

# ANT-INSPIRED DENSITY ESTIMATION VIA RANDOM WALKS

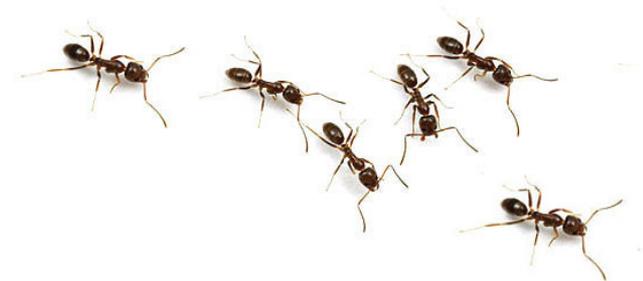
---

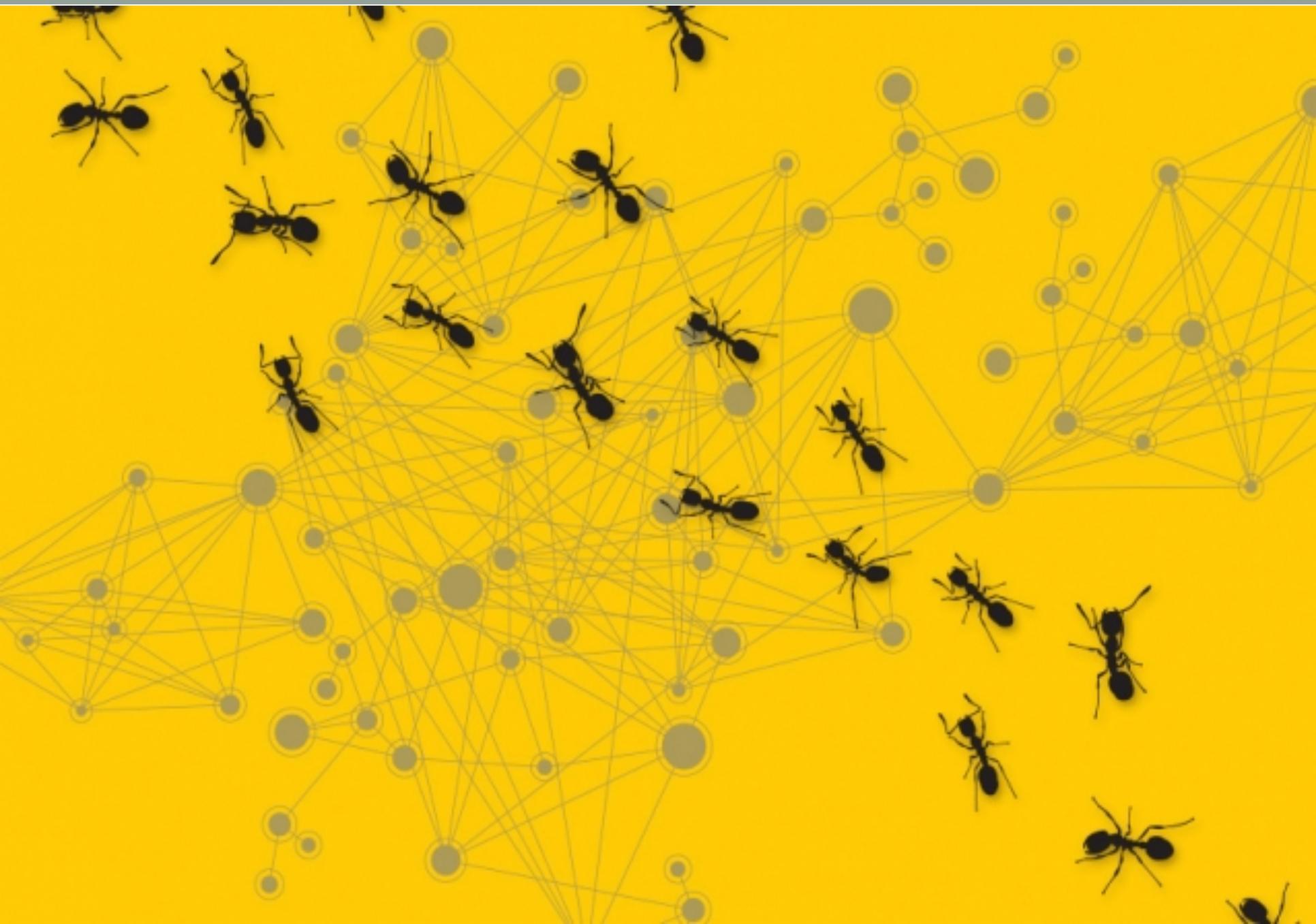
Nancy Lynch, Cameron Musco, Hsin-Hao Su

BDA 2016

July, 2016

Chicago, Illinois





# 1. Introduction

- Ants appear to use estimates of colony density (number of ants per unit area), in solving typical ant colony problems:
  - **Searching for a new nest:** Ants decide to accept a nest when they detect that the ant density in the nest has become sufficiently high [Pratt 05].
  - **Engaging or retreating:** Ants may decide to engage or retreat based on relative density of their own vs. an enemy colony [Adams 90] .
  - **Task allocation:** Ants may choose tasks based on densities of ants already allocated to various tasks [Gordon 99], [Schafer, Holmes, Gordon 06].
- Estimate density based on encounter rates [Gordon, Paul, Thorpe 93], [Pratt 05].
- **Q:** How might this work, and how accurate are the estimates?



# Density estimation in distributed systems

- Similarly, agents in distributed systems could use density estimates in solving distributed computing problems:
  - **Robot swarms:**
    - Robots can determine the frequency of certain properties within the swarm, such as detecting an environment event.
    - Robots can allocate themselves to tasks, or distribute themselves evenly around an area.
  - **Social networks:**
    - One could estimate the size of a network by launching agents and observe how frequently they encounter others [Katzir, Liberty, Somekh 11].
- Estimating density is equivalent to:
  - Estimating the number of agents, if the area is known, or
  - Estimating the area, if the number of agents is known.



# How we got interested:

- Distributed House-Hunting in Ant Colonies [Ghaffari, Lynch, Musco, Radeva PODC 15].
  - **Algorithm:** Ants evaluate nest desirability by determining numbers of ants in the nests and how the numbers change over time.
  - $O(\log n)$  time until termination.
  - Approximately matching lower bound,  $\Omega(\log n)$ .
- This assumes that an ant can determine the number of ants in a nest precisely.
  - Typical sort of assumption for distributed algorithms.
  - Not realistic for ants: they cannot count precisely, they move,...
  - Makes the algorithm too fragile, for a biological algorithm.
- Led us to study **approximate counting**, which could be implemented by estimating density.



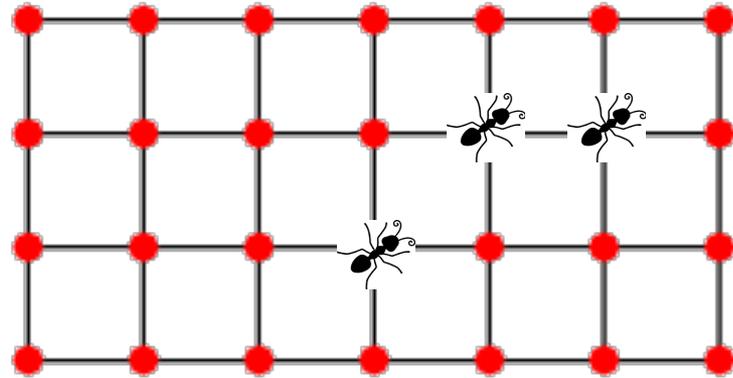
# Our latest algorithm

- Ant-Inspired Density Estimation via Random Walks [Lynch, Musco, Su PODC 16, arXiv]
- Uses encounter rates, as suggested by [Gordon, Paul, Thorpe 93], [Pratt 05].
- **Specifically:**
  - Ants wander in a 2-D plane, using independent random walks.
  - Each ant determines its **number of encounters per unit time**.
  - Uses that as a density estimate (number of ants per unit area).
- **Notes:**
  - This assumes that an ant can count its number of encounters, although ants cannot count precisely.
  - Actually, the algorithm is not so fragile---approximate counting should be good enough.
  - But for now, just pretend an ant can count its encounters precisely.

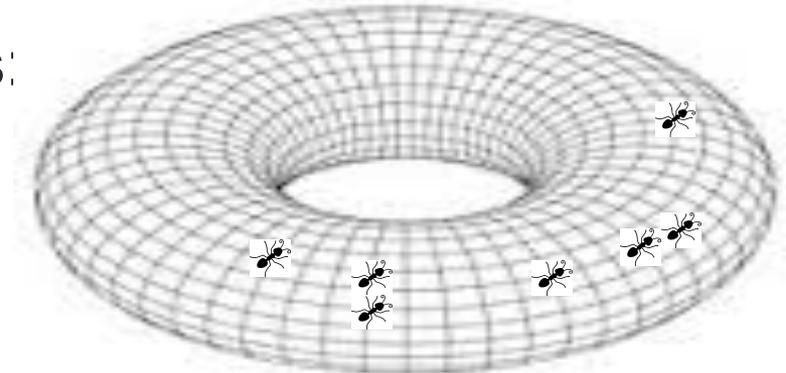


# Our algorithm

- Geometry is important for our results.
- 2-dimensional plane.
- **Discretize space:** Describe the plane as a grid, with ants on the nodes.



- Then fold the grid into a torus:



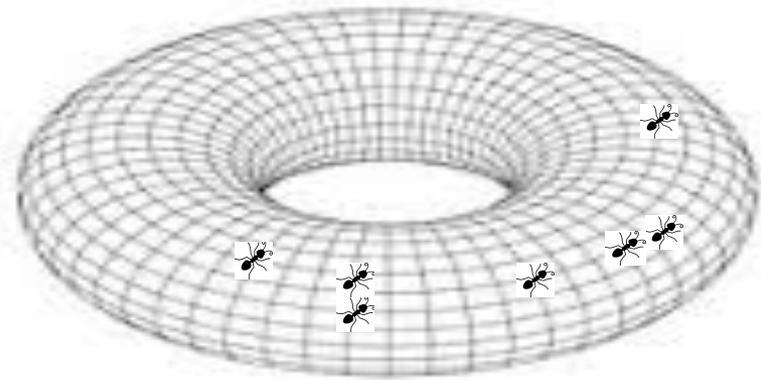
# Our algorithm

- **Discretize time:** Synchronous rounds.
- **Algorithm:**
  - In each round, each ant takes a step in a random direction, sees how many ants it encounters at the new position, and adds this number to a running *count*.
  - After  $t$  rounds, it outputs the value of the ratio  $\frac{\text{count}}{t}$ .
- **Claim:** This is a good estimate for the ant density  $d = \frac{n}{\text{area}}$ .
- **Q:** How good?
- **A:** With “high probability”, the estimate is correct to within a small inaccuracy  $\epsilon$ , provided that the number  $t$  of rounds is at least a certain constant times  $\frac{1}{d\epsilon^2}$  times  $\log\left(\frac{1}{d\epsilon}\right)$ .

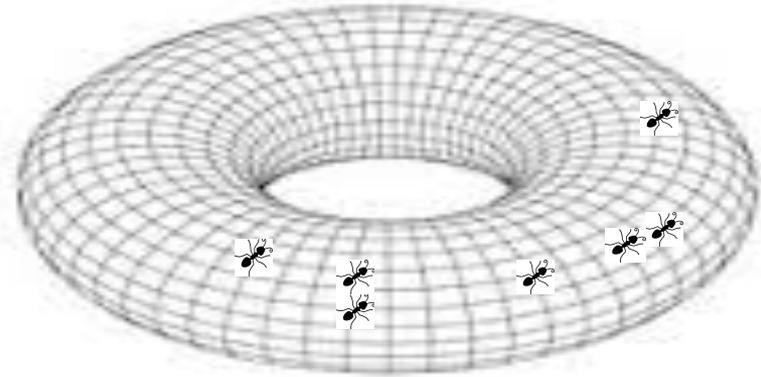


## 2. Model and Problem

- **Torus grid**,  $A$  locations,  $\sqrt{A}$  by  $\sqrt{A}$ .
- Ants start at (uniformly, independently chosen) random locations.
- Then they work in **synchronous rounds**.
- At every round, each ant can choose (deterministically or probabilistically) to move one step in any direction, or to not move.
- In every round, each ant can detect how many other ants have reached the same grid location in the same round.
- It can also remember these numbers, e.g., by accumulating them in a single internal *count* variable.

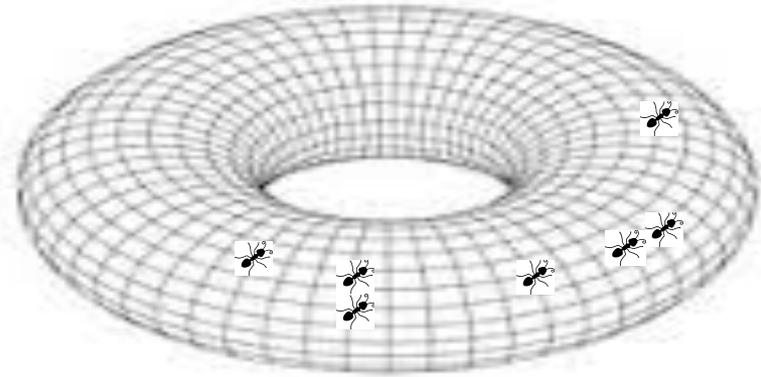


# The Density Estimation problem



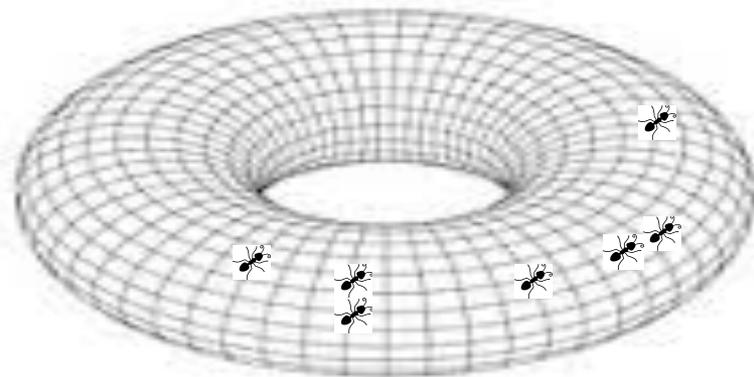
- Each ant should continually output its latest estimate of the **density**  $d = n/A$ , where  $n$  is the total number of ants and  $A$  is the total number of grid points in the torus.
- Ants are not assumed to know  $n$  or  $A$ , and don't need to determine these---just the ratio.
  - But if they happen to know  $n$  or  $A$ , the density estimate yields an estimate of the other.

# 3. The Algorithm



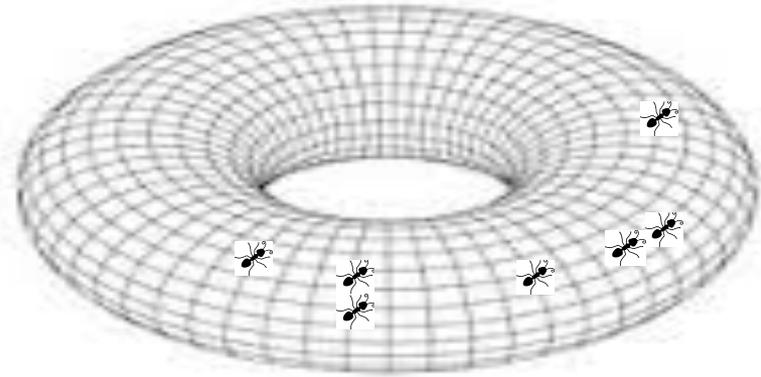
- Simplest possible!
- Ants are initially randomly placed at grid locations.
- **Algorithm for ant  $a_i$ :**
  - **Local variables:**
    - *count*, initially 0
    - *time*, initially 0
  - **At every round:**
    - Set  $time := time + 1$ .
    - Move in any of the four directions, each with probability  $\frac{1}{4}$ .
    - See how many other ants have reached the same grid location in the same round.
    - Add that number to *count*.
    - Output estimate  $est = \frac{count}{time}$ .

# The Algorithm



- Algorithm for ant  $a_i$ :
  - At every round:
    - Set  $time := time + 1$ .
    - Move in any of the four directions, each with probability  $\frac{1}{4}$ .
    - See how many other ants have reached the same grid location in the same round.
    - Add that number to  $count$ .
    - Output estimate  $est = \frac{count}{time}$ .
  - Q: Why is  $\frac{count}{time}$  a plausible estimate for density  $d = n/A$ ?
    - $d = n/A$  is the expected number of ants at any particular location at any particular time.
    - $\frac{count}{time}$  is the average number any particular ant **sees** at any time.
    - Those are the same.

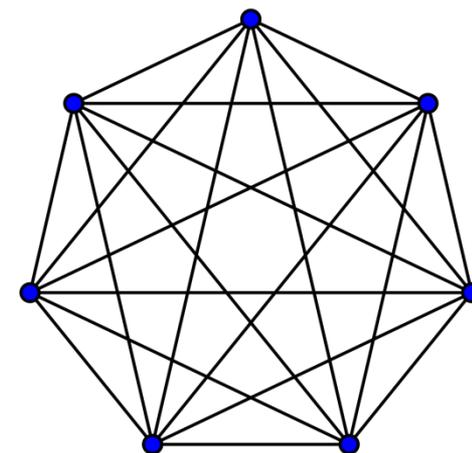
# 4. The Analysis



- How does this behave?
- **Theorem 1:** The expected value of any ant's estimate is equal to the actual ant density  $d = n/A$ .
- As we just argued.
- **But we also want a high-probability result:** With “high probability”, the estimate is correct to within  $\epsilon$ , provided that the number  $t$  of rounds is “sufficiently large”.
- Having the right expectation doesn't automatically imply high probability that our estimate is close to the expectation.

# Analysis

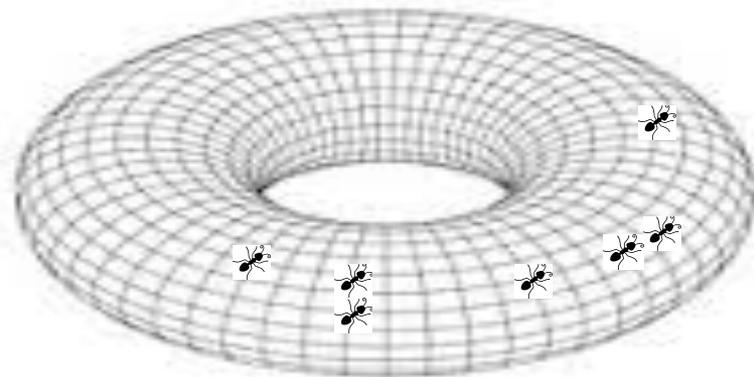
- **High-probability result:** With “high probability”, the estimate is correct to within  $\epsilon$ , provided that the number  $t$  of rounds is “sufficiently large”.
- In completely-connected graphs, a high-probability result follows easily:
  - Any ant is equally likely to go anywhere at each round.
  - Occurrences of encounters are essentially independent at each round.
  - Standard probability results (Chernoff bounds) yield a good high-probability result:
- **Theorem 2 (for complete graphs):** With “high probability”, the estimate is correct to within  $\epsilon$ , provided that the number  $t$  of rounds is at least a certain constant times  $\frac{1}{d\epsilon^2}$ .



# Analysis

- We say that the complete graph has **fast mixing time**, meaning there is little correlation between successive locations for an ant.
- On the other hand, the torus grid graph has **slow mixing time**--- strong correlation between successive locations for an ant.
- Thus, when ant  $a_i$  encounters ant  $a_j$  in some round, it is likely to encounter it again in the following rounds.
- High variance in time between successive encounters.
  
- Still, we obtain:
- **Theorem 3 (for torus grid graphs):** With “high probability”, the estimate is correct to within  $\epsilon$ , provided that the number  $t$  of rounds is at least a certain constant times  $\frac{1}{d\epsilon^2}$  times  $\log(\frac{1}{d\epsilon})$ .

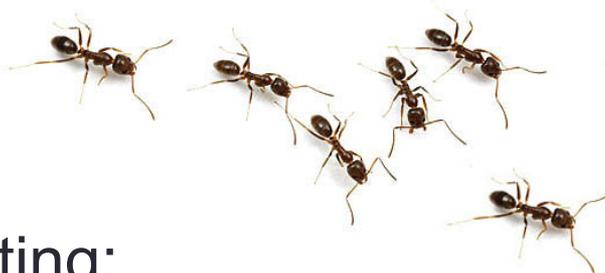
# Analysis



- **Theorem 3 (for torus grid graphs):** With “high probability”, the estimate is correct to within  $\epsilon$ , provided that the number  $t$  of rounds is at least a constant times  $\frac{1}{d\epsilon^2}$  times  $\log(\frac{1}{d\epsilon})$ .
- **Proof:**
  - Calculations, based on bounding the moments of the distribution of numbers of encounters.
  - See [Lynch, Musco, Su, PODC 16, arXiv] for details.
- **Key Lemma 4 (Re-collision bound):** If  $a_i$  and  $a_j$  collide in round  $r$ , then the probability that they collide again in round  $r + m$  is (approximately)  $\Theta\left(\frac{1}{m+1}\right) + O\left(\frac{1}{A}\right)$ .

# 5. Discussion

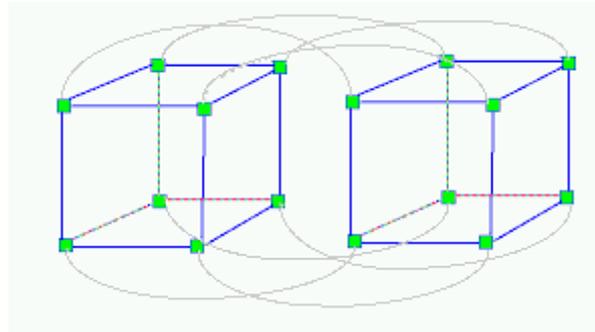
- We have shown that a very simple random exploration algorithm for the 2-dimensional plane gives accurate estimates of colony density, even though collisions at successive rounds are not independent.
- May be useful for understanding insect behavior:
  - Searching for a new nest
  - Engaging or retreating
  - Allocating ants to tasks
- And for distributed computing:
  - Robot swarms
  - Estimating the size of a large social network
  - See [Lynch, Musco, Su 16] for some examples.



# Results: Other graph classes

- Density estimation for other classes of graphs:

- Rings
- Higher-dimensional tori
- Regular expanders
- Hypercubes



- The key in each case is a re-collision bound, e.g., for a ring:
- **Key Lemma (Re-collision bound):** If  $a_i$  and  $a_j$  collide in round  $r$ , then the probability that they collide again in round  $r + m$  is (approximately)  $\Theta\left(\frac{1}{\sqrt{m+1}}\right) + O\left(\frac{1}{A}\right)$ .
- We use a general result that converts re-collision bounds to bounds for density estimation.

# Results: Network size estimation

- Estimate the size (area) of a social network by regarding it as a large directed graph, edges corresponding to network links.
- **Algorithm:**
  - Launch a number  $k$  of agents to follow links randomly and uniformly.
  - See how often the agents collide.
  - Use this to produce an estimate of density, which automatically yields an estimate of size since we know  $k$ .
- **Issues:**
  - Graph isn't regular, unlike grid. Compensate by using degree weights.
  - Initial distribution:
    - Can't place agents uniformly on nodes.
    - Instead, place them according to stationary distribution of a random walk of the network.
    - Implement by using an initial "burn-in" period.



# Future work: Robustness

- **Inexact counting of collisions:**
  - Ants cannot count exact numbers of encounters.
  - Consider approximate counting, e.g., to within a factor of 2.
  - How does this affect the bounds?
- **Inexact probabilities for choosing directions**
- **Dynamic setting:**
  - What happens if the number of agents, or the network, or both, change during execution of the algorithm?
  - Adjust the estimation procedure?

# Future work: Ant house-hunting

- [Ghaffari, Lynch, Musco, Radeva PODC 15].
- Ants evaluate nest desirability by determining the numbers of ants in the nests and how the numbers change over time.
- Assumes ants can count the number of ants in a nest exactly.
  
- Now reconsider house-hunting algorithms using inexact estimates of ant density instead of exact counts.
- Implement these estimates using our density-estimation algorithms.
- **Q:** How exactly do the algorithms fit together?

Thank you!



Thank you!

