

Automating the generation of algorithms for Generalized Least-Squares problems

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 - ➔ Smart mapping onto BLAS/LAPACK
 - ➔ The decomposition is not unique: many algorithms

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Input Matrix equation + **App-specific Knowledge**

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Output **Family** of algorithms

Approach Map onto high-performance kernels

Search: Not exhaustive. Guidelines. Led by knowledge.

- 1 Goal
- 2 Automation: Engine
- 3 Automation: Extensions
- 4 Conclusions

How to explore the search space

- Inverse operator:
 - A^{-1} : factorization
 - ➔ $LL^T = A, \quad QR = A, \quad ZWZ^T = A, \dots$

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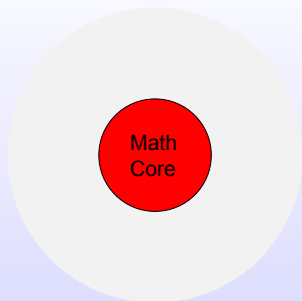
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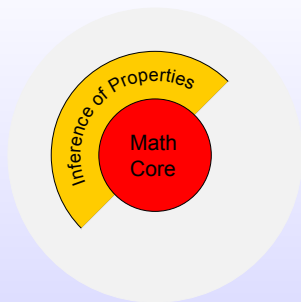
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 - Reducing flops: $S = R^{-1} Q^T L y$



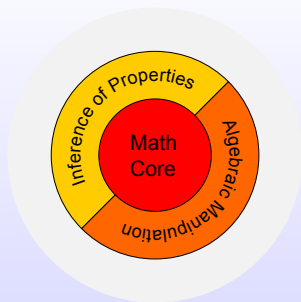
- Math core:
 - Matrix, Vector, Scalar, Size/Shape, ...
 - Diagonal, L/U triangular, Symm, ...
 - Operators: +, -, *, $^{-1}$, T . Properties.

- $X: \{\text{Matrix, FullRank, ColumnPanel}\}$
- $L: \{\text{Matrix, Square, Lower Triangular}\}$
- $(LL^T)^{-1} \rightarrow L^{-T}L^{-1}$
- $(X^T X)^{-1} \rightarrow (X^T X)^{-1}$



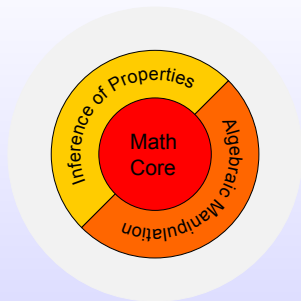
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- $A := X^T X \rightarrow A$ is SPD
- $QR = X \rightarrow Q$ is Orthonormal, R is Triangular



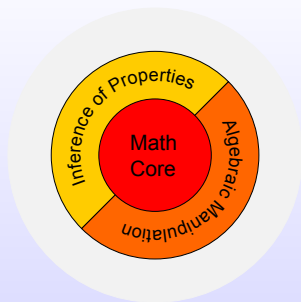
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- $(R^T Q^T Q R)^{-1} R^T Q^T$



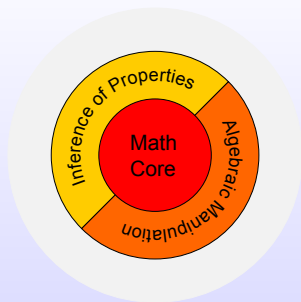
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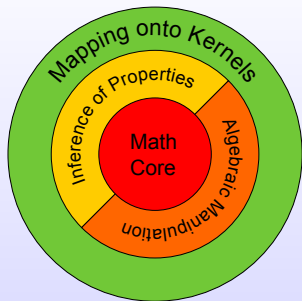
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- Kernels

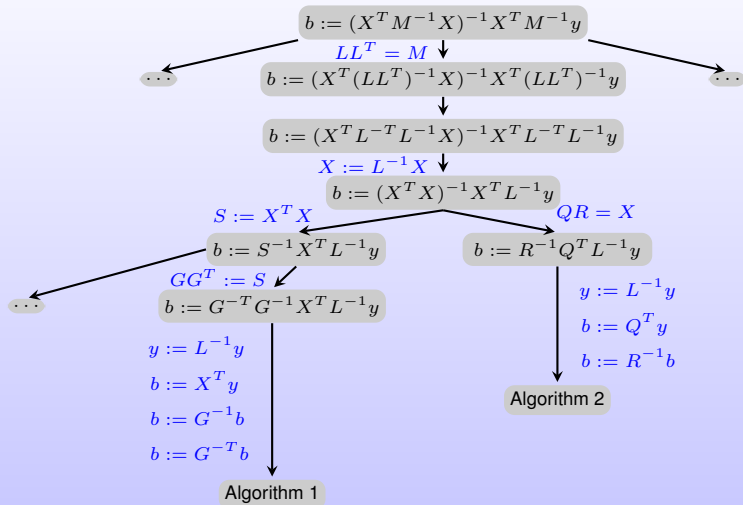
- Factorizations: QR, LU, Cholesky, Eigen, ...
- BLAS: GEMM, TRSM, GEMV, DOT, ...
- LAPACK: inverse of a triangular matrix, ...
- Extensible

$$\begin{cases} b := (X^T M^{-1} X)^{-1} X^T M^{-1} y \\ M := h\Phi + (1 - h)I \end{cases}$$

```
equation = {  
  equal[b,  
    times[ inv[ times[ trans[X], inv[M], X ] ],  
      ...  
      y ]  
] };
```

```
properties = {  
  {X, {"Input", "Matrix", "ColPanel", "FullRank"}}  
  {y, {"Input", "Vector" }}  
  ...  
  {b, {"Output", "Vector" }}  
};
```

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$$\begin{cases} b_{ij} = (X_i^T M_j^{-1} X_i)^{-1} X_i^T M_j^{-1} y_j & \text{with } 1 \leq i \leq m \\ M_j = h_j \Phi + (1 - h_j) I & \text{and } 1 \leq j \leq t. \end{cases}$$

- We have to solve not one but a sequence of **correlated** problems

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- Goal: **reuse of computation**

Naive approach: for i , for j , ...

$$b_{ij} = (X_i^T M_j^{-1} X_i)^{-1} X_i^T M_j^{-1} y_j$$

for $i = 1 : m$

 for $j = 1 : t$

$$LL^T = M_j$$

$$X^T \leftarrow X_i^T L^{-T}$$

$$QR = X$$

$$y \leftarrow L^{-1} y_j$$

$$b \leftarrow Q^T y$$

$$b_{ij} \leftarrow R^{-1} b$$

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$$Q_{ij} R_{ij} = X_{ij}$$

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Elmar Peise, *Hierarchical Performance Modeling for Ranking Dense Linear Algebra Algorithms*, 2012. <http://arxiv.org/abs/1207.5217>

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TO-DO

- Encode more available knowledge
- Rank algorithms to pick the “best”
- Matlab/Fortran code generator

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- Dr. Edoardo Di Napoli
- Matthias Petschow
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- Elmar Peise

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Deutsche
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DFG

More details in

D. Fabregat, P. Bientinesi, *A Domain-Specific Compiler for Linear Algebra Operations*, 2012.

<http://arxiv.org/abs/1205.5975>

Further questions?

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