ResTriplet/TripletRes: Learning contact-maps from a triplet of coevolutionary matrices

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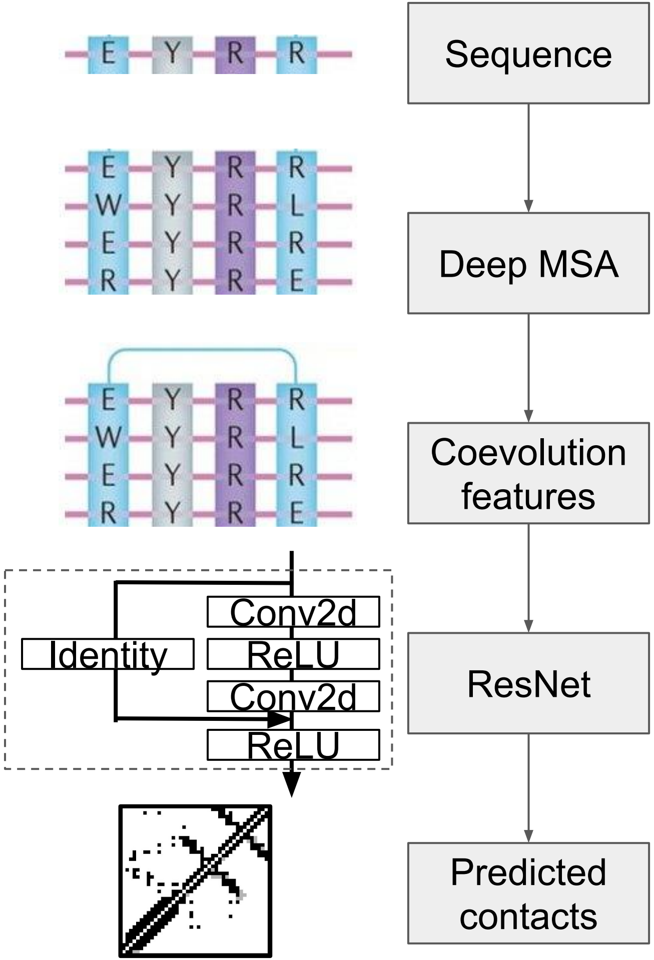
ResTriplet/TripletRes Method overview

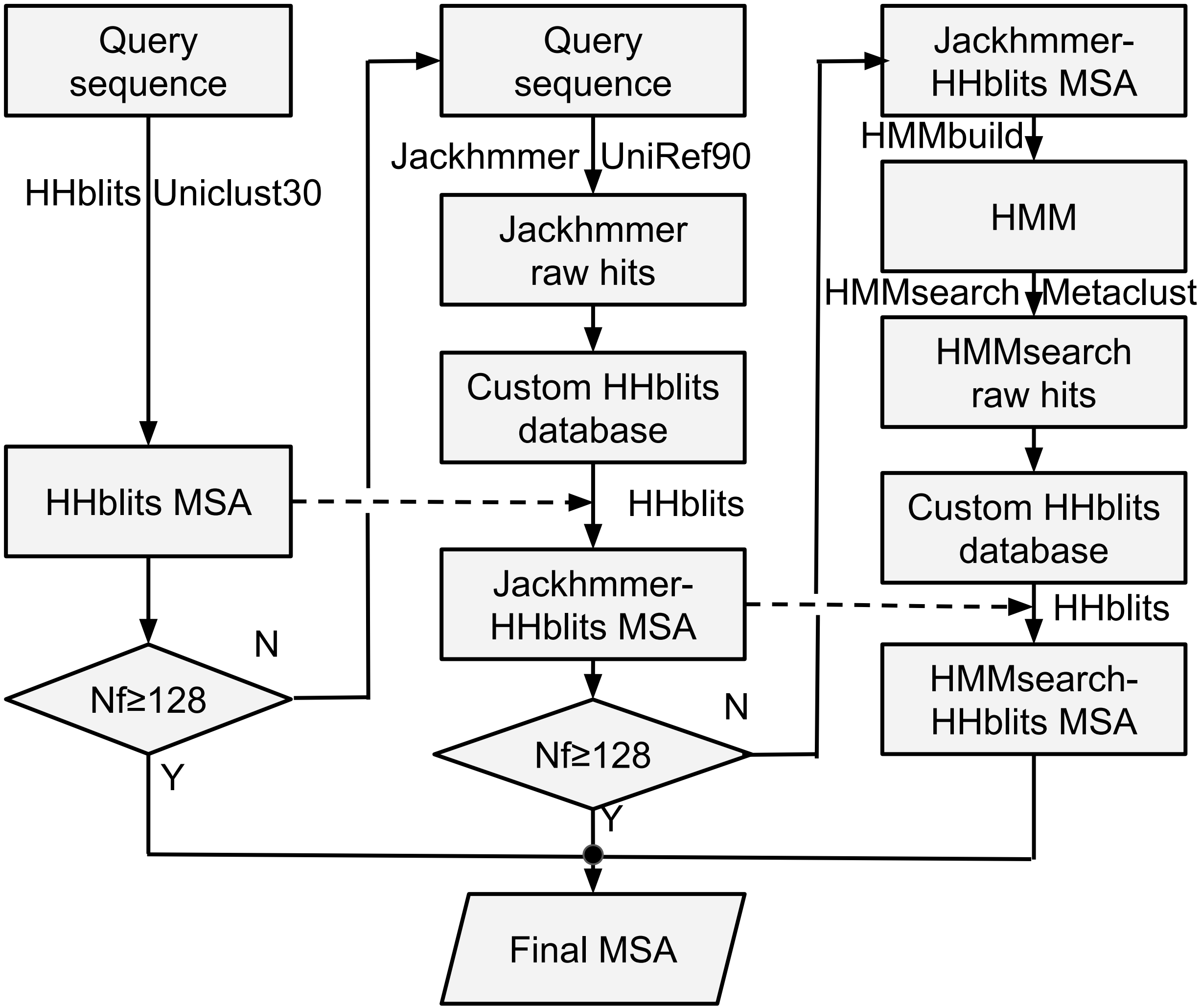


1. Deep MSA: build MSA from incremental sequence searching protocols

2. **Triple** coevolution features: covariance matrix, precision matrix, and pseudolikelihood maximization

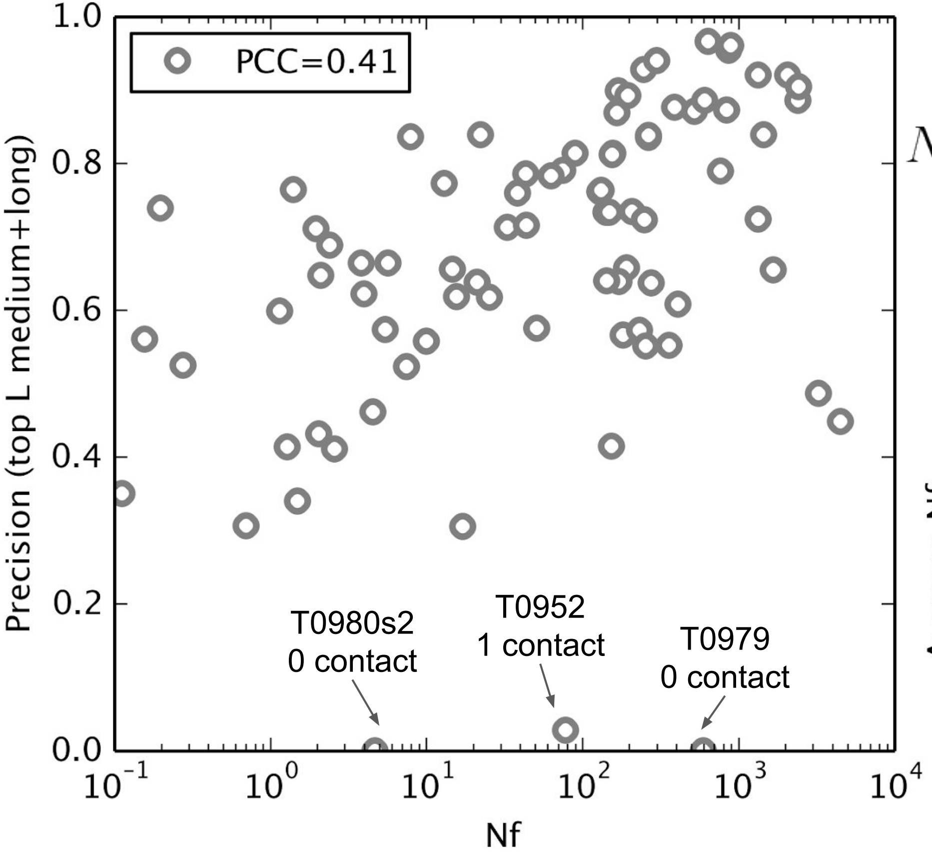
3. **Res**Net: fully convolutional neural network with residual blocks

Step 1: Deep MSA

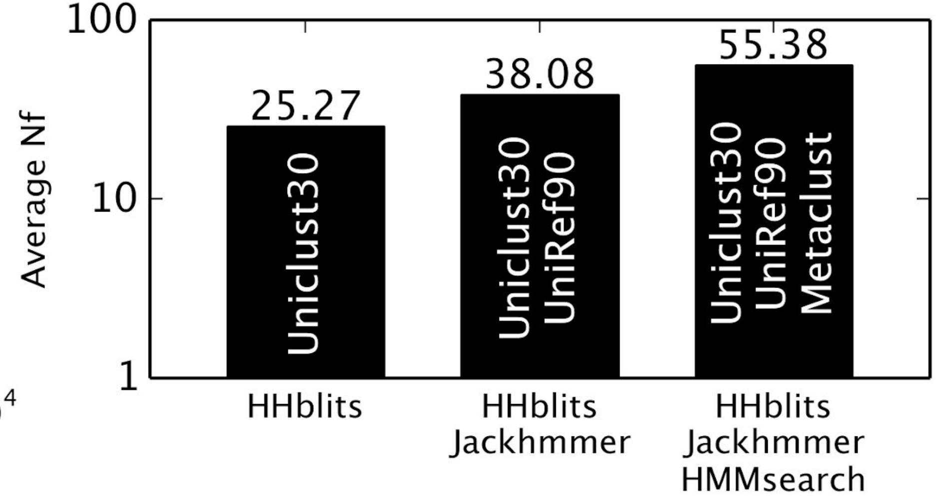


Nf: number of effective sequences in MSA

Step 1: Effect of MSA on contact prediction



$$Nf = \frac{1}{\sqrt{L}} \cdot \sum_{n=1}^{N} \frac{1}{1 + \sum_{m=1, m \neq n}^{N} \mathbb{I}[S_{m,n} \geq 0.8]}$$



Step 2: Three feature matrices derived from MSA

1. COVariance matrix (COV) *S*:

$$S_{i,j}(a,b) = f_{i,j}(a,b) - f_i(a) \cdot f_j(b)$$

2. PREcison matrix (PRE) *θ*:

$$\theta = \underset{\theta}{argmin} \left(tr(S \cdot \theta) - log(det(\theta)) + \rho \cdot \|\theta\|_2^2 \right)$$

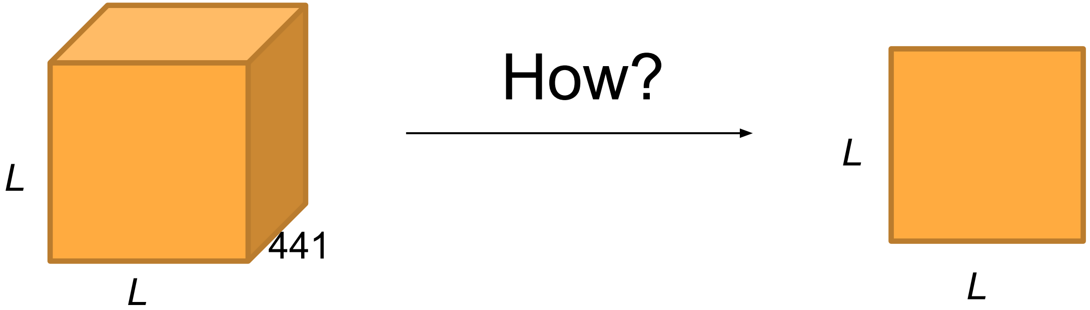
3. Pseudo-Likelihood Maximization (PLM) σ:

$$P(X|\sigma) = \prod_{n=1}^{N} \prod_{i=1}^{L} P(x_i^n | [x_1^n, ..., x_{i-1}^n, x_{i+1}^n, ..., x_L^N], \sigma)$$

$$= \prod_{n=1}^{N} \prod_{i=1}^{L} \frac{1}{Z_i^n} \cdot exp \left(\sigma_i(x_i^n) + \sum_{j=1, j \neq i}^{L} \sigma_{i,j}(x_i^n, x_j^n) \right)$$

Step 3: Predicting contact-map from features

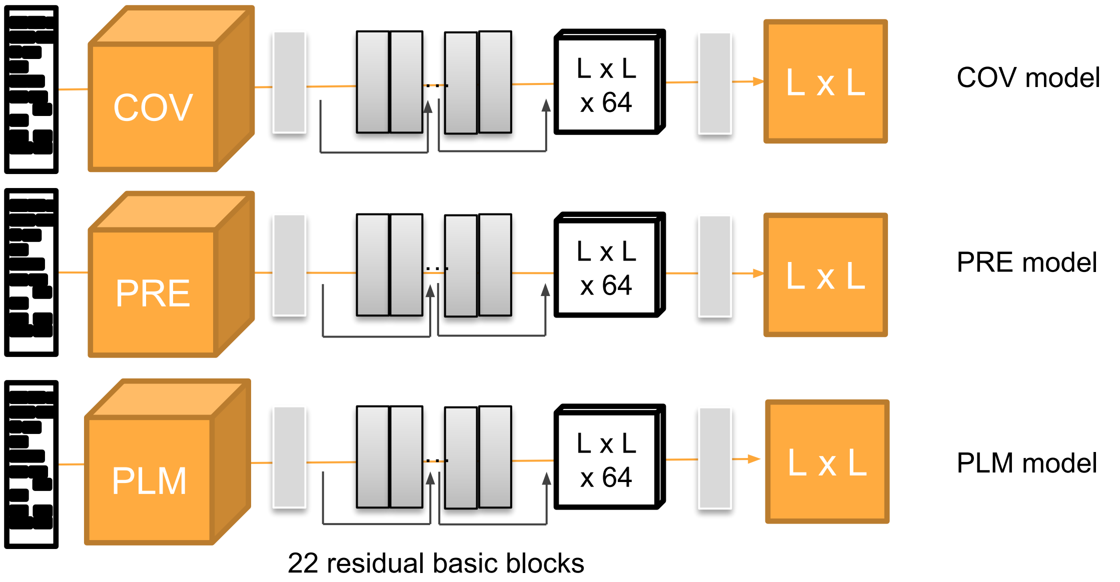
How do we convert $L \times L \times 441$ (=21 × 21) evolutionary coupling features to $L \times L \times 1$ contact map?



- L1 norm (λ=1) or L2 norm (λ=2): $$C_{i,j} = \left(\sum_{a,b} (\theta_{i,j}(a,b))^{\lambda} \right)^{1/\lambda}$$
- Or just leave it to deep learning: ResTriplet/TripletRes

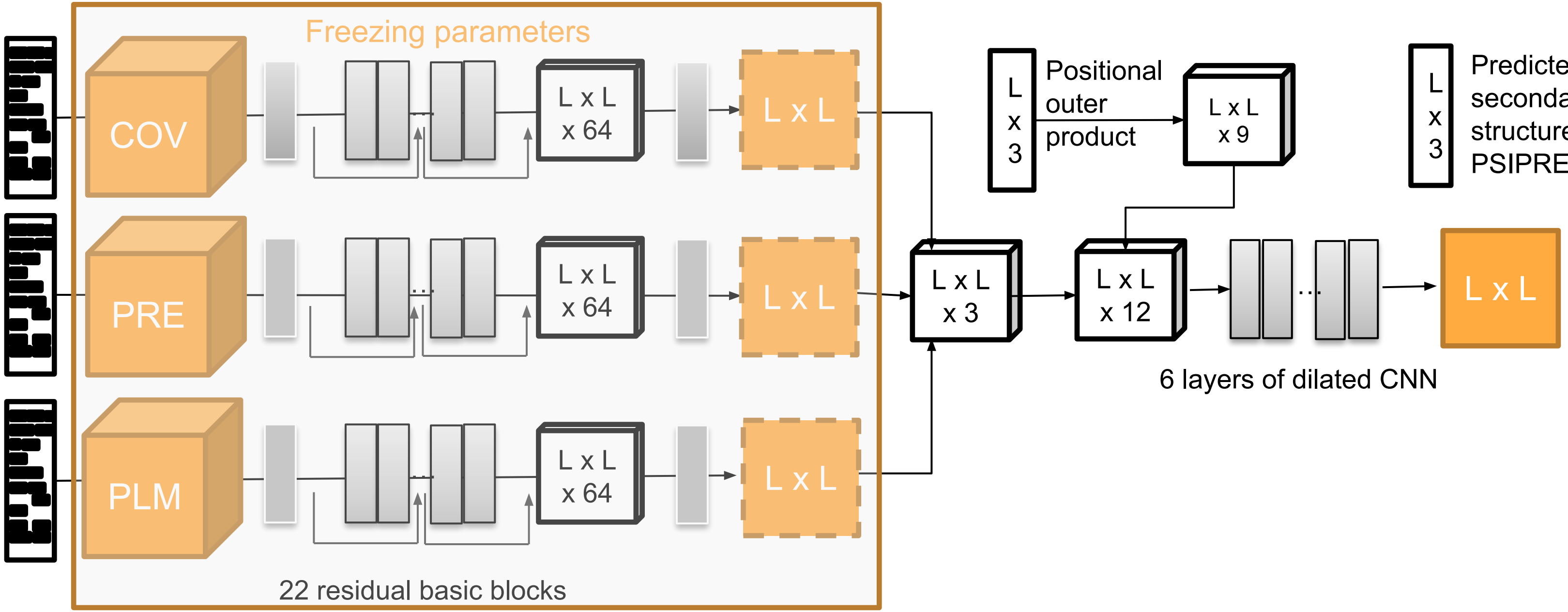
Step 3: ResTriplet neural network architecture

- First, train CNN models on COV, PRE and PLM features, separately.



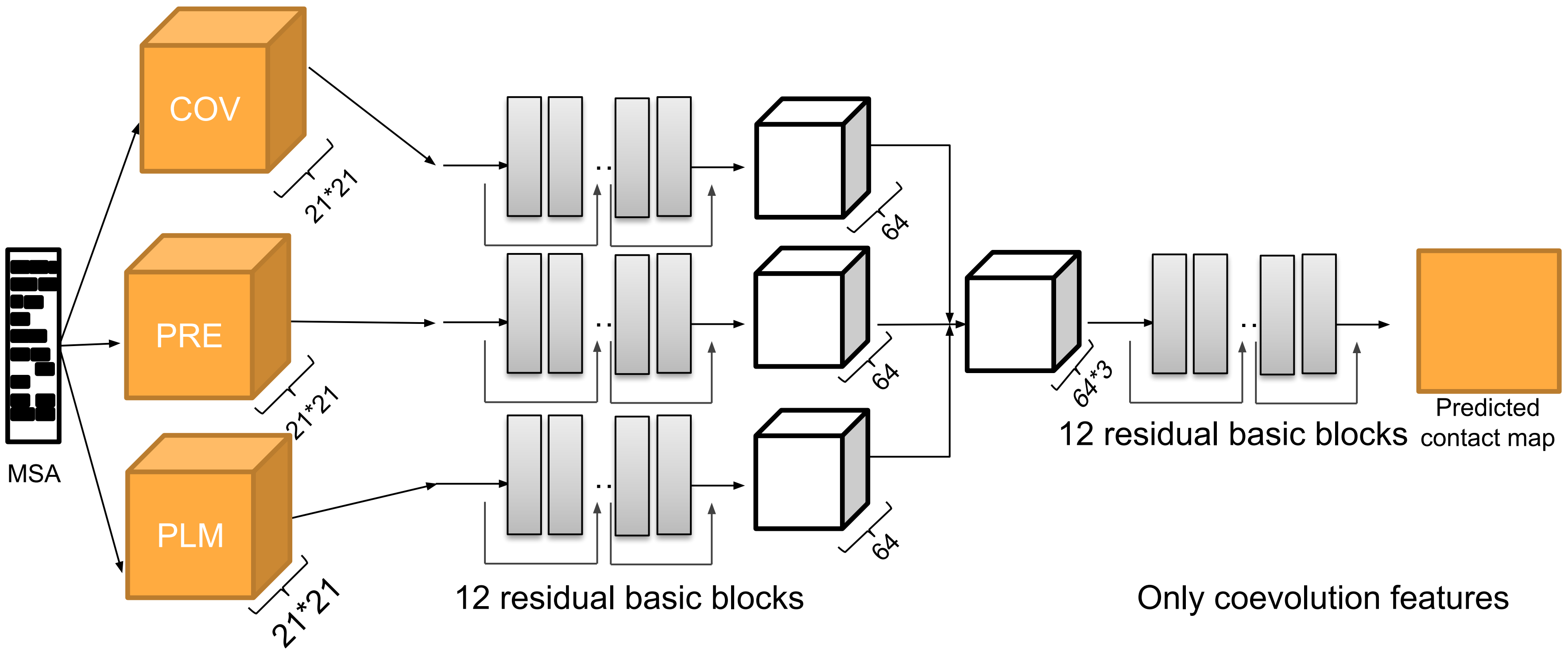
Step 3: ResTriplet neural network architecture

- First, train CNN models on COV, PRE and PLM features, separately.
- Second, stack 3 models with another dilated CNN model, with additional secondary structure features.

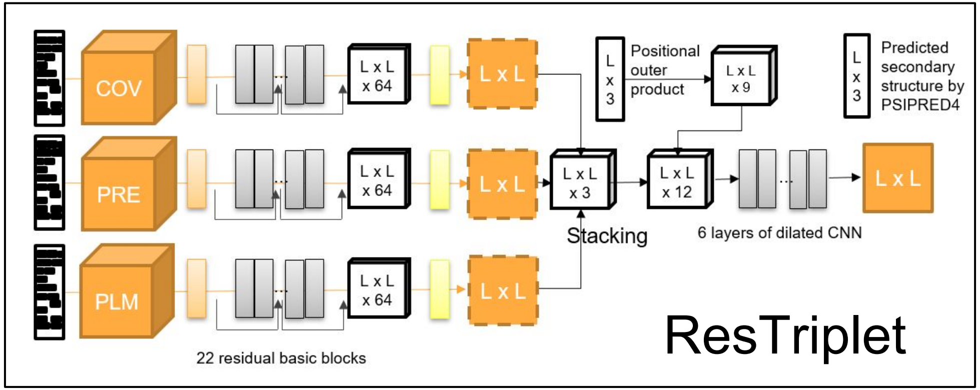


Step 3: TripletRes neural network architecture

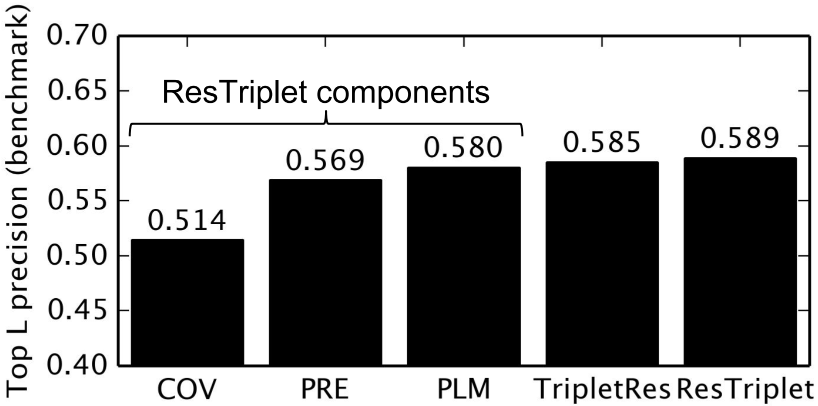
Train all CNN models together, in an end-to-end fashion.

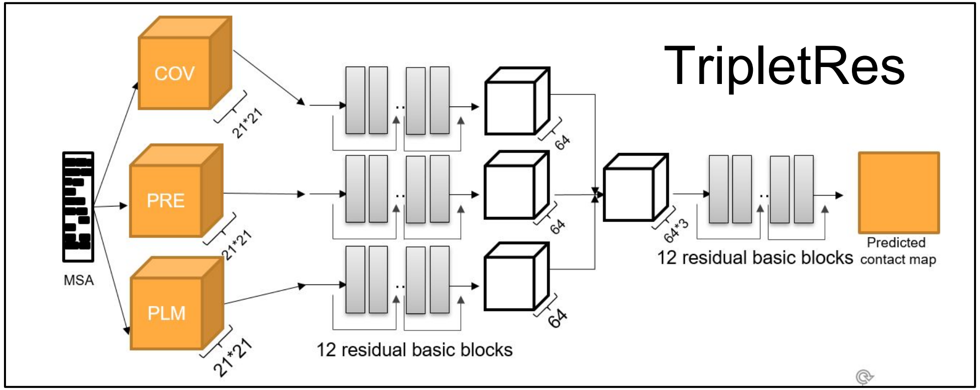


Step 3: ResTriplet vs TripletRes: neural network architecture



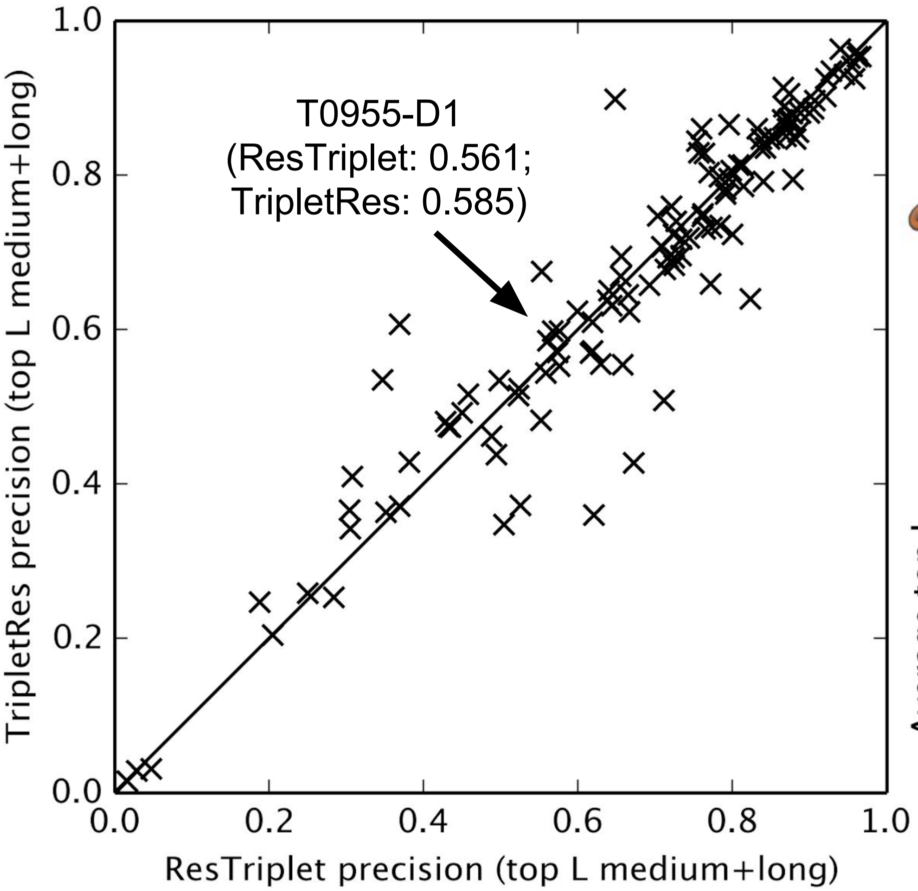
- Coevolution features + predicted secondary structure feature
- Training 4 models separately
- Can be trained with 1 GPU

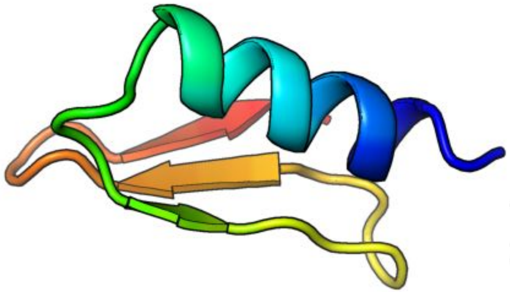




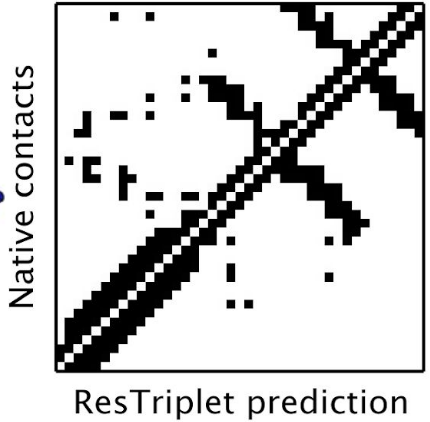
- ONLY coevolution features
- End-to-end training
- Requires 4 GPUs for training

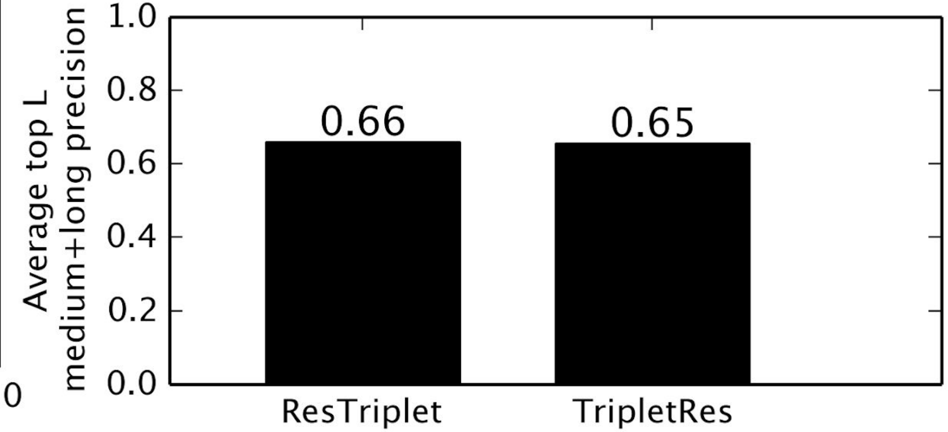
Result of ResTriplet/TripletRes on CASP13 Targets



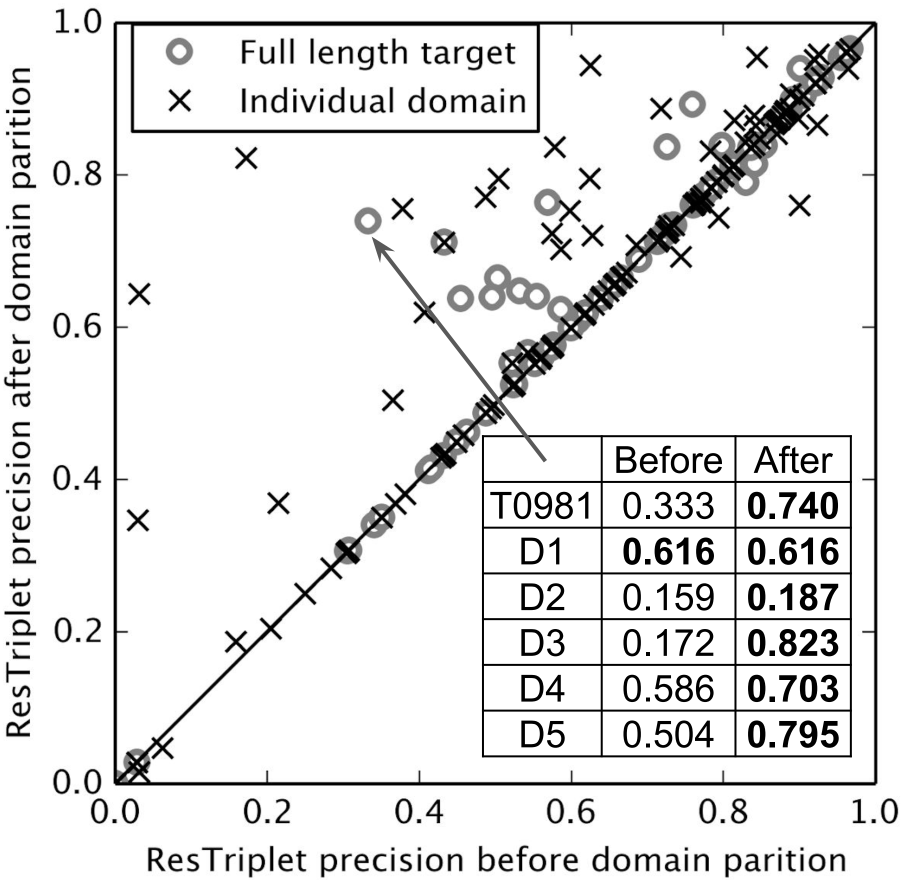


T0955-D1 (designed protein;
single sequence in MSA)

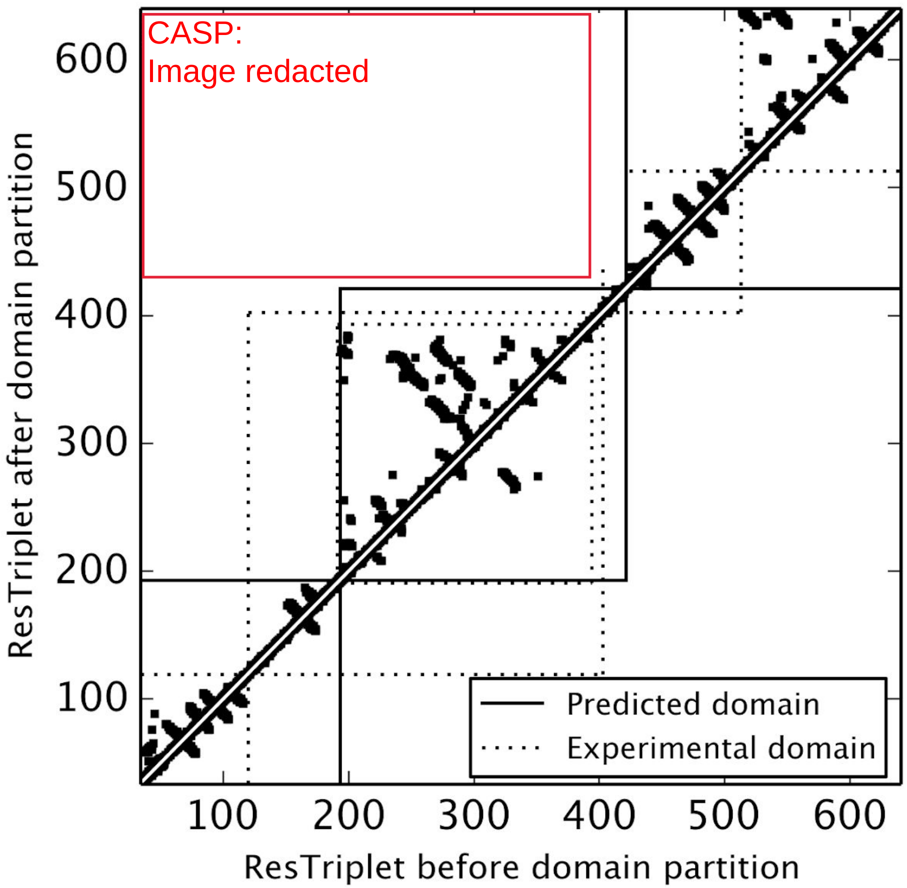




Effect of Domain Partition on Contact Prediction



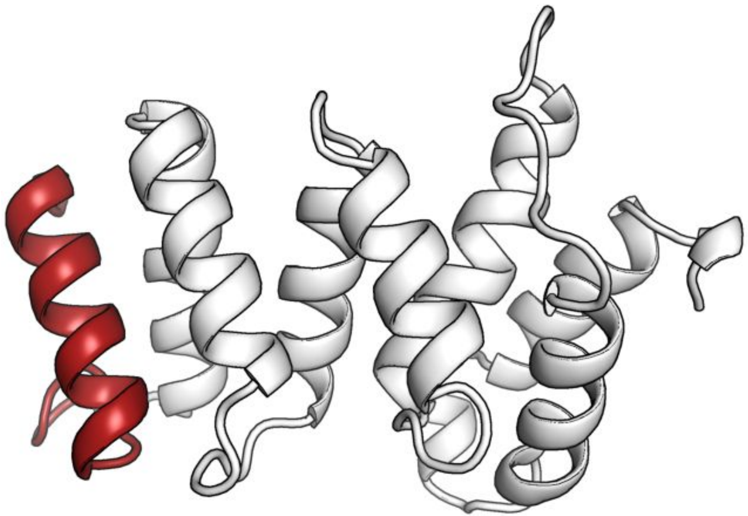
	Before	After
T0981	0.333	**0.740**
D1	**0.616**	**0.616**
D2	0.159	**0.187**
D3	0.172	**0.823**
D4	0.586	**0.703**
D5	0.504	**0.795**

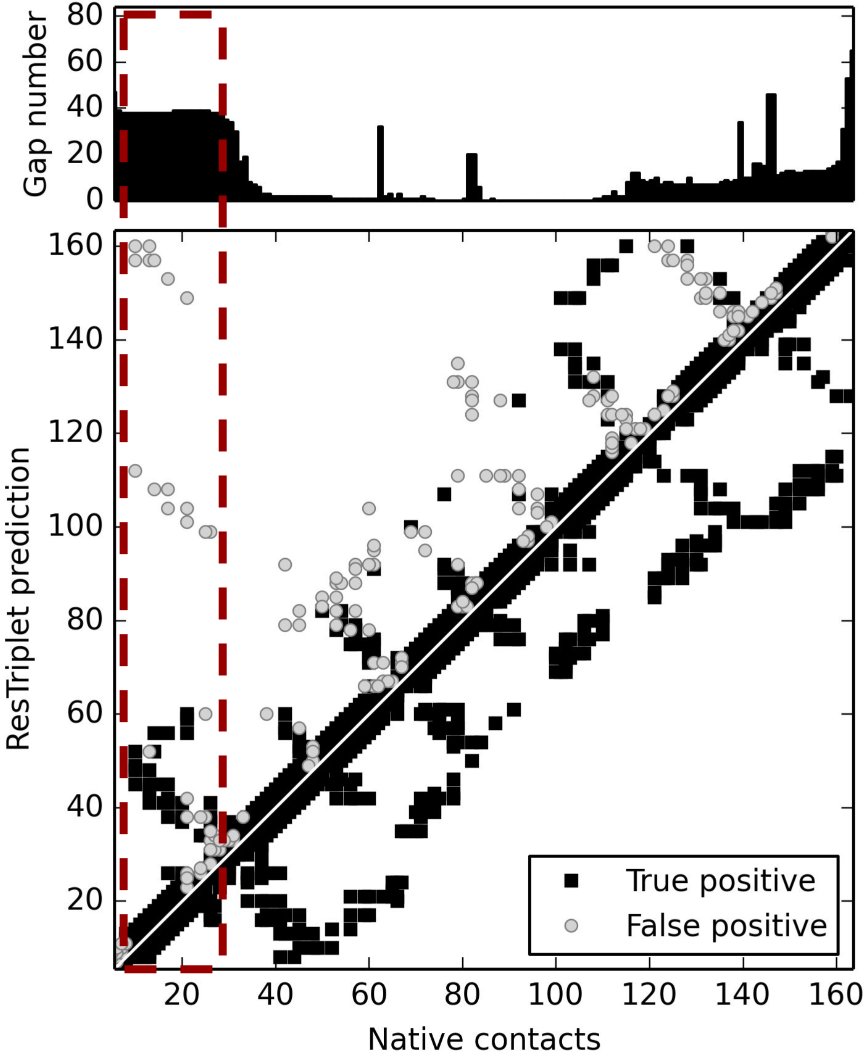


What went wrong?

T0957s2-D1: top *L* long range accuracy 0.342 (ResTriplet) and 0.394 (TripletRes)

Incorrectly predicted long range contacts for the first helix of T0957s2-D1 caused mainly by long stretch of gaps in MSA.





Summary

What went right?

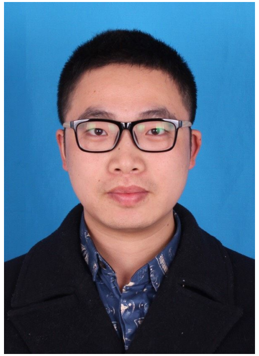
- DCA features (PRE and PLM) outperforms covariance feature (COV).
- Multiple feature fusion/ensemble with deep convolutional neural networks leads to highly accurate contact prediction.
- With the set of coevolutionary features, predicted one-dimensional features (secondary structure, sequence profile, solvent accessibility etc) is not strictly required for deep learning.
- Domain partition (even when domain boundary is not exact) improves precision.
- Combination of diverse multiple sequence alignment generation protocols (search algorithms and sequence databases) improves contact prediction.

What went wrong?

- How to appropriately consider large gaps in MSA is still an open question.

Acknowledgements

Zhang lab Research Group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MEDICAL SCHOOL
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XSEDE
Extreme Science and Engineering Discovery Environment

Thank You!