Parallelizing Word2Vec in Multi-Core and Many-Core Architectures

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Abstract

Word2vec is a widely used algorithm for extracting low-dimensional vector representations of words. State-of-the-art algorithms including those by Mikolov et al. [5, 6] have been parallelized for multi-core CPU architectures, but are based on vector-vector operations with “Hogwild” updates that are memory-bandwidth intensive and do not efficiently use computational resources. In this paper, we propose “HogBatch” by improving reuse of various data structures in the algorithm through the use of minibatching and negative sample sharing, hence allowing us to express the problem using matrix multiply operations. We also explore different techniques to distribute word2vec computation across nodes in a compute cluster, and demonstrate good strong scalability up to 32 nodes. The new algorithm is particularly suitable for modern multi-core/many-core architectures, especially Intel’s latest Knights Landing processors, and allows us to scale up the computation near linearly across cores and nodes, and process hundreds of millions of words per second, which is the fastest word2vec implementation to the best of our knowledge.

1 From Hogwild to HogBatch

We refer the reader to [5, 6] for an introduction to word2vec and its optimization problem. The original implementation of word2vec by Mikolov et al. [3] uses Hogwild [7] to parallelize SGD. Hogwild is a parallel SGD algorithm that seeks to ignore conflicts between model updates on different threads and allows updates to proceed even in the presence of conflicts. The psuedocode of word2vec Hogwild SGD is shown in Algorithm 1. The algorithm takes in a matrix \( M^{V \times D} \) in that contains the word representations for each input word, and a matrix \( M^{V \times D} \) out for the word representations of each output word. Each word is represented as an array of \( D \) floating point numbers, corresponding to one row of the two matrices. These matrices are updated during the training. We take in a target word, and a set of \( N \) input context words around the target as depicted in the top of Figure 1. The algorithm iterates over the \( N \) input words in Lines 2-3. In the loop at Line 6, we pick either the positive example (the target word in Line 8) or a negative example at random (Line 10). Lines 13-15 compute the gradient of the objective function with respect to the choice of input word and positive/negative example. Lines 17–20 perform the update to the entries \( M^{out}_{pos/neg \ example} \) and \( M^{in}_{input \ context} \). The psuedocode only shows a single thread; in Hogwild, the loop in Line 2 is parallelized over threads without any additional change in the code.

Algorithm 1 reads and updates entries corresponding to the input context and positive/negative words at each iteration of the loop at Line 6. This means that there is a potential dependence between successive iterations - they may happen to touch the same word representations, and each iteration must potentially wait for the update from the previous iteration to complete. Hogwild ignores such

[https://code.google.com/archive/p/word2vec/](https://code.google.com/archive/p/word2vec/)
Algorithm 1 word2vec Hogwild SGD in one thread.

1: Given model parameter $\Omega = \{M_{in}, M_{out}\}$, learning rate $\alpha$, 1 target word $w_{out}^t$, and N input words $\{w_{in}^0, w_{in}^1, \ldots, w_{in}^{N-1}\}$
2: for (i = 0; i < N; i++) {
  3:     input_word = $w_{in}^i$;
  4:     for (j = 0; j < D; j++) temp[j] = 0;
  5:     // negative sampling
  6:     for (k = 0; k < negative + 1; k++) {
    7:         if (k = 0) {
            8:             target_word = $w_{out}^t$; label = 1;
        9:         } else {
            10:         target_word = sample one word from V; label = 0;
        11:     }
      12:     inn = 0;
    13:     for (j = 0; j < D; j++) inn += $M_{in}[input_word][j] \times M_{out}[target_word][j]$;
    14:     err = label - $\sigma(inn)$;
    15:     for (j = 0; j < D; j++) temp[j] += err * $M_{out}[target_word][j]$;
    16:     // update output matrix
    17:     for (j = 0; j < D; j++) $M_{out}[target_word][j] += \alpha \times err \times M_{in}[input_word][j]$;
    18:   }
    19:   // update input matrix
    20:   for (j = 0; j < D; j++) $M_{in}[input_word][j] += \alpha \times temp[j]$;
  21: }

dependencies and proceeds with updates regardless of conflicts. In theory, this can reduce the rate of convergence of the algorithm as compared to a sequential run. However, the Hogwild approach has been shown to work well in case the updates across threads are unlikely to be to the same word; and indeed for large vocabulary sizes, conflicts are relatively rare and convergence is not typically affected.

Figure 1: The parallelization schemes of the original word2vec (left) and our optimization (right).

1.1 Shared Memory Parallelization: HogBatch

However, the original word2vec algorithm suffers from two main drawbacks that significantly affect runtimes. First, since multiple threads can update the same cache line containing a specific model entry, there can be significant ping-ponging of cache lines across cores. This leads to high access
latency and significant drop in scalability. Second and perhaps even more importantly, there is a significant amount of locality in the model updates that is not exploited in the Hogwild algorithm. As an example, we can easily see that the same target word \( w_{t} \) is used in the model updates for several input words. By performing a single update at a time, this locality information is lost, and the algorithm performs a series of dot-products that are level-1 BLAS operations \(^1\) and limited by memory bandwidth. It is indeed, as we show next, possible to batch these operations into a level-3 BLAS call \(^1\) which can more efficiently utilize the compute capabilities and the instruction sets of modern multi-core and many-core architectures.

We exploit locality in two steps. As a motivation, consider Figure 1. The figure to the left shows the parallelization scheme of the original word2vec. Note that we compute dot products of the word vectors for a given input word \( w_i \) with both the target word \( w_{t} \) as well as a set of \( K \) negative samples \( \{w_1^{t}, \ldots, w_K^{t}\} \). Rather than doing these one at a time, it is rather simple to batch these dot products into a matrix vector multiply, a level-2 BLAS operation \(^1\), as shown in the left side of Figure 1. However, this alone does not buy significant performance improvement. Indeed, most likely the shared input word vector may come from cache. In order to convert this to a level-3 BLAS operation, we also need to batch the input context words. Doing this is non-trivial since the negative samples for each input word could be different in the original word2vec implementation. We hence propose “negative sample sharing” as a strategy, where we share negative samples across a small batch of input words. Doing so allows us to convert the original dot-product based multiply into a matrix-matrix multiply call (GEMM) as shown on the right side of Figure 1. At the end of the GEMM, the model updates for all the word vectors of all input words and target/sample words that are computed need to be written back. Performing matrix-matrix multiplications (GEMMs) rather than dot-products allows us to leverage all the compute capabilities of modern architectures including vector units and instruction set features such as multiply-add instructions in the Intel AVX2 instruction set. It also allows us to leverage heavily optimized linear algebra libraries.

For multi-threading across the GEMM calls, we follow the same “Hogwild”-style philosophy - each thread performs its own GEMM call independently to other threads, and we allow for threads to potentially conflict when updating the models at the end of the GEMM operation. We therefore call our new parallelization scheme “HogBatch”.

While the original word2vec performs model updates after each dot product, our HogBatch scheme performs a number of dot products as a GEMM call before performing model updates. It is important to note that this locality optimization has a secondary but important benefit - we cut down on the total number of updates to the model. This happens since the GEMM operation performs a reduction (in registers/local cache) to an update to a single entry in the output matrix; while in the original word2vec scheme such updates to the same entry (same input word representation, for instance) happen at distinct periods of time with potential ping-pong traffic happening in between. As we will see in Sec. 2 when we present results, this leads to a much better scaling of HogBatch than the original word2vec.

### 1.2 Distributed Memory Parallelization

To scale out word2vec, we also explore different techniques to distribute its computation across nodes in a compute cluster. Essentially, we employ data parallelism for distributed computation. Due to limited space, we skip the details here and will report it in a full paper.

## 2 Experiments

We compare the performances of three different implementations of word2vec: (1) the original implementation from Google that is based on Hogwild SGD on shared memory systems (https://code.google.com/archive/p/word2vec/), (2) BIDMach (https://github.com/BIDData/BIDMach) which achieves the best known performance of word2vec on Nvidia GPUs, and (3) our optimized implementation on Intel architectures, including (1) 36-core Intel Xeon E5-2697 v4 Broadwell (BDW) CPUs, and (2) the latest Intel Xeon Phi 68-core Knights Landing (KNL) processors. We train the algorithm on the one billion word benchmark \(^3\) with the same parameter settings of BIDMach (\( dim=300, \) negative samples=5, \( window=5, \) sample=1e-4, vocabulary of 1,115,011 words). We evaluate the model accuracy on the standard word similarity benchmark WS-353 \(^4\) and Google word analogy benchmark \(^5\). Since all the implementations achieve similar accuracy and due to
lack of space, in the following we only report their performances in terms of throughput, measured as million words/sec. More details of the experimental comparison will be reported in a full paper. Our implementation and scripts are open sourced at https://github.com/IntelLabs/pWord2Vec.

![Particle Learning](image1)

Figure 2: (a) Scalabilities of the original word2vec and our optimization on all threads of an Intel Broadwell CPU; (b) Scalabilities of our distributed word2vec on multiple Intel Broadwell and Knights Landing nodes, and BIDMach on $N = 1, 4$ NVidia Titan-X nodes as reported in [2].

Figure 2 shows the throughputs measured as million words/sec of our algorithm and the original word2vec, scaling across cores and nodes of Intel BDW and KNL processors. When scaling to multiple threads (Figure 2(a)), our algorithm achieves near linear speedup until 36 threads. In contrast, the original word2vec scales linearly only until 8 threads and slows down significantly after that. In the end, the original word2vec delivers about 1.6 million words/sec, while our code delivers 5.8 million words/sec or a 3.6X speedup over the original word2vec. The superior performance highlights the effectiveness of our optimization in reducing unnecessary inter-thread communications and utilizing computation resource of modern multi-core architecture. When scaling across multiple nodes (Figure 2(b)), our distributed word2vec achieves near linear scaling until 16 BDW nodes or 8 KNL nodes while maintaining a similar accuracy to that of the original word2vec. As the number of nodes increases, to maintain a comparable accuracy, we need to increase the model synchronization frequency to mitigate the loss of convergence rate. However, this takes a toll on the scalability and leads to a sub-linear scaling at 32 BDW nodes or 16 KNL nodes. Despite this, our distributed word2vec delivers over 100 million words/sec with a small 1% accuracy loss. To the best of our knowledge, this is the best performance reported so far on this benchmark. Finally, Table 1 summarizes the best performances of the state-of-the-art implementations on different architectures, demonstrating superior performance of our algorithm.

| Processor            | Code     | Words/Sec |
|----------------------|----------|-----------|
| Intel BDW (Xeon E5-2697 v4) | Original | 1.6M      |
| Intel BDW (Xeon E5-2697 v4) | BIDMach | 2.5M      |
| Nvidia K40           | BIDMach  | 4.2M      |
| Intel BDW (Xeon E5-2697 v4) | Our     | 5.8M      |
| Nvidia GeForce Titan-X | BIDMach | 8.5M      |
| Intel KNL            | Our      | 8.9M      |
| Nvidia GeForce Titan-X (4 nodes) | BIDMach | 20M      |
| Intel KNL (4 nodes)  | Our      | 29.4M     |

1 Data from [2]

### 3 Conclusion

A high performance word2vec algorithm “HogBatch” is proposed for shared memory and distributed memory systems. The algorithm is particularly suitable for modern multi-core/many-core architectures, especially Intel’s KNL, on which we deliver the best known performance reported so far. Our implementation is publicly available for general usage.
References

[1] L. S. Blackford, J. Demmel, J. Dongarra, I. Duff, S. Hammarling, G. Henry, M. Heroux, L. Kaufman, A. Lumsdaine, A. Petitet, R. Pozo, K. Remington, and R. C. Whaley. An updated set of basic linear algebra subprograms (blas). ACM Trans. Mathematical Software, 28(2):135–151, 2002.

[2] J. Canny, H. Zhao, Y. Chen, B. Jaros, and J. Mao. Machine learning at the limit. In IEEE International Conference on Big Data. 2015.

[3] C. Chelba, T. Mikolov, M. Schuster, Q. Ge, T. Brants, P. Koehn, and T. Robinson. One billion word benchmark for measuring progress in statistical language modeling. In INTERSPEECH, pages 2635–2639, 2014.

[4] L. Finkelstein, E. Gabrilovich, Y. Matias, E. Rivlin, Z. Solan, G. Wolfman, and E. Ruppin. Placing search in context: The concept revisited. ACM Transactions on Information Systems, 20:116–131, 2002.

[5] T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient estimation of word representations in vector space. Proceedings of Workshop at ICLR, 2013.

[6] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In Advances in Neural Information Processing Systems 26, pages 3111–3119. 2013.

[7] F. Niu, B. Recht, C. Re, and S. J. Wright. Hogwild: A lock-free approach to parallelizing stochastic gradient descent. In Advances in Neural Information Processing Systems, pages 693–701. 2011.