

SimplePCFG: Simple Hardware-Efficient PCFGs with Independent Left and Right Productions

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Advantages Brought by Scaling

- Low-rank parameterization enables a dramatic increase in the numbers of nonterminals(NT) preterminals(PT), from just over **30** and **60** to upwards to **5,000** and **10,000** respectively
- The Sentence-F1 score in unsupervised parsing sees an increase from **55.2** to **64.1**, a significant improvement attributable to scaling

The Achilles' Heel of Low-rank PCFGs

- Despite benefiting from scaling in unsupervised parsing, low-rank PCFGs perform poorly as a **language model** and **underperform similarly-sized HMMs**
- On the Penn Treebank, PCFGs scaled via low-rank parameterization with thousands of states achieves ≈ 170
- However, it lags behind a similarly-sized HMM which obtains ≈ 130 perplexity, even though **HMMs are subclass of PCFGs**.

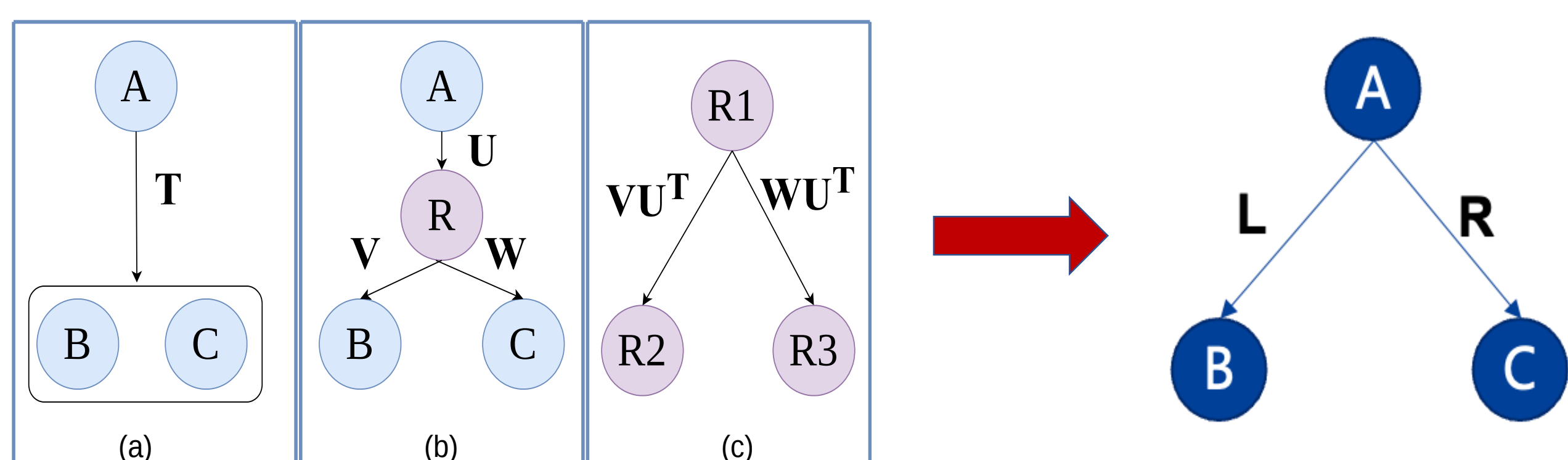
Low-Rank PCFGs

- The previous approach to scaling HMMs and PCFGs to thousands of nonterminals is parameterizing the rule probability tensor $\mathbf{T} \in \mathbb{R}^{|\mathcal{N}| \times |\mathcal{N}| \times |\mathcal{N}|}$ to be low-rank
- Low-rank PCFGs can be viewed as introducing a new latent variable, namely a "rank variable" R , where $\mathbf{U}, \mathbf{V}, \mathbf{W}$ are tensor/matrix representations of rule probabilities.
- In fact, a low-rank PCFG can be parameterized as a PCFG with independent left/right productions by marginalizing nonterminal variables and viewing the rank variables as new nonterminal variables
- As such, low-rank PCFGs parameterize $\mathbf{L}, \mathbf{R}$ in a more restrictive manner: $\mathbf{L} = \mathbf{V}\mathbf{U}^T, \mathbf{R} = \mathbf{W}\mathbf{U}^T$. We speculate that the shared $\mathbf{U}^T$ would restrict the expressiveness of low-rank PCFGs and thus hinder optimization, which motivates our simple PCFGs.

SimplePCFG

In simple PCFGs, we simplify all these things.

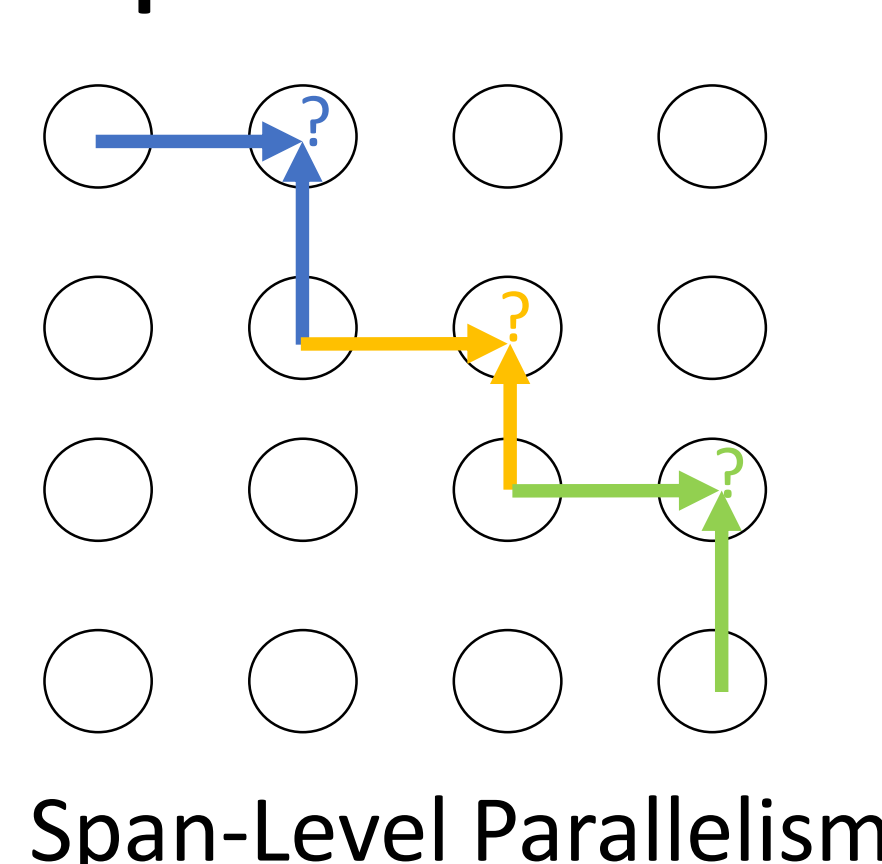
- We decompose $\pi_{A \rightarrow BC}$ into $\pi_{B \leftarrow A} \cdot \pi_{A \rightarrow C}$, effectively assuming that left and right children are generated independently
- In simplePCFG, we parameterize $\mathbf{L}, \mathbf{R}$ directly instead of through the shared $\mathbf{U}^T$, which in fact contributes to building a **more flexible parameterization**



FlashInside: A Hardware-efficient Inside Algorithm

To facilitate scaling of simple PCFGs, we introduce FlashInside, a hardware-efficient IO-aware implementation of the inside algorithm. It consists of four techniques:

Span-level Parallelism, The log-einsum-exp trick, Kernel Fusion and Recomputation



$$a_{ij} = x^\dagger + \log \left(\mathbf{L} \exp(o_{ij} - x^\dagger) \right)$$

$$b_{ij} = x^\dagger + \log \left(\mathbf{R} \exp(o_{ij} - x^\dagger) \right)$$

Log-einsum-Trick for SimplePCFG
 $\mathbf{a}, \mathbf{b}$ is used for computing inside probability and $\mathbf{L}, \mathbf{R}$ are left and right production rules

Speed & Memory Comparison

Algorithm	$ \mathcal{N} $	l	Speed	Memory
log-sum-exp	512	20	1x	100x
log-einsum-exp	512	20	4.8x	3x
FlashInside	512	20	9.5x	1x
log-einsum-exp	8192	20	1x	2x
FlashInside	8192	20	6x	1x
log-sum-exp	512	40	1x	50x
log-einsum-exp	512	40	16x	3x
FlashInside	512	40	44x	1x
log-einsum-exp	8192	40	1x	2.4x
FlashInside	8192	40	39x	1x

Language Modeling

- Simple Neural PCFG (SN-PCFG) outperforms previous low-rank PCFG with similar size
- SN-PCFG successfully **exceeds similarly-sized HMMs**

Model	NT	ppl (↓)
NHMM	4096	147
LHMM	16384	131.8
Rank HMM	16384	127.0
Rank HMM	32768	126.4
Rank PCFG [†]	4096	174.5 ± 11.1
Rank PCFG [†]	8192	161.2 ± 8.9
SN-PCFG	4096	125.4 ± 4.1
SN-PCFG	8192	119.0± 5.3

Unsupervised Parsing

- SC-PCFG is simple compound neural PCFG
- SN-PCFG or SC-PCFG outperforms previous PCFG models on unsupervised parsing benchmarks across different languages
- Simple PCFG vs. Neural PCFG: Despite the better scalability of simple PCFGs, we find that under the same number of NT (i.e. 128), SN-PCFG expectedly underperforms N-PCFG

Model	NT	S-F1 (↑)	ppl (↓)
N-PCFG	30	50.8	252.6
C-PCFG	30	55.2	-
TN-PCFG	500	57.7	210.0
Rank PCFG	4500	64.1	168.0
Rank PCFG [†]	4096	60.1 ± 7.6	165.1 ± 7.7
Rank PCFG [†]	8192	61.1 ± 5.9	171.2 ± 11.7
N-PCFG [†]	128	56.7 ± 3.7	181.1 ± 15.3
SN-PCFG	128	51.1 ± 4.1	231.7 ± 8.1
SN-PCFG	4096	65.1± 2.1	132.5± 4.9
SN-PCFG	8192	62.9 ± 2.8	134.6 ± 9.1
SC-PCFG	512	54.3 ± 4.8	-
SC-PCFG	2048	60.6 ± 3.6	-
PRPN	-	37.4	-
ON	-	47.7	-
DIORA ₊ span constraint	-	61.2	-
S-DIORA	-	57.6	-
Constituency test	-	62.8	-
StructFormer	-	54.0	-
Fast-R2D2	-	57.2	-
Right-Branching	-	39.5	-
Oracle Trees	-	84.3	-

Model	NT	Chinese		French		German	
		S-F1(↑)	ppl(↓)	S-F1(↑)	ppl(↓)	S-F1(↑)	ppl(↓)
Left-Branching	-	7.2	-	5.7	-	10.0	-
Right-Branching	-	25.5	-	26.4	-	14.07	-
Random Trees	-	15.2	-	16.2	-	13.9	-
kim-2022-revisiting	-	-	-	41.9	-	47.3	-
li-lu-2023-contextual	-	-	-	48.7	-	40.8	-
N-PCFG	30	26.3 ± 2.5	-	45.0 ± 2.0	-	42.3 ± 1.6	-
C-PCFG	30	38.7 ± 6.6	-	45.0 ± 1.1	-	43.5 ± 1.2	-
TN-PCFG	250	39.2 ± 5.0	-	39.1 ± 4.1	-	47.1 ± 1.7	-
Rank PCFG	4096	31.00 ± 8.9	409.4 ± 29.5	31.2 ± 9.3	355.8 ± 13.7	35.6 ± 9.1	215.3 ± 57.1
Rank PCFG	8192	32.4 ± 8.2	372.6 ± 31.4	32.9 ± 10.6	332.2 ± 60.8	38.9 ± 9.6	190.5 ± 65.9
SN-PCFG	4096	39.9 ± 6.3	328.3 ± 62.1	38.0 ± 3.1	379.7 ± 5.2	46.7 ± 4.9	157.8± 65.6
SN-PCFG	8192	41.2 ± 3.5	288.2± 11.7	43.3 ± 9.9	259.9± 70.2	46.9 ± 5.1	159.5 ± 77.2
SC-PCFG	512	38.4 ± 7.4	-	47.9 ± 1.2	-	47.7 ± 1.0	-
SC-PCFG	2048	42.9± 2.9	-	49.9± 1.7	-	49.1± 1.0	-