Discuss projects. People want extensions, see me.

## 1 Polynomial LP algorithms (cont)

Last time, saw ellipsoid and interior point.

### 1.1 Path Following

Potential function:

- Define

$$
P(\mu)=c x-\mu \sum \log x_{i}
$$

- minimize over $A x=b$
- When $\mu$ is tiny, barrier is negligible except right at edge of polytope
- so optimum is right near LP opt, just pushed away from boundary a bit.
- For each $\mu$, some optimum $x(\mu)$
- $\lim _{\mu \rightarrow 0} P(\mu)$ is LP opt.
- $P(\mu)$ as $\mu$ varies defines a function: central path
- starts where $\mu=\infty$, analytic center farthest from all boundaries.

Path following algorithm:

- repeatedly optimizes $P(\mu)$ for smaller and smaller $\mu$
- when $\mu$ small enough, round to (optimal) vertex
- need to start somewhere near central path-revise problem to make this easy.
- How optimize nonlinear $P(\mu)$ ? gradient descent (actually second order taylor)

Path following step:

- Suppose are at $P(\mu)$
- take $\bar{\mu}=(1-\beta) \mu$
- Then $P(\bar{\mu})$ near $P(\mu)$
- so gradient descent from $x(\mu)$ should converge fast to $x(\bar{\mu})$.

Actual implementation:

- don't wait to converge to $x(\bar{\mu})$.
- instead, trace out $y(\mu)$ that "follows" path without being on it.
- suppose have $y(\mu)$ near $x(\mu)$
- want $y(\bar{\mu})$ near $x(\bar{\mu})$
- take a (second order) taylor expansion of $P(\bar{\mu})$ near $y(\mu)$
- since $y(\mu)$ near $x(\bar{\mu})$, Taylor"accurate" (need $\beta \approx 1 / \sqrt{n})$
- take a "Newton step" from $y(\mu)$ towards minimizing $P(\bar{\mu})$
- takes us closer to $x(\bar{\mu})$
- update $\bar{\mu}$ and repear
- like potential method, $O(\sqrt{n} L)$ iterations halve potential.
- in practice, 9 iterations halve potential!


### 1.2 Randomized LP

New idea: focus on low dimension.
Standard incremental: $O\left(n^{d}\right)$ (poly!)
Randomization is crucial in geometry (actually everywhere; take class next year).
Seidel Randomized incremental algorithm

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

Bring in other random sampling techniques: best bound

$$
O\left(d^{2} n+b^{\sqrt{d \log d}} \log n\right)
$$

Best known bound on diameter (Kalai and Kleitman): $n^{2+\log d}$

## 2 Geometry

Field:

- We have been doing geometry
- But in computational geometry, key difference in focus: low dimension ${ }^{d}$
- Lots of algorithms that are great for $d$ small, but exponential in $d$


### 2.1 Convex Hull by RIC

- define
- good for: width, diameter, filtering
- assume no 3 points on straight line.
- output:
- points and edges on hull
- in counterclockwise order
- can leave out edges by hacking implementation
- $\Omega(n \log n)$ lower bound via sorting
algorithm (RIC):
- random order $p_{i}$
- insert one at a time (to get $S_{i}$ )
- update $\operatorname{conv}\left(S_{i-1}\right) \rightarrow \operatorname{conv}\left(S_{i}\right)$
- new point stretches convex hull
- remove new non-hull points
- revise hull structure
- Data structure:
- point $p_{0}$ inside hull (how find?)
- for each $p$, edge of $\operatorname{conv}\left(S_{i}\right)$ hit by $\overrightarrow{p_{0} p}$
- say $p$ cuts this edge
- To update $p_{i}$ in $\operatorname{conv}\left(S_{i-1}\right)$ :
- if $p_{i}$ inside, discard
- delete new non hull vertices and edges
- 2 vertices $v_{1}, v_{2}$ of $\operatorname{conv}\left(S_{i-1}\right)$ become $p_{i}$-neighbors
- other vertices unchanged.
- To implement:
- detect changes by moving out from edge cut by $\overrightarrow{p_{0} p}$.
- for each hull edge deleted, must update cut-pointers to $p_{i} \vec{v}_{1}$ or $p_{i} \vec{v}_{2}$

Runtime analysis

- deletion cost of edges:
- charge to creation cost
- 2 edges created per step
- total work $O(n)$
- pointer update cost
- proportional to number of pointers crossing a deleted cut edge
- BACKWARDS analysis
* run backwards
* delete random point of $S_{i}\left(\operatorname{not} \operatorname{conv}\left(S_{i}\right)\right)$ to get $S_{i-1}$
* same number of pointers updated
* expected number $O(n / i)$
- what $\operatorname{Pr}[$ update $p]$ ?
- $\operatorname{Pr}[$ delete cut edge of $p]$
- $\operatorname{Pr}$ [delete endpoint edge of $p]$
- $2 / i$
* deduce $O(n \log n)$ runtime
- 3 d convex hull using same idea, time $O(n \log n)$,


### 2.2 Orthogonal Range Queries

What points are in this box?

- goal: $O(n)$ space
- query time $O(\log n)$ plus number of points
- 1d: binary tree

Solve in each coordinate "separately"

- solve each coord, intersect too expensive.


### 2.2.1 kd trees

kd-trees:

- Split vertical, then horizontal
- size $O(n)$
- build time $O(n \log n)$

Query time:

- traverse subtree, descending into every node (region) that intersects query.
- pay one for each contained point
- this also amortizes cost of visiting any region completely contained in the box
- so only need measure number of region intersecting but not contained in region
- these hit one of the 4 boundaries
- let's see how many regions hit one vertical boundary
- vertical boundary on only one side of vertical split line
- but (worst case) on both sides of horizontal one
- so $Q(n)=2+2 Q(n / 4) \Theta(\sqrt{n})$


### 2.2.2 Range Trees

Basic idea:

- Build binary search tree on $x$ coords
- Each internal node represents an interval containing some points
- Our query's $x$ interval can be broken into $O(\log n)$ tree intervals
- We want to reduce dimension: on each subinterval, range search $y$ coords only amound nodes in that $x$ interval
- Solution: each internal node has a $y$-coord search tree on points in its subtree
- Size: $O(n \log n)$, since each point in $O(\log n)$ internal nodes
- Query time: find $O(\log n)$ nodes, range search in each $y$-tree, so $O\left(\log ^{2} n\right)$ (plus output size)
- more generally, $O\left(\log ^{d} n\right)$
- fractional cascading improves to $O(\log n)$


## 3 Plane Sweep Algorithms

Another key idea:

- dimension is low,
- so worth expending lots of energy to reduce dimension
- we saw this idea in LP
- plane sweep is a general-purpose dimension reduction
- Run a plane/line across space
- Study only what happens on the frontier
- Need to keep track of "events" that occur as sweep line across
- simplest case, events occur when line hits a feature


### 3.1 Segment intersections

We saw this one using persistent data structures.

- Maintain balanced search tree of segments ordered by current height.
- Heap of upcoming "events" (line intersections/crossings)
- pull next event from heap, output, swap lines in balanced tree
- check swapped lines against neighbors for new intersection events
- lemma: next event always occurs between neighbors, so is in heap
- note: next event is always in future (never have to backtrack).
- so sweep approach valid
- and in fact, heap is monotone!

