existing work on unconditional generation and use various statistics on a mini-batch of 600 sequences to asses diversity and quality (Fedus et al., 2018; Holtzman et al., 2018). For diversity, we use the ratio of unique sequences in the batch ρ and the average ratio of unique 2-grams and 4-grams per sequence ρ_2 and ρ_4 . For quality, we evaluate the output under the GPT-2 (Radford et al., 2019) language model and report perplexity. Finally, we report the average length of the generated sequences to asses how well the length distribution of the data is preserved. Figures 5 and 6 show

quality and diversity for our reward and the baseline reward over the course of the training. Table 3 summarizes the final performance obtained by the policies and compares to ML, the identical policy trained under maximum likelihood only. Also, we add DATA, a sample of the true data.

Our reward outperforms the reward based only on n-grams in all metrics. Under both rewards, the policies trained under RL deliver sequences with much better quality (as determined by GPT-2), yet much poorer variety. When increasing β to trade quality for more variety, we immediately obtained models with extremely high entropy under both reward functions. Unfortunately, GPT-2 does not detect all forms of degeneracy, in particular repeated punctuation (he went away.....) and repeated short sequences are sometimes assigned unreasonably high perplexity as similarly reported by Holtzman et al. (2019) recently.

Although the numbers in Table 3 suggest superior performance of the RL-trained models compared to the purely ML based model, a manual inspection reveals that the outputs of the RL-trained models are often instances of few "templates". For example, both reward functions seem to incentivize sentences with direct speech such as vinnie, i'm scared." or idiots, " she whispered. or jacques, i'll kill him." (we provide more examples in Appendix A). While direct speech appears in 40% of all sequences in the data, a model trained against n-GRAM generates direct speech 99% of the time and one trained against OURS 95% of the time. This is in line with recent work by Choshen et al. (2019) on conditional generation that criticizes standard RL methods in NLP and suggests that the main effect of RL training after pre-training is a decrease in entropy. Naturally, this surfaces much more pronouncedly when perform unconditional sampling instead of conditional argmax decoding.

6. Conclusion

In this work, we have proposed a reward function for unconditional text generation based on contextual BERT embeddings. Our reward employs embedding-based similarity instead of count-based similarity and in contrast to n-grambased reward provides per-word contributions by design. Using a clustering approach we condense the training corpus into a set of BERT-grams which allow efficient reward assignment independent of the corpus size.

Our investigations of the proposed reward confirm the expressiveness and versatility of contextualized embeddings. In particular, we also find these properties maintained when clustering word vectors aggressively. However, when employing the reward as learning signal in unconditional generation, we do notice the limits of the underlying REINFORCE training methodology and discover similar modes of collapse as found in GAN training.

References

- Arora, S., Li, Y., Liang, Y., Ma, T., and Risteski, A. Linear algebraic structure of word senses, with applications to polysemy. *CoRR*, abs/1601.03764, 2016.
- Arthur, D. and Vassilvitskii, S. K-means++: The advantages of careful seeding. volume 8, pp. 1027–1035, 01 2007. doi: 10.1145/1283383.1283494.
- Bahdanau, D., Brakel, P., Xu, K., Goyal, A., Lowe, R., Pineau, J., Courville, A. C., and Bengio, Y. An actor-critic algorithm for sequence prediction. *CoRR*, abs/1607.07086, 2016.
- Bengio, S., Vinyals, O., Jaitly, N., and Shazeer, N. Scheduled sampling for sequence prediction with recurrent neural networks. In *NIPS*, 2015.
- Bowman, S. R., Pavlick, E., Grave, E., Durme, B. V., Wang, A., Hula, J., Xia, P., Pappagari, R., McCoy, R. T., Patel, R., Kim, N., Tenney, I., Huang, Y., Yu, K., Jin, S., and Chen, B. Looking for elmo's friends: Sentence-level pretraining beyond language modeling. *CoRR*, abs/1812.10860, 2018.
- Caccia, M., Caccia, L., Fedus, W., Larochelle, H., Pineau, J., and Charlin, L. Language gans falling short. *CoRR*, abs/1811.02549, 2018.
- Callison-Burch, C., Osborne, M., and Koehn, P. Reevaluating the role of Bleu in machine translation research. In 11th Conference of the European Chapter of the Association for Computational Linguistics, Trento, Italy, April 2006. Association for Computational Linguistics.
- Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Y. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In *EMNLP*, pp. 1724– 1734, October 2014.
- Choshen, L., Fox, L., Aizenbud, Z., and Abend, O. On the weaknesses of reinforcement learning for neural machine translation. *CoRR*, abs/1907.01752, 2019.
- Clark, E., Celikyilmaz, A., and Smith, N. A. Sentence mover's similarity: Automatic evaluation for multisentence texts. In *Proceedings of the 57th Annual Meet*ing of the Association for Computational Linguistics, pp. 2748–2760, Florence, Italy, July 2019a. Association for Computational Linguistics.
- Clark, K., Khandelwal, U., Levy, O., and Manning, C. D. What does bert look at? an analysis of bert's attention. *ArXiv*, abs/1906.04341, 2019b.

- Clinchant, S., Jung, K. W., and Nikoulina, V. On the use of BERT for neural machine translation. In *Proceedings of the 3rd Workshop on Neural Generation and Translation*, pp. 108–117, Hong Kong, November 2019. Association for Computational Linguistics.
- Coenen, A., Reif, E., Yuan, A., Kim, B., Pearce, A., Viégas, F. B., and Wattenberg, M. Visualizing and measuring the geometry of BERT. *CoRR*, abs/1906.02715, 2019.
- Devlin, J., Chang, M., Lee, K., and Toutanova, K. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018.
- Elhadad, M. Book review: Natural language processing with python by steven bird, ewan Klein, and edward loper. *Computational Linguistics*, 36(4), 2010.
- Ethayarajh, K. How contextual are contextualized word representations? comparing the geometry of BERT, ELMo, and GPT-2 embeddings. In *EMNLP*, pp. 55–65, Hong Kong, China, November 2019. Association for Computational Linguistics.
- Fan, A., Lewis, M., and Dauphin, Y. N. Hierarchical neural story generation. *CoRR*, abs/1805.04833, 2018.
- Fedus, W., Goodfellow, I. J., and Dai, A. M. Maskgan: Better text generation via filling in the _____. In *ICLR*, 2018.
- Geva, M., Malmi, E., Szpektor, I., and Berant, J. Discofuse: A large-scale dataset for discourse-based sentence fusion. *CoRR*, abs/1902.10526, 2019.
- Goodfellow, I., Bengio, Y., and Courville, A. *Deep Learning*. MIT Press, 2016.
- Goyal, A., Lamb, A., Zhang, Y., Zhang, S., Courville, A. C., and Bengio, Y. Professor forcing: A new algorithm for training recurrent networks. In *NIPS*, 2016.
- Hewitt, J. and Manning, C. D. A structural probe for finding syntax in word representations. In *NAACL*, pp. 4129–4138, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics.
- Holtzman, A., Buys, J., Forbes, M., Bosselut, A., Golub, D., and Choi, Y. Learning to write with cooperative discriminators. *CoRR*, abs/1805.06087, 2018.
- Holtzman, A., Buys, J., Forbes, M., and Choi, Y. The curious case of neural text degeneration. *CoRR*, abs/1904.09751, 2019.
- Kiros, R., Zhu, Y., Salakhutdinov, R., Zemel, R. S., Torralba, A., Urtasun, R., and Fidler, S. Skip-thought vectors. arXiv preprint arXiv:1506.06726, 2015.

- Kryscinski, W., Keskar, N. S., McCann, B., Xiong, C., and Socher, R. Neural text summarization: A critical evaluation. In *EMNLP*, pp. 540–551, Hong Kong, China, November 2019. Association for Computational Linguistics
- Kusner, M. J., Sun, Y., Kolkin, N. I., and Weinberger, K. Q. From word embeddings to document distances. In *ICML*, 2015.
- Leblond, R., Alayrac, J., Osokin, A., and Lacoste-Julien, S. SEARNN: training rnns with global-local losses. In *ICLR*, 2018.
- Lin, C.-Y. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pp. 74–81, Barcelona, Spain, July 2004. Association for Computational Linguistics.
- Lo, C.-k. and Simard, M. Fully unsupervised crosslingual semantic textual similarity metric based on BERT for identifying parallel data. In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pp. 206–215, Hong Kong, China, November 2019. Association for Computational Linguistics.
- M. Ziegler, Z. and M. Rush, A. Latent normalizing flows for discrete sequences. *arXiv preprint arXiv:1901.10548*, 01 2019.
- Mathur, N., Baldwin, T., and Cohn, T. Putting evaluation in context: Contextual embeddings improve machine translation evaluation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 2799–2808, Florence, Italy, July 2019. Association for Computational Linguistics.
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. Distributed representations of words and phrases and their compositionality. In Burges, C. J. C., Bottou, L., Welling, M., Ghahramani, Z., and Weinberger, K. Q. (eds.), *NIPS*, 2013.
- Papineni, K., Roukos, S., Ward, T., and Zhu, W.-J. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pp. 311–318, Philadelphia, Pennsylvania, USA, July 2002. Association for Computational Linguistics.
- Peters, M., Neumann, M., Zettlemoyer, L., and Yih, W.-t. Dissecting contextual word embeddings: Architecture and representation. In *EMNLP*, pp. 1499–1509, Brussels, Belgium, October-November 2018a. Association for Computational Linguistics.
- Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., and Zettlemoyer, L. Deep contextualized word representations. *CoRR*, abs/1802.05365, 2018b.

- Qin, Y. and Specia, L. Truly exploring multiple references for machine translation evaluation. In *Proceedings of the* 18th Annual Conference of the European Association for Machine Translation, pp. 113–120, Antalya, Turkey, May 2015.
- Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., and Sutskever, I. Language models are unsupervised multitask learners. 2019.
- Ranzato, M., Chopra, S., Auli, M., and Zaremba, W. Sequence level training with recurrent neural networks. *CoRR*, abs/1511.06732, 2015.
- Rennie, S. J., Marcheret, E., Mroueh, Y., Ross, J., and Goel,V. Self-critical sequence training for image captioning.CoRR, abs/1612.00563, 2016.
- Schmidt, F. Generalization in generation: A closer look at exposure bias. pp. 157–167, 01 2019.
- Semeniuta, S., Severyn, A., and Gelly, S. On accurate evaluation of gans for language generation. In *ICML* workshop on Theoretical Foundations and Applications of Deep Generative Models, 2018.
- Serban, I. V., Sordoni, A., Bengio, Y., Courville, A. C., and Pineau, J. Building end-to-end dialogue systems using generative hierarchical neural network models. In *AAAI*, 2016.
- Tan, B., Hu, Z., Yang, Z., Salakhutdinov, R., and Xing, E. P. Connecting the dots between MLE and RL for sequence generation. *CoRR*, abs/1811.09740, 2018.
- Wang, A. and Cho, K. BERT has a mouth, and it must speak: BERT as a markov random field language model. *CoRR*, abs/1902.04094, 2019.
- Wang, A., Pruksachatkun, Y., Nangia, N., Singh, A., Michael, J., Hill, F., Levy, O., and Bowman, S. R. Superglue: A stickier benchmark for general-purpose language understanding systems. *ArXiv*, abs/1905.00537, 2019.
- Wieting, J., Berg-Kirkpatrick, T., Gimpel, K., and Neubig,
 G. Beyond BLEU:training neural machine translation with semantic similarity. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 4344–4355, Florence, Italy, July 2019. Association for Computational Linguistics.
- Williams, R. J. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine Learning*, 8(3):229–256, May 1992. ISSN 1573-0565.
- Williams, R. J. and Zipser, D. A learning algorithm for continually running fully recurrent neural networks. *Neural computation*, 1(2):270–280, 1989.

- Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., and Brew, J. Huggingface's transformers: State-of-theart natural language processing. *ArXiv*, abs/1910.03771, 2019.
- Wu, L., Tian, F., Qin, T., Lai, J., and Liu, T.-Y. A study of reinforcement learning for neural machine translation. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 3612–3621, Brussels, Belgium, October-November 2018. Association for Computational Linguistics.
- Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., Krikun, M., Cao, Y., Gao, Q., Macherey, K., Klingner, J., Shah, A., Johnson, M., Liu, X., Kaiser, L., Gouws, S., Kato, Y., Kudo, T., Kazawa, H., Stevens, K., Kurian, G., Patil, N., Wang, W., Young, C., Smith, J., Riesa, J., Rudnick, A., Vinyals, O., Corrado, G., Hughes, M., and Dean, J. Google's neural machine translation system: Bridging the gap between human and machine translation. *CoRR*, abs/1609.08144, 2016. URL http://arxiv.org/abs/1609.08144.
- Yu, L., Zhang, W., Wang, J., and Yu, Y. Seqgan: Sequence generative adversarial nets with policy gradient. In *AAAI*, 2017.
- Zhang, T., Kishore, V., Wu, F., Weinberger, K. Q., and Artzi, Y. Bertscore: Evaluating text generation with BERT. *CoRR*, abs/1904.09675, 2019.
- Zhao, W., Peyrard, M., Liu, F., Gao, Y., Meyer, C. M., and Eger, S. MoverScore: Text generation evaluating with contextualized embeddings and earth mover distance. In *EMNLP*, pp. 563–578, Hong Kong, China, November 2019. Association for Computational Linguistics.
- Zhu, Y., Kiros, R., Zemel, R., Salakhutdinov, R., Urtasun, R., Torralba, A., and Fidler, S. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. *arXiv preprint arXiv:1506.06724*, 2015.

Example Sentences

We show the first 20 sentences output in the 600 sentence batches used to evaluate the models in Table 3 of the main paper.

Output for training with n-GRAM

```
pam was the last . ' ' '
callum was n ' t lying .
gia , he ^{\prime} ll kill him . ^{\prime} ^{\prime}
music , i 'll try .''
phoenix , he ' ll kill him . ' ' '
apparently he 's dead . '''
harper was n ' t stupid .
busy , ^{\prime} ^{\prime} she added .
answer me , ' ' she said .
lissa 's eyes . '''
hopefully he ^{\prime} ll kill him . ^{\prime} ^{\prime}
justice was n ^{\prime} t kidding . ^{\prime} ^{\prime}
eliza was n ' t stupid .
elaine was n ' t stupid .
danger was n ^{\prime} t joking .
antonia was n ' t embarrassed .
az was n ^{\prime} t stupid .
acheron was n ^{\prime} t embarrassed . use the other . ^{\prime} ^{\prime} ^{\prime}
oklahoma , ' ' she added .
```

Output for training with OURS

```
lila 's eyes . '''
effectively was betting she was n ' t dead .
gia , i ' m scared . ' '
music , ^{\prime} ^{\prime} she whispered .
celtic , i ' m scared . ' '
aaron 's eyes . '''
harper , i ' m scared . ' '
maps of the first . ^{\prime} ^{\prime}
chris 's eyes . ' ' '
emergency , the first . ' ' '
hopefully , he ^{\prime} 11 call . ^{\prime} ^{\prime}
compelled to be a good man . ^{\prime} ^{\prime}
wizards i ' m scared . ' '
said , he was n ' t dead .
danger was n ' t dead .
wish i was n ' t dead .
irene 's eyes . '''
acheron was n ' t dead . ' '
use the door . ' '
oklahoma , i ' m scared . ' '
```

Output for training with ML

```
at young while we were girls from the dead . lucky , i didnt last night .
```

```
it 's my greatest metaphor, actually.
you need to get away from home !
` ` i want you . ' '
' ' please , tab , ' ' he added .
harper peered farther to the right side inside .
' ' i can set it up . ' '
it would rotauging as changes by some .
i give the ups to him close to him .
` ` jacob ' s shula . ' '
\lq \lq everything more than a military force . ' '
i fisted at my glossy trying red lipsbl .
your choice can go to the johnnie . ' '
' ' two hurting you . ' '
they would understand the plane , but anyway .
i ^{\prime} ve got ta talk ! ^{\prime} ^{\prime}
acheron had special kind of missing swallow .
use you on the lions , congrats me !
i leave in england , said bern .
```

Training data DATA

```
i will serve it faithfully , always .
i 'll be really nice to her . ^{\prime\prime}
they did n't smile .
^{\prime\prime} no , ^{\prime\prime} she finally said .
^{\,\,\,\,\,\,\,\,\,} where are they going ? ^{\prime\,\,\prime}
" i do n't know . "
you hear that , spyder ?
you ca n't be in here ! "
^{\prime\prime} i 'll finally be free . ''
i need to head to the administration building . ^{\prime\prime}
"women , " was his only explanation .
" what do you mean ? "
the mantra had screamed in her head .
lucivar shifted just enough to block entry into the kitchen .
" i do n't know .
le'ace sank into the shadows underneath the staircase .
perhaps they would even be justified in wishing for this .
a dirty , blood-stained apron .
'where can these two be found ? '
bad enough they wo n't have a father .
```