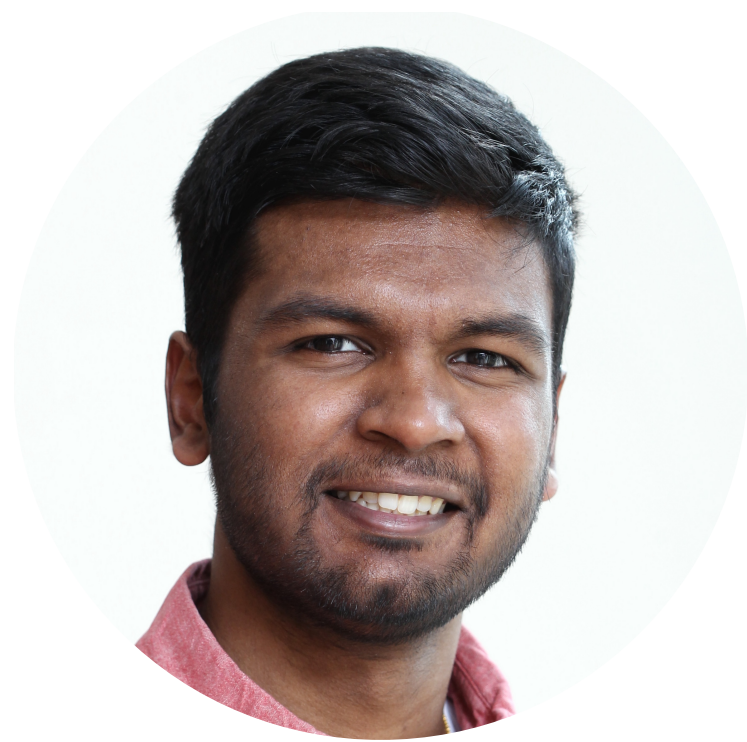


CryoBoltz



Multiscale Guidance of Protein Structure Prediction with Heterogeneous Cryo-EM Data



Rishwanth Raghu



Axel Levy



Gordon Wetzstein

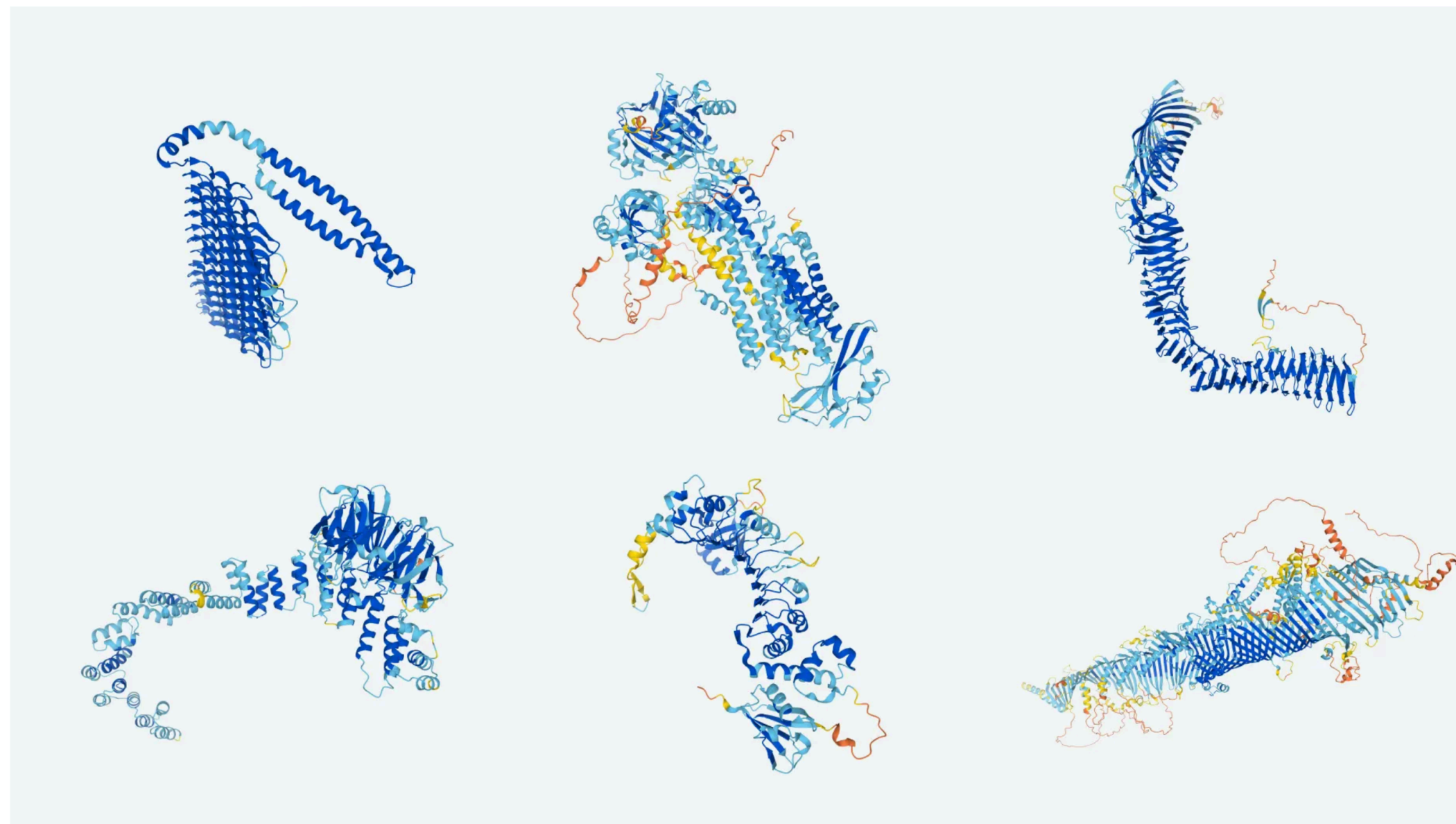


Ellen Zhong

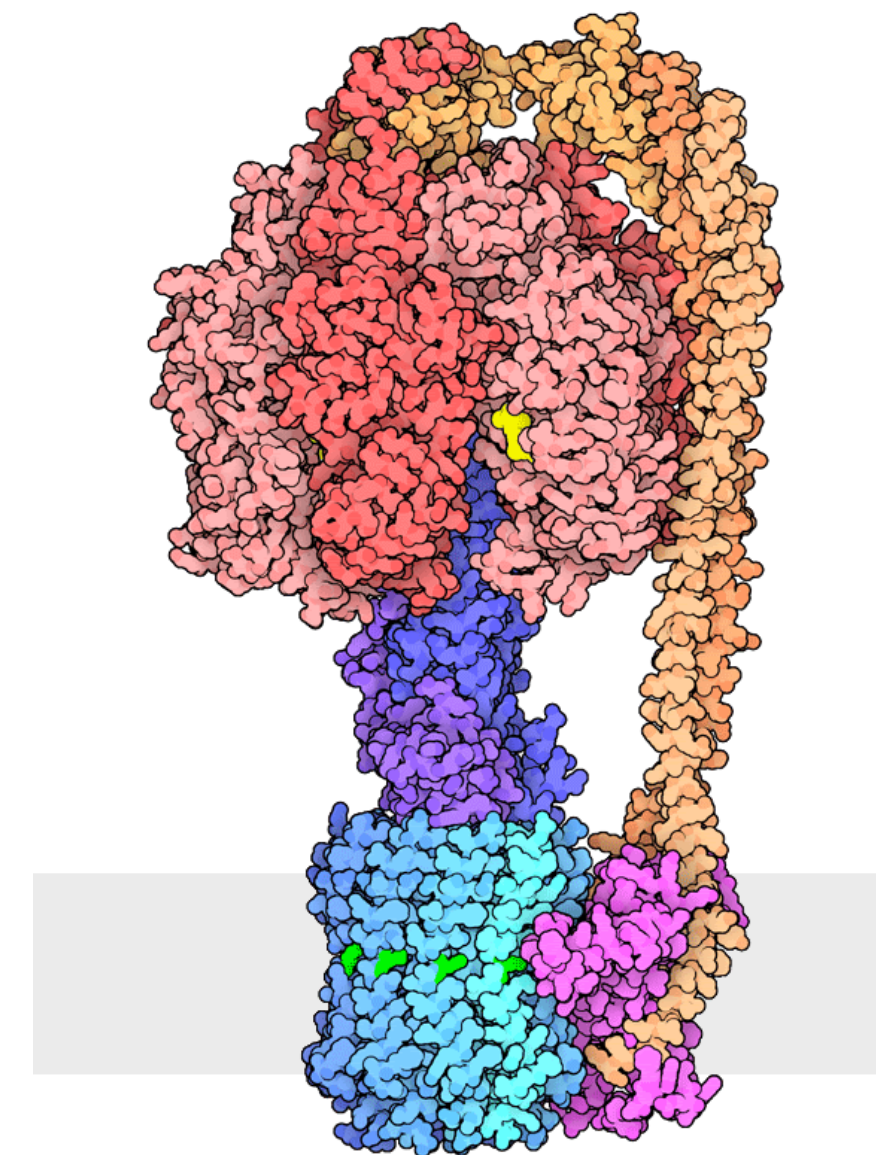


Protein Structure Prediction

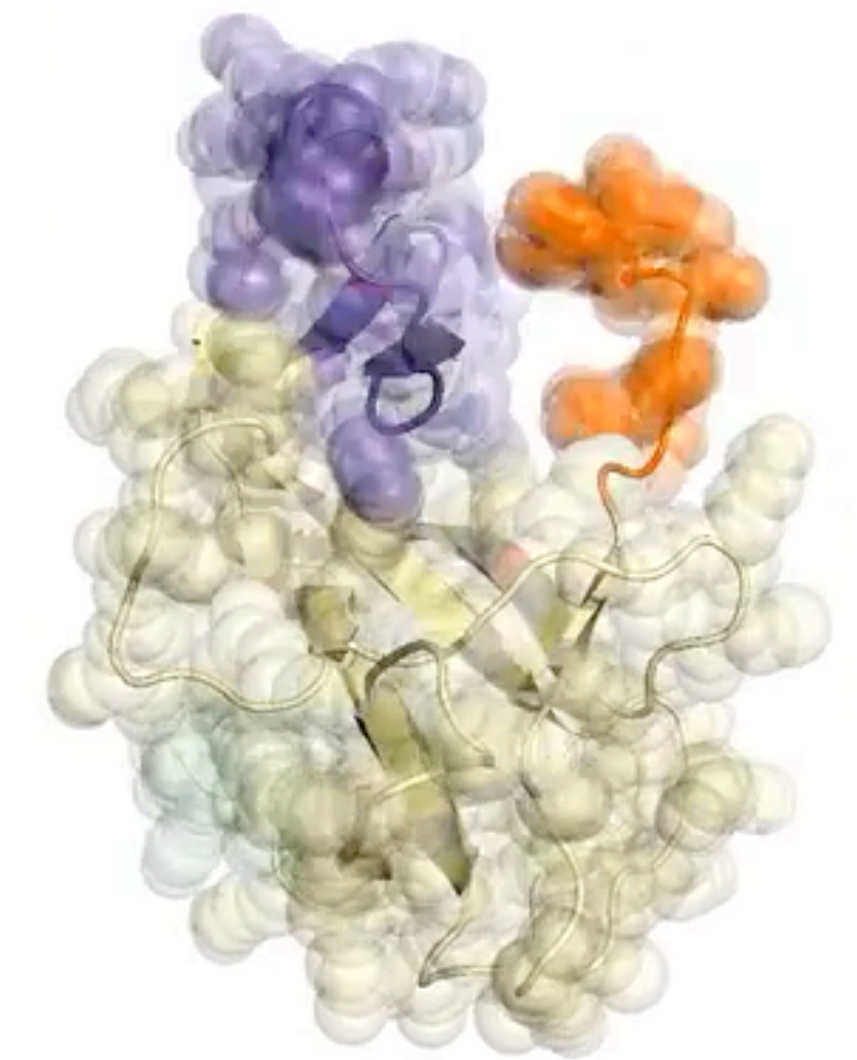
- Protein structure prediction models, e.g. AlphaFold [1], predict static 3D protein structure with high accuracy
- Protein structure is highly dynamic
- Predictive models are limited in their ability to predict multiple conformational states



AlphaFold Database. Tunyasuvunakool et al, 2021.



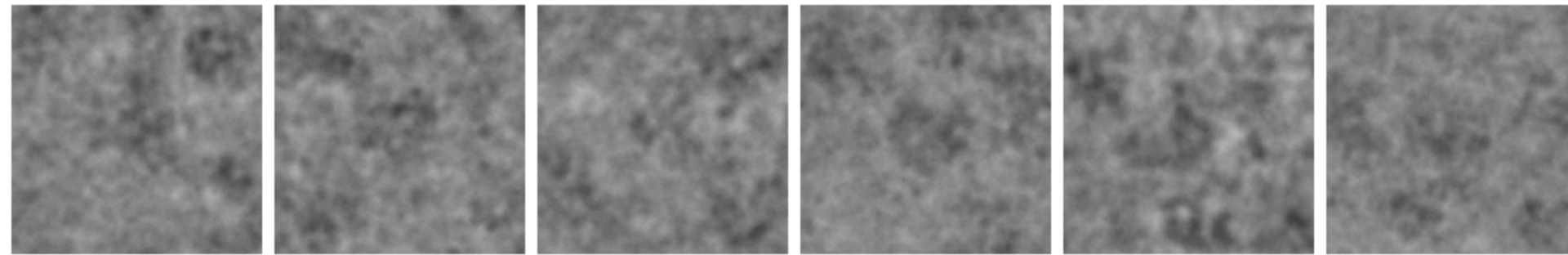
PDB 101



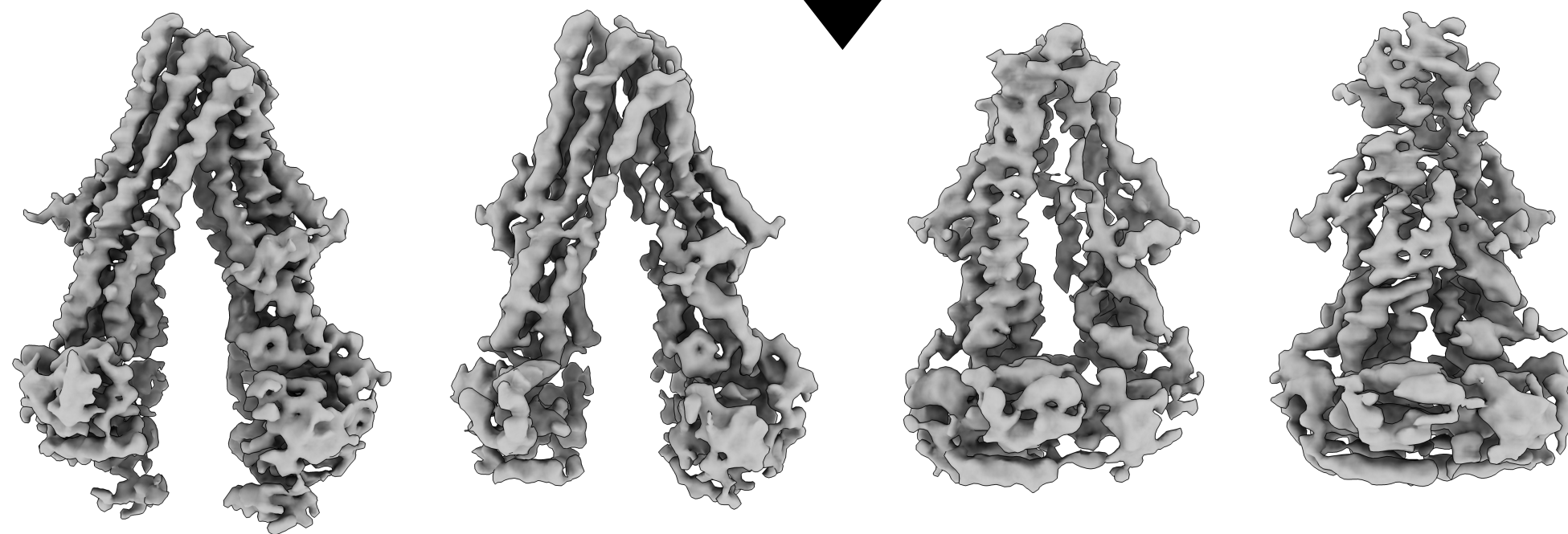
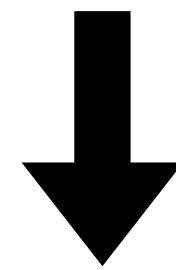
Chen et al eLife 2019

[1] Jumper et al. "Highly accurate protein structure prediction with AlphaFold." *Nature* 2021.

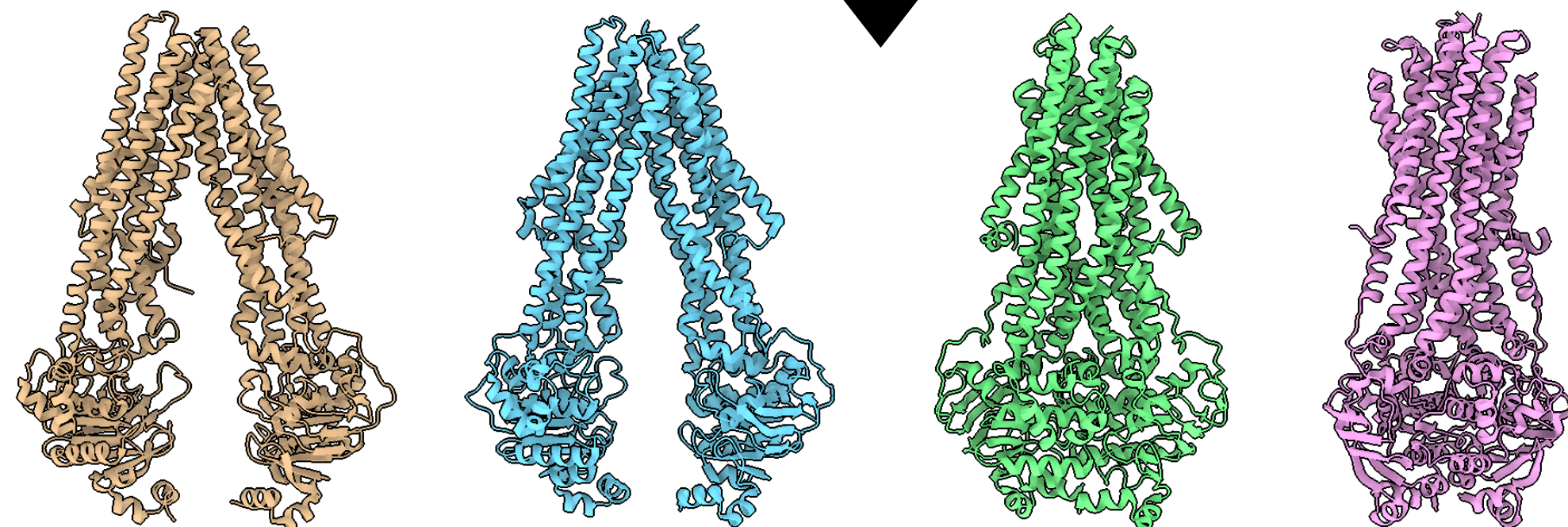
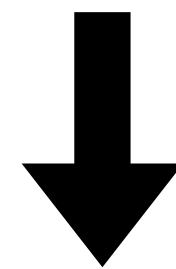
Conformational Ensembles from Cryo-EM



2D cryo-EM images



Ensemble of 3D density maps

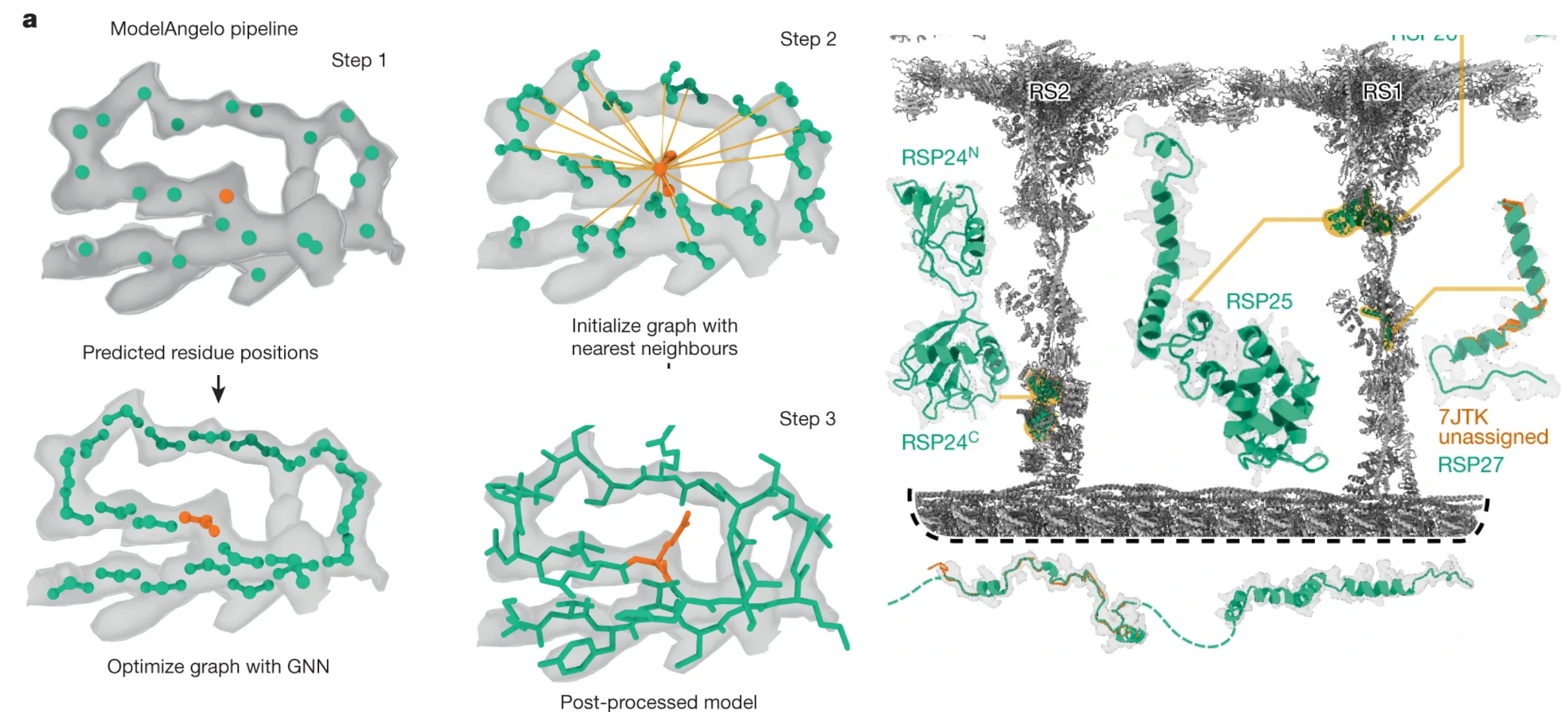


Ensemble of atomic models

- ✓ Captures near-native conformational ensembles
- ✗ Model building is challenging and unscalable

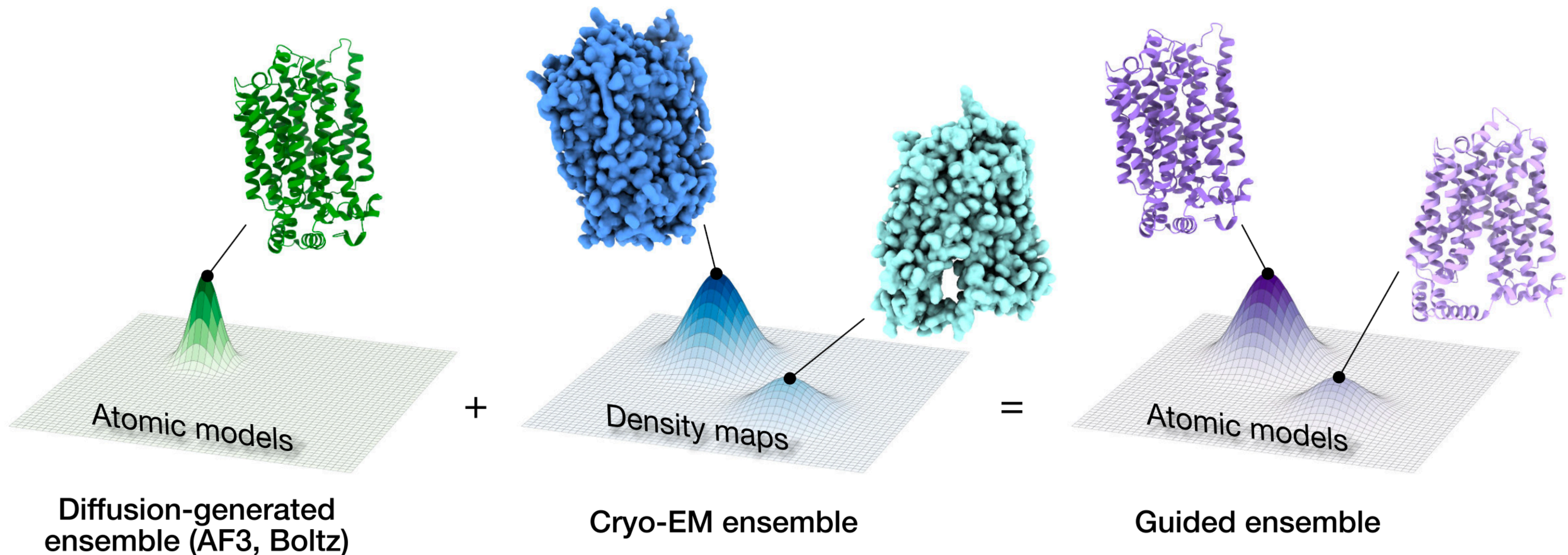
Model building

- Manual building
- MD simulation based flexible fitting
- ModelAngelo - Automated building for high-resolution maps [Jamali *et al.* 2024]



CryoBoltz Approach

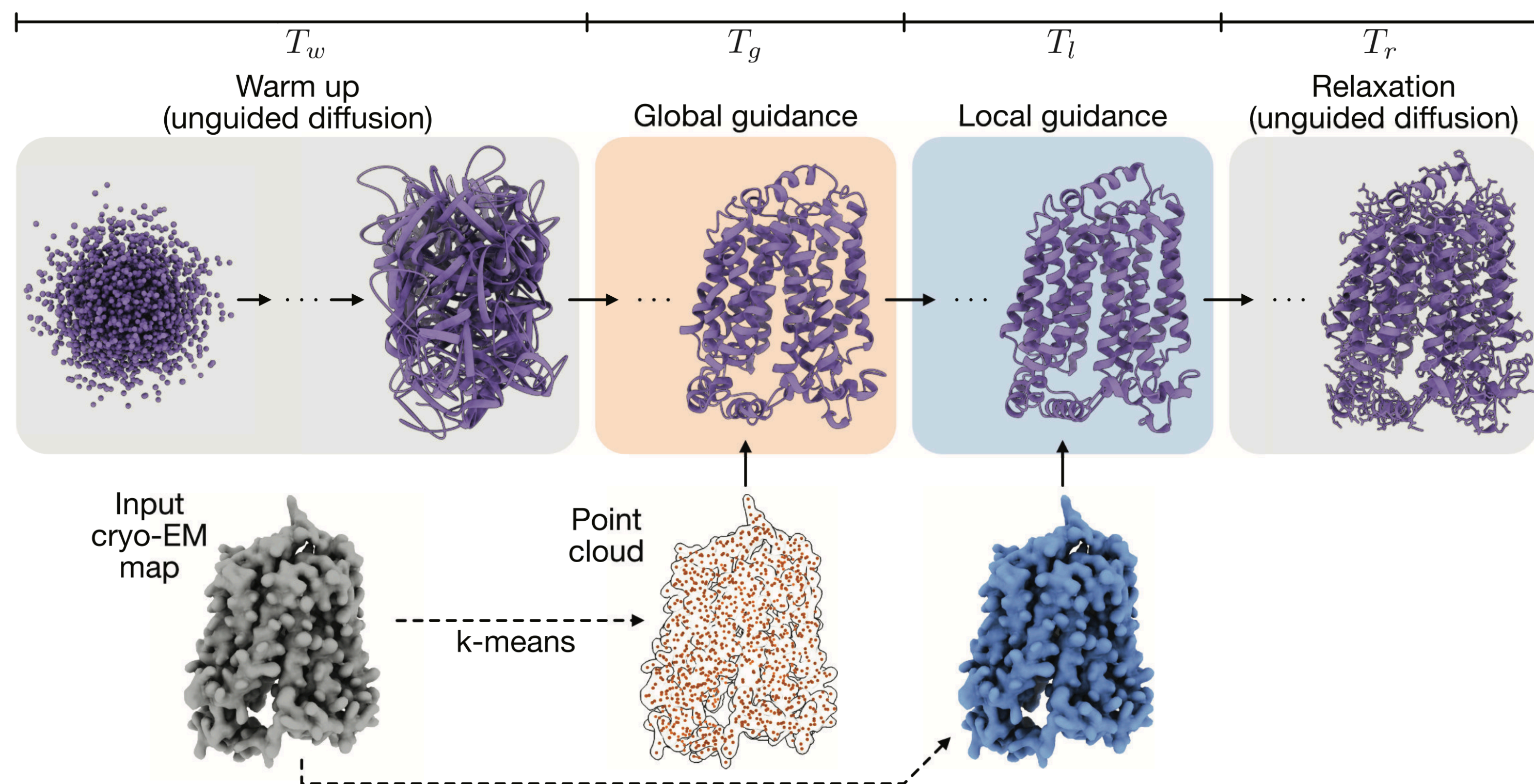
We combine **experimental cryo-EM data** with the biophysical priors learned by **protein structure prediction** models, to produce **ensembles of atomic models**



Diffusion Guidance with Cryo-EM Maps

- We use diffusion posterior sampling [1] to bias the sampling trajectory of Boltz-1 [2] towards structures consistent with an input cryo-EM map
- A coarse-to-fine fitting strategy combines optimal transport and physics-based guidance terms

$$d\mathbf{x} = \left(\mathbf{f}(\mathbf{x}, t) - g(t)^2 s_{\theta}(\mathbf{x}, t) - \underbrace{\lambda(t) \nabla_{\mathbf{x}} \log p(\mathbf{y} | \mathbf{x}_0 = \hat{\mathbf{x}}_{\theta}(\mathbf{x}, t))}_{\text{Experimental guidance}} \right) dt + g(t) d\mathbf{w}$$

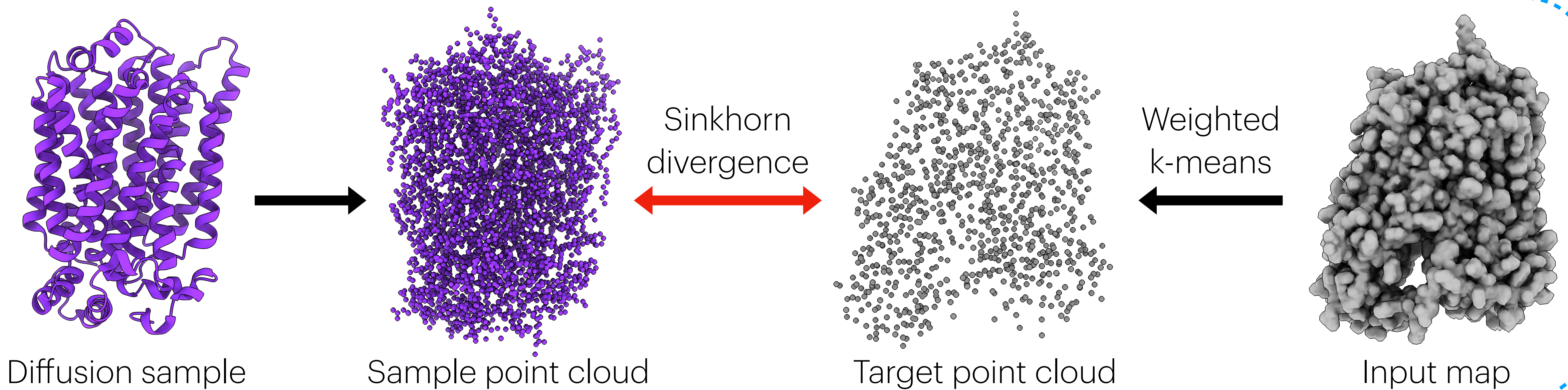


[1] Chung et al. "Diffusion posterior sampling for general noisy inverse problems." *ICLR* 2023.

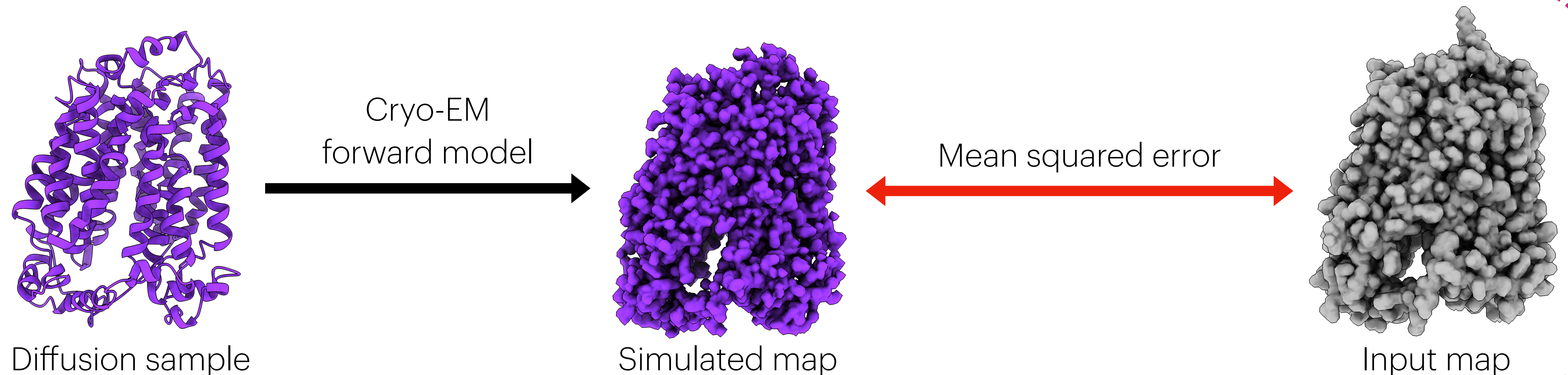
[2] Wohlwend et al. "Boltz-1 democratizing biomolecular interaction modeling." *bioRxiv*, 2024.

Diffusion Guidance with Cryo-EM Maps

Global

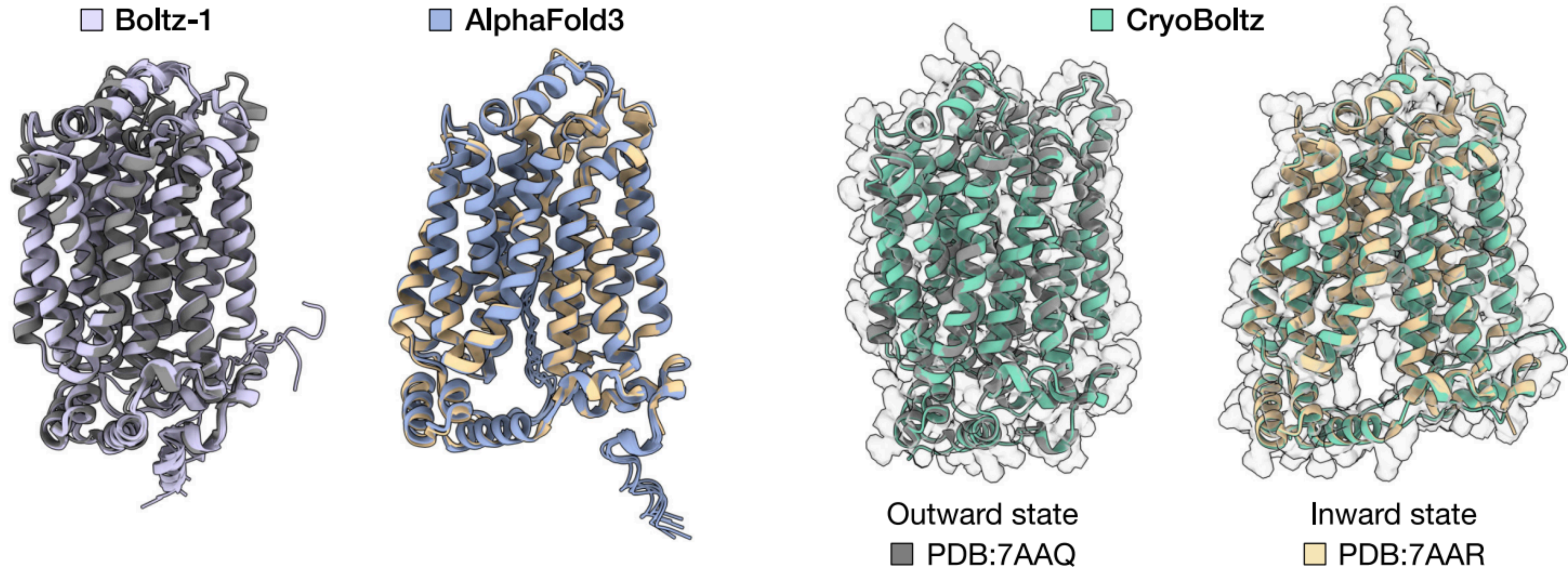


Local



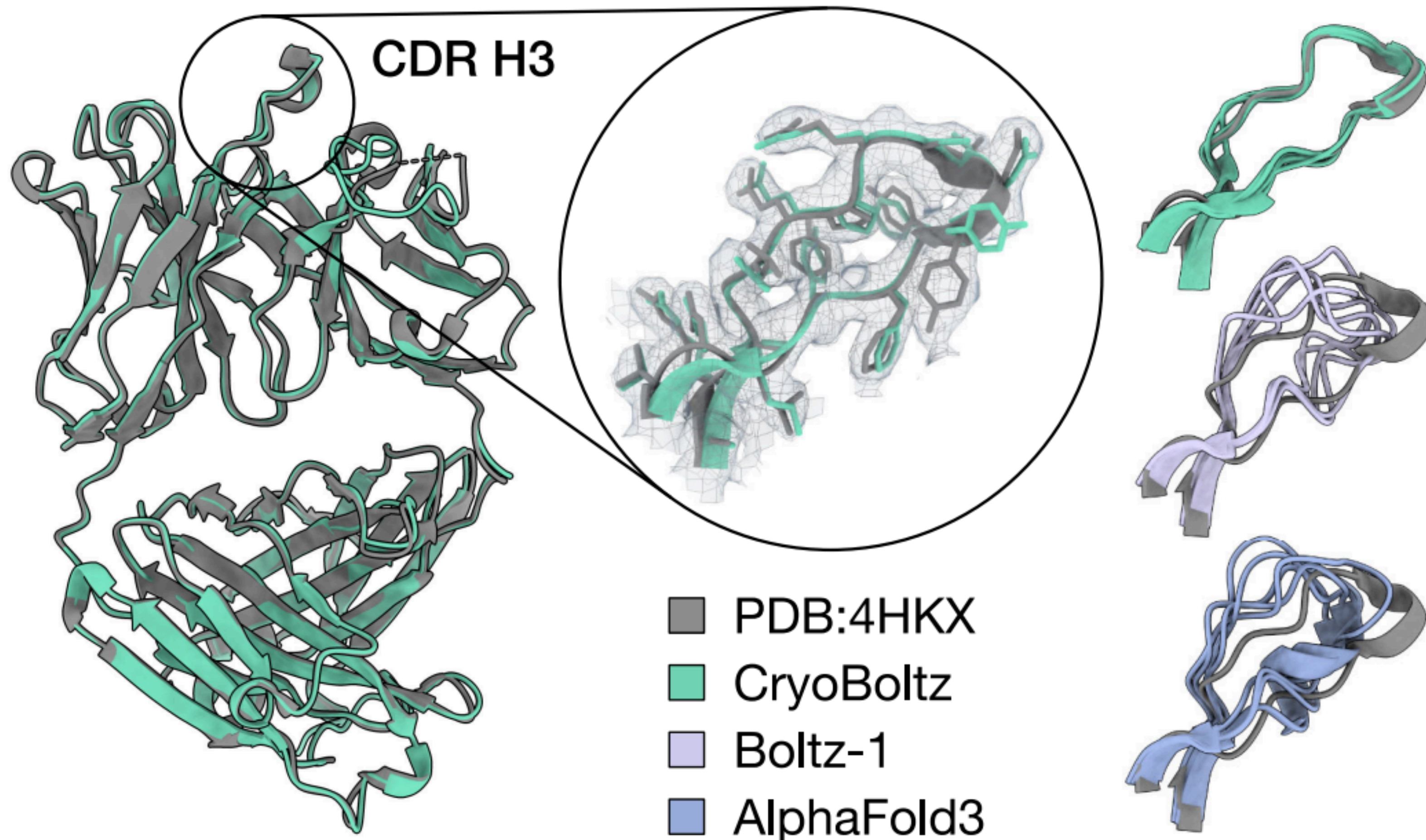
Guidance Overcomes Single-Structure Bias

Boltz-1 and AF3 predict only one conformation of the STP10 transporter, whereas guidance with synthetic maps achieves both



Local Fitting of Antibody CDR Loops

CryoBoltz accurately fits loops and side chains in a synthetic antibody map



Recovering Conformations from Real Maps

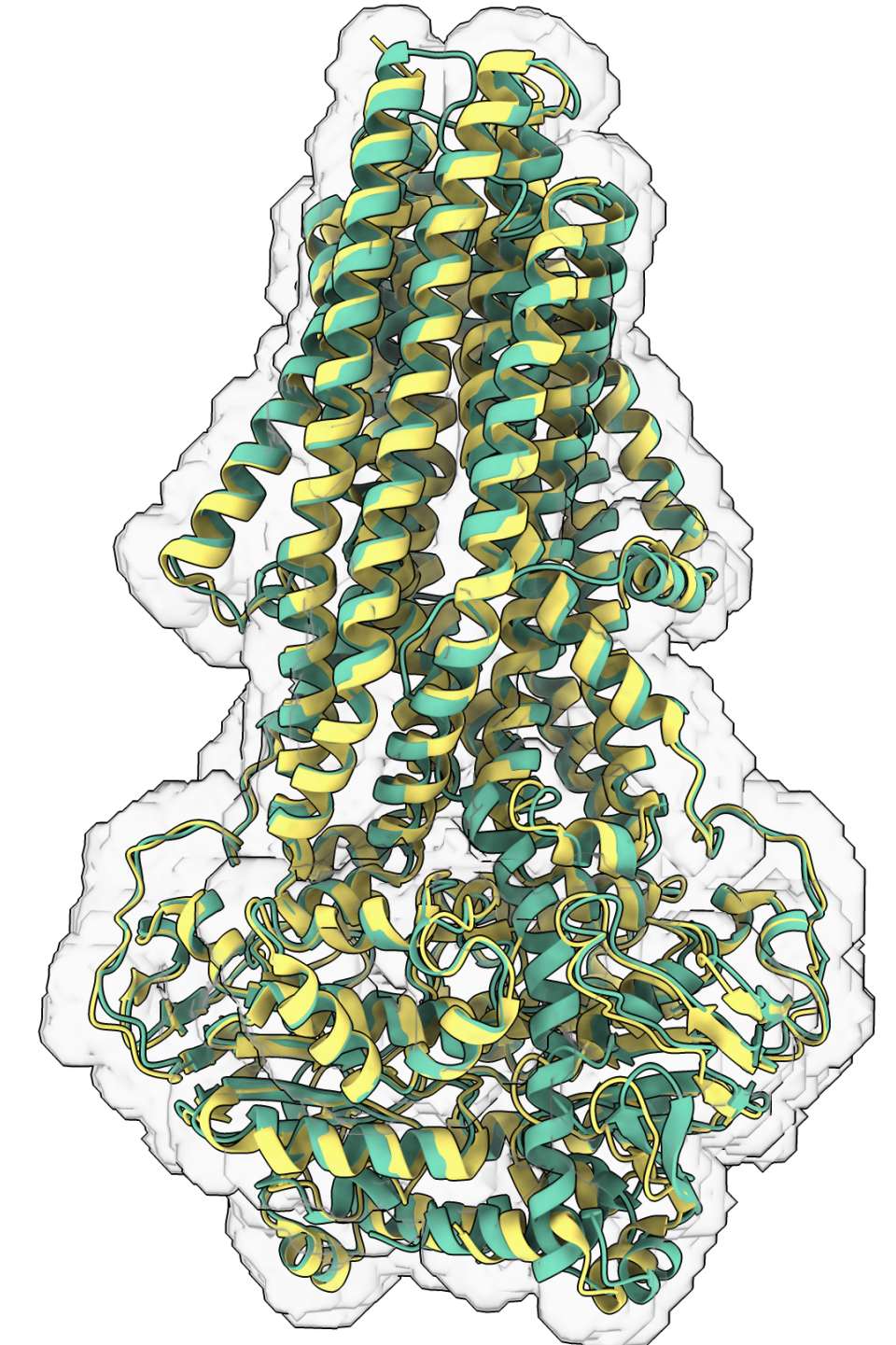
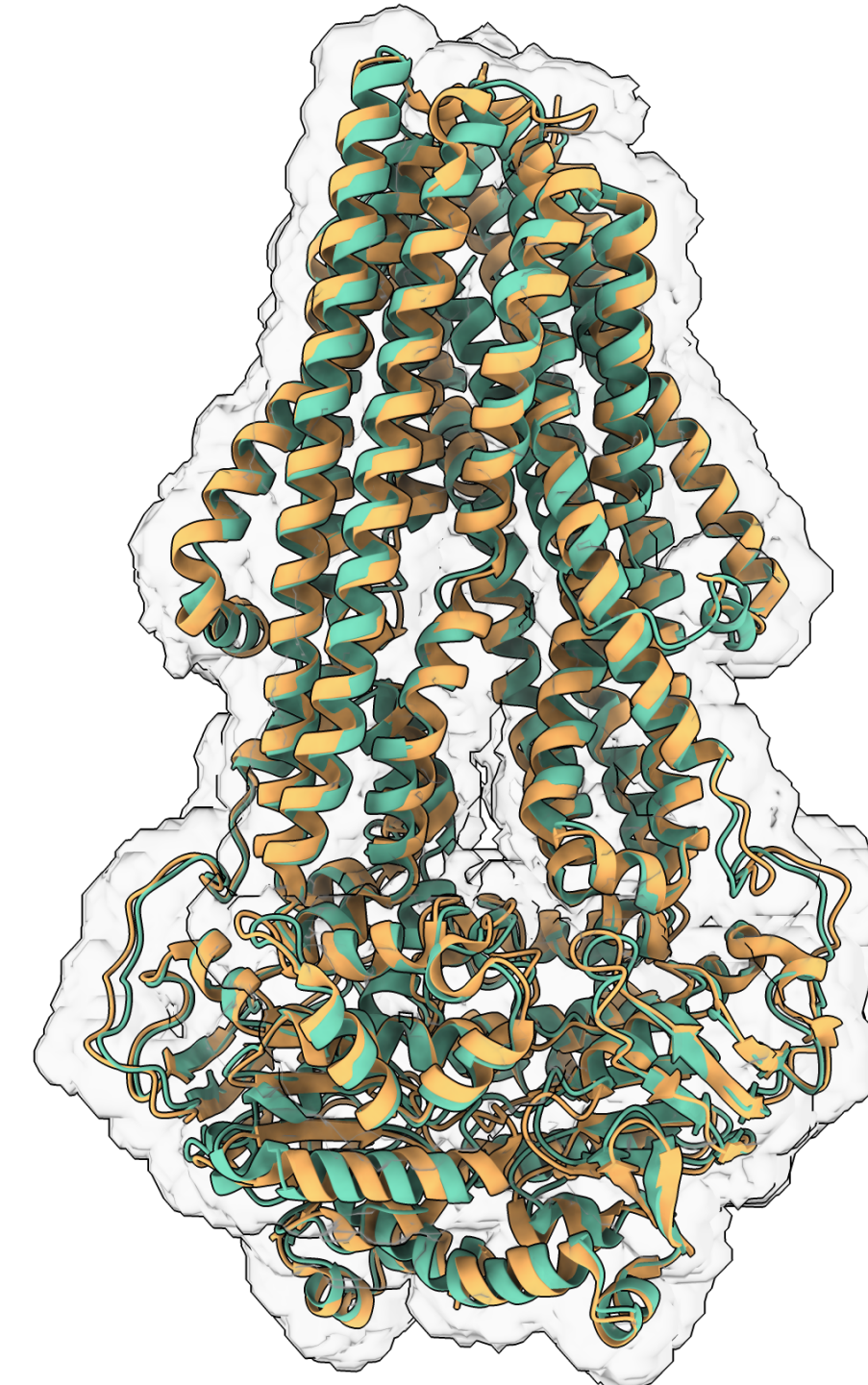
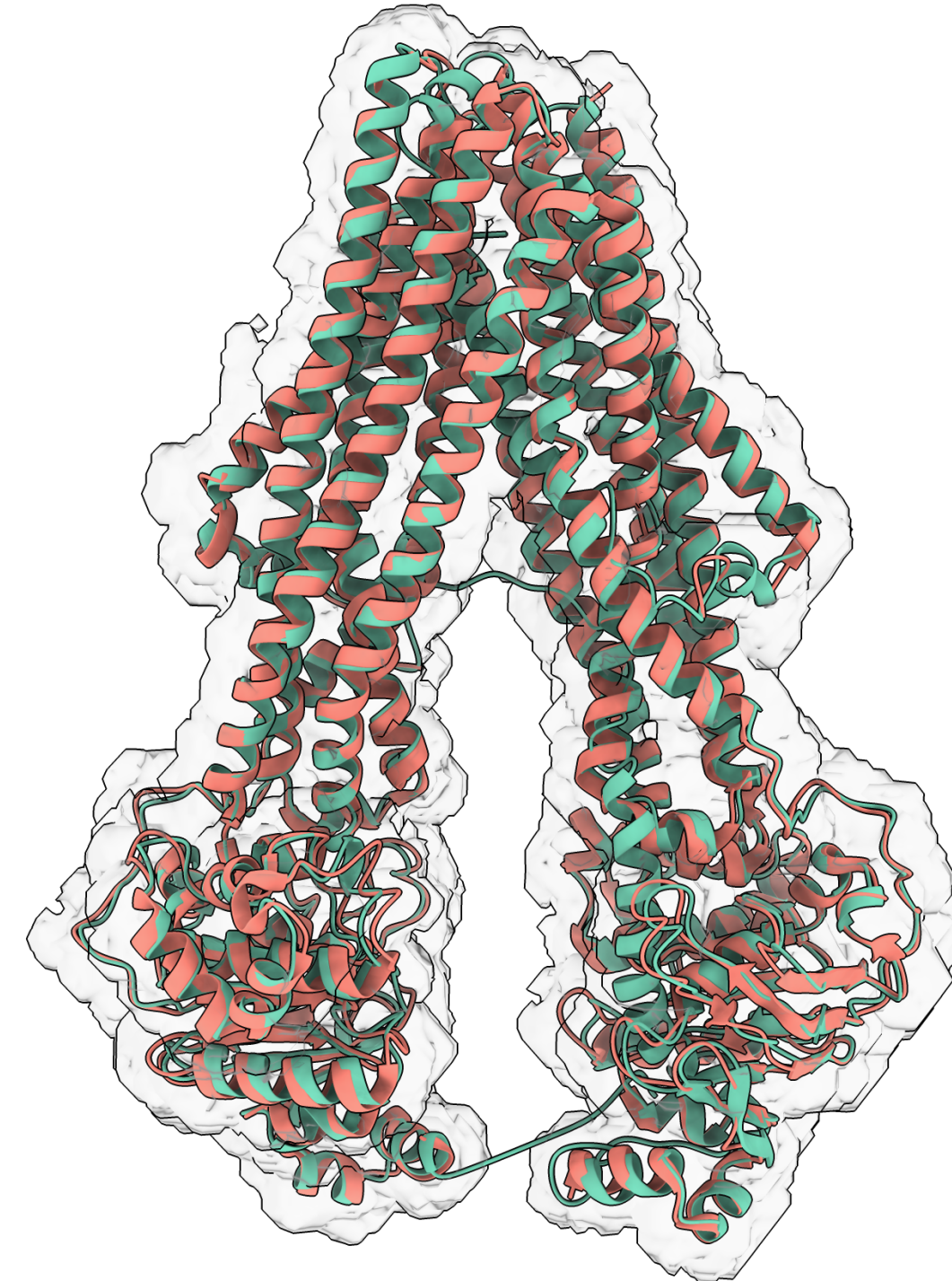
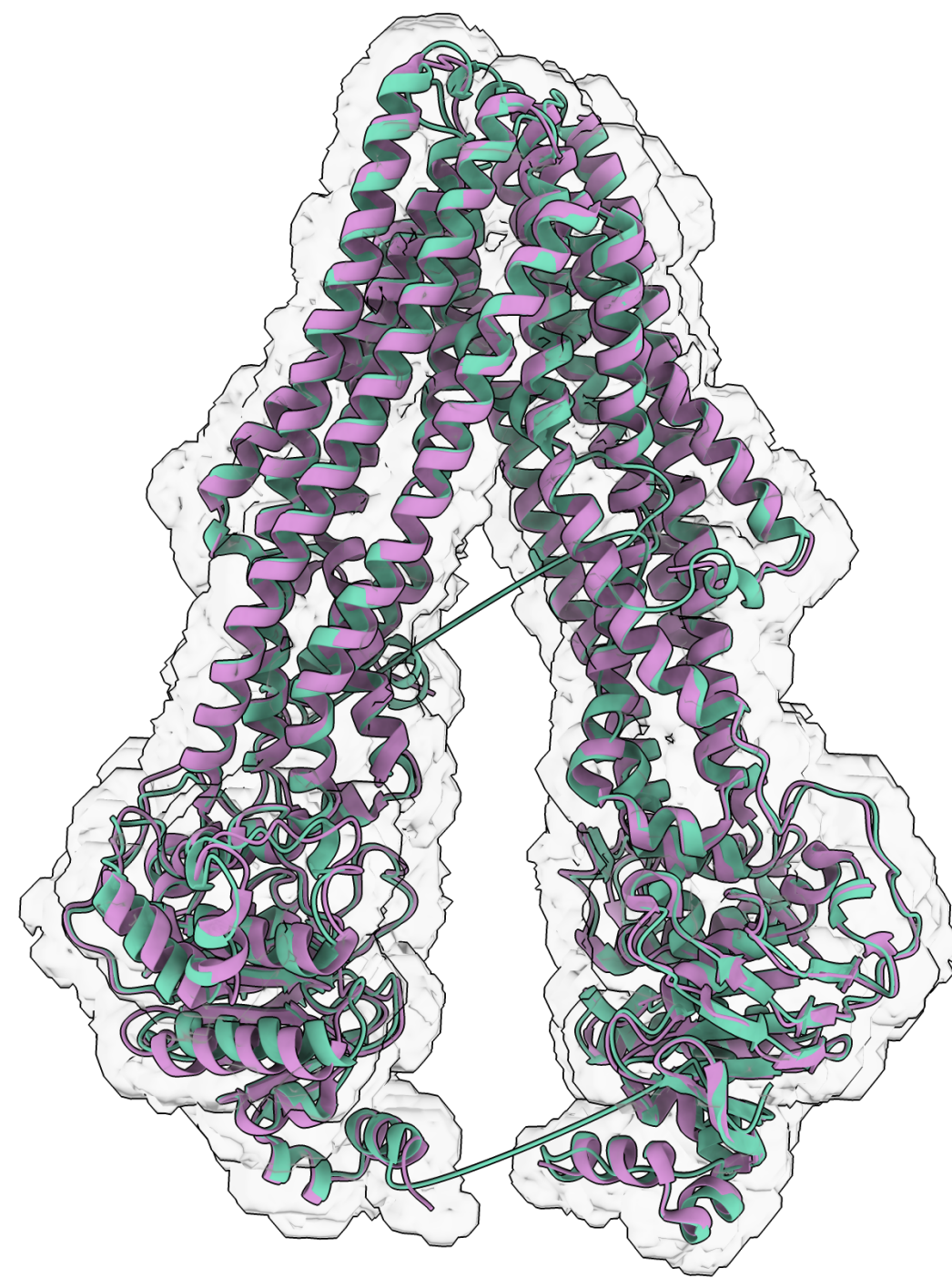
CryoBoltz accurately models 4 conformational states of P-glycoprotein

Apo State

Inward State

Occluded State

Collapsed State



■ PDB 8GMG

■ PDB 8SA1

■ PDB 8SA0

■ PDB 8GMJ

■ CryoBoltz

Quantitative Evaluation

CryoBoltz models structures more accurately than unguided predictors
and model building tools

<i>Structure</i>	Res. (Å)	CryoBoltz			Boltz-1			AlphaFold3			ModelAngelo	
		RMSD all	RMSD C α	TM score	RMSD all	RMSD C α	TM score	RMSD all	RMSD C α	TM score	Comp. (%)	TM score
Pgp (apo)	4.3	1.382	1.208	0.989	6.994	7.194	0.767	3.827	3.865	0.904	40.3	0.361
Pgp (inward)	4.4	1.348	1.187	0.989	5.630	5.692	0.828	2.692	2.663	0.947	18.3	0.134
Pgp (occluded)	4.1	1.727	1.677	0.979	2.929	2.904	0.942	3.440	3.420	0.921	2.3	0.010
Pgp (collapsed)	4.4	1.309	1.261	0.988	3.425	3.412	0.917	4.568	4.554	0.864	2.5	0.010
Pma1 (active)	3.25	2.046	1.776	0.973	2.987	2.752	0.935	6.628	6.389	0.769	91.5	0.889
Pma1 (inhibited)	3.52	1.999	1.590	0.979	6.140	5.829	0.794	8.017	7.776	0.723	72.8	0.721
CYP (open)	6.5	4.167	3.946	0.957	8.532	8.439	0.788	6.490	6.361	0.890	0.0	0.000
CYP (closed)	4.4	2.004	1.552	0.990	8.784	8.667	0.743	3.585	3.391	0.946	18.9	0.102
YbbAP (bound)	3.66	1.320	0.678	0.997	3.623	3.339	0.928	3.749	3.480	0.922	81.7	0.801
YbbAP (unbound)	4.05	2.454	2.039	0.974	7.842	7.654	0.776	4.022	3.744	0.913	55.4	0.548



cryoboltz.cs.princeton.edu