Title: The Big Data Approach to Quantum Gravity

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Abstract: <p>In both Causal Set Quantum Gravity as well as in the String Landscape, we face the challenging tasks of sifting through large state spaces and searching for the set of solutions which best model our physical universe. I demonstrate in this talk how efficient parallel algorithms can give us access to areas of physics previously unstudied due to computational barriers. I first present new methods to accelerate the evolution of causal set Markov chains, which enables us to look for the spontaneous emergence of manifoldlike structure. Then, I use a similar graph theoretic approach to show how a dynamic vacuum selection mechanism naturally emerges in F-Theory and Type IIB String Theory in the context of eternal inflation. We will discuss in detail relevant numerical aspects, including practical limitations and algorithms from graph theory, and how machine learning can be used in future work.</p>

The Big Data Approach to Quantum Gravity

Will Cunningham

Department of Physics
Network Science Institute
Northeastern University

December 14, 2017

1. Introduction to Big Data
   - Basic Concepts
   - Motivation
2. Causal Sets
   - Overview
   - Algorithmic Details
   - Current Work
3. Vacuum Selection in the String Landscape
   - Geometries in F-Theory
   - Networks of Geometries
   - Relation to Cosmology
   - Numerical Details
   - The Selection Mechanism
4. Other Work

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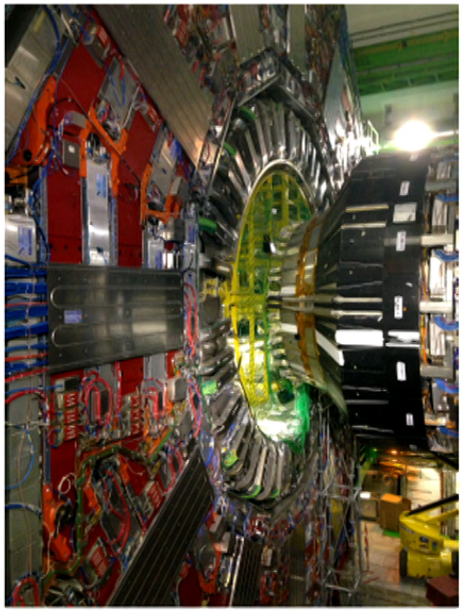

Image: Wikipedia

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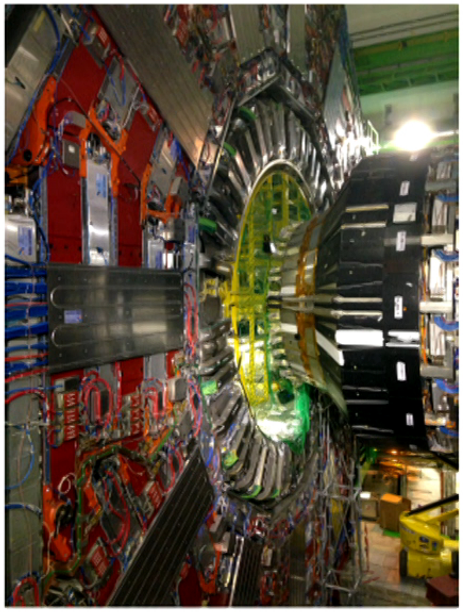

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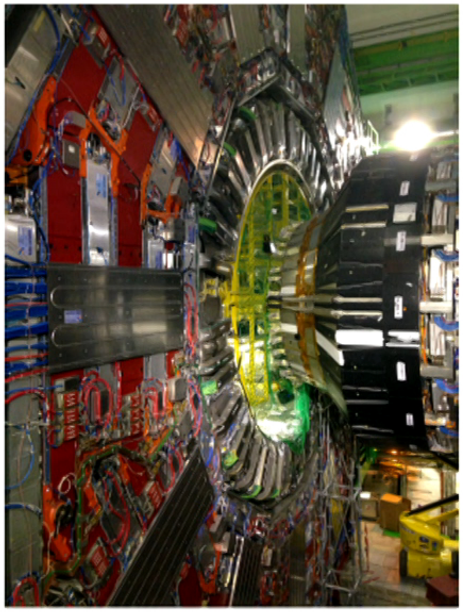
- 3Vs: Volume, Velocity, and Variety



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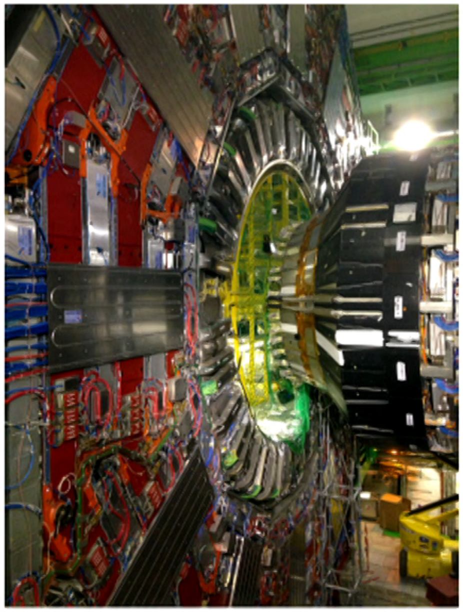
Big **graphs** are interesting



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Why Big Data?

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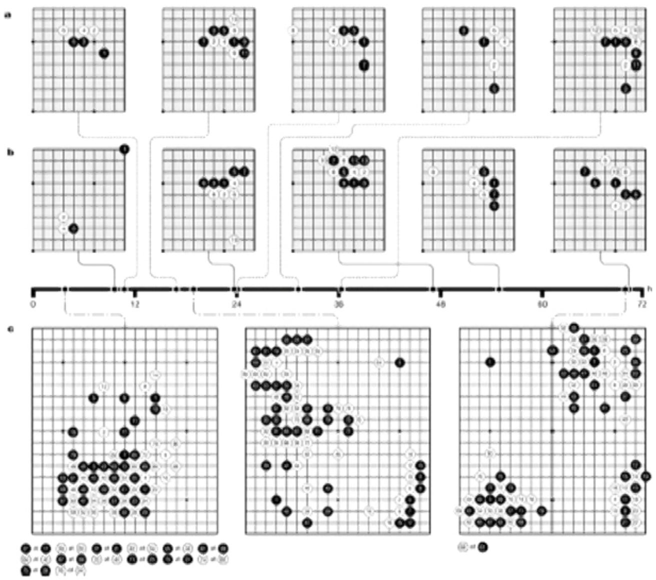

Image: Silver et al. Nature 550, 354 (2017).

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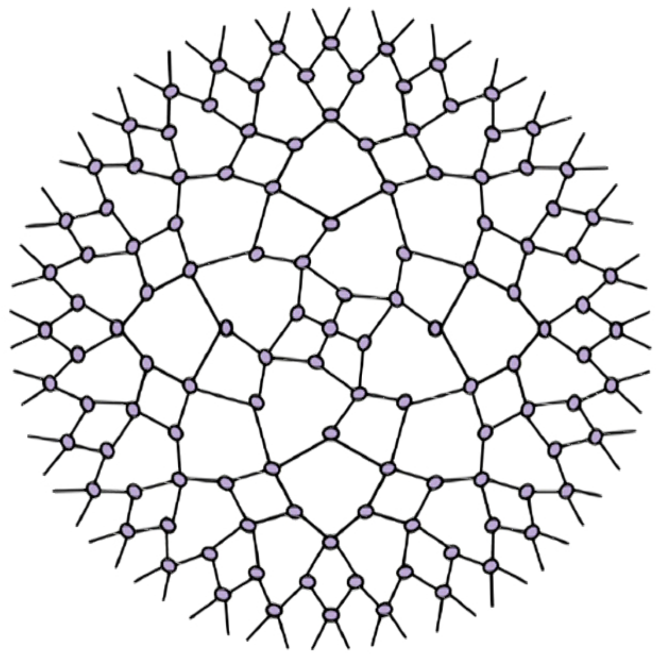

Image: Perimeter Institute

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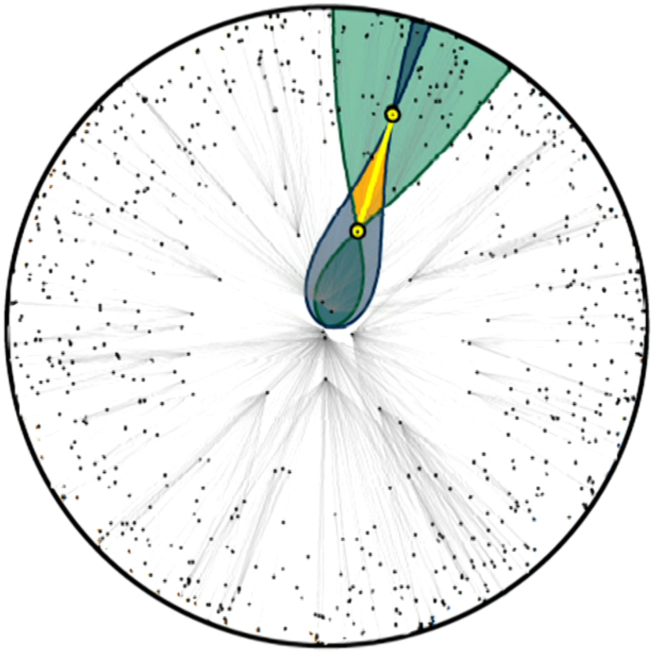

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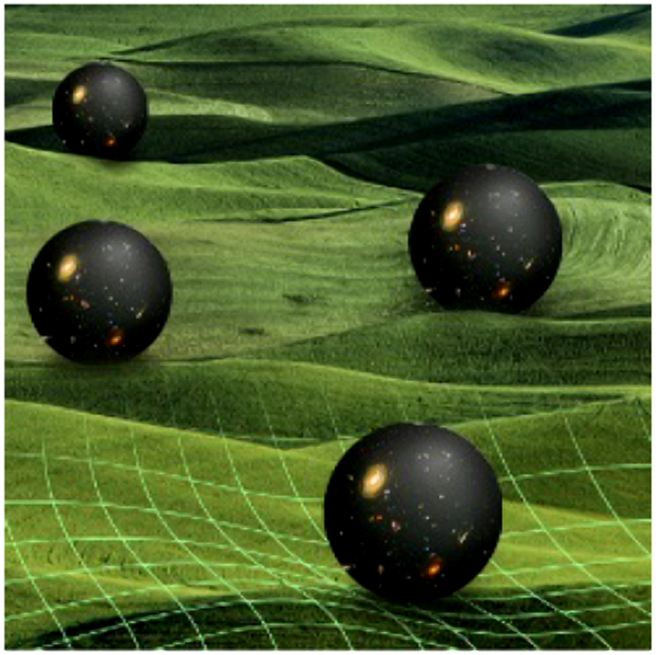

Image: Huffington Post

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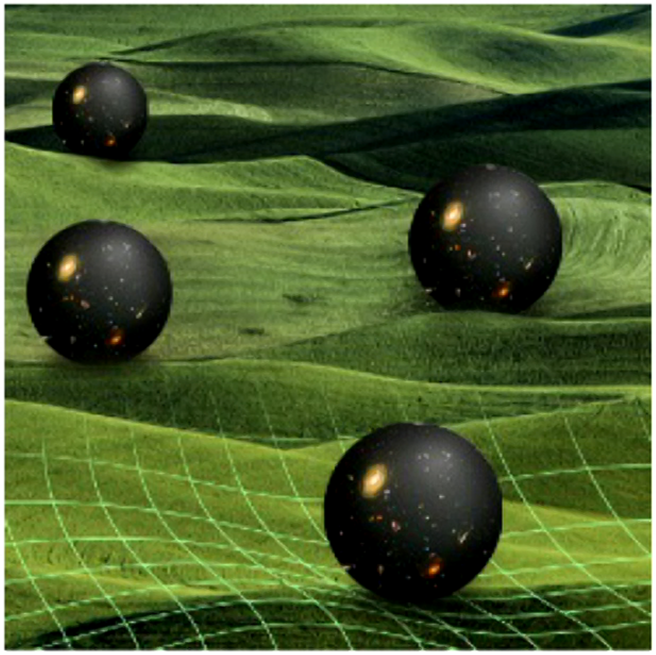
Big Data is all around us

- AlphaGo
- Tensor Networks
- **Causal Sets**
- **String Landscape**

We need efficient algorithms to study large complex systems



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Causal Set Quantum Gravity

Premise: Discrete spacetime with causal relations

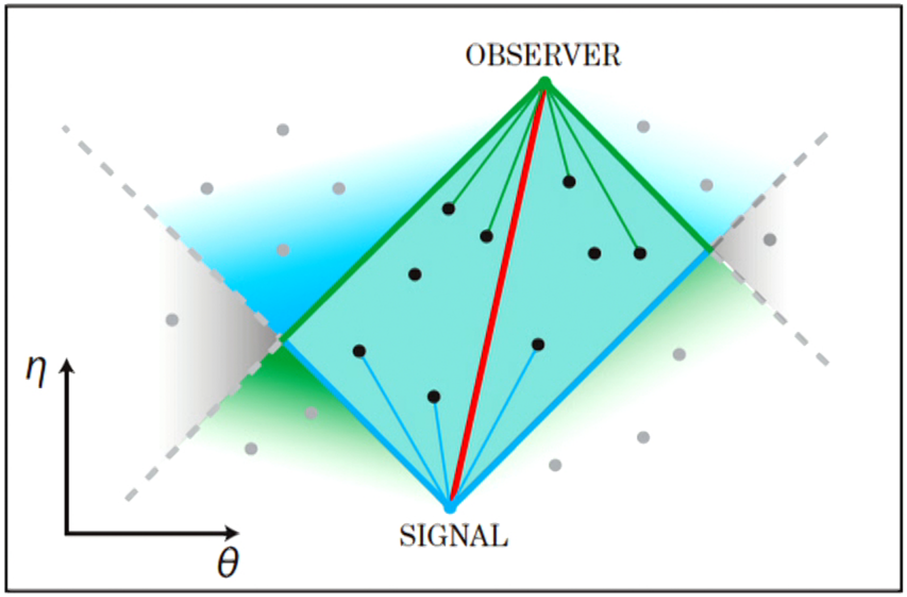

Image: Cunningham & Krioukov, arXiv:1709.03013 (2017).

Path Integral Approach

Problem: How do we measure observables?

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New Problems:

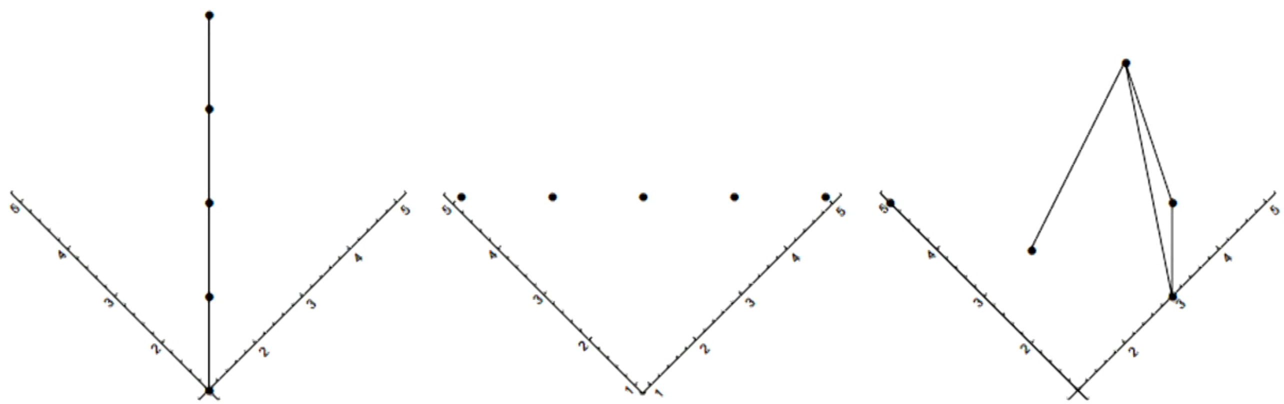
1) How do we deal with $\sum_{\mathcal{C}}$?

2) What is $S(\mathcal{C})$ for a causal set?

2D Orders in $\mathbb{M}^2$

Consider 2D partial orders built from total orders U, V

$$U = \{u_1, \ldots, u_N\} \qquad V = \{v_1, \ldots, v_N\}$$



$\Omega(N)$: All permutations of U and V

$$\sum_{\mathcal{C}} e^{iS(\mathcal{C})/\hbar} \longrightarrow \sum_{\mathcal{C}} e^{-\beta S(\mathcal{C})}$$

Brightwell, Henson & Surya, Class. Quantum Grav 25 (2008).

The Causal Set Action

The Benincasa-Dowker action S_{BD} converges to the Einstein-Hilbert action S_{EH} as $N \to \infty$

- There's a different expression for each dimension
- S_{BD} is a function of subgraphs in $\mathcal{C}$
- Computation is $O(N^3)$
- Boundary terms not included

$$\text{2D: } S_{BD} = 2(N - 2n_1 + 4n_2 - 2n_3)$$

Benincasa & Dowker, Phys. Rev. Lett. 104, 181301 (2010).

Benincasa, Ph.D. Thesis, Imperial College London (2013).

Phase Transitions

Metropolis Monte Carlo $\longrightarrow$ first order phase transition

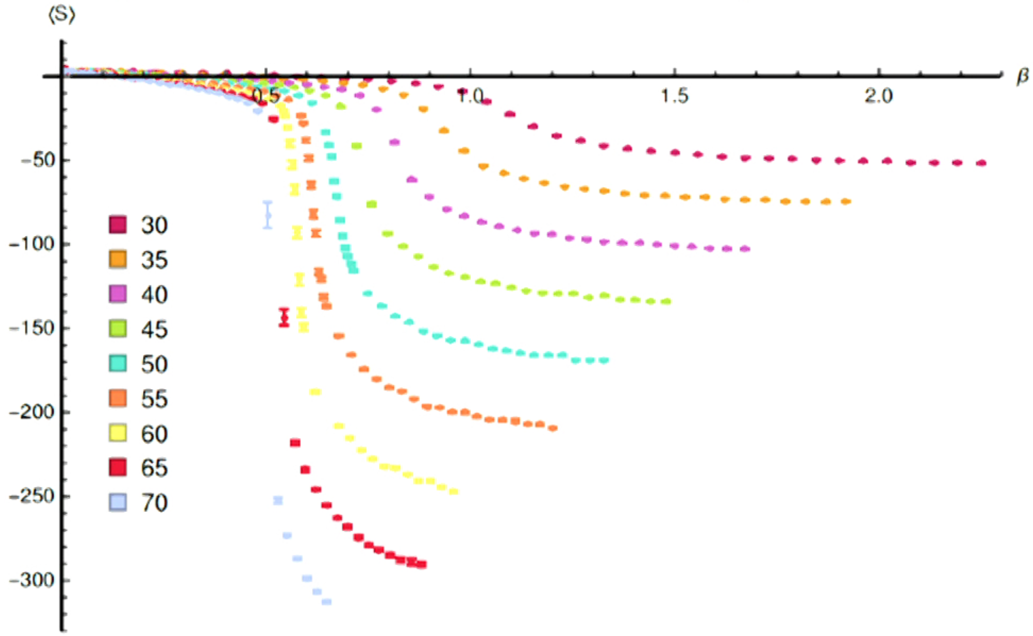


Image: Glaser, O'Connor & Surya, arXiv:1706.06432 (2017).

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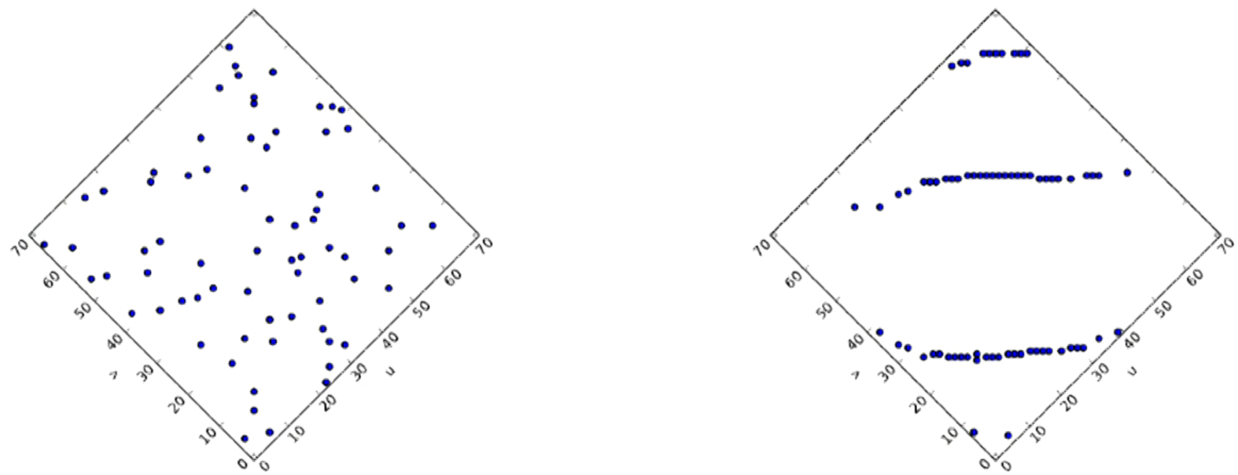

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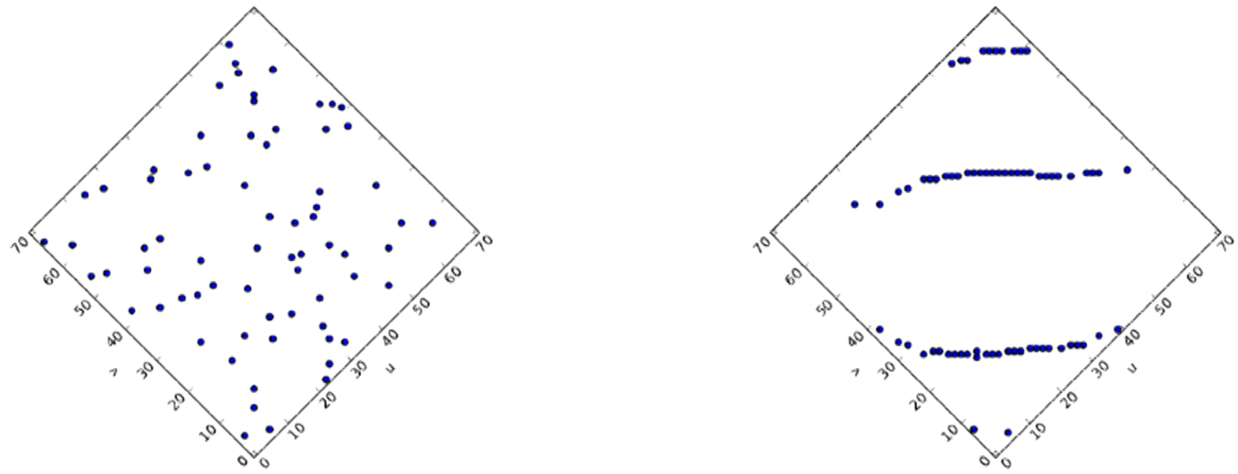
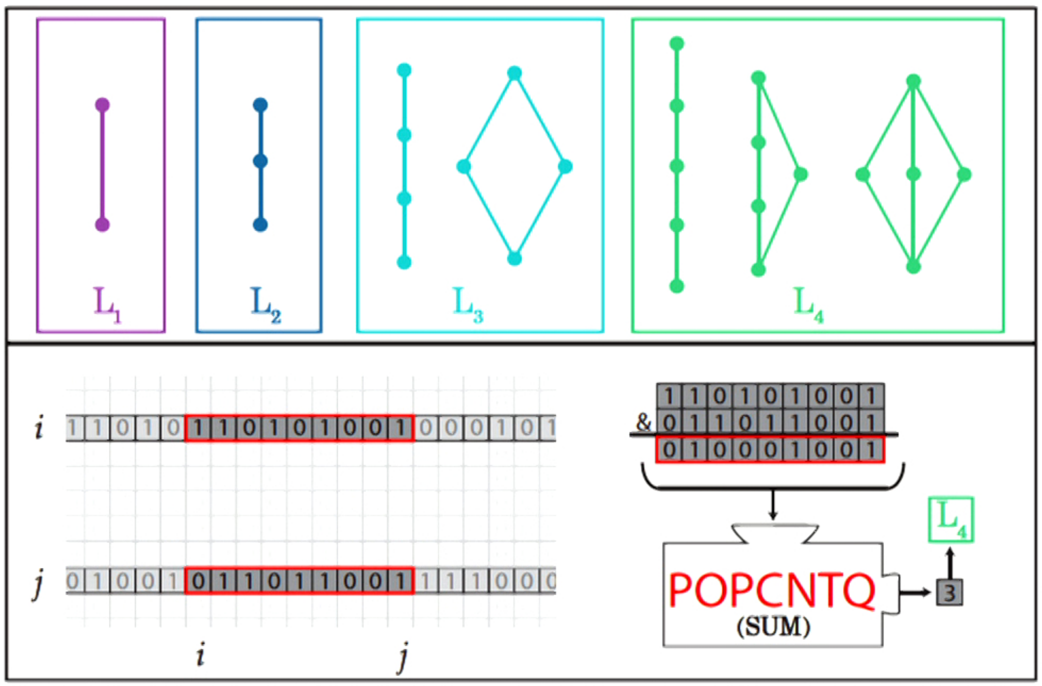


Claim: $\bar{\beta}_c \equiv \beta_c N = \mathrm{constant}$

Image: Glaser, O'Connor & Surya, arXiv:1706.06432 (2017).

Details of the Action

$$Z(N, d, \mathcal{T}) = \sum_{C} e^{-\beta S_d(C)/\hbar} \qquad S_2(C) = 2(N - 2n_1 + 4n_2 - 2n_3)$$



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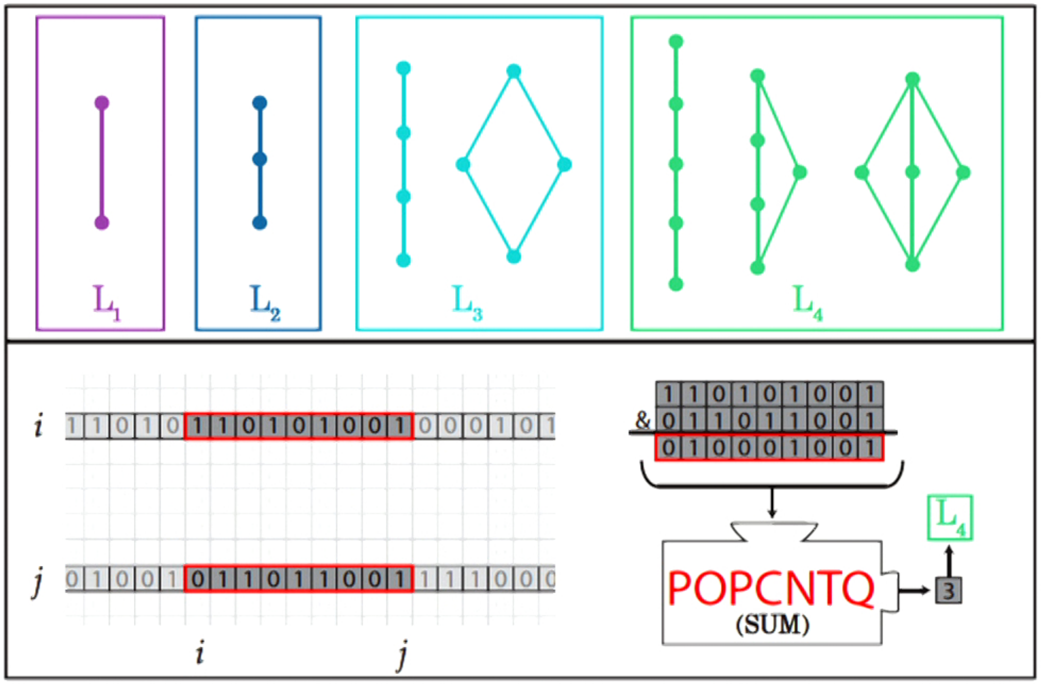

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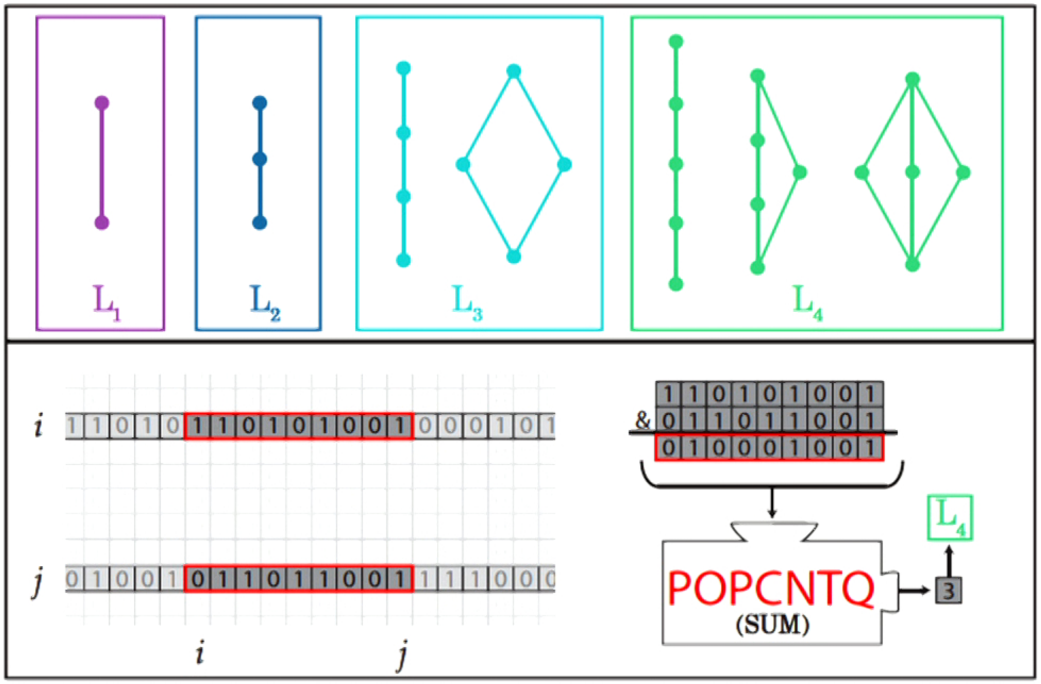

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Graphs with Known Properties

Causal sets can be constructed as **random geometric graphs** in a compact region of spacetime

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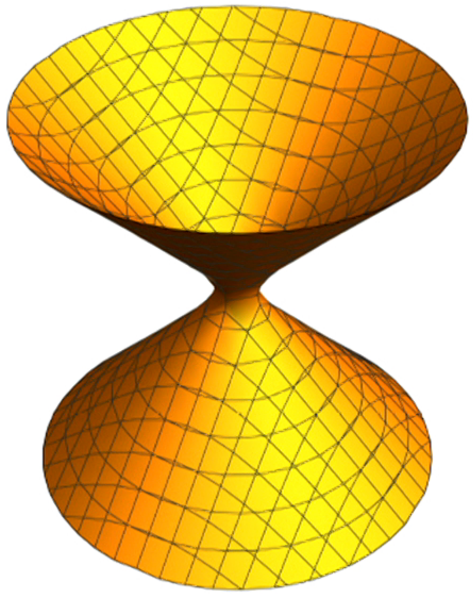
1+1 De Sitter Slab



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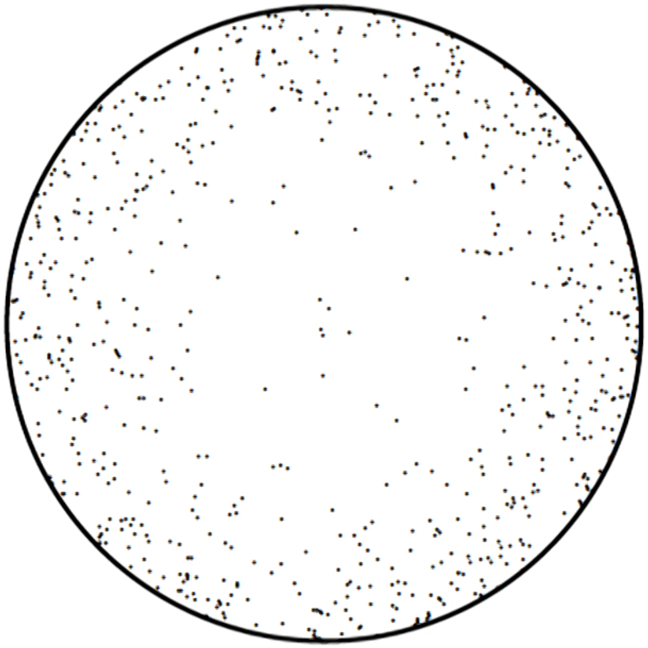

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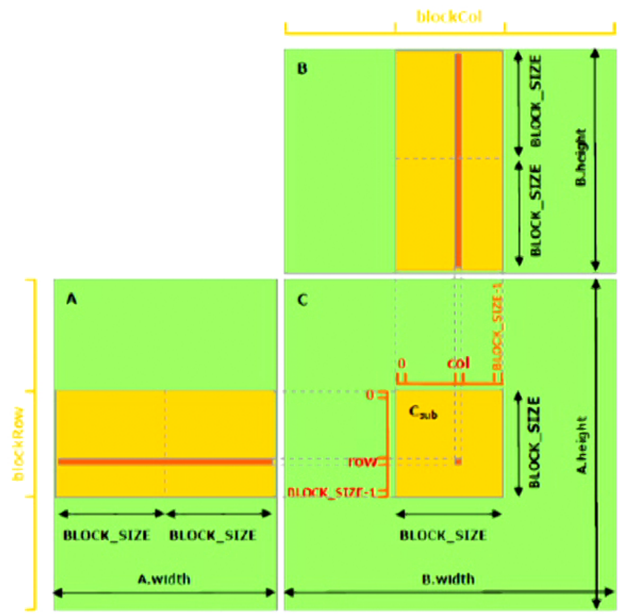

Image: NVIDIA

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3. Identify links (CUDA) (Use 48KB L1 cache for 10x speedup)

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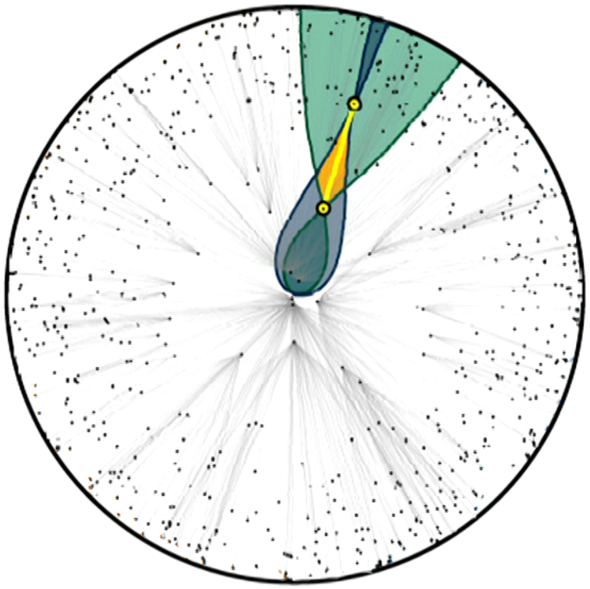

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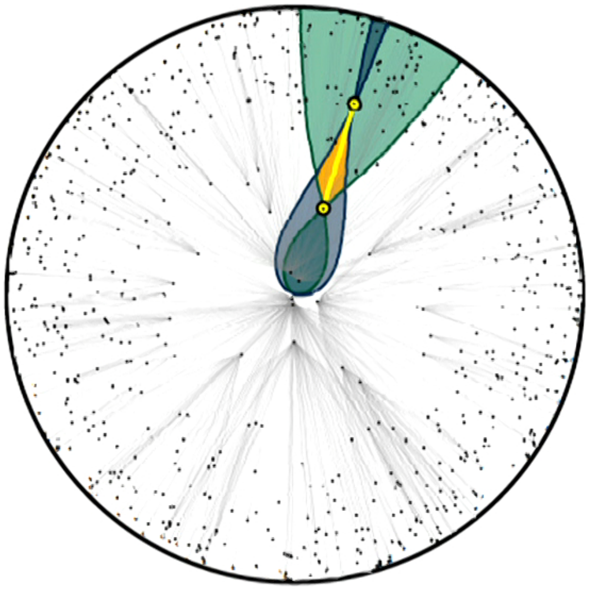

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This is the control group

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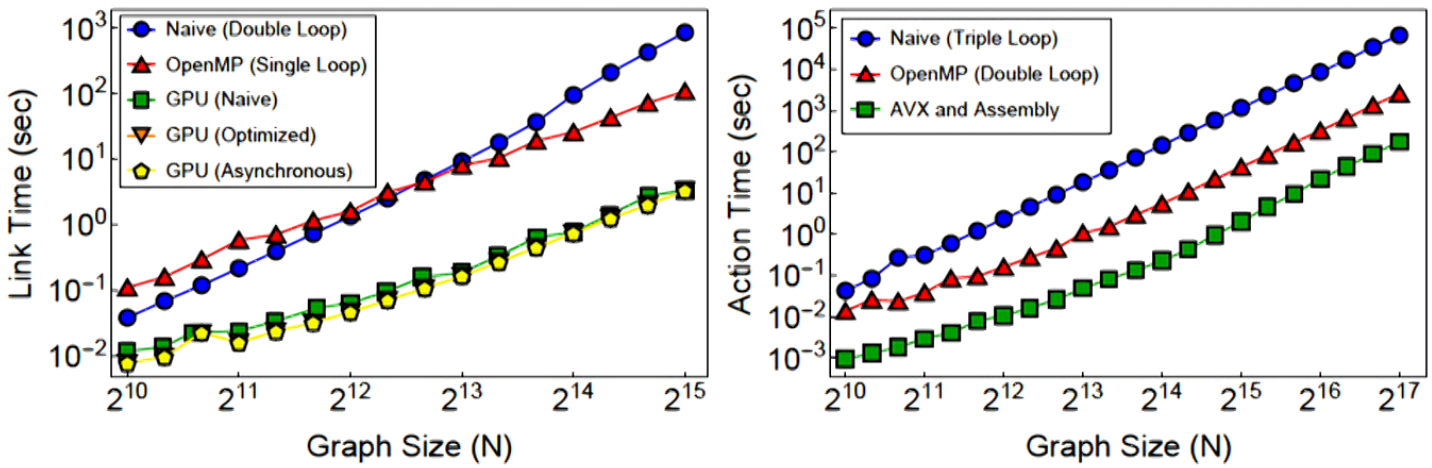
Perforamance

GPU + OpenMP + SIMD (AVX) + Assembly



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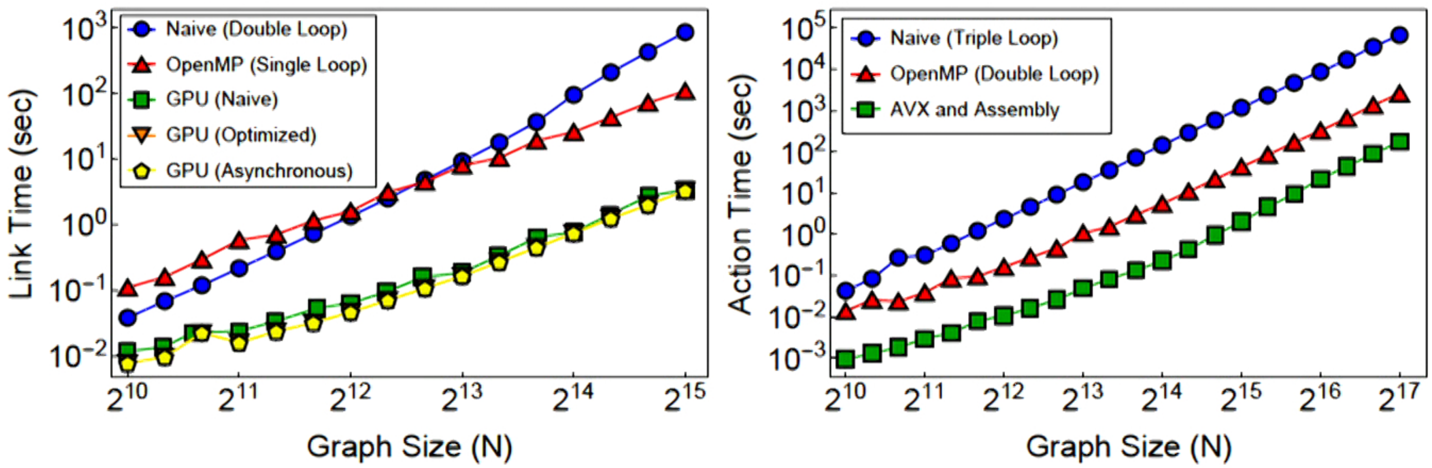
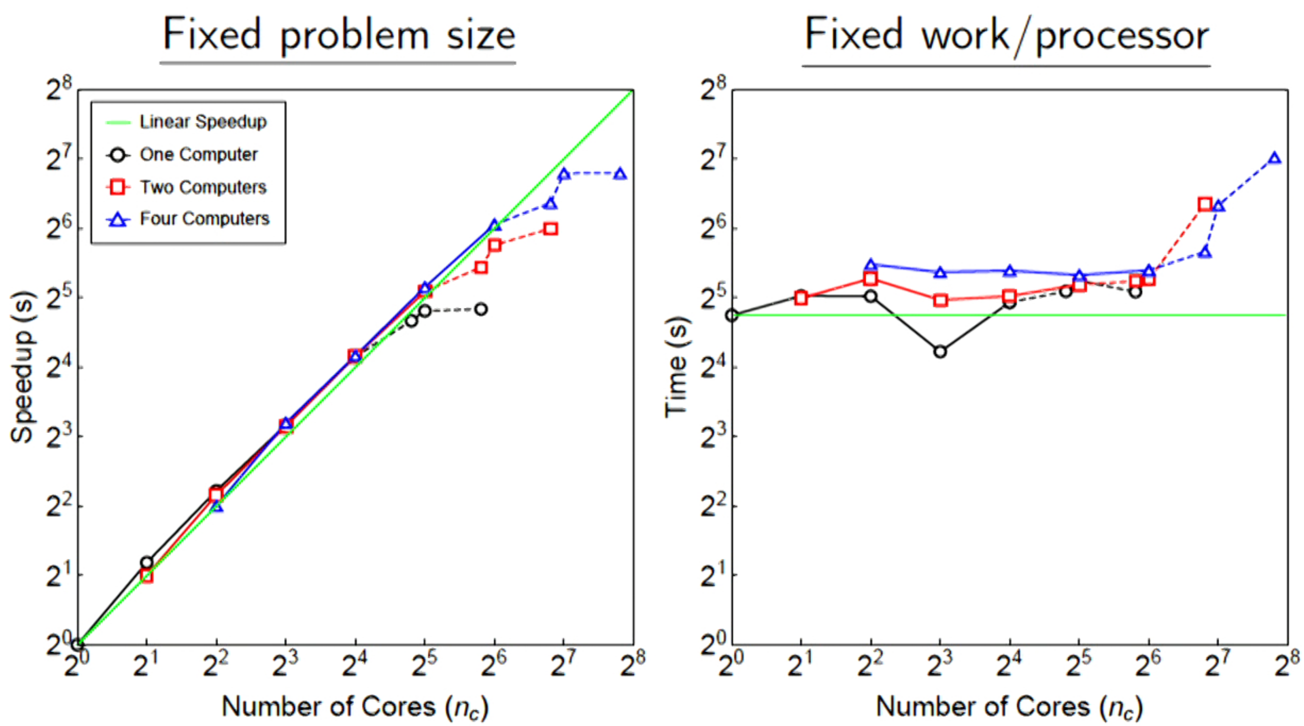


This gives a 1000x speedup!

Image: Cunningham & Krioukov, arXiv:1709.03013 (2017).

Strong & Weak Scaling



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Cannot answer these without high performance algorithms to compute the action!

Machine Learning

Newer: Classification of Geometric Structure

Supervised Learning:

- Training data $\rightarrow$ Random geometric graphs
- Construct a deep neural network (DNN)
- Classify according to spacetime dimension in $\mathbb{M}^d$
- Use DNN to monitor Markov chain properties efficiently

Reinforcement Learning:

- Grow causal sets while minimizing the action
- Use SL network to monitor growth
- Relate to Classical Sequential Growth
- Develop equations of motion

Collaboration: Benincasa, [Charles River Analytics], [Evans], [Northeastern]

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- 3-folds ($\mathbb{C}^3$) are triangulated 3-D reflexive polytopes (4319)

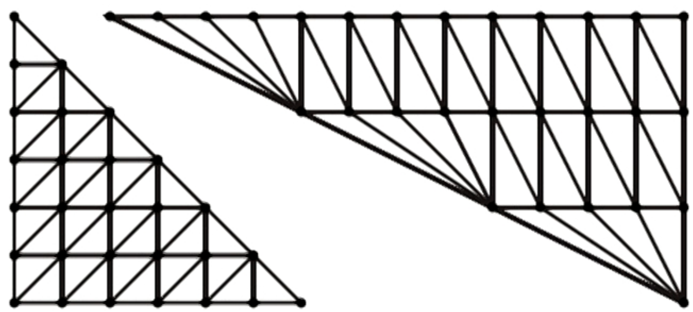
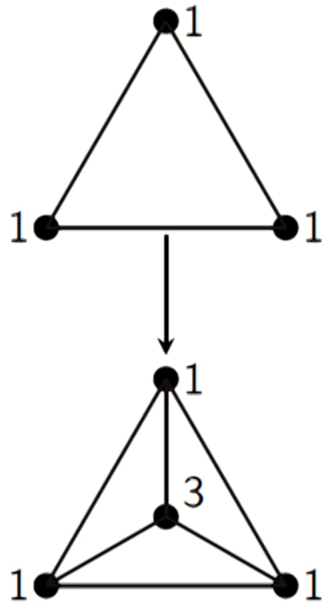


Image: Halverson et al. arXiv:1706.02299 (2017).

"Simple" Topological Transitions

Two 3-folds are related by a **blowup**; # **cones** += 2

Face Blowup



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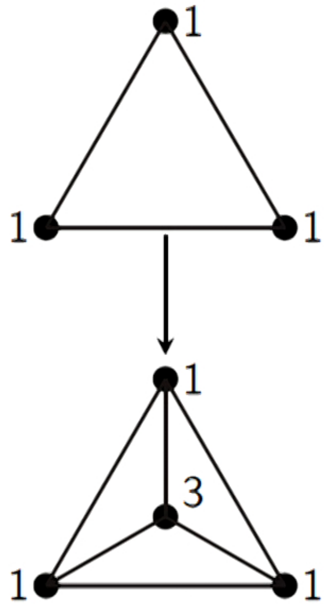

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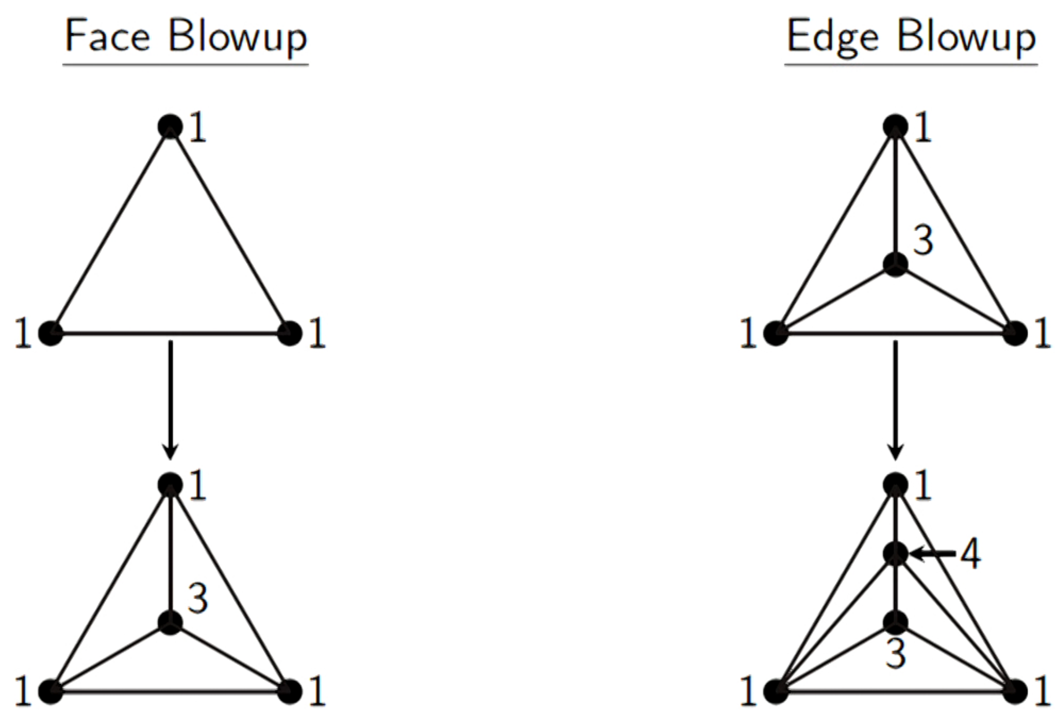

Height Restriction: $H \leq 6$

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- The entire network is a **cartesian product** of smaller ones
- Our adjacency matrix $\mathbf{A}$ contains transition rates $\mathbf{\Gamma}$
- Transitions make sense when we think about bubble cosmology in eternal inflation

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Bubble Cosmology

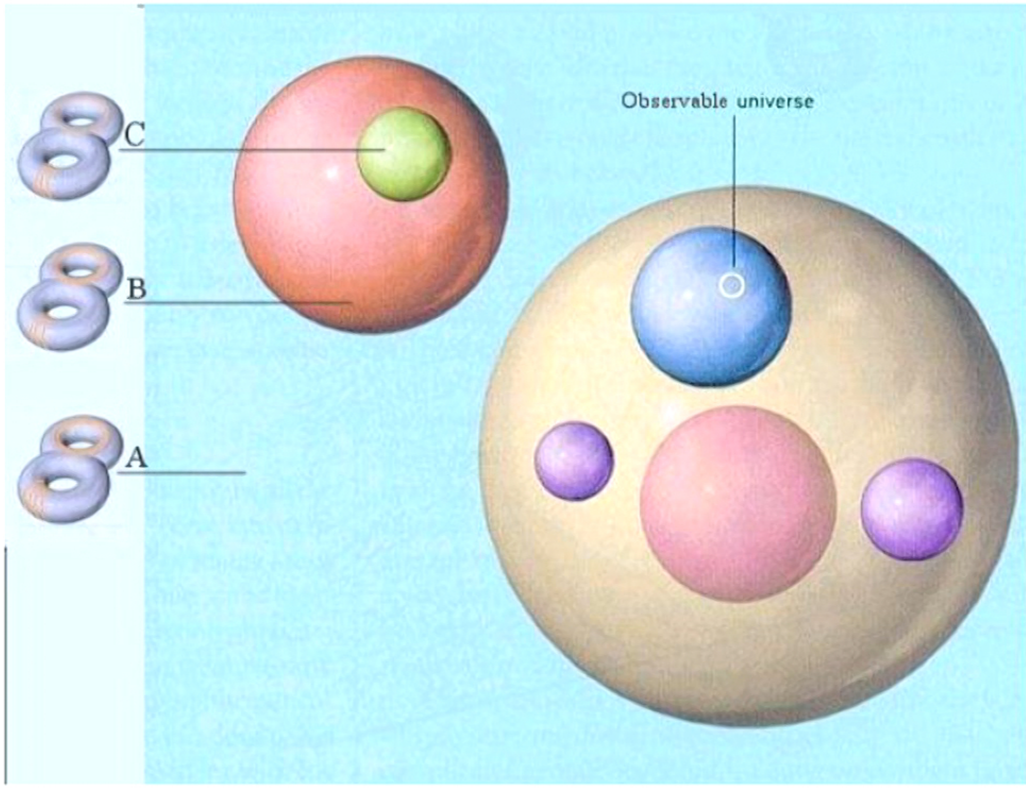

Image: *universe-review.ca*

Modeling Bubble Nucleation

Question: What is the distribution of vacua at $t \to \infty$?

Nucleation Rate: $\frac{d\mathbf{N}}{dt} = \mathbf{\Gamma}\mathbf{N}$

Solution: $\mathbf{N} = e^{\mathbf{\Gamma}t}\mathbf{N}_0 = \sum_p a_p e^{\gamma_p t}\mathbf{v}_p$

Late-Time Solution: $\mathbf{N} \to a_0 e^{\gamma_0 t}\mathbf{v}_0$ Normalize: $\mathbf{p} = \mathbf{N}/|\mathbf{N}|$

Toy Model: $\mathbf{\Gamma} = \mathbf{A}$

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But to use **A** would require ~210 TB memory...

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Same low-level code used here and for the causal set action!

The Eigenvector Centrality

We compute the eigenvector centralities of the (sparse) graph

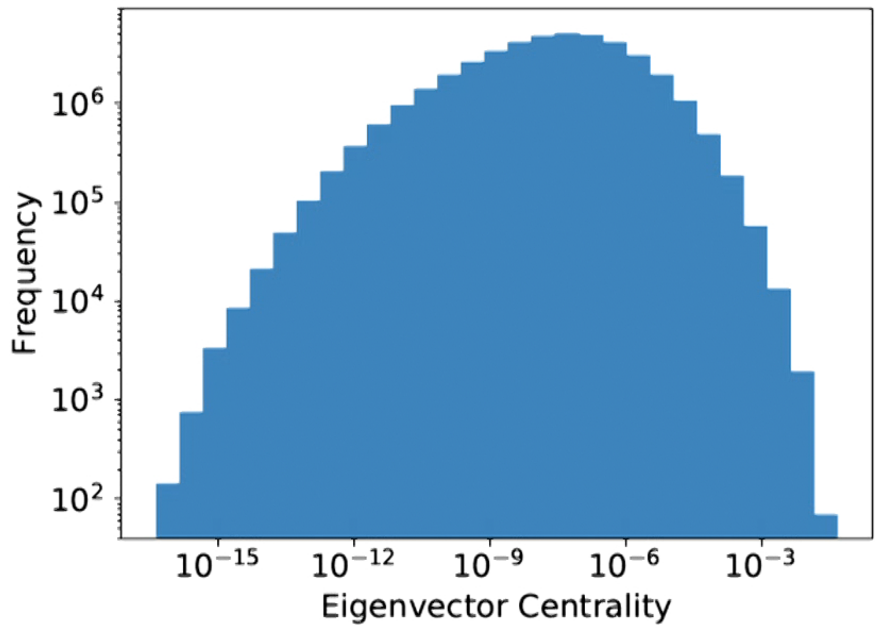
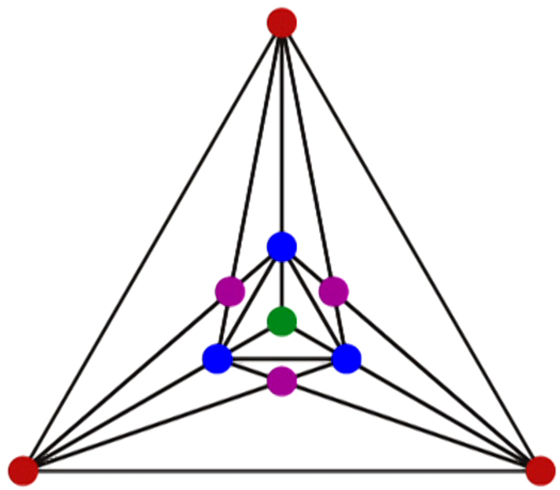


Image: Carifio, Cunningham, Halverson, Krioukov, Long & Nelson, arXiv:1711.06685 (2017)

The Selected Vacuum State



Selected Gauge Group: $E_8^3 \times G_2 \times SU(2)^3$

Full 10^{755} Network: $E_8^{37} \times F_4^{85} \times G_2^{220} \times SU(2)^{320}$

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- This is the *biggest* Big Data problem ever
- We can use deep neural networks to search for the MSSM (Ruehle, Halverson & Nelson)