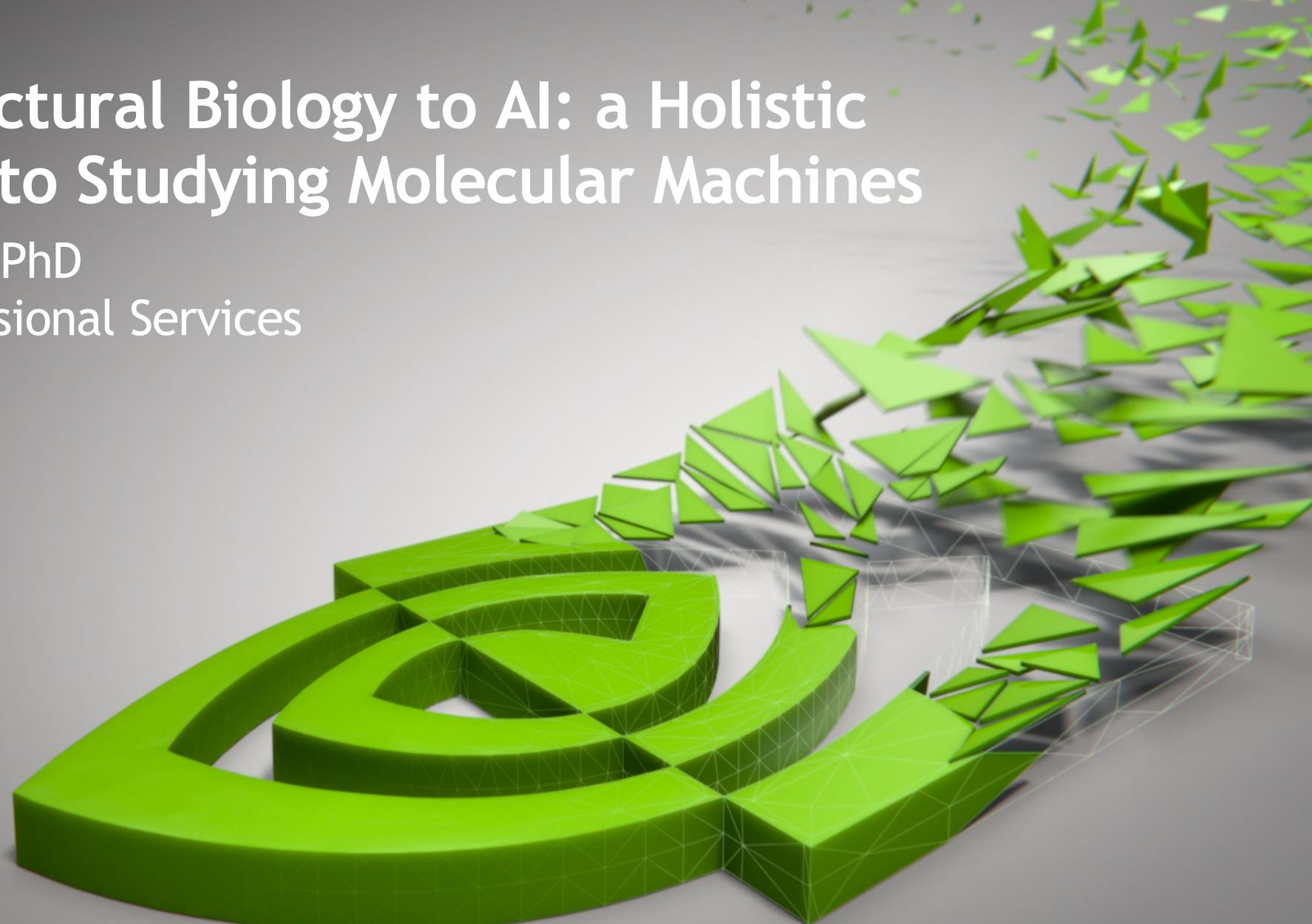


# From Structural Biology to AI: a Holistic Approach to Studying Molecular Machines

Michelle Gill, PhD  
NVIDIA Professional Services



# NVIDIA Professional Services

Our goal is to *enable* broader customer *adoption* of *Deep Learning* on *NVIDIA-accelerated* platforms

Enable

NVIDIA helps organizations get started or overcome roadblocks

Adoption

NVIDIA equips teams with the skills to plan, manage, and deliver projects going forward

Deep Learning

NVIDIA Professional Services is focused on Deep Learning

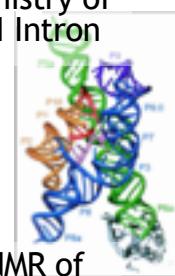
NVIDIA-  
Accelerated

NVIDIA supports customers adopting NVIDIA-accelerated infrastructure (on-premises, in the cloud, or at the edge)

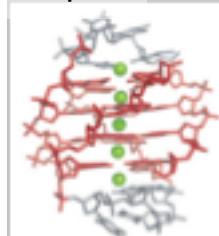
# From Scientist to Data Scientist (and Sometimes Both)

## Solution NMR Applications & Methods Development

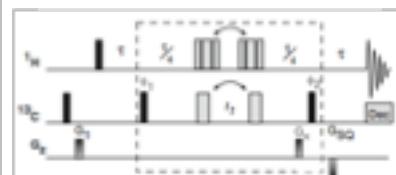
Biochemistry of Group I Intron



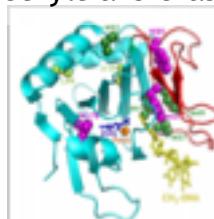
$^{205}\text{TL}$  NMR of G-Quadruplex



NMR Pulse Sequence Development

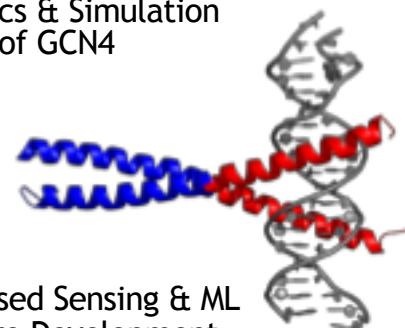


Dynamics of AlkB DNA Methyltransferase

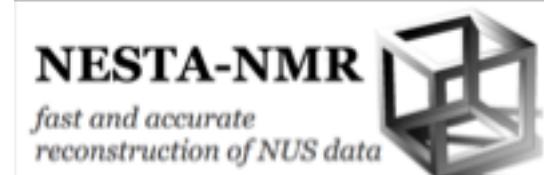


## Compressed Sensing & Molecular Dynamics

Dynamics & Simulation of GCN4

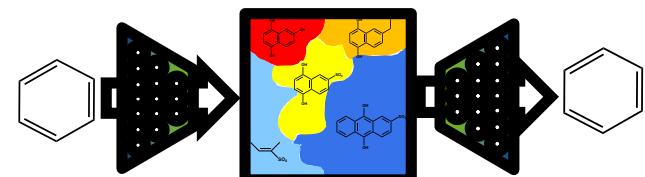


Compressed Sensing & ML Software Development

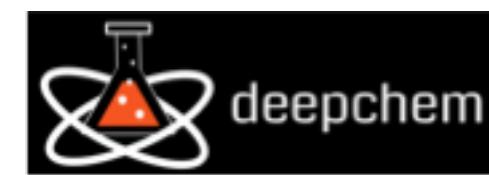


## Data Science & Deep Learning

Deep Learning in Materials Science & Pharma



DeepChem Committer (Early Days)



Graduate & Postdoctoral Research

Staff Scientist at NCI

Data Scientist

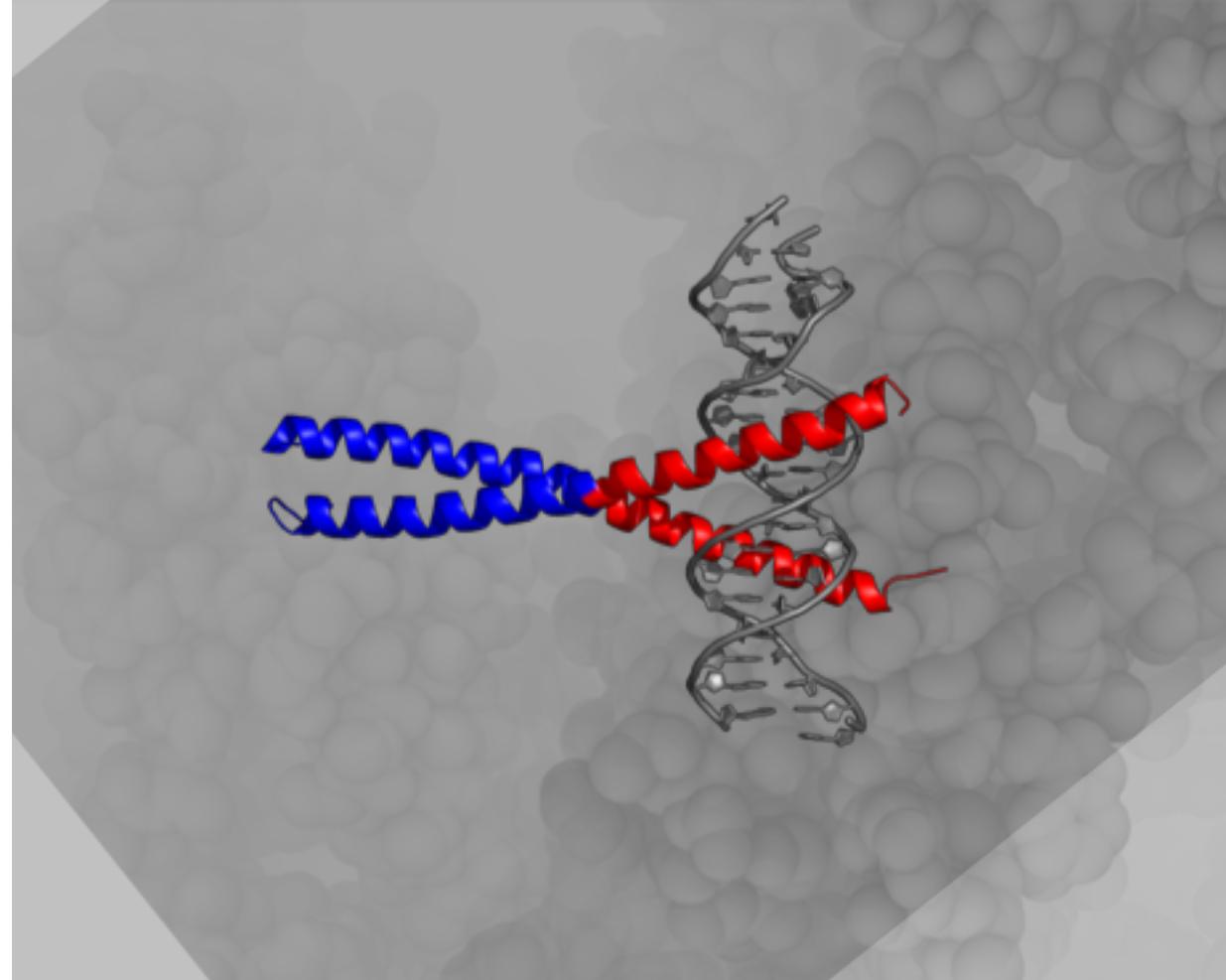
# Enzymes are Molecular Machines

Enzymes are nature's machines

Found throughout an organism

Perform the chemical reactions that make life possible

Malfunction of enzymes can contribute to disease states

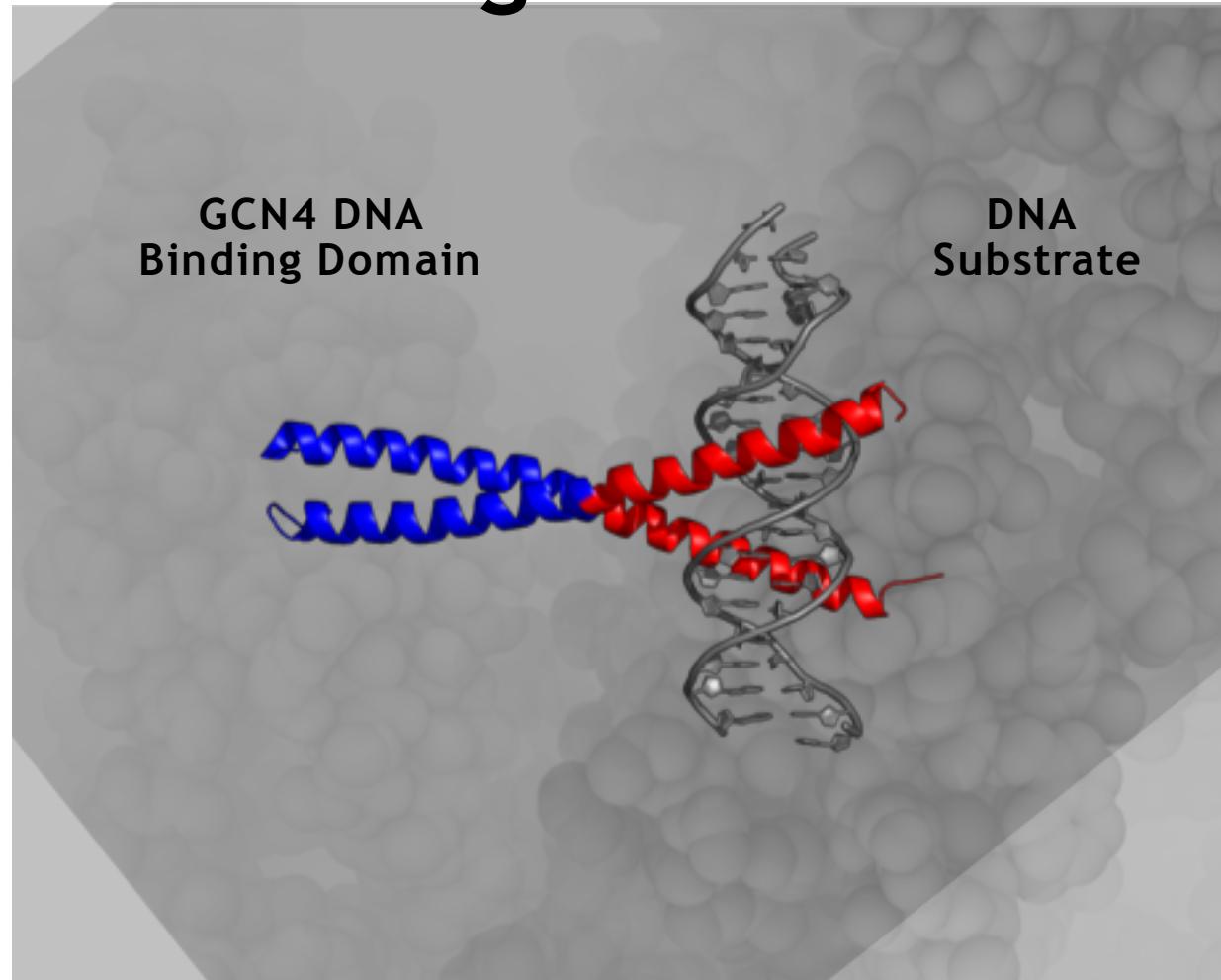


# Molecular Dynamics Control Substrate Recognition

GCN4 is an enzyme that belongs to the transcription factor family

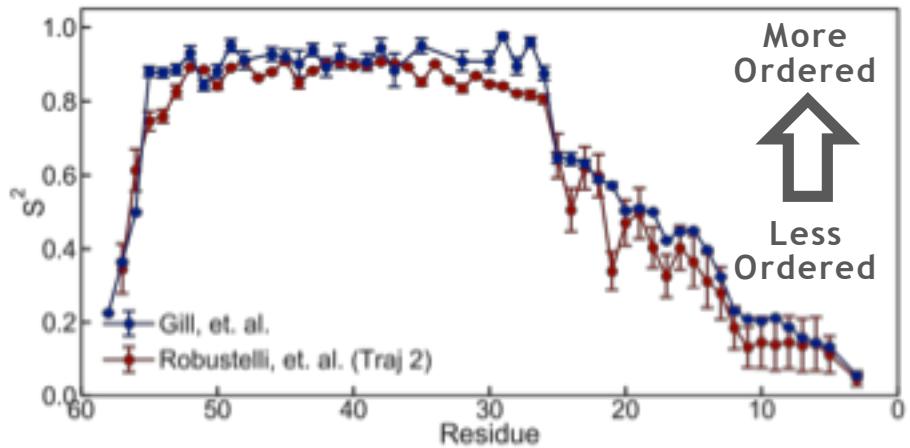
Binds to substrate (DNA) leading to expression of the nearby gene

Binding event requires motion of the enzyme – dynamics

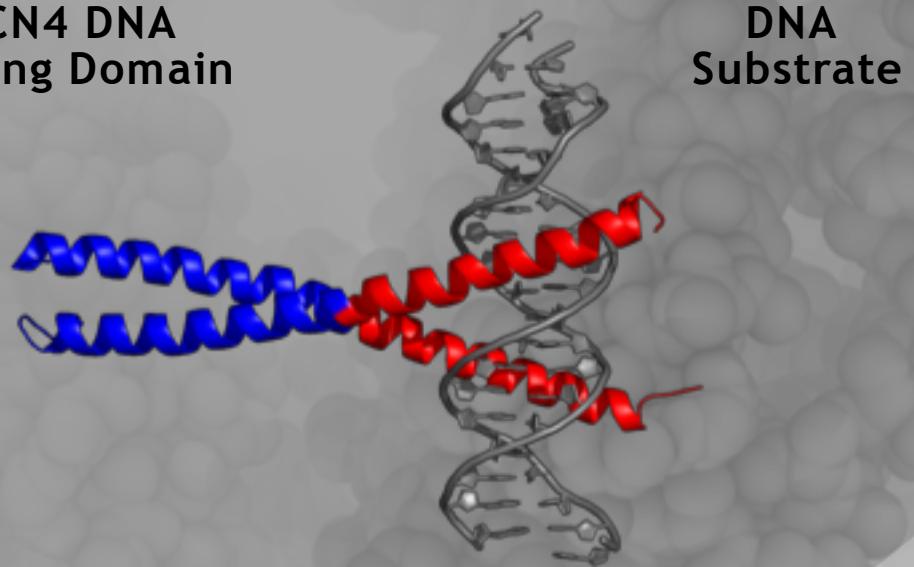


# Molecular Dynamics Control Substrate Recognition

Order Parameters ( $S^2$ ) from Solution NMR



GCN4 DNA Binding Domain



Gill, M.L., Byrd, R.A., Palmer, A.G. "Dynamics of GCN4 facilitate DNA interaction: a model-free analysis of an intrinsically disordered region", *Phys. Chem. Chem. Phys.*, 2016, 18, 5839-5849.

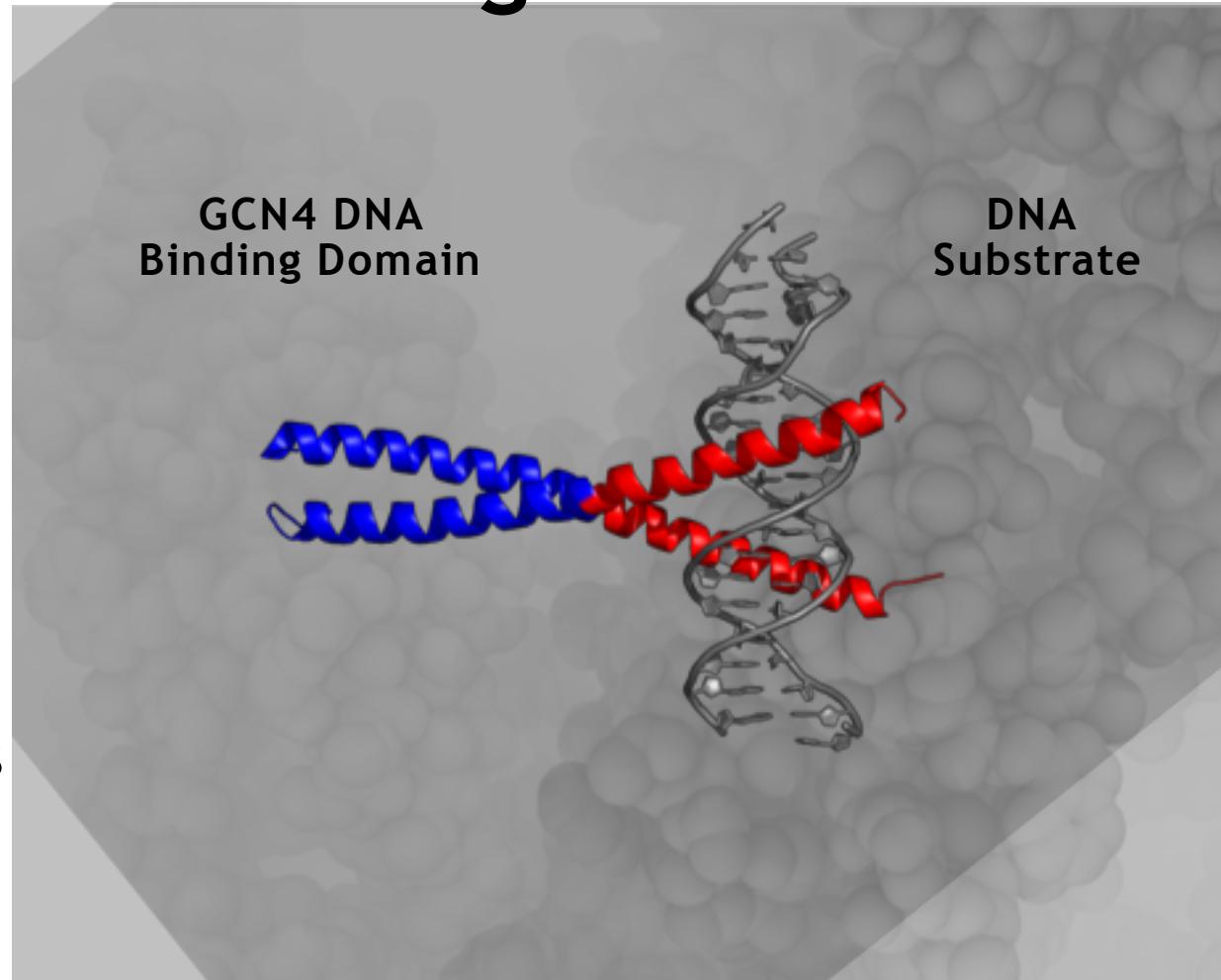
Robustelli, P., Trbovic, N., Friesner, R.A., Palmer, A.G. "Conformational dynamics of the partially disordered yeast transcription factor GCN4", *J. Chem Theory Comput.*, 2013, 9, 5190-5200.

# Molecular Dynamics Control Substrate Recognition

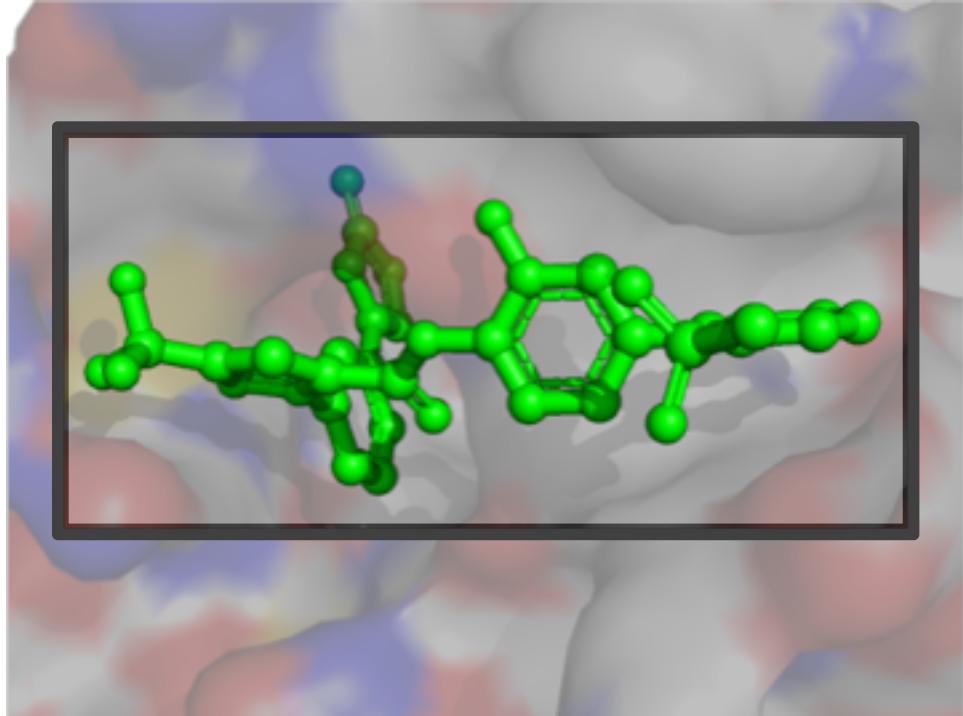
Over 30% of mammalian genome predicted to have regions of intrinsic disorder

Genes containing disordered regions associated with fundamental cellular processes (and cancer)

Disorder difficult to study with traditional structural biology methods



# Enzyme Structure and Dynamics are Key for Therapeutic Discovery



Many successful therapeutics (drugs) bind in place of substrates

Understanding enzyme dynamics critical for substrate binding and development of therapeutics

Deep learning excels at recognition of complex patterns

Potential for AI-assisted drug discovery

# Challenges Unique to Deep Learning With Chemistry

Limited availability of scientific data

Exploration of large chemical space

Representing chemical features

# Limited Availability of Scientific Data

## General Topics



Text, image, and sound data are readily available on internet

# Limited Availability of Scientific Data

## General Topics



Text, image, and sound data are readily available on internet

## Chemistry Specific



Access to scientific data limited - difficult to acquire, not shared publicly

# Exploration of Large Chemical Space

## General Topics



ImageNet classification uses 1000 categories ( $10^3$  magnitude)

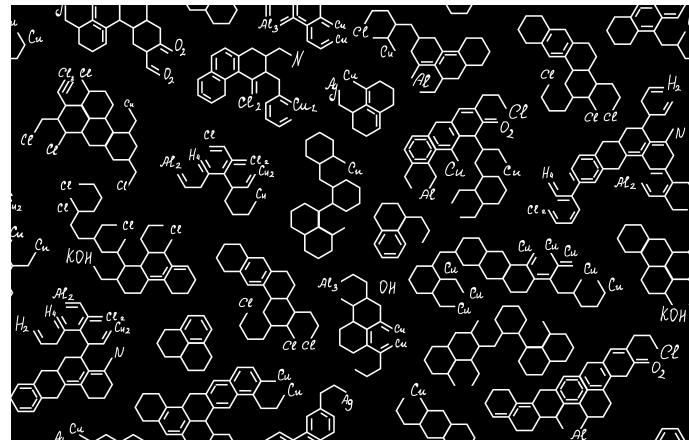
# Exploration of Large Chemical Space

## General Topics



ImageNet classification uses 1000 categories ( $10^3$  magnitude)

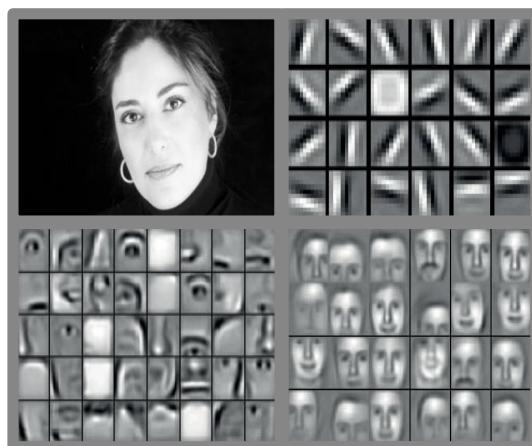
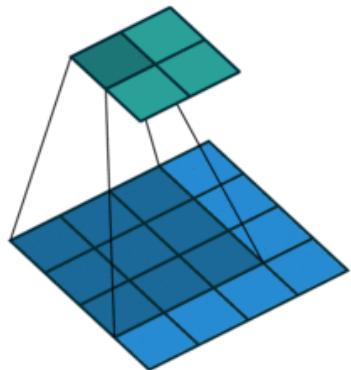
## Chemistry Specific



Molecule space encompasses  $10^{60}$  -  $10^{300}$  possibilities ( $10^8$  synthesized)

# Representing Chemical Features

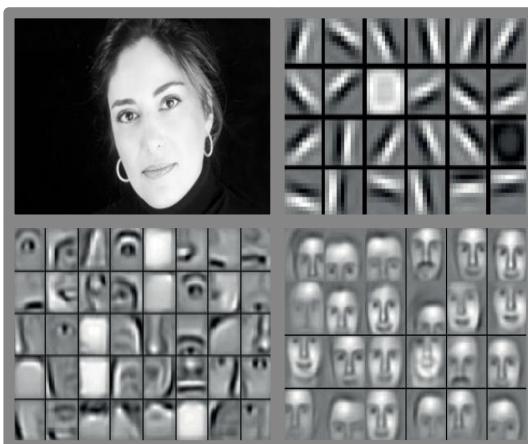
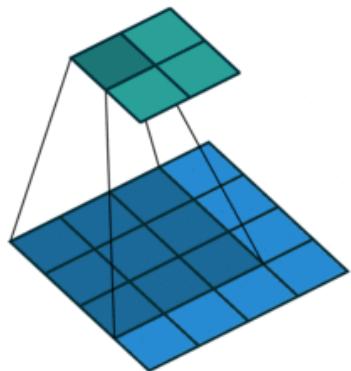
## General Topics



Two-dimensional convolutional filters  
learn image features

# Representing Chemical Features

## General Topics



Two-dimensional convolutional filters learn image features

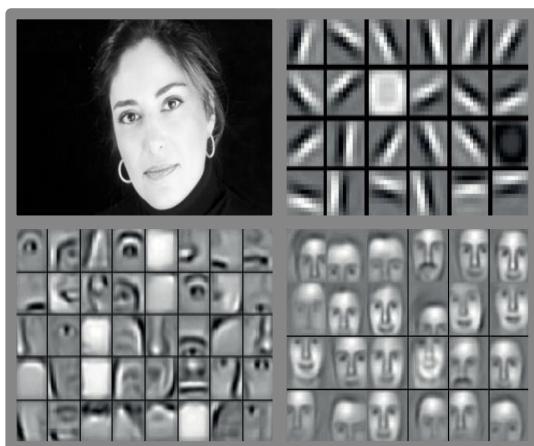
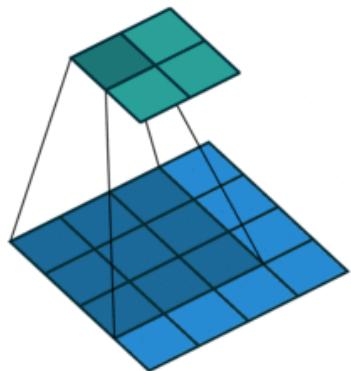
## Chemistry Specific



Representations can be one-, two-, and three-dimensional (or combination)

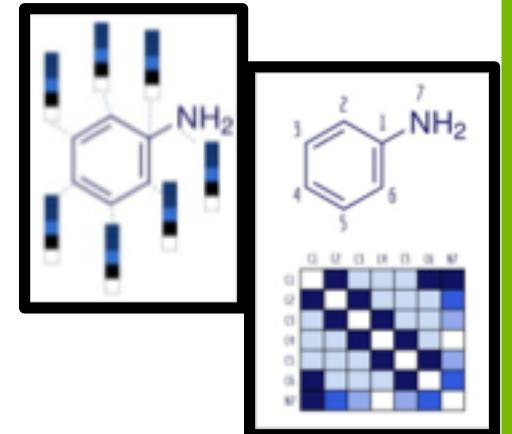
# Representing Chemical Features

## General Topics



Two-dimensional convolutional filters learn image features

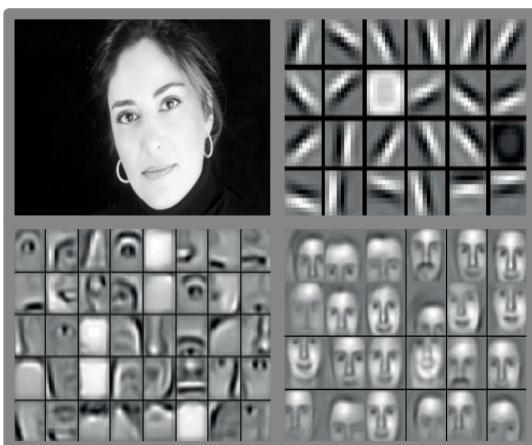
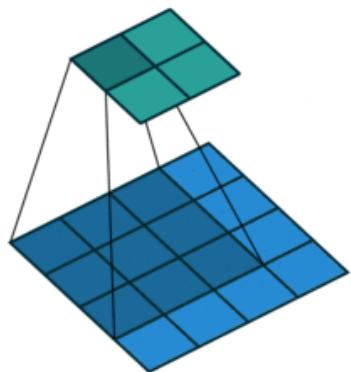
## Chemistry Specific



Representations can be one-, two-, and three-dimensional (or combination)

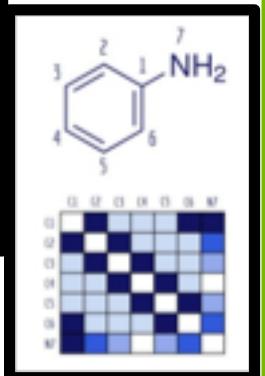
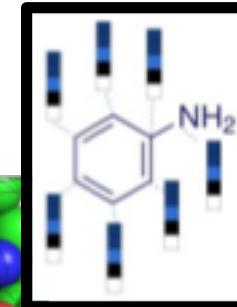
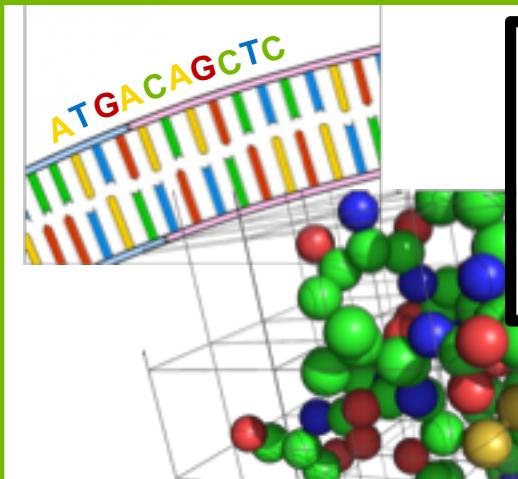
# Representing Chemical Features

## General Topics



Two-dimensional convolutional filters learn image features

## Chemistry Specific



Representations can be one-, two-, and three-dimensional (or combination)

# Deep Learning with Chemistry

Predicting enzyme-ligand binding using three-dimensional atomic convolutional networks

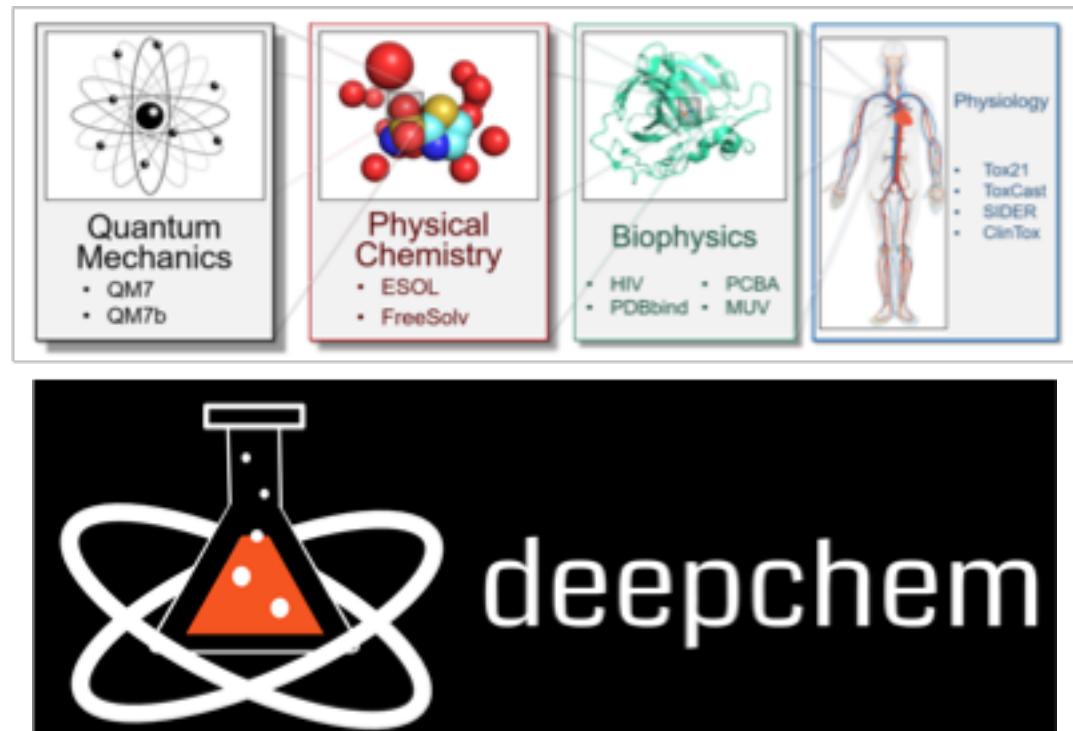
Generation of drug-like molecules using continuous latent spaces

# (Bio)Chemistry Data for Deep Learning

Public and proprietary data are a useful combination – for transfer learning and as supplement

Utilized MoleculeNet – benchmark datasets for chemistry, biophysics, and physiology

Part of DeepChem deep learning library

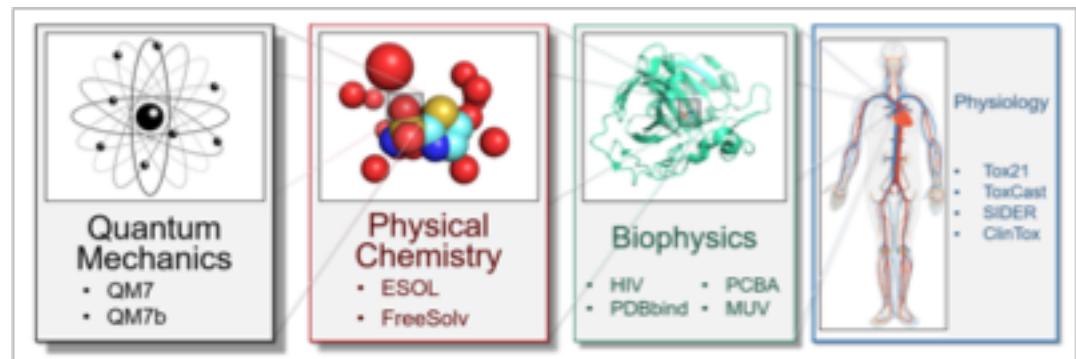


Wu, Z., Ramsundar, B., Feinberg, E. N., Gomes, J., Geniesse, C., Pappu, A. S., Leswing, K., Pande, V. "MoleculeNet: A Benchmark for Molecular Machine Learning." arXiv.org, 2017.

# (Bio)Chemistry Data for Deep Learning

PDBbind – 12K published measurements and 3D structures of enzyme-ligand complexes

ZINC12 – 35M chemicals and properties for drug discovery

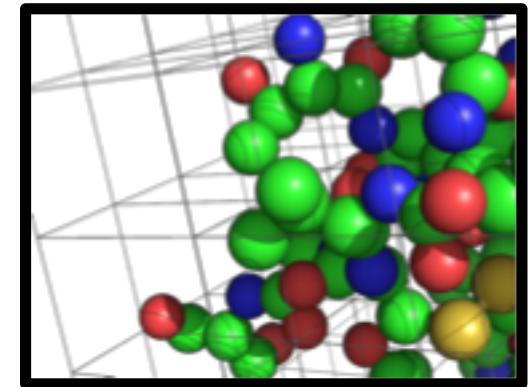


# Ligand Binding Featurization and Modeling

Utilizes a three-dimensional "atomic fingerprint"

Atom type (element) and distance  
calculated within threshold and pooled

Atom Type  
+  
Distance



Featurization based on: Gomes, J., Ramsundar, B., Feinberg, E. N., & Pande, V. S. "Atomic Convolutional Networks for Predicting Protein-Ligand Binding Affinity.", *arXiv*, 2017.

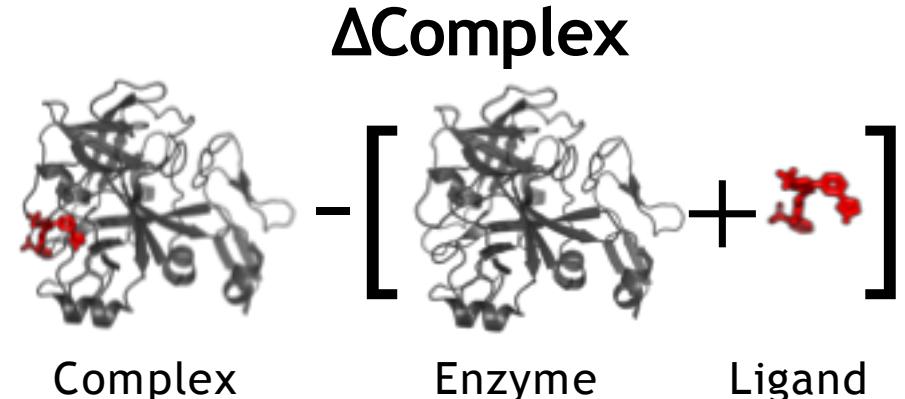
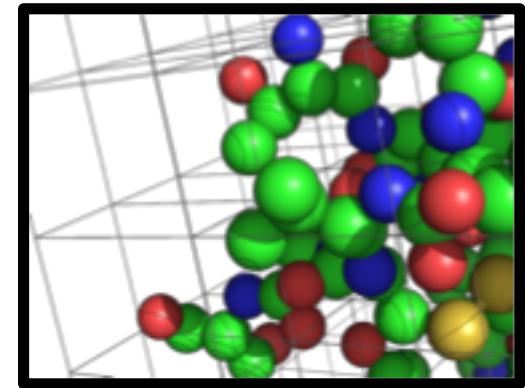
# Ligand Binding Featurization and Modeling

Utilizes a three-dimensional "atomic fingerprint"

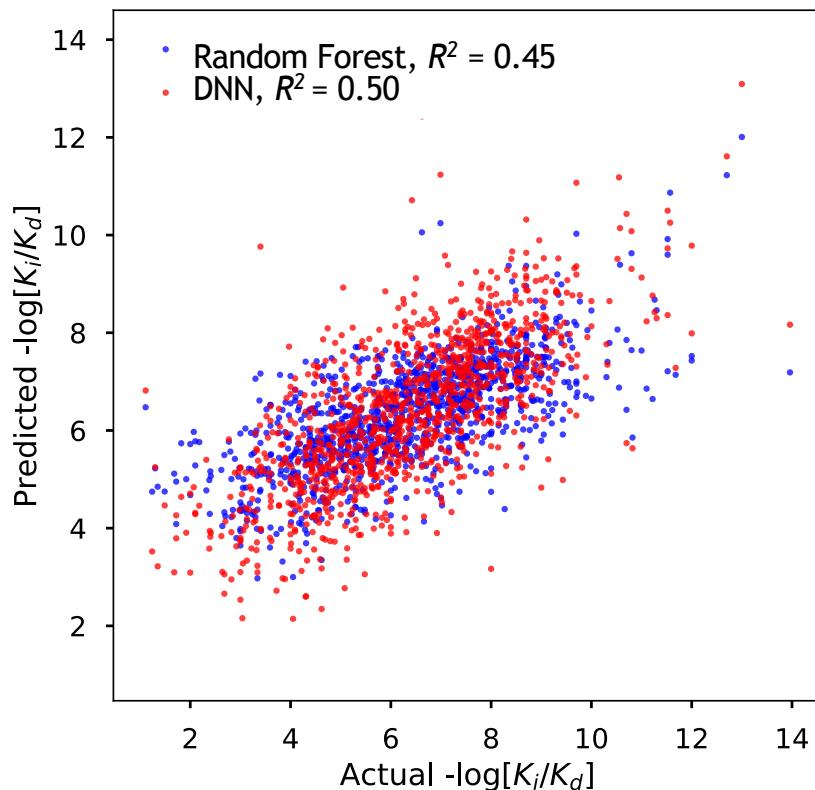
Atom type (element) and distance calculated within threshold and pooled

Three interlinked neural networks emphasize changes introduced by ligand binding

Atom Type  
+  
Distance



# Predicting Ligand Affinity



Compared binding predictions with Random Forest and DNN regression models

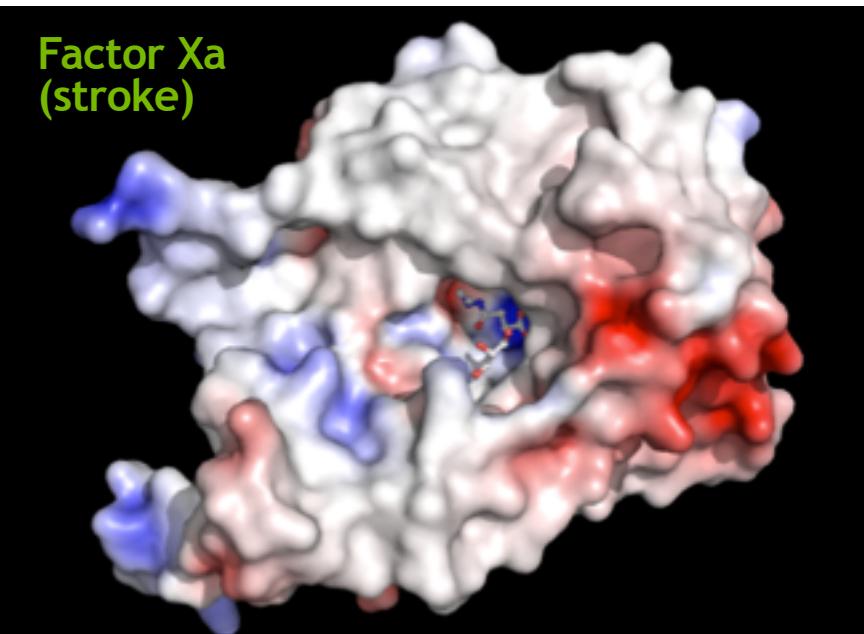
$R^2$  indicates DNN performs slightly better than Random Forest

DNN performance expected to improve with more data

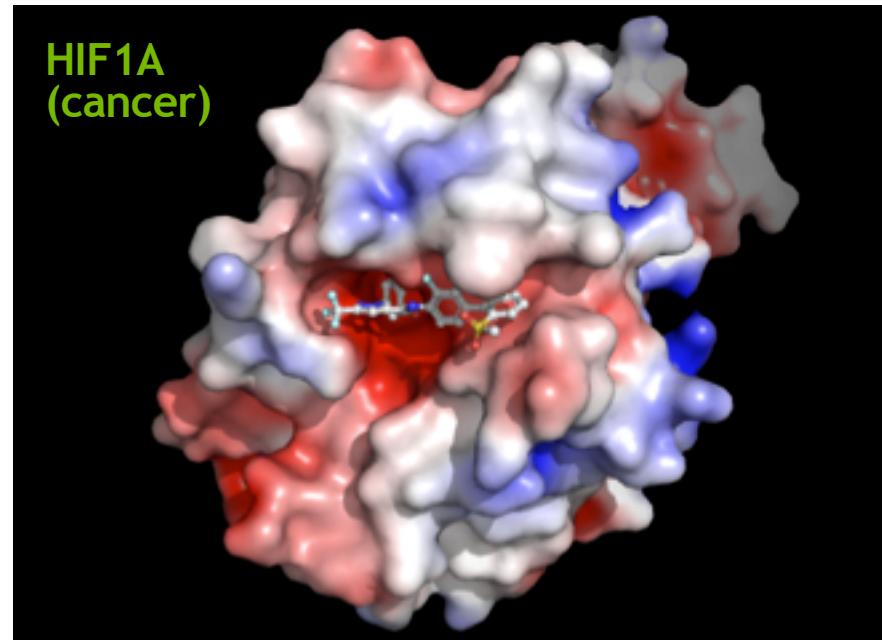
Predicting only successful ligand binding events (challenge)

# Visualizing Enzyme-Ligand Binding

Tightest Binding Ligand



Weakest Binding Ligand



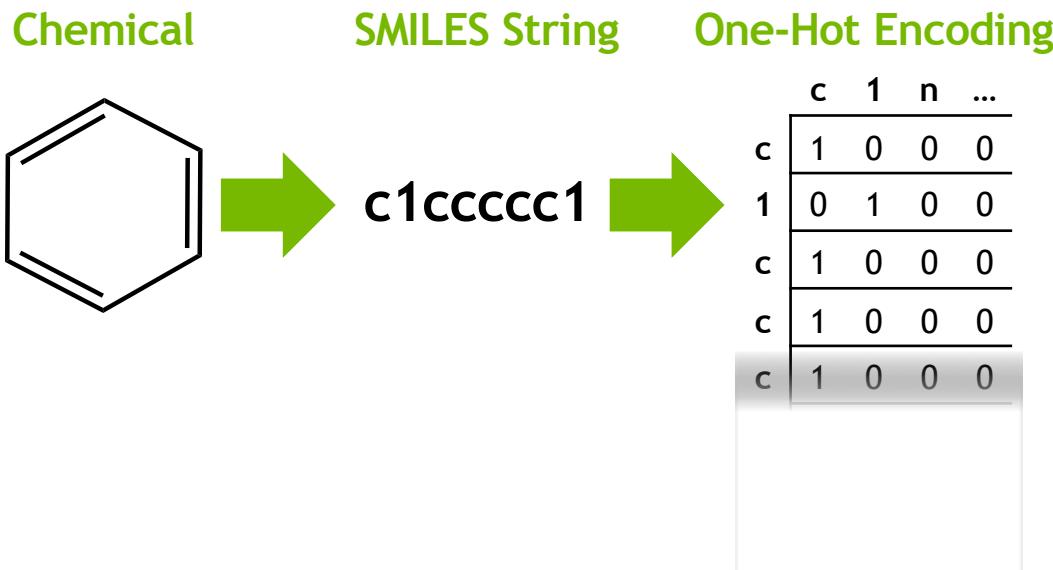
Opposite Protein-Ligand Charges Attract (+/-)

# Deep Learning with Chemistry

Predicting enzyme-ligand binding using three-dimensional atomic convolutional networks

Generation of drug-like molecules using continuous latent spaces

# Featurizing Chemicals for Deep Learning



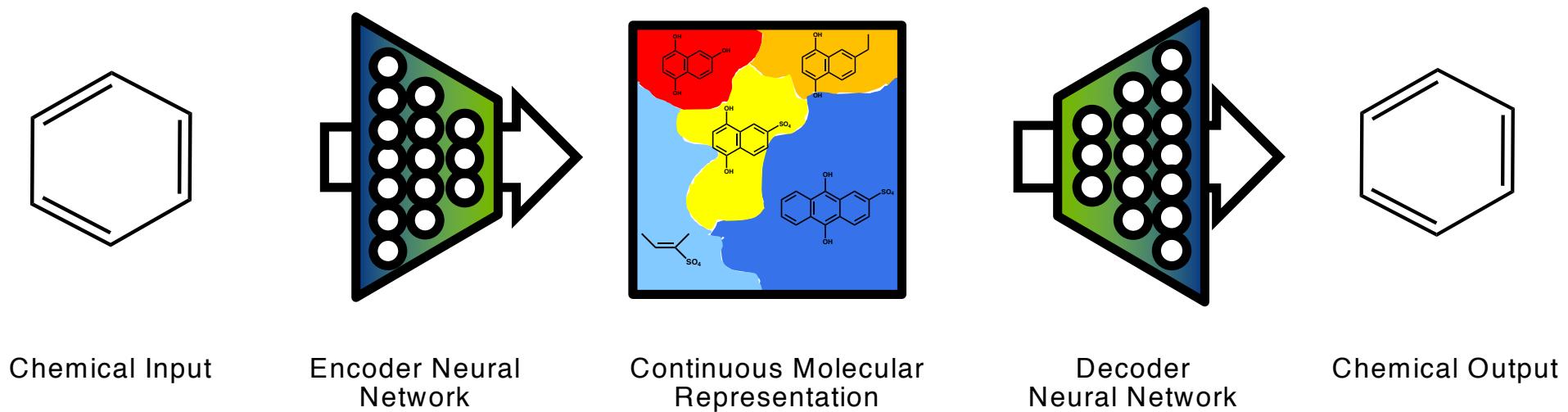
Chemicals first converted to SMILES strings

SMILES characters used to create one-hot encoded vectors

Vectors used as features for neural network

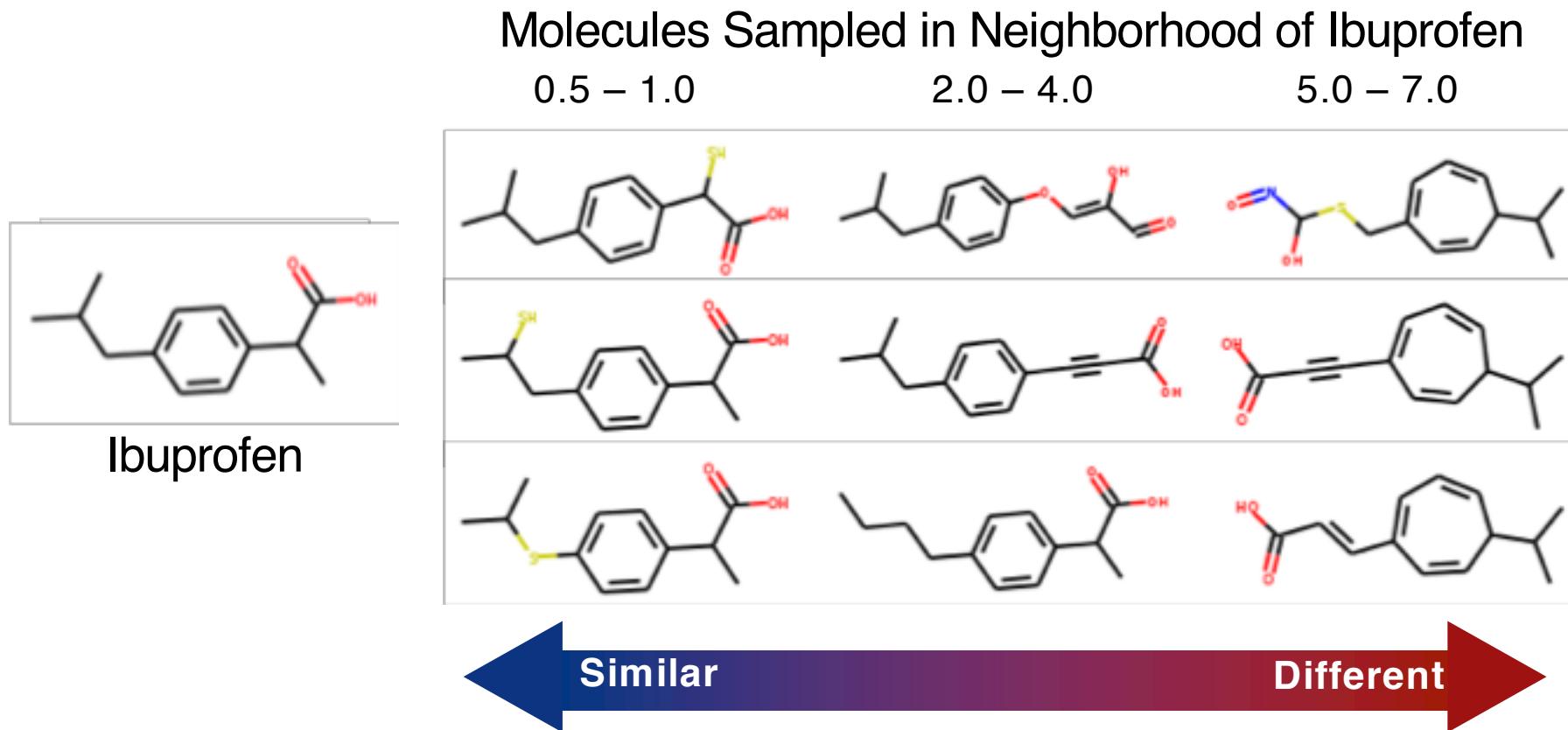
Character-level encodings don't always capture inherent rules of chemistry

# Deep Learning Assisted Chemical Design

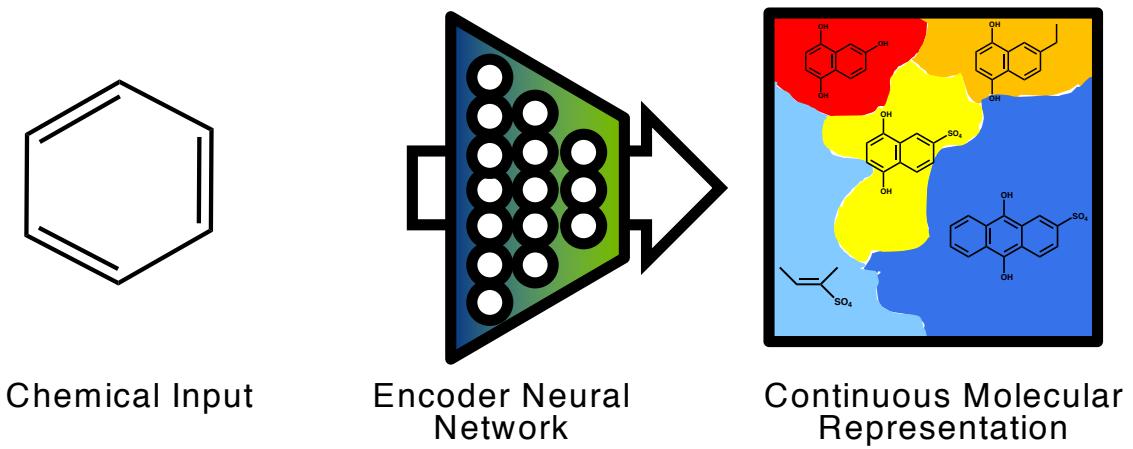


Network based on: Gómez-Bombarelli, R., Wei, J.N., Duvenaud, D., Hernández-Lobato, J. M., Sánchez-Lengeling, B., Sheberla, D., Augilera-Iparragirre, J., Hirzel, T.D., Adams, R.P., Aspuru-Guzik, A. "Automatic chemical design using a data-driven continuous representation of molecules." *ACS Cent. Sci.*, 2018.

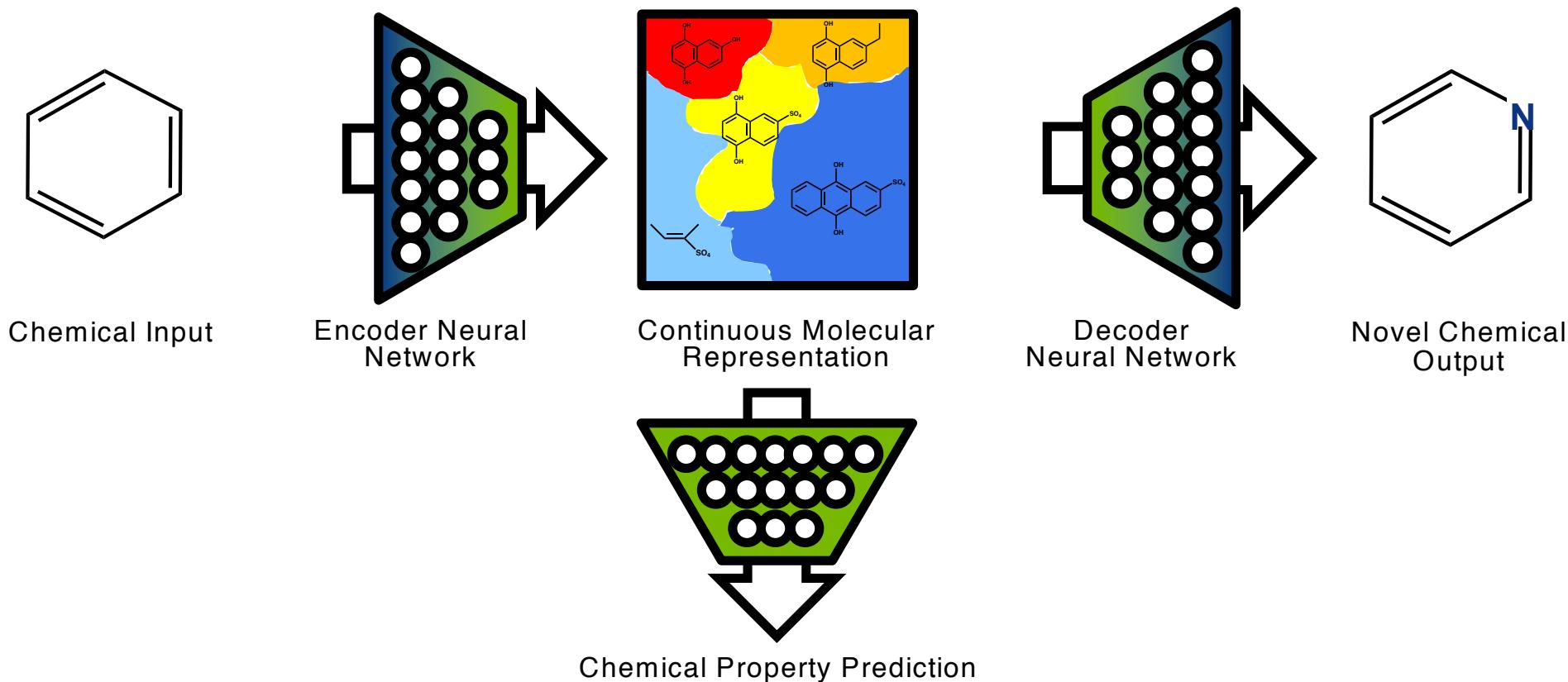
# Exploring Chemical Space



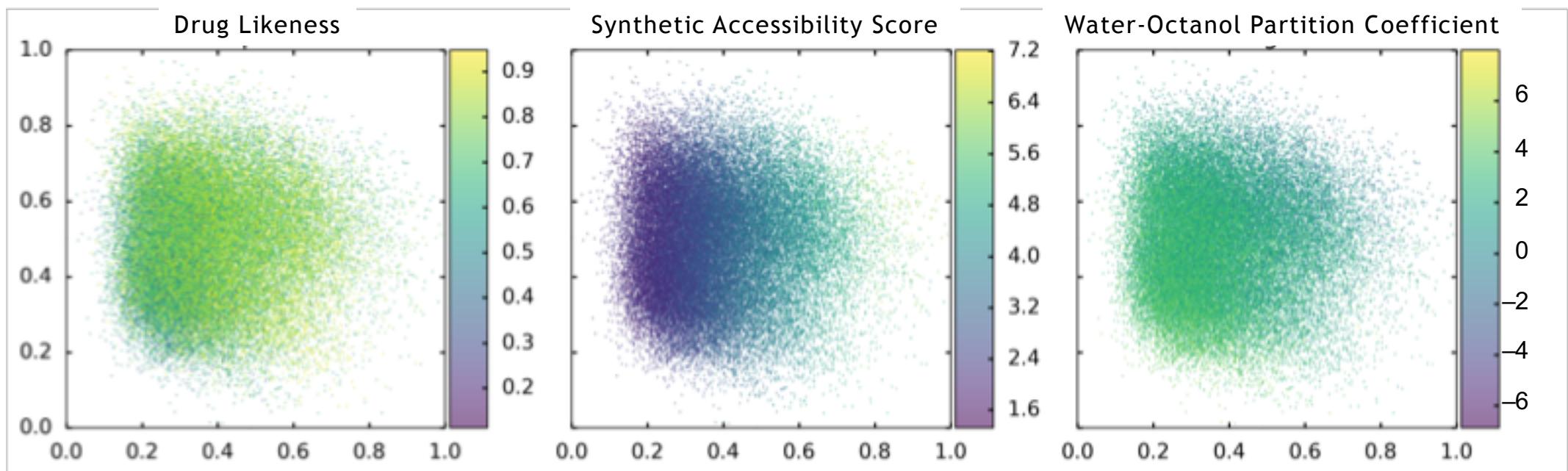
# Generating Novel Chemicals with Deep learning



# Generating Novel Chemicals with Deep learning



# Chemical Properties in Molecular Space



# Conclusions

Artificial intelligence provides a nascent but powerful toolkit for accelerating chemistry-focused innovation

Combining deep learning with experimental and simulation data further accelerates this iterative process

Tomorrow's basic and applied science breakthroughs will blend AI and traditional methodologies

