Software Report

CP_{dock}: The Complementarity Plot for Docking of Proteins: Implementing Multi-dielectric Continuum Electrostatics

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Abstract

The Complementarity plot (CP) is an established validation tool for protein structures, applicable to both, globular proteins (folding) as well as protein-protein complexes (binding). It computes the shape and electrostatic complementarities (S_m, E_m) for amino acid side-chains buried within the protein interior or interface and plots them in a two-dimensional plot having knowledge-based probabilistic quality estimates for the residues as well as for the whole structure. The current report essentially presents an upgraded version of the plot with the implementation of the advanced multi-dielectric functionality (as in Delphi version 6.2 or higher) in the computation of electrostatic complementarity to make the validation tool physico-chemically more realistic. The two methods (single- and multi-dielectric) agrees decently in their resultant E_m values and hence, provisions for both methods have been kept in the software suite. So to speak, the global electrostatic balance within a well-folded protein and / or a well-packed interface seems only marginally perturbed by the choice of different internal dielectric values. However, both from theoretical as well as practical grounds, the more advanced multi-dielectric version of the plot is certainly recommended for potentially producing more reliable results. The report also presents a new methodology and a variant plot, namely, CP_{dock}, based on the same principles of complementarity, specifically designed to be used in the docking of proteins. The efficacy of the method to discriminate between good and bad docked protein complexes have been tested on a recent state-of-the-art docking benchmark. The results unambiguously indicate that CP_{dock} can indeed be effective in the initial screening phase of a docking scoring pipeline before going into more sophisticated and computationally expensive scoring functions. CP_{dock} has been made available at https://github.com/nemo8130/CPdock

Keywords: Complementarity Plot, Multi-dielectric electrostatic complementarity, CP_{dock}, screening of docked protein models

Introduction

The Complementarity plot (CP) is an established graphical structure validation tool in the field of protein science originally proposed for globular proteins [1–3] and later extended for experimentally solved protein co-complexes [4]. So far, this has been constructed and applied to analyze complementarity in a residue-wise manner in proteins. CP has a wide array of applications ranging from serving as a component in protein crystallography, homology modeling, protein design and dynamics [1,2,5]. It computes the shape and electrostatic complementarities for amino acid side-chains deeply or partially buried within the protein interior or interface and plots these ordered pair values in a two-dimensional plot (E_m: ordinate, S_m: abscissa) according to the burial of the residues [1]. In effect, the term CP stands out to be a misnomer, while in reality, there exist three plots (CP1, CP2, CP3) corresponding to three different burial bins (see **Methods**) [1]. The design of CP is analogous to the famous Ramachandran Plot (RP) [6] though it is distinctly different in its physico-chemical nuances and accordingly in its particular uses in the validation pipeline. For example, structures with incorrectly assigned side-chain rotamers (frequently found in low-resolution atomic models) may indeed give rise to a sub-optimal distribution of points in their CP's, in spite of well satisfying the Ramachandran validation filters (or scores based on the RP – as in Procheck [7], Molprobity [8]) for having an optimal set of Φ, Ψ's [2]. For this very reason, the combined application of the two complementarity measures (S_m, E_m) has also found its wide use and superiority in performance to older methods in threading exercises [1] wherein the problem was to pick the correct native structure situated amid a set of decoys, with their main-chains being kept identical to that of the native (offering an identical set of Φ, Ψ's) while allowing variations only in their side-chain coordinates. Also, in the related problem of fold recognition, the methodology could prove its efficacy to identify the correct fold for a pair of sequences having low sequence similarity although belonging to the same fold [1].

The accurate determination of the local internal dielectric constant within proteins (as a function of the degree of solvent exposure of amino acid residues) has been a well posed problem in the field for decades. For electrostatic continuum models, there is still an ongoing debate among different values proposed for the parameter [9]. The subject has been further complicated by paradoxical observations like the presence of ionic groups in the hydrophobic protein interior without having to adapt to any specialized structures to get stabilized, demanding a considerably higher effect experienced locally at these sites than can be accounted for by the low dielectric constant traditionally assigned to represent the hydrophobic protein interior in continuum models [10]. Primarily contributed by this 'dielectric problem', electrostatic complementarity of individual amino acid residues (E_m) within a folded protein chain remained undetermined, until the problem was finally adequately addressed by the same study [1] that put forward the Complementarity Plot (CP). Briefly, the study had shown that electrostatic complementarity (being a correlation function between two troughs of potential values) is independent of any single dielectric constant assigned to the protein interior, treated as the internal dielectric of the continuum [1]. Even then, the methodology had room to implement more sophistication by means of actually quantifying the local internal dielectric *in situ* prior to calculating the electrostatic potential. This central concern of protein electrostatics has precisely been addressed recently in an advanced version of Delphi [11], the leading Poisson-Boltzmann solver in the field. More specifically, by means of their Gaussian-based approach in the multi-dielectric treatment of the protein interior [12], Delphi can now deliver the dielectric constant distribution throughout a protein. As a result, it presented a realistic opportunity to incorporate this functionality in CP and recompute E_m as a function of variable local internal dielectric, compare the results with the earlier method, and keep both options in the user interface of the software and this is the central theme of the current report. The study shows strong agreement in general in the E_m values for amino acid residues within proteins, computed by both

single and multi-dielectric methods. It is to be noted that large disagreement between the E_m values is rare and highly contextual, and, in such cases the more advanced multi-dielectric method is surely recommended. Subsequently, both softwares for CP (**Interior:** https://github.com/nemo8130/SARAMA-updated [3], **Interface:** https://github.com/nemo8130/SARAMAint-updated [4]) have been added with the provisions to implement both single and multi-dielectric methods as separate standalone packages.

In addition, here we also present a varient of the Complementarity Plot (namely, CP_{dock}) to be effectively used at the initial screening phase of a protein-protein docking scoring pipeline. CP_{dock} is based on single values of shape (Sc) and electrostatic complementarity (EC) raised at the protein-protein interface, as was in the original formulations of the two complementarity measures [13,14] .

Methods

Software Implementation

The multi-dielectric versions of CP (**Interior:** https://github.com/nemo8130/SARAMA-updated/tree/master/SARAMA-multidielectric-delphi, **Interface:** https://github.com/nemo8130/SARAMAint-updated/tree/master/SARAMAint-multidielectric-delphi) have appropriately been added with the functionality to implement the delphi multi-dielectric model [12]. For user-convenience as well as for future development, the single and multi-dielectric methods have been kept as separate standalone packages; and, as a consequence, there is no alteration required at the user interface. The user may simply download the desired version (single- or multi-dielectric) and run an identical set of commands (as detailed in the software-documentation) to execute either of them. The CP packages (SARAMA, SARAMAint) can also be found enlisted in the delphi tools page (http://compbio.clemson.edu/delphi_tools) redirecting to their source site (http://www.saha.ac.in/biop/www/sarama.html) having the same currently updated versions and also hyperlinks to the aforementioned github pages. For all future downloads and updates, we recommend the user to refer to the github pages.

Essential Measures

Solvent accessible surface area (ASA) was calculated for each protein atom by NACCESS [15] which were then summed up for all atoms pertaining to the same residue. As elaborated in a series of earlier studies [1,2,16,17], the burial (*bur*) of solvent exposure for any residue (X) embedded in a polypeptide chain was defined by the solvent accessible surface area (ASA) of X located in the protein divided by the ASA of the same amino acid in a Gly-X-Gly peptide fragment in its fully extended conformation. Residues were distributed in three different burial bins based on their *bur* value mapping to three different CP's: CP1: $0.00 \leq bur \leq 0.05$; CP2: $0.05 < bur \leq 0.15$; CP3: $0.15 < bur \leq 0.30$. The completely exposed residues with $bur > 0.3$ [16] were not considered in any of the CP's for lacking any notable packing constraints in their local neighborhood. The methododlogy to calculate S_m, E_m as well as the detailed construction of CP's could be found in their original reports [1–4].

For CP_{dock}, Sc was calculated precisely according to a previous report [18] while for EC, the only alteration in the previous protocol [18] was the permanent adaptation of the multi-dielectric continumm model [12].

Databases

For comparing the single- and multi-dielectric methods in terms of their effect in CP, the S_m, E_m values for individual buried / partially buried residues were calculated from a previously

standardized database (**DB2**) of globular proteins: https://github.com/nemo8130/DB2 which was used successfully in several earlier studies [1,2,19].

For the construction of CP_{dock}, the Sc, EC values raised at protein-protein interfaces were calculated from a previously standardized database (**DB3**: https://github.com/nemo8130/DB3), used successfully in several other studies [4,18,19].

Results and Discussion

Statistical Comparison of the single- and multi-dielectric methods

The overall distribution of points in the CP's doesn't really change by adapting to the multi-dielectric Gaussian model [12]. This was evident from the visual comparison of both distributions side-by-side across all three burial bins (**Fig.1, Supplementary Fig.S1, Fig.S2**). The agreement in the two methods was also quantified by the overlap in grid-probabilities (P_{grid}) [1] between the corresponding pair of plots. P_{grid} values were found to be 0.94, 0.93, 0.92 calculated over 22461, 10997 and 13767 points for CP1, CP2 and CP3 for the interior (calculated on **DB2**) while almost identical overlap-values obtained also for the interface CP's: 0.94, 0.94, 0.93 for 27479, 18376, 17868 points (calculated on **DB3**). In accordance, the corresponding pair of E_m values (calculated by the two methods) also had descent agreement between themselves as revealed from their root mean square deviations (rmsd's) and pair-wise Correlation (Pearson's). The numbers were found to be rmsd: 0.12, Pearson's: 0.90 (for 27479 residues in CP1), rmsd: 0.13, Pearson's: 0.88 (for 18376 residues in CP2) and (rmsd: 0.15, Pearson's: 0.86) for 17868 residues in CP3, calculated from the larger (**DB3**) of the two databases. Note, that the corresponding agreement between the equivalent single-valued term (EC) raised at protein-protein interfaces has already been reported (rmsd: 0.15, Pearson's Correlation: 0.94) in a previous study [18].

The contours to delineate the 'probable', 'less probable' and 'improbable' regions [1] of the plots based on the new (multi-dielectric) distributions were also redrawn for all three CP's (**Fig.2**, **Supplementary Fig.S3, Fig.S4**) following an identical method described in the original formulation of CP [1] and compared with the earlier contours [1,2]. The contours were largely similar with only marginal increase in length along the Y-axis (E_m) which is well within statistical limits of error. These ever-so-tiny differences could potentially also occur even if an identical methodology is implemented on two different / non-overlapping databases to delineate the contours. Note that the Complementarity Plot is probabilistic (knowledge-based) in nature. Based on this strong coherence between the two methods consistent across all three burial bins (CP1, CP2, CP3), the original contours were retained in both (single-dielectric, multi-dielectric) versions of the softwares.

CP_{dock}

In addition to the adaptation of the multi-dielectric method to compute electrostatic complementarity, here we also present an equivalent though new plot (namely, CP_{dock}) designed with the view to score docked inter-protein or peptide-protein complexes. CP_{dock} plots single ordered-pair complementarity values computed at the protein-protein interface (Sc, EC) in the background of equivalent non-overlapping contoured regions (i.e., 'probable', 'less probable', 'improbable') delineated from the distribution of the same set of complementarity measures (i.e., Sc, EC) from a database of high resolution protein-protein complexes. In effect, this is a back-track to the origin of the subject since the original idea to evaluate shape and electrostatic complementarities (Sc, EC) in proteins was emerged and implemented for interfaces only, based on single

complementarity scores [13,14] assigned to each interface. Here we take the opportunity to demonstrate the numbers pictorially.

To that end, 1880 high resolution protein co-complex crystal structures were assembled from a previously used database (**DB3**, see **Methods**); the (Sc, EC) values calculated at their interface (precisely according to an earlier report [18]) and plotted in accordance with the previous constructions of the plots [1]. The multi-dielectric Gaussian model [12] was implemented to compute EC. The whole two-dimensional area was divided into square grids (0.05 × 0.05 wide) and the probability of finding any point (representative of a protein-protein interface) in a particular grid (P_{grid}) was estimated as demonstrated earlier [1]. Likewise to its original constructions [1], the plots were then contoured based on their grid-probability values, P_{grid} >=0.005 for the first contour level and >0.002 for the second. The cumulative probabilities of locating a point within the first and the second contoured level were found to be in strong agreement with previous versions of the complementarity plots constructed to score proteins in a residue wise manner.

One noticeable point of difference between the residue-wise-multi-valued and single-valued versions of the plots is their range in the shape complementarity (**Fig.3**) defined along the horizontal axis. It is to be noted that Sc maps to an elevated range of values in comparison to the residue-wise equivalent measure S_m as evident from the two plots. This is because Sc is computed traditionally on the molecular Connolly surfaces [13] whereas S_m is computed on van der Wal's surfaces [16]. It is well-known [16] that the shape complementarity measure renders a higher value when computed on molecular Connolly surfaces than equivalent van der Waal's surfaces because of the re-entrant points of the van der Waal's surfaces making their contours (protrusions and crevices) sharper than the corresponding Connolly surfaces [16].

The fact that there is a 20% probability associated with attaining a negative EC at native inter-protein interfaces [18] is also reflected in the isolated islands at the negative half of EC in the plot. The constraints with respect to Sc is again much stronger than EC featured by the horizontal (Sc) and vertical (EC) widths of the corresponding contoured levels (say, the probable regions) in the plot. This difference in relative width (constraints) given rise by Sc and EC is consistent with the short and long range nature of the forces from which they have been originated.

Utility of CP_{dock} exemplified in a docking benchmark

The apt of the plot (CP_{dock}) in discriminating between good and bad realistic protein-protein docked complexes was tested on a recent docking benchmark [20] built using SwarmDock [21] to generate the models. The benchmark (named after the first author as 'Moal') originally contained 56015 models for 118 targets and was previously used to test, validate and compare the performance of another recent docking scoring function, ProQDock [18] trained by support vector regression machines using shape and electrostatic complementarities as two of its thirteen features. In the same study, it was found that the electrostatic complementarity can as well be negative for top ranked realistic docked protein complexes at a statistically non-negligible fraction (~21%), also true even for native experimentally solved protein complexes (~20%). In such cases, highly raised values of shape complementarity was found to compensate the deleterious electrostatic effect at the interfaces. When Sc, EC were calculated on the native Moal targets, the same fraction (i.e., negative EC) was found to be ~17%, similar to the larger datasets.

Our objective for the current calculation was clear that we wanted to test the efficacy of CP_{dock} in its discriminatory ability between good and bad docking models, only based on the two complementarity measures. If found to be efficient, one can then potentially use this tool as a means

to provide a meaningful delineation between good and bad docked models, to be used at the initial screening phase of a docking scoring pipeline, before actually going into expensive computation with more sophisticated trained machines like ProQDock [18]. To that end, one had to consider one or more subsets of (Moal) targets (and their corresponding models) for which their native Sc, EC values were found to be optimal falling in the 'probable' / 'less probable' regions of the plot. In other words, it probably won't make a sense to try out CP_{dock} on those targets where the native complex itself maps to the 'improbable' region of the plot, due to sub-optimal values being raised by one of its two components (EC in particular, hitting a negative value in ~1/5th of the cases).

Two separate calculations were conducted on two subsets based on two sets of cutoffs. The cutoffs were set according to the normalized frequency (or probability) distributions of the parameters as revealed from the database, **DB3**. The probability distribution of Sc was found to best fit to a sharp Gaussian curve (R^2=0.98) with tight bounds on either end of the peak value, while, the same for EC was negatively skewed fitting best to a Lorentzian distribution (R^2=0.97) accompanied by a long tail mapping to the negative EC values (**Fig.4**). The nature of the curves were identical to the characteristic patterns depicted earlier for the conditional probability estimates $P(S_m|\{Res, Bur\})$ and $P(E_m|\{Res, Bur\})$ calculated on their corresponding residue-wise parameters S_m and E_m for a given burial bin (Bur) and residue identity (Res) [1]. The contrasting features in terms of the stringent and relaxed curve-widths of the two distributions were also consistent with the nature of short- and long-range forces determining the Sc and EC respectively.

To determine the cutoffs based on these two distributions, first, their medians were calculated (μ(Sc): 0.73, μ(EC): 0.41) along with the corresponding absolute median deviations (σ(Sc): 0.06, σ(EC): 0.21). To note is that for EC, the median was certainly a better choice for central tendency because of the negatively skewed nature of the distribution while for Sc, either of the mean or median could have been the choice due to the symmetric nature of the distribution (mean: 0.71, median: 0.73). For consistency purposes, medians were considered for both.

For the first of the two calculations, a straight cutoff (or lower threshold) equaling to the aforementioned median values (Sc: 0.73, EC: 0.41) were set for both measures, while for the second, the corresponding lower thresholds were set to (μ-3σ) and (μ-σ) for Sc and EC, consistent with the stringent and relaxed curve-widths of their respective distributions. Note that the vertical EC-width encompassing the 'probable' region is about thrice the horizontal Sc-width in CP_{dock} (also true for the residue-wise CP1 corresponding to the first burial bin).

In effect, only the 'elite class' of targets (in terms of Sc, EC) were considered for the first calculation, which could secure highly elevated values of Sc ≥ 0.73, EC ≥ 0.41 in their respective native structures. Only 28 out of 118 targets could fall into this class. While, for the second calculation, those targets were considered for which the native structures could hit values in Sc, EC between closed intervals of the aforementioned lower thresholds (Sc: μ-3σ; EC: μ-σ) and the corresponding medians (μ). 39 targets could fall into this class satisfying the Sc, EC criteria of 0.55 ≤ Sc < 0.73 and 0.20 ≤ EC < 0.41 simultaneously. Hence, this class of targets could be viewed as the 'average class' and there's no overlap between the two ('elite' and 'average') classes totaling 67 targets (and the corresponding 31508 models) covered between them.

In effect, for both the 'elite' and the 'average' class of targets, the native Sc, EC values were optimal, falling into the 'probable' or 'less probable' regions of CP_{dock}, such that they could serve as valid reference native benchmarks (in terms of Sc, EC) against which the quality of the docked models could be judged. We were to test whether in such cases CP_{dock} was indeed able to suggest reasonably strong probability estimates that could delineate between incorrect and correct docked models as assigned to each model by the docking benchmark [20] based on the CAPRI classification scheme [22], in which, correct models refer to the 'acceptable or higher' category.

For all targets covered by both the classes (as detailed above) and their corresponding models, Sc, EC were calculated, plotted and overlaid on CP_{dock} with different colors assigned to the native (white), correct (black) and incorrect (red) models. For each target, the fraction of models falling into the 'probable', 'less probable' and 'improbable' regions of the plot were calculated separately for the correct and incorrect models. A descriptive statistics on these fractional counts were performed afterwards on the targets falling into the ‘elite’ and ‘average’ class (as defined above) individually.

For the incorrect models belonging to the ‘elite’ class of targets, the fractions (averaged over all targets in the class) falling into the ‘probable’, ‘less probable’ and ‘improbable’ regions of CP_{dock} were 23.0% (±7.4), 37.5% (±3.6) and 39.6% (±7.6) respectively (**Table 1**). In distinct contrast, the same fractions for the correct models in this class were 81.8% (±13.1), 14.9% (±10.8) and 3.3% (±3.7) respectively (**Table 2**).

A thorough visual examination of the individual plots revealed a few kinds of distribution patterns of the correct models among themselves as well as with respect to their corresponding native(s). In the most prevalent pattern observed, the correct models were found to be clustered together around the closely spaced native (**Fig.5**) mostly falling into the probable regions of the plots. While, another frequent pattern portrayed the distant residence of the native with respect to the cluster formed by the correct models (**Fig.6**). Yet another third pattern was observed where the correct models were themselves scattered, though again mostly falling into the probable regions of the plots (**Fig.7**). On the other hand, the incorrect models were mostly found to be gathering around the left bottom half of the less probable / improbable regions of the plots mapping to lower / sub-optimal Sc, EC values. Overall, the ability of the plot to delineate between the correct and incorrect models were clear and unambiguous in this ‘elite’ class of targets, the ones with optimal and elevated native Sc, EC values providing strong reference points for quality assessment of the docked models.

For the ‘average class’ of targets, the mean fractions of incorrect models falling into the ‘probable’, ‘less probable’ and ‘improbable’ regions of CP_{dock} were 19.6% (±7.2), 35.9% (±3.9) and 44.5% (±9.9) respectively (**Supplementary Table S1**) while the same fractions for the correct models in this class were 64.9% (±12.1), 32.8% (±11.4) and 2.3% (±2.5) respectively (**Supplementary Table S2**).

So to speak, the mean fractional counts (falling into the three disjoint regions of the plots) in both classes (‘elite’ and ‘average’) were fairly similar for incorrect models while for the correct models the ‘elite class’ could hit to a higher mean fractional count in the ‘probable’ regions (81.8%) than to that of the average class (64.9%) with standard deviations of the same order of magnitudes. This has been accompanied by a corresponding lower mean fractional count in the ‘less probable’ regions for the elite class (14.9%) compared to the average class (32.8%) again with roughly identical standard deviations while similar values obtained for both class in the ‘improbable regions’ of the plot. This third category of points could be treated as ‘false negatives’. The relative alterations in the corresponding mean fractional counts in the two class could as well be viewed as the transition of ~15% of points from the ‘probable’ to the ‘less probable’ region, brought about by switching from the 'elite' to the 'average' class. Note that the native Sc, EC values for the targets in the ‘average class’ is lower in magnitude to that of the ‘elite class’.

Although, the raw numbers suggest that the discriminatory ability of CP_{dock} in the ‘elite class’ is somewhat better than the ‘average class’, if viewed against their corresponding ranges of native reference values (Sc, EC), their performances might as well be interpreted as equivalent in both classes. Also, the dependence of the discriminatory ability of the methodology on the native (Sc, EC) reference values was evident. This said, CP_{dock} indeed appears to be more than useful to be incorporated in the initial screening phase of a docking scoring pipeline, especially effective for those targets which procure strong native reference values in their Sc, EC.

Conclusions

This brief software report essentially presents an upgraded version of the Complementarity Plot (CP), an established structure validation tool for proteins, based on the incorporation of the multi-dielectric functionality (as in the advanced Delphi version: 6.2 or higher) to make it physico-chemically more realistic. It also highlights the agreement between the two methods (single- and multi-dielectric) in terms of both residue-wise (E_m) as well as single-valued (EC) terms of electrostatic complementarity measures (computed both at protein interiors and interfaces). Hence, it was felt wise to keep both provisions in the software suite. In effect, the conclusions also support the previous observations that the impact of a variety of values chosen as the internal dielectric (in continuum electrostatic models) is rather passive on the electrostatic complementarity, a key determinant of the global long-range harmony in proteins. Having said that, we definitely recommend our users to switch to the more advanced multi-dielectric version of CP for having stronger theoretical foundations potentially giving rise to more reliable E_m / EC values. The difference between the E_m / EC values computed by the two methods might actually be meaningful in certain structural contexts, and, in such cases some local salient features might be portrayed by the advanced method that might otherwise be missed by the older method (e.g., in mutational studies, protein / peptide design). A full-scale analysis of this kind might serve the subject matter of future studies.

The current report also presents a new methodology and a variant plot, namely, CP_{dock}, based on the same principles of complementarity, specifically designed to be used in protein-protein docking. Calculations on a recent *state-of-the-art* docking benchmark reveals the fact that CP_{dock} can indeed be effectively used in the initial screening phase of a docking scoring pipeline, particularly effective for targets with strong native reference values in the two complementarity measures.

Figure Legends

Fig.1. Distribution of points in CP1 (corresponding to the first burial bin: $0 \leq bur \leq 0.05$) where E_m calculated by (A) single- and (B) multi-dielectric methods. S_m, E_m calculated for residues from the database DB2.

Fig.2. Contours to delineate the different regions (probable, less probable, improbable) in the Complementarity Plot: drawn for CP1 where E_m calculated by (A) single- and (B) multi-dielectric methods.

Fig.3. Contours to delineate the different regions (probable, less probable, improbable) in CP_{dock}. Sc, EC calculated for interfaces from the database DB3.

Fig.4. Normalized Frequency (or probability) distributions of (A) Sc and (B) EC and their best fit curves (C) and (D) respectively.

Fig.5. Distribution of points corresponding to the incorrect (red), correct (black) and native structures (white) for the Elite class of targets in CP_{dock}: (A) 1E6E, (B) 1E96, (C) 1KXP and (D) 1ML0. These distributions represent cases where the correct models cluster around their corresponding closely spaced natives.

Fig.6. Distribution of points corresponding to the incorrect (red), correct (black) and native structures (white) for the Elite class of targets in CP_{dock}: (A) 1D6R, (B) 1GPW, (C) 1JTG and (D) 7CEI. These represent cases where the native is far away from the cluster of the correct models.

Fig.7. Distribution of points corresponding to the incorrect (red), correct (black) and native structures (white) for the Elite class of targets in CP_{dock}: (A) 1L2M, (B) 2I25. These represent cases where the correct models are scattered in contrast to clustering as in Fig.5 and Fig.6.

Tables

Table 1. CP_{dock} statistics on Incorrect models in the 'Elite class' of targets selected from the Docking Benchmark 'Moal'. $F_{probable}$, $F_{less_probable}$, $F_{improbable}$ stands for the fraction of points falling into the 'probable', 'less probable' and 'improbable' regions of the plots. TotNM stands for the total number of models in the said category (incorrect / correct) as mentioned in the table title.

Target	$F_{Probable}$	$F_{Less_Probable}$	$F_{Improbable}$	TotNM
1AVX	0.165	0.397	0.438	424
1AY7	0.134	0.459	0.408	435
1AZS	0.186	0.355	0.459	484
1D6R	0.232	0.424	0.344	423
1E6E	0.248	0.368	0.385	424
1E96	0.229	0.361	0.410	501
1EAW	0.470	0.394	0.136	427
1FCC	0.257	0.371	0.371	427
1FQJ	0.208	0.389	0.403	463
1GPW	0.320	0.315	0.364	408
1GXD	0.143	0.362	0.494	463
1I2M	0.243	0.337	0.420	400
1J2J	0.188	0.363	0.449	409
1JTG	0.227	0.381	0.391	500
1K74	0.138	0.430	0.432	376
1KXP	0.158	0.371	0.471	497
1LFD	0.308	0.346	0.346	468
1ML0	0.306	0.338	0.356	488
1OC0	0.123	0.380	0.498	423
1SYX	0.286	0.423	0.291	414
1WDW	0.158	0.303	0.539	459
1XQS	0.262	0.379	0.359	448
2I25	0.292	0.333	0.375	498
2I9B	0.268	0.409	0.323	494

2MTA	0.245	0.378	0.378	431
2OZA	0.181	0.409	0.409	446
2PCC	0.214	0.331	0.455	501
7CEI	0.241	0.382	0.377	413
Average	0.230 (±0.074[1])	0.375 (±0.036)	0.396 (±0.076)	

Table 2. CP_{dock} statistics on correct models in the 'Elite class' of targets selected from the Docking Benchmark, Moal. $F_{probable}$, $F_{less_probable}$, $F_{improbable}$ stands for the fraction of points falling into the 'probable', 'less probable' and 'improbable' regions of the plots. TotNM stands for the total number of models in the said category (incorrect / correct) as mentioned in the table title.

Target	$F_{Probable}$	$F_{Less_Probable}$	$F_{Improbable}$	**TotNM**
1AVX	0.579	0.368	0.053	1
1AY7	0.923	0.000	0.077	12
1AZS	0.900	0.100	0.000	8
1D6R	0.867	0.133	0.000	5
1E6E	0.818	0.182	0.000	25
1E96	0.865	0.108	0.027	26
1EAW	0.771	0.200	0.029	4
1FCC	0.708	0.250	0.042	1
1FQJ	0.870	0.130	0.000	7
1GPW	0.860	0.120	0.020	29
1GXD	0.895	0.105	0.000	9
1I2M	0.535	0.395	0.070	26
1J2J	0.857	0.071	0.071	60
1JTG	0.955	0.000	0.045	28
1K74	0.510	0.353	0.137	52
1KXP	0.897	0.103	0.000	31
1LFD	0.884	0.093	0.023	3
1ML0	0.882	0.088	0.029	23
1OC0	1.000	0.000	0.000	1
1SYX	1.000	0.000	0.000	8
1WDW	0.818	0.182	0.000	12

1 Standard Devision

1XQS	0.615	0.288	0.096	8
2I25	0.806	0.161	0.032	13
2I9B	0.947	0.053	0.000	2
2MTA	0.727	0.182	0.091	2
2OZA	0.706	0.235	0.059	1
2PCC	0.865	0.115	0.019	10
7CEI	0.853	0.147	0.000	16
Average	0.818 (±0.131)	0.149 (±0.108)	0.033 (±0.037)	

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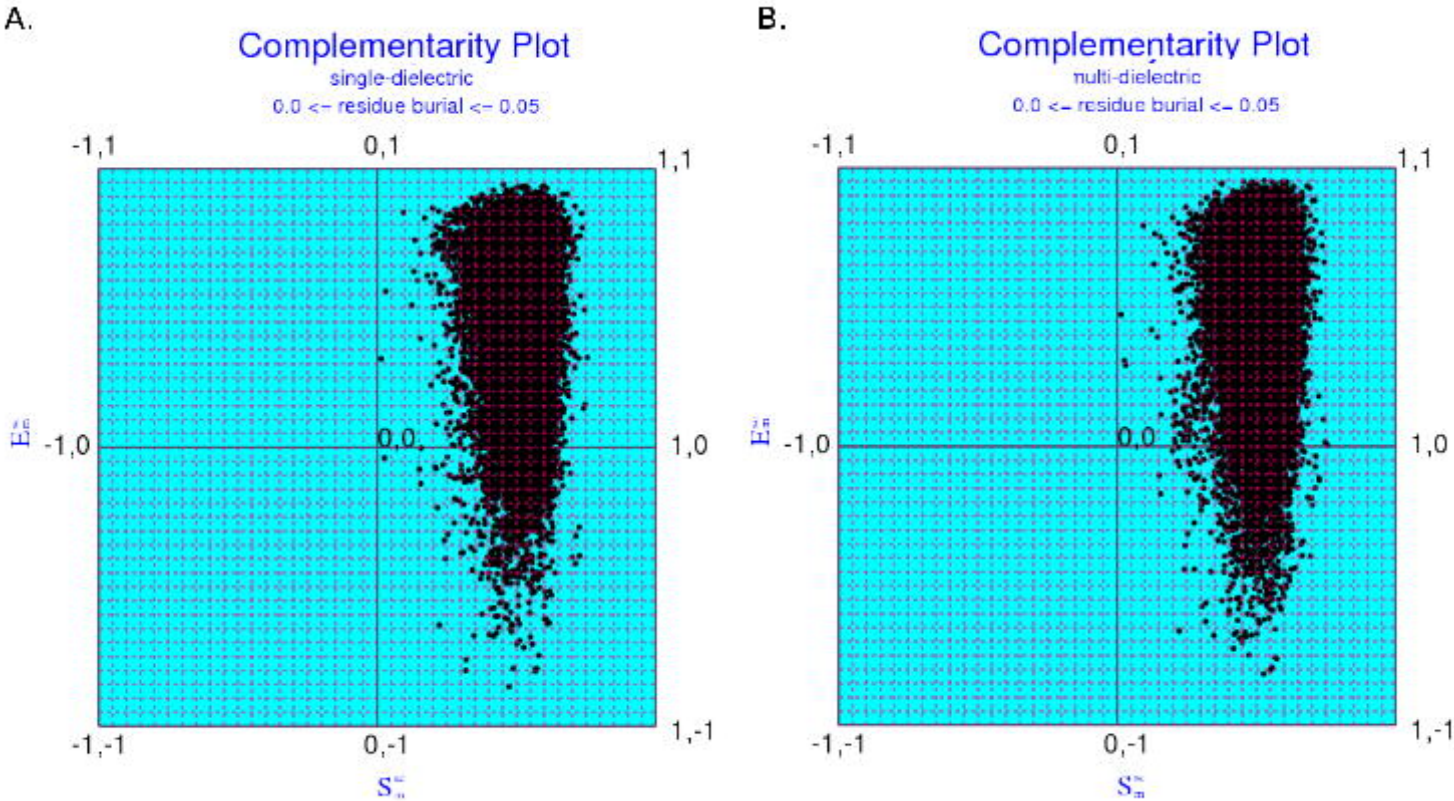
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Complementarity Plot
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0.0 <= residue burial <= 0.05
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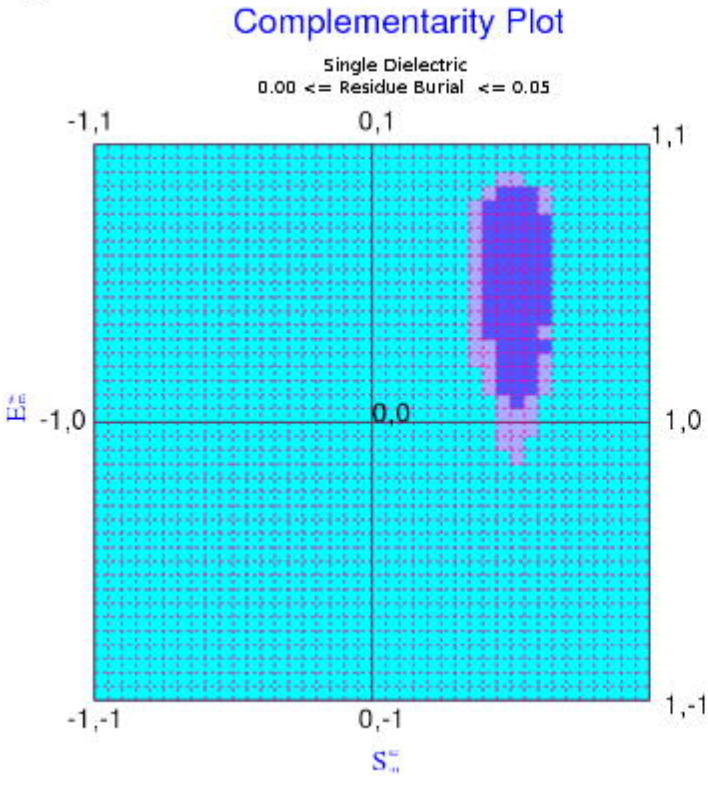
0,1
1,1
-1,0
0,0
1,0
-1,-1
0,-1
1,-1
B.
Complementarity Plot
multi-dielectric
0.0 <= residue burial <= 0.05
-1,1
0,1
1,1
-1,0
0,0
1,0
-1,-1
0,-1
1,-1

A.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Single Dielectric
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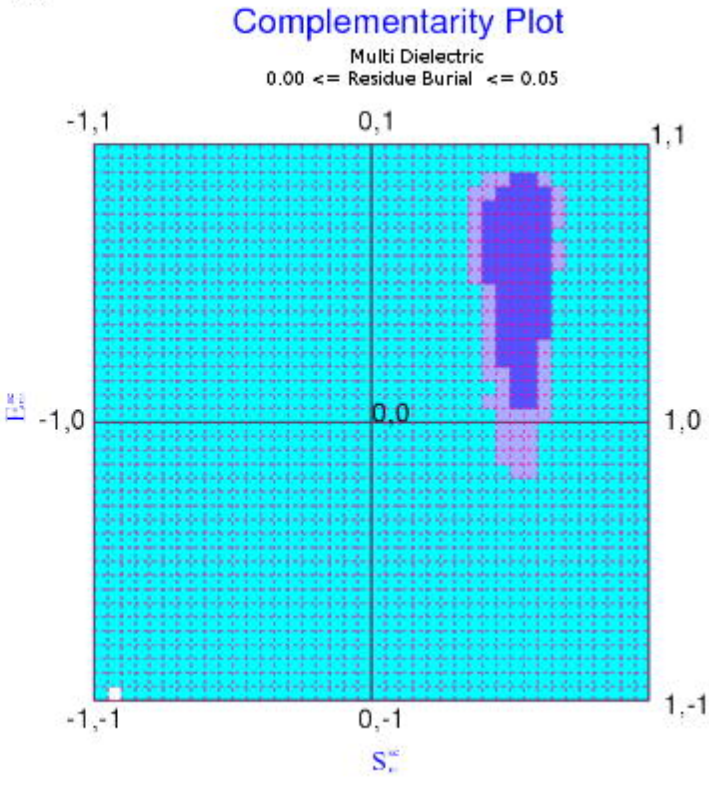
-1,-1
0,-1
1,-1

B.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Multi Dielectric
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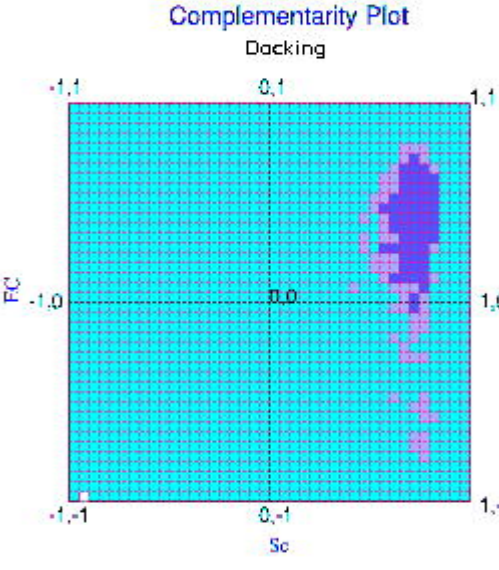
Complementarity Plot
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FC
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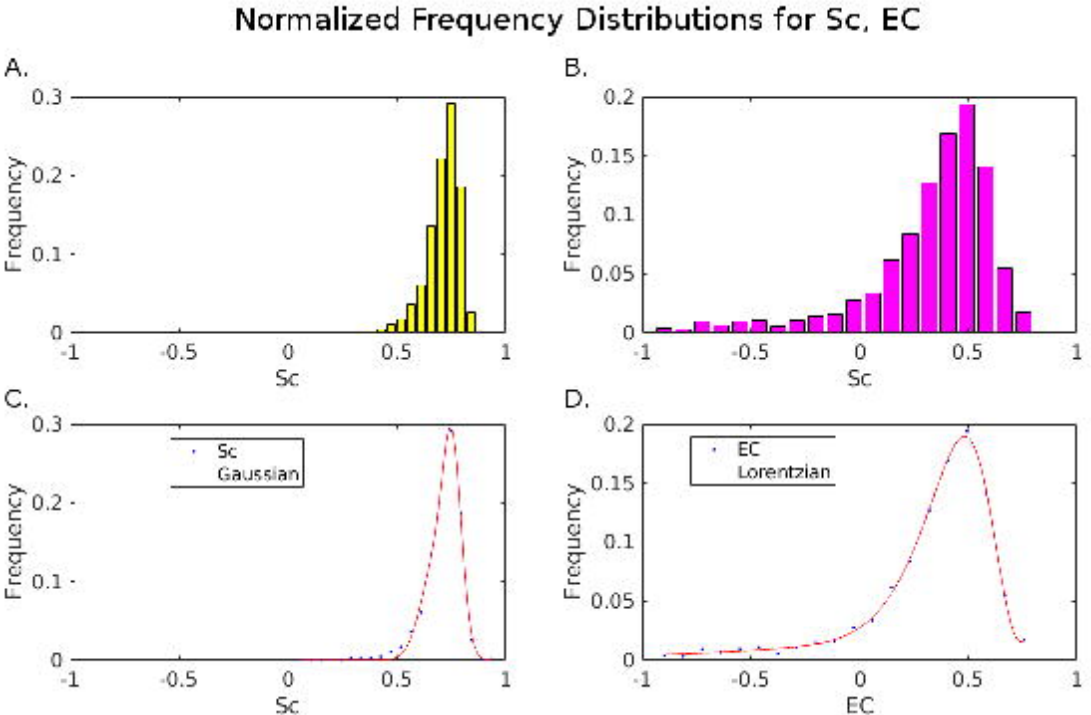
Sc


Normalized Frequency Distributions for Sc, EC
A.
B.
C.
D.
Frequency
Sc
EC
Sc
Gaussian
EC
Lorentzian
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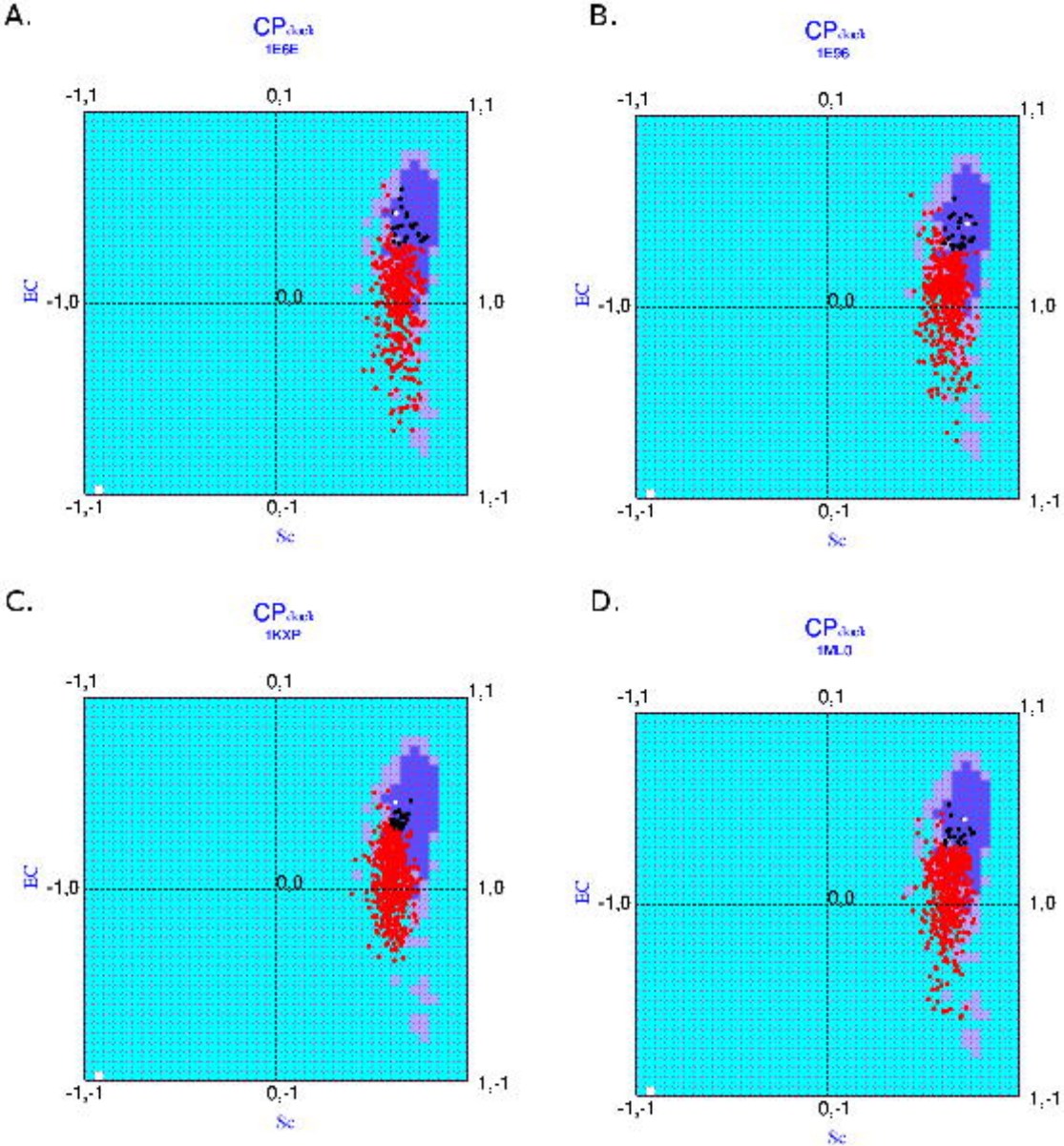
0.2
0.1
0
0.15
0.05
-1
-0.5
0
0.5
1


A.
CPdock
1E6E
B.
CPdock
1E96
C.
CPdock
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D.
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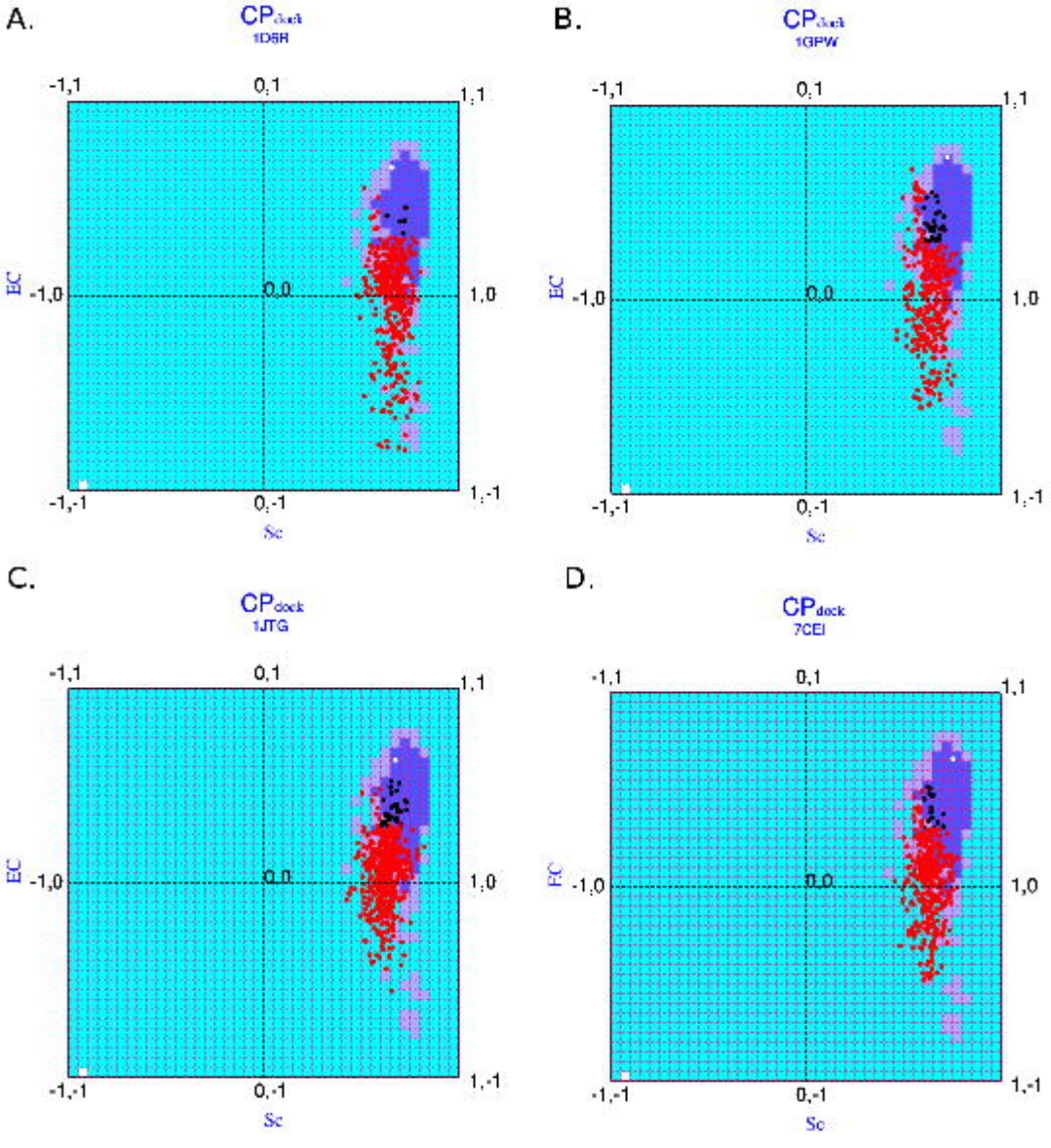
Sc


A.
CPdock
1D5R
B.
CPdock
1GPW
C.
CPdock
1JTG
D.
CPdock
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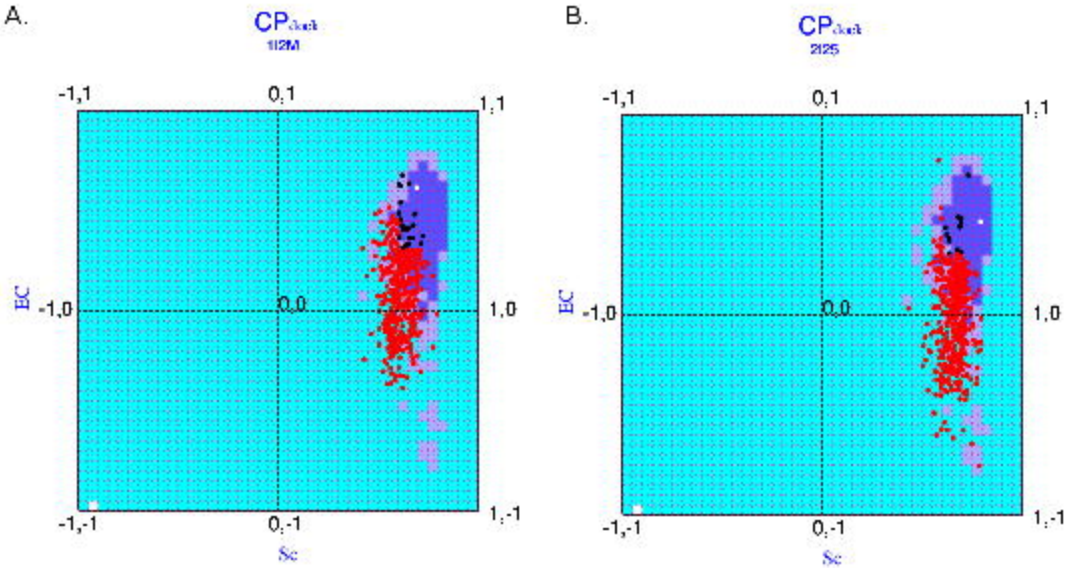
EC
Sc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Sc
B.
CPclock
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EC
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0,-1
1,-1
Sc