# A Lower Bound for the Distributed Lovász Local Lemma 

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## Outline

(1) The Lovász local lemma
(2) Our model of distributed computing
(3) A lower bound for the distributed LLL

## The probabilistic method

- Primarily used in combinatorics to give existence proofs.
- Randomly choose objects from a certain class, and show that the probability that the object is of the desired kind is larger than zero.
- It follows that at least one such object has to exist.


## The probabilistic method

- Primarily used in combinatorics to give existence proofs.
- Randomly choose objects from a certain class, and show that the probability that the object is of the desired kind is larger than zero.
- It follows that at least one such object has to exist.
- Let $\mathcal{E}=\left\{E_{1}, \ldots, E_{n}\right\}$ be a set of bad events that make the object undesirable.
- If the events are mutually independent and $\operatorname{Pr}\left(E_{i}\right)<1$ for each $i$, we have trivially $\operatorname{Pr}\left(\bigcap_{i=1}^{n} \overline{E_{i}}\right)>0$.
- What if there is some dependence between the events?


## The Lovász local lemma (LLL)

## Theorem (Erdős and Lovász, 1975)

Let $\mathcal{E}=\left\{E_{1}, \ldots, E_{n}\right\}$ be a finite set of events such that each $E_{i}$ depends on at most $d$ other events. If $\operatorname{Pr}\left(E_{i}\right) \leq p$ and $4 p d \leq 1$, then there is a positive probability that none of the events occur.

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## Theorem (Lovász, 1977)

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$e=2.718 \ldots$ is the base of the natural logarithm.

## LLL: example

## Proposition

Any instance $\phi$ of $k-S A T$ where no variable appears in more than $\frac{2^{k-2}}{k}$ clauses is satisfiable.

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## Proof.

(1) Pick a truth assignment uniformly at random.
(2) Let $E_{i}$ denote the event "clause $i$ is not satisfied".
(3) $\operatorname{Pr}\left(E_{i}\right)=2^{-k}=: p$.
(9) $E_{i}$ depends on at most $d:=k \frac{2^{k-2}}{k}=2^{k-2}$ other events.
(5) We have $4 p d=4 \cdot 2^{-k} \cdot 2^{k-2}=1$.
(6) Now LLL implies that $\operatorname{Pr}\left(\bigcap \overline{E_{i}}\right)>0$.

## The algorithmic LLL

- LLL itself does not give a method for finding the object whose existence it proves.
- Beck showed in 1991 that there exist a deterministic polynomial-time algorithm for a weaker variant of LLL.
- This inspired a long line of reseach about algorithms for various versions of LLL.
- The breakthrough result of Moser and Tardos (2010) shows that there is a simple randomised resampling algorithm for a very general form of LLL.
- But we are interested in the distributed algorithmic LLL.


## Distributed computing: the LOCAL model



A simple connected undirected graph $G=(V, E)$, where each node $v \in V$

- is given its own input,
- runs the same algorithm,
- communicates with its neighbours,
- produces its own output.


## Communication in synchronous rounds

Initially, each node $v$ knows the total number of nodes $n$, the maximum degree of the graph $\Delta$, and a task-specific local input $f(v)$.

In every round, each node $v \in V$

(1) sends messages to its neighbours,
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(1) sends messages to its neighbours,
(2) receives messages from its neighbours,
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After the final round, each node announces its output.

The running time of an algorithm is the number of communications rounds until all nodes have stopped, as a function of $n$.

## Input and output

- The same graph $G=(V, E)$ serves both as the communication network and as the problem instance.
- A graph problem is defined by a function $\Pi$ that maps each graph $G$ and each labelling $f: V \rightarrow X$ to a set $\Pi(G, f)$ of solutions $S: V \rightarrow Y$.
- The output of algorithm $A$ in $(G, f)$ is the function $g: V \rightarrow Y$ such that $g(v)$ is the local output of $v$ for each node $v$.
- Algorithm $A$ solves problem $\Pi$ if for each graph $G$ and labelling $f$ the output $g$ of $A$ in $(G, f)$ is in $\Pi(G, f)$.


## Randomised algorithms

- We assume that each node can toss a countably infinite number of random coins.
- Equivalently, each node $v$ is given a real number $x(v)$ taken uniformly at random from $[0,1]$.
- With probability 1 , the values $x(v)$ are globally unique and can thus be used as identifiers.


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- Monte Carlo algorithms:
- Running time is deterministic.
- Output is a valid solution with high probability (with probability at least $1-1 / n^{c}$ for an arbitrarily large constant $c$ ).


## The distributed Lovász local lemma

- Let $\mathcal{X}=\left\{X_{1}, \ldots, X_{m}\right\}$ be a set of mutually independent random variables and let $\mathcal{E}=\left\{E_{1}, \ldots, E_{n}\right\}$ be a set of events.
- Denote by $\operatorname{vbl}\left(E_{i}\right) \subseteq \mathcal{X}$ the subset of variables that $E_{i}$ depends on.
- Define a dependency graph $G_{\mathcal{E}}=(\mathcal{E}, \mathcal{D})$, where $\mathcal{D}=\left\{\left\{E_{i}, E_{j}\right\}: \operatorname{vbl}\left(E_{i}\right) \cap \operatorname{vbl}\left(E_{j}\right) \neq \emptyset\right\}$.


## Problem

Let the communication network be isomorphic to $G_{\mathcal{E}}=(\mathcal{E}, \mathcal{D})$; each node $v$ corresponds to an event $E_{v} \in \mathcal{E}$ and knows the set $\mathrm{vbl}\left(E_{v}\right)$. The task is to have each node output an assignment $a_{v}$ of the variables $\mathrm{vbl}\left(E_{v}\right)$ such that
(1) for any $\left\{E_{u}, E_{v}\right\} \in \mathcal{D}$ and $X \in \operatorname{vbl}\left(E_{u}\right) \cap \operatorname{vbl}\left(E_{v}\right)$ it holds that $a_{u}(X)=a_{v}(X)$,
(2) the event $E_{v}$ does not occur under assignment $a_{v}$.

## Existing algorithms and lower bounds

- The algorithm of Moser and Tardos (2010) can be adapted to the distributed setting; the running time is $O\left(\log ^{2} n\right)$ rounds.
- Chung et al. (2014) gave a distributed algorithm running in $O(\log n)$ rounds in bounded-degree graphs.
- LLL can be used to properly colour a cycle graph using a constant number of colours. This is known to require $\Omega\left(\log ^{*} n\right)$ rounds.


## Our lower bound

## Theorem

Let $f: \mathbb{N} \rightarrow \mathbb{R}$ be such that $f(4) \leq 16$. Let $A$ be a Monte Carlo distributed algorithm for LLL that finds an assignment avoiding all the bad events under the $L L L$ criteria $p f(d) \leq 1$ with high probability. Then the running time of $A$ is $\Omega(\log \log n)$ rounds.

Note that we can plug in, for example, either of the LLL criteria $e p(d+1) \leq 1$ or $4 p d \leq 1$.

## Outline of the proof

- Two new graph problems: sinkless orientation and sinkless colouring.
- LLL can be used to solve the sinkless orientation in 3-regular graphs.
- A mutual speedup lemma:
- If we can find a sinkless colouring in $t$ rounds, we can find a sinkless orientation in $t$ rounds.
- If we can find a sinkless orientation in $t$ rounds, we can find a sinkless colouring in $t-1$ rounds.
- By iterating the lemma, we obtain an algorithm that finds a sinkless orientation in 0 rounds, which leads to a contradiction.


## Orientations

- An orientation $\sigma$ of a graph $G=(V, E)$ assigns a direction $\sigma(\{u, v\}) \in\{u \rightarrow v, u \leftarrow v\}$ for each edge $\{u, v\} \in E$.
- For all $v \in V$ define in- $\operatorname{deg}(v, \sigma)=|\{u:(u, v) \in \sigma(E)\}|$, out-deg $(v, \sigma)=|\{u:(v, u) \in \sigma(E)\}|$ and $\operatorname{deg}(v)=\operatorname{in}-\operatorname{deg}(v, \sigma)+$ out-deg $(v, \sigma)$.
- A node $v$ with $\operatorname{in}-\operatorname{deg}(v, \sigma)=\operatorname{deg}(v)$ is called a sink. We call an orientation $\sigma$ sinkless if no node is a sink, that is, every node $v$ has out-deg $(v, \sigma)>0$.


## Colourings

- We write $[k]=\{0,1, \ldots, k-1\}$.
- $\psi: E \rightarrow[\chi]$ is a proper edge $\chi$-colouring if any two adjacent edges have a different colour.
- Given a properly edge $\chi$-coloured graph $G=(V, E, \psi)$, we call $\varphi: V \rightarrow[\chi]$ a sinkless colouring of $G$ if for all edges $e=\{u, v\} \in E$ it holds that $\varphi(u)=\psi(e) \Rightarrow \varphi(v) \neq \psi(e)$.


## Graph problem definitions

## Problem (Sinkless colouring)

Given an edge $d$-coloured $d$-regular graph $G=(V, E, \psi)$, find a sinkless colouring $\varphi$. That is, compute a colouring $\varphi$ such that for no edge $e=\{u, v\} \in E$ we have $\varphi(u)=\varphi(v)=\psi(e)$.

## Problem (Sinkless orientation)

Given an edge $d$-coloured $d$-regular graph $G=(V, E, \psi)$, find a sinkless orientation. That is, compute an orientation $\sigma$ such that out-deg $(v, \sigma)>0$ for all $v \in V$.

## Graph problem definitions: example

(a)

(b)

(c)


Figure: (a) A 3-regular edge 3-coloured graph. (b) A sinkless orientation. (c) A sinkless colouring.

## From LLL to Sinkless Orientation

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- We start with 4-regular graphs $G=(V, E)$.
- Set $\operatorname{vbl}\left(E_{v}\right)=\left\{X_{e}: v \in e\right\}$ for each $v \in V$
- For each $e=\{u, v\} \in E$, the variable $X_{e}$ ranges over $\{u \rightarrow v, u \leftarrow v\}$
- The bad event $E_{v}$ occurs exactly when for all neighbours $u$ of $v$ the variable $X_{\{v, u\}}$ takes the value $u \rightarrow v$


## From LLL to Sinkless Orientation

- If the variables $X_{e}$ are sampled uniformly at random, we have $\operatorname{Pr}\left(E_{v}\right)=1 / 2^{4}=1 / 16$ for each $v \in V$.
- Let $p=1 / 16$ and $d=4$. Now $\operatorname{Pr}\left(E_{v}\right) \leq p$ and $E_{v}$ depends on $d$ other events for each $v \in V$, and the condition $p f(d) \leq 1$ holds, given $f(4) \leq 16$.
- Run the algorithm $A$ and define an orientation $\sigma$ of $G$ by setting $\sigma(e)=a_{v}\left(X_{e}\right)$, where $v \in e$, for each $e \in E$.
- Now $\sigma$ is a sinkless orientation of $G$.


## From 3-regular to 4-regular graphs

- LLL is not directly applicable: the probability of bad events would be $p=1 / 2^{3}=1 / 8$ and thus ep $(d+1)>1$.
- Contract edges of one colour class to obtain a 4-regular graph.
- Simulate the algorithm for the 4-regular case in the 3-regular graph.


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## The Mutual Speedup Lemma

## Lemma

Suppose $B$ is a sinkless colouring algorithm that runs in $t$ rounds such that for any edge $e=\{u, v\}$ the probability of outputting a forbidden configuration $B(u)=\psi(e)=B(v)$ is at most $p$. Then there exists a sinkless orientation algorithm $B^{\prime}$ that runs in $t$ rounds such that for any node $u$ the probability of being a sink is at most $6 p^{1 / 3}$.

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## Lemma

Suppose $B^{\prime}$ is a sinkless orientation algorithm that runs in time $t$ such that the probability that any node $u$ is a sink is at most $\ell$. Then there exists a sinkless colouring algorithm $B^{\prime \prime}$ that runs in time $t-1$ such that the probability for any edge $e=\{u, v\}$ having a forbidden configuration $B^{\prime \prime}(u)=\psi(e)=B^{\prime \prime}(v)$ is less than $4 \ell^{1 / 4}$.

## From colouring to orientation: the proof idea

- Given a randomised sinkless colouring algorithm $B$ running in $t$ rounds, construct a randomised sinkless orientation algorithm $B^{\prime}$ that also runs in $t$ rounds.
- We write $B(u)$ for the colour that $u$ outputs according to $B$ and $B^{\prime}(e)$ for the orientation $B^{\prime}$ outputs for edge $e$.
- We denote the radius- $t$ neighbourhood of a node $u$ by $N^{t}(u)=\{v \in V: \operatorname{dist}(u, v) \leq t\}$, where $\operatorname{dist}(u, v)$ is the length of the shortest path between $u$ and $v$.
- The radius- $t$ neighbourhood of an edge $\{u, v\}$ is $N^{t}(\{u, v\})=N^{t}(u) \cap N^{t}(v)$.


## From colouring to orientation: the proof idea

Consider any node $u \in V$. Algorithm $B^{\prime}$ consists of three steps:
(1) Node $u$ gathers its radius- $t$ neighbourhood $N^{t}(u)$ in $t$ rounds.
(2) Node $u$ computes the set $C(u)$ of candidate colours:

$$
C(u)=\left\{\psi(e): \operatorname{Pr}\left[B(u)=\psi(e) \mid N^{t}(e)\right] \geq p^{1 / 3} \text { and } e=\{u, v\}\right\},
$$

In addition, for each $e=\{u, v\}$ node $u$ calculates the probability of $v$ outputting the colour $\psi(e)$ when executing $B$. Thus $u$ can determine whether $\psi(e) \in C(v)$.

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- If $\psi(e) \in C(u) \cap C(v)$ or $\psi(e) \notin C(u) \cup C(v)$, choose the orientation $B^{\prime}(e)$ of edge $e$ arbitrarily. Otherwise, edge $e$ is oriented according to the following rule:

$$
B^{\prime}(e)= \begin{cases}u \rightarrow v & \text { if } \psi(e) \in C(u) \text { and } \psi(e) \notin C(v), \\ u \leftarrow v & \text { if } \psi(e) \notin C(u) \text { and } \psi(e) \in C(v) .\end{cases}
$$

## Conclusion

- There is a randomised distributed algorithm for LLL that runs in $O(\log n)$ rounds in bounded-degree graphs.
- The best previously known lower bound was $\Omega\left(\log ^{*} n\right)$ rounds.
- We show that any randomised Monte Carlo algorithm for LLL that finds a satisfying assignment with high probability requires $\Omega(\log \log n)$ rounds.

