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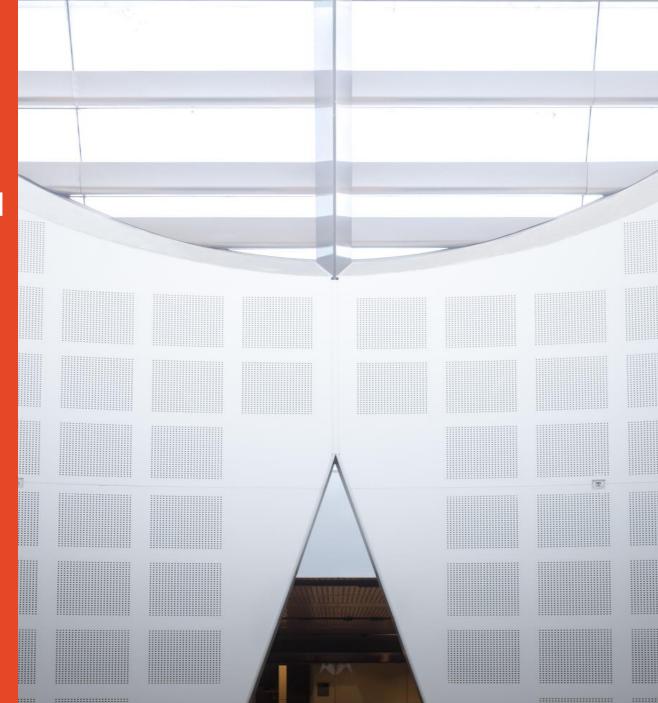
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COMPx270: Randomised and Advanced Algorithms
Lecture 4: Derandomisation

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A question

You have a randomised algorithm A which runs in time T(n) and solves task X (say, decision problem) with probability .99. Is there a deterministic algorithm B which solves X and runs in time...

- O(T(n))
- poly(T(n))
- exp(T(n))
- No/we don't know

A question

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- poly(T(n)) ?
- exp(T(n)) √
- No/we don't know

An answer?

That's **complicated**. This is what derandomization asks, and there is a lot of work on this: one of the major unsolved question in theoretical computer science.

P v. BPP

Let's not stop here though

We know how to derandomize **some** algorithms, and there are **some** general techniques.

Method 1: PRNG 🕡

The goal is to reduce the amount of randomness required, by generating a lot of "good enough" pseudorandom bits: good enough to fool the algorithm.

Method 1: PRNG 🕡

Why is that useful?

- Random bits don't grow on trees!
- Derandomisation (method 2)

Why is this bad?

Conditional (under assumptions)

If the algorithm uses a small number of random seeds, check 'em all.

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```
Require: Input x

1: for all r \in \{0,1\}^R do

2: y \leftarrow A(x;r) \triangleright Run A on x with randomness r

3: if V(x,y) = 1 then \triangleright Verify if y is a good solution

4: return y \triangleright If so, we are done
```

Details.

What if verifying is hard?

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- Majority vote!
- Median trick!

What if the algorithm does not use a small number of random bits?

What if the algorithm does not use a small number of random bits?

Or (sometimes) we can reduce the randomness by carefully looking at the proof.

Derandomizing Max-Cut

MAX-Cut: Given an (undirected) graph G = (V, E) on n vertices and m edges, output a cut (A, B) (partition of V) max-imising the number c(A, B) of edges between A and B.

(It's NP-Hard)

Derandomizing Max-Cut

MAX-Cut: Given an (undirected) graph G = (V, E) on n vertices and m edges, output a cut (A, B) (partition of V) max-imising the number c(A, B) of edges between A and B.

But we can get a ½-approximation!

```
1: (A, B) \leftarrow (\emptyset, \emptyset)

2: for all v \in V do

3: X_v \leftarrow \text{Bern}(1/2) \triangleright Independent of previous choices

4: if X_v = 1 then add v to A

5: else add v to B

6: return (A, B)
```

Theorem.

$$\mathbb{E}[c(A,B)] \ge \frac{1}{2}m \ge \frac{1}{2}\operatorname{OPT}(G).$$

Proof.

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Definition 22.1. A family of functions $\mathcal{H} \subseteq \{h \colon \mathcal{X} \to \mathcal{Y}\}$ is a family of pairwise independent hash functions, or a strongly universal hash family, if, for every $x, x' \in \mathcal{X}$ with $x \neq x'$ and every $y, y' \in \mathcal{Y}$,

$$\Pr_{h \sim \mathcal{H}} \left[h(x) = y, h(x') = y' \right] = \frac{1}{|\mathcal{Y}|^2}$$

where the probability is over the uniformly random choice of $h \in \mathcal{H}$.

Fact. Small families of pairwise independent hash functions exist.

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Proof of derandomization claim.

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(Important) Fact. If $\mathbb{E}[X]$ exists, then $\Pr[X \ge \mathbb{E}[X]] > 0$.

Proof.

Theorem. There exists a deterministic $\frac{1}{2}$ -approximation algorithm for Max-CUT which runs in time O(n(m+n)).

Method 3: The Method of Conditional Expectations

Idea: sequentially do the greedy choice. Sometimes it works!

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Details.

Method 3: The Method of Conditional Expectations

Theorem. There exists a deterministic $\frac{1}{2}$ -approximation algorithm for Max-CUT which runs in time O(mn).

Derandomisation: summary

- PRNG
- Brute-Force
- Pairwise (k-wise) independence
- Method of Conditional Expectations

(there is more!)

Bonus: The Probabilistic Method

"We can prove things exist without knowing how to build them."

(also can be derandomised, sometimes)