#### Algorithms and Data Structures

NP-Completeness (non-examinable)

## Running time hierarchy

 $O(\log n)$ O(n) $O(n^2)$  $O(n \log n)$  $O(n^{\alpha})$  $O(c^n)$ logarithmic polynomial linear quadratic exponential The algorithm The algorithm The algorithm The algorithm The algorithm The algorithm splits the inputs considers pairs performs many considers many accesses the does not even into two pieces of elements. nested loops. subsets of the read the input only of similar size, input elements. whole input. a constant solves each part number of and merges the times. solutions. O(1) $\omega(n)$ superlinear constant  $\omega(1)$  $\omega(n^{\alpha})$ superpolynomial superconstant  $o(c^n)$ o(n)subexponential sublinear

## Running time hierarchy

#### Polynomial time

o(n) subexponential  $o(c^n)$ 

sublinear

r oryman anno						
$O(\log n)$	O(n)	$O(n \log n)$	$O(n^2)$	$O(n^{\alpha})$	$O(c^n)$	
logarithmic	linear		quadratic	polynomial	exponential	
The algorithm does not even read the whole input.	The algorithm accesses the input only a constant number of times.	The algorithm splits the inputs into two pieces of similar size, solves each part and merges the solutions.	The algorithm considers pairs of elements.	The algorithm performs many nested loops.	The algorithm considers many subsets of the input elements.	
constant	O(1)	superlinear	$\omega(n)$			
superconstant	$\omega(1)$	superpolynomial	$\omega(n^{\alpha})$			

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What was the exception?

Is it possible to design a polynomial-time algorithm for *every* problem?

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Are there problems for which polynomial-time algorithms do not exist?

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Some problems were believed to not be solvable efficiently for many years, but then they were proven to be tractable.

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If there was an efficient algorithm for Problem A, we could use it to solve many other problems for which we don't have efficient algorithms.

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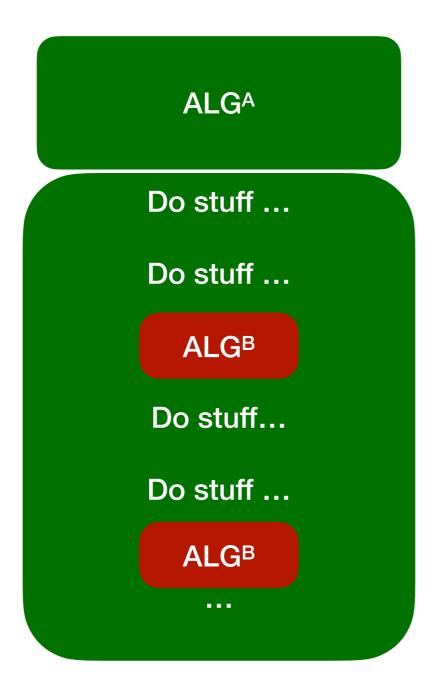
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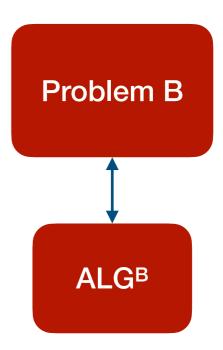
We can construct an algorithm ALG<sup>A</sup> for solving problem A, which uses calls to the algorithm ALG<sup>B</sup> as a subroutine.

If ALG<sup>A</sup> is a polynomial time algorithm, then this is a polynomial time reduction.

## Pictorially

Problem A





#### Notation

When problem A reduces to problem B in polynomial time, we write

 $A \leq p B$ 

We often say "there is a polynomial time reduction *from* A *to* B".

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Idea: If we want to provide strong evidence that a problem B cannot be solved by an efficient algorithm, we need to reduce another problem A to it, for which there is strong evidence that it cannot be solved by an efficient algorithm.

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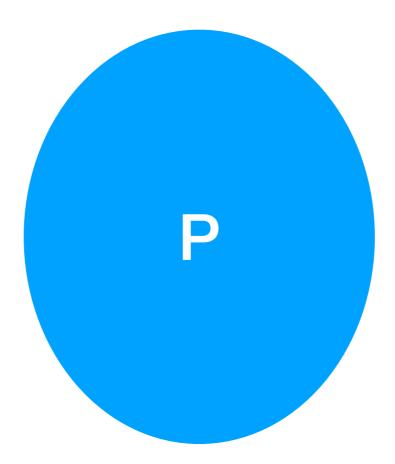
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We also say that they can be solved *efficiently*.

### The landscape of complexity



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Efficiently verifiable.

A CNF formula with m clauses and k literals.

$$\Phi = (X_1 \vee X_5 \vee X_3) \wedge (X_2 \vee X_6 \vee X_5) \wedge ... \wedge (X_3 \vee X_8 \vee X_{12})$$

("An AND of ORs").

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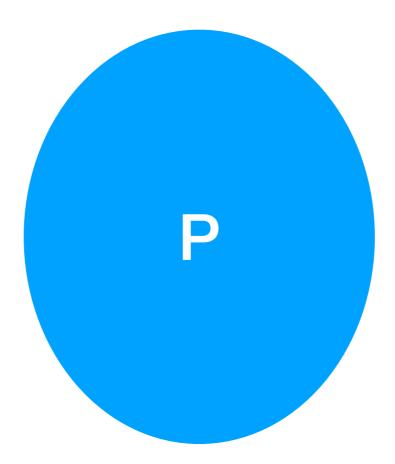
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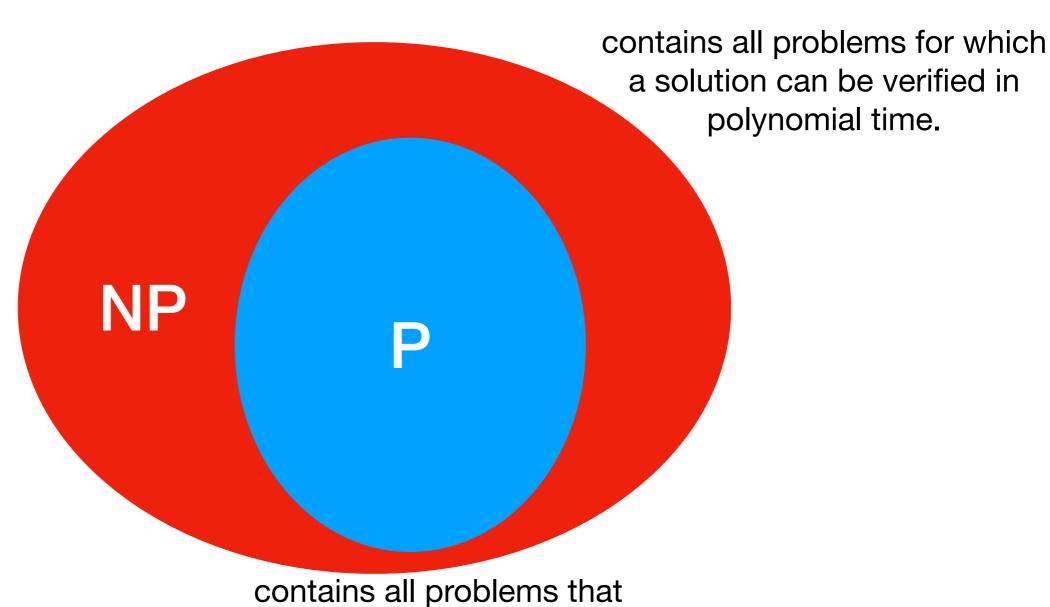
3 SAT is in NP (why?)

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#### How to work with reductions

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A problem B is NP-hard if for every problem A in NP, it holds that  $A \leq^p B$ .

If every problem in NP is "polynomial time reducible to B".

This captures the fact that B is at least as hard as the hardest problems in NP.

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This is not very useful!

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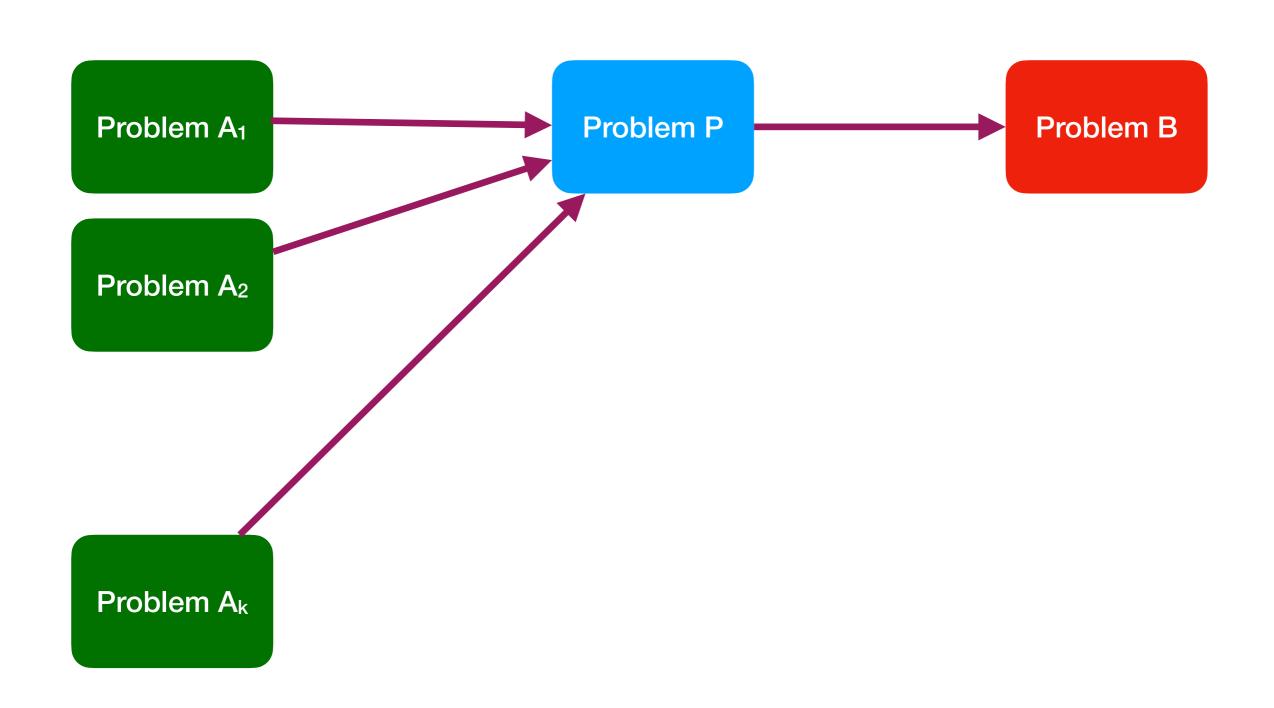
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A reduction from any other problem A to B goes "via" P.

## NP-hardness via P



#### NP-hardness

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This all works if we have an NP-hard problem to start with.

### 3 SAT

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#### Remark:

The first problem shown to be NP-complete was the SAT problem (more general than 3 SAT, the Cook-Levin Theorem), and this reduces to 3SAT.

Sorting
Minimum Spanning Tree

Longest Common Subsequence
Chain Matrix Multiplication
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**SAT** 

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**Vertex Cover** 

Subset Sum Knapsack **SAT** 

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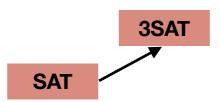
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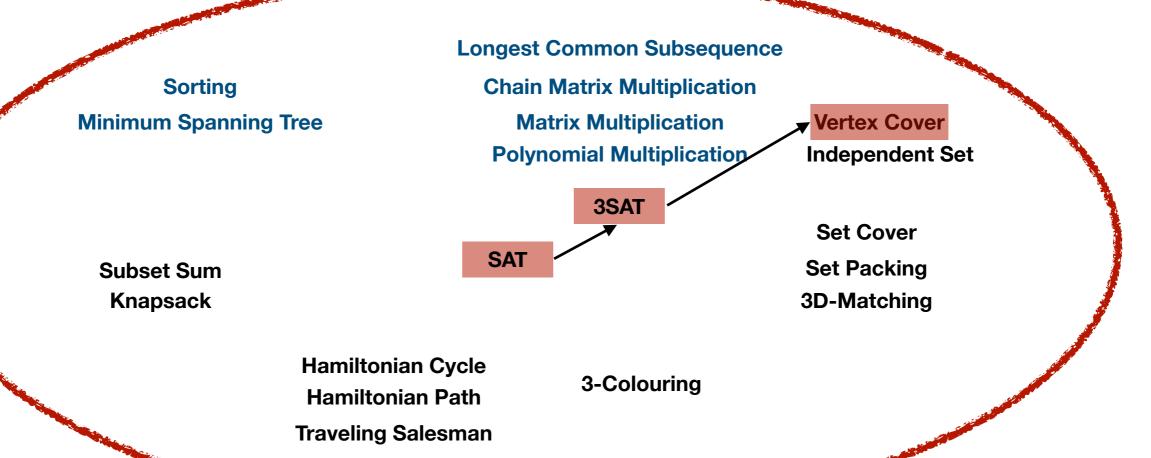
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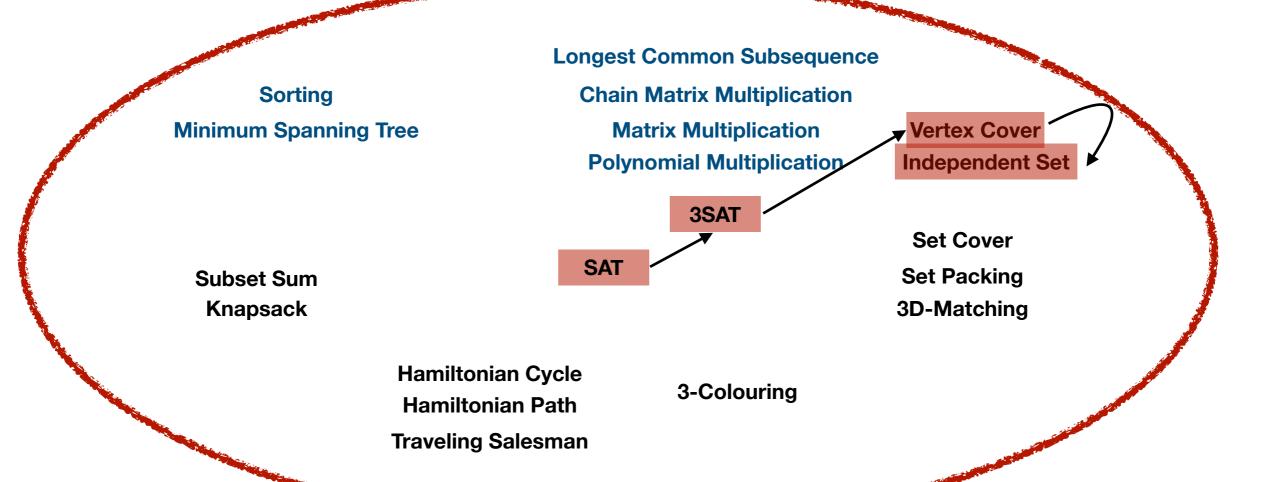
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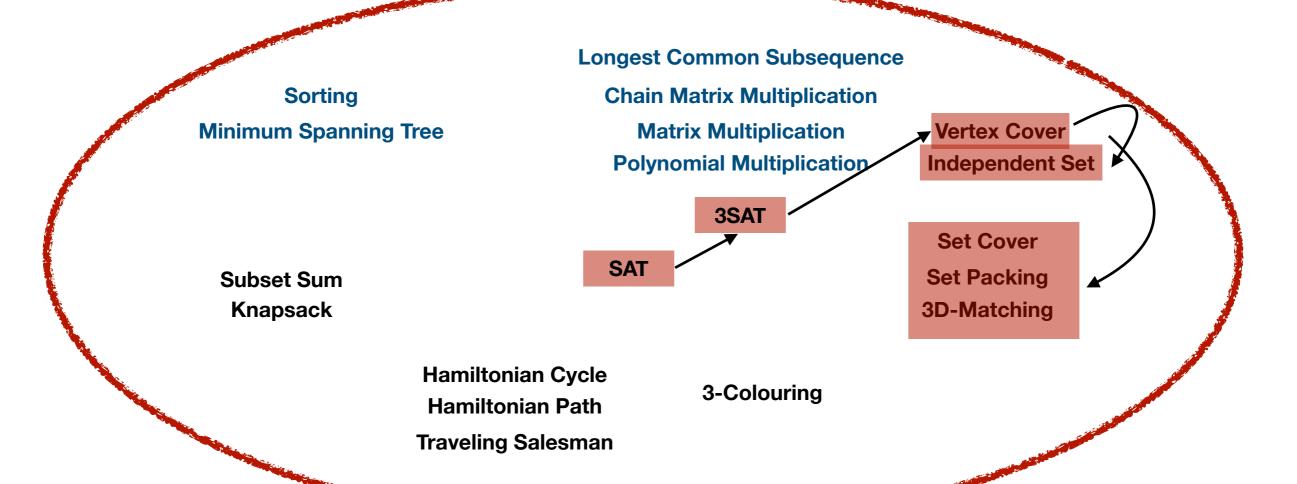
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Then prove that A is NP-hard.

Construct a polynomial time reduction from some NP-hard problem P.

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This takes time!

# NP-completeness, a taxonomy

Packing problems

Independent Set Set Packing

Covering problems

Vertex Cover Set Cover Partitioning problems

3D-Matching Graph Colouring

Hamiltonian Cycle Hamiltonian Path Traveling Salesman

Sequencing problems

Subset Sum Knapsack

Numerical problems

3 SAT

Constraint Satisfaction problems

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I don't know about you, but I would probably be convinced that I am not going to come up with a polynomial-time algorithm!

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