

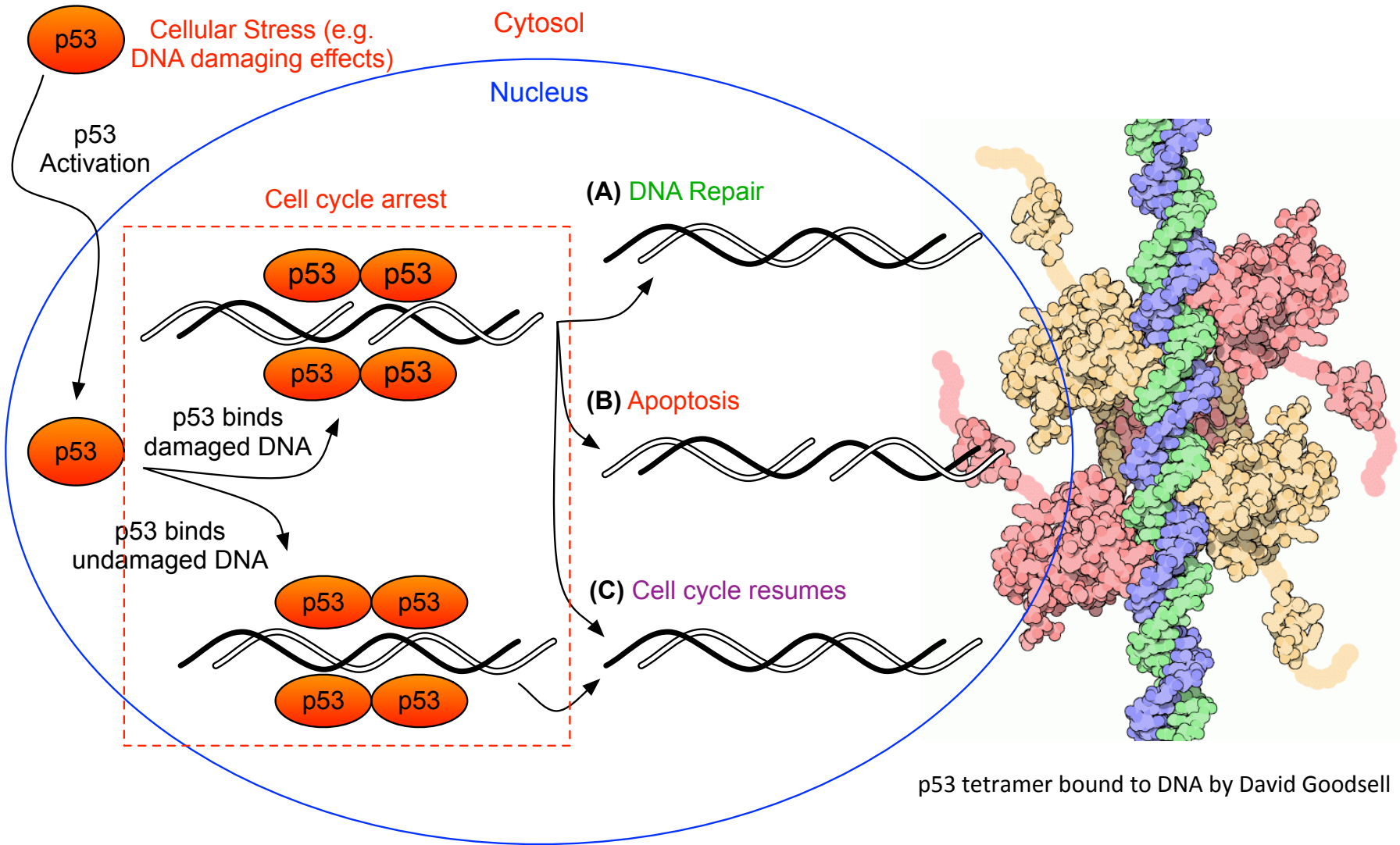


Probing the Chemical Similarity Network of Designed Inhibitors to the p53 binding site on MDM2

George A Pantelopulos, Asanga Bandara, Shanshan Song

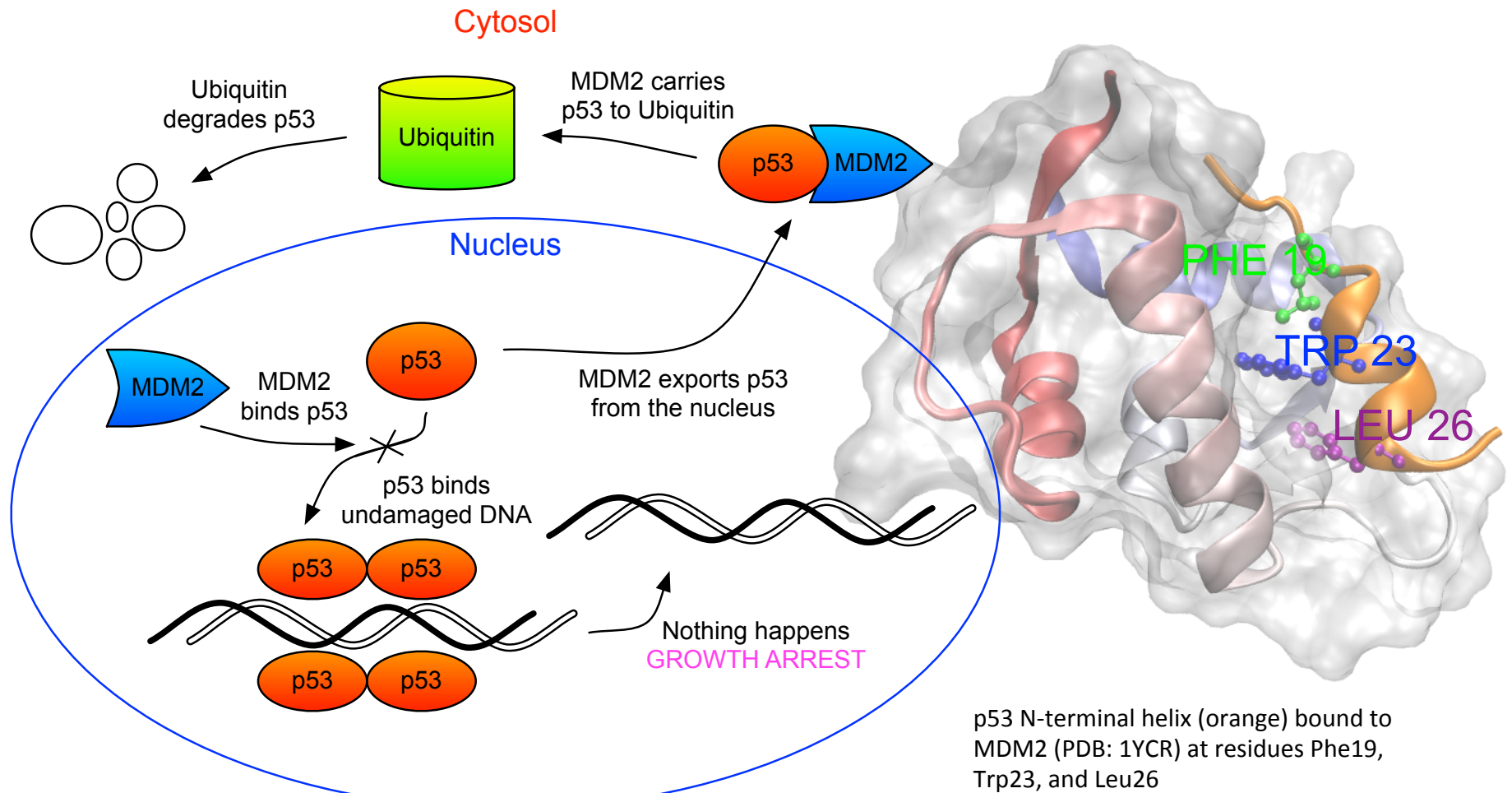
PY 895 – Network Science

p53 is the Guardian of the Genome

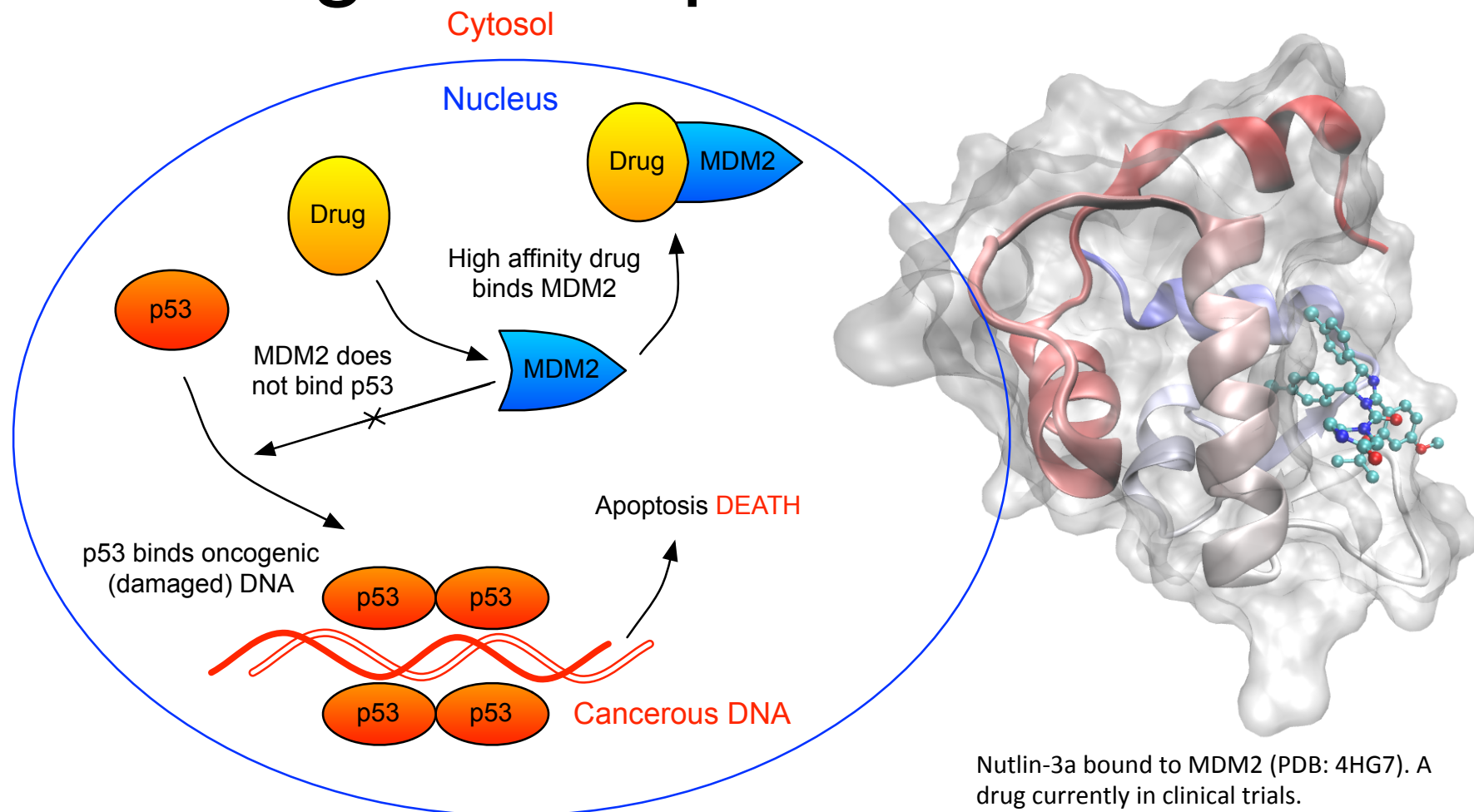


p53 tetramer bound to DNA by David Goodsell

MDM2 antagonizes p53 to promote healthy growth



MDM2 is an attractive target for anti-cancer drug development



Anil, B.; Riedinger, C.; Endicott, J. A.; Noble, M. E., The structure of an MDM2-Nutlin-3a complex solved by the use of a validated MDM2 surface-entropy reduction mutant. *Acta crystallographica. Section D, Biological crystallography* **2013**, 69 (Pt 8), 1358-66.

Many MDM2 inhibitor designs have been made, and have measured binding affinities

Binding DB has 2,389 entries for designs that bind MDM2

93 of these designs have exactly reported IC_{50} s

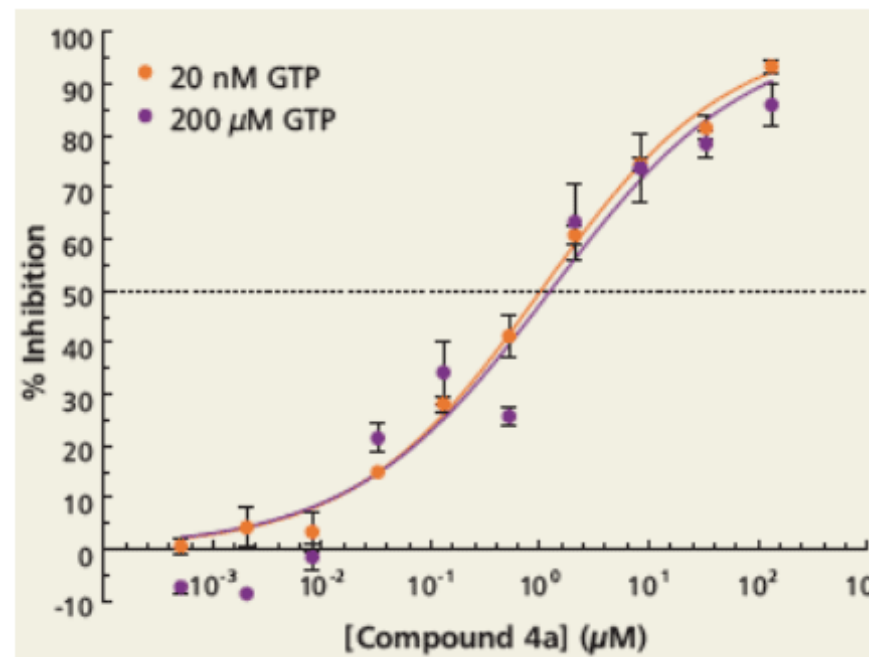
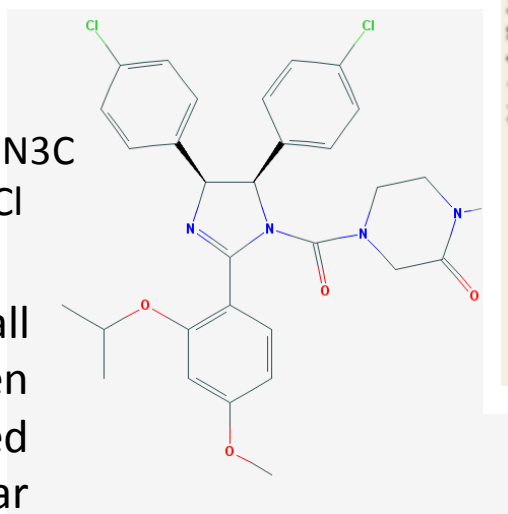
SMILES (simplified molecular-input line-entry system) strings define the 2D structure for each design.

e.g. the Nutlin-3a SMILES string

```
CC(C)OC1=C(C=CC(=C1)OC)C2=NC(C(N2C(=O)N3C(C(=O)C3)C4=CC=C(C=C4)Cl)C5=CC=C(C=C5)Cl
```

Could networks where nodes are small molecules and links are formed between all molecules of similar structure be used to find groups (communities) of similar molecules (chemotypes)?

What would such a network look like?



Example IC_{50} plot.¹ Dotted line represents IC_{50} .

We can define the similarity between molecules using SMILES strings based on bit-wise correlations!

Given strings that are 2D descriptors of molecular structure, we could use a string length-normalized string-similarity based method...

Tanimoto coefficients (T)! (Jaccard index)

$$T = (A \cap B) / (A + B - (A \cap B))$$

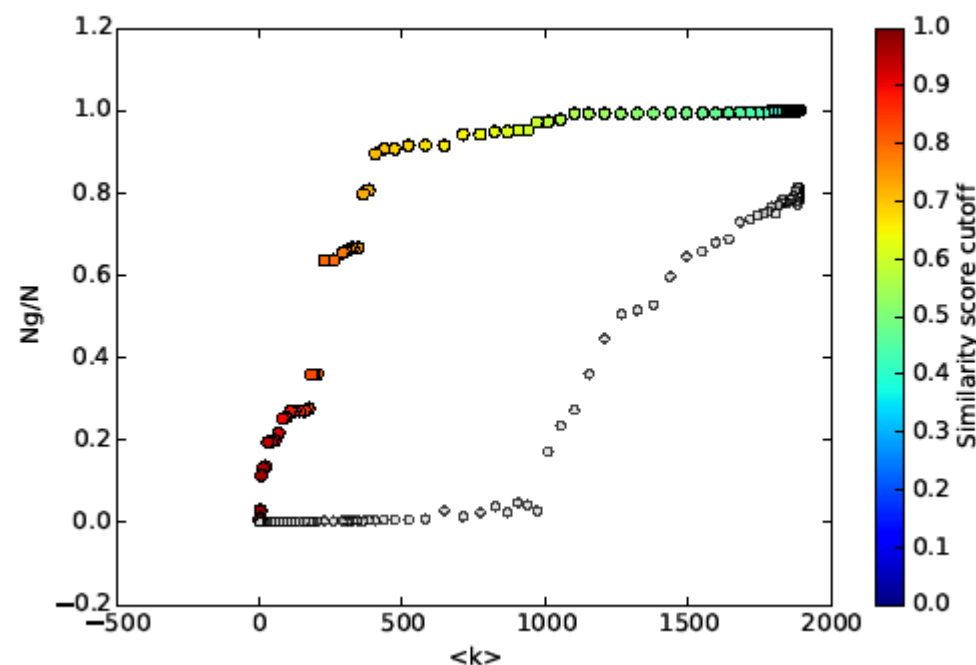
where A is the number of bits that are valued "1" in string A , B is the number of bits that are valued "1" in string B , and $A \cap B$ are the number of bits that are valued "1" that intersect between strings A and B .

Tanimoto similarity scores, T , vary from 0 to 1.

Connectivity of networks described using different similarity score linking cutoffs can give us a sense of a decent cutoff.

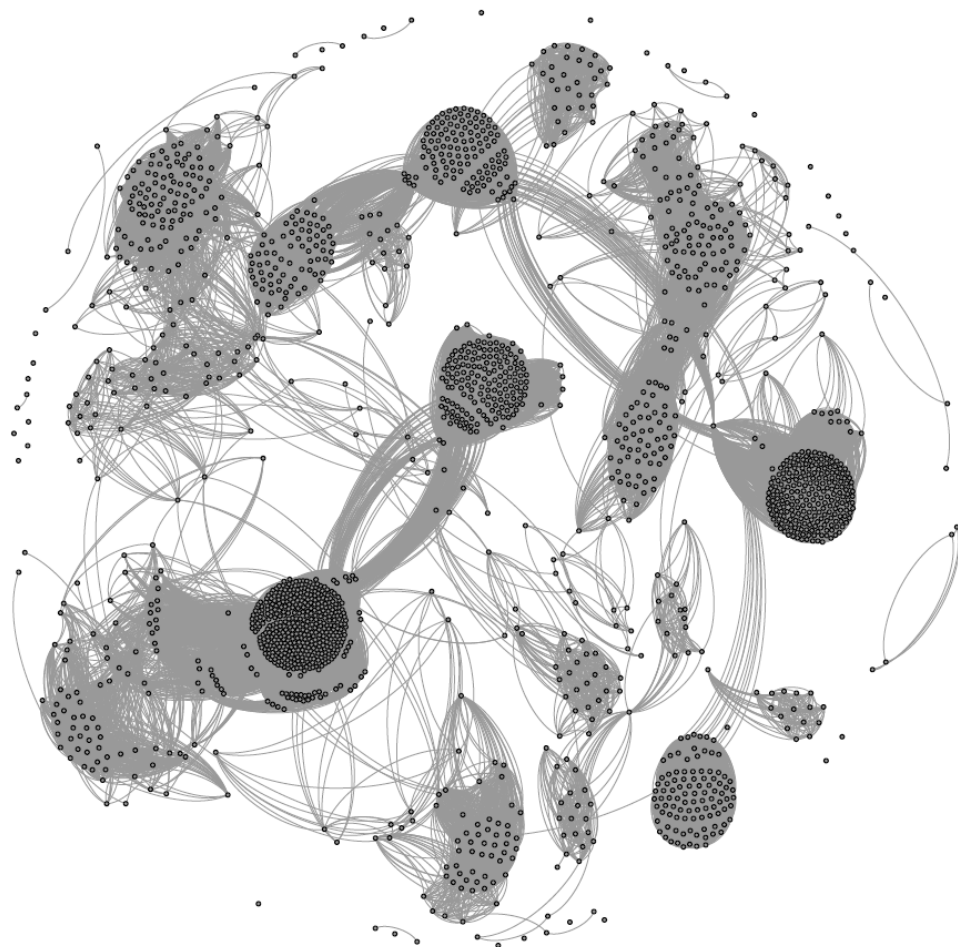
By constructing chemical similarity networks of these MDM2 inhibitors at many different similarity score cutoff values, we get a sense of the connectivity of the network for each cutoff...

A similarity score linking cutoff of 0.65 was selected to ensure a high connectivity while being far from a complete graph and far from above random.

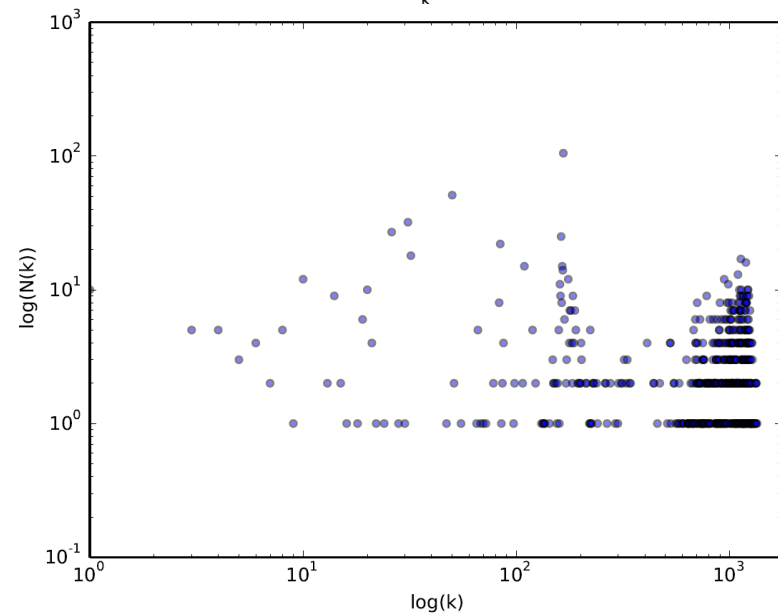
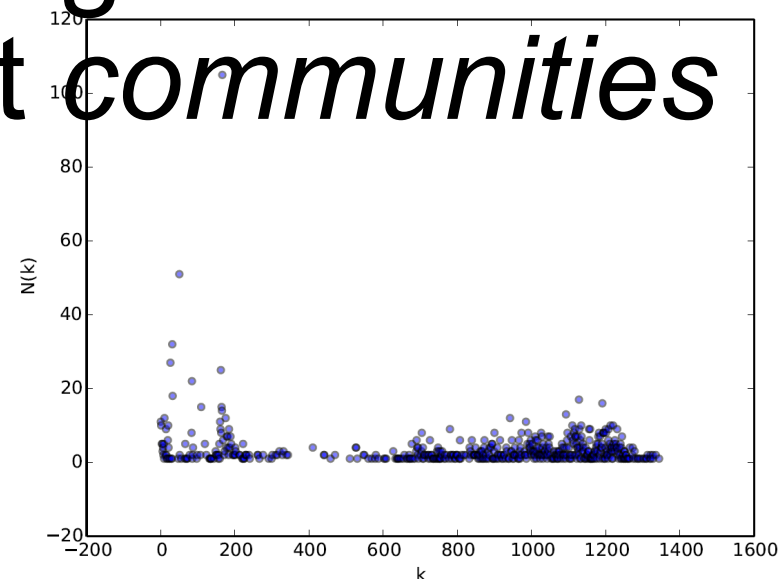


Phase diagram of MDM2 inhibitor chemical similarity networks at different similarity score linking cutoffs. N_g is the number of nodes in the largest connected component, N is the number of nodes in the network, and $\langle k \rangle$ is the average degree of nodes in the network. ER graphs are constructed at each $\langle k \rangle$ for comparison, and are represented in gray.

Our resulting network is large and appears to contain distinct *communities*



Representation with Fruchterman-Reingold force-directed drawing shows multiple possible partitions.



We partition our network into distinct communities via the Louvain Method

Optimizes the *modularity*, Q , a quantity that measures the density of links within communities of a network.

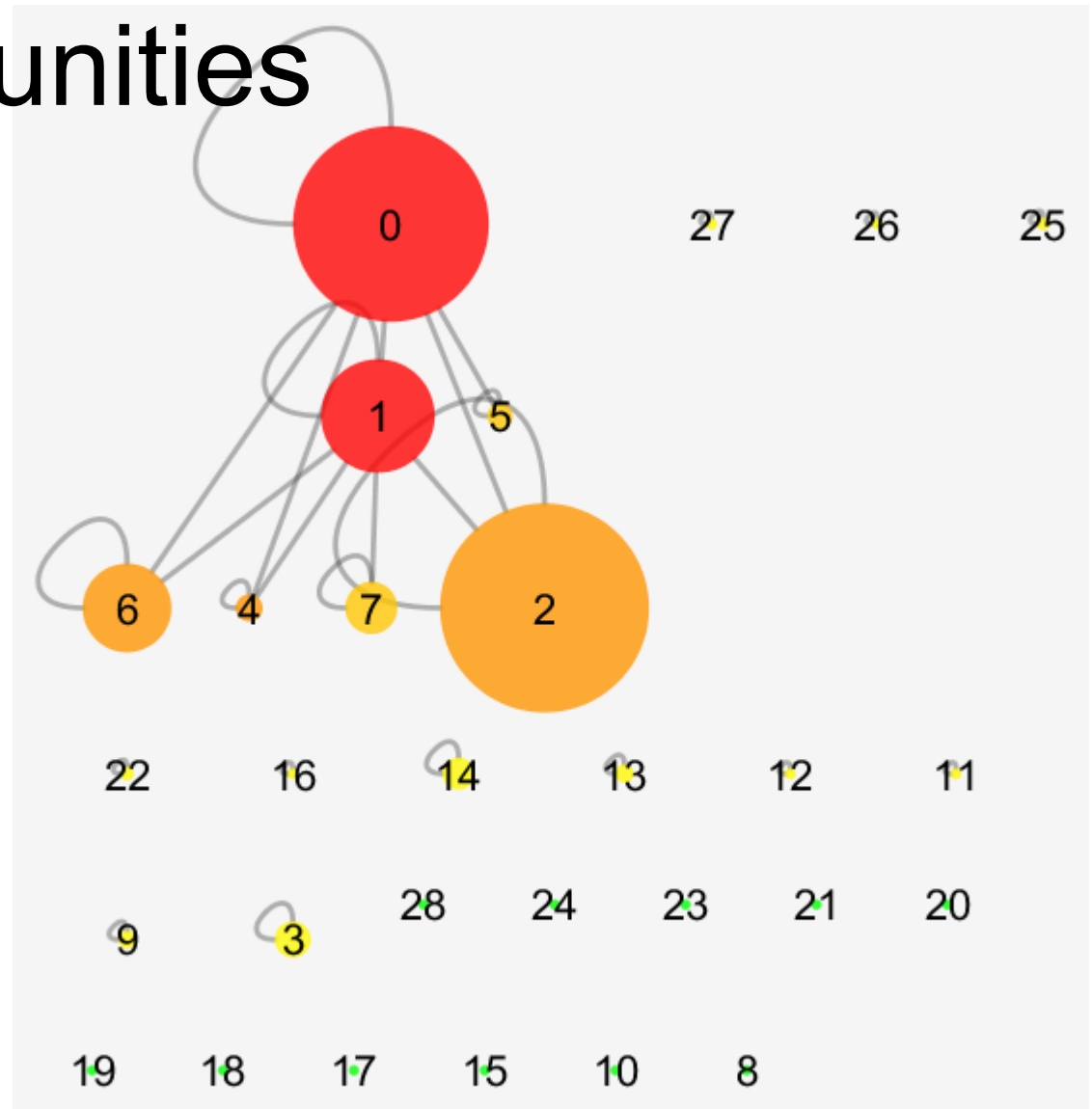
$$Q = \frac{1}{2m} \sum_{i,j} [A_{ij} - \frac{k_i k_j}{2m}] \delta(c_i, c_j)$$

Where i and j are the indices of nodes in the network, m is half the sum of edge weights in the graph (weights = 1 here), c_i and c_j are the communities which each node belongs, and A_{ij} is the edge weight between i and j (=1 here)

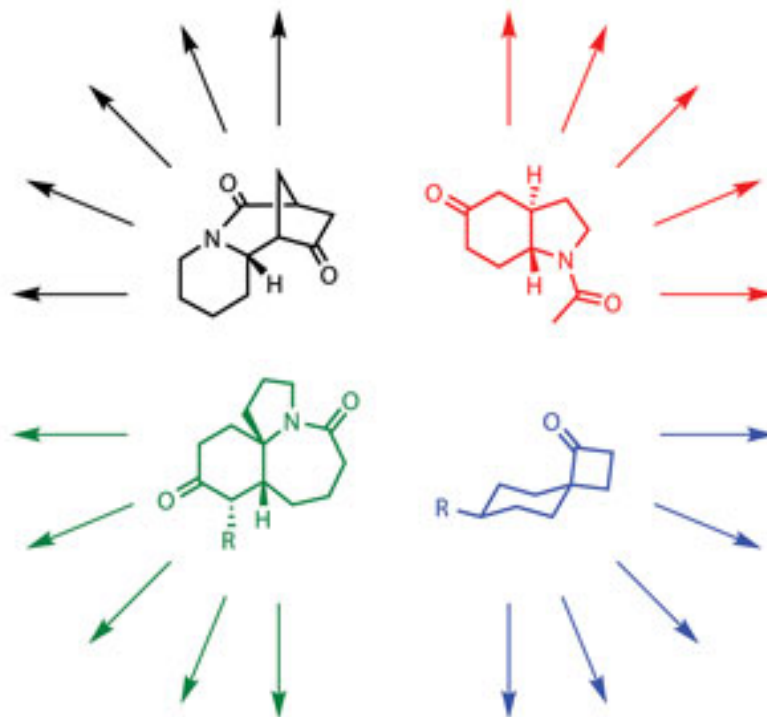
The assignments of nodes to communities is accomplished by whatever discretization of nodes into communities maximizes Q .

Our network contains a handful of well-populated communities

Community	Population
0	602
1	267
2	657
3	32
4	21
5	19
6	166
7	51
8	1
9	10
10	1
11	2
12	2
13	11
14	27
15	1
16	2
17	1
18	1
19	1
20	1
21	1
22	5
23	1
24	1
25	4
26	2
27	2



Community Representatives



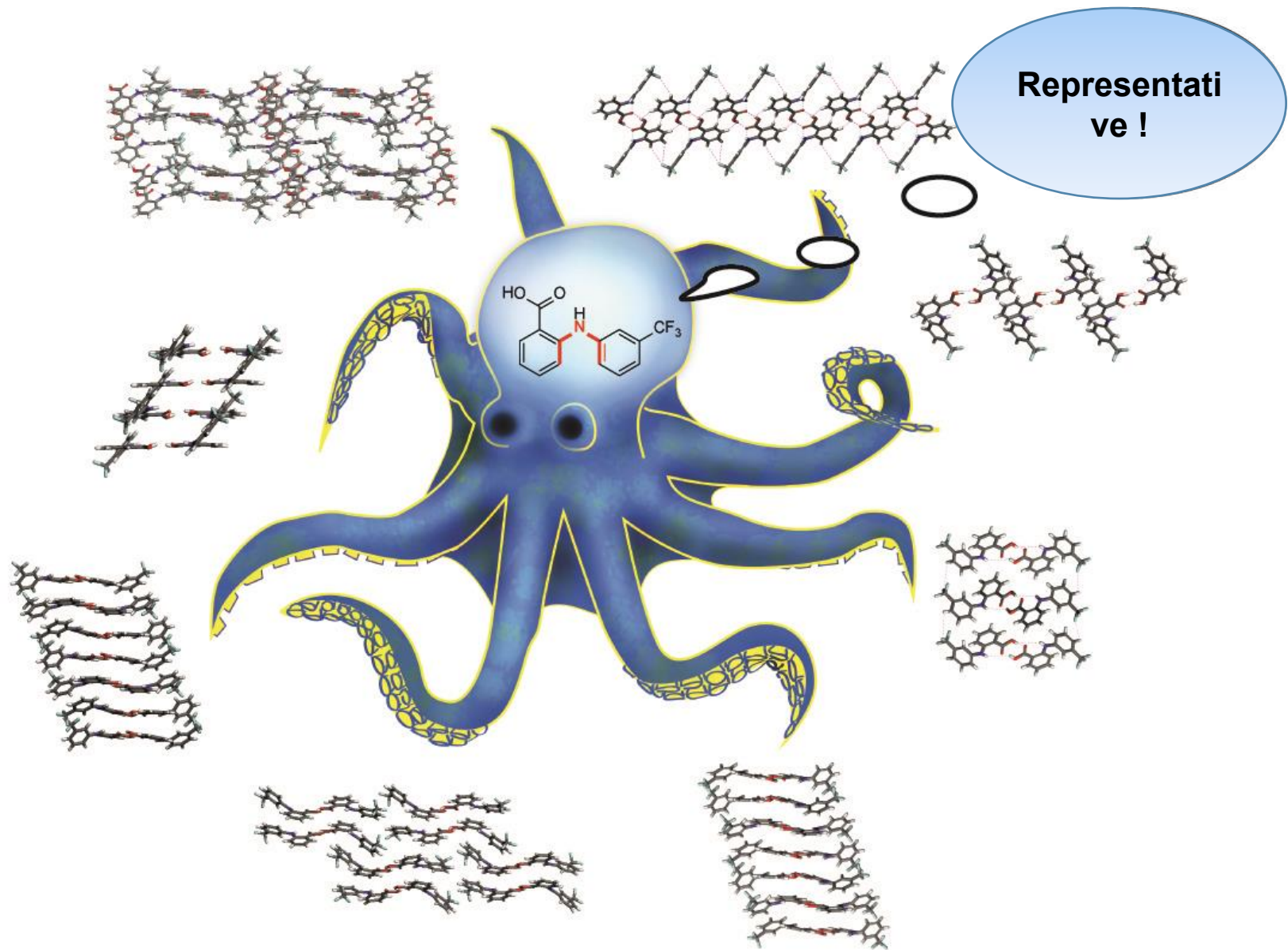
Motivation

Large number of members in a community.

Individual analysis is time consuming.

Chemical intuition is narrow with individual analysis.

Not member molecules but scaffolds (Functional groups, Steric groups) deemed more interesting !



Approach

Nodes with highest links : Representative ?

Links have different weights

Cumulative weighted links

**Representative Molecule for a
Community**

=

**Node with the Highest Weighted
Degree**

Investigating network and chemical structures in our communities may reveal interesting and useful features...

We briefly investigate network and chemical structures in our four most-populated communities via the following:

1. Visualization with force-directed drawing.
2. Log-log degree distributions
3. Representative molecule structures
4. Similarity maps for other molecules in communities in reference to community representatives



Similarity Maps

Structure features

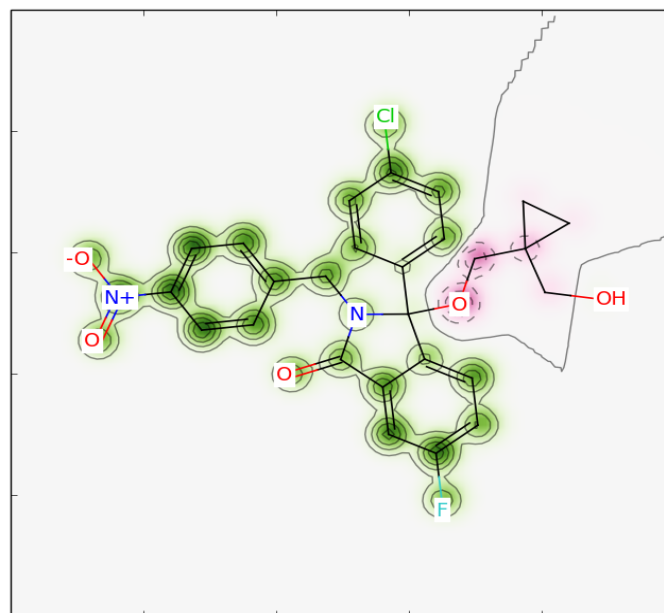
- functional group
- 3D structure

Weight -- Similarity

- Remove bits of one atom
- Green: positive difference
- Pink: negative difference
- Grey: no difference

Advantage of Conversion

- computationally efficient
- compare similarity



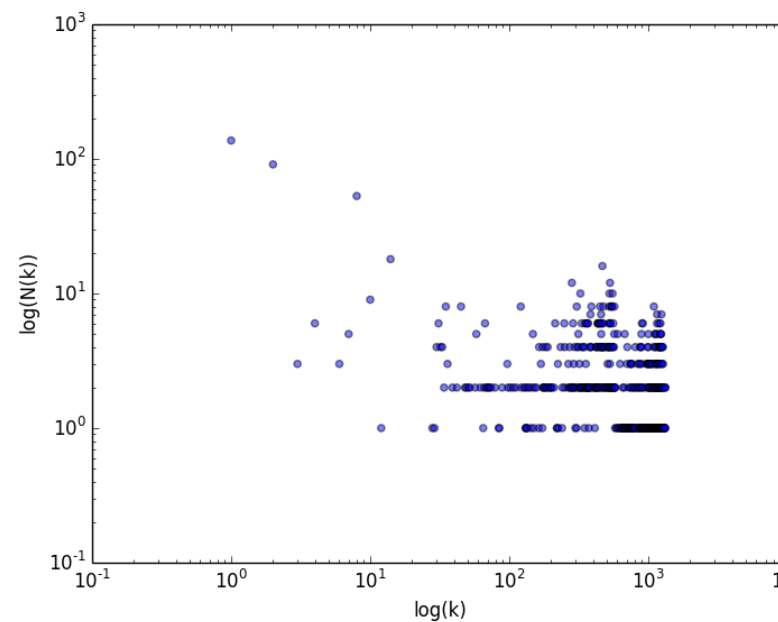
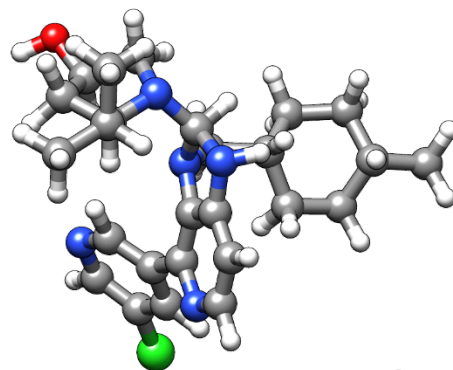
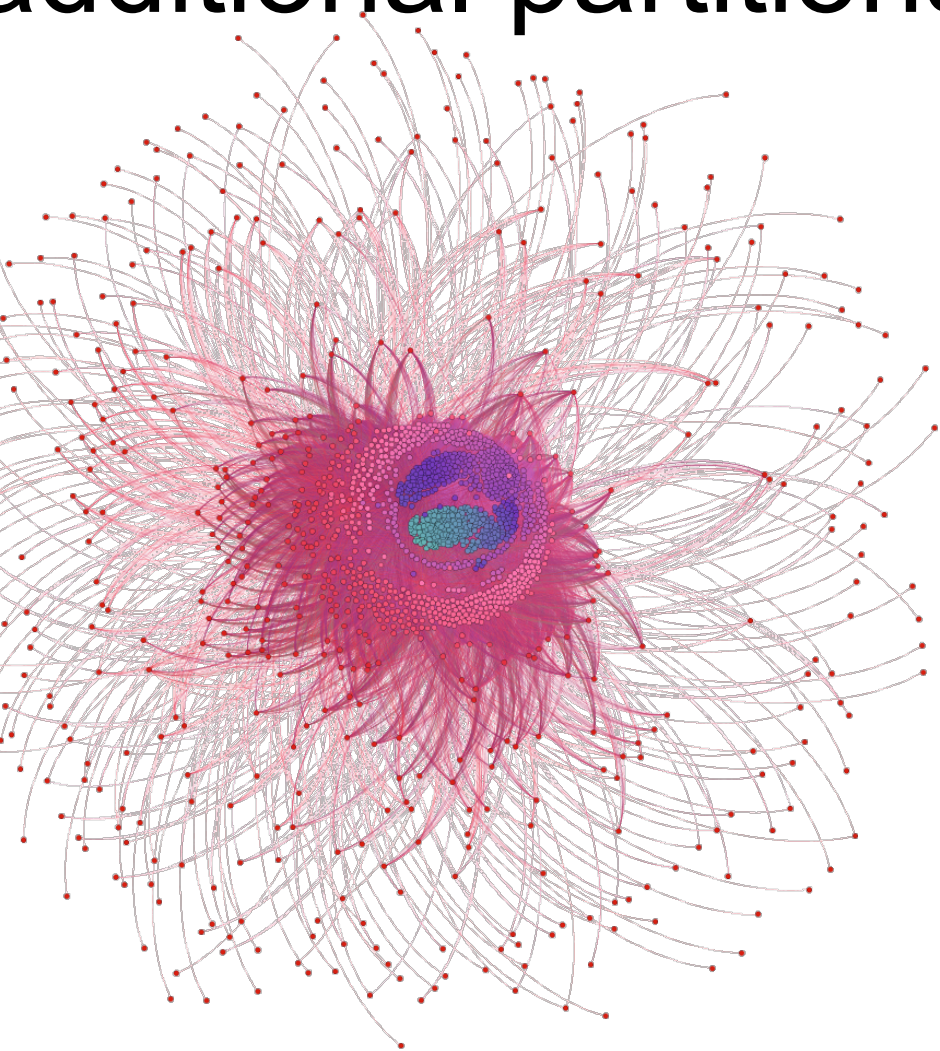
Fingerprints

- bits in vector
- count in vector

FeatMorgan2

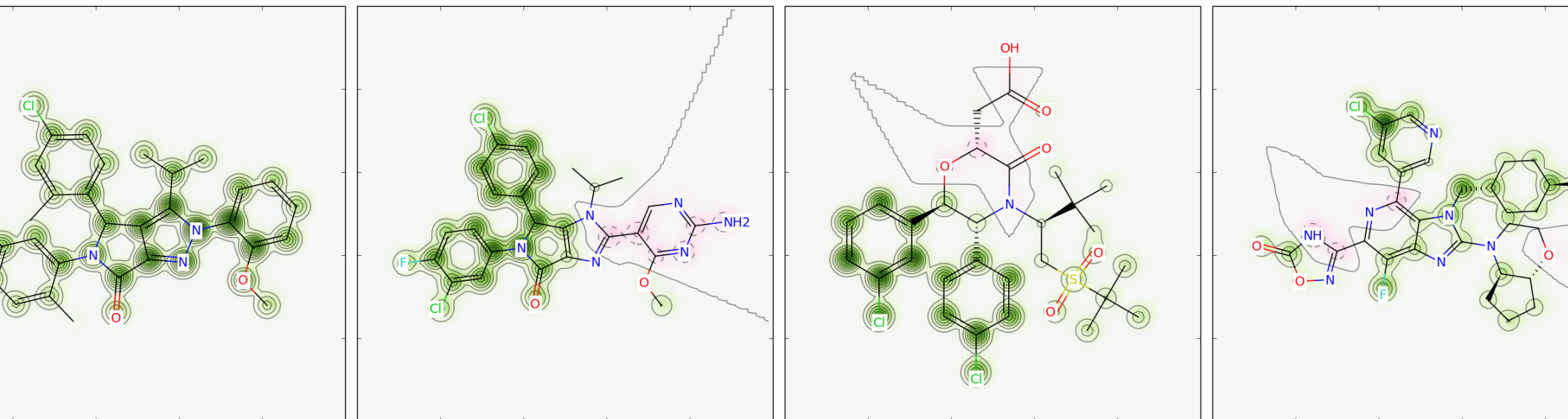
- FEATURE based
- donar, acceptor, aromatic, basic, acid
- CIRCULAR FINGERPRINT
- w/ RADIUS 2 (radius=2)
- as BIT VECTOR (size=1024bit)

Community 0 appears to show no additional partitions



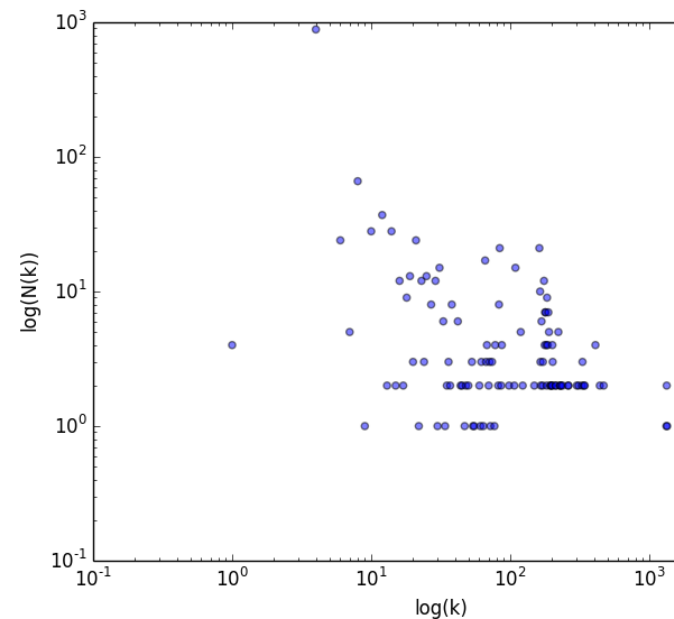
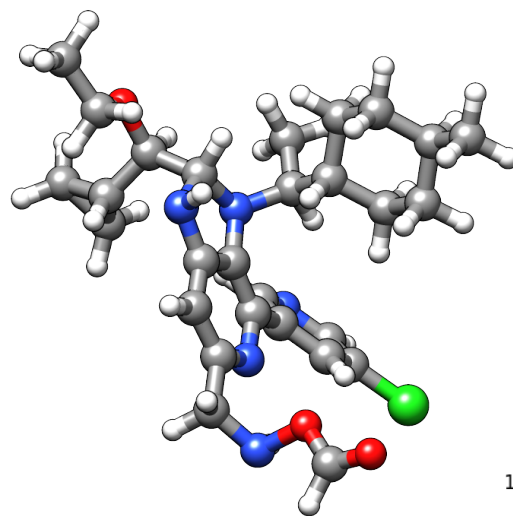
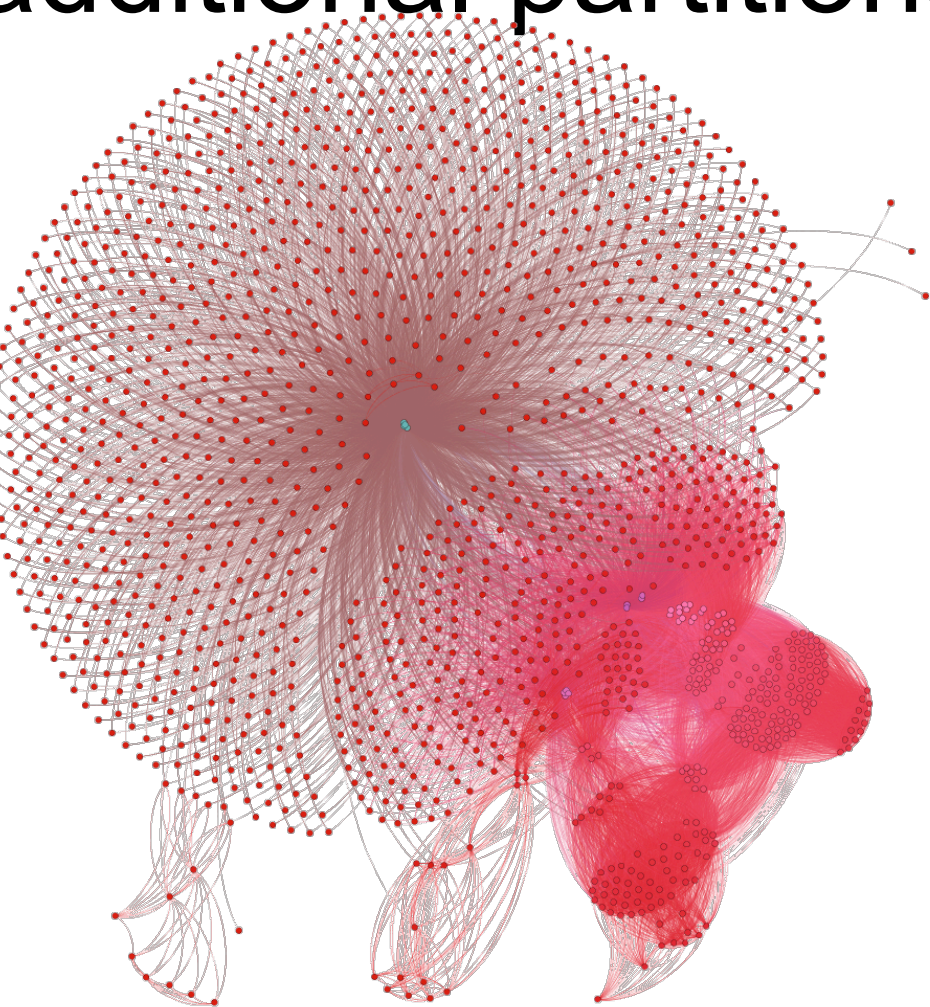
Man-Reingold force-directed drawing shows no partitions.

Community 0 similarity depends on aromatic nitrogen-containing scaffold and aromatic chlorine-containing sidechains.



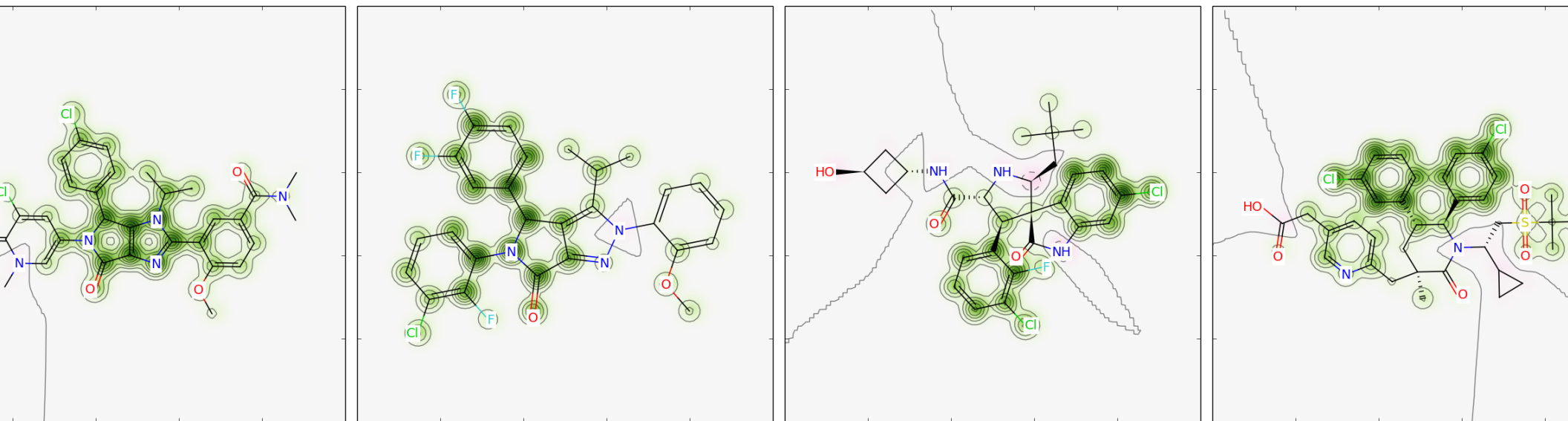
Similarity maps based on per-atom similarity with the representative molecule. 2nd, 3rd, 4th and 5th highest-similarity molecules presented from left to right.

Community 1 appears to contain additional partitions



Man-Reingold force-directed drawing shows possible further partitions.

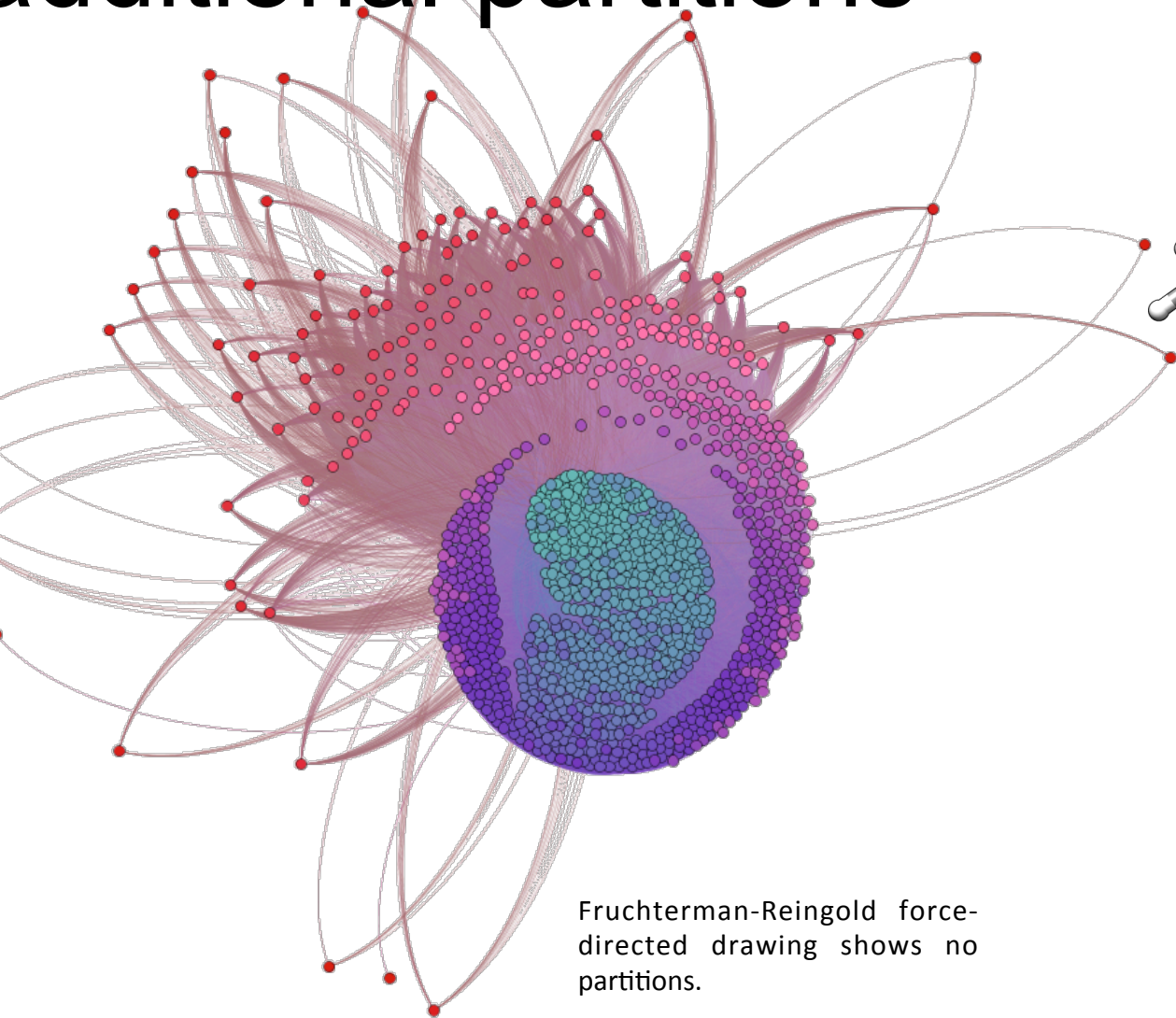
Community 1 similarity depends on aromatic chlorine and fluorine-containing side chains.



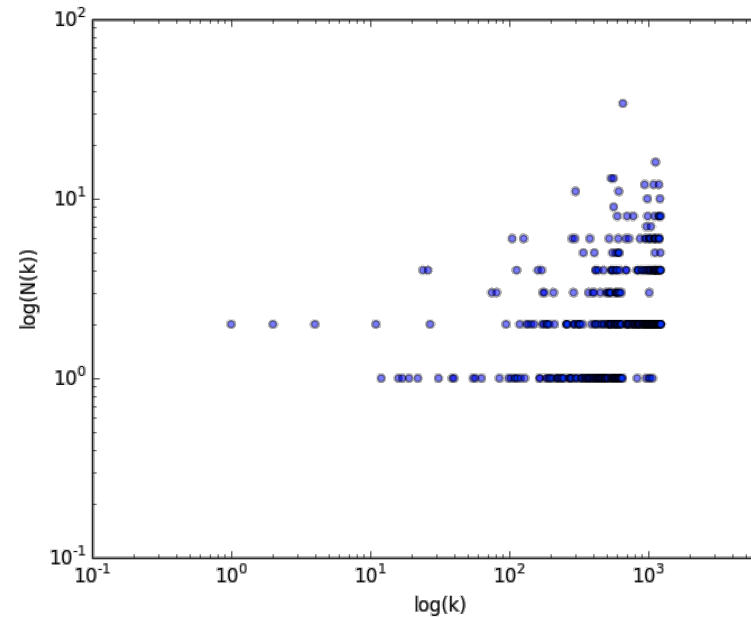
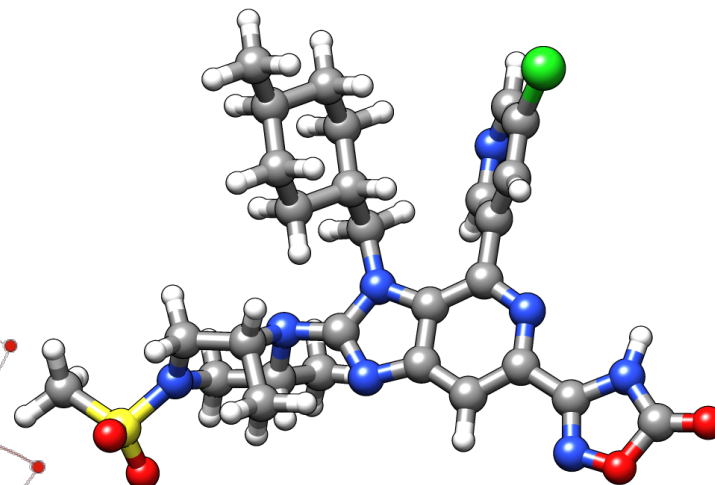
Similarity maps based on per-atom similarity with the representative molecule. 2nd, 3rd, 4th and most-representative molecules presented from left to right.

It is possible that molecules out of the top 3 most-representative molecules might be in need of further partitioning.

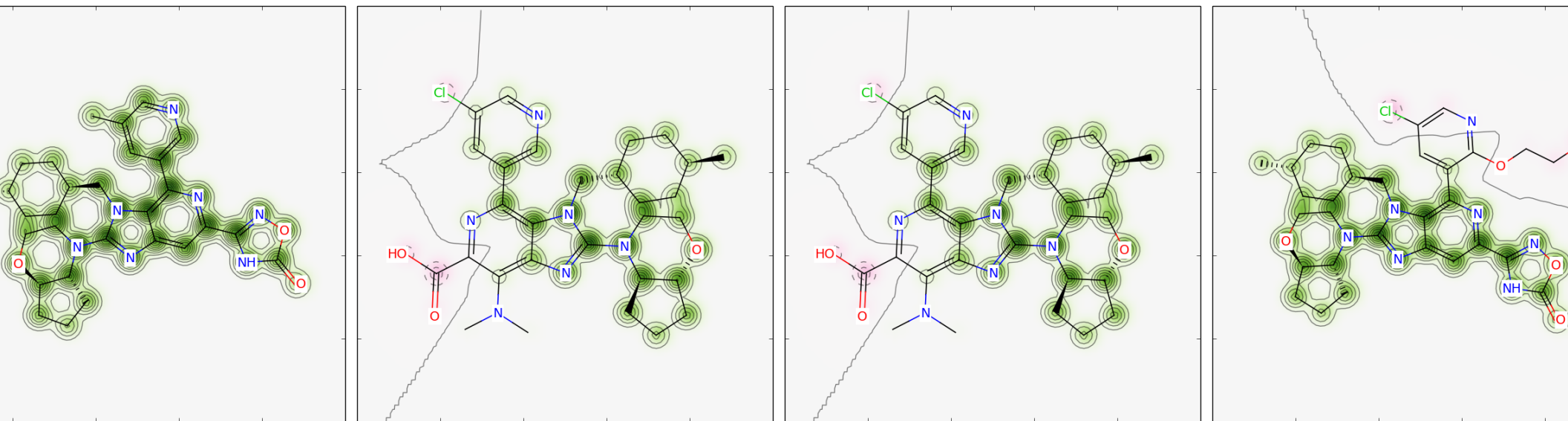
Community 2 appears to show no additional partitions



Fruchterman-Reingold force-directed drawing shows no partitions.

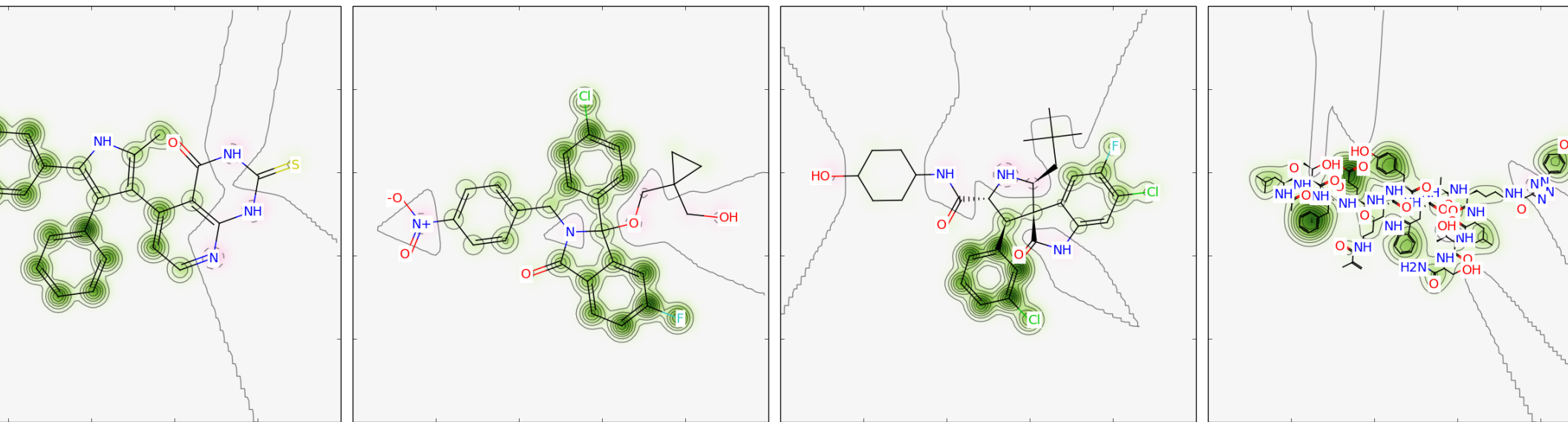


Community 2 is characterized by nitrogen-containing aromatic scaffolds.



Clarity maps based on per-atom similarity with the representative molecule. 2nd, 3rd, 4th and 5th most representative molecules presented from left to right.

Community 6 contains well-defined aromatic side chains.



Clarity maps based on per-atom similarity with the representative molecule. 2nd, 3rd, 4th and 5th most representative molecules presented from left to right.

Future work(?)

Building a small molecule inhibitor network where links are weighted by similarity score and there is no similarity score cutoff – would the communities be any more well-defined?

Using a different algorithm for partitioning molecules into communities?

Characterizing small molecules within communities in terms of their IC_{50} and unique molecular structure.

Generating semi-random new 2D molecular designs that would fall into our communities. Binding affinity could be approximately predicted using molecular docking to the p53 binding site on MDM2... Can we generate potent new designs algorithmically using our communities?