FASTER TRAINING OF WORD EMBEDDINGS

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ABSTRACT

Word embeddings have gained increasing popularity in the recent years due to the Word2vec library and its extension fastText that uses subword information. In this paper, we aim at improving the execution speed of fastText training on homogeneous multi- and manycore CPUs while maintaining accuracy. We present a novel open-source implementation that flexibly incorporates various algorithmic variants including negative sample sharing, batched updates, and a byte-pair encoding-based alternative for subword units. We build these novel variants over a fastText implementation that we carefully optimized for the architecture, memory hierarchy, and parallelism of current manycore CPUs. Our experiments on three languages demonstrate 3–20× speed-up in training time at competitive semantic and syntactic accuracy.

1 INTRODUCTION

Word embeddings have a long history (Rumelhart et al., 1986; Bengio et al., 2003; Collobert & Weston, 2008), but have received much attention in recent years due to word2vec (Mikolov et al., 2013) and its computationally efficient implementation via skip-gram with negative sampling. Word embeddings capture contextual relationships between the words, and have become a standard input representation for the majority of NLP tasks, benefitting, e.g., classification (Joulin et al., 2016; Deriu et al., 2017) or machine translation (Jansen, 2017; Conneau et al., 2017). More recently, state-of-the-art results on many language understanding tasks were achieved by deep transformer architectures such as BERT (Devlin et al., 2019), which however are very compute intensive both at training and inference time, even with pre-trained models and reduced parameter space. Thus, simpler and more lightweight static word embeddings such as fastText (Bojanowski et al., 2017) are still widely used, due to their fast execution, comparable results for particular tasks (Tseng et al., 2019), and ability to produce a single vector per word, which helps in information retrieval with interpretability and search index construction.

Contributions. In this paper, we present algorithmic and code optimization techniques to improve the training time of word2vec and fastText embeddings on modern general-purpose multicore and manycore computers. We present an optimized open-source implementation of word2vec and fastText that encapsulates a number of algorithmic variants including negative sample sharing, batched updates, and subword units based on byte-pair encoding approach. Our extensive evaluation on three languages shows that the best combinations of optimizations speed up training time by 2.7–20.6 times while maintaining accuracy of selected NLP tasks.

2 WORD EMBEDDINGS

Word2vec. Word2vec is built upon a simple bilinear regression model trained on word co-occurrence, resulting in numerical feature representations as floating point vectors of dimensionality d. Given a word in a sentence, the goal of the algorithm is to maximize the likelihood of predicting surrounding (context) words. To achieve this, the model is trained to increase the probability of predicting particular words if they appear close to a given current word in the training corpus. A popular variant also decreases the probability of predicting words that do not appear close to the current word (negative sampling (Mikolov et al., 2013; Goldberg & Levy, 2014)).

During training, the algorithm processes the corpus in a streaming fashion. Each word w_i (called current word) is processed together with its surrounding context words

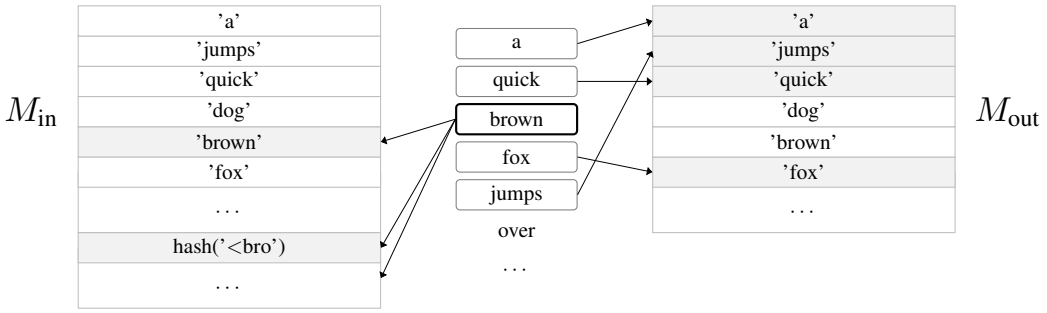


Figure 1: Representation of source and target words in the input (M_{in}) and output (M_{out}) matrix in fastText (skip-gram). The sentence is "a quick brown fox jumps over the lazy dog", the current word w_i is "brown" and the context window size is 2. The words in the corpus are represented as indices of the corresponding rows in M_{in} and M_{out}.

$\{w_{i-C}, ..., w_{i-1}\}, \{w_{i+1}, ..., w_{i+C}\}$, where C is the range of the context window. There are two modes of operation training the model for the following prediction tasks:

- *Skip-gram (SG)*: predict target context words using the current word w_i as the source.
- *CBOW*: predict the target current word w_i using context words as the source.

Each word w in the vocabulary of size V is represented as a source w_s by one row in the $V \times d$ *input* matrix M_{in} containing word embeddings and each word is represented as a target w_t by one row in the $V \times d$ *output* matrix M_{out} that is used to calculate the training objective function. The goal of the optimization is to maximize the inner products (minimize difference) of real pairs of source current words with the target context words or *vice versa*, using the binary logistic loss. This approach can be improved by the use of negative sampling, where the algorithm additionally maximizes the difference between the source current words and the words picked randomly out of the source's context. Training is performed using stochastic gradient descent (SGD). SGD is performed with p threads by splitting the training corpus into p parts and processing them asynchronously ("Hogwild" approach (Recht et al., 2011)). The final embedding of each word is its corresponding row in M_{in}. M_{out} is discarded at the end of training.

FastText. FastText (Bojanowski et al., 2017) improves word2vec by utilizing subwords of target words during the training. A typical run of fastText uses subwords of lengths $k = 3 \ldots 6$, containing delimiters $\langle, \rangle$ at the boundaries. For example, for the word *paris* and $k = 3$ the subwords are: $\langle$pa, par, ari, ris, is$\rangle$.

In fastText, M_{in} is extended to contain rows representing both entire words as well as hashes of all their subwords. Additionally, the representation of the entire word is added to the set of its subwords. During the execution of the algorithm, the hidden layer $\mathbf{h}$ is built by averaging vectors in M_{in} representing the source word's subwords. The final vector embedding for each word is obtained in the same way. M_{out} remains unchanged. Fig. 1 shows an example of how the word vectors are stored and accessed. A single update is described in Alg. 1.

Related work. FastText has been implemented as a part of the popular Gensim library (Rehurek & Sojka, 2011) using Cython and a default machine's BLAS library (e.g., Intel MKL) for algebraic operations. In our experiments we found the code memory-expensive and slow: training 5 epochs on a 1 GB English Wikipedia dump with 24 threads took approximately 11 hours on a Knights Landing CPU, about 10 times slower than the original fastText. Therefore, we use the original code provided by Facebook Research (2016a) as the baseline in all our experiments.

For skip-gram with negative sampling, pWord2Vec (Ji et al., 2016) transforms the "Hogwild" approach into "Hogbatch", by performing updates on multiple context words at once (effectively turning a series of dot products into a matrix-matrix operation) and sharing negative samples for the entire batch. We employ similar techniques in our implementation.

The work by Rengasamy et al. (2017) extends this approach by context combining, where multiple contexts can share a set of negative samples and be updated all at once. We do not adapt this approach as it requires careful preprocessing rewarded by a relatively small speedup over pWord2Vec.

Algorithm 1: A single iteration of the original fastText algorithm. In skip-gram, it is performed on each current-context word pair (as source-target). In CBOW, all context words are used as source words at the same time.

Data: source word(s) w_s, target word w_t, learning rate l, number of negative samples n

1 **if** *skip-gram* **then** // **Initialize.**
2 $\quad \mathbf{h} = \frac{M_{\text{in}}(w_s)+\sum_{z\in\text{subwords}(w_s)} M_{\text{in}}(z)}{\text{count}(\text{subwords}(w_s))+1}$; // Average vectors of the source word(s) and their
3 **else if** *CBOW* **then** // subwords to obtain the hidden layer.
4 $\quad \mathbf{h} = \frac{\sum_s (M_{\text{in}}(w_s)+\sum_{z\in\text{subwords}(w_s)} M_{\text{in}}(z))}{\sum_s (\text{count}(\text{subwords}(w_s))+1)}$;
5 $\mathbf{g} = 0$; // Reset the gradient.
// **Update the target word.**
6 $\alpha = l(1-\sigma(\mathbf{h}\cdot M_{\text{out}}(w_t)))$; // Compute positive score reflecting similarity between
// $\mathbf{h}$ and the row $M_{\text{out}}(w_t)$ representing w_t.
7 $\mathbf{g} = \mathbf{g} + \alpha \cdot M_{\text{out}}(w_t)$; // Build the gradient.
8 $M_{\text{out}}(w_t) = M_{\text{out}}(w_t) + \alpha \cdot \mathbf{h}$; // Update the target word.
9 **for** $t' \leftarrow 1$ **to** n **do** // **Update negative samples: negative score.**
10 $\quad$ pick a random negative sample $w_{t'} \neq w_t$;
11 $\quad \alpha = l(0-\sigma(\mathbf{h}\cdot M_{\text{out}}(w_{t'})))$; // Compute negative score.
12 $\quad \mathbf{g} = \mathbf{g} + \alpha \cdot M_{\text{out}}(w_{t'})$; // Build the gradient.
13 $\quad M_{\text{out}}(w_{t'})) = M_{\text{out}}(w_{t'})) + \alpha \cdot \mathbf{h}$; // Update the target word.
14 **end**
15 **if** *skip-gram* **then** // **Update the source rows(s).**
16 $\quad M_{\text{in}}(w_s) = M_{\text{in}}(w_s) + \mathbf{g}$;
17 $\quad$ **foreach** $z \in$ *subwords*(w_s) **do**
18 $\quad\quad M_{\text{in}}(z) = M_{\text{in}}(z) + \mathbf{g}$;
19 $\quad$ **end**
20 **else if** *CBOW* **then**
21 $\quad$ **foreach** w_s **do** // As a result, the difference between rows in $M_{\text{in}}(w_s)$
22 $\quad\quad M_{\text{in}}(w_s) = M_{\text{in}}(w_s) + \mathbf{g}$; // and M_{out} which corresponds to the positive samples
23 $\quad\quad$ **foreach** $z \in$ *subwords*(w_s) **do** // drops, and the difference between rows in M_{out}
24 $\quad\quad\quad M_{\text{in}}(z) = M_{\text{in}}(z) + \mathbf{g}$; // which correspond to the negative samples increases.
25 $\quad\quad$ **end**
26 $\quad$ **end**

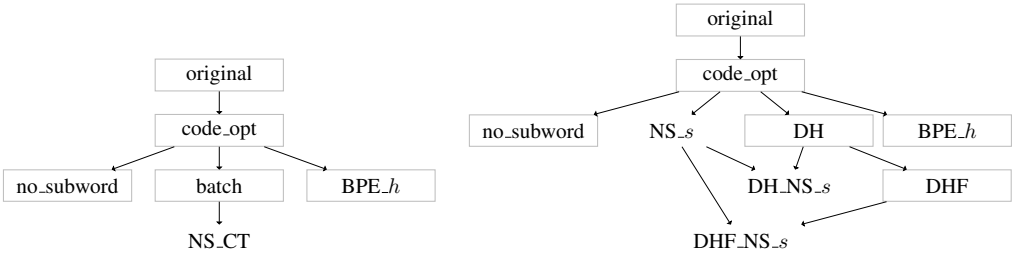
Word2Vec has been also implemented for GPU clusters. BlazingText (Gupta & Khare, 2017) tackles the problem of efficient batch size and synchronization for multiple GPUs. While this issue is of no concern on CPU, they report the execution time on a single GPU comparable to a 16-threaded CPU implementation. Li et al. (2019) discuss a distributed version for many GPUs aiming at the reduction of write conflicts in updates. Similarly (and independently), we made attempts at creating a structure of current-context word pairs, but we found the overhead of this preprocessing prohibitive.

3 Optimization techniques and algorithmic variants

To improve the training time, we first identify the most expensive operations. Assume that the source word(s) have a total of m subwords and that we use n negative samples per target word. Then each update comprises:

- Construction of $\mathbf{h}$: a sum of m vectors (line 2 or 4).
- Loss calculation: $n+1$ dot products and $2(n+1)$ vector additions (lines 6–8, 11–13).
- Gradient update: m vector additions (lines 16–19 or 21–26).

In skip-gram, $\mathbf{h}$ is built only from a single current word, while in CBOW, it is constructed from all context words. The loss function, in contrast, is computed once per each current-context word pair in skip-gram, while in CBOW, the loss is computed using the entire context. This means that for CBOW, the construction of $\mathbf{h}$ and the gradient update consumes most of the execution time, while for skip-gram, these operations take roughly the same amount of time as the loss function calculation (assuming the default parameter of $n = 5$). All operations listed above are memory-intensive and therefore memory bound: thus, the best approach to optimize them is by reducing memory movement and avoiding unnecessary updates. It is further supported by our observations



(a) skip-gram (SG) (b) CBOW

Figure 2: Dependency between our code variants of skip-gram and CBOW. The experiments for the "NS" variants (no box frames) are only shown in the appendix due to inferior experimental accuracy.

during the tests on isolated sections of the code. We noted that a large amount of execution time is taken by the latency of loading data from the rows scattered across M_{in} and M_{out}, which is an access pattern required to provide high quality embeddings.

To speed up the training, we first perform a number of code performance optimizations and then various algorithmic modifications compared to the original fastText. Some modifications depend on each other as illustrated in Fig. 2. Some, but not all, techniques apply to both modes of operation. We next discuss these variants, referring to specific parts of Alg. 1 that they modify.

Code performance optimizations (code_opt). For efficient execution we explicitly vectorize matrix and vector operations using AVX-512 intrinsics. We block and merge operations involving multiple reads from the same location in memory to make them more cache-friendly (temporal locality), like averaging the rows of M_{in} or subsequently reading from and writing to M_{out}.

During the creation of hidden layer $\mathbf{h}$ (line 2 or 4), we reduce the number of array accesses such that each element of $\mathbf{h}$ is stored only once during summing up the vector representations of subwords. This improves the original code which performs a separate store for each subword.

To speed up the binary logistic loss function, we vectorize the dot product (lines 6, 11) with the use of eight accumulators to increase instruction-level parallelism without too much register pressure. We merge the update of the gradient $\mathbf{g}$ and the relevant rows of M_{out} (lines 7–8, 12–13) to avoid multiple reads from the latter. We still call the loss function once per each w_t and w'_t.

Similar to the creation of $\mathbf{h}$, we improve the update of $M_{\text{in}}(w_s)$ with $\mathbf{g}$ (line 16 or 21–22) by reading each element of $\mathbf{g}$ only once for all words and subwords w_s.

The optimizations in the version code_opt are used in all algorithmic variants discussed next. Note that these optimizations can also be applied to other regularization schemes such as the hierarchical softmax used in the original word2vec (Mikolov et al., 2013).

No subwords (no_subword). Experiments in Section 4 show that it is sometimes useful to train word embeddings without any subword information. We provide a code variant which disables subwords, but applies all optimizations discussed above. It is algorithmically equivalent to word2vec. In Alg. 1, $subwords(w_s)$ in lines 1–4 and 15–26 becomes an empty set and needs not be processed.

Minibatching (batch for SG). For skip-gram, we implement a form of minibatching of the target words per each source word. Rather than following the work of Ji et al. (2016), which merges all $M_{\text{in}}(w_s)$ rows in a minibatch into a matrix, we follow the original fastText's approach hitherto only applied to CBOW, which simply averages all these rows. The advantage of our minibatching over the original fastText skip-gram is being able to execute a single update for each context window of the current word w_i, rather than per each current-context word pair. This means that $\mathbf{h}$ and the relevant rows of the input matrix M_{in} are updated only once per each current word, independent of context window size. Lines 2 and 16 are now executed only once per context window, in a similar fashion as in lines 4 and 21–22 respectively). This creates an additional delay between reading and writing a word's subword representations increasing the possibility of write conflicts, but our experiments later show that the accuracy remains nearly unaffected. Minibatching can bring significant speed improvements to subword-based training due to the relatively high cost of building $\mathbf{h}$ and updating

all subword representations. As mentioned, in fastText CBOW, this form of batching is already a part of its algorithmic structure.

Negative sharing (NS_CT and NS_s). We implement negative sharing proposed by Ji et al. (2016), but adapted for and built over SG_batch and the natural batching of fastText CBOW. For skip-gram, we share negative samples among all words in the entire context window of w_i (NS_CT). For CBOW, we share negative samples for s consecutive current words w_i (NS_s). In our implementation, s is a hyperparameter chosen by the user. Thus, line 10 is executed only n times every s-th update. Despite improvements in execution time we do not report the results in the paper due to the inferior obtained accuracy, but only present them in the appendix.

Dynamic hidden layer update (DH). CBOW spends a large portion of its execution time building $\mathbf{h}$ and updating relevant rows of M_{in} for each subsequent current word w_i and its context window. Therefore, we opt for adding and removing subwords only as their words move in and out of the context window as the algorithm processes the training text. After each shift of the context window, we update the rows of M_{in} for all removed subwords, readjust to the gradient $\mathbf{g}$, and add new subwords to $\mathbf{h}$. Thus, rather than performing the entire sum in line 4, the data is processed in five steps. Assuming that x embeddings remain inside the context window after a particular shift:

1. Denormalize $\mathbf{h}$.
2. Update M_{in} for subwords falling out of the context window.
3. Subtract embeddings of subwords falling out of the context window from $\mathbf{h}$.
4. Readjust to gradient $\mathbf{g}$: $\mathbf{h} = \mathbf{h} + x\mathbf{g}$.
5. Add subwords falling into the context window to $\mathbf{h}$.
6. Normalize $\mathbf{h}$.

Note that this creates additional delay between reading and writing to the rows of M_{in}, but empirically it does not harm the vector quality.

Fixed window for dynamic hidden layer update (DHF). Since the window size is picked randomly in each iteration, some words will fall in and out of the context window multiple times, forcing DH to remove and add the same subwords to $\mathbf{h}$ multiple times over a short period of time. To mitigate this, we fix the window size. While potentially saving time, this approach comes with a pitfall: the variable window size is a natural way of sampling context words that are closer to a current word w_i with greater probability, which reflects a greater contribution of these words to the current word's meaning. DHF effectively ignores the impact of the distance of context words.

Byte-Pair vocabulary (BPE_h). We also implement an alternative approach to subword embeddings, replacing the subwords by Byte-Pair Encoding (BPE) tokens (Sennrich et al., 2016). These are produced with the Hugging Face Tokenizers library (Moi, 2019) in the form of token IDs for the h most frequent word fragments, where h is a hyperparameter. We expect this to reduce execution time and memory consumption as the number of tokens is typically an order of magnitude smaller than that of subwords. To our knowledge, this is the first attempt to apply BPE tokenization to provide additional subword information in fastText-like fashion. In our experiments in Section 4, we train the tokenizer over the same training corpus as our embeddings, but both trainings could use different corpora. In case the BPE variant of fastText is unable to tokenize a word found in its training corpus (e.g., because it was absent from the corpus used for training the tokenizer), the word remains as it is, without additional embeddings. An alternative approach would be to create embeddings for tokens consisting of single characters: however, we found that if many words fail to be tokenized, this may cause a drastic slowdown, likely due to update conflicts on the single-character tokens. In Alg. 1, using the BPE variant means replacing "subwords" with "tokens".

4 EVALUATION

Setup. We use a dual-socket Intel(R) Xeon(R) Silver 4114 CPU processor (Skylake, 20 physical cores). For evaluation, we create an English corpus as described by Facebook Research (2016b). For other languages, we proceed in analogous fashion: download respective Wikipedia dumps (Wikimedia Foundation, 2001), sanitize and lowercase with the script wikifil.pl authored by Mahoney (2006). For each language, the script is modified to capture relevant characters and replace relevant words. We truncate the outputs to 1 billion characters. The resulting vocabulary sizes are: (a) 218,316 words for English, (b) 592,674 words for German, (c) 385,596 words for Russian.

The purpose of our experiments is to speed up training. We demonstrate the speed-ups of our implementation and show which algorithmic variants maintain accuracy at the same time.

The results for English are presented in Table 1. The names of modes match those from Section 3 and Fig. 2. We omit negative sharing (NS) due to low accuracy, but show the results in the appendix. In tokenized runs (BPE), we use $h = 20\text{K}, 40\text{K}, 200\text{K}$. All other hyperparameters are the fastText defaults. The speedups shown are over the original implementation, run with the same number of threads. Scaling means speedup of our code when run with 20 threads compared to 1 thread. Together with Fig. 2 the tables also show the incremental impact on accuracy and execution speed of each variant.

Table 1: Accuracy and speedup achieved with our library over fastText when training on English Wikipedia corpus. Blue: best accuracy in category, bold: Pareto-optimal accuracy, "speedup": over the original fastText run with the same number of threads, "scaling": speedup 20 threads vs. 1 thread for our code.

algorithmic variant	accuracy						speedup (times)		scaling
	QW		BATS		MUSE	Battig	1 thread	20 threads	
	sem.	syn.	sem.	syn.					
SG_original	**27.07**	**64.22**	**9.30**	**41.54**	**0.643**	**40.97**	1.0	1.0	15.2
Our work:									
SG_code_opt	**26.37**	**63.75**	**9.29**	**41.61**	**0.647**	**40.85**	3.7	2.7	11.2
SG_no_subword	**47.42**	**48.07**	**12.97**	**27.81**	**0.635**	**41.27**	10.2	8.8	13.1
SG_batch	**24.28**	**62.47**	**8.92**	**41.84**	**0.630**	**40.76**	4.4	3.6	12.2
SG_BPE_20K	**40.78**	**53.85**	**12.86**	**34.50**	**0.642**	**40.43**	4.9	4.2	13.0
SG_BPE_40K	**47.77**	**50.56**	**13.33**	**33.16**	**0.646**	**39.80**	4.8	4.2	13.2
SG_BPE_200K	**54.98**	**44.79**	**12.65**	**27.73**	**0.634**	**41.46**	4.8	4.2	13.4
CBOW_original	9.27	67.74	5.53	63.42	0.546	32.98	1.0	1.0	13.2
Our work:									
CBOW_code_opt	9.55	68.14	5.69	63.52	0.538	33.07	4.6	2.3	6.6
CBOW_no_subword	**51.00**	**54.49**	**14.84**	**32.29**	**0.614**	**40.68**	20.6	20.4	13.1
CBOW_DH	**11.38**	**68.73**	**6.51**	**63.58**	**0.583**	**36.30**	4.8	2.7	7.4
CBOW_DHF	**5.29**	**57.44**	**3.94**	**51.71**	**0.633**	**31.37**	4.8	3.3	9.2
CBOW_BPE_20K	**22.65**	**46.01**	**10.17**	**36.98**	**0.607**	**35.56**	11.4	11.0	12.8
CBOW_BPE_40K	30.85	40.47	10.13	33.38	0.614	36.07	11.5	11.1	12.8
CBOW_BPE_200K	43.33	26.40	8.12	24.70	0.606	40.39	11.4	11.3	13.0

We perform multiple intrinsic evaluation tasks to test the quality of our embeddings.

First, we test our embeddings with the word analogy task script provided with word2vec (Mikolov et al., 2013) for both *semantic* and *syntactic* accuracy. For English, we use the questions-words (QW) dataset (Mikolov, 2013). For other languages, we use its translations: German (Köper et al., 2015) and Russian (Kononova, 2017). Additionally, we employ the Vecto library (Vecto, 2018) to evaluate on the The Bigger Analogy Test Set (BATS) (Gladkova et al., 2016) on English embeddings, with 3CosAdd method. For all analogy benchmarks, we observe that fastText performs better for syntactic than semantic tasks as was already noted by Bojanowski et al. (2017).

Second, we compute word similarity scores with Facebook MUSE (Conneau et al., 2017), using monolingual evaluation with word similarity tasks on semantic datasets. For English and German, we use the tests provided by MUSE. For Russian, we use the HJ dataset (Panchenko et al., 2016).

Third, we use the scripts provided by the Word Embedding Benchmarks package (Jastrzebski, 2015) to perform the concept categorization (word clustering) task. We evaluate on the semantic Battig test set introduced by Battig & Montague (1969).

Finally, we show the speedups for CBOW and skip-gram variants calculated over the original implementations CBOW_original and SG_original, respectively, from Bojanowski et al. (2017), using the same number of threads e.g. 1-thread speedup denotes the speedup of single-threaded runs over a single-threaded run of the original fastText. We also illustrate scaling between 20- and 1-threaded runs. Multiple runs of the same variant show consistent execution times.

In the table, the best accuracy scores are marked in blue. We apply bold face to Pareto-optimal combinations. A combination of scores of algorithm A is Pareto-optimal if no other algorithm B yields a combination where *all* scores are better than those of A (B's scores do not dominate A's).

Evaluating English skip-gram. First, we evaluate multiple variants of skip-gram presented in the first section of Tab. 1. The dependencies between different variants is illustrated by Fig. 2(a). We observe that only optimizing for efficient execution yields for fastText a 2.7–3.7× speedup ($code_opt$) while maintaining accuracy. The $no_subword$ variant allows up to over 10× speedup over $original$ and up to over 3× speedup over $code_opt$. For word analogy, $no_subword$ improves the embeddings semantically. The tokenized versions roughly balance between the fastText- and word2vec-style embedding quality, with an exception of BPE_200K where the number of tokens is close to vocabulary size, effecting in turning only the most common subwords into separate tokens. This approach proves semantic accuracy even greater than $original$ for both BATS and QW, however at a price of syntactic quality, all including roughly 4–5× speedup over $original$ and up to 1.5× speedup over $code_opt$. For QW, the accuracies vary greatly, while BATS indicates that a smaller number of tokens is generally preferable. The $batch$ variant maintains or slightly handicaps the accuracy of fastText, and provides slightly smaller speedup than the tokenized versions. The different variants of skip-gram perform almost equally well on the word similarity and categorization tasks.

Evaluating English CBOW. Subsequently, we proceed with evaluation to CBOW (second section of Tab. 1) with the dependencies between variants illustrated in Fig. 2(b). The $code_opt$ variant allows 2.3–4.6× speedup over $original$, indicating a slightly greater benefit of code optimizations with fewer threads, but worse scaling than skip-gram. For word analogy, CBOW generally performs better on syntactic than semantic questions. The $no_subword$ variant diminishes the discrepancy between these scores, albeit impacting negatively the syntactic quality of the embeddings. Removing the subwords provides good scaling with over 20× speedup over $original$ and up to nearly 9× speedup over $code_opt$, while achieving highest scores for word similarity and categorization. None of the BPE variants was able to beat $no_subword$ both in speed and evaluation on these tasks, but they provide an improvement in semantic accuracy over $original$, as well as in word similarity and categorization. The DH variant provides only slight speedup over $code_opt$, but yields higher accuracies in all tasks, while DHF impacts negatively all scores except for MUSE, with speedup over DH visible only with multiple threads. Therefore, DH is more preferable than DHF.

Comparison between skip-gram and CBOW. As a rule of thumb, the fastText implementations of skip-gram perform much better on semantic questions in word analogy tasks and slightly better in word similarity and categorization tasks. For syntactic questions, the $CBOW_code_opt$ and $CBOW_DH$ variants are a better option. On the other hand, $CBOW_no_subword$ performs nearly as well for word similarity and categorization tasks as skip-gram. Therefore, in specific cases, we expect that the former can be used rather than skip-gram to boost the execution speed.

Evaluation on German and Russian corpora. Table 2 contains results for German and Russian, presented analogously to those in English. In terms of evaluation accuracy, they are largely consistent with English, with a small exception of $CBOW_BPE_20K$ which performs better than $CBOW_no_subword$ on the German corpus. This indicates the impact of the number of tokens used during training and opens opportunities for further investigation. Noteworthy, $CBOW_DH$ achieves the best scores in syntactic tasks for all evaluated languages. Using skip-gram with BPE tokens rather than fastText-style subwords performs very well in terms of both speedups and accuracy scores, all of which are Pareto-optimal. The $code_opt$ variants yields slightly better speedups than for English, and further optimizations lead to even two times greater speedups. The best achieved improvement is $CBOW_no_subword$, up to 50× for Russian. This shows that our improvements are particularly beneficial for morphologically-rich languages with a large number of subwords per word. For all languages, there is no universally best variant, which makes a case for our polyalgorithmic implementation and thorough evaluation of trade-offs.

5 CONCLUSIONS

We presented a thorough evaluation, and associated open-source implementation, of various optimization techniques for fastText and word2vec. In particular, these include code-level performance optimizations and the use of BPE tokens rather than subwords. For example, for English, our code offers practitioners speedups in the range of 2.7–20.6×, while maintaining a single or multi-

Table 2: Accuracy and speedup achieved with our library over fastText when training on (a) German and (b) Russian Wikipedia corpora. Blue: best accuracy in category, bold: Pareto-optimal accuracy, "speedup": over the original fastText run with the same number of threads, "scaling": speedup 20 threads vs. 1 thread for our code.

algorithmic variant	accuracy			speedup (times)		scaling
	QW		MUSE	1	20	
	sem.	syn.		thread	threads	
SG_original	**21.13**	**49.94**	**0.587**	1.00	1.00	8.5
Our work:						
SG_code_opt	19.41	49.12	0.575	3.54	4.94	11.8
SG_no_subword	**42.31**	**27.29**	**0.589**	11.47	18.75	13.9
SG_batch	17.43	49.13	0.573	4.60	7.01	12.9
SG_BPE_20K	**29.91**	**36.83**	**0.589**	5.48	8.94	13.9
SG_BPE_40K	**34.55**	**29.96**	**0.593**	5.22	8.99	14.6
SG_BPE_200K	**45.90**	**23.39**	**0.593**	5.26	9.03	14.6
CBOW_original	4.71	58.94	0.507	1.00	1.00	8.3
Our work:						
CBOW_code_opt	4.30	59.09	0.510	4.25	3.44	6.7
CBOW_no_subword	**37.75**	**27.66**	**0.559**	24.09	41.84	14.3
CBOW_DH	**5.96**	**59.81**	**0.527**	4.94	4.21	7.0
CBOW_DHF	**1.86**	**54.17**	**0.591**	5.18	4.54	7.2
CBOW_BPE_20K	11.19	31.31	0.542	13.12	21.14	13.3
CBOW_BPE_40K	18.67	23.25	0.557	13.26	22.01	13.7
CBOW_BPE_200K	27.81	16.14	0.560	12.87	22.61	14.5

(a) German

algorithmic variant	accuracy			speedup (times)		scaling
	QW		MUSE	1	20	
	sem.	syn.		thread	threads	
SG_original	**12.29**	**77.61**	**0.633**	1.00	1.00	10.2
Our work:						
SG_code_opt	**12.86**	**77.81**	**0.622**	4.08	4.17	10.4
SG_no_subword	**23.82**	**42.89**	**0.588**	12.08	16.54	14.0
SG_batch	10.58	76.32	0.629	5.11	5.24	10.5
SG_BPE_20K	**14.22**	**51.86**	**0.621**	5.83	7.87	13.8
SG_BPE_40K	**16.75**	**46.81**	**0.608**	5.80	7.92	13.9
SG_BPE_200K	**22.90**	**45.91**	**0.600**	5.78	7.99	14.1
CBOW_original	8.88	80.78	0.495	1.00	1.00	7.9
Our work:						
CBOW_code_opt	**9.18**	**79.79**	**0.497**	4.52	4.57	8.0
CBOW_no_subword	16.01	37.35	0.532	28.06	50.50	14.2
CBOW_DH	**9.17**	**81.43**	**0.523**	4.28	5.72	10.5
CBOW_DHF	**7.32**	**78.75**	**0.557**	4.61	6.22	10.6
CBOW_BPE_20K	8.28	34.82	0.513	14.96	25.24	13.3
CBOW_BPE_40K	8.96	40.66	0.493	15.20	26.12	13.6
CBOW_BPE_200K	11.13	35.96	0.537	15.28	27.00	14.0

(b) Russian

dimensional notion of accuracy. Our techniques should also apply to sent2vec (Pagliardini et al., 2018) for sentence embeddings.

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A DETAILS OF EXPERIMENTAL SETUP

For the experiments with questions-words and MUSE, we do not remove any questions containing out-of-vocabulary words. We use full test data sets for all modes, therefore our results are consistent.

For MUSE, we use the following tests provided by the library[1].

English:

EN_YP-130
EN_SIMLEX-999
EN_MTurk-771
EN_RG-65
EN_VERB-143
EN_SEMEVAL17
EN_MTurk-287
EN_MC-30
EN_RW-STANFORD
EN_WS-353-SIM
EN-TR-3k
EN_WS-353-ALL
EN_WS-353-REL

German:

DE_ZG222
DE_GUR65
DE_SIMLEX-999
DE_GUR350
DE_SEMEVAL17
DE_WS-353

For the final MUSE scores, we take arithmetic mean of individual scores obtained from these tests.

For Russian, MUSE provides no tests. Therefore, we download and use the HJ dataset[2].

B PREPARATION OF DATA

To prepare German and Russian Wikipedia dumps for training, we modify the wikifil.pl script such that it captures relevant characters and replaces all digits with relevant words in each language. For German, we add *äöüß* to the set of Latin characters. For Russian, we extract Cyrillic characters. Then, we manually truncate the parsed texts to 1 billion characters, and further truncate to the last complete word in the resulting text. For example, if the German enumeration was cut at the 1 billion boundary, such that

```
eins zwei drei vier
```

becomes

```
eins zwei dr
```

we truncate it to

```
eins zwei
```

.

Finally, we use `iconv` to ensure UTF-8 format.

For example, for the Russian Wikipedia dump, the order of actions is:

[1] https://dl.fbaipublicfiles.com/arrival/wordsim.tar.gz
[2] https://github.com/nlpub/russe-evaluation/blob/master/russe/evaluation/hj.csv

```
wget <wiki dump address>/<ru.dump>
perl wikifil-ru.pl <ru.dump> > ruwiki
head -c 1000000000 ruwiki > ruwiki9
# manually truncate the text
# to the last complete word
iconv -t utf-8 ruwiki9 -o ruwiki9-utf
```

We train the embeddings on the file `ruwiki9-utf`.

C COMPATIBILITY WITH HUGGING FACE TOKENIZERS

We implement tokenization in a way that it is compatible with the files produced by `ByteLevelBPETokenizer` in the Hugging Face Tokenizers library[3]. We apply the same character mapping for UTF-8 characters that use more than one byte, and preprocess the words from the vocabulary such that each begins with a special delimiter character $\dot{G}$.

Note that the number of tokens h must be selected **during** tokenization with the Tokenizers library.

```
bpe = ByteLevelBPETokenizer()
bpe.train([<corpus file>],
          vocab_size=<h>)
bpe.save(<path>, <filename>)
```

(Note the `[]` brackets.)

D HOW TO RUN EXPERIMENTS

We provide parameterized code [4] to replicate our experiments. It is a modification of the original fastText library[5]. Note that we disabled the production of .bin file to reduce saving time and save storage space. Our experiments apply to unsupervised training with skip-gram and CBOW.

In order to compile, CMake, Intel ICPC compiler and a CPU with AVX-512 support are required. Please compile with:

```
cmake .
make
```

To run, please use the command:

```
fasttext {cbow, skipgram} \
  -input  <corpus file> \
  -output <embeddings file> \
  <arguments>
```

Selecting code optimizations. To run a particular algorithm mode, use the argument `-mode <mode>`. Table 3 explains all available modes.

By default, s (the number of words sharing negative samples) is set to $2C + 1$, where C is the maximum context window size (set in the original fastText with the argument `-ws <c>`). To set a different s, use `-shared <s>`. Setting this argument to zero will result in the default setting.

Selecting BPE tokens or no_subword. To use BPE tokens instead of subwords, provide paths to the merge and vocab files produced by the Tokenizers library.

```
 -token-merges <path/to/f.txt >
 -token-vocab  <path/to/f.json>
```

[3] https://github.com/huggingface/tokenizers
[4] https://github.com/FT-Submit/ft-mod
[5] https://github.com/facebookresearch/fastText

Table 3: An overview of `-mode` arguments and their connection to our experiments. Parameter s is set with `-shared <s>`.

argument	mode
`-mode normal`	*_code_opt (default)
`-mode batched`	SG_batch (skip-gram only)
`-mode ns`	SG_NS_CT (skip-gram) CBOW_NS_s (CBOW)
`-mode dh`	CBOW_DH (CBOW only)
`-mode dhf`	CBOW_DHF (CBOW only)
`-mode dh-ns`	CBOW_DH_NS_s (CBOW only)
`-mode dhf-ns`	CBOW_DHF_NS_s (CBOW only)

Both these arguments must be set to enable the BPE run. The number of tokens h is obtained from the merge and vocab files. For our experiments, we produce these files using our training corpora. Note that these two arguments are incompatible with `-no-subwords`.

Finally, to run the no_subword (word2vec) version of our code, use the argument `-no-subwords`. Note that it is incompatible with `-token-merges` and `-token-vocab`.

We run both the BPE and no_subword experiments using `-mode normal` (default).

The remaining arguments are identical to those used by the original fastText code.

To obtain the results for SG_original and CBOW_original, please run the original library.

E COMPLETE RESULTS: ENGLISH, RUSSIAN AND GERMAN

We provide complete results for the embeddings trained on English (Tab. 4), German (Tab. 5) and Russian (Tab. 6) corpora. In negative sharing (NS), we use $s = 11, 80, 160$.

Table 4: Accuracy, runtime, and speedup achieved with our library over fastText when training with English Wikipedia corpus. Blue: best accuracy in category, bold: Pareto-optimal accuracy.

mode	accuracy			time [s]		speedup	
	semantic	syntactic	MUSE	1 thread	20 threads	1 thread	20 threads
SG_original (fastText)	**27.07**	**64.22**	**0.643**	33640	2221	1.0	1.0
SG_code_opt	**26.37**	**63.75**	**0.647**	9087	810	3.7	2.7
SG_batch	24.28	62.47	0.630	7631	625	4.4	3.6
SG_NS_CT	13.10	60.52	0.611	2537	257	13.3	8.7
CBOW_original (fastText)	9.27	67.74	0.546	19614	1484	1.0	1.0
CBOW_code_opt	9.55	68.14	0.538	4285	651	4.6	2.3
CBOW_NS_11	7.18	63.30	0.545	3623	605	5.4	2.5
CBOW_NS_80	6.11	63.41	0.570	3604	604	5.4	2.5
CBOW_NS_160	5.10	62.50	0.555	3584	602	5.5	2.5
CBOW_DH	**11.38**	**68.73**	**0.583**	4079	555	4.8	2.7
CBOW_DH_NS_11	9.19	64.19	0.564	3422	480	5.7	3.1
CBOW_DH_NS_80	6.64	56.76	0.574	3347	474	5.9	3.1
CBOW_DH_NS_160	3.90	54.84	0.536	3371	454	5.8	3.3
CBOW_DHF	5.29	57.44	0.633	4100	446	4.8	3.3
CBOW_DHF_NS_11	2.71	44.51	0.608	3214	398	6.1	3.7
CBOW_DHF_NS_80	2.84	47.19	0.582	3136	392	6.3	3.8
CBOW_DHF_NS_160	2.00	52.77	0.539	3132	392	6.3	3.8
SG_no_subword (word2vec)	47.42	48.07	0.635	3309	253	10.2	8.8
SG_BPE_20K	**40.78**	**53.85**	**0.642**	6843	527	4.9	4.2
SG_BPE_40K	**47.77**	**50.56**	**0.646**	6948	525	4.8	4.2
SG_BPE_200K	**54.98**	**44.79**	**0.634**	7041	526	4.8	4.2
CBOW_no_subword (word2vec)	**51.00**	**54.49**	**0.614**	951	73	20.6	20.4
CBOW_BPE_20K	22.65	46.01	0.607	1717	135	11.4	11.0
CBOW_BPE_40K	30.85	40.47	0.614	1710	133	11.5	11.1
CBOW_BPE_200K	43.33	26.40	0.606	1714	131	11.4	11.3

Table 5: Accuracy, runtime, and speedup achieved with our library over fastText when training with German Wikipedia corpus. Blue: best accuracy in category, bold: Pareto-optimal accuracy.

mode	accuracy			time [s]		speedup	
	semantic	syntactic	MUSE	1 thread	20 threads	1 thread	20 threads
SG_original (fastText)	**21.13**	**49.94**	**0.587**	51747.20	6094.62	1.00	1.00
SG_code_opt	19.41	49.12	0.575	14599.40	1232.77	3.54	4.94
SG_batch	17.43	49.13	0.573	11249.40	869.94	4.60	7.01
SG_NS_CT	7.08	47.41	0.547	4505.81	383.28	11.48	15.90
CBOW_original (fastText)	4.71	58.94	0.507	31674.20	3837.49	1.00	1.00
CBOW_code_opt	4.30	59.09	0.510	7451.51	1114.33	4.25	3.44
CBOW_NS_11	3.17	55.67	0.520	5754.08	1049.82	5.50	3.66
CBOW_NS_80	3.04	52.50	0.515	5663.71	1067.62	5.59	3.59
CBOW_NS_160	1.58	46.71	0.472	5614.96	1045.14	5.64	3.67
CBOW_DH	**5.96**	**59.81**	**0.527**	6405.56	911.22	4.94	4.21
CBOW_DH_NS_11	**4.57**	**55.56**	**0.530**	5531.81	841.33	5.73	4.56
CBOW_DH_NS_80	2.30	50.95	0.522	5811.81	831.03	5.45	4.62
CBOW_DH_NS_160	1.51	45.25	0.450	6096.92	829.48	5.20	4.63
CBOW_DHF	**1.86**	**54.17**	**0.591**	6117.06	845.38	5.18	4.54
CBOW_DHF_NS_11	0.82	46.36	0.562	5048.92	751.09	6.27	5.11
CBOW_DHF_NS_80	1.03	46.97	0.498	5028.07	736.84	6.30	5.21
CBOW_DHF_NS_160	1.08	41.07	0.420	5058.70	764.34	6.26	5.02
SG_no_subword (word2vec)	**42.31**	**27.29**	**0.589**	4511.47	325.00	11.47	18.75
SG_BPE_20K	**29.91**	**36.83**	**0.589**	9439.95	681.74	5.48	8.94
SG_BPE_40K	**34.55**	**29.96**	**0.593**	9908.2	677.83	5.22	8.99
SG_BPE_200K	**45.90**	**23.39**	**0.593**	9829.85	674.91	5.26	9.03
CBOW_no_subword (word2vec)	**37.75**	**27.66**	**0.559**	1314.89	91.73	24.09	41.84
CBOW_BPE_20K	11.19	31.31	0.542	2413.35	181.51	13.12	21.14
CBOW_BPE_40K	18.67	23.25	0.557	2388.83	174.36	13.26	22.01
CBOW_BPE_200K	27.81	16.14	0.560	2461.39	169.70	12.87	22.61

Table 6: Accuracy, runtime, and speedup achieved with our library over fastText when training with Russian Wikipedia corpus. Blue: best accuracy in category, bold: Pareto-optimal accuracy.

mode	accuracy			time [s]		speedup	
	semantic	syntactic	MUSE	1 thread	20 threads	1 thread	20 threads
SG_original (fastText)	**12.29**	**77.61**	**0.633**	30218.90	2958.98	1.00	1.00
SG_code_opt	**12.86**	**77.81**	**0.622**	7409.16	709.82	4.08	4.17
SG_batch	10.58	76.32	0.629	5913.83	565.20	5.11	5.24
SG_NS_CT	5.58	77.81	0.602	2288.52	253.59	13.20	11.67
CBOW_original (fastText)	8.88	80.78	0.495	20510.2	2599.34	1.00	1.00
CBOW_code_opt	**9.18**	**79.79**	**0.497**	4540.83	568.55	4.52	4.57
CBOW_NS_11	7.92	77.32	0.493	4166.32	519.48	4.92	5.00
CBOW_NS_80	7.46	75.83	0.490	4105.2	517.66	5.00	5.02
CBOW_NS_160	6.61	68.75	0.391	4311.11	517.78	4.76	5.02
CBOW_DH	**9.17**	**81.43**	**0.523**	4790.45	454.79	4.28	5.72
CBOW_DH_NS_11	7.82	78.95	0.513	4178.51	402.81	4.91	6.45
CBOW_DH_NS_80	7.41	75.63	0.449	3968.98	403.44	5.17	6.44
CBOW_DH_NS_160	6.23	66.47	0.368	3795.56	404.72	5.40	6.42
CBOW_DHF	**7.32**	**78.75**	**0.557**	4450.69	418.14	4.61	6.22
CBOW_DHF_NS_11	4.79	73.60	0.548	3400.10	366.18	6.03	7.10
CBOW_DHF_NS_80	5.50	66.22	0.458	2866.19	367.79	7.16	7.07
CBOW_DHF_NS_160	5.68	60.92	0.384	3023.92	365.95	6.78	7.10
SG_no_subword (word2vec)	**23.82**	**42.89**	**0.588**	2501.02	178.91	12.08	16.54
SG_BPE_20K	**14.22**	**51.86**	**0.621**	5179.27	375.95	5.83	7.87
SG_BPE_40K	**16.75**	**46.81**	**0.608**	5211.94	373.84	5.80	7.92
SG_BPE_200K	**22.90**	**45.91**	**0.600**	5230.31	370.40	5.78	7.99
CBOW_no_subword (word2vec)	16.01	37.35	0.532	731.05	51.47	28.06	50.50
CBOW_BPE_20K	8.28	34.82	0.513	1370.97	102.97	14.96	25.24
CBOW_BPE_40K	8.96	40.66	0.493	1348.92	99.50	15.20	26.12
CBOW_BPE_200K	11.13	35.96	0.537	1342.59	96.26	15.28	27.00