

Ant Colony Optimization for Model Checking

Introduction

Background

Ant Colony
Optimization

Experiments

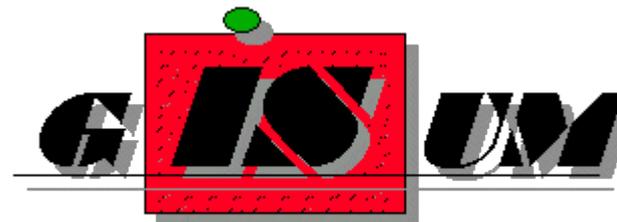
Conclusions &
Future Work



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Enrique Alba and Francisco Chicano

Introduction

- Nowadays **software is very complex**
- An error in a software system can imply the **loss of lot of money ...**



... and even **human lives**

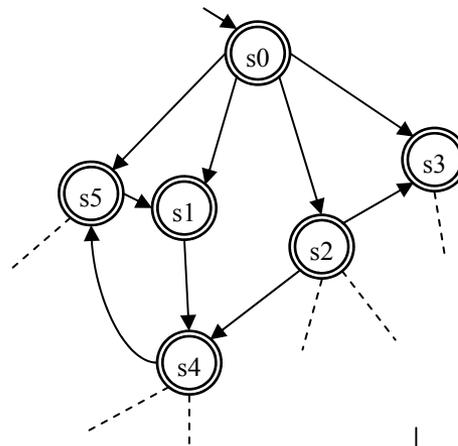


- Techniques for **proving the correctness of the software are required**
- **Model checking** → fully automatic

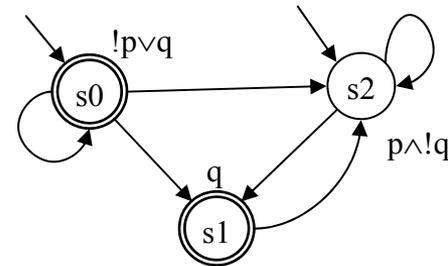
Explicit State Model Checking

- **Objective:** Prove that model M satisfies the property $f: M \models f$
- **SPIN:** the property f is an **LTL formula**

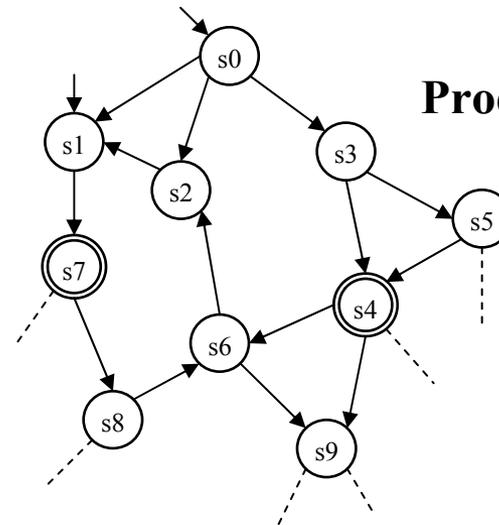
Model M



LTL formula $\neg f$

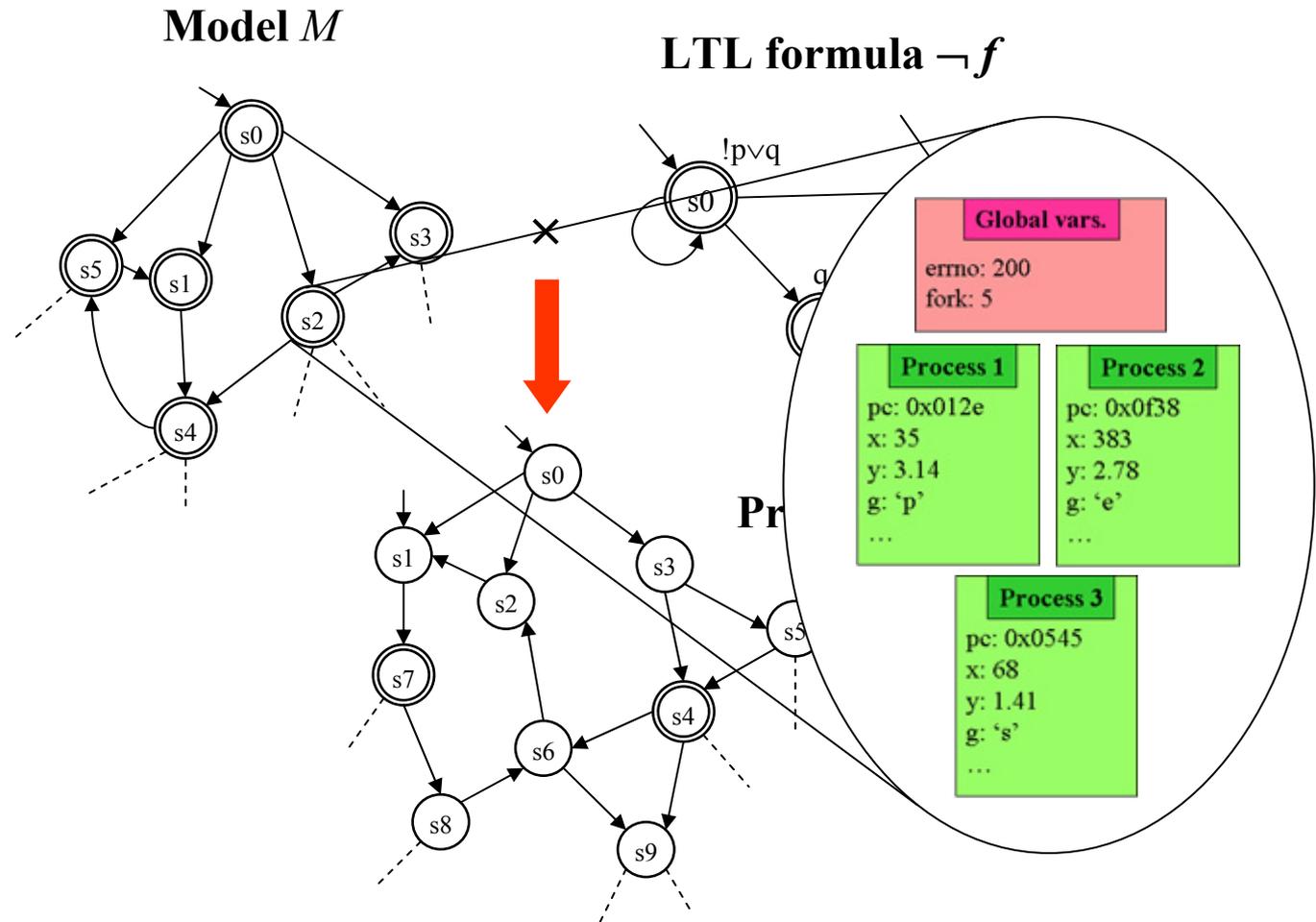


Product Büchi automaton



Explicit State Model Checking

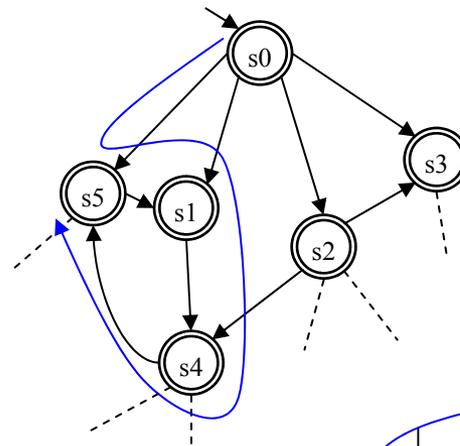
- **Objective:** Prove that model M satisfies the property $f: M \models f$
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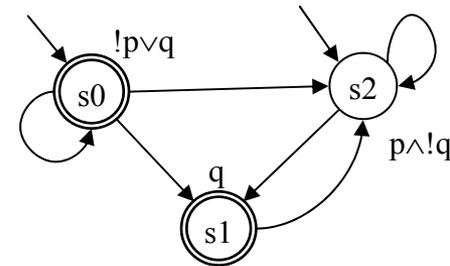
Explicit State Model Checking

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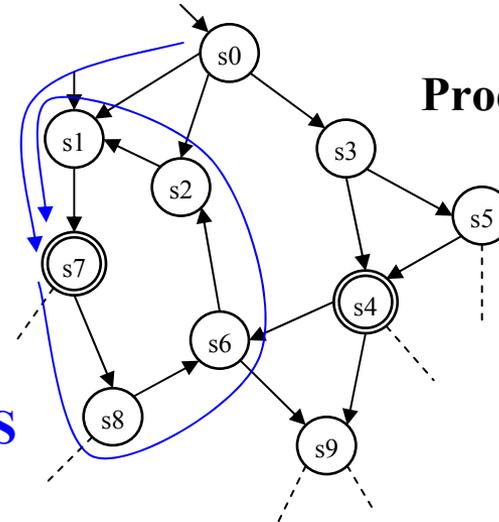
Model M



LTL formula $\neg f$



Product Büchi automaton



Using Nested-DFS



Introduction

Background

Ant Colony
Optimization

Experiments

Conclusions &
Future Work

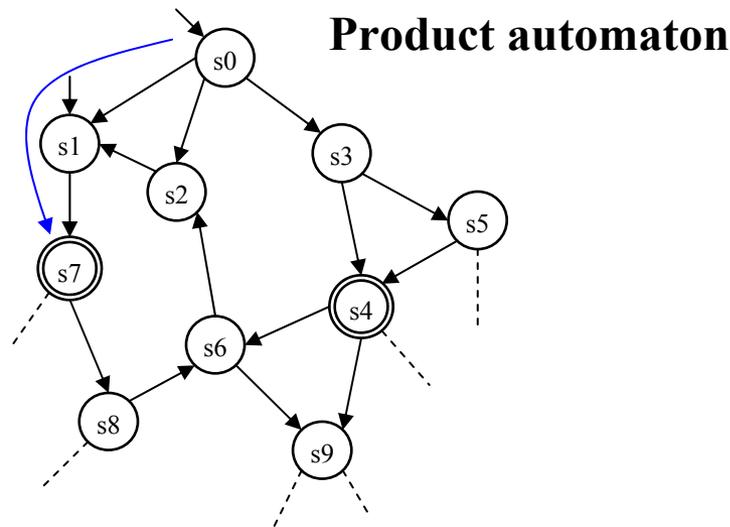
Safety Properties

- **Safety properties** are those expressed by an LTL formula of the form:

$$f = \square p$$

where p is a **past formula**

- Finding one counterexample \equiv finding one **accepting state**



Safety Properties

Deadlocks

Invariants

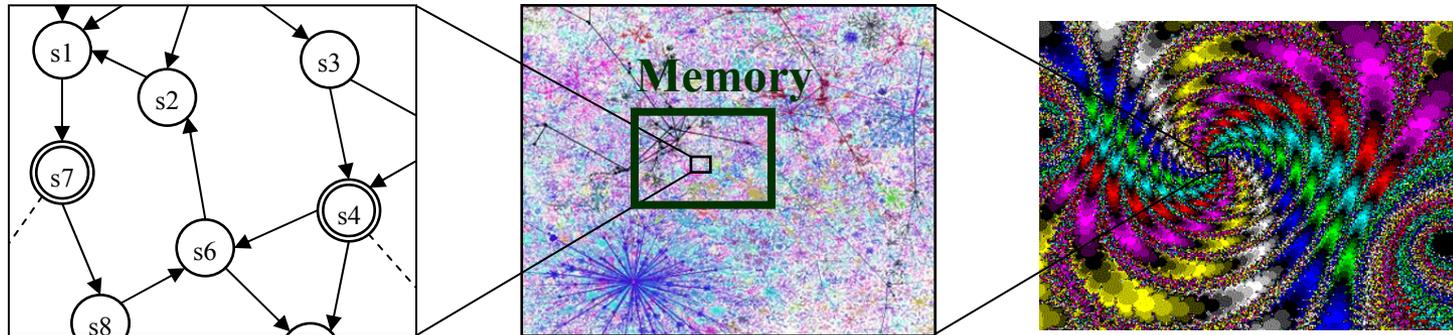
Assertions

...

- Classical algorithms for graph exploration can be used: **DFS** and **BFS**

State Explosion Problem

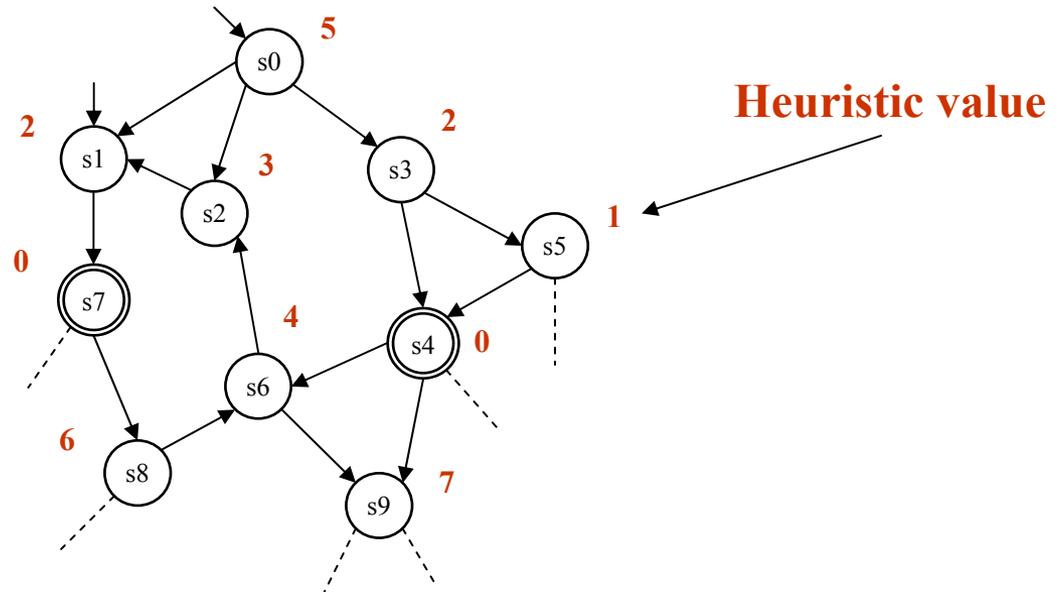
- Number of states **very large** even for small models



- Example: Dining philosophers with n philosophers $\rightarrow 3^n$ states
20 philosophers \rightarrow 1039 GB for storing the states
- **Solutions:** state compression, bitstate hashing, partial order reduction, symmetry reduction, symbolic model checking
- Large models cannot be verified but **errors can be found**

Heuristic Model Checking

- The search for errors can be directed by heuristics using algorithms like **A***, **IDA***, **WA***, **Best-First**, and so on



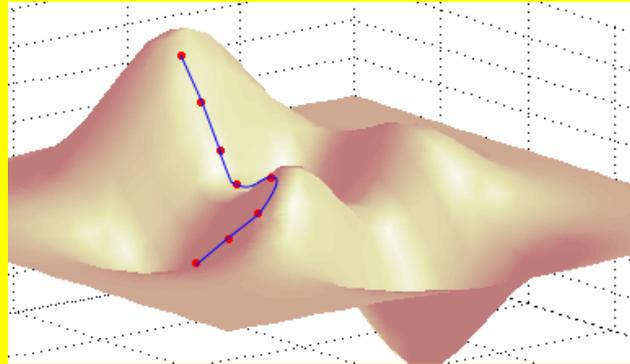
- Different kinds of heuristic functions have been proposed in the past:
 - Formula-based** heuristics: depends on the LTL formula
 - Structural** heuristics: code coverage
 - Deadlock-detection** heuristics: active process
 - State-dependent** heuristics: hamming distance

Metaheuristic Algorithms

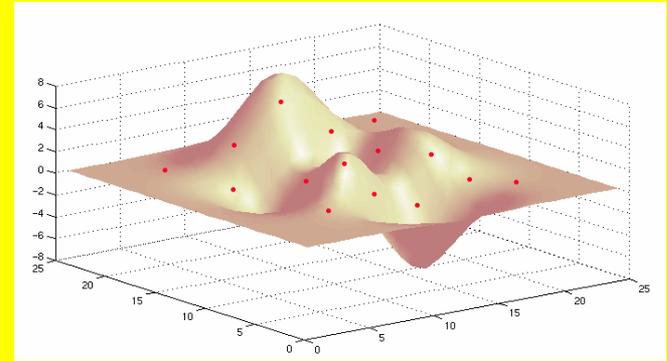
- Designed to solve **optimization problems**
 - Maximize or minimize a given function: the **fitness function**
- They can find “**good**” solutions with “**reasonable**” resources

Metaheuristic Algorithms

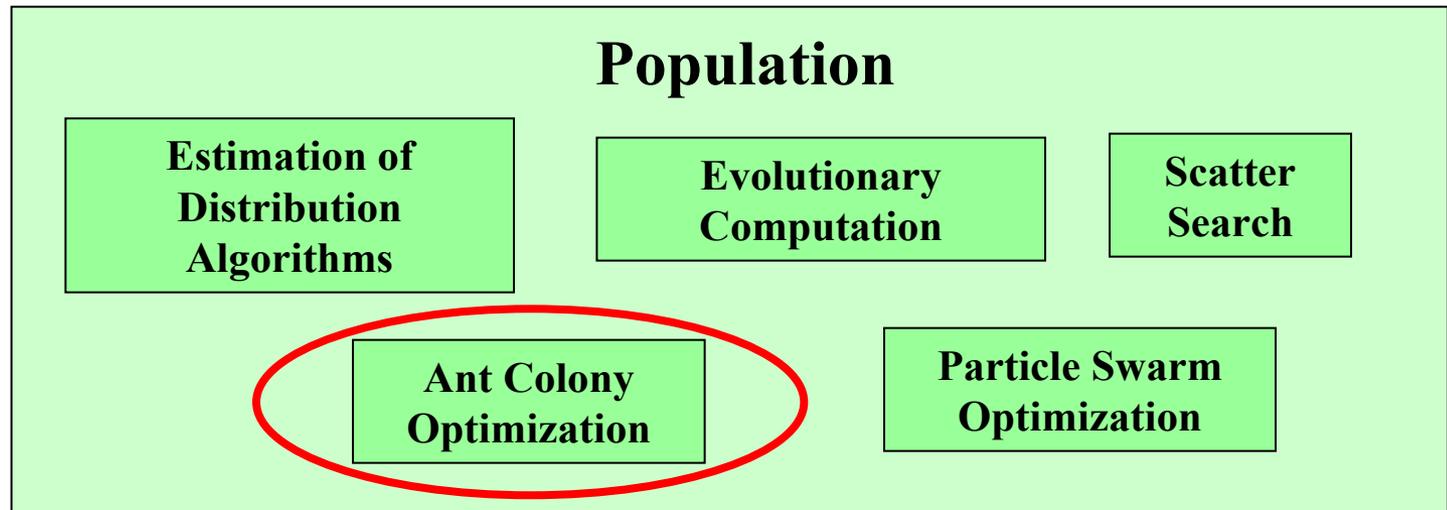
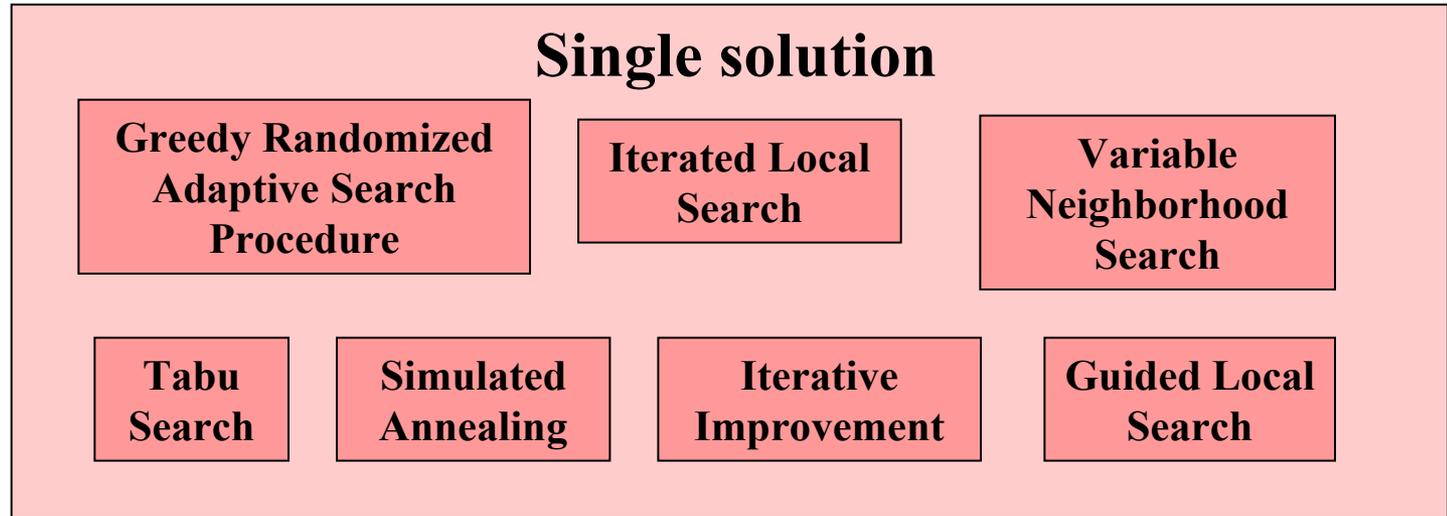
Single solution



Population



Metaheuristic Algorithms



Introduction

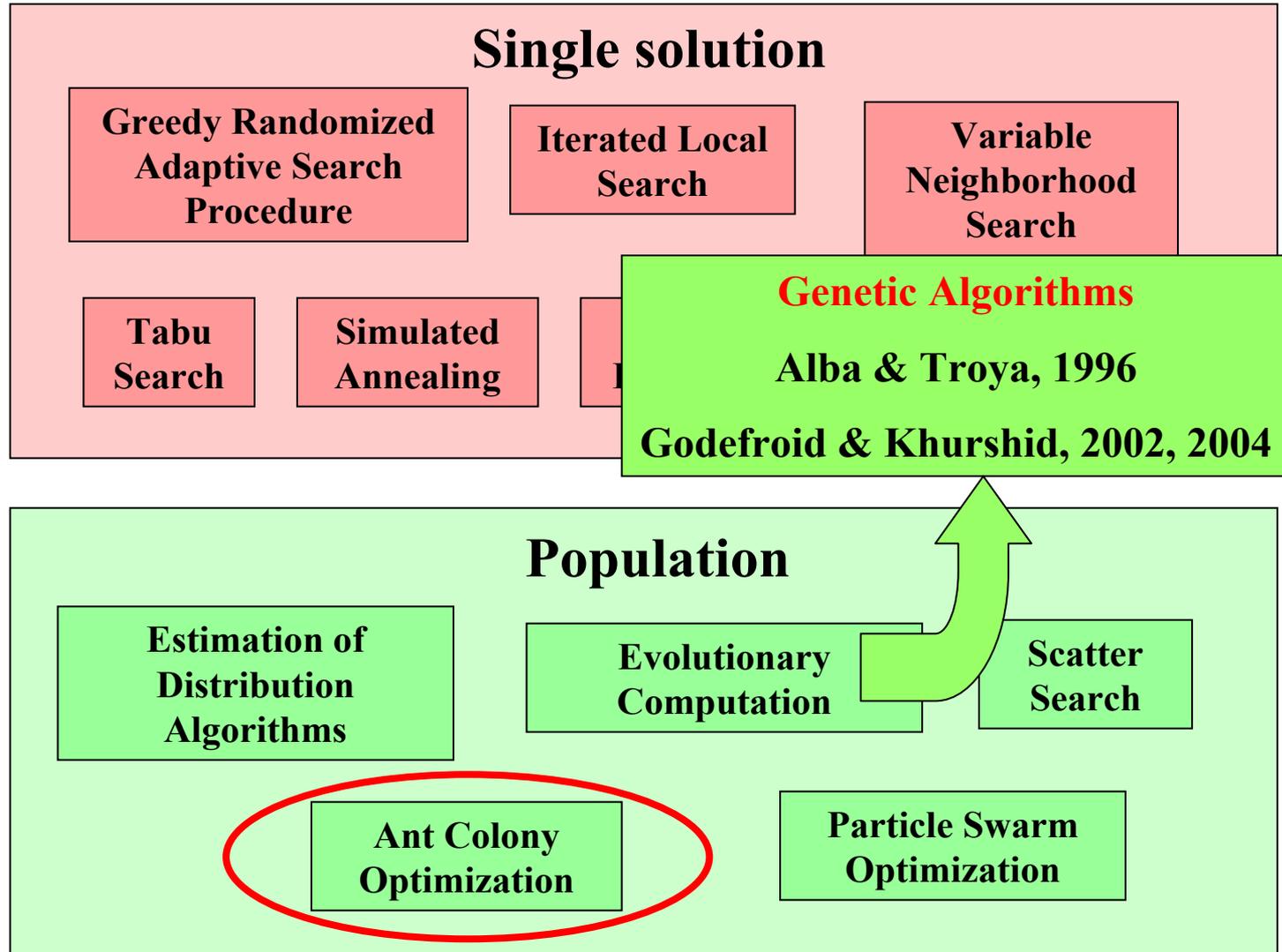
Background

Ant Colony Optimization

Experiments

Conclusions & Future Work

Metaheuristic Algorithms



Introduction

Background

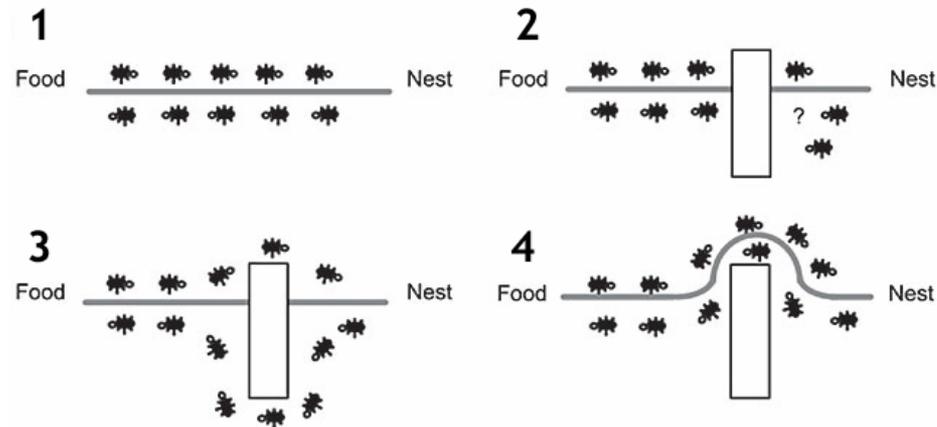
Ant Colony
Optimization

Experiments

Conclusions &
Future Work

Ant Colony Optimization

- Ant Colony Optimization (ACO) metaheuristic is inspired in the foraging behavior of the real ants



- ACO Pseudo-code

```

procedure ACOMetaheuristic
  ScheduleActivities
    ConstructAntsSolutions
    UpdatePheromones
    DaemonActions // optional
  end ScheduleActivities
end procedure
  
```

Introduction

Background

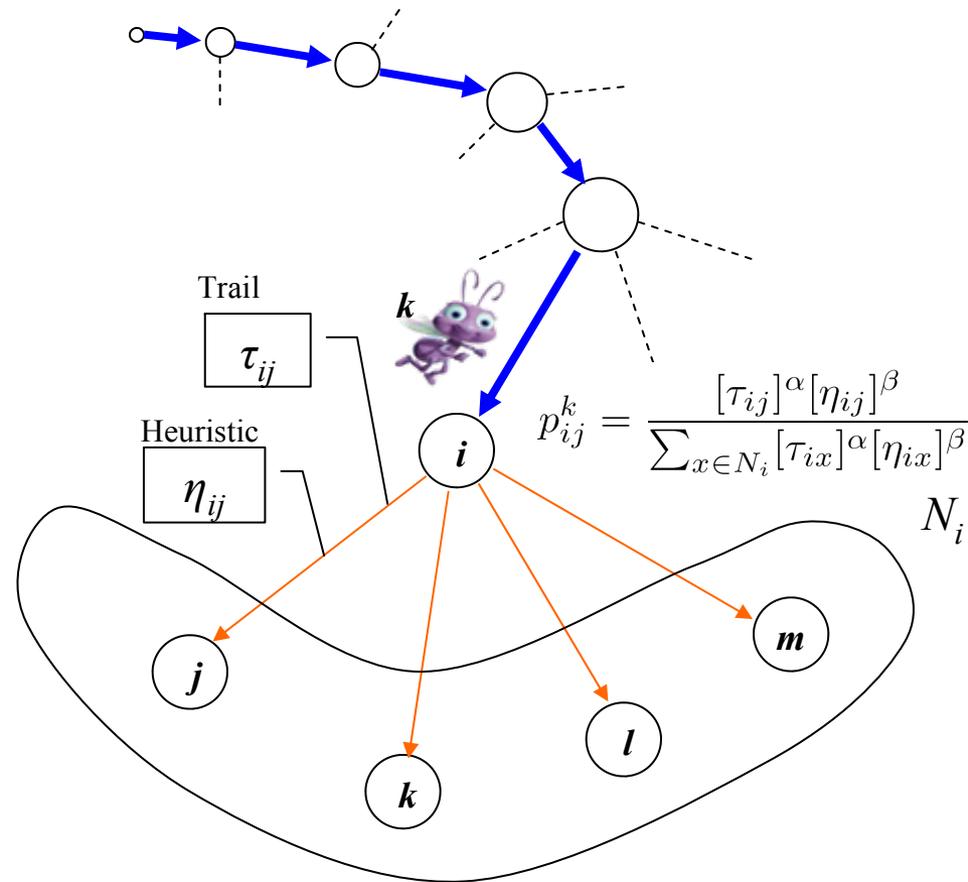
Ant Colony
Optimization

Experiments

Conclusions &
Future Work

Ant Colony Optimization

- Construction Phase



Introduction

Background

Ant Colony
Optimization

Experiments

Conclusions &
Future Work

Ant Colony Optimization

- **Pheromone update**

- **During the construction phase**

$$\tau_{ij} \leftarrow (1 - x_i) \tau_{ij} \quad \text{with} \quad 0 \leq x_i \leq 1$$

- **After the construction phase**

$$\tau_{ij} \leftarrow \rho \tau_{ij} + \Delta \tau_{ij}^{bs} \quad \text{with} \quad 0 \leq \rho \leq 1$$

- **Trail limits (particular of MMAS)**

- **Pheromones are kept in the interval $[\tau_{\min}, \tau_{\max}]$**

$$\tau_{max} = \frac{Q}{1 - \rho}$$

$$\tau_{min} = \frac{\tau_{max}}{a}$$

Introduction

Background

Ant Colony
Optimization

Experiments

Conclusions &
Future Work

ACO_{hg}: Motivation

- **Existing ACO models cannot be applied to the search for errors in concurrent programs**
 - **The graph is very large, the construction of a complete solution could require too much time and memory**
 - **In some models the number of nodes of the graph is used for computing the initial pheromone values**
- **We need a new model for tackling these problems: ACO_{hg} (ACO for Huge Graphs)**
 - **Constructs the ant paths and updates the pheromone values in the same way as the traditional models**
 - **Allows the construction of partial solutions**
 - **Allows the exploration of the graph using a bounded amount of memory**
 - **The pheromone matrix is never completely stored**

Introduction

Background

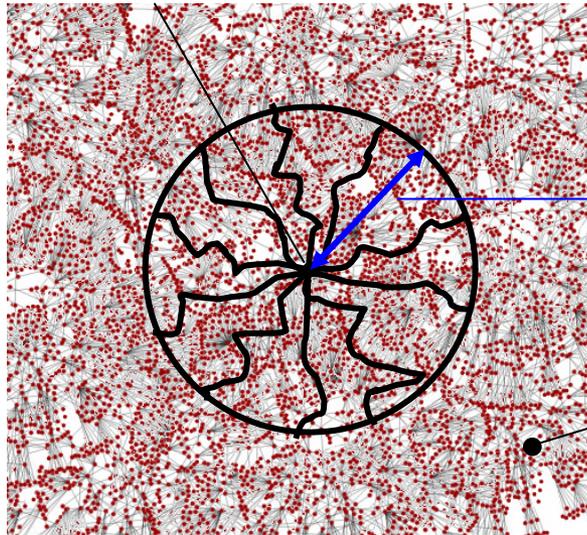
Ant Colony
Optimization

Experiments

Conclusions &
Future Work

ACO_{hg}: Ant Paths Length

- The length of the ant paths is limited by λ_{ant}



What if...?

Objective node

Introduction

Background

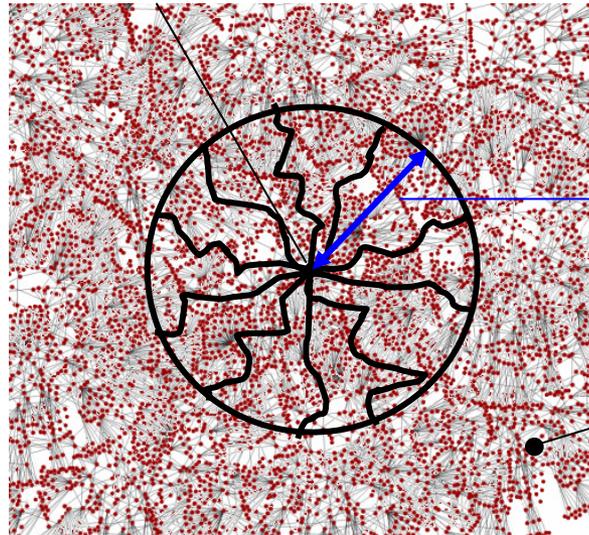
Ant Colony
Optimization

Experiments

Conclusions &
Future Work

ACO_{hg}: Ant Paths Length

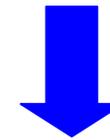
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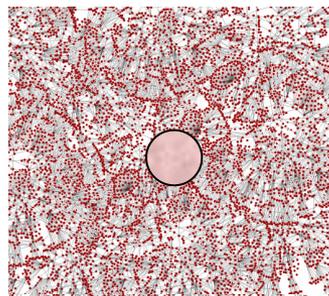
What if...?

Objective node

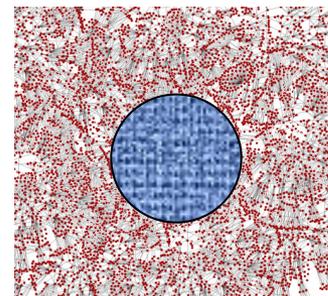
Two alternatives



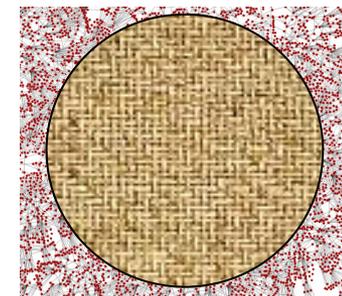
Expansion Technique: λ_{ant} changes



After σ_i steps



$$\lambda_{\text{ant}} = \lambda_{\text{ant}} + \delta_1$$



Introduction

Background

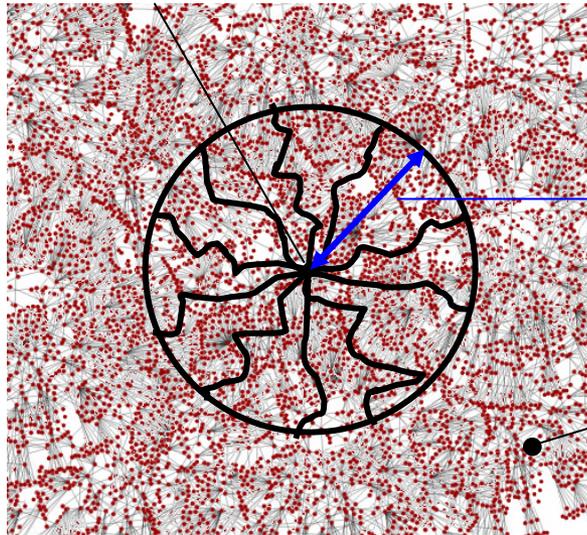
Ant Colony
Optimization

Experiments

Conclusions &
Future Work

ACO_{hg}: Ant Paths Length

- The length of the ant paths is limited by λ_{ant}



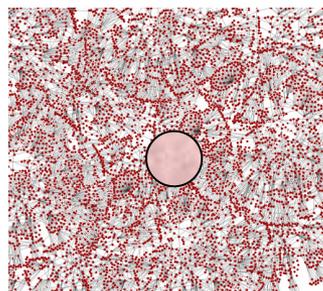
What if...?

Objective node

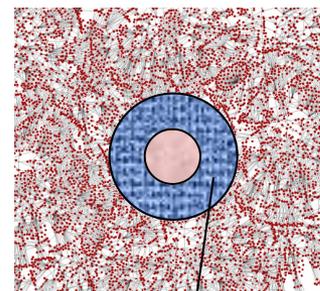
Two alternatives



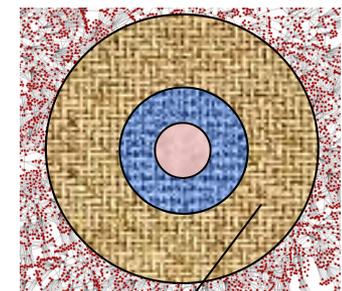
Missionary Technique: starting nodes for path construction change



After σ_s steps



Second stage



Third stage

Introduction

Background

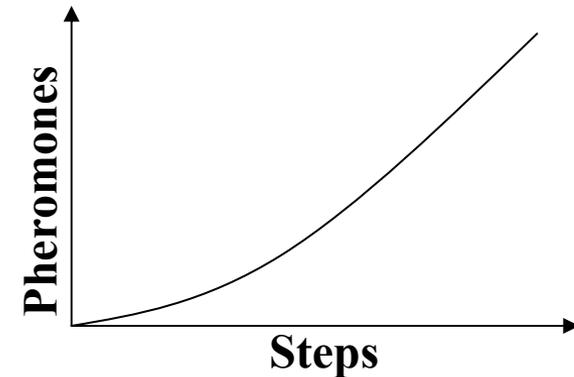
Ant Colony
Optimization

Experiments

Conclusions &
Future Work

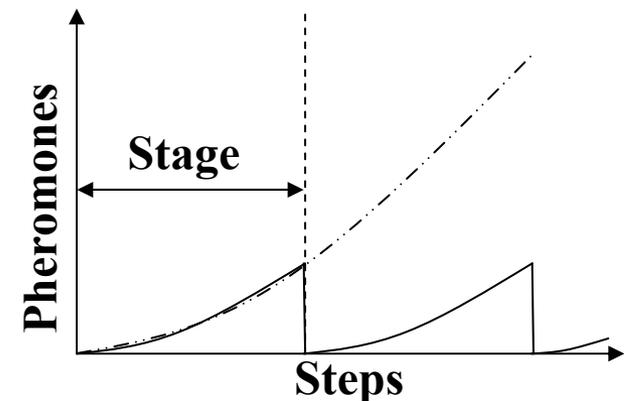
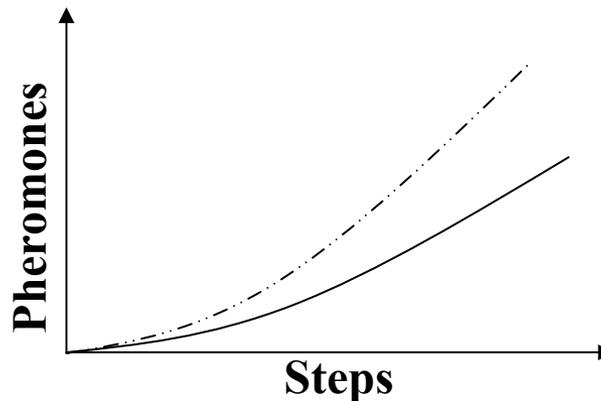
ACO_{hg}: Pheromones

- The **number of pheromone** trails increases during the search
- This leads to memory problems
- We must **remove** some pheromone trails from memory



Remove pheromone trails τ_{ij}
below a given threshold τ_θ

In the missionary technique,
remove **all** pheromone trails
after one stage



Introduction

Background

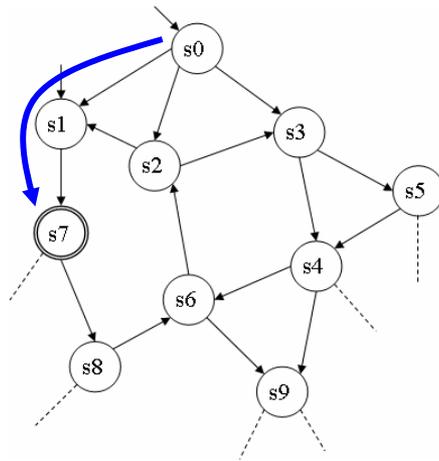
Ant Colony
Optimization

Experiments

Conclusions &
Future Work

ACO_{hg}: Fitness Function

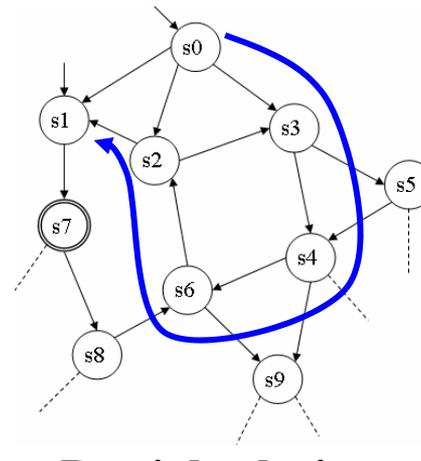
- The fitness function must be able to **evaluate partial solutions**
- Penalties are added for **partial solutions and solutions with cycles**



Complete solution

$$p = 0$$

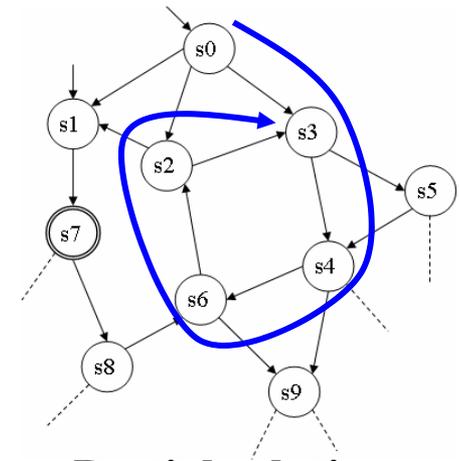
Total penalty



Partial solution
without cycle

$$p = p_p$$

Penalty constant for
partial solutions



Partial solution
with cycle

$$p = p_p + p_c \frac{\lambda_{ant} - l}{\lambda_{ant} - 1}$$

Penalty constant for
solutions with cycles

Path length

Experiments: Models

- We selected **5 Promela models** for the experiments

Model	LoC	States	Processes	Safety Property
basic_call2	198	33667	3	deadlock
garp	272	<i>unknown</i>	8	deadlock
giop12	717	27877	10	deadlock
marriers4	142	<i>unkown</i>	5	deadlock
phi8	34	6561	9	deadlock

- For **marriers4** and **garp** the states do not fit into the main memory of the computer

Introduction

Background

Ant Colony
Optimization

Experiments

Conclusions &
Future Work

Experiments: Parameters

- The ACOhg model was implemented inside the **MALLBA** library and and then included into the **HSF-SPIN** model checker

Parameter	Value
Steps	10
Colony size	10
λ_{ant}	10
x_i	0.0
ρ	0.9
α	1.0
β	0.0/1.0

- These parameters belong to a **Min-Max Ant System (MMAS)**
- **Fitness function:** length of the path + penalty
- Two variants: using no heuristic (**MMAS-b**) and using it (**MMAS-h**)
- **Machine:** Pentium 4 at 2.8 GHz with 512 MB

Introduction

Background

Ant Colony
Optimization

Experiments

Conclusions &
Future Work

Experiments: Comparison

- We compare *MMAS-b* and *MMAS-h* against DFS, BFS, and A*

Concurrent System		DFS	BFS	<i>MMAS-b</i>	A*	<i>MMAS-h</i>
basic_call2	Len.	82.00	26.00	30.24	26.00	31.30
Basic call protocol with 2 users	CPU (ms)	10.00	80.00	41.70	110.00	49.40
	Mem. (KB)	2713.00	16384.00	4219.44	17408.00	4278.44
	garp	Len.	65.00	17.00	24.70	17.00
Generic Attribute Registration Protocol	CPU (ms)	10.00	53180.00	6.00	2820.00	9.50
	Mem. (KB)	3357.00	480256.00	2532.28	122880.00	2634.44
giop12	Len.	48.00	43.00	43.45	43.00	43.00
CORBA General Inter-ORB Protocol (1 client, 2 servers)	CPU (ms)	10.00	350.00	41.20	490.00	26.80
	Mem. (KB)	2901.00	49152.00	4085.12	37888.00	3202.24
marriers4	Len.	-	-	85.79	-	88.76
Stable marriage problem with 4 suitors	CPU (ms)	-	-	148.60	-	91.90
	Mem. (KB)	-	-	15388.39	-	10625.80
phi8	Len.	1338.00	10.00	10.00	10.00	10.00
Dining philosophers with 8 philosophers	CPU (ms)	70.00	60.00	21.90	0.00	35.20
	Mem. (KB)	29696.00	17408.00	4333.92	2105.00	4986.68

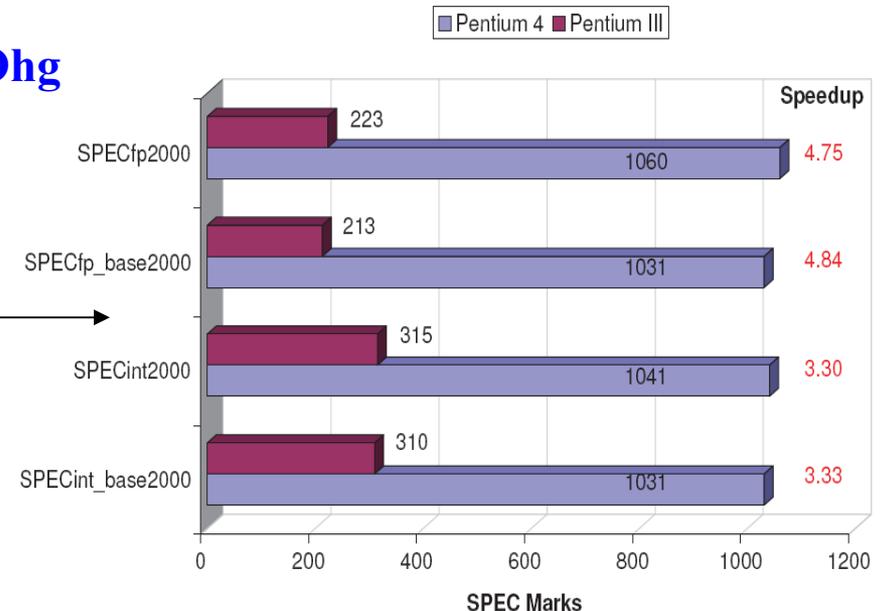
- MMAS* algorithms are **the only ones** able to find errors in *marriers4*
- MMAS* algorithms require **less memory than BFS**
- MMAS* algorithms get **shorter (better) error trails than DFS**
- We conclude that *MMAS* algorithms are the best trade-off between efficacy and efficiency (**good results with low resources**)

Experiments: ACOhg vs. GA

- **GA** is the previous metaheuristic algorithm applied to this problem
- We use **phi17** and **needham** for the comparison (Godefroid & Khurshid, 2002)

Model	Algorithm	Hit (%)	Time (s)	Mem. (KB)
phi17	GA	52	197.00	n/a
	ACOhg-h	100	0.28	11274
needham	GA	3	3068.00	n/a
	ACOhg-h	100	0.23	4865

- The results state that **ACOhg** has **higher efficacy and efficiency** than **GA** (even taking into account the differences in the machines)

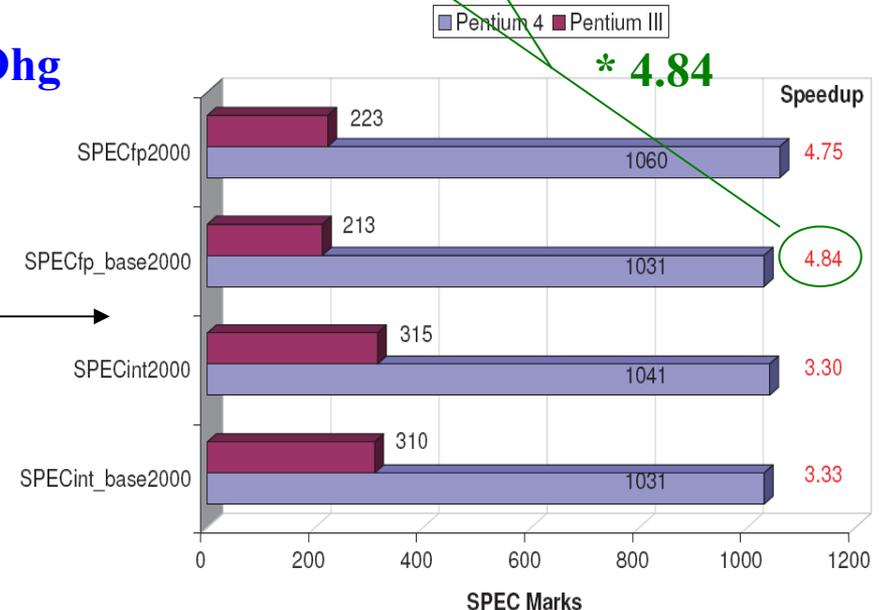


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Conclusions and Future Work

Conclusions

- ACOhg is able to **outperform state-of-the-art algorithms** used nowadays in current model checkers for finding errors
- The results obtained with ACOhg **improve by far** those obtained by **GAs** in the past
- This represents a **promising starting point** for the use of metaheuristic algorithms in model checking

Future Work

- We plan to **study ACOhg algorithms in depth**, exploring all the alternatives mentioned for the algorithm
- ACOhg algorithms can be combined with other techniques for reducing the amount of memory: e.g., **Partial Order Reduction**
- ACOhg can be extended **to work in parallel** and profit from the use of clusters of machines (parallel model checkers)

The End

Thanks for your attention !!!



Questions?

Introduction

Background

Ant Colony
Optimization

Experiments

Conclusions &
Future Work