IJCAI-19 Paper #6385 - Supplemental Material
Recommending Links to Maximize the Influence in Social Networks

Proof Theorem 2

For any graph H, we denote by $\mathcal{G}(H)$ the set of all possible live-edge graphs sampled from H. For LSS, we have that $\sigma_{\hat{G}}(A \cup S_{LSS}, \emptyset) = \sum_{G' \in \mathcal{G}(\hat{G})} \mathbf{P}(G') |R_{A \cup S_{LSS}}(G')|$, while for IMA, we have

$$\sigma_G(A, S_{IMA}) = \sum_{G'' \in \mathcal{G}(G(S_{IMA}))} \mathbf{P}\left(G''\right) |R_A(G'')|.$$

For any live-edge graph generated from $G(S_{IMA})$ there exists a live-edge graph generated from $\hat{G}$ with the same probability and viceversa since sets $E \cup S_{IMA}$ and $\hat{E}$ are associated with the same weights. For any $G' \in \mathcal{G}(\hat{G})$, let G'' be its corresponding graph in $\mathcal{G}(G(S_{IMA}))$, then we have $R_{A \cup S_{LSS}}(G') = R_A(G'') \cup S_{LSS}$. Therefore, $\sigma_{\hat{G}}(A \cup S_{LSS}, \emptyset) = \sigma_G(A, S_{IMA}) \cup S_{LSS}$. Since $\sigma_G(A, S_{IMA}) \cap S_{LSS} = \emptyset$ and $|S_{LSS}| = B$ the statement follows. $\square$

Experimental Study

Diffusion process approximation

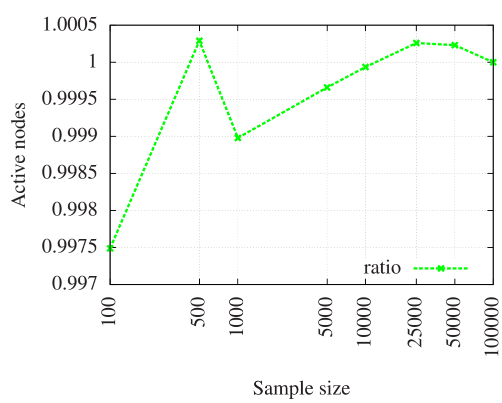

Figure 1: Approximation of $\sigma(A)$ using repeated sampling.

In Figure 1 we show that the quality of the approximation for $\sigma(A)$ after 500 simulations of the diffusion process (both ICM and LTM) is comparable to that after 100000 iterations. We report the results for the *Twitter* network ($n = 465017$ nodes and $m = 834797$ edges), the results for the other networks are similar and therefore omitted. We run the diffusion process selecting a random set of seed nodes A such that $|A| = 1\% \cdot n$. We plot the ratio between the number of active nodes using $100, 500, 1000, 5000, 10000, 25000, 50000, 100000$ samples and the number of active nodes using 100000 samples, we notice that the ratio is almost 1. Therefore, we choose 500 as the number of samples to use for our experiments.

Adding more than one edge incident to the same node

By means of experiments, we can show that even if we do not allow addition of edges from two, or more, different seeds $a_1, \ldots, a_i$ to the same node $v_i \in V \setminus A$, we do not affect much the approximation guarantee.

We run GREEDY1 on five randomly generated set of seeds choosing $|A| = 1\% \cdot |V|$, adding $|S| = 2 \times |A|$ edges and assigning probabilities according to the weighted model. In particular, we plot the results of the relative error for the network Wiki-Vote in Figure 2. In this graph, obtained from SNAP [7], nodes in the network represent Wikipedia users and a directed edge from node i to node j represents that user i voted on user j. It is easy to see that the two functions representing the number of influenced nodes coincide on most of the points.

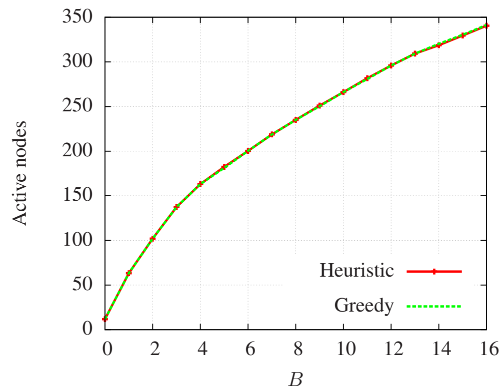

Figure 2: Approximation error for Wiki-Vote network.

The results for many other networks, taken from the ArnetMiner [1] repository, are similar and reported in Table 1: the first three columns report the name of the network, the number of nodes and the number of edges. The last column of the table reports the maximum error e_{max} among all the edge insertions and it is computed as

$$e_{max} = \left| \frac{\sigma(A, S_{all}) - \sigma(A, S)}{\sigma(A, S_{all})} \right|$$

where $\sigma(A, S_{all})$ is the expected number of active nodes computed using GREEDY1 and allowing multiple edges to the same node while $\sigma(A, S)$ is that obtained adding only one outgoing edge per seed to the same node v_i.

Name	$\|V\|$	$\|E\|$	e_{max}
Software Engineering (SE)	3141	14787	0.045
Theoretical CS (TCS)	4172	14272	0.035
High-Performance Comp. (HPC)	4869	35036	0.033
Wiki-Vote (Wiki)	7115	103689	0.033
Computer Graphic (CGM)	8336	41925	0.045
Computer Networks (CN)	9420	53003	0.035

Table 1: Real-world networks and relative approximation error.

We can conclude that it is very unlikely that two edges towards the same node in $V \setminus A$ are added to the solution.

Further experimental results on real networks

In Tables 2 and 3 we report the results on the number of nodes that are activated by GREEDY1 and GREEDY2 on real-word networks. We use $***$ when GREEDY1 was not able to compute the final solution for a given graph in the time limit that we set to four hours.

In Tables 4 and 5 we report the experimental comparisons between GREEDY2 and the alternative baselines on real-world networks.

In Figure 3 we compare the result obtained applying GREEDY1 and GREEDY2 algorithms to the Artificial Intelligence network given a seed set A. The expected number of active nodes is similar for both algorithms and a small difference is due to the sampling technique used to estimate $\tilde{\sigma}(A, S)$. The results for the other real-world and random networks are reported in Tables 2-3 and 7-8, respectively.

G	$\sigma(A,\emptyset)$	$\sigma(A,\emptyset)\%$	GREEDY1				GREEDY2			
			$\sigma(A,S)$	$\sigma(A,S)\%$	$I\%$	time (sec.)	$\sigma(A,S)$	$\sigma(A,S)\%$	$I\%$	time (sec.)
SE	13.38	0.43	103.09	3.28	670.56	5.74	103.45	3.29	670.95	0.04
TCS	9.49	0.23	97.54	2.34	928.26	10.44	97.63	2.34	928.76	0.07
HPC	9.36	0.19	164.92	3.39	1662.23	12.18	165.75	3.40	1670.83	0.07
Wiki	10.07	0.14	338.93	4.76	3266.84	35.31	333.37	4.69	3257.87	0.12
CGM	20.34	0.24	253.84	3.05	1148.13	35.88	257.62	3.09	1166.71	0.12
CN	22.21	0.24	408.69	4.34	1740.10	49.33	397.95	4.22	1765.86	0.10
AI	68.94	0.25	1055.76	3.82	1431.44	374.66	1017.82	3.69	1362.71	0.47
Sl	126.11	0.25	621.75	1.22	393.01	2050.65	612.52	1.20	408.63	1.72
Epi	352.17	0.46	1236.71	1.63	251.17	3884.27	1230.23	1.62	249.32	3.25
Sl-z	570.84	0.72	3485.02	4.41	510.50	3730.36	3425.87	4.40	505.14	2.63
Digg	3848.57	1.38	***	***	***	***	14835.40	5.31	285.48	14.32
Citeseer	683.16	0.18	***	***	***	***	13072.36	3.40	1813.52	12.20
Twitter	2861.20	0.62	***	***	***	***	207061.00	44.53	7136.87	10.23
Pokec	23472.20	1.44	***	***	***	***	83726.90	5.13	256.71	78.91

Table 2: Results for Real-world networks (ICM).

G	$\sigma(A,\emptyset)$	$\sigma(A,\emptyset)\%$	GREEDY1				GREEDY2			
			$\sigma(A,S)$	$\sigma(A,S)\%$	$I\%$	time (sec.)	$\sigma(A,S)$	$\sigma(A,S)\%$	$I\%$	time (sec.)
SE	12.40	0.39	49.33	1.57	297.83	2.10	59.45	1.89	276.88	0.10
TCS	8.34	0.20	47.39	1.14	468.58	2.95	51.78	1.24	430.62	0.13
HPC	7.91	0.16	73.75	1.51	832.21	3.26	87.98	1.81	935.87	0.39
Wiki	9.17	0.13	119.76	1.68	1205.96	6.68	120.93	1.70	1151.57	1.33
CGM	16.69	0.20	107.49	1.29	543.95	5.46	128.96	1.55	525.37	0.29
CN	18.30	0.19	174.92	1.86	856.03	6.84	204.73	2.17	936.94	0.43
AI	53.15	0.19	407.57	1.48	666.77	20.05	530.99	1.92	767.02	4.74
Sl	87.97	0.17	638.35	1.25	625.62	44.86	663.43	1.30	592.51	6.82
Epi	174.98	0.23	2216.56	2.92	1166.74	54.39	2248.09	2.96	999.34	37.42
Sl-z	206.35	0.26	2773.19	3.51	1243.94	47.69	3203.52	4.05	1160.21	36.48
Citeseer	623.82	0.16	***	***	***	***	5901.46	1.54	846.03	42.98
Twitter	1673.07	0.36	***	***	***	***	127414.00	27.40	7515.56	13.33

Table 3: Results for Real-world networks (LTM).

G	$B=0$		GREEDY2	AA	PA	J	D	TopK	Prob	KKT
	$\sigma(A,\emptyset)$	$\sigma(A,\emptyset)\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$
SE	13.38	0.43	670.56	101.66	57.67	66.03	53.30	353.60	156.58	396.32
TCS	9.49	0.23	928.26	114.78	100.74	115.99	102.56	82.94	351.27	343.37
HPC	9.36	0.19	1662.23	176.33	15.33	153.93	16.15	15.99	363.73	896.97
Wiki	10.07	0.14	3266.84	330.02	1404.37	157.00	2078.44	2054.02	228.10	2284.13
CGM	20.34	0.24	1148.13	158.46	43.18	124.91	48.38	45.97	238.87	271.13
CN	22.21	0.24	1740.10	153.82	375.71	102.83	661.84	662.23	221.30	575.31
AI	68.94	0.25	1431.44	78.30	24.42	72.80	30.69	143.37	192.22	522.45
Sl	126.11	0.25	393.01	60.30	80.95	79.39	76.16	83.46	131.67	95.24
Epi	352.17	0.46	251.17	62.65	123.09	48.13	94.54	102.32	75.97	115.44
Sl-z	570.84	0.72	510.50	106.56	125.05	29.39	153.94	93.42	57.57	99.65
Digg	3848.57	1.38	285.48	126.80	149.44	10.58	145.44	121.71	39.07	86.65
Citeseer	683.16	0.18	1813.52	124.74	446.49	91.89	931.10	498.96	215.97	389.25
Twitter	2861.20	0.62	7136.87	1718.20	6286.58	5721.36	6510.76	6649.86	75.99	5148.94

Table 4: Baseline results for real-world networks (ICM).

G	$B=0$		GREEDY2	AA	PA	J	D	KKT	Prob	TopK
	$\sigma(A,\emptyset)$	$\sigma(A,\emptyset)\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$
SE	12.40	0.39	276.88	54.00	83.70	40.08	86.25	166.39	58.13	192.33
TCS	8.34	0.20	430.62	69.12	152.37	69.57	139.31	315.47	115.80	99.71
HPC	7.91	0.16	935.87	105.65	128.70	75.12	126.80	508.44	116.18	115.30
Wiki	9.17	0.13	1151.57	196.90	914.84	84.37	873.36	889.14	105.12	864.51
CGM	16.69	0.20	525.37	96.86	183.59	74.57	188.57	327.83	119.88	131.10
CN	18.30	0.19	936.94	115.17	310.27	56.65	435.75	518.69	129.63	430.47
AI	53.15	0.19	767.02	59.18	181.75	45.21	206.81	407.02	105.22	198.18
Sl	87.97	0.17	592.51	81.88	489.49	47.09	505.79	525.57	79.86	498.96
Epi	174.98	0.23	999.34	529.37	1018.25	38.99	901.28	1039.70	56.72	851.96
Sl-z	206.35	0.26	1160.21	291.21	724.98	32.25	753.77	1004.12	57.90	903.31
Twitter	1673.07	0.36	7515.56	735.84	5324.15	4047.27	5505.72	7191.78	61.48	6329.72

Table 5: Baseline results for real-world networks (LTM).

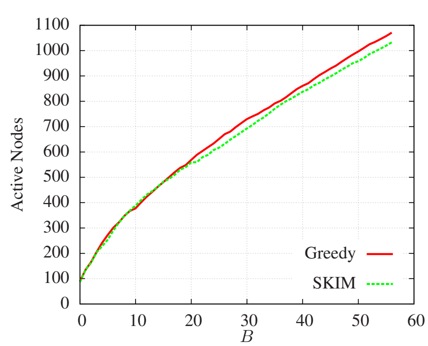

Figure 3: Comparison of GREEDY1 and GREEDY2 on AI network.

Experiments on random graphs

We evaluate the performance of the algorithm on four types of randomly generated directed networks which exhibit many of the structural features of complex networks, namely directed Preferential Attachment (in short, `PA`) [2], Erdős-Rényi (`ER`) [4], Copying (`COPY`) [5], Compressible Web (`COMP`) [3] and Forest Fire (`FF`) [6]. For each combination $(|V|, |E|)$, we generated five random directed graphs.

The size of the graphs is reported in Table 6. We choose 0.1% of the nodes in V as seeds and we add up to $B = 2 \cdot |A|$ edges. The seed nodes are chosen uniformly at random.

The experimental results are reported in Tables 7, 8 (activated nodes) and 9, 10 (comparison with baselines).

Name	$\|V\|$	$\|E\|$
PA5	5000	6500
PA10	10000	13000
PA15	15000	20000
FF5	5000	10000
FF10	10000	20000
FF15	15000	30000
COPY5	5000	5000, 10000, 25000
COPY10	10000	20000, 50000, 100000
COPY15	15000	45000, 100000
COMP5	5000	5000, 10000, 25000
COMP10	10000	20000,50000, 100000
COMP15	15000	45000, 100000
ER5	5000	10000, 25000, 50000
ER10	10000	40000, 100000, 200000
ER15	150000	90000, 225000, 450000

Table 6: Random networks.

G	$\sigma(A,\emptyset)$	$\sigma(A,\emptyset)\%$	GREEDY1				GREEDY2			
			$\sigma(A,S)$	$\sigma(A,S)\%$	$I\%$	time (sec.)	$\sigma(A,S)$	$\sigma(A,S)\%$	$I\%$	time (sec.)
PA5	7.30	0.17	333.37	7.67	4467.18	10.04	332.84	7.66	4448.94	0.03
PA10	15.05	0.17	688.57	7.84	4474.88	38.02	685.10	7.80	4474.17	0.07
PA15	20.51	0.16	1094.54	8.35	5237.70	86.93	1092.27	8.33	5230.44	0.12
FF5	10.07	0.20	137.94	2.76	1269.51	14.04	136.06	2.72	1246.09	0.07
FF10	19.08	0.19	276.40	2.76	1348.45	55.82	273.96	2.74	1343.34	0.15
FF15	28.34	0.19	432.76	2.89	1426.96	115.94	429.65	2.86	1420.92	0.25
COPY5-5	7.39	0.15	48.06	0.96	549.97	11.21	47.85	0.96	547.33	0.14
COPY5-10	9.12	0.18	81.71	1.63	795.56	13.61	80.43	1.61	783.16	0.09
COPY5-25	11.97	0.24	157.78	3.16	1218.38	12.45	154.85	3.10	1208.11	0.06
COPY10-20	17.99	0.18	167.47	1.67	830.95	51.26	164.63	1.65	809.46	0.21
COPY10-50	26.51	0.27	335.79	3.36	1166.53	48.53	329.07	3.29	1150.25	0.13
COPY10-100	31.98	0.32	559.43	5.59	1649.14	39.45	547.73	5.48	1608.47	0.11
COPY15-45	30.41	0.20	329.38	2.20	983.29	113.47	323.41	2.16	962.07	0.27
COPY15-100	40.40	0.27	630.23	4.20	1459.87	97.38	619.77	4.13	1446.42	0.20
COPY15-225	52.00	0.35	1128.13	7.52	2069.52	73.86	1102.94	7.35	2006.04	0.18
COMP5-5	9.39	0.19	62.43	1.25	564.61	15.14	61.92	1.24	562.24	0.11
COMP5-10	8.74	0.17	58.56	1.17	569.85	14.18	58.03	1.16	563.22	0.12
COMP5-25	7.97	0.16	55.81	1.12	600.02	12.74	54.46	1.09	583.92	0.12
COMP10-20	16.03	0.16	115.16	1.15	618.20	53.19	114.19	1.14	613.41	0.29
COMP10-50	16.85	0.17	112.70	1.13	568.72	48.59	109.95	1.10	554.42	0.29
COMP10-100	16.11	0.16	112.93	1.13	600.94	48.93	109.94	1.10	582.67	0.30
COMP15-45	24.79	0.17	170.61	1.14	588.17	114.11	167.55	1.12	573.56	0.46
COMP15-100	24.32	0.16	170.58	1.14	601.45	111.12	167.26	1.12	588.28	0.48
COMP15-225	24.82	0.17	171.82	1.15	592.36	107.07	169.09	1.13	582.21	0.50

Table 7: Results for random networks (ICM).

G	$\sigma(A,\emptyset)$	$\sigma(A,\emptyset)\%$	GREEDY1				GREEDY2			
			$\sigma(A,S)$	$\sigma(A,S)\%$	$I\%$	time (sec.)	$\sigma(A,S)$	$\sigma(A,S)\%$	$I\%$	time (sec.)
PA5	6.72	0.15	132.20	3.04	1866.23	3.33	141.42	3.25	1885.31	0.08
PA10	13.53	0.15	272.78	3.11	1916.24	6.89	297.09	3.38	1980.65	0.15
PA15	18.68	0.14	432.16	3.30	2213.32	10.31	470.22	3.59	2290.91	0.24
FF5	8.33	0.17	49.89	1.00	498.95	3.76	61.12	1.22	575.13	0.11
FF10	16.32	0.16	106.05	1.06	549.64	7.56	133.37	1.33	659.49	0.27
FF15	24.04	0.16	161.44	1.08	571.65	11.48	203.40	1.36	690.55	0.43
COPY5-5	6.70	0.13	22.01	0.44	228.31	4.78	22.69	0.45	224.33	0.24
COPY5-10	7.90	0.16	30.98	0.62	292.09	4.06	34.53	0.69	310.20	0.17
COPY5-25	9.53	0.19	49.43	0.99	418.47	3.22	61.04	1.22	498.48	0.18
COPY10-20	15.25	0.15	62.79	0.63	311.83	8.31	69.34	0.69	323.29	0.38
COPY10-50	19.85	0.20	103.34	1.03	420.53	7.06	125.60	1.26	465.98	0.36
COPY10-100	22.53	0.23	148.03	1.48	557.06	5.98	191.86	1.92	662.01	0.55
COPY15-45	25.08	0.17	114.71	0.76	357.41	11.88	128.55	0.86	376.51	0.60
COPY15-100	29.85	0.20	179.87	1.20	502.63	10.57	228.39	1.52	566.52	0.65
COPY15-225	34.89	0.23	276.52	1.84	692.65	9.22	389.49	2.60	869.25	1.21
COMP5-5	7.84	0.16	25.44	0.51	224.68	4.03	27.36	0.55	223.39	0.22
COMP5-10	7.55	0.15	27.26	0.55	261.32	4.08	29.18	0.58	263.29	0.21
COMP5-25	7.14	0.14	27.54	0.55	285.77	4.05	29.57	0.59	290.93	1.13
COMP10-20	14.26	0.14	52.24	0.52	266.39	8.28	54.73	0.55	268.17	0.45
COMP10-50	15.03	0.15	55.33	0.55	268.13	8.73	57.95	0.58	264.55	3.25
COMP10-100	14.60	0.15	56.53	0.57	287.18	8.88	59.95	0.60	291.71	20.05
COMP15-45	22.11	0.15	81.23	0.54	267.34	13.90	84.86	0.57	260.04	1.26
COMP15-100	21.96	0.15	85.23	0.57	288.15	13.41	90.21	0.60	290.18	16.70
COMP15-225	22.49	0.15	88.29	0.59	292.64	14.25	92.82	0.62	294.14	108.79

Table 8: Results for random networks (LTM).

G	$B=0$		GREEDY2	AA	PA	J	D	TopK	Prob	KKT
	$\sigma(A,\emptyset)$	$\sigma(A,\emptyset)\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$
PA5	7.30	0.17	4467.18	1996.92	2691.24	389.35	2877.88	3957.10	216.01	3900.63
PA10	15.05	0.17	4474.88	1785.58	3114.64	150.66	3183.03	3807.15	178.39	4030.14
PA15	20.51	0.16	5237.70	2587.99	3247.53	196.43	2049.33	4284.63	202.95	4079.94
FF5	10.07	0.20	1269.51	58.74	263.83	59.62	325.81	401.58	206.53	5079.94
FF10	19.08	0.19	1348.45	71.36	278.57	67.69	362.02	470.00	221.63	981.44
FF15	28.34	0.19	1426.96	63.68	322.10	68.29	425.73	515.21	225.89	929.24
COPY5-5	7.39	0.15	549.97	83.43	9.86	83.43	191.46	282.70	215.58	414.55
COPY5-10	9.12	0.18	795.56	43.29	3.70	50.57	168.26	477.72	206.25	537.71
COPY5-25	11.97	0.24	1218.38	52.57	0.72	51.10	137.23	785.68	246.65	990.36
COPY10-20	17.99	0.18	830.95	51.69	3.30	53.28	165.90	408.71	211.38	737.68
COPY10-50	26.51	0.27	1166.53	51.84	0.77	51.45	127.60	709.52	222.21	1038.17
COPY10-100	31.98	0.32	1649.14	55.77	0.29	51.15	76.79	788.38	317.94	1415.66
COPY15-45	30.41	0.20	983.29	53.59	1.84	52.69	172.67	567.75	225.81	880.44
COPY15-100	40.40	0.27	1459.87	45.39	0.54	41.39	109.73	995.94	297.03	1275.84
COPY15-225	52.00	0.35	1128.13	48.13	0.21	40.90	50.68	929.98	383.81	1073.52
COMP5-5	9.39	0.19	564.61	68.48	17	68.48	202.41	276.67	211.75	503.82
COMP5-10	8.74	0.17	569.85	60.91	2.83	60.91	186.71	268.85	217.59	530.11
COMP5-25	7.97	0.16	600.02	60.40	1.55	60.40	178.28	297.03	224.21	592.42
COMP10-20	16.03	0.16	618.20	61.62	3.86	61.62	195.86	254.23	221.14	589.87
COMP10-50	16.85	0.17	568.72	68.12	0.91	68.12	204.75	268.39	236.17	555.31
COMP10-100	16.11	0.16	600.94	68.44	1.29	68.44	185.98	272.92	227.66	568.24
COMP15-45	24.79	0.17	588.17	61.15	1.51	61.15	179.62	233.62	233.02	557.50
COMP15-100	24.32	0.16	601.45	57.70	1.35	57.70	178.75	249.61	228.20	597.35
COMP15-225	24.82	0.17	592.36	59.48	0.71	59.48	176.23	244.07	225.91	572.52

Table 9: Baseline results for random networks (ICM).

G	$B=0$		GREEDY2	AA	PA	J	D	TopK	Prob	KKT
	$\sigma(A,\emptyset)$	$\sigma(A,\emptyset)\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$	$I\%$
PA5	6.71	0.15	1885.31	987.99	1640.56	211.4	1776.95	1773.83	102.76	1795.10
PA10	13.57	0.15	1980.65	848.85	1707.63	79.77	1865.31	1687.18	91.02	1875.23
PA15	18.76	0.14	2290.91	1137.50	1944.29	102.85	2168.81	1847.77	101.28	2180.47
FF5	8.36	0.17	575.13	38.91	111.62	35.69	124.69	211.59	107.25	368.06
FF10	16.36	0.16	659.49	39.09	117.04	38.70	150.44	232.07	107.51	446.36
FF15	24.11	0.16	690.55	39.79	167.42	38.72	186.36	255.20	118.61	460.99
COPY5-5	6.70	0.13	224.33	43.91	18.98	43.91	91.27	134.12	107.79	221.25
COPY5-10	7.92	0.16	310.20	28.95	16.49	30.64	68.60	194.35	99.67	257.13
COPY5-25	9.52	0.19	498.48	30.49	12.40	30.32	58.28	291.20	118.23	384.06
COPY10-20	15.23	0.15	323.29	30.19	17.84	31.34	76.60	172.63	109.94	291.46
COPY10-50	19.91	0.20	465.98	30.69	13.60	30.78	56.53	275.64	117.36	386.69
COPY10-100	22.57	0.23	662.01	29.47	11.28	27.88	35.24	398.60	157.88	509.22
COPY15-45	25.09	0.17	376.51	32.16	13.76	31.83	74.09	218.13	110.36	334.18
COPY15-100	29.86	0.20	566.52	27.55	13.11	26.29	47.91	365.96	138.18	454.24
COPY15-225	34.95	0.23	869.25	26.81	10.56	24.24	24.86	464.83	186.77	597.01
COMP5-5	7.83	0.16	223.39	39.08	16.17	39.08	91.19	122.93	103.05	200.92
COMP5-10	7.52	0.15	263.29	36.61	15.43	36.61	83.17	124.97	107.51	249.83
COMP5-25	7.12	0.14	290.93	38.67	17.78	38.67	77.24	147.48	111.48	291.39
COMP10-20	14.25	0.14	268.17	36.86	19.53	36.86	86.20	115.92	112.93	268.57
COMP10-50	15.01	0.15	264.55	41.77	16.55	41.77	94.58	130.59	115.76	272.88
COMP10-100	14.61	0.15	291.71	39.22	16.26	39.22	83.68	142.97	117.31	291.30
COMP15-45	22.13	0.15	260.04	37.85	18.84	37.85	82.23	116.88	111.13	271.28
COMP15-100	21.94	0.15	290.18	35.71	16.97	35.71	81.55	130.94	111.85	293.32
COMP15-225	22.50	0.15	294.14	35.98	16.47	35.98	78.75	132.40	109.85	294.51

Table 10: Baseline results for random networks (LTM).

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