

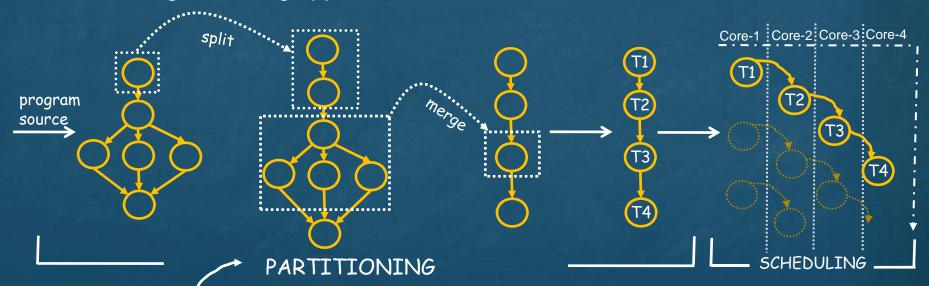
Partitioning Streaming Parallelism for Multicores: A Machine Learning Based Approach

Zheng Wang and Michael O'Boyle

PACT Vienna, Austria, September, 2010

Background

- Applications:
 - Stream programs written by high level programming languages
- The problem:
 - Partitioning streaming applications for multi-cores



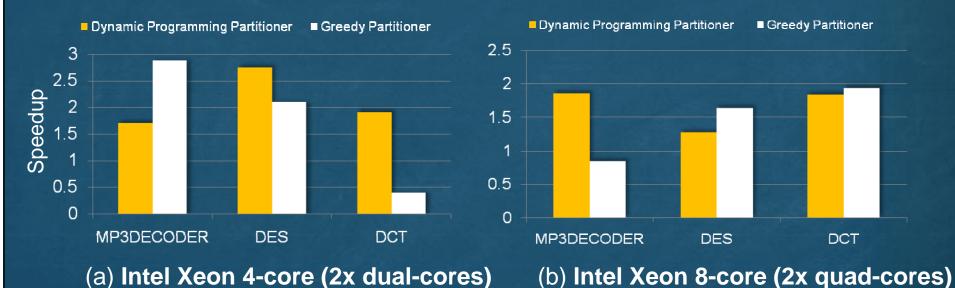
* We focus only on the partitioning stage in this work!



Why not Partitioning Heuristics?

Hardwired heuristics might not adapt to different platforms

*Baseline is a naïve graph partitioner.





^{*} The best partitioning strategy varies across programs and platforms.

Why Machine Learning?

It can automatically learn from data; then, reuses the learned knowledge



- Advantages:
 - Doesn't require expert knowledge and is portable across platforms
- We use supervised learning technique in this work
 - Classical supervised learning directly predicts the partitioning sequence



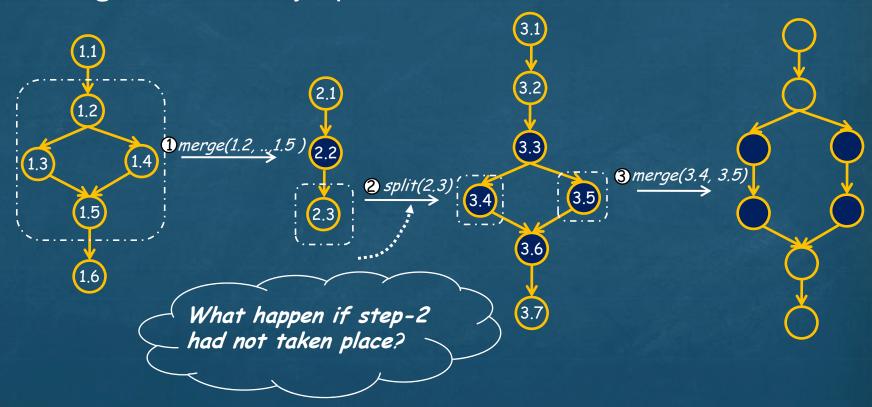
This is a Different Machine Learning Problem

- Previous machine learning based work limits on *fixed* targets
 - Determining the compiler flag settings
 - (Cavazos et al., CGO'07; Hoste and Eeckhout, CGO'08; Dubach et. al, MICRO'09)
 - Determining loop unroll factors
 - (Mark and Saman, CGO'05)
 - #Threads per parallel loop
 - (Wang and O'Boyle, PPoPP'09)
- We are dealing with a problem with unbounded graph structure
 - The graph structure changes after each operation



The Challenge

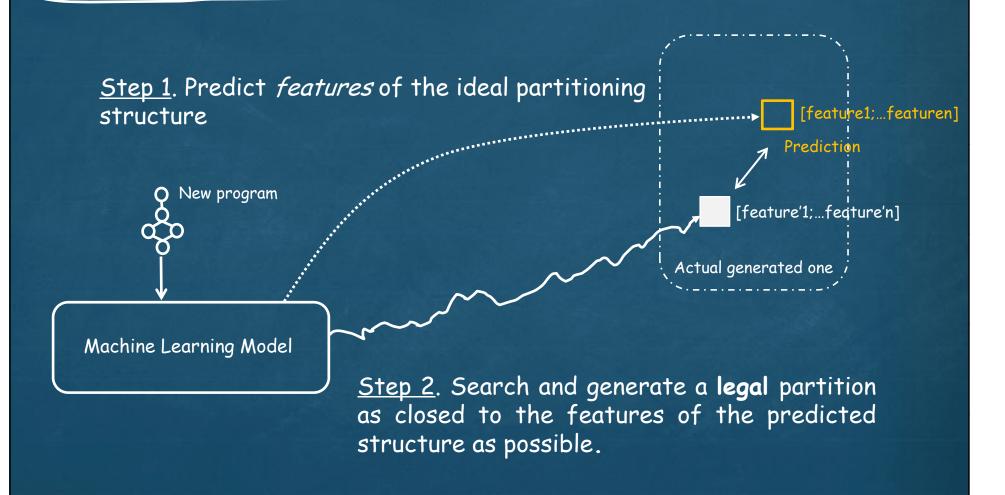
• The partitioning sequence is unbound and the graph changes after every operation.



^{*} It is difficult for a predictive model to make sure each intermediate stage is 100% correct!



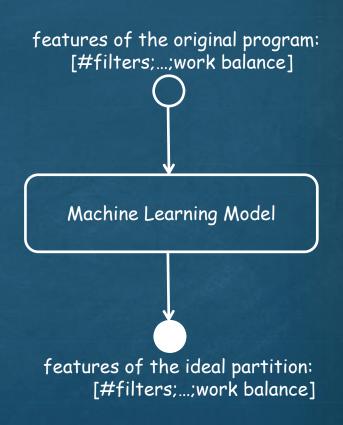
Our Two-Step Approach





Using Program Features to Characterise the Original Program and a Partition

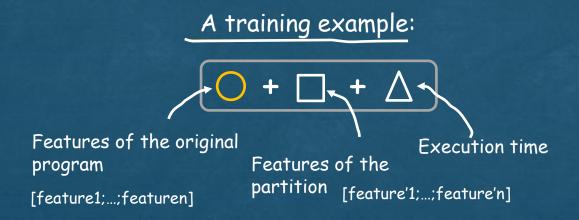
Static program features	
#Filters	#Joiners
Pipeline depth	Splitjoin width
Avg. unit work	Max unit work
Pipeline work	Splitjoin work
Computation	Computation of stateful filters
Branches per inst	Load/Store per inst
Avg. communication rate	Computation-communication ratio
Avg. commun. / unit work	Avg. bytes commun. / unit work
Max commun. /unit work	Work balance





Generate Training Data

- Using features to characterise both the program and generated partitions
 - Training is performed off-line using a set of training programs.

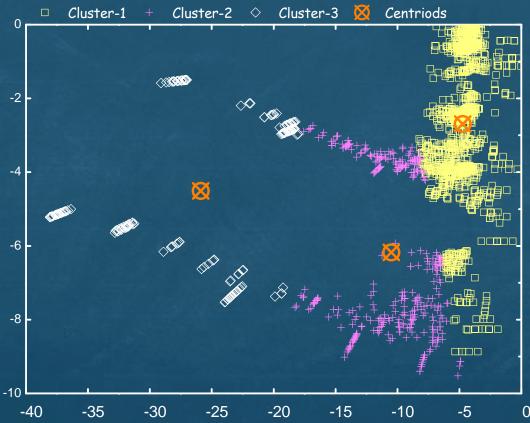


*The key point is to summarise features of the ideal partitioning structure.



Summarise the Ideal Partitioning Structure (Training)

 Using K-Means clustering algorithm to summarise the best partition of a program

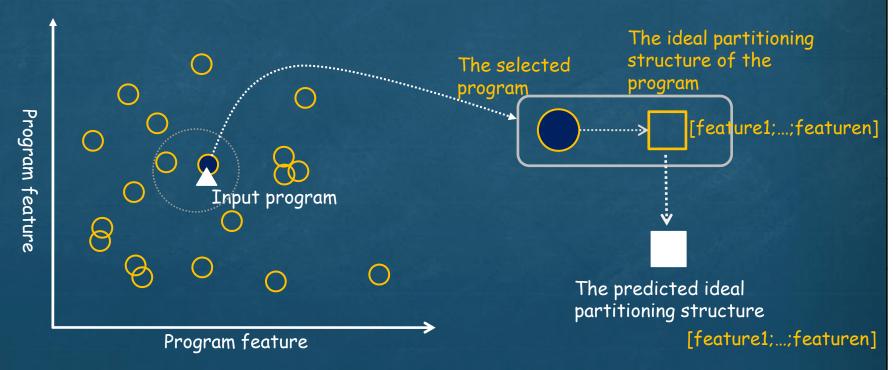


^{*} The multi-dimensional feature space has been projected to a two-dimensional one.



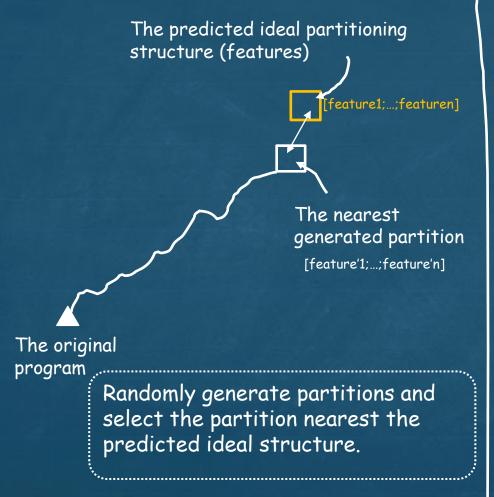
Train and Use the Model

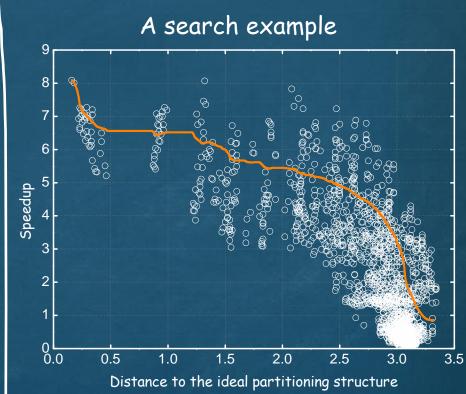
- Nearest-Neighbour Algorithm
 - Pick a program from the training set, whose features most closely match the input program's features





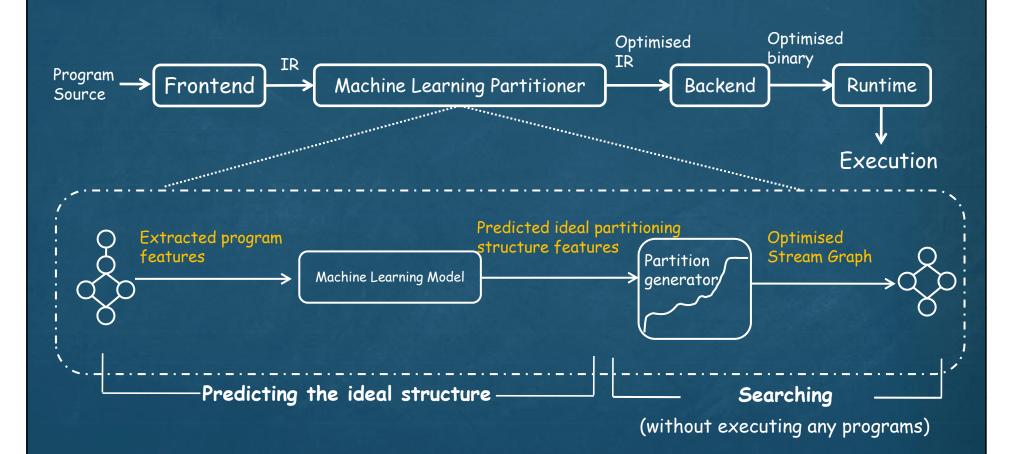
Searching and Generating a Legal Partition







The Compilation Framework





Experimental Setup

Platforms

- 2 x Dual Intel Xeon 5160 processors
 (4 cores in total)
- 2 x Quad Intel Xeon 5450 processors
 (8 cores in total)

Compilers:

- StreamIt version 2.1.1
- Intel ICC v11.0
 - -O3 -xT -aXT -ipo

Benchmarks:

17 StreamIt applications

Comparison:

- 2 StreamIt compiler built-in partitioners
- An analytical-based model (Navarro et al., PACT 2009)

Evaluation Methodology:

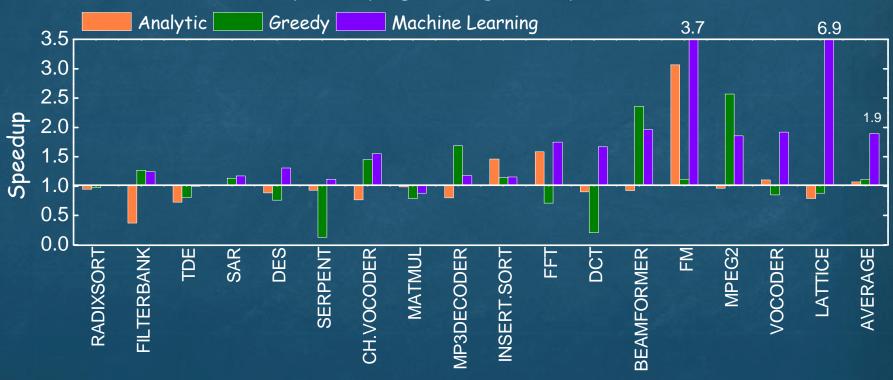
- Leave-one-out-cross-validation
 - Making sure the model has NOT seen the target program before.
- Baseline: StreamIt dynamic programmingbased partitioner



Results on the Intel 4-Core Platform (1.9x)

 Our approach achieves 1.9x speedup over the StreamIt default scheme

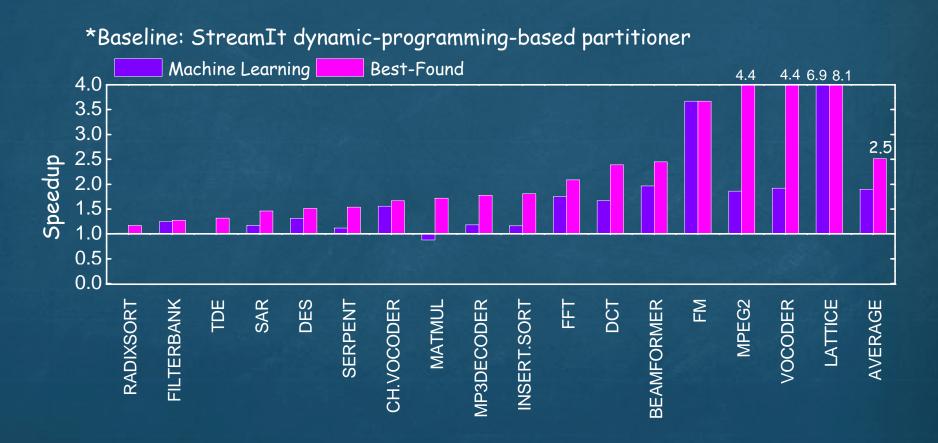
*Baseline: StreamIt dynamic-programming-based partitioner





Machine Learning vs. Best-Found (Intel 4-Core)

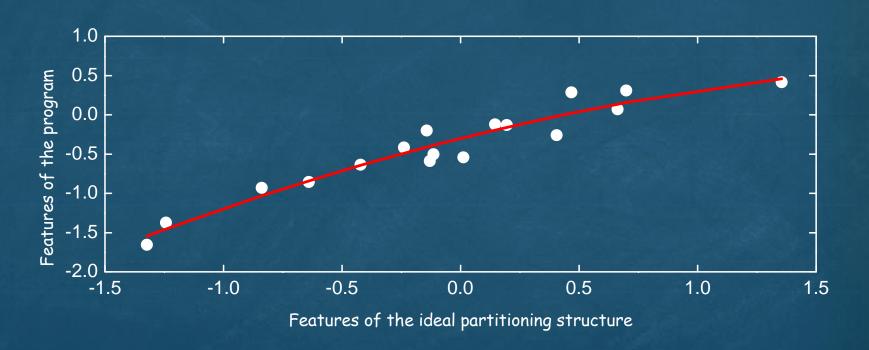
Our approach achieves 60% of the Best-Found performance





Similar Programs Have Similar Ideal Partitioning Structures

Correlation of programs and the ideal partitioning structures



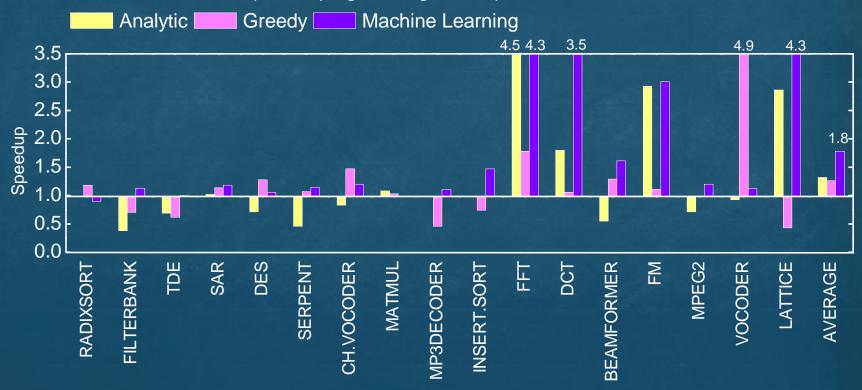
^{*}The original multi-dimensional feature space have been projected into a single value.



Adapt to the Intel 8-core Platform (1.8x)

Our approach achieves1.8x speedup over the StreamIt default scheme

*Baseline: StreamIt dynamic-programming-based partitioner





Conclusions

- A machine learning based approach for partitioning streaming applications
 - The model is firstly trained off-line
 - Predicting the ideal partitioning structure used the trained model
 - Searching a legal partition closest to the predicted structure (without running any code)
- Comparison with heuristics and analytical-based approaches
 - Better performance and more stable across programs and platforms
 - An automatic and portable scheme



Thank You

