## CPSC 420+500: Advanced Algorithm Design and Analysis January 18 \& 20, 2017

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## Lower Bound on Element Uniqueness

Lemma Any linear decision tree that computes some function F has height:

$$
\left\lceil\log _{3}\left(\sum_{\text {outputs } t} \# \text { connected components of } F_{t}\right)\right\rceil
$$

i.e., $\log _{3}$ of the number of connected components for each of the possible outputs of F .

Theorem Any linear decision tree that computes Element Uniqueness has height $\Omega(n \log n)$. The NO components for Element Uniqueness $=1$, since all hyperplanes are joined at the origin.

Proof. Let

$$
\begin{gathered}
x=(1,2, \ldots, n) \\
y=(2,1,3, \ldots, n)
\end{gathered}
$$

Are $x$ and $y$ in the same connected component? No. If you have $(1,2)$ and $(2,1)$, at some point a path between them would have to cross a NO region.

Let $v$ be a vector of $n$ unique numbers and $v \neq v^{\prime}$ be any permutation of $v$. There myst be indices $i$ and $j$ such that $v_{i}$ is smaller than $v_{j}$ and $v_{i}^{\prime}$ is bigger than $v_{j}^{\prime}$, i.e., $v_{i}<v_{j}, v_{i}^{\prime}>v_{j}^{\prime}$. Any continuous path from $v$ to $v^{\prime}$ must contain a point $z$ with $z_{i}=z_{j}$ (by the intermediate value theorem*). $z$ is a NO input, so $v$ and $v^{\prime}$ are not in the same connected component.
*Intermediate Value Theorem Let $p$ be a path from points $x$ to $y$ where

$$
p:[0,1] \in \mathbb{R}^{\mathrm{n}}, \mathrm{p}(0)=\mathrm{x}, \mathrm{p}(1)=\mathrm{y}
$$

Let $q(t)=p(t)_{j}-p(t)_{i}$ (the difference between $i^{t h}$ and $j^{t h}$ coordinate in point $\left.p(t)\right)$. At some point, $q(t)=0$ because $q(0)>0, q(1)<0$ so it had to have crossed from positive to negative.

Since there are $n$ ! different permutations of a list of $n$ numbers, and none of those permutations are in the same component, there are at least $n$ ! different connected components, i.e., $\# F_{Y E S} \geq n$ !. Therefore:

$$
\# F_{Y E S}+F_{N O}=n!+1
$$

Plugging this into our formula for the height of the decision tree:

$$
\begin{gathered}
\left\lceil\log _{3}\left(\sum \# F_{t}\right)\right\rceil=\left\lceil\log _{3}(n!+1)\right\rceil \\
\lceil\log (n!)\rceil=n \log n \in \Omega(n \log n)
\end{gathered}
$$

Practice Question: reduce Element Uniqueness to Convex Hull.
However, Linear Decision Trees aren't powerful enough to calculate the Convex Hull. Algebraic Decision Trees of the $d^{t h}$ order use internal node tests that are $d^{t h}$ order polynomials (i.e., Linear Decision Trees are Algebraic Decision Trees of the $1^{\text {st }}$ order.)

Jarvis March is $\in O(n h)$ and Graham's Scan is $\in O(n \log n)$ (where $h$ is the number of points on the hull); is there a more efficient algorithm?

## Chan's Algorithm

$(\sim 1996) \in O(n \log h)$ Given $n$ points in set $P$ and a guess $h$ :

1. $O(n)$ Divide points into $\lceil n / h\rceil$ groups of size $h$
2. $O(h \log h)$ per group,$\in O(n \log h)$ total Use Graham's Scan to find the convex hull of each group
3. $O(n)$ Find the lowest point $p_{0}$ in $P$
4. $O(h(n / h) \log h)=O(n \log h)$. Do giftwrapping (Jarvis March) for $h$ steps.

Note that we don't need to scan all the points in $P$, since we have $h$ hulls that are now sorted within themselves; we can find the rightmost tangent from $p_{i}$ for each sub-hull using binary search. $n / h$ binary searches each taking $O(\log h)$ time take a total of $O(n / h \log h)$ time. Since we do this gift-wrapping step $h$ times, the total time is $O(h n / h \log h)=O(n \log h)$. Let $p_{i+1}=$ point on the rightmost out of those tangents.
5. If $p_{i+1}=p_{0}$ in $\leq h$ steps, then output the hull. Otherwise output that $h$ is too small.

Where does our guess $h$ come from? Generate the guesses for the "true" $h, h *$, by squaring each time:

$$
\begin{gathered}
h=4,16,256 \ldots \\
t^{t h} \operatorname{tr} y=2^{2^{t}}
\end{gathered}
$$

The time complexity of all tries until $h \geq h *$

$$
\begin{gathered}
\sum_{h=2^{2^{t}}} O(n \log h) \text { until } h \geq h * \\
\sum_{t=1}^{\lceil\log \log h *\rceil} O\left(n 2^{t}\right)=n\left[\sum_{t=1}^{\lceil\log \log h *\rceil} O\left(2^{t}\right)=O(n \log h *)\right. \\
\approx 2^{\operatorname{lglg} h *}
\end{gathered}
$$

