

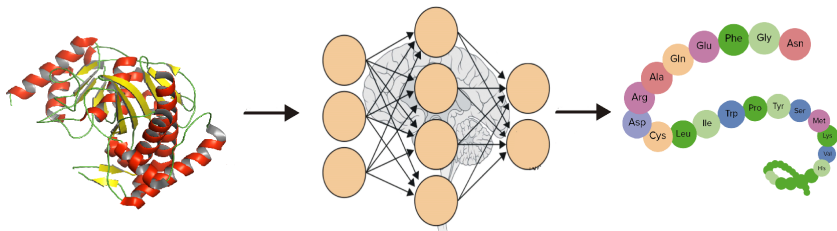
# Fast uncovering of protein sequence diversity from structure

Luca Alessandro Silva, Barthelemy Meynard-Piganeau  
Carlo Lucibello, Christoph Feinauer  
Bocconi University, Genbio.AI

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# Protein inverse folding

**Protein inverse folding:** given a 3D structure  $X$ , find  $\sigma$  folding into  $X$



- ▶ Given the task's complexity, recently deep-learning methods emerged.
- ▶ Models such as ESM-IF1, Protein-MPNN though only map a  $X \rightarrow \sigma_X$ .

# Sequence-structure data imbalance

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- ▶ Determined sequences  $\sim 200$  millions, determined structures  $\sim 200k \implies 0.1\%$  of sequences have a determined structure.
- ▶ Mapping  $X \rightarrow \sigma_X$  focuses on a very small part of sequences.
- ▶ Many proteins come from a common ancestor  $\implies$  their sequences have some very conserved regions.
- ▶ We can cluster such sequences  $\implies$  protein families.
- ▶ Such sequences evolve constrained by they function and hence structure.
- ▶ Crucial *many-to-one* nature of inverse folding



- ▶ MSA has long-range correlations  $\implies$  need a **global model**

- ▶ Probability of a sequence  $\sigma_i$  in a MSA is

$$p(\sigma_i|J, h) = \frac{1}{Z(J, h)} \exp \left\{ - \left[ \sum_{i < j} J_{ij}(\sigma_i, \sigma_j) + \sum_i h_i(\sigma_i) \right] \right\}$$

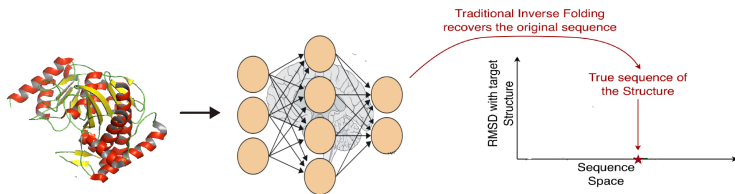
- ▶ *Couplings*  $J \in \mathbb{R}^{L \times q \times L \times q}$ .  $J_{i,j}(a, b)$  describe propensity of amino acids  $a, b$  to co-appear at position  $i, j$ .
- ▶ *Fields*  $h \in \mathbb{R}^{L \times q}$ .  $h_i(a)$  describe the marginal propensity of an amino acid  $a$  to appear at position  $a$ .
- ▶ Potts models can replicate **first and second order** patterns of MSA

# InvMSAFold architecture

- ▶ We propose a novel architecture, **InvMSAFold**, which forces the model to learn this variability
- ▶ **InvMSAFold** outputs the parameters of a light-weight low-rank approximation of the couplings  $J$

$$J_{i,j}[a, b] = \frac{1}{\sqrt{K}} V_i[a]^\top v_j[b],$$

trained on the *augmented* dataset  $(X, M_X)$ .

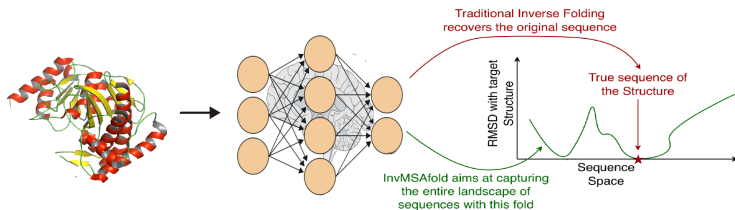


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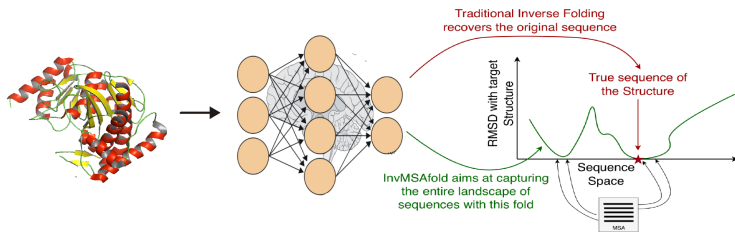


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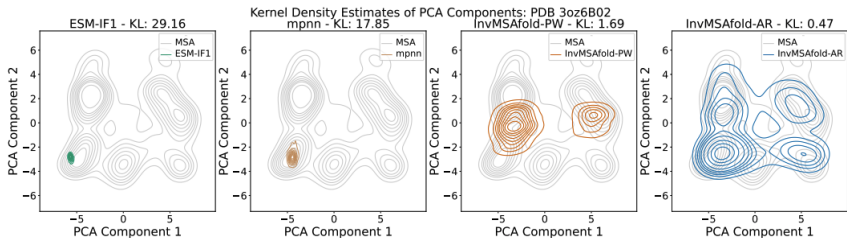
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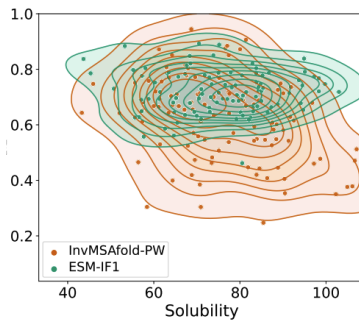
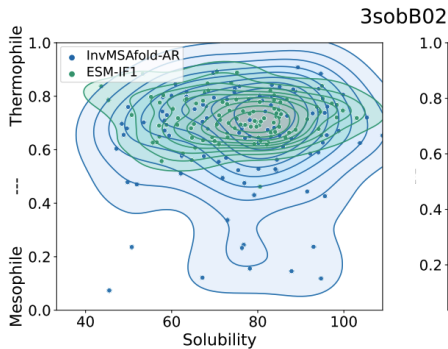




# PCA plots



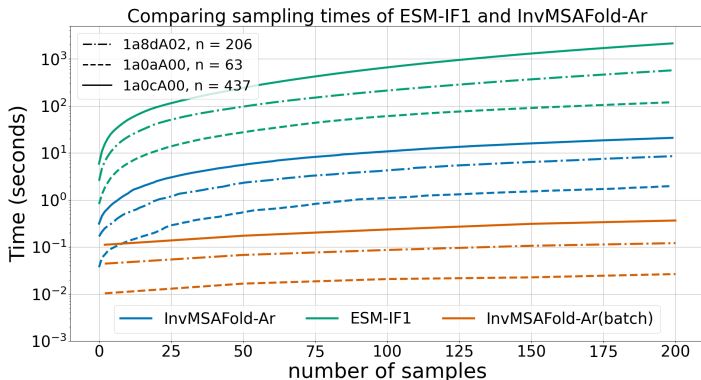
# Protein property sampling



# Sampling speed at generation

ESM-IF1, Protein-MPNN can be very expensive at inference

- ▶ Need  $\Theta(L)$  passes through the transformer
- ▶ Inv-MSAFold-AR needs just **one**!



# Thank you for your attention!

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- ▶ Paper available at:  
<https://openreview.net/forum?id=1iuaxjssVp>
- ▶ Hope to see you all at the poster presentation:  
**Fri 25 Apr 7 p.m. PDT 9:30 p.m. PDT!**