Aggregating and optimising AlphaFold2 structure predictions with templates



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CASP14 multimer refinement

Monomer refinement

Goal: Refine structural templates using AF2Input: Single sequence and template from diverse sources



0.6

CASP14 monomers

TM-score

0.7

Goal: Predict protein complexes with AF2 Input: Single sequences and monomer templates from diverse sources Proficient recovery of protein multimers when provided with structural

templates derived from oligomeric states; however, performance deteriorates when templates deviate from the oligomeric conformation

0.3



0.5 0.6 0.7

TM-score



0.5

TM-score

0.6 0.7

0.25

0.20

0.10

0.05

Q 20.15

Protein-protein interaction

Goal: Rigid body protein blind docking Input: Single sequences and monomer templates from DIPS[4] DIPS 100 dataset*

HDOCK	Comb	MSA	Omega
AF2	ESM	None	PDB

No improvement of poor predictions or enhancement of accurace ones No degradation in the quality of accurate predictions

0.5

0.8 O.8

0.3

0.4

0.7

0.6

0.4

Current state of the art for protein folding Can be used to rank quality of prediction [1] Relies on Multiple Sequence Alignment (MSA) for predictions

Research question

To what extent does AlphaFold 2 understand protein structure? Experimental approach

Evaluate accuracy and limitations by analyzing ability to predict protein structures using single sequence and template(s)



22.5 20.0 17.5 15.0 12.5 10.0 RMSD[Å]

> Limited success observed in recovering complexes, especially when compared to a multimer setting, likely attributed to the dynamic and transient nature of the interactions

Recovery

0.7

0.5

0.4

0.4

0.6

Goal: Recover original structure post-alteration through diffusion
Input: Single sequence and diffused template
Protein: Ubiquitin (UPID 014933)
RFDiffusion [2] + FASPR [3]
Template for AlphaFold2

AlphaFold 2 has difficulties in managing structural variations, indicating limitations in capturing dynamic molecular transformations
Successful packing of side chains suggests a better understanding of local structural features
Further supported by good performance for protein docking when provided with perfect templates
AlphaFold 2 has learnt a valid machine learning energy function, yet it has not fully mastered a robust and comprehensive physical energy function
Without MSA information, the local neighborhood to unroll a prediction to a better structure is prohibitively narrow



Side-chain packing

Goal: Side chain packing assessment of AF2 using a provided backbone **Input:** Single sequence and a template from CASP14 with side chains packed

Template aggregation

Goal: Aggregate structural information from several templates Input: Single sequence and pairs of partially truncated templates





 0.0^{1}



TM-score IDDT

Incapable of restoring the structure after alteration through RFdiffusion





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