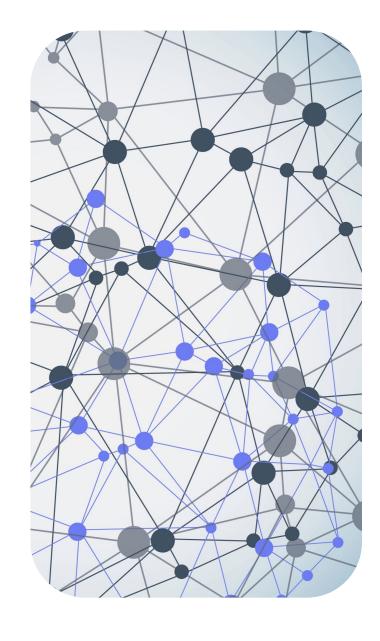
Introduction to AlphaFold2

Shirley (Xue) Li, PhD, Bioinformatician Research Technology, TTS, Tufts University

xue.li37@tufts.edu

tts-research@tufts.edu



The Research Technology Team

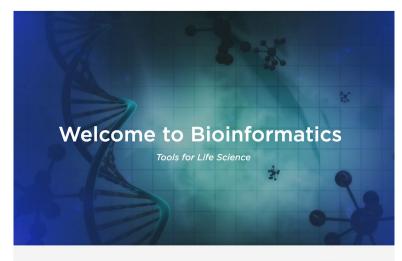
- Consultation on Projects and Grants
- High Performance Cluster Support
- Workshops

https://it.tufts.edu/bioinformatics

https://sites.tufts.edu/datalab/workshops/



Bioinformatics



We offer a range of services including bioinformatics tools on the HPC cluster secondary analysis pipelines for NGS data including DNA-seq, RNA-seq, and ChIP-seq, data visualization, and training and consultation!

Overview

01. The importance of protein structure

Levels of protein organization Approaches to study protein structure

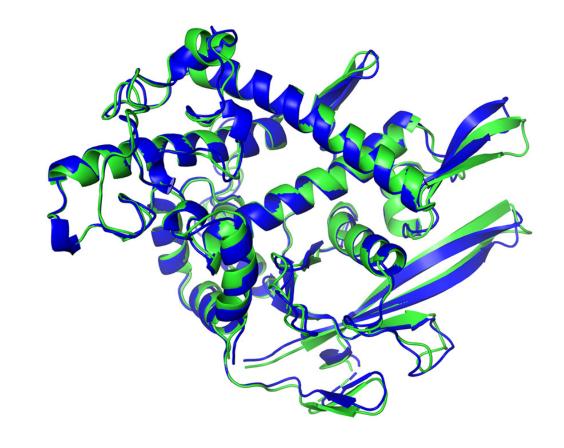
02. Introduction to AlphaFold2

AF architecture

03. Running AlphaFold2 on Tufts server

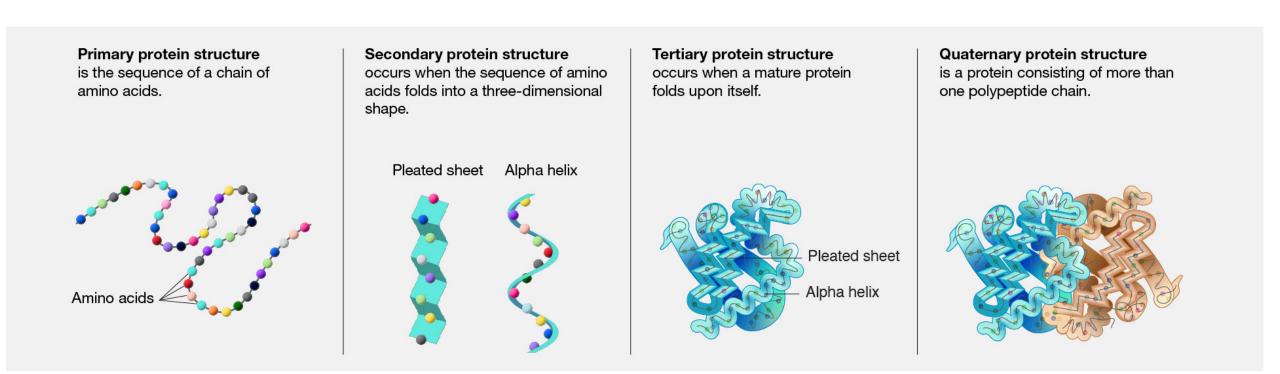
Open OnDemand
Command Line Interface

04. PyMOL: Visualizing Protein Structures



01. The importance of protein structure

Levels of protein structure

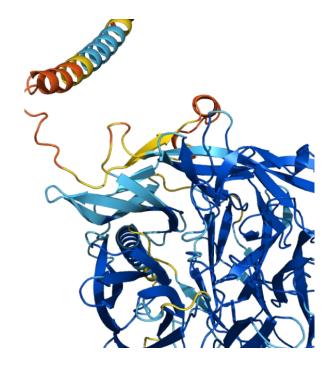


https://www.genome.gov/genetics-glossary/Protein

The importance of protein structure

- Function Determination
- Biological Mechanisms
- Disease Understanding
- Protein Engineering
- Drug Design
- Vaccine Development

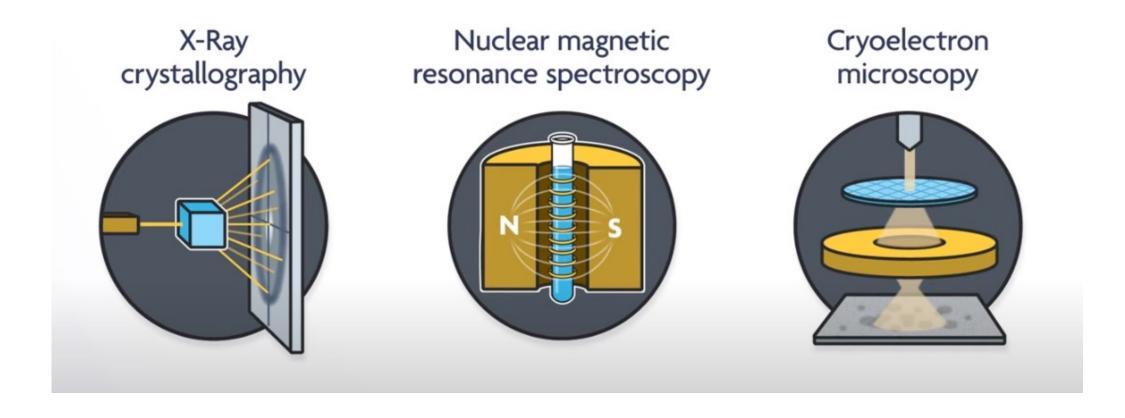




Q8I3H7: May protect the malaria parasite against attack by the immune system. Mean pLDDT 85.57.

https://alphafold.ebi.ac.uk/

Experimental approaches to study protein structure

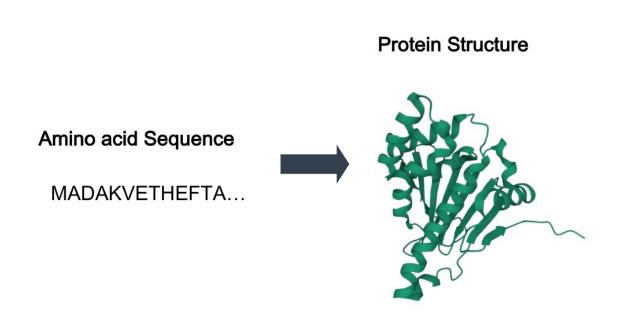


https://www.youtube.com/watch?v=7q8Uw3rmXyE

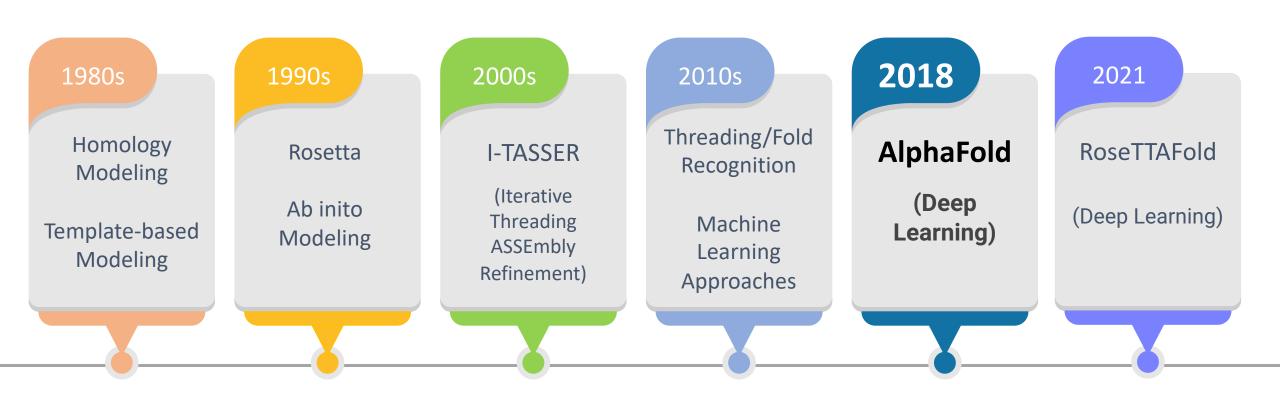
Computational approaches to study protein structure

- Instead of laboratory experimentation, there have been massive efforts to use a protein's sequence to determine structure.
- In 1994, the Critical Assessment of Structure Protein (CASP) was established. It's a scientific even focused on the assessment of protein structure prediction methods.

https://deepmind.google/discover/blog/alphafold-a-solution-to-a-50-year-old-grand-challenge-in-biology/



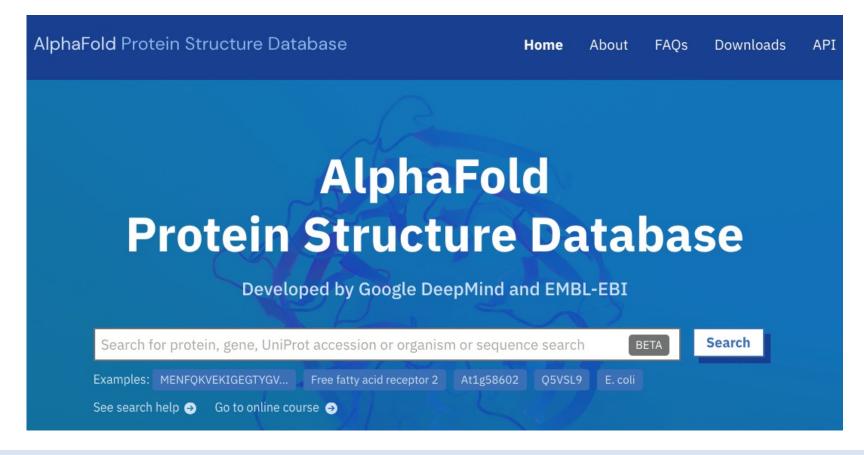
Computational approaches to study protein structure



02. Introduction to AlphaFold2

DeepMind's AlphaFold

AlphaFold - Developed by DeepMind, it made groundbreaking progress in 2018 with AlphaFold 1 and then in 2020 with AlphaFold 2, which marked a significant leap in the field.



Article | Published: 15 January 2020

Improved protein structure prediction using potentials from deep learning



Andrew W. Senior [™], Richard Evans, John Jumper, James Kirkpatrick, Laurent Sifre, Tim Green, Chongli Qin, Augustin Žídek, Alexander W. R. Nelson, Alex Bridgland, Hugo Penedones, Stig Petersen, Karen Simonyan, Steve Crossan, Pushmeet Kohli, David T. Jones, David Silver, Koray Kavukcuoglu & Demis

<u>Hassabis</u>

Nature 577, 706-710 (2020) | Cite this article

164k Accesses | 1704 Citations | 656 Altmetric | Metrics

AlphaFold2

Article Open access Published: 15 July 2021

Highly accurate protein structure prediction with AlphaFold

John Jumper ☑, Richard Evans, Alexander Pritzel, Tim Green, Michael Figurnov, Olaf Ronneberger, Kathryn Tunyasuvunakool, Russ Bates, Augustin Žídek, Anna Potapenko, Alex Bridgland, Clemens Meyer, Simon A. A. Kohl, Andrew J. Ballard, Andrew Cowie, Bernardino Romera-Paredes, Stanislav Nikolov, Rishub Jain, Jonas Adler, Trevor Back, Stig Petersen, David Reiman, Ellen Clancy, Michael Zielinski, ... Demis Hassabis ☑ + Show authors

Nature 596, 583–589 (2021) | Cite this article

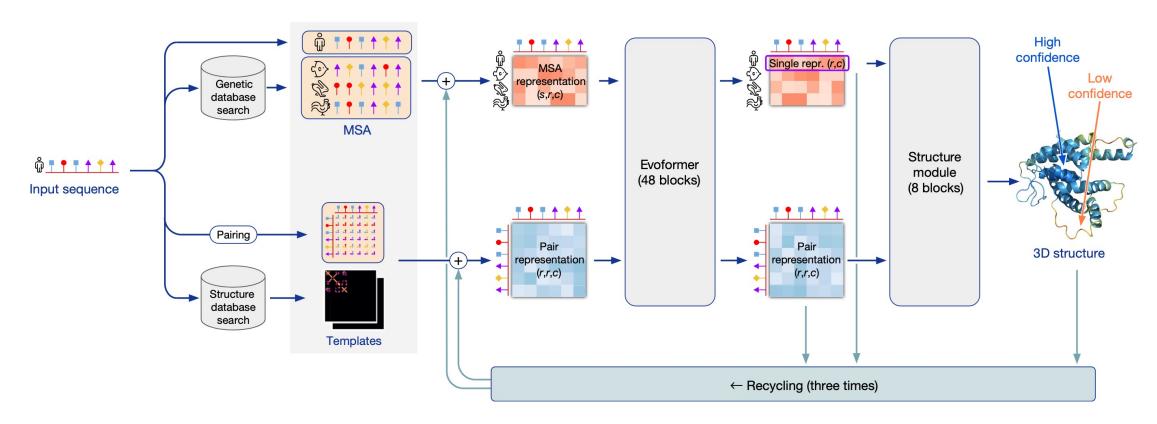
1.47m Accesses | 8815 Citations | 3517 Altmetric | Metrics

AlphaFold vs Other Computational Approaches

- Classical prediction methods require structure templates (e.g. MODELLER, I-TASSER) and they are <u>heavily dependent on</u> <u>sequence homology</u>.
 - These classical methods depend on the alignment of a target protein sequence with other sequences of known structure to infer the target's structure.
- AlphaFold employs deep learning, using a neural network to predict the "distance" and "angles" between residues in a protein, independent of templates.
 - This approach requires significant computational resources due to the complexity of the calculations involved.

AlphaFold 2 Architecture

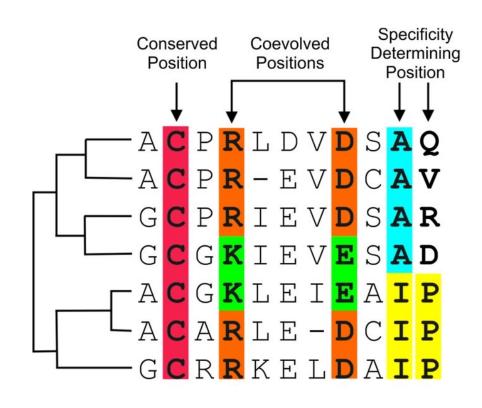
AlphaFold takes only sequence from the user



(Jumper, Evans et al. 2021)

Step 1: Database search and preprocessing

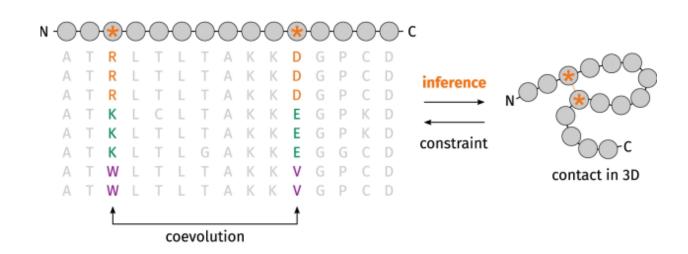
- Protein structural information can be gained by understanding multiple sequence alignments (MSA)
- When we align similar protein sequences we identify:
 - Conserved positions: where the letter does not change
 - Coevolved positions: where the letter will change with another letter
 - Specificity determining positions: where the letter is consistently different



https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9825149/

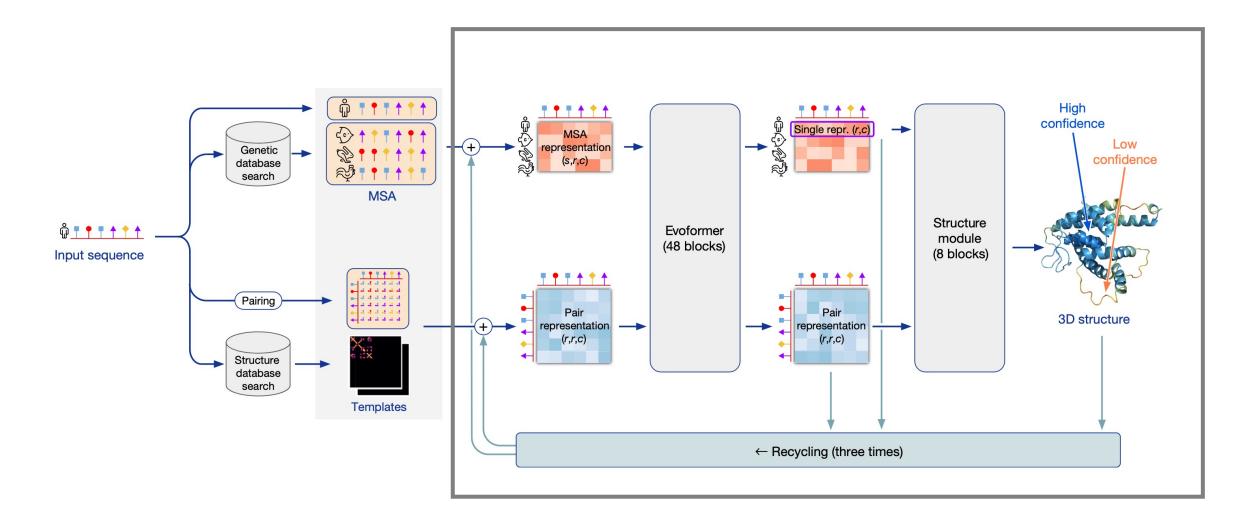
Residue Coevolution

- With an MSA we can identify residues that coevolve, or change together
- We can then reason that residues that change together must be close together in 3D space



https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9825149/

Step 2 & 3: Evoformer and Structure Module



Read the paper to understand the algorithm

Article | Published: 15 January 2020

Improved protein structure prediction using potentials from deep learning

Andrew W. Senior

Richard Evans, John Jumper, James Kirkpa

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Nature **596**, 583–589 (2021) | Cite this article

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AlphaFold represents the state of the art

- Thoroughly validated in competition, but not perfect.
- Not reliable when:
 - Too-sparse MSAs
 - Sequence are not evolutionary
 - Antibody-antigen interface
 - Point mutation studies
 - Large state-dependent structure differences

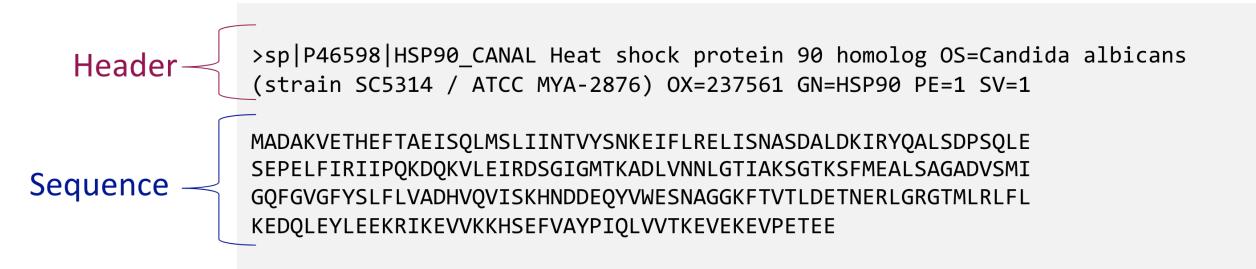
To download a copy of this slides, please go to

https://go.tufts.edu/chbe0165_af

03. Running AlphaFold on Tufts HPC

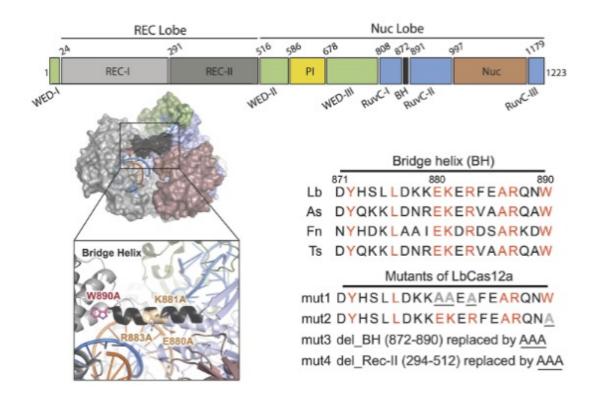
Protein Sequence Information

- Protein Sequence information
- Stored as a FASTA file. Consists of:



Today's study

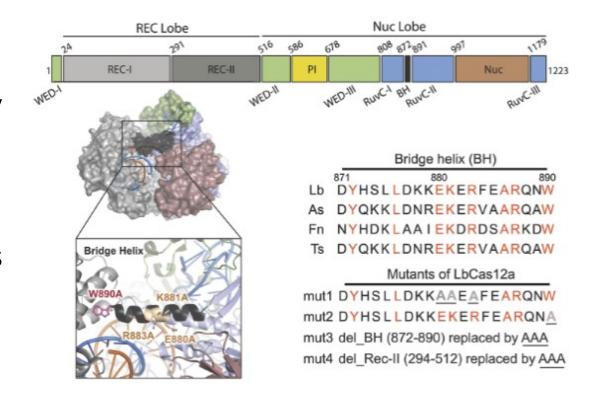
- Today we will be looking at a study by Ma et al. 2022, where they engineer Cas12a variants with reduced trans-activity while maintaining cis-activity
- They start by screening multiple mutants and identify mutant 2 as having reduced trans-activity
- Variants were then introduced in mutant 2 to create a variant with less trans-activity, and maintained cis-activity



https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9825149/

Today's study

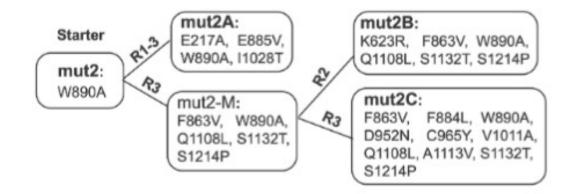
- Cas12a is used for gene editing across various organisms.
- The cis-activity of Cas12a refers to its ability to cleave DNA that is directly bound by the complex formed between Cas12a and its crRNA.
- The trans-cleavage activity of Cas12a refers to its capability to cut single-stranded DNA (ssDNA) molecules not bound by the Cas12a-crRNA complex, a process initiated upon the enzyme's activation through the recognition and cleavage of its target DNA.



https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9825149/

Variant Structure Prediction with AlphaFold2

- Three variants were ultimately refined: mut2B-W, mut2C-W, and mut2C-WF
- We will use AlphaFold2 to predict the structure of mut2C-WF



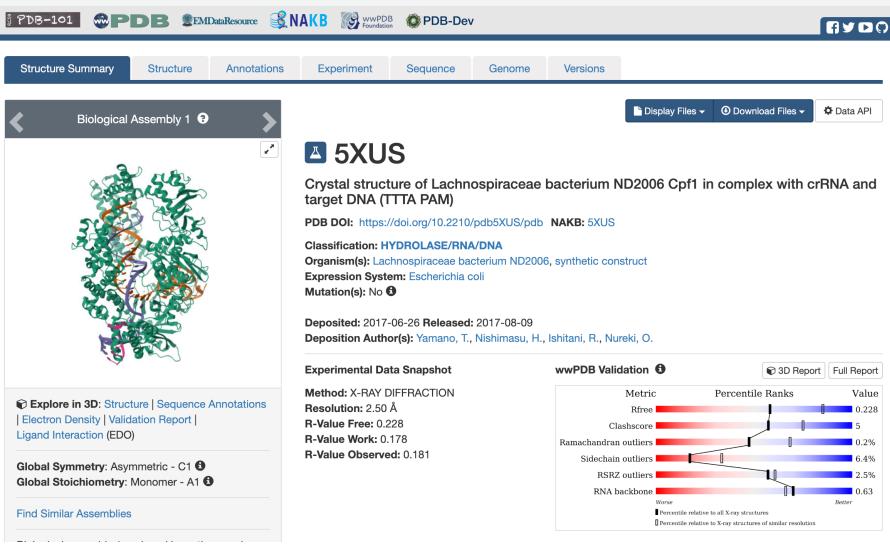
Variant Structure Prediction with AlphaFold2

- Three variants were ultimately refined: mut2B-W, mut2C-W, and mut2C-WF
- We will use AlphaFold2 to predict the structure of mut2C-WF

```
mut2C-WF
F863V, F884L, W890A,
D952N, C965Y, V1011A,
Q1108L, A1113V, S1132T,
S1214P
```



Cas12a protein (previously named Cpf1)



AA sequence of mut2C-WF

F863V, F884L, W890A, D952N, C965Y, V1011A, Q1108L, A1113V, S1132T, S1214P

>5XUS_1|Chain A|LbCpf1_mut2cwf|Lachnospiraceae bacterium ND2006 (1410628) MSKLEKFTNCYSLSKTLRFKAIPVGKTQENIDNKRLLVEDEKRAEDYKGVKKLLDRYYLSFINDVLHSIKLKNLNNYISLFRKKTRTEKENKELENLEINLRKEIAKAF KGNEGYKSLFKKDIIETILPEFLDDKDEIALVNSFNGFTTAFTGFFDNRENMFSEEAKSTSIAFRCINENLTRYISNMDIFEKVDAIFDKHEVQEIKEKILNSDYDVED FFEGEFFNFVLTQEGIDVYNAIIGGFVTESGEKIKGLNEYINLYNQKTKQKLPKFKPLYKQVLSDRESLSFYGEGYTSDEEVLEVFRNTLNKNSEIFSSIKKLEKLFKN FDEYSSAGIFVKNGPAISTISKDIFGEWNVIRDKWNAEYDDIHLKKKAVVTEKYEDDRRKSFKKIGSFSLEQLQEYADADLSVVEKLKEIIIC DADFVLEKSLKKNDAVVAIMKDLLDSVKSFENYIKAFFGEGKETNRDESFYGDFVLAYDILLKVDHIYDAIRNYVTQKPYSKDKFKLYFQNPQ ILRYGSKYYLAIMDKKYAKCLQKIDKDDVNGNYEKINYKLLPGPNKMLPKVFFSKKWMAYYNPSEDIQKIYKNGTFKKGDMFNLNDCHKLIDF FNFSETEKYKDIAGFYREVEEQGYKVSFESASKKEVDKLVEEGKLYMFQIYNKDFSDKSHGTPNLHTMYFKLLFDENNHGQIRLSGGAELFMRRASLKK<u>EE</u>LVVHPANS PIANKNPDNPKKTTTLSYDVYKDKRFSEDQYELHIPIAINKCPKNIFKINTEVRVLLKHDDNPYVIGIDRGERNLLYIVVVDGKGNIVEQYSLNEIINNVNGIRIKTDY HSLLDKKEKERFEARQNWTSIENIKELKAGYISQVVHKICELVEKYDAVIALEDLNSGFKNSRVKVEKQVYQKFEKMLINKLNYMVDKKSNPYATGGALKGYQITNKFE SFKSMSTQNGFIFYIPAWLTSKIDPSTGFANLLKTKYTSIADSKKFISSFDRIMYVPEEDLFEFALDYKNFSRI IRIFRNPKKNNVFDWEEVC LTSAYKELFNKYGINYQLGDIRVLLCEQSDKAFYSSFMALMTLMLQMRNSITGRTDVDFLISPVKNSDGIFYD ANGAYNIARKVLWAIGQFK D952N KAEDEKLDKVKIAIPNKEWLEYAQTSVKH

Running Alphafold2

Hardware Requirements

GPU: It requires NVIDIA GPUs with CUDA support, and for optimal performance, it's recommended to use a high-performance GPU such as the NVIDIA A100, V100, or at least a T4 or RTX 2080 Ti for smaller proteins.

CPU: A modern multi-core CPU (e.g., 8 cores or more) is important for efficient data processing.

Memory (RAM): The amount of system memory required can vary. For predicting structures of individual proteins (monomers), at least 16 GB of RAM is recommended, but 32 GB or more may be required for larger proteins or for multimer predictions.

Computational Time

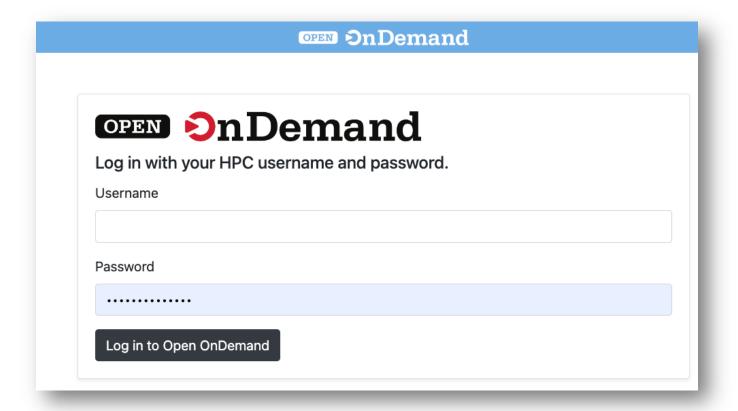
The time it takes to run a prediction can vary from a few hours to several days, depending on:

- The complexity of the protein or protein complex.
- The model_preset used (monomer vs. multimer).
- The performance of the hardware, especially the GPU.

Accessing AlphaFold2 on Tufts HPC

 Command Line Interface (CLI) xli37@login-prod-01:~>module load alphafold/2.3.2
xli37@login-prod-01:~>

OpenOnDemand



Run AlphaFold2 on Tufts HPC

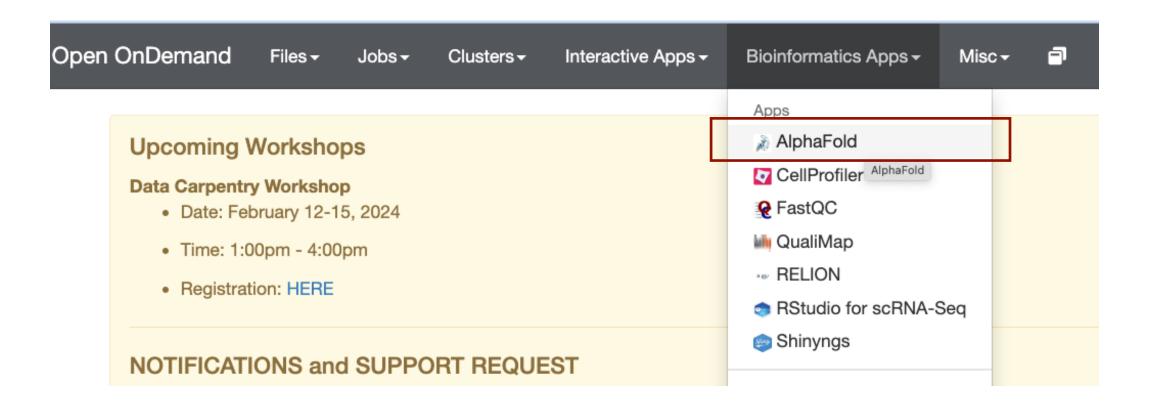
Example script is provided

/cluster/tufts/bio/tools/training/cas12a_af2_sp24/script/runaf.sh

```
#!/bin/bash
#SBATCH -p gpu
#SBATCH -n 8
#SBATCH --mem=64g
#SBATCH --time=2-0
#SBATCH -o output.%j
#SBATCH -e error.%i
#SBATCH -N 1
#SBATCH --gres=gpu:a100:1
# Load the AlphaFold2 and NVIDIA modules
module load alphafold/2.3.2
nvidia-smi
# Make the results directories
mkdir /cluster/home/xli37/cas12a af2 sp24/out/
# Specify where your output directories and raw data are
outputpath1=/cluster/home/xli37/cas12a af2 sp24/out/
fastapath=/cluster/home/xli37/cas12a_af2_sp24/5XUS_mut2cwf_modified.fasta
# Date to specify if you want to avoid using template
maxtemplatedate1=2020-01-01
run_alphafold.sh --output_dir=$outputpath1 \
        --fasta_paths=$fastapath \
        --max template date=$maxtemplatedate1 \
        --model_preset=multimer \
        --models to relax=best \
        --data_dir=/cluster/tufts/biocontainers/datasets/alphafold/db_20231031/
        --uniref90_database_path=/cluster/tufts/biocontainers/datasets/alphafold/db_20231031/uniref90/uniref90.fasta
        --mgnify_database_path=/cluster/tufts/biocontainers/datasets/alphafold/db_20231031/mgnify/mgy_clusters_2022_05.fa
        --pdb_segres_database_path=/cluster/tufts/biocontainers/datasets/alphafold/db_20231031/pdb_segres/pdb_segres.txt \
        --template_mmcif_dir=/cluster/tufts/biocontainers/datasets/alphafold/db_20231031/pdb_mmcif/mmcif_files \
        --max_template_date=2022-01-01 \
        --obsolete_pdbs_path=/cluster/tufts/biocontainers/datasets/alphafold/db_20231031/pdb_mmcif/obsolete.dat \
        --use_gpu_relax=True \
        --bfd_database_path=/cluster/tufts/biocontainers/datasets/alphafold/db_20231031/bfd/bfd_metaclust_clu_complete_id30_c90_final_seq.sorted_opt \
        --uniref30 database path=/cluster/tufts/biocontainers/datasets/alphafold/db 20231031/uniref30/UniRef30 2021 03 \
        --uniprot_database_path=/cluster/tufts/biocontainers/datasets/alphafold/db_20231031/uniprot/uniprot.fasta
```

Running AlphaFold2 with Open OnDemand

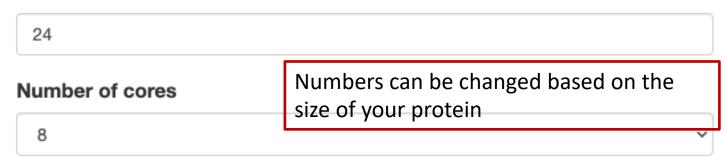
https://ondemand.pax.tufts.edu



AlphaFold

This app will launch AlphaFold. More information about AlphaFold can be found here (https://github.com/deepmind/alphafold).

Number of hours



Amount of memory



NOTE: jobs submitted to the preempt partition may get automatically killed to allow higher priority jobs to run

Select the GPU type



Software Version

2.3.2

Database

20231031

Working Directory

Change it to your own working directory

/cluster/home/tutln02/cas12a_af2_sp24/

Select your project directory; defaults to \$HOME

Output directory Name

/cluster/home/tutln02/cas12a_af2_sp24/

Change it to your own output directory

Where the results will be going to (relative to the working directory field above). Example: alphafold.out

fasta_paths

Input file. Fasta format.

/cluster/home/tutln02/cas12a_af2_sp24/5XUS_mut2cwf_modified.fasta

The fasta files containing amino acid sequence(s) to fold. If there are more multiple files, please separate them using comma(e.g. seq1.fasta,seq2.fasta)

model_preset

Let's use multimer for now

multimer

Select to run the monomer or multimer model for sequences.

models_to_relax

best

After generating the predicted model, AlphaFold runs a relaxation step to improve local geometry. By default, only the best model (by pLDDT) is relaxed (--models_to_relax=best), but also all of the models (--models_to_relax=all) or none of the models (--models_to_relax=none) can be relaxed.

num_multimer_predictions_per_model

How many predictions (each with a different random seed) will be generated per model. E.g. if this is 2 and there are 5 models then there will be 10 predictions per input. Note: this FLAG only applies if model_preset=multimer. (default: 5).

max_template_date

2020-01-01

Maximum template release date to d It can be any past date. DD). Important if folding historical tes

Extra parameters

This parameter is crucial for benchmarking and studies, ensuring predictions replicate original conditions without using future knowledge unavailable at the study time.

This date acts as a cutoff, meaning that only protein templates solved on or before this date will be considered during the structure prediction process.

Extra parameters to use. Multiple space-separated parameters can be used.

Launch

* The AlphaFold session data for this session can be accessed under the data root directory.

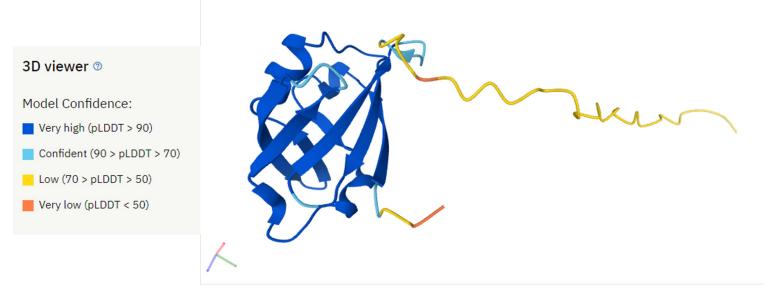
Output

```
the MSA information, processed to be given to AlphaFold as input (+ more)
4.8M Dec 6 17:26 features.pkl
                                           subdirectory with MSA information, in human-readable format
4.0K Dec 6 17:26 msas
125K Dec 6 17:29 unrelaxed model 1 ptm.pdb
125K Dec 6 17:32 unrelaxed model 2 ptm.pdb
                                                the (not yet relaxed) predictions from the
125K Dec 6 17:34 unrelaxed model 3 ptm.pdb
                                                five AlphaFold models.
125K Dec 6 17:35 unrelaxed model 4 ptm.pdb
125K Dec 6 17:37 unrelaxed model 5 ptm.pdb
243K Dec 6 17:29 relaxed model 1 ptm.pdb
243K Dec 6 17:32 relaxed_model_2_ptm.pdb
                                               the relaxed versions of the predicted
243K Dec 6 17:34 relaxed model 3 ptm.pdb
                                               structures
243K Dec 6 17:36 relaxed model 4 ptm.pdb
243K Dec
          6 17:37 ranked_0.pdb
243K Dec
                                   the relaxed versions of the predicted structures, but now ranked
243K Dec 6 17:37 ranked 2.pdb
                                   based on pLDDT (with highest pLDDT for ranked 0.pdb)
243K Dec 6 17:37 ranked 3.pdb
243K Dec 6 17:37 ranked 4.pdb
 29M Dec 6 17:29 result model 1 ptm.pkl
 29M Dec 6 17:32 result model 2 ptm.pkl
                                              extra outputs in .pkl format. Contains a lot of information,
 29M Dec 6 17:34 result model 3 ptm.pkl
                                              including pLDDT and PTM values
 29M Dec 6 17:35 result model 4 ptm.pkl
 29M Dec 6 17:37 result_model_5_ptm.pkl
 829 Dec 6 17:37 timings.json
                                                     information on how long the different parts of the
 370 Dec 6 17:37 ranking debug.json
                                                     AlphaFold run took, in seconds
                                   information on the pLDDT of each model,
                                   and how they were ranked
```

https://elearning.vib.be/courses/alphafold/lessons/alphafold-on-the-hpc/topic/alphafold-outputs/

AlphaFold2 Accuracy

Predicted Local Distance Difference Test



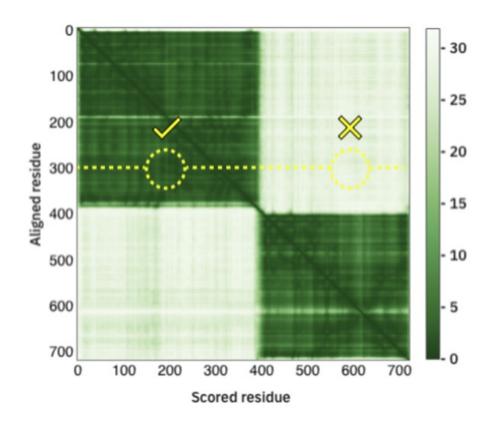
- The Predicted Local Distance Difference Test (pLDDT) is a per-residue confidence metric ranging from 0-100 (100 being the highest confidence)
- Regions below 50 could indicate disordered regions

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9825149/

AlphaFold2 Accuracy

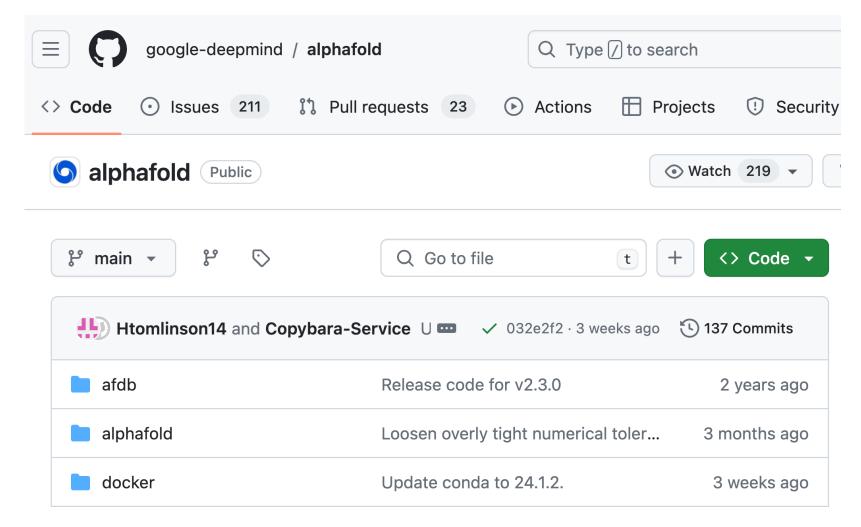
Predicted Alignment Error

- The Predicted Alignment Error (PAE) gives us an expected distance error based on each residue.
- If we are more confident that the distance between two residues is accurate, then the PAE is lower (darker green). If we are less confident that the distance between two residues is accurate, the PAE is higher (lighter green)



https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9825149/

Github page for AlphaFold

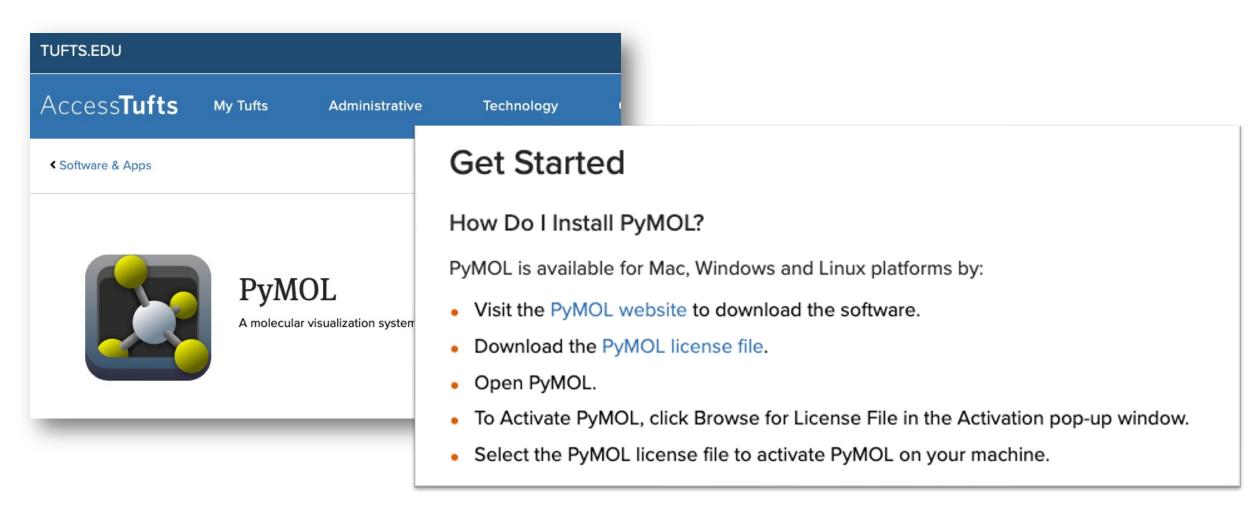


https://github.com/google-deepmind/alphafold/?tab=readme-ov-file#running-alphafold

04. PyMOL: Visualizing Protein Structures

Pymol is accessible for free with Tufts credentials

https://access.tufts.edu/pymol

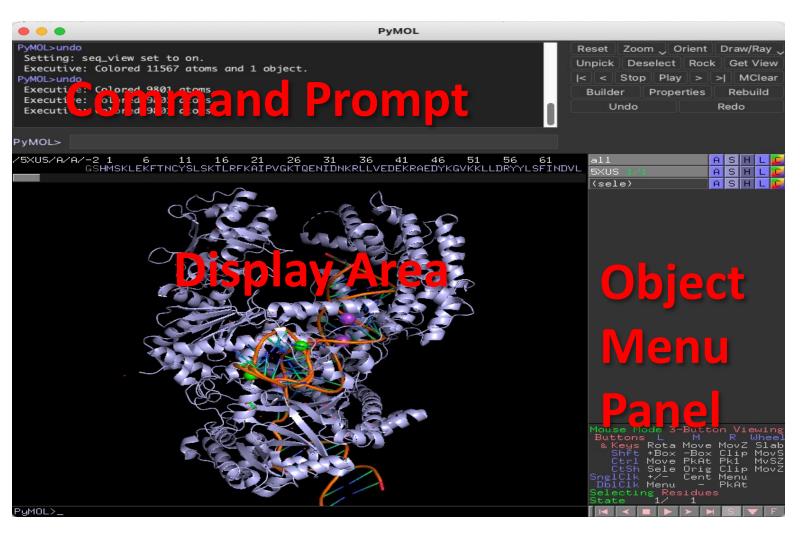


https://www.rcac.purdue.edu/files/training/AlphaFold Protein Structure Prediction.pdf

Molecular visualization software

- Given atomic coordinate or volumetric data
- X-ray, NMR, EM, AlphaFold, etc.
- Generates an interactive visualization
- Can render and save publication-quality images and videos.

https://www.rcac.purdue.edu/files/training/AlphaFold Protein Structure Prediction.pdf



Misc Controls

Misc Controls

Pymol Reference Card

Pymol Reference Card

Modes

Pymol supports two modes of input: point and click mode, and command line mode. The point and click allows you to quickly rotate the molecule(s) zoom in and out and change the clipping planes. The command line mode where commands are entered into the external GUI window supports all of the commands in the point and click mode, but is more flexible and possibly useful for complex selection and command issuing. Commands entered on the command line are executed when you press the return key.

command help

help keyword

Pymol Reference Card

Pymol Reference Card

Modes

Pymol supports two modes of input: point and click mode, and command line mode. The point and click allows you to quickly rotate the molecule(s) zoom in and out and change the clipping planes. The command line mode where commands are entered into the external GUI window supports all of the commands in the point and click mode, but is more flexible and possibly useful for complex selection and command issuing. Commands entered on the command line are executed when you press the return key.

Loading Files

Loading 1 nes	
file loading	load data/test/pept.pdb
loading from terminal	<pre>pymol data/test/pept.pdb</pre>
toggle between text and gray	phics Esc
toggle Y axis rocking	rock
stereo view	stereo on/off
stereo type stereo crosse	eye / walleye / quadbuffer
undo action	undo
reset view	reset
reinitialize Pymol	reinitialize
quit (force, even if unsaved)	quit

Mouse Control

	L Rota	M Move	$_{ m MovZ}$	Wheel Slab	
Shift	+Box	-Box	Clip	MovS	
Ctrl	+/-	PkAt	Pk1	_	
CtSh	Sele	Cent	Menu	_	
DblClk	Menu	Cent	PkAt	_	
set the cer	nter of ro	tation		origin	selection

Atom Selection

object-name/seqi-id/chain-id/resi-id/name-id

, , , , , , , , , , , , , , , , , , , ,	
molecular system selection	/pept
molecule selection	/pept/lig
chain selection	/pept/lig/a
residue selection	/pept/lig/a/10
atom	/pept/lig/a/10/ca
ranges	lig/a/10-12/ca
ranges	a/6+8/c+o
missing selections	/pept//a
naming a selection select	bb, name c+o+n+ca
count atoms in a selection	count_atoms bb
remove atoms from a selection	remove resi 5
general all, none, hydro, hetatm	, visible, present
atoms not in a selection select	sidechains, ! bb
atoms with a vdW gap $< 3 \text{ Å}$	resi 6 around 3
atom centers with a gap $< 1.0 \text{ Å}$ al.	l near 1 of resi 6
atom centers within < 4.0 Å all to	within 4 of resi 6

Basic Commands

Some commands used with atoms selections. If you are unsure about the selection, click on the molecule part that you want in the viewing window and then look at the output line to see the selection.

fill viewer with selection center a selection colour a selection force Pymol to reapply colours set background colour vdW representation of selection stick representation of selection	zoom /pept//a center /pept//a colour pink, /pept//a recolor bg_color white show spheres, 156/ca show sticks, a//
line representation of selection ribbon representation of selection dot representation of selection mesh representation of selection surface representation of selection nonbonded representation of selec-	show lines, /pept show ribbon, /pept show dots, /pept show mesh, /pept n show surface, /pept
nonbonded sphere representation nb.spheres, /pept cartoon representation of selectic clear all rotate a selection rotate of	

Cartoon Settings

Setting the value at the end to 0 forces the secondary structure to go though the CA position.

cylindrical helices set cartoon_cylindrical_helices,1 fancy helices [tubular edge] set cartoon_fancy_helices,1

flat sheets
smooth loops
set cartoon_smooth_loops,1
find rings for cartoon
cartoon_ring_finder,[1,2,3,4]

ring mode
nucleic acid mode
cartoon sidechains
rebuild
set cartoon_ring_mode,[1,2,3]
set nucleic_acid_mode,[0,1,2,3,4]
set cartoon_side_chain_helper;
rebuild

primary colour set cartoon_color,blue secondary colour set cartoon_highlight_color,grey a limit colour to ss set cartoon_discrete_colors,on a cartoon transparency set cartoon_transparency, 0.5 o cartoon loop cartoon loop, a// a cartoon loop cartoon loop, a// a cartoon rectangular cartoon rect, a// cartoon oval cartoon oval, a// cartoon tubular cartoon tube, a// cartoon arrow cartoon arrow, a// cartoon dumbell cartoon dumbell, a// b-factor sausage cartoon putty, a//

Image Output

low resolution	ray
high resolution	ray 2000,2000
ultra-high resolution	ray 5000,5000
change the default size [pts]	viewport 640,480
image shadow control	set ray_shadow,0
image fog control	set ray_trace_fog,0
image depth cue control	set depth_cue,0
image antialiasing control	set antialias,1
export image as .png	png image.png

Hydrogen Bonding

Draw bonds between atoms and label the residues that are involved.

draw a line between atoms	distance 542/oe1,538/ne
set the line dash gap	set dash_gap,0.09
set the line dash width	set dash_width,3.0
set the line dash radius	set dash_radius,0.0
set the line dash length	set dash_length,0.15
set round dash ends	set dash_round_ends,on
hide a label	hide labels, dist01
label a reside label	(542/oe1), "%s" %("E542")
set label font	set label_font_id,4
set label colour	set label_color,white

Electrostatics

There are a number of ways to apply electrostatics in Pymol. The user can use GRASP to generate a map and then import it. Alternatively the user can use the APBS Pymol plugin. Pymol also has a built in function that is quick and dirty.

generate electrostatic surface action > generate>vacuum
electrostatics > protein contact potential

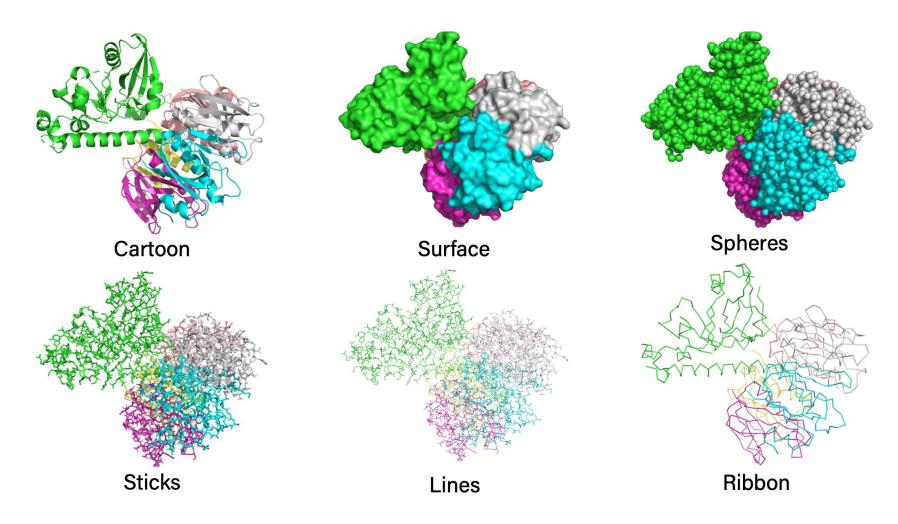
Pymol Movies (mac)

Loading Data

PyMOL handles PDB, mmCIF, MRC, SITUS, etc

- Can open files on your computer
 - File → Open
 - load <path to file>
- Can download directly from PDB
 - File → Get PDB
 - fetch <PDB code>

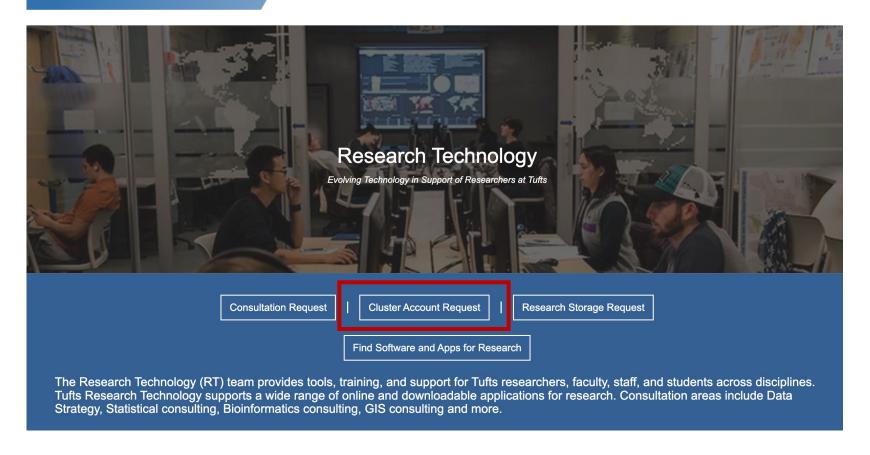
Representations for Atomic Coordinate Data



https://www.rcac.purdue.edu/files/training/AlphaFold Protein Structure Prediction.pdf

For those without access to an HPC account

Research Technology



https://it.tufts.edu/researchtechnology.tufts.edu

Hands-on tutorial 2024 Spring Latest version

https://go.tufts.edu/chbe0165_af

Hands-on session 1: Run AlphaFold2 on Tufts HPC with Open OnDemand App

https://github.com/tuftsdatalab/tuftsWorkshops/blob/main/docs/2024_workshops/cas12aAlphaFold2 sp24/02 Run AlphaFold2 OpenOndemandApp.md

Hands-on session 2: Visualize alphafold2 predicted structure with PYMOL

https://github.com/tuftsdatalab/tuftsWorkshops/blob/main/docs/2024_workshops/cas12aAlphaFold2_sp24/03_Vizualize_predicted_structure_with_PYMOL.md

Hands-on tutorial, 2023 Spring: Content developed by Jason Larid, former bioinformatics scientist.

https://github.com/tuftsdatalab/tuftsWorkshops/tree/main/docs/20 23_workshops/cas12aAlphaFold2

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