Supplementary Information for: GRAFENE: Graphlet-based alignment-free network approach integrates 3D structural and sequence (residue order) data to improve protein structural comparison

Fazle E. Faisal1,5,6,†**, Khalique Newaz**1,5,6,†**, Julie L. Chaney**² **, Jun Li**³ **, Scott J. Emrich**¹ **,** Patricia L. Clark^{2,4,6}, and Tijana Milenković^{1,5,6,*}

¹Department of Computer Science and Engineering, University of Notre Dame, Notre Dame, IN 46556, USA

²Department of Chemistry and Biochemistry, University of Notre Dame, Notre Dame, IN 46556, USA

³Department of Applied and Computational Mathematics and Statistics, University of Notre Dame, Notre Dame, IN 46556, USA

⁴Department of Chemical and Biomolecular Engineering, University of Notre Dame, Notre Dame, IN 46556, USA ⁵Interdisciplinary Center for Network Science and Applications, University of Notre Dame, Notre Dame, IN 46556, USA

⁶Eck Institute for Global Health, University of Notre Dame, Notre Dame, IN 46556, USA

†These authors equally contributed to this work

*To whom correspondence should be addressed

I Supplementary Sections

S1 Data

We collect 3D atomic structures of proteins from the Protein Data Bank (PDB)^{[1](#page-55-0)}. Since PDB contains multiple copies of the same or nearly identical proteins, we aim to reduce the redundancy by selecting a set of proteins from PDB such that each protein in the set is not more than 90% sequence identical to any other protein in the set. If a protein is not more than 90% sequence identical to any other protein from PDB, we immediately select the protein. If a protein is more than 90% sequence identical to one or more proteins from PDB, we select a "representative" protein from such a protein group so that the representative protein is of the highest quality (in terms of resolution) among all proteins in the group. This strategy results in the selection of 17,036 proteins. We denote this data set as *ProteinPDB*. Each protein in the data is comprised of the X, Y, and Z orthogonal Angstrom (\AA) coordinates of heavy atoms (i.e., *carbon, nitrogen, oxygen,* and *sulfur*) of each amino acid within the protein. The data is available at http://www.rcsb.org/pdb/home/home.do for free download.

Both Class, Architecture, Topology, Homology (CATH) and Structural Classification of Proteins (SCOP) are protein domain categorization databases^{2-[4](#page-55-2)}. A protein is typically composed of one or more domains (a domain refers to a part of a protein structure that can fold and often function independently). The purpose of CATH and SCOP is to annotate these domains. We use the protein domain categorization schemes of CATH and SCOP to assign labels to the protein domains from ProteinPDB.

S2 Synthetic networks

We generate synthetic networks by using different network models. A good approach should identify networks from the same network model (i.e., with the same label) as similar, and it should identify networks from different models (i.e., with different labels) as dissimilar. Specifically, we use three well-established network models: *Erdős-Rényi random graphs* (*ER*), *geometric* random graphs (GEO), and *scale-free random graphs* (SF)^{[5,](#page-55-3)[6](#page-55-4)}. We note that these models are not necessarily representative of PSNs. Instead, they are general-purpose models. This is intentional, because the models that we use are intended to illustrate wide applicability of our GRAFENE approach to any domain where data can be modeled as networks. It is our analyses of real-world PSNs that focus specifically on the task of PC.

First, we evaluate the considered approaches on synthetic networks of the same size but of different labels (originating from the three network models). To evaluate the robustness of GRAFENE to the choice of network size, we repeat this analysis three times, by increasing the size of the considered networks. That is, we perform three separate analyses of three different network data sets, where in a given data set, all networks are of the same size, and one third of the networks in the set comes from each of the three network models. We denote these network sets as *Synthetic-100*, *Synthetic-500*, and *Synthetic-1000* (Supplementary Table [S1\)](#page-30-0), where each set consists of 50 networks per model (totaling to $50 \times 3 = 150$ networks). The numbers of nodes and edges in these networks are set to mimic sizes of real-world PSNs.

Second, we evaluate the considered approaches on networks of different sizes as well as different labels, to check whether the approaches can correctly identify as similar networks from the same model despite the networks being of different sizes, as well as that they can correctly identify as dissimilar networks from different models despite the networks being of the same size. To generate a synthetic network set of different sizes, we combine networks from Synthetic-100, Synthetic-500, and Synthetic-1000 together. We denote the combined network set as *Synthetic-all* (Supplementary Table [S1\)](#page-30-0).

S3 Forming real-world PSNs

Here, we continue our discussion regarding the fourth PSN construction strategy that uses the α -carbon atom type and the 7.5 Å distance cut-off. Note that the original GR-Align study used a distance cut-off of 12 Å because this study argued that when considering the α -carbon atom type, this cut-off showed better performance compared to all other tested cut-offs (in the 5 Å-20 Å range)^{[7](#page-55-5)}. However, we use the 7.5 Å cut-off for the following reasons. First, even at this cut-off, GR-Align is already much slower than our proposed GRAFENE approach (as we show in our evaluation), and increasing the distance cut-off would only result in more edges and thus further slow down GR-Align. And it was the original GR-Align study that recommended using the 7.5 Å cut-off when aiming to achieve speed-up (as reflected by linear time complexity at this cut-off). Second, as demonstrated in the GR-Align study, for two out of three evaluated performance measures, the improvement when using the 12 \AA cut-off compared to when using the 7.5 \AA cut-off is negligible and thus not worth the extra increase in computational time that would result from using the 12 Å cut-off compared to using the 7.5 Å cut-off.

S4 Real-world PSNs with CATH categorization

ProteinPDB contains 17,884 protein domains that have CATH categorization, which for a given PSN construction strategy results in 17,884 PSNs. Of these PSNs, to ensure that PSNs are of reasonable "confidence", we focus for further analyses on those PSNs that meet all of the following criteria: 1) the given network has more than 100 nodes, 2) the maximum diameter of the network is more than five, and 3) the network is composed of a single connected component. For different PSN construction strategies, the above criteria can result in different numbers of PSNs. For the first PSN construction strategy (any heavy atom type, 4 Å distance cut-off), this results in 9,509 such PSNs. In the main paper (also, see Supplementary Table $S2$), we report the number of PSNs with respect to this PSN construction strategy. The number of PSNs resulting from using one of the other three PSN construction strategies is of the similar order.

First, we test how well the considered PC approaches can compare PSNs between the top hierarchical categories (i.e., labels) of CATH: *alpha* (α), *beta* (β), *alpha/beta* (α/β), and *few secondary structures*. Only for few secondary structures, none of the domains in ProteinPDB belong to this category, and so we remove the few secondary structures category from further consideration. Of the 9,509 PSNs, 2,628, 3,085, and 3,796 PSNs belong to (i.e., are labeled with) α , β , and α/β categories, respectively. We denote this PSN set as *CATH-primary* (Fig. [2](#page-6-0) in the main paper). The set contains a large enough number of PSNs in each category, which ensures enough statistical power for further analyses.

Second, we test how well the PC approaches can compare PSNs between the second-level hierarchical categories of CATH. That is, within each of the top-level categories of CATH, we compare PSNs belonging to their sub-categories, i.e., second-level categories of CATH. To ensure enough statistical power for further analyses, we focus only on those top-level categories that have at least two sub-categories with at least 30 PSNs each. Each of the three top-level CATH categories satisfies this, and hence, for each of them, we analyze all of their sub-categories that each contain at least 30 PSNs. This results in three PSN sets, denoted as α , β , and α/β (Fig. [2](#page-6-0) in the main paper).

Third, we test how well the PC approaches can compare PSNs between the third-level hierarchical categories of CATH. That is, within each of the second-level categories of CATH, we compare the PSNs belonging to their sub-categories, i.e., third-level categories of CATH. To ensure enough statistical power for further analyses, we focus only on those second-level categories that have at least two sub-categories with at least 30 PSNs each. This results in nine PSN sets, denoted as 1.10, 1.20, 2.30, 2.40, 2.60, 2.160, 3.10, 3.30, and 3.40 (Fig. [2](#page-6-0) in the main paper).

Fourth, we test how well the PC approaches can compare PSNs between the fourth-level hierarchical categories of CATH. That is, within each of the third-level categories of CATH, we compare PSNs belonging to their sub-categories, i.e., fourth-level categories of CATH. To ensure enough statistical power for further analyses, we focus only on those third-level categories that

have at least two sub-categories with at least 30 PSNs each. This results in six PSN sets, denoted as 2.60.40, 2.60.120, 3.20.20, 3.30.390, 3.30.420, and 3.40.50 (Fig. [2](#page-6-0) in the main paper).

Thus, in total, we analyze $1+3+9+6 = 19$ CATH PSN sets (Fig. [2](#page-6-0) in the main paper and Supplementary Tables [S3](#page-32-0)[-S5\)](#page-36-0).

S5 Real-world PSNs with SCOP categorization

ProteinPDB has 15,762 protein domains with SCOP categorization, which results in 15,762 PSNs. Of these PSNs, to ensure that PSNs are of reasonable "confidence", we focus on those PSNs that meet the same three criteria that PSNs with CATH categorization are also required to meet, resulting in 11,451 PSNs with SCOP categorization (again, for the first of the four PSN construction strategies). For details, see Supplementary Table [S2.](#page-31-0)

Again, first, we evaluate how well the considered PC approaches can compare PSNs between the top hierarchical categories of SCOP: α, β, α/β, *alpha plus beta* (α+β), *coiled coil*, *membrane*, *multi-domain*, *small*, *low resolution*, *peptide*, and *designed*. For small, low resolution, peptide, or designed, none of the domains in ProteinPDB belong to these categories, and so we remove these four categories from further consideration. Of the 11,451 PSNs, 1,678, 2,541, 3,835, 2,879, 44, 156, and 318 PSNs belong to α , β , α/β , $\alpha+\beta$, coiled coil, membrane, and multi-domain categories, respectively. This PSN set, denoted as *SCOP-primary* (Fig. [2](#page-6-0) in the main paper), contains enough PSNs in each category to ensure enough statistical power for further analyses. Second, we test how well the PC approaches can compare PSNs between the second-level hierarchical categories of SCOP. This results in five PSN sets, denoted as α , β , α/β , $\alpha+\beta$, and multi-domain (Fig. [2](#page-6-0) in the main paper). Third, we test how well the PC approaches can compare PSNs between the third-level hierarchical categories of SCOP. This results in six PSN sets, denoted as *a*.118, *b*.1, *c*.1, *c*.23, *c*.26, and *c*.55 (Fig. [2](#page-6-0) in the main paper). Fourth, we test how well the PC approaches can compare PSNs between the fourth-level hierarchical categories of SCOP. This results in four PSN sets, denoted as *b*.1.1, *c*.1.8, *c*.2.1, and *c*.37.1 (Fig. [2](#page-6-0) in the main paper).

Thus, in total, we analyze $1+5+6+4 = 16$ SCOP PSN sets (Fig. [2](#page-6-0) in the main paper and Supplementary Tables [S3](#page-32-0)[-S5\)](#page-36-0).

S6 Real-world PSNs of the same size

To benchmark PSN-based approaches for protein comparison in a way that the comparison cannot be biased by PSN size, we need PSN data of the same (or at least similar) network size (analogous to the synthetic network data sets). For this analysis, we focus on PSNs of α and β labels from the CATH-primary data set. First, within this data set, we aim to identify PSNs that are of reasonable size, i.e., that have ∼100 nodes. We further filter the resulting PSN set according to the following rules: 1) the number of nodes in all α and β PSNs is the same, 2) the number of edges in all α and β PSNs is statistically significantly similar (Mann-Whitney *U* test; *p*-value < 0.05), and 3) there are at least six PSNs in each of the two label categories. We end up with two such PSN sets. The first set is comprised of 24 PSNs having 95 nodes and 343-362 edges, where 12 PSNs are from α and 12 PSNs are from β. We denote this PSN set as *CATH-95*. The second set is comprised of 28 PSNs having 99 nodes and 347-374 edges, where 12 PSNs are from α and 16 PSNs are from β. We denote this PSN set as *CATH-99*. Second, within the CATH-primary data set, we aim to identify even larger PSNs, i.e., PSNs that have ∼250 nodes. We again further filter the resulting PSN set according to the same three rules as above, except that in rule 1, we do not force the number of nodes of all PSNs to match (as we could not identify multiple PSNs that satisfy this constraint) but instead it is sufficient that the PSNs are of statistically significantly similar size in terms of the number of nodes (Mann-Whitney U test; p -value $\lt 0.05$). This results in another PSN set, which is comprised of 16 PSNs having 251-265 nodes and 1,003-1,076 edges, where nine PSNs are from α and seven PSNs are from β. We denote this PSN set as *CATH-251-265*. Note that the reported numbers of PSNs in these three "equal size" PSN sets are with respect to the first PSN construction strategy (any heavy atom type, 4 A distance cut-off). Yet, ˚ the numbers remain the same for the other three PSN construction strategies.

S7 Existing approaches

S7.1 Existing network approaches

Existing approaches of this type that we use for PC (not all of which were proposed for PC but can be adapted to it) can be categorized into graphlet and non-graphlet approaches. None of them use PCA as we do.

Existing graphlet approaches. These include graphlet degree distribution agreement $(GDDA)^8$ $(GDDA)^8$, relative graphlet frequency distance (RGFD)^{[9](#page-55-8)}, graphlet correlation distance (GCD)^{[10](#page-55-9)}, and GR-Align^{[7](#page-55-5)}. Among them, GDDA, RGFD, and GCD can compare any type of networks, while GR-Align has been specifically designed to compare PSNs. GDDA, RGFD, and GCD are alignment-free, while GR-Align is alignment-based. For each network pair, each of the four existing graphlet-based network approaches outputs a similarity (or equivalently, a distance) score. Then, for each approach, we sort all network pairs in terms of their increasing distance and evaluate the given approach the given approach as discussed in Section "Evaluation of PC accuracy" of the main manuscript.

Two alternative graphlet approaches were used in the context of $PSNs^{11,12}$ $PSNs^{11,12}$ $PSNs^{11,12}$ $PSNs^{11,12}$, but they were used to predict (classify in a supervised manner) functional residues in PSNs (where residues are nodes in PSNs) and not for PSN comparison. Since these approaches compare nodes rather than networks, and since they are supervised (while our study is unsupervised, per our discussion in Section "Evaluation of PC accuracy" of the main manuscript), the approaches do not fit the context of our study. As such, we do not consider them further.

Existing non-graphlet approaches. Several PSN measures have already been used for PC: *average degree*, *average distance*, *maximum distance*, *average closeness centrality*, *average clustering coefficient*, *intra-hub connectivity*, and *assortativity*[13–](#page-55-12)[17](#page-55-13) . For each measure, for each pair of networks, we compute Euclidean distance between the networks' vectors (because all vectors are 1-dimensional, here we cannot use cosine similarity as for our GRAFENE approach). We describe these measures below. Average degree. The average degree of a network can be interpreted as a measure of the overall connectivity of the network. The degree of a node is the number of its network neighbors. The average degree of a network is the average of degrees of all nodes in the network. This measure has been used for analyzing protein structures by^{[13](#page-55-12)-17}.

Average distance. The distance between two nodes in a network is the length of the shortest path between the nodes. The average distance of a network is the average of distances over all pairs of nodes in the network. This measure has been used for analyzing protein structures by $16, 17$ $16, 17$ $16, 17$.

Maximum distance. The maximum distance of a network is the largest of all distances in the network. This measure has been used for analyzing protein structures by^{[16](#page-55-14)}.

Average closeness centrality. The *closeness centrality* of a node in a network can be interpreted to be the *nearness* of the node to all other nodes in the network. The closeness centrality $cl(v)$ of a node $v \in V$ is computed as $cl(v) = \frac{1}{\sum d(u,v)}$, where $d(v,u)$

is the distance between nodes *v* and *u*. The average closeness centrality of a network is the average of the closeness centrality values of all nodes in the network. This measure has been used for analyzing protein structures by $16, 17$ $16, 17$ $16, 17$.

Average clustering coefficient. The *clustering coefficient* of a node in a network can be interpreted as a measure of the connectivity between the neighbors of the node. Given a node ν with *m* neighbors, the clustering coefficient $cc(\nu)$ of the node ν is computed as $cc(v) = \frac{b}{m(m-1)}$, where *b* is the number of edges in the network connecting the *m* neighbors of *v*. The average

clustering coefficient of a network is the average of clustering coefficient values of all nodes in the network. This measure has been used for analyzing protein structures by $16, 17$ $16, 17$ $16, 17$.

Intra-hub connectivity. The intra-hub connectivity of a network can be interpreted as the overall connectivity of the hub nodes within the network.^{[14](#page-55-15)} defined a node to be a hub in a PSN if the degree of the node is at least three. We adopt the same strategy to define a hub node in this study. Given *k* such hub nodes in a network, the intra-hub connectivity of the network is computed as $\frac{m}{k(k-1)}$, where *m* is the number of connections between the hub nodes and $\frac{k(k-1)}{2}$ is the maximum possible number

of connections between the hub nodes. This measure has been used for analyzing protein structures by^{[14](#page-55-15)}.

Assortativity. The assortativity of a network can be interpreted as the tendency of the high degree nodes to be connected with other high degree nodes (see^{[18](#page-55-16)} for details). This measure has been used for analyzing protein structures by^{[16](#page-55-14)}.

We combine the seven measures into an eighth measure, *Existing-all*, to investigate whether the integration of different and complementary topological measures helps PC. We use Existing-all within our PCA framework. This way, we can fairly compare our graphlet measures (i.e., different versions of our GRAFENE approach) and the existing non-graphlet measures within the same framework.

S7.2 Existing 3D contact approaches

These include DaliLite^{[19](#page-55-17)} and TM-align^{[20](#page-55-18)}. Given two proteins (i.e., 3D co-ordinates of their residues), each of DaliLite and TM-align outputs the proteins' structural similarity score: *z*-score in the case of DaliLite and TM-score in the case of TM-align. In our evaluation framework, we sort all protein pairs in terms of their increasing distance, i.e., decreasing *z*-scores for DaliLite and decreasing TM-scores for TM-Align, and then we evaluate DaliLite and TM-Align as discussed in Section "Evaluation of PC accuracy" of the main manuscript.

S7.3 Existing sequence approach

The sequence-based approach that we use, which we call AAComposition, works as follows. For a given protein, for each amino acid type *i* (out of 20 possible types), we divide the number of amino acids of type *i* by the total number of amino acids in the protein sequence. We use the resulting 20 values, along with the length of the protein sequence, as the protein's sequence-based measure (i.e., feature vector). Then, we use this measure within our PCA framework. This way, we can fairly compare network- and sequence-based measures within the same framework.

S8 Performance trends of different PC approaches on same PSN sets and of same PC approaches on different PSN sets

Performance trends of different PC approaches on same PSN sets. We sometimes observe a difference in trends between different PC approaches for same PSN sets. Specifically, in the case of the CATH database, all approaches result in a consistent trend that their accuracy for CATH- α is higher than their accuracy for CATH- β . Similarly, in the case of the SCOP database, the majority of the approaches show a consistent trend that their accuracy for SCOP- β is higher than their accuracy for SCOP- α , except the GDDA, GCD, and AAComposition PC approaches, whose accuracy for $SCOP - \alpha$ is higher than their accuracy for SCOP-β. This difference in the trends between the different approaches (GDDA, GCD, and AAComposition versus all others) for SCOP is an approach-specific issue, meaning that some approaches might simply work better for (i.e., better capture patterns in) data of type 1 (e.g., α) than for data of type 2 (e.g., β), while other approaches might show the opposite trend (i.e., work better for data of type 2 than for data of type 1). It is hard to explain why this is, especially for the network-based approaches, because these approaches are heuristics (due to the computational intractability, i.e., NP-hardness, of the network comparison problem) without a theoretic guarantee on their accuracy (and especially on their accuracy on certain data types as opposed to other data types).

Performance trends of same PC approaches on different PSN sets. Additionally, we observe a difference in the performance of same PC approaches on different PSN sets. Specifically, a given approach might have higher accuracy for CATH- α than for CATH- β , but the same approach might have lower accuracy for SCOP- α than for SCOP- β . This trend inconsistency holds for all considered PC approaches except GDDA, GCD, and AAComposition; for both CATH and SCOP, the accuracy of these three approaches is higher for α than for β . This trend inconsistency is likely a data-specific issue: 1) CATH and SCOP do not necessarily contain the exact same PSNs (meaning that some PSNs that are in CATH might be missing from SCOP, and vice versa), and 2) for those PSNs that are in both CATH and SCOP, the PSNs might be categorized into some protein domain group (e.g., α) in CATH but to a different protein domain group (e.g., α/β) in SCOP, because the methodologies that CATH and SCOP use to categorize proteins into domain groups are not identical. If any of these two conditions is met, this could explain the observed trend inconsistency. Indeed, we find that:

- 1. Of all $(\alpha, \beta, \text{ or } \alpha/\beta)$ PSNs that are in CATH, only 27% are in SCOP. Similarly, of all $(\alpha, \beta, \alpha/\beta, \text{ or } \alpha+\beta)$ PSNs that are in SCOP, only 24% are in CATH. That is, most of the PSNs are unique to CATH and SCOP.
- 2. For all PSNs that are present in both CATH and SCOP:
	- 8% of the PSNs that are labeled as α in CATH are labeled as β , α/β , or $\alpha+\beta$ in SCOP.
	- 0.3% of the PSNs that are labeled as α in SCOP are labeled as β or α/β in CATH.
	- 37% of the PSNs that are labeled as β in CATH are labeled as α , α/β , or $\alpha+\beta$ in SCOP.
	- 38% of the PSNs that are labeled as β in SCOP are labeled as α or α/β in CATH.
	- 40% of the PSNs that are labeled as α/β in CATH are labeled as α or β in SCOP.
	- 43% of the PSNs that are labeled as α/β or $\alpha+\beta$ in SCOP are labeled as α or β in CATH.

Clearly, both of the above conditions are met, and hence, the observed trend inconsistency is not surprising.

Note that the above results are with respect to the first PSN construction strategy (any heavy atom, 4 Å) and the performance evaluation using AUPR.

II Supplementary Figures

Supplementary Figure S1. Illustration of the importance of "long-range(*K*)" ordered graphlets. A PSN is shown for a toy protein that consists of 42 amino acids in the sequence, i.e., nodes in the PSN (amino acids 4-19 and 23-39 are not shown for simplicity, as indicated by dashed lines). The nodes are denoted by their amino acid positions (i.e., residue order) in the sequence. Black solid lines are network edges that indicate sequence closeness of the corresponding amino acids (meaning that the amino acids are adjacent in the sequence), which in turn yields sufficient 3D spatial proximity of the amino acids. On the other hand, red solid lines are network edges that indicate only spatial proximity, without sequence adjacentness. On the one hand, both the three-node path 1–2–3 as well as the three-node path 2–21–41 correspond to the same ordered graphlet, namely O_1 from Fig. 3 in the main manuscript, under the traditional ordered graphlet approach. However, we argue that the latter is more interesting than the former, as the former is O_1 simply because of sequence adjacentness of amino acids 1 and 2 as well as 2 and 3, while the latter is *O*¹ because of spatial proximity of amino acids 2 and 21 as well as 21 and 41. On the other hand, even for *K* value as low as two, the path $1-2-3$ will not be detected as O_1 under the "long-range(*K*)" ordered graphlet approach, while the path 2–21–41 will, because all of its linked node pairs are at least two amino acids apart in the sequence. Note that the path 2–21–41 will be identified as O_1 up to *K* value of $min(21-2,41-21) = 19$.

Supplementary Figure S2. The performance comparison of the 15 considered approaches on each of the four considered synthetic network sets, with respect to AUROC, in terms of: (A) the approaches' ranks compared to one another, and (B) the approaches' raw AUROC values. In panel (A), for a given synthetic network set, the 15 approaches are ranked from the best (rank 1) to the worst (rank 15). So, the lower the rank, the better the approach. In panel (B), for each approach, its raw AUPR value is shown for each of the four synthetic network sets. So, the higher the AUROC value, the better the approach. For equivalent results with respect to AUPR values, see Fig. [4](#page-8-0) in the main manuscript.

Supplementary Figure S3. The PSN set group-specific performance comparison of the 24 considered approaches, averaged over all PSN sets in the given PSN set group, with respect to AUROC, in terms of: (A) the approaches' ranks compared to one another, and (B) the approaches' raw AUROC values. In panel (A), for a given PSN set, the 24 approaches are ranked from the best (rank 1) to the worst (rank 24). Then, for a given approach, its ranks over all group-specific PSN sets are averaged (the average ranks are denoted by circles, and bars denote the corresponding standard deviations). So, the lower the average rank, the better the approach. In panel (B), for each approach, its group-specific raw AUROC scores are averaged (the average values are denoted by circles, and bars denote the corresponding standard deviations). So, the higher the average AUROC value, the better the approach. The trends are very similar with respect to AUPR as well (Fig. [7](#page-11-0) in the main manuscript). These results are for the best PSN construction strategy. Equivalent results for each of the PSN construction strategies are shown in Supplementary Fig. [S4](#page-8-0)[-S7.](#page-11-0)

Supplementary Figure S4. The PSN set group-specific rank performance comparison of the 24 considered approaches, averaged over all PSN sets in the given PSN set group, with respect to AUPR, corresponding to the (A) first (any heavy atom, 4 A), (B) second (any heavy atom, 5 Å), (C) third (any heavy atom, 6 Å), and (D) fourth (α -carbon heavy atom, 7.5 Å) PSN construction strategy. For a given PSN set, the 24 approaches are ranked from the best (rank 1) to the worst (rank 24). Then, for a given approach, its ranks over all group-specific PSN sets are averaged (the average ranks are denoted by circles, and bars denote the corresponding standard deviations). So, the lower the average rank, the better the approach. The trends are very similar with respect to AUROC as well (Supplementary Fig. [S5\)](#page-9-0).

Supplementary Figure S5. The PSN set group-specific rank performance comparison of the 24 considered approaches, averaged over all PSN sets in the given PSN set group, with respect to AUROC, corresponding to the (A) first (any heavy atom, 4 Å), (B) second (any heavy atom, 5 Å), (C) third (any heavy atom, 6 Å), and (D) fourth (α -carbon heavy atom, 7.5 Å) PSN construction strategy. For a given PSN set, the 24 approaches are ranked from the best (rank 1) to the worst (rank 24). Then, for a given approach, its ranks over all group-specific PSN sets are averaged (the average ranks are denoted by circles, and bars denote the corresponding standard deviations). So, the lower the average rank, the better the approach. The trends are very similar with respect to AUPR as well (Supplementary Fig. [S4\)](#page-8-0).

Supplementary Figure S6. The PSN set group-specific performance comparison of the 24 considered approaches, averaged over all PSN sets in the given PSN set group, with respect to AUPR values (expressed as percentages), corresponding to the (A) first (any heavy atom, 4 Å), (B) second (any heavy atom, 5 Å), (C) third (any heavy atom, 6 Å), and (D) fourth $(\alpha$ -carbon heavy atom, 7.5 Å) PSN construction strategy. For each approach, its group-specific raw AUPR values are averaged (the average values are denoted by circles, and bars denote the corresponding standard deviations). So, the higher the average AUPR value, the better the approach. The trends are very similar with respect to AUROC as well (Supplementary Fig. [S7\)](#page-11-0).

Supplementary Figure S7. The PSN set group-specific performance comparison of the 24 considered approaches, averaged over all PSN sets in the given PSN set group, with respect to AUROC values (expressed as percentages), corresponding to the (A) first (any heavy atom, 4 Å), (B) second (any heavy atom, 5 Å), (C) third (any heavy atom, 6 Å), and (D) fourth (α -carbon heavy atom, 7.5 Å) PSN construction strategy. For each approach, its group-specific raw AUROC values are averaged (the average values are denoted by circles, and bars denote the corresponding standard deviations). So, the higher the average AUROC value, the better the approach. The trends are very similar with respect to AUPR as well (Supplementary Fig. [S6\)](#page-10-0).

Supplementary Figure S8. Distribution of PSN sets across four PSN construction strategies: 1, 2, 3, and 4. The results are with respect to AUPR. Each panel (one panel per PC approach) shows the following: for each PSN construction strategy, we calculate the percentage of all $3+35 = 38$ real-world PSN sets for which the given PSN construction strategy performs the best; this is what the height of the given bar shows. Then, within each bar, we label the PSN sets according to the PSN set groups to which they belong.

Supplementary Figure S9. Distribution of PSN sets across four PSN construction strategies: 1, 2, 3, and 4. The results are with respect to AUROC. Each panel (one panel per PC approach) shows the following: for each PSN construction strategy, we calculate the percentage of all $3+35 = 38$ real-world PSN sets for which the given PSN construction strategy performs the best; this is what the height of the given bar shows. Then, within each bar, we label the PSN sets according to the PSN set groups to which they belong.

Supplementary Figure S10. The ranking of the four PSN construction strategies: 1, 2, 3, and 4. The ranking is shown with respect to AUPR. Each panel (one panel per PC approach) shows the following: for each PSN construction strategy, we calculate the percentage of all $3+35 = 38$ real-world PSN sets in which the given PSN construction strategy performs the best, the second best, the third best, and the fourth best.

Supplementary Figure S11. The ranking of the four PSN construction strategies: 1, 2, 3, and 4. The ranking is shown with respect to AUPR. Each panel (one panel per PC approach) shows the following: for each PSN construction strategy, we calculate the percentage of all $3+35 = 38$ real-world PSN sets in which the given PSN construction strategy performs the best, the second best, the third best, and the fourth best. Note that unlike in Supplementary Fig. [S10,](#page-14-0) here we consider two AUPR values to be tied if the absolute difference between them is \leq 5% of the maximum achievable AUPR value.

Supplementary Figure S12. The ranking of the four PSN construction strategies: 1, 2, 3, and 4. The ranking is shown with respect to AUROC. Each panel (one panel per PC approach) shows the following: for each PSN construction strategy, we calculate the percentage of all $3+35 = 38$ real-world PSN sets in which the given PSN construction strategy performs the best, the second best, the third best, and the fourth best.

Supplementary Figure S13. The ranking of the four PSN construction strategies: 1, 2, 3, and 4. The ranking is shown with respect to AUROC. Each panel (one panel per PC approach) shows the following: for each PSN construction strategy, we calculate the percentage of all $3+35 = 38$ real-world PSN sets in which the given PSN construction strategy performs the best, the second best, the third best, and the fourth best. Note that unlike in Supplementary Fig. [S12,](#page-16-0) here we consider two AUROC values to be tied if the absolute difference between them is \leq 5% of the maximum achievable AUROC value.

Supplementary Figure S14. The PSN construction strategy-specific performance comparison of the 24 considered PC approaches, with respect to AUROC, in terms of: (A) the approaches' ranks compared to one another, and (B) the approaches' raw AUROC values. In panel (A), for each PSN construction strategy, for a given PSN set, the 24 approaches are ranked from the best (rank 1) to the worst (rank 24). Then, for a given approach, its 35 ranks (corresponding to the 35 PSN sets) are averaged (the average ranks are denoted by circles, and bars denote the corresponding standard deviations). So, the lower the average rank, the better the approach. In panel (B), for each PSN construction strategy, for each approach, its 35 raw AUROC values (corresponding to the 35 PSN sets) are averaged (the average values are denoted by circles, and bars denote the corresponding standard deviations). So, the higher the average AUROC value, the better the approach. The trends are very similar with respect to AUPR as well (Fig. [8](#page-12-0) in the main manuscript). These results are for the "all group" PSN set group that spans the 35 PSN sets of different sizes. Equivalent results for the individual groups 1-4 are shown in Supplementary Fig. [S15-](#page-19-0)[S18.](#page-22-0)

Supplementary Figure S15. The PSN construction strategy-specific rank performance comparison of the 24 considered PC approaches, with respect to AUPR, corresponding to PSN set group : (A) 1, (B) 2, (C) 3, and (D) 4. For each PSN construction strategy, for a given PSN set, the 24 approaches are ranked from the best (rank 1) to the worst (rank 24). Then, for a given approach, its 35 ranks (corresponding to the 35 PSN sets) are averaged (the average ranks are denoted by circles, and bars denote the corresponding standard deviations). So, the lower the average rank, the better the approach. The trends are very similar with respect to AUROC as well (Supplementary Fig. [S16\)](#page-20-0).

Supplementary Figure S16. The PSN construction strategy-specific rank performance comparison of the 24 considered PC approaches, with respect to AUROC, corresponding to PSN set group : (A) 1, (B) 2, (C) 3, and (D) 4. For each PSN construction strategy, for a given PSN set, the 24 approaches are ranked from the best (rank 1) to the worst (rank 24). Then, for a given approach, its 35 ranks (corresponding to the 35 PSN sets) are averaged (the average ranks are denoted by circles, and bars denote the corresponding standard deviations). So, the lower the average rank, the better the approach. The trends are very similar with respect to AUPR as well (Supplementary Fig. [S15\)](#page-19-0).

Supplementary Figure S17. The PSN construction strategy-specific performance comparison of the 24 considered PC approaches, with respect to AUPR values (expressed as percentages), corresponding to PSN set group : (A) 1, (B) 2, (C) 3, and (D) 4. For each PSN construction strategy, for each approach, its 35 raw AUPR values (corresponding to the 35 PSN sets) are averaged (the average values are denoted by circles, and bars denote the corresponding standard deviations). So, the higher the average AUPR value, the better the approach. The trends are very similar with respect to AUROC values as well (Supplementary Fig. [S18\)](#page-22-0).

Supplementary Figure S18. The PSN construction strategy-specific performance comparison of the 24 considered PC approaches, with respect to AUROC values (expressed as percentages), corresponding to PSN set group : (A) 1, (B) 2, (C) 3, and (D) 4. For each PSN construction strategy, for each approach, its 35 raw AUROC scores (corresponding to the 35 PSN sets) are averaged (the average values are denoted by circles, and bars denote the corresponding standard deviations). So, the higher the average AUROC value, the better the approach. The trends are very similar with respect to AUPR values as well (Supplementary Fig. [S17\)](#page-21-0).

Supplementary Figure S19. Statistical significance of the difference between average ranks of the PC approaches, with respect to: (A) AUPR and (B) AUROC. For aesthetics, these results are only for the best approach in each category, namely: the best of our proposed PCA graphlet-based network approaches (GRAFENE version NormOrderedGraphlet-3-4(K)), the best of the existing non-PCA graphlet-based network approaches (GR-Align), the best of the existing non-graphlet network approaches (Existing-all), the best of the existing non-network 3D structural approaches (DaliLite), and the sequence-based approach (AAComposition). For each of the 35 PSN sets, the five approaches are ranked from the best (rank 1) to the worst (rank 5). Hence, for each approach, there are 35 ranks (corresponding to the 35 PSN sets). For each pair of approaches, we compare the two given approaches' 35 ranks using paired *t*-test. In the figure, every cell (*i*, *j*) indicates the statistical significance (in terms of *p*-value) of approach *i* being superior to approach *j*. The results are similar when we use raw AUPR/AUROC values instead of ranks (Supplementary Fig. [S20\)](#page-24-0).

Supplementary Figure S20. Statistical significance of the difference between average raw values of the PC approaches, with respect to: (A) AUPR and (B) AUROC. For aesthetics, these results are only for the best approach in each category, namely: the best of our proposed PCA graphlet-based network approaches (GRAFENE version NormOrderedGraphlet-3-4(K)), the best of the existing non-PCA graphlet-based network approaches (GR-Align), the best of the existing non-graphlet network approaches (Existing-all), the best of the existing non-network 3D structural approaches (DaliLite), and the sequence-based approach (AAComposition). For each of the 35 PSN sets, raw AUPR/AUROC values for all five approaches are measured. Hence, for each approach, there are 35 raw AUPR/AUROC values (corresponding to the 35 PSN sets). For each pair of approaches, we compare the two given approaches' 35 raw AUPR/AUROC values using paired *t*-test. In the figure, every cell (i, j) indicates the statistical significance (in terms of *p*-value) of approach *i* being superior to approach *j*. The results are similar when we use ranks instead of raw AUPR/AUROC values (Supplementary Fig. [S19\)](#page-23-0).

Supplementary Figure S21. The performance comparison of only the best PC approach in each category (for aesthetics purposes) on all three "equal size" PSN sets and all 35 PSN sets of different size, with respect to raw AUROC values. Namely, results are shown for: the best of our proposed PCA graphlet-based network approaches (GRAFENE version NormOrderedGraphlet-3-4(K)), the best of the existing non-PCA graphlet-based network approaches (GR-Align), the best of the existing non-graphlet network approaches (Existing-all), the best of the existing non-network 3D structural approaches (DaliLite), and the sequence-based approach (AAComposition). The vertical dotted lines separate the PSN sets into the five PSN set groups, namely (from left to right): "equal size", group 1, group 2, group 3, and group 4. For the equivalent results in terms of raw AUPR values, see Fig. [9](#page-13-0) in the main manuscript.

Supplementary Figure S22. (A) Precision-recall (PR) and (B) receiver operating characteristic (ROC) curves for the best approach in each category, namely: the best of our proposed PCA graphlet-based network approaches (GRAFENE version NormOrderedGraphlet-3-4(K)), the best of the existing non-PCA graphlet-based network approaches (GR-Align), the best of the existing non-graphlet network approaches (Existing-all), the best of the existing non-network 3D structural approaches (DaliLite), and the sequence-based approach (AAComposition). The results are for the three "equal-size" PSN sets. Also, these results are for the best PSN construction strategy.

Supplementary Figure S23. Precision-recall (PR) curves for the best approach in each category, namely: the best of our proposed PCA graphlet-based network approaches (GRAFENE version NormOrderedGraphlet-3-4(K)), the best of the existing non-PCA graphlet-based network approaches (GR-Align), the best of the existing non-graphlet network approaches (Existing-all), the best of the existing non-network 3D structural approaches (DaliLite), and the sequence-based approach (AAComposition). These results are for the 35 PSN sets of different size. Also, these results are for the best PSN construction strategy.

Supplementary Figure S24. Receiver operating characteristic (ROC) curves for the best approach in each category, namely: the best of our proposed PCA graphlet-based network approaches (GRAFENE version NormOrderedGraphlet-3-4(K)), the best of the existing non-PCA graphlet-based network approaches (GR-Align), the best of the existing non-graphlet network approaches (Existing-all), the best of the existing non-network 3D structural approaches (DaliLite), and the sequence-based approach (AAComposition). These results are for the 35 PSN sets of different size. Also, these results are for the best PSN construction strategy.

Supplementary Figure S25. Ordered graphlets that are significantly represented in α (dark gray) or β (light gray) PSNs.

III Supplementary Tables

Supplementary Table S1. Synthetic network sets that we use. For the given data set, the second column indicates whether its networks are of the same size or different sizes, and the last three columns indicate the number of its networks as well as their size(s) in terms of the number of nodes and edges.

Supplementary Table S2. The number of categories and the number of PSNs averaged over all categories for each of the 35 real-world PSN sets, with respect to four different PSN construction strategies: first (any heavy atom, 4 Å), second (any heavy atom, 5 Å), third (any heavy atom, 6 Å), and fourth (α -carbon heavy atom, 7.5 Å).

Supplementary Table S3. Details about our PSN sets belonging to the second-level hierarchical categories of CATH and SCOP. At the top-level of the CATH hierarchy, there are three categories: α , β , and α/β . At the top-level of the SCOP hierarchy, there are five categories: α , β , α/β , $\alpha+\beta$, and Multi domain. Each top-level category has multiple second-level categories, as shown in the table. For example, the α top-level hierarchical category of CATH has four second-level categories: Orthogonal Bundle, Up-down Bundle, Alpha Horseshoe, and Alpha/Alpha Barrel. For each top-level hierarchical category, we specify its name and label (separated by semicolon), where the labels are as given by CATH/SCOP. For each second-level hierarchical category, we specify its name and the number of PSNs (shown in parentheses).

Supplementary Table S2 – continued on next page

Supplementary Table S4. Details about our PSN sets belonging to the third-level hierarchical categories of CATH and SCOP. At the second-level of the CATH hierarchy, there are nine categories: 1.10, 1.20, 2.160, 2.30, 2.40, 2.60, 3.10, 3.30, and 3.40. At the second-level of the SCOP hierarchy, there are six categories: *a*.118, *b*.1, *c*.1, *c*.23, *c*.26 and *c*.55. Each second-level category has multiple third-level categories, as shown in the table. For example, the 2.60 second-level hierarchical category of CATH has two third-level categories: Jelly-rolls and Immunoglobulin-like. For each second-level hierarchical category, we specify its name and label (separated by semicolon), where the labels are as given by CATH/SCOP. For each third-level hierarchical category, we specify its name and the number of PSNs (shown in parentheses).

Supplementary Table S3 – continued on next page

Supplementary Table S5. Details about our PSN sets belonging to the fourth-level hierarchical categories of CATH and SCOP. At the third-level CATH hierarchy, there are six categories: 2.60.120, 2.60.40, 3.20.20, 3.30.390, 3.30.420, and 3.40.50. At the third-level SCOP hierarchy, there are four categories: *b*.1.1, *c*.1.8, *c*.2.1, and *c*.37.1. Each third-level category has multiple fourth-level categories, as shown in the table. For example, the 3.40.50 third-level hierarchical category of CATH has two fourth-level categories: Vaccinia virus protein VP39 and P-loop containing nucleotide triphosphate hydrolase. For each third-level hierarchical category, we specify its name and label (separated by semicolon), where the labels are as given by CATH/SCOP. For each fourth-level hierarchical category, we specify its name and the number of PSNs (shown in parentheses).

Supplementary Table S6. Accuracy with respect to AUPR values (expressed as percentages) on synthetic networks. Results for non-normalized approaches are highlighted in 1) light gray for network data of the same size and 2) dark gray for network data of different sizes. Results for normalized approaches are not highlighted. Given a network data set (within a column), the AUPR of the best approach is shown in bold. For equivalent results with respect to AUROC values, see Supplementary Table [S7.](#page-38-0)

Supplementary Table S7. Accuracy with respect to AUROC values (expressed as percentages) on synthetic networks. Results for non-normalized approaches are highlighted in 1) light gray for network data of the same size and 2) dark gray for network data of different sizes. Results for normalized approaches are not highlighted. Given a network data set (within a column), the AUROC of the best approach is shown in bold. For equivalent results with respect to AUPR values, see Supplementary Table [S6.](#page-37-0)

Supplementary Table S8. Accuracy with respect to AUPR values (expressed as percentages) on the three real-world PSN sets that form the "equal size" group, each of which contains networks of the same size. Also, average accuracy over all three PSN sets is shown ("Average"), along with the corresponding standard deviation ("SD"). Results for non-normalized approaches are highlighted in light gray. Results for normalized approaches are not highlighted. Given a PSN set (within a given column), the AUPR of the best approach is shown in bold. For equivalent results with respect to AUROC values, see Supplementary Table [S9.](#page-40-0)

Supplementary Table S9. Accuracy with respect to AUROC values (expressed as percentages) on the three real-world PSN sets that form the "equal size" group, each of which contains networks of the same size. Also, average accuracy over all three PSN sets is shown ("Average"), along with the corresponding standard deviation ("SD"). Results for non-normalized approaches are highlighted in light gray. Results for normalized approaches are not highlighted. Given a PSN set (within a given column), the AUROC of the best approach is shown in bold. For equivalent results with respect to AUPR values, see Supplementary Table [S8.](#page-39-0)

Supplementary Table S10. Summary of method accuracy and running times. Accuracy of the given approach is shown with respect to its average ranking as well as its average raw score compared to all considered approaches across all 35 different-size PSN sets, and the results are shown based on AUPR as well as AUROC. We rank the approaches as follows. For the given PSN set, we determine which approach results in the highest accuracy (rank 1), the second highest accuracy (rank 2), etc. Then, we average the rankings of the given method over all PSN sets. So, the lower the average rank, the better the method. Since NormOrderedGraphlet-3-4(K) has the best average rank with respect to both AUPR and AUROC (shown in bold), we compute the statistical significance of the improvement of NormOrderedGraphlet-3-4(K) over each of the other approaches in terms of their ranks using paired *t*-test. We also do the same in terms of raw AUPR/AUROC values. Note that in the case of raw values, the higher the average AUPR/AUROC value, the better the approach. Running times of the approaches are shown when comparing proteins from the CATH- α set. Running times for the other data sets are qualitatively the same.

Supplementary Table S11. Detailed accuracy results for each PC approach, each PSN set, and each PSN construction strategy, with respect to AUPR values.

[http://nd.edu/˜cone/PSN/ST11.xlsx](http://nd.edu/~cone/PSN/ST11.xlsx)

Supplementary Table S12. Detailed accuracy results for each PC approach, each PSN set, and each PSN construction strategy, with respect to AUROC values.

[http://nd.edu/˜cone/PSN/ST12.xlsx](http://nd.edu/~cone/PSN/ST12.xlsx)

Supplementary Table S13. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of "equal size", group 1, and group 2. Given a PSN set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the first PSN construction strategy, (any heavy atom type, 4 Å distance cut-off).

Supplementary Table S14. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of "equal size", group 1, and group 2. Given a network data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the first PSN construction strategy, (any heavy atom type, 4 Å distance cut-off).

Supplementary Table S15. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of group 3. Given a PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the first PSN construction strategy, (any heavy atom type, 4 Å distance cut-off).

Supplementary Table S16. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of group 3. Given a third-level PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the first PSN construction strategy, (any heavy atom type, 4 Å distance cut-off).

Supplementary Table S17. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of group 4. Given a fourth-level PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the first PSN construction strategy, (any heavy atom type, 4 Å distance cut-off).

Supplementary Table S18. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of group 4. Given a fourth-level PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the first PSN construction strategy, (any heavy atom type, 4 Å distance cut-off).

Supplementary Table S19. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of "equal size", group 1, and group 2. Given a PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the second PSN construction strategy, (any heavy atom type, 5 Å distance cut-off).

Supplementary Table S20. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of "equal size", group 1, and group 2. Given a PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the second PSN construction strategy, (any heavy atom type, 5 Å distance cut-off).

Supplementary Table S21. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of group 3. Given a third-level PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the second PSN construction strategy, (any heavy atom type, 5 Å distance cut-off).

Supplementary Table S22. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of group 3. Given a third-level PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the second PSN construction strategy, (any heavy atom type, 5 Å distance cut-off).

Supplementary Table S23. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of group 4. Given a fourth-level PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the second PSN construction strategy, (any heavy atom type, 5 Å distance cut-off).

Supplementary Table S24. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of group 4. Given a fourth-level PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the second PSN construction strategy, (any heavy atom type, 5 Å distance cut-off).

Supplementary Table S25. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of "equal size", group 1, and group 2. Given a PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the third PSN construction strategy, (any heavy atom type, 6 Å distance cut-off).

Supplementary Table S26. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of "equal size", group 1, and group 2. Given a PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the third PSN construction strategy, (any heavy atom type, 6 Å distance cut-off).

Supplementary Table S27. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of group 3. Given a third-level PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the third PSN construction strategy, (any heavy atom type, 6 Å distance cut-off).

Supplementary Table S28. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of group 3. Given a third-level PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the third PSN construction strategy, (any heavy atom type, 6 Å distance cut-off).

Supplementary Table S29. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of group 4. Given a fourth-level PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the third PSN construction strategy, (any heavy atom type, 6 Å distance cut-off).

Supplementary Table S30. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of group 4. Given a fourth-level PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the third PSN construction strategy, (any heavy atom type, 6 Å distance cut-off).

Supplementary Table S31. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of "equal size", group 1, and group 2. Given a PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the fourth PSN construction strategy, (α -carbon heavy atom type, 7.5 Å distance cut-off).

Supplementary Table S32. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of "equal size", group 1, and group 2. Given a PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the fourth PSN construction strategy, (α -carbon heavy atom type, 7.5 Å distance cut-off).

Supplementary Table S33. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of group 3. Given a third-level PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the fourth PSN construction strategy, (α -carbon heavy atom type, 7.5 Å distance cut-off).

Supplementary Table S34. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of group 3. Given a third-level PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the fourth PSN construction strategy, (α -carbon heavy atom type, 7.5 Å distance cut-off).

Supplementary Table S35. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUPR values (expressed as percentages), corresponding to the PSN sets of group 4. Given a fourth-level PSN data set (within a given column), the AUPR for the "best" *K* is shown in bold. These results are with respect to the fourth PSN construction strategy, (α -carbon heavy atom type, 7.5 Å distance cut-off).

Supplementary Table S36. Accuracy of the NormOrderedGraphlet-3-4(K) approach when varying the value of *K*, with respect to AUROC values (expressed as percentages), corresponding to the PSN sets of group 4. Given a fourth-level PSN data set (within a given column), the AUROC for the "best" *K* is shown in bold. These results are with respect to the fourth PSN construction strategy, (α -carbon heavy atom type, 7.5 Å distance cut-off).

References

- 1. Berman, H. M. *et al.* The Protein Data Bank. *Nucleic Acids Research* 28, 235–242 (2000).
- 2. Sillitoe, I. *et al.* CATH: comprehensive structural and functional annotations for genome sequences. *Nucleic Acids Research* 43, D376–D381 (2015).
- 3. Orengo, C. A. *et al.* The CATH database provides insights into protein structure/function relationships. *Nucleic Acids Research* 27, 275–279 (1999).
- 4. Murzin, A. G., Brenner, S. E., Hubbard, T. & Chothia, C. SCOP: a structural classification of proteins database for the investigation of sequences and structures. *Journal of Molecular Biology* 247, 536–540 (1995).
- 5. Milenković, T., Lai, J. & Pržulj, N. GraphCrunch: a tool for large network analyses. *BMC Bioinformatics* 9 (2008).
- 6. Kuchaiev, O., Stevanović, A., Hayes, W. & Pržulj, N. GraphCrunch 2: Software tool for network modeling, alignment and clustering. *BMC Bioinformatics* 12 (2011).
- 7. Malod-Dognin, N. & Pržulj, N. GR-Align: fast and flexible alignment of protein 3D structures using graphlet degree similarity. *Bioinformatics* 30, 1259–65 (2014).
- 8. Pržulj, N. Biological network comparison using graphlet degree distribution. *Bioinformatics* 23, e177–e183 (2007).
- 9. Pržulj, N., Corneil, D. G. & Jurisica, I. Modeling interactome: Scale-free or geometric? *Bioinformatics* 20, 3508–3515 (2004).
- 10. Yaveroglu, O. N. *et al.* Revealing the Hidden Language of Complex Networks. *Scientific Reports* 4, 4547 (2014).
- 11. Vacic, V., Iakoucheva, L. M., Lonardi, S. & Radivojac, P. Graphlet Kernels for Prediction of Functional Residues in Protein Structures. *Journal of Computational Biology* 17, 55–72 (2010).
- 12. Lugo-Martinez, J. & Radivojac, P. Generalized graphlet kernels for probabilistic inference in sparse graphs. *Network Science* 2, 254–276 (2014).
- 13. Pabuwal, V. & Li, Z. Network pattern of residue packing in helical membrane proteins and its application in membrane protein structure prediction. *Protein Engineering, Design and Selection* 21, 55–64 (2008).
- 14. Pabuwal, V. & Li, Z. Comparative analysis of the packing topology of structurally important residues in helical membrane and soluble proteins. *Protein Engineering, Design and Selection* 22, 67–73 (2009).
- 15. Gao, J. & Li, Z. Conserved network properties of helical membrane protein structures and its implication for improving membrane protein homology modeling at the twilight zone. *Journal of Computer-Aided Molecular Design* 23, 755–763 (2009).
- 16. Emerson, I. A. & Gothandam, K. M. Network analysis of transmembrane protein structures. *Physica A* 391, 905–916 (2012).
- 17. Emerson, I. A. & Gothandam, K. M. Residue centrality in alpha helical polytopic transmembrane protein structures. *Journal of Theoretical Biology* 309, 78–87 (2013).
- 18. Newman, M. E. J. Assortative mixing in networks. *Physical Review Letters* 89, 208701 (2002).
- 19. Holm, L. & Rosenström, P. Dali server: conservation mapping in 3D. *Nucleic Acids Research* 38, W545–W549 (2010).
- 20. Zhang, Y. & Skolnick, J. TM-align: a protein structure alignment algorithm based on the TM-score. *Nucleic Acids Research* 33, 2302–09 (2005).