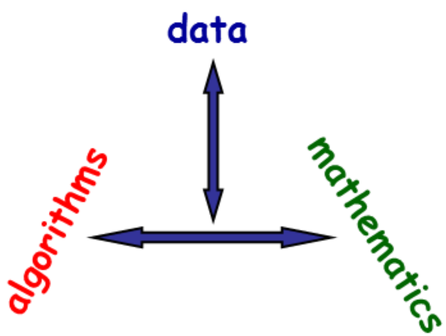
RandNLA
Randomized Numerical Linear Algebra

Organizers: H. Avron[1], C. Boutsidis[1], and P. Drineas[2]

([1]IBM Research, [2]Rensselaer Polytechnic Institute)



Goal: expose the participants to recent progress on developing randomized numerical linear algebra algorithms, as well as on the application of such algorithms to a variety of disciplines and domains.

Key question: How can randomization and sampling be leveraged in order to design faster numerical algorithms?

Google **RandNLA** for workshop web page.

Randomized algorithms

Randomization and sampling allow us to design provably accurate algorithms for problems that are:

- Massive

(e.g., matrices so large that can not be stored at all, or can only be stored in slow, secondary memory devices)

- Computationally expensive or NP-hard

(e.g., combinatorial optimization problems such as the Column Subset Selection Problem and the related CX factorization)

Randomized algorithms & Linear Algebra

- **Randomized algorithms**
  - By (carefully) sampling rows/columns/entries of a matrix, we can construct new matrices (that have smaller dimensions or are sparse) and have bounded distance (in terms of some matrix norm) from the original matrix (with some failure probability).
  - By preprocessing the matrix using random projections, we can sample rows/columns/ entries much less carefully (uniformly at random) and still get nice bounds (with some failure probability).

Randomized algorithms & Linear Algebra

- **Randomized algorithms**
  - By (carefully) sampling rows/columns/entries of a matrix, we can construct new matrices (that have smaller dimensions or are sparse) and have bounded distance (in terms of some matrix norm) from the original matrix (with some failure probability).
  - By preprocessing the matrix using random projections, we can sample rows/columns/ entries much less carefully (uniformly at random) and still get nice bounds (with some failure probability).
- **Matrix perturbation theory**
  - The resulting smaller/sparser matrices behave similarly (in terms of singular values and singular vectors) to the original matrices thanks to the norm bounds.

Many results in RandNLA have the above structure.

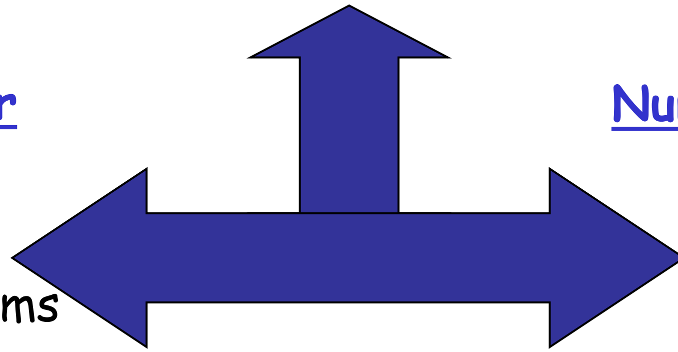
Interplay

Applications

(Data Mining, Machine Learning, etc.)

Theoretical Computer Science

Randomized and Approximation Algorithms



Numerical Linear Algebra

Matrix Computations and Linear Algebra (ie., perturbation theory)

Sessions 2, 3, and 4

Session 2: N. Harvey, N. Srivastava, I. Ipsen

Matrix concentration (theory and experiments) and applications to graph sparsification.

Session 3: H. Avron, I. Koutis, T. Zouzias

(Randomized) Preconditioners for systems of (Laplacian) linear equations.

Session 4: C. Boutsidis, D. Woodruff, B. Recht

Matrix reconstruction and low-rank approximations via column/row/element-wise sampling and (input sparsity time) random projections.

Coming up: Tutorial

M. W. Mahoney

Theory (and Some Practice) of Randomized Algorithms for Matrices and Data

An excellent review article for **RandNLA:**

M. W. Mahoney (2011), *Randomized Algorithms for Matrices and Data.*

(http://arxiv.org/abs/1104.5557)