High-performance and automatic computing

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RWTHAACHEN



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- 2 Application: Genome-Wide Association Studies
- Performance experiments



Overview

• High-performance computing

numerical computations, parallel architectures

 \rightarrow time-to-solution, efficiency, scalability, ...

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Automatic computing

optimization, search, but also derivation & deduction \rightarrow range of algorithms, productivity

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Applications

 \rightarrow application-specific properties & needs, large scale, full code

methods & applications				
P. Bientinesi				
• E. Di Napoli	Electronic structure calculations			
M. Petschow	Parallel eigensolvers			
 D. Fabregat 	Automation, Computational biology			
 D. Tameling* 	Molecular dynamics			
• E. Peise	Performance modeling & prediction			
• L. Beyer	Density Functional Theory			
• F. Kürten, Y. Madzh	unkov, A. Frank, P. Springer,			

hpac.rwth-aachen.de - group overview

methods & applications

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F Peise

L. Beyer

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 Parallel eigensolvers
- D. Fabregat Automation, Computational biology
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D. Fabregat



E. Peise



Y. Aulchenko



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 - 3 Performance experiments
- 4 Conclusions



Source: David Hall





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<u>Yurii</u>



<u>Yurii</u>	Paolo
"Mixed models"	???

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Linear regression with non-independent outcomes	???

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Generalized least-square problems	

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Mixed models $b := (X^T M^{-1} X)^{-1} X^T M^{-1} y$



Genome-wide association analysis

- y: **phenotype** (outcome; vector of observations) E.g.: height, blood pressure for a set of people
- X: genome measurements and covariates (design matrix; predictors)

E.g.: sex and age over height

- *M*: **dependencies** between observations E.g.: tall parents have tall children
- *b*: **relation** between a variation in the outcome (*y*) and a variation in the genome sequence (*X*)

Stats

n: Population size



Stats

m: Number of SNPs



Problem definition (1)



"to be repeated millions of times"

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$$b := \left(X^T M^{-1} X \right)^{-1} X^T M^{-1} y$$

"to be repeated millions of times"

$$\downarrow
b_i := \left(X_i^T M_i^{-1} X_i\right)^{-1} X_i^T M_i^{-1} y_i$$
for $i = 1, \dots, m$

Problem definition (1)

$b := (X^T M^{-1} X)^{-1} X^T M^{-1} y$			
"to b	e repeated millions	of times"	
	\Downarrow		
$b_i :=$	$\left(X_i^T M_i^{-1} X_i\right)^{-1} X_i$	$\sum_{i=1}^{T} M_i^{-1} y_i$	
for i	$=1,\ldots,m$		
	\Downarrow		
Problem size			
$M_i \in \mathbb{R}^{n \times n}$	$1000 \le n \le 20k\text{+}$	7.5MBs – 3GBs	
$X_i \in \mathbb{R}^{n \times p}$	$3 \le p \le 20$	30 – 625KBs	
$y_j \in \mathbb{R}^n$		8 – 780KBs	
$b_i \in \mathbb{R}^p$ 24 – 160 Bytes			
Total	$10^6 \le m \le 10^8$	7.5 – 3000 TBs	

Problem definition (2)

$$b_i := \left(X_i^T M_i^{-1} X_i\right)^{-1} X_i^T M_i^{-1} y_i$$

Problem definition (2)

$b_{i} := \left(X_{i}^{T} M_{i}^{-1} X_{i}\right)^{-1} X_{i}^{T} M_{i}^{-1} y_{i}$			
	\Downarrow		
$b_i := (X_i^T M^{-1} X_i)^{-1} X_i^T M^{-1} y$			
and $X_i = [X_L X_{Ri}],$			
fo	for $i=1,\ldots,m$		
	\Downarrow		
	Problem size	ze	
$M \in \mathbb{R}^{n \times n}$	$1000 \le n \le 100k$	7.5MBs – 74.5GBs	
$X_{Ri} \in \mathbb{R}^n$		8 – 780KBs	
$b_i \in \mathbb{R}^p$		24 – 160 Bytes	
Total	$10^6 \le m \le 10^8$	74GBs – 7 TBs	

Problem definition (3)

$$b_i := (X_i^T M^{-1} X_i)^{-1} X_i^T M^{-1} y$$

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$$b_i := (X_i^T M^{-1} X_i)^{-1} X_i^T M^{-1} y$$

$$\downarrow$$

$$b_{ij} := (X_i^T M_j^{-1} X_i)^{-1} X_i^T M_j^{-1} y_j$$
and
$$M_j = \sigma_j (\Phi + h_j I),$$
for $i = 1, \dots, m$ and $j = 1, \dots, t$

Moreover, either t = 1 or $t \le 10^5$.

GWAS: complete problem definition



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Problem size

$M \in \mathbb{R}^{n \times n}$	$1000 \le n \le 100k$	7.5MBs – 74.5GBs
$X_{Ri}, y_j \in \mathbb{R}^n$		8 – 780KBs
$b_{ij} \in \mathbb{R}^p$	$3 \le p \le 20$	24 – 160 Bytes
Total	$m \le 10^8, t \le 10^5$	1.5 – 100s TBs

Vision: domain-specific compiler



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Nov. 1954: The IBM Mathematical FORmula TRANslating System, <u>FORTRAN</u> "a set of programs to accept a concise formulation of a problem and to produce automatically a solution of the problem"

Automatic generation

$$\begin{array}{ll} Y \in \mathbb{R}^{n \times p}, & A \in \mathbb{R}^{n \times n}, & b \in \mathbb{R}^n \\ & v := (Y^T \ast A^{-1} \ast Y)^{-1} \ast b \\ & \downarrow \\ & < \mathsf{lin. alg. compiler} > \\ & \downarrow \\ & \text{algorithm, code} \end{array}$$

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Matrix algebra	Sequences of operations	
Inference of properties	Cost analysis	
Building blocks	Code generation	

Algorithms generated

Algorithm 1	Algorithm 2	 Algorithm 20	
$LL^T = M$	$LL^T = M$	$ZWZ^T = \Phi$	
$X := L^{-1}X$	$X := L^{-1}X$	$D := (hW + (1 - h)I)^{-1}$	
$S := X^T X$	QR := X	$KK^T = D$	
$GG^T = S$	$y := L^{-1}y$	$X := Z^T X$	
$y := L^{-1}y$	$b := Q^T y$	$X := K^T X$	
$b := X^T y$	$b := R^{-1}b$	QR := X	
$b := G^{-1}b$		$y := L^{-1}y$	
$b := G^{-T}b$		$b := Q^T y$	
		$b := R^{-1}b$	

Many algorithms! Predictions?

Flop count – rough estimate				
	Alg. 1	Alg. 2	Alg. 20	
Single instance $(t = 1)$	$O(n^3)$	$O(n^3)$	$O(n^3)$	
$\begin{array}{l} \text{2D sequence} \\ (t \gg 1) \end{array}$	$O(tn^3 + mtn^2)$	$O(tn^3 + mtn^2)$	$O(n^3 + mtn)$	

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Analytic models	Model-based prediction	
Roman lakymchuk	Elmar Peise	

ope	rands		
X	input	100s GBs – 2 TBs	streaming from disk
y	input	1 – 10 GBs	streaming from disk
M	input	MBs – 80 GBs	read once
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 YES ⇒ single node + multithreading streaming HD↔CPU, double buffering, in-core implementation

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Does M fit in GPU-memory?

• Yes \Rightarrow accelerator

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streaming HD \leftrightarrow CPU \leftrightarrow GPU, triple+double buffering, GPU implementation
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 NO ⇒ distributed memory + MPI partitioning + streaming HD↔CPUs, double buffering, data distribution



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Results t = 1

Single-trait analysis



Results t = 1, large-scale



MPI

Results t = 1, large-scale





Scalability



Results $t \gg 1$

Multi-trait analysis, "OMICS"-data





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HPC's perspective

- In-core efficiency
- How to sustain efficiency?

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App's perspective

- Many data formats
- Missing data, bogus data
- Output data. Post-processing?
- New features

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- New features
- HUGE gap: algorithm ↔ optimized implementation (data management, parallelism)
- Development cycle: several months!
- How to deal with BIG problems? Expose knowledge, exploit knowledge