

# Some Sequential Algorithms are Almost Always Parallel

Guy Blelloch

Carnegie Mellon University

July 2017

## Some Sequential Algorithms

?

are **Almost Always**

?

**Parallel**

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Joint work with Jeremy Fineman, Phil Gibbons, Yan Gu, Julian Shun, and Yihan Sun [BFS SPAA'12], [BFGS PPOPP'12], [SGuBFG SODA'15], [BGuSSu SPAA'16].

# Iterative Sequential Algorithms

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for i = 1 to n  
  do something
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for i = 1 to n  
  a[i] = f(a[i-1])
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**Fully Sequential** (for arbitrary  $f$ )  
Each iteration depends on all previous iterations.

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for i = 1 to n  
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## Fully “parallel”

No dependences among iterations.

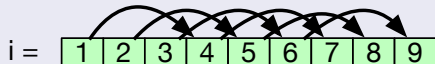


# Iterative Sequential Algorithms

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for  $i = \sqrt{n} + 1$  to  $n$   
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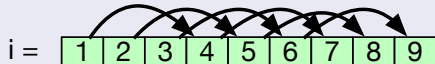
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$i \rightarrow j$  means  $j$  depends on  $i$

## Partially parallel.

Some dependences, but they are not affected by the data.

In this case dependence depth is  $\sqrt{n}$ .

?

```
A = an input array of length  $n$   
for  $i = n - 1$  downto 0  
     $H[i] = \text{rand}(\{0, \dots, i\})$   
     $\text{swap}(A[H[i]], A[i])$ 
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## Knuth's shuffle to generate a random permutation of $A$

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$i =$	0	1	2	3	4	5	6	7
$A[i]$	a	b	c	d	e	f	g	h
$H[i] =$	0	0	1	3	1	2	3	1

# Iterative Sequential Algorithms

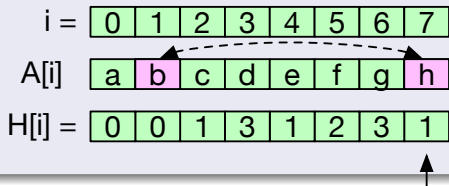
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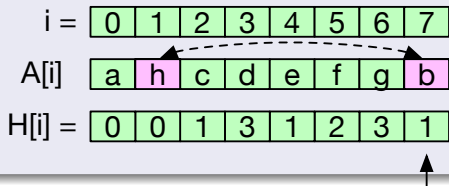
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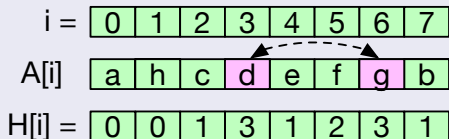




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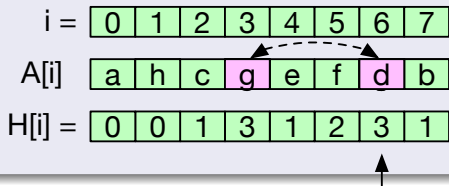
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Dependences?

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# Iterative Sequential Algorithms

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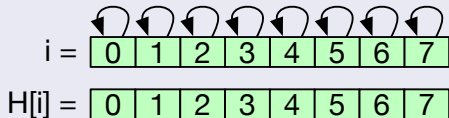
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In general?

```
 $i =$ 

|   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|
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|---|---|---|---|---|---|---|---|

  
 $H[i] =$ 

|   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|
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|---|---|---|---|---|---|---|---|

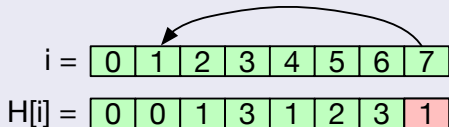

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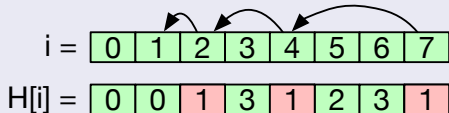


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Dependences **depend on data**.

**Question:** What can we say about dependence depth over the **random choices**?

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**Answer** [SGuBFG'15]:  $O(\log n)$  w.h.p.

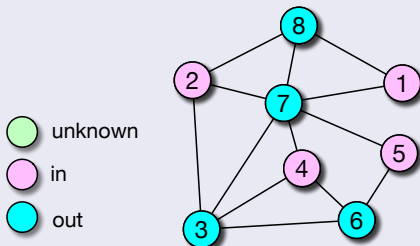
?

```
undirected graph  $G = (V, E)$ ,  $S[1, \dots, n] = \text{unknown}$   
for  $i = 1$  to  $|V|$   
  if for any earlier neighbor  $v_j$  of  $v_i$ ,  $S[j] = \text{in}$   
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# Iterative Sequential Algorithms

## Greedy Maximal Independent Set

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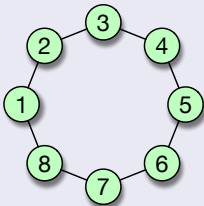


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Dependencies for this simple cycle graph?

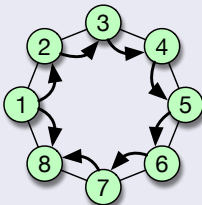


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## Fully sequential

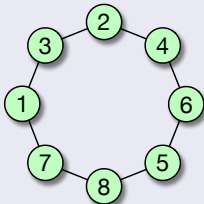


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Same graph, different ordering of  $V$ . Dependences now?



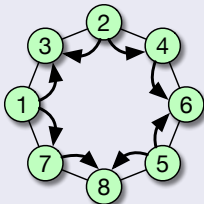


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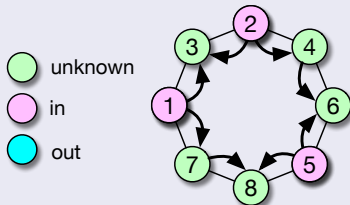


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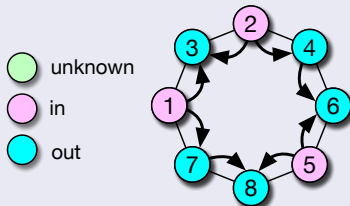


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Fully parallel order (two rounds)

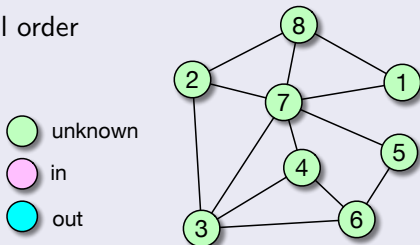


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## Partially parallel order

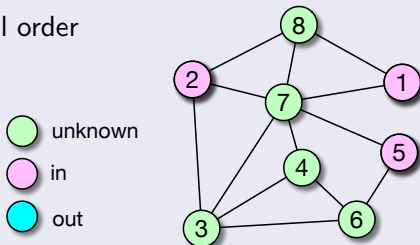


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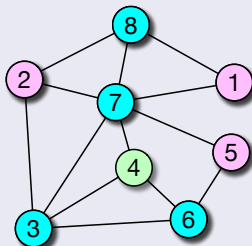


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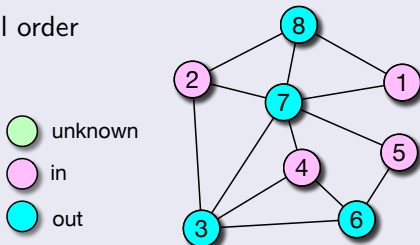


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**Answer** [BFS'12]:  $O(\log^2 n)$

(w.h.p. for random ordering of  $V$ , i.e. if we randomly permute  $V$ )

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**Open problem:**  $O(\log n)$  w.h.p.?

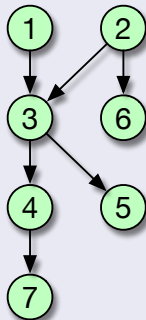
# Dependence Depth

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for i = 1 to n  
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Simple model:

- Each iterate is a vertex
- $i \rightarrow j$  means  $j$  depends on  $i$

Iterations



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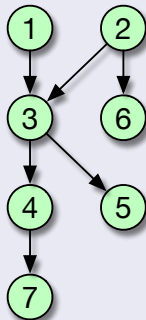
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**Iteration Depth:**

the longest chain of dependences.

Iterations



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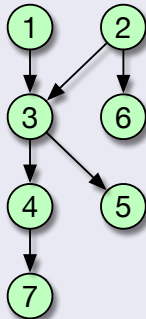
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**Overall Depth:**

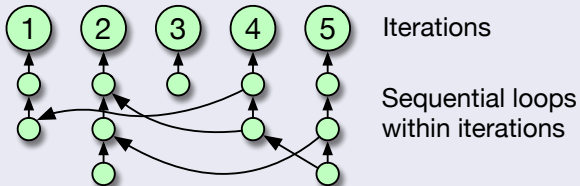
weighted by depth of each iteration.

Iterations



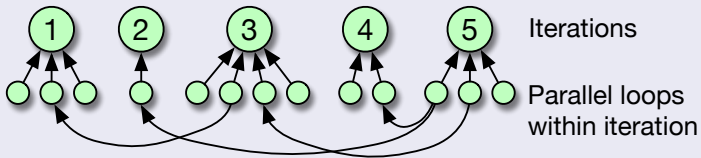
# Dependence Depth

## Nested iterations



# Dependence Depth

## Nested iterations



# Only Two Examples?

- 1 Knuth shuffle
- 2 Greedy MIS



# More Iterative Sequential Algorithms

## Greedy Maximal Matching

```
Graph  $G = (V, E)$  and  
 $A[1, \dots, |V|] = \text{true}$  //  $A[i]$  if vertex  $i$  is available  
 $M[1, \dots, |E|] = \text{false}$  //  $M[j]$  if edge  $j$  is in matching  
for  $i = 1$  to  $|E|$   
   $(u, v) = E[i]$   
  if  $(A[u]$  and  $A[v])$   
    then  $M[i] = \text{true}$ ,  $A[u] = \text{false}$ ,  $A[v] = \text{false}$ 
```

**Iteration Depth** [BFS'12]:  $O(\log^2 |V|)$   
(w.h.p. for random ordering of  $E$ )

# More Iterative Sequential Algorithms

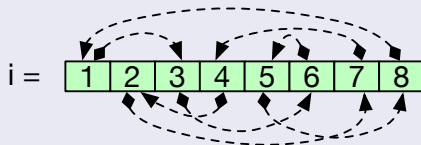
## List contraction

$A$  = an array containing  $n$  links of doubly linked lists

**for**  $i = 0$  **to**  $n - 1$

$A[i].next.previous = A[i].previous$

$A[i].previous.next = A[i].next$



# More Iterative Sequential Algorithms

## List contraction

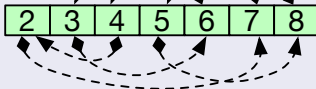
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Applications of:

- length of lists or list ranking
- size or number of cycles in a permutation
- Euler tour, biconnectivity,...

## List contraction

$A$  = an array containing  $n$  links of doubly linked lists

**for**  $i = 0$  **to**  $n - 1$

$A[i].next.previous = A[i].previous$

$A[i].previous.next = A[i].next$

**Iteration Depth** [SGuBFG'15]:  $O(\log n)$

(w.h.p. for random ordering of  $A$ )

# More Iterative Sequential Algorithms

## Sorting by insertion into a binary search tree (BST)

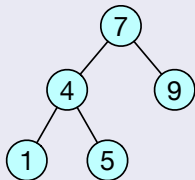
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A = an array of keys  
T = empty binary tree  
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## Example:



insert(2), insert(8) – no dependence

insert(2), insert(3) – dependence

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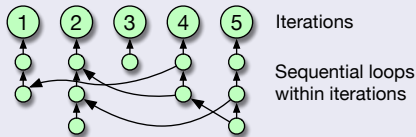
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**Overall Depth:**  $O(\log n)$

Analysis requires  
sub-iteration  
dependences, otherwise  
 $O(\log^2 n)$ .



# More Iterative Sequential Algorithms

## two-dimensional linear programming

Constraints (lines)  $C = c_1, \dots, c_n$

$p = (\infty, 0)$

**for**  $i = 1$  **to**  $n$

**if**  $p$  violates  $c_i$

$p = \text{min intersection of } c_1, \dots, c_{i-1} \text{ along } c_i$

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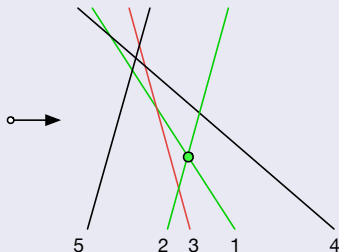
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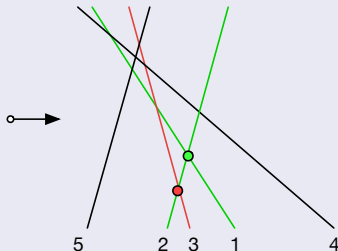
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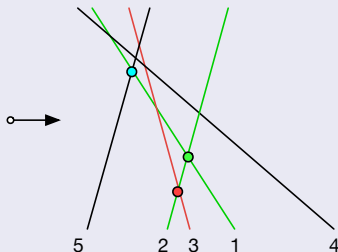
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**Overall Depth:**  $O(\log(n) \log \log(n))$

( $\log \log(n)$  term for min intersection)

# More Iterative Sequential Algorithms

## Delaunay triangulation

points  $P = p_1, \dots, p_n$

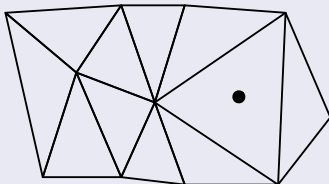
$T = \{\text{boundingTriangle of } P\}$

**for**  $i = 1$  **to**  $n$

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## Example:



# More Iterative Sequential Algorithms

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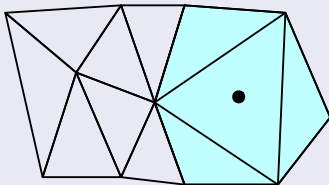
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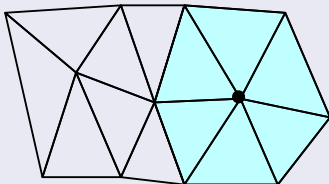
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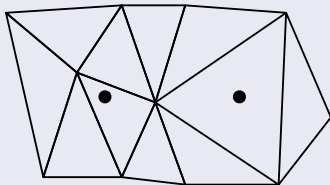
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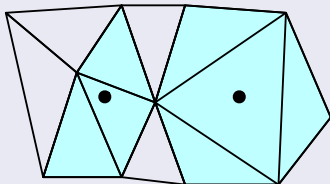
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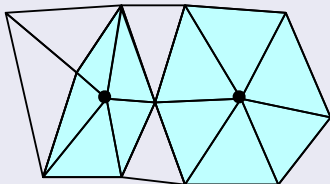
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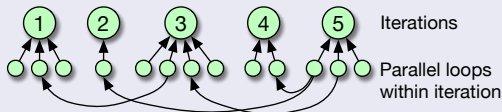
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Analysis requires allowing subiterations to proceed independently.



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Parallel incremental Delaunay is **widely used in practice**, but it was not previously known whether it is theoretically efficient.

## Graph Connectivity using union-find

```
graph  $G = (V, E)$ 
```

```
F = a union find data structure on  $V$ 
```

```
for  $i = 1$  to  $|E|$ 
```

```
     $u = F.find(E[i].u)$ 
```

```
     $v = F.find(E[i].v)$ 
```

```
    if  $(u \neq v)$  then  $F.union(u, v)$ 
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     $v = F.find(E[i].v)$   
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```

**Iteration Depth:** TDB (open problem)

# Some Sequential Algorithms

are **Almost Always**

**Parallel**

## ~~Some~~ Many Sequential Algorithms

- Iterative sequential algorithms such as:  
Knuth shuffle, greedy MIS, greedy maximal matching,  
list contraction, tree contraction, linear programming,  
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- Polylogarithmic dependence depth

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- Lots of work on parallel algorithms, but perhaps sequential ones are already parallel

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- Surprisingly simple solutions to basic problems
- Possible way to attack new problems
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## Application to parallel and distributed algorithms (Practice)

- Fast and simple code
- Generic techniques to parallelize code
- Determinacy

# How to Analyze Dependence Depth

# Knuth Shuffle: Iteration Depth

```
for  $i = n - 1$  downto 0  
   $H[i] = \text{rand}(\{0, \dots, i\})$   
  swap( $A[H[i]]$ ,  $A[i]$ )
```

$i =$ 

0	1	2	3	4	5	6	7
---	---	---	---	---	---	---	---

$H[i] =$ 

0	0	1	3	1	2	3	1
---	---	---	---	---	---	---	---

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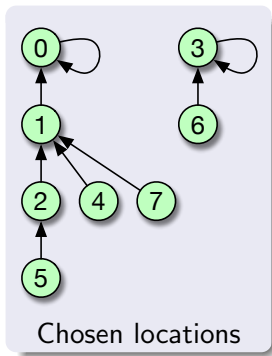
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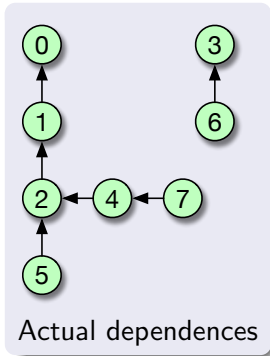
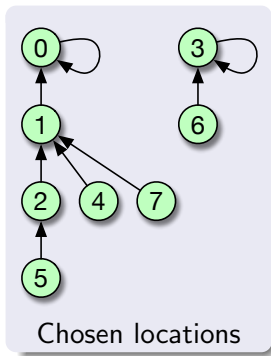
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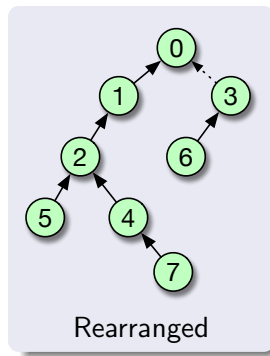
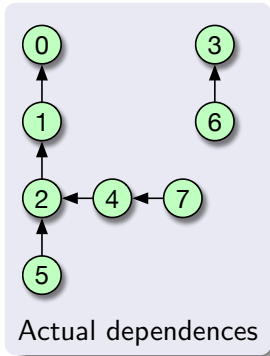
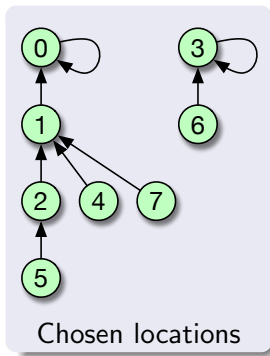
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# Knuth Shuffle: Iteration Depth

Adding one more, i.e., proof by induction

$i =$ 

0	1	2	3	4	5	6	7	8
---	---	---	---	---	---	---	---	---

$H[i] =$ 

0	0	1	3	1	2	3	1	?
---	---	---	---	---	---	---	---	---

# Knuth Shuffle: Iteration Depth

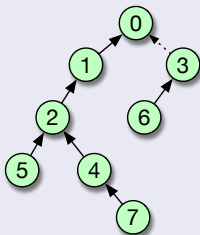
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Not including 8

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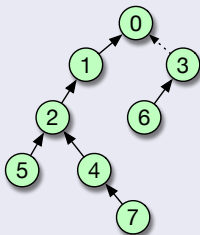
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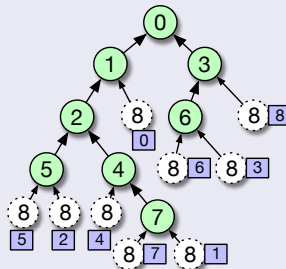
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Not including 8



Possible positions of 8

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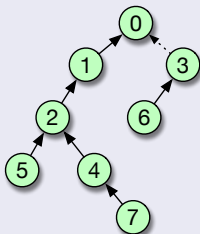
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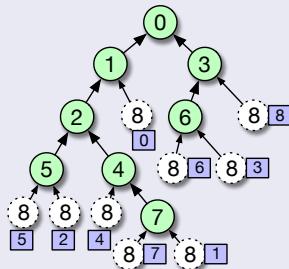
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Not including 8



Possible positions of 8

All equally likely, so equivalent to random BST.

# Maximal Independent Set, Bound on Depth

```
graph  $G = (V, E)$ ,  $S[1, \dots, n] = \text{unknown}$ ,  $n = |V|$   
for  $i = 1$  to  $n$   
  if for any earlier neighbor  $v_j$  of  $v_i$ ,  $S[j] = \text{in}$   
  then  $S[i] = \text{out}$  else  $S[i] = \text{in}$ 
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## Known results

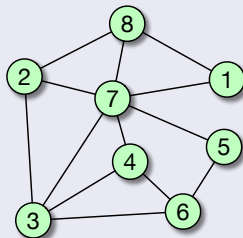
- Lexicographically first MIS is P-complete [Cook '85]
- $O(\log^2 n)$  dependence depth for random graphs w.h.p. [Coppersmith, Raghavan, Tompa '89]
- $O(\log n)$  depth for random graphs w.h.p. [Calkin, Frieze '90]
- $O(\log^2 n)$  depth for arbitrary graph in random order
- Many parallel algorithms (e.g. Luby).

# Maximal Independent Set, Bound on Depth

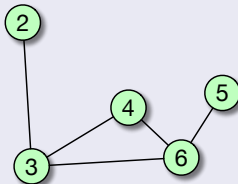
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## Definition (Residual graph on step $i$ )

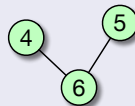
The graph that is left after step  $i$



After iteration 1



After iteration 2



# Maximal Independent Set, Bound on Depth

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```

## Lemma (Degree)

*After step  $i$ , the maximum degree in the residual graph is  $O(n \log n / i)$  w.h.p. (over orderings of  $V$ ).*

# Maximal Independent Set, Bound on Depth

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```

## Lemma (Degree)

*After step  $i$ , the maximum degree in the residual graph is  $O(n \log n / i)$  w.h.p. (over orderings of  $V$ ).*

For example:

For  $i = n/2$  (half done), the max degree is  $O(\log n)$  w.h.p.

# Maximal Independent Set, Bound on Depth

```
graph  $G = (V, E)$ ,  $S[1, \dots, n] = \text{unknown}$ ,  $n = |V|$   
for  $i = 1$  to  $n$   
  if for any earlier neighbor  $v_j$  of  $v_i$ ,  $S[j] = \text{in}$   
  then  $S[i] = \text{out}$  else  $S[i] = \text{in}$ 
```

## Lemma (Degree)

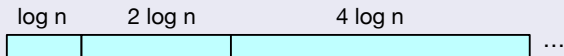
*After step  $i$ , the maximum degree in the residual graph is  $O(n \log n / i)$  w.h.p. (over orderings of  $V$ ).*

## Proof outline.

Consider a vertex with degree larger than  $d$  (in residual graph) on step  $i$ . The probability of selecting one of the neighbors on each step  $j$  ( $\leq i$ ) is at least  $d/n$ . The probability it survives all steps  $j$  is therefore at most  $(1 - d/n)^i$ , leading to the result.  $\square$

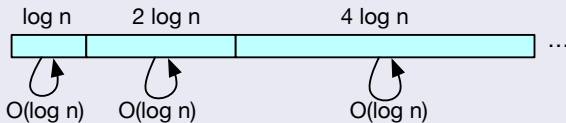
# Maximal Independent Set, Bound on Depth

Consider increasing sized blocks of the iterations



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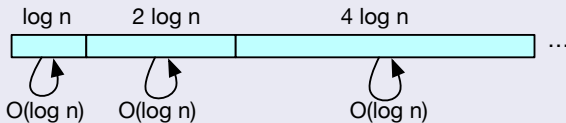
Consider increasing sized blocks of the iterations



w.h.p. no path within a block is greater than  $O(\log n)$

# Maximal Independent Set, Bound on Depth

Consider increasing sized blocks of the iterations



Proof outline: For each block  $i$

- Prob. of edge between two iterations is at most  $\frac{1}{2^i}$  (by Degree Lemma)
- number of paths of length  $l$  is  $\binom{2^i \log n}{l}$

By the union bound the prob. of any path of length  $l$  is at most

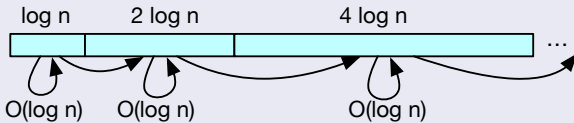
$$\left(\frac{1}{2^i}\right)^l \binom{2^i \log n}{l} < \left(\frac{1}{2^i}\right)^l \left(\frac{e 2^i \log n}{l}\right)^l = \left(\frac{e \log n}{l}\right)^l$$

**Therefore probability is very small that  $l > 2e \log n$ .**



# Maximal Independent Set, Bound on Depth

Consider increasing sized blocks of the iterations



## Summary

Since path within each block is  $O(\log n)$ , and number of blocks is  $O(\log n)$ , total depth is  $O(\log^2 n)$ .

Can be improved to  $O(\log n \log d_{max})$  by picking blocks of size  $2^i \frac{d_{max}}{n} \log n$ .

# Concrete Algorithms and Implementation

## Definition (Efficiently Checkable Dependences)

In a constant number of “rounds” each iteration can check if it has any unresolved dependences.

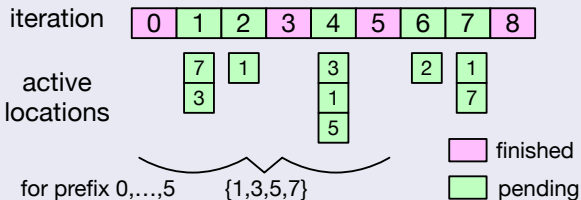
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## Sufficient condition (true for all our examples):

- 1 Each  $i$  independently can identify *active* locations  $l_i$ , s.t.,
- 2 pending iterations in every prefix  $0, \dots, i$  only update  $\cup_{j \in [i]} l_j$ .



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## Suggests an implementation strategy:

While there are pending iterations:

**reserve:** in parallel pending iterations find active locations and mark them

**commit:** in parallel each pending iteration runs, but aborts if it depends on an active previous location

# Implication For Algorithms

## Parallel (Priority PRAM)

	Work	Depth (Time)
MIS	$O( E )$	$O(\log^2  V  \log \Delta)$
Maximal Matching	$O( E )$	$O(\log^2  V  \log \Delta)$
BST Sort	$O(n \log n)$	$O(\log n)$
Knuth Shuffle	$O(n)$	$O(\log n \log^* n)$
List Contraction	$O(n)$	$O(\log n \log^* n)$
2d Linear Programming	$O(n)$	$O(\log n)$
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**All are work efficient.**

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## Distributed (CONGEST model)

	Rounds
MIS	$O(\log  V  \log \Delta)$
Maximal Matching	$O(\log  V  \log \Delta)$

# Implementation: Speculative For

```
struct step {  
    bool reserve(int i) {  
        reserves locations that will be written by iteration i}  
    bool commit(int i) {  
        checks locations iteration i depends on, and runs if safe}};
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Can dynamically choose size of prefix.

# Knuth Shuffle Code

```
struct knuth_step {
    bool reserve(int i) {
        write_min(R[i], i); write_min(R[H[i]], i);
        return 1; }

    bool commit (int i) {
        int h = H[i];
        if(R[H[i]] == i) {
            if(R[i] == i) {swap(A[i],A[H[i]]); R[i] = inf; return 1;}
            R[H[i]] = inf;}
        return 0; }
};
```

```
speculative_for(knuth_step(..), 0, n);
```

```
struct mis_step {
  bool reserve(int i) {
    flag = In;
    for (int j = 0; j < G[i].degree; j++) {
      int ngh = G[i].Neighbors[j];
      if (ngh < i) {
        if (S[ngh] == In) { flag = Out; return 1;}
        else if (S[ngh] == Unknown) flag = Unknown; }
    }
    return 1;}

  bool commit(int i) { return (S[i] = flag) != Unknown;}
};
```

```
speculative_for(mis_step(..), 0, n);
```

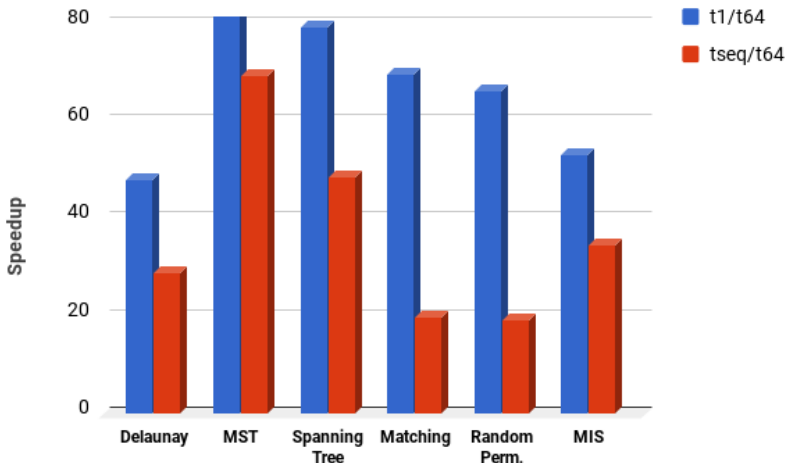
# Spanning Tree Code

```
struct union_find_step {
    bool reserve(int i) {
        u = UF.find(E[i].u);
        v = UF.find(E[i].v);
        if (u > v) swap(u,v);
        if (u != v) { write_min(R[v], i); return 1;
        } else return 0; }

    bool commit(int i) {
        if (R[v] == i) { UF.link(v, u); return 1; }
        else return 0; }
};
```

```
speculative_for(union_find_step(..), 0, m);
```

# Timings on a 64-core Xeon Phi

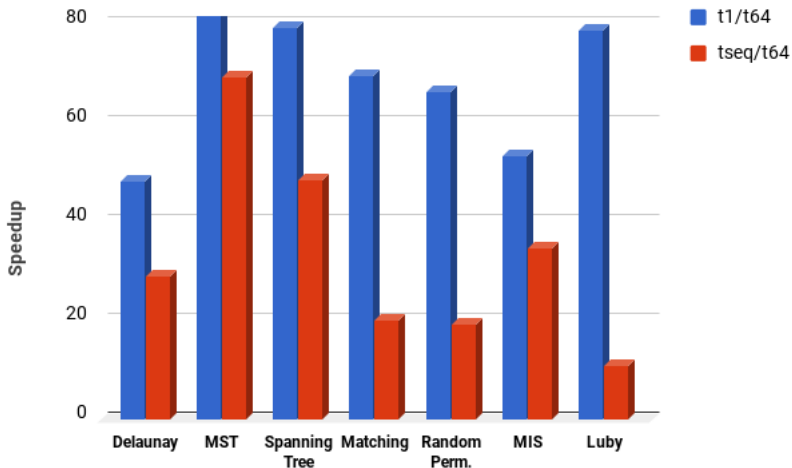


$tseq$  = best sequential algorithm

$t1$  = time on one core

$t64$  = time on all cores

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## Conclusions

- 1 Many sequential algorithms are “inherently” parallel, at least when randomly ordering.
  - Perhaps should be thinking of algorithms more abstractly in terms of their dependence graph instead of specific model.
- 2 Can often take advantage of the parallelism using reservations
- 3 Resulting code is **simple**, **fast**, and **deterministic**

## Conclusions

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  - Perhaps should be thinking of algorithms more abstractly in terms of their dependence graph instead of specific model.
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- 3 Resulting code is **simple**, **fast**, and **deterministic**

## Open Questions

- 1 Depth of MIS
- 2 Resolving dependences in a more general context.