

## Supplementary Material for Chapter 6



Table 1: Comparison of the methods in dataset emotions in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-315.71	0.28	<b>0.791</b>	1.03	2	2
1	DGS-clp	<b>-300.3</b>	0.28	0.78	1.03	2	2
1	GS-tw	-449.6	0.27	0.78	<b>0.6</b>	2	2
1	GS-clp	-317.61	<b>0.294</b>	0.79	<b>0.6</b>	2	2
1	GS-pruned	-361.94	0.27	0.78	0.65	4	2
2	DGS	-317.76	0.24	0.76	0.79	2	2
2	DGS-clp	-309.24	0.24	0.76	0.79	2	2
2	GS-tw	-389.42	<b>0.345</b>	<b>0.794</b>	0.63	2	2
2	GS-clp	<b>-301.9</b>	0.32	0.79	0.63	2	2
2	GS-pruned	-336.51	0.28	0.76	<b>0.6</b>	3	2
3	DGS	-293.23	0.28	0.77	0.77	2	2
3	DGS-clp	<b>-285.3</b>	<b>0.319</b>	0.78	0.77	2	2
3	GS-tw	-355.2	0.29	<b>0.794</b>	0.61	2	2
3	GS-clp	-313.23	0.23	0.76	0.61	2	2
3	GS-pruned	-298.79	0.23	0.78	<b>0.6</b>	3	2
4	DGS	-317.8	<b>0.288</b>	0.77	0.74	2	2
4	DGS-clp	<b>-309.2</b>	<b>0.288</b>	0.77	0.74	2	2
4	GS-tw	-429.35	0.25	0.77	<b>0.6</b>	2	2
4	GS-clp	-349.22	0.27	<b>0.777</b>	<b>0.6</b>	2	2
4	GS-pruned	-352.53	0.28	0.76	0.65	3	2
5	DGS	-305.74	<b>0.322</b>	0.79	0.75	2	2
5	DGS-clp	<b>-298.4</b>	<b>0.322</b>	0.78	0.75	2	2
5	GS-tw	-477.82	0.28	0.78	<b>0.6</b>	2	2
5	GS-clp	-343.7	0.25	0.76	<b>0.6</b>	2	2
5	GS-pruned	-338.7	<b>0.322</b>	<b>0.797</b>	0.93	4	2

Table 2: Comparison of the methods in dataset emotions in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-300.92	0.29	0.79	1.16	3	3
1	DGS-clp	<b>-279.3</b>	<b>0.311</b>	0.78	1.16	3	3
1	GS-tw	-357.54	0.29	0.78	0.75	3	3
1	GS-clp	-295.83	0.29	<b>0.789</b>	0.75	3	3
1	GS-pruned	-348.87	0.28	0.78	<b>0.6</b>	4	3
2	DGS	-317.76	0.24	0.76	0.72	2	2
2	DGS-clp	-309.24	0.24	0.76	0.72	2	2
2	GS-tw	-326.83	0.27	0.75	0.75	3	3
2	GS-clp	<b>-299.5</b>	<b>0.277</b>	<b>0.768</b>	0.75	3	3
2	GS-pruned	-322.52	0.2	0.76	<b>0.6</b>	4	3
3	DGS	-293.23	0.28	0.77	0.71	2	2
3	DGS-clp	-285.34	<b>0.319</b>	0.78	0.71	2	2
3	GS-tw	-287.87	0.3	<b>0.8</b>	0.73	3	3
3	GS-clp	<b>-273.5</b>	0.3	0.79	0.73	3	3
3	GS-pruned	-292.9	0.28	0.8	<b>0.6</b>	4	3
4	DGS	-317.8	0.29	0.77	0.71	2	2
4	DGS-clp	<b>-309.2</b>	0.29	0.77	0.71	2	2
4	GS-tw	-355.62	0.29	0.78	0.69	3	3
4	GS-clp	-313.92	<b>0.314</b>	<b>0.798</b>	0.69	3	3
4	GS-pruned	-347.44	0.3	0.79	<b>0.6</b>	4	3
5	DGS	-302.83	0.31	0.79	0.88	3	3
5	DGS-clp	<b>-295.5</b>	<b>0.322</b>	0.78	0.88	3	3
5	GS-tw	-348.01	0.31	0.79	0.72	3	3
5	GS-clp	-311.3	0.28	0.77	0.72	3	3
5	GS-pruned	-333.77	0.31	<b>0.802</b>	<b>0.7</b>	4	3

Table 3: Comparison of the methods in dataset emotions in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-300.92	0.29	<b>0.787</b>	0.77	3	3
1	DGS-clp	<b>-279.3</b>	<b>0.311</b>	0.78	0.77	3	3
1	GS-tw	-348.87	0.28	0.78	0.74	3	3
1	GS-clp	-286.26	0.28	0.79	0.74	3	3
1	GS-pruned	-348.87	0.28	0.78	<b>0.6</b>	4	3
2	DGS	-317.76	<b>0.244</b>	0.76	0.76	2	2
2	DGS-clp	-309.24	<b>0.244</b>	<b>0.763</b>	0.76	2	2
2	GS-tw	-322.52	0.2	0.76	0.78	4	3
2	GS-clp	<b>-305.3</b>	0.22	0.75	0.78	4	3
2	GS-pruned	-322.52	0.2	0.76	<b>0.6</b>	4	3
3	DGS	-293.23	0.28	0.77	0.81	2	2
3	DGS-clp	-285.34	<b>0.319</b>	0.78	0.81	2	2
3	GS-tw	-286.04	0.29	<b>0.801</b>	0.8	4	3
3	GS-clp	<b>-272.4</b>	<b>0.319</b>	0.78	0.8	4	3
3	GS-pruned	-292.9	0.28	0.8	<b>0.6</b>	4	3
4	DGS	-317.8	0.29	0.77	0.75	2	2
4	DGS-clp	-309.18	0.29	0.77	0.75	2	2
4	GS-tw	-348.21	<b>0.314</b>	0.78	0.75	3	3
4	GS-clp	<b>-304.7</b>	0.31	<b>0.794</b>	0.75	3	3
4	GS-pruned	-347.44	0.3	0.79	<b>0.6</b>	4	3
5	DGS	-302.83	0.31	0.79	0.78	3	3
5	DGS-clp	<b>-295.5</b>	<b>0.322</b>	0.78	0.78	3	3
5	GS-tw	-334.73	0.31	0.79	0.77	4	3
5	GS-clp	-309.08	0.31	0.78	0.77	4	3
5	GS-pruned	-333.77	0.31	<b>0.802</b>	<b>0.7</b>	4	3

Table 4: Comparison of the methods in dataset emotions in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-300.92	0.29	<b>0.787</b>	0.76	3	3
1	DGS-clp	<b>-279.3</b>	<b>0.311</b>	0.78	0.76	3	3
1	GS-tw	-348.87	0.28	0.78	0.79	3	3
1	GS-clp	-286.26	0.28	0.79	0.79	3	3
1	GS-pruned	-348.87	0.28	0.78	<b>0.7</b>	4	3
2	DGS	-317.76	<b>0.244</b>	0.76	0.74	2	2
2	DGS-clp	-309.24	<b>0.244</b>	<b>0.763</b>	0.74	2	2
2	GS-tw	-322.52	0.2	0.76	0.76	4	3
2	GS-clp	<b>-305.3</b>	0.22	0.75	0.76	4	3
2	GS-pruned	-322.52	0.2	0.76	<b>0.7</b>	4	3
3	DGS	-293.23	0.28	0.77	0.74	2	2
3	DGS-clp	-285.34	<b>0.319</b>	0.78	0.74	2	2
3	GS-tw	-292.9	0.28	<b>0.796</b>	0.76	4	3
3	GS-clp	<b>-274.1</b>	0.29	0.77	0.76	4	3
3	GS-pruned	-292.9	0.28	<b>0.796</b>	<b>0.7</b>	4	3
4	DGS	-317.8	0.29	0.77	0.72	2	2
4	DGS-clp	-309.18	0.29	0.77	0.72	2	2
4	GS-tw	-347.44	<b>0.297</b>	0.79	0.84	4	3
4	GS-clp	<b>-302.8</b>	<b>0.297</b>	<b>0.794</b>	0.84	4	3
4	GS-pruned	-347.44	<b>0.297</b>	0.79	<b>0.6</b>	4	3
5	DGS	-302.83	0.31	0.79	0.75	3	3
5	DGS-clp	<b>-295.5</b>	<b>0.322</b>	0.78	0.75	3	3
5	GS-tw	-333.77	0.31	<b>0.802</b>	0.81	4	3
5	GS-clp	-309.21	0.29	0.79	0.81	4	3
5	GS-pruned	-333.77	0.31	<b>0.802</b>	<b>0.7</b>	4	3

Table 5: Comparison of the methods in dataset foodtruck in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-342.28	<b>0.317</b>	<b>0.852</b>	0.23	2	2
1	DGS-clp	-342.34	<b>0.317</b>	<b>0.852</b>	0.23	2	2
1	GS-tw	-341.1	0.29	0.85	0.06	2	2
1	GS-clp	<b>-339.6</b>	<b>0.317</b>	0.84	0.06	2	2
1	GS-pruned	-341.1	0.29	0.85	<b>0</b>	2	2
2	DGS	-363.21	<b>0.244</b>	0.84	0.13	2	2
2	DGS-clp	-364.11	<b>0.244</b>	0.84	0.13	2	2
2	GS-tw	-366.04	<b>0.244</b>	0.84	0.05	2	2
2	GS-clp	<b>-360.3</b>	0.23	<b>0.845</b>	0.05	2	2
2	GS-pruned	-366.04	<b>0.244</b>	0.84	<b>0</b>	2	2
3	DGS	<b>-358</b>	<b>0.185</b>	0.84	0.12	2	2
3	DGS-clp	-358.5	<b>0.185</b>	0.84	0.12	2	2
3	GS-tw	-359.46	0.17	<b>0.845</b>	<b>0</b>	2	2
3	GS-clp	-361.47	<b>0.185</b>	0.84	<b>0</b>	2	2
3	GS-pruned	-359.46	0.17	<b>0.845</b>	0.07	2	2
4	DGS	<b>-361.4</b>	<b>0.296</b>	0.87	0.13	2	2
4	DGS-clp	-362.6	<b>0.296</b>	<b>0.866</b>	0.13	2	2
4	GS-tw	-365.01	0.28	0.85	<b>0.1</b>	2	2
4	GS-clp	-363.35	0.28	0.85	<b>0.1</b>	2	2
4	GS-pruned	-365.01	0.28	0.85	0.06	2	2
5	DGS	<b>-399.9</b>	<b>0.259</b>	<b>0.819</b>	0.12	2	2
5	DGS-clp	-400.81	<b>0.259</b>	<b>0.819</b>	0.12	2	2
5	GS-tw	-405.2	0.21	0.82	<b>0.1</b>	2	2
5	GS-clp	-400.49	0.25	<b>0.819</b>	<b>0.1</b>	2	2
5	GS-pruned	-405.2	0.21	0.82	0.06	2	2

Table 6: Comparison of the methods in dataset foodtruck in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-342.28	<b>0.317</b>	<b>0.852</b>	0.12	2	2
1	DGS-clp	-342.34	<b>0.317</b>	<b>0.852</b>	0.12	2	2
1	GS-tw	-341.1	0.29	0.85	0.06	2	2
1	GS-clp	<b>-339.6</b>	<b>0.317</b>	0.84	0.06	2	2
1	GS-pruned	-341.1	0.29	0.85	<b>0</b>	2	2
2	DGS	-363.21	<b>0.244</b>	0.84	0.12	2	2
2	DGS-clp	-364.11	<b>0.244</b>	0.84	0.12	2	2
2	GS-tw	-366.04	<b>0.244</b>	0.84	<b>0</b>	2	2
2	GS-clp	<b>-360.3</b>	0.23	<b>0.845</b>	<b>0</b>	2	2
2	GS-pruned	-366.04	<b>0.244</b>	0.84	0.06	2	2
3	DGS	<b>-358</b>	<b>0.185</b>	0.84	0.12	2	2
3	DGS-clp	-358.5	<b>0.185</b>	0.84	0.12	2	2
3	GS-tw	-359.46	0.17	<b>0.845</b>	0.05	2	2
3	GS-clp	-361.47	<b>0.185</b>	0.84	0.05	2	2
3	GS-pruned	-359.46	0.17	<b>0.845</b>	<b>0.1</b>	2	2
4	DGS	<b>-360.4</b>	<b>0.296</b>	0.87	0.13	3	3
4	DGS-clp	-361.78	<b>0.296</b>	<b>0.866</b>	0.13	3	3
4	GS-tw	-364.03	0.28	0.85	0.06	3	3
4	GS-clp	-362.48	0.28	0.85	0.06	3	3
4	GS-pruned	-364.03	0.28	0.85	<b>0.1</b>	3	3
5	DGS	<b>-399.9</b>	<b>0.259</b>	<b>0.819</b>	0.12	2	2
5	DGS-clp	-400.81	<b>0.259</b>	<b>0.819</b>	0.12	2	2
5	GS-tw	-405.2	0.21	0.82	<b>0.1</b>	2	2
5	GS-clp	-400.49	0.25	<b>0.819</b>	<b>0.1</b>	2	2
5	GS-pruned	-405.2	0.21	0.82	0.06	2	2

Table 7: Comparison of the methods in dataset foodtruck in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-342.28	<b>0.317</b>	<b>0.852</b>	0.12	2	2
1	DGS-clp	-342.34	<b>0.317</b>	<b>0.852</b>	0.12	2	2
1	GS-tw	-341.1	0.29	0.85	0.05	2	2
1	GS-clp	<b>-339.6</b>	<b>0.317</b>	0.84	0.05	2	2
1	GS-pruned	-341.1	0.29	0.85	<b>0</b>	2	2
2	DGS	-363.21	<b>0.244</b>	0.84	0.11	2	2
2	DGS-clp	-364.11	<b>0.244</b>	0.84	0.11	2	2
2	GS-tw	-366.04	<b>0.244</b>	0.84	<b>0</b>	2	2
2	GS-clp	<b>-360.3</b>	0.23	<b>0.845</b>	<b>0</b>	2	2
2	GS-pruned	-366.04	<b>0.244</b>	0.84	0.05	2	2
3	DGS	<b>-358</b>	<b>0.185</b>	0.84	0.13	2	2
3	DGS-clp	-358.5	<b>0.185</b>	0.84	0.13	2	2
3	GS-tw	-359.46	0.17	<b>0.845</b>	<b>0</b>	2	2
3	GS-clp	-361.47	<b>0.185</b>	0.84	<b>0</b>	2	2
3	GS-pruned	-359.46	0.17	<b>0.845</b>	0.06	2	2
4	DGS	<b>-360.4</b>	<b>0.296</b>	0.87	0.13	3	3
4	DGS-clp	-361.78	<b>0.296</b>	<b>0.866</b>	0.13	3	3
4	GS-tw	-364.03	0.28	0.85	<b>0.1</b>	3	3
4	GS-clp	-362.48	0.28	0.85	<b>0.1</b>	3	3
4	GS-pruned	-364.03	0.28	0.85	0.07	3	3
5	DGS	<b>-399.9</b>	<b>0.259</b>	<b>0.819</b>	0.12	2	2
5	DGS-clp	-400.81	<b>0.259</b>	<b>0.819</b>	0.12	2	2
5	GS-tw	-405.2	0.21	0.82	0.07	2	2
5	GS-clp	-400.49	0.25	<b>0.819</b>	0.07	2	2
5	GS-pruned	-405.2	0.21	0.82	<b>0.1</b>	2	2



Table 8: Comparison of the methods in dataset foodtruck in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-342.28	<b>0.317</b>	<b>0.852</b>	0.13	2	2
1	DGS-clp	-342.34	<b>0.317</b>	<b>0.852</b>	0.13	2	2
1	GS-tw	-341.1	0.29	0.85	0.06	2	2
1	GS-clp	<b>-339.6</b>	<b>0.317</b>	0.84	0.06	2	2
1	GS-pruned	-341.1	0.29	0.85	<b>0</b>	2	2
2	DGS	-363.21	<b>0.244</b>	0.84	0.12	2	2
2	DGS-clp	-364.11	<b>0.244</b>	0.84	0.12	2	2
2	GS-tw	-366.04	<b>0.244</b>	0.84	<b>0</b>	2	2
2	GS-clp	<b>-360.3</b>	0.23	<b>0.845</b>	<b>0</b>	2	2
2	GS-pruned	-366.04	<b>0.244</b>	0.84	0.05	2	2
3	DGS	<b>-358</b>	<b>0.185</b>	0.84	0.16	2	2
3	DGS-clp	-358.5	<b>0.185</b>	0.84	0.16	2	2
3	GS-tw	-359.46	0.17	<b>0.845</b>	<b>0</b>	2	2
3	GS-clp	-361.47	<b>0.185</b>	0.84	<b>0</b>	2	2
3	GS-pruned	-359.46	0.17	<b>0.845</b>	0.05	2	2
4	DGS	<b>-360.4</b>	<b>0.296</b>	0.87	0.12	3	3
4	DGS-clp	-361.78	<b>0.296</b>	<b>0.866</b>	0.12	3	3
4	GS-tw	-364.03	0.28	0.85	<b>0.1</b>	3	3
4	GS-clp	-362.48	0.28	0.85	<b>0.1</b>	3	3
4	GS-pruned	-364.03	0.28	0.85	0.08	3	3
5	DGS	<b>-399.9</b>	<b>0.259</b>	<b>0.819</b>	0.13	2	2
5	DGS-clp	-400.81	<b>0.259</b>	<b>0.819</b>	0.13	2	2
5	GS-tw	-405.2	0.21	0.82	0.06	2	2
5	GS-clp	-400.49	0.25	<b>0.819</b>	0.06	2	2
5	GS-pruned	-405.2	0.21	0.82	<b>0.1</b>	2	2

Table 9: Comparison of the methods in dataset birds in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-464.69	0.39	0.94	<b>4.3</b>	1	1
1	DGS-clp	<b>-463.2</b>	0.4	0.93	<b>4.3</b>	1	1
1	GS-tw	-764.85	0.39	0.93	8.02	2	2
1	GS-clp	-473.46	<b>0.419</b>	<b>0.939</b>	8.02	2	2
1	GS-pruned	-483.23	0.4	0.94	6.2	3	2
2	DGS	-432.34	0.47	0.95	<b>4.8</b>	1	1
2	DGS-clp	<b>-426.3</b>	0.43	0.95	<b>4.8</b>	1	1
2	GS-tw	-683.37	0.46	0.94	7.23	2	2
2	GS-clp	-439.78	<b>0.481</b>	<b>0.951</b>	7.23	2	2
2	GS-pruned	-451.61	0.42	0.95	6.39	3	1
3	DGS	<b>-414.8</b>	<b>0.45</b>	<b>0.944</b>	<b>4.9</b>	1	1
3	DGS-clp	-415.49	0.43	0.94	<b>4.9</b>	1	1
3	GS-tw	-629.66	0.44	0.93	7.12	2	2
3	GS-clp	-427.4	<b>0.45</b>	0.94	7.12	2	2
3	GS-pruned	-456.72	0.4	0.94	6.67	3	2
4	DGS	-364.14	0.55	<b>0.959</b>	<b>4.4</b>	2	1
4	DGS-clp	<b>-359.2</b>	0.55	0.96	<b>4.4</b>	2	1
4	GS-tw	-657.38	0.51	0.94	6.64	2	2
4	GS-clp	-381.86	<b>0.558</b>	<b>0.959</b>	6.64	2	2
4	GS-pruned	-396.29	0.53	0.96	6.28	3	2
5	DGS	<b>-371.8</b>	0.52	0.95	<b>4.4</b>	1	1
5	DGS-clp	-373.13	0.52	0.96	<b>4.4</b>	1	1
5	GS-tw	-615.19	0.45	0.93	6.8	2	2
5	GS-clp	-385.61	<b>0.55</b>	<b>0.956</b>	6.8	2	2
5	GS-pruned	-394.88	0.49	0.95	6.32	3	2

Table 10: Comparison of the methods in dataset birds in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-464.69	0.39	0.94	<b>4.3</b>	1	1
1	DGS-clp	<b>-463.2</b>	<b>0.403</b>	0.93	<b>4.3</b>	1	1
1	GS-tw	-493.39	0.36	0.94	7.81	3	3
1	GS-clp	-463.37	<b>0.403</b>	<b>0.938</b>	7.81	3	3
1	GS-pruned	-472.5	0.4	0.94	6.5	3	3
2	DGS	-432.34	0.47	0.95	<b>4.9</b>	1	1
2	DGS-clp	<b>-426.3</b>	0.43	0.95	<b>4.9</b>	1	1
2	GS-tw	-473.13	<b>0.481</b>	0.94	7.82	3	2
2	GS-clp	-440.55	0.44	<b>0.948</b>	7.82	3	2
2	GS-pruned	-447.78	0.44	0.95	8.09	3	3
3	DGS	<b>-414.8</b>	0.45	0.94	<b>5.7</b>	1	1
3	DGS-clp	-415.49	0.43	0.94	<b>5.7</b>	1	1
3	GS-tw	-433.59	<b>0.473</b>	0.94	8.36	3	2
3	GS-clp	-419.36	0.44	<b>0.947</b>	8.36	3	2
3	GS-pruned	-434.36	0.44	0.94	7.69	3	2
4	DGS	-364.14	0.55	<b>0.959</b>	<b>5.6</b>	2	1
4	DGS-clp	<b>-359.2</b>	0.55	0.96	<b>5.6</b>	2	1
4	GS-tw	-422.26	0.52	0.95	9.38	3	2
4	GS-clp	-377.26	<b>0.558</b>	0.96	9.38	3	2
4	GS-pruned	-393.49	0.52	0.96	6.83	4	2
5	DGS	<b>-371.8</b>	0.52	0.95	<b>4.4</b>	1	1
5	DGS-clp	-373.13	0.52	<b>0.955</b>	<b>4.4</b>	1	1
5	GS-tw	-426.54	<b>0.535</b>	0.95	7.84	3	2
5	GS-clp	-395.78	0.53	0.95	7.84	3	2
5	GS-pruned	-400.2	0.52	0.95	6.49	4	2

Table 11: Comparison of the methods in dataset birds in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-464.69	0.39	0.94	<b>4.4</b>	1	1
1	DGS-clp	<b>-463.2</b>	<b>0.403</b>	0.93	<b>4.4</b>	1	1
1	GS-tw	-472.5	0.4	0.94	7.46	3	2
1	GS-clp	-468	<b>0.403</b>	<b>0.94</b>	7.46	3	2
1	GS-pruned	-472.5	0.4	0.94	7.11	3	3
2	DGS	-432.34	<b>0.473</b>	<b>0.948</b>	<b>4.8</b>	1	1
2	DGS-clp	<b>-426.3</b>	0.43	<b>0.948</b>	<b>4.8</b>	1	1
2	GS-tw	-443.88	0.44	0.95	7.65	3	2
2	GS-clp	-440.34	0.43	0.95	7.65	3	2
2	GS-pruned	-447.78	0.44	0.95	7.04	3	3
3	DGS	<b>-414.8</b>	<b>0.45</b>	0.94	<b>5.6</b>	1	1
3	DGS-clp	-415.49	0.43	0.94	<b>5.6</b>	1	1
3	GS-tw	-434.81	0.43	0.94	7.64	4	2
3	GS-clp	-432.79	0.43	0.94	7.64	4	2
3	GS-pruned	-434.36	0.44	<b>0.945</b>	6.36	3	2
4	DGS	-364.14	0.55	<b>0.959</b>	<b>4.7</b>	2	1
4	DGS-clp	<b>-359.2</b>	0.55	0.96	<b>4.7</b>	2	1
4	GS-tw	-393.49	0.52	0.96	7.55	4	2
4	GS-clp	-371.88	<b>0.566</b>	0.96	7.55	4	2
4	GS-pruned	-393.49	0.52	0.96	7.18	4	2
5	DGS	<b>-371.8</b>	<b>0.519</b>	0.95	<b>4.5</b>	1	1
5	DGS-clp	-373.13	<b>0.519</b>	<b>0.955</b>	<b>4.5</b>	1	1
5	GS-tw	-400.2	<b>0.519</b>	0.95	8.54	4	2
5	GS-clp	-396.89	0.51	0.95	8.54	4	2
5	GS-pruned	-400.2	<b>0.519</b>	0.95	6.5	4	2

Table 12: Comparison of the methods in dataset birds in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-464.69	0.39	0.94	<b>4.3</b>	1	1
1	DGS-clp	<b>-463.2</b>	<b>0.403</b>	0.93	<b>4.3</b>	1	1
1	GS-tw	-472.5	0.4	0.94	7.47	3	2
1	GS-clp	-468	<b>0.403</b>	<b>0.94</b>	7.47	3	2
1	GS-pruned	-472.5	0.4	0.94	6.73	3	3
2	DGS	-432.34	<b>0.473</b>	<b>0.948</b>	<b>4.7</b>	1	1
2	DGS-clp	<b>-426.3</b>	0.43	<b>0.948</b>	<b>4.7</b>	1	1
2	GS-tw	-447.78	0.44	0.95	7.78	3	2
2	GS-clp	-444.87	0.43	0.95	7.78	3	2
2	GS-pruned	-447.78	0.44	0.95	6.53	3	3
3	DGS	<b>-414.8</b>	<b>0.45</b>	0.94	<b>5.5</b>	1	1
3	DGS-clp	-415.49	0.43	0.94	<b>5.5</b>	1	1
3	GS-tw	-434.36	0.44	<b>0.945</b>	7.89	4	2
3	GS-clp	-434.4	0.42	0.94	7.89	4	2
3	GS-pruned	-434.36	0.44	<b>0.945</b>	6.81	3	2
4	DGS	-364.14	0.55	<b>0.959</b>	<b>4.5</b>	2	1
4	DGS-clp	<b>-359.2</b>	0.55	0.96	<b>4.5</b>	2	1
4	GS-tw	-393.49	0.52	0.96	7.7	4	2
4	GS-clp	-371.88	<b>0.566</b>	0.96	7.7	4	2
4	GS-pruned	-393.49	0.52	0.96	6.26	4	2
5	DGS	<b>-371.8</b>	<b>0.519</b>	0.95	<b>4.5</b>	1	1
5	DGS-clp	-373.13	<b>0.519</b>	<b>0.955</b>	<b>4.5</b>	1	1
5	GS-tw	-400.2	<b>0.519</b>	0.95	8.84	4	2
5	GS-clp	-396.89	0.51	0.95	8.84	4	2
5	GS-pruned	-400.2	<b>0.519</b>	0.95	6.58	4	2

Table 13: Comparison of the methods in dataset scene in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-674.62	<b>0.6</b>	<b>0.897</b>	16.15	2	2
1	DGS-clp	<b>-643.3</b>	0.59	0.9	16.15	2	2
1	GS-tw	-3190.74	0.51	0.86	<b>11.8</b>	2	2
1	GS-clp	-1326.52	0.53	0.88	<b>11.8</b>	2	2
1	GS-pruned	-799.89	0.43	0.88	24.99	20	2
2	DGS	-813.7	0.53	0.88	17.53	2	2
2	DGS-clp	<b>-719.5</b>	<b>0.558</b>	<b>0.889</b>	17.53	2	2
2	GS-tw	-2629.79	0.48	0.86	<b>11.8</b>	2	2
2	GS-clp	-1242.91	0.5	0.86	<b>11.8</b>	2	2
2	GS-pruned	-882.71	0.45	0.86	21.39	17	2
3	DGS	-643.25	<b>0.613</b>	0.9	20.16	2	2
3	DGS-clp	<b>-615.2</b>	0.6	<b>0.899</b>	20.16	2	2
3	GS-tw	-3140.02	0.42	0.85	<b>12.2</b>	2	2
3	GS-clp	-1328.36	0.48	0.87	<b>12.2</b>	2	2
3	GS-pruned	-866.79	0.45	0.86	25.96	13	2
4	DGS	-686.13	0.61	0.89	19.57	2	2
4	DGS-clp	<b>-641.5</b>	<b>0.628</b>	<b>0.897</b>	19.57	2	2
4	GS-tw	-4030.28	0.41	0.84	<b>12.4</b>	2	2
4	GS-clp	-1161.97	0.51	0.87	<b>12.4</b>	2	2
4	GS-pruned	-815.36	0.47	0.87	22.82	16	2
5	DGS	-660.32	0.57	0.89	19.08	2	2
5	DGS-clp	<b>-634</b>	<b>0.599</b>	<b>0.897</b>	19.08	2	2
5	GS-tw	-3049.73	0.48	0.86	<b>12.4</b>	2	2
5	GS-clp	-1075.31	0.56	0.88	<b>12.4</b>	2	2
5	GS-pruned	-800.85	0.41	0.87	27.73	20	2

Table 14: Comparison of the methods in dataset scene in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-618.2	0.61	<b>0.899</b>	<b>17.7</b>	3	3
1	DGS-clp	<b>-594</b>	<b>0.616</b>	0.9	<b>17.7</b>	3	3
1	GS-tw	-1558.1	0.51	0.88	23.86	3	3
1	GS-clp	-737.24	0.55	0.88	23.86	3	3
1	GS-pruned	-733.82	0.49	0.88	22.92	21	3
2	DGS	-813.7	0.53	0.88	<b>18.7</b>	2	2
2	DGS-clp	<b>-719.5</b>	<b>0.558</b>	<b>0.889</b>	<b>18.7</b>	2	2
2	GS-tw	-1356.8	0.51	0.87	24.01	3	3
2	GS-clp	-801.73	0.55	0.88	24.01	3	3
2	GS-pruned	-842.93	0.45	0.86	27.15	17	3
3	DGS	-631.4	<b>0.626</b>	<b>0.901</b>	<b>18.1</b>	3	3
3	DGS-clp	<b>-605.8</b>	0.62	0.9	<b>18.1</b>	3	3
3	GS-tw	-1562.19	0.49	0.87	22.82	3	3
3	GS-clp	-758.8	0.52	0.88	22.82	3	3
3	GS-pruned	-773.21	0.49	0.87	25.7	22	3
4	DGS	-655.5	<b>0.632</b>	<b>0.899</b>	<b>18.5</b>	3	3
4	DGS-clp	<b>-623.5</b>	0.62	0.9	<b>18.5</b>	3	3
4	GS-tw	-1395.93	0.5	0.87	24.01	3	3
4	GS-clp	-758.86	0.55	0.88	24.01	3	3
4	GS-pruned	-726.98	0.54	0.88	22.93	15	3
5	DGS	-648.42	<b>0.599</b>	<b>0.894</b>	<b>17.4</b>	3	3
5	DGS-clp	<b>-630.7</b>	0.57	0.89	<b>17.4</b>	3	3
5	GS-tw	-1285.26	0.51	0.86	24.05	3	3
5	GS-clp	-738.85	0.53	0.87	24.05	3	3
5	GS-pruned	-750.37	0.46	0.86	23.8	21	3

Table 15: Comparison of the methods in dataset scene in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $\text{acc}_G$ ), the mean accuracy ( $\text{acc}_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$\text{acc}_G$	$\text{acc}_M$	time	tw	tw-pr
1	DGS	-625.01	<b>0.612</b>	<b>0.893</b>	<b>17.9</b>	4	4
1	DGS-clp	<b>-590.7</b>	<b>0.612</b>	0.89	<b>17.9</b>	4	4
1	GS-tw	-663.62	0.58	0.88	27.42	4	4
1	GS-clp	-656.09	0.55	0.88	27.42	4	4
1	GS-pruned	-678.54	0.53	0.88	24.42	20	4
2	DGS	-813.7	0.53	0.88	<b>18.4</b>	2	2
2	DGS-clp	-719.45	<b>0.558</b>	<b>0.889</b>	<b>18.4</b>	2	2
2	GS-tw	-756.76	0.51	0.86	26.66	4	4
2	GS-clp	<b>-699.3</b>	0.54	0.87	26.66	4	4
2	GS-pruned	-762.25	0.46	0.85	29.05	18	4
3	DGS	-631.4	<b>0.626</b>	<b>0.901</b>	<b>17.8</b>	3	3
3	DGS-clp	<b>-605.8</b>	0.62	0.9	<b>17.8</b>	3	3
3	GS-tw	-730.73	0.53	0.87	27.49	4	4
3	GS-clp	-678.2	0.55	0.88	27.49	4	4
3	GS-pruned	-703.37	0.55	0.87	24.96	17	4
4	DGS	-670.22	0.61	0.89	25.37	4	4
4	DGS-clp	<b>-604</b>	<b>0.626</b>	<b>0.896</b>	25.37	4	4
4	GS-tw	-667.99	0.58	0.88	25.65	4	4
4	GS-clp	-643.28	0.54	0.88	25.65	4	4
4	GS-pruned	-705.44	0.51	0.87	<b>23.3</b>	16	4
5	DGS	-574.27	<b>0.653</b>	0.9	<b>18.3</b>	4	4
5	DGS-clp	<b>-548</b>	0.64	<b>0.904</b>	<b>18.3</b>	4	4
5	GS-tw	-690.44	0.56	0.87	26.56	4	4
5	GS-clp	-669.79	0.54	0.87	26.56	4	4
5	GS-pruned	-708.94	0.57	0.87	26.72	22	4



Table 16: Comparison of the methods in dataset scene in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-625.01	0.61	<b>0.893</b>	<b>18.6</b>	4	4
1	DGS-clp	-590.68	0.61	0.89	<b>18.6</b>	4	4
1	GS-tw	<b>-566.4</b>	<b>0.639</b>	0.89	39.26	5	5
1	GS-clp	-581.01	0.61	0.88	39.26	5	5
1	GS-pruned	-590.17	0.62	0.88	25.07	20	5
2	DGS	-813.7	0.53	0.88	<b>19.9</b>	2	2
2	DGS-clp	-719.45	0.56	<b>0.889</b>	<b>19.9</b>	2	2
2	GS-tw	-645.7	0.58	0.87	29.56	5	5
2	GS-clp	<b>-616.1</b>	<b>0.604</b>	0.88	29.56	5	5
2	GS-pruned	-681.04	0.57	0.87	25.49	16	5
3	DGS	-631.4	<b>0.626</b>	<b>0.901</b>	<b>20.1</b>	3	3
3	DGS-clp	<b>-605.8</b>	0.62	0.9	<b>20.1</b>	3	3
3	GS-tw	-659.28	0.6	0.88	28.57	5	5
3	GS-clp	-665.85	0.58	0.87	28.57	5	5
3	GS-pruned	-670.17	0.58	0.87	25.43	18	5
4	DGS	-608.46	0.66	0.9	<b>18.8</b>	5	5
4	DGS-clp	<b>-527.1</b>	<b>0.672</b>	<b>0.898</b>	<b>18.8</b>	5	5
4	GS-tw	-587.14	0.63	0.89	32.9	5	5
4	GS-clp	-577.97	0.62	0.89	32.9	5	5
4	GS-pruned	-634.36	0.57	0.87	25.62	14	5
5	DGS	-574.27	<b>0.653</b>	0.9	<b>18.8</b>	4	4
5	DGS-clp	<b>-548</b>	0.64	<b>0.904</b>	<b>18.8</b>	4	4
5	GS-tw	-602.4	0.58	0.88	29.17	5	5
5	GS-clp	-591.39	0.58	0.88	29.17	5	5
5	GS-pruned	-623.14	0.58	0.87	27.33	22	5

Table 17: Comparison of the methods in dataset genbase in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-14.28	<b>0.985</b>	<b>0.999</b>	19.73	1	1
1	DGS-clp	<b>-3.8</b>	<b>0.985</b>	<b>0.999</b>	19.73	1	1
1	GS-tw	-19.79	<b>0.985</b>	1	<b>17.5</b>	2	2
1	GS-clp	-8.36	<b>0.985</b>	1	<b>17.5</b>	2	2
1	GS-pruned	-20.18	<b>0.985</b>	1	17.8	4	2
2	DGS	-31.35	<b>0.97</b>	1	19.58	1	1
2	DGS-clp	-42.69	<b>0.97</b>	1	19.58	1	1
2	GS-tw	-21.69	<b>0.97</b>	<b>0.999</b>	<b>17.8</b>	2	2
2	GS-clp	-35.97	<b>0.97</b>	1	<b>17.8</b>	2	2
2	GS-pruned	<b>-21.7</b>	<b>0.97</b>	<b>0.999</b>	18.28	4	2
3	DGS	-61.44	<b>0.962</b>	1	17.69	1	1
3	DGS-clp	-90.64	<b>0.962</b>	1	17.69	1	1
3	GS-tw	<b>-49.9</b>	0.95	1	<b>17.1</b>	2	2
3	GS-clp	-80.94	<b>0.962</b>	<b>0.998</b>	<b>17.1</b>	2	2
3	GS-pruned	-50.25	0.95	1	17.43	5	2
4	DGS	-24.61	<b>0.962</b>	<b>0.999</b>	18.6	2	1
4	DGS-clp	-25.92	<b>0.962</b>	<b>0.999</b>	18.6	2	1
4	GS-tw	<b>-19.5</b>	<b>0.962</b>	<b>0.999</b>	<b>16.7</b>	2	2
4	GS-clp	-31.44	<b>0.962</b>	<b>0.999</b>	<b>16.7</b>	2	2
4	GS-pruned	-20.1	<b>0.962</b>	<b>0.999</b>	17.05	5	2
5	DGS	-17.49	<b>0.985</b>	1	19.6	1	1
5	DGS-clp	-21.59	<b>0.985</b>	1	19.6	1	1
5	GS-tw	-12.11	<b>0.985</b>	1	<b>17.2</b>	2	2
5	GS-clp	<b>-12.1</b>	<b>0.985</b>	1	<b>17.2</b>	2	2
5	GS-pruned	-12.15	<b>0.985</b>	<b>1</b>	18.04	4	2

Table 18: Comparison of the methods in dataset genbase in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-14.28	<b>0.985</b>	<b>0.999</b>	19.76	1	1
1	DGS-clp	<b>-3.8</b>	<b>0.985</b>	<b>0.999</b>	19.76	1	1
1	GS-tw	-19.79	<b>0.985</b>	1	18.87	3	3
1	GS-clp	-9.88	<b>0.985</b>	1	18.87	3	3
1	GS-pruned	-19.79	<b>0.985</b>	1	<b>18.4</b>	3	3
2	DGS	-31.35	<b>0.97</b>	1	19.66	1	1
2	DGS-clp	-42.69	<b>0.97</b>	1	19.66	1	1
2	GS-tw	<b>-23.2</b>	<b>0.97</b>	<b>0.999</b>	20.86	3	3
2	GS-clp	-31.62	<b>0.97</b>	1	20.86	3	3
2	GS-pruned	-23.25	<b>0.97</b>	<b>0.999</b>	<b>18.6</b>	4	3
3	DGS	-61.44	<b>0.962</b>	1	18.25	1	1
3	DGS-clp	-90.64	<b>0.962</b>	1	18.25	1	1
3	GS-tw	<b>-50.2</b>	0.95	1	18.3	3	3
3	GS-clp	-71.64	<b>0.962</b>	<b>0.998</b>	18.3	3	3
3	GS-pruned	-50.21	0.95	1	<b>18.1</b>	5	3
4	DGS	-24.61	<b>0.962</b>	<b>0.999</b>	18.74	2	1
4	DGS-clp	-25.92	<b>0.962</b>	<b>0.999</b>	18.74	2	1
4	GS-tw	-20.04	<b>0.962</b>	<b>0.999</b>	<b>17.5</b>	3	3
4	GS-clp	-33.68	<b>0.962</b>	<b>0.999</b>	<b>17.5</b>	3	3
4	GS-pruned	<b>-20</b>	<b>0.962</b>	<b>0.999</b>	17.59	4	3
5	DGS	-17.49	<b>0.985</b>	1	19.98	1	1
5	DGS-clp	-21.59	<b>0.985</b>	1	19.98	1	1
5	GS-tw	<b>-12</b>	<b>0.985</b>	<b>1</b>	18.14	3	3
5	GS-clp	-14.28	<b>0.985</b>	1	18.14	3	3
5	GS-pruned	-12.09	<b>0.985</b>	<b>1</b>	<b>18.1</b>	4	3

Table 19: Comparison of the methods in dataset genbase in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-14.28	<b>0.985</b>	<b>0.999</b>	19.77	1	1
1	DGS-clp	<b>-3.8</b>	<b>0.985</b>	<b>0.999</b>	19.77	1	1
1	GS-tw	-19.86	<b>0.985</b>	1	18.87	4	4
1	GS-clp	-10.32	<b>0.985</b>	1	18.87	4	4
1	GS-pruned	-19.86	<b>0.985</b>	1	<b>18.8</b>	4	4
2	DGS	-31.35	<b>0.97</b>	1	19.45	1	1
2	DGS-clp	-42.69	<b>0.97</b>	1	19.45	1	1
2	GS-tw	<b>-23.3</b>	<b>0.97</b>	<b>0.999</b>	19.09	4	3
2	GS-clp	-41.76	<b>0.97</b>	1	19.09	4	3
2	GS-pruned	<b>-23.3</b>	<b>0.97</b>	<b>0.999</b>	<b>18.7</b>	4	3
3	DGS	-61.44	<b>0.962</b>	1	<b>18</b>	1	1
3	DGS-clp	-90.64	<b>0.962</b>	1	<b>18</b>	1	1
3	GS-tw	-49.29	0.95	1	18.24	4	3
3	GS-clp	-87.86	<b>0.962</b>	<b>0.998</b>	18.24	4	3
3	GS-pruned	<b>-49.3</b>	0.95	1	18.44	5	3
4	DGS	-24.61	<b>0.962</b>	<b>0.999</b>	18.75	2	1
4	DGS-clp	-25.92	<b>0.962</b>	<b>0.999</b>	18.75	2	1
4	GS-tw	-20.02	<b>0.962</b>	<b>0.999</b>	<b>17.5</b>	4	4
4	GS-clp	-49.4	<b>0.962</b>	<b>0.999</b>	<b>17.5</b>	4	4
4	GS-pruned	<b>-20</b>	<b>0.962</b>	<b>0.999</b>	18.02	5	4
5	DGS	-17.49	<b>0.985</b>	1	19.88	1	1
5	DGS-clp	-21.59	<b>0.985</b>	1	19.88	1	1
5	GS-tw	<b>-12.1</b>	<b>0.985</b>	<b>1</b>	18.53	4	3
5	GS-clp	-16.38	<b>0.985</b>	1	18.53	4	3
5	GS-pruned	<b>-12.1</b>	<b>0.985</b>	<b>1</b>	<b>18.4</b>	4	3

Table 20: Comparison of the methods in dataset genbase in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-14.28	<b>0.985</b>	<b>0.999</b>	19.57	1	1
1	DGS-clp	<b>-3.8</b>	<b>0.985</b>	<b>0.999</b>	19.57	1	1
1	GS-tw	-19.86	<b>0.985</b>	1	<b>18.6</b>	4	4
1	GS-clp	-10.32	<b>0.985</b>	1	<b>18.6</b>	4	4
1	GS-pruned	-19.86	<b>0.985</b>	1	18.71	4	4
2	DGS	-31.35	<b>0.97</b>	1	19.67	1	1
2	DGS-clp	-42.69	<b>0.97</b>	1	19.67	1	1
2	GS-tw	<b>-23.3</b>	<b>0.97</b>	<b>0.999</b>	18.83	4	3
2	GS-clp	-41.76	<b>0.97</b>	1	18.83	4	3
2	GS-pruned	<b>-23.3</b>	<b>0.97</b>	<b>0.999</b>	<b>18.7</b>	4	3
3	DGS	-61.44	<b>0.962</b>	1	<b>18</b>	1	1
3	DGS-clp	-90.64	<b>0.962</b>	1	<b>18</b>	1	1
3	GS-tw	<b>-49.3</b>	0.95	1	18.46	5	3
3	GS-clp	-87.07	<b>0.962</b>	<b>0.998</b>	18.46	5	3
3	GS-pruned	<b>-49.3</b>	0.95	1	18.48	5	3
4	DGS	-24.61	<b>0.962</b>	<b>0.999</b>	18.63	2	1
4	DGS-clp	-25.92	<b>0.962</b>	<b>0.999</b>	18.63	2	1
4	GS-tw	<b>-20</b>	<b>0.962</b>	<b>0.999</b>	17.95	5	4
4	GS-clp	-41.39	<b>0.962</b>	<b>0.999</b>	17.95	5	4
4	GS-pruned	<b>-20</b>	<b>0.962</b>	<b>0.999</b>	<b>17.9</b>	5	4
5	DGS	-17.49	<b>0.985</b>	1	19.79	1	1
5	DGS-clp	-21.59	<b>0.985</b>	1	19.79	1	1
5	GS-tw	<b>-12.1</b>	<b>0.985</b>	<b>1</b>	<b>18.2</b>	4	3
5	GS-clp	-16.38	<b>0.985</b>	1	<b>18.2</b>	4	3
5	GS-pruned	<b>-12.1</b>	<b>0.985</b>	<b>1</b>	18.2	4	3

Table 21: Comparison of the methods in dataset yeast in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-2192.33	0.14	0.78	2.84	2	2
1	DGS-clp	<b>-2173.3</b>	0.13	<b>0.784</b>	2.84	2	2
1	GS-tw	-2660.47	<b>0.143</b>	0.77	<b>1.9</b>	2	2
1	GS-clp	-2611.93	0.08	0.75	<b>1.9</b>	2	2
1	GS-pruned	-2260.46	0.12	0.78	2.4	5	2
2	DGS	-2098.62	0.17	0.79	2.59	2	2
2	DGS-clp	<b>-2089.3</b>	<b>0.178</b>	<b>0.791</b>	2.59	2	2
2	GS-tw	-2642.62	0.16	0.79	<b>1.7</b>	2	2
2	GS-clp	-2200.91	0.16	0.78	<b>1.7</b>	2	2
2	GS-pruned	-2185.57	0.17	0.79	2.43	6	2
3	DGS	-2137.6	0.16	0.79	2.7	2	2
3	DGS-clp	<b>-2111.1</b>	0.16	0.79	2.7	2	2
3	GS-tw	-2816.39	0.16	0.79	<b>1.7</b>	2	2
3	GS-clp	-2279.63	<b>0.18</b>	<b>0.798</b>	<b>1.7</b>	2	2
3	GS-pruned	-2182.17	0.12	0.78	2.3	4	2
4	DGS	-2194.79	0.12	0.78	2.5	2	2
4	DGS-clp	<b>-2182.1</b>	0.12	0.79	2.5	2	2
4	GS-tw	-2740.16	0.11	0.77	<b>2</b>	2	2
4	GS-clp	-2226.07	<b>0.128</b>	<b>0.788</b>	<b>2</b>	2	2
4	GS-pruned	-2270.94	0.09	0.77	2.36	5	2
5	DGS	-2089.25	<b>0.18</b>	0.79	2.45	2	2
5	DGS-clp	<b>-2078.1</b>	0.17	0.79	2.45	2	2
5	GS-tw	-2489.37	0.18	0.78	<b>1.6</b>	2	2
5	GS-clp	-2139.19	<b>0.18</b>	<b>0.79</b>	<b>1.6</b>	2	2
5	GS-pruned	-2115.9	<b>0.18</b>	0.79	2.5	6	2

Table 22: Comparison of the methods in dataset yeast in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-2045.9	0.19	0.78	2.83	3	3
1	DGS-clp	<b>-2018</b>	<b>0.194</b>	<b>0.78</b>	2.83	3	3
1	GS-tw	-2116.96	0.18	0.78	2.81	3	3
1	GS-clp	-2055.3	0.19	0.78	2.81	3	3
1	GS-pruned	-2109.76	0.17	0.77	<b>2.3</b>	6	3
2	DGS	-1984.15	<b>0.186</b>	0.79	2.78	3	3
2	DGS-clp	<b>-1969.7</b>	0.18	<b>0.795</b>	2.78	3	3
2	GS-tw	-2039.12	0.18	0.79	2.6	3	3
2	GS-clp	-1990.05	0.18	0.79	2.6	3	3
2	GS-pruned	-2036.01	0.18	0.78	<b>2.5</b>	5	3
3	DGS	-2017.79	0.18	<b>0.792</b>	2.95	3	3
3	DGS-clp	<b>-1988.3</b>	0.18	0.79	2.95	3	3
3	GS-tw	-2120.75	<b>0.19</b>	0.79	<b>2.3</b>	3	3
3	GS-clp	-1998.96	<b>0.19</b>	0.79	<b>2.3</b>	3	3
3	GS-pruned	-2058.6	0.17	0.78	2.38	5	3
4	DGS	-2008.69	<b>0.168</b>	0.78	2.77	3	3
4	DGS-clp	-2002.13	0.16	<b>0.784</b>	2.77	3	3
4	GS-tw	-2031.25	0.16	0.78	<b>2.3</b>	3	3
4	GS-clp	<b>-1997.6</b>	0.16	0.78	<b>2.3</b>	3	3
4	GS-pruned	-2066.41	0.15	0.78	2.55	6	3
5	DGS	-1979.35	0.2	0.79	2.64	3	3
5	DGS-clp	-1966.5	0.19	0.79	2.64	3	3
5	GS-tw	-1982.61	0.21	<b>0.795</b>	2.55	3	3
5	GS-clp	<b>-1947.1</b>	<b>0.217</b>	0.79	2.55	3	3
5	GS-pruned	-1964.74	0.2	0.79	<b>2.4</b>	6	3

Table 23: Comparison of the methods in dataset yeast in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-1998.73	0.19	0.78	3.2	4	4
1	DGS-clp	<b>-1973.6</b>	<b>0.205</b>	<b>0.783</b>	3.2	4	4
1	GS-tw	-2038.22	0.19	0.78	2.87	4	4
1	GS-clp	-2000.96	0.19	0.77	2.87	4	4
1	GS-pruned	-2030.35	0.19	0.78	<b>2.6</b>	6	4
2	DGS	-1962.04	<b>0.188</b>	0.79	2.97	4	4
2	DGS-clp	<b>-1947.8</b>	0.18	<b>0.794</b>	2.97	4	4
2	GS-tw	-2012.18	0.17	0.79	2.66	4	4
2	GS-clp	-1996.68	0.17	0.78	2.66	4	4
2	GS-pruned	-2015.46	0.18	0.78	<b>2.5</b>	5	4
3	DGS	-1980	<b>0.197</b>	0.79	3.04	4	4
3	DGS-clp	<b>-1955.5</b>	0.19	<b>0.794</b>	3.04	4	4
3	GS-tw	-2017.83	0.18	0.79	2.94	4	4
3	GS-clp	-1968.22	0.19	0.79	2.94	4	4
3	GS-pruned	-2023.37	0.18	0.78	<b>2.6</b>	5	4
4	DGS	-1973.53	<b>0.18</b>	0.79	2.85	4	4
4	DGS-clp	<b>-1966.7</b>	0.16	<b>0.786</b>	2.85	4	4
4	GS-tw	-2002.32	0.15	0.78	2.86	4	4
4	GS-clp	-1987.94	0.16	0.78	2.86	4	4
4	GS-pruned	-2038.18	0.15	0.77	<b>2.4</b>	5	4
5	DGS	-1927.96	0.19	<b>0.791</b>	3.13	4	4
5	DGS-clp	<b>-1910.8</b>	0.2	0.79	3.13	4	4
5	GS-tw	-1933.26	<b>0.209</b>	0.79	3.06	4	4
5	GS-clp	-1927.73	0.2	0.79	3.06	4	4
5	GS-pruned	-1934.79	0.2	0.79	<b>2.6</b>	6	4



Table 24: Comparison of the methods in dataset yeast in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-1979.19	0.2	0.78	3.52	5	5
1	DGS-clp	<b>-1955.7</b>	<b>0.213</b>	<b>0.783</b>	3.52	5	5
1	GS-tw	-2007.4	0.17	0.77	3.07	5	5
1	GS-clp	-1993.13	0.18	0.77	3.07	5	5
1	GS-pruned	-2023.76	0.18	0.77	<b>2.5</b>	6	5
2	DGS	-1962.04	<b>0.188</b>	0.79	3.2	4	4
2	DGS-clp	<b>-1947.8</b>	0.18	<b>0.794</b>	3.2	4	4
2	GS-tw	-2023.42	0.18	0.78	2.79	5	5
2	GS-clp	-2010.23	0.18	0.78	2.79	5	5
2	GS-pruned	-2023.37	0.18	0.78	<b>2.3</b>	5	5
3	DGS	-1976.93	<b>0.199</b>	0.79	3.54	5	5
3	DGS-clp	<b>-1952</b>	0.19	<b>0.795</b>	3.54	5	5
3	GS-tw	-2034.29	0.19	0.79	2.82	5	5
3	GS-clp	-1987.55	0.18	0.79	2.82	5	5
3	GS-pruned	-2031.61	0.18	0.78	<b>2.7</b>	5	5
4	DGS	-1955.15	<b>0.174</b>	<b>0.786</b>	3.04	5	5
4	DGS-clp	<b>-1948.8</b>	0.16	<b>0.786</b>	3.04	5	5
4	GS-tw	-1991.59	0.15	0.78	2.89	5	5
4	GS-clp	-1986.86	0.15	0.78	2.89	5	5
4	GS-pruned	-2018.41	0.15	0.77	<b>2.5</b>	6	5
5	DGS	-1922.15	0.19	<b>0.79</b>	2.89	5	5
5	DGS-clp	<b>-1903.6</b>	<b>0.203</b>	0.79	2.89	5	5
5	GS-tw	-1924.62	0.2	0.79	2.9	5	5
5	GS-clp	-1914.44	0.2	0.79	2.9	5	5
5	GS-pruned	-1930.62	<b>0.203</b>	0.79	<b>2.3</b>	6	5

Table 25: Comparison of the methods in dataset medical in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	<b>-297.1</b>	0.62	0.99	<b>88.5</b>	2	1
1	DGS-clp	-317.2	<b>0.663</b>	<b>0.989</b>	<b>88.5</b>	2	1
1	GS-tw	-459.99	0.55	0.99	182.41	2	2
1	GS-clp	-339.2	0.62	0.99	182.41	2	2
1	GS-pruned	-365.45	0.63	0.99	221.29	20	2
2	DGS	<b>-325.3</b>	0.67	0.99	<b>92.6</b>	2	1
2	DGS-clp	-327.56	<b>0.679</b>	<b>0.989</b>	<b>92.6</b>	2	1
2	GS-tw	-478.11	0.6	0.99	170.01	2	2
2	GS-clp	-368.45	0.62	0.99	170.01	2	2
2	GS-pruned	-343.09	0.61	0.99	203.29	18	2
3	DGS	<b>-249</b>	0.69	<b>0.991</b>	<b>97.1</b>	2	1
3	DGS-clp	-251.1	<b>0.704</b>	0.99	<b>97.1</b>	2	1
3	GS-tw	-376.55	0.6	0.99	188.42	2	2
3	GS-clp	-298.22	0.65	0.99	188.42	2	2
3	GS-pruned	-295.64	0.62	0.99	224.87	20	2
4	DGS	<b>-341.9</b>	0.59	0.99	<b>90.1</b>	2	2
4	DGS-clp	-376.74	0.59	0.99	<b>90.1</b>	2	2
4	GS-tw	-452.76	0.58	0.99	185.87	2	2
4	GS-clp	-382.54	0.58	0.99	185.87	2	2
4	GS-pruned	-377.71	<b>0.621</b>	<b>0.988</b>	237.23	19	2
5	DGS	<b>-277.7</b>	0.64	0.99	<b>89.9</b>	2	1
5	DGS-clp	-287.12	<b>0.682</b>	<b>0.99</b>	<b>89.9</b>	2	1
5	GS-tw	-378.15	0.62	0.99	181.93	2	2
5	GS-clp	-327.35	0.68	0.99	181.93	2	2
5	GS-pruned	-322.51	0.66	0.99	231.24	16	2

Table 26: Comparison of the methods in dataset medical in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	<b>-283.5</b>	0.65	0.99	<b>91.3</b>	3	2
1	DGS-clp	-291.64	<b>0.658</b>	0.99	<b>91.3</b>	3	2
1	GS-tw	-396.33	0.57	0.99	223.35	3	3
1	GS-clp	-368.83	0.64	<b>0.989</b>	223.35	3	3
1	GS-pruned	-361.57	0.61	0.99	241.87	20	3
2	DGS	<b>-308</b>	<b>0.663</b>	0.99	<b>91.9</b>	3	2
2	DGS-clp	-323.19	0.65	0.99	<b>91.9</b>	3	2
2	GS-tw	-384	0.62	0.99	212	3	3
2	GS-clp	-338.26	0.64	0.99	212	3	3
2	GS-pruned	-341.38	0.63	<b>0.988</b>	221.57	20	3
3	DGS	<b>-248.3</b>	0.69	<b>0.991</b>	<b>96.6</b>	3	1
3	DGS-clp	-251.98	<b>0.704</b>	0.99	<b>96.6</b>	3	1
3	GS-tw	-300.24	0.64	0.99	232.62	3	3
3	GS-clp	-319.13	0.62	0.99	232.62	3	3
3	GS-pruned	-298.75	0.65	0.99	245.04	22	3
4	DGS	<b>-331.2</b>	<b>0.605</b>	<b>0.988</b>	<b>92.3</b>	3	2
4	DGS-clp	-357.54	0.6	0.99	<b>92.3</b>	3	2
4	GS-tw	-432.17	0.57	0.99	231.52	3	3
4	GS-clp	-400.04	0.57	0.99	231.52	3	3
4	GS-pruned	-390.18	0.6	0.99	235.87	19	3
5	DGS	<b>-273.9</b>	0.64	0.99	<b>96.4</b>	3	1
5	DGS-clp	-289.16	<b>0.677</b>	<b>0.99</b>	<b>96.4</b>	3	1
5	GS-tw	-331.65	0.64	0.99	218.36	3	3
5	GS-clp	-333.48	0.65	0.99	218.36	3	3
5	GS-pruned	-329.74	0.63	0.99	231.44	16	3

Table 27: Comparison of the methods in dataset medical in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	<b>-283.5</b>	0.65	0.99	<b>93.7</b>	3	2
1	DGS-clp	-291.64	0.66	0.99	<b>93.7</b>	3	2
1	GS-tw	-386.58	0.58	0.99	220.73	4	3
1	GS-clp	-362.49	<b>0.658</b>	<b>0.989</b>	220.73	4	3
1	GS-pruned	-361.57	0.61	0.99	227.32	20	3
2	DGS	<b>-308</b>	<b>0.663</b>	0.99	<b>95.8</b>	3	2
2	DGS-clp	-323.19	0.65	0.99	<b>95.8</b>	3	2
2	GS-tw	-359.65	0.63	0.99	214.23	4	4
2	GS-clp	-375.46	0.63	0.99	214.23	4	4
2	GS-pruned	-342.07	0.63	<b>0.988</b>	209.79	20	4
3	DGS	<b>-248.3</b>	0.69	<b>0.991</b>	<b>99.1</b>	3	1
3	DGS-clp	-251.98	<b>0.704</b>	0.99	<b>99.1</b>	3	1
3	GS-tw	-302.69	0.65	0.99	226.99	4	3
3	GS-clp	-305.31	0.67	0.99	226.99	4	3
3	GS-pruned	-298.75	0.65	0.99	229.07	22	3
4	DGS	<b>-331.2</b>	<b>0.605</b>	<b>0.988</b>	<b>94.6</b>	3	2
4	DGS-clp	-357.54	0.6	0.99	<b>94.6</b>	3	2
4	GS-tw	-408.62	0.59	0.99	218.29	4	4
4	GS-clp	-398.08	0.6	0.99	218.29	4	4
4	GS-pruned	-394.87	0.6	0.99	227.9	19	4
5	DGS	<b>-273.9</b>	0.64	0.99	<b>95.5</b>	3	1
5	DGS-clp	-289.16	<b>0.677</b>	<b>0.99</b>	<b>95.5</b>	3	1
5	GS-tw	-324.49	0.63	0.99	213.73	4	3
5	GS-clp	-300.53	0.65	0.99	213.73	4	3
5	GS-pruned	-329.74	0.63	0.99	219.21	16	3

Table 28: Comparison of the methods in dataset medical in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	<b>-283.5</b>	0.65	0.99	<b>93.5</b>	3	2
1	DGS-clp	-291.64	<b>0.658</b>	<b>0.989</b>	<b>93.5</b>	3	2
1	GS-tw	-380.44	0.58	0.99	221.47	5	3
1	GS-clp	-356.73	0.65	0.99	221.47	5	3
1	GS-pruned	-361.57	0.61	0.99	230.65	20	3
2	DGS	<b>-308</b>	0.66	0.99	<b>91</b>	3	2
2	DGS-clp	-323.19	0.65	0.99	<b>91</b>	3	2
2	GS-tw	-352.29	0.63	0.99	216.3	5	4
2	GS-clp	-325.75	<b>0.668</b>	<b>0.989</b>	216.3	5	4
2	GS-pruned	-342.07	0.63	0.99	211.38	20	4
3	DGS	<b>-248.3</b>	0.69	<b>0.991</b>	<b>99.2</b>	3	1
3	DGS-clp	-251.98	<b>0.704</b>	0.99	<b>99.2</b>	3	1
3	GS-tw	-294.97	0.64	0.99	234.83	5	3
3	GS-clp	-313.04	0.68	0.99	234.83	5	3
3	GS-pruned	-298.75	0.65	0.99	230.21	22	3
4	DGS	<b>-331.2</b>	<b>0.605</b>	<b>0.988</b>	<b>93.9</b>	3	2
4	DGS-clp	-357.54	0.6	0.99	<b>93.9</b>	3	2
4	GS-tw	-405.3	0.59	0.99	223.41	5	3
4	GS-clp	-385.28	0.59	0.99	223.41	5	3
4	GS-pruned	-394.87	0.6	0.99	226.14	19	4
5	DGS	<b>-273.9</b>	0.64	0.99	<b>93.3</b>	3	1
5	DGS-clp	-289.16	<b>0.677</b>	<b>0.99</b>	<b>93.3</b>	3	1
5	GS-tw	-318.9	0.63	0.99	230.34	5	3
5	GS-clp	-302.74	0.67	0.99	230.34	5	3
5	GS-pruned	-329.74	0.63	0.99	217.13	16	3

Table 29: Comparison of the methods in dataset enron in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-2230	0.18	0.95	516.89	2	2
1	DGS-clp	<b>-2208.9</b>	<b>0.208</b>	<b>0.954</b>	516.89	2	2
1	GS-tw	-4945.07	0.16	0.95	<b>465.2</b>	2	2
1	GS-clp	-2509.63	0.15	0.95	<b>465.2</b>	2	2
1	GS-pruned	-2540.47	0.18	0.95	879.31	301	2
2	DGS	-2343.35	0.13	0.95	502.19	2	2
2	DGS-clp	<b>-2328.4</b>	0.12	<b>0.95</b>	502.19	2	2
2	GS-tw	-6225.88	0.12	0.95	<b>499.8</b>	2	2
2	GS-clp	-3354.15	0.12	0.95	<b>499.8</b>	2	2
2	GS-pruned	-2601.76	<b>0.138</b>	0.95	865.86	290	2
3	DGS	-2598.96	0.12	0.95	525.1	2	2
3	DGS-clp	<b>-2585</b>	0.13	<b>0.948</b>	525.1	2	2
3	GS-tw	-6974.26	0.12	0.95	<b>466.3</b>	2	2
3	GS-clp	-2786.05	0.13	0.94	<b>466.3</b>	2	2
3	GS-pruned	-2955.42	<b>0.147</b>	0.95	832.53	285	2
4	DGS	-2369	0.13	<b>0.951</b>	527.42	2	2
4	DGS-clp	<b>-2362.3</b>	0.13	0.95	527.42	2	2
4	GS-tw	-5536.03	0.13	0.95	<b>502.1</b>	2	2
4	GS-clp	-3175.06	0.11	0.94	<b>502.1</b>	2	2
4	GS-pruned	-2640.17	<b>0.138</b>	0.95	852.39	321	2
5	DGS	-2481.97	0.14	0.95	511.71	2	2
5	DGS-clp	<b>-2468.7</b>	<b>0.153</b>	<b>0.951</b>	511.71	2	2
5	GS-tw	-6744.56	0.12	0.95	<b>470.6</b>	2	2
5	GS-clp	-3092.26	0.12	0.95	<b>470.6</b>	2	2
5	GS-pruned	-3112.37	0.14	0.95	817.18	280	2

Table 30: Comparison of the methods in dataset enron in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-2228.26	0.18	0.95	<b>566</b>	3	3
1	DGS-clp	<b>-2206.5</b>	<b>0.208</b>	<b>0.954</b>	<b>566</b>	3	3
1	GS-tw	-3546.09	0.18	0.95	737.09	3	3
1	GS-clp	-2506.06	0.17	0.95	737.09	3	3
1	GS-pruned	-2487.65	0.19	0.95	861.36	278	3
2	DGS	-2320.67	0.12	0.95	<b>589.1</b>	3	3
2	DGS-clp	<b>-2300.6</b>	0.12	<b>0.951</b>	<b>589.1</b>	3	3
2	GS-tw	-3954.07	<b>0.138</b>	0.95	694.1	3	3
2	GS-clp	-2972.07	0.12	0.95	694.1	3	3
2	GS-pruned	-2668.47	0.13	0.95	892.97	306	3
3	DGS	-2581.5	0.14	0.95	<b>565</b>	3	3
3	DGS-clp	<b>-2571.4</b>	0.13	<b>0.948</b>	<b>565</b>	3	3
3	GS-tw	-4502.73	0.13	0.95	649.7	3	3
3	GS-clp	-3464.55	0.13	0.94	649.7	3	3
3	GS-pruned	-2976.54	<b>0.147</b>	0.95	858.14	295	3
4	DGS	-2334.63	0.14	<b>0.95</b>	<b>578</b>	3	3
4	DGS-clp	<b>-2325.6</b>	0.14	0.95	<b>578</b>	3	3
4	GS-tw	-3371.59	<b>0.162</b>	0.95	687.44	3	3
4	GS-clp	-2875.02	0.12	0.95	687.44	3	3
4	GS-pruned	-2669.71	0.15	0.95	868.05	302	3
5	DGS	-2450.76	0.15	0.95	<b>555.8</b>	3	3
5	DGS-clp	<b>-2436.6</b>	<b>0.153</b>	<b>0.952</b>	<b>555.8</b>	3	3
5	GS-tw	-5049.49	0.12	0.95	629.29	3	3
5	GS-clp	-2770.65	0.12	0.95	629.29	3	3
5	GS-pruned	-3085.85	0.13	0.95	830.34	286	3

Table 31: Comparison of the methods in dataset enron in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-2185.81	0.2	0.95	<b>643.1</b>	4	4
1	DGS-clp	<b>-2163.9</b>	<b>0.226</b>	<b>0.954</b>	<b>643.1</b>	4	4
1	GS-tw	-3171.39	0.19	0.95	680.08	4	4
1	GS-clp	-2527.01	0.17	0.95	680.08	4	4
1	GS-pruned	-2436.24	0.2	0.95	889.45	287	4
2	DGS	-2320.25	0.12	0.95	<b>635</b>	4	4
2	DGS-clp	<b>-2299.1</b>	0.13	<b>0.951</b>	<b>635</b>	4	4
2	GS-tw	-3709.44	<b>0.141</b>	0.95	680.87	4	4
2	GS-clp	-2808.06	0.1	0.95	680.87	4	4
2	GS-pruned	-2660.41	0.13	0.95	888.34	312	4
3	DGS	-2578.17	0.14	0.95	644.82	4	4
3	DGS-clp	<b>-2569.6</b>	0.14	<b>0.948</b>	644.82	4	4
3	GS-tw	-4157.39	0.13	0.95	<b>631.3</b>	4	4
3	GS-clp	-2993.42	0.14	<b>0.948</b>	<b>631.3</b>	4	4
3	GS-pruned	-2941.35	<b>0.147</b>	0.95	867.92	288	4
4	DGS	-2335.72	0.14	0.95	<b>633</b>	4	4
4	DGS-clp	<b>-2326.1</b>	<b>0.15</b>	0.95	<b>633</b>	4	4
4	GS-tw	-3008.88	0.14	0.95	687.45	4	4
4	GS-clp	-2483.79	0.13	<b>0.951</b>	687.45	4	4
4	GS-pruned	-2646.01	<b>0.15</b>	0.95	903.22	299	4
5	DGS	-2416.73	0.14	0.95	<b>625.3</b>	4	4
5	DGS-clp	<b>-2405</b>	<b>0.153</b>	<b>0.95</b>	<b>625.3</b>	4	4
5	GS-tw	-4523.7	0.13	0.95	627.91	4	4
5	GS-clp	-3014.18	0.11	0.95	627.91	4	4
5	GS-pruned	-3075.93	0.14	0.95	849.94	272	4



Table 32: Comparison of the methods in dataset enron in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-2182.96	0.2	0.95	<b>685.1</b>	5	4
1	DGS-clp	<b>-2161.1</b>	<b>0.223</b>	<b>0.954</b>	<b>685.1</b>	5	4
1	GS-tw	-3075.4	0.19	0.95	729.43	5	5
1	GS-clp	-2485.14	0.2	0.95	729.43	5	5
1	GS-pruned	-2472.03	0.18	0.95	914.53	298	5
2	DGS	-2320.25	0.12	0.95	<b>686.1</b>	4	4
2	DGS-clp	<b>-2299.1</b>	0.13	<b>0.951</b>	<b>686.1</b>	4	4
2	GS-tw	-3450.06	<b>0.129</b>	0.95	693.06	5	5
2	GS-clp	-2784.21	0.12	0.95	693.06	5	5
2	GS-pruned	-2655.29	<b>0.129</b>	0.95	888.46	303	4
3	DGS	-2582.09	0.14	0.95	769.64	5	4
3	DGS-clp	<b>-2573.8</b>	0.14	0.95	769.64	5	4
3	GS-tw	-3944.27	0.14	0.94	<b>669</b>	5	5
3	GS-clp	-2943.77	0.14	<b>0.949</b>	<b>669</b>	5	5
3	GS-pruned	-2970.11	<b>0.147</b>	0.95	898.75	286	4
4	DGS	-2338.75	0.15	0.95	<b>728.8</b>	5	4
4	DGS-clp	<b>-2330.1</b>	0.15	<b>0.95</b>	<b>728.8</b>	5	4
4	GS-tw	-3002.33	<b>0.156</b>	0.95	759.91	5	5
4	GS-clp	-2686.29	0.12	0.95	759.91	5	5
4	GS-pruned	-2642.63	0.15	0.95	931.31	310	4
5	DGS	-2417.49	0.14	0.95	671.63	5	4
5	DGS-clp	<b>-2405.2</b>	<b>0.153</b>	<b>0.95</b>	671.63	5	4
5	GS-tw	-4351.29	0.13	0.95	<b>655.9</b>	5	5
5	GS-clp	-2888.93	0.13	0.95	<b>655.9</b>	5	5
5	GS-pruned	-3072.84	0.12	0.95	872.62	282	5

Table 33: Comparison of the methods in dataset ohsumed in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-10585.72	<b>0.239</b>	0.94	513.48	2	2
1	DGS-clp	<b>-10516.5</b>	0.23	0.94	513.48	2	2
1	GS-tw	-13210.81	0.2	0.94	<b>233.5</b>	2	2
1	GS-clp	-10683.48	0.23	0.94	<b>233.5</b>	2	2
1	GS-pruned	-10745.48	0.23	<b>0.945</b>	473.26	177	2
2	DGS	-10511	<b>0.239</b>	<b>0.944</b>	515.66	2	2
2	DGS-clp	<b>-10456.9</b>	0.24	0.94	515.66	2	2
2	GS-tw	-13114.68	0.2	0.94	<b>239.6</b>	2	2
2	GS-clp	-10613.86	0.23	0.94	<b>239.6</b>	2	2
2	GS-pruned	-10738.35	0.24	0.94	482.9	172	2
3	DGS	-10703.43	0.24	<b>0.944</b>	527.64	2	2
3	DGS-clp	<b>-10659.4</b>	<b>0.246</b>	0.94	527.64	2	2
3	GS-tw	-13287.28	0.21	0.94	<b>234.1</b>	2	2
3	GS-clp	-10801.13	0.23	0.94	<b>234.1</b>	2	2
3	GS-pruned	-10794.84	0.24	0.94	468.76	171	2
4	DGS	-10697.67	0.24	0.94	544.44	2	2
4	DGS-clp	<b>-10640.4</b>	0.24	<b>0.943</b>	544.44	2	2
4	GS-tw	-13091.09	0.21	0.94	<b>239.9</b>	2	2
4	GS-clp	-11199.58	0.23	0.94	<b>239.9</b>	2	2
4	GS-pruned	-10879.39	<b>0.239</b>	0.94	487.51	173	2
5	DGS	-10695.9	0.23	0.94	531.76	2	2
5	DGS-clp	<b>-10629</b>	0.23	<b>0.944</b>	531.76	2	2
5	GS-tw	-13430.92	0.21	0.94	<b>238</b>	2	2
5	GS-clp	-11380.13	0.22	0.94	<b>238</b>	2	2
5	GS-pruned	-10925.12	<b>0.239</b>	0.94	467.16	170	2

Table 34: Comparison of the methods in dataset ohsumed in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-10470.96	0.24	0.95	596.33	3	3
1	DGS-clp	<b>-10416.1</b>	0.24	0.95	596.33	3	3
1	GS-tw	-11908.4	0.22	0.94	<b>314.7</b>	3	3
1	GS-clp	-10789.73	<b>0.244</b>	0.94	<b>314.7</b>	3	3
1	GS-pruned	-10663.21	0.24	<b>0.945</b>	499.53	175	3
2	DGS	-10506.17	0.24	<b>0.944</b>	604.36	3	3
2	DGS-clp	<b>-10452.1</b>	0.24	0.94	604.36	3	3
2	GS-tw	-11638.21	0.23	0.94	<b>320.4</b>	3	3
2	GS-clp	-10525.21	0.24	0.94	<b>320.4</b>	3	3
2	GS-pruned	-10663.87	<b>0.246</b>	0.94	491.28	169	3
3	DGS	-10600.59	<b>0.251</b>	<b>0.945</b>	639.68	3	3
3	DGS-clp	<b>-10571.8</b>	<b>0.251</b>	0.94	639.68	3	3
3	GS-tw	-11994.52	0.22	0.94	<b>323.4</b>	3	3
3	GS-clp	-10879.78	0.23	0.94	<b>323.4</b>	3	3
3	GS-pruned	-10779.47	0.25	<b>0.945</b>	488.49	175	3
4	DGS	-10686.93	0.23	0.94	602.6	3	3
4	DGS-clp	<b>-10633.9</b>	0.23	0.94	602.6	3	3
4	GS-tw	-11902.49	0.23	0.94	<b>326.2</b>	3	3
4	GS-clp	-10876.01	0.24	<b>0.944</b>	<b>326.2</b>	3	3
4	GS-pruned	-10846.24	<b>0.242</b>	0.94	496.2	167	3
5	DGS	-10703.08	0.23	0.94	609.17	3	3
5	DGS-clp	<b>-10638.5</b>	0.23	<b>0.944</b>	609.17	3	3
5	GS-tw	-12153.04	0.22	0.94	<b>319.2</b>	3	3
5	GS-clp	-11089.49	0.23	0.94	<b>319.2</b>	3	3
5	GS-pruned	-10896.06	<b>0.244</b>	0.94	469.98	180	3

Table 35: Comparison of the methods in dataset ohsumed in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-10379.37	0.24	0.95	638.99	4	4
1	DGS-clp	<b>-10325.3</b>	0.24	0.95	638.99	4	4
1	GS-tw	-11508.74	0.23	0.94	<b>356.6</b>	4	4
1	GS-clp	-10663.18	<b>0.244</b>	0.94	<b>356.6</b>	4	4
1	GS-pruned	-10645.1	0.24	<b>0.945</b>	525.42	176	4
2	DGS	-10457.92	<b>0.248</b>	<b>0.944</b>	761.95	4	4
2	DGS-clp	<b>-10403</b>	0.24	0.94	761.95	4	4
2	GS-tw	-11495.26	0.24	0.94	<b>353.7</b>	4	4
2	GS-clp	-10736.82	0.24	0.94	<b>353.7</b>	4	4
2	GS-pruned	-10681.22	0.25	0.94	504.34	175	4
3	DGS	-10539.04	0.25	<b>0.945</b>	779.53	4	4
3	DGS-clp	<b>-10508.9</b>	<b>0.253</b>	0.94	779.53	4	4
3	GS-tw	-11634.14	0.23	0.94	<b>364.4</b>	4	4
3	GS-clp	-10691.9	0.24	0.94	<b>364.4</b>	4	4
3	GS-pruned	-10737.43	0.25	0.94	520.56	173	4
4	DGS	-10636.07	0.24	0.94	715.77	4	4
4	DGS-clp	<b>-10587.5</b>	0.23	0.94	715.77	4	4
4	GS-tw	-11554.26	0.24	0.94	<b>363.3</b>	4	4
4	GS-clp	-10654.76	0.24	<b>0.944</b>	<b>363.3</b>	4	4
4	GS-pruned	-10786.37	<b>0.254</b>	0.94	510.39	176	4
5	DGS	-10626.17	0.24	0.94	729.99	4	4
5	DGS-clp	<b>-10562.7</b>	0.24	0.94	729.99	4	4
5	GS-tw	-11673.81	0.24	0.94	<b>384.3</b>	4	4
5	GS-clp	-10846.8	0.25	0.94	<b>384.3</b>	4	4
5	GS-pruned	-10835.45	<b>0.252</b>	<b>0.944</b>	496.44	170	4

Table 36: Comparison of the methods in dataset ohsumed in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-10384.76	0.24	0.95	771.87	5	5
1	DGS-clp	<b>-10326.2</b>	0.24	0.95	771.87	5	5
1	GS-tw	-11287.85	0.23	0.94	<b>400.5</b>	5	5
1	GS-clp	-10443.61	<b>0.247</b>	0.95	<b>400.5</b>	5	5
1	GS-pruned	-10558.59	0.24	<b>0.946</b>	533.56	163	5
2	DGS	-10465.5	<b>0.253</b>	<b>0.944</b>	896.56	5	5
2	DGS-clp	<b>-10410.9</b>	0.25	0.94	896.56	5	5
2	GS-tw	-11265.4	0.24	0.94	<b>386.1</b>	5	5
2	GS-clp	-10560.3	0.25	0.94	<b>386.1</b>	5	5
2	GS-pruned	-10652.25	0.25	0.94	508	175	5
3	DGS	-10534.18	<b>0.251</b>	<b>0.945</b>	894.1	5	5
3	DGS-clp	<b>-10505.3</b>	0.25	0.94	894.1	5	5
3	GS-tw	-11471.09	0.23	0.94	<b>421.6</b>	5	5
3	GS-clp	-10605.64	0.24	0.94	<b>421.6</b>	5	5
3	GS-pruned	-10683.44	0.25	0.94	514.42	175	5
4	DGS	-10619.17	0.24	0.94	877.31	5	5
4	DGS-clp	<b>-10566.8</b>	0.24	0.94	877.31	5	5
4	GS-tw	-11437.73	0.24	0.94	<b>398.5</b>	5	5
4	GS-clp	-10642.31	<b>0.256</b>	<b>0.944</b>	<b>398.5</b>	5	5
4	GS-pruned	-10715.44	0.25	0.94	516.16	169	5
5	DGS	-10552.22	0.25	<b>0.944</b>	920.54	5	5
5	DGS-clp	<b>-10494.9</b>	0.24	<b>0.944</b>	920.54	5	5
5	GS-tw	-11597.13	0.24	0.94	<b>406.8</b>	5	5
5	GS-clp	-10788.52	0.24	0.94	<b>406.8</b>	5	5
5	GS-pruned	-10806.91	<b>0.25</b>	0.94	491.91	174	5

Table 37: Comparison of the methods in dataset reutersk500 in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-7006.06	0.03	0.99	14.96	2	2
1	DGS-clp	-7005.76	0.03	0.99	14.96	2	2
1	GS-tw	-7011.71	0.03	0.99	<b>8.1</b>	2	2
1	GS-clp	-7011.37	0.03	0.99	<b>8.1</b>	2	2
1	GS-pruned	<b>-7003.8</b>	<b>0.061</b>	<b>0.986</b>	8.05	3	2
2	DGS	-6863.31	0.03	0.99	15.1	2	2
2	DGS-clp	-6862.38	0.03	0.99	15.1	2	2
2	GS-tw	-6857.9	0.03	0.99	<b>8</b>	2	2
2	GS-clp	<b>-6856.9</b>	0.03	0.99	<b>8</b>	2	2
2	GS-pruned	-6862.44	<b>0.044</b>	<b>0.986</b>	8.07	4	2
3	DGS	<b>-6934.8</b>	<b>0.022</b>	<b>0.986</b>	15.39	2	2
3	DGS-clp	-6935.61	<b>0.022</b>	<b>0.986</b>	15.39	2	2
3	GS-tw	-6946.74	<b>0.022</b>	<b>0.986</b>	<b>8</b>	2	2
3	GS-clp	-6947.38	<b>0.022</b>	<b>0.986</b>	<b>8</b>	2	2
3	GS-pruned	-6947.91	0.01	0.99	8.09	3	2
4	DGS	-6988.74	0.03	0.99	14.96	2	2
4	DGS-clp	<b>-6988.6</b>	0.03	0.99	14.96	2	2
4	GS-tw	-6989.59	0.03	0.99	<b>7.8</b>	2	2
4	GS-clp	-6989.34	0.03	0.99	<b>7.8</b>	2	2
4	GS-pruned	-6990.22	<b>0.047</b>	<b>0.986</b>	7.84	4	2
5	DGS	-7068.12	<b>0.02</b>	<b>0.986</b>	16.13	2	2
5	DGS-clp	-7067.88	<b>0.02</b>	<b>0.986</b>	16.13	2	2
5	GS-tw	-7064.29	<b>0.02</b>	<b>0.986</b>	<b>8.5</b>	2	2
5	GS-clp	-7064	<b>0.02</b>	<b>0.986</b>	<b>8.5</b>	2	2
5	GS-pruned	<b>-7054.9</b>	0.02	0.99	8.71	4	2

Table 38: Comparison of the methods in dataset reutersk500 in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-6905.89	0.05	<b>0.986</b>	16.04	3	3
1	DGS-clp	-6902.71	0.05	<b>0.986</b>	16.04	3	3
1	GS-tw	-6898.37	0.05	<b>0.986</b>	<b>8.5</b>	3	3
1	GS-clp	-6894.58	0.05	<b>0.986</b>	<b>8.5</b>	3	3
1	GS-pruned	<b>-6876.6</b>	<b>0.066</b>	0.99	8.62	4	3
2	DGS	-6775.64	0.04	<b>0.986</b>	16.93	3	3
2	DGS-clp	-6769.52	0.04	<b>0.986</b>	16.93	3	3
2	GS-tw	-6776.23	0.05	<b>0.986</b>	<b>8.6</b>	3	3
2	GS-clp	-6769.78	0.04	<b>0.986</b>	<b>8.6</b>	3	3
2	GS-pruned	<b>-6767.4</b>	<b>0.062</b>	0.99	8.78	4	3
3	DGS	-6845.91	0.03	0.99	16.61	3	3
3	DGS-clp	-6840.59	0.03	0.99	16.61	3	3
3	GS-tw	-6852.63	0.04	0.99	<b>8.7</b>	3	3
3	GS-clp	-6846.91	0.03	<b>0.986</b>	<b>8.7</b>	3	3
3	GS-pruned	<b>-6840.5</b>	<b>0.054</b>	0.99	8.71	4	3
4	DGS	-6933.33	0.04	0.99	16.12	3	3
4	DGS-clp	-6930.54	0.04	0.99	16.12	3	3
4	GS-tw	-6928.91	<b>0.057</b>	0.99	<b>8</b>	3	3
4	GS-clp	<b>-6925.9</b>	0.04	0.99	<b>8</b>	3	3
4	GS-pruned	-6927.49	0.05	<b>0.986</b>	8.19	5	3
5	DGS	-6956.92	0.03	0.99	17.41	3	3
5	DGS-clp	-6958.15	0.03	0.99	17.41	3	3
5	GS-tw	-6959.44	0.03	<b>0.986</b>	8.94	3	3
5	GS-clp	-6959.69	0.03	<b>0.986</b>	8.94	3	3
5	GS-pruned	<b>-6936.3</b>	<b>0.045</b>	0.99	<b>8.9</b>	5	3

Table 39: Comparison of the methods in dataset reutersk500 in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-6829.29	0.06	0.99	16.7	4	4
1	DGS-clp	-6827.11	0.07	0.99	16.7	4	4
1	GS-tw	-6829.82	0.05	0.99	<b>8.8</b>	4	4
1	GS-clp	-6826.43	0.05	<b>0.986</b>	<b>8.8</b>	4	4
1	GS-pruned	<b>-6818.5</b>	<b>0.072</b>	0.99	8.88	5	4
2	DGS	-6720.48	0.08	0.99	17.38	4	4
2	DGS-clp	-6719.38	0.06	0.99	17.38	4	4
2	GS-tw	-6708.65	<b>0.084</b>	<b>0.986</b>	<b>8.7</b>	4	4
2	GS-clp	<b>-6703.2</b>	0.07	<b>0.986</b>	<b>8.7</b>	4	4
2	GS-pruned	-6703.77	0.06	<b>0.986</b>	8.96	5	4
3	DGS	-6766.23	0.08	0.99	17.27	4	4
3	DGS-clp	-6767.42	0.06	0.99	17.27	4	4
3	GS-tw	-6780.41	<b>0.081</b>	<b>0.986</b>	<b>8.8</b>	4	4
3	GS-clp	-6777.84	0.05	<b>0.986</b>	<b>8.8</b>	4	4
3	GS-pruned	<b>-6757.3</b>	0.06	0.99	9.01	5	4
4	DGS	-6889.86	0.07	0.99	16.67	4	4
4	DGS-clp	-6887.8	0.06	0.99	16.67	4	4
4	GS-tw	-6845.49	0.07	<b>0.986</b>	<b>8.5</b>	4	4
4	GS-clp	<b>-6841.5</b>	<b>0.074</b>	<b>0.986</b>	<b>8.5</b>	4	4
4	GS-pruned	-6844.63	0.06	0.99	8.63	5	4
5	DGS	-6875.33	<b>0.065</b>	0.99	18.19	4	4
5	DGS-clp	-6874.72	0.05	0.99	18.19	4	4
5	GS-tw	-6864.08	0.06	0.99	<b>9.2</b>	4	4
5	GS-clp	-6865.68	0.02	<b>0.986</b>	<b>9.2</b>	4	4
5	GS-pruned	<b>-6854.4</b>	0.06	0.99	9.37	5	4



Table 40: Comparison of the methods in dataset reutersk500 in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-6794.44	0.08	0.99	17.98	5	5
1	DGS-clp	<b>-6792.1</b>	0.08	<b>0.986</b>	17.98	5	5
1	GS-tw	-6801.82	0.08	<b>0.986</b>	<b>9.1</b>	5	5
1	GS-clp	-6801.04	<b>0.087</b>	<b>0.986</b>	<b>9.1</b>	5	5
1	GS-pruned	-6801.82	0.08	<b>0.986</b>	9.13	5	5
2	DGS	-6660.87	<b>0.076</b>	0.99	18.34	5	5
2	DGS-clp	-6659.51	0.06	0.99	18.34	5	5
2	GS-tw	-6649.62	0.07	<b>0.986</b>	<b>8.9</b>	5	5
2	GS-clp	<b>-6644.4</b>	0.07	<b>0.986</b>	<b>8.9</b>	5	5
2	GS-pruned	-6655.26	0.07	0.99	8.94	6	5
3	DGS	<b>-6719.4</b>	<b>0.075</b>	<b>0.986</b>	18.24	5	5
3	DGS-clp	-6720.43	0.04	<b>0.986</b>	18.24	5	5
3	GS-tw	-6739.97	0.06	0.99	9.21	5	5
3	GS-clp	-6738.14	0.06	0.99	9.21	5	5
3	GS-pruned	-6739.97	0.06	0.99	<b>9.2</b>	5	5
4	DGS	-6833.36	0.07	0.99	17.5	5	5
4	DGS-clp	-6831.15	0.06	0.99	17.5	5	5
4	GS-tw	-6806.98	<b>0.074</b>	<b>0.986</b>	<b>8.7</b>	5	5
4	GS-clp	<b>-6803</b>	<b>0.074</b>	0.99	<b>8.7</b>	5	5
4	GS-pruned	-6812.67	0.06	<b>0.986</b>	8.85	6	5
5	DGS	-6834.56	<b>0.065</b>	0.99	19.16	5	5
5	DGS-clp	-6833.87	0.05	<b>0.986</b>	19.16	5	5
5	GS-tw	<b>-6827.5</b>	0.05	<b>0.986</b>	<b>9.7</b>	5	5
5	GS-clp	-6828.42	0.05	<b>0.986</b>	<b>9.7</b>	5	5
5	GS-pruned	<b>-6827.5</b>	0.05	<b>0.986</b>	9.72	5	5

Table 41: Comparison of the methods in dataset mediamill in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-63335.47	<b>0.091</b>	0.97	661.77	2	2
1	DGS-clp	<b>-63004.6</b>	0.09	<b>0.967</b>	661.77	2	2
1	GS-tw	-230702.76	0.04	0.96	<b>13.5</b>	2	2
1	GS-clp	-66996.52	0.08	0.97	<b>13.5</b>	2	2
1	GS-pruned	-65127.5	0.07	0.97	23.72	35	2
2	DGS	-62152.82	0.09	0.97	619.41	2	2
2	DGS-clp	<b>-61765.1</b>	<b>0.091</b>	<b>0.968</b>	619.41	2	2
2	GS-tw	-225868.26	0.04	0.96	<b>13.7</b>	2	2
2	GS-clp	-70425.73	0.07	0.97	<b>13.7</b>	2	2
2	GS-pruned	-64141.2	0.08	0.97	23.48	42	2
3	DGS	-63169.85	<b>0.084</b>	0.97	606.22	2	2
3	DGS-clp	<b>-62675.5</b>	0.08	<b>0.968</b>	606.22	2	2
3	GS-tw	-230041.11	0.04	0.96	<b>13.6</b>	2	2
3	GS-clp	-70842.95	0.07	0.97	<b>13.6</b>	2	2
3	GS-pruned	-64703.39	0.07	0.97	23.59	45	2
4	DGS	-63369.16	<b>0.074</b>	0.97	630.16	2	2
4	DGS-clp	<b>-63015.2</b>	0.07	<b>0.968</b>	630.16	2	2
4	GS-tw	-230803.25	0.03	0.96	<b>13.8</b>	2	2
4	GS-clp	-66036.85	0.07	0.97	<b>13.8</b>	2	2
4	GS-pruned	-65069.46	0.07	0.97	23.54	42	2
5	DGS	-63703.38	<b>0.084</b>	0.97	652.26	2	2
5	DGS-clp	<b>-63230</b>	0.08	<b>0.968</b>	652.26	2	2
5	GS-tw	-230562.66	0.04	0.96	<b>14.2</b>	2	2
5	GS-clp	-65908.34	0.08	0.97	<b>14.2</b>	2	2
5	GS-pruned	-65745.22	0.07	0.97	23.69	37	2

Table 42: Comparison of the methods in dataset mediamill in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-61521.56	<b>0.095</b>	0.97	986.28	3	3
1	DGS-clp	<b>-61239.4</b>	0.09	<b>0.968</b>	986.28	3	3
1	GS-tw	-260184.35	0.03	0.96	<b>17.7</b>	3	3
1	GS-clp	-70348.16	0.08	0.97	<b>17.7</b>	3	3
1	GS-pruned	-62980.4	0.08	0.97	28.95	38	3
2	DGS	-61091.35	<b>0.095</b>	0.97	893.15	3	3
2	DGS-clp	<b>-60783</b>	0.09	<b>0.968</b>	893.15	3	3
2	GS-tw	-260044.28	0.04	0.96	<b>17.4</b>	3	3
2	GS-clp	-137287.94	0.03	0.96	<b>17.4</b>	3	3
2	GS-pruned	-62803.99	0.07	0.97	29.8	37	3
3	DGS	-61447.42	0.09	0.97	852.45	3	3
3	DGS-clp	<b>-60943.1</b>	<b>0.092</b>	<b>0.968</b>	852.45	3	3
3	GS-tw	-268497.53	0.03	0.96	<b>17.3</b>	3	3
3	GS-clp	-69728.8	0.08	0.97	<b>17.3</b>	3	3
3	GS-pruned	-62681.33	0.07	0.97	29.62	40	3
4	DGS	-61759.03	0.08	0.97	842.94	3	3
4	DGS-clp	<b>-61428.1</b>	<b>0.084</b>	<b>0.968</b>	842.94	3	3
4	GS-tw	-262699.9	0.04	0.96	<b>16.9</b>	3	3
4	GS-clp	-72954.53	0.07	0.97	<b>16.9</b>	3	3
4	GS-pruned	-62464.53	0.08	0.97	28.71	42	3
5	DGS	-62317.84	<b>0.086</b>	0.97	976.3	3	3
5	DGS-clp	<b>-61971.7</b>	0.08	<b>0.968</b>	976.3	3	3
5	GS-tw	-262344.27	0.04	0.96	<b>17.4</b>	3	3
5	GS-clp	-71138.28	0.07	0.97	<b>17.4</b>	3	3
5	GS-pruned	-62650.41	0.08	0.97	28.88	34	3

Table 43: Comparison of the methods in dataset mediamill in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-60934.34	<b>0.093</b>	0.97	1673.88	4	4
1	DGS-clp	<b>-60641.9</b>	0.09	<b>0.968</b>	1673.88	4	4
1	GS-tw	-261727.4	0.04	0.96	<b>20.9</b>	4	4
1	GS-clp	-144692.3	0.03	0.96	<b>20.9</b>	4	4
1	GS-pruned	-61661.65	0.08	0.97	33.84	40	4
2	DGS	-59978.94	<b>0.09</b>	0.97	1145.26	4	4
2	DGS-clp	<b>-59649.4</b>	0.09	<b>0.968</b>	1145.26	4	4
2	GS-tw	-258541.44	0.04	0.96	<b>21.3</b>	4	4
2	GS-clp	-165912.91	0.03	0.96	<b>21.3</b>	4	4
2	GS-pruned	-61737.62	0.08	0.97	33.92	36	4
3	DGS	-60469.24	0.09	0.97	1193.82	4	4
3	DGS-clp	<b>-60029.9</b>	0.09	0.97	1193.82	4	4
3	GS-tw	-264572.27	0.04	0.96	<b>21</b>	4	4
3	GS-clp	-64719.1	<b>0.093</b>	<b>0.968</b>	<b>21</b>	4	4
3	GS-pruned	-61631.92	0.09	0.97	33.8	40	4
4	DGS	-60310.1	<b>0.085</b>	0.97	1274.16	4	4
4	DGS-clp	<b>-59959.1</b>	0.08	<b>0.968</b>	1274.16	4	4
4	GS-tw	-272078.14	0.04	0.96	<b>20.8</b>	4	4
4	GS-clp	-155287.25	0.03	0.96	<b>20.8</b>	4	4
4	GS-pruned	-61270.81	0.08	0.97	33.8	37	4
5	DGS	-60978.42	<b>0.088</b>	0.97	1407.1	4	4
5	DGS-clp	<b>-60532.4</b>	0.08	0.97	1407.1	4	4
5	GS-tw	-262981.07	0.04	0.96	<b>20.7</b>	4	4
5	GS-clp	-67988.49	<b>0.088</b>	<b>0.968</b>	<b>20.7</b>	4	4
5	GS-pruned	-61992.07	0.08	0.97	33.41	42	4

Table 44: Comparison of the methods in dataset mediamill in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-60371.47	0.09	0.97	2502.95	5	5
1	DGS-clp	<b>-60028.3</b>	<b>0.091</b>	0.97	2502.95	5	5
1	GS-tw	-90368.71	0.06	0.96	<b>30</b>	5	5
1	GS-clp	-60294.09	0.08	<b>0.968</b>	<b>30</b>	5	5
1	GS-pruned	-61429.4	0.07	0.97	34.45	44	5
2	DGS	-59653.79	0.09	0.97	1918.17	5	5
2	DGS-clp	<b>-59340.9</b>	0.09	0.97	1918.17	5	5
2	GS-tw	-102520.34	0.06	0.96	<b>29.3</b>	5	5
2	GS-clp	-65278.33	<b>0.093</b>	<b>0.968</b>	<b>29.3</b>	5	5
2	GS-pruned	-61258.64	0.08	0.97	33.61	41	5
3	DGS	-60021.5	0.09	0.97	2302.43	5	5
3	DGS-clp	<b>-59558.9</b>	0.09	0.97	2302.43	5	5
3	GS-tw	-95421.69	0.07	0.96	<b>30.2</b>	5	5
3	GS-clp	-60433.8	<b>0.095</b>	<b>0.968</b>	<b>30.2</b>	5	5
3	GS-pruned	-61086.39	0.07	0.97	35.33	41	5
4	DGS	-60096.82	0.09	0.97	1970.78	5	5
4	DGS-clp	<b>-59788.2</b>	0.08	0.97	1970.78	5	5
4	GS-tw	-93889.54	0.06	0.96	<b>29.3</b>	5	5
4	GS-clp	-60794.68	<b>0.095</b>	<b>0.968</b>	<b>29.3</b>	5	5
4	GS-pruned	-61700.14	0.08	0.97	33.92	43	5
5	DGS	-60381.59	0.09	0.97	2380.98	5	5
5	DGS-clp	<b>-59976.4</b>	<b>0.095</b>	0.97	2380.98	5	5
5	GS-tw	-92636.48	0.07	0.96	<b>29.7</b>	5	5
5	GS-clp	-61024.52	0.09	<b>0.968</b>	<b>29.7</b>	5	5
5	GS-pruned	-61922.54	0.08	0.97	33.61	40	5

Table 45: Comparison of the methods in dataset corel5k in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-12888.47	0	0.99	254.62	2	2
1	DGS-clp	<b>-12862</b>	0	<b>0.99</b>	254.62	2	2
1	GS-tw	-12982.03	<b>0.007</b>	0.99	<b>98.5</b>	2	2
1	GS-clp	-12937.48	<b>0.007</b>	0.99	<b>98.5</b>	2	2
1	GS-pruned	-12970.06	0	0.99	119.03	42	2
2	DGS	-12738.84	0.01	0.99	260.18	2	2
2	DGS-clp	<b>-12716.7</b>	0.01	<b>0.99</b>	260.18	2	2
2	GS-tw	-12961.6	<b>0.009</b>	0.99	<b>97.7</b>	2	2
2	GS-clp	-12924.43	<b>0.009</b>	0.99	<b>97.7</b>	2	2
2	GS-pruned	-12934.12	0.01	0.99	119.27	58	2
3	DGS	-12852.12	0.01	0.99	241.69	2	2
3	DGS-clp	<b>-12834.5</b>	0.01	<b>0.99</b>	241.69	2	2
3	GS-tw	-12899.4	<b>0.014</b>	0.99	<b>100.1</b>	2	2
3	GS-clp	-12869.72	<b>0.014</b>	0.99	<b>100.1</b>	2	2
3	GS-pruned	-12890.29	0.01	0.99	119.93	45	2
4	DGS	-13033.48	0	0.99	241.61	2	2
4	DGS-clp	-13008.65	0	<b>0.99</b>	241.61	2	2
4	GS-tw	-13030.36	<b>0.012</b>	0.99	<b>97.3</b>	2	2
4	GS-clp	<b>-12994</b>	0.01	0.99	<b>97.3</b>	2	2
4	GS-pruned	-13014.81	0.01	0.99	120.77	40	2
5	DGS	-12910.67	0.02	0.99	253.19	2	2
5	DGS-clp	<b>-12882.5</b>	0.02	<b>0.991</b>	253.19	2	2
5	GS-tw	-12972.62	<b>0.02</b>	0.99	<b>98.7</b>	2	2
5	GS-clp	-12936.61	<b>0.02</b>	0.99	<b>98.7</b>	2	2
5	GS-pruned	-12950.17	0.02	0.99	127.47	51	2

Table 46: Comparison of the methods in dataset corel5k in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-12767.68	0	0.99	248.38	3	3
1	DGS-clp	<b>-12740.9</b>	0	<b>0.99</b>	248.38	3	3
1	GS-tw	-12831.43	<b>0.006</b>	0.99	<b>113.4</b>	3	3
1	GS-clp	-12792.95	<b>0.006</b>	0.99	<b>113.4</b>	3	3
1	GS-pruned	-12837.21	<b>0.006</b>	0.99	124.83	44	3
2	DGS	-12697.59	0.01	0.99	262.58	3	3
2	DGS-clp	<b>-12674.1</b>	<b>0.008</b>	<b>0.99</b>	262.58	3	3
2	GS-tw	-12827.13	0.01	0.99	<b>111.1</b>	3	3
2	GS-clp	-12791.64	0.01	0.99	<b>111.1</b>	3	3
2	GS-pruned	-12832.62	<b>0.008</b>	0.99	133.28	52	3
3	DGS	-12738.77	0.01	0.99	249.18	3	3
3	DGS-clp	<b>-12719.4</b>	0.01	0.99	249.18	3	3
3	GS-tw	-12760.2	<b>0.016</b>	0.99	<b>111.2</b>	3	3
3	GS-clp	-12731.13	0.02	<b>0.99</b>	<b>111.2</b>	3	3
3	GS-pruned	-12795.29	0.01	0.99	128.75	51	3
4	DGS	-12979.8	0	0.99	254.93	3	3
4	DGS-clp	-12955.87	0	<b>0.99</b>	254.93	3	3
4	GS-tw	-12904.04	<b>0.011</b>	0.99	<b>107.7</b>	3	3
4	GS-clp	<b>-12870.2</b>	<b>0.011</b>	0.99	<b>107.7</b>	3	3
4	GS-pruned	-12934.33	<b>0.011</b>	0.99	127.05	48	3
5	DGS	-12803.18	<b>0.021</b>	0.99	263.84	3	3
5	DGS-clp	<b>-12775.1</b>	0.02	<b>0.991</b>	263.84	3	3
5	GS-tw	-12832.31	<b>0.021</b>	0.99	<b>108.6</b>	3	3
5	GS-clp	-12797.31	0.02	0.99	<b>108.6</b>	3	3
5	GS-pruned	-12817.6	0.02	0.99	124.77	55	3

Table 47: Comparison of the methods in dataset corel5k in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-12721.19	0	0.99	271.93	4	4
1	DGS-clp	<b>-12693.1</b>	0	<b>0.99</b>	271.93	4	4
1	GS-tw	-12800.96	0.01	0.99	<b>113.8</b>	4	4
1	GS-clp	-12760.81	0.01	0.99	<b>113.8</b>	4	4
1	GS-pruned	-12830.52	<b>0.008</b>	0.99	131.04	46	4
2	DGS	-12651.61	0.01	0.99	271.98	4	4
2	DGS-clp	<b>-12628.4</b>	0.01	<b>0.99</b>	271.98	4	4
2	GS-tw	-12779.1	0.01	0.99	<b>112.2</b>	4	4
2	GS-clp	-12743.09	0.01	0.99	<b>112.2</b>	4	4
2	GS-pruned	-12778.24	<b>0.01</b>	0.99	130.39	56	4
3	DGS	-12652.39	0.01	0.99	275.77	4	4
3	DGS-clp	<b>-12635.2</b>	0.01	<b>0.99</b>	275.77	4	4
3	GS-tw	-12674.03	<b>0.016</b>	0.99	<b>113.3</b>	4	4
3	GS-clp	-12646.15	0.02	0.99	<b>113.3</b>	4	4
3	GS-pruned	-12706.9	0.01	0.99	130.27	53	4
4	DGS	-12912.24	0	0.99	305.56	4	4
4	DGS-clp	-12889.31	0	<b>0.99</b>	305.56	4	4
4	GS-tw	-12809.5	0.01	0.99	<b>110.4</b>	4	4
4	GS-clp	<b>-12779.5</b>	0.01	0.99	<b>110.4</b>	4	4
4	GS-pruned	-12836.54	<b>0.011</b>	0.99	128.42	47	4
5	DGS	-12750.36	0.02	0.99	304.35	4	4
5	DGS-clp	<b>-12721.7</b>	0.02	<b>0.99</b>	304.35	4	4
5	GS-tw	-12793.31	<b>0.022</b>	0.99	<b>109.5</b>	4	4
5	GS-clp	-12759.07	0.02	0.99	<b>109.5</b>	4	4
5	GS-pruned	-12785.62	0.02	0.99	129	56	4



Table 48: Comparison of the methods in dataset corel5k in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-12728.1	0	0.99	305.44	5	5
1	DGS-clp	<b>-12699.6</b>	0	<b>0.99</b>	305.44	5	5
1	GS-tw	-12824.47	0.01	0.99	<b>115.2</b>	5	5
1	GS-clp	-12787.43	0.01	0.99	<b>115.2</b>	5	5
1	GS-pruned	-12832.04	<b>0.008</b>	0.99	139.98	51	5
2	DGS	-12635.71	0.01	0.99	322.18	5	5
2	DGS-clp	<b>-12613.1</b>	0.01	<b>0.99</b>	322.18	5	5
2	GS-tw	-12774.04	0.01	0.99	<b>114.4</b>	5	5
2	GS-clp	-12737.61	0.01	0.99	<b>114.4</b>	5	5
2	GS-pruned	-12783.79	<b>0.012</b>	0.99	143.67	52	5
3	DGS	-12641.14	0.01	0.99	315.76	5	5
3	DGS-clp	-12623.01	0.01	<b>0.991</b>	315.76	5	5
3	GS-tw	-12649.94	<b>0.019</b>	0.99	<b>121</b>	5	5
3	GS-clp	<b>-12620.7</b>	0.02	0.99	<b>121</b>	5	5
3	GS-pruned	-12685.71	0.01	0.99	145.14	47	5
4	DGS	-12875.75	0.01	0.99	304.58	5	5
4	DGS-clp	-12852.74	0.01	<b>0.99</b>	304.58	5	5
4	GS-tw	-12806.13	0.01	0.99	<b>123</b>	5	5
4	GS-clp	<b>-12777.3</b>	0.01	0.99	<b>123</b>	5	5
4	GS-pruned	-12835.98	<b>0.011</b>	0.99	143.36	44	5
5	DGS	-12706.61	0.02	0.99	292.79	5	5
5	DGS-clp	<b>-12677.9</b>	0.02	<b>0.991</b>	292.79	5	5
5	GS-tw	-12803.46	0.02	0.99	<b>121.2</b>	5	5
5	GS-clp	-12765.85	0.02	0.99	<b>121.2</b>	5	5
5	GS-pruned	-12776.74	<b>0.021</b>	0.99	159.4	54	5

Table 49: Comparison of the methods in dataset tmc2007\_500 in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-20250.13	0.26	0.93	612.09	2	2
1	DGS-clp	<b>-20063.4</b>	<b>0.265</b>	0.93	612.09	2	2
1	GS-tw	-28030.39	0.24	0.93	<b>55.7</b>	2	2
1	GS-clp	-20628.18	0.25	<b>0.935</b>	<b>55.7</b>	2	2
1	GS-pruned	-21116.28	0.26	0.93	102.67	74	2
2	DGS	-20244.04	0.26	0.93	546.33	2	2
2	DGS-clp	<b>-20055.8</b>	0.26	0.93	546.33	2	2
2	GS-tw	-27084.77	0.24	0.93	<b>54</b>	2	2
2	GS-clp	-21603.03	0.26	0.93	<b>54</b>	2	2
2	GS-pruned	-20496.28	<b>0.266</b>	<b>0.935</b>	101.32	62	2
3	DGS	-19863.35	0.26	0.94	591.37	2	2
3	DGS-clp	<b>-19587.1</b>	0.26	0.94	591.37	2	2
3	GS-tw	-26223.62	0.25	0.93	<b>54.5</b>	2	2
3	GS-clp	-19811.79	<b>0.271</b>	0.94	<b>54.5</b>	2	2
3	GS-pruned	-20218.88	0.27	<b>0.936</b>	103.64	66	2
4	DGS	-20191.89	<b>0.279</b>	0.94	605.42	2	2
4	DGS-clp	<b>-19797.8</b>	0.28	0.94	605.42	2	2
4	GS-tw	-28104.55	0.24	0.93	<b>54.4</b>	2	2
4	GS-clp	-20240.57	0.27	<b>0.935</b>	<b>54.4</b>	2	2
4	GS-pruned	-21134.37	0.26	0.93	101.45	62	2
5	DGS	-20167.57	0.26	0.93	593.13	2	2
5	DGS-clp	<b>-19950</b>	<b>0.266</b>	<b>0.934</b>	593.13	2	2
5	GS-tw	-27389.33	0.22	0.93	<b>54.5</b>	2	2
5	GS-clp	-21832.16	0.22	0.93	<b>54.5</b>	2	2
5	GS-pruned	-20851.24	0.24	0.93	106.29	64	2

Table 50: Comparison of the methods in dataset tmc2007\_500 in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-19944.63	0.27	0.94	881.13	3	3
1	DGS-clp	<b>-19771</b>	0.27	0.93	881.13	3	3
1	GS-tw	-26100.14	0.24	0.93	<b>75.1</b>	3	3
1	GS-clp	-20302.07	0.27	0.93	<b>75.1</b>	3	3
1	GS-pruned	-20768.92	<b>0.272</b>	<b>0.936</b>	110.03	59	3
2	DGS	-19857.24	0.28	0.93	840.87	3	3
2	DGS-clp	<b>-19683.9</b>	0.28	0.94	840.87	3	3
2	GS-tw	-25537.51	0.27	0.93	<b>74.1</b>	3	3
2	GS-clp	-20127.96	0.29	0.94	<b>74.1</b>	3	3
2	GS-pruned	-20455.26	<b>0.293</b>	<b>0.938</b>	112.16	54	3
3	DGS	-19555.06	0.28	0.94	816.24	3	3
3	DGS-clp	<b>-19320.8</b>	0.28	0.94	816.24	3	3
3	GS-tw	-24578.89	0.26	0.93	<b>74.3</b>	3	3
3	GS-clp	-21347.79	0.22	0.93	<b>74.3</b>	3	3
3	GS-pruned	-20002.24	<b>0.284</b>	<b>0.938</b>	112.05	59	3
4	DGS	-19865.92	<b>0.286</b>	0.94	838.1	3	3
4	DGS-clp	<b>-19471.1</b>	0.29	0.94	838.1	3	3
4	GS-tw	-26518.1	0.26	0.93	<b>74.2</b>	3	3
4	GS-clp	-19626.01	<b>0.286</b>	<b>0.937</b>	<b>74.2</b>	3	3
4	GS-pruned	-21013.55	0.27	0.94	109.68	56	3
5	DGS	-19806.17	0.28	0.93	860.03	3	3
5	DGS-clp	-19609.32	0.28	0.94	860.03	3	3
5	GS-tw	-25099.09	0.25	0.93	<b>76</b>	3	3
5	GS-clp	<b>-19451.6</b>	<b>0.282</b>	<b>0.937</b>	<b>76</b>	3	3
5	GS-pruned	-20521.63	0.27	0.94	110.38	61	3

Table 51: Comparison of the methods in dataset tmc2007\_500 in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-19785.19	0.27	0.93	1104.03	4	4
1	DGS-clp	<b>-19580.8</b>	0.26	0.94	1104.03	4	4
1	GS-tw	-24785.8	0.25	0.93	<b>87.9</b>	4	4
1	GS-clp	-20132.67	<b>0.285</b>	<b>0.937</b>	<b>87.9</b>	4	4
1	GS-pruned	-21042.06	0.27	0.94	112.29	63	4
2	DGS	-19804.44	0.28	0.94	1120.51	4	4
2	DGS-clp	<b>-19626.6</b>	0.29	0.94	1120.51	4	4
2	GS-tw	-24063.92	0.27	0.93	<b>88.2</b>	4	4
2	GS-clp	-19979.22	<b>0.295</b>	<b>0.938</b>	<b>88.2</b>	4	4
2	GS-pruned	-20619.86	0.29	0.94	112.54	51	4
3	DGS	-19304.48	0.28	0.94	1080.47	4	4
3	DGS-clp	<b>-19045</b>	0.28	0.94	1080.47	4	4
3	GS-tw	-23033.78	0.28	0.94	<b>89.1</b>	4	4
3	GS-clp	-19063.55	<b>0.297</b>	<b>0.939</b>	<b>89.1</b>	4	4
3	GS-pruned	-20042.36	0.29	0.94	114.89	60	4
4	DGS	-19613.78	<b>0.286</b>	0.94	1197.77	4	4
4	DGS-clp	<b>-19422.6</b>	0.28	<b>0.936</b>	1197.77	4	4
4	GS-tw	-24891.71	0.26	0.93	<b>87.3</b>	4	4
4	GS-clp	-20134.32	0.28	0.94	<b>87.3</b>	4	4
4	GS-pruned	-21046.37	0.28	0.94	111.19	62	4
5	DGS	-19580.98	0.28	0.93	1156.26	4	4
5	DGS-clp	<b>-19388.2</b>	0.28	0.94	1156.26	4	4
5	GS-tw	-23842.49	0.26	0.93	<b>88.7</b>	4	4
5	GS-clp	-20077.99	<b>0.284</b>	<b>0.936</b>	<b>88.7</b>	4	4
5	GS-pruned	-20602.67	0.28	0.94	112.8	60	4

Table 52: Comparison of the methods in dataset tmc2007\_500 in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-19691.57	0.27	0.93	1611.95	5	5
1	DGS-clp	<b>-19498.3</b>	0.26	0.94	1611.95	5	5
1	GS-tw	-23431.19	0.27	0.93	<b>95</b>	5	5
1	GS-clp	-19586.56	<b>0.282</b>	<b>0.937</b>	<b>95</b>	5	5
1	GS-pruned	-20993.18	0.27	0.94	113.26	62	5
2	DGS	-19725.29	0.29	0.94	1488.23	5	5
2	DGS-clp	-19549.15	0.29	0.94	1488.23	5	5
2	GS-tw	-23068.58	0.27	0.94	<b>93.9</b>	5	5
2	GS-clp	<b>-19142.3</b>	<b>0.301</b>	<b>0.938</b>	<b>93.9</b>	5	5
2	GS-pruned	-20984.62	0.27	0.94	111.53	50	5
3	DGS	-19323.68	0.28	0.94	1380.7	5	5
3	DGS-clp	-19054.92	0.28	0.94	1380.7	5	5
3	GS-tw	-22342.69	0.28	0.94	<b>95.8</b>	5	5
3	GS-clp	<b>-19052.7</b>	<b>0.293</b>	<b>0.94</b>	<b>95.8</b>	5	5
3	GS-pruned	-20419.94	0.29	0.94	114.15	61	5
4	DGS	-19467.8	0.29	0.94	1699.84	5	5
4	DGS-clp	-19140.63	0.29	0.94	1699.84	5	5
4	GS-tw	-23616.57	0.28	0.93	<b>94.2</b>	5	5
4	GS-clp	<b>-19068.1</b>	<b>0.307</b>	<b>0.939</b>	<b>94.2</b>	5	5
4	GS-pruned	-21111.88	0.29	0.94	112	53	5
5	DGS	-19647.84	0.28	0.93	1584.57	5	5
5	DGS-clp	-19448.1	0.28	0.94	1584.57	5	5
5	GS-tw	-22894.14	0.27	0.93	<b>96.9</b>	5	5
5	GS-clp	<b>-19252.1</b>	<b>0.288</b>	<b>0.938</b>	<b>96.9</b>	5	5
5	GS-pruned	-20876.97	0.27	0.94	114.3	58	5

Table 53: Comparison of the methods in dataset bibtex in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-10668.67	0.17	0.99	3195.46	2	2
1	DGS-clp	<b>-10622.9</b>	<b>0.166</b>	0.99	3195.46	2	2
1	GS-tw	-13425.81	0.15	0.98	<b>1298.6</b>	2	2
1	GS-clp	-10845.99	0.16	<b>0.987</b>	<b>1298.6</b>	2	2
1	GS-pruned	-11299.4	0.16	0.99	2227.37	157	2
2	DGS	-10821.1	0.16	0.99	3222.08	2	2
2	DGS-clp	<b>-10761.2</b>	0.16	0.99	3222.08	2	2
2	GS-tw	-12858.09	0.16	0.99	<b>1413.9</b>	2	2
2	GS-clp	-10772.04	0.17	<b>0.987</b>	<b>1413.9</b>	2	2
2	GS-pruned	-11240.62	<b>0.176</b>	0.99	2222.64	157	2
3	DGS	-10702.02	0.16	0.99	3074.02	2	2
3	DGS-clp	<b>-10642.5</b>	0.16	0.99	3074.02	2	2
3	GS-tw	-13169.12	0.15	0.99	<b>1401.5</b>	2	2
3	GS-clp	-10738.04	0.17	<b>0.988</b>	<b>1401.5</b>	2	2
3	GS-pruned	-11108.49	<b>0.17</b>	0.99	2112.64	168	2
4	DGS	-10542.38	0.16	0.99	3008.42	2	2
4	DGS-clp	<b>-10485.6</b>	0.16	0.99	3008.42	2	2
4	GS-tw	-12769.65	0.17	0.99	<b>1437.6</b>	2	2
4	GS-clp	-10674.65	0.18	<b>0.987</b>	<b>1437.6</b>	2	2
4	GS-pruned	-10871.39	<b>0.183</b>	0.99	2108.82	170	2
5	DGS	-10668.06	0.15	0.99	2999.46	2	2
5	DGS-clp	<b>-10609.3</b>	0.15	0.99	2999.46	2	2
5	GS-tw	-13374.59	0.14	0.98	<b>1454</b>	2	2
5	GS-clp	-10689.19	<b>0.159</b>	<b>0.987</b>	<b>1454</b>	2	2
5	GS-pruned	-11352.09	0.15	0.99	2165.53	173	2

Table 54: Comparison of the methods in dataset bibtex in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-10659.93	0.17	0.99	3603.34	3	3
1	DGS-clp	<b>-10610.8</b>	0.16	0.99	3603.34	3	3
1	GS-tw	-13031.31	0.15	0.98	<b>1659.8</b>	3	3
1	GS-clp	-10691.18	0.16	<b>0.987</b>	<b>1659.8</b>	3	3
1	GS-pruned	-11090.35	<b>0.17</b>	0.99	2252.57	161	3
2	DGS	-10793.71	0.16	0.99	3558.33	3	3
2	DGS-clp	-10738.01	0.16	0.99	3558.33	3	3
2	GS-tw	-12384.95	0.16	0.99	<b>1695.3</b>	3	3
2	GS-clp	<b>-10524.3</b>	0.17	<b>0.987</b>	<b>1695.3</b>	3	3
2	GS-pruned	-11093.07	<b>0.181</b>	0.99	2209.16	168	3
3	DGS	-10591.06	0.16	0.99	3458.82	3	3
3	DGS-clp	-10534.01	0.16	0.99	3458.82	3	3
3	GS-tw	-12785.68	0.16	0.99	<b>1612.8</b>	3	3
3	GS-clp	<b>-10455.9</b>	0.17	<b>0.988</b>	<b>1612.8</b>	3	3
3	GS-pruned	-11098.76	<b>0.169</b>	0.99	2166	161	3
4	DGS	-10467.39	0.16	0.99	3404.01	3	3
4	DGS-clp	<b>-10407</b>	0.16	0.99	3404.01	3	3
4	GS-tw	-12406.06	0.16	0.99	<b>1730.5</b>	3	3
4	GS-clp	-10573.98	0.18	<b>0.987</b>	<b>1730.5</b>	3	3
4	GS-pruned	-10869.41	<b>0.184</b>	0.99	2264.55	153	3
5	DGS	-10631.63	0.15	0.99	3331.59	3	3
5	DGS-clp	-10568.99	0.15	0.99	3331.59	3	3
5	GS-tw	-12640.94	0.16	0.99	<b>1724.1</b>	3	3
5	GS-clp	<b>-10345.3</b>	<b>0.169</b>	<b>0.987</b>	<b>1724.1</b>	3	3
5	GS-pruned	-11343.91	0.16	0.99	2241.75	163	3

Table 55: Comparison of the methods in dataset bibtex in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-10625.38	0.17	0.99	3984.99	4	4
1	DGS-clp	-10576.58	0.16	0.99	3984.99	4	4
1	GS-tw	-12030.82	<b>0.17</b>	0.99	<b>1795.5</b>	4	4
1	GS-clp	<b>-10475.5</b>	0.17	<b>0.987</b>	<b>1795.5</b>	4	4
1	GS-pruned	-11163.7	0.17	0.99	2344.13	154	4
2	DGS	-10752.18	0.16	0.99	4087.34	4	4
2	DGS-clp	-10696.34	0.16	0.99	4087.34	4	4
2	GS-tw	-11615.69	0.17	0.99	<b>1913.5</b>	4	4
2	GS-clp	<b>-10466.4</b>	0.18	<b>0.987</b>	<b>1913.5</b>	4	4
2	GS-pruned	-11044.28	<b>0.185</b>	0.99	2403.38	158	4
3	DGS	-10570.34	0.17	0.99	3782.72	4	4
3	DGS-clp	-10511.02	0.17	0.99	3782.72	4	4
3	GS-tw	-11871.06	0.17	0.99	<b>1873</b>	4	4
3	GS-clp	<b>-10475.6</b>	0.17	<b>0.988</b>	<b>1873</b>	4	4
3	GS-pruned	-11112.76	<b>0.17</b>	0.99	2351.94	183	4
4	DGS	-10434.02	0.16	0.99	4062.21	4	4
4	DGS-clp	-10374.54	0.16	0.99	4062.21	4	4
4	GS-tw	-11594.91	<b>0.185</b>	0.99	<b>1863.2</b>	4	4
4	GS-clp	<b>-10294.9</b>	0.18	<b>0.987</b>	<b>1863.2</b>	4	4
4	GS-pruned	-10837.86	0.18	0.99	2199.8	153	4
5	DGS	-10567.59	0.16	0.99	3686.44	4	4
5	DGS-clp	-10508.51	0.16	0.99	3686.44	4	4
5	GS-tw	-12038.81	<b>0.171</b>	0.99	<b>1868.8</b>	4	4
5	GS-clp	<b>-10340.3</b>	0.17	<b>0.987</b>	<b>1868.8</b>	4	4
5	GS-pruned	-11335.94	0.16	0.99	2360.88	171	4



Table 56: Comparison of the methods in dataset bibtex in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $acc_G$ ), the mean accuracy ( $acc_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$acc_G$	$acc_M$	time	tw	tw-pr
1	DGS	-10599.53	0.17	0.99	4141.01	5	5
1	DGS-clp	<b>-10550.3</b>	0.17	<b>0.987</b>	4141.01	5	5
1	GS-tw	-11909.28	0.17	0.99	<b>1886.9</b>	5	5
1	GS-clp	-11807.36	<b>0.172</b>	0.99	<b>1886.9</b>	5	5
1	GS-pruned	-11179.94	0.17	0.99	2349.92	167	5
2	DGS	-10723.1	0.16	0.99	4085.36	5	4
2	DGS-clp	<b>-10667.7</b>	0.16	0.99	4085.36	5	4
2	GS-tw	-11584.34	0.18	0.99	<b>1910.9</b>	5	5
2	GS-clp	-11503.89	0.17	0.99	<b>1910.9</b>	5	5
2	GS-pruned	-11029.72	<b>0.182</b>	<b>0.987</b>	2359.26	172	5
3	DGS	-10550.99	0.16	0.99	4087.37	5	5
3	DGS-clp	<b>-10491.7</b>	0.16	<b>0.987</b>	4087.37	5	5
3	GS-tw	-11680.54	0.17	0.99	<b>1979.9</b>	5	5
3	GS-clp	-11589.85	<b>0.168</b>	0.99	<b>1979.9</b>	5	5
3	GS-pruned	-11107.63	0.17	0.99	2376.38	184	5
4	DGS	-10424.31	0.16	0.99	4211.13	5	5
4	DGS-clp	<b>-10364.3</b>	0.16	<b>0.987</b>	4211.13	5	5
4	GS-tw	-11392.62	0.17	0.99	<b>1936.3</b>	5	5
4	GS-clp	-11299.44	0.17	0.99	<b>1936.3</b>	5	5
4	GS-pruned	-10837.48	<b>0.185</b>	0.99	2319.04	172	5
5	DGS	-10532.02	0.16	0.99	4130.05	5	4
5	DGS-clp	<b>-10473.5</b>	0.16	<b>0.987</b>	4130.05	5	4
5	GS-tw	-11974.16	<b>0.169</b>	0.99	<b>1995.7</b>	5	5
5	GS-clp	-11868.68	0.17	0.99	<b>1995.7</b>	5	5
5	GS-pruned	-11437.38	0.16	0.99	2284.55	172	5

Table 57: Comparison of the methods in dataset imdb in 5-fold cross-validation, using a treewidth bound of 2. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $\text{acc}_G$ ), the mean accuracy ( $\text{acc}_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$\text{acc}_G$	$\text{acc}_M$	time	tw	tw-pr
1	DGS	-130004.63	0.11	0.93	1689.36	2	2
1	DGS-clp	<b>-129932.2</b>	0.11	<b>0.929</b>	1689.36	2	2
1	GS-tw	-131700.79	0.09	0.93	<b>383.9</b>	2	2
1	GS-clp	-131045.72	0.11	0.93	<b>383.9</b>	2	2
1	GS-pruned	-130185.53	<b>0.118</b>	0.93	824.91	147	2
2	DGS	-130559.47	0.11	0.93	1735.31	2	2
2	DGS-clp	<b>-130489.6</b>	0.11	0.93	1735.31	2	2
2	GS-tw	-132110.88	0.11	0.93	<b>394.8</b>	2	2
2	GS-clp	-131494.44	0.11	0.93	<b>394.8</b>	2	2
2	GS-pruned	-130732.96	<b>0.118</b>	<b>0.928</b>	803.65	133	2
3	DGS	-129531.21	0.06	0.93	1873.71	2	2
3	DGS-clp	<b>-129467.9</b>	0.11	0.93	1873.71	2	2
3	GS-tw	-131500.83	0.08	0.93	<b>390.9</b>	2	2
3	GS-clp	-130803.19	0.11	0.93	<b>390.9</b>	2	2
3	GS-pruned	-129653.49	<b>0.118</b>	<b>0.929</b>	820.19	144	2
4	DGS	-130982.75	0.11	0.93	1841.36	2	2
4	DGS-clp	<b>-130907.2</b>	0.11	<b>0.928</b>	1841.36	2	2
4	GS-tw	-133351.94	0.09	0.93	<b>399</b>	2	2
4	GS-clp	-132525.99	0.11	0.93	<b>399</b>	2	2
4	GS-pruned	-131302.48	<b>0.109</b>	0.93	846.24	152	2
5	DGS	-130113.36	0.11	0.93	1703.97	2	2
5	DGS-clp	<b>-130063.6</b>	0.1	<b>0.929</b>	1703.97	2	2
5	GS-tw	-132272.68	0.08	0.93	<b>396.3</b>	2	2
5	GS-clp	-131524.7	0.11	0.93	<b>396.3</b>	2	2
5	GS-pruned	-130542.74	<b>0.114</b>	0.93	833.14	141	2

Table 58: Comparison of the methods in dataset imdb in 5-fold cross-validation, using a treewidth bound of 3. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $\text{acc}_G$ ), the mean accuracy ( $\text{acc}_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$\text{acc}_G$	$\text{acc}_M$	time	tw	tw-pr
1	DGS	-127954.11	0.11	0.93	2434.01	3	3
1	DGS-clp	<b>-127868.8</b>	0.11	0.93	2434.01	3	3
1	GS-tw	-128290.35	0.12	0.93	<b>535.4</b>	3	3
1	GS-clp	-127971.75	<b>0.117</b>	0.93	<b>535.4</b>	3	3
1	GS-pruned	-128035.66	0.12	<b>0.929</b>	848.91	160	3
2	DGS	-128517.17	0.12	0.93	2101.35	3	3
2	DGS-clp	<b>-128444.5</b>	0.12	<b>0.928</b>	2101.35	3	3
2	GS-tw	-128794.85	0.12	0.93	<b>552.8</b>	3	3
2	GS-clp	-128477.51	0.12	0.93	<b>552.8</b>	3	3
2	GS-pruned	-128606.61	<b>0.123</b>	0.93	812.61	128	3
3	DGS	-126950.48	0.12	0.93	2435.7	3	3
3	DGS-clp	<b>-126871.1</b>	0.12	<b>0.929</b>	2435.7	3	3
3	GS-tw	-127440.46	0.12	0.93	<b>564.8</b>	3	3
3	GS-clp	-127113.91	0.12	0.93	<b>564.8</b>	3	3
3	GS-pruned	-127059.64	<b>0.126</b>	0.93	832.76	134	3
4	DGS	-128693.12	0.11	0.93	2312.82	3	3
4	DGS-clp	<b>-128623.5</b>	0.11	<b>0.928</b>	2312.82	3	3
4	GS-tw	-129254.32	0.11	0.93	<b>531.4</b>	3	3
4	GS-clp	-128915.3	<b>0.111</b>	0.93	<b>531.4</b>	3	3
4	GS-pruned	-128954.35	0.11	0.93	860.87	154	3
5	DGS	-128273.41	0.11	0.93	2177.14	3	3
5	DGS-clp	<b>-128205.7</b>	0.11	<b>0.929</b>	2177.14	3	3
5	GS-tw	-128661.81	0.11	0.93	<b>534.7</b>	3	3
5	GS-clp	-128353.72	0.11	0.93	<b>534.7</b>	3	3
5	GS-pruned	-128508.74	<b>0.117</b>	0.93	840.93	137	3

Table 59: Comparison of the methods in dataset imdb in 5-fold cross-validation, using a treewidth bound of 4. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $\text{acc}_G$ ), the mean accuracy ( $\text{acc}_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$\text{acc}_G$	$\text{acc}_M$	time	tw	tw-pr
1	DGS	-126593.67	0.12	0.93	2971.53	4	4
1	DGS-clp	-126478.99	<b>0.125</b>	0.93	2971.53	4	4
1	GS-tw	-126695.81	0.12	0.93	<b>591.2</b>	4	4
1	GS-clp	<b>-126443.4</b>	0.12	0.93	<b>591.2</b>	4	4
1	GS-pruned	-126716.17	0.12	<b>0.929</b>	846.6	139	4
2	DGS	-127786.02	0.12	0.93	2741.12	4	4
2	DGS-clp	-127719.93	0.12	<b>0.928</b>	2741.12	4	4
2	GS-tw	-127781.78	0.12	0.93	<b>591.4</b>	4	4
2	GS-clp	<b>-127566.5</b>	<b>0.122</b>	0.93	<b>591.4</b>	4	4
2	GS-pruned	-127860.67	0.12	0.93	816.94	142	4
3	DGS	-125785.55	0.12	0.93	2822.44	4	4
3	DGS-clp	<b>-125698</b>	<b>0.123</b>	<b>0.929</b>	2822.44	4	4
3	GS-tw	-126046.37	0.12	0.93	<b>605.3</b>	4	4
3	GS-clp	-125840.88	0.12	0.93	<b>605.3</b>	4	4
3	GS-pruned	-125959.52	0.12	0.93	848.1	147	4
4	DGS	-127045.18	0.11	0.93	3059.47	4	4
4	DGS-clp	<b>-126950.3</b>	0.12	<b>0.928</b>	3059.47	4	4
4	GS-tw	-127299.75	<b>0.118</b>	0.93	<b>606.5</b>	4	4
4	GS-clp	-126987.52	0.12	0.93	<b>606.5</b>	4	4
4	GS-pruned	-127236.8	0.12	0.93	859.36	137	4
5	DGS	-127021.17	0.12	0.93	2857.09	4	4
5	DGS-clp	<b>-126944.3</b>	<b>0.118</b>	<b>0.929</b>	2857.09	4	4
5	GS-tw	-127398.88	0.12	0.93	<b>598.7</b>	4	4
5	GS-clp	-127125.43	0.12	0.93	<b>598.7</b>	4	4
5	GS-pruned	-127246.2	0.12	0.93	857.86	153	4

Table 60: Comparison of the methods in dataset imdb in 5-fold cross-validation, using a treewidth bound of 5. For each fold and method, the conditional log-likelihood in the test dataset (CLL), the global accuracy ( $\text{acc}_G$ ), the mean accuracy ( $\text{acc}_M$ ), the learning time (time), the treewidth (tw) and the treewidth of the pruned graph (tw-pr) are shown. The optimal results are denoted in boldface.

Fold	Method	CLL	$\text{acc}_G$	$\text{acc}_M$	time	tw	tw-pr
1	DGS	-126123.47	0.12	0.93	3677.5	5	5
1	DGS-clp	-126031.13	<b>0.125</b>	<b>0.929</b>	3677.5	5	5
1	GS-tw	-126132.06	0.12	0.93	<b>658.5</b>	5	5
1	GS-clp	<b>-125895.8</b>	0.12	0.93	<b>658.5</b>	5	5
1	GS-pruned	-126097.03	0.12	0.93	879.83	141	5
2	DGS	-126800.73	0.12	0.93	3369.75	5	5
2	DGS-clp	-126715.08	0.12	<b>0.928</b>	3369.75	5	5
2	GS-tw	-126770.5	0.12	0.93	<b>638.1</b>	5	5
2	GS-clp	<b>-126598.4</b>	0.12	0.93	<b>638.1</b>	5	5
2	GS-pruned	-126820.89	<b>0.12</b>	0.93	835.69	134	5
3	DGS	-124402.12	0.12	0.93	3935.6	5	5
3	DGS-clp	<b>-124379.2</b>	<b>0.126</b>	<b>0.929</b>	3935.6	5	5
3	GS-tw	-124590.43	0.13	0.93	<b>673.5</b>	5	5
3	GS-clp	-124452.15	0.12	0.93	<b>673.5</b>	5	5
3	GS-pruned	-124662.1	0.12	0.93	854.26	152	5
4	DGS	-126101.27	0.12	0.93	3783.08	5	5
4	DGS-clp	-126009.97	0.12	<b>0.928</b>	3783.08	5	5
4	GS-tw	-126162.79	<b>0.121</b>	0.93	<b>669.1</b>	5	5
4	GS-clp	<b>-125892.6</b>	0.12	0.93	<b>669.1</b>	5	5
4	GS-pruned	-126195.54	0.12	0.93	887.45	148	5
5	DGS	-125751.19	0.12	0.93	3686.68	5	5
5	DGS-clp	<b>-125685.3</b>	<b>0.121</b>	<b>0.929</b>	3686.68	5	5
5	GS-tw	-125914.8	0.12	0.93	<b>658.2</b>	5	5
5	GS-clp	-125760.31	0.12	0.93	<b>658.2</b>	5	5
5	GS-pruned	-126091.93	0.12	0.93	876.82	138	5