

Mathematical Embeddings of Complex Systems

Daryl DeFord

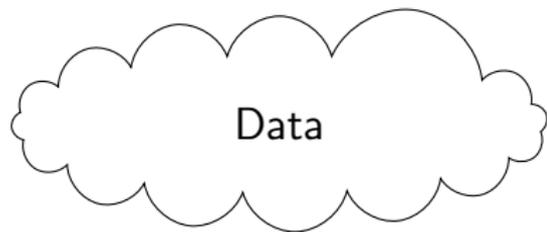
Dartmouth College
Department of Mathematics

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Santa Fe Institute
Santa Fe, NM
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Outline

- 1 Introduction
- 2 Time Series Entropy
- 3 SFCs for Parallel Computing
- 4 Multiplex Dynamics
- 5 Conclusion

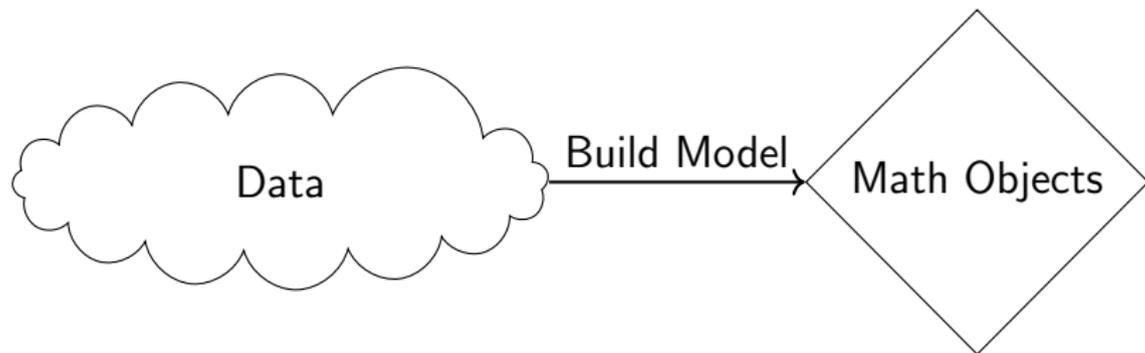
Philosophy



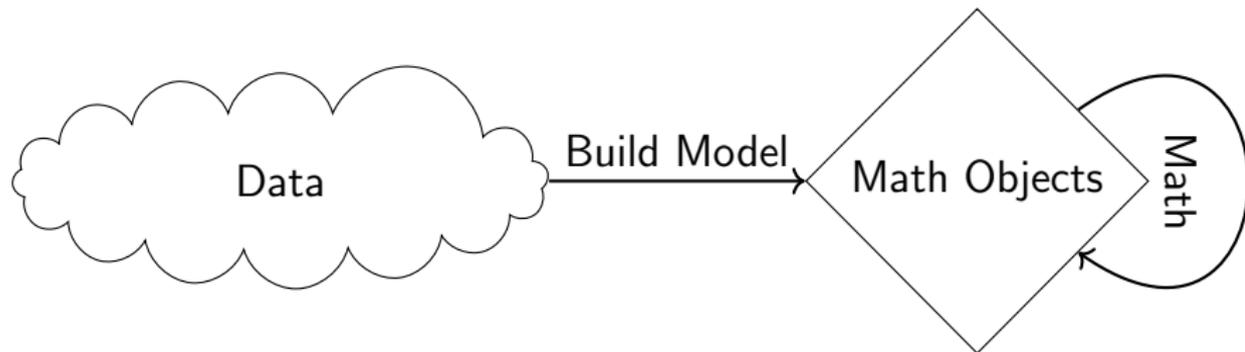
Philosophy



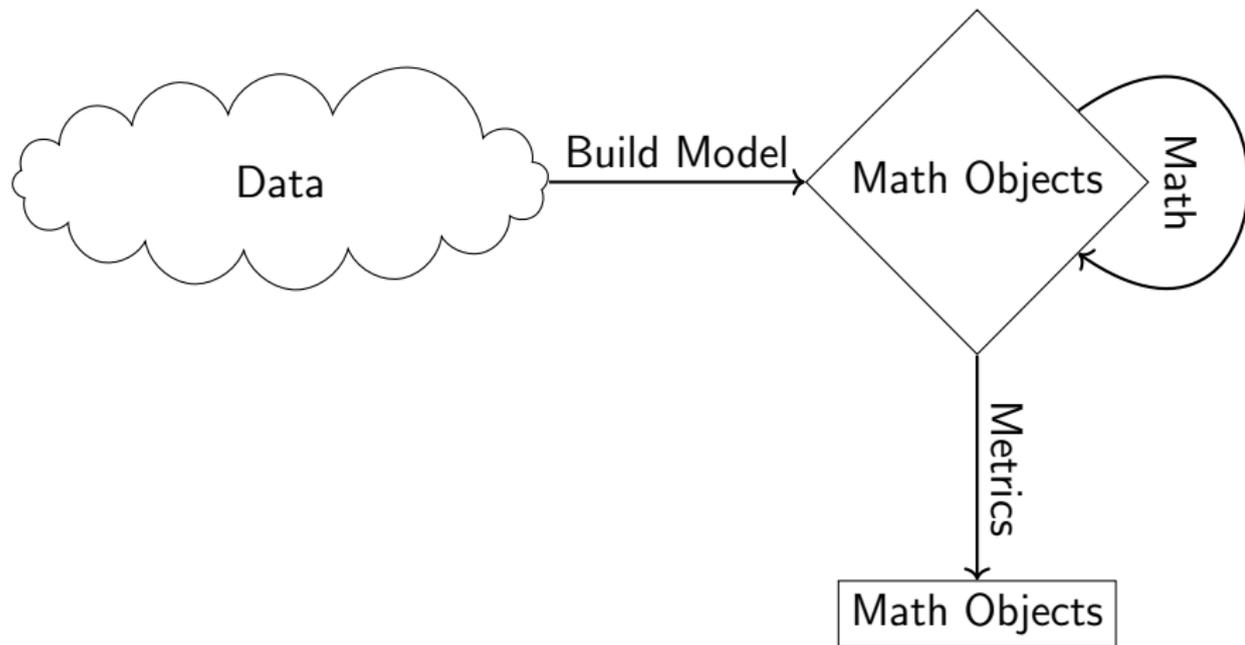
Philosophy



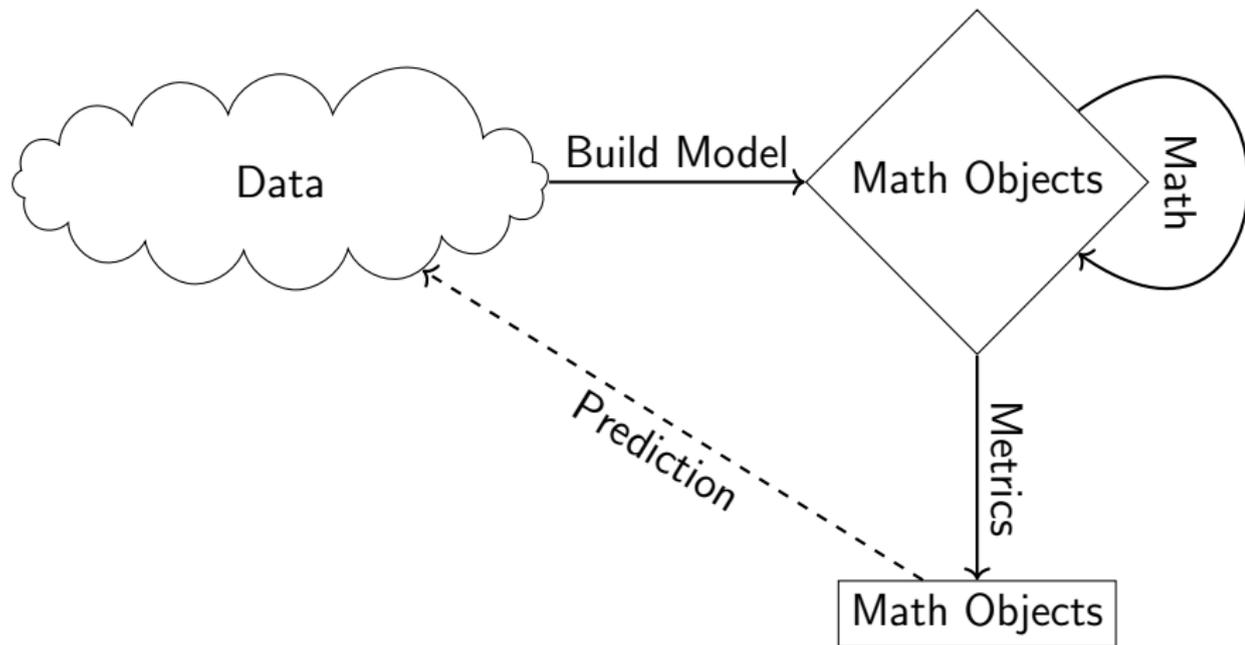
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Philosophy



Motivating Examples



(a) C.O.M.P.A.S.

Images from Wikipedia.

Motivating Examples



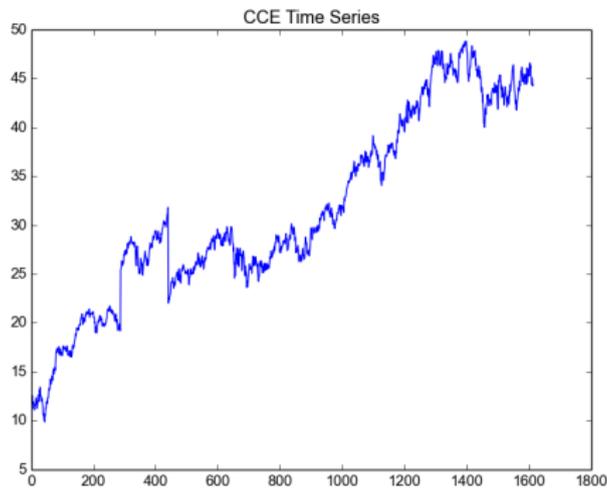
(a) C.O.M.P.A.S.



(b) Gerrymandering

Images from Wikipedia.

Time Series



Iterated Maps

Given a function $f : [0, 1] \rightarrow [0, 1]$ and a point $x \in [0, 1]$, consider the behavior of $\{x, f(x), f(f(x)), f(f(f(x))), \dots\}$.

Iterated Maps

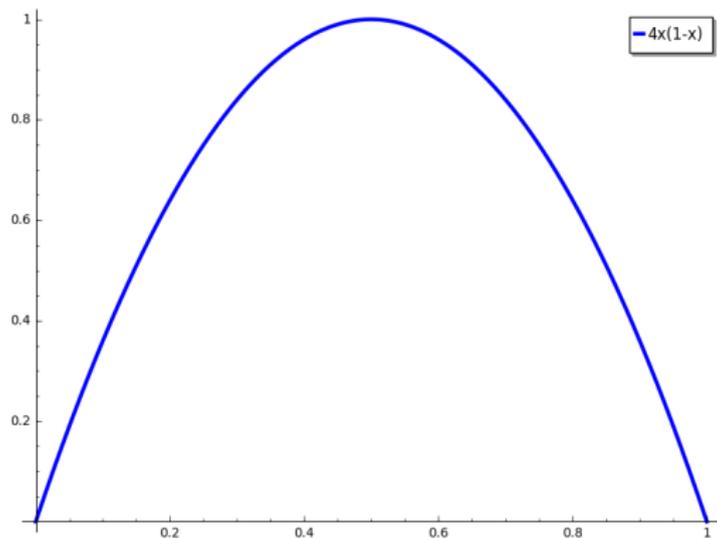
Given a function $f : [0, 1] \rightarrow [0, 1]$ and a point $x \in [0, 1]$, consider the behavior of $\{x, f(x), f(f(x)), f(f(f(x))), \dots\}$.

Example

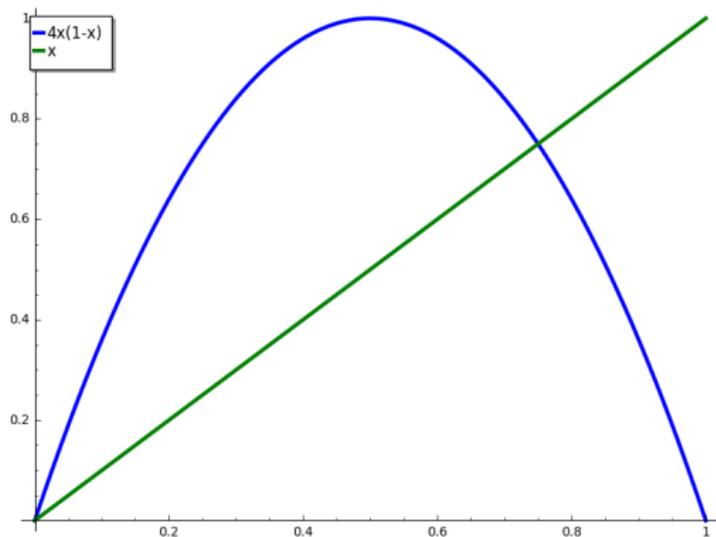
Let $f(x) = 4x(1 - x)$ and $x_0 = .2$. Then, the list of values is:

$[0.20, 0.64, 0.92, 0.28, 0.82, 0.58, 0.97, 0.11, 0.40, \dots]$.

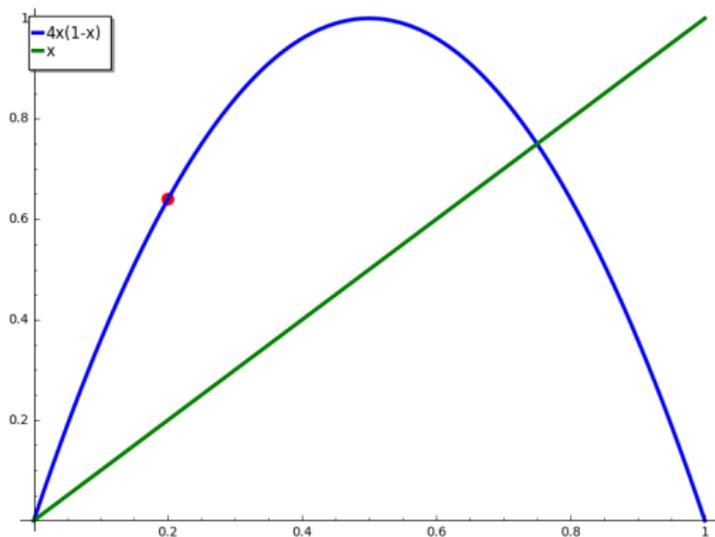
Iterated Example



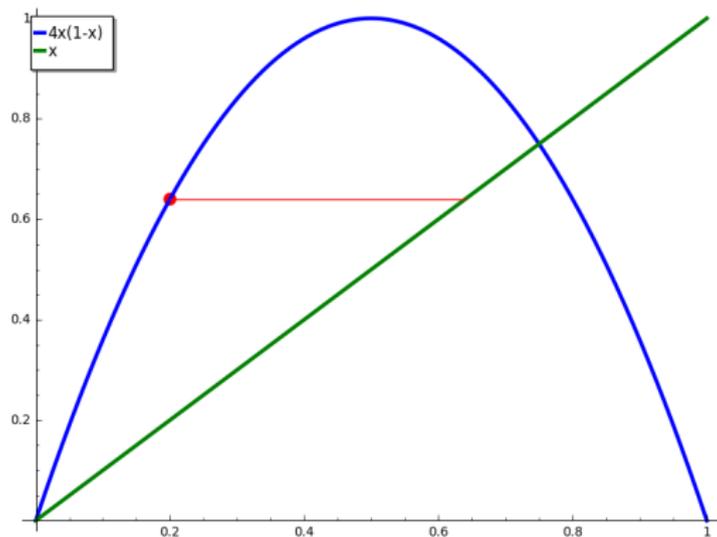
Iterated Example



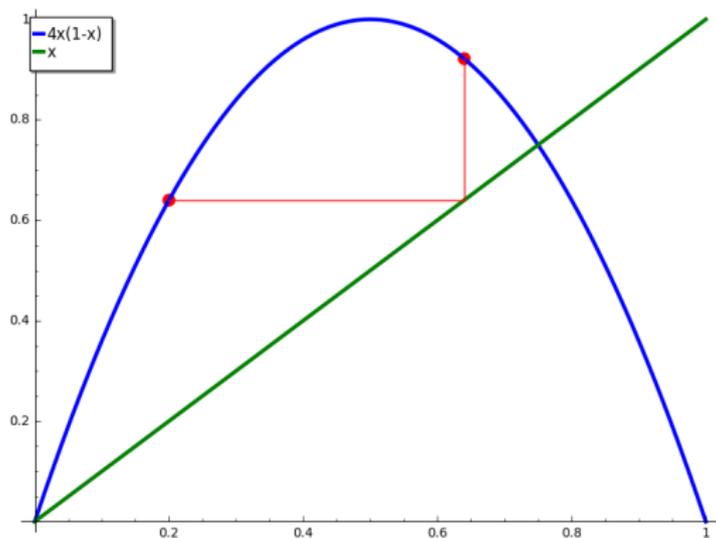
Iterated Example



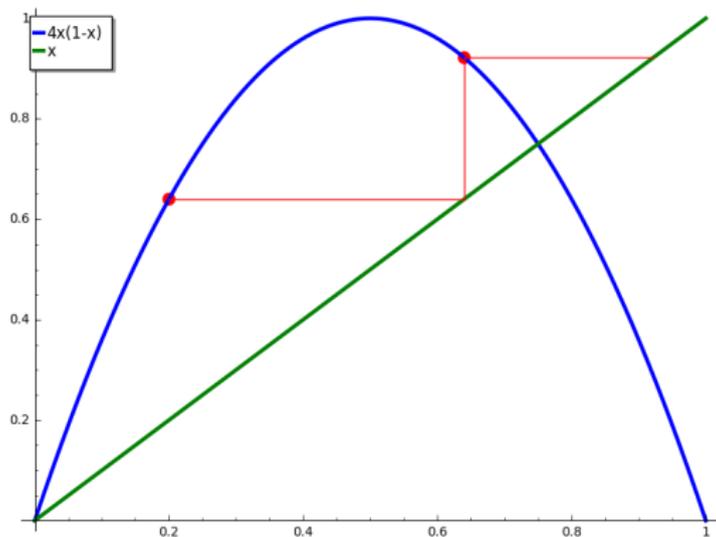
Iterated Example



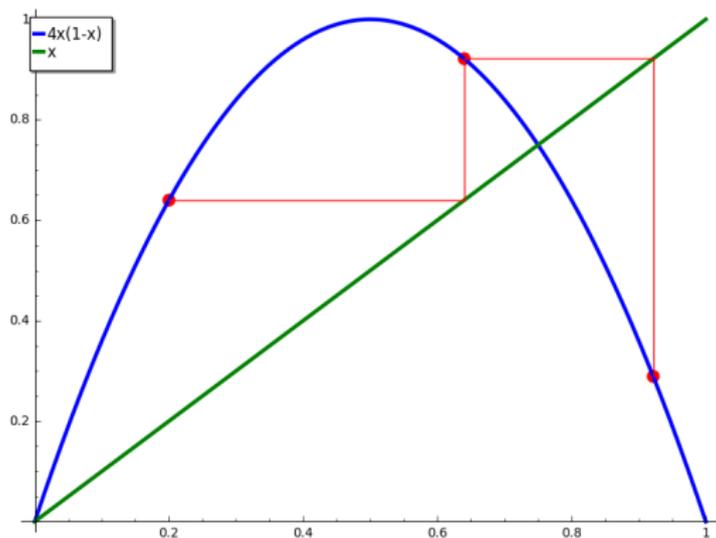
Iterated Example (12)



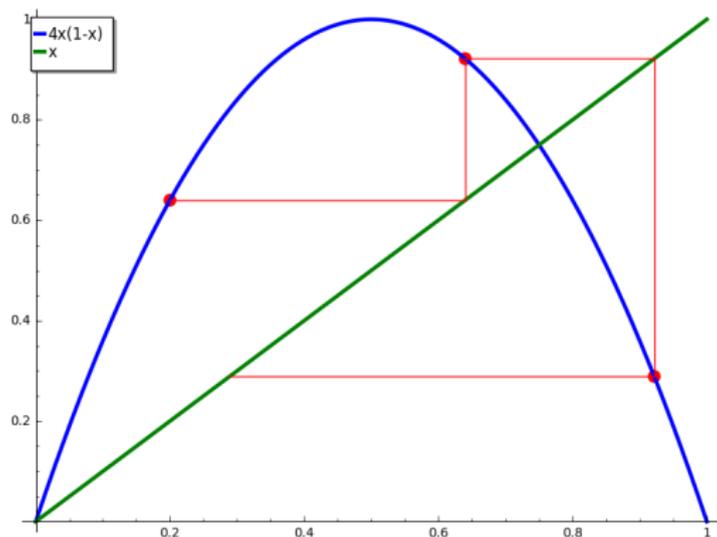
Iterated Example (12)



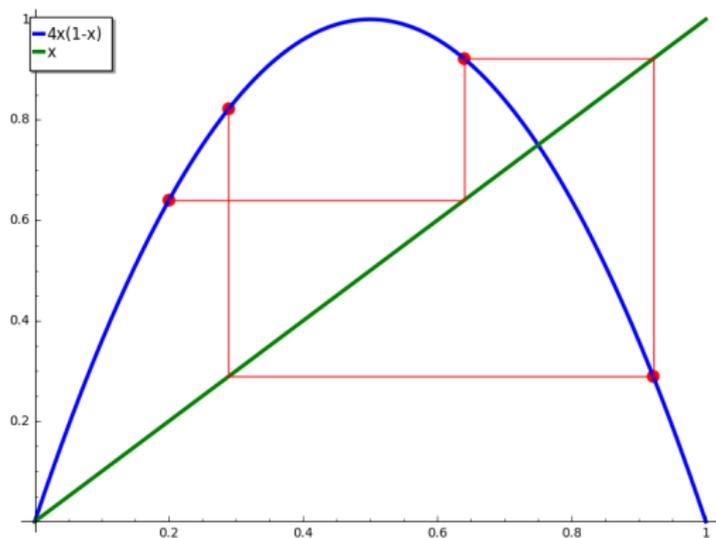
Iterated Example (231)



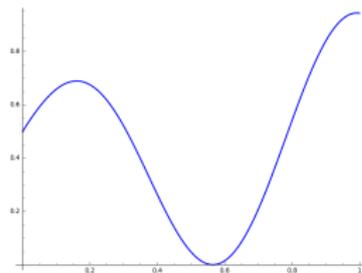
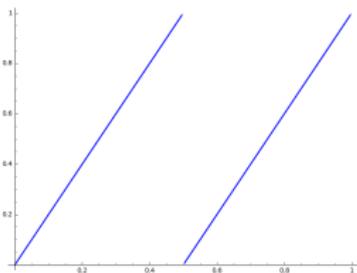
Iterated Example (231)



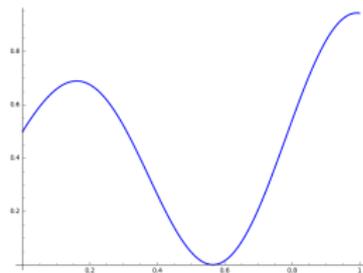
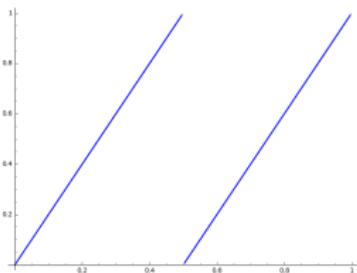
Iterated Example (2413)



Forbidden Patterns



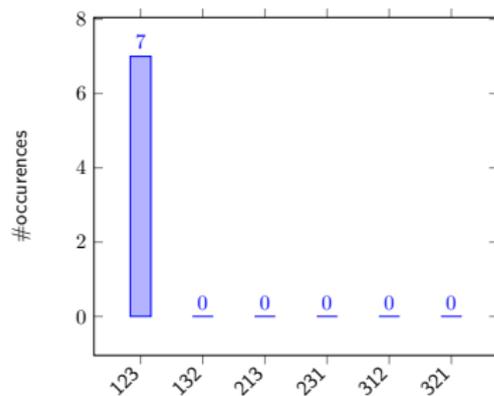
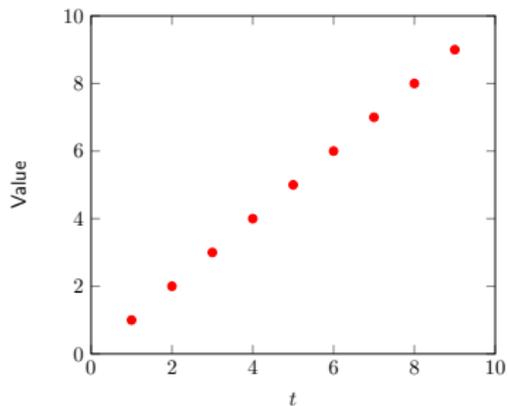
Forbidden Patterns



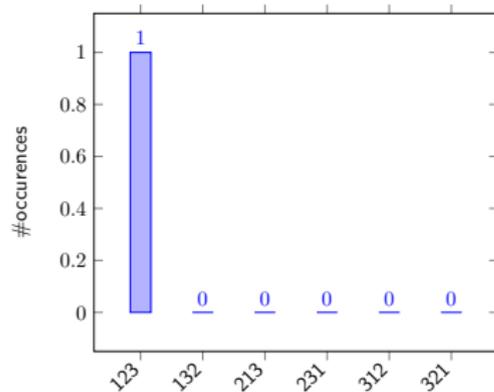
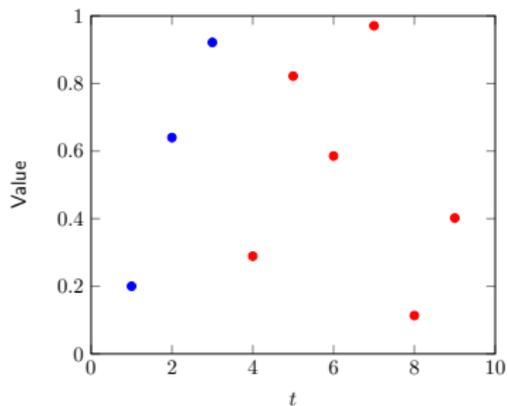
Definition (Topological Entropy)

$$TE = \lim_{n \rightarrow \infty} \frac{\log(|\text{Allow}(f)|)}{n - 1}$$

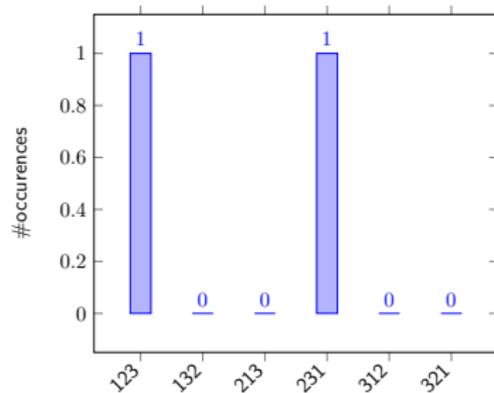
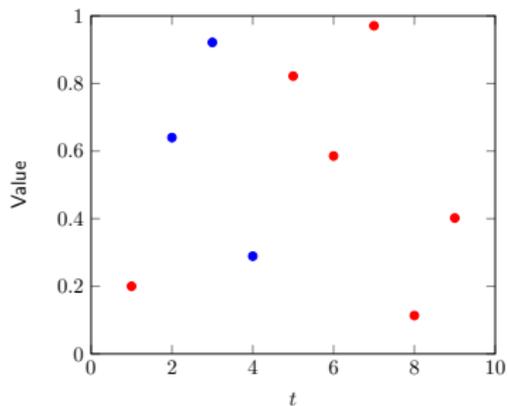
Simple Time Series



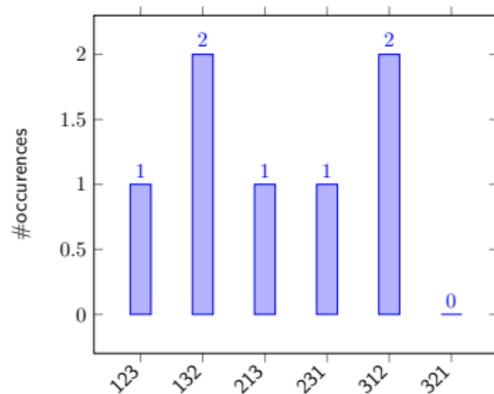
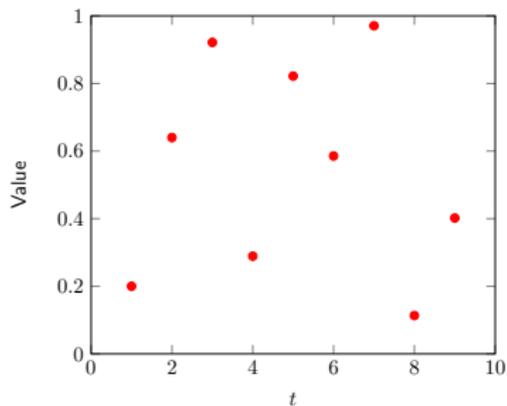
Complex Time Series



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Complexity Measures

Definition (Normalized Permutation Entropy)

$$NPE(\{X_i\}) = -\frac{1}{\log(N!)} \sum_{\pi \in S_n} p_\pi \log(p_\pi)$$

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$$D_{KL}(\{X_i\} || \text{UNIFORM}) = \sum_{\pi \in S_n} p_\pi \log\left(\frac{p_\pi}{\frac{1}{n!}}\right)$$

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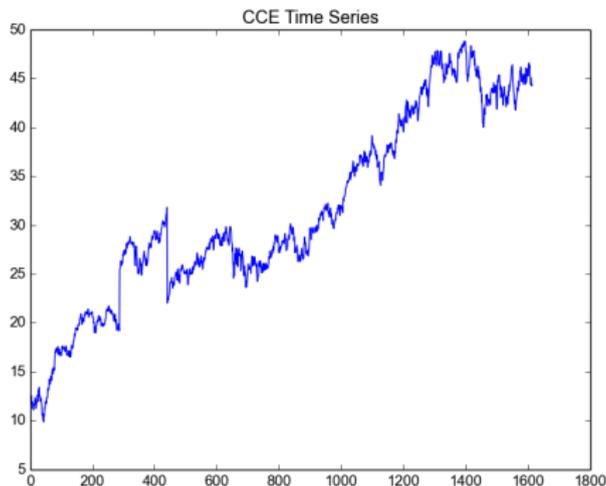
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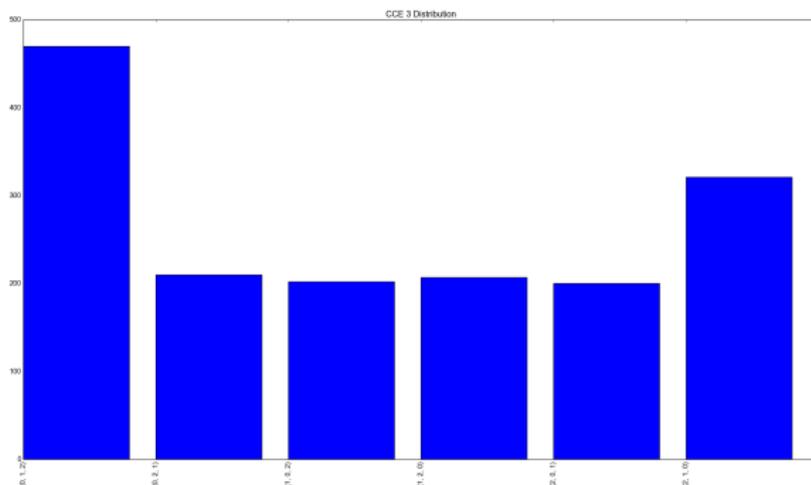
Observation

$$1 - NPE(\{X_i\}) = \frac{1}{\log(N!)} D_{KL}(\{X_i\} || \text{UNIFORM})$$

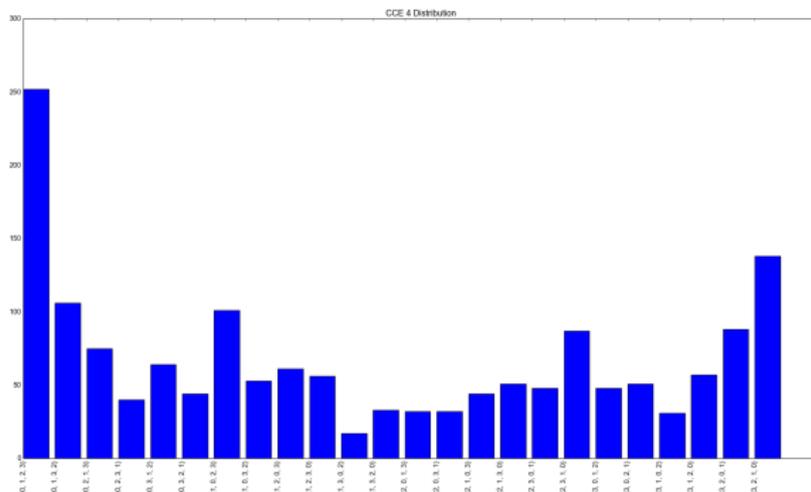
Stock Data (Closing Prices)



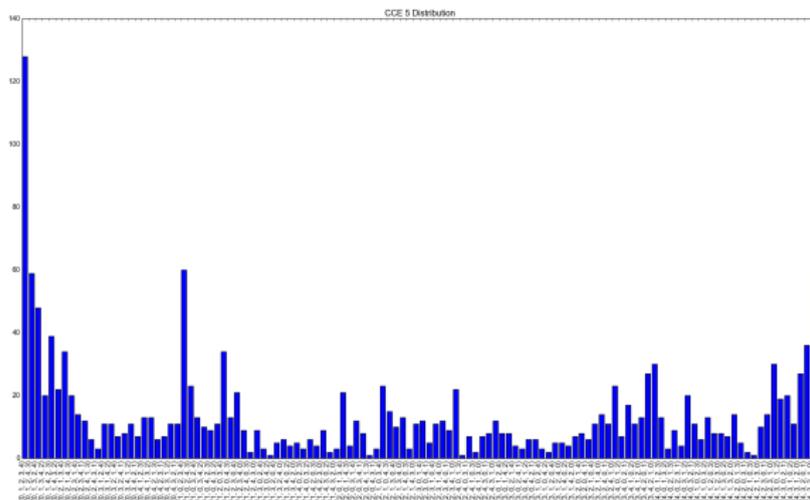
Stock Data (n=3)



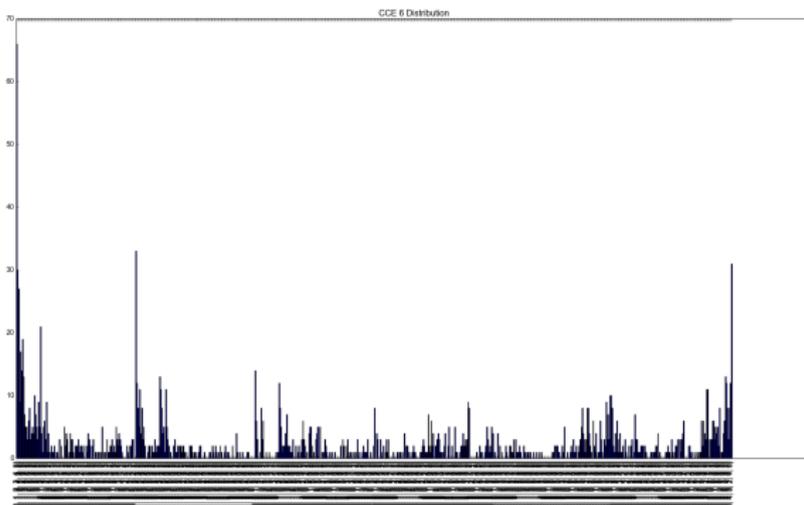
Stock Data (n=4)



Stock Data (n=5)



Stock Data (n=6)



Random Walk Null Models

Definition (Random Walk)

Let $\{X_i\}$ be a set of I.I.D. continuous random variables and define $\{Z_i\}$ by $Z_j = \sum_{i=0}^j X_i$. Usually the steps $\{X_i\}$ will be uniformly or normally distributed.

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Proposition (No Forbidden Patterns)

If $\{Z_i\}$ are defined as above then every permutation occurs with some positive probability.

Proposition (No Uniform Distribution)

If $\{Z_i\}$ are defined as above and $n \geq 3$ then the expected distribution of permutations is not uniform.

New Complexity Measure

Definition (Null Model KL Divergence)

$$D_{\text{KL}n}(X) := D_{\text{KL}n}(X||Z) = \sum_{\pi \in \mathcal{S}_n} p_{\pi} \log \left(\frac{p_{\pi}}{q_{\pi}} \right),$$

where p_{π} is the relative frequency of π in X and q_{π} is the relative frequency of π in Z .

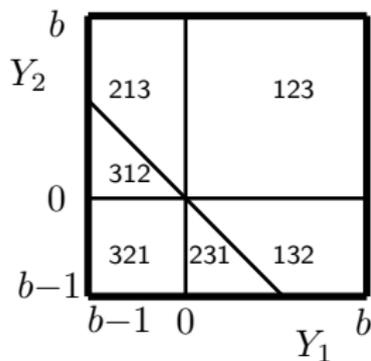
Hyperplanes

Example (Uniformly distributed steps)

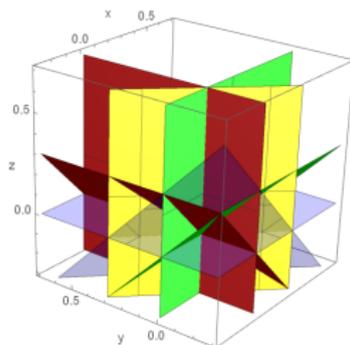
In order for the pattern 1342 to appear in the random walk time series we need the following inequalities to hold:

- $X_1 > 0$
- $X_2 > 0$
- $X_3 < 0$
- $X_3 > X_2$
- $X_3 < X_1 + X_2$

Integration Regions



(a)



(b)

Figure: The regions of integration for patterns in uniform random walks for (a) $n = 3$ and (b) $n = 4$, sketched here for $b = 0.65$.

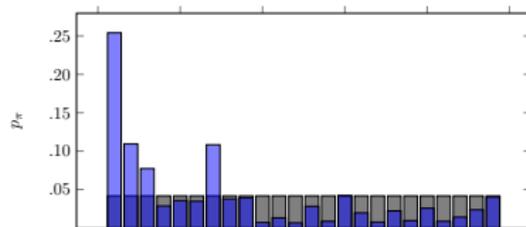
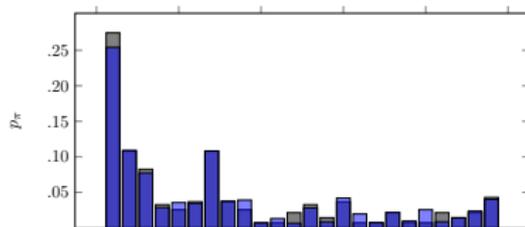
Null Distributions ($n = 3$)

Pattern	Normal: $\mu = 0$	Uniform: $\mu = 0$	Uniform: $\mathbb{P}(Y > 0) = b$
{123}	1/4	1/4	b^2
{132, 213}	1/8	1/8	$(1/2)(1 - b)^2$
{231, 312}	1/8	1/8	$(1/2)(b^2 + 2b - 1)$
{321}	1/4	1/4	$(1 - b)^2$

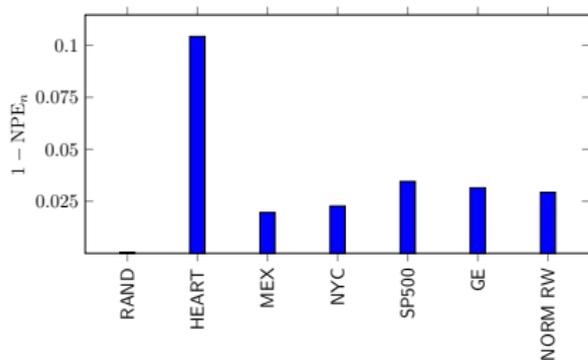
Null Distributions ($n = 4$)

Pattern	Normal: $\mu = 0$	Uniform: $\mu = 0$	Uniform: $\mathbb{P}(Y > 0) = b$
{1234}	0.1250	1/8	b^3
{1243, 2134}	0.0625	1/16	$(1/2)b(1-b)(3b-1)$
{1324}	0.0417	1/24	$(1/3)(1-b)(7b^2-5b+1)$
{1342, 3124}	0.0208	1/24	$(1/6)(1-b)^2(4b-1)$
{1423, 2314}	0.0355	1/48	$(1/6)(1-b)^2(5b-2)$
{1432, 2143, 3214}	0.0270	1/48	$\begin{cases} (1/6)(2-24b+48b^2-15b^3) & \text{if } b \leq 2/3 \\ (b-1)^2(2b-1) & \text{if } b > 2/3 \end{cases}$
{2341, 3412, 4123}	0.0270	1/48	$(1/6)(1-b)^3$
{2413}	0.0146	1/48	$(1/6)(1-b)^3$
{2431, 4213}	0.0208	1/24	$\begin{cases} (1/6)(24b^3-45b^2+27b-5) & \text{if } b \leq 2/3 \\ (1/2)(1-b)^3 & \text{if } b > 2/3 \end{cases}$
{3142}	0.0146	1/48	$\begin{cases} (1/6)(25b^3-48b^2+30b-6) & \text{if } b \leq 2/3 \\ (1/3)(1-b)^3 & \text{if } b > 2/3 \end{cases}$
{3241, 4132}	0.0355	1/48	$(1/6)(1-b)^3$
{3421, 4312}	0.0625	1/16	$(1/2)(1-b)^3$
{4231}	0.0417	1/24	$(1/3)(1-b)^3$
{4321}	0.1250	1/8	$(1-b)^3$

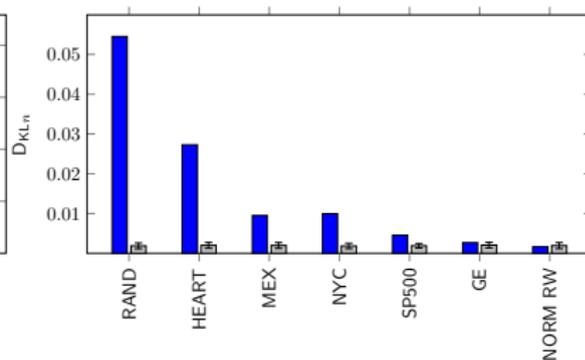
Uniform Steps S&P 500



Data Comparisons

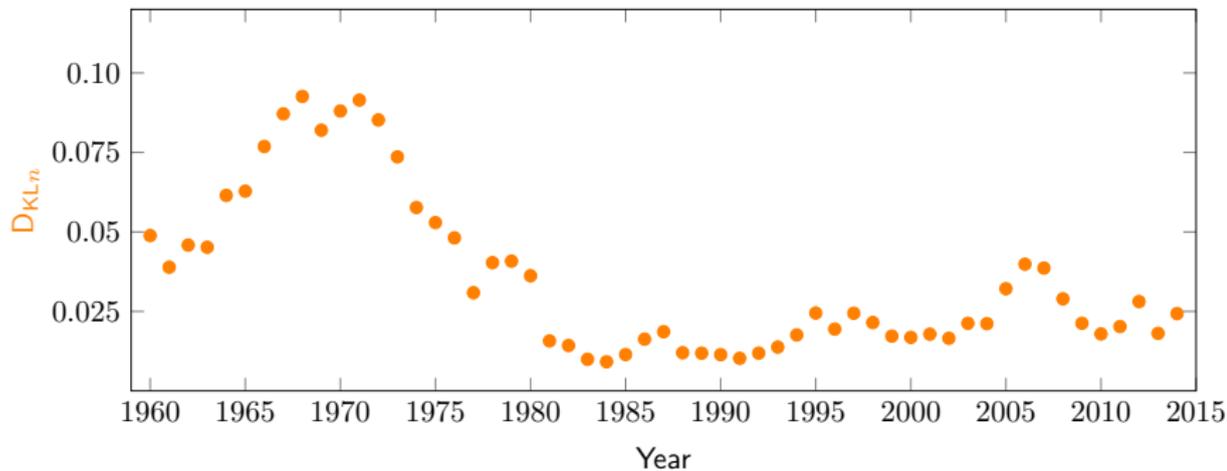


(a)

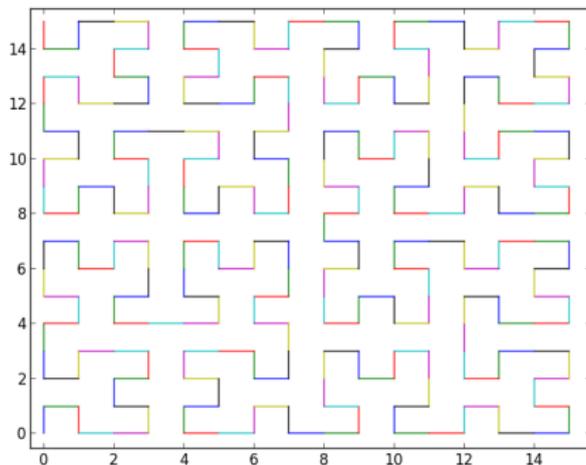


(b)

Stock Market Example



Hilbert Curve



Parallel Computing

- Latency in communication overhead has become a limiting factor in designing parallel algorithms
- Designing ways to efficiently embed problems to minimize communication is an important problem

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- Factors:
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 - ...
- Previous Approaches
 - Database Methods
 - Average Nearest Neighbor Stretch

Discrete Space Filling Curves

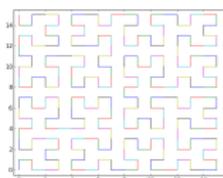
Definition

A Discrete Space Filling Curve is a mapping from multi-dimensional space to a linear order that allows for a unique indexing of the points.

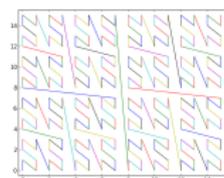
Discrete Space Filling Curves

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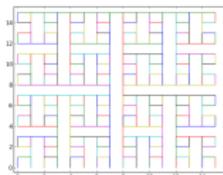
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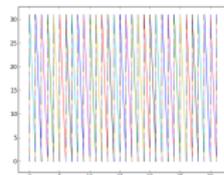
(a) Hilbert Curve \mathcal{H}_4



(b) Z-Curve \mathcal{Z}_4

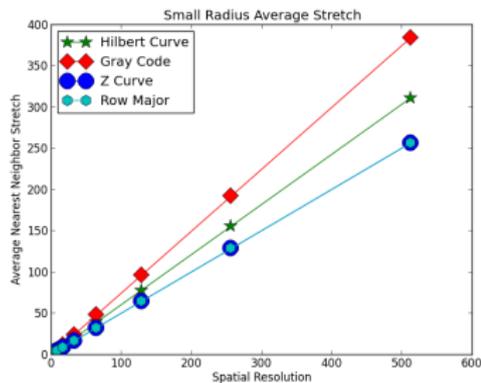


(c) Gray Order \mathcal{G}_4

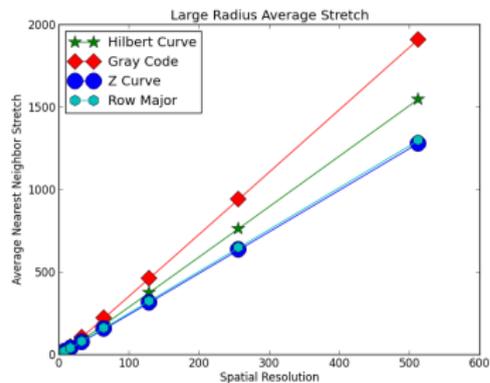


(d) Column Order

ANNS Result



(a) Standard ANNS



(b) Large Radius ANNS

Average Communicated Distance

Definition (ACD)

Given a particular problem instance, the *Average Communicated Distance (ACD)* is defined as the average distance for every pairwise communication made over the course of the entire application. The communication distance between any two communicating processors is given by the length of the shortest path (measured in the number of hops) between the two processors along the network intraconnect.

Average Communicated Distance

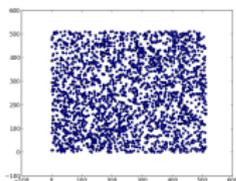
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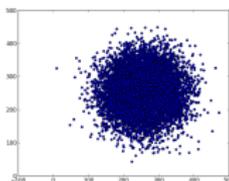
Definition (FMM)

The Fast Multipole Method (FMM) is an algorithm for approximating the interactions in an n body problem. The computations can be separated into two components: Near Field Interactions (NFI) and Far Field Interactions (FFI), with very different communications profiles.

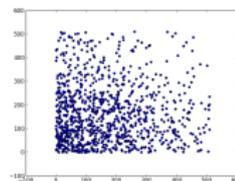
Point Distributions



(a) Uniform

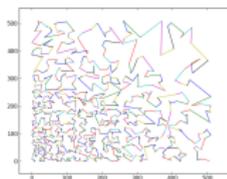


(b) Normal

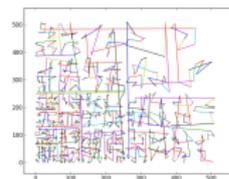


(c) Exponential

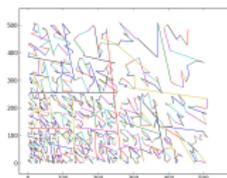
Ordered Points



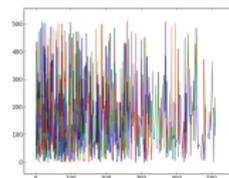
(a) Hilbert Ordering



(b) Gray Ordering



(c) Z Ordering



(d) Row Major
Ordering

Main Results (NFI)

Table: A comparison of different particle/processor-order SFC combinations for NFI under various distributions. The lowest ACD value within each row is displayed in **boldface blue**, while the lowest ACD value within each column is displayed in *red italics*. The best option for each distribution is displayed in **bold green italics**.

	Particle Order			
Processor Order ↓	Hilbert Curve	Z-Curve	Gray Code	Row Major
Hilbert Curve	4.008	<i>4.308</i>	<i>4.939</i>	<i>13.117</i>
Z-Curve	5.486	5.758	6.573	18.127
Gray Code	5.802	6.010	6.970	19.220
Row Major	9.126	9.763	11.713	70.353

Table: Uniform Distribution

Main Results (NFI) Continued

	Particle Order			
Processor Order ↓	Hilbert Curve	Z-Curve	Gray Code	Row Major
Hilbert Curve	8.561	<i>9.297</i>	<i>10.123</i>	<i>20.340</i>
Z-Curve	11.003	11.551	12.984	26.842
Gray Code	11.881	12.595	13.249	28.188
Row Major	20.143	22.221	24.053	66.719

(a) Normal Distribution

	Particle Order			
Processor Order ↓	Hilbert Curve	Z-Curve	Gray Code	Row Major
Hilbert Curve	5.238	<i>5.654</i>	<i>6.271</i>	<i>14.943</i>
Z-Curve	6.943	7.070	8.235	20.851
Gray Code	7.276	7.663	8.760	22.269
Row Major	12.483	13.017	15.289	61.227

(b) Exponential Distribution

Main Results (FFI)

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	Particle Order			
Processor Order ↓	Hilbert Curve	Z-Curve	Gray Code	Row Major
Hilbert Curve	19.494	<i>20.841</i>	<i>22.572</i>	<i>31.124</i>
Z-Curve	24.217	24.793	27.787	37.709
Gray Code	24.622	25.446	27.997	39.282
Row Major	44.513	48.762	50.118	57.880

Table: Uniform Distribution

Main Results (NFI) Continued

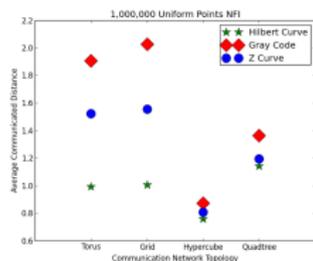
	Particle Order			
Processor Order ↓	Hilbert Curve	Z-Curve	Gray Code	Row Major
Hilbert Curve	26.336	<i>26.824</i>	31.963	<i>32.542</i>
Z-Curve	29.160	28.036	34.241	36.663
Gray Code	29.449	27.981	<i>31.909</i>	37.291
Row Major	43.639	44.636	49.133	45.475

(a) Normal Distribution

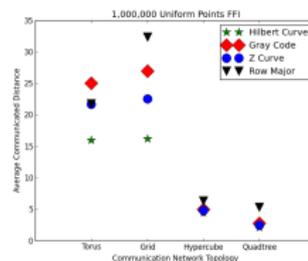
	Particle Order			
Processor Order ↓	Hilbert Curve	Z-Curve	Gray Code	Row Major
Hilbert Curve	18.960	<i>19.841</i>	<i>23.007</i>	<i>31.368</i>
Z-Curve	24.672	23.316	26.315	37.576
Gray Code	23.762	24.076	27.973	37.863
Row Major	42.447	44.067	46.872	50.963

(b) Exponential Distribution

Topology Comparison



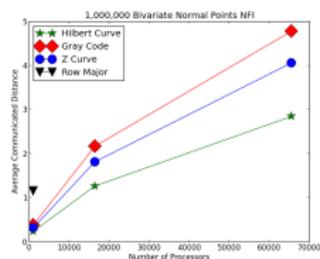
(e) Near-Field Interactions



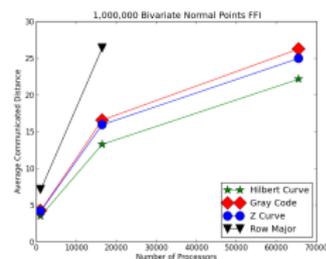
(f) Far-Field Interactions

Figure: The charts show the results of comparing different network topologies for a) NFI and b) FFI, respectively. All experiments were performed using 1,000,000 uniformly distributed particles on a 4096×4096 spatial resolution. This plot is representative of all the experiments we performed to evaluate the topologies. It is important to note that quadtree structures have disproportionately large issues with contention in high volume communications.

Processor Scaling



(a) NFI



(b) FFI

Figure: These plots show ACD values for a) NFI, and b) FFI, as a function of the number of processors and the SFC used. The input used was fixed at 1,000,000 uniformly distributed particles. This demonstrates the effect scale on processor ranking SFCs. Some of the row-major data has been excluded from these plots because for this SFC, the ACD values at larger processor numbers were significantly higher than the other data-points.

What is a multiplex?

What is a multiplex?

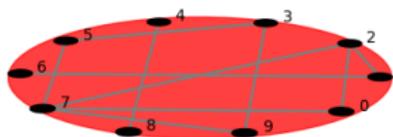
Definition

A *multiplex* is a collection of graphs all defined on the same node set.

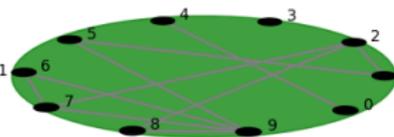
What is a multiplex?

Definition

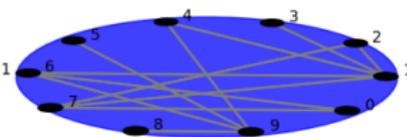
A *multiplex* is a collection of graphs all defined on the same node set.



(a) Family



(b) Colleagues



(c) Facebook

World Trade Web¹



Figure: World trade networks

¹ R. Feenstra, R. Lipsey, H. Deng, A.C. Ma, and H. Mo. World Trade Flows: 1962-2000. NBER Working Paper 11040, (2005).

WTW Layers

Layer	Description	Volume	% Total	Transitivity
0	Food and live animals	291554437	5.1	.82
1	Beverages and tobacco	48046852	0.9	.67
2	Crude materials	188946835	3.3	.79
3	Mineral fuels	565811660	10.0	.62
4	Animal and vegetable oils	14578671	0.3	.64
5	Chemicals	535703156	9.5	.83
6	Manufactured Goods	790582194	13.9	.87
7	Machinery	2387828874	42.1	.85
8	Miscellaneous manufacturing	736642890	13.0	.83
9	Other commodities	107685024	1.9	.56
All	Aggregate Trade	5667380593	100	.93

Table: Layer information for the 2000 World Trade Web.

Disjoint Layers

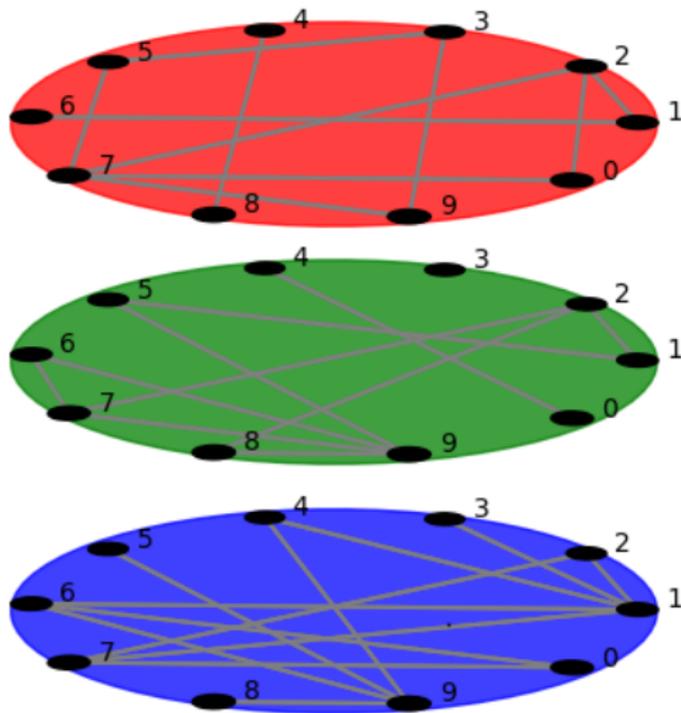
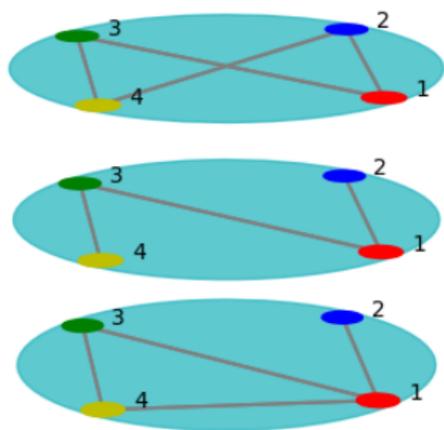
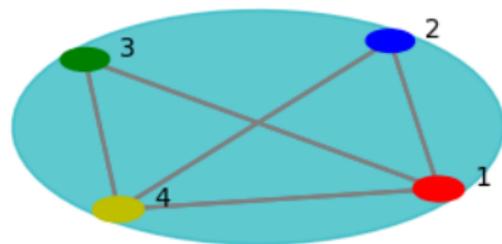


Figure: Disjoint Layers

Aggregate Models

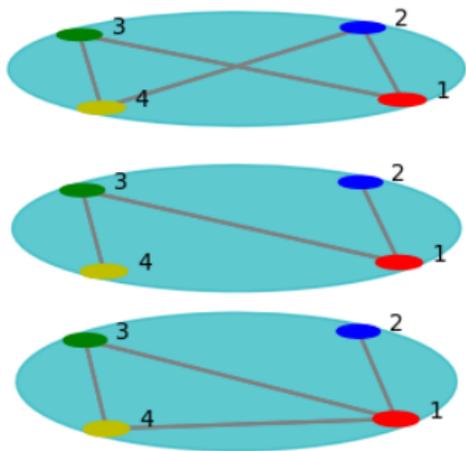


(a) Disjoint Layers

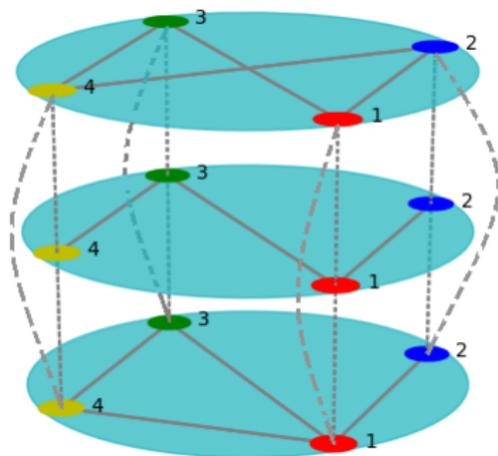


(b) Aggregate

Matched Sum



(a) Disjoint Layers



(b) Matched Sum

Structural Asymptotics

As the number of layers grows, what happens to the:

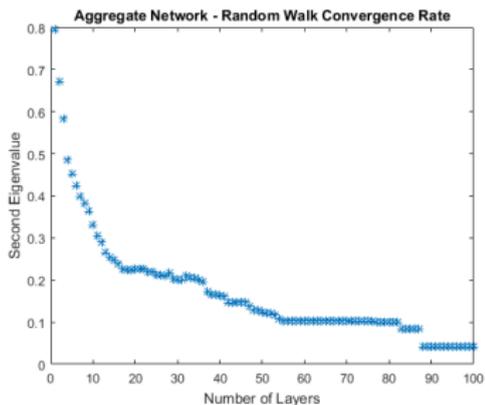
- Density?
- Degree Distribution?
- Transitivity?
- Average Path Length?
- Diameter?
- Clique Number?
- ...

Structural Asymptotics

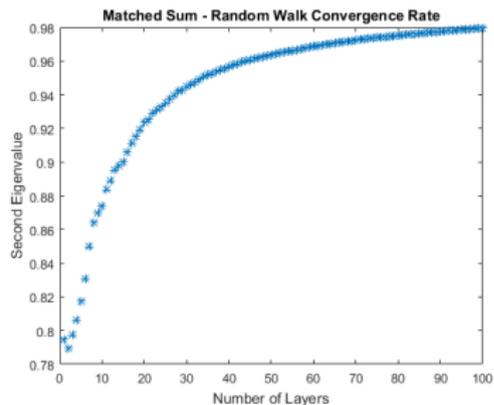
As the number of layers grows, what happens to the:

- Density?
- Degree Distribution?
- Transitivity?
- Average Path Length?
- Diameter?
- Clique Number?
- ...
- **Dynamics?!?**

Random Walk Convergence



(a) Aggregate



(b) Matched Sum

Dynamics on Multiplex Networks

- Two types of interactions
 - Within the individual layers
 - Between the layers
- Effects should “pass through” nodes
- Two step iterative model

Dynamics on Multiplex Networks

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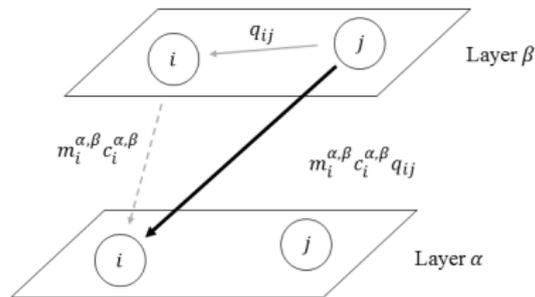
$$v' = \mathcal{D}v$$
$$(v')_i^\alpha = \sum_{\beta=1}^k m_i^{\alpha,\beta} c_i^{\alpha,\beta} (Dv)_i^\beta$$

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Multiplex Random Walks

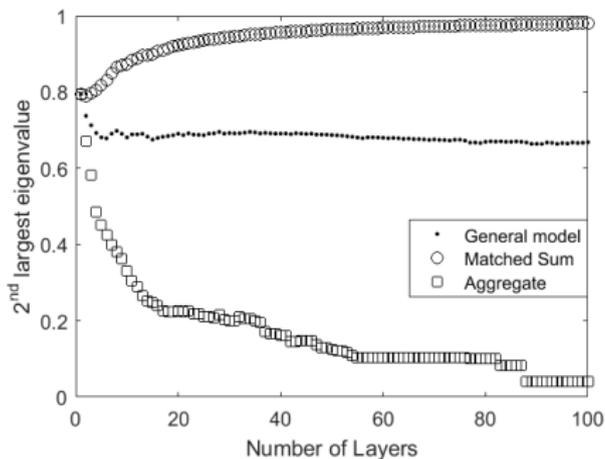
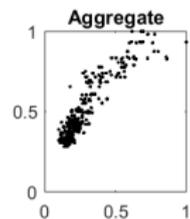
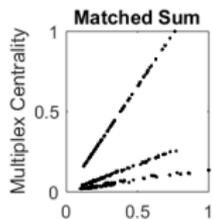
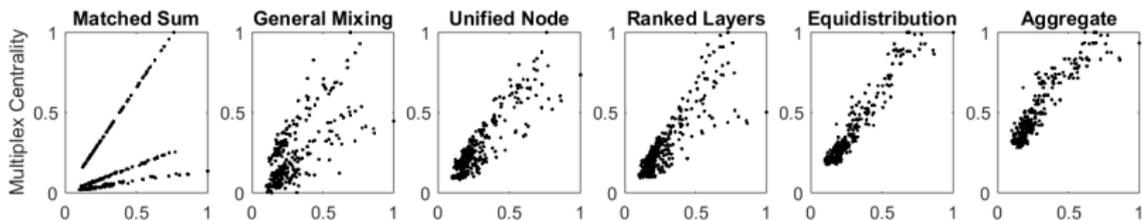


Figure: Comparison of random walk convergence for multiplex models.

Centrality Comparison



Centrality Comparison



Global Aggregate Rankings

Year	1970	1980	1990	2000
1	US	US	US	US
2	Germany	Germany	Germany	Germany
3	Canada	Japan	Japan	Japan
4	UK	UK	France	China
5	Japan	France	UK	UK
6	France	Saudi Arabia	Italy	France

Table: RWBC values for the aggregate WTW.

Full Multiplex RWBC

Ranking	Country	Layer
1	US	7
2	Germany	7
3	China	7
4	UK	7
5	Japan	7
6	US	8
7	Canada	7
8	France	7
9	Japan	3
10	US	6
12	US	3
13	Netherlands	7
14	Germany	6
15	Italy	7

Table: Multiplex RWBC values for the 2000 WTW.

Commodity Appearance

Layer	Ranking	Country
0	22	Japan
1	199	Germany
2	47	China
3	9	Japan
4	184	Australia
5	23	Germany
6	10	US
7	1	US
8	6	US
9	39	US

Table: First appearance of each layer in the rankings.

Ranking Movement

Layer 7 Ranking	Country	Multiplex Ranking
1	USA	1
2	Japan	5
3	Germany	2
4	China	3
5	France	8
6	UK	4
7	South Korea	18
8	Canada	7
9	Malaysia	16
10	Mexico	20

Table: Comparison of the relative rankings of the RWBC on Layer 7 versus the multiplex RWBC.

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That's all..

Thank You!