### • Welcome

- Welcome
- Committee
  - Dr. Arvin Agah, Professor in Charge
  - Dr. Victor Frost
  - Dr. Costas Tsatsoulis

## Problem and Solution Overview Playing Go

## Problem and Solution Overview Playing Go Relevant Computational Methods

- Playing Go
- Relevant Computational Methods
- State of the Art
  - Genetic algorithms
  - Traditional programs

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- Implementation
- Experiments and Results
- Conclusion
  - Contributions
  - Limitations
  - Future

Introduction to Go

### • Perfect Information

**Introduction to Go** 

## Perfect Information Board is 19 by 19

# Perfect Information Board is 19 by 19 Two players

Perfect Information
Board is 19 by 19
Two players
Territory

- Perfect Information
- Board is 19 by 19
- Two players
- Territory
- Capturing

- Go has simple rules, but tactics and strategies are complex
  - Go has emergent complexity
  - Multiagent systems have emergent complexity

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- Current go programs play on a beginner level, why?

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- Current go programs play on a beginner level, why?

<ul> <li>Search space</li> </ul>	Search Ply	Go	Chess	Checkers
	1	361	20	7
	2	129,960	400	49
	3	445,145,640	approx. 10,000	approx. 343

• Use multiple agents to suggest solutions based on a narrow world perspective • Use multiple agents to suggest solutions based on a narrow world perspective

Bring these solutions together to obtain a better overall solution

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- Algorithmic composition of individual agent solutions
- Illustrate this method in a non-trivial environment: go

### • Multiagent Architecture

- Specialized agents
- Each has its own perspective of the game
- Outputs an array representing move qualities

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- Specialized agents
- Each has its own perspective of the game
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- Agents connected via a summation network to generate output
  - No communication

– Allows a passive combination of agent output into a solution

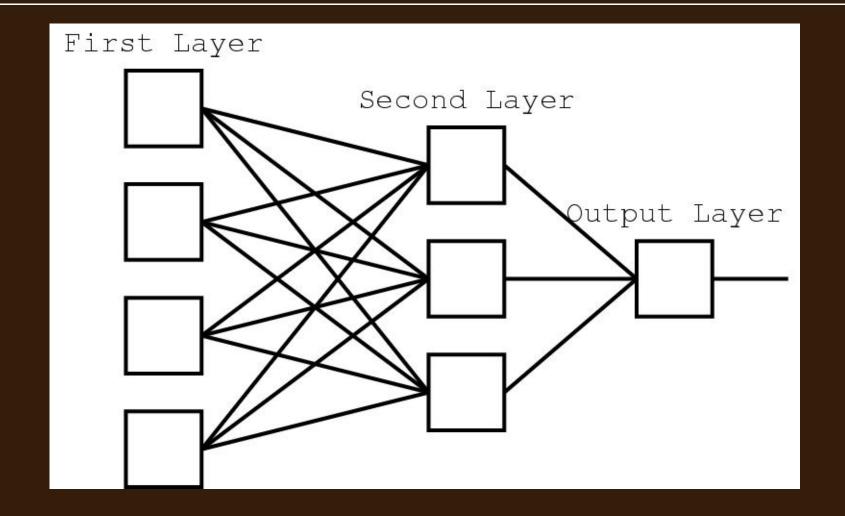
### • Multiagent Architecture

- Specialized agents
- Each has its own perspective of the game
- Outputs an array representing move qualities
- Agents connected via a summation network to generate output
  - No communication
  - Allows a passive combination of agent output into a solution
- Weights for this network were evolved using genetic algorithms

### • Network weights are four-bit integers

### Network weights are four-bit integers These four-bit integers make up chromosome

- Network weights are four-bit integers
- These four-bit integers make up chromosome
- Extra bits at the end of chromosome are available
  - Extra bits for internal use by agents
  - Extender agent uses these extra bits



### Traditional search provides little help

## Traditional search provides little help Complex

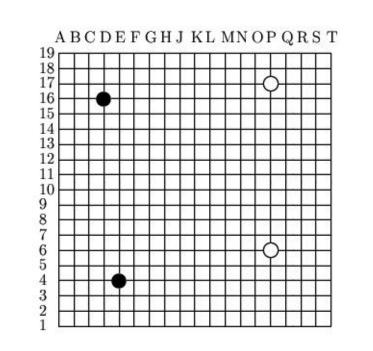
## Traditional search provides little help Complex

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- Unsolved now and in the near future

- Traditional search provides little help
  Complex
- Heavily pattern-oriented
- Unsolved now and in the near future
- Analogues to more complex environments
  - Local versus global concerns
  - Many choices at any point
  - Adversarial

#### The Go Board



**Playing Go (continued)** 

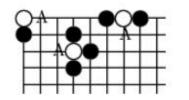


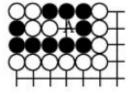
**Playing Go (continued)** 

#### • Groups • Eyes

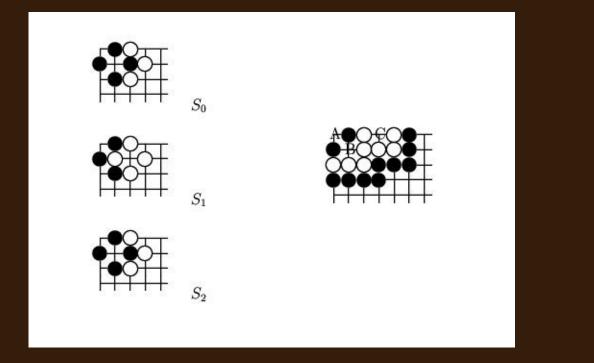
## Groups Eyes Live and Dead Stones

Capturing

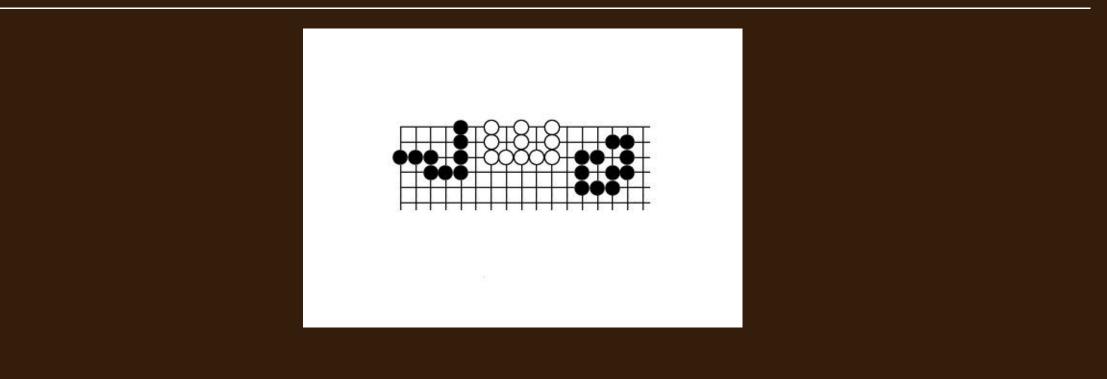




#### Ko and Seki Rules



Territory



**Playing Go (continued)** 



## ScoringOther board sizes

# Scoring Other board sizes Handicaps

#### • Random search

## Random search Populations

#### • Random search

- Populations
- Chromosomes representing parameters or solutions

- Random search
- Populations
- Chromosomes representing parameters or solutions
  Fitness functions

- Random search
- Populations
- Chromosomes representing parameters or solutions
- Fitness functions
- Crossover, mating, and mutations

#### • Autonomous agents

## Autonomous agentsSense environment

### Autonomous agentsSense environment

• Interacts with environment

- Autonomous agents
- Sense environment
- Interacts with environment
- Cooperative or adversarial

#### • No Soft Methods

#### No Soft Methods

#### • Müller

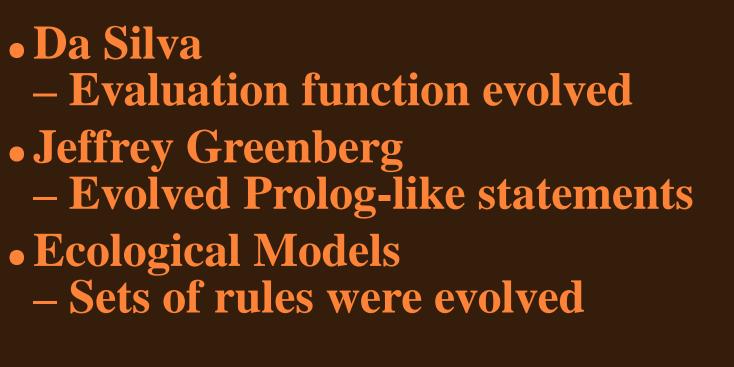
- Patricia trees variant
- 3000 pattern database

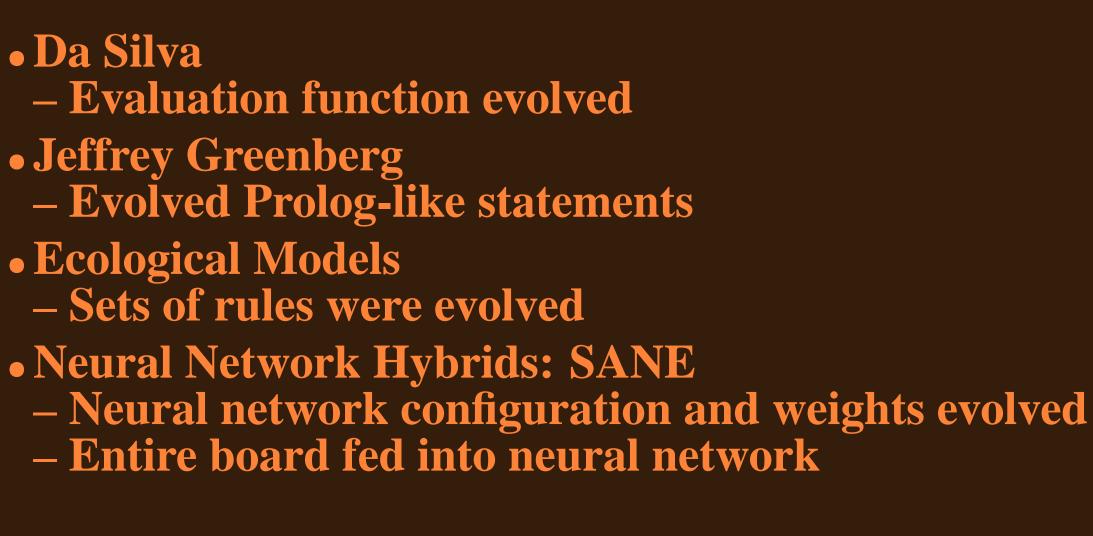
- No Soft Methods
- Müller
  - Patricia trees variant
  - 3000 pattern database
- Many Faces of Go
  - Opening database of 45,000 moves
  - Pattern database of 1000 patterns
  - 200 rules hardcoded

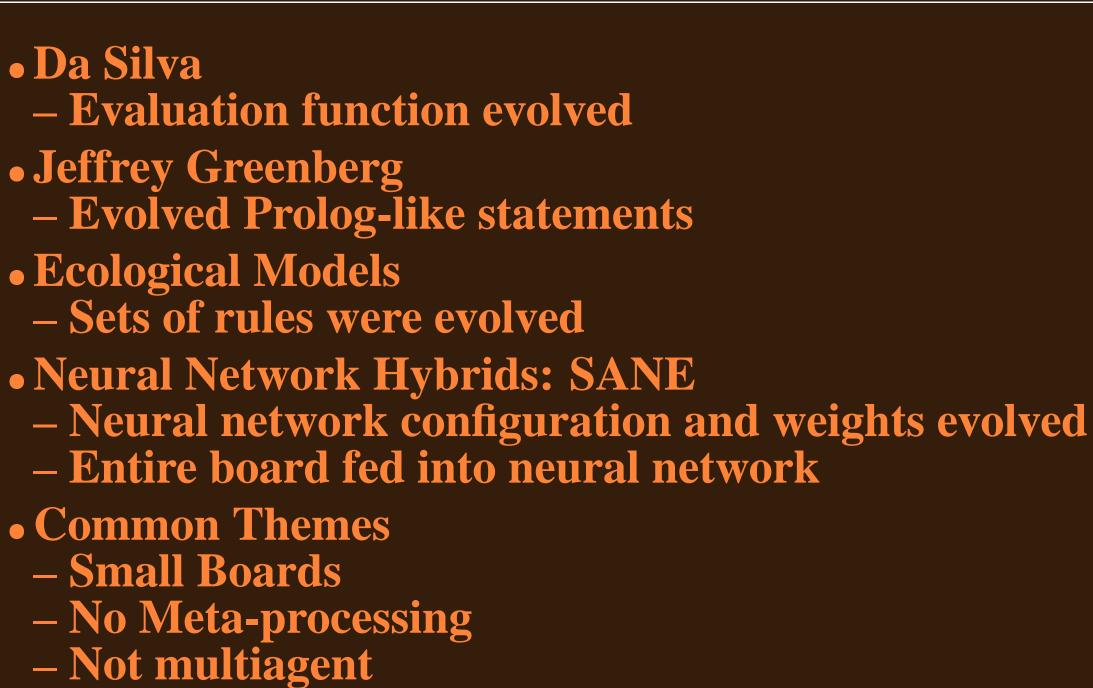
- No Soft Methods
- Müller
  - Patricia trees variant
  - 3000 pattern database
- Many Faces of Go
  - Opening database of 45,000 moves
  - Pattern database of 1000 patterns
  - 200 rules hardcoded
- Others
  - Patterns
  - Try to create small set of possible moves to look into

#### • Da Silva – Evaluation function evolved

# Da Silva Evaluation function evolved Jeffrey Greenberg Evolved Prolog-like statements







**Support Classes** 

#### • Bit-level operations for Stone class for speed

## Bit-level operations for Stone class for speed Board class is a 1D array of stone classes

# Bit-level operations for Stone class for speed Board class is a 1D array of stone classes Game class is a linked list of Boards

- Bit-level operations for Stone class for speed
- Board class is a 1D array of stone classes
- Game class is a linked list of Boards
- Probability Board class
  - Parallel to board array
  - Each offset is a move quality
  - Summation, normalization, and scaling provided
    Spin

Interfaces

#### • Moderator class, a template

Interfaces

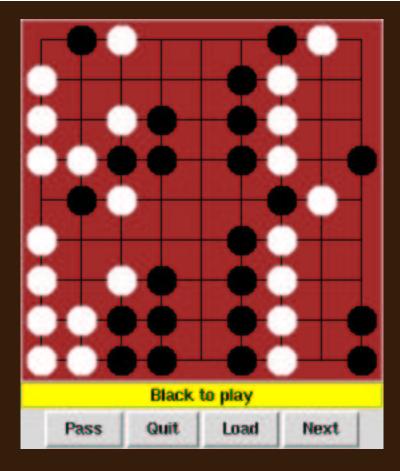
## Moderator class, a template Multiagent genetic algorithm player

Interfaces

Moderator class, a template
Multiagent genetic algorithm player
Genetic algorithm trainer player

Fitness function





Agents

#### • Random

### Random Follower



- Random
  Follower
  Opener
- Capture

- Random
- Follower
- Opener
- Capture
- Tiger's Mouth

- Random
- Follower
- Opener
- Capture
- Tiger's Mouth
- Extender
  - Uses GA values internally

**Experiments Overview** 

#### • Each Agent Individually

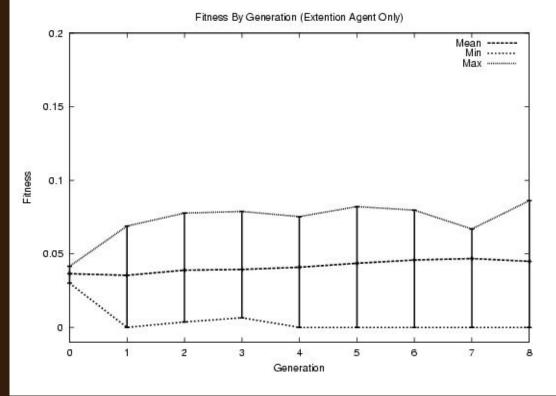
# Each Agent IndividuallyRandom Agent

# Each Agent Individually Random Agent Multiagent

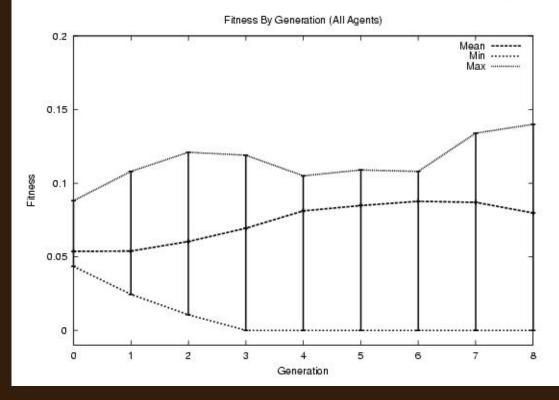
- Each Agent Individually
- Random Agent
- Multiagent
- GA parameters
  - Crossover 0.4
  - Mutation 0.0333
  - Population size: 10 and 100

		Generation	Max	Min	Mean	Std. Dev.	Sumfitness	]
		0	0.0777	0.0777	0.0777	7.85e-09	0.777	
		1	0.0777	0.0777	0.0777	2.95e-05	0.777	
		2	0.0777	0.0777	0.0777	2.95e-05	0.777	
		3	0.0777	0.0777	0.0777	0.00181	0.777	
		4	0.0777	0.0777	0.0777	0.00181	0.777	1
		5	0.0777	0.0777	0.0777	0.0142	0.777	
		6	0.0777	0.0777	0.0777	0.0142	0.777	
		7	0.0777	0.0777	0.0777	0.0397	0.777	
		8	0.0777	0.0777	0.0777	0.0397	0.777	
			F	itness By Ge	eneration (Ca	apturer Agent)		
	0.2					1	- i - i -	
	-							
	0.15	-						1
52								
Fitness	0.1	•						1
ш		·····				·····	-++	
		9 B			22	<u>80</u>	92 - 24	
	0.05	_						
	0.05	59						
	0							
	1	<u> </u>	1				1 1	
	0	1	2	з	4 Generation	5	6 7	8
					Generation			

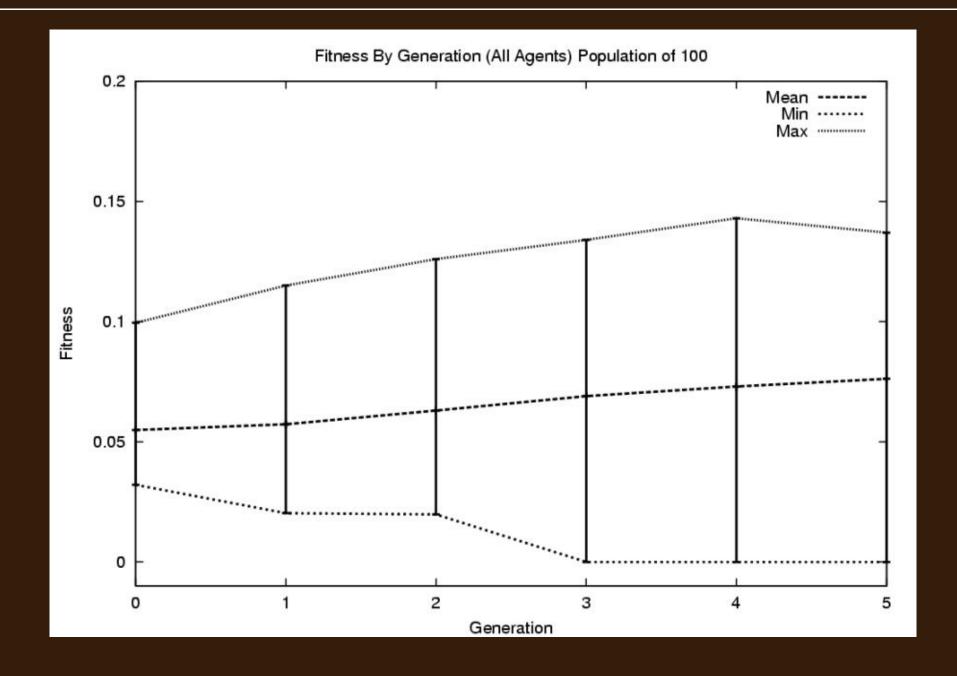
Generation	Max	Min	Mean	Std. Dev.	Sumfitness
0	0.0415	0.0301	0.0365	0.00428	0.365
1	0.0689	0	0.0354	0.0319	0.354
2	0.0777	0.0037	0.0389	0.0347	0.389
3	0.0788	0.00656	0.0394	0.0641	0.394
4	0.0753	2.76e-10	0.0409	0.0667	0.409
5	0.0821	8.1e-09	0.0436	0.0899	0.436
6	0.0797	5.57e-09	0.0458	0.0893	0.458
7	0.0669	0	0.0468	0.102	0.468
8	0.0861	0	0.0449	0.105	0.449



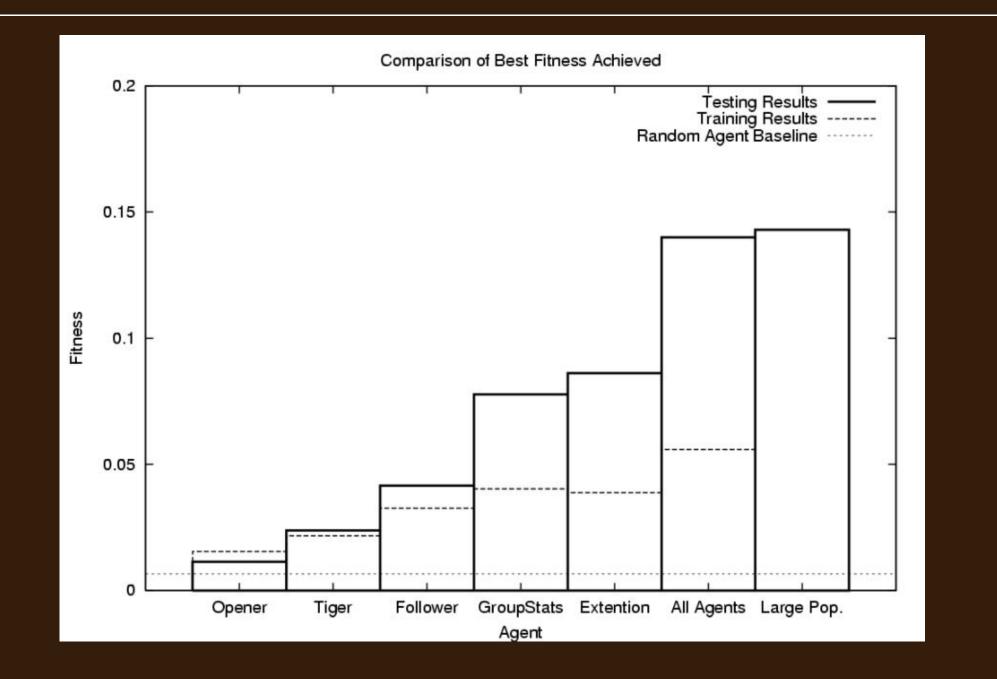
Generation	Max	Min	Mean	Std. Dev.	Sumfitness
0	0.0881	0.0435	0.0537	0.0138	0.537
1	0.108	0.0245	0.0539	0.0454	0.539
2	0.121	0.0106	0.0604	0.0575	0.604
3	0.119	3.49e-10	0.0694	0.0865	0.694
4	0.105	3.15e-09	0.0812	0.0867	0.812
5	0.109	2.82e-09	0.0848	0.103	0.848
6	0.108	2.15e-09	0.0877	0.103	0.877
7	0.134	0	0.087	0.113	0.87
8	0.14	0	0.0798	0.118	0.798



#### **Results of Multiagent Experiment: Large Population**



#### **Comparison Plot**



**Results Summary (Multiagent, Population 100)** 

#### • 0.143 Highest fitness

## 0.143 Highest fitness 0.076 Highest mean fitness

- 0.143 Highest fitness
- 0.076 Highest mean fitness
- Student's T-test
  - T-test, 100 population confidence: 3.89E-21
  - T-test, 10 population confidence: 5.04E-4

Contributions

### • Unique approach to go

Contributions

### Unique approach to go Probabilistic methods for go

Contributions

Unique approach to go
Probabilistic methods for go
Multiagent paradigm

- Unique approach to go
  Probabilistic methods for go
  Multiagent paradigm
- Scalability

#### • Board Size

# Board SizeNumber of Agents

- Board Size
- Number of Agents
- Time to run genetic algorithms
  - Training sets
  - Populations
  - Larger summation networks
  - Generations

- Board Size
- Number of Agents
- Time to run genetic algorithms
  - Training sets
  - Populations
  - Larger summation networks
  - Generations
- Programmer's knowledge of go

### • Larger population size

### Larger population size Larger board size

Larger population size
Larger board size
More agents

- Larger population size
- Larger board size
- More agents
- Agents of higher complexity

- Larger population size
- Larger board size
- More agents
- Agents of higher complexity
- Larger summation network

#### • Thank You

### Thank You Thread Pools

- Thank You
  Thread Pools
- Search

- Thank You
- Thread Pools
- Search
- Minimax

- Thank You
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- Texts
  - Genetic Algorithms in Search Optimization, and Machine Learning
  - Numerical Recipes in C: The Art of Scientific Computing