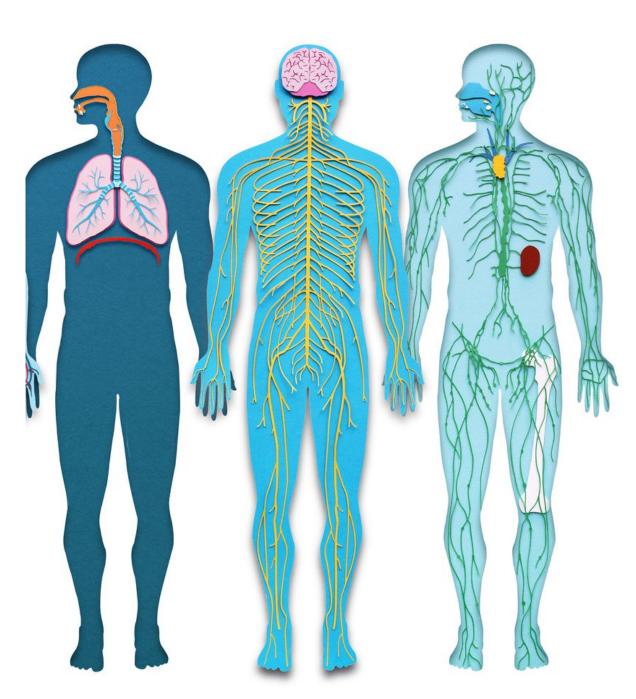
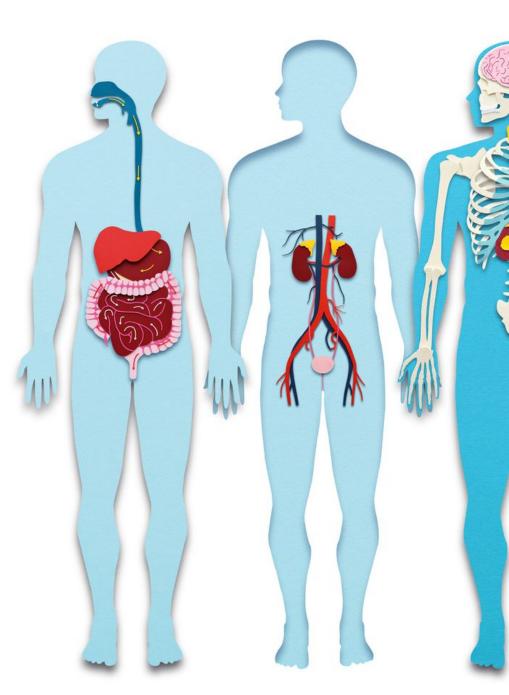
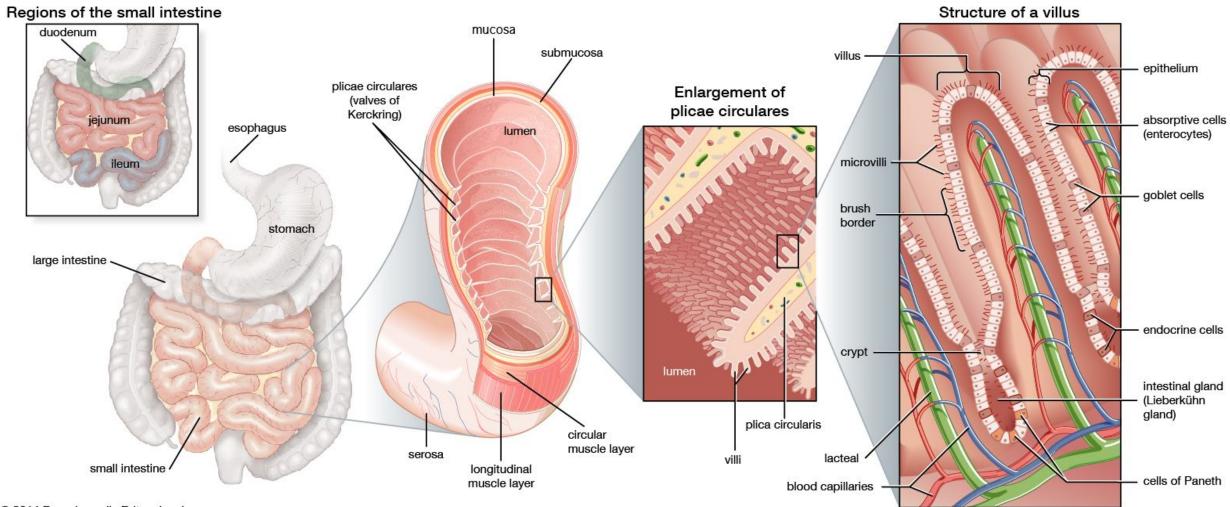
Deep Learning in Structural Biology and Protein Design: Where, How, and Why

> Deep Learning Theory Workshop and Summer School Aug 5, 2022 @ Simons Institute By Chloe Hsu (UC Berkeley)

Intro: A view of biology from living beings to molecules

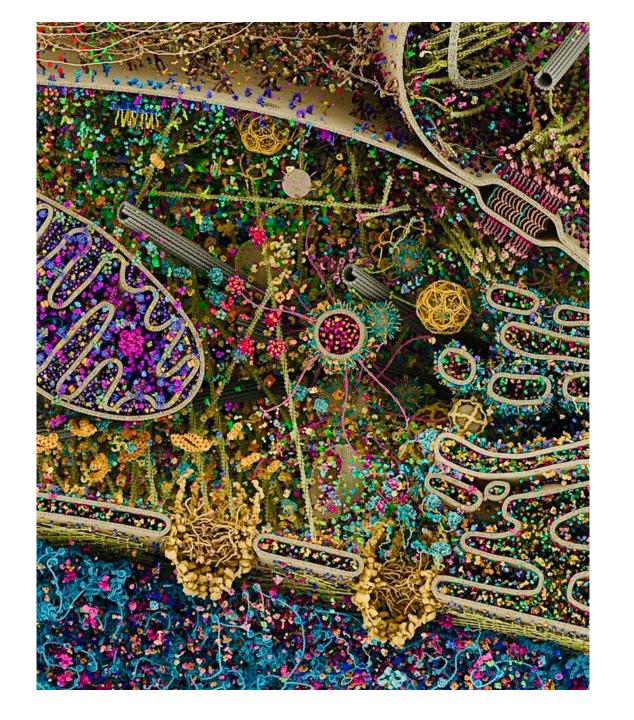


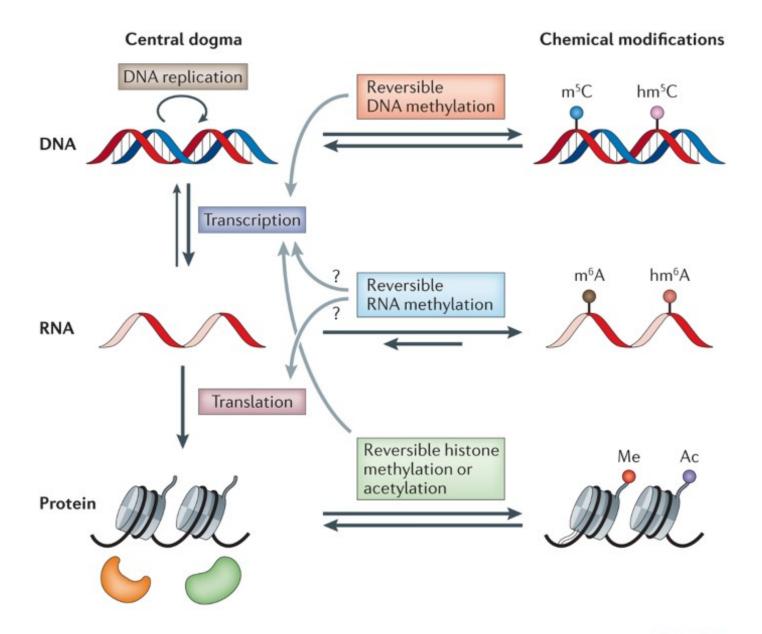




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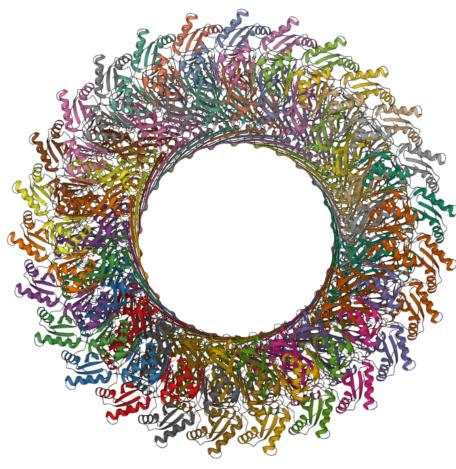


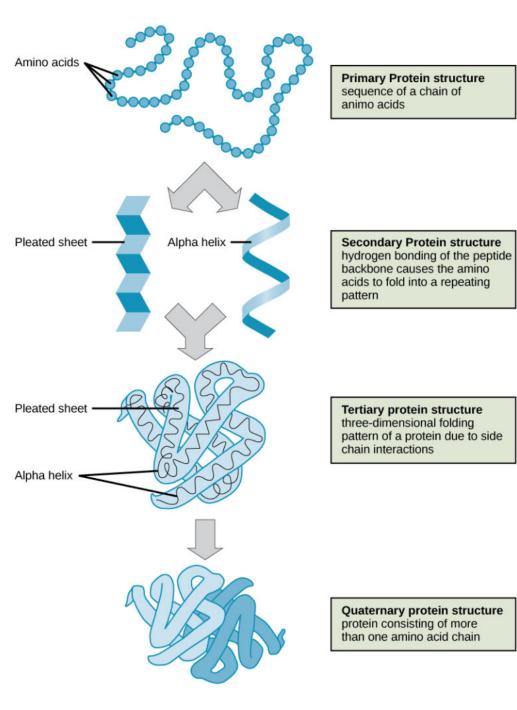




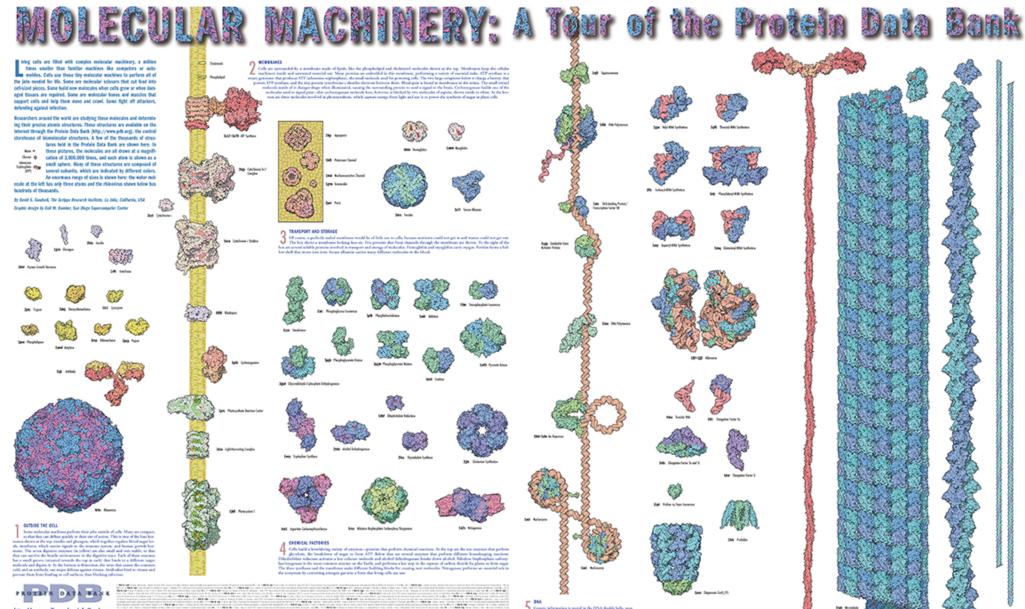
"Where": Advances in structural biology and protein design

Protein structures





Salmonella LP ring (It moves and swims!)



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5 Senset information is mored in the DNA should belies, non-regarding theorem up to horizon hum. Name promises are used to experiment, and the source horizon the source of the source conversion of two provides. In a monitor for programmer, which down memoirs when the belie is source of a downerse, and pair of an appropriate starting pairs by the sense is sourced on the source of the sour or is filling a gap in the double hole. Some provine, We the spread, gods DNA and head is charake, or even wear is all the

other. He do too makes on the bound

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BUILDING NON PROTEINS

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Structure prediction

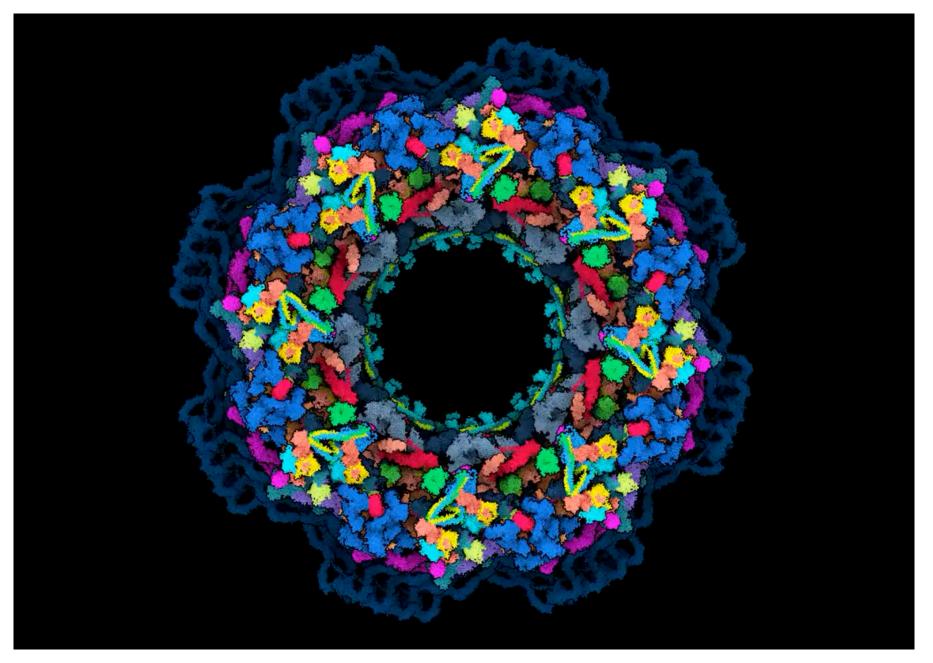
Substantial improvement in structure prediction from AlphaFold2

Also notable in new capabilities for predicting protein-protein interactions (although not perfect yet)

Applications:

- Interprets complex experimental data in structural biology at a new speed
- Creates an unprecedented size of predicted structures for data mining & learning

•



Mosalaganti, Shyamal, et al. "Artificial intelligence reveals nuclear pore complexity." BioRxiv (2021).

Structure prediction

Substantial improvement in structure prediction from AlphaFold2

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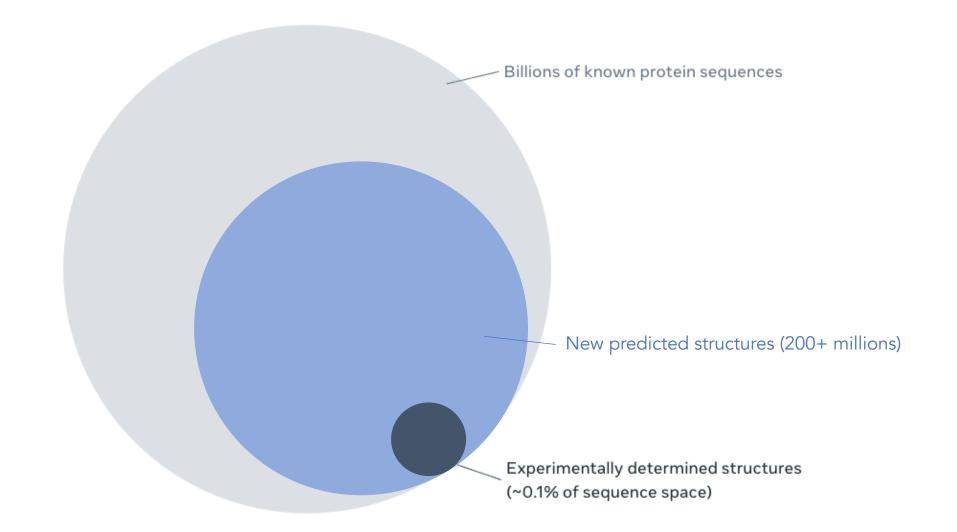
Applications:

- Interprets complex experimental data in structural biology at a new speed
- Creates an unprecedented size of predicted structures for data mining & learning

•

- Billions of known protein sequences

Experimentally determined structures (~0.1% of sequence space)

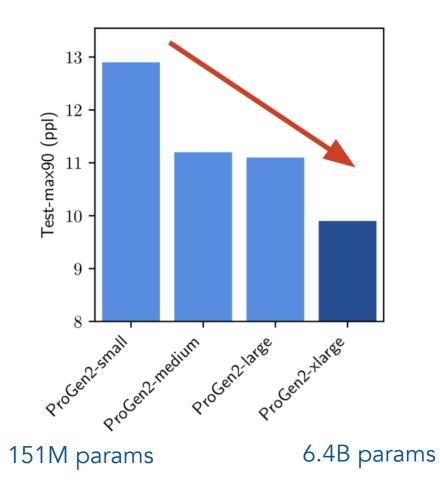


Protein sequence models

• Modeling the distribution of protein sequences through language models or other density models

• Bigger is better??

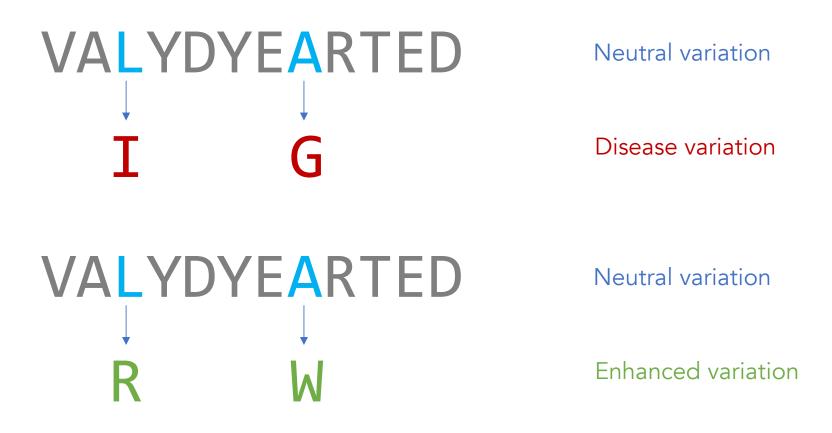
- Applications
 - Predicts effects of genetic mutations
 - Guides sequence choices in protein engineering

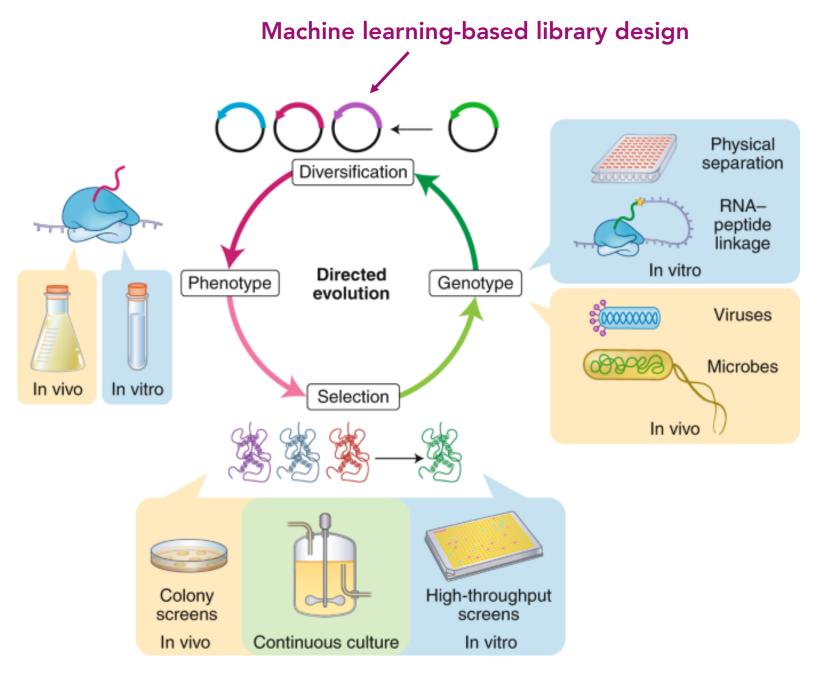


Sequence density model (language model)

Protein sequence

Sequence likelihood

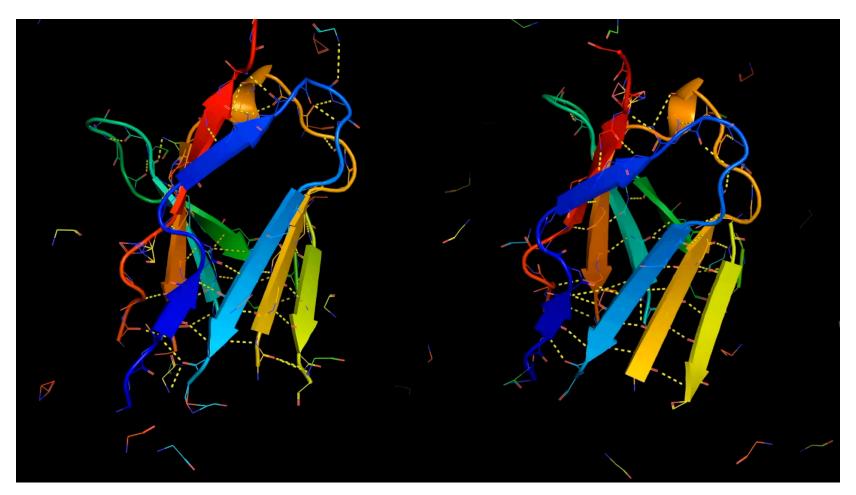




Morrison, M.S., Podracky, C.J. & Liu, D.R. The developing toolkit of continuous directed evolution. Nat Chem Biol 16, 610–619 (2020).

Generative models for protein design

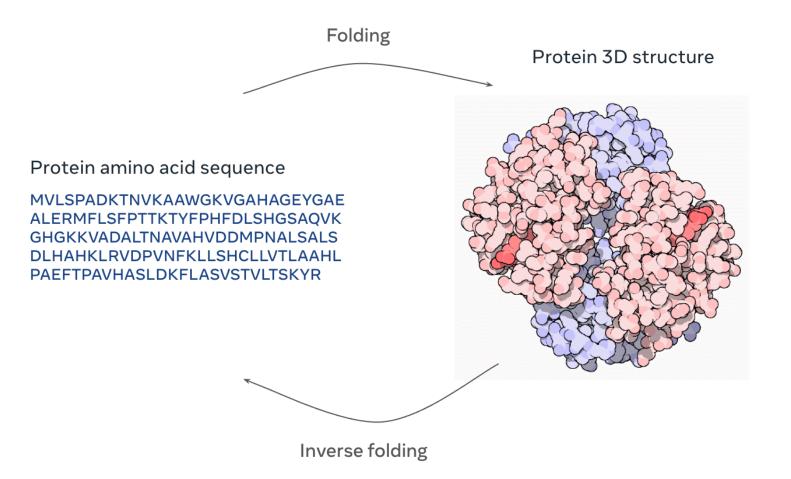
Denoising diffusion probabilistic model for protein structure and sequence



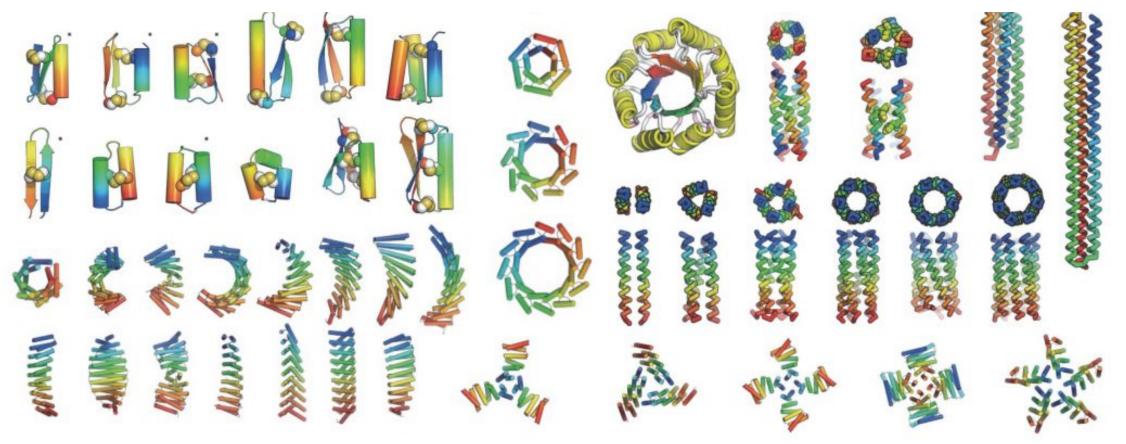
Anand, Namrata, and Tudor Achim. "Protein Structure and Sequence Generation with Equivariant Denoising Diffusion Probabilistic Models." arXiv preprint arXiv:2205.15019 (2022).

Generative models for protein design

Conditional generative models for protein design, e.g. inverse folding models



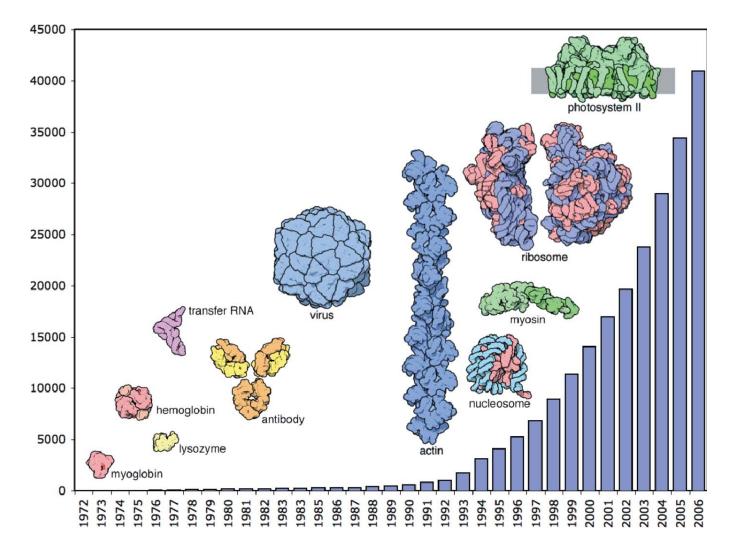
Beyond naturally existing proteins: De novo proteins



Huang, Po-Ssu, Scott E. Boyken, and David Baker. "The coming of age of de novo protein design." Nature 537.7620 (2016): 320-327.

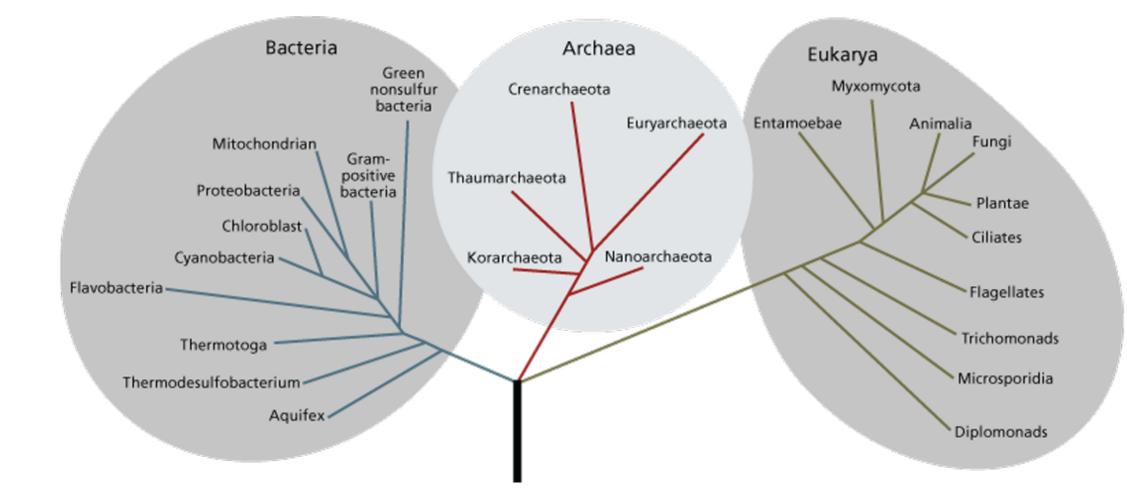
"How": The data and the learning algorithms

Protein structures: Protein Data Bank



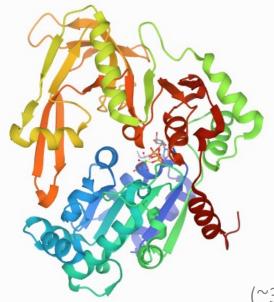
(Today over 100,000)

Evolutionary data: observing the products of evolution

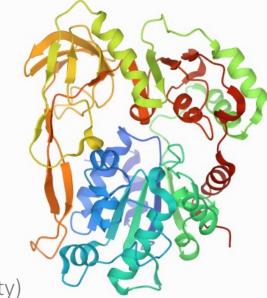


Evolutionary data: observing the products of evolution

Human PIF1 helicase (PDB: 6HPH)



Thermophilic bacteria PIF1 helicase (PDB: 6S3E)





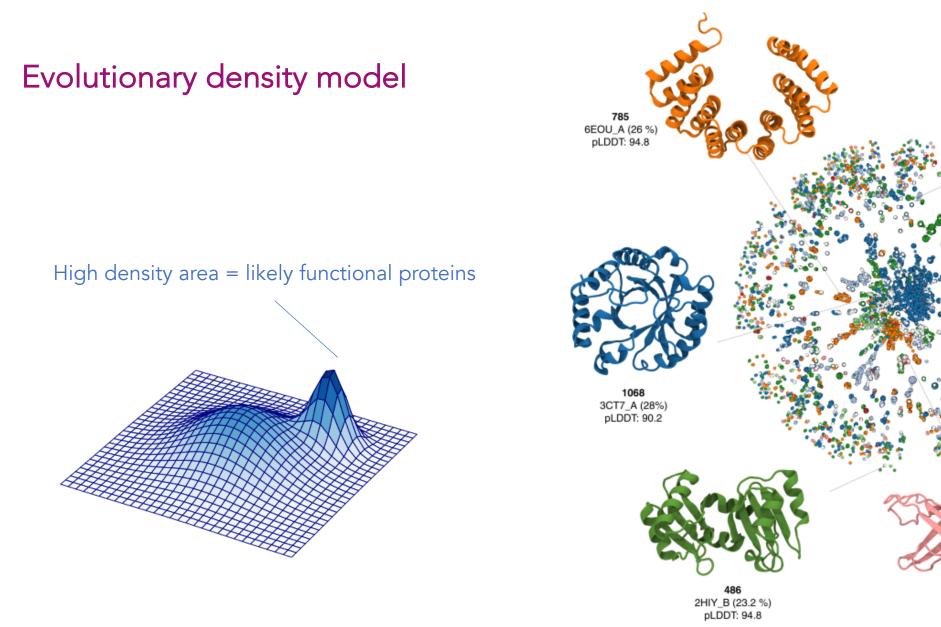
(~30% sequence identity)

Evolutionary data: observing the products of evolution

Multiple sequence alignment (MSA)

WALRKTRKRLEEPFGGVKVLLLGDTRQLEPVVPGGEEALYIARTWGGPFFFQAHVWEE R R++ +PFGG+++++ GD QL PV G + F FQ+ W+	180
AVARAVRQQ-NKPFGGIQLIICGDFLQLPPVTKGSQPPRFCFQSKSWKRCV	168
-VALRVHRLWESQRQREDPLFAELLKRLRQGDPQALETLNRAAVRPDGGEEPGTLILT V L + ++W ++ D F LL+ +R G + L A G + L	237
PVTLELTKVWRQADQTFISLLQAVRLGRCSDEVTRQLQATASHKVGRDGIVATRLC	224
PRRKEADALNLKRLEALPGKPLEYQAQVKG-EFAETDFPTEAALTLKKGAQVILLRN + + N +RL+ LPGK ++A E A T P L LK GAOV+L++N	293
THQDDVALTNERRLQELPGKVHRFEAMDSNPELASTLDAQCPVSQLLQLKLGAQVMLVKN	284
DPLGE-YFNGDLGWVEDLEAEALAVRLKRNGRRVVIRPFVWEKIVYTYDSEREEIKPQ + NG G V EAE + R G VI W T + ++ +	350
LSVSRGLVNGARGVVVGFEAEGRGLPQVRFLCGVTEVIHADRWTVQATGGQLLSR	339
VVGTFRQVPVRLAWALTVHKAQGLTLDKVHLELGRGLFAHGQLYVALTRVRRLQDL 406 +Q+P++LAWA+++HK+QG+TLD V + LGR +FA GQ YVAL+R R LQ L	
QQLPLQLAWAMSIHKSQGMTLDCVEISLGR-VFASGQAYVALSRARSLQGL 389	

PIF1 helicase



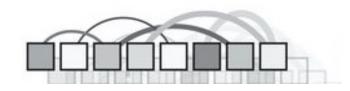
Ferruz, N., Schmidt, S. & Höcker, B. ProtGPT2 is a deep unsupervised language model for protein design. *Nat Commun* **13**, 4348 (2022). 27

4307 3QRC_B (18 %) pLDDT: 70.4 751 4GZV_H (13 %) pLDDT: 81.4

4266 *5B48_C (9%, 67aa) pLDDT: 72.5 Before deep learning: Simple models on evolutionary data



Hidden Markov Models (HMMs) only model the site-specific amino acid features.



Potts models, also known as Markov Random Fields (MRFs), model the site-specific amino acid features and the pairwise interactions between sites.

They work quite well, too

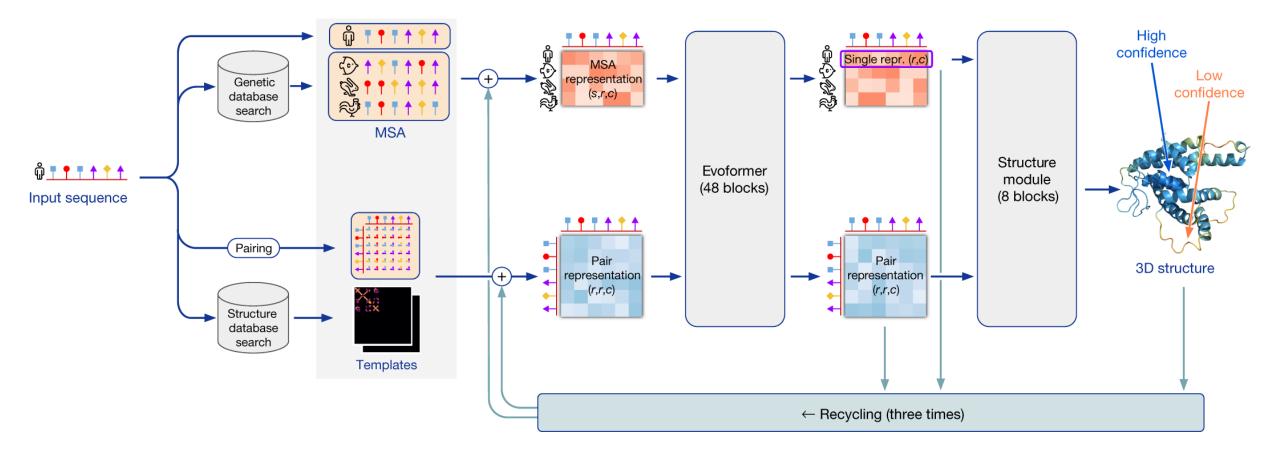
(when used on specific protein families in combination with search algorithms)

Replacing multiple sequence alignments with deep learning models (Protein language models)

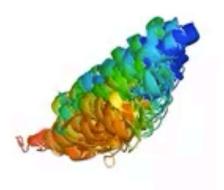
PIF1 helicase			
Insulin			
Casein			

New ability to jointly model all protein families regardless of "alignments"

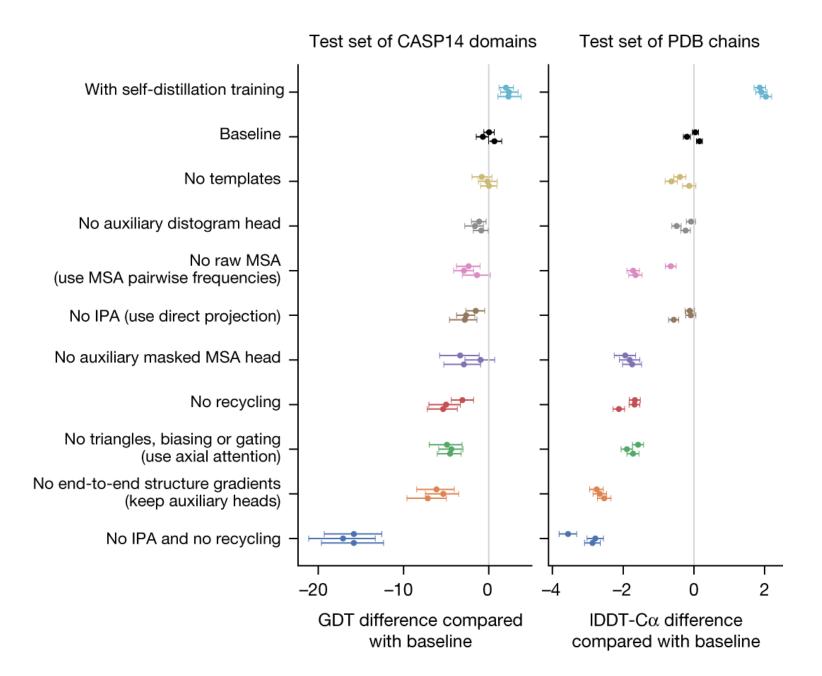
AlphaFold2 also relies on evolutionary data (multiple sequence alignments)



Jumper, J., Evans, R., Pritzel, A. et al. Highly accurate protein structure prediction with AlphaFold. Nature 596, 583–589 (2021).



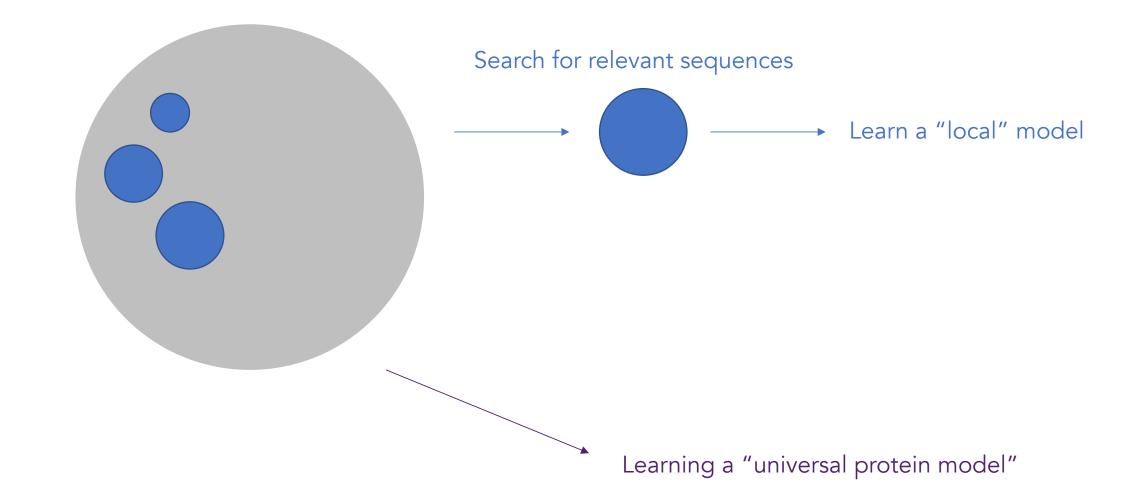
Recycling iteration 0, block 01 Secondary structure assigned from the final prediction



Jumper, J., Evans, R., Pritzel, A. et al. Highly accurate protein structure prediction with AlphaFold. Nature 596, 583–589 (2021).

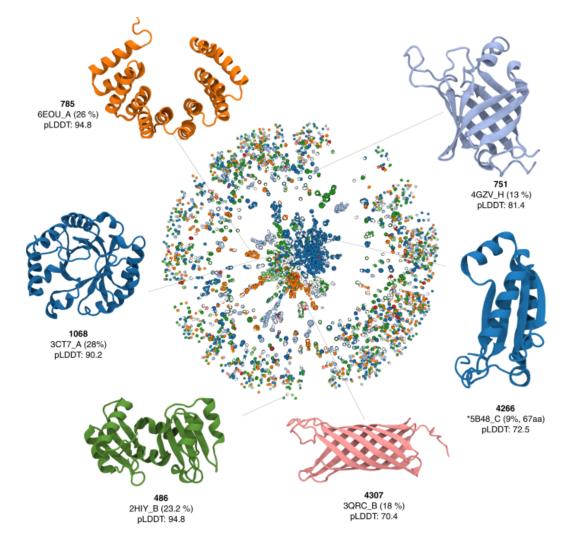
"Why": Common themes and open questions

"Search & learn" vs. "universal learning"



"Generalization" vs "memorization"

Are language models / single-sequence folding models effectively memorizing the evolutionary database?



Ferruz, N., Schmidt, S. & Höcker, B. ProtGPT2 is a deep unsupervised language model for protein design. *Nat Commun* **13**, 4348 (2022).