BlackOut: Speeding up RNNLMs with Very Large Vocabularies

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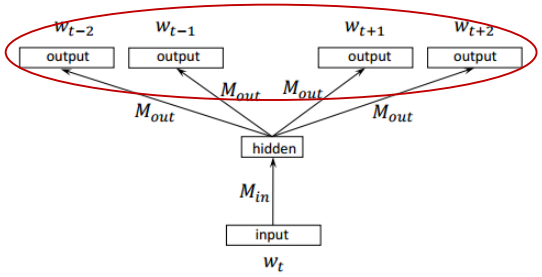
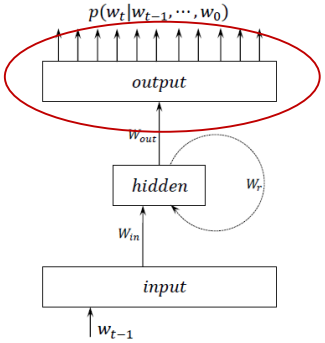
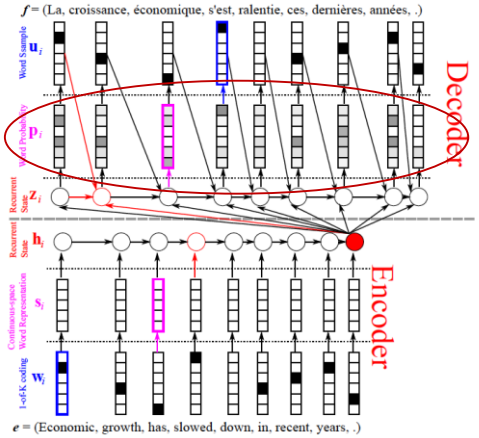
Prevalence of Large Softmax Output Layers



Word2Vec

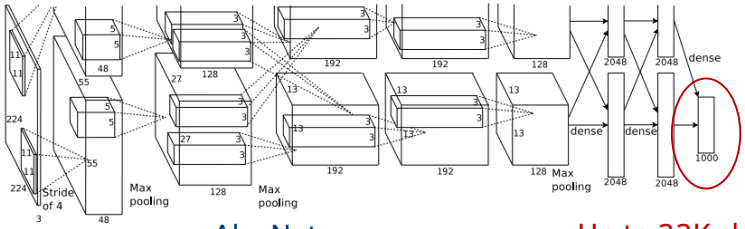


RNNLM



Neural Machine Translation (Kyunghyun Cho, etc.)

Typical vocabulary size ≈ 1M words (classes) in NLP applications



AlexNet (Alex Krizhevsky, etc)

Up to 22K classes for ImageNet

Case Study: RNNLM

Objective: Given previous word sequence (history), predict next word

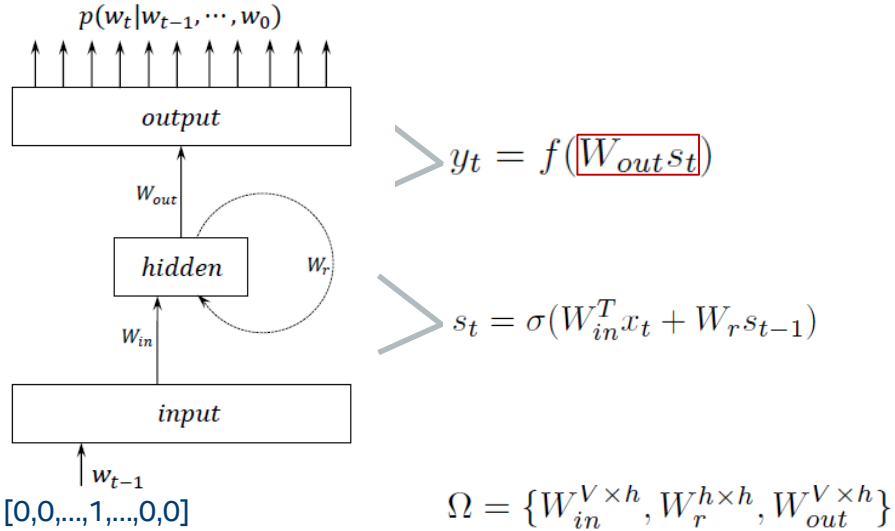
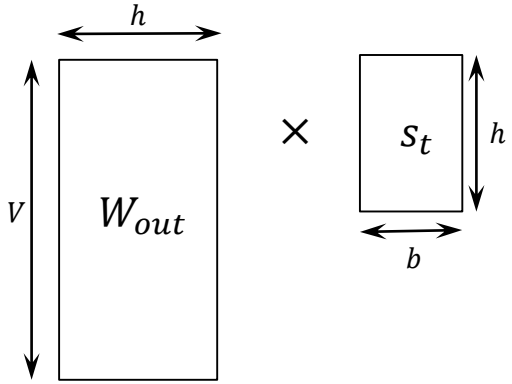


Fig. 1 The standard RNNLM architecture.

Tall-Skinny SGEMM (e.g., V=1M, h=1K, b=128)



- Efficiency is low due to low arithmetic intensity and high BW requirements
- Matrix transpose incurs additional high overheads
- Latest Intel MKL has significant improvements to this case.

System Optimization

Vocabulary size= **20K** (Google's One Billion Words LM benchmark)

	Throughput (words/sec)		
	Published Result [1]		Our Result (w/o approx.)
	GPU[1]	CPU[2]	CPU[3]
RNN 512	9.9k	0.37k	12.6k

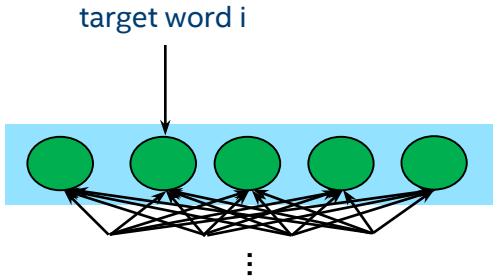
[1] Nvidia Geforce GTX Titan
[2] Intel Xeon E5-2670 2.6GHz
[3] Intel Xeon Haswell E5-2697 v3

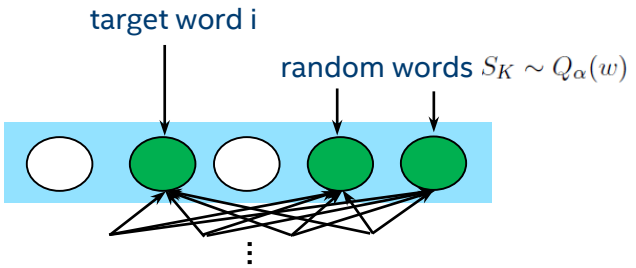
[1] X. Chen, Y. Wang, X. Liu, M. Gales, and P. Woodland. *Efficient gpu-based training of recurrent neural network language models using spliced sentence bunch*. In INTERSPEECH, 2014.

Strategies to Speed up Softmax

$$f(W_{out}s_t) \iff p_\theta\left(w_i|s\right) = \frac{\exp\left(\langle\theta_i, s\rangle\right)}{\sum_{j=1}^{V}\exp\left(\langle\theta_j, s\rangle\right)}$$

- Hierarchical softmax (Morin & Bengio, 2005, Mnih & Hinton. 2008)
  - Instead of a flat output layer, a hierarchical binary tree is used to encode $p_\theta(w_i|s)$
- Sampling-based approximations (IS, NCE, LSH, BlackOut)
  - Select at random or heuristically a small subset of the output layer
- Self normalization (Devlin et al., 2014)
  - Regularize the cross-entropy loss by explicitly encouraging the partition function to be as close to 1.0 as possible
- Exact gradient on limited loss functions (Vincent et al., 2015)
  - Algorithmic approach to efficient compute the exact loss and gradient; only applies to squared error and spherical softmax, but not standard softmax





	Traditional ML	Blackout Training
Softmax	$p_\theta(w_i\|s) = \frac{\exp(\langle\theta_i, s\rangle)}{\sum_{j=1}^{V}\exp(\langle\theta_j, s\rangle)} \doteq p_i \quad \forall i \in \{1,\cdots,V\}$	$\tilde{p}_\theta(w_i\|s) = \frac{q_i \exp(\langle\theta_i, s\rangle)}{\sum_{j\in\{t\}\cup S_K} q_j \exp(\langle\theta_j, s\rangle)} \doteq \tilde{p}_i \quad \forall i \in \{t\}\cup S_K$ where $Q_\alpha(w) \propto p_{uni}^{\alpha}(w), \quad \alpha \in [0,1] \qquad q_j := \frac{1}{Q(w_j)}$
Objective function	$J_{ml}^{s}(\theta) = \log p_\theta(w_i\|s)$	$J_{disc}^{s}(\theta) = \log \tilde{p}_\theta(w_i\|s) + \sum_{j\in S_K} \log(1-\tilde{p}_\theta(w_j\|s))$
Gradient	$\frac{\partial J_{ml}^{s}(\theta)}{\partial u_i} = 1 - p_i$ $\frac{\partial J_{ml}^{s}(\theta)}{\partial u_j} = -p_j$	$\frac{\partial J_{disc}^{s}(\theta)}{\partial u_i} = 1 - \left(K+1-\sum_{j\in S_K}\frac{1}{1-\tilde{p}_j}\right)\tilde{p}_i$ $\frac{\partial J_{disc}^{s}(\theta)}{\partial u_j} = -\left(K+1-\sum_{k\in S_K\setminus\{j\}}\frac{1}{1-\tilde{p}_k}\right)\tilde{p}_j, \quad \text{for } j \in S_K$

Connection to Importance Sampling

$$\frac{\partial}{\partial\theta}\log\tilde{p}_\theta(w_i|s) = \frac{\partial}{\partial\theta}\langle\theta_i, s\rangle - \frac{1}{\sum_{k\in\{i\}\cup S_K} q_k \exp(\langle\theta_k, s\rangle)} \sum_{j\in\{i\}\cup S_K} q_j \exp(\langle\theta_j, s\rangle)\frac{\partial}{\partial\theta}\langle\theta_j, s\rangle$$

$$= \frac{\partial}{\partial\theta}\langle\theta_i, s\rangle - \mathbb{E}_{\tilde{p}_\theta(w|s)}\left[\frac{\partial}{\partial\theta}\langle\theta_w, s\rangle\right].$$

Differences to previous IS-based approximations (e.g., Bengio & Senecal, 2003; 2008; Jean et al., 2015)

- Proposal density function $Q_\alpha(w) \propto p_{uni}^\alpha(w), \quad \alpha \in [0, 1]$
  - Uniform distribution ($\alpha = 0$, large bias)
  - Unigram distribution ($\alpha = 1$, high variance)
- ML training vs. Discriminative training

Connection to Noise Contrastive Estimate (NCE)

Convert density estimation to learning by comparison, e.g., estimating the parameters of a binary classifier that distinguish samples from the data distribution $p_\theta(w|s)$ from samples generated by a noise distribution $p_n(w|s)$ (Gutmann & Hyvarinen, 2012).

Typically, unigram is used for $p_n(w|s)$. Here we propose to use

$$p_n(w_i|s) = \frac{1}{K} \sum_{j \in S_K} \frac{q_j}{q_i} p_\theta(w_j|s)$$

Theorem 1 *The noise distribution function $p_n(w_i|s)$ defined in Eq. 13 is a probability distribution function under the expectation that K samples in S_K are drawn from $Q(w)$ randomly, $S_K \sim Q(w)$, such that $\mathbb{E}_{S_K \sim Q(w)}(p_n(w_i|s)) = Q(w_i)$ and $\mathbb{E}_{S_K \sim Q(w)}(\sum_{i=1}^{V} p_n(w_i|s)) = 1$.*

Assume noise samples are K times more frequent than data samples, the posterior of w_i being generated from data dist. is

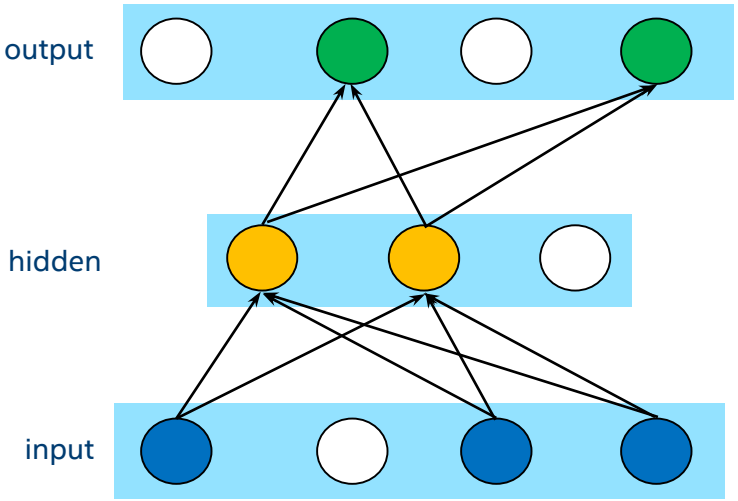
$$p_\theta(D = 1|w_i, s) = \frac{p_\theta(w_i|s)}{p_\theta(w_i|s) + K p_n(w_i|s)}$$

$$= \frac{q_i \exp(\langle \theta_i, s \rangle)}{q_i \exp(\langle \theta_i, s \rangle) + \sum_{j \in S_K} q_j \exp(\langle \theta_j, s \rangle)}$$

Advantages:

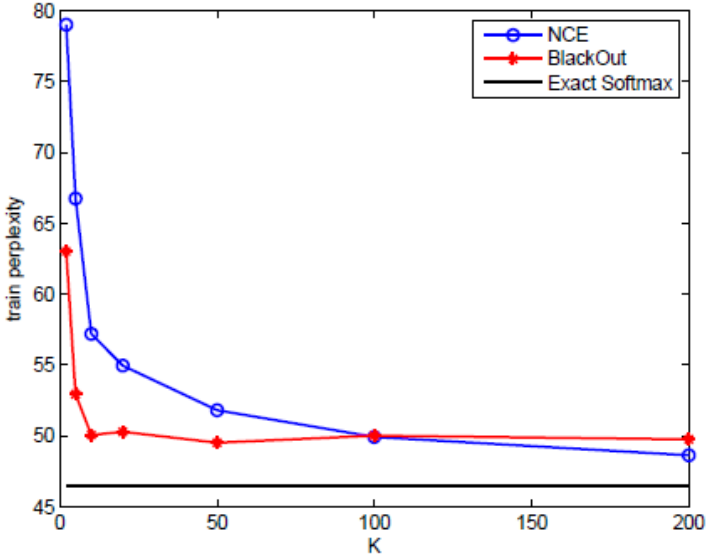
- the expensive partition function of $p_\theta(w|s)$ is cancelled out
- log-sum-exp trick can still be used for numerical stability

Comparison to Dropout

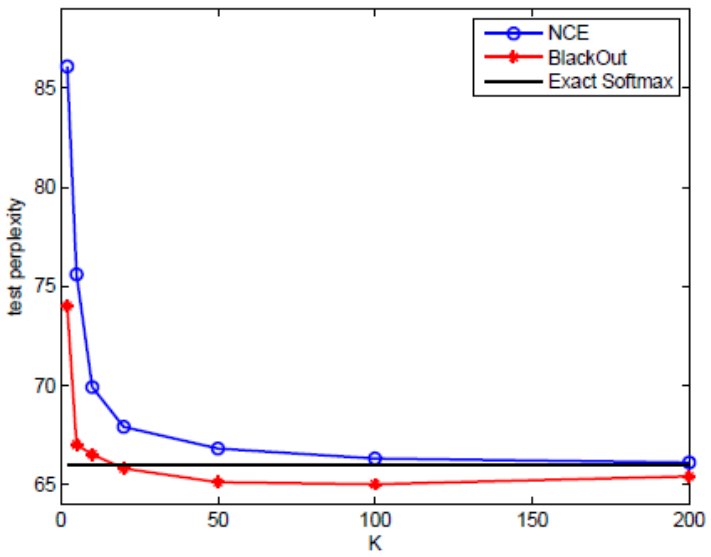


	Dropout	Blackout
Application	input, hidden layers	(softmax) output layer
Training	retain a node with a fixed probability p	sample K nodes from Q(w), each selected node is weighted by 1/Q(w) for a weighted softmax with discriminative training
Test	full network participates with scaled-down weights pW	full network participates with the trained weights W
Benefits	➢ speed up training, but not test ➢ model averaging, avoid overfitting (with some theoretical justifications)	➢ speed up training, but not test ➢ avoid overfitting empirically (need more theoretical justifications)

Experiments on Small Dataset



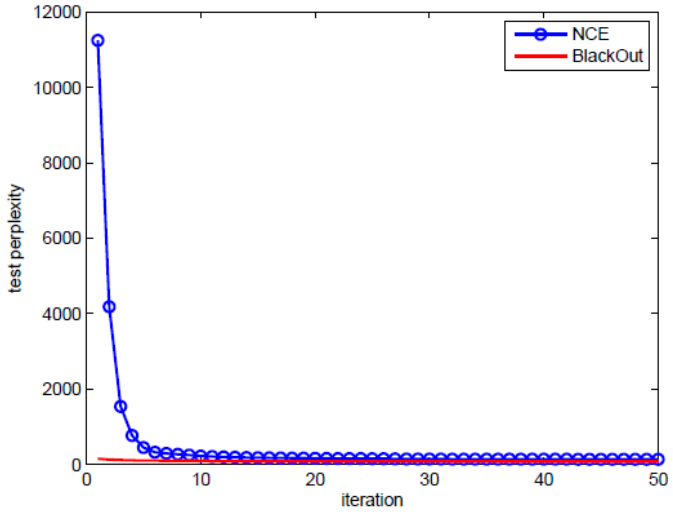
(a) On training data



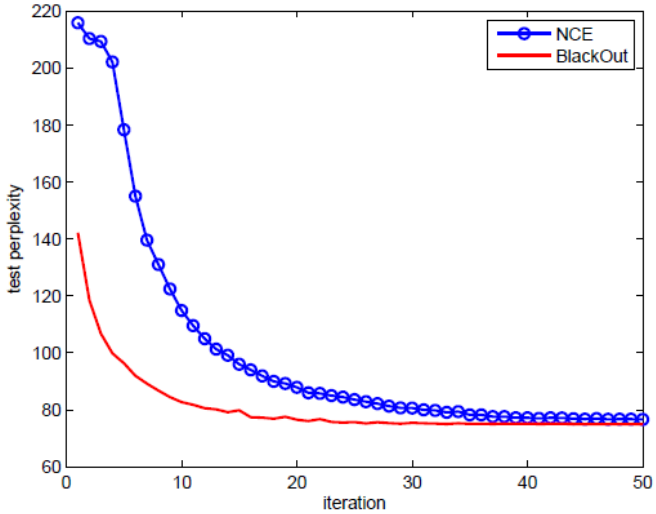
(b) On test data

Fig. 2 Sample efficiency and regularization effect

Experiments on Small Dataset (cont'd)



(a) K=10



(b) K=50

Fig. 3 Rate of Convergence of NCE and BlackOut

Experiments on 1-Billion Word Benchmark

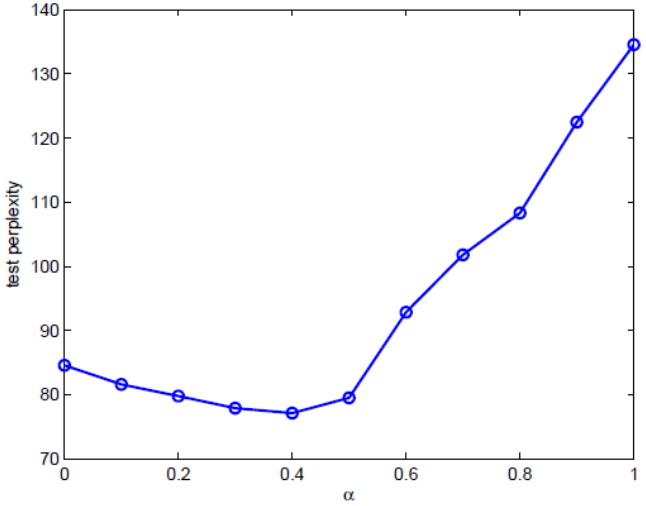


Fig. 4 Impact of α $Q_\alpha(w) \propto p_{uni}^{\alpha}(w), \quad \alpha \in [0,1]$

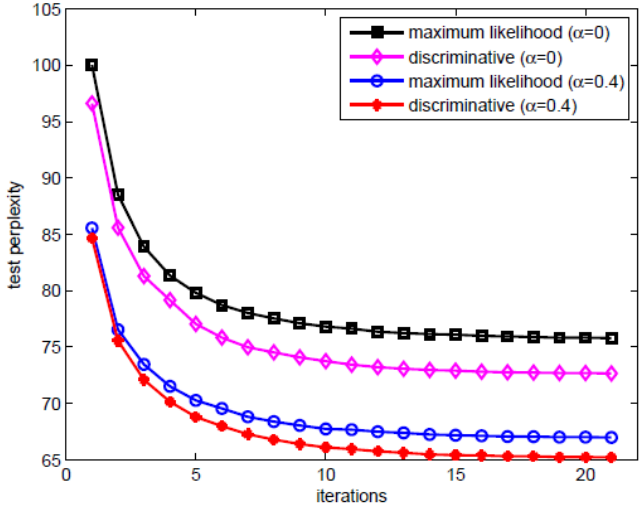


Fig. 5 Traditional ML training vs. Discriminative training

Comparison to State-of-The-Arts

Compared to GPU performance

Table 1: Performance on the one billion word benchmark by interpolating RNNLM on a 64K word vocabulary with a full-size KN 5-gram LM.

Model	#Params [millions]	Test Perplexity		Time to Solution	
		Published[1]	BlackOut	Published[1]	BlackOut
KN 5-gram	1,748	66.95		45m	
RNN-128 + KN 5-gram	1,764	60.8	59.0	6h	9h
RNN-256 + KN 5-gram	1,781	57.3	55.1	16h	14h
RNN-512 + KN 5-gram	1,814	53.2	51.5	1d2h	1d
RNN-1024 + KN 5-gram	1,880	48.9	47.6	2d2h	1d14h
RNN-2048 + KN 5-gram	2,014	45.2	43.9	4d7h	2d15h
RNN-4096 + KN 5-gram	2,289	**42.4**	**42.0**	14d5h	10d

[1] Data from Table 1 of Williams et al. (2015).

GPU: Nvidia GTX Titan, CPU: 28-core Intel Xeon Haswell

Compared to CPU cluster performance

Table 2: Performance on the one billion word benchmark with a vocabulary of 1,000,000 words.

	Model	Perplexity
Le et al. (2015) 32 machines 60 hours	LSTM (512 units)	**68.8**
Our Results 1 machine 175 hours	RNN (1 layer, 2048 sigmoid units)	**68.3**

Conclusion

- BlackOut is a sampling-based approximation to speed up large softmax output layers of any networks;
- We established its connection to importance sampling, NCE and the analogy to Dropout; Blackout is complementary to Dropout to train DNNs;
- The application of BlackOut to RNNLM demonstrated its stability, sample efficiency and rate of convergence on the 1-billion word benchmark;
- An optimized CPU code matched or outperformed the best known performance on GPUs and CPU clusters.

source code: https://github.com/IntelLabs/rnnlm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