An Empirical Study of Compound PCFGs

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Abstract

Compound probabilistic context-free grammars (C-PCFGs) have recently estabilished a new state-of-the-art performance in phrase-structure grammar induction. However, due to the high time-complexity of chart-based learning and inference, it is difficult to investigate them comprehensively. In this work, we rely on a fast implementation of C-PCFGs to conduct evaluation complementary to that of Kim et al. (2019). We highlight three key findings: (1) C-PCFGs are data-efficient, (2) C-PCFGs make the best use of the compound distribution (of sentence embeddings) in preterminal rule probabilities, and (3) the best-performed C-PCFG on English does not always generalize to morphology-rich languages.

1 Introduction

Probabilistic context-free grammars (PCFGs) have been used for unsupervised constituency grammar learning since decades ago (Lari and Young, 1990; Klein and Manning, 2002), while learning PCFGs with the Expectation Maximization (Dempster et al., 1977) has been difficult as being involving non-convex optimization. Recently, Kim et al. (2019) propose compound PCFGs, an over-parameterized neural model that extend corpus-level PCFGs by defining a mixture of PCFGs per sentence. C-PCFGs have achieved the state-of-the-art performance on English and Chinese treebanks. They are also shown to be effective in a visually-grounded learning setting (Zhao and Titov, 2020). However, because of the high time-complexity of chart-based learning and infernece, it is still hard to inspect C-PCFGs comprehensively.

In this work, we use a fast implementation[1] of C-PCFGs to conduct a set of experiments complementary to those of Kim et al. (2019). Our first experiment concerns data efficiency and generalizability of C-PCFGs. We empirically find that a C-PCFG, trained only on short sentences (e.g., shorter than 30 tokens), can generalize to longer sentences while maintaining a high testing performance (54.8% F1). The surprisingly good performance of C-PCFGs further motivates us to investigate the factors that affect the model performance. As C-PCFGs differ from vanilla PCFGs in that they use an additional sentence embedding in three types of rules (see model details in Section 2), we ablate C-PCFGs by removing it from the three types of rules, individually. Our experimental results show that the sentence embedding is most effective for preterminal rules, presumably because it encodes part-of-speech tags which are important for parsing. Despite the impressive performance on English, it is still unclear whether C-PCFGs can generalize to other languages. We thus conduct multilingual evaluation of C-PCFGs on the SPMRL dataset (Seddah et al., 2014). We find that a C-PCFG performing best on English does not necessarily generalize to morphology-rich languages.

We organize the rest of paper as follows: we briefly describe the background of C-PCFGs in Section 2. Section 3 summarizes datasets, evaluation methods, and implementation details. In Section 4 we present comprehensive evaluation and analysis of C-PCFGs .

2 Compound PCFGs

Compound PCFGs extends PCFG. Unlike PCFGs which assign each rule r a non-negative scalar π_r such that $\sum_{r:A\rightarrow\gamma} \pi_r = 1$, C-PCFGs assume rule probabilities follow a compound distribution:

$$\pi_r = g_r(\mathbf{z};\theta), \quad \mathbf{z} \sim p(\mathbf{z}).$$

where $p(\mathbf{z})$ is a prior distribution. Considering grammar rules in the Chomsky normal form, for a

[1] https://github.com/zhaoyanpeng/cpcfg

binary rule $r : A \rightarrow BC$, its probability is defined by $g_r(\mathbf{z}; \theta)$ and takes the following form:

$$\pi_{A \rightarrow BC} = \frac{\exp(\mathbf{u}_{BC}^T f([\mathbf{w}_A; \mathbf{z}]))}{\sum_{B',C'} \exp(\mathbf{u}_{B'C'}^T f([\mathbf{w}_A; \mathbf{z}]))},$$

where $\mathbf{w}$ indicates nonterminal embeddings and $\mathbf{u}$ represents learnable parameters; $f(\cdot)$ takes as the input the concatenation of $\mathbf{w}$ and $\mathbf{z}$ and yields a vector representation (parameters are dropped for simplicity). Notice that $\pi_{A \rightarrow \gamma}$ follows a categorical distribution as in PCFGs. $g_r(\mathbf{z}; \theta)$ can be generalized to unary rules[2] in a similar way.

A C-PCFG defines a mixture of PCFGs in the sense that a PCFG can be parameterized by sampling a $\mathbf{z}$. Learning C-PCFGs is formulized as maximizing the log likelihood of each observed sentence $\boldsymbol{w} = w_1 w_2 \dots w_n$:

$$\log p_\theta(\boldsymbol{w}) = \log \int_{\mathbf{z}} \sum_{t \in \mathcal{T}_\mathcal{G}(\boldsymbol{w})} p_\theta(t|\mathbf{z}) p(\mathbf{z}) \, d\mathbf{z},$$

where $\mathcal{T}_\mathcal{G}(\boldsymbol{w})$ consists of all parses of the sentence $\boldsymbol{w}$ under a PCFG $\mathcal{G}$. As a typical practice in learning latent variable models, C-PCFGs resort to variational inference for a tractable learning and instead maximize the evidence lower bound (ELBO):

$$\log p_\theta(\boldsymbol{w}) \geq \text{ELBO}(\boldsymbol{w}; \phi, \theta) = \quad (1)$$
$$\mathbb{E}_{q_\phi(\mathbf{z}|\boldsymbol{w})}[\log p_\theta(\boldsymbol{w}|\mathbf{z})] - \text{KL}[q_\phi(\mathbf{z}|\boldsymbol{w})||p(\mathbf{z})],$$

where the first term computes the expected log likelihood under a varitional posterior $q_\phi(\mathbf{z}|\boldsymbol{w})$; the KL term can be estimated analytically when $p(\mathbf{z})$ and $q_\phi(\mathbf{z}|\boldsymbol{w})$ are normally distributed. $q_\phi(\mathbf{z}|\boldsymbol{w})$ is parameterized by a neural network and defines a distritbuion over the latent sentence embedding $\mathbf{z}$.

C-PCFGs satisfy the context-free assumption conditioned on $\mathbf{z}$ and thus admit tractable inference for each given $\mathbf{z}$. Inference with C-PCFGs seeks for the most probable parse t^* of $\boldsymbol{w}$:

$$t^* = \text{argmax} \int_{\mathbf{z}} p_\theta(t|\mathbf{w}, \mathbf{z}) p_\theta(\mathbf{z}|\boldsymbol{w}) \, d\mathbf{z}.$$

Though given $\mathbf{z}$, the maximum a posterior (MAP) inference over $p_\theta(t|\mathbf{w}, \mathbf{z})$ can be exactly solved by using the CYK algorithm, the integral over $\mathbf{z}$ renders inference intractable. The MAP inference is instead approximated by:

$$t^* \approx \text{argmax} \int_{\mathbf{z}} p_\theta(t|\mathbf{w}, \mathbf{z}) \delta(\mathbf{z} - \boldsymbol{\mu}_\phi(\boldsymbol{w})) \, d\mathbf{z}, \quad (2)$$

where $\delta(\cdot)$ is the Dirac delta function and $\boldsymbol{\mu}_\phi(\boldsymbol{w})$ is the mean vector of the variational posterior.

3 Experimental setup

3.1 Datasets and evaluation

Datasets: We investigate the parsing performance of C-PCFGs across ten languages. Specifically, we conduct experiments on the Wall Street Journal (WSJ) corpus of the Penn Treebank (Marcus et al., 1994) for English, the Penn Chinese Treebank 5.1 (CTB) (Xue et al., 2005) for Chinese, and eight treebanks from the SPMRL 2014 shared task (Seddah et al., 2014) for other eight languages (Basque, German, French, Hebrew, Hungarian, Korean, Polish, Swedish). We use the standard data splitting for each treebank. Following Kim et al. (2019), punctuation is removed from all data; the top 10000 frequent tokens in the training data of each treebank are kept as the vocabulary. Unless otherwise specified, we train C-PCFGs on sentences no longer than 40 tokens.

Evaluation: We train C-PCFGs for each language separately. On each treebank we run C-PCFGs four times with different random seeds and for 30 epochs. The best model in each run is selected according to the perplexity on the validation data. At test time, trivial spans such as single-word and sentence-level spans are ignored. We report average corpus- and sentence-level F1 numbers as well as the unbiased standard deviations.

3.2 Model hyperparameters

We re-implement C-PCFGs relying on Torch-Struct (Rush, 2020) and adopt the same hyperparameter settings as in Kim et al. (2019).

4 Results and discussion

We analyze C-PCFGs on WSJ in Section 4.1-4.3. We give a quantitative analysis as to the correlation between model performance and data distribution in Section 4.1. Section 4.2 concerns data efficiency of C-PCFGs and presents a length generalization test of C-PCFGs. Section 4.3 focuses on the role of sentence embeddings (i.e., the latent vector $\mathbf{z}$) in C-PCFGs. In Section 4.4 we conduct multilingual evaluation of C-PCFGs.

[2]Unary rules consist of preterminal rules which generate a word from a nonterminal symbol (e.g., $A \rightarrow w$) and start rules which generate a nonterminal symbol from the start symbol S (e.g., $S \rightarrow A$).

Model	NP	VP	PP	SBAR	ADJP	ADVP	C-F1	S-F1
Left Branching	10.4	0.5	5.0	5.3	2.5	8.0	6.0	8.7
Right Branching	24.1	**71.5**	42.4	**68.7**	27.7	38.1	36.1	39.5
Random Trees	$22.5_{\pm 0.3}$	$12.3_{\pm 0.3}$	$19.0_{\pm 0.5}$	$9.3_{\pm 0.6}$	$24.3_{\pm 1.7}$	$26.9_{\pm 1.3}$	$15.3_{\pm 0.1}$	$18.1_{\pm 0.1}$
†N-PCFG	71.2	33.8	58.8	52.5	32.5	45.5		50.8
N-PCFG	$72.2_{\pm 4.8}$	$31.4_{\pm 9.7}$	$66.8_{\pm 4.7}$	$50.2_{\pm 9.1}$	$46.3_{\pm 5.7}$	$55.2_{\pm 5.0}$	$49.0_{\pm 3.5}$	$50.8_{\pm 3.8}$
†C-PCFG	74.7	41.7	68.8	56.1	40.4	52.5		55.2
C-PCFG	$76.7_{\pm 2.0}$	$40.7_{\pm 5.5}$	$71.3_{\pm 2.1}$	$53.8_{\pm 3.1}$	$45.9_{\pm 2.8}$	$64.2_{\pm 2.8}$	$53.5_{\pm 1.4}$	$55.7_{\pm 1.3}$
L50C-PCFG	$\mathbf{76.9}_{\pm 3.6}$	$40.7_{\pm 3.7}$	$\mathbf{72.3}_{\pm 0.6}$	$60.1_{\pm 5.5}$	$\mathbf{46.9}_{\pm 5.8}$	$63.2_{\pm 5.0}$	$\mathbf{53.8}_{\pm 2.1}$	$\mathbf{55.9}_{\pm 1.9}$
L40C-PCFG	$76.7_{\pm 2.0}$	$40.7_{\pm 5.5}$	$71.3_{\pm 2.1}$	$53.8_{\pm 3.1}$	$45.9_{\pm 2.8}$	$64.2_{\pm 2.8}$	$53.5_{\pm 1.4}$	$55.7_{\pm 1.3}$
L30C-PCFG	$74.5_{\pm 2.8}$	$38.4_{\pm 1.7}$	$71.1_{\pm 1.2}$	$59.7_{\pm 4.8}$	$44.2_{\pm 4.1}$	$\mathbf{64.3}_{\pm 3.1}$	$52.5_{\pm 1.5}$	$54.8_{\pm 1.4}$
L20C-PCFG	$72.4_{\pm 2.3}$	$36.5_{\pm 1.1}$	$69.2_{\pm 1.7}$	$54.1_{\pm 3.2}$	$41.9_{\pm 2.3}$	$58.1_{\pm 7.1}$	$50.6_{\pm 0.9}$	$52.8_{\pm 0.7}$
L10C-PCFG	$67.1_{\pm 3.8}$	$31.0_{\pm 9.8}$	$61.3_{\pm 2.2}$	$45.9_{\pm 8.2}$	$36.7_{\pm 2.3}$	$41.3_{\pm 6.0}$	$45.5_{\pm 2.4}$	$48.2_{\pm 2.3}$

Table 1: Recall on six frequent constituent labels (NP, VP, PP, SBAR, ADJP, ADVP) in the WSJ test data, corpus-level F1 (C-F1), and sentence-level F1 (S-F1) results. The best mean number in each column is in bold. † denotes results reported by Kim et al. (2019). L# indicates that the models are trained on sentences shorter than # tokens.

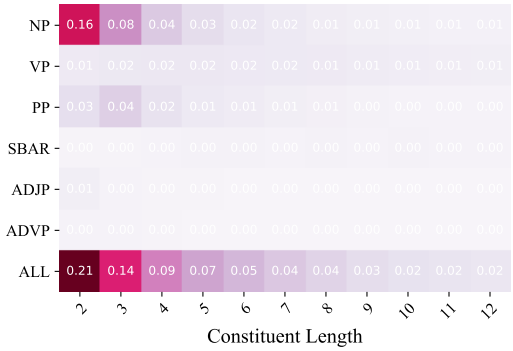


Figure 1: Label distribution over constituent lengths on the WSJ test data. *All* denotes frequencies of constituent lengths. Zero frequencies are due to the limited numerical precision.

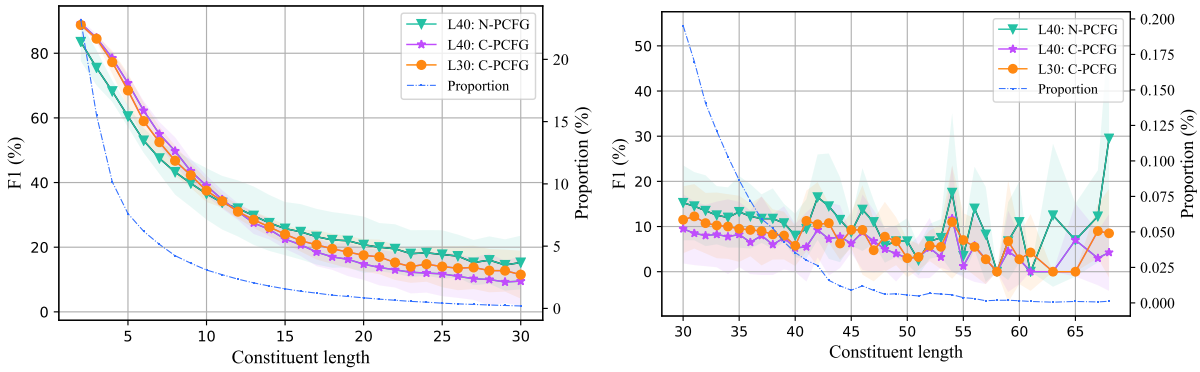
4.1 Main results

We compare C-PCFGs against three trivial baselines (left- / right-branching model and random trees) and a neural PCFG model (N-PCFG). In short, C-PCFGs beats all baselines in terms of corpus- / sentence-level F1 (see the second row of Table 1). Our re-implementation of C-PCFGs reaches the highest sentence-level F1, slightly outperforming the model of Kim et al. (2019) by 0.5% F1. We will focus on sentence-level F1 for a consistent comparison in the following discussion. To give an in-depth analysis of the model gains, we present recall numbers on six most frequent constituent labels in the test data (NP, VP, PP, SBAR, ADJP, ADVP). Unsurprisingly, C-PCFGs achieve the best recall for most labels (4 out of 6 constituent labels). However, on verb phrases (VPs) they fall far behind the right-branching baseline (-30.8% recall), presumably because VPs are longer and involve more complex linguistic structures. We further plot distributions of the six labels across constituent lengths (see Figure 1). We can see that VPs are nearly uniformly distributed over different constituent lengths. In contrast, noun phrases (NPs) account for 61% of short constituents that have less than 6 tokens and cover 51% of total constituents. It suggests that C-PCFGs can recognize local and short constituents with a high accuracy but struggles with long constituents; a better overal performance would be achieved if we could improve C-PCFGs on VPs.

4.2 Data efficiency and length generalization

A crucial aspect of human languages is that they exhibit compositional structures. Humans can derive grammar rules from a few sentences and combine the rules to generate new sentences compositionally. As C-PCFGs are backed by context-free grammar (CFGs), we expect them to be data-efficient and to have a good generalizability. We design a length generalization test to verify this hypothesis. Specifically, we train C-PCFGs using training sentences of length equal to or below a chosen sentence length. At test time, we evaluate C-PCFGs either on the test data of WSJ (to check data efficiency) or on the training data of WSJ (to perform length generalization test).

We choose five sentence lengths, 10, 20, 30, 40 and 50, indicated by L10, L20, L30, L40 and L50, respectively (see the third row of Table 1)). Figure 3 illustrates sentence-level F1 numbers on the test data of WSJ. Overall, training C-PCFGs on more / longer sentences results in higher F1 num-



(a) F1 w.r.t. constituent length **below** 30

(b) F1 w.r.t. constituent length **above** 30

Figure 2: F1 numbers broken down by constituent lengths on the WSJ training data. During training, constituents (sentences) longer than 30 tokens (L30) are unseen to L30C-PCFG and are unseen to L40C-PCFG and L40N-PCFG when longer than 40 tokens (L40).

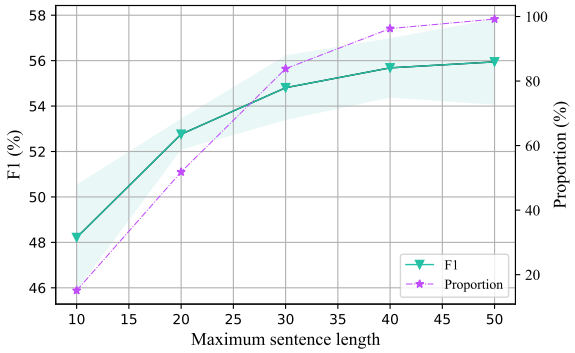


Figure 3: F1 numbers on the WSJ test data with varying maximum lengths of training sentences.

bers. While using training sentences longer than 40 tokens trivially improve the performance (+0.2% F1). Given that 97% test sentences are shorter than 40 tokens, we conjecture that training sentences shorter than 40 tokens can adequately cover lexical / structural characteristics in the test data. On the other hand, longer sentences have a larger tree space and probably make it harder for the model to learn. Notably, discarding training sentences longer than 30 tokens only decreases the model performance by 1.2% F1, showing that C-PCFGs are data-efficient.

Next, we perform the length generalization test. Since the test data of WSJ does not have enough statistics of long constituents, we test C-PCFGs on training sentences and report F1 numbers across *constituent lengths* (see Figure 2). In general, F1 numbers become worse as constituent length increases. This is resonable because large constituents merge from small constituents; errors in small constituents accumulate when consposing larger constituents.

Instead, we investigate how training data influences length generalization. We use sentence lengths 30 and 40 as an illustration. Compare with L40C-PCFG, when tested on constituents longer than 40 tokens, L30C-PCFG shows a slightly better generalizability (see Figure 2b). It consistently outperforms L40C-PCFG on sentences of length ranging from 30 to 40, though L40C-PCFG can access all sentences shorter than 40 tokens during training. This implies that C-PCFGs can learn to generalize from short sentences. We also plots the propotions of constituent lengths, which shows that the generalizability exhibited by L30C-PCFGs is indeed reliable.

Figure 2b also visualizes the performance of an L40N-PCFG. Surprisingly, L40N-PCFG shows the best generalizability on long constituents. *Where does the F1 improvement of* C-PCFGs *over* N-PCFGs *come from?* Look at the F1 numbers on shorter constituents in Figure 2a, clearly C-PCFGs are better on constituents that are shorter than 11 tokens, while L40N-PCFGs consistently outperform C-PCFGs on constituents of length below 11. L30C-PCFGs fall in between L40C-PCFGs and L40N-PCFGs, once again showing that short sentences can endow C-PCFGs good parsing performance as well as nice generalizability.

4.3 Model ablation

C-PCFGs have demonstrated a significant improvement over N-PCFGs. Compare with N-PCFGs, C-PCFGs use an additional sentence embedding (i.e., the latent variable $\mathbf{z}$, see Section 2) to parame-

Model	Chinese	Basque	German	French	Hebrew	Hungarian	Korean	Polish	Swedish	Mean
Left Branching	7.2	17.9	10.0	5.7	8.5	13.3	18.5	10.9	8.4	11.2
Right Branching	25.5	15.4	14.7	26.4	30.0	12.7	19.2	**34.2**	**30.4**	23.2
N-PCFG	30.1$_{\pm 4.6}$	**30.2**$_{\pm 0.9}$	**37.8**$_{\pm 1.7}$	**42.2**$_{\pm 1.4}$	**41.0**$_{\pm 0.6}$	37.9$_{\pm 0.8}$	25.7$_{\pm 2.8}$	31.7$_{\pm 1.8}$	14.5$_{\pm 12.7}$	32.3
C-PCFG	**35.1**$_{\pm 6.1}$	27.9$_{\pm 2.0}$	37.3$_{\pm 1.8}$	40.5$_{\pm 0.8}$	39.2$_{\pm 1.2}$	**38.3**$_{\pm 0.7}$	**27.7**$_{\pm 2.8}$	32.4$_{\pm 1.1}$	23.7$_{\pm 14.3}$	**33.6**

Table 2: Sentence-level F1 numbers on multilingual treebanks. Similarly to Kim et al. (2019), we observe that C-PCFGs suffer a huge variance, e.g., on the Chinese and Swedish treebanks.

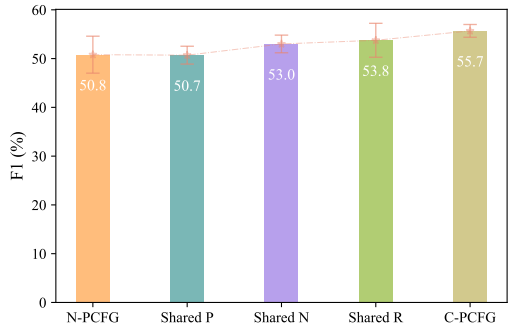


Figure 4: F1 numbers on the WSJ test data. Shared P / N / R indicates C-PCFGs that use corpus-level parameters for preterminal / nonterminal / start rules (see Section 4.3).

terize a sentence-specific PCFG. We would like to understand the role of the sentence embedding in the parameterization.

In CPCFGs there are three types of rules using the sentence embedding: preterminal rules (P), nonterminal rules (N), and start rules (R). We instead study influences of the sentence embedding in the paramenterization of different rule types, i.e., we hope to answer the question: *which type of rules make the best use of the sentence embedding?* To this end, we let a C-PCFG use corpus-level parameters for the three types of rules, individually, i.e., parameters for a rule type are shared among sentences. Interestingly, C-PCFGs degenerate into N-PCFGs when using corpus-level parameters for preterminal rules (see Figure 4). It implies that the sentence embedding is most crucial for the parameterization of preterminal rules, presumably because the sentence embedding help preterminal rules derive the knowledge of part-of-speech tags, which are beneficial for parsing (Klein and Manning, 2004).

4.4 Multilingual evaluation

Despite the surprisingly good performance on English, it is still unclear whether C-PCFGs can generalize to languages beyond English. We thus conduct miltilingual evaluation of C-PCFGs on another nine languages (see Tablel 2). When training C-PCFGs on the nine languages, we use the hyperparameters of the best-performed C-PCFG on English, i.e., we tune C-PCFGs only on WSJ and then test their generalizability on other treebanks. We can see that C-PCFGs achieve the highest overall mean F1 (average F1 number over all treebanks), though they have two fewer winning treebanks than N-PCFGs. Notably, both C-PCFGs and N-PCFGs are worse than the right-branching baseline on the Polish and Swedish treebanks. As these languages have rich morphologies, we anticipate an improvement by encoding more knowledge of morphologies into the sentence embedding.

5 Conclusion

We have presented an in-depth analysis of C-PCFGs from a quantitative perspective. The analysis concerns three aspects of C-PCFGs: data efficiency and length generalization, the role of the latent sentence embedding, and multilingual performance. Our experimental results show that C-PCFGs can learn well only from short sentences and maintain a good performance at test time. The latent sentence embedding is crucial for the good performance. Among three rule types, preterminal rules make the most of the sentence embedding. However, the best-performed C-PCFGs on English does not always generalize to other morphology-rich languages.

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