A Framework for Multi-Model EDAs with Model Recombination

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Foundations

Evolutionary Algorithms (EA)

- Based on „survival of the fittest“
- Select the fittest individuals from the current generation
- Use crossover and mutation to create new individuals

Estimation of Distribution Algorithms (EDA)

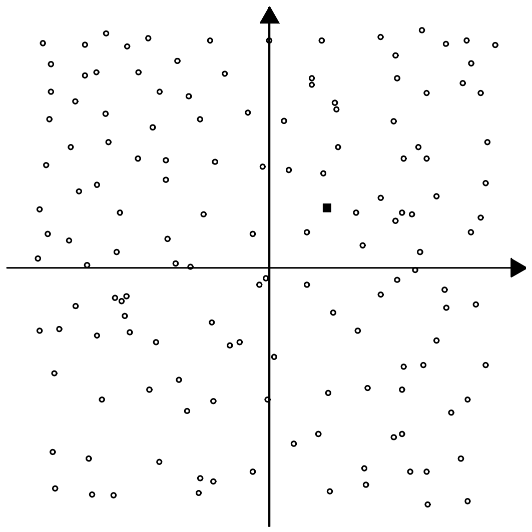
- Creating models by analysing of the selected individuals
- Sample new individuals using the model
- Learn „how a good solution should look like“
- Conventional EDAs: only one model

Motivation

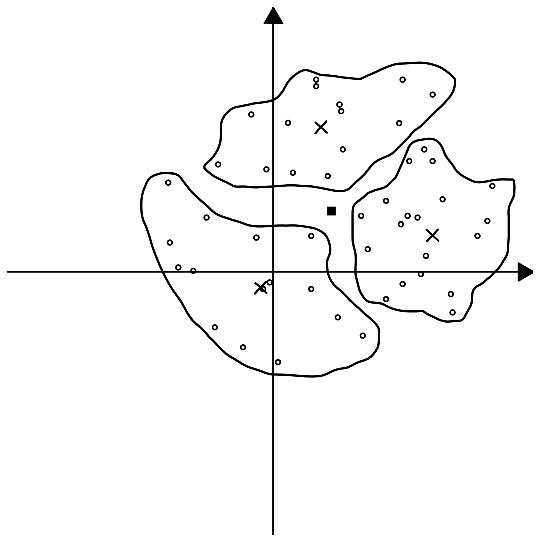
- Single-model EDAs have problems with
  - premature convergence
  - high degree of neutrality
- Goals
  - Exploring different areas of the search space in parallel
  - Using crossover for a higher adaption on the problem specific search space
  - Provide a simple framework which combines EAs and EDAs
- Idea
  - Clustering of similar individuals
  - For each cluster computing one model -> multi-model
  - Model crossover

Algorithm

1. Create first generation with ***n*m*** new individuals
2. Evaluate the fitness of each candidate
3. Select the best ***s*** individuals with truncation selection
4. Create ***c*** clusters, with ***c***
   1. as a fixed parameter
   2. subject to self-adaption
   3. determined by the clustering algorithm



Step 1



Step 4

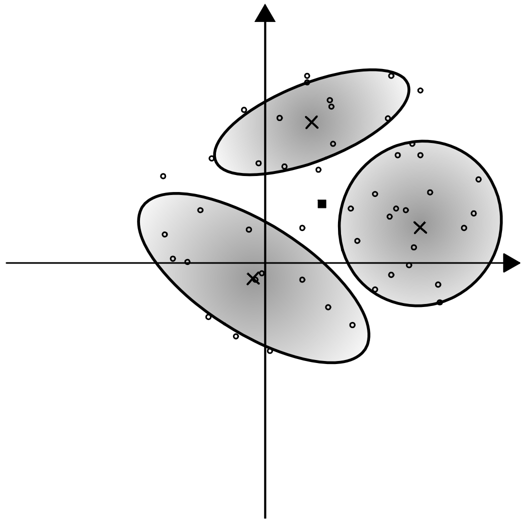
Algorithm

5. Create a model for each cluster

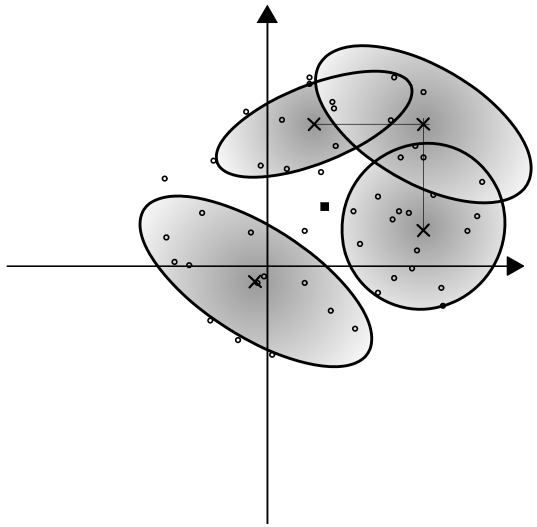
6. Generate ***n*** – ***c*** additional models by crossover

7. Sample **m** new individuals from each of the ***n*** models

8. Terminate if criterion not met, continue at step 2

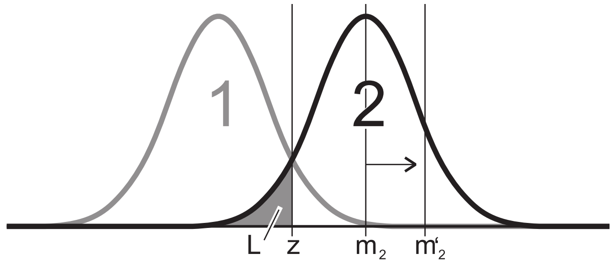


Step 5



Step 6

Multi-Model EDAs



- Preventing intersection of models
  - Two clusters border each other
  - Intersection of the created models
  - In next generation: no intersection of the new clusters

- Unite EAs and EDAs
  - In multi-model EDA the population is split in ***n*** models
    n * ***m*** = population size
  - ***n*** = 1, the multi-model EDA is like a regular EDA
  - ***n*** = ***ps***, the multi-model EDA is like a regular EA

The Real-Valued Multi-Model EDA (RVMMEDA)

- Model: mean vector $\boldsymbol{\mu}$ + covariance matrix $\boldsymbol{\Sigma}$
- K-means as clustering algorithm, with a fixed number of clusters
- Sampling:
  1. Create a vector of standard normally-distributed random values
  2. Scale by square root of the Eigen value from corresponding dimension of $\boldsymbol{\Sigma}$
  3. Rotate with the covariance matrix $\boldsymbol{\Sigma}$
  4. Move by adding $\boldsymbol{\mu}$
- Crossover:
  - New mean vector: mixing two parent mean vectors
  - New covariance matrix: compute from the three mean vectors

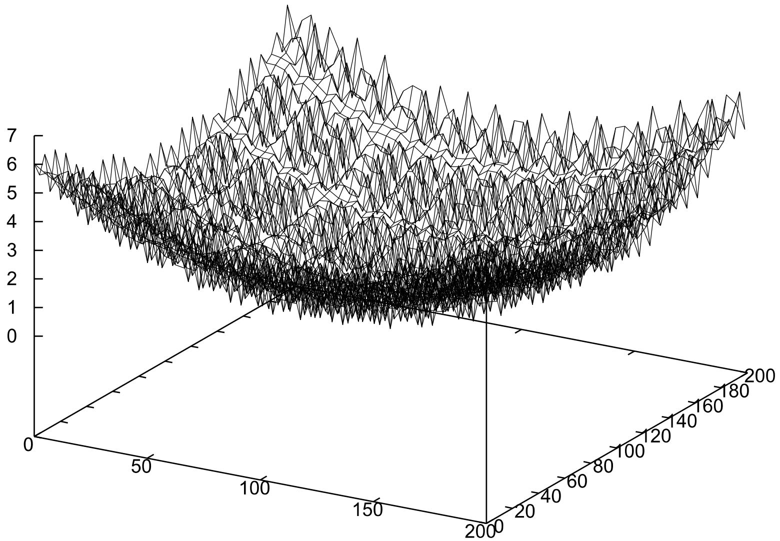
Experiments

- Five numerical benchmark functions
  - **Griewank Function**, Michalewicz Function, **Rosenbrock Function**, Summation Cancellation Function, and **Stair Function**
- Settings:
  - Search space dimension: 5, 25
  - Population size: 1000 individuals
  - Generations: maximal 10000
  - Model count: 1 to 10
  - Cluster count: 1 to 10, with cluster count < model count
  - Selection count: 200, 300, 400, 500, 600

Functions

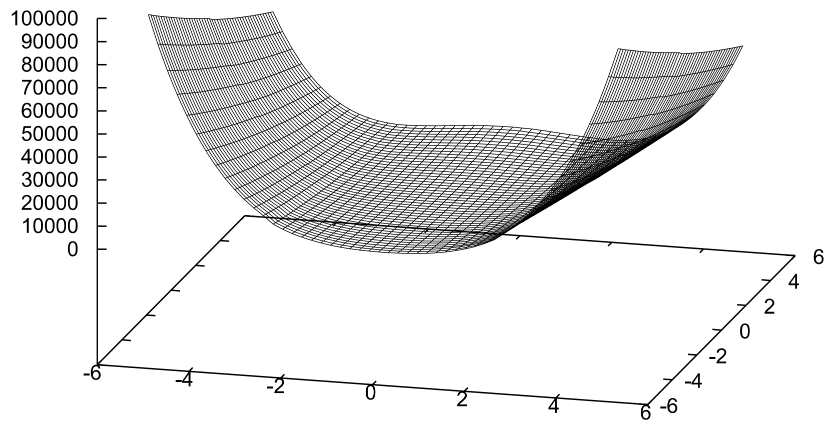
Griewank Function

$$\frac{1}{4000}\sum_{i=0}^{n-1}(x_i-100)^2-\prod_{i=0}^{n-1}\cos\left(\frac{x_i-100}{\sqrt{i+1}}\right)+1$$



Rosenbrock Function

$$\sum_{i=0}^{n-2}100\left(x_{i+1}-x_i^2\right)^2+\left(1-x_i\right)^2$$

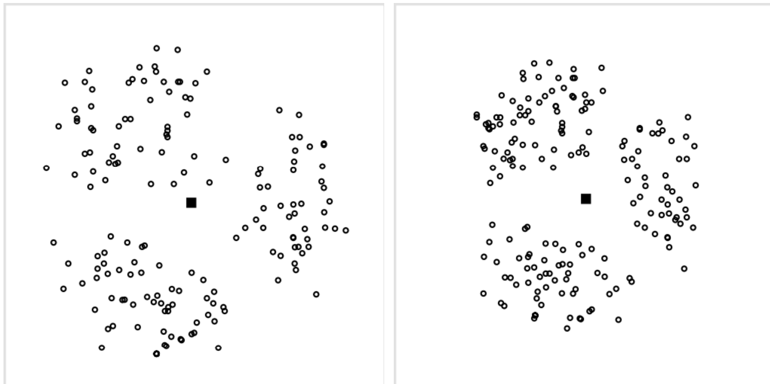


Results Griewank Function

- Regular EDA
  - Finds the optimum in every test run
  - Cloud of points creates a circle around the optimum
  - The cloud becomes smaller in each generation
- Real-Valued Multi-Model EDA
  - The cloud does not become any smaller after some generations
  - Cluster repel each other
  - The algorithm prevents premature convergence in a too high degree

Regular EDA

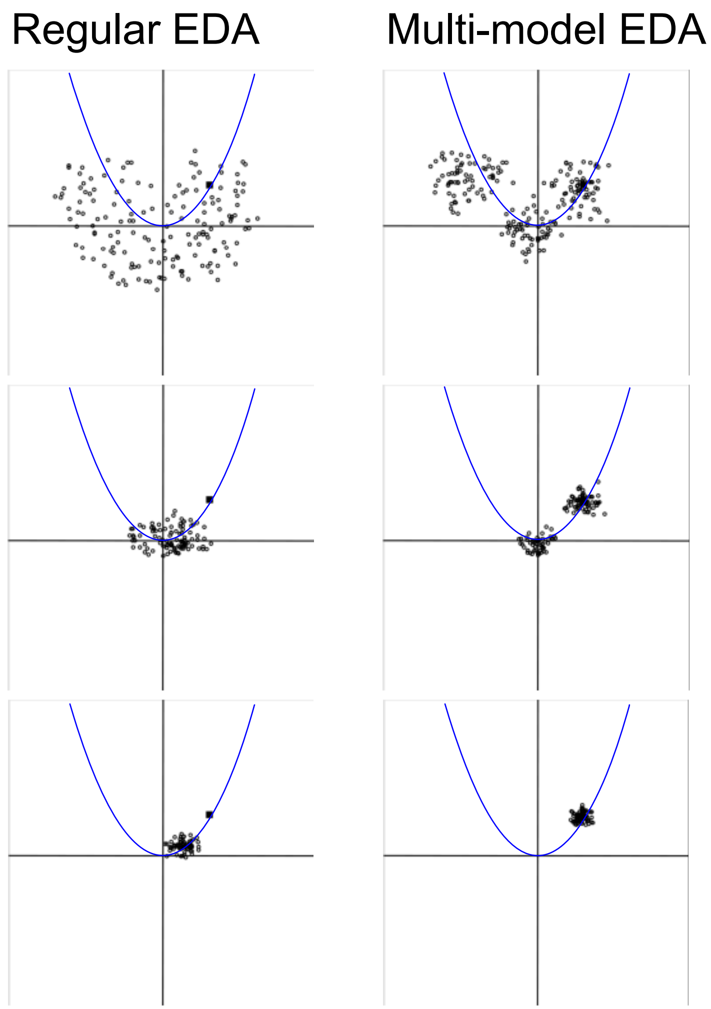
Real-Valued Multi-Model EDA



Results Rosenbrock Function

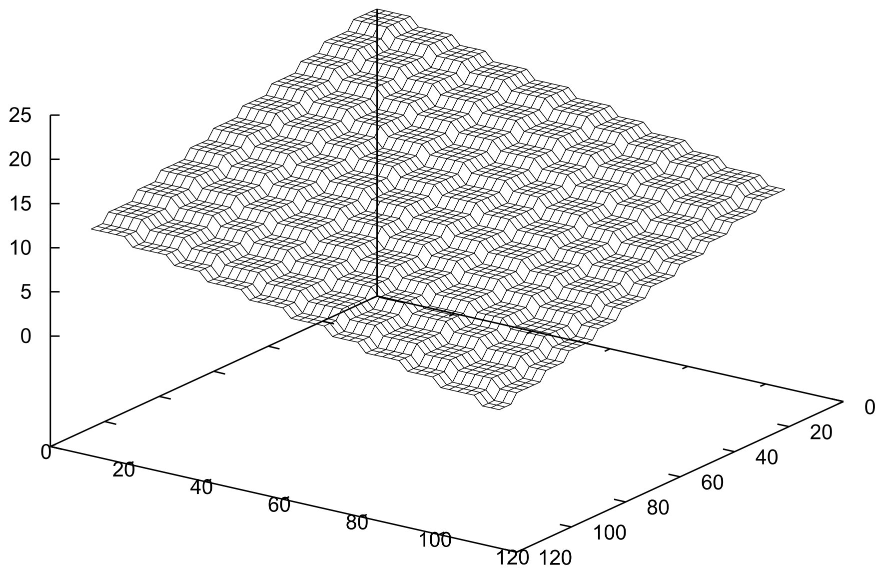
- Regular EDA
  - Quickly finds the small channel
  - Does not explore the channel
  - Converges towards a local optimum

- Real-Valued Multi-Model EDA
  - Explores multiple areas of the search space
  - Finds the area of the gobal optimum
  - Cluster repel each other
  - The cloud does not becomes smaller, the optimum was not found



Results Stair Function

$$\sum_{i=0}^{n-1}\left(10-\frac{round(x_i)}{10}\right)$$



- Regular EDA
  - Does not find the global optimum in a single run
  - High degree of neutrality on each step
  - Does not sample individuals outside of the selected cloud of points
- Real-Valued Multi-Model EDA
  - Easily located the global optimum for the most settings
  - Use the crossover operator to jump onto other stairs

Conclusion

- Multi-model EDA
  - Unites EAs and EDAs
  - Preventing premature convergence by using multiple models in parallel
  - Allows model crossover

- Evaluation with implementation for real-valued problems
  - RVMMEDA prevents premature convergence
  - Simply locates the area of the global optimum
  - Drawback of the repelling: does not finds the optimum

Thank you

Thank you for your interest.

Questions?

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