Techniques for Dynamic Workload Partitioning in High-Performance Heterogeneous Computing Platforms

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Introduction

THALES

- The proper allocation/mapping of data-parallel processes (kernels) in a High-Performance Computing (HPC) platform is crucial to exploit the system full potential
- Dynamic Heterogeneous Platforms: type and amount of available devices may change at runtime
- Applications requirements (Quality of Service Qos): also may change at runtime





GOAL

Develop a system manager able to sense and react at runtime to variations in the High-Performance **Heterogeneous Computing platform** as well as in the QoS requirements



Scenario 1: new application needs to be mapped

Problem Formulation

- **Simple scenario**: single-kernel data-parallel application \rightarrow preliminary study
- Only two devices: CPU and GPU
- Workload partitioning Data partitioning
- Estimate the amount of data to be allocated to each device
- **Definition: Best partitioning** is the one that enforces





Design of the System Manager (SM)



- It is assumed a **performance profile** of the kernel in each device is available \rightarrow Matrix R
- HPC feedback: measurement of devices performances in order to update profiles in R
- **QoS requirements:** application dependent
- SM uses those to estimate the workload partitioning that minimizes kernel execution time

Mathematical Representation

error e_k : Measure of how well the can be combined resources to achieve the QoS requirements

 $e_k = \left(d - \sum_{j}^{N} r_j \lambda(j)\right) = \left(d - R\lambda_k\right)$

 $d \rightarrow QoS$ requirements $R \rightarrow resources$ matrix vector $r_j \rightarrow \text{column of } R$

The Intelligence embedded in the SM

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Workload Partitioning → Minimization Problem
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\min_{\lambda} J(\lambda) = \mathbf{E} |\boldsymbol{e}_k|^2 = \mathbf{E} |\boldsymbol{d} - \boldsymbol{R}\lambda_k|^2
subject to \lambda(j) \ge 0, j \in [1, N], \ \mathbb{1}^T \lambda_k = \sum_{k=1}^N \lambda(j) = 1
```

Results

- Test: variation in the QoS requirements
 - d changes while R remains fix
- Adaptive Filter is able to provide a new workload partitioning at runtime → Fast reaction

j=1

Adaptive Filter - Reweighted LMS

- Naturally fit for real-time estimation: no need for previous training
- Able to **track variations** in the HPC resources (matrix R) and in the Qos requirements (vector d)
- **Easy to be scaled up** towards several applications (kernels) and computing devices

$$\begin{split} \lambda_{k,i} &= P[\lambda_{k,i-1} + \mu D_{\lambda} R_i^T e_k(i)] + F \\ P &= I - \frac{1}{N} \mathbb{1} \mathbb{1}^T \ F = \frac{1}{N} \mathbb{1} \quad D_{\lambda} \text{= diag}\{\text{entries of } \lambda\} \end{split}$$



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