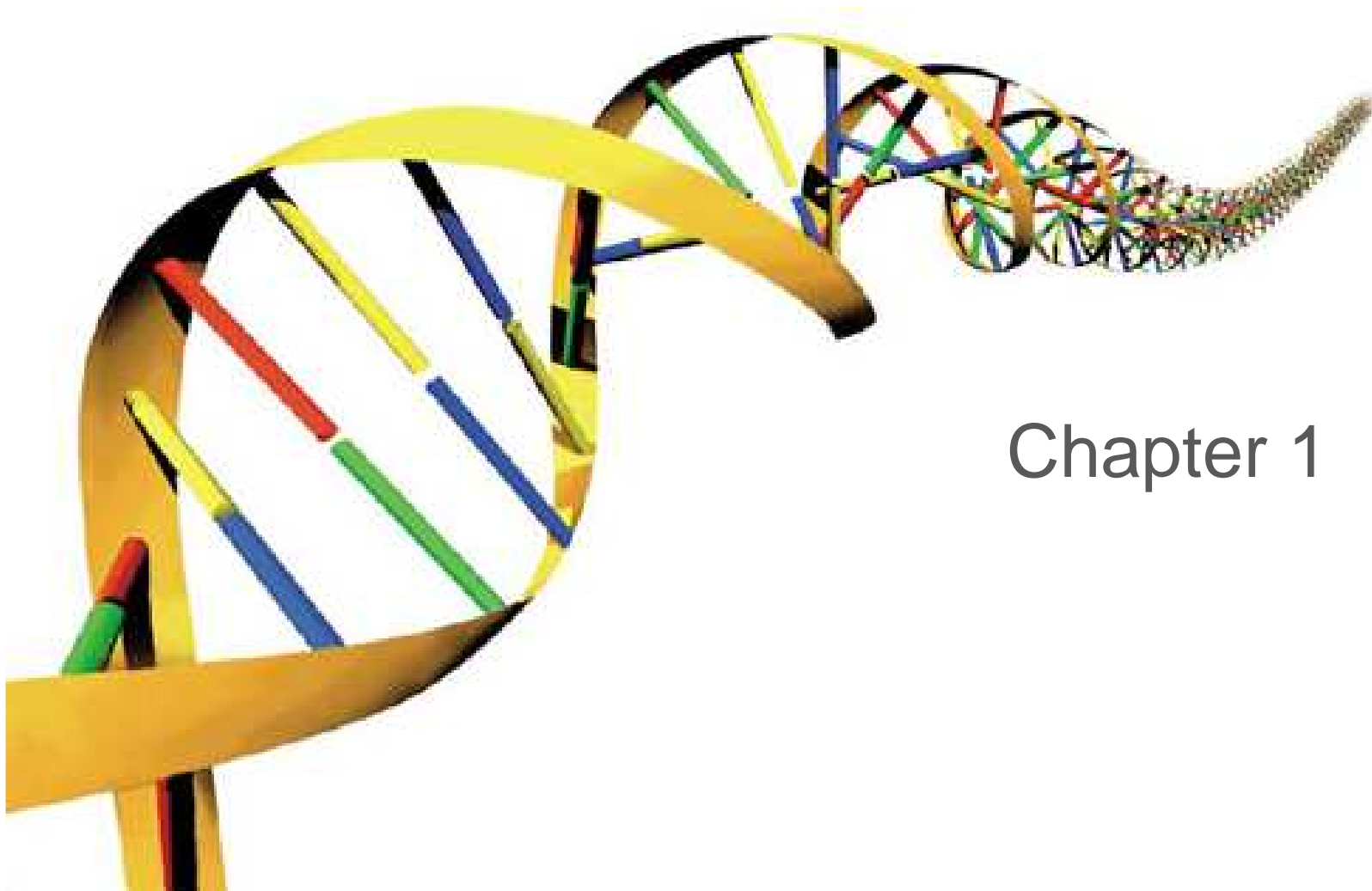


Evolutionary Computing



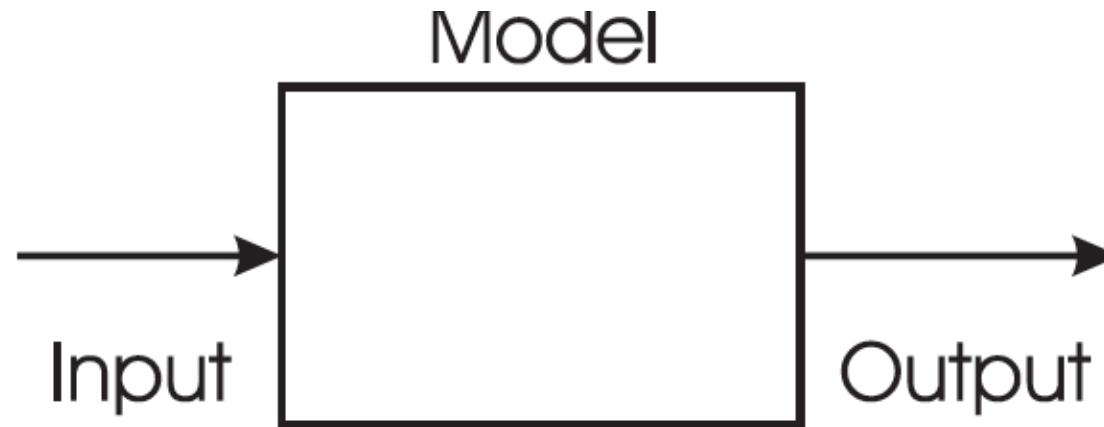
Chapter 1

Chapter 1: Problems to be solved

Problems can be classified in different ways:

- Black box model
- Search problems
- Optimisation vs constraint satisfaction
- NP problems

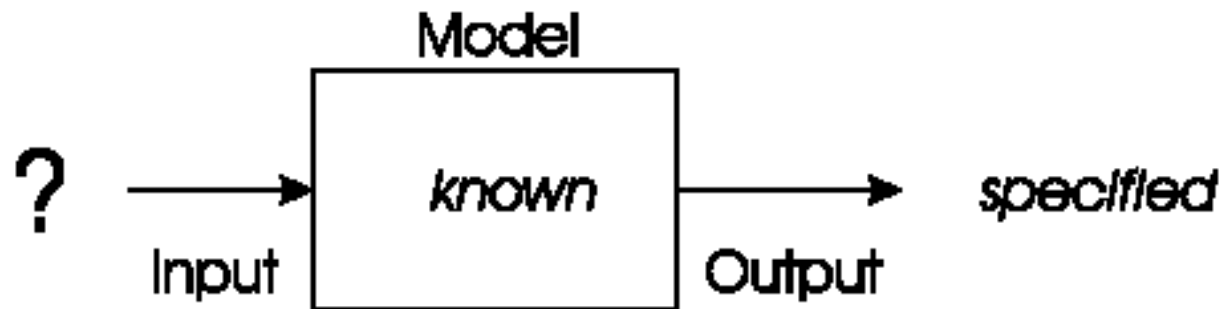
“Black box” model



- “Black box” model consists of 3 components
- When one component is unknown: new problem type

“Black box” model: Optimisation

- Model and desired output is known, task is to find inputs

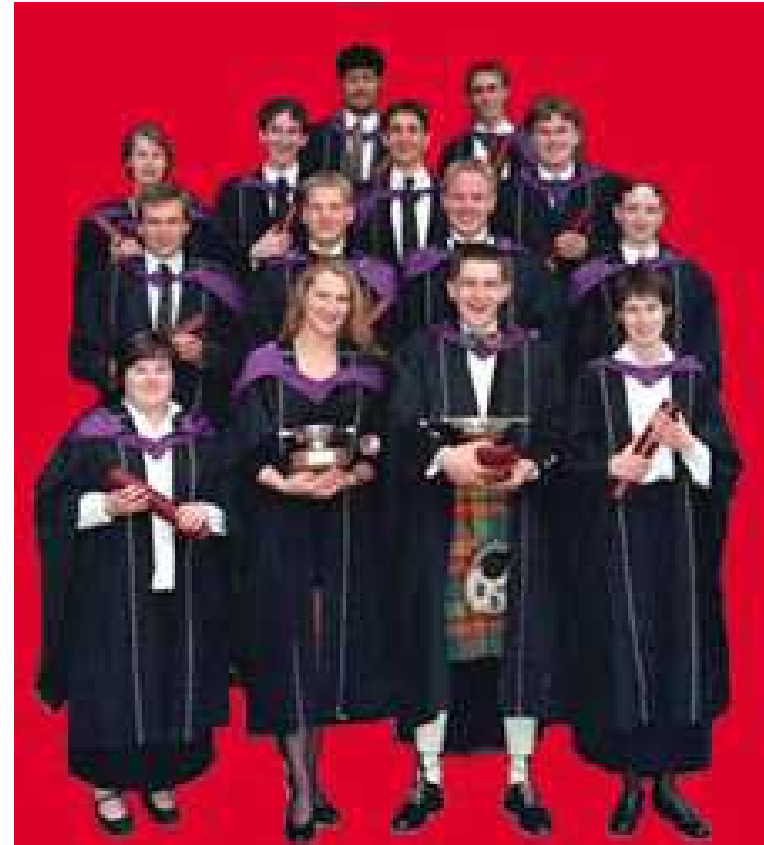


- Examples:
 - Time tables for university, call center, or hospital
 - Design specifications
 - Traveling salesman problem (TSP)
 - Eight-queens problem, etc.

“Black box” model:

Optimisation example 1: university timetabling

- Enormously big search space
- Timetables must be *good*
- “Good” is defined by a number of competing criteria
- Timetables must be feasible
- Vast majority of search space is infeasible





Evaluations: 717 Last change at: 431 Evaluations per minute: 14952 Displaying: Best

Run No: 0

Placing Events is a Special Priority

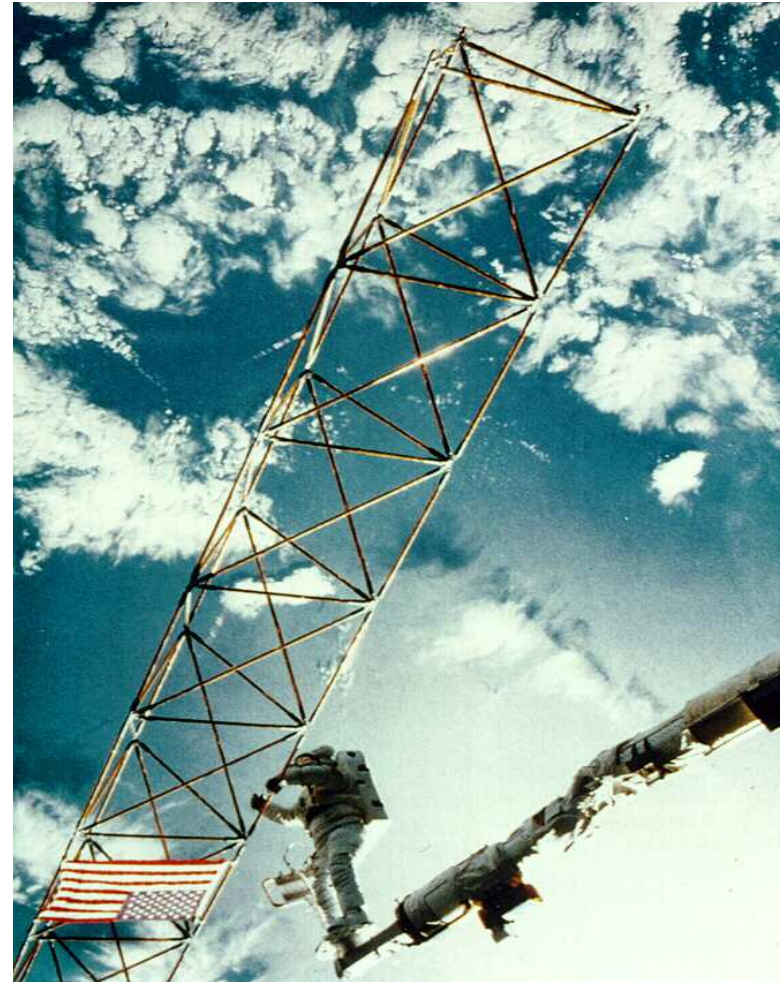
Targets		Weights	
22		Unplaced Events: 1	100
0		Changes: 0	0
1		Five O'Clock Classes: 13	100
6		Wed Afternoon Classes: 13	24
60		Gaps in Student Day: 7046	82
0		Lone Classes: 17708	100
30		Long Intensive: 0	100
0		Overloaded Lecturers: 26	27
0		No Teaching Free Day: 52	46
0		Instant Site Changes: 0	30
0		Site Changes: 0	43
210		Location Changes: 49738	8
100		Room Changes: 11869	13

Progress: 55%

“Black box” model:

Optimisation example 2: satellite structure

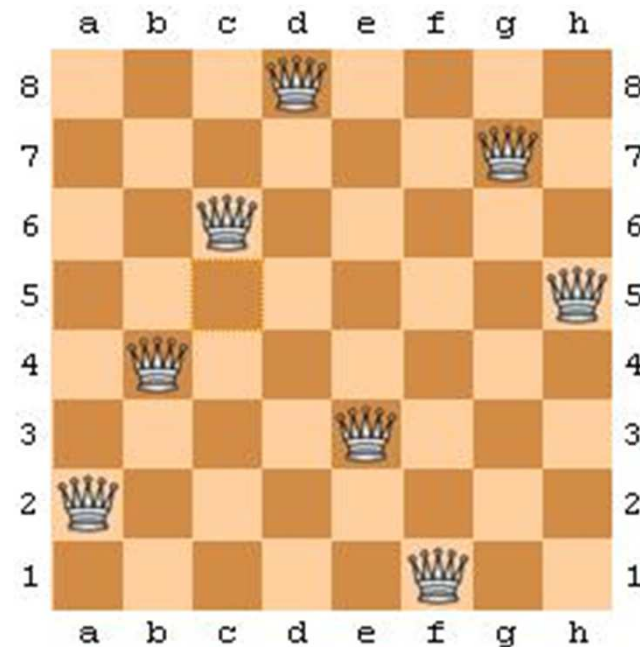
- Optimised satellite designs for NASA to maximize vibration isolation
- Evolving: design structures
- Fitness: vibration resistance
- Evolutionary “creativity”



“Black box” model:

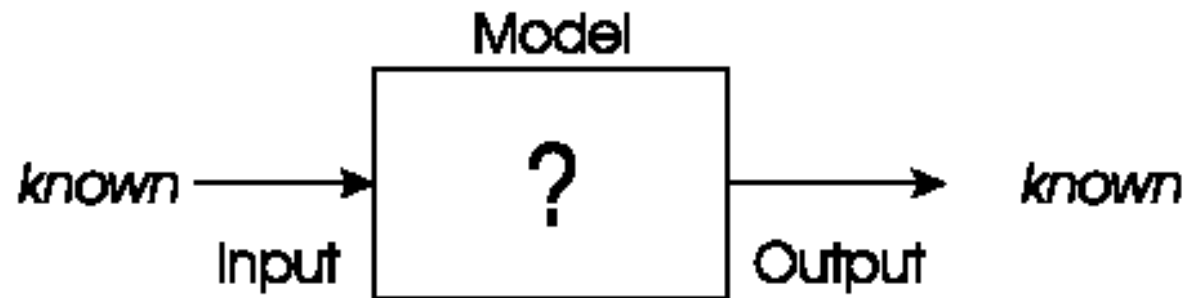
Optimisation example 3: 8 queens problem

- Given an 8-by-8 chessboard and 8 queens
- Place the 8 queens on the chessboard without any conflict
- Two queens conflict if they share same row, column or diagonal
- Can be extended to an n queens problem ($n > 8$)



“Black box” model: Modelling

- We have corresponding sets of inputs & outputs and seek model that delivers correct output for every known input



- Note: modelling problems can be transformed into optimisation problems
 - Evolutionary machine learning
 - Predicting stock exchange
 - Voice control system for smart homes

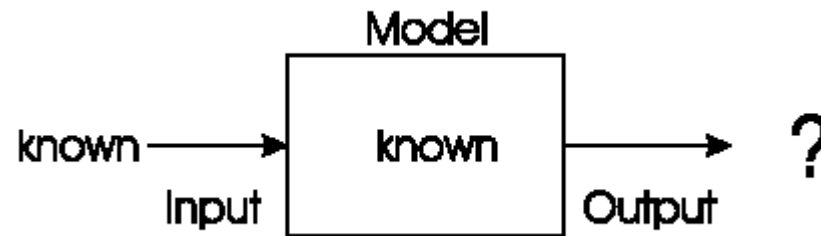
“Black box” model: Modelling example: loan applicant creditability

- British bank evolved creditability model to predict loan paying behavior of new applicants
- Evolving: prediction models
- Fitness: model accuracy on historical data



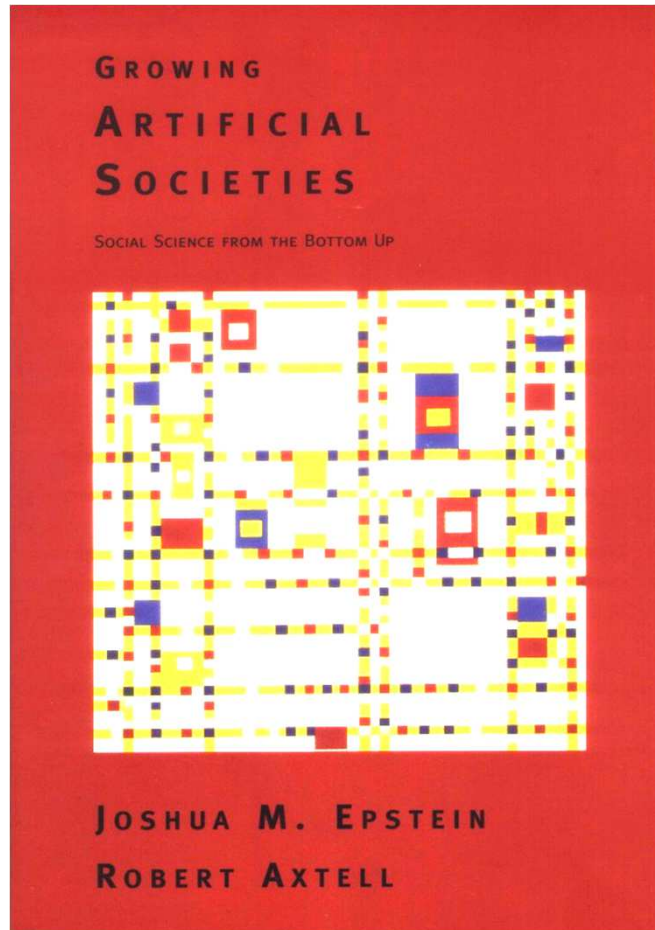
“Black box” model: Simulation

- We have a given model and wish to know the outputs that arise under different input conditions



- Often used to answer “what-if” questions in evolving dynamic environments
 - Evolutionary economics, Artificial Life
 - Weather forecast system
 - Impact analysis new tax systems

“Black box” model: Simulation example: evolving artificial societies



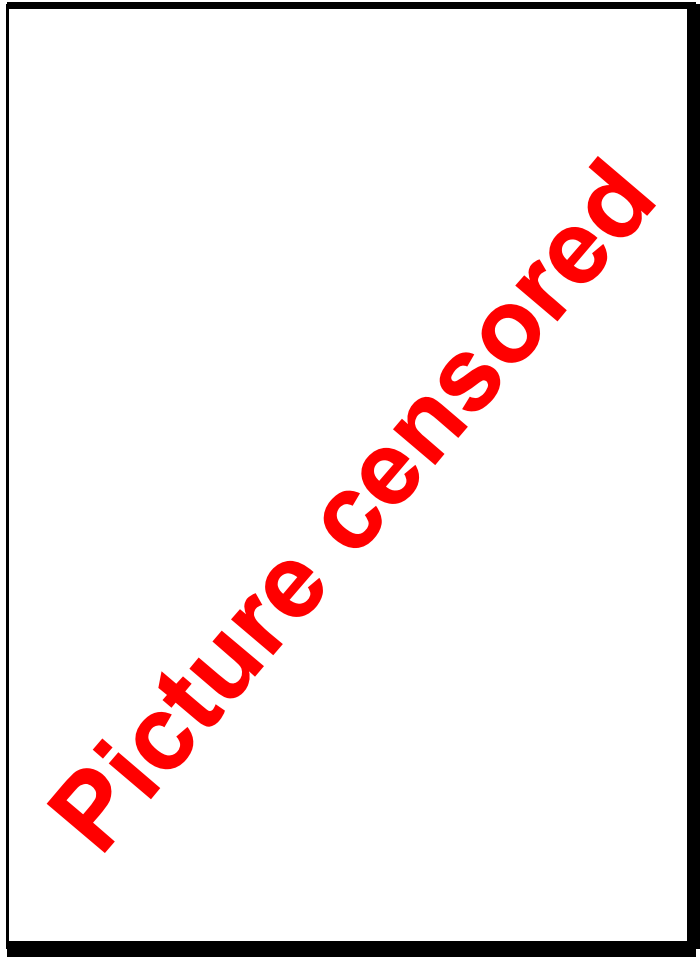
Simulating trade, economic competition, etc. to calibrate models

Use models to optimise strategies and policies

Evolutionary economy

Survival of the fittest is universal (big/small fish)

“Black box” model: Simulation example 2: biological interpretations



Incest prevention keeps
evolution from rapid
degeneration
(we knew this)

Multi-parent reproduction,
makes evolution more
efficient
(this does not exist on Earth
in carbon)

2nd sample of Life

Search problems

- Simulation is different from optimisation/modelling
- Optimisation/modelling problems search through huge space of possibilities
- Search space: collection of all objects of interest including the desired solution
- **Question:** how large is the search space for different tours through n cities?

Benefit of classifying these problems: distinction between

- search problems, which define search spaces, and
- problem-solvers, which tell how to move through search spaces.

Optimisation vs. constraint satisfaction (1/2)

- Objective function: a way of assigning a value to a possible solution that reflects its quality on scale
 - Number of un-checked queens (maximize)
 - Length of a tour visiting given set of cities (minimize)
- Constraint: binary evaluation telling whether a given requirement holds or not
 - Find a configuration of eight queens on a chessboard such that no two queens check each other
 - Find a tour with minimal length where city X is visited after city Y

Optimisation vs. constraint satisfaction (2/2)

- When combining the two:

	Objective function	
Constraints	Yes	No
Yes	Constrained optimisation problem	Constraint satisfaction problem
No	Free optimisation problem	No problem

- Where do the examples fit?
- Note: constraint problems can be transformed into optimisation problems
- Question: how can we formulate the 8-queens problem in to a FOP/CSP/COP?

NP problems

- We only looked at classifying the problem, not discussed problem solvers
- This classification scheme needs the properties of the problem solver
- Benefit of this scheme: possible to tell how difficult the problem is
- Explain the basics of this classifier for combinatorial optimisation problems (booleans or integers search space)

NP problems:

Key notions

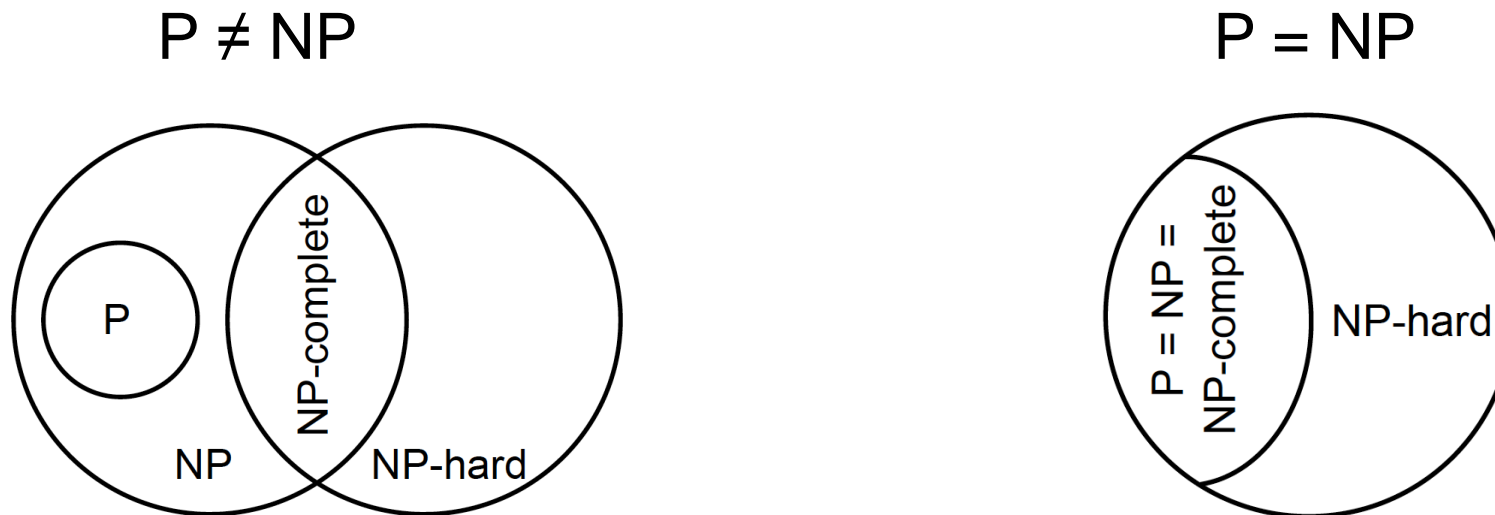
- **Problem size**: dimensionality of the problem at hand and number of different values for the problem variables
- **Running-time**: number of operations the algorithm takes to terminate
 - Worst-case as a function of problem size
 - Polynomial, super-polynomial, exponential
- **Problem reduction**: transforming current problem into another via mapping

NP problems: Class

- The difficultness of a problem can now be classified:
 - **Class P**: algorithm can solve the problem in polynomial time (worst-case running-time for problem size n is less than $F(n)$ for some polynomial formula F)
 - **Class NP**: problem can be solved and any solution can be verified within polynomial time by some other algorithm (P subset of NP)
 - **Class NP-complete**: problem belongs to class NP and any other problem in NP can be reduced to this problem by an algorithm running in polynomial time
 - **Class NP-hard**: problem is at least as hard as any other problem in NP -complete but solution cannot necessarily be verified within polynomial time

NP problems: Difference between classes

- P is different from NP-hard
- Not known whether P is different from NP



- For now: use of approximation algorithms and metaheuristics