

On the Search Efficiency of Parallel Lévy Walks on \mathbb{Z}^2

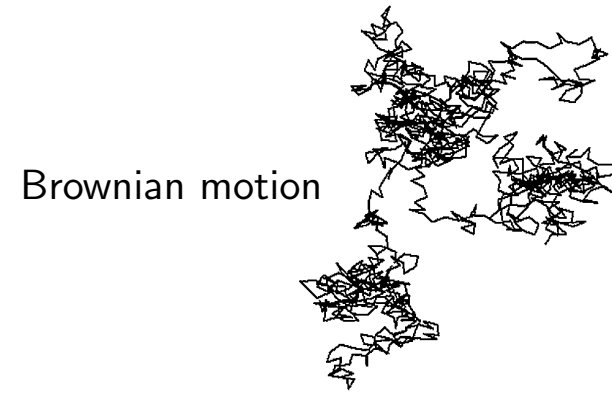
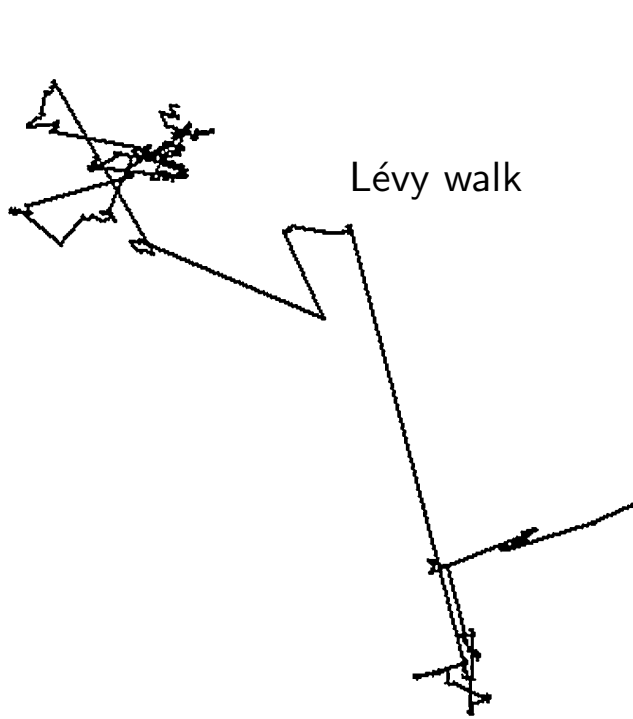
Francesco d'Amore



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

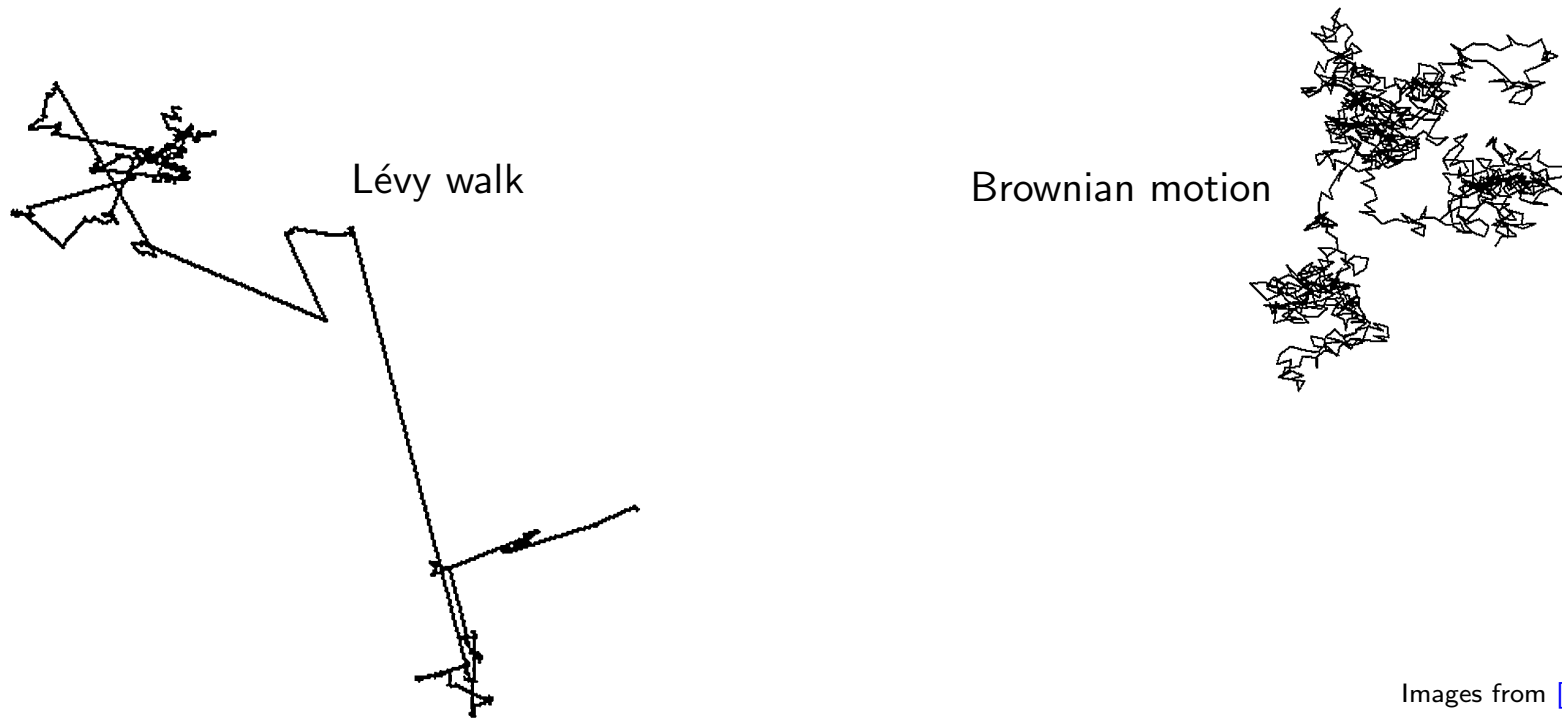
Coati seminar, 30 April 2020

What are Lévy Walks?



Images from [\[Reynolds, '15\]](#)

What are Lévy Walks?



Images from [\[Reynolds, '15\]](#)

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**

Why are Lévy walks interesting?

Lévy walks are used to model **movement patterns** [Biology Open, '18]

Examples:

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



Australian desert ants

Image from [professor Gibb, La Trobe University](#)

Why are Lévy walks interesting?

Lévy walks are used to model **movement patterns** [Biology Open, '18]

Examples:

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



Australian desert ants

Image from [professor Gibb, La Trobe University](#)

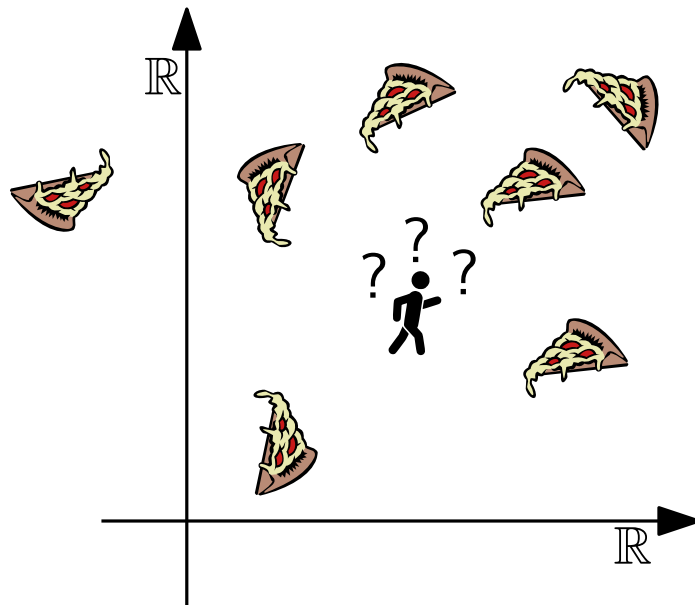
Some fun: [mussels Lévy walk video](#) [Science, '11]

The Theory of Foraging

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

The Theory of Foraging

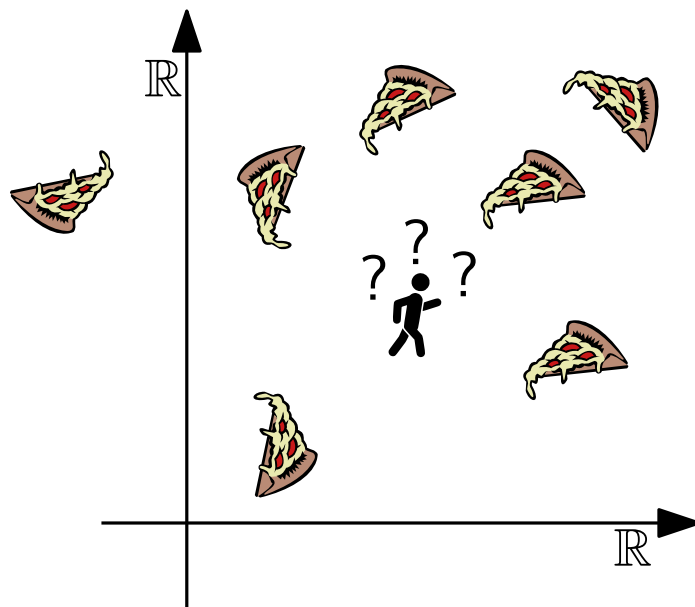
- Scenario:
- a density distribution ρ in \mathbb{R}^n describing **food locations**
 - an **uninformed** walker searching for food in \mathbb{R}^n



Slices of pizza from [Ubiquitous Phire](#)

The Theory of Foraging

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



Slices of pizza from [Ubiquitous Phire](#)

Question: which strategy **maximizes** the expected food discovery rate?

The Theory of Foraging

[Nature, '99] analyzes three random search strategies:

- (a) normal diffusion
- (b) ballistic diffusion
- (c) super diffusion

The Theory of Foraging

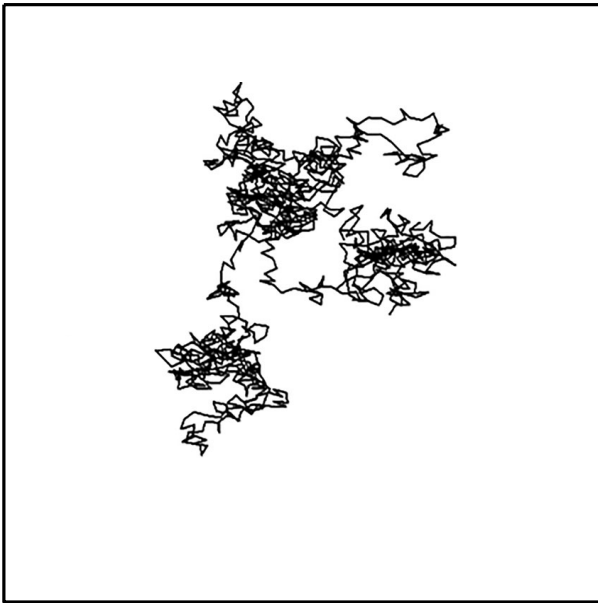
[Nature, '99] analyzes three random search strategies:

(a) normal diffusion

(b) ballistic diffusion

(c) super diffusion

(random walk/brownian motion)



Images from [Reynolds, '15]

The Theory of Foraging

[Nature, '99] analyzes three random search strategies:

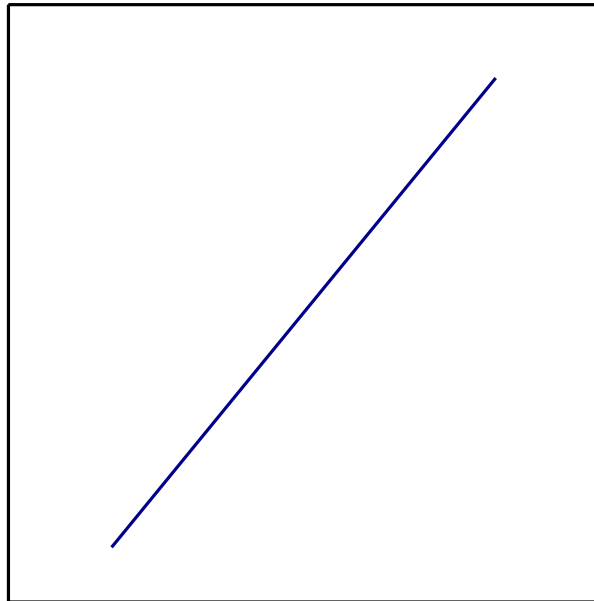
(a) normal diffusion

(random walk/brownian motion)

(b) ballistic diffusion

(straight/ballistic walk)

(c) super diffusion



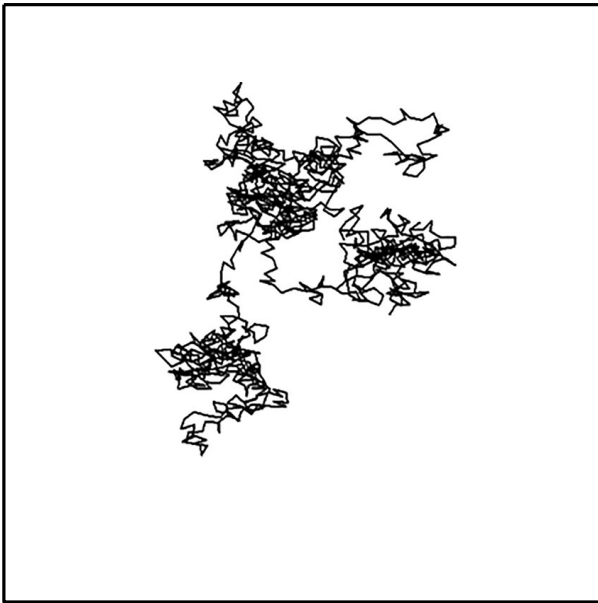
Images from [Reynolds, '15]

The Theory of Foraging

[Nature, '99] analyzes three random search strategies:

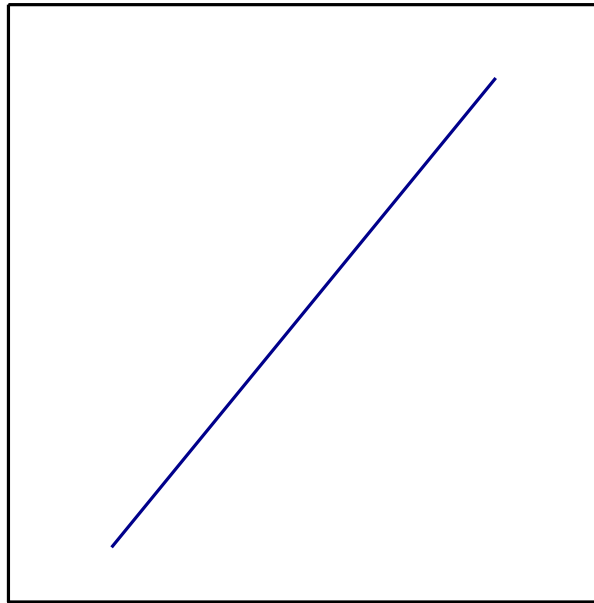
(a) normal diffusion

(random walk/brownian motion)



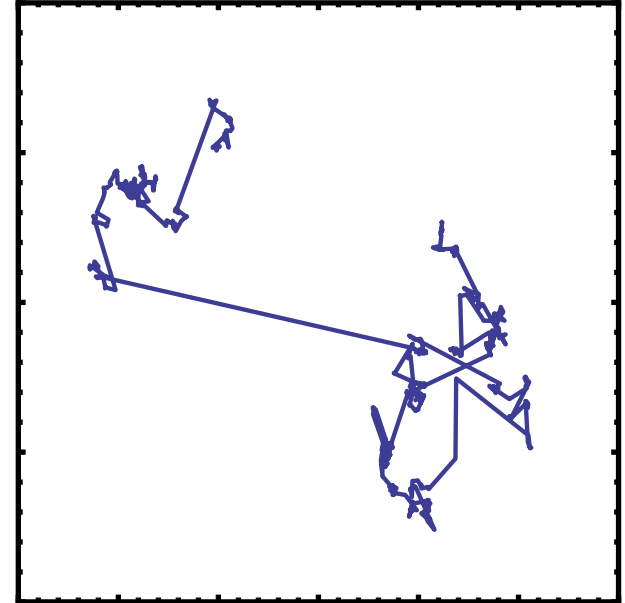
(b) ballistic diffusion

(straight/ballistic walk)



(c) super diffusion

(between (a) and (b))



Images from [Reynolds, '15]

The Lévy Walk Regimes

Reminder: the density distribution of the step-length is $f(d) \sim 1/d^\alpha$

Case $\alpha \geq 3$: the Lévy walk has normal diffusion

(Idea) In one dimension, and for $\alpha > 3$.

The Lévy Walk Regimes

Reminder: the **density distribution** of the **step-length** is $f(d) \sim 1/d^\alpha$

Case $\alpha \geq 3$: the Lévy walk has **normal diffusion**

(Idea) In one dimension, and for $\alpha > 3$.

Finite step-length **variance**: $\sim \int_1^\infty 1/x^{\alpha-2} dx < +\infty$.

From the **central limit theorem**, the long-term position of the walk has **Gaussian distribution**.

The same holds for the **brownian motion** (known result).

The Lévy Walk Regimes

Reminder: the **density distribution** of the **step-length** is $f(d) \sim 1/d^\alpha$

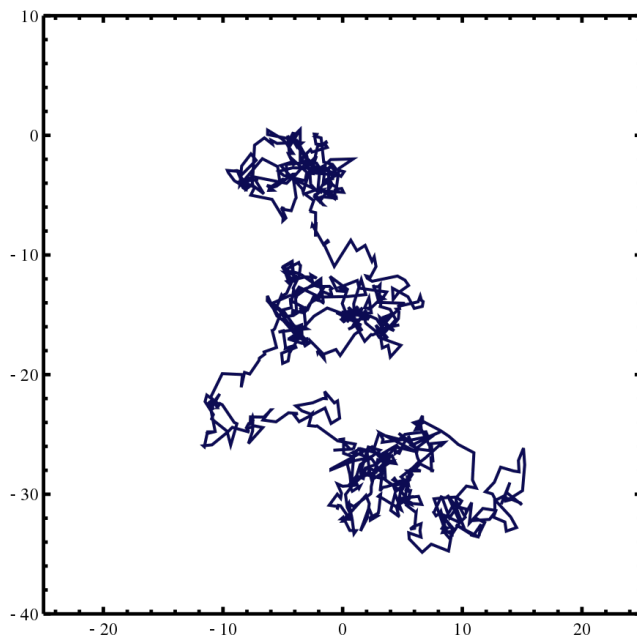
Case $\alpha \geq 3$: the Lévy walk has **normal diffusion**

(Idea) In one dimension, and for $\alpha > 3$.

Finite step-length **variance**: $\sim \int_1^\infty 1/x^{\alpha-2} dx < +\infty$.

From the **central limit theorem**, the long-term position of the walk has **Gaussian distribution**.

The same holds for the **brownian motion** (known result).



A Lévy walk with parameter $\alpha = 3$ approximates a brownian motion

The Lévy Walk Regimes

Reminder: the density distribution of the step-length is $f(d) \sim 1/d^\alpha$

Case $1 < \alpha \leq 2$: the Lévy walk has ballistic diffusion

(Idea)

The Lévy Walk Regimes

Reminder: the density distribution of the step-length is $f(d) \sim 1/d^\alpha$

Case $1 < \alpha \leq 2$: the Lévy walk has ballistic diffusion

(Idea)

Infinite step-length expectation: $\sim \int_1^\infty 1/x^{\alpha-1} dx = +\infty$.

Thus, just one step brings the walker to distance t in time t , on average.

The same holds for the ballistic walk (trivial).

The Lévy Walk Regimes

Reminder: the **density distribution** of the **step-length** is $f(d) \sim 1/d^\alpha$

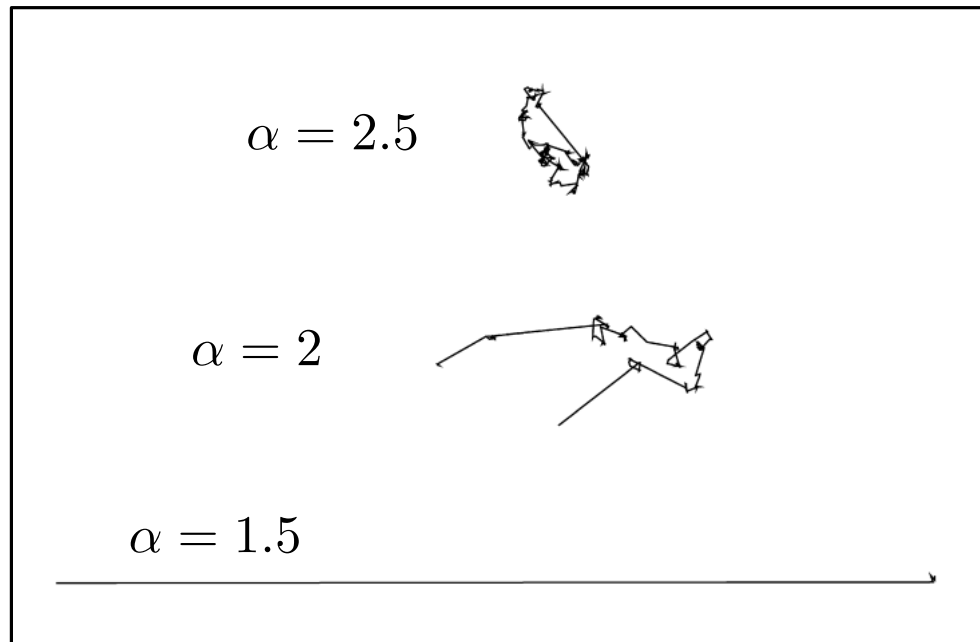
Case $1 < \alpha \leq 2$: the Lévy walk has **ballistic diffusion**

(Idea)

Infinite step-length **expectation**: $\sim \int_1^\infty 1/x^{\alpha-1} dx = +\infty$.

Thus, just one step brings the walker to distance t in time t , on average.

The same holds for the **ballistic walk** (trivial).



Examples of Lévy walks for different values of α

The Lévy Walk Regimes

Reminder: the density distribution of the step-length is $f(d) \sim 1/d^\alpha$

Case $2 < \alpha < 3$: the Lévy walk has super diffusion

The Lévy Walk Regimes

Reminder: the density distribution of the step-length is $f(d) \sim 1/d^\alpha$

Case $2 < \alpha < 3$: the Lévy walk has super diffusion

- Finite step-length expectation: $\sim \int_1^\infty 1/x^{\alpha-1} dx < +\infty$
- Infinite step-length variance: $\sim \int_1^\infty 1/x^{\alpha-2} dx = +\infty$

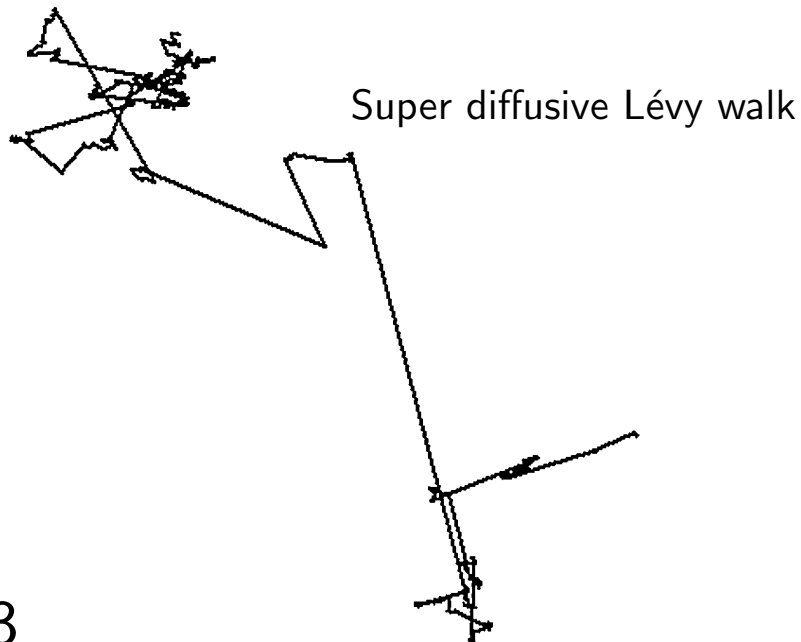
The Lévy Walk Regimes

Reminder: the **density distribution** of the **step-length** is $f(d) \sim 1/d^\alpha$

Case $2 < \alpha < 3$: the Lévy walk has **super diffusion**

- **Finite** step-length **expectation**: $\sim \int_1^\infty 1/x^{\alpha-1} dx < +\infty$
- **Infinite** step-length **variance**: $\sim \int_1^\infty 1/x^{\alpha-2} dx = +\infty$

Note: in **between normal** and **ballistic** diffusion



Optimality of Lévy Walk

[Nature, '99] takes into account two different settings:

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

Optimality of Lévy Walk

[Nature, '99] 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 (number of discovered food locations over travelled distance), the walker should perform

Optimality of Lévy Walk

[Nature, '99] 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 (number of discovered food locations over travelled distance), the walker should perform

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



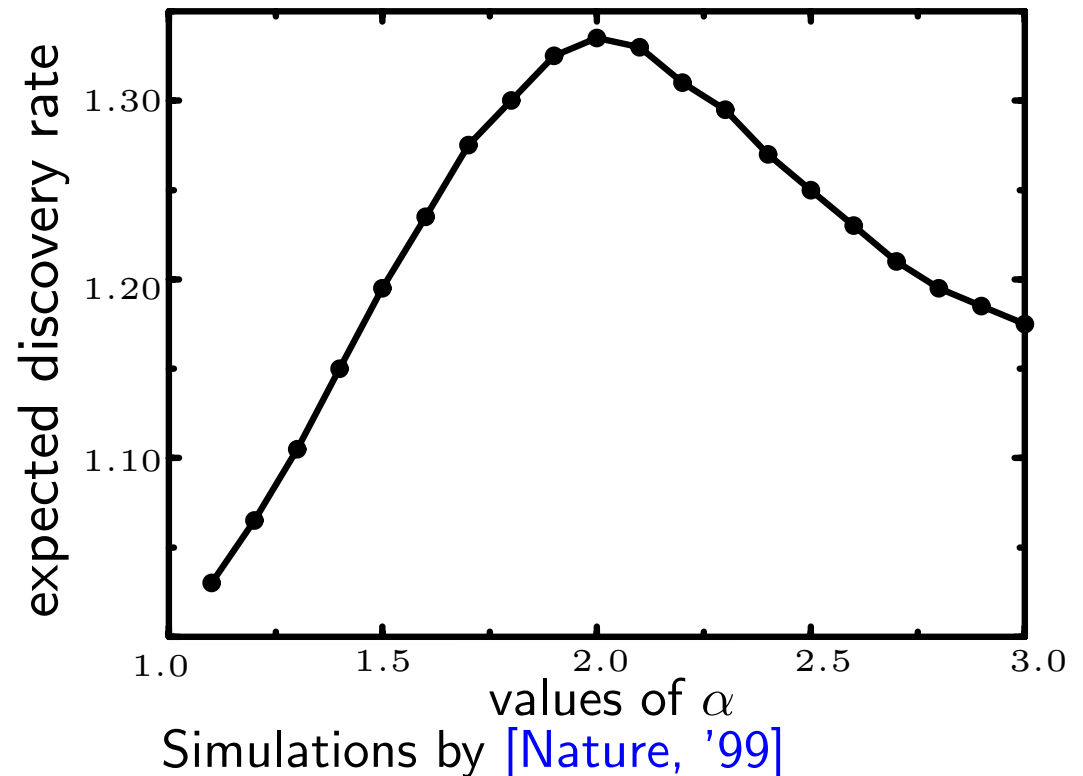
The Lévy Flight Foraging Hypothesis

Non-destructive foraging is considered to be the more realistic hypothesis [Nature, '99], leading to the optimality of Lévy walk as random search strategy

The Lévy Flight Foraging Hypothesis

Non-destructive foraging is considered to be the **more realistic** hypothesis [Nature, '99], leading to the **optimality of Lévy walk** as random search strategy

The Lévy flight foraging hypothesis [Physics of Life Reviews, '08]: since Lévy flights/walks (with exponent $\alpha = 2$) optimize random searches, biological organisms must have therefore evolved to exploit Lévy flights/walks

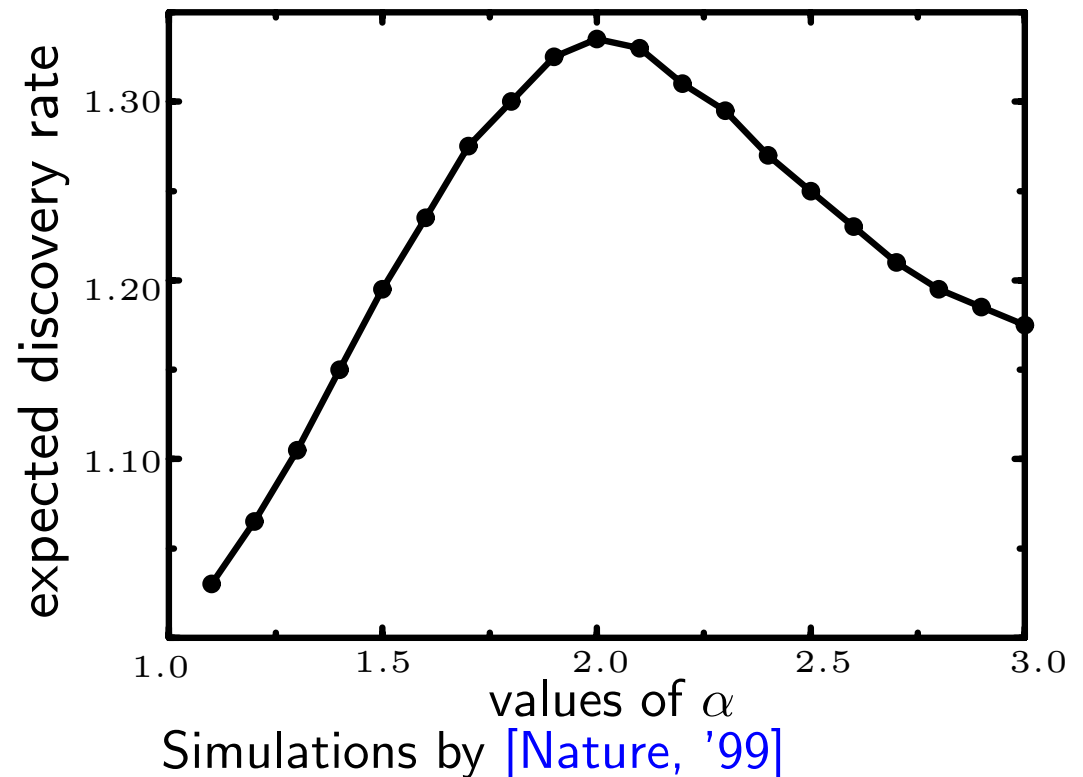


The Lévy Flight Foraging Hypothesis

Non-destructive foraging is considered to be the **more realistic** hypothesis [Nature, '99], leading to the **optimality of Lévy walk** as random search strategy

The Lévy flight foraging hypothesis [Physics of Life Reviews, '08]: since Lévy flights/walks (with exponent $\alpha = 2$) optimize random searches, biological organisms must have therefore evolved to exploit Lévy flights/walks

These results shaped much of subsequent research



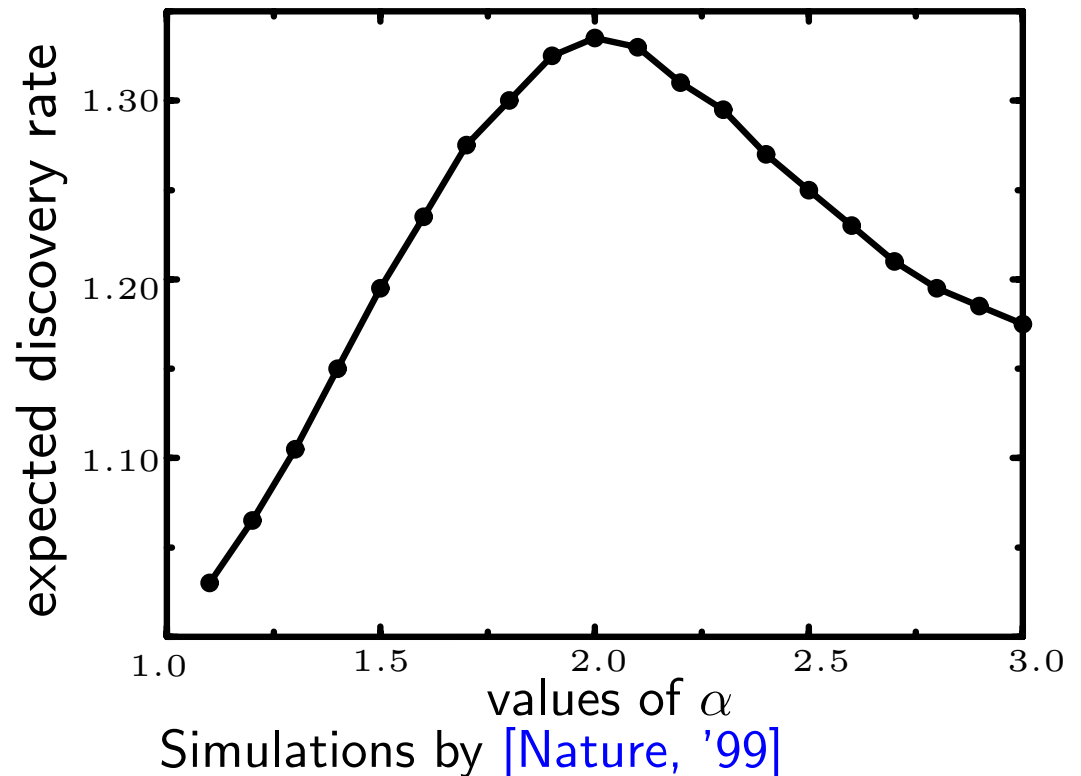
The Lévy Flight Foraging Hypothesis

Non-destructive foraging is considered to be the **more realistic** hypothesis [Nature, '99], leading to the **optimality of Lévy walk** as random search strategy

The Lévy flight foraging hypothesis [Physics of Life Reviews, '08]: since Lévy flights/walks (with exponent $\alpha = 2$) optimize random searches, biological organisms must have therefore evolved to exploit Lévy flights/walks

These results shaped much of subsequent research

HOWEVER...



Considerations and Breaking News

We *failed* to find rigorous mathematical treatment of the claimed results

Considerations and Breaking News

We *failed* to find **rigorous mathematical treatment** of the claimed results

[Physical Review Letters, '20] claims the results of [Nature, '99] **do not apply** in dimension $d \geq 2$, thus **questioning** the **validity** of the Lévy flight foraging hypothesis.

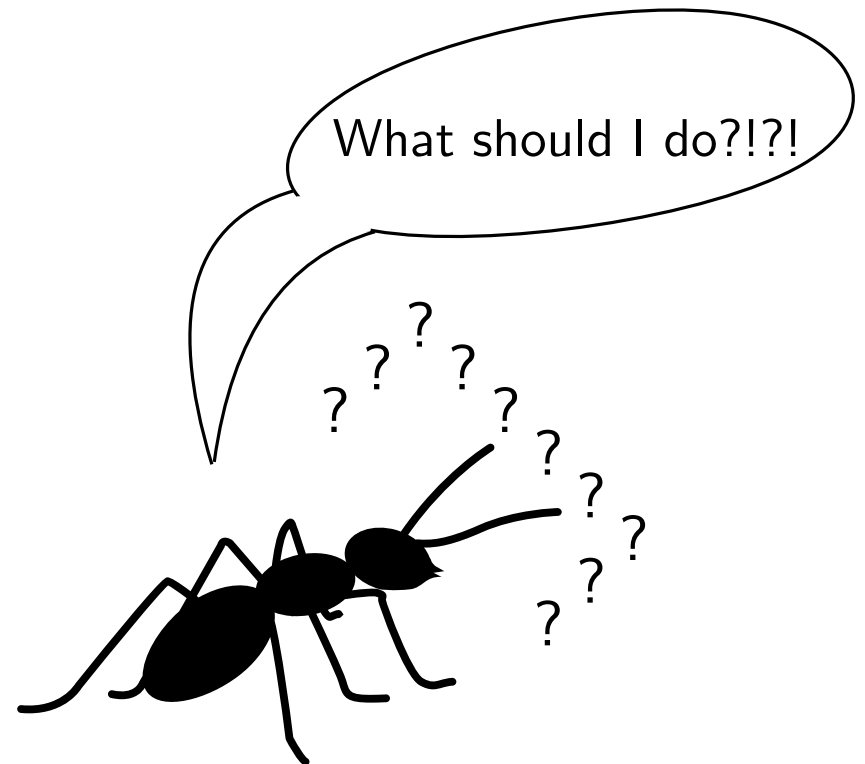


Image from [Jacob Eckert](#), from [The Noun Project](#)

Considerations and Breaking News

We *failed* to find **rigorous mathematical treatment** of the claimed results

[Physical Review Letters, '20] claims the results of [Nature, '99] **do not apply** in dimension $d \geq 2$, thus **questioning** the **validity** of the Lévy flight foraging hypothesis.

The Lévy walk has **never been studied** in the discrete setting

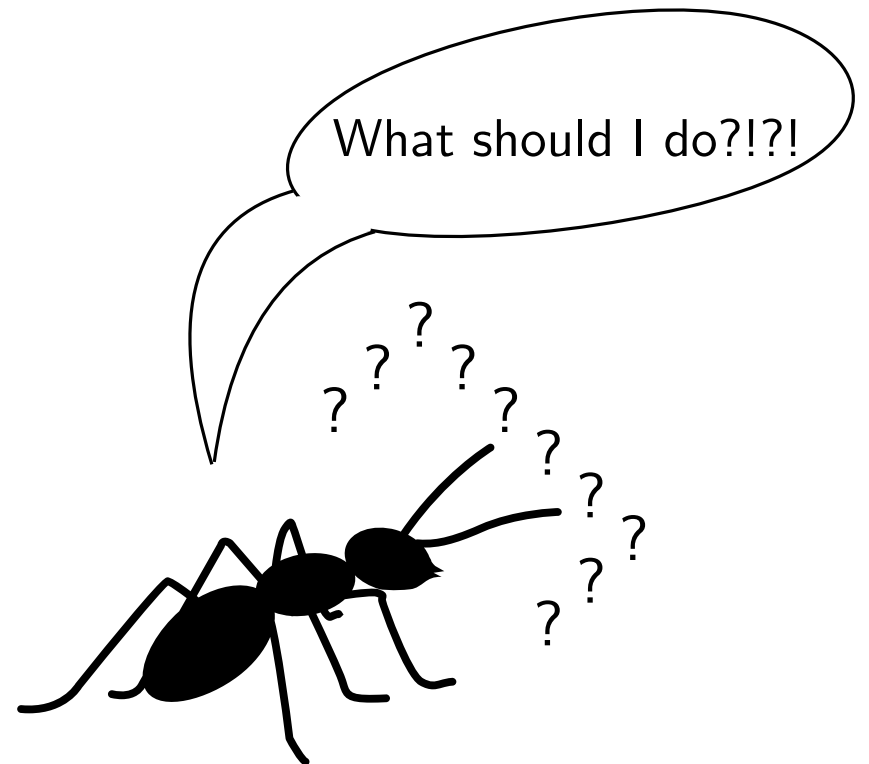


Image from [Jacob Eckert](#), from [The Noun Project](#)

The ANTS Problem

[PODC, '12] introduces the Ants Nearby Treasure Search (ANTS) Problem

The ANTS Problem

[PODC, '12] introduces the Ants Nearby Treasure Search (ANTS) Problem

- Setting:
- k (mutually) **independent walkers** (agents) start moving in \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 ***treasure***, at (Manhattan) distance ℓ from the origin

The ANTS Problem

[PODC, '12] introduces the Ants Nearby Treasure Search (ANTS) Problem

- Setting:
- k (mutually) **independent walkers** (agents) start moving in \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 **treasure**, at (Manhattan) distance ℓ from the origin

Question: which strategy is the **best one** to find the treasure?

Ant Race



image from <https://www.youtube.com/watch?v=2M4gXkUhK6M>

Some Preliminaries

We denote

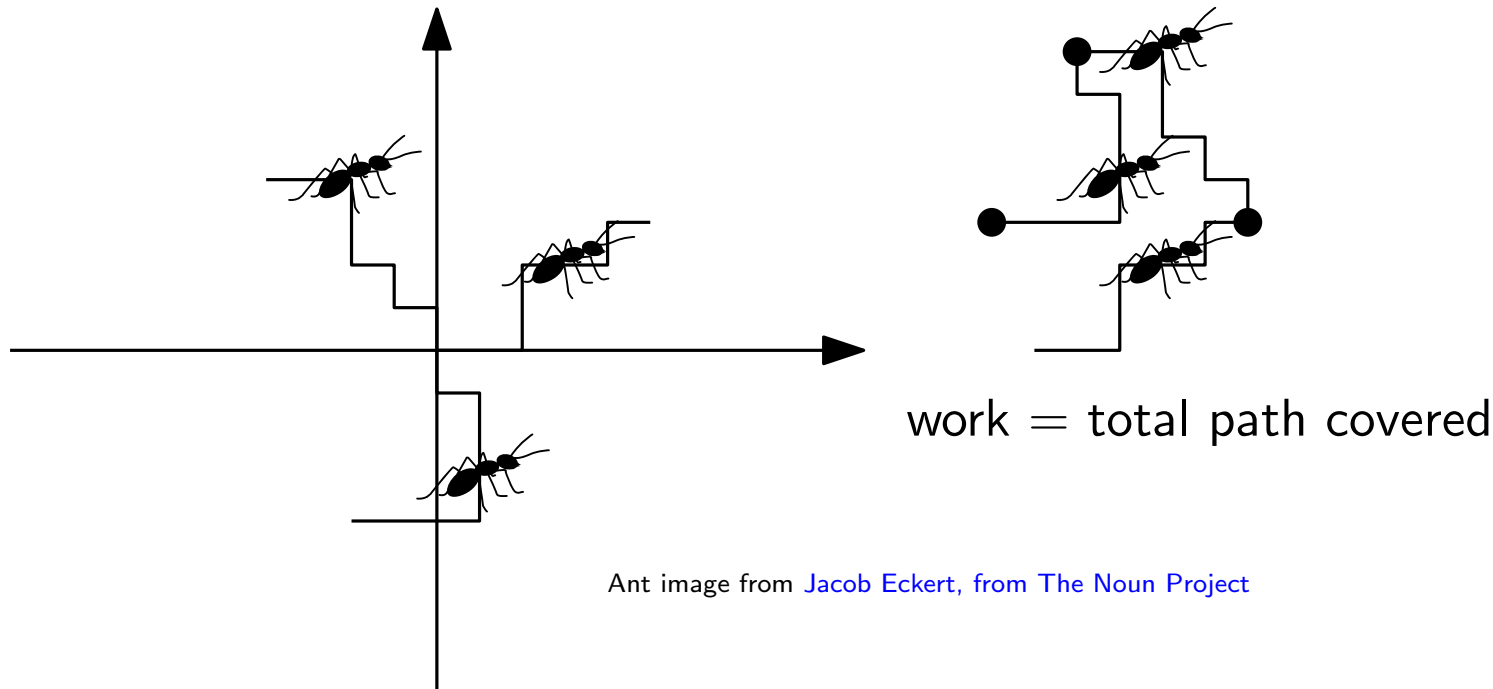
- *step* a move that takes one time unit
- $B_d(u)$ the set of nodes of \mathbb{Z}^2 having Manhattan distance at most d from u

Some Preliminaries

We denote

- *step* a move that takes one time unit
- $B_d(u)$ the set of nodes of \mathbb{Z}^2 having Manhattan distance at most d from u

Definition (*work*): k agents moving for t steps make a *work* equal to $k \cdot t$



Ant image from [Jacob Eckert](#), from [The Noun Project](#)

Lower Bound on the Work

By a simple extension of a result in [PODC, '12], we prove the following lower bound on the work

Lower Bound on the Work

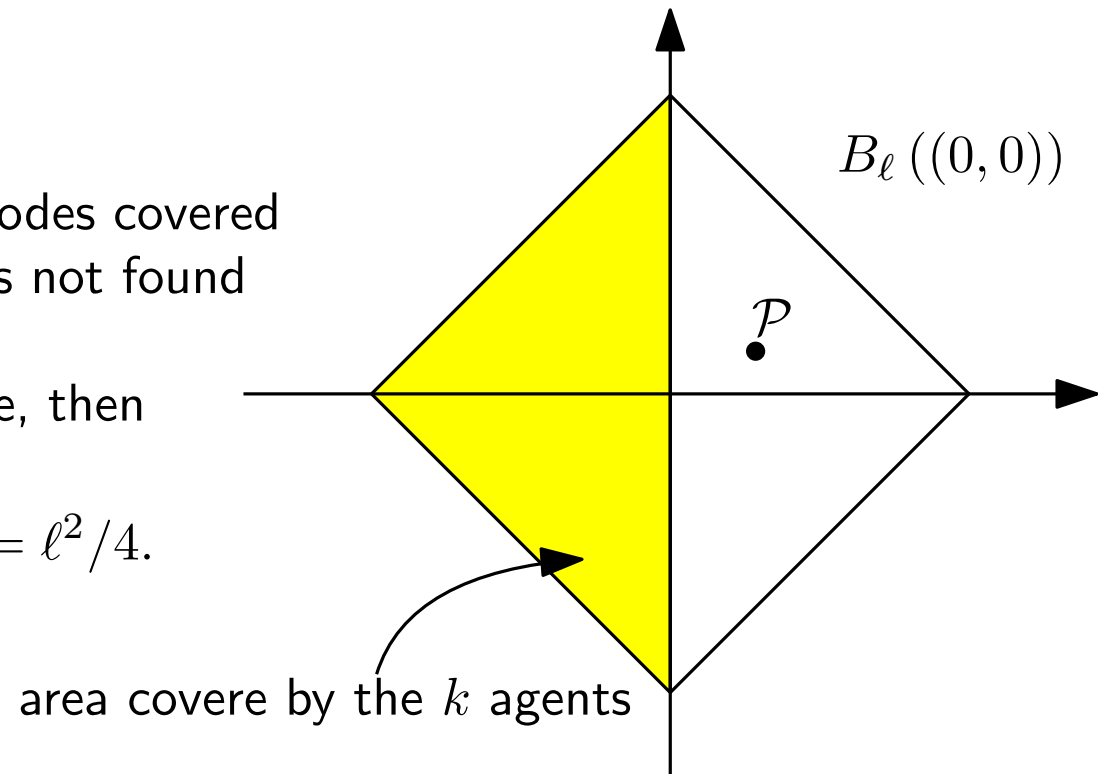
By a simple extension of a result in [PODC, '12], we prove the following **lower bound** on the **work**

Lemma: locate \mathcal{P} u.a.r. in one node in $B_\ell((0,0))$. For any $k \geq 1$, and for **any search algorithm** \mathcal{A} adopted, the **work required** to find \mathcal{P} is $\Omega(\ell^2)$ 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
- probability at least $1/2$ the treasure is not found within time $2t$
- $H =$ first hitting time for the treasure, then

$$\mathbb{E}[\text{work}] = \mathbb{E}[kH] \geq 2kt \cdot \frac{1}{2} = \ell^2/4.$$

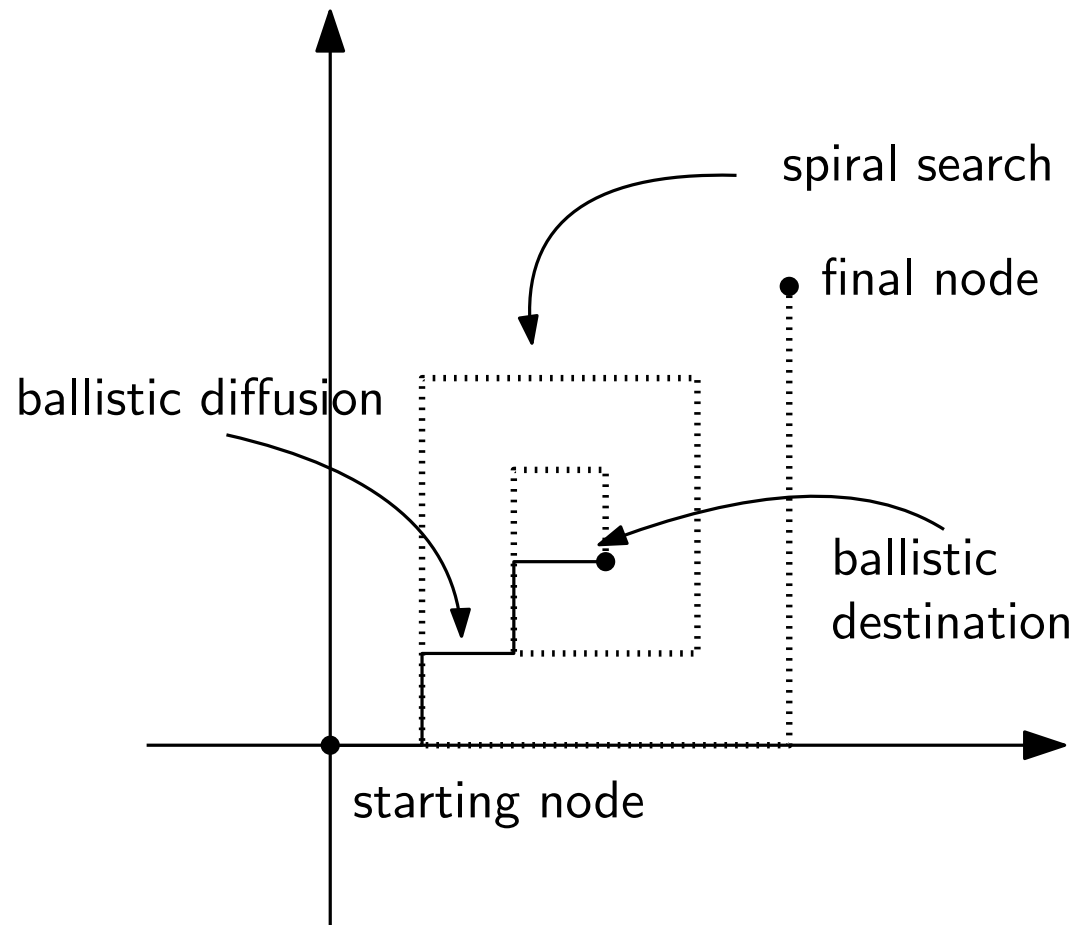


The Harmonic Search Algorithm

[PODC, '12] proposes a search algorithm which is **almost optimal** and which is *natural*

The Harmonic Search Algorithm

[PODC, '12] proposes a search algorithm which is **almost optimal** and which is *natural*



One iteration of the
harmonic search algorithm:

The Harmonic Search Algorithm

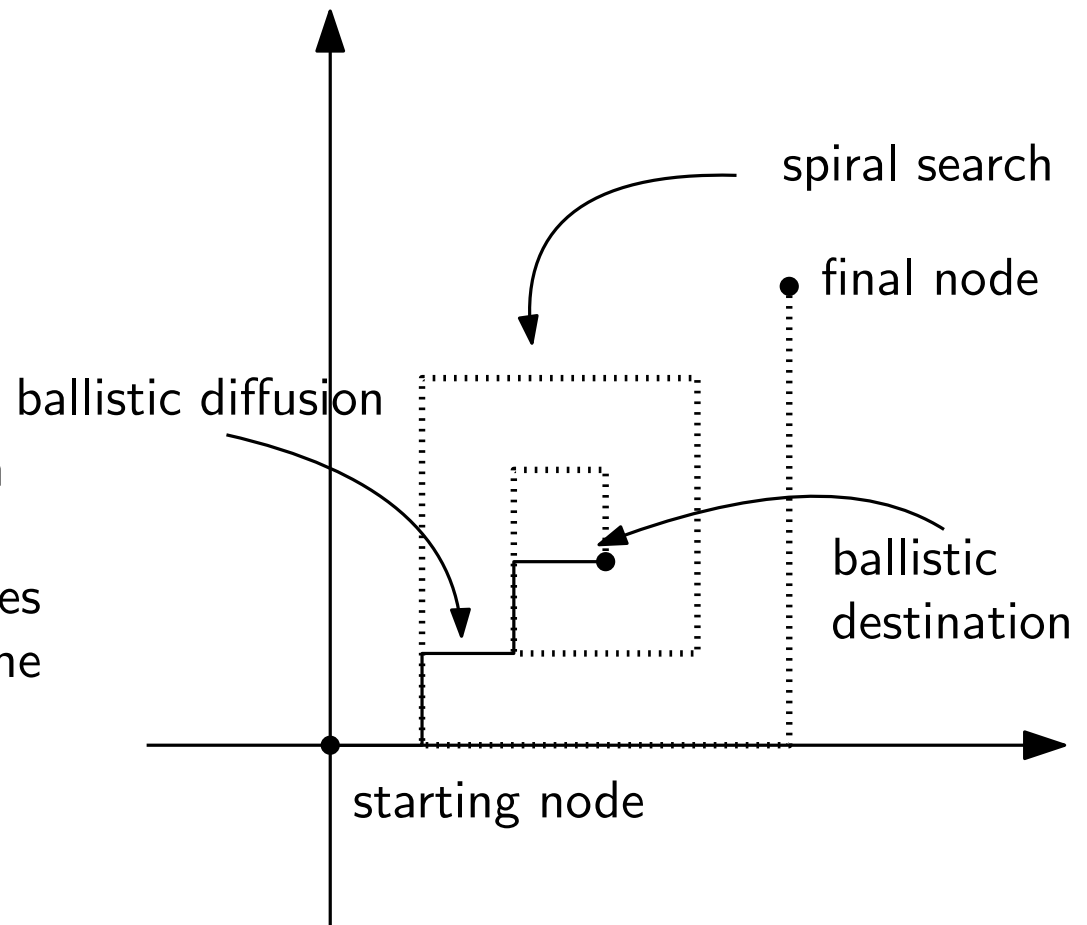
[PODC, '12] proposes a search algorithm which is **almost optimal** and which is *natural*

Let $\alpha > 1$ be a real constant

The Harmonic Search algorithm:

each agent performs the following instructions

- it samples a Lévy jump-length d with probability c_α/d^α
- (ballistic diffusion) in d steps, it moves to a destination at distance d from the starting node chosen u.a.r.
- (normal diffusion) once at the destination, it starts exploring the around area with a spiral search for $d^{\alpha+1}$ steps
- it returns in the origin and repeats



One iteration of the harmonic search algorithm:

The Harmonic Search Algorithm

Remark: the algorithm **allows** the walker to **look for the treasure** only during **step (c)**, namely the “normal diffusion” phase

The Harmonic Search Algorithm

Remark: the algorithm **allows** the walker to **look for the treasure** only during **step (c)**, namely the “normal diffusion” phase

Results [PODC, '12] (informal):

- the **smaller** $\alpha > 1$, the **better** the performances
- the **work** made by k walkers is $\mathcal{O}(\ell^{\alpha+1}) = \mathcal{O}(\ell^{2+(\alpha-1)})$ with probability $\geq 1 - \epsilon$, for any $\epsilon > 0$ and $k \geq \Theta(f(\epsilon)\ell^{\alpha-1})$

The Harmonic Search Algorithm

Remark: the algorithm **allows** the walker to **look for the treasure** only during **step (c)**, namely the “normal diffusion” phase

Results [PODC, '12] (informal):

- the **smaller** $\alpha > 1$, the **better** the performances
- the **work** made by k walkers is $\mathcal{O}(\ell^{\alpha+1}) = \mathcal{O}(\ell^{2+(\alpha-1)})$ with probability $\geq 1 - \epsilon$, for any $\epsilon > 0$ and $k \geq \Theta(f(\epsilon)\ell^{\alpha-1})$

Reminder: the lower bound on the work is $\Omega(\ell^2)$ with constant probability

Our Work

We give the *first definition* of Lévy walk in the *discrete setting* in \mathbb{Z}^2 , the *Pareto walk*, which is *natural* and *time-homogeneous*

- the jump-length distribution we choose is a common variant of the Pareto distribution, which is a power-law

Our Work

We give the **first definition** of Lévy walk in the **discrete setting** in \mathbb{Z}^2 , the *Pareto walk*, which is **natural** and **time-homogeneous**

- the jump-length distribution we choose is a common variant of the Pareto distribution, which is a power-law

The ANTS Problem setting:

- one special node \mathcal{P} of \mathbb{Z}^2 (the **treasure**) at distance ℓ from the origin
- k (mutually) **independent agents** starting at the origin of \mathbb{Z}^2 and moving around looking for the treasure

Our Work

We give the **first definition** of Lévy walk in the **discrete setting** in \mathbb{Z}^2 , the *Pareto walk*, which is **natural** and **time-homogeneous**

- the jump-length distribution we choose is a common variant of the Pareto distribution, which is a power-law

The ANTS Problem setting:

- one special node \mathcal{P} of \mathbb{Z}^2 (the **treasure**) at distance ℓ from the origin
- k (mutually) **independent agents** starting at the origin of \mathbb{Z}^2 and moving around looking for the treasure

Task:

- **minimize** the **work** to find the treasure
- estimate the **distribution** of the **hitting time**

Some Preliminaries

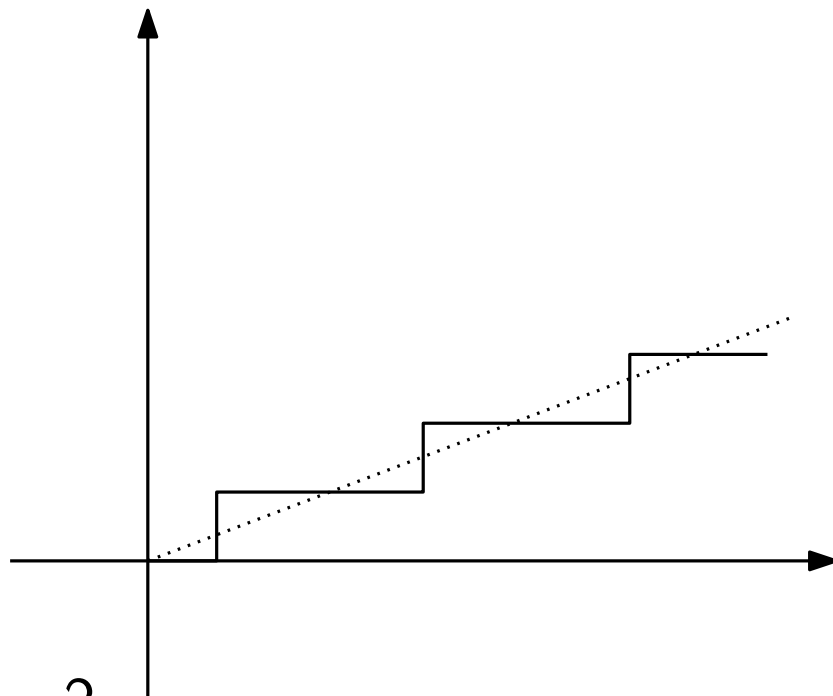
Definition: we say that an event E depending on a parameter $n \in \mathbb{N}$ holds *with high probability* (w.h.p. in short) w.r.t. n if $\mathbb{P}(E) \geq 1 - 1/n^{\Theta(1)}$

Some Preliminaries

Definition: we say that an event E depending on a parameter $n \in \mathbb{N}$ holds *with high probability* (w.h.p. in short) w.r.t. n if $\mathbb{P}(E) \geq 1 - 1/n^{\Theta(1)}$

Two notions:

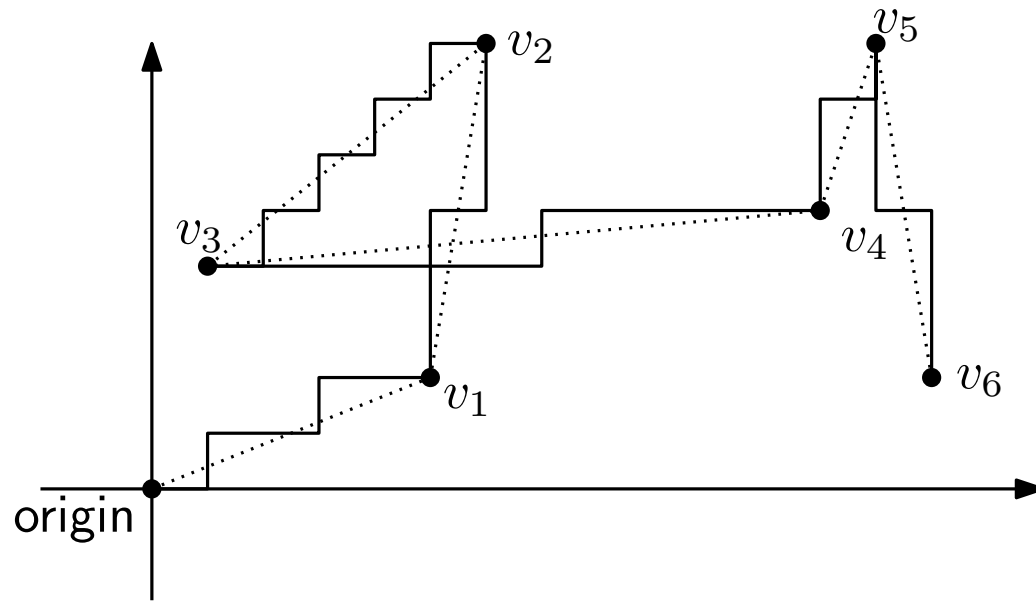
- choice of a **direction** u.a.r. in \mathbb{Z}^2
- selection of a “**direction-approximating**” path



..... direction chosen
— path performed

Direction and approximating
path example

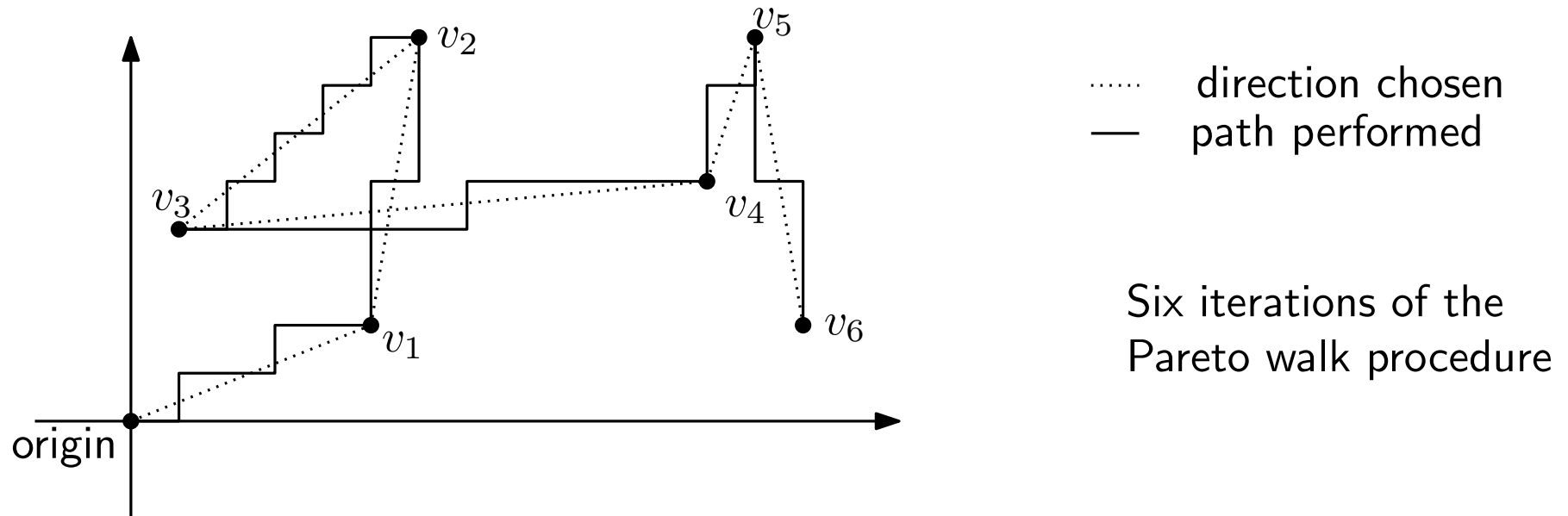
Some Preliminaries



..... direction chosen
— path performed

Six iterations of the
Pareto walk procedure

Some Preliminaries

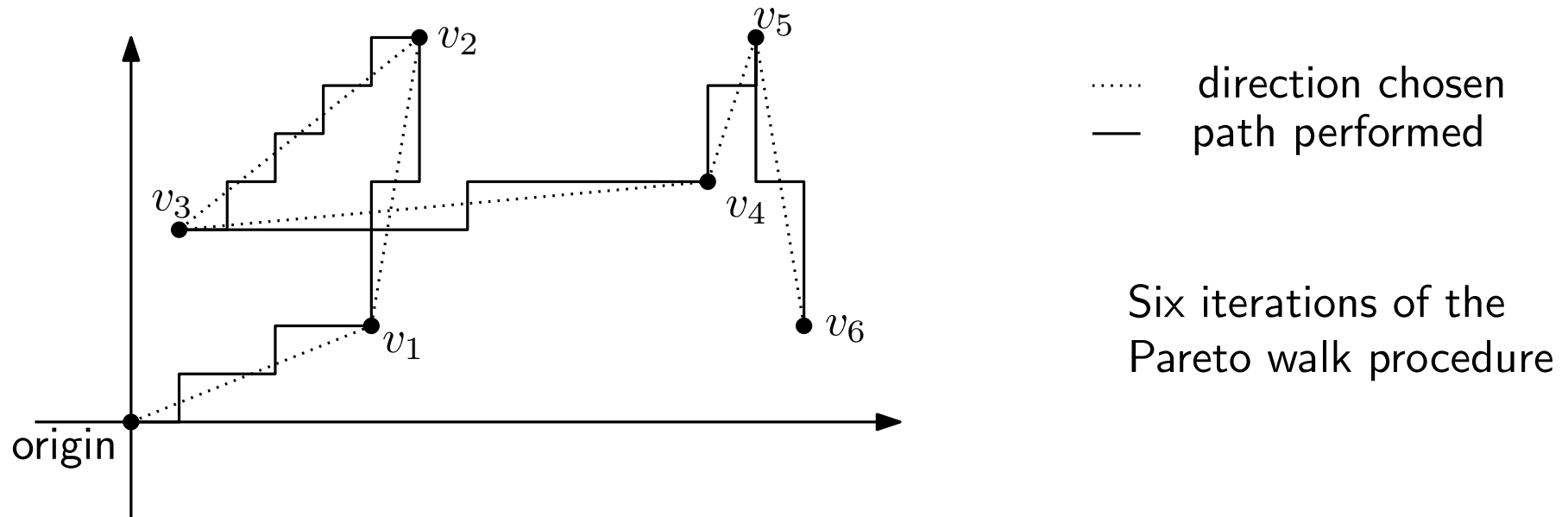


Let $\alpha > 1$ be a real constant

Pareto walk: each agent performs the following instructions

- it chooses a **distance** $d \in \mathbb{N}$ with probability $c_\alpha / (1 + d)^\alpha$
- it chooses a **direction** u.a.r.
- it walks along the corresponding **direction-approximating path** for d steps, one edge at a time, crossing d nodes
- it **repeats** the procedure

Some Preliminaries



Let $\alpha > 1$ be a real constant

Pareto walk: each agent performs the following instructions

- it chooses a **distance** $d \in \mathbb{N}$ with probability $c_\alpha / (1 + d)^\alpha$
- it chooses a **direction** u.a.r.
- it walks along the corresponding **direction-approximating path** for d steps, one edge at a time, crossing d nodes
- it **repeats** the procedure

Remark: the probability distribution in (a) is a known variant of the **Pareto distribution**

Our Results

Reminder: the lower bound on the work is $\Omega(\ell^2)$ with constant probability

Result (up to polylogarithms): for each choice of $\alpha > 1$ there is just one polynomial value (in ℓ) for k such that, w.h.p., the work is equal to ℓ^2 , thus optimal

Our Results

Reminder: the lower bound on the work is $\Omega(\ell^2)$ with constant probability

Result (up to polylogarithms): for each choice of $\alpha > 1$ there is just one polynomial value (in ℓ) for k such that, w.h.p., the work is equal to ℓ^2 , thus optimal

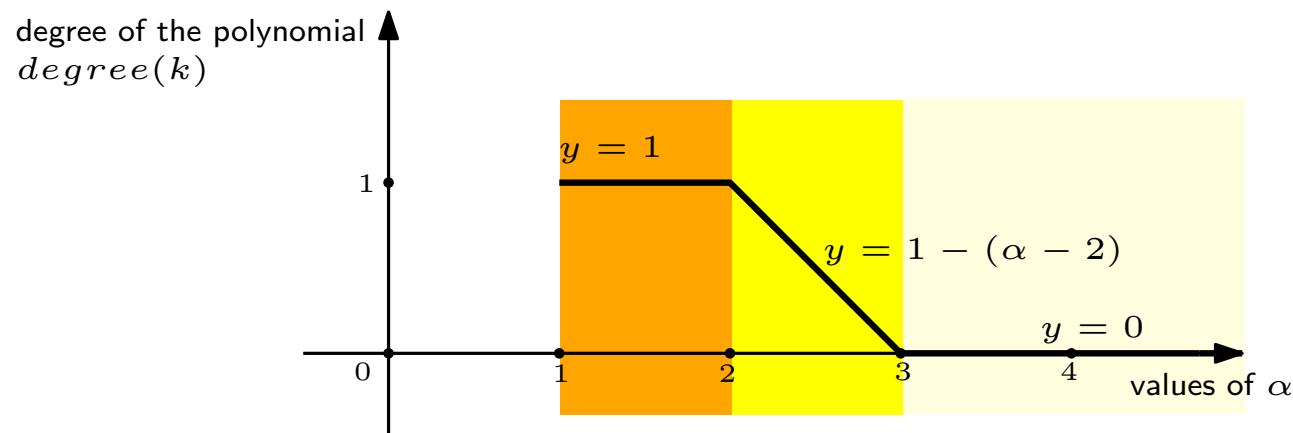
Exponent	Value of k	Hitting time	Work
$\alpha \geq 3$	$\log^{\Theta(1)} \ell$	$\tilde{\Theta}(\ell^2)$	$\tilde{\Theta}(\ell^2)$
$2 < \alpha < 3$	$\tilde{\Theta}(\ell^{1-(\alpha-2)})$	$\tilde{\Theta}(\ell^{1+(\alpha-2)})$	$\tilde{\Theta}(\ell^2)$
$1 < \alpha \leq 2$	$\tilde{\Theta}(\ell)$	$\tilde{\Theta}(\ell)$	$\tilde{\Theta}(\ell^2)$

Our Results

Reminder: the lower bound on the work is $\Omega(\ell^2)$ with constant probability

Result (up to polylogarithms): for each choice of $\alpha > 1$ there is just one polynomial value (in ℓ) for k such that, w.h.p., the work is equal to ℓ^2 , thus optimal

Exponent	Value of k	Hitting time	Work
$\alpha \geq 3$	$\log^{\Theta(1)} \ell$	$\tilde{\Theta}(\ell^2)$	$\tilde{\Theta}(\ell^2)$
$2 < \alpha < 3$	$\tilde{\Theta}(\ell^{1-(\alpha-2)})$	$\tilde{\Theta}(\ell^{1+(\alpha-2)})$	$\tilde{\Theta}(\ell^2)$
$1 < \alpha \leq 2$	$\tilde{\Theta}(\ell)$	$\tilde{\Theta}(\ell)$	$\tilde{\Theta}(\ell^2)$



Other Results

The results in the previous slide are *almost-tight*:

- **changing** by a polynomial factor the value of k leads the work to **worsen** by at least polynomial factor, w.h.p.

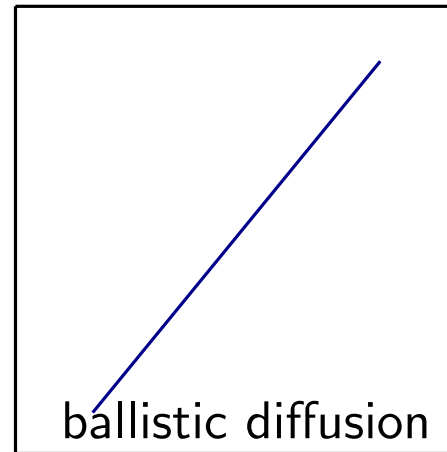
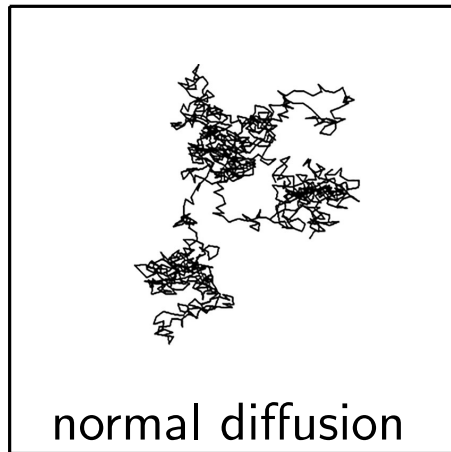
Other Results

The results in the previous slide are *almost-tight*:

- **changing** by a polynomial factor the value of k leads the work to **worsen** by at least polynomial factor, w.h.p.

We also prove the following **equivalences**, in terms of work-efficiency

- $\alpha \geq 3 \sim$ **simple random walk** (normal diffusion)
- $1 < \alpha \leq 2 \sim$ **ballistic walk** (ballistic diffusion)



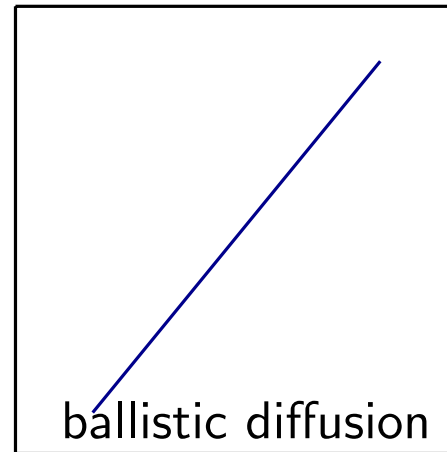
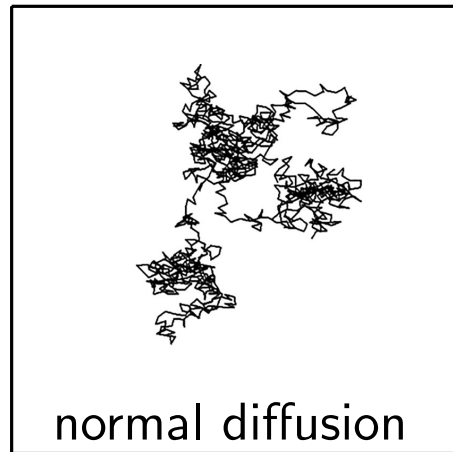
Other Results

The results in the previous slide are *almost-tight*:

- **changing** by a polynomial factor the value of k leads the work to **worsen** by at least polynomial factor, w.h.p.

We also prove the following **equivalences**, in terms of work-efficiency

- $\alpha \geq 3 \sim$ **simple random walk** (normal diffusion)
- $1 < \alpha \leq 2 \sim$ **ballistic walk** (ballistic diffusion)



Now, **some details** on how we prove the upper bound on the hitting time for the super-diffusive regime...

Some Considerations

The **exponent** $\alpha = 2$ **does not play** any **crucial role** in our setting

Some Considerations

The **exponent** $\alpha = 2$ **does not play** any **crucial role** in our setting

Instead, for **each choice** of α there is **some value** for k such that the **work** performed is **optimal** (up to polylogarithms)

Some Considerations

The **exponent** $\alpha = 2$ **does not play** any **crucial role** in our setting

Instead, for **each choice** of α there is **some value** for k such that the **work** performed is **optimal** (up to polylogarithms)

Hint: the **optimal search strategy** **depends** on the **chosen setting** (i.e., the environment)

Some Analysis: $2 < \alpha < 3$

Remark: if $2 < \alpha < 3$, the **expected jump-length** of the Pareto walk is **constant**

Proof: indeed, the expectation is

$$\sum_{d \geq 0} c_\alpha d / (1 + d)^\alpha \sim \sum_{d \geq 0} c_\alpha / (1 + d)^{\alpha-1} < +\infty$$

Some Analysis: $2 < \alpha < 3$

Remark: if $2 < \alpha < 3$, the **expected jump-length** of the Pareto walk is **constant**

Proof: indeed, the expectation is

$$\sum_{d \geq 0} c_\alpha d / (1 + d)^\alpha \sim \sum_{d \geq 0} c_\alpha / (1 + d)^{\alpha-1} < +\infty$$

Hint: in each jump, the walker **visits** only a **constant number of nodes** in expectation, thus we don't lose much if we look only at jump-destination nodes

Some Analysis: $2 < \alpha < 3$

Remark: if $2 < \alpha < 3$, the **expected jump-length** of the Pareto walk is **constant**

Proof: indeed, the expectation is

$$\sum_{d \geq 0} c_\alpha d / (1 + d)^\alpha \sim \sum_{d \geq 0} c_\alpha / (1 + d)^{\alpha-1} < +\infty$$

Hint: in each jump, the walker **visits** only a **constant number of nodes** in expectation, thus we don't lose much if we look only at jump-destination nodes

Pareto flight: the Pareto flight is a Pareto walk in which the agent takes just **one step/time unit** to reach a jump-destination, without visiting intermediate nodes



Wow! This is a
Markov chain in \mathbb{Z}^2 !!

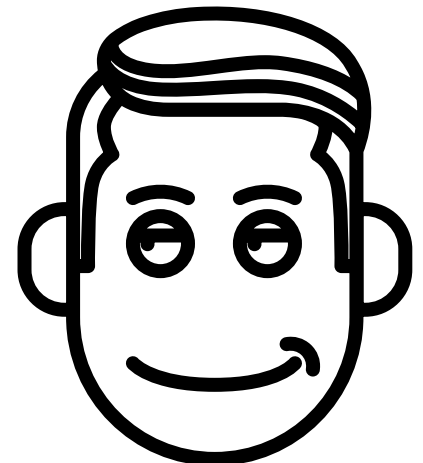
Coupling Result

Coupling result: if one single **Pareto flight** finds the treasure within t steps with probability $p(t)$ conditional on the event that all the performed jump lengths are less than $(t \log t)^{\frac{1}{\alpha-1}}$, then one **Pareto walk** finds the treasure within $\Theta(t)$ steps with probability at least $[p(t) - \exp(-t^{\Theta(1)})]/2$, without any conditional event

Coupling Result

Coupling result: if one single **Pareto flight** finds the treasure within t steps with probability $p(t)$ conditional on the event that all the performed jump lengths are less than $(t \log t)^{\frac{1}{\alpha-1}}$, then one **Pareto walk** finds the treasure within $\Theta(t)$ steps with probability at least $[p(t) - \exp(-t^{\Theta(1)})]/2$, without any conditional event

Basically, we **reduce** ourselves to study the **hitting time** distribution for the treasure of the **Pareto flight** to get the same result on the Pareto walk

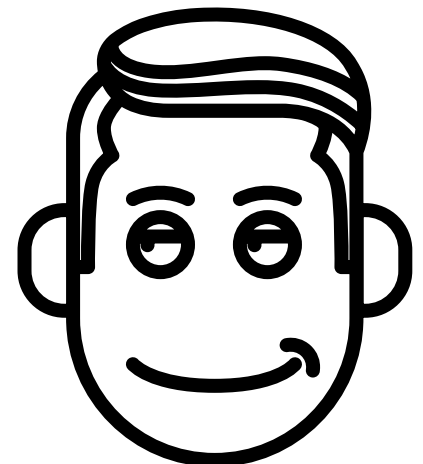


Coupling Result

Coupling result: if one single **Pareto flight** finds the treasure within t steps with probability $p(t)$ conditional on the event that all the performed jump lengths are less than $(t \log t)^{\frac{1}{\alpha-1}}$, then one **Pareto walk** finds the treasure within $\Theta(t)$ steps with probability at least $[p(t) - \exp(-t^{\Theta(1)})]/2$, without any conditional event

Basically, we **reduce** ourselves to study the **hitting time** distribution for the treasure of the **Pareto flight** to get the same result on the Pareto walk

We look at **one single** Pareto flight to determine $p(t)$ in order to use the coupling result...



Trying to get $p(t)$...

- Let
- \mathcal{P} be the **treasure**
 - $|\mathcal{P}|_1 = \ell$ its **Manhattan distance** from the origin
 - $Z_{\mathcal{P}}(t)$ = random variable of **number of visits** in \mathcal{P} until time t
 - \mathcal{E}_t = the **event** first t jumps have length $\leq (t \log t)^{\frac{1}{\alpha-1}}$
 - $a_t = \mathbb{E} [Z_{(0,0)}(t) \mid \mathcal{E}_t]$

Trying to get $p(t)$...

- Let
- \mathcal{P} be the **treasure**
 - $|\mathcal{P}|_1 = \ell$ its **Manhattan distance** from the origin
 - $Z_{\mathcal{P}}(t)$ = random variable of **number of visits** in \mathcal{P} until time t
 - \mathcal{E}_t = the **event** first t jumps have length $\leq (t \log t)^{\frac{1}{\alpha-1}}$
 - $a_t = \mathbb{E} [Z_{(0,0)}(t) \mid \mathcal{E}_t]$

For the Pareto flight, it holds

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

Trying to get $p(t)$...

- Let
- \mathcal{P} be the **treasure**
 - $|\mathcal{P}|_1 = \ell$ its **Manhattan distance** from the origin
 - $Z_{\mathcal{P}}(t)$ = random variable of **number of visits** in \mathcal{P} until time t
 - \mathcal{E}_t = the **event** first t jumps have length $\leq (t \log t)^{\frac{1}{\alpha-1}}$
 - $a_t = \mathbb{E} [Z_{(0,0)}(t) \mid \mathcal{E}_t]$

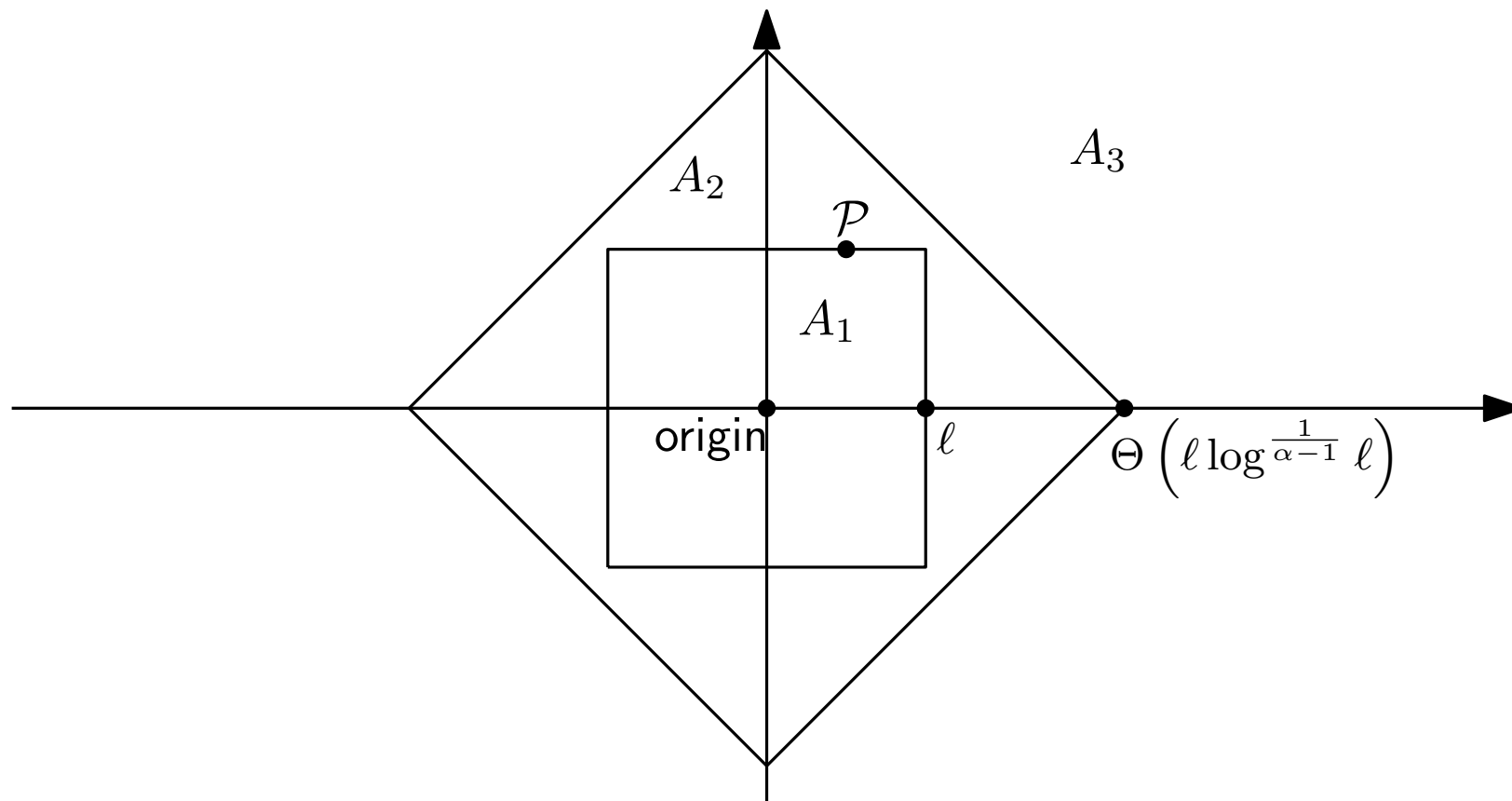
For the Pareto flight, it holds

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

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

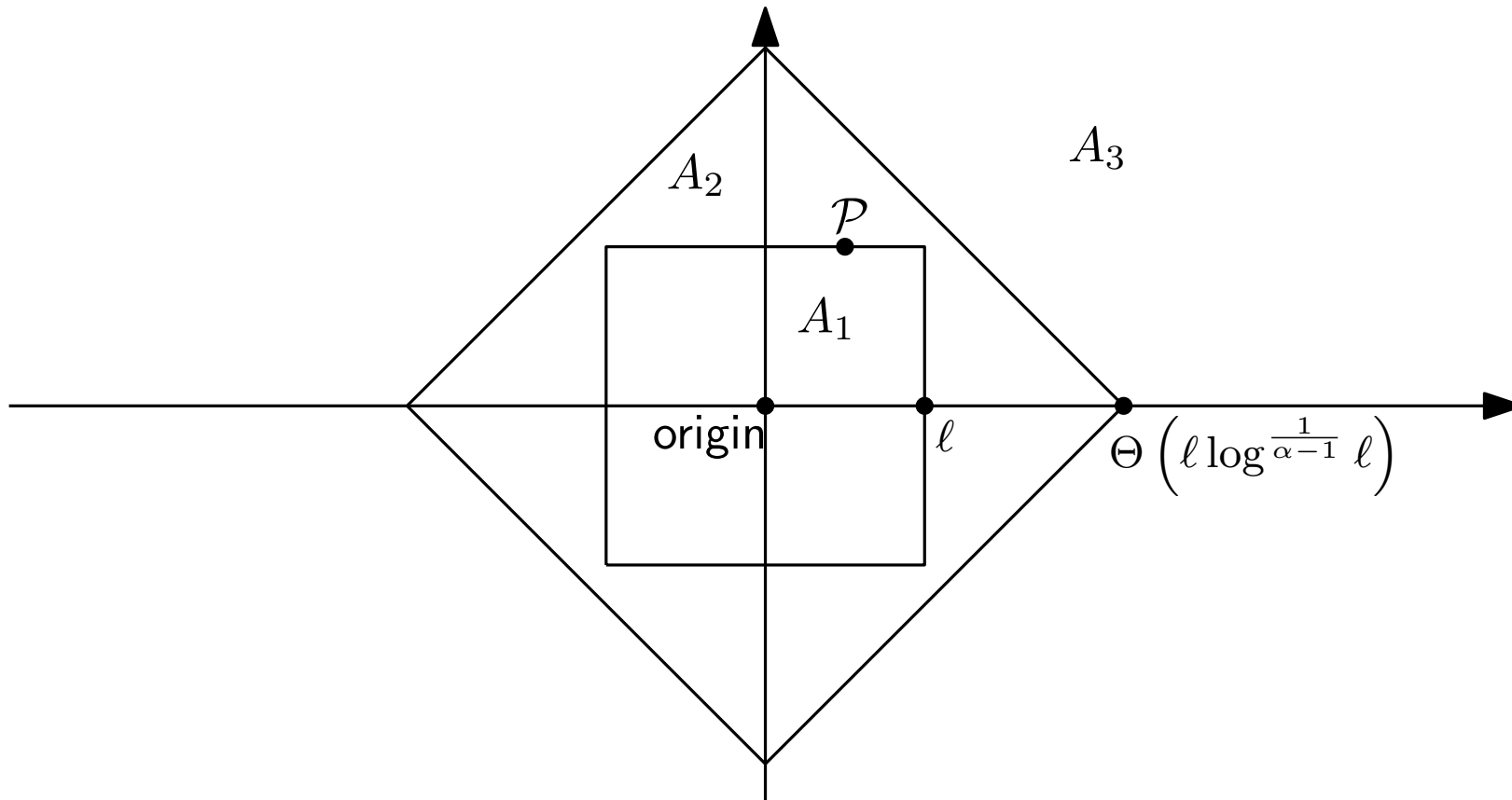
Trying to get $\mathbb{E}[Z_{\mathcal{P}}(t) \mid \mathcal{E}_t] \dots$

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



Trying to get $\mathbb{E}[Z_{\mathcal{P}}(t) \mid \mathcal{E}_t] \dots$

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



- $A_1 = Q(\ell) = \{(x, y) \in \mathbb{Z}^2 : \max(|x|, |y|) \leq \ell\}$
- $A_2 = B_{\Theta\left(\ell \log^{\frac{1}{\alpha-1}} \ell\right)}((0, 0)) \setminus A_1$
- $A_3 = \mathbb{Z}^2 \setminus (A_1 \cup A_2)$

Trying to get $\mathbb{E} [Z_{\mathcal{P}} (t) \mid \mathcal{E}_t] \dots$

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

Trying to get $\mathbb{E} [Z_{\mathcal{P}} (t) \mid \mathcal{E}_t] \dots$

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 a walker makes is, clearly, t , we get that

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

Trying to get $\mathbb{E} [Z_{\mathcal{P}} (t) \mid \mathcal{E}_t] \dots$

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 a walker makes is, clearly, t , we get that

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

For some $t = \Theta (\ell^{1+(\alpha-2)})$, we **prove** that:

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

$$(c) \quad \mathbb{E} [Z_{A_2} (t) \mid \mathcal{E}_t] \leq \mathbb{E} [Z_{\mathcal{P}} (t) \mid \mathcal{E}_t] \cdot \Theta \left(\ell^2 \log^{\frac{2}{\alpha-1}} \ell \right)$$

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

Trying to get $\mathbb{E} [Z_{\mathcal{P}} (t) \mid \mathcal{E}_t] \dots$

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 a walker makes is, clearly, t , we get that

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

For some $t = \Theta (\ell^{1+(\alpha-2)})$, we **prove** that:

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

$$(c) \quad \mathbb{E} [Z_{A_2} (t) \mid \mathcal{E}_t] \leq \mathbb{E} [Z_{\mathcal{P}} (t) \mid \mathcal{E}_t] \cdot \Theta \left(\ell^2 \log^{\frac{2}{\alpha-1}} \ell \right)$$

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

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

$$\mathbb{E} [Z_{\mathcal{P}} (t) \mid \mathcal{E}_t] = \tilde{\Omega} \left(1 / \ell^{1-(\alpha-2)} \right)$$

Back to $p(t)$...

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

Back to $p(t)$...

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

Through an involved argument, we show that a_t is **constant** w.r.t. t

Lemma: for $t = \Theta(\ell^{1+(\alpha-1)})$, it holds that $p(t) = \tilde{\Omega}(1/\ell^{1-(\alpha-2)})$

Back to $p(t)$...

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

Through an involved argument, we show that a_t is **constant** w.r.t. t

Lemma: for $t = \Theta(\ell^{1+(\alpha-1)})$, it holds that $p(t) = \tilde{\Omega}(1/\ell^{1-(\alpha-2)})$

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

Back to $p(t)$...

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

Through an involved argument, we show that a_t is **constant** w.r.t. t

Lemma: for $t = \Theta(\ell^{1+(\alpha-1)})$, it holds that $p(t) = \tilde{\Omega}(1/\ell^{1-(\alpha-2)})$

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

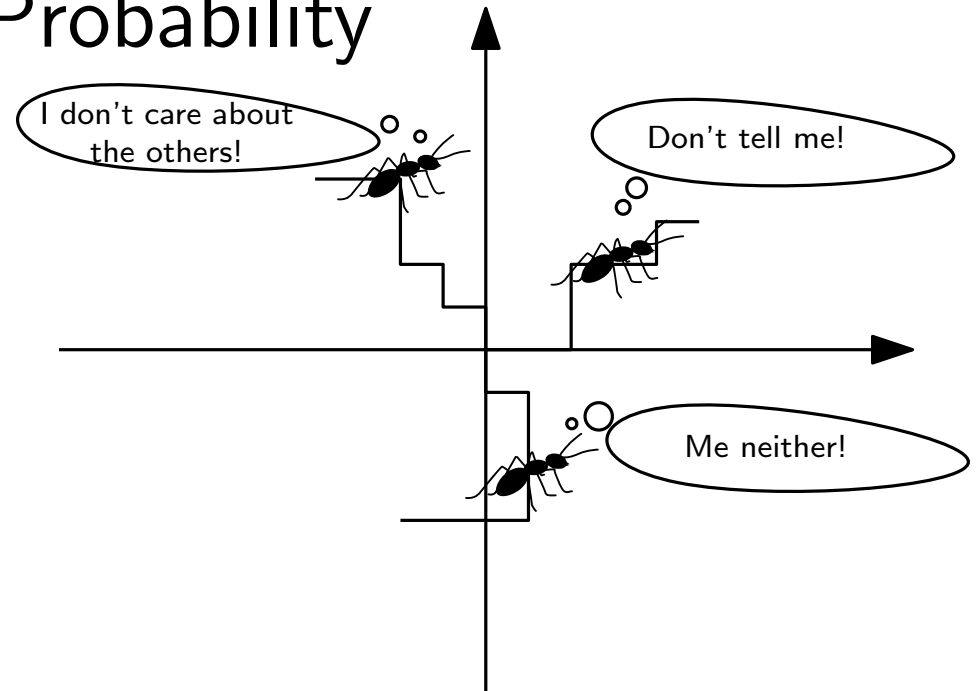
Question: how to get the **high probability**?



© Can Stock Photo

The High Probability

We exploit *independence!*



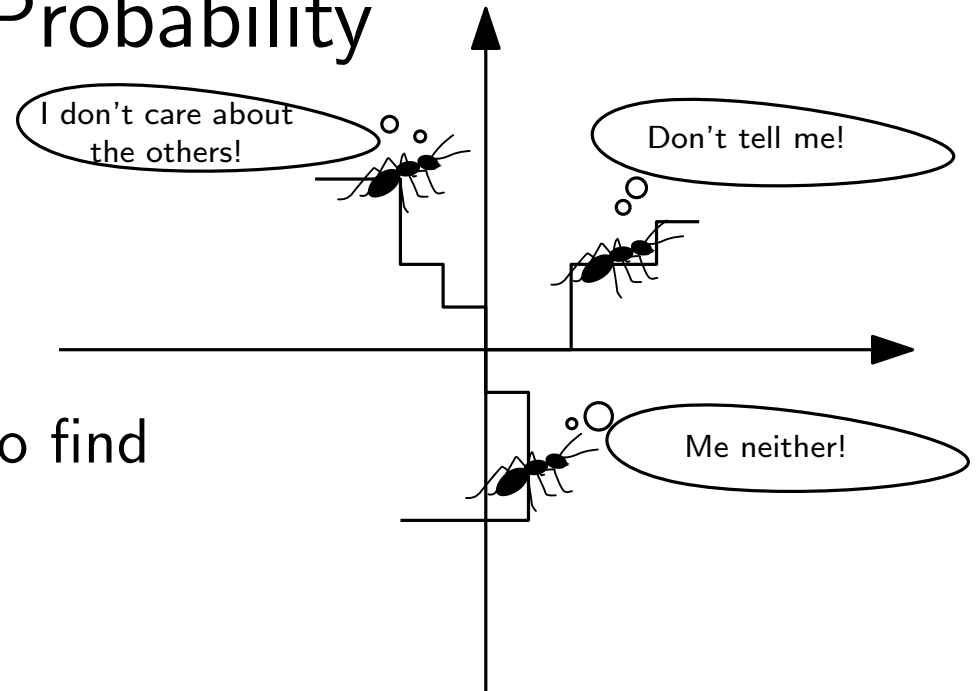
Ant images from [Jacob Eckert, The Noun Project](#)

The High Probability

We exploit *independence*!

k walkers, each has probability $p(t)$ to find
the treasure within time
 $t = \Theta(\ell^{1+(\alpha-2)}) \dots$

k walkers **don't find** the treasure within time t with probability $[1 - p(t)]^k$



Ant images from [Jacob Eckert, The Nolin Project](#)

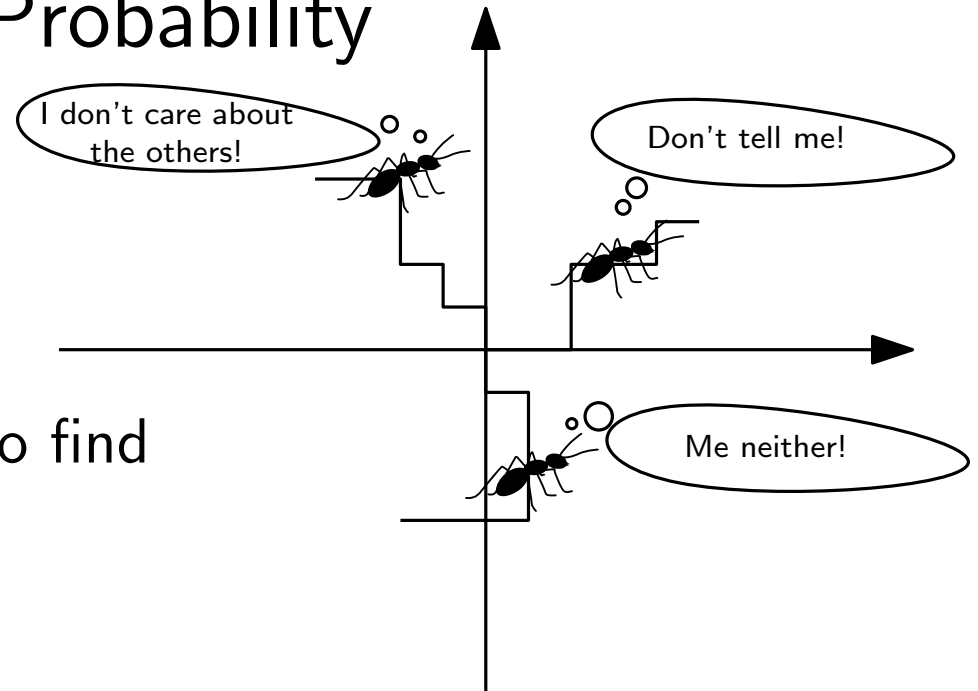
The High Probability

We exploit *independence*!

k walkers, each has probability $p(t)$ to find the treasure within time $t = \Theta(\ell^{1+(\alpha-2)}) \dots$

k walkers **don't find** the treasure within time t with probability $[1 - p(t)]^k$

Set $k = \log \ell \cdot (p(t))^{-1} \dots$

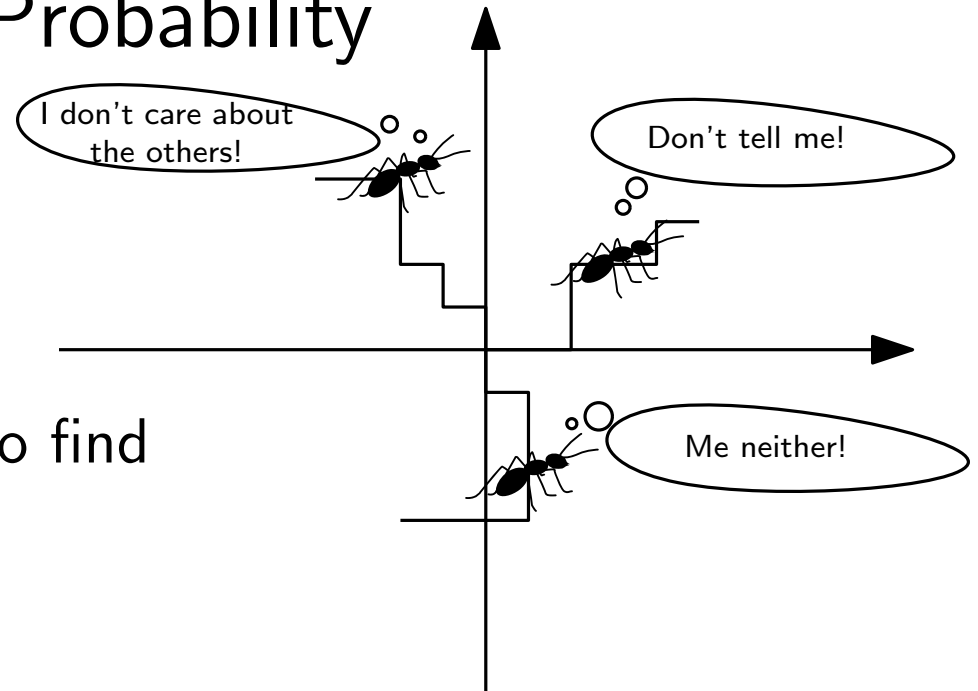


Ant images from [Jacob Eckert, The Nolin Project](#)

The High Probability

We exploit *independence*!

k walkers, each has probability $p(t)$ to find the treasure within time $t = \Theta(\ell^{1+(\alpha-2)}) \dots$



k walkers **don't find** the treasure within time t with probability $[1 - p(t)]^k$

Set $k = \log \ell \cdot (p(t))^{-1} \dots$

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

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

We thus **need** $\log \ell / p(t) = \tilde{O}(\ell^{1-(\alpha-2)})$ **walkers** to find the treasure **within time** $t = \Theta(\ell^{1+(\alpha-2)})$, **making a work** equal to $\tilde{O}(\ell^2)$, w.h.p.

THANK YOU FOR YOUR ATTENTION

