

# Search via Parallel Lévy Walks on $\mathbb{Z}^2$

Francesco d'Amore



Joint work with **Andrea Clementi**, **George Giakkoupis**,  
and **Emanuele Natale**

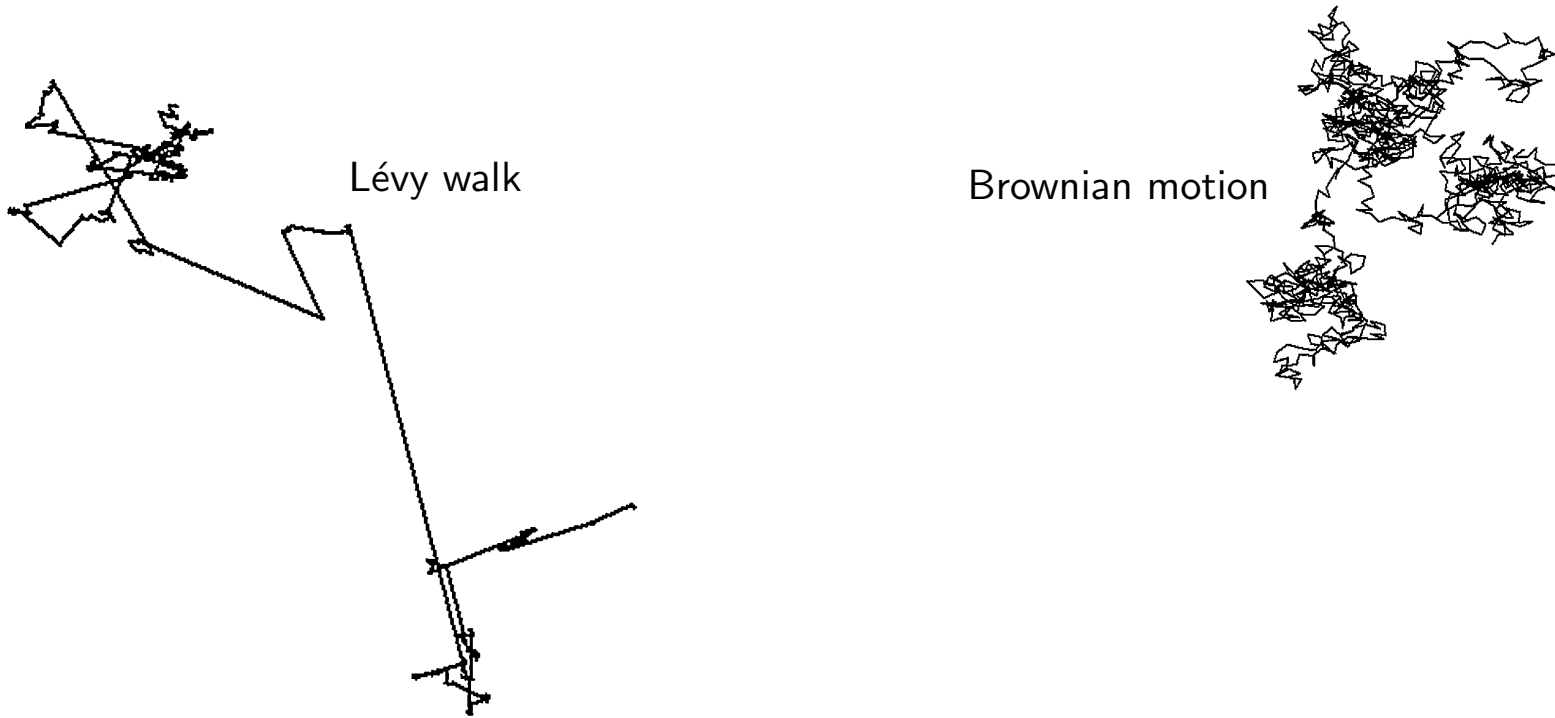
Seminario di Logica e Informatica Teorica

Dipartimento di Matematica e Fisica

Università degli studi Roma Tre

4 June 2021

# What are Lévy walks?



**Lévy walk** (informal):

*A Lévy walk is a random walk whose step-length density distribution is proportional to a power-law, namely, for each  $d \in \mathbb{R}$ ,  $f(d) \sim 1/d^\alpha$ , for some  $\alpha > 1$*

**Note:** the **speed** of the walk is **constant**

# Movement models and foraging theory

Lévy walks are used to model **movement patterns** [Reynolds, Biology Open 2018]

Examples:

- T cells within the brain
- swarming bacteria
- midge swarms
- termite broods
- schools of fish
- Australian desert ants
- a variety of molluscs



Australian desert ants

# Movement models and foraging theory

Lévy walks are used to model **movement patterns** [Reynolds, Biology Open 2018]

Examples:

- T cells within the brain
- swarming bacteria
- midge swarms
- termite broods
- schools of fish
- Australian desert ants
- a variety of molluscs



Australian desert ants

Widely employed in the **Foraging theory**

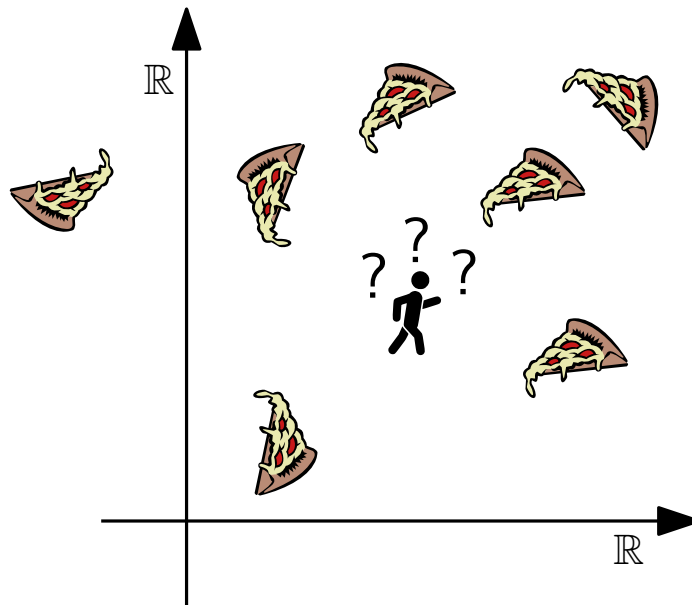
**Some fun:** **mussels Lévy walk video** [de Jager et al., Science 2011]

# Foraging theory

- Setting:
- a density distribution  $\rho$  in  $\mathbb{R}^n$  describing food locations
  - an uninformed walker searching for food

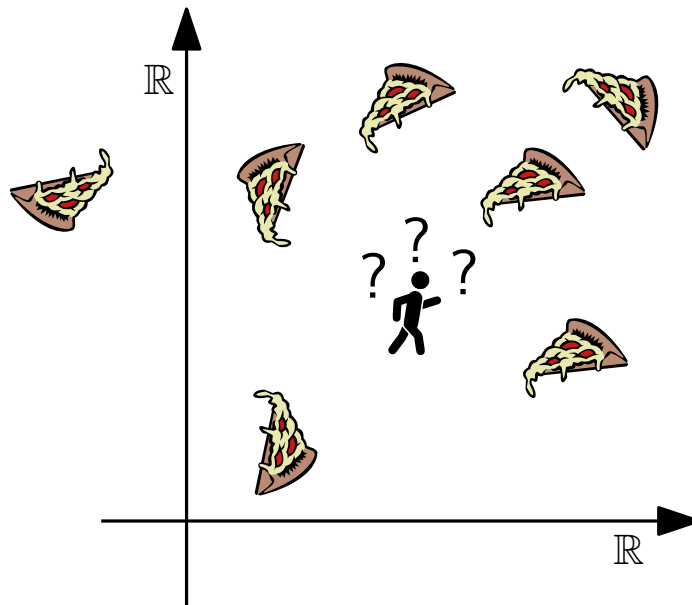
# Foraging theory

- Setting:
- a density distribution  $\rho$  in  $\mathbb{R}^n$  describing food locations
  - an **uninformed walker** searching for food



# Foraging theory

- Setting:
- a density distribution  $\rho$  in  $\mathbb{R}^n$  describing food locations
  - an uninformed walker searching for food



**Task:** find a strategy which maximizes the expected food discovery rate

# Lévy walk optimality

[Viswanathan et al., Nature 1999] takes into account two different settings:

- non-destructive foraging (the food regenerates once found)
- destructive foraging (the food does not regenerate once found)



# Lévy walk optimality

[Viswanathan et al., Nature 1999] takes into account two different settings:

- non-destructive foraging (the food regenerates once found)
- destructive foraging (the food does not regenerate once found)

**Result:** in order to maximize the expected food discovery rate, the walker should perform

# Lévy walk optimality

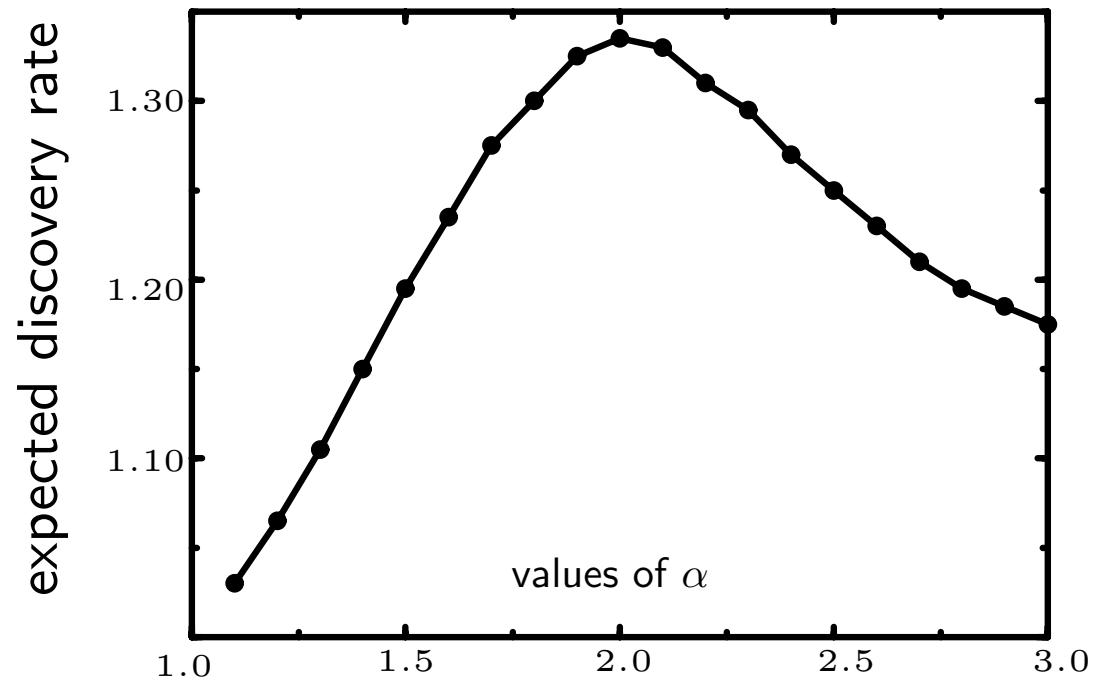
[Viswanathan et al., Nature 1999] takes into account two different settings:

- non-destructive foraging (the food regenerates once found)
- destructive foraging (the food does not regenerate once found)

**Result:** in order to maximize the expected food discovery rate, the walker should perform

- a Lévy walk with exponent  $\alpha = 2$ , for non-destructive foraging
- a ballistic walk, for destructive foraging

Simulations by [Viswanathan et al., 1999]



# The Lévy flight foraging hypothesis

Non-destructive foraging is more realistic

This has lead to an evolutionary hypothesis

# The Lévy flight foraging hypothesis

Non-destructive foraging is more realistic

This has lead to an evolutionary hypothesis

**The Lévy flight foraging hypothesis** [Viswanathan et al., *Physics of Life Reviews* 2008]: since Lévy flights/walks optimize random searches, biological organisms must have therefore evolved to exploit Lévy flights/walks

# The Lévy flight foraging hypothesis

Non-destructive foraging is more realistic

This has lead to an evolutionary hypothesis

**The Lévy flight foraging hypothesis** [Viswanathan et al., *Physics of Life Reviews* 2008]: since Lévy flights/walks optimize random searches, biological organisms must have therefore evolved to exploit Lévy flights/walks

These results shaped much of subsequent research

The performance of Lévy walks has been analyzed in a wide range of search problems



# The Lévy flight foraging hypothesis

Non-destructive foraging is more realistic

This has lead to an evolutionary hypothesis

**The Lévy flight foraging hypothesis** [Viswanathan et al., *Physics of Life Reviews* 2008]: since Lévy flights/walks optimize random searches, biological organisms must have therefore evolved to exploit Lévy flights/walks

These results shaped much of subsequent research

The performance of Lévy walks has been analyzed in a wide range of search problems



We focus on the ANTS problem

# The ANTS problem

Introduced by [Feinerman et al., PODC 2012]

- Setting:
- $k$  (mutually) **independent walkers** (agents) start moving on  $\mathbb{Z}^2$  from the origin
  - time is **synchronous** and marked by a global clock
  - one special node  $\mathcal{P} \in \mathbb{Z}^2$ , the **target**, placed by an **adversary** at unknown (Manhattan) distance  $\ell$  from the origin

# The ANTS problem

Introduced by [Feinerman et al., PODC 2012]

- Setting:
- $k$  (mutually) **independent walkers** (agents) start moving on  $\mathbb{Z}^2$  from the origin
  - time is **synchronous** and marked by a global clock
  - one special node  $\mathcal{P} \in \mathbb{Z}^2$ , the **target**, placed by an **adversary** at unknown (Manhattan) distance  $\ell$  from the origin

**Task:** **find** the target **as fast as possible**

## Ant Race





# A lower bound on the hitting time

[Feinerman et al., PODC 2012] shows the following:

**Lemma:** for any  $k \geq 1$ , and for any search algorithm  $\mathcal{A}$ , the hitting time to find  $\mathcal{P}$  is  $\Omega(\ell^2/k + \ell)$  both with constant probability and in expectation

**Proof:**

# A lower bound on the hitting time

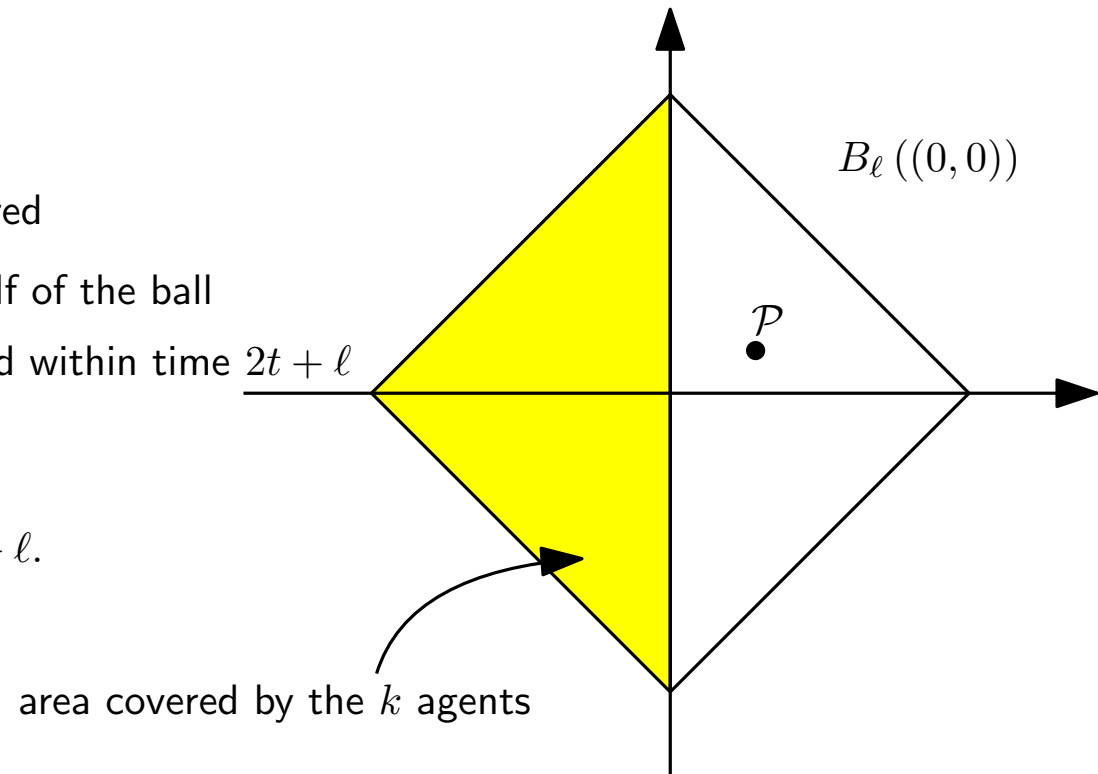
[Feinerman et al., PODC 2012] shows the following:

**Lemma:** for any  $k \geq 1$ , and for **any search algorithm**  $\mathcal{A}$ , the **hitting time** to find  $\mathcal{P}$  is  $\Omega(\ell^2/k + \ell)$  both with **constant probability** and in **expectation**

**Proof:**

- $|B_\ell((0,0))| = \ell^2$
- set  $t = \ell^2/(4k)$
- within time  $2t$ , at most  $2kt = \ell^2/2$  nodes covered
- the adversary locates the target in the other half of the ball
- probability at least  $1/2$  the treasure is not found within time  $2t + \ell$
- $H$  = first hitting time for the treasure, then

$$\mathbb{E}[H] \geq 2t \cdot \frac{1}{2} + \ell = \ell^2/(4k) + \ell.$$



# No advice, no communication

[Feinerman et Korman, DC 2017] proposes many solutions to the problem

Many considered settings, in which

- agents exchange information at the source node
- agents receive some advice on the number of agents  $k$
- there is no communication and no advice

# No advice, no communication

[Feinerman et Korman, DC 2017] proposes many solutions to the problem

Many considered settings, in which

- agents **exchange information** at the source node
- agents **receive** some **advice** on the number of agents  $k$
- there is **no communication** and **no advice**

We focus on the case **no advice, no communication**

# No advice, no communication

[Feinerman et Korman, DC 2017] proposes many solutions to the problem

Many considered settings, in which

- agents **exchange information** at the source node
- agents **receive** some **advice** on the number of agents  $k$
- there is **no communication** and **no advice**

We focus on the case **no advice, no communication**

Their **best algorithm** in this case achieves **expected hitting time**

$$\mathcal{O} \left( (\ell^2/k + \ell) \log^{1+\epsilon} \ell \right) ,$$

for any fixed constant  $\epsilon > 0$

# No advice, no communication

Uniform algorithm proposed in [Feinerman et Korman, DC 2017]

(idea)

- i fix a subset of  $k_i$  **agents** to be moved
- ii fix a **ball** of some radius  $\ell_i$
- iii agents go to **random nodes** in the ball
- iv agents perform a **spiral search** of length  $d_i$  around the chosen nodes
- v agents **return** to the source node
- vi increase  $k_i, \ell_i, d_i$  and repeat (i)-(v)

However, the above algorithm is not that **natural**

# No advice, no communication

Uniform algorithm proposed in [Feinerman et Korman, DC 2017]

(idea)

- i fix a subset of  $k_i$  **agents** to be moved
- ii fix a **ball** of some radius  $\ell_i$
- iii agents go to **random nodes** in the ball
- iv agents perform a **spiral search** of length  $d_i$  around the chosen nodes
- v agents **return** to the source node
- vi increase  $k_i$ ,  $\ell_i$ ,  $d_i$  and repeat (i)-(v)

However, the above algorithm is not that **natural**

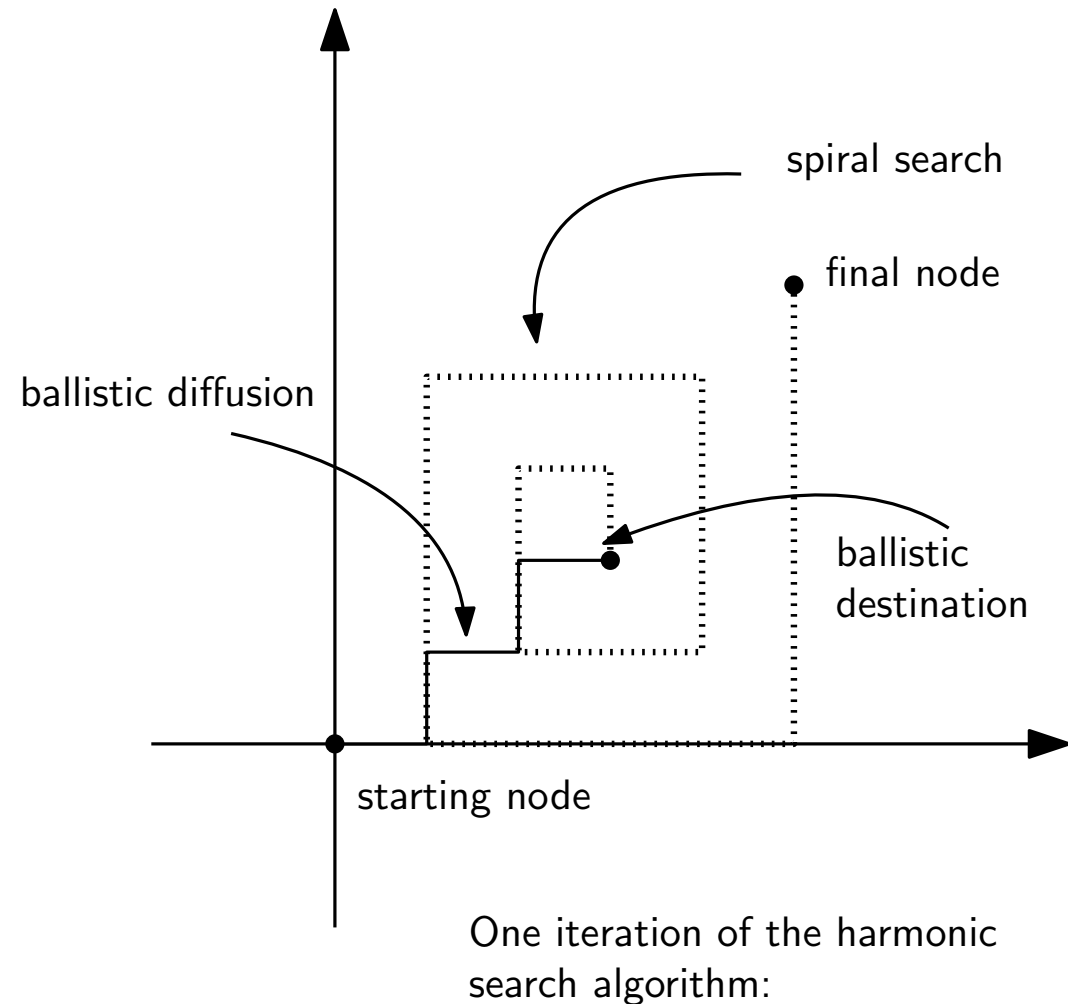
[Feinerman et Korman, DC 2017] proposes a more natural algorithm, the **Harmonic search algorithm** (HSA)

# The Harmonic search algorithm

HSA **worsens performance**, but **increases probability**: the **hitting time** is

$$\mathcal{O}(\ell^{2+\delta}/k + \ell)$$

with probability  $1 - \epsilon$  for any fixed constants  $0 < \delta, \epsilon < 1$





# The Harmonic search algorithm

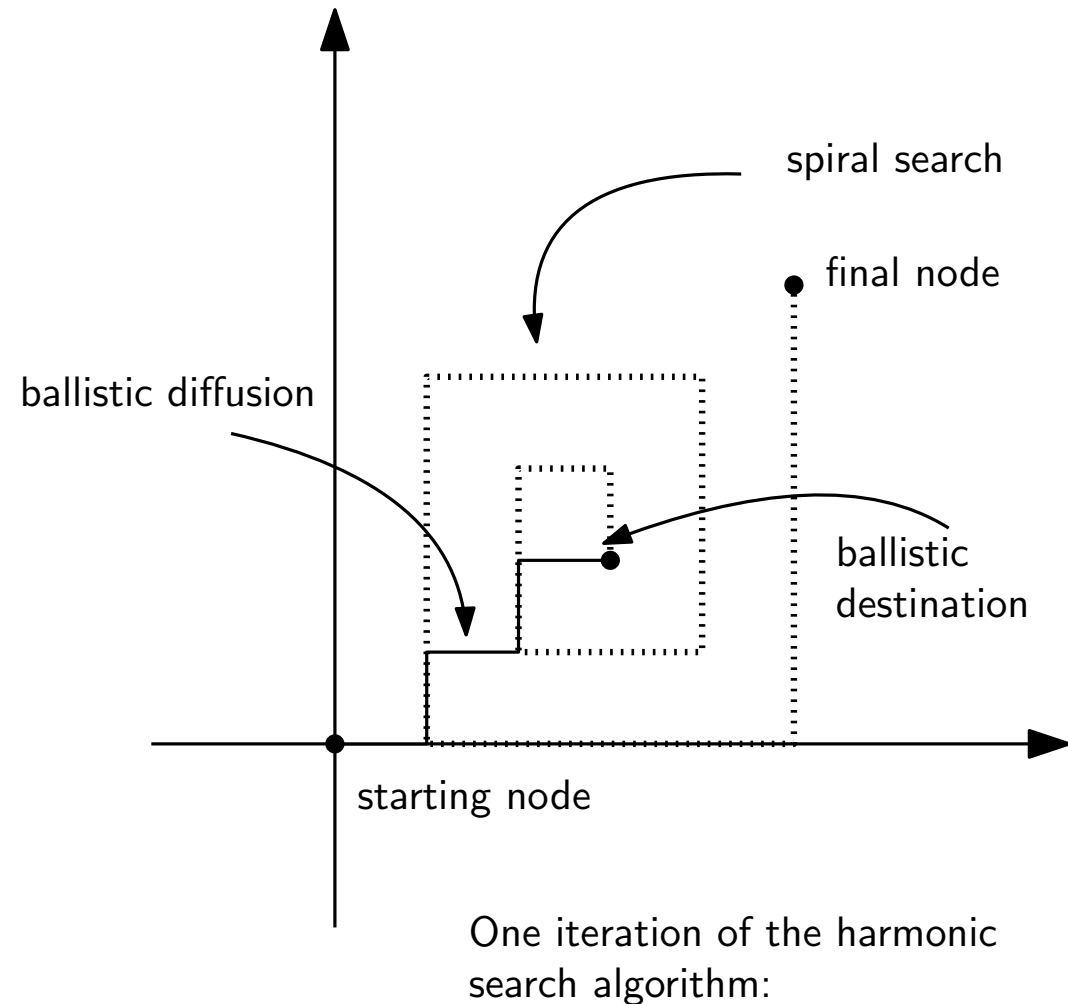
HSA **worsens performance**, but **increases probability**: the **hitting time** is

$$\mathcal{O}(\ell^{2+\delta}/k + \ell)$$

with probability  $1 - \epsilon$  for any fixed constants  $0 < \delta, \epsilon < 1$

**HSA**: each agent

- samples a **jump-length**  $d$  with a **power-law distribution** with exponent  $\alpha = 1 + \delta$  (small)
- (**ballistic diffusion**) moves to a destination at distance  $d$  chosen u.a.r.
- (**normal diffusion**) starts a spiral search for  $d^{\delta+2}$  steps
- returns** in the origin and repeats



# Our contributions

(i) we give the **first definition** of Lévy walk in the **discrete setting** in  $\mathbb{Z}^2$ , which is **natural** and **time-homogeneous**

# Our contributions

- (i) we give the **first definition** of Lévy walk in the **discrete setting** in  $\mathbb{Z}^2$ , which is **natural** and **time-homogeneous**
- (ii) to the best of our knowledge, we give the **first analysis** of the **hitting time** distribution of  $k$  parallel walks

# Our contributions

- (i) we give the **first definition** of Lévy walk in the **discrete setting** in  $\mathbb{Z}^2$ , which is **natural** and **time-homogeneous**
- (ii) to the best of our knowledge, we give the **first analysis** of the **hitting time** distribution of  $k$  parallel walks
- (iii) we show how the Lévy walks can be employed to give a natural, **almost-optimal** solution to the **ANTS problem** (no advice, no communication)

# Our contributions

- (i) we give the **first definition** of Lévy walk in the **discrete setting** in  $\mathbb{Z}^2$ , which is **natural** and **time-homogeneous**
- (ii) to the best of our knowledge, we give the **first analysis** of the **hitting time** distribution of  $k$  parallel walks
- (iii) we show how the Lévy walks can be employed to give an **almost-optimal** solution to the **ANTS problem**

# Defining the discrete Lévy walk

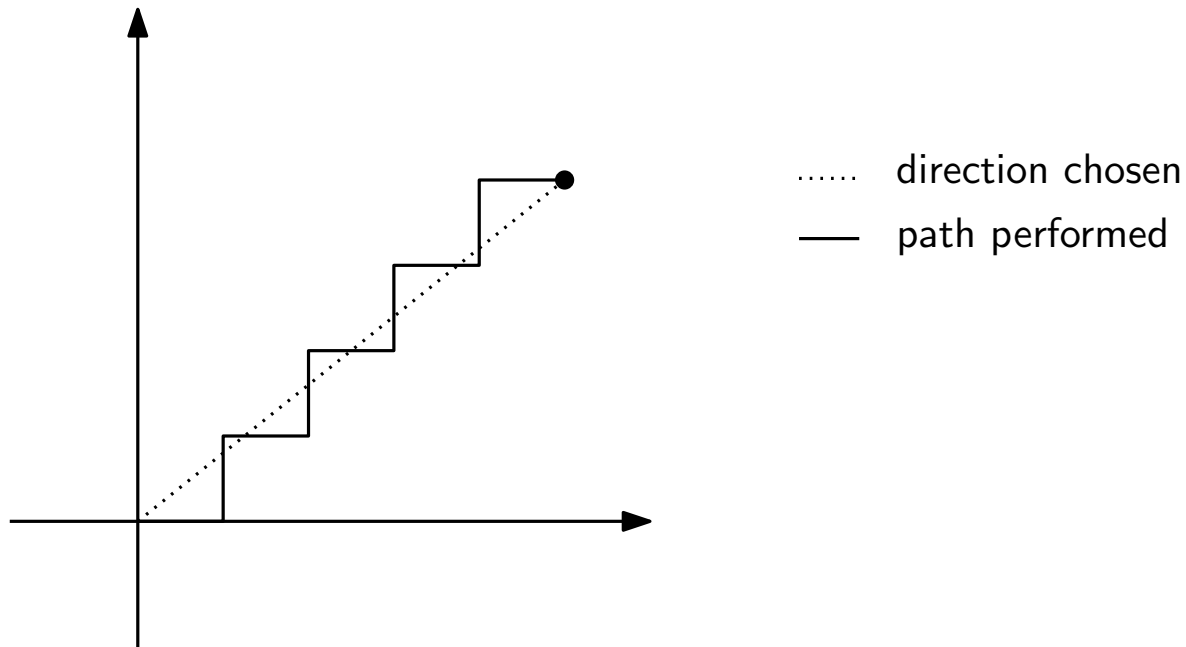
Two choices to make:

- define the **jump-length distribution**
- define a **notion** of **approximating** a **line-segment**

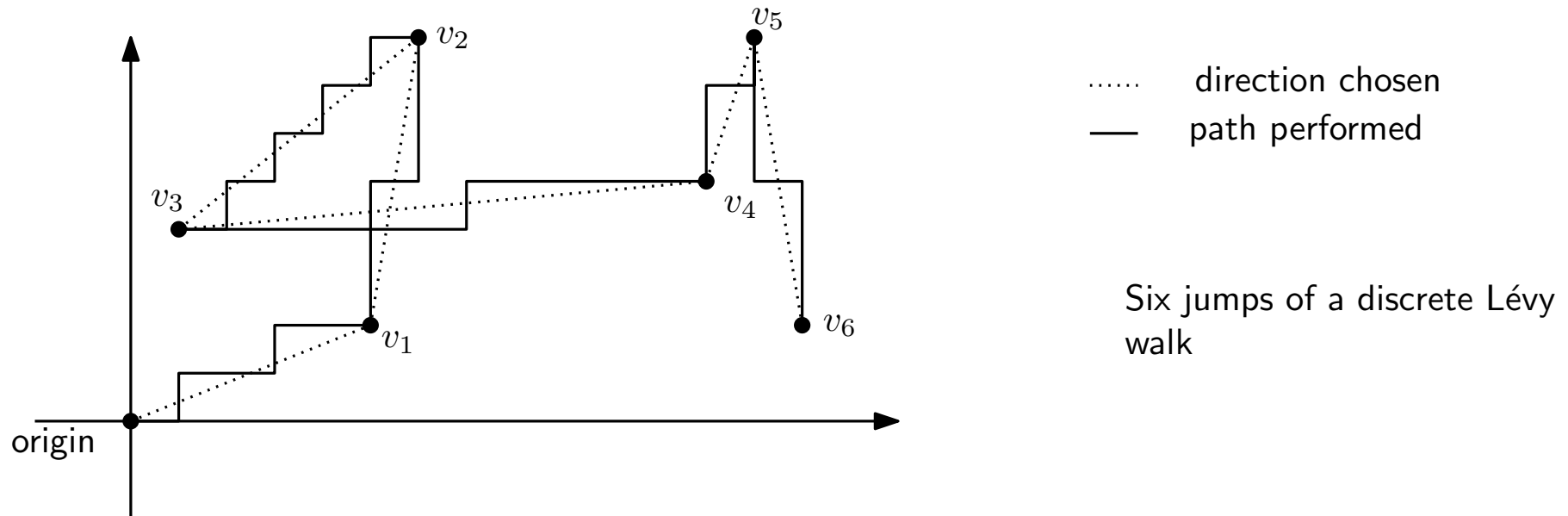
## Jump length distribution

- $d = 0$  with probability  $1/2$
- $d \geq 1$  with probability  $c_\alpha/d^\alpha$

## Approximation of a line-segment



# Discrete Lévy walk



Let  $\alpha > 1$  be a real constant

**Lévy walk:** the agent

- chooses a **distance**  $d \in \mathbb{N}$  as follows:  $d = 0$  w.p.  $1/2$ , and  $d \geq 1$  w.p.  $c_\alpha/d^\alpha$
- chooses a **destination** u.a.r. among those at distance  $d$
- walks along an **approximating path** for  $d$  steps, one edge at a time, crossing  $d$  nodes
- repeats** the procedure

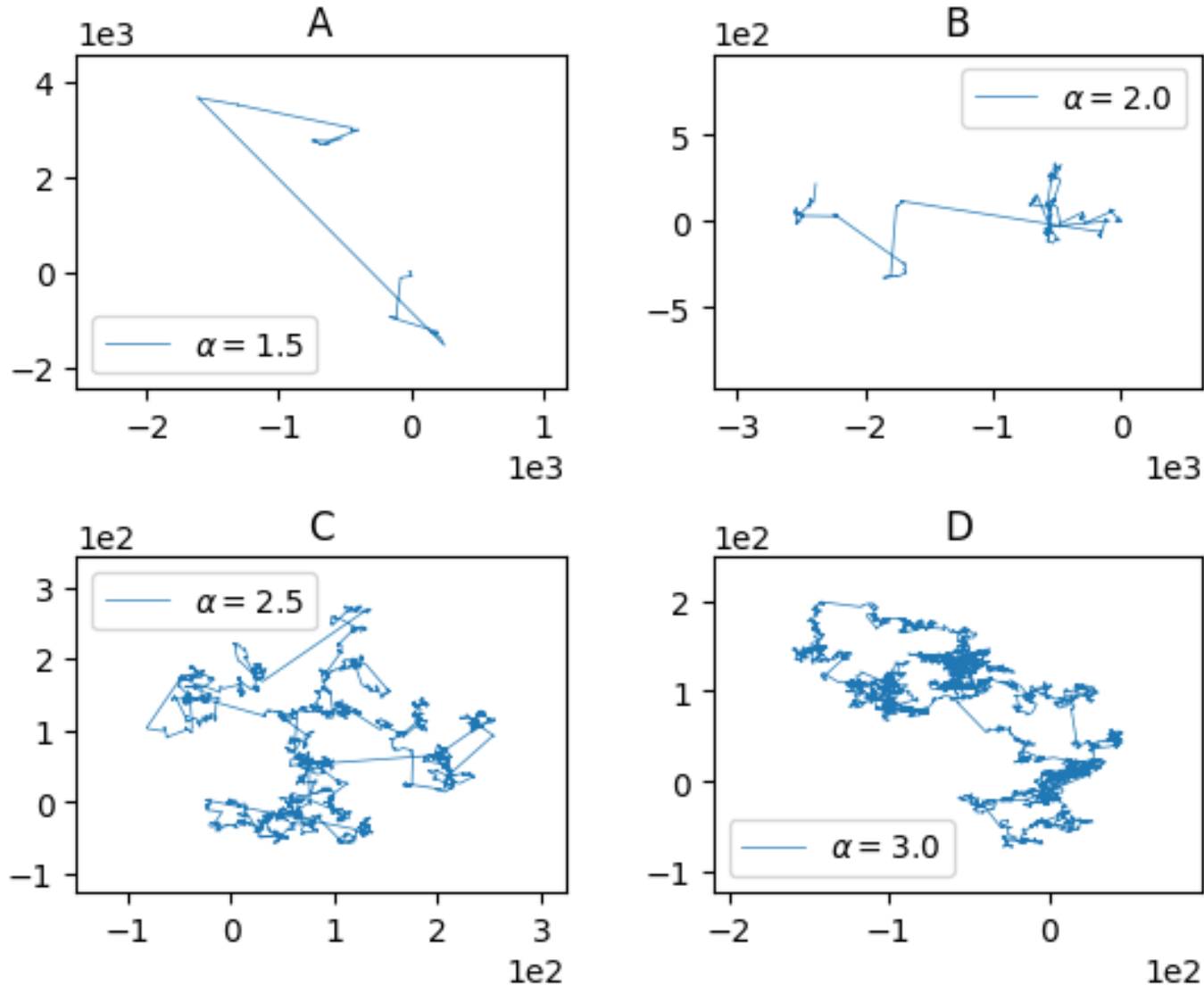
# Our contributions

- (i) we give the **first definition** of Lévy walk in the **discrete setting** in  $\mathbb{Z}^2$ , which is **natural** and **time-homogeneous**
- (ii) to the best of our knowledge, we give the **first analysis** of the **hitting time** distribution of  $k$  parallel walks
- (iii) we show how the Lévy walks can be employed to give an **almost-optimal** solution to the **ANTS problem**



# Known facts about the continuous Lévy walk

- $1 < \alpha \leq 2$  ballistic diffusion (fig.s A and B)
- $2 < \alpha < 3$  super diffusion (fig. C)
- $3 \leq \alpha$  normal diffusion (fig. D)



# Other known facts

## Expected jump-length

- $1 < \alpha \leq 2$ :  $\int_1^\infty x^{-\alpha+1} dx = \infty$
- $2 < \alpha$ :  $\int_1^\infty x^{-\alpha+1} dx = \Theta(1)$

## Jump-length second moment

- $1 < \alpha \leq 3$ :  $\int_1^\infty x^{-\alpha+2} dx = \infty$
- $3 < \alpha$ :  $\int_1^\infty x^{-\alpha+1} dx = \Theta(1)$

# Other known facts

## Expected jump-length

- $1 < \alpha \leq 2$ :  $\int_1^\infty x^{-\alpha+1} dx = \infty$
- $2 < \alpha$ :  $\int_1^\infty x^{-\alpha+1} dx = \Theta(1)$

## Jump-length second moment

- $1 < \alpha \leq 3$ :  $\int_1^\infty x^{-\alpha+2} dx = \infty$
- $3 < \alpha$ :  $\int_1^\infty x^{-\alpha+1} dx = \Theta(1)$

The secret lies in the range  $2 < \alpha < 3...$

# Three ranges for $k$ and $\ell$

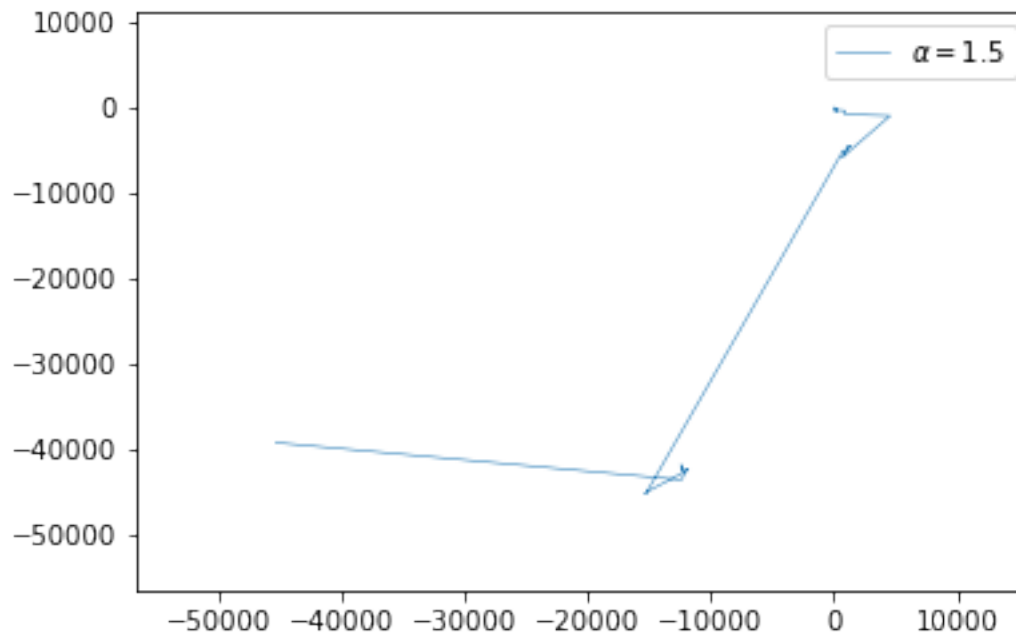
Recall:  $\ell$  target distance,  $k$  number of agents

Three different possible settings:

1. **close target:**  $\ell \leq k/\text{polylog}(k)$
2. **far target:**  $k/\text{polylog}(k) \leq \ell \leq \exp(k^{\Theta(1)})$
3. **very far target:**  $\exp(k^{\Theta(1)}) \leq \ell$

Close target:  $\ell \leq k/\text{polylog}(k)$

Best strategy = **ballistic walks**: any  $\alpha$  in  $(1, 2]$

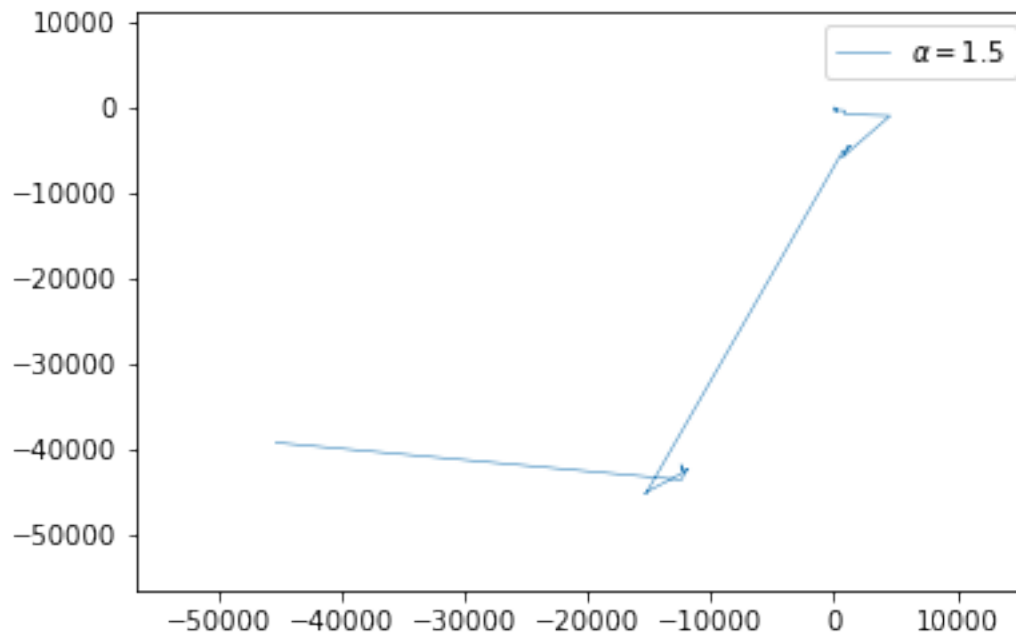


Close target:  $\ell \leq k/\text{polylog}(k)$

Best strategy = **ballistic walks**: any  $\alpha$  in  $(1, 2]$

With high probability in  $\ell$ , the hitting time is

$$\mathcal{O}(\ell \text{polylog}(\ell))$$



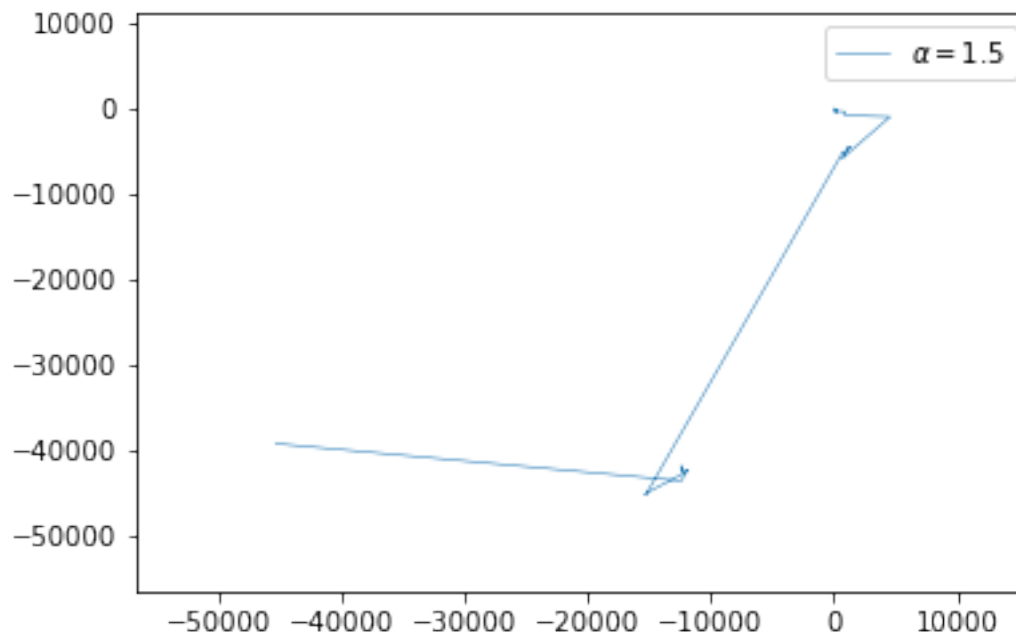
Close target:  $\ell \leq k/\text{polylog}(k)$

Best strategy = **ballistic walks**: any  $\alpha$  in  $(1, 2]$

With high probability in  $\ell$ , the hitting time is

$$\mathcal{O}(\ell \text{polylog}(\ell))$$

**Recall:** an event  $E$  depending on a parameter  $\ell$  holds with high probability in  $\ell$  if  $\mathbb{P}(E) \geq 1 - \ell^{-\Theta(1)}$



Vey far target:  $\exp(k^{\Theta(1)}) \leq \ell$

More problematic interval...

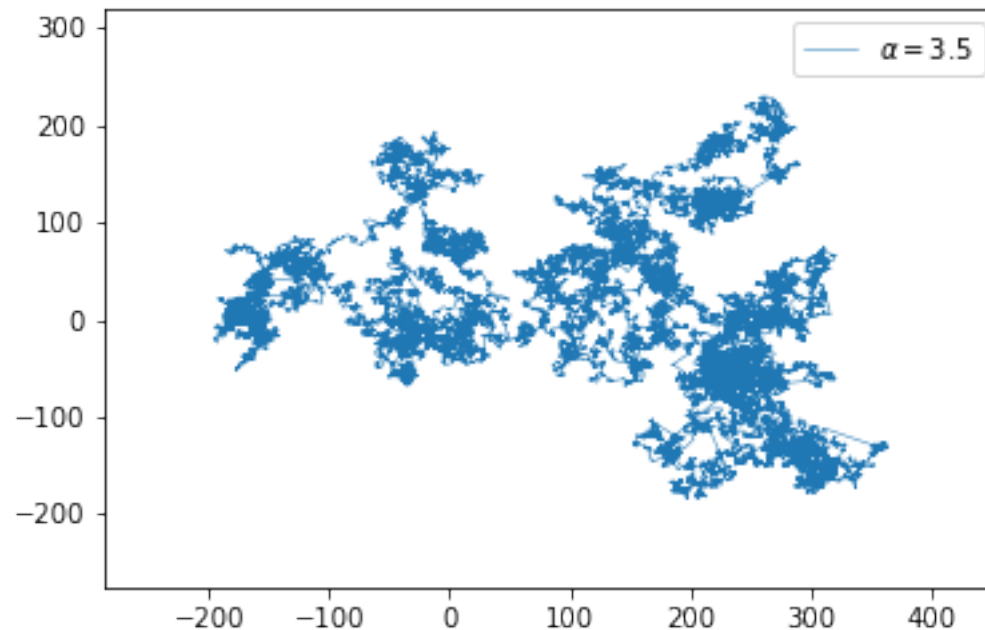


Vey far target:  $\exp(k^{\Theta(1)}) \leq \ell$

More problematic interval...

Best strategy = **diffusive walks**: any  $\alpha$  in  $[3, +\infty)$  (brownian-like behavior)

With probability 1, the walks will **eventually** find the target

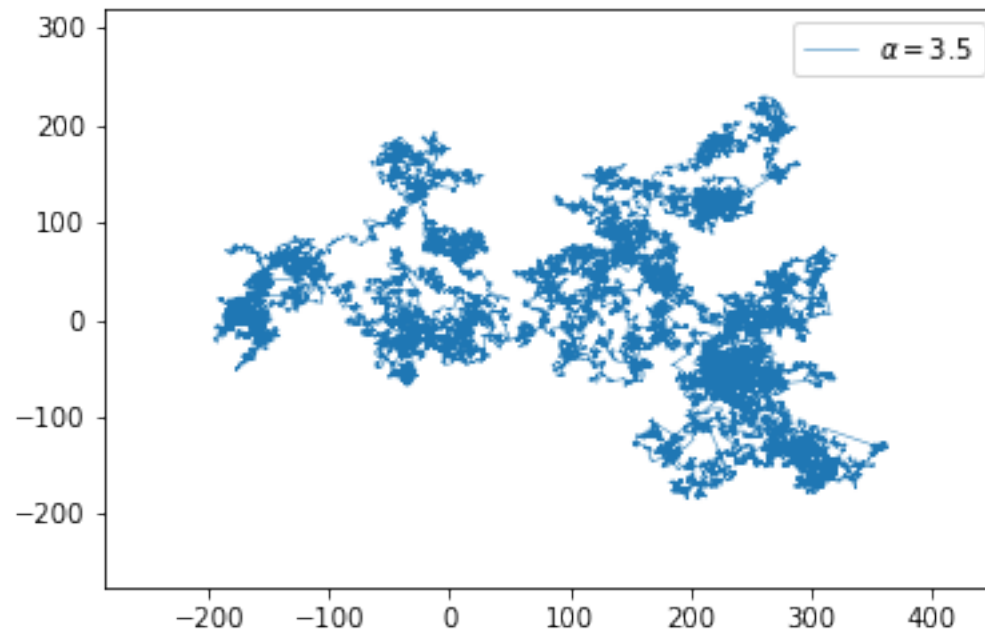


Vey far target:  $\exp(k^{\Theta(1)}) \leq \ell$

More problematic interval...

Best strategy = **diffusive walks**: any  $\alpha$  in  $[3, +\infty)$  (brownian-like behavior)

With probability 1, the walks will **eventually** find the target



If  $\alpha = 3 - \epsilon$ , with high probability the target **is not found**

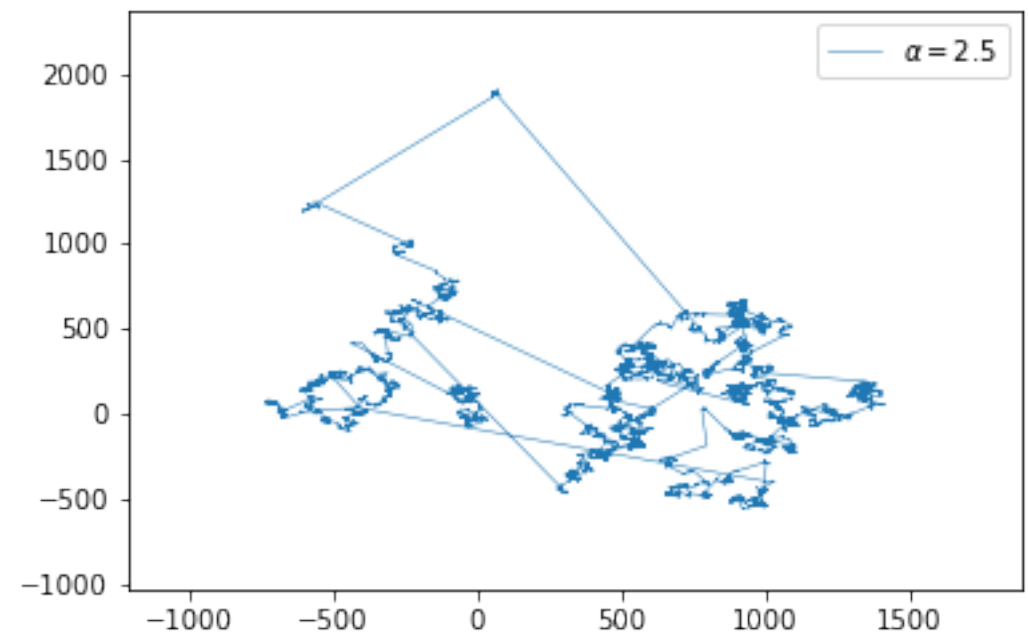
Far target:  $k/\text{polylog}(k) \leq \ell \leq \exp(k^{\Theta(1)})$

Best strategy: ... **it depends!**

Far target:  $k/\text{polylog}(k) \leq \ell \leq \exp(k^{\Theta(1)})$

Best strategy: ... **it depends!**

Fix  $\alpha^* = 3 - \log k / \log \ell$ : **super-diffusive** range



Far target:  $k/\text{polylog}(k) \leq \ell \leq \exp(k^{\Theta(1)})$

Best strategy: ... **it depends!**

Fix  $\alpha^* = 3 - \log k / \log \ell$ : **super-diffusive** range

The followings hold w.h.p. in  $\ell$

- if  $\alpha = \alpha^* + \mathcal{O}(\log \log \ell / \log \ell)$ ,  
the hitting time is

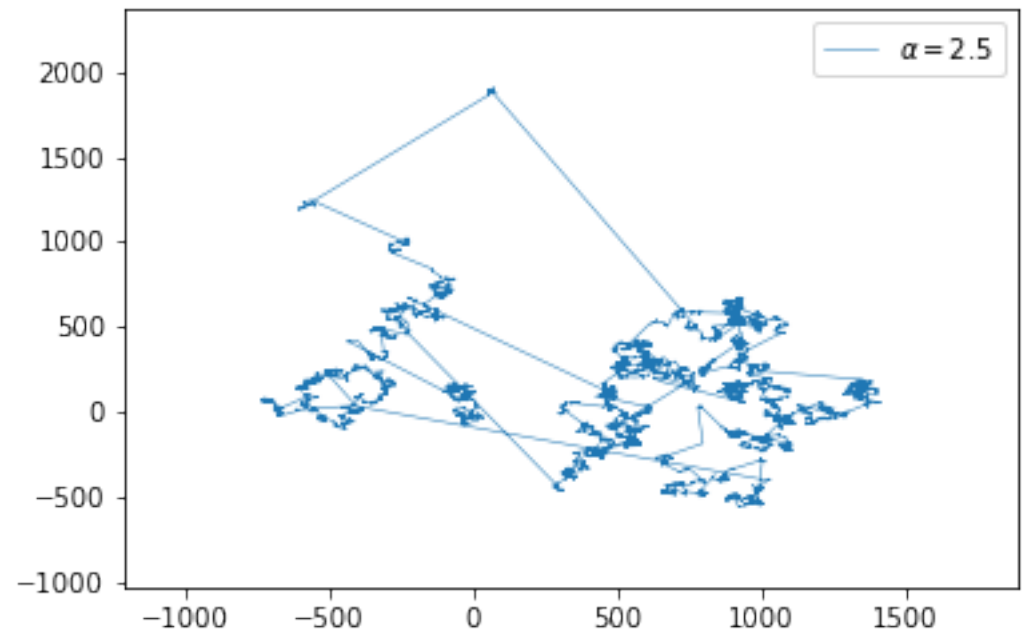
$$\mathcal{O}\left((\ell^2/k + \ell) \text{polylog}(\ell)\right)$$

- if  $\alpha = \alpha^* + \epsilon$ , the hitting time is

$$\Omega\left((\ell^2/k + \ell) \ell^c\right),$$

for some constant  $c > 0$

- if  $\alpha = \alpha^* - \epsilon$  the hitting time is  
**infinite**



But... No advice, no communication!

How can we find  $\alpha^*$ ?

# Our contributions

- (i) we give the **first definition** of Lévy walk in the **discrete setting** in  $\mathbb{Z}^2$ , which is **natural** and **time-homogeneous**
- (ii) to the best of our knowledge, we give the **first analysis** of the **hitting time** distribution of  $k$  parallel walks
- (iii) we show how the Lévy walks can be employed to give an **almost-optimal** solution to the **ANTS problem**

But... No advice, no communication!

How can we find  $\alpha^*$ ?



# But... No advice, no communication!

How can we find  $\alpha^*$ ?

**We don't have to!**

**Algorithm:** each agent  $u$  *samples* u.a.r. a real number  $\alpha_u \in (2, 3)$ .  
Then, it *performs* a discrete *Lévy walk* with *exponent*  $\alpha_u$

# But... No advice, no communication!

How can we find  $\alpha^*$ ?

**We don't have to!**

**Algorithm:** each agent  $u$  *samples* u.a.r. a real number  $\alpha_u \in (2, 3)$ .  
Then, it *performs* a discrete *Lévy walk* with *exponent*  $\alpha_u$

If  $\ell \leq \exp(k^{\Theta(1)})$ , the hitting time is  $\mathcal{O}((\ell^2/k + \ell) \text{polylog}(\ell))$  w.h.p.

# The idea behind the algorithm

Fix some  $\epsilon = \mathcal{O}(\log \log \ell / \log \ell)$

We use:  $\ell < \exp(k^{\Theta(1)})$  ( $\iff k \geq \text{polylog}(\ell)$ ) + Chernoff bound

$\implies$  at least  $\Theta(\epsilon k)$  agents choose an exponent in the range  $(\alpha^* - \epsilon, \alpha^* + \epsilon)$  w.h.p.

$\Theta(\epsilon k)$  agents are sufficient to ensure high probability to find the target fast enough

# Recap

Accepted at [\[PODC 2021\]](#). Join work with Andrea Clementi, George Giakkoupis and Emanuele Natale.

# Recap

Accepted at [PODC 2021]. Joint work with Andrea Clementi, George Giakkoupis and Emanuele Natale.

In this work, we

- provide a **definition** of a discrete version of the **Lévy walk**
- analyze the **hitting time** of  $k$  parallel **Lévy walks**
- show that for any choices of  $k$  and  $\ell$  from a wide range, **Lévy walks** are an **almost-optimal search strategy** for the ANTS problem

# Recap

Accepted at [PODC 2021]. Joint work with Andrea Clementi, George Giakkoupis and Emanuele Natale.

In this work, we

- provide a **definition** of a discrete version of the **Lévy walk**
- analyze the **hitting time** of  $k$  parallel **Lévy walks**
- show that for any choices of  $k$  and  $\ell$  from a wide range, **Lévy walks** are an **almost-optimal search strategy** for the ANTS problem
  - very **natural** and **time-homogeneous** random process
  - **improves** the HSA (just polylog factor worse than optimum, not polynomial)
  - does **not** improve their **optimal** solution

# Recap

Accepted at [PODC 2021]. Joint work with Andrea Clementi, George Giakkoupis and Emanuele Natale.

In this work, we

- provide a **definition** of a discrete version of the **Lévy walk**
- analyze the **hitting time** of  $k$  parallel **Lévy walks**
- show that for any choices of  $k$  and  $\ell$  from a wide range, **Lévy walks** are an **almost-optimal search strategy** for the ANTS problem
  - very **natural** and **time-homogeneous** random process
  - **improves** the HSA (just polylog factor worse than optimum, not polynomial)
  - does **not** improve their **optimal** solution
- argue the non (universal) optimality of exponent  $\alpha = 2$

# The idea to find $\alpha^*$

We analyze the hitting time of a single Lévy flight (Markov chain on  $\mathbb{Z}^2$ !)



# The idea to find $\alpha^*$

We analyze the hitting time of a single Lévy flight (Markov chain on  $\mathbb{Z}^2$ !)

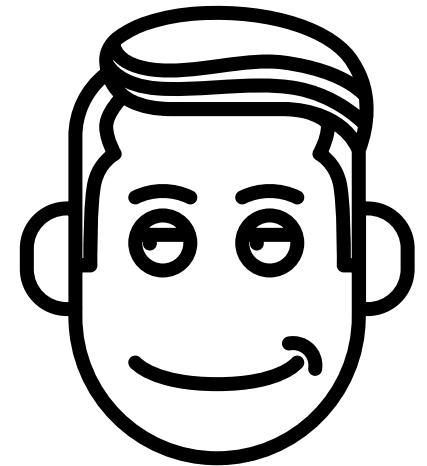
We derive bounds for a single Lévy walk through a coupling argument

# The idea to find $\alpha^*$

We analyze the hitting time of a single Lévy flight (Markov chain on  $\mathbb{Z}^2$ !)

We derive bounds for a single Lévy walk through a coupling argument

We exploit independence to get results for the  $k$  walks

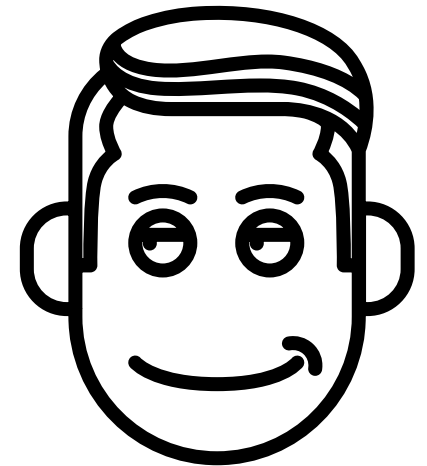


# The idea to find $\alpha^*$

We analyze the hitting time of a single Lévy flight (Markov chain on  $\mathbb{Z}^2$ !)

We derive bounds for a single Lévy walk through a coupling argument

We exploit independence to get results for the  $k$  walks



**Remark:** Here, we **DON'T** show why other values for  $\alpha$  are worse than  $\alpha^*$ . We just show how to find  $\alpha^*$

# Analyzing a single Lévy flight

- Let
- $Z_u(t)$  = random variable of **number of visits** in  $u$  until time  $t$
  - $\mathcal{E}_t$  = the **event** first  $t$  jumps have length  $\leq (t \log t)^{\frac{1}{\alpha-1}}$
  - $a_t = \mathbb{E} [Z_{(0,0)}(t) \mid \mathcal{E}_t]$
  - $p(t) = \mathbb{P} (Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t)$

# Analyzing a single Lévy flight

- Let
- $Z_u(t)$  = random variable of **number of visits** in  $u$  until time  $t$
  - $\mathcal{E}_t$  = the **event** first  $t$  jumps have length  $\leq (t \log t)^{\frac{1}{\alpha-1}}$
  - $a_t = \mathbb{E} [Z_{(0,0)}(t) \mid \mathcal{E}_t]$
  - $p(t) = \mathbb{P} (Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t)$

**Lemma:**  $p(t) = \mathbb{P} (Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t) \geq \mathbb{E} [Z_{\mathcal{P}}(t) \mid \mathcal{E}_t] / a_t$

Comes from two facts

- (i)  $\mathbb{E} [Z_{\mathcal{P}}(t) \mid Z_{\mathcal{P}}(t) > 0, \mathcal{E}_t] \leq a_t$
- (ii)  $\mathbb{E} [Z_{\mathcal{P}}(t) \mid Z_{\mathcal{P}}(t) > 0, \mathcal{E}_t] \cdot \mathbb{P} (Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t) = \mathbb{E} [Z_{\mathcal{P}}(t) \mid \mathcal{E}_t]$

# Analyzing a single Lévy flight

- Let
- $Z_u(t)$  = random variable of **number of visits** in  $u$  until time  $t$
  - $\mathcal{E}_t$  = the **event** first  $t$  jumps have length  $\leq (t \log t)^{\frac{1}{\alpha-1}}$
  - $a_t = \mathbb{E} [Z_{(0,0)}(t) \mid \mathcal{E}_t]$
  - $p(t) = \mathbb{P} (Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t)$

**Lemma:**  $p(t) = \mathbb{P} (Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t) \geq \mathbb{E} [Z_{\mathcal{P}}(t) \mid \mathcal{E}_t] / a_t$

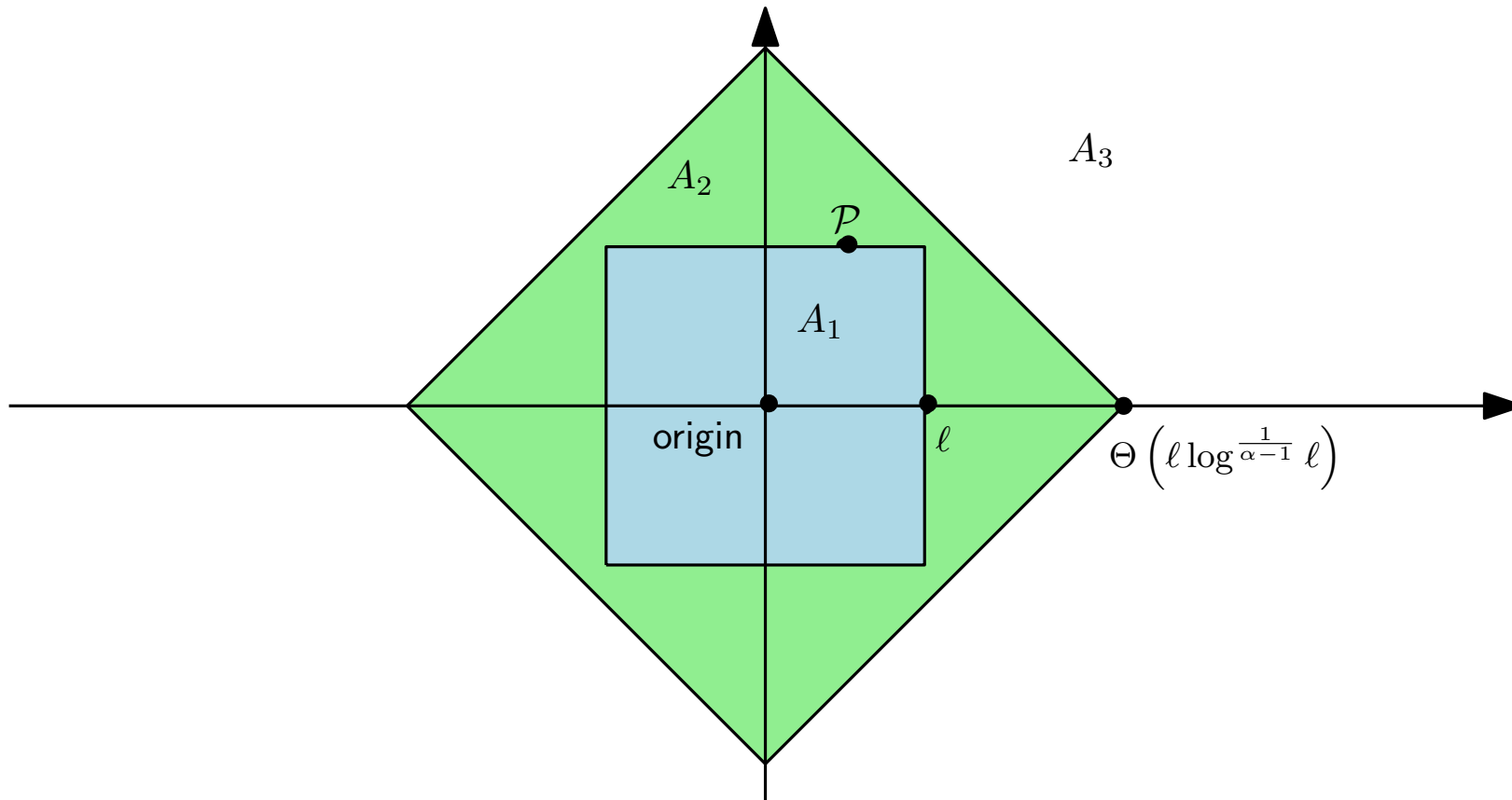
Comes from two facts

- (i)  $\mathbb{E} [Z_{\mathcal{P}}(t) \mid Z_{\mathcal{P}}(t) > 0, \mathcal{E}_t] \leq a_t$
- (ii)  $\mathbb{E} [Z_{\mathcal{P}}(t) \mid Z_{\mathcal{P}}(t) > 0, \mathcal{E}_t] \cdot \mathbb{P} (Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t) = \mathbb{E} [Z_{\mathcal{P}}(t) \mid \mathcal{E}_t]$

We now look for  $\mathbb{E} [Z_{\mathcal{P}}(t) \mid \mathcal{E}_t]$  and  $a_t \dots$

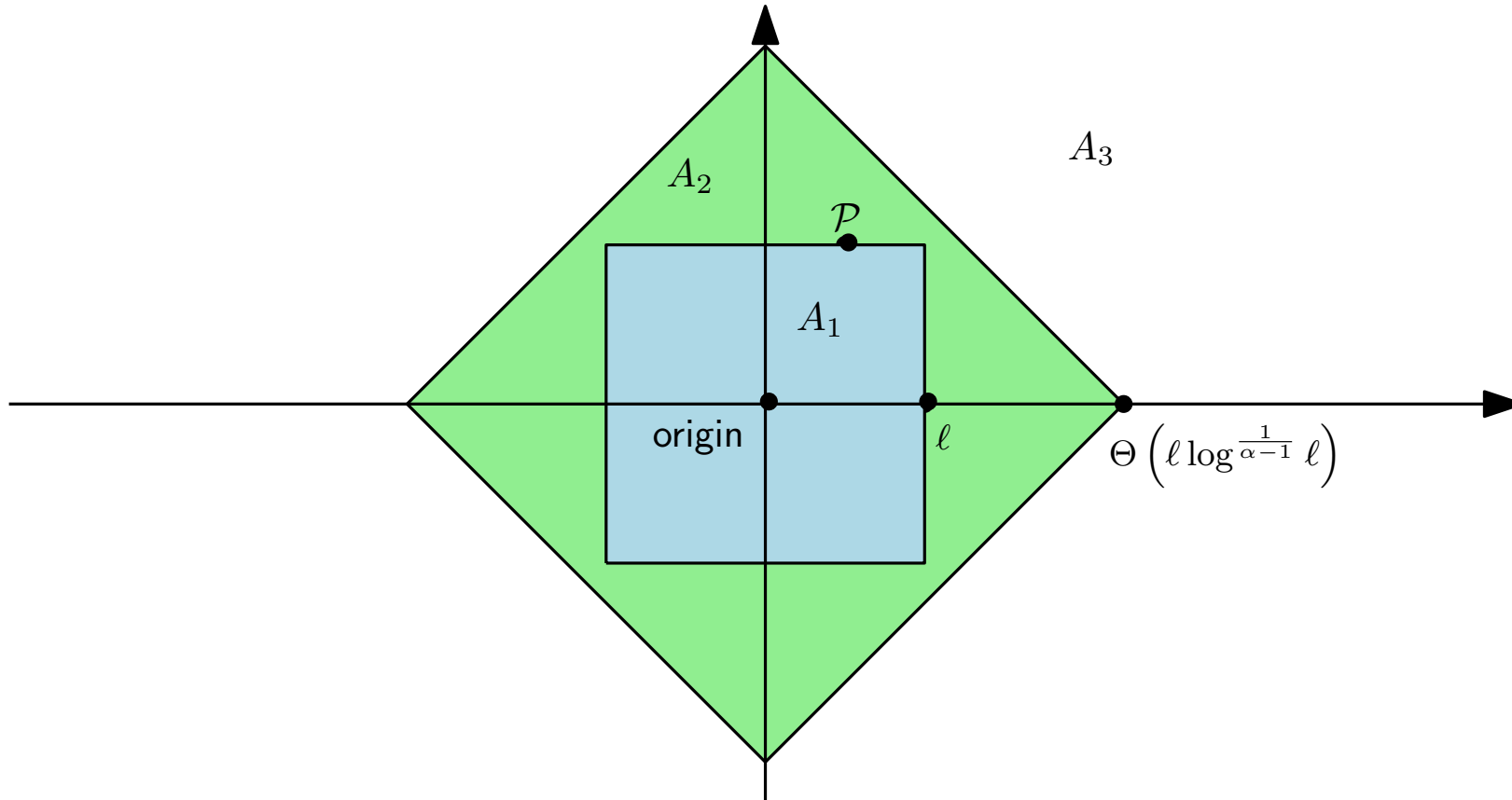
# Partition of the space

We **partition**  $\mathbb{Z}^2$  in three areas in the following way



# Partition of the space

We **partition**  $\mathbb{Z}^2$  in three areas in the following way



- $A_1 = Q(\ell) = \{(x, y) \in \mathbb{Z}^2 : \max(|x|, |y|) \leq \ell\}$
- $A_2 = B_{\ell \text{polylog}(\ell)}((0, 0)) \setminus A_1$
- $A_3 = \mathbb{Z}^2 \setminus (A_1 \cup A_2)$



## Getting $\mathbb{E} [Z_{\mathcal{P}} (t) | \mathcal{E}_t]$

Denote by  $Z_S (t)$  the **total number of visits** in the set  $S$  until time  $t$

## Getting $\mathbb{E} [Z_{\mathcal{P}} (t) | \mathcal{E}_t]$

Denote by  $Z_S (t)$  the **total number of visits** in the set  $S$  until time  $t$

Since the **total number of visits** until time  $t$  is, clearly,  $t$ , we get that

$$\text{a) } \mathbb{E} [Z_{A_1} (t) | \mathcal{E}_t] + \mathbb{E} [Z_{A_2} (t) | \mathcal{E}_t] + \mathbb{E} [Z_{A_3} (t) | \mathcal{E}_t] = t$$

## Getting $\mathbb{E} [Z_{\mathcal{P}} (t) | \mathcal{E}_t]$

Denote by  $Z_S (t)$  the **total number of visits** in the set  $S$  until time  $t$

Since the **total number of visits** until time  $t$  is, clearly,  $t$ , we get that

$$\text{a) } \mathbb{E} [Z_{A_1} (t) | \mathcal{E}_t] + \mathbb{E} [Z_{A_2} (t) | \mathcal{E}_t] + \mathbb{E} [Z_{A_3} (t) | \mathcal{E}_t] = t$$

For some  $t = \Theta (\ell^{\alpha-1})$ , we **prove** that:

$$\text{b) } \mathbb{E} [Z_{A_1} (t) | \mathcal{E}_t] \leq \frac{3}{4}t$$

$$\text{c) } \mathbb{E} [Z_{A_2} (t) | \mathcal{E}_t] \leq \mathbb{E} [Z_{\mathcal{P}} (t) | \mathcal{E}_t] \cdot \Theta (\ell^2 \text{polylog} (\ell))$$

$$\text{d) } \mathbb{E} [Z_{A_3} (t) | \mathcal{E}_t] = \mathcal{O} (t / \log t)$$

## Getting $\mathbb{E} [Z_{\mathcal{P}} (t) | \mathcal{E}_t]$

Denote by  $Z_S (t)$  the **total number of visits** in the set  $S$  until time  $t$

Since the **total number of visits** until time  $t$  is, clearly,  $t$ , we get that

$$\text{a) } \mathbb{E} [Z_{A_1} (t) | \mathcal{E}_t] + \mathbb{E} [Z_{A_2} (t) | \mathcal{E}_t] + \mathbb{E} [Z_{A_3} (t) | \mathcal{E}_t] = t$$

For some  $t = \Theta (\ell^{\alpha-1})$ , we **prove** that:

$$\text{b) } \mathbb{E} [Z_{A_1} (t) | \mathcal{E}_t] \leq \frac{3}{4}t$$

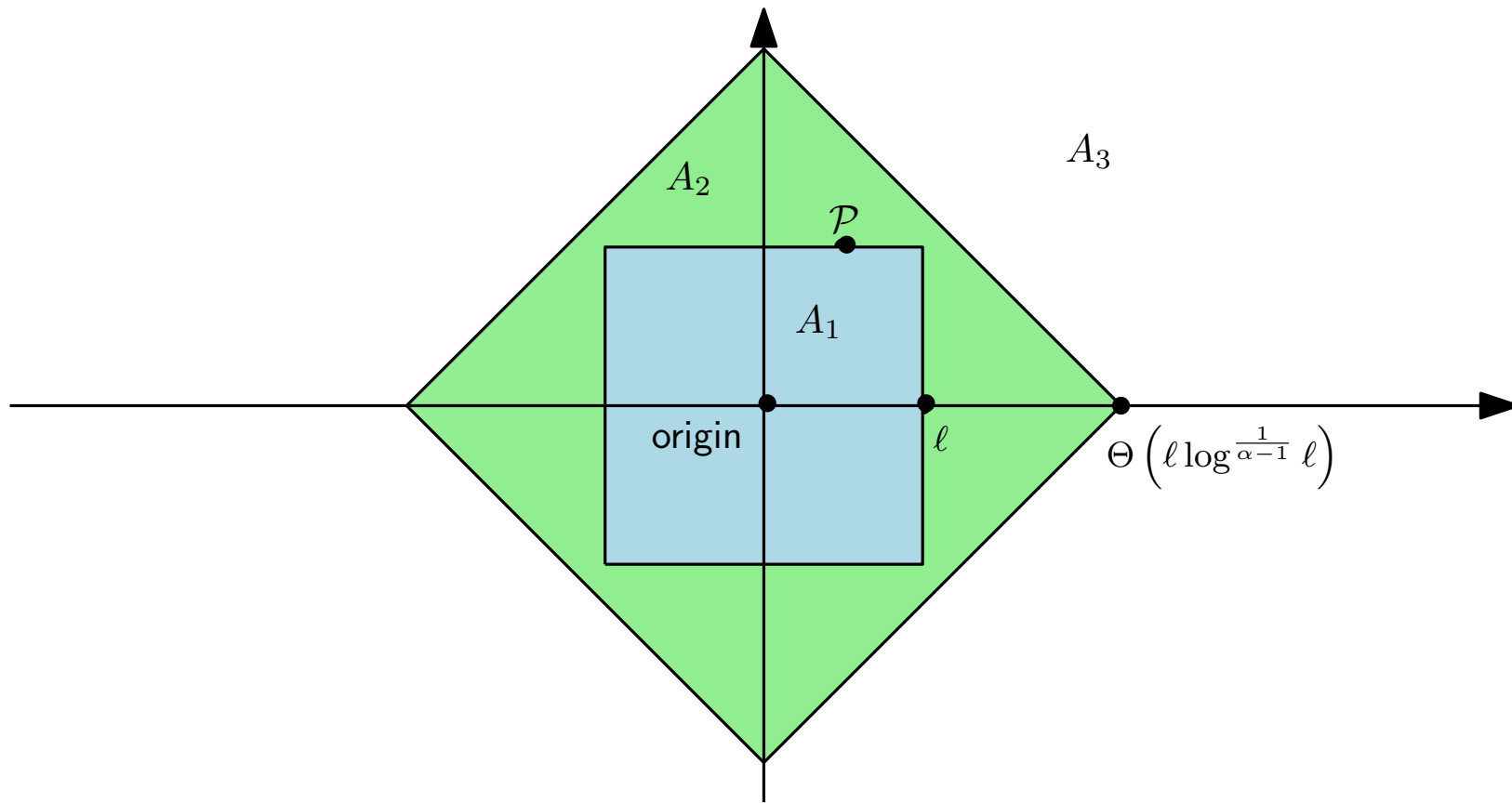
$$\text{c) } \mathbb{E} [Z_{A_2} (t) | \mathcal{E}_t] \leq \mathbb{E} [Z_{\mathcal{P}} (t) | \mathcal{E}_t] \cdot \Theta (\ell^2 \text{polylog} (\ell))$$

$$\text{d) } \mathbb{E} [Z_{A_3} (t) | \mathcal{E}_t] = \mathcal{O} (t / \log t)$$

**Combine** (a) with (b), (c), and (d) to get

$$\mathbb{E} [Z_{\mathcal{P}} (t) | \mathcal{E}_t] = \Omega (1 / (\ell^{3-\alpha} \text{polylog} (\ell)))$$

# Getting $\mathbb{E}[Z_{\mathcal{P}}(t) | \mathcal{E}_t]$



b)  $\mathbb{E}[Z_{A_1}(t) | \mathcal{E}_t] \leq \frac{3}{4}t$

c)  $\mathbb{E}[Z_{A_2}(t) | \mathcal{E}_t] \leq \mathbb{E}[Z_{\mathcal{P}}(t) | \mathcal{E}_t] \cdot \Theta(\ell^2 \text{polylog}(\ell))$

d)  $\mathbb{E}[Z_{A_3}(t) | \mathcal{E}_t] = \mathcal{O}(t / \log t)$

c) comes from a **monotonicity property**

## Getting $p(t)$

*Reminder:*  $p(t) = \mathbb{P} (Z_{\mathcal{P}} (t) > 0 \mid \mathcal{E}_t) \geq \mathbb{E} [Z_{\mathcal{P}} (t) \mid \mathcal{E}_t] / a_t$

## Getting $p(t)$

*Reminder:*  $p(t) = \mathbb{P}(Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t) \geq \mathbb{E}[Z_{\mathcal{P}}(t) \mid \mathcal{E}_t] / a_t$

We prove that  $a_t = \mathbb{E}[Z_{(0,0)}(t) \mid \mathcal{E}_t]$  is constant w.r.t.  $t$

# Getting $p(t)$

*Reminder:*  $p(t) = \mathbb{P}(Z_{\mathcal{P}}(t) > 0 \mid \mathcal{E}_t) \geq \mathbb{E}[Z_{\mathcal{P}}(t) \mid \mathcal{E}_t] / a_t$

We prove that  $a_t = \mathbb{E}[Z_{(0,0)}(t) \mid \mathcal{E}_t]$  is constant w.r.t.  $t$

**Lemma:** for  $t = \Theta(\ell^{\alpha-1})$ , it holds that

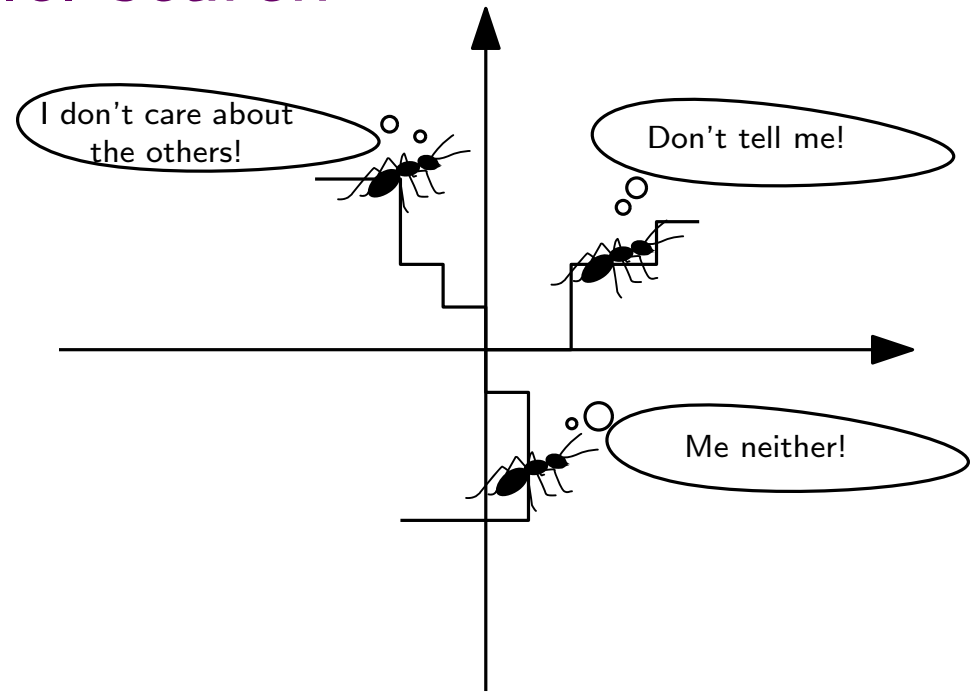
$$p(t) = \Omega(1 / (\ell^{3-\alpha} \text{polylog}(\ell)))$$

**Note:** the coupling result gives us the same asymptotic bound for the Lévy walk



# The parallel search

We exploit *independence*!

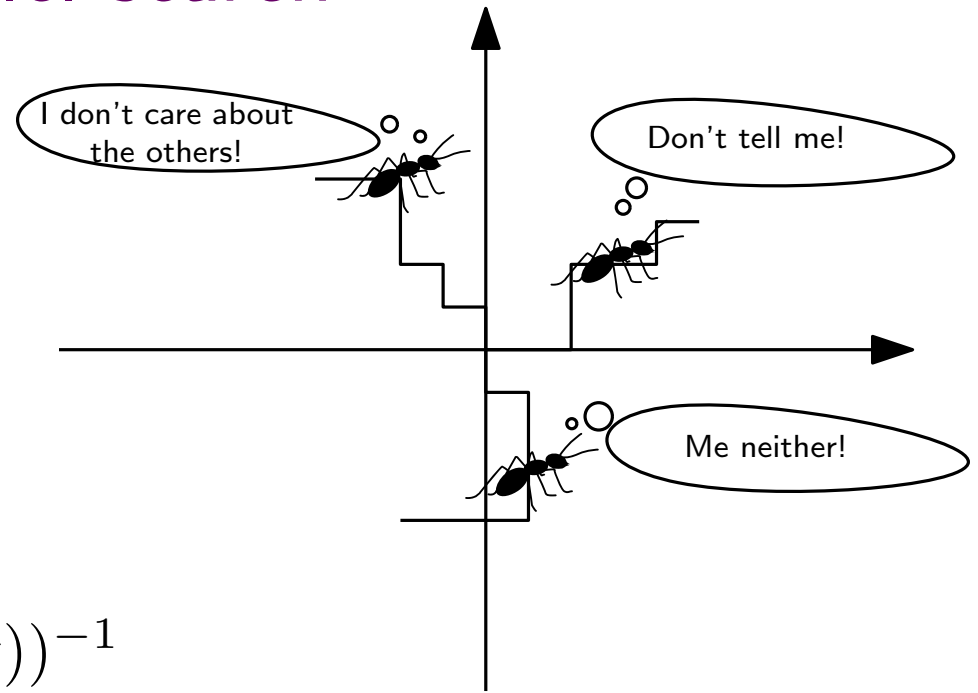


# The parallel search

We exploit *independence!*

$$p(t) = \Omega \left( 1 / \left( \ell^{3-\alpha} \text{polylog}(\ell) \right) \right)$$

For  $t = \mathcal{O}(\ell^{\alpha-1})$ , set  $k = \log \ell \cdot (p(t))^{-1}$

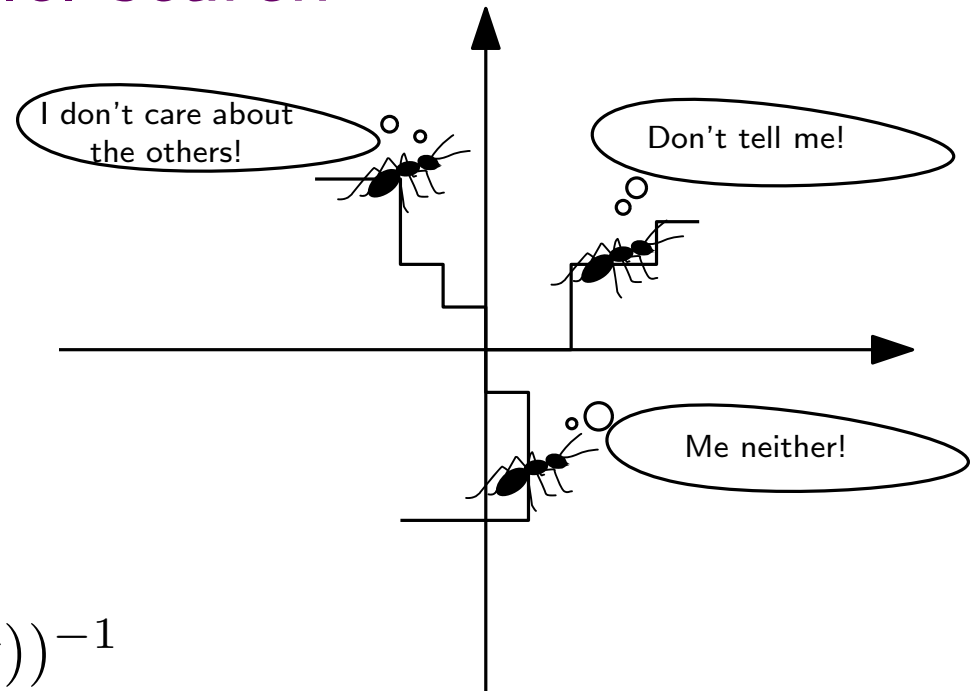


# The parallel search

We exploit *independence*!

$$p(t) = \Omega \left( 1 / \left( \ell^{3-\alpha} \text{polylog}(\ell) \right) \right)$$

For  $t = \mathcal{O}(\ell^{\alpha-1})$ , set  $k = \log \ell \cdot (p(t))^{-1}$



The probability that **at least one** walker finds the treasure within time  $t$  is

$$1 - [1 - p(t)]^{\frac{\log \ell}{p(t)}} \sim 1 - e^{-\log \ell} = 1 - \frac{1}{\ell}$$

$k$  **walkers** find the target **within time**  $t = \Theta(\ell^{\alpha-1})$ , w.h.p.

# Finding $\alpha^*$

$$p(t) = \Omega \left( 1 / \left( \ell^{3-\alpha} \text{polylog}(\ell) \right) \right)$$

# Finding $\alpha^*$

$$p(t) = \Omega \left( 1 / \left( \ell^{3-\alpha} \text{polylog}(\ell) \right) \right)$$

Find  $\alpha$  such that  $k = \log \ell / p(t)$

# Finding $\alpha^*$

$$p(t) = \Omega \left( 1 / \left( \ell^{3-\alpha} \text{polylog}(\ell) \right) \right)$$

Find  $\alpha$  such that  $k = \log \ell / p(t)$

$$\alpha = 3 - \log k / \log \ell + \mathcal{O}(\log \log \ell / \log \ell)$$

# Finding $\alpha^*$

$$p(t) = \Omega \left( 1 / \left( \ell^{3-\alpha} \text{polylog}(\ell) \right) \right)$$

Find  $\alpha$  such that  $k = \log \ell / p(t)$

$$\alpha = 3 - \log k / \log \ell + \mathcal{O}(\log \log \ell / \log \ell)$$

$$\implies \alpha^* = 3 - \log k / \log \ell$$

Questions?

THANK YOU FOR YOUR  
ATTENTION

