PreFIQs: Face Image Quality Is What Survives Pruning

Supplementary Material

7. Supplementary Material Overview

This supplementary material contains the following supporting content:

- Detailed pAUC results across all four evaluated FR models and pruning ratios ρ. These are provided for unstructured L_1 magnitude pruning (Table 6), unstructured random pruning (Table 7), and structured pruning (Table 8).
- A comprehensive comparison of FR verification accuracy across different pruning granularities (unstructured vs. structured) and parameter selection criteria (unstructured L_1 magnitude vs. unstructured random pruning), detailed in Table 9.
- An extended comparison of PreFIQs (using unstructured L_1 magnitude pruning at $\rho = 0.4$) against recent state-of-the-art FIQA approaches. Table 10 provides the pAUC results evaluated at an FMR of 10^{-4} to complement the results provided in the main paper.
- Error-Versus-Discard Characteristic (EDC) curves comparing PreFIQs ($\rho = 0.4$) against recent FIQA methods. These curves are plotted for an FMR of 10^{-3} in Figure 4 and an FMR of 10^{-4} in Figure 5.
- Additional evaluations utilizing a ResNet50 backbone. Table 11 presents the pAUC results at an FMR of 10^{-3} across all four FR models using unstructured L_1 magnitude pruning.

Table 6. Performance of **unstructured L_1 magnitude pruning** on four FR models using pAUC scores (discard rate = 0.3, FMR = 10^{-3}). We exclude XQLFW from this average, as its quality labels were derived using SER-FIQ. The best pAUC value is shaded.

ArcFace [11] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured L_1 Magnitude Pruning ρ =0.1	9.933	6.866	3.779	0.849	21.913	*20.809*	*139.497*	10.691
Unstructured L_1 Magnitude Pruning ρ =0.2	10.088	7.129	**3.479**	0.912	21.963	**20.761**	**137.626**	10.722
Unstructured L_1 Magnitude Pruning ρ =0.3	9.798	6.991	3.972	**0.779**	22.219	21.045	143.120	10.801
Unstructured L_1 Magnitude Pruning ρ =0.4	10.009	6.876	3.755	0.921	**20.979**	21.180	141.716	10.620
Unstructured L_1 Magnitude Pruning ρ =0.5	**9.734**	6.910	*3.631*	0.880	21.502	21.284	143.139	10.657
Unstructured L_1 Magnitude Pruning ρ =0.6	*9.765*	**6.699**	3.832	*0.788*	*21.190*	23.145	146.722	10.903
Unstructured L_1 Magnitude Pruning ρ =0.7	9.979	*6.747*	4.354	0.873	21.791	26.264	148.950	11.668
Unstructured L_1 Magnitude Pruning ρ =0.8	11.466	8.280	8.139	0.832	22.271	41.568	160.413	15.426
Unstructured L_1 Magnitude Pruning ρ =0.9	14.394	8.932	11.292	0.856	23.614	56.227	183.969	19.219

CurricularFace [25] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured L_1 Magnitude Pruning ρ =0.1	8.986	*7.018*	3.732	0.921	21.154	*17.853*	124.686	9.944
Unstructured L_1 Magnitude Pruning ρ =0.2	9.153	7.593	**3.484**	0.952	21.252	**17.598**	**121.306**	10.005
Unstructured L_1 Magnitude Pruning ρ =0.3	*8.842*	7.032	3.868	**0.779**	21.441	18.011	124.430	9.995
Unstructured L_1 Magnitude Pruning ρ =0.4	8.968	7.020	3.752	0.921	*20.577*	18.239	123.709	9.913
Unstructured L_1 Magnitude Pruning ρ =0.5	**8.786**	7.345	*3.554*	0.892	20.875	18.171	124.025	9.937
Unstructured L_1 Magnitude Pruning ρ =0.6	8.882	**6.927**	3.864	*0.808*	**20.554**	18.380	*123.356*	9.903
Unstructured L_1 Magnitude Pruning ρ =0.7	9.058	7.333	4.493	0.873	21.031	22.024	133.094	10.802
Unstructured L_1 Magnitude Pruning ρ =0.8	10.412	8.578	8.283	0.832	21.529	33.501	145.322	13.856
Unstructured L_1 Magnitude Pruning ρ =0.9	13.144	9.495	11.581	0.856	22.612	45.848	162.629	17.256

ElasticFace [7] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured L_1 Magnitude Pruning ρ =0.1	10.651	**6.314**	*3.201*	0.785	21.125	*19.664*	131.822	10.290
Unstructured L_1 Magnitude Pruning ρ =0.2	10.954	6.958	3.229	0.796	21.144	**19.391**	*129.852*	10.412
Unstructured L_1 Magnitude Pruning ρ =0.3	*10.592*	*6.586*	3.396	**0.664**	21.356	19.740	**129.723**	10.389
Unstructured L_1 Magnitude Pruning ρ =0.4	10.664	6.600	3.287	0.805	*20.324*	19.926	135.726	10.268
Unstructured L_1 Magnitude Pruning ρ =0.5	**10.584**	6.657	**3.102**	0.776	20.690	19.889	139.316	10.283
Unstructured L_1 Magnitude Pruning ρ =0.6	10.662	6.667	3.358	0.725	**20.318**	20.120	148.875	10.308
Unstructured L_1 Magnitude Pruning ρ =0.7	11.088	6.686	3.879	0.757	20.884	23.476	146.510	11.128
Unstructured L_1 Magnitude Pruning ρ =0.8	13.191	7.920	7.247	*0.715*	21.358	35.078	159.555	14.252
Unstructured L_1 Magnitude Pruning ρ =0.9	16.575	9.039	10.293	0.739	22.483	48.956	172.481	18.014

MagFace [35] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured L_1 Magnitude Pruning ρ =0.1	10.128	**7.040**	**4.672**	0.910	21.547	23.441	152.317	11.290
Unstructured L_1 Magnitude Pruning ρ =0.2	10.299	7.999	*4.683*	0.921	21.637	**22.645**	**148.797**	11.364
Unstructured L_1 Magnitude Pruning ρ =0.3	9.979	7.236	4.924	**0.788**	21.880	*23.096*	*150.416*	11.317
Unstructured L_1 Magnitude Pruning ρ =0.4	10.146	7.432	4.805	0.947	*20.981*	23.261	154.940	11.262
Unstructured L_1 Magnitude Pruning ρ =0.5	*9.894*	7.285	4.749	0.936	21.258	23.174	153.128	11.216
Unstructured L_1 Magnitude Pruning ρ =0.6	**9.881**	*7.177*	5.053	*0.834*	**20.826**	23.531	157.902	11.217
Unstructured L_1 Magnitude Pruning ρ =0.7	10.115	7.499	5.591	0.917	21.640	29.432	171.570	12.532
Unstructured L_1 Magnitude Pruning ρ =0.8	11.667	9.018	9.489	0.841	22.207	54.756	179.703	17.996
Unstructured L_1 Magnitude Pruning ρ =0.9	14.919	10.391	13.723	1.016	23.270	81.149	192.868	24.078

Figure 4. Comparison of EDC curves (FNMR at FMR=$1e^{-3}$) of PreFIQs against recent FIQA approaches. The results are shown for four FR models on eight benchmarks. Unsupervised approaches are visualized using dotted lines. Supervised methods are visualized with dashed lines. PreFIQs is visualized using a continous line with shaded AUC. For PreFIQs, unstructured L_1 magnitude pruning with $\rho = 0.4$ is used.

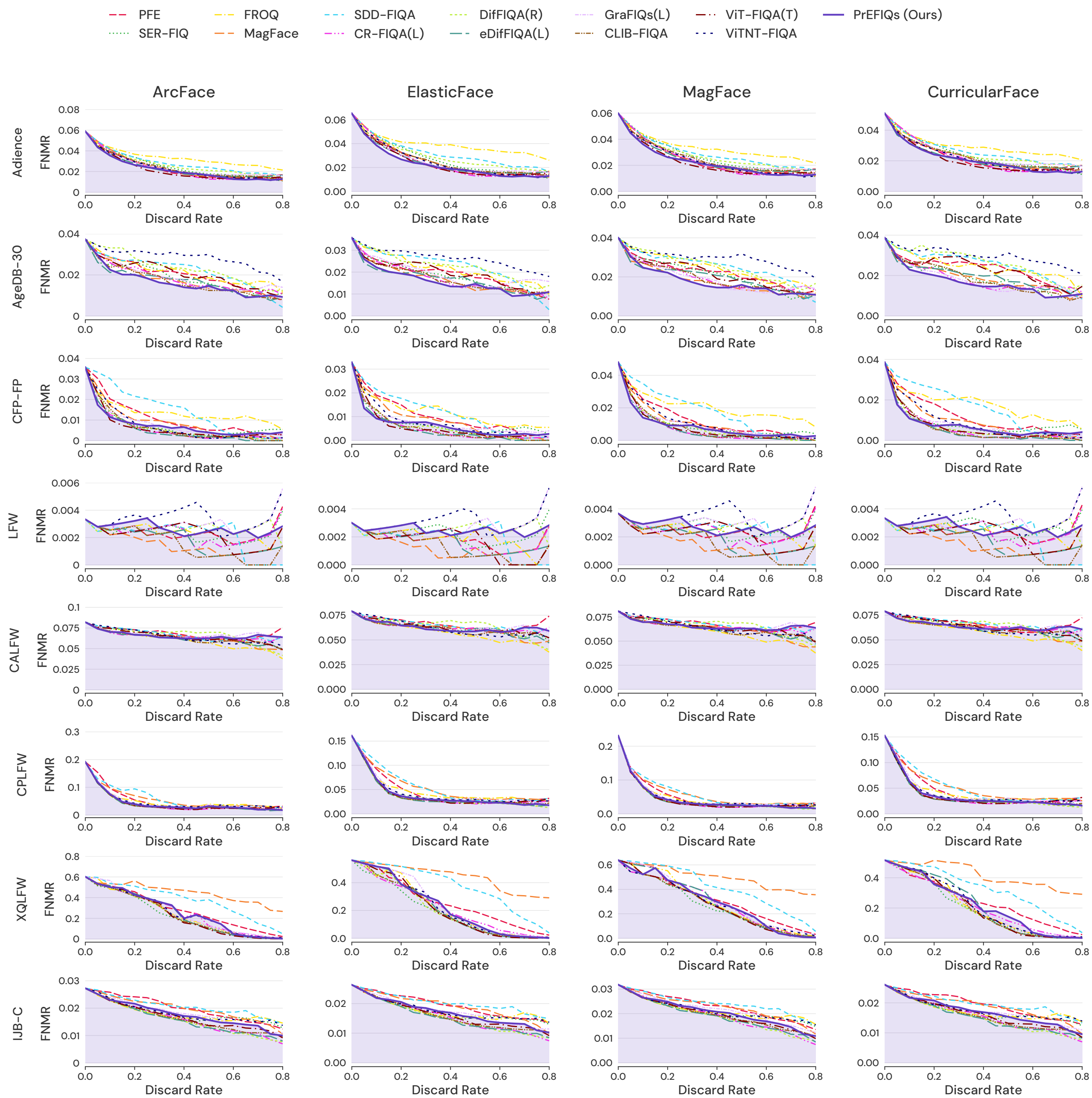

Figure 5. Comparison of EDC curves (FNMR at FMR=$1e^{-4}$) of PreFIQs against recent FIQA approaches. The results are shown for four FR models on eight benchmarks. Unsupervised approaches are visualized using dotted lines. Supervised methods are visualized with dashed lines. PreFIQs is visualized using a continous line with shaded AUC. For PreFIQs, unstructured L_1 magnitude pruning with $\rho = 0.4$ is used.

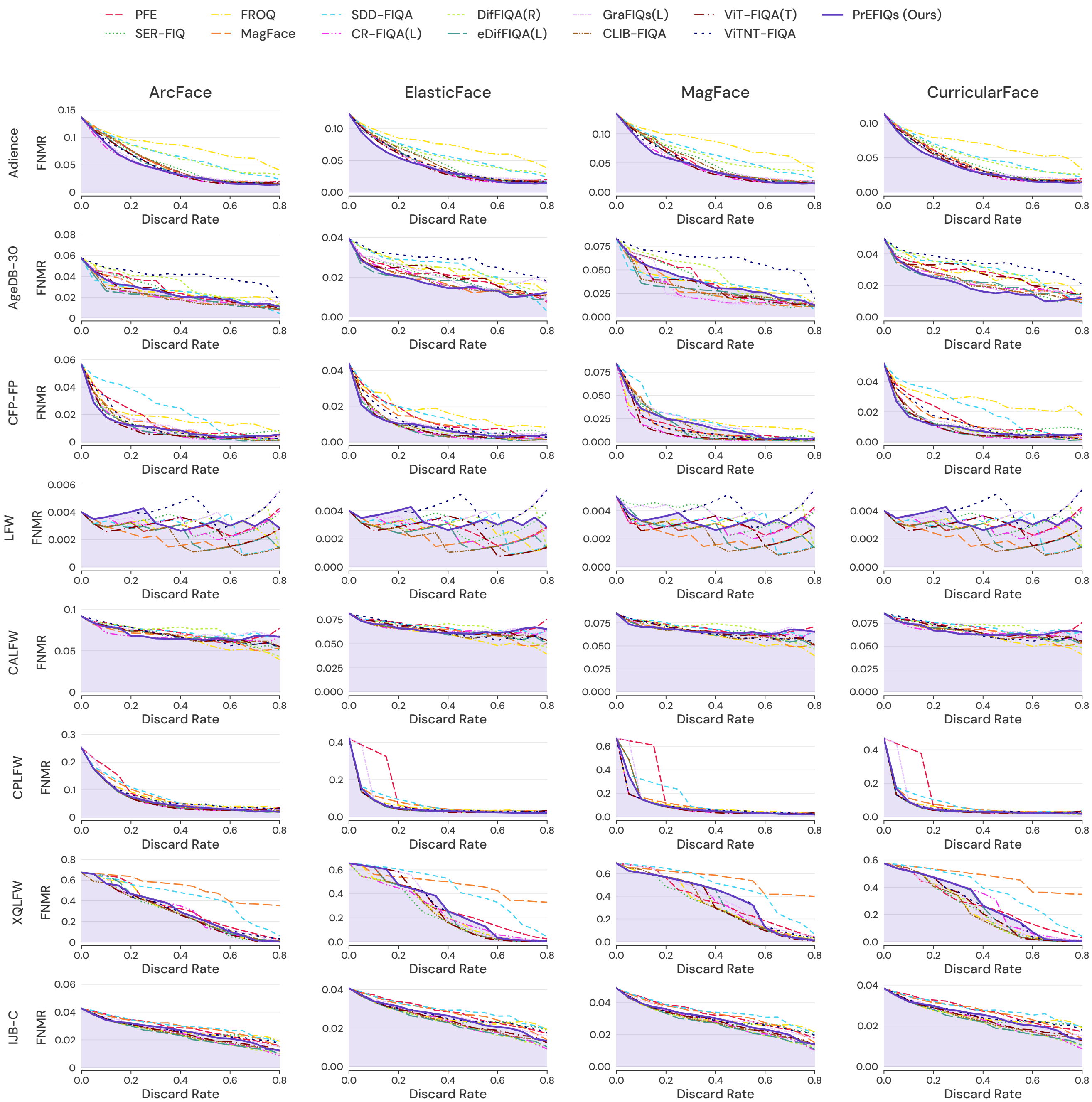

Table 7. Performance of **unstructured random pruning** on four FR models using pAUC scores (discard rate = 0.3, FMR = 10^{-3}). We exclude XQLFW from this average, as its quality labels were derived using SER-FIQ. The best pAUC value is shaded.

ArcFace [11] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured Random Pruning ρ =0.1	**15.057**	**8.802**	**10.271**	**0.738**	**22.996**	**50.725**	185.933	18.098
Unstructured Random Pruning ρ =0.2	17.838	*9.569*	12.682	1.122	24.483	60.280	187.807	20.996
Unstructured Random Pruning ρ =0.3	16.583	10.460	12.331	0.912	24.369	60.005	**180.625**	20.777
Unstructured Random Pruning ρ =0.4	16.307	10.440	12.339	0.892	*24.160*	60.143	*183.353*	20.713
Unstructured Random Pruning ρ =0.5	*15.748*	10.466	12.097	0.925	24.225	60.499	185.443	20.660
Unstructured Random Pruning ρ =0.6	15.963	10.769	*12.005*	0.917	24.687	*58.891*	184.489	20.539
Unstructured Random Pruning ρ =0.7	16.281	10.393	12.139	0.991	24.426	59.896	183.915	20.688
Unstructured Random Pruning ρ =0.8	17.055	10.729	12.192	0.908	24.665	59.558	185.973	20.851
Unstructured Random Pruning ρ =0.9	16.982	10.296	12.013	*0.891*	24.739	59.662	186.222	20.764

CurricularFace [25] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured Random Pruning ρ =0.1	**13.073**	**10.041**	**10.247**	**0.738**	**22.443**	**42.386**	166.993	16.488
Unstructured Random Pruning ρ =0.2	15.459	*10.792*	12.186	1.122	23.692	47.304	166.937	18.426
Unstructured Random Pruning ρ =0.3	14.480	11.283	11.765	0.912	23.264	49.333	162.053	18.506
Unstructured Random Pruning ρ =0.4	14.282	11.352	11.831	0.892	*23.069*	46.203	*161.380*	17.938
Unstructured Random Pruning ρ =0.5	*14.103*	11.350	11.629	0.925	23.155	47.227	163.548	18.065
Unstructured Random Pruning ρ =0.6	14.334	11.735	11.667	0.917	23.542	48.328	**158.221**	18.420
Unstructured Random Pruning ρ =0.7	14.583	11.140	11.578	0.991	23.213	46.416	162.351	17.987
Unstructured Random Pruning ρ =0.8	15.101	11.521	11.629	0.908	23.502	46.217	164.159	18.147
Unstructured Random Pruning ρ =0.9	15.174	11.329	*11.404*	*0.891*	23.603	*46.027*	164.509	18.071

ElasticFace [7] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured Random Pruning ρ =0.1	**17.014**	**8.479**	**8.921**	**0.621**	**22.330**	**44.025**	175.487	16.898
Unstructured Random Pruning ρ =0.2	19.909	*9.445*	11.197	1.005	23.520	51.749	176.004	19.471
Unstructured Random Pruning ρ =0.3	18.670	9.683	10.557	0.796	23.383	51.002	**170.618**	19.015
Unstructured Random Pruning ρ =0.4	18.352	9.976	10.935	0.776	*23.089*	51.820	*170.678*	19.158
Unstructured Random Pruning ρ =0.5	*17.806*	9.854	10.513	0.809	23.295	51.880	173.129	19.026
Unstructured Random Pruning ρ =0.6	18.054	10.289	10.548	0.854	23.671	*50.339*	171.993	18.959
Unstructured Random Pruning ρ =0.7	18.405	9.777	10.423	0.874	23.376	51.147	171.672	19.000
Unstructured Random Pruning ρ =0.8	19.179	10.138	10.359	0.792	23.619	50.854	173.737	19.157
Unstructured Random Pruning ρ =0.9	19.155	9.768	*10.309*	*0.775*	23.754	51.312	173.965	19.179

MagFace [35] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured Random Pruning ρ =0.1	**15.261**	**9.712**	**12.488**	**0.822**	**23.015**	**68.953**	196.552	21.708
Unstructured Random Pruning ρ =0.2	18.076	*10.819*	15.366	1.292	24.345	*87.547*	197.676	26.241
Unstructured Random Pruning ρ =0.3	17.095	11.352	14.751	0.992	24.040	87.775	*193.409*	26.001
Unstructured Random Pruning ρ =0.4	16.734	11.402	15.136	0.972	*23.896*	88.859	193.840	26.167
Unstructured Random Pruning ρ =0.5	*16.289*	11.336	14.845	1.005	23.924	89.931	195.817	26.222
Unstructured Random Pruning ρ =0.6	16.681	11.614	14.803	0.997	24.359	87.955	**193.222**	26.068
Unstructured Random Pruning ρ =0.7	17.001	11.159	14.704	1.069	24.148	88.618	194.451	26.117
Unstructured Random Pruning ρ =0.8	17.618	11.563	14.634	0.989	24.376	88.542	196.422	26.287
Unstructured Random Pruning ρ =0.9	17.572	11.068	*14.375*	*0.970*	24.555	89.114	196.850	26.276

Table 8. Performance of **structured pruning** on four FR models using pAUC scores (discard rate = 0.3, FMR = 10^{-3}). We exclude XQLFW from this average, as its quality labels were derived using SER-FIQ. The best pAUC value is shaded.

ArcFace [11] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Structured Pruning ρ =0.1	**10.682**	**8.092**	**4.214**	**0.798**	**21.534**	**22.337**	**146.636**	11.276
Structured Pruning ρ =0.2	*11.866*	*9.480*	*8.575*	0.964	*22.461*	*48.433*	*160.614*	16.963
Structured Pruning ρ =0.3	16.136	10.348	11.902	1.170	23.726	58.509	174.307	20.299
Structured Pruning ρ =0.4	16.447	11.296	12.291	0.932	25.109	55.601	174.252	20.279
Structured Pruning ρ =0.5	16.254	11.354	11.728	*0.909*	24.631	57.294	176.949	20.362
Structured Pruning ρ =0.6	15.875	11.021	11.655	0.929	24.645	57.736	177.852	20.310
Structured Pruning ρ =0.7	17.205	10.568	11.681	1.005	24.748	57.508	173.673	20.452
Structured Pruning ρ =0.8	16.181	10.400	11.986	1.011	24.774	58.010	175.532	20.394
Structured Pruning ρ =0.9	16.529	9.951	12.482	0.967	24.638	59.317	178.910	20.647

CurricularFace [25] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Structured Pruning ρ =0.1	**9.438**	**8.264**	**4.576**	**0.851**	**20.940**	**19.171**	**133.453**	10.540
Structured Pruning ρ =0.2	*10.507*	*10.131*	*9.091*	0.964	*21.591*	*39.515*	*139.968*	15.300
Structured Pruning ρ =0.3	14.202	10.617	12.293	1.170	22.872	48.333	158.205	18.248
Structured Pruning ρ =0.4	14.424	12.192	12.186	0.932	23.906	47.932	156.167	18.595
Structured Pruning ρ =0.5	14.431	11.997	11.473	*0.909*	23.468	47.403	155.834	18.280
Structured Pruning ρ =0.6	14.240	11.372	11.365	0.929	23.537	46.968	156.709	18.069
Structured Pruning ρ =0.7	15.091	10.823	11.632	1.005	23.723	47.080	157.546	18.226
Structured Pruning ρ =0.8	14.372	11.092	11.446	1.011	23.659	47.229	155.716	18.135
Structured Pruning ρ =0.9	14.664	10.698	11.942	0.967	23.536	48.810	162.417	18.436

ElasticFace [7] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Structured Pruning ρ =0.1	**11.861**	**7.862**	**3.872**	**0.692**	**20.568**	**20.907**	**138.529**	10.960
Structured Pruning ρ =0.2	*13.507*	*9.249*	*8.052*	0.846	*21.444*	*41.140*	*156.850*	15.706
Structured Pruning ρ =0.3	18.070	9.691	10.516	1.053	22.736	50.392	167.648	18.743
Structured Pruning ρ =0.4	18.709	10.760	10.807	0.815	24.068	49.996	165.012	19.192
Structured Pruning ρ =0.5	18.484	10.698	10.304	*0.793*	23.627	49.438	164.708	18.891
Structured Pruning ρ =0.6	18.115	10.198	10.425	0.813	23.675	49.046	165.614	18.712
Structured Pruning ρ =0.7	19.485	9.707	10.470	0.890	23.947	49.210	165.305	18.952
Structured Pruning ρ =0.8	18.584	9.732	10.521	0.906	23.850	49.320	168.750	18.819
Structured Pruning ρ =0.9	18.753	9.396	10.646	0.851	23.601	50.980	171.624	19.038

MagFace [35] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Structured Pruning ρ =0.1	**10.798**	**8.508**	**5.147**	**0.824**	**21.508**	**23.844**	**158.485**	11.771
Structured Pruning ρ =0.2	*12.385*	*10.379*	*11.155*	1.052	*22.203*	*68.994*	*171.634*	21.028
Structured Pruning ρ =0.3	16.519	11.074	15.199	1.307	23.296	85.109	179.578	25.417
Structured Pruning ρ =0.4	17.022	12.235	15.101	0.993	24.704	86.582	186.718	26.106
Structured Pruning ρ =0.5	16.890	12.097	14.587	*0.988*	24.281	86.486	187.859	25.888
Structured Pruning ρ =0.6	16.528	11.688	14.496	1.009	24.339	82.950	187.531	25.168
Structured Pruning ρ =0.7	17.828	11.149	14.474	1.085	24.584	85.853	187.248	25.829
Structured Pruning ρ =0.8	16.881	11.296	14.667	1.091	24.497	86.012	191.370	25.741
Structured Pruning ρ =0.9	17.257	10.736	15.155	1.064	24.268	87.703	194.474	26.031

Table 9. Verification accuracy (%) of ResNet-100 under different pruning strategies at rates $\rho \in \{0.1, \ldots, 0.9\}$. The **best** and *second-best* results per dataset are highlighted.

Granularity of Pruning - Comparison between unstructured and structured model pruning [↑]

Methods	LFW	CFP-FP	CFP-FF	AgeDB-30	CALFW	CPLFW	$\overline{\text{Acc}}$ [↑]
ResNet-100 (unpruned)	**99.80**	*96.67*	*99.89*	98.35	*96.15*	**93.32**	97.36
Unstructured ρ=0.1	**99.80**	*96.67*	*99.89*	**98.43**	**96.17**	*93.23*	97.37
Unstructured ρ=0.2	**99.80**	**96.70**	*99.89*	**98.43**	**96.17**	*93.23*	97.37
Unstructured ρ=0.3	**99.80**	96.59	*99.89*	*98.42*	96.08	93.17	97.32
Unstructured ρ=0.4	**99.80**	96.44	*99.89*	98.32	96.08	93.18	97.29
Unstructured ρ=0.5	**99.80**	96.36	**99.90**	98.20	96.00	92.70	97.16
Unstructured ρ=0.6	**99.80**	95.79	**99.90**	98.05	96.02	92.22	96.96
Unstructured ρ=0.7	99.75	94.87	99.79	97.50	95.85	90.38	96.36
Unstructured ρ=0.8	99.57	87.50	99.39	94.70	94.35	82.92	93.07
Unstructured ρ=0.9	90.45	65.76	91.87	75.27	78.37	58.87	76.76
Structured ρ=0.1	*99.77*	95.30	99.84	97.82	95.88	91.07	96.61
Structured ρ=0.2	98.17	81.74	98.01	89.85	90.63	76.20	89.10
Structured ρ=0.3	82.90	58.71	79.10	71.93	68.22	56.72	69.60
Structured ρ=0.4	73.83	57.83	73.36	60.85	60.67	54.62	63.53
Structured ρ=0.5	72.47	59.39	71.50	58.35	58.92	52.77	62.23
Structured ρ=0.6	65.63	55.69	69.29	53.88	56.70	51.63	58.80
Structured ρ=0.7	51.12	50.19	51.26	50.10	50.17	50.60	50.57
Structured ρ=0.8	50.72	50.43	51.31	50.20	50.12	50.08	50.48
Structured ρ=0.9	50.00	50.00	50.00	50.00	50.00	50.00	50.00

Pruning Criterion - Comparison between L_1 magnitude and random model pruning [↑]

Methods	LFW	CFP-FP	CFP-FF	AgeDB-30	CALFW	CPLFW	$\overline{\text{Acc}}$ [↑]
ResNet-100 (unpruned)	**99.80**	*96.67*	*99.89*	98.35	*96.15*	**93.32**	97.36
L_1 **Magnitude** ρ=0.1	**99.80**	*96.67*	*99.89*	**98.43**	**96.17**	*93.23*	97.37
L_1 **Magnitude** ρ=0.2	**99.80**	**96.70**	*99.89*	**98.43**	**96.17**	*93.23*	97.37
L_1 **Magnitude** ρ=0.3	**99.80**	96.59	*99.89*	*98.42*	96.08	93.17	97.32
L_1 **Magnitude** ρ=0.4	**99.80**	96.44	*99.89*	98.32	96.08	93.18	97.29
L_1 **Magnitude** ρ=0.5	**99.80**	96.36	**99.90**	98.20	96.00	92.70	97.16
L_1 **Magnitude** ρ=0.6	**99.80**	95.79	**99.90**	98.05	96.02	92.22	96.96
L_1 **Magnitude** ρ=0.7	99.75	94.87	99.79	97.50	95.85	90.38	96.36
L_1 **Magnitude** ρ=0.8	99.57	87.50	99.39	94.70	94.35	82.92	93.07
L_1 **Magnitude** ρ=0.9	90.45	65.76	91.87	75.27	78.37	58.87	76.76
Random ρ=0.1	97.43	77.86	98.03	82.82	89.18	73.52	86.47
Random ρ=0.2	77.00	59.67	75.30	57.85	62.23	58.23	65.05
Random ρ=0.3	71.73	59.83	73.21	56.63	57.88	55.07	62.39
Random ρ=0.4	64.80	56.89	71.83	57.47	56.75	54.48	60.37
Random ρ=0.5	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Random ρ=0.6	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Random ρ=0.7	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Random ρ=0.8	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Random ρ=0.9	50.00	50.00	50.00	50.00	50.00	50.00	50.00

Table 10. Performance comparison of four FR models using pAUC scores (discard rate = 0.3, FMR = 10^{-4}). The **best** and *second-best* results per dataset are highlighted. The final column displays the average pAUC across all benchmarks. We exclude XQLFW from this average to prevent evaluation bias, as its quality labels were derived using SER-FIQ. The best average pAUC is highlighted in GREEN for supervised approaches (marked using green stripes) , and BLUE for unsupervised approaches (marked with blue stripes).

ArcFace [11] - $pAUC * 10^3$ (FMR= 10^{-4}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	IJB-C	$\overline{pAUC}$
RankIQ [9]	35.792	17.131	13.301	0.929	25.432	48.441	172.415	12.200	21.889
PFE [46]	27.089	12.675	8.976	0.921	24.361	42.758	171.946	11.003	18.255
SDD-FIQA [37]	29.760	10.189	12.499	0.963	24.245	41.998	178.950	11.039	18.670
MagFace [35]	27.522	10.816	7.495	**0.841**	22.829	39.988	190.526	10.883	17.196
CR-FIQA(L) [8]	**22.352**	9.983	6.166	1.012	**21.958**	**33.201**	159.127	10.114	14.970
DifFIQA(R) [4]	29.121	13.729	6.707	0.930	24.367	33.550	158.615	*9.872*	16.897
eDifFIQA(L) [5]	25.487	**8.878**	6.048	0.908	23.466	*33.348*	166.808	**9.790**	15.418
CLIB-FIQA [40]	27.319	*9.436*	6.769	0.915	23.340	33.627	**150.932**	9.957	15.909
ViT-FIQA(T) [2]	25.664	10.734	**5.663**	*0.896*	23.614	33.388	*156.275*	10.118	15.725
FROQ [6]	31.630	10.388	8.296	0.959	23.453	37.003	167.705	9.919	17.378
SER-FIQ [48]	27.434	12.283	6.305	0.975	24.202	35.086	156.847	10.093	16.625
FaceQnet [20, 21]	35.469	12.704	11.470	1.132	25.723	65.278	202.213	12.698	23.496
GraFIQs(L) [31]	23.757	11.034	7.103	1.040	23.900	37.669	158.682	10.294	16.399
ViTNT-FIQA [42]	25.196	14.276	7.340	1.149	24.402	35.678	158.107	10.233	16.896
PreFIQs (Ours)	*23.200*	10.744	*5.884*	1.142	*22.737*	34.380	160.838	10.192	<u>15.469</u>

CurricularFace [25] - $pAUC * 10^3$ (FMR= 10^{-4}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	IJB-C	$\overline{pAUC}$
RankIQ [9]	28.973	13.897	12.347	0.929	23.731	44.689	152.020	11.229	19.399
PFE [46]	22.063	10.451	8.741	0.921	23.196	79.334	**137.743**	10.231	22.134
SDD-FIQA [37]	24.334	11.549	11.167	0.963	23.413	44.873	162.193	10.053	18.050
MagFace [35]	22.276	9.427	7.489	**0.841**	21.915	38.775	163.263	9.987	15.816
CR-FIQA(L) [8]	21.058	9.511	5.964	1.012	**21.397**	29.961	149.557	9.247	14.021
DifFIQA(R) [4]	23.109	11.749	5.982	0.930	22.762	*29.538*	141.513	9.163	14.747
eDifFIQA(L) [5]	*20.309*	**8.948**	*5.693*	0.908	21.994	**29.462**	148.370	**9.044**	13.766
CLIB-FIQA [40]	21.731	9.634	6.076	0.915	21.897	29.973	141.835	9.251	14.211
ViT-FIQA(T) [2]	20.890	10.593	5.800	*0.896*	22.717	29.590	144.613	9.322	14.258
FROQ [6]	26.215	10.810	10.309	0.959	22.092	33.024	142.794	*9.119*	16.075
SER-FIQ [48]	23.264	9.451	5.808	0.975	22.653	32.754	*138.231*	9.210	14.874
FaceQnet [20, 21]	29.768	11.695	11.412	1.132	24.303	125.926	175.338	11.664	30.843
GraFIQs(L) [31]	20.743	9.199	6.143	1.040	22.502	47.312	141.425	9.456	16.628
ViTNT-FIQA [42]	21.473	12.199	7.714	1.149	23.177	31.136	144.810	9.464	15.187
PreFIQs (Ours)	**19.560**	*9.020*	**5.533**	1.142	*21.648*	32.238	148.557	9.425	<u>14.081</u>

ElasticFace [7] - $pAUC * 10^3$ (FMR= 10^{-4}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	IJB-C	$\overline{pAUC}$
RankIQ [9]	32.314	11.553	9.822	0.929	22.184	43.910	153.491	11.891	18.943
PFE [46]	23.534	7.988	7.174	0.921	22.110	70.252	160.004	10.694	20.382
SDD-FIQA [37]	26.484	9.384	7.541	0.963	22.013	41.128	185.308	10.579	16.870
MagFace [35]	23.591	7.355	6.552	**0.841**	20.984	37.621	170.809	10.497	15.349
CR-FIQA(L) [8]	22.961	7.895	4.795	1.012	*20.747*	29.283	*145.298*	9.764	13.779
DifFIQA(R) [4]	25.311	9.199	4.956	0.870	21.605	**28.757**	149.565	*9.596*	14.328
eDifFIQA(L) [5]	23.121	**7.031**	**4.566**	0.848	20.828	*28.759*	161.211	**9.511**	13.523
CLIB-FIQA [40]	24.724	7.561	5.055	*0.842*	20.782	29.149	159.775	9.701	13.974
ViT-FIQA(T) [2]	*22.535*	8.123	4.803	0.896	21.569	29.220	172.150	9.764	13.844
FROQ [6]	28.572	9.162	7.599	0.959	**20.723**	32.372	154.630	9.615	15.572
SER-FIQ [48]	25.769	8.272	4.833	0.975	21.701	31.266	**143.390**	9.659	14.639
FaceQnet [20, 21]	32.043	9.529	9.728	1.059	23.390	112.090	195.806	12.382	28.603
GraFIQs(L) [31]	22.707	8.521	5.193	1.040	21.409	43.509	177.210	10.044	16.060
ViTNT-FIQA [42]	23.405	9.884	5.827	1.149	22.154	30.853	166.858	9.907	14.740
PreFIQs (Ours)	**20.954**	*7.150*	*4.711*	1.142	20.936	30.677	166.140	9.964	<u>13.648</u>

MagFace [35] - $pAUC * 10^3$ (FMR= 10^{-4}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	IJB-C	$\overline{pAUC}$
RankIQ [9]	35.315	23.671	20.646	1.207	23.341	120.130	178.752	13.872	34.026
PFE [46]	26.848	18.720	9.904	0.946	22.728	121.181	178.028	12.481	30.401
SDD-FIQA [37]	29.644	14.141	14.142	0.987	22.965	91.491	196.530	12.468	26.548
MagFace [35]	25.897	14.706	10.157	**0.865**	21.743	62.562	190.811	12.241	21.167
CR-FIQA(L) [8]	*23.460*	13.942	**6.347**	0.961	21.650	**48.232**	177.183	11.418	18.001
DifFIQA(R) [4]	28.100	19.892	11.839	0.990	22.712	63.122	176.827	*11.162*	22.545
eDifFIQA(L) [5]	25.601	**12.583**	10.986	1.003	21.536	62.819	176.440	**11.076**	20.801
CLIB-FIQA [40]	27.333	*13.463*	11.688	0.993	*21.473*	63.054	180.233	11.278	21.326
ViT-FIQA(T) [2]	25.507	15.333	*7.463*	*0.938*	22.271	*48.300*	176.617	11.378	18.741
FROQ [6]	32.243	15.344	10.360	1.020	21.775	51.720	*175.071*	11.189	20.522
SER-FIQ [48]	27.398	18.478	10.351	1.343	22.145	57.925	**164.777**	11.301	21.277
FaceQnet [20, 21]	34.071	17.753	18.253	1.175	23.538	189.005	201.488	14.358	42.593
GraFIQs(L) [31]	24.288	14.670	12.381	1.280	21.873	72.939	183.078	11.785	22.745
ViTNT-FIQA [42]	25.230	21.339	9.409	1.116	22.425	50.261	176.733	11.507	20.184
PreFIQs (Ours)	**23.223**	16.512	11.027	1.105	**21.322**	56.892	176.660	11.559	<u>20.234</u>

Table 11. Performance of **ResNet50 trained on CASIA-Webface [51] using ArcFace [11]** on four FR models using pAUC scores (discard rate = 0.3, FMR = 10^{-3}). ResNet-50 is pruned using unstructured L_1 magnitude pruning. The **best** and *second-best* results per dataset are highlighted. The final column displays the average pAUC across all benchmarks. We exclude XQLFW from this average, as its quality labels were derived using SER-FIQ.

ArcFace [11] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured ρ =**0.1**	*13.045*	*10.076*	**8.743**	1.006	22.172	**48.064**	*187.383*	17.185
Unstructured ρ =**0.2**	13.636	10.374	9.044	0.946	22.022	*49.660*	188.583	17.614
Unstructured ρ =**0.3**	13.174	**9.905**	9.106	0.933	*21.853*	54.262	191.440	18.205
Unstructured ρ =**0.4**	**12.951**	10.837	*8.758*	*0.874*	**21.769**	51.052	189.925	17.707
Unstructured ρ =**0.5**	13.887	10.856	8.859	**0.798**	22.416	50.924	192.805	17.957
Unstructured ρ =**0.6**	13.572	11.265	8.937	1.092	22.836	51.588	193.798	18.215
Unstructured ρ =**0.7**	13.677	10.464	9.877	1.170	22.623	57.639	194.791	19.242
Unstructured ρ =**0.8**	14.668	10.758	12.219	1.133	23.531	61.064	189.744	20.562
Unstructured ρ =**0.9**	15.590	10.300	12.350	1.127	22.830	63.394	**186.573**	20.932

CurricularFace [25] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured ρ =**0.1**	**11.564**	*10.730*	9.258	1.006	21.376	**42.766**	*168.681*	16.116
Unstructured ρ =**0.2**	12.336	**10.176**	**8.556**	1.001	21.218	*43.182*	169.495	16.078
Unstructured ρ =**0.3**	11.935	10.887	9.140	0.987	**20.985**	44.248	171.296	16.364
Unstructured ρ =**0.4**	*11.659*	11.070	*8.867*	*0.929*	*21.081*	43.385	170.833	16.165
Unstructured ρ =**0.5**	12.453	10.971	9.344	**0.818**	21.500	44.401	172.527	16.581
Unstructured ρ =**0.6**	12.117	11.424	9.312	1.092	21.901	44.949	172.224	16.799
Unstructured ρ =**0.7**	12.250	11.015	9.771	1.170	21.788	48.376	172.332	17.395
Unstructured ρ =**0.8**	12.980	11.548	12.407	1.133	22.365	47.928	169.064	18.060
Unstructured ρ =**0.9**	13.900	10.890	13.347	1.127	21.893	47.166	**165.039**	18.054

ElasticFace [7] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured ρ =**0.1**	**14.466**	**9.271**	8.451	0.887	21.282	**44.853**	*176.500*	16.535
Unstructured ρ =**0.2**	15.203	*9.298*	**7.565**	0.827	21.222	45.541	177.543	16.609
Unstructured ρ =**0.3**	14.698	9.927	*7.782*	0.814	**20.682**	46.239	179.343	16.690
Unstructured ρ =**0.4**	*14.509*	10.038	7.969	*0.755*	*20.973*	*45.307*	178.396	16.592
Unstructured ρ =**0.5**	15.394	10.054	8.633	**0.679**	21.245	46.766	180.910	17.129
Unstructured ρ =**0.6**	14.837	10.378	8.448	0.974	21.735	47.489	180.965	17.310
Unstructured ρ =**0.7**	15.012	9.671	8.915	1.053	21.732	50.233	182.343	17.769
Unstructured ρ =**0.8**	16.532	9.672	10.682	1.017	22.475	53.326	177.513	18.951
Unstructured ρ =**0.9**	17.572	9.808	11.265	1.043	22.113	54.480	**173.979**	19.380

MagFace [35] - $pAUC * 10^3$ (FMR= 10^{-3}) [↓]

Methods	Adience	AgeDB-30	CFP-FP	LFW	CALFW	CPLFW	XQLFW	$\overline{pAUC}$
Unstructured ρ =**0.1**	**13.332**	**10.689**	10.886	1.032	21.774	**52.677**	**196.726**	18.399
Unstructured ρ =**0.2**	14.026	*10.845*	**10.483**	*0.954*	21.749	*54.247*	199.101	18.717
Unstructured ρ =**0.3**	13.640	10.886	10.822	0.977	**21.512**	61.676	202.518	19.919
Unstructured ρ =**0.4**	*13.384*	11.082	*10.506*	0.958	*21.532*	56.992	199.355	19.076
Unstructured ρ =**0.5**	14.278	11.076	10.957	**0.823**	21.962	55.992	202.837	19.181
Unstructured ρ =**0.6**	13.875	11.975	10.926	1.118	22.564	57.054	204.008	19.585
Unstructured ρ =**0.7**	14.082	11.216	11.737	1.239	22.528	77.373	205.857	23.029
Unstructured ρ =**0.8**	15.140	11.339	15.235	1.250	23.172	86.173	200.850	25.385
Unstructured ρ =**0.9**	15.902	11.143	16.631	1.298	22.454	92.730	*197.217*	26.693

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