

# Supplementary Figures

## Improved predictions of phase behaviour of intrinsically disordered proteins by tuning the interaction range

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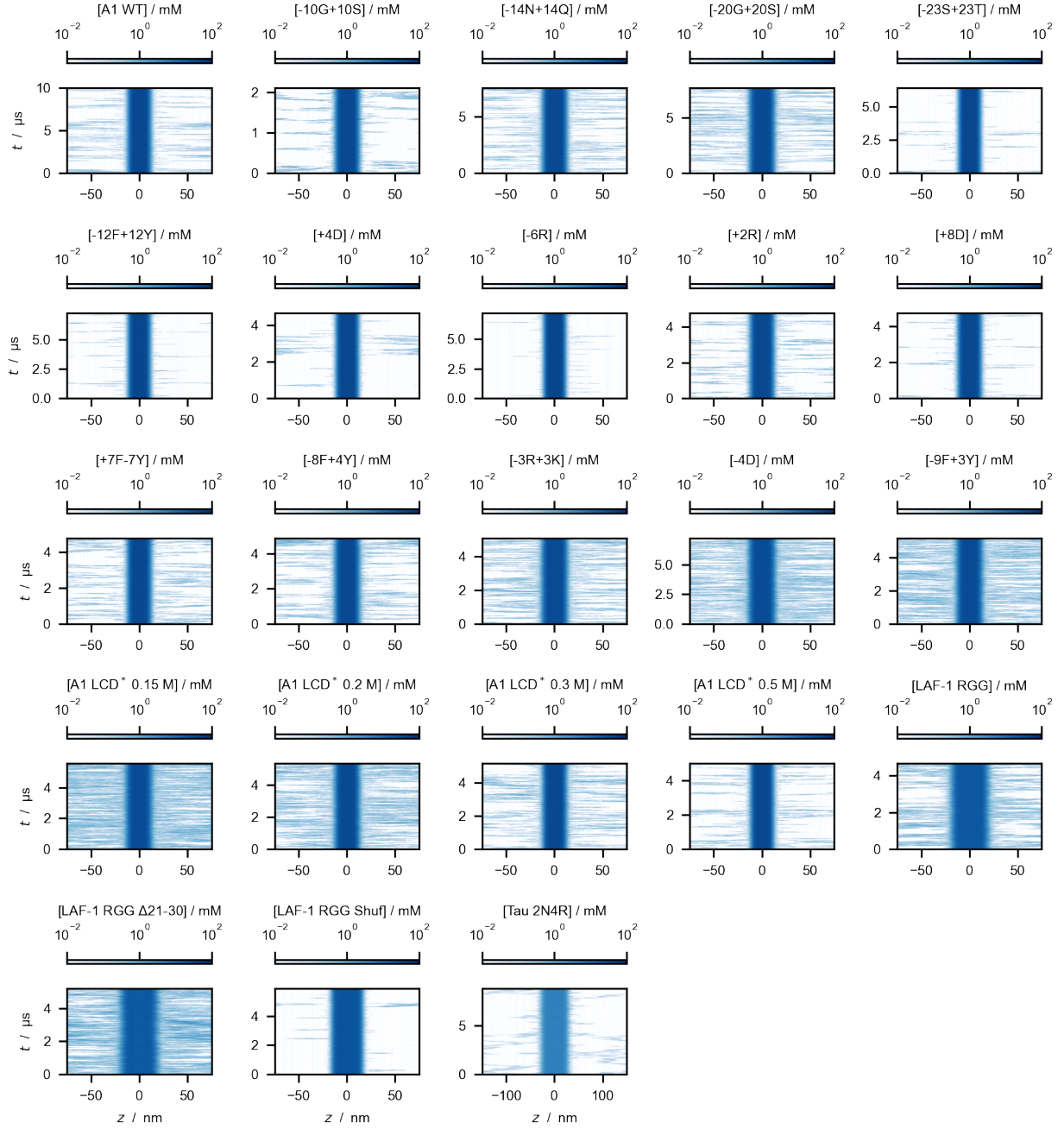


Figure S1: Time evolution of protein concentration along the  $z$ -axis of the simulation cell, as obtained from direct-coexistence simulations performed with the CALVADOS 1 model and  $r_c = 4$  nm.

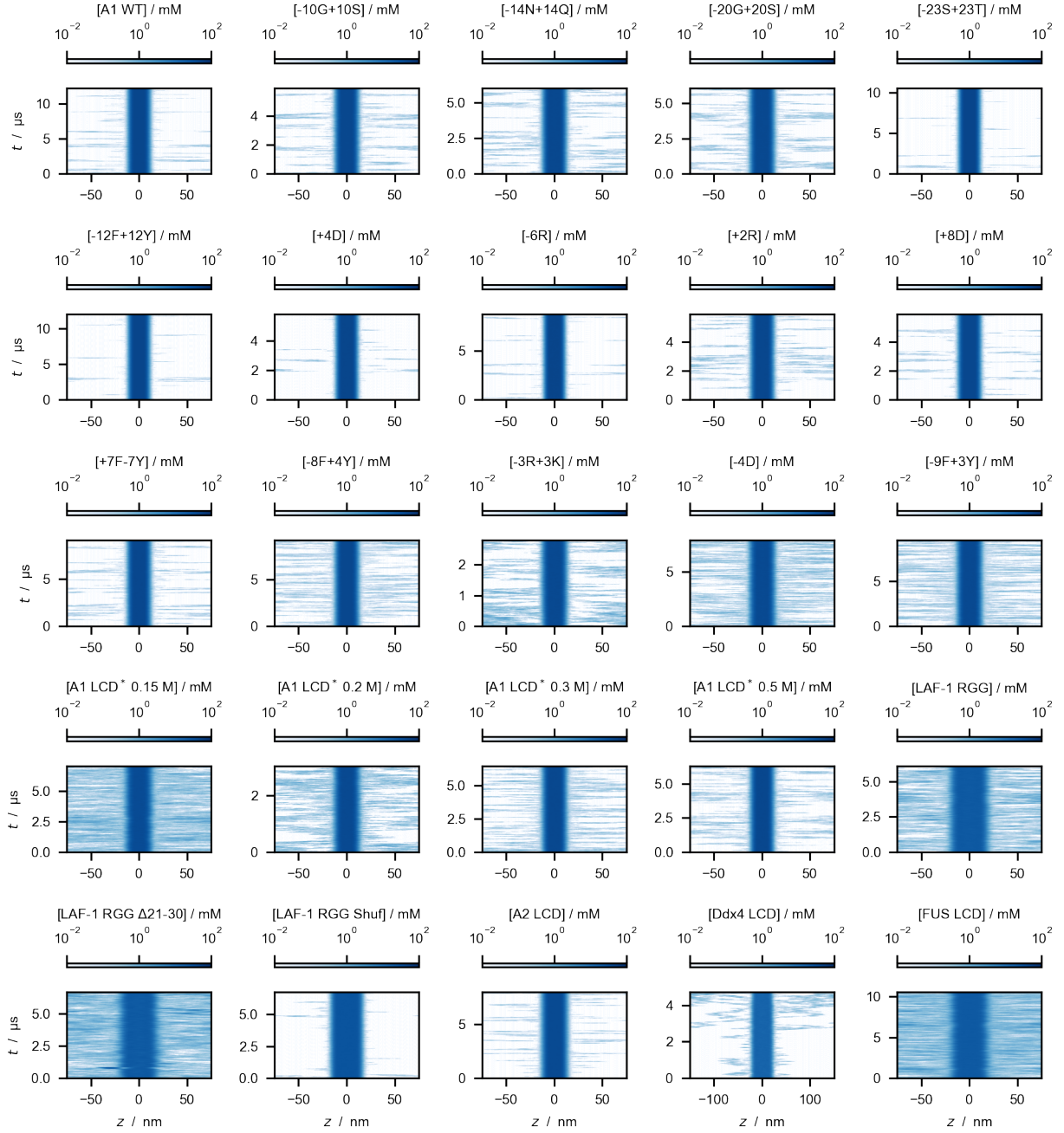


Figure S2: Time evolution of protein concentration along the  $z$ -axis of the simulation cell, as obtained from direct-coexistence simulations performed with the CALVADOS 1 model and  $r_c = 2$  nm.

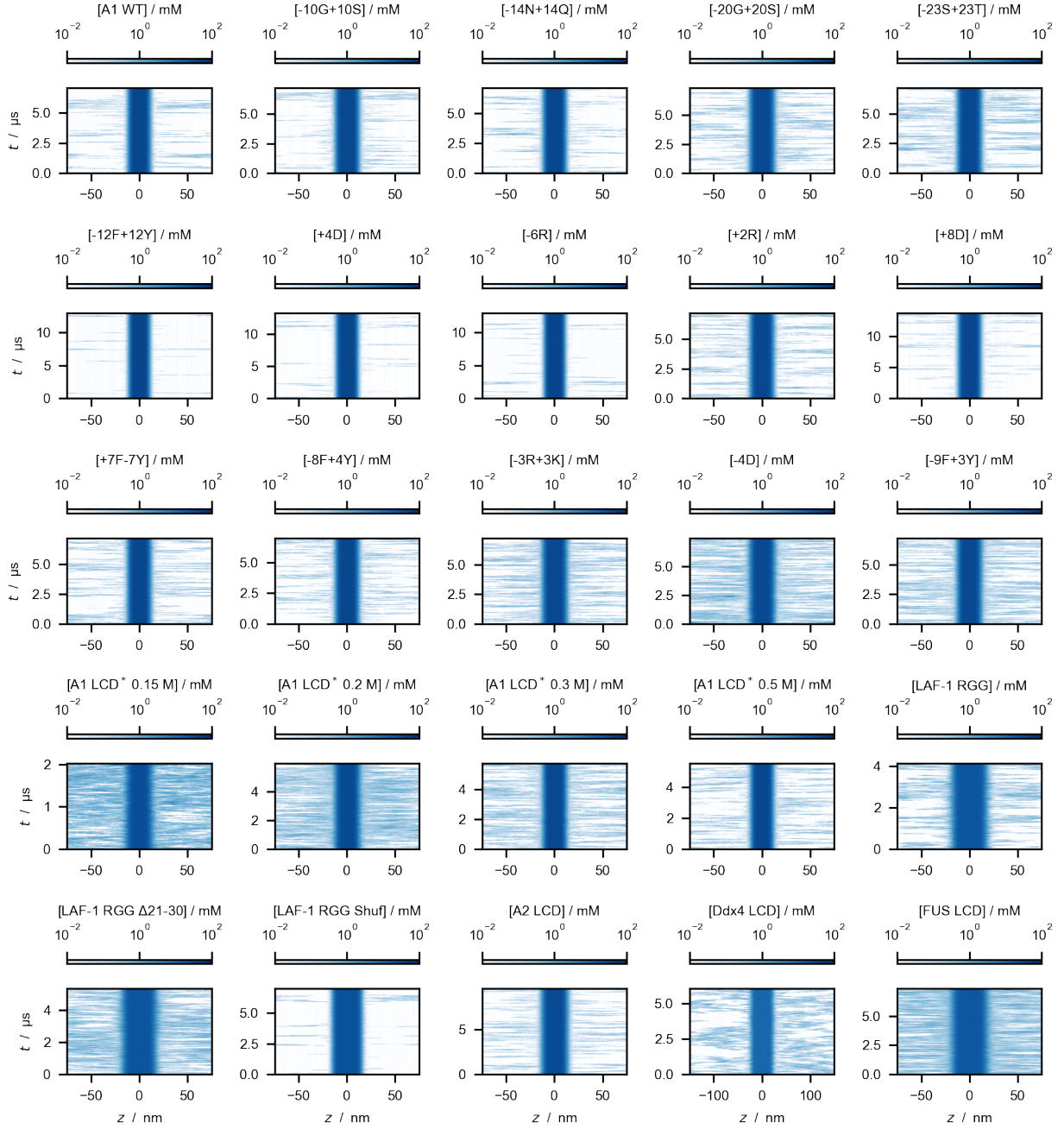


Figure S3: Time evolution of protein concentration along the  $z$ -axis of the simulation cell, as obtained from direct-coexistence simulations performed with the CALVADOS 2 model and  $r_c = 2$  nm.

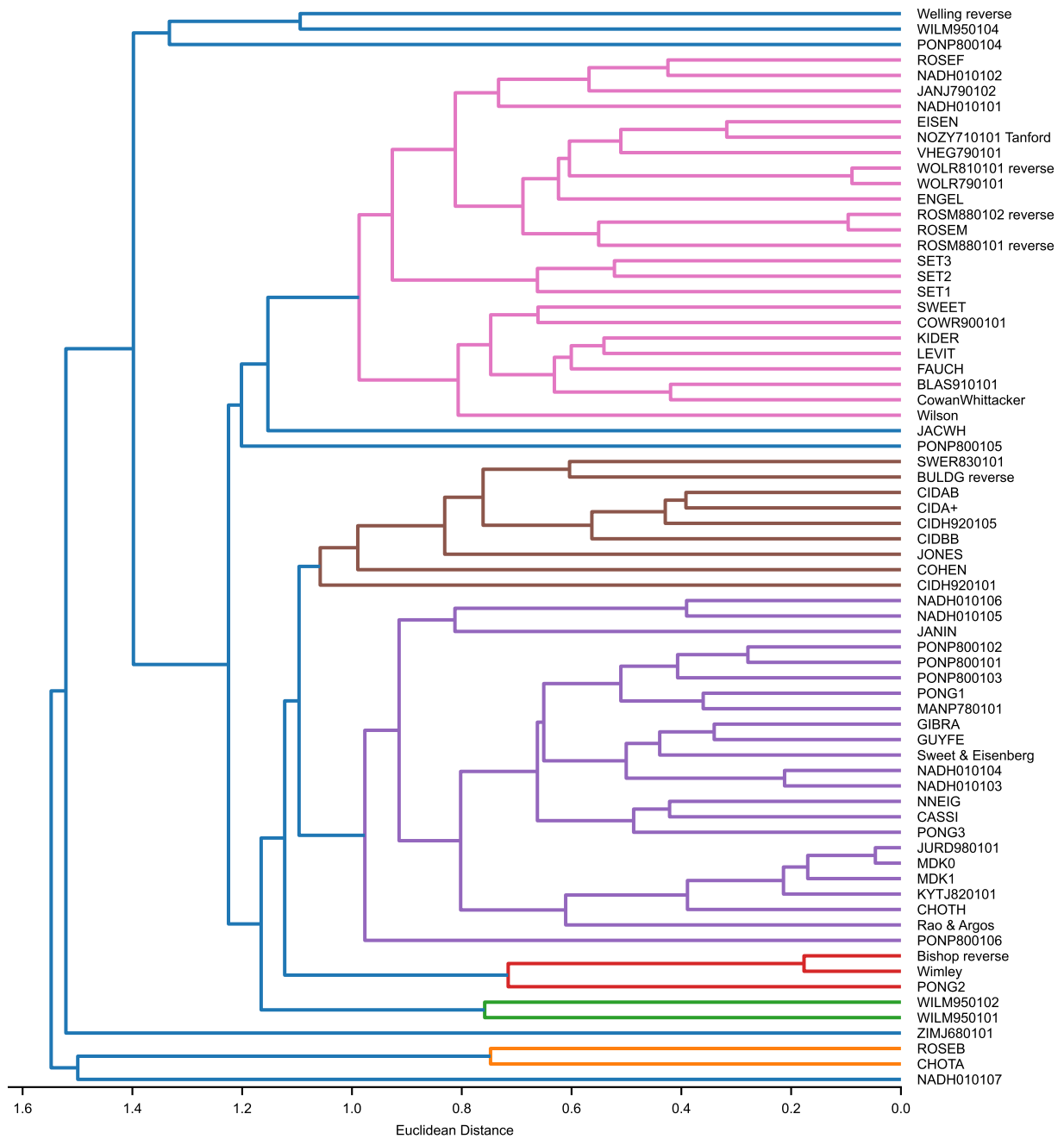


Figure S4: Hierarchical clustering dendrogram of 70 min-max normalized hydrophobicity scales selected from the set by Simm et al. [1]. Agglomerative clustering is performed using Euclidean distances and the average linkage method as implemented in the Python scikit-learn package [2].

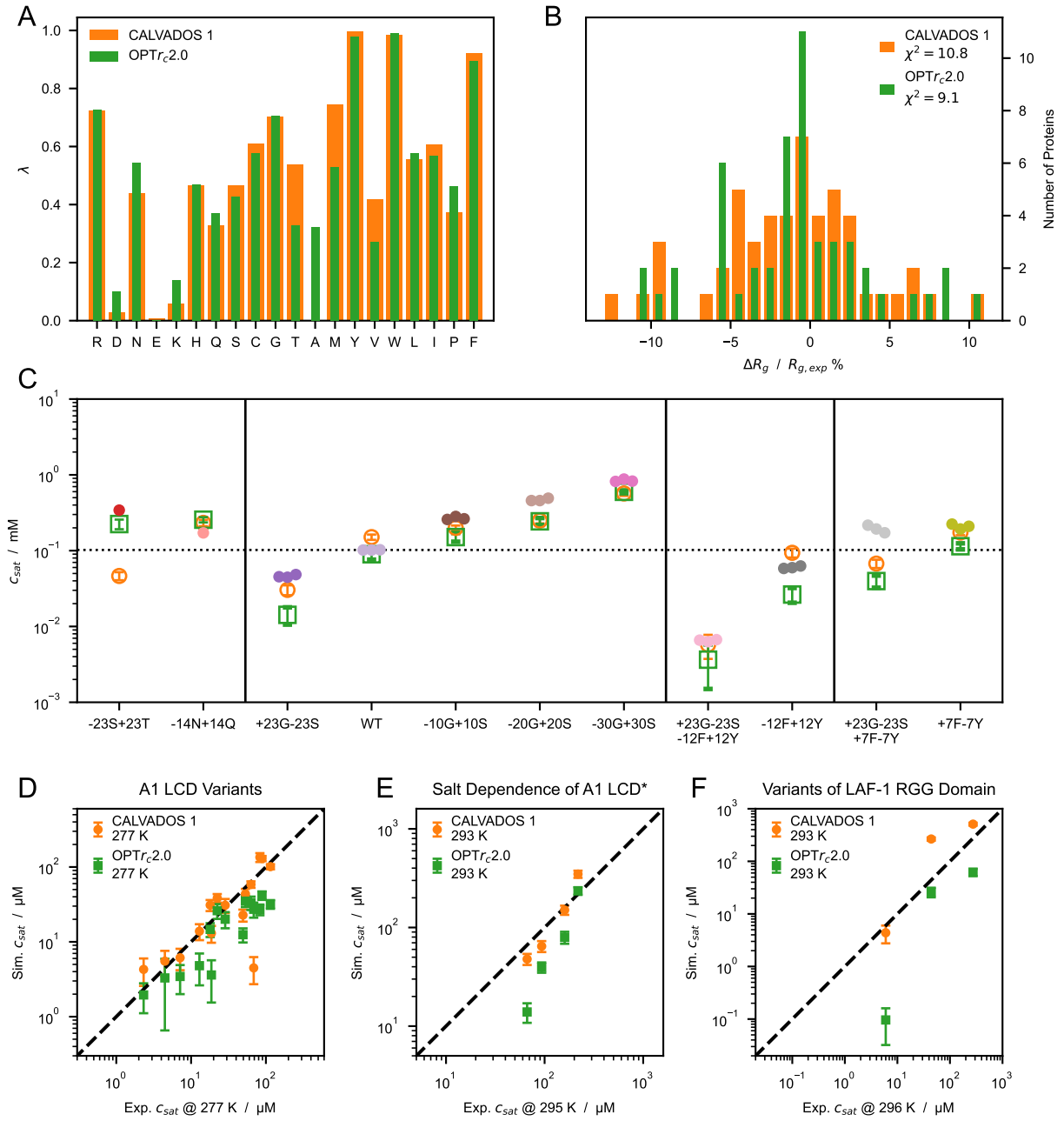


Figure S5: (A) Comparison between  $\lambda$  sets of CALVADOS 1 (orange) and the model resulting from the optimization with  $r_c = 2.0$  nm (OPT $r_c$ 2.0, green). (B) Distribution of the relative difference between experimental (Table 1) and predicted radii of gyration,  $\langle R_g \rangle$ , for CALVADOS 1 (orange) and OPT $r_c$ 2.0 (blue). (C) Comparison between saturation concentrations,  $c_{sat}$ , at 293 K of variants of hnRNPA1 LCD measured by Bremer, Farag, Borchers et al. [3] (closed circles) and corresponding predictions of CALVADOS 1 (open orange circles) and OPT $r_c$ 2.0 (open green squares). (D–F) Correlation between  $c_{sat}$  from simulations and experiments for (D) A1 LCD variants, (E) A1 LCD\* WT at  $[\text{NaCl}] = 0.15, 0.2, 0.3$  and  $0.5$  M and (F) variants of LAF-1 RGG domain (Table 4).

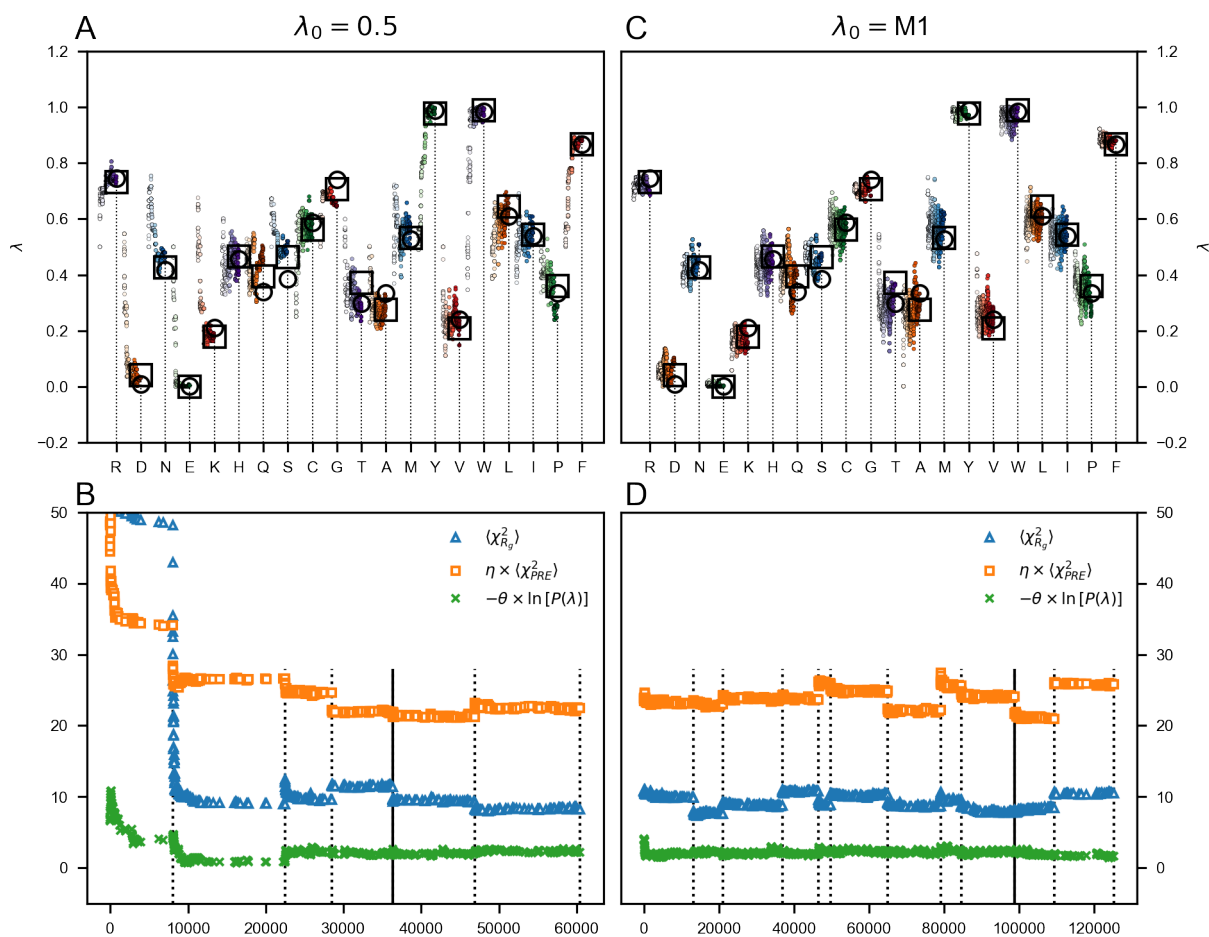


Figure S6: Optimization of the  $\lambda$  parameters starting from  $\lambda_0 = 0.5$  (A and B) and  $\lambda_0 = M1$  (C and D). (A and B) Evolution of the  $\lambda$  parameters during three consecutive optimization cycles. The color gradient from light to dark shade indicates increasing number of iterations. Open squares and circles show optimal  $\lambda$  sets obtained from independent optimizations starting from  $\lambda_0 = 0.5$  and  $\lambda_0 = M1$ , respectively. (C and D) Evolution of  $\chi^2_{R_g}$  (blue triangles),  $0.1 \times \chi^2_{PRE}$  (orange squares), and the regularization term  $0.05 \times \ln[P(\lambda)]$  (green circles). Dotted vertical lines indicate updated sampling by molecular simulations, whereas the remaining points are estimated from reweighted ensembles. Solid vertical lines indicate the optimal  $\lambda$  set corresponding to the lowest total cost function,  $\mathcal{L}$ .

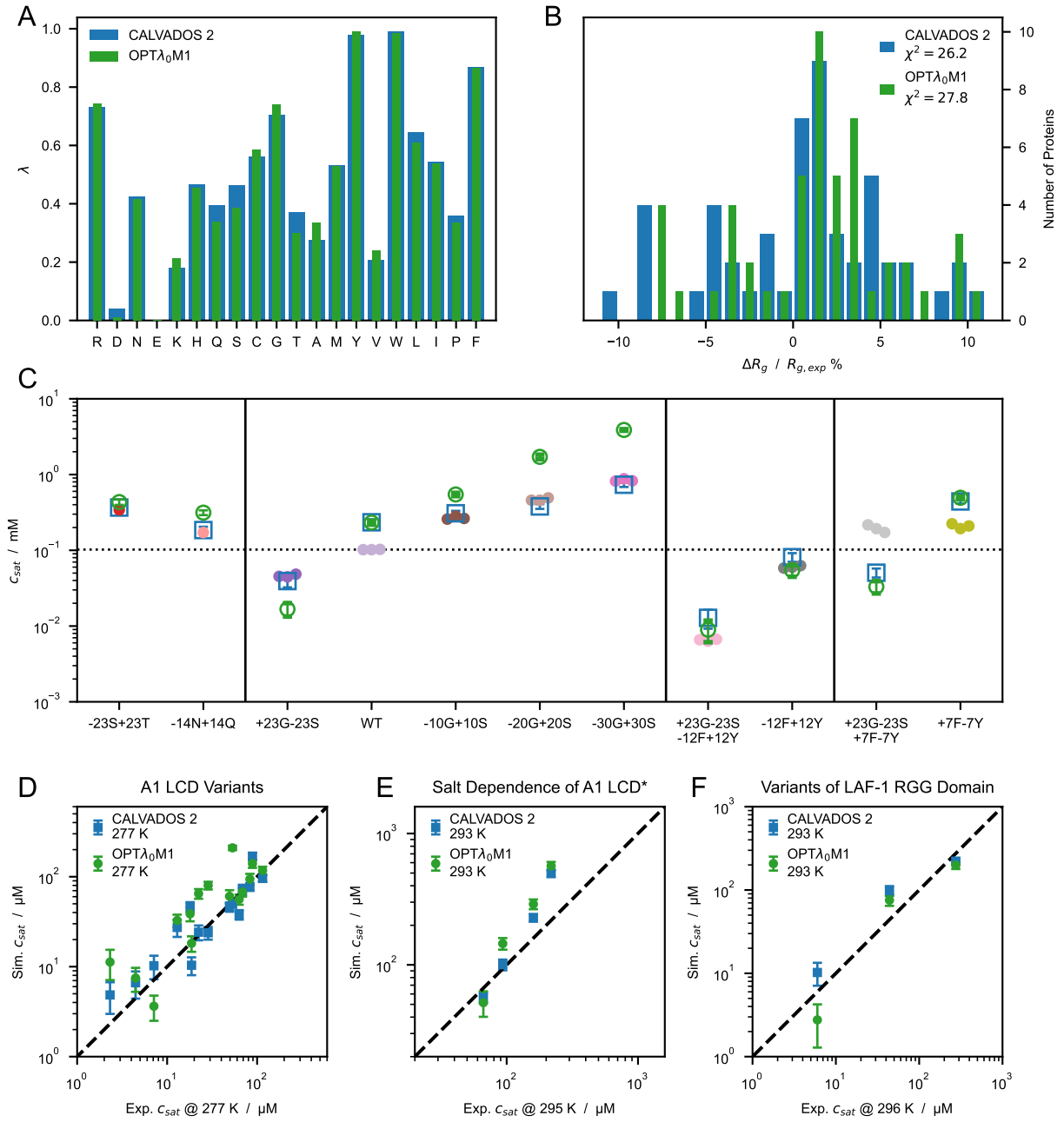


Figure S7: (A) Comparison between  $\lambda$  sets optimized starting from  $\lambda_0 = 0.5$  (CALVADOS 2, blue) and  $\lambda_0 = M1$  (OPT $\lambda_0$ M1, green) using  $r_c = 2.4$  nm. (B) Distribution of the relative difference between experimental (Table 1) and predicted radii of gyration,  $\langle R_g \rangle$ , for CALVADOS 2 (blue) and OPT $\lambda_0$ M1 (green). (C) Comparison between saturation concentrations,  $c_{sat}$ , at 293 K of variants of hnRNPA1 LCD measured by Bremer, Farag, Borchers et al. [3] (closed circles) and corresponding predictions of CALVADOS 2 (open blue squares) and OPT $\lambda_0$ M1 (open green circles). (D–F) Correlation between  $c_{sat}$  from simulations and experiments for (D) A1 LCD variants, (E) A1 LCD\* WT at  $[NaCl] = 0.15, 0.2, 0.3$  and  $0.5$  M and (F) variants of LAF-1 RGG domain (Table 4).



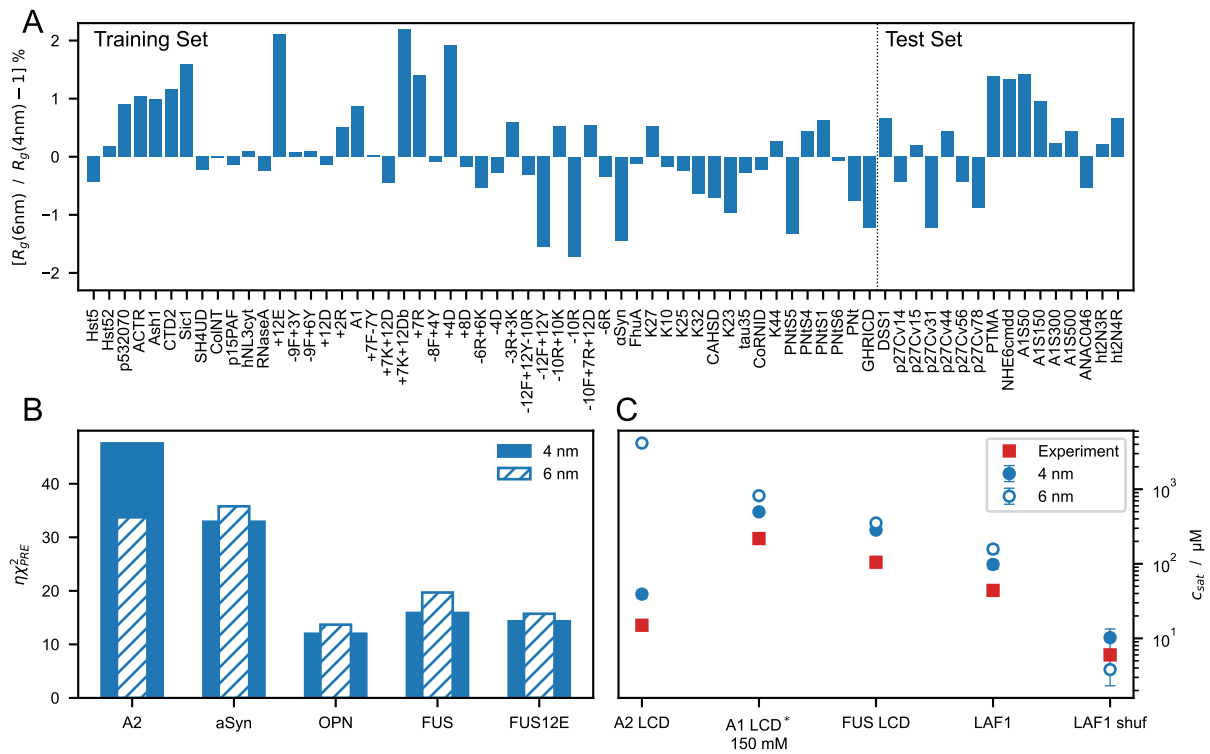


Figure S8: (A) Relative change in predicted  $R_g$  values upon increasing the cutoff for the ionic interactions from 4 to 6 nm. (B) Comparison between  $\chi^2_{PRE}$  values for PRE data estimated from simulations performed using a cutoff of 4 (closed) and 6 nm (hatched) for the ionic interactions. (C) Comparison between experimental  $c_{sat}$  values (red squares) and predictions for A2 LCD ( $c_s = 10$  mM), A1 LCD\* ( $c_s = 150$  mM), FUS LCD ( $c_s = 150$  mM), LAF-1 RGG domain ( $c_s = 150$  mM), and its shuffled variant ( $c_s = 150$  mM) (Table 4) from simulations performed using a cutoff of 4 (closed blue circles) and 6 nm (open blue circles) for the ionic interactions.

Table 1: Solution conditions and experimental radii of gyration of proteins included in the training set for the Bayesian parameter-learning procedure.

Protein	$N$	$R_g$ (nm)	$T$ (K)	$c_s$ (M)	pH	Ref.
Hst5	24	$1.38 \pm 0.05$	293	0.15	7.5	[4]
(Hst5) <sub>2</sub>	48	$1.87 \pm 0.05$	298	0.15	7.0	[5]
p53 (20-70)	62	$2.39 \pm 0.05$	277	0.1	7.0	[6]
ACTR	71	$2.6 \pm 0.1$	278	0.2	7.4	[7]
Ash1	81	$2.9 \pm 0.05$	293	0.15	7.5	[8, 9]
CTD2	83	$2.61 \pm 0.05$	293	0.12	7.5	[10, 9]
Sic1	92	$3.0 \pm 0.4$	293	0.2	7.5	[11]
SH4UD	95	$2.7 \pm 0.1$	293	0.2	8.0	[12]
ColNT	98	$2.8 \pm 0.1$	277	0.4	7.6	[13]
p15PAF	111	$2.8 \pm 0.1$	298	0.15	7.0	[14]
hNL3cyt	119	$3.2 \pm 0.2$	293	0.3	8.5	[15]
RNaseA	124	$3.4 \pm 0.1$	298	0.15	7.5	[16]
A1	137	$2.76 \pm 0.02$	298	0.15	7.0	[3]
-10R	137	$2.67 \pm 0.01$	298	0.15	7.0	[3]
-6R	137	$2.57 \pm 0.01$	298	0.15	7.0	[3]
+2R	137	$2.62 \pm 0.02$	298	0.15	7.0	[3]
+7R	137	$2.71 \pm 0.01$	298	0.15	7.0	[3]
-3R+3K	137	$2.63 \pm 0.02$	298	0.15	7.0	[3]
-6R+6K	137	$2.79 \pm 0.01$	298	0.15	7.0	[3]
-10R+10K	137	$2.85 \pm 0.01$	298	0.15	7.0	[3]
+12D	137	$2.80 \pm 0.01$	298	0.15	7.0	[3]
+4D	137	$2.72 \pm 0.03$	298	0.15	7.0	[3]
+8D	137	$2.69 \pm 0.01$	298	0.15	7.0	[3]
-9F+3Y	137	$2.68 \pm 0.01$	298	0.15	7.0	[3]
+12E	137	$2.85 \pm 0.01$	298	0.15	7.0	[3]
+7K+12D	137	$2.92 \pm 0.01$	298	0.15	7.0	[3]
+7K+12D blocky	137	$2.56 \pm 0.01$	298	0.15	7.0	[3]
-4D	137	$2.64 \pm 0.01$	298	0.15	7.0	[3]
-8F+4Y	137	$2.71 \pm 0.01$	298	0.15	7.0	[3]
-10F+7R+12D	137	$2.86 \pm 0.01$	298	0.15	7.0	[3]
+7F-7Y	137	$2.72 \pm 0.01$	298	0.15	7.0	[3]
-12F+12Y	137	$2.60 \pm 0.02$	298	0.15	7.0	[3]
-12F+12Y-10R	137	$2.61 \pm 0.02$	298	0.15	7.0	[3]
-9F+6Y	137	$2.65 \pm 0.01$	298	0.15	7.0	[3]
$\alpha$ Syn	140	$3.55 \pm 0.1$	293	0.2	7.4	[17]
FhuA	144	$3.34 \pm 0.1$	298	0.15	7.5	[16]
K27	167	$3.70 \pm 0.2$	288	0.15	7.4	[18]
K10	168	$4.00 \pm 0.1$	288	0.15	7.4	[18]
K25	185	$4.10 \pm 0.2$	288	0.15	7.4	[18]
K32	198	$4.20 \pm 0.3$	288	0.15	7.4	[18]
CAHSD	227	$4.8 \pm 0.2$	293	0.07	7.0	[19]
K23	254	$4.9 \pm 0.2$	288	0.15	7.4	[18]
Tau35	255	$4.7 \pm 0.1$	298	0.15	7.4	[20]
CoRNID	271	$4.7 \pm 0.2$	293	0.2	7.5	[21]
K44	283	$5.2 \pm 0.2$	288	0.15	7.4	[18]
PNt	334	$5.1 \pm 0.1$	298	0.15	7.5	[16, 22]
PNt Swap1	334	$4.9 \pm 0.1$	298	0.15	7.5	[22]
PNt Swap4	334	$5.3 \pm 0.1$	298	0.15	7.5	[22]
PNt Swap5	334	$4.9 \pm 0.1$	298	0.15	7.5	[22]
PNt Swap6	334	$5.3 \pm 0.1$	298	0.15	7.5	[22]
GHRICD	351	$6.0 \pm 0.5$	298	0.35	7.3	[23, 24]

Table 2: Solution conditions and experimental radii of gyration of proteins simulated in this study but not included in the training set for the Bayesian parameter-learning procedure.

Protein	$N$	$R_g$ (nm)	$T$ (K)	$c_s$ (M)	pH	Ref.
DSS1	71	$2.5 \pm 0.1$	288	0.17	7.4	[24]
p27Cv14	107	$2.936 \pm 0.13$	293	0.095	7.2	[25]
p27Cv15	107	$2.915 \pm 0.10$	293	0.095	7.2	[25]
p27Cv31	107	$2.81 \pm 0.18$	293	0.095	7.2	[25]
p27Cv44	107	$2.492 \pm 0.13$	293	0.095	7.2	[25]
p27Cv56	107	$2.328 \pm 0.10$	293	0.095	7.2	[25]
p27Cv78	107	$2.211 \pm 0.03$	293	0.095	7.2	[25]
PTMA	111	$3.7 \pm 0.2$	288	0.16	7.4	[24]
NHE6cmdd	116	$3.2 \pm 0.2$	288	0.17	7.4	[24]
A1 LCD*	131	$2.645 \pm 0.02$	293	0.05	7.5	[26]
A1 LCD*	131	$2.65 \pm 0.02$	293	0.15	7.5	[26]
A1 LCD*	131	$2.62 \pm 0.02$	293	0.3	7.5	[26]
A1 LCD*	131	$2.528 \pm 0.02$	293	0.5	7.5	[26]
ANAC046	167	$3.6 \pm 0.3$	298	0.14	7.0	[24]
Tau 2N3R	410	$6.3 \pm 0.3$	298	0.15	7.4	[20]
Tau 2N4R	441	$6.7 \pm 0.3$	298	0.15	7.4	[20]

Table 3: Protein and conditions related to the intramolecular PRE data included in the training set.

Protein	$N$	$N_{labels}$	$\omega_I/2\pi$ (MHz)	$T$ (K)	$c_s$ (M)	pH	Ref.
FUS	163	3	850	298	0.15	5.5	[27]
FUS12E	164	3	850	298	0.15	5.5	[27]
OPN	220	10	800	298	0.15	6.5	[28]
$\alpha$ Syn	140	5	700	283	0.2	7.4	[29]
A2	155	2	850	298	0.005	5.5	[30]

Table 4: Proteins and conditions used for the direct-coexistence simulations performed in this study and references to the experimental data. Shaded rows highlight systems which are not included in the correlation plot of Figure 7C.

Protein	$N$	$c_s$ (mM)	pH	Ref.	$T$ (K)		
					4 nm	2 nm	Figure 3D
6His-TEV-Lge1 <sub>1-80</sub> -StrepII WT	114	100	7.5	[31]	-	293	-
6His-TEV-Lge1 <sub>1-80</sub> -StrepII -11R+11K	114	100	7.5	[31]	-	293	-
6His-TEV-Lge1 <sub>1-80</sub> -StrepII -14Y+14A	114	100	7.5	[31]	-	293	-
A1 LCD WT	137	150	7.0	[32, 3]	310 & 323	277 & 293	310
A1 LCD +7F-7Y	137	150	7.0	[3]	310 & 323	277 & 293	-
A1 LCD -12F+12Y	137	150	7.0	[3]	310 & 323	277 & 293	-
A1 LCD -23S+23T	137	150	7.0	[3]	310 & 323	277 & 293	-
A1 LCD -14N+14Q	137	150	7.0	[3]	310 & 323	277 & 293	-
A1 LCD -10G+10S	137	150	7.0	[3]	310 & 323	277 & 293	-
A1 LCD -20G+20S	137	150	7.0	[3]	310 & 323	277 & 293	-
A1 LCD -30G+30S	137	150	7.0	[3]	323	293	-
A1 LCD +23G-23S	137	150	7.0	[3]	323	293	-
A1 LCD +23G-23S+7F-7Y	137	150	7.0	[3]	323	293	-
A1 LCD +23G-23S-12F+12Y	137	150	7.0	[3]	323	293	-
A1 LCD -9F+3Y	137	150	7.0	[3]	310	277	-
A1 LCD -8F+4Y	137	150	7.0	[3]	310	277	-
A1 LCD -3R+3K	137	150	7.0	[3]	310	277	-
A1 LCD -6R	137	150	7.0	[3]	310	277	-
A1 LCD -4D	137	150	7.0	[3]	310	277	-
A1 LCD +4D	137	150	7.0	[3]	310	277	-
A1 LCD +8D	137	150	7.0	[3]	310	277	-
A1 LCD +2R	137	150	7.0	[3]	310	277	-
A1 LCD* WT	131	150	7.0	[33]	323	293	-
A1 LCD* WT	131	200	7.0	[33]	323	293	-
A1 LCD* WT	131	300	7.0	[33]	323	293	-
A1 LCD* WT	131	500	7.0	[33]	323	293	-
LAF-1 RGG Domain	176	150	7.5	[34]	323	293	293
LAF-1 RGG Domain Shuffled	176	150	7.5	[34]	323	293	323
LAF-1 RGG Domain $\Delta$ 21-30	166	150	7.5	[34]	323	293	-
A2 LCD	155	10	5.5	[35]	-	297	-
FUS LCD	163	150	7.4	[36]	-	297	-
Ddx4 LCD	236	130	6.5	[37]	-	297	-
Human Full-Length Tau (2N4R)	441	70	7.4	-	-	-	277

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