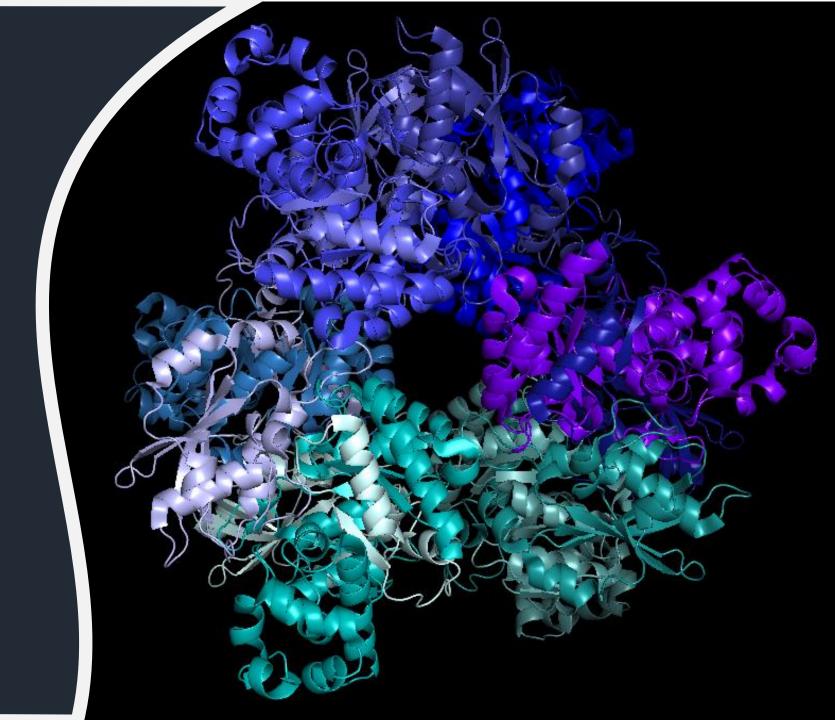
Introduction to Protein Structure Prediction With AlphaFold 2

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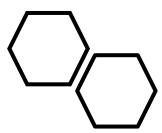


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- ✓ Consultation on Projects and Grants
- ✓ High Performance Compute Cluster
- ✓ Workshops

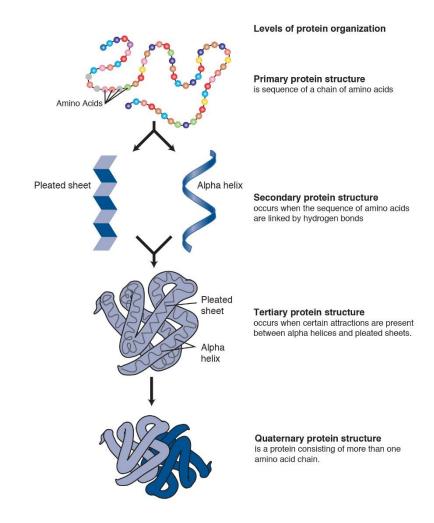
https://it.tufts.edu/research-technology

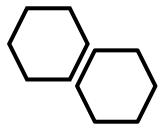




Protein Organization

- Primary Structure: amino acid sequence
- Secondary Structure: amino acid sequences linked by hydrogen bonds
- Tertiary Structure: organization of secondary structures
- Quaternary Structure: organization of multiple amino acid chains



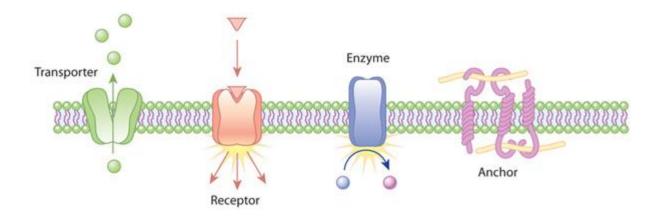


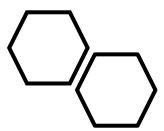
The Importance of Protein Structure

Can help determine what a protein does

 Often more conserved than the amino acid sequences that form them

Examples of Different Proteins

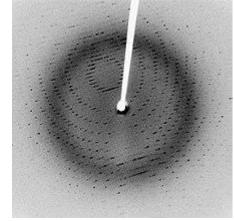




Laboratory Means To Determine Protein

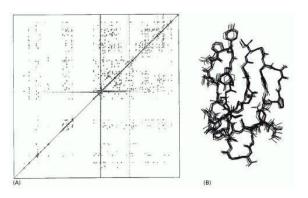
Structure

X-ray Crystallography



- X-ray Crystallography
- Nuclear Magnetic Resonance (NMR)
 Spectroscopy
- 3D Electron Microscopy

NMR Spectroscopy



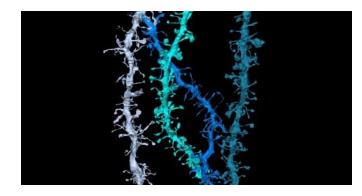
https://directorsblog.nih.gov/tag/serial-scanning-3d-electron-microscopy/

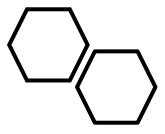
https://www.ncbi.nlm.nih.gov/books/NBK26820/

https://pdb101.rcsb.org/learn/guide-to-understanding-pdb-data/methods-for-determining-structure

https://simple.wikipedia.org/wiki/X-ray crystallography

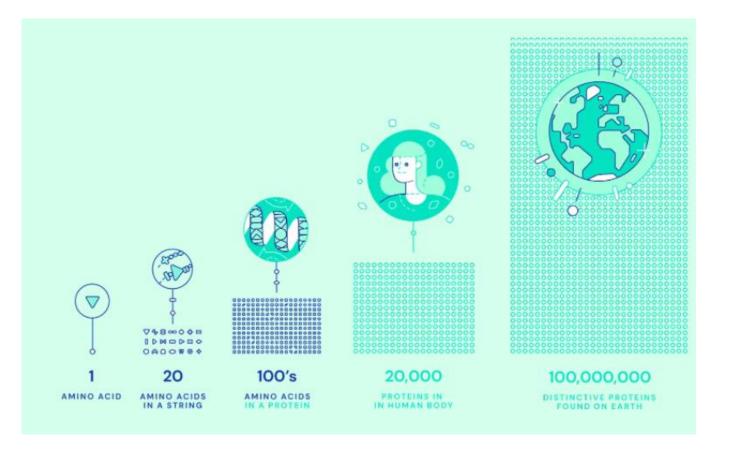
3D Electron Microscopy





The Protein Structure Problem

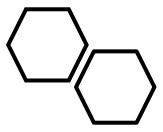
- 100,000,000 known distinct proteins
- Each has a unique structure that determines function
- Determining protein structure is time consuming
- Only a small fraction of exact 3D structures are known





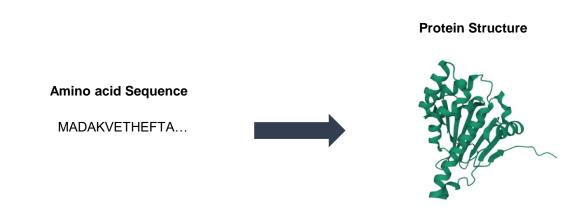
- Finding the native folded state of a protein by random searching of all possible configurations would take an enormous amount of time
- However, proteins can often fold within seconds
- Meaning some process must be guiding this folding





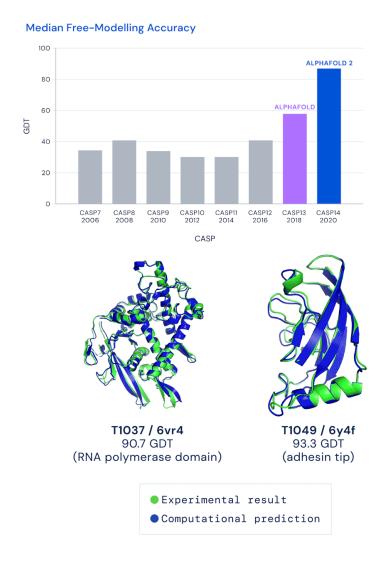
Using Sequence To Predict Structure

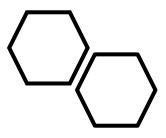
- Instead of laboratory experimentation, there have been massive efforts to use a protein's sequence to determine structure
- 1994, the Critical Assessment of Structure Protein (CASP) was established as a biennial assessment of methods to predict structure from sequence





- Google's DeepMind team Entered AlphaFold 2 in CASP14
- Achieved a median Global Distance Test Score of 92.4
- AlphaFold 2 works by finding similar sequences to the query, extracts the information using a neural network, then passes that information to another neural network that construct a theoretical structure

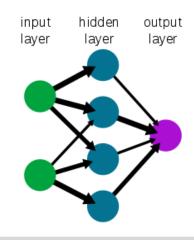




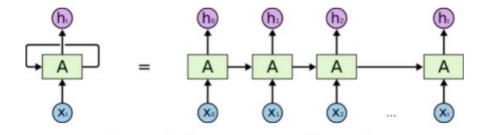
Simple v. Recurrent Neural Network

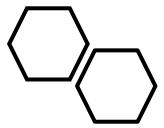
- A neural network is a machine learning algorithm commonly used in predictive modelling
 - Composed of an input layer, hidden layer, and an output layer
 - Traditionally learn from training
- A Recurrent Neural Network learns from training and from previous inputs
- However, the memory is poor when pulling from old connections

Simple Neural Network



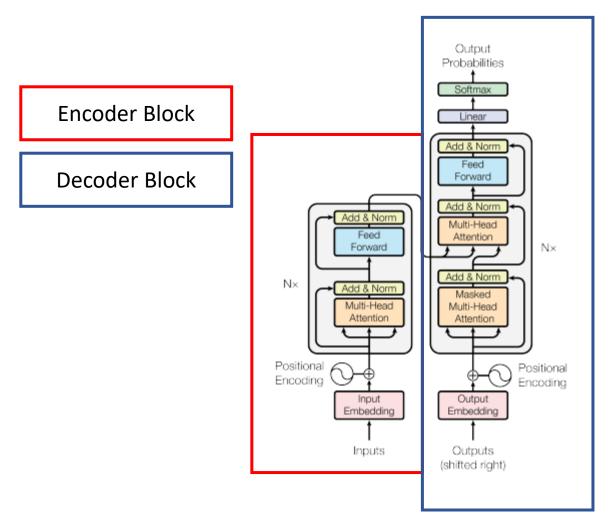
Recurrent Neural Network

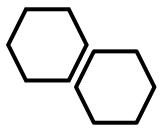




The Transformer

- AlphaFold 2 uses an evolution of the Recurrent Neural Network called a Transformer
- The Transformers can be broken up into two blocks: the Encoder Block and the Decoder Block
- Encoder Block: turn sequences into vectors w/ positional information, the attention is limited by each character's interaction w/ the rest of the sequence
- Decoder Block: information from the previous block is converted to probability distributions





Transformer Benefits

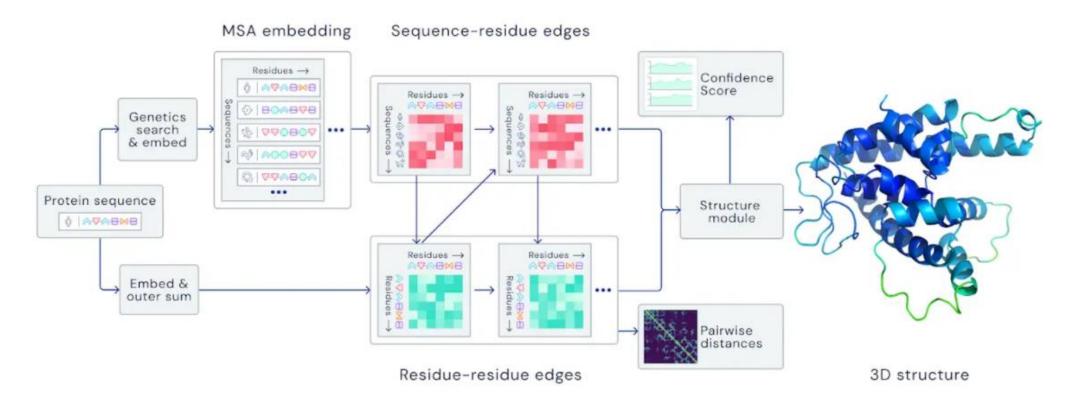
- Limited attention means better memory utilization
- Faster model training times
- Overcome the issue of the memory being poor when pulling from old connections



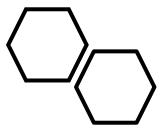




The AlphaFold 2 Workflow







Protein Sequence Information

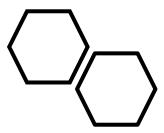
 Protein sequence information stored as a fasta file. Consists of

a:

- Header
- sequence

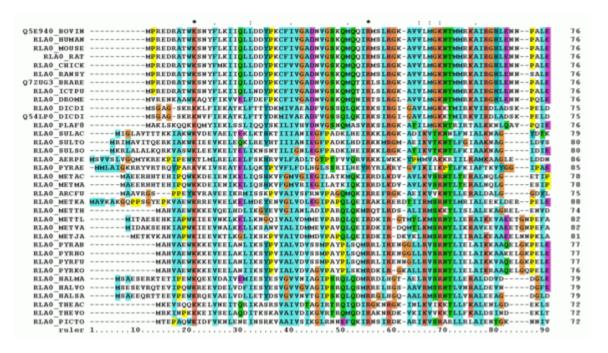
>sp|P46598|HSP90_CANAL Heat shock protein 90 homolog OS=Candida albicans (strain SC5314 / ATCC MYA-2876) OX=237561 GN=HSP90 PE=1 SV=1

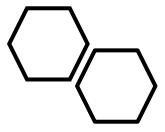
MADAKVETHEFTAEISQLMSLIINTVYSNKEIFLRELISNASDALDKIRYQALSDPSQLE
SEPELFIRIIPQKDQKVLEIRDSGIGMTKADLVNNLGTIAKSGTKSFMEALSAGADVSMI
GQFGVGFYSLFLVADHVQVISKHNDDEQYVWESNAGGKFTVTLDETNERLGRGTMLRLFL
KEDQLEYLEEKRIKEVVKKHSEFVAYPIQLVVTKEVEKEVPETEEEDKAAEEDDKKPKLE
EVKDEEDEKKEKKTKTVKEEVTETEELNKTKPLWTRNPSDITQDEYNAFYKSISNDWEDP
LAVKHFSVEGQLEFRAILFVPKRAPFDAFESKKKKNNIKLYVRRVFITDDAEELIPEWLS
FIKGVVDSEDLPLNLSREMLQQNKILKVIRKNIVKKMIETFNEISEDQEQFNQFYTAFSK
NIKLGIHEDAQNRQSLAKLLRFYSTKSSEEMTSLSDYVTRMPEHQKNIYYITGESIKAVE
KSPFLDALKAKNFEVLFMVDPIDEYAMTQLKEFEDKKLVDITKDFELEESDEEKAAREKE
IKEYEPLTKALKDILGDQVEKVVVSYKLVDAPAAIRTGQFGWSANMERIMKAQALRDTTM
SSYMSSKKTFEISPSSPIIKELKKKVETDGAEDKTVKDLTTLLFDTALLTSGFTLDEPSN
FAHRINRLIALGLNIDDDSEETAVEPEATTTASTDEPAGESAMEEVD



Building a Multiple Sequence Alignment (MSA)

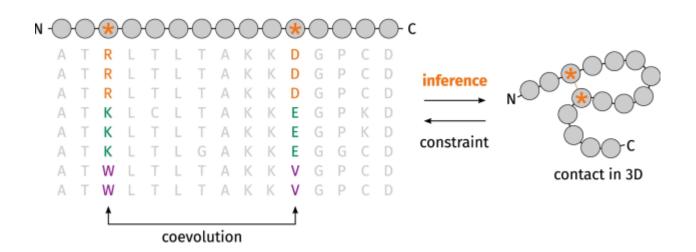
- The sequence is checked against a reference database of sequences -UniRef90 database
- Sequences with sections that align well to our query are then used as input

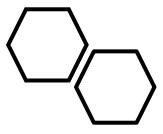




Coevolution of Residues

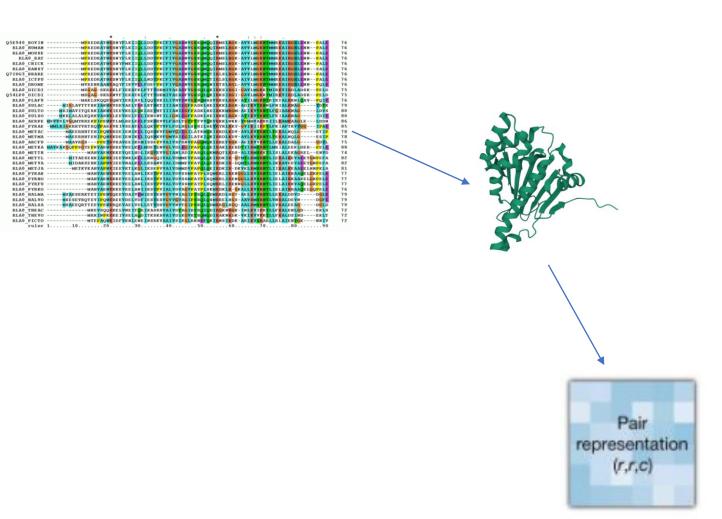
- So how does one go from an alignment to a structure?
- The theory is that residues that coevolve are generally close to each other in the protein's folded state

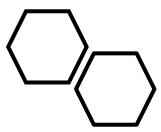




Template Information

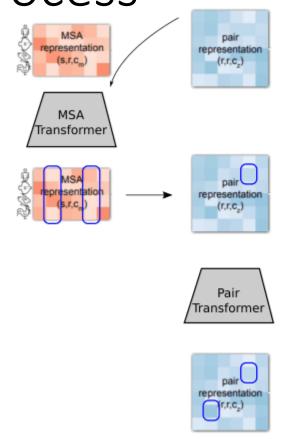
- The similar sequences pulled from also have structural information
- These templates can be converted into distance matrices to determine the distance between residues

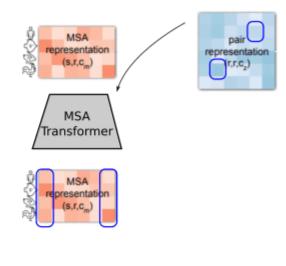


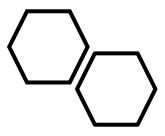


The Evoformer Process

- Takes the MSA representation and the pair representation
- Uses the pair representation to limit the attention of the MSA transformer
- Model then determines two residues are close
- Given this information, the Pair Transformer notes that another two residues could be close
- Process is iterated until a possible structure is resolved

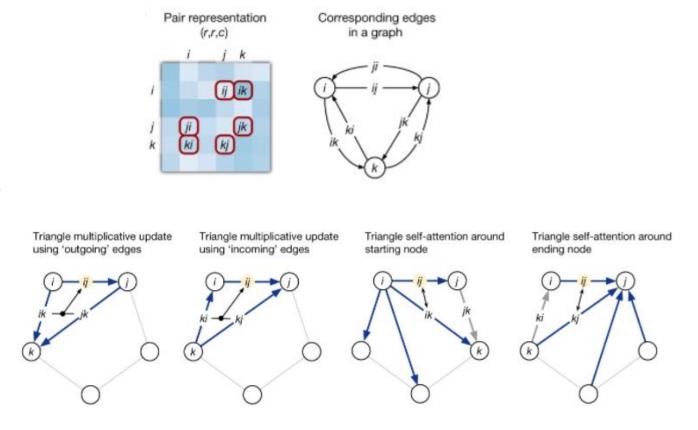


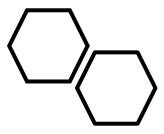




A Closer Look at the Pair Transformer

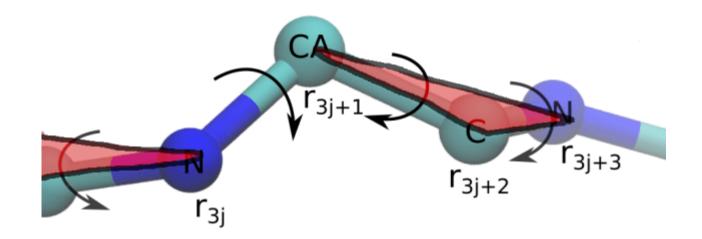
- The pair transformer works on the principle of Triangle inequality, where the sum of two sides must be greater than or equal to the third side.
- Using this theorem, we can determine the likely distance residues have from one another because the distance between three points can never break that theorem

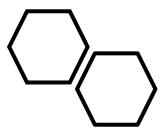




The Structure Module

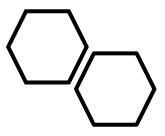
- Begins with each amino acid as a residue gas, or triangle with points at Nitrogen, R group Carbon and the Alpha Carbon
- These "gases" start at an origin point and are moved by the model using the pair distances and the information from the pairwise distance matrix and the MSA





AlphaFold File Output

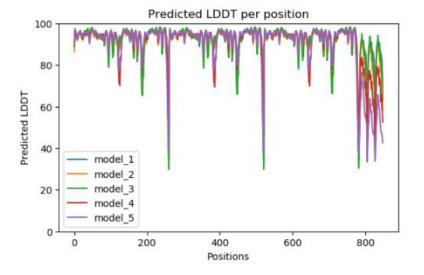
features.pkl	unrelaxed_mode l_*.pdb	relaxed_model_ *.pdb	ranked_*.pdb	ranking_debug.js on	timings.json	msas/	result_model_*. pkl
A pickle file w/ input feature NumPy arrays	A PDB file w/ predicted structure, exactly as outputted by the model	A PDB file w/ predicted structure, after performing an Amber relaxation procedure on the unrelaxed structure prediction	A PDB file w/ relaxed predicted structures, after reordering by model confidence (using predicted LDDT (pLDDT) scores). ranked_0.pdb = highest confidence ranked_4.pdb = lowest confidence	A JSON file w/pLDDT values used to perform the model ranking, and a mapping back to the original model names.	A JSON file w/ times taken to run each section of the AlphaFold pipeline.	A directory containing the files describing the various genetic tool hits that were used to construct the input MSA.	 A pickle file w/ a nested dictionary of the various NumPy arrays directly produced by the model: Structure Module Output Distograms Per-residue pLDDT scores predicted TM-score predicted pairwise aligned errors



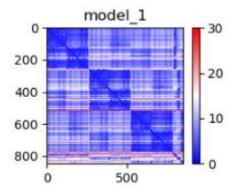
Assessing AlphaFold Accuracy

- We can assess the accuracy of the AlphaFold prediction using:
 - Predicted Local Distance Difference Test (pLDDT)
 - Predicted Alignment Error

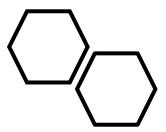
Predicted Local Distance Difference Test (pLDDT)



Predicted Alignment Error (PAE)

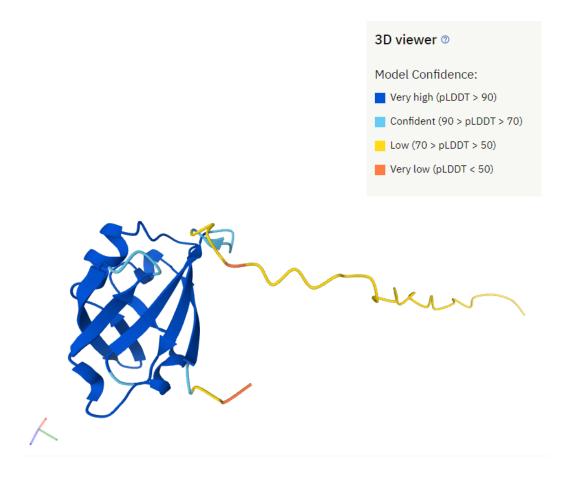


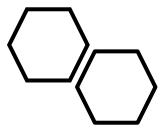
https://github.com/deepmind/alphafold



Predicted Local Distance Difference Test (pLDDT)

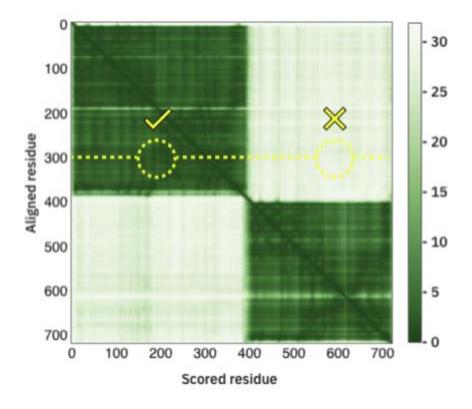
- per-residue confidence metric ranging from 0-100 (100 being the highest confidence)
- Regions below 50 could indicate disordered regions
- This information can be found in each model's result_model_*.pkl file where * is the model number

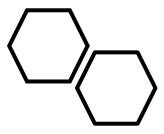




Predicted Alignment Error (PAE)

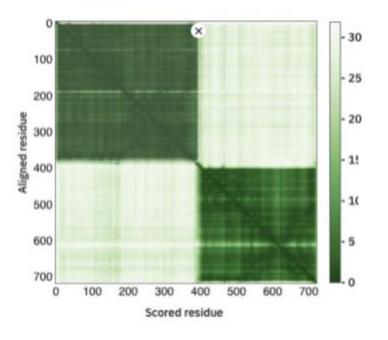
- The color at (x, y) corresponds to the expected distance error in residue x's position, when the prediction and true structure are aligned on residue y.
- So, in the example to the right:
 - The darker color indicates a lower error
 - When we are aligning on residue 300, we are more confident in the position of residue 200 and less confident in the position of residue 600





Predicted Alignment Error (PAE) cont.

- The example in the previous slide came from a multimer prediction
- Here we see that the error is higher when assessing the position between the two chains



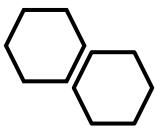


Acknowledgement

Much of this tutorial has been adapted from the Oxford Protein Informatics Group's explanation on AlphaFold 2

References

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- 20. https://github.com/deepmind/alphafold
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Next: Preparing the Batch Script

