# **Optimization in Machine Learning**

# **Evolutionary Algorithms GA / Bit Strings**





#### Learning goals

- Recombination
- Mutation
- Simple examples

# **BINARY ENCODING**

- In theory: Each problem can be encoded binary
- In practice: Binary not always best representation (e.g., if values are numeric, trees or programs)

We typically encode problems with **binary decision variables** in binary representation.

#### Examples:

- Scheduling problems
- Integer / binary linear programming
- Feature selection
- ...



# **RECOMBINATION FOR BIT STRINGS**

Two individuals  $\mathbf{x}, \tilde{\mathbf{x}} \in \{0, 1\}^d$  encoded as bit strings can be recombined as follows:

• 1-point crossover: Select crossover  $k \in \{1, ..., d-1\}$  randomly. Take first k bits from parent 1 and last d-k bits from parent 2.

1	1		1
0	0		0
0	1	$\Rightarrow$	1
1	1		1
1	0		0

• **Uniform crossover:** Select bit j with probability p from parent 1 and 1 - p from parent 2.

1	0		1
0	0		0
0	1	$\Rightarrow$	1
0	1		1
1	0		1



# **MUTATION FOR BIT STRINGS**

Offspring  $\mathbf{x} \in \{0,1\}^d$  encoded as a bit string can be mutated as follows:

• **Bitflip:** Each bit *j* is flipped with probability  $p \in (0, 1)$ .



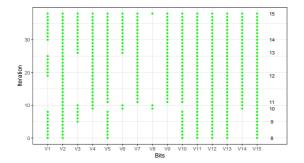


# **EXAMPLE 1: ONE-MAX EXAMPLE**

 $\mathbf{x} \in \{0, 1\}^d, d = 15$  bit vector representation.

Goal: Find the vector with the maximum number of 1's.

- Fitness:  $f(\mathbf{x}) = \sum_{i=1}^{d} x_i$
- ullet  $\mu=$  15,  $\lambda=$  5,  $(\mu+\lambda)$ -strategy, bitflip mutation, no recombination



**Green:** Representation of best individual per iteration. Right scale shows fitness.



# **EXAMPLE 2: FEATURE SELECTION**

We consider the following toy setting:

- Generate design matrix  $\mathbf{X} \in \mathbb{R}^{n \times p}$  by drawing n = 1000 samples of p = 50 independent normally distributed features with  $\mu_j = 0$  and  $\sigma_j^2 > 0$  varying between 1 and 5 for  $j = 1, \dots, p$ .
- Linear regression problem with dependent variable y:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\theta} + \epsilon$$

with  $\epsilon \sim \mathcal{N}(0, 1)$ .

Parameter  $\theta$ :

$$heta_0 = -1.2$$
  $heta_j = egin{cases} 1 & ext{for } j \in 1,7,13,19,25,31,37,43 \ 0 & ext{otherwise} \end{cases}$ 

⇒ Only 8 out of 50 equally influential features

