

# Word Ordering Without Syntax

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## Abstract

Recent work on word ordering has argued that syntactic structure is important, or even required, for effectively recovering the order of a sentence. We find that, in fact, an n-gram language model with a simple heuristic gives strong results on this task. Furthermore, we show that a long short-term memory (LSTM) language model is even more effective at recovering order, with our basic model outperforming a state-of-the-art syntactic model by 11.5 BLEU points. Additional data and larger beams yield further gains, at the expense of training and search time.

## 1 Introduction

We address the task of recovering the original word order of a shuffled sentence, referred to as bag generation (Brown et al., 1990), shake-and-bake generation (Brew, 1992), or more recently, linearization, as standardized in a recent line of research as a method useful for isolating the performance of text-to-text generation models (Zhang and Clark, 2011; Liu et al., 2015; Liu and Zhang, 2015; Zhang and Clark, 2015). The predominant argument of the more recent works is that jointly recovering explicit syntactic structure is crucial for determining the correct word order of the original sentence. As such, these methods either generate or rely on given parse structure to reproduce the order.

Independently, Elman (1990) explored linearization in his seminal work on recurrent neural networks. Elman judged the capacity of early recurrent neural networks via, in part, the network’s ability to predict word order in simple sentences. He notes,

The order of words in sentences reflects a number of constraints... Syntactic structure, selective restrictions, subcategorization, and discourse considerations are among the many factors which join together to fix the order in which words occur... [T]here is an abstract structure which underlies the surface strings and it is this structure which provides a more insightful basis for understanding the constraints on word order... It is, therefore, an interesting question to ask whether a network can learn any aspects of that underlying abstract structure (Elman, 1990).

Recently, recurrent neural networks have reemerged as a powerful tool for learning the latent structure of language. In particular, work on long short-term memory (LSTM) networks for language modeling has provided improvements in perplexity.

We revisit Elman’s question by applying LSTMs to the word-ordering task, without any explicit syntactic modeling. We find that language models are in general effective for linearization relative to existing syntactic approaches, with LSTMs in particular outperforming the state-of-the-art by 11.5 BLEU points, with further gains observed when training with additional text and decoding with larger beams.

## 2 Background: Linearization

The task of linearization is to recover the original order of a shuffled sentence. We assume a vocabulary  $\mathcal{V}$  and are given a sequence of out-of-order phrases  $x_1, \dots, x_N$ , with  $x_n \in \mathcal{V}^+$  for  $1 \leq n \leq N$ . Define  $M$  as the total number of tokens (i.e., the sum of the lengths of the phrases). We consider two varieties of the task: (1) WORDS, where each  $x_n$  consists of a single word and  $M = N$ , and (2) WORDS+BNPNS,

where base noun phrases (noun phrases not containing inner noun phrases) are also provided and  $M \geq N$ . The second has become a standard formulation in recent literature.

Given input  $x$ , we define the output set  $\mathcal{Y}$  to be all possible permutations over the  $N$  elements of  $x$ , where  $\hat{y} \in \mathcal{Y}$  is the permutation generating the true order. We aim to find  $\hat{y}$ , or a permutation close to it. We produce a linearization by (approximately) optimizing a learned scoring function  $f$  over the set of permutations,  $y^* = \arg \max_{y \in \mathcal{Y}} f(x, y)$ .

### 3 Related Work: Syntactic Linearization

Recent approaches to linearization have been based on reconstructing the syntactic structure to produce the word order. Let  $\mathcal{Z}$  represent all projective dependency parse trees over  $M$  words. The objective is to find  $y^*, z^* = \arg \max_{y \in \mathcal{Y}, z \in \mathcal{Z}} f(x, y, z)$  where  $f$  is now over both the syntactic structure and the linearization. The current state of the art on the Penn Treebank (PTB) (Marcus et al., 1993), without external data, of Liu et al. (2015) uses a transition-based parser with beam search to construct a sentence and a parse tree. The scoring function is a linear model  $f(x, y) = \theta^\top \Phi(x, y, z)$  and is trained with an early update structured perceptron to match both a given order and syntactic tree. The feature function  $\Phi$  includes features on the syntactic tree. This work improves upon past work which used best-first search over a similar objective (Zhang and Clark, 2011).

In follow-up work, Liu and Zhang (2015) argue that syntactic models yield improvements over pure surface n-gram models for the WORDS+BNPS case. This result holds particularly on longer sentences and even when the syntactic trees used in training are of low quality. The n-gram decoder of this work utilizes a single beam, discarding the probabilities of internal, non-boundary words in the BNPs when comparing hypotheses. We revisit this comparison between syntactic models and surface-level models, utilizing a surface-level decoder with heuristic future costs and an alternative approach for scoring partial hypotheses for the WORDS+BNPS case.

Additional previous work has also explored n-gram models for the word ordering task. The work of de Gispert et al. (2014) demonstrates improve-

ments over the earlier syntactic model of Zhang et al. (2012) by applying an n-gram language model over the space of word permutations restricted to concatenations of phrases seen in a large corpus. Horvat and Byrne (2014) models the search for the highest probability permutation of words under an n-gram model as a Travelling Salesman Problem; however, direct comparisons to existing works are not provided.

## 4 LM-Based Linearization

In contrast to the recent syntax-based approaches, we use an LM directly for word ordering. We consider two types of language models: an n-gram model and a long short-term memory network (Hochreiter and Schmidhuber, 1997). For the purpose of this work, we define a common abstraction for both models. Let  $\mathcal{H}$  be the current state of the model, with  $\mathbf{h}_0$  as the initial state. Upon seeing a word  $w_i \in \mathcal{V}$ , the LM advances to a new state  $\mathbf{h}_i = \delta(w_i, \mathbf{h}_{i-1})$ . At any time, the LM can be queried to produce an estimate of the probability of the next word  $q(w_i, \mathbf{h}_{i-1}) \approx p(w_i | w_1, \dots, w_{i-1})$ . For n-gram language models,  $\mathcal{H}$ ,  $\delta$ , and  $q$  can naturally be defined respectively as the state space, transition model, and edge costs of a finite-state machine.

LSTMs are a type of recurrent neural network (RNN) that are conducive to learning long-distance dependencies through the use of an internal memory cell. Existing work with LSTMs has generated state-of-the-art results in language modeling (Zaremba et al., 2014), along with a variety of other NLP tasks.

In our notation we define  $\mathcal{H}$  as the hidden states and cell states of a multi-layer LSTM,  $\delta$  as the LSTM update function, and  $q$  as a final affine transformation and softmax given as  $q(*, \mathbf{h}_{i-1}; \theta_q) = \text{softmax}(\mathbf{W}\mathbf{h}_{i-1}^{(L)} + \mathbf{b})$  where  $\mathbf{h}_{i-1}^{(L)}$  is the top hidden layer and  $\theta_q = (\mathbf{W}, \mathbf{b})$  are parameters. We direct readers to the work of Graves (2013) for a full description of the LSTM update.

For both models, we simply define the scoring function as

$$f(x, y) = \sum_{n=1}^N \log p(x_{y(n)} | x_{y(1)}, \dots, x_{y(n-1)})$$

where the phrase probabilities are calculated word-by-word by our language model.

**Algorithm 1** LM beam-search word ordering

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1: procedure ORDER( $x_1 \dots x_N, K, g$ )
2:    $B_0 \leftarrow \langle \langle \rangle, \{1, \dots, N\}, 0, \mathbf{h}_0 \rangle$ 
3:   for  $m = 0, \dots, M - 1$  do
4:     for  $k = 1, \dots, |B_m|$  do
5:        $(y, \mathcal{R}, s, \mathbf{h}) \leftarrow B_m^{(k)}$ 
6:       for  $i \in \mathcal{R}$  do
7:          $(s', \mathbf{h}') \leftarrow (s, \mathbf{h})$ 
8:         for word  $w$  in phrase  $x_i$  do
9:            $s' \leftarrow s' + \log q(w, \mathbf{h}')$ 
10:           $\mathbf{h}' \leftarrow \delta(w, \mathbf{h}')$ 
11:          $j \leftarrow m + |x_i|$ 
12:          $B_j \leftarrow B_j + (y + x_i, \mathcal{R} - i, s', \mathbf{h}')$ 
13:         keep top- $K$  of  $B_j$  by  $f(x, y) + g(\mathcal{R})$ 
14:   return  $B_M$ 

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Searching over all permutations  $\mathcal{Y}$  is intractable, so we instead follow past work on linearization (Liu et al., 2015) and LSTM generation (Sutskever et al., 2014) in adapting beam search for our generation step. Our work differs from the beam search approach for the WORDS+BNPs case of previous work in that we maintain multiple beams, as in stack decoding for phrase-based machine translation (Koehn, 2010), allowing us to incorporate the probabilities of internal, non-boundary words in the BNPs. Additionally, for both WORDS and WORDS+BNPs, we also include an estimate of future cost in order to improve search accuracy.

Beam search maintains  $M + 1$  beams,  $B_0, \dots, B_M$ , each containing at most the top- $K$  partial hypotheses of that length. A partial hypothesis is a 4-tuple  $(y, \mathcal{R}, s, \mathbf{h})$ , where  $y$  is a partial ordering,  $\mathcal{R}$  is the set of remaining indices to be ordered,  $s$  is the score of the partial linearization  $f(x, y)$ , and  $\mathbf{h}$  is the current LM state. Each step consists of expanding all next possible phrases and adding the next hypothesis to a later beam. The full beam search is given in Algorithm 1.

As part of the beam search scoring function we also include a future cost  $g$ , an estimate of the score contribution of the remaining elements in  $\mathcal{R}$ . Together,  $f(x, y) + g(\mathcal{R})$  gives a noisy estimate of the total score, which is used to determine the  $K$  best elements in the beam. In our experiments we use a very simple unigram future cost estimate,  $g(\mathcal{R}) = \sum_{i \in \mathcal{R}} \sum_{w \in x_i} \log p(w)$ .

Model	WORDS	WORDS+BNPs
ZGEN-64	30.9	49.4
ZGEN-64+POS	–	50.8
NGRAM-64 (NO $g$ )	32.0	51.3
NGRAM-64	37.0	54.3
NGRAM-512	38.6	55.6
LSTM-64	40.5	60.9
LSTM-512	42.7	63.2
ZGEN-64+LM+GW+POS	–	52.4
LSTM-64+GW	41.1	63.1
LSTM-512+GW	44.5	65.8

Table 1: BLEU score comparison on the PTB test set. Results from previous works (for ZGEN) are those provided by the respective authors, except for the WORDS task. The final number in the model identifier is the beam size, +GW indicates additional Gigaword data. Models marked with +POS are provided with a POS dictionary derived from the PTB training set.

## 5 Experiments

**Setup** Experiments are on PTB with sections 2-21 as training, 22 as validation, and 23 as test<sup>1</sup>. We utilize two UNK types, one for initial uppercase tokens and one for all other low-frequency tokens; end sentence tokens; and start/end tokens, which are treated as words, to mark BNPs for the WORDS+BNPs task. We also use a special symbol to replace tokens that contain at least one numeric character. We otherwise train with punctuation and the original case of each token, resulting in a vocabulary containing around 16K types from around 1M training tokens.

For experiments marked GW we augment the PTB with a subset of the Annotated Gigaword corpus (Napoles et al., 2012). We follow Liu and Zhang (2015) and train on a sample of 900k Agence France-Presse sentences combined with the full PTB training set. The GW models benefit from both additional data and a larger vocabulary of around 25K types, which reduces unknowns in the validation and test sets.

We compare the models of Liu et al. (2015)

<sup>1</sup>In practice, the results in Liu et al. (2015) and Liu and Zhang (2015) use section 0 instead of 22 for validation (author correspondence).

BNP	$g$	GW	1	10	64	128	256	512
LSTM								
•			41.7	53.6	58.0	59.1	60.0	60.6
•	•		47.6	59.4	62.2	62.9	63.6	64.3
•	•	•	48.4	60.1	64.2	64.9	65.6	66.2
			15.4	26.8	33.8	35.3	36.5	38.0
		•	25.0	36.8	40.7	41.7	42.0	42.5
		•	23.8	35.5	40.7	41.7	42.9	43.7
NGRAM								
•			40.6	49.7	52.6	53.2	54.0	54.7
•	•		45.7	53.6	55.6	56.2	56.6	56.6
			14.6	27.1	32.6	33.8	35.1	35.8
		•	27.1	34.6	37.5	38.1	38.4	38.7

Table 2: BLEU results on the validation set for the LSTM and NGRAM model with varying beam sizes, future costs, additional data, and use of base noun phrases.

(known as ZGEN), a 5-gram LM using Kneser-Ney smoothing (NGRAM)<sup>2</sup>, and an LSTM. We experiment on the WORDS and WORDS+BNPs tasks, and we also experiment with including future costs ( $g$ ), the Gigaword data (GW), and varying beam size. We retrain ZGEN using publicly available code<sup>3</sup> to replicate published results.

The LSTM model is similar in size and architecture to the medium LSTM setup of Zaremba et al. (2014)<sup>4</sup>. Our implementation uses the Torch<sup>5</sup> framework and is publicly available<sup>6</sup>.

We compare the performance of the models using the BLEU metric (Papineni et al., 2002). In generation if there are multiple tokens of identical UNK type, we randomly replace each with possible unused tokens in the original source before calculating BLEU. For comparison purposes, we use the BLEU script distributed with the publicly available ZGEN code.

**Results** Our main results are shown in Table 1. On the WORDS+BNPs task the NGRAM-64 model scores nearly 5 points higher than the syntax-based model ZGEN-64. The LSTM-64 then surpasses

<sup>2</sup>We use the KenLM Language Model Toolkit (<https://kheafield.com/code/kenlm/>).

<sup>3</sup><https://github.com/SUTDNLP/ZGen>

<sup>4</sup>We hypothesize that additional gains are possible via a larger model and model averaging, ceteris paribus.

<sup>5</sup><http://torch.ch>

<sup>6</sup>[https://github.com/allenschmaltz/word\\_ordering](https://github.com/allenschmaltz/word_ordering)

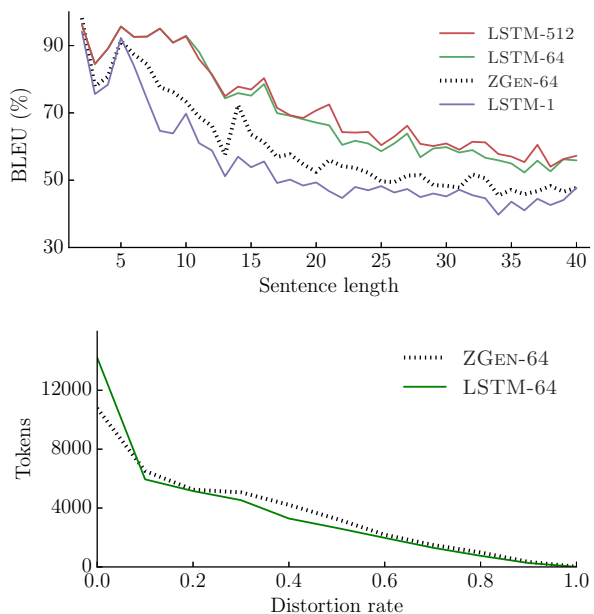


Figure 1: Experiments on the PTB validation on the WORDS+BNPs models: (a) Performance on the set by length on sentences from length 2 to length 40. (b) The distribution of token distortion, binned at 0.1 intervals.

NGRAM-64 by more than 5 BLEU points. Differences on the WORDS task are smaller, but show a similar pattern. Incorporating Gigaword further increases the result another 2 points. Notably, the NGRAM model outperforms the combined result of ZGEN-64+LM+GW+POS from Liu and Zhang (2015), which uses a 4-gram model trained on Gigaword. We believe this is because the combined ZGEN model incorporates the n-gram scores as discretized indicator features instead of using the probability directly.<sup>7</sup> A beam of 512 yields a further improvement at the cost of search time.

To further explore the impact of search accuracy, Table 2 shows the results of various models with beam widths ranging from 1 (greedy search) to 512, and also with and without future costs  $g$ . We see that for the better models there is a steady increase in accuracy even with large beams, indicating that search errors are made even with relatively large beams.

<sup>7</sup>In work of Liu and Zhang (2015), with the given decoder, N-grams only yielded a small further improvement over the syntactic models when discretized versions of the LM probabilities were incorporated as indicator features in the syntactic models.

Model	WORDS	WORDS+BNPs
ZGEN-64( $z^*$ )	39.7	64.9
ZGEN-64	40.8	65.2
NGRAM-64	46.1	67.0
NGRAM-512	47.2	67.8
LSTM-64	51.3	71.9
LSTM-512	52.8	73.1

Table 3: Unlabeled attachment scores (UAS) on the PTB validation set after parsing and aligning the output. For ZGEN we also include a result using the tree  $z^*$  produced directly by the system. For WORDS+BNPs, internal BNP arcs are always counted as correct.

One proposed advantage of syntax in linearization models is that it can better capture long-distance relationships. Figure 1 shows results by sentence length and distortion, which is defined as the absolute difference between a token’s index position in  $y^*$  and  $\hat{y}$ , normalized by  $M$ . The LSTM model exhibits consistently better performance than existing syntax models across sentence lengths and generates fewer long-range distortions than the ZGEN model.

Finally, Table 3 compares the syntactic fluency of the output. As a lightweight test, we parse the output with the Yara Parser (Rasooli and Tetreault, 2015) and compare the unlabeled attachment scores (UAS) to the trees produced by the syntactic system. We first align the gold head to each output token. (In cases where the alignment is not one-to-one, we randomly sample among the possibilities.) The models with no knowledge of syntax are able to recover a higher proportion of gold arcs.

## 6 Conclusion

Strong surface-level language models recover word order more accurately than the models trained with explicit syntactic annotations appearing in a recent series of papers. This has implications for the utility of costly syntactic annotations in generation models, for both high- and low- resource languages and domains.

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