

# A Machine Learning Based Parallelization Assistant

Aleksandr Maramzin, Christos Vasiladiotis, Roberto Castañeda Lozano,  
Björn Franke, Murray Cole

The University of Edinburgh  
United Kingdom



AI-SEPS 2019 workshop



**SPLASH**  
ATHENS 2019

# A Machine Learning Based Parallelization Assistant

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“It Looks Like You’re Writing a Parallel Loop”



AI-SEPS 2019 workshop



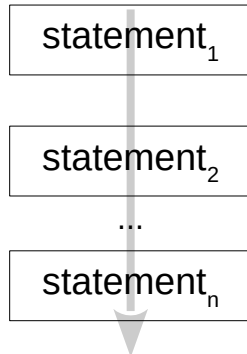
**SPLASH**  
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# Problem Statement

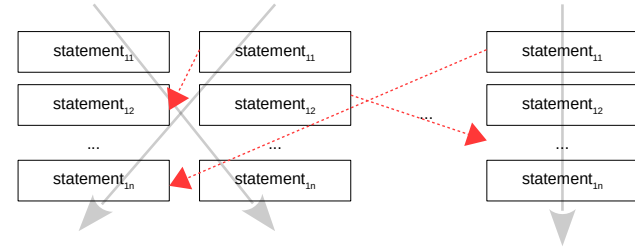
**Parallel Hardware  
is Ubiquitous**



**Software  
is Sequential**



**Automatic Parallelization  
is Limited**



**Manual Parallelization  
is Hard**



# Problem Statement

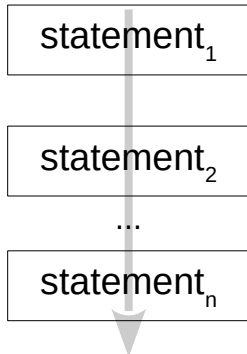
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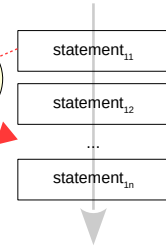
The **assistant solution** we propose alleviates  
the process of manual parallelization



Software  
is Sequential

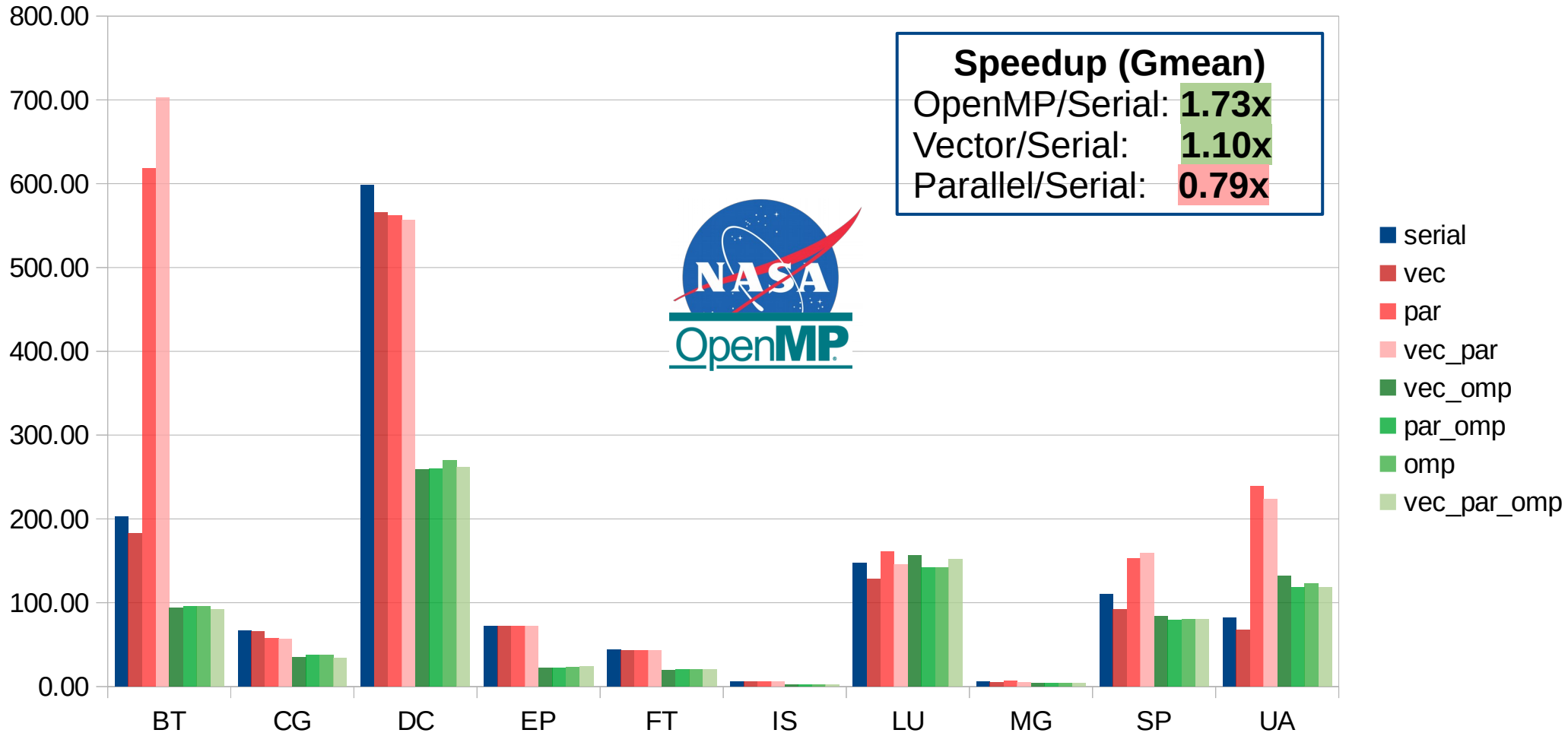


Manual Parallelization  
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# Problem Statement

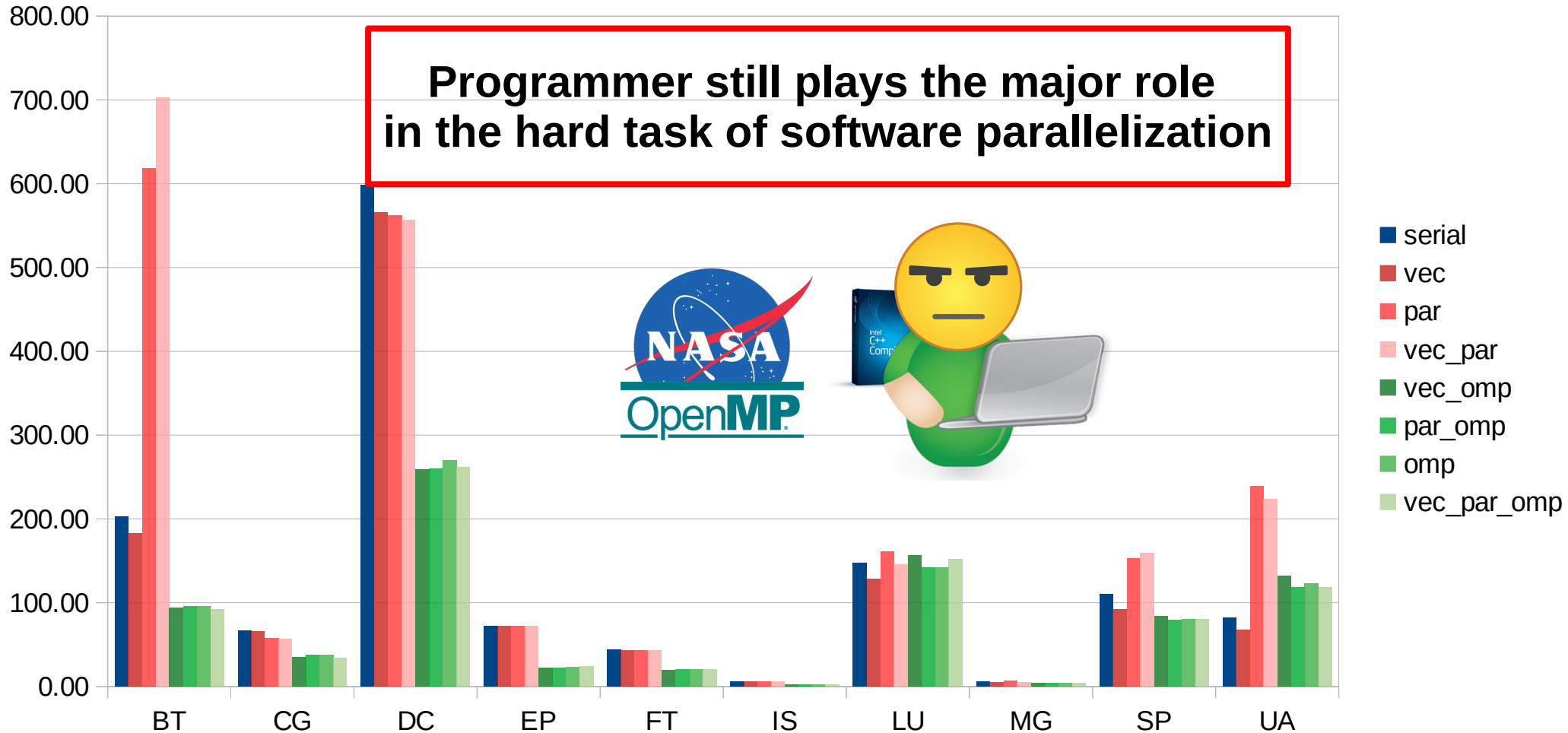
## NAS Parallel Benchmarks (NPB)



# Problem Statement

## NAS Parallel Benchmarks (NPB)

**Programmer still plays the major role  
in the hard task of software parallelization**



# Manual Parallelization: Where Should I Start?

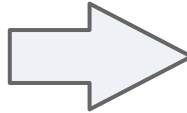
*Source Code*

$L_0$ :  
**for** (int i=0; ... ) {  
 ...  
}

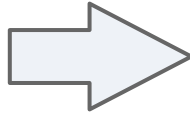
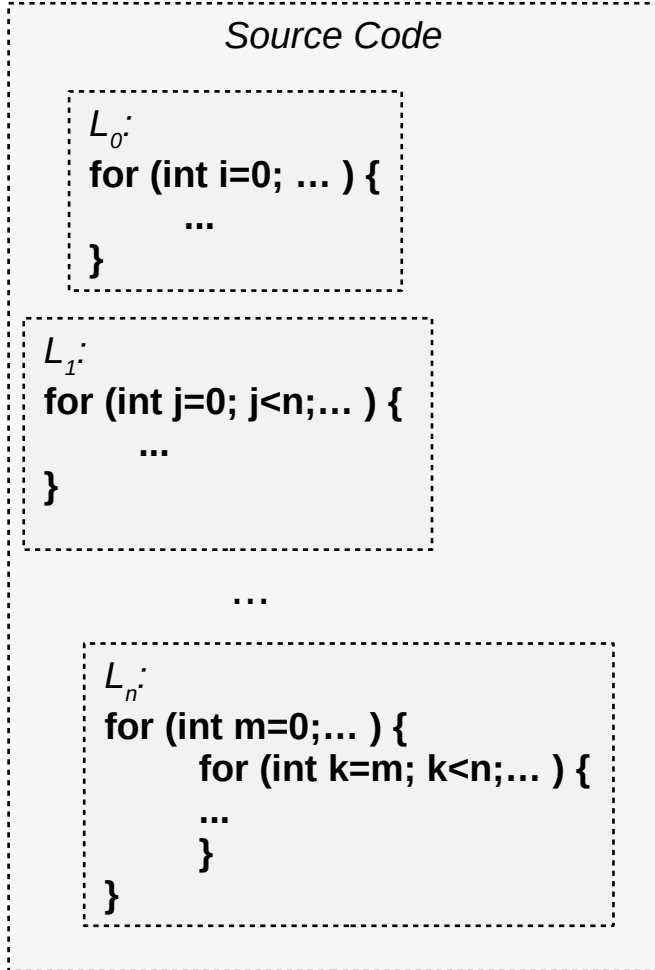
$L_1$ :  
**for** (int j=0; j<n;... ) {  
 ...  
}

...

$L_n$ :  
**for** (int m=0;... ) {  
 **for** (int k=m; k<n;... ) {  
 ...  
 }  
}



# Manual Parallelization: Where Should I Start?



Where Should I Start?



# Manual Parallelization: Where Should I Start?

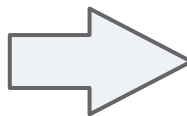
*Source Code*

$L_0$ :  
for (int i=0; ... ) {  
 ...  
}

$L_1$ :  
for (int j=0; j<n;... ) {  
 ...  
}

...

$L_n$ :  
for (int m=0;... ) {  
 for (int k=m; k<n;... ) {  
 ...  
 }  
}

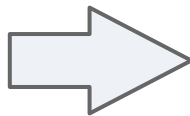
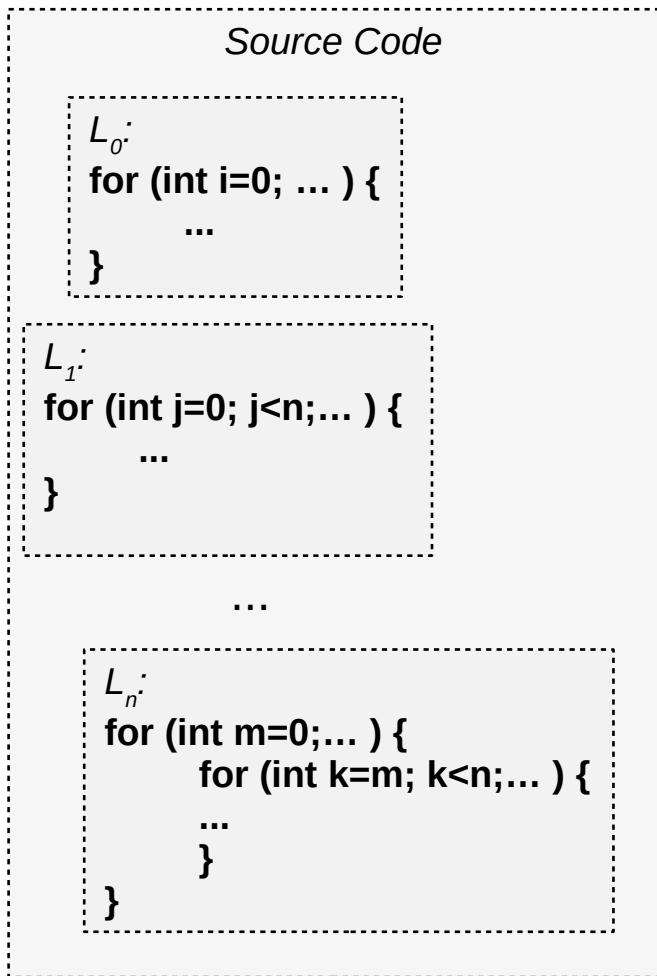


**Program Loop Rankings**

*Source Order*

$L_0, L_1, \dots, L_n$

# Manual Parallelization: Where Should I Start?

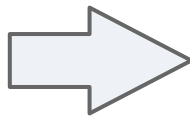
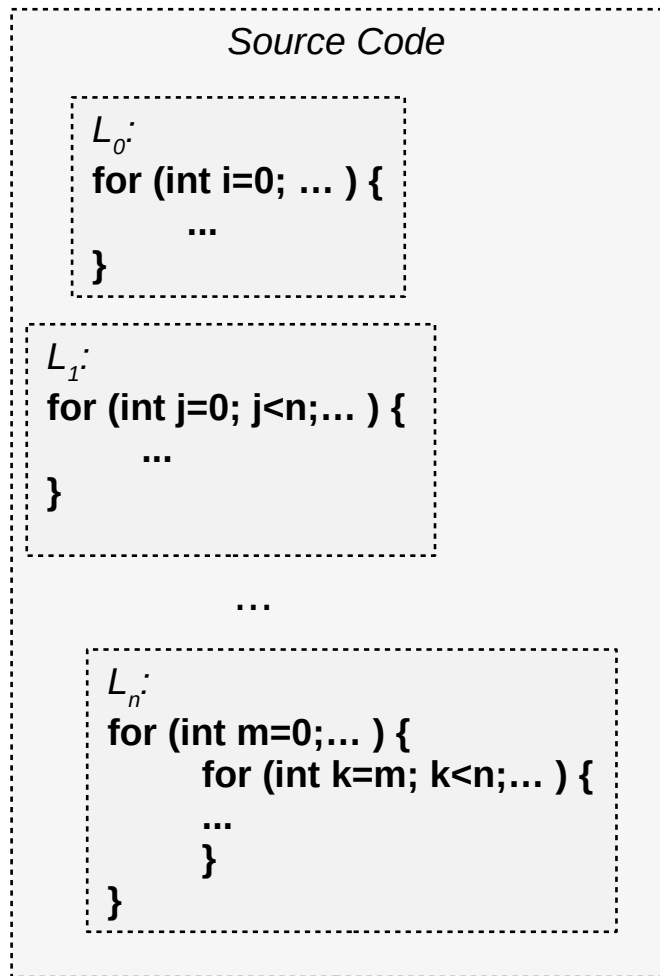


## Program Loop Rankings

Source Order  
 $L_0, L_1, \dots, L_n$



# Manual Parallelization: Where Should I Start?



## Program Loop Rankings

Source Order

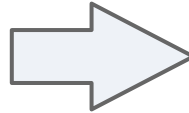
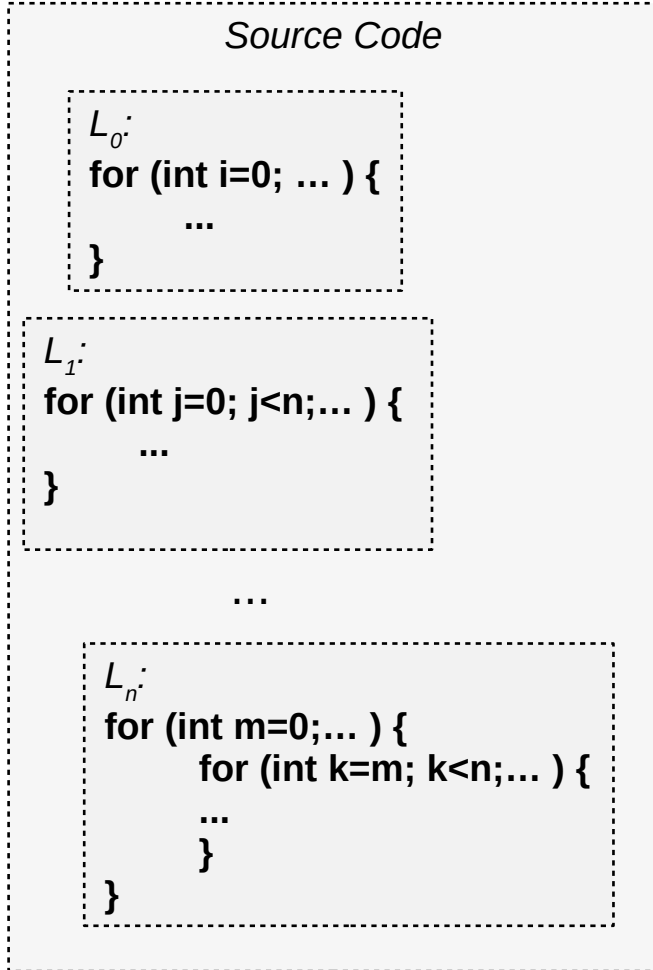
$L_0, L_1, \dots, L_n$



Profile Order

$L_{17}, L_{12}, \dots, L_1$

# Manual Parallelization: Where Should I Start?



## Program Loop Rankings

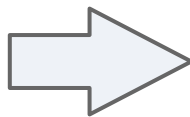
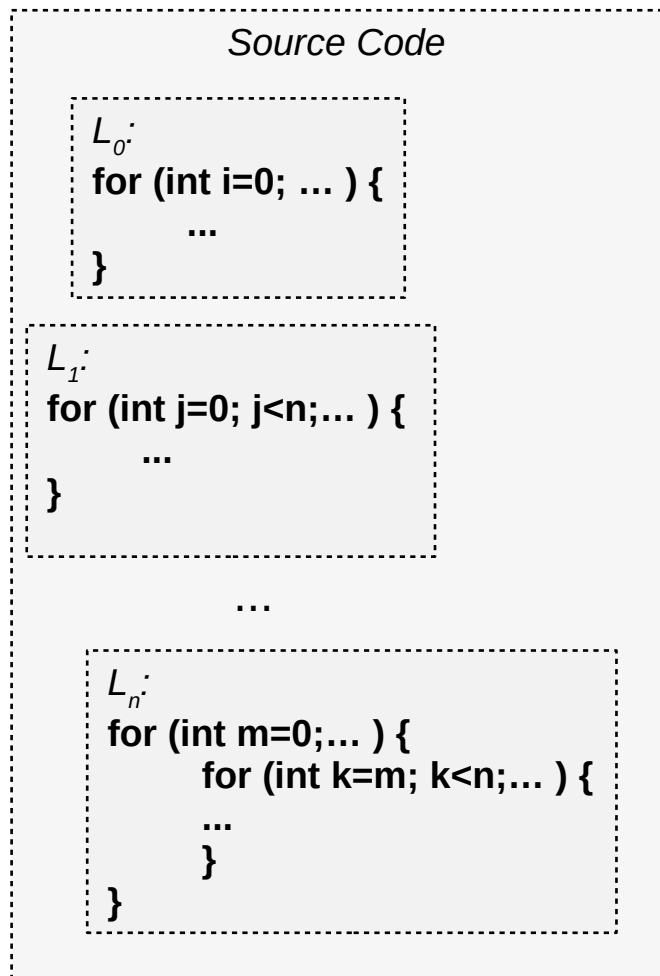
Source Order  
 $L_0, L_1, \dots, L_n$



Profile Order  
 $L_{17}, L_{12}, \dots, L_1$



# Manual Parallelization: Where Should I Start?



Traditional Empirical and Experimental Method

## Program Loop Rankings

Source Order

$L_0, L_1, \dots, L_n$



Profile Order

$L_{17}, L_{12}, \dots, L_1$



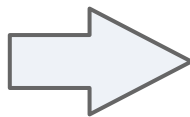
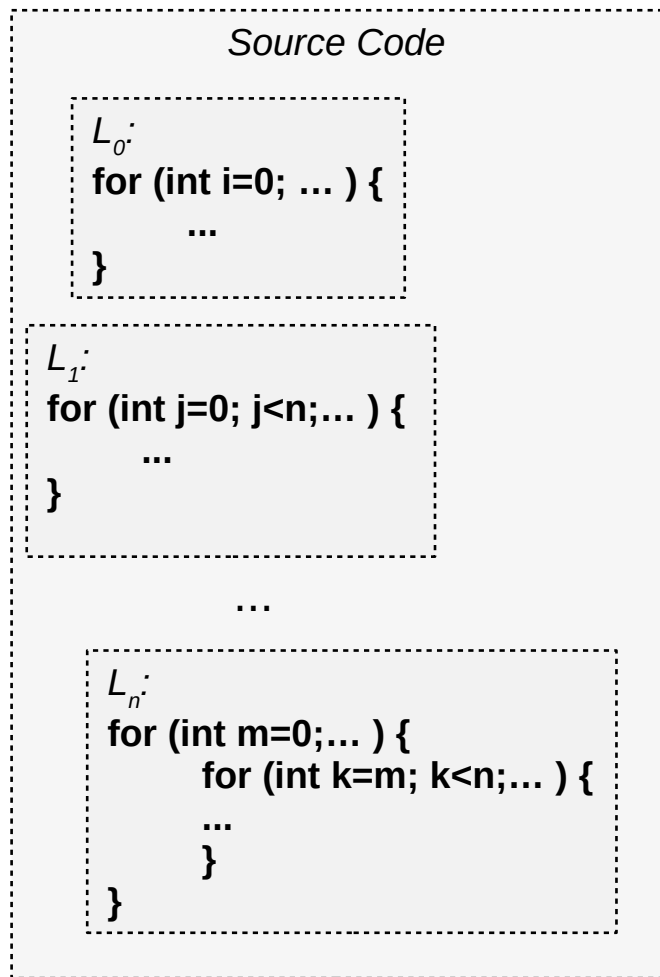
Profitability\* Order

$L_{12}, L_7, \dots, L_3$

AI-inspired Method

$$* \text{Profitability} = F\left(\frac{\text{Performance Gain}}{\text{Programmer Effort}}\right)$$

# Manual Parallelization: Where Should I Start?



Traditional Empirical and  
Experimental Method

## Program Loop Rankings

Source Order

$L_0, L_1, \dots, L_n$



Profile Order

$L_{17}, L_{12}, \dots, L_1$



Profitability\* Order

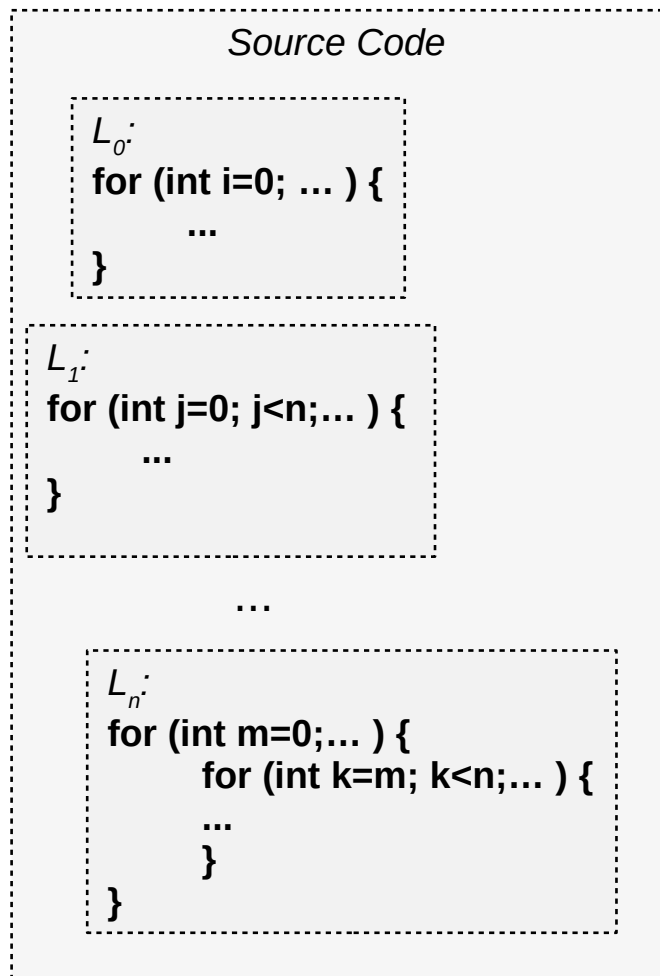
$L_{12}, L_7, \dots, L_3$



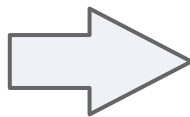
AI-inspired Method

$$* \text{Profitability} = F\left(\frac{\text{Performance Gain}}{\text{Programmer Effort}}\right)$$

# Manual Parallelization: Where Should I Start?



**Final Programmer  
Decision**



**Traditional Empirical and  
Experimental Method**



## Program Loop Rankings

Source Order  
 $L_0, L_1, \dots, L_n$



Profile Order  
 $L_{17}, L_{12}, \dots, L_1$



Profitability\* Order  
 $L_{12}, L_7, \dots, L_3$

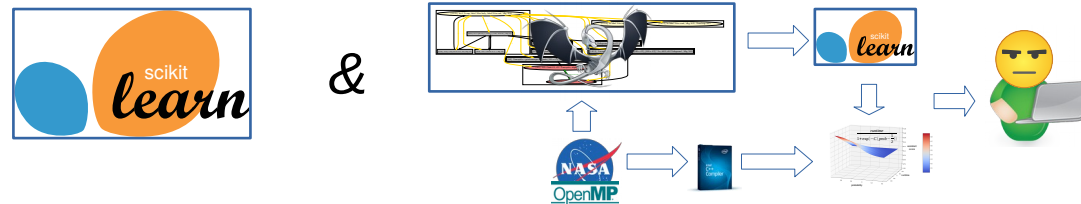


**AI-inspired Method**

$$* \text{Profitability} = F\left(\frac{\text{Performance Gain}}{\text{Programmer Effort}}\right)$$

# Proposed Solution: Software Parallelization Assistant

Tool                      Methodology

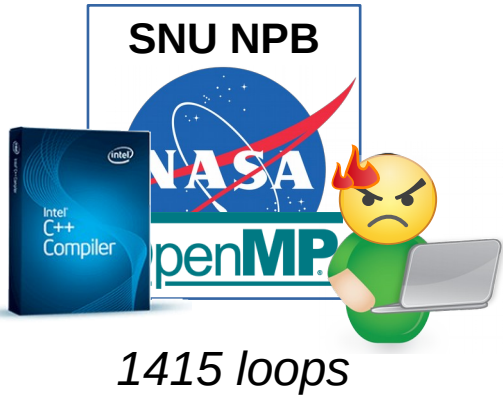


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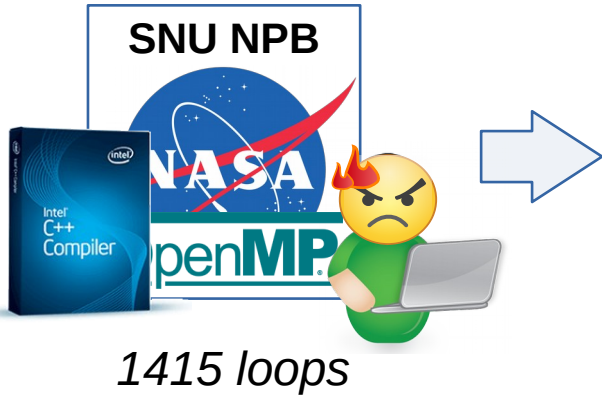


# Assistant Training

# Assistant Training



# Assistant Training



## Training Data Set

### Parallelizable loops

```
for (int i=...) { ... } [ f1, f2, ..., fn ]  
...  
for (int j=...) { ... } [ f1, f2, ..., fn ]
```

995 loops \*

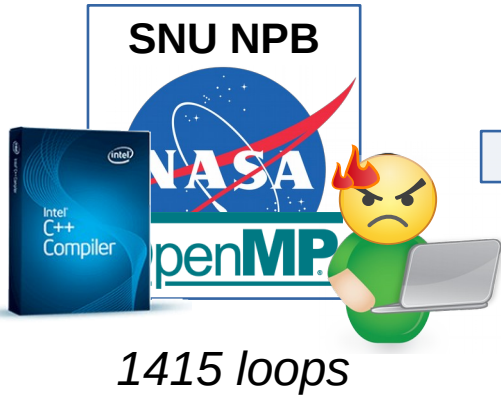
### Non-parallelizable loops

```
while (true) { ... } [ f1, f2, ..., fn ]  
...  
for (int k=...) { ... } [ f1, f2, ..., fn ]
```

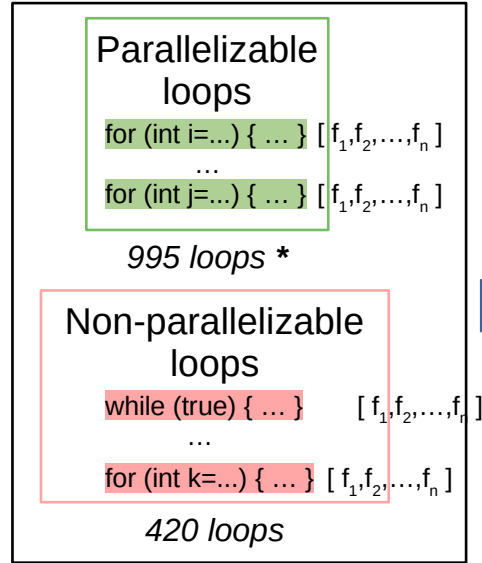
420 loops

\* Intel Compiler succeeds in parallelizing 812 loops

# Assistant Training



## Training Data Set

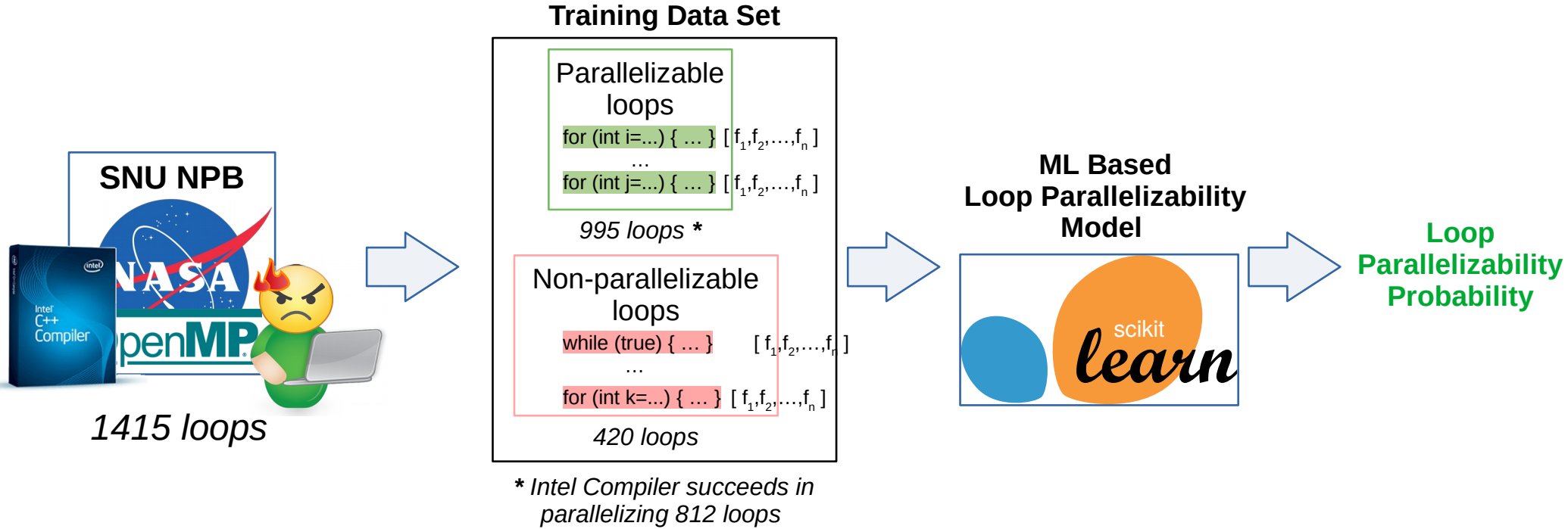


\* Intel Compiler succeeds in parallelizing 812 loops

## ML Based Loop Parallelizability Model

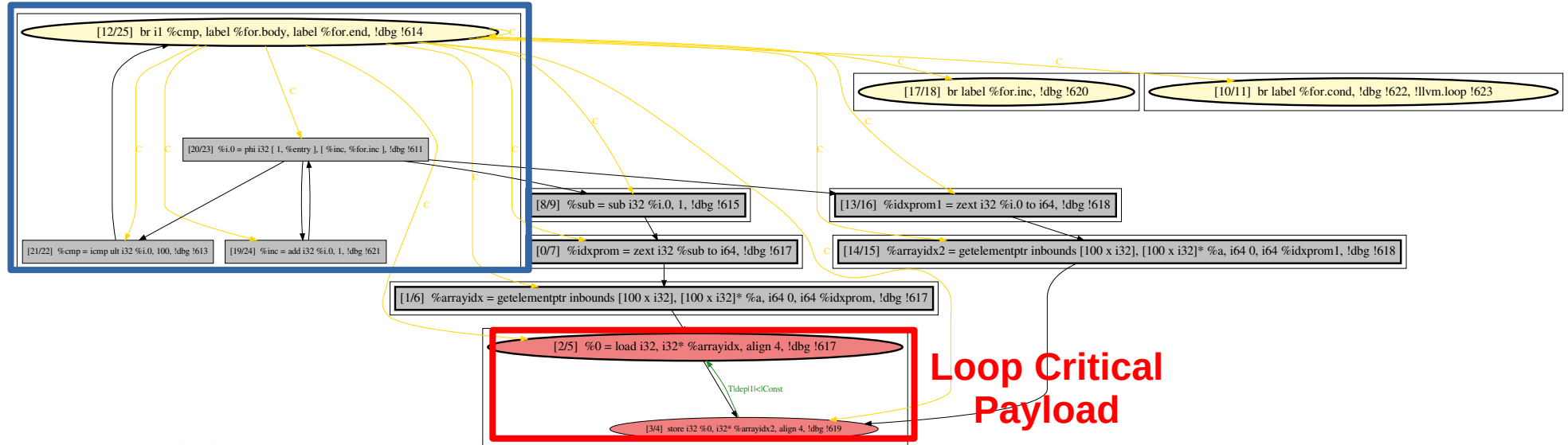


# Assistant Training



# Loop Features

## Loop Iterator



**Loop features** are based on static structural properties of loop program dependence graphs (PDGs):

- Absolute size
- Loop Iterator/Payload cohesion
- Number of dependence edges
- Instruction types (calls, loads/stores, etc.)
- etc.

# Loop Ranking Score

ML Based  
Loop Parallelizability  
Model



# Loop Ranking Score

ML Based  
Loop Parallelizability  
Model



Not Aware of Loop  
Running Time



# Loop Ranking Score

**Profiler**



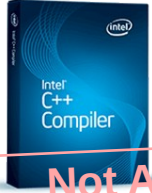
**ML Based  
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# Loop Ranking Score

## Profiler



Not Aware of Loop  
Parallelizability

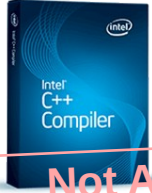
## ML Based Loop Parallelizability Model



Not Aware of Loop  
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# Loop Ranking Score

**Profiler**



**Not Aware of Loop  
Parallelizability**

**ML Based  
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Model**



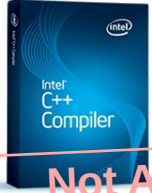
**Predicted Probability  
of Parallelization**



**Not Aware of Loop  
Running Time**

# Loop Ranking Score

Profiler



Potential Contribution  
to Speedup



Not Aware of Loop  
Parallelizability

ML Based  
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Predicted Probability  
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Not Aware of Loop  
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# Loop Ranking Score

Profiler



Not Aware of Loop Parallelizability

Potential Contribution to Speedup

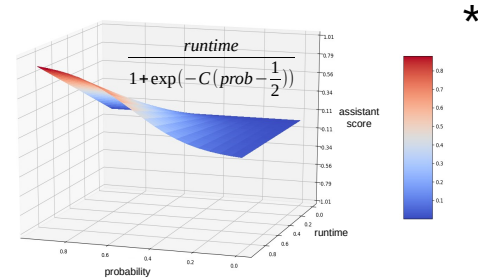


ML Based Loop Parallelizability Model



Not Aware of Loop Running Time

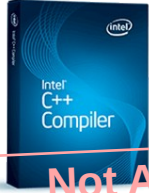
Predicted Probability of Parallelization



$$* \text{Profitability} = F\left(\frac{\text{Performance Gain}}{\text{Programmer Effort}}\right)$$

# Loop Ranking Score

Profiler



Not Aware of Loop Parallelizability

Potential Contribution to Speedup

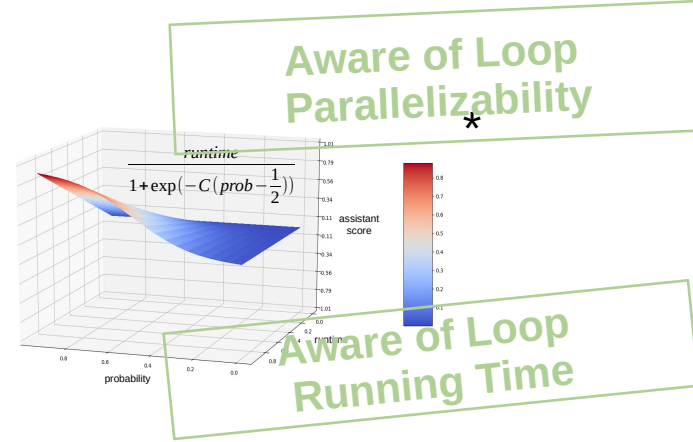


ML Based Loop Parallelizability Model



Not Aware of Loop Running Time

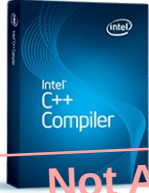
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# Loop Ranking Score

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Not Aware of Loop Parallelizability

Potential Contribution to Speedup

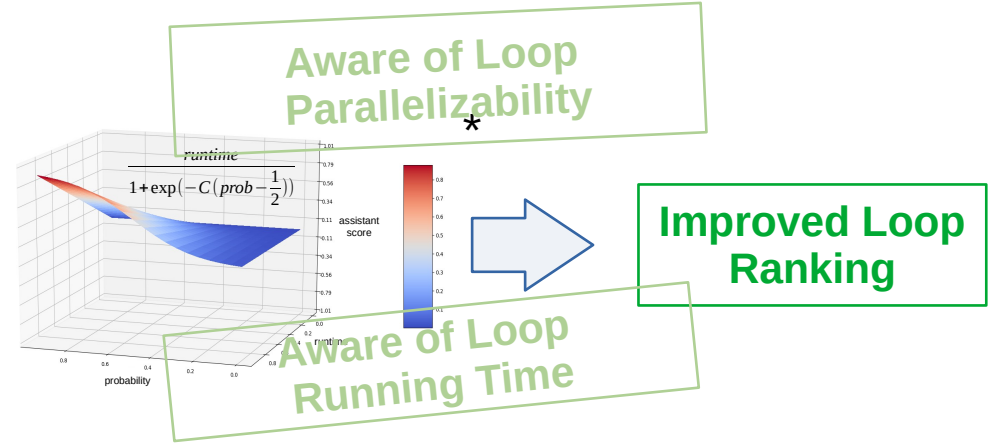


ML Based Loop Parallelizability Model



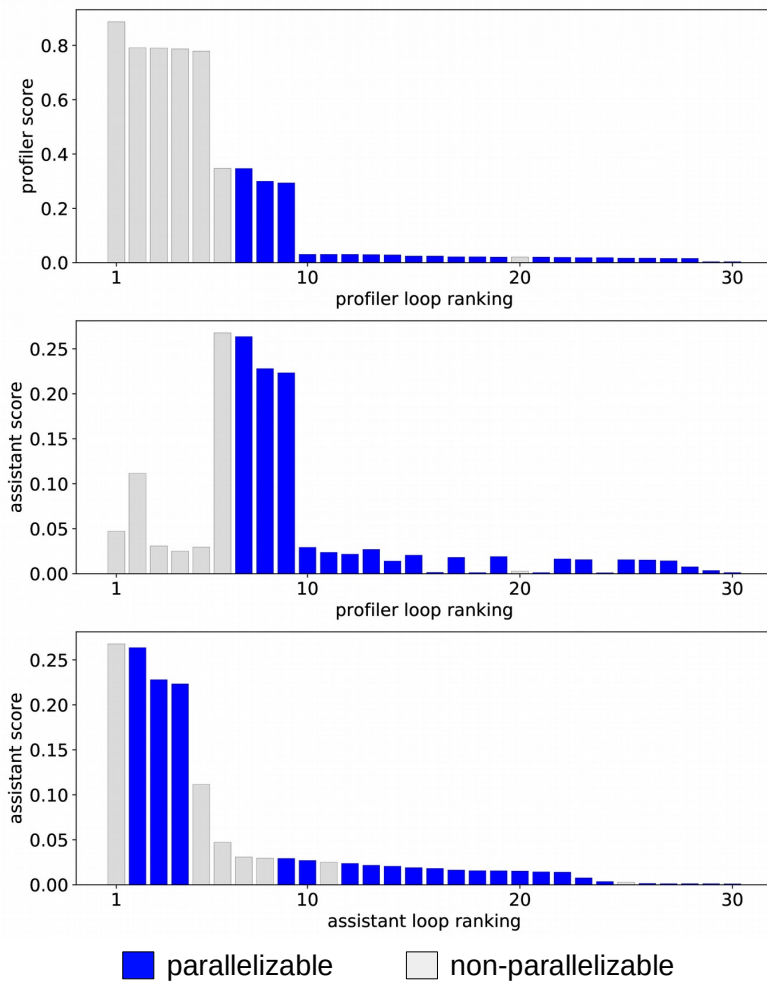
Not Aware of Loop Running Time

Predicted Probability of Parallelization



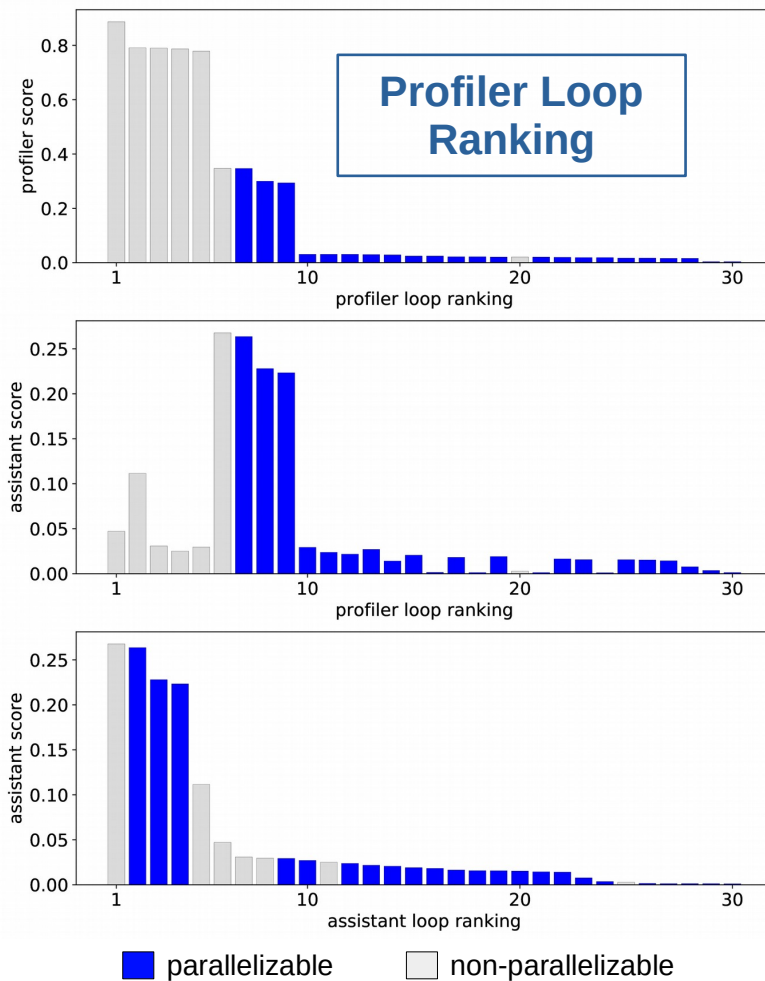
$$* Profitability = F\left(\frac{Performance\ Gain}{Programmer\ Effort}\right)$$

# Loop Rankings: Profiler vs. Assistant

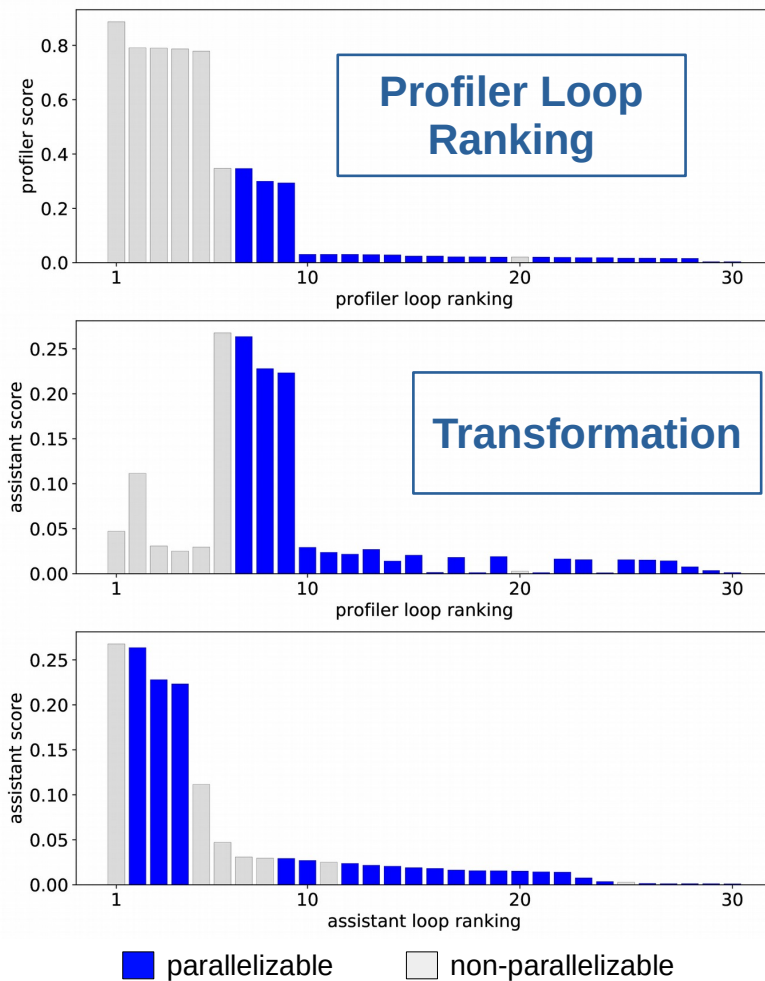




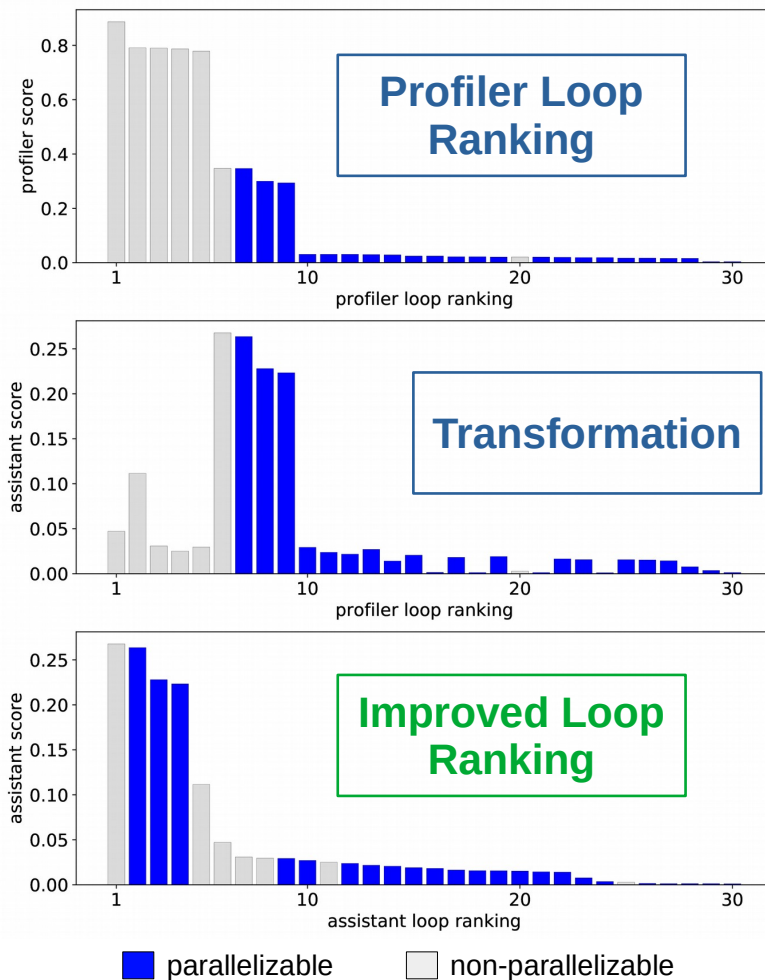
# Loop Rankings: Profiler vs. Assistant



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# Loop Rankings: Profiler vs. Assistant



## Results



Predictive performance of our ML based loop parallelizability model



Deployment of our assistant on SNU NPB benchmarks



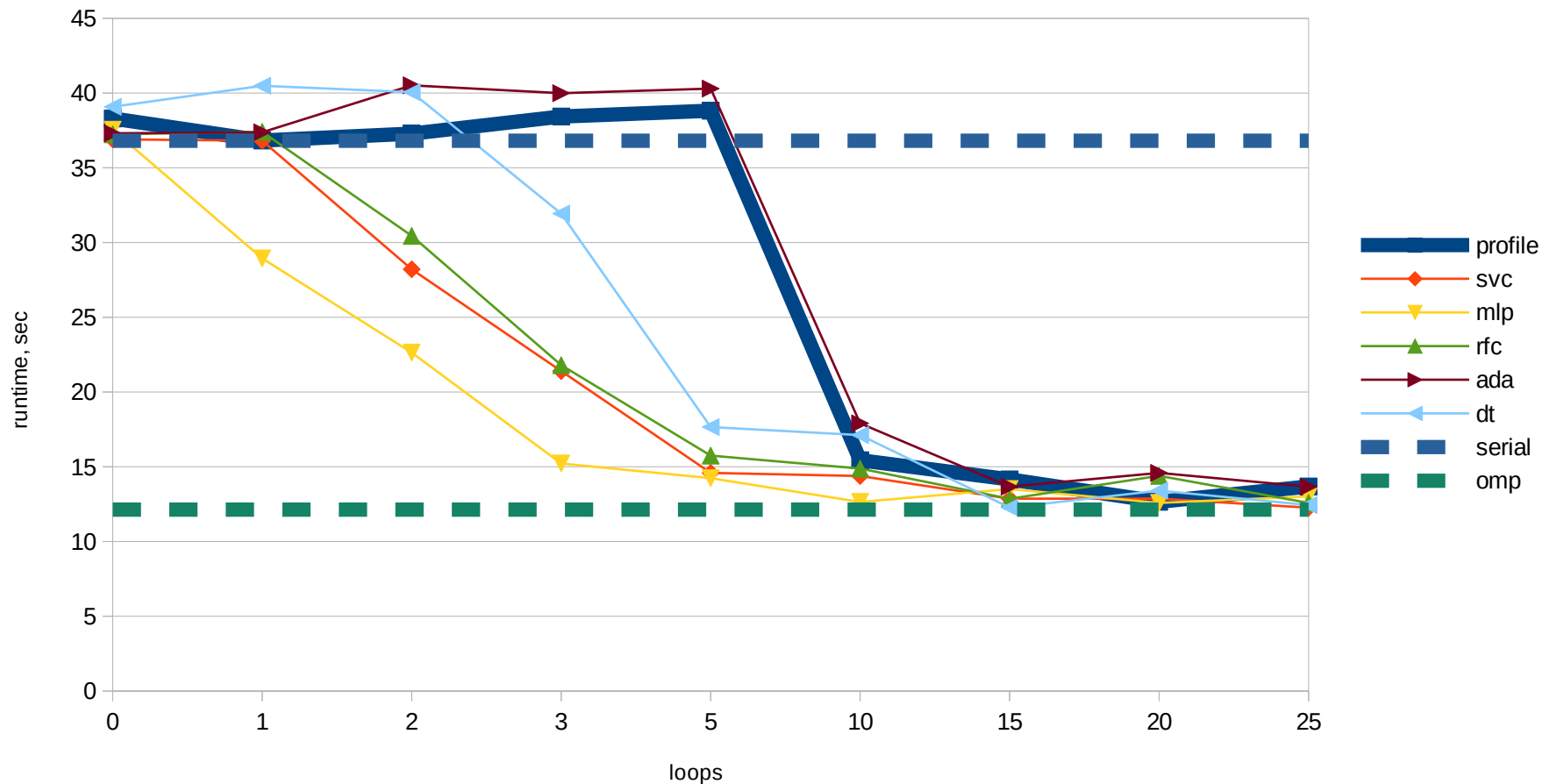
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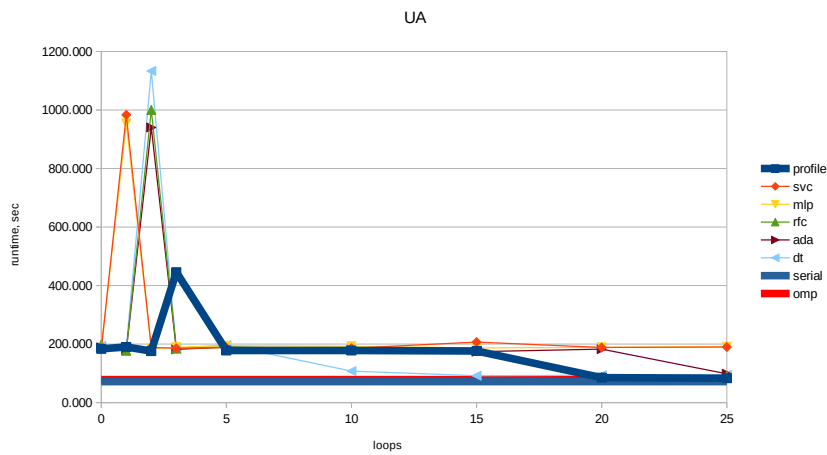
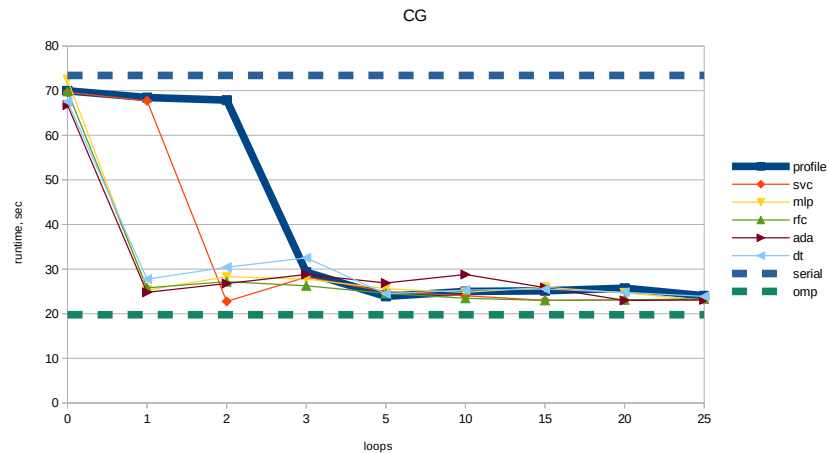




# How well do we do?

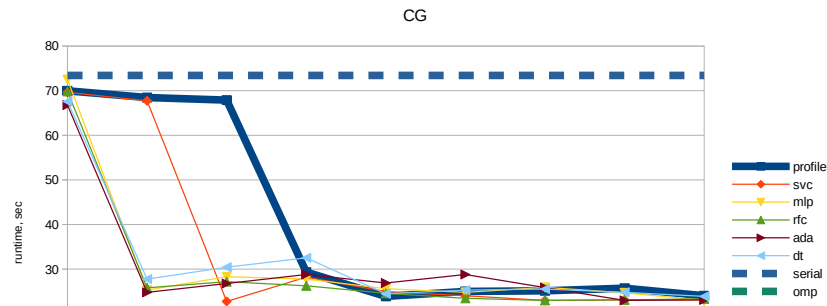
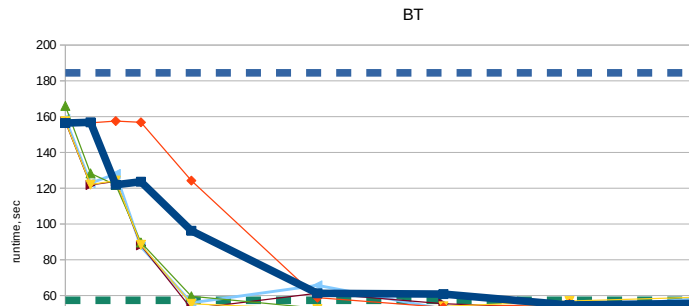
FT



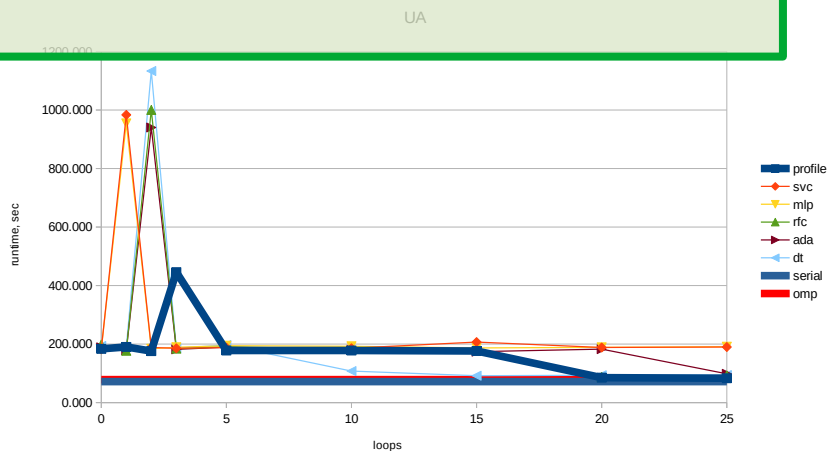
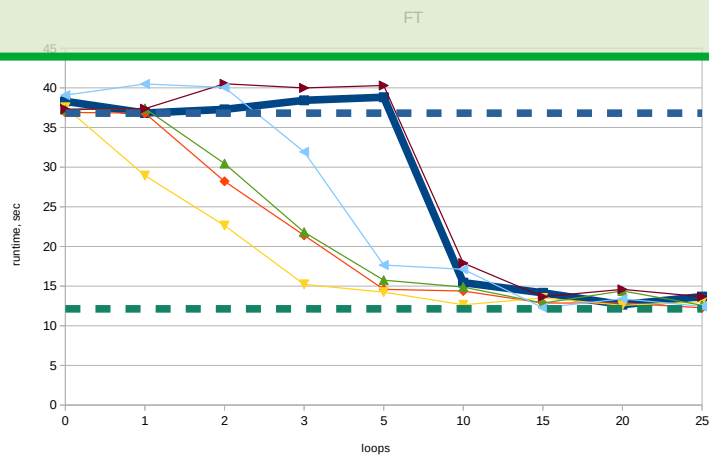




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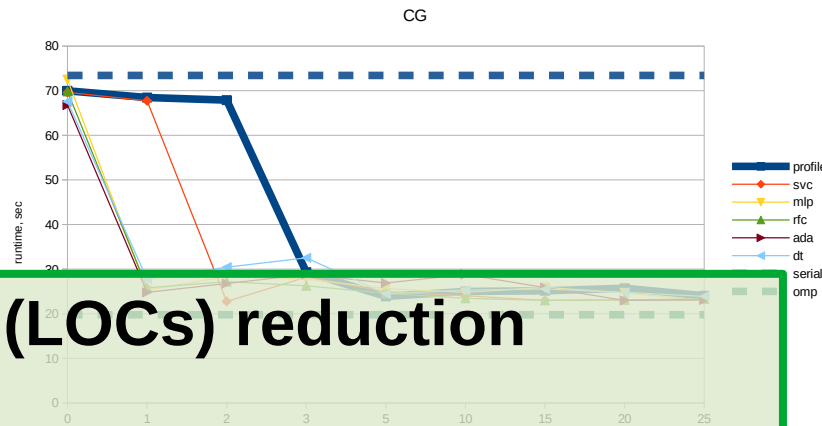
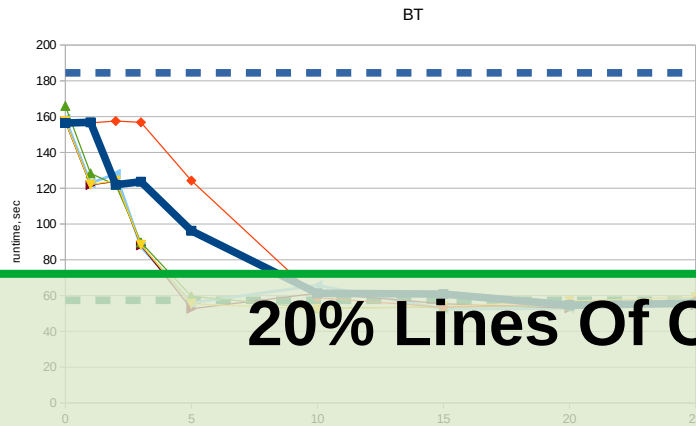


8 benchmarks in total: 4 wins / 4 draws



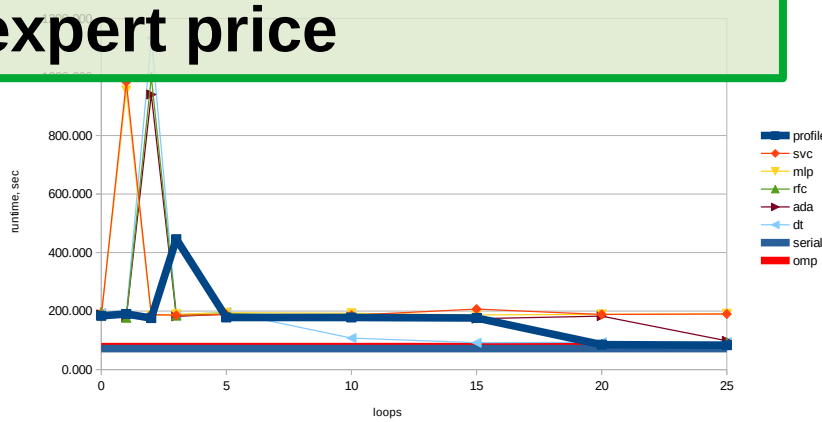
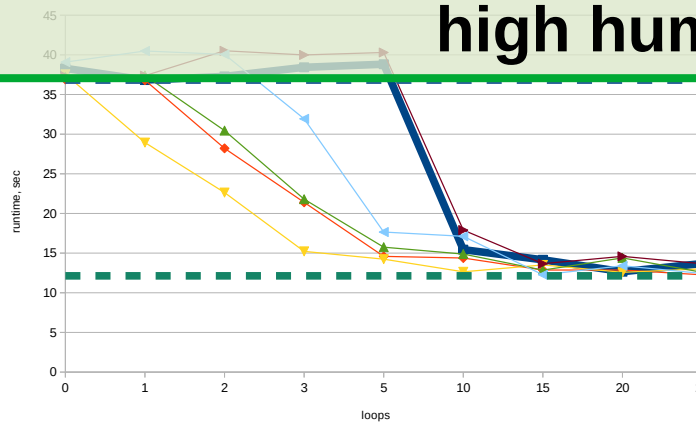


# How well do we do?



**20% Lines Of Code (LOCs) reduction**

**Might result into significant cost savings given a high human expert price**





## Reference

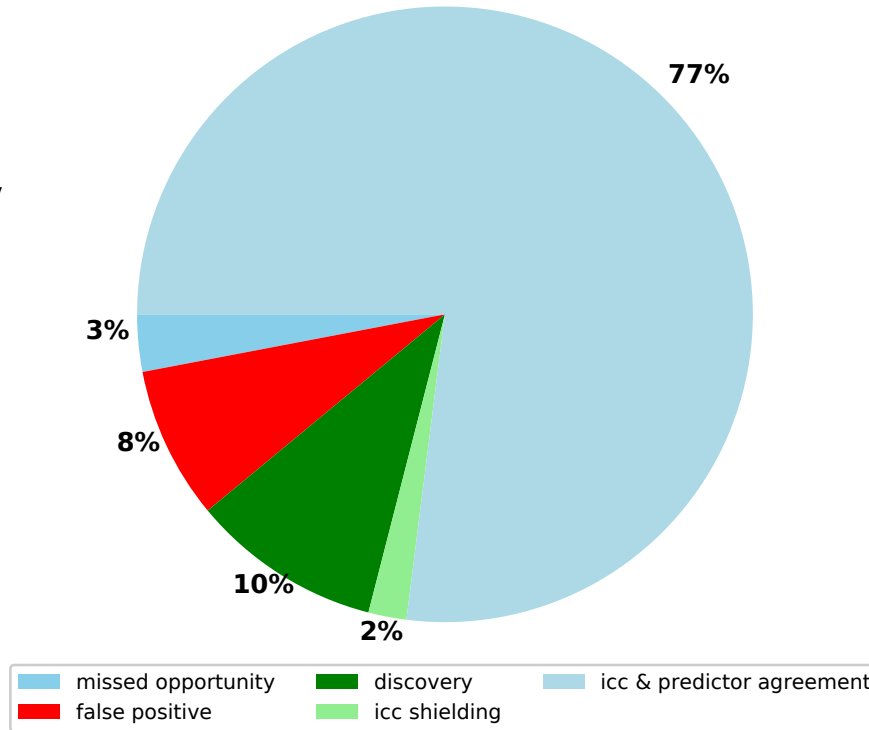
ML model	accuracy	recall	precision
constant	70.32	100	70.32
uniform	46.27	41.50	69.79
SVC	90.04	95.24	91.06
AdaBoost	86.96	92.92	89.06
DT	84.36	89.57	87.90
RFC	86.65	93.22	88.47
MLP	89.40	93.77	91.39

**Around 90% predictive accuracy**



# ML Model Predictive Performance

ML Based  
Loop Parallelizability  
Model



Agreement rate of 80%

Discovery rate of 10%

False positive rate of 8%  
is not critical

# Summary & Conclusions

- Human experts still play the major role in the task of software parallelization
- Loop parallelizability is learnable property (we introduce a ML model and train it to work with the accuracy of above 90%)
- ML model of loop parallelizability has been integrated into parallelization assistant
- Deployed against SNU NPB benchmarks our assistant showed a faster parallelization process: 20% Lines Of Code (LOC) reduction

**Thank you!**



Sun 20 - Fri 25 October 2019 Athens, Greece

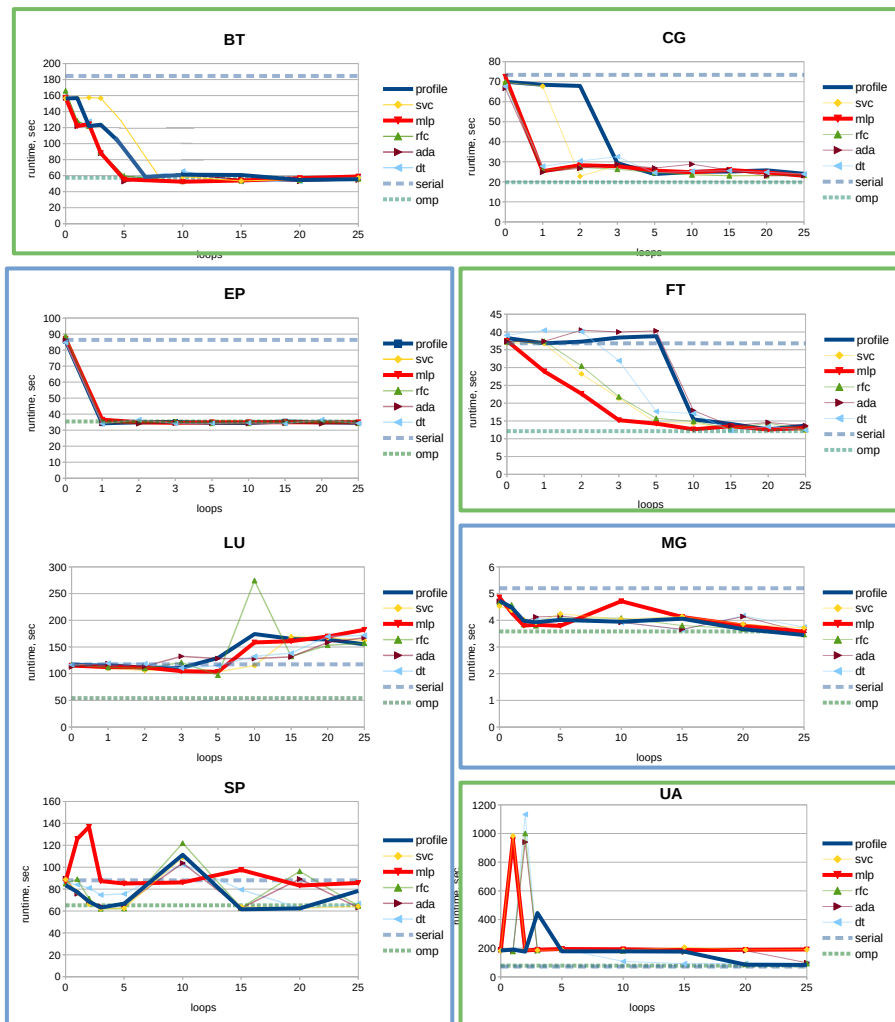
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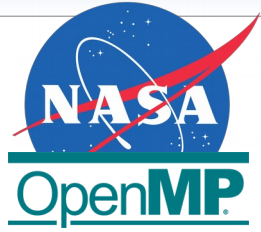
**SPLASH**  
ATHENS 2019



# How well do we do?



# Motivating example



## SNU NPB Conjugate Gradient (CG) benchmark

```
for (j = 0; j < lastrow-firstrow+1; j++) {  
    sum1 = 0.0;  
    for (k = rowstr[j]; k < rowstr[j+1]; k++)  
        sum1 = sum1 + a[k]*p[colidx[k]];  
    q[j] = sum1;  
}
```

**cg.c:509**

```
for (it = 1; it <= NITER; it++) {  
    ...  
    if (timeron) timer_start(T_conj_grad);  
    conj_grad(colidx,rowstr,x,z,a,p,q,r,&rn timer);  
    if (timeron) timer_stop(T_conj_grad);  
    ...  
    printf("      %5d      %20.14E%20.13f\n", it,  
           rn timer, zeta);  
    ...  
}
```

**cg.c:326**

### Profiler's Loop Ranking

- 1 **cg.c:326**
- 2 **cg.c:484**
- 3 **cg.c:509**

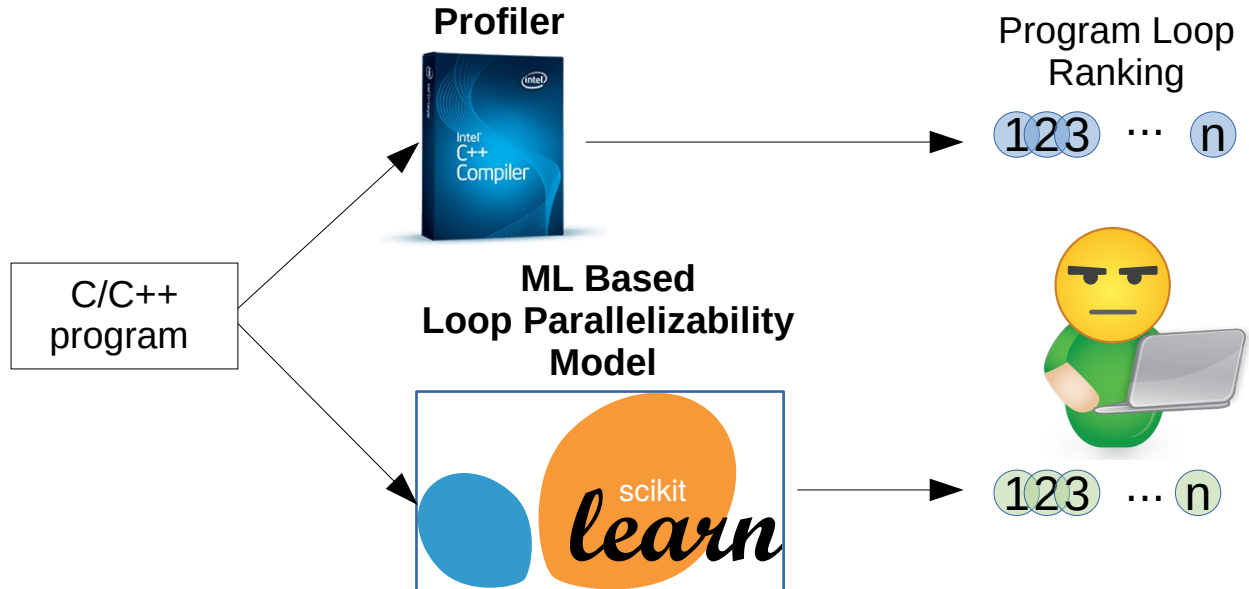
VS.

### Assistant's Loop Ranking

- 1 **cg.c:509**
- 2 **cg.c:326**
- 3 **cg.c:484**

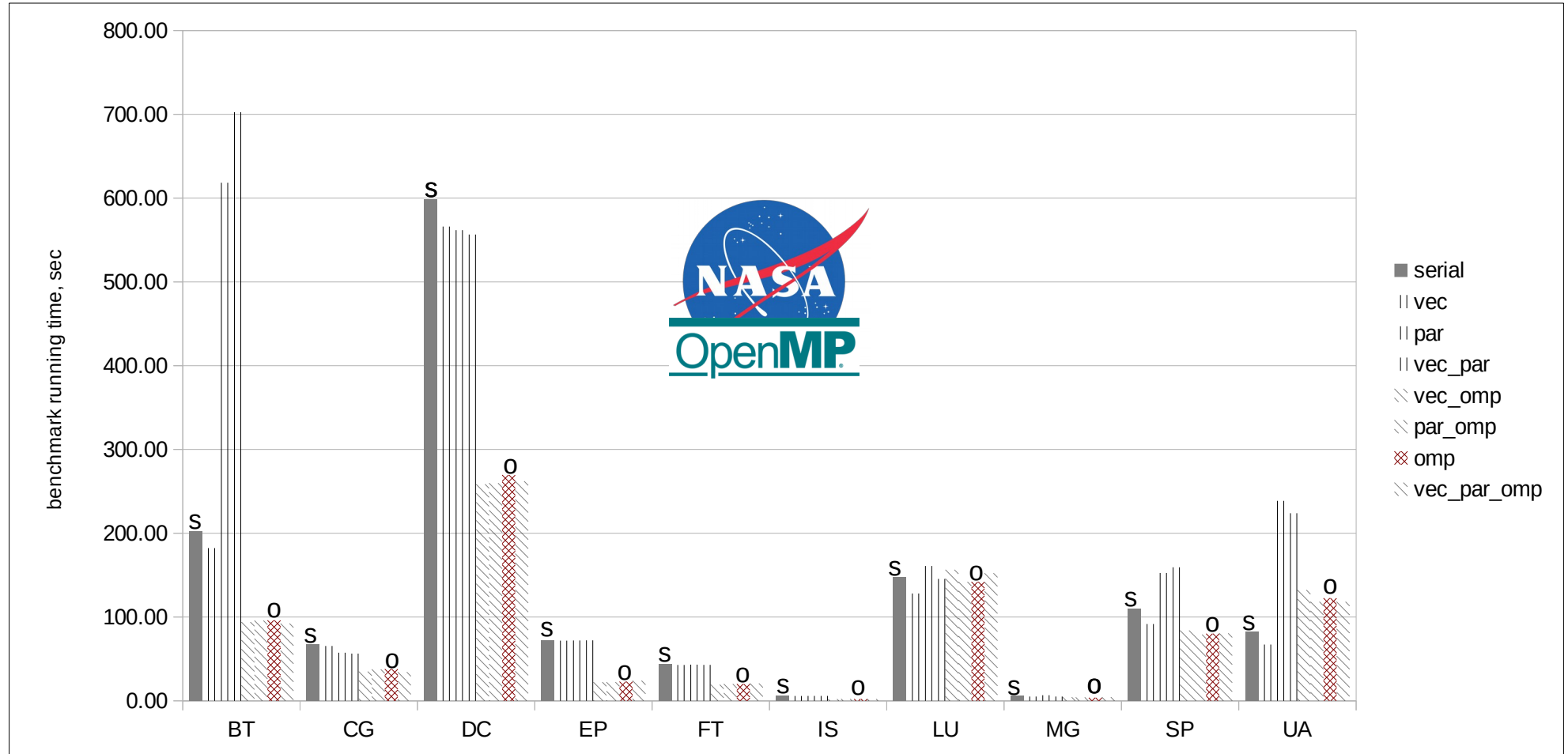
### Assistant's Parallel Loop Probability

- [ 85% ]
- [ 29% ]
- [ 8% ]



# Problem Statement 2/2

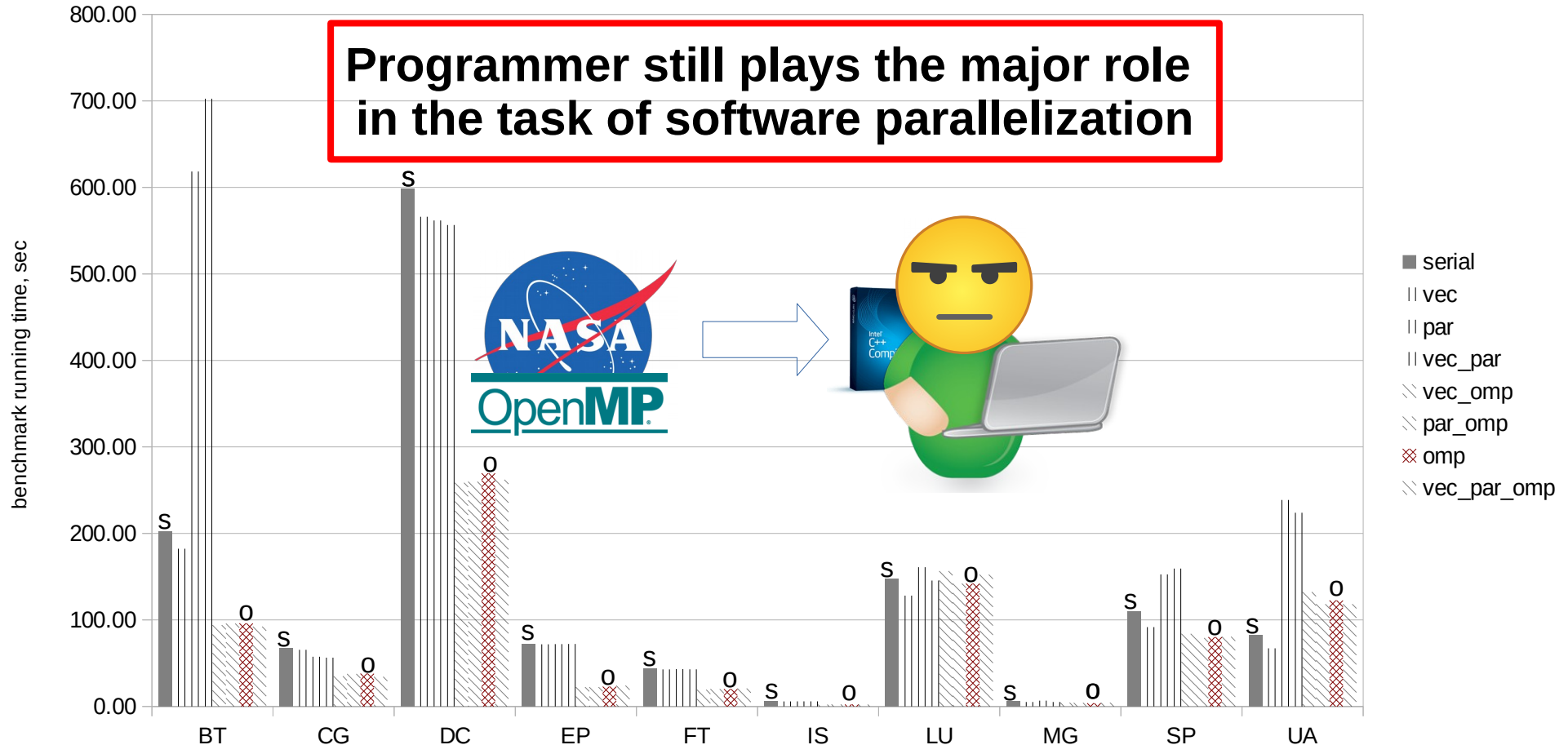
## NAS Parallel Benchmarks (NPB)



# Problem Statement 2/2

## NAS Parallel Benchmarks (NPB)

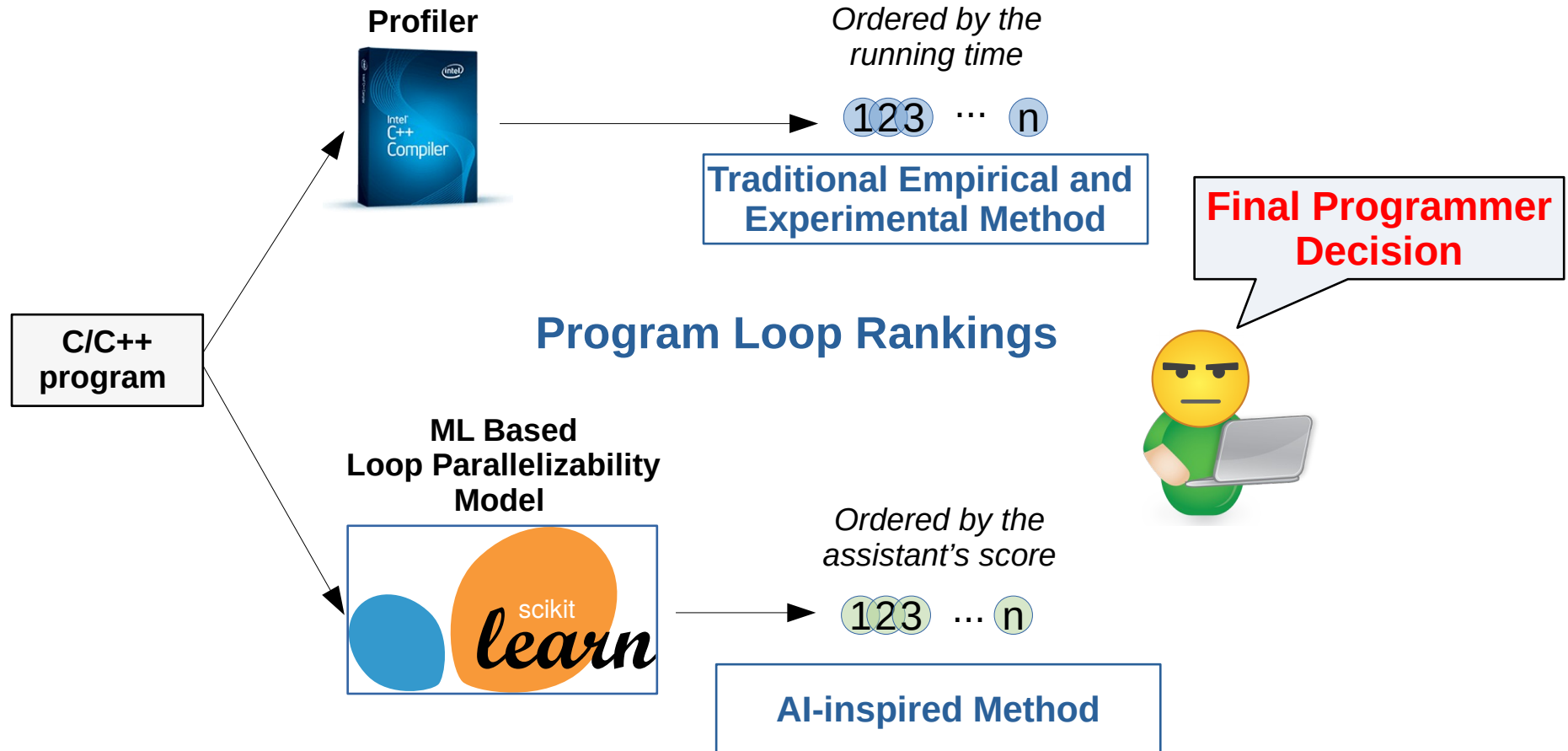
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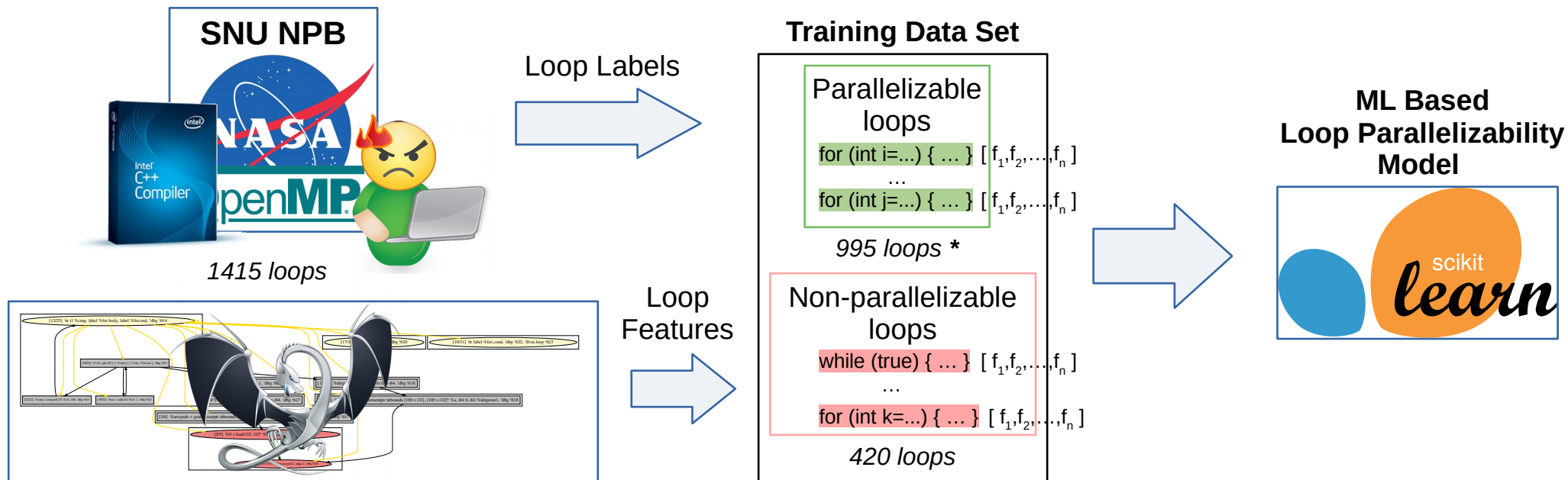


# How to use the assistant

(from the programmers perspective)



# Solution Scheme [1/2]



\* Intel Compiler succeeds in parallelizing 812 loops

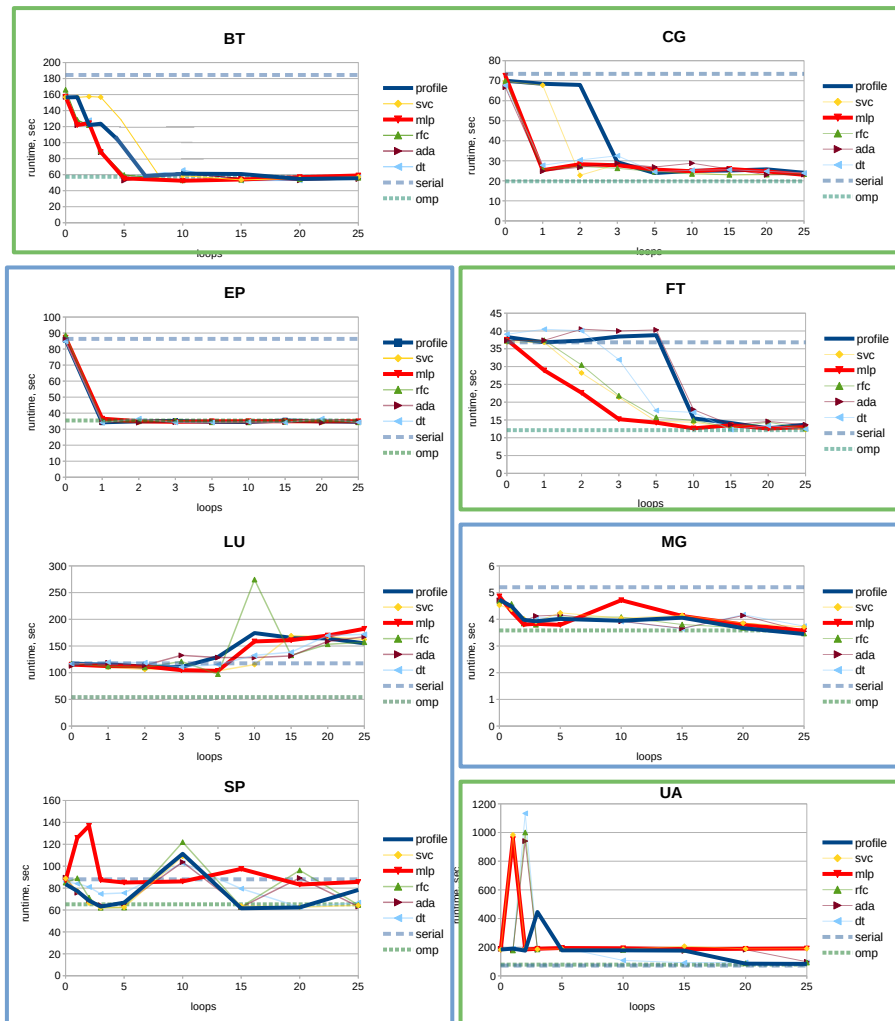
**Loop features** are based on static structural properties of loop program dependence graphs (PDGs):

- Absolute size
- Loop Iterator/Payload cohesion
- Number of dependence edges
- Instruction types (calls, loads/stores, etc.)

**Loop labels** are derived out of OpenMP pragmas present in parallelized SNU NPB versions as well as from the Intel Compiler's parallelization/vectorization reports.

# How well do we do?

Improvement in  
4 benchmarks



No change in  
4 other  
benchmarks