

# Distance geometry for computing conformations

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## Outline

- 02. Distance geometry
- 07. Distance matrices
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- 28. Noisy data: triangular inequality
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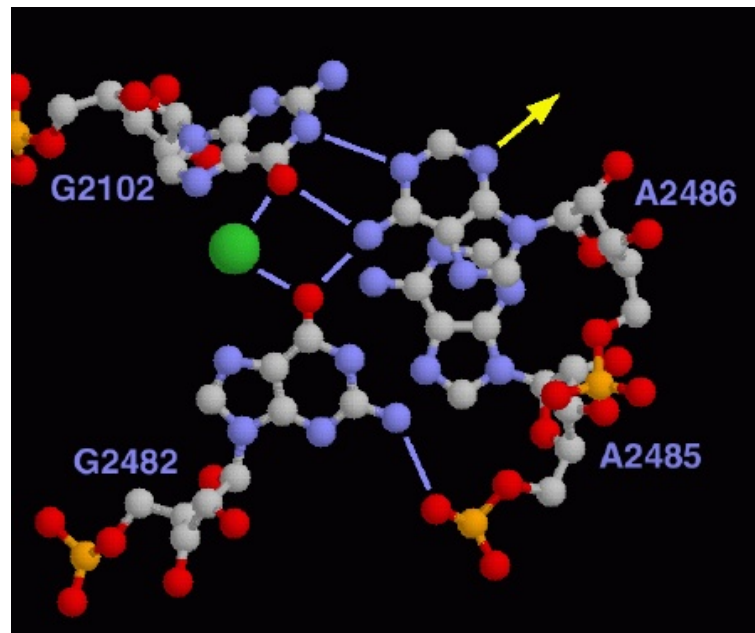
# Distance geometry

## 3D protein conformation

**Goal:** match pharmacophores, screen databases, identify function...

**Principle:** At a first level of approximation, **bond distances** and **planar angles** require too much energy to be altered in a protein  
⇒ a 3D conformation depends upon the **dihedral angles** about the bonds.

**Assume point masses**, ignore chemical properties (e.g. hydrophobicity), angle limitations (postprocess).



## Structure from Distances

- Treat arbitrary number (e.g. 5000 atoms) of DOFs with:
  - Nuclear Magnetic Resonance (NMR) approximates distances [K.Wüthrich, ETHZ, Chemistry Nobel'02] "for his development of NMR spectroscopy for determining the 3-dimensional structure of biological macromolecules in solution"
  - X-ray crystallography gives accurate distances (error  $\leq 1\text{\AA}$ ) but in crystal state, takes  $\sim 1$  research year.

Distance geometry Software effective for molecules of  $> 100$  atoms:

- DYANA [Guntert,Mumenthaler,Wüthrich'97], EMBED [Crippen,Havel'88].
- DISGEO: #507 <http://qcpe.chem.indiana.edu> [Havel,Wüthrich'98].
- DGSOL: open [Moré,Wu].
- ABBIE [Hendrickson], DGEOM, XPLOR module, ...
- <http://www.netsci.org/resources/software/modeling/conf>
- Main phases of Distance geometry:
  - Triangle/tetrahedron inequalities used for bound smoothing
  - minimize error function within distance intervals.

# Nuclear Magnetic Resonance (NMR)

- Specific isotopes have spin ( $\pm 1/2$ ) e.g.: H,  $C^{13}$
- Each isotope absorbs and radiates back energy from electromagnetic (EM) pulse of specific “resonance” frequency

## Steps of NMR:

1. Constant magnetic field applied to isotopes, spins aligned (polarized).
2. EM pulse applied, specific nuclei stimulated, and radiate energy
3. Stimulated nuclei form pairs whose distance depends on EM frequency

## Experiments of NMR spectroscopy:

- Nuclear Overhauser Effect Spectroscopy (NOESY)
- Other 2D (distance) experiments: Correlation Spectroscopy (COSY), J- or Exchange (EXSY) Spectroscopies.
- Not 2D: Residual Dipolar Coupling (RDC) yields angles.

# Nuclear Enhanced Overhauser Spectroscopy (NOESY)

- Different frequencies  $f \neq f' \Rightarrow$  different distances  $d \neq d'$ .
- Triplet  $(i, j, k)$  of nuclei, stimulated:  $\text{dist}(i, j) = d$ ,  $\text{dist}(j, k) = d'$ .

**Problem 1:** Match measurements to specific nuclei pairs.

Semi-automatic, human intervention still important.

**Problem 2:** Given some distances, embed nuclei in  $\mathbb{R}^3$

- Only upper / lower bounds of distances are known.
- Only nuclei pairs with distance  $\leq 5 - 6 \text{ \AA}$ .

Global optimization has high time complexity.

[Havel, Guntert, Wüthrich] [E-Nikitopoulos]

## Residual Dipolar Coupling (RDC)

- Consider the vector between each atom and its H.
- Measures angle of vector with a constant but unknown vector.

[Donald et al] [E-Pantos'07]

# Distance matrices

## Distance matrices

**Definition (and structure):**

A distance matrix  $M$  is square,  $M_{ii} = 0$ ,  $M_{ij} = M_{ji} \geq 0$ .

**Definition.** A distance matrix  $M$  is Euclidean and embeddable in  $\mathbb{R}^d$  iff

$$\exists \text{ points } p_i \in \mathbb{R}^d : M_{ij} = \frac{1}{2} \text{dist}(p_i - p_j)^2.$$

Embeddable matrices in  $\mathbb{R}^3$  correspond to 3D conformations.



## Embeddability

**Thm** [Schoenberg'35,Blumenthal'53] Take border (Cayley-Menger) matrix

$$B = \begin{bmatrix} 0 & 1 & \dots & 1 \\ 1 & & & \\ \vdots & & M & \\ 1 & & & \end{bmatrix}.$$

Then, distance matrix  $M$  embeds in  $\mathbb{R}^d$  iff

- $\text{rank}(B) \leq d + 2$  [Cayley 1841], and
- $(-1)^k D(i_1, \dots, i_k) \geq 0$ ,  $\forall k \geq 2$  [Menger 1928],

where  $D(\dots)$  is any minor of  $B$  indexed by rows/columns  $0, i_1, \dots, i_k$ .

**Cor.** A distance matrix  $M$  expresses a 3D conformation iff

- $\text{rank}(B) = 5 \Rightarrow$  all  $6 \times 6$  minors  $= 0 \Rightarrow \det \text{Border}(5 \text{ points}) = 0$ .
- satisfies the triangle and tetrahedral inequalities.

## Small minors

Given points  $i_1, \dots, i_k$ , the corresponding border matrix contains these rows/columns and the artificial (zeroth) row/column of 1's.

- $\det \text{Border}(\text{points } i, j) = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & d_{ij}^2/2 \\ 1 & d_{ij}^2/2 & 0 \end{bmatrix} \geq 0 \Leftrightarrow d_{ij}^2 \geq 0.$

- **Triangular** inequality:  $\det \text{Border}(\text{points } 1, 2, 3) = (d_{12} + d_{13} + d_{23})(d_{12} + d_{13} - d_{23})(d_{12} + d_{23} - d_{13})(d_{13} + d_{23} - d_{12}) \geq 0$   
Recall classical inequalities:  $d_{ij} + d_{jk} \geq d_{ik} \geq |d_{ij} - d_{jk}|.$

- **Tetragonal** inequality:  $\det \text{Border}(4 \text{ points}) \geq 0.$

## Embeddability, again

**Cor.** Let border (Cayley-Menger) matrix  $B$  contain distance matrix  $M$ ; the latter embeds in  $\mathbb{R}^d$  and not in  $\mathbb{R}^{d-1}$  iff

- $\text{rank}(B) = d + 2$  [Cayley], and
- $(-1)^k D(i_1, \dots, i_k) > 0$ ,  $k = 2, \dots, d + 1$  [Menger],

where  $D(\dots)$  is any  $(k + 1) \times (k + 1)$  border minor of  $B$  indexed by rows/columns  $0, i_1, \dots, i_k$ .

Distance matrices express many geometric properties: orthogonality, convexity etc [Michelucci].

## Cyclohexane's distance matrix

$$\begin{array}{c}
 \\
 \\
 p_1 \\
 p_2 \\
 p_3 \\
 p_4 \\
 p_5 \\
 p_6
 \end{array}
 \begin{bmatrix}
 & p_1 & p_2 & p_3 & p_4 & p_5 & p_6 \\
 0 & 1 & 1 & 1 & 1 & 1 & 1 \\
 1 & 0 & u & c & x_{14} & c & u \\
 1 & u & 0 & u & c & x_{25} & c \\
 1 & c & u & 0 & u & c & x_{36} \\
 1 & x_{14} & c & u & 0 & u & c \\
 1 & c & x_{25} & c & u & 0 & u \\
 1 & u & c & x_{36} & c & u & 0
 \end{bmatrix}$$

**Known:**  $u \simeq 1.526$  (adjacent),  $\phi \simeq 110.4^\circ \Rightarrow c \simeq 2.285$  (triangle).

Rank condition ( $= 5$ ) equivalent to the vanishing of all  $6 \times 6$  minors.  
This yields a  $3 \times 3$  system of quadratic **polynomials** in the  $x_{14}, x_{25}, x_{36}$ .

If all  $c, u$  same, then 2 isolated conformations, one 1-dim set.

If the  $c, u$  perturbed, then  $\leq 16$  solutions  $\in \mathbb{R}$  [E-Mourrain].

## Point coordinates from distances

**Input:** distances  $d_{ij}$  among  $n + 1$  points  $(i, j = 0, \dots, n)$  in  $\mathbb{R}^3$ .

**Output:** point coordinates (up to rigid transforms) in  $\mathbb{R}^3$ .

Consider points  $p_i \in \mathbb{R}^d$  as (column) vectors,  $i = 0, \dots, n$ , where

$$d_{ij}^2 = |p_i - p_j|^2, \quad d_{i0}^2 = |p_i|^2, \quad \text{setting } p_0 = 0.$$

$$\text{Now } d_{ij}^2 = |p_i|^2 - 2p_i^T p_j + |p_j|^2 \Leftrightarrow p_i^T p_j = \frac{d_{i0}^2 - d_{ij}^2 + d_{j0}^2}{2} =: G_{ij}$$

defines (Gram)  $n \times n$  matrix  $G$  of inner products:

$$G = \begin{pmatrix} p_1^T p_1 & p_1^T p_2 & \dots & p_1^T p_n \\ p_2^T p_1 & p_2^T p_2 & \dots & p_2^T p_n \\ \vdots & \vdots & \ddots & \vdots \\ p_n^T p_1 & p_n^T p_2 & \dots & p_n^T p_n \end{pmatrix}$$

## Coordinates from inner products

Gram matrix expresses coordinate vectors:

$$[G_{ij}] = [p_i^T p_j] = P^T \cdot P, \text{ where } P = [p_1, \dots, p_n] \text{ is } 3 \times n.$$

$G$  is real symmetric, so eigen-values/vectors  $\in \mathbb{R}$  and  $U = V$ :

The Singular Value Decomposition (SVD) yields

$$G = V \Sigma V^T, \quad V^T V = I, \quad \Sigma = \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{bmatrix}, \quad \sigma_i = |\text{eigenval}_i|.$$

Since  $\text{rank}(d_{ij}) = 3 \Rightarrow \text{rank}(G) = 3$ , therefore can have:

- singular vector matrix  $V$  be  $n \times 3$ , and
- singular value matrix  $\Sigma$  positive,  $3 \times 3$  diagonal.

Then,  $G = V \sqrt{\Sigma} \sqrt{\Sigma} V^T = P^T P \Rightarrow P := \sqrt{\Sigma} V^T$ .

## Embeddability Theorem

**Theorem.**  $\{p_1, \dots, p_n\}$  embed in  $\mathbb{R}^3$  (and not  $\mathbb{R}^2$ ) iff Gram matrix  $G = P^T P$  defined by coordinates  $P$  has  $\text{rk} G = 3$ .

[ $\Leftarrow$ ] SVD: symmetric real  $G = V S V^T$  (previous slide), where  $V^T V = V V^T = I$ ,  $S = \text{diag}[\sigma_1, \dots, \sigma_n]$ ,  $\sigma_i = |\text{eigenvalue}_i| \geq 0$ .  $\text{rk} G = 3 \Rightarrow S = \text{diag}[\sigma_1, \sigma_2, \sigma_3, 0, \dots]$ ,  $\sqrt{S} = [\sqrt{\sigma_i}]$ ,  $G = V \sqrt{S} \cdot \sqrt{S} V^T$ .  $P := V \sqrt{S}$  is  $n \times 3$ : defines  $n$  points  $p_i \in \mathbb{R}^3$ .

- SVD =  $O(n^3)$  and well implemented, e.g. Matlab.

[ $\Rightarrow$ ]  $P = [p_1, \dots, p_n]$  is  $3 \times n$ .

$\text{rk}(AB) = \min\{\text{rk} A, \text{rk} B\} \Rightarrow \text{rk} G = \text{rk} P$ .

Embed  $\Rightarrow \exists p_a, p_b, p_c$  linearly independent  $\Rightarrow \text{rk} P = 3$ .

- $\forall y \in \mathbb{R}^n, y^T P^T P y = (P y)^T (P y) \geq 0 \Rightarrow G = P^T P \succeq 0$ .

## Positive (semi)definite matrices

**Def.** An  $n \times n$  real matrix  $M$  is positive (semi)definite if

$$x^T M x > 0, \quad (x^T M x \geq 0), \quad \forall x \neq 0.$$

Denoted  $M \succ 0$ ,  $M \succeq 0$ .

Examples:  $\begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}$      $\begin{bmatrix} 3 & -1 & -2 \\ -2 & 2 & 0 \\ 1 & 0 & 1 \end{bmatrix}$

Lemma [Sylvester]: For all  $i \times i$  upper-left minor  $M_i$ :

$$M \succ 0 \Leftrightarrow \det M_i > 0, \quad M \succeq 0 \Rightarrow \det M_i \geq 0.$$



## Symmetric P(S)D matrices

Hypothesis: Real symmetric  $M = M^T$  (or complex Hermitian  $M = M^*$ )

- $M \succeq 0 \Leftrightarrow$  all eigenvalues  $\geq 0$ ,  $M \succ 0 \Leftrightarrow$  all eigenvalues  $> 0$ .
- $M \succ 0 \Leftrightarrow \exists B : \det B \neq 0, M = BB^T$ .
- $M \succ 0 \Leftrightarrow \exists$  low-triangular  $B : M = B^2$ , then  $B = \sqrt{M}$ .  
Unique  $B : B \succ 0, B = B^T$ .

## Complexity

- Given **complete** set of exact distances: Embed  $\in P$ .
- Given **incomplete** set of exact distances: Embed- $\mathbb{R} \in \text{NP-hard}$ .  
Reduction of set-partition [Saxe'79].
- Embed- $\mathbb{R}^k \in \text{NP-hard}$ , for  $k \geq 2$ , even if weights  $\in \{1, 2\}$  [Saxe'79].
- (approximate) Embed- $\mathbb{R}^2 \in \text{NP-hard}$  for planar graphs: weights = 1 [Demaine, Rote Et al]
- Given distances  $\pm\epsilon$ , approximate-Embed  $\in \text{NP-hard}$  [Moré, Wu'96].

**Incomplete data**

## Matrix completion

**Prob.** Given incomplete  $M$ , **complete** it to PSD (or distance) matrix.  
This is a feasibility question on a PSD program.

**Def.** PSD **program** (feasibility): Given matrices  $A_1, \dots, A_m, b_1, \dots, b_m \in \mathbb{R}$ ,  
 $\exists$  ? matrix  $X$  s.t.:

$$X \succeq 0, \quad b_k = A_k \cdot X := \sum_{i,j} A_{i,j}^{(k)} X_{i,j}, \quad k = 1, \dots, m.$$

Note  $A_k \cdot X = \text{trace}(A_k^T X)$ .

Full PSD program includes also linear objective function on the  $X_{i,j}$ .

- If  $M$  contains determined line/column, completion reduces to that of submatrix.

## Complexity of PSD

- Solving PSD programs with arbitrary precision  $\in P_{\mathbb{R}}$ : interior-point [Karmarkar], ellipsoid method [Khachiyan].
- Unknown whether PSD-program  $\in NP_{bit}$ .
- Unknown whether PSD-feasibility  $\in P_{bit}$ .
- LP  $\in P_{bit}$  (weak polytime) interior-point [Karmarkar], ellipsoid [Khachiyan]
- Open whether LP in  $P_{\mathbb{R}}$  (strong polytime).
- Typically, symmetric  $M = M^T$ , diagonal entries known.
- Focus on polynomial instances of PSD completion [Laurent].

## Further into partial PSD matrices

**Def.**  $M$  is **partial-PSD** if  $\forall$  principal specified submatrix is PSD.

**Lem.** If incomplete matrix  $M$  has a **P(S)D** / **distance** matrix completion,  
 $\Rightarrow M$  is **partial-P(S)D** / **partial-distance** matrix.

Necessary (not sufficient) conditions for completing  $M$ .

**Counter-example:** Partial-PSD but  $\nexists$  PSD-completion:

$$\begin{bmatrix} 1 & 1 & ? & 0 \\ & 1 & 1 & ? \\ & & 1 & 1 \\ & & & 1 \end{bmatrix}$$

Note: cycle of length 4.

## Chordal Graphs: poly-1

**Defn.** A graph is **chordal** if its largest cycle is of length 3.

**Defn.** Given symmetric matrix  $M$ , construct graph  $G$  with nodes corresponding to rows/columns and edges to every specified matrix entry.

**Thm** [Johnson,Wolkowitz,etal'84,Bakonyi,Johnson'95].

Every **partial-PSD** (or partial-distance) matrix  $M$  with graph  $G$  has a **PSD** (or distance-matrix) completion iff  $G$  is chordal.

Proof: [ $\Leftarrow$ ] algorithm in  $P_{bit}$  [Laurent'98].

Moreover:  $\forall$  principal submatrices embed in  $\mathbb{R}^k \Rightarrow$  entire matrix in  $\mathbb{R}^k$ .

## Chordal filling: poly-2

**Thm** [Laurent]. Given  $M, G$ , if  $\min \#edges$  added to make  $G$  chordal is  $O(1)$ , then PSD-completion  $\in P_{bit}$ .

Proof. PSD program with  $\#constraints = O(1)$ .

- Generally, minimizing  $\#edges$  to make  $G$  chordal is NP-hard.



## No $K_4$ , class $G_{p,q}$ : poly-3, -4

**Def** Graph  $G'$  is **similar** to  $G$  if obtained by adding vertices to edges of  $G$

**Thm [Laurent]**. Given  $M$  and  $G$ , where  $G$  has no subgraph similar to clique  $K_4$ . Then,  $M$  can be completed to a PSD matrix in  $P_{\mathbb{R}}$ .

**Def.** Let be  $p, q \geq 1$ . **Class  $G_{p,q}$**  contains graphs  $G = (V, E)$  s.t.:

1.  $\exists V_1, V_2 \subset V, V_1 \cap V_2 = \emptyset, \min(|V_1|, |V_2|) = p,$
2.  $F := \{ij | i \in V_1, j \in V_2\} \Rightarrow F \cap E = \emptyset,$
3. Graph  $H := (V, E \cup F)$  is chordal,
4.  $H$  has  $q$  max-cliques that are not cliques of  $G$ .

**Thm [Laurent]**. For integers  $p, q \geq 1$ , matrices with graph  $G \in G_{p,q}$  can be completed to a PSD matrix in weak Polytime.

## Dense Graphs: poly-5

- Consider a clique missing edges incident to a vertex  $v$ . Then, in poly-time,  $M$  is PSD-completed and its minimum embedding dimension (MED) computed. E.g.:

$$\text{MED}(v - G_1 \equiv G_2) = \max\{\text{MED}(v - G_1), \text{MED}(G_1 \equiv G_2)\}.$$

- Same for star of cliques  $K_i$ :

$$\text{MED}(\text{star}) = \max_i \{\text{MED}(K_i)\}.$$

[E-Fragoudakis-Markou]

## Graph embedding

- [Bourgain'93]. Every graph with  $n$  vertices can be embedded in *some* Euclidean space (*of any dimension*) with distortion  $O(\log n)$ .
- [Barvinok]. If graph embedded in  $\mathbb{R}^d$ , for some  $d$ , then embedded in dimension  $d^*$  s.t.:

$$d^* = \lfloor \frac{\sqrt{8E+1}-1}{2} \rfloor, \quad E+1 \leq \binom{d^*+2}{2}.$$

- Conj.  $d^* < \# \text{vertices}$ , or  $\leq \max \deg(\text{graph})$ .

**Noisy data: triangular inequality**

## Minors

- $6 \times 6$  minors vanish  $\Leftrightarrow \det \text{Border}(5 \text{ points}) = 0$ .

- $\det \text{Border}(2 \text{ points}) = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & d_{ij}^2/2 \\ 1 & d_{ij}^2/2 & 0 \end{bmatrix} \geq 0 \Leftrightarrow d_{ij}^2 \geq 0$ .

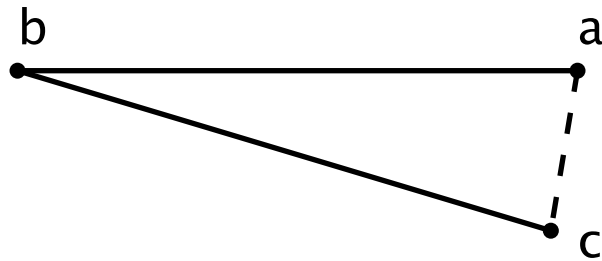
- **Triangular** inequality:  $\det \text{Border}(3 \text{ points}) = (d_{12} + d_{13} + d_{23})(d_{12} + d_{13} - d_{23})(d_{12} + d_{23} - d_{13})(d_{13} + d_{23} - d_{12}) \geq 0$

- **Tetragonal** inequality:  $\det \text{Border}(4 \text{ points}) \geq 0$ .

## Smoothing triangular inequalities

- **Triangle** inequalities (equality iff coliner): For any 3 points in Euclidean space of any dimension (including  $\mathbb{R}^3$ ) the triangle inequality holds:

$$|d_{ik} - d_{kj}| \leq d_{ij} \leq d_{ik} + d_{kj}.$$



## Bound smoothing

- Improve **upper** bound by forcing:

$$u_{ij} \leq u_{ik} + u_{kj}.$$

All-min-paths in single pass:  $\Omega(VE)$ ,  
 $O(V^3)$  [FloydWarshal],  $O(V(V + m) \lg V)$ ,  $m$  edges in minpaths [KargerEtal91]

- Improve **lower** bound by forcing:

$$l_{ij} \geq l_{ik} - u_{kj}, l_{kj} - u_{ik} \Rightarrow l_{ij} \geq l_{km} - u_{ik} - u_{mj},$$

where indices  $i, j, k, m$  not necessarily all distinct.

Independent of upper bounds; also reduces to all-minpaths.

## Example

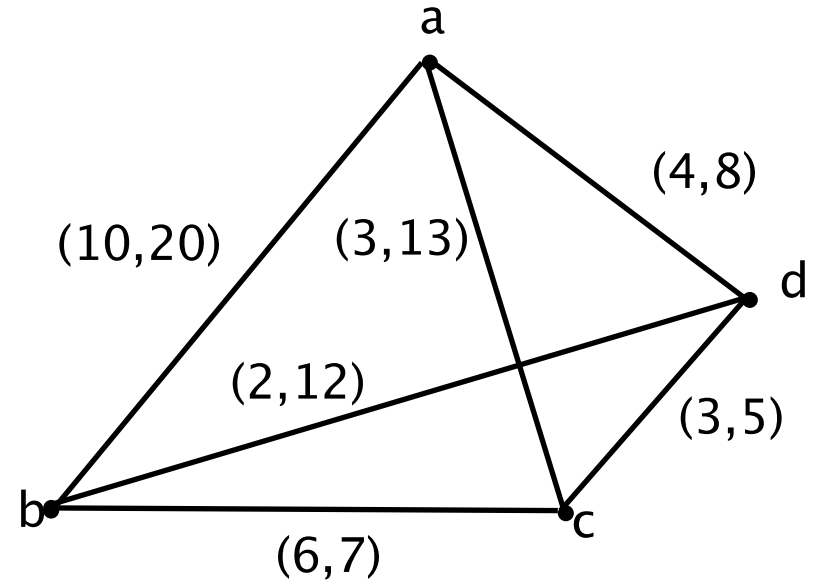
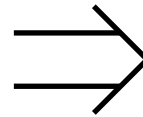
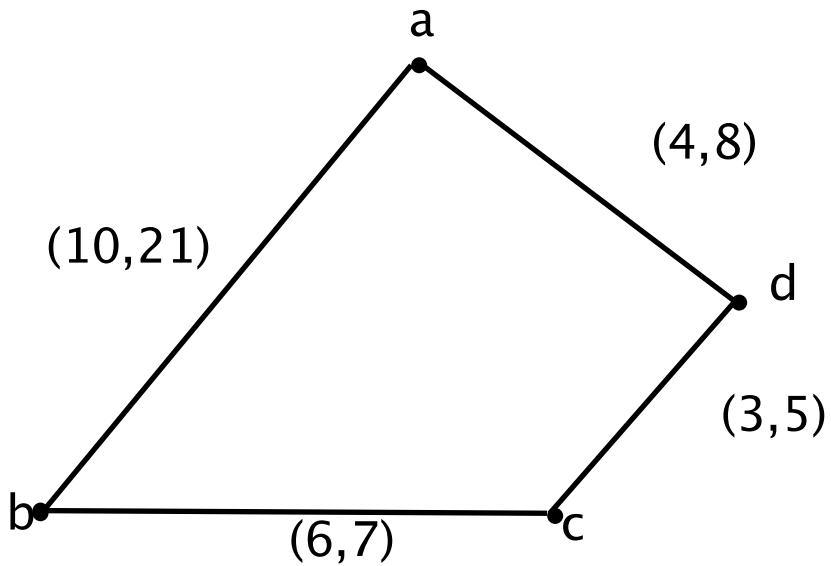
$$l_{bd} \geq l_{ab} - u_{ad} = 2$$

$$l_{ac} \geq l_{ab} - u_{bc} = 3$$

$$u_{bd} \leq u_{bc} + u_{cd} = 12$$

$$u_{ac} \leq u_{ad} + u_{cd} = 13$$

$$u_{ab} \leq u_{ad} + u_{bd} = 20$$





## Simple algorithm for upper bounds

1. Check all triplets of nodes, applying the inequality for upper bounds. Repeat until no improvement is possible.
2. The runtime =  $2\binom{n}{r} = O(n^3)$ . Second pass merely confirms that 1st pass found best possible bounds.
3. Algorithm is essentially Floyd's,  $O(n^3)$  is best for dense graphs.

## A better algorithm

1. For every graph node  $i$  consider all  $j, k$  such  $(i, j), (i, k), (j, k) \in E$ .
2. This correctly checks all triplets with 3 edges. Runtime is

$$n \sum_i \deg(i) = O(nm)$$

3. For edges not in  $E$ , apply the procedure "Fillin" below.
4. Connected graph,  $m = O(n)$ : best  $\binom{n}{2}$  bounds in  $= O(n^2)$

"Fillin" procedure:

- 3.1. For every  $i$  construct BFS-tree by picking "closest" neighbors first depending on refined upper bounds.
- 3.2.  $G$  connected  $\Rightarrow$  tree is spanning.
- 3.3.  $\forall j$  s.t.  $(i, j) \notin E$ , set as  $\hat{u}_{ij}$  the distance of  $i, j$  on tree.
- 3.3. The running time is linear per  $i$ , hence  $O(n^2)$  in total.

New (?) algorithm [Palios'05].

## Exotic data structures

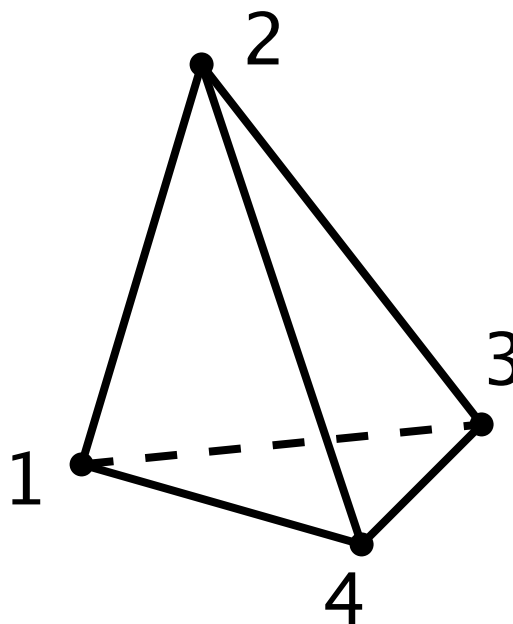
- Improve Floyd using Dijkstra's algorithm for single-source min paths. Using **binary heaps** Dijkstra =  $O((m + n) \log n)$ ; with **Fibonacci heaps** it is  $O(m + n \log n)$ , but with high hidden constant.
- [Karger,Koller,Philips'91] single-source minpaths =  $O((n + \mu) \log n)$  using binary heaps;  $O(\mu + n \log n)$  using Fibonacci heaps, where  $\mu \leq m$  is number of edges actually participating in some minpath.
- If  $m = \Theta(n) \Rightarrow$  runtime for  $n$  executions becomes  $O(n^2 \log n)$  with either kind of heaps.

**Noisy data: tetragonal inequality**

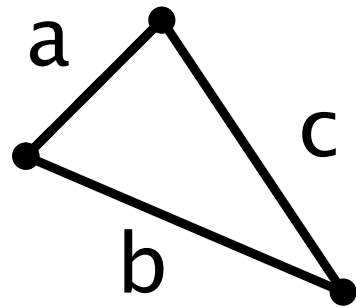
## Four points

Four atoms (1, 2, 3, 4), Cayley-Menger determinant:

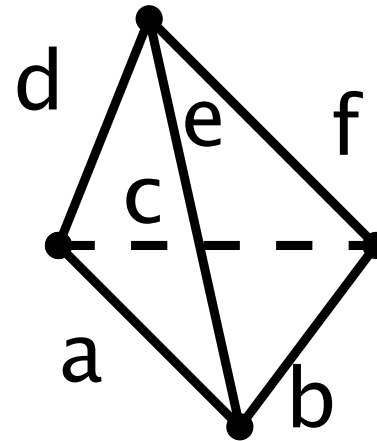
$$\begin{vmatrix} 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & d_{12}^2 & d_{13}^2 & d_{14}^2 \\ 1 & d_{21}^2 & 0 & d_{23}^2 & d_{24}^2 \\ 1 & d_{31}^2 & d_{32}^2 & 0 & d_{34}^2 \\ 1 & d_{41}^2 & d_{42}^2 & d_{43}^2 & 0 \end{vmatrix} > 0$$



# Heron's formula ( $'H\rho\omega\nu$ )



T



T

- Triangular:  $CM(a, b, c) = 16(\text{Area of } T)^2 =$   
 $= (a + b + c)(-a + b + c)(a - b + c)(a + b - c).$
- Tetrangular:  $CM(a, b, c, d, e, f) = 288(\text{Volume of } T)^2.$

## Independence

- To tighten bounds for a point pair, we have to solve 64 inequalities.
- If given bounds satisfy triangle inequality, only 7 are non-redundant.
- Consider the (3,4) distance: For upper limit  $u_{34}$ :

$$CM(l_{12}, u_{13}, u_{14}, u_{23}, u_{24}, u_{34}) \geq 0,$$

$$CM(u_{12}, l_{13}, l_{14}, u_{23}, u_{24}, u_{34}) > 0,$$

$$CM(u_{12}, u_{13}, u_{14}, l_{23}, l_{24}, u_{34}) > 0,$$

For the lower limit  $l_{34}$  we have:

$$CM(u_{12}, u_{13}, l_{14}, l_{23}, u_{24}, l_{34}) > 0,$$

$$CM(u_{12}, l_{13}, u_{14}, u_{23}, l_{24}, l_{34}) > 0,$$

$$CM(l_{12}, l_{13}, u_{14}, l_{23}, u_{24}, l_{34}) > 0,$$

$$CM(l_{12}, u_{13}, l_{14}, u_{23}, l_{24}, l_{34}) > 0.$$

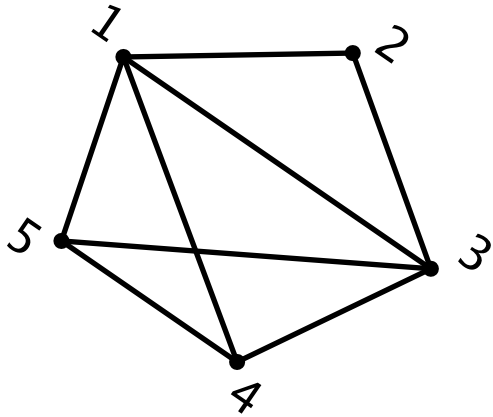
## Bound smoothing

Algorithm:

0. Fix a Tolerance value.
  1. Initialize using the triangle inequality.
  2. Check all  $\binom{n}{4}$  quadruples of nodes, applying 7 inequalities.
  3. Repeat until max change in any bound is  $<$  Tolerance.
- 
- Order of quadruples/inequalities does not affect output.
  - BUT: may get in cycle and progress very slowly to final result.
  - Tetrahedron inequalities much tighter than triangular, but slow.



## Example of cycling



- 5 edges:  $u = l = 1$ ,
- 3 shown diagonals:  $l = 1.617$ ,
- true diagonal  $= 1.618 = 2 \cos 36^\circ$

- Triangle-Bound-Smoothing yields upper bound  $= 2$  for each of 5 diagonals. New  $u_{24}$  by using quadruple  $(2,3,4,5)$ , which is used in  $(2,4,5,1)$  to update  $u_{25}$ .
- After 30 passes, tolerance  $= 10^{-14}$ , we have  $u_{24} = 1.6207323507579925$ ,  $u_{25} = 1.6207323507579441$ .

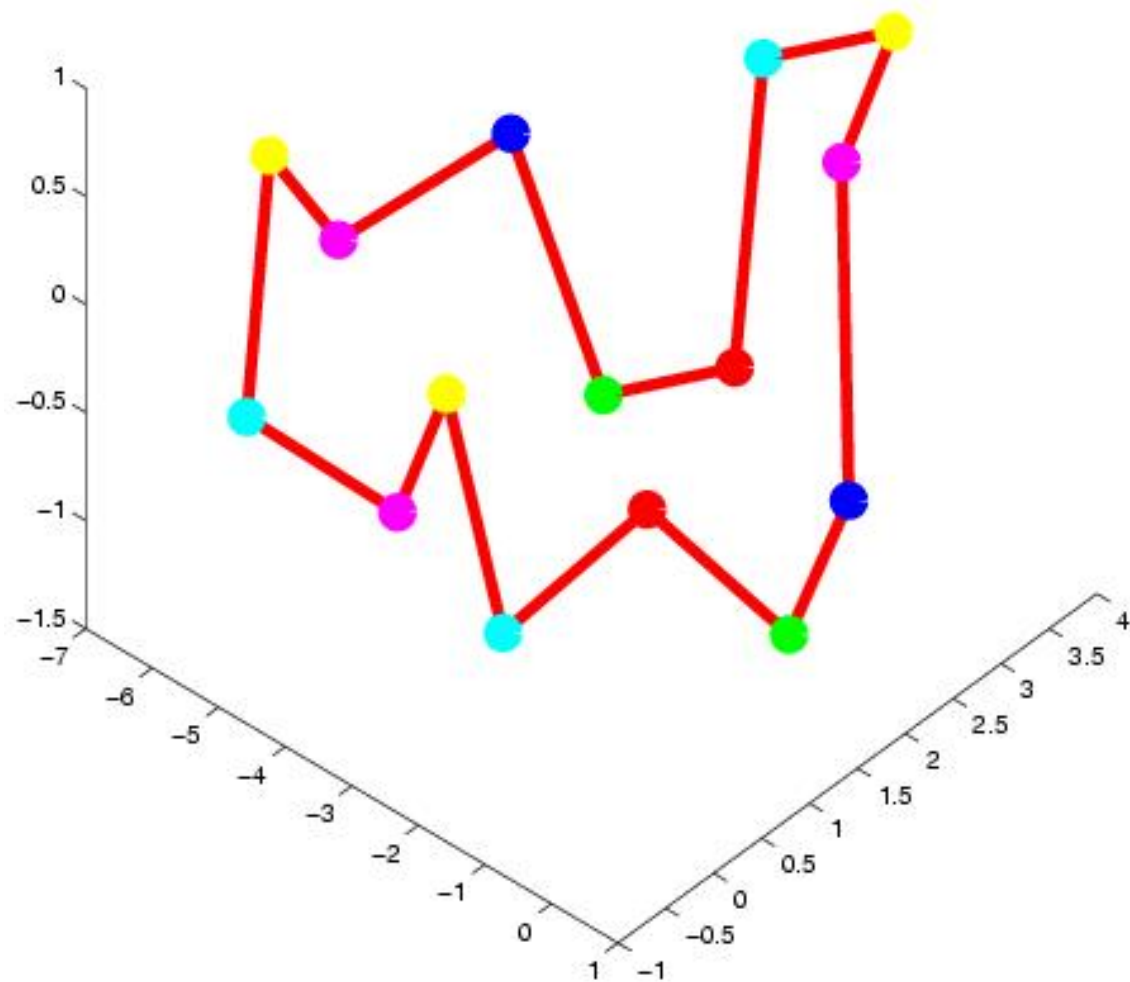
# Matrix perturbations

## Performance on ring molecules

Matlab/Scilab implementation reduces the 6-th eigenvalue; precision = 16 decimal digits, 500-MHz Pentium-III. [Nikitop-E'02].

#atoms	Init. eigval	Final eigval	Iterations	Time [sec.]	KFlop
7	2.98e-02	6.64e-14	3	0.01	36
8	2.57e-02	4.43e-12	3	0.05	49
9	2.10e-02	6.29e-11	3	0.05	73
10	2.38e-02	2.95e-13	3	0.11	109
11	3.16e-02	2.60e-12	3	0.16	165
12	8.13e-02	1.20e-07	3	0.22	282
13	8.09e-02	8.49e-08	3	0.30	450
14	3.72e-02	6.04e-13	3	0.49	606
15	3.53e-02	2.02e-14	3	0.77	940
16	3.78e-02	1.72e-12	3	1.15	1404
17	3.83e-02	1.70e-13	3	1.54	2082
18	3.53e-02	3.93e-13	3	2.14	3039
19	3.80e-02	4.59e-14	3	2.91	4344
20	4.00e-02	7.09e-13	3	3.79	6136

## Example: 15-atom molecular backbone



## Distance matrices: **done** / **to do**

- Triangle and tetrahedron **inequalities** for bound smoothing.
  - Find **conformation** if started in its neighborhood.
  - Bound locally the number of DOFs on the **conformation manifold** [E-Nikitopoulos].
- 
- Treat **family** of known proteins, or just with common features.
  - **Partial distance information** (“on-line” or false data), or probability distribution, to avoid full NMR-spectra assignment.
  - Determine the **minimum** set of required distances.