

### Overview

Optimization in multi-modal search spaces

A study of attraction basins

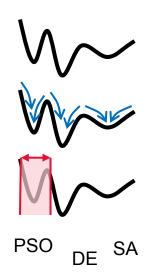
An introduction to thresheld convergence

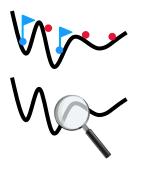
Applications of thresheld convergence

An introduction to leaders and followers

Conclusions about search in multi-modal spaces

Current and future work

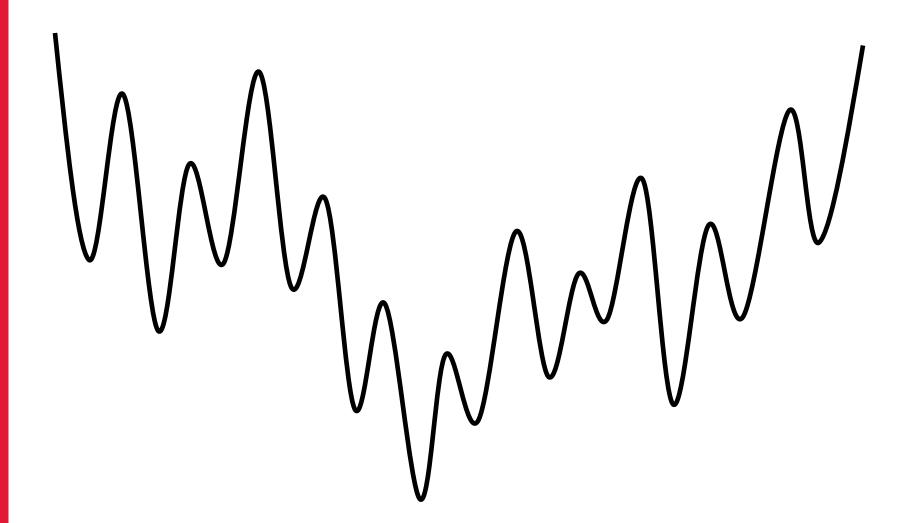






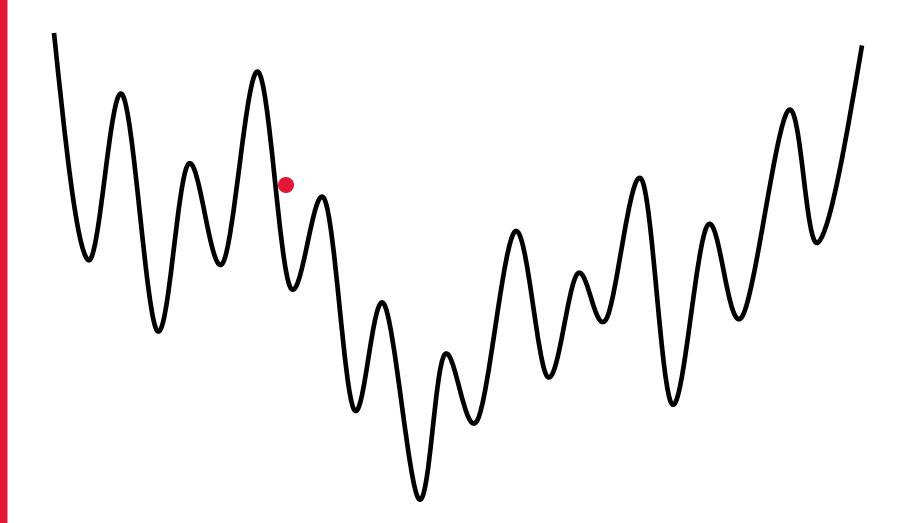


## Optimization in Multi-Modal Search Spaces



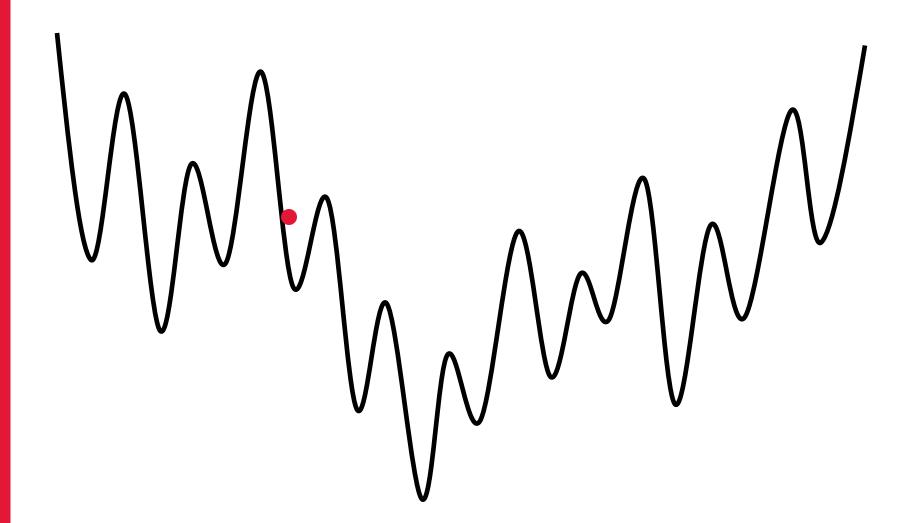






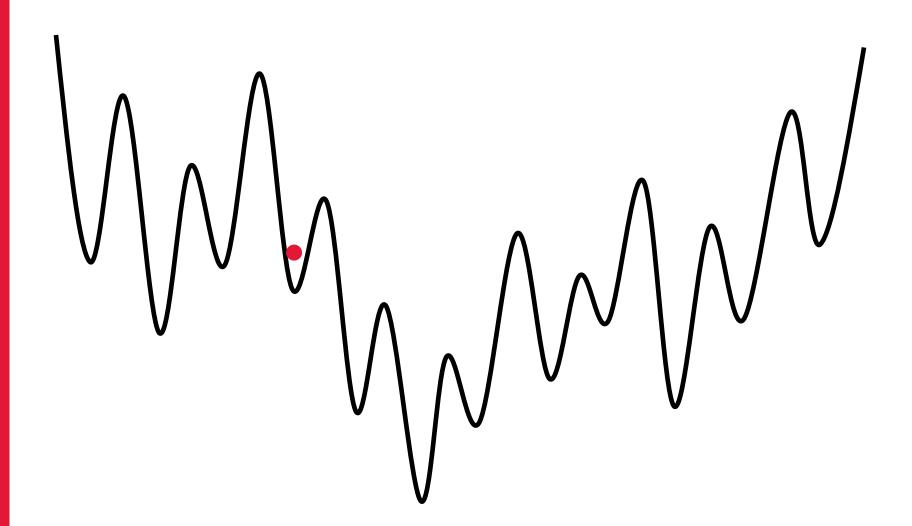






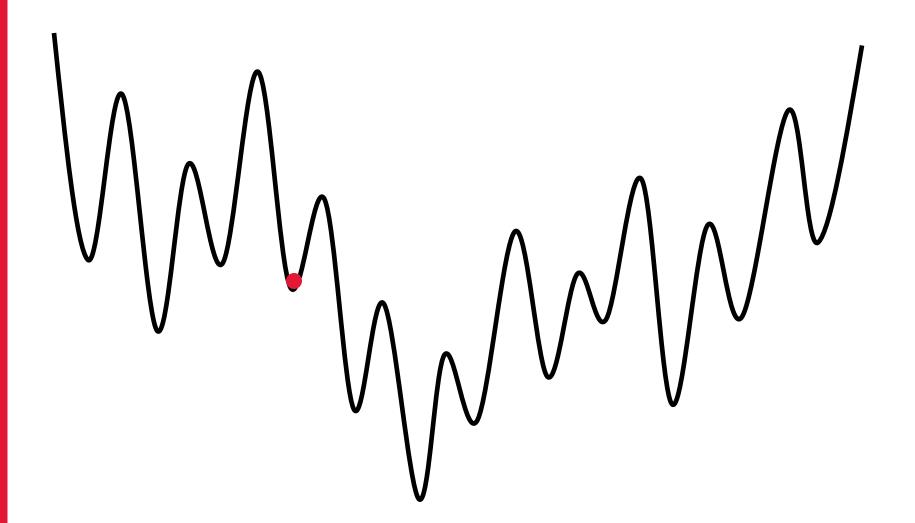






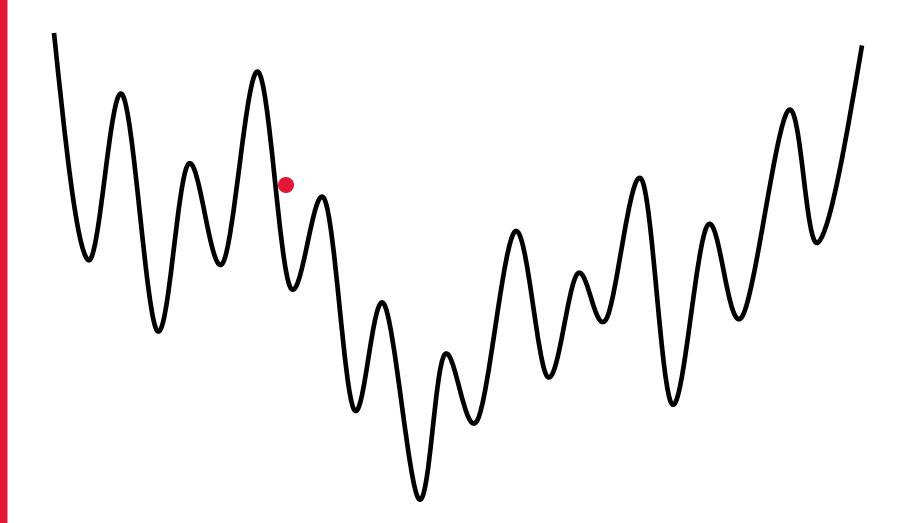






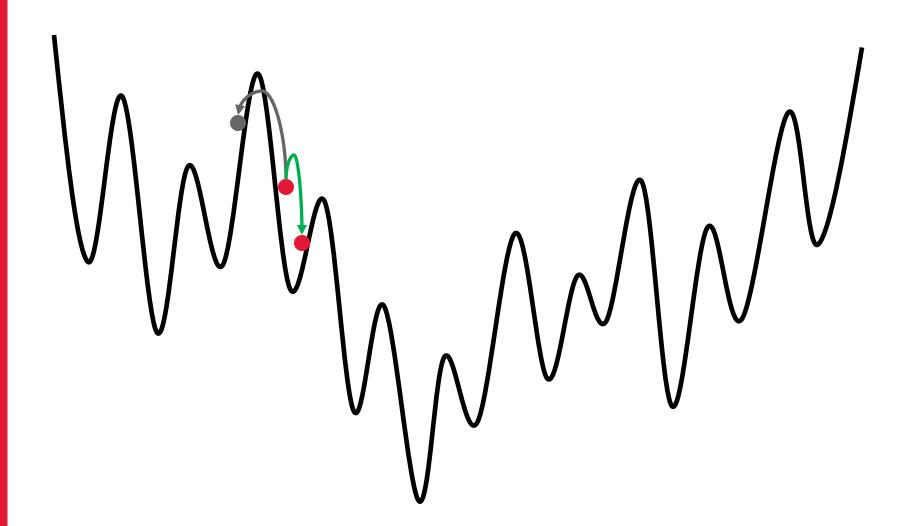






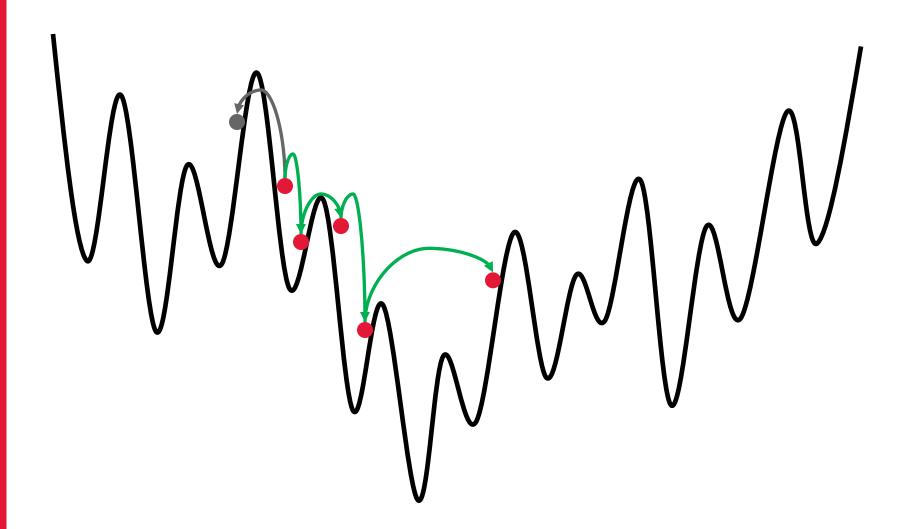






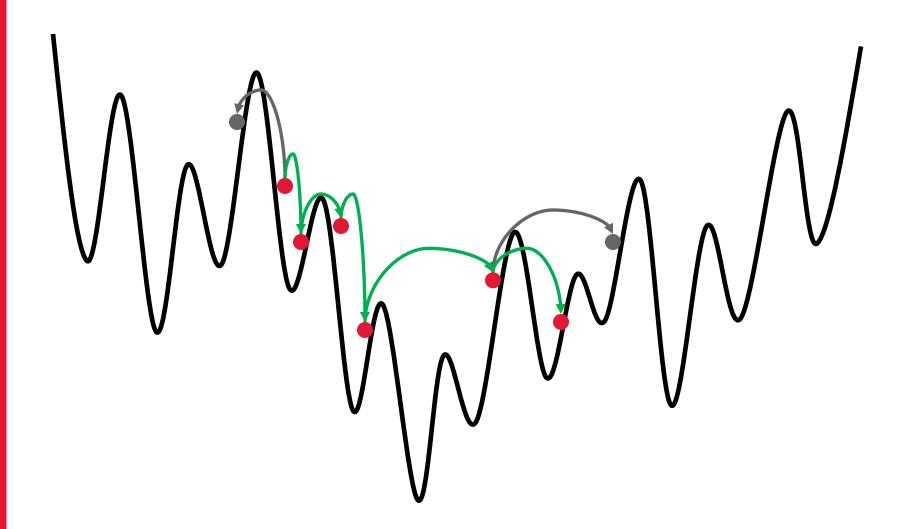
















### **Escape from Local Optima**

- The definition of fitness landscapes, multi-modality, and local optima is often based on Hill Climbing/Descent
- This perspective leads to the mindset of needing to escape local optima
- Key example: Simulated Annealing
- Are other perspectives possible?





### Rethinking Multi-Modal Optimization

- Stop thinking about local optima
  - Escaping from local optima
  - Finding multiple local optima
- Start thinking about attraction basins
  - Exploration → search among different attraction basins
  - Exploitation → search within the same attraction basin
- Distinct two-phase process
  - Find the fittest attraction basin
  - Find its local optimum





### Two Phase Process for Metaheuristics

### Phase 1 – Exploration

- Find the fittest attraction basin
  - (Not necessarily the fittest search point)

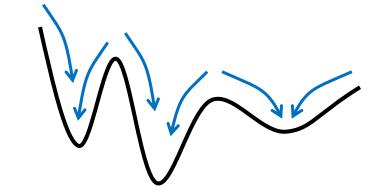
### Phase 2 – Exploitation

Stay within the fittest attraction basin (no further exploration)









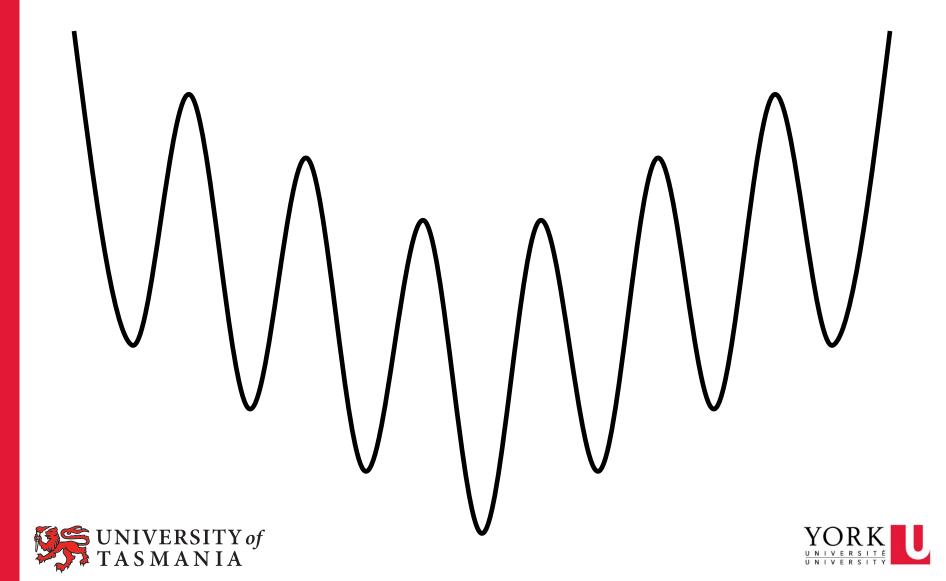


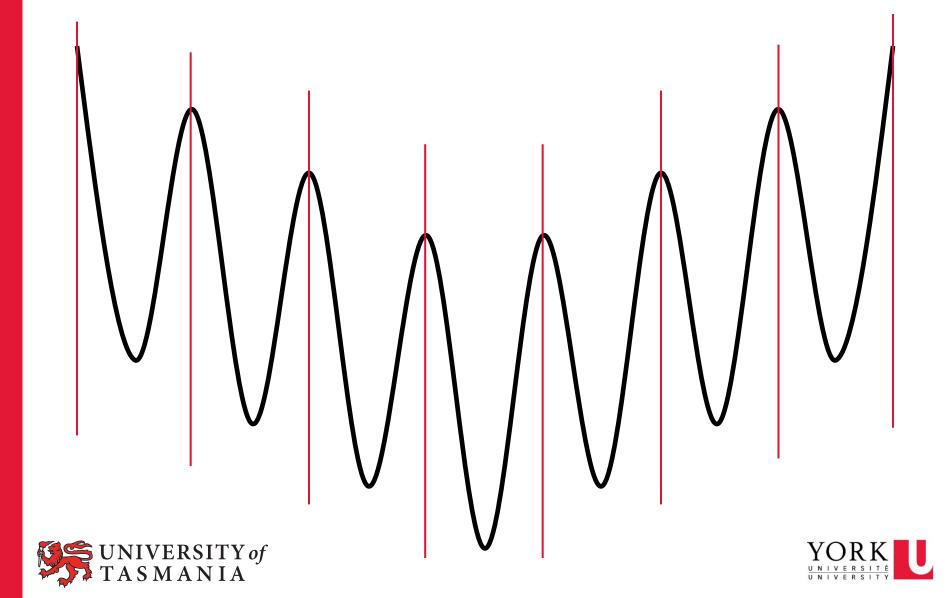
### **Definitions**

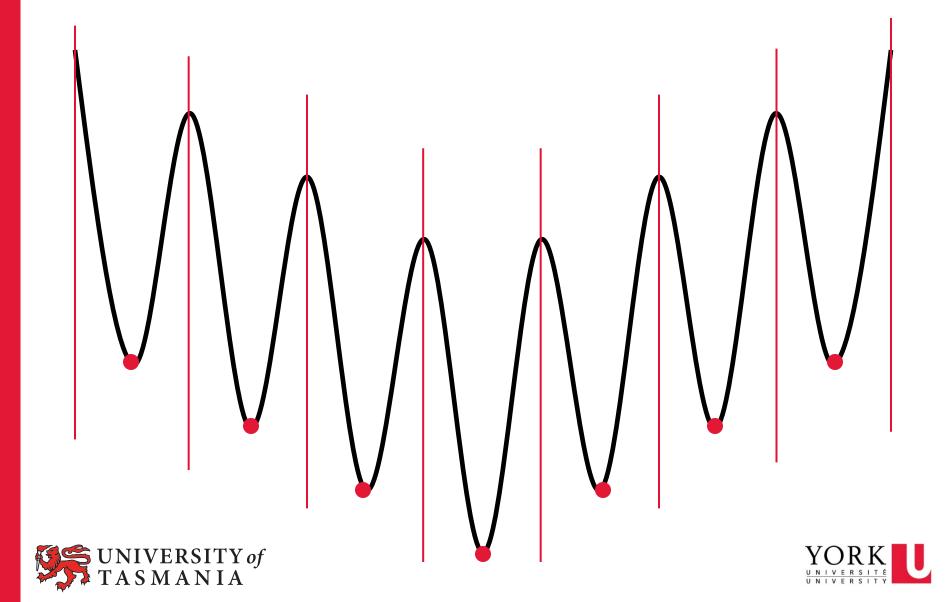
- An attraction basin is all of the points around a local optimum that lead to that optimum when greedy local search is used
- The fitness of the an attraction basin is the fitness of its local optimum











### A Two-Phase Search Process

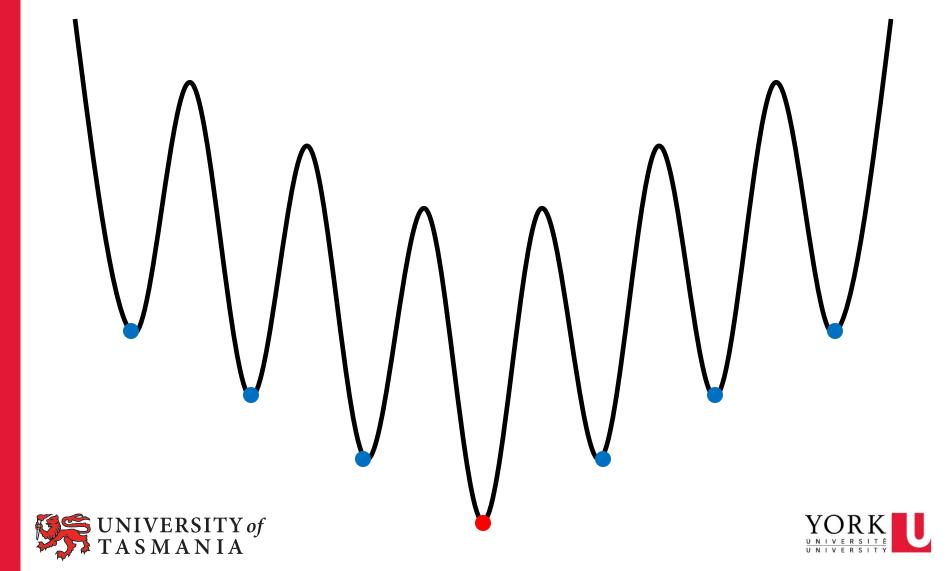
The global optimum is the local optimum in the fittest attraction basin

- 1. Find the fittest attraction basin (exploration)
- Find the local optimum in this attraction basin (exploitation)

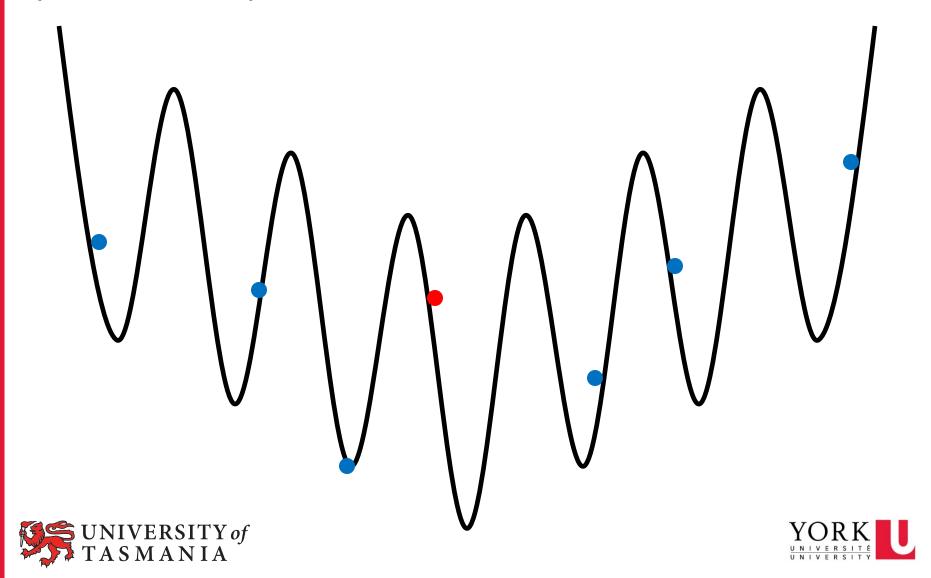




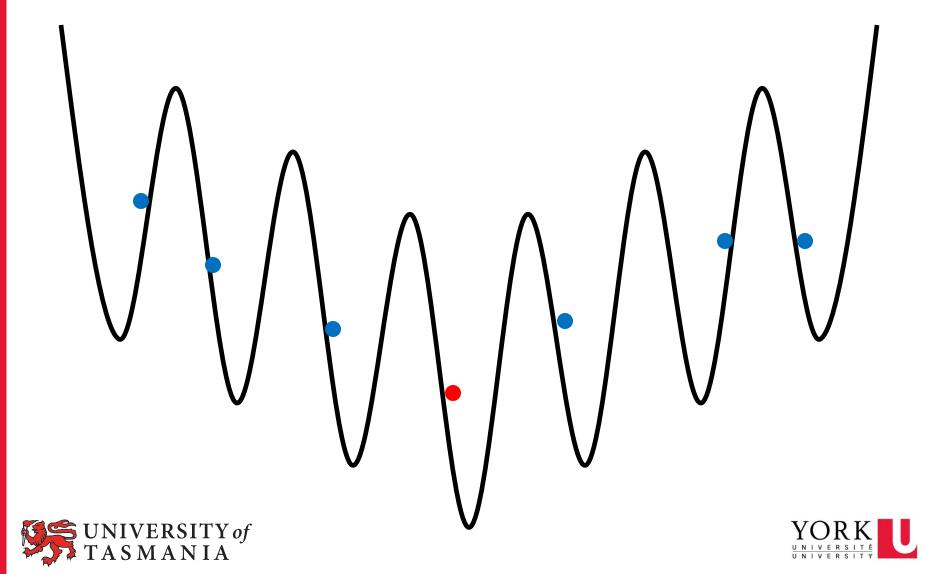
# Finding the Fittest Attraction Basin (Trivial Case)



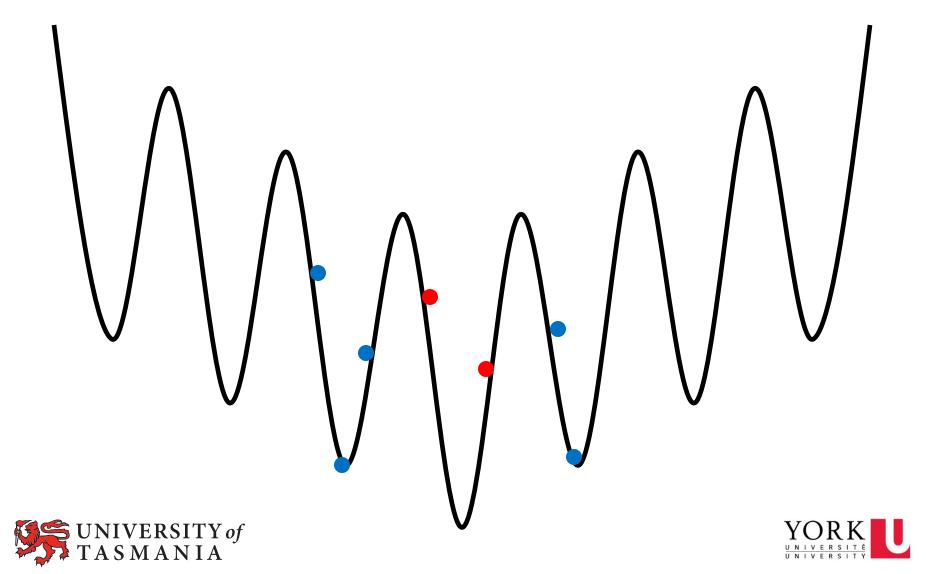
# Finding the Fittest Attraction Basin (Hard Case)



# Finding the Fittest Attraction Basin (Typical Case – Early)



# Finding the Fittest Attraction Basin (Typical Case – Late)



### Attraction basins of known size, shape, and location

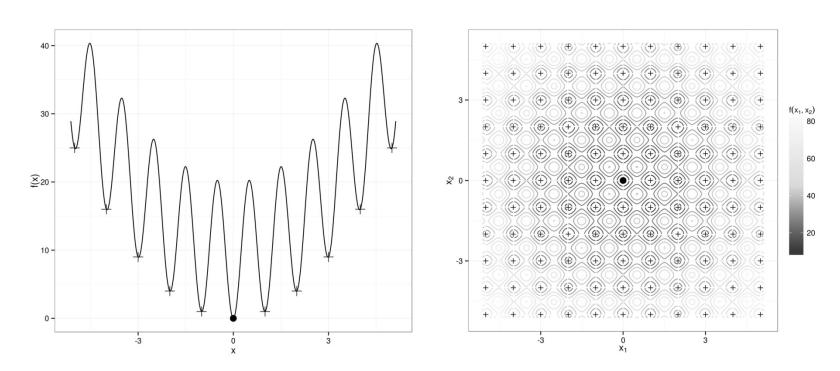


Image from Y. Gonzalez-Fernandez and S. Chen, "Leaders and Followers – A New Metaheuristic to Avoid the Bias of Accumulated Information", IEEE CEC, 2015.





- Focus on exploration
  - The ability to identify the fitter attraction basin based on the fitness of random sample solutions
- Demonstrate the negative effects of concurrent exploration and exploitation
  - Comparing only random solutions is the Easy Case
  - Comparing random solutions against a local optimum is the Hard Case





#### Success of exploration goes down with exploitation

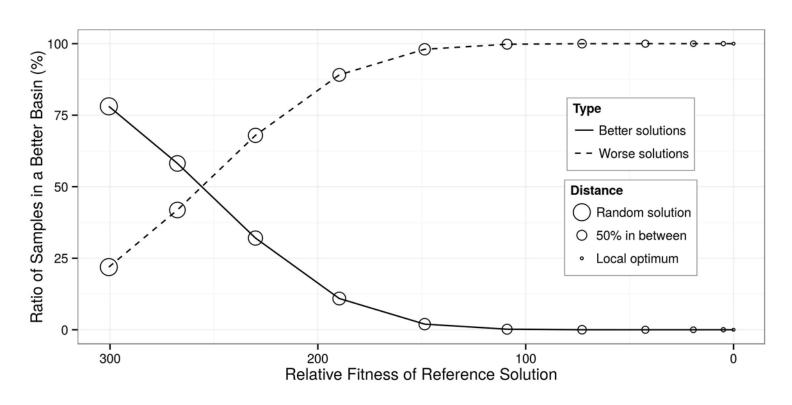
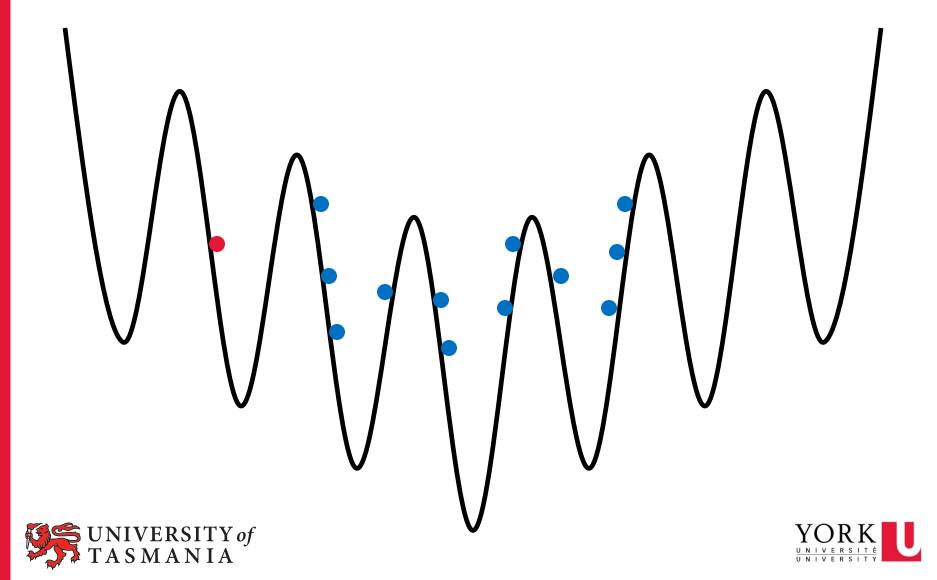


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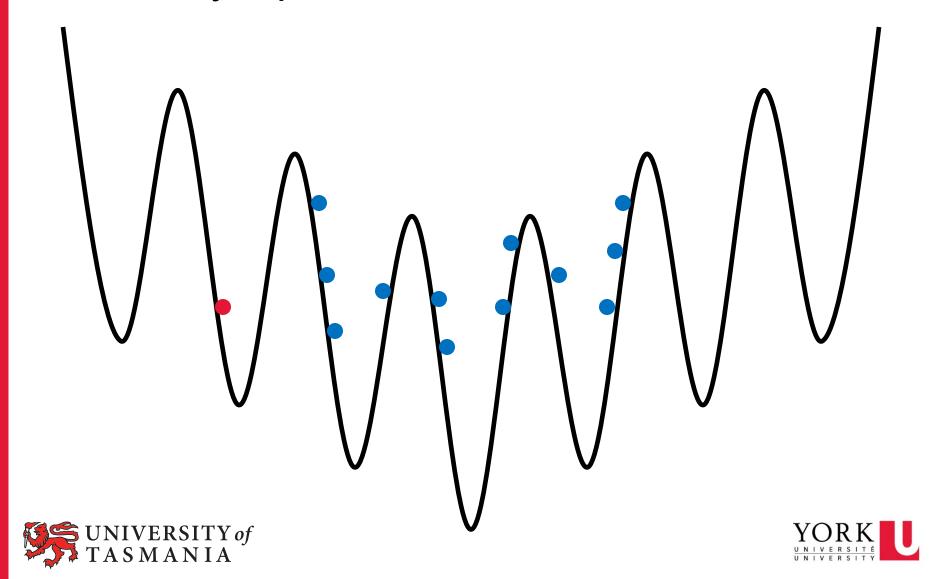




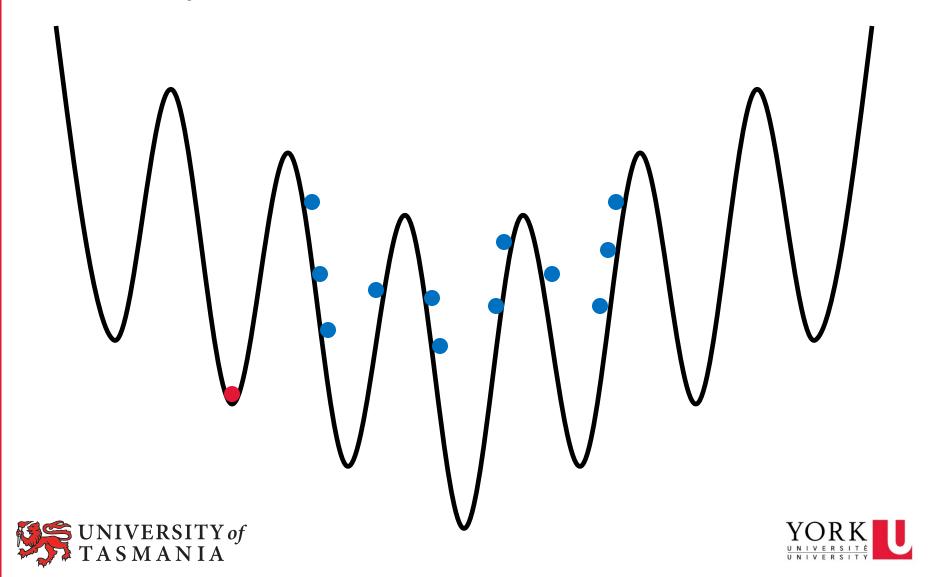
- Initial Random Solution



- Partially Optimized Solution



- Locally Optimal Solution



#### 50% optimization makes exploration almost impossible

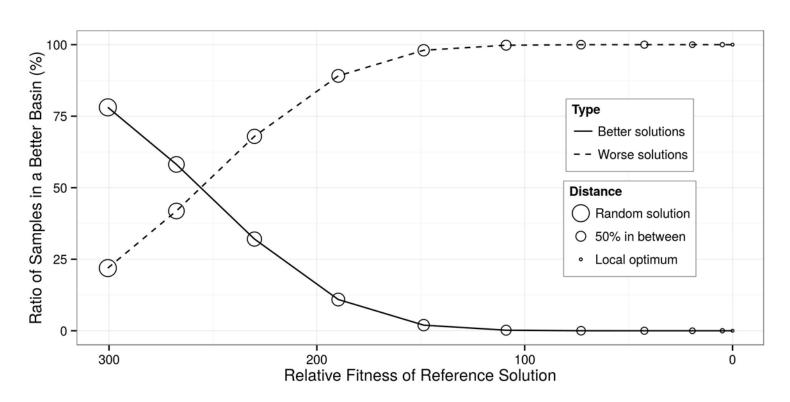


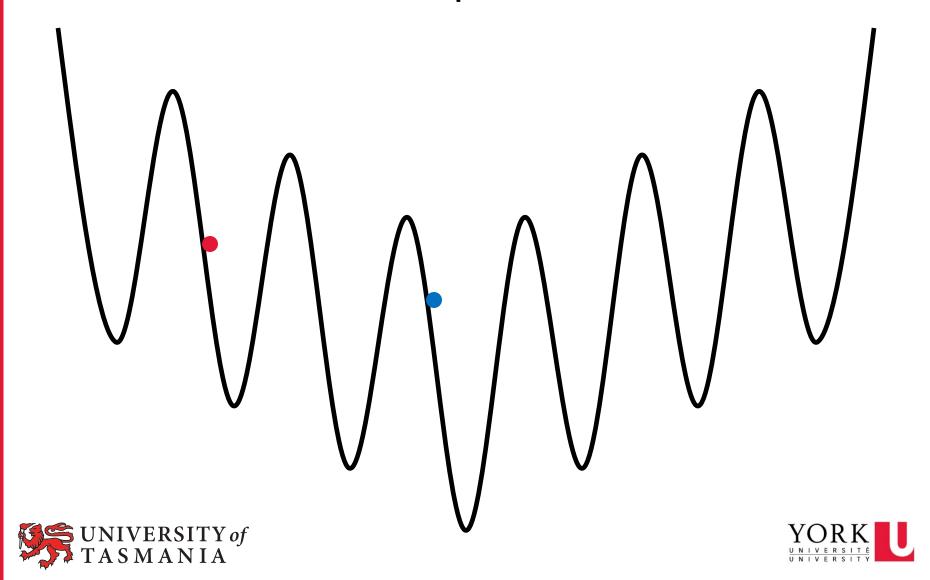
Image from Y. Gonzalez-Fernandez and S. Chen, "Leaders and Followers – A New Metaheuristic to Avoid the Bias of Accumulated Information", IEEE CEC, 2015.





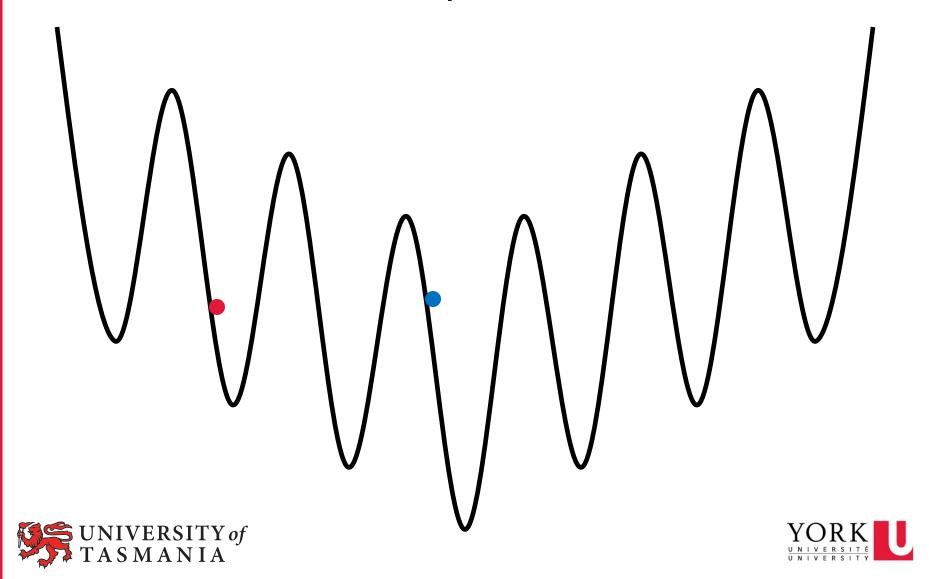
### Concurrent Exploration and Exploitation

- From Successful Exploration



### Concurrent Exploration and Exploitation

- To Unsuccessful Exploration



### PSO and DE perform local optimization very early

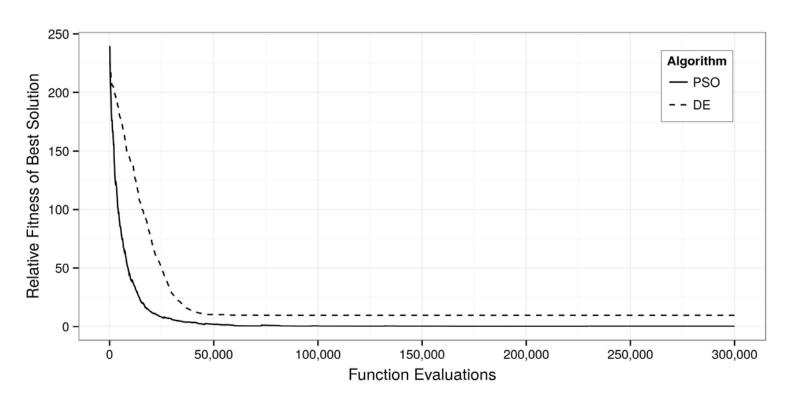


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#### PSO and DE stall quickly – no more exploration

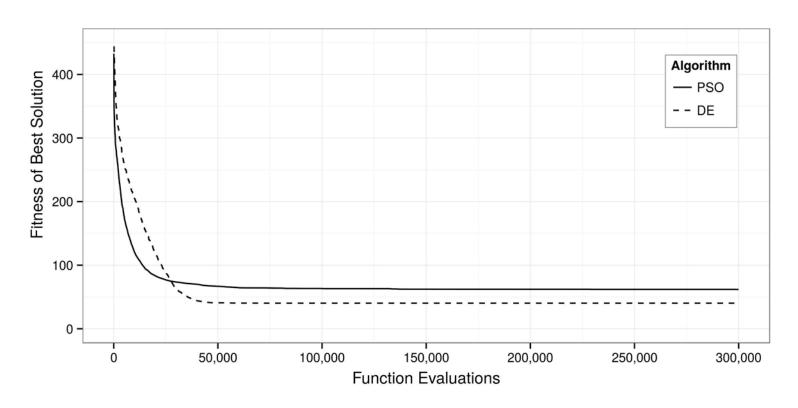


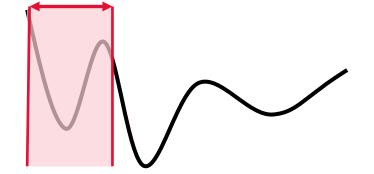
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## Thresheld Convergence

#### an introduction







## Optimization in Multi-Modal Search Spaces

#### Phase 1: Find the fittest attraction basin

- Concurrent exploration and exploitation interferes with exploration
- Eliminate exploitation during this phase

### Thresheld convergence

- Convergence is "held" back by a threshold function
- Small, exploitative moves which are smaller than the threshold value are disallowed
- Create an initial phase of pure exploration





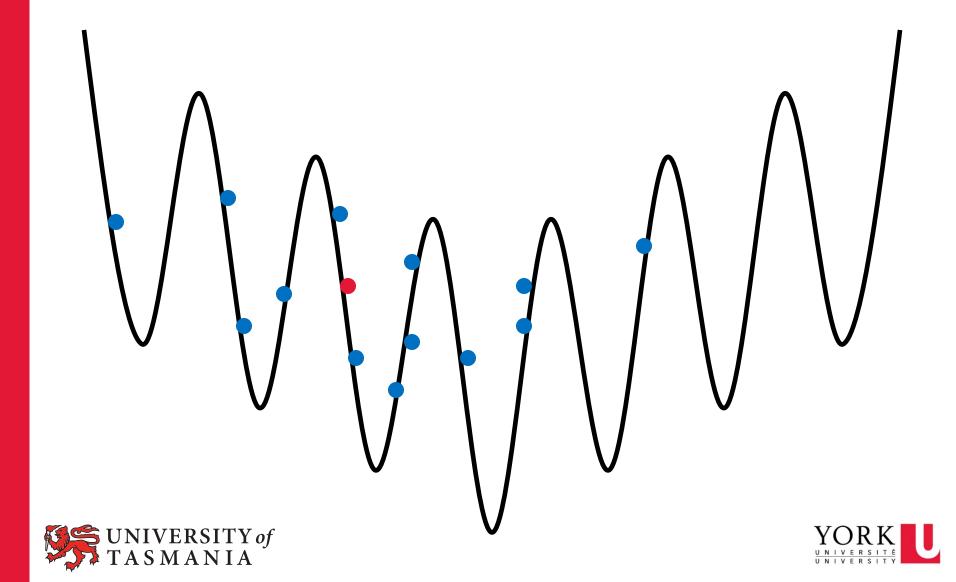
## Working Definitions

- A new search point in a new attraction basin is exploration
- A new search point in the same attraction basin is exploitation
- The first search point in a new attraction basin is likely to have a random/average fitness
- Exploitation within an existing attraction basin leads to solutions of better-than-random/above-average fitness

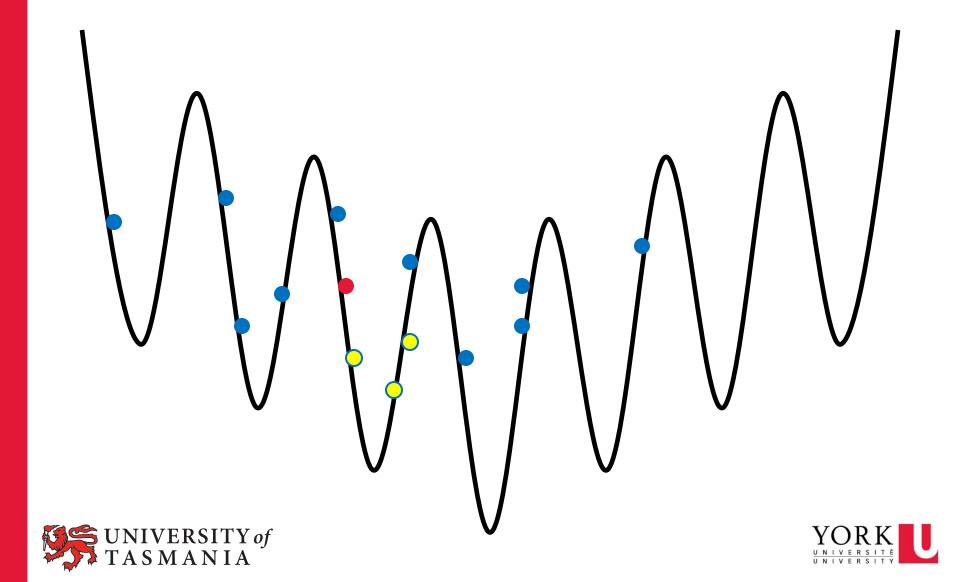




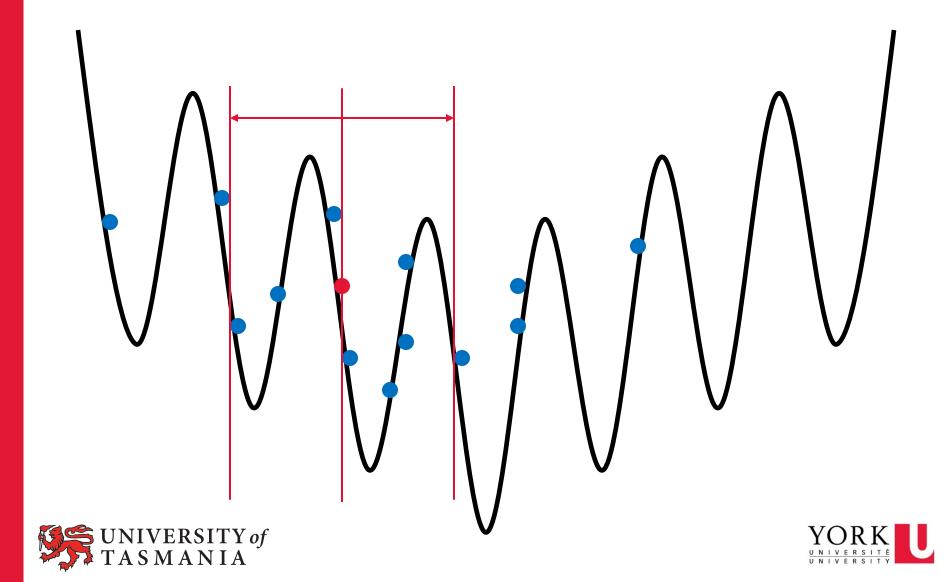
## Normal Search – No Minimum Step



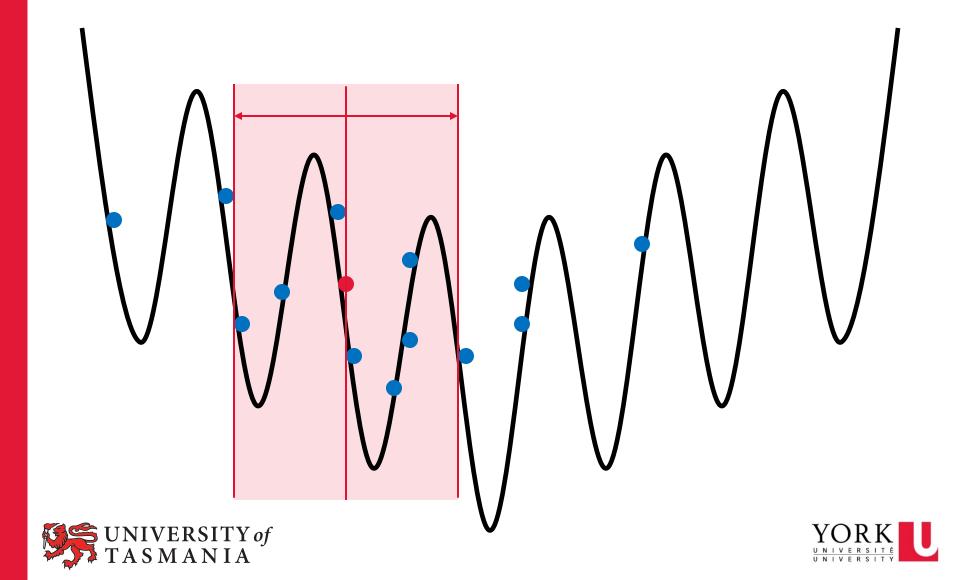
## Normal Search – Exploitation Possible



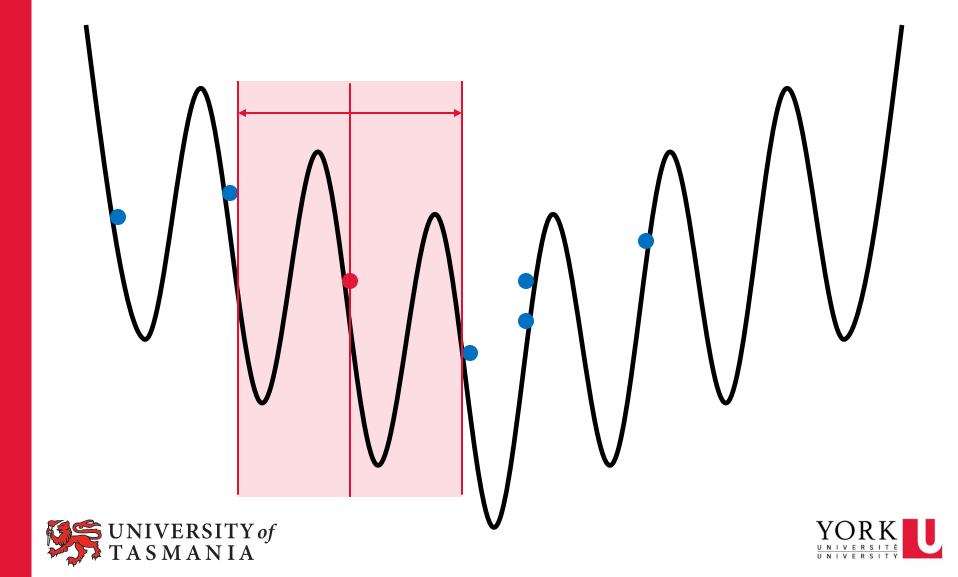
## Thresheld Convergence – Minimum Step



## Thresheld Convergence – No Exploitation



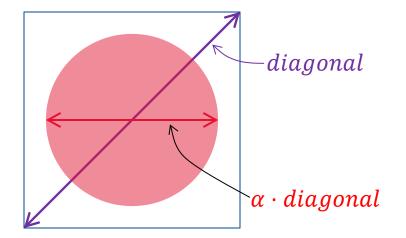
## Thresheld Convergence – Exploration Only



## A Simple Threshold Function

- Early applications used a polynomial decay function
- In effect, this is exhaustive search to find the size of attraction basins

$$threshold = (\alpha \cdot diagonal) \cdot \left(\frac{FEs - i}{FEs}\right)^{\gamma}$$







## Applications of Thresheld Convergence

PSO, DE, and SA





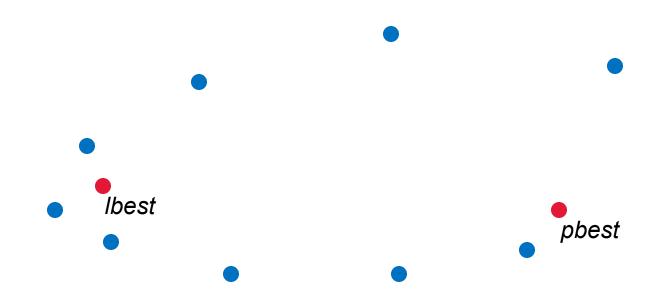
Original update

```
if f(x) < f(pbest)
  pbest = x;
end if</pre>
```

New update

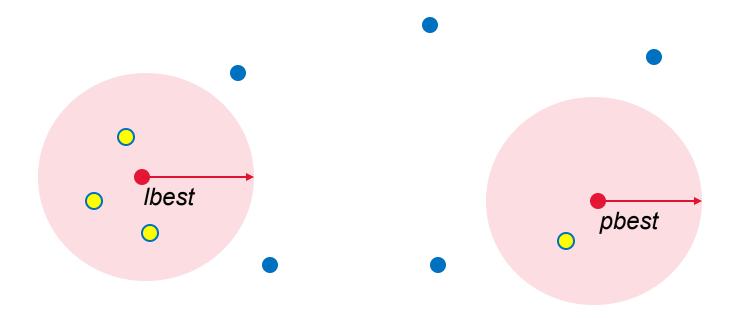
















- Eliminating search points within the threshold wastes FEs
- Despite inefficiency, performance improves in multi-modal search spaces
- Successful proof of concept





Modified update

```
if ||new - base|| < threshold
direction = Normalize(new - base)
new' = base + threshold \cdot direction
end if
```



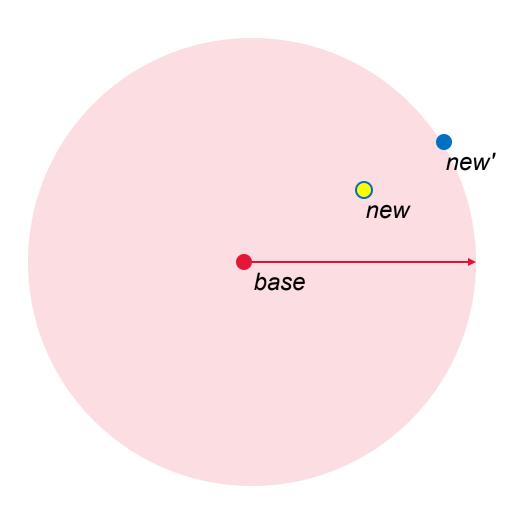




base









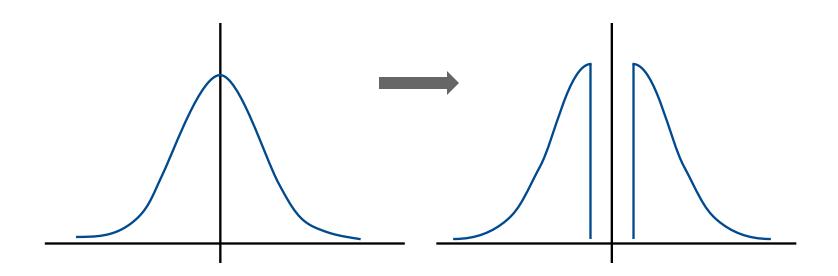


- No wasted FEs
- Minimum step size both improves exploration (in multimodal search spaces) and prevents premature convergence (in all search spaces)
- Improved performance across a broad range of benchmark functions





Create "hollow" sampling distribution

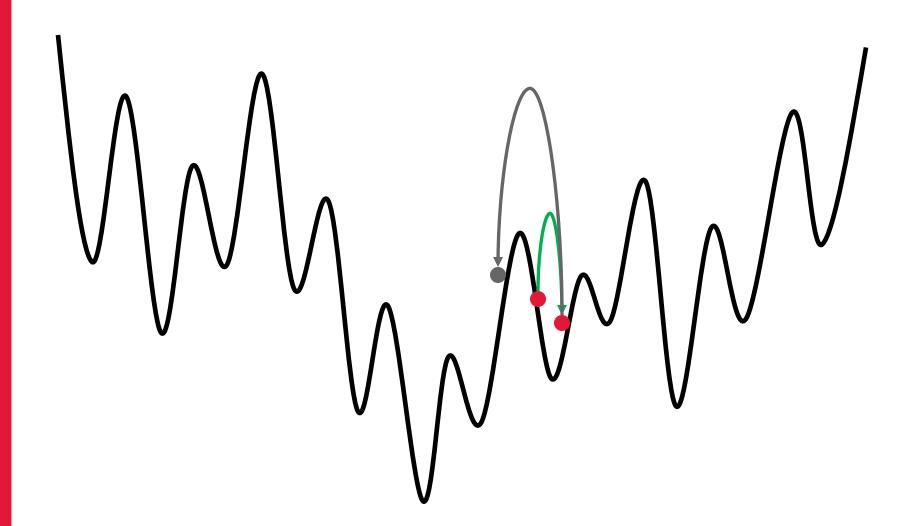


Images from S. Chen, C. Xudiera, and J. Montgomery, "Simulated Annealing with Thresheld Convergence", IEEE CEC, 2012.



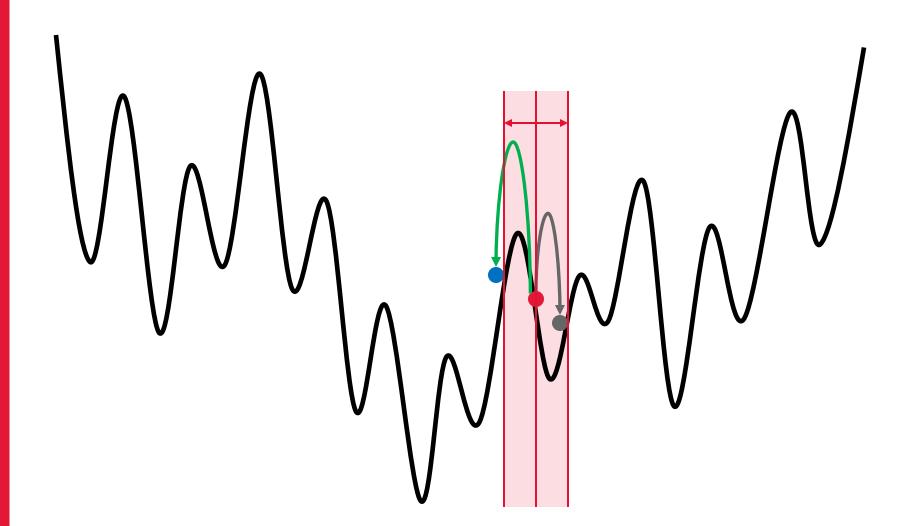


## Original Simulated Annealing













- Local search/optimization makes escaping from the current attraction basin more difficult
- With threshold, search becomes almost random
  - Concurrent exploration and exploitation is required for useful convergence in a memory-less search system
  - E.g. simulated annealing like a real physical system, genetic algorithms like a real biological system
- SA with thresheld convergence requires a memory





## Early Applications of Thresheld Convergence

- Many metaheuristics allow (even require) concurrent exploration and exploitation
- Adding minimum step size reduces, but does not eliminate concurrent exploration and exploitation
- Experiments on benchmark problems led to improved results in the targeted multi-modal search spaces
- Improvements limited by the simple, preliminary threshold function





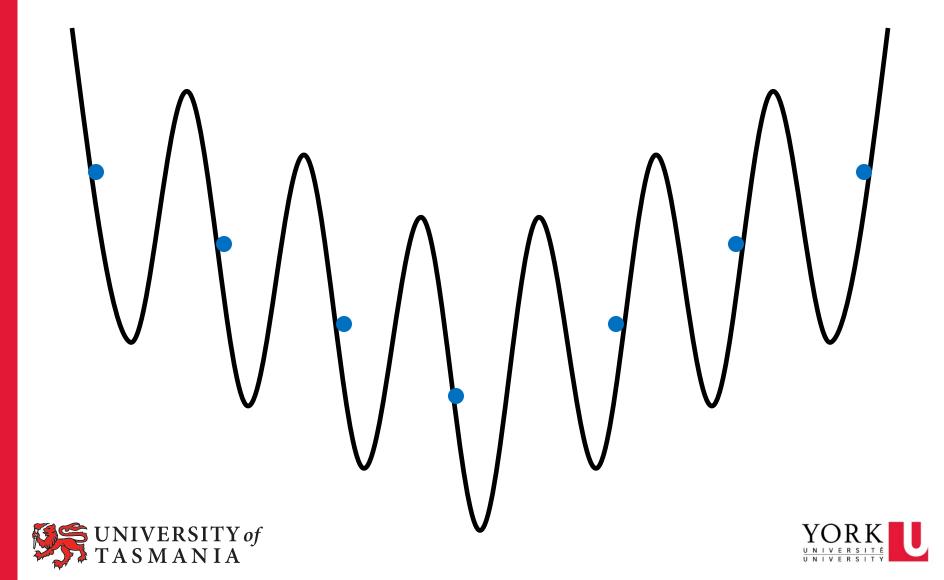
## Limitations of Thresheld Convergence

- Ideal case assumes same relative fitness for each sample solution
- Random variations naturally occur in the relative fitness of sample solutions
- Random variations lead to random search
  - Relative fitness improves over time
  - Even when threshold size is larger than attraction basins
  - Even when no exploitation is possible
- Exploration with thresheld convergence still stalls

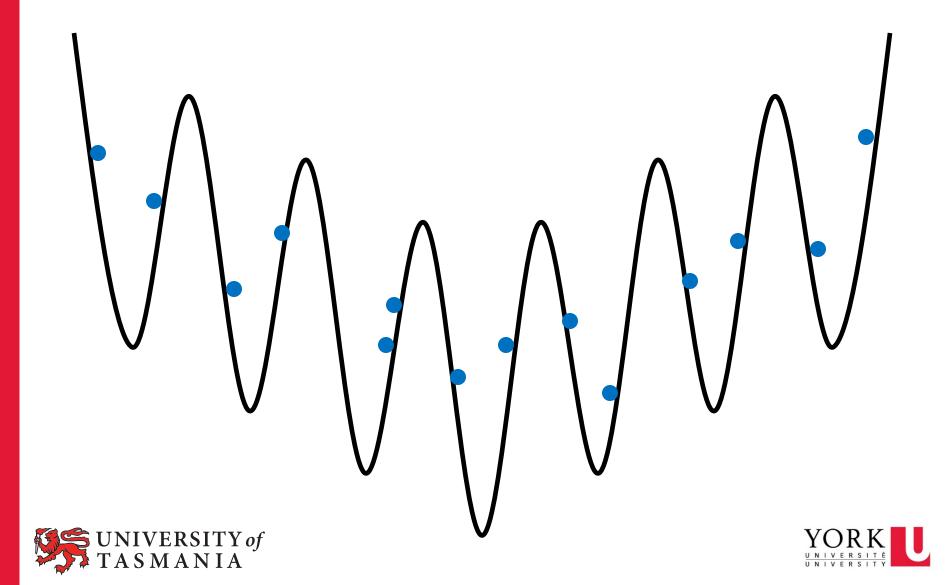




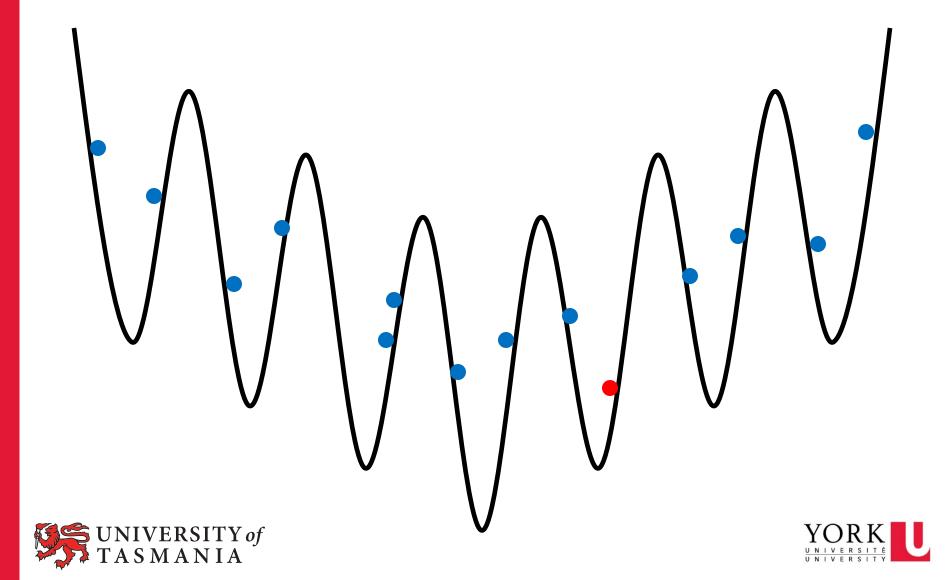
## **Ideal Case**



## **Typical Case**



## **Typical Case**



## Limitations of Thresheld Convergence

#### Random search leads to improved relative fitness

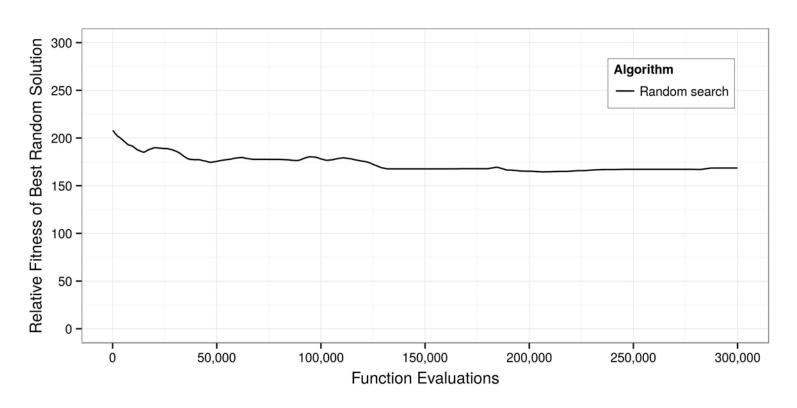


Image from Y. Gonzalez-Fernandez and S. Chen, "Leaders and Followers – A New Metaheuristic to Avoid the Bias of Accumulated Information", IEEE CEC, 2015.





## Limitations of Thresheld Convergence

#### Better relative fitness means less effective exploration

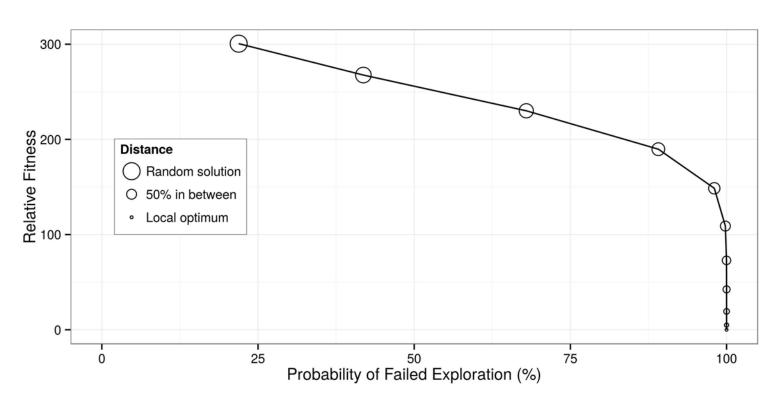


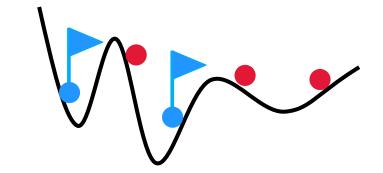
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#### Towards a New Metaheuristic

#### Leaders and Followers







#### Towards a New Metaheuristic

- Exploration is only effective for a very few number of iterations
- Need rapid restarts
  - Each restart renews opportunity for effective exploration
- Goal of optimization is to find better solutions
  - Better solutions reduce effectiveness of exploration
- Solution: two populations
  - Leaders: best solutions which guide the search
  - Followers: new solutions which can explore effectively





- A new metaheuristic explicitly developed for multi-modal search spaces
- Population control scheme designed to promote accurate comparison of attraction basins





## Leaders



#### The best solutions found to date

#### Guide the search

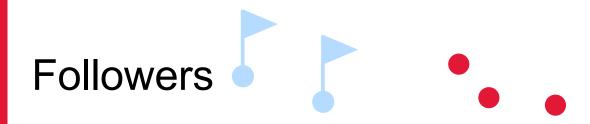
Like pbests in PSO which guide/attract the current solutions

#### Do not evaluate the search

 Unlike PSO, new solutions are not compared to leaders/pbests







#### The current solutions looking for better attraction basins

#### Cannot be compared with leaders

- New search points are likely to have poor relative fitness
- Direct comparison with leaders/solutions with high relative fitness will lead to inaccurate comparisons

#### Compare with other followers

After each restart, followers can have similar relative fitness





- Leaders lead
- Followers follow
- How can search progress unless followers can become leaders?
- When can leaders and followers be compared fairly?
- Ideally, when both populations have similar relative fitness
- Practically, when both populations have the same median fitness





Initialize Leaders (to random solutions)

**Loop** allowed iterations/function evaluations

Initialize Followers to random solutions

Loop until Followers have similar relative fitness

Each follower moves towards a leader

Each follower is best of current or previous position

**End Loop** 

Select new Leaders

**End Loop** 

Return best leader





#### Relative fitness of *pbests* in PSO improves rapidly

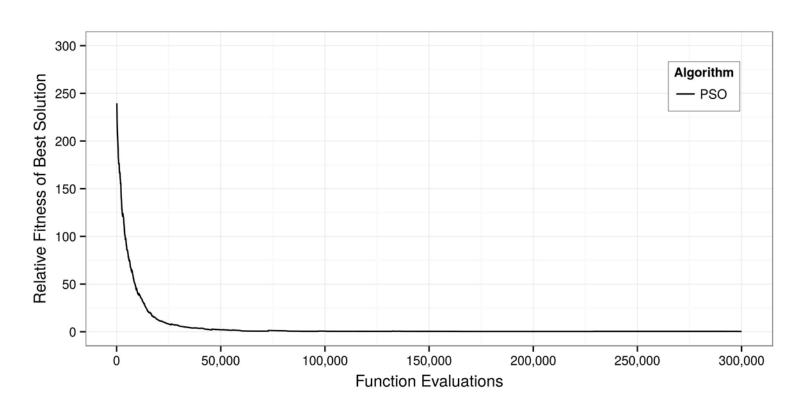


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#### Relative fitness of leaders also improves rapidly

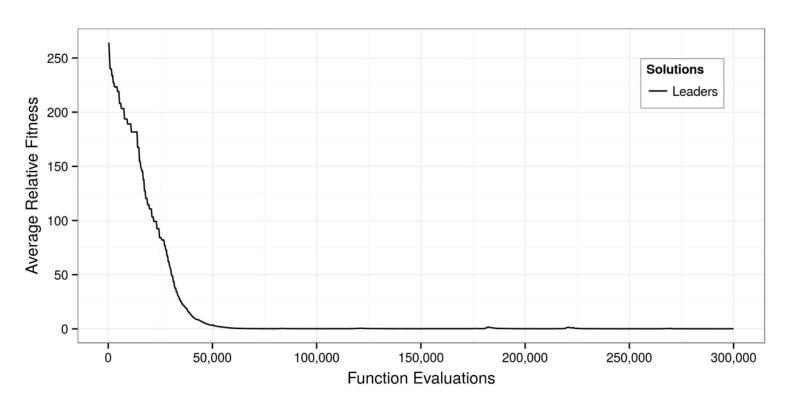


Image from Y. Gonzalez-Fernandez and S. Chen, "Leaders and Followers – A New Metaheuristic to Avoid the Bias of Accumulated Information", IEEE CEC, 2015.





Search stalls in PSO, does not stall in Leaders and Followers – followers are not compared against leaders

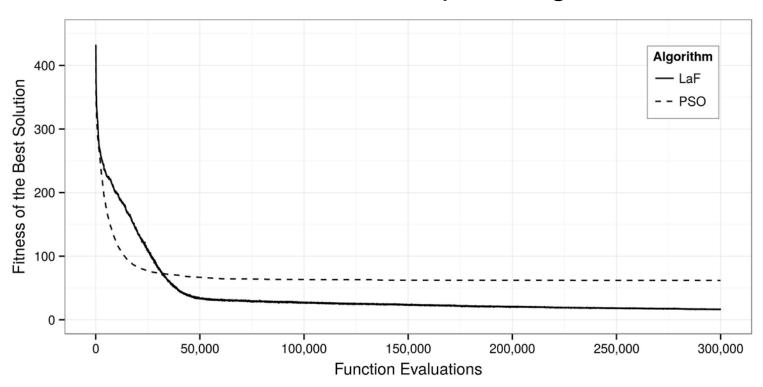
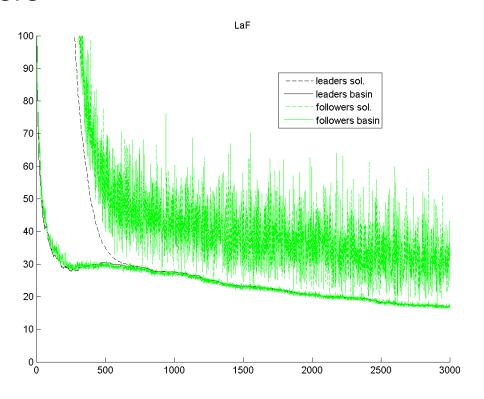


Image from Y. Gonzalez-Fernandez and S. Chen, "Leaders and Followers – A New Metaheuristic to Avoid the Bias of Accumulated Information", IEEE CEC, 2015.





Each wave of Followers can still find better attraction basins than the Leaders







## Leaders and Followers - Operation

- Followers reset every time their median fitness reaches the median fitness of the Leaders
- Each reset allows unbiased comparison of attraction basins
- Improved comparisons lead to improved performance in multi-modal search space
- Rapid restarts are implicit thresheld convergence
  - No threshold function used to encourage diversity





#### Leaders and Followers - Performance

- LaF performs 20% better than PSO on multi-modal functions in CEC2013 benchmark
- LaF performs 10% better than DE on multi-modal functions in CEC2013 benchmark
- LaF is simpler than both PSO and DE
  - Fewer parameters
  - Less-optimized parameters





#### Leaders and Followers - Future Work

- Add explicit thresheld convergence
  - Better exploration in Followers
    - Don't create followers in the same attraction basins
    - Lots of wasted time in unnecessary exploitation
  - Better diversity in Leaders
    - Each leader in its own attraction basin
- Improve search distribution for Followers





## Leaders and Followers – Why Bother?

- K. Sörensen, "Metaheuristics—the metaphor exposed," International Transactions in Operational Research, 2013.
- Leaders and Followers is not metaphor based
  - Based on a detailed study of exploration in multi-modal search spaces (using the Rastrigin function)
- Leaders and Followers is distinctly different from other metaheuristics
  - Key feature is how solutions are compared
  - Explicitly designed for multi-modal search spaces





## Thresheld Convergence

and what we have learned from its development





# Optimization in multi-modal spaces should be two distinct phases

Thresheld convergence focuses on attraction basins in multimodal search spaces

#### Optimization should be a two-phase process:

- Phase 1: Exploration → find the fittest attraction basins
- Phase 2: Exploitation → find its local optimum

Accuracy of comparing attraction basins is affected by the relative fitness of their sample solutions

Goal of thresheld convergence is to maintain similar relative fitness of all search solutions





## Metaheuristic design should focus on how solutions are compared

Leaders and followers is a new metaheuristic designed explicitly for multi-modal search spaces

#### Key focus is on how solutions are compared

Avoid comparison of solutions with dissimilar relative fitness

#### Most metaheuristics focus on how solutions are created

- PSO → attraction vectors
- DE → difference vectors
- UMDA → distributions

Improvements to how solutions are created should lead to large performance gains in leaders and followers





## Key papers

#### A Review of Thresheld Convergence

S. Chen, J. Montgomery, A. Bolufé-Röhler, Y. Gonzalez-Fernandez GECONTEC: Revista Internacional de Gestión del Conocimiento y la Tecnología, Vol. 3(1), pp 1-13, 2015.

## Leaders and Followers – A New Metaheuristic to Avoid the Bias of Accumulated Information

Y. Gonzalez-Fernandez and S. Chen CEC2015, pp 776-783.



