Swarms and evolution

The concept of Zero-Intelligence agents
Principle of swarms
Evolution and adaption
Genetics

Swarms


Proceedings of the
European Conference
on Artificial Life 2015
edited by
Paul Andrews, Leo Caves, René Doursat,
Simon Hickinbotham, Fiona Polack,
Susan Stepney, Tim Taylor and Jon Timmis

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What is Swarm Intelligence?

Swarm intelligence (SI) is a subfield of artificial intelligence. The concept originated in the field of robotics and refers to the amplified intelligence of flocks of birds, colonies of ants or swarms of bees, vs the performance of their individual members. SI is concerned with the design of multiagent systems modelled after the collective behavior of these self-organized animal populations.

The brainpower, self-organization and problem-solving abilities of such collectives in nature have always exercised fascination on researchers and scientists. More recently, they've inspired advances and applications in robotics and optimization. Now artificial swarm intelligence is brought within the reach of human groups as well.

http://www.megamification.com/unu-the-platform-that-gamifies-human-swarm-intelligence/

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newsweek.com/swarm-intelligence-ai-algorithm-predicts-future-418707

Newsweek

TECH & SCIENCE

Swarm Intelligence: AI Algorithm Predicts the Future

BY ANTHONY CUTHBERTSON ON 1/25/16 AT 1:45 PM EST

A new A.I. algorithm that enables decision making through swarm intelligence could revolutionize democracy and transform healthcare.

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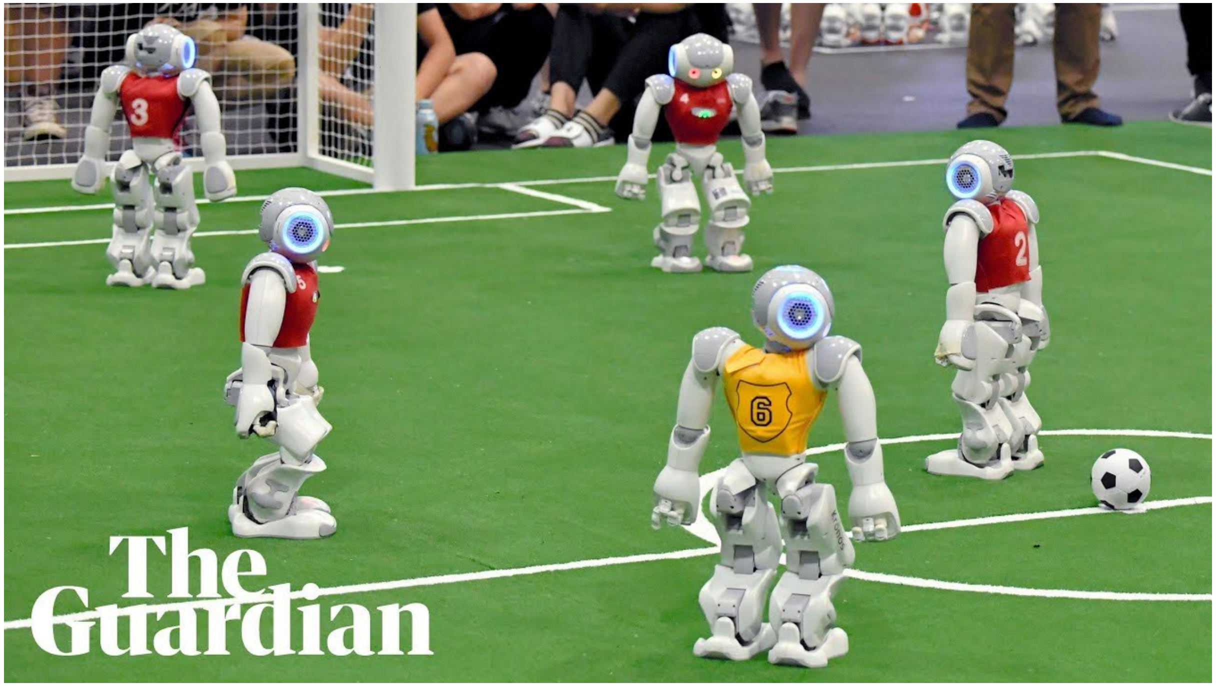
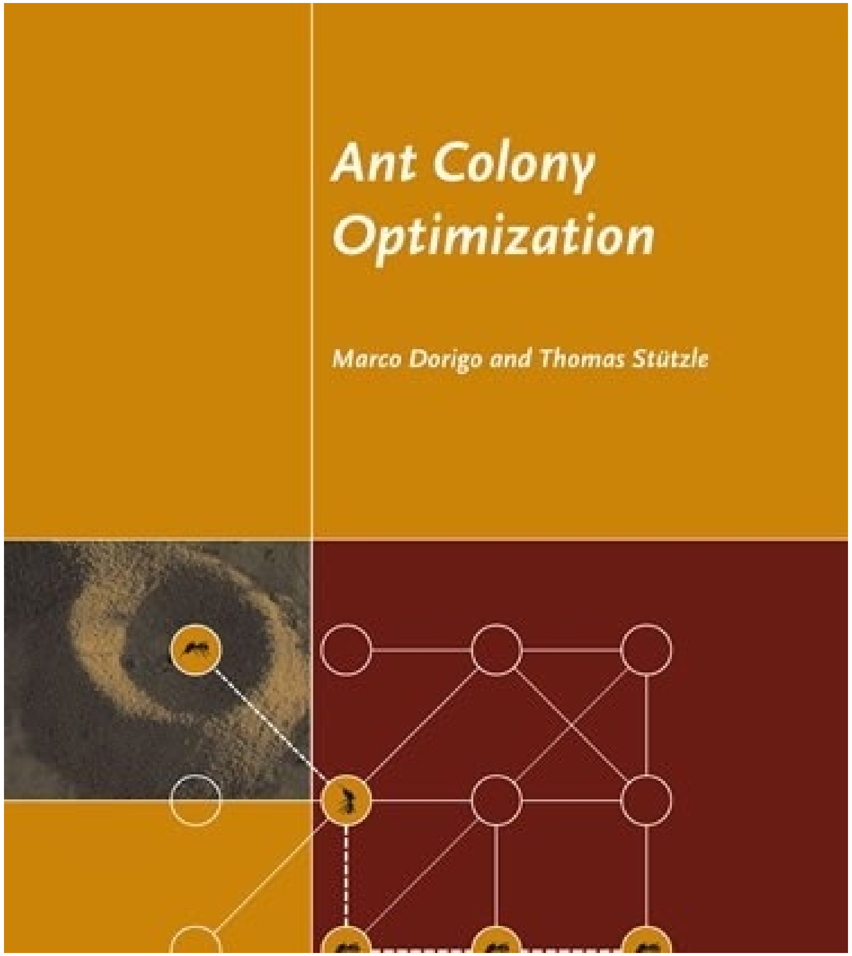
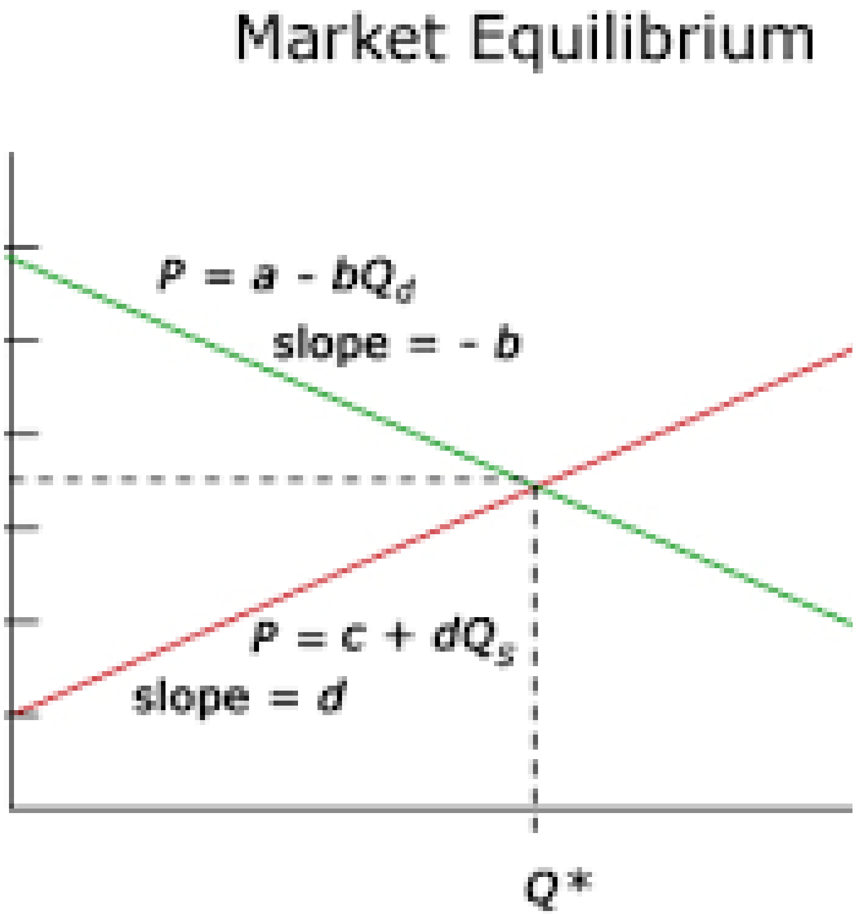
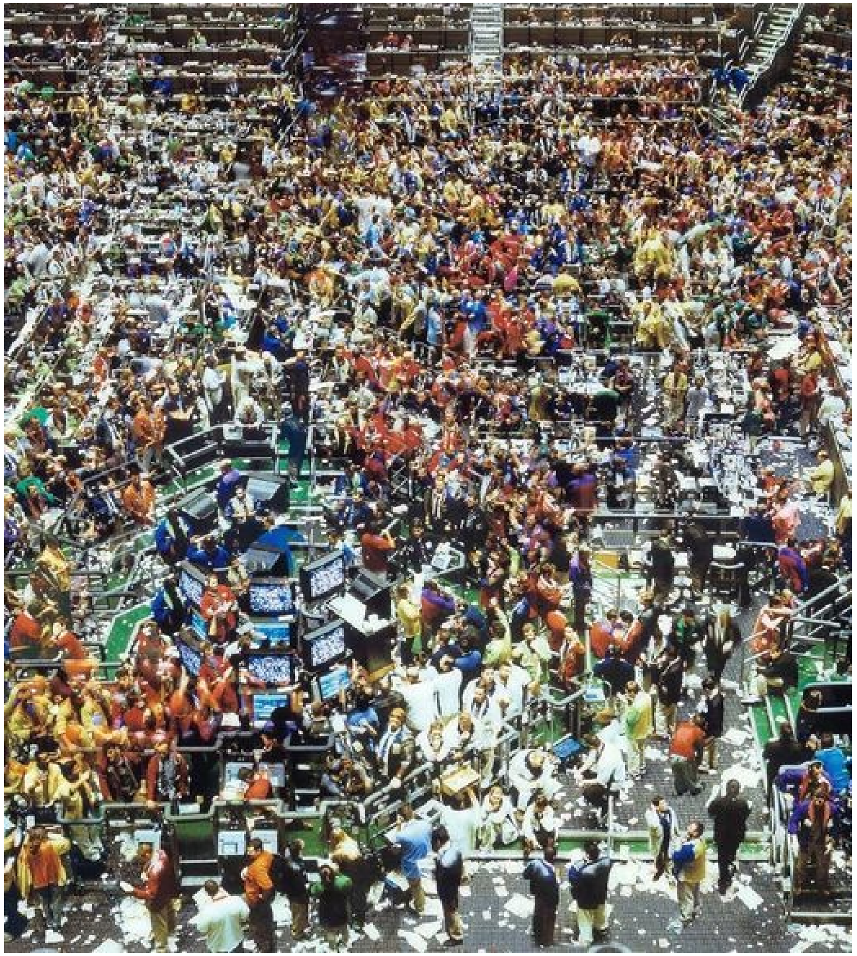


Colonies



Markets





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Principal papers on swarms

Artificial Swarm Intelligence vs Vegas Betting Markets

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***Abstract*— In the natural world, Swarm Intelligence (SI) is a commonly occurring process in which biological groups amplify their collective intelligence by forming closed-loop systems. It is well known in schools of fish, flocks of bird, and swarms of bees. In recent years, new AI technologies have enabled networked human groups to form systems modeled after natural swarms. Known as Artificial Swarm Intelligence (ASI), the technique has been shown to amplify the effective intelligence of human groups. This study compares the predictive ability of ASI systems against large betting markets when forecasting sporting events. Groups of average sports fans were tasked with predicting the outcome of 200 hockey games (10 games per week for 20 weeks) in the NHL. The expected win rate for Vegas favorites was 62% across the 200 games based on the published odds. The ASI system achieved a win rate of 85%. The probability that the system outperformed Vegas by chance was extremely low ($p = 0.0057$), indicating a significant result. In addition, researchers compared the winnings from two betting models – one that wagered weekly on the Vegas favorite, and one that wagered weekly on the ASI favorite. At the end of 20 weeks, the Vegas model generated a 41% financial loss, while the ASI model generated a 170% financial gain.**

Keywords*— Swarm Intelligence, Artificial Swarm Intelligence, Collective Intelligence, Human Swarming, Artificial Intelligence.

I. Background

Prior studies on Artificial Swarm Intelligence (ASI) have shown that by forming real-time "human swarms," networked human groups can significantly amplify their accuracy in a wide

While prior studies have documented the ability of artificial swarms to outperform individuals and outperform traditional Wisdom of Crowd methods across a range of forecasting tasks, no formal study has compared the predictive ability of artificial swarms against largescale markets. To address this need, a study was run to compare human swarms to Vegas betting markets, assessing the accuracy rates and the financial returns across a large set of predictions. Specifically, this study required human participants to forecast the outcome of 200 games in the National Hockey League (NHL), structured as 10 games per week for 20 consecutive weeks.

II. Swarms vs Crowds

When comparing the accuracy of real-time swarms against traditional crowd-based methods, it's worth reviewing the structural differences between them. The prime differentiator between "crowds" and "swarms" is that in crowd-based methods, human participants provide input in isolation for aggregation in external statistical models, while in swarm-based methods, human participants "think together" in real-time, their interactions governed by intelligence algorithms. This means that swarms are closed-loop systems in which participants act, react, and interact with each other, converging on optimized solutions in synchrony. The swarming process is generally modeled after biological systems such as schools of fish, flocks of birds, and swarms of bees. The present study uses Swarm AI technology from Unanimous AI Inc, which is modeled largely on the decision-making processes of honeybee swarms [4].

Behav Ecol Sociobiol (1999) 45: 19–31

ORIGINAL ARTICLE

Thomas D. Seeley · Susannah C. Buhrman

Group decision making in swarms of honey bees

Received: 26 February 1998 / Accepted after revision: 16 May 1998

Abstract This study renews the analysis of honey bee swarms as decision-making units. We repeated Lindauer's observations of swarms choosing future home sites but used modern videorecording and bee-labelling techniques to produce a finer-grained description of the decision-making process than was possible 40 years ago. Our results both confirm Lindauer's findings and reveal several new features of the decision-making process. Viewing the process at the group level, we found: (1) the scout bees in a swarm find potential nest sites in all directions and at distances of up to several kilometers; (2) initially, the scouts advertise a dozen or more sites with their dances on the swarm, but eventually they advertise just one site; (3) within about an hour of the appearance of unanimity among the dancers, the swarm lifts off to fly to the chosen site; (4) there is a crescendo of dancing just before liftoff, and (5) the chosen site is not necessarily the one that is first advertised on the swarm. Viewing the process at the individual level, we found: (1) the dances of individual scout bees tend to taper off and eventually cease, so that many dancers drop out each day; (2) some scout bees switch their allegiance from one site to another, and (3) the principal

accurate but also the most demanding in terms of information processing, because it takes account of all of the information relevant to a decision problem. Despite being composed of small-brained bees, swarms are able to use the weighted additive strategy by distributing among many bees both the task of evaluating the alternative sites and the task of identifying the best of these sites.

Key words *Apis mellifera* · Communication · Dance language · Decision making · Swarming

Introduction

One of the most spectacular examples of an animal group functioning as an adaptive unit is a swarm of honey bees choosing its future home. This phenomenon occurs in the late spring and early summer when a colony outgrows its hive and proceeds to divide itself by swarming. The mother queen and approximately half the worker bees leave the parental hive to establish a

JOURNAL OF THE ROYAL SOCIETY Interface

J. R. Soc. Interface (2009) **6**, 1065–1074
doi:10.1098/rsif.2008.0511
Published online 25 February 2009

On optimal decision-making in brains and social insect colonies

James A. R. Marshall[1,*], Rafal Bogacz[1], Anna Dornhaus[2], Robert Planqué[3], Tim Kovacs[1] and Nigel R. Franks[4]

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[2] *Department of Ecology and Evolutionary Biology, University of Arizona, PO Box 210088, Tucson, AZ 85721, USA*
[3] *Department of Mathematics, VU University Amsterdam, De Boelelaan 1081a, 1081 HV Amsterdam, The Netherlands*
[4] *School of Biological Sciences, University of Bristol, Woodland Road, Bristol BS8 1UG, UK*

The problem of how to compromise between speed and accuracy in decision-making faces organisms at many levels of biological complexity. Striking parallels are evident between decision-making in primate brains and collective decision-making in social insect colonies: in both systems, separate populations accumulate evidence for alternative choices; when one population reaches a threshold, a decision is made for the corresponding alternative, and this threshold may be varied to compromise between the speed and the accuracy of decision-making. In primate decision-making, simple models of these processes have been shown, under certain parametrizations, to implement the statistically optimal procedure that minimizes decision time for any given error rate. In this paper, we adapt these same analysis techniques and apply them to new models of collective decision-making in social insect colonies. We show that social insect colonies may also be able to achieve statistically optimal collective decision-making in a very similar way to primate brains, via direct competition between evidence-accumulating populations. This optimality result makes testable predictions for how collective decision-making in social insects should be organized. Our approach also represents the first attempt to identify a common theoretical framework for the study of decision-making in diverse biological systems.

Keywords: decision-making; diffusion model; optimality; neurons; social insects; sequential probability ratio test

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UNU: The Platform that Gamifies Human Swarm Intelligence

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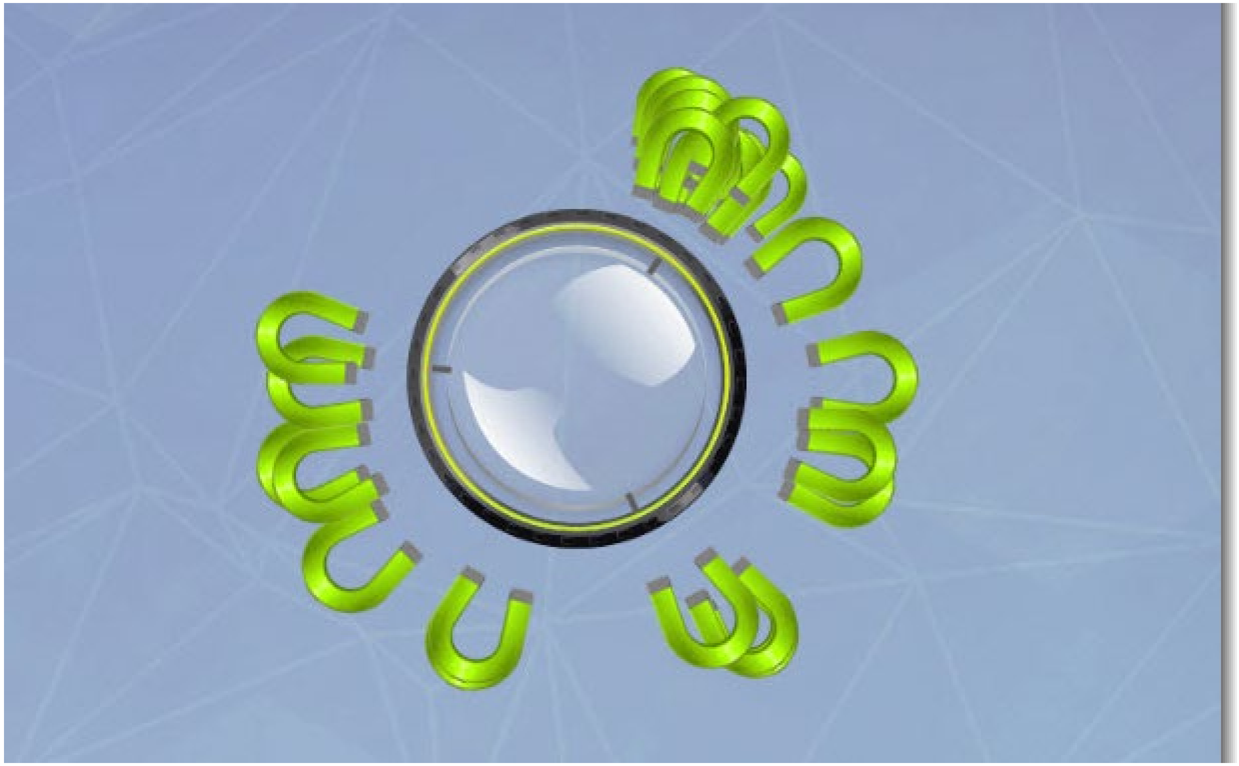
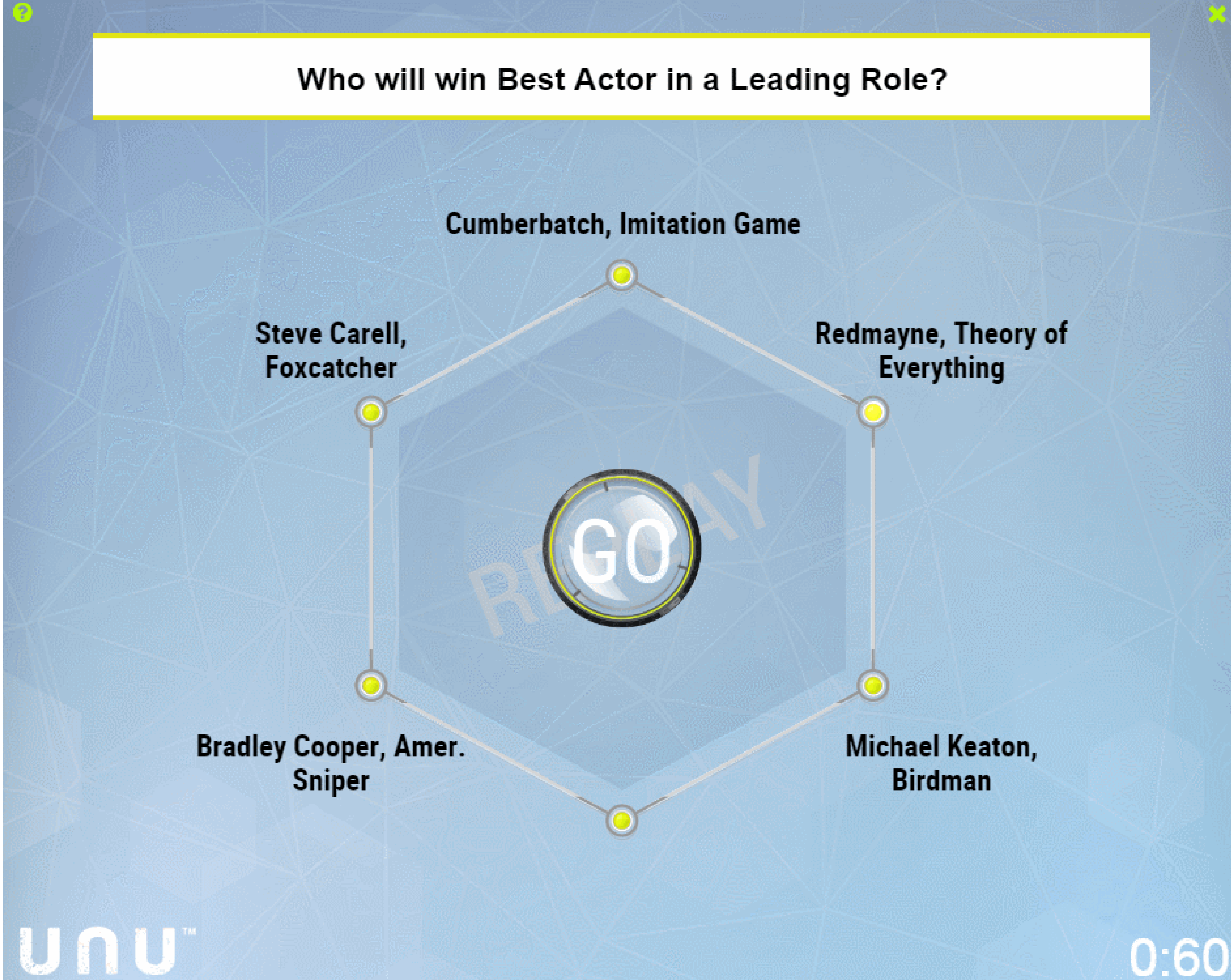
The Puck of Unu



http://www.megamification.com/unu-the-platform-that-gamifies-human-swarm-intelligence/


Who will win Best Actor in a Leading Role?
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Steve Carell, Foxcatcher
Redmayne, Theory of Everything
GO
Bradley Cooper, Amer. Sniper
Michael Keaton, Birdman
0:60

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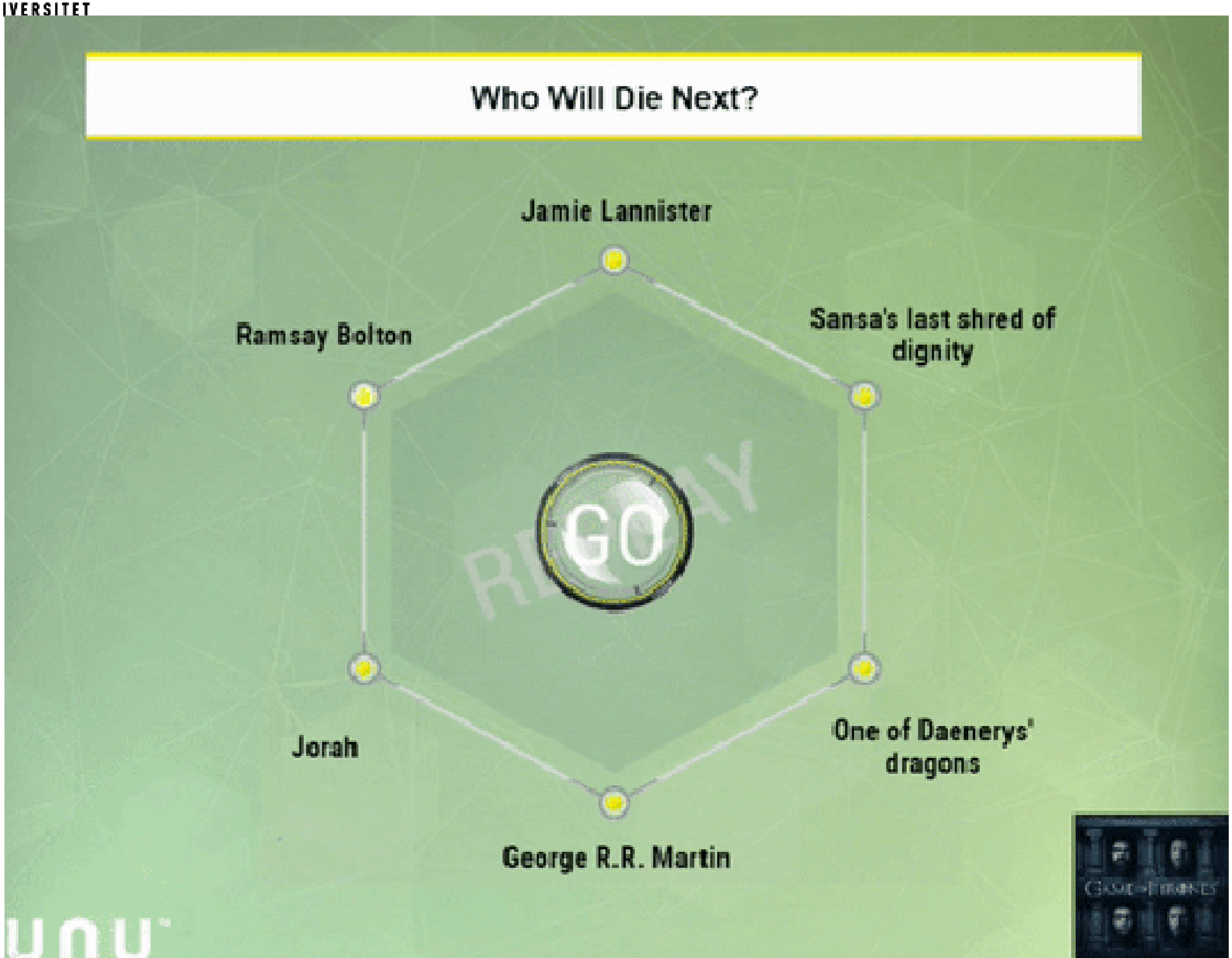

Marshall et al.

- In ***both brains and social insect colonies***, mutually interacting populations must reach an ***activation threshold to precipitate a decision***.

- We argue that the ***interaction patterns*** between populations are the crucial part of the decision-making process at both these levels of ***biological complexity, organismal and super-organismal.***

Marshall et al. (2)

- Notwithstanding their impressive individual abilities (Koch 1999), ***neurons are simple*** in comparison with ***individually sophisticated social insects*** (Giurfa et al. 2001; Chittka et al. 2003; Franks et al. 2003b; Franks & Richardson 2006; Richardson et al. 2007).

- ***Simple interaction patterns*** in both these systems, however, may implement ***robust, efficient decision-making*** regardless of how sophisticated their individual components are.

Swarm principles

- **Principle #1: Awareness**
- Each member must be aware of its surroundings and abilities.
- **Principle #2: Autonomy**
- Each member must operate as an autonomous master (not as a slave;) this is essential to self-coordinate allocation of labor.
- **Principle #3: Solidarity**
- Each member must cooperate in solidarity: when a task is completed, each member should autonomously look for a new task (leveraging its current position.)
- **Principle #4: Expandability**
- The system must permit expansion where members are dynamically aggregated.
- **Principle #5: Resiliency**
- The system must be self-healing: when members are removed, the remaining members should undertake the unfinished tasks.

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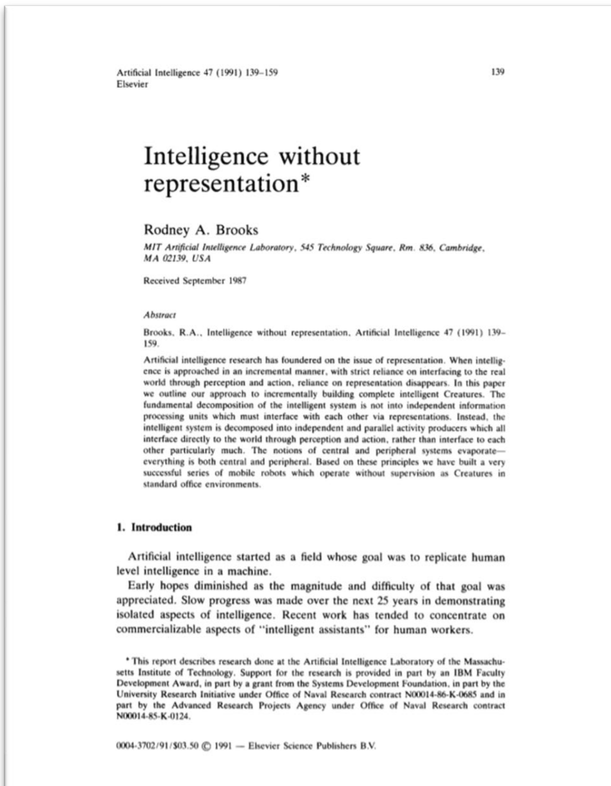
Take aways on swarms

- Collective intelligence operating in a **synchronous** manner
  - Similar to fuzzy systems based on voting (which is asynchronous) and explicit reasoning
  - Similar to crowd sourcing which is asynchronous
  - Related to cellular automata
  - Shares some features with ensembles
- Each agent adopts a specific role to solve a problem or make a decision for the best of the hive/colony
- Even small swarms can beat "intelligent indiviudals"
- Social insect systems similar to neuron based systems

Rodney Brooks:
Smartness in a simple way



Artificial Intelligence 47 (1991) 139–159
Elsevier

Intelligence without representation*

Rodney A. Brooks
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Received September 1987

Abstract

Brooks, R.A., Intelligence without representation, Artificial Intelligence 47 (1991) 139–159.

Artificial intelligence research has foundered on the issue of representation. When intelligence is approached in an incremental manner, with strict reliance on interfacing to the real world through perception and action, reliance on representation disappears. In this paper we outline our approach to incrementally building complete intelligent Creatures. The fundamental decomposition of the intelligent system is not into independent information processing units which must interface with each other via representations. Instead, the intelligent system is decomposed into independent and parallel activity producers which all interface directly to the world through perception and action, rather than interface to each other particularly much. The notions of central and peripheral systems evaporate—everything is both central and peripheral. Based on these principles we have built a very successful series of mobile robots which operate without supervision as Creatures in standard office environments.

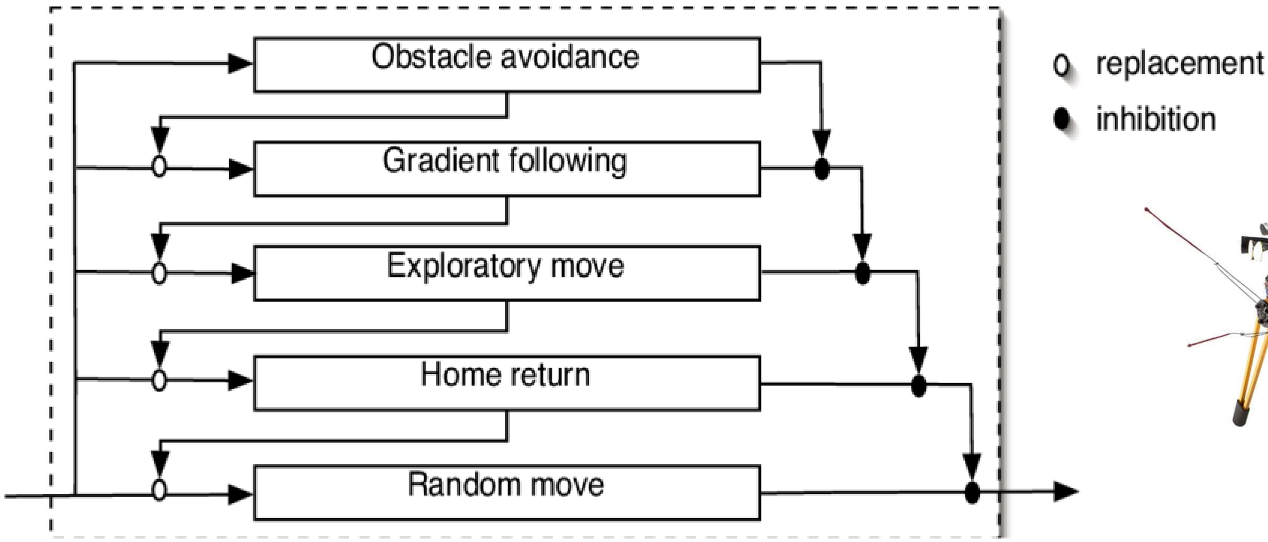
1. Introduction

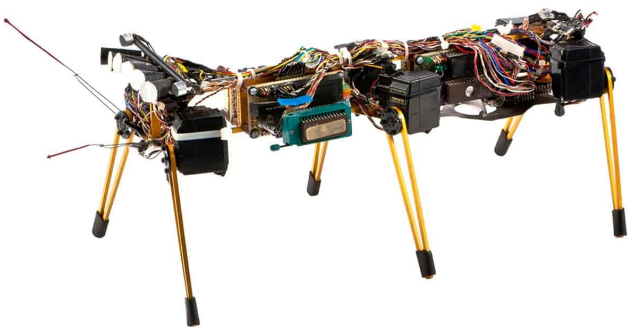
Artificial intelligence started as a field whose goal was to replicate human level intelligence in a machine.

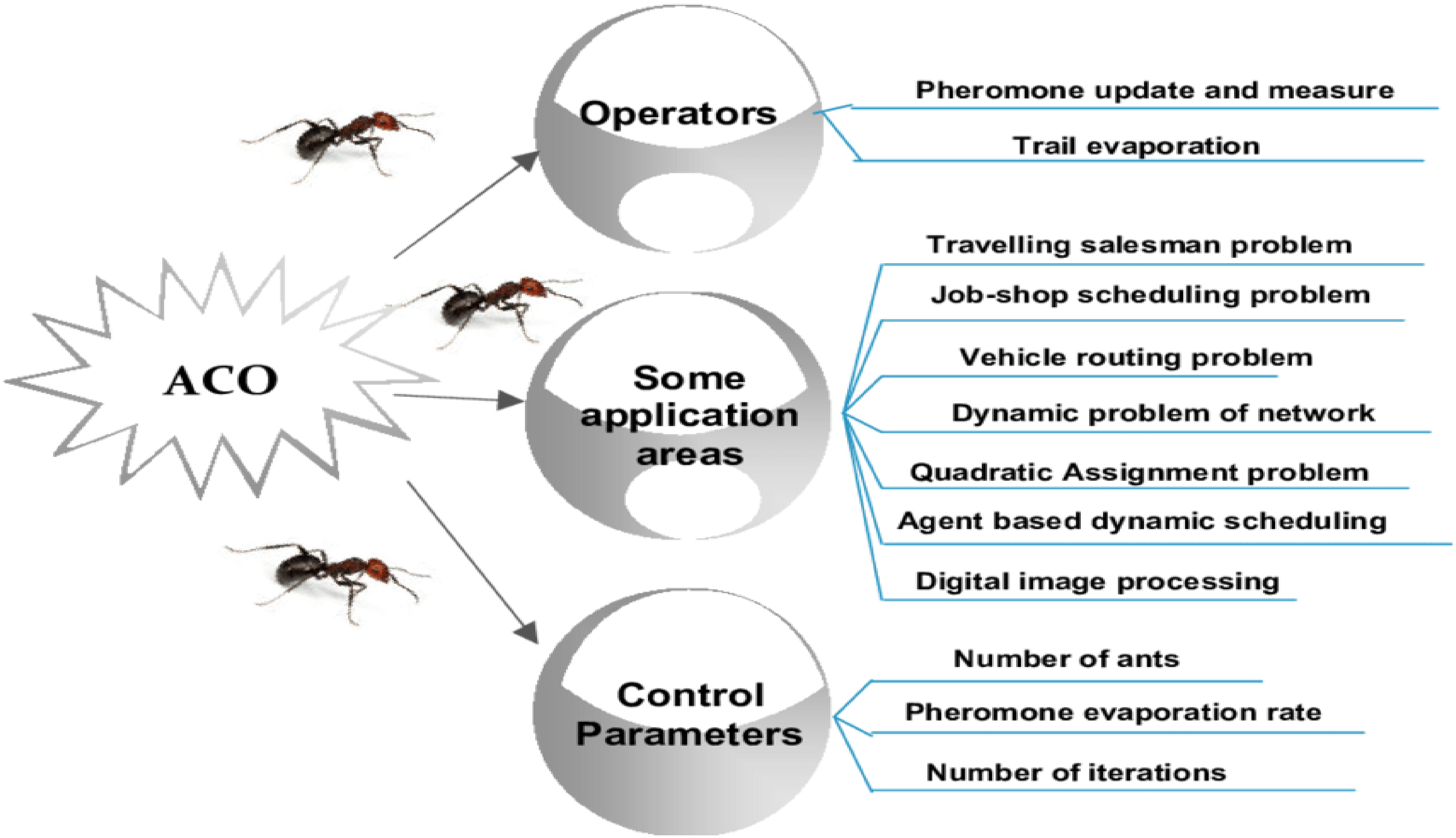
Early hopes diminished as the magnitude and difficulty of that goal was appreciated. Slow progress was made over the next 25 years in demonstrating isolated aspects of intelligence. Recent work has tended to concentrate on commercializable aspects of "intelligent assistants" for human workers.

* This report describes research done at the Artificial Intelligence Laboratory of the Massachusetts Institute of Technology. Support for the research is provided in part by an IBM Faculty Development Award, in part by a grant from the Systems Development Foundation, in part by the University Research Initiative under Office of Naval Research contract N00014-86-K-0685 and in part by the Advanced Research Projects Agency under Office of Naval Research contract N00014-85-K-0124.

Take aways: Rodney Brooks' robots






ACO
Operators
Pheromone update and measure
Trail evaporation
Some application areas
Travelling salesman problem
Job-shop scheduling problem
Vehicle routing problem
Dynamic problem of network
Quadratic Assignment problem
Agent based dynamic scheduling
Digital image processing
Control Parameters
Number of ants
Pheromone evaporation rate
Number of iterations

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Relevant papers

Don’t Go with the Ant Flow: Ant-inspired Traffic Routing in Urban Environments

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ABSTRACT

Traffic routing is a well established optimization problem in traffic management. We address here dynamic routing problems where the load of roads is taken into account dynamically, aiming at the optimization of required travel times. We investigate ant-based algorithms that can handle dynamic routing problems, but suffer from negative emergent effects like road congestions. We propose an *inverse* ant-based routing algorithm to avoid these negative emergent effects. We evaluate our approach with the agent-based traffic simulation system MAINS^{2}IM. For evaluation, we use a synthetic and two real world scenarios. Evaluation results indicate that the proposed inverse ant-based routing can lead to a reduction of travel time.

1. INTRODUCTION

Traffic routing is a well established research and optimization problem in traffic management [6]. Most research has been done for static problems, i.e., settings where the problem structure does not change. In static problems the routing decision boils down to find the shortest path between the start and the goal point. Once a solution has been found for all routes the optimal ones can be used whenever needed. These algorithms typically are based on shortest path algorithms, like the well known A* algorithm.

The situation becomes more complex if we regard dynamic problems. In a dynamic problem, the problem structure changes while solving the problem. For routing decisions this

Using Ant Colony Optimization to determine influx of EVs and charging station capacities

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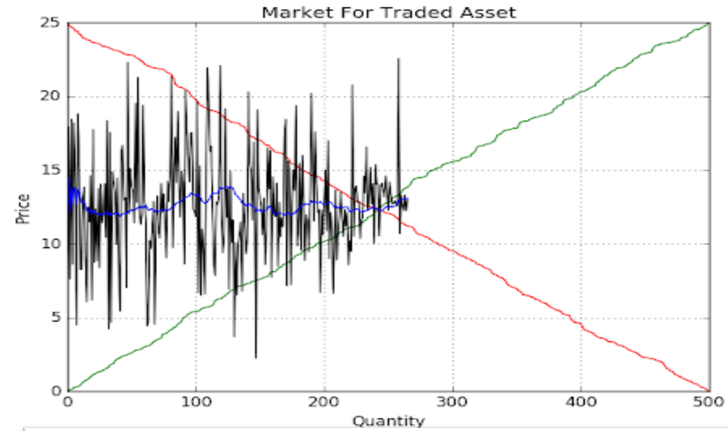
***Abstract*—This paper presents a novel method for determining plug-in Elecric Vehicle (EV) traffic and associated recharging needs based on an ACO (Ant Colony Optimization) method. The method is used to analyze traffic patterns and to determine their impact on the local grid and the design of charging stations. The research reported here also supports the design of a portfolio of Charging Stations (CSs) across a limited geographical area and use this to determine the required capacities of each station. An empirical basis for the research presented has been gathered from Norway where the number of EVs are growing fast and where use of EVs for different purposes, including long-range driving, are becoming very pronounced. The research presented also shows how demand for charging at different times can be determined. This lays the foundation for estimating peak loads in the local grid due to EV charging. For the individual driver the system presented can be used to find preferred routing under different circumstances such as traffic congestion.**

***Index Terms*—Ant Colony Optimization, Charging Stations,**

II. INTRODUCTION

Understanding the traffic pattern under various conditions and to determine the potential recharging needs of plug-in vehicles (EV) in the future is essential in the Flex-ChEV project. This can help to determine where CSs should be located and the potential loads that the recharging needs could impose on the CS itself and the local grid. For an off-grid facility such loads should be absorbed by an ESS, and the magnitude of these loads would therefore be essential for its design. The approach documented here is based on Ant Colony Optimization (ACO). The aim of the paper is thus to highlight the validity of the method applied for the purpose presented above and to compare it with other, more traditional approaches, like Dynamic Programming (DP). The method developed can cater for a number of dynamic and transient aspects such as traffic congestion, seasonal changes and road

Markets and ZI-agents



Allocative Efficiency of Markets with Zero-Intelligence Traders: Market as a Partial Substitute for Individual Rationality

Dhananjay K. Gode; Shyam Sunder

The Journal of Political Economy, Vol. 101, No. 1. (Feb., 1993), pp. 119-137.

Stable URL:
http://links.jstor.org/sici?sici=0022-3808%28199302%29101%3A1%3C119%3AAEOMWZ%3E2.0.CO%3B2-3

The Journal of Political Economy is currently published by The University of Chicago Press.

Zero is Not Enough: On The Lower Limit of Agent Intelligence for Continuous Double Auction Markets*

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Abstract

Gode and Sunder's (1993) results from using "zero-intelligence" (ZI) traders, that act randomly within a structured market, appear to imply that convergence to the theoretical equilibrium price in continuous double-auction markets is determined more by market structure than by the intelligence of the traders in that market. However, it is demonstrated here that the average transaction prices of ZI traders can vary significantly from the theoretical equilibrium value when the market supply and demand are asymmetric, and that the degree of difference from equilibrium is predictable from *a priori* probabilistic analysis. In this sense, it is shown here that Gode and Sunder's results are artefacts of their experimental regime. Following this, 'zero-intelligence-plus' (ZIP) traders are introduced: like ZI traders,

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Humans as “ants”

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'Zero intelligence' trading closely mimics stock market

LIFE 1 February 2005

By Katharine Davis

A model that assumes stock market traders have zero intelligence has been found to mimic the behaviour of the London Stock Exchange very closely.

However, the surprising result does not mean traders are actually just buying and selling at random, say researchers. Instead, it suggests that the movement of markets depend less on the strategic behaviour of traders and more on the structure and constraints of the trading system itself.

The research, led by J Doyne Farmer and his colleagues at the Santa Fe Institute, New Mexico, US, say the finding could be used to identify ways to lower volatility in the stock markets and reduce transaction costs, both of which would benefit small investors and perhaps bigger investors too.

A spokesperson for the London Stock Exchange says: “It’s an interesting bit of work that mirrors things we’re looking at ourselves.”

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Smart Innovation Norway, UiT and Skagerak Energy

The Skagerak Market in E-Regio


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Sustainable Planet

The E-Regio project: for a distributed local energy market

30th June 2020

With a focus on pure energy trade, the E-Regio project investigates different local energy market concepts for energy storage, whilst also conducting research on local flexibility trade.

At E-Regio, we investigate different local market concepts for energy. This is primarily for the pure energy trade, but local flexibility trade is also subject to research. An overview of local energy markets and associated literature can be found in Sumper, 2019.1 In particular, the concepts described by Bremdal and Ilieva (2019) have been important for the type of work that has been conducted in E-Regio.2 Multiple models are reviewed and discussed regarding

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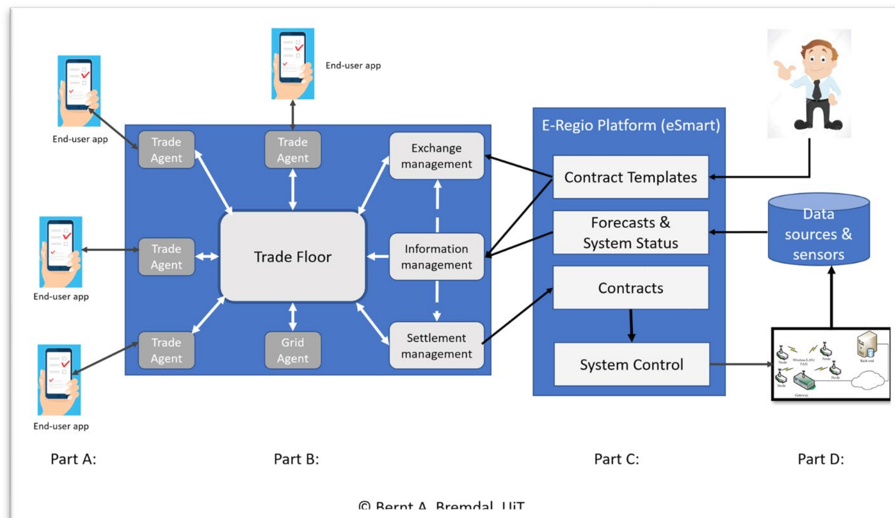
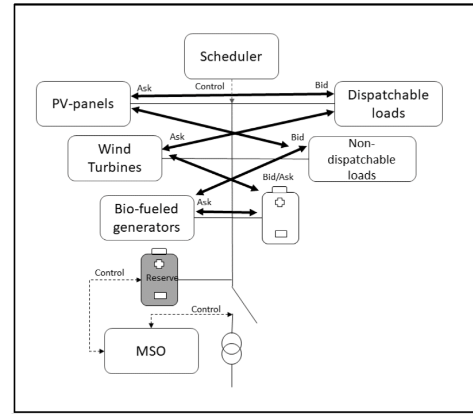


Trade floor

Agents' performances



Peer-to-peer concept w/ self-interested agents

User specifies trade limits – the agent does the rest

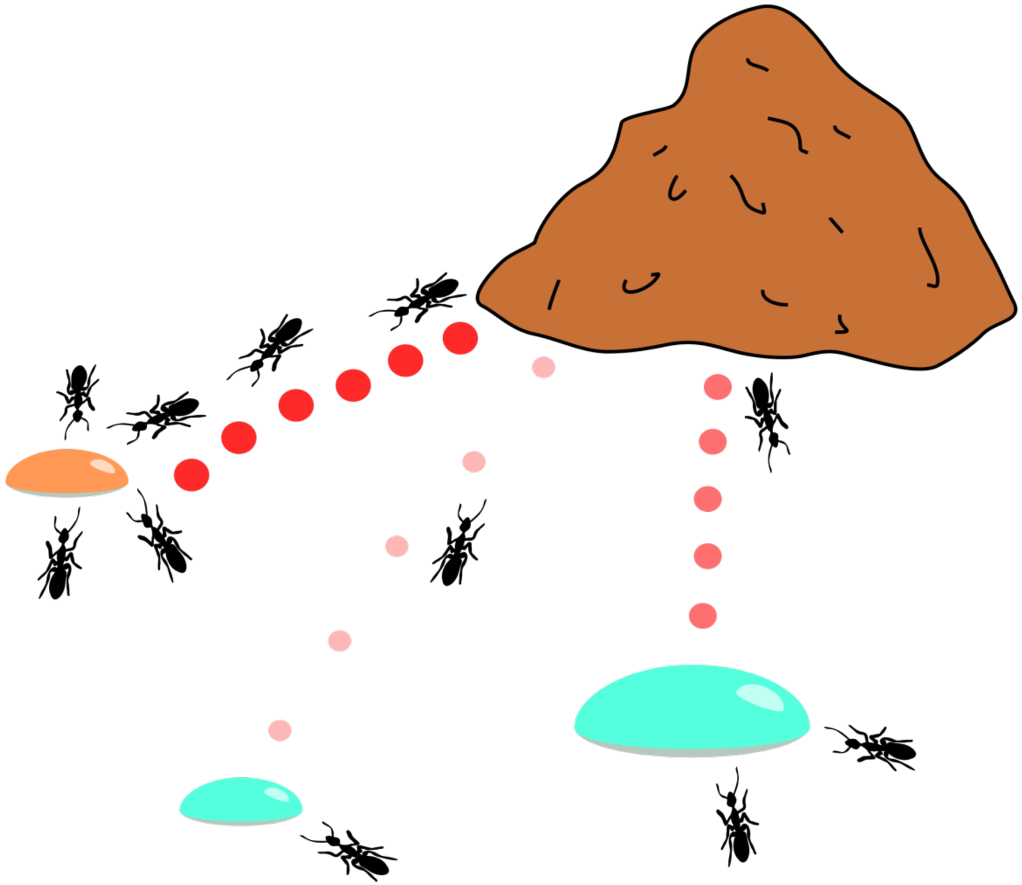
Ants as agents

Bernt A. Bremdal

UiT 2019

On collective intelligence & memory

Ant Colony Optimization



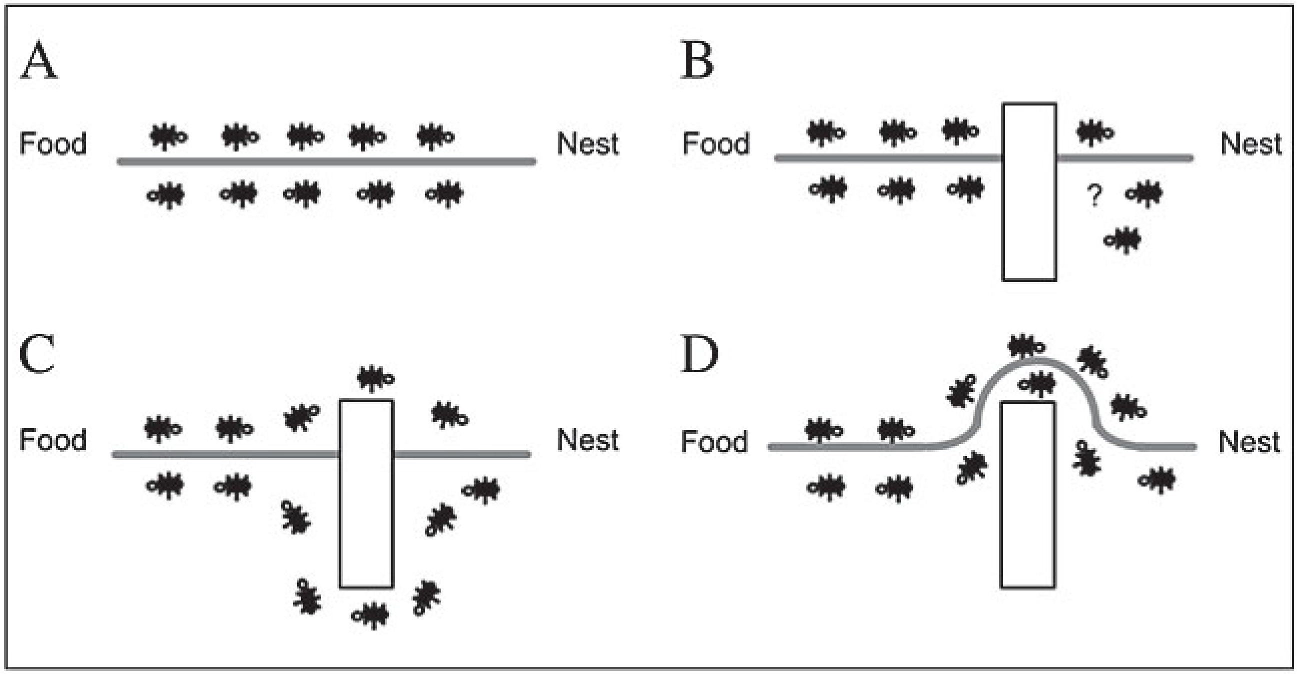
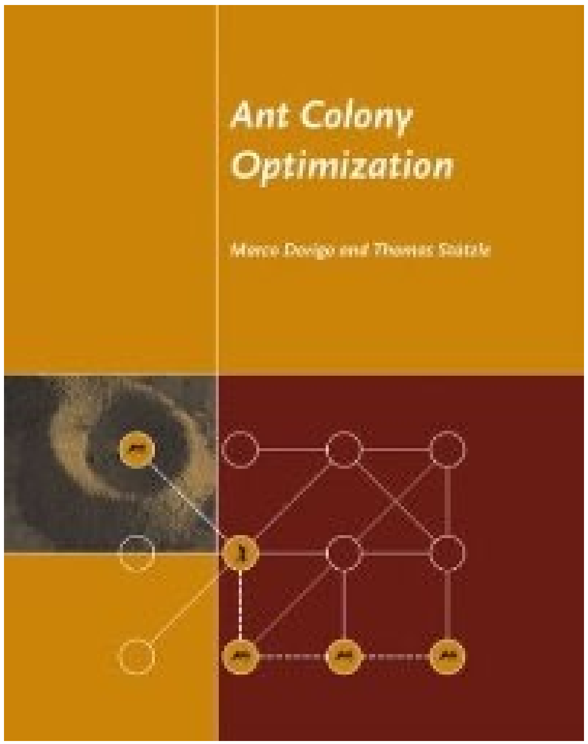


Figure 2. A. Ants in a pheromone trail between nest and food; **B.** an obstacle interrupts the trail; **C.** ants find two paths to go around the obstacle; **D.** a new pheromone trail is formed along the shorter path.

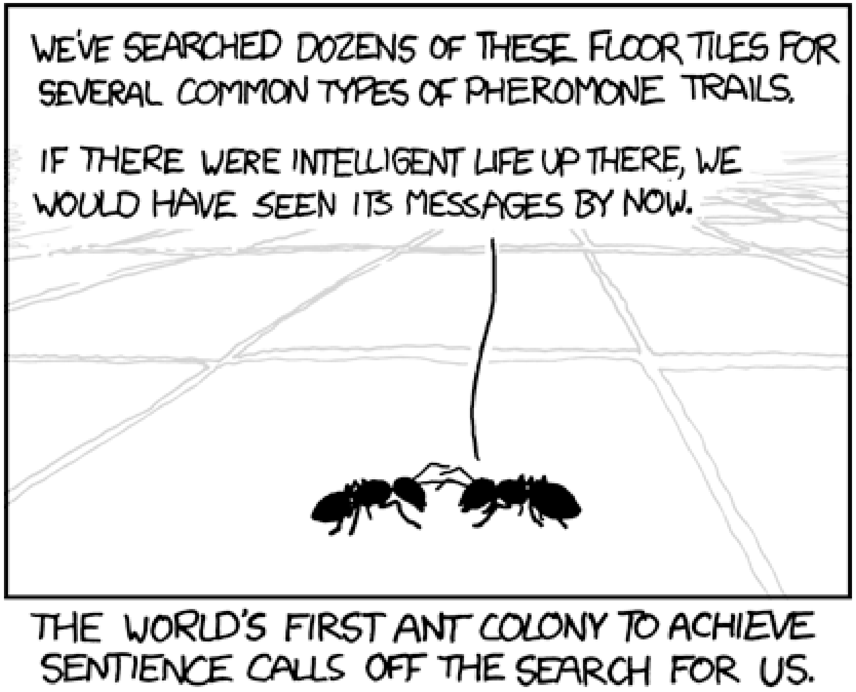
Ant colony intelligence



Ant Colony Optimization (Ch. 12)
Invented by Marco Dorigo in 1991

- An ant is a type of agent that solves a problem iteratively together with other ants
- Ants collaborate
- Partial solutions in the problem solving process are considered states
- Cyclic process
- Each ant moves from one state to another

Basic concepts



- Reward
- Attraction
- Profitability per path
- Pheromone and pheromone level
- Pheromone decay

Basic behavior of ants

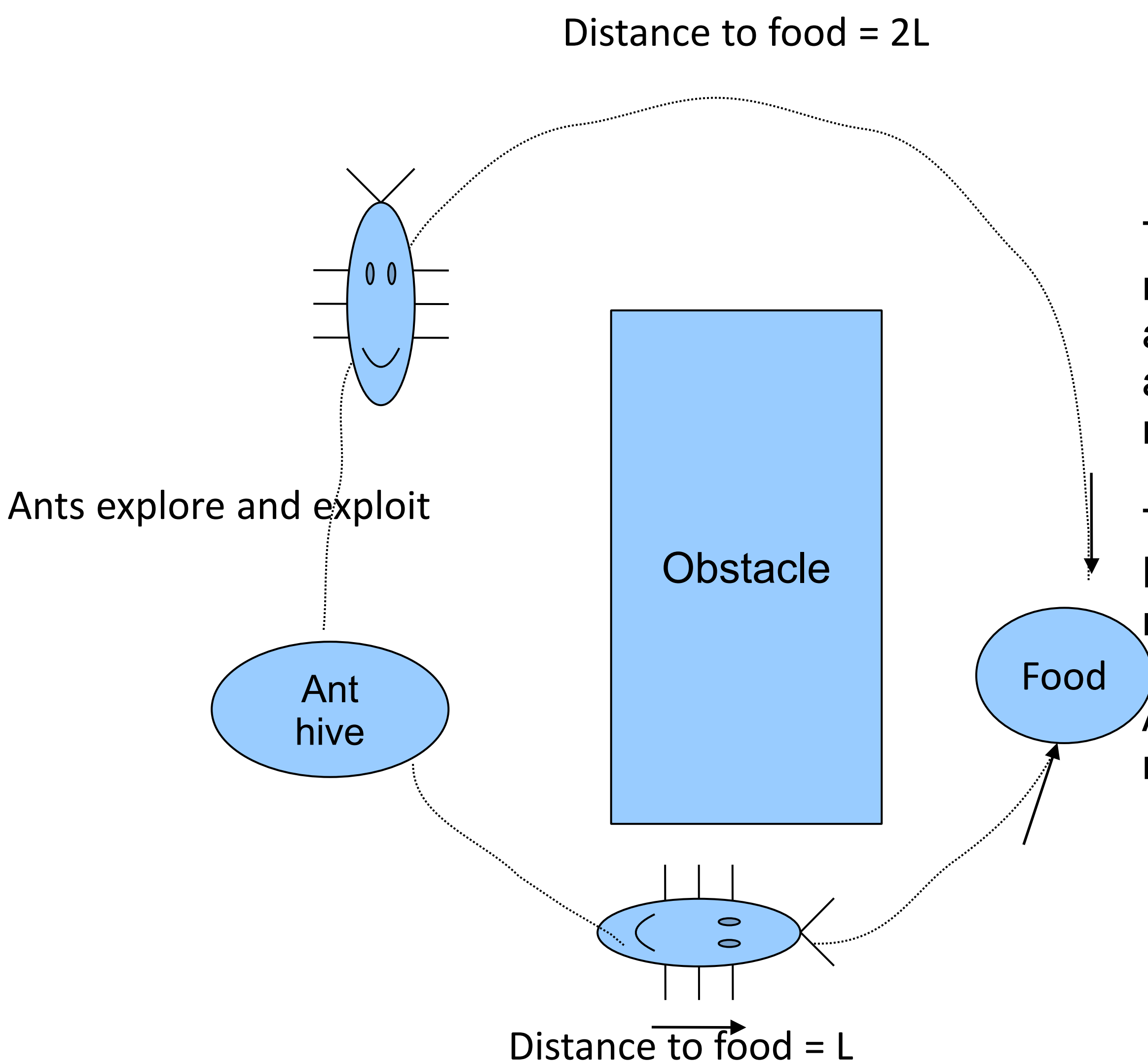
The ant workers are always on the road for food.

If food resources are depleted new ones must be found

Ants shift between exploration and exploitation

If we assumed that two ants where in search for new sources of nourishment the situation that follows could occur……………………

Basic principle of work

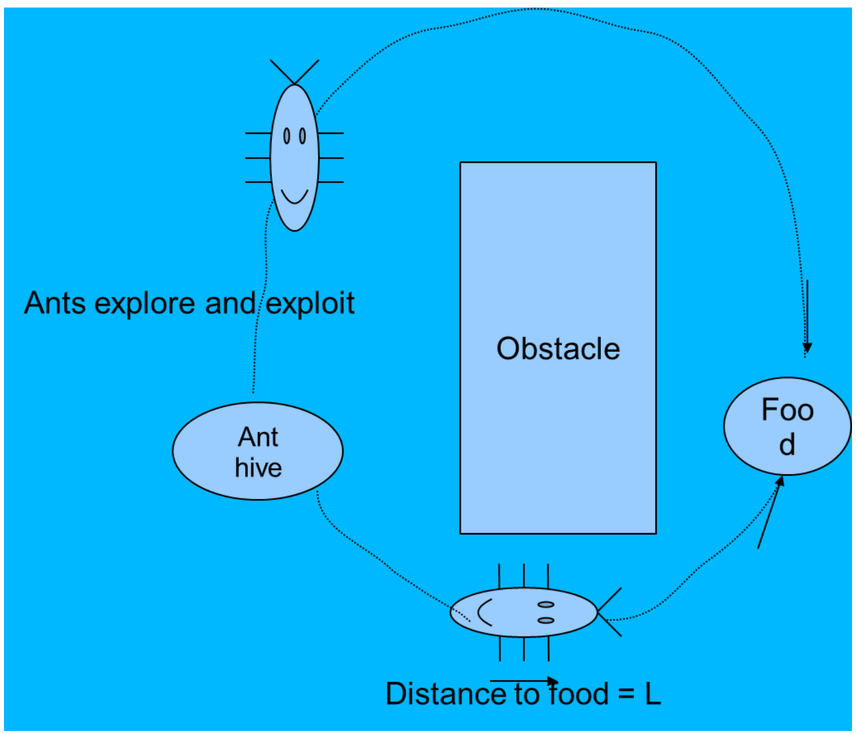


The ant that selects the shortest route will be able to move back and forth during the same time as the other spends his way to reach the food.

The pheronome level will increase More rapidly along the shorter route.

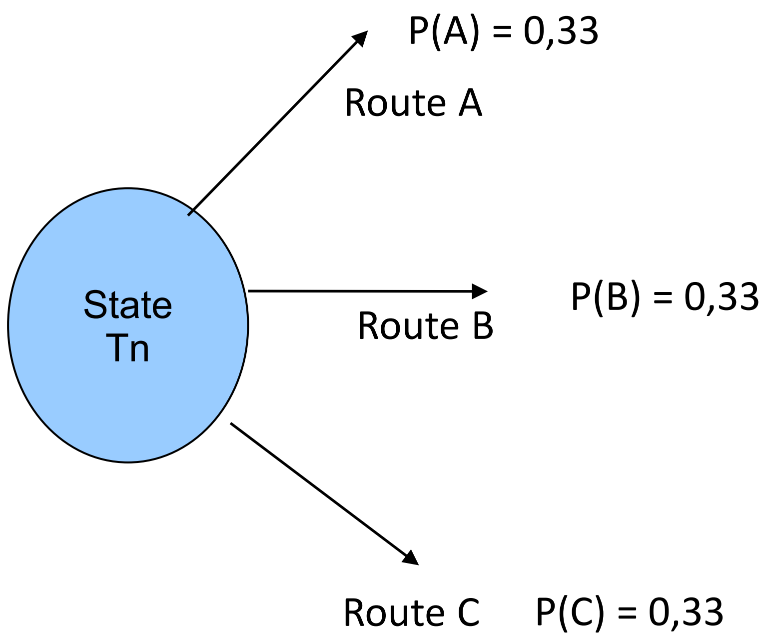
Actually twice that of the longer route

We can describe this in terms of states (Ti)



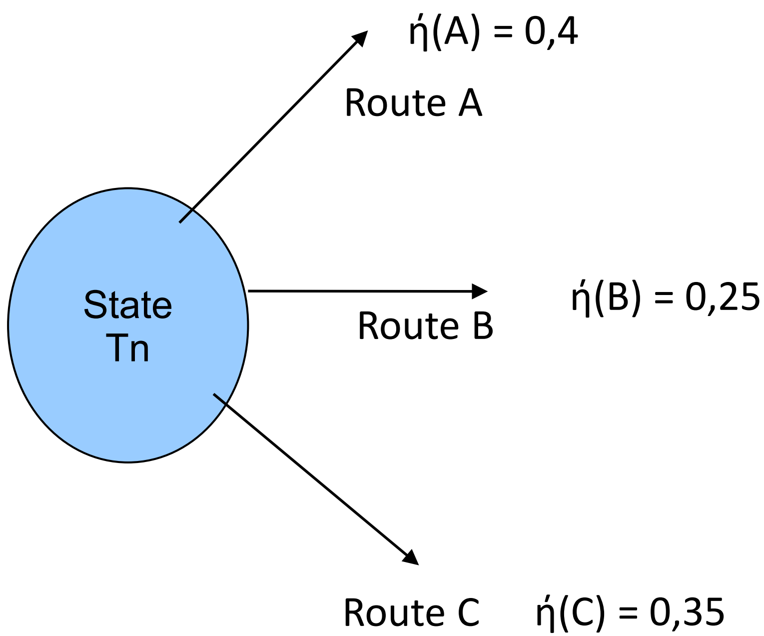
- Situation at T1: Ant 1 reaches the new source of forage or other food. It leaves a pheromone track. Ant 2 is only half way there yet.
- Situation T2: Ant 1 has returned to the hive with its load of food. Ant 2 has reached the new food source.
- Situation T3: Ant 1 is back at the food spot. The level of pheromone deposited along the track increases accordingly. If Ant 2 chooses his original track back home it has half the distance to og still.
- Situation T4: Ant 1 is once more at the hive. This time he meets up with Ant 2 who will arrive at the same time
- Etc.
- Pheromone attracts other ants. When new ones comes around which path are they likely to follow?

Assume the ants had no knowledge or information – a pure probabilistic model – which path will it choose?



Perfect entropy! Any direction is just as good

A probabilistic model reflects pure exploration



ή(i) is here a «weighted probability» reflecting the cost of a path.
The attractiveness of a path can b established «a priori».

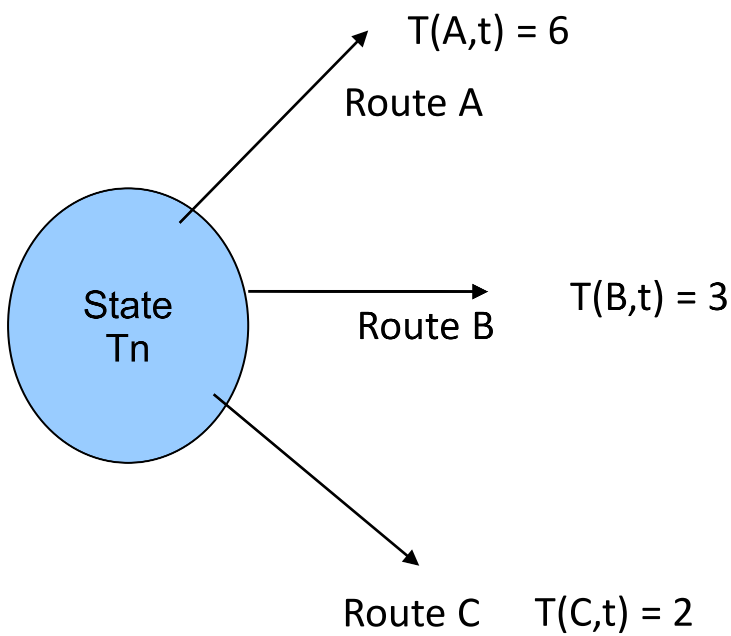
How experience influences choice

Pheromone level provides information which the ants senses

The change of pheromone level reflects the «degree of exploitation»

It makes salient the collective experience of the ants

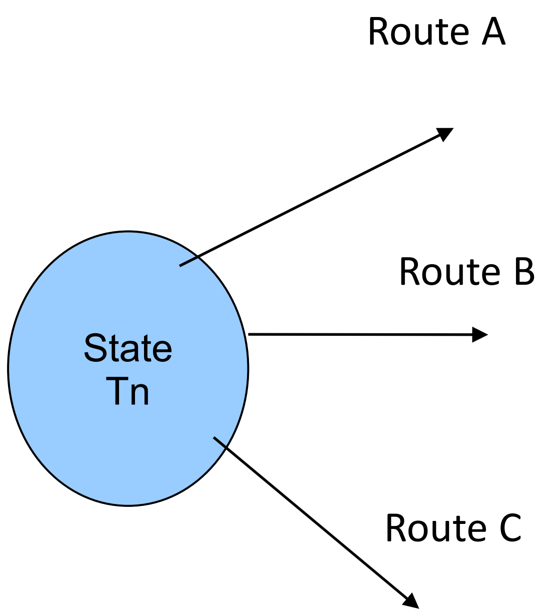
Assume that pheromone deposits can be expressed as a at a given time t by means of the level T(i,t)



T(i,t) reflects the collective experience at t. The relative level of any path stemming from Tn can therefore also be expressed as a probability.

$$P'(A,t) = T(A,t) / (T(A,t) + T(A,t) + T(A,t))$$

Experience thus have an impact on choice



Which path is the ant likely to choose?

$$P(r,u) = \frac{T(r,u)^{\alpha} * n(r,u)^{\beta}}{\sum_k T(r,k)^{\alpha} * n(r,k)^{\beta}}$$

$$P(r,u) = \frac{T(r,u)^{\alpha} * \ n(r,u)^{\beta}}{\sum_k T(r,k)^{\alpha} * n(r,k)^{\beta}}$$

r,u is the path between node r og u in a graph or matrix
r,k are any path from r

P(r,u) is the probability that the path r-u will be picked

T(r-u) = intensity of pheromone along the path r-u

T is a heuristic function expressed T = Q * 1/D where D is the distance between r og u.
Q is a scalar.

Alpha, α is the relative influence of pheromone, a user defined number between 0 and 1
Beta, β, is the relative influence of heuristics, a number between 0 and 1.

ή is the attraction level of the path r-u

K is the number of paths that fork out from the present state or node that the ant is

$$P(r,u) = \frac{T(r,u)^{\alpha} * \ n(r,u)^{\beta}}{\sum_k T(r,k)^{\alpha} * n(r,k)^{\beta}}$$

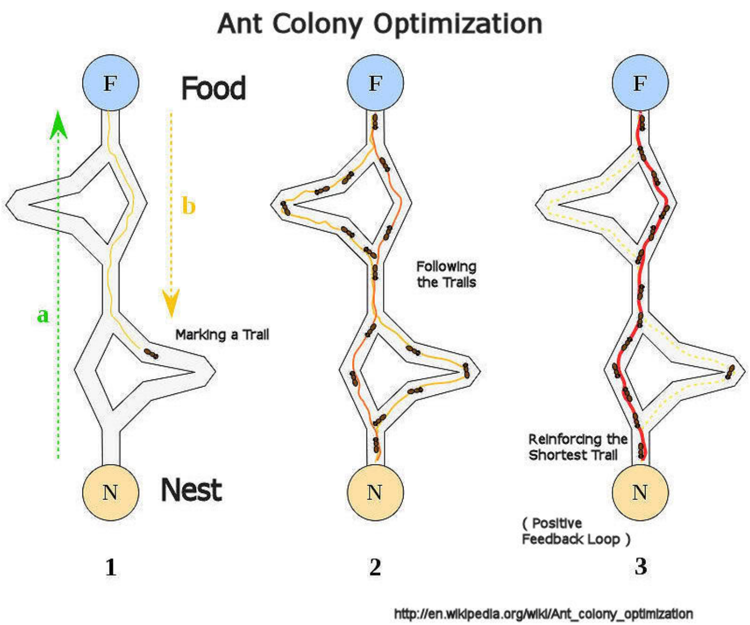
Consequently we are working with weighted probabilities.
The likelihood of choosing the path is a weigthed function of its attractiveness divided by the sum of all the paths weigthed in terms of their attractiveness

The full expression is a function of the pheromone level and some heuristics related to i.e. length, cost, risk, rewards etc.
(just like with informed search such A*)

Note

- Exploitation deals with the pheromone level.
- Exploration is often based on the heuristic about distance (or cost/reward like for regular search problems).
  - If we look away from the exploitation part and focus on the distance, the attractiveness of a path is related to how short the distance is.
- The probability of a shorter path being picked is the weighted probability of that choice compared to the all the others.
  - Consequently attractiveness and thus the weight that we use must be the inverse of the distance, not the distance itself. Many use the distance. This favors the longest distance. In most cases this would be wrong. If we were addressing rewards (not distance or cost) then we would not use the inverse. I might not have stressed this well enough in class.
- Attractiveness must be the inverse of the distance, n= 1/d.

The ants will always find the path that yields the best cost-benefit ratio



- The tension between exploration and exploitation
- The use of pheromone allows the ants to communicate
- More ants on the same trail → more pheromone deposited → the more ants will be attracted
- Decay means that pheromone level decreases
  - Once popular trails that does not produce rewards will loose its p-level and be subdued
- ACO captures dynamics well

The trip that an ant makes

- A trip that an ant makes is complete if an ant has been through the whole set of nodes in the graph

- But – only one visit per node per trip (The Hamilton Path)

- When the trip is complete the full distance can be calculated

- This also allows the total amount of pheromone to be calculated

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Learning, sharing and optimizing

$$T_{ij}(t) = T_{i,j}(t-1) + \Delta T_{i,j}(k)^{*}\rho$$

$\Delta T_{i,j}$ is the pehoromone deposited by one ant k on its trip

This is added to the existing level of pheromone that is already present along the paths of the trip, $T_{i,j}(t-1)$.

i-j is the path from i to j.

ρ is a heuristic factor.

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The amount of pheromone deposited per trip

$\Delta T = Q * 1/D$

D = distance

Q = is the pheromone deposition capability

Decay reduces the pheromone level on a path

$$T_{ij}(t) = T_{i,j}(t - 1)\ (1 - \rho)$$

ρ is the heuristic factor used for pheromone deposition

Example 1 : Simple probability

The chance of taking choice 2 might be calculated like this:

$$\frac{\tau_2}{\sum \tau_{t_i}} = \frac{0.7}{0.2 + 0.7 + 0.1 + 0.6 + 0.8}$$

Choice	**Variable Name**	**Pheromone Value**	**Chance of Chosing**
1	t_1	0.2	0.083
2	t_2	0.7	0.291
3	t_3	0.1	0.041
4	t_4	0.6	0.25
5	t_5	0.8	0.333

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Example 2: Now we add more weight to the pheromone

- We can increase the differences by raising the pheromones value to a power α:

$$\frac{\tau_2^\alpha}{\sum \tau_{t_i^\alpha}} = \frac{0.7^\alpha}{0.2^\alpha + 0.7^\alpha + 0.1^\alpha + 0.6^\alpha + 0.8^\alpha}$$

Choice	Variable Name	Pheromone Value	$t_i^{\alpha=2}$	Chance of Chosing
1	t_1	0.2	0.04	0.026
2	t_2	0.7	0.49	0.318
3	t_3	0.1	0.01	0.006
4	t_4	0.6	0.36	0.233
5	t_5	0.8	0.64	0.415

Example 3: Combining it with heuristics

	Route alternative	Variable name	Pheromone value	Variable name	Heuristic value	T^{α}	n^{β}	Product	Probability of choice	%
α	1	T1	0,2	n1	0,5	0,04	0,70710678	0,02828427	0,03464737	3,4
2	2	T2	0,7	n2	0,6	0,49	0,77459667	0,37955237	0,46494011	46,4
β	3	T3	0,1	n3	0,8	0,01	0,89442719	0,00894427	0,01095646	1
0,5	4	T4	0,6	n4	0,3	0,36	0,54772256	0,19718012	0,24153965	24,1
	5	T5	0,8	n5	0,1	0,64	0,31622777	0,20238577	0,24791641	24,7
							SUM	0,8163468	1	100

$$P(r,u) = \frac{T(r,u)^{\alpha} * \ n(r,u)^{\beta}}{\sum_k T(r,k)^{\alpha} * n(r,k)^{\beta}}$$

Heuristics example: admissible estimate of relative reward (or 1/cost) of path

Excellent for route planning and logistics

Can model human behavior and include

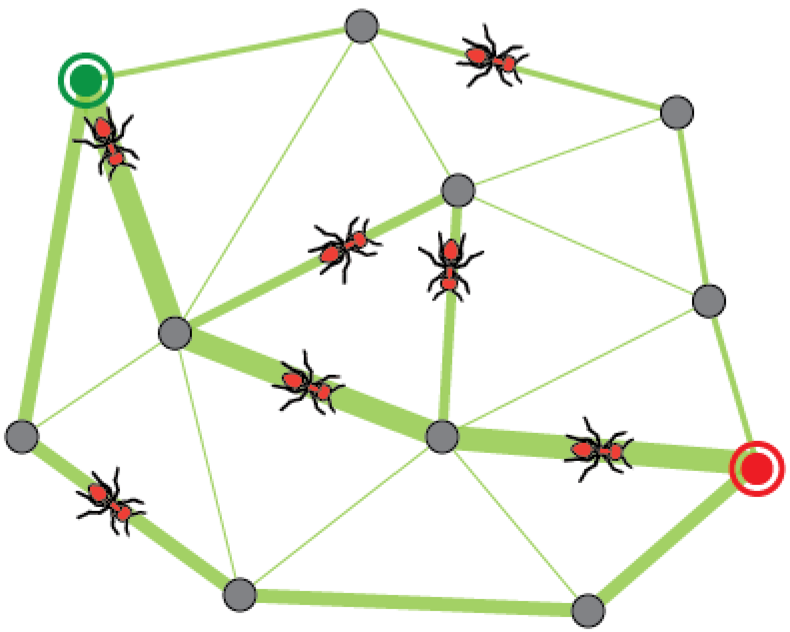
- Panic
- Rational choice
- Sentiments

Can model obstacles

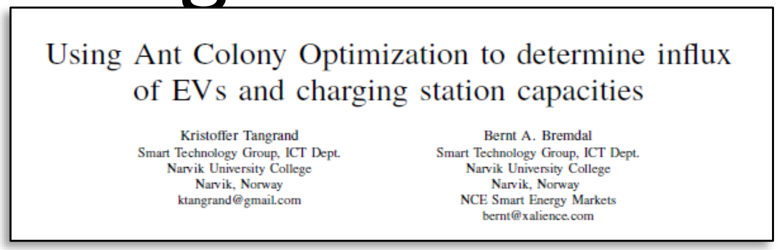
- Permanent
- Temporary

Can model rewards

- Permanent
- Temporary



Collective and individual planning


Using Ant Colony Optimization to determine influx of EVs and charging station capacities

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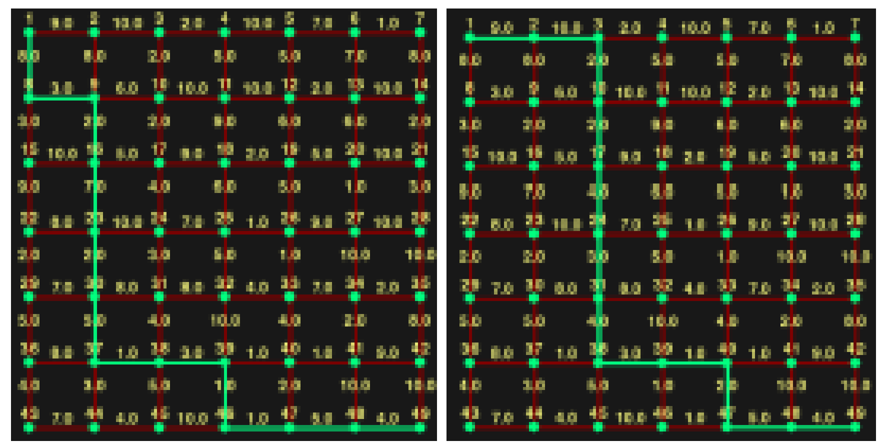
(a) Optimal solution to the 7x7 graph. d_{ij} shown on arcs

(b) The optimal route for inhomogeneous nodes

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