Iterative Compilation Optimization Based on Metric Learning and Collaborative Filtering

HONGZHI LIU, School of Software and Microelectronics, Peking University, P.R. China

JIE LUO, Center for Data Science, Peking University, P.R. China

YING LI, National Engineering Center of Software Engineering, Peking University, P.R. China

ZHONGHAI WU, National Engineering Center of Software Engineering, Peking University, P.R. China

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Pass selection and phase ordering are two critical compiler auto-tuning problems. Traditional heuristic methods cannot effectively address these NP-hard problems especially given the increasing number of compiler passes and diverse hardware architectures. Recent research efforts have attempted to address these problems through machine learning. However, the large search space of candidate pass sequences, the large numbers of redundant and irrelevant features, and the lack of training program instances make it difficult to learn models well. Several methods have tried to use expert knowledge to simplify the problems, such as using only the compiler passes or subsequences in the standard levels (e.g., -O1, -O2, and -O3) provided by compiler designers. However, these methods ignore other useful compiler passes that are not contained in the standard levels. **Principal component analysis (PCA)** and **exploratory factor analysis (EFA)** have been utilized to reduce the redundancy of feature data. However, these unsupervised methods retain all the information irrelevant to the performance of compilation optimization, which may mislead the subsequent model learning.

To solve these problems, we propose a compiler pass selection and phase ordering approach, called **Iterative Compilation based on Metric learning and Collaborative filtering (ICMC)**. First, we propose a data-driven method to construct pass subsequences according to the observed collaborative interactions and dependency among passes on a given program set. Therefore, we can make use of all available compiler passes and prune the search space. Then, a supervised metric learning method is utilized to retain useful feature information for compilation optimization while removing both the irrelevant and the redundant information. Based on the learned similarity metric, a neighborhood-based collaborative filtering method is employed to iteratively recommend a few superior compiler passes for each target program. Last, an iterative data enhancement method is designed to alleviate the problem of lacking training program instances and to enhance the performance of iterative pass recommendations. The experimental results using the LLVM compiler on all 32 cBench programs show the following: (1) ICMC significantly outperforms several state-of-the-art compiler phase ordering methods, (2) it performs the same or better than the standard level -O3 on

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Authors' addresses: H. Liu (corresponding author), School of Software and Microelectronics, Peking University, No. 24 Jinyuan Road, Beijing, P.R. China; email: liuhz@pku.edu.cn, J. Luo, Center for Data Science, Peking University, No. 5 Yiheyuan Road, Beijing, P.R. China; email: isluojie@pku.edu.cn, Y. Li, National Engineering Center of Software Engineering, Peking University, No. 5 Yiheyuan Road, Beijing, P.R. China; email: li.ying@pku.edu.cn, Z. Wu (corresponding author), National Engineering Center of Software Engineering, Peking University, No. 5 Yiheyuan Road, Beijing, P.R. China; email: wuzh@pku.edu.cn.

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all the test programs, and (3) it can reach an average performance speedup of 1.20 (up to 1.46) compared with the standard level -O3.

CCS Concepts: • **Software and its engineering** → **Compiler**; • **Information system** → *Recommender systems*;

Additional Key Words and Phrases: Compiler auto-tuning, iterative compilation, metric learning, collaborative filtering

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1 INTRODUCTION

The goal of compilers is to translate program codes written by humans into executable binaries for efficient execution by a target computing hardware. For each program, there are many different correct translations having varying performance characteristics. The key is to find the best one among these correct translations [45]. The selection of a sequence of suitable compiler passes for a given program has usually been done manually [5]. However, the increasing number of candidate compiler passes and diverse hardware architectures make it difficult to do this by hand.

Modern compilers provide a large number of optimization passes targeting various code segments. For example, GCC has more than 200 compiler passes [32], and LLVM has over 150 transformation passes [5]. Most of these compiler passes are disabled by default. Compiler designers assume software developers know which compiler passes will be beneficial for their programs. To simplify the problem, compiler designers always provide several standard optimization levels, such as -O1, -O2, and -O3. Each of these standard levels is a fixed and program-independent sequence of compiler passes. However, these standard sequences leave much to be desired performance for most programs [2, 24, 38]. Many experiments have verified that the performance of compilers' standard levels is not good enough for specific benchmarks and that the best pass sequence is program-specific [6, 31]. For each program, choosing the right set of compiler passes (aka *pass selection*) and finding the best ordering of them (aka *phase ordering*) are two critical problems for compiler auto-tuning [6, 24, 25].

Recent research efforts have attempted to utilize machine learning models to deal with these two NP-hard problems, pass selection and phase ordering [45]. However, the large search space of candidate pass sequences, the large numbers of redundant and irrelevant features, and the lack of training program instances make it difficult to learn models well [12, 13]. To deal with the problem of large search space, several studies have tried to use expert knowledge to prune the search space of candidate pass sequences [8, 41, 43]. For example, Ashouri et al. [3, 4] used compiler designers' knowledge to construct pass subsequences from a standard optimization level and then utilized the subsequences as basic optimization units to form the search space. These methods can greatly prune the search space. However, they are limited to the passes and their orderings used in the standard level while ignoring other useful passes. To solve this problem, we propose a data-driven method to construct pass subsequences. It tries to mine the collaborative interactions and dependency among passes according to the collected performance records of candidate passes and pass-pairs on a given set of programs. Therefore, all available passes provided by compilers can be utilized to further optimize programs. In addition, it can help us to discover the interactions and dependency among passes that have been ignored by experts and to further design new standard optimization sequences for compilers.

To deal with the problem of large numbers of redundant and irrelevant features, principal component analysis (PCA) [1, 12, 44] and exploratory factor analysis (EFA) [6] have been utilized for compiler auto-tuning. These unsupervised methods are good at removing the redundancy of feature data. However, all the irrelevant information, for example, the number of indirect pointers and the number of occurrences of constant 1, is retained because these methods ignore the effects of features on the performance of compilation optimization, which may mislead the subsequent model learning. To solve this problem, we utilize a supervised metric learning method, which tries to retain useful feature information for compilation optimization while removing both the irrelevant and the redundant information. Based on the learned similarity metric, a neighborhood-based collaborative filtering method is designed to iteratively recommend a few superior compiler passes for each target program. In addition, a data enhancement method is designed to alleviate the problem of lacking training program instances.

The main contributions of this article are summarized as follows:

- (1) We propose a data-driven method to construct pass subsequences according to the observed collaborative interactions and dependency among passes on a given program set. Therefore, we can make use of all available passes while reducing the search space. In addition, it can find out some collaborative interactions ignored by experts.
- (2) We propose an iterative compilation optimization method based on metric learning and collaborative filtering, which tries to recommend passes for the target program according to the observed preferences of similar programs. It utilizes a supervised metric learning method to embed programs into a latent representation space with the supervision of their preference similarities on candidate pass subsequences, which can remove both the irrelevant and the redundant information in program features for compilation optimization.
- (3) An iterative data enhancement method is designed to alleviate the problem of lacking training program instances and to enhance the performance of iterative pass recommendations.
- (4) We evaluate the proposed method and make a comparison with several state-of-the-art compiler phase ordering methods on all 32 cBench programs. Extensive experiments demonstrate the promise of our method, which performs the same or better than the standard level -O3 on all the test programs and can reach an average performance speedup of 1.20 (up to 1.46).

The rest of this article is organized as follows: Section 2 introduces some related work. Section 3 formulates the problem and Section 4 describes our method in detail. Comparison with several state-of-the-art methods and empirical evaluations are presented in Section 5. Finally, Section 6 concludes the article.

2 RELATED WORK

2.1 Reduction of Search Space

The main difficulty of compiler pass selection and phase ordering is the large and intractable search space caused by hundreds of candidate passes. Evolutionary algorithms (EAs), such as genetic algorithms (GAs) and genetic programming (GP), have been used to find good optimization solutions (pass sequences) from the large search space for each given program [5]. Cooper et al. [15, 16] proposed to use a GA to find the pass sequences that can generate smaller object codes to reduce the code size for embedded systems. Kulkarni et al. [30] used two complementary GAs to shorten the search time by pruning unnecessary optimization configurations and to increase the variety of choices. Stephenson et al. [42] proposed to use GP to heuristically explore the space. EAs are useful for exploring the large search space. However, they rely on excessive fitness evaluations and expensive exploration time [32, 45].

To reduce the search space, several methods have been proposed to construct pass subsequences and search the best whole sequence based on these subsequences [28]. Ashouri et al. [3] directly took some fragments of a standard level provided by compiler designers as subsequences. Later, Ashouri et al. [4] proposed to cluster the passes used in a standard level into several groups with a hierarchical clustering algorithm and combine each group as a subsequence. These methods can greatly reduce the search space. However, they depend on the information of expert-designed pass sequences. In addition, they ignore other useful passes that are not contained in the standard level.

2.2 Machine Learning Based Sequence Prediction

To avoid excessive online evaluations for each target program, several machine learning–based methods have been proposed to predict the optimization effects of candidate pass sequences on each given program. These methods can be roughly divided into two categories according to the search space exploration strategy, namely (1) complete sequence prediction and (2) iterative intermediate prediction. The former strategy tries to directly predict the global best pass sequence for a given program based on the characteristics of the program in its original state [4, 10, 39, 40]. The latter strategy tries to iteratively predict the next-best pass to further optimize the given program based on the characteristics of the program in its current optimized state and/or performance feedback [1, 6, 32, 33].

Ashouri et al. [4] proposed to learn a prediction model that takes a tuple (F, T) as an input, where F denotes the code-feature vector of the program being optimized and T denotes one of the possible compiler pass sequences. A similar machine learning–based method [10] was proposed for pass selection. These methods can greatly reduce the requirement of online evaluations using models learned offline. However, the code features extracted by different tools contain much redundant and irrelevant information for compilation optimization, which makes it difficult for model learning. In recent years, several reaction-feature based learning methods have been proposed for compiler auto-tuning. Cereda et al. [11] assumed that if two programs receive similar performance improvements from the same set of passes, they will show similar reactions on other sets. Furthermore, they proposed a collaborative filtering-based method to deal with the pass selection problem. This method can be extended for phase ordering problem by regarding each optimization configuration as a complete pass sequence rather than a pass set. Christoforidis et al. [14] proposed to use a matrix factorization based method to learn a regression model according to collected reaction data to deal with the phase ordering problem. These methods can avoid the problems of redundant and irrelevant code-features. However, they require several online evaluations to characterize each new program and make predictions because of ignoring the useful information contained in code features, which makes them heavy time-overhead during the online compilation phase.

In contrast to complete sequence prediction methods that try to directly optimize each whole program, intermediate prediction methods try to iteratively optimize different segments of a given program according to the current state of the program [3, 5, 29, 32]. They use an iterative process to select the next-best compiler pass based on the current intermediate state of the given program, i.e., the state of the program optimized by several previously selected passes. At each intermediate step, they only require evaluating or predicting the performance of all candidate passes instead of all candidate pass sequences, which greatly reduces the computational complexity.

Kisuki et al. [29] treated the compilation optimization as an iterative tree-based search process. The next-best compiler pass is predicted for the current optimized program according to the program's feedback. Therefore, it can iteratively generate further efficient codes. However, this method requires all candidate passes to be evaluated at each sequence node, which is expensive for general compilation. In addition, it ignores the interactions among passes, which is important and significant for optimization effectiveness and efficiency of phase ordering.

Ashouri et al. [3] proposed to use a linear regression model to predict the intermediate speedup value of candidate compiler optimizations and select the next-best optimization given the current state of the program. It avoids the evaluations of all candidate passes at each intermediate state. In addition, it tries to capture the interactions among passes by using subsequences of standard level -O3 as the candidate optimizations. However, this method ignores other useful compiler passes outside of -O3. In addition, it only makes use of dynamic features to characterize programs while ignoring useful static code-features.

2.3 Data Transformation and Enhancement

The existence of large numbers of redundant and irrelevant features and the lack of training program instances are two common problems for machine learning-based methods [35].

To deal with the problem of large numbers of redundant features, several data transformation methods have been utilized for compiler auto-tuning [6, 7, 44]. Principal component analysis (PCA) [3, 12, 44] and exploratory factor analysis (EFA) [6] are two commonly used data transformation methods [5]. They are good at removing the redundancy of feature data. However, these unsupervised methods only try to maintain the main characteristics of data while ignoring their effects on the performance of compilation optimization. Therefore, the information irrelevant to compilation optimization is also retained.

To deal with the problem of lacking program instances, several methods have been proposed to generate synthetic training programs. Chiu et al. [13] designed a programming language that allows users to annotate a template program to customize its code using statistical distributions and to generate program instances based on those distributions. Cummins et al. [18] tried to use deep learning techniques to automatically construct models for how humans write programs from open source repositories. Then, they synthesized programs through a process of iterative model sampling. These methods can generate more synthetic programs for model training. However, they rely on manual programming or a large source code repository.

3 PROBLEM DEFINITION

Let $O = \{o_1, o_2, \dots, o_m\}$ denote a set of candidate compiler passes and $P = \{p_1, p_2, \dots, p_n\}$ denote a set of programs, where $m = |O|$ and $n = |P|$ denote the number of passes and programs, respectively. Let $s_j = (o_{j1}, o_{j2}, \dots, o_{js})$ denote a sequence of compiler passes and Ω denote the set of all possible pass sequences. Compilation optimization can be regarded as a function G . Its input is a program p_i and a pass sequence s_j , based on which it outputs p_i 's semantically equivalent code optimized by s_j , i.e.,

$$p_i^j = G(p_i, s_j). \quad (1)$$

The goal of pass selection and phase ordering is to select the best sequence $s^* \in \Omega$ for each program $p_i \in P$, i.e.,

$$s^*(p_i) = \max_{s_j \in \Omega} f(p_i, s_j), \quad (2)$$

where $f(p_i, s_j)$ denotes the performance improvement of program p_i with the help of pass sequence s_j .

The pass selection and phase ordering problem is an NP-hard problem. Let L denote the maximum length of the pass sequence. The size of the search space is

$$|\Omega| = \sum_{i=0}^L m^i, \quad (3)$$

where m denotes the number of candidate passes.

4 THE PROPOSED METHODOLOGY

The framework of the proposed pass selection and phase ordering model, called **Iterative Compilation based on Metric learning and Collaborative filtering (ICMC)**, is shown in Figure 1. To alleviate the problem of a large search space caused by hundreds of candidate passes, we first propose a data-driven pass subsequence construction method. It makes use of the observed collaborative interactions and dependency among passes on the training program set to automatically generate a set of pass subsequences (Section 4.1). Then, we propose an iterative compilation method based on metric learning and collaborative filtering (Section 4.2). It iteratively recommends the next-best subsequence according to the current state of the target program and the performance of candidate subsequences on similar programs (Section 4.2.2). To avoid the misleading effects of both the irrelevant and the redundant features on similarity measurement, we utilize a supervised metric learning method to automatically learn an appropriate similarity metric for the subsequence recommendation task. It makes use of the observed preferences of training programs on candidate pass subsequences (Section 4.2.1). Furthermore, we propose a data enhancement method to deal with the problem of lacking training program instances for metric learning and subsequence recommendation (Section 4.2.3).

4.1 Construction of Collaborative Pass Subsequences

We assume that there are collaborative interactions among passes and that some of these interactions are useful for improving the performance of compilation optimization and controlling the search space [28]. For a given program p , if pass sequence (A, B) performs better than both pass A and pass B alone and even better than the sequence (B, A) , i.e.,

$$f(p, (A, B)) > f(p, (A)) \ \& \ f(p, (A, B)) > f(p, (B)) \ \& \ f(p, (A, B)) > f(p, (B, A)), \quad (4)$$

we say that pass A improves the effectiveness of pass B for program p , which means that pass B *depends on* pass A . These kinds of relationships among passes are called *collaborative interactions* in this article.

The interactive effects of pass pairs depend on the characteristics of the programs being optimized. We assume that if one collaborative interaction exists on a vast number of programs, it is a strong collaborative interaction. Based on this assumption, we design a data-driven method to make use of all available passes besides those not contained in the standard levels.

Algorithm 1 describes the process of constructing pass subsequences according to the collaborative interactions among passes on a given program set P . First, we remove some inefficient passes to reduce the complexity of subsequence construction while excluding few potentially useful passes. Second, we collect collaborative pass pairs on all programs to construct a collaboration matrix M . The element M_{ij} of matrix M denotes the frequency of collaborative pass pair (o_i, o_j) appearing in the program set P , where o_i and o_j denote the i th and j th pass, respectively. Third, we construct a dependency graph G according to the collected collaboration matrix. The dependency graph G is a directed weighted graph, whose nodes denote compiler passes. If there exist collaborative interactions between two passes o_i and o_j , there is an edge between the two corresponding nodes in the graph G and the weight of this edge is M_{ij} . Fourth, we utilize a graph cut algorithm [46] to cut down a few weak connections while keeping the strong collaborative connections. The graph is segmented into several subgraphs. Finally, each subgraph is stretched as a subsequence according to the collaborative connections inside it. Figure 2 shows an example of the graph cut process, which cuts down the weak connections and generates two strongly connected subgraphs. For each subgraph, we use a depth-first traversal algorithm to construct a corresponding pass subsequence. First, we find the root node of the subgraph according to the

Fig. 1. Framework of the proposed ICMC model. It consists of three main components. I) Pass subsequence construction and data enhancement denotes the preprocessing phase, which aims to reduce the search space by subsequence construction and generate more training program instances by data enhancement. II) Supervised metric learning aims to automatically learn an appropriate similarity metric for the subsequence recommendation task. III) Online iterative recommendation aims to iteratively recommend the next-best pass subsequence according to the current feature state of the given program, the learned metric model, and the collected training data.

principle of minimum in-degree. Then, we recursively traverse the subtrees of the root which are ranked according to their weights connected to the root, i.e., M_{ij} . It ensures that the pass which can enhance the effectiveness of subsequent passes is used first.

4.2 Iterative Compilation Based on Metric Learning and Collaborative Filtering

The optimization passes provided by compilers are targeted for different code segments of programs, such as some for loop unrolling while some others for register allocation. Based on this fact, we assume that the same pass subsequence has similar effects on similar programs. Furthermore, we design a neighborhood-based collaborative filtering method to iteratively recommend pass subsequences for a given program (Section 4.2.2). The key of this method is to determine the neighborhood according to similarities between programs. However, similarities based on the original feature vectors of programs may mislead the recommendations because of the numerous redundant and irrelevant features. To deal with this problem, we utilize a supervised metric learning method to automatically learn an appropriate similarity metric for pass subsequence

Fig. 2. An example of data-driven subsequence construction. Nodes of the graph denote compiler passes, arrows denote directed collaborative interactions, and weights of edges denote the frequencies of collaborative interactions that appear in the training program set. Two weak connections are cut down, and the constructed subsequences are as follows: A-C-D-G (-inline -dse -loops -lcssa) and E-F-I-H-B (-loop-deletion -mem2reg -basiccg -mldst-motion -lower-expect).

recommendation (Section 4.2.1). The performance of both metric learning and subsequence recommendation relies on a set of sufficient training samples. However, the available programs are always limited. To deal with this problem, we design a data enhancement method to generate more training programs based on the available programs and compiler passes (Section 4.2.3).

4.2.1 Program Similarity Based on Metric Learning and Programs' Preferences. We assume that similar programs have similar preferences on candidate pass subsequences with the same running environment [37]. To profile programs comprehensively, we make use of both dynamic and static features to characterize them. Dynamic features characterize the behavior of the target program when executing, while static features characterize the source code of the program without execution. However, because of the vastness and variety of features collected through different feature extractors, there may be a large number of redundant or irrelevant features for performance prediction of compilation optimization. Therefore, similarity based on the original program feature vectors may not satisfy our assumption. To deal with this problem, we utilize a supervised metric-learning framework [36] to embed the programs into a latent representation space with consideration of programs' preferences on candidate passes or subsequences.

As shown in Figure 3, in the learned latent representation space, we hope the program pair (p_i, p_i^+) with similar preferences on candidate pass subsequences becomes closer while the encounter pair (p_i, p_i^-) becomes more distant.

Let (F_i, Υ_i) denote the instance of program p_i , where F_i denotes its feature vector and Υ_i denotes its preference vector on candidate pass subsequences. The feature vector F_i contains both static features and dynamic features of program p_i , which are extracted by different tools, such as MICA [27] and Milepost GCC [22]. The preference vector Υ_i represents the performance improvement of program p_i compiled with the candidate pass subsequences constructed in Section 4.1. Its element Υ_{ij} denotes the performance improvement of program p_i after being optimized with the subsequence s_j , i.e., the speedup value $f(p_i, s_j)$. And the length of Υ_i is the number of

Fig. 3. Illustration of the supervised metric learning. The program p_i^+ with similar preferences on candidate pass subsequences is pulled closer while the dissimilar program p_i^- is pushed away.

ALGORITHM 1: Data-driven Construction of Pass Subsequences

Input: Compiler pass set O , program set P , number of efficient passes to be kept K , number of pass subsequences to be constructed c .

Output: Constructed pass subsequence set S

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1 for each  $o_j \in O$  do
2   Calculate its harmonic average speedup on the whole program set  $P$ :
      
$$\bar{f}_{o_j} = \frac{|P|}{\sum_{p_i \in P} \frac{1}{f(p_i, o_j)}} = \frac{|P|}{\sum_{p_i \in P} \frac{t_{ij}}{t_i}}$$

      where  $t_i$  denotes the execution time of program  $p_i$  without optimization, and  $t_{ij}$  denotes the
      execution time of program  $p_i$  optimized by single compiler pass  $o_j$ .
3 end
4 Keep the top  $K$  passes  $O^*$  with the sorted average speedup  $\bar{f}$  from high to low;
5 Initialize all elements of the collaboration matrix  $M$  with 0;
6 for each  $p_i \in P$  do
7   for each  $o_j \in O^*$  do
8     for each  $o_k \in O^*, j \neq k$  do
9       if  $f(p_i, (o_j, o_k)) > 1$  and  $f(p_i, (o_j, o_k)) > \max\{f(p_i, o_j), f(p_i, o_k), f(p_i, (o_k, o_j))\}$  then
10         $M_{jk} = M_{jk} + 1$ ;
11      end
12    end
13  end
14 end
15 Construct a dependency graph  $G$  according to the collaboration matrix  $M$ ;
16 Segment the dependency graph  $G$  into  $c$  subgraphs using a graph cut algorithm [46];
17 Stretch each subgraph as a pass subsequence with a depth-first traversal algorithm.
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candidate subsequences. To learn the latent representations of programs with consideration of their preferences on candidate pass subsequences, we utilize the LSML model [36] and try to learn a Mahalanobis transformation matrix M to minimize the following squared hinge loss function:

$$Loss_{ML} = \sum_{(p_i, p_i^+, p_i^-) \in TrainSet} H(D_M(p_i, p_i^+) - D_M(p_i, p_i^-)) + D_{ld}(M, M_0), \quad (5)$$

$$H(x) = \begin{cases} 0 & (x \leq 0) \\ x^2 & (x > 0) \end{cases} \quad (6)$$

$$D_{ld}(M, M_0) = \text{trace}(MM_0^{-1}) - \log \det(M), \quad (7)$$

$$D_M(p_i, p_j) = \sqrt{(F_i - F_j)^T M (F_i - F_j)}, \quad (8)$$

where $D_M(p_i, p_j)$ represents the Mahalanobis distance between program p_i and program p_j after being embedded with the transformation matrix M , and $D_{ld}(M, M_0)$ represents the LogDet divergence between the learned metric M and a given prior metric M_0 (usually set as the identity matrix). A triplet (p_i, p_i^+, p_i^-) represents that program p_i^+ is more similar than program p_i^- for a given program p_i according to their preferences on candidate pass subsequences. The preference similarity between two programs is computed as the cosine similarity of their preference vectors with respect to the candidate pass subsequence set S :

$$S_{\text{preference}}(p_i, p_j) = \frac{\sum_{s_k \in S} \Upsilon_{ik} \Upsilon_{jk}}{\sqrt{\sum_{s_k \in S} \Upsilon_{ik}^2} \sqrt{\sum_{s_k \in S} \Upsilon_{jk}^2}} \quad (9)$$

where $\Upsilon_{ik} = f(p_i, s_k)$ represents the performance improvement of program p_i with the help of candidate pass subsequence s_k . The more similarity there is between two programs, i.e., the more similar the candidate subsequences' speedup on the two programs, the closer the value $S_{\text{preference}}(p_i, p_j)$ is to 1. To learn the transformation matrix M given a set of programs P with their instances $\{(F_i, \Upsilon_i) | p_i \in P\}$, we adopt a projected gradient method to optimize the objective function in Equation (5) as in [36].

With the learned metric M , we can calculate the similarity between programs to select the neighborhood for a new program according to Equation (10), which normalizes the similarity to the interval of (0, 1].

$$\text{sim}(p_i, p_j) = \frac{1}{1 + D_M(p_i, p_j)} \quad (10)$$

where $D_M(p_i, p_j)$ denotes the distance between program p_i and program p_j according to the learned metric model M and their features F_i and F_j as in Equation (8).

4.2.2 Personalized Recommendation Based on Collaborative Filtering. Based on the learned similarity metric, we take each program as a user and design a neighborhood-based collaborative filtering method to iteratively recommend pass subsequences for a new given program. Figure 4 shows an example of this program-based collaborative filtering. As shown in the figure, for a new program p_{new} , the recommendation is made based on the preferences of its similar program p_1 and p_2 on candidate pass subsequences.

Assume we have collected a set of instances $I = \{(F_i, \Upsilon_i) | p_i \in P\}$ for a given program set P . Each instance (F_i, Υ_i) , which contains a feature vector F_i and a preference vector Υ_i , corresponds to a program sample $p_i \in P$. The preference vector Υ_i contains the preferences of program p_i on all candidate pass subsequences. The preference of program p_i on a pass subsequence s_j is measured by the performance improvement of program p_i after being compiled with subsequence s_j , i.e., the speedup value $f(p_i, s_j)$.

The instances of the k most similar programs in P are used to recommend subsequences for a new given program $p_{\text{new}} \notin P$. The preference of program p_{new} on a candidate pass subsequence s_j can be estimated as follows:

$$r(p_{\text{new}}, s_j) = \sum_{p_v \in N(p_{\text{new}}, k)} \text{sim}(p_{\text{new}}, p_v) R_{vj}, \quad (11)$$

where $N(p_{\text{new}}, k)$ denotes the program set of the k nearest neighbors of program p_{new} in P , $\text{sim}(p_{\text{new}}, p_v)$ represents the similarity between program p_{new} and program p_v as in Equation (10), and R_{vj} represents the effectiveness of subsequence s_j on program p_v . Considering the large deviation of subsequences' performance on programs, we take R_{vj} as a binary variable to represent

Fig. 4. Illustration of the iterative optimization process and an example of program-based collaborative filtering.

the interaction rather than the speedup value. The positive interaction $R_{vj} = 1$ is defined such that the program p_v compiled with the subsequence s_j can obtain the top- n best performance among all subsequences with a speedup $f(p_v, s_j)$ greater than 1.

The pseudocode of the iterative compilation algorithm based on collaborative filtering is shown in Algorithm 2. As shown in Figure 4, the new target program p_{new} is first transformed as an intermediate representation IR_{new}^0 without any optimizations. Then, the target program is further optimized with the iteratively recommended pass subsequences. Specifically, in the l th iteration, the temporary optimized intermediate representation IR^l is chosen as follows:

$$IR_{new}^l = G(IR_{new}^{l-1}, \max_{s_j \in S_n} f(IR_{new}^{l-1}, s_j)), \quad (12)$$

where IR_{new}^{l-1} denotes the optimization result of the $(l - 1)$ -th iteration and S_n denotes the subsequence set recommended in the l th iteration. When the number of iteration arrives at a preset threshold L or the program cannot be further optimized with the recommended pass subsequences, the iterative optimization process stops and it outputs the optimized program with the corresponding pass sequence.

4.2.3 Iterative Data Enhancement. As shown in Figure 4, the recommendation effectiveness in each iteration depends on not only a proper similarity metric but also sufficient program instances. However, the number of programs in most benchmarks and real applications is limited [12, 13]. To deal with this problem, we propose an iterative data enhancement method to generate new training programs based on a given set of programs.

A *program* can be defined as an instruction sequence with a given computer instruction set, for example, SSE2 and X86 [20]. At the instruction level, the optimized state of a program by a compiler pass or sequence can be regarded as a new instruction sequence, which means that it is a new program. Therefore, we use the Intermediate Representations (IRs) to represent the program as in [9] and treat a program optimized by one or more compiler passes as a new program. In this

ALGORITHM 2: Iterative Compilation Based on Collaborative Filtering

Input: Program p_{new} , candidates pass subsequence set S , a set of collected program instances I , learned metric transformation matrix M , number of nearest neighbors k , maximum sequence length L , number of recommended subsequences in each iteration n .

Output: Recommended sequence of pass subsequences $\text{Recipe}_{\text{Best}}$ for program p_{new} and the corresponding speedup $\text{Speedup}_{\text{Best}}$.

- 1 Transform program p_{new} into Intermediate Representation (IR) IR_{Orig} with compiler front-end;
- 2 Initialization: $\text{Recipe}_{\text{Cur}} = \text{EmptyList}$, $\text{Recipe}_{\text{Best}} = \text{EmptyList}$, $\text{IR}_{\text{Best}} = \text{IR}_{\text{Orig}}$, $\text{Speedup}_{\text{Best}} = 1$, $\text{iterNum} = 0$;
- 3 **while** $\text{iterNum} < L$ **do**
- 4 Compile IR_{Best} into an executable program p_t and collect its feature vector F_{new} ;
- 5 Find the k nearest neighbors of program p_t in I according to Equation (10);
- 6 Calculate the preference scores of program p_t on all candidate subsequences S according to Equation (11);
- 7 Select the top n subsequences according to preference scores as the recommendation set $S_n \subset S$;
- 8 **for each** $s \in S_n$ **do**
- 9 $\text{Recipe}_{\text{Temp}} = (\text{Recipe}_{\text{Cur}}, s)$;
- 10 Generate IR_{Temp} by applying $\text{Recipe}_{\text{Temp}}$ to IR_{Orig} ;
- 11 Compile IR_{Temp} into an executable program and evaluate its speedup $\text{Speedup}_{\text{Temp}}$ with respect to the original version IR_{Orig} ;
- 12 **if** $\text{Speedup}_{\text{Temp}} > \text{Speedup}_{\text{Best}}$ **then**
- 13 $\text{Recipe}_{\text{Best}} = \text{Recipe}_{\text{Temp}}$; $\text{Speedup}_{\text{Best}} = \text{Speedup}_{\text{Temp}}$; $\text{IR}_{\text{Best}} = \text{IR}_{\text{Temp}}$;
- 14 **end**
- 15 **end**
- 16 $\text{Recipe}_{\text{Cur}} = \text{Recipe}_{\text{Best}}$;
- 17 $\text{iterNum} = \text{iterNum} + 1$;
- 18 **end**

way, we can generate more training program instances based on a given set of programs and a set of compiler passes or subsequences.

As shown in Figure 5, each program instance is defined as an intermediate representation IR , and the intermediate representation of source program p_i is denoted as IR_i^0 . An intermediate representation IR_i^j generated through applying a given pass sequence s_j on IR_i^0 can be regarded as a new program instance. i.e.,

$$\text{IR}_i^j = G(\text{IR}_i^0, s_j). \quad (13)$$

In this way, we can iteratively generate more program instances, i.e., $\text{IR}_i^{(j,k)} = G(\text{IR}_i^j, s_k)$. These program instances can help us learn a more suitable similarity metric for the iterative collaborative recommendation with consideration of the combination effects of subsequences. For the newly generated program instances, dynamic program features are directly extracted from those IR s. Static features are extracted from the original source code (e.g., the root of the tree in Figure 5) and integrated with dynamic features to represent the generated program instances. Then these newly generated programs combined with the raw programs are used to collect training samples as usual, i.e., optimizing them with given pass sequences and evaluating the corresponding performance improvement.

Combined with the supervised pairwise metric learning method (Section 4.2.1), the proposed data enhancement method can help us to capture some high-order interactions among passes, i.e.,

Fig. 5. Flowchart of the iterative data enhancement process. The Intermediate Representations (IR) of a program compiled with one or more subsequences are taken as new program samples.

the interactions between subsequences, which may be ignored during the phase of pass subsequence construction (Section 4.1).

5 EXPERIMENTS

In this section, we first introduce the experimental setup and evaluation methodology in Section 5.1. Then, the performance of our pass subsequence construction method and iterative compilation method are evaluated and compared with several state-of-the-art methods in Section 5.2 and 5.3, respectively. Last, we employ a series of experiments to evaluate the effectiveness of module design and the effects of parameter settings in Section 5.4 and 5.5, respectively.

5.1 Experimental Setup

5.1.1 Dataset and Experiment Platform. The full set of programs from the cTuning cBench benchmark v1.1 [21] are used as the experimental data, which contains 32 different programs ranging from automotive, security, and office sectors to telecommunications.

Experiments are run on a quad-core Intel(R) CPU i7-3630QM with Linux Ubuntu 16.4 OS. LLVM is adopted as the compiler. LLVM-clang and LLVM-link are used as the front-end and back-end, by which the source code is converted into an IR and the optimized IR is linked into an executable program, respectively. LLVM-opt is used as the optimization tool which apply an optimization sequence, such as -O3, on the IR. Since some of the passes provided by LLVM-opt are used for structural code analysis or code debugging, such as *-deadarghaXOr*, *-view-cfg*, and *-transform-warning*, we exclude these passes as they do not contribute to the performance improvement or even degrade the performance. In default, we use LLVM v3.8 as the compiler because several baseline methods like IS Pred. [3] and MiCOMP [4] used it and some results of these methods depend on it. With consideration of the rapid development of LLVM, we also do a comparison experiment using the latest LLVM, i.e., LLVM v12.0, in Section 5.3.

The execution time of each program is estimated by the *time* tool provided by Linux OS. A PIN-based dynamic instrumentation framework, called MICA [27], is used to characterize the dynamical behavior of a target program while executing. A plugin tool based on GCC, named Milepost-GCC [22, 23], is used to capture the static features of the source code without execution.

A script written with Python language is used to automatically read, store, and analyze the raw data obtained by these tools.

5.1.2 Evaluation Metric and Methodology. To evaluate the empirical performance of different methods, we adopt the average speedup on all benchmark programs as the evaluation metric. Specifically, we use the harmonic mean speedup as in [4] and [26].

The speedup of a compiler option (i.e., a pass sequence) o_j on a program p_i is defined as:

$$\text{speedup}(p_i, o_j) = \frac{t(p_i, o_{\text{base}})}{t(p_i, o_j)}, \quad (14)$$

where $t(p_i, o_{\text{base}})$ denotes the execution time of program p_i optimized by the base compiler option, e.g., -O3, and $t(p_i, o_j)$ denotes the execution time of program p_i optimized by the compiler option o_j . The default dataset setting of cBench is used as the input for each program. With consideration of the execution time and measurement bias, we adjust the number of execution repetitions for each evaluation to make the measurement results stable and low-overhead.

All studies are cross-validated. **Leave-one-out cross-validation (LOOCV)** is adopted to better evaluate the performance of different methods as in [3], [4], and [11]. Each time, one program p_i of the given program set P is used as the test data, while the other programs are put together to form a training set. The process is repeated $|P|$ times with each program $p_i \in P$ used exactly once as the test data. The experimental results are recorded as the harmonic mean of the $|P|$ runs, i.e.,

$$\text{speedup_Hmean} = \frac{|P|}{\sum_{p_i \in P} \frac{1}{\text{speedup}(p_i)}}. \quad (15)$$

5.2 Performance Evaluation of Pass Subsequence Construction

The goal of this experiment is to evaluate the performance of the proposed pass subsequence construction method which is presented in Section 4.1.

5.2.1 Experimental Design. Two subsequence construction methods are used as baseline methods, including IS Pred. subsequences [3] and MiCOMP subsequences [4].

- **IS Pred. subsequences** [3] are fragments from the LLVM -O3 standard sequence with carefully considered collaborations among passes.
- **MiCOMP subsequences** [4] are automatically derived from the LLVM -O3 standard sequence using a hierarchical clustering method with consideration of the ordering information in the standard sequence.

In this experiment, we use an exhaustive search to evaluate the effectiveness of different subsequence construction methods, i.e., completely exploring the whole search space to determine the global optimal configuration of each subsequence group for each program with a given length of configuration. The harmonic mean speedups of all programs with various lengths of configuration are recorded. To ensure a fair comparison, we only use the passes in the LLVM standard level -O3 in this experiment. We construct five pass subsequences using the proposed method (Algorithm 1).

5.2.2 Experimental Results. Figure 6 shows the performance of different subsequence construction methods with various lengths. The speedups of different methods increase as the length of the sequence increases. However, the search space increases exponentially as the length of the sequence increases.

With different lengths of sequences, our data-driven method consistently performs better than both IS Pred. and MiCOMP. This result demonstrates the effectiveness of our data-driven subsequence construction method. In addition, the results compared with the subsequences designed

Fig. 6. Harmonic mean speedup of different subsequence construction methods using exhaustive search with various lengths of sequences.

by experts in IS Pred. show that our data-driven method can find some collaborative interactions that were ignored by the experts.

To further analyze the effectiveness of the constructed pass subsequences, we evaluate the performance of individual pass subsequences on all the 32 programs. As shown in Table 1, even using the constructed pass subsequences individually, programs can be optimized well and the best performance improvement can achieve 1.106. It is worth mentioning that these results are better than the results in Figure 6 with the length set as 1, because each of these subsequences can get better performance on its 31 training programs than on the one test program that was left out. Three passes, *-mem2reg*, *-dse*, and *-correlated-propagation*, appear in all the five best subsequences. Besides, we can find some characteristics of and interactions between the passes from these subsequences. For example, as a hardware independent pass, *-sroa* is used as the first pass in four of the five best subsequences, because it is used to do scalar replacement of aggregates, which seems to not dependent on other passes. After applying *-sroa*, some variables become dead stores, then the *-dse* pass, which intends to remove assignments of variables that are not read by any subsequent instructions, can be used to eliminate these stores. And after merging the same constant or the same variable with the pass *-constmerge*, the *-correlated-propagation* pass can be used to propagate values more effectively.

5.3 Comparison with State-of-the-Art Methods

The goal of this experiment is to evaluate the performance of the proposed iterative compilation method ICMC and make a comparison with several state-of-the-art compiler phase ordering methods.

5.3.1 Experimental Design. Five compiler phase ordering methods are used as baseline methods, including Focus Search [1], IS Pred. [3], MiCOMP [4], CF-TUNE [14], and CF-PS [11].

Table 1. The 5 Best Pass Subsequences and Their Harmonic Average Speedup with Respect to LLVM -O3

Pass subsequences	Speedup
-mem2reg -correlated-propagation -scoped-noalias -globals-aa -lcssa -jump-threading -tti -lazy-value-info -adce -dse -globalopt	1.106
-sroa -assumption-cache-tracker -dse -tailcallelim -constmerge -correlated-propagation -inferattrs -mem2reg -argpromotion -ipsccp -loops	1.106
-sroa -dse -assumption-cache-tracker -tailcallelim -constmerge -correlated-propagation -inferattrs -argpromotion -ipsccp -loops -mem2reg -scoped-noalias	1.104
-sroa -assumption-cache-tracker -dse -constmerge -loop-vectorize -lazy-value-info -argpromotion -correlated-propagation -globals-aa -inferattrs -mem2reg -ipsccp -loops -scoped-noalias	1.095
-sroa -assumption-cache-tracker -dse -constmerge -correlated-propagation -argpromotion -inferattrs -mem2reg -ipsccp -loops -scoped-noalias	1.093

- *Focus Search* [1] is a search-based compiler-phase ordering method that employs a Markov model to automatically search in those areas likely to achieve the best performance.
- *Intermediate Speedup Predictor (IS Pred.)* [3] is an iterative compilation method that tries to predict the next-best pass or subsequence iteratively with a learned linear regression model given the current state of the target program.
- *MiCOMP* [4] is a complete sequence prediction method that uses a regression model to directly predict the best whole sequence for a given program.
- *CF-TUNE* [14] is a complete sequence prediction method based on matrix factorization.
- *CF-PS* [11] is a collaborative filtering-based method proposed for pass selection. We extend it for phase ordering by considering complete pass sequences rather than pass sets as the items to be recommended.

For Focus Search, we run a random search of 1,000 evaluations for each program with passes used in LLVM -O3 as offline training data as in [1]. Moreover, we use Laplace smoothing to avoid the sparse Markov transition matrix problem. For regression-based baselines, IS Pred. and MiCOMP, we set the parameter of PCA as $k = 10$ to retain over 98% of the overall variance across all training data as in [3]. For CF-TUNE and CF-PS, we randomly choose 1,000 configurations composed of the subsequences used in MiCOMP [4] and IS Pred. [3], and other parameters are set as [14] and [11], respectively. Table 2 lists the parameter settings used in this experiment for our ICMC method. An aggregated pass subsequence set, which includes 5 subsequences constructed with passes used in LLVM -O3 and 5 subsequences constructed with passes not used in LLVM -O3 by Algorithm 1, is used in ICMC. To ensure a fair comparison, all methods are set to run the same number of evaluations to evaluate the performance of predicted pass sequences for each test program, which is set as 15. For CF-TUNE, it requires another 15 evaluations for each test program to collect reaction features to make predictions.

5.3.2 Experimental Results. Table 3 shows the speedups of different methods with respect to the LLVM standard optimization level -O3. The proposed method ICMC gets the best performance on 29 out of the 32 programs compared with the baseline methods. In addition, it performs the same or better than LLVM -O3 on all the 32 programs. ICMC can reach an average speedup of 1.20 (up to 1.46) compared with the standard level -O3. On average, ICMC can achieve a performance

Table 2. Parameter Settings of ICMC

Parameter	Value
Number of kept effective passes K in Algorithm 1	40
Number of constructed subsequences c	5
Number of nearest neighbors k in Algorithm 2	5
The maximum number of iterations L	5
Number of recommended subsequences in each iteration n	3

Fig. 7. Friedman test on performance speedup of different methods. The midpoint on each horizontal line indicates the average ranking of the corresponding method's performance. The horizontal line shows the confidence interval with the significance level of 0.05 in the Bonferroni test. If the horizontal lines of two methods do not overlap, it means that there is a significant difference between them.

improvement of 17.65%, 11.10%, 7.14%, 10.09%, and 11.11% compared with Focus Search, IS Pred. MiCOMP, CF-TUNE, and CF-PS, respectively.

To further compare the performance of different methods, we appeal to statistical tests. The Friedman test results are shown in Figure 7. ICMC achieves the best performance among all the compared methods. It is significantly better than all the other methods involved in the comparison. Among the compared methods, Focus Search performs the worst, as it uses only a transition probability model on the passes while ignoring the program-specific features. These results confirm that with proper program features, machine learning-based methods can attain better performance.

Table 4 shows the time cost of different methods in the training and the test stages. The time cost is measured by the number of evaluations. For each evaluation, we compile and run a training or test program to collect the performance information of compilation optimization, e.g., running time of the compiled program. Compared with the complete sequence prediction methods, e.g., MiCOMP, CF-TUNE and CF-PS, the iterative intermediate compilation methods such as IS Pred. and ICMC greatly shorten the training process. Even taking the subsequence construction utilized in the preprocessing phase into consideration, the running time of ICMC is still shorter than that of MiCOMP. It is worth mentioning that both the subsequence construction and the model training are done offline and once. Compared with the offline time consumption of these processes, we focus more on the online time consumption of model test and application. However, with the

Table 3. Speedup of Different Methodswith Respect to LLVM -O3

Applications	Focus Search	IS Pred.	MiCOMP	CF-TUNE	CF-PS	ICMC
automotive_bitcount	0.99	1.00	0.93	0.96	<u>1.03</u>	1.07
automotive_qsort1	0.89	<u>0.92</u>	0.90	0.89	0.91	1.04
automotive_susan_c	1.10	1.19	1.33	1.32	<u>1.36</u>	1.38
automotive_susan_e	1.06	1.13	<u>1.32</u>	1.27	1.13	1.35
automotive_susan_s	1.12	1.18	1.16	1.06	<u>1.20</u>	1.23
bzip2d	<u>1.22</u>	1.18	1.21	1.17	1.19	1.40
bzip2e	1.02	1.08	1.28	1.10	1.20	1.28
consumer_jpeg_c	1.01	1.17	<u>1.31</u>	1.15	1.16	1.37
consumer_jpeg_d	1.06	1.20	1.20	<u>1.30</u>	1.23	1.35
consumer_mad	1.05	1.10	1.03	1.05	<u>1.08</u>	1.12
consumer_lame	1.10	1.13	1.18	1.11	<u>1.19</u>	1.22
consumer_tiff2bw	1.33	1.37	1.37	1.36	1.27	1.34
consumer_tiff2rgba	1.08	<u>1.39</u>	1.35	1.09	1.22	1.40
consumer_tiffdither	1.03	1.30	1.23	<u>1.31</u>	1.22	1.38
consumer_tiffmedian	1.07	<u>1.41</u>	1.39	1.18	1.25	1.45
network_dijkstra	1.00	<u>1.04</u>	1.03	0.86	0.91	1.04
network_patricia	0.96	0.92	1.01	<u>1.03</u>	0.86	1.05
office_ghostscript	1.15	1.22	1.20	1.25	1.23	1.37
office_ispell	1.01	1.00	1.04	1.09	<u>1.11</u>	1.15
office_rsynth	0.99	0.93	<u>1.04</u>	1.01	0.94	1.05
office_stringsearch1	0.89	<u>0.92</u>	0.78	0.87	0.82	1.04
security_blowfish_d	1.03	1.05	<u>1.06</u>	1.04	0.91	1.08
security_blowfish_e	1.03	1.08	1.10	1.07	0.94	1.06
security_pgp_d	0.98	1.02	1.05	<u>1.12</u>	1.08	1.33
security_pgp_e	0.92	1.03	1.10	1.14	<u>1.17</u>	1.22
security_rijndael_d	0.96	0.95	0.98	<u>0.99</u>	0.98	1.02
security_rijndael_e	<u>0.99</u>	0.96	0.98	0.96	0.98	1.00
security_sha	0.92	<u>1.02</u>	1.00	<u>1.02</u>	1.01	1.08
telecom_adpcm_c	1.04	1.23	<u>1.40</u>	1.23	1.39	1.46
telecom_adpcm_d	1.07	1.13	<u>1.18</u>	1.10	1.16	1.20
telecom_crc32	<u>1.04</u>	0.98	1.02	1.01	0.99	1.09
telecom_gsm	0.92	0.87	1.24	1.24	1.17	1.21
Harmonic Mean	1.02	1.08	1.12	1.09	1.08	1.20
# of best perf.	0	1	4	1	0	29

The best results are bolded and the best baseline results are underlined. The last row denotes the number of best speedups of each method out of the 32 test applications.

same online time consumption, the offline time consumption determines the relative execution efficiency of different methods.

Considering the rapid development of LLVM, we also compare the proposed method ICMC with three baselines, including Focus Search [1], CF-TUNE [14] and CF-PS [11], using the latest LLVM v12.0. We simply use the last program of each sector in alphabetical order as test programs, including automotive_susan_s, bzip2e, consumer_tiffmedian, network_patricia, office_stringsearch1, security_sha and telecom_gsm. The other 25 programs are used as training programs. As shown in Table 5, the proposed method ICMC performs the best on all seven test programs and achieves

Table 4. Time Cost of Different Methods Measured by the Number of Evaluations (# of Evals Per Program)

Method	Subsequence construction	Training phase	Test phase
Focus Search	-	1000	15
IS Pred.	-	4	15
MiCOMP	0	3906	15
CF-TUNE	-	1000	15 + 15
CF-PS	-	1000	15
ICMC	3331	10	15

Table 5. Speedup of Different Methods with Respect to -O3 Using LLVM v12.0

Applications	Focus Search	CF-TUNE	CF-PS	ICMC
automotive_susan_s	1.09	<u>1.20</u>	<u>1.20</u>	1.26
bzip2e	1.10	<u>1.27</u>	1.21	1.31
consumer_tiffmedian	1.32	1.37	<u>1.40</u>	1.47
network_patricia	0.92	<u>0.94</u>	0.85	1.06
office_stringsearch1	0.78	0.84	<u>0.91</u>	1.01
security_sha	0.90	<u>1.06</u>	1.03	1.12
telecom_gsm	0.95	1.18	<u>1.22</u>	1.28

a performance improvement of 21.76%, 9.43% and 10.18% compared with Focus Search, CF-TUNE and CF-PS, respectively, on average.

5.4 Ablation Studies

The goal of this experiment is to evaluate the effectiveness of module design of ICMC.

5.4.1 Experimental Design. There are several key modules in ICMC, including pass subsequence construction, metric learning, data collection, and enhancement. To evaluate the effectiveness of these modules, we replace them with some traditional methods and compare the performance of ICMC before and after the replacement. For pass subsequence construction, we try to replace our data-driven method with MiCOMP's method. For metric learning, we try to replace the supervised metric learning method with traditional PCA. For data collection and enhancement, we try to compare the performance of ICMC with and without data enhancement on different feature sets.

To evaluate the relative effectiveness of different methods, we define a metric, called *improvement ratio*, to measure the relative effectiveness of a method B over another method A on a program p as follows:

$$\text{improvement_ratio}(p, A, B) = \frac{t(p, A)}{t(p, B)}, \quad (16)$$

where $t(p, A)$ and $t(p, B)$ denote the execution time of the program p optimized by method A and method B , respectively. $\text{Improvement_ratio}(p, A, B) > 1$ means that method B is more effective than method A for program p .

5.4.2 Experimental Results. Figure 8 shows the effectiveness of subsequence construction and metric learning of ICMC. Compared with unsupervised PCA, the supervised metric learning method is more effective when combined with different pass subsequence sets. It confirms that the supervised metric learning method can help to capture the preference similarity between

Fig. 8. Effectiveness of subsequence construction and supervised metric learning. (a) Harmonic mean speedup with different module settings with respect to LLVM -O3. (b) Improvement ratios of the proposed modules compared with traditional methods. ICMC-MiCOMPSQ denotes ICMC with subsequences replaced by MiCOMP's subsequences. ICMC-O3 denotes ICMC with only passes in -O3. ICMC-AP denotes ICMC with all available passes. ICMC-ML denotes ICMC with the supervised metric learning method. ICMC-PCA denotes ICMC with metric learning replaced by traditional PCA.

programs while mitigating the effects of redundant and irrelevant features for compilation optimization. Compared with MiCOMP's subsequence construction method, our subsequence construction method is more effective with only the passes in the standard -O3 sequence. It shows the ability of our data-driven method to capture the collaborations among passes. In addition, our data-driven method can make use of passes not contained in the -O3 sequence. Experimental results show that it can significantly improve the performance of ICMC with the help of these passes on most programs. This finding confirms that the use of extra passes can provide more useful optimization options for different code segments and produce better optimization effects.

Figure 9 shows the effectiveness of data collection and enhancement of ICMC. Compared with using only dynamic program features, the adding of static code features can improve the performance of iterative compilation. With the help of the proposed data enhancement method, we can significantly improve the performance of ICMC.

5.5 Effects of Different Parameter Settings

The goal of this experiment is to evaluate the effects of different parameter settings on the performance of ICMC.

5.5.1 Experimental Design. There are several key parameters for ICMC, including the number of passes retained to construct subsequences K , the number of constructed pass subsequences c , the number of nearest neighbors used for personalized recommendation k , the length of the recommendation list in each iteration n , and the maximum number of iterations L , i.e., the maximum length of sequences. We evaluate the effects of different settings of these parameters on the performance of ICMC.

5.5.2 Experimental Results. Figure 10 shows the effects of different settings of the number of retained passes K and the number of constructed subsequences c . It demonstrates that the performance of ICMC is relatively stable when the values of K and c are not too small or too large. When the value of K , i.e., the number of passes used to construct subsequences, is too small, ICMC yields

Fig. 9. Effectiveness of data collection (feature choices) and enhancement. (a) Harmonic mean speedup with different module settings with respect to LLVM -O3. (b) Improvement ratios of the proposed modules compared with traditional methods. ICMC-woSF denotes ICMC without using static code-features. ICMC-woDE denotes ICMC without using data enhancement.

Fig. 10. The effects of different settings of the number of retained passes K (rows) and the number of constructed subsequences c (columns).

a poor performance for ignoring many useful passes. In consideration of both performance and complexity, we suggest to set $K = 40$ and $c = 5$.

Table 6 shows the effects of different settings of the neighborhood size k and the length of the recommendation list in each iteration n . As the value of n increases, the performance of ICMC first increases significantly and then remains stable. The effect of parameter k is similar. In consideration of both performance and complexity, we suggest to set $k = 5$ and $n = 3$.

Table 6. The Effects of Different Settings of the Neighborhood Size k and the Length of the Recommendation List in Each Iteration n

	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
$k = 3$	1.131	1.149	1.172	1.171	1.190
$k = 5$	1.140	1.170	1.196	1.204	1.199
$k = 7$	1.148	1.163	1.196	1.199	1.195
$k = 9$	1.148	1.166	1.183	1.181	1.188

Fig. 11. Effect of the max length of the sequence L .

Figure 11 shows the performance of ICMC with various maximum numbers of iterations L , i.e., the maximum length of sequences. As the value of L increases, the performance of ICMC first increases and then tends to be stable. In consideration of both performance and complexity, we suggest to set $L = 5$.

6 CONCLUSIONS

To address the compiler pass selection and phase ordering problem, which is an NP-hard problem, we first proposed a data-driven subsequence construction method. It can not only prune the search space but can also make use of all available passes besides those not contained in standard compiler levels. Then, we proposed an iterative compilation method based on collaborative filtering and metric learning, which can effectively find some suitable pass sequences for a new program with a few compilations and evaluations.

In this article, we only took the reduction of execution time as the objective. However, there are several other objectives in real applications, such as the reduction of the code size or energy consumption. In the future, we will evaluate the performance of ICMC with these objectives and study the multi-objective compiler auto-tuning problem [19]. Furthermore, during the construction of the pass subsequence, we focused on the pairwise dependency among passes. In the future, we will mine more complex and high-order dependency among passes. In addition, since we only used the program features extracted by two existing tools, some useful information for our task may have been overlooked. Therefore, in the future, we will try to directly learn features from program source codes or intermediate representations [17, 34].

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