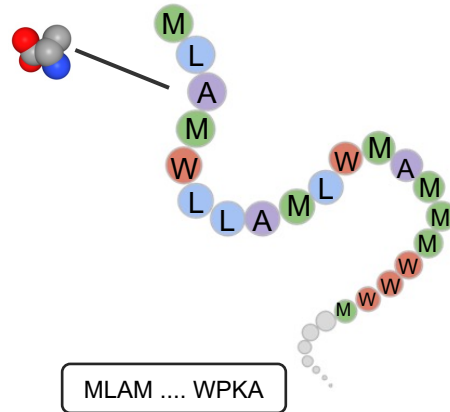


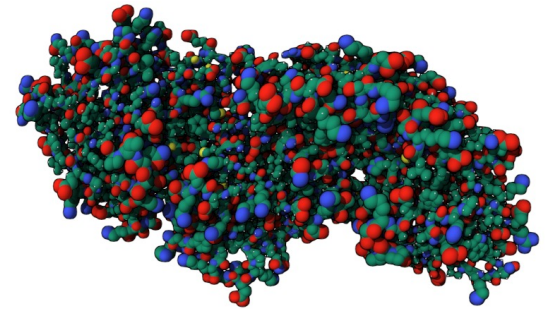
# Determining protein 3D structures

- Proteins consist of amino acid sequences that fold into 3D structures

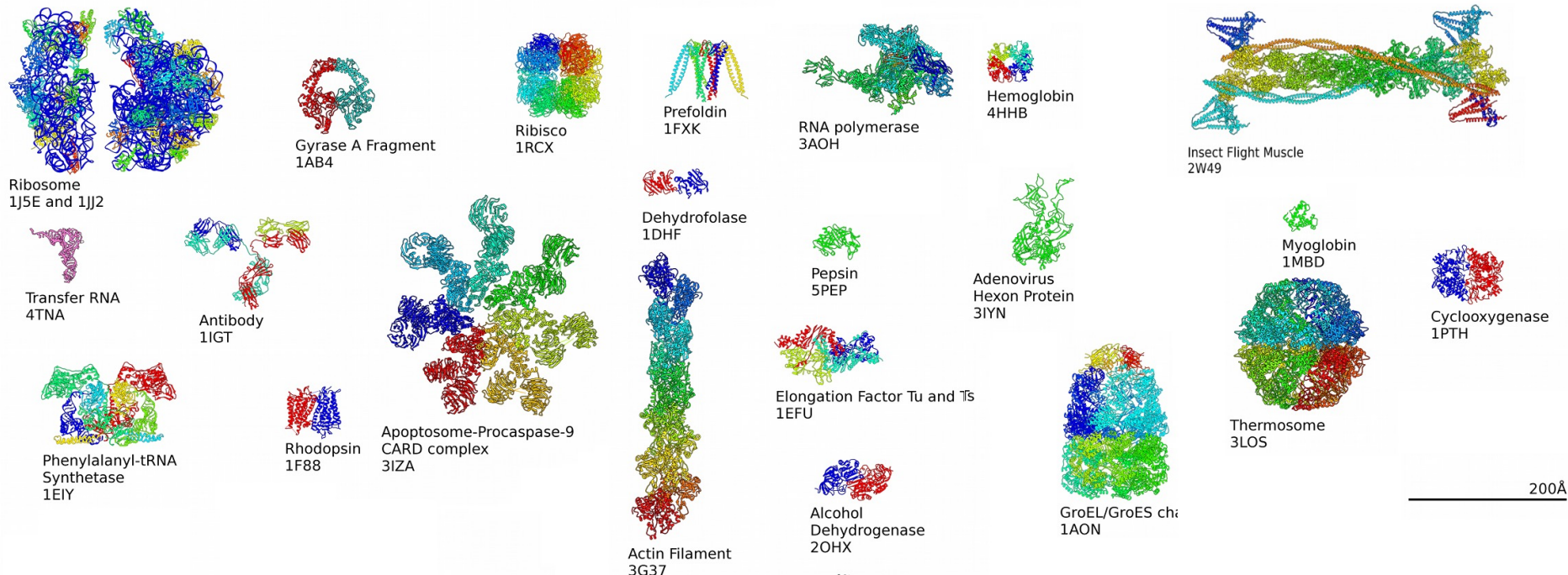
20 different amino acids;  
each amino acid is a small  
molecule



Folding into  
3D structure

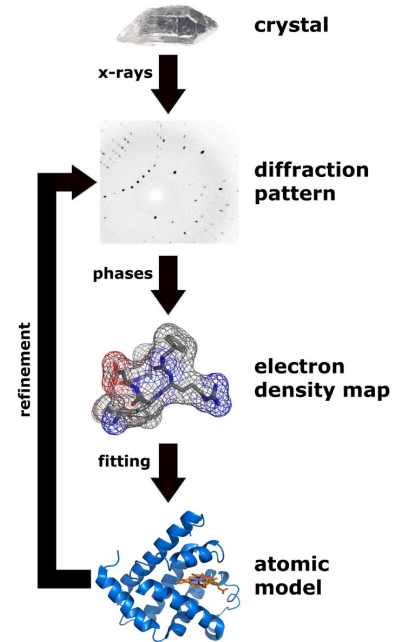


# Protein structure space



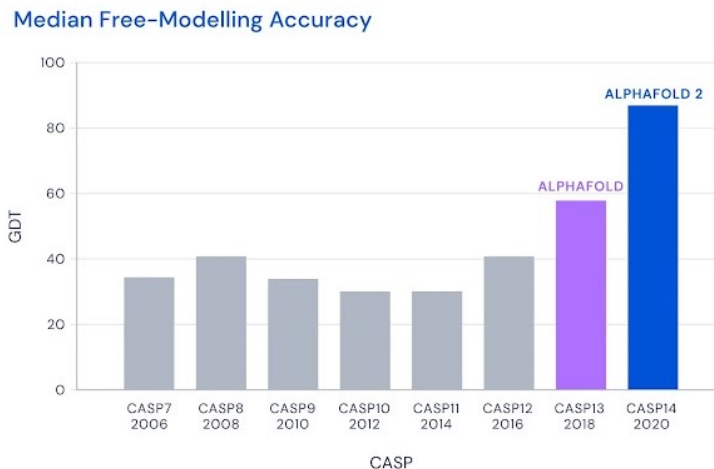
# Experimentally determining 3D structures

- Nuclear Magnetic Resonance (NMR) Spectroscopy
- Cryogenic Electron Microscopy (Cryo-EM)
- Electron Crystallography
- X-ray Crystallography
  - 1. Protein Purification
  - 2. Protein Crystallization
  - 3. X-ray Diffraction
  - 4. Electron Density Maps
  - 5. Atom Model
  - 6. Refinements
- For novel proteins, this process typically takes several months or even up to over a year
- Protein Data Bank (PDB): stores ~180,000 experimentally determined protein 3D structures (~600M proteins are sequenced)



# Predicting protein 3D structures

- Predicting protein 3D structure from protein sequence is desirable
  - Was not possible (with high accuracy) until 2020:



- Deep Learning Models that can predict protein 3D structures
  - AlphaFold 2
  - ESMFold
  - RoseTTAFold

# AlphaFold2 - Input

Multiple Sequence Alignment (MSA)

M	L	A	M	...	K	A
M	L	D	M		V	A
M	L	K	M		E	A
...	...	...	...	...	...	...
M	L	K	M		E	A

MSA

MLAM .... WPKA

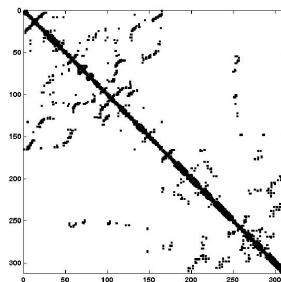
embedding

M	L	A	M	...	K	A
M	L	D	M		V	A
M	L	K	M		E	A
...	...	...	...	...	...	...
M	L	K	M		E	A

$\in (N_{seq}, N_{res}, c_m)$

co-evolution

Structure templates



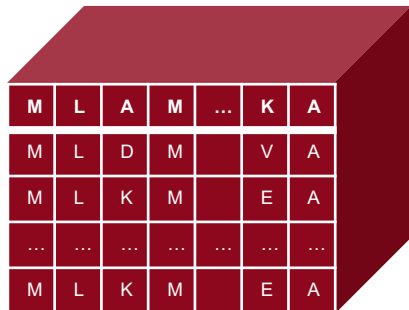
embedding

		(i,j)		

$\in (N_{res}, N_{res}, c_r)$

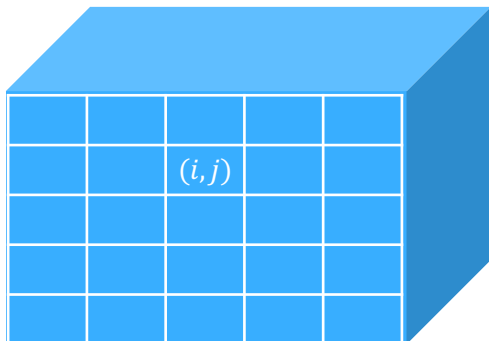
# AlphaFold2 - Evoformer

MSA



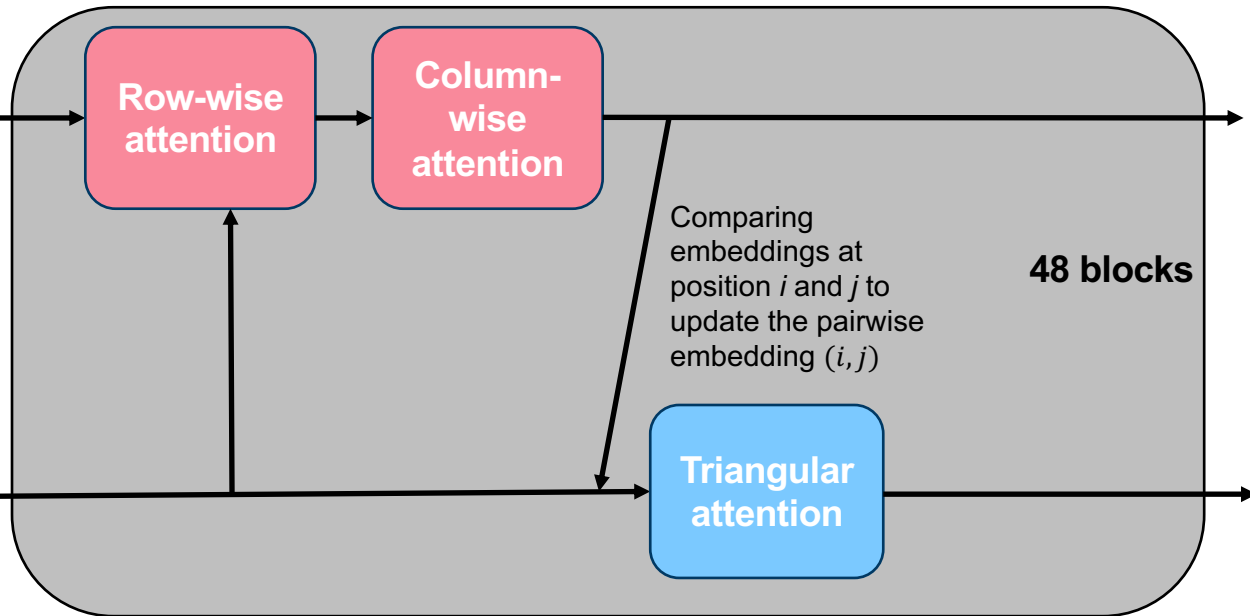
$\in (N_{seq}, N_{res}, c_m)$

Pair representations



$\in (N_{res}, N_{res}, c_r)$

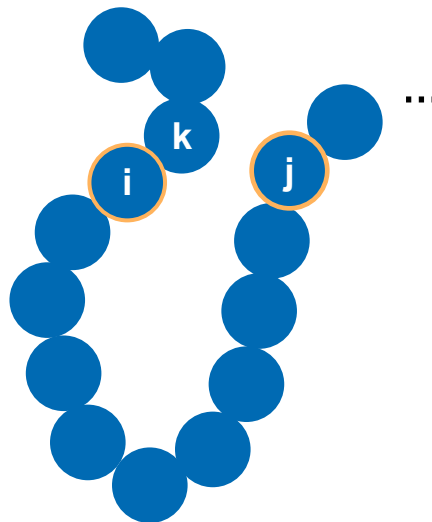
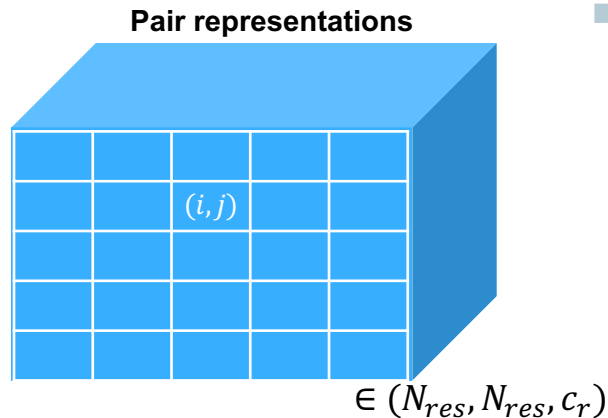
Evoformer



- Triangular attention: Node rep.  $(i, j)$  is updated using all edges between  $i$  &  $k$  and  $j$  &  $k$

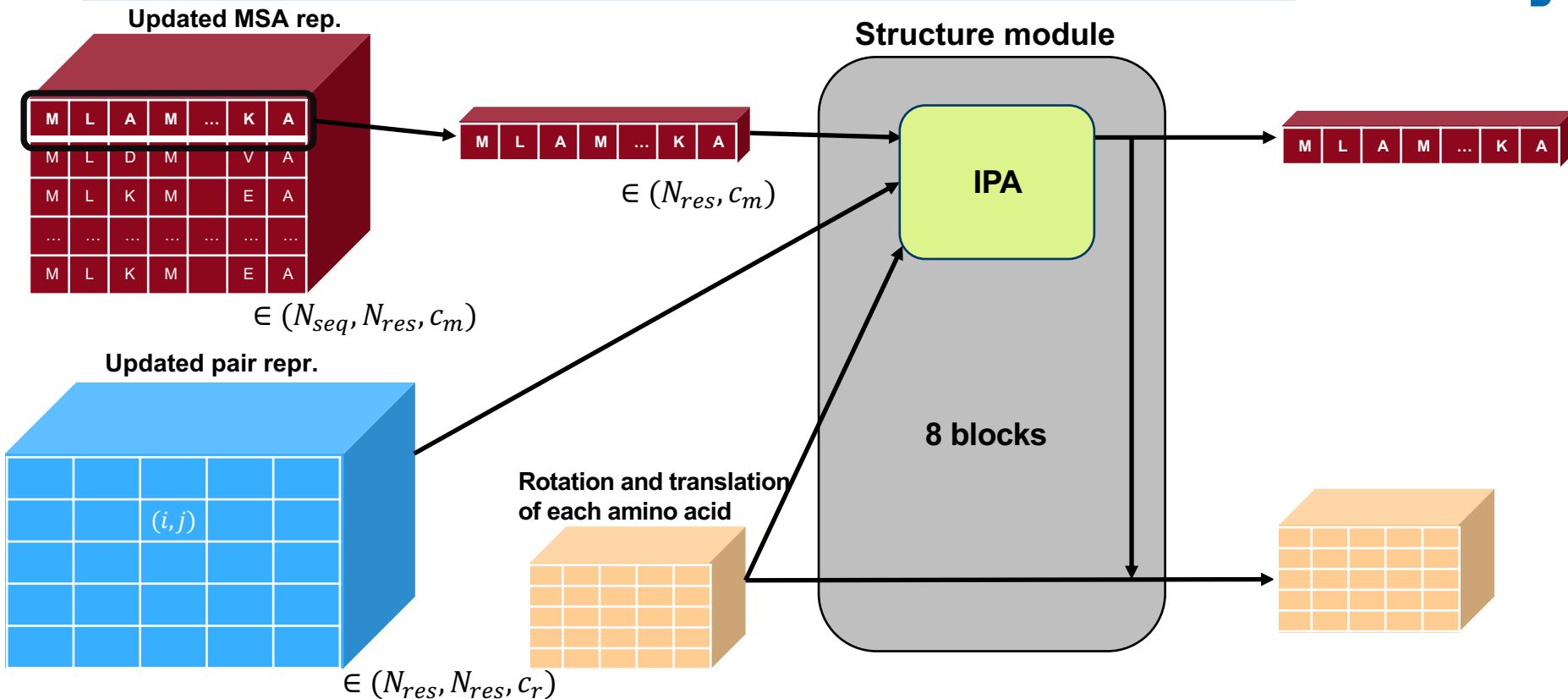
# AlphaFold2 – Triangular Attention

- Triangular attention: Node rep.  $(i, j)$  is updated using all edges between  $i$  &  $k$  and  $j$  &  $k$ 
  - Integrating Euclidean geometry into the network:  
Knowing distance between  $i$  &  $k$  and between  $j$  &  $k$  put a strong constraint of distance between  $i$  &  $j$

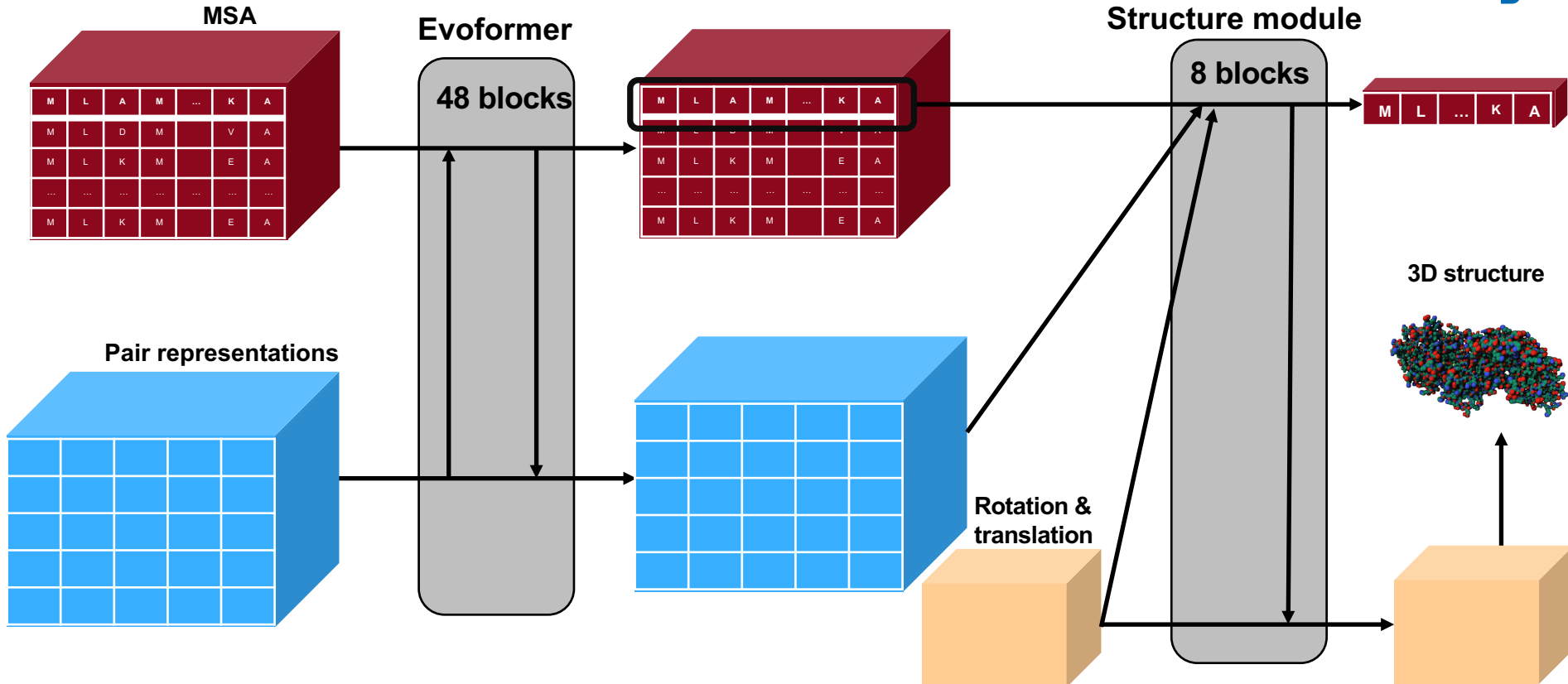




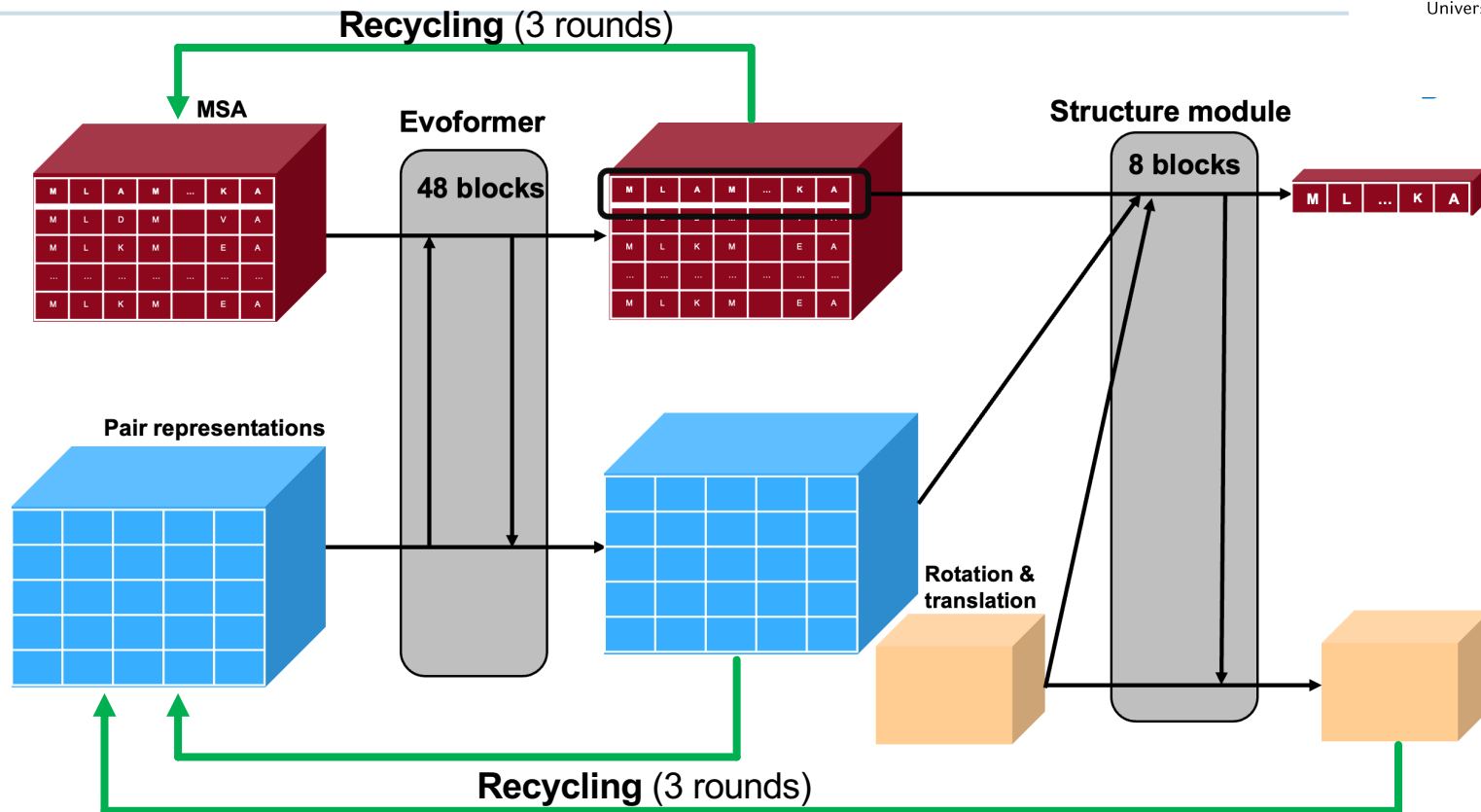
# AlphaFold2 – Structure module



# AlphaFold2 – Full Model



# AlphaFold2 – Recycling



- Loss function:
  - Structural loss named FAPE: Similar to RMSD (root mean squared deviation) of atomic positions
  - Auxiliary losses:
    - Distogram loss: Comparing the pairwise distances between amino acids to ground truth
    - MSA masking: Some tokens of the MSA are masked out and are predicted during training
    - ...
- Training data:
  - ~120k experimentally determined protein 3D structures from the PDB
  - After first run of training:
    - Predicting structures of ~350k proteins with yet unknown structures
    - New training on experimental and predicted 3D structures

# AlphaFold2 – Capabilities and limitations

## ■ Capabilities

- Single protein chains
- Protein multimers
- Protein-protein complexes
- AlphaFold2 can often predict protein structure, even if there are no known related protein structures, if a sequence has many related sequences

## ■ Limitations

- Struggles to predict the structures of protein with few closely related protein sequences
- Cannot predict effect of point mutations
- AlphaFold2 does not capture such conformational changes
- Cannot predict interactions with other molecules, e.g., small molecules