Scientific Data Mining & Machine Learning

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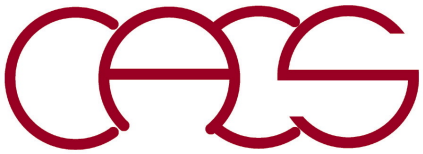
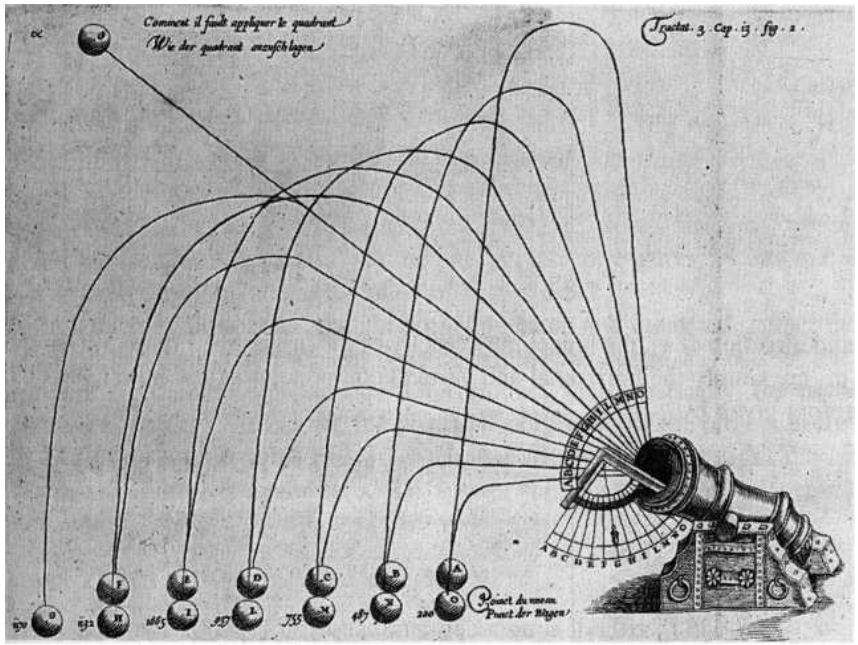


Scientific Data Mining

- **Scientific data mining:** Automated detection of knowledge hidden in large & often noisy scientific (experimental, simulation, *etc*.) datasets
- **Knowledge:** Simplest (*i.e*., minimal description length) explanation to replace exhaustive enumeration of the original data



Data

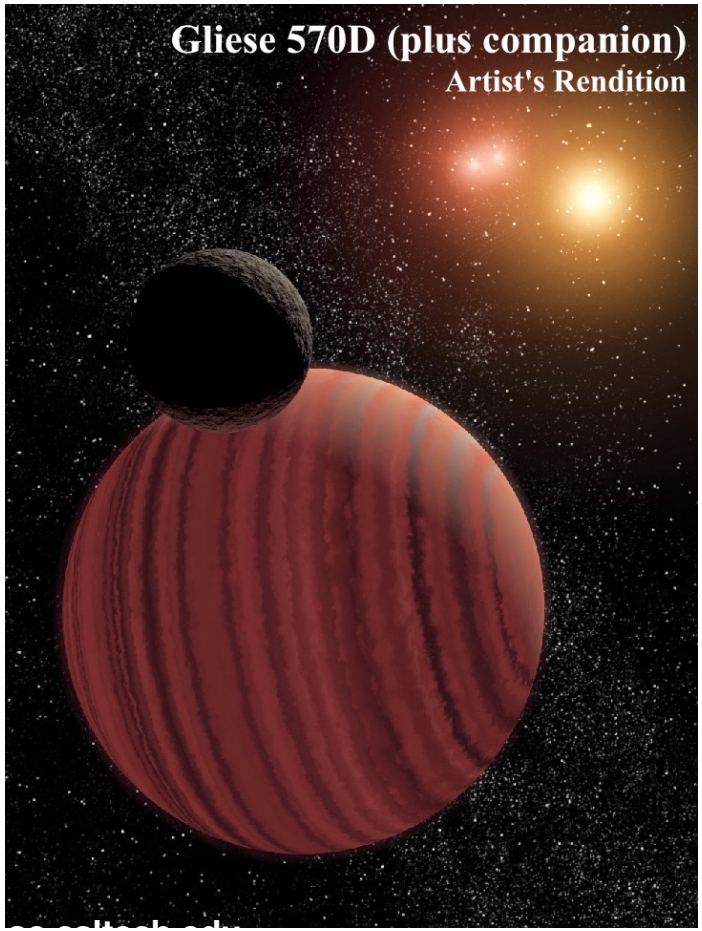
$$m\frac{d^2}{dt^2}\vec{r}(t) = \vec{F}$$

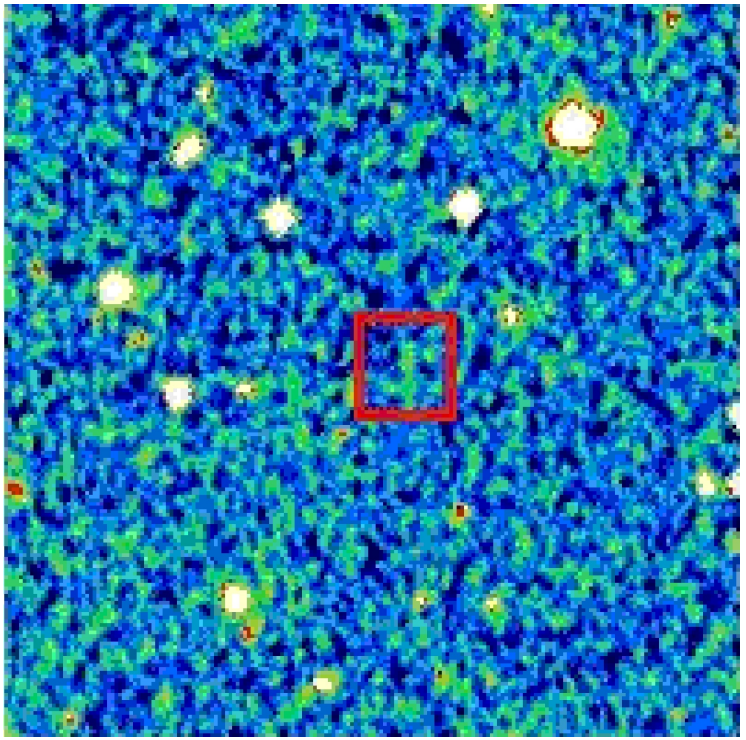
Knowledge

cf. Occam's razor
Kolmogorov complexity

Google Science in the Flat World

Parallel computing on globally distributed supercomputers & visualization platforms will revolutionize & democratize science & engineering (*e.g.*, Google astronomy in the flat world)





SDSS image of brown dwarf, 2MASSI J0104075-005328

Atomistic Data as a Graph

- **Molecular dynamics data**
  - —**Atomic data: species, positions, velocities, stresses,…**

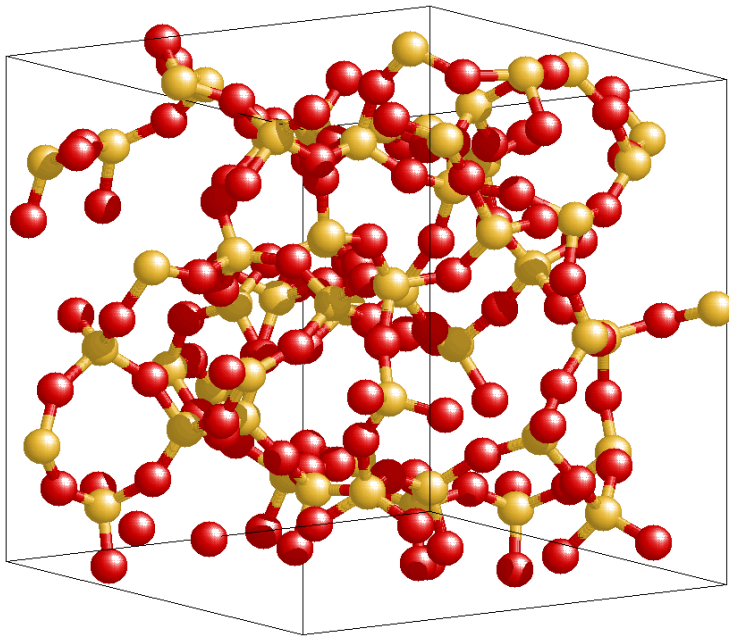
$$\{\lambda_i, \vec{r}_i, \vec{v}_i, \overleftrightarrow{\sigma}_i, \ldots | i = 1, \ldots, N\}$$

  - —**Atomic-pair data: bond order, pair distance,…**

$$\{B_{ij}, \vec{r}_{ij}, \ldots | i, j = 1, \ldots, N; i \neq j\}$$

- **Chemical bond network**
  - —**Node degrees**
  - —**Paths**
  - —**Rings**
  - —**Frequently occurring subgraphs**

G **= (*V*,*E*)**
V**: Set of atoms**
E**: Set of bonds**

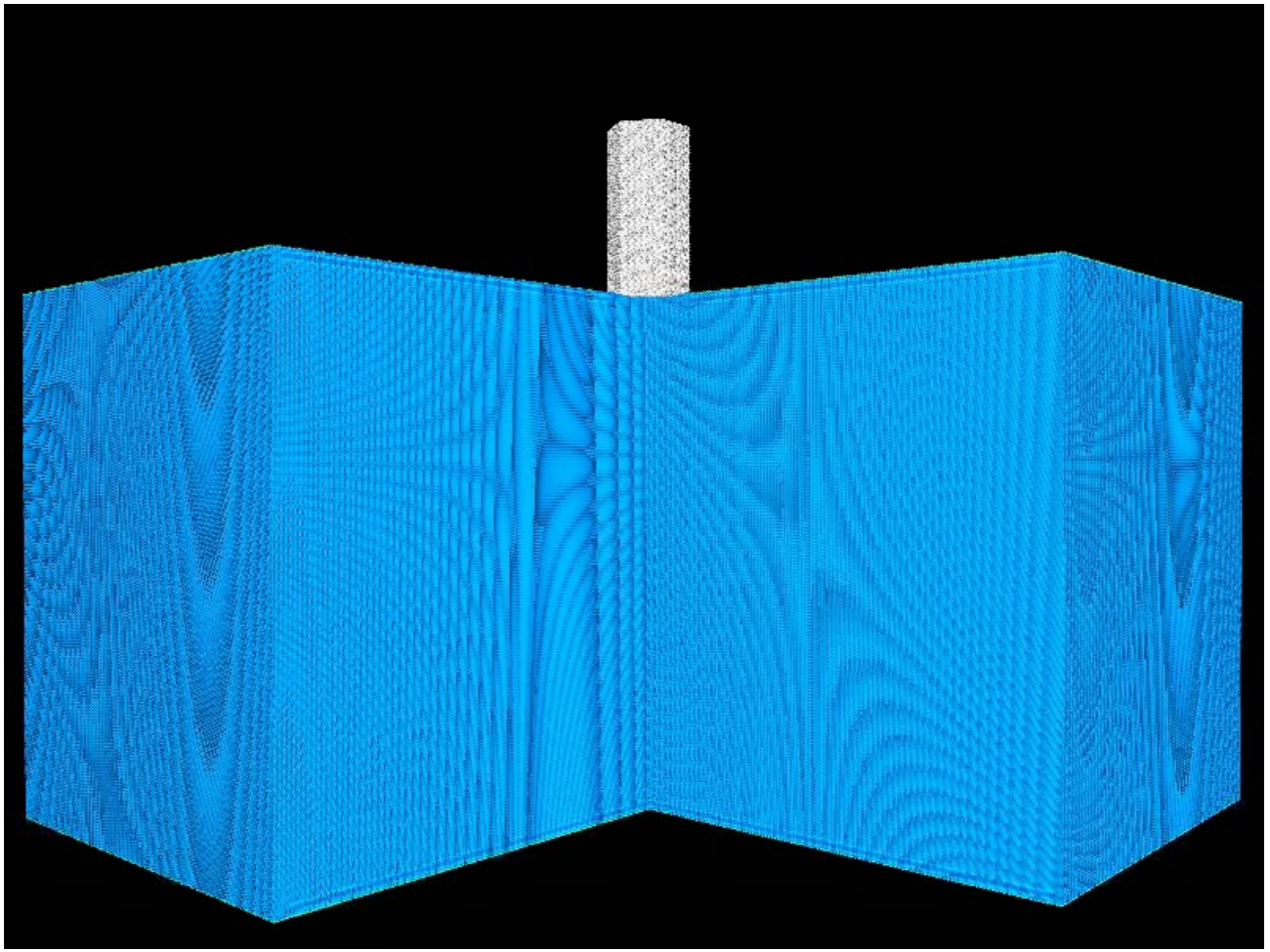


Hypervelocity Impact on Ceramics

- 209M-atom MD of AlN
- 300M-atom MD of SiC
- 540M-atom MD of Al_2O_3

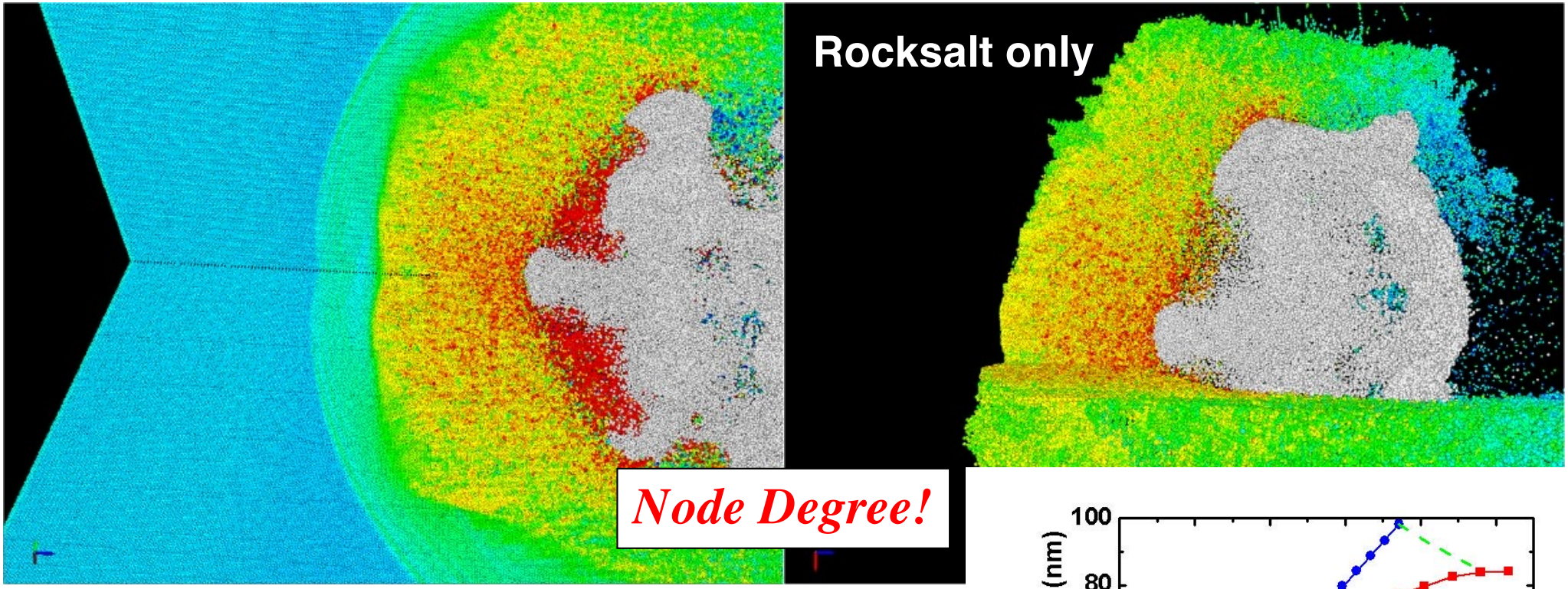
↑ [0001]

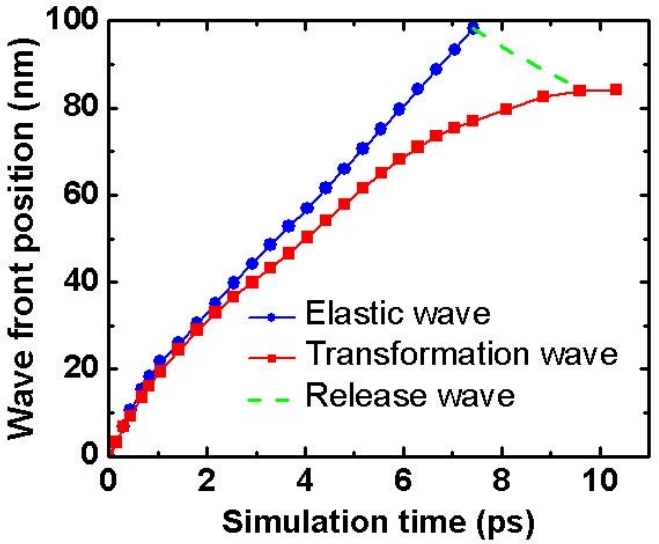
- Al_2O_3 plate
- 18 km/s impact



0.2μm

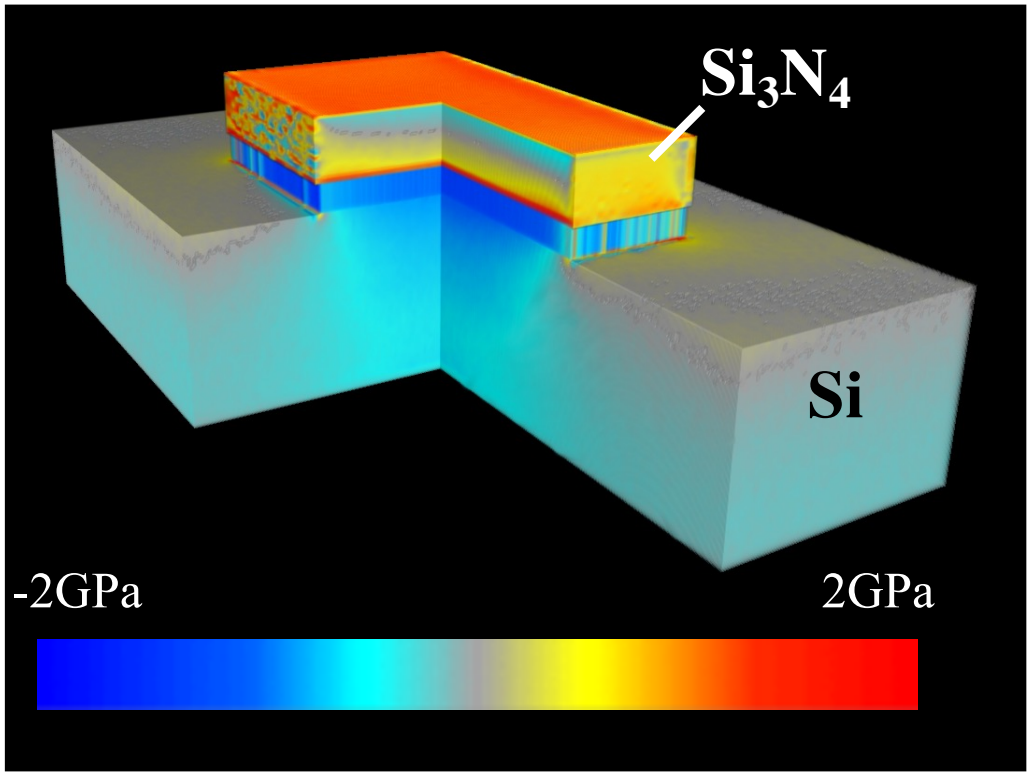
Shock-Induced Structural Phase Transformation in AlN

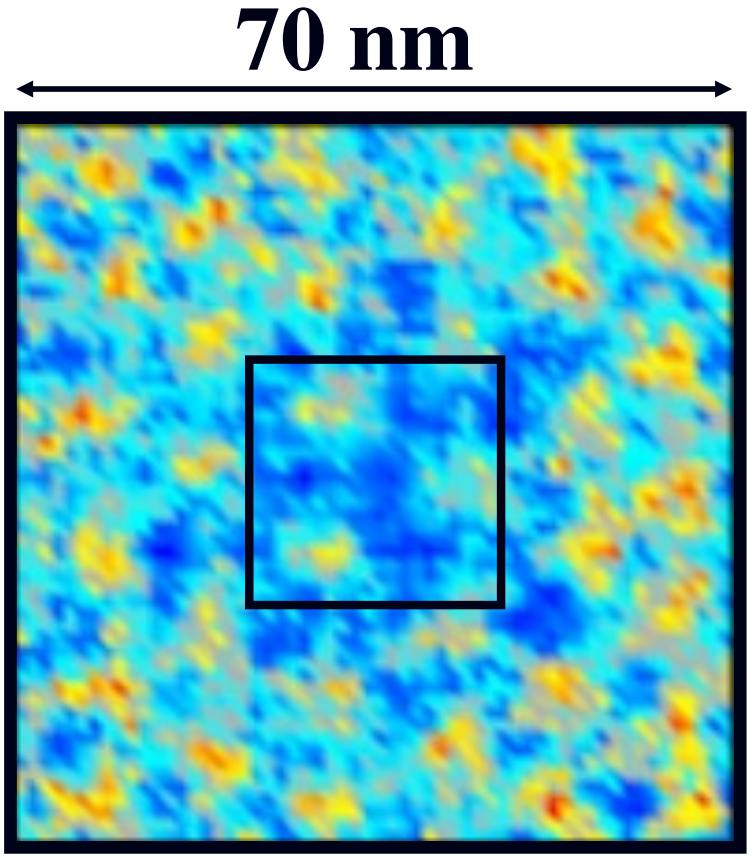




- **Wurtzite (4-coordinated) to rocksalt (6-coordinated) phase transformation at 20 GPa**

Stress Domains in Si_3N_4/Si Nanopixels

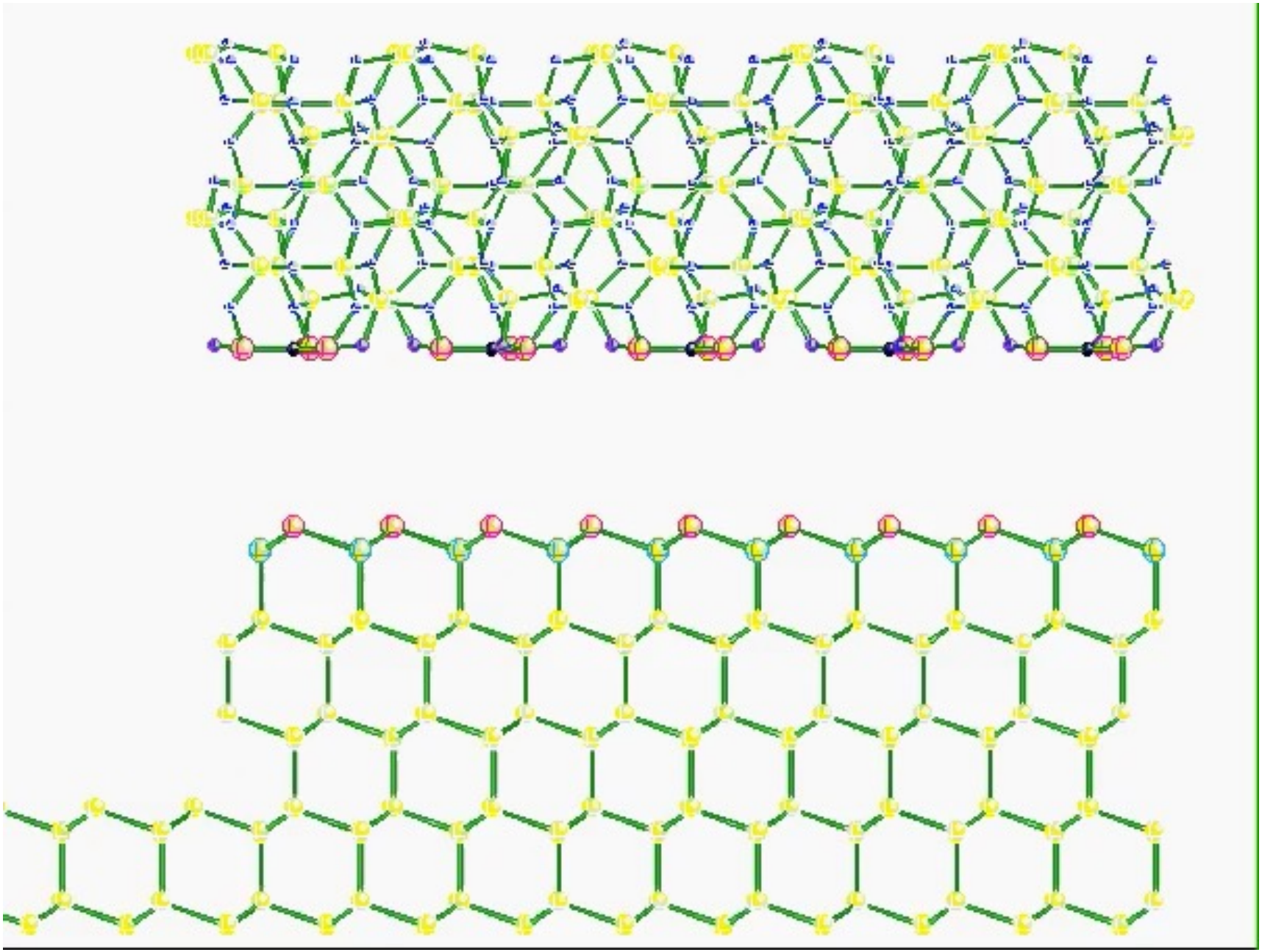




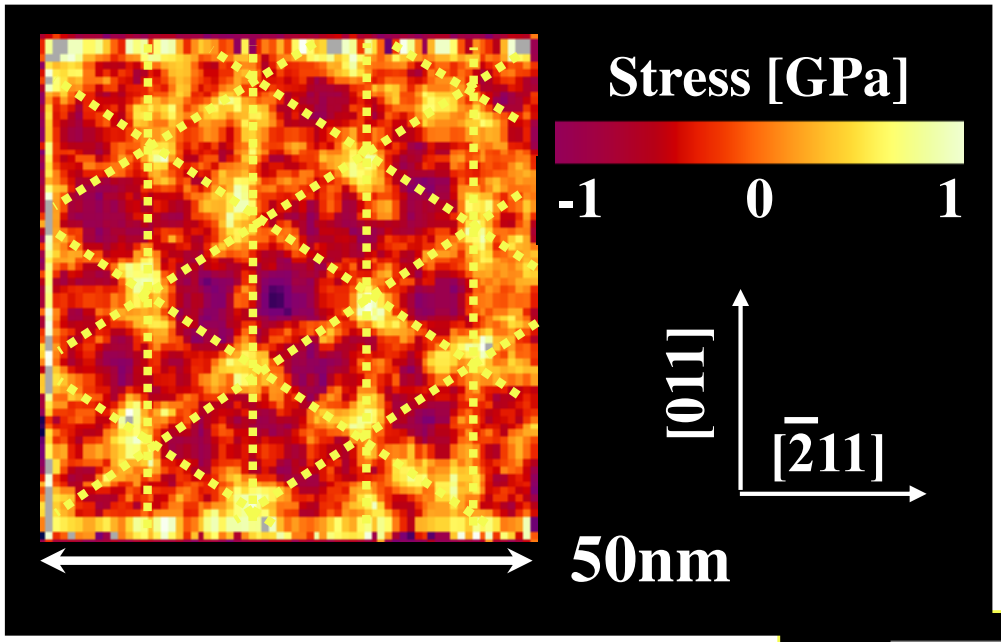
Stress well in Si with a crystalline Si_3N_4 film due to lattice mismatch

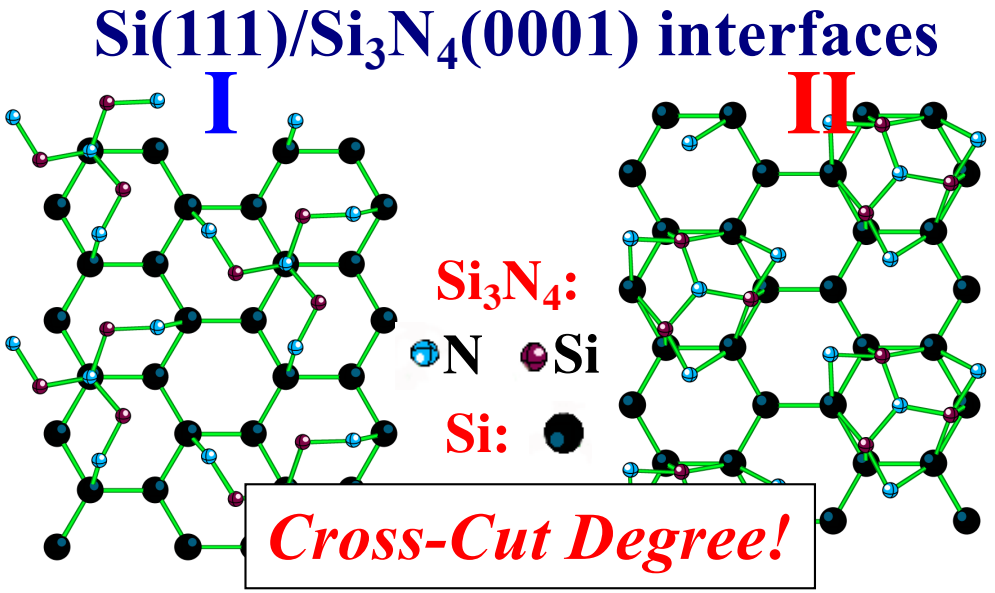
Stress domains in Si due to an amorphous Si_3N_4 film

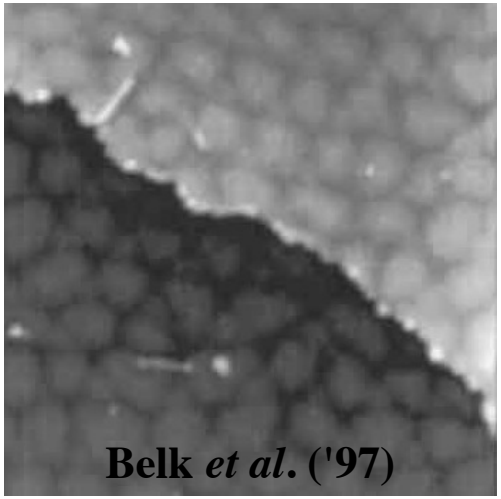
$Si(111)/Si_3N_4(0001)$ Interface



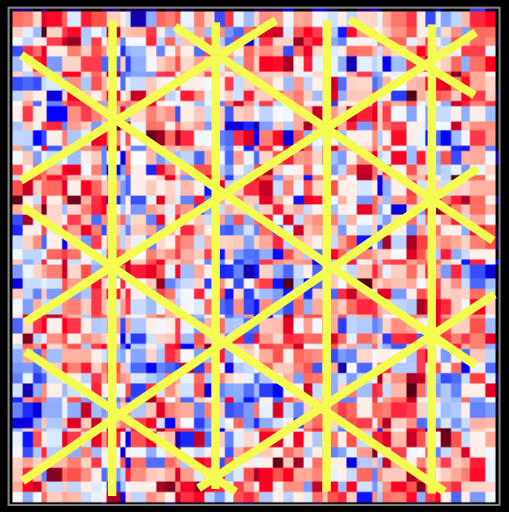
Stress Domains in Si/Si_3N_4 Nanopixel



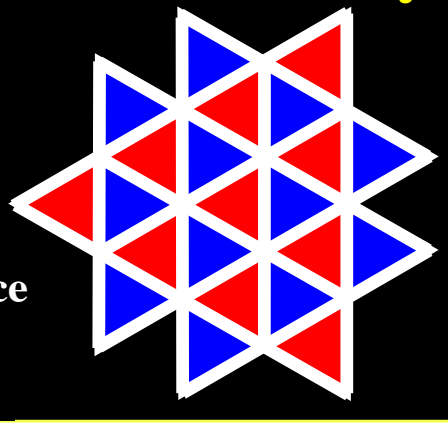




Misfit dislocation network in InAs/GaAs(111)

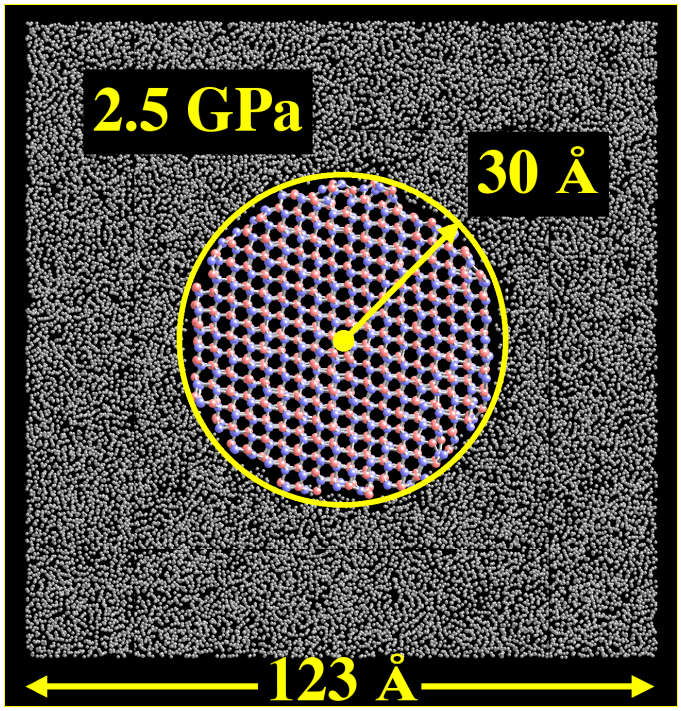


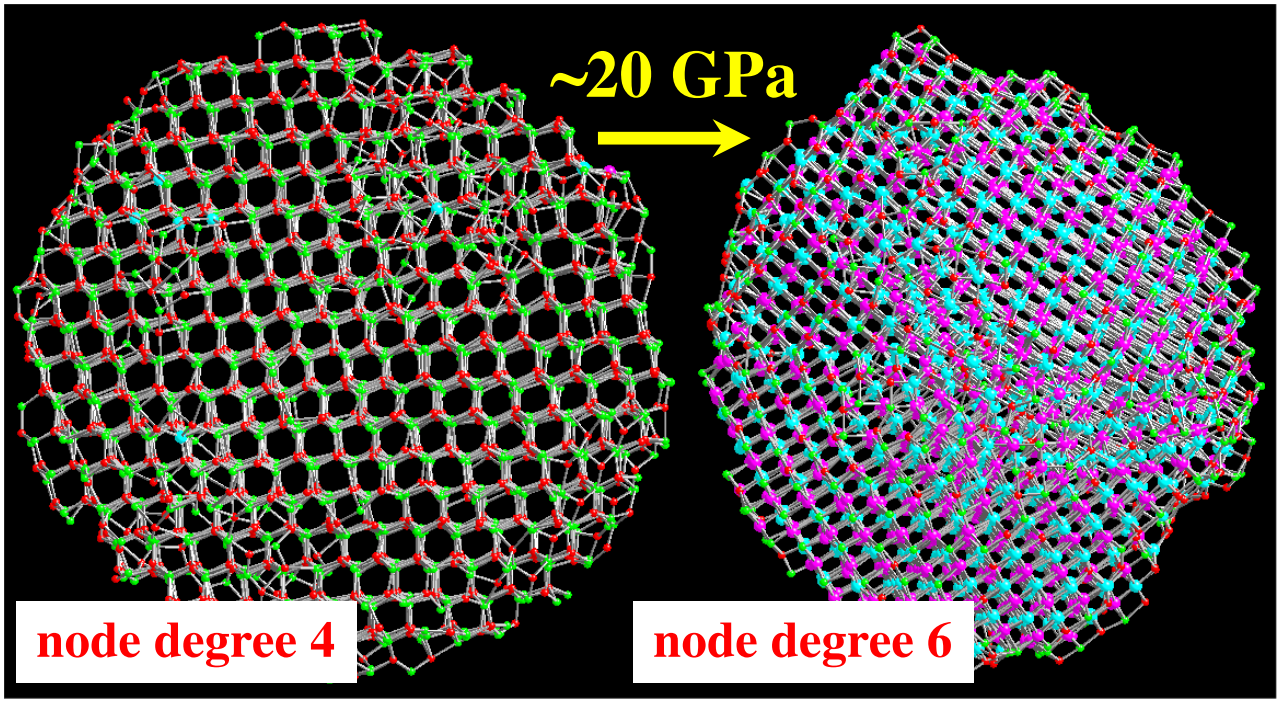
Lattice mismatch (1%) induced interfacial domain array



High-Pressure Structural Transformation

- Wurzite (node degree 4) to rocksalt (node degree 6) structural transformation of a GaAs nanoparticle under high pressure

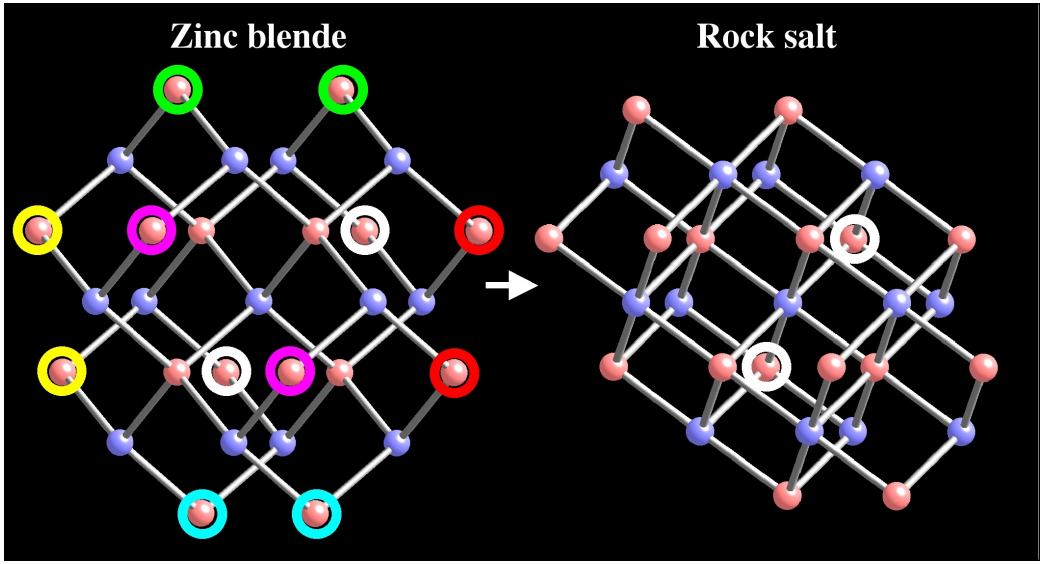


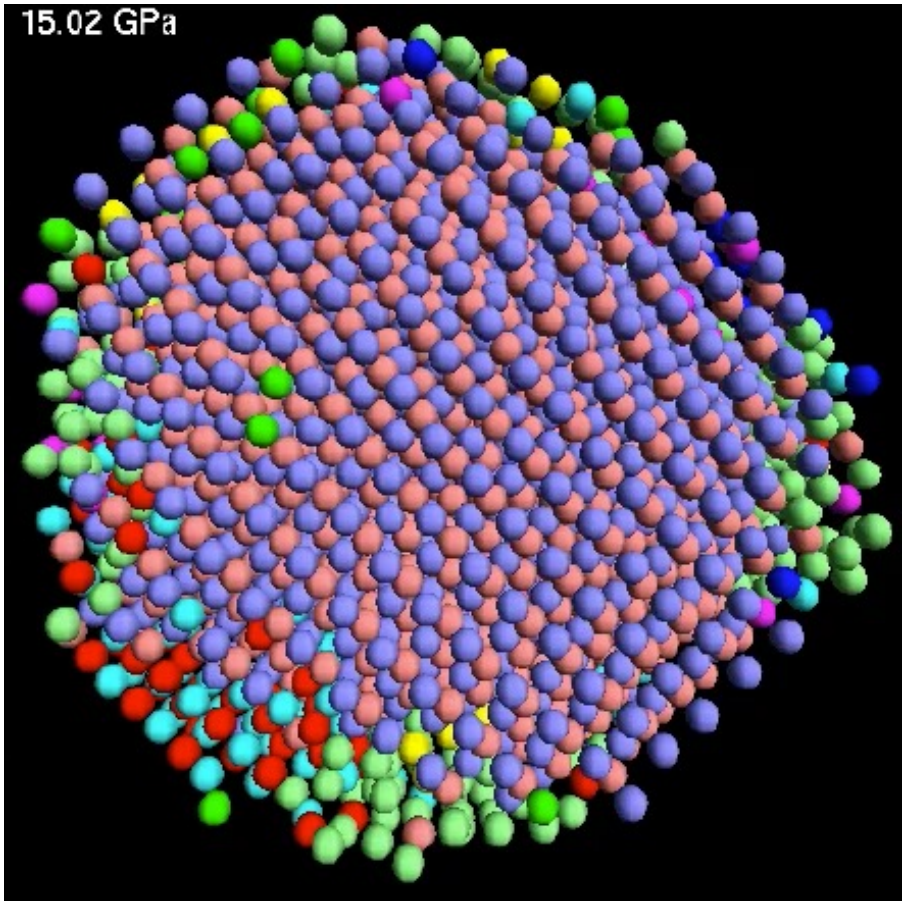


- Existence of multiple domains?

Graph-Transition Tracking

- **Finite set of graph transitions as a classifier**



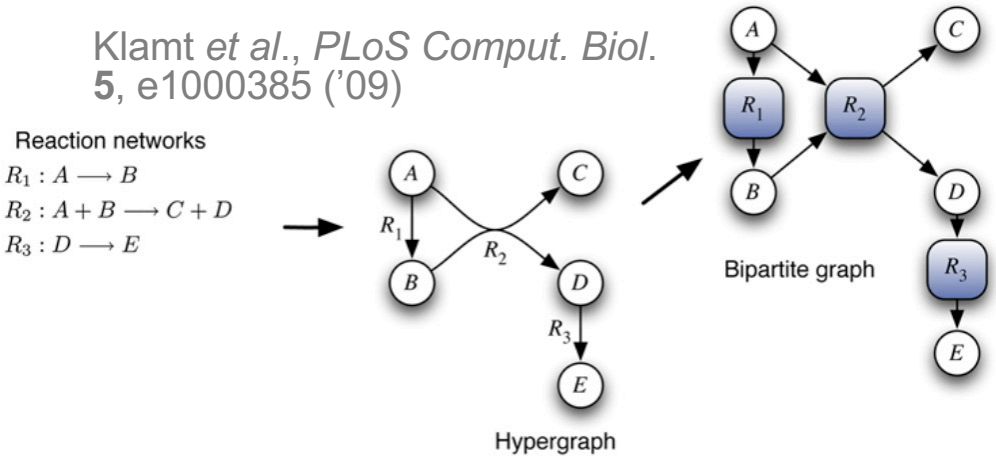


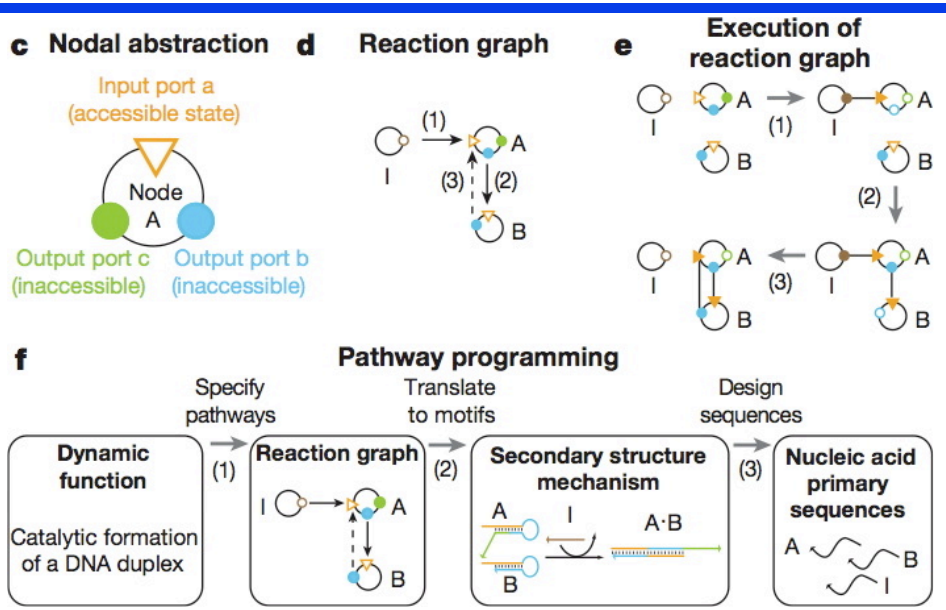
$$G = (V,E)$$
$$\downarrow$$
$$G' = (V,E')$$
$$E \subset E'$$

Graph Transition!

Chemical Reaction Network

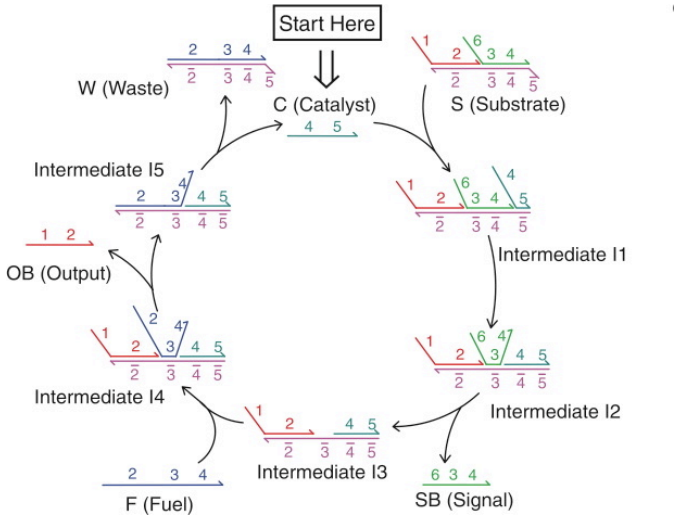
Klamt *et al.*, *PLoS Comput. Biol.* **5**, e1000385 ('09)

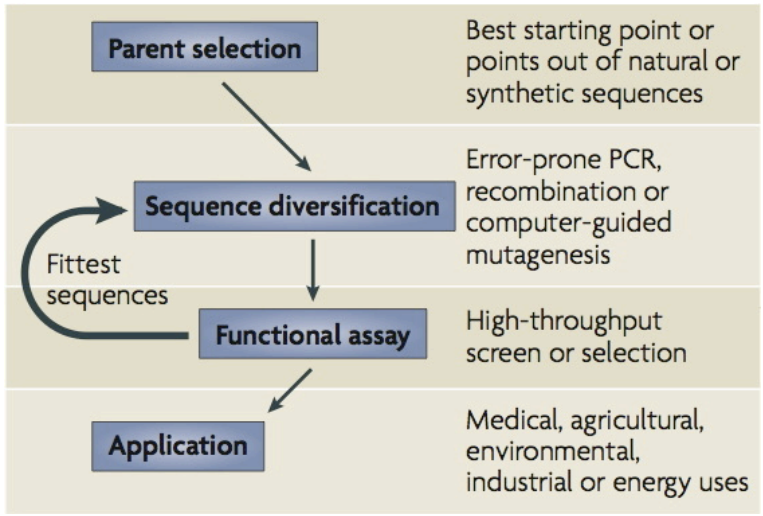


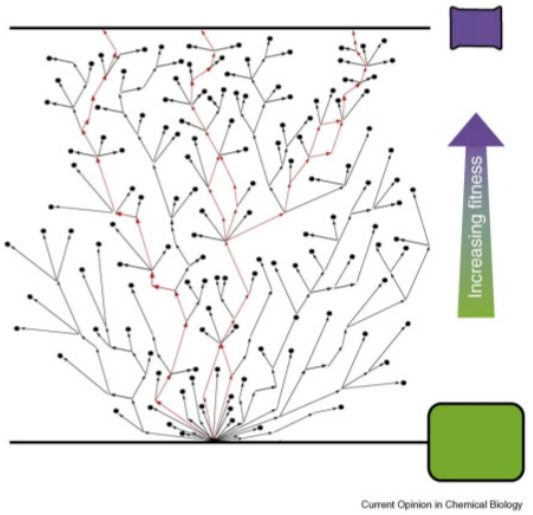


Yin *et al.*, *Nature* **451**, 318 ('08)

Zhang *et al.*, *Science* **318**, 1121 ('07)







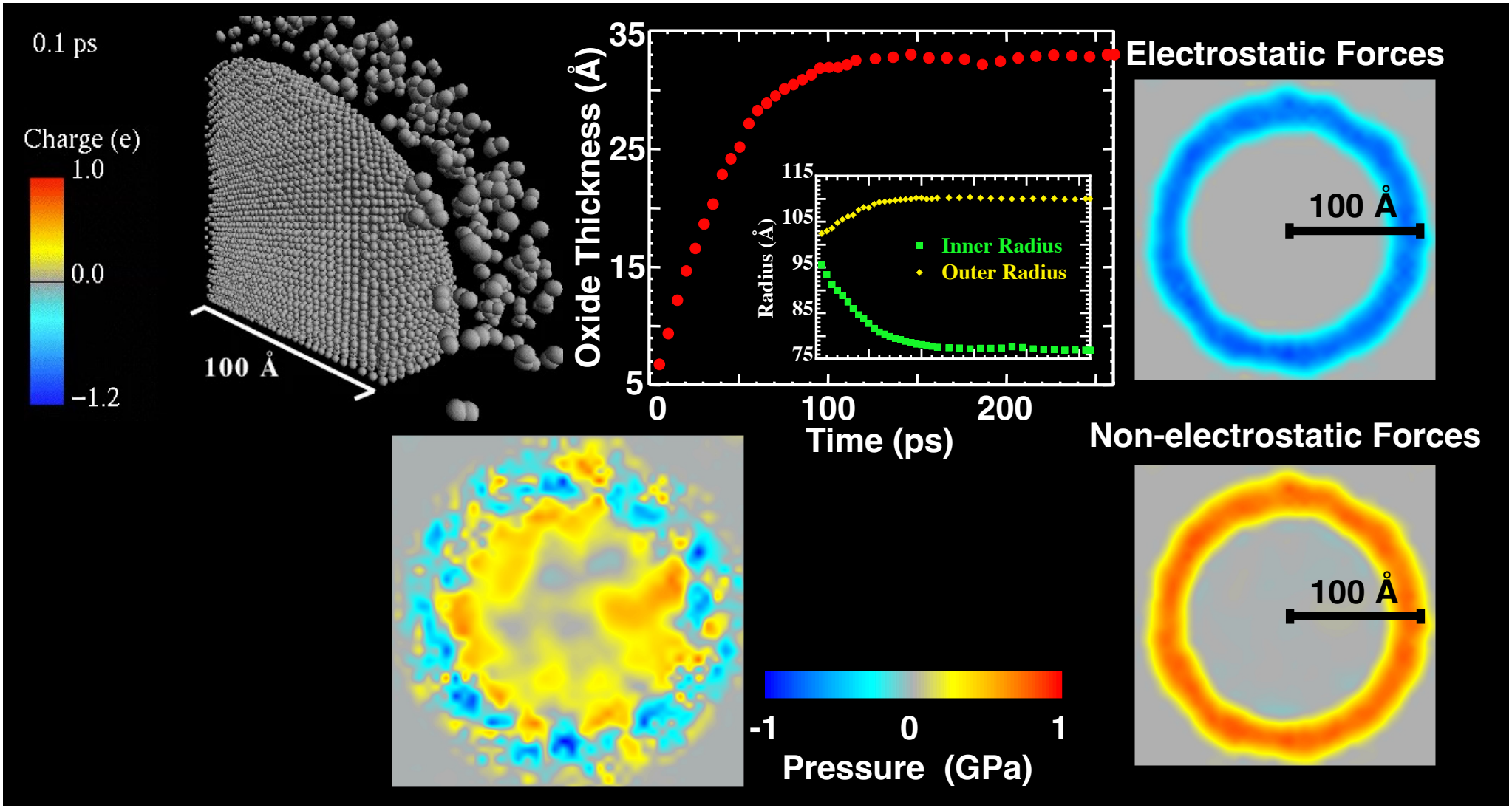
Arnold group, *Nature Rev. MCB* **10**, 867('09); *COCB* **13**, 3 ('09)

Reaction graph = language for self-assembly & catalytic cycle design

Directed & accelerated evolution

Chen *et al.*, *Nature Nanotechnol.* **8**, 755 ('13)

Oxidation of an Al Nanoparticle (n-Al)

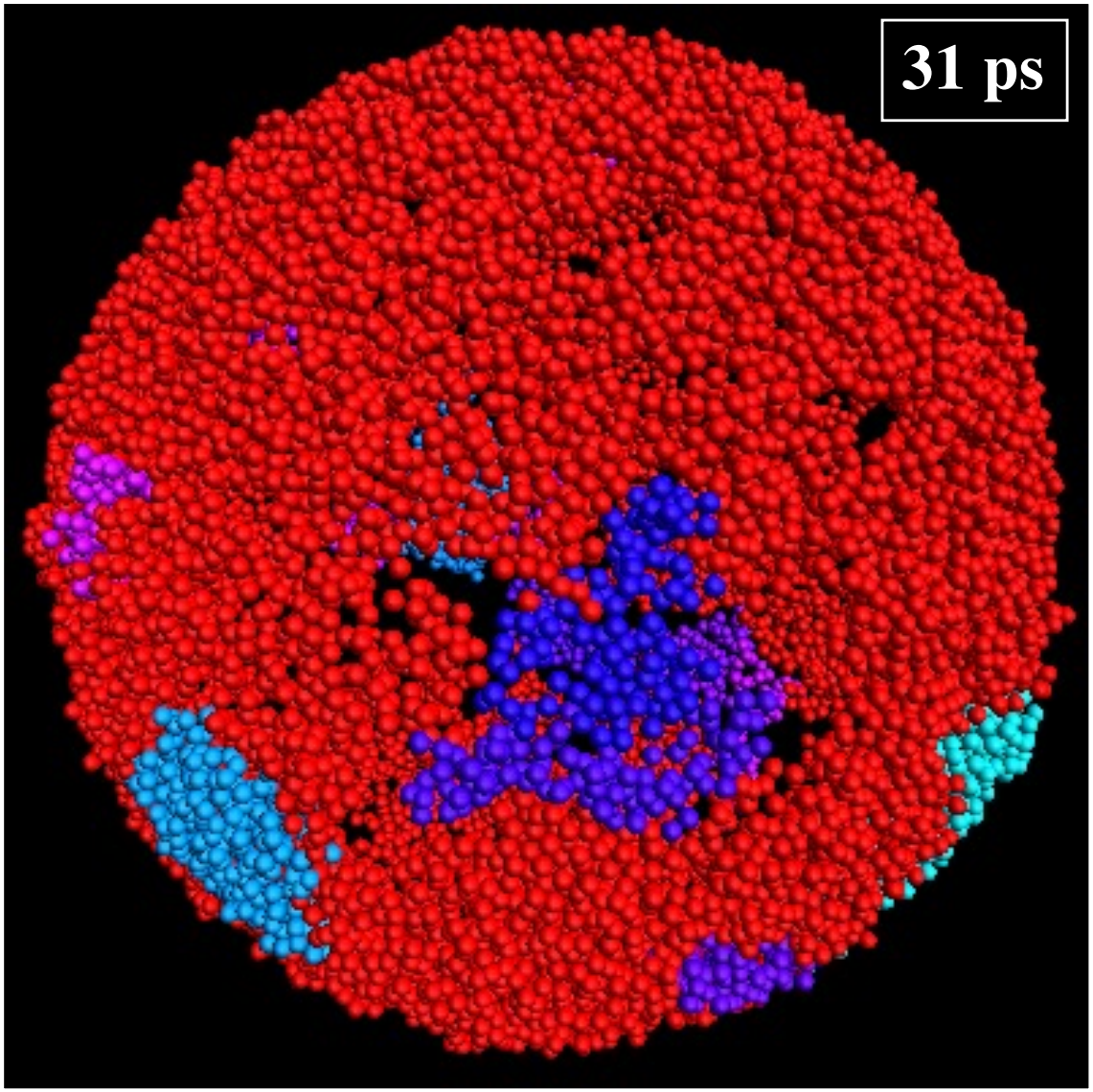


- Oxide thickness saturates at 40 Å after 0.5 ns, in agreement with experiments
- Oxide region/metal core is under negative/positive pressure
- Attractive Al-O Coulomb forces contribute large negative pressure in the oxide

Oxidative Percolation

Clusters of OAl_4 coalesce to form a neutral, percolating tetrahedral network that impedes further growth of the oxide

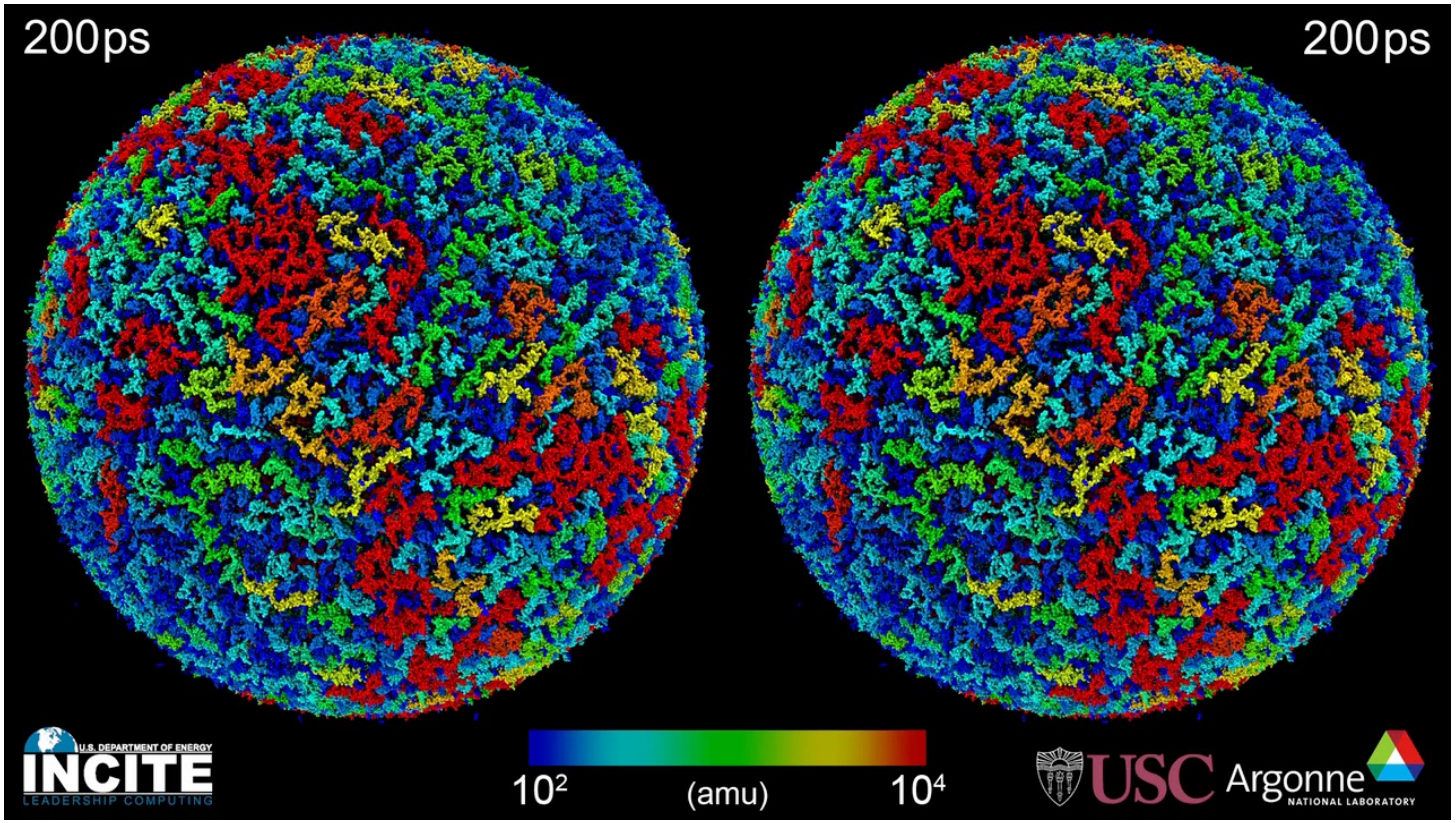
Percorative Connected Components!

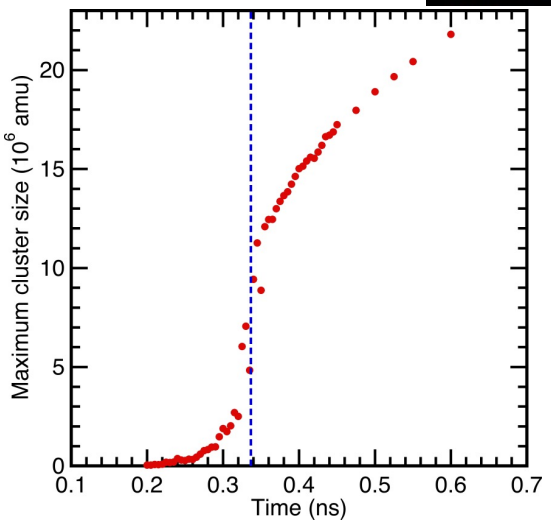


Fractal Nanocarbon Product

Oxidation of SiC particle

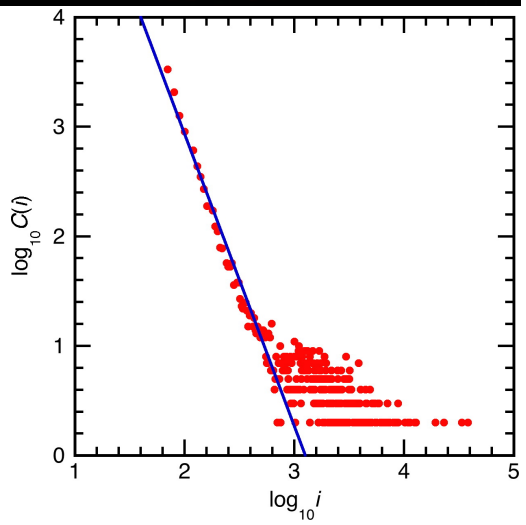
- **Percolation transition causes carbon clusters to exhibit power-law distribution of sizes: $C(i) \sim i^{-\tau}$**





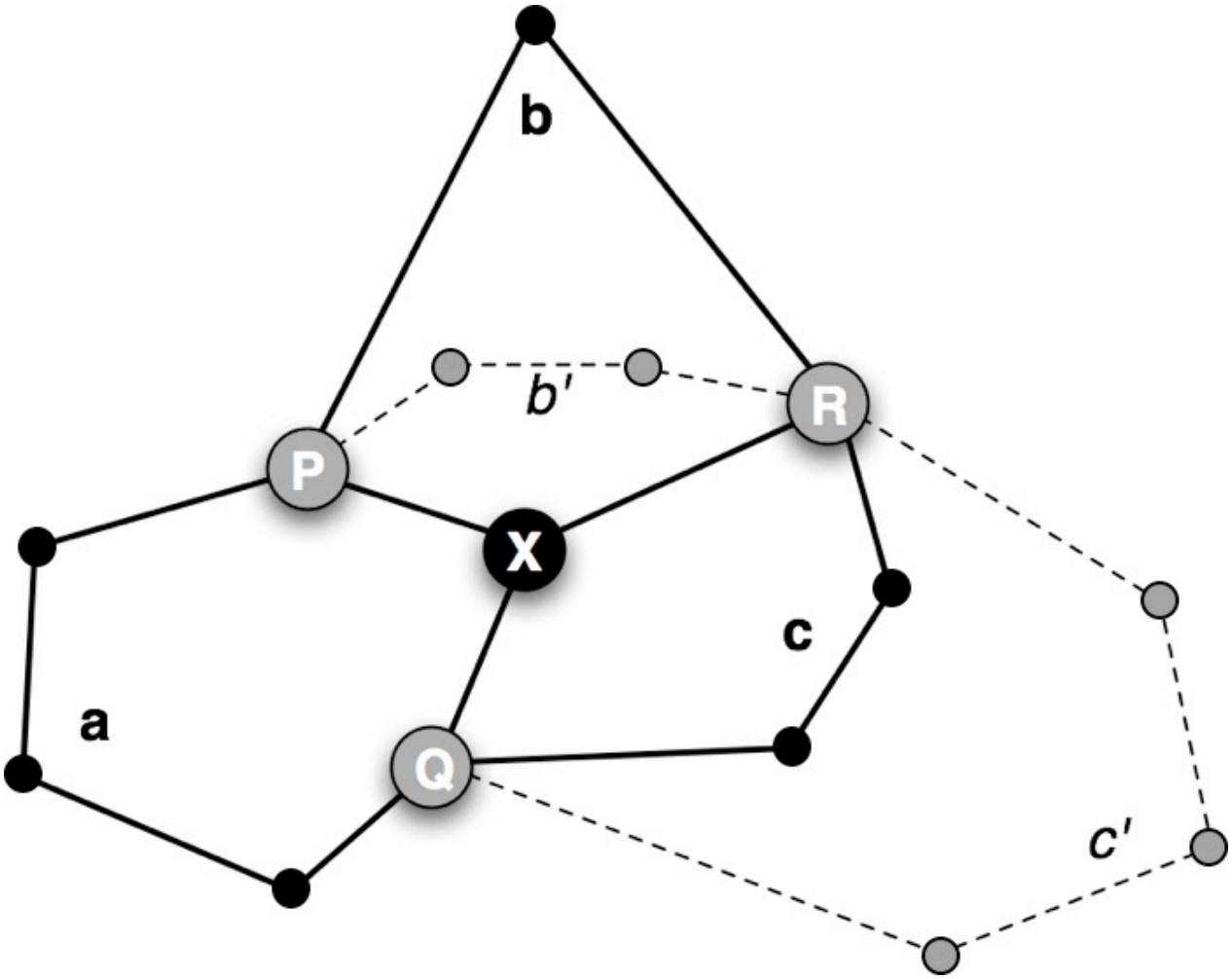
- **Fractal nanocarbon product with large surface areas may find supercapacitor, battery-electrode & mechanical metamaterial applications: $d_f = d/(\tau - 1) \sim 1.85$**

K. Nomura *et al.*, *Sci. Rep.* **6**, 24109 ('16)
J. Insley *et al.*, *IEEE/ACM SC16*



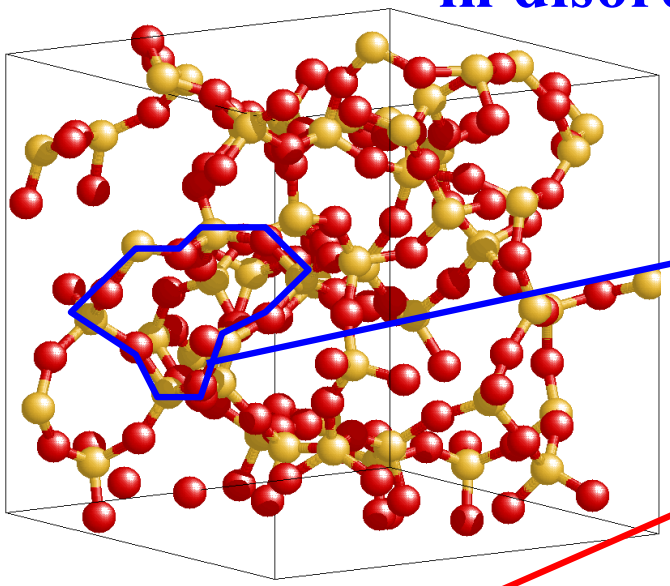
Shortest-Path Rings

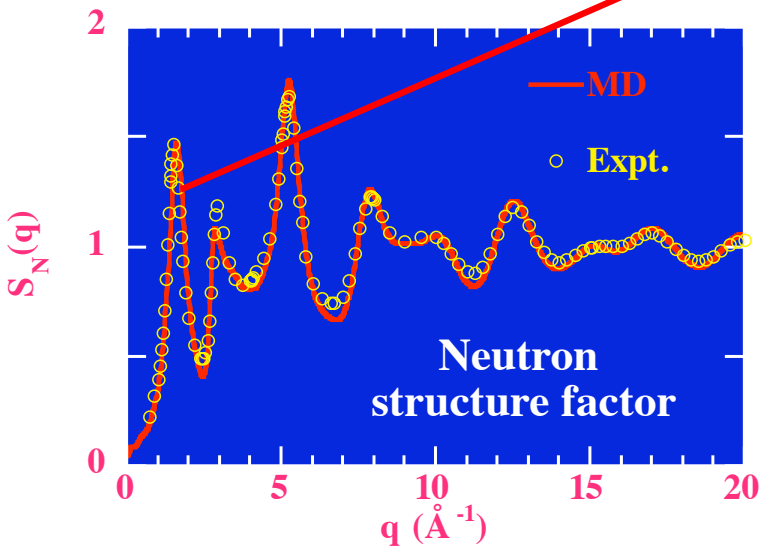
- **K-ring:** Given a vertex x & two of its neighbors w & y, a K-ring generated by the triplet w–x–y is any ring containing the edges [w–x], [x–y] and a shortest path w–y path in G–x

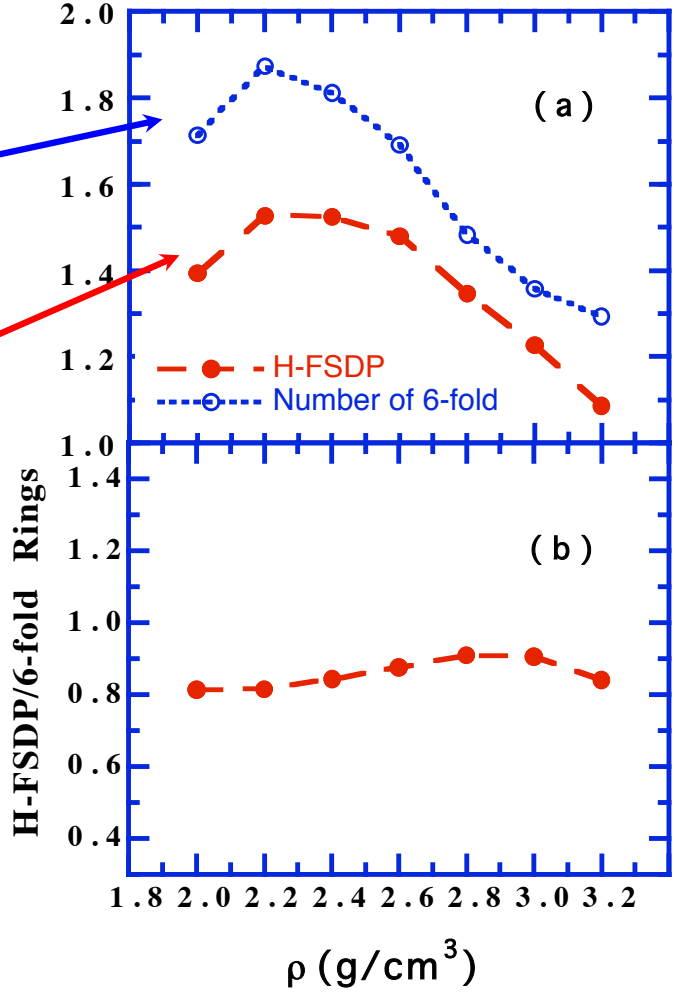


Ring-based Data Mining

Shortest-path ring analysis of intermediate-range order (IRO) in disordered materials

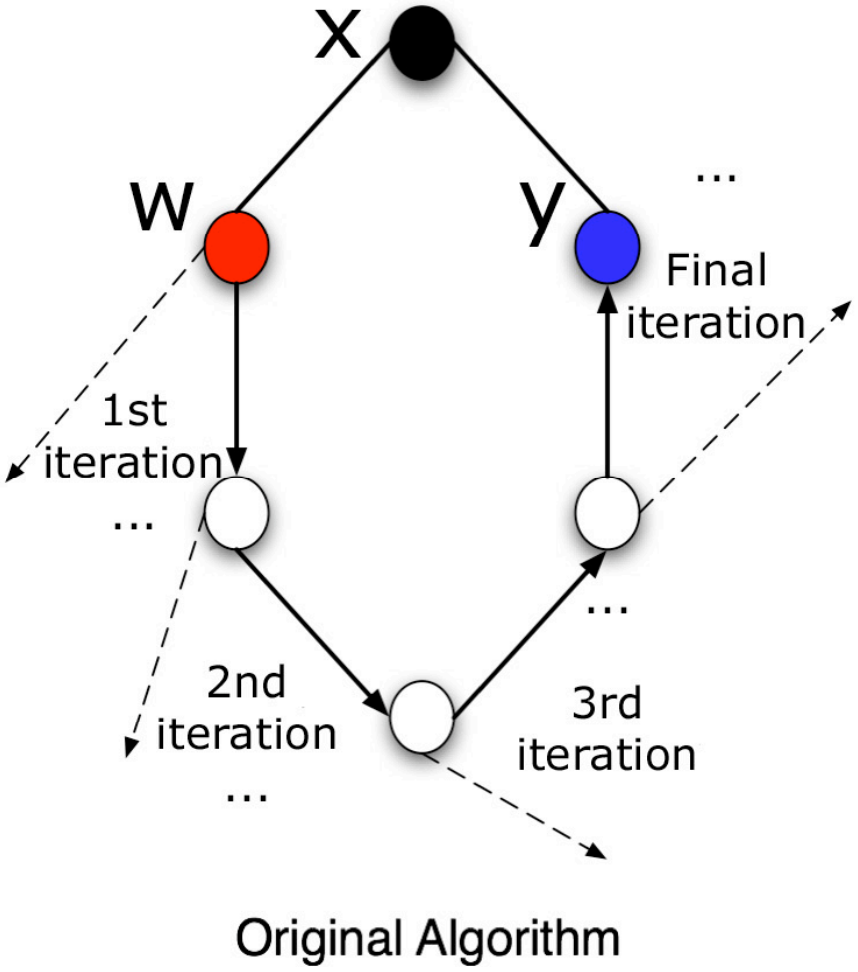




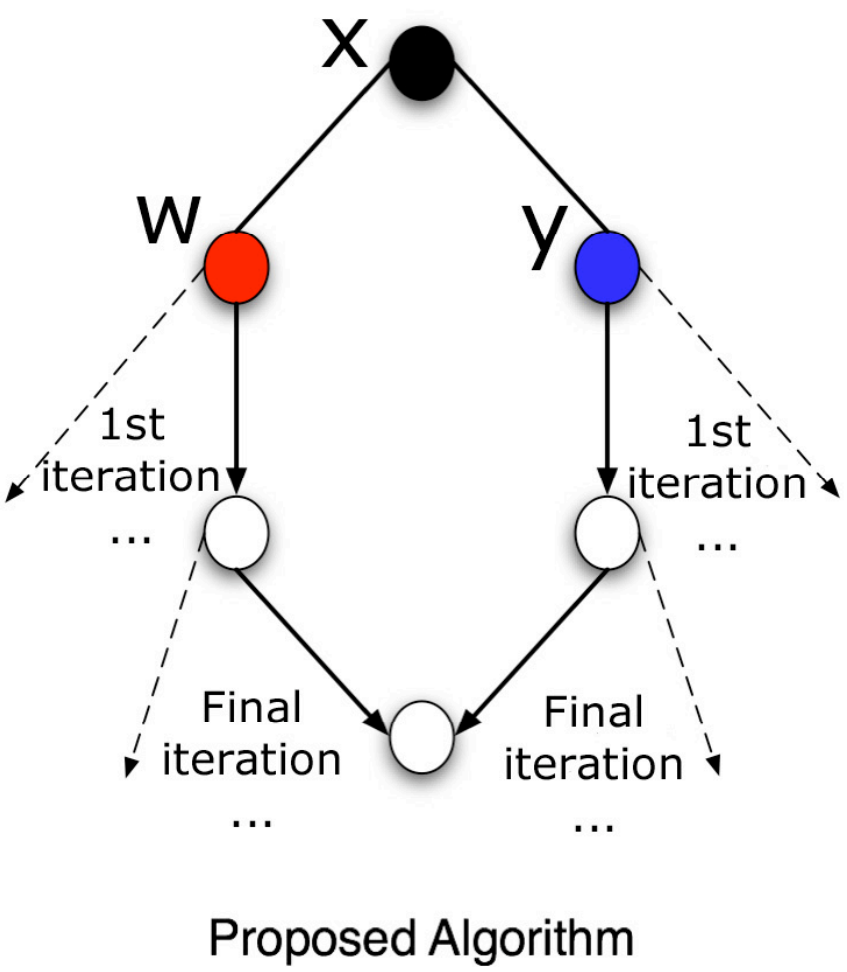


Correlation between IRO in neutron scattering & ring distribution

Fast Ring Analysis: Dual-Tree Expansion



Original Algorithm



Proposed Algorithm

C. Zhang *et al.*, *Computer Physics Communications* **175**, 339 ('06)

DTE Algorithm

Algorithm dual_tree_expansion()

Input:

V = Set of all vertices (i.e., atoms)
R_c = Ring cutoff range (Euclidean)
R_{bc} = Bond cutoff distance (Euclidean)
L_{MAX} = Maximum length of ring (integer)
P = Number of compute nodes

Output:

The K-ring statistics for all vertices in the network
List of atoms with abnormal ring profile

Variables:

Neighbors(V) = Set of vertices that share an edge with vertex V
$K_v(p)$ = Number of p-member rings that go through vertex V
L_b = Length of the ring formed with path (V_i, V, V_j)

Steps:

0 coarse grained spatial decomposition of atoms on P compute nodes with a thin boundary extension of R_c distance (This step is for the parallel version only)
1 create adjacency list G for all node in V_p using R_{bc} as cutoff distance
2 for every vertex $V \in V_p$
  for each vertex pair V_i and V_j in Neighbors(V) do
    $A_1 = \{V_i\}$
    $A_2 = \{V_j\}$
    $L_b = 0$
    while ($A_1 \cap A_2 = \varnothing$ AND $L_b < L_{MAX}$) do
      $L_b = L_b + 2$
      if ($A_1 \cap$ Neighbors(A_2) $\neq \varnothing$ OR $A_2 \cap$ Neighbors(A_1) $\neq \varnothing$)
        $L_b = L_b + 1$
        break
      else if (Neighbors(A_1) $\cap$ Neighbors(A_2) $\neq \varnothing$)
        $L_b = L_b + 2$
      A_1 = Neighbors(A_1)
      A_2 = Neighbors(A_2)
    if ($L_b < L_{MAX}$) ++ $K_v(L_b)$

Spatial Hash-Function Tagging

Algorithm spatial hash function tagging (SHAFT)

Input:

$C(V)$ = 3D coordinates of all vertices (i.e., atoms)
R_c = Ring cutoff range (Euclidean)
R_{bc} = Bond cutoff distance (Euclidean)
L_{MAX} = Maximum length of ring (integer)

Output:

The integer index that is unique for all vertices in the maximum ring span

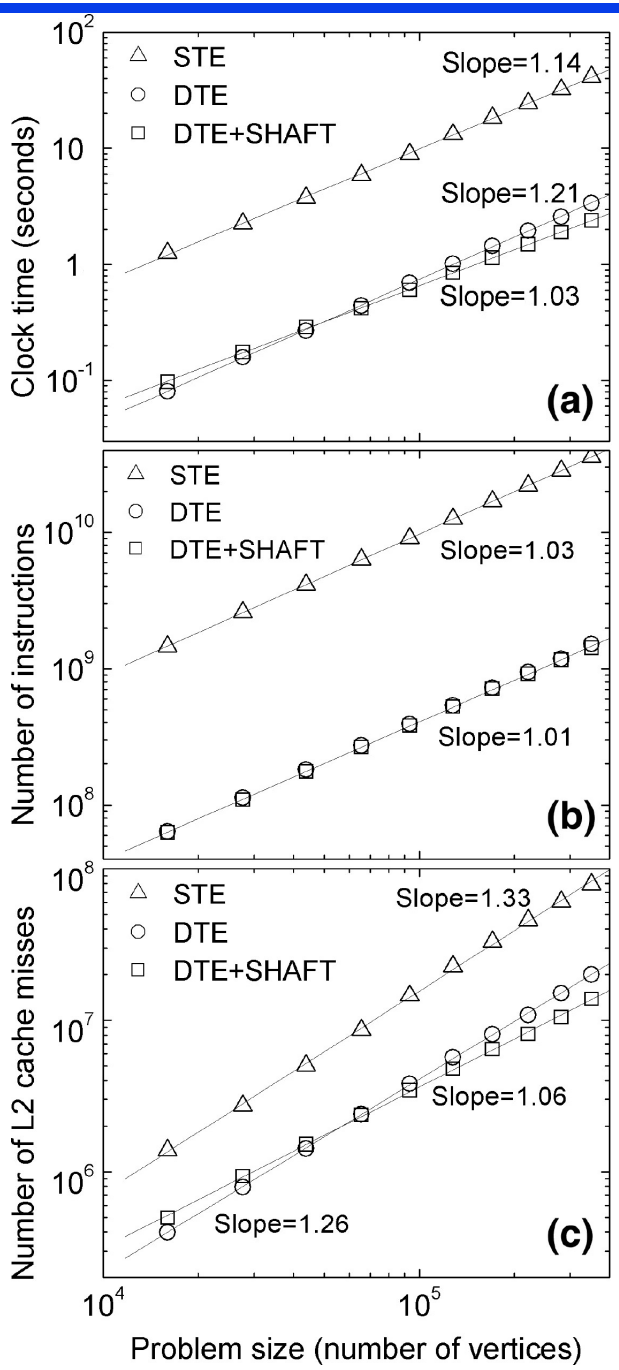
$b = R_{lower} / \sqrt{3}$
$c = R_{upper} L_{max}$
$m = \lceil c/b \rceil$

Step:

for each vertex
for each spatial dimension i from 1 to 3
$q_i = \lfloor C_i/b \rfloor$
$q_i \% = m$
return $q = q_3 \times m^2 + q_2 \times m + q_1$

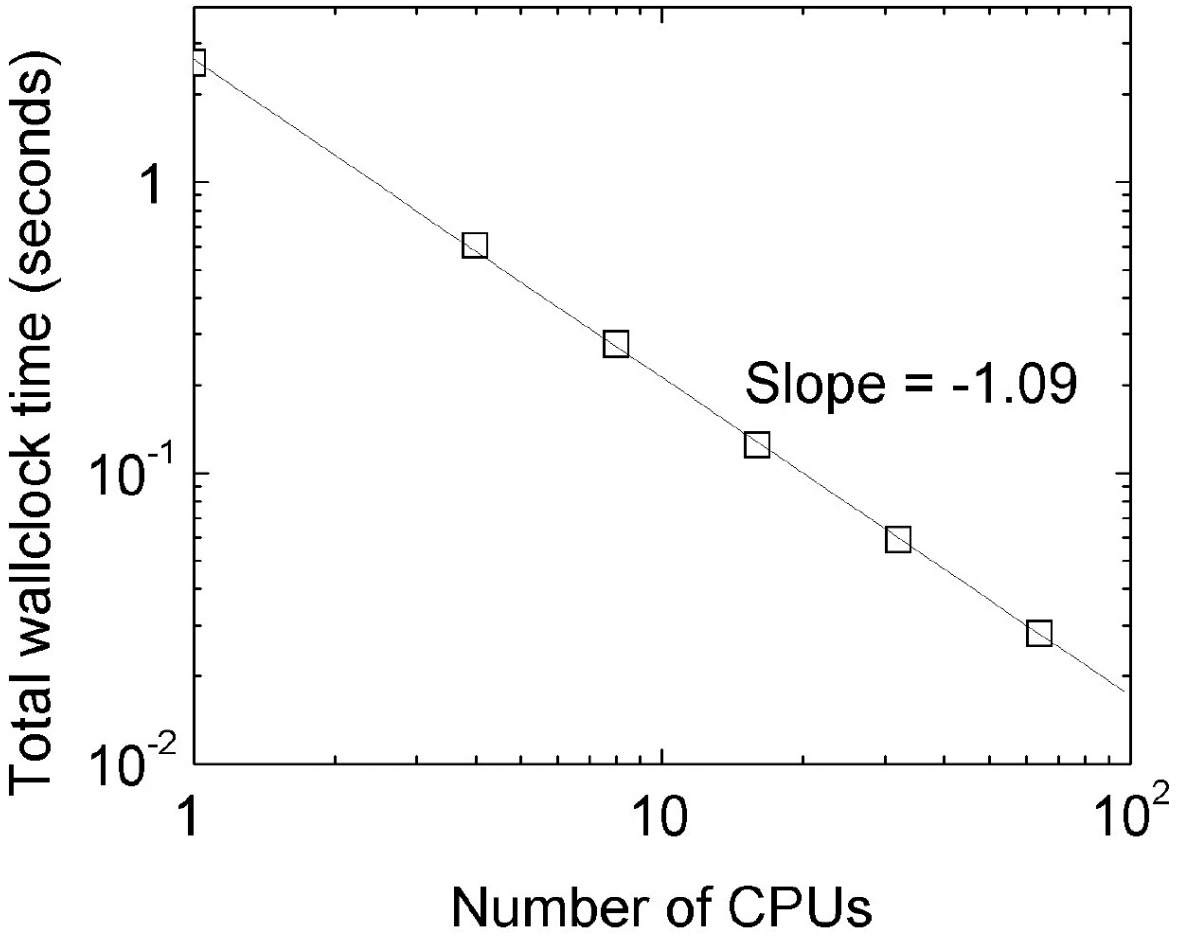
0	1	2	3	4	0	1	2	3	4
5	6	7	8	9	5	6	7	8	9
10	11	12	13	14	10	11	12	13	14
15	16	17	18	19	15	16	17	18	19
20	21	22	23	24	20	21	22	23	24
0	1	2	3	4	0	1	2	3	4
5	6	7	8	9	5	6	7	8	9
10	11	12	13	14	10	11	12	13	14
15	16	17	18	19	15	16	17	18	19
20	21	22	23	24	20	21	22	23	24

Numerical Tests



Linear scaling on the problem size

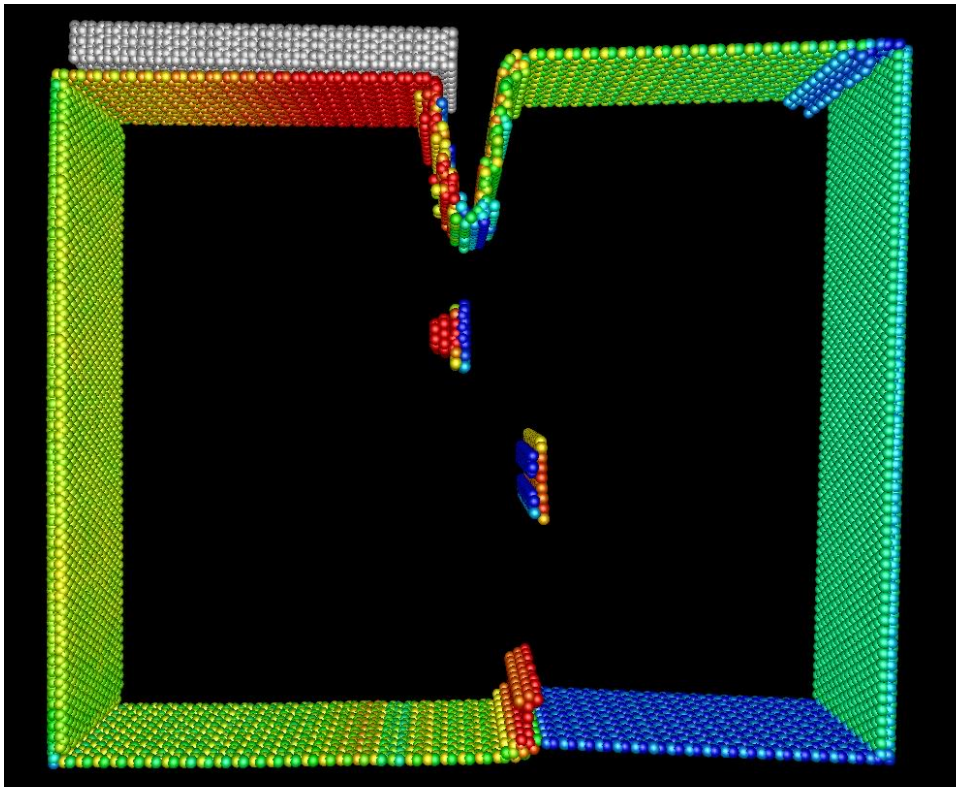
Superlinear (strong) scaling on the number of CPUs



Dislocation Mining

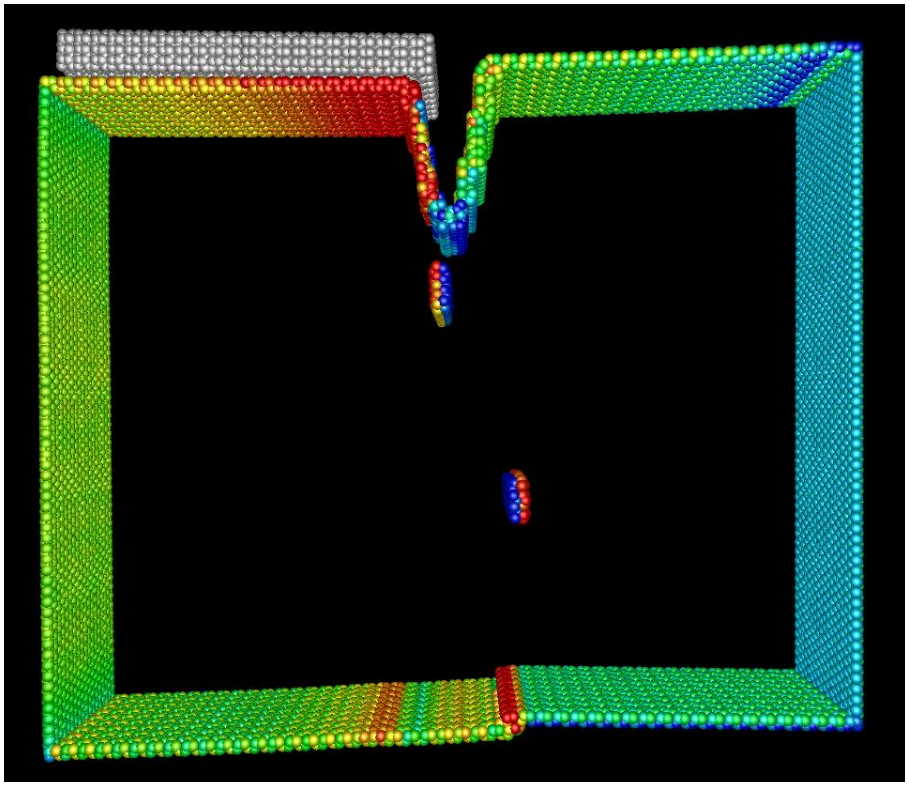
Based on potential energy

Shown atoms with high energy compared to bulk



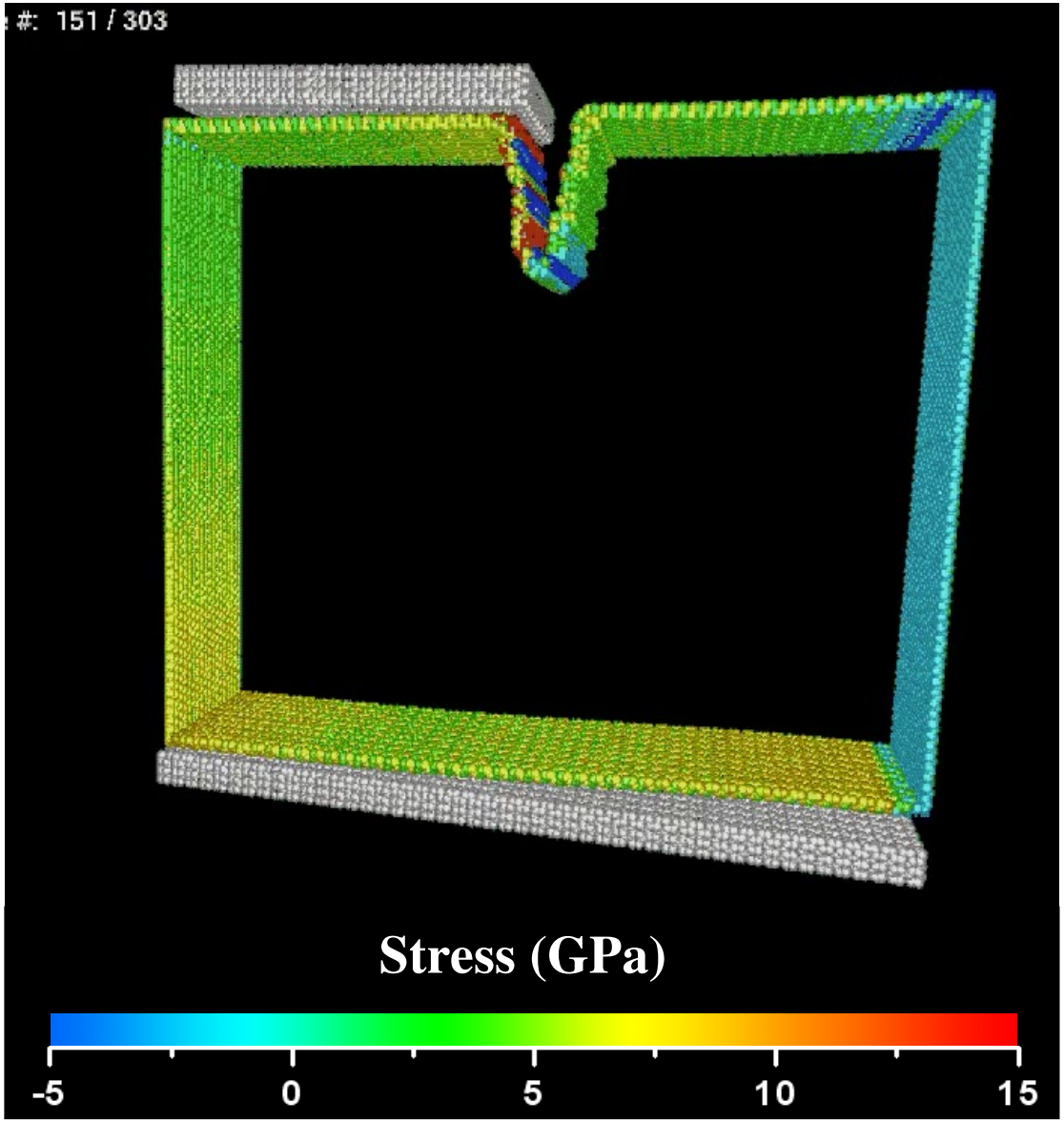
Based on shortest-path ring statistics

Shown atoms with less than 12 6-membered rings



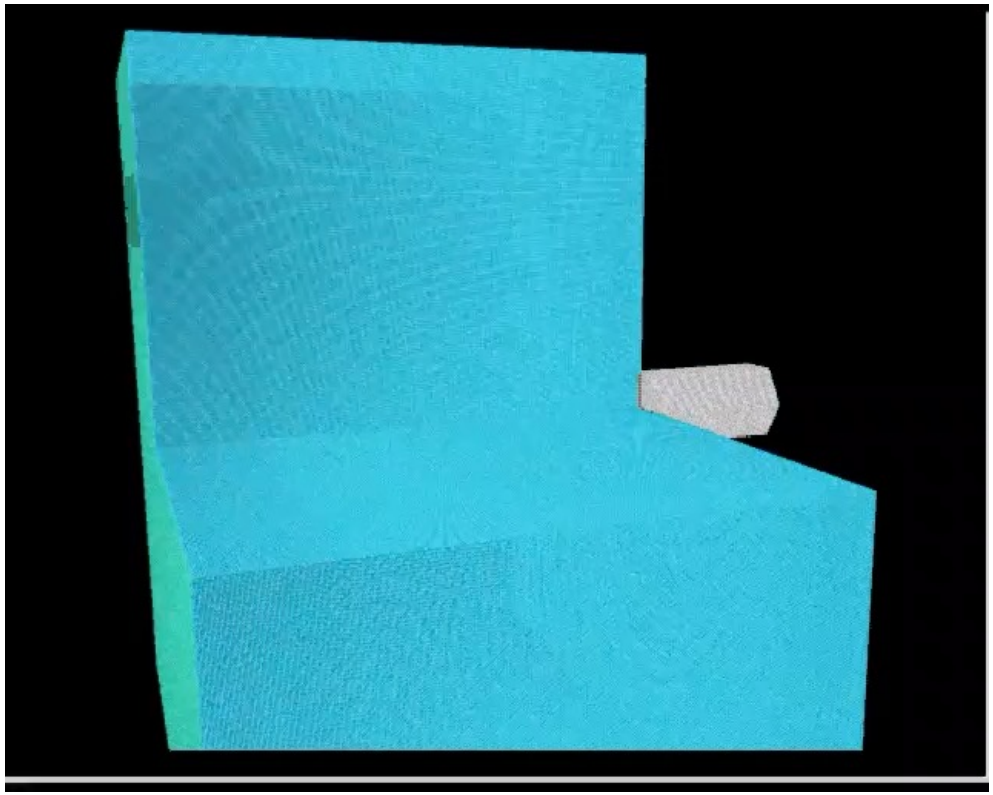
100 km/s Impact on Notched AlN

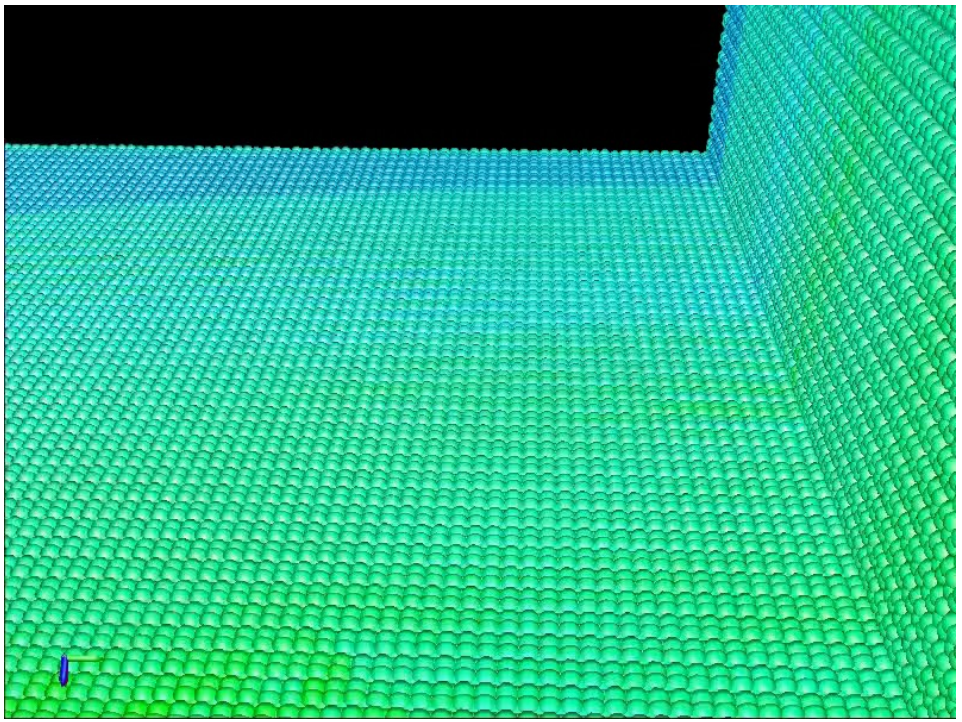
- Dislocation nucleation & emission from notch during impact
- Dislocations & surface atoms mined by ring statistics

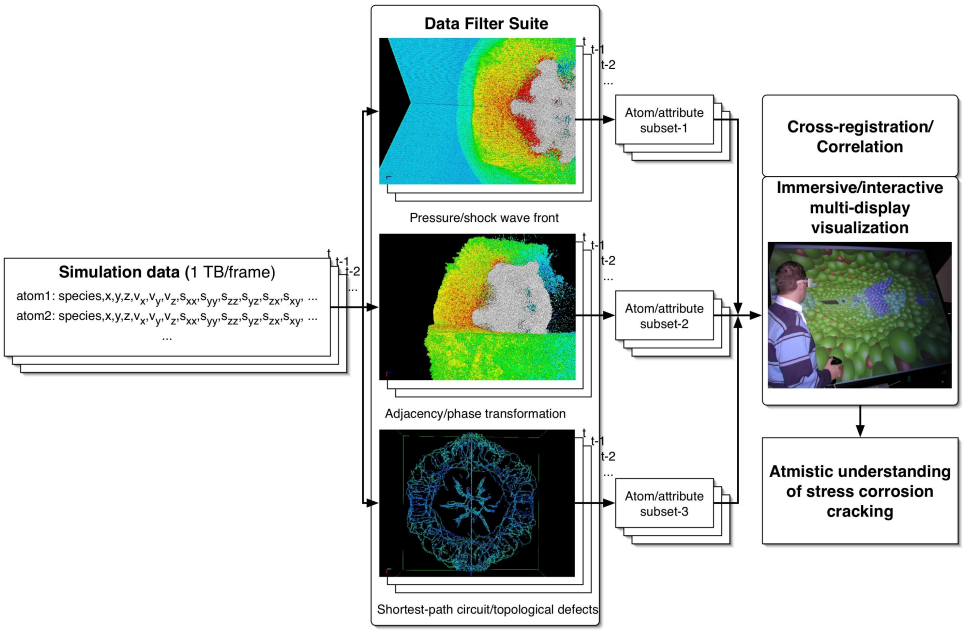


Impact-Damage Tolerant Ceramics?

Inverse problem: design materials with desired properties

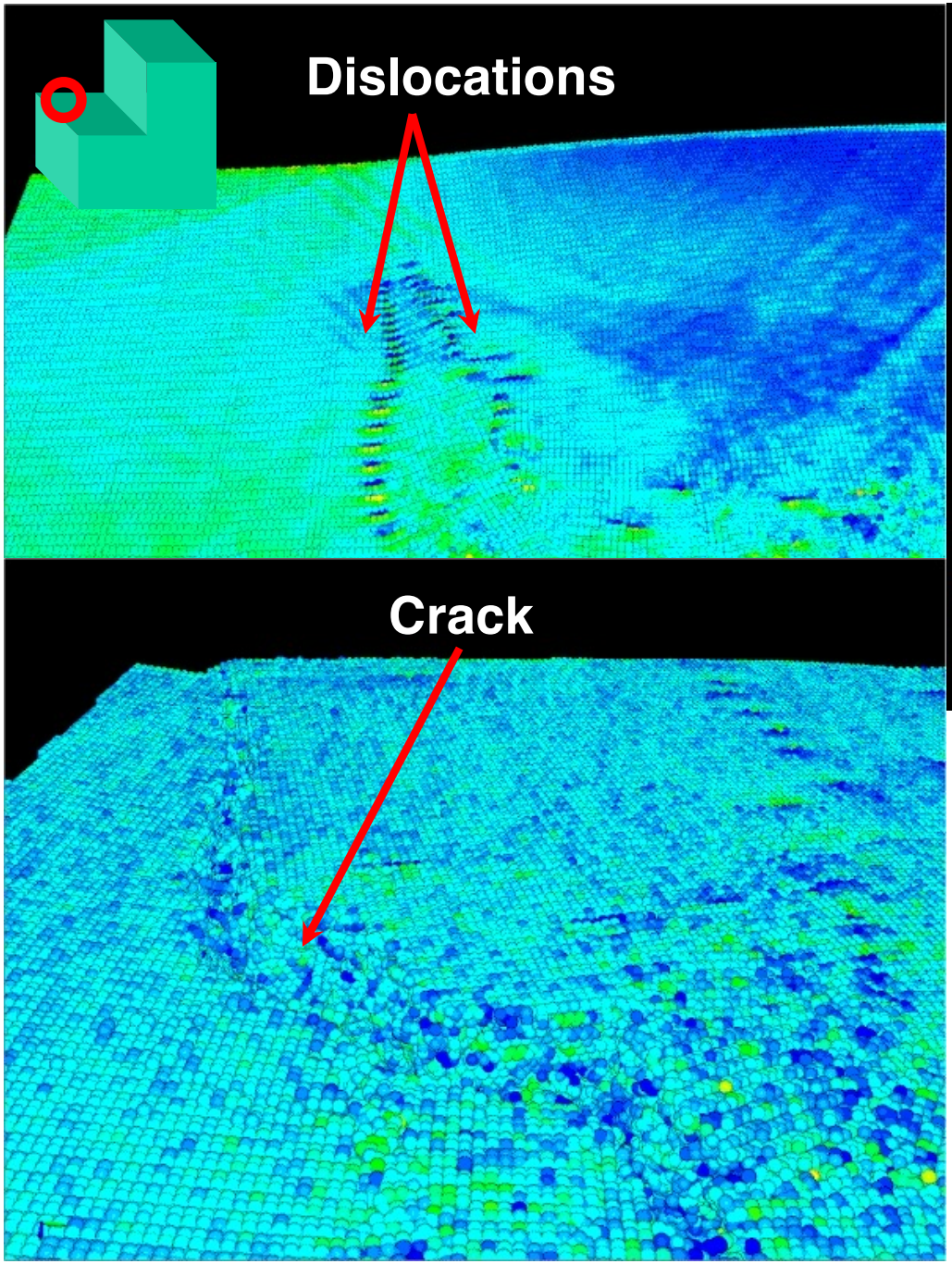


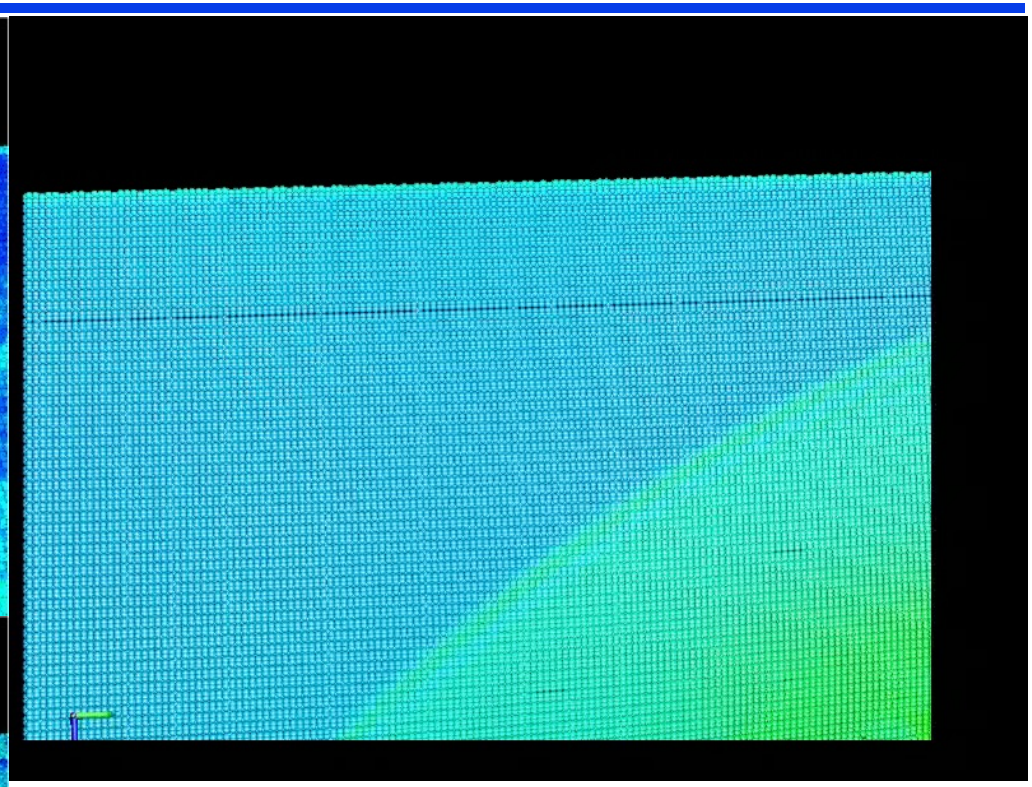




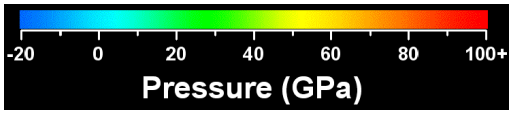
209 million atom MD of hypervelocity impact in AlN for the design of light-weight ceramic armors

Crack Nucleation at Kink Bands



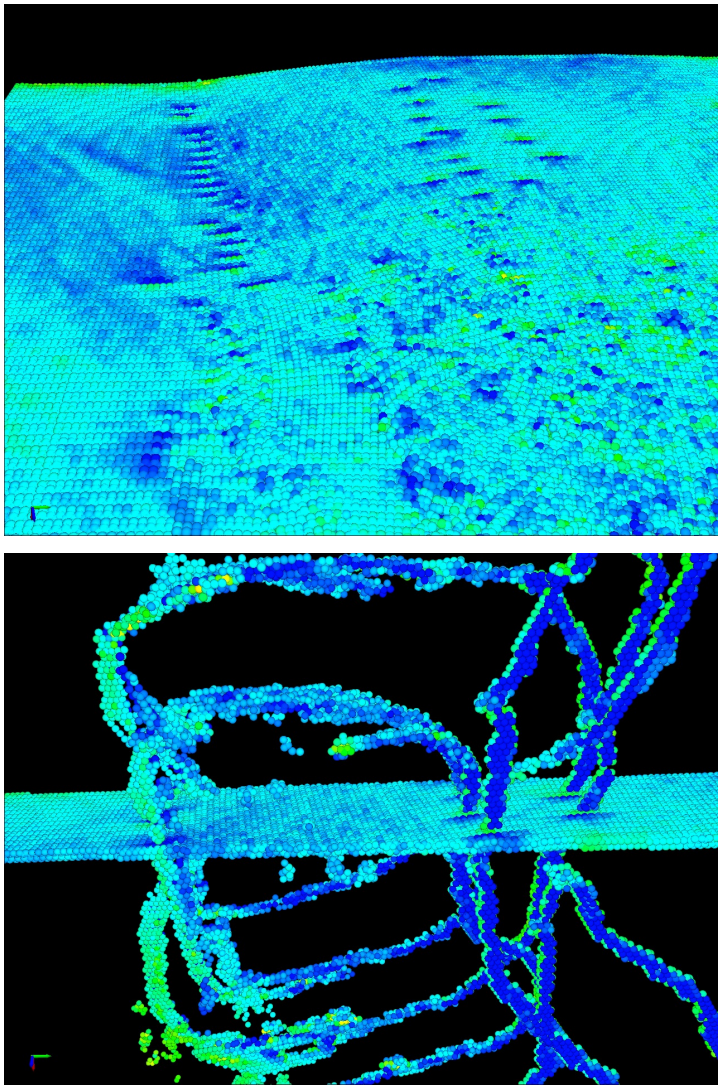


- Series of dislocation dipoles with opposite Burgers vectors form a kink band to releases stress
- Tilt grain boundaries of the kink bands act as sources of mode-II (shear) crack nucleation

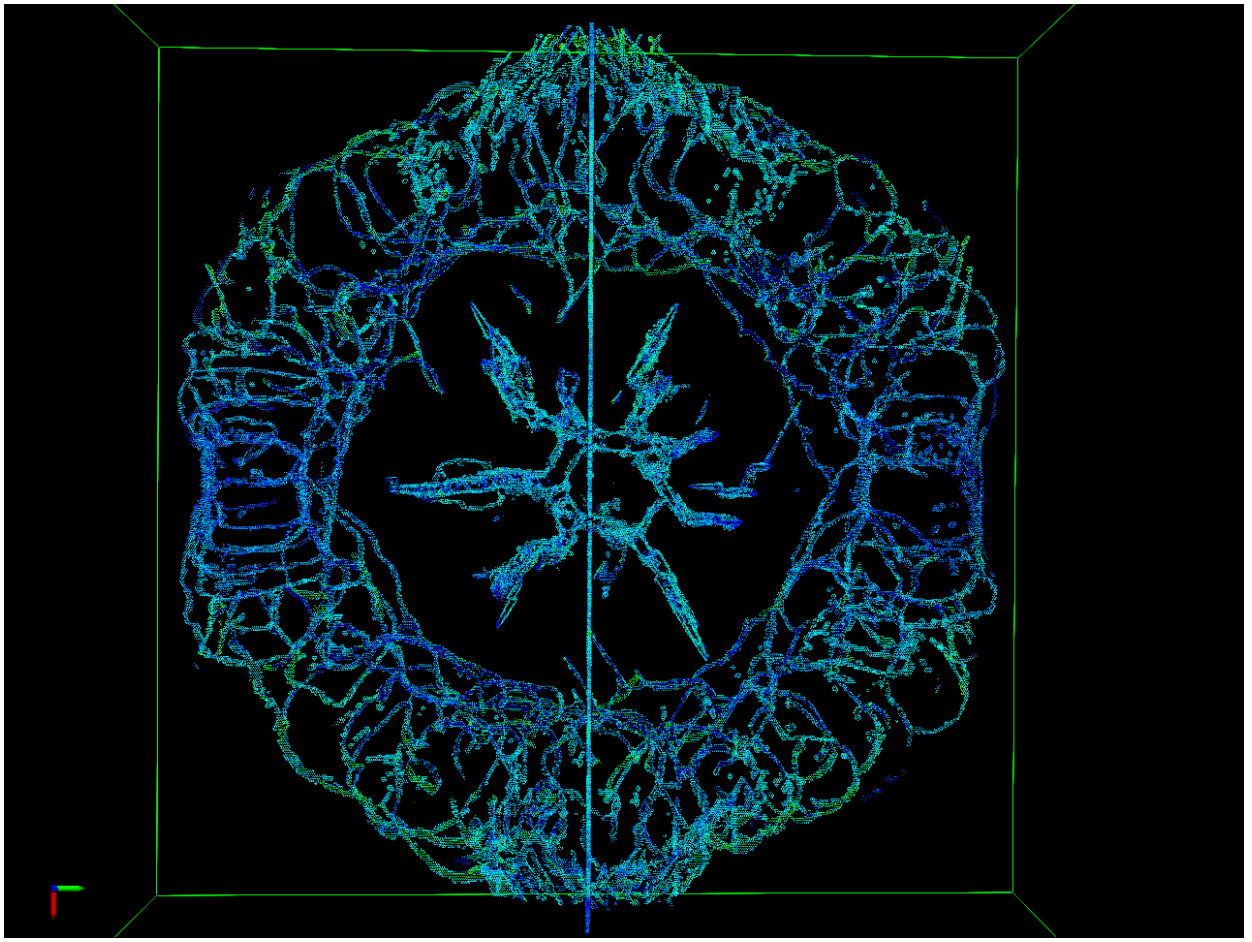


Dislocation Loops at Kink Bands

Graph (shortest-path circuit) based mining of topological defects



Atoms participating in non-6-member circuits



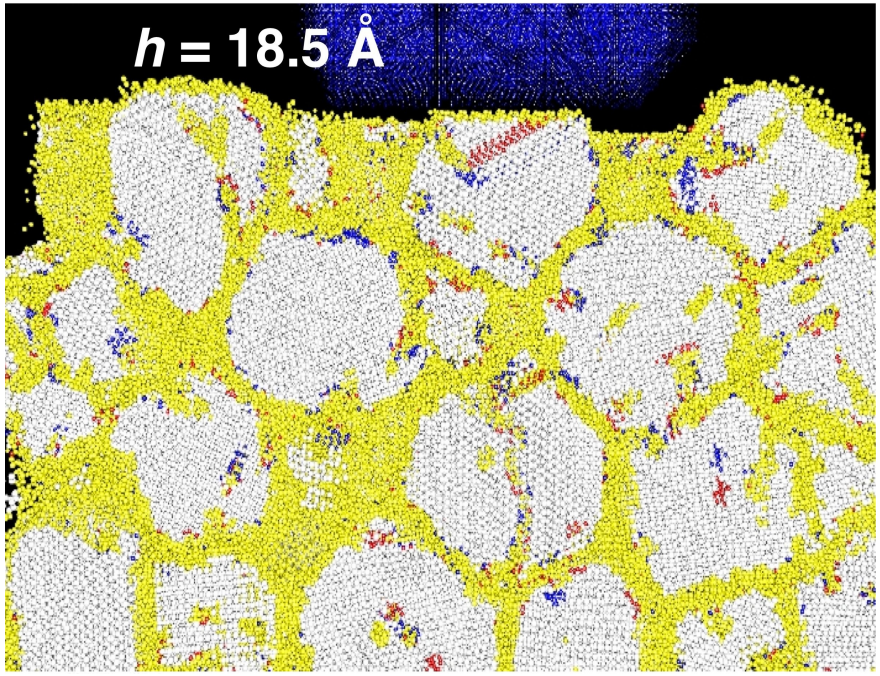
Dislocation network

Nanoindentation on Nanophase SiC

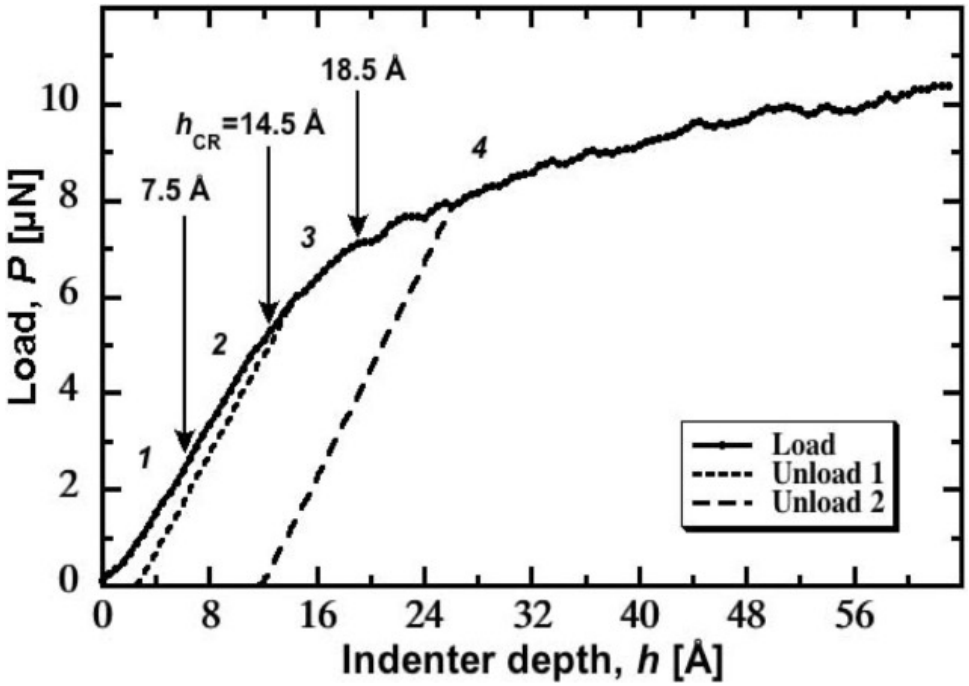
Superhardness

MD: 39 GPa
(grain size, d = 8 nm)

Expt.: 30-50 GPa
(d = 5-20 nm)
[Liao *et al.*, *APL*, '05]



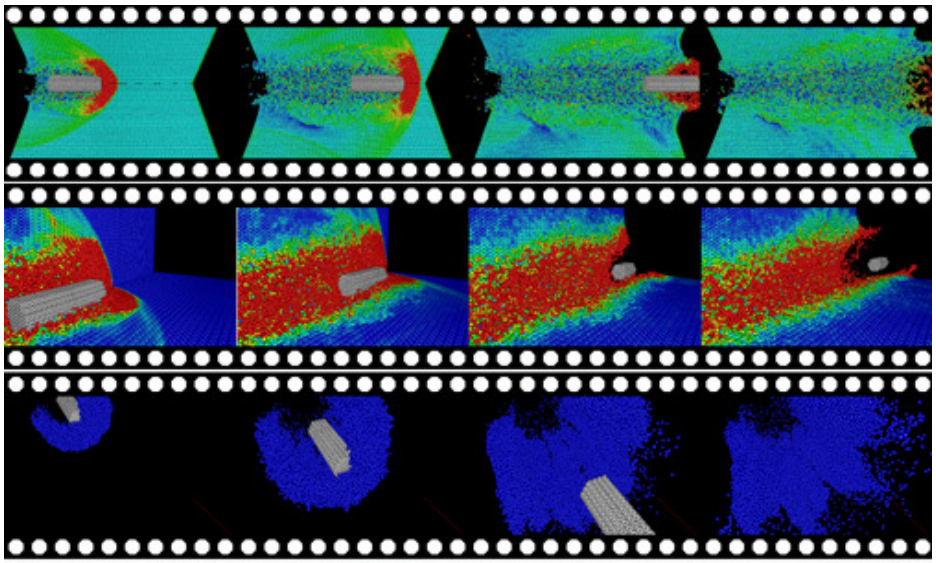
Load-displacement curve

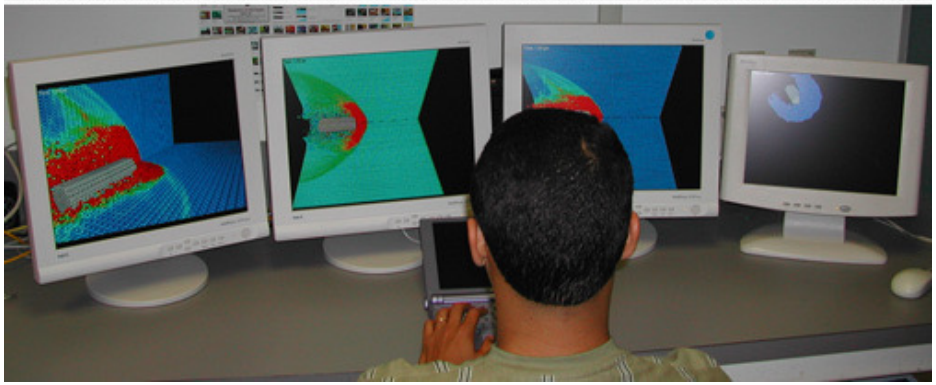


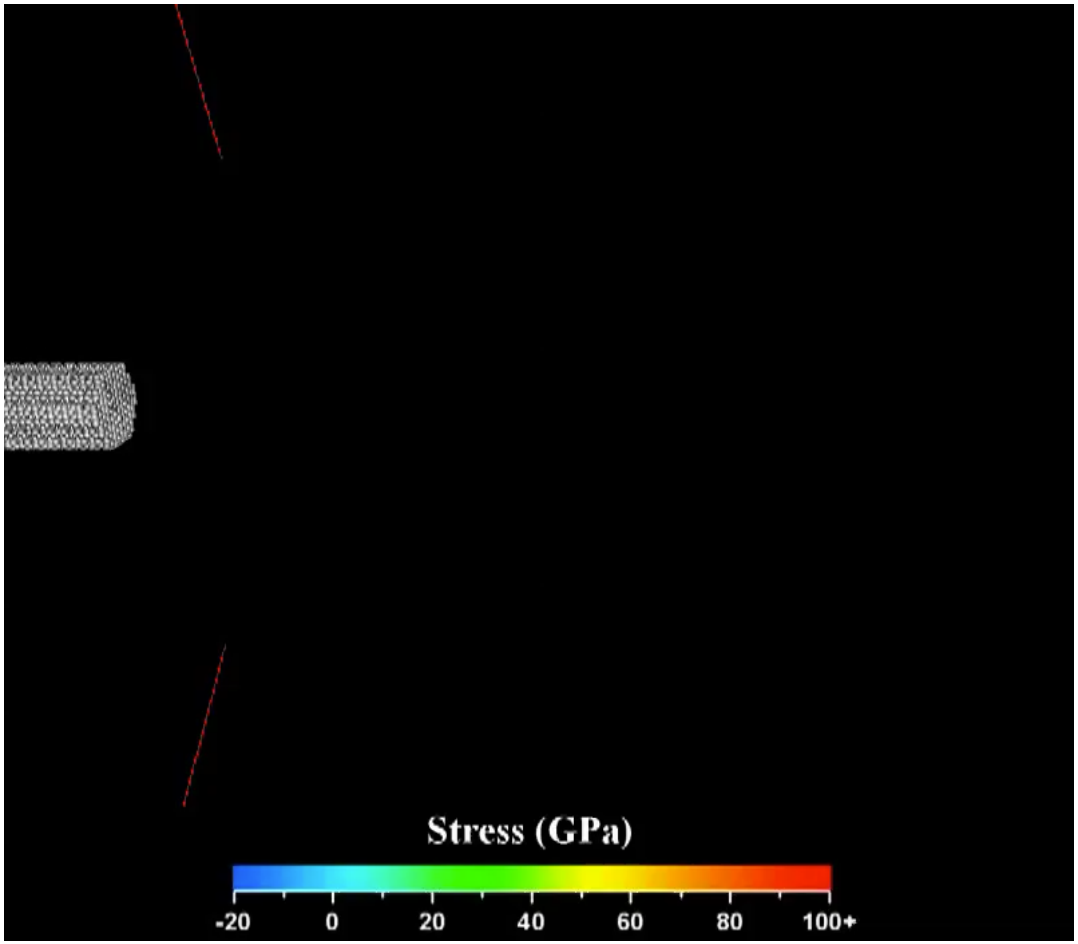
Crossover from intergrain continuous response to intragranular discrete response

Szlufarska, Nakano & Vashishta, *Science* **309**, 911 ('05)

Multimodal Multidisplay Visualization







Hypervelocity penetration through an AlN plate

Singular Value Decomposition

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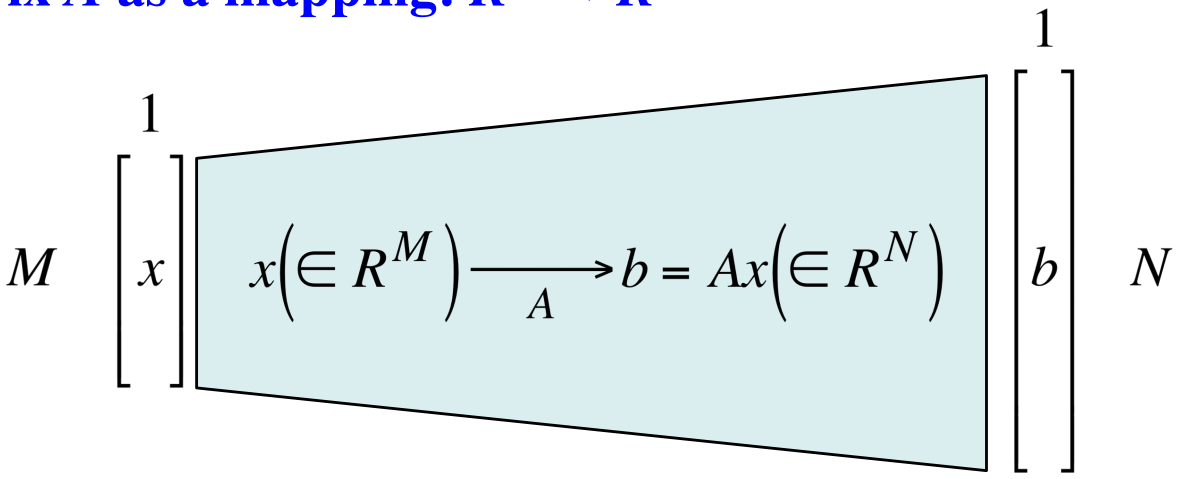
Goal: Another matrix decomposition (SVD) for low-rank matrix approximation

cf. Eigen decomposition
$A = Q[\searrow]Q^T$
QR decomposition
$A = Q[\blacktriangleright]$

See note on "least square fit" & *Numerical Recipes* Sec. 2.6

Rank of a Matrix

- ***N*×*M* matrix *A* as a mapping: $R^M \rightarrow R^N$**



- **Range of *A*: Vector space $\{b = Ax | \forall x\}$**
- **Rank of *A*: Number, *m*, of linearly-independent vectors in the range, *i.e.*, how many linearly-independent *N*-element vectors are there in the range, such that**

$$b = A^{\forall} x = \sum_{\nu=1}^{m} c_\nu |\nu\rangle$$

Low Rank Approximations of a Matrix

- **Rank-1 approximation: $NM \rightarrow N + M$**

$$\underbrace{\begin{matrix} N \\ \end{matrix}\begin{bmatrix} \overset{M}{\overset{\downarrow}{\quad}} \\ \psi \end{bmatrix}}_{N\times M} \cong \underbrace{\begin{bmatrix} u \end{bmatrix}}_{N\times 1}\underbrace{\begin{bmatrix} v \end{bmatrix}}_{1\times M}$$

$$|u\rangle\langle v|\forall x\rangle \propto |u\rangle$$

- **Rank-2 approximation: $NM \rightarrow 2(N + M)$**

$$\begin{bmatrix} \psi \end{bmatrix} \cong \begin{bmatrix} u_1 \end{bmatrix} w_1 \begin{bmatrix} v_1 \end{bmatrix} + \begin{bmatrix} u_2 \end{bmatrix} w_2 \begin{bmatrix} v_2 \end{bmatrix}$$

- **Rank-m ($m \ll N, M$) approximation: $NM \rightarrow m(N + M)$**

$$\begin{bmatrix} \psi \end{bmatrix} \cong \sum_{\nu=1}^{m} \begin{bmatrix} u_\nu \end{bmatrix} w_\nu \begin{bmatrix} v_\nu \end{bmatrix}$$

Singular Value Decomposition

- **Problem:** Optimal approximation of an $N\times M$ matrix ψ of rank-m ($m \ll N$)?
- **Theorem:** An $N\times M$ matrix ψ (assume $N \geq M$) can be decomposed as

$$\psi = UDV^T = \sum_{\nu=1}^{M} U_{i\nu} d_\nu V_{j\nu} = \sum_{\nu=1}^{M} u_i^{(\nu)} d_\nu v_j^{(\nu)}$$

where $U \in R^N \times R^M$ & $V \in R^M \times R^M$ are column orthogonal & D is diagonal

$$U^T U = V^T V = I_M$$

$$\underset{N}{\left[\begin{array}{c}\\ \psi \\ \\ \end{array}\right]}_{M} = \underset{N\times M}{\left[\begin{array}{c}\\ U \\ \\ \end{array}\right]} \underset{M\times M}{\left[\begin{array}{ccc} d_1 & & \\ & \ddots & \\ & & d_M \end{array}\right]} \underset{M\times M}{\left[\begin{array}{c}\\ V^T \\ \\ \end{array}\right]}$$

See appendix on polar & singular decompositions

- **Theorem:** Sort the SVD diagonal elements in descending order, $d_1 \geq d_2 \geq \ldots \geq d_M \geq 0$, & retain the first m terms

$$\psi^{(m)} \equiv \sum_{\nu=1}^{m} u^{(\nu)} d_\nu v^{(\nu)T}$$

which is optimal among ∀rank-m matrices in the 2-norm sense with the error

$$\min_{rank(A)=m} \|A - \psi\|_2 = \left\|\psi^{(m)} - \psi\right\|_2 = d_{m+1}$$

cf. singular.c & svdcmp.c cc -o singular singular.c svdcmp.c -lm

Use the program!

SVD for Image Compression

Original Image

5 Iterations

10 Iterations

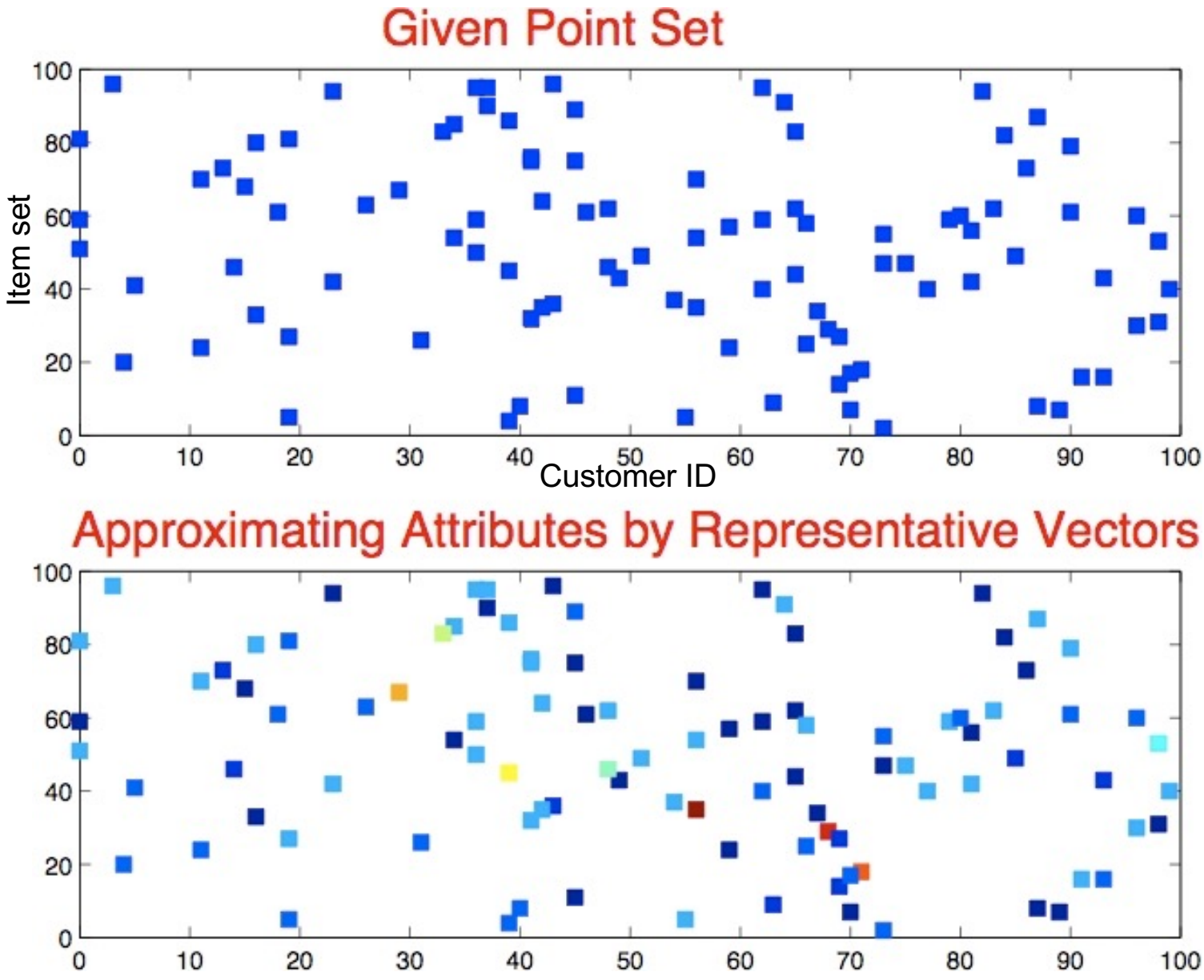
D. Richards & A. Abrahamsen

20 Iterations

60 Iterations

100 Iterations

SVD in Data Mining



N. Ramakrishnan & A. Y. Grama

Reduced Density Matrix

- **Quantum system coupled to an environment**

$$\{|i\rangle = \psi_i(x) | i = 1, \ldots, N\} \quad \{|j\rangle = \phi_i(X) | j = 1, \ldots, M\}$$

- **∀Quantum state of block + environment**

$$|\psi\rangle = \sum_{i=1}^{N} \sum_{j=1}^{M} \psi_{ij} |i\rangle |j\rangle \quad \text{or} \quad \Psi(x,X) = \sum_{i=1}^{N} \sum_{j=1}^{M} \psi_{ij} \psi_i(x) \phi_j(X)$$

- **Reduced density matrix**

$$\left\langle {}^{\forall}A \right\rangle = \sum_{i} \sum_{j} \psi_{ij}^{*} \langle j | \langle i | A \sum_{i'} \sum_{j'} \psi_{i'j'} | i' \rangle | j' \rangle$$

Arbitrary operator in the block

$$= \sum_{i} \sum_{j} \sum_{i'} \sum_{j'} \psi_{i'j'} \psi_{ij}^{*} \langle i | A | i' \rangle \underbrace{\langle j | j' \rangle}_{\delta_{jj'}}$$

$$= \sum_{i} \sum_{i'} \sum_{j} \psi_{i'j} \psi_{ij}^{*} \langle i | A | i' \rangle \equiv \sum_{i} \sum_{i'} \rho_{i'i} A_{ii'} = \mathrm{tr}_{\mathrm{B}}(\rho A)$$

$$\rho_{i'i} \equiv \sum_{j} \psi_{i'j} \psi_{ij}^{*} \qquad A_{ii'} \equiv \langle i | A | i' \rangle$$

Low-Rank Approx. to Reduced Density Matrix

$$\psi \cong \psi^{(m)} = \sum_{\nu=1}^{m} u^{(\nu)} d_\nu v^{(\nu)T} \qquad \psi_{ij}^{(m)} = \sum_{\nu=1}^{m} u_i^{(\nu)} d_\nu v_j^{(\nu)}$$

$$\rho = \psi\psi^T \cong \psi^{(m)}\psi^{(m)T} = \sum_{\nu=1}^{m}\sum_{\nu'=1}^{m} u^{(\nu)} d_\nu \left(v^{(\nu)T} v^{(\nu')}\right) d_{\nu'} u^{(\nu')T}$$

$$= \sum_{\nu=1}^{m}\sum_{\nu'=1}^{m} u^{(\nu)} d_\nu \left(\delta_{\nu\nu'}\right) d_{\nu'} u^{(\nu')T} = \sum_{\nu=1}^{m} u^{(\nu)} d_\nu^2 u^{(\nu)T} \equiv \rho^{(m)}$$

$$\rho_{ii'}^{(m)} = \sum_{\nu=1}^{m} u_i^{(\nu)} d_\nu^2 u_{i'}^{(\nu)}$$

- **Density matrix renormalization group = systematic procedure to accurately obtain a quantum ground state:**
  1. **Incrementally add environment to a block**
  2. **Solve the global (= block + environment) ground state**
  3. **Construct a low-rank approx. to represent the block with reduced d.o.f.**

S. R. White, *Phys. Rev. B* **48**, 10345 ('93);
G. K.-L. Chan & S. Sharma, *Annu. Rev. Phys. Chem.* **62**, 465 ('11) (Eqs. 3-10)

More SVD in quantum chemistry

J. F. Gonthier & M. Head-Gordon, *J. Chem. Phys.* **147**, 144110 ('17)

Entanglement Entropy & Quantum Computing

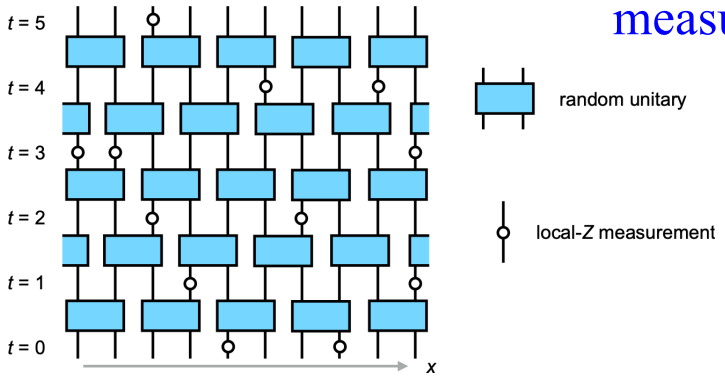
- **Entanglement entropy:** A measure of quantum entanglement between two subsystems. If a state describing two subsystems A and B is a ***separable*** state $|\Psi_{AB}\rangle = |\phi_A\rangle|\phi_B\rangle$ (*i.e.*, tensor product), then the reduced density matrix $\rho_A = \mathrm{Tr}_B|\Psi_{AB}\rangle\langle\Psi_{AB}| = |\phi_A\rangle\langle\phi_A|$ is a ***pure state***. Thus, the entropy of the state is zero. A reduced density matrix having a non-zero entropy is therefore a signal of the existence of entanglement in the system.
- **Area law:** A quantum state satisfies an ***area law*** if the leading term of the entanglement entropy grows at most proportionally with the ***boundary*** between the two partitions. Area laws are remarkably common for ground states of local ***gapped*** quantum many-body systems. ***It greatly reduces the complexity of quantum many-body systems***. ***The density matrix renormalization group and matrix product states, for example, implicitly rely on such area laws***.

https://en.wikipedia.org/wiki/Entropy_of_entanglement

Measurement-driven entanglement transition in hybrid quantum circuits

"With increasing measurement rate, the volume law phase is unstable to a disentangled area law phase, passing through a single entanglement transition at a critical rate of measurement."

Y. Li *et al.*, *Phys. Rev. B* **100**, 134306 ('19)



Machine Learning in Simulation

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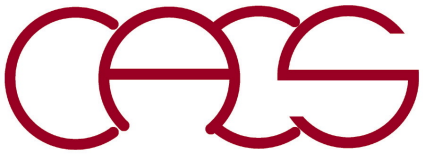
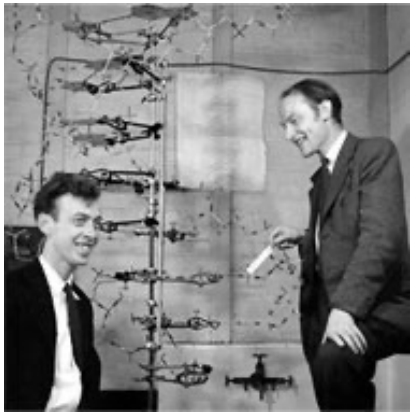
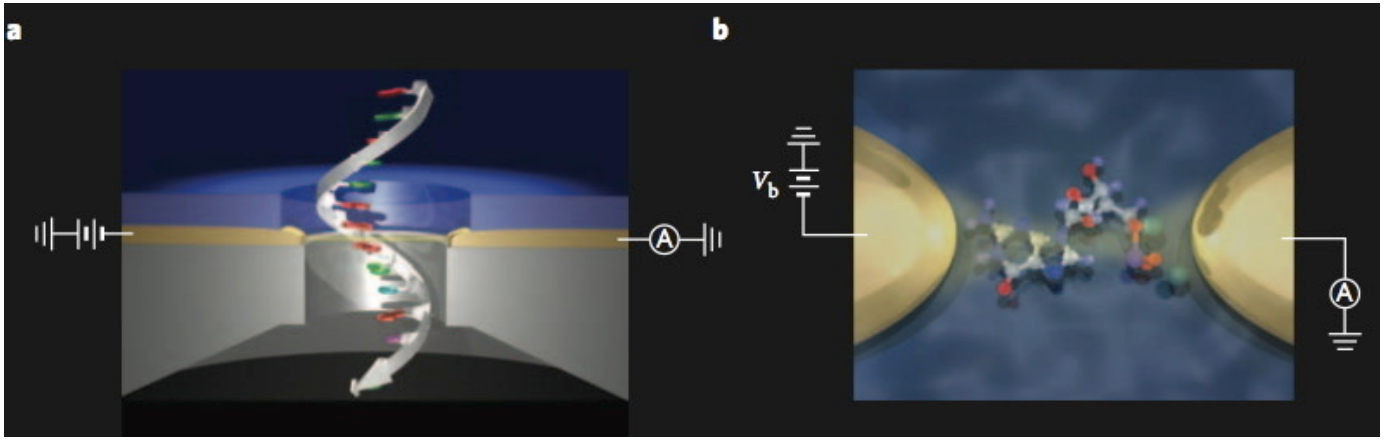


SVD for Rapid Genome Sequencing

- **$10M Archon X prize for decoding 100 human genomes in 10 days & $10K per genome (**http://genomics.xprize.org**): Preemptive attack on diseases**

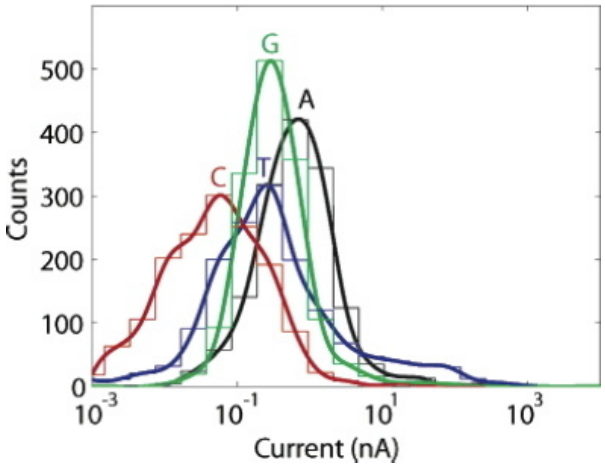


- **Quantum tunneling current for rapid DNA sequencing?**



Tsutsui *et al.*, *Nature Nanotechnology* ('10)

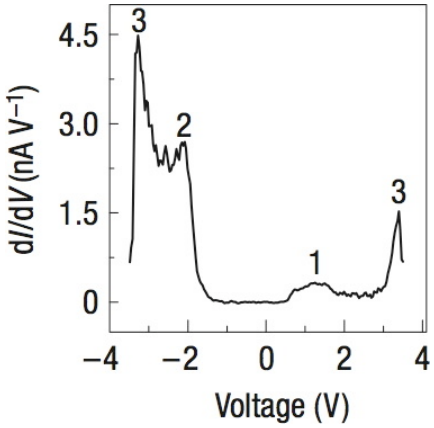
Lagerqvist *et al.*, *Nano Letters* ('06)



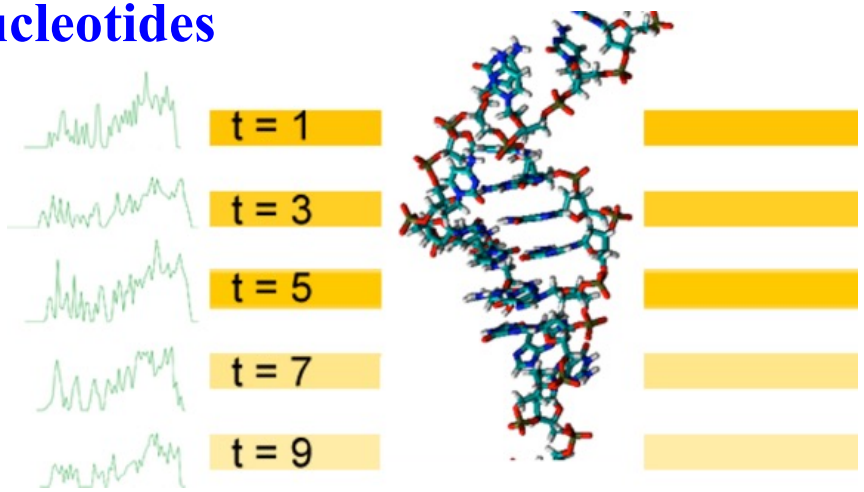
- **Tunneling current alone cannot distinguish the 4 nucleotides (A, C, G, T)**

Rapid DNA Sequencing *via* Data Mining

- **Use tunneling current (I)-voltage (V) characteristic (or electronic density-of-states) as the 'fingerprints' of the 4 nucleotides**

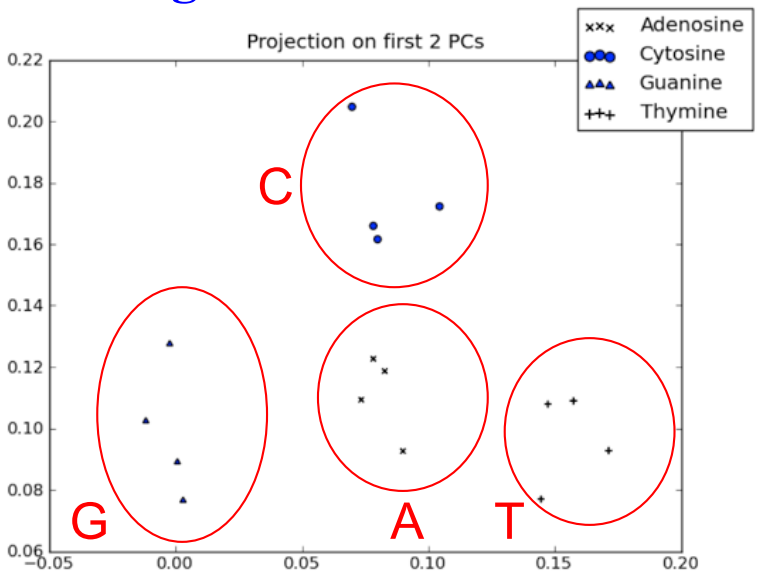


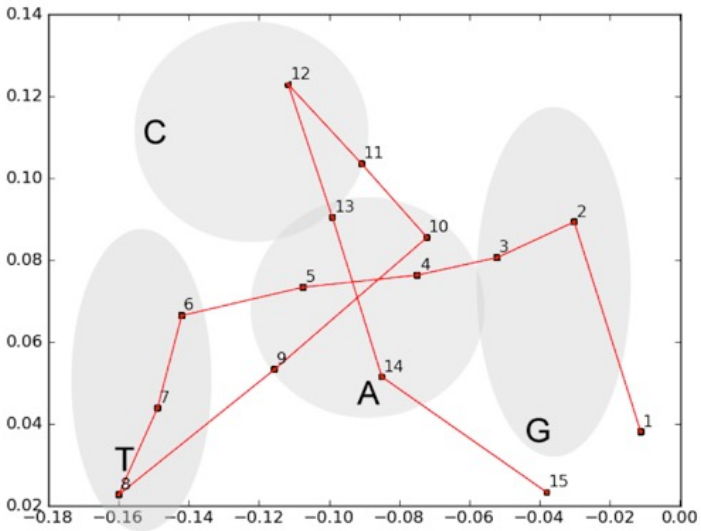
Shapir *et al.*, *Nature Materials* ('08)



- **Principal component analysis (PCA) & fuzzy c-means clustering clearly distinguish the 4 nucleotides**

H. Yuen *et al.*, *IJCS* **4**, 352 ('10)





http://www.henryyuen.net/

- **Viterbi algorithm for even higher-accuracy sequencing**

See Henry's landmark discovery

SVD *vs.* PCA (in Economics)

- **SVD of N (number of companies) × T (number of time points) of stock-price time series**

$$\underset{T\times N}{\Xi}^{T} = \underset{T\times N}{\mathbf{U}}\ \underset{N\times N}{\Sigma}\ \underset{N\times N}{\mathbf{V}}^{T}$$

- **Stock correlation matrix**

$$\underset{N\times N}{\mathbf{C}} = \underset{N\times T}{\Xi}\ \underset{T\times N}{\Xi}^{T}$$

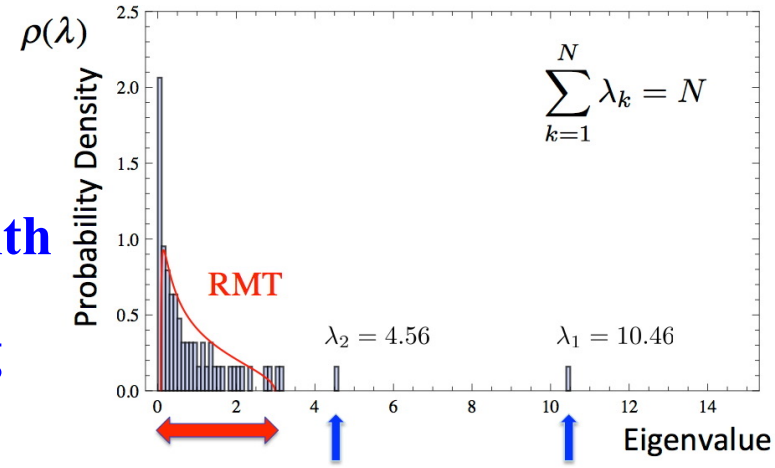
Apply it in your area!

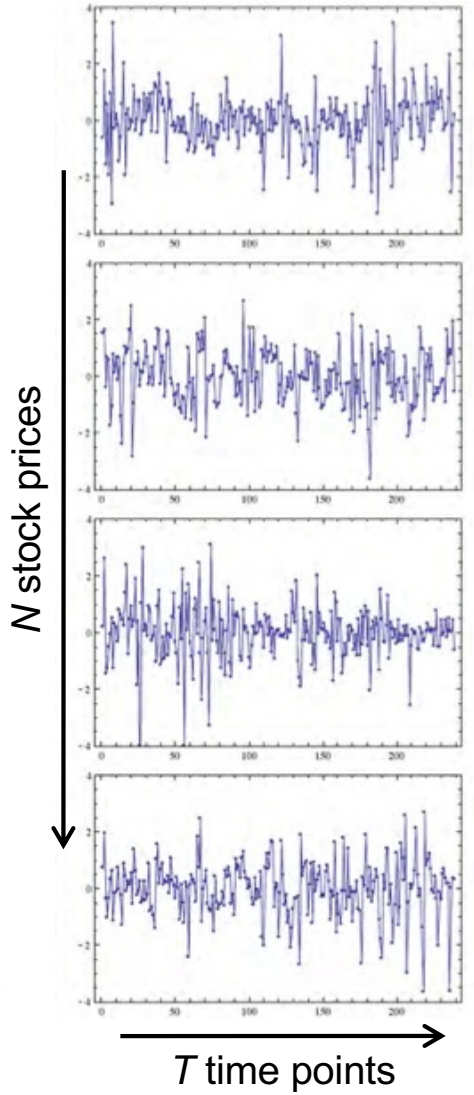
- **Principal component analysis (PCA): Eigen decomposition of the correlation matrix**

$$\mathrm{C} = \Xi\Xi^{T}$$
$$= \mathrm{V}\Sigma\overbrace{\mathrm{U}^{T}\mathrm{U}}^{\mathrm{I}}\Sigma\mathrm{V}^{T}$$
$$= \mathrm{V}\Sigma^{2}\mathrm{V}^{T}$$

- **Compare the spectrum with that of random matrix theory (RMT) for judging statistical significance**

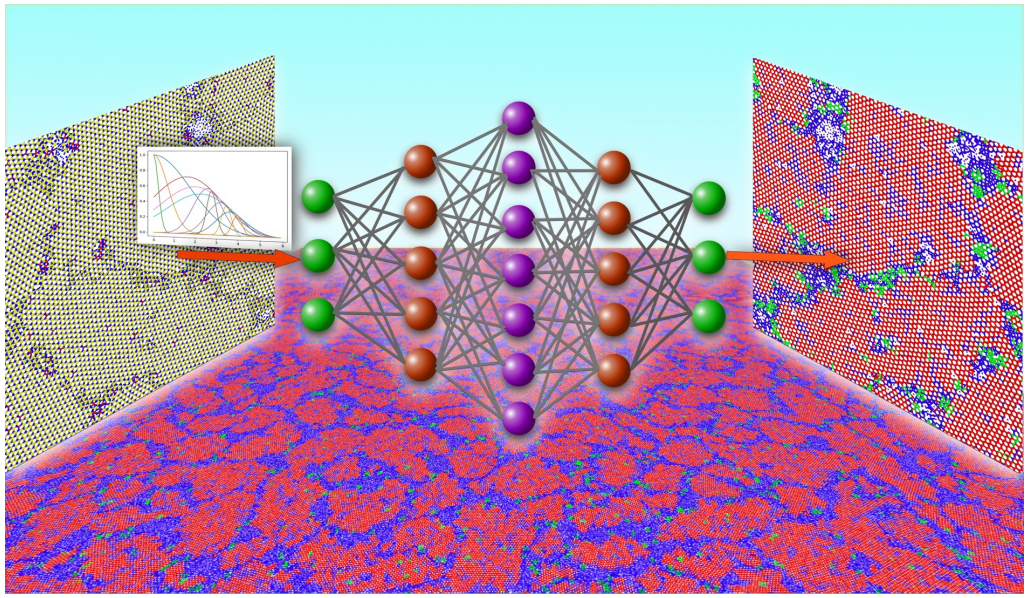
$$\rho_{\mathrm{RMT}} = \frac{Q}{2\pi}\frac{\sqrt{(\lambda_{+}-\lambda)(\lambda-\lambda_{-})}}{\lambda}$$
$$\lambda_{\pm} = \left(1+\frac{1}{\sqrt{Q}}\right)^{2}$$
$$Q = T/(2N) \quad N,T\to\infty$$





Y. Kichikawa *et al.*, *Proc. Comp. Sci.* **60**, 1836 ('15)

Learning Materials Phases & Defects

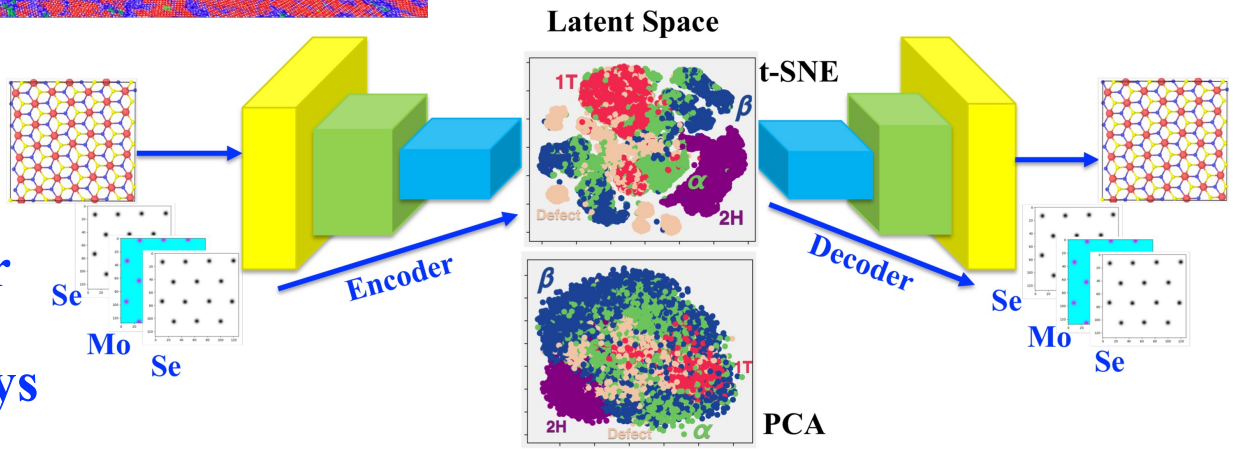


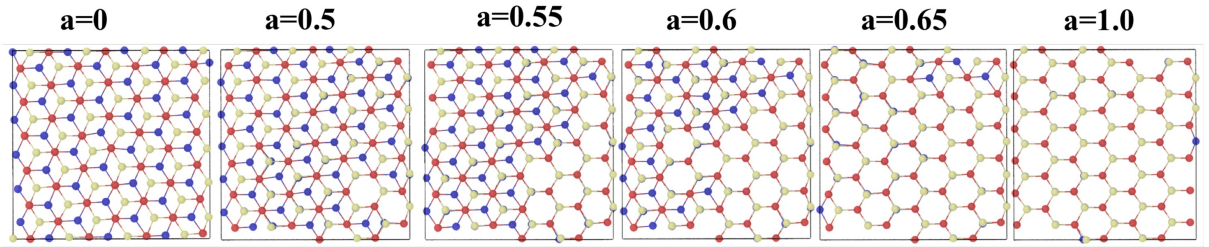
- **Feedforward neural network to learn phases from local symmetry functions**

K. Liu *et al.*, *Proc. ScalA18* ('18)
S. Hong *et al.*, *JPCL* **10**, 2739 ('19)

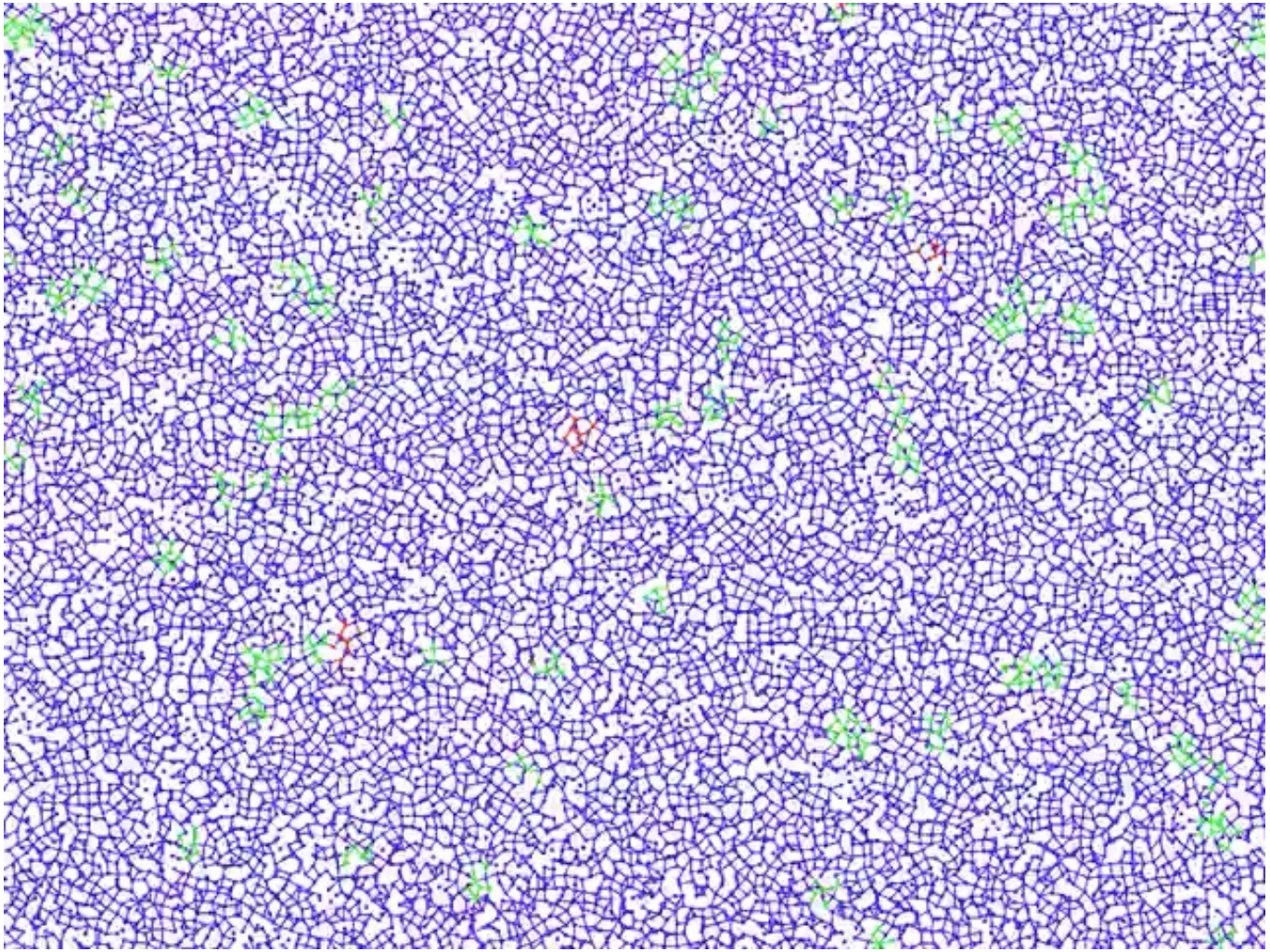
- **Variational autoencoder to generate transformation pathways from images & latent-space algebra**

P. Rajak *et al.*, *Phys. Rev. B* **100**, 014108 ('19)





Learning Transformation Pathways



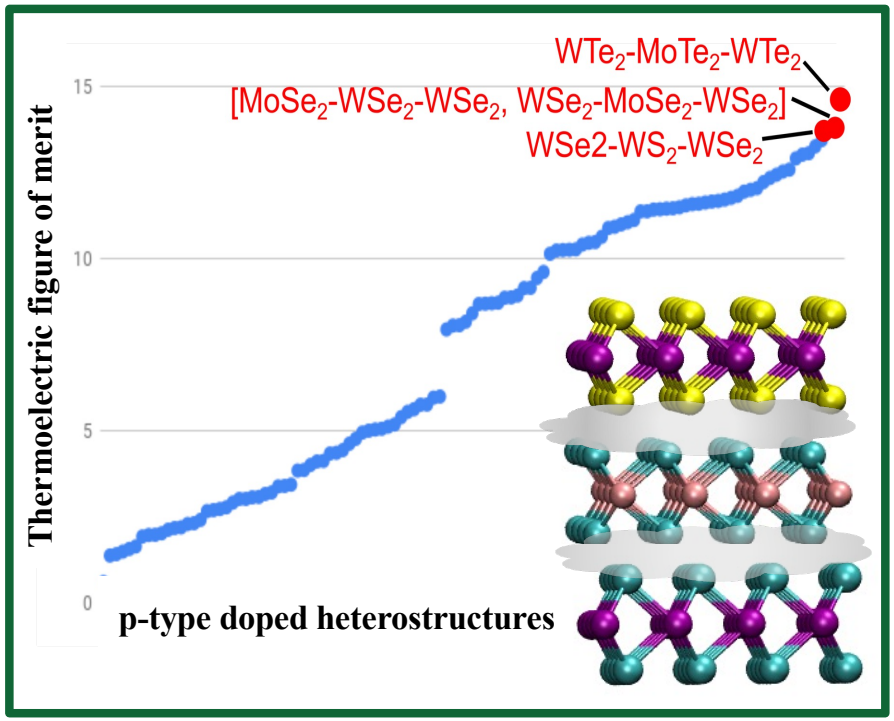
2H
1T
disorder

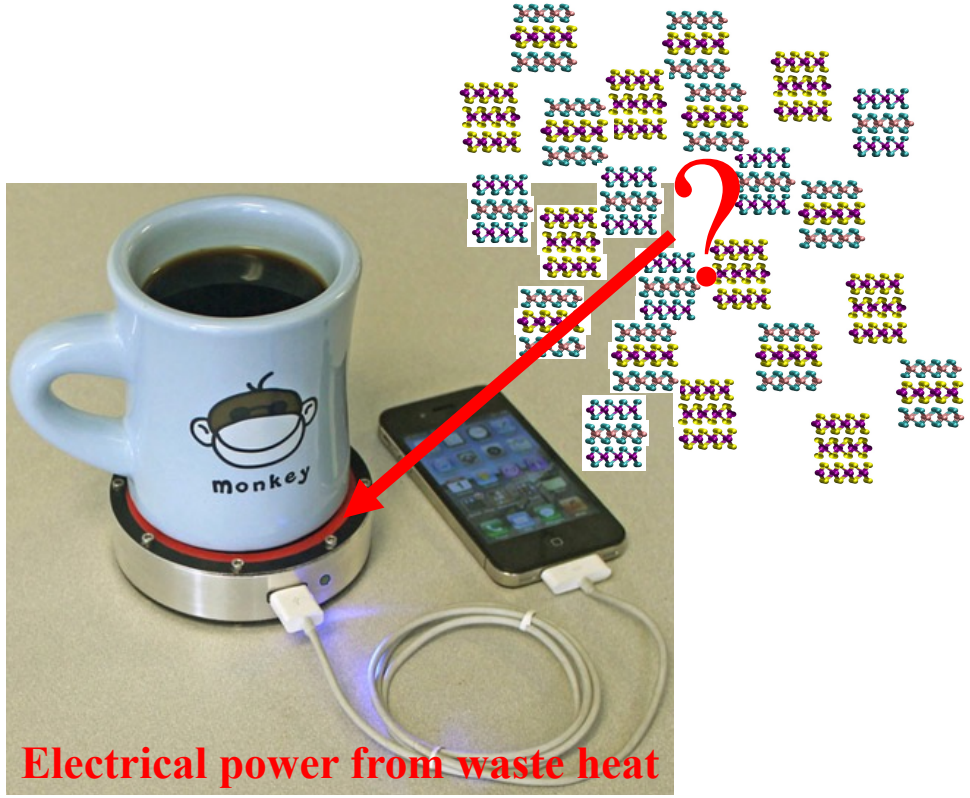
- **Found novel transformation pathways to the stable 2H phase *via* the metastable 1T phase during chemical vapor deposition (CVD) growth of MoS_2**

S. Hong *et al.*, *J. Phys. Chem. Lett.* **10**, 2739 ('19)

Active Learning of Optimal Materials

- **Bayesian optimization balances exploitation & exploration to find a structure with the desired property with a minimal number of quantum-mechanical calculations**
- **Predicted three-layered transition-metal chalcogenide (TMDC) heterostacks with the largest thermoelectric figure-of-merit**

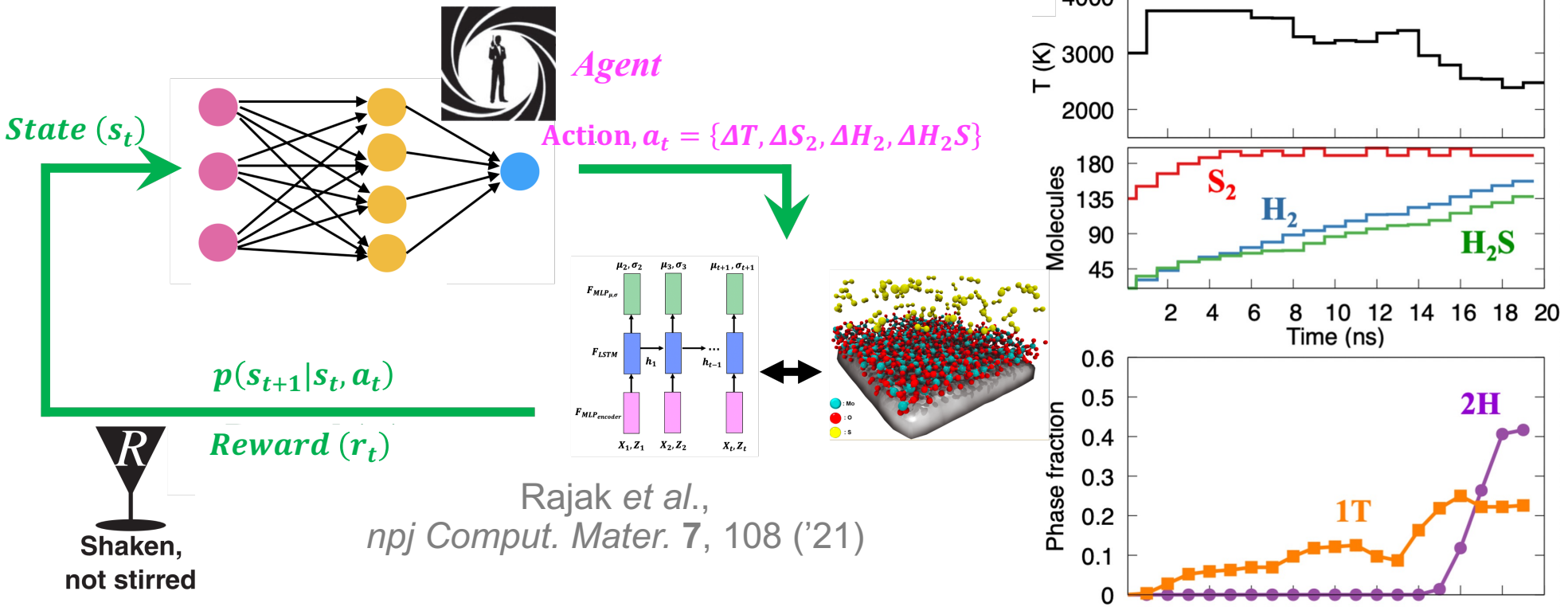




L. Bassman *et al.*, *npj Comput. Mater.* **4**, 74 ('18)

Reinforcement Learning for Growth

- **In a manner AI plays a board game of Go, use reinforcement learning (RL) to design optimal growth conditions (*e.g.*, temperature & gas-pressure control) to achieve desired properties such as minimal defect density**
- **AI model combines:**
  1. **RL agent to design actions**
  2. **Nesural network-based dynamic model trained by molecular-dynamics (MD) simulation to predict new states**



Rajak *et al.*,
npj Comput. Mater. **7**, 108 ('21)

cf. Sgroi *et al.*, *Phys. Rev. Lett.* ***126***, 020601 ('21)

AI Meets Kirigami

- **Reinforcement learning to design optimal kirigami with maximal stretchability**

Rajak *et al*., *npj Comput. Mater.* **7**, 102 ('21)

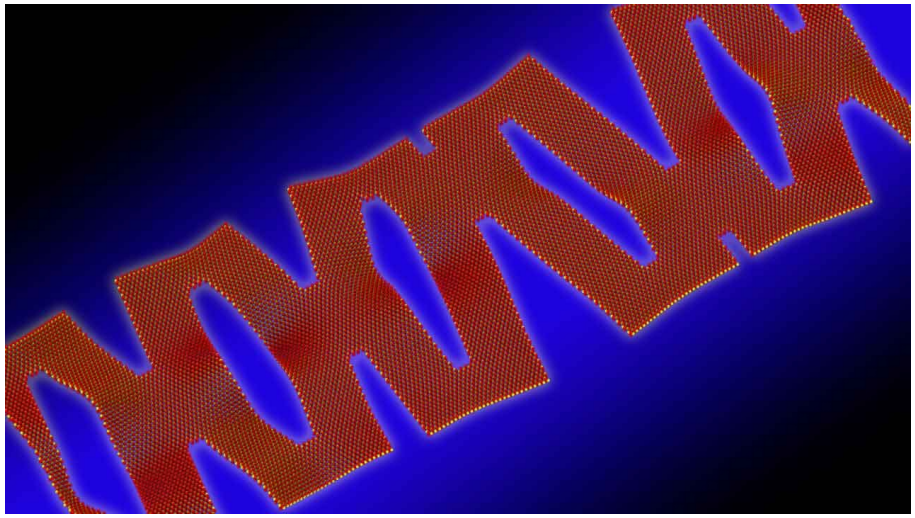
FEATURE STORY | ARGONNE NATIONAL LABORATORY

Ancient art meets AI for better materials design

BY JOHN SPIZZIRRI | APRIL 7, 2022

Ancient Japanese art of kirigami guides artificial intelligence (AI) technique for durable, wearable electronics.

Kirigami is the Japanese art of paper cutting. Likely derived from the 剪纸 Chinese art of jiǎnzhǐ, it emerged around the 7th century in Japan,



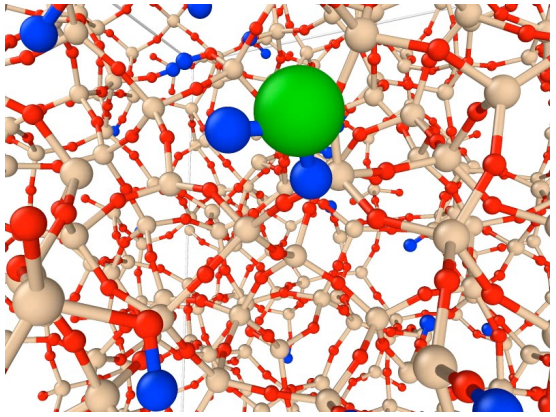
https://www.anl.gov/article/ancient-art-meets-ai-for-better-materials-design

Reinforcement Learning for Long-Time Dynamics

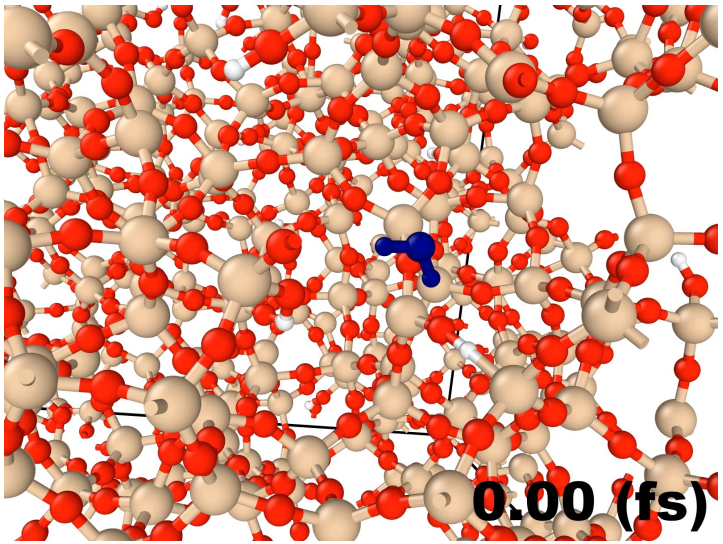
- **Phase 1—explore (agent parallelism): Multiple reinforcement learning (RL) agents autonomously discover *long low-activation-barrier pathways***
  Mnih, *Nature* **518**, 529 ('15); Hessel, *AAAI* **32**, 11796 ('18)
- **Phase 2—refine (time parallelism): Concurrent nudged-elastic-band (NEB) refinements of multiple *minimum-energy path (MEP) segments***
- **Estimate time based on transition-state theory**

$$t_{\text{migration}} = \sum_{i\in\{\text{activation events}\}} \frac{\hbar}{k_B T} \exp\left(\frac{E_i^{\text{activation}}}{k_B T}\right)$$

Agent guiding O in H_2O

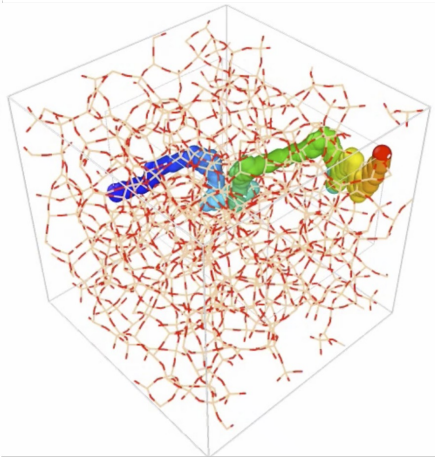


H_2O diffusion & reaction in SiO_2

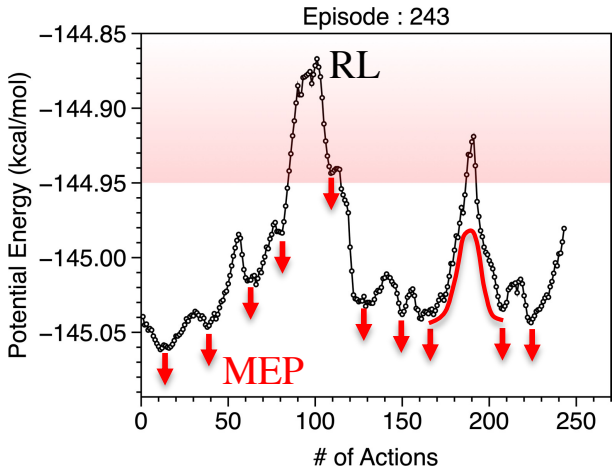


2-seconds trajectory

1. Explore



2. Refine



Nomura *et al.*, *J. Phys. Chem. Lett.* **15**, 5288 ('24)

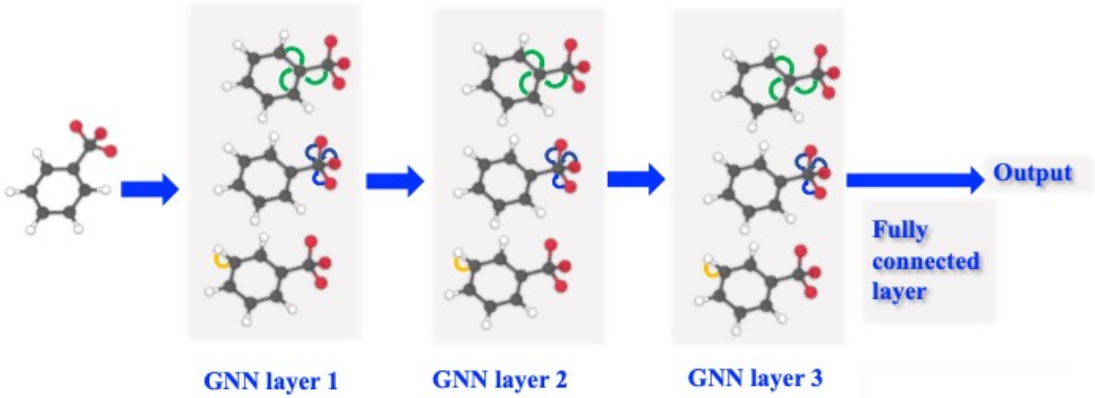
AI for long time!

Dielectric Polymer Genome

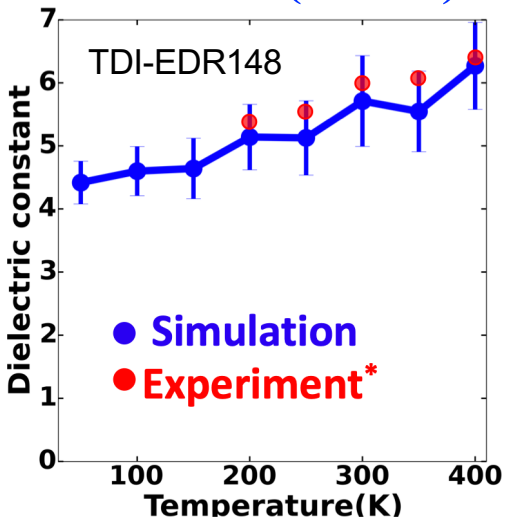
Recurrent neural network for polymer property prediction

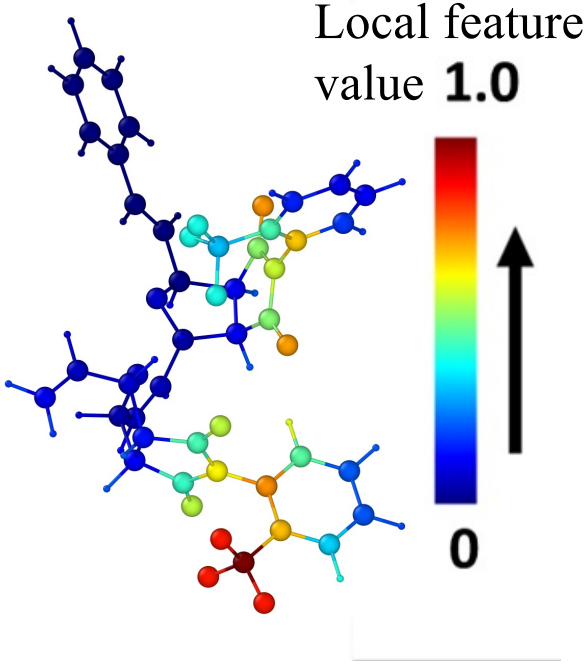
Nazarova *et al.*,
J. Chem. Info. Model. **61**, 2175 ('21)

Graph attention neural network for explainable property prediction



Experimental validation (Uconn)

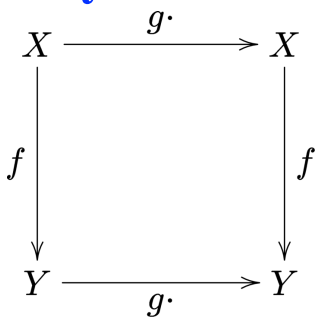




Graph Neural Network

- **Allegro (fast) NNQMD: State-of-the-art *accuracy & speed* founded on *group-theoretical equivariance & local descriptors***
  Musaelian *et al*., *Nat. Commun.* **14**, 579 ('23)
- **An equivariant function f acts on an atomic geometry $x \in X$ under a group action g (*e.g.*, rotation) as $f(g \cdot x) = g \cdot f(x)$**
  Thomas *et al*., *arXiv.* 1802.08219v3 ('18)

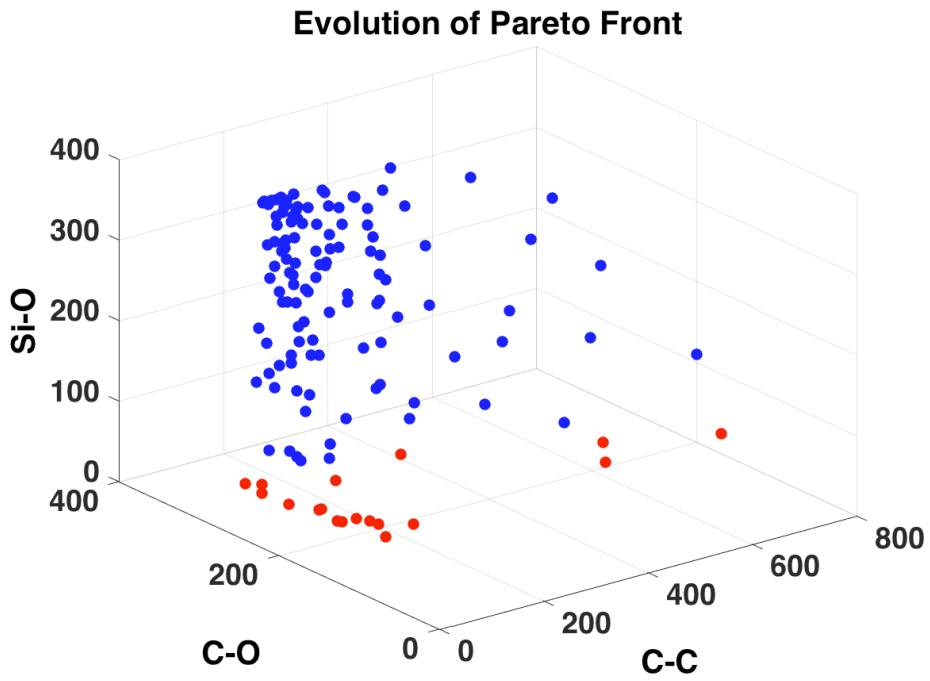
  NNQMD: Neural network quantum molecular dynamics

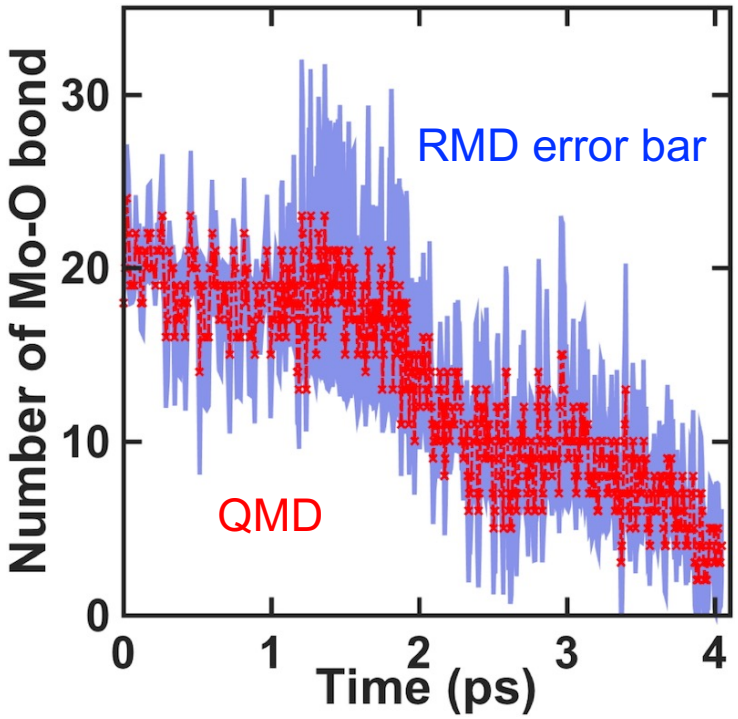


- **Allegro speeds-up an equivariant message-passing (or graph neural-network) NNQMD, NequIP** [Batzer et al., *Nat. Commun*. **13**, 2453 ('22)]**, by localizing atomic-environment descriptors, *i.e.*, restricting message passing to the nearest neighbor**
- **A complete set of atomic-environment descriptors is provided by atomic cluster expansion (ACE)** [Drautz, *Phys. Rev. B* **99**, 014104 ('19)]**; relationship between NequIP & ACE has been discussed in** Batatia *et al*., *arXiv.* 1802.08219v3 ('18)

Pareto-Frontal Uncertainty Quantification

- **Train reactive force-field parameters by dynamically fitting reactive molecular dynamics (RMD) trajectories to quantum molecular dynamics (QMD) trajectories on-the-fly**
- **Pareto optimal front in multiobjective genetic algorithm (MOGA) provides an ensemble of force fields to enable uncertainty quantification (UQ)**





- Pareto-optimal solutions during genetic training (RMD errors for three quantities-of-interest)
- Converged Pareto-optimal front

A. Mishra *et al.*, *npj Comput. Mater.* **4**, 42 ('18)