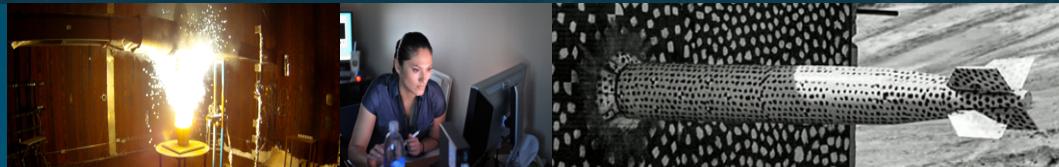




Sandia  
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# Exploring Chapel Productivity Using Some Graph Algorithms

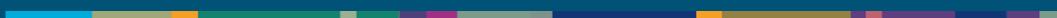


*Richard Barrett*

Chapel Implementors and Users Workshop 2020

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SAND 2020 – 5317 C



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# Team

Omar Aaziz : node performance analysis

Richard Barrett : application development

Jeanine Cook : node performance analysis

Chris Jenkins : architecture

Stephen Oliver : runtime systems

Courtenay Vaughan : distributed memory performance analysis



# Overview

*Investigating Chapel performance for some linear algebra based graph analytics*

Compute hitting time moments and triangle enumeration.

*Sparse matrix-vector and matrix-matrix multiplication.*

Compare with existing implementations

- Grafiki hitting time : C++/Kokkos/MPI
  - “Advantages to modeling relational data using hypergraphs versus graphs”, Wolf, Klinvexm, and Dunlavy, IEEE HPEC, 2016.
- miniTri : C++/OpenMP/MPI
  - “A Task-Based Linear Algebra Building Blocks Approach for Scalable Graph Analytics”, Wolf, Stark, and Berry, IEEE HPEC 2015.



# Outline

Graph hitting time

Key computation

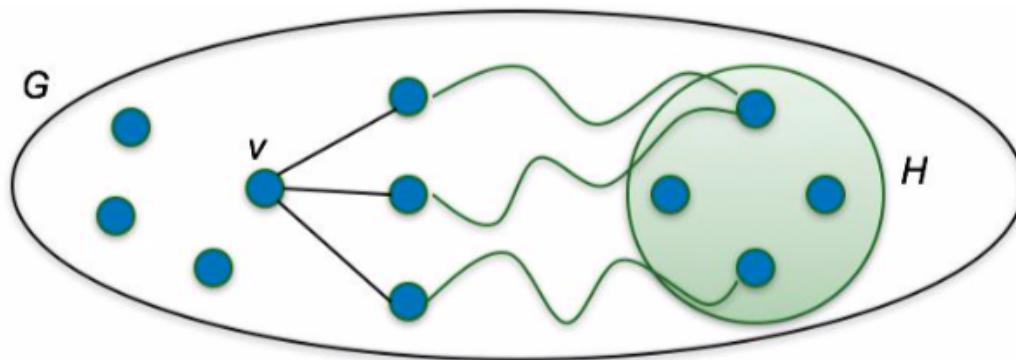
Performance

Preview of triangle enumeration

Summary

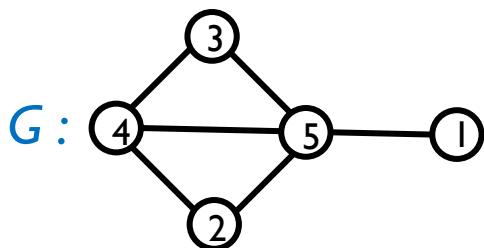
# Graph hitting time

- A random variable for the number of (Markov chain) steps to reach a set of hitting set vertices  $H$  of a graph  $G$



- Compute random variable distribution, i.e., the hitting time moments : mean, standard deviation, skew, and kurtosis.

# Setting up linear system



Simple undirected graph

$$A = \begin{pmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

Adjacency matrix

Configured as linear system :  $(D - A)x_k = f(D, A, x_{k-1})$

for  $D$  = diagonal matrix of vertex degrees,  $x$  = moments

where  $x_1$  mean,  $x_2$  standard deviation,  $x_3$  skew,  $x_4$  kurtosis

Solved using the *Conjugate Gradient* algorithm

- Key kernel: *matrix-vector product*

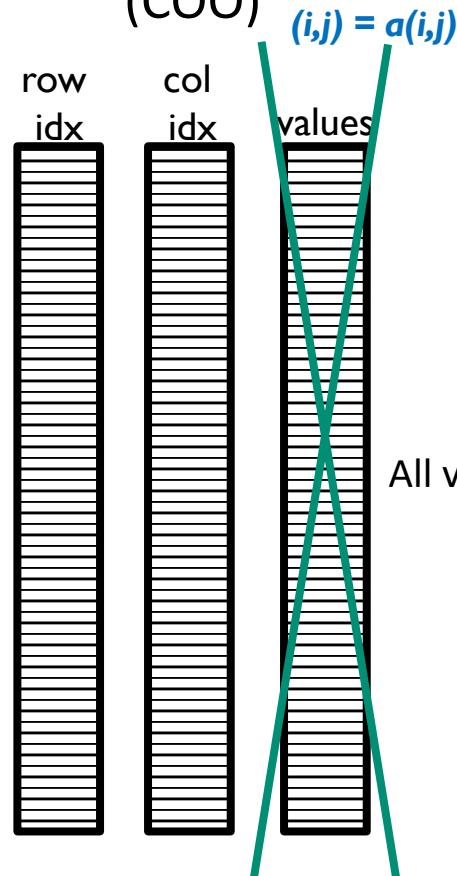
# Storing the sparse matrix

## Chapel sparse domain

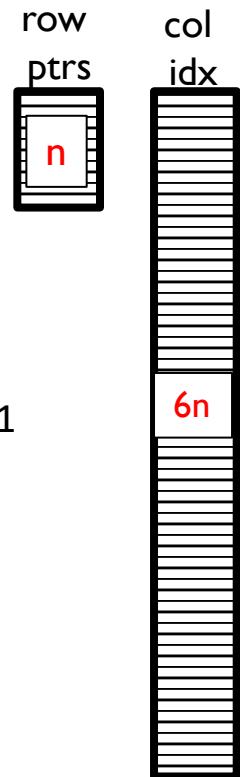
- Define dense domain
- Define subset of it: sparse domain
- Not (yet) performant (Brad)
- Using for miniTri in unique way

(not allocating anything  
using the sparse domain)

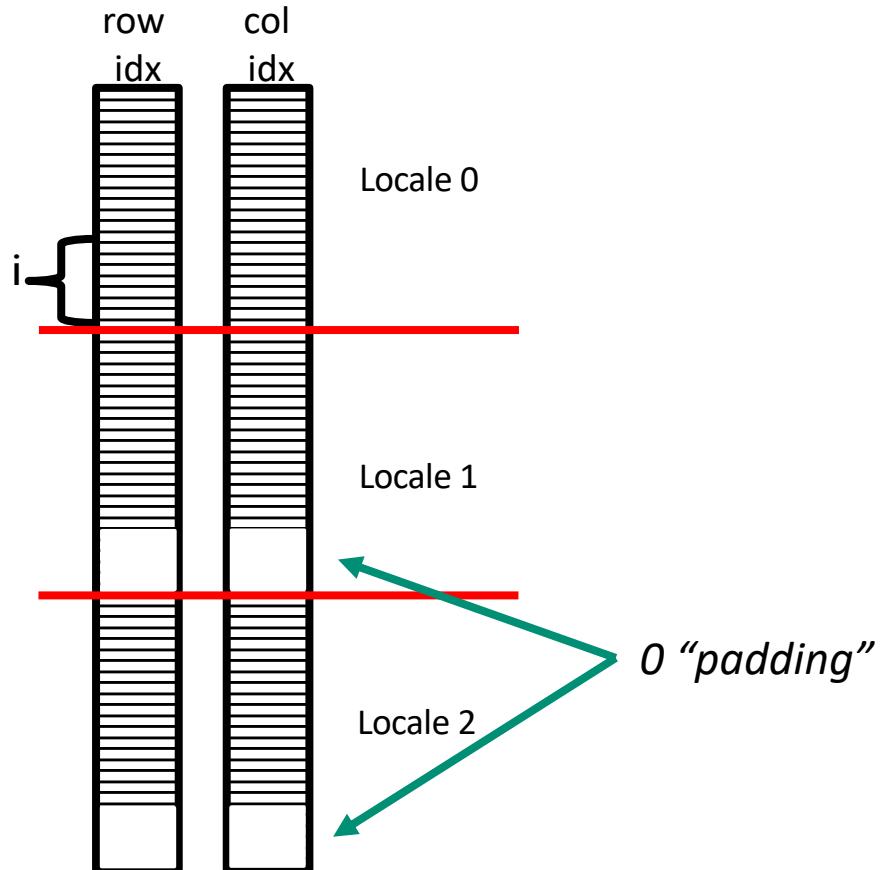
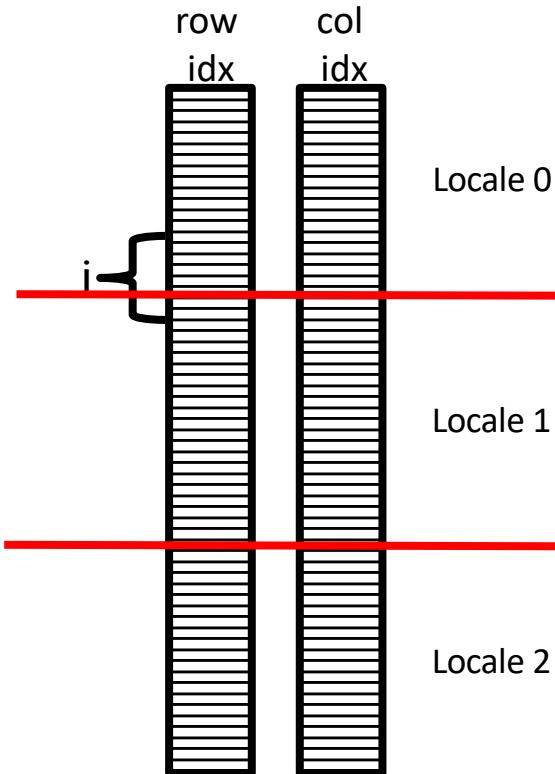
## Coordinate storage (COO)



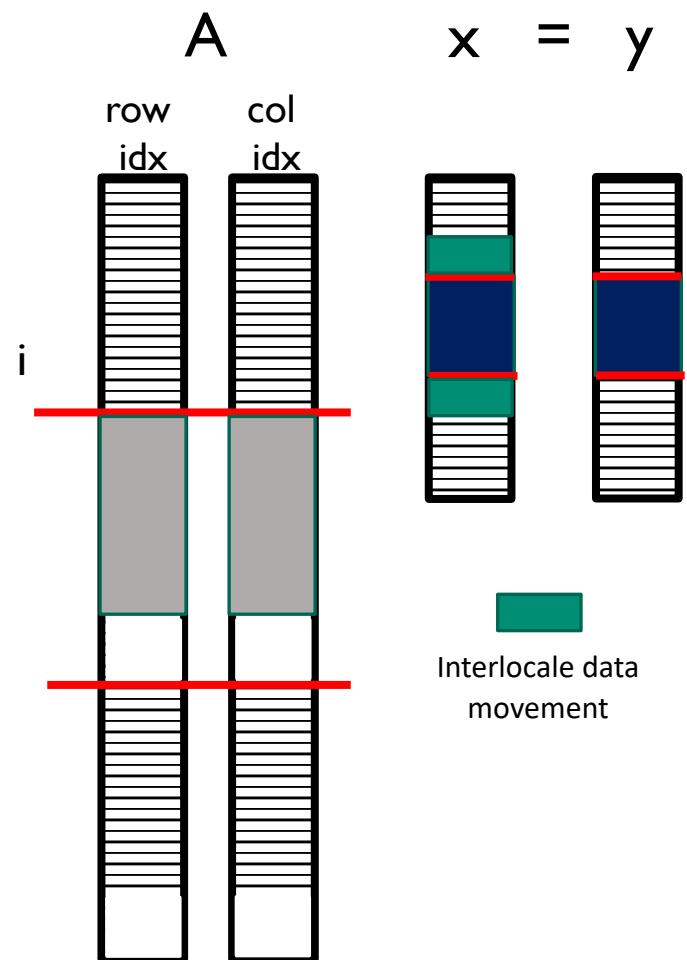
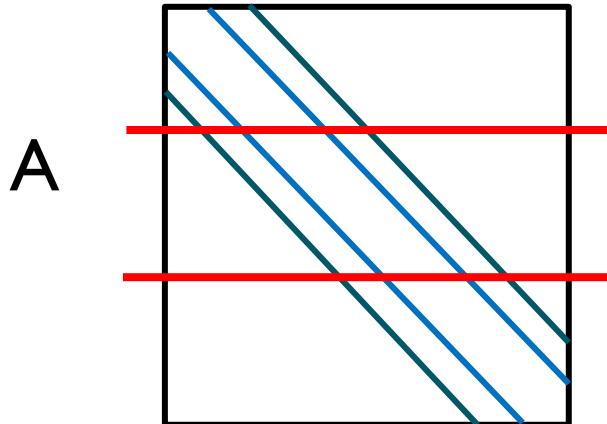
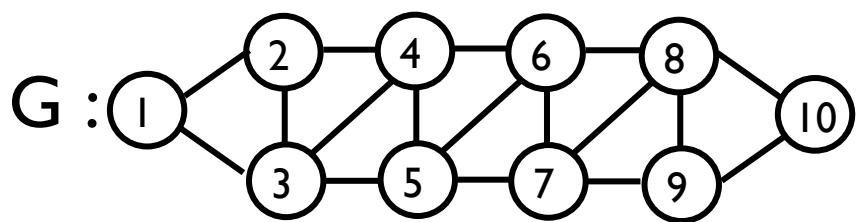
## Row compressed (CSR)



# Balance the load (COO)



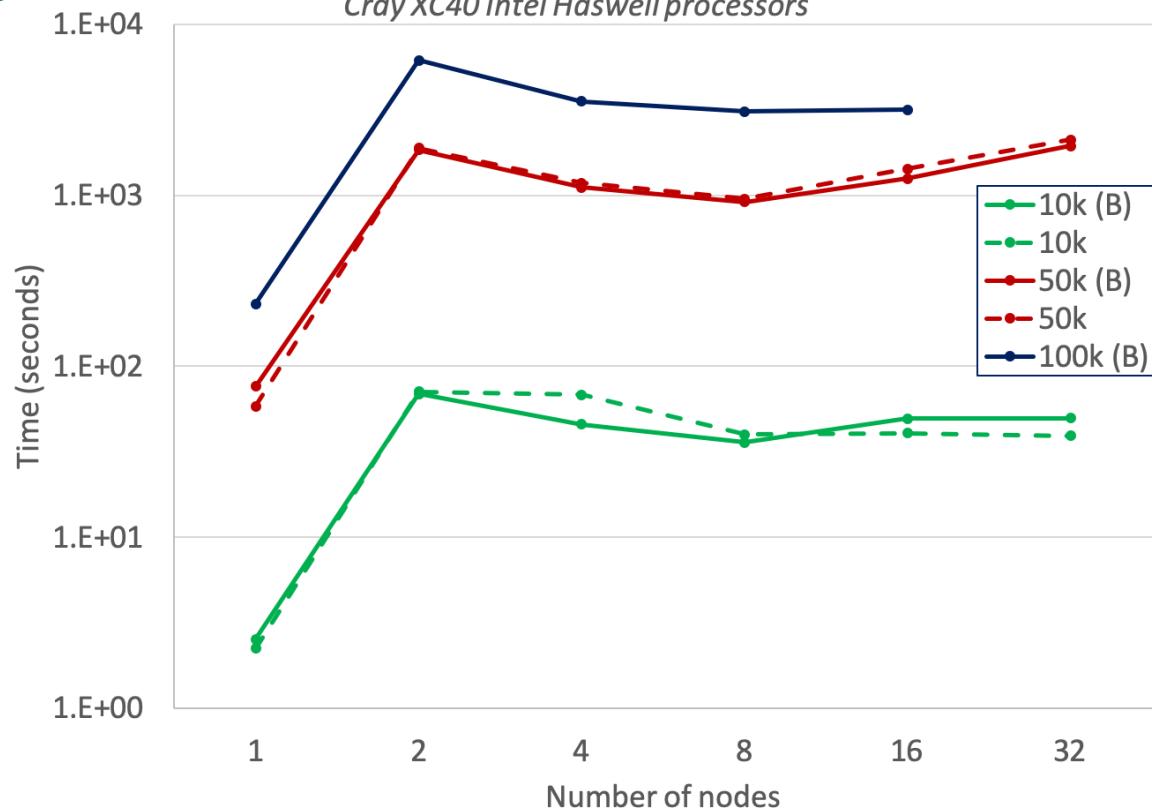
# Example: banded matrix A, in COO format



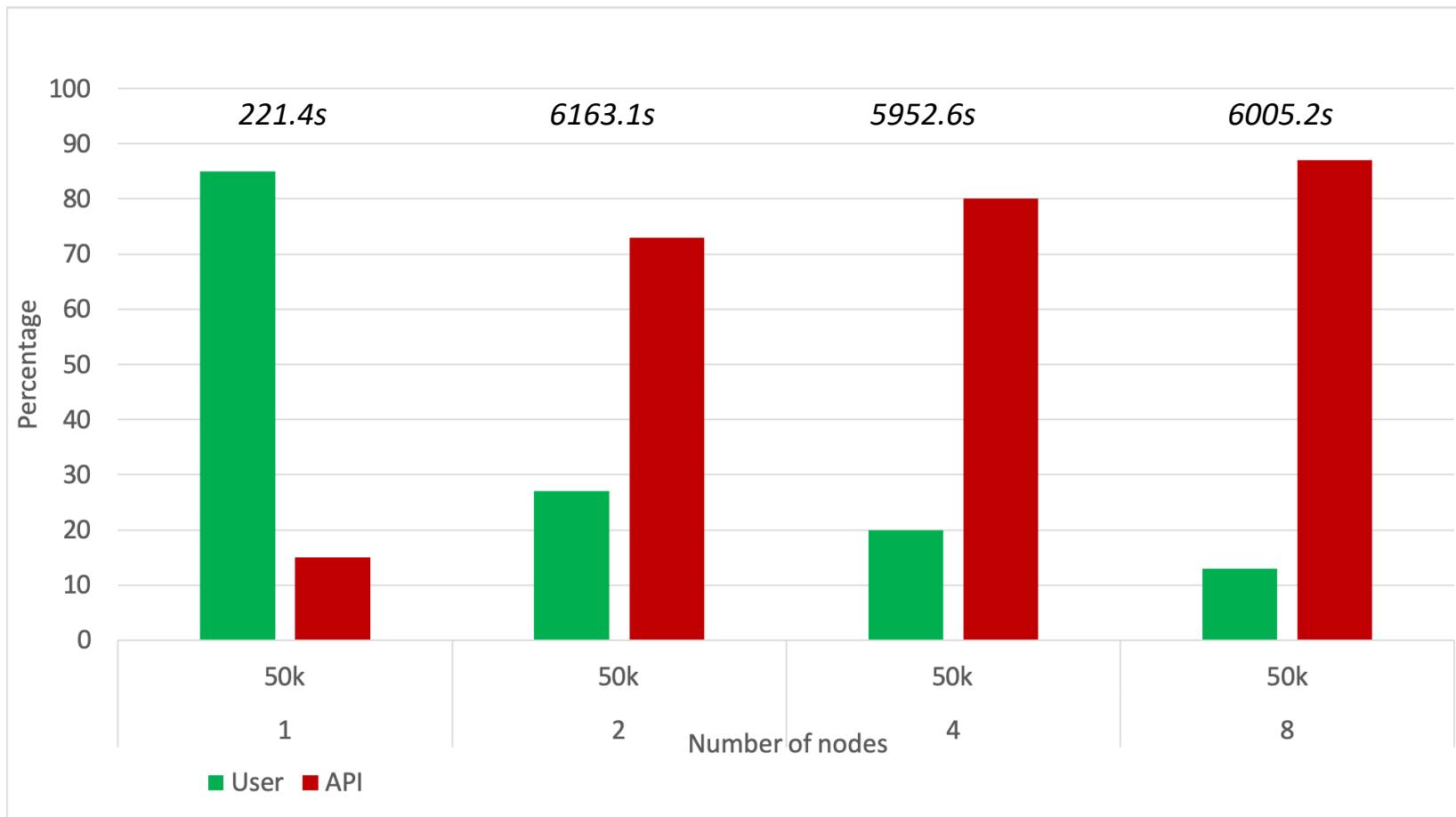
# Strong Scaling

Lower is better

Matrix-vector product in Hitting Time Moments CG  
Cray XC40 Intel Haswell processors



# User vs API runtime





# Performance Tools

## CrayPat

- Results look like it's mostly monitoring runtime, not user code.
- No longer supports Chapel.

## HPCToolKit

- Returns profile with missing function names, even when compiling with -g

## LDMS

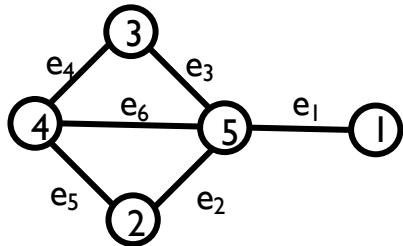
- Papi sampler runs with Chapel code, but gives '0' for all data collected.
- Network samplers should work to show communication (TBD).

## ChplBlamer

- Academic tool from University of Maryland (Jeff Hollingsworth); supported?

# Triangle enumeration

## Key computation: sparse MatMat



## Adjacency matrix

$$\begin{array}{c}
 \text{vertex} \quad \text{edge} \\
 \downarrow \quad \downarrow \\
 \left( \begin{array}{cccccc} 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 \end{array} \right) * \left( \begin{array}{cccccc} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 \end{array} \right) = \left( \begin{array}{cccccc} \emptyset & \emptyset & \emptyset & \emptyset & \emptyset & \emptyset \\ \emptyset & \emptyset & \emptyset & \emptyset & \emptyset & \{2,4,5\} \\ \emptyset & \emptyset & \emptyset & \emptyset & \emptyset & \{3,4,5\} \\ \emptyset & \{4,2,5\} & \{4,3,5\} & \emptyset & \emptyset & \emptyset \\ \emptyset & \emptyset & \emptyset & \{5,3,4\} & \{5,2,4\} & \emptyset \end{array} \right)
 \end{array}$$

## Incidence matrix



# Summary

Scaling performance currently poor.

We're assuming no known graph structure.

Exploring various matrix storage formats:

- COO, CSR, Chapel sparse domain

User supplied Chapel operator capability.

Need tools!

Future work

- Matrix “in place” implementation, to support full application.
- Additional processors, eg ARM, GPU and interconnects.



# Additional slides



# Productivity

*Time from idea to solution (DARPA HPCS motivator)*

- Expressiveness
- Performance
- Portability
- Robustness
- Code development tools



# Conjugate gradient method solving $A^*x=b$

For symmetric positive definite matrix  $A$  in  $R^{nxn}$ ,  $x$  and  $b$  in  $R^{nx1}$

```
r = b - A*x;
error = norm( r ) / bnrm2;
if ( error < tol ) return, end

for iter = 1:max_it

    z = M \ r; Preconditioning. Ax=b => M-1Ax = M-1b; Jacobi: M = diag(A)
    rho = (r'*z); inner product

    if ( iter > 1 ),
        beta = rho / rho_1;
        p = z + beta*p; vector update (daxpy)
    else
        p = z;
    end

    q = A*p; Matrix-vector product
    alpha = rho / (p'*q); inner product
    x = x + alpha * p; vector update (daxpy)

    r = r - alpha*q; vector update (daxpy)
    error = norm( r ) / bnrm2;
    if ( error <= tol ), break, end

    rho_1 = rho;

end
```



# Matrix-vector multiplication: COO and CSR matrix storage

COO: Arrays for row indices, column indices (values: n/a for us)

```
for i in y.dom {      // For nnz nonzero coefficients
    y[rowidx[i]] += x[colidx[i]] * A[rowidx[i]];
}
```

CSR:  $\text{rowptr}[i+1] - \text{rowptr}[i] - 1$  = number of nonzeros in row i.  
(For a 6 banded matrix,  $\text{rowptr} = 1, 7, 13, 19, \dots$ )

```
for i in y.dom{      // For n matrix rows
    for j in rowptr[i]..rowptr[i+1]-1 {
        y[i] += x[colidx[j]] * A[i];
    }
}
```

Analogous for Compressed Column (CSC)