Evolution of collective behavior in social insects:

a model for complex systems

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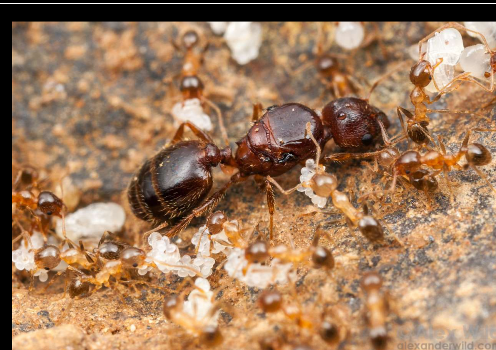
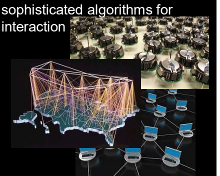


Complex 'systems'

Complexity

Modularity and interaction

- *recursivity* → apparent unpredictability
- *specialization* of subunits → 'visual' complexity
- unit behaviors optimized for collective outcome → sophisticated algorithms for interaction



Anna Dornhaus research

Collective strategies

- Task allocation/Division of labor
  - Specialists are not always more efficient
  - Cheap, poor performers can be optimal
  - A lot of unit variation is not specialization on tasks, but on other dimensions (robustness, cost/accuracy, life history)
- Information exchange/search
  - Positive feedback reduces innovation
  - Communication has opportunity costs

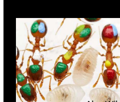
What are the benefits & costs = why / when does it evolve?

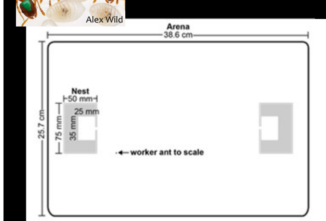
Empirical model system

Rock ants: *Temnothorax rugatulus*

Allocation to defense

Ant fights



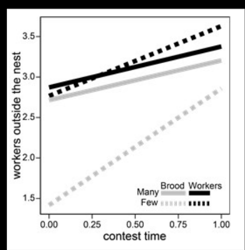


- Competition with other colonies is a major selection pressure in ants
- Rich theory in biology on animal contests and information use

Study by Victor 'Blue' Paat, Kenny Chapin, Anna Dornhaus

Allocation to defense

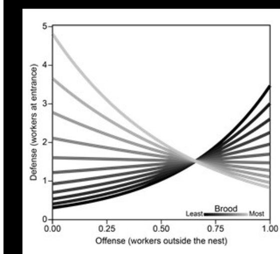
Ant fights – offense (workers out)



- Ant colonies use own & opponent worker number (=fighting ability?) and brood number (=resource value?) to decide investment in attack
- More ~ more

Allocation to defense

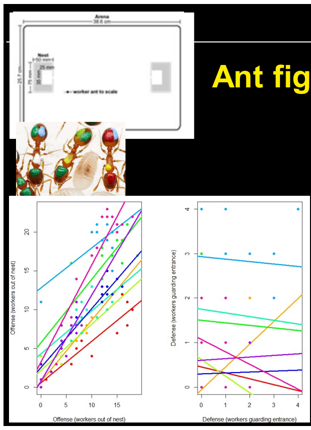
Ant fights – defense (guarding)



- Defense is a result of complex interplay between number of brood & workers…
- More brood ~ more defense when weak offense

Allocation to defense

Ant fights



- Number of searching/attacking workers may be matched to opponent
- Own and opponent traits are assessed to determine investment

Study by Victor 'Blue' Paat, Kenny Chapin, Anna Dornhaus

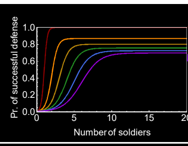
Defense deployment

Deploying resources across sites

'Turtle ants' – few soldiers, multiple sites, varying in quality, defensibility, and risk levels

Study by Matina Donaldson-Matasci, Scott Powell, Anna Dornhaus

A model of soldier defense



Small entrance: fewer soldiers needed (h=1)

Large entrance: even maximal defense isn't enough (h=6)

Defensibility

Defense function (one cavity)

$$d(k;h) = \frac{h^{-1/5}}{1 + e^{5(1-k/h)}}$$

entrance size

1) Chance of k soldiers successfully defending a nest against an attack

Threat

Survival function (one cavity)

$$s(k;a,h) = e^{-a(1-d(k;h))}$$

attack intensity (Poisson process)

2) Chance of nest surviving for one season

Quality

Fitness function (multiple cavities)

$$f(\vec{k};\vec{v},\vec{a},\vec{h}) = \sum_i v_i \cdot s(k_i;a_i,h_i)$$

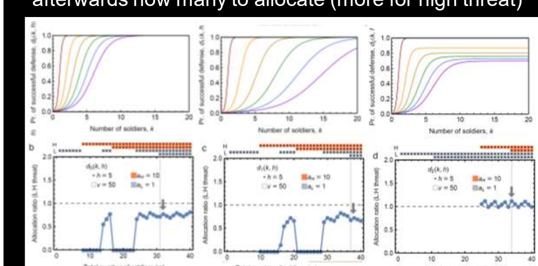
brood capacity

3) Total expected number of surviving brood in all nests

Defense deployment

Model results

To defend or not is the first choice (low threat first); afterwards how many to allocate (more for high threat)



Defense deployment

Do ants use the 'optimal' strategy?

	Model Predictions		Experimental results	
	Which to defend?	Defense level?	Which to defend?	Defense level?
Quality	Choose to defend high-quality cavities	Defend high & low quality nests at same level	Choose to defend high-quality cavities	Defend high & low quality nests at same level
Defensibility	Choose to defend cavities that are easy to defend	Defend vulnerable cavities more heavily	No preference based on defensibility	Defend vulnerable cavities more heavily
Threat	Defend fewer cavities (esp. hard-to-defend ones)	Shift defense away from vulnerable cavities	Defend fewer cavities (no defensibility preference)	Shift defense away from vulnerable cavities

Not in one respect: hard-to-defend sites are not avoided. Limitation based on distributed allocation algorithm?

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Broad relevance

Why study collective behavior in social insects?

Many reasons!

- Philosophical: Complexity out of simpler parts
- Specific: Ecological (more biomass than vertebrates) and economic importance (pollinators, pests)
- Model for Cognition: (Collective) intelligence in tractable system
- Model for Organismic traits: Evolutionary principles applied to different 'major transition' or organizational level (e.g. evolution of life history, intraspecific variation, etc.)
- Practical: Application to engineering

Social insects

Research areas

1. Communication & Information flow – push & pull, network structure, resource distribution, symmetry breaking, personal vs social information and reliability
2. Collective decision-making – individual vs collective, latent learning, colony size & consensus, speed & accuracy
3. Optimal search – adaptive random walks, group size effects
4. Spatial sorting – creates variation, stigmergy, self-organized group size effects
5. Division of labor – inactive workers, specialization, response threshold distributions, reserves, algorithms/mechanisms, task switching, elites
6. Individual vs collective intelligence – learning complex tasks without reward

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