# **Integrative structural modeling using SAXS data**



#### **Dina Schneidman**

האוניברסיטה העברית בירושלים THE HEBREW UNIVERSITY OF JERUSALEM





*Ward A, Sali A, Wilson I. Integrative structural biology. Science 2013. Rout M, Sali A. Principles for Integrative Structural Biology Studies. Cell 2019.*

#### **Thanks!**

**Lab Edan Patt Tomer Cohen Ben Shor** Alon Aronson Matan Halfon Amir Weinfeld Tanya Hochner Adi Weshler Gal Passi Meitar Sela Danielle Zaccai Merav Braitbard Jerome Tubiana Shon Cohen



**BERKELEY LAB** 

Michal Hammel Greg Hura Rob Rambo Susan Tsutakawa John Tainer





#### Icahn<br>School of Medicine at **Mount**

Sinai

#### **EGFR antibodies** Arvind Sivasubramanian









**ISRAEL** 

**SCIENCE** 







National Institute of Allergy and **Infectious Diseases** 





### **What are the modeling tasks to address with SAXS?**

**validation** of protein structure prediction

assembly of multidomain proteins



assembly of multiprotein complexes



#### structural characterization of protein dynamics





RNA

#### **Scoring: Fast open-source X-ray Scattering**

#### Forward modeling



A rapid method for computing a SAXS profile of a given structure and for matching of the computed and experimental profiles



# **Scoring:**<br>**Excluded Volume and Hydration Layer Density**





vacuum solvent excluded volume hydration layer  $f_i(q) = f_i^{\nu}(q) - \widehat{C_1(q)} f_i^{\nu}(q) + \widehat{C_2} s_i f^{\nu}(q)$ 

Increase/decrease atomic radii to obtain the best fit to the experimental profile

Add water form factor to solvent accessible atoms (*si* measures solvent accessibility [0-1])

5% variance in radius 0.32 e/Å3 ≤*ρ*≤0.38 e/Å3

**enumeration of 2 fitting parameters: c1, c2**

#### **X-ray structure vs. SAXS - good fits —> publish**



#### **X-ray structure vs. SAXS - good fits —> publish**



#### 14 experimental datasets with x-ray structures

*Schneidman-Duhovny D, Hammel M, Tainer J, Sali A. Biophys J 2013*

#### **X-ray structure vs. SAXS - they don't fit!**



#### **X-ray structure vs. SAXS**

- Data quality
- Missing residues/sugars
- Compositional heterogeneity
- Conformational heterogeneity
- both







**Fast SAXS Profile Computation with Debye Formula** 

#### · About FOXS · Web Server · Help · FAQ · Download · Sali Lab · IMP · Links



#### Can't see interactive display? Use old interface







#### **LASSA GP1**



*Data from Ron Diskin*

#### **X-ray structure vs. SAXS**

- Data quality
- Missing residues/sugars
- Compositional heterogeneity
- Conformational heterogeneity
- both



#### **AbnA structures vs. SAXS**

**?**

• 3 X-ray structures in different conformations do not fit the data



*Collaboration with Shifra Lansky and Gil Shoham*

# **Dynamics Comes in Flavors and it is<br>Common**



#### **Dynamics and SAXS**

- SAXS data can be easily collected for proteins that include disordered regions
- Data interpretation is challenging



while(noSuccess) tryAgain(); if(Dead) break;

# **Heterogeneous Sample Requires Multi-State Model**

**Heterogeneous sample**

compositional or conformational heterogeneity in the sample used to generate the data

**Multi-state model** a model that specifies two or more co-existing structural states and values for any other parameter









*Schneidman-Duhovny, Hammel, Tainer, Sali. NAR 2016*

### **Conformational sampling**

Proteins and robots have similar degrees of freedom





Robotic arm AbnA protein

We rely on methods for Motion Planning developed in Robotics *(La Valle, Latomb, Kavraki, Cortes)*

# **Mapping collision free space with Rapidly exploring Random Tree (RRT)**

Collision free space for robot Collision free space for protein chain



#### **Enumeration of multi-state models**

**branch & bound** deterministic algorithm Multi-state models of size **i+1** are generated by extending **best K** (=10000) multi-state models of size **i**

best K multi-state models of size 1:

best K multi-state models of size 2:

best K multi-state models of size 3:



### **Scoring of Multi-State Models**



- weights optimization is needed for each set of structural states
- Non-negative least square fitting (NNLS, Lawson & Hanson 1974)

- $\cdot$  c<sub>1</sub> (excluded volume), and c<sub>2</sub> (hydration layer) are enumerated
- $\cdot$  a single pair of  $c_1$  and  $c_2$  is used for all states in a multi-state model

#### **AbnA structures vs. SAXS**

• 3 X-ray structures in different conformations do not fit the data



#### **Multi-state Modeling**

• Good fit to data obtained with open and closed conformations





### **BilboMD: high-temperatu**

#### **SAXS Data Analysis with BILBOMD**

**BILBOMD Home** Check your jobs **Experiment Title:** LIGIV XRCC4 (letters, numl C (up to 10 PDB files. Each chainID are Enter number of segments you have:  $\mathbf{3}$ Select segment 1 (PDB name): Choose File XRCC4 1.pdb XRCC4\_2.pdb Select segment 2 (PDB name): Choose File Select segment 3 (PDB name): LIGIV.pdb Choose File Upload or create const.inp file: Choose File No file chosen or **Edit File Experimental data:** Choose File | |4x4new.dat **Extent of Conformational Sampling:** 800 conformations per Rg  $\Diamond$  $R_q$  min (Å):  $30 (10-100)$  $R_q$  max: (Å)  $90 (10-100)$ Enter email to receive results: consulting@saxs.org

**SUBMIT** 

#### <https://bl1231.als.lbl.gov/bilbomd> *Pelikan M, Hura GL, Hammel M.2009*

### **SAXS profile calculator for RNA structure validation**

RNA binds  $Mg<sup>2+</sup>$  ions that are required for proper folding and charge neutralization



#### X-ray scattering Length density



#### **SCOPER: Solution Conformation Predictor for RNA**



## **Sampling RNA while preserving base pairing**

**KGSRNA sampling**

Kinematics-based approach to efficiently explore the native ensemble of RNA molecules



#### **Normal mode sampling**

- The base pair interactions not preserved
- **Oversampling**
- Nonrealistic RNA structure



Normal Mode - best-fit conformer w/o Mg2+ Overfit the SAXS data with nonrealistic conformers



*Fonseca et al. 2015*





### **IonNet: Mg2+ binding site predictor**



### **Using IonNet to predict Mg2+ positions for an RNA structure**

- RNA 3D structure is covered with probes that are classified by the model
- The probes are added to the RNA, starting with the most likely one
- Fit to the experimental SAXS profile is used to select the optimal number of ions









## **High-quality benchmark dataset**

#### Size exclusion coupled SAXS (SEC-SAXS) applied for RNAs benchmark of 12 RNA's





## **High-quality benchmark dataset**







0 0.05 0.1 0.15 0.2 0.25 0.3 0.35 0.4 0.45 0.5  $q(\hat{A}^{-1})$ 



### **Flexibility, Mg2+, and multiple states**



## **Flexibility, Mg2+, and multiple states**



w/o w w/o w w/o w

**Mg2+**

- RNA flexibility is responsible for poor SAXS fit
- The addition of Mg<sup>2+</sup> ions improves the SAXS fit for the best scoring structure
- Multistate models have a minimal impact on the improvement of SAXS fit

## **SCOPER webserver**

#### https://bilbomd.bl1231.als.lbl.gov

D







Scoper Model - scoper\_combined\_newpdb\_73.pdb - I vs. q



#### ginal Model - model5.pdb - Chi<sup>2</sup> residuals Chi<sup>2</sup>: 6.23 C<sub>i</sub>: 0.99 C<sub>2</sub>: -0.03



Scoper Model - scoper\_combined\_newpdb\_73.pdb - Chi<sup>2</sup> residuals





### **Integrative Modeling and SAXS**



*Schneidman-Duhovny, Pellarin, Sali. COSB 2014*

#### **Modeling protein interactions with or without SAXS**



# **AlphaFold2 is effective in predicting complexes**

- On typical benchmarks, 40-70% of the complexes are correctly modeled vs. 20-30% for docking algorithms
- Docking methods generate thousands of models including models that are close to the correct complex (PatchDock, ZDock, ClusPro…)
- Additional data, such as SAXS or crosslinks, helps to identify and validate correct models



- success rate  $=$  # of benchmark complexes with acceptable or higher accuracy models, usually specified for topN predictions
- accuracy according to the CAPRI criteria (Acceptable, Medium, and High)

### **BUT…**

Large assemblies are still difficult to model with AlphaFold-Multimer:

- GPU memory limitations
- sampling limitations
- out-of-domain inference
- converges to a single minima

Antibody-antigen systems

interactions via highly variable loops





#### **Combinatorial assembly based on AlphaFold2**



*Shor, Schneidman-Duhovny Nat Methods 2024*

#### Ben Shor

### **Benchmarking heteromers**

- 35 complexes (no overlap with the AFM training set)
- 5-20 chains
- 1,700-8,000 amino acids



Top-1 Top-5

- CombFold high CombFold acceptable
	- AFMv2 high
	- AFMv2 acceptable



- High: TM-score > 0.8
- Acceptable: TM-score > 0.7

### **Modeling subunits that are missing in PDB structures**



eIF2B:eIF2 complex (PDB 6I3M) 4,680 amino acids TM-Score 0.79 6,114 amino acids

• 20% increase in structural coverage compared to PDB entries in our Benchmark

## **Why antibodies?**



- A key component of the adaptive immune system
- A rapidly growing class of human therapeutics for a range of diseases, including **cancer, autoimmunity**, **inflammatory diseases**, **viral infections**
- There are over 100 approved antibody-based therapeutics and over 1,000 in clinical studies for a wide range of diseases.
- Nanobodies, heavy chain only antibodies small, stable, highly similar to IgGs
- Accurate high-throughput computational methods have the potential to greatly accelerate the **discovery of new therapeutic antibodies**



#### **Antibodies have a conserved frame region and variable loops**



FR<sub>3</sub>

**CDR2** 

CDR<sub>3</sub>

FR4

regions (heavy chain)

FR<sub>1</sub>

CDR1

FR<sub>2</sub>

### **Open challenges**

#### **Folding**

Input: antibody sequence Output: 3D structure

#### **Docking/specificity**

Input: structures (or sequences) Output: antibody-antigen complex 3D structure





#### **Design**

Input: antigen structure and epitope (in red) **Output:** antibody sequence/structure that binds to the given epitope

*Ruffolo, Jeffrey A., and Jeffrey J. Gray. Fast, accurate antibody structure prediction from deep learning on massive set of natural antibodies." Biophysical Journal 2022 Yin, Rui, et al. Benchmarking AlphaFold for protein complex modeling reveals accuracy determinants. Protein Science 2022 Watson, Joseph L., et al. De novo design of protein structure and function with RFdiffusion. Nature 2023*

#### **Integrative modeling of antibody-antigen complexes**



*SARS-CoV-2 nanobodies with crosslinks Xiang et al. Science 2020* *PCSK9 antibody with 2D EM Schneidman et al. Bioinformatics 2012*

*EGFR antibodies with SAXS profiles Cohen et al. Meth. Enzymol 2023*

### **Data gaps for ML**



#### **NanoNet: end-to-end antibody, nanobody, and TCR modeling without MSA**





Tomer Cohen

- Invariance to rotations and translations can be achieved by frame region alignment
- All the structures of the training set were aligned on a randomly selected reference structure



*Cohen at al. 2022 Front Immunol.*

#### **NanoNet architecture**



- Trained on ~1,800 antibody and nanobody structures
- Coordinates MSF as a loss function
- Structure prediction: ~6ms on GPU or ~20ms on a CPU
- $\Rightarrow$  1M structures in less than an hour on a CPU!
- https://github.com/dina-lab3D/tutorials/tree/main/NanoNet

#### **NanoNet performance for nanobodies**



• Accuracy comparable to AlphaFold2, IgFold, ABLooper...

#### **Antibody folding and docking to antigen**



• the main problem is the accuracy of the antibody models

#### **Can we fold & dock simultaneously?**



Input: antibody sequence + antigen structure Output: complex structure

#### **Transformational invariance**

• **Antibody** – aligning the training set structures on a single representative structure for the heavy and the light chains

• **Antigen** – constructing an amino acid reference frame for the antigen (N-CA-C atoms) and transforming it to the global reference frame.





#### **Fold & dock architecture**

Designed to simulate the **biological antibody-antigen recognition**

Consists of several layers of **G**eometric **P**air **A**ttention (**GPA**) each containing **four** dedicated **Distance Transformer** modules

Each of the **four Distance Transformers** is responsible for a different aspect of the antibody-antigen interaction



#### **Fold & Dock accuracy**



Success rate: fraction of test set complexes with Acceptable or higher quality models, usually specified for topN predictions Quality: High, Medium, Acceptable, and Incorrect

#### **Docking with SAXS profile of the complex FOXSDock**



*Schneidman-Duhovny D, Hammel M, Sali A. J Struct Biol. 2011 Schneidman-Duhovny D, Hammel M, Tainer J, Sali A. NAR 2016*



Schneidman-Duhovny D, Hammel M, Sali A. Macromolecular docking restrained by a small angle X-

Contact: dina@salilab.org

### **EGFR-antibody complex with SAXS profiles**

- SAXS profiles collected for EGFR, antibody, and their complex
- 4 antibodies



### **EGFR is flexible and glycosylated**



### **Fabs vary their elbow angle**





### **Let's dock!**

 $10^{0}$ 

 $\frac{1}{2}$ <sub>10</sub><sup>1</sup>  $\frac{1}{9}$  10<sup>2</sup>  $10^3$  $10<sup>4</sup>$ 

I(q) log−scale



- antibody, antigen, complex
- 2. Antibody and antigen modeling
- single- or multi-state
- 3. Docking with all conformations
- 4. Scoring
- SAXS multiple states
- interaction interface



### **Docking Results**







4/5

### **What are the modeling tasks to address with SAXS?**

**validation** of protein structure prediction

assembly of multidomain proteins



assembly of multiprotein complexes



#### structural characterization of

protein dynamics

RNA



 $(50)$ 



#### **Links**

SAXS profile calculator https://modbase.compbio.ucsf.edu/fox-Multi-state modeling https://modbase.compbio.ucsf.edu/r  $BilboMD - MD + Multif\o XS$ [https://bilbomd.bl1231.als.lbl.gov](https://bilbomd.bl1231.als.lbl.gov/) SCOPER [https://bilbomd.bl1231.als.lbl.gov](https://bilbomd.bl1231.als.lbl.gov/) SAXS-based docking https://modbase.compbio.ucsf.edu/fox [Antibody-antigen structure p](https://folddock.cs.huji.ac.il/)rediction https://folddock.cs.huji.ac.il/ AlphaFold-based assembly of comp https://github.com/dina-lab3D/Comb