

Masterthesis

External DLA

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1 Introduction



2 Preliminaries

2.1 Symbols

Here we list all Symbols which will be used in this paper. Let $d \in \mathbb{N}$ and $q \in \{0, \dots, d\}$.

$\mathbb{N} = \{1, 2, 3, \dots\}$, the set of natural numbers (without 0)

$\mathbb{N}_0 = \mathbb{N} \cup \{0\}$

\mathcal{K}^d , the set of convex and compact sets in \mathbb{R}^d

$B_d(r, x) = \{y \in \mathbb{R}^d \mid |x - y| \leq r\}$, the d -dimensional closed ball of radius r around x

$S_{d-1}(r, x) = \partial B_d(r, x)$, the $(d - 1)$ -dimensional surface of the d -dimensional ball

$A(d, q)$, the set of q -dimensional affine subspaces of \mathbb{R}^d

$\mathcal{A}(d, q)$, the σ -algebra of $A(d, q)$, as constructed later in the paper

$\mathcal{G} := A(2, 1)$, the set of lines in the real plane

$SO_d := \{\nu \in \mathbb{R}^{d \times d} \mid \nu \nu^\top = I_d \text{ and } \det \nu = 1\}$, identify $SO_2 = \{\nu_\beta := e^{i\beta} \in \mathbb{C} \mid \beta \in [0, 2\pi)\}$

$G_d := \{\varphi : \mathbb{R}^d \rightarrow \mathbb{R}^d, x \mapsto \nu x + b \mid \nu \in SO_d, b \in \mathbb{R}^d\}$, the set of euclidean motions

2.2 Basic structures

We prepare this script with the following preliminaries. Let $d \in \mathbb{N}$.

Graphs. We will be interested in the graph (\mathbb{Z}^d, E) with its canonical graph structure, which is two vertices (or points) $x = (x_1, \dots, x_d), y = (y_1, \dots, y_d) \in \mathbb{Z}^d$ form an edge (e.q. $\{x, y\} \in E$) if and only if there exists exactly one $i \in \{1, \dots, d\}$ such that $|x_i - y_i| = 1$ and $x_j = y_j$ for all $j \neq i$. For a point $x \in \mathbb{Z}^d$ its set of *neighbours* is defined as

$$N(x) := \{y \in \mathbb{Z}^d \mid (x, y) \in E\}.$$

For a set $A \subset \mathbb{Z}^d$ the *outer boundary* ∂A of A is defined as

$$\partial A := \{y \in \mathbb{Z}^d \setminus A \mid \exists x \in A : (x, y) \in E\}$$

Instead of (\mathbb{Z}^d, E) we will write \mathbb{Z}^d from now on.

Probability Space. Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space. For our space of interest \mathbb{Z}^d we will always use the discrete σ -algebra which is the power set of \mathbb{Z}^d . If for $A \in \mathcal{F}$ we have $\mathbb{P}(A) = 1$ we will say that " A holds \mathbb{P} -a.s.", or short " A holds a.s." (almost sure).

Random Walk. A family $(S_n)_{n \in \mathbb{N}}$ of measurable functions $S_n : \Omega \rightarrow \mathbb{Z}^d$ is called a *Random Walk on \mathbb{Z}^d (starting at $x \in \mathbb{Z}^d$)* if and only if $S_0 = x$, a.s. and

$$\mathbb{P}(S_n = y \mid S_{n-1} = z) = \frac{1}{|N(z)|} = \frac{1}{2d}, \quad \text{for all } y \in N(z) \text{ and } z \in \mathbb{Z}^d.$$

Note that $|N(z)| = 2d$ for all $z \in \mathbb{Z}^d$ since every point has two neighbours in every dimension. We can therefore follow easily that $\mathbb{P}(S_n = y \mid S_{n-1} = z) = 0$ for all $y \notin N(z)$ and $z \in \mathbb{Z}^d$. So a Random Walk can be understood as a particle starting from some point x and moving randomly on the grid choosing its next step uniformly from its neighbours. Further define

$$\mathbb{P}_x(S_n \in A) := \mathbb{P}(S_n \in A \mid S_0 = x)$$

for any subset $A \subset \mathbb{Z}^d$. We define the *hitting times* of A by

$$T_A := \min\{n \geq 0 \mid S_n \in A\} \text{ and } T_A^+ := \min\{n \geq 1 \mid S_n \in A\},$$

$T_x := T_{\{x\}}$ and $T_x^+ := T_{\{x\}}^+$ for one element sets and $x \in \mathbb{Z}^d$. The *heat kernel* of the random walk S_n is defined to be

$$p_n(x, y) := \mathbb{P}_x(S_n = y)$$

2 Preliminaries

and the *Green function* as

$$G(x, y) := \sum_{n \geq 0} p_n(x, y).$$

G is well-defined and finite since \mathbb{Z}^2 is transient. Similarly for a subset $A \subset G$ the *killed* or *stopped Green function* is defined as

$$G_A(x, y) := \sum_{n \geq 0} \mathbb{P}_x(S_n = y, T_A > n).$$

3 Incremental Aggregate

In this paper we will look at stochastic processes on the set of finite subsets of \mathbb{Z}^d , where we start with a one point set at $\{0\}$ and incrementally add a point on the outer boundary of the current cluster according to some distribution. What we get is a randomly, point by point growing connected cluster which we will call *Incremental Aggregate*. Define

$$\mathcal{P}_f := \{A \subset \mathbb{Z}^d \mid A \text{ is finite}\}, \quad (3.1)$$

the set of finite subsets of \mathbb{Z}^d . Furthermore we will be interested in distributions on those sets, so for $A \in \mathcal{P}_f$ we define

$$\mathcal{D}_A := \{\mu : \mathbb{Z}^d \rightarrow [0, 1] \mid \mu(y) = 0 \text{ for all } y \notin A \text{ and } \sum_{y \in A} \mu(y) = 1\}, \quad (3.2)$$

the set of distributions on A . Now we define *Incremental Aggregate* as follows.

Definition 3.0.1. Let $\mu = (\mu_A)_{A \in \mathcal{P}_f}$ be a family of distributions with $\mu_A \in \mathcal{D}_A$ for all $A \in \mathcal{P}_f$. *Incremental Aggregate (with distribution μ)* is a stochastic process $(\mathcal{E}_n)_{n \in \mathbb{N}_0}$ which evolves as follows. The process starts with one point $\mathcal{E}_0 = \{0\}$ at the origin of \mathbb{Z}^d . Knowing the process \mathcal{E}_n at time n , let y_n be a random point in $\partial\mathcal{E}_n \in \mathcal{P}_f$ with distribution

$$\mathbb{P}(y_n = y \mid \mathcal{E}_n) := \mu_{\partial\mathcal{E}_n}(y), \quad y \in \mathbb{Z}^d. \quad (3.3)$$

We then define $\mathcal{E}_{n+1} := \mathcal{E}_n \cup \{y_n\}$.

For all incremental aggregates in this paper we will have $d = 2$. From now on we will identify \mathbb{R}^2 with \mathbb{C} .

4 External DLA

External DLA is a model of an Incremental Aggregate as defined above using a very natural family of distributions, called the *harmonic measures*.

Definition 4.0.1. (*Harmonic Measure*) Let $A \in \mathcal{P}_f$. Remembering the definitions in (2), especially the heat kernel $p_n(x, y) = \mathbb{P}_x(S_n = y)$ of a random walk, for $x \in \mathbb{Z}^2$ the *harmonic measure* (from x) of A is

$$h_A(x, y) := \mathbb{1}\{y \in A\} p_{T_A}(x, y) = \mathbb{1}\{y \in A\} \mathbb{P}_x(S_{T_A} = y), \quad \text{for } y \in \mathbb{Z}^2.$$

We now define the *harmonic measure* (from infinity) of A as the family $h = (h_A)_{A \in \mathcal{P}_f}$ with

$$h_A(y) := \lim_{|x| \rightarrow \infty} h_A(x, y), \quad y \in \mathbb{Z}^2.$$

This is well-defined because ... CONTINUE

Definition 4.0.2. (*External Diffusion Limited Aggregate*) *External Diffusion Limited Aggregate*, short *External DLA*, is a incremental aggregate with the harmonic measure h as distribution.

5 Integral Geometry

In the next section we want to define an approximation for External DLA. This approximation will be an incremental aggregate for which distribution definition we need some concepts and results from Integral Geometry which we will discuss and develop in this section. In the process we want to define we will want to choose a random line out of all lines which intersect with the current cluster of the aggregate. This random choosing is not obvious since most of the time the cluster will be strongly non symmetric and it is even less obvious how to actually get a realisation of a random line when simulating with Python. In our case we are looking for a parametrisation of lines in the plane and a reasonable way of choosing parameters randomly.

We will introduce a possible solution for this problem first through the abstract and general concepts of integral geometry and later through a simple parametrisation for the case of lines in the plane which goes hand in hand with the general result.

5.1 General results

In the general context we are in \mathbb{R}^d for $d \in \mathbb{N}$ and consider q -dimensional affine subspaces where $q \in \{0, \dots, d\}$, short q -flats in \mathbb{R}^d . The set of q -flats in \mathbb{R}^d is denoted by $A(d, q)$. Later we will be interested in choosing random lines in the real plane (i.e. 1-flats in \mathbb{R}^2). In order to get a probability measure on some set of q -flats, we first need a measure and a σ -algebra on $A(d, q)$ in total.

Definition 5.1.1. For $K \in \mathcal{K}^d$ define $A_K := \{F \in A(d, q) \mid F \cap K \neq \emptyset\}$. Then the σ -algebra $\mathcal{A}(d, q)$ on $A(d, q)$ shall be defined by

$$\mathcal{A}(d, q) := \sigma(\{A_K \mid K \in \mathcal{K}^d\}).$$

Theorem 5.1.1. On $A(d, q)$ there exists a unique G_d -invariant Radon measure μ_q such that

$$\mu_q(A_{B_d(1,0)}) = \kappa_{d-q}, \tag{5.1}$$

where $\kappa_n := \lambda_n(B_n(1,0))$ is the n -dimensional Lebesgue measure of the n -dimensional unit ball for $n \in \mathbb{N}$, and $\kappa_0 := 1$.

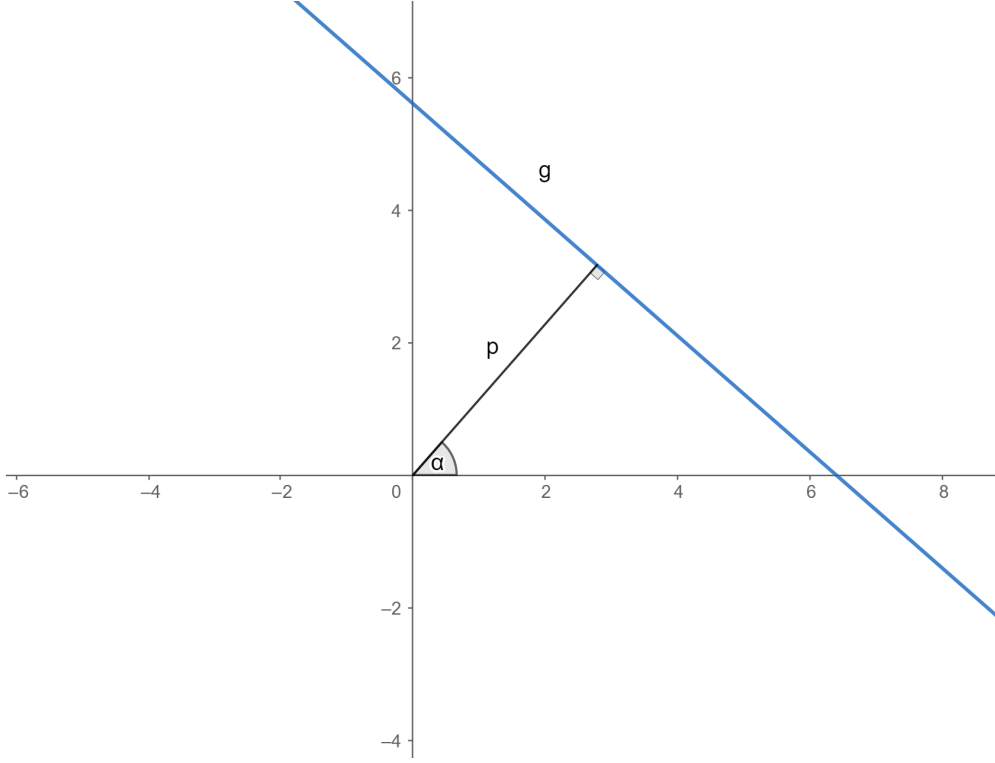
Proof. [2] Theorem 4.26

MAKE PROOF CLEARER

□

5.2 Construction in the plane

For our special case we choose $d = 2$ and $q = 1$, thus lines in the plane. We denote this set of lines by \mathcal{G} . The following construction in this chapter is completely motivated by [3] 2.1.1. Firstly we propose a parametrisation of lines which works as follows. Every


 Figure 1: Line parameters α and p

line can be uniquely determined by an angle $\alpha \in [0, \pi)$ and a real number $p \in \mathbb{R}$. Let $e_\alpha := e^{\alpha i} = \cos(\alpha) + \sin(\alpha)i$ be the unit vector 1 rotated by α counterclockwise. It is easy to realize that $g_{\alpha,p} := \{x \in \mathbb{C} \mid \langle x, e_\alpha \rangle = p\}$ defines a line and that every line has a unique pair of α and p for such a representation (see in *Figure 1*). With $\Phi := [0, \pi) \times \mathbb{R}$ this naturally defines a bijection

$$\chi : \Phi \rightarrow \mathcal{G}, \quad (\alpha, p) \mapsto g_{\alpha,p}.$$

We take the subspace Borel- σ -algebra $\mathcal{B}_\Phi := \mathcal{B}^2 \cap \Phi$ on Φ and define the σ -algebra \mathfrak{G} on \mathcal{G} by $\mathfrak{G} := \chi(\mathcal{B}_\Phi)$. This works well since χ is a bijection. The next lemma shows that this way of defining a σ -algebra on \mathcal{G} makes sense as it is indeed equivalent to the general context as defined above.

Lemma 5.2.1. We have $\mathcal{A}(2, 1) = \mathfrak{G}$.

Proof. To proof this it is helpful to consider generators of these σ -algebras. Define the set of closed rectangles in Φ as $R := \{[\alpha, \beta] \times [c, d] \subset \mathbb{C} \mid 0 \leq \alpha < \beta < \pi, c < d\}$. Then by measure theory we know that $\mathcal{B}_\Phi = \sigma(R)$ and since χ is a bijection, we have $\chi(\sigma(R)) = \sigma(\chi(R))$ and finally $\mathfrak{G} = \sigma(\chi(R))$. For $\tilde{A} := \{A_K \mid K \in \mathcal{K}^2\}$ we have by

definition $\mathcal{A}(2, 1) = \sigma(\tilde{A})$.

\subset : Let $K \in \mathcal{K}^2$. We will show that $\chi^{-1}(A_K)$ is a closed set in Φ . If that is the case we can write $\chi^{-1}(A_K) = \cup_{i=1}^{\infty} R_i$ for some rectangles $R_i \in R$, hence $A_K = \cup_{i=1}^{\infty} \chi(R_i)$ and therefore $A_K \in \sigma(\chi(R)) = \mathfrak{G}$. Therefore we have $\tilde{A} \subset \mathfrak{G}$ and finally $\sigma(\tilde{A}) = \mathcal{A}(2, 1) \subset \mathfrak{G}$. To show that $\chi^{-1}(A_K)$ is a closed let $(\alpha_0, p_0) \in \Phi \setminus \chi^{-1}(A_K)$. Then $\chi(\alpha_0, p_0) \notin A_K$ and therefore $\chi(\alpha_0, p_0) \cap K = \emptyset$. Since K is closed we can find small values $\tilde{\alpha}, \tilde{p} > 0$ such that $\chi(\alpha, p) \cap K = \emptyset$ for all $(\alpha, p) \in [\alpha_0, \alpha_0 + \tilde{\alpha}] \times [p_0, p_0 + \tilde{p}] =: \tilde{R}$. Hence we have $\tilde{R} \subset \Phi \setminus \chi^{-1}(A_K)$, so $\Phi \setminus \chi^{-1}(A_K)$ is open. Hence $\chi^{-1}(A_K)$ is closed.

\supset : CONTINUE □

Definition 5.2.1. A \mathcal{F} - \mathfrak{G} -measurable function $g : \Omega \rightarrow \mathcal{G}$ is called a *random line*.

Definition 5.2.2. We define the measure $\mu := \lambda_{2|\Phi} \circ \chi^{-1}$ on $(\mathcal{G}, \mathfrak{G})$ where $\lambda_{2|\Phi}$ is the 2-dimensional Lebesgue measure restricted to Φ . We say a measure ν on $(\mathcal{G}, \mathfrak{G})$ is locally finite if for any $K \in \mathcal{K}^2$ we have $\nu(A_K) < \infty$.

Lemma 5.2.2. μ is locally finite and G_2 -invariant.

Proof. Let $K \in \mathcal{K}^2$ and since K is compact choose $r > 0$ such that $K \subset B_r$. Then we have $A_K \subset A_{B_r}$ and

$$\mu(A_K) \leq \mu(A_{B_r}) = \lambda_{2|\Phi}(\chi^{-1}(A_{B_r})) = \lambda_{2|\Phi}([0, \pi) \times [-r, r]) = 2\pi r < \infty,$$

hence μ is locally finite. To show that μ is G_2 -invariant, that means euclidean motion invariant, we must show it is translation and rotation invariant. First we clarify what exactly translation and rotation mean for lines. We denote x modulo r as $(x)_r$. For $b \in \mathbb{C}$ and $\beta \in [0, 2\pi)$ we define

$$T_b : \Phi \rightarrow \Phi, \quad (\alpha, p) \mapsto (\alpha, p + \langle e_\alpha, b \rangle) \quad (5.1)$$

and

$$D_\beta : \Phi \rightarrow \Phi, \quad (\alpha, p) \mapsto ((\alpha + \beta)_\pi, \delta((\alpha + \beta)_{2\pi})p), \quad (5.2)$$

where

$$\delta : [0, 2\pi) \rightarrow \{-1, 1\}, \quad \gamma \mapsto \begin{cases} 1, & \gamma \in [0, \pi) \\ -1, & \gamma \in [\pi, 2\pi) \end{cases}.$$

It is easy to see that both functions are well-defined. T_b defines a translation by b and D_β a rotation by β . Let's prove that first. Let $(\alpha, p) \in \Phi$, then

$$\begin{aligned} x \in \chi(\alpha, p) + b &\Leftrightarrow x - b \in \chi(\alpha, p) \\ &\Leftrightarrow \langle e_\alpha, x - b \rangle = p \\ &\Leftrightarrow \langle e_\alpha, x \rangle = p + \langle e_\alpha, b \rangle \end{aligned}$$

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$$\Leftrightarrow x \in \chi(\alpha, p + \langle e_\alpha, b \rangle)$$

$$\Leftrightarrow x \in \chi(T_b(\alpha, p))$$

and therefore $\chi(\alpha, p) + b = \chi(T_b(\alpha, p))$. Hence $T_b(\alpha, p)$ are indeed the parameters for the by b translated line. For the rotation lets divide it into two cases. First let $(\alpha + \beta)_{2\pi} \in [0, \pi)$, then $\delta((\alpha + \beta)_{2\pi}) = 1$ and $(\alpha + \beta)_\pi = \alpha + \beta$ and therefore

$$D_\beta(\alpha, p) = (\alpha + \beta, p).$$

In the second case with $(\alpha + \beta)_{2\pi} \in [\pi, 2\pi)$ we have $\delta((\alpha + \beta)_{2\pi}) = -1$ and $(\alpha + \beta)_\pi = \alpha + \beta - \pi$ and therefore

$$D_\beta(\alpha, p) = (\alpha + \beta - \pi, -p).$$

In the second case we have to carefully understand the parametrisation of \mathcal{G} , but finally we can see that $D_\beta(\alpha, p)$ are indeed the parameters of the by β rotated line.

We will further show now, that μ is invariant in respect to both these functions. Let $A \in \mathfrak{G}$, $b \in \mathbb{C}$ and $\nu_\beta \in SO_2$. We will understand $A + b = \{g + b \in \mathcal{G} \mid g \in A\}$ and $\nu_\beta A = \{\nu_\beta g \in \mathcal{G} \mid g \in A\}$ pointwise, and $g + b = \{x + b \mid x \in g\}$ and $\nu_\beta g = \{\nu_\beta x \mid x \in g\}$ pointwise aswell. We furthermore define $A_p := \{\alpha \in [0, \pi) \mid (\alpha, p) \in \chi^{-1}(A)\}$ and $A_\alpha := \{p \in \mathbb{R} \mid (\alpha, p) \in \chi^{-1}(A)\}$ for $(\alpha, p) \in \Phi$. For a translation we get

$$\begin{aligned} \mu(A + b) &= \int_{\mathfrak{G}} \mathbb{1}_{A+b}(g) \mu(dg) \\ &= \int_{\mathfrak{G}} \mathbb{1}_A(g - b) \mu(dg) \\ &= \int_{\mathfrak{G}} \mathbb{1}_A(g - b) \lambda_{2|\Phi}(\chi^{-1}(dg)) \\ &= \int_{\chi^{-1}(\mathfrak{G})} \mathbb{1}_{\chi^{-1}(A)}(\chi^{-1}(g - b)) \lambda_{2|\Phi}(d(\chi^{-1}(g))) \\ &\stackrel{(5.1)}{=} \int_{\Phi} \mathbb{1}_{\chi^{-1}(A)}(\alpha, p - \langle e_\alpha, b \rangle) \lambda_{2|\Phi}(d(\alpha, p)) \\ &= \int_0^\pi \int_{\mathbb{R}} \mathbb{1}_{A_\alpha}(p - \langle e_\alpha, b \rangle) \lambda_1(dp) \lambda_{1|[0, \pi)}(d\alpha) \\ &= \int_0^\pi \int_{\mathbb{R}} \mathbb{1}_{A_\alpha + \langle e_\alpha, b \rangle}(p) \lambda_1(dp) \lambda_{1|[0, \pi)}(d\alpha) \\ &= \int_0^\pi \lambda_1(A_\alpha + \langle e_\alpha, b \rangle) \lambda_{1|[0, \pi)}(d\alpha) \\ &\stackrel{(+)}{=} \int_0^\pi \lambda_1(A_\alpha) \lambda_{1|[0, \pi)}(d\alpha) \\ &= \dots \\ &= \mu(A), \end{aligned}$$

and for a rotation we get

$$\mu(\nu_\beta A) = \int_{\mathcal{G}} \mathbb{1}_{\nu_\beta A}(g) \mu(dg)$$

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$$\begin{aligned}
&= \int_{\mathcal{G}} \mathbb{1}_A(\nu_{-\beta}g) \lambda_{2|\Phi}(\chi^{-1}(dg)) \\
&= \int_{\chi^{-1}(\mathcal{G})} \mathbb{1}_{\chi^{-1}(A)}(\chi^{-1}(\nu_{-\beta}g)) \lambda_{2|\Phi}(d(\chi^{-1}(g))) \\
&\stackrel{(5.2)}{=} \int_{\Phi} \mathbb{1}_{\chi^{-1}(A)}((\alpha - \beta)_{\pi}, \delta((\alpha - \beta)_{2\pi})p) \lambda_{2|\Phi}(\alpha, p) \\
&= \int_{\Phi} \mathbb{1}_{\chi^{-1}(A)}((\alpha - \beta)_{\pi}, \delta((\alpha - \beta)_{2\pi})p) \lambda_{2|\Phi}(\alpha, p) \\
&= \int_0^{2\pi} \int_{\mathbb{R}} \mathbb{1}_{\chi^{-1}(A)}((\alpha - \beta)_{\pi}, \delta((\alpha - \beta)_{2\pi})p) \lambda_1(dp) \lambda_{1|[0,\pi)}(d\alpha) \\
&= \int_0^{2\pi} \int_{\mathbb{R}} \mathbb{1}_{A_{(\alpha-\beta)\pi}}(\delta((\alpha - \beta)_{2\pi})p) \lambda_1(dp) \lambda_{1|[0,\pi)}(d\alpha) \\
&\stackrel{(+)}{=} \int_0^{2\pi} \int_{\mathbb{R}} \mathbb{1}_{A_{(\alpha-\beta)\pi}}(p) \lambda_1(dp) \lambda_{1|[0,\pi)}(d\alpha) \\
&= \int_{\mathbb{R}} \int_0^{2\pi} \mathbb{1}_{\chi^{-1}(A)}((\alpha - \beta)_{\pi}, p) \lambda_{1|[0,\pi)}(d\alpha) \lambda_1(dp) \\
&= \int_{\mathbb{R}} \int_0^{2\pi} \mathbb{1}_{A_p}((\alpha - \beta)_{\pi}) \lambda_{1|[0,\pi)}(d\alpha) \lambda_1(dp) \\
&\stackrel{(+)}{=} \int_{\mathbb{R}} \int_0^{2\pi} \mathbb{1}_{A_p}(\alpha) \lambda_{1|[0,\pi)}(d\alpha) \lambda_1(dp) \\
&= \int_{\mathbb{R}} \int_0^{2\pi} \mathbb{1}_{\chi^{-1}(A)}(\alpha, p) \lambda_{1|[0,\pi)}(d\alpha) \lambda_1(dp) \\
&= \dots \\
&= \mu(A).
\end{aligned}$$

where in (+) we used the translation and rotation invariance of the Lebesgue measure. This completes the proof. \square

By 5.1.1 we know that μ is, up to a factor, the only euclidean motion invariant measure on \mathcal{G} . Since it is locally finite, for $K \in \mathcal{K}^2$ we can define a probability measure on \mathcal{G} by

$$\mathbb{P}_{\mu}^K(A) := \frac{\mu(A \cap A_K)}{\mu(A_K)}, \quad A \in \mathfrak{G}.$$

Definition 5.2.3. Let $K \in \mathcal{K}^2$. A random line $g : \Omega \rightarrow \mathcal{G}$ is called *K-isotropic* if it is distributed as

$$\mathbb{P}(g \in A) = \mathbb{P}_{\mu}^K(A), \quad A \in \mathfrak{G}.$$

Lemma 5.2.3. Let $M, K \in \mathcal{K}^2$ with $M \subset K$. Let f be a random K -isotropic and g be a random M -isotropic line. Then for all $A \in \mathfrak{G}$ we have

$$\mathbb{P}(f \in A \mid f \in A_M) = \mathbb{P}(g \in A).$$

Proof. Note that since $M \subset K$ it is $A_M \subset A_K$. For $A \in \mathfrak{G}$ we therefore directly get

$$\mathbb{P}(f \in A \mid f \in A_M) = \frac{\mathbb{P}(f \in A \cap A_M)}{\mathbb{P}(f \in A_M)}$$

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$$\begin{aligned}
&= \frac{\mu(A \cap A_M \cap A_K)}{\mu(A_K)} \frac{\mu(A_K)}{\mu(A_M \cap A_K)} \\
&= \frac{\mu(A \cap A_M)}{\mu(A_M)} \\
&= \mathbb{P}(g \in A).
\end{aligned}$$

□

If we choose a simple convex set such as $K = B_r := B_2(r, 0)$ then choosing random K -isotropic lines becomes a very intuitive and easy realizable task as the following lemma shows.

Lemma 5.2.4. Let $K = B_r \in \mathcal{K}^2$ and let $(\alpha, p) \sim \mathcal{U}(\tilde{\Phi})$ with $\tilde{\Phi} := [0, \pi) \times [-r, r] = \chi^{-1}(A_K) \subset \Phi$. Then $\chi(\alpha, p)$ is a random K -isotropic line.

Proof. For $A \in \mathfrak{G}$ we get

$$\begin{aligned}
\mathbb{P}(\chi(\alpha, p) \in A) &= \mathbb{P}((\alpha, p) \in \chi^{-1}(A)) = \frac{\lambda_{2|\tilde{\Phi}}(\chi^{-1}(A \cap A_K))}{\lambda_{2|\tilde{\Phi}}(\chi^{-1}(A_K))} \\
&= \frac{\lambda_{2|\Phi}(\chi^{-1}(A \cap A_K))}{\lambda_{2|\Phi}(\chi^{-1}(A_K))} = \frac{\mu(A \cap A_K)}{\mu(A_K)}.
\end{aligned}$$

□

Both lemmas 5.2.3 and 5.2.4 give a useful help for realizing K -isotropic lines for complicated sets K . Lemma 5.2.3 tells us that if we are looking for a K -isotropic line, we can actually take a convex, compact set B which contains K and realize B -isotropic lines. If we realize such a line and it happens that it intersects K , we know that its distribution is equal to trying to realize K -isotropic lines directly. And how to realize B -isotropic lines? Lemma 5.2.4 tells us that if we choose $B = B_r$ a ball with a big enough radius such that it contains K , then realizing B -isotropic lines comes by choosing the line parameters α and p uniformly in $[0, \pi)$ and $[-r, r]$. Finally we have a practicable process of choosing random K -isotropic lines, even if K happens to be very asymmetric and complicated. This gives the base to define a new Incremental Aggregate in the next section which tries to approximate External DLA.

6 Line Hitting Aggregate

In the following we will look at a process which is the approach of a simple approximation of external DLA on \mathbb{Z}^2 . The idea is to let particles move on straight lines coming from infinity and add to the cluster when hitting it. Obviously in most cases particles cannot move completely straight on \mathbb{Z}^2 . Therefore we will consider points in \mathbb{Z}^2 as the centers of unit squares and let the particles move on straight lines in the full plane \mathbb{R}^2 . We consider a line hitting a point in \mathbb{Z}^2 if and only if it intersects with its unit square as defined in the following.

Definition 6.0.1. Define

$$\mathbb{C}_{sq} := \{[k - \frac{1}{2}, k + \frac{1}{2}] + [l - \frac{1}{2}, l + \frac{1}{2}]i \in \mathbb{C} \mid k, l \in \mathbb{Z}\}, \quad (6.1)$$

note that $\mathbb{C} = \bigcup_{s \in \mathbb{C}_{sq}} s$. The canonical function

$$sq : \mathbb{Z}^2 \rightarrow \mathbb{C}_{sq}, \quad (k, l) \rightarrow [k - \frac{1}{2}, k + \frac{1}{2}] + [l - \frac{1}{2}, l + \frac{1}{2}]i \quad (6.2)$$

is bijective and intuitively identifies points in \mathbb{Z}^2 with squares in \mathbb{C} which is p is the center of the square $sq(p)$ for all $p \in \mathbb{Z}^2$. In the following when using a point $p \in \mathbb{Z}^2$ it will reference the point in \mathbb{Z}^2 or the corresponding square in \mathbb{C} respecting the context. This bijection also naturally defines a graph structure on \mathbb{C}_{sq} , which is two squares $s_1, s_2 \in \mathbb{C}_{sq}$ form an edge if and only if $sq^{-1}(s_1)$ and $sq^{-1}(s_2)$ form an edge in \mathbb{Z}^2 . For the following context we say a line g *hits* a point $p \in \mathbb{Z}^2$ if and only if $g \cap sq(p) \neq \emptyset$.

BILD Linie durch squares "hitting"

Definition 6.0.2. Let $g = g_{\alpha, p} \in \mathcal{G}$ and $A \in \mathcal{P}_f$. We define

$$g \cap A := \{p \in A \mid g \text{ hits } p\}$$

which is the subset of all points in A which are hit by g . For the following we suppose $g \cap A \neq \emptyset$. We will define a total ordered relation \triangleleft on $g \cap A$ which shall be defined equivalently for all $g \in \mathcal{G}$ and $A \in \mathcal{P}_f$ with $g \cap A \neq \emptyset$. We choose two points $x, y \in g \cap A$ and divide the definition of the relation \triangleleft into four cases, which are the line going from left-bottom to right-top, left-top to right-bottom, parallel to the x -axis and parallel to the y -axis. Denote the real part of x with $x.\text{real}$ and the imaginary one with $x.\text{imag}$.

Case 1 : g is parallel to the x -axis $\Leftrightarrow \alpha = \frac{\pi}{2}$

$$x \triangleleft y \quad :\Leftrightarrow \quad x.\text{real} < y.\text{imag}$$

Case 2 : g is parallel to the y -axis $\Leftrightarrow \alpha = 0$

$$x \triangleleft y \quad :\Leftrightarrow \quad x.\text{imag} < y.\text{imag}$$

Case 3 : g is going from left-bottom to right-top $\Leftrightarrow \alpha \in (\frac{\pi}{2}, \pi)$

$$x \triangleleft y \quad :\Leftrightarrow \quad \begin{cases} x.\text{real} < y.\text{real}, & \text{if } x.\text{real} \neq y.\text{real}, \\ x.\text{imag} < y.\text{imag}, & \text{if } x.\text{real} = y.\text{real}. \end{cases}$$

Case 4 : g is going from left-top to right-bottom $\Leftrightarrow \alpha \in (0, \frac{\pi}{2})$

$$x \triangleleft y \quad :\Leftrightarrow \quad \begin{cases} x.\text{real} < y.\text{real}, & \text{if } x.\text{real} \neq y.\text{real}, \\ x.\text{imag} > y.\text{imag}, & \text{if } x.\text{real} = y.\text{real}. \end{cases}$$

It is easy to see that this well-defines a relation on $g \cap A$. In the following we will quickly prove that this relation is totally ordered.

Lemma 6.0.1. For a line $g = g_{\alpha,p} \in \mathcal{G}$ and $A \in \mathcal{P}_f$ with $g \cap A \neq \emptyset$ the relation \triangleleft on $g \cap A$ is totally ordered.

Proof. We will only prove the case where g is going from left-bottom to right-top, which is Case 3 of the definition. In this case we have $\alpha \in (\frac{\pi}{2}, \pi)$. Note, that the proof for Case 4 will work very similar and in the case of g being parallel to one of the axes (Case 1 or 2), all properties for a totally ordered relation follow directly from the totally ordered relation $<$ on \mathbb{R} . So let $\alpha \in (\frac{\pi}{2}, \pi)$.

Antisymmetry : For antisymmetry let $x \triangleleft y$ and $y \triangleleft x$. Suppose $x.\text{real} \neq y.\text{real}$, then $x.\text{real} < y.\text{real}$ and $y.\text{real} < x.\text{real}$, therefore $x.\text{real} = y.\text{real}$ by antisymmetry of the standard order $<$ in \mathbb{R} , a contradiction, hence $x.\text{real} = y.\text{real}$. But then we have $x.\text{imag} < y.\text{imag}$ and $y.\text{imag} < x.\text{imag}$ and therefore also $x.\text{imag} = y.\text{imag}$.

Transitivity : For transitivity let $x \triangleleft y$ and $y \triangleleft z$. We find four cases. In case $x.\text{real} \neq y.\text{real}$ and $y.\text{real} \neq z.\text{real}$ we get $x.\text{real} < z.\text{real}$ by transitivity of $<$, hence $x \triangleleft z$. In case $x.\text{real} \neq y.\text{real}$ and $y.\text{real} = z.\text{real}$ we get $x.\text{real} < y.\text{real} = z.\text{real}$, therefore $x \triangleleft z$. In case $x.\text{real} = y.\text{real}$ and $y.\text{real} \neq z.\text{real}$ we get $x.\text{real} = y.\text{real} < z.\text{real}$, similar as the last case. In the last case $x.\text{real} = y.\text{real} = z.\text{real}$ we get $x.\text{imag} < y.\text{imag}$ and $y.\text{imag} < z.\text{imag}$ and again by transitivity of $<$ we get $x.\text{imag} < z.\text{imag}$, hence $x \triangleleft z$ again.

Connexity : Connexity is given since for any two points $x, y \in g \cap A$ we have either $x.\text{real} \neq y.\text{real}$ or $x.\text{real} = y.\text{real}$ and therefore either $x \triangleleft y$ or $y \triangleleft x$. □

Remark 6.0.1. The relation \triangleleft on $g \cap A$ basically orders the hitpoints of g with A from left to right (or bottom to top in case of a line parallel to the y -axis). This order allows us to identify the outest hitting points which are minimum and maximum of $g \cap A$ respecting \triangleleft . To clarify, we define $\min(g \cap A) := x_0$ if and only if $x_0 \triangleleft x$ for all $x \in g \cap A$, analogously $\max(g \cap A)$. This means when moving on g facing A coming from infinity this order allows to know where in A the line g hits first when "entering" A and where it hits last when "leaving" A .

6 Line Hitting Aggregate

Remind, for a bounded subset $A \subset \mathbb{C}$ the convex hull $\text{conv}(A)$ of A is defined to be the smallest convex set containing A , formally

$$\text{conv}(A) := \bigcap_{A \subset K \in \mathcal{K}^2} K.$$

Note that $\text{conv}(A) \in \mathcal{K}^2$ for all bounded subsets $A \subset \mathbb{C}$. For a set $A \in \mathcal{P}_f$ we define

$$\text{conv}(A) := \text{conv}\left(\bigcup_{p \in A} sq(p)\right)$$

and since $\bigcup_{p \in A} sq(p)$ is a bounded set we have $\text{conv}(A) \in \mathcal{K}^2$ here aswell.

Definition 6.0.3. (*Random Line Hitting Distribution*) Let $A \in \mathcal{P}_f$ and $g : \Omega \rightarrow \mathcal{G}$ be a random $\text{conv}(A)$ -isotropic line. Then define a distribution $\mu_A \sim \mathcal{U}(\{\min(g \cap A), \max(g \cap A)\})$, which chooses uniformly out of the outest hitting points of g with A . We call this family $(\mu_A)_{A \in \mathcal{P}_f}$ of distributions the *Random Line Hitting Distribution*.

Definition 6.0.4. (*Line Hitting Aggregate*) An Incremental Aggregate with the Random Line Hitting Distribution we call *Line Hitting Aggregate*, short *LHA*.

7 Python Simulation

Part of the work in this paper is the attempt to build simulations for both incremental aggregates *External DLA* and *LHI* which were presented in the previous sections. For calculating the simulations we use *Python* and for rendering pictures we use the package *Pygame*. Each vertex in \mathbb{Z}^2 is naturally mapped to its coordinate and is represented in this way in python code. In graphics each coordinate basically can be represented by squares in \mathbb{C} as presented in Definition 6.0.1, and each square will be represented by exactly one pixel, so every picture about incremental aggregates you'll see in the following consists of pixels each representing exactly one vertex in \mathbb{Z}^2 in the most natural way. Our aim will be to simulate the aggregates as close as possible to their mathematical definitions. This is much easier for LHI, and less obvious for External DLA. We start of with External DLA in the following.

7.1 External DLA Simulation

By identifying each vertex in \mathbb{Z}^2 with its square in \mathbb{C} and a pixel when rendering, the representation of the space we are moving is exact. For any simulation of randomness we use the package *random*. Respecting the error behaviour of this package, random walks on \mathbb{Z}^2 can be simulated directly and therefore very exact. For External DLA we let a particle move randomly on the grid and wait for it to hit the actual cluster. The problem which will have to be solved is where to start the moving particle and how to handle a particle when it is moving away from the actual cluster, therefore creating a too long waiting time for it coming back to the cluster. In the definition of External DLA new particles start the random walk from infinity. Obviously this is not possible in simulation so this has to be solved differently.

7.2 LHI Simulation

8 Questions

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Erklärung

Hiermit versichere ich, dass ich diese Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt, die wörtlich oder inhaltlich übernommen Stellen als solche kenntlich gemacht und die Satzung des Karlsruher Instituts für Technologie zur Sicherung guter wissenschaftlicher Praxis in der jeweils gültigen Fassung beachtet habe.

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