A deep learning method for predicting interactions for intrinsically disordered regions of proteins

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Summary

Intrinsically disordered proteins or regions (IDPs/IDRs) adopt diverse binding modes with different partners, from coupled-folding-and-binding, to fuzzy binding, to fully-disordered binding. Characterizing IDR interfaces is challenging experimentally and computationally. The state-of-the-art AlphaFold-multimer and AlphaFold3 can be used to predict IDR binding sites, although they are less accurate at their benchmarked confidence cutoffs. Here, we developed Disobind, a deep-learning method that predicts inter-protein contact maps and interface residues for an IDR and its partner, given their sequences. It uses sequence embeddings from the ProtT5 protein language model. Disobind outperforms state-of-the-art interface predictors for IDRs. It also outperforms AlphaFold-multimer and AlphaFold3 at multiple confidence cutoffs. Combining Disobind and AlphaFold-multimer predictions further improves the performance. In contrast to current methods, Disobind considers the context of the binding partner and does not depend on structures and multiple sequence alignments. Its predictions can be used to localize IDRs in large assemblies and characterize IDR-mediated interactions.

Keywords: Intrinsically disordered proteins (IDP), intrinsically disordered regions (IDR), protein structure, deep learning (DL), protein language model (pLMs)

Introduction

Intrinsically disordered proteins or regions (IDPs or IDRs) lack a well-defined three-dimensional structure in their monomeric state (Oldfield & Dunker, 2014; Wright & Dyson, 1999). They exist as an ensemble of interconverting conformers in equilibrium and hence are structurally heterogeneous (Lindorff-Larsen & Kragelund, 2021; Oldfield & Dunker, 2014; Uversky, 2013b). Here, we use the term IDR for both IDPs and IDRs. The heterogeneity of IDRs provides several functional advantages including the ability to overcome steric restrictions, have a large capture radius, undergo functional misfolding, and interact with multiple partners (Fonin et al., 2018). They play critical roles in cellular processes including signaling, intracellular transport, protein folding, and condensate formation (Fonin et al., 2018; Uversky, 2013b).

IDRs are known to mediate a large number of protein-protein interactions (Tompa et al., 2014). They exhibit considerable diversity in their binding modes within complexes (Holehouse & Kragelund, 2024; Olsen et al., 2017). Upon binding to a partner protein, they may adopt an ordered state (disorder-to-order or DOR) or may remain disordered (disorder-to-disorder or DDR) (Holehouse & Kragelund, 2024; Miskei et al., 2017, 2020; Orand & Jensen, 2025). Moreover, depending on the binding partner, the same IDR may undergo DOR and DDR transitions (Miskei et al., 2020; Orand & Jensen, 2025). For example, IDRs with short linear motifs (SLiMs) may form multivalent interactions with their partner, exchanging between conformations where one or more motifs bind at a time (Orand & Jensen, 2025). This heterogeneity in binding makes their structural characterization in complexes challenging.

Here, we develop a deep learning method to determine the binding sites of an IDR and an interacting partner protein given their sequences. Several methods have been developed for predicting interface residues, inter-protein contact maps, and structures of complexes formed by two proteins. Some of them are limited by the requirement of a structure of the input proteins (Christoffer & Kihara, 2020; Dai & Bailey-Kellogg, 2021; Gainza et al., 2020; Guo et al., 2022; Lin et al., 2023; Pittala & Bailey-Kellogg, 2020). Sequence-based methods that require a multiple sequence alignment (MSA) are often limited by the low sequence conservation of IDRs (Abramson et al., 2024; Bret et al., 2024; Jumper et al., 2021; B.-G. Lee et al., 2020). Other sequence-based

methods for IDRs use physicochemical features or embeddings from protein language models (pLMs) but do not account for the partner protein (Jahn et al., 2024; Mészáros et al., 2009; Singh et al., 2022; F. Zhang et al., 2022). However, the knowledge of the partner protein is crucial in understanding IDR interactions as these are context-dependent. To this end, FINCHES predicts intermolecular interactions for two IDRs based on their chemical specificity, given their sequences. However, it is currently limited to IDRs that remain disordered upon binding (Ginell et al., 2025).

State-of-the-art methods like AlphaFold2 (AF2) and AlphaFold3 (AF3) tend to provide low-confidence predictions for IDRs (Abramson et al., 2024; Evans et al., 2022; Jumper et al., 2021). Even though the low-confidence regions predicted by AF2 often correspond to the presence of IDRs, the predicted structure cannot be considered a representative IDR structure (Alderson et al., 2022; Ruff & Pappu, 2021). Recent studies showed that AlphaFold-multimer (referred to as AF2 hereon) could predict the structures of complexes where the IDR undergoes a DOR transition, including protein-peptide complexes and domain-motif complexes (Bret et al., 2024; B.-G. Lee et al., 2020; Omidi et al., 2024). However, the results may be sensitive to the inputs, such as the sequence fragment size, the fragment delimitation, and the alignment mode for the MSA (Bret et al., 2024; B.-G. Lee et al., 2020). In general, predicting the binding interfaces for IDRs at high resolution remains a challenge for current methods (Verburgt et al., 2022).

Our method, Disobind, predicts the inter-protein contact maps and interface residues for an IDR and its partner from their sequences. Predicting inter-protein contact maps for IDRs presents several challenges. The structural data for IDRs in complexes is limited, the IDRs may retain their heterogeneity in complexes, and the inter-protein contact maps can be sparse. Here, we leverage the pLM ProtT5 to train our model with limited data, without the need for large, resource-intensive architectures. Predicting coarse-grained inter-protein contact maps and interface residues reduces problems associated with sparsity and heterogeneity. Disobind performs better than state-of-the-art interface predictors for IDRs and better than AF2 and AF3 across multiple confidence cutoffs used in this study. Combining the Disobind and AF2 predictions further improves the performance. We demonstrate the performance of Disobind+AF2 on several IDR complexes, on multiple examples, including several

DOR and DDR complexes. Predictions from the method can be used to localize IDRs in integrative structures of large assemblies. They can be used to characterize protein-protein interactions involving IDRs, identify novel motifs, and modulate IDR-mediated interactions.

Results

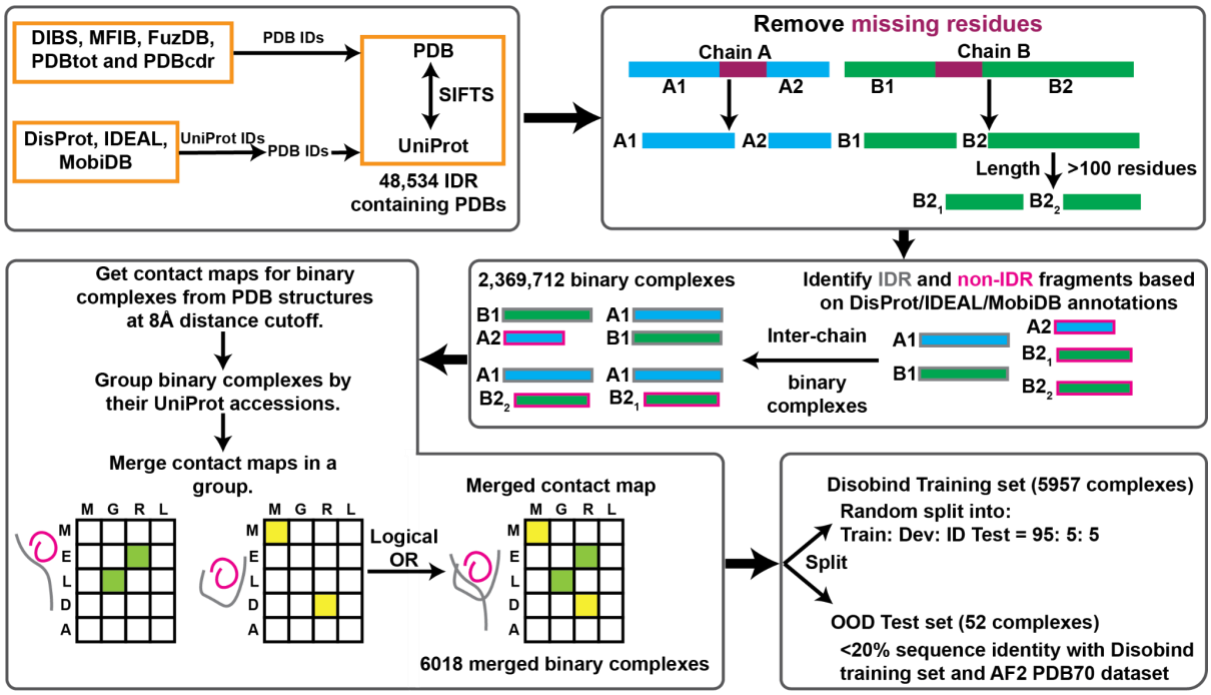

Figure 1: Disobind dataset creation pipeline. We compiled our dataset by gathering structures of IDR-containing complexes from DIBS, MFIB, FuzDB, PDBtot, PDBcdr, DisProt, IDEAL, and MobiDB. For each PDB chain, missing residues in the structures are excluded, resulting in sequence fragments. Further, we restrict the maximum length of a sequence fragment to 100 residues. We use annotations from DisProt, IDEAL, and MobiDB to classify a sequence fragment as an IDR. Next, we obtain inter-chain binary complexes comprising at least one IDR fragment. Contact maps are obtained for all binary complexes which are subsequently grouped based on the UniProt accessions of the sequence fragment pair. The contact maps of all binary complexes in a group are merged, creating merged contact maps. A sequence fragment pair and its corresponding merged contact map comprise a merged binary complex. The merged binary complexes are redundancy reduced at a 20% sequence

identity cutoff to create an out-of-distribution (OOD) test set. The remaining complexes comprise the Disobind training set which is split into train, dev, and in-distribution (ID) test sets.

Disobind dataset creation

Given a pair of protein sequences, at least one of which is an IDR, Disobind predicts binary inter-protein contact maps and interface residues for the pair (Fig 1). We compile our dataset by gathering structures of IDR-containing complexes from an array of existing IDR databases and datasets, including DIBS, MFIB, FuzDB, PDBtot, PDBcdr, DisProt, IDEAL, and MobiDB, covering a range of IDR binding modes (Fig 1) (See Methods). Missing residues in the structures are excluded from the input sequences, resulting in sequence fragments for each PDB chain. Further, we restrict the maximum length of a sequence fragment to 100 residues for computational reasons.

We classify a sequence fragment as an IDR based on annotations supported by experimental evidence and sequence-based homology obtained from DisProt, IDEAL, and MobiDB; an IDR fragment has at least 20% residues annotated as disordered (See Methods). Next, we obtain inter-chain binary complexes from each PDB structure, in which at least one of the two fragments is an IDR (Fig 1). We obtain contact maps for all binary complexes. The contact maps are grouped based on the UniProt accessions of the corresponding sequence fragment pair. Next, we merge all contact maps with overlapping sequences in a group using a logical OR operation to obtain a merged contact map, ensuring that the length of each sequence fragment is up to 100 residues. Together, the sequence fragments for the pair and the corresponding merged contact map form a merged binary complex. Disobind is trained on a dataset of merged binary complexes with the sequence fragments as input and the merged contact map as output. The merged contact map encompasses contacts formed across all available structures of the complex, accounting for the multiple conformations of an IDR in a complex. This simplified output representation avoids making any assumptions about binding mode, allowing it to be applicable to DOR and DDR cases. Further, this provides for a less sparse output representation compared

to an ensemble of contact maps, while also mitigating the bias caused by having an unequal number of structures for different sequence fragment pairs.

We then create an out-of-distribution (OOD) test set comprising merged binary complexes where the input sequence fragments share less than 20% identity with the Disobind dataset and with the AlphaFold2 PDB70 dataset. The remaining complexes are further split into a train, validation, and an in-distribution (ID) test set. The ID and OOD test sets comprise 297 and 52 merged binary complexes respectively. Adding more complexes to the OOD test set may be achieved by increasing the sequence identity cutoff but would also increase similarity to the AF2 training dataset, which we attempted to avoid.

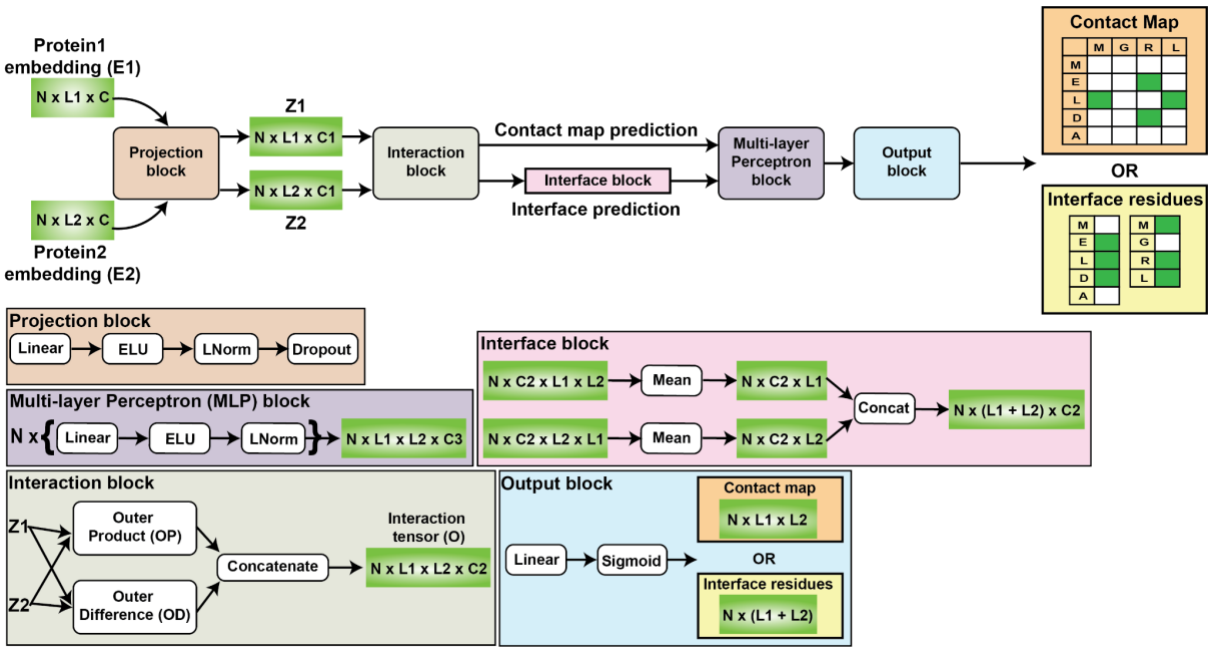

Figure 2: Disobind architecture. The inputs to Disobind are the sequence embeddings for the sequence pair obtained using a pLM. The sequence embeddings are projected to a lower dimension using a projection block. Next, in the interaction block, the projected embeddings are used to compute the outer product and outer difference, which is subsequently concatenated along the feature dimension, resulting in an interaction tensor. For contact map prediction, this interaction tensor is processed by a multi-layer perceptron (MLP). For interface residue prediction, the interaction tensor is reduced by computing row-wise and column-wise averages and further processed by an MLP. Next, an output block provides element-wise sigmoid

scores, with a score greater than 0.5 representing a contact or interface residue. Here, N, L, C represent the batch size, sequence length, and feature dimension respectively.

Model architecture

Disobind uses a shallow feedforward neural network architecture with the sequence embeddings obtained from a protein language model as input (Fig 2). The input embeddings are projected to a lower dimension using a projection block. Next, in the interaction block, the projected embeddings are used to compute the outer product and outer difference, which are subsequently concatenated along the feature dimension. This allows the model to capture complementarity between the input sequences and yields an interaction tensor. This interaction tensor is processed by a multi-layer perceptron (MLP) for contact map prediction. For interface residue prediction, the interaction tensor is first reduced by computing row-wise and column-wise averages and further processed by an MLP. Finally, an output block provides element-wise sigmoid scores, with a score greater than 0.5 representing a contact or interface residue. The outputs are binary contact maps or binary interface residue predictions on the fragments. The model is trained with the singularity-enhanced loss (SE loss) (Si & Yan, 2021) using the AdamW optimizer with weight decay (Fig S1). This loss is a modified form of the binary cross-entropy (BCE) loss used for class-imbalanced training. We varied the hyperparameters of the network including the projection dimension, the number of layers in the MLP, and the SE loss parameters (Table S1-S4, Fig S1). We use recall, precision, and F1-score to evaluate model performance.

Evaluating Disobind

Inter-protein contact map prediction

First, we evaluate Disobind on predicting residue-wise inter-protein contact maps on the ID and OOD test sets. Disobind achieves an F1-score of 0.57 and 0.33 on the ID and OOD test sets respectively (Table 1 and Table S5, contact map prediction at coarse-grained (CG) resolution 1). It performs better than a random baseline (see Methods) on the OOD test set (Table 1). However, predicting residue-wise inter-

protein contact maps is challenging due to their sparsity (Table S6). This leads to a class imbalance, biasing the model to predict just the majority class, *i.e.,* 0's or non-contacts. The heterogeneity of IDRs in complexes poses another challenge. For example, the multivalency of IDRs may result in different sets of contacts in different conformations with the same partner (J. Zhang et al., 2024).

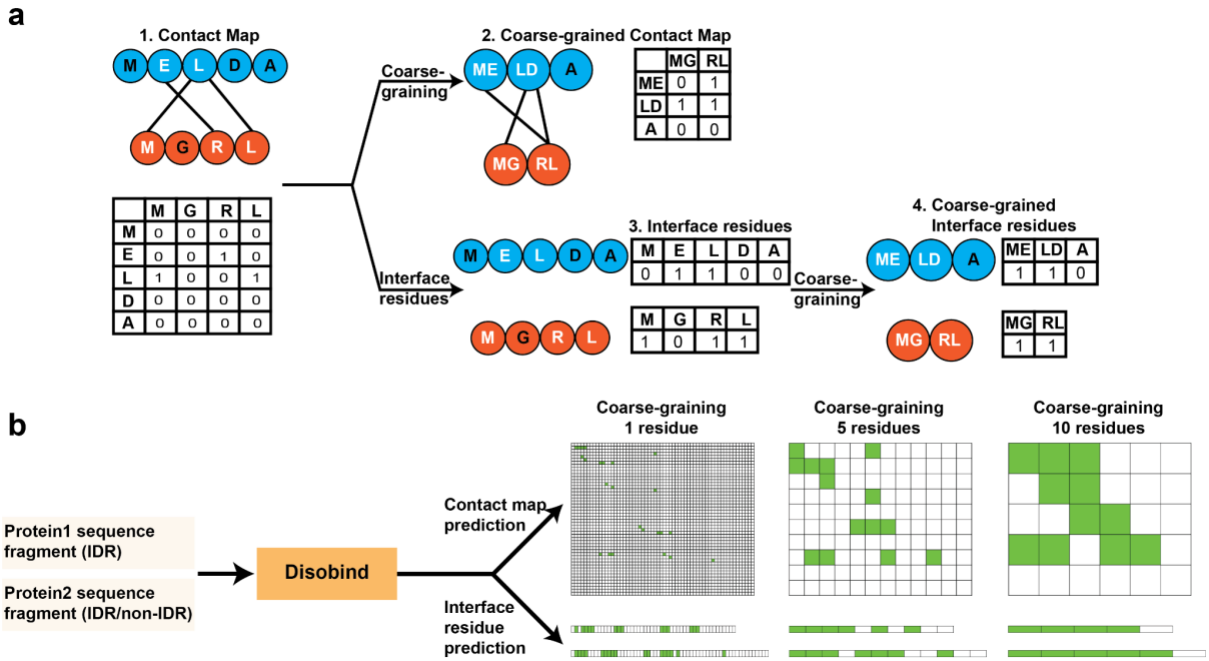

Figure 3: Predicting coarse-grained contact maps and interface residues. (a) We use coarse-graining and predict interface residues as an alternative to predicting residue-wise inter-protein contact maps. This addresses the problems associated with the multivalency of IDRs and the sparsity of inter-protein contact maps. **(b)** Disobind can predict inter-protein contact maps and interface residues at multiple coarse-grained resolutions (1, 5, 10).

Interface residue prediction

As an alternative to predicting inter-protein residue-wise contact maps, next, we predict interface residues for the IDR and its partner (Fig 3a). For two input sequence fragments of length L_1 and L_2, this reduces the number of predicted elements from $L_1 \times L_2$ in the contact map prediction to $L_1 + L_2$ in the interface residue prediction (Fig 3b). This helps mitigate the class imbalance as the interface residue predictions

are less sparse (Fig 3a, Fig 3b Table S6, interface residue prediction at coarse-grained (CG) resolution 1). Interface residue prediction is also less affected by the heterogeneity of IDRs in complexes. The prediction for each residue is simplified to determining whether it binds to the partner, rather than identifying the specific residues within the partner it interacts with.

As expected, Disobind performs better in interface residue prediction than in contact map prediction. It achieves an F1 score of 0.70 and 0.48 on the ID and OOD test sets respectively (Fig S2, Table 1 and Table S5, interface residue prediction at coarse-grained (CG) resolution 1). It performs better than a random baseline evaluated on the OOD test set (Table 1).

Coarse-graining improves the performance

To further improve the performance of our model, we predict coarse-grained contact maps and interface residues (Fig 3a, Fig 3b). Coarse-graining has been widely used for modeling biological systems (Arvindekar et al., 2024; Noid, 2013). Coarse-graining over a set of residue pairs in a contact map or a set of residues in the interfaces further reduces the sparsity and class imbalance, and mitigates the problems posed by the multivalency of IDR interactions (Fig 3a, Fig 3b, Table S6). Notably, we coarse-grain over embeddings from pLMs, which provide context-aware, abstract representations of the sequence. Further, coarse-graining along the sequence is well-suited for the modular and patch-driven nature of IDR interactions, that are mediated by charge patterning, attractive sticker regions, conserved short linear motifs (SLiMs) and molecular recognition features (MoRFs), and/or less conserved low-complexity regions (LCRs) (Christensen et al., 2019; Cumberworth et al., 2013; Holehouse & Kragelund, 2024; Mohan et al., 2006).

We train Disobind to predict coarse-grained contact maps and coarse-grained interface residues at resolutions of 5 and 10 contiguous residues along the backbone. The coarse-grained embeddings are obtained by averaging the input embeddings (Elnaggar et al., 2022). As expected, coarse-graining further improves the performance of Disobind on the ID and OOD test sets for both the contact map and

interface residue prediction (Fig S2, Table 1, Table S5). For all cases, Disobind performs better than a random baseline on the OOD test set.

Comparison to AlphaFold2 and AlphaFold3

We further compare the performance of Disobind with the state-of-the-art methods AF2 and AF3 on the OOD test set. For evaluating AF2 and AF3 outputs, we mask out interactions predicted at low confidence based on the interface-predicted template matching (ipTM) score, predicted local distance difference test (pLDDT), and predicted aligned error (PAE) metrics (see Methods).

Using different ipTM cutoffs for AF2 and AF3

The ipTM score is a metric provided by AF2 and AF3 to assess the confidence in the predicted interfaces in a complex (Abramson et al., 2024; Evans et al., 2022). A prediction with an ipTM score greater than 0.75 is considered highly confident, while an ipTM lower than 0.6 indicates a likely failed prediction (O'Reilly et al., 2023; Yin et al., 2022). We first evaluate the performance of AF2 and AF3 with an ipTM cutoff of 0.75. Disobind performs better than AF2 and AF3 for all tasks, *i.e.,* contact map and interface residue predictions across different coarse-grained resolutions (Table 1, ipTM = 0.75). Disordered residues, however, are known to impact the pTM and ipTM metrics negatively (Abramson et al., 2024; Magana & Kovalevskiy, 2024). Considering this, we relaxed the ipTM cutoff to 0.4 to assess the performance of AF2 and AF3, keeping the per-residue metric, *i.e.* pLDDT and PAE cutoffs as is, guided by recent benchmarks and the AF3 guide (Abramson et al., 2024; Omidi et al., 2024). Here also, Disobind performs better than both AF2 and AF3 for both contact map and interface residue prediction (Table 1, ipTM = 0.4). AF3 performs worse than both Disobind and AF2. Furthermore, this trend remains more or less the same even when we do not apply an ipTM cutoff (Table 1, ipTM = 0.0). Additionally, we show that predictions derived from the structure and the contact probabilities are largely similar, indicating a good agreement between the predicted structure and the contact probabilities (Table S7, see supplementary text).

AF2 performs better than AF3

Similar to Disobind, coarse-graining improves the performance of both AF2 and AF3 for both contact map and interface predictions (Table 1). Across all tasks, AF2 performs better than AF3. Moreover, AF3 predictions have lower confidence as measured by their ipTM scores (Fig S3). For 35 of 52 OOD test set entries, the ipTM score of the best AF2 model was greater than that of the best AF3 model. Overall, only 8 of 52 predictions from AF2 and 2 of 52 predictions from AF3 had a high confidence prediction, *i.e.*, ipTM score higher than 0.75.

Combining Disobind and AlphaFold2 predictions

Next, we sought to combine the predictions from Disobind and AF2, to see if we could further improve over either method. We combine the predictions from Disobind and AF2 using a logical OR operation and evaluate the performance on the OOD test set. The combined model, “Disobind+AF2”, performs better than either of the methods (Table 2).

Performance by residue types

Next, we assess the performance of Disobind, AF2, and Disobind+AF2 by residue type to examine which regions each method tends to perform better on (See Methods). Disobind outperforms AF2 on both the contact map and interface residue prediction in disordered regions, whereas AF2 performs slightly better than Disobind for ordered regions (Table S8). Importantly, the combined model Disobind+AF2 performs better for both disordered and ordered regions, likely because the two models learn complementary information by focusing on different regions.

Further, Disobind predictions are more accurate than AF2 for disorder-promoting and hydrophobic, whereas AF2 and Disobind perform similarly for aromatic and polar residues (Table S9). Disobind is more accurate than AF2 in predicting contacts and interface residues involving LIPs (Table S9). The combined model is better across all residue types (Table S9).

Comparison with interface predictors for IDRs

We compared Disobind with partner-independent interface predictors for IDRs, including AIUPred, MORFchibi, and DeepDISOBind, which are comparable to the state-of-the-art in the Critical Assessments of protein Intrinsic Disorder prediction (CAID2) (Conte et al., 2023; Erdős et al., 2025; Malhis & Gsponer, 2025; F. Zhang et al., 2022). For a fair comparison, we evaluated interface residue predictions for only the IDR protein in the OOD set (See Methods). Disobind outperforms AIUPred, MORFchibi, and DeepDISOBind at predicting interface residues for the IDR (Table 3).

Input Embeddings

Next, we investigate the effect of using embeddings from various pLMs and the different embedding types on the performance of Disobind.

Protein language models allow for a shallow architecture

Protein language models (pLMs) provide context-aware representations of protein sequences that facilitate training models for downstream tasks like contact map prediction *via* transfer learning. They allow using a shallow downstream architecture when training with limited data (Bepler & Berger, 2021; Jahn et al., 2024). Several pLMs have been developed including the ESM series of models (Rives et al., 2021), ProstT5 (Heinzinger et al., 2024), ProtT5 (Elnaggar et al., 2022), ProtBERT (Elnaggar et al., 2022), and ProSE (Bepler & Berger, 2019).

The pLMs differ in the model architecture, the training datasets, and the training regime. These can affect their ability to learn contextual representations for protein sequences. ProSE uses a bidirectional LSTM trained on UniRef protein sequences and structures with a multitask loss combining similarity and contact prediction objectives (Bepler & Berger, 2019). The other pLMs use variants of the transformer architecture. ProtBERT uses the Bidirectional Encoder Representations from Transformers (BERT) architecture, an encoder-only model, trained on the UniRef100 and BFD100 datasets. It is trained to reconstruct corrupted tokens given the context of the neighbouring tokens (Elnaggar et al., 2022). ProtT5 uses the Text-to-Text Transfer Transformer (T5) architecture, an encoder-decoder model, trained on the

UniRef50 and BFD100 datasets. In contrast to the BERT-style training objective, ProtT5 is trained to reconstruct spans of corrupted tokens (Elnaggar et al., 2022; Raffel et al., 2023). ProstT5 is a newer version of ProtT5, fine-tuned with AlphaFold2 predicted protein structures (Heinzinger et al., 2023).

Disobind uses embeddings from ProtT5, one of the best performing pLMs in our comparison (Table S10). The T5-based models, ProtT5 and ProstT5, perform similarly, but outperform the BERT-styled ProtBERT and LSTM-based ProSE models. Due to limitations in memory, we could not generate ESM2-650M-global embeddings for the entire training set. Hence, we do not include ESM in our comparison.

Global embeddings perform better than local embeddings

We then evaluate whether models trained with global sequence embeddings perform better than those with local embeddings. Local embeddings are obtained by providing the sequence of the fragment as input to the pLM. Global embeddings, in contrast, are obtained by providing the entire protein sequence corresponding to the fragment as input to the pLM, followed by extracting the embeddings corresponding to the fragment (Fig S4). Models with global embeddings perform better than those with local embeddings across all the pLMs we tested (Table S10). Using the global embeddings provides the context of the complete protein sequence corresponding to the fragment, plausibly resulting in better performance. This context may contain information relevant to binding: for example, the binding of IDRs is known to be affected by the flanking regions (Olsen et al., 2017).

Case studies

IDRs enable dynamic interactions, molecular recognition, and functional adaptability, making them a crucial component of various signaling and regulatory pathways. We used Disobind+AF2 for predicting interface residues for several IDR complexes (Fig 4, Fig S5). Here, we discuss in detail two cases in which the IDR becomes ordered upon binding (DOR) and two cases where the IDR remains disordered (DDR). A larger set of NMR examples of mostly DDR cases from MobiDB, PEDS, BMRB, and LLPSdb

are also shown separately (Fig S5) (Ghafouri et al., 2024; Hoch et al., 2023; Li et al., 2020; Piovesan et al., 2024).

The cellular prion protein (PrP^{C}) plays an important role in several cellular processes, including synapse formation, regulating circadian rhythm, and maintaining ion homeostasis (Kraus et al., 2021; Sigurdson et al., 2019). It is known to convert to an infectious PrP^{Sc} form, which forms amyloid fibrils associated with several diseases, including Creutzfeldt-Jakob disease and bovine spongiform encephalopathy (Kraus et al., 2021; Sigurdson et al., 2019). PrP^{C} has an N-terminal disordered region and a primarily α-helical C-terminal region, whereas the conversion to PrP^{Sc} involves significant structural changes, resulting in a β-sheet-rich structure. Disobind+AF2 could accurately predict the interface residues in the β-sheet-rich PrP^{Sc} dimer, achieving an F1-score of 0.71 (Fig 4a).

Chemokines are small secretary molecules that play several important roles, including immune cell trafficking, wound healing, and lymphoid cell development (Rossi & Zlotnik, 2000; Sepuru et al., 2020). Dysregulation of chemokine release is associated with several diseases, including chronic pancreatitis, inflammatory bowel disease, and psoriasis (Rossi & Zlotnik, 2000; Sepuru et al., 2020). Chemokines bind to chemokine receptors that belong to the G-protein coupled receptor (GPCR) family. Tha latter contains an N-terminal disordered region that becomes structured and adopts an extended conformation upon binding. Disobind + AF2 accurately predicts the interface residues for the chemokine Interleukin-8 binding to the N-terminus of its cognate receptor, CXCR1 with an F1 score of 0.73 (Fig 4b).

The death domain-associated protein 6 (Daxx) is a transcriptional coregulator that plays a key role in apoptosis (Chang et al., 2011; Salomoni & Khelifi, 2006). It contains a C-terminal disordered region that attains an extended conformation upon binding to its partner SUMO-1 (Chang et al., 2011). This interaction is crucial for its localization to nuclear PML bodies, the absence of which leads to disruption of PML nuclear bodies as seen in acute myelocytic leukaemia (Salomoni & Khelifi, 2006). Disobind+AF2 could accurately capture interface residues in this region, achieving an F1-score of 0.81 (Fig 4c).

UV-stimulated scaffold protein A (UVSSA) is a crucial component for transcription-coupled nucleotide excision repair (TC-NER) pathway (Okuda et al., 2017; Schwertman et al., 2012). Disruption of the TC-NER pathway is associated with various diseases, including xeroderma pigmentosa and UV-sensitive syndrome (Okuda et al., 2017). In complex with USP7, UVSSA is involved in processing the stalled RNA pol II and recruiting TFIIH. A short acidic region in UVSSA is an IDR and interacts with the N-terminal PH domain in the p62 subunit of the TFIIH complex, which is crucial for the recruitment of TFIIH to the TCR site (Okuda et al., 2017). Disobind+AF2 was able to capture the interface residues in this case with an F1-score of 0.71 (Fig 4d). In summary, across all the cases, our combined model achieves high accuracy in predicting interface residues for IDR complexes.

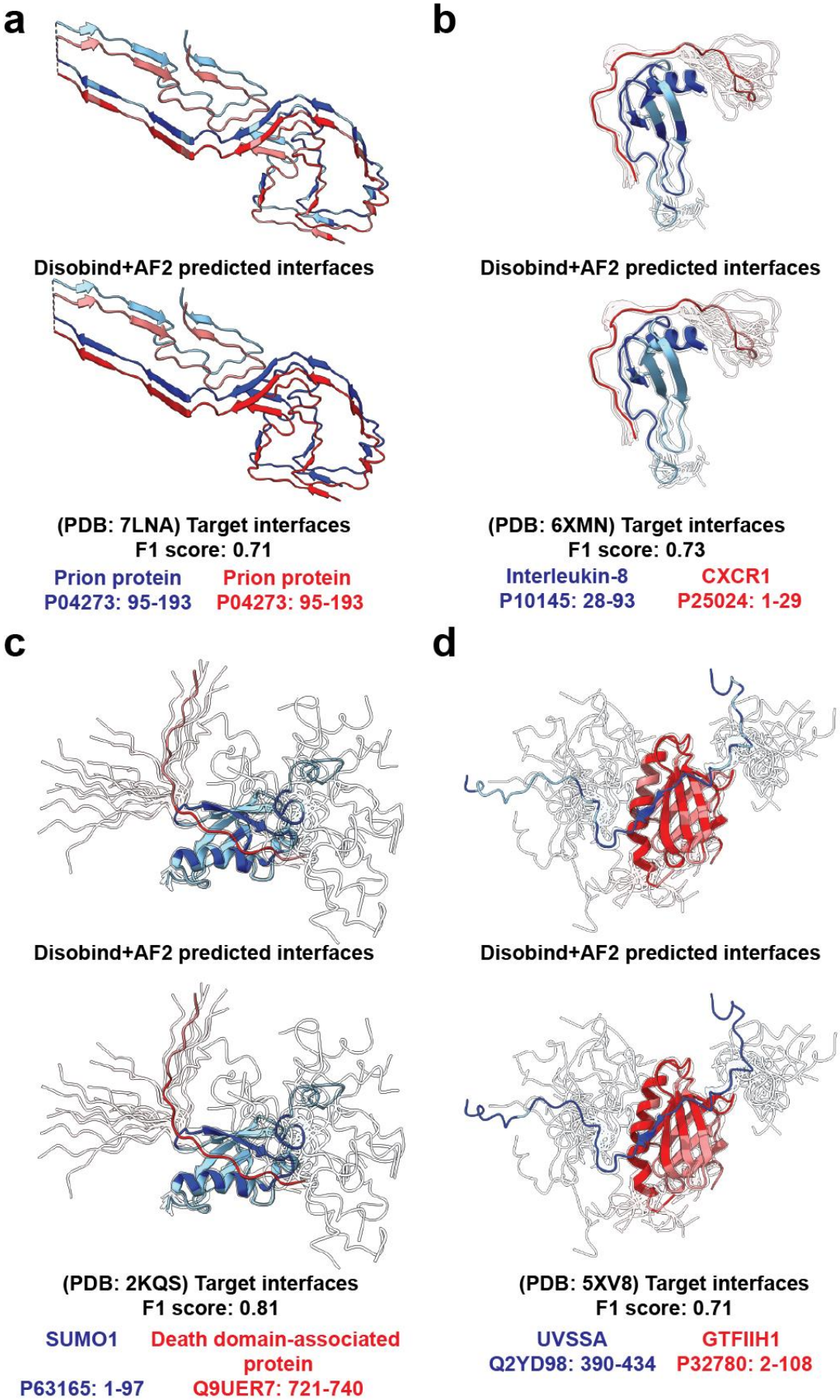
a
Disobind+AF2 predicted interfaces
(PDB: 7LNA) Target interfaces
F1 score: 0.71
Prion protein
P04273: 95-193
Prion protein
P04273: 95-193
b
Disobind+AF2 predicted interfaces
(PDB: 6XMN) Target interfaces
F1 score: 0.73
Interleukin-8
P10145: 28-93
CXCR1
P25024: 1-29
c
Disobind+AF2 predicted interfaces
(PDB: 2KQS) Target interfaces
F1 score: 0.81
SUMO1
P63165: 1-97
Death domain-associated protein
Q9UER7: 721-740
d
Disobind+AF2 predicted interfaces
(PDB: 5XV8) Target interfaces
F1 score: 0.71
UVSSA
Q2YD98: 390-434
GTFIIH1
P32780: 2-108

Figure 4: Case studies visualizing Disobind+AF2 predictions. The figures visualize the Disobind+AF2 predicted and target interface residues for both proteins in complexes where IDRs undergo a DOR (panels a and b) or DDR (panels c and d) transition. The protein chains are coloured in blue and red, where the lighter shade represents the chain and the darker shade represents the interface residues for the respective chains. For all NMR structures, the ensemble is represented with reduced transparency in the background, whereas the first model is shown in the foreground. The PDB IDs, protein names, and corresponding UniProt accession, along with the residue numbers for which the predictions were made, are shown for all complexes.

Discussion

Here, we discuss about the uses and limitations of Disobind, challenges involved, the performance of AlphaFold, and future directions.

Uses and limitations

Predictions from Disobind+AF2 may be used to improve the localization of IDRs in integrative models of large assemblies, our primary motivation for developing the method. Macromolecular assemblies contain significant portions of IDRs, for example, the Fg Nups in the nuclear pore complex, the MBD3-IDR in the nucleosome remodeling and deacetylase (NuRD) complex, and the N-terminus of Plakophilin1 in the desmosome (Akey et al., 2022; Arvindekar et al., 2022; Pasani et al., 2024). These regions typically lack data for structural modeling, resulting in integrative models of poor precision (Arvindekar et al., 2022; Pasani et al., 2024). The predictions from Disobind+AF2 can be used in integrative modeling methods such as IMP, HADDOCK, and Assembline as inter-protein distance restraints (Dominguez et al., 2003; Rantos et al., 2022; Russel et al., 2012). Even the coarse-grained contact map and interface residue predictions would be useful in such cases to improve the precision of these regions in the integrative model. Further, the predicted contacts can be combined with molecular dynamics (MD) simulations to generate ensembles of IDRs in complexes, providing mechanistic insights into their dynamic behaviour. Additionally, our method can be used to characterize interactions involving IDRs across proteomes. This may

aid in identifying new binding motifs for IDRs, potentially linked to their sub-cellular localization or function. Finally, predictions from our method may aid in modulating interactions involving IDRs, for example, by suggesting plausible mutations.

However, our method also has several limitations. First, it is limited to binary IDR-partner complexes. For complexes formed by three or more subunits, binary predictions from Disobind would need to be combined. Second, it assumes that the IDR and its partner are known to bind. Disobind cannot reliably distinguish binders from non-binders (see Supplementary text). Third, the accuracy of the predictions depends on the ability of the pLM to provide accurate representations of the IDR and its partner. Finally, our method cannot be used to assess the effects of post-translational modifications as the pLM used does not distinguish post-translationally modified amino acids.

Challenges

Predicting contact maps and interface residues for IDRs in a complex with a partner is challenging. First, a limited number of experimental structures are available for IDRs in complexes (Jahn et al., 2024; J. Zhang et al., 2024). Second, IDRs adopt an ensemble of conformations, and the available structures may only partially capture this conformational diversity. Third, inter-protein contact maps are typically sparse, with only a few residues forming contacts. Although not sufficient, we gather all available structures for IDRs in complexes. With these, we create a dataset of merged binary complexes for training Disobind. Using merged binary complexes helps overcome the issue of sparsity associated with training on an ensemble of contact maps. Predicting interface residues instead of contacts and using coarse-graining helps overcome the challenges associated with the multivalency of IDRs and the sparsity of inter-protein contact maps (Fig 3a).

Performance of AF2 and AF3

Several studies indicate that the low-confidence regions in AF2 predictions overlap with the presence of disordered regions, although these low-confidence regions cannot be considered as a representative conformation for IDRs (Alderson et al., 2022; Escobedo et al., 2023; Ruff & Pappu, 2021). Despite the success of AF2 and AF3 for

ordered proteins, their performance on IDR complexes remains limited, as shown in benchmarks (Alderson et al., 2022; Bret et al., 2024; C. Y. Lee et al., 2024; Omidi et al., 2024). This could potentially be due to several reasons. First, IDRs show low sequence conservation, resulting in poor quality MSAs (Holehouse & Kragelund, 2024). Second, IDRs are best described by an ensemble of conformations which capture their dynamic behaviour. AF2 and AF3, however, predict a single best structure, which may not be representative of IDRs (Ruff & Pappu, 2021). Further, the diversity of binding modes of IDRs in complexes, *e.g.,* DOR and DDR, poses a significant challenge. In particular, AlphaFold predictions are less accurate for fuzzy complexes or DDR complexes, compared to DOR complexes (Alderson et al., 2022; Omidi et al., 2024). Third, the confidence metrics of AF2 and AF3 may not reliably reflect structural accuracy (Elofsson, 2025; Guan & Keating, 2025). Particularly, the presence of IDRs is known to negatively impact the confidence metrics (Dunbrack, 2025; Magana & Kovalevskiy, 2024; Omidi et al., 2024; Varga et al., 2024).

On our OOD test set, most of the predictions from AF2 and AF3 had low confidence, with an ipTM score lower than 0.75. Notably, compared to AF2, AF3 predictions were less accurate and had lower confidence. It is possible that the confidence cutoffs used for ordered proteins do not apply to IDRs and predictions involving the latter might require different cutoffs. A recent benchmark suggested a lower ipTM score of 0.4 for assessing interfaces involving IDRs (Omidi et al., 2024). Further, the per-residue metrics such as pLDDT and PAE may be more relevant for assessing AF2 and AF3 predictions than the global metrics such as the ipTM and pTM, as is also suggested by a recent benchmark and the AF3 guide (Abramson et al., 2024; Omidi et al., 2024). Thus, AlphaFold confidence metrics might need to be interpreted differently for IDRs, and this requires rigorous benchmarking (Chakravarty et al., 2025; Kim et al., 2024; Varga et al., 2024).

AF2 has been shown to successfully predict the structures of protein-peptide complexes and domain-motif complexes, although the results could be sensitive to the sequence fragment size, fragment delimitation, and the MSA alignment mode (Bret et al., 2024; B.-G. Lee et al., 2020). Some studies show that MSA subsampling (del Alamo et al., 2022), clustering the sequences in the MSA (Wayment-Steele et al., 2024), and using sliding fragments as input to AF2 (Bret et al., 2024) result in better

predictions and can be used to predict multiple conformations. In our comparison, we did not explore these strategies, though they may improve the model predictions.

Future Directions

One of the major roadblocks in training methods such as Disobind is the lack of data. More experimental structures of IDRs in complexes would be valuable (Jahn et al., 2024; J. Zhang et al., 2024). Whereas IDR ensembles derived from MD can be used, generating MD ensembles for IDR complexes is computationally expensive and challenging, and the existing databases like PED contain very few such ensembles for IDR complexes (Ghafouri et al., 2024; Majila et al., 2024). Alternatively, deep generative models can be used to generate ensembles for IDRs in complexes (Janson & Feig, 2024; Majila et al., 2024; Mansoor et al., 2024). However, the current methods are limited to generating ensembles for monomers.

Disobind and similar methods can be further enhanced by improving the existing pLMs to provide better representations for IDRs plausibly by incorporating physical priors and/or structural information (Majila et al., 2024; Rogers et al., 2023; Wang et al., 2024). Additionally, these methods could be extended to predict protein-protein interactions (PPIs) involving IDRs, and aid in the design of IDR binders. The behaviour of IDRs within cells remains largely unexplored. Methods like Disobind are expected to facilitate an improved understanding of the interactions, function, and modulation of IDRs.

Data and Code availability

The data is deposited to Zenodo at https://doi.org/10.5281/zenodo.14504762. The deposition contains all datasets (train, dev, ID, OOD) along with the input sequences and target contact maps, AF2 and AF3 predictions for the OOD test set, and the PDB structures, SIFTS mappings, PDB API files, and Uniprot Sequences used to create the datasets.

The Disobind model and scripts to create datasets, train the model, use Disobind/Disobind+AF2, and perform analysis are available at GitHub https://github.com/isblab/disobind.
Any additional information required to reanalyze the data reported in this paper is available from the lead contacts upon request.

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Author contribution

Conceptualization: K.M., S.V.
Reading and synthesis: K.M., S.V.
Data curation: K.M.
Methodology: K.M., V.U., S.V.
Writing – original draft: K.M.
Writing – review & editing: K.M., V.U., S.V.
Resources, Supervision, Funding acquisition: S.V.

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Declaration of interests

None declared.

Declaration of generative AI and AI-assisted technologies

During the preparation of this work, the authors used ChatGPT to refine the wording. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Supplemental information titles and legends

Supplementary_material.docx – Figures S1-S4 and Tables S1-S10.
Table S1: Hyperparams.xlsx – Excel file containing hyperparameters for model training.

STAR★Methods

Key resources table

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Antibodies		
NA		
NA		
NA		
NA		
Bacterial and virus strains		
NA		
NA		
NA		
NA		
Biological samples		
NA		
NA		
NA		
NA		
Chemicals, peptides, and recombinant proteins		
NA		
NA		
NA		
NA		
Critical commercial assays		
NA		
NA		
NA		
NA		
Deposited data		
DIBS	Schad E. et. al. (2018) Bioinform.	https://dibs.enzim.ttk.mta.hu/
MFIB	Fichó E. et. al. (2017) Bioinform.	https://mfib.pbrg.hu/
FuzDB	Miskei M. et. al. (2017) NAR	https://fuzdb.org/

PDBtot, PDBcdr	Miskei M. et. al. (2020) JMB	https://doi.org/10.1016/j.jmb.2020.02.017
MobiDB	Piovesan D. et. al. (2024) NAR	https://mobidb.org/
DisProt	Aspromonte M.C. et. al. (2024) NAR	https://disprot.org/
IDEAL	Fukuchi S. et. al. (2014) NAR	https://www.ideal-db.org/
PDB	Berman H.M. et. al. (2000) NAR	https://www.rcsb.org/
UniProt	The UniProt Consortium (2025) NAR	https://www.uniprot.org/
Experimental models: Cell lines		
NA		
NA		
NA		
NA		
Experimental models: Organisms/strains		
NA		
NA		
NA		
NA		
NA		
Oligonucleotides		
NA		
NA		
NA		
NA		
Recombinant DNA		
NA		
NA		
NA		
NA		
Software and algorithms		
SIFTS	Velanker S. et. al. (2013) NAR	10.1093/nar/gks1258
AlphaFold2	Jumper J. et. al. (2021) Nature	https://github.com/google-deepmind/alphafold

AlphaFold3 server	Abramson J. et. al. (2024) Nature	https://alphafoldserver.com/
MMSeqs2	Steinegger M. et. al. (2017) Nat. Biotechnol.	https://github.com/soedinglab/MMseqs2.git
Pytorch v 2.0.1		
CUDA v 11.8		
AIUPred	Erdős G et. al. (2025) JMB	https://doi.org/10.1093/nar/gkae385
MORFchibi 2.0	Malhis N and Gsponer J (2025) bioRxiv	https://doi.org/10.1101/2025.01.31.635962
DeepDISOBind	Zhang F et al (2021) Brief. in Bioinform.	https://doi.org/10.1093/bib/bbab521
ProtT5, ProtBERT	Elnaggar A. et. al. (2023) IEEE PAMI	https://github.com/agemagician/ProtTrans.git
ProstT5	Heinzinger M. et. al. (2024) NAR genom. bioinform.	https://github.com/mheinzinger/ProstT5.git
ProSE	Bepler and Berger (2019) ICLR	https://github.com/tbepler/prose.git
Other		
Disobind GitHub	Majila K. et. al. (2024) bioRxiv	https://github.com/isblab/disobind
Disobind Zenodo		https://doi.org/10.5281/zenodo.14504762

Experimental model and study participant details

Not applicable

Method details

Creating the dataset for Disobind

Gathering PDB structures of IDRs in complexes

First, we gathered the available PDB entries for protein complexes containing IDRs from databases on structures of disordered proteins: DIBS (Schad et al., 2018), MFIB (Fichó et al., 2017), and FuzDB (Miskei et al., 2017) (Fig 1). We also included PDB entries from the PDBtot and PDBcdr datasets (Miskei et al., 2020). PDBtot consists of IDRs that either undergo a DOR or DDR transition, whereas PDBcdr consists of IDRs that undergo both DOR and DDR transitions depending upon the partner. We considered all PDB entries associated with each database. This resulted in a set of 4252 PDB entries. PEDS is another source of conformational ensembles of IDRs (Ghafouri et al., 2024). However, PEDS entries were not used: several PED entries were already incorporated into our pipeline and the remaining entries correspond to monomers.

We then supplemented this set by querying the PDB for additional complexes containing IDRs. For this, we first obtained Uniprot identifiers (IDs) of proteins containing IDRs from DisProt (Aspromonte et al., 2024), IDEAL (Fukuchi et al., 2014), and MobiDB (Piovesan et al., 2024) (Fig 1). Specifically, from Disprot, we obtained all UniProt IDs corresponding to each DisProt entry. From IDEAL, we obtained UniProt IDs for entries annotated as "verified ProS". These sequences are experimentally verified to be disordered in isolation and ordered upon binding. From MobiDB, we obtained UniProt IDs for entries annotated "curated-disorder-priority", "homology-disorder-priority", "curated-lip-priority", and "homology-lip-priority". These correspond to sequences with curated experimental evidence for disorder (“curated-disorder”), their homologs (“homology-disorder”), sequences with experimental evidence for disorder with binding motifs such as SLIMs (“curated-lip”), and their homologs (“homology-lip”), respectively. Homology-based annotations were incorporated due to the lack of sufficient experimentally curated data available for IDRs. Importantly, the annotations were based on the source with the highest confidence (“priority”), and annotations based on indirect sources of evidence or predictions were not considered.

Choosing the highest confidence annotation may reduce false positive “disorder” or “lip” annotations that may arise from homology-based evidence.

A total of 357734 unique Uniprot IDs across MobiDB, Disprot, and IDEAL were obtained. The PDB REST API was queried to obtain all the PDB entries associated with a given Uniprot ID, resulting in 48534 PDB entries (Table S1) (Rose et al., 2021). Combining these with the PDB entries obtained in the previous step, we obtained 50294 unique PDB entries. As an aside, we note that MobiDB now provides the PDB IDs for IDR-containing complexes, however, this functionality was not available when this project started.

Defining binary complexes containing IDRs

The above PDB entries were downloaded using the Python requests library and mapped to the sequences in UniProt using the SIFTS (Structure Integration with Function, Taxonomy, and Sequence) tool (Velankar et al., 2013). Entries with an obsolete PDB ID and those lacking a SIFTS mapping were removed, and deprecated PDB IDs were replaced with superseding PDB IDs. Further, entities corresponding to chimeric proteins or non-protein molecules, those having an obsolete UniProt ID, and those containing more than 10000 residues were removed.

Next, for each PDB entry, we obtained sequence fragments by removing missing residues from the sequence of each chain. The length of these fragments was kept to between 20 and 100 residues. Fragments longer than 100 residues were further divided due to constraints on GPU memory, that limited the scalability of the model architecture. We then identified the disordered residues in these fragments (Fig 1). This was achieved by cross-referencing the UniProt mapping of the fragment with the disorder annotations from DisProt, IDEAL, and MobiDB as obtained above; a residue was considered disordered if it was annotated as such in any of these three databases. Fragments comprising at least 20% disordered residues were considered as IDR fragments whereas the others were considered as non-IDR fragments. This cutoff balances an over-representation of ordered residues while ensuring enough training data. This is also consistent with proteome-wide analyses which indicate that proteins

with IDRs have 13–28% disordered residues. Specifically, annotations based on experiments indicate a 17% disorder fraction (Piovesan et al., 2024).

Subsequently, a set of binary complexes was constructed from each PDB entry. Each binary complex consisted of an IDR fragment paired with another IDR or non-IDR fragment. Binary complexes comprising solely of intra-chain fragments or non-IDR fragments were excluded (Fig 1). This resulted in a total of 2369712 binary complexes.

Creating merged binary complexes

We then created contact maps from these binary complexes. A contact map is a binary matrix of zeros (non-contacts) and ones (contacts); two residues are in contact if the distance between their $C\alpha$ atoms is less than 8 Å. We merged the contact maps across different binary complexes of a sequence fragment pair, to create "merged contact maps" (Fig 1). This allows us to account for contacts from all available complexes. Further, a merged contact map is less sparse and therefore easier to learn compared to an ensemble of contact maps. It also mitigates the bias caused by having different numbers of structures for different sequence fragment pairs.

We first grouped the binary complexes across all the PDB entries by the UniProt ID of the constituent proteins in the sequence fragment pair, resulting in 14599 UniProt ID pairs/groups. For computational efficiency, all binary complexes with no contacts were eliminated. The remaining binary complexes in a group were sorted based on the UniProt start residue positions of the protein fragments in the pair and further partitioned into sets. Each set comprised binary complexes containing overlapping sequences (more than one residue overlap) for both fragments such that the sequence length for each fragment, merged across the overlapping sequences, does not exceed the maximum fragment length (100 residues). Contact maps for all binary complexes in a set were aggregated using a logical OR operation to form "merged contact maps". A sequence fragment pair with the corresponding merged contact map comprises a merged binary complex. We obtained 24442 merged binary complexes. Finally, we filtered merged binary complexes for which the contact density was very high (>5%) or very low (<0.5%), resulting in 6018 merged binary complexes (Fig 1).

Creating the training set and OOD test set

We created an out-of-distribution (OOD) test set that is sequence non-redundant with our training dataset and the PDB70 dataset used for training AlphaFold. We first removed merged binary complexes whose sequence fragments were derived from a PDB chain in PDB70. We then obtained a non-redundant set of sequences by clustering our dataset of sequence fragments and the PDB70 cluster representatives using MMSeqs2 (Steinegger & Söding, 2017). MMSeqs2 was used at a 20% sequence identity threshold and cluster mode 1. Since the PDB70 dataset is already clustered at 40% sequence similarity, we consider only the representative cluster members for sequence identity comparisons.

For the OOD test set, we selected clusters without any chain from PDB70 that are singleton (only one cluster member *i.e.* self) or doublet (two member sequences, both belonging to the same merged binary complex) clusters. This resulted in 53 merged binary complexes for the OOD test set. We removed an OOD test set entry for which AF2 predictions could not be obtained, resulting in 52 OOD test set complexes. The remaining dataset was split into a training (train), development (dev), and an in-distribution (ID) test set in the ratio 0.9:0.05:0.05, resulting in 5362 train, 298 dev, and 297 ID test set merged complexes.

Disobind Model Architecture and Training

Notations

Here, we define the notation used in this paper.

$R^{A\times B\times C\times D}$: 4D tensor with the axes i, j, k, l corresponding to the four dimensions of size A, B, C, D respectively

N: batch size used for training.

L_1, L_2: lengths of protein sequence fragments 1 and 2 indicating the number of residues in each protein.

C, C_1, C_2, C_3: the sizes of embedding or feature dimensions.

E_1, E_2: embeddings for protein sequence fragments 1 and 2.

O: interaction tensor obtained post-concatenation.

O_{red}: output from the multi-layer perceptron block, reduced from the interaction tensor.

I_1, I_2 interface tensors for proteins 1 and 2.

I: concatenated interface tensors.

$Linear$: applies a linear transformation, $Linear(X) = XW^T + b$.

ELU: exponential linear unit, $ELU(x) = max(x, \alpha(e^x - 1))$.

$Sigmoid(x)$: $\frac{1}{1+e^{-x}}$.

$Dropout$: regularization technique that randomly sets weights to 0.

$LNorm$: layer normalization.

$Concat([A, B]_i)$: concatenate tensors A, B along the axis i.

$A_{ijkl \to ikjl}$: permute tensor A along the specified axes.

Inputs and outputs for training

We train six separate models, corresponding to six prediction tasks. These correspond to two types of predictions: a) inter-protein contact map and b) interface residue predictions at three coarse-grained (CG) resolutions (1, 5, and 10 sequence-contiguous residues). Coarse-graining at resolution 1 is equivalent to no coarse-graining, *i.e.*, residue-level predictions. The input to the model is the embedding for the two sequence fragments from the ProtT5 pLM $E_1 \in R^{L_1 \times C}, E_2 \in R^{L_2 \times C}$ (Elnaggar et al., 2022). The outputs for the two types of predictions respectively are a) a binary contact map, $ContactMap \in R^{L_1/k \times L_2/k}$ and b) a binary interface residue vector, $Interface \in R^{L_1/k + L_2/k}$ at a particular CG resolution, where $k \in [1, 5, 10]$ represents the CG resolution.

For coarse-grained predictions, the input embeddings were coarse-grained using an AvgPool1d whereas the corresponding contact maps were coarse-grained using a MaxPool2d; the kernel size and stride were set to the CG resolution in both cases.

The target vectors for interface residue predictions were obtained by reducing the rows and columns of the corresponding contact maps by an OR operation. The input embeddings, output contact maps, and interface residue vectors were zero-padded to the maximum length (100 residues).

Model architecture

Disobind comprises a projection block, an interface block, a multi-layer perceptron (MLP) block, and an output block (Fig 2). The models for contact map and interface residue prediction employ a contact map block and interface block respectively.

Projection block

The input embeddings E_1, E_2 are projected to a lower dimension, C_1 using a linear layer.

$Z_1 = Dropout(\ ELU(\ Linear(\ E_1\ )\ )\ )\ ;\ Z_1 \in R^{N \times L_1 \times C_1}$ – (1)

$Z_2 = Dropout(\ ELU(\ Linear(\ E_2\ )\ )\ )\ ;\ Z_2\ \in R^{N \times L_2 \times C_1}$ – (2)

Interaction block

The model captures complementarity between the projected embeddings Z_1, Z_2 by concatenating the outer product and the absolute value of the outer difference between the projected embeddings along the feature dimension.

$O\ = Concat(\ [OuterProduct(\ Z_1, Z_2\ ), |OuterDifference(\ Z_1, Z_2\ )|]_l);\ O \in R^{N \times L_1 \times L_2 \times C_2}$ – (3)

Interface block

To capture the interface residues for both proteins I, we compute row-wise and column-wise averages followed by concatenating along the length.

$I_1 = Mean(O_{ijkl \rightarrow iljk});\ I_1 \in R^{N \times C_2 \times L_1}$ – (4)

$I_2 = Mean(O_{ijkl \rightarrow ilkj});\ I_2 \in R^{N \times C_2 \times L_2}$ – (5)

$I = Concat([I_1, I_2]_k);\ I_2 \in R^{N \times C_2 \times (L_1 + L_2)}$ – (6)

$I = I_{ijk \rightarrow ikj}; I\ \in R^{N \times (L_1 + L_2) \times C_2}$ – (7)

Multi-layer perceptron (MLP) block

The feature dimension of the interaction tensor O is progressively decreased using a multilayer perceptron (MLP) to obtain O_{red}.

$O_{red}\ = m \times \{\ LNorm(\ ELU(\ Linear(\ x\ )\ )\ )\};\ O_{red} \in R^{N \times L_1 \times L_2 \times C_3}$ – (8)

We used a 3-layer ($m = 3$) MLP for contact map prediction whereas it was not used for interface residue prediction ($m = 0$).

Output block

It comprises a $Linear$ layer followed by a $Sigmoid$ activation.

$ContactMap = Sigmoid(Linear(O_{red}))$; $ContactMap \in R^{N \times L_1 \times L_2}$ – (9)

$Interface = Sigmoid(Linear(I))$; $Interface \in R^{N \times (L_1 + L_2)}$ – (10)

Training

The models were trained using PyTorch version 2.0.1 and CUDA version 11.8, using an NVIDIA A6000 GPU. The model was trained using the Singularity Enhanced (SE) loss function (Si & Yan, 2021), a modified form of the binary cross-entropy (BCE) loss used for class-imbalanced training, with $\alpha = 0.9, \beta = 3$ and AdamW (amsgrad variant) optimizer with a weight decay of 0.05. We used an exponential learning rate scheduler for slowly decaying the base learning rate.

$$SELoss = \sum \quad (\alpha \cdot y \, log(\hat{y}) + (1 - \alpha) \cdot (1 - y) \, log((1 - \hat{y})) \cdot (1 + \hat{y})^{\beta}) \text{ – (10)}$$

A binary mask was used to exclude the padding from the loss calculation. The train and dev set loss were monitored to check for over/under-fitting (Fig S1).

Evaluating predictions

The Disobind predicted score was converted to a binary output using a threshold of 0.5. The model performance was evaluated on the train, dev, and ID test set using recall, precision, and F1-score. All metrics were calculated using the torchmetrics library.

$$Recall = \frac{TP}{TP + FN} \qquad Precision = \frac{TP}{TP + FP} \qquad F1\ score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \text{ – (11)}$$

Hyperparameter tuning and ablations

Here, we explore the effect of select hyperparameters on the model performances in the dev and ID test sets. Hyperparameters were tuned for the contact map and

interface prediction at CG 1 and minimally modified for the CG 5 and CG 10 models. The final set of hyperparameters is provided (Table S1).

Projection dimension

We tuned the projection dimension C_1 for the projection block (Table S2).

Number of layers in the MLP

$Linear$ layers in the MLP were used to either upsample (upsampling layers, US) or downsample (downsampling layers, DS) the feature dimension by a factor of 2. We tuned the number of US (DS) layers. Additionally, we removed the MLP for interface residue prediction (Table S3).

α, β for SE loss

We tuned the α and β parameters for SE loss; these weigh the contribution of the contact and non-contact elements to the loss (Table S4).

pLM embeddings

We compared the model performance using embeddings from ProtT5 $(C = 1024)$, ProstT5 $(C = 1024)$, ProSE $(C = 6165)$, and ProtBERT (Bepler & Berger, 2019; Elnaggar et al., 2022; Heinzinger et al., 2024)$(C = 1024)$.

Further, we compared two types of embeddings: global and local embeddings (Fig S4, Table S10). Local embeddings were obtained using the sequence of the fragment as input to the pLM. In contrast, global embeddings were obtained by using the complete UniProt sequence as input to the pLM and extracting fragment embedding from it.

Assessment

Random baseline

To compute random baseline predictions, we predicted random contacts and interface residues based on their frequencies in the training set. For the prediction tasks involving coarse-graining, these frequencies were determined from the coarse-grained contact maps and coarse-grained interface residues in the training set.

AlphaFold predictions on the OOD test set

We used a local AF2 installation and the AF3 webserver for obtaining OOD test set predictions (Abramson et al., 2024; Evans et al., 2022). AF2 was run with the default arguments as specified in their GitHub repository. Due to the failure of AF2 to relax several of the OOD test set entries we switch off the Amber relaxation step and consider the unrelaxed models for further evaluation. Additionally, we removed an OOD test set entry for which we were unable to obtain the AF2 prediction. We considered the best models from AF2 (based on the ipTM+pTM score) and AF3 (based on the ranking score) for comparison with Disobind. The ipTM score was used to assess the overall model confidence and the pLDDT and PAE metrics assessed the per-residue confidence. pLDDT scores higher than 70 and PAE values lower than 5 are considered as confident (Edmunds et al., 2024). An ipTM score higher than 0.8 represents a high-confidence prediction whereas an ipTM score lower than 0.6 represents a likely incorrect prediction; predictions with ipTM scores between 0.6-0.8 require further validation (Abramson et al., 2024; Evans et al., 2022; O'Reilly et al., 2023; Yin et al., 2022). Given that only five AF2 predictions and none of the AF3 predictions in the OOD test set have an ipTM score greater than 0.8, we initially applied an ipTM cutoff of 0.75 as recommended in benchmarks on AlphaFold2 (O'Reilly et al., 2023; Yin et al., 2022). Later we relaxed the ipTM cutoffs to 0.4 and 0 (*i.e.*, no ipTM cutoff).

To compare the AlphaFold outputs to those from our models, we first derive the binary contact maps from the best-predicted model. We then apply binary masks on this output to ignore low-confidence interactions (pLDDT<70 and PAE>5). Both the pLDDT and PAE masks are applied on the CG 1 contact map obtained from AF2 and AF3 before proceeding further. To apply an ipTM cutoff, we zero the contact maps for AlphaFold predictions with an ipTM lower than the cutoff. The binary contact map was zero-padded to the maximum length (100 residues). The interface residues and coarse-grained predictions were derived from the CG 1 contact map as mentioned previously (See Inputs and Outputs for training).

Disobind+AF2 predictions

The Disobind+AF2 predictions were obtained by combining the corresponding predictions from Disobind and AF2 using a logical OR operation. We ignore low-confidence AF2 predictions having a pLDDT less than 70 and a PAE greater than 5. No ipTM cutoff was used.

Performance by residue type

Given a protein sequence, disordered regions were identified by combining DisProt, IDEAL, and MobiDB annotations as described in Creating dataset for Disobind section. Residues in these regions were annotated as “disordered residues”, the remaining residues in the sequence were considered “ordered”. Linear interacting peptide (LIP) annotations were obtained from MobiDB as described earlier. We categorized residues into disorder-promoting amino acids (R, P, Q, E, G, S, A, K), aromatic amino acids (F, Y, W), hydrophobic amino acids (A, V, L, I, P, M, F, W), and polar amino acids (S, T, C, N, Q, Y, D, E, K, R, H) (Uversky, 2013, 2019). For LIPs, we evaluated contacts between residues in LIPs and any residue on the partner protein. For all other residue types, we evaluated contacts between residues of the same type. To assess the predictions on specific residue types, we applied a binary mask on the predictions and the target to ignore interface residues (contacts) not involving the relevant residues (residue pairs). We only considered confident predictions from AF2 having pLDDT scores higher than 70 and PAE values lower than 5. No ipTM cutoff was used.

Comparison with interface predictors for IDRs

We selected state-of-the-art interface predictors including AIUPred, MORFchibi, and DeepDISOBind for comparison to Disobind on the OOD test set (Erdős et al., 2025; Malhis & Gsponer, 2025; F. Zhang et al., 2022). These methods have been shown to be comparable to the state-of-the-art in CAID2 (Conte et al., 2023). They provide partner-independent interface residue predictions. For comparison to Disobind, we assess their interface residue predictions on the IDR sequence of the binary complexes in the OOD set. AIUPred predictions were obtained using programmatic access as mentioned in their GitHub repository. For MORFchibi and DeepDISOBind, predictions were obtained using their respective webservers, using defaults. DeepDISOBind provides binary interface predictions. AIUPred predictions are

converted to binary interfaces using a 0.5 threshold as specified in the paper (Erdős et al., 2025). For MORFchibi, we use a 0.77 threshold for interface residues as recommended; interface residue regions shorter than four residues are eliminated (Malhis & Gsponer, 2025).

Quantification and statistical analysis

Not applicable

Additional resources

Not applicable

Tables

Table 1: Comparing Disobind, AF2, and AF3 performance. We compare the performances of Disobind, AF2, and AF3 on the OOD set for contact map and interface residue prediction for different coarse-grained (CG) resolutions. We also include a random baseline (RB) for comparison. For AF2 and AF3 we only consider the confident predictions (pLDDT >= 70 and PAE <= 5) at multiple ipTM cutoffs (0, 0.4, 0.75) for evaluation. The number after the '_' represents the ipTM cutoff used.

Model	Recall	Precision	F1 score	Recall	Precision	F1 score
	Contact map			Interface		
	Coarse Graining 1					
Disobind	0.22	0.63	0.33	0.5	0.46	0.48
RB	0.51	0.01	0.02	0.5	0.26	0.34
AF2_0.75	0.12	0.58	0.2	0.18	0.76	0.29
AF3_0.75	0.02	0.41	0.04	0.02	0.43	0.04
AF2_0.4	0.2	0.45	0.28	0.35	0.7	0.47
AF3_0.4	0.08	0.33	0.13	0.18	0.6	0.27
AF2_0.0	0.2	0.45	0.28	0.35	0.7	0.47
AF3_0.0	0.08	0.31	0.13	0.18	0.57	0.27
	Coarse Graining 5					
Disobind	0.38	0.61	0.47	0.73	0.56	0.63
RB	0.52	0.08	0.13	0.53	0.45	0.49
AF2_0.75	0.15	0.58	0.24	0.2	0.79	0.32
AF3_0.75	0.02	0.34	0.03	0.02	0.5	0.04
AF2_0.4	0.29	0.52	0.37	0.43	0.76	0.54
AF3_0.4	0.14	0.47	0.22	0.22	0.72	0.34
AF2_0.0	0.29	0.52	0.37	0.43	0.76	0.54

AF3_0.0	0.14	0.45	0.22	0.23	0.7	0.34
	Coarse Graining 10					
Disobind	0.42	0.49	0.45	0.8	0.61	0.69
RB	0.54	0.17	0.26	0.48	0.52	0.5
AF2_0.75	0.16	0.62	0.25	0.2	0.83	0.32
AF3_0.75	0.02	0.4	0.04	0.03	0.59	0.05
AF2_0.4	0.32	0.57	0.41	0.44	0.8	0.57
AF3_0.4	0.16	0.52	0.25	0.24	0.78	0.36
AF2_0.0	0.32	0.57	0.41	0.44	0.8	0.57
AF3_0.0	0.16	0.51	0.25	0.24	0.75	0.37

Table 2: Evaluating the performance of Disobind+AF2 on the OOD test set. We combine Disobind and AF2 predictions using a logical OR operation and evaluate the performance on the OOD test set for contact map and interface residue prediction. For AF2 we consider the confident predictions (pLDDT >= 70 and PAE <= 5) for evaluation. No ipTM cutoff is applied for AF2 and Disobind+AF2 predictions.

Model	Recall	Precision	F1 score	Recall	Precision	F1 score
	Contact map			Interface		
	Coarse Graining 1					
Disobind	0.22	0.63	0.33	0.5	0.46	0.48
AF2_0.0	0.2	0.45	0.28	0.35	0.7	0.47
Disobind+AF2	0.33	0.49	0.4	0.6	0.46	0.52
	Coarse Graining 5					
Disobind	0.38	0.61	0.47	0.73	0.56	0.63
AF2_0.0	0.29	0.52	0.37	0.43	0.76	0.54
Disobind+AF2	0.49	0.5	0.5	0.78	0.54	0.64
	Coarse Graining 10					
Disobind	0.42	0.49	0.45	0.8	0.61	0.69
AF2_0.0	0.32	0.57	0.41	0.44	0.8	0.57
Disobind+AF2	0.55	0.46	0.5	0.86	0.61	0.71

Table 3: Comparison with interface predictors for IDRs. We compare the performance of Disobind with interface predictors for IDRs, including AIUPred, MORFchibi, and DeepDISOBind, on the IDR sequences from the OOD test set.

Model	Recall	Precision	F1 score
	Interface residue prediction, CG1		
Disobind	0.5	0.49	0.5
Aiupred	0.36	0.38	0.37
Morfchibi	0.97	0.24	0.39
Deepdisobind	0.22	0.45	0.29

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