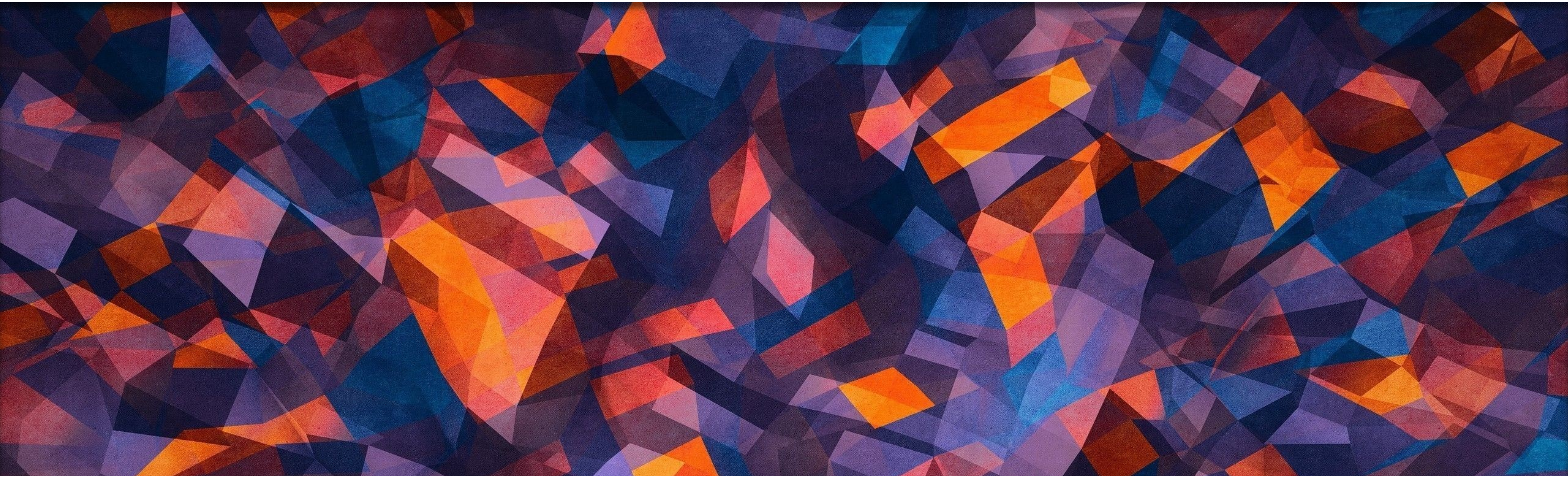
Universität St.Gallen



Web-based Autonomous Systems

Coordination II: Self-Organization and Stigmergy

Chair for Interaction- and Communication-based Systems (ICS-HSG)

Our Journey

Prerequisites:
- **ASSE**
- **(…)**

Week 1:
Introduction

Week 2:
A Web for Machines

Week 3:
Knowledge Representation and Reasoning for the Web

Week 4:
Linked Data and Distributed Knowledge Graphs

Week 5:
Autonomous Agents (Arch. and Programming)

Week 6 (Coordination I):
Agent Communication and Interaction

Week 7 (Coordination II):
Self-Organization and Stigmergy

Week 8 (Coordination III):
Normative MAS and Organizations

Week 9 (Coordination IV):
Trust & Reputation

Week 10:
Game Theory and Social Choice

Week 11:
Reinforcement Learning and Multi-Agent Learning

Week 12:
An Industry Perspective

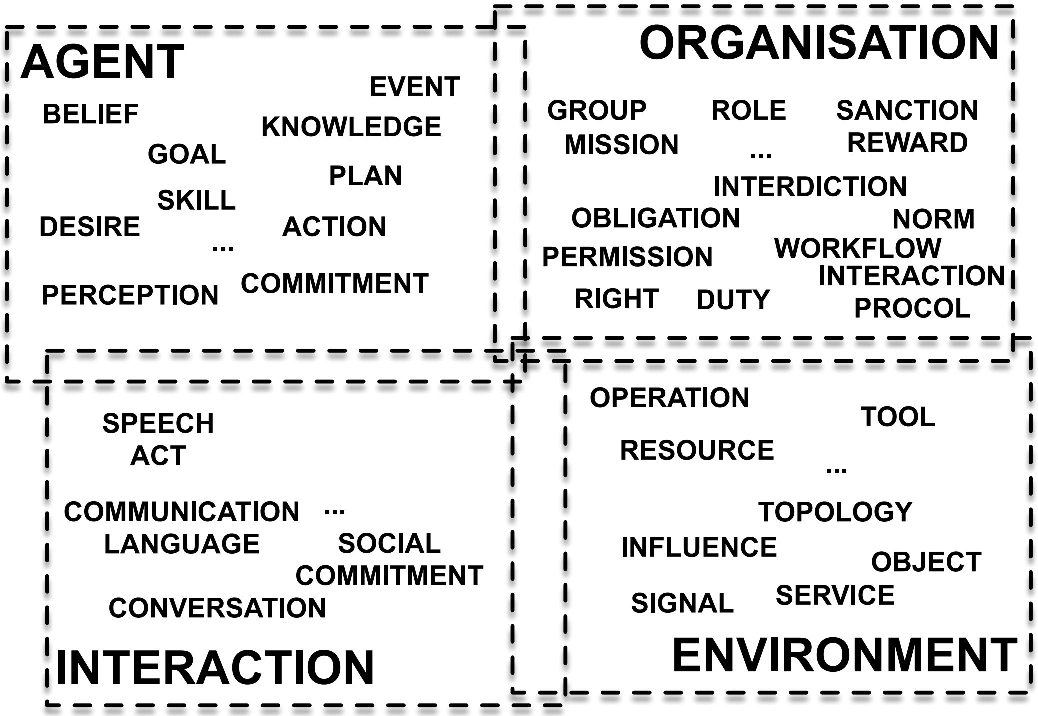
Exercises

Ex1: Writing Your First Agent(s)!
Ex2: Automated Planning
Ex3: Web Ontologies
Ex4: Operating on Linked Data
Ex5: BDI Agents
Ex6: Interacting Agents on the Web
Ex7: Ant Colony Optimization
Ex8: Organized Agents
Ex9: Trustworthy Agents
Ex10: Axelrod's Agents
Ex11: Reinforcement Learning Agents
Course Review and Q&A

Coordination in Multi-Agent Systems

Week 9 (Coordination IV):
Trust & Reputation

Week 6 (Coordination I):
Communication and Interaction



Week 8 (Coordination III):
Normative MAS and Organizations

Week 7 (Coordination II):
Self-Organization and Stigmergy

Modelling Dimensions for Multi-Agent Systems
[Demazeu, 1995]

O. Boissier, *Multi-Agent Coordination Course*, MINES Saint-Étienne, 2021.
Y. Demazeau. From Interactions To Collective Behaviour In Agent-Based Systems, 1st European Conf. on Cognitive Science, 1995.

Today's Agenda

- Self-Organization and Swarm Intelligence
  - Flocking Behavior: Bird-oid Objects (Boids)
  - Swarm Robotics
  - Non-Functional Properties of Self-Organizing Systems
  - Design Principles for Self-Organizing Systems
- Stigmergy
  - Ant Colony Optimization
  - Cognitive Stigmergy

Self-Organization and Swarm Intelligence

Simple rules of local interaction create **global emergent behavior**






Self-Organization: emergent behavior

Swarm Intelligence: “the **emergent collective intelligence** of groups of **simple agents**” [Bonabeau et al., 1999]

E. Bonabeau et al. Swarm intelligence: from natural to artificial systems. 1999.

Flocking Behavior: Flight of the Starlings

https://youtube.com/clip/UgkxI1WN-GiufL3V81Q1MOsAw4FAIrQQLLSx

Common Starling

How to model/simulate **flocking behavior?**

https://en.wikipedia.org/wiki/Common_starling

Flocking Behavior: Bird-oid Objects (Boids)

Flocks, Herds, and Schools: A Distributed Behavioral Model [1]

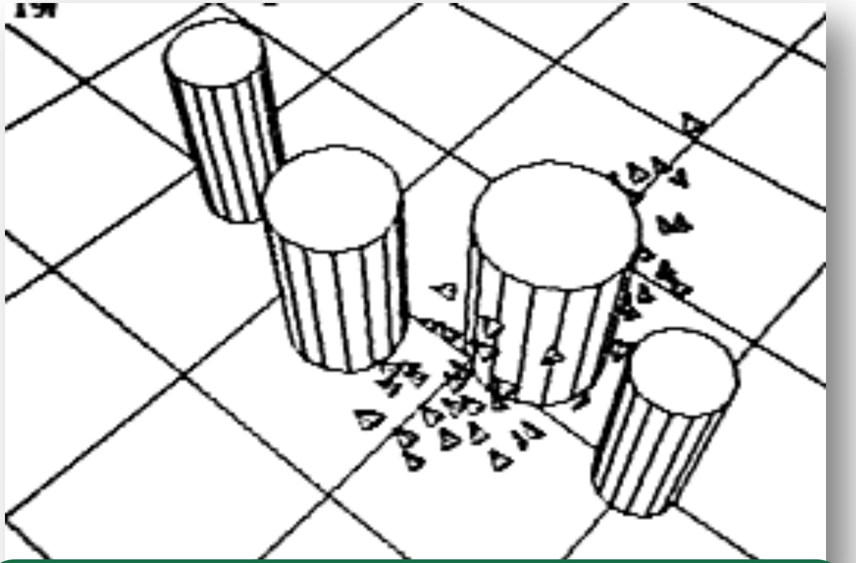
Craig W. Reynolds
Symbolics Graphics Division

[obsolete addresses removed[2]]

Abstract

The aggregate motion of a flock of birds, a herd of land animals, or a school of fish is a beautiful and familiar part of the natural world. But this type of complex motion is rarely seen in computer animation. This paper explores an approach based on simulation as an alternative to scripting the paths of each bird individually. The simulated flock is an elaboration of a particle system, with the simulated birds being the particles. The aggregate motion of the simulated flock is created by a distributed behavioral model much like that at work in a natural flock; the birds choose their own course. Each simulated bird is implemented as an independent actor that navigates according to its local perception of the dynamic environment, the laws of simulated physics that rule its motion, and a set of behaviors programmed into it by the "animator." The aggregate motion of the simulated flock is the result of the dense interaction of the relatively simple behaviors of the individual simulated birds.

[Reynolds, SIGGRAPH 1987]



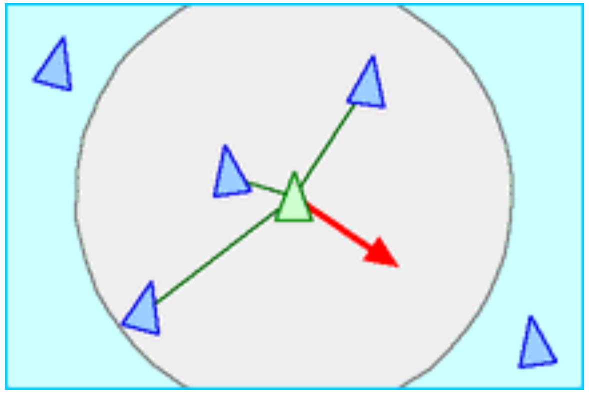
Original demo reel (1987)
https://www.youtube.com/watch?v=xBniZYiyrb4

Craig W. Reynolds. *Flocks, herds and schools: A distributed behavioral model*. ACM SIGGRAPH 1987.

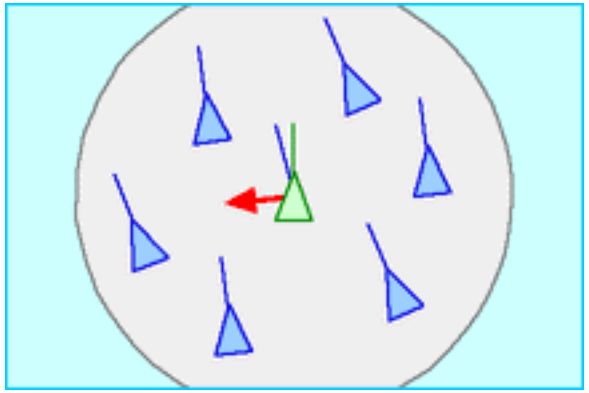
Flocking Behavior: Bird-oid Objects (Boids)

Each bird in the flock implements **3 simple steering behaviors**

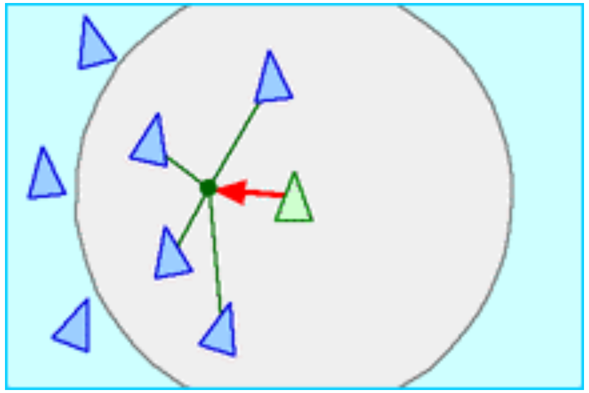
– local information: positions and headings of nearby flockmates



Separation
steer to avoid crowding local flockmates



Alignment
steer towards the average heading of local flockmates



Cohesion
steer to move towards the average position of local flockmates

Let's see how this works (hands-on)!
View at home: https://youtu.be/QbUPfMXXQIY

Craig Reynolds, *Boids: Background and Update*, http://www.red3d.com/cwr/boids/

Boids in the Motion Picture Industry

Batman Returns (1992)
Bat swarms: https://youtu.be/YpoT-QRgOK4
Penguin flocks: https://youtu.be/APs3qbAE1FY
(Craig Reynolds was part of the crew)

The Lion King (1994)
The stampede:
https://youtu.be/YpoT-QRgOK4?t=10

Multiple Agent Simulation System in Virtual Environment (MASSIVE)
https://massivesoftware.com/

The Lord of the Rings Trilogy
(2001, 2002, 2003)
https://youtu.be/YpoT-QRgOK4

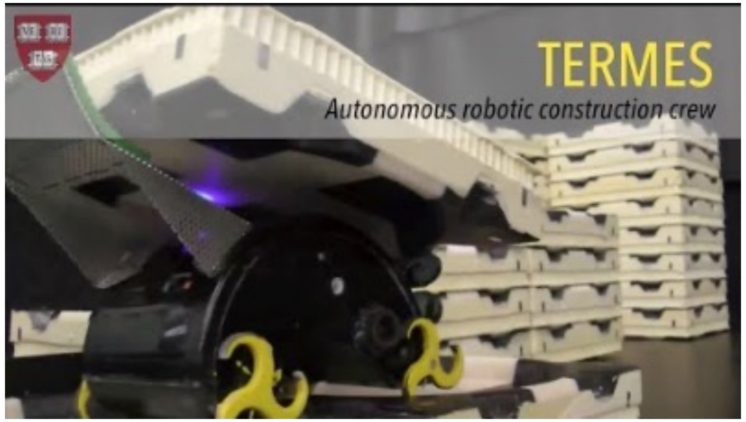
Craig Reynolds, *Boids: Background and Update*, http://www.red3d.com/cwr/boids/

Swarm Robotics



Swarm-bots [Gross et al., 2006]: https://youtu.be/seGqyO32pv4

Kilobots [Rubenstein et al., 2012]
https://youtu.be/G1t4M2XnIhI?t=94

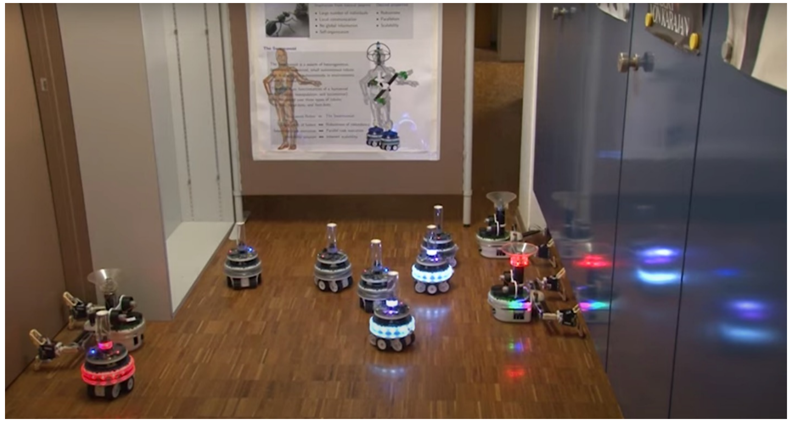


Termes [Petersen et al., 2011]
https://youtu.be/nFjtRONfae4?t=38

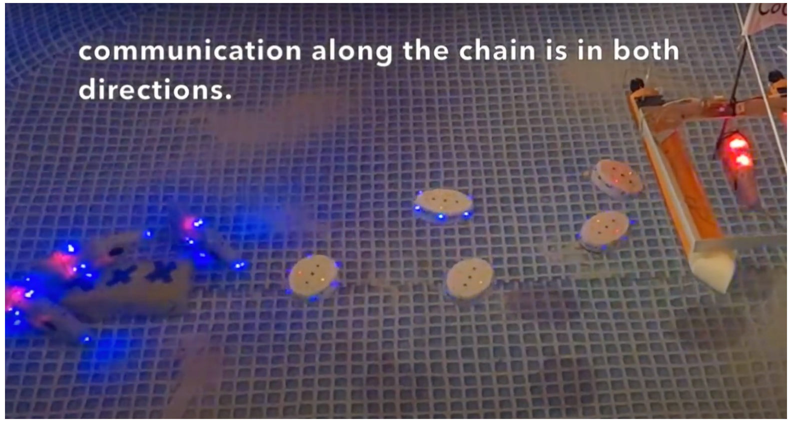
Particle Robots [S. Li et al., 2019]
https://youtu.be/aXrljS7wBic

R. Gross et al., *Autonomous Self-Assembly in Swarm-Bots*. IEEE Transactions on Robotics, vol. 22. 2006.
M. Rubenstein et al.. *Kilobot: A low cost scalable robot system for collective behaviors*. ICRA 2012.
K.H. Petersen et al.. *Termes: An autonomous robotic system for three-dimensional collective construction*. Robotics: science and systems VII. 2011.
S. Li et al. Particle robotics based on statistical mechanics of loosely coupled components. Nature 567. 2019.

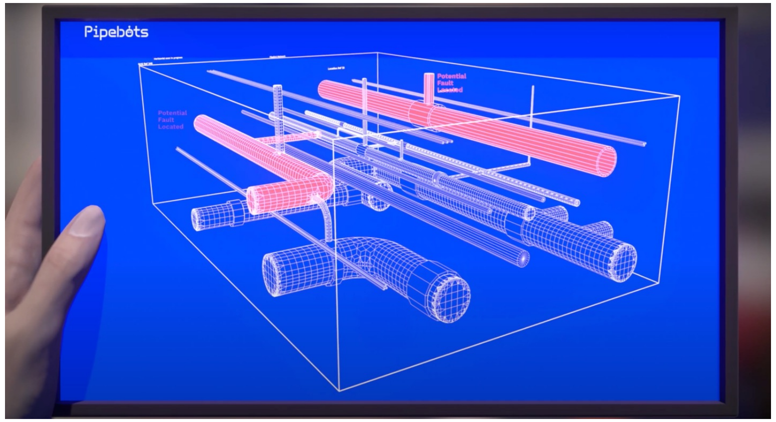
Swarm Robotics



Swarmanoid (2011):
https://youtu.be/M2nn1X9Xlps



CoCoRo (2011):
https://youtu.be/WjDeFzAGJSs



Pipebots (ongoing):
https://youtu.be/pppxa9MpoeY

Pipebots: http://pipebots.ac.uk/
Swarmanoid: http://www.swarmanoid.org/
CoCoRo project: https://www.thomasschmickl.eu/projects/eu-project-cocoro

Non-Functional Properties of SOS

Scalability

– addition or removal of new individuals does not impact overall system performance significantly

Robustness

– the system continues to operate as intended if individuals are lost or malfunction (within some limits)

Flexibility

– the system adapts to dynamic environments and changing working conditions

Discussion:
What are the drawbacks?

Design Principles for SOS

Decentralized Control

- the systems are composed of (many) interacting individuals with no central coordinator
- individuals are generally assumed to be homogeneous (identical or from a small set of classes)
- individuals are generally assumed to implement simple behavioral rules

Local Interaction

- individuals interact based on local information: they do not know the global state of the swarm and its overall objective
- individuals are agnostic to who their neighbors are
- interactions among individuals can be direct or through the environment (stigmergy)

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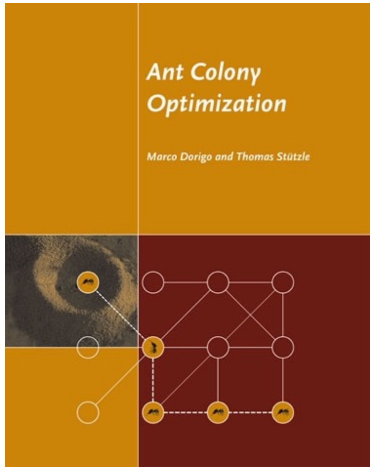


[Dorigo and Stützle, 2004]

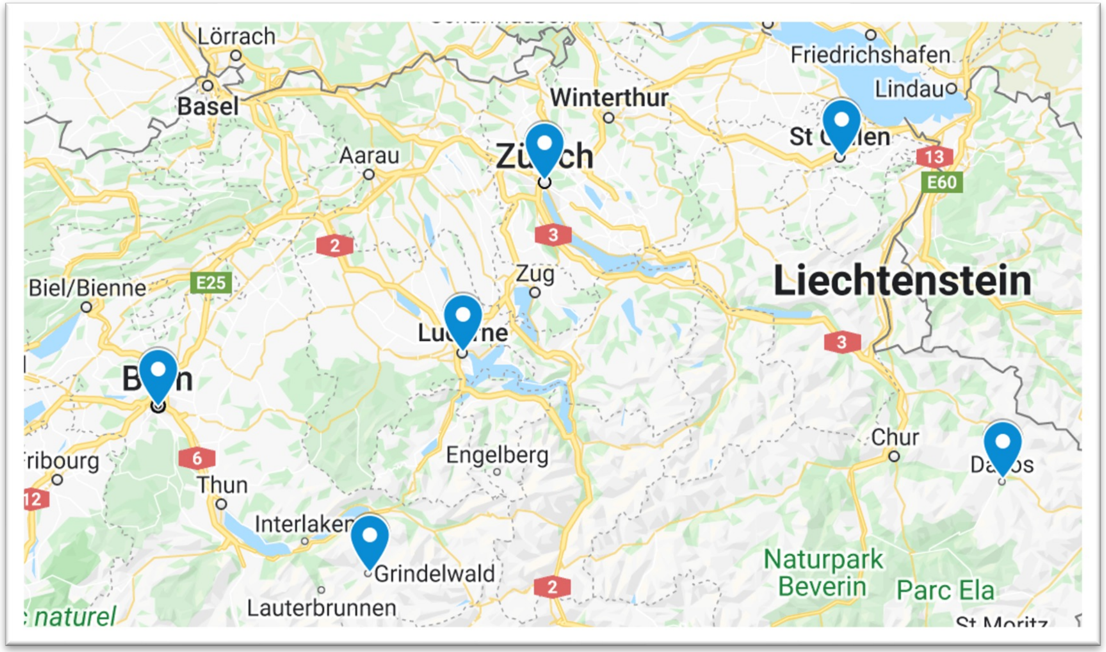
Chapter 3.1
Chapter 3.3.1

M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.

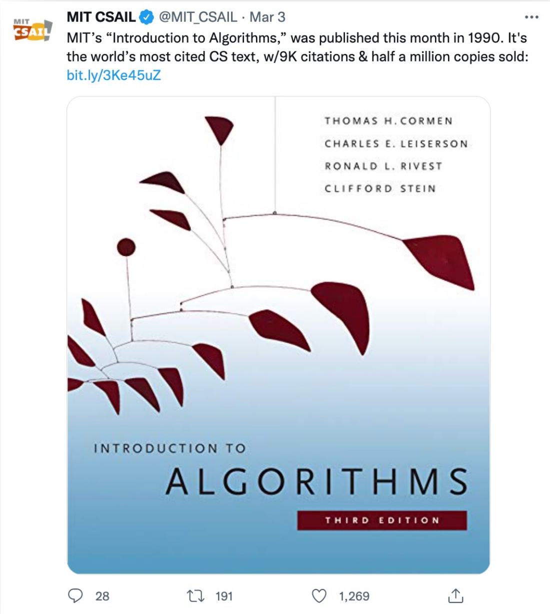
The Traveling-Salesman Problem

Formulation: A salesperson wants to find a shortest tour that takes them through a set of customer cities and back to the initial city, visiting each city exactly once.

– NP-hard problem, standard testbed for new algorithmic ideas



The Traveling-Swiss-Salesman Problem


MIT CSAIL @MIT_CSAIL · Mar 3

MIT's "Introduction to Algorithms," was published this month in 1990. It's the world's most cited CS text, w/9K citations & half a million copies sold: bit.ly/3Ke45uZ

THOMAS H. CORMEN
CHARLES E. LEISERSON
RONALD L. RIVEST
CLIFFORD STEIN

INTRODUCTION TO
ALGORITHMS
THIRD EDITION

28 191 1,269

The Traveling-Salesman Problem

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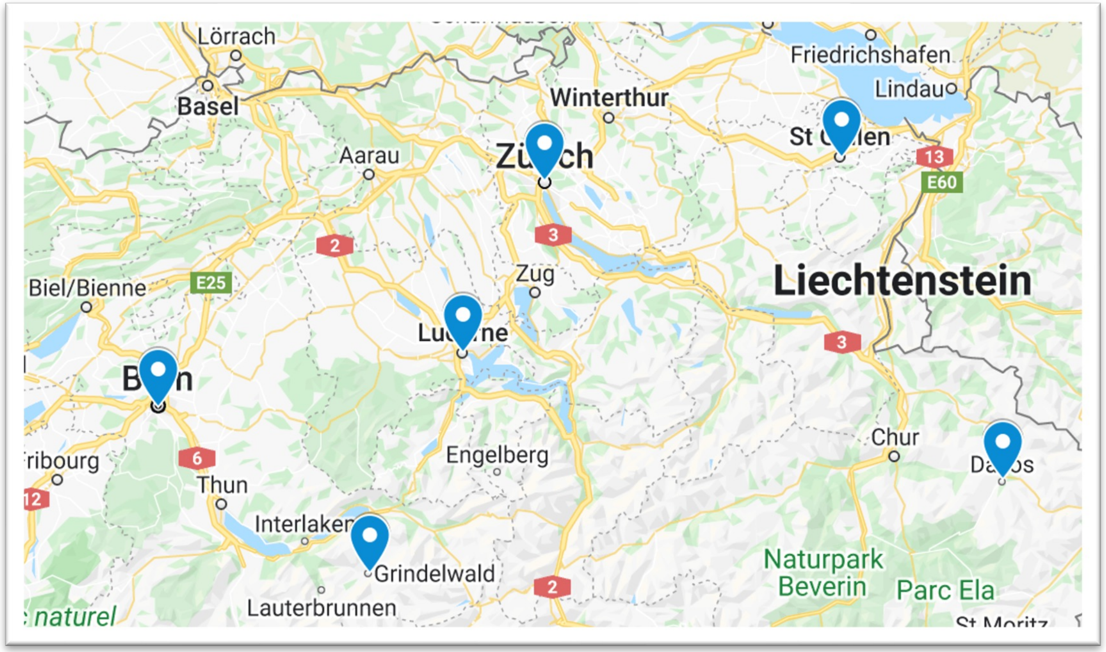
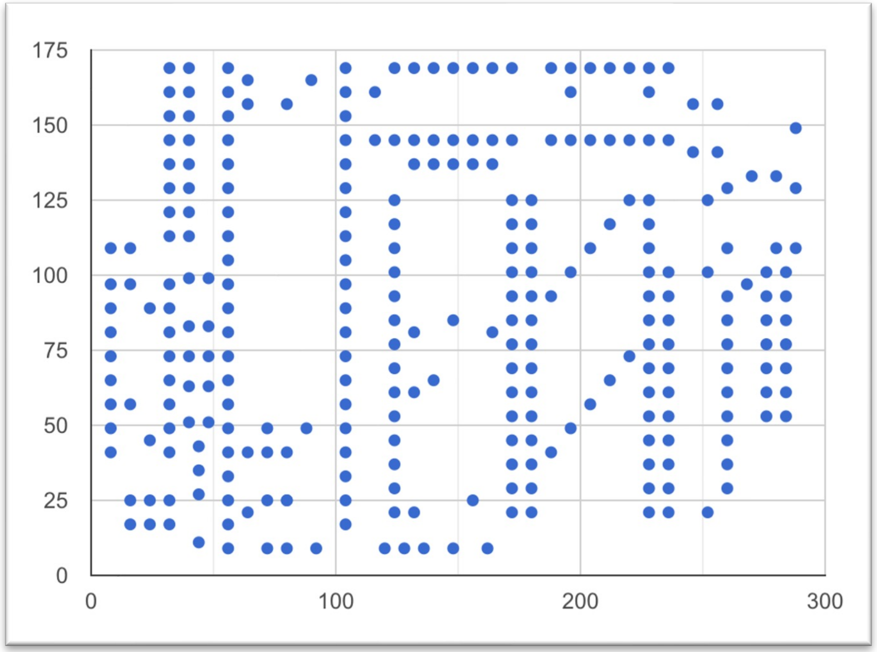


The Traveling-Swiss-Salesman Problem



Drilling holes in a circuit board (Google OR-Tools)
https://developers.google.com/optimization/routing/tsp

The Traveling-Salesant Problem

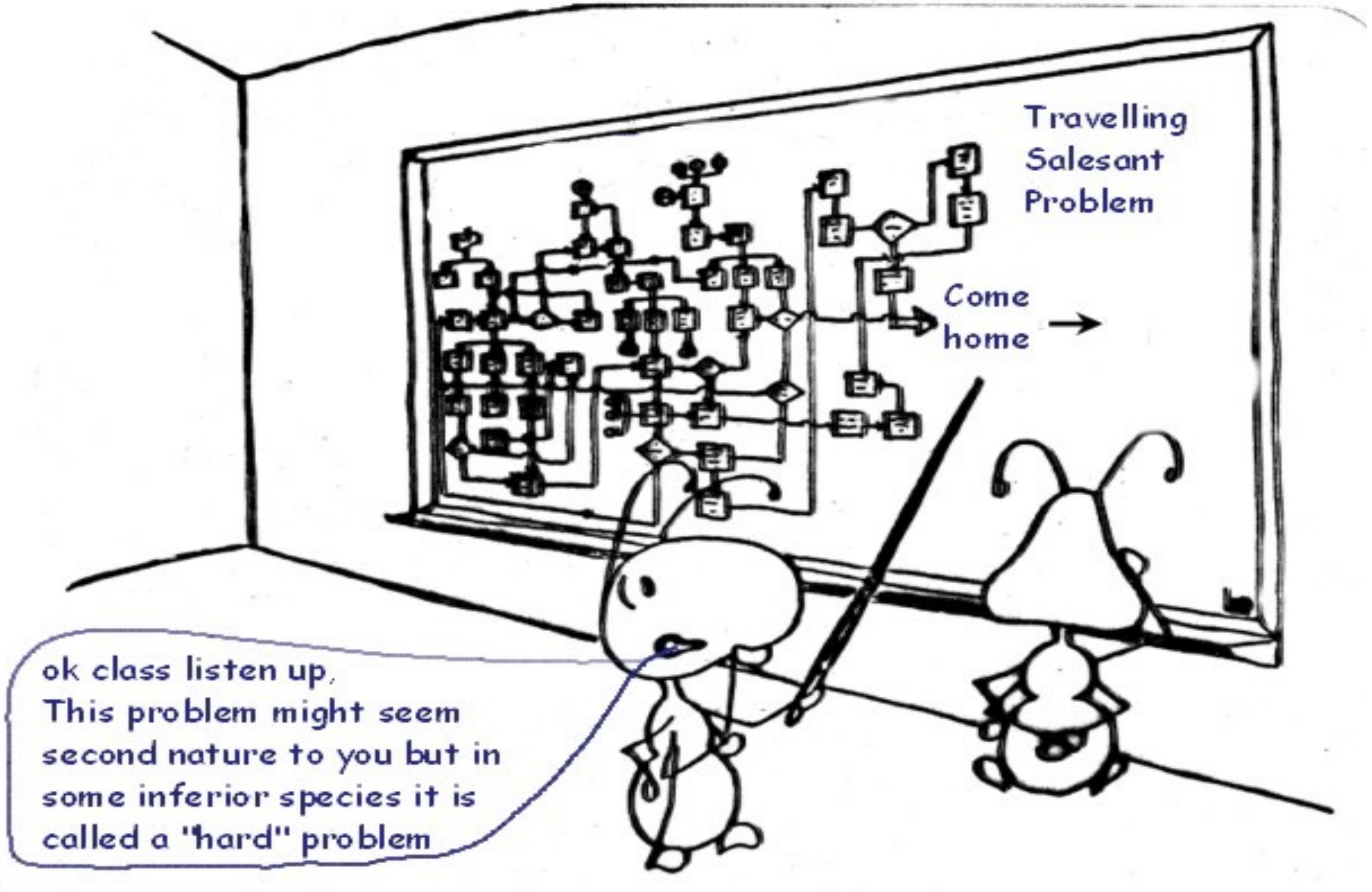


Image: unknown source

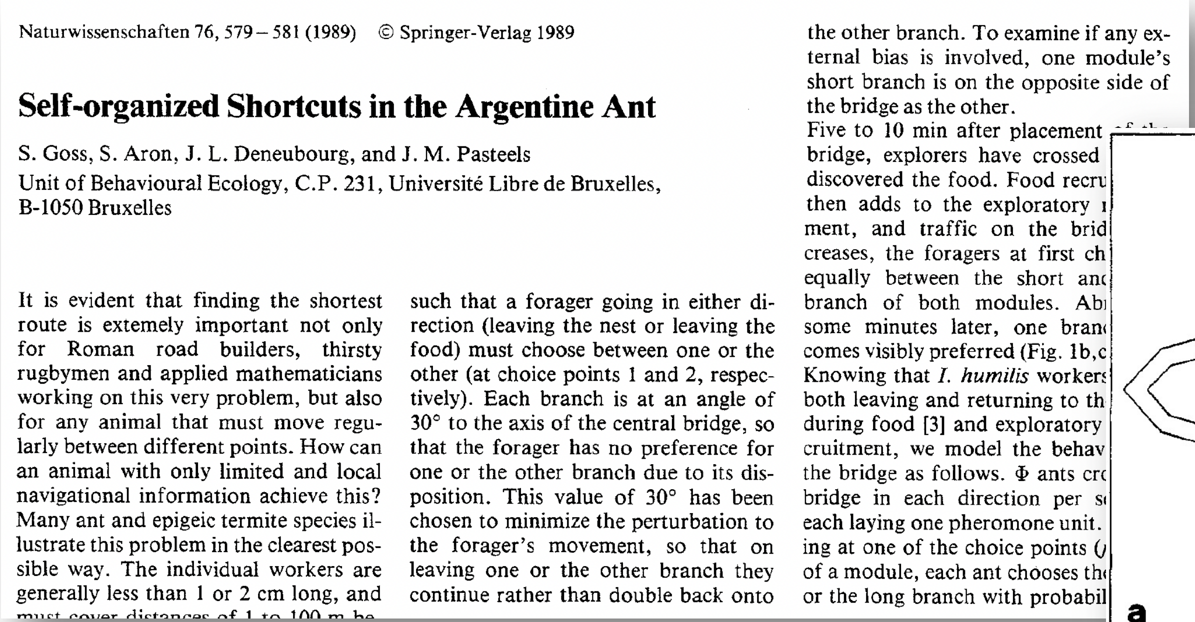
The Double Bridge Experiments

Ants are navigation experts — not individually, but as a colony [Goss et al., 1989]

– a series of controlled experiments studied the built-in path-optimization ability of Argentine ants

– the experiments used a double bridge to connect a nest to a food source

– the authors proposed a stochastic model that describes the observed dynamics of the ant colony through probabilistic rules and local information



Naturwissenschaften 76, 579 – 581 (1989) © Springer-Verlag 1989

Self-organized Shortcuts in the Argentine Ant

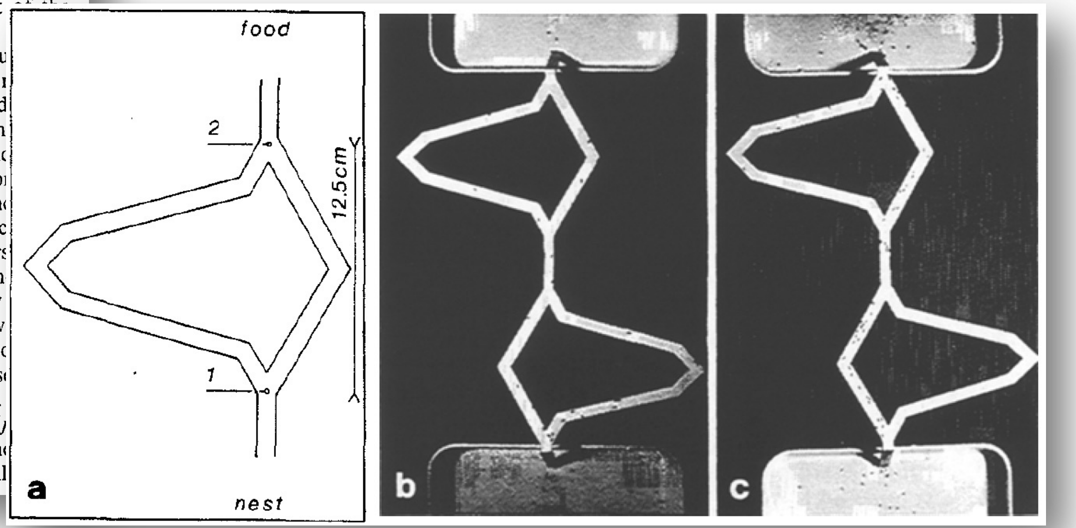
S. Goss, S. Aron, J. L. Deneubourg, and J. M. Pasteels
Unit of Behavioural Ecology, C.P. 231, Université Libre de Bruxelles, B-1050 Bruxelles

It is evident that finding the shortest route is extemely important not only for Roman road builders, thirsty rugbymen and applied mathematicians working on this very problem, but also for any animal that must move regularly between different points. How can an animal with only limited and local navigational information achieve this? Many ant and epigeic termite species illustrate this problem in the clearest possible way. The individual workers are generally less than 1 or 2 cm long, and must cover distances of 1 to 100 m be-

such that a forager going in either direction (leaving the nest or leaving the food) must choose between one or the other (at choice points 1 and 2, respectively). Each branch is at an angle of 30° to the axis of the central bridge, so that the forager has no preference for one or the other branch due to its disposition. This value of 30° has been chosen to minimize the perturbation to the forager's movement, so that on leaving one or the other branch they continue rather than double back onto

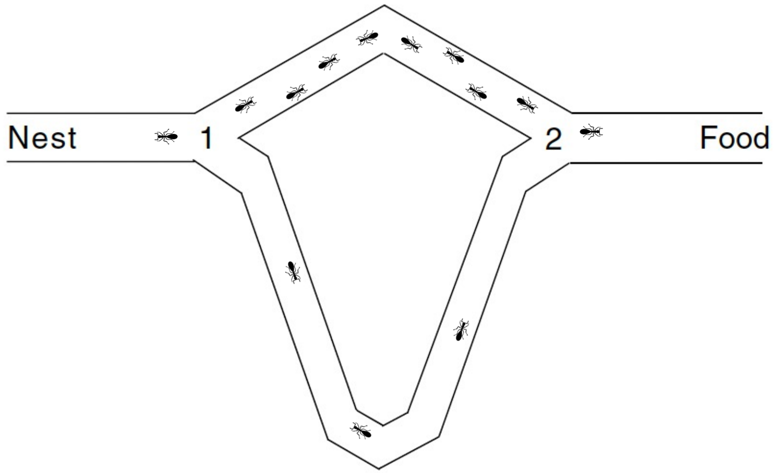
the other branch. To examine if any external bias is involved, one module's short branch is on the opposite side of the bridge as the other.
Five to 10 min after placement of the bridge, explorers have crossed discovered the food. Food recru then adds to the exploratory r ment, and traffic on the brid creases, the foragers at first ch equally between the short and branch of both modules. Ab some minutes later, one branc comes visibly preferred (Fig. 1b,c Knowing that *I. humilis* workers both leaving and returning to th during food [3] and exploratory cruitment, we model the behav the bridge as follows. Φ ants cro bridge in each direction per s each laying one pheromone unit. ing at one of the choice points (of a module, each ant chooses the or the long branch with probabil

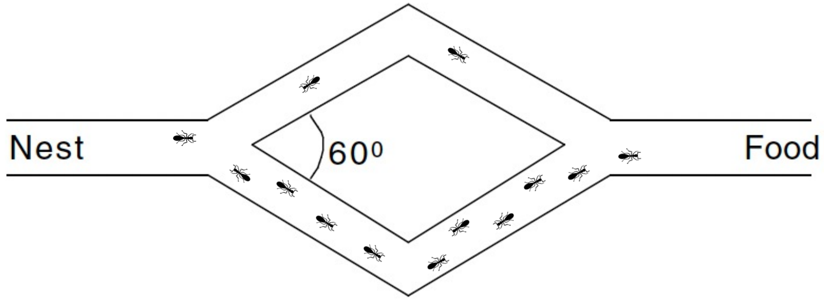
Theoretical foundation for colonies of **artificial ants**



S. Goss et al. Self-organized shortcuts in the Argentine ant. Naturwissenschaften 76. 1989.

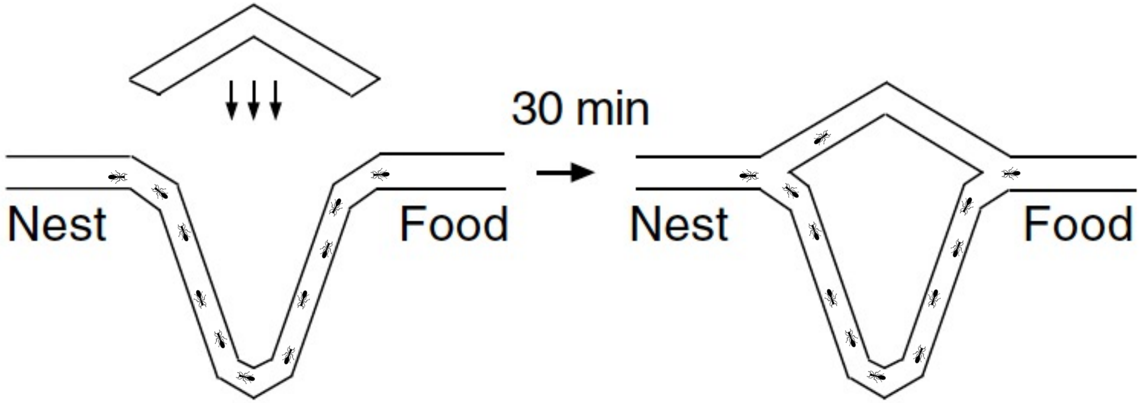
The Double Bridge Experiments





path that form a labyrinth worthy of the Minotaur. The Argentine ant *Iridomyrmex humilis* studied in this article has only a limited individual capacity for orientation [2], yet we shall see how by interacting with each other via their trail pheromone, they are capable of selecting with great reliability the shortest route between nest and food.

[S. Goss et al., 1989]



M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.
S. Goss et al. Self-organized shortcuts in the Argentine ant. Naturwissenschaften 76. 1989.

Stigmergy

Stigmergy: “Stimulation of workers by the performance they have achieved” [Grassé, 1959]

– initially defined to describe the indirect interaction mediated by modifications of the environment in the workers caste of some species of termites

stigma (Gk.)
mark, sign

+

ergon (Gk.)
work, action

Coordinated work/action through the environment

M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.
Pierre-Paul Grassé. La reconstruction du nid et les coordinations interindividuelles chez Bellicositermes natalensis et Cubitermes sp. La théorie de la stigmergie: Essai d’interprétation du comportement des termites constructeurs. Insectes Sociaux, 6, 1959.

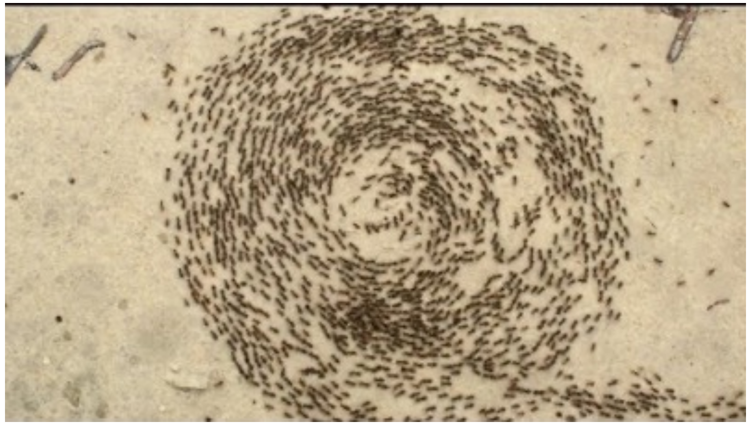
From Natural to Artificial Ants

Ant Colony Optimization

- a family of algorithms for finding **minimum cost paths** in **graphs**
- inspired by the behavioral model from the double bridge experiments, but with adaptations

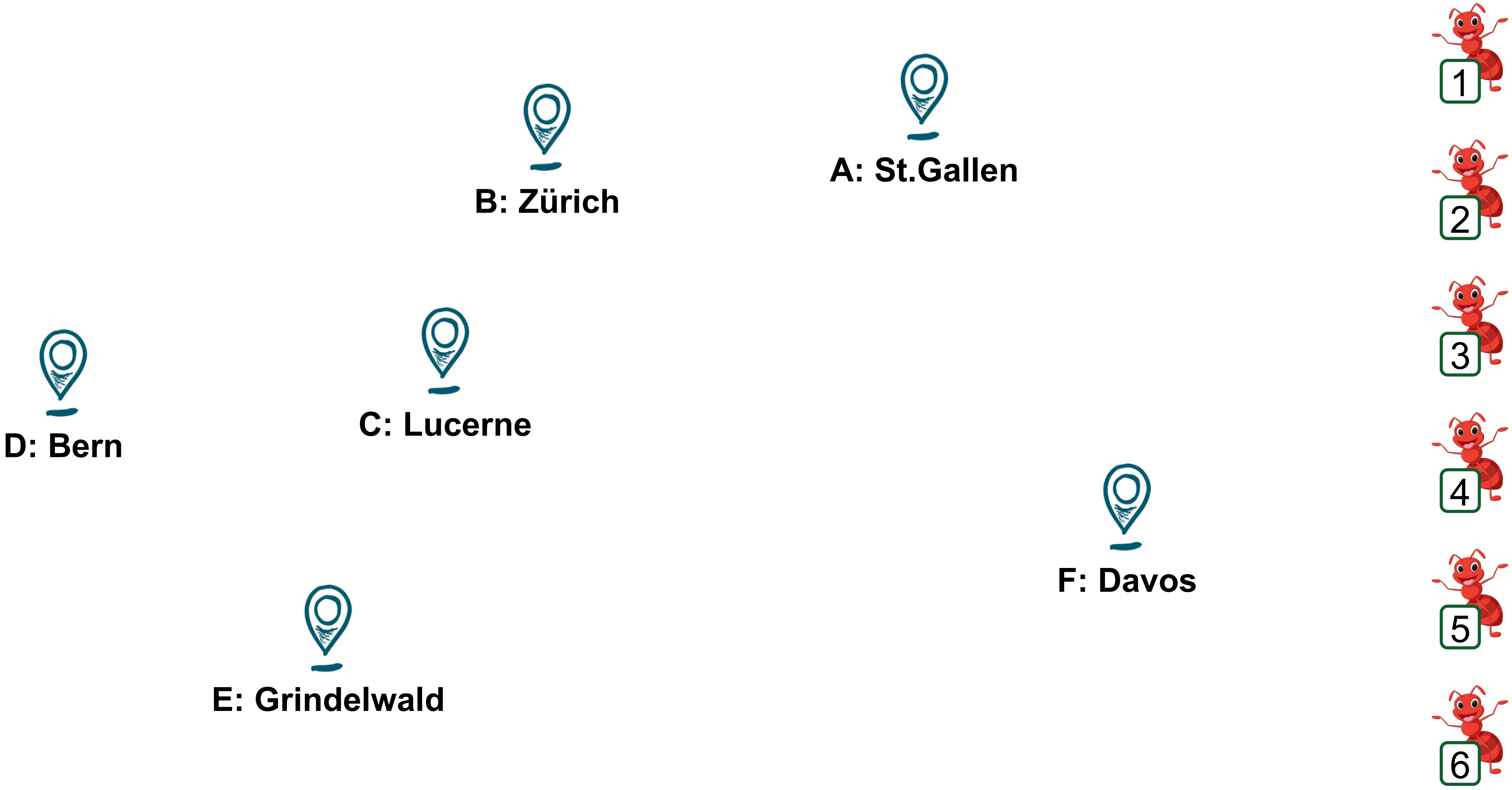
Artificial ants are equipped with a **small memory** that allows them to avoid loops and to find minimal cost paths

- used to store the partial paths they have followed so far (used in **path construction**)
- used to store the cost of the links they have traversed (solution quality determines the **amount of pheromone** to be deposited)



https://youtu.be/LEKwQxO4EZU

Ant System [Dorigo et al., 1996]: Overview



M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.
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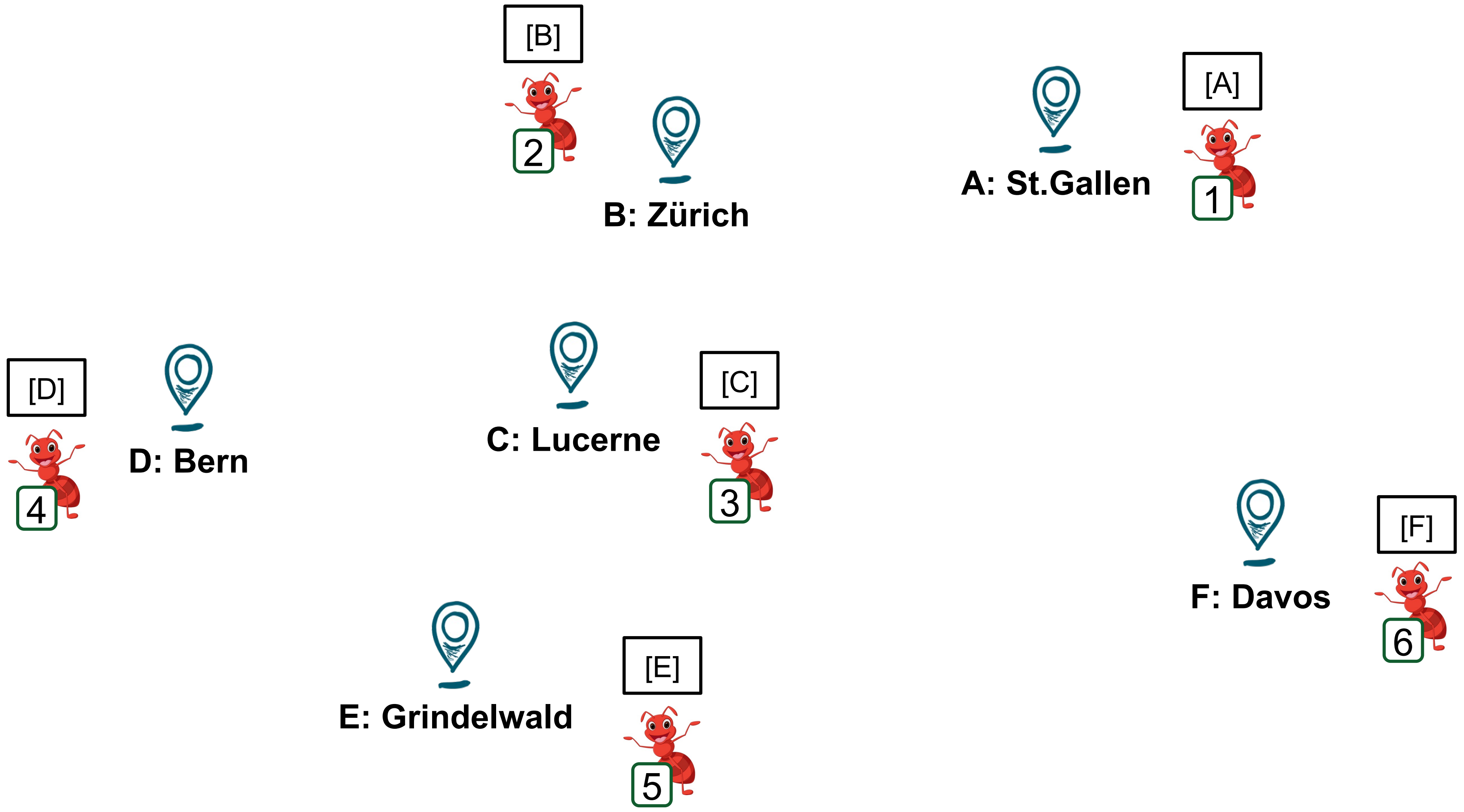
Ant System [Dorigo et al., 1996]: Overview



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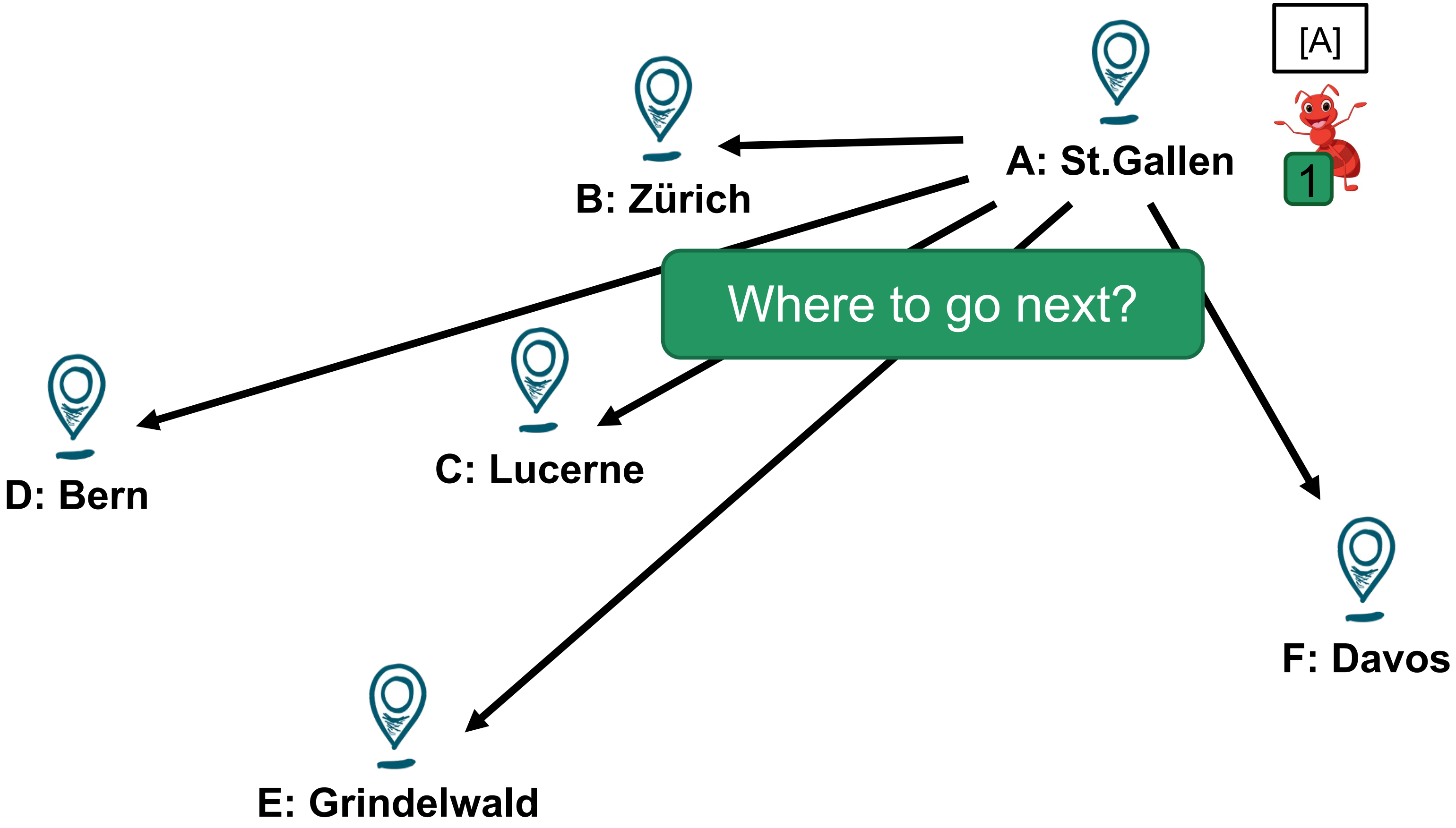

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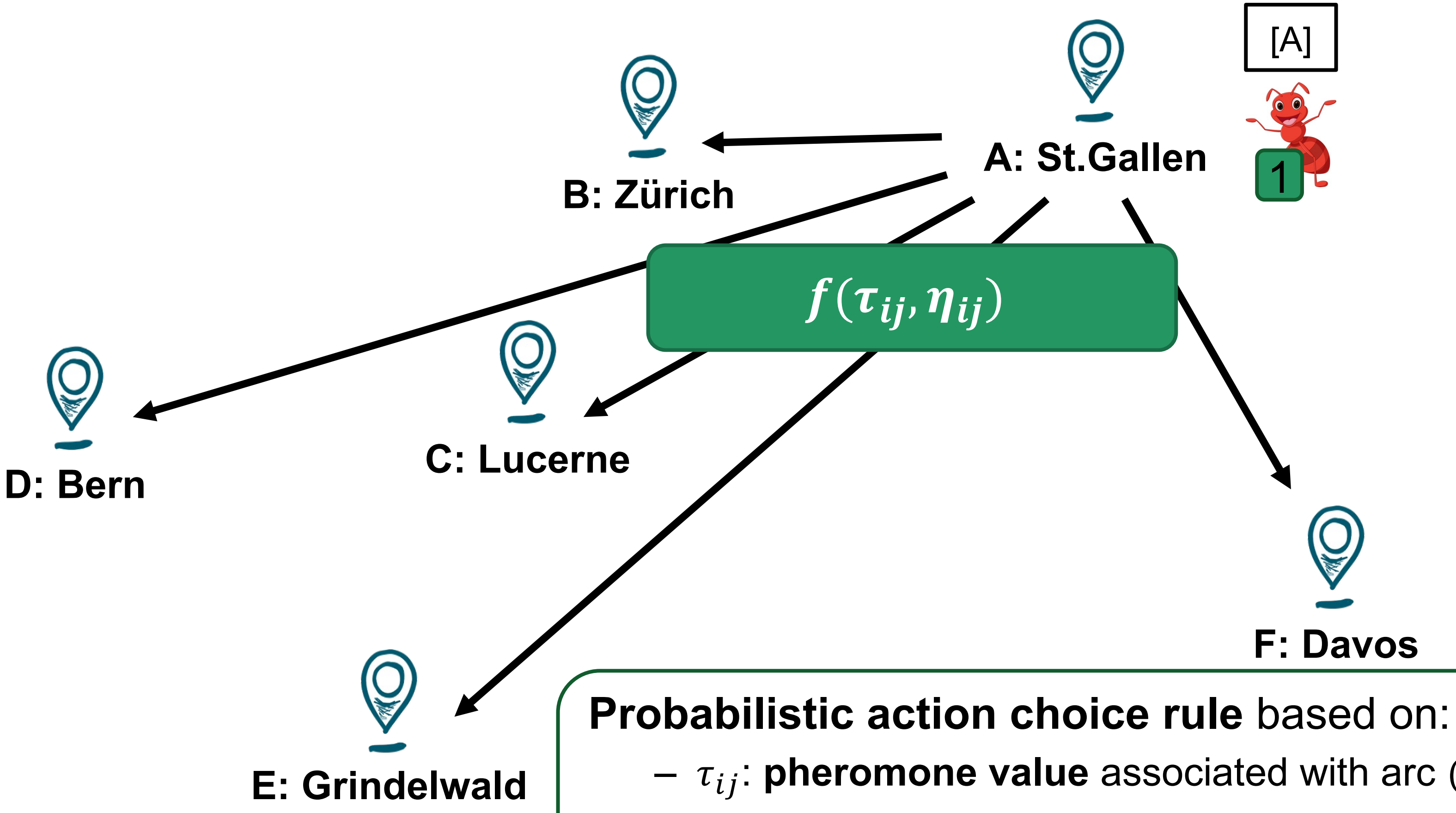

Probabilistic action choice rule based on:

- τ_{ij}: **pheromone value** associated with arc (i, j)
- η_{ij}: **heuristic information**, a priori information about the problem instance or run-time information from a source different from the ants

M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.
M. Dorigo et al., Ant System: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics, vol. 26, 1996.

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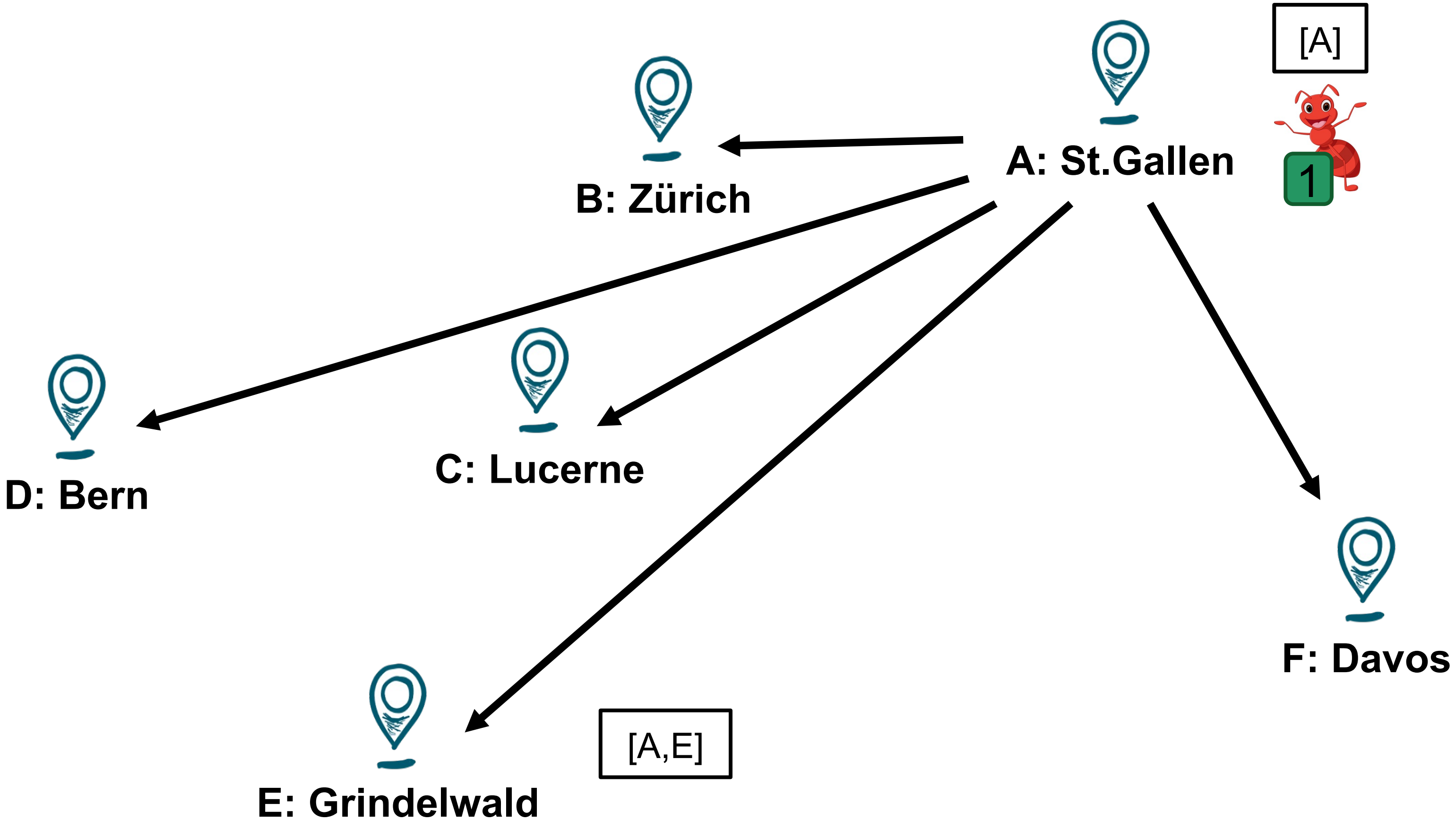

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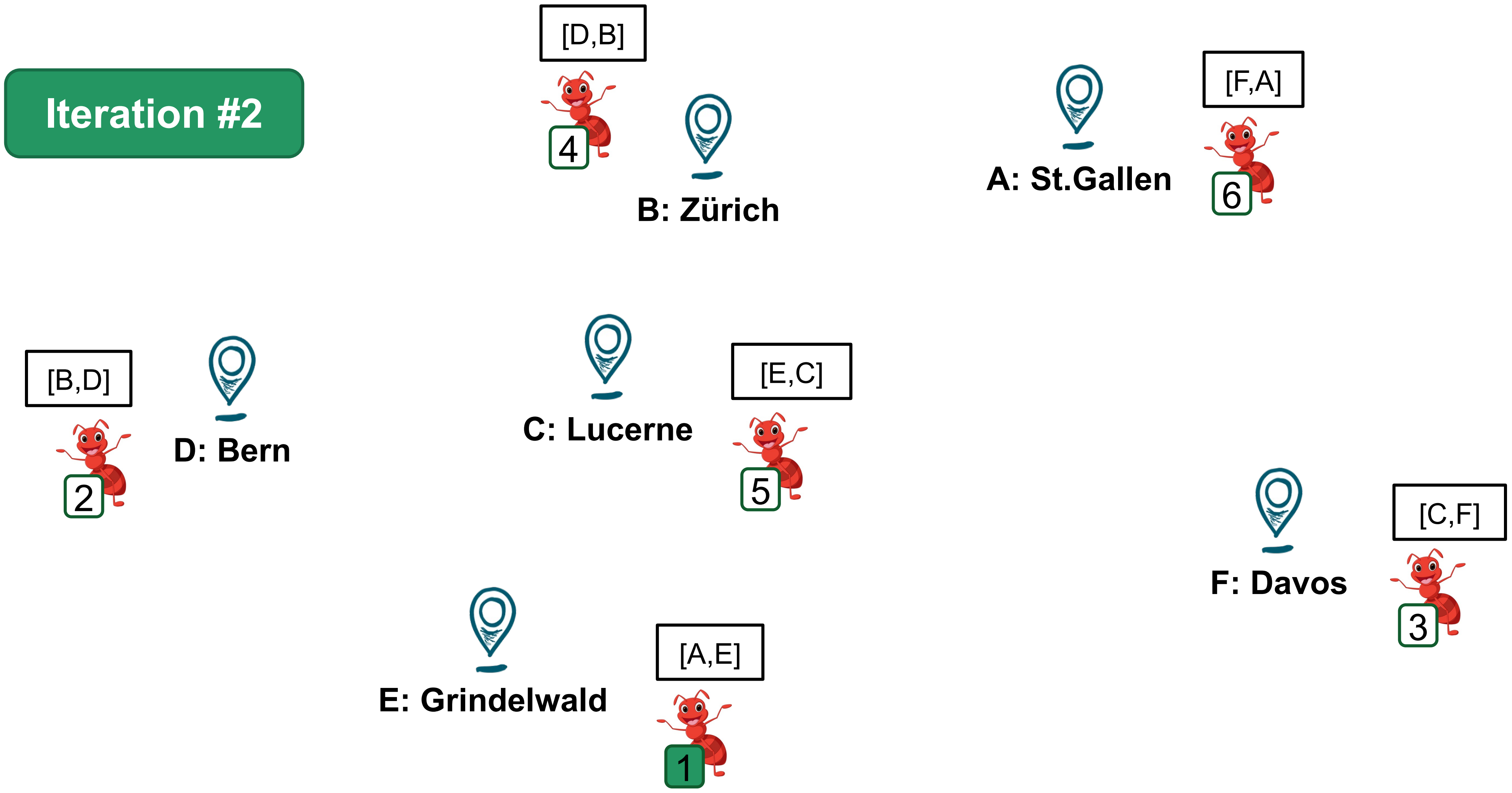
Ant System [Dorigo et al., 1996]: Overview

Iteration #2



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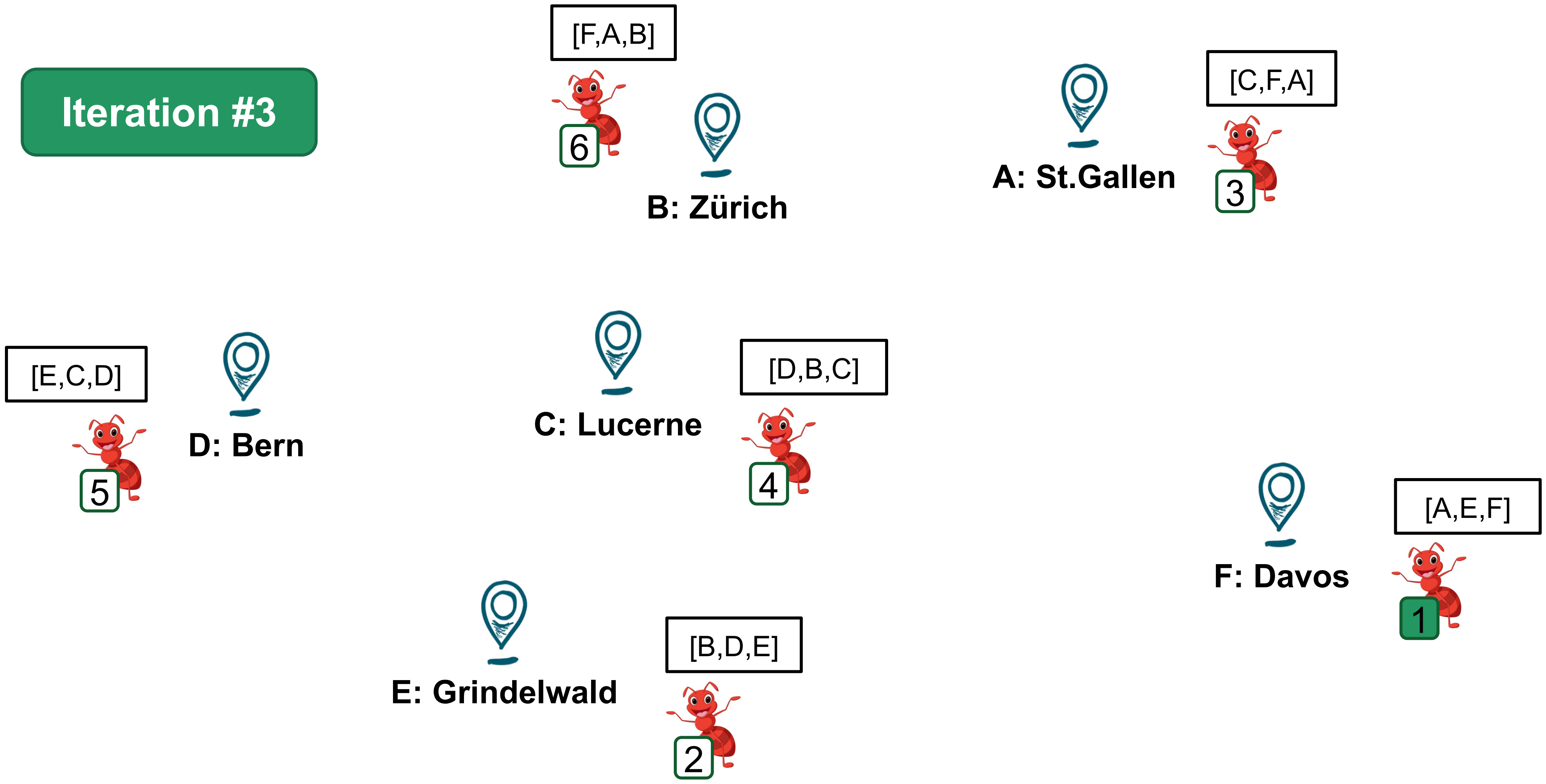
Ant System [Dorigo et al., 1996]: Overview



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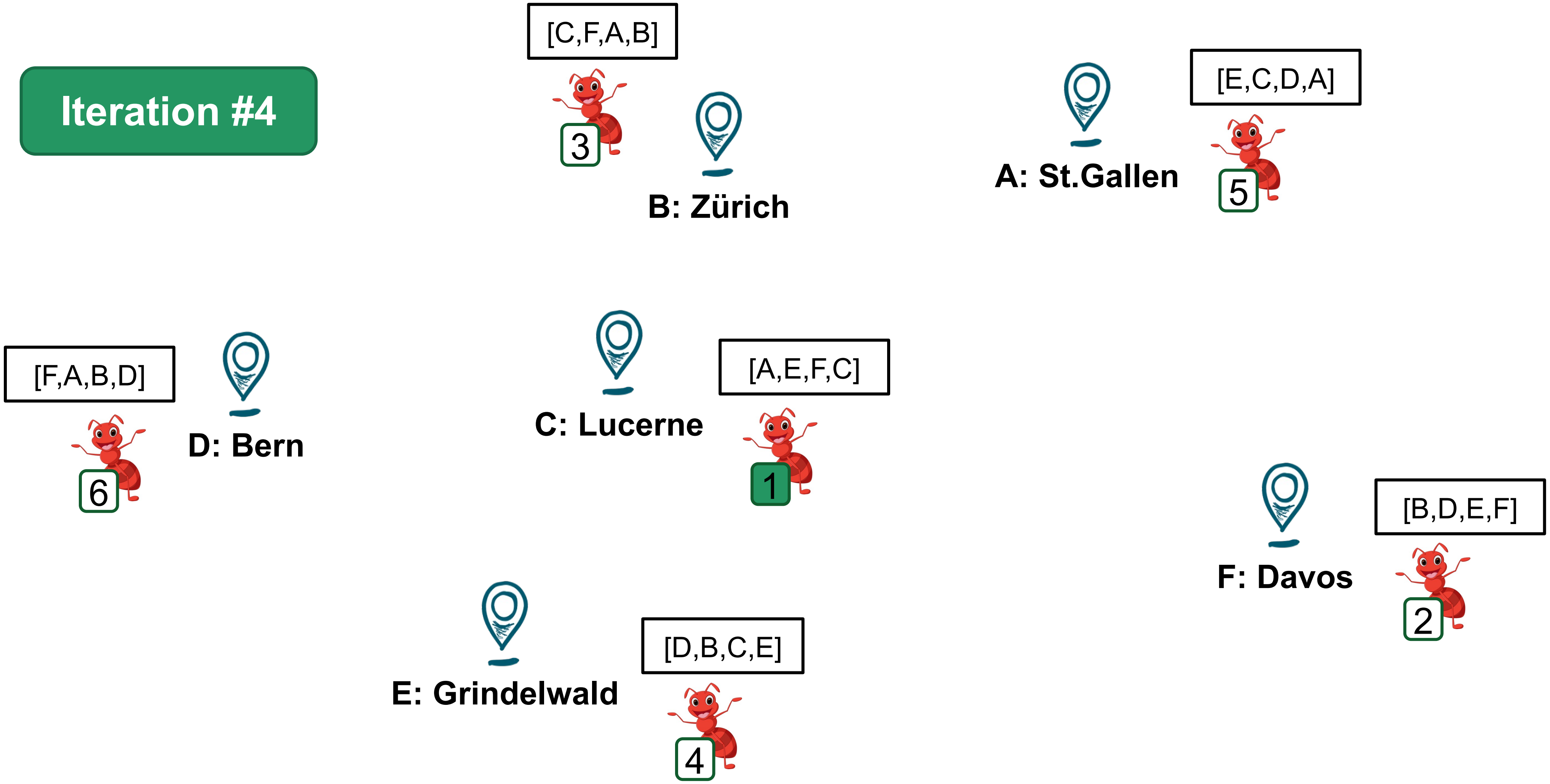
Ant System [Dorigo et al., 1996]: Overview

Iteration #4



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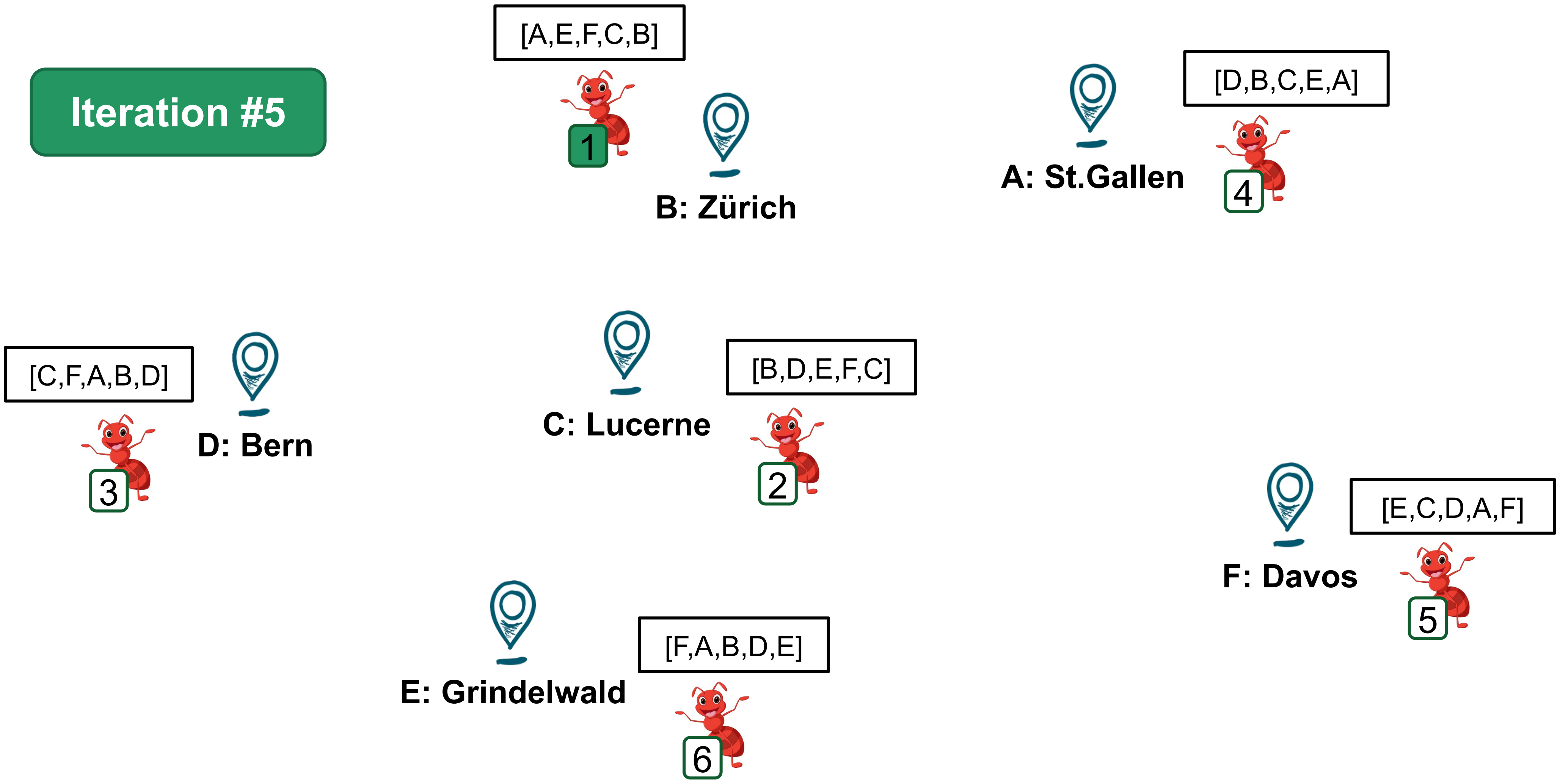
M. Dorigo et al., Ant System: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics, vol. 26, 1996.

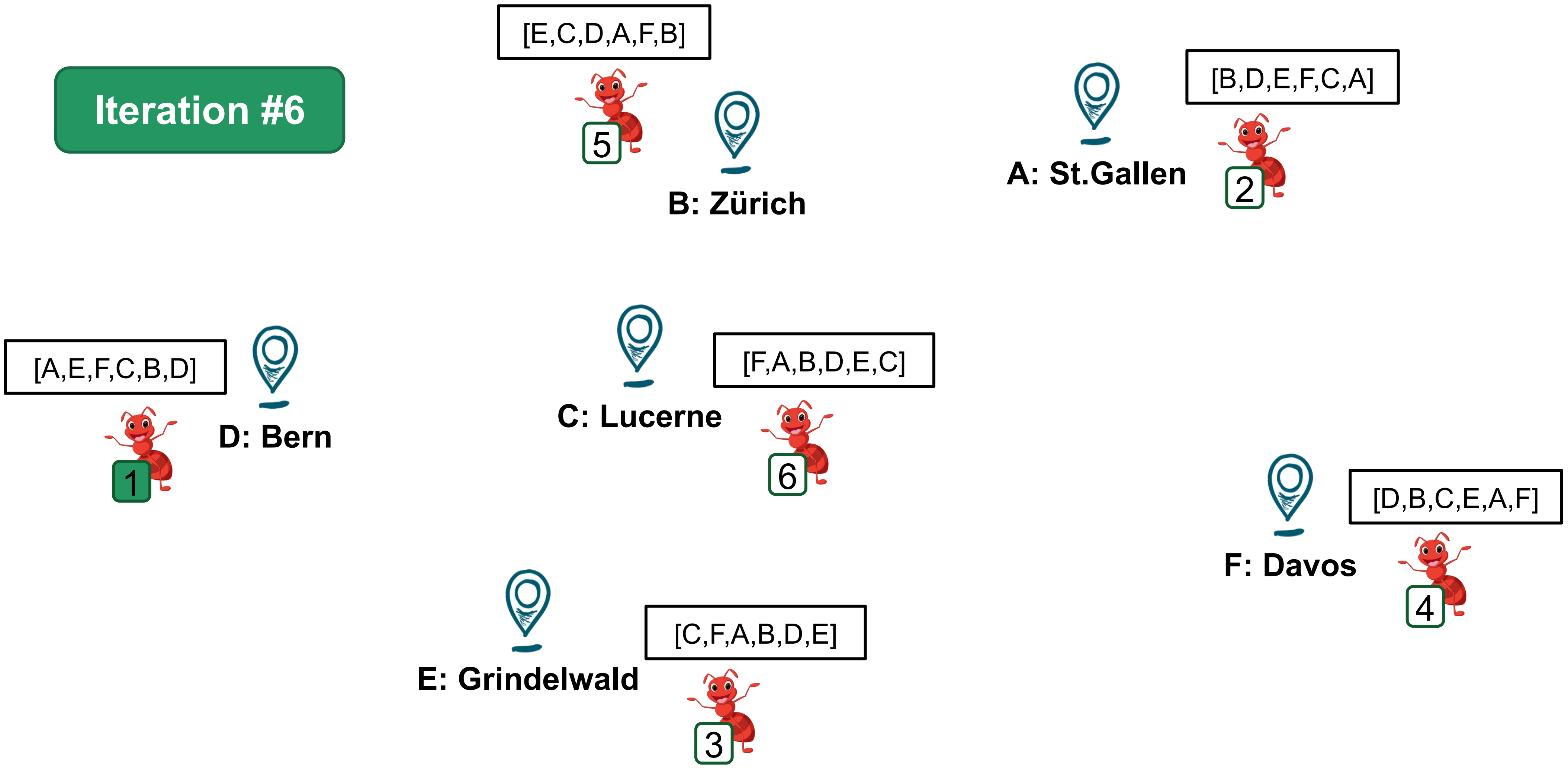
Ant System [Dorigo et al., 1996]: Overview



M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.
M. Dorigo et al., Ant System: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics, vol. 26, 1996.

Ant System [Dorigo et al., 1996]: Overview

Iteration #6



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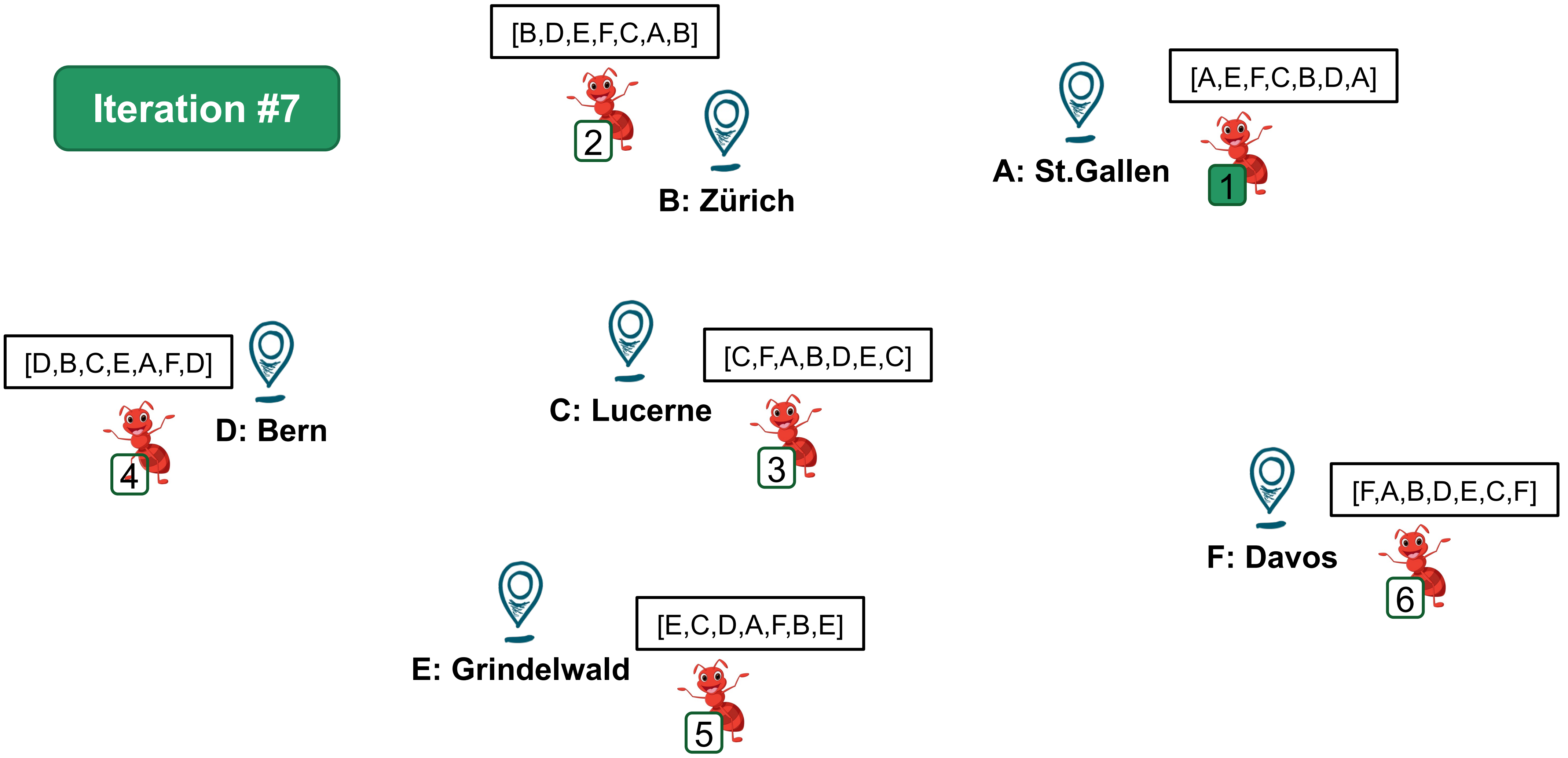
Ant System [Dorigo et al., 1996]: Overview



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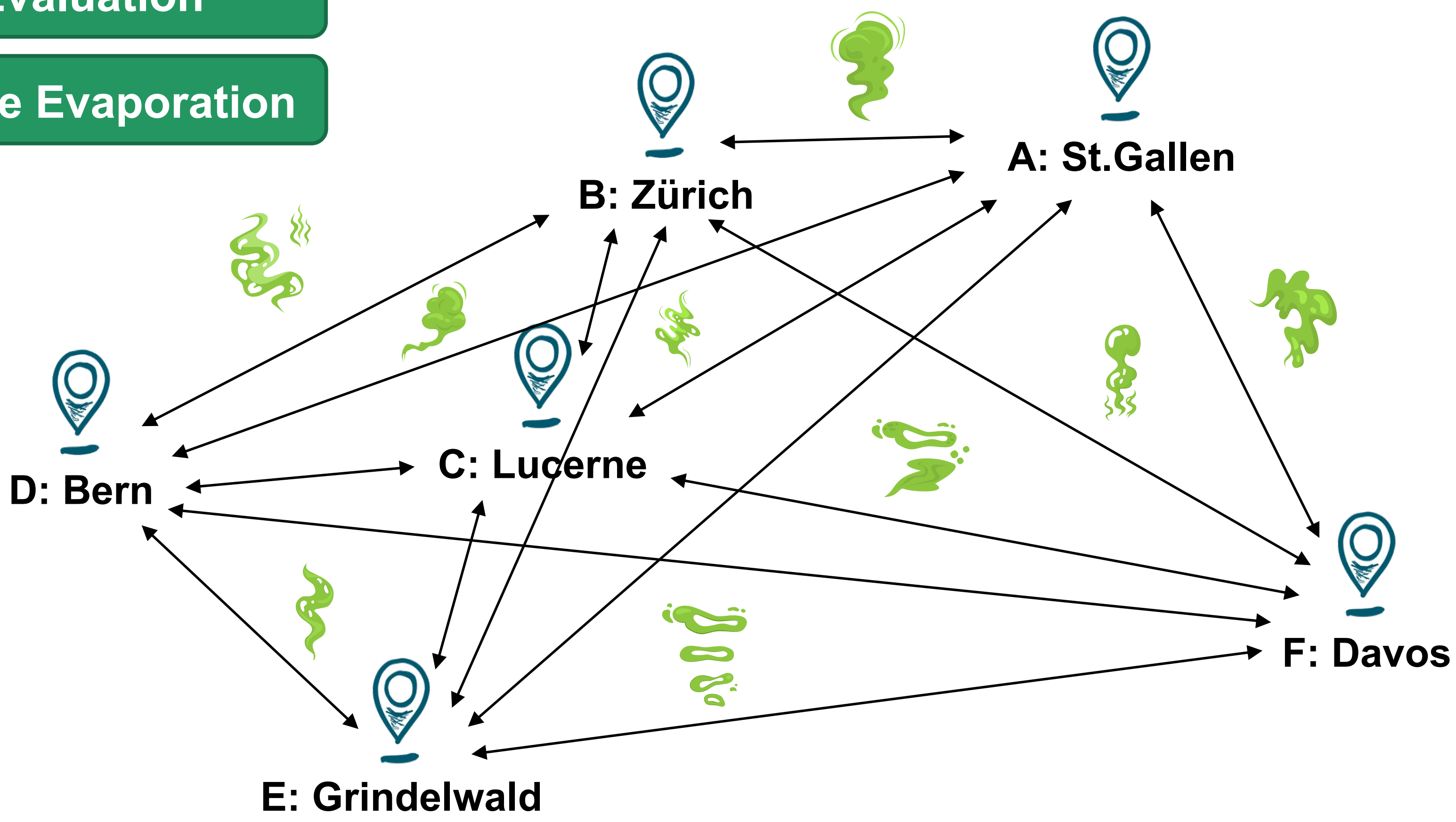
Ant System [Dorigo et al., 1996]: Overview

Tour Evaluation

Pheromone Evaporation



1. $C^1 = 1024$ [A,E,F,C,B,D,A]
2. $C^2 = 847$ [B,D,E,F,C,A,B]
3. $C^3 = 675$ [C,F,A,B,D,E,C]
4. $C^4 = 884$ [D,B,C,E,A,F,D]
5. $C^5 = 815$ [E,C,D,A,F,B,E]
6. $C^6 = 675$ [F,A,B,D,E,C,F]

M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.
M. Dorigo et al., Ant System: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics, vol. 26, 1996.

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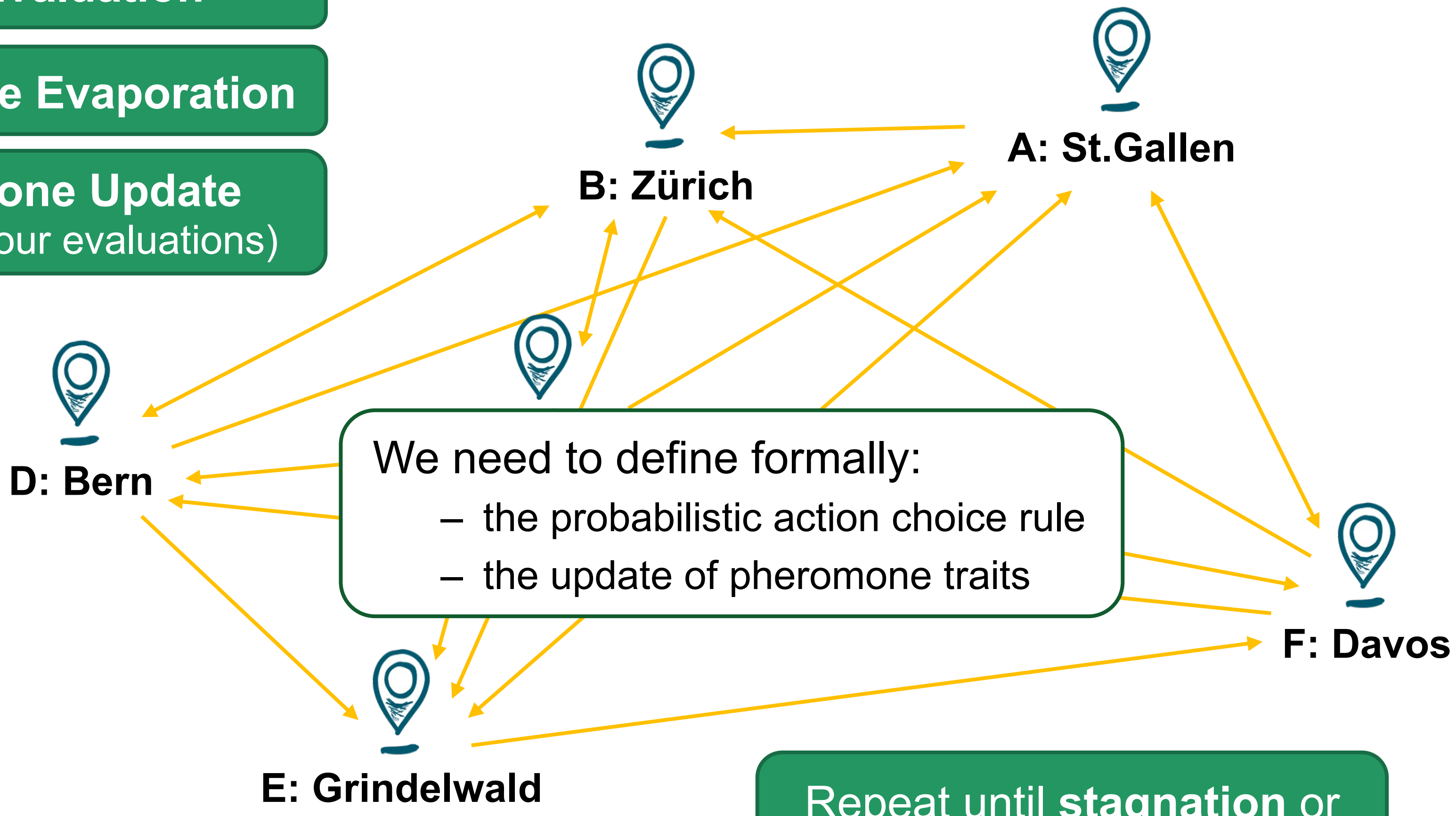
Ant System [Dorigo et al., 1996]: Overview

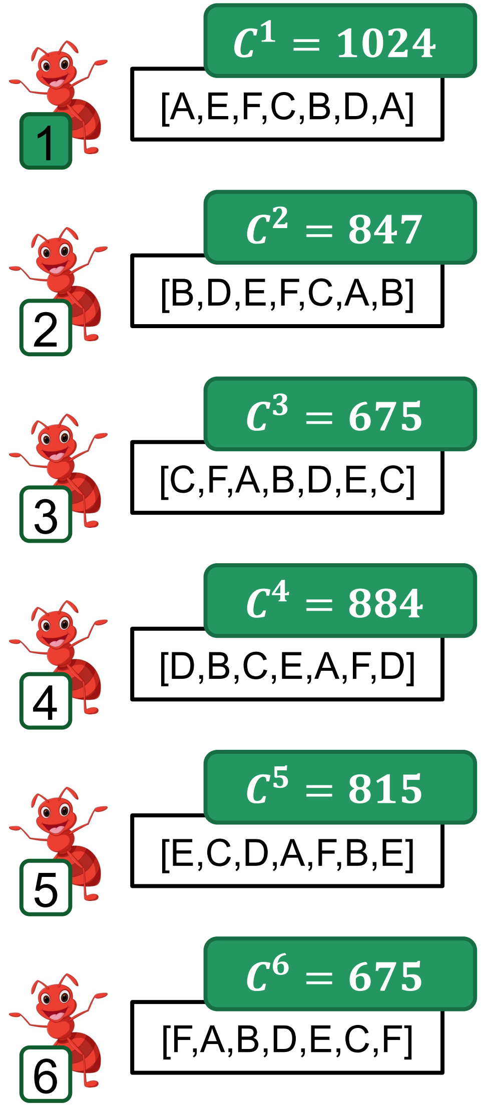
Tour Evaluation

Pheromone Evaporation

Pheromone Update
(based on tour evaluations)



We need to define formally:
- the probabilistic action choice rule
- the update of pheromone traits



Repeat until **stagnation** or **max. iterations reached**

M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.
M. Dorigo et al., Ant System: Optimization by a colony of cooperating agents. IEEE Transactions on Systems, Man, and Cybernetics, vol. 26, 1996.

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Ant System: Tour Construction

Probability with which ant k at city i chooses to go to city j:

$$p_{ij}^{k} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in \mathcal{N}_i^k}[\tau_{il}]^{\alpha}[\eta_{il}]^{\beta}}, & \text{if } j \in \mathcal{N}_i^k \\ 0, & \text{otherwise} \end{cases}$$

where:

- $\mathcal{N}_i^k$ is the set of cities reachable from city i that ant k has not visited yet (the *feasible neighborhood*)
- τ_{ij} is the amount of pheromone on the arc from city i to city j;
- $\eta_{ij} = 1/d_{ij}$ is a heuristic value based on the distance d_{ij} between city i and city j (available a priori);
- α and β are two parameters that determine the relative influence of the pheromone trail and the heuristic information

Exploration vs. Exploitation

- if $\alpha = 0$, the closest cities are most likely to be selected next
- if $\beta = 0$, only the pheromone values are used

In practice, good parameter values are chosen empirically

Common values [Dorigo & Stützle, 2004]: $\alpha = 1$ and $\beta = 2$ to 5

M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.

Ant System: Update of Pheromone Trails

Pheromone trails are updated after all the ants have constructed their tours (*ant-cycle* variant [Dorigo, 1992])

Step 1: Pheromone is first removed from all arcs (pheromone evaporation):

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \forall (i,j) \in E$$

where E is the set of all arcs and $0 < \rho \leq 1$ is the pheromone evaporation rate

– pheromone evaporation allows to "forget" bad decisions taken previously: if an arc is not chosen by the ants, its associated pheromone value decreases exponentially in the number of iterations

Common evaporation rate value [Dorigo & Stützle, 2004]:
$\rho = 0.5$

Step 2: Pheromone is then added on the arcs the ants have crossed in their tours:

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \forall (i,j) \in E$$

where m is the total number of ants, and $\Delta\tau_{ij}^{k}$ is the amount of pheromone ant k deposits on the arcs it has visited and is defined as:

$$\Delta\tau_{ij}^{k} = \begin{cases} 1/C^k, & \text{if } (i,j) \in T^k \\ 0, & \text{otherwise} \end{cases}$$

A common value for m is the number n of nodes in the graph [Dorigo & Stützle, 2004]

where T^k is the tour built by ant k and C^k is the tour's cost (the sum of the distances of all arcs in T^k)

M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.
M. Dorigo. *Optimization, Learning and Natural Algorithms*, PhD Thesis, Politecnico di Milano, 1992.

Ant System: Initializing Pheromone Trails

Pheromone trails are initialized to a value slightly higher than the expected amount of pheromone deposited by the ants in one iteration

- if the initial pheromone values are too high, many iterations are lost until pheromone evaporation reduces enough pheromone values such that the pheromone added by the ants can bias the search
- if the initial pheromone values are too low, the search is quickly biased towards the first tours generated by the ants

$$\forall(i,j), \tau_{ij} = \tau_0 = m/C^{nn}$$

where:

- m is the number of ants
- C^{nn} is the expected cost of a tour generated using a *nearest-neighbor heuristic* (e.g., choosing the next closest city that was not yet visited)

M. Dorigo and T. Stützle. Ant Colony Optimization. MIT Press. 2004.

Today's Agenda

- Self-Organization and Swarm Intelligence
  - Flocking Behavior: Bird-oid Objects (Boids)
  - Swarm Robotics
  - Non-Functional Properties of Self-Organizing Systems
  - Design Principles for Self-Organizing Systems
- Stigmergy
  - Ant Colony Optimization
  - Cognitive Stigmergy

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Cognitive Stigmergy

Stigmergy in self-organizing multi-agent systems generally brings two biases [Ricci et al., 2007]:
- the agent model is assumed to be very simple, such as ant-like agents
- the environment model is often quite elementary, such as a pheromone infrastructure

Cognitive Stigmergy: Towards a Framework Based on Agents and Artifacts

Alessandro Ricci, Andrea Omicini, Mirko Viroli, Luca Gardelli, and Enrico Oliva

ALMA MATER STUDIORUM—Università di Bologna
via Venezia 52, 47023 Cesena, Italy
a.ricci@unibo.it, andrea.omicini@unibo.it, mirko.viroli@deis.unibo.it, luca.gardelli@unibo.it, enrico.oliva@unibo.it

Abstract. *Stigmergy* has been adopted in MAS (multi-agent systems) and in other fields as a technique for realising forms of emergent co-ordination in societies composed by a large amount of ant-like, non-

How can **stigmergy** be transposed in systems of **cognitive agents**?

Artifacts as enablers for stigmergy

Workspaces capture locality

From pheromones to **annotations**:
- annotations hold a **symbolic value** referring to some **ontology**
- can be both **intentional** (created by agents) or **unintentional** (created by artifacts)

A. Ricci, A. Omicini, M. Viroli, L. Gardelli, E. Oliva. Cognitive Stigmergy: Towards a Framework Based on Agents and Artifacts. LNCS, 2007.

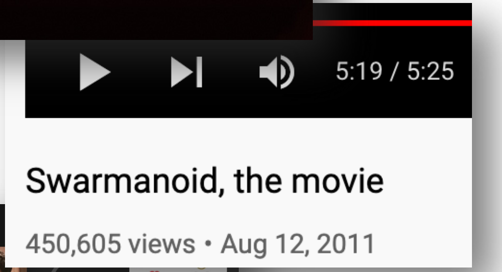
"Trails" of Cognitive Stigmergy on the Web

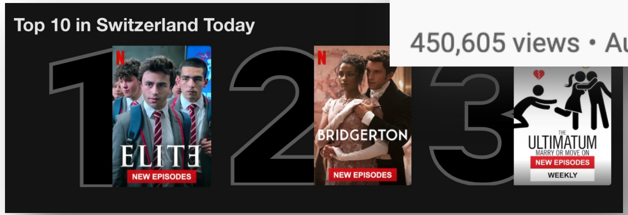
Promote **awareness** of others' activity

Some are **unintentional**, others are **intentional**

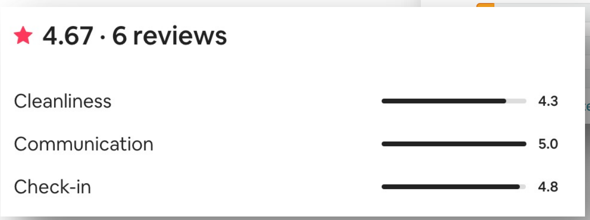
Useful both for **people** and **artificial agents**

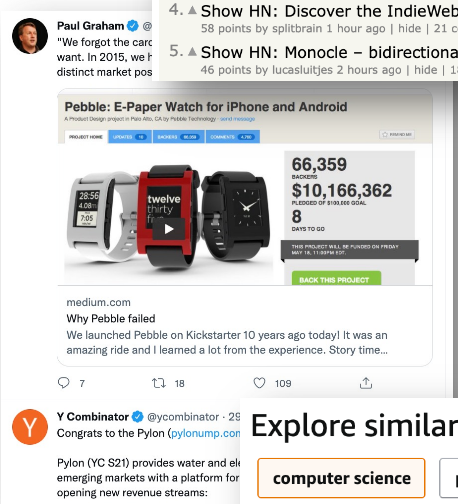
Usage Metrics

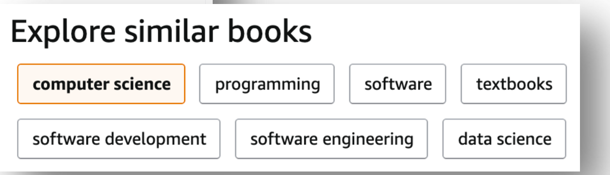




Product/Service Ratings

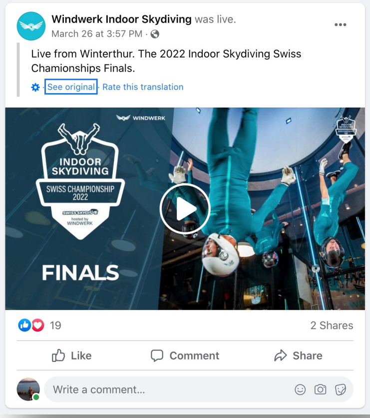






Aggregation & Difusion of Information

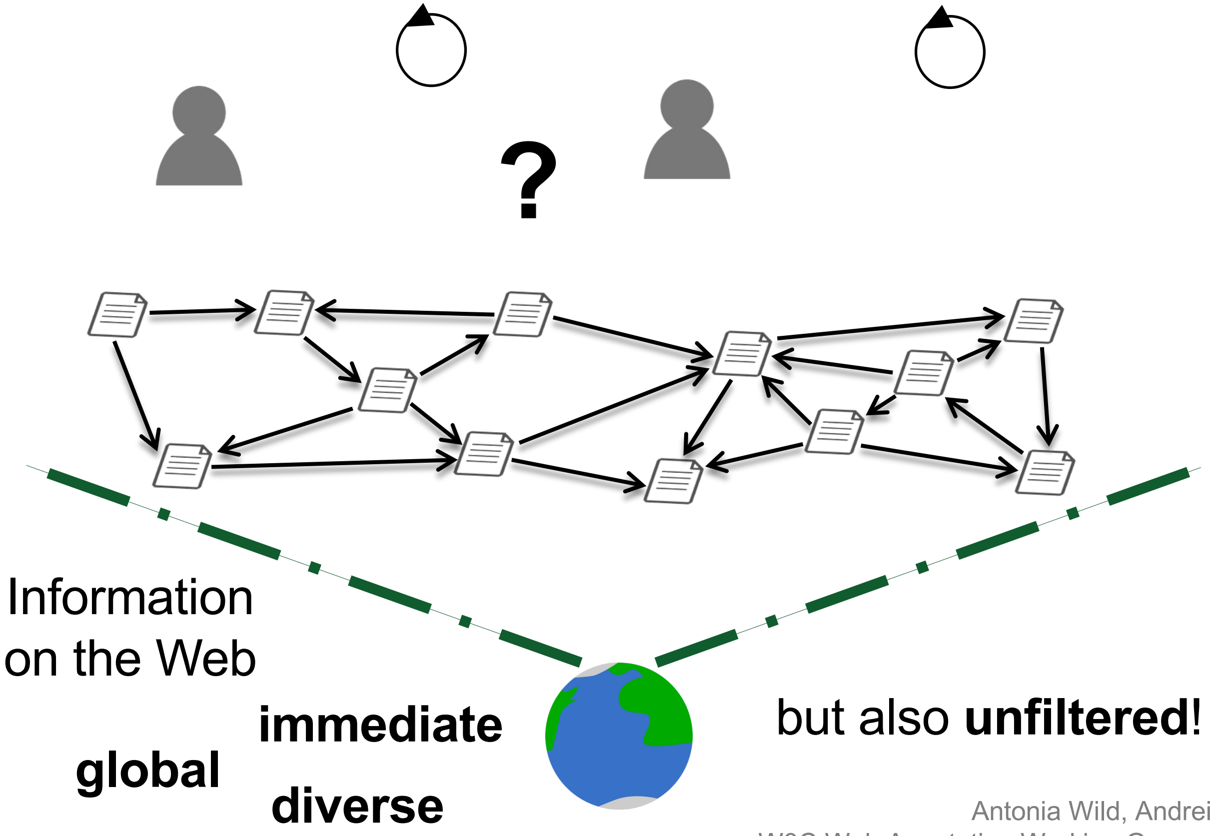
Social Cues



Etc...

Case Study: Tackling Online Disinformation

Credibility analysis of online information is hard
- automated fact-checking can **scale** but **lacks accuracy**
- manual fact-checking is more **accurate** but **lacks scale**



https://euvsdisinfo.eu/

Antonia Wild, Andrei Ciortea, and Simon Mayer. Designing Social Machines for Tackling Online Disinformation, DecentWeb 2020.
W3C Web Annotation Working Group: https://www.w3.org/annotation/; W3C CredWeb Community Group: https://www.w3.org/community/credibility/

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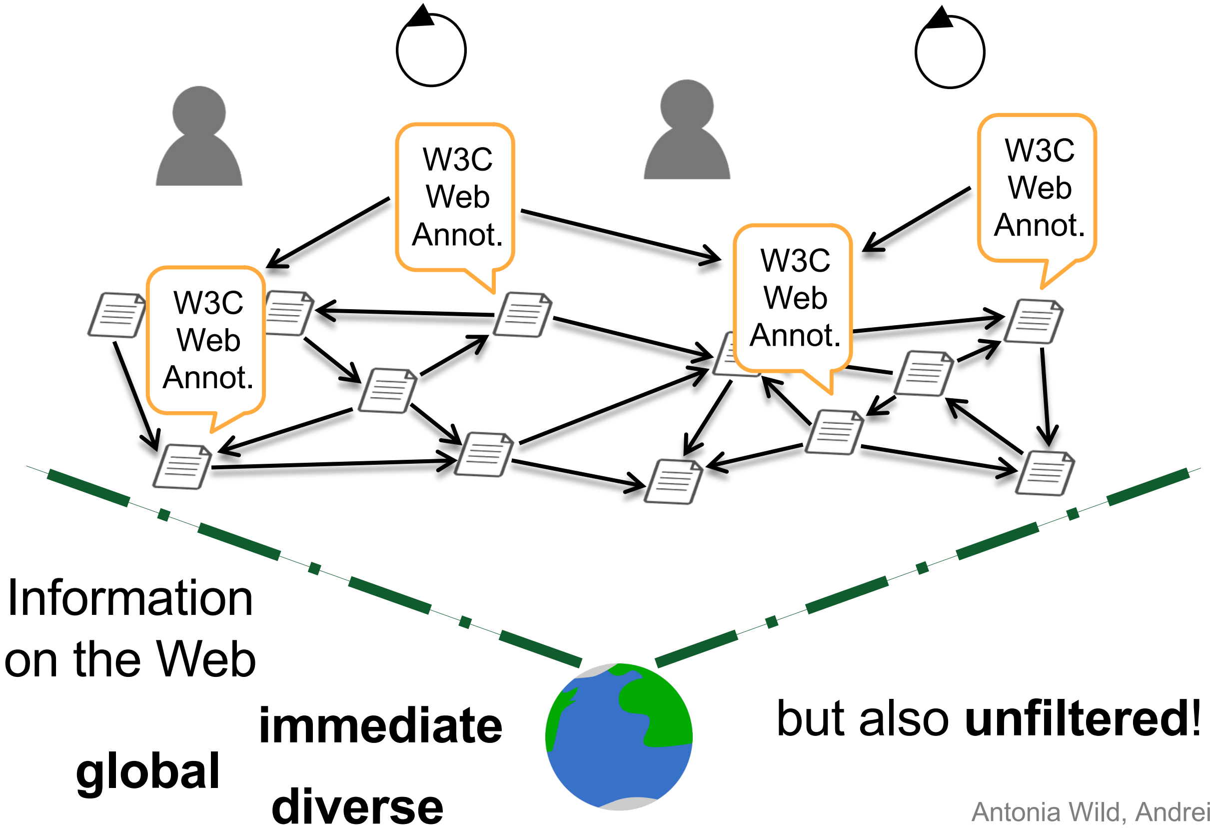
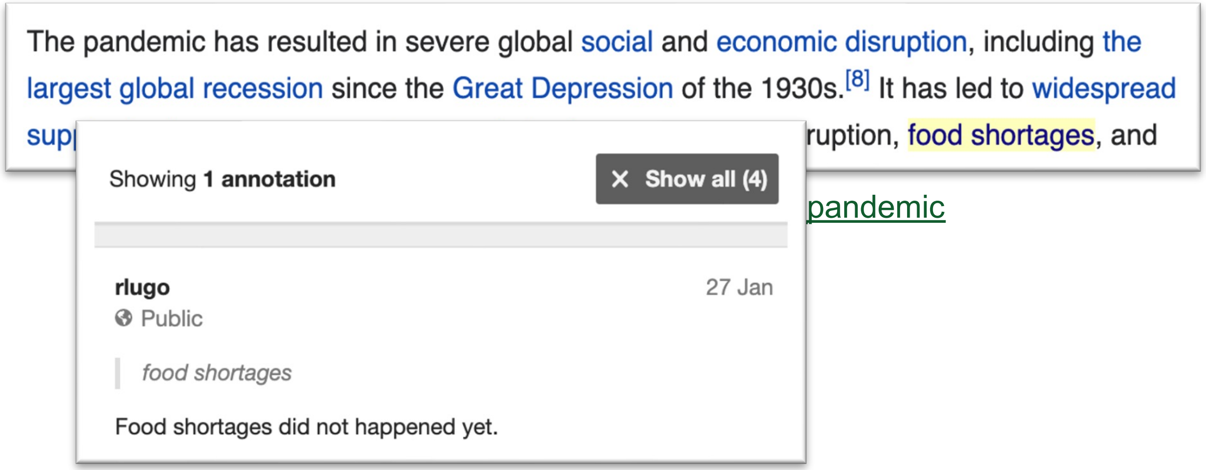


Information on the Web

global **immediate** **diverse**

but also **unfiltered!**

W3C Web Annotations: transparency **at source** on the **open Web**



Antonia Wild, Andrei Ciortea, and Simon Mayer. Designing Social Machines for Tackling Online Disinformation, DecentWeb 2020.
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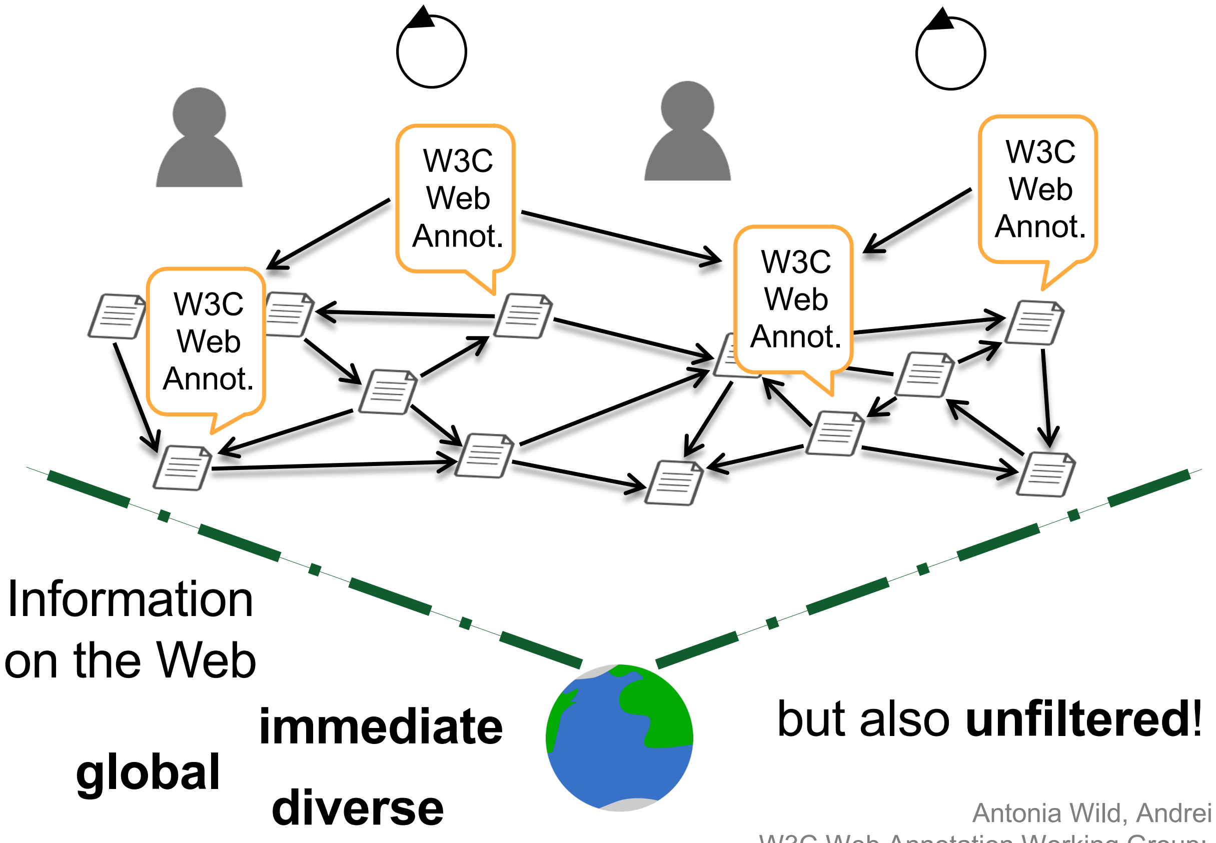

W3C Web Annotations: transparency **at source** on the **open Web**

Fact-checking workflows defined by experts

What's missing: designing hybrid organizations of people and autonomous agents

— and deploying them **at scale**!

Antonia Wild, Andrei Ciortea, and Simon Mayer. Designing Social Machines for Tackling Online Disinformation, DecentWeb 2020.
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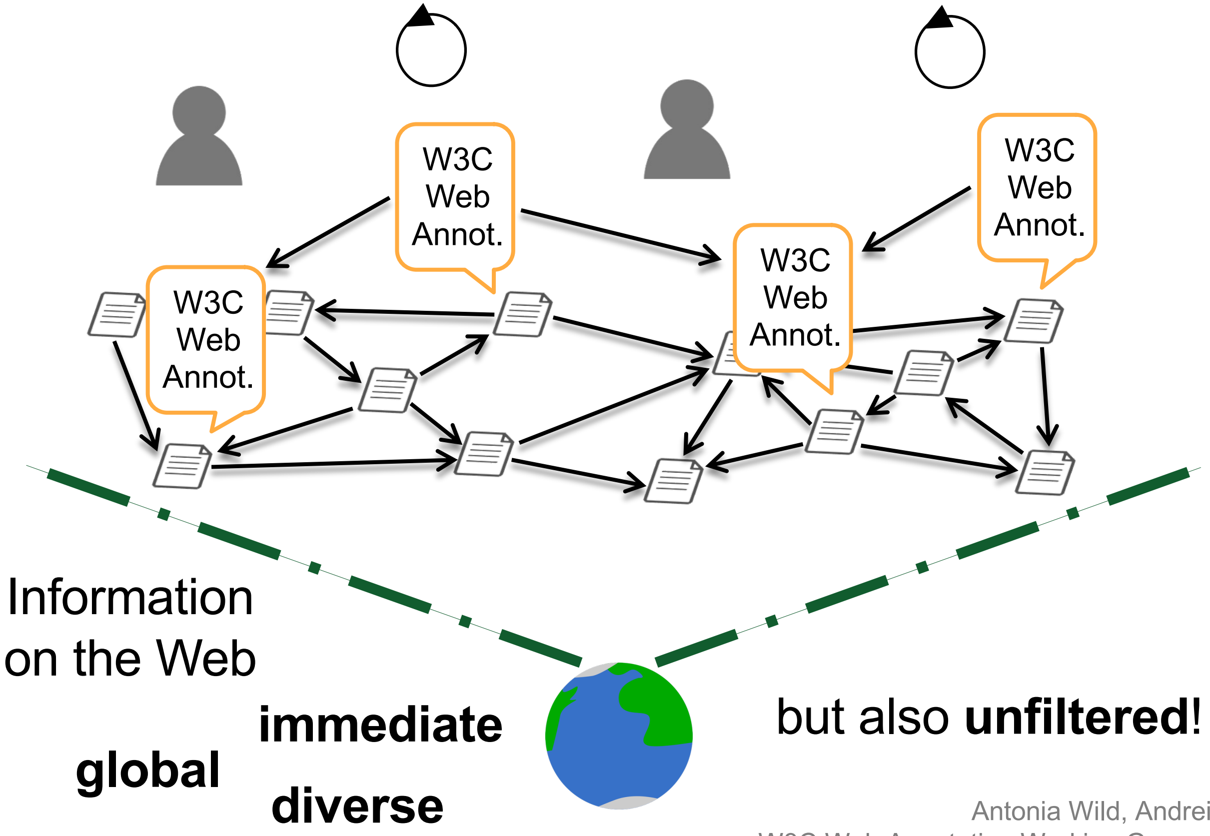
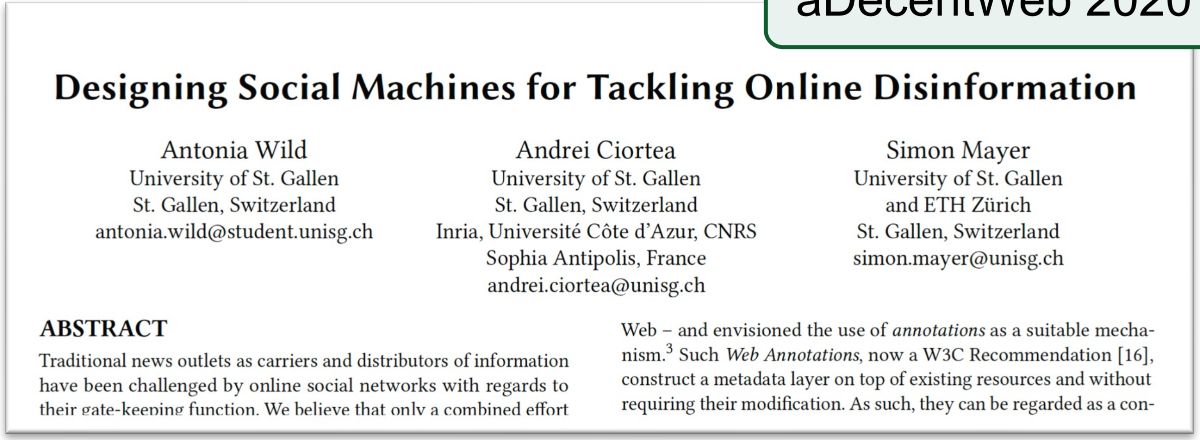


aDecentWeb 2020



Designing Social Machines for Tackling Online Disinformation

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ABSTRACT

Traditional news outlets as carriers and distributors of information have been challenged by online social networks with regards to their gate-keeping function. We believe that only a combined effort

Web – and envisioned the use of *annotations* as a suitable mechanism.[3] Such *Web Annotations*, now a W3C Recommendation [16], construct a metadata layer on top of existing resources and without requiring their modification. As such, they can be regarded as a con-

Next week:
More on **organizations** and **cognitive stigmergy** for **coordination**

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Our Journey

Prerequisites:
- **ASSE**
- **(…)**

Week 1:
Introduction

Week 2:
A Web for Machines

Week 3:
Knowledge Representation and Reasoning for the Web

Week 4:
Linked Data and Distributed Knowledge Graphs

Week 5:
Autonomous Agents (Arch. and Programming)

Week 6 (Coordination I):
Agent Communication and Interaction

Week 7 (Coordination II):
Self-Organization and Stigmergy

Week 8 (Coordination III):
Normative MAS and Organizations

Week 9 (Coordination IV):
Trust & Reputation

Week 10:
Game Theory and Social Choice

Week 11:
Reinforcement Learning and Multi-Agent Learning

Week 12:
An Industry Perspective

Exercises

Ex1: Writing Your First Agent(s)!
Ex2: Automated Planning
Ex3: Web Ontologies
Ex4: Operating on Linked Data
Ex5: BDI Agents
Ex6: Interacting Agents on the Web
Ex7: Ant Colony Optimization
Ex8: Organized Agents
Ex9: Trustworthy Agents
Ex10: Axelrod’s Agents
Ex11: Reinforcement Learning Agents
Course Review and Q&A

Any Questions / Comments / Doubts / Concerns?

Images

https://www.istockphoto.com/
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http://www.wikipedia.com