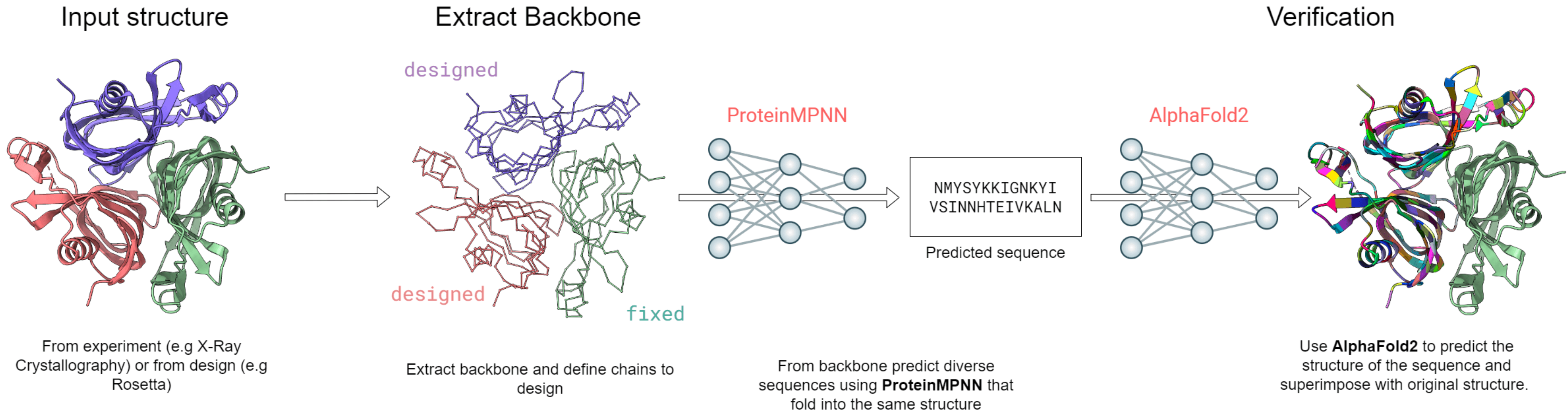


‘Generative AI’ for protein design

Structure-based protein design workflow

Assumption: Structure → Function



Not shown: **protein Language Models** (purely sequence-based)

Analogy to ChatGPT



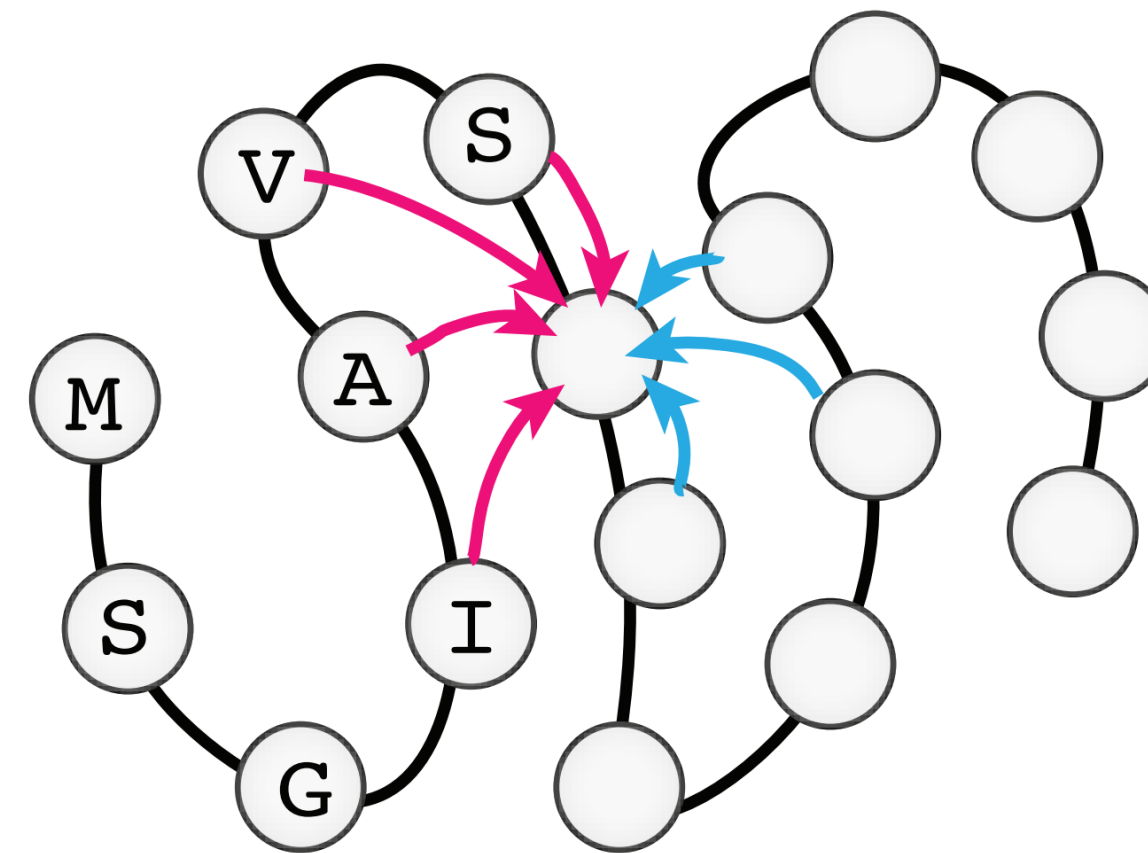
Natural language models

S = Where are we going

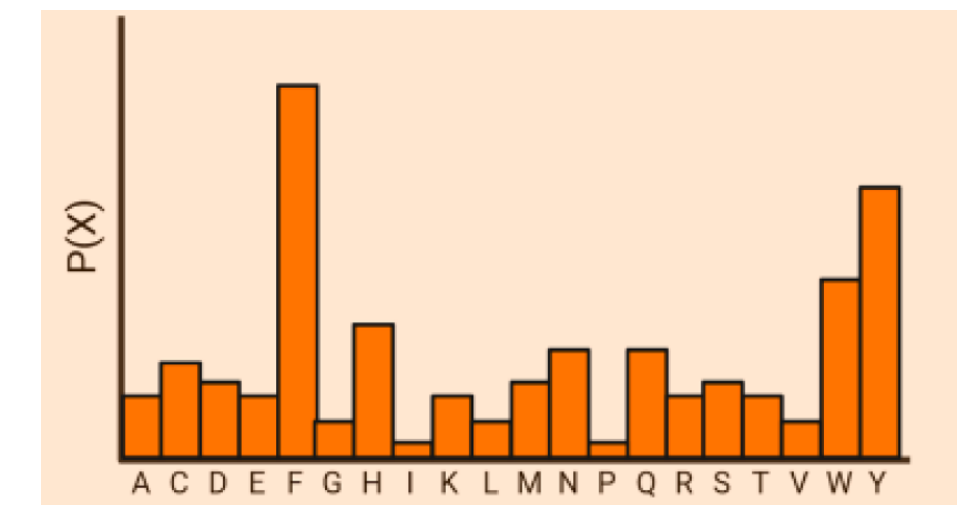
Previous words
(Context)

Word being
predicted

$$P(S) = P(\text{Where}) \times P(\text{are} \mid \text{Where}) \times P(\text{we} \mid \text{Where are}) \times P(\text{going} \mid \text{Where are we})$$



Trained on PDB structures:
Samples are biased towards
thermal stability, expression.

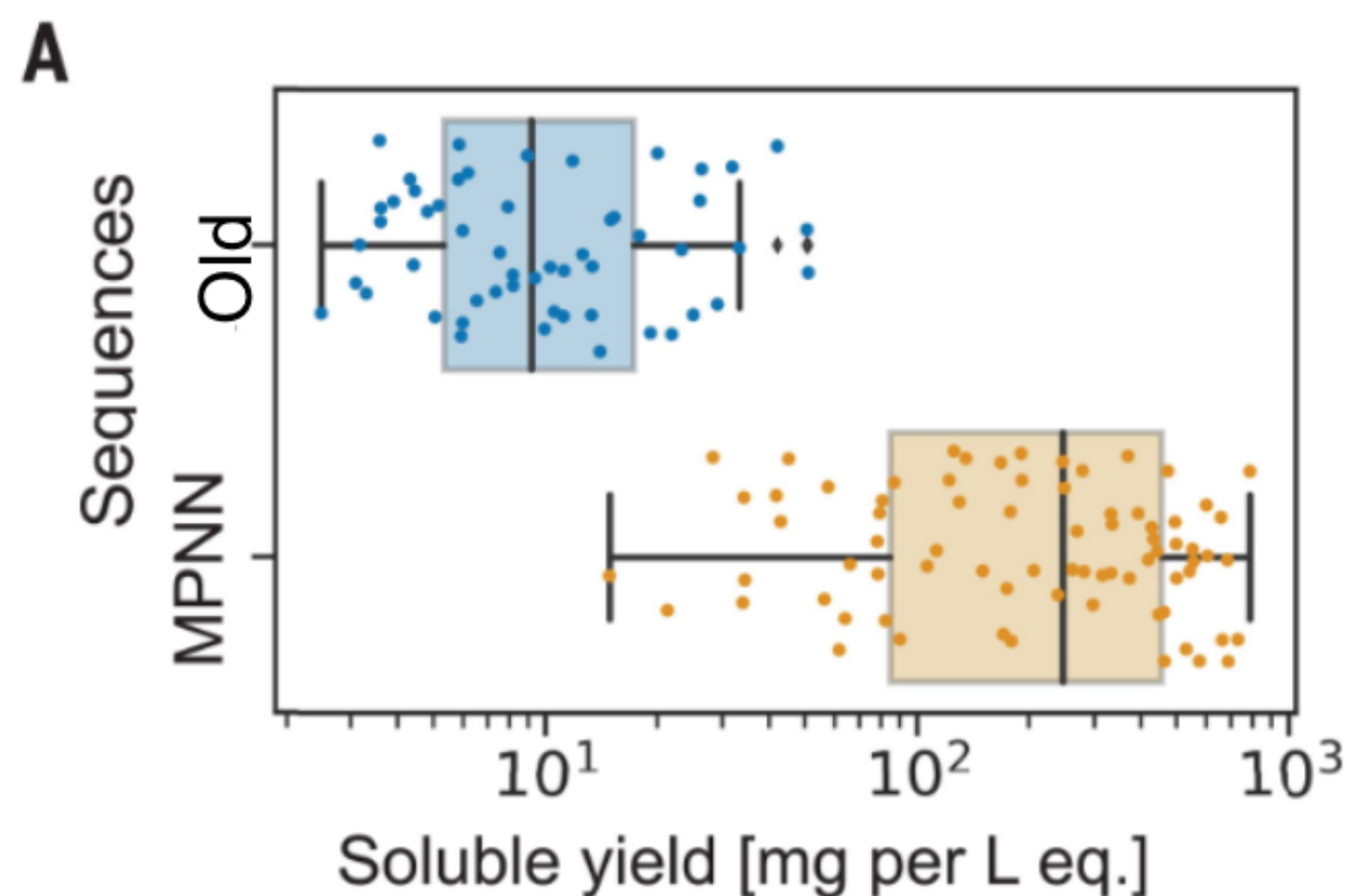


Sequence generation: **Language model**

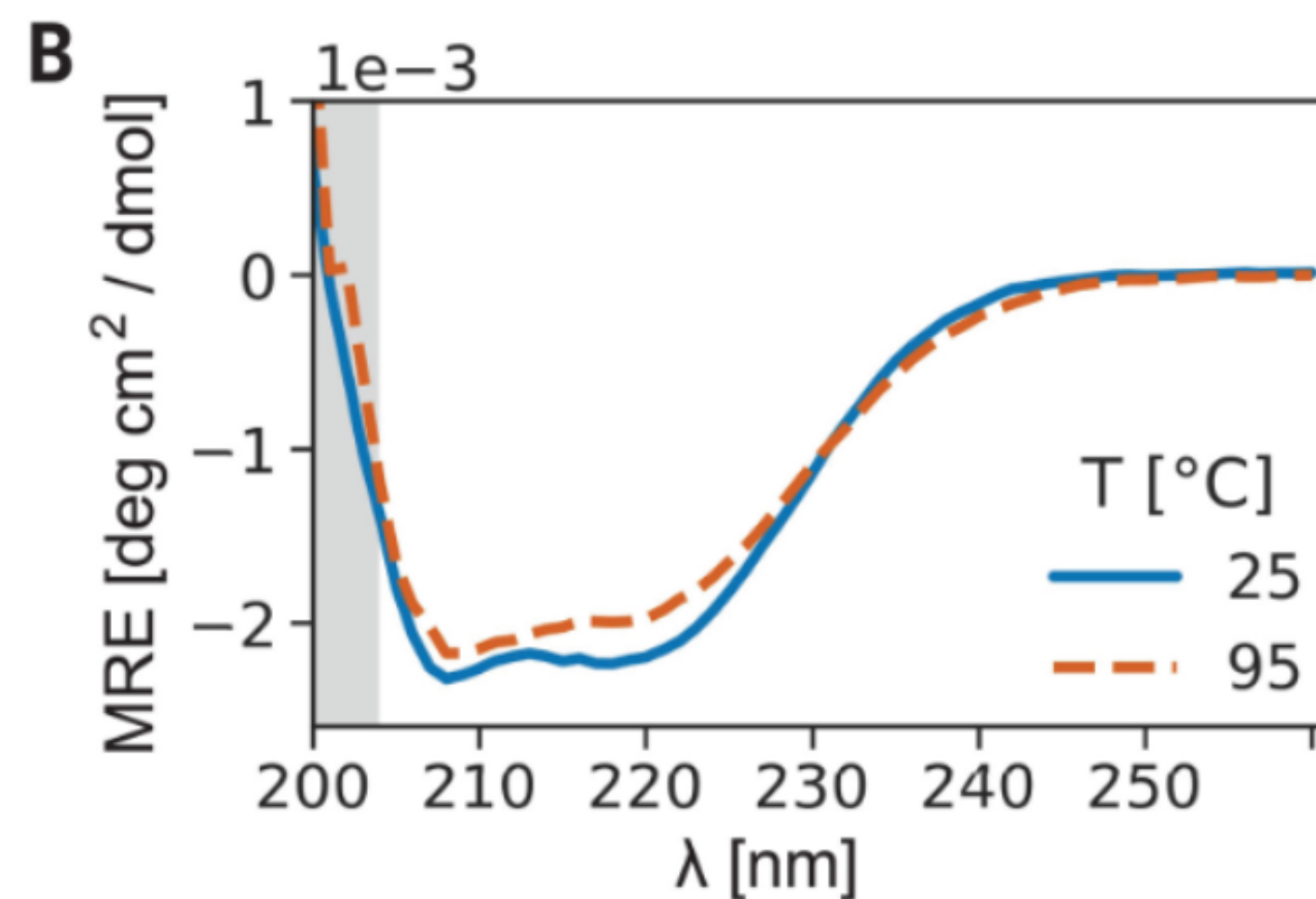
Sequence generation conditioned on structure: **ProteinMPNN** (inverse folding)

ProteinMPNN improves over physics-based tools

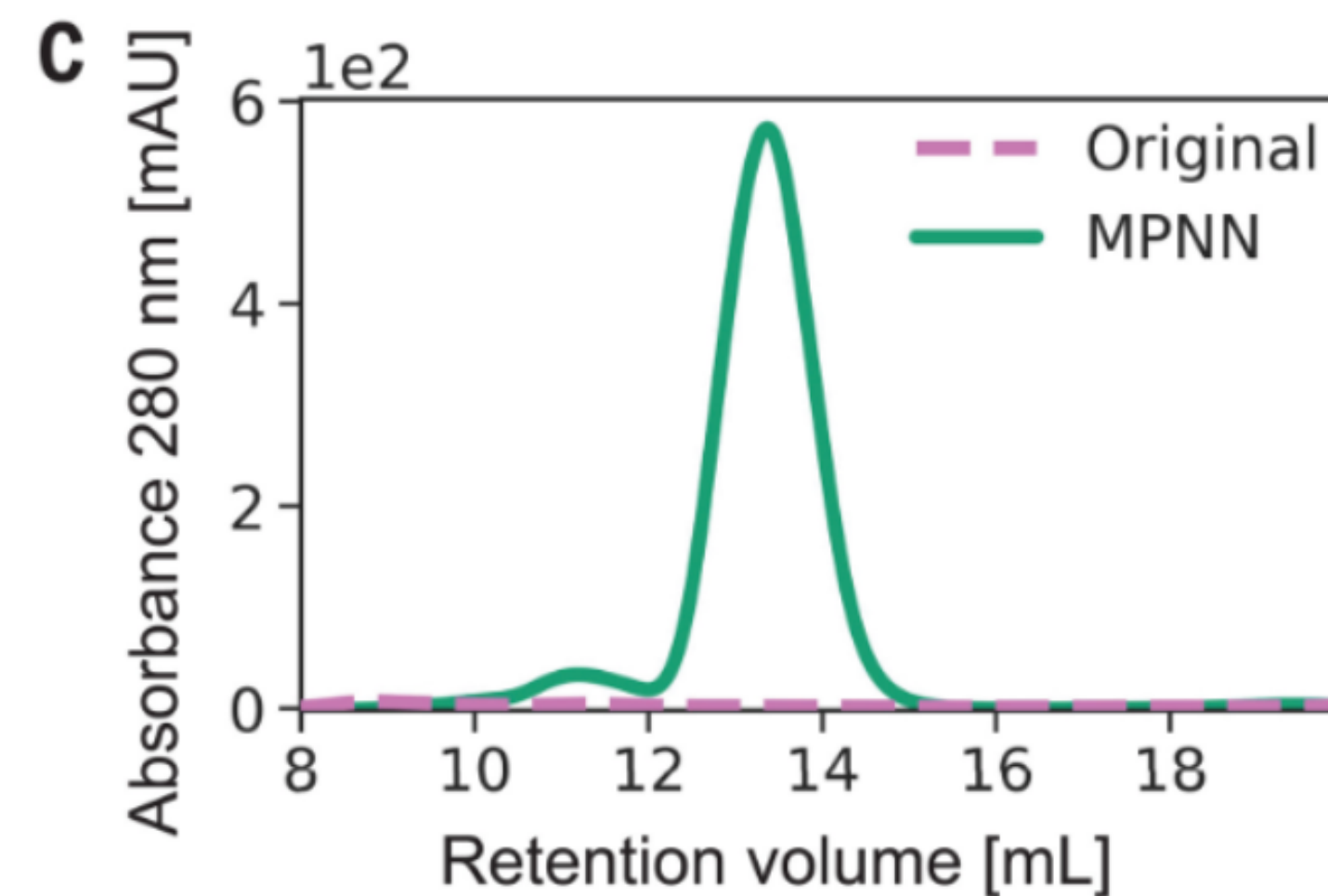
Fixed backbone re-design of structures from Rosetta



Soluble protein yield after expression in E.coli for old designs vs. re-designs (129 proteins)



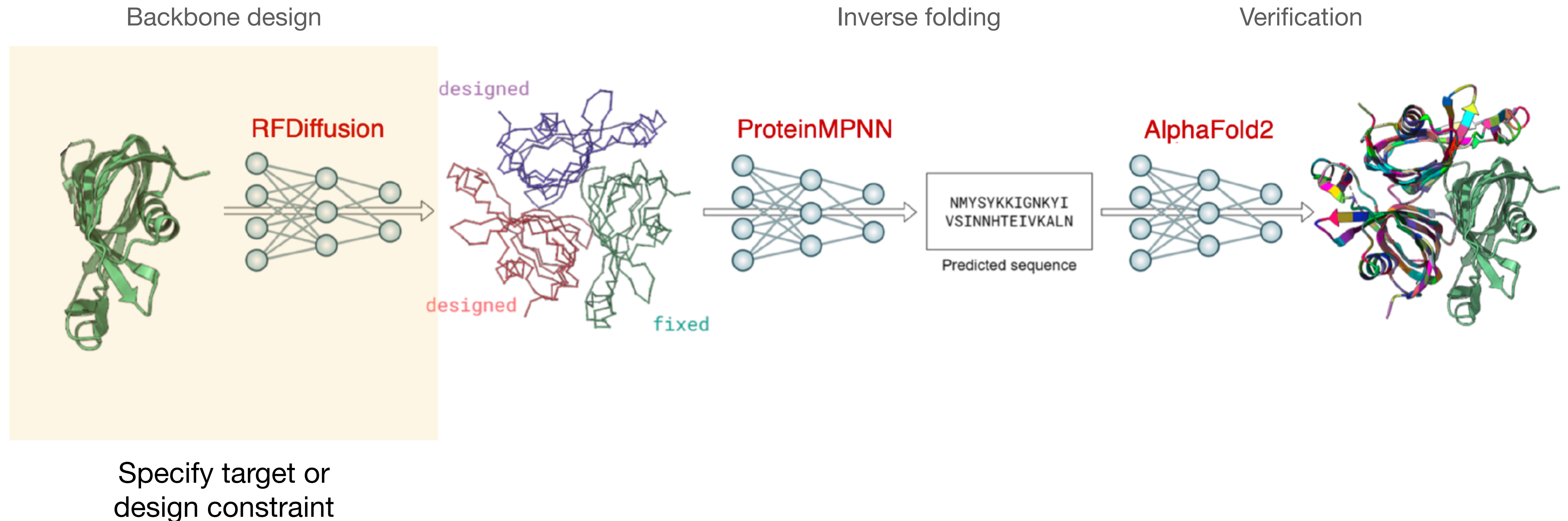
A highly thermostable design, sec. structure maintained up to 95°C



Size exclusion chromatography profile of a failed design vs. re-design.

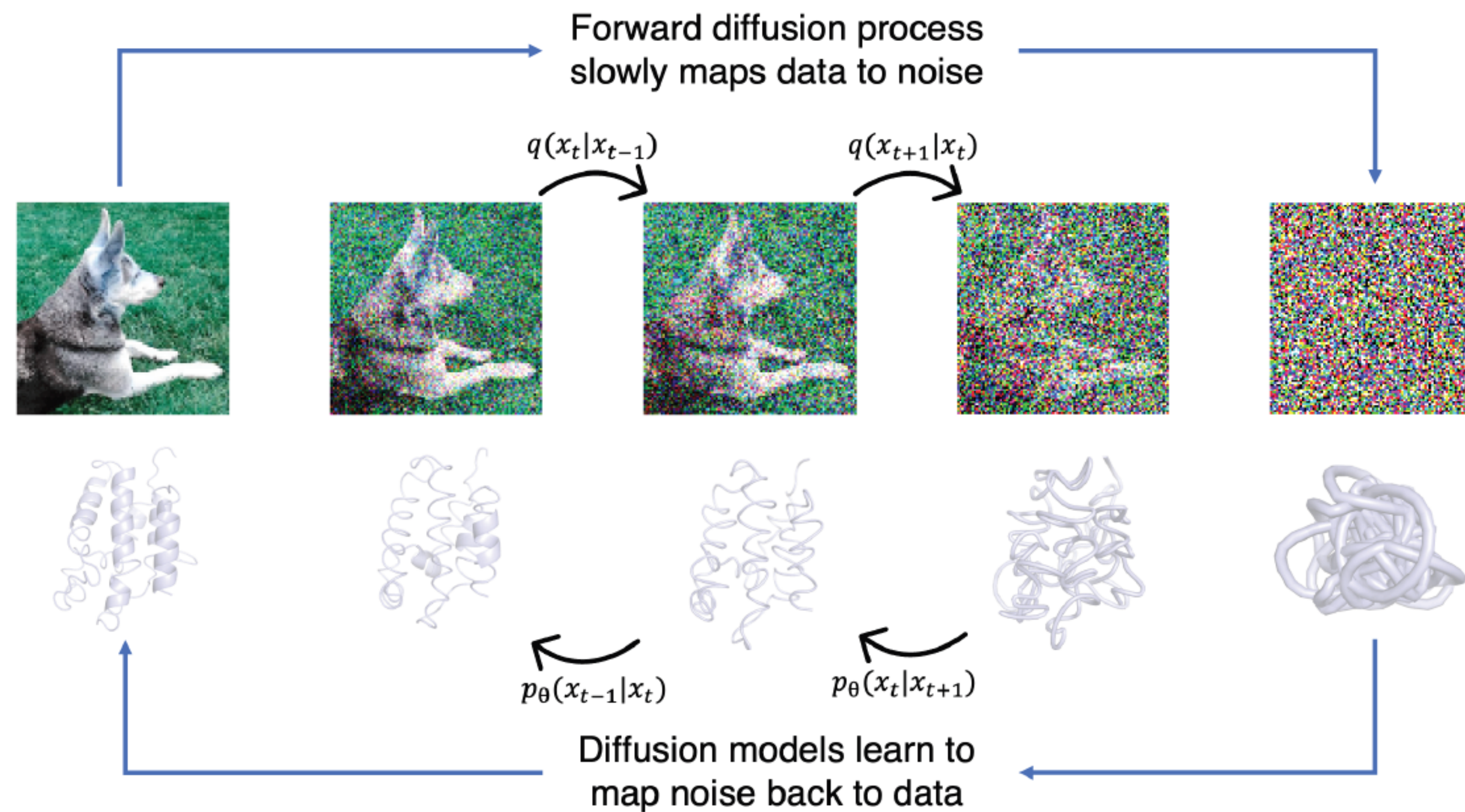
De-novo protein design workflow

Starting from scratch



Analogy to DALL-E

DALL-E
Image generation models



Trained on PDB structures:
Learn to mix and match real protein sub-structures.

Backbone design: **RFdiffusion**

RFdiffusion designs functional proteins

Task: scaffold a p53 helix for improved binding to MDM2

Among 96 designs, they find 0.5 nM binders. This is 3 orders of magnitude better compared to native 600nM affinity of p53 alone.

