Computational Intelligence

Winter Term 2024/25

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Computational Intelligence

Fakultät für Informatik

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- Design of Evolutionary Algorithms
  - Design Guidelines
  - Genotype-Phenotype Mapping
  - Maximum Entropy Distributions

Three tasks:

1. Choice of an appropriate problem representation.
2. Choice / design of variation operators acting in problem representation.
3. Choice of strategy parameters (includes initialization).

ad 1) different "schools":

    (a) operate on binary representation and define genotype/phenotype mapping
      + can use standard algorithm
      − mapping may induce unintentional bias in search

    (b) no doctrine: use "most natural" representation
      − must design variation operators for specific representation
      + if design done properly then no bias in search

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ad 1a) genotype-phenotype mapping

original problem $f: X \rightarrow \mathbb{R}^d$

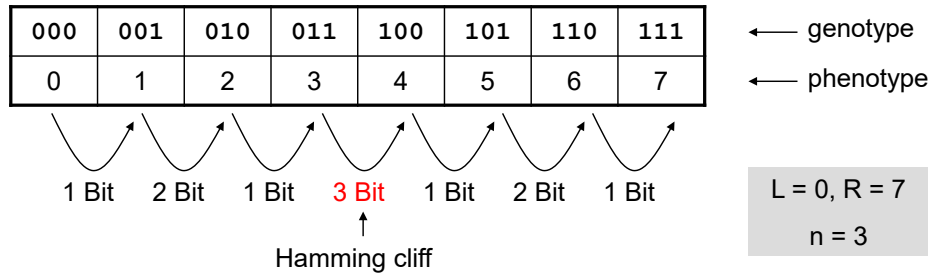scenario: no standard algorithm for search space X available
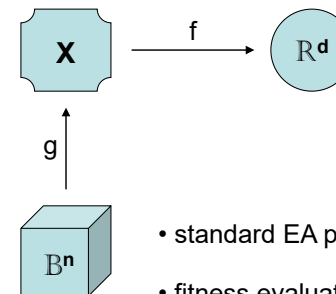
- standard EA performs variation on binary strings $b \in \mathbb{B}^n$

- fitness evaluation of individual b via $(f \circ g)(b) = f(g(b))$

    where $g: \mathbb{B}^n \rightarrow X$ is genotype-phenotype mapping

- selection operation independent from representation

Genotype-Phenotype-Mapping $\mathbb{B}^n \rightarrow [L, R] \subset \mathbb{R}$

- Standard encoding for $b \in \mathbb{B}^n$

$$x = L + \frac{R - L}{2^n - 1} \sum_{i=0}^{n-1} b_{n-i}\, 2^i$$

$\rightarrow$ Problem: *hamming cliffs*

000	001	010	011	100	101	110	111	$\longleftarrow$ genotype
0	1	2	3	4	5	6	7	$\longleftarrow$ phenotype

1 Bit 2 Bit 1 Bit **3 Bit** 1 Bit 2 Bit 1 Bit

↑ Hamming cliff

L = 0, R = 7

n = 3

Genotype-Phenotype-Mapping $\mathbb{B}^n \rightarrow [L, R] \subset \mathbb{R}$

- Gray encoding for $b \in \mathbb{B}^n$

  Let $a \in \mathbb{B}^n$ standard encoded. Then $b_i = \begin{cases} a_i, & \text{if } i = 1 \\ a_{i-1} \oplus a_i, & \text{if } i > 1 \end{cases}$

  $\oplus$ = XOR

000	001	011	010	110	111	101	100	$\longleftarrow$ genotype
0	1	2	3	4	5	6	7	$\longleftarrow$ phenotype

OK, no hamming cliffs any longer …

$\Rightarrow$ small changes in phenotype „lead to" small changes in genotype

since we consider evolution in terms of Darwin (not Lamarck):

$\Rightarrow$ small changes in genotype lead to small changes in phenotype!

but: 1-Bit-change: $000 \rightarrow 100 \Rightarrow$ ☹

Genotype-Phenotype-Mapping $\mathbb{B}^n \rightarrow \mathbb{P}^{\log(n)}$ (example only)

- e.g. standard encoding for $b \in \mathbb{B}^n$

individual:

010	101	111	000	110	001	101	100	$\longleftarrow$ genotype
0	1	2	3	4	5	6	7	$\longleftarrow$ index

consider index and associated genotype entry as unit / record / struct;

sort units with respect to genotype value, old indices yield permutation:

000	001	010	100	101	101	110	111	$\longleftarrow$ genotype
3	5	0	7	1	6	4	2	$\longleftarrow$ old index

= permutation

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ad 1a) genotype-phenotype mapping

typically required: strong causality

$\rightarrow$ small changes in individual leads to small changes in fitness

$\rightarrow$ small changes in genotype should lead to small changes in phenotype

but: how to find a genotype-phenotype mapping with that property?

necessary conditions:

1) g: $\mathbb{B}^n \rightarrow X$ can be computed efficiently (otherwise it is senseless)

2) g: $\mathbb{B}^n \rightarrow X$ is surjective (otherwise we might miss the optimal solution)

3) g: $\mathbb{B}^n \rightarrow X$ *preserves closeness* (otherwise strong causality endangered)

Let $d(\cdot, \cdot)$ be a metric on $\mathbb{B}^n$ and $d_X(\cdot, \cdot)$ be a metric on X.

$\forall x, y, z \in \mathbb{B}^n : d(x, y) \leq d(x, z) \Rightarrow d_X(g(x), g(y)) \leq d_X(g(x), g(z))$

ad 1b) use "most natural" representation

typically required: strong causality

→ small changes in individual leads to small changes in fitness

→ need variation operators that obey that requirement

but: how to find variation operators with that property?

⇒ need design guidelines ...

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ad 2) **design guidelines for variation operators**

a) *reachability*

   every x ∈ X should be reachable from arbitrary x_0 ∈ X
   after finite number of repeated variations with positive probability bounded from 0

b) *unbiasedness*

   unless having gathered knowledge about problem
   variation operator should not favor particular subsets of solutions
   ⇒ formally: <u>maximum entropy principle</u>

c) *control*

   variation operator should have parameters affecting shape of distributions;
   known from theory: weaken variation strength when approaching optimum

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ad 2) **design guidelines for variation operators in practice**

<u>binary search space</u> X = $\mathbb{B}^n$

variation by k-point or uniform crossover and subsequent mutation

a) *reachability*:
   regardless of the output of crossover
   we can move from x ∈ $\mathbb{B}^n$ to y ∈ $\mathbb{B}^n$ in 1 step with probability

$$p(x,y) = p_m^{H(x,y)} (1 - p_m)^{n-H(x,y)} > 0$$

   where H(x,y) is Hamming distance between x and y.

   Since   min{ p(x,y): x,y ∈ $\mathbb{B}^n$ } = δ > 0   we are done.

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b) *unbiasedness*

don't prefer any direction or subset of points without reason

⇒ use maximum entropy distribution for sampling!

   properties:

   - distributes probability mass as uniform as possible

   - additional knowledge can be included as constraints:
     → under given constraints sample as uniform as possible

Design of Evolutionary Algorithms — Lecture 07

Formally:

Definition:

Let X be discrete random variable (r.v.) with $p_k = P\{X = x_k\}$ for some index set K. The quantity

$$H(X) = -\sum_{k \in K} p_k \log p_k$$

is called the **entropy of the distribution** of X. If X is a continuous r.v. with p.d.f. $f_X(\cdot)$ then the entropy is given by

$$H(X) = -\int_{-\infty}^{\infty} f_X(x) \log f_X(x)dx$$

The distribution of a random variable X for which H(X) is maximal is termed a **maximum entropy distribution**. ∎

Excursion: Maximum Entropy Distributions — Lecture 07

Knowledge available:

Discrete distribution with support $\{x_1, x_2, \dots x_n\}$ with $x_1 < x_2 < \dots x_n < \infty$

$$p_k = P\{X = x_k\}$$

⇒ leads to nonlinear constrained optimization problem:

$$-\sum_{k=1}^{n} p_k \log p_k \quad \rightarrow \text{max!}$$

s.t. $\qquad \sum_{k=1}^{n} p_k = 1$

solution: via Lagrange (find stationary point of Lagrangian function)

$$L(p, a) = -\sum_{k=1}^{n} p_k \log p_k + a\left(\sum_{k=1}^{n} p_k - 1\right)$$

Excursion: Maximum Entropy Distributions — Lecture 07

$$L(p, a) = -\sum_{k=1}^{n} p_k \log p_k + a\left(\sum_{k=1}^{n} p_k - 1\right)$$

partial derivatives:

$$\frac{\partial L(p, a)}{\partial p_k} = -1 - \log p_k + a \overset{!}{=} 0 \qquad \Rightarrow \quad p_k \overset{!}{=} e^{a-1}$$

$$\frac{\partial L(p, a)}{\partial a} = \sum_{k=1}^{n} p_k - 1 \overset{!}{=} 0$$

$$\Rightarrow \sum_{k=1}^{n} p_k = \sum_{k=1}^{n} e^{a-1} = n\, e^{a-1} \overset{!}{=} 1 \quad \Leftrightarrow \quad e^{a-1} = \frac{1}{n}$$

$$p_k = \frac{1}{n}$$

uniform distribution

Excursion: Maximum Entropy Distributions — Lecture 07

Knowledge available:

Discrete distribution with support $\{1, 2, \dots, n\}$ with $p_k = P\{X = k\}$ **and** E[X] = ν

⇒ leads to nonlinear constrained optimization problem:

$$-\sum_{k=1}^{n} p_k \log p_k \quad \rightarrow \text{max!}$$

s.t. $\qquad \sum_{k=1}^{n} p_k = 1 \qquad$ and $\qquad \sum_{k=1}^{n} k\, p_k = \nu$

solution: via Lagrange (find stationary point of Lagrangian function)

$$L(p, a, b) = -\sum_{k=1}^{n} p_k \log p_k + a\left(\sum_{k=1}^{n} p_k - 1\right) + b\left(\sum_{k=1}^{n} k \cdot p_k - \nu\right)$$

$$L(p, a, b) = -\sum_{k=1}^{n} p_k \log p_k + a \left(\sum_{k=1}^{n} p_k - 1 \right) + b \left(\sum_{k=1}^{n} k \cdot p_k - \nu \right)$$

partial derivatives:

$$\frac{\partial L(p, a, b)}{\partial p_k} = -1 - \log p_k + a + b\,k \overset{!}{=} 0 \qquad \Rightarrow \quad p_k = e^{a - 1 + b\,k}$$

$$\frac{\partial L(p, a, b)}{\partial a} = \sum_{k=1}^{n} p_k - 1 \overset{!}{=} 0$$

$$\frac{\partial L(p, a, b)}{\partial b} \,(*) = \sum_{k=1}^{n} k\,p_k - \nu \overset{!}{=} 0 \qquad \sum_{k=1}^{n} p_k = e^{a-1} \sum_{k=1}^{n} (e^b)^k \overset{!}{=} 1$$

(continued on next slide)

$$\Rightarrow \quad e^{a-1} = \frac{1}{\sum\limits_{k=1}^{n} (e^b)^k} \qquad\qquad \Rightarrow \quad p_k = e^{a-1+b\,k} = \frac{(e^b)^k}{\sum\limits_{i=1}^{n} (e^b)^i}$$

$$\Rightarrow \quad \text{\textbf{discrete Boltzmann distribution}} \qquad p_k = \frac{q^k}{\sum\limits_{i=1}^{n} q^i} \qquad (q = e^b)$$

$$\Rightarrow \quad \text{value of q depends on } \nu \text{ via third condition: } (*)$$

$$\sum_{k=1}^{n} k\,p_k = \frac{\sum\limits_{k=1}^{n} k\,q^k}{\sum\limits_{i=1}^{n} q^i} = \frac{1 - (n+1)\,q^n + n\,q^{n+1}}{(1-q)\,(1-q^n)} \overset{!}{=} \nu$$
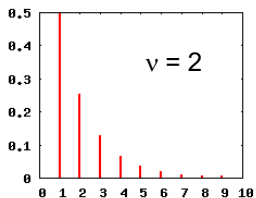
Boltzmann distribution

(n = 9)
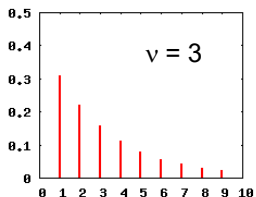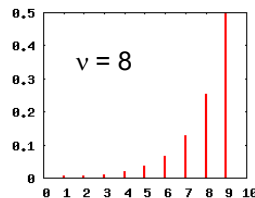
specializes to uniform distribution if $\nu = 5$

(as expected)
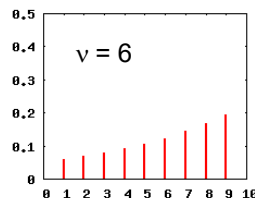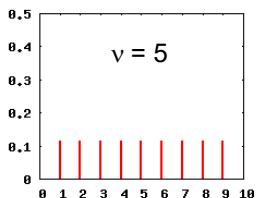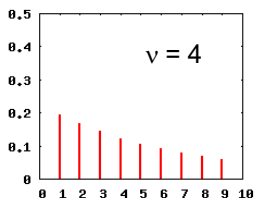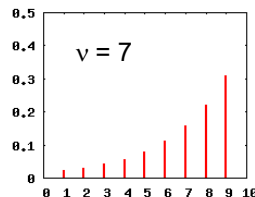
Knowledge available:

Discrete distribution with support { 1, 2, …, n } with E[X] = ν **and** V[X] = η^2

$\Rightarrow$ leads to nonlinear constrained optimization problem:

$$-\sum_{k=1}^{n} p_k \log p_k \quad \rightarrow \max!$$

$$\text{s.t.} \quad \sum_{k=1}^{n} p_k = 1 \quad \text{and} \quad \sum_{k=1}^{n} k\,p_k = \nu \quad \text{and} \quad \sum_{k=1}^{n} (k - \nu)^2\,p_k = \eta^2$$

solution: in principle, via Lagrange (find stationary point of Lagrangian function)

but very complicated analytically, if possible at all
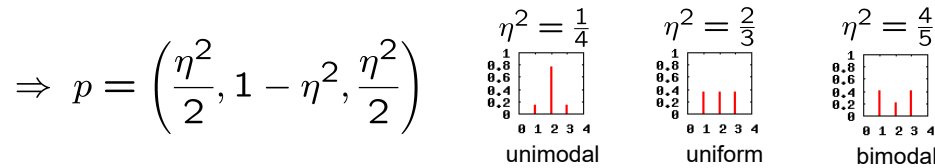
$\Rightarrow$ consider special cases only

note: constraints are linear equations in p_k

Special case: **n = 3** and **E[X] = 2** and **V[X] = η^2**

Linear constraints uniquely determine distribution:

$$
\begin{array}{llllllll}
\text{I.} & p_1 & + & p_2 & + & p_3 & = & 1 \\
\text{II.} & p_1 & + & 2\,p_2 & + & 3\,p_3 & = & 2 \\
\text{III.} & p_1 & + & 0 & + & p_3 & = & \eta^2
\end{array}
$$

$$
\begin{array}{llll}
\text{II} - \text{I:} & p_2 & + & 2\,p_3 & = & 1 \\
\text{I} - \text{III:} & p_2 & & & = & 1 - \eta^2
\end{array}
$$

$$
p_1 = \frac{\eta^2}{2}
$$

↑ insertion in III.

$$
p_3 = \frac{\eta^2}{2}
$$

$$
\Rightarrow \; p = \left(\frac{\eta^2}{2}, 1 - \eta^2, \frac{\eta^2}{2} \right)
$$

$\eta^2 = \frac{1}{4}$ $\eta^2 = \frac{2}{3}$ $\eta^2 = \frac{4}{5}$

unimodal   uniform   bimodal

Knowledge available:

Discrete distribution with unbounded support { 0, 1, 2, … } and **E[X] = ν**

$\Rightarrow$ leads to <u>infinite-dimensional</u> nonlinear constrained optimization problem:

$$
-\sum_{k=0}^{\infty} p_k \log p_k \quad \rightarrow \max!
$$

$$
\text{s.t.} \qquad \sum_{k=0}^{\infty} p_k = 1 \qquad \text{and} \qquad \sum_{k=0}^{\infty} k\, p_k = \nu
$$

<u>solution:</u> via Lagrange (find stationary point of Lagrangian function)

$$
L(p,a,b) = -\sum_{k=0}^{\infty} p_k \log p_k + a \left(\sum_{k=0}^{\infty} p_k - 1 \right) + b \left(\sum_{k=0}^{\infty} k \cdot p_k - \nu \right)
$$

$$
L(p,a,b) = -\sum_{k=0}^{\infty} p_k \log p_k + a \left(\sum_{k=0}^{\infty} p_k - 1 \right) + b \left(\sum_{k=0}^{\infty} k \cdot p_k - \nu \right)
$$

partial derivatives:

$$
\frac{\partial L(p,a,b)}{\partial p_k} = -1 - \log p_k + a + b\,k \stackrel{!}{=} 0 \qquad \Rightarrow \; p_k = e^{a-1+b\,k}
$$

$$
\frac{\partial L(p,a,b)}{\partial a} = \sum_{k=0}^{\infty} p_k - 1 \stackrel{!}{=} 0
$$

$$
\frac{\partial L(p,a,b)}{\partial b} \stackrel{(\textcolor{red}{*})}{=} \sum_{k=0}^{\infty} k\, p_k - \nu \stackrel{!}{=} 0 \qquad \sum_{k=0}^{\infty} p_k = e^{a-1} \sum_{k=0}^{\infty} (e^b)^k \stackrel{!}{=} 1
$$

(continued on next slide)

$$
\Rightarrow \quad e^{a-1} = \frac{1}{\sum\limits_{k=0}^{\infty} (e^b)^k} \qquad\qquad \Rightarrow \quad p_k = e^{a-1+b\,k} = \frac{(e^b)^k}{\sum\limits_{i=0}^{\infty} (e^b)^i}
$$

set $q = e^b$ and insists that $q < 1$ $\Rightarrow$ $\sum\limits_{k=0}^{\infty} q^k = \dfrac{1}{1-q}$ insert

$$
\Rightarrow \; p_k = (1-q)\,q^k \quad \text{for} \quad k = 0, 1, 2, \dots \quad \textcolor{blue}{\textbf{geometrical distribution}}
$$

it remains to specify q; to proceed recall that $\qquad \sum\limits_{k=0}^{\infty} k\, q^k = \dfrac{q}{(1-q)^2}$

$\Rightarrow$ value of q depends on ν via third condition: (✱)

$$\sum_{k=0}^{\infty} k\, p_k \;=\; \frac{\sum_{k=0}^{\infty} k\, q^k}{\sum_{i=0}^{\infty} q^i} \;=\; \frac{q}{1-q} \;\overset{!}{=}\; \nu$$

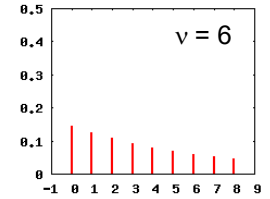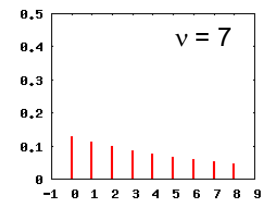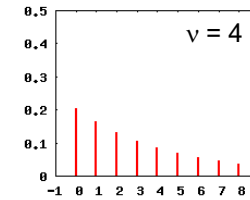$$\Rightarrow \quad q \;=\; \frac{\nu}{\nu+1} \;=\; 1 - \frac{1}{\nu+1}$$

$$\Rightarrow \quad p_k \;=\; \frac{1}{\nu+1}\left(1 - \frac{1}{\nu+1}\right)^k$$

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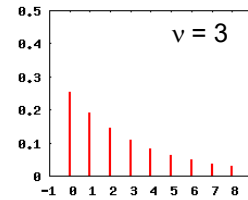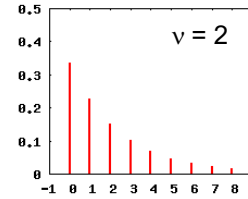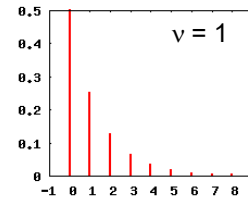
geometrical distribution

with E[x] = ν

p_k only shown
for k = 0, 1, …, 8
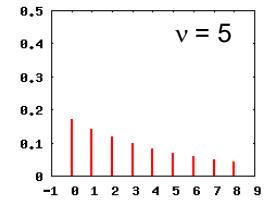
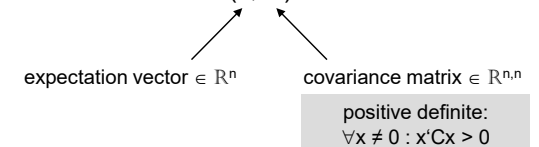
Overview:

support { 1, 2, …, n } $\Rightarrow$ *discrete uniform* distribution

and require E[X] = θ $\Rightarrow$ *Boltzmann* distribution

and require V[X] = η^2 $\Rightarrow$ N.N. (**not** Binomial distribution)

support $\mathbb{N}$ $\Rightarrow$ not defined!

and require E[X] = θ $\Rightarrow$ *geometrical* distribution

and require V[X] = η^2 $\Rightarrow$?

support $\mathbb{Z}$ $\Rightarrow$ not defined!

and require E[|X|] = θ $\Rightarrow$ *bi-geometrical* distribution (*discrete Laplace* distr.)

and require E[|X|²] = η^2 $\Rightarrow$ N.N. (*discrete Gaussian* distr.)

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support [a,b] $\subset \mathbb{R}$ $\Rightarrow$ uniform distribution

support $\mathbb{R}^+$ with E[X] = θ $\Rightarrow$ Exponential distribution

support $\mathbb{R}$
with E[X] = θ, V[X] = η^2 $\Rightarrow$ normal / Gaussian distribution N(θ, η^2)

support $\mathbb{R}^n$
with   E[X] = θ
and Cov[X] = C $\Rightarrow$ multinormal distribution N(θ, C)

expectation vector $\in \mathbb{R}^n$ covariance matrix $\in \mathbb{R}^{n,n}$

positive definite:
$\forall x \neq 0 : x'Cx > 0$

for permutation distributions ?

→ uniform distribution on all possible permutations

```
set v[j] = j for j = 1, 2, ..., n

for i = n to 1 step -1

  draw k uniformly at random from { 1, 2, ..., i }

  swap v[i] and v[k]

endfor
```

generates permutation uniformly at random in $\Theta(n)$ time

Guideline:

Only if you know something about the problem *a priori* or

if you have learnt something about the problem *during the search*

⇒ include that knowledge in search / mutation distribution (via constraints!)