## Effective Protein-Protein Interaction Exploration with PPIretrieval First deep-learning retrieval framework for https://arxiv.org/pdf/2402.03675.pdf

Chenqing William Hua @ McGill&Mila



#### • Thanks to all my collaborators :)





McGill&Mila

MIT

• This work is impossible without their resources and suggestions.





UdeM&Mila



DeepMind&McGill&Mila



SJTU&Aureka



- Protein-Protein Interactions (PPIs) are crucial in regulating cellular functions.
- Pressing need for strategies aimed at designing new protein binders.
- Help understand underlying mechanisms of protein interactions.

• Help advance therapeutic interventions.



## Motivation

## Motivation

• Proteins can be modeled as graphs, meshes, point clouds.



**Protein Residue** 

- Geometric deep learning for modeling PPIs.



**Point Cloud Representation of Protein as different scales** 

#### • Geometric deep learning for geometric and chemical mechanisms governing PPIs.

# Retrieval (Inference) Stage



- (1) PPIretrieval takes an unseen protein *P* with its corresponding binding site.
- (2) Encoder network generates surface representation  $\mathbf{H}_P$ .
- (3) PPIretrieval identifies a binding partner B with surface  $\mathbf{H}_B$  from our database.
- (4) Decoder network takes  $\mathbf{H}_{P}$ ,  $\mathbf{H}_{B}$  and predictes their binding interface.





- (1) PPIretrieval takes a paired proteins *R*, *L* with their binding interface.
- (2) Encoder network generates surface representations  $\mathbf{H}_R$ ,  $\mathbf{H}_L$ .
- (3) These surface representations are stored in our database.
- (4) Decoder network takes  $\mathbf{H}_R$ ,  $\mathbf{H}_L$  and learns their interactions.
- (5) PPI retrieval is optimized to learn the 'lock-and-key' structure between R, L.



## PPIretrieval Encoder

## • Encoding Stage

• (1) Surface Generation

Protein flow

Input Protein Residue

- Define heat operator  $\Delta_P$  on P.
- Calculate first k eigenfunctions of heat operator  $\Phi_P$  with eigenvalues  $\{\lambda_i\}_{i=1}^k$ .
- Calculate Moore-Penrose pseudo-inverse  $\Phi_P^+$ .
- (2) Geometric Descriptor
  - Calculate Mean curvature  $\mathbf{F}_{Mean}$  on P.
  - Calculate Gaussian curvature  $\mathbf{F}_{\text{Gauss}}$  on P.
  - Calculate Heat Kernel Signatures  $\mathbf{F}_{HKS}$  on P.
  - Transform geometric features  $\mathbf{F}_{Geom} \leftarrow MLP([\mathbf{F}_{Mean}, \mathbf{F}_{Gauss}, \mathbf{F}_{HKS}])$ .





**Protein Surface Representation** 

```
erator \Phi_P with eigenvalues \{\lambda_i\}_{i=1}^k.
\Phi_P^+.
```

P. *P*. MLP([**F**<sub>Mean</sub>, **F**<sub>Gauss</sub>, **F**<sub>HKS</sub>]).

# **PPIretrieval Encoder**

### • Encoding Stage

- (3) Chemical Descriptor
  - Compute residue-level chemical features:
    - Compute chemical features  $\mathbf{F}_{\text{Res}} \leftarrow \text{MLP}([P, Y_P^{\text{res}}])$ .
    - Augment chemical features  $\mathbf{F}_{\text{Res}} \leftarrow \text{EGNN}([\mathbf{F}_{\text{Res}}, v_P])$ .
  - For every every surface point  $x_i$ , compute surface-level chemical features from  $\mathbf{F}_{Res}$ :
  - Find k nearest neighboring residues  $\{r_1^i, \ldots, r_k^i\}$  with features  $\{f_{\text{Res}}^{i,1}, \ldots, f_{\text{Res}}^{i,k}\}$ • Compute chemical features  $f_{\text{Chem}}^i \leftarrow \text{MLP}(\sum_{i=1}^k f_{\text{COS}}(\|x_i - r_j^i\|) \cdot \text{MLP}([f_{\text{Res}}^{i,j}, 1/\|x_i - r_j^i\|]))$ • Compute surface features  $\mathbf{F}_{Surf} \leftarrow MLP([\mathbf{F}_{Geom}, \mathbf{F}_{Chem}])$ .
- (4) Message Passing
  - Compute aggregated surface features  $\mathbf{H}_P$  via heat diffusion defined by  $\Delta_P$ ,  $\Phi_P$ ,  $\Phi_P^+$  (details see paper).
- **During Training** 
  - Encoder network generates  $\mathbf{H}_{R}$ ,  $\mathbf{H}_{L}$  for input paired receptor and ligand proteins.



# **PPIretrieval Decoder**

### • Decoding Stage

- Aiming to predict ligand's binding site conditioned on receptor's binding site
  - (1) Interaction Block
    - Augment receptor surface features  $\mathbf{H}_R \leftarrow \text{EGNN}([\text{MLP}(\mathbf{H}_R, \mathbf{Y}_R^{\text{surf}}), x_R])$ .
  - (2) Binding Site Prediction
    - Predict ligand's binding site  $\hat{\mathbf{Y}}_{L}^{\text{surf}} \leftarrow \sigma(\text{MLP}(\mathbf{F}_{I}))$
  - For every every resiue *i*, compute residue-level binding site from  $\hat{\mathbf{Y}}_{I}^{surf}$ :
    - Find k nearest neighboring residues  $\{\hat{\mathbf{y}}_1^{\text{surf}}, \dots, \hat{\mathbf{y}}_k^{\text{surf}}\}$  with features  $\{\mathbf{f}_1, \dots, \mathbf{f}_k\}$
    - Compute chemical features  $\hat{\mathbf{f}}_i \leftarrow \text{Mean}(\sum_{i=1}^k \mathbf{f}_i)$
    - Compute binding site  $\hat{\mathbf{y}}_i^{\text{res}} \leftarrow \text{Mean}(\sum_{j=1}^k \hat{\mathbf{y}}_j^{\text{surf}})$
- During Training
  - Each PPI sample is treated as two training instances.



```
• Augment ligand surface features \mathbf{H}_L \leftarrow \text{EGNN}([\text{MLP}(\mathbf{H}_L), x_L]).
• Compute cross-attention \mathbf{F}_L \leftarrow \text{softmax}\left(\frac{(\mathbf{H}_L W_Q)(\mathbf{H}_R W_K)^T}{\sqrt{d}}\right)(\mathbf{H}_R W_V).
```

# **PPIretrieval** Optimization

- Utilize the 'lock-and-key' structure between the receptor and ligand.
- Achieve by three training objectives:
  - (1) Lock-and-Key Optimization
    - Assemble the Jigsaw puzzles of receptor and ligand.
  - (2) Contrastive Optimization
    - Bring residues of the binding interface closer.
    - Push residue that do not belong to the binding interface farther apart.
  - (3) Binding Interface Optimization
    - Optimize the predictions of binding interfaces.



# Lock-and-Key Optimization • Ground-truth matching matrix $\mathbf{X} \in \{0,1\}^{N_R \times N_L}$ , $\mathbf{x}_{ii} = 1$ if $d_{ii} \leq d_{\text{cut}}$ .

- Construct a soft-matching matrix
  - $\hat{\mathbf{X}} = \operatorname{sinkhorn}(\exp(\hat{\mathbf{F}}_R^T W \hat{\mathbf{F}}_L / \tau)) \in [0, 1]^{N_R \times N_L}$ .
  - $\hat{\mathbf{X}}$  is a doublystochastic matrix,  $\hat{\mathbf{X}}_{ii}$  measures soft-matching score between residues *i*, *j* in receptor and ligand.
- $\mathscr{L}_{match} = cross-entropy(\mathbf{X}, \hat{\mathbf{X}})$ .
- $\mathscr{L}_{match}$  serves the dual purpose:



#### • Encourage alignment between soft-matching scores and the ground truth. • Ensure residues are matched with its complementary part in the opposite protein.

# **Contrastive** Optimization

- Bring residues of the binding interface closer.

• 
$$\mathscr{L}_{\text{contra}} = -\sum_{i \in Y_R^{\text{res}}} \sum_{j \in Y_L^{\text{res}}} \log \frac{\exp(\hat{\mathbf{f}}_R^i, \hat{\mathbf{f}}_L^j / \tau)}{\sum_{k \in Y_L^{\text{res}}} \exp(\hat{\mathbf{f}}_R^i, \hat{\mathbf{f}}_L^k / \tau)}$$

maximizes the distance between non-corresponding residues.



# • Push residue that do not belong to the binding interface farther apart.

# • $\mathscr{L}_{contra}$ minimizes the distance between corresponding residues and

# **Binding Interface Optimization**

- Directly optimize the predictions of binding interfaces.

• 
$$\mathscr{L} = \mathscr{L}_{match} + \mathscr{L}_{contra} + \mathscr{L}_{b}$$

inherent in PPI complexes.



# • $\mathscr{L}_{\text{bind}} = \text{cross-entropy}(\mathbf{Y}_{R}^{\text{res}}, \hat{\mathbf{Y}}_{R}^{\text{res}}) + \text{cross-entropy}(\mathbf{Y}_{L}^{\text{res}}, \hat{\mathbf{Y}}_{L}^{\text{res}}).$

### oind

• Overall optimization strategy is to leverage the 'lock-and-key' structure

# **Retrieval Visualization**





(f) Interface dockO similarity: 0.5280

• Visualization of PPIretrieval results for proteins in the PDB test set, evaluated by dockQ. Proteins colored in blue are input query proteins; proteins colored in red are binding partners. Left column displays the ground-truth structures; right column shows the structures predicted by PPIretrieval.







# Case Study



RKRVTSSDPAALKRAATERRSARKLQRMKQLED LLSKNYHLENVEALRKKLVGER

RRRVSPFGGGHLRLREALELFDENLPPLLELFD GEANMLPPNMPLELRGGEAPTKR

- id: 5J28), while the other not (pdb id: 1DGC).
- Although the query protein in the two ground-truth structures shares the same sequence representation, there are slightly different in their geometry.
- PPIretrieval identifies the protein in the database that most closely matches in both sequential and geometric representation



RRRVSPFGGGHLRLREALELFDENLPPLLELFD GEANMLPPNMPLELRGGEAPTKR

• The query protein has two binding partners: one stored in our surface database (pdb





Query protein and protein B fed into interactive decoder model to predict B's binding site



## Evaluation

• For a PPI in the test set, a query protein with a known binding site, we compare between

 $dockQ(Y_{true}, Y_{B}^{ref}), dockQ(Y_{true}, Y_{B}^{masif})),$  $dockQ(Y_{true}, Y_{B}^{dmasif}), dockQ(Y_{true}, Y_{B}^{pred})),$  $TM(Y_{true}, Y_R^{ref}), TM(Y_{true}, Y_R^{masif}),$  $TM(Y_{true}, Y_B^{dmasif}), TM(Y_{true}, Y_B^{pred}),$  $\operatorname{rmsd}(\mathbf{Y}_{\operatorname{true}}, \mathbf{Y}_{B}^{\operatorname{ref}}), \operatorname{rmsd}(\mathbf{Y}_{\operatorname{true}}, \mathbf{Y}_{B}^{\operatorname{masif}}),$  $\operatorname{rmsd}(\mathbf{Y}_{\operatorname{true}}, \mathbf{Y}_{B}^{\operatorname{dmasif}}), \operatorname{rmsd}(\mathbf{Y}_{\operatorname{true}}, \mathbf{Y}_{B}^{\operatorname{pred}}).$ 





# **Emperical Results**

Dataset	M	letrics	PDB	DIPS	PPBS		
	$dockO(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{ref}}_B$	0.4073	0.4177	0.5535		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_{B}$	0.4220	0.4304	0.5946		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{masif}}$	0.1334	0.1021	0.1228		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	0.1155	$\begin{array}{ c c c } \textbf{DIPS} \\ \hline 0.4177 \\ \hline 0.4304 \\ \hline 0.1021 \\ \hline 0.0837 \\ \hline 0.6617 \\ \hline 0.6649 \\ \hline 0.0981 \\ \hline 0.0981 \\ \hline 0.0831 \\ \hline 11.33 \\ \hline 6.02 \\ \hline 19.66 \\ \hline 23.55 \\ \end{array}$	0.1036		
	$TM(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{ref}}_B$	0.2134	0.6617	0.4622		
Site Quality		$TM(\uparrow)$	$TM(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	0.2366	<u>0.6649</u>	0.4735
		$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{masif}}  0.0773  0.09$	0.0981	0.0911			
			$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	0.0665	$\begin{array}{c c} 0.4177 \\ 0.4304 \\ 0.1021 \\ 0.0837 \\ \hline 0.6617 \\ \underline{0.6649} \\ 0.0981 \\ 0.0981 \\ \hline 0.0831 \\ \hline 11.33 \\ \underline{6.02} \\ 19.66 \\ 23.55 \\ \end{array}$	0.0871	
	$rmsd(\downarrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{ref}}_B$	11.40	11.33	<u>8.20</u>		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	10.44	<u>6.02</u>	9.77		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{masif}}$	15.73	19.66	17.32		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	17.87	23.55	19.65		

Table 1. dockQ, TM, and rmsd for evaluation of **Top1 hit** binding sites predicted by PPIretrieval in comparison with other binding sites over three runs. The database for each test set comprises surface representations from the training and validation sets of each respective dataset.



Dataset	Μ	letrics	PDB	DIPS	PPBS		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{ref}}$	0.4250	0.4367	0.6014		
	$dock O(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	0.4678	0.4410	0.6045		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{masif}}$	0.1345	0.1026	0.1249		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	0.1235	0.0998	0.1261		
	$TM(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{ref}}_B$	0.3222	0.6914	0.6014		
Site Quality		$TM(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	<u>0.3300</u>	0.6944	0.6045	
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{masif}}$	0.0833	0.1002	0.1004		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	0.0823	0.0911	0.1144		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{ref}}$	9.30	9.65	9.96		
	$\mathit{rmsd}(\downarrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{pred}}$	10.70	5.67	$\underline{6.52}$		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{masif}}$	15.56	19.05	16.82		
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	16.81	21.22	16.08		

Table 2. dockQ, TM, and rmsd for evaluation of **Top1 hit** binding sites predicted by PPIretrieval in comparison with other binding sites over three runs. The database comprises all surface representations from the training and validation sets of PDB, DIPS, and **PPBS** datasets.



# **Cross-Dataset Validation**

DIPS and PPBS training and validation sets, respectively.

Dataset	М	etrics	PDB	DIPS	PPBS
	$dockO(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{ref}}_B$	0.4073	0.4177	0.5535
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	0.4220	0.4304	0.5946
	uccag()	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{masif}}$	0.1334	$\begin{array}{ c c c } \textbf{DIPS} \\ 0.4177 \\ 0.4304 \\ 0.1021 \\ 0.0837 \\ \hline 0.6617 \\ \underline{0.6649} \\ 0.0981 \\ 0.0981 \\ \hline 0.0831 \\ 11.33 \\ \underline{6.02} \\ 19.66 \\ 23.55 \\ \end{array}$	0.1228
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	0.1155		0.1036
	$TM(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{ref}}_{B}$	0.2134	0.6617	0.4622
Site Quality		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_{B}$	0.2366	0.6649	0.4735
	(1)	$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{masif}} = 0.0773 = 0.0$	0.0981	0.0911	
		$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{dmasif}}$	0.0665	0.0831	0.0871
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{ref}}$	$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{ref}}$ 11.40 11	11.33	<u>8.20</u>
	$rmsd(\downarrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	10.44	6.02	9.77
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{masif}}$	15.73	19.66	17.32
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	17.87	23.55	19.65

Table 3. dockQ, TM, and rmsd for evaluation of Top1, Top10 hit Table 1. dockQ, TM, and rmsd for evaluation of **Top1 hit** binding binding sites predicted by PPIretrieval in comparison with other sites predicted by PPIretrieval in comparison with other binding binding sites on cross-datasets over three runs. The database for sites over three runs. The database for each test set comprises each test set comprises surface representations from the training surface representations from the training and validation sets of and validation sets of each respective dataset. each respective dataset.



# • We take the model trained on PDB training set only to encode the PPIs in

Dataset	Μ	letrics	DIPS-Top1	DIPS-Top10	PPBS-Top1	PPBS-Top10
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{ref}}$	0.4030	0.4156	0.5231	0.5611
	$dockO(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	0.4207	0.4435	0.5579	0.5857
	ubeng(1)	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{masif}}$	0.0515	0.0523	0.0621	0.0633
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{dmasif}}$	0.0434	0.0515	0.0601	0.0633
Site Quality	$TM(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{ref}}$	0.5330	0.6714	0.4202	0.3725
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	0.5419	0.6792	0.4421	<u>0.3889</u>
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{masif}}$	0.0499	0.0511	0.0611	0.0620
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{dmasif}}$	0. <mark>0</mark> 433	0.0491	0.0519	0.0602
	rmsd(1)	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{ref}}$	11.12	7.35	8.92	8.91
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	5.84	10.50	11.76	10.49
	(1)	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{masif}}$	20.73	19.21	19.81	19.55
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmasif}}$	23.89	22.05	20.66.	20.04



# **More Emperical Results**

PDB Dataset	Metrics		Top1	Top10	Top20	Top50	<b>Top100</b>		PDB Dataset	Μ	etrics	Top1	Top10	Top20	Top50	To
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_{B}^{ ext{ref}}$	0.4073	0.4362	0.4379	0.4411	0.3507		Site Quality	$dockQ(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{ref}}$	0.4126	0.4331	0.4480	0.4491	0.
	$dockO(\uparrow)$	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_{B}$	<u>0.4220</u>	0.4375	0.4459	0.4569	<u>0.4688</u>				$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_{B}$	0.4235	0.4402	0.4531	0.4649	<u>0</u> .
	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{masif}}$	0.1334	0.1338	0.1355	0.1401	0.1405				$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{masif}}$	0.1433	0.1436	0.1455	0.1458	0.
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmassif}}$	0.1155	0.1194	0.1212	0.1247	0.1301				$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{dmasif}}$	0.1225	0.1266	0.1301	0.1398	0.
		$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{ref}}$	0.2134	0.2078	0.2059	0.2059	0.2108			<i>TM</i> (†)	$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{R}^{\text{ref}}$	0.3944	0.3877	0.3833	0.3554	0.
Site Quality $TM(\uparrow)$	$TM(\uparrow)$	$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{pred}}$	<u>0.2366</u>	<u>0.2266</u>	0.2241	0.2231	0.2265				Vtrue Vpred	0 4041	0 3969	0.3863	0 3625	0
		$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{mastr}}$	0.0773	0.0775	0.0774	0.0758	0.0702				$\mathbf{V}_{i}$ $\mathbf{V}_{B}^{\text{masif}}$	0.0787	0.0766	0.0750	0.0791	$\int \frac{\nabla}{\Omega}$
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmassif}}$	0.0665	0.0668	0.0679	0.0698	0.0701				$\mathbf{v}$ $\mathbf{v}$ dmasif	0.0101	0.0700	0.0750	0.0721	0.
		$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{ref}}$	11.40	9.74	9.59	9.50	9.34				<b>I</b> true, <b>I</b> B	0.0550	0.0546	0.0566	0.0562	0.
		$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{P}^{\text{pred}}$	10.44	9.33	8.94	8.52	8.16				$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{ref}}$	10.41	9.73	9.70	9.49	6
$rmsa(\downarrow)$	$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{masif}}$	15.98	15.88	15.84	15.76	15.53			rmsd(1)	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}^{ ext{pred}}_B$	<u>10.04</u>	8.97	<u>8.66</u>	8.20		
		$\mathbf{Y}_{\text{true}}, \mathbf{Y}_{B}^{\text{dmasif}}$	17.87	17.31	17.03	16.55	16.02			(*)	$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{masif}}$	15.73	15.71	15.54	15.26	1
Cost	<i>PPIretrieval runtime</i> ( $\downarrow$ )	second/protein	0.29	0.91	1.97	4.64	9.44				$\mathbf{Y}_{ ext{true}}, \mathbf{Y}_B^{ ext{dmassif}}$	17.75	17.22	17.02	16.40	1

Table 5. dockQ, TM, and rmsd for evaluation of Top1, Top10, Table 4. dockQ, TM, and rmsd for evaluation of Top1, Top10, **Top20, Top50, Top100 hit** binding sites predicted by PPIretrieval **Top20, Top50, Top100 hit** binding sites predicted by PPIretrieval in comparison with other binding sites in the PDB test set over in comparison with other binding sites in the PDB test set over three runs. The database comprises surface features from training three runs. The database comprises surface features from training and validation sets from PDB, DIPS, and PPBS dataset. and validation sets from PDB dataset only.







## Future Direction

- Improving model size and training.
- Including more high-qiality PPI data.
- Designing interpretable embedding space for visualization, like foldseek.
- Establishing webserve for PPIretrieval, like foldseek.





Personal Website

Paper







Will Hua 华辰清 Montreal, Canada



Scan the QR co



Code (private)

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