# Election vs. Selection: How Much Advice is Needed to Find the Largest Node in a Graph? 

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## Application - Shared Resource



Microsoft Docs, Leader Election Pattern, 23.06.2017
https://docs.microsoft.com/en-us/azure/architecture/patterns/leader-election

## Application - Shared Resource

Access to shared resource -> need coordinator

Failure resilience -> need new leader


## Application - Radiocom


G. Le Lann, Distributed Systems - Towards a Formal Approach Proc. IFIP Congress, 1977, 155-160, North Holland.

## Application - Radiocom



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# Election vs. Selection: <br> How Much Advice is Needed to Find the Largest Node in a Graph? 

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## Election

Find a leader
Everyone knows its identity


## Election

Find a leader

Everyone knows its identity


# Election 

Find a leader

Everyone knows its identity


## Selection

Leader outputs 1

Every other node outputs $\mathbf{0}$


## Selection

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## Election vs Selection



## Synchronous Algorithms

In each round:

- Send messages to neighbours
- Receive messages from neighbours
- Do some computation

Time complexity is the number of rounds

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## Algorithm with advice

Oracle with full knowledge

Gives same advice to each node

Goal: make computation faster


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## Algorithm with advice

Example : Election without advice


Notations:
$K(r, v)=$ knowledge of $v$ after $r$ rounds
$\Lambda(r, v)$ set of labels induced by $K(r, v)$


## Algorithm with advice

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$\Lambda(0,4)=\{4\}$


Round 0

## Algorithm with advice

Example : Election without advice


Notations:
$K(r, v)=$ knowledge of $v$ after $r$ rounds
$\Lambda(r, v)$ set of labels induced by $K(r, v)$
$K(1,4)$
$\Lambda(1,4)=\{4,6\}$


Round 1

## Algorithm with advice

Example : Election without advice


Notations:
$K(r, v)=$ knowledge of $v$ after $r$ rounds
$\Lambda(r, v)$ set of labels induced by $K(r, v)$

$\Lambda(2,4)=\{3,4,6\}$


Round 2

## Algorithm with advice

Example : Election without advice


Notations:
$K(r, v)=$ knowledge of $v$ after $r$ rounds
$\Lambda(r, v)$ set of labels induced by $K(r, v)$

$\Lambda(3,4)=\{3,4,5,6,12\}$


## Algorithm with advice

Example : Election without advice
Notations:
$K(r, v)=$ knowledge of $v$ after $r$ rounds
$\Lambda(r, v)$ set of labels induced by $K(r, v)$

$\Lambda(4,4)=\{1,3,4,5,6,10,12\}$


## Algorithm with advice

Example : Election without advice


## Algorithm with advice

Example : Election without advice


## Task - Measure of Difficulty

Time constraint for the execution

How much advice needed ?

Upper and lower bound the size of advice

## Tight Bounds on Advice

Tight bounds are given on the size of advice.

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## Tight Bounds on Advice

Tight bounds are given on the size of advice.
$\Theta(f(x)) \Leftrightarrow \Omega(f(x)) \wedge O(f(x))$

Lower bound $l$
Find a class of graphs for which a least $l$ advice needed for any algorithm

Upper bound $u$
Find an algorithm for which at most $u$ advice needed on all graphs

## How is it helpful?

Can rule out entire classes of algorithms

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Can rule out entire classes of algorithms
Given result: Task $T$ needs $\Theta(\log n)$ bits of advice
Proposed algorithm: Needs linear upper bound on $n$ as advice.
Contradiction: Advice can be given by $\lceil\log n\rceil$, using $\Theta(\log \log n)$ bits.

## Results - Election

| Time | Advice |
| :---: | :---: |
| $>$ diam | 0 |
| diam | $\Theta(\log$ diam $)$ |
| $<$ diam | $\Theta(\log n)$ |

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Provide the diameter of the graph

## Results - Election

| Time | Advice |
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| $>$ diam | 0 |
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| $<$ diam | $\Theta(\log n)$ |

No better advice than to give the solution

## Results - Election



## Results - Selection



| Time | Advice |
| :---: | :---: |
| $>$ diam | 0 |
| $a \cdot \operatorname{diam}$, <br> $a \in(0,1)$ | $\Theta(\log \log \operatorname{diam})$ |
| diam $^{e}$, <br> $e<1$ | $\Theta(\log$ diam $)$ |

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## Only valid for rings

## Results - Selection



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We will go through the algorithm for the upper bound

## Results - Selection



| Time | Advice |
| :---: | :---: |
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For rings $\Theta(\log$ diam $)=$ $\Theta(\log n)$

## Results - Selection



## Results

| Time | Advice |
| :---: | :---: |
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## Results



Inter-task jump


## Selection - Example



Time constraint: $\mathrm{t}=a \cdot \operatorname{diam}, a \in(0,1)$
Goal : Prove that size of advice is $\mathrm{O}(\log \log \operatorname{diam}(R))$ for any ring $R$

Simplification: $a=1$, so $t=\operatorname{diam}$

## Selection - Example

Algorithm consists of two stages

1. Round-by-round discovery
2. Eliminate resulting nodes from first stage

Advice string split in two parts $A=A_{1} A_{2}$

## Selection - Example

Algorithm - Stage 1
$A_{1}=\lfloor\log (\operatorname{diam}(R))\rfloor$
On each node $v$
Run $r=2^{A_{1}}$ rounds to learn $\Lambda(r, v)$


Selection - Example
Algorithm - Stage 1

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## Selection - Example

Algorithm - Stage 1

$$
A_{1}=\lfloor\log (\operatorname{diam}(R))\rfloor \quad\lfloor\log (5)\rfloor=2
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On each node $v$

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\text { Run } r=2^{A_{1}} \text { rounds to learn } \Lambda(r, v) \quad r=4
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On each node $v$
Run $r=2^{A_{1}}$ rounds to learn $\Lambda(r, v) \quad r=4$
If $v \neq \max (\Lambda(r, v))$ output 0


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## Selection - Example

Algorithm - Stage 2: Advice construction
$C_{R}=\left\{\gamma_{0}, \gamma_{1}, \ldots, \gamma_{\left|C_{R}\right|-1}\right\}=$ set of resulting nodes where $\gamma_{0}$ is largest
Goal: eliminate all but $\gamma_{0}$

## Selection - Example

Algorithm - Stage 2: Advice construction
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Solution: for each $\gamma_{j, j>0}$, find difference with $\gamma_{0}$ and provide it as advice

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$C_{R}=\left\{\gamma_{0}, \gamma_{1}, \ldots, \gamma_{\left|C_{R}\right|-1}\right\}=$ resulting set of nodes where $\gamma_{0}$ is largest
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Solution: for each $\gamma_{j, j>0}$, find difference with $\gamma_{0}$ and provide it as advice

$$
\begin{aligned}
& \gamma_{0}=100111 \\
& \gamma_{1}=100011
\end{aligned}
$$

## Selection - Example

Algorithm - Stage 2: Advice construction
$C_{R}=\left\{\gamma_{0}, \gamma_{1}, \ldots, \gamma_{\left|C_{R}\right|-1}\right\}=$ resulting set of nodes where $\gamma_{0}$ is largest
Goal: eliminate all but $\gamma_{0}$
Solution: for each $\gamma_{j, j>0}$, find difference with $\gamma_{0}$ and provide it as advice

$$
\begin{aligned}
& \gamma_{0}=100111 \\
& \gamma_{2}=100101
\end{aligned}
$$

## Selection - Example

Algorithm - Stage 2: Advice construction
$A_{2}$ set of indices satisfying:
For all $\gamma_{j, j>0}$, there exists $i \in A_{2}$ such that $\gamma_{j}[i]=0$ and $\gamma_{0}[i]=1$
Construction Example

$$
A_{2}=\emptyset
$$

## Selection - Example

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Construction Example

$$
A_{2}=\{3\}
$$

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\begin{aligned}
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\end{aligned}
$$

## Selection - Example

Algorithm - Stage 2: Advice construction
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Algorithm - Stage 2: Advice construction
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For all $\gamma_{j, j>0}$, there exists $i \in A_{2}$ such that $\gamma_{j}[i]=0$ and $\gamma_{0}[i]=1$
Construction Example

$$
A_{2}=\{3,4\}
$$

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\begin{aligned}
& \gamma_{0}=100111 \\
& \gamma_{2}=100101
\end{aligned}
$$

## Selection - Example

Algorithm - Stage 2: Advice construction
$A_{2}$ set of indices satisfying:
For all $\gamma_{j, j>0}$, there exists $i \in A_{2}$ such that $\gamma_{j}[i]=0$ and $\gamma_{0}[i]=1$
Construction Example

$$
A_{2}=\{3,4\}
$$

$$
\begin{aligned}
& \gamma_{0}=100111 \\
& \gamma_{3}=100001
\end{aligned}
$$

## Selection - Example

Algorithm - Stage 2: Algorithm

On each node $\gamma$ in $\mathrm{C}_{\mathrm{R}}$
If there exists $\mathrm{i} \in A_{2}$ such that $\gamma[i]=0$
Output 0
Else
Output 1

## Selection - Example

Algorithm - Stage 2: Algorithm

On each node $\gamma$ in $\mathrm{C}_{\mathrm{R}}$
If there exists $i \in A_{2}$ such that $\gamma[i]=0$
Output 0
Else

$$
\text { Output } 1
$$

Algorithm at $\gamma_{2}$

$$
A_{2}=\{3,4\}
$$

$$
\gamma_{2}=100101
$$

## Selection - Example

Algorithm - Stage 2: Algorithm

On each node $\gamma$ in $\mathrm{C}_{\mathrm{R}}$
If there exists $\mathrm{i} \in A_{2}$ such that $\gamma[i]=0$
Output 0
Else

$$
\text { Output } 1
$$

Algorithm at $\gamma_{2}$

$$
\begin{aligned}
& A_{2}=\{3,4\} \\
& \qquad \gamma_{2}=100101 \quad \Rightarrow \text { Output 0 }
\end{aligned}
$$

## Selection - Example

Algorithm - Recap
$A=A_{1} A_{2}$
$A_{1}=\lfloor\log (\operatorname{diam}(R))\rfloor$
$A_{2}:$ For all $\gamma_{j, j>0}$, there exists $i \in A_{2}$ such that $\gamma_{j}[i]=0$ and $\gamma_{0}[i]=1$
On each node $v$
Run $r=2^{A_{1}}$ rounds to learn $\Lambda(r, v)$
If $v \neq \max (\Lambda(r, v))$ output 0
On each node $\gamma$ in $\mathrm{C}_{\mathrm{R}}$
If there exists $\mathrm{i} \in A_{2}$ such that $\gamma[i]=0$
Output 0
Else
Output 1

## Selection - Example

Algorithm - Size of Advice
$A_{1}=\lfloor\log \operatorname{diam}(R)\rfloor$
Size of $A_{1}$ is $O(\log \log \operatorname{diam}(R))$
$A_{2}=$ is a set of at most $\left|C_{R}\right|$ indices
Size of each index is $\mathrm{O}(\log \log \operatorname{diam}(R))$
$\left|C_{R}\right|$ is a constant
Size of $A_{2}$ is $\mathrm{O}\left(\left|C_{R}\right| \cdot \log \log \operatorname{diam}(R)\right)=\mathrm{O}(\log \log \operatorname{diam}(R))$

Size of advice $A$ is $O(\log \log \operatorname{diam}(R))$
Note that the time constraint is also respected.

## Summary



- Election vs Selection
- Algorithm with advice
- Measure of difficulty - size of advice
- Results
- Algorithm overview for selection in time linear in the diameter (upper bound)


## Questions?

## Related Work

- Message complexity
- Non-unique labels
- Non-labelled graphs
- Election of arbitrary node
- Algorithms with advice for other problems
- Different advice for each node
- Different kind of difficulty measurement.

