# Trapezoidal decomposition:

Motivation:

- manipulate/analayze a collection of *segments*
- e.g. detect segment intersections
- e.g., point location data structure
  - Draw verticals at all points
  - binary search for slab
  - binary search inside slab
  - problem:  $O(n^2)$  space

### Definition.

- draw altitudes from each intersection till hit a segment.
- trapezoid graph is *planar* (no crossing edges)
- each trapezoid is a *face*
- show a face.
- one face may have many vertices (from altitudes that hit the *outside* of the face)
- max vertex degree is 6 (assuming nondegeneracy)
- so total space O(n+k) for k intersections.
- number of faces also O(n+k) (each face needs one edge)
- (or use Euler's theorem:  $n_v n_e + n_f \ge 2$ )
- standard clockwise pointer representation lets you walk around a face

Randomized incremental construction:

- to insert segment, start at left endpoint
- draw altitudes from left end (splits a trapezoid)
- traverse segment to right endpoint, adding altitudes whenever intersect
- traverse again, erasing (half of) altitudes cut by segment

### Implementation

• clockwise ordering of neighbors allows traversal of a face in time proportional to number of vertices

- for each face, keep a (bidirectional) pointer to all not-yet-inserted left-endpoints in face
- to insert line, start at face containing left endpoint
- traverse face to see where leave it
- create intersection,
  - update face (new altitude splits in half)
  - update left-end pointers
- segment cuts some altitudes: destroy half
  - removing altitude merges faces
  - update left-end pointers

#### Analysis:

- Overall, update left-end-pointers in faces neighboring new line
- time to insert s is

$$\sum_{f \in F(s)} (n(f) + \ell(f))$$

where

- F(s) is faces s bounds after insertion
- -n(f) is number of vertices in face f
- $-\ell(f)$  is number of left-ends in f.
- So if  $S_i$  is first *i* segmenets inserted, expected work of insertion *i* is

$$\frac{1}{i} \sum_{s \in S_i} \sum_{f \in F(s)} (n(f) + \ell(f))$$

- Note each f appears at most 4 times in sum
- so  $O(\frac{1}{i}\sum_{f}(n(f) + \ell(f))).$
- Bound endpoint contribution:
  - note  $\sum l(f) = n i$
  - so contributes n/i
  - so total  $O(n \log n)$
- Bound intersection contribution
  - $-\sum n(f)$  is  $O(k_i + i)$  if  $k_i$  intersections

- so cost is  $E[k_i]$
- intersection present if both segments in first *i* insertions
- so expected cost is  $O((i^2/n^2)k)$
- so cost contribution  $(i/n^2)k$
- sum over *i*, get O(k)
- **note:** adding to RIC, assumption that first *i* items are random.
- Total:  $O(n \log n + k)$

#### Search structure

Goal: apply binary search in slabs, without  $n^2$  space

- Idea: trapezoidal decomp is "important" part of vertical lines
- problem: slab search no longer well defined
- but we show ok

The structure:

- A kind of search tree
- "x nodes" test against an altitude
- "y nodes" test against a segment
- leaves are trapezoids
- each node has two children
- so works like a search tree
- bf But node may have many parents
- sharing descendants saves space.

Inserting an edge contained in a trapezoid

- update trapezoids
- build a 4-node subtree to replace leaf

Inserting an edge that crosses trapezoids

- sequence of traps  $\Delta_i$
- if  $\Delta_0$  has left endpoint, replace leaf with x-node for left endpoint and y-node for new segment

- Same for last  $\Delta$
- middle  $\Delta$ :
  - cut off pieces form new trapezoids (leaves)
  - replace each cut trapezoid with a *y*-node for new segment
  - two children of *y*-node point to appropriate traps
  - note trap can have several incoming nodes

Proof of correctness:

- Claim after each insert, valid search for current segments
- consider last insertion
- search gets to correct place before insertion
- new nodes continue search to correct place

#### Search time analysis

- depth increases by one for new trapezoids "below" new segment
- RIC argument shows depth  $O(\log n)$

### Linear programming.

- define
- assumptions:
  - nonempty, bounded polyhedron
  - minimizing  $x_1$
  - unique minimum, at a vertex
  - exactly d constraints per vertex
- definitions:
  - hyperplanes  ${\cal H}$
  - **basis** B(H) of hyperplanes that define optimum
  - optimum value O(H)
- Simplex
  - exhaustive polytope search:
  - walks on vertices
  - runs in  $O(n^{\lceil d/2 \rceil})$  time in theory

- often great in practice

- polytime algorithms exist (ellipsoid)
- but bit-dependent (weakly polynomial)!
- OPEN: strongly polynomial LP
- goal today: polynomial algorithms for small d

Random sampling algorithm

- Goal: find B(H)
- Plan: random sample
  - solve random subproblem
  - keep only violating constraints V
  - recurse on leftover
- problem: violators may not contain all of B(H)
- bf BUT, contain **some** of B(H)
  - opt of sample better than opt of whole
  - but any point feasible for B(H) no better than O(H)
  - so current opt not feasible for B(H)
  - so some B(H) violated
- revised plan:
  - random sample
  - discard useless planes, add violators to "active set"
  - repeat sample on whole problem while keeping active set
  - claim: add one B(H) per iteration
- Algorithm **SampLP**:
  - set S of "active" hyperplanes.
  - if  $n < 9d^2$  do simplex  $(d^{d/2+O(1)})$
  - pick  $R \subseteq H S$  of size  $d\sqrt{n}$
  - $-x \leftarrow \mathbf{SampLP}(R \cup S)$
  - $V \leftarrow$  hyperplanes of H that violate x
  - if  $V \leq 2\sqrt{n}$ , add to S
- Runtime analysis:

- mean size of V at most  $\sqrt{n}$
- each iteration adds to S with prob. 1/2.
- each successful iteration adds a B(H) to S
- deduce expect 2d iterations.
- -O(dn) per phase needed to check violating constraints:  $O(d^2n)$  total
- recursion size at most  $2d\sqrt{n}$

$$T(n) \le 2dT(2d\sqrt{n}) + O(d^2n) = O(d^2n\log n) + (\log n)^{O(\log d)}$$

(Note valid use of linearity of expectation)

Must prove claim, that mean  $V \leq \sqrt{n}$ .

- Lemma:
  - suppose |H S| = m.
  - sample R of size r from H S
  - then expected violators d(m-r-1)/(r-d)
- $\bullet$  book broken: only works for empty S
- Let  $C_H$  be set of optima of subsets  $T \cup S, T \subseteq H$
- Let  $C_R$  be set of optima of subsets  $T \cup S$ ,  $T \subseteq R$
- note  $C_R \subseteq C_H$ , and  $O(R \cup S)$  is only point violating no constraints of R
- Let  $v_x$  be number of constraints in H violated by  $x \in C_H$ ,
- Let  $i_x$  indicate  $x = OPT(R \cup S)$

$$E[|V|] = E[\sum v_x i_x]$$
$$= \sum v_x \Pr[i_x]$$

- decide  $\Pr[v_x]$ 
  - $-\binom{m}{r}$  equally likely subsets.
  - how many have optimum x?
  - let  $q_x$  be number of planes defining x **not** already in S
  - must choose  $q_x$  planes to define x
  - all others choices must avoid planes violating x. prob.

$$\binom{m - v_x - q_x}{r - q_x} / \binom{m}{r} = \frac{(m - v_x - q_x) - (r - q_x) + 1}{r - q_x} \binom{m - v_x - q_x}{r - q_x - 1} / \binom{m}{r}$$
  
$$\leq \frac{(m - r + 1)}{r - d} \binom{m - v_x - q_x}{r - q_x - 1} / \binom{m}{r}$$

- deduce

$$E[V] \le \frac{m-r+1}{r-d} \sum v_x \binom{m-v_x-q_x}{r-q_x-1} / \binom{m}{r}$$

- summand is prob that x is a point that violates exactly one constraint in r.

- \* must pick  $q_x$  constraints defining x
- \* must pick  $r q_x 1$  constraints from  $m v_x q_x$  nonviolators
- \* must pick one of  $v_x$  violators
- therefore, sum is expected number of points that violate exactly one constraint in R.
- but this is only d (one for each constraint in basis of R)

Result:

- saw sampling LP that ran in time  $O((\log n)^{O(\log d)} + d^2n\log n + d^{O(d)})$
- key idea: if pick r random hyperplanes and solve, expect only dm/r violating hyperplanes.

### Iterative Reweighting

Get rid of recursion and highest order term.

- idea: be "softer" regarding mistakes
- plane in V gives "evidence" it's in B(H)
- Algorithm:
  - give each plane weight one
  - pick  $9d^2$  planes with prob. proportional to weights
  - find optimum of R
  - find violators of R
  - if

$$\sum_{h \in V} w_h \le (2\sum_{h \in H} w_h)/(9d-1)$$

- then double violator weights
- repeat till no violators
- Analysis
  - show weight of basis grows till rest is negligible.
  - claim  $O(d \log n)$  iterations suffice.
  - claim iter successful with prob. 1/2

- deduce runtime  $O(d^2 n \log n) + d^{d/2 + O(1)} \log n$ .
- proof of claim:
  - \* after each iter, double weight of some basis element
  - \* after kd iterations, basis weight at least  $d2^k$
  - \* total weight increase at most  $(1 + 2/(9d 1))^{kd} \le n \exp(2kd/(9d 1))$
- after  $d \log n$  iterations, done.
- so runtime  $O(d^2 n \log n) + d^{O(d)} \log n$
- Can improve to linear in n

## Randomized incremental algorithm

$$T(n) \le T(n-1,d) + \frac{d}{n}(O(dn) + T(n-1,d-1)) = O(d!n)$$

Incomparable to prior bound. Can improve to  $O(d^4 2^d N)$  (see book) Can improve to  $O(d^2 n + b^{\sqrt{d \log d} \log n})$