

# Probabilistic Proofs, Kolmogorov Complexity and Laszlo Lovasz Local Lemma

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- ▶ If a random variable has an expectation greater than  $c$ , it is sometimes greater than  $c$

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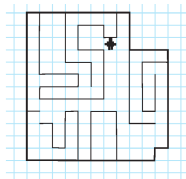
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- ▶ Similar argument: every 3-CNF has an assignment that satisfies at least  $7/8$  of all clauses

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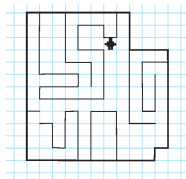
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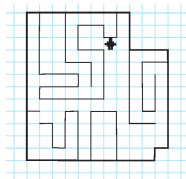


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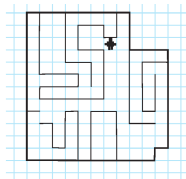
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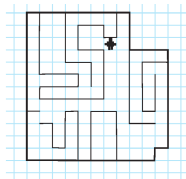
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- ▶ Theorem: for every board size there exists a sequence that guarantees that the robot visits all cells (independent of the maze and initial position).

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- ▶ for this  $k$  a random program of length  $kN$  with positive probability works for all mazes and initial positions

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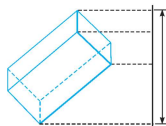
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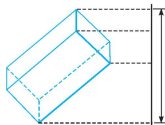
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- ▶ (Expected value of the projection to a random line is proportional to the sum of dimensions)



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- ▶ Probability argument: take a random  $n \times n$  matrix. For a given position of a minor the probability to see an uniform minor there is  $2^{-k^2} \times 2$ . There are at most  $n^{2k}$  positions for a  $k \times k$  minor. So if  $n^{2k} 2^{-k^2+1} < 1$ , a matrix without uniform minors exists. Taking logarithms, we get  $2k \log n - k^2 + 1 < 0$  which is guaranteed if  $k > 2 \log n + 1$ .

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- ▶ Complexity version: let us prove that a incompressible matrix has no uniform minors. In other words, a matrix that has uniform minor is compressible. Indeed, it can be described by specifying the position of that minor ( $2k$  indices in  $1 \dots n$  range, i.e.,  $2k \log n$  bits), the bit in the minor (1 bit) and the remaining  $n^2 - k^2$  bits in the matrix, so if  $2k \log n + 1 + n^2 - k^2 < n^2$ , the matrix is compressible

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- ▶ This is not a rigorous proof since complexity is defined up to a constant.

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- ▶ Sometimes an open problem (e.g., the existence of Boolean functions that require circuits of exponential size)
- ▶ Sometime explicit constructions exist but are rather complicated and do not achieve the best possible parameters (expanders, codes)



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- ▶ Laslo Lovasz Local Lemma deals with partial independence
- ▶ Each node in a rectangular grid may have one of 10 colors; each edge prohibits one of 100 color combinations (different for different edges). LLLL guarantees that there exists a coloring that satisfies all restrictions.

## Laszlo Lovasz Local Lemma

Let  $A_1, \dots, A_n$  are events indexed by vertices of an (undirected) graph. Let  $N(i)$  be the set of all neighbors of  $i$  (not including  $i$ ). Assume that for every  $i$  the event  $A_i$  is independent with the tuple of all events  $A_j$  with  $j \notin N(i)$ . Assume that for every  $i$  an upper bound  $\varepsilon_i < 1$  for  $\Pr[A_i]$  is chosen and, moreover,

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- ▶ If all  $A_i$  are independent,  $\varepsilon_i = \Pr[A_i]$
- ▶ If there is no information about dependence (complete graph), and  $\sum \Pr[A_i] < 1/4$ , one can let  $\varepsilon_i = 2 \Pr[A_i]$ : the product of  $(1 - \varepsilon_i)$  is at least  $1 - \sum \varepsilon_i > 1/2$ .



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- ▶ In our example events correspond to edges; neighbors are edges that share a vertex (6 of them). Choosing the same  $\varepsilon$  for every edge, we need

$$1/100 < \varepsilon(1 - \varepsilon)^6$$

If  $\varepsilon = 1/6$ , the rhs is about  $1/6e \gg 1/100$ .

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- ▶ separating neighbors and non-neighbors ( $j, k$  are neighbors,  $l, \dots$  are not):

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- ▶ using induction (less events in the condition)

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- ▶ Let  $\alpha < 1$ . Assume that for every  $n$  there is at most  $2^{\alpha n}$  forbidden (bit) strings. Then there exists a number  $c$  and a bit sequence  $\omega$  that has no forbidden substrings of length  $> c$ .
- ▶ (Kolmogorov complexity version) There exists a sequence  $\omega$  such that any substring  $x$  of  $\omega$  has complexity at least  $\alpha|x| - O(1)$ .

Statements are equivalent: there is at most  $2^{\alpha n}$  sequences of length  $n$  and complexity  $< \alpha n$ ; on the other hand, if  $X$  is a set of forbidden strings and there is at most  $2^{\alpha n}$  forbidden strings of length  $n$ , they are all simple (have complexity  $\alpha n + o(n)$ ) relative to  $X$ . (Non-relativized version can be also used.)

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- ▶ such a block exists since we can take a block that is random relative to the prefix of the sequence; each group of  $s$  consecutive blocks increases complexity at least by  $\beta s M$  and therefore has complexity at least  $\beta s M$ . For non-aligned blocks we discard some part of them (using the difference between  $\alpha$  and  $\beta$  to compensate for the losses).

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- ▶ so there is a sequence such that every substring has high complexity
- ▶ and a two-dimensional sequence such that every rectangle has a high complexity (close to its area)

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- ▶ The proof of the most general result (Moser and Tardos) is a bit mysterious
- ▶ but a very simple argument exists for special cases (as explained by Fortnow using complexity)

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- ▶ ...and it can be found with high probability by a polynomial probabilistic algorithm

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(induction: if recursive calls are correct, the calling procedure is correct)
- ▶ The only problem is why  $Fix(S)$  terminates in reasonable time with high probability.

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- ▶ Main observation: random bits can be reconstructed from the current values and the (chronological) list of resampled clauses
- ▶ Indeed, each clause is violated only for one combination of bits, so resampling can be “undone” and random bits can be extracted
- ▶ So if we can describe the sequence of resampled clauses using less than  $m$  bits per clause, we get a contradiction ( $N$  is fixed and for the large number of steps we get a contradiction with incompressibility)

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- ▶ so we need an additional bit (up/down) for recursive call (down step) and one bit to describe exits (up steps)
- ▶ so instead of  $\log t$  per resampling we get  $(\log t + 1) + 1$  – still less than  $m$  by assumption ( $\log t < m - 3$ )