# RANDOM-EDGE is slower than RANDOM-FACET on abstract cubes 

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- Linear programming: Maximize a linear objective function subject to linear constraints.
- The simplex algorithm: Move from vertex to vertex along edges while improving the objective.
- This operation is called a pivot.


## Pivoting rules



- A pivoting rule chooses which improving pivot to make.
- Random-Edge: Repeatedly use a uniformly random improving pivot.


## Orientations



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- Many pivoting rules only rely on this orientation.
- Random-Edge: Perform a random walk until reaching the sink where all edges are incoming.


## The Random-Facet pivoting rule

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## Properties of the orientation


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(2) The unique sink property: In every face there is a unique sink (optimal vertex within the face).

## Abstract cubes



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- Acyclic unique sink orientations (AUSOs) (or abstract objective functions) are orientations that are
(1) acyclic and
(2) have the unique sink property.
- AUSOs can be defined for arbitrary polytopes. We focus on the case where the underlying polytope is a hypercube.


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## Acyclic unique sink orientations



- An algorithm asks an oracle for the orientation of the edges adjacent to a vertex.
- Goal: Find the global sink with as few oracle calls as possible.


## AUSOs and some applications



## Results about RANDOM-FACET

Bounds for the expected number of steps performed by Random-Facet on $n$-dimensional AUSOs with $m$ facets.

- Kalai [1992] and Matoušek, Sharir and Welzl [1992]: $2^{O(\sqrt{(m-n) \log n})}$
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- Matoušek [1994]: $2^{\Omega(\sqrt{n})}$ for abstract cubes ( $m=2 n$ )
- Friedmann, Hansen, and Zwick [2011]: $2^{\tilde{\Omega}(\sqrt[3]{m})}$ for linear programs


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Open problem: Is Random-Edge subexponential?

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- Goal: Construct a slightly larger AUSO C for which Random-Edge performs $2 T$ steps with high probability.
- Construction: Randomized product $C=A \times_{R} B$.



## Random walk on product AUSO

- Every step in $A$ brings us to a previously unvisited copy of $B$.
- Every copy of $B$ has its coordinates randomly permuted.
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## Random walk with reshuffles



- Main challenge: Ensure that $B$ does not reach its sink before A.
- Random-ReshuFfle $k$ : Random walk on $B$ where at least $k$ edges are always available in $A$.
- A larger $k$ delays progress in $B$.


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- A larger $k$ delays progress in $B$.
- Matoušek and Szabó [2004] use many copies of the Klee-Minty cube to get a large $k$.
- We simplify and improve their analysis by using only two copies (and therefore $k=2$ ) of a path AUSO.


## Path AUSOs

- Every vertex of a hypercube can be identified by a binary vector.
- Path AUSO: The $i$-th edge is outgoing iff the $i$-th coordinate is 0 and all previous coordinates are 1 , or the $i$-th coordinate is 1 and some previous coordinate is 0 .

In/Out: 11100110

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## In/Out: 11011101

- A reshuffle permutes the coordinates; the number of 0 's and 1's remain unchanged.


## RANDOM-RESHUFFLE 2 on a path AUSO

## In/Out: $11100110 \quad k=5, j=2$

- Suppose a vertex has $k 1$ 's, $j$ of which are non-leading.
- Let $r \geq 2 /(j+3)$ be the reshuffle probability for Random-Reshuffle 2 on $B$.


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- Let $r \geq 2 /(j+3)$ be the reshuffle probability for Random-Reshuffle 2 on $B$.
- In the next step in $B$, the number of 1 's increases with probability:

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p=(1-r) \cdot \frac{1}{j+1}+r \cdot \sum_{j^{\prime}=0}^{k} \frac{\binom{n-\left(k-j^{\prime}+1\right)}{j^{\prime}}}{\binom{n}{k}} \frac{1}{j^{\prime}+1}
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- Lemma: For $8 \leq k \leq n-9$, the number of 1 's increases with probability at most 5/12.
- The process can be analyzed as a biased random walk on $\{0,1, \ldots, n-17\}$.


## Choosing the size of $B$

By analyzing the biased random walk on $\{0,1, \ldots, n\}$ we get:

## Lemma

Let $P_{m}$ be the $m$-dimensional path AUSO. There are constants $\alpha, \beta>0$ such that the probability that Random-Reshuffle 2 on $P_{m}$, starting from a random vertex, performs less than $2^{\alpha m}$ steps before reaching the sink is at most $2^{-\beta m}$.

- We let $A_{0}=P_{m}$ and $A_{i}=A_{i-1} \times_{R}^{2} P_{m}$ for $i>1$.
- We show that the probability that Random-Edge performs less than $2^{\ell}$ steps when started at a random vertex of $A_{\ell}$, where $\ell<\alpha m$, is at most $4 \cdot 2^{\ell-\beta m}$.


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- Choosing $\ell=\Theta(m)$ gives a $2^{\Omega(\sqrt{n})}$ lower bound, where $n=\Theta(\ell m)$.


## Improving the bound further

- We show that Random-Reshuffle 2 on the $m$-dimensional path AUSO in two steps almost always increases the number of 1 's with probability at most $O(1 / \sqrt{m})$.
- The improved analysis gives a $2^{\Omega(\sqrt{n \log n})}$ lower bound.


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- Can we do better?


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- The improved analysis gives a $2^{\Omega(\sqrt{n \log n})}$ lower bound.
- Can we do better? No:
- Any $m$-dimensional AUSO has a path of length at most $m$ to its sink from every vertex.
- This is true for any choice of $B$ in $A_{i}=A_{i-1} \times_{R} B$.
- Random-Edge on $A_{\ell}$ follows this path in $B$ with probability at least $1 / n^{m}$, where $m$ is the dimension of $B$ and $n=m \ell$ is the dimension of $A_{\ell}$.

$$
\# \text { steps } \leq \min \left\{2^{\ell}, n^{n / \ell}\right\} \text { poly }(n)
$$

- It is impossible to get a better $\ell$ relative to $m$, regardless of the choice of $B$.


## Concluding remarks

- We gave a $2^{\Omega(\sqrt{n \log n})}$ lower bound for Random-Edge on abstract cubes (AUSOs), showing that Random-Edge is slower than Random-Facet for this problem.
- Open problem: Is Random-Edge subexponential? Can the lower bound be further improved?
- Open problem: Improve the $2^{\Omega(\sqrt[4]{n})}$ lower bound for linear programming by Friedmann, Hansen, and Zwick [2011].
- Open problem: Is there an algorithm for AUSOs that is faster than $2^{O(\sqrt{n})}$ ?
- Schurr and Szabó [2004]: Any deterministic algorithm requires $\Omega\left(n^{2} / \log n\right)$ queries.


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Thank you for listening!

