# Nature-inspired optimization in Dynamic Environments

**- An Introduction -**

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# Motivation

- Many real-world applications are dynamic
  - Scheduling
  - Control problems
  - Vehicle routing
  - Portfolio optimization
  - etc.
  - Also: Co-evolutionary approaches, model-refinement
- Current approaches
  - Ignore dynamics and re-optimize regularly
  - Use very simple control rules
- Large potential when dynamism is addressed explicitly
- Nature-inspired optimization algorithms seem particularly promising, as nature is a continuously changing environment

# Robustness or adaptability

To succeed in a dynamic environment

- Be robust (show good performance in a variety of environments)

1. Adapt (adjust quickly to changed conditions)
   - The problem of convergence
   - Remedies
   - Benchmarks
     (in particular: Moving Peaks)
   - Additional aspects
     - Learning
     - Theory
   - Other metaheuristics
     - Ant Colony Optimization
     - Particle Swarm Optimization

# Nature is able to adapt

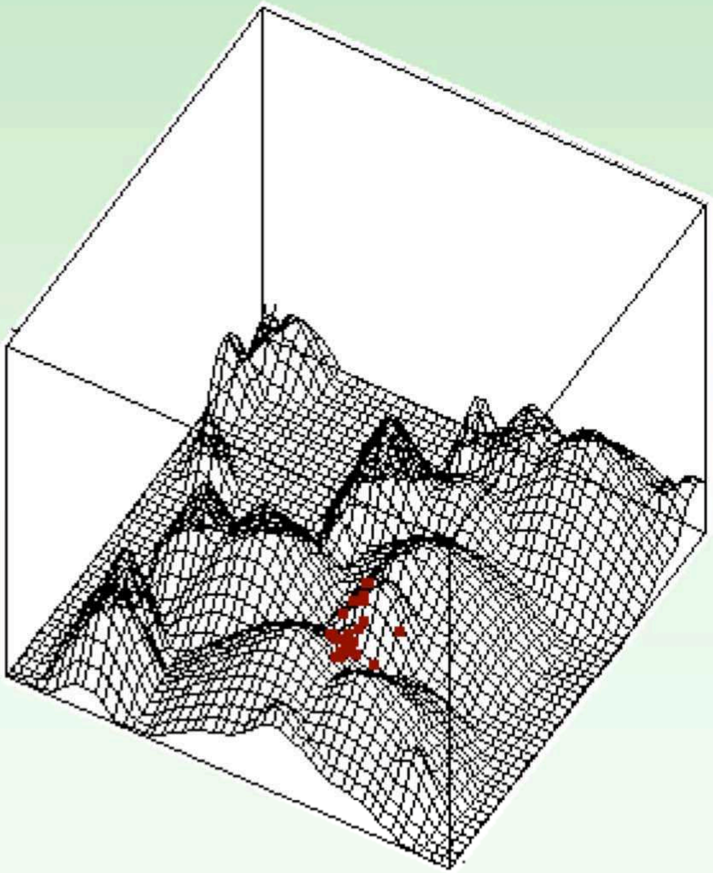
Evolutionary Algorithms

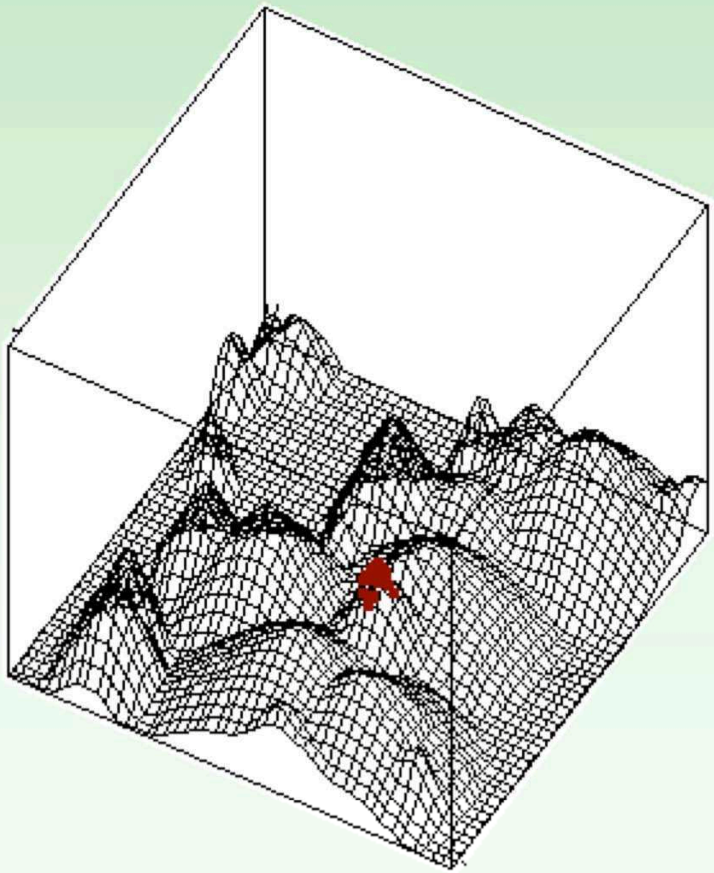
Dynamic Optimization Problems

# The problem of convergence

For static optimization problems, convergence is desired.

If the problem is dynamic, convergence is dangerous.





# Possible Remedies

1. Restart after a change
   (only choice if changes are too severe)

But: Too slow

2. Generate diversity after a change
   – Hypermutation [Cobb 1990]
   – Variable Local Search [Vavak et al. 1997]

But: Randomization destroys information,
   only local search or similar to restart

# Possible Remedies (2)

3. Maintain diversity throughout the run
   – Random Immigrants [Grefenstette 1992]
   – Sharing/Crowding [Andersen 1991, Cedeno & Vemuri 1997]
   – Thermodynamical GA [Mori et al. 1996]
   – Sentinels [Morrison 2004]
   – Diversity as second objective [Bui et al. 2005]

But: Disturbes optimization process

4. Memory-enhanced EAs
   – Implicit memory [Goldberg & Smith 1987, Ng & Wong1995, Lewis et al. 1998]
     • Redundant genetic representation (e.g. diploid)
     • EA is free to use additional memory
   – Explicit memory [Ramsey & Grefenstette 1993, Trojanowski et al. 1997, Mori et al. 1997, Branke 1999, Yang 2005]
     • Explicit rules which information to store in and retrieve from the memory

But: Only useful when optimum reappears at old location,
Problem of convergence remains

# Possible Remedies (3)

5. Multi-Population approaches
   – Maintain different subpopulations on different peaks
     - adaptive memory
     - able to detect new optima
     - distance/similarity metric required
   – Self-Organizing Scouts [Branke et al. 2000, Branke 2001]
   – Multi-National EA [Ursem 2000]

Maintains useful diversity

6. Anticipation & Prediction

-> see next talk

# Thermodynamical GA [Mori et al. 1996]

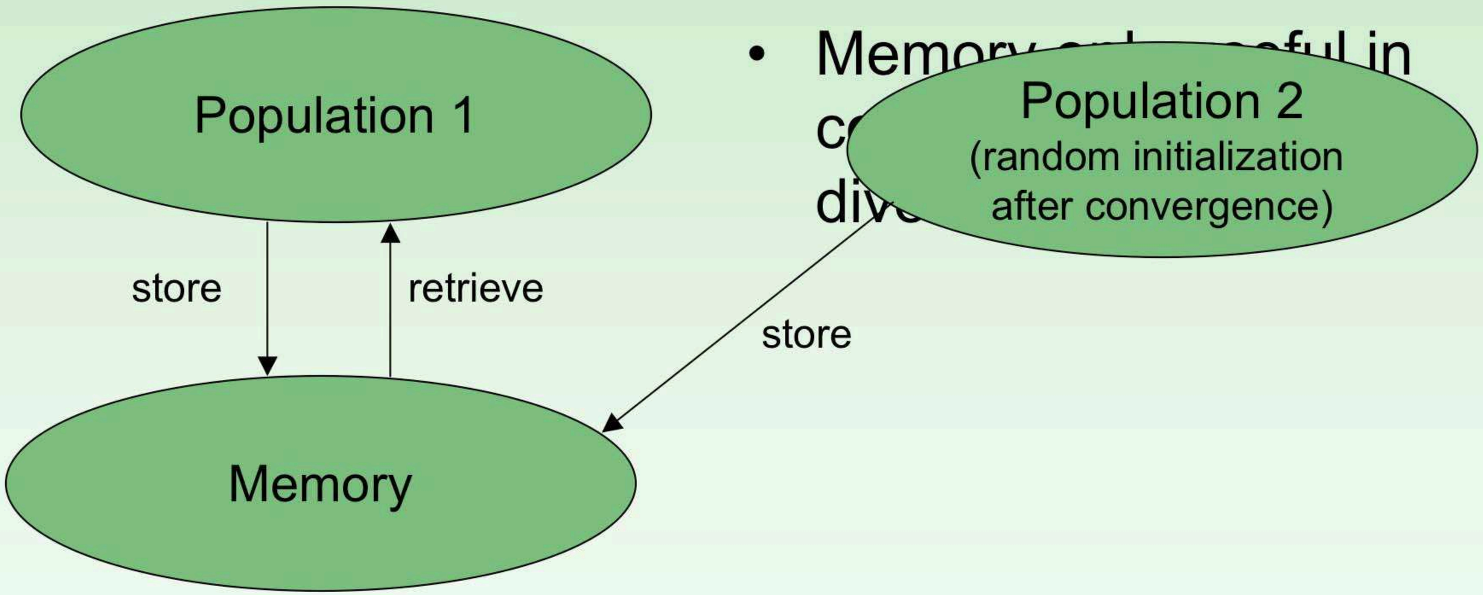
- Select next parent generation such that they are a good compromise between quality and diversity
- Select parents one by one such that the resulting (incomplete) parent generation minimizes

$$\min \underbrace{F}_{\text{free energy}} = \underbrace{\langle E \rangle}_{\text{average population fitness}} - T\underbrace{H}_{\text{diversity}}$$

- Requires to tune parameter T
- Computationally expensive

# Memory/Search-Approach [Branke 1999]

- Explicit memorization of individuals
- Keep the better of the two most similar
- Memory ful in c dive




⇨ Sensible balance of exploration vs. exploitation

# Self Organizing Scouts (SOS) [Branke 2001]

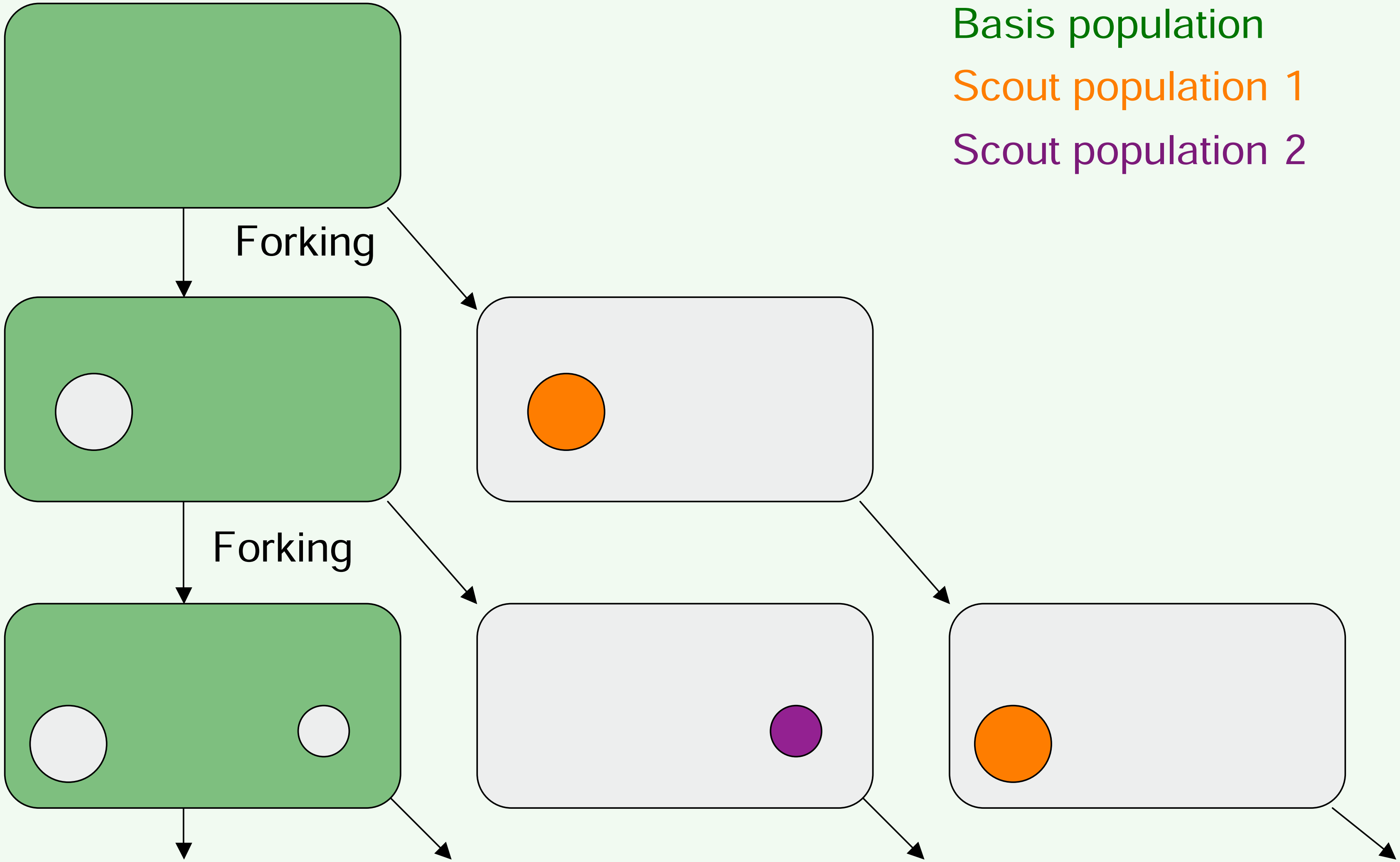
- Idea: Collect information about search space
- Whenever a local optimum has been found
  ⇨ watch it with some scouts
- Base population should search for new peak
- Scouts should be able to track "their" peak

# How does it work, really?

- When a cluster is detected in basis population
  ⇒ Forking

# Forking [Tsutsui et al. 1997]

Basis population
Scout population 1
Scout population 2



# How does it work, really?

- When a cluster is detected in basis population
  ⟹ Forking
- Invalid individuals are replaced by random individuals
  ⟹ Diversification
- Best individual defines center ⟹ Tracking
- Number of individuals in scout population depends on quality and trend ⟹ Efficiency
- Size of the scout population's search space
  - Shrinks continuously
  - Is increased when two scout populations merge

  ⟹ Adaptation

# Typical benchmark problems

- Moving Peaks Benchmark [Branke 1999, Morrison & DeJong 1999]
- XOR problem generator [Yang & Yao, 2005]
- Dynamic knapsack problem, e.g. [Mori et al. 1996, Branke et al. 2005]
- Dynamic bit-matching, e.g. [Stanhope & Daida 1999, Droste 2003]
- Scheduling with new jobs arriving over time, e.g. [Mattfeld & Bierwirth 2004]
- Greenhouse control problem [Ursem et al. 2002]

# XOR benchmark generator [Yang & Yao 2005]

- For any problem/algorithm with bitstring representation
- Idea: before evaluation, XOR individual with mask

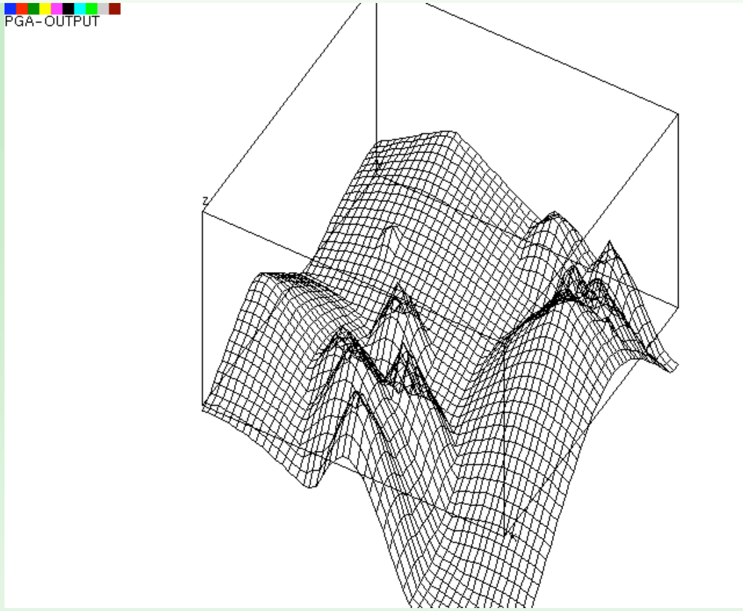
$$
\begin{array}{lr}
\text{Individual:} & 0110100 \\
\otimes\ \text{Mask:} & 1101001 \\
\hline
\text{Evaluate:} & 1011101
\end{array}
$$

- Inverts each bit where mask is "1"
- Dynamics: modify m bits in mask
- Change severity = m
- Landscape characteristics remain the same

# Moving peaks benchmark [Branke 1999]

available at http://www.aifb.uni-karlsruhe.de/~jbr/MovPeaks

- Multi-modal environment characterised by moving peaks of varying widths and heights
- Small continuous changes in f can lead to discontinuous changes in $x_{opt}$
- Parameters:
  – Change frequency
  – Number of peaks
  – Severity (length of shift vector, height and width)
  – Correlation of shifts
  – Number of dimensions
  – Shape of the peaks



# Performance Measure: Offline Error

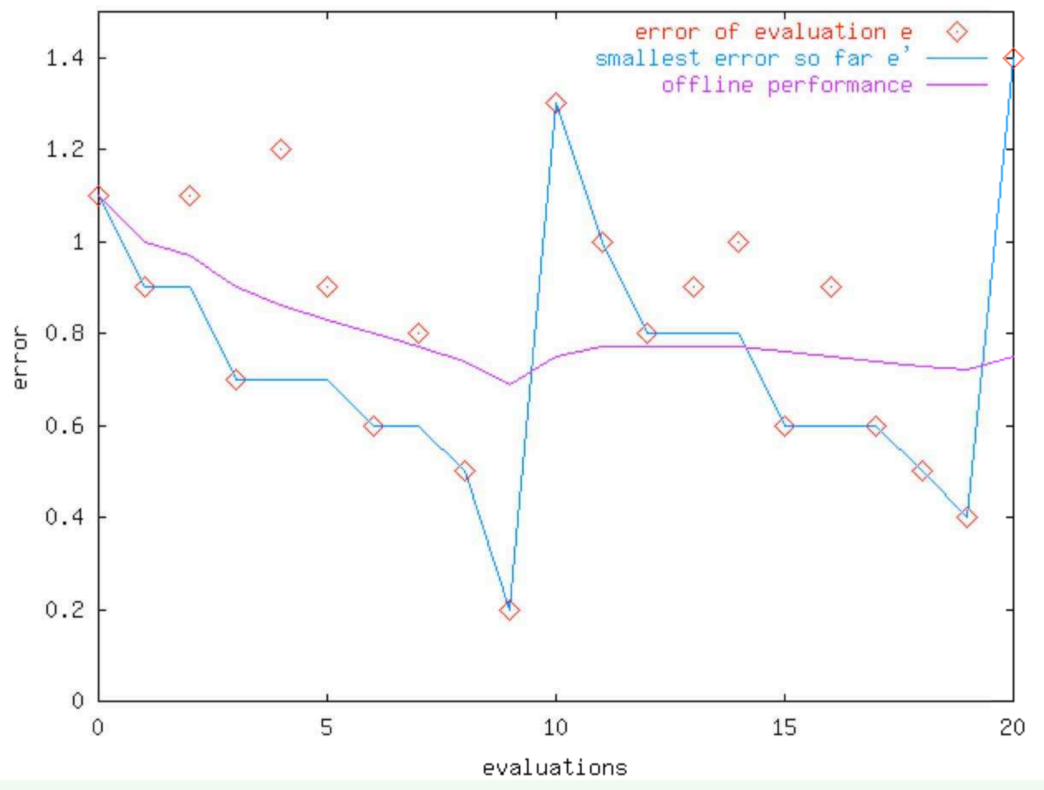
Difficulty: best solution found is not sufficient

⇨ Use modified offline error $\varepsilon^*(T)$

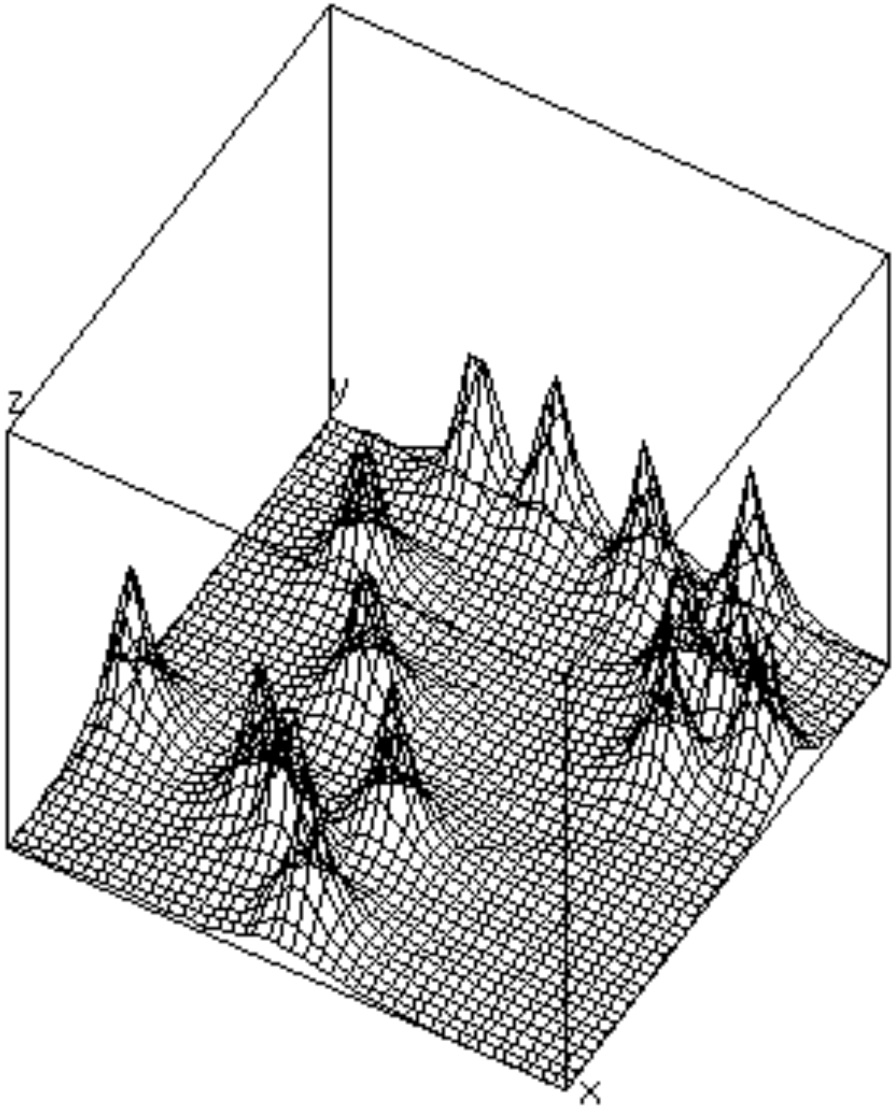
$$\varepsilon^*(T) = \frac{1}{T}\sum_{t=1}^{T}(opt_t - e_t')$$

$$e_t' = \max(e_\tau, e_{\tau+1}, \ldots, e_t)$$

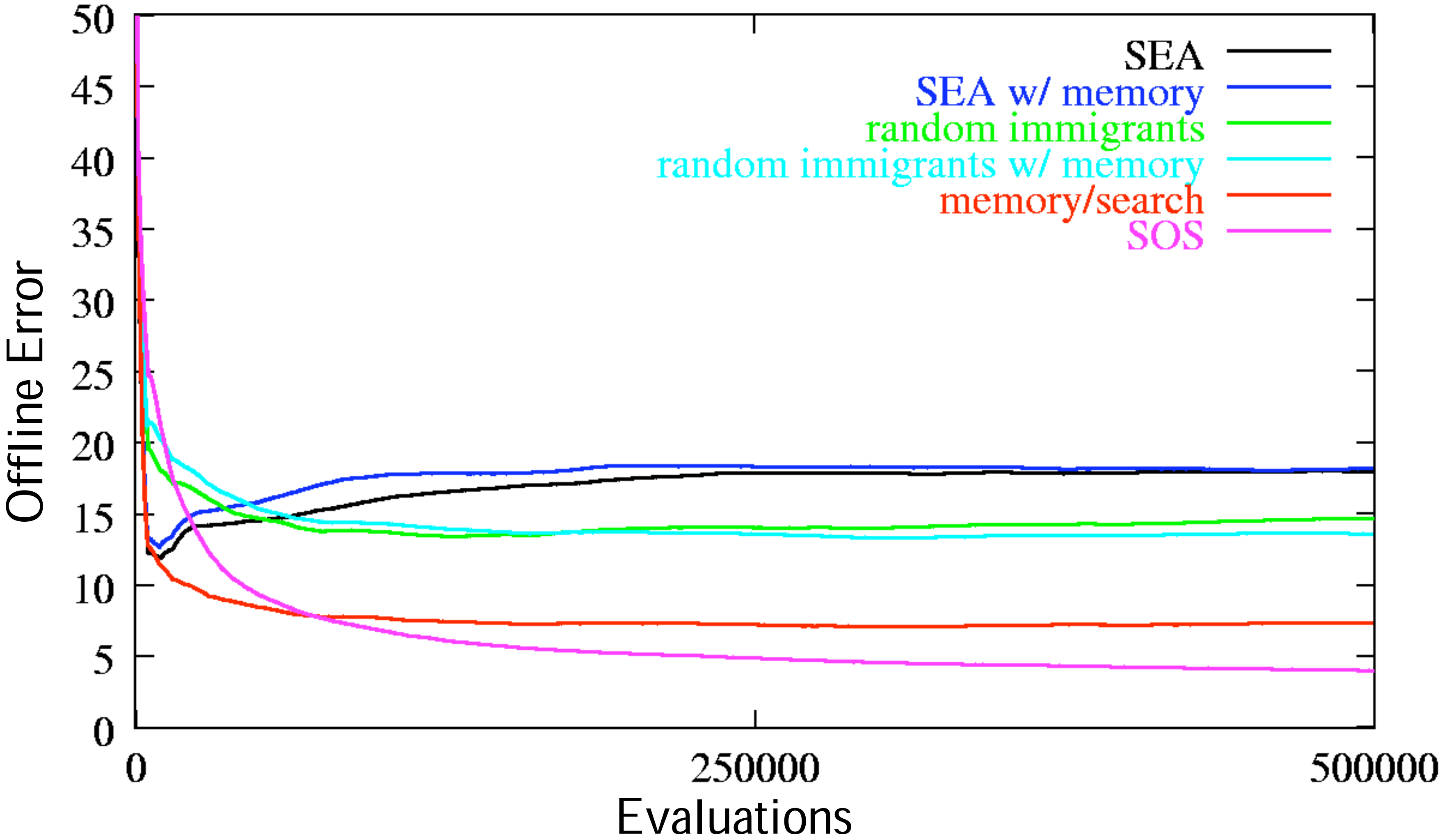
$\tau$ : time of last change



# Demo: Self-Organizing Scouts

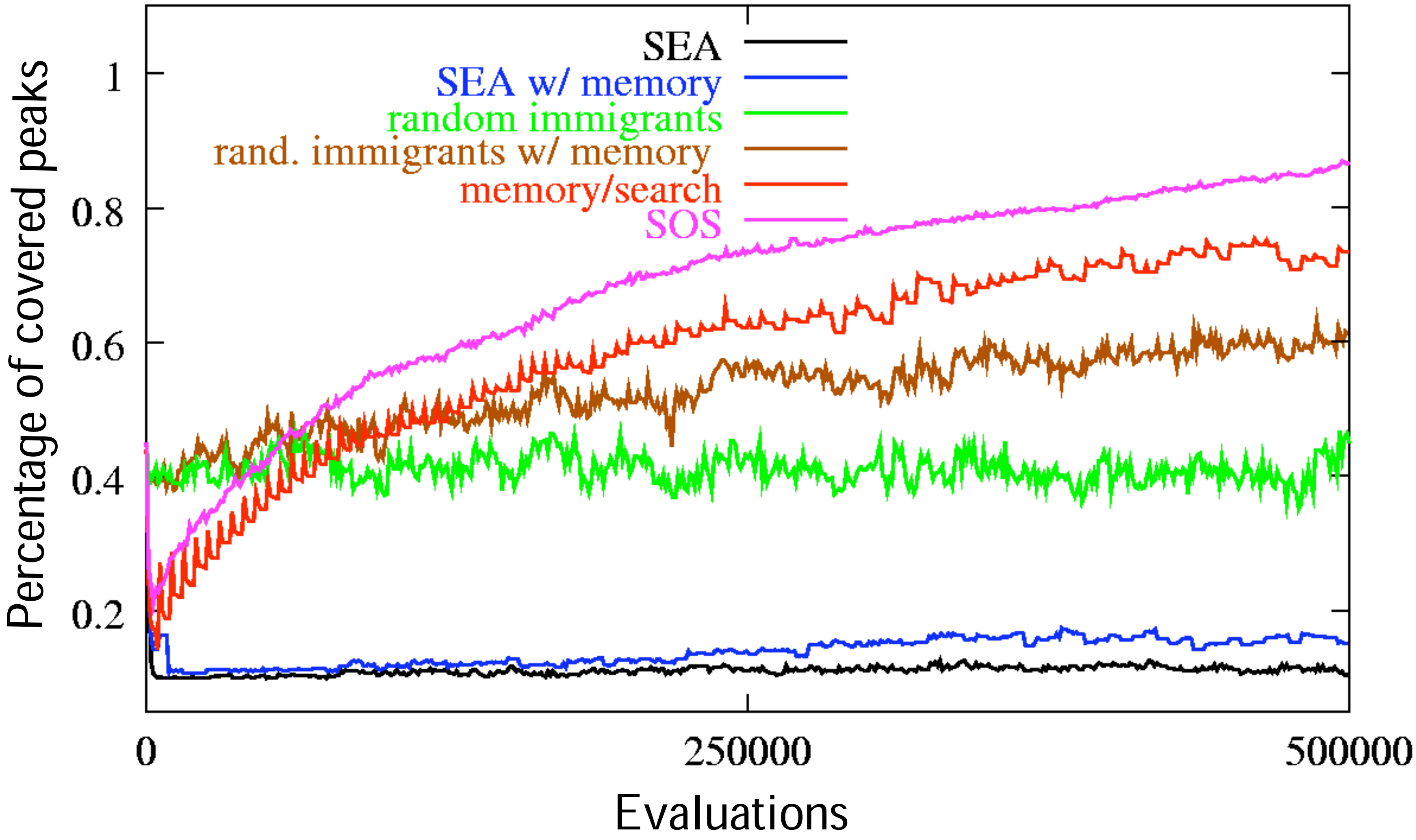


# Comparison of offline error



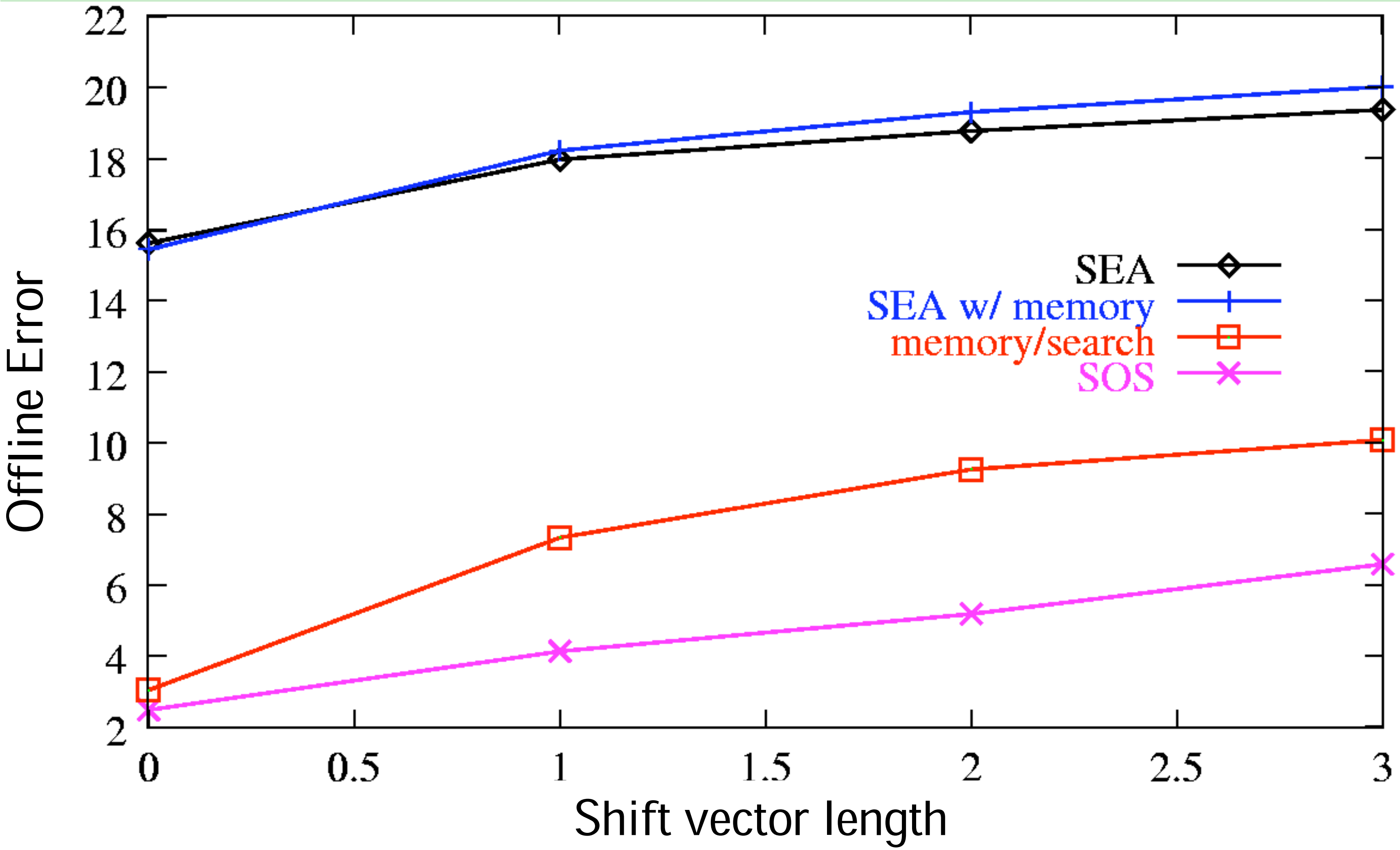

(Population size 100, 10 peaks, step size 1.0)

# Percentage of covered peaks




(Population size 100, 10 peaks, step size 2.0)

# Influence of step size




(After 5000 generations, 10 peaks)

# Summary of Observations

- Standard EA gets stuck on single peak
- Diversity preservation slows down convergence
- Random immigrants introduce high diversity from the beginning, but benefit is limited
- Memory without diversity preservation is counterproductive
- Non-adaptive memory suffers significantly if peaks move
- Self-organizing scouts performs best

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# *Questions*

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