Syntax-driven Iterative Expansion Language Models for Controllable Text Generation

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Abstract

The dominant language modeling paradigms handle text as a sequence of discrete tokens. While these approaches can capture the latent structure of the text, they are inherently constrained to sequential dynamics for text generation. We propose a new paradigm for introducing a syntactic inductive bias into neural language modeling and text generation, where the dependency parse tree is used to drive the Transformer model to generate sentences iteratively, starting from a root placeholder and generating the tokens of the different dependency tree branches in parallel, using either word or subword vocabularies.

In this work, we propose a new paradigm for text generation and language modeling called Iterative Expansion Language Model, which generates the final sequence following a token ordering defined by the sentence dependency parse by iteratively expanding each level of the tree.

In the rest of this article, we provide an overview of the related work (§2) and present the proposed approach (§3). We describe our experimental setup (§4), present the obtained results (§5), and subsequently discuss them (§6). Finally, we draw the conclusions of this work (§7).

1 Introduction

The currently dominant text generation paradigm is based on generating a sequence of discrete tokens in a left-to-right autoregressive way. Most neural language models (LMs) fall into the autoregressive generation category. Some neural architectures are intrinsically sequential in nature, such as those based on recurrent neural networks (RNNs), lending themselves naturally to the autoregressive generation approach when used together with teacher forcing (Williams and Zipser, 1989). Other architectures, such as Transformer (Vaswani et al., 2017), while not intrinsically sequential, have also been directly targeted for the sequential paradigm.

On the other hand, some recent lines of research have focused on nonsequential generation, such as recurrent neural network grammars (RNNG; Dyer et al., 2016) or the insertion transformer (Stern et al., 2019).

2 Related Work

In this section, we provide an overview of works related to ours, including those using syntactic dependencies for LMs (§2.1), constituent-driven generation (§2.2), insertion-based approaches (§2.3), non-causal LMs (§2.4) or iterative refinement (§2.5).

2.1 Dependency LMs

The use of dependency parse trees to drive a language model was first proposed by Chelba et al. (1997), with a similar structure to an n-gram LM, but where the context of a word is its preceding bigram plus a list of preceding words whose parent does not precede it. Shen et al. (2008) make use of the dependency tree in a probabilistic LM, computing the probability of each word conditioned on its parent and the sibling words between both.

Mirowski and Vlachos (2015) propose a dependency LM based on RNNs, where the dependency tree is decomposed into a collection of unrolls, that is, paths from the root to one of the leaves, and where the probability of a word can be predicted from these unrolls. Buys and Blunsom (2018) propose a shift-reduce transition-based LSTM (Hochreiter and Schmidhuber, 1997) dependency LM that can be used for language modeling and generation by means of dynamic programming.
2.2 Syntactic Constituent-driven Generation

Recurrent neural network grammars (Dyer et al., 2016) are recursive models that operate with a stack of symbols that can be populated with terminals or nonterminals or “reduced” to generate a syntactic constituent, obtaining as a result a sentence and its associated constituency parse tree.

Shen et al. (2018) propose parsing-reading-predict networks, where skip-connections are used to integrate constituent dependency relations with RNNs. Their model does not need syntactic supervision but can learn the underlying dependency structures by leveraging a syntactic distance together with structured attention.

Syntactically supervised transformers (Akoury et al., 2019) make use of a simplified form of the constituency parse tree as latent variables, modeling it autoregressively in a supervised way to later use it as input for a fully non-autoregressive transformer that generates the output sentence.

Ordered neurons (Shen et al., 2019) are a modified version of LSTMs where the latent sentence tree structure is used to control the dependencies between recurrent units by means of special “master” input and forget gates.

2.3 Insertion-based Generation

Stern et al. (2019) propose Insertion Transformer, a conditional generative model that iteratively generates pairs of tokens plus the position at which they should be inserted within the sequence, with the ability to generate text from left to right or in a parallel fashion, by decoding according to a balanced binary tree. Emelianenko et al. (2019) simultaneously propose the same approach, going one step further and optimizing the generation order by sampling from the ordering permutations. Chan et al. (2019) propose a similar idea but optimizing a lower bound of the marginalized probability over every possible ordering.

Gu et al. (2019a) propose a latent variable model where the generation order is treated as latent and captured as the relative position through self-attention, optimizing the ELBO to train the model.

Gu et al. (2019b) propose Levenshtein Transformer, a model trained with reinforcement learning to generate token insertion and deletion actions.

Welleck et al. (2019) propose a cost minimization imitation learning framework where a policy is learned to generate a binary tree that is used to drive the token generation.

2.4 Non-causal LMs

BERT (Devlin et al., 2019) is a masked language model that drops the causal mask in transformers’ decoder self-attention blocks, thereby predicting masked tokens based on the whole sentence context. XLNet (Yang et al., 2019), on the other hand, makes use of the causality mask to impose different permutations over the tokens’ probability factorization. While masked LMs and permutation LMs are only meant to learn representations for transfer learning and not for text generation, they are the foundation of ideas on which non-autoregressive iterative generation approaches rely.

2.5 Iterative Refinement

Lee et al. (2018) propose a latent variable non-autoregressive machine translation model where first the target length is predicted by the model, and then, the decoder is iteratively applied to its own output to refine it.

Mask-predict (Ghazvininejad et al., 2019) also predicts the target sentence length and then non-autoregressively predicts the sentence itself, iteratively refining it a fixed number of times, masking out and regenerating the tokens it is least confident about. Lawrence et al. (2019) follow a similar approach and start with a sequence of placeholder tokens (all the same) of a specified length, and they iteratively replace them with normal tokens via masked LM-style inference. As the masking strategy for the training data, the authors propose different stochastic processes to randomly select which placeholders are to be uncovered.

3 Iterative Expansion LMs

We propose to train a new kind of language model where the token generation order is driven by the dependency parse tree of the sentence and where the generation process is iterative.

![Figure 1: Example of dependency parse tree.](image)

The input vocabulary contains terminal tokens as well as special tokens called dependency placeholders, each of which is associated with one of
the possible dependency relations to the heads. For the dependency tree in Figure 1, the dependency placeholders are [poss], [nsubj], [advmod], [xcomp], [dobj] and [ROOT].

The input of the first iteration is the sequence with the [ROOT] element. At each iteration, the model receives as input a sequence of indexes to the input vocabulary, referred to as “previous level tokens” (PLT), and non-autoregressively generates two new sequences, each of them of the same length as the input.

The first output sequence contains tokens from a vocabulary with all possible textual tokens (terminal tokens). This sequence is referred to as “next level tokens” (NLT). The second output is a sequence of tokens called expansion placeholders, which are taken from a separate vocabulary. This sequence is referred to as “next level expansions” (NLE). Each expansion placeholder is associated with a pattern describing the left and right dependencies of the token at that position in the next level token sequence. An example of dependency expansion could be [nsubj-advmod-HEAD-xcomp] for the word “likes” in the dependency parse tree from Figure 1.

After each iteration, the output of the model is expanded. This consists of creating a new sequence by combining the tokens from the previous level, the predicted next level tokens and expansions. This process is illustrated in Figure 2, making use of the dependency tree from Figure 1.

When there is a padding token [pad] in the output (either the next level tokens or next level expansions), this means that the output at that position is ignored when computing the loss function. This occurs when the terminal token has already been computed in previous iterations and has therefore been received as part of the previous level tokens, and the model does not need to compute it again.

Note also that an empty dependencies token [HEAD] marks the end of a branch and that there is no need for an end of sequence token (typically \(</s> \) or \(<\text{eos}>\)). As shown in the example from Figure 1, the generation of independent branches occurs in parallel, needing only 3 iterations to generate a 6-token sentence.

### 3.1 Tree Sequentialization

The strategy for composing tree expansion tokens (e.g., [nsubj-advmod-HEAD-xcomp]) previously described may not scale well when single words present many direct dependencies. To alleviate this problem, we propose to introduce a preprocessing step where the dependency parse tree is modified so that every single word has at most one dependency to the left and one dependency to the right. For each word with more than one dependency on any of its sides, we modify the tree to impose a left-to-right ordering.

![Sequentialized dependency parse tree.](image)

This process is illustrated in Figure 3, where the sequentialized version of the dependency tree from Figure 1 is shown. The only difference between the original tree and the modified version is the word “also”, whose head has changed from “likes” to “dog” because “likes” had two left dependencies.

![Ratio of dep. tree depth and sentence length.](image)

Tree sequentialization reduces the degree of parallelism of the text generation process of iterative...
expansion LMs, as shown in Figure 4. This figure depicts the histogram of ratios between the sentence length and the depth of its dependency parse tree for sequentialized and nonsequentialized trees, as well as a reference for the ideal depth if the sentence dependency tree were a balanced binary tree \((\log_2 n)\), for a sample of the training data of the WMT17 dataset, which is used later in our experiments. Despite the impact on the level of parallelism, tree sequentialization reduces data sparsity and allows handling constructions where the number of dependencies of a word may otherwise be too large for the model to properly capture, such as enumerations (e.g., “I bought a pair of shoes, an umbrella, a beautiful jacket and a bracelet”).

3.2 Extension to Subword-level Vocabularies

The proposed approach can be naturally extended to subword-level vocabularies, such as byte-pair encoding (BPE; Sennrich et al., 2016): for each word, we decompose its node in the tree into as many nodes as subwords that the word contains, rearranging the tree so that the head of the old word node is now the head of the first subword node, and each subsequent subword depends on the previous one, while every dependency of the old word node now depends on the last subword node. This is illustrated in Figure 5, where the dependency tree from Figure 3 is modified to use subwords.

![Figure 5: Subwords in the dependency parse tree.](image)

3.3 Neural Architecture

The neural architecture proposed is based on a Transformer decoder (Vaswani et al., 2017). While our approach could be used in any sequence-to-sequence neural model, we have chosen Transformer because it is inherently parallel, as opposed to recurrent architectures based on LSTMs (Hochreiter and Schmidhuber, 1997) or GRUs (Cho et al., 2014), which are inherently sequential.

To generate the dual output, comprised of terminal tokens and expansion placeholders, we propose two alternatives: **independent generation of terminals and expansions**: the categorical distributions over terminal token space and expansion token space are independently generated by using two different projections from the last hidden states, and **conditioned generation of terminals**: the probability distribution over the expansion token space is generated first by projecting from one of the intermediate layers’ hidden states. We sample from such a distribution and use the resulting expansion IDs as an index to a trainable expansion token embedding layer; the embedded vectors are added to the hidden state used to generate them for use as input to subsequent layers.

As described in section 3, the input and output token vocabularies are different: the latter only contains terminal tokens (plus some special tokens such as \([PAD]\)); the former also contains dependency placeholders. However, for practical purposes, at the model level, we define both vocabularies to be the same, both with terminal tokens and dependency placeholders, and we mask the entries of dependency placeholders in the final softmax.

To inject the syntactic dependency information as input into the model, we add a layer of learned positional embeddings containing the position of the head of each token, and we refer to this embedding layer as **head position embedding**.

In terms of the self-attention mask, we propose two variants of the architecture. The **unconstrained attention** variant does not make use of the self-attention matrix normally used in Transformer to ensure causality in training. The input is therefore not masked at all, and the token predictions have access to the full input sequence, which are the previous level tokens. The **constrained attention** variant makes use of the self-attention matrix to force each prediction to attend only to their head words, recursively up to the root of the sentence. This mask is received as input by the model. Examples are shown in Appendix D.

3.4 Training

In sequential LMs, during training, the expected output of the model is a batch of token sequences, while the model’s input is the same batch but with the tokens shifted one position to the right.

For training iterative expansion LMs, the main input of the model is the tokens at one of the levels of the dependency parse tree (previous level tokens, PLT), while the output is the following level tokens (next level tokens, NLT) and expansion placeholders (next level expansions, NLE). Secondary inputs
to the model are the dependency indexes (which are used in the head position embedding) and the mask used for the constrained attention variant. Training takes place in minibatches: as the “trainable unit” is a level transition, given the usual data shuffling, a training batch is composed of level transitions from many different sentences.

The model is trained with maximum likelihood estimation, using the categorical cross-entropy for both tokens and expansion placeholders and then adding both sublosses into the final loss. Tokens generated in previous iterations appear as [PAD] tokens in the expected output and are ignored when computing the loss.

### 3.5 Inference and Text Generation

In iterative expansion LMs, inference takes place iteratively. The initial state is a batch of [ROOT] tokens, together with the head positions initialized to the special value representing the root node and, in constrained attention variants, a mask with the self-dependency of the single node in each sentence in the batch. At each iteration, the model generates the probability distributions for terminal tokens and expansion tokens. Following the conclusions from Holtzman et al. (2019), we use nucleus sampling to sample from them. The terminal token sequences are expanded according to the expansion tokens (see §3), and these are the inputs for the following iteration if there are still unfinished branches. Before sampling from the token and expansion probability distributions, we mask the <unk> token and the dependency placeholders to avoid generating them.

Although iterative expansion LMs could be subject to beam search across iterations, we have not covered such a possibility as part of this work.

### 3.6 Probabilities from the Language Model

In a sequential LM, the probability of a sentence is computed by factorizing it, applying the chain rule over the token sequence, as

$$ p(x_1, \ldots, x_n) = \prod p(x_i | x < i) \ldots $$

In iterative expansion LMs, we need a dependency parse tree of the sentence in order to compute its probability. Given a dependency tree $D$, taking into account that the token predictions at a specific iteration are independent from one another but dependent on the ones from previous iterations, we approximate the factorized probability as

$$ p(x_1, \ldots, x_n | D) \approx \prod p(x_i | A(x_i)), \quad (1) $$

where $A(x_i)$ represents the tokens $x_{\text{prev}}$ and expansions $e_j$ generated at previous iterations. Note that the probability in (1) only depends on the expansions $e_j$ that have been generated in previous iterations. Likewise, we can compute the joint probability of the sentence and the tree $D$ by including the probability of the expansions $e_j$:

$$ p(x_1, \ldots, x_n, D) = p(x_1, \ldots, x_n | D) p(D) \quad (2) $$

$$ \approx \prod p(x_i | A(x_i)) \prod p(e_j | A(e_j)). $$

Note that the probabilities of tokens $x_i$ are taken from the NLT output of the model and the probabilities of expansions $e_j$ are taken from the NLE output of the model (see Figure 2).

To compute $p(x_1, \ldots, x_n)$, we need to marginalize over all possible dependency trees $D$. As this is not tractable, following Chelba et al. (1997), we can assume that the summation is dominated by the most probable tree $D^\star$ and approximate it as (3).

This can be computed for an iterative expansion LM by means of (2).

$$ p(x_1, \ldots, x_n) = \sum_D p(x_1, \ldots, x_n, D) \approx p(x_1, \ldots, x_n, D^\star). \quad (3) $$

This approximation of the probability of a sentence can be used to compute the corpus level perplexity on an iterative expansion LM, although given the nature of the approximation, the resulting approximated value will be greater than or equal to the perplexity computed with the true marginalized (and intractable) form.

### 3.7 Iterative Refinement

As described in the text generation approach in §3.5, once a terminal token is predicted at a specific iteration, it is kept as is throughout the subsequent iterations. We could, however, complement iterative expansion LMs by applying iterative refinement to improve the already generated tokens in subsequent iterations. This can be approached by injecting noise into the training data and taking into account all tokens in the output instead of only the new ones for the loss definition. In our iterative refinement experiments, we inject both token duplication noise and token corruption noise.

Adding iterative refinement to iterative expansion LMs prevents applying the factorization needed to compute the probabilities (and therefore perplexity). This, however, is not a problem for text generation-only scenarios.
4 Experimental Setup

In this section, we describe the experiments carried out to evaluate iterative expansion LMs (IterExp). Except when explicitly stated, the configuration used consists of unconstrained attention, head position embeddings and conditioned generation of terminal tokens, with tree sequentialization. The full hyperparameters of the models and baselines can be found in Appendix C while details on the data processing are described in Appendix B.

4.1 Unconditional Text Generation

We conducted experiments on unconditional text generation following the methodology used by Caccia et al. (2018). The goal is to assess both the quality and diversity of the text generated by the model under different values of the temperature $\tau$ in the model’s final softmax. For the quality evaluation, we use the BLEU score (Papineni et al., 2002) over the test set, where each generated sentence is evaluated against the whole test set as a reference. For diversity, we used the self-BLEU score (Zhu et al., 2018), computed using as references the rest of the generated sentences. For each different value of $\tau$, each model under evaluation is used to generate 2000 sentences, which are then evaluated in terms of BLEU against the test set and self-BLEU. The negative test BLEU and self-BLEU values are plotted as $(x, y)$ coordinates for different values of $\tau$, forming a curve that reflects the quality and diversity trade-off in the different generation regimes.

Iterative expansion LMs are compared against a standard LM baseline model, namely, AWD-LSTM\(^2\) (Merity et al., 2018), at both word (w) and BPE subword (sw) levels. The models were trained on the WMT17 news dataset, using corenlp to add dependency annotations. When sampling from both models, we use nucleus sampling (Holtzman et al., 2019) (with $p = 0.9$), a form of ancestral sampling that constrains the candidate pool by discarding the distribution tail. For reference, we also measure a sample of 2000 sentences from the training data and a sample of 2000 sentences from the validation data.

Apart from the described measures, we study the generated text and compare it against real text in terms of sentence length, dependency tree depth and similarity between generated trees and trees obtained by parsing their lexicalized forms.

4.2 Style Variation

Given that iterative expansion LMs are inherently controllable and offer full access to the syntactic constructions of the text being generated, it is possible to influence some of their traits. To demonstrate this, we created a modified version of the decoding process of iterative expansion LMs in which the probability to generate adjectival constructions is artificially increased, aiming at generating a more descriptive text style. For this, during decoding, we multiply the probabilities of the expansion placeholders that express adjectival dependencies (those containing adjectival modifier “amod” relations), and then, we renormalize the probabilities by dividing by the sum.

We conducted this experiment with the word-level models trained on the WMT17 dataset, computing the ratio of adjectives per sentence, as well as quality measurements over the generated text to control for potential quality degradation.

4.3 Language Modeling

We performed language modeling experiments on annotated datasets (treebanks) and textual datasets annotated by means of automatic annotation tools.

For the experiments on treebanks, we experimented with data from multiple languages: the Penn Treebank (PTB; Marcus et al., 1993) for English, the GSD Traditional Chinese Universal Dependencies (UD) treebank, the AnCora Spanish UD treebank, the GSD Japanese UD treebank, the UD Prague Arabic Dependency Treebank (PADT) and the SynTagRus Russian UD treebank\(^3\). We trained iterative expansion LMs on the mentioned treebanks. We also trained a sequential LM on the unannotated text as a baseline, using AWD-LSTM (Merity et al., 2018) as the model with appropriate hyperparameters for each specific dataset.

For the experiments on plain text datasets, we used corenlp (Manning et al., 2014) to generate the dependency parse trees. The dataset used for these experiments was Wikitext-2\(^4\), as well as the WMT17 news dataset, also referred to as the EMNLP2017 dataset, from Lu et al. (2019).

For AWD-LSTM, we show the perplexities computed with full context (ctx) and at sentence level, without previous context (sent).

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\(^2\)Abbreviation of ASGD weight-dropped LSTM, where ASGD stands for averaged stochastic gradient descent.

\(^3\)https://universaldependencies.org

\(^4\)https://blog.einstein.ai/the-wikitext-long-term-dependency-language-modeling-dataset/
5 Results

The ability of iterative expansion LMs to unconditionally generate text is assessed in the quality vs. diversity plot in Figure 6. We can appreciate that the quality and diversity (based on BLEU-5) of the text generated by iterative expansion LMs are analogous to those of AWD-LSTM with word-level vocabulary in the $\tau$ regime closest to the training and validation data and surpass those of the version with subword-level vocabulary. We can also see that the sampling $\tau$ implies less variation for our approach. Appendix E contains plots for other $n$-gram orders supporting the same conclusions.

![Figure 6: Quality vs. diversity on WMT17 (BLEU-5).](image)

Table 1 contains the most relevant data from Figure 6, along with extra quality references: the perplexity obtained by OpenAI GPT-2 (1.5 B parameters) (Radford et al., 2019) on the generated text and perplexity obtained by an AWD-LSTM word LM also trained on WMT17.

|          | test | self | test | self | GPT-2 | test | self | test | self |
|----------|------|------|------|------|-------|------|------|------|------|
|          | BLEU-5 |      | AWD-LSTM |      | GPT-2 |      | AWD-LSTM |      | GPT-2 |
| AWD-LSTM (w) | 22.7 | 15.8 | 82.9 | 101.6 |
| AWD-LSTM (sw) | 23.3 | 22.5 | 95.4 | 112.3 |
| ITEXP (w) | 23.4 | 16.3 | 41.4 | 87.1 |
| ITEXP (sw) | 23.2 | 16.3 | 45.9 | 98.8 |
| Train sample | 21.4 | 12.5 | 39.3 | 24.3 |
| Valid sample | 21.0 | 15.3 | 42.1 | 23.7 |

Table 1: Quality and diversity ($\tau = 1.0$) on WMT17.

Illustrative samples of the generated text are presented in Appendix F.

Given that the generation process in iterative expansion LMs is not sequential, we studied the distribution of the sentence lengths it generates. This is shown in Figure 7 for the text generated by a word-level iterative expansion LM and AWD-LSTM, both trained on WMT17, along with the lengths of a sample from the training data.

![Figure 7: Distribution of generated text length.](image)

We studied the depths of the dependency trees of generated text in relation to those parsed from the training data and generated by AWD-LSTM (also trained on WMT17), as shown in Figure 8.

![Figure 8: Histogram of generated text tree depth.](image)

We measured the degree to which the generated trees adhere to the trees obtained by parsing their lexicalized representation. Specifically, as shown in Table 3, we computed the labeled and unlabeled attachment scores between both for the text generated at different softmax temperatures $\tau$.

| $\tau$ | 0.7 | 0.8 | 0.9 | 1.0 | 1.2 |
|-------|-----|-----|-----|-----|-----|
| LAS   | 96.4 | 95.3 | 94.2 | 92.3 | 86.2 |
| UAS   | 98.0 | 97.3 | 96.5 | 95.2 | 90.7 |

Table 3: (Un)labeled att. scores of the generated trees.

To study the influence of the different possible configurations of our approach, we computed ablations of the model, presented in Table 2.

The transparent nature of the decoding process of iterative expansion LMs allows to influence the generated syntactic constructions. We leverage this to increase the probability of generating adjectival constructions, making the text more descriptive. As shown in Table 4, the style of the resulting text can be successfully modulated to the desired degree.

Regarding the use of iterative expansion LMs to model language, Table 5 shows the perplexities obtained over the test split for different treebank datasets, while Table 6 is the analogous content for textual datasets. Note that, as described in sec-
The results of iterative expansion LMs presented in section 5, specifically in Figure 6 and Tables 1 and 2, show how the generated text is comparable to text by sequential LMs (AWD-LSTM) in terms of quality and diversity. Based on the perplexity computed by AWD-LSTM itself and by GPT-2, trained on much more data, the quality of the text generated by iterative expansion LMs is higher.

As shown in Figures 7 and 8, the length and tree depth of the generated text are very close to the real data, and the generated dependency trees match those computed with an annotation tool.

Furthermore, as shown in Figure 4, the generation time for iterative expansion LMs is on average only 45% of the decoding steps of a sequential LM.

From the ablations in Table 2, we see that the constrained attention variant fails to properly generate text and that conditioning of terminal tokens on expansions implies a large gain in performance, while head position embeddings only add a small gain. Moreover, iterative refinement is shown to harm the quality of the text.

The training of iterative expansion LMs can be naturally computed in batches; they are amenable to subword-level vocabularies and not specifically tied to a neural architecture, though they lend themselves to parallel architectures than can profit from non-autoregressive generation of each tree level. As shown in Table 4, our approach allows inducing stylistic variations in the generated text. On the other hand, the current formulation of iterative expansion LMs needs a syntactic supervision signal.

Finally, as shown in Tables 5 and 6, the approximated nature of the perplexities computed with iterative expansion LMs prevents their comparison with traditional LMs. Nevertheless, this does not preclude their use for sentence ranking.

### Analysis and Discussion

In this work, we presented iterative expansion LMs, iterative non-autoregressive text generation models that rely on syntactic dependency trees to generate sentence tokens in parallel, saving half of the decoding steps with respect to sequential LMs. We showed that the text generated with iterative expansion LMs is comparable to or better than sequential LMs in terms of quality and diversity. Our source code is available as open source code.

In future work, we would like to study alternatives to dependency parse trees that relieve the need for a syntactic supervision signal, as well as the application of conditional iterative expansion LMs to tasks such as machine translation or dependency parsing. We would also like to further explore their controllability aspects, with applications to sentence completion, style transfer and register variations.

### Table 2: Ablations in text generation (at $\tau = 1.0$) on WMT17 for word-level models.

|                             | test BLEU-5 | self-BLEU-5 | AWD-LSTM ppl | GPT-2 ppl |
|-----------------------------|-------------|-------------|--------------|-----------|
| Constrained Attention       | 3.4         | 2.7         | 642.5        | 1006.6    |
| Independent Terminal-Expansion | 15.6        | 10.5        | 127.2        | 211.8     |
| No Head Embeddings          | 23.2        | 16.1        | 53.5         | 87.1      |
| Base ITEXP                  | 23.4        | 16.3        | 41.4         | 87.1      |
| ITEXP + Refinement (dedup)  | 21.1        | 17.1        | 54.3         | 119.8     |
| ITEXP + Refinement (dedup + denoise) | 20.9 | 14.2 | 60.3 | 137.5 |
| Train sample                | 21.4        | 12.5        | 39.3         | 24.3      |
| Valid sample                | 21.0        | 15.3        | 42.1         | 23.7      |

Table 2: Ablations in text generation (at $\tau = 1.0$) on WMT17 for word-level models.

| Adj. Probability | Adj. / sentence | 1 | 10 | 20 | 50 | 100 |
|------------------|------------------|---|----|----|----|-----|
| Adj. / sentence  | test BLEU-5      | 23.4 | 21.5 | 20.5 | 19.3 | 18.0 |
|                  | self-BLEU-5      | 16.3 | 15.5 | 15.4 | 15.3 | 14.9 |
|                  | AWD-LSTM ppl     | 41.4 | 51.3 | 57.3 | 65.3 | 72.9 |
|                  | GPT-2 ppl        | 87.1 | 109.4 | 122.7 | 140.9 | 158.8 |

Table 4: ITEXP(w), increased adjective generation.

### Table 5: Perplexities over treebank datasets.

|       | en   | es   | zh   | ru   | ja   | ar   |
|-------|------|------|------|------|------|------|
| LSTM ctx | 39.2 | 51.5 | 97.4 | 47.9 | 56.2 | 99.2 |
| LSTM sent | 58.7 | 63.7 | 118.2 | 64.8 | 66.9 | 123.4 |
| ITEXP   | 112.4 | 182.1 | 376.3 | 383.3 | 170.3 | 555.2 |

Table 5: Perplexities over treebank datasets.

|       | wikitext-2 | wmt17 |
|-------|------------|-------|
| LSTM ctx | 64.9 | 37.6 |
| LSTM sent | 106.9 | 42.9 |
| ITEXP   | 204.6 | 57.7 |

Table 6: Perplexities over textual datasets.

### 6 Analysis and Discussion

The perplexities computed with iterative expansion LMs are approximated higher bounds.

Table 3: Perplexities over treebank datasets.

### 7 Conclusion

In this work, we presented iterative expansion LMs, iterative non-autoregressive text generation models that rely on syntactic dependency trees to generate sentence tokens in parallel, saving half of the decoding steps with respect to sequential LMs. We showed that the text generated with iterative expansion LMs is comparable to or better than sequential LMs in terms of quality and diversity. Our source code is available as open source code.

In future work, we would like to study alternatives to dependency parse trees that relieve the need for a syntactic supervision signal, as well as the application of conditional iterative expansion LMs to tasks such as machine translation or dependency parsing. We would also like to further explore their controllability aspects, with applications to sentence completion, style transfer and register variations.
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Supplementary Material: Appendix

A Dataset Statistics

Table 7 summarizes the statistics of the different treebanks used in our experiments, including number of sentences in the training, validation and test splits, terminal vocabulary size (imposed by us), percentage of out of vocabulary (OOV) words, expansion vocabulary size (unconstrained) and total number of resulting iterations (see §2 or Appendix F for examples of the decomposition of a sentence into iterations), along with the language of the text. These statistics have been extracted after preprocessing (see Appendix B for details).

|                  | train | valid | test |
|------------------|-------|-------|------|
| **PTB**          |       |       |      |
| sentences        | 40k   | 1.7k  | 2.4k |
| iterations       | 462k  | 20k   | 27k  |
| expansion vocab   | 776   |       |      |
| terminal vocab    | 10k   |       |      |
| OOV               | 5.6%  |       |      |
| **UD Chinese GSD** |     |       |      |
| sentences        | 4k    | 0.5k  | 0.5k |
| iterations       | 40k   | 5k    | 5k   |
| expansion vocab   | 650   |       |      |
| terminal vocab    | 10k   |       |      |
| OOV               | 7.2%  |       |      |
| **UD AnCora**    |       |       |      |
| sentences        | 14k   | 1.7k  | 1.7k |
| iterations       | 178k  | 20k   | 20k  |
| expansion vocab   | 503   |       |      |
| terminal vocab    | 10k   |       |      |
| OOV               | 7.8%  |       |      |
| **UD Japanese GSD** |    |       |      |
| sentences        | 7k    | 0.5k  | 0.5k |
| iterations       | 68k   | 5k    | 5k   |
| expansion vocab   | 263   |       |      |
| terminal vocab    | 10k   |       |      |
| OOV               | 8.5%  |       |      |
| **UD PADT**      |       |       |      |
| sentences        | 6k    | 0.9k  | 0.7k |
| iterations       | 143k  | 20k   | 18k  |
| expansion vocab   | 403   |       |      |
| terminal vocab    | 10k   |       |      |
| OOV               | 6.6%  |       |      |
| **UD SynTagRus** |       |       |      |
| sentences        | 49k   | 6.5k  | 6.5k |
| iterations       | 416k  | 57k   | 56k  |
| expansion vocab   | 747   |       |      |
| terminal vocab    | 32k   |       |      |
| OOV               | 9.9%  |       |      |

Table 7: Statistics of the used treebanks.

Table 8 summarizes the statistics of the different textual datasets used in our experiments, with content analogous to the previous table, except for the language, which is English in all cases. Note that the WMT17 training/validation/test split was taken from Holtzman et al. (2019).

|                  | train | valid | test |
|------------------|-------|-------|------|
| **wikitext-2**   |       |       |      |
| sentences        | 83k   | 8.6k  | 10k  |
| iterations       | 914k  | 95k   | 108k |
| expansion vocab   | 712   |       |      |
| terminal vocab    | 33319 |       |      |
| OOV               | 0%    |       |      |
| **wmt17**        |       |       |      |
| sentences        | 268k  | 10k   | 10k  |
| iterations       | 3.2M  | 122k  | 122k |
| expansion vocab   | 904   |       |      |
| terminal vocab    | 8195  |       |      |
| OOV               | 0%    |       |      |

Table 8: Statistics of the textual datasets (English).

B Data Processing Details

Penn Treebank (PTB). The version from Mikolov et al. (2010) that is frequently used as a sequential LM benchmark contains multiple transformations: lowercasing, numeral masking, punctuation removal and limitation of the vocabulary to the 10k most frequent symbols, masking the rest with <unk>. Instead of that version, we used the one normally used for constituency parsing, that is, the original Wall Street Journal portion of PTB annotated with syntactic constituents, using sections 2 to 21 as training data (~40k sentences), section 22 for validation (1700 sentences) and section 23 as test data (~2400 sentences). We converted the constituent annotations to dependency trees by means of corenlp, converted the text to lower case, masked numerals (tokens with NUM as the part of speech (POS) tag) and extracted a vocabulary of the 10k most frequent symbols.

Universal Dependencies (UD) treebanks. For each UD treebank (Nivre et al., 2019), following the preprocessing done for PTB, we masked numerals (tokens with NUM as the POS tag), converted the text to lower case (for languages with Roman script) and extracted a vocabulary of the 10k most frequent symbols, except for Russian, which, being morphologically rich and having a larger treebank, needed a vocabulary size of 32k to keep OOV words below 10%. Moreover, the sentences containing words with spaces among their characters were removed.
WikiText-2 dataset. This corpora contains \texttt{<unk>} tokens in its word LM-oriented version. While for sequence modeling, this may not be a problem, for iterative expansion LMs, it is: we need to obtain the sentence dependency parse tree before actually using the information in the sentence, and \texttt{<unk>} tokens may prevent the syntactic annotation tools from computing an appropriate parse. To mitigate this problem while aiming to make our work comparable with others, we used the raw version of WikiText-2 as input to the syntactic annotation tool, and in the resulting dependency parses, we masked the \texttt{<unk>} tokens according to the word LM version. Wikitext-2 also contains lines with complete paragraphs. In sequential LMs, the whole paragraph is used to create “continuous” training batches. Given that iterative expansion LMs are sentence-oriented, we need to separate paragraphs into sentences. For this, we used spaCy’s sentenceizer (Honnibal and Montani, 2017) with the original space tokenization.

WMT17 dataset. The tokenization of the WMT17 dataset is very nonstandard. To appropriately prepare it to be used as input to the syntactic annotation tool \texttt{corenlp}, we detokenized the text and then retokenized it again with the Moses tokenizer. For the experiments with BPE, we created the subword vocabulary with 4000 merge operations and without further constraining the size of the resulting vocabulary.

Quality vs. diversity plots. The generated text was un-BPE’ed (for the subword-level models) and detokenized by means of the Moses \texttt{detokenizer.perl} script. Then, it was tokenized with the Moses \texttt{tokenizer.perl} script, and the BLEU scores were computed with the NLTK \texttt{corpus_bleu} function (Loper and Bird, 2002), without smoothing.

GPT-2 perplexity computation. The text that served as input to GPT-2 was properly detokenized before applying the model’s own BPE tokenization.

Text generation with AWD-LSTM. AWD-LSTM is trained with “continuous” text batches. This implies that when used for text generation, it likewise generates text. To obtain a predetermined number of sentences, we used AWD-LSTM to generate a fixed number of tokens (e.g., 200). Then, we split this text at the \texttt{<eos>} boundaries and removed the first and last sentences to avoid incomplete ones. We repeated this procedure until we had the target number of sentences.

C Hyperparameters

In this section, we present the detailed hyperparameters used in the experiments presented in this work. They were obtained by manual exploration, observing the behavior of the loss over the training and validation sets of each dataset.

C.1 Text Generation Experiments

The models used for the text generation experiments are presented in Figure 6; both the word and subword vocabulary variants are shown in Table 9.

| num. layers | 6       |
| num. heads  | 8       |
| embed. size | 1024    |
| batch size  | 16384   |
| params      | 96M     |

Table 9: Hyperparameters of the text generation experiments in Figure 6.

These hyperparameters are the same as those used for the language modeling experiments on WMT17, which are presented in Table 10.

C.2 Language Modeling Experiments

Table 10 presents the hyperparameters for the models in Tables 5 and 6, which were trained with treebank and textual datasets, respectively.

Note that the AWD-LSTM variant used as a baseline is the base LM without the continuous cache pointer mechanism, with tied weights. Additionally, note that the terminal and expansion vocabulary sizes are different, which leads to a different size of the expansion embedding table and therefore to a different total number of parameters for the same values of the rest of the hyperparameters.

The batch size for ITExP is expressed as the total number of tokens, while that for AWD-LSTM is expressed as the number of sentences, which, when multiplied by the back-propagation through time (BPTT) length, gives the total number of tokens per batch. Note that the criteria for the optimum batch size differ for transformers and LSTMs.

D Constrained Attention Examples

The normal causal self-attention mask used in the training of autoregressive Transformer models forces each token to be only able to attend to the previous ones. This allows the model to be used autoregressively during inference. An example of such a type of causality mask is shown in Figure
A WD-LSTM

| en PTB | es UD | zh UD | ru UD | ja UD | ar UD | wikitext-2 | wmt17 |
|--------|-------|-------|-------|-------|-------|------------|-------|
| hidden size | 1150 | 1150 | 256   | 1150  | 256  | 1150  | 1150 |
| embed. size | 400   | 400   | 128   | 400   | 128  | 400   | 400  |
| num. layers | 3     | 3     | 3     | 3     | 3    | 3     | 3    |
| batch size | 20    | 20    | 20    | 20    | 20   | 20    | 20   |
| BPTT    | 70    | 70    | 70    | 70    | 70   | 70    | 70   |
| params (M) | 24.2  | 24.2  | 2.4   | 24.2  | 2.4  | 24.2  | 23.5 |

Our approach

| num. layers | 6     | 6     | 6     | 6     | 6    | 6     | 6    |
| num. heads | 8     | 8     | 4     | 8     | 4    | 8     | 8    |
| embed. size | 512   | 256   | 256   | 512   | 256  | 512   | 256  |
| batch size | 4096  | 4096  | 4096  | 4096  | 4096 | 4096  | 4096 |
| params | 24.4M | 10.4M | 10.5M | 24.4M | 10.3M | 10.4M | 147M |

Table 10: Hyperparameters of LM experiments with treebank and textual data corresponding to Tables 5 and 6.

9, where the black cells represent that the token of that row is allowed to attend to the token in that column.

Figure 9: Causal self-attention mask in Transformer.

Figure 10 shows the attention masks used in the constrained attention variant of iterative expansion LMs throughout the iterations in Figure 2. On the right side, we present the input (previous level tokens (PLT)) and outputs (next level tokens (NLT), next level expansions (NLE)).

Figure 10: Dependency mask at each iteration of the example in Figure 2 (without tree sequentialization).

E Extra Evaluation of the Generated Text

Figure 11 shows the quality (BLEU against the test set) vs. diversity (self-BLEU) plot for \( n \)-gram orders with \( n = 2, 3, 4 \). The same conclusions can be drawn as that for \( n = 5 \) in Figure 6. Note that in all BLEU vs. self-BLEU figures, each model is shown as a different line (each with its own color and/or dashed pattern) and that the data points computed for each temperature value are plotted with a specific marker shape (square, diamond, triangle, or flipped triangle). We can appreciate that the temperature regimes affect AWD-LSTM and iterative expansion LMs differently, with the latter concentrating around the training/validation sample points. Note that for each \( n \)-gram order, the plot axis limits have been fit to the values corresponding to the most typical \( \tau \) normally used for sampling.

F Generated Text Samples

F.1 Iterative Expansion Intermediate States

Figure 12 shows the full generation process of iterative expansion LMs for a sample sentence, presenting the input and outputs at all iterations.

F.2 Text generated at different values of \( \tau \)

Table 11 presents sentences generated by iterative expansion LMs trained on WMT17 at different values of the final softmax temperature \( \tau \). They have not been cherry-picked.

F.3 Style Variation Samples

Table 12 show samples of sentences generated with an altered probability of generating adjectival constructions that is ten times higher, which are not cherry-picked.
Figure 11: Quality (BLEU) vs. diversity (self-BLEU), for \( n \)-gram orders \( n = 4 \) (left), \( 3 \) (middle), and \( 2 \) (right).

Iteration 1

PLT: [ROOT]
NLT: failure
NLE: [nsubj-HEAD-punct]

Iteration 2

PLT: [nsubj] failure [punct]
NLT: It [pad] .
NLE: [HEAD-cop] [pad] [HEAD-cc]

Iteration 3

PLT: It [cop] failure , [cc]
NLT: [pad] was [pad] and
NLE: [pad] [HEAD-det] [pad] [pad] [head] [HEAD-conj]

Iteration 4

PLT: It [det] failure , and [conj]
NLT: [pad] [pad] a [pad] [pad] knew
NLE: [pad] [pad] [HEAD] [pad] [pad] [pad] [nsubj-HEAD-ccomp]

Iteration 5

PLT: It was [det] failure , and [nsubj] knew [ccomp]
NLT: [pad] [pad] [pad] [pad] [pad] [we] [pad] be
NLE: [pad] [pad] [pad] [pad] [pad] [pad] [HEAD] [pad] [ADVmod-HEAD-punct]

Iteration 6

PLT: It was a failure , and [nsubj] knew [advmod] be [punct]
NLT: [pad] [pad] [pad] [pad] [pad] [we] [pad] [pad] [pad] far [pad]
NLE: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [ADVmod-HEAD-nsubj] [pad] [HEAD-dep]

Iteration 7

PLT: It was a failure , and we knew [advmod] far [nsubj] be , [dep]
NLT: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] how [pad] ball [pad] [pad] so
NLE: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [HEAD] [pad] [det-HEAD-aux] [pad] [pad] [HEAD-parataxis]

Iteration 8

PLT: It was a failure , and we knew how far [det] ball [aux] be , so [parataxis]
NLT: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [the] [pad] would [pad] [pad] [pad] have
NLE: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [HEAD] [pad] [HEAD] [pad] [pad] [pad] [nsubj-HEAD-xcomp]

Iteration 9

PLT: It was a failure , and we knew how far the ball would be , so [nsubj] have [xcomp]
NLT: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] the [pad] would [pad] [pad] [pad] have
NLE: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [HEAD] [pad] [HEAD] [pad] [pad] [pad] [nsubj-HEAD-xcomp]

Iteration 10

PLT: It was a failure , and we knew how far the ball would be , so you have [mark] wait [punct]
NLT: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [you] [pad] wait
NLE: [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [pad] [HEAD] [pad] [HEAD] [pad] [pad] [pad] [nsubj-HEAD-punct]

Figure 12: Generation of sentence “It was a failure, and we knew how far the ball would be, so you have to wait.”
We're really looking forward to seeing the world in a positive way from the main stage in my life, "he said. I will do everything to make me feel comfortable with myself, and tell you that I can go out and play my part.

\[ \tau = 0.7 \]

I think I'm one of the first people I think we need the people to make the most of it.

The company said she would go on TV and was concerned for the welfare of hundreds of thousands of customers.

"It was a one - child policy by one," Mr. Trump told the Financial Times.

\[ \tau = 0.8 \]

The good news is that the government is likely to build a wall between the country's population and younger voters.

We can't imagine the figures will increase our interest rates in December and December, with a cost of around £2 billion.

\[ \tau = 0.9 \]

We feel it feels as if this was the result of someone acting in life - threatening, and it made sense.

I like the president - elect, I would want to play fair, and I want someone who is more conservative than that.

We have to show that we have the sort of thing we need as we want of doing what we do.

He also sent out a letter to Tony Abbott, who asked him for a response to Russia's intervention in Ukraine.

\[ \tau = 1.0 \]

She said she encouraged her husband to start the company "to fight State and Qaeda," and that he would send them to Iraq.

Clinton's appeal means that Bill Clinton on Monday is limited to the amount of the national education budget for the Democrats.

But the weak drinks industry may leave an impression, that key cash restrictions would be a disaster for your business of car.

When Hillary Clinton reporters considered the moment after the election he would bring out their criticism of women for the attacks "black identity.

A Home Office spokesperson said: "We are aware of the game and are travelling as people are far away from Europe.

\[ \tau = 1.2 \]

He produced a decent player, and became the fifth player in the eighth game, and helped Williams to his rally to Miami.

George Osborne, which exposed Labor last month, was reportedly referring to Mr Trump's launch by a senior campaign policy official on Jan.

Almost 60 per cent of them believe it was the first time they had joined the coalition to promote civil war and human rights.

We won't get anywhere, so we had to make that decision and it was a present and say, "Is it?

I see what happens, I'm just trying to do something this way, and I don't want

I tell our friends to write stories about their mixed ways: can you ask if something is obvious again?

Researchers also noted that jobs' growth assets fear UK taxpayers will forget if real estate wages and a free living wage could be affected by the plan.

"All on the street, players and events are speaking up with other teams because they are tired that we should have stuck faster, we don't agree with how our players looks, so you really enjoy playing more," he said.

Labour were eventually advised over a quiet situation within two groups "eat and exercise with speed at all, however, say.

The result may be to leave the house in 12 seasons or complete with a personal outdoor work between 6 - year - old.

Table 11: Samples of text generated by iterative expansion LMs (w) for different softmax temperatures (not cherry-picked).

The last judge appeal is to focus on the single many main causes of attempted murder," he said.

"I ask if you are willing to it to say yes and have a serious conversation about the way that I’ve been prepared," he said.

I can just make improvements we need to keep this message going, and we cannot believe that we treat the British Labour badly.

I had guys created, and I couldn’t see that stronger, and I thought they could do, but it turned out.

The same poll leaves 75% of the voters vote and 48 points in 2012, a standard national measure released last month.

Table 12: Samples of style variation with adj. probability×10 from Table 4 (not cherry-picked).