

Hyperuniformity of 1D Point Patterns

Week 1 Progress

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February 25, 2026

2026-02-25

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Week 1 progress update on the 1D hyperuniformity project.

Background

A point pattern is **hyperuniform** if density fluctuations are suppressed relative to random (Torquato & Stillinger, 2003):

$$S(k) \sim |k|^\alpha \text{ as } k \rightarrow 0, \quad \sigma^2(R) \sim \begin{cases} R^{d-\alpha} & 0 < \alpha < 1 \\ R^{d-1} \ln R & \alpha = 1 \\ R^{d-1} & \alpha > 1 \end{cases}$$

Three chains built from substitution rules on tiles $S=1, L=\mu$:

Chain	Rule	Metallic mean μ	ρ
Fibonacci	$S \rightarrow L, L \rightarrow LS$	$\tau \approx 1.618$	0.724
Silver	$S \rightarrow L, L \rightarrow LLS$	$\mu_2 \approx 2.414$	0.500
Bronze	$S \rightarrow L, L \rightarrow LLLS$	$\mu_3 \approx 3.303$	0.361

Goal: numerically verify the eigenvalue prediction $\alpha = 3$ (Oğuz et al., 2019) for all three chains, using diffusion spreadability (Torquato, 2021).

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└ Background

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Hyperuniformity: Torquato & Stillinger (2003). Eigenvalue formula: Oğuz et al. (2019), Acta Cryst. A 75. Spreadability method: Torquato (2021), Phys. Rev. E 104.

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A point pattern is **hyperuniform** if density fluctuations are suppressed relative to random (Torquato & Stillinger, 2003):

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Code Validation: Poisson Benchmark

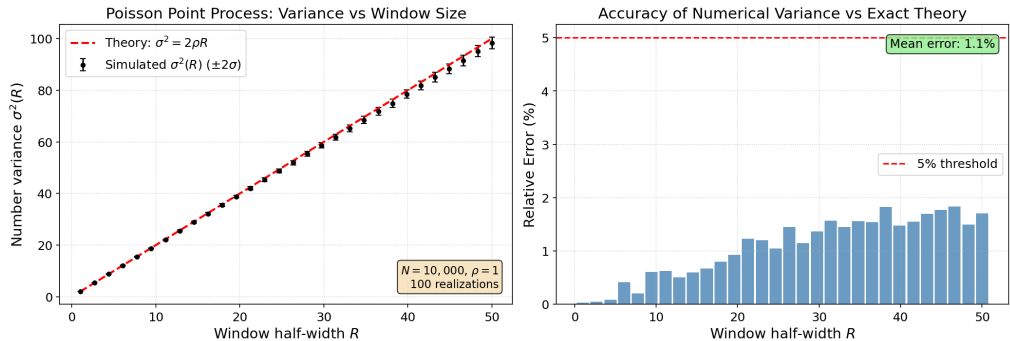


Figure 1: Code Validation — Poisson number variance matches exact result $\sigma^2 = 2\rho R$

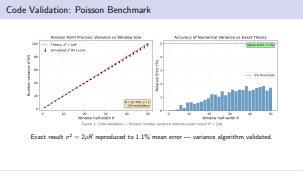
Exact result $\sigma^2 = 2\rho R$ reproduced to 1.1% mean error — variance algorithm validated.

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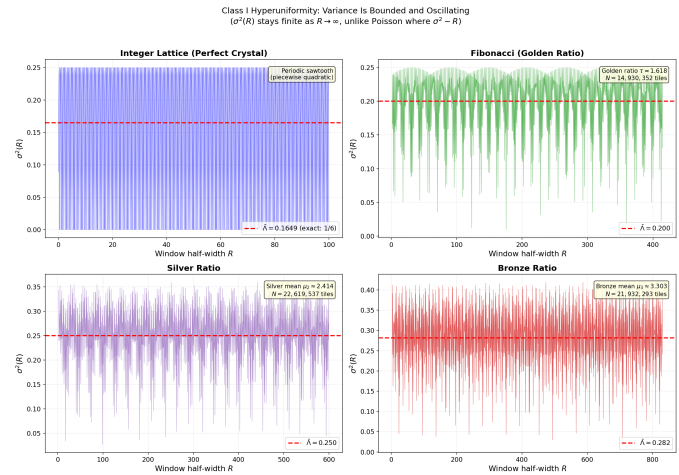
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- Validation
- Code Validation: Poisson Benchmark

100 independent Poisson patterns, $N=10,000$. This validates the sliding-window algorithm used for all subsequent measurements.



Bounded Variance — Class I Confirmed



Pattern	$\bar{\Lambda}$	Exact
Lattice	0.165	$1/6$
Fibonacci	0.200	—
Silver	0.250	—
Bronze	0.282	—

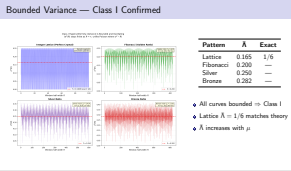
- All curves bounded \Rightarrow Class I
- Lattice $\bar{\Lambda} = 1/6$ matches theory
- $\bar{\Lambda}$ increases with μ

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- Results

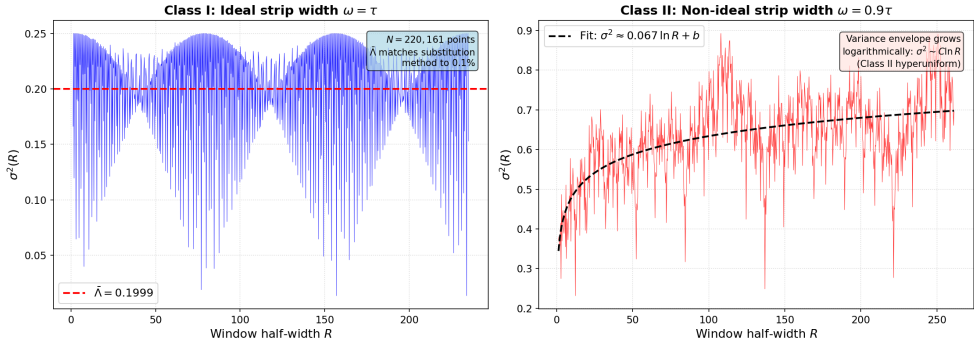
Bounded Variance — Class I Confirmed

Lattice $\bar{\Lambda} = 1/6$ exact (Torquato & Stillinger, 2003). Fibonacci $\bar{\Lambda} = 0.201$ reported numerically in Zachary & Torquato (2009); our 0.200 matches to 0.5%.



Projection Method: Class I vs. Class II

Projection (Cut-and-Project) Method: Strip Width Controls Hyperuniformity Class
Ideal $\omega = \tau$ gives Class I (bounded); non-ideal $\omega \neq \tau$ degrades to Class II (log growth)



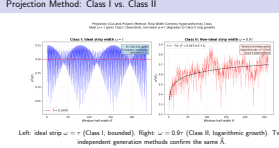
Left: ideal strip $\omega = \tau$ (Class I, bounded). Right: $\omega = 0.9\tau$ (Class II, logarithmic growth). Two independent generation methods confirm the same $\bar{\lambda}$.

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Results

Projection Method: Class I vs. Class II



The cut-and-project method provides an independent realization. Any deviation from ideal strip width degrades Class I to Class II.

Problem: $S(k)$ has dense Bragg peaks \implies can't read off α directly (Torquato, 2021).

Solution: embed points in a two-phase medium (Torquato, 2002) and measure diffusion spreadability (Torquato, 2021):

- 1 Decorate each point with a solid rod (packing fraction $\phi_2 = 0.35$)
- 2 Compute spectral density $\tilde{\chi}_V(k) = \rho |\tilde{m}(k)|^2 S(k)$
- 3 Evaluate excess spreadability $E(t)$ via Gaussian-smoothed sum
- 4 Extract α from long-time power-law decay: $E(t) \sim t^{-(1+\alpha)/2}$

The Gaussian kernel e^{-k^2Dt} naturally smooths over the dense Bragg peaks, revealing the underlying α (Torquato, 2021; Hitin-Bialus et al., 2024).

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└ Results

└ Spreadability Method

Two-phase media: Torquato (2002), Random Heterogeneous Materials, Ch. 2. Spreadability method: Torquato (2021), Phys. Rev. E 104, 054102. Applied to quasicrystals: Hitin-Bialus et al. (2024), Princeton thesis. Packing fraction $\phi_2 = 0.35$ follows from Hitin-Bialus (2024).

Spreadability Method

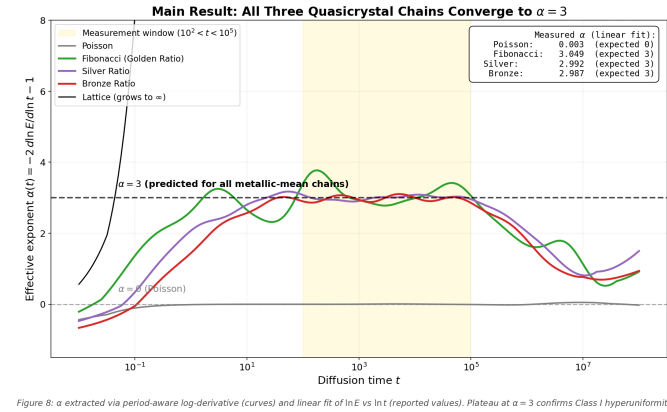
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Main Result: $\alpha = 3$ for All Three Chains



Pattern	α	Exp.
Poisson	0.003	0
Fibonacci	3.049	3
Silver	2.992	3
Bronze	2.987	3

Errors: Fib 1.6%, Ag 0.3%, Br 0.4%.
Linear fit over $t \in [10^2, 10^5]$.

$\alpha = 3$ confirmed,
matching Oğuz et al. (2019).

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Results

Main Result: $\alpha = 3$ for All Three Chains

Main result: all three chains give $\alpha \approx 3$, matching the eigenvalue prediction $\alpha = 1 - 2 \ln |\lambda_2| / \ln \lambda_1$ from Oğuz et al. (2019). Poisson baseline confirms $\alpha \approx 0$.

