

# Programming languages and linear algebra computations

Christos Psarras, Henrik Barthels, **Paolo Bientinesi**

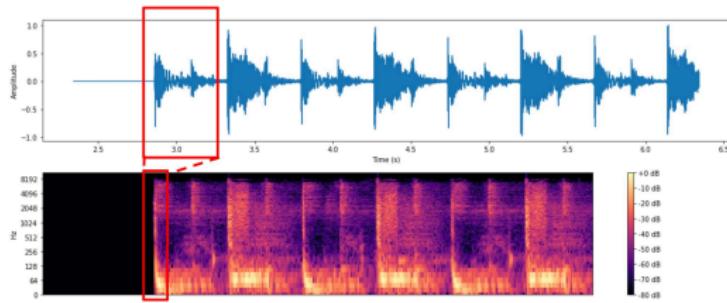
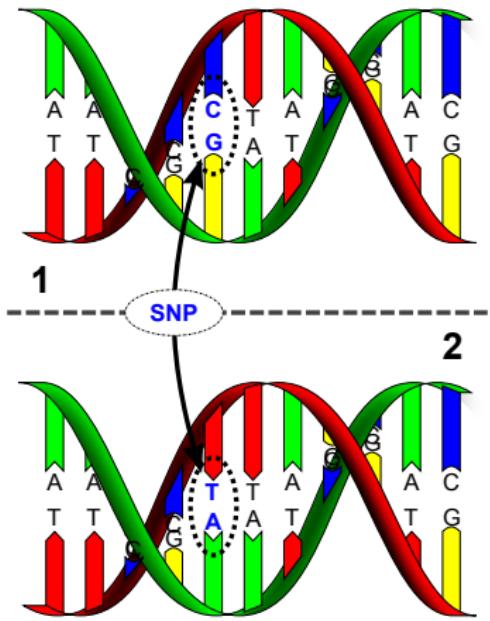
RWTH Aachen University

Umeå University

April 22, 2020  
Uppsala University (via Zoom)

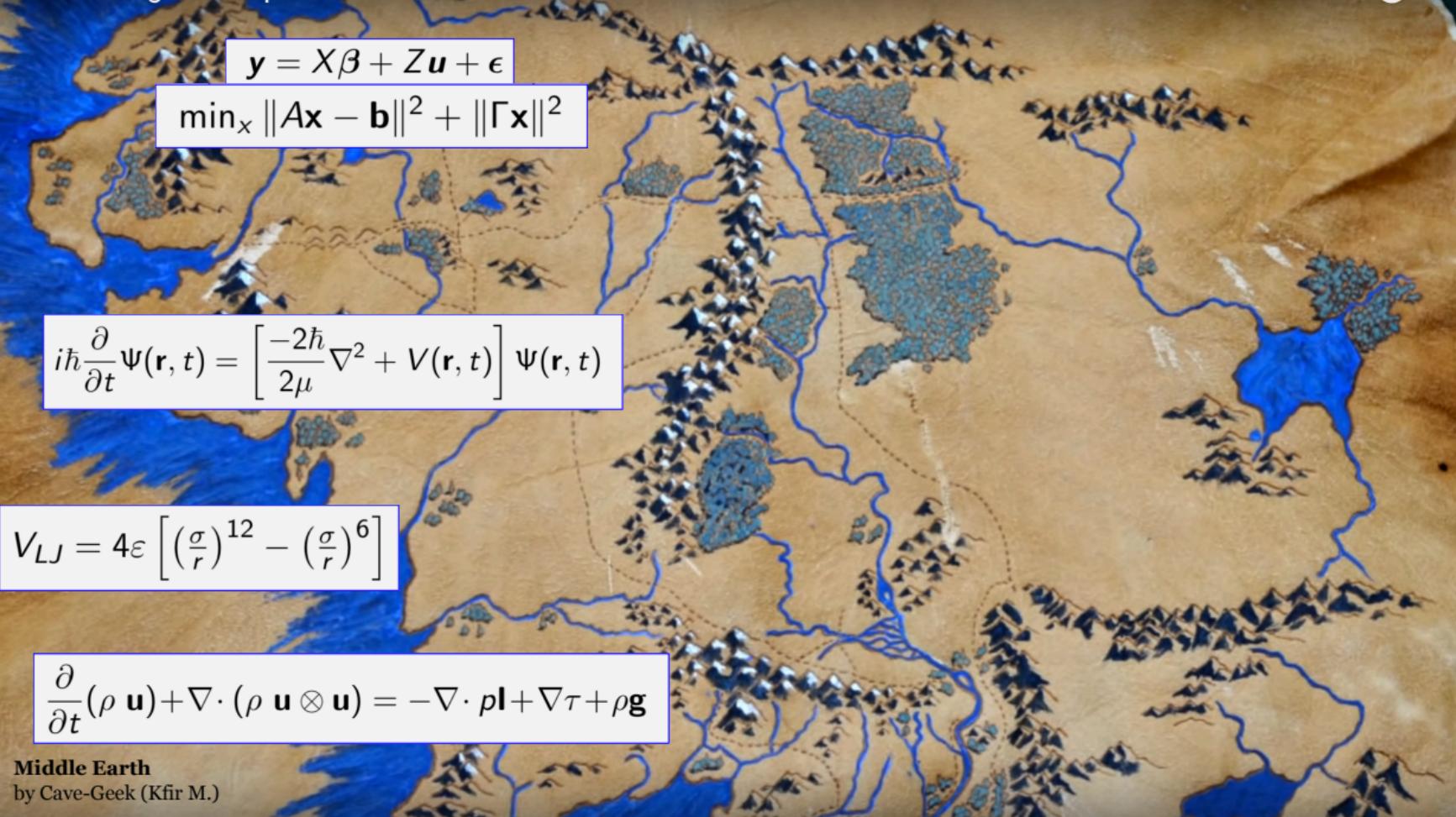


# High-Performance & Scientific Computing



# The computing world




$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + \boldsymbol{\epsilon}$$

$$\min_{\mathbf{x}} \|\mathbf{Ax} - \mathbf{b}\|^2 + \|\Gamma \mathbf{x}\|^2$$

$$i\hbar \frac{\partial}{\partial t} \Psi(\mathbf{r}, t) = \left[ \frac{-2\hbar}{2\mu} \nabla^2 + V(\mathbf{r}, t) \right] \Psi(\mathbf{r}, t)$$

$$V_{LJ} = 4\varepsilon \left[ \left( \frac{\sigma}{r} \right)^{12} - \left( \frac{\sigma}{r} \right)^6 \right]$$

$$\frac{\partial}{\partial t} (\rho \mathbf{u}) + \nabla \cdot (\rho \mathbf{u} \otimes \mathbf{u}) = -\nabla \cdot p \mathbf{I} + \nabla \tau + \rho \mathbf{g}$$

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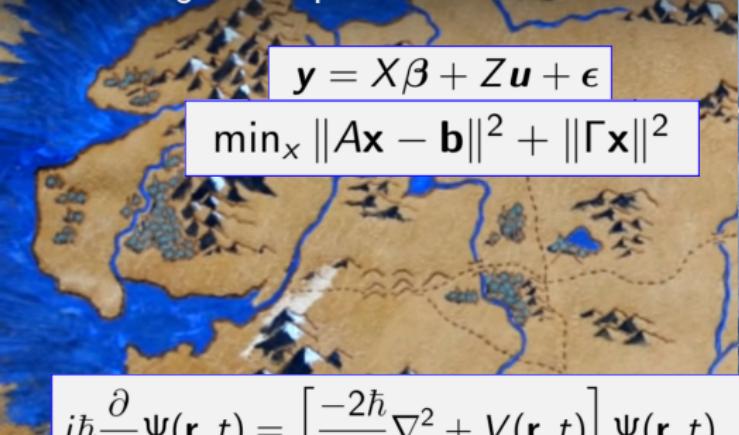
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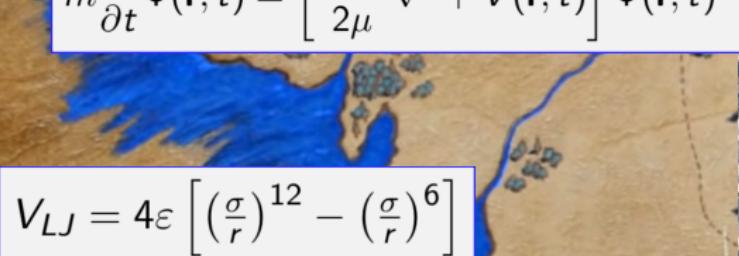
Middle Earth  
by Cave-Geek (Kfir M.)

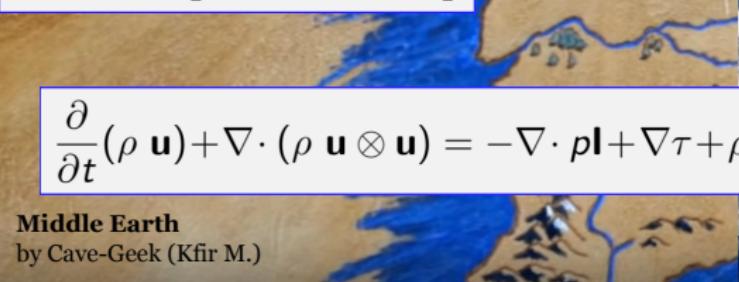



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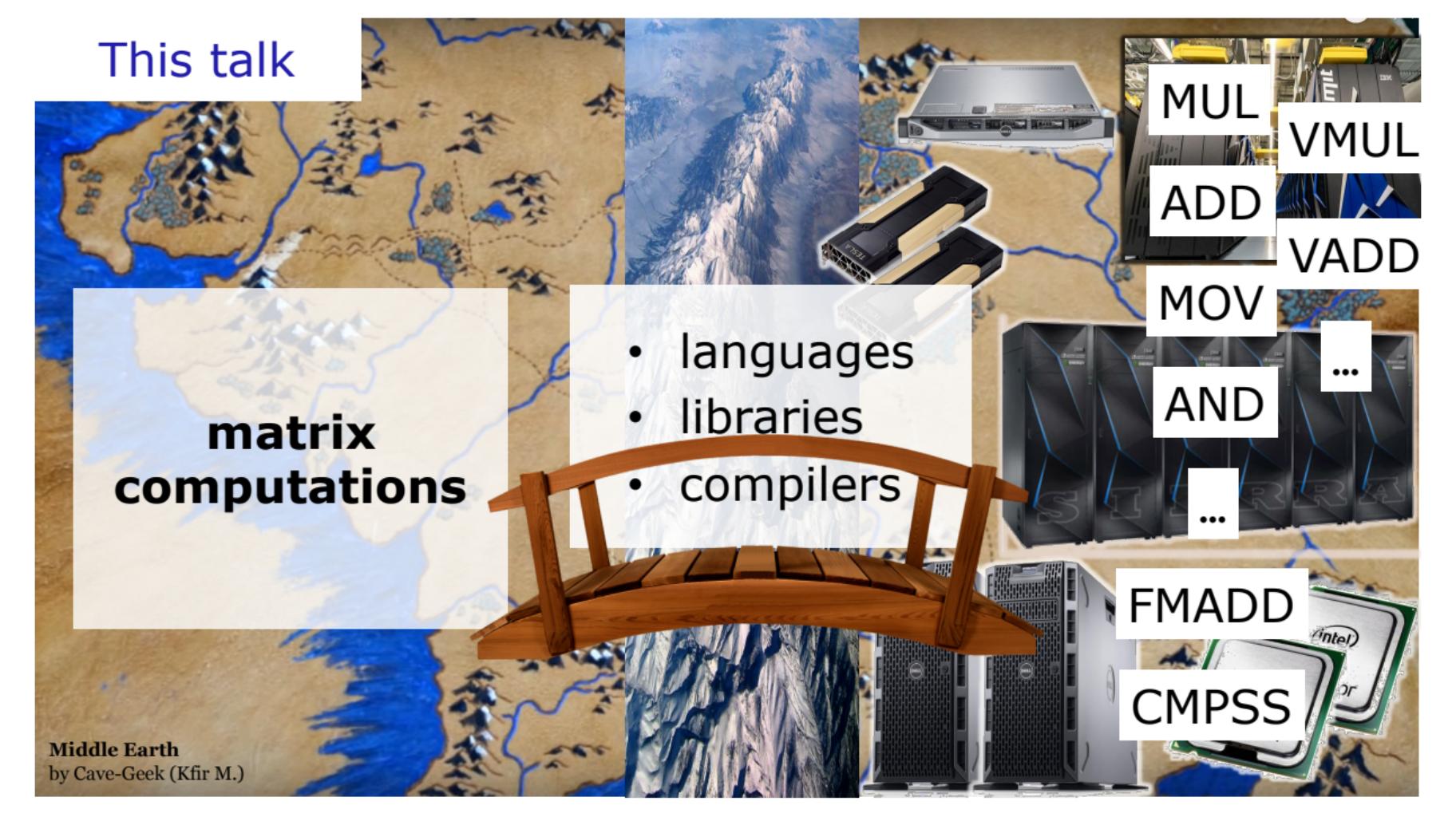
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## Issues

- ▶ ...
- ▶ language mismatch
- ▶ ...



# This talk



matrix computations

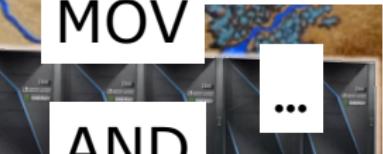
- languages
- libraries
- compilers



MUL



VMUL



ADD



VADD



MOV



...



AND



...



FMADD



CMPSS

# Matrix computations

**Signal Processing**

$$x := (A^{-T} B^T B A^{-1} + R^T L R)^{-1} A^{-T} B^T B A^{-1} y \quad R \in \mathbb{R}^{n-1 \times n}, \text{ UT}; L \in \mathbb{R}^{n-1 \times n-1}, \text{ DI}$$

**Kalman Filter**

$$K_k := P_k^b H^T (H P_k^b H^T + R)^{-1}; \quad x_k^a := x_k^b + K_k (z_k - H x_k^b); \quad P_k^a := (I - K_k H) P_k^b$$

**Ensemble Kalman Filter**

$$X^a := X^b + (B^{-1} + H^T R^{-1} H)^{-1} (Y - H X^b) \quad B \in \mathbb{R}^{N \times N} \text{ SSPD}; R \in \mathbb{R}^{m \times m}, \text{ SSPD}$$

**Ensemble Kalman Filter**

$$\delta X := (B^{-1} + H^T R^{-1} H)^{-1} H^T R^{-1} (Y - H X^b)$$

**Ensemble Kalman Filter**

$$\delta X := X V^T (R + H X (H X)^T)^{-1} (Y - H X^b)$$

**Image Restoration**

$$x_k := (H^T H + \lambda \sigma^2 I_n)^{-1} (H^T y + \lambda \sigma^2 (v_{k-1} - u_{k-1}))$$

**Image Restoration**

$$H^\dagger := H^T (H H^T)^{-1}; \quad y_k := H^\dagger y + (I_n - H^\dagger H) x_k$$

**Rand. Matrix Inversion**

$$X_{k+1} := S (S^T A S)^{-1} S^T + (I_n - S (S^T A S)^{-1} S^T A) X_k (I_n - A S (S^T A S)^{-1} S^T)$$

**Rand. Matrix Inversion**

$$X_{k+1} := X_k + W A^T S (S^T A W A^T S)^{-1} S^T (I_n - A X_k) \quad W \in \mathbb{R}^{n \times n}, \text{ SPD}$$

**Rand. Matrix Inversion**

$$X_{k+1} := X_k + (I_n - X_k A^T) S (S^T A^T W A S)^{-1} S^T A^T W$$

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## Matrix computations (2)

**Generalized Least Squares**  $b := (X^T M^{-1} X)^{-1} X^T M^{-1} y$   $n > m; M \in \mathbb{R}^{n \times n}, \text{SPD}; X \in \mathbb{R}^{n \times m}; y \in \mathbb{R}^{n \times 1}$

**Stochastic Newton**  $B_k := \frac{k}{k-1} B_{k-1} (I_n - A^T W_k ((k-1)I_l + W_k^T A B_{k-1} A^T W_k)^{-1} W_k^T A B_{k-1})$

**Optimization**  $x_f := W A^T (A W A^T)^{-1} (b - A x); \quad x_o := W (A^T (A W A^T)^{-1} A x - c)$

**Optimization**  $x := W (A^T (A W A^T)^{-1} b - c)$

**Triangular Matrix Inv.**  $X_{10} := L_{10} L_{00}^{-1}; \quad X_{20} := L_{20} + L_{22}^{-1} L_{21} L_{11}^{-1} L_{10}; \quad X_{11} := L_{11}^{-1}; \quad X_{21} := -L_{22}^{-1} L_{21}$

**Tikhonov Regularization**  $x := (A^T A + \Gamma^T \Gamma)^{-1} A^T b$   $A \in \mathbb{R}^{n \times m}; \Gamma \in \mathbb{R}^{m \times m}; b \in \mathbb{R}^{n \times 1}$

**Tikhonov Regularization**  $x := (A^T A + \alpha^2 I)^{-1} A^T b$

**Gen. Tikhonov Reg.**  $x := (A^T P A + Q)^{-1} (A^T P b + Q x_0)$   $P \in \mathbb{R}^{n \times n}, \text{SSPD}; Q \in \mathbb{R}^{m \times m}, \text{SSPD}; x_0 \in \mathbb{R}^{m \times 1}$

**Gen. Tikhonov reg.**  $x := x_0 + (A^T P A + Q)^{-1} (A^T P (b - A x_0))$

**LMMSE estimator**  $K_{t+1} := C_t A^T (A C_t A^T + C_z)^{-1}; \quad x_{t+1} := x_t + K_{t+1} (y - A x_t); \quad C_{t+1} := (I - K_{t+1} A) C_t$

**LMMSE estimator**  $x_{\text{out}} = C_X A^T (A C_X A^T + C_Z)^{-1} (y - A x) + x$

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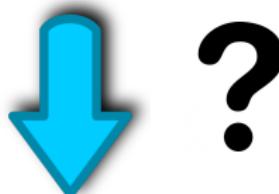


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MUL	ADD	MOV
MOVAPD		
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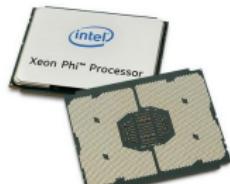
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2-step solution



MUL	ADD	MOV
MOVAPD		
VFMADDPD	...	

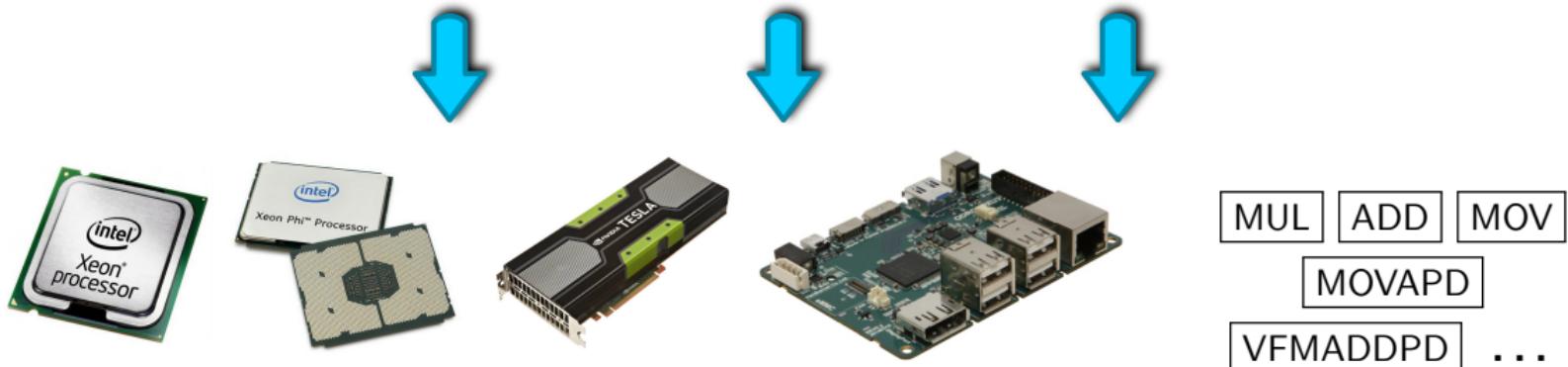
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MUL	ADD	MOV
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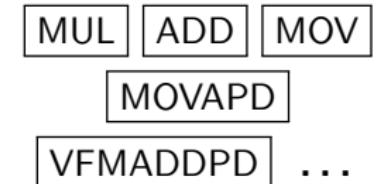
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$$= Q^{-1} U(I + U^T Q^{-1} U)^{-1} U^T$$

**Step 2: “LAMP”  
LINEAR  
ALGEBRA  
MAPPING  
PROBLEM**

$$y := \alpha x + y$$

$$LU = A$$

...

$$C := \alpha AB + \beta C$$

$$X := A^{-1}B$$

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$$QR = A$$

...



**BLAS**



**LAPACK**

...



MUL	ADD	MOV
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- ▶ Suboptimal solution easy
- ▶ Optimality NP complete reduction from Ensemble Computation

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Slow solutions → “2-language problem”

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Seven languages/libraries. Not an exhaustive survey.

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Main criterion: high level of **abstraction**. Also: popularity, expressiveness, (performance...)

```
C = A * B' + B * A' + C; // Matlab, Octave
```

```
C = A * transpose(B) + B * transpose(A) + C // Julia
```

```
C = A * trans(B) + B * trans(A) + C; // Armadillo
```

```
C = A * B.transpose() + B * A.transpose() + C; // Eigen
```

```
ct = at @ bt.T + bt @ at.T + ct // NumPy
```

```
ct <- at %*% t(bt) + bt %*% t(at) + ct // R
```

## Do they map? matrix products

Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
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$C = AB$

## Do they map?

matrix products

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$C = AB$	0.29	0.28	0.30	0.31	0.29	0.29	0.29	0.27

## Do they map? matrix products

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$C = AB$	0.29	0.28	0.30	0.31	0.29	0.29	0.29	0.27
GEMM	✓	✓	✓	✓	✓	✓	✓	

## Do they map? matrix products

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$C = AB$	0.29	0.28	0.30	0.31	0.29	0.29	0.29	0.27
GEMM	✓	✓	✓	✓	✓	✓	✓	
<hr/>								
$C = C + AA'$								

## Do they map? matrix products

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$C = AB$	0.29	0.28	0.30	0.31	0.29	0.29	0.29	0.27
GEMM	✓	✓	✓	✓	✓	✓	✓	
$C = C + AA'$	0.18	0.17	0.21	0.32	0.29	0.17	0.18	0.14

## Do they map?

matrix products

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$C = AB$	0.29	0.28	0.30	0.31	0.29	0.29	0.29	0.27
GEMM	✓	✓	✓	✓	✓	✓	✓	
<hr/>								
$C = C + AA'$	0.18	0.17	0.21	0.32	0.29	0.17	0.18	0.14
SYRK	✓	✓	✓	✗	✗	✓	✓	
<hr/>								

## Do they map? matrix products

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$C = AB$	0.29	0.28	0.30	0.31	0.29	0.29	0.29	0.27
GEMM	✓	✓	✓	✓	✓	✓	✓	
$C = C + AA'$	0.18	0.17	0.21	0.32	0.29	0.17	0.18	0.14
SYRK	✓	✓	✓	✗	✗	✓	✓	
$C = C + AB' + BA'$	0.57	0.59	0.69	0.59	0.58	0.57	0.58	0.28

## Do they map? matrix products

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$C = AB$	0.29	0.28	0.30	0.31	0.29	0.29	0.29	0.27
GEMM	✓	✓	✓	✓	✓	✓	✓	
$C = C + AA'$	0.18	0.17	0.21	0.32	0.29	0.17	0.18	0.14
SYRK	✓	✓	✓	✗	✗	✓	✓	
$C = C + AB' + BA'$	0.57	0.59	0.69	0.59	0.58	0.57	0.58	0.28
SYR2K	✗	✗	✗	✗	✗	✗	✗	

Do they map?       $Ax = b \equiv x := A \setminus b \not\equiv \text{inv}(A) * b$

---

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
--	--------	--------	-------	---	-------	--------	-------	---

---

$x := A \setminus b$

Do they map?  $Ax = b \equiv x := A \setminus b \not\equiv \text{inv}(A) * b$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$x := A \setminus b$	0.71	0.72	0.63	0.68	0.64	0.63	0.72	0.61

Do they map?  $Ax = b \equiv x := A \setminus b \not\equiv \text{inv}(A) * b$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$x := A \setminus b$	0.71	0.72	0.63	0.68	0.64	0.63	0.72	0.61
$\text{inv}(A) * b$	1.76	1.82	1.69	2.20	2.21	<b>0.63</b>	2.49	1.71

Do they map?  $Ax = b \equiv x := A \setminus b \not\equiv \text{inv}(A) * b$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$x := A \setminus b$	0.71	0.72	0.63	0.68	0.64	0.63	0.72	0.61
$\text{inv}(A) * b$	1.76	1.82	1.69	2.20	2.21	<b>0.63</b>	2.49	1.71
LinSolve	-	-	-	-	-	✓	-	-

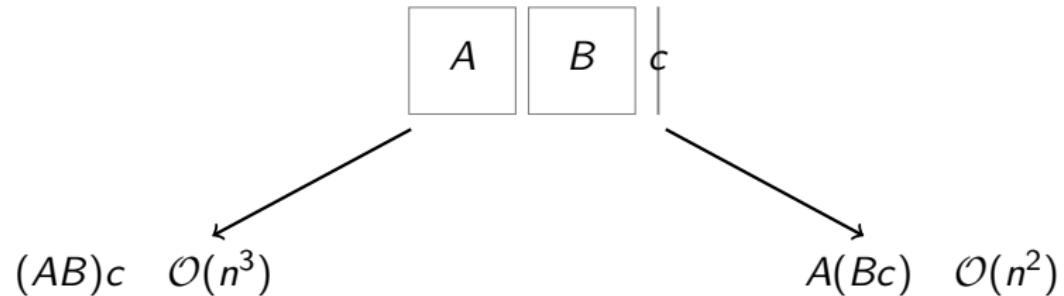
but ...

Do they map?  $Ax = b \equiv x := A \setminus b \not\equiv \text{inv}(A) * b$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
$x := A \setminus b$	0.71	0.72	0.63	0.68	0.64	0.63	0.72	0.61
$\text{inv}(A) * b$	1.76	1.82	1.69	2.20	2.21	<b>0.63</b>	2.49	1.71
LinSolve	-	-	-	-	-	✓	-	-

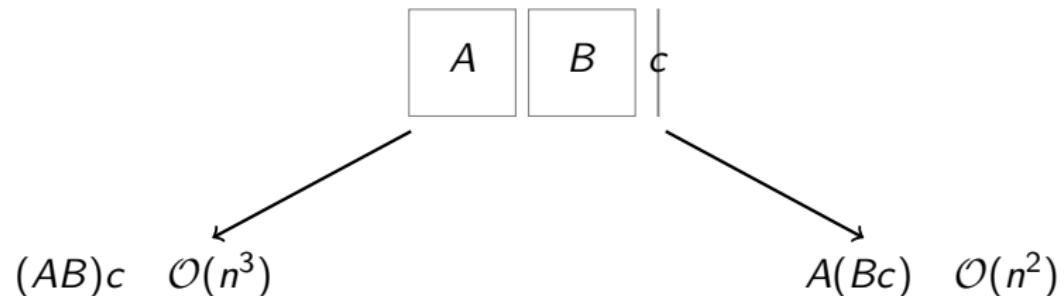
but . . . should they map?

## Optimal parenthesisation



Product is associative, but its cost is not

## Optimal parenthesisation



Product is associative, but its cost is not

Matrix Chain Algorithm

$\mathcal{O}(k \log k)$  Hu & Shing 1982;  $\mathcal{O}(k^3)$  dynamic programming

## Matrix Chain?

<b>Chain</b>	<b>Optimal Evaluation</b>
1) "left-to-right" (LtR)	$((A B) C)$
2) "right-to-left" (RtL)	$(A (B C))$
3) "mixed" (Mix)	$((A B) (C D))$

## Matrix Chain?

<b>Chain</b>	<b>Optimal Evaluation</b>
1) "left-to-right" (LtR)	$((A B) C)$
2) "right-to-left" (RtL)	$(A (B C))$
3) "mixed" (Mix)	$((A B) (C D))$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy
1) LtR no par.	0.056	0.056	0.055	0.061	0.058	0.056	0.055
	0.056	0.056	0.055	0.061	0.058	0.056	0.055

# Matrix Chain?

Chain	Optimal Evaluation
1) "left-to-right" (LtR)	((A B) C)
2) "right-to-left" (RtL)	(A (B C))
3) "mixed" (Mix)	((A B) (C D))

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy
1)	LtR no par.	0.056	0.056	0.055	0.061	0.058	0.056
	LtR guided	0.056	0.056	0.055	0.061	0.058	0.056
2)	RtL no par.	0.42	0.43	0.42	0.44	0.42	<b>0.055</b>
	RtL guided	0.055	0.056	0.054	0.059	0.056	0.056

# Matrix Chain?

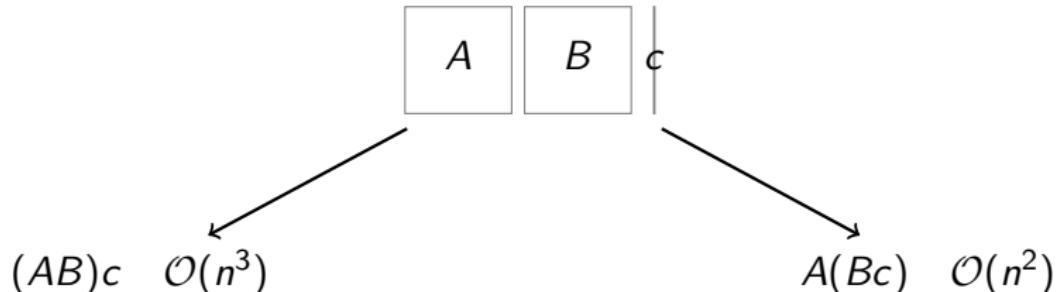
Chain	Optimal Evaluation
1) "left-to-right" (LtR)	$((A B) C)$
2) "right-to-left" (RtL)	$(A (B C))$
3) "mixed" (Mix)	$((A B) (C D))$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy
1) 1) LtR no par.	0.056	0.056	0.055	0.061	0.058	0.056	0.055
	0.056	0.056	0.055	0.061	0.058	0.056	0.055
2) 2) RtL no par.	0.42	0.43	0.42	0.44	0.42	<b>0.055</b>	0.42
	0.055	0.056	0.054	0.059	0.056	0.055	0.056
3) 3) Mix no par.	0.32	0.33	0.33	0.33	0.35	0.31	0.33
	0.21	0.22	0.22	0.22	0.23	0.20	0.22

# Matrix Chain?

Chain	Optimal Evaluation
1) "left-to-right" (LtR)	$((A B) C)$
2) "right-to-left" (RtL)	$(A (B C))$
3) "mixed" (Mix)	$((A B) (C D))$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy
1) 1) LtR no par.	0.056	0.056	0.055	0.061	0.058	0.056	0.055
	0.056	0.056	0.055	0.061	0.058	0.056	0.055
2) 2) RtL no par.	0.42	0.43	0.42	0.44	0.42	<b>0.055</b>	0.42
	0.055	0.056	0.054	0.059	0.056	0.055	0.056
3) 3) Mix no par.	0.32	0.33	0.33	0.33	0.35	0.31	0.33
	0.21	0.22	0.22	0.22	0.23	0.20	0.22
Matrix chains	×	×	×	×	×	≈	×



In practice

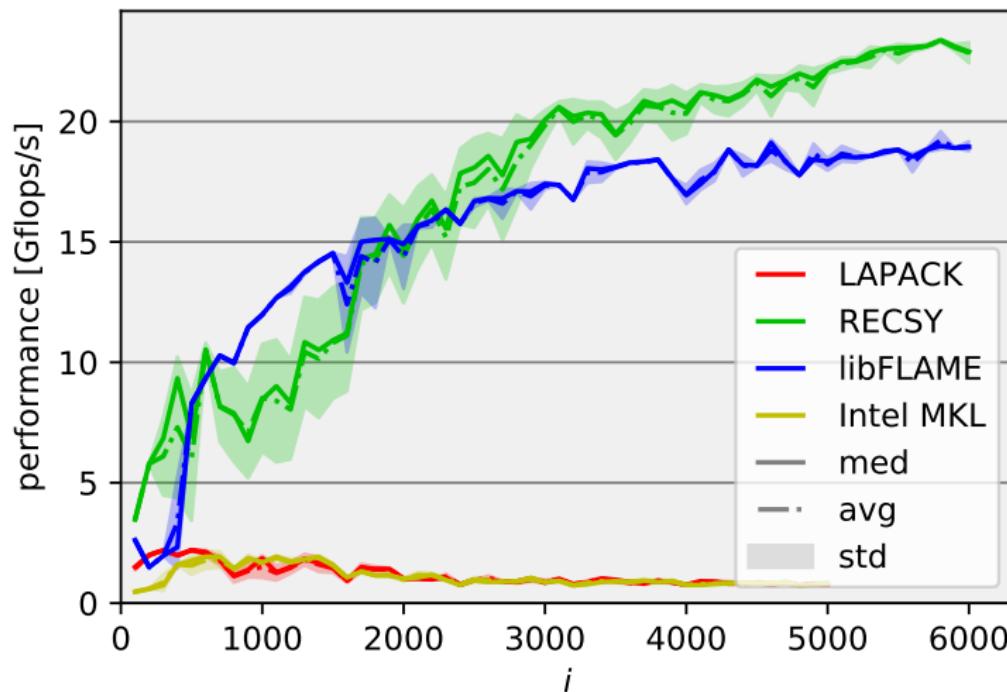
- ▶ Unary operators: transposition, inversion  $(X := AB^T C^{-T} D + \dots)$
- ▶ Overlapping kernels  $(\text{e.g., } L \leftarrow L^{-1}, X = A^{-1}B)$
- ▶ Decompositions  $(\text{e.g., } A \rightarrow Q^T D Q, A \rightarrow L U)$
- ▶ Properties & specialized kernels  $(\text{GEMM, TRMM, SYMM, \dots})$

## Challenge: Not all flops were created equal

#FLOPs vs. execution time (vs. numerical stability)

$$\underset{\mathcal{A}}{\operatorname{argmin}}(\text{FLOPs}(\mathcal{A})) \neq \underset{\mathcal{A}}{\operatorname{argmin}}(\text{time}(\mathcal{A}))$$

Triangular Sylvester equation – all libraries perform the same # of flops



#FLOPs vs. execution time (vs. numerical stability)

$$\underset{\mathcal{A}}{\operatorname{argmin}} (\text{ FLOPs}(\mathcal{A})) \neq \underset{\mathcal{A}}{\operatorname{argmin}} (\text{ time}(\mathcal{A}))$$

⇒ **Performance prediction:** efficiency

#FLOPs vs. execution time (vs. numerical stability)

$$\underset{\mathcal{A}}{\operatorname{argmin}} (\text{ FLOPs}(\mathcal{A})) \neq \underset{\mathcal{A}}{\operatorname{argmin}} (\text{ time}(\mathcal{A}))$$

⇒ **Performance prediction:** efficiency

## Big Challenge: Parallelism

$$X := A((B^T C^{-T})D) \quad \text{vs.} \quad X := (AB^T)(C^{-T}D) \quad \text{vs.} \quad \dots$$

## Properties?

Operation	Property	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
Linear System	-	0.71	0.74	0.62	0.67	0.63	0.62	0.65	0.61

## Properties?

Operation	Property	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
Linear System	-	0.71	0.74	0.62	0.67	0.63	0.62	0.65	0.61
	Symmetric	0.71	0.73	0.62	0.69	N/A	0.62	0.65	0.46

## Properties?

Operation	Property	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
Linear System	-	0.71	0.74	0.62	0.67	0.63	0.62	0.65	0.61
	Symmetric	0.71	0.73	0.62	0.69	N/A	0.62	0.65	0.46
	SPD	<b>0.41</b>	<b>0.40</b>	0.60	0.63	N/A	<b>0.34</b>	0.62	0.31

## Properties?

Operation	Property	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
Linear System	-	0.71	0.74	0.62	0.67	0.63	0.62	0.65	0.61
	Symmetric	0.71	0.73	0.62	0.69	N/A	0.62	0.65	0.46
	SPD	<b>0.41</b>	<b>0.40</b>	0.60	0.63	N/A	<b>0.34</b>	0.62	0.31
	Triangular	<b>0.03</b>	<b>0.04</b>	<b>0.03</b>	0.63	N/A	0.62	0.65	0.03

## Properties?

Operation	Property	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
Linear System	-	0.71	0.74	0.62	0.67	0.63	0.62	0.65	0.61
	Symmetric	0.71	0.73	0.62	0.69	N/A	0.62	0.65	0.46
	SPD	<b>0.41</b>	<b>0.40</b>	0.60	0.63	N/A	<b>0.34</b>	0.62	0.31
	Triangular	<b>0.03</b>	<b>0.04</b>	<b>0.03</b>	0.63	N/A	0.62	0.65	0.03
	Diagonal	0.03	0.05	<b>0.01</b>	0.63	N/A	<b>0.03</b>	0.62	0.001
		≈	≈	≈	×	×	≈	×	

## Properties?

Operation	Property	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy	C
Linear System	-	0.71	0.74	0.62	0.67	0.63	0.62	0.65	0.61
	Symmetric	0.71	0.73	0.62	0.69	N/A	0.62	0.65	0.46
	SPD	<b>0.41</b>	<b>0.40</b>	0.60	0.63	N/A	<b>0.34</b>	0.62	0.31
	Triangular	<b>0.03</b>	<b>0.04</b>	<b>0.03</b>	0.63	N/A	0.62	0.65	0.03
	Diagonal	0.03	0.05	<b>0.01</b>	0.63	N/A	<b>0.03</b>	0.62	0.001
		≈	≈	≈	×	×	≈	×	
Multiplication	-	1.44	1.48	1.47	1.47	1.45	1.44	1.44	1.46
	Triangular	1.44	1.48	<b>0.75</b>	1.47	1.45	1.44	1.44	0.74
	Diagonal	1.44	1.48	<b>0.03</b>	1.47	1.45	1.42	1.44	0.06
		×	×	✓	×	×	×	×	

## Challenge: Inference of properties

► **easy**

$$E := L_1 * U^T * L_2$$

triangular(  $E$  ) ?

## Challenge: Inference of properties

▶ **easy**

$$E := L_1 * U^T * L_2$$

triangular(  $E$  ) ?

▶ **hard**

$$\lambda(L^{-T} A L^{-1})$$

symmetric(  $L^{-T} A L^{-1}$  ) ?

## Challenge: Inference of properties

- ▶ **easy**       $E := L_1 * U^T * L_2$        $\text{triangular}( E ) ?$
- ▶ **hard**       $\lambda(L^{-T} A L^{-1})$        $\text{symmetric}( L^{-T} A L^{-1} ) ?$
- ▶ **impossible?**     $E := Q^{-1} U(I + U^T Q^{-1} U)^{-1} U^T$        $\text{properties}( I + U^T Q^{-1} U ) ?$

## Challenge: Inference of properties

- ▶ **easy**       $E := L_1 * U^T * L_2$        $\text{triangular}( E ) ?$
- ▶ **hard**       $\lambda(L^{-T} A L^{-1})$        $\text{symmetric}( L^{-T} A L^{-1} ) ?$
- ▶ **impossible?**     $E := Q^{-1} U(I + U^T Q^{-1} U)^{-1} U^T$        $\text{properties}( I + U^T Q^{-1} U ) ?$

⇒ **Symbolic analysis:** pattern matching

## Challenge: Common Subexpressions

[arXiv:1710.06915]

$$\begin{cases} X := AB^{-T}C \\ Y := B^{-1}A^TD \end{cases} \rightarrow \begin{cases} Z := AB^{-T} \\ X := ZC \\ Y := Z^TD \end{cases}$$

$$\begin{cases} X := AB^{-T}C \\ Y := B^{-1}A^TD \end{cases} \rightarrow \begin{cases} Z := AB^{-T} \\ X := ZC \\ Y := Z^TD \end{cases}$$

BUT

$$X := ABABv \not\rightarrow \begin{cases} Z := AB \\ X := ZZv \end{cases}$$

## Common Subexpressions?

$$\begin{cases} X := AB \\ Y := AB \end{cases} \rightarrow \begin{cases} X := AB \\ Y := X \end{cases}$$

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$$\begin{cases} X := AB \\ Y := AB \end{cases} \rightarrow \begin{cases} X := AB \\ Y := X \end{cases}$$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy
copy	0.27	0.31	0.36	0.30	0.30	0.26	0.30

## Common Subexpressions?

$$\begin{cases} X := AB \\ Y := AB \end{cases} \rightarrow \begin{cases} X := AB \\ Y := X \end{cases}$$

	Matlab	Octave	Julia	R	Eigen	Armad.	NumPy
copy	0.27	0.31	0.36	0.30	0.30	0.26	0.30
direct	0.54	0.6	0.61	0.56	0.58	0.52	0.55
	×	×	×	×	×	×	×

## Other features (challenges)

- ▶ Code motion

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```
for i = 1:n,  
    X = A*B;  
    d[i] = C[i,i];  
end
```

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→ ?  
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for i = 1:n,  
    d[i] = C[i,i];  
end
```

×

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for i = 1:n,  
    X = A*B;  
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end
```

→ ?

```
X = A*B;  
for i = 1:n,  
    d[i] = C[i,i];  
end
```

×

- ▶ Blocked operands

$$M = \begin{bmatrix} M_1 & 0 \\ 0 & M_2 \end{bmatrix}$$

## Other features (challenges)

### ▶ Code motion

```
for i = 1:n,  
    X = A*B;  
    d[i] = C[i,i];  
end
```

→ ?

```
X = A*B;  
for i = 1:n,  
    d[i] = C[i,i];  
end
```

×

### ▶ Blocked operands

$$M = \begin{bmatrix} M_1 & 0 \\ 0 & M_2 \end{bmatrix}$$

→ ?

$$\left\{ \begin{array}{l} M_1 x_T = y_T \\ M_2 x_B = y_B \end{array} , \quad \left\{ \begin{array}{l} y_T := M_1 x_T \\ y_B := M_2 x_B \end{array} \right. \right.$$

## Other features (challenges)

### ▶ Code motion

```
for i = 1:n,  
    X = A*B;  
    d[i] = C[i,i];  
end
```

→ ?

```
X = A*B;  
for i = 1:n,  
    d[i] = C[i,i];  
end
```

×

### ▶ Blocked operands

$$M = \begin{bmatrix} M_1 & 0 \\ 0 & M_2 \end{bmatrix}$$

→ ?

$$\begin{cases} M_1x_T = y_T, \\ M_2x_B = y_B, \end{cases}$$

$$\begin{cases} y_T := M_1x_T \\ y_B := M_2x_B \end{cases}$$

×, ×

## Other features (challenges)

- ▶ Code motion

```
for i = 1:n,  
    X = A*B;  
    d[i] = C[i,i];  
end
```

→ ?

```
X = A*B;  
for i = 1:n,  
    d[i] = C[i,i];  
end
```

×

- ▶ Blocked operands

$$M = \begin{bmatrix} M_1 & 0 \\ 0 & M_2 \end{bmatrix} \quad \rightarrow ?$$

$$\begin{cases} M_1x_T = y_T, \\ M_2x_B = y_B, \end{cases} \quad \begin{cases} y_T := M_1x_T \\ y_B := M_2x_B \end{cases} \quad \times, \times$$

- ▶  $\text{diag}(A + B)$  vs.  $\text{diag}(A) + \text{diag}(B)$

## Other features (challenges)

- ▶ Code motion

```
for i = 1:n,  
    X = A*B;  
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end
```

→ ?

```
X = A*B;  
for i = 1:n,  
    d[i] = C[i,i];  
end
```

×

- ▶ Blocked operands

$$M = \begin{bmatrix} M_1 & 0 \\ 0 & M_2 \end{bmatrix} \quad \rightarrow ?$$

$$\begin{cases} M_1x_T = y_T, \\ M_2x_B = y_B, \end{cases} \quad \begin{cases} y_T := M_1x_T \\ y_B := M_2x_B \end{cases} \quad \times, \times$$

- ▶  $\text{diag}(A + B)$  vs.  $\text{diag}(A) + \text{diag}(B)$

→

Armadillo

## Other features (challenges)

- ▶ Code motion

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for i = 1:n,  
    X = A*B;  
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→ ?

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X = A*B;  
for i = 1:n,  
    d[i] = C[i,i];  
end
```

×

- ▶ Blocked operands

$$M = \begin{bmatrix} M_1 & 0 \\ 0 & M_2 \end{bmatrix} \quad \rightarrow ?$$

$$\begin{cases} M_1x_T = y_T, \\ M_2x_B = y_B, \end{cases} \quad \begin{cases} y_T := M_1x_T \\ y_B := M_2x_B \end{cases} \quad \times, \times$$

- ▶  $\text{diag}(A + B)$  vs.  $\text{diag}(A) + \text{diag}(B)$  → Armadillo
- $\text{diag}(AB)$  vs. ...

## Other features (challenges)

### ▶ Code motion

```
for i = 1:n,  
    X = A*B;  
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end
```

→ ?

```
X = A*B;  
for i = 1:n,  
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end
```

×

### ▶ Blocked operands

$$M = \begin{bmatrix} M_1 & 0 \\ 0 & M_2 \end{bmatrix} \quad \rightarrow ?$$

$$\begin{cases} M_1x_T = y_T, \\ M_2x_B = y_B, \end{cases} \quad \begin{cases} y_T := M_1x_T \\ y_B := M_2x_B \end{cases} \quad \times, \times$$

- ▶  $\text{diag}(A + B)$  vs.  $\text{diag}(A) + \text{diag}(B)$  → Armadillo
- $\text{diag}(AB)$  vs. ... → ×

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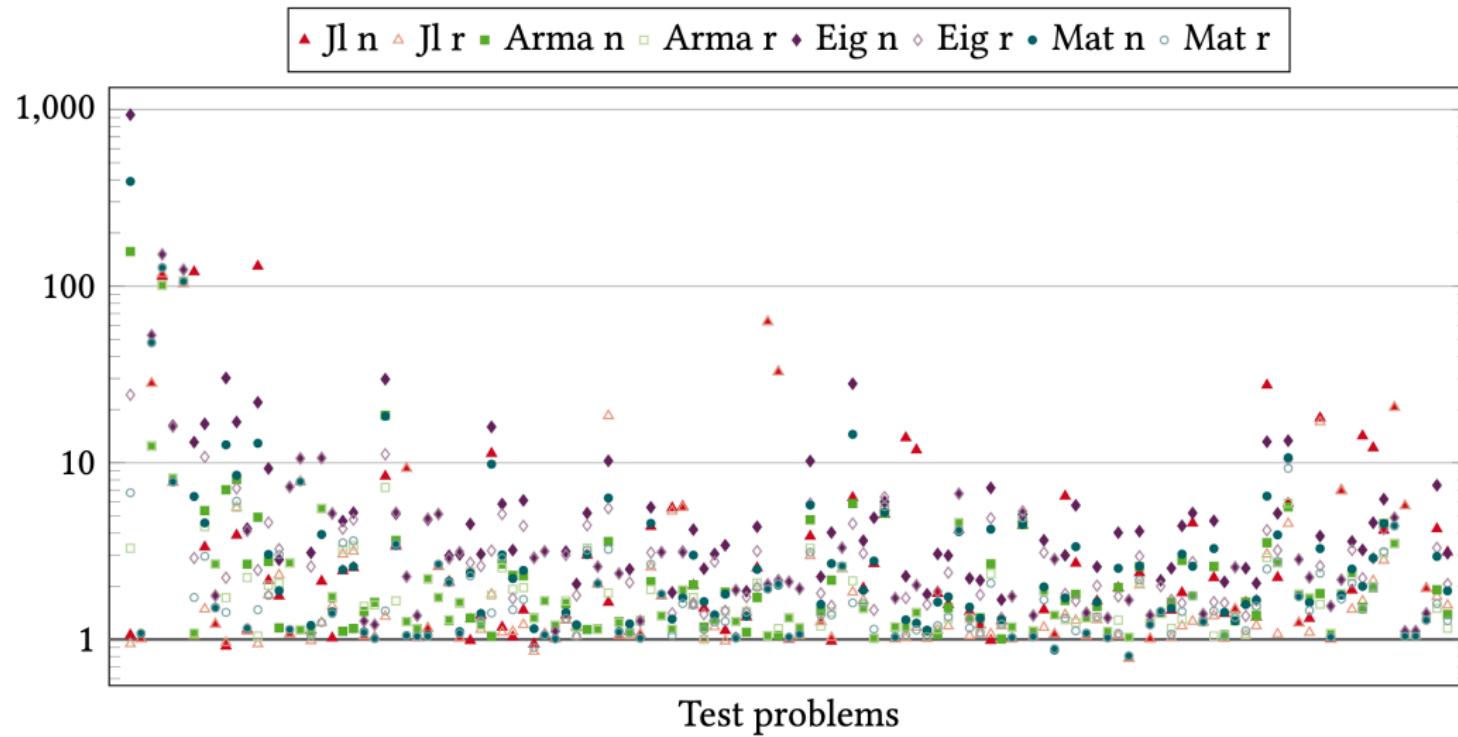
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THANK YOU

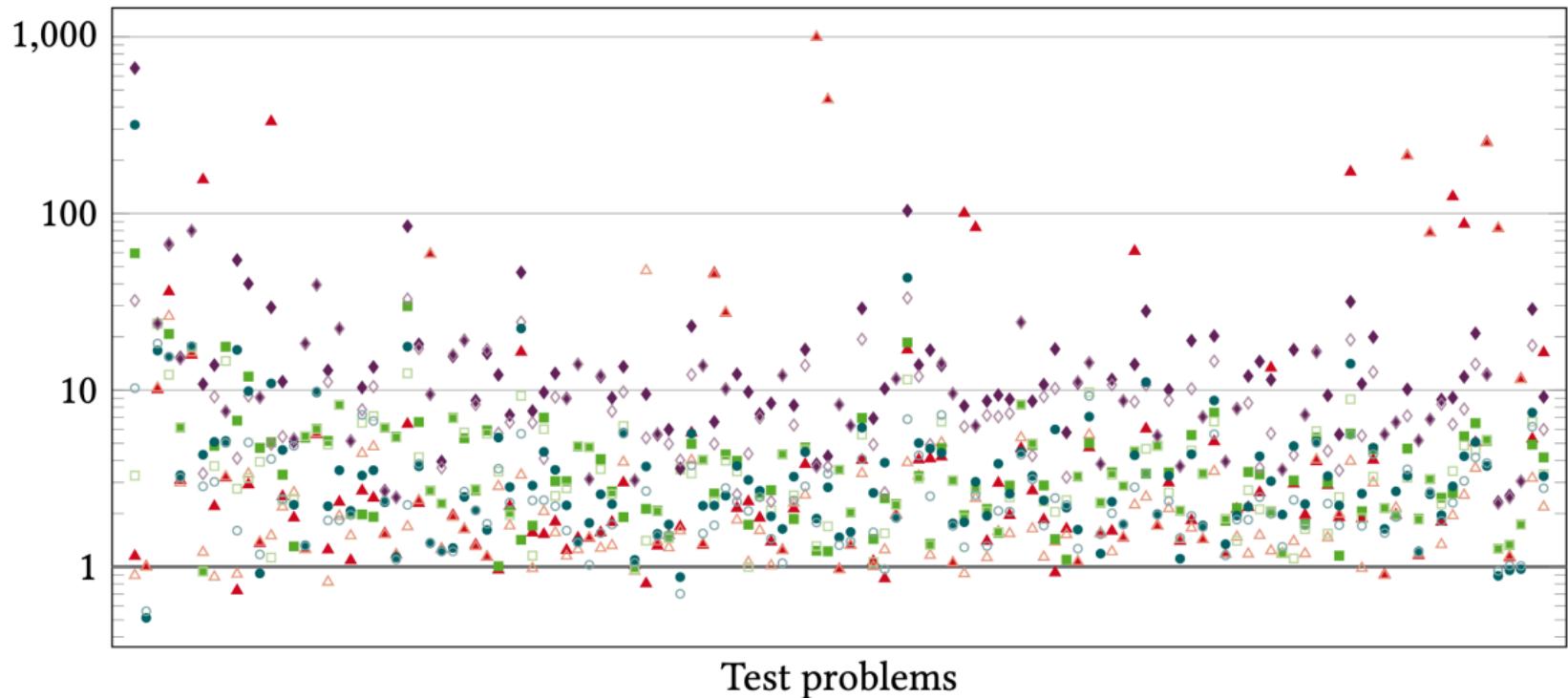
# Linnea speedup: 1 thread



Jl: Julia, Arma: Armadillo, Eig: Eigen, Mat: Matlab.

n/r: naive/recommended implementation

## Linnea speedup: 24 threads



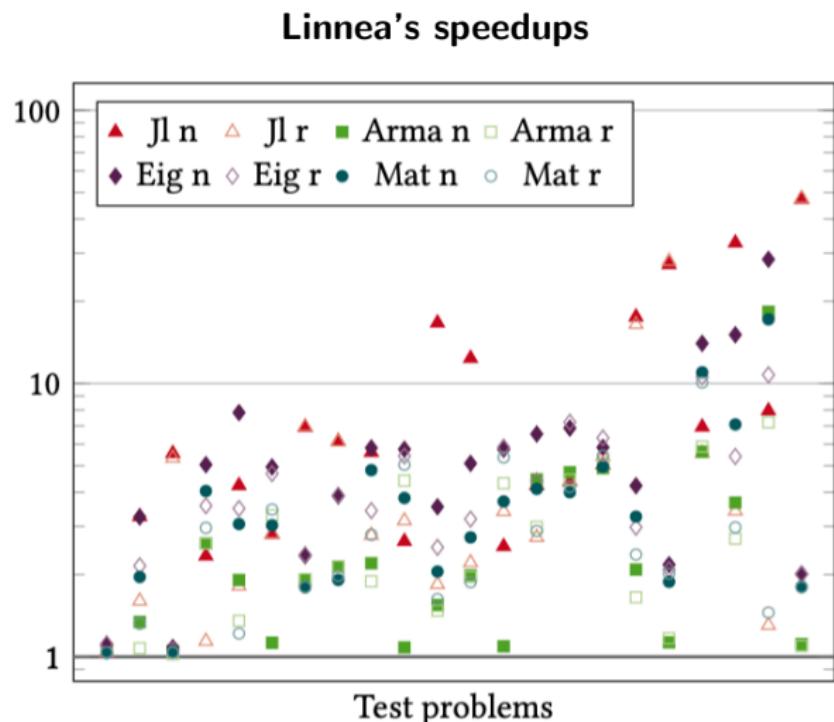
**Jl:** Julia, **Arma:** Armadillo, **Eig:** Eigen, **Mat:** Matlab.

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**Linear algebra knowledge:** operators, identities, properties, theorems

- Distributivity, commutativity, partitionings, ...
- $((QR)^T QR)^{-1}(QR)^T y \rightarrow (R^T Q^T QR)^{-1} R^T Q^T y \rightarrow R^{-1} R^{-T} R^T Q^T y \rightarrow R^{-1} Q^T y$
- $\text{SPD}(A) \rightarrow \text{SPD}(A_{BR} - A_{BL} A_{TL}^{-1} A_{BL}^T)$  Schur complement
- ...

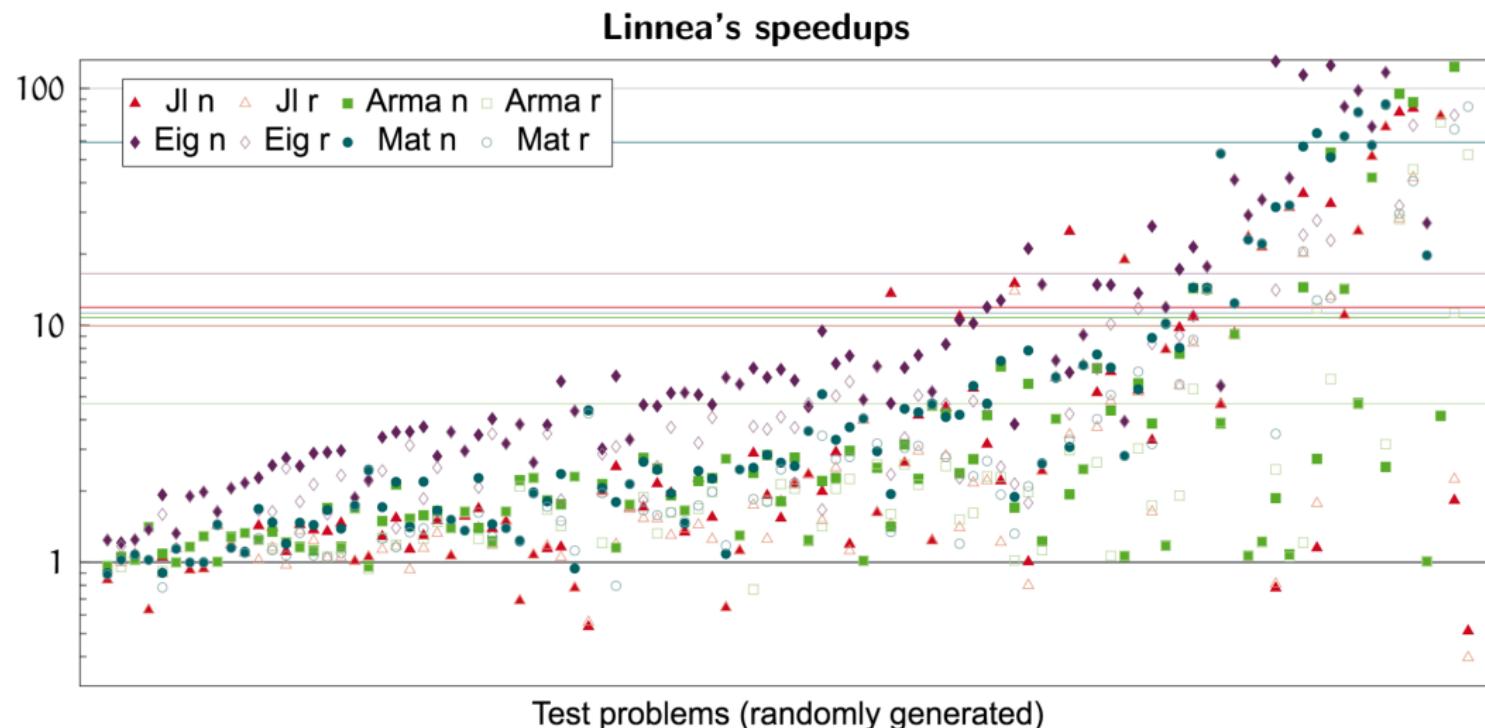
# Linnea: Results for real applications



**Jl:** Julia, **Arma:** Armadillo, **Eig:** Eigen, **Mat:** Matlab.

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# Linnea: Results for random expressions



**Jl:** Julia, **Arma:** Armadillo, **Eig:** Eigen, **Mat:** Matlab.

**n/r:** naive/recommended implementation

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- ▶ Applications

$$\mathcal{E} : \text{explicit assignments} \quad \mathcal{K} : \text{libraries} \quad \mathcal{M} : \text{execution time} + \dots$$



Transposition

Khatri-Rao

Contraction

SpMTTKRP

Alternating LS

TTV, TTM

HPTT

TCL

BLAS



MUL

ADD

MOV

MOVAPD

VFMADDPD

...

## Linnea: Example

$$w := AB^{-1}c, \quad \text{SPD}(B)$$

### Naive

```
w = A*inv(B)*c
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### Recommended

```
w = A*(B\c)
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### Expert

```
L = Chol(B)
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### Generated

```
m10 = A; m11 = B; m12 = c;  
potrf!('L', m11)  
trsv!('L', 'N', 'N', m11, m12)  
trsv!('L', 'T', 'N', m11, m12)  
m13 = Array{Float64}(10)  
gemv!('N', 1.0, m10, m12, 0.0, m13)  
w = m13
```