Predicting Protein Folding

"Improved protein structure prediction using potentials from deep learning"

By Andrew W. Senior et al @ DeepMind

Nature, 2020





ANDRE YE | FEBRUARY 2021



How proteins fold is an important but complex problem.

- Protein function is <u>dependent on shape</u>.
- If protein shape is known, it can be engineered to serve a function.
- Protein structures are highly complex and difficult to predict.



Amino acid (polypeptide) chain



Folded (Functional) Protein



Recent protein modeling is a two-part process.



Predicted Folded Protein



An animation of the gradient descent method predicting a structure for CASP13 target T1008



Previous attempts relied on predicting <u>residue contact</u>.

- The model returns whether two residues should be in contact.
- This method is **not** information-rich.







AlphaFold relies on predicting the <u>distance</u> between residues.

- The model returns the predicted distance between any two residues.
- This method is information-rich.







Putting it all together...



The AlphaFold System

Predicted Folded Protein



An animation of the gradient descent method predicting a structure for CASP13 target T1008



AlphaFold can model both template and free forms.

Proteins are split into domains, or significant parts of proteins. Domains fold independently.

Template-Based Modelling (TBM)

The structure of a domain with a similar sequence is known.

Make modifications to an existing template structure.

Free-Modelling (FM)

There is no homologous (similar) structure known.

Generate a completely novel structure.



Result: AlphaFold is astoundingly accurate.

"FM + FM/TBM domain count":

- Measures how many domains can be predicted with a TM score \geq the cutoff.
- Considers both TBM and FM domains
- <u>Bigger is better</u>



"TM-score": between 0 and 1, indicating how close the predicted structure is to the ground truth

"Other groups": referring to other efforts or solutions to this problem



Thanks for listening!





Deep neural networks learn the dynamics of chemistry to predict distances.



• Highly complex algorithms capable of learning highly complex phenomena. • Trained on a dataset to predict distances between residues given the amino acid sequence.





Structures: Ground truth (green) Predicted (blue)









Residues

Residue x

Residues

