

# Multi-armed Bandit Based Covariance Matrix Adaptation Evolution Strategy

Chuan-Che Yen  
Advisor: Dr. Tian-Li Yu

TEILab

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# Outline

- 1 Real-valued Function Optimization
- 2 Related Approaches
- 3 Summary
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# Real-valued Function Optimization

- Real-valued function

- $f: \mathcal{S} \subset \mathbb{R}^n \rightarrow \mathbb{R}, x \mapsto f(x)$
- $\mathcal{S}$ : search space
- Elements of  $\mathcal{S}$ : candidates or solutions

- Optimization

- $\arg \min_x f(x)$ , where  $x$  are within given bounds.
- Maximizing  $f$  is equivalent to minimizing  $-f$ .

- Example

- $\arg \min_x 2x^3 - 3x^2 - 36x - 14$ .
- Design of aircraft wings.

# Black-box Optimization

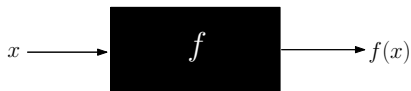


Figure: Black-box function

- The only information is the interaction between input and output.
- The key point is investigating the trade-off between **exploration** and **exploitation**.
  - Exploration is the capability of **having an overview for the search space**.
  - Exploitation is the capability of **generating high resolution candidates**.

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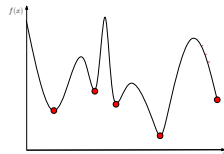


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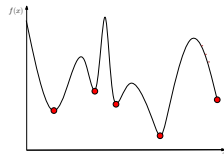


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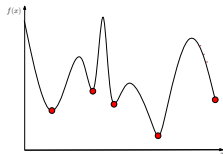


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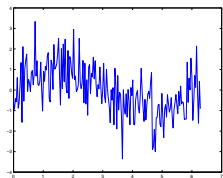


Figure:  $\sin(x)$  with noise

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  - Non-smooth.

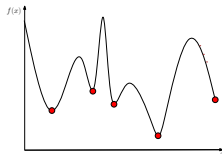


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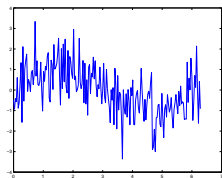


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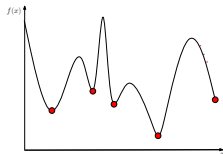


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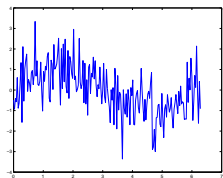


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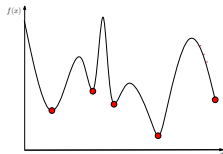


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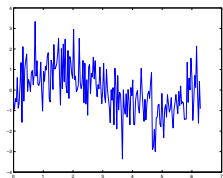


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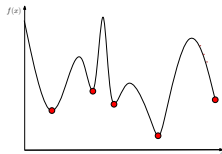


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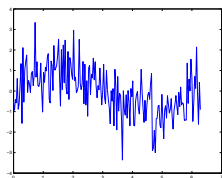


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- Non-separable
  - Dependencies between decision variables

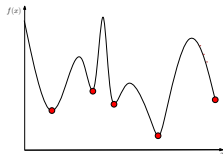


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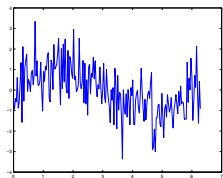


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- Ill-conditioned

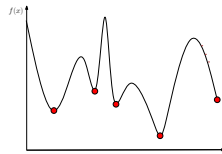


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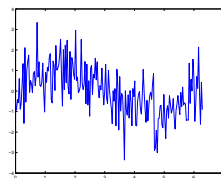


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- Ill-conditioned
  - Unable to extract gradient information

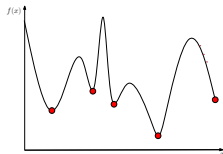


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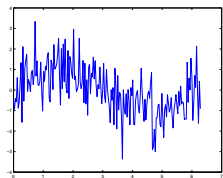


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# Related Approaches

- Optimizing black-box problems
  - No deterministic way to evolve global optimum
  - Applying meta heuristic for approximation
- Stochastic algorithms
  - Iteratively generating better solutions
- Two major approaches
  - Estimation of distribution algorithm (EDA)
  - Evolution strategy (ES)

# Discretization

- Continuous domain  $\rightarrow$  Discrete domain
- Finding good solutions  $\rightarrow$  Finding promising regions
- 2 traditional discretization methods
  - Fixed Height Histogram (FHH)
  - Fixed Width Histogram (FWH)

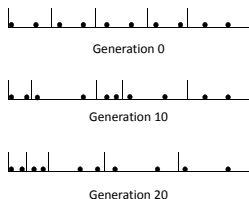


Figure: Illustration of FHH

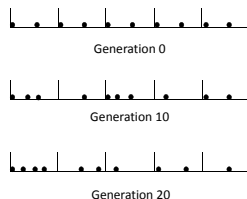


Figure: Illustration of FWH

# Split on Demand

- Solutions in each bin should not exceed  $\gamma N$ .
  - $N$  is the population size.
  - $\gamma$  defines the rate of one region.
- $\gamma$  decays with a factor  $\epsilon$ .

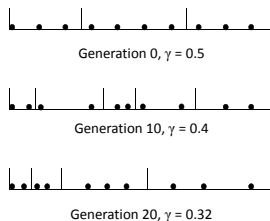


Figure: Illustration of SoD

# EDA

- Sometimes known as Probabilistic Model Building GA (PMBGA).
  - Building model explicitly.
  - Linkage between decision variables are provided.
- Extended Compact Genetic Algorithm (ECGA).
  - Model is built according to population distribution.
  - Applying greedy search to refine model iteratively.

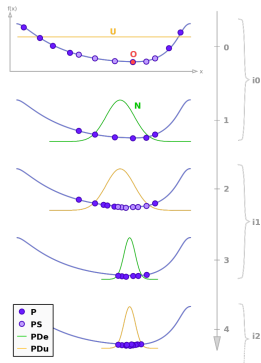


Figure: EDA

# Real-coded ECGA with SoD

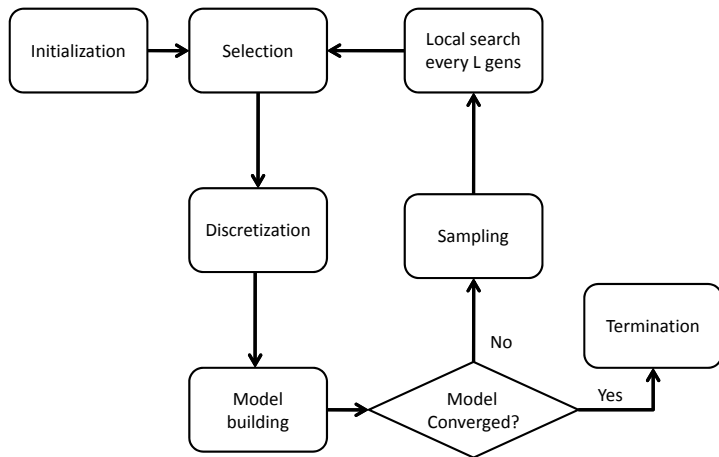


Figure: Integrating SoD into ECGA

# Evolution Strategy (ES)

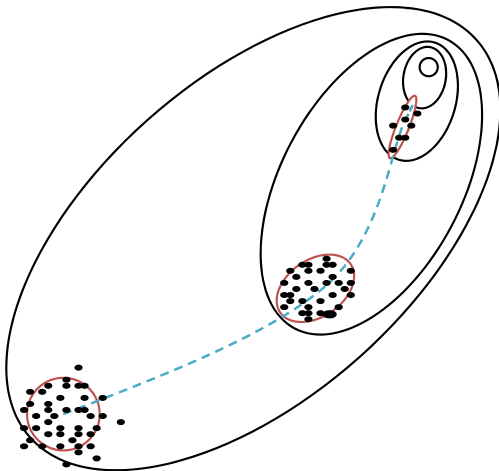
- A search template for black-box optimization.
  - Encoded in continuous domain.
- New search points are generated based on current population.
- $(\mu, \lambda)$ -ES and  $(\mu + \lambda)$ -ES.
- $x_i^{t+1} = m^t + \sigma N_i(0, C)$ .
  - $x_i^{t+1}$ :  $i$ -th generated solution at generation  $t + 1$ .
  - $m^t$ : weighted mean of population at generation  $t$ .
  - $\sigma$ : step size.
  - $C$ : Estimated distribution.

# Covariance Matrix Adaptation Evolution Strategy (CMA-ES)

- A famous derivation of ES.
- Importance of  $\sigma$  and  $C$ .
  - Larger step size reinforces exploration while smaller reinforces exploitation.
    - Choosing an fixed, appropriate number?
  - Covariance matrix determines the shape of estimated distribution.
    - Determining the length of each axis.
    - Representing the dependency among decision variables.
- CMA-ES features in the adoption of historical information.
  - $\sigma$  and  $C$  are adjusted accordingly.



# Illustration of CMA-ES



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