

# Protein 3D Structure Computed from Evolutionary Sequence Variation

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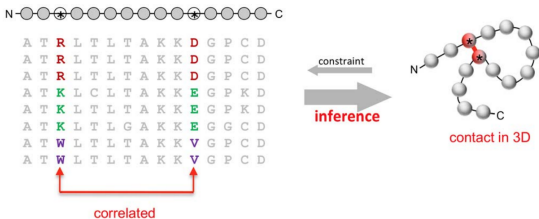
<https://qdata.github.io/deep2Read>

# Motivation

- ▶ A protein family: group of proteins that share a common evolutionary origin, reflected by their related functions and similarities in sequence or structure.
- ▶ Very large space of sequences, only few observed
- ▶ conservation of function imposes boundaries on sequence variation and ensures 3D structure similarity

# Motivation

- ▶ to maintain energetically favorable interactions, residues in spatial proximity may co-evolve across a protein family
- ▶ suggests that residue correlations could provide information about amino acid residues that are close in structure



# Residue-Residue Correlation

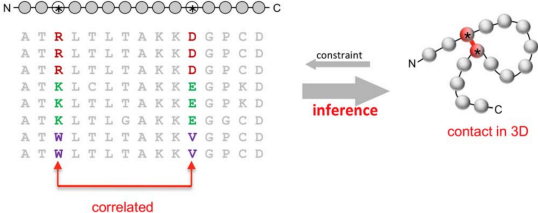
- ▶ correlated residue pairs within a protein are not necessarily close in 3D space
- ▶ Confounding Correlations:
  - ▶ transitivity of correlations: if  $(i,j)$ ,  $(j,k)$  correlated,  $(i,k)$  also correlated
  - ▶ technical noise, oligomerization, protein-protein, or protein-substrate interactions or other spatially indirect or spatially distributed interactions can result in co-variation between residues not in close spatial proximity.

# Motivation

This Paper:

Infer evolutionary constraints from a set of sequence homologs of a protein.

Predicting 3D Protein Structure from these evolutionary interactions.

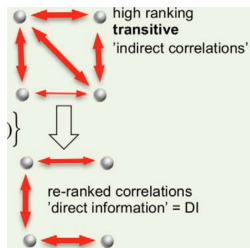


## Methods: Pipeline

1. Protein sequence alignment of an iso-structural protein family (from PFAM database) of length  $L$
2. **Residue-Residue Coupling Scores**( $DI \in R^{L \times L}$ ) **for all pairs of residues in [1]**
3. Derivation of a ranked set of evolutionarily inferred contacts (EICs) from [2]
4. Prediction of 3D structures by using EICs



## Step 2: Residue Coupling Scores



- ▶ For sequence length  $L$  for a protein family, a matrix  $DI \in R^{L \times L}$  is inferred:

$$MI_{ij} = \sum_{A_i, A_j=1}^q f(A_i, A_j) \ln \left( \frac{f(A_i, A_j)}{f_i(A_i) f_j(A_j)} \right) \quad (1)$$

$$DI_{ij} = \sum_{A_i, A_j=1}^q P_{ij}^{Dir} \ln \left( \frac{P_{ij}^{Dir}}{f_i(A_i) f_j(A_j)} \right) \quad (2)$$

- ▶  $q$ : types of residues (20)
- ▶  $L$ : length of sequence (50-250 in these experiments)



## Computing Residue Coupling Scores

- ▶ Estimate a  $p(A_1, \dots, A_L)$  such that it maximizes entropy  $S = -\sum P(A_1, \dots, A_L) \ln P(A_1, \dots, A_L)$  subject to the following constraints:

$$P_i(A_i) = \sum_{A_k=\{1, \dots, q\}, k \neq i} P_i(A_1, \dots, A_L) = f_i(A_i) \quad (3)$$

$$P_{ij}(A_i, A_j) = \sum_{A_k=\{1, \dots, q\}, k \neq i, j} P_i(A_1, \dots, A_L) = f_{ij}(A_i, A_j) \quad (4)$$

- ▶ Make empirical correlation matrix

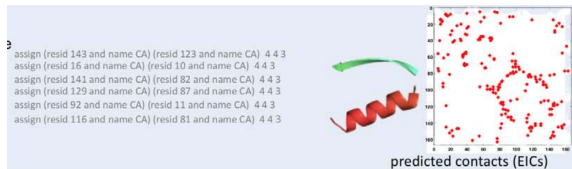
$$C_{ij} = f_{ij}(A_i, A_j) - f_i(A_i)f_j(A_j) \quad (5)$$

- ▶  $e_{ij} = C_{ij}^{-1}$

$$P_{ij}^{Dir} = \frac{1}{Z} \exp\left(e_{ij}(A_i, A_j) + h_i(A_i) + h_j(A_j)\right) \quad (6)$$

### 3. Derivation of a ranked set of evolutionary inferred contacts (EICs)

- ▶ evolutionary inferred contacts (EICs): predicted to be close in 3D space
- ▶ Convert the above  $DI$  matrix into EICs using rules:
  - ▶ Remove residue pairs close in sequence
  - ▶ consistent with predicted secondary structure: PredictProtein and PsiPred Algorithms
  - ▶ ..

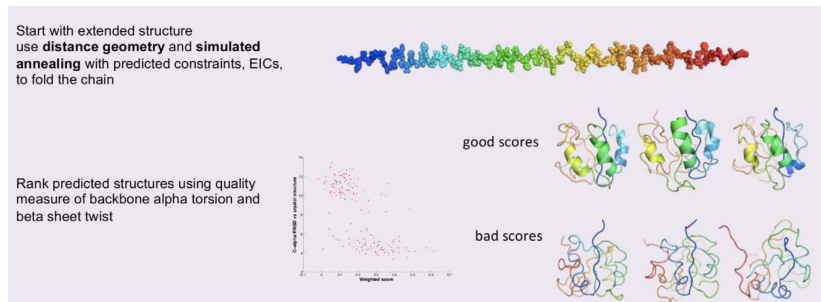


- ▶ The first  $N_c$  inferred EIC pairs are ranked according to the  $DI$  scores and used as distance constraints to distance geometry and simulated annealing calculations

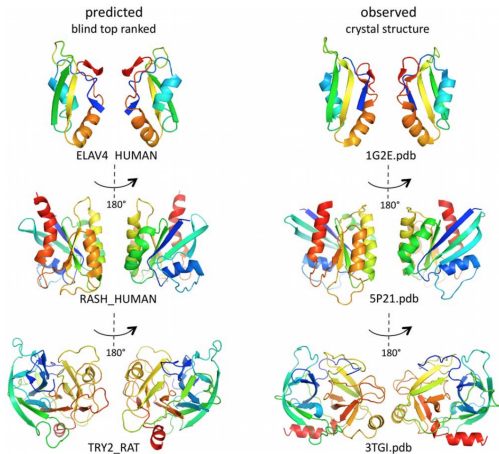
## Step 4: Prediction of 3D structures

EICs used as input to distance geometry and simulated annealing calculations.

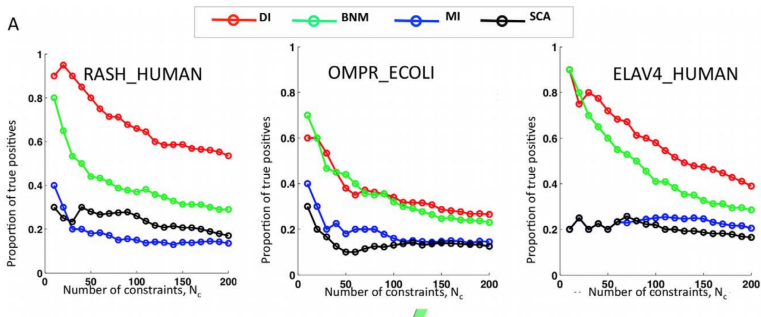
tested on multiple protein families (from PFAM database) with range of Multiple Sequence Alignment of 71/161/223



# Results: Prediction of 3D structures

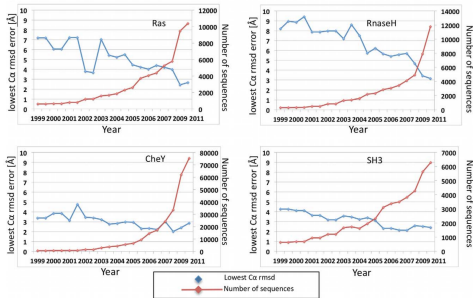


# Evaluation of residue-residue contact prediction:



- ▶ BNM: Bayesian network model (also global)
- ▶ SCA: statistical coupling analysis (local)
- ▶ MI: Mutual Information(local) coupling analysis (local)

# $C_{\alpha}$ – $RMSD$ <sup>1</sup> Error as a function of number of sequences



Other factors:

- ▶ Which sequences are used/distribution of sequences in the protein family? For example, this algorithm removes sequences with over 70% residue identity to family neighbors are down-weighted
- ▶ uneven sampling in the space of natural sequences, due to experimental ascertainment bias during sequencing.

<sup>1</sup>the root-mean-square deviation of atomic positions- average distance between the atoms (usually the backbone atoms) of superimposed proteins.

# Conclusion

- ▶ pairwise without indirect/confounding interactions for residue-residue contact prediction
- ▶ DI based(global) works better than MI based (local)
- ▶ Lots of feature engineering: data selection, removal of invalid correlations, etc