

A Holistic, High Dimensional Perspective on Extracting and Encoding Chemical Data

**a problem for soft matter materials design



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An Integrated Math + Chemistry Team









Henry Adams Colo. State

Brittany Story CSU/U Tenn (PhD stud)





Biswajit Sadhu BARC (post-doc)

Harnessing the Data Revolution (HDR) Frameworks – Clark PI

Complementarity With Prior Talks

Jörg Neugebauer - Enabling next-generation materials science simulations by automated workflows Methodological challenges

Exploring and navigating high-dimensional configuration spaces



Partition Function Encodes State Dist. and Energy



- In solid/crystalline phase contributors to Z directly connect structure and energy distributions (vib, rot, elect, config contributions)
- What about soft matter? (ignoring liquid crystals and other weird things)
 - Liquids, solutions often very heterogeneous
 - Interfacial regions (L/L interfaces)
 - Gels
- Intrinsically disordered
 - Varying correlation lengths in space. (configuration states harder to define)
 - Correlation times how easy to escape out of minima
- Often the dynamical phenomena <u>are a key property of the material</u>

Soft Matter Ensembles - Emulsions



• Very complex and rich multicomponent phase diagrams



An Energy Landscape Perspective



***let's be agnostic to the type of EL at this point



Find the global minimum using some approximate Hamiltonian

An Energy Landscape Perspective



Sampling configurational space - finding all relevant local minima on the EL

-index 0 critical points

An Energy Landscape Perspective



Sampling the fluctuations means sampling minima and maxima -including index 1 CP's and higher order CP's for some processes

Key Challenges for Soft Matter Design



If we sample configuration space (using molecular dynamics)

- How to define states?
- How to relate to energy landscape? (choosing higher dimensional representations)

Key Challenges for Soft Matter Design



Soft Matter Design Workflow



Key Challenges for Soft Matter Design



If we sample configuration space (using molecular dynamics)

- How to define states?
- How to relate to energy landscape?

An Example Using Microemulsions







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Polar Cosolutes and Reverse Micelle Formation





 $\hfill\square$ H₂O and HNO₃ increase TODGA micelle size



What's molecular origin of this?
Can we reduce dimension of the EL to be conceptually meaningful?



Feature Selection



Features	Feature descriptions	Features	Feature descriptions
P-13 xyz	xyz coordinates of 13 polar core atoms of TODGA	P-13 distances	Intramolecular distances involving 13 polar core atoms of TODGA.
P-7 xyz	xyz coordinates of 7 polar core atoms of TODGA	P-7 distances	Intramolecular distances involving 13 polar core atoms of TODGA.
PT-2 torsion	Two torsions	PT-4 torsions	Four torsions

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Feature Selection







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	xyz coordinates of 13 polar core atoms of TODGA	P-13 distances	Intramolecular distances involving 13 polar core atoms of TODGA.
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	Two torsions		Four torsions



BMSM for Conformational Landscapes Coarse-graining of microstates into macrostates **Finalizing Number** using PCCA++ Analysis of Microstates Generate transitior □ Choose # of dimensions to keep 95% of variance **22** dimensions were kept for solutions with no polar solutes (**NonPol**) 20 dimensions were kept for solutions with polar solutes (Pol) Discretization of TICA space with k-means using 100 clusters Hajculury •MD data



BMSM for Conformational Landscapes



BMSM for Conformational Landscapes



BMSM for Conformational Landscapes





Sadhu & Clark, In Prep



4 coarse-grained macrostates observed in non-polar and polar conditions
Free energy landscape in terms of independent components of PCA++





4 coarse-grained macrostates observed in non-polar and polar conditions
Free energy landscape in terms of independent components of PCA++
non-polar
polar

Free energy landscapes appear similar...but this is misleading.

What are the structures/configurations in the ³²/₂ P1 macrostates?



 Very different transition probabilities are observed, different conformational ensembles comprise a macrostate non-polar
polar





Very different transition probabilities are observed, different conformational ensembles comprise a macrostate non-polar polar

- Free energy landscapes appear similar...but this is misleading.
 - What are the structures/configurations in the macrostates?





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Polar Solute - Conformation Relationships



Polar solute changes the free energy barrier of dihedral rotation



Obtained from welltempered metadynamics simulation

Polar Solute - Conformation Relationships



Polar solute changes the free energy barrier of dihedral rotation

This was very hard – it took a long time

It does not easily scale across space and time

Dihedral I (°)

Alternative Approaches for Defining States





Alternative Approaches for Defining States





Graph Theory Tools for Soft Matter Structure



- Graph representations of chemical systems
 - Molecular graphs \rightarrow date back to 1870's
 - intermolecular/interparticle interactions --> identify micelles
- Descriptors of graph connectivity & patterns (similar to molecular graphs)
 - Local and non-local, spectral GT approaches
- Hierarchical partitioning
 - Robust cluster or community analysis
- Time dependent evolution
Birth of Structure Theory (Aided by Graph Theory)



• Derived generating functions to identify all possible isomers of tree alkanes with a given number of nodes

Arthur Cayley



[Cay75a] A. Cayley, On the analytic forms called trees, with applications to the theory of chemical combinations, *Reports British Assoc. Adv. Sci.*, **45** (1875), 257-305 = *Math. Papers*, Vol. 9, pp. 427-460 (see p. 451).

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GT and Chemistry Over Time (Some Highlights)



- Chemical reaction mechanisms based upon minimal edge changes and distances btw. adjacency matrices of reactants and products
- Principle of minimal structure change - Kolbe 1850

Definition 3.2. The *chemical distance* between two isomeric graphs $G_1 = (V_1, E_1, L_1)$ and $G_2 = (V_2, E_2, L_2)$ with maximal common subgraph $G_1 \cap G_2 = (V_{12}, E_{12}, L_{12})$ is determined by

$$CD(G_1, G_2) = |E_1| + |E_2| + |L_1| + |L_2| - 2|E_{12}| - 2|L_{12}|.$$
(3.1)



Figure 2. Constitution of imaginary transition structures (ITS's). This example is the hydrolysis of ethyl acetate catalyzed by hydrochloric acid. The abbreviations S and P correspond to the starting and product stages, respectively.

Fujita, S. J. Chem. Inf. Comput. Sci. 1986, 26, 4, 205–212; Balaz, V. et. al. Disc. Appl. Math 1992, 35, 1-19.

GT and Chemistry Over Time (Some Highlights)



pubs.acs.org/CF

Quantum graphs – many different types here, though original formulation was for electron movement as in a wire along bonds (relevant to understanding magnetism, e- transport, and a wealth of condensed matter physics applications)





Quantum Interference, Graphs, Walks, and Polynomials

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Pauling, L. J. Chem. Phys. 4, 673 (1936); Ruedenberg, K.; Scherr, C. W. J. Chem. Phys. 21, 1565 (1953)

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Molecular Graphs and Partition Functions



Statistical-mechanical theory of topological indices

Ernesto Estrada

Institute for Cross-Disciplinary Physics and Complex Systems (IFISC, UIB-CSIC), Campus Universitat de les Illes Balears E-07122, Palma de Mallorca, Spain

***also some work relating Shannon Entropy to thermodynamic entropy, etc.



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Our Contributions to Descriptors

Spectral GT side:

- Determining Polyhedral Arrangements of Atoms Using PageRank, Journal of Mathematical Chemistry, 2012, 50, 2342.
- Novel Analysis of Cation Solvation Using Graph Theoretic Approaches, *Journal of Physical Chemistry B*, **2012**, *116*, 4263.

----many applications ensued---

• PageRank as a Collective Variable to Study Complex Chemical Transformations and Their Energy Landscapes, *Journal of Chemical Physics*, **2019**, *150*, 134102.

Centrality Measures:

• Deconstructing the Confinement Effect upon the Organization and Dynamics of Water in Hydrophobic Nanoporous Materials: Lessons Learned from Zeolites, *Journal of Physical Chemistry C*, **2017**, *121*, 22015

---many applications using different measures to understand speciation---

Graph Theory Tools for Soft Matter Structure



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From Molecules to Micelles



Hierarchical Graph Partitioning



- Modularity optimization helps identifying cluster in a generalized manner
- Find cluster partition that maximizes Q







 Do in multiple passes to coarse-grain and obtain hierarchical partitioning

Journal of Physical Chemistry B, 2021, 125, 3986-3993

Modularity Optimization in Time



Journal of Chemical Theory and Computation, **2022**, 18, 7043 – 7051

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Modularity Optimization in Time





 Increased computational efficiency by using statistics of edge addition/deletion in time

Journal of Chemical Theory and Computation, 2022, 18, 7043 – 7051

Temporal Communities for Separations



Temporal Graph Theory Analyses



Molecular dynamics of an actively transporting oil/water interface



Journal of Chemical Theory and Computation, 2022, 18, 7043 – 7051

Graph Theory and Comp. Topology as a Framework





Graph Theory and Comp. Topology as a Framework





1. Choose a ball radius that forms the complex

2. Vary ball radius and track how components change



Persistent Homology – Distance Filtered Graphs



 Graphs formed by different distance filtrations of <u>point cloud</u> <u>data</u>

- Recording the number of components of the simplicial complex (zero dimensional information, β₀)
- Recording the number of holes in the simplicial complex (1dimensional information, β₁)



Structures of Surfactant Aggregates



Journal of Physical Chemistry B, **2020**, 124, 10822.

Sub- or Superlevelset Persistent Homology

- Not only for point cloud data, but also functions
- Filtration starts from the lowest to highest sublevelset
- Filtration starts from highest to lowest superlevelset







Sublevelset PH for Separations





Sublevelset PH



• Molecular dynamics of surfactants at oil/water interfaces

Create time-dependent density images



Journal of Chemical Theory and Computation, **2023**, In Press <u>https://doi.org/10.26434/chemrxiv-2023-vwrxj</u>







FIG. 3. Representative density surfaces analyzed in this study. (A) Adsorption density surface of ~ 72 TBP adsorbed at the water/vapor interface (x = y = 60 Å). (B) Stochastic distribution model surface representing ~ 72 TBP on a x = y = 52 Å surface, (C), and an average of ~ 79 TBP adsorbed at LiNO_{3(aq)}/hexane interface (x = y = 52 Å).

PH Descriptors



- Goal capture organization at surface by surfactants
- Excess Betti Curves
 - Compares the real betti curves with those from purely random images (at same density)

$$\tilde{\beta}_{n}(\rho) = \beta_{n}(\rho) - \beta'_{n}(\rho).$$

Persistent entropy - measures variations in persistent lifetimes of the components

$$PE = \sum_{i} -\frac{l_{i}}{L} \log \frac{l_{i}}{L},$$

 Non-ideality index for surfaces – if surfactants don't interact we know # of components, variations indicate non-ideal interactions

Journal of Chemical Theory and Computation, **2023**, In Press <u>https://doi.org/10.26434/chemrxiv-2023-vwrxj</u>

 $I = \frac{\text{number of observed cycles}}{\text{average number of adsorbates}}$





FIG. 7. The correlation between the interfacial tension (γ) with (A) 0- and (B) 1-d persistent entropy and (C) 0- and (D) 1-d Betti-index for the systems with 72, 96, 120 and 144 TBP per interface at the water/vapor surface. The data is fitted to a linear regression model to obtain the slopes provided in the inset.





What have we learned?



- Huge number of tools available for creating new representations of "states" in soft matter systems
- Across lengthscales (locally, globally)
- Capturing dynamical phenomena
- Now...how do we connect to energy landscapes?
 - Brute force mapping along collective variables (like PR)
 - Use dynamical information to obtain energetics (Markov)
 - Encode topological information
 - Use to predict EL?

Compact Representations of PELs





Sublevelset Persistent Homology of PEL



Journal of Chemical Physics, 2021, 154, 114114

Higher Dimensionality Information is Impt!



Distinguishing between PEL
 Understanding chemical dynamics
 Relevance of 2nd order pathways



Phys. Chem. Chem. Phys., 2019, 21, 12837-12842

Sublevelset PH of PEL



- Visualization of higher-dimensions of PEL (no dim. red. needed!)
- Capturing more information about PEL topology
 - Bar lengths are barrier heights
 - # of bars are # of barriers
 - Include all indices of critical points (all dimensions of PEL)
- Create a platform for quantifying differences in PEL in highdimensional space?
- What patterns emerge and can they be used for predicting PEL?



Journal of Chemical Physics, 2021, 154, 114114



What's notable about these barcodes?
of n-dimensional bars







What's notable about these barcodes?
of n-dimensional bars



I Birth and death times of features
I Relative energy differences of minima and maxima



What's notable about these barcodes?
of n-dimensional bars



Birth and death times of features
 Relative energy differences of minima and maxima

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Sublevelset PH of Conformational PEL



What's notable about these barcodes?
of n-dimensional bars





Birth and death times of features
 Relative energy differences of minima and maxima

Sublevelset PH of Conformational PEL



Patterns in the barcodes for n-alkanes

- The rotation about 1 dihedral has a PEL that can be plotted on the circle (1-dim torus)
- 6 critical points for each dihedral PEL (3 maxima and 3 minima)

- For every added C-atom, add a
- dihedral degree of freedom



Patterns in the barcodes for n-alkanes



- The rotations of butane are 2x in pentane, all rotations are translated copies
- True as n C-atoms are added to alkane PEL
- PEL are nested functions if they are constructed additively
- Mathematically prove the # of bars in *k*-dimensions, birth and death times for any *n*-alkane



FIG. 3. Morse–Smale complexes for the analytical PEL for (A) butane, (B) pentane, and (C) hexane. The critical points are indicated and are colored by their index. For pentane and hexane, the unique flows between critical points whose indices differ by one are also indicated; see Appendix \boxed{D} . For (A) and (B), the energy scales are indicated by the vertical direction.

Journal of Chemical Physics, 2021, 154, 114114

Predicted Sublevelset PH





- Energy landscape $V \colon X
 ightarrow \mathbb{R}$
- is a function over a product spac $X=X_1 imes\ldots imes X_n$.
- These are composed of building block functions $g_i \colon X_i o \mathbb{R}$
- Thus

$$V(x_1,...,x_n) = g_1(x_1) + ... + g_n(x_n) = \sum_{i=1}^n g_i(x_i)$$

• Building blocks could be on the circle (dihedrals), HO's, etc.

J. Chem. Phys. 2023 158, 164104



J. Chem. Phys. 2023 158, 164104



J. Chem. Phys. 2023 158, 164104





2-methylpentane $2 - \frac{1}{2}$

(c)





 The sublevel set filtration for V is a "tensor product" of the sublevelset filtrations of g_n

Branched Alkane Examples

Building block units



Building block functions



Branched Alkane Examples

Building block sublevel set PH

 $0^+_{\dot{\mathbf{0}}}$

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1-3-2-1

1-4-2-1

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1-4-4-1

1-2-2-1

1-3-3-1

1-4-3-1

0⊥

0[⊥]

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Building block functions

Generalizing the pric

- □ *n* building block functions on the circle □ Domain of V is $(S^1)^n$.
- n-dimensional torus has k-dimensional homology of rank $\binom{n}{k}$
- \Box The semi-infinite bars in a filtration space recover the homology of the space - thus

Lemma 1. The energy landscape $V: (S^1)^n \to \mathbb{R}$ for any branched alkane built from n building block functions has $\binom{n}{k}$ semi-infinite bars in dimension k.



- How to know total # c
 - semi-infinite + finit

 $\binom{n}{k}$ semi-infinite bars in dimension k, for each $0 \le k \le n$

- $\sum_{k=0}^{n} {n \choose k} = 2^{n}$ semi-infinite bars
- Every building block function is a Morse function, hence every V is a Morse function
- Birth and death times correspond directly to CP's (p_i) of V

 2^n belong to semi-infinite bars

 $\prod_{i=1}^{n} p_i - 2^n$ must be split between the birth and death times of the finite bars

• # of CP's is even on the circle – thus $\prod_{i=1}^{n} p_i - 2^n$ is even

*







• # of finite bars is then

$$\frac{1}{2} \left(\prod_{i=1}^{n} p_i - 2^n \right)$$

Theorem 1. Suppose the additive energy function $V : (S^1)^n \rightarrow \mathbb{R}$ is given by $V(\phi_1, \dots, \phi_n) = g_1(\phi_1) + \dots + g_n(\phi_n)$ with each Morse function $g_i : S^1 \rightarrow \mathbb{R}$ having p_i critical points. The total number of bars in the sublevelset persistent homology of V is

(2ⁿ) semi-infinite bars +
$$\frac{1}{2}\left(\prod_{i=1}^{n} p_i - 2^n\right)$$
 finite bars.







- How many bars in each dimension?
 - Use the # of bars in *n* to identify # of bars in n+1 (nested aspect of V_n)
 - Begin with any building block function
 - Example dihedral angle (on the circle) 6 CPs, 3 k=0 bars





$$\binom{1}{0} + (3^{1} - 1)\binom{1-1}{0} = 3$$
 bars of dimension 0
 $\binom{1}{1} + (3^{1} - 1)\binom{1-1}{1} = 1$ bar of dimension 1

• Does this equation hold as n (# building blocks) is increased? $V_n: (S^1)^n \to \mathbb{R} \longrightarrow V_{n+1}: (S^1)^{n+1} \to \mathbb{R}.$

where

$$V_{n+1}(\phi_1, \dots, \phi_{n+1}) = V_n(\phi_1, \dots, \phi_n) + g_{n+1}(\phi_{n+1})$$

 $g_{n+1}: S^1 \to \mathbb{R}$



- If you know the # of bars of each dimension of the building block, then there is a finite # of combinations of how to add them (Kunneth formula)
 - Find each k-dimensional bar in V_{n+1} in terms of the sublevelset persistence bars of V_n and g_{n+1}
 - (i) combining *k*-dimensional bars of V_n with 0-dimensional bars of g_{n+1} ,
 - (ii) combining (k-1)-dimensional bars of V_n with 1-dimensional bars of g_{n+1} , or
 - (iii) combining (k-1)-dimensional bars of V_n with 0-dimensional bars of g_{n+1} via torsion.



$$3 \left[\binom{n}{k} + (3^{n} - 1)\binom{n-1}{k} \right] + \left[\binom{n}{k-1} + (3^{n} - 1)\binom{n-1}{k-1} \right] + 2 \left[(3^{n} - 1)\binom{n-1}{k-1} \right]$$

$$= 3 \binom{n}{k} + 3(3^{n} - 1)\binom{n-1}{k} + \binom{n}{k-1} + 3(3^{n} - 1)\binom{n-1}{k-1}$$

$$= 3 \binom{n}{k} + 3^{n+1}\binom{n-1}{k} - 3\binom{n-1}{k} + \binom{n}{k-1} + 3^{n+1}\binom{n-1}{k-1} - 3\binom{n-1}{k-1}$$

$$= 3\binom{n}{k} + \binom{n}{k-1} + 3^{n+1} \left[\binom{n-1}{k} + \binom{n-1}{k-1} \right] - 3 \left[\binom{n-1}{k} + \binom{n-1}{k-1} \right]$$

$$= 3\binom{n}{k} + \binom{n}{k-1} + 3^{n+1}\binom{n}{k} - 3\binom{n}{k}$$

$$= \binom{n}{k-1} + \binom{n}{k} + (3^{n+1} - 1)\binom{n}{k}$$

$$= \binom{n+1}{k} + (3^{n+1} - 1)\binom{n}{k}, \quad \text{# of bars of each dimension k for a given n building blocks}$$



Topology of 2,2-dimethylpentane PEL



- 7-dim dihedral angle PEL
- 840,000 total CP's
- 32 global minima
- 186 index-0 local minima under 1 kcal/mol
- 1,200 index-0 CP before you overcome any index-1 barriers at 2.75 kcal/mol

Topology of change to PEL w/bond addition



New Opportunities



- Direct connection between structure and location on a PEL
- Learn about patterns in EL barriers and minima related to structure and changes to composition of the system
 - Experimental design strategies → stabilizing specific structure or dynamic phenomena for the application of interest
- Employ in enhanced sampling of EL \rightarrow accelerate computational workflows

***other great into on applied topology can be found on the AATRN YouTube (Henry Adams)

Soft Matter Design Workflow



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