Applying Logistic Regression Model on HPX Parallel Loops

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***Abstract*—The performance of many parallel applications depend on the loop-level parallelism. However, manually parallelizing all loops may result in degrading parallelization performance, as some of the loops cannot scale desirably on more number of threads. In addition, the overheads of manually setting chunk sizes might avoid an application to reach its maximum parallel performance. We illustrate how machine learning techniques can be applied to address these challenges. In this research, we develop a framework that is able to automatically capture the static and dynamic information of a loop. Moreover, we advocate a novel method for determining execution policy and chunk size of a loop within an application by considering those captured information implemented within our learning model. Our evaluated execution results show that the proposed technique can speed up the execution process up to 45%.**

I. Introduction

Runtime information is often speculative, solely relying on it doesn't guarantee maximizing parallelization performance, since the parallelization performance of an application depends on both the values measured at runtime and the related transformations performed at compile time. Collecting outcome of the static analysis performed by the compiler could significantly improve the runtime performance. These captured information should be analyzed to optimize the application's parameters for achieving maximum parallelization. However, manually tuning parameters becomes ineffective and almost impossible when too many features are given to the program. Hence, many researches have extensively studied machine learning algorithms to optimize such parameters automatically.

For example in [1], nearest neighbors and support vector machines are used for predicting unroll factors for different nested loops based on the extracted static features. In [2], clustering algorithm is implemented for examining different benchmarks for their similarities to reduce the time needed for evaluating other similar benchmarks and estimating their performances. In [3], neural network and decision tree are applied on the training data collected from different observations to predict the branch behavior in a new program.

Most of these existing optimization techniques require users to compile their application twice, first compilation for extracting static information and the second one for recompiling application based on those extracted data. Also, none of them considers both static and dynamic information. The goal of this research is to optimize an HPX performance by predicting optimum execution policy and efficient chunk size for its parallel algorithms by considering both static and dynamic information and to develop a technique to avoid unnecessary compilation. To the best of our knowledge, we present a first attempt in implementing learning model for the loop parameters prediction at runtime, in which designing these runtime techniques and capturing learning models features are automatically performed at compile time.

II. Learning Algorithm

A. Binary Logistic Regression Model

For predicting optimum execution policy (sequential or parallel), we implement a binary logistic regression model [4] for analyzing extracted information from a loop. The wights parameters $W^T = [\omega_0, \omega_1, \omega_2, ...]$ are determined by considering features values $x_r(i)$ of each experiment $X(i) = [1, x_1(i), x_2(i), ...]^T$ for minimizing log-likelihood of the Bernoulli distribution value $\mu(i) = 1/(1 + e^{-W^T x(i)})$. The values of ω are updated as follow:

$$\omega_{k+1} = (X^T S_k X)^{-1} X^T (S_k X \omega_k + y - \mu_k) \tag{1}$$

In equation (1), S is a diagonal matrix with $S(i,i) = \mu(i)(1 - \mu(i))$. The output is determined by considering decision rule as follow:

$$y(x) = 1 \longleftrightarrow p(y = 1|x) > 0.5 \tag{2}$$

B. Multinomial Logistic Regression Model

For predicting optimum chunk size, we implement a multinomial logistic regression model [4] for analyzing extracted information from a loop. The posterior probabilities are computed by using softmax transformation of the feature variables linear functions as follow:

$$y_{nk} = y_k(\phi_n) = \frac{exp(W_h^T \phi(X_n))}{\sum_j exp(W_j^T \phi(X_n))} \tag{3}$$

The cross entropy error function is defined as follow:

$$E(\omega_1, \omega_2, ..., \omega_k) = -\sum_n \sum_k t_{nk} ln y_{nk} \tag{4}$$

, where T is a matrix of target variables with t_{nk} elements. The gradient of E is computed as follow:

$$\nabla_{\omega_j} E(\omega_1, \omega_2, ..., \omega_k) = \sum_n (y_{nj} - t_{nj}) \phi(x_n) \tag{5}$$

We use the Newton-Raphson for updating the weights values:

$$\omega_{new} = \omega_{old} - H^{-1} \nabla E(\omega) \tag{6}$$

, where H is the Hessian matrix defined as follow:

$$\nabla_{\omega_k} \nabla_{\omega_j} E(\omega_1, \omega_2, ..., \omega_k) = \sum_n y_{nk} (I_{kj} - y_{nj}) \phi(x_n) \phi^T(x_n) \tag{7}$$

III. Proposed Model

In this section, we propose a new technique categorized as follow for applying learning models described in section II.

A. Special Execution Policies and Parameter

We introduce new execution policy and parameter in HPX, which applying them on the loops makes implementing learning model on those loops. *par_if* is a new execution policy for implementing binary logistic regression model for determining optimum execution policy. *adaptive_chunk_size* is a new execution policy's parameter for implementing multinomial logistic regression model for choosing efficient chunk size. Fig.1 shows two loops defined with these new execution policy and parameter.

```
for_each(par_if, range1.begin(), range1.end(), lambda1);

for_each(policy.with(adaptive_chunk_size),range2.begin(),
      range2.end(),lambda2);
```

Figure 1: Before compilation.

static/dynamic	Information
dynamic	number of threads*
dynamic	number of iterations*
static	number of total operations*
static	number of float operations*
static	number of comparison operations*
static	deepest loop level*
static	number of integer variables
static	number of float variables
static	number of if statements
static	number of if statements within inner loops
static	number of function calls
static	number of function calls within inner loops

Table I: Collected static and dynamic features.

B. Feature Extraction

We collect 10 static features at compile time and 2 dynamic features at runtime to determine a learning model that are listed in Table I. Although it may not be the best possible set, but it is very similar to those considered in the other works [1], [5], in which their results proved that set is sufficient to design a learning model. The first two features are measured dynamically at runtime and the rest of features are collected at compile time. For this purpose, we introduce a new class named *ForEachCallHandler* in the Clang compiler as shown in fig.2 that is intended to collect static information at compile time for the loops that use *par_if* as their execution policy or *adaptive_chunk_size* as their execution policy parameter. Each feature has a member in that class and they are calculated for each detected loop. These features are extracted from $lambda$ function of the loop by applying *getBody()* on a $lambda$ operator *getLambdaCallOperator()*. Then, the value of each of them are recorded by passing $lambda$ to *analyze_statement*. Dynamic features are also measured by implementing *hpx::get_os_thread_count()* and *std::distance(range.begin(), range.end())*.

For avoiding overfitting problem, we choose 5 critical features marked with red* color in Table I by implementing Principal Component Analysis Algorithm [4].

C. Learning Model Implementation

1) Implementing binary logistic regression model for determining efficient execution policy: A new function *seq_par* is proposed to pass the extracted features for the loops that use *par_if* as their execution policy. In this technique, the compiler adds extra lines within a user's code automatically as shown in fig.3a that makes runtime to decide whether execute a loop sequentially or parallel based on the output of *seq_par* from eq.2, in which the output 0 results in executing loop sequentially and the output 1 results in executing loop in parallel. The input of this function includes the extracted static information that is initialized during compilation. Number of threads and number of iterations are also measured and included in that features

```
class ForEachCallHandler:public MatchFinder::MatchCallback{
  virtual void run(const MatchFinder::MatchResult &Result){
    ...
    const SourceManager *SM = Result.SourceManager;
    //Capturing lambda function from a loop
    const CXXMethodDecl* lambda_callop =
          lambda_record->getLambdaCallOperator();
    Stmt* lambda_body = lambda_callop->getBody();
    //Capturing policy
    SourceRange policy(call->getArg(0)->getExprLoc(),
       call->getArg(1)->getExprLoc().getLocWithOffset(-2));
    std::string policy_string = Lexer::getSourceText(
         CharSourceRange::getCharRange(policy), *SM,
         LangOptions()).str();
    //Determining policy if a current policy is par_if
    if (policy_string.find("par_if") != string::npos){
      //Extracting static information from lambda function
         analyze_statement(lambda_body);
         policy_determination(call, SM);   }
    //Determining chunk size if a current policy's
         parameter is adaptive_chunk_size
    if(policy_string.find("adaptive_chunk_size")!=string::
         npos){
      //Extracting static information from lambda function
         analyze_statement(lambda_body);
         chunk_size_determination(call, SM); }}}
```

Figure 2: The proposed *ForEachCallHandler*.

```
if(seq_par({f0,f1,...fn}))
  for_each(seq, range1.begin(),range1.end(),lambda1);
else
  for_each(par, range1.begin(),range1.end(),lambda1);
```

(a) After compilation

```
bool seq_par(F &&features){
  return policy_costs_fnc(features,weights("weights.dat"));}
```

(b) Determining execution policy at runtime.

Figure 3: The proposed *seq_par*.

set at runtime. Fig.3b shows the policy determination approach implemented within *seq_par* for computing cost function by considering features and weights.

2) Implementing multinomial logistic regression model for determining efficient chunk size: A new function *chunk_size_determination* is proposed to pass the extracted features for a loop that uses *adaptive_chunk_size* as its execution policy's parameter. In this technique, a Clang compiler changes a user's code automatically as shown in fig.4a that makes runtime to choose an optimum chunk size by considering the output of *chunk_size_determination* from eq.3, that is based on the chunk size candidate's probability. In addition to the extracted compile time static information, number of threads and number of iterations are also automatically measured and included in this function at runtime. Fig.4b shows the chunk size determination approach implemented within *chunk_size_determination* for computing cost function by considering features and weights values.

```
for_each(policy.with(chunk_size_determination({f0,f1,...fn})
    )), range2.begin(),range2.end(),lambda2);
```

(a) After compilation

```
dynamic_chunk_size chunk_size_determination(F &&features){
  return chunk_costs_fnc(features,weights("weights.dat"));}
```

(b) Determining chunk size at runtime.

Figure 4: The proposed *chunk_size_determination*.

test	loop	*itr.	*opr.	*flt opr.	*comp. opr.	lvl	policy	chunk size
1	l_1	10	400	200	101	2	par	0.001
	l_2	20	450	250	150	2	par	0.001
	l_3	20	502	250	103	2	par	0.001
	l_4	0.5	550	200	150	1	par	0.1
2	l_1	150	350	101	0.5	2	par	0.001
	l_2	0.1	10050	5000	2505	3	seq	0.1
	l_3	0.1	25000	3010	1500	3	seq	0.1
	l_4	50	4000	200	100	1	par	0.01
3	l_1	0.5	4504	250	150	2	par	0.01
	l_2	0.4	3502	200	100	1	par	0.01
	l_3	2	250	150	103	3	seq	0.1
	l_4	2.5	350	150	100	3	seq	0.1
4	l_1	20	204	100	10	2	par	0.001
	l_2	30	400	150	10	2	par	0.001
	l_3	0.3	550	44	20	3	seq	0.1
	l_4	0.4	450	50	10	3	seq	0.1
5	l_1	0.2	4502	150	101	3	par	0.01
	l_2	0.7	400	300	150	3	par	0.01
	l_3	0.3	302	20	14	2	par	0.01
	l_4	0.1	50	20	10	2	seq	1

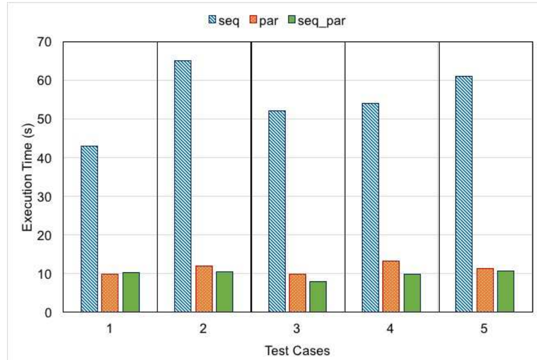
Table II: Execution policy and chunk size determined by *seq_par* and *chunk_size_determination* implementation. The values of the fields marked with * are divided by 10^3 because of the limited space.

IV. Experimental Results

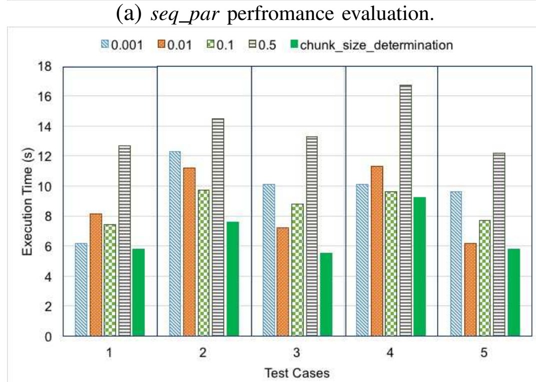
In this section, we evaluate the performance of the proposed techniques over different test cases with different characteristics shown in Table II, using Clang $4.0.0$ and HPX $0.9.99$ and on the test machine with two Intel Xeon E5-2630 processors, each with 8 cores clocked at $2.4GHZ$ and $65GB$.

1) seq_par: This function is able to make runtime to decide whether execute a loop sequentially or in parallel by considering static and dynamic features of that loop. Fig.5a shows the execution time for tests with 4 loops per each in Table II by choosing *seq* or *par* as an execution policy of all of its loops and implementing this proposed technique for choosing execution policy of those loops. Their determined final execution policies are included in Table II. Fig.5a illustrates that as the execution policy of all of the four loops of the first test case is determined as *par* by implementing this technique, due to the overhead of the *policy_costs_fnc* cost function, manually setting their execution policy as *par* resulted in having a better performance. However for the rest of the test cases, it illustrates that execution policy *seq* is determined for some of the loops that cannot scale desirably on more number of threads, which results in outperforming manually parallelized code by around $15\% - 20\%$.

2) chunk_size_determination: This function is able to make runtime to choose an efficient chunk size for a loop by considering static and dynamic features of that loop. It should be noted that the multinomial logistic regression model requires to know the chunk size candidates for choosing efficient one among them, which are chosen to be 0.001, 0.01, 0.1, and 0.5 of the number of iteration of a loop in this research. Fig.5b shows the execution time for tests with 4 loops per each in Table II by setting chunk size of all of its loops to be one of the candidates and determining efficient one using this proposed technique. Their determined chunk size are included in the last column of the Table II. The overall performance of these cases show up to 45%, 32%, 37% and 58% improvement over setting chunks to be 0.001, 0.01, 0.1, or 0.5 iterations.



(a) *seq_par* perfromance evaluation.



(b) *chunk_size_determination* perfromance evaluation.

Figure 5: The execution time comparisons for tests with 4 loops per each.

V. Conclusion and Future Works

In this paper, we developed new techniques that are able to implement the binary and multinomial logistic regression model to determine an optimum execution policy and chunk size for an HPX loop. These techniques are able to consider both static and dynamic features of a loop and to implement a learning technique at runtime to make an optimum decision for its execution without requiring extra compilation. We illustrated that the parallel performance of our test cases were improved by around $15\% - 45\%$ using our proposed technique. These results proved that combining machine learning technique, compiler and runtime methods helps in utilizing maximum resource availability for optimizing HPX parallel performance.

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