

EUNICE RESEARCH SUMMER SCHOOL 2025

**APPLICATIONS OF AI** 

## Introduction to Evolutionary Computation

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## Verifying questions – do you know....

#### Motivation

- Applications
- Popular optimization problems
- Landscapes
- Algorithms
- On-site experiment

• Can optimization be used for maximization, or only for minimization?

- Applications
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- Can optimization be used for maximization, or only for minimization?
- Are optimization algorithms used in machine learning?

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- Can optimization be used for maximization, or only for minimization?
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- What is the difference between **numerical** and **combinatorial** optimization problems?

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- What is a fitness landscape?

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- What is NP-hard?

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- What is NP-hard?
- What is local search?

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- What is a fitness landscape?
- What is **NP-hard**?
- What is local search?
- What are the main steps in an evolutionary algorithm?
- What is the role of **mutation** and **crossover** in evolutionary algorithms?

# Optimization?

- Applications
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- Landscapes
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- On-site experiment:

- $\bullet\,$  How to find good (best) solutions (to improve quality, time, cost...)
- In hard problems

# Optimization?

- Applications
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- How to find good (best) solutions (to improve quality, time, cost...)In hard problems
- without the need to be an expert in solving each particular problem and in its domain

### Motivation

**Applications** 

Popular optimization problems

Problem

Landscapes

Algorithms

### Motivation

#### **Applications**

Popular optimization problems

Landscapes

Algorithms

- Problem
- An instance of a problem

### Motivation

#### **Applications**

Popular optimization problems

Landscapes

Algorithms

- Problem
- An instance of a problem
- Solution space

### Motivation

#### Applications

Popular optimization problems

Landscapes

Algorithms

- Problem
- An instance of a problem
- Solution space
- Constraints

### Motivation

#### Applications

Popular optimization problems

Landscapes

Algorithms

- Problem
- An instance of a problem
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- Constraints
- Evaluation criteria

### Motivation

#### Applications

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- Goal function

### Motivation

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### Problem:

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On-site experiment Invest M money in K assets, expected gain of each is  $G_k$ , risk of each is  $R_k$ 

### Motivation

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On-site experiment

### Problem:

Invest M money in K assets, expected gain of each is  $G_k$ , risk of each is  $R_k$ 

• An instance of a problem:

Invest €100k in 4 stocks, gains (1.01, 1.03, 1.02, 1.11), risks (0.7, 0.54, 0.6, 0.95)

### Motivation

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• Solution space: All combinations of amounts invested,  $x_1, x_2, x_3, x_4$ 

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### Problem:

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 and each  $x_i \geq 0$ 

• Evaluation criteria:

Expected gain (maximize), variance of the portfolio return (minimize)

### Motivation

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- Goal function: Maximize (gain risk)
- Algorithm: ...

## What are combinatorial optimization problems?

(as opposed to *numerical* optimization problems)

#### Motivation

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- Many real world problems can be expressed as a combination of elements
  - e.g., Traveling Salesman Problem is a permutation of integers

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- Many real world problems can be expressed as a combination of elements
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- More formally:
  - minimizing (or maximizing)
  - a function f(x)
  - subject to constraints, e.g., g(x) > 0
  - x is a solution, often encoded with vectors of symbols

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- NP-hard!

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• Time and memory complexity – examples

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- Time and memory complexity examples
  - pair comparison/confrontation:

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- Time and memory complexity examples
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- Time and memory complexity examples

  - selection of a subset of features:

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- Time and memory complexity examples

  - shortest path:
- **Applications**
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- Time and memory complexity examples

  - shortest path: A B C D E | B A C D E | D E B A C | ...

- **Applications**
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- On-site experiment:

- Time and memory complexity examples

  - shortest path: A B C D E | B A C D E | D E B A C | ...
- Plot: number\_of\_solutions(*n*)

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- Time and memory complexity examples

  - shortest path: A B C D E | B A C D E | D E B A C | ...
- Plot: number\_of\_solutions(n)
- Plot: time\_to\_find\_optimum(n)

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- Time and memory complexity examples

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. . .

 Complexity classes: P (easy to find the optimum, easy to verify), NP (easy to verify), NP-C, strongly NP-C,



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  - shortest path: A B C D E | B A C D E | D E B A C | ...
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. . .

Complexity classes:
P (easy to find the optimum, easy to verify),
NP (easy to verify),
NP-C,
strongly NP-C,



• The simplest algorithms: a heuristic, random, exhaustive

### A large number of possible solutions

### Motivation

#### Applications

Popular optimization problems

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Algorithms

On-site experiments For example, the Boolean satisfiability problem (SAT):

$$F(x) = (x_{13} \lor \overline{x}_{23} \lor x_{34}) \land (\overline{x}_{13} \lor x_{23} \lor \overline{x}_{34}) \land \ldots = TRUE$$

For 100 variables (two possible values per variable)

|S| =

### A large number of possible solutions

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On-site experiments For example, the Boolean satisfiability problem (SAT):

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For 100 variables (two possible values per variable)

 $|S| = 2^{100} pprox 10^{30}$ 

SA7

299

Kraków

Warszawa







SA7

299

Kraków

Warszawa



SA7

Kraków

299

Warszawa

584

304



### Traveling salesman problem (TSP) and NP-hardness

#### Motivation

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On-site experiment 10 cities 20 cities 50 cities

$$|S| = \frac{n!}{2n} = \frac{(n-1)!}{2}$$

Each route is expressed in 2*n* different ways, *n*! ways of permutation of *n* items

181 440 60 822 550 204 416 000 304 251 932 017 133 780 436 126 081 660 647 688 443 776 415 689 605 120 000 000 000

### Traveling salesman problem (TSP) and NP-hardness

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On-site experiment  $|S| = \frac{n!}{2n} = \frac{(n-1)!}{2}$ 

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10 cities	181 440
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<b>—</b>			6		
For	comparison:	selection	ot	а	subset
	companioon	5010011011	<b>··</b>	-	546566

$n{=}10$	1 024
n=20	1 048 576
n=50	1 125 899 906 842 624

### Traveling salesman problem (TSP) and NP-hardness

#### Motivation

Applications

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On-site experiment

S	n!	(n-1)!
	$\frac{2n}{2n}$	2

Each route is expressed in 2n different ways, n! ways of permutation of n items

10 cities	181 440
20 cities	60 822 550 204 416 000
50 cities	304 251 932 017 133 780 436 126 081 660 647 688 443 776 415 689 605 120 000 000 000

	n=10	1 024
For comparison: selection of a subset	n=20	1 048 576
	n=50	1 125 899 906 842 624

	n=10	45
For comparison: evaluation of pairs	n=20	190
	n—50	1 225

### Problems, models, instances, algorithms



### Motivation Application

Popular optimization problems

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### Problems, models, instances, algorithms - relationships



Motivation Application

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### Motivations for developing optimization methods

### Motivation

#### **Applications**

- Popular optimization problems
- Landscapes
- Algorithms
- On-site experiment:

- Economy
- Machine vision
- Molecular biology
- Optimal power flow
- Structural optimization
- Robotics
- Database systems
- Computer graphics

- Medicine
- Telecommunications
- Artificial intelligence
- Integrated circuit design automation
- Computer architecture design
- Computer networks
- Image processing
- Security

# Motivations for developing optimization methods

### Motivation

#### Applications

- Popular optimization problems
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- Algorithms
- On-site experiments

- Economy
- Machine vision
- Molecular biology
- Optimal power flow
- Structural optimization
- Robotics
- Database systems
- Computer graphics

### NP-hard.

- Medicine
- Telecommunications
- Artificial intelligence
- Integrated circuit design automation
- Computer architecture design
- Computer networks
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- Security

### Sample applications of optimization methods

#### Motivatior

### Applications

- Popular optimization problems
- Landscapes
- Algorithms
- On-site experiment:

- Design of electronic circuits (VLSI)
- Telecommunication network design
- Knowledge discovery / Machine Learning
- Neural network training & design
- Automatic control
- Business scheduling and planning
- Games
- Self-adapting computer programs
- Test-data generation
- Medical image analysis
- DNA Sequencing

# Examples of NP-hard problems from my experience (1/6)

#### Motivation

### Applications

Popular optimization problems

Landscapes

Algorithms

On-site experiment

### OptiFacility, http://optifacility.mooncoder.com/

Logistics, transport, suppliers, routes...





# Examples of NP-hard problems from my experience (2/6)

#### Motivation

#### Applications

Popular optimization problems

Landscapes

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### Framsticks, http://www.framsticks.com/

Designs, control systems, neural networks...





# Examples of NP-hard problems from my experience (3/6)

#### Motivation

#### Applications

Popular optimization problems

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### Top Sailor, http://sailor.mooncoder.com/

Route planning, control, strategy...





#### Motivatior

#### Applications

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• Create groups of people according to their competencies

#### Motivatior

#### Applications

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- Algorithms
- On-site experiment

- Create groups of people according to their competencies
- Assign offices to locations in a building

#### Motivation

#### Applications

- Popular optimization problems
- Landscapes
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- On-site experiment

- Create groups of people according to their competencies
- Assign offices to locations in a building
- Determine the route for the garbage truck

#### Motivatior

#### Applications

Popular optimization problems

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Algorithms

On-site experiment:

- Create groups of people according to their competencies
- Assign offices to locations in a building
- Determine the route for the garbage truck
- Draw the most readable diagram/graph based on the specification

#### Motivation

#### Applications

Popular optimization problems

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On-site experiments

- Create groups of people according to their competencies
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- Decide where to place pictures in the text

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- Select some of the office staff to transfer to another location

#### Motivatior

#### Applications

Popular optimization problems

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On-site experiment:

- Create groups of people according to their competencies
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- Determine the route for the garbage truck
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- Decide where to place pictures in the text
- Select some of the office staff to transfer to another location
- Choose the best route for the metro line and its stops

#### Motivation

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On-site experiment:

- Create groups of people according to their competencies
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- Determine the route for the garbage truck
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- Decide where to place pictures in the text
- Select some of the office staff to transfer to another location
- Choose the best route for the metro line and its stops
- Suggest the best order in which cars are assembled on the assembly line

#### Motivation

#### Applications

Popular optimization problems

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On-site experiment

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- Assign offices to locations in a building
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- Suggest the best order in which cars are assembled on the assembly line
- Provide a schedule for shutting down and maintenance of the power plant

#### Motivatior

### Applications

Popular optimization problems

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On-site experiment

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- Select some of the office staff to transfer to another location
- Choose the best route for the metro line and its stops
- Suggest the best order in which cars are assembled on the assembly line
- Provide a schedule for shutting down and maintenance of the power plant
- Find identical fragments in DNA sequences

#### Motivation

#### Applications

Popular optimization problems

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On-site experiment • Assign hospital wards to available locations

#### Motivation

#### Applications

- Popular optimization problems
- Landscapes
- Algorithms
- On-site experiment

- Assign hospital wards to available locations
- Make a schedule of classes

#### Motivation

#### Applications

- Popular optimization problems
- Landscapes
- Algorithms
- On-site experiment:

- Assign hospital wards to available locations
- Make a schedule of classes
- Design the best antenna or wing of the aircraft
#### Motivation

- Popular optimization problems
- Landscapes
- Algorithms
- On-site experiments

- Assign hospital wards to available locations
- Make a schedule of classes
- Design the best antenna or wing of the aircraft
- Provide variable values for which the logical expression is true

#### Motivation

- Popular optimization problems
- Landscapes
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- Assign hospital wards to available locations
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- $\bullet\,$  Specify the order and time of advertising on radio/TV

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- $\bullet\,$  Specify the order and time of advertising on radio/TV
- Route the network to connect buildings in the most economical way

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- Select the stocks in which you will invest your funds

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- Assign hospital wards to available locations
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- Design the best antenna or wing of the aircraft
- Provide variable values for which the logical expression is true
- $\bullet\,$  Specify the order and time of advertising on radio/TV
- Route the network to connect buildings in the most economical way
- Select the stocks in which you will invest your funds
- Assign work to employees taking into account skill constraints

#### Motivation

### Applications

Popular optimization problems

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On-site experiment • "Dating site": find matching pairs

### Motivation

- Popular optimization problems
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- "Dating site": find matching pairs
- Specify the flight trajectory of satellites (best photo coverage of Earth)

### Motivation

### Applications

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- "Dating site": find matching pairs
- Specify the flight trajectory of satellites (best photo coverage of Earth)
- Decide how much and what types of grain to grow in a given year

### Motivation

### Applications

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### • "Dating site": find matching pairs

- Specify the flight trajectory of satellites (best photo coverage of Earth)
- Decide how much and what types of grain to grow in a given year
- Create a chess program

### Motivation

- Popular optimization problems
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- "Dating site": find matching pairs
- Specify the flight trajectory of satellites (best photo coverage of Earth)
- Decide how much and what types of grain to grow in a given year
- Create a chess program
- Detect the minimum set of differences in two texts

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- "Dating site": find matching pairs
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- Create a chess program
- Detect the minimum set of differences in two texts
- Simplify logical or algebraic expressions

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- On-site experiment:

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- Create a chess program
- Detect the minimum set of differences in two texts
- Simplify logical or algebraic expressions
- Recruitment: assign candidates to specializations, taking into account their preferences

### Motivation

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- "Dating site": find matching pairs
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- Recruitment: assign candidates to specializations, taking into account their preferences
- Adjust weights in the neural network ("train" it)

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- Create a chess program
- Detect the minimum set of differences in two texts
- Simplify logical or algebraic expressions
- Recruitment: assign candidates to specializations, taking into account their preferences
- Adjust weights in the neural network ("train" it)
- Provide a proof of a theorem

## Discussion

### Motivatior

### Applications

Popular optimization problems

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On-site experiments Choose a few of the problems listed on the slides 3/6, 4/6, and 5/6, and specify

- what constitutes the set of solutions,
- how big and how limited it is,
- how to enumerate all of its elements,
- what are the evaluation criteria, and
- how to automatically calculate their values for every possible solution.

# Graph bisection problem (2-GPP)



Landscapes

Algorithms

On-site experiment



Applications:

VLSI design, networks design, data mining, geographical information systems, job scheduling

## Knapsack problem

#### Motivation

### **Applications**

Popular optimization problems

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Algorithms

- A set of I items
- Each item i = 1, ..., I has weight  $w_i$  and value  $c_i$
- The backpack with a maximum weight capacity W should contain items with the maximum total value and the total weight not exceeding W
- Example interpretation selection of investment projects
  - Items investment projects
  - Weights project costs
  - Values profits from projects

## **Common Problems**

### Motivatior

Applications

Popular optimization problems

Landscapes

Algorithms

- General function optimization
- Traveling Salesman Problem (TSP)
- Quadratic Assignment Problem (QAP)
- Graph Coloring & Partitioning (GPP)
- Minimum Spanning Tree Problem (MSTP)
- Vehicle Routing (VRP)
- Single & Multiple Knapsack
- Set Partitioning (SPP) & Set Covering Problems (SCP)
- Cutting stock problem (CSTP)
- 2-Dimensional Packing Problem (2PP)
- Processor Allocation Problem
- Staff Scheduling Problems
- Job Shop & Project Scheduling (PSP)

# Compendium of NP optimization problems

#### https://www.csc.kth.se/tcs/compendium/

- Motivatior
- Applications

Popular optimization problems

Landscapes

Algorithms

- Graph Theory
  - Covering and Partitioning
  - Subgraphs and Supergraphs
  - Vertex Ordering
  - Iso- and Other Morphisms
- Network Design
  - Spanning Trees
  - Cuts and Connectivity
  - Routing Problems
  - Flow Problems
- Sets and Partitions
  - Covering, Hitting and Splitting
  - Weighted Set Problems
- Storage and Retrieval
  - Data Storage
  - Compression and Representation

- Sequencing and Scheduling
  - Sequencing on One Processor
  - Multiprocessor Scheduling
  - Shop Scheduling
- Mathematical Programming
- Algebra and Number Theory
  - Solvability of Equations
- Games and Puzzles
- Logic
  - Propositional Logic
- Automata and Language Theory
  - Automata Theory
  - Formal Languages
- Program Optimization
  - Code Generation

# Compendium of NP optimization problems

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## Network design NP problems

#### **Motivation**

### **Applications**

Popular optimization problems

Landscapes

Algorithms

On-site experiment

#### Spanning Trees

- MIN K-SPANNING TREE
- MIN DEGREE SPANNING TREE
- MIN GEOMETRIC 3-DEGREE SPANNING TREE
- MAX LEAF SPANNING TREE
- MAX MIN METRIC K-SPANNING TREE
- MIN DIAMETER SPANNING SUBGRAPH
- MIN COMMUNICATION COST SPANNING TREE
- MIN STEINER TREE
- MIN GEOMETRIC STEINER TREE
- MIN GENERALIZED STEINER NET
- MIN ROUTING TREE CONGESTION
- MAX MIN SPANNING TREE DELETING K EDGES
- MIN UPGRADING SPANNING TREE

#### Routing Problems

- MIN TRAVELING SALESPERSON
- MIN METRIC TRAVELING SALESPERSON PROBLEM
- MIN GEOMETRIC TRAVELING SALESPERSON
- MIN METRIC TRAVELING K-SALESPERSON PROBLEM
- MIN METRIC BOTTLENECK WANDERING SALESPERSON PROBLEM
- MIN CHINESE POSTMAN FOR MIXED GRAPHS
- MIN K-CHINESE POSTMAN PROBLEM
- MIN STACKER CRANE PROBLEM
- MIN K-STACKER CRANE PROBLEM
- MIN GENERAL ROUTING
- LONGEST PATH
- SHORTEST WEIGHT-CONSTRAINED PATH
- MIN RECTILINEAR GLOBAL ROUTING
- MIN TRAVELING REPAIRMAN
- MAX QUADRATIC ASSIGN

### • Cuts and Connectivity

- MAX CUT
- MIN CROSSING NUMBER
- MAX DIRECTED CUT
- MAX K-CUT
- MIN NET INHIBITION ON PLANAR GRAPHS
- MIN K-CUT
- MIN VERTEX K-CUT
- MIN MULTIWAY CUT
- MIN MULTI-CUT
- MIN RATIO-CUT
- MIN B-BALANCED CUT
- MIN B-VERTEX SEPARATOR
- MIN QUOTIENT CUT
- MIN K-VERTEX CONNECTED SUBGRAPH
- MIN K-EDGE CONNECTED SUBGRAPH
- MIN BICONNECTIVITY AUGMENTATION
- MIN STRONG CONNECTIVITY AUGMENTATION
- MIN BOUNDED DIAMETER AUGMENTATION

#### • Flow Problems

- MAX PRIORITY FLOW
- MAX INTEGRAL K-MULTICOMMODITY FLOW ON TREES
- MAX DISJOINT CONNECTING PATHS
- MIN MAX DISJOINT CONNECTING PATHS
- MIN SINGLE-SINK EDGE INSTALLATION
- MIN UNSPLITTABLE FLOW

## ...And even more network design NP problems...

#### Motivation

#### **Applications**

Popular optimization problems

Landscapes

Algorithms

On-site experiments

### Miscellaneous

- MIN BROADCAST TIME
- MIN K-CENTER
- MIN K-CLUSTERING
- MIN K-CLUSTERING SUM
- MIN K-SUPPLIER
- MIN K-MEDIAN
- MIN DIAMETERS DECOMPOSITION
- MAX K-FACILITY DISPERSION
- MIN FACILITY LOCATION
- MAX K-FACILITY LOCATION
- MIN K-SWITCHING NET
- MIN BEND NUMBER
- MIN LENGTH TRIANGULATION
- MIN SEPARATING SUBDIVISION

# Minimal spanning tree (MST) problem

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12

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 $X_5$ 

 $X_{\neg}$ 



- Total cost of the links used is a minimum
- All the points are connected together

Constraint:  $x_1 + x_2 + x_6 \le 1$  $x_1 \le x_3$ 

Penalty: 50

## Vehicle routing problem (VRP) with constraints





Popular optimization problems

Landscapes

Algorithms

On-site experiment



capacity and time window constraints!

# RC PSP - Resource-constrained project scheduling problem



# Ship scheduling

#### Motivation

- Popular optimization problems
- Landscapes
- Algorithms
- On-site experiment



## Ship schedule table

### Motivation

### **Applications**

Popular optimization problems

Landscapes

Algorithms







#### Applications

Popular optimization problems

Landscapes

Algorithms







#### Applications

Popular optimization problems

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Motivation

### Applications

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Algorithms



## Optimization landscape

Motivation

Applications

Popular optimization problems

Landscapes

Algorithms



## Optimization landscape

#### Motivation

Applications

Popular optimization problems

Landscapes

Algorithms



# Some landscapes

http://en.alife.pl/opt/e/index.html

#### Motivatior

#### Applications

Popular optimization problems

### Landscapes

Algorithms



## Some landscapes

http://en.alife.pl/opt/e/index.html

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#### **Applications**

Popular optimization problems

### Landscapes

Algorithms



## Some landscapes

http://en.alife.pl/opt/e/index.html

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#### **Applications**

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### Landscapes

Algorithms



### Local search

#### Motivation

**Applications** 

Popular optimization problems

Landscapes

Algorithms

On-site experiments

# *current* := random solution **repeat**

generate a neighbor of current
if the neighbor is better than current then current := neighbor
} until all neighbors are worse than current

### Local search

#### Motivation

**Applications** 

Popular optimization problems

Landscapes

Algorithms

On-site experiments *current* := random solution **repeat** 

generate a neighbor of current
if the neighbor is better than current then current := neighbor
} until all neighbors are worse than current

http://en.alife.pl/files/opt/d/OptiVisJS/OptiVisJS.html?lang=en

## Evolutionary/genetic algorithm: the main loop

#### Motivation

**Applications** 

Popular optimization problems

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}

Landscapes

### Algorithms

On-site experiments

```
t := 0
initialize P(t)
evaluate P(t)
while (not stopping-condition)
```

```
t := t + 1
select P(t) from P(t - 1) // reproduce better solutions
modify P(t) // crossover, mutate
evaluate P(t)
```

// P is a population (a set of solutions)

### Evolutionary/genetic algorithm: the main loop

#### Motivation

**Applications** 

Popular optimization problems

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Landscapes

### Algorithms

On-site experiments

```
t := 0
initialize P(t)
evaluate P(t)
while (not stopping-condition)
```

```
\begin{array}{ll} t := t + 1 \\ \text{select } P(t) \text{ from } P(t-1) & // \text{ reproduce better solutions} \\ \text{modify } P(t) & // \text{ crossover, mutate} \\ \text{evaluate } P(t) \end{array}
```

// P is a population (a set of solutions)

http://en.alife.pl/files/opt/d/OptiVisJS/OptiVisJS.html?lang=en

#### Motivation

- Applications
- Popular optimization problems

Landscapes

### Algorithms

- Can optimization be used for maximization, or only for minimization?
- Are optimization algorithms used in machine learning?
- What is the difference between **numerical** and **combinatorial** optimization problems?
- What is a fitness landscape?
- What is **NP-hard**?
- What is local search?
- What are the main steps in an evolutionary algorithm?
- What is the role of **mutation** and **crossover** in evolutionary algorithms?

### Hardware and software for on-site experiments

• Will you have a laptop with you?

Linux/macOS/Windows?Android or iOS phone/tablet?

#### Motivation

#### Applications

- Popular optimization problems
- Landscapes
- Algorithms
- On-site experiments