Graph Clustering Approaches using Quantum Annealing

QUBITS 2018 D-Wave Users Conference

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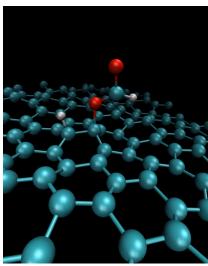
Introduction

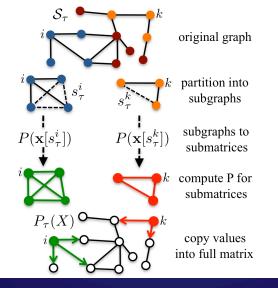
- Motivated by graph-based methods for quantum molecular dynamics (QMD) simulations
- Explored graph partitioning/clustering methods and implementations that run on the D-Wave
 - Initially, 2-partitioning, 2-clustering
 - Recursive methods
 - k-Concurrent methods
 - Iterative multi-level graph partitioning with D-Wave refinement
- Used sapi and hybrid classical-quantum qbsolv software tools
- Demonstrated "proof of principle" results on benchmark graphs, example graphs and electronic structure graphs
- Results are shown to equal or out-perform current "state of the art" methods

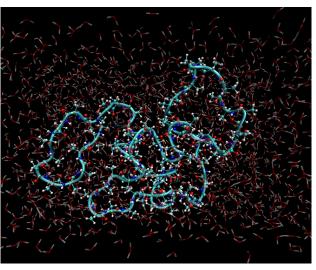
Graph partitioning/clustering implementations on the D-Wave.

Motivation

- Multi-year research program on Next Generation Quantum Molecular Dynamics
- Quantum-based models capture the making and breaking of covalent bonds, charge transfer between species of differing electronegativities, and long-range electrostatic interactions - reactions
- Graph-based methods for quantum molecular dynamics (QMD) simulations A. M. N. Niklasson et al, Graph-based linear scaling electronic structure theory, *J. Chem. Phys.* **144**, 234101 (2016).
- Density matrix generated each timestep from many small sub-matrices (or sub-graphs)
- Shown to be equivalent to traditional methods (ex. diagonalization)

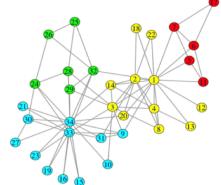






Graph Clustering - Description

- **Definition:** Unsupervised machine learning data classification
 - Identify structure based on a similarity measure Given a graph G = (V, E)
 - V ~ nodes, E ~ edges (possibly weighted)
- **Goal:** Partition V into up to k clusters/communities
- **NP-hard:** Uses heuristics and approximation algorithms
- **Methods:** Modularity, K-Means, Spectral, Hierarchical, etc.
- Approaches: 2-clustering, recursive bisection, k-concurrent, multi-level with refinement
- Applications:
 - Graph-based data decomposition for distributed HPC simulations
 - Document analysis, text classification
 - Image segmentation
 - Networks computer, communications, physical, VLSI circuit, telephone
 - Load balancing minimize total communication between processors
 - Biosystems, social networks, cyber networks

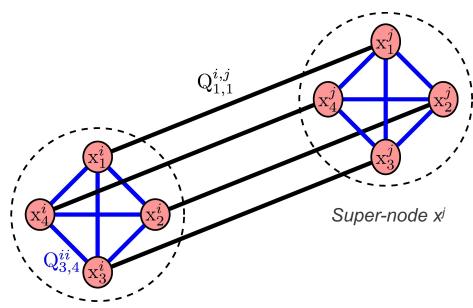


Graph Clustering using Community Detection

- Using modularity or community network analysis for natural clusters
 - M. E. J. Newman, Modularity and community structure in networks, 2006, PNAS, vol. 103, no. 23, 8577-8582.
- Identifying communities in social networks
- Identifying secondary structures in proteins
 - I. Rivalta, M. M. Sultan, N.-S. Lee, G. A. Manley, J. P. Loria, V. S. Batista, Allosteric pathways in imidazole glycerol phosphate synthase, *PNAS*, vol. 109, no. 22, pp. 1428-1436 (2011).
- Maximize modularity metric: $Q = 1/4m s^T Bs$
- 2-Clustering fits naturally on D-Wave machine, no reformulation required
- New *k*-Concurrent community detection formulation

k-Concurrent Clustering – Multiple parts in parallel

- Cluster into k parts in parallel
- Uses super-node concept
- Unary encoding
- k logical qubits per vertex
- New formulation requires a kN x kN QUBO
- Results in 1 of k qubits set on for each vertex
- Similar to graph coloring problem
- Useful for graph partitioning and community detection



Super-node xⁱ

Super-node Concept

QUBO/Ising Modularity Clustering Formulation

Construct adjacency matrix A

 $A_{ij=.} \begin{bmatrix} 0, & \text{if } i = j \\ w_{ij}, & \text{if } i \neq j \end{bmatrix}$ Where w_{ij} is the weight on the edge between nodes i and j

Construct modularity matrix B

 $B_{ij} = A_{ij} - g_i g_j / 2m = A_{ij} - g_i g_j / \sum (g_i)$, where g_i is the degree of node *i*

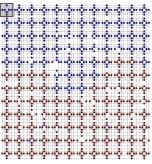
- Maximize objective for the optimal modularity for QUBO or Ising Ising: $max_s Q(s) = s^TBs$, where $s_i \in \{-1, 1\}$ or QUBO: $max_x Q(x) = x^TBx$, where $x_i \in \{0, 1\}$
- Calculate modularity metric to evaluate a set of clusters $-Q_{metric} = \sum (B_{ij} \phi(c_i, c_j)) / 2m$, where $\phi(c_i, c_j)$ is 1 when $c_i = c_j$, else 0

Data and Examples

- Determine at most k communities, maximizing modularity in parallel
- Similar formulation as k-concurrent graph partitioning
 - *kN x kN* QUBO
 - Constraint: each node in only 1 community
 - Penalty constants, β =1, γ dependent on data
- Using *qbsolv* on D-Wave 2X and 2000Q
- Examples and results
 - Newman's benchmark social networks (www-personal.umich.edu/~mejn/netdata/)
 - Alex Arena's network data sets (deim.urv.cat/~alexandre.arenas/data/welcome.htm)
 - The Koblenz Network Collection (konect.uni-koblenz.de)
 - Molecular electronic structure Phenyl dendrimer, Peptide 1 aft
 - Protein structure IGPS enzyme
- Comparison metrics # of communities and modularity
- Next, apply to more bio-systems and social networks

Using D-Wave's qbsolv on 2X and 2000Q

- Hybrid classical-quantum approaches are required for problems that are too large for embedding into D-Wave's *Chimera* Graph.
- D-Wave's *qbsolv* is a tool that solves large quadratic unconstrained binary optimization (QUBO) problems by partitioning into subproblems for execution on the D-Wave quantum annealer.
- A QUBO is generated for the full problem to be used as input.
- SubQUBO size: 46 for D-Wave 2X and 64 for D-Wave 2000Q.



- Call directly through D-Wave Ocean API response = QBSolv().sample(bqm_qubo, solver=EmbeddingComposite(DWaveSampler())
- Or from the command line

qbsolv -- i example.qubo -- o (-m) dwave_output.out

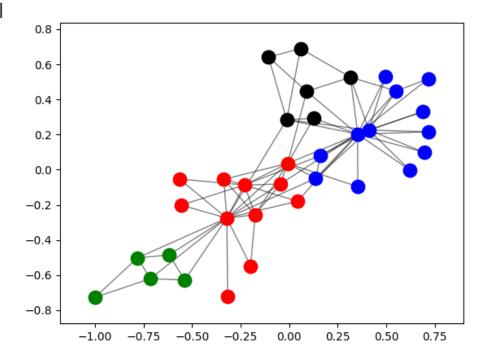
 Resulting bitstring of 0's and 1's is translated based on the optimization problem's representation

Benchmark Social Network – Karate Club

- Social network of friendships between 34 members of a karate club at a US university in the 1970s.
 - W. W. Zachary, An information flow model for conflict and fission in small groups, *Journal of Anthropological Research* 33, 452-473 (1977).
- Matches best known results for communities and modularity (Blondel et al.)

# Communities	Modularity
2	0.3717949
3	0.4020381
4	0.4197896

Karate club graph (N = 34, E = 78) 4 communities, modularity = 0.419789

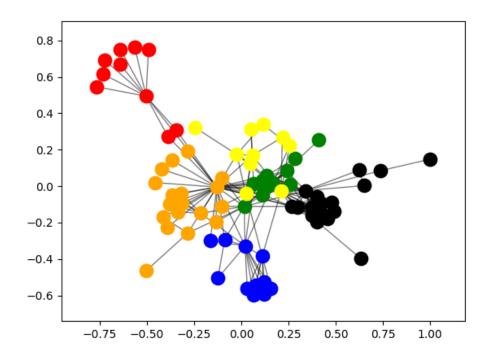


Benchmark Social Network – Les Miserables

- Coappearance network of characters in the novel *Les Miserables*.
 - D. E. Knuth, *The Stanford GraphBase: A Platform for Combinatorial Computing*, Addison-Wesley, Reading, MA (1993).
- Matches best known results for communities and modularity

# Communities	Modularity
2	0.3827887
3	0.4973274
4	0.5428343
5	0.5555388
6	0.5586134

Les Miserables graph (N = 77, E = 254) 6 communities, modularity = 0.5586134

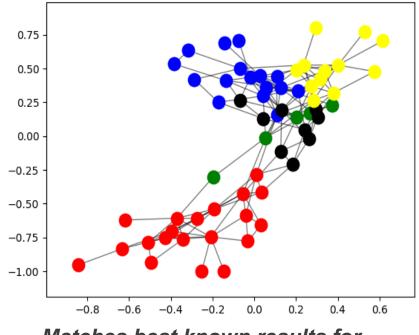


Benchmark Social Network – Dolphins

- An undirected social network of frequent associations between 62 dolphins in a community living off Doubtful Sound, New Zealand.
 - D. Lusseau, K. Schneider, O. J.
 Boisseau, P. Haase, E. Slooten, and S.
 M. Dawson, *Behavioral Ecology and Sociobiology* 54, 396-405 (2003).

# Communities	Modularity
2	0.4027333
3	0.4941853
4	0.5267987
5	0.5285194

Dolphins graph (N = 62, E = 159) 5 communities, modularity = 0.5285194



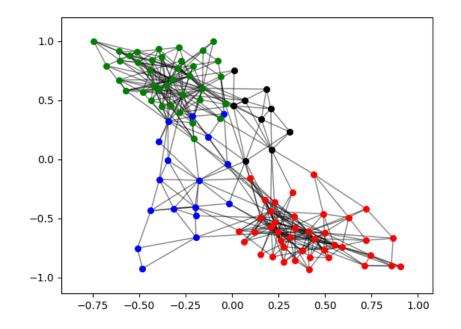
Matches best known results for communities and modularity.

Benchmark Social Network – Political Books

- Book co-purchasing network. Nodes represent books about US politics and edges represent frequent co-purchasing of books.
 - M. E. J. Newman, Modularity and Community Structure in Networks, *PNAS*, vol. 103, no. 23, 8577-8582 (2006).

# Communities	Modularity
2	0.45687
3	0.52207
4	0.52555

Political books graph (N = 105, E = 441) 4 communities, modularity = 0.52555



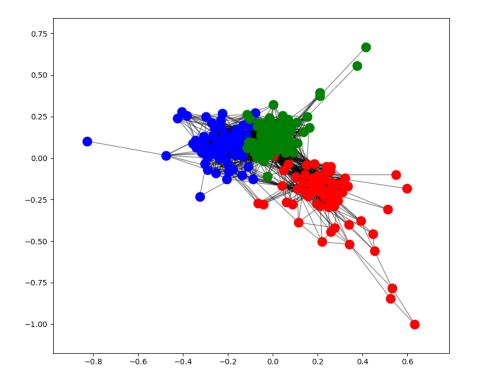
Matches best known results for communities and modularity.

Benchmark Social Network – Jazz Musicians Network

- Collaboration network of Jazz
 musicians.
 - P.Gleiser and L. Danon, Community Structure in Jazz, Adv. Complex Syst.6, 565 (2003).
- Comparable results for communities and modularity
- Race and recording location determine communities

# Communities	Modularity
2	0.3206093
3	0.4444694

Jazz graph (N = 198, E = 2742) 3 communities, modularity = 0.4444694

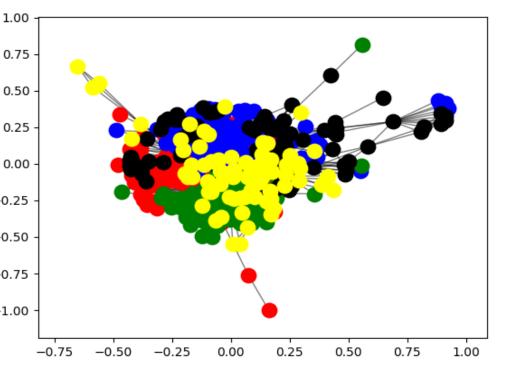


Benchmark Social Network – C. elegans metabolic network

- Metabolic network of the nematode C. elegans. Nodes are proteins, edges are interactions.
 - J. Duch and A. Arenas, Community identification using Extremal Optimization, Physical Review E, vol. 72, 027104, (2005).
- Comparable results for communities and modularity.

# Communities	Modularity	-0
2	0.3199541	-0
3	0.3929653	-0
4	0.4091737	-1
5	0.4172796	

C. elegans graph (N = 453, E = 2040) 5 communities, modularity = 0.4172798



Koblenz Networks – k-Concurrent Clustering

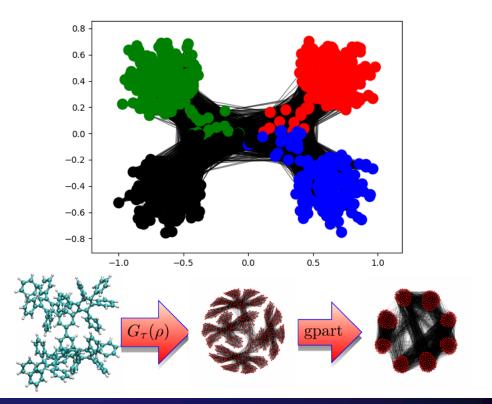
					Infectious
Dataset	Nodes	Edges	Comms	Mod	
Cont. USA (spatial)	49 state	107 border	6	0.5970	
Infectious (social net)	410 visitor	2765 contact	8	0.7067	Contiguous USA
Contact (cell phone contacts)	274 person	2124 phone contact	4	0.1315	
Brunson (affiliation network)	136 person	159 membership	5	0.5795	
Moreno_oz (friendship)	217 person	1839 friend	6	0.4282	
					<u>Brunson</u>

Molecule electronic structure – Phenyl Dendrimer

- Molecular electronic structure graph for Phenyl Dendrimer protein.
 - H. N. Djidjev, G. Hahn, S. M. Mniszewski, C.
 F. A. Negre, A. M. N. Niklasson, V. B.
 Sardeshmukh, Graph partitioning Methods for Fast Parallel Quantum Molecular
 Dynamics, SIAM Workshop on Combinatorial Scientific Computing 2016 (CSC16).
- Density matrix used for adjacency

# Communities	Modularity
2	0.4773614
3	0.5724155
4	0.6651407

Phenyl dendrimer graph (N = 730, E = 31877) 4 communities, modularity = 0.6651407



Molecule electronic structure – Peptide 1 aft + H₂O

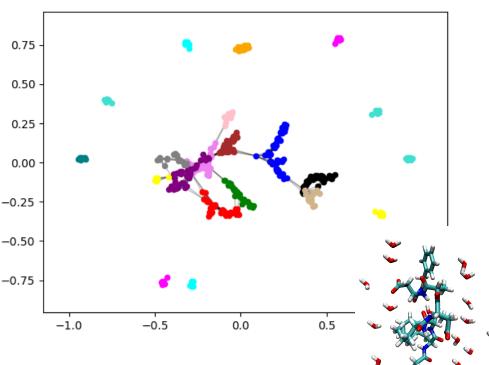
• Molecular electronic structure graph for Peptide 1 aft protein.

 H. N. Djidjev, G. Hahn, S. M. Mniszewski, C.
 F. A. Negre, A. M. N. Niklasson, V. B.
 Sardeshmukh, Graph partitioning Methods for Fast Parallel Quantum Molecular
 Dynamics, SIAM Workshop on Combinatorial Scientific Computing 2016 (CSC16).

Amino acid sequence

- PHE-ASP-ALA-ASP-LEU-THR-PHE
 - (PHEnylalanine, ASPartic acid, LEUcine, THyRosine)
- Solvated in water
- LATTE QMD after SCF convergence
- Orbitals as nodes
- Density matrix used for adjacency

Peptide 1 aft graph (N = 384, E = 2217) 16 communities, modularity = 0.875424



Molecule electronic structure – Peptide 1 aft (No water)

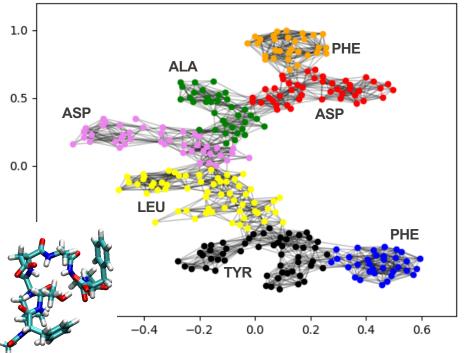
• Molecular electronic structure graph for Peptide 1 aft protein.

 H. N. Djidjev, G. Hahn, S. M. Mniszewski, C.
 F. A. Negre, A. M. N. Niklasson, V. B.
 Sardeshmukh, Graph partitioning Methods for Fast Parallel Quantum Molecular
 Dynamics, SIAM Workshop on Combinatorial Scientific Computing 2016 (CSC16).

Amino acid sequence

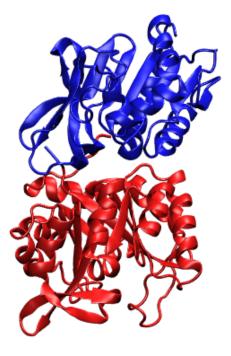
- PHE-ASP-ALA-ASP-LEU-TYR-PHE
 - (PHEnylalanine, ASPartic acid, ALAnine, LEUcine, TYRosine)
- LATTE QMD after SCF convergence
- Communities correspond to amino acids

Peptide 1 aft graph (N = 300, E = 1794) 7 communities, modularity = 0.765666



Protein Structure Communities in Bio-Systems

- IGPS is an enzyme in bacteria (454 residues)
- Applying community detection using *qbsolv* resulted in communities corresponding to IGPS's 2 molecules
- The modularity matrix is calculated from a correlation matrix based on a molecular dynamics (MD) simulation



Correlation matrix (for CNA)
$$\mathbf{r}_{ij}^{MI} = g(\mathbf{I}[\mathbf{x}_i, \mathbf{x}_j])$$

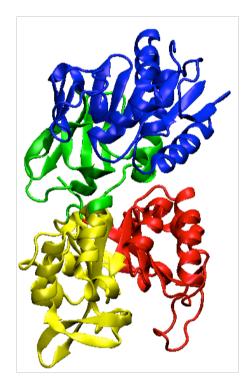
Girvan-Newman

Modularity Matrix

IGPS Protein Structure

Protein Structure Communities in Bio-Systems

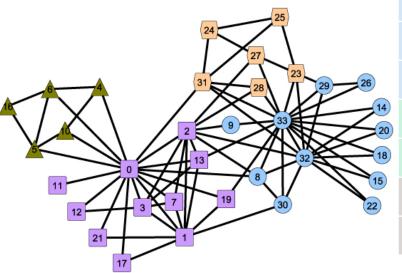
- IGPS is an enzyme in bacteria consisting of 2 molecules (454 residues)
- Applying quantum community detection using *qbsolv* for up to k = 4 communities
- The 4 resulting communities each share common sub-structure
 - Each molecule is composed of 2 domains
 - Each domain has a specific function
- Results are comparable with classical methods
 - C. F. A. Negre, H. Hendrickson, R. Pal, I. Rivalta, J. Ho, V. S. Batista, Eigenvector Centrality Distribution for Characterization of Protein Allosteric Pathways, arXiv preprint arXiv:1706.02327 [q-bio.BM].



IGPS Protein Structure

k-Clustering Community Detection with Thresholding

- Using community detection for natural clusters
- Compare for up to 4 clusters
- Threshold modularity matrix weights
- Results in reduction in qubit chains
 and couplers



Karate club graph (N = 34) using *qbsolv*

Threshold	# weights	# clusters	modularity
0	561	4	0.4197896
0.02	544	4	0.4197896
0.05	411	4	0.4197896
0.06	334	4	0.4197896
0.07	300	4	0.4151052
0.08	244	3	0.3990795
0.10	227	3	0.3990795
0.15	169	2	0.3717948
0.25	110	2	0.3717948

K-Means Clustering of Numerical Data

- Given X data points partition into k disjoint subsets
 - Zero mean data
 - Clusters defined by centroids
- Even 2-means clustering is NP-hard
- Typically minimize the <u>within cluster scatter</u> $|| x mean(x_i)||^2$
- Alternatively maximize the <u>between cluster scatter</u> $|| mean(x_i) mean(x_j) ||^2$
- Reduce to an Ising Model formulation
 - Minimize $\sum Q_{ij} s_i s_j$, where $Q = X^T X$ which is a Gram Matrix
 - Gram matrix elements are dot products of the X data pairs
- Bauckhage C., Brito E., Cvejoski K., Ojeda C., Sifa R., Wrobel S. (2018) Ising Models for Binary Clustering via Adiabatic Quantum Computing. In: Pelillo M., Hancock E. (eds) Energy Minimization Methods in Computer Vision and Pattern Recognition. EMMCVPR 2017. Lecture Notes in Computer Science, vol 10746.

2-Means clustering of Iris Data

- Iris Data UCI Machine Learning Repository
- Fisher, R.A. "The use of multiple measurements in taxonomic problems" Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to Mathematical Statistics" (John Wiley, NY, 1950).
- Best known database to be found in the pattern recognition literature
- 150 instances with 4 features
 - sepal length, sepal width, petal length, petal width
 - 3 classes: Iris Setosa, Iris Versicolour, Iris Virginica
- Processing required:
 - Zero mean centered data
 - Calculate Gram matrix dot product of pairs of data
- Results using Quantum Annealing
 - Partitioned into Iris Setosa and Iris Versicolour + Iris Virginica



Summary

- Quantum annealing for modularity-based community detection results in equal or comparable results to existing classical approaches
- Demonstrated a hybrid classical-quantum approach for existing benchmark graphs, example graphs, and electronic structure graphs
- Quantum-based k-means clustering is possible as demonstrated for 2means clustering
- Future plans include exploring quantum computing approaches to other clustering methods

Publications

- S. M. Mniszewski, H. Ushijima-Mwesigwa, C. F. A. Negre, 2017, Graph Partitioning using the D-Wave for Electronic Structure Problems, SIAM Annual Meeting, Minisymposium MS43: Identifying Computational Methods for early Benefit from Quantum Computing,.
- P. Goddard, S. M. Mniszewski, F. Neukart, S. Pakin, S. Reinhardt, 2017, How Will Early Quantum Computing Benefit Computational Methods? *SIAM News*, Vol. 50, No. 10.
- H. Ushijima-Mwesigwa, C. F. A. Negre. S. M. Mniszewski, 2017, Graph Partitioning using Quantum Annealing on the D-Wave System, arxiv preprint arxiv.org/abs/1705.03082.
- H. Ushijima-Mwesigwa, C. F. A. Negre, S. M. Mniszewski, 2017, Graph Partitioning using Quantum Annealing on the D-Wave System, *Proceedings of the 2nd International Workshop on Post Moore's Era Supercomputing (PMES)*, 22-29, SC 2017.
- S. M. Mniszewski, C. F. A. Negre, Ushijima-Mwesigwa, 2018, Graph Clustering Approaches using Nearterm Quantum Computing, Argonne Quantum Computing Workshop.
- H. Ushijima-Mwesigwa, C. F. A. Negre, S. M. Mniszewski, I. Safro, 2018, Multilevel Quantum Annealing for Graph Partitioning, Argonne Quantum Computing Workshop.
- C. F. A. Negre, H. Ushijima-Mwesigwa, S. M. Mniszewski, 2018, Community Detection using Quantum Annealing on the D-Wave System, (in preparation).



Thank You!